# The Unsung Principles of Dynamics

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## Abstract

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# The Unsung Principles of Dynamics

We – organizational psychologists – are increasingly interested in dynamics and process 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 terms "dynamics" and "dynamical" 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 a number of great reviews on dynamic models (Wang, Zhou, & Zhang, 2016) and issues of time (Beal, 2015; Shipp & Cole, 2015). Moreover, this interest covers many content areas, including self-regulation, leadership, and team performance (Hardy, Day, & Steele, 2018; Schaubroeck, Lam, & Peng, 2016).

We have noticed a pattern in how people think about and describe dynamics in empirical studies. Researchers tend to study and convey their dynamic process of interest with respect to a statistical model or class of models. For example, researchers that are familiar with growth models will talk about the importance of growth in a variable or how within-person trajectories have been ignored in prior research, they will then estimate a growth curve, and ultimately convey something about trends or growth over time and how this has added a new dynamic perspective to our understanding. "Growth model thinking," as well as other recent ways of discussing how things happen over time, have produced wonderful insights into important processes in organizational science, and we see them as initial steps toward dynamics.

When researchers couch their thinking in a model, however, some concepts naturally go unnoticed. We are accumulating tremendous knowledge about our core variables and processes by opening the door of dynamics, but there are even more principles that have yet to be exposed in our literature – we have not yet stepped fully through the door. In this paper we discuss a variety of dynamics principles; some are concepts that will reorient how researchers think about dynamics, and others are statistical properties that, if ignored, could result in biased inferences.

Below, we first discuss two broad classes of "thinking with respect to a statistical model" that have done the hard work – they are sets of empirical studies taking initial steps towards dynamics. The first we refer to as "growth," and the second as "relationships," and we discuss example studies in each to briefly show our field's interest in dynamics and how some researchers approach it. This first section is not exhaustive, we are simply sampling a few of the common ways researchers currently think about dynamics to motivate the core of the paper. There, we will unpack a variety of dynamics principles that must be incorporated as we enter this domain.

## Stepping Toward Dynamics – Growth

It is becoming increasingly popular to examine whether something goes up or down over time – its trend or growth pattern. Sometimes this idea is also called "change."

Hülsheger (2016) examines fatigue trends. He motivates his study by stating that his examination of the "the continuous ebb and flow of fatigue over the course of the day and about the factors that influence this temporal ebb and flow" responds to calls to "empirically address the dynamic process of recovery and thereby helps refine recovery theory" (p. 906). For 5 consecutive workdays he employes fatigue surveys – one in the morning, another at the first work break, a third at the end of work, and the last in the evening – among a sample of Dutch employees. All surveys measure fatigue, and the morning survey also assessses sleep quality whereas the fourth measures psychological detachment. He estimates growth curves for fatigue across his sample and correlates sleep quality and psychological detachment with both the fatigue intercept and slope, respectively.

Dunford, Shipp, Boss, Angermeier, and Boss (2012) examine burnout trajectories over two years. They motivate their study by stating that, “theoretically, much of the burnout literature suggests that burnout should be progressive and dynamic, yet most empirical research has focused on explaining and testing the antecedents of static levels of burnout,” therefore “knowing for whom burnout changes and when this pattern of change occurs leads to a more realistic view of the dynamism of human experience and better managerial prescriptions for addressing burnout” (p. 637). Over two years they assess healthcare workers with five measurements, each separated by six months. All surveys measure burnout (all dimensions), and the researchers also collect between person assessments of job transitions (a categorical variable indicating whether an employee is a newcomer, recently underwent an internal job change, or remained at the same position throughout). They estimate a sequence of growth curves and examine linear and quadratic slope terms for all three burnout dimensions. They also covary job transition type with the intercept and slope terms.

### Summary

These authors are clearly interested in dynamics, and in this framework they examine within-person trajectories, whether those trajectories exhibit trends (growth), and correlate other variables with those trends.

## Stepping Toward Dynamics – Relationships

Another popular approach is to examine relationships across time rather than trends or covariates of trend.

Gabriel, Koopman, Rosen, and Johnson (2018) study the association among helping acts, depletion, and self-serving political acts. They motivate their study by highlighting the limitations of between-person research and then stating that “a more appropriate empirical test of this process requires an intraindividual lens that allows researchers to consider how

OCBs, resources, and subsequent behaviors vary daily. That is, not assessing the dynamic relations between helping behaviors and related constructs potentially misaligns the theoretical underpinnings of the construct and the level of analysis used to assess their relationships (i.e., taking dynamic processes and assessing them with static, 'in general' assessments of constructs; Klein & Kozlowski, 2000)" (p. 2). For ten work days they collect surveys twice a day (morning and afternoon). Both the morning and afternoon surveys assess helping acts, depletion, and political acts. They regress afternoon depletion on afternoon helping acts and morning depletion. They regress afternoon political acts on afternoon depletion and morning political acts. They regress afternoon helping acts on afternoon depletion and morning helping acts.

Johnson, Lanaj, and Barnes (2014) study the relationship between justice behaviors, depletion, and OCBs – they argue that exhibiting procedural justice behaviors is depleting and can negatively influence OCBs. They motivate their study by stating that our current justice knowledge comes from "cross-sectional studies examining between-person differences," but "there is a need for longitudinal, daily investigations of justice experiences that take a dynamic person-centric view" (p. 1). Ultimately they argue that their research design enabled them to "examine dynamic, within-person effects" and test a model "via a more granular approach to time" (p. 11). Their participants responded to surveys twice a day for 10 working days (morning and afternoon). The morning survey measured sleep quantity, whereas the afternoon survey measured justice behaviors, depletion, and OCBs. They regress afternoon depletion on the morning sleep quantity, the prior day's afternoon justice behavior, and the prior day's afternoon depletion.

Rosen, Koopman, Gabriel, and Johnson (2016) explore the relationship between incivility and self-control. They motivate their research by stating that "although examinations of incivility have gained momentum in organizational research, theory and empirical tests involving dynamic, within-person processes associated with this negative interpersonal behavior are limited" (p. 1). They also argue that "previous studies focused almost exclusively on chronic forms of incivility that occur on average during unspecified periods of time, which overlooks the dynamic and temporal nature of incivility and its effects. Consistent with ego depletion theory, we consider a dynamic process that explains why employees become more uncivil." (p. 2). Their participants respond to three surveys a day (morning, afternoon, and evening) for 10 workdays. The morning survey assesses self-control, the afternoon survey assesses self-control, experienced incivlity, and instigated incivility, and the evening survey measures experienced incivility and instigated incivility. They regress afternoon self-control on afternoon incivility and morning self-control. Another model regresses evening incivility on afternoon self-control.

Koopman, Lanaj, and Scott (2016) examine the costs and benefits of OCBs on behalf of the actor – specifically how OCBs relate to positive affect and work goal progress. They motivate their study by stating that they "respond to calls in the literature to examine the consequences of OCB on a more dynamic basis" (p. 415). Their respondents fill out three surveys (morning, afternoon, and evening) for ten workdays. The morning survey assesses OCBs, positive affect, and work goal progress. The afternoon survey measures work goal progress, and the evening survey assesses outcome variables irrelevant to the discussion here. They examine the relationship between OCBs and positive affect by regressing afternoon positive affect on morning OCB and morning work goal progress. They examine the relationship between OCBs and work goal progress by regressing afternoon work goal progress on morning OCB and morning work goal progress.

## Summary

These authors are also interested in dynamics. All test for within-person variance and motivate their studies by stating that "the good stuff" resides in the within-person relationships. They examine concurrent or lagged relationships across their variables over time, and they are able to examine many observations due to their frequent sampling designs.

# Dynamics

Both frameworks above get things moving toward dynamics. They bring up great notions like within-person trajectories and lag relationships, but there are many more principles left to appreciate, and we want to expose our field to them so that researchers have an even greater number of tools to explore this domain.

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. Below, we unpack a number of important principles couched in this simple idea.

## Concepts

states vs. variables memory self-similarity constraints boundary space on the system reciprocal ando and simon timing. within person dynamics vs. entire room temperature

### Statistics

lags equilibrium random walks white noise stationarity

## 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.

### Stocks and Flows

One common approach to explaining how things happen over time is to identify stocks and flows. (**???**) 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 (**???**): (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.

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Insert Figure 2 Here

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## 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 (1990) 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? That is, if the independent variable causes the dependent variable to change to a new value, does the dependent value remain at that new value indefinitely?

## 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 (**???**; 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 (**???**; 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.

## Examples

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).

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Insert Figure 3 Here

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## 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.

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

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.

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

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," "periodicity," or "feedback" 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 (**???**).

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 required to explain 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

# Discussion

Having presented the principles and terms like process, longitudinal, and dynamics, we close with our opinion about how the term "process" should be used. In our view, only explanations about the proposed "true" mechanism should be called "process." If a researcher, instead, simply observes and describes manifest behavior like trend or correlates of trend then they are not explaining process – but it is still a useful study!

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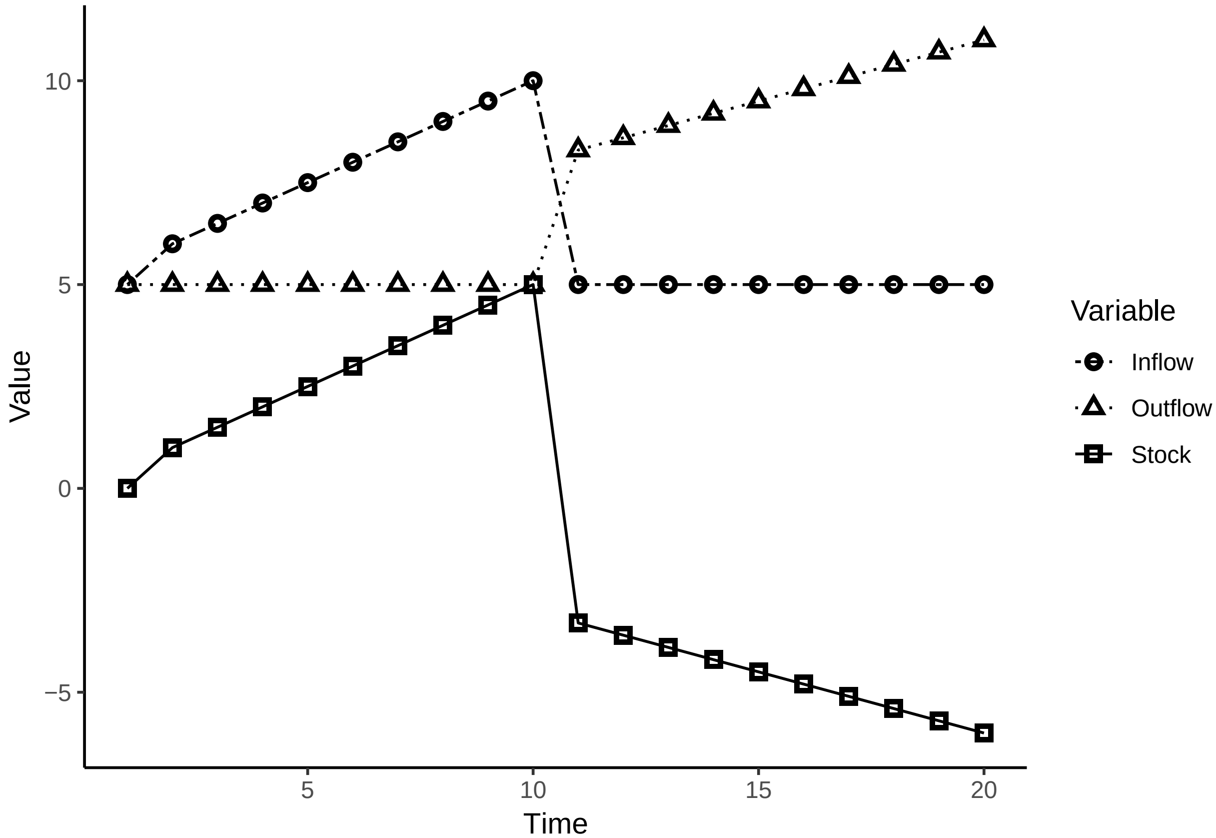


*Figure 1*. the ol stock system

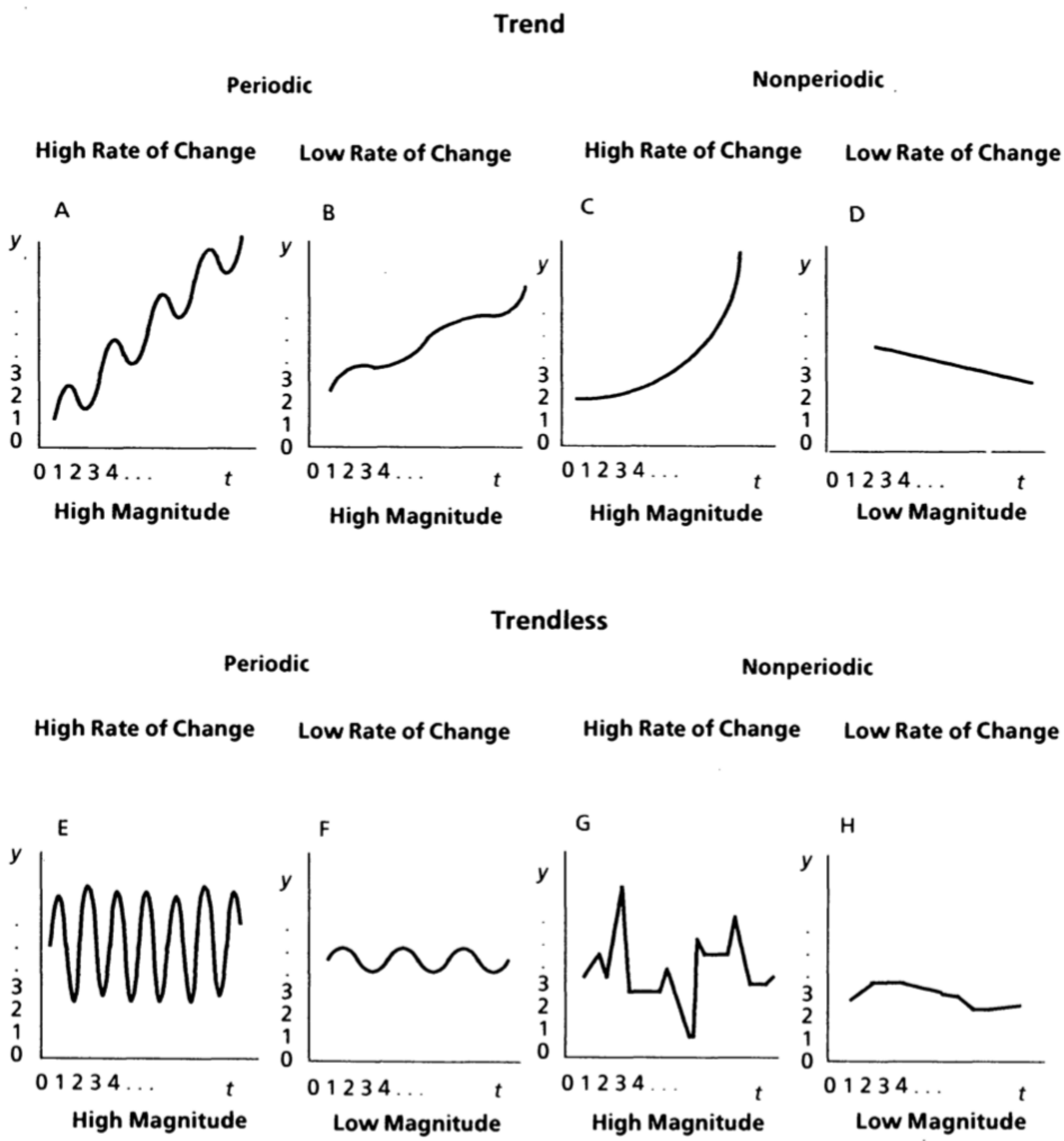


*Figure 2*. monge image

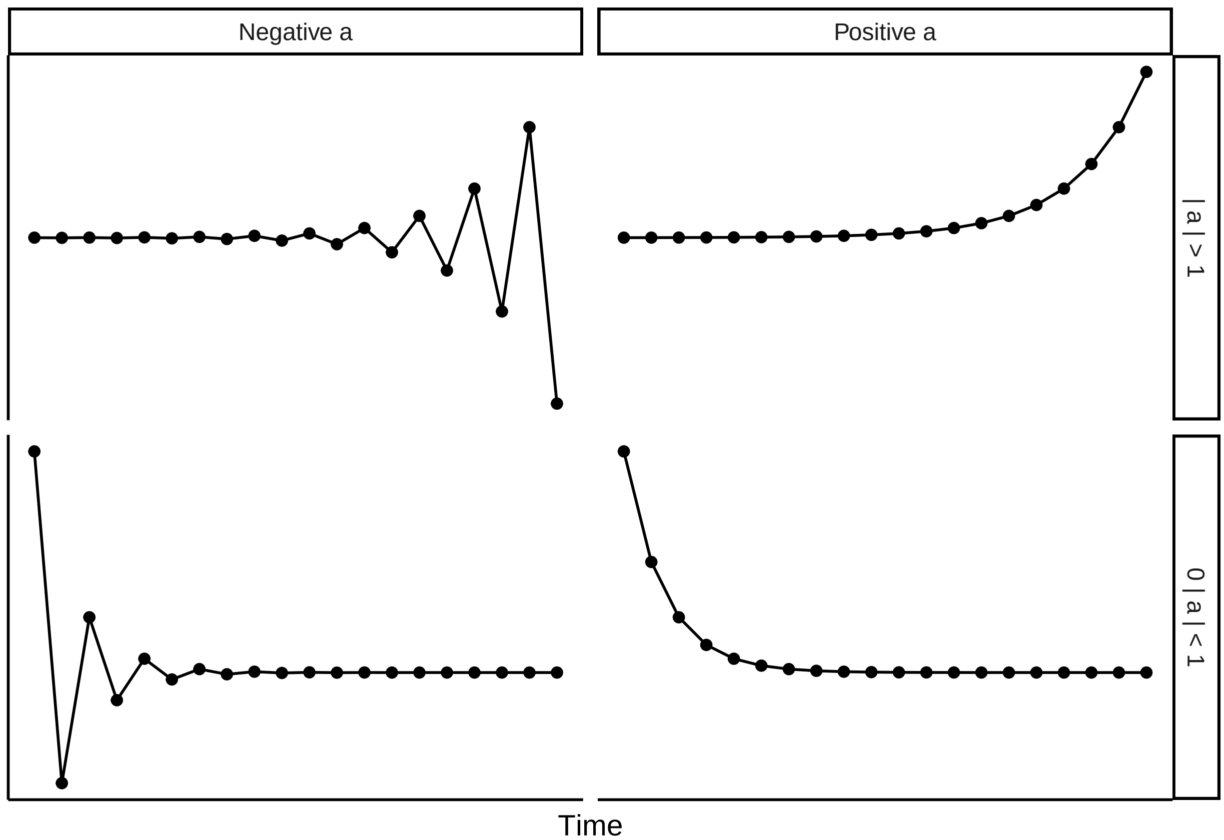


*Figure 3*. dynamic equilibrium fig

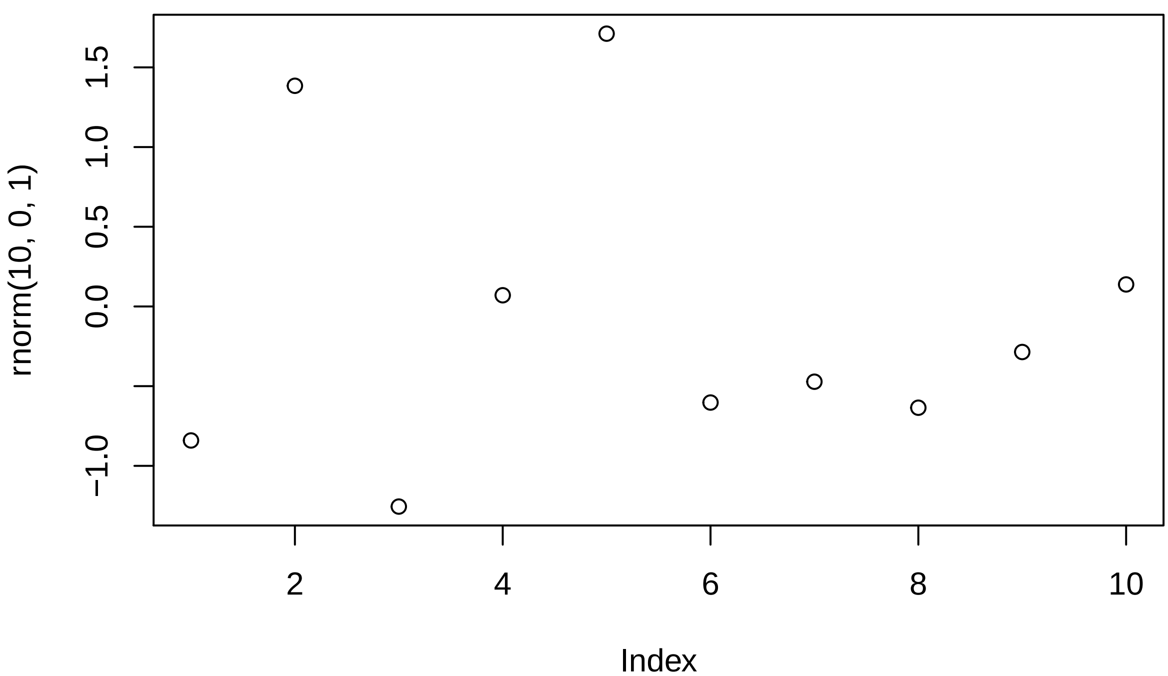


*Figure 4*. this one will be a white noise process and a random walk