Simulating the potential of applying recurrence quantification analysis on ecological momentary assessment data

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Introduction

Ecological momentary assessment has made it possible to construct time series on the basis of self-report scales. The constructs that are generated using these methods have been shown to display all markers of complex dynamics, which means that the patterning of 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, Hasselman, and Lichtwarck-Aschoff 2020). Traditional statistical methods are often used to analyze the data that is generated using EMA, but these methods are not suitable to capture complex temporal patterns of psychological constructs (Jenkins et al. 2020). E.g., the popular root mean squared successive difference (RMSSD) method averages out change between two time points, and can only be used to indicate total variability of a certain range. It does not capture how that variability is patterned.

Recurrence quantification analysis is an analysis technique that can be used to aid in understanding psychological dynamics. This method aims to capture repeating patterns in time series by quantifying which observations x_{t+y} are equivelent to x_t, where t refers to the time of an observation, x to an observation, and y is the distance to t where that point recurs (Webber Jr and Zbilut 2005). The method results in several indicators that can be used to understand patterns in the data.

Recurrence quantification measures were developed under the assumption that measurements can be retrieved at great frequency and at high resolution. However, measures in ecological momentary assessment rely on the admission of tests taken several times a day, meaning that the sampling frequency is limited (Haslbeck and Ryan 2022). Moreover, the psychological constructs that are measured using EMA cannot be measured without relying on ordinal self-report questionnaires. This necessitates that research methods that are developed or adapted from the physical to the behavioural sciences take these particularities into account.

The current project

This project aims to find out at what point decreased data quality limits the ability of EMA to capture idiographic dynamics. We present an analysis pipeline consisting of multiple stages. We will use the `DynamicalSystems.jl` and `Statistics.jl` julia-packages to simulate the toy model and perform the analysis (Bezanson et al. 2017; Datseris 2018; Datseris and Parlitz 2022).

Stage 1: Data generation

In the first stage, we use a toy model developed to simulate the data based on a 3+1 dimensions model (Gauld and Depannemaecker 2023). This model captures clinical observations found in psychiatric symptomology by modeling internal factors, environmental noise, temporal specificities, and sympomatology. By changing these variables systematically, we aim to model a large variety of possible psychological constructs, and we save each one of these models as a separate time series. For the purpose of our study, we redefine "symptomatology" as any naturally occurring dynamical development 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 every k^{th} observation of the simulated data. We systematically decrease the value of n and min and increase the value of k and max, storing any combination of these values.

Stage 3: Data analysis

We will judge the sensitivity of the data by calculating summary statistics and recurrence indicators (recurrence rate, determinism, Shannen entropy,) for each time series in each state of degradation. We judge the sensitivity of the data to degredation by looking at the change in values for each of the indicators, where the full dataset is used as the baseline. We will then map the .

Ethical approval and proof of concept

The project has been approved by the ethical committee [!not yet done]. We

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