

Fractals Beyond Hierarchy—Analyzing the Temporal Patterns of Contact Networks in a French Public Sector Organization

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Abstract

Fractals describe structural details at arbitrarily small scales, but are mathematically not necessarily complex, presenting a pragmatic way of describing nature. They are also common in social settings, including the organizational space. However, attention has been devoted to temporal fractal patterns in heterarchical or networked organizations. This article leverages data on face-to-face interactions collected by the SocioPatterns collaboration in a public sector organization to investigate temporal fractal patterns in interaction networks and three types of processes have been identified in this. White noise exhibits no correlation in time with rapid, chaotic changes. Brown noise entails a diffusion process with stable, structural patterns, but no quick adaptation. Pink noise exhibits an equilibrium between the two, producing dynamics that maintain stable patterns of interactions, remaining flexible to regulate interaction. The interaction network is described with metrics of social network analysis, and analyzed with detrended fluctuation analysis (DFA) to detect temporal fractal patterns within the three largest departments as well as the whole organization. Results indicate high levels of pink noise with traces of white noise in the departments as well as pink noise with traces of brown noise on the organizational level. While previous research found pink noise processes in self-organizing networks, this article extends them to structured intraorganizational networks. The low levels of brown noise question the influence of rigid organizational structures and processes on the temporal structure of interaction. Hence, the fractal temporal structure of the interactions themselves is a factor that contributes to the stability of interactions between individuals over time.

Keywords

Fractal Organization, Temporal Network, Social Network, Detrended Fluctuation Analysis

Introduction

Nature is beautiful and is organized in complex patterns, often defying the description by calculus in their roughness. These patterns are called fractals and are defined as geometric shape with the property of detailed structure at arbitrarily small

scales (Mandelbrot, 1982). Their fractal dimension usually exceeds the topological dimension (Briggs, 1992). Interestingly, fractals describe structural details at arbitrarily small scales but are mathematically not necessarily more complex than calculus. They are not a mathematical exercise either, but rather a pragmatic way of describing nature.

Our perception of organic design and organization is inherently linked to their fractal nature. This is directly related to the fractal organization of biological organisms and ecosystems. A striking example of the organic and natural appearance of fractal design and organization comes from architecture in the form of the houses designed by Frank Lloyd Wright, which audiences described as “oddly natural” (Joye, 2011; Ostwald et al., 2015).

However, fractals can not only be found in mathematical or architectural design processes. They are everywhere around us. Mandelbrot modeled coastlines, lake-shores, and even cauliflowers as fractals (Mandelbrot, 1982). Not long after, the concept was also picked up in more social domains, like management studies. In the wake of computer integrated manufacturing (CIM) in the late 1990s and early 2000s, scholars predicted a fundamental transformation of production processes toward more agility and smaller batch sizes while increasing variety (Fowler et al., 2001). Among “bionic organization” and “holonic organization,” “fractal organization” was one of the structural and functional solutions proposed (Ryu & Jung, 2003; Tharumarajah, 1996). This concept did not remain limited to the industrial manufacturing process and was extended to “fractal social organizations” (FSO), in an attempt to homogeneously model collective behaviors of different complexity and scale (De Florio et al., 2013a). While discussing fractal architecture in depth, both fractal manufacturing and FSO put a strong emphasis on the hierarchical organization of fractal systems in the organizational context. While the hierarchy is not necessarily one of control, it is a functional and structural hierarchy that results from the fractal architecture (Ryu & Jung, 2003; Tharumarajah, 1996). The hierarchical focus is a limitation of modeling fractals in social networks or organizations, as many forms of organization or interactions are heterarchical (Stark, 1999).

While hierarchy is a central element of FSOs and structural fractals in the social domain, there is good reason to assume that nonhierarchical forms of organization and interaction also exhibit fractal features. One dimension in which this is possible is the *temporal* fractal nature of (social) systems that are created by interaction patterns or exchanges over time. Other studies on fractal patterns in social environments, like the behavior of animals (Alados & Huffman, 2000; MacIntosh et al., 2013), the growth of the internet (Tadić, 2002), or the self-organization of social movements (Aguilera et al., 2013), show fractal patterns not only in space use but also in temporal sequences across multiple orders of magnitude. Temporal fractal structures are correlated with positive

outcomes, such as health (Alados & Huffman, 2000), or stability over time (Aguilera et al., 2013). While there is research on temporal fractal patterns in human behavior (Aguilera et al., 2013; Fan et al., 2010; Likens et al., 2015), this does not extend to structured, formal organizations. Therefore this article aims to explore temporal fractal patterns in a contact network between individuals in different departments of a French public sector organization, by first outlining previous research on fractals in the organizational space, and carving out characteristics of temporal fractal patterns, based on previous research on such patterns in self-organizing social movements, before investigating the existence of different temporal fractal patterns using detrended fluctuation analysis (DFA) (Peng et al., 1992). The research question guiding the process therefore is:

To which degree do structured intraorganizational networks exhibit temporal fractal structures and how does the fractal nature manifest in temporal social networks?

Background

Fractal Geometry and the Social Space

Coming to a definition of what “fractal” entails in the social space is not particularly easy. The definition “fractal geometry is a workable geometric middle ground between the excessive geometric order of Euclid and the geometric chaos of general mathematics. It is based on $[]$ invariance under contraction or dilation” (Mandelbrot, 1989, p. 3) does introduce one of the basic concepts of fractal geometry, invariance of detail to scale, but does not give clear implications about fractal patterns in social interactions, organizations, and networks. The statement of invariance under contraction or dilation refers to the fact that fractals retain detailed structure at arbitrarily small scales. While this is often equated with self-similarity at arbitrarily small scales, like in the “Koch snowflake” (von Koch, 2004) or the “Sierpinski triangle” (Sierpinski, 1915), the fractal reality of nature is not typically self-similar. In a temporal context, for example, fluctuations over different time scales might exhibit different properties but are invariant to dilation in the sense that fluctuations remain regardless of the scale of the time series (Evertsz, 1995). Besides this, only mathematical fractals are infinite, thus the invariance of detail to scale in natural (physical) fractals only holds true for some orders of magnitude, leading to some scholars calling them “pseudo-fractals” (Kautz, 2011).

Early on, researchers also identified fractals in social and organizational spaces, which remained predominantly at the structural level. The first contribution on fractal organizations by Zimmerman and Hurst (1993) departed from the tension at and between different levels that underlies fractals in nature and generalized it to firms, attested self-similarity and fractal boundaries in organizations (Zimmerman & Hurst, 1993). The fractal structure of organizations comes as a little surprise, as many social groups have a discrete hierarchical organization that is fractal with a consistent scaling ratio of three (Zhou et al., 2005). Later organizational research on the “fractal organization” developed the concepts of self-similar “basic fractal units,” which are parts of a greater system but also a fully contained system with subsystems in them to arbitrarily small scales (Ryu & Jung, 2003; Tharumarajah, 1996). They notably included an interactionist component, pointing out that basic fractal units are networked via an efficient information and communication system. The concept of “fractal organization” was later extended to and formalized in the “fractal social organization” (FSO) (De Florio et al., 2012; De Florio et al., 2013a,b). In de Florio’s model, FSOs are characterized by a distributed, bio-inspired, and hierarchical architecture, in which a basic building block, similar to a basic fractal unit, is applied recursively at different levels. This provides a homogeneous way to model collective behaviors of different scales and complexity (De Florio et al., 2013a). In practice, FSOs have a higher performance, as the recursive application of the same structure, enabled by self-similarity, creates a high potential for parallel processing in the systems (De Florio et al., 2013b).

In the original definitions of both fractal organization and FSO, strong emphasis is placed on *hierarchical* federation in nested systems. While this applies to many firms, and based on evidence from hierarchical mammalian societies (Hill et al., 2008), it effectively excludes nonhierarchical forms of organization, such as networks and heterarchical federations from the discussion of fractal (social) organizations. Furthermore, the organization is only structurally fractal. No direct consideration is paid to the fractal patterns in interaction between individuals or units in the fractal system(s). Hence, the research into fractal patterns in organizations so far is predominantly atemporal, meaning that there are few insights into the fractal patterns of interaction or the development of organizational structure over time.

Temporal Fractal Patterns

An important contribution to the analysis of temporal fractal patterns in the social and organizational space is the article of Aguilera et al. (2013) about political self-organization on social media. Building on work from the field of physics (Bak et al., 1987), they identify fractal scaling as a characteristic of self-organizing systems in the social space. They observe an “interesting mix between stability and instability creating complex structures of the variability of the systems activity” (Aguilera et al., 2013, p. 296). The temporal fractal patterns in a network can be described with a spectral density function $S(f)$, or more specifically

$$S(f) \propto f^\beta$$

for fractal scaling, where f stands for the different frequencies of the interaction activity, and β defines a log-linear relationship between the spectral power content at different scales of f , delivering insights into the relative influence of each scale in the system. In cognitive neuropsychology, this approach is commonly used to describe interactivity among components in the system, as well as predict the emergence of new cognitive structures (Dixon et al., 2012). This approach is especially suitable for the analysis of organizational structures with distinct components, such as the departments in the data used for this article.

Three different types of processes can be identified from different values of the relative influence of each scale in the system (β):

- White noise ($\beta=0$) entails no correlations in time. They display fast changes in their activity, as well as high adaptation to rapid environmental changes, but are unable to maintain structured and coherent patterns.
- Brown noise ($\beta=2$), corresponding to Brownian motion, entails a diffusion process with no correlation between short-scale events, but a high correlation between the position of one sample and the next. These processes are long-range dependent and produce stable structural patterns, but unable to adapt to fast changes in the environment. Brown and white noise are directly related to each other, as Brownian motion is the integral of white noise and white noise is differentiated brown noise (Keshner, 1982).
- Pink noise ($\beta=1$) describes the equilibrium between White and Brown noise. Hence it is also an equilibrium between disorder with high adaptation and structure with low adaptation. Pink

noise processes tend to produce dynamics that maintain stable patterns of activity while remaining flexible to regulate activity (Aguilera et al., 2013).

White noise processes exhibit high fluctuations on a short time scale but normalize across a longer scale. On the other hand, Brown noise diffusion processes exhibit larger fluctuations on longer time scales, limited by the end of the diffusion process. On shorter time scales, the fluctuation per time becomes negligible. Pink noise processes are inherently fractal as the combination of white and brown noise leads to an invariance of fluctuation to scale. Insights from cognitive neuroscience (Dixon et al., 2012) as well as the human and nonhuman social space (Aguilera et al., 2013; Alados & Huffman, 2000) indicate that this particular mix of fluctuation size and frequency is a core component of functional and healthy systems of interactions. However, Aguilera et al. (2013) analyzed critically self-organizing systems. Other research on temporal fractal patterns such as fractal time series in the social and organizational space considered power-law distributions in the growth of the internet (Tadić, 2002) and the multifractal characteristics of warehouse-out behavioral sequences (Yao et al., 2017). Organizations with a clear structure despite the absence of a formal hierarchy among actors may present a different case, one has not yet investigated for its fractal scaling and temporal fractal properties. It remains unclear whether the three processes outlined above also replicate in environments that constrain flexibility and long-range structural patterns by the presence of structure external to the interactions. The remainder of this article will therefore investigate the (multi-)fractal properties of interaction sequences between humans in a structured, though not formally hierarchical organizational setting. Besides pink noise, higher levels of brown noise than in the context of Aguilera and colleagues are expected due to the more rigid structure of the organization.

Data

The data used were collected by the SocioPatterns collaboration in one of the two office buildings of Institut de Veille Sanitaire (InVS), the French Institute for Public Health Surveillance, located near Paris and lasted 2 weeks in 2015 (Génois et al., 2015). The data collection was carried out using wearable sensors that can detect the proximity of individuals wearing them using radio signals. The body acts as a shield for the radio frequencies, resulting only in the detection of proximity if individuals face each other at a range of <1.5 m (Barrat et al. 2014; Cattuto et

al., 2010). Furthermore, RFID readers located in the environment enabled the definition of a spatial location for each sensor (Génois & Barrat, 2018). As each RFID reader covered a range of approximately 30 m, two individuals within such a distance (assuming low overlap between sensors) were defined to have a co-presence, as their signal is picked up by the same sensor. This resulted in a temporal network of face-to-contacts and a temporal co-presence network, at a temporal resolution of 20 s each. Genois and Barrat (2018) provide a detailed description of the data collection process and data structure.

Furthermore, the data can be subdivided into groups corresponding to the five functional departments, with department sizes ranging from 5 to 60 people. A detailed description of the organizational structure can be found in Genois et al. (2015), which is the first fielding of the measurement at InVS in 2013, later repeated in 2015 (Génois & Barrat, 2018). The more recently collected data will be used in this analysis. Appendix 1 displays contact networks based on all contacts during the data collection period, both for the whole organization and the three most contact intensive departments separately.

A first visual inspection of the contact frequencies indicated that the time stamps (t) of the 20 s intervals were continuous and not limited to office hours. Hence, there were prolonged periods with no contacts during the evenings, nights, and weekends in the 2 weeks of measurement. These periods were excluded from the analysis, as they would bias the patterns of fluctuation. This yielded a data set of 18,488 with 20 s intervals. The analyses were performed on the face-to-face contact network.

Methods

DFA

DFA (Peng et al., 1992) method is widely used for discovering fractal properties of time series by determining the statistical self-affinity of a signal. As the name suggests, the time series is detrended globally by integrating it, before dividing it into “windows” of equal size t . This process is repeated for a range of different values of t , resulting in different number of windows. For each value of t a standard least squares line is fit to the data, which allows for computing the size of the fluctuation $F(t)$ for every window individually. Usually, $F(t)$ increases with t . While Aguilera et al. (2013) use the DFA results to calculate the Hurst exponent, an approximation of β in the spectral density function, which in turn is used to estimate β , as the relationship between the Hurst

exponent and the spectral power content at different scales is $\beta=2 * \alpha-1$, this article takes the more parsimonious approach of estimating β directly from the DFA results. As $F(t) t^\beta$, β can be estimated directly from the DFA results by regressing $F(t)$ on t . The range of the regression is determined by the window sizes for which a linear relation in the log-log plot of t and $F(t)$ holds true. The exponent of this regression is beta (Penzel et al., 2003).

For the interpretation of the DFA results, it is crucial to recognize the cited β values of white noise (0), brown noise (2), and pink noise (1) as ideal values, situated on a spectrum from $\beta=0$ to $\beta=2$. Hence the pink noise is observed as values *tend toward* 1 instead of only if they are exactly 1. This is coherent with the practically imperfect nature of fractals, both as “pseudo-fractals” (Kautz, 2011), limited in their dimensionality by the temporal resolution and length of observation, as well as the randomness of an observational context such as InVS. Previous research using DFA to detect fractal patterns in temporal data has not specified clear boundaries on the white-pink-brown noise spectrum (Aguilera et al., 2013; Alados & Huffman, 2000), but described values between $\beta=0.8$ and $\beta=1.2$ as “quite close to pink noise” (Aguilera et al., 2013, 2). Also Alados and Huffman (2000) confirm the presence of fractal scaling at $\beta=1.247$.

For the three biggest departments in terms of contacts (DMI, DSE, DISQ, with 14,945, 9,528, and 8,658 measured contacts, respectively), as well as for the whole organization, time series were created that were composed of number of contacts for each 20 s interval. The DFA procedure was performed on 200 window sizes of t , ranging from 30 (600 s) to 18,488 (369,760 s) intervals, resulting in a range of $t=30$ to $t=18,488$ for the time series, obtaining the $F(t)$ values for each window size t across the different cases. Following this, the value of t was identified where the shape of $F(t)$ began to have a log-linear relationship, indicating fractal scaling. This allows for an estimation of a range of scales across which the fractal relationship within the time series held true.

Network Analysis

Furthermore, a network analysis was performed to gain descriptive insights into the underlying networks of the time series. Factors that were deemed to deliver insights into structural elements influencing the contact frequency and fluctuation were network size, density, average and maximum degree centrality in the network, the clustering coefficient (transitivity), and the size and percentage of the largest component.

Network Size

The size of a network is simply the sum of all nodes in the network, regardless of whether they share edges or not. *Ceteris paribus*, the larger the network, the greater the sum of all contacts between the nodes.

Network Density

The network density is obtained by dividing the number of edges in the observed network by the maximum number of edges observable given the number of nodes. Again, a higher network density entails more contacts.

Degree Centrality

The degree centrality is a measure of the number of ties/contacts a person has within the network, where the *average degree* also indicates the expected number of other individuals an individual is in contact with and the *maximum degree* indicates whether certain individuals have many contacts disproportionately. Degree centrality can deliver insights into the fluctuations of contact frequency in the network and a Removing two nodes with different degree centralities from the network (temporarily) will have differing effects on the contact frequency.

Clustering Coefficient

The clustering coefficient, or transitivity, is a measure of redundancy in networks. The clustering coefficient for a node (A) is defined as the proportion of all possible contacts between the contacts of A. In a network in which A serves as a hub and intermediates all contacts between its connections, A's (temporary) removal from the network would lead to an inevitable drop of the contact frequency to 0.

Components

A component refers to a part of the network within all nodes that are connected to each other via some finite path. Components are different from groups or *cliques* within the network as they are not connected to each other. All isolated individuals in the network are their own components, however, they are not all considered in this analysis as they do not have any contacts with other individuals.

The network was constructed using the contact matrix and thus includes individuals from all departments across the whole period of data collection. The network was constructed as a nondirected, nonweighted, and nonmultiplex network, thus not

considering the initiation or frequency of the contact between two individuals. Appendix 2 provides a visual representation of the resulting network.

Results

Network Analysis

The results of the network analysis summarized in Table 1 show a higher network density within departments, than across the whole organization. While for the whole organization, 9% of the possible contacts between individuals were realized over the 10-day period of data collection, this increases to 22%, 29%, and 45% in the respective departments. From this it is also evident that the percentage of other individuals a given individual has contact with over the time period increases as the department size decreases.

Significant differences are found in degree centrality at organizational and departmental levels. While the network density decreased with network size, the opposite seems to hold true for the degree centrality. This is predominantly because the smaller n of the departmental networks limits the maximum number of unique contacts an individual can have within the network. Comparing the average degree across the whole organization (39.39) to the average degree within departments, it is evident that the degree within the departments examined is consistently lower than across the whole organization. In all but the DISQ department where the maximum degree equals $n-1$, individuals also are not directly connected to all other members of their department.

Similarly to the network density, the clustering coefficient, as a measure of redundancy in the network, is also inversely related to network size. Finally, not only within departments but also across the whole organization all individuals are linked via some finite path, which entails that a message transmitted exclusively in face-to-face contacts could have reached all 217 individuals over the course of the 10-day data collection period.

The results of the network analysis analyzing both the structure of the three most contact intensive departments individually, as well as the organization as a whole, indicate that there are substantial differences between departments, mainly due to their differences in size. While departments as clusters can be analyzed as sub-networks, there is also a need for analyzing the organization as a whole. Hence, the article will proceed by first analyzing the fractal scaling for the DMI, DISQ, and DSE departments separately, before analyzing the aggregate results of

Table 1. Descriptive network statistics.

	InVS	Departments		
		DMI	DISQ	DSE
Network size	217	56	18	32
Network density	0.09	0.22	0.45	0.29
Average degree	39.39	25.07	15.33	18.13
Maximum degree	84	41	17	29
Clustering coefficient	0.36	0.56	0.92	0.71
Size of largest Component	217	56	18	32
% of largest component	100	100	100	100

InVS, Institut de Veille Sanitaire

the whole organization, also including the other, less contact-intensive departments.

Fractal Scaling within Departments

DMI

Figure 1 presents a visual summary of the DFA results for the contacts within the DMI department. The global value for β across all window sizes $t=30$ - $t=18,488$ was estimated to be 0.801. However, limiting the estimation to the range of t in which the log-log plot exhibits a linear relationship and thus indicates fractal scaling ($t=30$ - $t=2,500$), yields $\beta=0.947$. While the global value of β indicates the presence of predominantly pink and some white noise, the limited range with $\beta=0.947$ is very close to pink noise ($\beta=1$).

DISQ

Figure 2 displays a visual summary of the DFA results for the DISQ department. The value of β across all window sizes t is slightly lower than in the DMI department ($\beta=0.796$) but still indicates the presence of pink noise as it is substantially closer to $\beta=1$ than $\beta=0$. Limiting the estimation of the exponent to the range of t in which the linear relationship in the log-log plot holds true ($t=30$ - $t=2,200$) yields $\beta=0.836$, which is substantially closer to pink noise. Notably, the plot displays heterogeneity of variance as the variance increases between $t=30$ and $t=2,500$.

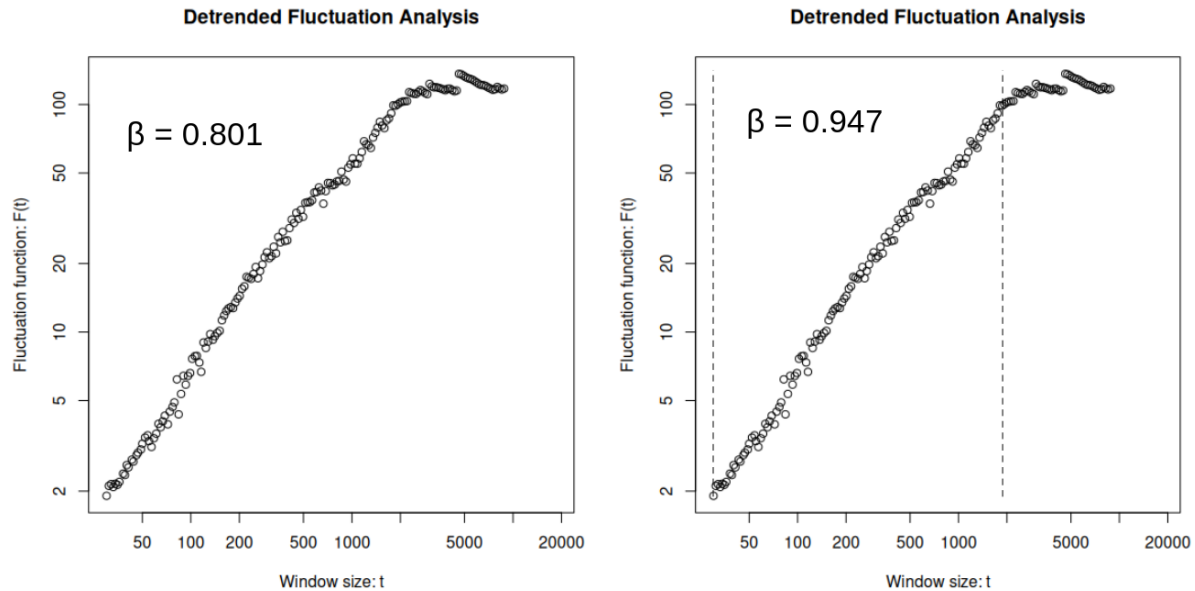


Figure 1:

DSE

Figure 3 visually summarizes the DFA results for the frequencies of face-to-face contacts in the DSE department. Globally, ($t=30$ - $t=18,488$) the value of β indicates the presence of pink noise processes, with some white noise elements, similar to the DMI and DISQ departments ($\beta=0.832$ compared to $\beta=0.801$ and 0.796 respectively). For the data from the DSE department, the linear relationship in the log-log plot holds true between $t=30$ and $t=2,200$ approximately. For this range, the value of β is very close to pink noise, as $\beta=0.985$. Out of all three departments, the DSE department's values are closest to pink noise, both across all window sizes t as well as in the limited range.

Fractal Scaling Globally

Figure 4 displays the DFA organizations across all functional departments in the organization. For the range $t=30$ - $t=18,488$, $\beta=0.913$, which is higher than in all previously examined departments separately. This is at least partly because of the limited range where the linear relationship in the log-log plot holds true ($t=30$ - $t=2,000$), $\beta=1.170$. In contrast to the within-department data on interaction frequencies, the data for the whole organization yields a β value exceeding 1, indicating the presence of traces of brown noise in the pink noise, rather than white noise. Hence, the

organization as a whole displays the highest β values out of all samples, both across all window sizes t and in the limited range.

Discussion

The results indicated the presence of pink noise processes or fractal scaling in the frequency of face-to-face contacts in all three departments as well as the whole organization. Among the three departments, DSE had the highest values of β both for the whole range of different window sizes t as well as for the limited range in which fractal scaling was expected based on a log-linear relationship between the window size t and fluctuation function $F(t)$. The results from the intradepartment analyses all exhibit similar features: pink noise processes were identified in all three departments, and the value of β was close to 1 when restricting the range to the window sizes t in which fractal scaling was expected. Furthermore, the deviation of the empirical β values from 1 was toward 0 in all three departments, indicating the presence of traces of white noise in the pink noise identified. For all three departments though, the evidence of white noise remains rather limited, and with no β values exceeding 1, there is no empirical evidence of any brown noise processes.

When analyzing the whole organization, it is observed the value of β for an unrestricted range exceeded the ones of the intradepartment

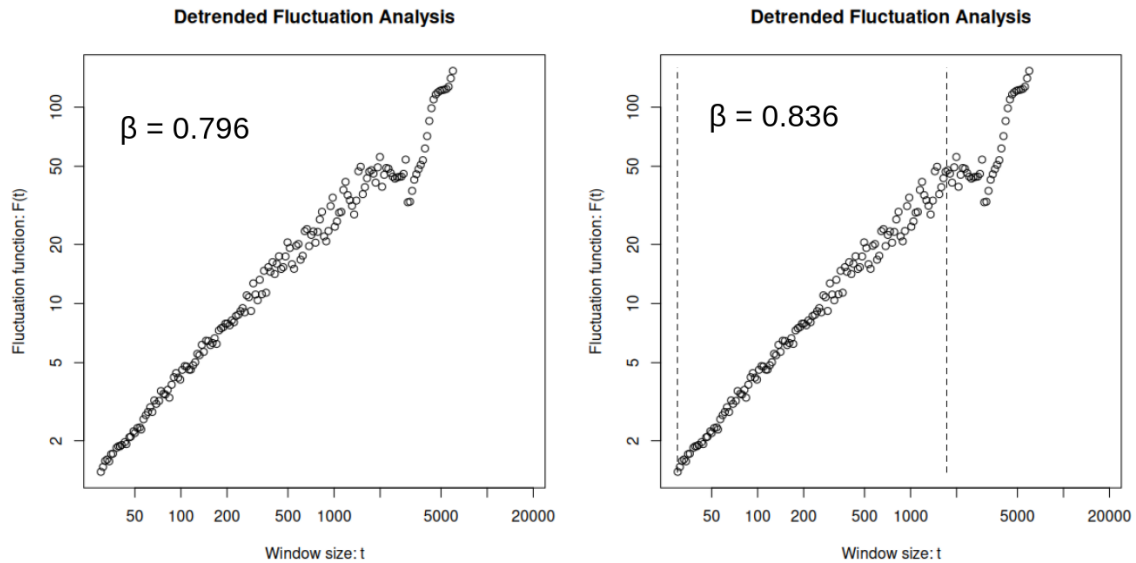


Figure 2:

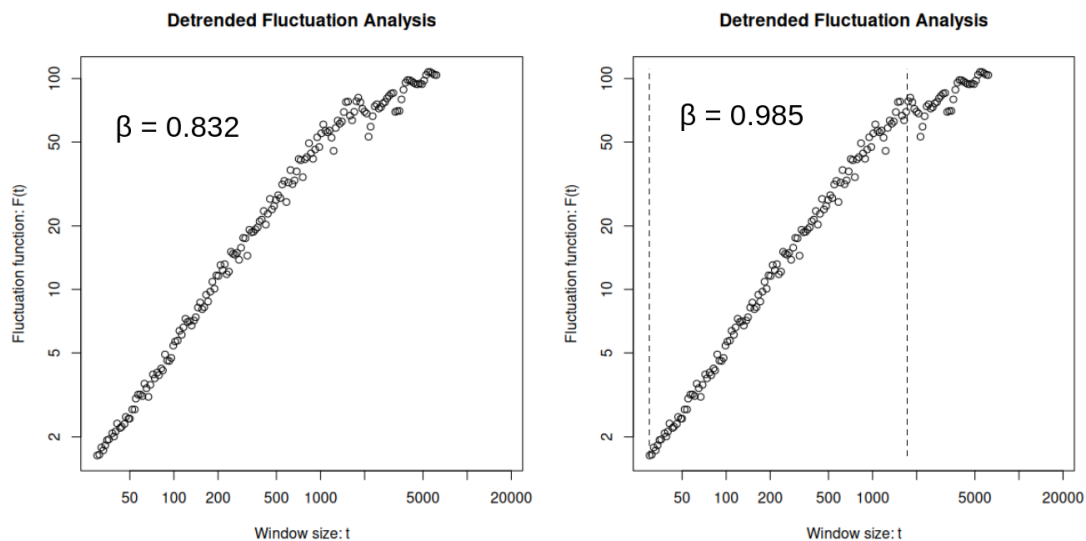


Figure 3:

analyses, which also held true for the limited range. Considering interaction frequencies of all individuals within the organization, that being all departments and both intra- and interdepartment face-to-face contacts, is the only case in which β exceeds 1, indicating the presence of brown noise. As the brown noise is exclusively observed in the analysis of the whole organization it either originated from the departments not analyzed, or more likely, a result of the interdepartment contacts.

Finally, for all intradepartment as well as interdepartment analyses, the linear relation in the log-log plot held true for a range of 30 to 2,000–2,500. This entails the time series of interaction frequencies to be considered fractal when analyzing ranges of 600 s (10 min) to 40,000 or 50,000 s (666–833 min). For larger window sizes t , the DFA results indicate lower exponents β meaning that the temporal patterns of interaction, as measured by their frequency per 20 s time unit, exhibit no correlations

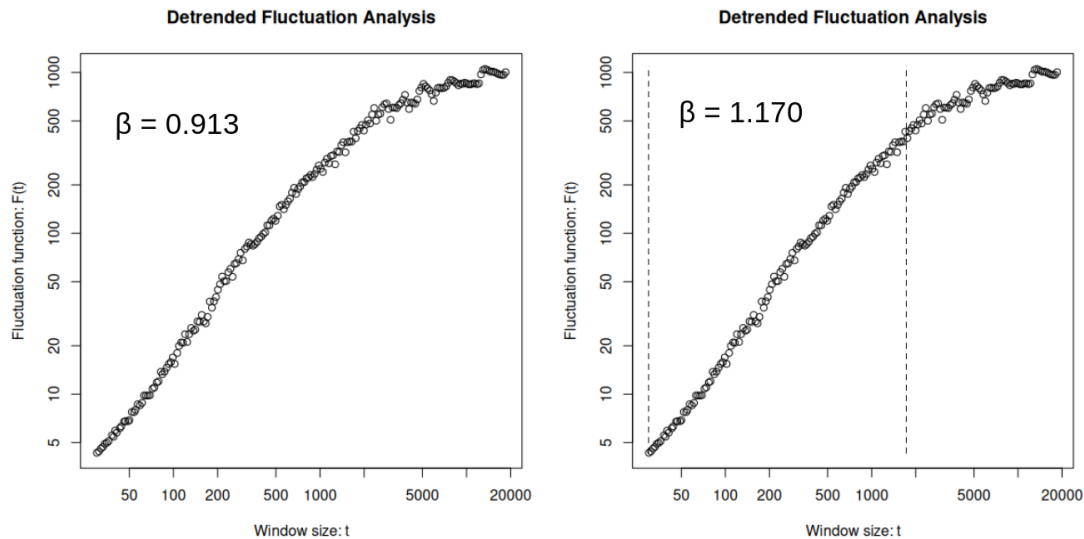


Figure 4:

in time and do not maintain stable or structured patterns.

Practically, these results entail that the contacts of the employees within the organization are adaptive to rapid changes, but defy the disorder and chaos of random interactions by producing stable patterns of interaction. Both within the single departments and the whole organization, this mechanism seems most effective in ranges of 10 min to 666–833 min, which corresponds to slightly more than a working day. For longer ranges, the fluctuations indicate a stronger presence of spontaneous, more chaotic responses in the contact frequency. This, however, remains moderate as all values of β remain relatively close to 1, indicating pink noise. Against previous expectations, the comparatively rigid organizational structure of InVS did not lead to higher levels of brown noise than in self-organizing social movements. Much the contrary, brown noise was only observed in the analysis of the whole organization when considering all window sizes t .

The absence of brown noise, despite a more rigid organizational structure that was hypothesized to produce more long-range dependent, stable patterns in the contact frequencies, provides confounding evidence to the assumption that the structure of an organization influences the temporal contact patterns. Similarly, the results of the network analysis for the three departments show that structural features of the network, such as size, density, and average degree, while being systematically related to each other, are not systematically related to the temporal patterns of interaction.

An interesting observation and also the main practical limitation of the research is the range of window sizes t for which the relationship was linear and tangible statements about the nature of the fluctuations in the interaction frequency could be made. As the range is from 10 min to less than a working day, the insights gathered from the analysis of this time period cannot be used to make tangible statements about the long-term structure of interactions within the organization. While the insights into the short time period at hand are interesting, it is questionable if the organizational structure has a great influence on the frequency fluctuations over less than an hour. When hypothesizing the relationship between organizational structure and fractality or long-term memory of the signal, the theoretical argument for more brown noise was the more rigid structure of the organization, with regular meetings, scripted interactions, and exchanges. These however are not choreographed down to sub-10 min intervals, which detaches the theoretical mechanism from the practical unit of analysis. This also serves as a potential explanation as to why there was less long-term memory in the interaction frequencies than anticipated. Another limitation of this research is the power of the fractal analysis. Besides the usual emergence of fractal patterns in time series as a result of self-organizing processes, they can also emerge as a product of linear combinations without fractal scaling (Hausdorff & Peng, 1996). In this case, the relationship between any organizational structure and the fractal patterns of the contact frequencies would be merely random. To mitigate this problem,

previous research has suggested multifractal analysis to verify the nonlinear nature of interactions and not a linear superposition of random components on multiple timescales (Ihlen & Vereijken, 2010). This, however, was beyond the scope of this article.

Considering the general presence of fractal temporal structures in functional and healthy systems of interaction (Aguilera et al., 2013; Alados & Huffman, 2000; Dixon et al., 2012), there is real practical value of temporal fractal analyses, also for large, structured organizations. Organizational network dysfunction on the level of communication is often intangible, and difficult to spot and pinpoint. Analyzing the temporal patterns of interaction, with DFA in particular can function as a warning system for dysfunctional organizational interactions. While it cannot engage with the content of communication, it can highlight the absence of fractal temporal structures associated with functional interactions. In previous analyses, DFA performs well on this task in the offline (Alados & Huffman, 2000) and in the online (Aguilera et al., 2013) space of interactions. With current technology, this is implementable both in person (e.g., using the RFID tags in office badges) and in online interactions (e.g., monitoring email traffic meta-data). Computationally DFA as a method of analysis is relatively inexpensive compared to survey-based or qualitative methods of monitoring communication in the company. Appendix 2 provides a conceptual overview of such a tool with R code for implementation.

Conclusion

This article investigated the fractal scaling in the frequency of contacts in a French public organization (InVS). Fractals are not only a mathematical phenomenon and a parsimonious way of accurately describing the nature, they are also a recurring theme in the social and organizational space. Previous research focused predominantly on the structural fractal nature of organizations, which is not only descriptively accurate but also normatively desirable. Fractal organizational structure is self-similar, with basic fractal units. This makes it modular, as well as scalable, leading to an unprecedented potential in adapting to the challenges of a complex, dynamic, and at times contradictory environment. This approach to fractal patterns in organizations had two drawbacks though, which stood in the way of comprehensively exploring and exploiting the fractal nature of organizations. One of them is the focus on hierarchy when identifying fractal structures. This is predominantly because one of the primary characteristics of fractals is their invariance

to scale, and scale is mostly defined by means of hierarchy. Heterarchical, nested and federated forms of organization are thus outside the bounds of the theory of fractal organizations. Second, the research on fractal patterns in organizations is predominantly atemporal, which is in stark contrast with the established presence of fractals in a multitude of time series and signals. The contribution of the present research therefore is twofold: First, it extended the theory of fractal (social) organization to a nonhierarchical and temporal dimension by investigating the fractal scaling of contact networks at InVS. Second, it aimed to answer the empirical question of whether structured organizations with little structural flexibility exhibit the same fractal scaling (pink noise) as self-organized social networks and movements. The results were somewhat surprising: Against the original assumption of a prevalence of long-range correlated, stable, diffusion-like processes in the contact frequencies, there was a prevalence of fractal scaling, pink noise processes. While this held true across all analyzed departments, as well as the organization as a whole, it only held true for time scales between 10 min and 33–42 min. This leaves us with a strong case for the presence of fractal scaling in the contact frequency and thus with a strong case for the extension of the theory of fractal (social) organization into the temporal and therefore also nonhierarchical space, but also leaves questions about the determinants of such fractal scaling. In the short time scales it seems unlikely for the organizational structure to be the determinant and without more information on the qualitative nature of interactions claims are hard to make. Therefore, a multifractal analysis to verify the nonlinear nature of interactions and more extensive research on the influence of organizational structure on the fractal scaling of contact frequencies are a fruitful avenue of future research. In general, more research on the interaction between (fractal) organizational structure and the fractal nature of contact frequencies, as well as the stability of contact frequencies over time, promises to yield valuable insights into the complex patterns and dynamics of organizations. For this, it is necessary to undertake further research that empirically validates the range of β values around 1 associated with fractal scaling and more importantly the correlation of different β values with the adaptability and stability of organizational processes. A future tool to assess the functionality of communication in organizational networks based on temporal fractal patterns can only work if the critical β values are triangulated with empirical data of organizational processes. As society is structured

in organizations and organizations take care of the major problem-solving processes of our times, the more holistic understanding of organizations through a fractal lens developed in this article can also practically contribute to solving great challenges, wicked problems, and advancing society.

DFA in Organizational Practice

Research such as Aguilera et al. (2013) or Alados and Huffman (2000) shows the value of tracking temporal fractal patterns in various contexts, ranging from the online organization of social movements to the behavior of chimpanzees. This article substantiates their findings with insights from the organizational/institutional space, highlighting a certain universality of temporal fractal patterns in situations of social interaction. The theory also suggests however that they are only present in “functional” or “healthy” systems, and that systems without these patterns will not retain adaptability and stability over time (Dixon et al., 2012).

Based on this, it is possible to automatize the tracking and analysis of organizational contact data. Here, strategically crucial is the decision of “which interactions to track.” They should represent the primary form of functional interactions in the organization, which can present a considerable challenge in many organizations that heavily rely both on email communication as well as physical interactions. Practically, digital interactions such as emails can easily be tracked in organizations’ IT systems, while physical interactions can be tracked using either the GPS function in the employees’ smartphones or RFID badges in chipcards or company badges similar to the Sociopatterns collaboration (Génois & Barrat, 2018). To implement a continuous tracking system, it is possible to automatize and implement the creation of data sets and their analysis using DFA on a rolling basis (e.g., every week with the interaction data of the previous month).

To ensure compatibility with the standard DFA implementation in *R*, the data should have the format *t, i, j* where *t* refers to the time stamp of the interaction and *i* and *j* are the respective identifiers of the interacting individuals. The code below gives insight into the import of raw data in the specified format, including metadata on which departments’ individuals are in and the subsequent steps necessary to create a data set ready to use for DFA. In practice, this script could be automated to run for every wave of collected data.

#----data import, inspection and cleaning----

```
data <- read.table("path/to/file")
```

```
metadata <- read.table("path/to/file")
```

```
colnames(data) <- c("t","i","j") #where t = time, i and j are  
IDs of the people in contact
```

```
sum(is.na(data)) #no missing data?
```

```
colnames(metadata) <- c("i","di") #where i = ID of  
individual and d = department
```

#combining the interaction information with
information on the departments

```
data <- merge(data,metadata, by = "i")
```

```
colnames(metadata) <- c("j","dj")
```

```
data <- merge(data,metadata, by = "j")
```

```
list_of_departments <- unique(data$di)
```

#removing out of office hours from the data

```
unique_t <- sort(as.data.frame(unique(data$t)))
```

```
unique_t$n <- seq.int(nrow(unique_t))
```

```
colnames(unique_t) <- c("t","ID")
```

```
data <- merge(data,unique_t, by = "t")
```

#create data on interaction frequencies (whole
organisation)

```
frequency_whole <- data %>%
```

```
count(ID) %>%
```

```
sort(ID, decreasing = F)
```

Once the data concerning interaction frequencies is prepared, it is possible to perform DFA and produce both numerical and visual output. The code below shows a simple, computationally inexpensive implementation of DFA in *R* that can be automatized. Here, the user can specify the window size range. This corresponds to rows in the data, not necessarily seconds or minutes, so the relationship between the number and the actual window size is contingent on the temporal resolution in the data. The window size range depends on the practical setting and needs for information on fluctuation. In an organization with a high frequency of interaction and high adaptability, the lower bound of window size ranges should consequently be lower. If an organization is primarily concerned with long-term stability of interactions, the upper bound should be adjusted accordingly. Furthermore the user can specify the number of specific window sizes to perform DFA on in this range (i.e., *n* points). A lower number of window sizes to be integrated and detrended promise higher computational efficiency, whereas a higher number provides for a more fine-grained analysis.

```
# -----detrended fluctuation analysis (DFA)-----
#DFA for whole organisation
dfa_whole <- dfa(time.series = frequency_whole$n,
window.size.range = c(30,18488), npoints = 200)
#hurst_whole <- hurstexp(frequency_whole$n, d = 30)

#----visualisation----
#whole organisation
ggplot(data=frequency_whole, aes(x=ID, y=n)) +
  geom_line()
```

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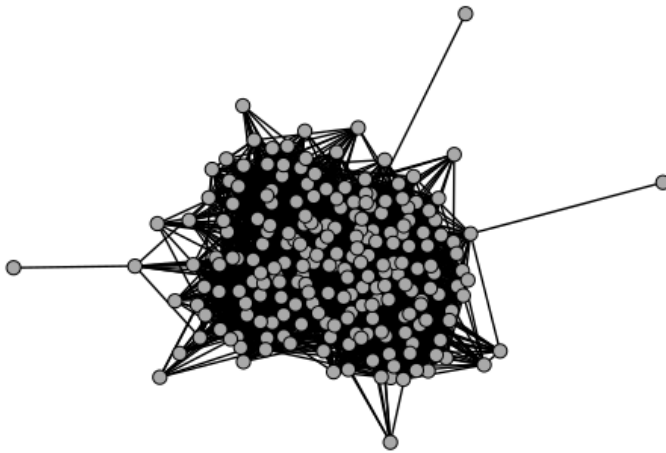
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Appendix

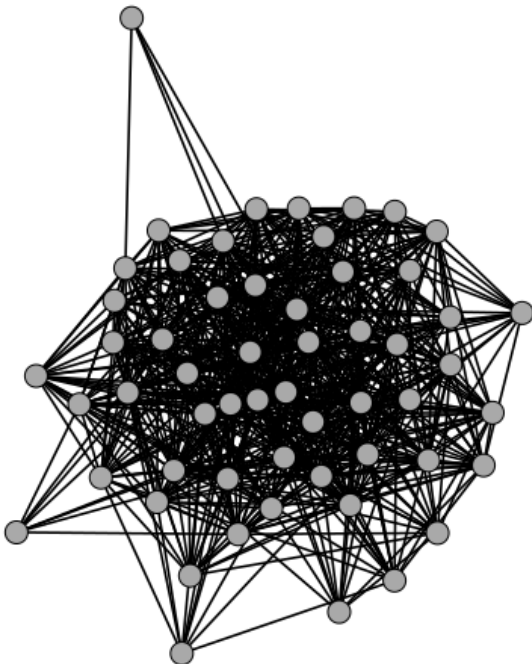
Appendix 1—Contact Networks

InVS contact network



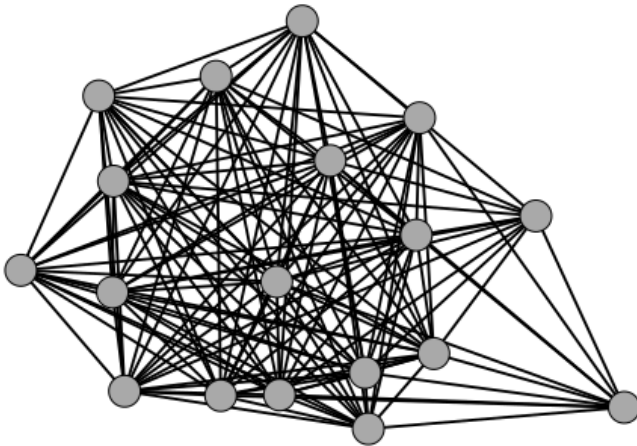
Appendix 1A: InVS contact network. InVS, Institut de Veille Sanitaire

DMI department contact network



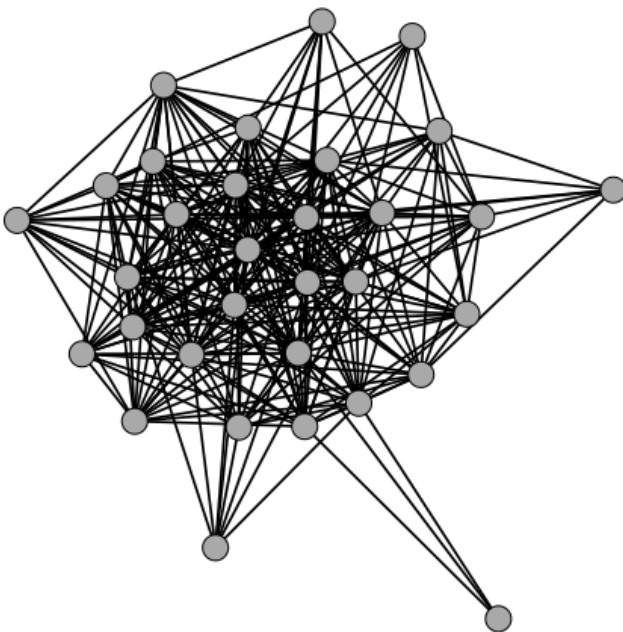
Appendix 1B: DMI department contact network

DISQ department contact network



Appendix 1C: DISQ department contact network

DSE department contact network



Appendix 1D: DSE department contact network.