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# The Episodic Nature of Experience: A Dynamical Systems Analysis

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**Abstract**

Context is an important construct in many domains of cognition, including learning, memory, and emotion. We used dynamical systems methods to demonstrate the episodic nature of experience by showing a natural separation between the scales over which within-context and between-context relationships operate. To do this, we represented an individual's emails extending over about 5 years in a high-dimensional semantic space and computed the dimensionalities of the subspaces occupied by these emails. Personal discourse has a two-scaled geometry with smaller within-context dimensionalities than between-context dimensionalities. Prior studies have shown that reading experience (Doxas, Dennis, & Oliver, 2010) and visual experience (Sreekumar, Dennis, Doxas, Zhuang, & Belkin, 2014) have a similar two-scaled structure. Furthermore, the recurrence plot of the emails revealed that experience is predictable and hierarchical, supporting the constructs of some influential theories of memory. The results demonstrate that experience is not scale-free and provide an important target for accounts of how experience shapes cognition.

*Keywords:* Dynamical systems; Human experience; Context; Memory; Rational analysis; Structure and dynamics

## 1. Introduction

People naturally divide their everyday experience into a sequence of events and use these representations to organize perception, memory, and communication (Zacks & Tversky, 2001; Zacks, Tversky, & Iyer, 2001). Even under passive viewing conditions,

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neural data suggest that people do not perceive time in a continuous stream, but rather spontaneously parse their experience into distinct context representations (Zacks, Braver, et al., 2001). However, is there a natural separation in the structure and dynamics of experience which supports this parsing by the cognitive apparatus? Contexts are typically operationally defined by referring to a study list, aspects of the experimental task, or the physical attributes of the laboratory environment (Johnson, Hashtroudi, & Lindsay, 1993; Smith & Vela, 2001). However, it remains unclear to what extent the contexts used in the laboratory resemble those that people typically employ outside the laboratory (cf. Conway & Pleydell-Pearce, 2000). Furthermore, a focus on the laboratory has led to a focus on certain temporal scales—namely those that can easily be studied within an hour long experimental paradigm. However, the cognitive system is sensitive to much longer time scales (Anderson & Conway, 1993; Barsalou, 1988; Radvansky, Copeland, & Zwaan, 2005; Rathbone, Moulin, & Conway, 2008). A complete understanding entails characterizing what occurs at all temporal scales.

Although it has long been argued that cognitive research that is focused solely on laboratory work is futile (Neisser, 1976), the difficulty has been how to proceed when the experience and behavior of the participant outside the laboratory cannot be rigorously quantified. One approach is to look for generic proxies to an individual's experience. For example, Anderson and Schooler (1991) conducted analyses on newspaper headlines, corpora of child speech, and emails. They observed a remarkable correspondence between the patterns of recurrence in the data and the form of memory retention and practice curves collected in the laboratory. The rational analysis of memory (Anderson & Milson, 1989; Anderson & Schooler, 1991, 2000; Schooler & Anderson, 1997) suggested that memory performance (and possibly performance in other cognitive domains) may reflect the structure of the environment.

In the following sections, we first summarize results from prior studies that used both generic proxies of experience such as text corpora (proxy for reading experience; Doxas, Dennis, & Oliver, 2010), as well as data collected from individuals such as images extending over temporal scales of 2 weeks collected using smartphones (proxy for visual experience; Sreekumar, Dennis, Doxas, Zhuang, & Belkin, 2014). We then describe this study, where we analyze the structure and dynamics of an email corpus extending over 5 years (proxy for personal discourse). Taken together, dynamical systems analyses reveal a striking similarity in the structure and dynamics of reading, visual experience, and personal discourse, with a clear separation between within-context and between-context relationships.

## 2. Prior relevant work

### 2.1. Reading experience

To analyze the structure of reading experience, Doxas et al. (2010) selected five text corpora in four languages: English, French, Greek, and German. Semantic spaces were constructed for each corpus using latent semantic analysis (LSA; Landauer & Dumais, 1997). LSA is a high-dimensional model that generates vector representations from a corpus of natural language text that capture word–word, document–document, and word–document semantic relationships. More details are provided in the Data S1. Euclidean distances between the LSA vectors were computed and the dimensionality of the semantic trajectories through each corpus was described using the correlation dimension. The correlation dimension (Grassberger & Procaccia, 1983a,b) is a widely used measure of fractal dimensionality which is commonly used to describe trajectories of dynamical systems. The trajectory of a dynamical system may not visit all parts of the state-space equally frequently. The correlation dimension measures the space-filling properties of the set of points visited by such a trajectory. For some systems, the structure of such a set may be adequately represented by one fractal dimension number, in which case it is a monofractal. Alternately, a system may exhibit multiple scaling regimes and therefore be described by a small number of different fractal dimensions, as we shall see is the case for the structure of human experience. A more detailed description of the correlation dimension is provided later when discussing the analysis of personal discourse which is the novel empirical contribution of the current article. While more sophisticated multi-fractal methods have recently garnered attention in the cognitive science literature (Ihlen & Vereijken, 2010), we aimed to detect transitions between within- and between-context relationships in semantic space and the simpler correlation dimension analysis proved sufficient and provides a direct extension of the previous work on the structure of different domains of human experience.

Doxas et al. (2010) showed that reading experience has a universal two-scaled structure with the dimensionality at shorter distance scales being smaller ($\approx 8$) than the dimensionality at longer distance scales ($\approx 12$–$23$). These dimensionalities are surprisingly small considering that many LSA applications typically use 300 dimensions (Landauer, Foltz, & Laham, 1998) to construct vector representations of documents. Doxas et al. (2010) used a version of the topics model (Griffiths, Steyvers, & Tenenbaum, 2007) to suggest a generative model of prose construction that would give rise to the two-scaled structure of reading experience that was observed across languages and genres. The upper scale was dominated by paragraph pairs pertaining to different topics, whereas the lower scale captured relationships between paragraphs pertaining to similar topics.

### 2.2. *Visual experience*

Sreekumar et al. (2014) analyzed the structure and dynamics of visual experience. To do this, they built a system which consisted of an Android app, server infrastructure, and user interfaces. The app continuously acquired data, including visual images, audio (short subsecond snippets to preserve privacy), location, and accelerometry. Users wore the phone around their neck to allow an unobstructed view for the camera.

Participants collected data for a period of 1–2 weeks and the time series of the images provided the trajectories through visual space for each participant. The images were represented as color correlograms (Huang, Kumar, Mitra, Zhu, & Zabih, 1997) and Euclidean distances between the reduced singular value decomposition (SVD) 300 dimensional image vectors were computed as in Doxas et al. (2010). The correlation dimension plot of each participant's visual experience was two-scaled with a smaller dimension at shorter distance scales ($\approx$ 4–6) than at longer distance scales ($\approx$ 10–14), much like the structure of reading experience trajectories. The upper scale was dominated by image pairs that came from different visual contexts, and the lower scale captured within-context relationships.

Furthermore, they demonstrated using Takens's embedding theorem that the two-scaled geometry is a signature of the dynamics of visual experience and is not just a property of the static distributions of images. Takens's theorem (Takens, 1981) guarantees that a *delay embedding* of any observable of the dynamical system will produce the same estimate for the correlation dimension. Sreekumar et al. (2014) chose the time series of the first dimension of the image representations as the observable of the system. A moving window over this time series was used to construct vectors. The correlation dimension was calculated for the system of vectors. The window size was increased until the correlation dimension estimate no longer changed. The value of this asymptote was found to be the original lower scale correlation dimension calculated using all available dimensions of the image representations. There was not enough data to construct a sufficient number of vectors based on window sizes large enough for recovering the upper scale correlation dimension. Thus, they were able to recover the lower scale correlation dimension based on just a unidimensional time series, but critically not from a permuted time series of the same observable. Their analyses demonstrate that the structure of visual experience is intricately linked to the dynamics of how people move through their visual environment.

## 3. This study: Personal discourse

To further test the generality of findings across domains and temporal scales, in this study, we analyze the structure of personal discourse as represented by a corpus of senior author S.D's emails extending over 5 years. All sent and received emails were included, both professional and personal. Email corpora have been used in the past as representations of human experience. For example, Anderson and Schooler (1991) provided an environmental explanation for the power-law retention and practice functions and spacing effects in memory. They showed that memory functions reflect the structure of environmental input. In one analysis, environmental input was represented by the emails that J.A received from 1985 to 1989. It was assumed that any time an email was accessed, that demanded a memory about the sender. The empirical odds of needing a memory about a sender on day $n$ was calculated as a function of the frequency of emails received on the previous $n - 1$ days. The relationship between the need odds and frequency of receipt of emails was shown to be a power law. Anderson and Schooler (1991) proposed that the memory retention function was a reflection of the need probabilities of memories as captured by the statistics of the environmental input. Similarly, we analyze the structure and dynamics of our experience to look for phenomena which may be reflected in the constructs posited by current theories of memory.

To analyze the structure of personal discourse, we followed the analysis in Doxas et al. (2010) and obtained the LSA vectors of emails and computed Euclidean distances between them. In the following sections, we first present recurrence plots (RPs; Eckmann, Kamphorst, & Ruelle, 1987; Marwan, Romano, Thiel, & Kurths, 2007) of the email data to visualize regularities in personal discourse. We then quantify the structure of personal discourse by computing the correlation dimension (Grassberger & Procaccia, 1983a,b, described in the corresponding section).

A number of preprocessing steps were taken to reduce noise and focus attention on the semantic content of the messages. First, dates and authors were removed. Dates will tend to have a linear structure and so it was thought they might distort the estimation of the dimensionality of the semantic content. Similarly, a given author will often correspond on a wide variety of topics potentially distorting the space. Second, we removed a number of complete lines that recurred often. Third, we removed lines that began with the “>” character which had been included from previous emails and thus were not semantic content specific to this email. Fourth, the text was tokenized, reduced to lowercase, and punctuation was removed. Fifth, stopwords were removed and any word that appeared less than five times was eliminated. Finally, emails with fewer than 50 words were removed because they have insufficient content for LSA to reliably capture their meaning and emails with more than 10,000 words were also eliminated as they typically contained very large attachments that included corpora and other data files. The resulting corpus contained 5,495,264 tokens (instances) distributed across 20,195 types (words). After preprocessing, there was a total of 30,823 emails. The majority of these occurred between 2007 and 2012.

### *3.1. Recurrence structure*

Our experience of reading emails has a certain structure to it due to the contents in emails being reflective of the patterns of our life. For example, the themes that govern the emails that you compose and read when you are a student are generally different from those that you engage with when you have entered a stage where work and family predominantly occupy your life. Within these themes, there is likely to be certain periodicities in personal discourse that reflect periodicities in life. For example, if one has a recurring meeting on every Monday, then one would expect to find a weekly periodic structure corresponding to that meeting in the themes of emails composed and read over a period of time. Similarly, if one has to take/teach a class every Monday, Wednesday, and Friday, then those structures are likely reflected in the email patterns as well. We visualize these regularities by plotting RPs (Eckmann et al., 1987; Marwan et al., 2007).

Fig. 1 shows the unthresholded RP, sometimes also known as a global RP, for S.D.’s emails. Both $X$ and $Y$ are time axes. The global RP is a heat map of the matrix of distances between the emails. Darker colors denote smaller distances and lighter colors denote larger distances. A dark point therefore in the RP denotes a time pair for which the dynamical system trajectory visited approximately the same region in state space (or in our case, the semantic space constructed by the contents of the emails). Since it is not

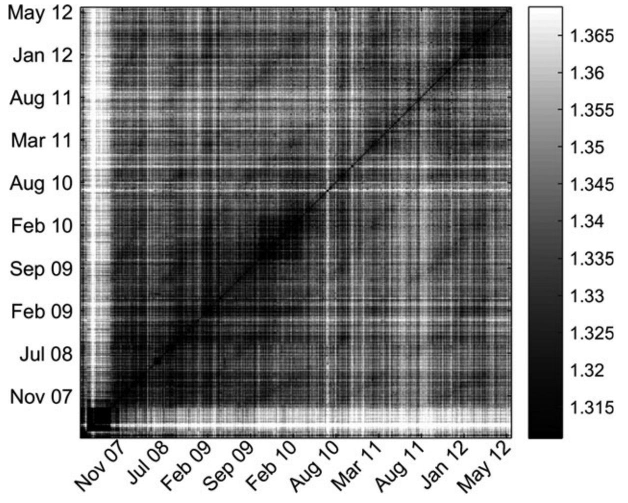


Fig. 1. Recurrence plot for S.D.'s emails. The emails are ordered in time on both *X* and *Y* axes. The substantial dark structure around the diagonal implies that emails about similar topics were sent/received close in time. The off-diagonal structures imply that S.D. returned to similar themes in his emails at different points in time. The diagonal line patterns spaced by about a year signal repeating sequences of themes with yearly periodicities.

possible to represent a 30,823 × 30,823 matrix without some sort of averaging, we decided to plot the average distance within 50 × 50 squares to produce a 617 × 617 RP.[1] This resolution preserves the finer grained structures of importance that we note below in addition to showing recurrence patterns over longer scales.

The resulting RP shows substantial structure around the diagonal which means that similar semantic themes are experienced close in time. The dark off-diagonal structures in the RP show that similar themes are visited far apart in time as well. A closer inspection of the RP reveals a hierarchical structure that reflects the various lifetime periods S.D. went through from 2007 to 2012 and the associated patterns within those periods. At the highest level, there are two distinct structures that are visible in the RP, one that is a tiny dark box on the left bottom corner of the RP and one that is a big dark structure that occupies most of the rest of the RP. Looking at the dates revealed that S.D. worked in Australia prior to August 2007 and then moved to the United States. The tiny black box on the bottom left of the RP covers the lifetime period spent in Australia, and the larger structure reflects the distinct lifetime period corresponding to life in the United States. Within the US period, the dark square extending from September 2009 to March 2010 corresponds to the period when S.D. was the interim director of the Cognitive Science center at the Ohio State University.

Human movement has been shown to be highly predictable (Song, Qu, Blumm, & Barabási, 2010). The RP in Fig. 1 also reveals a substantial degree of determinism in the dynamical system of personal discourse. When a similar theme is encountered at a later time, if the ensuing dynamics are also similar, a darker line parallel to the diagonal is obtained (Webber & Zbilut, 1994). The diagonal patterns in Fig. 1 therefore imply that movement through the semantic space of personal discourse is predictable to an extent. In addition, the diagonal bands span about a year's time and signals strong recurrent dynamics with a yearly periodicity. The RP clearly shows that these repeating patterns follow the calendar.

The RP is therefore a useful visualization of an individual's life experience and reveals important aspects of the dynamics. In the next section, we quantify the structure of personal discourse by computing the correlation dimension of the semantic space formed by the emails.

### 3.2. Correlation dimension

The correlation dimension is a measure of the dimensionality of the space occupied by a set of points and is a type of fractal dimension (Mandelbrot, 1967) because it allows non-integer values. Grassberger and Procaccia (1983a,b) introduced the correlation dimension to characterize phase space-filling properties of attractors. Of several possible dimension measurements, the correlation dimension ($D_2$) is the most widely used due to its ease of calculation.

The correlation dimension is based on the correlation sum $C(r)$, which is the number of pairs of points separated by a distance $< r$. $C(r)$ increases as we relax the distance threshold $r$, and the correlation dimension $D_2$ measures how $C(r)$ scales with $r$. For $N$ points in an M-dimensional space, the normalized correlation sum is given by

$$C(r) = \frac{2}{N(N-1)} \sum_{i=1}^{N} \sum_{j=1, j \neq i}^{N} H(r - |\mathbf{X_i} - \mathbf{X_j}|), \tag{1}$$

where $H$ is the Heaviside kernel function $H(x) = 0$ if $x \leq 0$ and $H(x) = 1$ if $x > 0$. Therefore, $C(r)$ is the number of pairs of points which are separated by $< r$. For sufficiently small $r$ and large number of points $N, C(r) \sim r^{D_2}$. Taking logarithms of each side, we get

$$\lim_{N \to \infty, r \to 0} D_2 \sim \frac{\log[C(r)]}{\log(r)}. \tag{2}$$

$D_2$ is calculated from the slope of the straight line scaling region of a $\log[C(r)]$ versus $\log(r)$ plot. The correlation dimension is only defined for $r \to 0$ and $N \to \infty$. However, in practice, $r \to 0$ means $r << L$, where $L$ is some "natural" scale of the system. So we avoid computing the slope at length scales that are comparable to the length scales of the system.

Let us first consider an example to understand what the correlation dimension describes. In panel A of Fig. 2 is a set of points forming a weave pattern. The threads of the weave are spaced by exp(1.5) so that the spacing can be readily identified on a natural log-log correlation dimension plot. Each thread has 500 uniformly randomly spaced

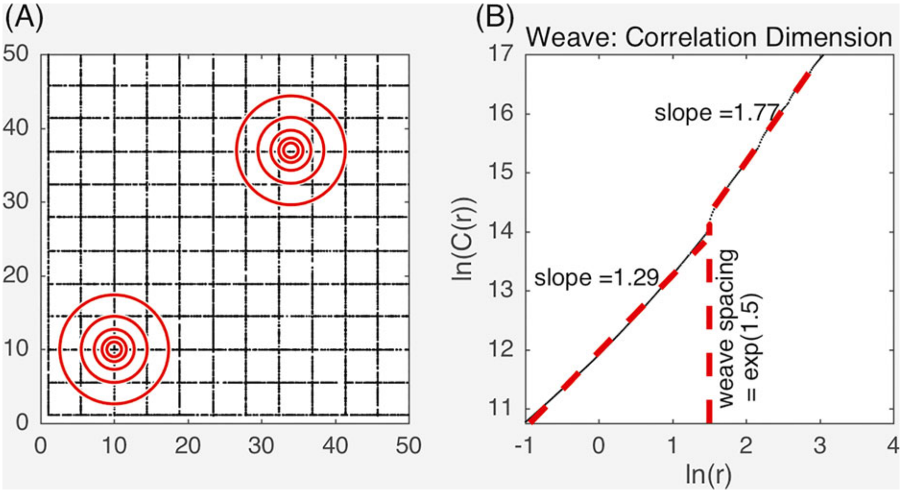


Fig. 2. Measuring the dimensionality of a weave pattern of points. (A) The points enclosed by a circle of radius $r$, when summed over all points, is the correlation sum $C(r)$, which increases with $r$ as $r^D$. At the shortest scales, expanding the radius increases the correlation sum slightly faster than linearly, since the smallest circles mostly "see" only single threads (e.g., top right set of circles) or less frequently two threads (e.g., bottom left set of circles). In contrast, expanding circles at the longer scales see more of the weave pattern which is closer to, yet not fully 2D since the pattern does not fill the 2D space, and the correlation sum increases more dramatically which is captured by a larger D. (B) Aligning with our expectation of smaller dimensionality of the weave pattern at shorter than longer scales, the lower scale correlation dimension is 1.29 and the longer scale correlation dimension is 1.77.

points. This set of points clearly does not fill all of the 2D space available, so we would expect the data to have non-integer dimensionality $d$, where $1 < d < 2$. To compute the correlation dimension, we first count the points that are within a distance $r$ from a given point. This number summed over all points, after accounting for double counting of pairs, is $C(r)$. At the shorter scales, as the threshold $r$ is relaxed, $C(r)$ increases approximately linearly since the smallest circles mostly "see" points on a single thread (the top right set of circles in panel A, Fig. 2). However, circles centered at grid points may see points that lie on two threads (e.g., the smallest circles in the bottom left of panel A of Fig. 2), and we would expect the smaller scale dimensionality to be close to but greater than 1. At the longer scales, points begin to come in more rapidly, indicating an increased dimensionality (closer to but $< 2$) as the larger circles "see" more of the weave pattern. Note that this transition happens as the radius crosses the weave spacing of exp(1.5). The correlation dimension plot is shown in panel B of Fig. 2. The slope is 1.29 at the smaller scales and the plot transitions to a regime of slope 1.77 at the weave spacing of exp(1.5) indicated by the vertical dashed line. The largest radius considered in the calculation is $\exp(3) = 20$, which is much less than the total length covered by the weave (= 50) to meet the $r \ll L$ condition mentioned in the preceding paragraph. Extremely small radii for which sufficient data are not available are also not considered. Therefore, in this example, we see that the correlation dimension describes the space-filling properties of the weave pattern at different scales.

The correlation dimension plot of S.D.'s emails in Fig. 3 is two-scaled like that of the weave pattern in the example. To estimate the dimensions at each of these scales, we used the same procedure as those used in the earlier papers (Doxas et al., 2010; Sreekumar et al., 2014) and employed the "bent-cable" regression model (Chiu, 2002) which has two linear segments joined smoothly by a quadratic bend. The quadratic segment has a half width of $\gamma$. The two linear segments, if extrapolated, intersect at $x = \mu$. In Fig. 3, dashed vertical lines are drawn at $\mu$ and $\mu \pm \gamma$. The use of this model to fit the correlation dimension plots helps avoid contaminating the slope estimates due to otherwise having to manually specify the location of the bend. We performed $K$-fold ($K = 10$) cross-validation demonstrating that the bent-cable regression model is superior to the linear, second degree polynomial, and third degree polynomial regression models in predictive value and generalizability. The mean residual sum of squares and the standard deviation for cross-validation over the $K$ folds are provided in Table 1. Thus, it is established that the correlation dimension plot is best interpreted as having two separate linear scales governed by the corresponding estimates of correlation dimension. The bent-cable slope estimates, or the correlation dimension estimates, for the lower and upper scales, respectively, are 2.83 and 20.14.

To rule out the possibility that the two-scaled structure observed here is due to artifacts introduced by LSA, we performed a surrogate analysis where the words in the emails

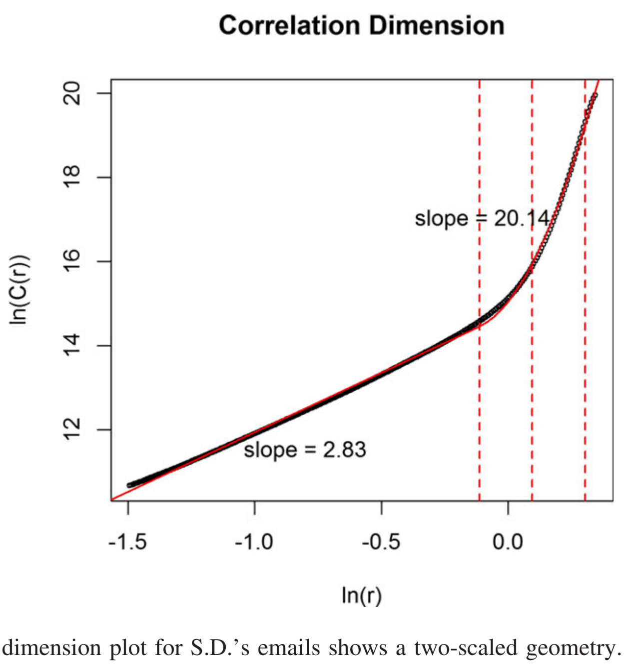


Fig. 3. The correlation dimension plot for S.D.'s emails shows a two-scaled geometry. The bent-cable regression lower scale correlation dimension estimate is 2.83, and the top scale correlation dimension estimate is 20.14.

Table 1
Mean and standard deviation (in brackets) of the cross-validated residual sum of squares over $K$ = 10 folds

| Linear | Second-Degree Polyn. | Third-Degree Polyn. | Bent-Cable Model |
|---|---|---|---|
| 15.27 (5.78) | 5.88 (2.12) | 1.78 (0.53) | 0.11 (0.03) |

*Note*. The models include polynomial regression (polyn.) with degree 1 through 3 and the bent-cable regression model.

were randomly shuffled across documents. Specifically, the number of documents (emails) and the number of words within a given document were kept the same as in the original data. The documents were then reconstructed by choosing words at random without replacement from all the words in the corpus, thereby also preserving word frequency. The analysis was repeated on this surrogate dataset and a single-scaled correlation dimension plot was obtained (Fig. 4) which suggests that the two-scaled structure of the intact emails is not an artifact of the analysis methods employed. Furthermore, this surrogate dataset is more space-filling with a much higher dimensionality (~70 at the shorter scales) than the original data. Therefore, the relatively low-dimensional and two-scaled structure exhibited by the unshuffled email data is a consequence of word choice or semantic content of the emails rather than word frequency or email lengths.

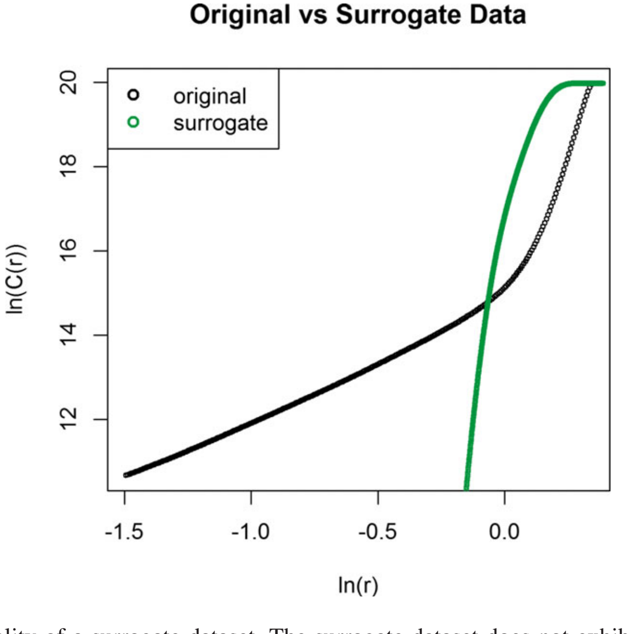


Fig. 4. The dimensionality of a surrogate dataset. The surrogate dataset does not exhibit a two-scaled geometry; instead, it is "space-filling" with a large dimensionality (~70), which means that the relatively low-dimensional, two-scaled structure of S.D.'s emails is a consequence of the semantic content/word choice and not due to word frequency, email lengths, or any other artifacts of the analysis methods.

### 3.3. What do the two scales capture?

The lower of the two scales was found to capture within-context relationships, and the upper scale captured between-context relationships in the case of reading experience (Doxas et al., 2010) and visual experience (Sreekumar et al., 2014). The same difference between the scales is observed here in personal discourse. An examination of email pairs randomly chosen from the lower scale suggests that these were related to the same event. For instance, in one case the two emails both referred to the organization of the Context and Episodic Memory Symposium. In another case, both emails referred to interactions when S.D. was purchasing a home in Adelaide. Pairs taken from above the bend appeared to be taken from different contexts. For instance, one pair contained an email about the Context and Episodic Memory Symposium, and an email about the Neural Information Processing Conference.

The probability that a given pair of emails pertains to the same theme/conversation is related to the time difference between them. Two emails within 10 min of each other are more likely to be from within the same conversation than a pair separated by 3 weeks. If the lower scale captures within-context relationships, we would expect the relative contribution of the lower scale to decrease as the time between the emails increases. Therefore, we plotted the ratio of distances from the top scale (i.e., distances greater than $\mu + \gamma$) to the bottom scale (i.e., distances $< \mu - \gamma$) as a function of log-spaced bins of time differences between the emails (see fig. 3 in Sreekumar et al., 2014, for the equivalent visual experience ratio plot). Given that there is a far greater number of upper scale distances than lower scale ones, it is certainly possible that this ratio is much greater than one for all time differences. In Fig. 5, the ratio stays low and often $<1$ for time differences $<8$ min, which is likely related to S.D.'s propensity to respond to emails during the work day at comparable latencies.

In addition, for some of the longer time bins, we observe decreases in the ratio from the previous time bin (marked by vertical dotted lines in Fig. 5). These decreases correspond to time differences in around 1 day, 2 days, 3 days, and 1 week. We know from the RP that context repetitions happen periodically, at least up to yearly recurrent patterns. A decrease in the ratio is to be expected at these periods if context recurrences are captured by the lower scale. Whereas the RP captures the longer scale recurrent patterns, the use of time difference bins allowed us to detect signatures of recurrences at the shorter day and week scales in the ratio plot. Note that the log-spaced bins in Fig. 5 increase in size as the time differences get larger and hence it may be difficult to detect the longer scale periods, however, we have observed signatures of those longer scale recurrences in the RP already.

The ratio plot along with our inspection of the contents of email pairs suggests that the lower scale corresponds to within-context experiences, while the higher scale corresponds to between-context experiences, as was the case in our analyses of visual experience (Sreekumar et al., 2014).

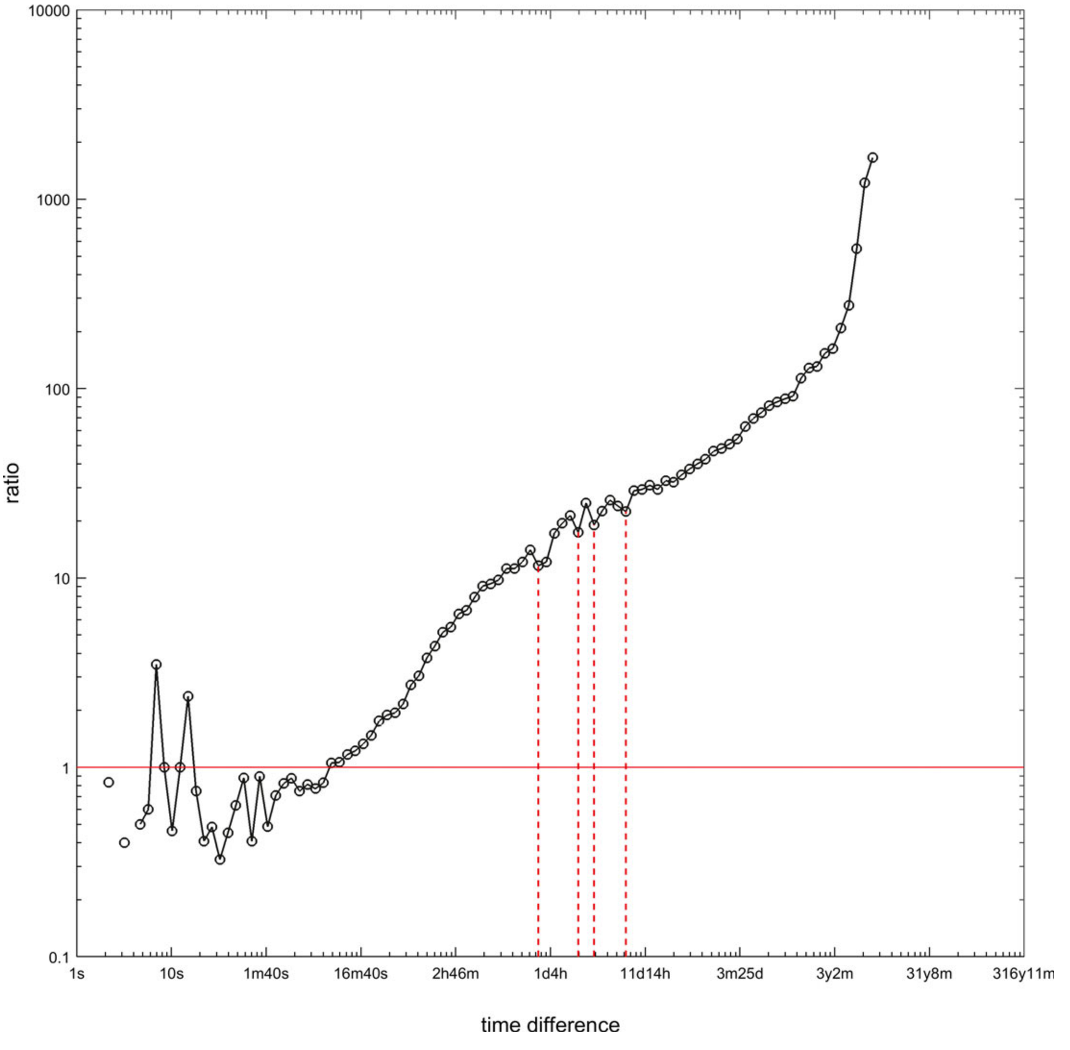


Fig. 5. Ratio of top scale to bottom scale pairs of emails as a function of log-spaced binned time differences. The ratio mostly remains under 1 (horizontal line) for time differences less than ~8 min. Vertical dashed lines denote points where the ratio drops relative to the previous time bins and indicate increased contributions from the lower scale at periodicities of 1 day, 2 days, 3 days, and 1 week.

## 4. Discussion

The application of dynamical systems methods has proven fruitful in revealing the structure of cognitive processes (e.g., Gilden, 2001; Holden, Van Orden, & Turvey, 2009; Ihlen & Vereijken, 2010). We used methods selected from the dynamical systems toolbox to analyze an email corpus of 30,823 emails and showed that the structure of personal discourse as described by the correlation dimension is two-scaled as are the structures of reading experience (fig. 2 in Doxas et al., 2010) and visual experience (Fig. 2 and fig. S6 in Sreekumar et al., 2014). The lower scale primarily captures relationships between emails referring to the same event that were separated by several minutes, whereas the upper scale captures relationships between emails referring to different events that were sent/received across longer time differences. Previous work also shows similar results where the lower scale captures within-context and the upper scale captures between-context relationships (Doxas et al., 2010; Sreekumar et al., 2014). These results signify the physical reality of a fundamental unit of experience (i.e., a context/episode), which is an important construct in theories of memory and learning (e.g., Anderson & Bower, 1972; Dennis & Humphreys, 2001; Gillund & Shiffrin, 1984; Howard & Kahana, 2002; Humphreys, Bain, & Pike, 1989; Mensink & Raaijmakers, 1988; Murdock, 1997; Shiffrin & Steyvers, 1997). Furthermore, the natural separation in the structure of within and between-context relationships likely supports the spontaneous parsing of experience into episodes (Zacks, Braver, et al., 2001).

The structure and dynamics of human experience described in this series of studies (Doxas et al., 2010; Sreekumar et al., 2014; this study) validate the assumptions of some theories of memory and call into question the assumptions of others. An influential verbal model (Conway & Pleydell-Pearce, 2000) proposed that autobiographical memories arise from an interaction between components of an underlying *knowledge base* and a current set of goals maintained in the *working self* mediated by control processes. Critically, the knowledge base contains information at multiple levels of specificity. At the broadest level, knowledge is organized into lifetime periods. For example, the lifetime period "when I was an undergrad" contains general knowledge about people, locations, activities, etc., that are characteristic to the period. In addition to details about the common thematic elements that define the period, the contents of lifetime periods also represent temporal information such as the boundaries of the period. Different lifetime periods may overlap and thematic links between them can be used to form higher order themes such as "work" or "relationships." *General events* are more specific and may include both repeated and single events. For example, "attending PSY100" is a general event which encompasses repeated visits to a classroom over a semester. Finally, *event-specific knowledge* contains details that are specific to an episode such as "he wore a blue shirt," "the rock station on the radio was playing The Dark Side of the Moon," and "I felt nostalgic."

The RP of emails reveals the temporal patterns of S.D.'s life. In particular, one can see the various lifetime periods spent working in different universities in Australia and the USA in different professional capacities (see fig. 5 in Conway, 2005, for a depiction of a similar academic work theme and its organization in autobiographical memory). The RP, if viewed at an appropriate resolution, can also reveal subpatterns within each lifetime period (e.g., general events such as a class that is taught in the Fall semester of each year). Therefore, the RP reveals that the organization of the autobiographical knowledge base in Conway's (2005) self-memory system mirrors the organization of our experience of the environment (cf. Anderson & Schooler, 1991).

Understanding how people isolate when events occurred is fundamental to our understanding of episodic memory and provides insight into the mechanisms by which people conceptualize time more generally. Friedman (1993, 2004) proposed that people primarily rely on *location-based* processing when retrieving the time of occurrence of events. For example, consider the following question: When was the last time you taught a specific class? This question might be answered by retrieving information about the university's academic calendar. Was this a first- or second-semester class? Did it run M/W/F or T/Th? Using a process of deduction, one can combine the answers to these questions to arrive at the required response. The retrieval of such *locations* within the temporal patterns of our lives is a reconstructive process. The RP shows signatures of recurrent dynamics with a yearly periodicity corresponding to the academic calendar with which S.D.'s life was aligned and indicates a degree of predictability in the dynamical system of human experience (Song et al., 2010). Predictable sequences of experience combined with knowledge about the temporal boundaries that define lifetime periods support the reconstructive processes employed in inferences about the time of occurrence of events (Friedman, 1993; Thompson, Skowronski, Larsen, & Betz, 1996). The RP allows us for the first time to directly observe the environmental structures that are required for theories such as Friedman's to operate.

We have demonstrated, across multiple domains that experience is not scale-free. A recent influential memory model, scale-independent memory, perception, and learning (Brown, Neath, & Chater, 2007) assumes that the retrieval processes operating at multiple scales are similar. Brown et al. (2007) review human memory phenomena such as serial position and recency effects that are similar across multiple scales, and argue that memory modeling should start with a default scale-free assumption. However, if cognition (e.g., learning, memory) is indeed scale-free, our models must specify how scale-free cognition emerges from experience which is not scale-free. Although the correlation dimension analysis identified different exponents characterizing different spatial scales (in semantic space), it is likely that the system is more complex than this analysis reveals. Many cognitive and other natural time series exhibit multifractality (Ihlen & Vereijken, 2010, 2013), which is described in terms of a smooth spectrum of exponents rather than a single average exponent or a small number of exponents. Whereas future efforts will address whether human experience is more appropriately described using multifractal formalisms, the correlation dimension adequately captures the differences between spatial scales characterizing within- and between-context relationships.

Correlation dimension analyses of reading experience (Doxas et al., 2010), visual experience (Sreekumar et al., 2014), and personal discourse suggest that the environments to which people are exposed are commonly not scale-free, but rather appear to be divided into episodes/contexts with within-context dimensionalities typically being less than between-context dimensionalities. These observations place constraints on the models of human memory that should be considered and demonstrate the utility of applying dynamical systems techniques to analyze the environmental structures that shape human cognition.

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## Note

1. The last row (column) contained averages of 23 × 50 (50 × 23) sub-matrices and one 23 × 23 square, but this is a tiny portion of the entire plot.

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## Supporting Information

Additional Supporting Information may be found online in the supporting information tab for this article:

**Data S1.** Latent semantic analysis (LSA)