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# Stars, holes, or paths across your Facebook friends: A graphlet-based characterization of many networks

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## Abstract

Network science gathers methods coming from various disciplines which sometimes hardly cross the boundaries between these disciplines. Widely used in molecular biology in the study of protein interaction networks, the enumeration, in a network, of all possible subgraphs of a limited size (usually around four or five nodes), often called graphlets, can only be found in a few works dealing with social networks. In the present work, we apply this approach to an original corpus of about 10,000 non-overlapping Facebook ego networks gathered from voluntary participants by a survey application. To deal with so many similar networks, we adapt the relative graphlet frequency to a measure that we call graphlet representativity, which we show to be more effective to classify random networks having slight structural differences. From our data, we produce two clusterings, one of graphlets (paths, star-like, holes, light triangles, and dense), one of networks. The latter is presented with a visualization scheme using our representativity measure. We describe the distinct structural characteristics of the five clusters of Facebook ego networks so obtained and discuss the empirical differences between results obtained with 4-node and 5-node graphlets. We also provide suggestions of follow-ups of this work, both in sociology and in network science.

**Keywords:** graphlets, ego networks, big Data

## 1. Introduction

For nearly 20 years, there has been a broad interest on networks across many fields of research, gathered into the terms of complex networks (Newman, 2003) or network science (Brandes et al., 2013). This trend comes after a long tradition of research in social sciences, traced back to the early 20th century with G. Simmel's social circles (Simmel, 1908), then J.-L. Moreno's sociograms (Moreno, 1934). After a frenzy of activity of anthropologists in the 1950s among which J. Barnes who coined the expression *social networks* (Barnes, 1954), an extensive quantitative framework has been formalized in the 1970s around H. White. Many accounts can be found of the formation of this field known as social network analysis (SNA) (Scott, 2017; Freeman, 2004).

A new boom of interest has come after the discovery and formalization of non-trivial properties that are shared by large networks coming from very diverse contexts (Faloutsos et al., 1999; Barabási & Albert, 1999; Watts & Strogatz, 1998; Newman, 2003). To study these so-called complex/small-world networks, new methods and tools have been designed, coming from statistical physics, computer science, applied mathematics, computational biology, economics, etc. (Bornholdt & Schuster, 2006; Easley & Kleinberg, 2010), sometimes with little (if any) reference to previous works from now classical SNA.

Along these two paths of research on networks (namely SNA and the complex networks field), some methodological approaches may produce sophisticated developments which remain quite concurrent and separate according to the disciplines in which they are used and spread. An example of this phenomenon is provided by structural analyses based on the enumeration of elementary structures. Triads, that is, triples of entities and the possible ties between them, have been extensively used since the 1970s as a methodological tool in SNA [(Holland & Leinhardt, 1976); for a survey, see (Faust, 2010)]. Decades later, this trend has led to a very active subfield on a statistical method called *ergm*, for exponential random graph models, in which specific (small) patterns are enumerated in the studied networks, and the result compared to an expected value, given a specific type of probabilistic model of random networks (Robins et al., 2007). Meanwhile in the study of biological networks (protein–protein interaction networks, for instance), a now widely used method based on the seminal work of Milo et al. (Milo, 2002) is to enumerate so-called *motifs*, which are small structures overrepresented in comparison to random networks with similar properties. The two approaches are thus very similar but the references, the exact methods, and also the terms used are widely distinct.

In the motif trend in biological networks, many works have been published during the last 15 years in computational biology, in computer science, and in statistics on the question of enumerating what has been called *graphlets*, small networks of size up to 5 or 6 (Pržulj et al., 2004). Algorithms have been devised to do it efficiently (Wernicke, 2006), including the enumeration of all possible positions of nodes in the graphlets (Stoica & Prieur, 2009; Hocevar & Demšar, 2014; Hočevar & Demšar, 2017), sometimes called *orbits*, and measures have been defined to use the results of the enumeration to compare networks of various origins (Pržulj, 2007; Yaveroglu et al., 2015). As suggested above, the motif or graphlet framework, mostly used on biological networks, has had a very low impact on the field of SNA, where the *ergm* method is prominent. On the specific case of ego networks, a key topic in SNA where the focus is made on individuals and their relational environment, only a few works have been done using the graphlet approach (Stoica & Prieur, 2009; Cunningham et al., 2013).

Dating back to the classical work of E. Bott on the network structure of households (Bott, 1957), the study of personal networks, or ego-centered networks, or ego networks, has long been an important trend to address questions ranging from homophily to agency, life change, or social capital [see, for instance, (Wellman, 2007) for a survey]. Studying ego networks retrieved from Facebook has then been a very stimulating perspective to study tie strength (Backstrom & Kleinberg, 2014), cohesion (Friggeri et al., 2011), social capital (Brooks et al., 2014), or online ties and the uses of Facebook itself (Spiliotopoulos & Oakley, 2013; Park et al., 2012), until Facebook decided to remove access to the users' ego networks for third-party applications as of May 2015 (Hogan, 2018; Nasim et al., 2016).

In the present work, we apply the graphlet approach to a corpus of about 10,000 Facebook ego networks. They have been gathered by a survey application using the platform's programming interface (API) which collected participants' data. Each network has been gathered independently from the others and no connection is made between them, for privacy reasons that have been agreed with the participants. Rather than using graphlets to categorize networks of different types (such as biological, social, or transportation networks, for instance), we describe a research framework enabling to compare similar networks to exhibit fine-grained structural properties.

Considering that random network models are hard to deal with in a graphlet-oriented study (Artzy-Randrup et al., 2004; Kovanen et al., 2011), we have designed a so-called *graphlet representativity* measure which provides insights for the analysis of specific individuals or groups of networks, as well as clustering them, without referencing to any null model. For each network of the corpus, our indicator compares the proportion of its graphlets with the proportions in the whole corpus. The same measure is used also to cluster the graphlets themselves, providing reading guides for the analysis of the corpus. Since the graphlet representativity is adapted from the relative graphlet frequency (RGF) (Pržulj et al., 2004), we used random graphs to assess the

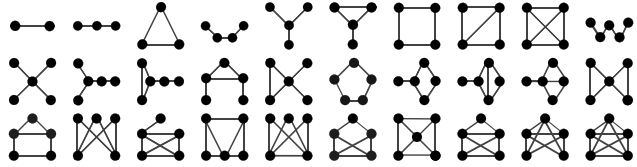


Figure 1. The 30 graphlets of size 5 or less.

benefit of using it, generating a corpus of four classes of networks structurally similar but with slight differences [stochastic block models (SBMs) with four different sets of parameters]. The precision–recall results show that the graphlet representativity clearly sharpens the performances of RGF to infer the classes of the generated graphs.

The outcome is twofold, in network science and in sociology. Indeed, it carries on the graphlet approach to work on corpuses of similar networks, which may occur in many contexts (biology, sociology, etc.). In the sociological study of personal networks in particular, our work is a contribution to bringing methodological tools and clues from the (mainly bio-informatics) graphlet community for future research on structural properties of networks of relationships.

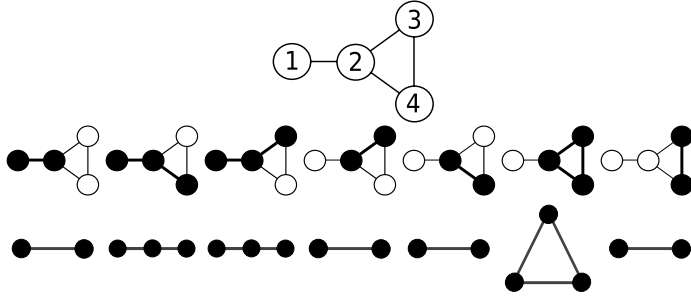
The paper is structured as follows. In Section 2, we recall the basic notions of graphlet counting, define our measure of graphlet representativity, adapted from the RGF, and present the data we will use, showing the distribution of graphlets among our corpus, distribution which constitute the reference set of values for the representativity measure. In Section 3, we look at the similarities between the different graphlets of size 5 within our dataset, providing a clustering of graphlets based on these. We then consider, in Section 4, clustering a set of networks using the graphlet representativity. We first assess the method using probabilistic generative models, and then apply it to our corpus of Facebook ego networks and exhibit five clusters of ego networks which provide significant structural characteristics. Finally, in Section 5, we discuss the interest of counting the graphlets only up to the size 4. In conclusion, we provide many suggestions of follow-ups of this work, both in sociology and in network science.

## 2. Framework

### 2.1 Graphlets

A network is usually modeled as a *graph*, which is a pair  $(V, E)$  where  $V$  is a set of *vertices* (or *nodes*) and  $E$  a set of *edges* (or *links*, or *ties*), pairs of vertices defining a binary relation between them. In the present paper, we only consider undirected graphs, that is, where the relation  $E$  is symmetric. A graph is said to be *connected* if for any pair of its nodes, there exists a sequence of edges that form a path from one node to the other. Following (Pržulj et al., 2004), we call *graphlets of size  $k$*  the collection of connected graphs with  $k$  vertices. The list of all graphlets of size up to 5 is presented in Figure 1. In order to avoid notations which would be too heavy, we consider in the whole paper that the set of graphlets is given as a numbered sequence, so we denote a graphlet by its number.

Given a graph  $G = (V, E)$  and a subset  $V'$  of  $V$ , a graph  $G' = (V', E')$  with  $V' \subseteq V$  and  $E' \subseteq E$  is called a *subgraph* of  $G$ . It is said to be *induced by  $V'$*  if  $E'$  is obtained by removing from  $E$  all the edges containing at least one vertex outside  $V'$ . The enumeration of graphlets within a graph (a network) consists in visiting (and counting) all of its connected induced subgraphs. An example for 2- and 3-node graphlets is illustrated in Figure 2. In practice, the maximum number of nodes within the combinations is usually of 3 for directed networks (Holland & Leinhardt, 1976; Milo, 2002) and 4 or 5 for undirected ones (Ali et al., 2014; Pržulj et al., 2004; Yaveroglu et al., 2015), due to combinatorial limitations. Indeed, both the number of different graphlets and the time of computation increase drastically with the value of  $k$  [for a study on the complexity for size 4, see (Ortmann & Brandes, 2017)]. Like (Ali et al., 2014), we choose here not to have a concomitant use of graphlets of different sizes. Indeed, each one of them being induced from some graphlets of higher size, we prefer to avoid being confronted with uncertain combinatorial constraints.



**Figure 2.** Example of graphlet counting up to size 3 for a small graph (on top). The middle line shows the induced subgraphs as they are visited. These subgraphs are identified to their corresponding graphlets (bottom line). All connected induced subgraphs of size less than 4 have been visited during the process. Notice that, in particular, the 2-path  $\bullet\text{---}\bullet$  is only visited twice even though it is a subgraph of the right-most portion of the graph (vertices 2, 3, 4), but the subgraph induced by {2, 3, 4} is the triangle graphlet  $\triangle$ .

With graphlets comes the notion of *orbits* [once again using the term proposed by Pržulj (2007)]. We do not use it in the work presented here but mention it for possible extensions and state of the art. The orbits of a graphlet are the equivalence classes defined on its vertices by the automorphic equivalence. Two vertices of a graph are *automorphic* if they cannot be distinguished

from each other. For instance, in the star  $\bullet\text{---}\bullet\text{---}\bullet\text{---}\bullet$ , the four nodes at the end of the branches are in the same orbit while the central node is the only one in its orbit. Another example: all the cliques  $\triangle$  have only one orbit each. There are 73 different orbits included in the 30 graphlets up to size 5.

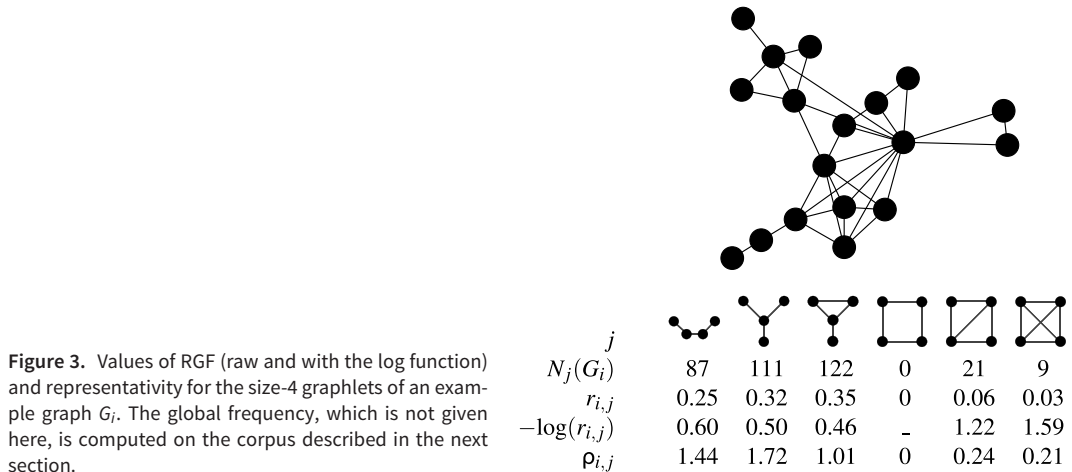
From an algorithmic point of view, graphlet counting is very expensive in terms of time of computation and thus different approaches have been proposed. Some algorithms are designed to exactly compute the number of appearances of each graphlet, with or without the orbits (Wernicke, 2006; Stoica & Prieur, 2009; Hocevar & Demsar, 2014; Pinar et al., 2017; Ortmann & Brandes, 2017) while others propose sampling strategies to have an approximate value for each graphlet (Wernicke & Rasche, 2006; Zhao et al., 2012).

**2.2 RGF and graphlet representativity**

Given a graph  $G$  and an integer  $i \in [2, 30]$ , the *relative (graphlet) frequency (RGF)* of the  $i$ -th graphlet is the ratio  $N_i(G)/T(G)$ , where  $N_i(G)$  is the number of occurrences of the graphlet within  $G$  and  $T(G) = \sum_{i=2}^{30} N_i(G)$  is the total amount of graphlets in  $G$ . This definition has been stated by N. Pržulj to design a graphlet-based distance for networks that they call the *relative graphlet frequency distance* (Pržulj et al., 2004). In his seminal paper, R. Milo uses the very similar notion of *concentration* on directed graphs (Milo, 2002). To tone down the difference of importance

between graphlets which occur a lot in real-world networks (like the fork  $\bullet\text{---}\bullet\text{---}\bullet$  or the star-like  $\bullet\text{---}\bullet\text{---}\bullet$ , for instance) and unusual graphlets (like many with a hole  $\bullet\text{---}\bullet\text{---}\bullet\text{---}\bullet$ ), a logarithmic function is applied to reduce the amplitude of the proportions. Formally, the distance between two graphs  $G_1$  and  $G_2$  is defined as:

$$D(G_1, G_2) = \sum_{i=2}^{30} |F_i(G_1) - F_i(G_2)|, \quad \text{where } F_i(G) = -\log(N_i(G)/T(G))$$



**Figure 3.** Values of RGF (raw and with the log function) and representativity for the size-4 graphlets of an example graph  $G_i$ . The global frequency, which is not given here, is computed on the corpus described in the next section.

They used it to compare protein–protein interaction networks with graphs generated according to four different random graph models.

Most of the graphlet-based methods aim at studying the deviation between networks coming from empirical data and randomly generated networks. They may even be used (Yaveroglu et al., 2015) to discriminate networks coming from various fields (social networks, protein interaction networks, various types of random networks, etc.). Some of these works compare two (typically large) graphs based on the count of the graphlets in ego networks *extracted* from each of the two graphs. Ego networks in this case are induced by 2-neighborhoods: for a given vertex  $v$ , its 2-neighborhood is the set of vertices which can be reached from  $v$  by a path of length at most 2. The graphlet count is then compared to an expectation which is computed from a reference input graph. The deviation from this reference is the basis for the comparison between the two graphs (Ali et al., 2014).

Unlike these, in our setting, we have a (possibly large) set of (not necessarily large) networks coming from one homogeneous corpus and we want to study the deviation between each network and the rest of the corpus. The corpus may be, for instance, a set of ego networks from a sociological survey (in which case, these ego networks are not extracted from a larger network), a set of protein–protein interaction networks, or of urban street networks of various cities. The input is then a set of graphs  $\mathcal{C} = \{G_1, \dots, G_{|\mathcal{C}|}\}$ .

We call *global (graphlet) frequency* of the  $j$ -th graphlet the ratio of its total number of appearances among all the graphs of  $\mathcal{C}$ , over the sum of appearances of all the graphlets of the same size in all the graphs. The idea of the graphlet representativity is then to normalize the RGF according to this global frequency, with an additional center cut operation that we describe now.

Let  $r_{ij}$  and  $R_j$  denote, respectively, the relative frequency of the graphlet  $j$  within the graph  $G_i$  and its global frequency. The ratio  $\frac{r_{ij}}{R_j}$  indicates whether the graphlet is over- or under-represented in  $G_i$ . However, it is either between 0 and 1 in the latter case or greater than 1 in the former. We thus normalize that value so that it fits between 0 and 2. The *representativity*  $\rho_{i,j}$  of the graphlet  $j$  within the graph  $i$  is defined as follows:

$$\rho_{i,j} = \begin{cases} \frac{r_{ij}}{R_j} & \text{if this value is under 1} \\ 2 - \frac{R_j}{r_{ij}} & \text{otherwise} \end{cases}$$

Figure 3 shows the values computed on a sample (ego) network from our corpus (see below for the description of the dataset).

We will also use an extended definition of the representativity applied to sets of graphs included in the main corpus. Let  $\mathcal{C}'$  be such a subset of  $\mathcal{C}$ , then we define  $r_{\mathcal{C}',j}$  as the *relative frequency* in

$\mathcal{C}'$ , which is the ratio between the number of occurrences of the  $j^{th}$  graphlet and the total number of graphlets in  $\mathcal{C}'$ . This value is actually the relative frequency (as defined in the previous section) of a graph made of the union of the graphs in  $\mathcal{C}'$ . Likewise,  $\rho_{\mathcal{C}',j}$  computed from  $r_{\mathcal{C}',j}$  and  $R_j$  like previously is the representativity of the  $j^{th}$  graphlet in  $\mathcal{C}'$ .





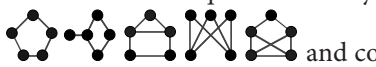



We can think of some limitations of representativity. First, a natural consequence of its very purpose is that network representativities cannot be compared to each other if they do not come from the same dataset. Now, focusing on a sub-corpus, every graphlet representativity converges to 1 (the null value) as the portion of the whole corpus in this sub-corpus grows, which means that it should not be too big in order to carry significant information.

**2.3 Data**

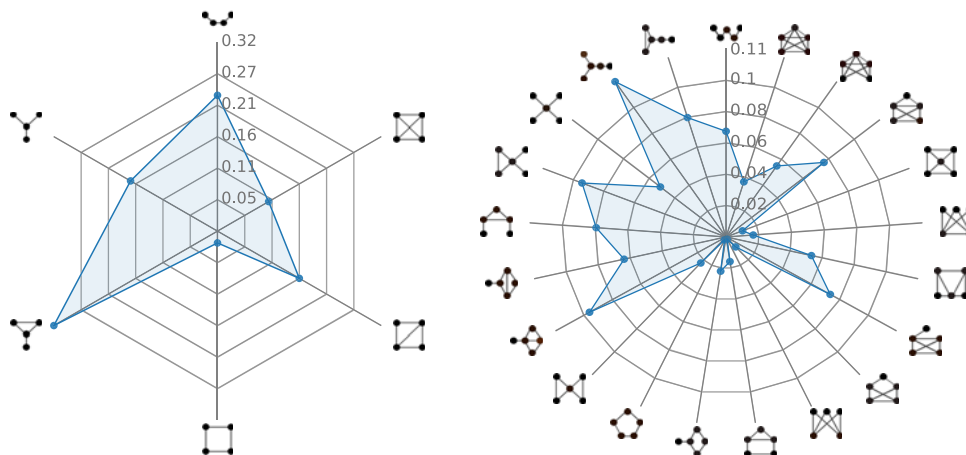
We have applied the graphlet representativity to a corpus of ego networks collected from 2013 to 2015 by an application designed for a survey on the uses of Facebook<sup>1</sup>. Besides a few questions, this application was asking for respondents' agreement to collect their (anonymized) data on Facebook (including the ties between friends, information which was available via the API until April 2015). As an incentive for their participation, the application provided, among other utilities, an interactive visualization tool showing their network of friends. Before accessing this tool, they had also to answer a few questions about their relationship to five of the friends among the most active on their Facebook page (or "wall"). They could (and some did) answer these relationship questions about more friends, by clicking on them on the map of their network. More than 16,000 people participated in the survey, among which more than 800 from a controlled representative sample recruited by a poll institute (as the application spread word-of-mouth on the web mostly through a technophile academic environment, young urban males are overrepresented among the respondents).

For each respondent (that we call *ego*), the ego network so retrieved is composed of (cryptographically anonymized) ego's Facebook friends (that we call *alters*), along with the "Facebook-friendship" ties between them, except for the alters who have opted out from their default visibility to third-party applications (in our data, these appear to have no ties at all). As is common practice in sociology [see, for instance, (Brooks et al., 2014) on Facebook ego networks as well], ego is not included as a node of the network, since it is by definition tied to all the nodes of the ego network and it would introduce a strong structural bias in the measures (besides making the visualization much less effective). Note that to make the anonymization process more effective, each respondent's network data were anonymized using a different hash key, so that there is no known overlap between any of the ego networks.





For computational reasons, in the present work, we have restricted the corpus to networks according to their size. We have kept two corpuses: one with  $N_5 = 3,694$  networks with fewer than 150 nodes for counting size-5 graphlets, one with  $N_4 = 10,252$  with fewer than 350 nodes for size-4 graphlets. Only networks with at least 15 links have been considered. Figure 4 shows the global graphlet frequency computed on these two corpuses.

The first thing one can see is that the values vary a lot. To ease the description, we will use figurative nicknames for some graphlets or groups of graphlets along with their graphical representation. The most represented graphlets of size 4 are those we call the hanger  and the path , while the clique  is less common and the square  very unusual. So are the 5-node graphlets with one or several holes  and conversely, the fork , the star-like , and some others which are quite dense , are frequent.






**Figure 4.** Relative frequencies of graphlets of our corpus of personal networks (of 4 nodes on the left, and of 5 nodes on the right). These constitute the reference values for the computation of the graphlet representativity.


It is interesting to note that the most common graphlets are not necessarily those with the most obvious structure, like the path , the star , the cycle , or the clique , which would have been easier to interpret and compute. This confirms the interest of an exhaustive counting of the graphlets.





### 3. Clustering the graphlets

Figure 4 shows that similar graphlets may not occur in similar proportions. We use here the values of graphlet representativity computed for all the networks of our corpus, to study the relationships between the graphlets themselves (focusing on size 5 in the present section). Identifying correlations might help reduce the complexity of an analysis of the networks.

Moreover, some graphlets can be seen as witnesses of clear social interactions between the alters (ego's friends) while for others it may be much more complicated. Clusters of graphlets occurring in the same networks might be more easily interpretable than isolated graphlets. For example, the

clique  is the marker of a group of classmates, coworkers, family members, usually related to

bonding ties. The central orbit of the star  indicates a special connection between ego and this alter, which is in relation with four other alters that do not know each other (try to think about who is in this position in your personal network and you will probably find your partner, closest friends or parents). Conversely, some other graphlets seem to be more difficult to read during the process of interpreting social relationships through networks, and there are several possible explanations. For example, some seem too similar to others to bring a significant difference in

terms of interpretation: the 4-clique plus 1 , very close to the 5-clique , or the star-like  to the star .

We use the *k-means* algorithm. This standard method aims at finding clusters of variables, that is, groups of variables which are closer to each other than to the ones from the other clusters. In our case, the variables representing a given graphlet are composed of ( $N_5 =$ ) 3,694 values, the representativity value of the graphlet in each network. Thus, if two graphlets have close

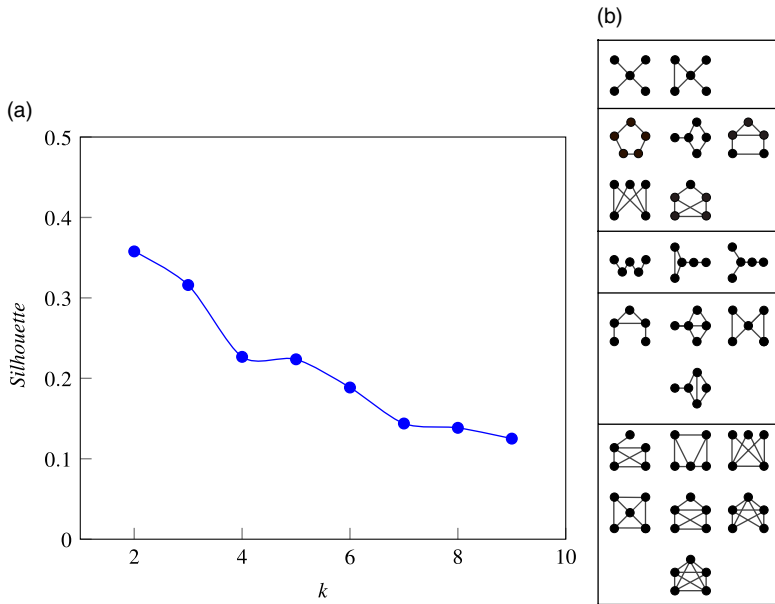





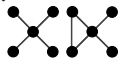



Figure 5. (a) The silhouette score of the clusterings obtained from  $k = 2$  to 9. (b) The resulting clustering of five groups.

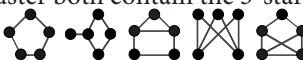

representativities for an important number of networks, they will be part of the same cluster of graphlets.

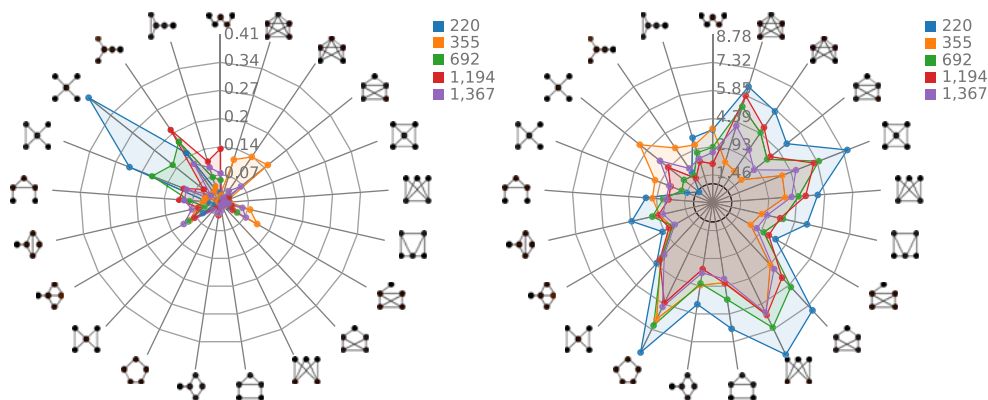
Since the  $k$ -means algorithm is not deterministic, and the number  $k$  of clusters has to be set as a parameter, we ran 100 iterations for each value of  $k$  between 2 and 9. To choose among the clusterings performed, we use the *silhouette* score (Rousseeuw, 1987), an indicator of the consistency of a cluster. Figure 5(a) that displays the average silhouette of each cluster of the best clustering per value of  $k$  suggests to cluster the graphlets into five groups. This is reinforced by an examination of the alternative choices. The 4-group clustering gathers graphlets in an unbalanced way, with a group containing half of them, while in the 6-group clustering, one graphlet is alone in its cluster. The resulting five clusters are presented in Figure 5(b). Note that most of the graphlets of size 5 from the same clusters contain the same induced graphlets of size 4.

Here are the five clusters of graphlets:


**The paths**  This cluster contains the graphlets with long paths and very few induced cycles (only one triangle in the case of the hanger ). All of them have the 4-path  twice as an induced subgraph which is also the only subgraph that they have in common.


**The star-like**  These two graphlets have a central node tied with all the other four nodes. Having the same property, the bowtie  is however separated from them. This may indicate that being a bridge between three or more nodes (and possibly cohesive groups of nodes) is quite different from linking only two. Indeed, the two graphlets of this cluster both contain the 3-star  which is not the case of the bowtie .



**The holes**  These are the graphlets containing cycles without a chord. It is interesting to note that the 5-cycle  is close to the others while it has no

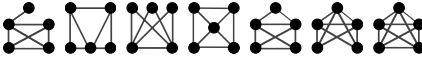





**Figure 6.** Displaying clusters using the RGF: unnormalized on the left, log-normalized on the right. The number beside each colored square gives the number of networks in the corresponding cluster.


combinatorial dependence from the square , that is included in all the other graphlets of this cluster. This suggests that most of the networks having five-node cycles also have squares.

**The light triangles**  These patterns contain triangles but do not have an important density. Underlining that, we notice that none of them contains more than twice

the triangle  and thus, more than once the diamond , which is the second densest graphlet of size 4.

**The dense**  This cluster gathers the graphlets with the

highest densities, even though three of them, the closed envelope , the Sydney opera , or the pyramid  do include subgraphs having a low density.

As we have underlined here, except for the 5-cycle , each cluster of graphlets in our corpus is in relationship with a shared subgraphlet. This suggests that they are likely to be robust on different corpuses.

#### 4. Clustering the networks

Clustering data is a good way to have an idea of how it is distributed within more or less similar groups. It also enables to compare these groups according to other variables. While the graphlet measures proposed in the literature and mentioned above successfully separate groups of networks of different origins, we have to deal here with a continuum of networks. We will thus have to keep in mind that a clustering algorithm will necessarily result in quite arbitrary frontiers between groups.

Before discussing a clustering method, we first present the visualization technique our framework uses to help interpret the clusters. Figure 6 shows the RGF of five clusters represented on a radar chart where the graphlets are put on the angle axis (as was done in (Harrigan et al., 2012) with Milo's motifs). In order to limit the visual bias which is attached to this graphic representation, we used the graphlet clustering built in the previous section to group the graphlets on the axis (a total ordering of the graphlets could be worth considering as well). The figure shows two

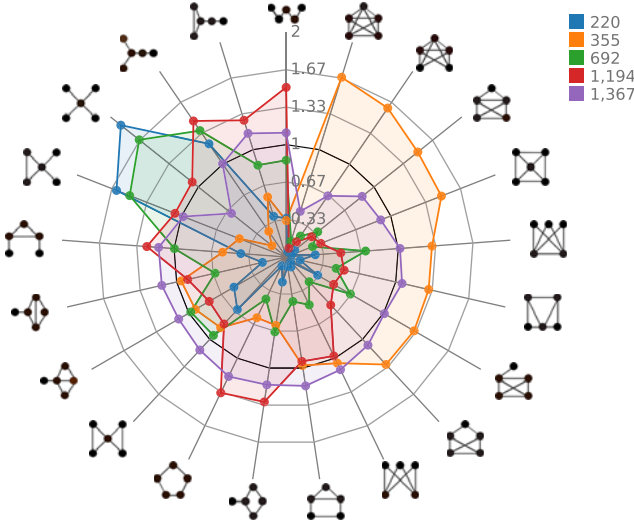


Figure 7. Displaying clusters using the graphlet representativity (clusters obtained from the RGF).

versions of the frequency defined by Pržulj et al. (2004): raw and log-normalized. In both cases, the clusters look very similar. This can be easily explained by the comparison to the RGF of the whole corpus, represented in Figure 4: as already mentioned, the frequency values are very heterogeneous over all the graphlets. This is precisely why we have defined the graphlet representativity, which we will thus use to represent the clusters, in Figure 7 as well as in the forthcoming radar charts. In this visualization, the reference value, defined as 1 for the representativity, is shown by a black solid “circle.” A dot outside this circle means the corresponding graphlet is overrepresented, a dot inside shows an underrepresentativity.

**4.1 Representativity versus RGF**

We have used the *k*-means algorithm to cluster the graphlets, we will now use that same algorithm to group the networks of our corpus. Indeed, the representativity values for the graphlets of size 5 make 21-dimension vectors for each network, which provides the input of the *k*-means algorithm. In order to assess the benefits of using our measure of graphlet representativity for this task, we compared it to the plain RGF values. More precisely, we used the *k*-means algorithm alternatively with the representativity vectors and with the RGF vectors, of graphs generated by several variations of one given probabilistic model.

We chose to use the SBM (Holland et al., 1983) to generate four classes of 50 graphs of size 50. The generated graphs are all composed of two blocks (that we will call communities), with the following parameters, selected from the ground-truth observation of our dataset:

- size of the largest community: 28 nodes
- size of the smallest community: 22 nodes
- density of the smallest community: 0.41.

Two parameters vary to produce four distinct classes:

	Density of the largest community	Connectivity between the two communities
First class	0.3	0.004
Second class	0.3	0.04
Third class	0.5	0.004
Fourth class	0.5	0.04

**Table 1.** Comparison of representativity-based or RGF-based  $k$ -means (or random clustering) to infer the classes of the ( $4 \times 50 =$ ) 200 graphs generated by SBMs.

Precision/Recall	Global		First class		Second class		Third class		Fourth class	
	P	R	P	R	P	R	P	R	P	R
Representativity	0.93	0.93	0.85	0.92	1.00	0.90	0.92	0.88	0.94	1.00
RGF	0.66	0.66	0.63	0.78	0.81	0.92	0.46	0.22	0.63	0.72
Random	0.31	0.31	0.31	0.33	0.32	0.36	0.36	0.28	0.26	0.27

To determine the sizes of the two communities, we have applied the Louvain algorithm for community detection (Blondel et al., 2008) on each of the networks in our corpus and computed the ratio of the sizes of the two largest communities. The mean ratio for the largest one is 28.6% (and the median 27.6%), while it is 22.2% for the second largest (median 21.5%). The chosen sizes respect these proportions.

The two possible values for the density of the largest community (0.3 and 0.5) have been chosen by noticing that for 33.4% of the networks, the largest detected community has a density lower than 0.3 while for 38% this value is higher than 0.5.

In a similar way, we selected the connectivity between the two communities to vary between 0.04 and 0.004, observing that 50.0% of the corpus have less than 0.4% of the possible edges between their two main communities and 19.4% have more than 4%. We took higher percentiles than previously since 37.7% of the graphs have no connections at all between their two largest communities.

We set the density of the second community to 0.41, the median of the corpus. In some previous trials, we made this value change like the density of the largest community, but it had no significant effect on either representativity or RGF, while increasing the complexity of the model and thus decreasing the performances of both measures. We have also tried to add as a parameter of our model the existence, or not, of a central node, connected to a large proportion of the other nodes, but is also had no significant effect on the graphlet measures.

We then applied a  $k$ -means algorithm to both the vectors of representativity and of RGF values for the corpus of ( $4 \times 50 =$ ) 200 randomly generated graphs and then computed the recall and precision scores of the resulting four clusters. Note that the  $k$ -means algorithm is a clustering and not a classification algorithm. Thus, in each case, we tested all the possible mappings of clusters onto the initial classes and took the best possible precision–recall values. The results, presented in Table 1, confirm that graphlet counting is a good tool to infer the initial classes in a corpus of similar networks, and moreover that our representativity measure clearly sharpens the performances of RGF. It is also worth noting that these good performances are obtained by counting only graphlets (21 values per network) and not orbits (58 values for the 5-node graphlets, with higher computational cost), unlike more recent works mentioned above.

#### 4.2 Five families of Facebook ego networks

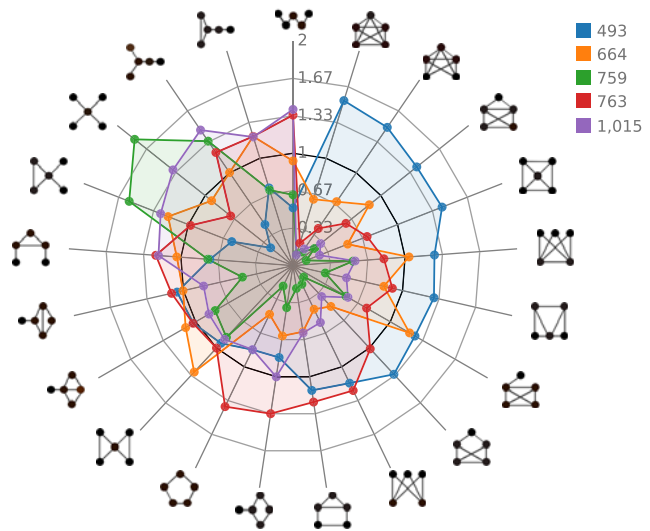
Now that we have seen the effectiveness of a representativity-based  $k$ -means to separate networks according to slight structural differences, we describe in this section the outcome of this method applied on our corpus of Facebook ego networks.

Clusters have been computed with  $k$  ranging from 3 to 10. As in Section 3, we ran the process 100 times for each value of  $k$ , keeping the partitioning with the highest silhouette score. The resulting clusters are depicted in Figure 8.

As can be seen visually, all clusters are significant and show properties of their own, while the networks of the corpus are rather well distributed. This section is devoted to a description of the characteristics of the five clusters, along with a visualization (on Figures 9 to 13) of a typical example of network for each of them, which is the closest to its centroid (the vector whose 21

**Table 2.** Structural measures per cluster.

	Dense	Bowties	Stars	Holes	Paths
Density	0.18	0.12	0.08	0.11	0.07
Clustering coefficient	0.7	0.64	0.46	0.52	0.47
Diameter	5.63	6.26	6.3	6.47	7.06
Betweenness centralization	0.15	0.2	0.35	0.17	0.23
Number of nodes	84	81	89	98	94
Number of links	625	365	291	530	327
Number of nodes in main connected component	58.1	58.2	70.8	75.5	74.1
Number of Louvain communities of size > 5	4.01	4.4	5.09	4.74	5.16
Modularity	0.39	0.52	0.56	0.46	0.58

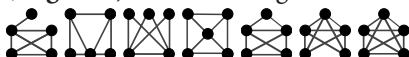


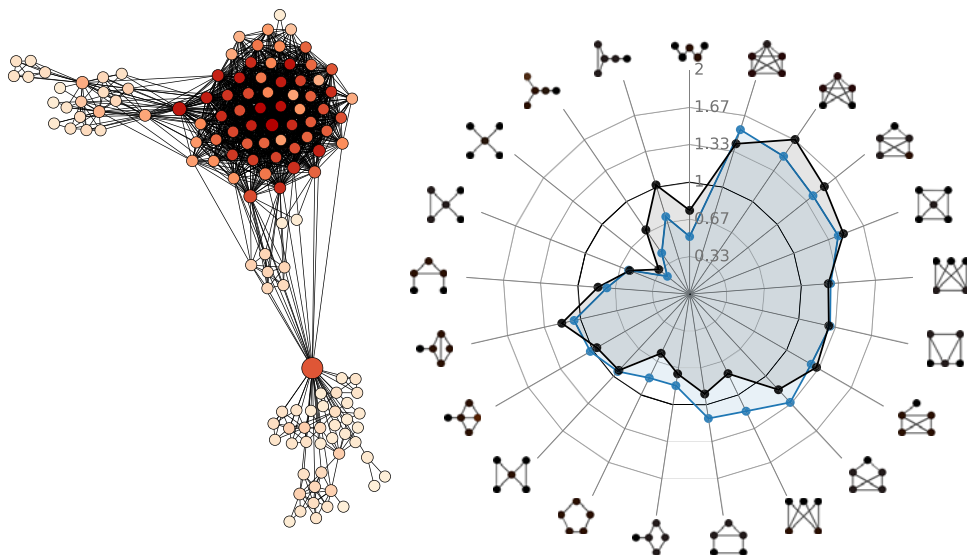
**Figure 8.** The clusters obtained from the graphlet representativity.

coordinates are average among all the elements of the cluster). For each cluster, next to the radar chart, a traditional node-link drawing of the illustrative centroid network is shown, where the size of the nodes is set according to the betweenness centrality, and the color according to the degree. The radar chart shows the representativity values of both the centroid network (in black) and its cluster (drawn in the same colour as in Figure 8).



Note that the names given to these five clusters of networks are quite similar to the names we have given to the five clusters of graphlets in the previous section. There is definitely some correlation between them that will be developed in Section 5 but these should however not be confused. Table 2 gives the mean values of some classical structural measures for the five clusters. Note that among these measures, the result of the non-deterministic Louvain community detection algorithm may vary. The last two rows of the table are computed on a single run (the modularity is computed from the result of Louvain).

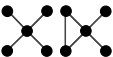
The description given below is based both on the representativity values, the structural properties, and the observation of many examples of networks picked randomly among the clusters.

**Dense cluster – 493 (13% of the corpus; Figure 9).** This cluster gathers many networks with high representativity for the dense graphlets , while low values for






**Figure 9. Dense centroid.** It is composed of many cliques and quasi-cliques inside its main group of alters (at the top of the figure). The broker between the main group and the one at the bottom has many neighbors in both groups, but when taken in one same group, they are likely to be tied to each other. It explains why there are so few graphlets from the star-like group.

paths  or star-like graphlets . On average, the networks are among the smallest of the corpus in terms of number of nodes and, quite logically, the densest. A correlation between the representativity of the dense graphlets and the density of the networks is indeed not a surprise (but we will see for other clusters that there is no equivalence). The very low representativity of


the star-like graphlets  suggests that these networks either do not have brokers (alters who create a bridge between communities), or if they do, then these brokers are not very central, as can be confirmed by the low mean value of Freeman's betweenness centralization. Accordingly, this group also has the lowest average values of diameter, number of Louvain communities, and modularity.

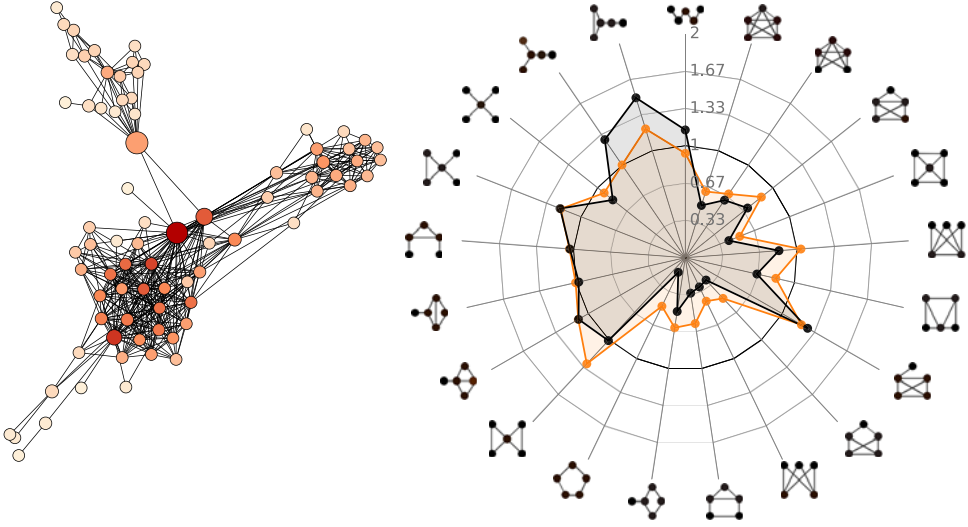
**Bowtie cluster – 664 (18% of the corpus; Figure 10).** We have chosen this group's name because


of the bowtie graphlet , whose representativity value is clearly distinct from the other clusters'. These networks are composed of different groups of alters tied by brokers. The relatively high density and clustering coefficient of the networks in this cluster, despite low representativity values for dense graphlets, indeed suggest the presence of at least small groups of connected nodes. Now these brokers are not necessarily so-called alter-egos, alters that would share most of ego's friends: these brokers most likely connect no more than two groups each, contrarily to what is observed in the forthcoming Star cluster. This interpretation is reinforced by the fact that


the star  is lightly underrepresented. Among the star-like graphlets  that appear, the two peripheral nodes probably occur most of the time in the same group but not tied to each other, or as nearly isolated nodes in the network. Evidence of pairwise connections between groups of

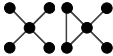



nodes may also be given by two other overrepresented graphlets . The clique-plus-one


 is particularly interesting with an overrepresentativity highest than any other dense graphlet for this cluster.



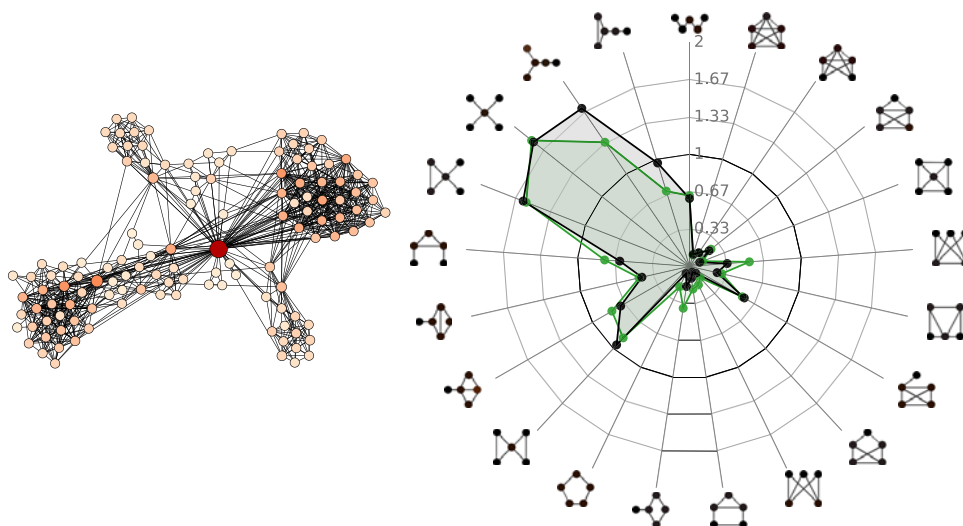
**Figure 10. Bowtie centroid.** This network offers an interesting situation. There are three groups as well as three main brokers that are connected together, forming a triangle. The two in the bottom are involved in many bowties , either including the mentioned triangle or not. Since the groups of nodes are not very dense, many path graphlets are found that probably cross the whole network.

We can also mention that the holes  have very low representativity values, which might be related to the presence of many brokers.


**Star cluster – 759 (20% of the corpus; Figure 11).** The most important representativities of star-like graphlets  are found in this cluster indicating that it is composed of many networks where one or several alters create bridges between others. This star group, unexpectedly, has the lowest representativity of the bowtie graphlet , which shows again that there is no specific relationship between this graphlet and the star-like graphlet, even though all of them contain an alter in a position of broker. It means that there is quite a difference between connecting two groups like the bowtie  does and connecting three or more groups as with the star-like graphlets . This cluster contains the networks with the highest mean Freeman betweenness centralization, which is common for star-shaped networks, and also a high mean modularity value. This once again underlines similarities between the properties of a network and of its most represented graphlets, as was seen earlier for the Dense cluster. The Star cluster has, by the way, one of the lowest representativity values for the dense graphlet, while the star graphlet itself has a low density, and the mean density value of the networks in this cluster is nearly the lowest.

**Hole cluster – 763 (21% of the corpus; Figure 12).** Here are the egos with overrepresented hole graphlets  within their network. The holes are very unlikely in general, occurring much less than other graphlets, as can easily be seen on Figure 4 with the relative frequencies. This cluster may thus put into evidence a social structure that usually remains unnoticed. There may be two structural explanations for the appearance of a hole: in a large sparse



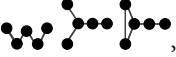






**Figure 11. Star-like centroid.** This network has a very central alter, that can be considered as a so-called alter-ego of the respondent. It is the center of many of the star-like graphlets that appear. The presence of other alters that link the groups

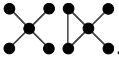
one-by-one explain why so many fork graphlets  are to be found within that network.

group of nodes or through several groups. The idea with the latter case is that if several ties exist

between two or more groups, the nodes of the square  or of the 5-node cycle  can be picked in several of these groups, with edges as bridges between them. With a sparse group or several groups connected together, it is also natural to find so many path graphlets , since the length-four path  is a shared subgraphlet.

**Sparse cluster – 1015 (28% of the corpus; Figure 13).** Here, we have the cluster with the most

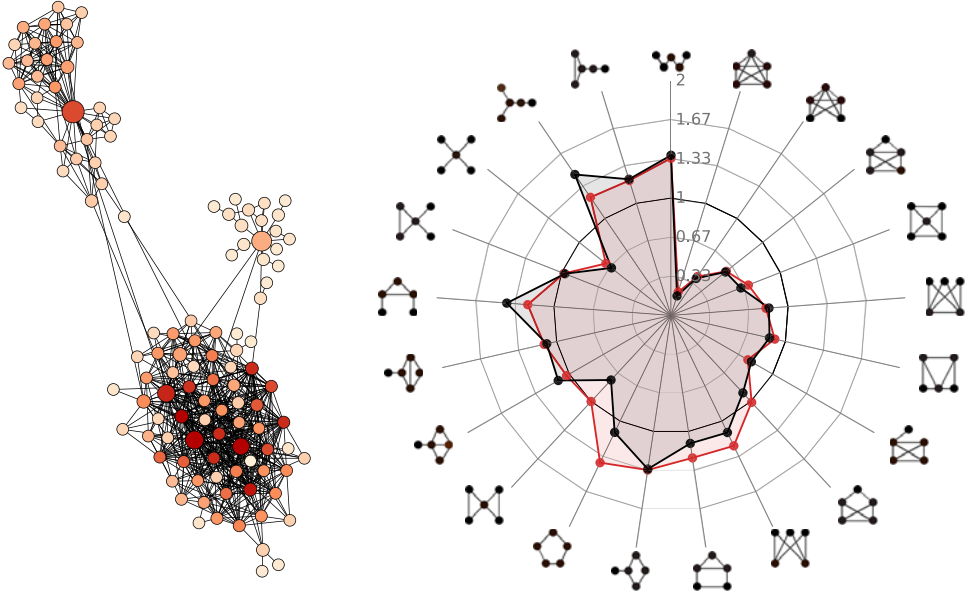
important representativities of path graphlets  with also a high representativ-

ity of star-like graphlets . Not surprisingly, these graphs have the highest diameter in average since many of them are composed of several groups that form chains of node knots. Quite logically, the networks in this cluster are poor in terms of graphlets of high density, since nodes from different groups are poorly interconnected. Note that this cluster shares, with the Hole (763) cluster, high representativity values for path graphlets, but they differ on the star-like


graphlets (more representative here) and obviously on the hole graphlets 

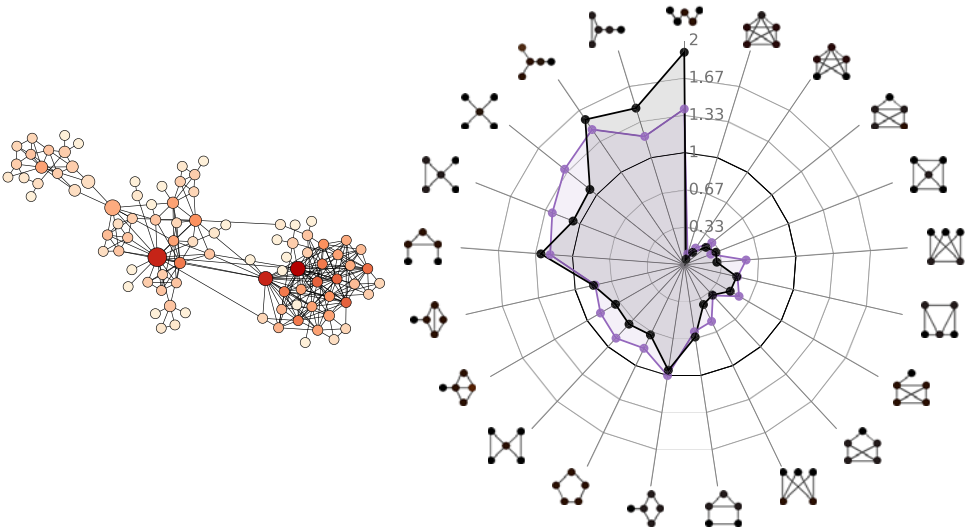
 (underrepresented here).

The observation of these five clusters of ego networks stresses the relationship between the values of structural indicators at the network level and at the graphlet level. It is indeed clear concerning the densest graphlets, overrepresented within the densest networks, for the star-like graphlets with modularity or Freeman centralization and for the path graphlets and the diameter. Moreover, the graphlet representativities are both correlated with the inner structure of groups of alters and with the ties between those groups since they also can be distributed among several of them.



**Figure 12. Hole centroid.** This network has several groups, a main one which is quite sparse, as can be guessed from the heterogeneous betweenness and degrees among the nodes, and two smaller groups that are both organized around central

alters. The largest group, much less dense than it appears, actually contains holes and the clique  is highly underrepresented in the network. This makes this network very different –structurally speaking– from the one in Figure 9 despite visual similarities (this illustrates a well-known visual bias induced by common node-link visualizations where the actual density is hard to evaluate from a packed set of lines). Also, several edges going between the main group and the two others are likely to be part of any hole graphlet.



**Figure 13. Sparse centroid.** This network is built like paths linking small groups of alters. These being sparse, there are many opportunities of finding, as induced subgraphs, paths that cross them. As there are no central alters that reach several groups, the star-like graphlets as well as the bowtie are a bit less represented in this specific network than on average in the rest of the cluster of networks.

**Table 3.** Age distribution among each cluster of networks (those described in Section 4.2). The sum of each column is 1 up to rounding errors. The age is the one declared by the respondents in the survey application.

Age	Dense	Fork	Star-like	Hole	Bowtie	All
18–25	0.42	0.26	0.11	0.42	0.26	0.28
26–40	0.32	0.46	0.56	0.31	0.45	0.43
41–60	0.22	0.25	0.3	0.24	0.27	0.26
60+	0.03	0.03	0.03	0.03	0.02	0.03
Pop.	322	614	487	494	401	2318

**Table 4.** Distribution of the relationship status among each cluster of networks (those described in Section 4.2). The sum of each column is 1 up to rounding errors. The relationship is the one declared on the Facebook page of the respondents, when available.


Facebook relationship	Dense	Fork	Star-like	Hole	Bowtie	All
Single	0.42	0.27	0.14	0.4	0.31	0.29
Couple	0.27	0.39	0.36	0.34	0.32	0.35
Married	0.31	0.34	0.5	0.26	0.37	0.36
Pop.	197	450	414	328	278	1667

### 4.3 Hints on socio-demographic data


We have provided a clustering of our corpus of networks based on the graphlet representativity, along with interpretative elements in terms of network structure. We now add supplementary data from our survey, in order to show that graphlets may be a useful element in a sociological analysis based on a corpus of ego networks. We have combined two variables, the age and the relationship status of our respondents, with the clusters obtained in the previous section. The results are presented in Tables 3 and 4.

We find two classical results. Young persons have denser networks (42% of dense networks' egos are less than 25 years old), which is due to the number of different social groups that they usually have met in their lifetime (Bidart & Lavenu, 2005; Kalmijn, 2012) (and this is even truer for students). Moreover, groups of young adults appear to have much more Facebook friendship ties (university cohorts, for instance).

The Hole cluster of networks is, with the Dense cluster, the one with the youngest population.

We make the hypothesis that a high representativity of hole graphlets  in a network may often be explained by a high homophily among the alters despite a relatively low density: friends of ego may, for instance, have similar ages or social backgrounds. Young people are more likely to be associated with other persons of their age and cultural environment, which should lead to either big groups of alters with a rather low density or unexpected ties between several denser groups through alters that are not necessarily very central in the network.

The other unsurprising result is the prominence of married persons in the star-like cluster that confirms previous findings (Bidart & Lavenu, 2005; Kalmijn, 2012; Backstrom & Kleinberg,

2014). Since a central node of the star-like graphlets  is in relation with at least three persons that do not know each other, it surely has a central position within the whole network. Moreover, there are chances that the central position of these most frequent graphlets is to be matched with the same few nodes (or even one node) in each network, and that one of them is ego's lover (partner, spouse, etc.)

The discrepancy between the populations of the two tables comes from the fact that some people did not answer all the questions of the survey or did not inform their relationship status on

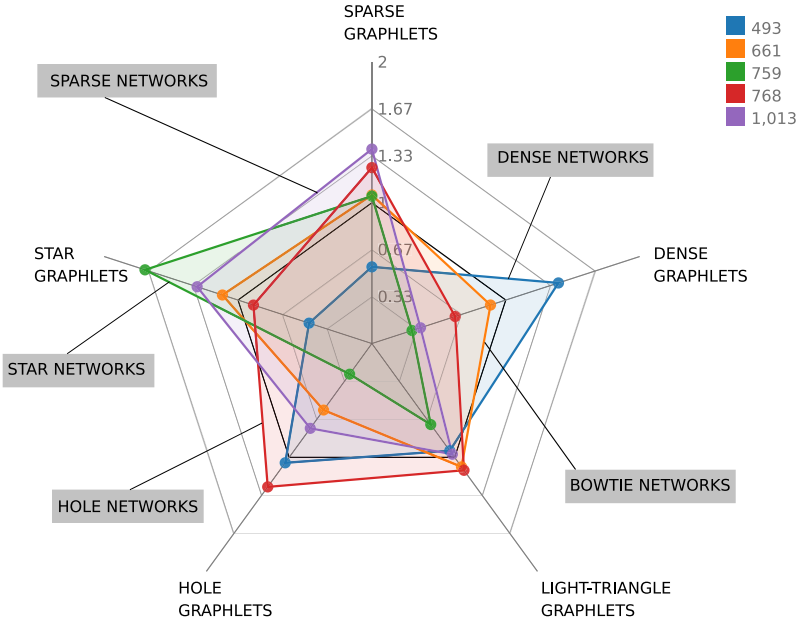






Figure 14. Network clusters depending on the clusters of graphlets.

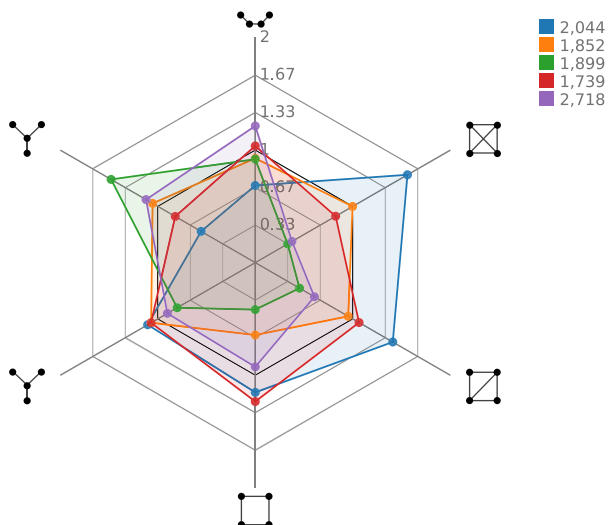
Facebook. It is the occasion to question the variability of the willingness to share private information with a platform like Facebook versus with sociologists. For instance, some respondents gave Facebook aberrant values for their age while giving more credible answers to our survey. Our survey did not ask for the romantic status but it is noteworthy that the ratio between the number of persons who gave it to Facebook and the number of those who gave us their age varies significantly from one cluster of networks to another: it is 0.61 and 0.66 in the Dense cluster and the Hole cluster, respectively, while 0.72 in average. This might indicate that young people (more present in these two clusters) are less eager to give their relationship status to Facebook. In the meantime, the Star cluster is the one with the highest value for this ratio, so it may just indicate that married people (more present in this cluster) are more likely to advertize it than single people (of course more present among young users).

**5. Shifting to 4-node graphlets?**






We have obtained in Section 3 five clusters of rather similar graphlets, and in Section 4 five clusters of networks grouped according to the distributions of the graphlet representativity values. Figure 14 sums up the combination of these two clusterings, presenting our corpus of networks in a very sketchy visualization. A much simpler way of simplifying the analysis would have been to count only the 6 graphlets of size 4 instead of clustering the 21 graphlets of size 5. As already mentioned, the time complexity of the computation of the graphlet enumeration made us choose to put an upper limit to the size of the networks in our corpus.

Figure 15 shows the result of a clustering of the networks of our larger corpus of 10,252 networks. As with the previous clustering, we obtain a (blue, 2,044) cluster with high representativities of the dense graphlets and a (purple, 2,718) cluster with overrepresented paths  and stars .

The (orange, 1,852) cluster is more likely to correspond to the Bowtie cluster since it has a bit more cliques  and hangers  than other clusters. Unfortunately, this cluster as



**Figure 15.** Clusters obtained by a  $k$ -means algorithm with the representativity data of the graphlets of four nodes.

well as the one with the highest representativity of squares  (red, 1,739) are clearly more difficult to read here than in the case of 5-node graphlets since they do not have representativities very far from 1. The specificity of the bowtie graphlet  compared to the star-like graphlets   , discussed in the previous section, is an example of structural properties that can hardly be caught with the size-4 graphlets.

To be able to formally compare these two clusterings, we have used the Rand index, a measure of how two clusterings are close to each other. Its result is between 0 (for two identical clusterings) and 1 (for two clusterings with no agreement). In the comparison of the clustering made through 21-dimensional vectors from the graphlets of size 5, and the clustering made through 6-dimensional vectors from the graphlets of size 4, we can compute the Rand index limited to the smaller networks that appear in both cases. The score of 0.79 we obtain indicates that there is a high similarity between them. Of course, some networks were moved from a cluster to another but their cores are preserved.

The clustering based on graphlets of size 5 is more interesting in the sense that the various clusters are easier to interpret and to understand, with much richer structural configurations. But the relatively good value of the Rand index suggests an empirical trade-off between insight and performance: once clusters have been computed the expensive way with 5-node graphlets for networks of limited sizes, the larger networks may be attributed to clusters according to the faster computation based on the 4-node graphlets.

## 6. Conclusion, future work, and applications

After recalling the principle of graphlet counting, and the measure of RGF mostly used in bioinformatics (Pržulj et al., 2004), we have defined what we call graphlet representativity, to study structural variations between networks from a possibly large homogeneous corpus, and applied it to a corpus of Facebook ego networks. With this measure, we have first produced a clustering of the 21 graphlets of size 5 into 5 groups of graphlets (path, star-like, hole, light triangle, and dense). Both these graphlet clusters and the representativity itself provide a useful visualization scheme with radar charts [which can be compared to what was done by (Harrigan et al., 2012), helping the process of designing a clustering of the ego networks of our corpus. We have assessed

the ability of the graphlet representativity to infer the initial classes of random networks generated by SBMs, with a clear benefit over the RGF, even without using orbit counts (which gives more structural information). We have then been able to exhibit five clusters of networks with shapes that are consistent with the structure of their most represented graphlets (dense, bowtie, star, hole, and sparse), putting into evidence non-trivial structural properties such as the distinction between bowtie graphlets (for more local centrality) and star-like graphlets (for more global centrality), or overrepresentativity of (generally unlikely) holes in some networks. This shows the relevance of counting all the graphlets rather than selecting only some of them, despite the computational cost. As for computation, we have shown that the enumeration of the 4-node graphlets is a powerful tool even if it is not as rich as the enumeration of 5-node graphlets. We have thus proposed a progressive analytical workflow, joining the richness of the latter and the efficiency of the former.

Now from a sociological point of view, with the graphlet representativity measure and five categories of ego networks based on it, one can investigate many questions about the nature of Facebook ties, the structure of personal networks, and the relationships between the two. A first lead to address these would be to explore, for each ego, the subpart of the network of friends induced by the alters who comment on ego's posts. A network of friends can be seen as a base map upon which the activity is performed by only a fraction of alters who play the actual Facebook game in ego's social life. The graphlet representativity might be used to compare the structure of the networks of Facebook friends and of Facebook commenters. One would of course consider the networks of commenters as a separate corpus, by recomputing the reference graphlet frequencies for the computation of the representativity values, and then compare, for each ego, their two networks. With or without the structures of the networks of commenters, one might investigate the social meaning of some characteristic structures: what types of activity and interaction take place among networks with overrepresented dense graphlets? Are path-like graphlets only a sign of a lack of engagement in the platform? Do networks from the Bowtie or Star clusters contain distinct cohesive subgroups with separate public conversations with ego? This question is also related to qualifying the social meaning of subgroups of alters among the ego networks, which can be addressed with the answers to the short survey about ties between ego and at least five of their most active alters (which are qualified as family, coworkers, lover, spouse, etc.), and with the co-occurrences of alter comments on ego's posts, of tags, etc. This may also be a way to investigate whether, as was hypothesized in Section 4.3, networks with an overrepresented amount of hole graphlets indicate a high level of social homophily.

Working on subgroups may also be done by considering a corpus of "communities" in the heuristic sense of groups returned by the so-called Louvain community detection algorithm (Blondel et al., 2008). The networks in our corpus have a mean number of about six such groups, which would make a corpus of about 60,000 small networks upon which to compute reference graphlet frequency values, then graphlet representativities. Ego networks would thus be analyzed according to the types of groups they are composed of. Another method to untangle the ego networks is to investigate structural roles of alters, which may be done by keeping tracks of the alters which appear in each position of each graphlet while counting. These positions are what is called orbits in the graphlet literature. One could compute the graphlet representativity of all the orbits in the ego networks of our corpus, which would exhibit social roles among the networks. These structural roles are of course to be related to the interaction data of the alters with the egos, and with the information the respondents have given about their relationships with some selected friends. The special case of the structural positions of lovers (partners, spouse, etc., categorized as such by the respondents) is a first issue that can easily be addressed. Furthermore, to all the issues mentioned above, the findings may vary according to socio-demographic variables such as ego's profession, age, and city of residence, which have been collected in the survey. Now more generally, all these directions are indications of analyses that can be performed on other corpuses of personal networks, regardless of how they are collected, including traditional surveys with manual recording by the respondents themselves.

Of course, our approach is applicable to other types of networks, including non-ego networks, including networks of non-social ties, as, of course, protein–protein interaction, but also functional connectivity among brain regions, citation links between documents, etc. As soon as one needs to compare and categorize many networks of the same kind, the approach presented here is relevant. Moreover, on networks of various origins, one could investigate how the graphlet representativity compares to methods mentioned in Section 2.1 to categorize them.

Regarding the technical aspects of graphlet counting, there may also be follow-ups to the present work. In particular, the relationships between graphlets of size  $k$  and of size  $k + 1$  are of course a key issue in the combinatorial and probabilistic aspects of the problem. Comparing the relative representativities of dependent graphlets might be a way to investigate and measure these dependences.

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**Resources.** Both the source code (to enumerate the graphlets, compute their representativity, detect the clusters, and display the radar charts<sup>2</sup>) and the data (Facebook ego networks and socio-demographic information on the egos<sup>3</sup>) are available online.

**Conflict of interest.** Raphaël Charbey and Christophe Prieur have nothing to disclose.

## Notes

1 The dataset is available at <http://www.enst.fr/~cprieur/algopol>. The (anonymized) data collection process was designed in close relationship with the national public organization in charge of the privacy policies.

2 [https://github.com/rcharbey/Graphlet\\_Representativity](https://github.com/rcharbey/Graphlet_Representativity)

3 <http://www.enst.fr/~cprieur/algopol/>

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