1   Process Principles

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4   Author Note

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7   Abstract

8   Begin here. . .

9   *Keywords:* ....

10   Word count: 95

11   Process Principles

12   sys theory math

13   comp models in computer I could just put these things into the computer. direct code

14   like a difference equation. but there are other properties that become apparent when you do

15   so. here they are.

16   We – organizational psychologists – are increasingly interested in process and dynamic

17   phenomena. Longitudinal studies are becoming more prevalent in our literature and the

18   number of time points they employ appears to be growing (**???**). The empirical literature

19   uses the term "dynamics" at an expoentially larger rates in recent years (**???**). A majority of

20   published methods literature now focuses on longitudinal data analysis (**???**), and there are

21   now many great reviews on the conceptual and methodological issues related to process and

22   dynamics (**???**; **???**; **???**; **???**). Moreover, this interest covers many content areas, including

23   emotional labor (**???**; **???**; **???**), workplace stress and well-being (**???**; **???**), organizatiional

24   performance (**???**), self-regulation (**???**), newcomer adjustment (**???**), justice and trust

25   (**???**), leadership (**???**; **???**; **???**), decision-making (**???**), team performance (**???**),

26   counterproductive work behaviors (**???**), work-family conflict (**???**), job satisfaction (**???**),

27   and team emergent states (**???**). In summary, explaining how a process functions appears to

28   be of great interest to current organizational science.

29   There are many ways to do so – alternative representations that we might use when we

30   want to describe sequences of events and their relationships. Just as different statistical

31   models can be used to draw the same inference given the appropriate assumptions about the

32   data generating process, we can use different forms of explanation to describe process. For

33   example, Bandura (**???**) and Kuwabara et al. (**???**), respectively, explain self regulation and

34   lay beliefs about networking with verbal theories, (**???**) presents a mathematical explanation

35   of social impressions, and (**???**) employ both mathematical and computational approaches

to explain self-regulation. People use different labels for these strategies – for example,

qualitative versus quantitative (**???**) or computational, mathematical, and verbal (**???**) –

but the point is that researchers describe process in various ways. Moreover, each approach

uses its own terms and principles to represent the phenomenon.

In this paper, we point out these principles and discuss the different ways researchers

explain process. Our discussion will move across literature that uses verbal, mathematical,

and computational explanations. These are all ways to represent relationships over time at

different levels of abstraction. For example, we could use a difference equation to explain the

trajctory of one variable over time, or we could use terms like autoregression, cycles, or

periodicity that describe the same emergent behavior but in a different way. 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 graduate-level training. The

literature on the principles is technical and hard 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 trajectories. What is the behavior of the trajectory? What is the system of trajectories? How are they related? Explain the behavior of how things happen over time. Causal or non causal. What is the sequence of events. What happens?

¹⁰⁷ **Systems Theory Principles**

¹⁰⁸ **Stocks and Flows**

¹⁰⁹ One common approach to explaining how things happen over time is to identify stocks

¹¹⁰ and flows. Meadows (**???**) defines both with the following:

> ¹¹¹ A stock is a store, a quantity, an accumulation of material or information that
>
> ¹¹² has built up over time. It may be the water in a bathtub, a population, the books
>
> ¹¹³ in a bookstore, the wood in a tree, the money in a bank, your own self confidence.
>
> ¹¹⁴ A stock does not have to be physical. Your reserve of good will toward others or
>
> ¹¹⁵ your supply of hope that the world can be better are both stocks.
>
> ¹¹⁶ Stocks change over time through the actions of flows. Flows are filling and
>
> ¹¹⁷ draining, births and deaths, purchases and sales, growth and decay, deposits and
>
> ¹¹⁸ withdrawals, successes and failures. A stock, then, is the present memory of the
>
> ¹¹⁹ history of changing flows within the system (18).

¹²⁰ That last sentence is what makes a stock imply behavior over time. We speak about stocks

¹²¹ by both referring to what they contain right now but also how they have developed and

¹²² where they are likely to go. Also note that stocks do not have to change.

¹²³ Many organizational phenomena can be viewed as combinations of stocks and flows.

¹²⁴ Stocks: Affect (**???**), helping behaviors, depletion, number of customers, justice perceptions,

¹²⁵ work-family conflict. Flows: turnover, stressful events, goal assignments. Sometimes the

¹²⁶ same thing can be expressed as both a stock and a flow, depending on how the researcher

¹²⁷ abstracts the situation. For example, the number of work tasks could be a stock, where it

¹²⁸ increases when we are given more assignments and decreases when we finish them. Or it

¹²⁹ 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 dynamics 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. Each of these is shown respectively in figure 2.

———————

Insert Figure 2 Here

———————

Trend

Dividing figure two into two portions – the top and bottom – reveals differences in trend. All of the panels on the top of figure two 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; Cycles; Oscillations

Periodicity is the amount of time before a pattern repeats itself, and it is equivalent to terms like cycles or oscillations. 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 put feedback loops as a central component to their discussion or analysis. This idea is also a common explanation in our own literature.

Feedback loops describe processes where a variable eventually relates back to itself. For example, EXAMPLE HERE.

Researchers often focus on the behavior that results as a function of this feedback. 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.

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:

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

₂₁₂ where the value of y is the same at each t, and the emergent behavior would be a flat line

₂₁₃ across time. In systems theory terms, there would be no trend.

₂₁₄   Although equation 1 seems simple, it introduces a fundamental concept in dynamics:

₂₁₅ memory. The variable now depends on where it was in the past. It is constrained, there are

₂₁₆ boundaries on where it can go.

₂₁₇   As we add terms to this basic difference equation the behavior of the variable becomes

₂₁₈ more complex. Adding a forcing constant, c in equation 1 produces positive or negative

₂₁₉ trend depending on whether c is, respectively, positive or negative. For example, the

₂₂₀ following equation:

$$y = y_{t-1} + c$$
$$c = -4 \tag{2}$$

₂₂₁ produces a line that decreases by four units at each time point.

₂₂₂   Autoregressive terms represent the extent to which the variable relates to itself over

₂₂₃ time. Here:

$$y = a y_{t-1}$$
$$a = 0.5 \tag{3}$$

₂₂₄ the variable is described over time but it does not retain the same value at each t. Instead,

₂₂₅ the variable is *similar* over time and the autoregressive term, a, describes the extent of that

226   similarity. The term is 0.5, meaning that the relationship between the variable now and itself

227   at the next time point will be 0.5.

228   There are fundamental properties of dynamic variables based on their autoregressive

229   terms, and these are shown in figure 3. The top row of figure 3 shows the trajectory of a

230   variable with autoregressive terms that are greater than one in absolute value. These large

231   terms produce explosive behavior – exponential growth when a is positive and oscillating

232   CHAOS? when a is negative. When the autoregressive term falls between zero and one,

233   conversely, the variable converges to an equilibrium value – shown in the bottom two panels.

234   Either the variable oscillates at a decreasing rate until it reaches equilibrium (when a is

235   negative) or it converges there smoothly (when a is positive).

236   ——————

237   Insert Figure 3 Here

238   ——————

239   **Stochastics**

240   **Random Walks**

241   **Stationarity**

242   **Cointegration**

243   **Granger Causality and Directionality**

244   X granger causes Y if Y can be better predicted by the histories of both X and Y than

245   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.

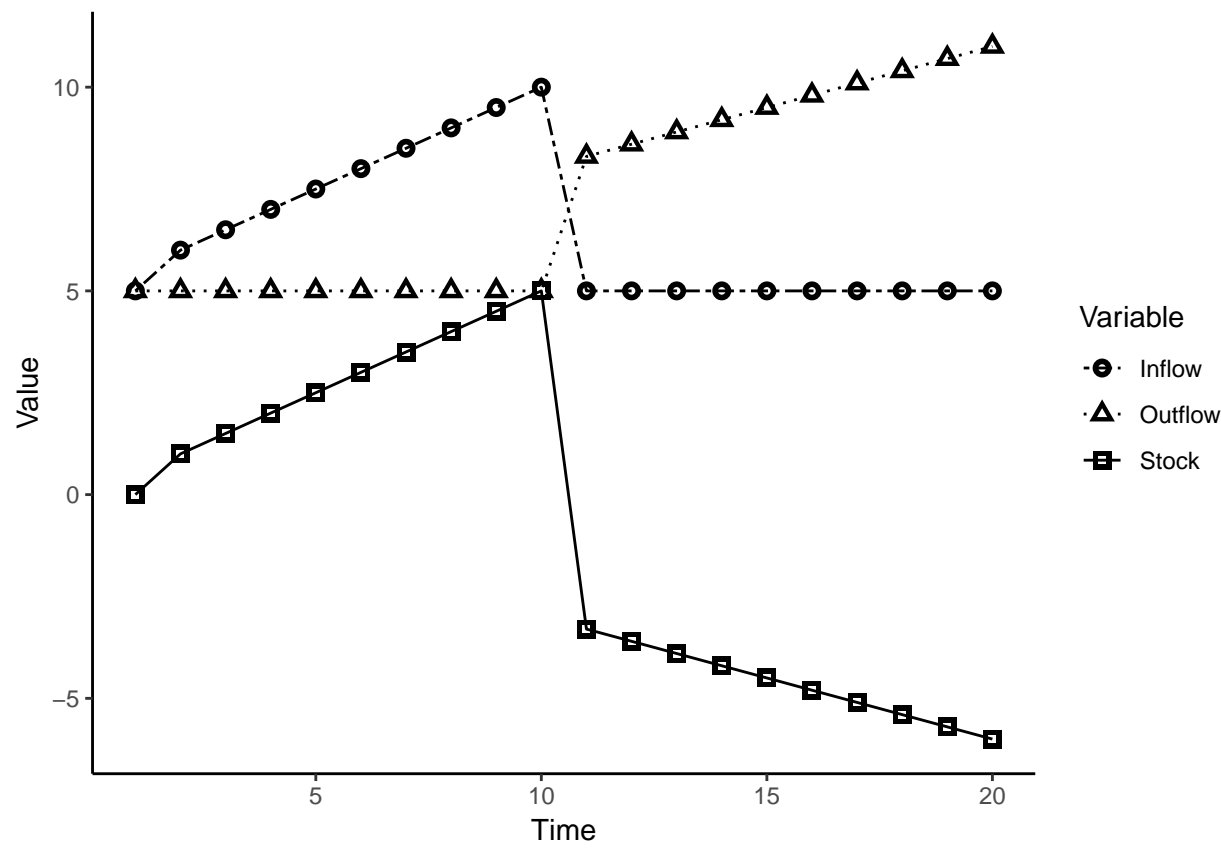**Diffusion**

Damping

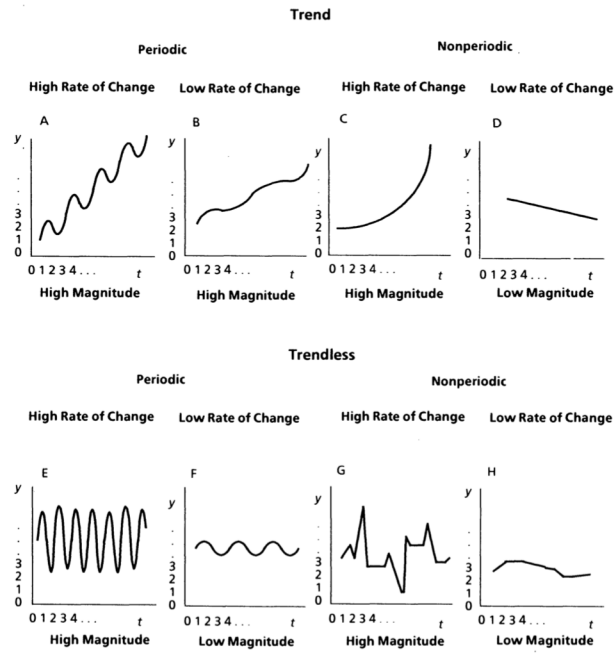**Markov Process**

262

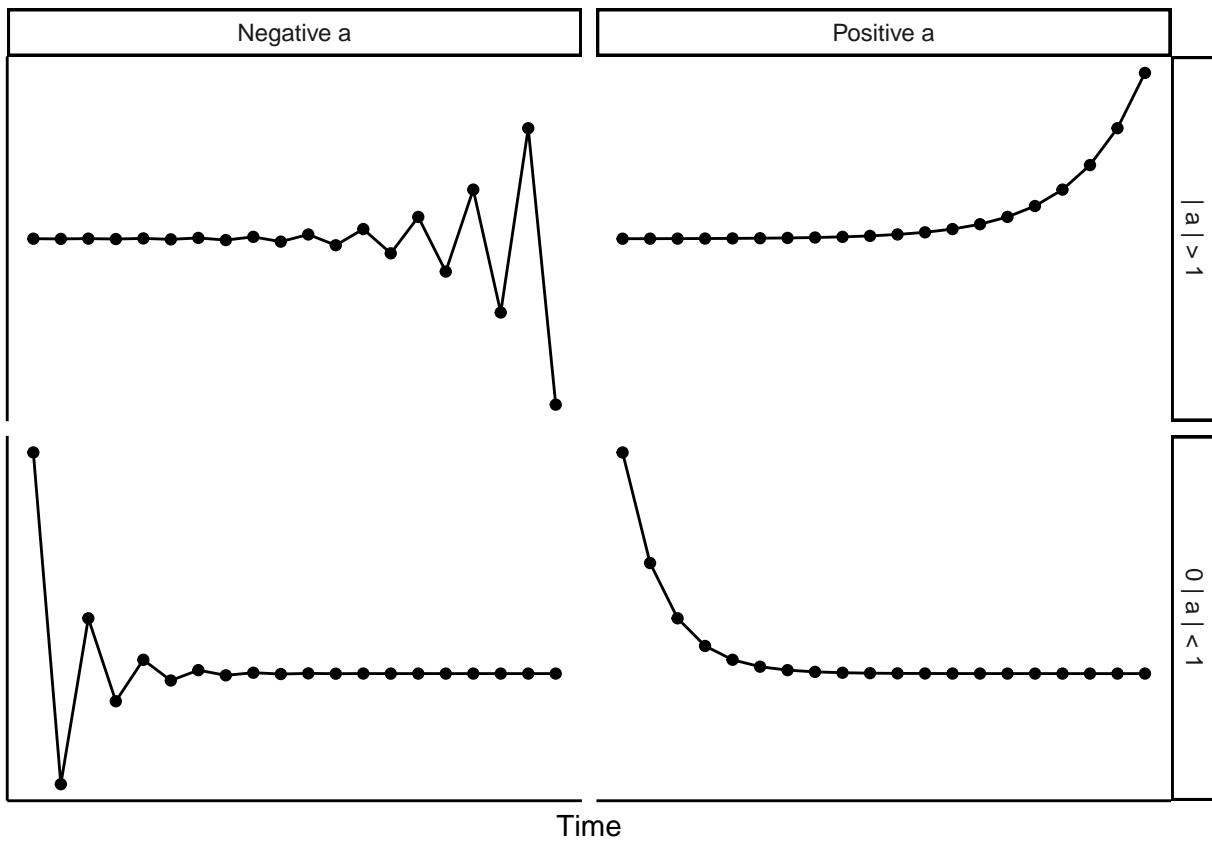# References

Figure 1. something

Figure 2. something else

Figure 3. something here