1   Process Principles

2                                       $\ldots$ [1]

3   [1] ...

4   Author Note

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7 Abstract

8 Begin here...

9 *Keywords:* ....

10 Word count: 95

11   Process Principles

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

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

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

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

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

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

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

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

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

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

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

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

24 be of great interest to current organizational science.

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

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

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

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

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

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

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

32 to explain self-regulation. All of these authors use different techniques and forms of

33 representation, but they are all trying to convey how the processes they study behave.

34   In this paper, we present some of the fundamental principles researchers use to convey

35 process. The principles come from a number of areas, including mathematics, systems theory,

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

We provide several contributions in doing so. First, we believe our discussion will help researchers augment their current approach to explaining process. It can be helpful to be exposed to different approaches, provide ideas etc., and we hope our paper provides new ideas to seasoned researchers in this area. Second, some of the principles are technical and sophisticated and may not transfer well to researchers with only graduate-level training in basic statistics. The technical literature on dynamics is technical and can be difficult to follow. Much of this work is not easily accessible to researchers with the usual methodological and statistical background obtained from doctoral level training in managemenet; we want to help distill it. Finally, we discuss ways to study process for researchers who may not want to want to develop sophisticated math or computational models. Some people claim that math is the only option. For example, Pearl (2009) states that any explanation "worthy of the title theory must be able to represent causal questions in some mathematical language" (p. 102). There is also some pressure to produce computational theories. For example, VANCOUVER COMP MODELS ARE BETTER; AND KOZLOWSKI COMP FRAMEWORKS ARE BETTER. But there are not many comp modelers in organizational psychology VANCOUVER ORM; and the social sciences do not emphasize mathematics as much as some of the more physical sciences (vancouver point out cites). Moreoever, Renee Thom points out that sometimes qualitative representations produce more error than their quantitative counterparts but nonetheless are better clues to the underlying process. We do not claim that one approach is better or worse than another;

63 we simply want to describe process principles from different domains to give researchers

64 alternative ways of talking about, specifying, and representing process behavior.

65 Below, we do these things. There are other excellent papers on aspects that we will not

66 cover. Ployhart and Vandenberg discuss how to design and analyze a longitudinal study,

67 Pitariu and Ployhart how to propose dynamic hypotheses, and Wang provides an overview of

68 dynamic statistical models. In this paper, conversely, we focus solely on principles

69 researchers use when they explain process.

What is process

Dymamics

72 The system has memory. The past has memory. Monge: "In most forms of dynamic

73 analysis it is essential to know how variables depend unpon their own past history" p. 409

74 Wang: "A dynamic model can be defined as a representation of a system that evolves over

75 time. In particular it describes how the system evolves from a given state at time t to

76 another state at time $t + 1$ as goverened by the transition rules and potential external

77 inputs." p. 242 Vancouver 2012 orm. "Dynamic variables behave as if they have memory;

78 that is, their value at any one time depends somewhat on their previous value." p. 604

79 pitariu and ployhart. "A dynamic relationship is defined as a longitudinal relationship

80 between two variables" p. 406 – but this doesn't say anything about memory

Longitudinal and Change

82 PLoyhart and Vandenberg. "Longitudinal research emphasizes the study of change and

83 contains at minimum three repeated observations on at least one of the substantive

84 constructs of interest" p. 97. Notice that they emphasize change. "an emphasis on change

85 permits researchers to capture two important characteristics of change: a) within-unit

86 change across time, or growth trajectories, and b) interunit differences in change that can be

87 either predicted or used for prediction" p. 97

88   Notice that ployhart tends to align with the growth modeling literature, where the

89 modes of exploration are:

90   Baltes and nesselraode 1979 *identify intra-individual change + how* i* changes over

91 time *identify interindividual differences in intra-individual change + how Julie changes over*

92 *time is different from how Tom changes over time* interrelationships of change + similarities

93 and differences in change on two or more variables *determinants of intra-individual change +*

94 *predicting intercepts and slopes* determinants of inter-individual differences in

95 intra-invididual change + predict individual differences in intercepts and slopes

96   "The study of phenomena in their time-related constancy and change is the aim of

97 longitudinal methodology" baltes and nesselroade 1979

Process

99   things that happen over time. Mememory may or may not matter... but it usually does.

100 Change – and by change I mean non-stationary – may or may not happen. Process is about

101 sequences of events and trajectories. What is the behavior of the variables and the system

102 over time? What happens? Explain how things happen over time. Causal or non causal.

¹⁰³ **Systems Theory Principles**

¹⁰⁴ **Stocks and Flows**

¹⁰⁵ One common approach to explaining how things happen over time is to identify stocks

¹⁰⁶ and flows. Meadows (**???**) defines both with the following:

¹⁰⁷ A stock is a store, a quantity, an accumulation of material or information that

¹⁰⁸ has built up over time. It may be the water in a bathtub, a population, the books

¹⁰⁹ in a bookstore, the wood in a tree, the money in a bank, your own self confidence.

¹¹⁰ A stock does not have to be physical. Your reserve of good will toward others or

¹¹¹ your supply of hope that the world can be better are both stocks.

¹¹² Stocks change over time through the actions of flows. Flows are filling and

¹¹³ draining, births and deaths, purchases and sales, growth and decay, deposits and

¹¹⁴ withdrawals, successes and failures. A stock, then, is the present memory of the

¹¹⁵ history of changing flows within the system (18).

¹¹⁶ That last sentence is what makes a stock imply behavior over time. We speak about stocks

¹¹⁷ by both referring to what they contain right now but also how they have developed and

¹¹⁸ where they are likely to go. Also note that stocks do not have to change.

¹¹⁹ The behavior of a stock – whether it rises, falls, or remains the same – depends on the

¹²⁰ nature of flows. We can learn about stock behavior by subtracting outflows from inflows.

¹²¹ Doing so leads to three general principles about stocks. They will (**???**):

¹²² 1. rise when inflows exceed outflows

¹²³ 2. fall when outflows exceed inflows

¹²⁴ 3. remain the same when inflows equal outflows.

¹²⁵ In other words, stocks change with respect to the summative properties of their flows. Stocks

126   also set the pace for the cumulative rhythm of the system. Even when flows are changing

127   rapidly, the stock may change slowly because accumulation occurred over a long period of

128   time.

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

130   —————————

131   Insert Figure 1 Here

132   —————————

133   Beginning at the first time point, inflows are equal to outflows and the stock therefore sits at

134   zero. Over the first ten time points, however, outflows remain the same whereas inflows

135   increase. With inflows exceeding outflows the stock also increases up until time point ten. At

136   this time, inflows drop back down to five whereas outflows increase – leading to a large

137   reduction in the stock. As outflows continue to rise over time – with no counterbalancing

138   movement from the inflow – the stock ultimately decreases.

139   Systems theory uses stocks and flows as general labels for each of the things in the

140   system. Above, we described the behavior of the stocks and flows with simple terms –

141   increasing, decreasing, or constant. Systems theory also provides a more systematic way of

142   describing trajectories and explaining behavior over time. These are unpacked in an excellent

143   paper by Monge (1990), and the framework includes trend, magnitude, rate of change, and

144   periodicity. These are shown respectively in figure 2.

145   —————————

146   Insert Figure 2 Here

147   —————————

Trend

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

Magnitude

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

Rate of Change

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

Periodicity

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

Now two variables

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

Lags

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

Permanence

Once the effect happens, how long does it last?

Feedback Loops

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

There are two common ways to describe the behavior of a focal variable within a feedback loop. When feedback causes the variable to move in the opposite direction than it initially moved, this is known as negative feedback, deviation counteraction, or a balancing feedback loop (**???**; **???**). Here, an initial increase in x leads to subsequent changes in the

system that, through time, eventually cause x to decrease. Now that x has gone down, more changes happen in the system that, through time, eventually cause x to increase.

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

Example

Literature example of someone using these terms to explain something.

Summary

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

Mathematical, Statistical and Dynamics Principles

Difference Equations

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

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

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

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

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

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

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:

$$y_t = ay_{t-1}$$
$$a = 0.5 \tag{3}$$

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

₂₂₀ similarity. In equation 3, a is 0.5, meaning that the relationship between the variable now

₂₂₁ and itself at the next time point will be 0.5.

₂₂₂   There are fundamental behaviors of dynamic variables based on their autoregressive

₂₂₃ terms, and these are shown in figure 3. The top row of figure 3 shows the trajectory of

₂₂₄ variables with autoregressive terms that are greater than one in absolute value. These large

₂₂₅ terms produce explosive behavior – exponential growth when a is positive and oscillating

₂₂₆ chaos when a is negative. When the autoregressive term falls between zero and one in

₂₂₇ absolute value, conversely, the variable converges to equilibrium – shown in the bottom two

₂₂₈ panels. Either the variable oscillates at a decreasing rate until it reaches equilibrium (when a

₂₂₉ is negative) or it converges there smoothly (when a is positive).

₂₃₀   _____

₂₃₁   Insert Figure 3 Here

₂₃₂   _____

₂₃₃ **Equilibrium**

₂₃₄   Equilibrium, then, describes the state of a variable that no longer changes unless

₂₃₅ disturbed by an outside force. It can also be used to describe multiple variable systems. In

₂₃₆ these contexts, equilibrium again means that the state remains constant unless disturbed by

₂₃₇ an outside force, but here state refers to the the entire system (i.e., all of the variables). In

₂₃₈ *static* equalibriums, the system has reached a point of stability with no change, whereas

₂₃₉ *dynamic* equilibrium refers to systems with changes and fluctuations but no net change.

₂₄₀ That is, the variables fluctuate across time in periodic ways but the general state of the

₂₄₁ system does not diverge so as to change the behavior of the entire system.

₂₄₂   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.

System of Equations

A difference equation with X influencing Y – now I have lags represented in math. A difference equation with X influencing Y and Y influencing X – now I have a feedback loop represented in a difference equation. I may also get priodicity, trend, and equilibrium – we could work that out analytically but it is easier just to graph it.

Our route so far has been deterministic – the mathematical representations do not contain error. When we want to convey that the underlying process – the data generating mechanism – contains error we can consider a host of additional principles.

Stochastics

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

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

where all terms are defined above but e_t represents an error 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 (**???**). 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.

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

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.

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

281   This representation is also an error process, but there is self-similarity across time. Panel "B"

282   of figure 4 presents a random walk. Although random walks can sometimes appear to be

283   moving in a systematic direction, ultimately their behavior is unpreditable: they could go up

284   or down at any moment.

285   Random walks and white noise are error processes over time. White noise processes

286   fluctuate randomly, whereas random walks fluctuate randomly while retaining some

287   self-similarity through time. These two principles are the null hypotheses of time-series

288   analysis in econometrics – where the first task in a longitudinal study is to demonstrate that

289   you are investigating something that is not a random walk or white noise.

290   Now that we have added the conept of error our focus changes from the exact values of

291   variables over time to their distributions.

292   **Stationarity**

293   Stationary is a term that describes the properties of a process. If a process is

294   stationary, its mean and variance are stable – they are similar across all t. In simple terms,

295   this means that we expect the properties (mean and variance) of a time series at time t to be

296   the same at time $t + 1$.

Cointegration and Granger Causality

Cointegration

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

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

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

where the variable is exactly what it was at the prior time point but also accumulates error across time. These series may increase, decrease, or change directions at any instant. A series

with trend is simply one that increases or decreases over time. Again, the steps required to demonstrate cointegration change if the analyst is dealing with trends or random walks. The analysis also changes if the variables are single-units or panels. Cointegration was developed for time-series data but panel techniques are also available now (**???**). At this point we recommend ensuring data are stationary. Cointegration merits another paper entirely.

Granger Causality

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

Example: Dishop (maybe) Denrell

Goal sampling over time.

- Difference equations

- Autoregression

- Error terms

Summary

In our prior discussions we cared about describing and explaining behavior over time. The emphasis was on what people are used to: verbal descriptions, plots, and math. There has recently been a push to comp model. These people are trying to do the same thing, but represent their process in a computer.

Think of it this way. Above, we were representing process on graphs, through equations, and through terms. To do so required certain principles. When we want to describe something in a computer language we also need certain principles: certain requirements about how we explain the process.

Vancouver has pointed out some of these. He framed them as difficult pieces to putting stuff into code.

Computational Principles

Key States

What are the important states? A variable is an entity that can take different values at one point in time. A state is a variable that fluctuates over time. In information technology and computer science, a program is described as stateful if it is designed to remember preceding events or user interactions; the remembered information is called the state of the system.

We can also talk about the global state of the system as a whole – its cumulative form. The state of the *system* describes enough about the system to determine its future behavior in the absence of any external forces affecting the system. The set of possible combinations of state variables is called the state space of a system.

State Dynamics

Constants

Values that do not change over time. Usually constants occur in the coefficients, or the weights. Vancouver's comp model 2018 included a weight relating assigned goal difficulty and goal specificity to self-efficacy that did not change over time.

Actions

Action selection

Context/Environment

How is the process situated? Simon's mouse behavior environment. He defines the context in which it can move around. Things happen with respect to the environment.

Noise

Is there error in the system, if so, where?

Time Scale

How long does the process operate for? How many iterations does my for loop go for?

Example: Simon 1956

key states:

- hunger and thirst
- It is easier to think of these as stocks: food and water.

State dynamics:

- The body requires energy, so the food and water stocks decrease over time (i.e., hunger and thirst increase)

Actions used to satisfy those states:

- resting, exploration, goal striving

Action selection

- If the food and water stocks are above threshold, the agent rests

- When the stock of any need dips below threshold, the agent explores

- During exploration

  - agent randomly runs into objects. If they encounter a single object relevant to one of the needs, the agent acquires it
  - If the agent encounters two or more need-relevant objects, they evoke a simple ratio to make a decision
    * compare energy required to meet the need (M) to the storage capacity with respect to the need (S)
    * or the effort required to get the object to how large the stock for this need is. Super large stocks take precedence

Environment

- a space with goals within which the entity moves
- the individual is located in an environment that contains spatially distributed goal-relevant objects such as sources of food and water (239).
- 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 storage requirements are greater. Similarly, breathable air is easier to obtain than water and so its storage requirements are less than both food and water (239).

Key * Dynamics of the environment + position of goal-relevant objects in the environments changes and new goal objects appear as the agent moves * Internal dynamics + internal states change and decay over time * To understand behavior you need to know internal agent dynamics and the distribution of goal-relevant objects in the environment
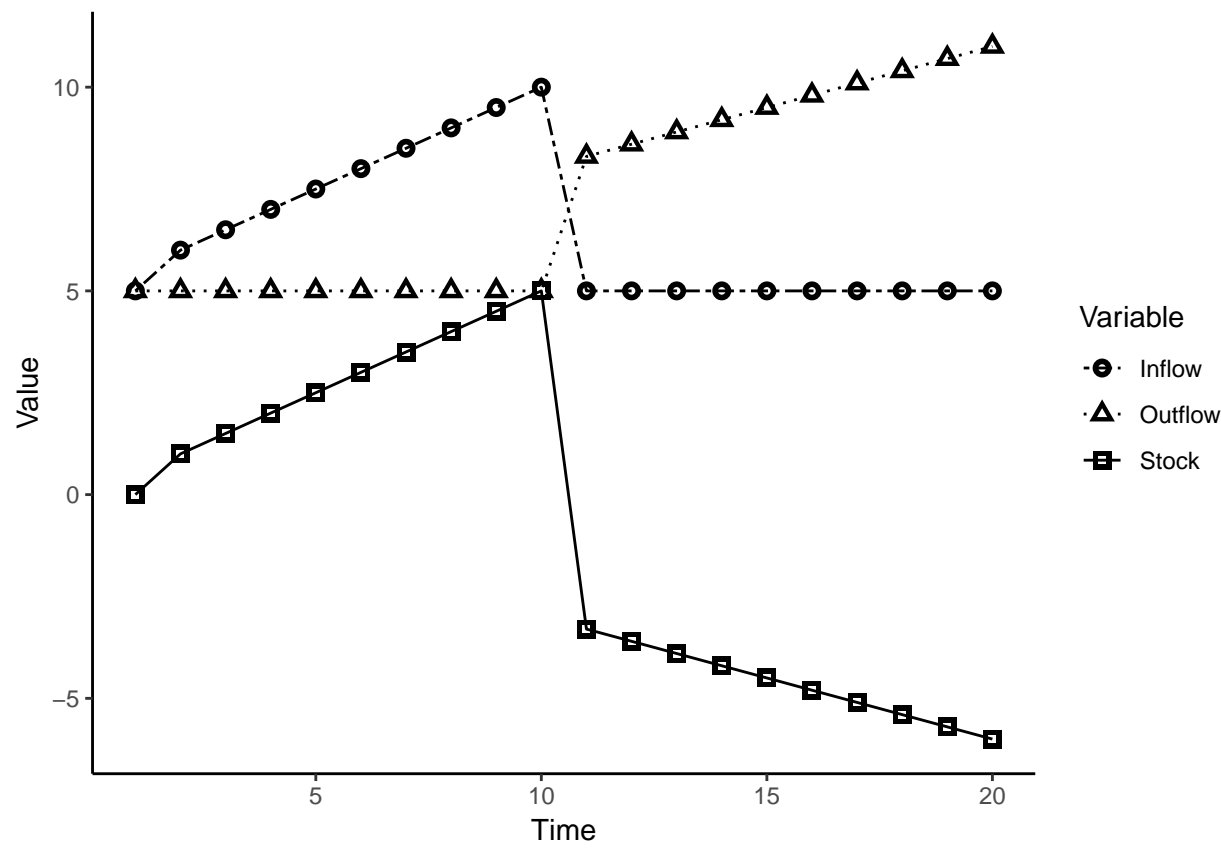
Summary

415   **References**
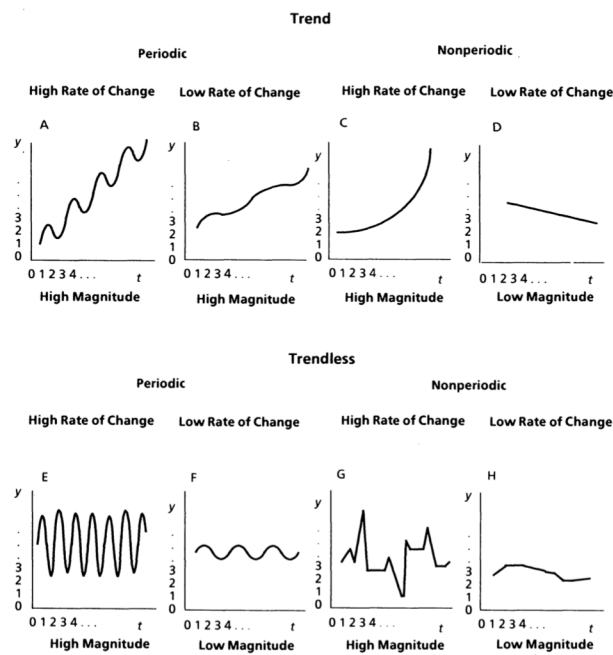
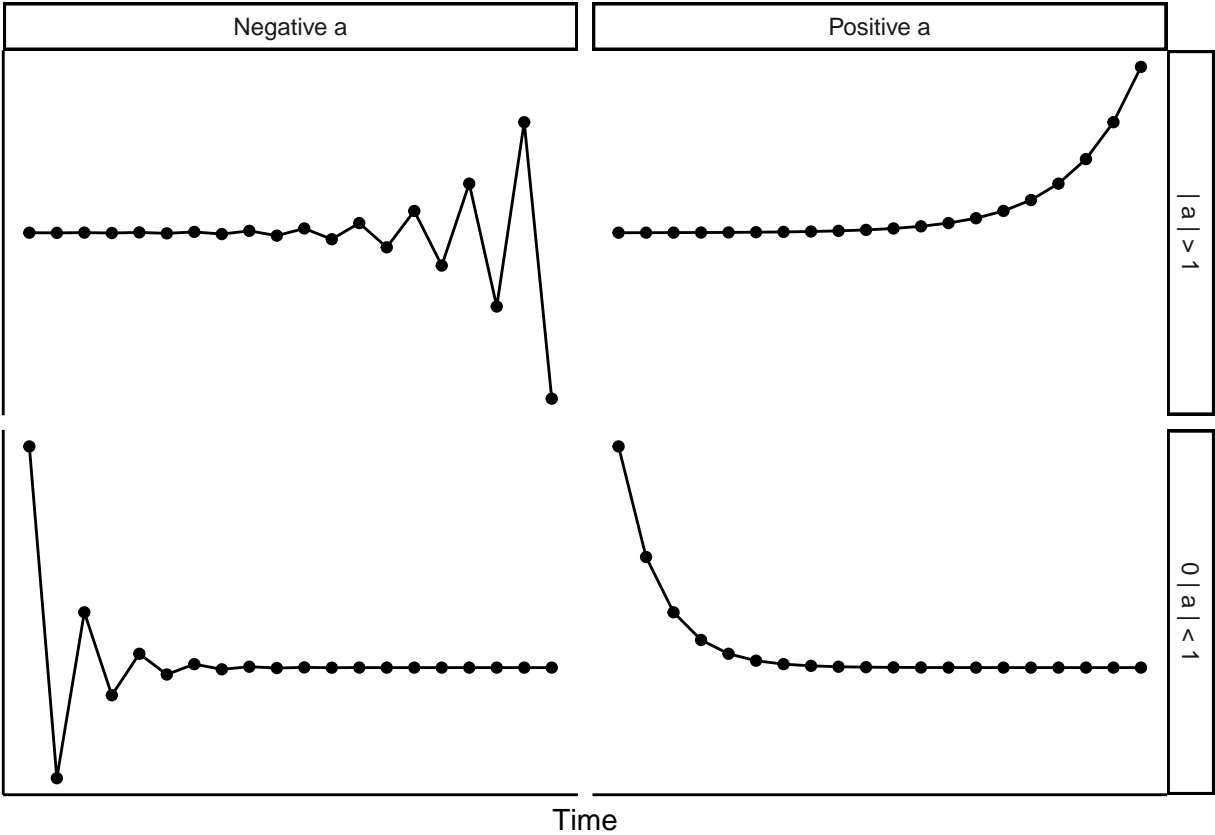*Figure 1*. something

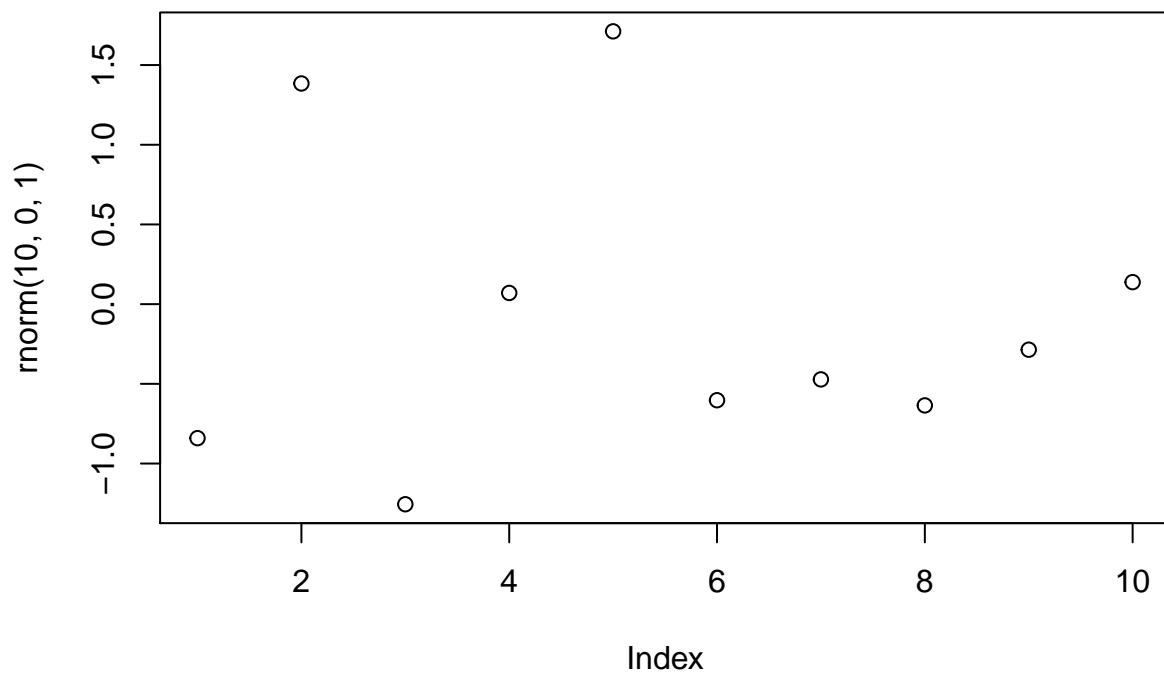*Figure 2.* something else

Figure 3. something here

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