Process Principles

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Author Note

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Correspondence concerning this article should be addressed to ..., ... E-mail: ...

Abstract

Begin here...

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Process Principles

sys theory math

comp models in computer I could just put these things into the computer. direct code like a difference equation. but there are other properties that become apparent when you do so. here they are.

SHOULD WE SAY SOMETHING LIKE, THERE IS MORE TO PROCESS THAN MEDIATION?

We – organizational psychologists – are increasingly interested in process and dynamic phenomena. Longitudinal studies are becoming more prevalent in our literature and the number of time points they employ appears to be growing (**???**). The empirical literature uses the term "dynamics" at an expoentially larger rates in recent years (**???**). A majority of published methods literature now focuses on longitudinal data analysis (**???**), and there are now many great reviews on the conceptual and methodological issues related to process and dynamics (**???**; **???**; **???**; **???**). Moreover, this interest covers many content areas, including emotional labor (**???**; **???**; **???**), workplace stress and well-being (**???**; **???**), organizatiional performance (**???**), self-regulation (**???**), newcomer adjustment (**???**), justice and trust (**???**), leadership (**???**; **???**; **???**), decision-making (**???**), team performance (**???**), counterproductive work behaviors (**???**), work-family conflict (**???**), job satisfaction (**???**), and team emergent states (**???**). In summary, explaining how a process functions appears to be of great interest to current organizational science.

There are many ways to do so – alternative representations that we might use when we want to describe sequences of events and their relationships. Just as different statistical models can be used to draw the same inference given the appropriate assumptions about the data generating process, we can use different forms of explanation to describe process. For example, Bandura (**???**) and Kuwabara et al. (**???**), respectively, explain self regulation and lay beliefs about networking with verbal theories, (**???**) presents a mathematical explanation of social impressions, and (**???**) employ both mathematical and computational approaches to explain self-regulation. All of these authors use different techniques and forms of representation, but they are all trying to convey how the processes they study behave.

In this paper, we present some of the fundamental principles researchers use to convey process. The principles come from a number of areas, including mathematics, systems theory, dynamics, and computational modeling, and they are all ways to represent and describe relationships over time at different levels of abstraction. For example, we could use a difference equation to explain the trajctory of one variable, or we could use terms like trend or cycles that describe the emergent behavior of the variable but through a different lens. What is important is that there are fundamental principles/concepts that go into to describing a process over time. Don't necessarily need to be causal; we can explain something and it can be causal or non causal.

We provide several contributions in doing so. First, we believe our discussion will help researchers augment their current approach to explaining process. It can be helpful to be exposed to different approaches, provide ideas etc., and we hope our paper provides new ideas to seasoned researchers in this area. Second, some of the principles are technical and sophisticated and may not transfer well to researchers with only graduate-level training in basic statistics. The technical literature on dynamics is technical and can be difficult to follow. Much of this work is not easily accessible to researchers with the usual methodological and statistical background obtained from doctoral level training in managemenet; we want to help distill it. Finally, we discuss ways to study process for researchers who may not want to want to develop sophisticated math or computational models. Some people claim that math is the only option. For example, Pearl (2009) states that any explanation "worthy of the title theory must be able to represent causal questions in some mathematical language" (p. 102). There is also some pressure to produce computational theories. For example, VANCOUVER COMP MODELS ARE BETTER;

AND KOZLOWSKI COMP FRAMEWORKS ARE BETTER. But there are not many comp modelers in organizational psychology VANCOUVER ORM; and the social sciences do not emphasize mathematics as much as some of the more physical sciences (vancouver point out cites). Moreoever, Renee Thom points out that sometimes qualitative representations produce more error than their quantitative counterparts but nonetheless are better clues to the underlying process. We do not claim that one approach is better or worse than another; we simply want to describe process principles from different domains to give researchers alternative ways of talking about, specifying, and representing process behavior.

Below, we do these things. There are other excellent papers on aspects that we will not cover. Ployhart and Vandenberg discuss how to design and analyze a longitudinal study, Pitariu and Ployhart how to propose dynamic hypotheses, and Wang provides an overview of dynamic statistical models. In this paper, conversely, we focus solely on principles researchers use when they explain process.

What is process

Dymamics

The system has memory. The past has memory. Monge: “In most forms of dynamic analysis it is essential to know how variables depend unpon their own past history” p. 409 Wang: “A dynamic model can be defined as a representation of a system that evolves over time. In particular it describes how the system evolves from a given state at time t to another state at time $t + 1$ as goverened by the transition rules and potential external inputs.” p. 242 Vancouver 2012 orm. “Dynamic variables behave as if they have memory; that is, their value at any one time depends somewhat on their previous value.” p. 604 pitariu and ployhart. “A dynamic relationship is defined as a longitudinal relationship between two variables” p. 406 – but this doesn’t say anything about memory

Longitudinal and Change

PLoyhart and Vandenberg. “Longitudinal research emphasizes the study of change and contains at minimum three repeated observations on at least one of the substantive constructs of interest” p. 97. Notice that they emphasize change. “an emphasis on change permits researchers to capture two important characteristics of change: a) within-unit change across time, or growth trajectories, and b) interunit differences in change that can be either predicted or used for prediction” p. 97

Notice that ployhart tends to align with the growth modeling literature, where the modes of exploration are:

Baltes and nesselraode 1979 *identify intra-individual change + how* i* changes over time *identify interindividual differences in intra-individual change + how Julie changes over time is different from how Tom changes over time* interrelationships of change + similarities and differences in change on two or more variables *determinants of intra-individual change + predicting intercepts and slopes* determinants of inter-individual differences in intra-invididual change + predict individual differences in intercepts and slopes

“The study of phenomena in their time-related constancy and change is the aim of longitudinal methodology” baltes and nesselroade 1979

Process

things that happen over time. Mememory may or may not matter…but it usually does. Change – and by change I mean non-stationary – may or may not happen. Process is about sequences of events and trajectories. What is the behavior of the variables and the system over time? What happens? Explain how things happen over time. Causal or non causal.

Systems Theory Principles

Stocks and Flows

One common approach to explaining how things happen over time is to identify stocks and flows. Meadows (**???**) defines both with the following:

> A stock is a store, a quantity, an accumulation of material or information that has built up over time. It may be the water in a bathtub, a population, the books in a bookstore, the wood in a tree, the money in a bank, your own self confidence. A stock does not have to be physical. Your reserve of good will toward others or your supply of hope that the world can be better are both stocks.
>
> Stocks change over time through the actions of flows. Flows are filling and draining, births and deaths, purchases and sales, growth and decay, deposits and withdrawals, successes and failures. A stock, then, is the present memory of the history of changing flows within the system (18).

That last sentence is what makes a stock imply behavior over time. We speak about stocks by both referring to what they contain right now but also how they have developed and where they are likely to go. Also note that stocks do not have to change.

Many organizational phenomena can be viewed as combinations of stocks and flows. Stocks: Affect (**???**), helping behaviors, depletion, number of customers, justice perceptions, work-family conflict. Flows: turnover, stressful events, goal assignments. Sometimes the same thing can be expressed as both a stock and a flow, depending on how the researcher abstracts the situation. For example, the number of work tasks could be a stock, where it increases when we are given more assignments and decreases when we finish them. Or it could be a flow that leads into something like stress.

The behavior of a stock – whether it rises, falls, or remains the same – depends on the nature of flows. We can learn about stock behavior by subtracting outflows from inflows. Doing so leads to three general principles about stocks. They will (**???**):

1. rise when inflows exceed outflows
2. fall when outflows exceed inflows
3. remain the same when inflows equal outflows.

In other words, stocks change with respect to the summative properties of their flows. Stocks also set the pace for the cumulative rhythm of the system. Even when flows are changing rapidly, the stock may change slowly because accumulation occurred over a long period of time.

Figure 1 plots a simple stock and flow system over 20 time periods.

Insert Figure 1 Here

Beginning at the first time point, inflows are equal to outflows and the stock therefore sits at zero. Over the first ten time points, however, outflows remain the same whereas inflows increase. With inflows exceeding outflows the stock also increases up until time point ten. At this time, inflows drop back down to five whereas outflows increase – leading to a large reduction in the stock. As outflows continue to rise over time – with no counterbalancing movement from the inflow – the stock ultimately decreases.

Systems theory uses stocks and flows as general labels for each of the things in the system. Above, we described the behavior of the stocks and flows with simple terms – increasing, decreasing, or constant. Systems theory also provides a more systematic way of describing trajectories and explaining behavior over time. These are unpacked in an excellent paper by Monge (1990), and the framework includes trend, magnitude, rate of change, and periodicity. These are shown respectively in figure 2.

Insert Figure 2 Here

Trend

Dividing figure 2 into two portions – the top and bottom – reveals differences in trend. All of the panels on the top of the figure have trend, whereas those on the bottom do not. Trend is the systematic increase or decrease of a variable over time.

Magnitude

Magnitude is the level, value, or amount of the variable at each time point – the number on the y axis at each respective point in time. For example, in panel C of figure two the magnitude is low at times 1, 2, and 3, but is high at later points in time. Additionally, panel E and F have the same magnitude if we average their values over time, but panel E contains both high and low magnitude, whereas the magnitude for the trajectory in panel F remains relatively constant.

Rate of Change

Monge refers to rate of change as "How fast the magnitude increases or decreases per one unit of time." Panels G and H reveal differences in rates of change.

Periodicity

Periodicity is the amount of time before a pattern repeats itself, and it is equivalent to the term cycle. The most important piece about periodicity is that it must be couched with "controlling for trend." Notice that panel A is periodic because, after controlling for trend, there are repeated patterns over time.

Now two variables

It is of course possible to combine these notions when researchers are studying processes with more than one variable. For example, a researcher might describe the magnitude in their presumed dependent variable with respect to the magnitude of their independent variable, or the rates of change across the system of variables. When we turn to the behavior and relationships among a system of variables a few additional principles are available.

Lags

How long does it take for the presumed independent variable to produce an effect on the outcome? This is the notion of lag.

Permanence

Once the effect happens, how long does it last?

Feedback Loops

Systems theory researchers often convey process by using feedback loops. This idea is also becomming common in our own litearture. Feedback loops describe processes where a variable eventually relates back to itself. For example, EXAMPLE HERE.

There are two common ways to describe the behavior of a focal variable within a feedback loop. When feedback causes the variable to move in the opposite direction than it initially moved, this is known as negative feedback, deviation counteraction, or a balancing feedback loop (**???**; **???**). Here, an initial increase in x leads to subsequent changes in the system that, through time, eventually cause x to decrease. Now that x has gone down, more changes happen in the system that, through time, eventually cause x to increase.

When feedback, instead, causes the variable to move in the same direction that it initially moved, this is known as postive feedback, deviation ampliciation, or a reinforcing feedback loop (**???**; **???**). Here, changes in x in one direction lead to eventual changes in x in the same direction and thus produce exponential, explosive, or amplifying behavior. Of course, we can also identify whether there is positive or negative feedback for every variable in the system.

Summary

These systems theory notions are valuable tools to explain and describe process. Note that we did not cover everything to keep the reading concise and consistent. For example, (**???**) also covers discontinuous systems, so please refer to his excellent paper for an even deeper discussion. Now we turn to mathematics and statistics and describe principles from these domains that are used to explain process.

Mathematical, Statistical and Dynamics Principles

Difference Equations

In mathematics, a basic representation of a process over time is a difference equation:

$$y_t = y_{t-1} \tag{1}$$

where y_t represents y now and y_{t-1} is the variable at the prior time point. Here, the value of y is the same at each t, and the emergent behavior would be a flat line across time. In systems theory terms, there would be no trend.

Although equation 1 seems simple, it introduces a fundamental concept in dynamics: memory. The variable now depends on where it was in the past. It is constrained, there are boundaries on where it can go.

As we add terms to this basic difference equation the behavior of the variable becomes more complex. Adding a forcing constant, c in equation 1 produces positive or negative trend depending on whether c is, respectively, positive or negative. For example, the following equation:

$$\begin{aligned} y_t &= y_{t-1} + c \\ c &= -4 \end{aligned} \tag{2}$$

produces a line that decreases by four units at each time point.

The next level of complexity comes from autoregressive terms, which represent the extent to which the variable relates to itself over time. Here:

$$\begin{aligned} y_t &= a y_{t-1} \\ a &= 0.5 \end{aligned} \tag{3}$$

the variable is described over time but it does not retain the same value at each t. Instead, the variable is *similar* over time and the autoregressive term, a, describes the extent of that similarity. In equation 3, a is 0.5, meaning that the relationship between the variable now and itself at the next time point will be 0.5.

There are fundamental behaviors of dynamic variables based on their autoregressive terms, and these are shown in figure 3. The top row of figure 3 shows the trajectory of variables with autoregressive terms that are greater than one in absolute value. These large terms produce explosive behavior – exponential growth when a is positive and oscillating chaos when a is negative. When the autoregressive term falls between zero and one in absolute value, conversely, the variable converges to equilibrium – shown in the bottom two panels. Either the variable oscillates at a decreasing rate until it reaches equilibrium (when a is negative) or it converges there smoothly (when a is positive).

Insert Figure 3 Here

Equilibrium

Equilibrium, then, describes the state of a variable that no longer changes unless disturbed by an outside force. It can also be used to describe multiple variable systems. In these contexts, equilibrium again means that the state remains constant unless disturbed by an outside force, but here it refers to the state of the entire system (i.e., all of the variables). In *static* equalibriums, the system has reached a point of stability with no change, whereas *dynamic* equilibrium refers to systems with changes and fluctuations but no net change. That is, the variables fluctuate across time in periodic ways but the general state of the system does not diverge so as to change the behavior of the entire system.

Predator-prey relationships are a typical example of a system in dynamic equilibrium. For example, consider a predator-prey relationship between bobcats and rabbits. As the rabbit population increases, the amount of available food for the bobcats goes up. Over time, this raises the population of the bobcats as well. Now with a greater bobcat population, the rabbit population decreases because more are being killed. Over time, this reduction in food opportunity decreases the bobcat population. This back and forth oscillating pattern between variables describes a dynamic equilibrium. The variables change and there may be random disturbances to the system across time, but the net dynamics of the system remain stable.

Our route so far has been deterministic. That is, the mathematical representations do not contain error. Conveying that the underlying process – the data generating mechanism – contains error presents us with a host of additional principles.

Stochastics

Stochastics, stated simply, refers to processes with error. Consider our simple difference equation from above, adding an error component produces:

$$y_t = ay_{t-1} + c + e_t \tag{4}$$

where all terms are defined above but e_t represents an error component that is incorporated into y at each time point. Errors cause y to be higher or lower at specific points in time than we would have expected given a deterministic process. For example, at time t the error might push y to a higher value, and at $t + 1$ to a lower value. Errors are therefore said to be random because we cannot predict their value at any specific t. In aggregation (i.e., averaged across time), however, positive errors cancel negative errors, and large errors are less likely than small errors. Any time we have an accumulation of random error we get a normal distribution (**???**). In stochastic systems, therefore, the errors are said to be distributed $N(0, 1)$ – that is, random and unpredictable at any specific t but distributed with certain constraints across time.

It can also be helpful to think about what error is not. Anything that is systematic, predictable, or common (using those in layman's terms) cannot be error.

White Noise and Random Walks

There are two fundamental stochastic processes: white noise and random walks. White noise is a process that only has error. Setting c and a to zero in equation 4 produces a white noise process.

$$\begin{aligned} y_t &= ay_{t-1} + c + e_t \\ a &= 0 \\ c &= 0 \end{aligned} \tag{5}$$

Here, all we have is error over time. Panel "A" of figure 4 shows the behavior of a white noise process over time. Random walks are similar, but a is now equal to one.

$$\begin{aligned} y_t &= ay_{t-1} + c + e_t \\ a &= 1 \\ c &= 0 \end{aligned} \tag{6}$$

This representation is also an error process, but there is self-similarity across time. Panel "B" of figure 4 presents a random walk. Although random walks can sometimes appear to be moving in a systematic direction, ultimately their behavior is unpreditable: they could go up or down at any moment.

Random walks and white noise are error processes over time. White noise processes fluctuate randomly, whereas random walks fluctuate randomly while retaining some self-similarity through time. These two principles are the null hypotheses of time-series analysis in econometrics – where the first task in a longitudinal study is to demonstrate that you are investigating something that is not a random walk or white noise.

Stationarity

Modeling techniques make assumptions about the data generating process they attempt to capture, and a key assumption in dynamic models is stationarity, or the stability of properties in a time series. Stationarity subsumes two requirements: mean stationarity, which refers to a series with a constant mean, and variance stationary, which refers to a series with a constant variance. Almost all dynamic models used in the organizational literature are stationary models and assume the data they model are realizations of a stationary process. In simple terms, this means that we expect the properties (mean and variance) of a time series at time t to be the same at time $t+1$.

In general, we are interested in the relationships between one or more time series or panel trajectories. Acknowleding stationarity is critical for analyzing these relationships because two series that are non-stationary will be related regardless of the data generating process (**???**; **???**). That is, two (or more) independent variables that share no causal relationship will appear related in the observed data when they have trend. The first step in a dynamic analysis, then, is to check whether there is evidence of trend (i.e., non-stationarity).

The most common method for checking stationarity is the Dickey-Fuller (ADF) test (**???**) in which the null hypothesis is that the time series contains a time-*dependent* error term. If the series is stationary, it will contain a time-*invariant* error term and thus the ADF significance test will be rejected. This test was designed in the econometrics literature where single time-series are more prevalent than panel data (repeated measures designs with many N), but equivalent tests are now available for data structures more consistent with those found in the organizational literature.

Complete explanations of stationarity tests for both time-series and panel data are available in (**???**) and (**???**). Because our interest here, consistent with the organizational literature, is on panel data and not single time-series relationships we use a panel version of the Dickey-Fuller test.

Cointegration

In the current paper we assessed stationarity before moving to formal data modeling because Granger and Newbold (**???**) demonstrated that regressions between independent non-stationary series will likely produce significant coefficient estimates and large R^2 values. Analyzing series with independent (i.e., unrelated/not causal) trends, random walks, or uneven variance across time, therefore, will likely result in spurious inference. It is also possible, however, that two non-stationary processes are related. We then need a way to assess that relationship without biasing our results in the manner presented by Granger and Newbold (1974). In a later paper, Granger (**???**) showed that, under very specific circumstances, we can garner evidence for a relationship between two non-stationary series. Formally, two series, x and y are said to be cointegrated if 1) both are integrated of the same order, $I(d)$, and 2) they share a linear combination that is $I(0)$. In other words, there is a linear combination of x and y that is stationary (requirement #2) and they both require the same number of steps to make them stationary (requirement #1).

The basis for cointegration is simple: do we have evidence for a relationship between series in a situation where we know spurious relationships are likely (i.e., non-stationarity)? Implementing cointegration techniques, however, is much more difficult. The analyst needs to be sensitive to the type of non-stationarity present in the series: trends or random walks. A random walk is defined as

$$y_t = 1 * y_{(t-1)} + e_t \tag{7}$$

where the variable is exactly what it was at the prior time point but also accumulates error across time. These series may increase, decrease, or change directions at any instant. A series with trend is simply one that increases or decreases over time. Again, the steps required to demonstrate cointegration change if the analyst is dealing with trends or random walks. The analysis also changes if the variables are single-units or panels. Cointegration was developed for time-series data but panel techniques are also available now (**???**). At this point we recommend ensuring data are stationary. Cointegration merits another paper entirely.

Granger Causality and Directionality

X granger causes Y if Y can be better predicted by the histories of both X and Y than the history of Y alone. If lagged values of X help predict current values of Y in a forecast formed from lagged values of both X and Y, then X is said to Granger cause Y. We implement this notion by regressing eggs on lagged eggs and lagged chickens; if the coefficients on lagged chickens are significant as a group, then chickens cause eggs. A symetric regression tests the reverse causality. We perform the Granger causality tests using one to four lags. The number of lags in each equation is the same for eggs and chickens. To conclude that one of the two "came first," we must find unidirectional causality from one to the other. In other words, we must reject the noncausality of the one to the other and at the same time fail to reject the noncausality of the other to the one. If either both cause each other or neigher causes the other, the question will remain unanswered. Results reject that eggs do not Granger cause chickens. They provide no such reject of the hypothesis that chickens do not Granger cause eggs. Therefore, we conclude that eggs cause chickens. A better phrasing might be "temporally related" (Granger & Newbold, p. 225) – Thurman and Fisher 1988 call it temporally ordered.

Diffusion

Damping

Markov Process

References

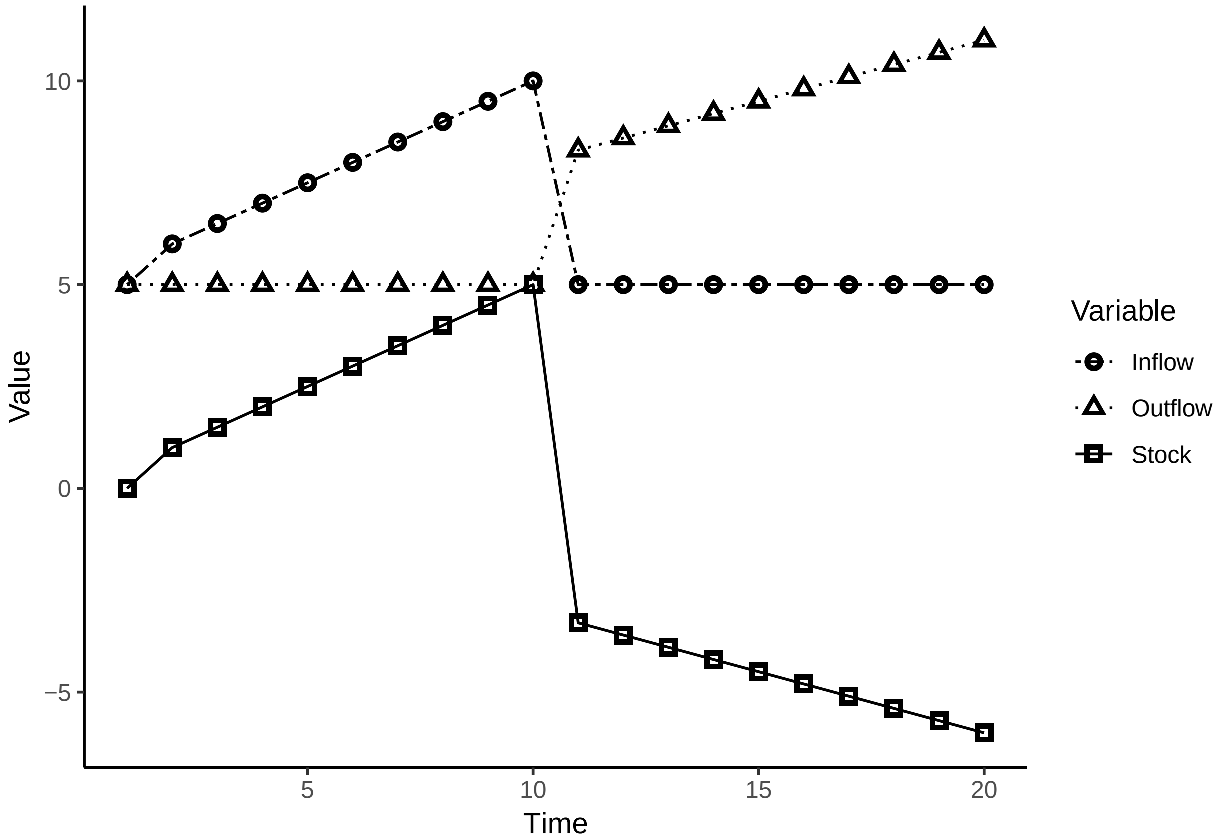

Figure 1. something

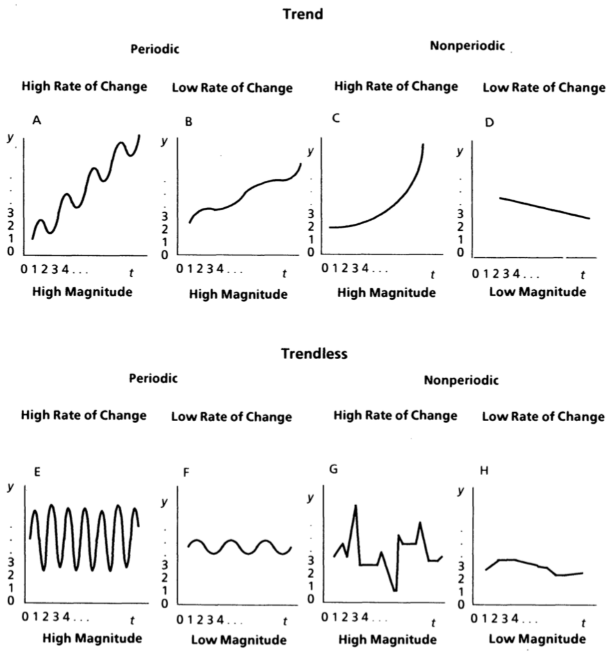

Figure 2. something else

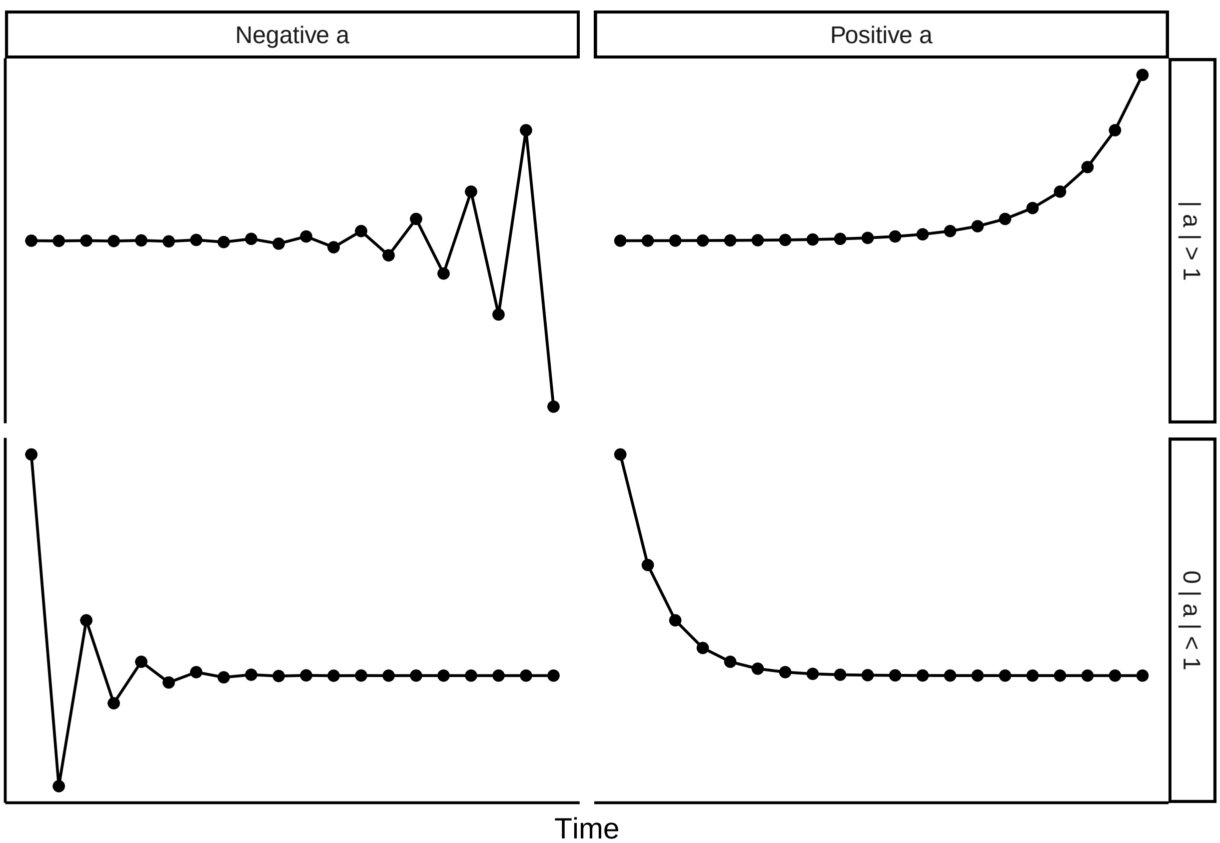

Figure 3. something here

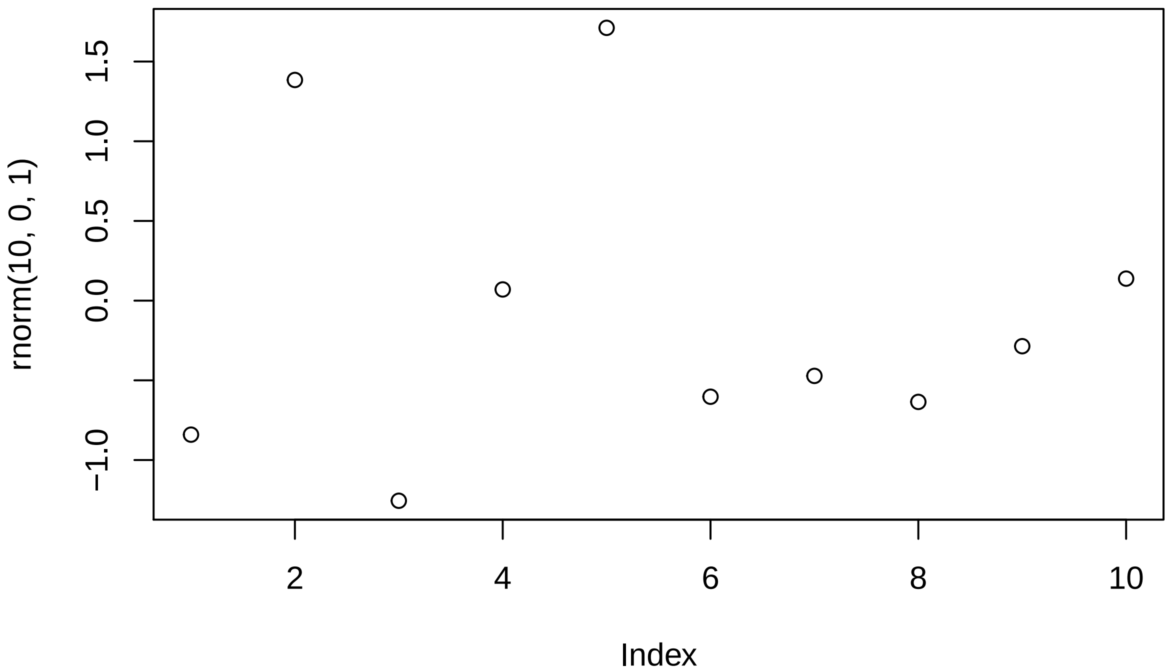

Figure 4. another