Lurking in Social Networks: Topology-based Analysis and Ranking Methods

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Abstract The massive presence of silent members in online communities, the so-called *lurkers*, has long attracted the attention of researchers in social science, cognitive psychology, and computer-human interaction. However, the study of lurking phenomena represents an unexplored opportunity of research in data mining, information retrieval and related fields. In this paper, we take a first step towards the formal specification and analysis of lurking in social networks. We address the new problem of *lurker ranking* and propose the first centrality methods specifically conceived for ranking lurkers in social networks. Our approach utilizes only the network topology without probing into text contents or user relationships related to media. Using Twitter, Flickr, FriendFeed and GooglePlus as cases in point, our methods' performance was evaluated against datadriven rankings as well as existing centrality methods, including the classic PageRank and alpha-centrality. Empirical evidence has shown the significance of our lurker ranking approach, and its uniqueness in effectively identifying and ranking lurkers in an online social network.

Keywords lurker ranking \cdot lurking coefficient \cdot LurkerRank \cdot delurking

1 Introduction

The majority of members of online communities play a passive or silent role as individuals that do not readily

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Dept. Computer Engineering, Modeling, Electronics, and Systems Sciences. University of Calabria, Italy E-mail: {tagarelli,rinterdonato}@dimes.unical.it contribute to the shared online space. Such individuals are called *lurkers*, since they belong to a community but remain quite unnoticed while watching, reading or, in general, benefiting from others' information or services without significantly giving back to the community.

Lurking characterization in online communities has been a controversial issue from a social science and computer-human interaction perspective [20]. Since the early works on social motivations and implications of lurking [45, 47], one common perception of lurking is that based on the infrequency of active participation to the community life, but other definitions have been given under the hypotheses of free-riding [32], legitimate peripheral participation [36,28], individual information strategy of microlearning [30], and knowledge sharing barriers (e.g., interpersonal or technological barriers) [6]. Lurkers might also be perceived as a menace for the cyberspace as they maliciously feed on others' intellects. For instance, in P2P file sharing systems [19], lurking may correspond to a leeching behavior whenever a user wastes valuable bandwidth by downloading much more than what s/he uploads. In the realm of online social networks (OSNs), negative views of the lurkers have been however supplanted with a neutral or even marginally positive view. A neutral perception of lurkers is related to the fact that their silent presence is seen as harmless and reflects a subjective reticence (rather than malicious motivations) to contribute to the community wisdom; half of times, a lurker simply feels that gathering information by browsing is enough without the need of being further involved in the community [47]. However, lurking can be expected or even encouraged because it allows users (especially newcomers) to learn or improve their understanding of the etiquette of an online community before they can decide to provide a valuable contribution over time.

Lurking is responsible for a *participation inequal*ity phenomenon that is shared by all large-scale online communities. This phenomenon is explained by the so-called "1:9:90" rule, which states that while 90% of users do not actively contribute, 9% of users may contribute (i.e., comment, like or edit) from time to time, and only 1% of users create the vast majority of social content [45,47]. Consequently, such inequities lead to a biased understanding of the community, whereby a major risk is that we will never hear from the silent majority of lurkers. Therefore, a challenge is to attract, or *de-lurk*, the crowd of lurkers, whereby online advertising strategies should be tailored to the lurkers' behavioral profile. Moreover, since lurkers have knowledge about the online community (as a result of the substantial time they dedicate towards learning from the community), delurking can mainly be seen as a mix of strategies aimed at encouraging lurkers to return their acquired social capital, through a more active participation to the community life.

Understanding user behaviors has long been studied in online social networks. A key element that is shared by all studies is the use of a social graph model as the basic tool to represent relationships among users [55]. Relationships, or *ties* [26], can vary over a spectrum that include friendships and followships [33,4,43,34, 15,57], visible interactions [17,37,54,57,41], and latent interactions (based on, e.g., browsing profiles or clickstream data) [50,9,29].

Surprisingly, despite the fact that lurking has been recognized and surveyed in social sciences, we are not aware of any previous study on lurking in social networks from a graph data management or mining perspective. Particularly, no computational method has been so far conceived to determine, and eventually, rank lurkers in an OSN graph. Note that, beyond the frequent vet trivial case of users that exhibit a peripheral unstructured membership, hidden forms of lurking are massively present in OSNs, which make it challenging to mine lurkers. While lurking is hard to track from a personal dispositional viewpoint, it appears that ranking lurkers is still possible by handling the situational variables that are related to the network of relationships between members. Moreover, a well-founded principle of eigenvector centrality, which is adopted in this work, will enable the determination of each node's lurking score in function of the lurking scores of the nodes that it is connected to.

One may notice that ranking influential people is clearly valuable as we naturally tend to follow leaders and learn from them, and conversely wonder "why ranking lurkers?". We argue that scoring community members as lurkers, rather than limiting to solely recognize (potential or actual) lurkers, should be seen as essential to determine the contingencies in the network under which different lurking behaviors occur, and ultimately to aid devising both generic and ad-hoc delurking plans and strategies. In effect, ordering members by decreasing lurking score would enable to manage priority in de-lurking applications, to identify the sub-communities particularly affected by lurkers, and to define personalized triggers of active participation. For example, lurkers of a given sub-community developed around an entity of interest (e.g., a person, or theme) would welcome messages that highlight the key topics (a service that is already delivered to its users by Twitter, for example), social events that describe how to approach a discussion in a forum or to start off your own project in a collaboration network, or introduce the role of forum moderators or team leaders.

Moreover, in order to alleviate information overload, which is recognized as a major negative factor for participation, various mechanisms of filtering (e.g., recommending threads of discussion, providing visual maps of the categories of activities) or promotion of lightweight contribution tasks (e.g., [22]) could be applied with the ultimate goal of revealing the lurker's value (i.e., ideas, opinions, expertise) to the community.

Contributions. This paper extends our previous work [53], in which we took a first step towards mining lurkers in OSNs. We scrutinize the concept of lurking in OSNs to determine the essential criteria that can be taken as the basis for mining lurkers. We lay out a *topology-driven lurking* definition upon a network representation modeling the directed relationships from information-producer to information-consumer. Our lurking definition is based on three principles that respectively express in/out-degree related properties of a given node, its in-neighborhood, and its out-neighborhood. We also define a lurking coefficient to characterize the topology of a network in terms of lurking degree.

The proposed lurking definition lends itself naturally to score the users in an OSN according to their lurking behavior, thus enabling the development of ranking mechanisms. We hence focus on the problem of *lurker ranking*, and define three formulations of it that rely on the different aspects of our topology-driven lurking concept. By resorting to classic link-analysis ranking algorithms, PageRank and alpha-centrality, we provide a complete specification of lurker ranking methods. We also propose a randomization-like model that simulates a mechanism of "self-delurking" of a network, and a lurking-oriented percolation analysis to unveil possible relations between lurkers and users that act as bridges over subnetworks.

We conducted experiments on Twitter, Flickr, Friend-Feed, and GooglePlus networks. Quantitative and qualitative results have shown the effectiveness of our lurker ranking approach, highlighting superior performance against PageRank, alpha-centrality and the Fair-Bets model, which conversely might fail to correctly identify and rank presumed lurkers. We have finally provided a preliminary exploration of relations between lurking and trustworthiness in an OSN.

The remainder of this paper is organized as follows. Section 2 introduces our definitions of topology-driven lurking and lurking coefficient of a network. Our lurker ranking methods are described in Section 3. Section 4 and Section 5 present experimental methodology and results. Section 6 discusses related work. Pointers for future research are provided in Section 7, and Section 8 concludes the paper.

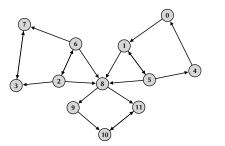


Fig. 1 An example OSN graph for our lurking-oriented ranking analysis.

2 In-degree, Out-degree, and Lurking

User interactions in an OSN are typically modeled as influence relationships, whose varying strengths are used to determine and rank the influential users. In effect, ranking methods, such as PageRank, follow the conventional model of *influence graph*, which implies that the more incoming links a node has the more important or authoritative it is; for example, translated to Twitter terms, the more followers a user has, the more interesting his/her published tweets might be. Actually, as is well-known in spam detection, a node's in-degree can easily be affected by malicious manipulation, and hence the number of incoming links is not to be trusted as unique estimator of the node's importance score. Rather, as discussed in [24] in the Twitter scenario, the follower-to-followee ratio should in principle be considered: if the number of followers exceeds those of followees then the user is likely to be an opinion-maker, otherwise her/his tweets are not that interesting.

We however observe that classic authority-based ranking methods (i.e., PageRank and related methods) cannot be directly applied to lurking analysis because they assume that links across users carry the meaning of node influence propagation, which is related to the *a*mount of information (number of walks) a node produces. By contrast, lurking behaviors build on the amount of information a node consumes; again, in Twitter terms, if user v follows user u, then v is benefiting from u's information (i.e., v is receiving u's tweets).

A question might arise whether there is any evident correlation between the in/out-degree ratio and the in-degree distribution in an OSN graph. To roughly answer the question, we empirically investigated this aspect on the networks we used for our experimental evaluation (cf. Section 4.1); Figure 2 displays the average in/out-degree for each in-degree k, on some selected datasets. While the charts show substantially different trends, they all provide evidence on the poor correlation between in/out-degree ratio and the in-degree distribution. For the *FriendFeed* and *GooglePlus* cases, it can be observed a slightly upward trend for low indegree values, while for *Twitter-UDI*, the initial uptrend rapidly decreases for low-mid in-degrees. All cases however present high dispersion of in/out-degrees for mid-high in-degrees.

2.1 Topology-driven Lurking

Upon the in/out-degree ratio intuition, we now provide a basic definition of lurking which aims to lay out the essential hypotheses of a lurking status based solely on the topology information available in an OSN.

Definition 1 (Topology-driven lurking) Let $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$ denote the directed graph representing an OSN, with set of nodes (members) \mathcal{V} and set of edges \mathcal{E} , whereby the semantics of any edge (u, v) is that v is consuming information produced by u. A node v with infinite in/out-degree ratio (i.e., a sink node) is trivially regarded as a lurker. A node v with in/out-degree ratio not below 1 shows a lurking status, whose strength is determined based on:

- **Principle I: Overconsumption**. The excess of information-consumption over information-production. The strength of v's lurking status is proportional to its in/out-degree ratio.
- Principle II: Authoritativeness of the information received. The valuable amount of information received from its in-neighbors. The strength of v's lurking status is proportional to the influential (non-lurking) status of the v's in-neighbors.
- **Principle III: Non-authoritativeness of the information produced.** The non-valuable amount of information sent to its out-neighbors. The strength of v's lurking status is proportional to the lurking status of the v's out-neighbors.

To support this intuition, let us consider the example of network in Figure 1. Nodes 3, 7, 8, 10, 11 have the highest in/out-degree ratio (i.e., 2), and as such they are candidate lurkers in the network. However, node 8 should be scored higher than others, since it benefits from information coming from two connected components, which are likely to contain influential nodes in the network (i.e., 5, 6). By contrast, nodes 10, 11 should be scored as lurkers lower than node 8, since they are mainly fed by 8 itself; similarly, nodes 3, 7 should be scored higher than 10, 11 but lower than 8, since they receive information that propagates from a smaller subgraph. Note that the example allows us to shed light on a crucial aspect related to the role that node 8 has in the network. In effect, one may say that 8 is a "bridge"

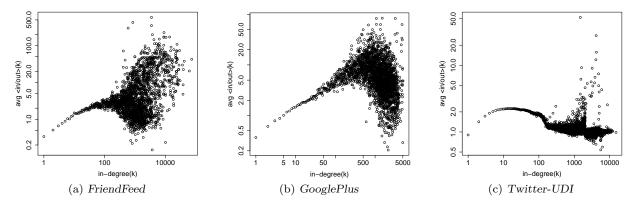


Fig. 2 Average in/out-degree as function of the in-degree k, on double-logarithmic scale. Sink and source nodes are discarded.

as it allows readers 9, 10, and 11 to peek into two otherwise separated communities. However, in our network model oriented to information consumption, the notion of bridge is also revised: the communication received from 9, 10, and 11 is likely to be less significant (in terms of amount and/or quality) than the bandwidth of information flow originated from the two largest components and received from 8. In Section 5.4, we shall investigate the relationship between lurkers and bridges, which will confirm that it's correct to regard node 8 as top-lurker.

2.2 Lurking Coefficient of a network

The participation inequality "1:9:90" rule loosely tells us that the majority of users shows a potential lurking behavior, in any generic online community. But, can we have a more precise indication of the presence of lurkers given a particular network? To answer this question we introduce here a measure, named *Lurking Coefficient*, as a basic lurking-related property of the topology of a network.

Given the directed graph $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$ representing an OSN, for any node $i \in \mathcal{V}$ let $B_i = \{j | (j,i) \in \mathcal{E}\}$ and $R_i = \{j | (i,j) \in \mathcal{E}\}$ denote the set of in-neighbors (i.e., backward nodes) and out-neighbors (i.e., reference nodes) of *i*, respectively. The sizes of sets B_i and R_i are the in-degree and the out-degree of *i*, denoted as in(i)and out(i), respectively. The local Lurking Coefficient of a node is first introduced to measure how likely any given node *i* is a lurker within its neighborhood. We define this quantity as:

$$lc_{i} = \frac{1}{|\mathcal{V}_{i}|} \left(\sum_{j \in B_{i}} \mathbb{1}\left\{ \frac{in(j)}{out(j)} < \frac{in(i)}{out(i)} \right\} + \sum_{j \in R_{i}} \mathbb{1}\left\{ \frac{in(j)}{out(j)} \ge \frac{in(i)}{out(i)} \right\} \right) \quad (1)$$

where \mathcal{V}_i is the set of neighbors of *i*, and $\mathbb{1}\{A\}$ is the *indicator* function, which is equal to 1 when the event *A* is true, 0 otherwise. Note that the two additive terms in Eq. (1) are in accordance with Principle II and Principle III, respectively, of Def. 1. The *Lurking Coefficient* of a graph \mathcal{G} is then given by the weighted average of the local Lurking Coefficients over the nodes in \mathcal{G} :

$$LC_{\mathcal{G}} = \frac{1}{|\mathcal{V}|} \sum_{i \in \mathcal{V}} p_i \cdot lc_i \tag{2}$$

where p_i is the weight of lc_i . This weight, unitary by default, can be set in accordance with Principle I, hence it is defined as the in/out-degree ratio of *i* normalized over all nodes in its neighborhood. We will refer to the variant of LC with non-unitary weights as weighted Lurking Coefficient (wLC).

3 Lurker Ranking

In this section we formulate our solutions to the problem of lurker ranking. To this aim, we will capitalize on the three principles stated in our topology-driven lurking definition. Note that, as a general premise valid for all lurker ranking methods that we shall present, we introduce a Laplace smoothing factor in the calculation of both in-degree and out-degree of node, i.e., in(i) (resp. out(i)) is meant hereinafter as the actual in-degree (resp. out-degree) of node i plus one. This allows us to deal with sink nodes and avoid infinite in/out-degree ratios.

According to Principle I in Definition 1, a basic way of scoring a node as a lurker is by means of its in/outdegree ratio. However, this way has clearly the disadvantage of assigning many nodes the same or very close ranks and, as we previously discussed, it ignores that the status of both the in-neighbors (Principle II) and out-neighbors (Principle III) contributes to the status of any given node. In the following we elaborate on each of those aspects separately.

In-neighbors-driven lurking. According to Principle II in Definition 1, an in-neighbors-driven lurking measure can be defined as:

$$r_i = \sum_{j \in B_i} \frac{out(j)}{in(j)} r_j$$

Hence, the score of node i increases with the number of its in-neighbors and with their likelihood of being nonlurkers, which is expressed by a relatively high out/indegree. The above formula can be enhanced by including a factor that is inversely proportional to the i's out-degree. Formally, we define the *in-neighbors-driven lurking* score of node i as:

$$r_i = \frac{1}{out(i)} \sum_{j \in B_i} \frac{out(j)}{in(j)} r_j \tag{3}$$

Note that Eq. (3) accounts for both the contribution of a node's in-neighbors and its own in/out-degree property.

Out-neighbors-driven lurking. The exclusive contribution of out-neighbors for the calculation of a node's lurking score, according to Principle III of Definition 1, can be formalized as:

$$r_i = \sum_{j \in R_i} \frac{in(j)}{out(j)} r_j$$

However, this method would let the score of a node increase with the tendency of its out-neighbors of being lurkers, while ignoring the status of the node itself; as a consequence, not only reciprocal lurkers will be scored high but also every node from which lurkers receive information. A correction factor should hence be introduced as proportional to the in-degree of the target node. Formally, we define the *out-neighbors-driven lurking* score of node *i* as:

$$r_i = \frac{in(i)}{\sum_{j \in R_i} in(j)} \sum_{j \in R_i} \frac{in(j)}{out(j)} r_j$$
(4)

Note that in Eq. (4), the in-degree of node i is divided by the sum of in-degrees of its out-neighbors in order to score i higher if it receives more than what its outneighbors receive.

In-Out-neighbors-driven lurking. The two previous definitions of lurking can in principle be combined

to obtain an integrated representation of all three principles in Definition 1. To this aim, we define the *in-out-neighbors-driven lurking* score of node i as:

$$r_{i} = \left(\frac{1}{out(i)} \sum_{j \in B_{i}} \frac{out(j)}{in(j)} r_{j}\right)$$
$$\left(1 + \left(\frac{in(i)}{\sum_{j \in R_{i}} in(j)} \sum_{j \in R_{i}} \frac{in(j)}{out(j)} r_{j}\right)\right) \quad (5)$$

Note that in Eq. (5) we have emphasized the aspect related to the strength of non-lurking behavior of inneighbors, which is expected to have a better fit of the hypothetical likelihood function for a given node.

3.1 LurkerRank methods

We now define our lurker ranking methods, dubbed LurkerRank (for short LR), upon the previously defined lurking models. In order to provide a complete specification of our models, we resorted to the classic eigenvector-centrality schemes offered by PageRank [11] and alpha-centrality [10]. Note that while being widely applied to a variety of application domains with the purpose of scoring the influence or prestige in information networks, PageRank and alpha-centrality rely on different assumptions which make it worth the exploration of lurker ranking through both approaches.

Let us first recall the PageRank mathematics. The PageRank vector is the unique solution of the iterative equation $\mathbf{r} = \alpha \mathbf{Sr} + (1 - \alpha) \mathbf{v}$. **S** denotes the columnstochastic transition probability matrix, which is defined as $(\mathbf{D}_{out}^{-1}\mathbf{A})^{\mathrm{T}} + \mathbf{ea}^{\mathrm{T}}/|\mathcal{V}|$, where **A** is the adjacency matrix of the network graph $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$, with $A_{ij} = 1$ if $(v_i, v_j) \in \mathcal{E}$, and $A_{ij} = 0$ otherwise; $\mathbf{D}_{out} =$ $diag(\mathbf{Ae})$ is the out-degree diagonal matrix; \mathbf{e} denotes a $|\mathcal{V}|$ -dimensional column vector of ones; and **a** is defined such that $a_i = 1$ if node *i* has zero out-degree, and 0 otherwise. Vector **v** is typically defined as $(1/|\mathcal{V}|)\mathbf{e}$, but can be modeled to bias the PageRank to boost a specific subset of nodes in the graph. Term α is a realvalued coefficient ($\alpha \in [0, 1]$, commonly set to 0.85), which acts as a damping factor so that the random surfer is expected to discontinue the chain with probability $1 - \alpha$, and hence to randomly select a page each with relevance $1/|\mathcal{V}|$ (teleportation).

We formulate three of our methods according to a PageRank-like scheme, i.e., at a high level, according to a combination of a random walk term with a random teleportation term. Our first LurkerRank method is named *in-neighbors-driven LurkerRank* (hereinafter denoted as LRin) since it is built upon Eq. (3):

$$r_i = \alpha \left(\frac{1}{out(i)} \sum_{j \in B_i} w(j, i) \frac{out(j)}{in(j)} r_j \right) + \frac{1 - \alpha}{|\mathcal{V}|}$$
(6)

Note that with Eq. (6), we introduce edge weights to deal with weighted graphs as well, for the sake of generality; although, as in our experimental setting, they are set as unitary by default. Analogously, the *outneighbors-driven LurkerRank* (hereinafter denoted as LRout) is defined as:

$$r_{i} = \alpha \left(\frac{in(i)}{\sum_{j \in R_{i}} in(j)} \sum_{j \in R_{i}} w(i,j) \frac{in(j)}{out(j)} r_{j} \right) + \frac{1 - \alpha}{|\mathcal{V}|} \quad (7)$$

Finally, the *in-out-neighbors-driven LurkerRank* (hereinafter denoted as LRin-out) is defined as:

$$r_{i} = \alpha \left[\left(\frac{1}{out(i)} \sum_{j \in B_{i}} w(j, i) \frac{out(j)}{in(j)} r_{j} \right) \left(1 + \left(\frac{in(i)}{\sum_{j \in R_{i}} in(j)} \sum_{j \in R_{i}} w(i, j) \frac{in(j)}{out(j)} r_{j} \right) \right) \right] + \frac{1 - \alpha}{|\mathcal{V}|} \quad (8)$$

Alpha-centrality [10] expresses the centrality of a node as the number of paths linking it to other nodes, exponentially attenuated by their length. Moreover, it takes into account the possibility that each node's status may also depend on information that comes from outside the network or that may regard solely the member. Alpha-centrality is defined as $\mathbf{r} = \alpha \mathbf{A}^{\mathrm{T}} \mathbf{r} + \mathbf{v}$, where \mathbf{v} is the vector of exogenous source of information ($\mathbf{v} =$ **e** as default), and α here reflects the relative importance of endogenous versus exogenous factors in the determination of centrality. High values of α (e.g., 0.85) make the close neighborhood contribute less to the centrality of a given node. The rank obtained using alphacentrality can be considered as the steady state distribution of an information spread process on a network, with probability α to transmit a message or influence along a link.

We will denote our alpha-centrality based Lurker-Rank methods with prefix ac- to distinguish them from the PageRank-based counterparts. The alpha-centralitybased in-neighbors-driven LurkerRank (ac-LRin) is defined as:

$$r_i = \alpha \left(\frac{1}{out(i)} \sum_{j \in B_i} w(j, i) \frac{out(j)}{in(j)} r_j \right) + 1$$
(9)

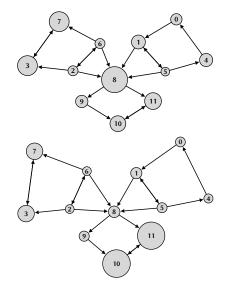


Fig. 3 Lurker ranking in the example OSN graph of Fig. 1: LRin (on top) versus PageRank (on bottom). Nodes are sized proportionally to their ranking scores.

Analogously, other two methods, denoted as ac-LRout and ac-LRin-out, are defined according to the out-neighborsdriven and in-out-neighbors-driven lurking models, respectively.

Figure 3 compares the rankings obtained by our LRin and basic PageRank on the example network of Figure 1 (α set to the default 0.85). Using LRin, node 8 was ranked highest (0.146), followed by 3 and 7 (0.112), and then 11 (0.094), 10 (0.088): this sheds light on the ability of LRin to match our definition of lurking (cf. discussion about Fig. 1 in Section 2). By contrast, Page-Rank ranked first nodes 10 and 11 (both around 0.256), and then 3 and 7 with a significant gap in score from the first two (0.116), followed by 8 (0.052), 1 (0.048); moreover, node 5 was ranked eighth, despite it is a major feeder of the lurker 8, while it was correctly ranked lowest by LRin. Similarly, alpha-centrality (results not shown) did not fare well as it ranked first nodes 11 (0.317) and 10 (0.308), before ranking node 8 (0.095), and nodes 3 and 7 in ninth and tenth position both with a score of 0.004.

3.2 Limit $\alpha \to 0$ of the LR functions

We investigate the behavior of LR functions to understand whether LR rank can be reduced to either the in/out-degree or the out/in-degree rank as α approaches 0. We take the LR in functional form as case in point, while analogous conclusions can be drawn for the other LR functions.

In the extreme case $\alpha = 0$, the LRin score of each vertex is equal to $1/|\mathcal{V}|$. If $\alpha \approx 0$, then $(1 - \alpha) \rightarrow 1$,

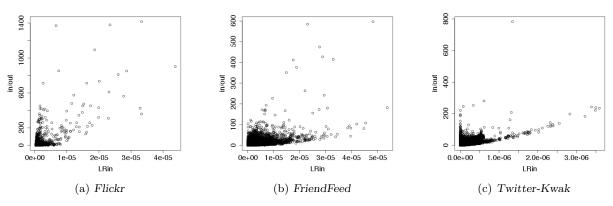


Fig. 4 LRin rank versus in/out-degree rank. Damping factor α is set to 0.01. Sink and source vertices are discarded.

therefore we write $1 - \alpha = 1 - \epsilon$, with $\epsilon \ll 1$, and $r_i \approx 1/|\mathcal{V}|$. Substituting these into Eq. (6), with unitary edge weights for the sake of simplicity, we have:

$$r_{i} = \epsilon \left(\frac{1}{out(i)} \sum_{j \in B_{i}} \frac{out(j)}{in(j)} r_{j} \right) + \frac{1 - \epsilon}{|\mathcal{V}|}$$
$$\approx \frac{1}{|\mathcal{V}|} \left[1 + \epsilon \left(\frac{1}{out(i)} \sum_{j \in B_{i}} \frac{out(j)}{in(j)} - 1 \right) \right] \quad (10)$$

A crucial part in Eq. (10) is the estimation of the sum. This term would be estimated as proportional to the in/out-degree of vertex i and to the average out/in-degree $\langle \frac{out}{in} \rangle$:

$$r_i \approx \frac{1}{|\mathcal{V}|} \left[1 + \epsilon \left(\frac{in(i)}{out(i)} \left\langle \frac{out}{in} \right\rangle - 1 \right) \right]$$
(11)

The above approximation is however admissible only if a relatively small dispersion can be assumed to hold for the out/in-degree distribution. Unfortunately, in all our evaluation network datasets (cf. Sect. 4.1), this does not seem the case since the out/in-degree distribution is always found to be less narrow than the corresponding in/out-degree distribution, as reported in Table 1. This would indicate that in principle LRin rank distribution is likely not to follow exactly the same trend as that of in/out-degree as $\alpha \approx 0$. In effect, although a moderate to strong positive correlation may still occur -0.568 on FriendFeed (Fig. 4(b)), 0.674 on Twitter-UDI, 0.679 on Flickr (Fig. 4(a)), 0.686 on Twitter-Kwak (Fig. 4(c)), and 0.745 on GooglePlus — Fig. 4 shows that topranked vertices by LRin often do not correspond to topranked in/out.

4 Experimental Evaluation

4.1 Data

We used five OSN datasets for our evaluation, namely *Twitter* (with two different dumps), *Flickr*, *FriendFeed*, and *GooglePlus*:

- From the Twitter dump studied in [34], which we will refer to as Twitter-Kwak, we extracted the followerfollowee topology starting from a connected component of one hundred thousands of users and their complete neighborhoods. A partial copy of the tweet data used in [34] was exploited to define a Twitterbased data-driven ranking and also to perform a qualitative evaluation on Twitter-Kwak, as we shall describe in Section 4.2.
- The Twitter-UDI dataset [38] was originally collected in May 2011, hence it's more recent and also larger than Twitter-Kwak. Tweet data however could not be exploited for our analysis since they are available only for a very small subset of users in Twitter-UDI (less than 0.6%) and they are also upper-bounded (limit of 500 tweets per user) [38].
- We used the entire *Flickr* data studied in [42], originally collected in 2006-2007. Information on the number of views and number of favorite markings every photo had, was exploited for our definition of Flickr-based data-driven ranking.
- We used the latest version of the FriendFeed dataset studied in [14]. Due to the recognized presence of spambots in this OSN dataset, we filtered out users with an excessive number of posts (above 20 posts per day) as suggested in [14].
- GooglePlus dataset was originally studied in [40], and consists of *circles* from GooglePlus. The dataset was collected from users who had manually shared their circles using the *share circle* feature, and the

		in/c	out *	in/o	ut **	out	/in *	out/in **		
		mean	sd	mean	sd	mean	sd	mean	sd	
	Flickr	1.096	3.377	2.731	10.557	1.263	4.583	5.554	20.085	
	FriendFeed	1.664	5.693	10.359	15.353	8.682	71.771	63.269	219.387	
	GooglePlus	3.947	11.200	24.350	27.665	3.739	46.235	27.984	144.051	
	Twitter-Kwak	2.647	3.863	11.662	9.442	1.263	46.078	6.910	145.665	
	Twitter-UDI	1.541	1.530	5.517	3.582	1.202	15.758	4.946	50.321	
* Sink nodes and source nodes are discarded. ** Like *, but only 90th percentile is considered										

Table 1 Mean and standard deviation values of in/out-degree and out/in-degree.

Table 2 Main structural characteristics of the evaluation network datasets.

data	# nodes	# links	avg in-degree	avg path length	clustering coefficient	assortativity	# sources # sinks	LC wLC
	0.000.005	00.140.010	, , , , , , , , , , , , , , , , , , ,		55	0.015	360,416	0.573
Flickr	2,302,925	33,140,018	14.39	4.36*	0.107	0.015	57,424	0.248
FriendFeed	493,019	19,153,367	38.85	3.82	0.029	-0.128	41,953 292,003	$0.955 \\ 0.354$
GooglePlus	107,612	13,673,251	127.06	3.32	0.154	-0.074	35,341 22	0.869 0.096
Twitter-Kwak	16,009,364	132,290,000	8.26	5.91*	1.26E-4	-0.095	1,067,936 10,298,788	0.914 0.435
Twitter-UDI	24,984,590	284,884,500	11.40	5.45*	4.96E-3	-0.297	3,380,805 8,065,287	0.790 0.470

Value estimated	$^{\mathrm{as}}$	$(\log(\mathcal{V}))$	$/\log(2 \mathcal{E} / \mathcal{V}).$	
-----------------	------------------	-------------------------	--	--

topology was built by combining the edges from each node's ego network.

Beyond the complexity of their technical and sociological aspects, the five networks have been selected since they naturally provide asymmetric relationships — recall that in our setting, a link from user i to user j means that j is a follower or subscriber of i — and also because they offer a variety of topological properties, as shown in Table 2. The table also reports each network's Lurking Coefficient (LC), in the upper row, and weighted LC (wLC), in the bottomer row (cf. Section 2.2). Notably, a high LC (ranging from about 0.8) to 0.95) was found for all networks except for Flickr: this may prompt us to suppose that lurkers would not characterize Flickr as much as other OSNs; in effect, differently from the other selected networks, users would subscribe and join the Flickr community when they are willing to upload and share their photos, thus showing a normal attitude to participate. Moreover, the lower value of weighted LC that characterizes GooglePlus could be explained due to a clustering coefficient, along with variation of in/out degree (Table 1), exhibited by this network, which are both relatively higher than in the other ones. Yet, note that the values of assortativity reported in Table 2 are always negative or close to zero, which would indicate no tendency of vertices with similar degree to connect to each other; interestingly, Twitter-UDI which has the most negative degree of assortativity, has also the largest value of weighted LC.

4.2 Assessment methodology

Competing methods and notations. We compared our proposed methods against PageRank (henceforth PR),

alpha-centrality (henceforth AC), and Fair-Bets model [13] (henceforth FB). The latter method was included in the comparative evaluation as it also exploits the notion of in/out-degree ratio to rank users, which is seen as a fairbets model of social capital accumulation and expenditure; originally conceived to rank players in round-robin tournaments, the Fair-Bets model assumes that users are paying each other to accept invitations on an on-line community, then the fair bets score of a user is the amount she/he can afford to pay on average. Fair-Bets computes the score of any node i as

$$r_i = \frac{1}{out(i)} \sum_{j \in B_i} r_j$$

Finally, we included in the evaluation the in/out-degree distribution of the nodes in a network dataset, as a baseline method (henceforth IO).

Data-driven evaluation. Given the novelty of the problem at hand, we had to cope with an issue relating to the lack of ground-truth data for lurker ranking. In the attempt of simulating a ground-truth evaluation, we generated a *data-driven ranking* (henceforth DD) for a network dataset and used it to assess the proposed and competing methods.

On Twitter-Kwak, we calculated the score of a node as directly proportional to its in/out-degree (Laplace add-one smoothed, cf. Section 3) and inversely exponentially with a Twitter-specific measure of influence:

$$r_i^* = \frac{in(i)}{out(i)} \exp(-EI(i))$$

 $EI(\cdot)$ denotes the *empirical measure of influence* [8] which is used to estimate the influence of a user based

on the amount of information s/he posted (i.e., tweets) and that her/his followers have retweeted. For a user i,

$$EI(i) = \frac{1}{out(i)} \sum_{j \in R_i} nRetweets(j)$$

where nRetweets(j) is the number of retweets by follower j. Note that, as found in [34], a ranking based on retweets differs from that based on the number of followers, and this prompted us to combine the two aspects in our data-driven ranking.

We defined an analytically similar function for the *FriendFeed* data-driven ranking, in which the *empirical* measure of influence has been redefined as:

$$EI(i) = \left(\frac{1}{out(i)} \sum_{j \in R_i} nCom(j,i)\right) \log_{10}\left(nPosts(i) + 10\right)$$

where nCom(j, i) is the number of comments from user j to posts by user i, and nPosts(i) is the total number of posts by user i. Note that this combination of indicators of user's activity with user's influence was needed since only a limited portion (below 10%) of users in *FriendFeed* had information on the number of received comments.

For *Flickr* we produced two data-driven rankings, dubbed DD-F and DD-V. While still related to the in/out degree as for the previously defined DD, we used the number of *favorites* (DD-F), or alternatively the number of *views* (DD-V), received by a user's photos to set the exponent (with negative sign) in the data-driven ranking function.

Unfortunately, for both *Twitter-UDI* and *Google-Plus* we were unable at the time of this writing to gather adequate information to produce a data-driven ranking, also due to the restrictive usage limits of both networks APIs. Note that the information used to generate DD for *Twitter-Kwak* was substantially incomplete and obsolete to be used for *Twitter-UDI*.

Assessment criteria. In order to comparatively evaluate our proposed methods' performance with respect to the competing methods, we resorted to well-known assessment criteria, namely *Kendall tau rank correlation coefficient* [1] *Fagin's intersection metric* [21] and *Bpref* [12].

Kendall correlation evaluates the similarity between two rankings, expressed as sets of ordered pairs, based on the number of inversions of pairs which are needed to transform one ranking into the other. Formally:

$$\tau(\mathcal{L}', \mathcal{L}'') = 1 - \frac{2\Delta(\mathcal{P}(\mathcal{L}'), \mathcal{P}(\mathcal{L}''))}{M(M-1)}$$

where \mathcal{L}' and \mathcal{L}'' are the two rankings to be compared, $M = |\mathcal{L}'| = |\mathcal{L}''|$ and $\Delta(\mathcal{P}(\mathcal{L}'), \mathcal{P}(\mathcal{L}''))$ is the symmetric difference distance between the two rankings, calculated as number of unshared pairs between the two lists. The score returned by τ is in the interval [-1, 1], where a value of 1 means that the two rankings are identical and a value of -1 means that one ranking is the reverse of the other.

Fagin measure allows for determining how well two ranking lists are in agreement with each other. This is regarded as the problem of comparing "partial rankings", since elements in one list may not be present in the other list. Moreover, according to [56], a ranking evaluation measure should consider top-weightedness, i.e., the top of the list gets higher weight than the tail. Applied to any two top-k lists $\mathcal{L}', \mathcal{L}''$, the Fagin score is defined as:

$$F(\mathcal{L}', \mathcal{L}'', k) = \frac{1}{k} \sum_{q=1}^{k} \frac{|\mathcal{L}'_{:q} \cap \mathcal{L}''_{:q}|}{q}$$

where $\mathcal{L}_{:q}$ denotes the sets of nodes from the 1st to the qth position in the ranking. Therefore, F is the average over the sum of the weighted overlaps based on the first k nodes in both rankings.

Bpref [12] evaluates the performance from a different view, i.e., the number of non-relevant candidates. It computes a preference relation of whether judged relevant candidates R of a list \mathcal{L}' are retrieved, i.e., occur in a list \mathcal{L}'' , ahead of judged irrelevant candidates N, and is formulated as

$$Bpref(R,N) = \frac{1}{|R|} \sum_{r} \left(1 - \frac{\text{\#of } n \text{ ranked higher than } r}{|R|} \right)$$

where r is a relevant retrieved candidate, and n is a member of the first |R| irrelevant retrieved candidates. In our setting, we first determined N as the set of nodes with data-driven ranking score below or equal to 1, and used it for comparisons with DD, when available; whereas, for comparisons among competing methods, N was defined as either the bottom of the corresponding method's ranking having the same size as N in the data-driven ranking, or (when DD is not available) as the bottom-25% of the method's ranking. R was selected as the set of nodes having top-l% score from the complement of N.

Both F and Bpref are within [0, 1], whereby values closer to 1 correspond to better scores. For the experiments discussed in the following, we setup the size k of the top-ranked lists for Fagin evaluation to $k = 10^2, 10^3, 10^4$, and the l% of relevant candidates for Bpref evaluation to l = 10, 25, 50 (i.e., relevant candidates in the 90th percentile, the third quartile and the

median). Moreover, unless otherwise specified, F scores will correspond to ranking lists without sink nodes, in order to avoid biasing (presumably overstating) our evaluation with trivial lurkers.

5 Results

We present here our experimental results, which are organized as follows. We begin first with an analysis of reciprocity and attachment behaviors of lurkers. Section 5.2 is devoted to present quantitative results on the ranking performance obtained by the proposed and competing methods. In Section 5.3, we introduce a randomization-like model to study how to support "selfdelurking" of a network, whereas in Section 5.4 we present a lurking-oriented percolation analysis. Finally, in Section 5.5, we provide a qualitative insight into the methods' ranking behavior.

Notations: Here we briefly recall main notations that will be used throughout this section. LR and ac-LR prefixed abbreviations refer to our proposed Lurker-Rank methods (cf. Section 3.1). The following notations are abbreviations for the competing methods (cf. Section 4.2): IO stands for in/out-degree ratio ranking; PR, PR, and FB stand for PageRank, alpha-centrality, and Fair-Bets model, respectively. Moreover, DD symbols refer to data-driven rankings.

5.1 Lurker reciprocity and attachment

We aimed at understanding two different aspects of the lurking behaviors: (1) how lurkers relate to each other, in terms of *link reciprocity*, and (2) how lurker distribution grows with respect to active users, which can be explained in terms of *attachment* mechanisms.

Reciprocity. We examined the impact of the presence of lurkers on measures of reciprocity in the various network graphs, under three different settings that correspond to the top-25%, top-10% and top-5%, respectively, of a LR ranking solution. Specifically, we considered four measures of reciprocity, namely (i) the number of reciprocal lurking edges (i.e., reciprocal edges in the lurking-induced network graph), (ii) the percentage of reciprocal lurking edges to the total number of edges in the original graph (denoted as rle), (iii) the fraction of reciprocal edges in the original network graph that connect lurkers to each other, and (iv) the fraction of edges that connect lurkers to each other within a lurking-induced subgraph.

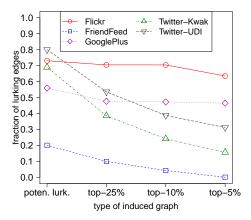


Fig. 5 Fraction of reciprocal edges in the lurking-induced subnetworks.

Table 3 reports results obtained by the LRin-out method. A first remark is that *rle* was very small or negligible regardless of the portion of LR ranking solution considered. An exception was represented by Flickr, whose rle varied from about 50% to 10%; this could be explained as an effect of the crawling mechanism used to build the *Flickr* network dataset, since unlike the other datasets, it was obtained starting from a single seed user and then performing a breadth-first search on the social network graph. Considering the fraction of reciprocal edges in the original network graph that connect lurkers to each other (results not shown), again with the exception of *Flickr* we observed a very small value even for the case of top-25% lurkers (around 23%) for GooglePlus, 5% for Twitter-UDI, and below 1% for FriendFeed and Twitter-Kwak), while approaching zero when the top-ranked solution is narrowed to 10% or smaller.

Note that, while LRin behaved very similarly to LRinout, results obtained by LRout showed that rle values were significantly higher than those observed in Table 3, with averages over the datasets equal to 35% (top-25%), 27% (top-10%), and 20% (top-5%). Even higher were the values of the fraction of reciprocal edges in the original network graph connecting lurkers, with peaks above 90% in the top-25% case, and averages of 85%(top-25%), 63% (top-10%), and 45% (top-5%). These findings were actually not surprising since LRout is designed to emphasize the lurking attitude of any node from which a target node receives information.

Figure 5, as complementary to Table 3, shows the fraction of edges that connect lurkers to each other within a lurking-induced subgraph. In the figure, we also included for comparison the case of "potential lurkers", regarding them as those nodes having in/out-degree ratio above 1. An evident remark is that the reciprocity between lurkers generally followed a decreasing trend

		top-25% of th	ne LRin-out solut	ion	top-10% of th	ne LRin-out solut	ion	top-5% of the LRin-out solution		
	# recip. edges	# edges	# reciprocal	% rle	# edges	# reciprocal	% rle	# edges	# reciprocal	% rle
	(full graph)	(induced graph)	lurking edges		(induced graph)	lurking edges		(induced graph)	lurking edges	
Flickr	20,603,483	23,352,367	16,440,872	49.61	12,349,595	8,704,922	26.27	5,030,759	3,192,712	9.63
FriendFeed	3,014,306	340,935	33,654	0.18	1,096	46	< 0.01	2	0	0.00
GooglePlus	2,870,336	1,413,468	667,422	4.88	49,481	23,562	0.17	5,310	2,624	0.02
Twitter-Kwak	52,137,192	7,293	2,806	< 0.01	216	52	< 0.01	64	10	< 0.01
Twitter-UDI	191,858,256	18,839,845	10,078,339	3.54	3,094,341	1,198,615	0.42	872,332	271,751	0.10

Table 3 Reciprocity and lurking. *rle* is the number of reciprocal lurking edges (i.e., reciprocal edges in the lurking-induced network graph) divided by the total number of edges in the original graph.

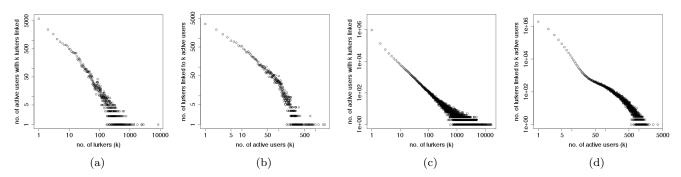


Fig. 6 Distribution of active users as a function of the lurkers-followers (a)-(c) and distribution of lurkers as a function of the active users-followees (b)-(d). (GooglePlus, two plots from the left, and Twitter-UDI, two plots from the right).

varying from the "potential lurkers" to the top-5% setting; this trend was quite slow or roughly stagnant on three out of five datasets (i.e., *Flickr*, *GooglePlus*, and *FriendFeed*) but much sharper in the two largest networks (i.e., the two Twitter datasets). Interestingly, when considering LRout instead of LRin-out or LRin, the fraction of reciprocal edges in the lurking-induced subgraph was in general not longer observed as a decreasing function by decreasing sizes of lurker sets; the trend was rather increasing for the Twitter datasets (upper values of 0.78 for *Twitter-UDI* and 0.60 for *Twitter-Kwak*) and for *FriendFeed* (upper value of 0.32).

Attachment. We focus now on the relation between lurkers and the "active" users they are linked to. Specifically, we analyzed the distribution of lurkers as function of the degree of attached active users, and dually for the distribution of active users. For this analysis, we selected the same fraction (25%) from the top and from the bottom of the LRin-out ranking solution in order to choose the set of lurkers and the set of active users, respectively, under examination.

Our goal was to understand whether the probability of observing active users with a certain degree of attached lurkers, and vice versa, can be predicted by a power law. Therefore, for each dataset, we learned the best fit of a power law distribution to the observed data, where the statistical significance of this fitting was assessed based on a Kolmogorov-Smirnov test. The resulting plots obtained on our datasets showed a power law behavior for both the distribution of lurkers (fol-

lowing k active users) and the distribution of active users (followed by k lurkers); Figure 6 shows the plots for GooglePlus and Twitter-UDI. The exponent of the fitted power law distributions varied from 1.67 (Google-Plus and Twitter-Kwak) to 2 (FriendFeed, Twitter-UDI), for the distribution of active users, and from 1.36 (Flickr, Twitter-Kwak) to 1.86 (GooglePlus), for the distribution of lurkers. Significant fitting was actually found in general for both distributions in each dataset, which would indicate that they may follow a preferential attachment mechanism: active users, who already are followed by a large number of lurkers, are likely to attract even more lurkers; analogously, lurkers, who already follow a large number of active users, are more likely to do so. Moreover, as smaller values of the Kolmogorov-Smirnov statistic denote better fit, we observed a slight tendency of better explaining the growing of the number of lurkers (rather than of active users) by preferential attachment on GooglePlus and Twitter-UDI, while an opposite situation was found on Flickr.

5.2 Ranking evaluation

Correlation analysis with data-driven rankings. Table 4 shows the Kendall tau rank correlation obtained by our LurkerRank methods and by the competing methods with respect to the data-driven ranking (DD) for all eligible datasets.

dataset	10	PR	AC	FB	LRin	LRout	LRin-out	ac-LRin	ac-LRout	ac-LRin-out
FriendFeed	.169 (± .003)	.128 (± .004)	$.230 (\pm .005)$	$.373 (\pm .004)$	$.661 (\pm .003)$	169 (± .005)	.497 (± .003)	.664 (± .003)	$189 (\pm .005)$.470 (± .003)
Flickr vs DD-V	$.046 (\pm .008)$	$.043 (\pm .005)$	$.043 (\pm .008)$	$.047 (\pm .002)$	$.247 (\pm .007)$	007 (± .013)	$.239 (\pm .014)$.234 (± .014)	$.011 (\pm .014)$.251 (± .013)
Flickr vs DD-F	$.052 (\pm .007)$	$.049 (\pm .005)$	$.049 (\pm .008)$	$.053 (\pm .002)$	$.231 (\pm .006)$	$.003 (\pm .012)$	$.260 (\pm .013)$	$.255 (\pm .013)$	$.011 (\pm .014)$.273 (± .012)
Twitter-Kwak	$.171 (\pm .006)$	$.004 (\pm .011)$	$.215 (\pm .010)$	$.235 (\pm .012)$.671 (± .007)	$082 (\pm .004)$	$.559 (\pm .008)$	$.659 (\pm .008)$	$073 (\pm .004)$	$.560 (\pm .008)$

Table 4 Comparative performance of LurkerRank methods and competitors with respect to data-driven rankings: Kendalltau rank correlation values (with 95% confidence intervals in parentheses).

Bold values refer to the highest correlation per dataset. All values except those in italic are statistically significant (under the null hypothesis of independence of two rankings).

The in-neighbors-driven and in-out-neighbors-driven LurkerRank methods generally obtained the highest correlation with DD (e.g., 0.67 by LRin on *Twitter-Kwak*, 0.66 by ac-LRin on *FriendFeed*). Results confirmed that LRin and LRin-out (and their ac- counterparts) significantly improved upon all competing methods, with maximum gains of 0.59 against IO, 0.66 against PR, 0.45 against AC and 0.43 against FB.

Note that LRout and ac-LRout obtained the lowest scores on all datasets: interestingly, this behavior confirms our intuition that determining the strength of lurking of a given node should not depend solely on the strength of the lurking behavior shown by the out-neighbors of that node (i.e., Principle III of Definition 1).

Concerning correlation of each of the competing methods with DD, we observed on *FriendFeed* and *Twitter-Kwak* some correlation for FB (up to 0.37) and AC (up to 0.23), while IO and PR showed poor correlation. However, on *Flickr*, all competing methods tended to be uncorrelated with the two DD, with an average correlation of 0.05 over all competitors. More interestingly, it is worth noting that IO generally showed poor correlation with DD, which not only would justify the use of in/out-degree ranking as a baseline competing method, but also gives evidence that in/out-degree cannot be considered as a basic approximation of LurkerRank.

$Comparative \ evaluation \ with \ LurkerRank \ methods.$

Tables 5–9 compare our LurkerRank methods against PageRank, alpha-centrality, Fair-Bets (all at convergence) as well as against DD (where possible) and IO. Note that results are organized on 3-row groups, where each row in a group corresponds to a specific variation of the Fagin's or Bpref's parameters.

On Twitter-Kwak (Table 5), LRin and LRin-out along with their ac- counterparts showed a relatively much higher F intersection with DD (0.516 on average) and IO (0.473) than with FB (0.08), and a nearly empty F with respect to PR and AC. By contrast, LRout and ac-LRout exhibited a larger F with PR, although below 0.316 on average, while scoring even lower with respect to the other methods. Bpref evaluation led to mostly similar remarks on the relative comparison be-

								D		
			F					Bpref		
		$k = 10^{2}$	$// 10^{3}$	$// 10^4$			l = 10	// 25 /	/ 50	
	DD	10	PR	AC	FB	DD	10	PR	AC	FB
LRin	.527	.404	0.0	0.0	.112	.997	.992	.121	.790	.441
	.289	.209	0.0	0.0	.127	.995	.989	.473	.914	.704
	.581	.617	.001	.001	.068	.985	.962	.521	.866	.606
LRout	.030	.032	.181	.010	.034	.045	0.0	.754	.311	.313
	.008	.008	.351	.024	.015	.055	.001	.757	.650	.600
	.003	.002	.437	.048	.005	.109	.074	.641	.678	.648
LRin-out	.475	.364	0.0	0.0	.064	.968	.981	.039	.826	.204
	.314	.277	0.0	0.0	.063	.979	.977	.387	.929	.524
	.666	.688	.001	.001	.032	.961	.925	.453	.878	.489
ac-LRin	.583	.459	0.0	0.0	.174	.993	.990	.072	.808	.339
	.573	.570	0.0	0.0	.122	.992	.988	.443	.921	.653
	.767	.810	.001	.001	.048	.982	.967	.501	.872	.575
ac-LRout	.038	.032	.244	.006	.036	.049	0.0	.796	.339	.307
	.009	.008	.319	.017	.011	.059	0.0	.775	.659	.598
	.003	.002	.362	.042	.004	.120	.081	.654	.687	.643
ac-LRin-	.473	.363	0.0	0.0	.062	.957	.981	.039	.828	.203
out	.278	.234	0.0	0.0	.062	.975	.976	.386	.930	.464
	.663	.685	.001	.001	.031	.957	.933	.453	.880	.454

Bold values refer to the highest scores per LurkerRank method and assessment criterion. Underlined bold values refer to the highest scores per assessment criterion.

Table 6 Comparative performances on Twitter-UDI.

	r	F	,			Bpr	ef	
	k =	10^2 //	$10^3 //$	10^{4}	1:	= 10 //		0
	10	PŔ	AC	FB	10	PR	ÁĆ	FB
LRin	.337	0.0	0.0	.184	.809	.254	.230	.477
	.245	0.0	0.0	.136	.917	.645	.633	.546
	.455	0.0	0.0	.292	.927	.709	.715	.568
LRout	0.0	0.0	0.0	0.0	0.0	.867	.767	.164
	0.0	.004	0.0	.002	0.0	.876	.766	.339
	.001	.021	.006	.001	.275	.810	.732	.531
LRin-out	.305	0.0	0.0	.160	.762	.130	.123	.299
	.178	0.0	0.0	.078	.897	.546	.550	.405
	.172	0.0	0.0	.076	.902	.646	.656	.443
ac-LRin	.343	0.0	0.0	.186	.825	.216	.202	.454
	.267	0.0	0.0	.152	.924	.617	.617	.524
	.446	0.0	0.0	.324	.932	.690	.704	.550
ac-LRout	0.0	0.0	0.0	0.0	0.0	.861	.765	.159
	0.0	.004	0.0	.002	0.0	.873	.765	.338
	.001	.021	.006	.001	.272	.807	.730	.530
ac-LRin-out	.306	0.0	0.0	.161	.877	.113	.153	.140
	.176	0.0	0.0	.076	.947	.482	.607	.293
	.153	0.0	0.0	.060	.949	.598	.692	.399

Bold values refer to the highest scores per LurkerRank method and assessment criterion. Underlined bold values refer to the highest scores per assessment criterion.

tween proposed and other methods: LRin, LRin-out and their ac- counterparts highly matched DD and IO (around 0.97 on average), but also a moderately high *Bpref* with respect to AC (0.87) and mid-low *Bpref* with respect to FB (0.47). Again, as already observed for both the Kendall evaluation and the Fagin evaluation, LRout and ac-LRout showed no significant matches in practice with DD (while scoring pretty high with respect to PR).

Table 7Comparative performances on Flickr.

	1		ŀ	7					Bp	ref		
		k =	10 ² //	$10^3 //$	10^{4}			ı	= 10 //		50	
	DD-F	DD-V	10	PR	AC	FB	DD-F	DD-V	10	PR	AC	FB
LRin	.576	.574	.639	0.0	0.0	.552	.361	.327	.921	.465	.769	.502
	.451	.433	.511	.003	.007	.463	.532	.496	.953	.522	.783	.488
	.297	.286	.383	.018	.008	.313	.650	.630	.931	.499	.987	.570
LRout	.102	.101	.123	.045	0.0	.037	.071	.060	.206	.620	.862	.138
	.124	.121	.107	.064	0.0	.008	.252	.218	.509	.503	.868	.229
	.015	.014	.126	.237	.007	.033	.460	.446	.645	.411	.878	.392
LRin-out	.561	.559	.626	0.0	0.0	.536	.353	.321	.878	.441	.761	.520
	.462	.444	.520	.004	.007	.462	.305	.292	.883	.474	.766	.509
	.311	.301	.398	.021	.008	.310	.430	.417	.667	.478	.748	.594
ac-LRin	.609	.607	.676	0.0	0.0	.587	.349	.316	.878	.458	.784	.498
1 1	.535	.513	.604	.004	.007	.538	.523	.487	.940	.484	.792	.482
	.348	.336	.447	.018	.009	.352	.644	.625	.921	.481	.795	.573
ac-LRout	.102	.009	.123	.051	0.0	.037	.071	.060	.209	.622	.660	.138
	.105	.101	.107	.072	0.0	.008	.256	.220	.514	.510	.670	.232
	.115	.114	.127	.229	.007	.034	.477	.464	.645	.413	.675	.392
ac-LRin-	.443	.440	.510	0.0	0.0	.432	.375	.345	.958	.604	.640	.520
out	.305	.293	.337	.002	.004	.291	.569	.533	.970	.675	.677	.466
	.232	.224	.293	.013	.006	.215	.676	.655	.954	.569	.706	.494

Bold values refer to the highest scores per LurkerRank method and assessment criterion. Underlined bold values refer to the highest scores per assessment criterion.

Table 8Comparative performances on FriendFeed.

			F					Bpref		
		$k = 10^{2}$	-	$// 10^4$) // 25 /	// 50	
	DD	10	PR	AC	FB	DD	10	PR	AC	FB
LRin	.542	.690	.024	.010	.453	1.0	.980	.331	.606	.985
	.488	.586	.108	.118	.384	.998	.976	.570	.802	.977
	.576	.628	.126	.153	.493	.986	.953	.678	.843	.898
LRout	.015	.009	.479	.620	.011	.008	0.0	.691	.672	.031
	.138	.163	.550	.725	.167	.030	.038	.764	.746	.066
	.154	.156	.498	.704	.184	.062	.110	.739	.737	.258
LRin-out	.207	.297	.032	.042	.170	.972	.910	.252	.604	.879
	.278	.320	.061	.064	.166	.955	.910	.553	.794	.870
	.424	.455	.076	.099	.338	.914	.874	.642	.815	.813
ac-LRin	.575	.735	.025	.014	.467	1.0	.980	.300	.605	.980
	.520	.627	.118	.131	.403	.999	.977	.548	.803	.969
	.603	.660	.130	.161	.503	.988	.954	.661	.845	.882
ac-LRout	.015	.009	.479	.620	.011	.008	0.0	.691	.672	.031
	.138	.163	.550	.725	.167	.030	0.0	.749	.726	.066
	.154	.156	.498	.704	.184	.040	.080	.723	.718	.257
ac-LRin-	.169	.243	0.0	0.0	.126	.958	.891	.237	.594	.852
out	.240	.273	.001	.001	.122	.942	.892	.546	.785	.836
	.400	.426	.041	.064	.310	.898	.853	.634	.803	.782

Bold values refer to the highest scores per LurkerRank method and assessment criterion. Underlined bold values refer to the highest scores per assessment criterion.

Table 9 Comparative performances on GooglePlus.

		F	۰			Bp	ref	
	k =	$10^2 //$	$10^3 //$	10 ⁴	<i>l</i> =	= 10 //	25 // 5	50
	10	PR	AC	FB	10	PR	AC	FB
LRin	.742	0.0	0.0	.363	1.0	.434	.582	.976
	.850	.001	0.0	.480	.993	.584	.695	.962
	.881	.063	.144	.592	.987	.684	.722	.937
LRout	.011	.079	0.0	.015	.972	.796	.796	.686
	.015	.107	.012	.015	.971	.793	.790	.815
	.223	.322	.144	.213	.964	.782	.774	.807
LRin-out	.629	0.0	0.0	.318	1.0	.462	.587	.907
	.721	0.0	0.0	.419	.991	.572	.688	.910
	.799	.045	.130	.547	.989	.677	.731	.886
ac-LRin	.747	0.0	0.0	.361	1.0	.456	.578	.976
	.851	.001	0.0	.477	.992	.546	.702	.963
	.882	.063	.143	.591	.988	.699	.724	.937
ac-LRout	.011	.077	0.0	.015	.972	.796	.796	.687
	.015	.107	.012	.015	.971	.793	.790	.815
	.223	.322	.145	.212	.965	.782	.774	.807
ac-LRin-out	.647	0.0	0.0	.328	1.0	.489	.586	.896
	.729	0.0	0.0	.422	.994	.612	.675	.899
	.795	.042	.125	.543	.983	.702	.727	.875

Bold values refer to the highest scores per LurkerRank method and assessment criterion. Underlined bold values refer to the highest scores per assessment criterion.

Results on *Twitter-UDI* (Table 6) corroborated the advantage of LRin and ac-LRin with respect to the other LR methods. LRin-out and ac-LRin-out achieved lower

F than LRin and ac-LRin, respectively, with respect to IO and FB, especially for higher k. Compared to the Twitter-Kwak case, Bpref values were relatively higher (respectively, lower) with respect to PR (respectively, AC), except for LRout and ac-LRout which had higher Bpref with respect to AC than in Twitter-Kwak.

On Flickr (Table 7), once again the best performance against the data-driven ranking (DD-F and DD-V) was obtained by LRin and LRin-out along with their ac- counterparts, and also roughly similar F values were obtained with respect to IO and FB. Note that both data-driven ranking (the *favorites*-based one, DD-F, and the *views*-based one, DD-V) corresponded to nearly identical results, with a slightly better agreement of the LR algorithms with respect to DD-F. In terms of *Bpref*, LRin, LRin-out and their ac- counterparts highly matched IO. *Bpref* values were also moderately high with respect to AC and mid-low with respect to PR and FB.

Looking at *FriendFeed* results (Table 8), LRin and LRin-out along with their ac- counterparts were again the best-performing methods against DD (0.42 F and 0.97 *Bpref*), and also showed mid F (0.34) and high *Bpref* (0.89) with respect to FB. Yet, LRout and ac-LRout were moderately in agreement with PR and AC in terms of F, whereas all LR generally achieved mid *Bpref* with both PR and AC.

GooglePlus evaluation results (Table 9) led us to draw conclusions similar to the other network datasets in terms of F values: in- and in-out-based algorithms outperformed the out-based ones when comparing with IO and FB, while nearly empty intersection was found with respect to PR and AC. LRin, LRin-out and their accounterparts achieved very high Bpref with respect to IO, and also showed good agreement with FB.

Statistical significance testing. We also determined the statistical significance of the better performance of LurkerRank methods with respect to the competing ones, through two stages of statistical testing analysis; in both cases, we fixed the Fagin parameter as $k = 10^4$ (which ensured a larger overlap between the ranking lists to be compared) and the Bpref parameter as l = 25(for which |R| was always smaller than |N|). Results refer here to Twitter-Kwak and FriendFeed, nevertheless similar conclusions were actually reached for the other evaluation networks.

Tables 10–11 show the p-values resulting from an unpaired two-tail t-test, in which the performance scores obtained for each iteration by a ranking method with respect to DD were regarded as the statistical samples, under the null hypothesis of no difference in performance with respect to DD between a LurkerRank method and a competing method. Note that in all cases,

	Fag	gin evaluati	on	Bpref evaluation				
	PR	AC	FB	PR	AC	FB		
LRin	4.4E-65	4.4E-65	8.4E-11	5.2E-110	1.1E-25	2.1E-65		
LRout	2.8E-41	2.7E-41	1.8E-04	3.2E-50	5.5E-79	9.2E-71		
LRin-out	4.3E-277	4.4E-277	2.9E-12	1.5E-89	6.7E-21	7.6E-65		
ac-LRin	5.6E-228	5.6E-228	4.8E-14	1.2E-91	2.1E-25	2.7E-65		
ac-LRout	6.5E-34	6.2E-34	1.8E-04	4.1E-54	1.8E-71	2.3E-73		
ac-LRin-out	3.8E-213	3.3E-265	3.4E-12	5.8E-85	2.1E-21	1.0E-64		

Table 10Twitter-Kwak t-test on the per-iteration performances.

Table 11FriendFeedt-testontheper-iterationperformances.

		gin evaluatio		Bpref evaluation			
	PR	AC	FB	PR	AC	FB	
LRin	1.3E-116	1.3E-103	2.6E-10	4.5E-195	5.9E-197	6.1E-10	
LRout	8.5E-12	1.6E-101	1.5E-38	6.8E-252	1.3E-264	2.5E-271	
LRin-out	6.0E-193	2.4E-166	2.1E-24	1.3E-298	2.1E-212	2.2E-116	
ac-LRin	1.0E-195	1.0E-172	4.4E-13	5.0E-298	3.9E-189	7.8E-10	
ac-LRout	2.6E-12	5.1E-88	1.3E-38	4.1E-99	5.9E-299	1.4E-282	
ac-LRin-out	8.1E-63	1.3E-96	2.1E-25	8.3E-82	5.1E-226	1.5E-75	

the number of iterations (samples) was adequate to perform a t-test (generally above 50). Looking at the two tables and both F and Bpref evaluation, the p-values turned out to be extremely low in most cases, thus giving a strong evidence that the null hypothesis was always rejected, at 1% significance level. This finding was useful to confirm that a certain difference (actually, the improvement) in performance between the LR methods and the competing ones, also on *FriendFeed* for which relatively high Bpref scores were observed in the previous analysis.

In the second stage of statistical testing, we analogously performed a paired two-tail t-test in which the samples corresponded to the F scores respectively obtained by two ranking methods with respect to DD over the same randomly generated subgraph. For each of the network datasets, we extracted 100 subgraphs, each time starting from a randomly picked seed node and roughly covering a fixed number of nodes (around 1/100 of the original network size). This test was hence intended to stress the ranking methods performing over a pool of subnetworks having different characteristics from each other, and from the whole original network as well; for instance, on Twitter-Kwak, the subnetworks had average path length mean of 2.52 (0.86 stdev), and in/out-degree ratio mean of 0.07 (0.13 stdev) — this might be explained because of the adopted approach of breadth-first traversal of the network, which led to connect the majority of nodes with a few source nodes having very high out-degree. On Twitter-Kwak, we observed a close behavior between the LurkerRank methods (except LRout and ac-LRout) and AC (around 0.19 F on average), and between PR and FB, which however achieved a lower average F(0.029) — note that k was still set to 10^4 , hence very high for such network sizes (i.e., around 200,000 nodes). In any case, i.e., for each pair of LurkerRank method vs. competing method, the

 Table 12 Comparative performances on FriendFeed damping factor depending on the average path length.

	F							Bpref		
	$k = 10^2 / / 10^3 / / 10^4$						l = 10	0 // 25	// 50	
	DD	10	PR	AC	FB	DD	10	PR	AC	FB
LRin	.450	.686	.012	.003	.445	.955	.978	.318	.601	.985
	.422	.582	.079	.078	.341	.914	.975	.567	.800	.974
	.529	.627	.111	.134	.472	.678	.952	.673	.839	.897
LRout	.015	.072	.510	.620	.015	.011	0.0	.689	.672	.027
	.138	.070	.571	.725	.184	.033	.041	.762	.747	.059
	.154	.208	.508	.704	.189	.155	.121	.738	.737	.199
LRin-out	.205	.294	.020	.031	.191	.759	.909	.250	.604	.871
	.274	.317	.053	.055	.182	.744	.910	.553	.792	.860
	.421	.448	.074	.096	.352	.602	.872	.642	.813	.804
ac-LRin	.485	.727	.016	.004	.479	.961	.978	.291	.600	.981
	.450	.623	.088	.090	.367	.916	.975	.545	.800	.967
	.553	.656	.115	.141	.488	.679	.951	.656	.841	.883
ac-LRout	.015	.072	.510	.620	.015	.011	0.0	.689	.672	.027
	.138	.070	.571	.725	.184	.033	.008	.747	.726	.059
	.154	.208	.508	.704	.189	.142	.102	.721	.718	.199
ac-LRin-	.169	.239	0.0	0.0	.140	.745	.889	.237	.594	.850
out	.240	.271	.001	.001	.136	.722	.891	.547	.785	.833
	.400	.421	.042	.064	.325	.592	.854	.636	.803	.780

Bold values refer to the highest scores per LurkerRank method and assessment criterion. Underlined bold values refer to the highest scores per assessment criterion.

 Table 13 Comparative performances on GooglePlus with damping factor depending on the average path length.

		F	,			Bp	ref		
	k =	10^2 //	$10^3 //$	104	1		$\begin{array}{c c c c c c c c c c c c c c c c c c c $		
	10	PR	AC	FB	10	PR	AC	FB	
LRin	.729	0.0	0.0	.551	1.0	.438	.584	.985	
	.829	.001	0.0	.631	.989	.585	.700	.963	
	.864	.061	.140	.690	.983	.689	.725	.927	
LRout	.011	.085	0.0	.022	.972	.994	.996	.671	
	.015	.148	.012	.018	.971	.993	.990	.795	
	.223	.356	.144	.232	.964	.981	.974	.783	
LRin-out	.629	0.0	0.0	.474	.997	.467	.590	.940	
	.720	0.0	0.0	.546	.989	.576	.689	.915	
	.798	.047	.129	.642	.980	.679	.734	.876	
ac-LRin	.732	0.0	0.0	.551	1.0	.459	.579	.986	
	.830	.001	0.0	.629	.990	.550	.702	.963	
	<u>.864</u>	.061	.139	.689	.986	.711	.726	.927	
ac-LRout	.011	.083	0.0	.022	.972	.994	.996	.671	
	.015	.148	.012	.018	.971	.993	.990	.796	
	.223	.356	.145	.232	.965	.981	.974	.783	
ac-LRin-out	.647	0.0	0.0	.488	.998	.492	.590	.935	
	.729	0.0	0.0	.550	.991	.623	.678	.907	
	.795	.044	.125	.638	.984	.709	.728	.866	

Bold values refer to the highest scores per LurkerRank method and assessment criterion. Underlined bold values refer to the highest scores per assessment criterion.

null hypothesis of equal means was rejected even at 1% significance level, since the p-values were ranging from 1.4E-3 to 2.8E-19. Analogous final remarks were drawn for *FriendFeed*.

Relation between damping factor and average path length. In our proposed methods, the damping factor α is chosen to be 0.85, in analogy with the default setting of the parameter in the original PageRank algorithm. Recall this finds an explanation based on the empirical observation that a web surfer is likely to navigate following 6 hyperlinks (before discontinuing this navigation chain and randomly jumping on another page), which corresponds to a probability $\alpha = 1 - (1/6) \approx 0.85$. On the other hand, research on degrees-of-separation in directed network graphs has shown that for many OSNs the average path length is typically below 6 (e.g., [7, 43]). Here we leverage on this result, confirmed in our network datasets as well, to understand how the ranking performance may change as the damping factor is varied in function of a network-specific structural characteristic like the average path length. Precisely, we set α as $\alpha = 1 - (1/apl)$, being *apl* the average path length of the particular network. For this evaluation stage, we focused on *FriendFeed* and *GooglePlus*, which exhibit the lowest average path lengths, i.e., 3.82 and 3.32, respectively (cf. Table 2).

Comparing the results in Table 13 that correspond to $\alpha = 0.7$ with the results obtained with default α (Table 9) on *GooglePlus*, *F* values were slightly lower (resp. unvaried) for the in- and in-out-based algorithms, (resp. for the out-based algorithms) with respect to IO, generally higher with respect to FB, and equal or higher with respect to PR and AC. Again comparing with the results in Table 9, *Bpref* slightly increased with respect to PR and AC and decreased with respect to IO. As for *FriendFeed*, comparing Table 8 with Table 12, we found that *F* values were generally lower when using $\alpha = 0.74$ for in- and in-out-based algorithms, and higher for outbased ones. A decrease in the performance of in- and in-out-based algorithms was observed for *Bpref* as well, especially with respect to DD.

Overall, it appears that the average path length cannot be regarded as a good estimator of damping factor in our methods, in the sense of a necessarily better alternative to the default 0.85. However, we would tend to take this sort of conclusion with a grain of salt, due to the heterogeneity of such networks and the lack of more example networks with average path length significantly below 6.

Efficiency results. Figure 7 shows the runtime performance of LurkerRank algorithms. The times do not include the graph building step.¹ Firstly, it was interesting to observe on all datasets that the Lurker-Rank methods consistently reached a ranking stability very quickly, in the range $35 \div 75$ iterations, with the exception of ac-LRin-out which always reached convergence with fewer iterations. The latter fact is however explained by a generally poor diversification of the ranking scores achieved by ac-LRin-out, which particularly affects the top of the ranking results: in fact, in most datasets, the scores at the maximum as well as the third quartile are of the same order of magnitude as the mean or even as the first quartile scores. LRin and LRout mostly required pretty similar running

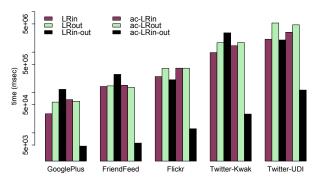


Fig. 7 Runtime performance of LurkerRank methods.

times, while LRin-out was slower than the other algorithms on 3 out of 5 networks — about twice the running time of LRin and LRout, which is clearly explained since LRin-out needs to iterate both on the inand out-neighborhood of each node. As concerns the alpha-centrality based formulations, ac-LRin always required a higher number of iterations to reach ranking stability than LRin, while ac-LRout performed similarly and sometimes faster than LRout, considering that in most cases both algorithms needed the same number of iterations until ranking stability. As a side remark, it should be noted that our power-iteration-method implementation of the LR algorithms caused quite different performance for networks with a number of edges of the same order of magnitude, but a greater difference in the number of nodes (e.g., FriendFeed and Flickr).

5.3 Delurking-oriented randomization

As we discussed in the Introduction, the ultimate objective of lurker analysis is in principle to attract the lurkers to the community life, that is, to change their status to that of active players in the network. Although devising real delurking plans (which might rely on marketing aspects) goes beyond our study, we are still interested in conceiving a general topology-based model that can support "self-delurking" of a network.

For this purpose, we introduce a novel randomizationlike model, named *delurking-oriented randomization*. Randomized models are commonly used to monitor how varying a certain topological feature may impact on the dynamics of the network. The most widely applied randomized model uses the concept of rewiring, so that the edges of the original (undirected) network are randomly rewired pairwise. The key idea behind our delurkingoriented randomization model is to simulate a mechanism of disclosure of the presence of lurkers, by letting more-likely-active users virtually hear from less-likelyactive users.

 $^{^1\,}$ Experiments were carried out on an Intel Core i7-3960X CPU @ 3.30GHz, 64GB RAM machine.

Algorithm 1 Delurking-oriented randomization

- **Input:** The topology graph $\mathcal{G} = \langle \mathcal{V}, \mathcal{E} \rangle$ of an OSN. The ranking *L* corresponding to a LR solution for \mathcal{G} . Cut-off percentage thresholds t_1, t_2 of ranking order in *L*. Probability *p*. Maximum fraction *d* of new edges to add to \mathcal{G} .
- **Output:** A randomized graph \mathcal{G}' .
- $1: \ \mathcal{E}' \leftarrow \emptyset$
- 2: Sort *L* by decreasing lurking score
- 3: Let L_{top} (resp. L_{bottom}) be the top- t_1 (resp. bottom- t_2) of the sorted L
- 4: $E_{al} \leftarrow \{e = (a, l) \in \mathcal{E} \mid a \in L_{\text{bottom}}, l \in L_{\text{top}}\}$
- 5: repeat
- 6: Pick randomly with probability p an edge $(a_1, l_1) \in E_{al} \setminus \mathcal{E}'$
- 7: Pick randomly with probability p an edge $(a_2, l_2) \in E_{al} \setminus \mathcal{E}'$, with $a_2 \neq a_1, l_2 \neq l_1$
- 8: $\mathcal{E}' \leftarrow \mathcal{E}' \cup \{(l_1, a_2), (l_2, a_1)\}$ /* add the new edges */ 9: until $(|\mathcal{E}'| \ge d|E_{al}|)$
- 10: $\mathcal{G}' \leftarrow \langle \mathcal{V}, \mathcal{E}' \cup \mathcal{E} \rangle$

Algorithm 1 shows our delurking-oriented randomization method, which substantially works by inserting new connections into the network each of which randomly links a vertex selected from the top of a predetermined LR ranking solution to a vertex selected from the bottom of that ranking. The algorithm hence requires cut-off thresholds to control the selection of the head and tail of the LR distribution, and a percentage threshold to control the degree of delurking-oriented randomization (i.e., the fraction of potentially new edges to add to the graph). At each step of insertion of a new pair of edges, it is to be ensured that both the new formed edges do not already exist in the graph — this restriction prevents the appearance of multiple edges connecting the same pair of vertices. It should be noted that Algorithm 1 does not provide a proper randomization model in its usual definition, since both the size of the network and the degree of vertices will change.

We applied Algorithm 1 to our networks, with the following setting: p = 0.5, $t_1 = t_2 = 25\%$, and d ranging from 0.2 to 1.0 (with increment by 0.2). Note that this setup of the algorithm was chosen to allow us to focus mainly on the degree of delurking-oriented randomization (d); as for the partition of the lurker ranking list, we decided to leave the middle 50% out and hence select one quartile both for the top (t_1) and the bottom (t_2) of the ranking list.

For this stage of evaluation, we mainly focused on two features of the network: the LR distribution and the in/out-degree distribution (either with and without the inclusion of sink and source vertices), and analyzed the pairwise correlations between a LR (resp. in/outdegree) ranking on a particular network and the LR (resp. in/out-degree) rankings obtained on the corresponding delurking-randomized networks.

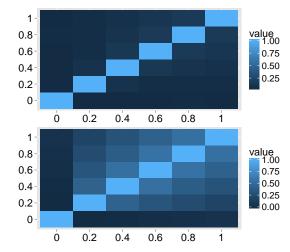


Fig. 8 Delurking-oriented randomization analysis: pairwise correlation between LRin solutions, as obtained on original network and randomized networks, for increasing degree of delurking-oriented randomization, on *Flickr* (top) and *FriendFeed* (bottom).

Considering the case where all vertices were included in the evaluation, we observed no clear trend both in the pairwise correlations between the LR ranking solutions at the different degrees of delurking-oriented randomization, which were either moderate (Flickr) or high, and in the correlations between an original LR and each of the LR solutions in the randomized networks, which were either absent (Flickr and FriendFeed) or moderate/high. However, when sink and source vertices were discarded from the analysis, trends become more evident: in one case (corresponding to the Twitter networks), the pairwise correlations between the LR ranking solutions at the different degrees of delurkingoriented randomization were moderate, while absent or moderate with respect to the original LR ranking; however, in the other case (corresponding to GooglePlus, Flickr, and FriendFeed), the LR ranking solutions at the different degrees of delurking-oriented randomization turned out to be not or scarcely correlated to each other as well as totally uncorrelated to the original LR ranking.

Interestingly, the above remarks indicate that upon a delurking-oriented randomization process, the topranked lurkers can significantly change, not only with respect to the original configuration of the network but also with respect to a configuration corresponding to a different degree of delurking-oriented randomization (shown in Fig. 8 for the LRin evaluation). Clearly, as expected, when considered as a global feature of the network, the delurking-oriented randomization impact can be lower for larger networks (e.g., *Twitter*), which have much lower (resp. higher) clustering coefficient (resp. average path length) than the other network datasets.

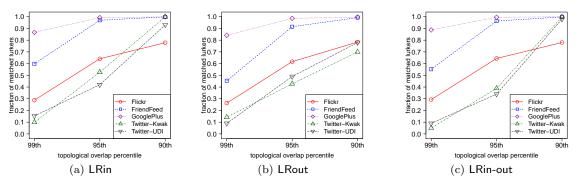


Fig. 9 Percolation analysis: fraction of lurkers matched as function of the vertices removed based on directed topological overlap.

By contrast, the delurking-oriented randomization seems to negligibly affect the in/out-degree distribution: correlations turned out to be moderate to high (when sinks and sources were considered) both between the in/out ranking in the original network and each of the in/out rankings of the randomized networks, and between the randomized in/out rankings pairwise. This result would indicate that an apparently "invasive" alteration of the topology (through the insertion of new links) actually will not significantly change the topological features based on in- and out-degree distributions.

5.4 Percolation analysis

Percolation analysis corresponds to studying the effect of network disruption via edge removal strategies, generally with the purpose of assessing topological integrity properties of the network or its vulnerability to (random) failures/attacks. An edge removal strategy is typically based on local structural properties of edges, such as topological overlap. Topological overlap is a measure originally introduced in [46] for undirected networks, which evaluates the number of neighbors shared by two given vertices i and j. Edges between connected components are expected to have a low number of common neighbors, and hence low topological overlap.

Removing edges by increasing order of topological overlap has shown to effectively detect the edges that act as *bridges* between different communities [25,48]. Upon this we build our intuition that if we would discover a certain correlation between the result of our lurker detection and the result of percolation based on topological overlap, then we could claim that *lurkers are likely to behave as bridges between communities*.

Our network model however implies that edges are directed from information-producer to information-consumer, therefore the notion of bridge as highly active user must be revised as less active user. Therefore, we needed first to adapt the basic topological overlap to our setting of directed networks, whereby the neighbor sets of any two selected vertices are partly considered according to the orientation of the edge drawn between the two vertices. Given edge (i, j), we define the *directed topological overlap* as:

$$O(i,j) = \frac{|R_i \cap B_j|}{(|R_i|-1) + (|B_j|-1) - |R_i \cap B_j|} \quad (12)$$

We developed a stage of evaluation in which two sets of vertices are compared with each other: the one resulting from an edge removal strategy based on increasing order of our directed variant of topological overlap, and the other one corresponding to the highest-ranked lurkers detected by one of our LR algorithms.

Figure 9 plots the fraction of top-25% of lurkers that matched the sets of vertices respectively included in the 99th, 95th and 90th percentile of the edges with lowest directed topological overlap. LRin, LRout, and LRin-out were used to rank lurkers. The methods appear to behave very closely to each other for all data, with some relative differences on the two *Twitter* networks. At 90th percentile of the edges with lowest directed topological overlap, almost all top-lurkers were matched on *FriendFeed*, *GooglePlus*, and only by LRin and LRinout, on the two *Twitter* networks as well. Moreover, on *FriendFeed* and *GooglePlus*, most top-lurkers were matched already at 95th percentile.

Clearly, this relatively easy tendency of covering the set of top-lurkers needs to be interpreted in relation to the ratio of the number of vertices removed (by increasing directed topological overlap) with respect to the total number of vertices in the network. While on *Friend-Feed* and *GooglePlus* the number of vertices removed corresponded to more than 90% of the total vertex set (which hence explains the high rate of coverage over the top-lurkers), on both the two *Twitter* networks, the above percentage was instead less than 27%. The latter, being observed on the two largest evaluation networks, should be taken as an important finding, which would

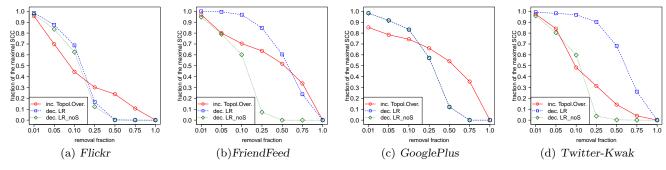


Fig. 10 Percolation analysis: fraction of the maximal strongly CC as function of removed vertices.

confirm the relationship between the lurkers and the bridges between communities.

We also analyzed the resilience of the various networks when vertices are removed by decreasing lurking order. To better evaluate the impact of sinks on the network disruption, we distinguished two cases: either sinks were preliminarily filtered out or they were included when selecting the fraction of lurkers to remove from the network. As shown in Figure 10 for LRin, the removal strategy with the most disruptive effects was that based on decreasing LR rank (with pre-filtering of sink vertices, denoted as LR_noS in the figure), which led to mostly dismantle the maximal strongly connected component (i.e., 80 to 90% of its size) already for 25% of vertex removal in all networks except GooglePlus (for which 50% of vertex removal was needed). By contrast, the removal strategy based on increasing topological overlap produced disruptive effects smoother with respect to the two LR-based strategies, on all networks. Interestingly, by including sink vertices in the selection of lurkers to remove, the network resilience was the same as in the case of sink-pre-filtering on GooglePlus and Flickr, whereas on the two Twitter and FriendFeed the resilience was higher than for the other strategies, since a level of dismantling below 70-60% was reached only by a removal fraction of 50% or higher. Note that Twitter and FriendFeed are the networks with a strong presence of sink vertices, and with a sink/source ratio greater than 10.

5.5 Qualitative evaluation

We investigated the meaningfulness of the rankings produced by LurkerRank methods as well as produced by the competing methods. For this analysis, we retrieved the OSN pages of top-ranked users and examined the available information about their profile and neighborhoods. Our goal was to understand whether a user actually looks like a lurker, or conversely s/he takes another role in the network. Tables 14–15 show the top-20 ranked users obtained on *Twitter-Kwak* and *FriendFeed* by PageRank, alphacentrality, Fair-Bets, and LRin. Table 14 also reports the number of times a user was retweeted (#rt), whereas Table 15 reports the total number of posts by a user (#posts). Moreover, we left sink nodes out of consideration in order to avoid biasing our evaluation with trivial lurkers.

By comparing the top-ranked lists, it is evident that LRin behaved differently from the other algorithms, since it shared just two users with FB (dark-grey shaded) and no users at all with PR and AC. Interestingly, the LRin top-ranked list contains only users who have never been retweeted; by retrieving the tweet post dates from Twitter, those users were all found as quite longer-time users, as in fact they joined Twitter much earlier (e.g., #8, #10 and #12 joined in 2007) than most users in the AC and PR top-ranked lists. Conversely, in the latter two lists most users have been significantly retweeted although they joined later (e.g., 2009).

PR and AC showed a certain association, with ten users in common (light-grey shaded). Most users in both AC and PR lists however were retweeted hundreds times, and hence they should not be considered as lurkers. Our hypothesis of non-lurking for those users was fully confirmed as we observed that those users' retweets were actually spread over a relatively short period of time (e.g., second half of 2009). Moreover, AC and PR ranked the same user on top, who is also the one having the highest number of retweets in the lists; indeed, that user is a very influential person, and in fact s/he has a followee/follower ratio much below 1: this would indicate that both AC and PR were not able to correctly handle this case (i.e., scoring it low enough), because their performance would be more affected by highly influential incoming links (i.e., followees) — which is a clear indication of tendency to absorb valuable knowledge — rather than by the number and type of followers. We also found other cases with characteristics similar to #1, e.g., #12 in the PR list, #10 and #14 in

the AC list, and the common users "ZAP." (#3 in both lists) and "SCO." (#17 in PR, #12 in AC).

As concerns FB, it was surprising to find that 15 out of 20 top-ranked users refer to spammers (#4, a fashion/cosmetic marketing spammer, #9, in advertising, and #15, a porn spammer), or in general to suspended accounts (#2-3, #5, #8, #10-11, #13-14, #17-20). Only #6, #12 and #16 appear to be lurkers, which might be confirmed by their high in/out-degree ratio coupled with a zero retweet-count. By contrast, #1 is an art director and designer, and #7 refers to an account actively used for academic advising purposes; probably, the high number of followees (e.g., about 1800 for #7) has misled the method. Therefore, like PR and AC, FB might also fail to correctly recognize real lurkers.

In FriendFeed (Table 15), a large intersection was found among the top-20 users not only between PR and AC (like in Twitter-Kwak) but also between FB and LRin. Looking at the users' profiles and at the contents of their posts, we can state that most of the users shared by the top20 lists of FB and LRin are recognized either as content spammers (i.e., users that have produced spamming contents, regardless of the popularity and number of their posts), or as professionals who aim to improve their visibility while staying as observers in the community (e.g., #9 in LRin/#7 in FB is a marketing expert, #7 in LRin/#5 in FB is a graphic designer). Some distinct profiles are also found to be clones, as they are associated to the same spamming contents (e.g., #1 and #4 in LRin, which correspond to #1 and #17 in FB, both probably related to a Russian commercial site). A reason for this massive presence of spammers probably can be found in the nature of the FriendFeed social network: being a real-time cross-network feed aggregator makes it a desirable and user-friendly means for spammers to reach high visibility, producing a number of user profiles for spamming attempts having very similar characteristics to lurker ones (e.g., high in/out degree ratio, low interaction with other members). Looking at PR and AC top-20 users we found that, as in the Twitter-Kwak case, most of them are not recognizable as lurkers, but rather as active and authoritative users (e.g., #7 in PR/#3 in AC is a finance blogger, #1 in both PR and AC is an industrial designer, #5 in PR/#2 in AC represents a philanthropic foundation). We also found a user shared by PR and FB top-20s: although the account does not exist anymore, its name would hint that the user was probably a spammer for a hosting solutions company.

Concerning *GooglePlus* (results not shown), the topranked list by LRin is mainly comprised of users that show poor public activity, and that added a lot of people to their circles although scarcely reciprocated. FB

Table 14 Top-20 Twitter-Kwak users by lurking score.

rank	P	2	A	r	FB		LRin	
/ Crite	user	#rt	user	#rt	user	#rt	user	#rt
1	B.O.	17811	B.O.	17811	D.W.S.	0	R.F.	0
2	W.F.	1676	ZAI.	10902	n.a.	0	R.J.	0
3	ZAP.	8707	ZAP.	8707	APA.	0	R.M.K.	0
4	TH.	7169	AS.	1172	T.S.C.	1	B.B.P.	0
5	L.E.	683	M.M.	7	n.a.	0	TR.	0
6	J.B.	1248	W.F.	1676	CON.	0	MU.	0
7	M.S.	476	M.K.	48	К.Т.	0	B.R.	0
8	AS.	1172	P.B.	328	n.a.	0	AZ.	0
9	OH.	1009	W.A.	2814	S.M.	0	O.L.	0
10	H.T.	43	C.B.	11943	n.a.	0	N.T.	0
11	E.T.	2435	EL.	902	n.a.	0	FR.	0
12	SCH.	3277	SCO.	6970	M.P.	0	D.W.S.	0
13	RE.	1467	WI.	811	n.a.	0	AW.	0
14	H.S.	1346	O.W.	1803	n.a.	0	O.B.	0
15	M.M.	7	T.B.B.	102	M.E.	0	N.C.	0
16	ZAI.	10902	T.S.	74	B.B.P.	0	D.P.	0
17	SCO.	6970	S.S.	789	n.a.	0	AU.	0
18	M.K.	48	M.W.	363	n.a.	0	EM.	0
19	WI.	811	H.R.	750	n.a.	0	DI.	0
20	W.A.	2814	A.K.	1572	n.a.	0	M.A.	0

For privacy reasons, users' names were replaced with their initials or abbreviations.

Table 15 Top-20 FriendFeed users by lurking score.

rank	PF	2	A	C	FB		LRi	in
	user	#posts	user	#posts	user	#posts	user	#posts
1	N.D.P.	350	N.D.P.	350	M.C.D.	11	M.C.D.	11
2	FRE.	3	C.T.	5	BOG.	367	BOG.	367
3	BR.	71	J.D.A.	282	L.H.	1	B.I.	61
4	A.C.	142	MBL.	37	DIM.	1	N.D.	13
5	C.T.	5	BR.	71	B.I.	61	G.A.	11
6	MBL.	37	U.R.	52	G.A.	11	L.H.	1
7	J.D.A.	282	TAV.	65	A.C.	2	R.W.	7
8	U.R.	52	D.H.	89	W.H.O.	10	ZAH.	3
9	S.M.	106	P.B.	13	ASR.	0	A.C.	2
10	W.H.O.	10	C.E.	447	H.P.B.	3	E.J.S.	24
11	RID.	886	RID.	886	MUA.	5	M.P.	2
12	D.G.	35	W.B.	5	E.J.S.	24	Y.P.	1
13	L.A.C.	4	R.T.	68	SVL.	1	S.E.	72
14	JSI.	49	K.K.	134	R.W.	7	J.N.	110
15	K.K.	134	D.S.	105	S.F.T.	4	H.P.B.	3
16	S.O.	12	L.A.C.	4	D.G.	5	P.C.	3
17	W.M.	108	JSI.	49	N.D.	13	MRT.	3
18	STR.	2	B.C.	14	I.P.G.	10	I.K.G.	2
19	C.F.	3	D.V.	85	ARG.	2	N.L.	1
20	R.T.	68	M.M.H.	34	E.E.M.	5	F.F.	764

For privacy reasons, users' names were replaced with their initials or abbreviations.

showed a behavior nearly similar to LRin, however its top-20 list contains less real lurkers than those detected by LRin. PR and AC ranked high users that are likely to be pretty influential, such as a classical guitarist with more than 60 thousand followers (ranked #1 by PR), a landscape photographer with more than 42 thousand followers (ranked #1 by AC), and even a social media director with nearly 400 thousand followers (ranked #6 by PR). In contrast to the other network datasets, there were no shared users among PR and AC top-20s, while FB shared 2 users with PR and 7 with LRin.

5.6 Some lessons learned

Our study so far allows us to draw some interesting conclusions, which are briefly summarized as follows.

Quantitative and qualitative results have demonstrated the ability of our approach in unveiling lurking cases that are intuitive yet non-trivial. The bestperforming ranking methods are those based on in-neighbors-driven and in-out-neighbors-driven lurking, i.e., the models emphasizing the first two principles underlying our lurking definition. These methods have shown high correlation with the data-driven ranking, and outperform competing methods, i.e., PageRank, alpha-centrality, Fair-Bets model, and the baseline in/out-degree ranking. Moreover, results tend to be relatively consistent over the PageRank-based and the alpha-centrality-based formulations of the lurker ranking methods. (We expect however that a different setting in the damping factor along with the introduction of a term modeling personalization or exogenous information in the respective formulas would bring to a more evident differentiation of the two ranking approaches.) From a runtime efficiency viewpoint, LRin tends to perform faster than ac-LRin, while ac-LRin-out achieves the highest rate of convergence although at the cost of much less diversified ranking scores. Furthermore, our qualitative analysis of the OSN pages of the top-ranked users has provided clear evidence that: (i) our approach successfully detects lurkers in an OSN, and conversely (ii) the competing methods fail in doing this — PageRank and alpha-centrality still detect influential users, whereas Fair-Bets tends rather to identify spammers.

From a pure network-analysis perspective, lurkers are not very prone to reciprocate each other, whereas preferential attachment is likely to occur between lurkers and the active users they are linked to. Under a percolation analysis framework, lurkers tend to be matched by users that are involved in links with low (directed) topological overlap: this would hint at a relation existing between lurkers and users playing the role of bridges between communities, under the assumption of lurking-oriented topological graph of an OSN. Finally, our proposed delurking-oriented randomization strategy reveals that self-delurking can be useful to change the top-ranked lurkers in the network, while scarcely affecting the in/out degree distribution.

6 Related Work

The topic of lurking has been long studied in social science and recently has gained renewed interest in the computer-human interaction community. [51] investigates relations between lurking and cultural capital, i.e., a member's level of community-oriented knowledge. Cultural capital is found positively correlated with both the degree of active participation and, except for longertime lurkers, with de-lurking. [18] leverages the significance of conceptualizing the lurking roles in relation to their boundary spanning and knowledge brokering activities across multiple community engagement

spaces. The study proposed in [16] raises the opportunity of rethinking of the nature of lurking from a group learning perspective, whereby the engagement of intentional lurkers is considered within the collective knowledge construction activity. The interactive/interpassive connotation of social media users' behavior is studied in [31], under a qualitative and grounded-theory-based approach. In the context of multiple online communities in an enterprise community service, lurking is found as only partially driven by the member's engagement but significantly affected by the member's disposition toward a topic, work task or social group [44]. Exploring epistemological motivations behind lurking dynamics is the main focus of the study in [49], which indeed reviews major relevant literature on epistemic curiosity in the context of online communities and provides a set of propositions on the propensity to lurk and de-lurk. However, as with [18], the paper only offers insights that might be useful to guide an empirical evaluation of lurkers' emotional traits. The study in [28] examines peripheral participation in Wikipedia, and designs a system to elicit lightweight editing contributions from Wikipedia readers.

To the best of our knowledge, there has been no study other than ours that provides a formal computational methodology for lurker ranking. The study in [23], which aims to develop classification methods for the various OSN actors, actually treats the lurking problem marginally, and in fact lurking cases are left out of experimental evaluation. Similarly, [35] analyzes various factors that influence lifetime of OSN users, also distinguishing between active and passive lifetime; however, analyzing passive lifetime is made possible only when the user's last login date is known, which is a rarely available information.

We finally mention some research studies that have focused on latent relationships or side-effect benefits in an OSN. For instance, [5] defines a Stackelberg game to maximize the benefit each user gains extending help to other users, hence to determine the advantages of being altruistic. Some interesting remarks relate the altruism of users to their level of capabilities, and indicate that the benefit derived from being altruistic is larger than that reaped by selfish users or free riders. [39] also builds upon game theory to study the property of users' departure dynamics, i.e., the tendency of individuals to leave the community. [58] studies the problem of identifying the off-line real-life social community of a given user, by analyzing the topological structure in an on-line social network like Twitter. To the purpose, user interactions are modeled in the form followee-to-follower (like in our setting), and a PageRank-like algorithm is applied over a probability transition matrix that embeds three key principles underlying the notion of off-line community, namely mutual reachability, friendship retainability, and community affinity. It should be noted that mutual reachability is not a peculiar characteristic of lurkers, i.e., it can hold for active users as well. Moreover, as for the community affinity principle, lurkers are usually not grouped into communities such that each community members are (indirectly) connected to each other; rather, as we have discussed in this paper, lurkers may lay on the boundary of a component and bridge over other components.

Relations with existing definitions of lurking. Our definition of lurking is substantially consistent with the various existing perspectives on lurking, previously mentioned in the Introduction. It can in general recognize and measure behaviors that rely on phenomena of lack of information production (i.e., inactivity or occasional activity) as well as on phenomena of information hoarding or overconsumption, like free-riding and leeching.

It is worth emphasizing that taking into account the authoritativeness of the information received as well as the non-authoritativeness of the information produced by lurkers is essential to the correct scoring of lurkers. Therefore, our definition of lurking can also explain more complex perspectives, such as legitimate peripheral participation. In this case, a lurker is regarded as a novice, for which it's legitimate to learn from experts as a form of cognitive apprenticeship. Indeed, by applying our LurkerRank methods, in [52] we have addressed an exemplary form of legitimate peripheral participation, known as vicariously learning, in the context of research collaboration networks.

Finally, note that other interpretations of lurking, such as microlearning and knowledge sharing barriers, actually aim to understand the various reasons for lurking, and to what extent they might be perceived as fruitful, rather than neutral or harmful, for the knowledge sharing in the online community. Therefore, they mostly involve sociological and psychological aspects whose study is beyond the objective of our work.

7 Challenges and future directions

The inherent complexity of lurking would advise that more information besides the network topology needs to be considered for an enhanced detection and ranking of lurkers. Some of the most challenging issues for research in this context are discussed next.

Temporal, context-biased lurking. Starting as visitors and newcomers, members of a community naturally evolve

over time playing different roles, thus showing a stronger or weaker tendency toward lurking on different times. Lurkers have unusual frequency of online presence, and hence any knowledge on the online participation frequency of the users could guide the identification of critical time intervals to reveal lurking behaviors. Moreover, the user's engagement level in the community clearly depends also on the number and type of contexts in which the user is involved.

Boundary-spanning and cross-network lurking. Some of the members that lay on the boundary of a component may bridge over other components. In Section 5.4, we have found out that indeed relations may exist between lurkers and users that act as bridges over different components of an OSN graph. To a larger extent, and given the increased interest towards cross-network services (see the latest examples of YouTube and Google-Plus), members who lurk inside an OSN may not lurk, or even take on the role of experts, in other OSNs. An analysis of the lurker ranking problem across different OSNs would represent a great potential to get a more complete picture of their users.

Lurking and trust contexts. Active users tend to avoid wasting their time with people who are very likely to not reply or show slow responsiveness, or who have few/bad feedbacks; as a consequence, lurkers could in principle be perceived as untrustworthy users. Another challenge would hence be modeling the dynamics of lurking behaviors in trust contexts [2], and ultimately understanding relations between lurkers and trustworthy/untrustworthy users in ranking problems.

While we believe this represents an important issue that deserves much attention in future studies, we nevertheless provide here a preliminary insight into a comparison of our LurkerRank methods with a classic method for ranking pages/users according to their trustworthiness, namely *TrustRank* [27]. Moreover, we further propose to integrate the ability of detecting trustworthy users (featured by TrustRank) into our LurkerRank in order to improve the *trustworthiness* of the lurkers to be detected. The result is a new set of methods, we call *TrustRank-biased LurkerRank* methods, in which the uniform personalization vector of a Lurker-Rank method is replaced by the ranking vector produced by TrustRank over the same network.

We recall that TrustRank is substantially a biased PageRank in which the teleportation set corresponds to the "good part" of an a priori selected seed set. The seed set is comprised of a relatively small subset of nodes in the graph, each of which is labeled as either trustworthy or untrustworthy by some *oracle* function. Note

Table 16 Comparative performance (Kendall tau rank correlation) of TrustRank-biased LurkerRank methods against original TrustRank and LurkerRank methods, on *Flickr*.

	LR vs. TrustRank	trust-LR vs. TrustRank	trust-LR vs. LR
LRin	.393	.436	.639
LRout	.562	.556	.980
LRin-out	.441	.640	.688
ac-LRin	.445	.434	.728
ac-LRout	.561	.559	.945
ac-LRin-out	.402	.724	.498

Bold values refer to the highest scores per method.

that unlike trust network data, OSNs do not contain explicit trust assessments among users. However, behavioral trust information in social media networks can be inferred from some forms of user interaction that would provide an intuitive way of indicating trust in another user [3]. Here we leverage information on the number of favorite markings received by a user's photographs in Flickr as implicit trust statements. (We will refer to Flickr as case in point for this evaluation, although the approach we shall present can straightforwardly be generalized to any social media network). In order to define the oracle function based on the above indicators of trust, we simply postulate that the higher the number of users that indicate trust in a user i, the more likely is the trustworthiness of i. We formalize this intuition as an entropy-based oracle function H, in such a way that for any user *i*:

$$H(i) = -\frac{1}{\log|\mathcal{V}_i|} \sum_{j \in \mathcal{V}_i} p_j \log p_j$$

with $p_j = ET(j,i)/(\sum_{k \in \mathcal{V}_i} ET(k,i))$, where \mathcal{V}_i is the set of neighbors of node i, and ET(j,i) is the empirical trust function measuring the number of implicit trust statements (i.e., favorites) assigned by node j to node i. A user i will be regarded as "good" if the corresponding H(i) belongs to the third quartile of the distribution of H values over all users.²

It is important to point out that TrustRank requires a graph model with edge orientation that is inverse with respect to LurkerRank. That is, if *i* likes a post by *j*, an edge from *j* to *i* $(j \rightarrow i)$ is created in the LurkerRank graph, whereas the opposite $(i \rightarrow j)$ is created in the TrustRank graph, as *i* indicates trust in *j*.

Table 16 summarizes Kendall correlation values obtained on *Flickr* by a pairwise comparison between our LurkerRank methods, their TrustRank-biased versions (denoted as trust-LR), and the original TrustRank. Several observations stand out. First, looking at the firstcolumn group of results, all LurkerRank methods showed positive correlation with TrustRank. This is interesting as it would indicate that the trustworthiness of users is likely to be considered when ranking lurkers; note that the LurkerRank behavior against untrustworthy users or spammers was already observed in our qualitative evaluation (cf. Section 5.5). By personalizing a LurkerRank method with TrustRank, the correlation with TrustRank itself generally increased (up to 0.72), as we expected. More interestingly, trust-LR methods still showed a strong correlation with their respective original LurkerRank methods. This suggests that introducing a trust-oriented bias in LurkerRank methods would not significantly decrease their lurker ranking effectiveness while also accounting for the user trustworthiness.

8 Conclusion

We addressed the previously unexplored problem of ranking lurkers in an OSN. We introduced a topologydriven lurking definition that rely on three basic principles to model lurking in a network, namely overconsumption, authoritativeness of the information received, and non-authoritativeness of the information produced. We proposed various lurker ranking models, for which we provided a complete specification in terms of the well-known PageRank and alpha-centrality. We have been positively impressed by results achieved on a number of real-world networks by some of our lurker ranking methods, especially in terms of significance and higher meaningfulness with respect to other competing methods. Future directions of research have also been issued.

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 $^{^2\,}$ Inferring and modeling trust in OSNs is a challenging topic per se: more refined alternatives to our entropy-based inference of trust can certainly be found.

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