Social network in the 2015 dreams of a male dreamer

Michael Schredl[1] and Richard Schweickert[2]

[1]Central Institute of Mental Health, Medical Faculty Mannheim/Heidelberg University, Germany

[2]Department of Psychological Sciences, Purdue University, USA

Summary. Social interactions play an important role in dreams and, thus, the question arises whether the characteristics of the dream social network based on co-occurrence of persons within dreams is comparable with the characteristics of waking-life social networks. The present analysis included 696 dreams reported by a male dreamer in the course of one year. Overall, the findings support the notion that a dream social network shows the characteristics of a small world network (small average distances, high clustering), and the power law distribution of co-occurrences – similar to waking-life social networks. The clustering was most obvious for the core family members of the dreamer; they are more likely to co-occur than occur with persons of other social areas. More studies are needed to link inter-individual differences within the properties of the dream social network to differences in the current and former waking-life social networks of the dreamer.

Keywords: Dream content, social network, continuity hypothesis

1. Introduction

Social interactions play an important role in dreams (Domhoff, 1996; Hall & Van de Castle, 1966; Schredl, 2018b). Compared to other activities like reading and writing, waking-life social life seems to be preferentially incorporated into dreams (McNamara et al., 2005; Schredl & Hofmann, 2003; Tuominen et al., 2019). These findings led to the formulation of Social Simulation Theory, postulating that one function of dreams might be training of social skills (Revonsuo et al., 2015). As the Social Simulation Theory is based in evolutionary psychology, it is assumed that the social skills trained within dreams increase reproductive success (Revonsuo et al., 2015). The continuity hypothesis, which postulates that waking-life experiences (especially emotionally relevant ones) are incorporated into dreams (Schredl, 2003), and the strengthening hypothesis of Social Simulation Theory (Tuominen et al., 2021) predict that close relationships are very common in dreams and, indeed, research indicates that family members (Schredl, 2013, 2021), partners (Schredl, 2018a; Schredl et al., 2020; Schredl & Wood, 2021), or one's own children (Schredl et al., 2021) are found in 20% to 30% of the dreams of persons having a partnership and/or children in waking life. Less attention has been directed to the social networks within dreams. Schweickert (2007c) put forward the idea of analyzing the properties of the dream social network and testing whether these properties are similar to those of waking-life social networks. Whereas a waking-life social network is defined by the existing relationships between the persons belonging to the network, the dream social network is based on their co-occurrence within dreams, that is, persons are related if they appear in a dream together. The underlying assumption is that dreams rely on the cognitive social network (Krackhardt, 1987) represented in the dreamer's memory (Schweickert et al., 2020), that is, dream characters do not occur in a random way but based on their association within the cognitive social network. Even though some researcher, e.g., Domhoff (2019), focused their attention to neurocognitive models of dreaming, it should be emphasized that the cognitive social network within the dreamer's memory is based on waking-life experiences, e.g., the inter-relationships within the network, e.g., between core family members have been part of the dreamer's waking life and, therefore, are stored in the memory system as a representation of his or her network. This imply that the concept of a cognitive social network fits very well into the general framework of the continuity hypothesis of dreaming (Schredl, 2003) postulating that dreaming reflects waking-life experiences.

Corresponding address:
Michael Schredl, Sleep laboratory, Central Institute of Mental Health, PO Box 12 21 20, 68072 Mannheim, Germany.
Email: Michael.Schredl@zi-mannheim.de

Submitted for publication: January 2022
Accepted for publication: February 2022
DOI: 10.11588/ijodr.2022.1.85607

Analyzing five dreams series, the authors (Han et al., 2016; Schweickert, 2007a) found that dream social networks show small world network characteristics (Watts & Strogatz, 1998), that is, small average distances (persons in the network are connected on average with a small number of links) and high clustering (if two people are linked to a third, probability is high that the two are linked themselves). Further, parameters vary systematically over individuals, and a power law distribution (Zipf-Mandelbrot law) was found (Schweickert, et al., 2020) for the frequency of dream characters (very few persons occur very often and many persons occur seldom in dreams). It is noteworthy that one dream social network (of the Engine man) had a different form from the others. The largest component is spoke and hub shaped in outline, with vertices on one spoke mainly for coworkers, vertices on another for members of a sister's family, and so on. This indicates that inter-individual differences in the properties of the dream social network exist.

An in-depth comparison between the waking-life social network and the dream social network was carried out by Han and Schweickert (2016). The dream social network was based on 4,254 dreams of “Barb Sanders” (a pseudonym) available on dreambank.net (see: Domhoff, 2003; Domhoff, 2018), whereas the authors obtained information from the dreamer about the waking-life social network of the dreamer encompassing 120 persons. “Barb Sanders” estimated her closeness to the person on a five-point scale and used a similar scale for estimating the closeness of relationships between two individuals of her social network. The findings clearly indicated that persons close to the dreamer in waking life were more likely to occur in dreams, and persons who were more closely related in waking life were more likely to co-occur in the dreams of “Barb Sanders”, with the top value of 150 dreams including the father and the mother of the dreamer. This study showed that the waking-life social network is clearly related to the dream social network. However, Schweickert (2007c) pointed out that the relationship between waking-life and dream social networks is not always straightforward, as in the Merri dream series the most prominent character was the dreamer’s sister Dora who died before the dreams were recorded, therefore, the emphasis on the cognitive social network within the dreamer’s memory. In addition, Schweickert (2007b) pointed out that including all dream characters into the analysis might be problematic as ‘police men’, ‘bus drivers’, ‘clerks’ are typically not included in waking-life social networks, perhaps producing, for example, the low fit of Zipf-Mandelbrot law regarding low frequency levels, that is, dream characters that only occur once or twice within the dreamer series (because these also encompass strangers). Therefore, the approach of Han and Schweickert (2016) including only persons that are known to the dreamer in waking-life seems more promising.

The present analysis is based on a dream series of *N* = 696 dreams recorded within one year. On a descriptive level, it was studied how strong the overlap was between different waking life social groups (family, private social network, work-related network, and persons from the dreamer’s past). It was considered whether there is modularity, i.e., whether persons co-occur in dreams in communities. In addition, the characteristics of the dream social network were determined based on the methodology applied by Schweickert (2007a) and Schweickert et al. (2020). It was expected that the dream social network will reflect the cognitive representation of the dreamer’s waking-life social network and, therefore, show characteristics like small average distances, high clustering coefficient, and a power law distribution of the number of co-occurrences per person.

2. Method

2.1. Participant and dream diary

The male participant started to keep an unstructured dream diary from the age of 22, with the first dream recorded on 5 September, 1984. For the present analysis, all 696 dreams recorded in 2015 were included. The mean length of the dreams was 165.56 ± 82.77 words. In 2015, the dreamer (age 53) was single, had no children, and was working part-time in a research institute.

2.2. Procedure

Dream reports were originally hand-written but were then typed and entered into a database (Alchera 3.72, created by Harry Bosma, www.mythwell.com) by the dreamer himself. This database allows the assigning of keywords to the dreams – this task was also carried out by the dreamer. For each dream, the dreamer coded the occurrence of persons who are known to the dreamer in his waking life: core family members, relatives, friends, neighbors, colleagues, former schoolmates, former partners, celebrities etc. This type of coding is following guidelines proposed by Schredl (2018b) and Schweickert (2007a), that is, not coding persons in dreams that are not “physically” present, e.g., talked about or owning objects in the dream. In order to keep the dream characters’ names confidential, specific labels, e.g., G1 (former schoolmates), Z1 (colleagues) etc., were used for each person (except for the family members).

The Alchera software provides a word count for each dream report. Reports included only dream experience-related words and all redundancies, e.g. repetitions that occurred in writing down the dream in the morning, were excluded. The analysis unit was an individual dream report. The data were exported into an Excel spreadsheet (Microsoft) and the descriptive data analysis was carried out using the SAS 9.4 software package for Windows (Cary, North Carolina, USA).

In addition, the distribution of the frequencies of dreams with a particular character were analyzed. The number of dreams a character appears in is the frequency of that character. Some frequencies occur more often than others. The number of characters having a certain frequency is the count of that frequency. The empirical values were compared to the Zipf-Mandelbrot distribution which is a form of power law probability distribution. With it, for counts $k = 1, \ldots, N$ the probability of count k is $P(k) = 1/c(k + b)a$, where a is greater than 0, b is greater than or equal to 0, and c is a constant, determined by a, b and N, that constrains the probabilities to sum to 1. Parameters were estimated by minimizing G^2, which maximizes the likelihood. If the population has the distribution specified by the model, then G^2 has approximately a chi-square distribution (Bishop et al., 1975). Note that the value of N that maximizes the likelihood is the largest observed frequency and if a frequency does not occur, i.e., has a count of 0, the maximum likelihood estimate of its count is 0. Parameter estimation was done in Excel using Solver.

The next step was to analyze the dream social network. The dream characters are represented by *vertices*. In a dream social network two characters are joined by an *edge* (line joining the vertices) if they were present in at least one dream together. (An edge is sometimes called a link.) The drawing and network computations were done in Pajek (Batagelj & Mrvar, 1998). Several packages for social network analysis are available, including Pajek, UCINet and R. The major ones accept a variety of input formats, calculate commonly used network measures, and draw networks. Unless the user has a special need, the choice among them can be based on familiarity and personal preference.

A *component* of a network is a subnetwork that is as large as possible such that every pair of vertices in the subnetwork is connected by a path. A community is a set of vertices with many edges between its members and few edges between a member and nonmember. A popular measure of how well a network is partitioned into such communities is *modularity* (Newman & Girvan, 2004). The *degree* of a vertex is the number of vertices joined to it by an edge. If a vertex is chosen at random with all vertices equally likely, the probability the degree of the vertex equals k, for $k = 1, 2, \ldots$ is the *degree distribution*. Waking life social networks such as

Table 1. Frequency of the known dream persons

Social group	Persons	Number of dreams	Number of occur-rences	Most often occurring persons
Core family	4	109	182	Sister (59), mother (58), brother (57), father (8)
Private network (relatives, friends, Acquaintances)	24	53	58	Friend1 (8), friend2 (5), acquaintance1 (7), acquaintance2 (4), friend3 (3),
Work-related network	55	79	103	Colleague1 (7), colleague2 (7), Head of the institute (7), Colleague3 (5), colleague4 (4)
Persons from the dreamer's past (former partners, former schoolmates, former neighbors)	59	91	114	Former partner (25), former school friend1 (5), former school friend2 (5), former school friend3 (3), former neighbor1 (3), former neighbor2 (3)
Celebrities	7	8	9	Magnus Carlsen (3), Colin Firth (1), Andrew McCutchen (1), Gregory Peck (1), Lex Barker (1), Pierce Brosnan (1), Richard Gere (1)

friendship networks often have a power law degree distribution for high degrees (e.g., Newman, 2003). The median degree was considered as the highest degree such that half or more of the vertices have degree at or higher than it.

In a small world network, the average distance between vertices is near that of a random network, approximately (ln n)/(ln d), where n is the number of vertices and d is the average degree (Watts & Strogatz, 1998). The *clustering coefficient* of a vertex is the number of completed triangles that include the vertex divided by the number of possible completed triangles at the vertex. The clustering coefficient of a network is the average of the clustering coefficients over all vertices. In a small world network, the clustering coefficient is much higher than that of a random network, which would be approximately d/n. For completeness, we also report a different way to quantify clustering, transitivity. A *connected triple* consists of vertices a, b and c such that a and b are joined by an edge as are b and c. In a *completed triangle* of vertices a, b and c, every pair of vertices is joined by an edge. Clustering is higher when there are more completed triangles. Vertices in a connected triple may or may not be in a completed triangle. *Transitivity* is three times the number of completed triangles in the network divided by the number of connected triples. The number of completed triangles is multiplied by 3 because each completed triangle has 3 connected triples. They are counted in the denominator and so need to be included in the numerator. Each edge in a network has two vertices and the correlation over edges between the degrees at the end vertices is called the *assortativity*. Newman and Park (2003) found that social networks differ from other networks in two main ways, having high clustering and high positive assortativity.

3. Results

Overall, 150 known persons occurred in 299 dreams (42.96% of the total dreams recorded in 2015). In 192 dreams one person occurred, in 59 dreams two, in 34 dreams three, in 12 dreams four, and in two dreams five persons, totaling to 470 occurrences. Core family members occurred most often (see Table 1), the other known persons were divided into three categories: private (relatives, friends, acquaintances), work-related and persons from the dreamers past (no contact in 2015). Celebrities were put into a separate category, encompassing a chess player (Magnus Carlsen), a baseball player (Andrew McCutchen) and male actors (see Table 1).

In Table 2, dreams with two or more known persons are classified with respect to the categories the people belong to. The percentages represent the proportion of dreams with two or more persons present, e.g., in 41.28% of the 109 family member dreams there were two or more family members, i.e., a family member was connected with another family member. On the other hand, only 3.67% of the family member dreams (including at least one family member) also included a person from the dreamer's work environment. The celebrities were not included as they was no overlap to the other categories, that is, celebrities did not occur with other known persons within the same dream (solely, in one dream two celebrities occurred). In more than 40% of the dreams including at least one family member, a second family member was also present; the percentages of dreams with at least one family member and persons from the private or work-related network or persons from the dreamers past were much lower (Table 2). This effect (higher frequency of within-category persons compared to the overlap with persons of another category) – albeit not so pronounced – was also found for the work-related network

Table 2. Overlap between the categories in dreams with two or more persons

Social group	Number of dreams	Core family	Private network	Work-related network	Persons from the dreamers past
Core family	109	41.28%	8.26%	3.67%	12.84%
Private network	53	16.98%	9.43%	11.32%	11.32%
Work-related network	79	5.06%	7.59%	20.25%	13.92%
Persons from the dreamer's past	95	14.74%	6.32%	11.58%	17.89%

Table 3. Fits of Poisson and Zipf-Mandelbrot distribution to counts of character frequencies

Distribution		Value
	N	59
Poisson	λ	2.97
	G^2	921.47
	df	57
	p	< .001
ZM	a	2.17
	b	0.16
	G^2	39.89
	df	56
	p	n. s.

Note. For the Poisson distribution, λ is the mean. N is the highest observed frequency. ZM stands for Zipf-Mandelbrot, df for degrees of freedom. For the Zipf-Mandelbrot distribution, when b is set to 0, the value of G^2 increases to 40.11 with 57 degrees of freedom. The slight increase is not significant.

Table 4. Fits of Poisson and Zipf-Mandelbrot distribution to counts of degrees at or above median

Distribution		Value
	Highest Degree	19
Poisson	λ	2.76
	G^2	112.50
	df	17
	p	< .001
ZM	a	3.69
	b	4.13
	G^2	14.61
	df	16
	p	n. s.

Note. For the Poisson distribution, λ is the mean. ZM stands for Zipf-Mandelbrot, df for degrees of freedom.

and the persons from the dreamers past, that is, if a colleague showed up in the dream the likelihood that another colleague occurred in the dreams was higher compared to the occurrence of a family member or persons from the past or the current private network (see Table 2). Solely for the private network there was no preference for co-occurring of these persons within the same dream.

A version of the power law (Zipf-Mandelbrot) was fit to the frequency counts over all characters known to the dreamer in his waking life. Clearly, the distribution presented in Figure 1 fits observed counts very well. The parameters for the best fit are in Table 3.

The dream social network considered here has 150 vertices and 140 edges (see Figure 2). The dream social network has 67 components. One is considerably larger than the others are, as often occurs in social and other complex networks. The largest component has 68 vertices, 45 percent of all 150 vertices. For the entire network, when communities that maximize modularity are formed, there are 75 communities (Figures 2 and 3). The modularity is .53, which falls in the mid-range of modularities of social networks in a short list of (Newman, 2006).

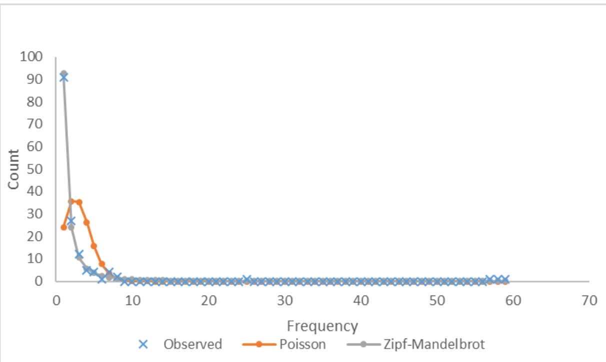

Figure 1. Fits of Zipf-Mandelbrot and Poisson Distributions to Observed Counts of Frequencies.

The small components are each a community on their own, not surprising because of their small sizes. The largest component has eight communities (Figure 3), indicated with different symbols. The largest community has 24 members, but is not the most important. The second largest, with 14 members, is most important because it is connected to each of the other communities and its members include the three high frequency characters Bruder (brother), Mutter (mother), and Schwester (sister). Its connections to other communities are all via edges to one or more of the three characters Bruder (brother), Mutter (mother), Schwester (sister). The other communities are either connected only to the most important community or to it and one other. Even with the tendency for core family members to co-occur with other family members, and so on (Table2), the small component communities and those of the largest component contain people from different waking life categories; the communities are heterogeneous.

For the dream social network here, the average degree (number of co-occurrences per dream character) is 1.87 and the median degree is 1. Figure 4 shows results of fitting the Zipf-Mandelbrot and Poisson distributions to counts of degrees, both distributions truncated at the median and at the highest observed degree. Clearly, the Zipf-Mandelbrot fits well and the Poisson does not (see Table 4 for statistical details).

The *distance* between two vertices is the number of edges on the shortest path from one to the other. In the largest component of the dream social network, the average distance between pairs of vertices is 3.64. In a small world network, the average distance between vertices is near that of a random network, approximately (ln n)/(ln d), where n is the number of vertices and d is the average degree (Watts & Strogatz, 1998). In the largest component, the number of vertices is 68 and the average degree is 3.62. Hence in a comparable random network the average distance would be approximately 3.28. This is indeed close to the average distance in the largest component, 3.64. The first property of a small world network, short paths, is satisfied. In the dream social network the clustering coefficient for the largest component is .68. In a corresponding random network the clustering coefficient would be approximately d/n = .05

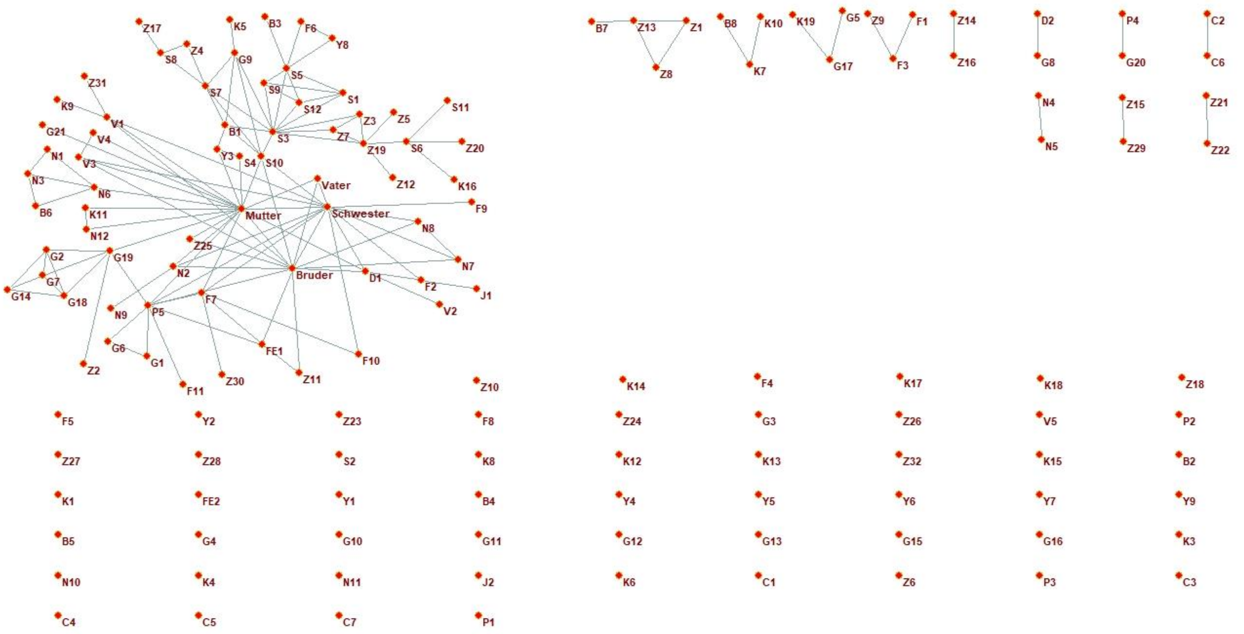

Figure 2. Dream Social Network.

(Watts & Strogatz, 1998). The clustering coefficient is much higher than that of a corresponding random network, so both properties of a small world network are satisfied by the largest component.

Transitivity for the entire dream social network is .318. Assortativity for the entire network is -.006, negative although close to 0, and negative for the largest component, -.129. (See the Appendix for a remark.) Assortativity for the dream social network is different from that of waking life social networks, which tend to have high positive assortativity (Newman & Park, 2003). The dream social network is heterogeneous in this respect, high degree people are not joined by an edge primarily to other high degree people.

4. Discussion

Overall, the present findings support the notion that a dream social network shows the characteristics of a small world network (small average distances, high clustering), and the power law distribution of co-occurrences – similar to waking-life social networks. The clustering was most obvious for the core family members of the dreamer; they are more likely to co-occur than occur with persons of other social areas.

Before discussing the findings in detail, several methodological issues have to be addressed. First, the analysis was based on a single dreamer. As we do not know very much how properties of dream social networks vary from person to person, additional analysis in larger groups of dreamers are necessary. In contrast to previous studies (Han et al., 2016; Schweickert, 2007a), the dream characters included in the analysis were only persons the dreamer knows in waking-life, that is, part of his waking-life social network. That might explain why the Zipf-Mandelbrot law fits less well for dream characters with infrequent occurrences or infrequent co-occurrences. This would suggest that for constructing a dream social network, this approach – also applied in Han and Schweickert (2016) – seems more promising compared to including all characters, even unfamiliar ones like policemen, bus drivers etc. Although studying dream characters

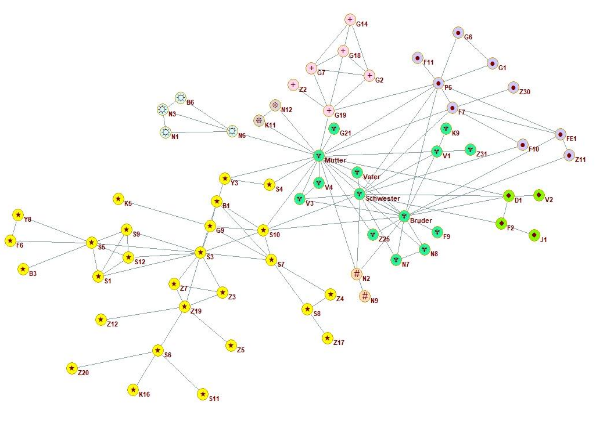

Figure 3. Communities Largest Component.

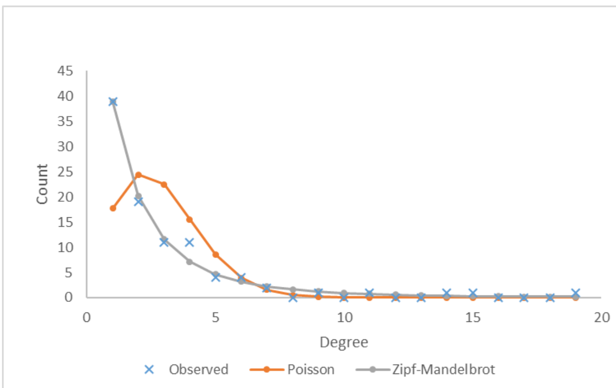

Figure 4. Fits of Zipf-Mandelbrot and Poisson Distributions to Observed Counts of Degrees at or above the Median Degree of 1.

not known to the dreamer might be interesting, e.g., if they are threatening, this is beyond the scope of this paradigm looking for parallels between the waking-life social network and the dream social network. Future research might focus on a broader definition of waking-life social network including strangers; the communities (cities, countries etc.) the dreamer live in.

The time interval the dreams were recorded encompasses one year in this study; this seems to be an advantage as social networks change over time (see the large number of dream characters belonging to the social network of dreamer's past). The duration of the five dream series analyzed in Han et al. (2016) ranged from 3 months (Engine man) to about 10 years (Alta). Han (2014) studied changes over time in the long dream series (over 30 years) of "Barb Sanders." It would be very interesting to study changes in more dream social networks over time.

The clustering coefficient (0.68), transitivity (0.318), and assortivity (total network: -.006; largest component: -.129) are comparable with the values of Merri's dream series (N = 312 dreams, N = 1127 characters, 2-year period) (Han et al., 2016), thus suggesting that the extraordinary findings regarding the Engine man series (high transitivity and assortivity) cannot be explained solely by gender differences. Negative assortativity indicates that dreaming may maintain weak connections in memory (Schweickert, 2007a). As time passes, connections between representations in memory degrade. At first, there may seem to be no harm in letting weak connections fade away. But Granovetter (1973) showed that weak connections in social networks are important. For example, people who found their current job through a contact reported most often that the contacted person was someone seen only occasionally. "In many cases, the contact was someone only marginally included in the current network of contacts, such as an old college friend or former workmate or employer" (p. 1371). In order to draw help from an acquaintance or friend from the past, one must remember this person. So maintaining weak connections in memory is useful. It is plausible that Hebbian learning occurs (Hebb, 1949), so if two people occur in a dream together, the strength of connection between their representations in memory is increased a little. There is little need to strengthen connections between high degree people, because those connections are likely maintained by waking life events. So co-occurrence in dreams is tuned to be somewhat frequent between high and low degree people. According to Social Simulation Theory, "dreams are *specialized* in simulating *the most important social connections*" (Revonsuo, et al, 2015, p. 20, emphasis in original). If so, weak connections must be included among those important.

The distribution of the frequency of dream characters occurring in the dream and the distribution of the number of co-occurrences with other dream characters per dream character were excellently modeled by a Zipf-Mandelbrot power law. That is, the number of persons who occur very often is very small, whereas many persons occur very rarely. This could be explained by a random walk through an associative memory network (Schweickert et al., 2020) supporting the idea that the dream social network reflects the cognitive social network as represented in the dreamer's memory. This idea is supported by the finding that persons from the dreamer's past – as Merri's deceased sister in her dream series (Schweickert, 2007c) – also play an important role in the current dream social network, even though they are not part of the waking-life social network anymore. That is, the dream social network is an amalgam of the current waking-life social network and the networks of the dreamer's past. This finding fits very well with the idea that dreams might be associated with sleep-dependent memory consolidation, integrating new information acquired during the day with information already existing within the memory (Klepel & Schredl, 2019; Wamsley & Stickgold, 2019), in this case the current waking-life social network into the global social network (all social contacts of the dreamer). In addition, the part showing that the current waking-life social network is clearly reflected in dreams, especially close relationship (core family members), is supporting partly the Social Simulation Theory (Revonsuo et al., 2015). However, the finding that persons that are no longer part of the social network of the dreamer occur in dreams is more difficult to explain within this theory, i.e., the question remains why strengthening relationships that are no longer relevant? Within the framework of the continuity hypothesis, these mixture of current and former social networks is easier to integrate as dreams reflect all waking-life experiences (current and former) of the dreamer, not only the current ones (Schredl, 2003).

So far, the method of characterizing the dream social network has only be applied to seven dream series (Han & Schweickert, 2016; Han et al., 2016; Schweickert, 2007a), raising the question about inter-individual differences. For example, the most frequent co-occurring pair of dream characters in the Barb Sanders series was mother and father (N = 150 co-occurrences). In the current dream series, the parents were simultaneously present in only four dreams, whereas the most frequent pair was brother and sister, very likely reflecting the fact that the parents of the dreamer divorced when he was twelve years old and had very rare contacts with his father since then.

To summarize, analyzing the dream social network, that is, co-occurrences of familiar dream characters, can help to understand how waking-life social relationships are reflected in dreams, e.g., the small world network properties. More studies are needed to link inter-individual differences within the properties of the dream social network to differences in the current and former waking-life social networks of the dreamer.

Note

As the present article refers to a previous paper of the second author (Schweickert, 2007a) and the journal did not publish the errata note sent by the second author, we would like to include the corrections here.

Table 1 of Schweickert (2007a) has two errors:

a. Clustering coefficients should be .44, .31, and .82 for Arlie, Merri, and The Natural Scientist (Engine Man), respectively. Those in Table 1 used the formula of Watts and Strogatz (1998). Those here (present paper) use the formula of Newman et al. (2002) and are often called transitivity. They are appropriate for comparison with the random affiliation network clustering coefficients of Table 1.

b. For the truncated power law the correct formula is $1/[\zeta(a+1) - H(m\text{-}1,a+1)]\ k^{a+1}$, where m is the median degree and $H(m\text{-}1,a+1)$ is the sum from k = 1 to m-1 of $1/k^{a+1}$. The correct formula was actually used to estimate parameter a and calculate r^2.

References

Barabási, A.-L. (2022). Network science. http://networksciencebook.com/ (accessed Jan 2022).

Batagelj, V., & Mrvar, A. (1998). Pajek - A Program for Large Network Analysis. Connections 21(2).

Bishop, Y. M. M., Feinberg, S. E., & Holland, P. W. (1975). Discrete multivariate analysis. MIT Press.

Domhoff, G. W. (1996). Finding meaning in dreams: a quantitative approach. Plenum Press.

Domhoff, G. W. (2003). The scientific study of dreams: neural networks, cognitive development and content analysis. American Psychological Association.

Domhoff, G. W. (2018). The emergence of dreaming: Mind-wandering, embodied simulation, and the default network. Oxford University Press.

Domhoff, G. W. (2019). The neurocognitive theory of dreams at age 20: An assessment and a comparison with four other theories of dreaming. Dreaming, 29(4), 265-302. https://doi.org/10.1037/drm0000119

Granovetter, M. S. (1973). The strength of weak ties. American Journal of Sociology, 78(6), 1360-1380.

Hall, C. S., & Van de Castle, R. L. (1966). The content analysis of dreams. Appleton-Century-Crofts.

Han, H. J. (2014). Structural and longitudinal analysis of cognitive social networks in dreams. Ph. D. Disseration.

Han, H. J., & Schweickert, R. (2016). Continuity: Knowing each other, emotional closeness, and appearing together in dreams. Dreaming, 26(4), 299-307. https://doi.org/10.1037/drm0000038

Han, H. J., Schweickert, R., Xi, Z., & Viau-Quesnel, C. (2016). The Cognitive Social Network in Dreams: Transitivity, Assortativity, and Giant Component Proportion Are Monotonic. Cognitive Science, 40(3), 671-696. https://doi.org/10.1111/cogs.12244

Hebb, D. O. (1949). The organization of behavior: A neuropsychological theory. John Wiley.

Klepel, F., & Schredl, M. (2019). Correlation of task-related dream content with memory performance of a film task – A pilot study. International Journal of Dream Research, 12(1), 112-118. https://doi.org/10.11588/ijodr.2019.1.59320

Krackhardt, D. (1987). Cognitive social structures. Social Networks, 9(2), 109–134. https://doi.org/10.1016/0378-8733(87)90009-8

McNamara, P., McLaren, D., Smith, D., Brown, A., & Stickgold, R. (2005). A “Jekyll and Hyde” within: aggressive versus friendly interactions in REM and Non-REM dreams. Psychological Science, 16, 130-136.

Newman, M. E. J. (2003). The structure and function of complex networks. SIAM Review, 45, 167-256. https://doi.org/10.1137/S003614450342480

Newman, M. E. J. (2006). Modularity and community structure in networks. Proceedings of the National Academy of Sciences, 103(23), 8577–8582.

Newman, M. E. J., & Girvan, M. (2004). Finding and evaluating community structure in networks. Physical Review E, 69(2), 026113.

Newman, M. E. J., & Park, J. (2003). Why social networks are different from other types of networks. Physical Review E, 68(3), 036122. https://doi.org/10.1103/PhysRevE.68.036122

Newman, M. E. J., Watts, D. J., & Strogatz, S. H. (2002). Random graph models of social networks. Procedings of the National Academy of Sciences, 99(Suppl 1), 2566-2572. https://doi.org/10.1073/pnas.012582999

Revonsuo, A., Tuominen, J., & Valli, K. (2015). The Avatars in the Machine. In T. K. Metzinger & J. M. Windt (Eds.), Open MIND (pp. 1-28). MIND Group. https://doi.org/10.15502/9783958570375

Schredl, M. (2003). Continuity between waking and dreaming: a proposal for a mathematical model. Sleep and Hypnosis, 5, 38-52.

Schredl, M. (2013). Dreams of core family members in a long dream series. International Journal of Dream Research, 6, 114-118. http://archiv.ub.uni-heidelberg.de/ojs/index.php/IJoDR/article/view/11055

Schredl, M. (2018a). Reminiscences of love: Former romantic partners in dreams. International Journal of Dream Research, 11(1), 69-73. https://doi.org/10.11588/ijodr.2018.1.43842

Schredl, M. (2018b). Researching Dreams: The Fundamentals. Palgrave Macmillan.

Schredl, M. (2021). Family members in a long dream series. International Journal of Dream Research, 14(2), 323-326. https://doi.org/10.11588/ijodr.2021.2.82662

Schredl, M., Cadiñanos Echevarria, N., Saint Macary, L., & Weiss, A. F. (2020). Partners and ex-partners in dreams: An online survey. International Journal of Dream Research, 13(2), 274-280. https://doi.org/10.11588/ijodr.2020.2.75338

Schredl, M., Cadiñanos Echevarria, N., Saint Macary, L., & Weiss, A. F. (2021). Dreaming about one’s own children: An online survey. Imagination, Cognition and Personality, 41(2), 222-237. https://doi.org/10.1177/02762366211017421

Schredl, M., & Hofmann, F. (2003). Continuity between waking activities and dream activities. Consciousness and Cognition, 12, 298-308. https://doi.org/10.1016/S1053-8100(02)00072-7

Schredl, M., & Wood, L. C. (2021). Partners and Ex-Partners in Dreams: A Diary Study. Clocks & Sleep, 3(2), 289–297. https://doi.org/10.3390/clockssleep3020018

Schweickert, R. (2007a). Properties of the organization of memory for people: evidence from dream reports. Psychonomic Bulletin and Review, 14, 270-276.

Schweickert, R. (2007b). Social networks of characters in dreams. In D. Barrett & P. McNamara (Eds.), The new science of dreaming - Volume 3: Cultural and theoretical perspectives (pp. 277-297). Praeger.

Schweickert, R. (2007c). The Structure of Semantic and Phonological Networks and the Structure of a Social Network in Dreams. In J. S. Nairne (Ed.), The foundations of remembering: Essays in honor of Henry L. Roediger, III. (pp. 281-296). Psychology Press.

Schweickert, R., Xi, Z., Viau-Quesnel, C., & Zheng, X. (2020). Power law distribution of frequencies of characters in dreams explained by random walk on semantic network. International Journal of Dream Research, 13(2), 192-201. https://doi.org/10.11588/ijodr.2020.2.71370

Tuominen, J., Olkoniemi, H., Revonsuo, A., & Valli, K. (2021). ‘No Man is an Island’: Effects of social seclusion on social dream content and REM sleep. British Journal of Psychology, online first. https://doi.org/10.1111/bjop.12515

Tuominen, J., Stenberg, T., Revonsuo, A., & Valli, K. (2019). Social contents in dreams: An empirical test of the Social Simulation Theory. Consciousness and Cognition, 69, 133-145. https://doi.org/https://doi.org/10.1016/j.concog.2019.01.017

Wamsley, E. J., & Stickgold, R. (2019). Dreaming of a learning task is associated with enhanced memory consolidation: Replication in an overnight sleep study. Journal of Sleep Research, 28(1), 1-8. https://doi.org/10.1111/jsr.12749

Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. Nature, 393(6684), 440-442. https://doi.org/10.1038/30918

Appendix

Remark on Negative Assortativity in the Largest Component

In the dream social network there is a single edge between two people who occur in a dream together, no matter how many dreams they co-occur in. Restriction to a single edge may produce by artifact a negative degree correlation when the degree distribution is a power law, see Barabási (2022) for discussion. With a positive correlation, two high degree vertices would tend to be frequently joined by an edge. But with only a single edge allowed, such joining can occur only once, not frequently. This constraint could lead to a negative degree correlation explained entirely by the degree distribution, a consequence called structural disassortativity. A negative degree correlation is not necessarily an artifact, and seems not an artifact here. Here, only one vertex could be the source of a structural disassortativity and when that vertex is removed the remaining network is still disassortative.

The following considerations are based on discussion in Barabási (2022). A negative degree correlation can only be caused by structural disassortativity if there are vertices whose degree is greater than the structural cutoff k_s, although such vertices may exist without causing structural disassortativity. The structural cuttoff ks is approximately (dn)1/2. In the largest component, d = 3.62 and n = 68, so the structural cutoff is k_s = 15.68. Only one vertex in the largest component has degree higher than k_s, Mutter, with degree 19. When this vertex and edges incident with it are removed, the remaining network still has negative assortativity, – .110. In the remaining network, the number of vertices is 67 and the average degree is 3.10, so the structural cutoff is 14.42. The largest degree in the remaining network is 14, for Schwester. No vertex in the remaining network has degree greater than the structural cutoff. Hence, most or all of the largest component has negative assortativity that is not completely accounted for by structural disassortativity.