The Effect of Low Sampling Frequency and Bandwidth of Idiographic Ecological Momentary Assessment On Recurrence Quantification Analysis

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Introduction

Ecological momentary assessment (EMA) has made it possible to construct time series based on self-report scales. This approach allows mapping within-person fluctuations of psychological constructs in a systematic manner (Conner et al., 2009). Data collected using these methods display all markers of complex dynamics, which means that the future trajectory of the data generated using these methods is only predictable in the short-term, and that observations are dependent on the state of the system and its externalities at earlier timepoints (Olthof et al., 2020a). While traditional statistical methods are frequently and fruitfully employed to analyze data generated using EMA, these methods are not suitable for capturing complex temporal idiographic patterns (Jenkins et al., 2020; Olthof et al., 2020b).

Within psychology, time-dependent within-person dynamics have historically been neglected (Molenaar, 2004). The methods in this paradigm are still in relative infancy within a psychological context. They are often imported from complex dynamical systems theory, which is an area of mathematics that concerns itself with the study of time-dependent dynamics of systems. A popular analysis technique is called Recurrence Quantification Analysis (RQA). It results in the identification of recurrent patterns, or repetitions, in a time series (Webber Jr and Zbilut, 2005). One can then derive several indicators of the stability, predictability, and the dynamical behavior of the time series from these recurrences. This method was developed in the physicial sciences under the assumption that measurements can be retrieved at great frequency and at high resolution, to an extent that is impossible when relying on self-report scales.

Given that EMA relies on limited sampling frequency and precision, it is necessary to systematically assess the consequences of utilizing data on the quality of RQA output(Haslbeck and Ryan, 2022).

The current project

The research question is *"At what point does reduced data quality limit EMA's ability to capture idiographic dynamics using RQA?"*. We present an analysis pipeline consisting of multiple stages. To simulate the toy model and perform the analysis, we will utilize the `DynamicalSystems.jl` and `Statistics.jl` julia-packages (Bezanson et al., 2017; Datseris, 2018; Datseris and Parlitz, 2022). Our hope, and hypothesis, is that the trajectory of indicators under degraded data quality possesses a degree of predictability. This would enable us to estimate the reliability of inferences drawn from lower quality data.

For the purposes of this project, we assume that the underlying psychological construct is a continuously changing dynamical value (Boker, 2002). We also assume that EMA output values are accurate ordinal, low sampling frequency attempts to measure continuous underlying dynamical processes. It is important to note that this idealized assumption is made specifically for studying the consequences of low sampling frequency and data bandwidth. It does not, however, consider other potential challenges to validity (Stinson et al., 2022; Maul et al., 2016).

Stage 1: Data generation

In the first stage, we use a toy model to simulate the data based on the *3 + 1 Dimensions Model* introduced by Gauld and Depannemaecker (2023). This model captures clinical observations found in psychiatric symptomology by modeling internal factors (y), environmental noise (z), temporal specificities (f), and sympomatology (x) using coupled differential equations. Symptomatology will be the outcome variable of this study. By changing all four of these coefficients systematically, we aim to model a large variety of possible trajectories. We save each one of these models as a separate time series. For the purpose of our study, we redefine "symptomatology" as any dynamical fluctuations of psychological constructs.

Stage 2: Binning data and removing time points

Now, we aim to systematically reduce the quality of the data. We bin a range of the width of the data into n intervals of equal length, where n stands for the number of bins. We also vary the minimum (min) and maximum (max) value of this range to simulate ceiling and floor-effects. Moreover, we remove time points from the data by keeping the first and every k^{th} observation of the simulated data. We systematically decrease the number of bins, the range, number of time points, and re-analyze the data.

Stage 3: Data analysis

We will judge the sensitivity of the data by deriving the recurrence indicators (recurrence rate, determinism, entropy of the distribution) for each time series in each state of degradation. We judge the sensitivity of the data to degredation by calculating the deviation of each of these values from the baseline, which are the recurrence values derived for the intact dataset. We will then map the changes in the indicators as the difference for that indicator between the baseline and for that set of degraded data.

Ethical approval

The project has been approved by the ethical committee (23-1844). The target journal is Frontiers in Psychology, section Quantitative Psychology and Measurement.

Additional papers

Theoretical background:

Dynamical systems:

- Theoretical introductions to dynamical systems and chaos theory (Ayers, 1997)
- "Red flags" for applying dynamical systems in the behavioural sciences

Recurrence Quantification Analysis

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Measurement:

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Possible extensions:

- Network approach to recurrence analysis (Donner et al., 2010; Eroglu et al., 2018).

Philosophy of Science:

- Difference between measurement in physics and in the behavioural and social sciences (Michell, 1999; Bringmann and Eronen, 2016)
- Dynamical systems contrasted against classical viewpoints (Georgescu-Roegen, 1971)

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