

Network properties of dream sources

Umberto Barcaro¹, and Maria Chiara Carboncini²

¹Istituto di Scienza e Tecnologie dell'Informazione, Consiglio Nazionale delle Ricerche, Pisa, Italy

²Dipartimento di Ricerca Traslationale e delle Nuove Tecnologie in Medicina e Chirurgia, Università di Pisa, Pisa, Italy

Summary. Vast research in the last decades has shed interesting light on a variety of heterogeneous systems, including the human brain, by studying their network properties. Our investigation aimed to see whether the system of dream sources and of the semantic links between them shares the network properties of the brain. The investigation was carried out by means of an appropriate graph representation of data obtained according to a protocol oriented to eliciting episodic dream sources. The main results were the following: most dream sources belonged to compact clusters; important hubs, i.e. sources very closely connected to numerous other sources, were present; the vertex-degree distribution presented two significant peaks; small-world properties were valid for most pairs of sources; forms of self-similarity or of partial self-similarity at different scales were observed; the graphs of dreams sources exhibited a very high level of integration between overlapping clusters.

Keywords: Dream sources, brain networks, vertex-degree distribution, small-world, self-similarity

1. Introduction

In the last decades of the 20th century, interesting properties of a variety of social, economic, and biological systems were recognized and described by focusing on their network properties. Examples are very heterogeneous: e.g., the list given by Albert and Barabási (2002) included the following items: world wide web, Internet, movie actor collaboration networks, science collaboration graphs, webs of human sexual contacts, cellular networks, ecological networks, phone call networks, citation networks, networks in linguistics, power networks, neural networks, and protein folding networks.

The basic instrument applied for these studies was the representation of systems by means of graphs, i.e., sets consisting of vertices (e.g., the documents in the world-wide web) and edges joining pairs of vertices (e.g., links between documents in the world-wide web). Graph representation is still the primary tool for the study of network systems, because it offers conceptual simplicity, enhanced by the visual impact of graphical representation, as well as remarkable descriptive and quantitative effectiveness, provided by the mathematical achievements of graph theory.

The application of statistical methods allowed significant aspects of complex networks to be evidenced. In particular, it was observed that a number of biological, technological, and social networks were neither completely regular (i.e., with all the vertices having the same number of incident

edges) nor completely random (i.e., with edges that existed or did not exist, among the possible edges, according to a purely random criterion): most systems lay between the two extremes of regular and random networks (Watts and Strogatz, 1998). As a result of the exploitation of statistical methods applied to graphs, three concepts occupied a prominent place in thinking about complex networks: small-world, clustering, and degree distribution (Albert and Barabási, 2002). The small-world concept derived from the famous assertion, advanced about half a century ago, that a path of at most six consecutive edges (six “degrees of separation”) could connect any pair of people in the United States (Milgram, 1967). Clustering consisted in the existence of strongly interconnected subgraphs, e.g., sets of web documents presenting a high number of links between each other. The degree distribution (the degree of a vertex is defined as the number of incident edges) in complex systems was found to significantly deviate from the Poisson distribution typical of random graphs and to display either an exponential tail or a power-law tail. These heterogeneous degree distributions implied the existence of highly connected vertices, often referred to as “hubs”. The networks presenting power-law distribution were called “scale-free” (Barabási & Albert, 1999), because power functions have the mathematical property of being self-similar under a scale change. The application of the idea of self-similarity to complex networks was connected with significant advancements in the study of non-linear systems that can present behaviors described by fractals, mathematical entities that are precisely or approximately self-similar at different scales.

In the last decades, these powerful methods of network analysis have been interestingly extended to the human brain. In the light of brain graphs constructed by means of conventional and functional magnetic resonance imaging, electroencephalography, magnetoencephalography, diffusion tensor imaging and diffusion spectrum imaging (for references and review of results, see, e.g., Bullmore & Bassett, 2011, and Bassett and Bullmore, 2016), it has been

Corresponding address:

Umberto Barcaro, Istituto di Scienza e Tecnologie dell'Informazione, Consiglio Nazionale delle Ricerche, Pisa, Italy

Email: umberto.barcaro@isti.cnr.it

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shown that the brain networks basically present the properties of small-world, modularity (i.e., decomposability into sub-systems), and heterogeneous degree distribution. As a consequence of these properties, both segregation and integration can be viewed as characterizing the brain networks in a balanced way. Indeed, the idea of a co-existence of segregation and integration can offer a general, conceptually simple schema of important brain functions. For instance, higher-order cognitive processes can be described as involving a large, integrated “global neuronal workspace” (Dehaene and Naccache, 2001; Dehaene and Changeux, 2011), composed of specialized sub-systems that are at the same time spatially separated and functionally connected. Another example of brain network exhibiting segregation and integration is given by the “default mode network” (Raichle et al. 2001), which consists of regions that are more active during resting states than while performing goal-oriented tasks.

Functional networks have also been recognized during the various stages of sleep, including REM sleep, as a result of analysis of the electroencephalographic (in particular high-density) signal (see, e.g., Langheim et al., 2011). Using functional magnetic resonance imaging, Wehrle et al. (2007) described a thalamocortical network including limbic and parahippocampal areas specifically active during phasic REM periods. Chow et al. (2013) observed that REM sleep is characterized by a widespread, temporally dynamic interaction between two major brain systems: unimodal sensorimotor areas and higher-order association cortices including the Default Mode Network. These results can have interesting implications for the study of dreaming: indeed, REM sleep is connected with dreaming in a privileged, although not exclusive, way (as to the complex relationship between dreaming and REM sleep, see Nir and Tononi, 2010; Siclari et al., 2017). In fact, we can wonder whether the network properties of the brain are reflected in the contents of dreams and can be investigated by the methods proper to dream analysis. Indeed, a basic feature of dreams is that of making connections (see, e.g., Hartmann, 1995). The episodic memory sources of a dream are linked according to complex patterns that can effectively be represented by means of graphs (Barcaro et al., 2005) whose vertices correspond to sources and whose edges correspond to links among sources. Thus, these patterns can provide a useful tool for a quantitative study of the relationship between waking life and dreaming experience, a basic issue in the debate about dream significance (for a discussion about this point, see Hobson & Schredl, 2011; see also Vogelsang et al., 2016). In particular, quantitative studies have identified a “dream-lag effect”: in addition to day residues, events or memory elements from approximately five to seven days are significantly incorporated into dreams (Nielsen et al., 2004; Blagrove et al., 2011).

The objective of our research has been to see if the basic concepts that have proved useful to the study of brain networks could be helpful in the study of the graphs that represent dream sources, in spite of the extremely large size difference between brain networks and dream-source graphs. Among the reasons why this analysis should not be viewed as purely formal is the semantic value of the link patterns between dream sources. In fact, these patterns constitute the layout for phenomena such as the existence of precise circumstantiated episodic sources, the existence of pervasive links (i.e., links that connect more than two sources),

the validity of a heuristic rule plausibly accounting for the establishment of links between sources, and the presence of more than one present concern among the basic sources (Barcaro et al., 2016).

2. Method

2.1. Construction and initial quantitative characterization of graphs

The present study was carried out on the same experimental data used for a previous research (Barcaro et al., 2016), which were obtained from 12 participants (women in the age range from 34 to 48 years) according to the “Associations for Dream Reports Protocol”. This protocol asked the dreamer to report a recent dream, to select significant dream items, and to provide associations with each selected item by filling in a form oriented to the elicitation of sources related to episodes of the dreamer’s life and current present concerns (about the significance of episodic sources and present concerns, see, e.g., Domhoff, 2011). The length of the dream report was limited to no more than five lines; the average number of (Italian) words was 76. The protocol only required associations with time- and space-definite memory sources. Precise correspondences were generally found between elements of the recollected episodes and elements of the dream experience, thus strongly supporting the validity of the dream-source recognition. Interestingly, the participants found it rather difficult to fill in the form without the assistance of one of the researchers. The terms of this assistance were rigorously defined: they only consisted in forms of encouragement and thoroughly excluded any kind of even implicit suggestion.

For each of the 12 dreams, links between each pair of sources were recognized on the basis of the presence, in the associations concerning the two sources, of words that had the same stem or were closely connected semantically. A graph was thus constructed whose vertices represented the sources and whose edges joined those pairs of sources between which at least one link existed. Each edge was appropriately labeled by means of a letter or more letters, each link being indicated by a letter. Thus, the relationship between links and edge labels was not one-to-one, because a same letter (link) could be included in different edge labels and the edge labels could consist of more than one letter. A first quantitative description of each of the obtained labeled graphs was obtained by calculating the number of vertices, of edges, and of links. It was also checked whether each graph was connected, i.e., whether, for each pair of vertices, a path (i.e., a set of consecutive edges) connecting them existed.

2.2. Recognition of complete subgraphs

A commonly performed basic analysis of graphs consists in the identification of complete subgraphs, i.e., subgraphs whose edges join all the pairs of vertices. In particular, edges joining sources determine the simplest complete subgraphs, i.e., triangles.

With regard to dream-source graphs, each complete subgraph can be viewed as a cluster of sources, i.e. sources that are closely semantically connected to each other. A significant subset of complete subgraphs is given by subgraphs determined by links connecting more than two

sources (called “pervasive links” because of their primary and extended effectiveness in the construction of the dream). Clusters determined by pervasive links are semantically very rich, because they often contain, in addition to at least three sources and a pervasive link, other links, thus establishing a set of close relationships between sources and links.

2.3. Study of the degree distribution

A study of the degree distribution was carried out to assess basic aspects of the examined patterns, such as the presence of hubs. For each dream, the degree of each vertex was calculated and the histogram of the degree distribution was built. The histogram was then averaged over the 12 graphs.

2.4. Calculation of the distances between pairs of vertices

To see whether the graphs enjoyed small-world properties, the distance between each pair of sources (number of edges of the shortest path connecting them) was measured. The histogram of the distances between pairs of vertices was calculated for each dream and then averaged over the 12 dreams.

2.5. Analysis of possible elements of self-similarity at different scales

Our approach to the study of self-similarity at different scales was based on three considerations regarding triangles: first, these elementary complete subgraphs have often played a useful role in the study of the brain networks (see, e.g., DeDeo & Krakauer, 2012; Lord et al., 2016); second, in dream-source graphs triangles are significant subgraphs indicating a close connection between different sources; third, these subgraphs appear as closely connected among themselves as well. For this reason we aimed to see if triangles could also be observed on a broader scale. Our method, which consisted in a slight modification of a previously applied method (Barcaro & Rizzi, 2010), was founded on the

construction, starting from the initial graph, of a broader-scale graph whose vertices were the triangles in the initial graph and whose edges were given by vertices shared by the triangles in the initial graph: a possible recognition of triangles in the new graph would indicate an interesting form of self-similarity. Considering that pervasive links that involve more than three sources determine complete subgraphs that contain more than one triangle, we only considered one triangle for each pervasive link to avoid an artefactual excess of triangles at the broader scale.

3. Results

3.1. Construction and initial quantitative characterization of graphs

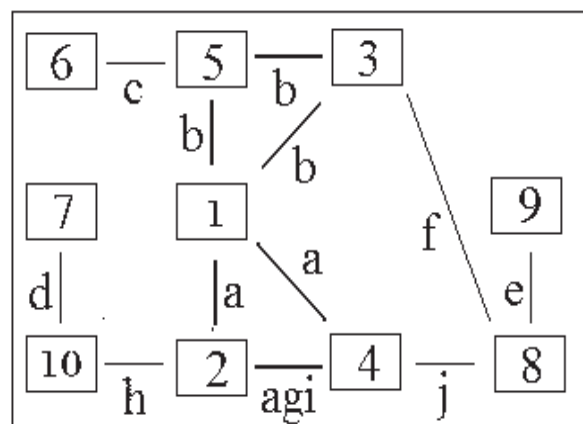
Figure 1 shows an example of a graph, built for the dream of Participant 6. The 10 vertices corresponded to the following dream sources: (1) I made a *journey* at ten without *Mother*; (2) During a *journey* in the Riviera with my *daughter* we visited *gardens* near the sea; (3) *Mother* was silent because she was *afraid* of something; (4) A *trip* to a village on the *seaside* gave me a feeling of *well-being*, especially when walking in its *gardens*; (5) *Mother* took me to learn how to *skate*; (6) During adolescence I often went *skating*; (7) Physiotherapists, who wear white *coats*, are giving me a feeling of *well-being*; (8) I recently felt a sense of *well-being* after overcoming the *fear* of not being able to fulfill a *work* task; (9) Yesterday I interrupted my *work* to take a coffee; (10) My *daughter* wears a *coat* at the school lab. (In this list of sources, words providing links are in italics.) The links were: (a) journey, trip; (b) Mother; (c) skating; (d) coat; (e) work; (f) afraid, fear; (g) sea; (h) daughter; (i) gardens, (j) well-being. A basic property of all of the graphs was immediately evident by means of visual observation: not only was no vertex isolated, but all pairs of sources were connected by a path. This initial result highlighted a fundamental property of the link patterns, their overall unitary structure.

Table 1 reports the number of vertices, the number of edges, and the number of links for the 12 dreams of the data set.

Table 1. Number of vertices, number of edges, and number of links for the 12 examined dreams

Participant	Number of vertices	Number of edges	Number of links
1	11	16	7
2	11	23	9
3	10	15	7
4	12	29	8
5	8	15	5
6	10	12	10
7	11	15	7
8	6	9	6
9	5	6	6
10	9	11	8
11	7	10	5
12	10	17	8

Figure 1. Dream-source graph for the dream of Participant 6. Pervasive links (links connecting more than two sources) determine the two triangles in the central column



3.2. Recognition of complete subgraphs

Two examples of complete subgraph are given by the two triangles of Figure 1, which are determined by pervasive Link (a) and pervasive Link (b), respectively. It can be observed that the vertex corresponding to Source 1 is common to the two triangles; we will return to this point later. The triangle determined by Link (a), which is shown again in the left part of Figure 2, is also labeled by other two links, thus establishing a compact interplay of links and sources: sub-structures of this kind are characterized by semantic richness and complexity.

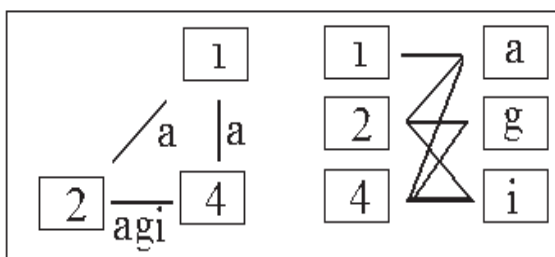
The right part of Figure 2 shows an alternative graph representation of the same triangle by means of a bipartite graph, in which not only sources (left column), but also links (right column) are indicated by vertices. Although the bipartite-graph representation is effective as well, for the sake of simplicity we have preferred to only use labeled graphs in this paper.

Table 2 reports, for each dream, the percentage of vertices that belonged to a complete subgraph and describes, for each dream, the properties of the recognized subgraphs determined by pervasive links. The very high percentage of vertices belonging to complete subgraphs indicates that the link patterns were not only unitary, as observed above, but very compact. Furthermore, all of the graphs contained pervasive links, and in some cases the number of the sources involved by a single pervasive link was high. For instance, the dream of Participant 4 was characterized by a link involving six sources. In the graph representation, this determined a complete subgraph with six vertices. This greatly increased the number of edges for this participant, as reported above in Table 1.

3.3. Study of the degree distribution

Table 3 reports the average and the maximum degree value for each dream. The fairly large values of the average degree quantitatively show that the graph pattern was generally distant from the simple pattern of a serial chain, because the vertices were largely interconnected, thus confirming the general existence of clusters. Furthermore, high values of the maximum degree demonstrated the existence of proper hubs, i.e., dream sources particularly important for the dream construction. For instance, considering the graph of Figure 1 again, the vertex representing Source 1

Figure 2. At left: subgraph (triangle) determined by Link (a), a pervasive link, in the graph of Figure 1. Two links additional to Link (a) label one of the edges of the subgraph. At right: alternative representation of the subgraph as a bipartite graph, in which the vertices in the left column stand for the sources and the vertices in the right column stand for the links



has the highest degree: this source, which concerned a journey (pervasive Link a) that the dreamer made without Mother (pervasive Link b), was directly connected to other 4 sources of the dream.

Figure 3 shows the average histogram over the 12 dreams: it presents a marked peak at about 3: this means that a large number of sources were directly linked to 3 other sources; it also presents a peak at 6, again indicating the presence of important hubs.

3.4. Calculation of the distances between pairs of vertices

Table 4 reports, for each dream, the average distance (i.e., the number of edges of the shortest path) between the pairs of vertices. The maximum value of distance (the “diameter” of the graph) is also reported for each dream. The average distances were in the range 1.46 – 2.40, thus indicating a marked small-world property of the graph, as could be expected considering the high level of interconnection among the vertices. However, in some cases the diameter was not very small, thus suggesting that for some vertices (very few) the small-world property was not so substantial. It might be conjectured, however, that some distant sources had not been as distant in the actual construction of the dream as they appeared in the graph representation, because some latent connection might not have been recognized by our method of analysis. For instance, coming back again to Figure 1, the most distant sources were Source 6 and Source 7, respectively concerning a movement activity (skating) and

Table 2. For each of the examined dreams, the percentage of vertices belonging to at least one complete subgraph is indicated. Pervasive links are also indicated (right column), together with the number of sources that each of them joined

Participant	Vertices belonging to a complete subgraph	Pervasive links
1	81.8%	• 1 link joining 4 sources • 3 links joining 3 sources
2	100%	• 3 links joining 4 sources • 2 links joining 3 sources
3	90.0%	• 1 link joining 4 sources • 2 links joining 3 sources
4	100%	• 1 link joining 6 sources • 2 links joining 4 sources • 2 links joining 2 sources
5	100%	• 1 link joining 5 sources • 2 links joining 3 sources
6	50.0%	• 2 links joining 3 sources
7	81.8%	• 1 link joining 4 sources • 2 links joining 3 sources
8	83.3%	• 4 links joining 3 sources
9	80.0%	• 1 link joining 3 sources
10	55.6%	• 2 links joining 3 sources
11	85.7%	• 3 links joining 3 sources
12	90.0%	• 2 links joining 4 sources • 2 links joining two sources

Table 3. For each dream, the average degree of the vertices is reported together with its maximum value

Participant	Average degree	Maximum degree
1	2.91	5
2	4.18	6
3	3.00	5
4	4.83	9
5	3.75	7
6	2.40	4
7	2.73	6
8	3.00	5
9	2.40	3
10	2.44	5
11	2.86	5
12	3.40	6

the fact that the dreamer needed physiotherapy because of some momentary movement difficulty. It can be reasonably hypothesized that a connection between these two sources actually played a role in the dream construction.

The average histogram of distances (Figure 4) highlights the marked small-world property for most pairs of vertices, because most of the distances are very small (1 and 2).

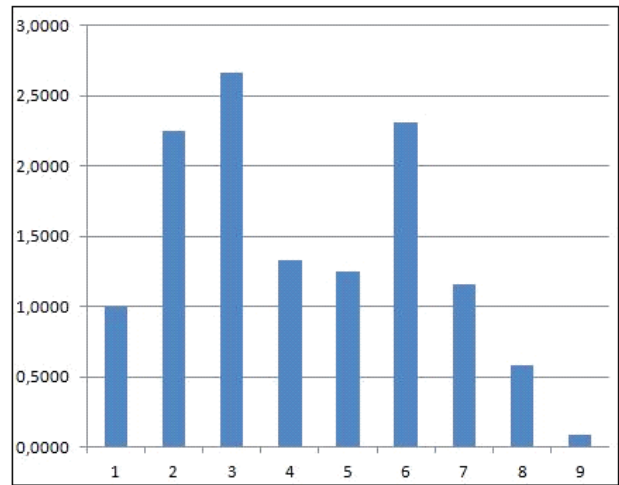
3.5. Analysis of possible elements of self-similarity at different scales

Figure 5 shows an example of how triangles were constructed at a broader scale. This example refers to a subgraph (at top right in the figure) of the graph for the dream of Participant 12 (at left in the figure; the labels have been omitted). This subgraph contained three triangles. A new broader-scale triangle was obtained (at bottom right) whose vertices were the triangles in the initial graph and whose edges were given by shared sources.

Table 4. For each dream, the average distance is reported over the pairs of vertices of the graph. The maximum distance (diameter of the graph) is also reported for each dream

Participant	Average distance	Diameter
1	2.24	4
2	1.89	4
3	2.13	5
4	1.68	3
5	1.46	2
6	2.38	5
7	2.40	5
8	1.42	2
9	1.49	3
10	2.06	4
11	1.57	3
12	1.78	3

Figure 3. Histogram of the vertex degrees averaged over the 12 dreams

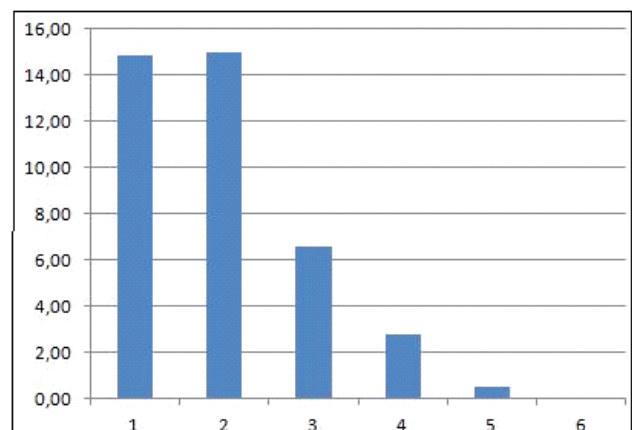


As Table 5 shows, a construction of self-similar triangles was only possible for 6 out of the 12 examined dreams; in the other 6 cases we only obtained a pattern of two joined vertices. These patterns, although failing exact self-similarity, can be viewed as partially self-similar, because they however indicate a very close connection between different triangles in the initial graph. More precisely, not only the existence of self-similar triangles, but also that of simpler two-vertex patterns highlighted a basic property of the link patterns: generally, semantically significant subgraphs were not fully separated, but were overlapped. In other words, the modularity model often effectively proposed for the brain, consisting in both segregation and integration, does not seem to be fully valid for the graphs of dream sources, because generally the various clusters were not segregated.

4. Discussion

We carried out an analysis of the link patterns among dream sources focused on central concepts that have been useful and enlightening for the study of a number of networks, including brain networks: possible presence of clusters, possible presence of hubs, properties of the degree distribution.

Figure 4. Histogram of the distances between pairs of vertices averaged over the 12 dreams



bution, possible small-world property, possible modularity, and possible forms of self-similarity.

The results can be summarized in this way: most sources belonged to compact clusters; important hubs generally existed; the degree distribution presented two distinct peaks, the first confirming the existence of clusters and the second corresponding to hubs; most vertices presented marked small-world properties; forms of self-similarity and of partial self-similarity showed that the graph of dream sources presented a very high level of integration between overlapping clusters.

The network properties of the links between dream sources offer the structural layout for the existence of semantically significant phenomena, which constitute a meaningful aspect of the complex relationship between waking life and dreaming experience. For instance, the generally observed phenomenon of the simultaneous presence of more than one present concern among the dream sources highlights that a multiplicity of simultaneous meanings can be attributed to a dream: this well corresponds to the fact that the various clusters that compose the graphs, each of which presents specific semantic properties, are overlapped, so that dream sources and links among them play parallel multifold roles in the dream experience. This is confirmed by the remarkable presence of hubs, i.e., sources that, being conceptually linked to numerous other sources, assume multifold significance.

As a consequence of the above described results, it can be confirmed that dreams enjoy marked network properties, as a number of systems, including the human brain, do. We can wonder whether this happens because the brain, while building a dream, leaves a trace of its properties, or because dreams present network properties independently from the properties of the brain, in the same way as other systems do that have little to do with our brain.

Considering that the hypothesis is solidly founded that dreams are reflective of sleep-dependent consolidation of

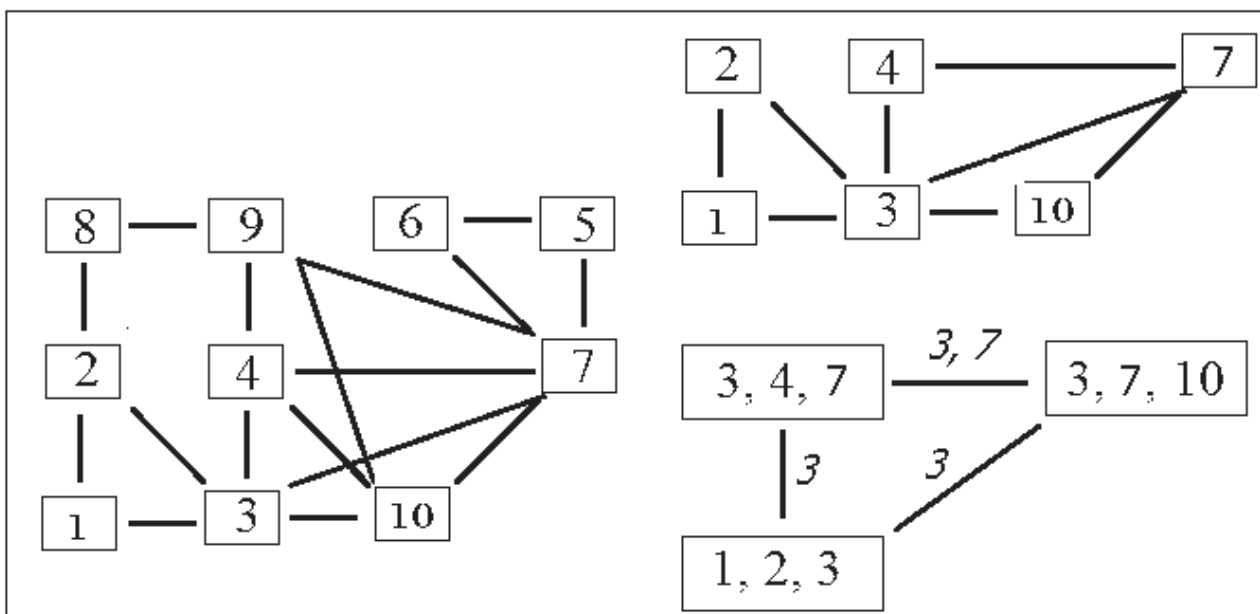
Table 5. For each dream, the existence at a broader scale is reported either of self-similar triangles or of patterns consisting of two joined vertices

Participant	Relevant pattern at broader scale
1	Self-similar triangle
2	Two joined vertices
3	Two joined vertices
4	Self-similar triangle
5	Self-similar triangle
6	Two joined vertices
7	Two joined vertices
8	Self-similar triangle
9	Two joined vertices
10	Two joined vertices
11	Self-similar triangle
12	Self-similar triangle

memories (Blagrove et al., 2011), it can also be hypothesized that the above described network patterns are reflective of network properties of the memory system. This idea suggests that future research should investigate the connection between the patterns of dream sources and the temporal properties of memories involved in the construction of dreams. Indeed, it will be interesting to study how at least three distinct categories of memory sources interplay in the construction of a dream: day residues, events related to the dream-lag effect, and time-remote episodes (e.g., as often happens, events in the dreamer's adolescence).

The fact that the brain, in addition to enjoying network properties, is able to build products, such as dreams, that enjoy this same property, poses a further interesting but dif-

Figure 5. Construction of triangles at a broader scale for the dream of Participant 12. At left: the initial graph. At top right: subgraph of the initial graph containing three triangles. At bottom right: broader-scale triangle whose vertices are the triangles in the initial graph and whose edges are given by shared sources



ficult question, concerning the extent to which it can be expected that the results obtained for dreams could be valid for other products of our mind.

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