Principles for Describing or Explaining Process

. . .[1]

[1] ...

Author Note

. . . .

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

Abstract

Begin here...

Keywords: ....

Word count: 95

Principles for Describing or Explaining Process

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 exponentially larger rates in recent years (DeShon, 2012). A majority of published methods literature now focuses on longitudinal data analysis (Aguinis, Pierce, Bosco, & Muslin, 2009), and there are now many great reviews on the conceptual and methodological issues related to dynamic and within-person models (Beal, 2015; Shipp & Cole, 2015; Wang, Zhou, & Zhang, 2016). Moreover, this interest covers many content areas, including self-regulation, leadership, and team performance (Hardy, Day, & Steele, 2018; Schaubroeck, Lam, & Peng, 2016).

Given our interest in "process" phenomena, what distinguishes a process from a non-process study? What are some fundamentals for people wanting to study process? Consider the following set of studies and, while reading, ask yourself which you feel appropriately represents process. Imagine that we are interested in weight gain among US males who are 50 years or older, and to investigate it we conduct three longitudinal studies. **Option A**. In the first, we find and report that the average male gains one pound every year for the rest of his life. In the second, we find and report a positive relationship between male weight and caloric intake across time, and suggest that caloric intake has an effect on weight. In the third, we propose that weight on any day determined by its value from the day before and the difference between today's caloric intake and expenditure.

Option B. In the first, we model weight over time, find a significant, positive trend, and suggest that the average male gains one pound every year for the rest of his life. In the second, we model weight and the number of consumed calories over time, find a significant, positive relationship between them, and suggest an effect of caloric intake and weight. In the third, we model initial weight, weight, and the number of consumed and expended calories over time and suggest that weight is a function of prior weight and difference between caloric intake and expenditure.

Which of these is a process study? Where is the line between explaining a process versus describing its manifest properties? What are the different ways that we can represent it? In this paper we call attention to these questions and provide a number of principles to help researchers convey some components of process. We are agnostic as to which of the studies above is a "true" process study – we feel that, at the current state of our literature, it is more important to raise attention to the issue and initiate discussion and debate over the coming years. All three studies have meaningful pieces to convey, what we want to do here is give researchers the tools to talk about each aspect. We do so in two parts.

In the first section we contrast process with other, "over time" concepts. There are loose and formal ways to use terms and notions about behavior over time, and we point out the differences to locate process within that concept map. We then provide a definition drawn from Pettigrew (1992) and Pettigrew (1997). Although the term is used in a variety of ways in the literature – including, for example, as a construct when something like "team process" is placed in a box with an arrow directed at "team performance" – we present a definition that describes what researchers actually look for when they unpack that "team process" box. We also discuss the difference between explaining versus describing a process. Both are valuable, but researchers should be aware of how they differ.

In the second section we then discuss principles for either describing or explaining 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 trajectory of one variable, or we could use terms like trend or cycles that describe its manifest behavior but through a different lens. We want to point researchers to principles that they can use to represent or convey variables/behavior over time – regardless of whether they are truly causal or non causal explanations.

(**Not clean paragraph** - may not even need it). 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, although there is a substantial amount of literature on mathematical process principles and dynamics, it is sophisticated and technical. Much of this work is not easily accessible to researchers with the usual methodological and statistical background obtained from doctoral level training in OP/OB; 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 orm). 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.

Process

Before jumping to a definition of process it is helpful to consider other, related concepts.

Dynamics. Dynamics refers to a specific branch of mathematics/mechanics, but the term is used in different ways throughout our literature. It is used informally to mean "change", "fluctuating," "volatile," "longitudinal," or "over time" (among others), whereas formal definitions in our literature are presented within certain contexts. Wang (2016) defines a dynamic *model* 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 governed by the transition rules and potential external inputs" (p. 242). Vancouver, Wang, and Li (2018) state that dynamic *variables* "behave as if they have memory; that is, their value at any one time depends somewhat on their previous value" (p. 604). Finally, Monge (1990) suggests that in dynamic *analyses*, "it is essential to know how variables depend upon their own past history" (p. 409).

The crucial notion to take from dynamics, then, is memory. When the past matters, and future states are constrained by where they were at prior points in time, dynamics are at play.

Longitudinal. Longitudinal is a broad term that is usually paired with one additional term to refer to an investigation's method, data, or aim. A study that uses a longitudinal *method* is different from a cross-sectional design due to the number of observations, such that longitudinal designs employ repeated observations, whereas cross-sectional studies do not. Longitudinal *data* are repeated observations on multiple units, whereas panel or time series data – the common data structure in economics – are repeated observations on one unit.

The other distinction surrounding longitudinal studies is what researchers hope to discover by using them. Ployhart and Vandenberg (2010) state that “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). Similarly, Baltes and Nesselroade (1979) note, “the study of phenomena in their time-related constancy and change is the aim of a longitudinal methodology” (p. 6). Both of these definitions reveal the recent tendency to focus on change in longitudinal studies. For example, a longitudinal investigation could observe increasing or decreasing trajectories (or other forms of change) across time. This change emphasis is likely due to the increasing knowledge and application of growth models, where change is the main interest.

Process. We presented the notions above to help pinpoint what process refers to. Dynamic systems have memory, where current states are driven to future states by transition rules and external inputs. Longitudinal studies collect data on multiple units across time, and some suggest that they ought to emphasize change. Process is about sequences of events with or without memory and with or without change. Pettigrey (1997) provides a formal definition: process is “a sequence of individual and collective events, actions, and activities unfolding over time in context” (p. 2).

This definition is consistent with sentiments found in Ilgen and Hulin (2000). These authors indirectly define process by describing their dissatisfaction with static research. They compare (some) OP/OB research to individual snapshots of behavior that – even if compiled and aggregated to form a longitudinal study – only reveal fleeting glances of the flow of the system. “Frozen moments do not capture…a process, nor do statistical interactions make a sequence” (71). Process, then, seems to entail sequences of events that, as stated above, must be couched in context.

Another point we want to reiterate is how words like “dynamics,” “change,” and “process” tend to be coupled. It is common to pair two or more of these terms with a phrase like “the dynamic process.” But each of these words has a precise meaning. Dynamics is used for systems or variables with memory. Growth describes the systematic increase or decrease of a variable or system over time. Change has been used in two ways. It is sometimes used synonymously with growth: systematic increase or decrease. At other times, researchers partial prior observations of their dependent variable and in a regression model to emphasize the effect of an IV on the change in the DV (e.g., Johnson, Lanaj, & Barnes, 2014). In this second way, change does not mean “growth” but instead, “how a variable is different from the last point in time.”

Process is distinct from each of these terms, and it does not need to be paired with any. Processes can grow, or they can not grow; they can change or not change; they can contain dynamics or no dynamics. Stated differently, “no change” in not synonymous with “not process.” There is still process to be found in behavior that does not change over time.

Having discussed the differences between terms like process, longitudinal, and dynamics, we now unpack the principles. All of these are ways to represent process behavior – to talk about how things unfold over time. Some are explanatory, whereas others simply describe the manifest behavior of the undiscovered true underlying mechanism, but all help convey process behavior.

Systems Theory Principles

We start with principles from systems theory – a gentle place to begin given that some of the terms will overlap with the growth modeling literature that people in our field are now familiar with.

Stocks and Flows

One common approach to explaining how things happen over time is to identify stocks and flows. Meadows (2008) 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.

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 (Cronin, Gonzalez, & Sterman, 2009): (1) rise when inflows exceed outflows, (2) fall when outflows exceed inflows, and (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.

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 two or more variables – i.e., 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. Feedback loops describe processes where a variable eventually relates back to itself.

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 (Meadows, 2008; Monge, 1990). 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 (Meadows, 2008; Monge, 1990). 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.

Example

People from our literature using these terms and principles to explain something. Study 1 measured X and Y and described trend. Study 2 measured X and Y and talked about cycles. Study 3 measured X and Y and reported lags.

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 dynamics and describe principles from these domains that are used to explain or describe process.

Mathematics 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

Notice that we introduced a new term in our description above: equilibrium. Equilibrium 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 – where equilibrium again means that the state remains constant unless disturbed by an outside force, but here state refers to the 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 – and therefore this situation is still called "equilibrium."

Stochastics

Our route so far has been deterministic – the mathematical representations do not contain error. When we want to convey a process with error we can consider a host of additional principles. 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 term 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 (McElreath, 2016). 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 – leaving error to be the random "left overs." An aggregation of randomness is a normal distribution.

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.

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

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.

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

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.

System of Equations

Our discussion so far has focused on one variable. Before moving to two or more variables we want to pause and highlight how much researchers can explore with single variables. It is of course interesting and fun to ask how two or more variables are related, or posit a complex sequence among a set of variables. But understanding whether or not one variable exhibits white noise or random walk behavior across time is a valuable study in itself. We feel that our field could substantially benefit from spending more time plotting and analyzing the individual trajctories of every measured variable in a study.

With multivariate systems we need multiple equations – one for each variable. Before, we demonstrated a simple difference equation for y. In a multivariate system with two variables, x and y, we need one equation for each:

$$y_t = ay_{t-1} + e_t \tag{7}$$

$$x_t = ax_{t-1} + e_t \tag{8}$$

where both equations posit that their variable is a function of its prior self to the extent of the autoregressive term (a). Notice that there are no cross-relationships, we are simply representing a system with two independent variables across time. It is of course also possible to introduce relationships among the different variables with more terms.

First, consider a system where x concurrently causes y. A more appropriate way to say this would be that x_t causes y_t:

$$y_t = ay_{t-1} + bx_t + e_t \tag{9}$$

$$x_t = ax_{t-1} + e_t \tag{10}$$

where all terms are defined above but now the equation for y also includes x_t, the value of x and time t, and b, the coefficient relating x to y. This set of equations says that x is simply a product of itself over time (with error), whereas y is a function of itself and also x at the immediate time point.

What if there is a lag between when x causes y? That is, perhaps we posit that x does not immediately cause y but instead causes y after some period of time. If the lag effect were 2, that would mean that x_t causes y_{t+2}, and to express the "lag 2 effect" mathematically we would use the following.

$$y_t = ay_{t-1} + bx_{t-2} + e_t \tag{11}$$

$$x_t = ax_{t-1} + e_t \tag{12}$$

Here, all terms are nearly identical to what we saw above but now there is a lag-two effect from x to y. y is now a function of both its immediately prior self and the value of x from two time points ago.

What if we want to convey feedback, or a reciprocal relationship between x and y? That is, now we posit that both x causes y and y causes x. To do so we update our equations with a simple change:

$$y_t = ay_{t-1} + bx_{t-2} + e_t \tag{13}$$

$$x_t = ax_{t-1} + by_{t-2} + e_t \tag{14}$$

where all terms are defined above but now x and y are reciprocally related. Both are determined by themselves at the immediately prior time point and the other variable two time points in the past. x happens, and two moments later this influences y, and two moments later this influences x, and so on throughout time. All the while, both variables retain self-similarity – they change and develop but only under the constraints afforded by the autoregressive terms.

We can make the equations more complicated by continuing to add variables or longer/shorter lag effects, but the beauty of math is its freedom to capture whatever the researcher desires. These equations are language tools to help researchers convey a process over time. If we were to plug values into the coefficients and variables we would produce trajectories over time, and to describe those trajectories we could then use terms like “trend” or “cycles” like we saw in the systems theory section.

Examples

People from our literature using these principles to explain something. Study 1 argued for random walk behavior in X. Study 2 measured X and Y and posited an equation.

Summary

Computational Principles

Above, we unpacked representations most people are familiar with: verbal descriptions, plots, and math. There has recently been a push to use computational models – where the goal is still to convey process but in computer code. In this section we discuss several principles that researchers can use when they are explaining a process and expect that explanation to eventually be evaluated with a computational model. We are not going to show code or a set of scripts or “if statements” (although doing so would be a valuable paper on its own). Instead, the principles below are pieces that should be incoporated into an explanation if the researcher hopes to eventually evaluate it in a computer simulation. This section will also be different from the sections above because we will use a running example throughout, and the example comes from Simon (1956).

While developing his notion of satisficing Simon wrote a paper exploring simple rules that could yield adaptive behavior. His paper was not framed as a "computational model," but his writing is a great example of how authors can write verbal explanations that lend themselves to computer simulations. Writing equations is of course preferred, but the concepts below are tools/criteria for researchers without a strong mathematical background.

Key States

Simon's (1956) paper is about how agents move through an environment and choose among multiple goals – it is about multiple goal self-regulation. He begins by arguing that agents choose among multiple goals to satisfy needs, and need satisfaction is the core driver of behavior. There are of course other causes, but everything is done with respect to the need requirements. The two needs he includes are food and water.

Simon begins his explanation with needs, and although there are other causes of behavior he makes the assumption that needs are the lowest level of abstraction that he needs to provide a full explanation of his model. They can be thought of as the "foundation" variables to build from. Researchers should be clear about the core variables that drive all other behavior in their models. Variables are called "states" when we talk about them over time, so the first principle is to adequately identify and describe the key states.

State Dynamics

Once we identify the states we need to describe their behavior over time. Again, Simon's (1956) key states are food and water, and he then goes on to describe how they unfold as time progresses. He posits that an agent's food and water states decrease over time because his or her body requires energy. The body is constantly using food and water in its stores, so as time passes the key states naturally decrease.

Actions

The key states are the assumed "proximate" causes of behavior, and we have now explained how they unfold over time. Next, we need to explain the list of possible behaviors that the causes lead to. In other words, we need actions that result given the set of states and their current dynamics. In Simon's model he lists three agent actions: resting, exploring, and goal striving. These actions satisfy the internal state dynamics. How so? That is the next criteria.

Action Selection

Assuming a set of actions, how does the agent select among them? Action selection is the principle for explaining how one of the actions actually occurs given the states and their dynamics. Simon argues that if the food and water states are above threshold then the agent rests. That is, he suggests that the food and water states act like stores (although they constantly decrease) and only produce action when some negative discrepancy exists. When one of the states dips below threshold the agent explores its environment. During exploration the agent randomly runs into objects, and if he or she encounters a single object relevant to one of the needs the agent acquires it. If instead the agent encounters two or more need-relevant objects he or she makes a decision based on the ratio of effort required to get the object versus the size of the state discrepancy. In summary, action selection is about how behavior occurs given the states and their dynamics, whereas actions are simply the names of the behaviors themselves.

Environment

Finally, computer simulations require a structure or environment for agents to operate within. The environment could be a lattice, a well-mixed population, or any number of network arrangements, but the core idea is that context shapes what ultimately happens. Simon explains his simple rules model within a grid that contains spatially distributed sources of food and water. The size of the food and water stocks are determined by the availability of the resources in the environment. Water is easier to come by than food and so food requirements are greater.

Summary

References

Aguinis, H., Pierce, C. A., Bosco, F. A., & Muslin, I. S. (2009). First decade of Organizational Research Methods: Trends in design, measurement, and data-analysis topics. *Organizational Research Methods*, *12*(1), 69–112.

Baltes, P. B., & Nesselroade, J. R. (1979). *Longitudinal research in the study of behavior and development*. Academic Press New York, NY.

Beal, D. J. (2015). ESM 2.0: State of the art and future potential of experience sampling methods in organizational research. *Annu. Rev. Organ. Psychol. Organ. Behav.*, *2*(1), 383–407.

Cronin, M. A., Gonzalez, C., & Sterman, J. D. (2009). Why don't well-educated adults understand accumulation? A challenge to researchers, educators, and citizens. *Organizational Behavior and Human Decision Processes*, *108*(1), 116–130.

DeShon, R. P. (2012). Multivariate dynamics in organizational science. *The Oxford Handbook of Organizational Psychology*, *1*, 117–142.

Hardy, J. H., Day, E. A., & Steele, L. M. (2018). Interrelationships Among Self-Regulated Learning Processes: Toward a Dynamic Process-Based Model of Self-Regulated Learning. *Journal of Management*, 0149206318780440. doi:10.1177/0149206318780440

Ilgen, D. R., & Hulin, C. L. (2000). *Computational modeling of behavior in organizations: The third scientific discipline.* American Psychological Association.

Johnson, R. E., Lanaj, K., & Barnes, C. M. (2014). The good and bad of being fair: Effects of procedural and interpersonal justice behaviors on regulatory resources. *Journal of Applied Psychology*, *99*(4), 635.

McElreath, R. (2016). *Statistical Rethinking: A Bayesian Course with Examples in R and Stan* (Vol. 122). CRC Press.

Meadows, D. H. (2008). *Thinking in systems: A primer.* chelsea green publishing.

Monge, P. R. (1990). Theoretical and analytical issues in studying organizational processes. *Organization Science*, *1*(4), 406–430.

Pettigrew, A. M. (1992). The character and significance of strategy process research. *Strategic Management Journal*, *13*(S2), 5–16.

Pettigrew, A. M. (1997). What is a processual analysis? *Scandinavian Journal of Management*, *13*(4), 337–348. doi:10.1016/S0956-5221(97)00020-1

Ployhart, R. E., & Vandenberg, R. J. (2010). Longitudinal research: The theory, design, and analysis of change. *Journal of Management*, *36*(1), 94–120.

Schaubroeck, J. M., Lam, S. S., & Peng, A. C. (2016). Can peers' ethical and transformational leadership improve coworkers' service quality? A latent growth analysis. *Organizational Behavior and Human Decision Processes*, *133*, 45–58.

Shipp, A. J., & Cole, M. S. (2015). Time in individual-level organizational studies: What is it, how is it used, and why isn't it exploited more often? *Annu. Rev. Organ. Psychol. Organ. Behav.*, *2*(1), 237–260.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*(2), 129.

Vancouver, J. B., Wang, M., & Li, X. (2018). Translating Informal Theories Into Formal Theories: The Case of the Dynamic Computational Model of the Integrated Model of Work Motivation. *Organizational Research Methods*, 109442811878030. doi:10.1177/1094428118780308

Wang, M., Zhou, L., & Zhang, Z. (2016). Dynamic modeling. *Annual Review of Organizational Psychology and Organizational Behavior*, *3*(1), 241–266. doi:10.1146/annurev-orgpsych-041015-062553

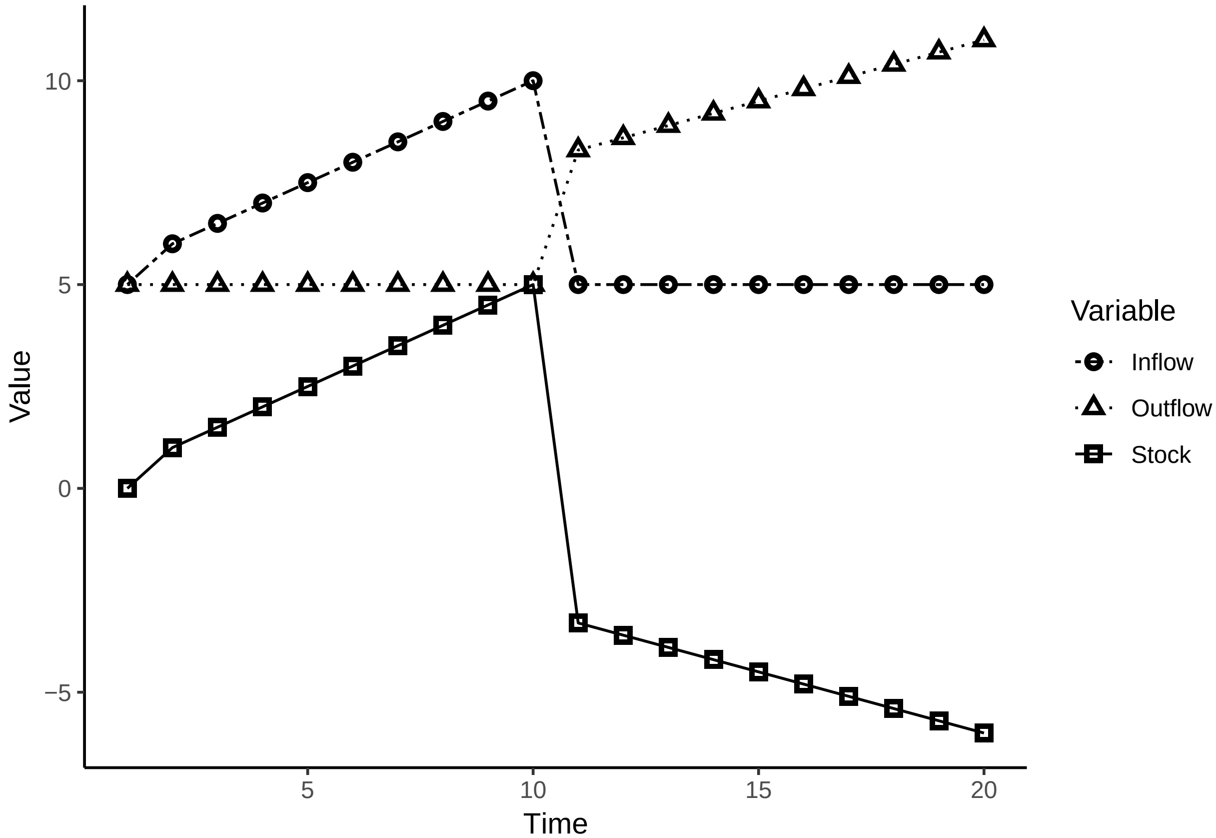

Figure 1. the ol stock system

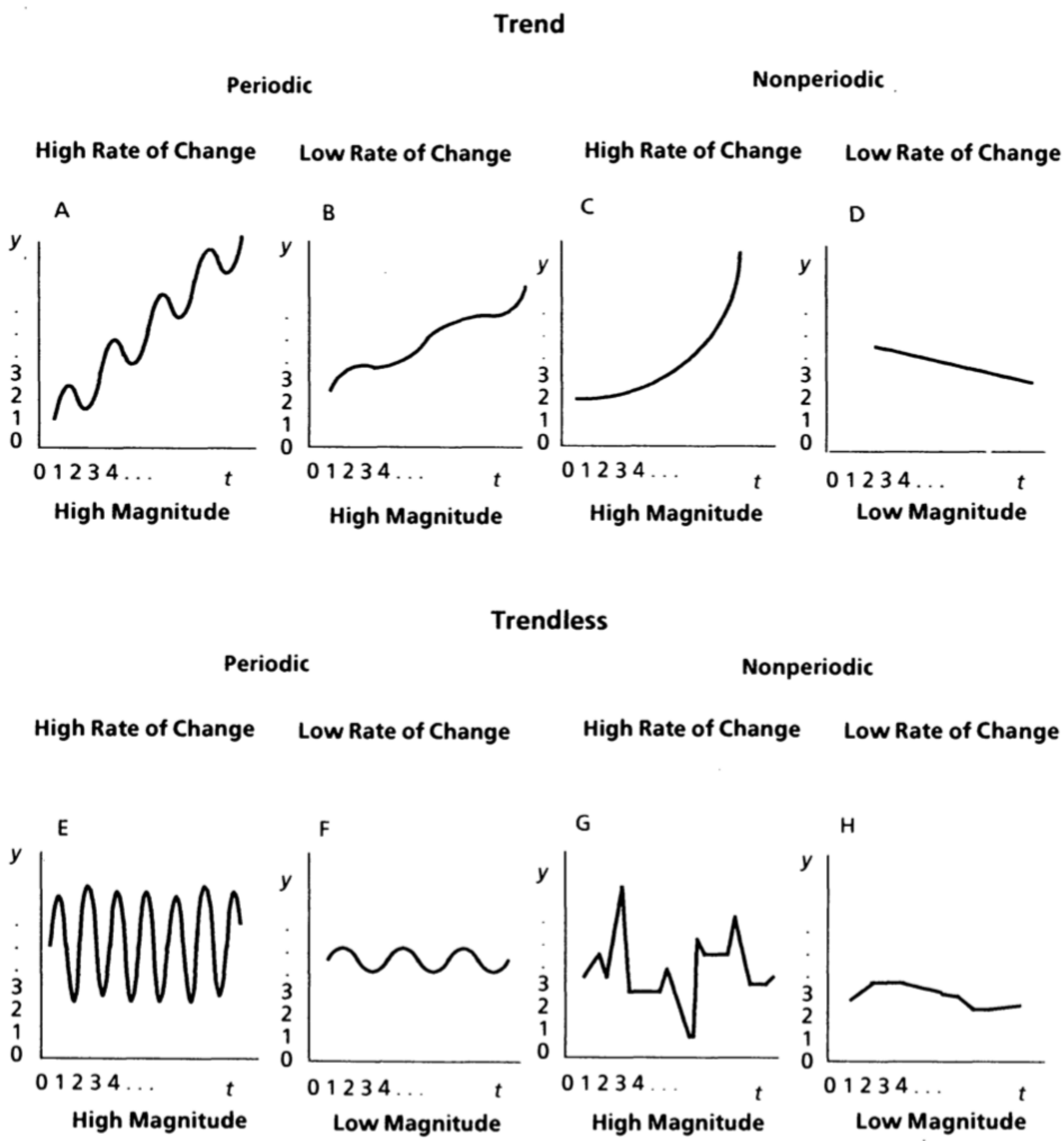

Figure 2. monge image

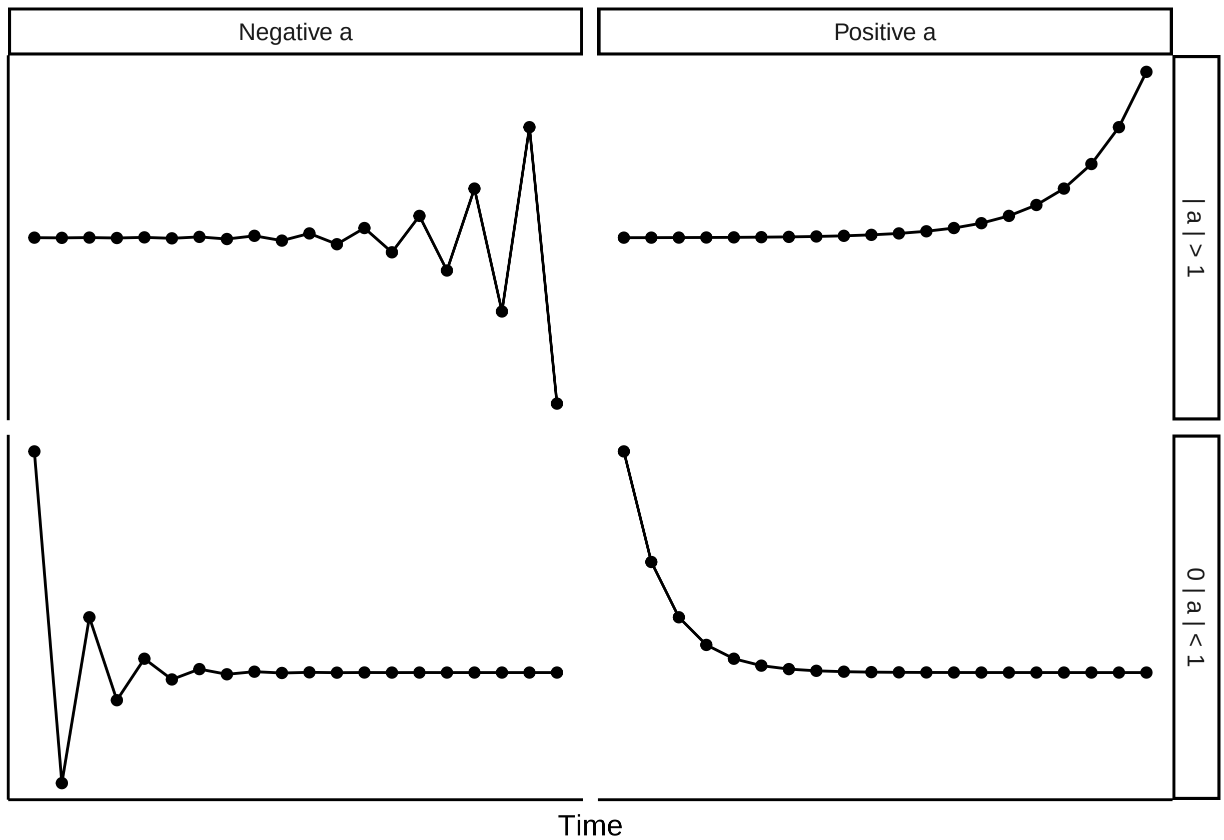

Figure 3. dynamic equilibrium fig

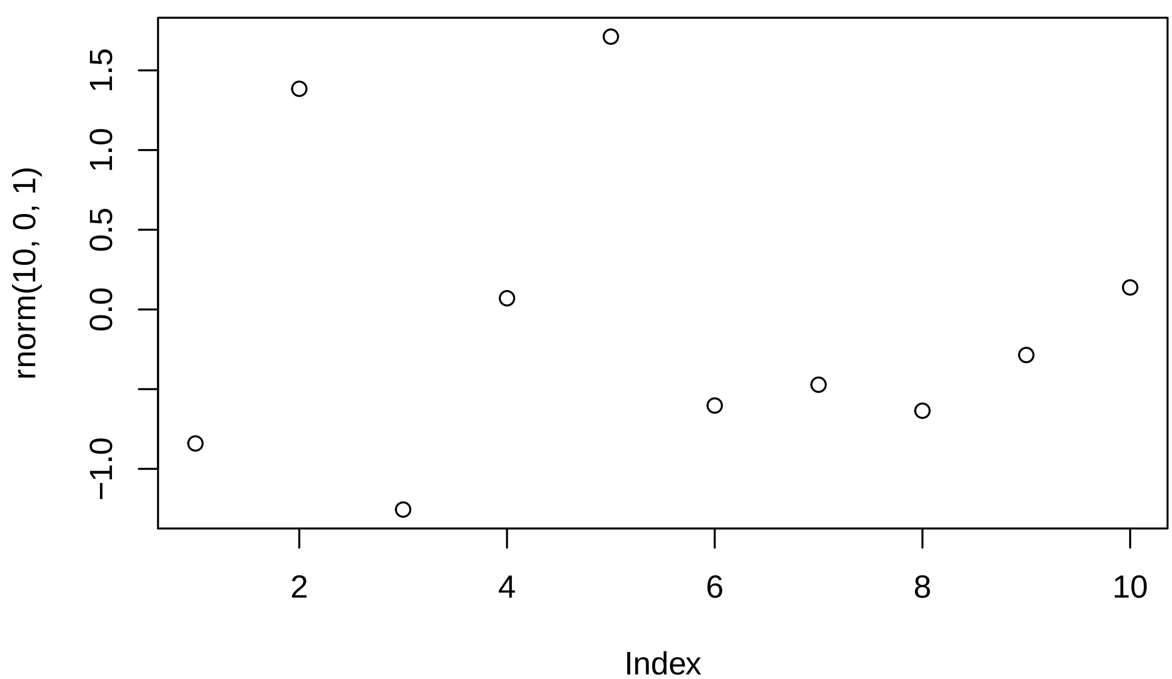

Figure 4. this one will be a white noise process and a random walk