Unfolding #Anonymous on Twitter: The networks behind the mask
by Davide Beraldo

Abstract
This paper presents a comprehensive empirical investigation of the range of actors, issues and sub-groups related to the hashtag Anonymous on Twitter between 2012 and 2015. Complementing existing studies that have provided in-depth accounts of Anonymous from a specific point of view, this research provides an overview of the network related to the discursive construction of Anonymous on Twitter from a synoptic standpoint. In particular, the analysis covers three dimensions: the structure and dynamics of the #Anonymous interaction network; the range of issues that Anonymous has been associated with; and the relation between Anonymous and its offshoots. This research provides a descriptive characterization of the topological and semantic complexity of Anonymous and invites to reflect on the simplifications that our vocabulary and methods entail vis à vis the complexity of digital entities delimited by and individuated through hashtags.

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Introduction: What is Anonymous?

Started around 2004 as a collective noun adopted on the online platform 4chan, Anonymous quickly evolved into a proper, though *sui generis*, actor of political contention (Coleman, 2013). It kept mutating through a series of ‘saltations’, signalling a shifting organizational logic (Uitermark, 2017), partly related to the affordances of the media platforms it appropriated. The emergence and reproduction of Anonymous as an entity should be understood as the effect of processes of ‘designation’ (Dunn Cavelty and Jaeger, 2015), according to which a variety of actors recognize its identity and attribute it with agency. Its internal composition derives from recurrent ‘identity claims’ (Dobusch and Schoeneborn, 2015), resulting from conflict and negotiation around the authenticity of the attribution of specific actions to the collective. Its symbolism works as a ‘memetic signifier’ (Gerbaudo, 2015), an ‘improper name’ (Deseriis, 2015), or a ‘contentious brand’ (Beraldo, 2020a, 2020b) — it is a set of semiotic elements open to be appropriated by a variety of actors and contributing to contrasting political (and non-political) causes (Fuchs, 2013). For all these reasons, it is extremely challenging to grasp Anonymous’ ontological status, which is somewhere in between categories such as movement, network, swarm and multitude (Wiedemann, 2014).
The journalistic discourse often tends to misrepresent Anonymous, reporting it as a unified and unique entity, and opportunistically alternate its framing (Klein, 2015). By contrast, existing in-depth studies on Anonymous (e.g., Coleman, 2015; Firer-Blaess, 2016; Olson, 2013) highlight its counter-intuitive character, as well as the heterogeneity in biographies and motivations that characterize the many faces of Anonymous activism. Nonetheless, these contributions tend to focus on a selected core of biographies, phases, and platforms, mainly depicting Anonymous as a loose, global network tied together by the cult of Internet freedom. Complementing existing knowledge, this study offers a descriptive characterization of Anonymous between 2012 and 2015 from a global/holistic perspective, as afforded by digital methods applied to Twitter data. Despite few exceptions (Beraldo, 2020a), very limited attention has been put on unfolding the complex articulation of the actions, mobilizations and groups ‘branded’ with the name and symbols of Anonymous, especially in recent years.

While the users including the hashtag #Anonymous in their tweets do not all necessarily correspond to Anonymous participants stricto sensu, mapping the structural and substantial properties of the discourse and publics related to Anonymous on this specific platform, in this specific time span, and through these specific methods allows us to learn about a number of trajectories relevant to Anonymous as a whole, as well as to reflect on the implications of the methods adopted. Consequently, the goals of the paper are both descriptive and methodological: it contributes original knowledge about Anonymous on a global scale; and it invites to reflect upon the entanglement between the methods adopted and the ‘stories’ that can be told through them.

This paper presents a comprehensive empirical investigation of the range of actors, issues and sub-groups related to the hashtag #Anonymous on Twitter between 2012 and 2015. What story does a large dataset of tweets marked with the #Anonymous hashtag tell us about this elusive (non-)collective? Based on previous knowledge, we can expect that the results of the analyses provide a fragmented, multifarious picture of Anonymous both from a structural and dynamic, as well as topological and semantic point of view. More in particular, the question is addressed along three dimensions: 1) What are the structure and dynamics of the #Anonymous interaction network?; 2) What is Anonymous concerned with and fighting for?; 3) What is the relation between Anonymous and its offshoots?

Unfolding the #Anonymous network on Twitter

This paper explores the structural-dynamic properties of an online network of interaction (Borge-Holthoefer, et al., 2011). The analysis is inspired by approaches such as digital methods (Rogers, 2013) and (digital) actor-network theory (Latour, et al., 2012; Venturini, 2012).

The empirical sections investigate different networks on Twitter related to the hashtag #Anonymous. The reason for choosing Twitter data is related to the prominent role this platform plays for Anonymous’ ‘PR’ and propaganda activity, as well as the research affordances (Weltevrede and Borra, 2016) it provides: the possibility to trace large-scale and long-term networks of communicative interaction related to publics (Bruns and Burgess, 2011). The strategy is to ‘follow the hashtag’, so as to open up the black box of what is commonly referred to as a unique entity (Beraldo, 2020a).

The main corpus of analysis is a dataset of three years of activity on Twitter (1 December 2012 — 30 November 2015), collected by exploiting Twitter Streaming API, following the hashtag ‘#Anonymous’ [1]. The resulting dataset corresponds to 6,754,197 tweets carried out by 1,296,589 unique users. Networks have been variously filtered and split for specific analytical purposes, as detailed in each section.

It must be stressed that this dataset, no matter how huge, is not a statistically representative sample of Anonymous’ overall activity on Twitter (Morstatter, et al., 2013), and by no means is it a comprehensive outlook on Anonymous as a whole. First, the time span included leaves out crucial phases of Anonymous’ evolution; however, this contributes partial coverage provides enough information in terms of general trends and peculiar associations. Second, Twitter is only one among the many media adopted by Anonymous, so this
work is not an exploration of Anonymous as a whole, but rather of Anonymous on Twitter. As already said, though, the publicity scope associated with Twitter is in line with the goals of this analysis. Third, the hashtag-based selection of data leaves out relevant tweets and introduces sampling biases; nonetheless, the emphasis on long-term dynamics and the exploratory character of the analyses largely temper this concern.

**Anonymous-as-entity and Anonymous-as-discourse**

There is also a more elaborate epistemological consideration which deserves to be put forward. On a more general level, the set of tweets including the hashtag #Anonymous does not correspond to Anonymous as such. In more appropriate terms, the dataset relates to the discourse around Anonymous and the publics articulating and articulated through such discourse.

This focus is at the core of digital methodological approaches to social phenomena on digital media, understood as issues and controversies articulated by a range of actors (Marres and Moats, 2015; Venturini, 2012). Twitter and hashtags-articulated publics are considered an elective entry point for this type of analysis, considering its publicity, real-timeness and accessibility (Bruns and Burgess, 2011).

Even though the dataset collected does not only comprise ‘authentic members of Anonymous’, but includes a range of actors (sympathizers, commentators, detractors), it does trace dynamics relevant for Anonymous as such, especially considering the fact that, in relation to this entity, notions such as membership and authenticity loose substantial meaning (Beraldo, 2020b).

Studying Anonymous through digital methods, then, means studying the discourse articulated by publics around it (Beraldo, 2020a; Marres and Moats, 2015; Venturini, 2012), an epistemological choice even more reasonable considering Anonymous’ identity being a purely discursive construction (Dobusch and Schoneborn, 2015; Dunn Cavelty and Jaeger, 2015).

Besides these epistemological considerations, there are also methodological reasons to justify translating claims made about Anonymous-as-discourse to claims made about Anonymous-as-entity.

For what concerns the first analysis (users’ interactions), it is true that users’ interacting on Twitter do not include only participants directly and substantially engaged with Anonymous. However, an overview of the most central nodes shows notorious accounts directly associated to Anonymous activities (e.g., @AnonOps, @AnonCentral, @YourAnonNews). Moreover, the dataset has been reduced by filtering out less recurrent users, which ensure that a consistent and/or persistent interest of the users towards Anonymous is present. This interest might take several forms, but it cuts out random bystanders and occasional commentators, leaving key actors that altogether contribute to the discursive construction of Anonymous.

The second analysis, in turn, concerns itself with the level of the objectives and themes of Anonymous in the time span considered. There are good reasons to assume that focusing on Twitter publics is a suitable option for this goal. Whereas the sampling might be biased by the selectivity and specificity of Anonymous’ presence on Twitter, the focus on a specific set of hashtags (the meta-hashtag ‘#Op-’, denoting actions directed towards a specific goal) and the ‘real-time’ logic of the platform ensure that the analysis captures existing, likely ongoing Anonymous operations. This does not allow to make exact generalizations about the distributions encountered (e.g., the exact relative proportion of an issue over the total), but allows to make descriptive claims about the focus of Anonymous actions in the time span considered.

A similar argument is valid for the third section’s focus on sub-groups. There is no guarantee that the numbers and visual representations elaborated by the analysis correspond to actors participating in the entities. However, what is relevant to the analysis is the discursive existence of these offshoots, as well as their structural relation among each other.

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**Interactions, issues, offshoots**
**The dynamics of the #Anonymous interaction network**

This section focuses on the structural evolution of the network of interactions between users. It will concentrate on patterns of stability, compactness and centralization, showing how the network surrounding the hashtag #Anonymous on Twitter demonstrates oscillating behavior.

A network of interaction has been built, linking each user who sent a tweet with each of the users included in the text of the tweet; thus, different Twitter relations (retweets, mentions and replies) are treated as general signatures of interaction. For simplicity, the network has been treated as non-directed. A threshold of five tweets sent has been set: under this threshold, users were discarded from the network. This operative choice should increase the validity of the operationalization, since it cuts off random noise and retain only users who are consistently associated with Anonymous. This operation resulted in a network of 113,743 nodes, tied by 1,025,904 edges. The network was then divided into monthly snapshots, so as to derive a structure more reflective of the dynamic nature of the phenomenon, and in order to allow for the observation of patterns of evolution. Due to a consistent number of missing observations, the month of July 2014 and its other related variables have been discarded.

**Stability**

Stability is assessed here across each contiguous month, considering three elements: the users involved — *i.e.*, network nodes; the links among users — *i.e.*, network edges; and the clusters of interaction among users — *i.e.*, network modules. The first variable (stable nodes) simply considers the proportion of active or mentioned users that are present in both months constituting each time interval. The second variable (stable edges) focuses instead on the persistence of a link between two users across months. The third variable (stable modules) considers whether users tend to belong to the same cluster of interaction, as computed by a so-called community detection algorithm.

**Table 1** summarizes the results, presenting the minimum, maximum, average and standard deviations of each variable.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Average</th>
<th>Standard deviation</th>
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<tbody>
<tr>
<td>% stable nodes</td>
<td>32.0</td>
<td>61.0</td>
<td>47.8</td>
<td>7.4</td>
</tr>
<tr>
<td>% stable edges</td>
<td>4.0</td>
<td>19.0</td>
<td>12.5</td>
<td>3.1</td>
</tr>
<tr>
<td>% stable clusters</td>
<td>2.0</td>
<td>17.0</td>
<td>7.4</td>
<td>4.1</td>
</tr>
</tbody>
</table>

Despite the fact that the lack of a benchmark does not allow for making definite claims concerning absolute values, the data are nevertheless quite clear in depicting the unstable character of the network. On average, the stability of nodes scores 47.8 percent, which means that more than a half of the nodes observed in one month are not included in the network of the following month. However, nodes stability oscillates quite a lot around
this average, ranging between 32 percent and 62 percent. As for the recurrence of links between users, the average stability across months is 12.6 percent and oscillates quite a lot across various time intervals: from 4 percent to 19 percent. Consequently, the vast majority of connections among nodes are rather contingent. Similarly, the stability of clusters of interaction is extremely low, scoring 7.4 percent on average, and oscillating between 2 percent and 18 percent. This means that the network is not composed of recurrent communities of nodes that are tightly connected to each other. Comparing the first and the last snapshot — December 2012 and November 2015 — gives a better understanding of how the network has mutated over three years. Out of the 22,042 final users, only 1,851 were part of the network in its first instance, corresponding to 8.4 percent. Similarly, the share of persistent connections amounts to 0.25 percent, while the proportion of nodes belonging to the same cluster of interaction is 0.01 percent. As noted, the level of stability is itself rather unstable. Is this associated with a trend toward progressively greater stability or instability? In order to answer this question, Figure 1 plots the data on a longitudinal axis.

Figure 1: Interaction network. Trend of stability measures across time (month/previous month). The proportion of stable nodes (red line), edges (black line) and clusters (gray) is plotted against each time interval. The components of the network are in general non-recurrent.

The distribution across time intervals of the different definitions of stability — nodes, edges and cluster stability — highly correlates, though no specific trend can be observed. We can observe peaks of stability between January and February 2013, November and December 2013, and November and December 2014. Conversely, between October and November 2013, October and November 2014, and June and July 2015 there is a wide reshuffling in the composition of the network. It is worth noting that 5 November is a topical day for Anonymous: the anniversary of the plot perpetrated by Guy Fawkes — the British plotter whose mask is Anonymous’ well-known icon. This may explain the recurrence of peaks of instability in the snapshot preceding the event and of peaks of stability in its aftermath: the resonance of the celebration provides a boost of new recruits, whose involvement lasts throughout the following month.

The analysis of the stability of nodes, links and clusters suggests that the Twitter network around the hashtag #Anonymous presents an ever-shifting composition; the turnover oscillates itself, but without exhibiting any
pattern of evolution. There is no evidence for the emergence of a stable community around ‘the Anonymous movement’ at any point in the time considered.

**Compactness**

Another possibility that is worth inquiring into is whether the network presents any trend toward an increasing concentration of interactions, signaling a progressive integration of its structure into a compact network.

Compactness is operationalized through two network measures: the average shortest path and the modularity index. The first variable is defined as the average value of the shortest path between every possible pair of nodes in the network [2], and gives information about the size of the network measuring whether it takes a lot of ‘hops’ to move from one node to another following the existing links. The second variable defines instead the modularity [3] of the network, which evolution provides insights into to which extent nodes tend to concentrate in a core module or to aggregate in isolated clusters.

Table 2 reports the minimum, maximum, average and standard deviation values of the two indicators of compactness calculated.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>average shortest path</td>
<td>3.92</td>
<td>8.32</td>
<td>4.69</td>
<td>0.78</td>
</tr>
<tr>
<td>modularity index</td>
<td>0.46</td>
<td>0.67</td>
<td>0.58</td>
<td>0.06</td>
</tr>
</tbody>
</table>

The mean of the average shortest path across month is 4.69. This value, however, oscillates between 3.92 and 8.32, signaling that the size varies across different timespans. Concerning the second indicator of compactness, the monthly network presents on average a modularity index of 0.58. However, it also ranges between a minimum of 0.46 and a maximum of 0.67. The network, consequently, presents an oscillating degree of integration.

What is of concern for the present analysis is the evolution in time of these parameters, in order to identify whether the interaction evolves toward a more compact structure. For this purpose, Figure 2 plots the normalized value of the average shortest path and of the modularity index for each month, in order to understand whether there is a trend in their fluctuation. The size of the network in terms of number of nodes is also included as a reference.
Figure 2: Interaction network. Evolution of compactness measures across months (normalized values). The values of the average shortest path (red line) and the modularity index (black line) are plotted against each month; the size of the network is also included as a reference (gray line). The network fluctuates between moments of highest compactness without following any trend.

No specific trend in the evolution of the compactness of the network can be identified. The two variables highly correlate with each other through time, though they reach several local maxima and minima. The compactness, moreover, sometimes follows the size of the network, while in other cases it does not. In the time of observation, the networks start quite scattered, becoming more compact from June 2013 onwards, then experiencing an inverse trend that reaches its peak in November 2013; compactness progressively increases thereafter, reaching a maximum peak around April 2014, but then starts decreasing again.

To give a better characterization of this result, the following visualizations (Figure 3) compare the pair of months which correspond to the greatest variation of compactness [4].
Figure 3a: Cluster structure of #Anonymous interaction network, May 2013.
Figure 3b: Cluster structure of #Anonymous interaction network, July 2013.
Figure 3c: Cluster structure of #Anonymous interaction network, August 2014.
The comparison of the networks’ divergent community structures allows a clear understanding of the evolving compactness of the interaction network. On May 2013 the network consists of a largely predominant cluster with few sparse independent nodes, while on July 2013 (just two months) it turns into an array of almost equally sized and relatively disconnected modules. Analogously, on August 2014 at least four very compact clusters of the same magnitude are visible, which on November 2014 evolve into a much more integrated structure.

As the analysis of the compactness of the network shows, there is no evidence for an evolution toward a more
integrated and compact structure, nor toward a more fragmented and sparse one; rather, the network alternates in phases of greater integration and greater fragmentation.

**Centralization**

The following analysis evaluates whether the network progressively verticalizes, following a trend toward greater formalization of its structure. In operative terms, this requires assessing the centralization of the network, that is to say the skewness of the distribution of the centrality of users.

There are a number of network measures to define the centrality of a node and this analysis will focus on two of these: degree centrality and betweenness centrality. The first defines centrality in terms of the number of connections held by a node, while the second elaborates on the number of shortest paths on which a node lies. Thus, in this context, degree centrality measures the level of popularity and activity of a user, while betweenness centrality reflects how strategic is the position occupied by a user in holding the network together. In order to provide a synthetic indicator of whether each snapshot of the network is more or less centralized, the analysis relies on the coefficient of the variation of the distribution of the centralization parameters mentioned above. This measure corresponds to the standard deviation of the centrality distribution divided by the mean, and allows observation taken across different months to be comparable.

Table 3 reports the minimum, maximum and average value of the centralization in terms of degree centrality and betweenness centrality.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Average</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>degree centralization</td>
<td>4.14</td>
<td>10.81</td>
<td>6.45</td>
<td>1.79</td>
</tr>
<tr>
<td>betweenness centralization</td>
<td>7.83</td>
<td>27.83</td>
<td>13.19</td>
<td>4.99</td>
</tr>
</tbody>
</table>

Whereas it is not possible to make any inference with respect to the level of centralization itself, the most striking observation is the extent to which centralization varies across different monthly snapshots of the network: degree centralization ranges between a minimum of 4.14 and a maximum of 10.81, while betweenness centralization oscillates between 7.83 and 27.83.

In order to understand whether this corresponds to a trend toward increased verticalization, or increased horizontality, of the network structure, the normalized values of the two indexes of centralization are plotted in Figure 4, in regard to their evolution in time.
Figure 4: Interaction network. Evolution of centralization measures across months (normalized values). The values of degree centralization (red line) and betweenness centralization (black line) are plotted against each month; the size of the network is also included as a reference (gray line). The network fluctuates between moments of highest and lower centralization, without following a trend.

Again, the two indicators follow a very similar evolution, strengthening the validity of the measure; the plot shows that the centralization does not follow any specific trend. The network starts as very centralized, following a trend toward increased horizontality that culminates between July and August 2013; then it reaches a relative peak of centralization between November 2013 and February 2014; centralization declines around April 2014 and then suddenly increases in August 2014; in the following months the network remains relatively decentralized, but a new wave of centralization can be seen in the last observations available. In general, network centralization is strongly associated with network size: the higher the number of nodes involved, the more uneven the distribution of centrality measures is.

It is possible to reinforce this deduction examining the network visualized in Figure 5, referring to the months in which the greatest fluctuation of centralization measures takes place. The network layout is computed with the Fruchterman Reingold algorithm, which tends to move central nodes in the middle of the graph; the size of nodes is linearly proportional to the weighted in-degree (scale 1:50), another measure of centrality that considers the number of links received by a node and includes the frequency of each interaction.
Figure 5a: Centrality distribution of #Anonymous interaction network, April 2013.
**Figure 5b:** Centrality distribution of #Anonymous interaction network, July 2013.
Figure 5c: Centrality distribution of #Anonymous interaction network, April 2014.
Figure 5d: Centrality distribution of #Anonymous interaction network, August 2014.

Figure 5a-d: Centrality distribution of #Anonymous interaction network over time in 2013 and 2014. The four network visualizations highlight the cluster structure of the network in different months, corresponding to extreme levels of integration and fragmentation.

The transition across different and oscillating stages of centralization is clear from the network representations. In April 2013 one single node concentrates a large share of connections, while in July 2013 influence is distributed across a set of distinct users. In April 2014, analogously, there is no clear center of the network and users tend to converge around the core, while in August 2014 a vast share of users is pushed to the boundaries and influence is concentrated in a couple of nodes (including a node with high weighted in-degree, but with low centrality in terms of number of connections).

Just as was observed for stability and compactness, the level of centralization of the network oscillates without...
The complex articulation of Anonymous’ issues

This section moves to the ‘semantic’ level of Anonymous’ goals and issues of concern, elaborating on the hashtags included in the Twitter corpus already presented. In particular, the focus is on the hashtags related to Anonymous operations.

An Anonymous operation is a sustained campaign that is concerned with a specific issue or target. In the syntax of online communication, it commonly follows the standard format Op[name of the operation]. Tweets related to a specific operation consequently include a hashtag in the form #Op[name of the operation]. It is thus possible to explore the dataset of tweets available for the specific operations in which the shifting Anonymous network has been involved. Whereas the data nominally relate to the discourse around Anonymous on Twitter, the existence of such discourse is a strong indicator of the existence of a concurrent engagement of Anonymous ‘itself’ with such issues, no matter which type of users (hardcore participants, sympathizers, commentators) are responsible for such stream of tweets. The list of hashtags included in the corpus has been parsed so as to retain those starting with the characters ‘#OP’; this resulted in a long list of 7,815 hashtags related to operations. A threshold of 50 occurrences has then been set to filter out the more insignificant ones, which produced a list of 911 distinct relevant markers of operations.

The word cloud in Figure 6 presents the most recurrent hashtags related to operations detected in the dataset. The size of each tag is proportional to its occurrence in the text of the tweets.

The most recurrent operations in the dataset are #OpIsrael (136,388 tweets), #OpISIS (92,828 tweets) and
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#OpKKK (69,975 tweets). Thus, the three most important operations related to Anonymous in the last three years have been targeting three entities as different as the state of Israel, the Jihadist organization ISIS, and the white-supremacist group the Ku Klux Klan (KKK). Quite surprisingly, the theme of Internet freedom, which has been predominant in the first big wave of Anonymous’ political commitment, seems to have been more marginal in the three years covered by this dataset: the only higher-ranked related operation is #OpNSA. Next to these top operations stands a long tail of medium-sized and minor ones, encompassing an array of formulations as varied as #OpFerguson, #OpNSA, #OpSeaWorld, #OpBahrain, #OpChemtrails and #OpCannabis.

Operation dynamics

Is there a stable core of operations or, alternatively, does the attention shift among different issues of concern? To answer this question, the distribution across months of the occurrence of hashtags related to operations has been computed. Out of this list, a core of 77 operations has been retained, corresponding to the five most tweeted operations per month. In this way it is possible to observe the dynamics of the focus of actions related to Anonymous on Twitter in the time span considered. The chart in Figure 7 represents the ‘ebbs and flows’ of Anonymous operations over time. The size of each pipe is proportional to the number of tweets that refer to each operation and values are normalized to increase readability.

Figure 7: Volume of monthly top-five operations over time (normalized values), December 2012 — November 2015. The ‘bump chart’ shows the evolution of the relative tweet volume of the 77 operations that fall into the five most consistent operations (at least) in a month. As the shape of the pipes show, some operations remain in the top five throughout the whole dataset, while others reach...
This visualization allows us to make two important inferences: one related to the dynamics of the operations themselves and the second concerning the shifting focus of Anonymous actions as reported on Twitter.

It can be easily noticed that different operations present a distinct evolution. The only constant presence in the overall period is #OpIsrael. Other operations present a likewise persistent character, such as #OpLeakageJP. Conversely, other operations appear prominent at the beginning of the timespan, but die out before the end, such as in the case of #OpBigBrother. To conclude, some operations present a more contingent character, suddenly rising and then declining in a relatively short time, as in the case of #OpUkraine, #OpHongKong and #OpInnocence, etc.

More interestingly, the data show that not only is Anonymous made up of heterogeneous components: the prominence of these shifts dramatically over time. The five most consistent operations each month do not recur — indeed, they amount to 77 in total — signaling a continuously evolving structure of attention of the network at large.

The shifting character of the discourse around Anonymous toward issues, as expressed by the dynamic of operations on Twitter, is even clearer in Figure 8, which allows us to make more exact inferences regarding the monthly quantitative composition of the operation set. It shows the evolution in time of a total of 611 operations, corresponding to the aggregation of the 50 most prominent operations in each month. Each pipe of a different color represents an operation and its size is proportional to the absolute value of its count.

![Figure 8: Volume of monthly top-50 operations across time (absolute values), December 2012 — November 2015. The ‘bump chart’ shows the evolution of the absolute tweet volume of the 611 operations that fall into the 50 most consistent operations (at least) in a month. Some phases present a concentration of activity around one operation, while in other phases Anonymous’ activity is](image-url)
spread across a number of operations.

The articulation of the chart reflects the unstable character of the ‘semantic core’ of Anonymous. The evolution shows the cyclic transition from periods in which attention is concentrated around a specific issue (such as around April 2013, or before July 2014) and thus other operations are less popular, to phases in which the attention is given in an equal share to a number of different concerns (such as at the beginning of 2013 or before October 2015).

**Operations structure**

Another aspect that is worth inspecting is the structural relation between operations, in terms of overlap among the users involved. How can we characterize the structure and evolution of this ‘socio-semantic’ network? In particular, two alternative scenarios are possible: operations are largely disconnected one from each other, in the sense that a specific set of users tends to converge around a specific set of operations; or operations are densely associated, meaning that users tend to shift between different operations.

In order to inquire into this dimension, a bipartite graph connecting users and operations has been built. A bipartite graph is a network composed of two classes of nodes, in which edges link nodes of different classes. Any bipartite network can be translated into a unipartite network, by following a procedure of ‘projection’: nodes belonging to one of the two classes are connected one with each other, considering the number of shared connections with the nodes of the other class. For the purpose of this analysis, the bipartite users-to-operations graph has been projected into a unipartite operation network: operations are linked according to whether they have overlaps of active users who include the operation-related hashtag in their tweets. Links among operations are assigned a weight corresponding to the number of overlapping users.

If users tend to aggregate around distinct sets of operations, the resulting graph should be rather sparse and clustered; and on the other hand a denser and more integrated graph would signal a large share of users that are active across different operations.

The visualization of the graph in Figure 9 makes quite clear which of the two scenarios is reflected by the data. It is worth noticing that the algorithm of spatialization adopted (OpenOrd) is meant to emphasize the community structure of a network.
Figure 9: User operations projected network (nodes are operations; links are shared users). The network visualization shows the dense structure of the network between operations linked by overlapping users, revealing the existence of overlapping users across a large number of distinct operations.

The network of overlapping participants among operations is strikingly dense and compact. The projected network counts 911 nodes, which corresponds to operation hashtags; nodes are linked by 54,111 unique edges, which correspond to the existence of shared users. Despite the presence of a few isolated nodes (most of which correspond to slight variations on, or mistyping of, the names of other operations), the vast majority of nodes coalesce in a tightly connected principal component, which includes 85.18 percent of the operation hashtags.

The static vision provided by Figure 9, however, does not reflect the dynamic character of the underlying data. For this reason, the following graph (Figure 10) reports the flows of users from operation to operation across
time. The top-five operations per month are retained and spatialized following the time evolution: the upper-left corner correspond to the first month, January 2012, and the curve progresses with time, ending in the upper-right corner with the last month, November 2015.

Figure 10: Dynamic operations network based on shared users, December 2012 — November 2015. The dynamic network shows, in a counterclockwise direction, the spillovers of users across monthly top-five operations over time. Some phases present consistent spillovers, while in other phases operations do not inherit many of their users from previous operations.

The network represented in Figure 10 allows us to infer the dynamics of the transitions of users among operations across time. An emerging aspect related to the structure of network paths is the clear alternation between phases in which a consistent number of users flow to other operations in the next month — in the areas where many strong links are shown — and phases in which the base of the core operations is largely regenerated. In certain cases the flow involves the same operation, which is part of the core for two consecutive months (e.g., there is a long #OpISIS path), while in other cases the transition involves two operations which have clear overlapping issue (e.g., #OpKKK and #OpFerguson, both related to the broker issue of racial discrimination); and in other cases the relation in terms of shared users is not reflected by a close relation in semantic terms (e.g., #OpMonsanto and #OpTurkey — an ecologist mobilization and an anti-
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In general, paths have a clear semantic coherence, though transitions of users among highly heterogeneous operations are present, though they are unlikely to occur.

These results, and in particular Figure 9, could give the impression that overall, despite its many ambiguities, the discourse around Anonymous is a highly integrated, since the heterogeneous actions associated to its name are structurally linked by overlapping participants. In order to understand to what extent this is the case, however, the relative values of the overlaps should be estimated, by referring to the volume of the operations involved. The networks in Figure 9 and Figure 10 show that there are a certain amount of users who create a layer of connectivity among most of the heterogeneous operations, though they do not show the actual share of users moving from operation to operation. Consequently, for each operation, a list of relative overlaps with every other operation has been computed; that is to say: the proportion between overlapping users and the occurrences of the operation. In this way, a list of the distribution of relative overlaps is generated. The list of operations has been limited to the 77 top-five operations per month, so as not to include minor hashtags that would bring a lot of noise to the analysis. Table 4 reports, for each operation, the number of operations connected via overlapping users, and the minimum, maximum and average shares of users between that operation and the operations to which it is connected.

Table 4: Descriptive variables of the distributions of relative overlaps between monthly top-50 operations. The table reports, for each of the monthly top-five operations, the number of linked operations via overlapping users, and the minimum, maximum and average overlap of users with other operations. The distributions imply that, despite the fact that operations are frequently connected one with each other through shared users, the proportion of overlapping users is generally very low.

<table>
<thead>
<tr>
<th>Operation hashtag</th>
<th>Number of linked operations</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>#OPANONDOWN</td>
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<td>17.74%</td>
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<tr>
<td>#OPANGEL</td>
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<td>17.12%</td>
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</tr>
<tr>
<td>#OPBAHRAIN</td>
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<td>0.00%</td>
<td>12.87%</td>
<td>2.21%</td>
</tr>
<tr>
<td>#OPBANGLADESH</td>
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<td>0.00%</td>
<td>17.68%</td>
<td>3.90%</td>
</tr>
<tr>
<td>#OPICEISIS</td>
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<td>0.00%</td>
<td>23.51%</td>
<td>2.99%</td>
</tr>
<tr>
<td>#OPBIGBROTHER</td>
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<td>12.46%</td>
<td>2.45%</td>
</tr>
<tr>
<td>#OPCHARLIEHEBDO</td>
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<td>18.40%</td>
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</tr>
<tr>
<td>#OPDEATTHEATERS</td>
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<td>0.00%</td>
<td>7.94%</td>
<td>1.42%</td>
</tr>
<tr>
<td>#OPDEATHEATERS</td>
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<td>0.00%</td>
<td>12.25%</td>
<td>1.28%</td>
</tr>
<tr>
<td>#OPFREEWILDAN</td>
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<td>0.00%</td>
<td>14.00%</td>
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<td>#OPGPII</td>
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<tr>
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<tr>
<td>#OPHONGKONG</td>
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<td>75</td>
<td>0.00%</td>
<td>23.51%</td>
<td>2.99%</td>
</tr>
</tbody>
</table>
From [Table 4](#) we can make the following observations. First, looking at the number of links per operation, we notice that almost all of the operations connect with almost all the others — most of the values are between 75 and 76; only one operation connects with a minority of others #OpInformacion, with 22. Nonetheless, the

<table>
<thead>
<tr>
<th>Operation</th>
<th>Links</th>
<th>0.00%</th>
<th>70.00%</th>
<th>3.82%</th>
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<td>#OPINFORMACION</td>
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<tr>
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<td>9.87%</td>
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<td>6.19%</td>
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<td>#OPWORLDCUP</td>
<td>76</td>
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<td>17.43%</td>
<td>2.97%</td>
</tr>
</tbody>
</table>
maximum minimum share of overlapping users is 0.05 percent, indicating that all the operations have at least some extremely weak connections with others. Looking at the distribution of maxima, we can indeed observe that there are at least some strong connections, thus cases where two operations shares a large number of users; the maximum of the maxima of shared users is 70 percent, reached by the two Latin American-based operations #OpInformacion, devoted to collaboratively sharing counter-information, and #OpPedofilia, against child abuse. Many operations, though, present very low maximum maxima: the most extreme cases are #OpIsraelReborn and #OpLeakageJP, which, respectively, share only 0.33 percent and 0.59 percent of users with the operation to which they are most connected. The distribution of the average relative overlaps, to conclude, oscillates between the 0.07 percent of #OpIsraelReborn (thus, a more ‘autonomous’ operation) and the 9.84 percent of #OpJustice4Kaitlyn (an operation that shares more users with others). The average value of the average relative overlap is 3.13 percent, a value that reinforces the conclusion that despite the fact that some Anonymous’ users do move from operation to operation, thus integrating the heterogeneous activity in an overall connected network, this does not imply a ‘unity of action’.

To obtain a better understanding of this process of users brokering operations, resulting in such a densely connected network, the histogram below (Figure 11) plots the distribution of the number of operations-related hashtags to which each user is connected. The number of operations is represented in a logarithmic scale, while the frequency is represented on an exponential scale, so as to increase the readability of the values.

**Figure 11:** Frequency distribution of number of operations per user (logarithmic-exponential scale). The histogram represents the frequency of each number of operations related to a user. The extremely skewed distribution shows that few hubs account for the overall connectivity of the co-
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The distribution clearly shows that the large majority of users connect to a limited amount of operations, while there is a limited cluster of users that are involved in dozens, and sometimes hundreds, of them. Consequently, the overall connectivity of the co-users operation network not only reflects largely weak connections, but also depends on the role of a minority of brokers and not on the generalized involvement of users in distinct operations.

**Anonymous as an umbrella brand and its offshoots**

Anonymous has often intertwined its destiny with other organizations, mobilizations and causes, promoting campaigns that were found worthy of its endorsement. Interestingly, a number of more or less related offshoots have arisen. This section intends to shed a light on the process of ‘brand variation’, by assessing the structural relation between Anonymous as a whole and some of its (many) offshoots.

**Anonymous’ sub-brands**

In order to identify the interaction between Anonymous and other entities in a grounded manner, the following heuristic procedure has been followed. The lists of hashtags and usernames extracted from the Twitter dataset have been matched, looking for patterns of occurrence of the former within the latter. In order to increase the relevance of the results, only hashtags occurring more than 1,000 times and users occurring more than five times have been considered. Subsequently, the list of terms obtained have been filtered for all the meaningful words, names of locations, institutions etc. The analysis of the resulting list of most recurrent terms that appear within both hashtags and usernames allows us to make some interesting inferences.

A first class of terms refers to direct variations related to the Anonymous brand, which characterizes influential accounts or Web sites. For example, ‘AnonOps’ (Anonymous Operations) relates to the IRC servers network that hosts Anonymous’ communication channels; and ‘YourAnon’ refers to influential accounts devoted to sharing information about, and giving visibility to, various operations. Similarly, other direct variations express a specific connotation related to the messages. For example, ‘AnonFamily’ emphasizes the feeling of ‘unity within diversity’; ‘FreeAnons’, and expresses solidarity toward imprisoned comrades. Particularly interesting is the case of ‘AnonyMiss’, a derivation which includes dozens of accounts and involves a specific variation of the logo, which has emerged to identify female activists.

Another cluster is related to more autonomous groups, which have been interacting with Anonymous: ‘OWS’ (Occupy Wall Street), for whose emergence the role of Anonymous has been crucial; ‘Wikileaks’, whose struggle for government transparency and against surveillance has become one of the central issues for Anonymous; and ‘RedHack’, a Turkish Marxist-Leninist hacker crew that has cooperated closely with Anonymous.

However, the group of terms that is more interesting here is a class that, in a sense, stands in between the mostly syntactic variations pertaining to the first group and the external interactions associated with the second. This is a set of ‘sub-brands’ that have developed at various stages of Anonymous’ history, whose relation to Anonymous as a whole is sometimes more directly evoked, while at other times it exists only in the background.

The main sub-brands identified by carrying out the heuristic procedure described above are the following:

- ‘LulzSec’: a well-known spinoff created by hardcore Anonymous hackers in 2011, which has been involved in spectacular defacement and leaking actions which exist at the boundary between the ‘lulz’ and the political;
- ‘AntiSec’ (Anti-Security): a branch, which refers to a preexisting 1990s movement, which has targeted the Internet security industry;
- ‘MMM’ (Million Mask March): an offshoot of Anonymous, often depicted as its ‘off-line version’,
related to a worldwide network of protest events that take place on the fifth of November;
- ‘Trutherbot’: the name of a vast array of accounts associated with the most conspiracy theory-oriented
  soul of Anonymous;
- ‘GhostSec’: a spinoff focused on fighting the presence of Islamic terrorist groups on the Internet;
- ‘CtrlSec’: a derivation of GhostSec, focusing on reporting ISIS sympathizers on Twitter;
- ‘AnonGhost’: an Islamist offshoot particularly active in #OpIsrael and other Middle-East operations; and
- ‘Sector404’: a South American spinoff of Anonymous.

As the recurrence of these terms in the usernames and in the hashtags shows, these derivations have branded
themselves as somewhat autonomous entities, despite their common origin linked to Anonymous’ activities.
However, looking at the associated Twitter profiles and Web site makes it clear that they often maintain a more
or less strong reference to the ‘umbrella brand’ and its visual identity, as Figure 12 makes clear.

Figure 12a: Logo of AnonGhost.
There is thus an apparent ambiguity when it comes to assessing the boundaries between Anonymous and its derivations; on the one hand, there are elements of explicit differentiation; on the other hand, there are elements of implicit continuity.

*Structural relations of Anonymous’ offshoots*

It is important to stress that these more or less autonomous offshoots, despite having developed a distinct focus and visual identity, still maintain a more or less direct reference to Anonymous as a whole and, often, to its...
In order to understand how the different sub-brands identified relate to each other from a structural point of view, Figure 13 represents their network clustering. The network is a bipartite graph between users and hashtags containing one of the sub-brands; the hashtags have then been collapsed to a single node representing the sub-brand itself. The closer the ‘audiences’ — represented by red nodes — of each of the offshoots, the more overlap among them.

Figure 13: User-offshoot network (nodes are users, labels are offshoots). The network visualizations show the clustering of users around Anonymous’ offshoots. Users seem to converge around certain offshoots (Sector404, Trutherbot), but also seem to share references with many of them (GhostSec, MMM, CtrlSec).

The resulting network presents some relatively disconnected clusters — in particular, Trutherbot and Sector404 — but also an overlapping core: for example, GhostSec and MMM are highly associated, despite the fact that the first is a counter-Jihadist group and the second is a protest network with rather distinct concerns. This leads to a quite counterintuitive inference: despite the process of differentiation that fosters the emergence of distinct offshoots with a specific branding, these offshoots are in reality still consistently embedded in the structural network of Anonymous as an entity as a whole, without clear differentiation among them.

Nonetheless, the network above considers users as an undifferentiated group, while it was already clear from the network among operations that some ‘super users’ act as brokers that account for much of the integration of
the network. When filtering out the top fifth percentile of active users, indeed, the structure of the network changes dramatically, as shown by Figure 14.

![Figure 14](image)

**Figure 14:** User-offshoot network, excluding top five percent of active users (nodes are users, labels are offshoots). The network visualizations show clustering of users around Anonymous’ offshoots when the layer of super-connectivity users is removed. Each offshoot presents a distinct constituency.

The comparison of the two network structures suggests that, similarly to what was observed in regard to the network of operations, each offshoot has a quite distinct constituency in general, but a layer of highly active users contributes to integrating the network of the various Anonymous offshoots.

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**Conclusions: Anonymous is (more than) one, anonymous is (less than) many**

This paper unfolds the discourse around Anonymous’ by following the #Anonymous hashtag on Twitter and analyzing the resulting dataset from a structural-relation perspective. The goal was to map what lies behind a specific hashtag related to a complex online entity, not yet investigated on a systematic, global level. Altogether, these results contribute to expand our understanding of Anonymous as a contradictory, multitudinous actor, as well as to reflect upon the operative choices associated with conducting research on an elusive Internet phenomenon.
Whereas it is clear from previous contributions how Anonymous is manifold, incoherent and even contradictory, to date the actual complexity underlying this intriguing (non-)collective remained substantially unexplored. Other studies (e.g., Coleman, 2015; Firer-Blaess, 2016; Olson, 2013; Uitermark, 2017), by leveraging in-depth qualitative methods, told stories about Anonymous from the local perspective they embraced, focusing on the level of agency and meaning. Conversely this study, adopting digital methods on Twitter, characterizes (the discursive construction of) Anonymous on a global level, focusing on relational structures and dynamics.

The first empirical section shows that the network of interactions between users is erratic and in constant flux: tendencies toward stabilization, integration and centralization are regularly countered by opposing trends toward instability, fragmentation and diffusion. The second part unwraps the heterogeneous components that emerge from the vast array of issues that are the targets of Anonymous’ operations; it makes evident the plurality of concerns discursively associated to #Anonymous, and their ever-shifting nature. The third analysis puts into focus the ambiguous relation between the discourse around Anonymous and its offshoots: on the one hand, they demarcate their individuality by rebranding themselves and appear structurally autonomous; on the other hand, they are still discursively tied to Anonymous as a whole by a super-layer of connectivity and by persistent symbolic references.

Is Anonymous always one entity, despite the fact that its constituency continuously shifts, falls apart and re-aggregates, and that it alternates between phases of concentration and phases of dispersion? Is the Anonymous that fights to expose the existence of a pedophile ring involving influential British celebrities and politicians the same Anonymous that fights against the killing of dolphins in Taji bay? Is the Million Mask March taking the streets to protest against governments and corporations part of the same movement calling itself AnonGhost and hiding in cyber-space to bring a cyber-holocaust to Israel? Existing in-depth, long-lasting studies on Anonymous (e.g., Coleman, 2015; Firer-Blaess, 2016; Olson, 2013; Uitermark, 2017) point out its multifaceted and contradictory character; nonetheless, they objectively tend to highlight a core of activities and activists — generally the hackers, pranksters and/or Internet freedom fighters operating on 4chan or IRC channels between 2008 and 2012. This paper, instead, focuses on Anonymous’ representation on Twitter between 2013 and 2015, and engages with its complexity from a holistic perspective, further characterizing its multiplicituous nature. The question ‘who is Anonymous?’, the results suggest, might have very different answers based on the point in time, space, platform and network topology in which the observer is situated.

Starting from a single analytical unit, the #Anonymous hashtag on Twitter, this paper describes the several multiple trajectories that lie behind it. However, despite that it lacks a stable constituency or a characteristic structure; that it condenses heterogeneous components with a shifting focus on diverse issues; and that it gives rise to relatively autonomous offshoots, Anonymous is also designated as a center of agency and possess a recognizable organizational identity (Dobusch and Schoeneborn, 2015; Dunn Cavelty and Jaeger, 2015). The set of sensibilities and epistemological tools associated with actor network theory (Law, 1992; Mol, 2010) and with the mapping of issues and controversies on digital platforms (Marres and Moats, 2015; Venturini, 2012) becomes then almost essential to be able to ‘tell stories’ about Anonymous on a more global levels, without making selective simplifications.

An irreducible tension between the ‘unit’ and the ‘multiple’ characterizes this entity. Anonymous explicitly exists as an ontological multiplicity occupying a fractional dimension: it is ‘more than one, but less than many’ (Law, 1999; Mol, 2002). The concept of punctualization (Law, 1992) is particularly useful to make sense of Anonymous: whereas reality is made up of heterogeneous connections among distributed elements, once successfully assembled those are generally designated and act as singular centres of agency. Through this process, the complexity of reality is ‘black-boxed’ (Callon, 1986) and cease to be perceived as a multiplicity. Similarly, when Anonymous is narrated from a specific point of view, the resulting story might be different than the picture that results from a bird-eye analysis.

The most apparent difference between this and other studies is indeed a methodological one and, arguably, transcends the specificity of Anonymous and suggest a broader reflection on digital research. Traditional qualitative endeavors require specific entry points and focuses; subsequently, whereas they manage to bring up important insights on participants motivations, individual trajectories, or specific case studies, they risk getting trapped in specific cliques — with the consequence of representing heterogeneous, ever-shifting phenomenon
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unfolding on digital network from a partial, situated perspective. In the specific case of Anonymous, they do acknowledge multiplicity, but the cannot account for it.

To the contrary, analyzing the digital traces starting from a general, albeit concrete entry point allows to unfold a complex object at different levels of granularity. This permitted to include within the picture the many (partly independent, partly intersecting) trajectories contained within Anonymous, raising points that could have gone otherwise unnoticed. In a sense, Anonymous as a whole represents a paradigmatic case of object of analysis onto which the application of digital methods manifest its full potential (Beraldo, 2020a; Latour, et al., 2012; Rogers, 2013).

Why did Anonymous survive so long, besides its contradictions, and to what extent are its participants aware of its extreme variety? What implications these considerations have for other online movements individuated and delimited by hashtags? How to complement the synoptic, mapping potential of digital methods with the in-depth, interpretative power of traditional qualitative methods? The bird-eye view on the many faces of Anonymous presented in this paper opens up as further research paths based on these and related questions.

About the author

Davide Beraldo is assistant professor of new media, data and information in the Department of Media Studies and the Institute for Logic, Language and Computation at the University of Amsterdam. His research interests include digitally mediated movements, digital and computational methods, the politics of data and algorithms and epistemology of complexity.

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Notes

1. This main dataset has been collected through the Twitter Capture and Analysis Toolset (Borra and Rieder, 2014) on the servers of the Digital Methods Initiatives at the University of Amsterdam.

2. The shortest path is the lowest number of nodes that indirectly connect a couple of nodes.

3. That is to say, a measure of the extent to which a network tends to be composed of relatively isolated clusters of interaction, characterized by higher internal density.

4. The algorithm adopted to spatialize the nodes is OpenOrd, which is designed to highlight the ‘community structure’ of a network (Martin, et al., 2011).

5. The chart was generated using the Bump Chart model provided by the tool Raw (https://app.raw.densitydesign.org/) developed by the research lab Density Design, Politecnico di Milano (https://www.densitydesign.org/).

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