Chapter 1 - Incomplete Pictures

W.E. Deming is quoted as saying "You can expect what you inspect". Not exactly a phrase that roles off the tongue, but an important premise nonetheless. It implies that since most systems can be decomposed into inputs, outputs and connecting processes, intelligence into the details of each of these can facilitate precise mappings of cause-effect relationships; Relationships necessary for the anticipation of risks and opportunities, and therefore the discerning of means for improvement. In the absence of complete details, such mappings suffers.

Yet, despite being much more widely (and incorrectly) referenced, Deming never actually suggested "*You can't manage what you can't measure*". Human decision makers are not incapable of making very good, even optimal, decisions in the absence of complete information. After all that's almost always what we are confronted with, even in the age of 'big data'. The trick is being able to make use of smart rules, and not falling into traps formed by our own biases.

In this chapter we begin with a description of the boundedly rational mind, drawing on now traditional economic literature on decision theory. We describe the assumptions and implications of this perspective, in practical terms focusing on manner in which individuals make sense of the world around them. We then extend this discussion by considering three families of biases that specifically affect the way individuals extrapolate from limited data in an effort to make intelligent decisions. Specifically we discuss what we refer to as Set Biases (beliefs in data Homogeneity, Uniformity, Normality), Trend Biases (beliefs in associative data Linearity, Continuity, Unboundedness, Stasis), and Causal Biases (beliefs in relational data Immediacy, No coincidences, Absence of feedback loops). We describe the implications of such biases in the presence of contemporary visual depictions of data; depictions which often do not provide enough details that might otherwise avoid boundedly rational extrapolations and better inform decisions on immediate inspection.

1.1 How we make lemonade

As stated, most of the decisions we make are done in the absence of complete information. Out of practical necessity. Nevertheless humans have survived as a species so far, so we must be doing something right. It turns out, when handed the lemon-equivalent of data, humans have a remarkable knack for making lemonade; and more often than not… it tastes pretty good.

How do we do it? What is this talent?

In large part we benefit from our ability to construct and reference rules for making sense of our environment. This is a skill developed over the eons of the evolution of our species. Those that maintained efficient and effective rule sets could scan their environment for risks and opportunities, formulate tactics for evading or leveraging, and out-perform those who held less efficient or less effective rules. From a translational perspective, it was as if the high performers had Google maps advising them on how to plan their routes, while the low performers only had an aerial photograph; i.e. the difference in large part was in how the data available was converted to actionable compositions.

Today we often discuss the process by which we transform data that we observe into potential action as 'sensemaking'. Sensemaking as a concept is something we'll talk about a lot in this text, as it is not simple an inherent ability that individual possess but also an ability that can be developed. It is also something that is key in the development of artificial intelligence. Granted, sometimes that development is in the wrong direction; individuals or artificial agents latch on to a new rule based on erroneous observation. But in other instances it can lead to much more intelligent decision making, in some cases superseding older less effective rule. And thankfully, course corrections in development are also always possible albeit at some cost.

Whether correct or not, these rules that we construct include beliefs regarding simple associations as well as complex causal relationships. These are mental maps that draw connections between observations and outcomes desired, peppered with details regarding the constraints within which these nodes and connections exist. They also include details regarding the lags between action and response, though as humans we do have some difficulty remembering to account for these at times.

We also tend to hold more than one line of reasoning, more than one mental map, in our arsenals. After all, we are social creatures. We encounter others who have different views of causality, and no matter how much we might like to we never completely ignore these views. That of course does complicate how we make sense of our environment. Ultimately our choices of rule sets to go with rely on higher level meta-rules. Metaheuristics, and at the highest level something that would seem so basic but has been long been far too ignored in management: Preference.

There are other words you'll encounter when discussing decision making with scholars. The rules that define how inputs are converted into decisions often fall into the category of 'heuristics', with metaheuristics again referring to those higher level rules that help develop and select which heuristic best applies to a certain scenario. The term 'bias' also tends to come up, although any quick examination of extant sources (including the more credible corners of Wikipedia) will reveal a good deal of blurring between what falls into the classification of bias versus heuristics. For the purpose of a concrete discussion, let's borrow a page again from the Operations Management field and think about sensemaking from an input-process-output (IPO) perspective.

As shown in Figure 2, heuristics and metaheuristics are nicely positioned as processes by which inputs are converted into decisions. What are inputs then? Certainly the observations we are able to make or data are by other means provided regarding the context of the decision. However inputs also include personal tendencies to give more weight to certain kinds of data than to others. The biases are the adjectives to the nouns that comprise our decision making environments, and often serve as adverbs to color the heuristics we apply in decision making. Some examples of these biases, drawn from the elder disciplines of Economics and Psychology are provided in Figure 1.1. Although it isn't the intent of this text to provide a comprehensive examination of biases and heuristics suggested by researchers, it benefits our present discussion to go through just some of these.

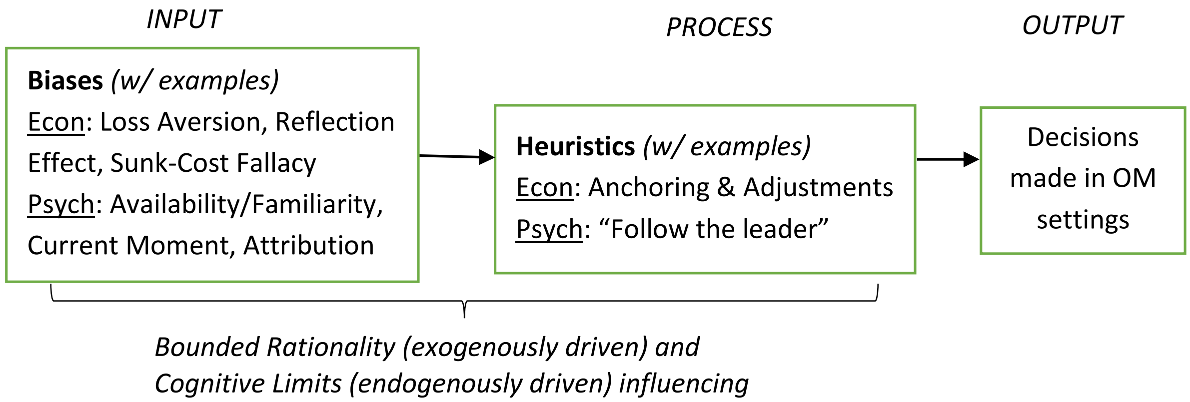

Figure 1.1. An Input-Process-Output view of Sensemaking (*pro tem. omitting Feedback*)

1.2 Biases in Everyday Life

To be sure, biases and heuristics are not all bad. They have a history of being absolutely critical to decision making; without them many great decisions may never have been made in the timely fashion in which they were needed. But it should also be clear that their presence, persistence and acceptance is not without some very risks. Sometimes the lemonade we make gives us an ulcer. It can even be lethal, and sadly not only to the decision maker.

On the input side, focusing on the various ways inherent biases might be influencing us, we'll start our review with a big one. A bias that is embedded in many, if not most of data interpretations and selections of / mediations of decision processes people face on a daily basis: Loss Aversion.

<u>*Loss Aversion*</u> – The tendency for individuals to strongly prefer (a) avoiding losses versus (b) acquiring gains. Made famous by Kahneman and Tversky (1981, 1986), and their investigation of the Allais Paradox, this bias has been studied extensively. The initial observations of this bias involved examining the following question posed to physicians:

> The U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows: If program A is adopted, 200 people will be saved. If program B is adopted, there is a one-third probability that 600 people will be saved and a two-thirds probability that no people will be saved. Which of the two programs would you favor?

72% of those asked chose option A, the certainty of 200 survivals over the possibility of 600 deaths. Interestingly the same exact options were provided in a somewhat different wording to examine how phrasing along might impact choice:

> The U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows: If program C is adopted, 400 people will die. If program D is adopted, there is a one-third probability that nobody will die and a two-thirds probability that 600 people will die. Which of the two programs would you favor?

To their surprise only 22% selected option C (equivalent in lives saved to option A), with 78% preferring option D (exact wording as B). A dramatic swing in what one might view as apparent "preference". The swing captures what is referred to as the Reflection Effect – the tendency for the preferences of individuals in Loss (or Loss framed) scenarios to appear to be the mirror opposite of those apparent in Gain (or Gain framed) scenarios.

A somewhat more striking comparison is the consideration of the following two choice scenarios. In one, the choice is one between a certain gain of $20 or a one-third chance of gaining $60. In the other the choice is between a certain loss of $20 and a one-third chance of losing $60. Two equal gains in one case, two equal losses in the other. Studies demonstrate a strong preference for certain gains in the first case, but a strong preference for uncertain losses in the other.

Again, a swing in preference?

Not technically, and this is something that often scholars get wrong. The fundamental nature of "preference" (the individual bias against loss) wasn't swinging at all – People prefer to avoid loss. That's what they were doing in both cases. What was different was the "perception" of the presence of loss. The salience of loss. In the second case, the perception of loss was amplified by explicit wording to that effect. That is the power of framing, and something that applies both to words and visual images.

This is also not an isolated contextual finding. De Martino et al. (2006) in an article in Science describe their more recent observations of this bias through an experiment in which individuals are asked to make choices in one setting for which certain options are described, or 'framed', as losses, and another in which certain options are frames as gains. The two settings are detailed in Table 1.1 along with the associated percent of participants choosing each option.

	Setting 1 – Start with $50		Setting 2 – Start with $50	
Choices	Keep $30	50/50 chance of keeping or losing $50	Lose $20	50/50 chance of keeping or losing $50
% who Chose	**57%**	43%	**39%**	61%

Table 1.1 Results of a Loss Framing Experiment

Note specifically that the first choice in both settings is to walk away with $30 (leave behind $20) of the $50 originally given. However, simply framing this as a loss is enough to shift participants towards a more risky option, and one with a lower expected value of $25. Findings like these emphasize the power of loss aversion as it impacts the choices we make. If the rule, or heuristic, or verb in the decision process is "select the option that lets you experience the most gain”, loss aversion serves to color those possible gains (or color their respective losses). It changes the perception of things. Through these perceptions it influences the manner in which an otherwise sound heuristic might play out.

While Loss Aversion focuses on the perception of prospective losses and gains simply by virtue of the loss-orientation or loss-framing of choices, other related biases can also impact these perceptions. Some emerge from past experience, as in the case of the Sunk Cost Fallacy.

Sunk-Cost Fallacy – The belief that additional investment in an option is needed based on past investment, often with the associated belief that such past investments would otherwise be lost and despite the potential risk of loss from further investment. The past investments in this case are unrecoverable expenditures of money, time, capital, etc.; In other words what are referred to as sunk costs. The “fallacy” here is that individuals tend to disproportionately weigh the value of options for which unrecoverable past investments (sunk costs) have been made, relative to new options all other things being equal. In many cases individuals chose options that are explicitly less favorable because of past investments. In experiments, much like the emphasis of loss, an emphasis on prior investments in an option has been shown to greatly influence choice – Again coloring perception and allowing otherwise effective choice heuristics to go awry.

How might that impact the views of individuals well versed in the construction of visual data representations of one sort when asked to expand their analysis? Are they more likely to start from scratch with a potentially new and valuable perspective, or invest further in simply tweaking artifacts they have spent time developing?

There have been some recent counter arguments regarding whether a bias towards options with greater sunk costs is in fact ‘irrational’. Some have suggested that further commitment to such options fulfills a social-psychological need: specifically to demonstrate to others that you knew what you were doing all along (if success is gained) or to demonstrate simply that you are unwavering in your commitments. These additional factors of course change the actual value of the option, with the potential to make it more favorable in real terms relative to other options not yet invested in. In other words, this doesn’t prevent individuals from still disproportionately weighing options with sunk costs… it just makes such overweighing irrelevant; In such cases the “all other things being equal” no longer applies.

It’s easy to have the presence and influence of biases masked by other details. That doesn’t mean they are not present or influential. Indeed it is not uncommon for both the Sunk Cost Fallacy and Loss Aversion to simultaneously impact the perceived value of choices. Consider the two additional related biases of Availability and Current Moment.

Availability Bias – Individuals tend to overly weigh the value of options that they are able to recall the most detail. As a result, those options for which individuals have the most recent or most extensive experience and familiarity are favored, all other things being equal, to options for which less familiarity exists. This aspect of the Availability bias has led to a common reference to what scholars refer to as the Familiarity Bias.

Current Moment Bias – Often referred to by the term Hyperbolic Discounting, the Current Moment bias is the tendency for individuals to overweigh more near-term payoffs relative to payoffs available later (Laibson 1997).

While these biases can stand alone in their own right, it is clear that there are many instances in which these also will have a dual presence. The details of the near-term are typically clearer than the details of the long-term. It's not uncommon for current payoffs therefore to appeal not only because they seem more readily available, but also because the amount of information available about these (their familiarity) is also often greater. Still more confounding, past investments (sunk cost) in certain options can often provide familiarity with such options. Many options are also positioned to yield short-term gains, albeit at long-term expense. It is no surprise that much of commercial marketing emphasizes familiarity and near term benefit, while pitching costs as existing substantially further in the future and de-emphasizing that such costs entail.

The only real question is why society as a whole remains boggled by the systematic nature and permanency of debt.

1.3 Biases in the Perception of Data

The biases just discussed have been discussed generally in reference to the facts presented when individuals are faced with isolated decisions. In other words "data" that they are often thought to be coloring is typically very limited. The value of a lottery ticket. The number of individuals surviving an epidemic. The lowest cost option for obtaining a vehicle. But biases also apply to assumptions made about collectives, groups of things. Consider for example the various biases that have been identified by social-psychologists in the study of behavior in group settings. Case in point is the Group Attribution Error, or the bias towards imagining that one or a subset of entities is characteristic of the larger set as a whole; a bias that can stubbornly remain even in light of new information to the contrary. Because individuals are making generalizations regarding the attributes of and within groups of people, places or things, we refer to biases such as this as intrascopic; with the prefix "intra" emphasizing the biases' implications on how the internal nature of collections is perceived.

Similar intrascopic biases also play a particularly important role in our perception of more complex forms of data. Distributions that have more than "a dot"; Histories and cross-sections of data collected across multiple populations. Data where multiple mechanisms comprising distinct forms of risks and paths for evolution may exist. To understand why it is important to think about more than monolithic views of biases, it is critical to appreciate how we approach non-monolithic data and in particular what we risk losing when we don't have all the dots we need. For discussion purposes we will group these biases as they relate to aspects of descriptive, predictive and prescriptive analysis.

Set Biases

In the process of examining data, individuals tend to make a number of assumptions right of the bat. The most common of these includes the assumption of homogeneity across samples. This implies a singular constituency, and subsequently often leads to difficulty in accounting for the noise in data; occasionally leading to misdirected conclusions. Simpson's Paradox (or Amalgamation Paradox) as depicted in Figure 1.2 is nice example of how easily the homogeneity Set Bias can wreak havoc with analysis. In this Paradox, best fits to subsets of data suggest trends diametrically contrary to those that would be estimated if the subsets were not distinguished.

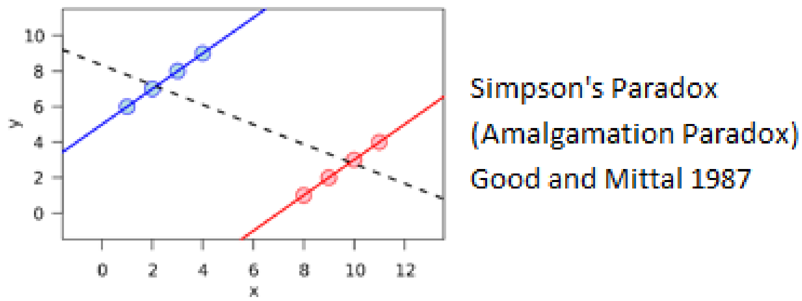

Figure 1.2 Homogeneity Set Biases as represented by Simpson's Paradox

Another common bias is the belief that the distribution of the data set adheres to a common symmetrical form (e.g. uniform and normal being the most common, largely due to how students are first introduced to distributions in basic statistics). This symmetry Set Bias can be more easily checked against by modern statistical methods, and it often does not critically impact analysis… in the case of bimodal distributions, subset distinction can even be resolved. Unfortunately often these checks are not made prior to model estimation, and in some instances these Set Biases can prove problematic as well.

In contrast it is also clearly possible to imagine instances where populations are not neatly captured by samples, particularly in the case of small samples. In such cases individuals examining data may perceived of clusters that that don't actually exist. Such a phenomena has been referred to as the Clustering Illusion (Iverson 2008). It has also been applied to explain how individuals develop perceptions of how data outside of observable samples might be interpolated or extrapolated. This bring us to our second general category of data biases.

Trend Biases

The Clustering Illusion just described has been associated with the tendency of individuals to excessively focus on small runs or streaks in data observed, and subsequently extrapolating or interpolating based on such limited information. The reason why this is problematic lays in the tendencies by which such extrapolation takes place. Once again largely an artifact of the way individuals have been taught, two major but fundamental assumptions are typically made: (1) that trends are linear, (2) that trends are continuous. These Trend Biases (linearity and continuity) are outcomes of other fundamental biases, such as the belief that over the relevant range trends are unbounded. Interestingly, once individuals question these more fundamental behaviors they are less likely to fall into linearity and continuity bias traps.

Are there additional situational reasons why some individuals default to linear assumptions? Certainly. When individuals personally benefit from conclusions drawn from linearity assumptions, they will tend to make such assumptions (Self-serving bias). If linearity is what they have always experienced in a data set for which they make decisions, there will also be a tendency for new data, even if seemingly deviating from linearity, to be under weighed or ignored. This is related to the Semmelweis reflex (the tendency to ignore contrary evidence) and the Status Quo bias from Psychology.

The other interesting thing about Trend Biases is that individuals strongly influenced by one are also often influenced by others. There are often broader mindsets, mental models of how data behaves and what to expect of it, which have higher level influences on the maintenance of biases. A metabias towards linear-continuity for example may be more common than isolated intrascopic biases towards either linearity or continuity.

As an example, consider the following observation. In past talks and classes we often present audiences with the classic Anscomb's Quartet data sets, as shown in Figure 1.3. The neat bit about each of these four data sets is that their basic descriptive statistics (means and variances for X and Y) are all the same. As are the best fit parameters of a linear fit of Y as a function of X.

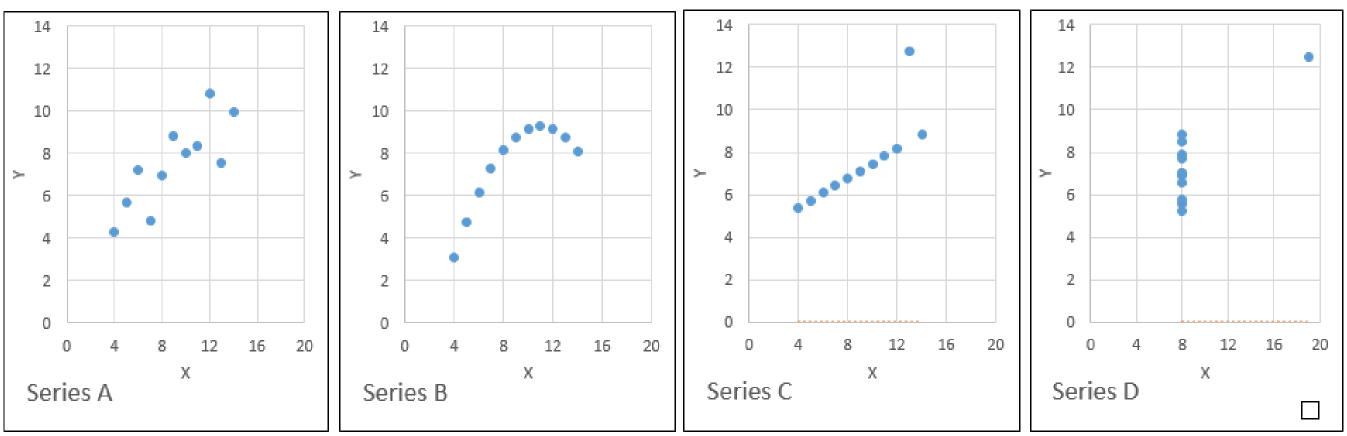

Figure 1.3 Anscomb's Quartet (For all sets, $\mu X=9$, $\mu Y=7.5$, $\sigma X=10$, $\sigma Y=3.75$; Linear model estimates: $Y = 0.5X + 3$, $R^2=0.67$))

Of course we don't tell the audience that before we show the set. Rather we ask them to draw what they feel the "true relationship" between X and Y is. Most people to draw straight continuous lines, in some cases simply filtering out points that don't adhere to that line. Some draw curves in particular instances (especially for the second panel's data set as one might expect). A handful draw discontinuous lines.

Figure 1.4 summarizes the typical distribution of results we get from audiences, regardless of background. The responses for depictions in last panel are crossed with other responses to emphasize how metabiases can playout in guiding intrascopic Trend Biases. Specifically, around 55% of respondents tend to filter out the seeming outliers from the last two panels, and draw best fit non-curved lines running through the rest of the points in these panels.

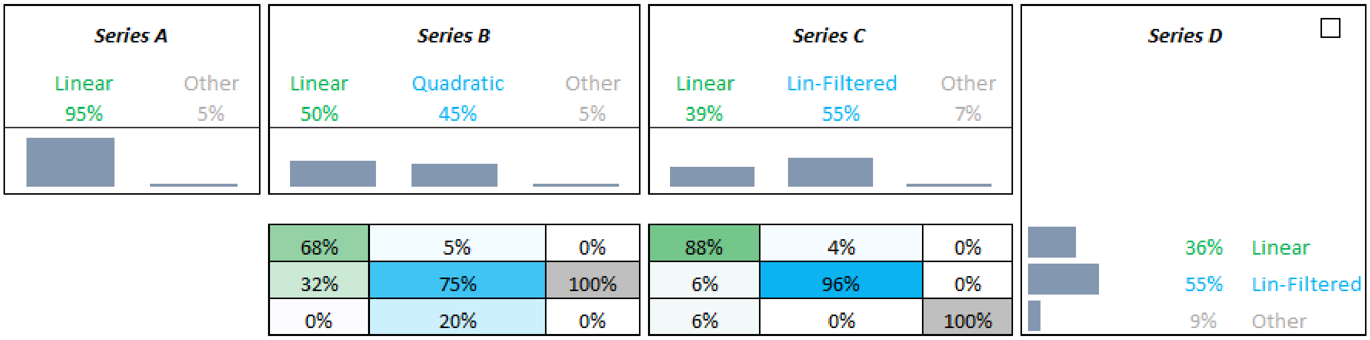

Figure 1.4 Responses from Practitioners when asked to Draw Relationships between X and Y in each Series

These are not simply random choices being made. Almost all of those who filter in one case will filter in the other (96%). Even more strikingly, 75% of those who draw quadratic forms in the second panel will tend to filter in the 3rd and 4th. 68% of those who draw straight lines in the second panel draw straight lines without filtering in the fourth panel. Why? Assumptions of linearity and assumptions regarding the need to filter otherwise discontinuous data, these two can be discussed fairly distinctly. Certainly it is possible for one to exist but not the other (as we have seen). The reason why they tend to be observed together has more to do with the willingness of individuals to entertain the potential complexity of data over their bias towards more simplistic albeit potentially facile views of the world. Something we will discuss in additional depth in the next chapter.

Causal Biases

Whereas intrascopic Trend Biases describe assumptions regarding the form of associations, and thus influence predictive analytics, formalized decision making assisted by prescriptive analysis typically presumes the development of mental models of cause and effect. In other words, not only does one presume “X and Y increase together”, but moreover “increasing X forces increases in Y”. The difference is between taking a stance as a passive anticipator of dynamics, and being poised for the active management of those dynamics. Both Set and Trend biases can influence the structure of these mental models, however other uniquely Causal Biases may also prove strongly influential in how we form beliefs of cause and effect.

Returning again to the concept of attribution, the Fundamental Attribution Error suggests individuals tend to assign more credit to individual actors and their personalities than to the other situational factors, which are often out of the control of such actors. If this bias is active it clearly can have a significant impact on perspectives of causality in data observed. Data specific to human actors may tend to be viewed as causal to outcomes more often than simply as associative. This can lead not only to poor decision making, but also to undue social stressors that further undermine the effectiveness of processes – Not to mention difficult to resolve.

However attributions of causality do no need to be restricted to the humans involved in the data. As humans we’re hard wired to see causality in observations all around us, even when it doesn't exist. This 'non-coincidence' metabias drives us to attribute a wide range of human and non-human factors with the capability of driving outcomes. Often erroneously.

What makes certain elements more likely to be attributed as causes of outcomes? The Availability and Current Moment biases certainly offer some suggestions. Generally speaking, humans are also extremely susceptible to the intrascopic Causal Bias of immediacy – That outcomes immediately follow actions that drive them. This tends to limit our search for likely suspects to actions and agents present at or just prior to the outcome's observation. Obviously that can be a problem, since two events that take place close to each other in time might be separate outcomes of a third factor and otherwise unrelated. When we find nothing proximal to the outcome, we may also concede to a relative lack of control over the outcome. Neither of these suppositions are necessary, provided we are willing to look back far enough and carefully at the systems in which outcomes arise.

Related is the Causal Bias of non-feedback – Specifically than an action/agent impacting an outcome will not result in counter-effects that will force subsequent changes in that action/agent. In reality, feedback loops are all around us. They have been widely studied and shown to be critical in the studies of systems. We even create social and legal structures that enforce reciprocity. Yet when faced with decision making, when confronted with visual representations of data that we are unfamiliar with, we have a tendency to overlook the existence of these loops. It implies a bit of egotism regarding the control one has over the decision environment. It also often happens hand in hand with the immediacy bias – If you are only looking for temporally proximal causes, you're also unlikely to recognize feedback mechanisms that take time to play out.

1.4 Heuristics, Metaheuristics and Sensemaking

What ultimately are the implications of all these biases? Specifically how might they influence the interpretation of contemporary visual depictions of data? Depictions which often do not provide enough details that might otherwise avoid boundedly rational extrapolations and better inform decisions on immediate inspection.

How might/should they influence the design of visual artifacts?

Universally, the ethical design of visual representations of data should be focused on truth and clarity for the audiences targeted. This means not selectively excluding or emphasizing certain aspects contrary to the intent of the conveyance. It also means being deliberate in providing clarity that dodges the kind of erroneous interpretations that common Set, Trend and Causal Biases can drive. Design still benefits from having an organized structure focusing on one or more key messages or with a subset of typical exploration paths in mind. However, these should be developed with transparency. The possibility of counter interpretations should not be constrained deliberately by visual designs, only by the nature of the underlying data (if at all).

Assuming truthfulness is a foremost concern, the question becomes one of how to ensure clarity. As designers, our ability to be clear requires that we both guard against our own possible biases and anticipate those for whom we design. This anticipation requires an appreciation not only of the possibility of biases already mentioned but also of the processes (heuristics) individuals use in the formation of the models; the processes that these biases color.

Not all of these processes are straightforward. Not all of them are easily explained. Most are short cuts, not comprehensive. But that doesn't mean they don't work in a lot of cases. It just means understanding them will help us design things to help make them work better (or even correct for them).

Consider the Nearest-Next heuristic individuals often use when asked to manually solve routing problem (e.g. travelling salesman scenarios as discussed in Bendoly 2013). By this process individuals start with a single element such as location in a route, and select each subsequent element based on closest proximity. It turns out that for highly complex routes, for which a comprehensive search for cost minimizing options increases factorally as a function of sites (N! solutions for a N-site routing problem), this simple process of coming up with a solution will tend to do fairly well. Often missing the true optimal path, but also often appearing in the top 10% of performing solutions. It's fast and frugal – Effective. If we want people to capitalize on such a heuristic in a data representation, we would benefit from the clear presentation of all sites, and a simple visual means by which to connect these dots. If we want our audience to avoid this, if we believe it to be problematic in the specific context, we need to design interfaces that make other interpretations and decision processes easy to conduct.

Another common heuristic is that of Anchoring & Adjustment. The use of this heuristic is often cited in decision making settings where data continues to be revealed over time. But studies also show that individuals tend to be poor at selecting anchors in certain circumstances, and often insufficiently adjust. The Bayesian concept of Conservatism suggests that many have an inherent tendency to not adjust as much as we often should when presented with new data. If this is a concern, again we need to design data representations that emphasize the importance of new data. Perhaps offer intelligent recommendations on how best to anchor.

A seemingly simpler heuristic, at least one that doesn't involve a great deal of processing, is sometimes referred to colloquially as "Follow the leader". Essentially it entails accepting interpretations and decision patterns from other sources, human or automated. Goddard et al. (2011) provide a fascinating study of how individuals can very easily adopt without question the guidance of automated systems, regardless of effectiveness. We do tend to put a great deal of faith in automated systems, rightly so in many cases. We are just as ready to assign blame to these other sources, which to some extent makes 'Follow the leader' and associated phenomena such as Group Think to be more of coping mechanisms than anything else. However blind attribution of accuracy and optimality to other sources can be a problem; coping with difficult interpretations and decisions by depending on others is generally not in the best interest of analysis. A designers we need to be careful about how much we automate for our users – When we want to promote active management, allowing them to be strictly passive undermines this goal.

How can we encourage active use? By helping individuals appreciate the systematic nature of the data they are confronted with. By emphasizing its dynamic nature. By emphasizing how data can be viewed as not only associated but potentially causally linked to other data. In the visual representation of data, effective interpretation of such dynamics is strongly facilitated by explicitly denoting direction and feedback, and allowing explorations of incremental changes.

This bring us to a mantra we will continue to reiterate:

System visualizations require systems of visuals.

That is, when there is a need to convey the nature of a complex system of inputs and processes that generate outputs of interest, a single visual idiom is unlikely to be sufficient. Here we conservatively adopt Haber and McNabb's classic definition of a visualization idiom: "any specific sequence of data enrichment and enhancement transformations, visualization mappings, and rendering transformations that produce an abstract display of a specific data set" (1990). Singular idioms, conservatively speaking, are self-contained renderings and tend to be limited, rationally, by a constrained selection of data and choice in abstraction. Because of this any stand-alone rendering will tend to, in isolation, pose a risk of inappropriate interpolations and erroneous extrapolations. In short it can lead to ineffective mental models of cause and effect, and subsequently to suboptimal, potentially disastrous decision making.

What is the alternative to a single visual depiction of a complex system? The answer might seem obvious, but in fact is a bit nuanced. In the case of truly complex systems, the best means of conveying critical dynamics is in fact not providing a comprehensive compilation of all possible system scenarios depicted in multidimensional space. Just as overwhelming an audience with a talk that provides too many details can lose a message, overwhelming an audience with endless depictions can fail to deliver. As we shall see in the next section there are some good reasons why, returning us again to a consideration of human cognitive constraints. Ultimately the best solutions to complex conveyance require sufficiency as well as selectivity in the design; the construction of efficient systems within which stand-alone idioms can be selectively considered and reconsidered in turn towards the development of sufficient system-wide understanding.

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Chapter 2 - Coping with Haystacks

In contrast to the first chapter, we devote our discussion here to the pitfalls of information overloads in visual depictions. In doing so we focus on another very real aspect of the human condition: cognitive limits.

Let's start with a curious anecdote.

At the start of 2015, as we were ramping up for our university-wide data visualization competition, a colleague came to talk of his personal views on human cognition. The discussion began unassumingly. We were in strong agreement regarding many points recognized in psychological, communication and design theory. Our colleague clearly had a strong appreciation of the problems that insufficient data representation might create, as well as the roles that biases and heuristics leveraged by designers and audiences can play; points discussed in Chapter 1.

And then he voiced something that immediately took us back. He expressed his belief that there was no such thing as too much information when it came to visual depictions. He dismissed wholesale the notion that individuals might have difficulty meaningfully focusing, filtering or aggregating increasingly complex presentations. His argument: The rule of 7+/-2 (the so-called Miller's Law) didn't hold water in most of the successful visual representations he and others had experience with. Specifically, since one could come up with countless highly effective examples in which many more than just 7 pieces of information are simultaneously graphically and meaningfully displayed… considerations of cognitive limits were largely irrelevant to design.

Our colleague was fairly adamant, despite our suggestion that he might want to reread Tufte's commentary on the subject. He seemed surprised to hear others might not share his fairly cut and dry perspective. I almost felt like hugging the guy.

It can be difficult to separate the robustness of general concepts from the applicability of their specific operationalizations; the forms they are given for tangible albeit specific discussion purposes. This is where our colleague faltered. Miller's Law (not self-named) outlines a very specific numerical instance that was applied to a very specific case context. Miller never suggested the 7+/-2 rule to be literally applicable regardless of context. He intended it to be an exemplar of the broader recognition of human cognitive limitations; limitations that take many forms. Just as no researcher worth her salt would presume a mean or median to be a holistic representation of a distribution (let alone a stable measure of a population or other samples of that population), it is clear that harping about a universally relevant count of anything would be misguided.

We agreed, it's ridiculous to expect any pre-defined specific number of "things" would represent a limit on visual design. However that doesn't mean that limits in general are absent in cognition as it relates to visual design and interpretation. Certainly Miller's point, and later related discussions by Tufte, emphasize that throwing this figurative baby out with the literal bath water is in short gross neglect. Of course cognitive limits exist, we just can't easily assign a single number to universally encapsulate them.

How do these limits show themselves in data visualization contexts? Often they emerge when there is so much content confronting us that the boundaries between relevant and irrelevant data, spurious and real relationships, are blurred. It's one of the downsides of data wealth. The more elements you have in a depiction the more likely these blurry lines will show up somewhere. When we push ourselves to show more than is necessary, we often introduce things that distract from interpretation simply because their presence can make it that much harder to focus. It leaves a door open for novel interpretations, but also at extremes it raises the risk that messages are overlooked, that meaningful deduction is frozen. At these extremes, not defined by any one number, ambiguity can shut things down if not completely mislead.

Those in the field of visual design have a similar view. Designers often cite the Law of Prägnanz, another principle based in psychology, which states that individuals have a tendency to interpret ambiguous images as simple and complete, versus complex and incomplete. Notice both the terms "simple" and "complete". In other words, when presentations of data are incomplete, individuals tend to complete these pictures in simple ways – enter the data set, trend and causality biases discussed in Chapter 1. However when data presentations are excessively complex, individuals lacking the cognitive resources to easily process such information are either forced to or choose to engage in reduction.

Again we can ask the question of how.

2.1 The Gestalt Laws of Grouping

To answer this, we'll start with a consideration of the seminal work by Kurt Koffka in 1935, the Principles of Gestalt Psychology - A work still referenced heavily today in the fields of design. In fact the overarching Law of Good Gestalt is often used interchangeably with the Law of Prägnanz. According to the Gestalt principles, depictions of sufficient data benefit from fewer rather than more elements, symmetric rather than asymmetric composition, and generally characteristics aligned with other principles and biases in human perception (aka Gestalt principles of perception). These include principles that emphasize what makes elements in visual depictions appear more related to each other (Gestalt laws of grouping) as well as, in contrast, what might allow individuals to more effectively compartmentalize when relevant; i.e. separate signals from noise, delineate units of analysis and generally systematically leverage meaningful distinctions via Figure-ground organization.

Law of Past Experience

Particularly reminiscent of the discussion of Biases in Chapter 2 is the Gestalt Law of Past Experience. Essentially this law suggests that past experiences strongly color the way in which we categorize visual representations (e.g. of data). No big surprise there. In the simplest of examples, the law implies that if you have most recently seen data arranged in a particular manner (e.g. geographically), you are likely to group new data with comparable attributes (e.g. the net revenues of firms with off-shore headquarters) in a similar manner… even if doing so is not always ideal or appropriate. The closer in time the two depictions the greater the likelihood of this effect.

Past experience of course can have much pervasive impacts. Regular exposure to certain forms of visual representations will predispose audiences to certain approaches to interpretation, and even make alternative visual forms of visual representation appear less relevant. When used to the interpretation of data presented in bar-chart formats, for example, encountering data presented in a partially seemingly related format (e.g. scatter plots with error bars) can inadvertently lead to the reduction of meaning. Conversely, repeated recent exposure to graphical representations intending to depict association over time (say a line chart) might bias individuals in their interpretation of graphs that don't explicitly depict longitudinal associations (e.g. viewing the points on the right side of an X-Y scatter to be somehow more relevant/timely than those on the left). In such a case, past visual experience is introducing properties that don't actually exist, thus again detracting from interpretation.

At the extreme, in cases of depictions that do not easily translate into recently considered familiarized forms (e.g. network diagrams for those only recently exposed to pie charts), cognitive dissonance may trigger filtering such depictions in their entirety; "That's neat, but I think I'll wait for the next pie." Clearly there is something to be said of the virtue of varied exposure to visual representations, as well as the virtues of designing for easy transitions between visual artifacts. Inducing skips in visual examination is not something designers should shoot for.

Law of Proximity

Related to the Past Experience which focuses on how time can impact assumptions of relatedness is the Law of Proximity which focuses on how space can impact such assumptions. The law states that when individuals observe a set of elements (e.g. data points in a plot, sets of entire graphical idioms in a dashboard, etc.) they tend to interpret those close to one another as more related than those distant. Once again, this can be a useful bias provided those proximal items are in fact strongly and meaningfully related. However, our tendency to make spurious associations based on proximity, or at least perceived proximity, can also get us in trouble.

Take for example the case presented in Figure 2.1. In the left panel, a set of data is presented in an X-Y scatterplot along two of the perhaps many dimensions that the set may ultimately be characterized by. From the perspective of the left pane, the data appear as a continuous cloud with relatively Normal univariate distributions. This vantage point might reinforce a belief that the data in fact represents a single continuous population, and hence only a singular approach to modelling and decision consideration might be warranted.

However, a simply expansion of the view by a third dimension of the data (call it "Z") might put this homogeneity believe in question. The right panel in Figure 2.1 provides this vantage point. Where the left panel can be thought of an aerial view where the z-axis is coming out of the plane towards the viewer, the right panel rotates this data set to reveal only very tenuous connections between three subsets. The reality and relevance of this distinction only raises additional research questions that would need their own additional examination, but these are questions that might yield much greater intelligence; And ones that might have been ignored had this only slightly more nuanced vantage point not been considered.

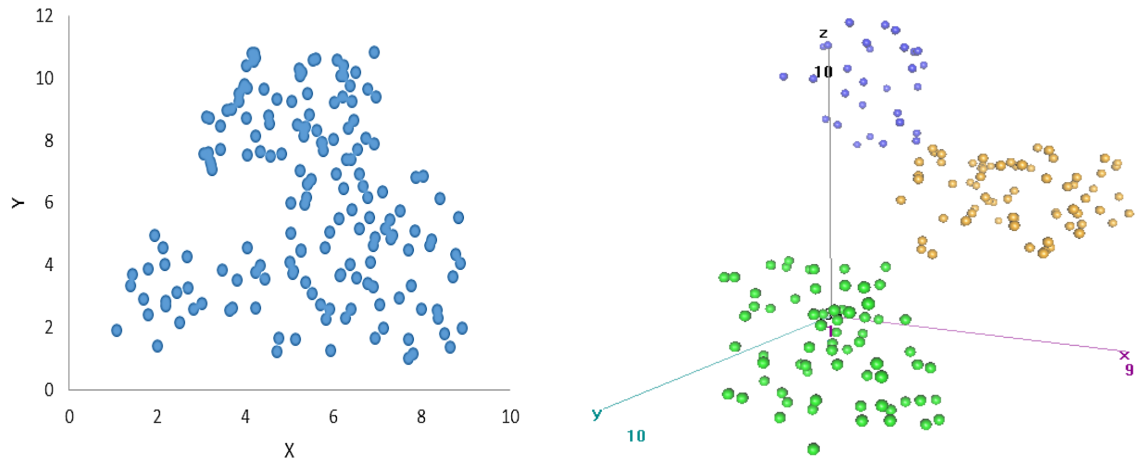


Figure 2.1 The Same Data: Proximity Bias as a Function of Dimensional Vantage Point

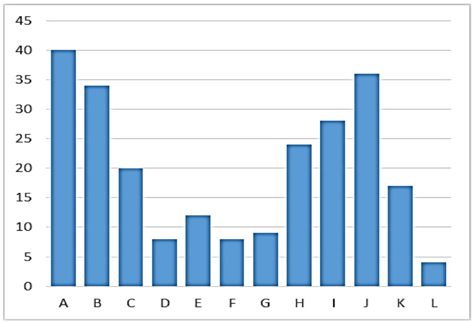
Our biases, in some cases reinforced by much of what we are taught methodologically, have an insidious way of convincing us that exploration or even targeted checks for greater complexity is not necessary. We are often the worse for it.

Law of Similarity

Clearly not all characteristics of data are defined by time and space. Other attributes describe the state of things. Physical properties might be captured in data as temperature, viscosity, weight; personal properties characteristic of individuals or organizations may include level of training, risk tolerance, altruistic tendencies, system criticality, etc. These attributes may also be the foundations of group associations that may or may not be real.

The law of similarity generally addresses this. It states that elements within a set tend to be grouped when their attributes (beyond timing and location) are comparable. Less comparable elements will tend to be excluded from such groups, perhaps being binned into their own distinct groups. The greater the similarity/dissimilariy the greater the likelihood of such groupings. Graphically the choice of renderings (color, iconography, etc.) may also serve as artificial attributes further complicating these grouping tendencies. This makes the selection of not only represented data and dimensional vantage points, but also the internal and relative forms of such representation, an extremely delicate one.

Consider the following example. A single data set, a single numerical dimension of that set in fact, is arranged by the alphabetical order of an associated nominal dimension. The first bar chart in Figure 2.2 provides the resulting depiction. In contrast, the right panel of Figure 2.1 presents that same data presented in a Pareto chart format (descending in numerical value). As difficult as it may be to believe, countless tests with human respondents show that in the first case individuals are much more likely to see two groups in the first panel. This curious tendency and those revealed by other tests if the law of similarity show this phenomena to transcend the professional backgrounds of those viewing such idioms.



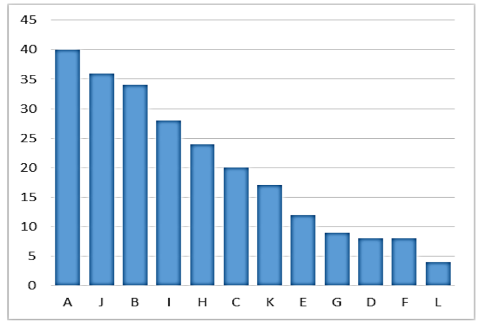


Figure 2.2 The Same Data II: Complications of Similarity and Ordinal Proximity Effects

Law of Symmetry

Human beings evolved to recognize, and indeed depend on, certain regularities in nature. One of these is symmetry. Most of the living organisms we have learned to interact with demonstrate significant symmetry in at least their external appearance. Many demonstrate bilateral symmetry being approximately equal on either side of a line (the sagittal plane in biology). Some have more complex symmetrical forms such as radial or rotational symmetry (think starfish but also plants).

Symmetry also exists in the non-biological natural world. We encounter symmetry in everything from that which is visible at the atomic level, to the just naturally visible (e.g. snow-flakes) to the massive (think the generally spherical or rotational structure of astronomical bodies). Our own architecture and the design of everyday consumer goods are permeated throughout with centuries of social evolution influenced by symmetry. Everything from tooth brushes to airplanes to skyscrapers.

In short, we are used to symmetry. We have come to expect it. As a result, sometimes, we assume it exists even when it does not.

How does this relate to our natural tendencies when it comes to interpreting visual representations of data? Designing for that interpretation? The law of symmetry recognizes the mind's tendency to anticipate symmetry around a central point, line or plane. In the absence of sufficient presentation (e.g. presenting only the upper half of a distribution beyond a critical level), we will tend to fill in the blanks with reflection. However, and particularly relevant to the way in which audiences may reduce overly complex visual presentations, the law also suggests that when presented with two seemingly symmetrical visual artifacts the mind will have a tendency to connect them as a single whole.

Consider two plots. One showing how an outcome Y_1 is related to a managerially controlled independent factor X_1, another doing the same for an alternate set of factors Y_2 and X_2. Say that both of these depictions suggest significant positive relationships between the outcomes and the independent variables. Imagine showing these two graphs to a set of individuals and asking them a series of questions including the likelihood of synergies and tradeoffs existing in the pursuit of Y_1 and Y_2. Interestingly in simple experiments such as this, individuals appear much more inclined to assume synergies exist when the two trends in the exact same direction (grouping by the law of similarity) and much more likely to assume the existence of tradeoffs when the trends are in opposing directions (i.e. when the X_2-Y_2 trend line is an exact and opposite reflection of the X_1-Y_1 relationship). This is a fairly remarkable finding in that nothing is ever said of the relationship between X_1 and X_2, or Y_1 and Y_2. In other words, even in the absence of any evidence of connections between two subsystems, there joint presentation and the existence of either high similarity or high levels of reflection can have very different (and in both cases misleading) implications on interpretation. Increasing proximity exacerbates this effect.

Law of Closure

In the previous example we witnessed the possible joint and contrasting impacts that multiple Gestalt laws might have on the perception of data structure in visual data representations. Although focusing on structural perceptions, it is important to appreciate that these laws not only apply to static attributes in the sense of intrascopic Set Biases. The Gestalt laws of perception also extend to misperceptions akin to intrascopic Trend and Causal Biases.

The Law of Closure represents the embodiment of how in that it refers once again to the tendency of individuals to interpolate and extrapolate. This of course can happen both in low information as well as high information settings. The law itself is fairly generic, in that the manner by which closure takes place is not predefined by the law. Closure may borrow from symmetry, similarity, proximity and or past experience in its accomplishment. It may also draw on other laws that associate in trends. To better appreciate the form that closure can take, especially in the context of data visualization it is worth considering the more nuanced nature of its associated laws.

Law of Continuity

The foundations of the law of continuity are attributed to works of many historically significant research efforts. Johannes Kelper's work in trigonometric estimation, relevant to his study of planetary motion in the late 16th and early 17th century. Specifically the original law of continuity as later formally outlined by Gottfried Leibniz (1701) is stated as follows:

> "*In any supposed continuous transition, ending in any terminus, it is permissible to institute a general reasoning, in which the final terminus may also be included*"

In other words interpretations made of the finite can be used as the foundation for extrapolations to the infinite. The assumption here is that the finite that is examined is actually a subset of something infinite (or at least something significantly more extensive). The problem is that for most of the settings for which visual representations of data could be informative… infinite continuation isn't a very reasonable or useful assumption.

It's easy to come up with examples of why the law of continuity applied to a data visualization context could be problematic when insufficient data is presented. Our intrascopic biases towards linearity and continuity can lead us to draw some unreasonable assumptions about what might exists outside of a range depicted. If we didn't know any better and saw a graph of a positive relationship between the use of water and plant growth, a relationship that tends to be positive at least in the range of "very limited watering" to "moderate", we might suspect that this positive trend continues and that our best option would be to continue to add water. Of course there are downsides to excess that exist in almost all settings. Graphically however these downsides are not always apparent, and without sufficient counterbalancing experience we are apt to overwater things when we don't know any better.

In the context of overabundant data visualization, we can also be misled by our tendencies to see continuity where it might not exist. Take for example a stylized portion of a graphical network depiction of traffic flow as presented in Figure 2.3. In the left panel all flow through a node is shown simultaneously. If asked to extrapolate what might occur if inward flow of 12/min from due-West was reduced by half, the typical response would be that the outward flow of 12/min East would be reduced to 6/min. However a more fragmented (and realistic in this case) depiction would demonstrate that the assumption of linear continuity that led to this assumption was itself flawed. In the right panel, where the same information is provided, a slight adjustment supports greater clarity into what happens at the node.

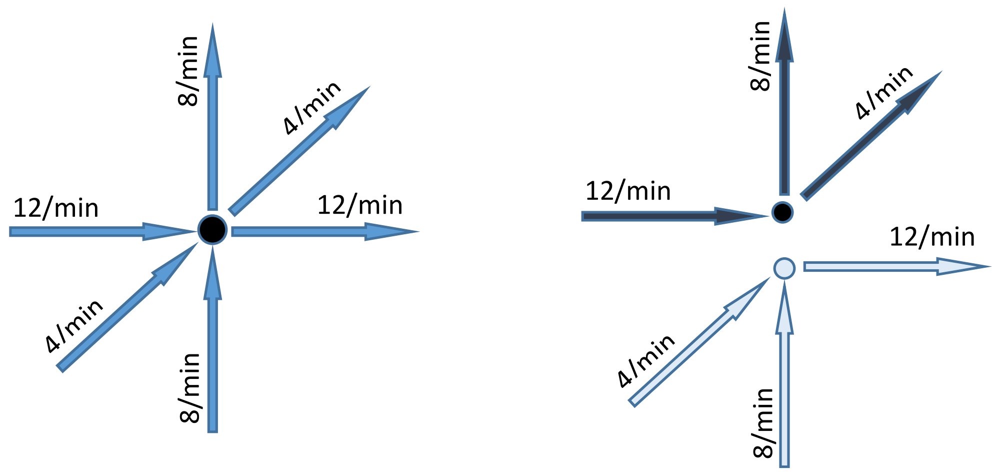


Figure 2.3 The Same Data III: Two Subsystems Merge and Continuity Misleads

The lesson from the law of continuity is that when an abrupt discontinuity exists in data and data relationships, show it. Sometimes trying to do everything with a single visual makes comprehension a difficult task. System visualizations require systems of visuals.

<u>*Law of Common Fate*</u>

Similar to the law of continuity, the law of common fate assumes that individuals may respond to exposure to movement paths of one type (e.g. graphics that show changes in state over time) and apply those same paths characteristics to the interpretation other depictions of change. As in the prior example, it is easy for movement to be a complex attribute for visual depiction. Complicating things is the option many designers engage in when attempting to make their visual artifacts interactive. In general an option that makes a great deal of sense, but also one that can in itself mislead regarding the actual dynamics inherent to a data set. For example, permitting an individual to scroll through values of one variable X in an ordinal sequence, to observe associated values in Y, could be misleading if X cannot actually be modified linearly or only takes on fairly discrete and discontinuous levels.

The law of common fate suggests that as human beings we have a tendency to assume a prior that transitions occur along smooth continuous paths – Which is ironic given the abundance of discontinuity we explicitly build into the processes we manage. There have even been pupilometric studies showing this tendency to view movement and extrapolations of movement as continuing along smooth paths of progress. More to the point, in data visualization contexts, we can easily fall for the expectation that the kind of trends we observe in either static or interactive settings apply commonly across broad swaths of a data set. It lulls us into assuming systems are much less complex than they are. That the data might not actually consist of multiple fairly independent systems, and that one-size-fits-all solutions are our best solutions.

2.2 The Virtues of Good Fences

Let's take a step back for a moment. Yes, the laws just outlined are useful ones and demonstrate a reinforcement of the prior discussions of psychological biases and heuristics that play so powerful a role in the absence of sufficient data. They suggest these kinds of biases and heuristics can be just as dangerous in the presence of excessive data. In many cases, the visual representations of one data set need to be viewed as emblematic of a distinct system from that of another. In some cases even portions of larger systems are disparate enough to warrant consideration from distinct and overtly separate vantage points.

But sometimes sets of data or entire visual idiom systems really should be thought of as connected… because they ARE connected. Although designs must avoid spurious visual associations, there are many cases where design benefits from an ability to make visible both association and distinction. In fact some of the best visual designs are predicated on the ability to continuously reinforce association both explicitly and aided through perception-driven implication. It is therefore critical that we recognize tactics that are useful to ensure distinctions between elements in a visual representation can also be useful to emphasize the connectedness within subgroups of those representations.

These tactics are not without theoretical foundations themselves. Whereas the Gestalt laws discussed provide insights into how one might devise implied connectedness in visual designs, when that connectedness is real and relevant, they clearly also suggest things kinds of distinctions that can help imply disconnectedness. Figure-ground organization, or the general ability to distinguish objects from their surroundings and highlight signals from noise, essentially relies on the success of these grouping laws as well as, and critically, their failure.

Working backwards then, what kinds of demarcations can accomplish the kind of fences that reinforce separation where needed. The proximity principle suggests that if we want to ensure implied distinctions between groups of elements within visualization idioms or among a set of complete idioms, we would do well to create as great a spatial separation between such distinct groups relative to within-group distances as possible; a method not unlike the approach used by mathematical discretization and clustering techniques. However all of this must be done with a strong caveat. If otherwise distinct system data overlaps over a finite set of dimensions, in a single graph say, we can't simply change the data to appear otherwise… We can however present the two data sets in separate graphs. Designers should not force separation or proximity when such action actually distorts the reality of the data. Truthful presentation remains tantamount. We must pursue clarity, but always place truth ahead of these efforts.

According to the law of similarity, within-group association is facilitated by implied commonality. Most visual designers recognize this and distinguish unrelated elements that otherwise might appear similar by strikingly diametric colors or iconography, reinforcing the relatedness of those elements that are in fact directly related through common colors and iconography. The similarity of color schemes is of course complicated by the ability of individuals to distinguish between certain colors, and the still epidemic dominance of non-color printers.

Spatial placement of elements within individual idioms, as well as of such idioms within a larger system interface, can also help reinforce the true relationships present in data and deter latent tendencies towards misinterpretations. The law of symmetry provides some additional guidance here. For example, if it is likely that bilateral symmetry might be perceived horizontally between two otherwise unrelated elements, and if close proximity cannot be avoided (or serves other design purposes) simply configure them vertically. In certain contexts, a tendency to associate elements across a horizontal may exist regardless, but the consideration of additional effects in either direction due to misperceptions of symmetry is a useful design exercise. Another more overt option, that is not always possible without other issues in misperception arising, is to distinguish these elements by the amount of space they occupy in a system. Such differentiation breaks up symmetric association and reduces the likelihood of intrascopic Set Biases emerging from it.

Intrascopic Trend and Causal Biases can also be mitigated when the risk of misinterpretation appears high. As case in point, there are several tactics for deterring inappropriate extrapolations of continuous linear trends into spatial regions where such trends cannot apply. These include the explicit depiction of strict practical or theoretical limits or cutoffs within the space of the graphic. If approaches to these limits are thought to be asymptotic, or taking on some other non-linear or discontinuous form, the embedding of a minigraph or sparkline can provide considerable guidance in interpretation (see dashed curves in upper right and lower right corners of left panel of Figure 2.4). In the case of multiple forms of dynamics captured by a data set, perhaps delineated by condition, subpopulation represented or region of examination, providing exemplar extremes as juxtapositions along with focal graphs can also reduce the likelihood of erroneous common fate assumptions (as per additional cases presented in right panel of Figure 2.4).

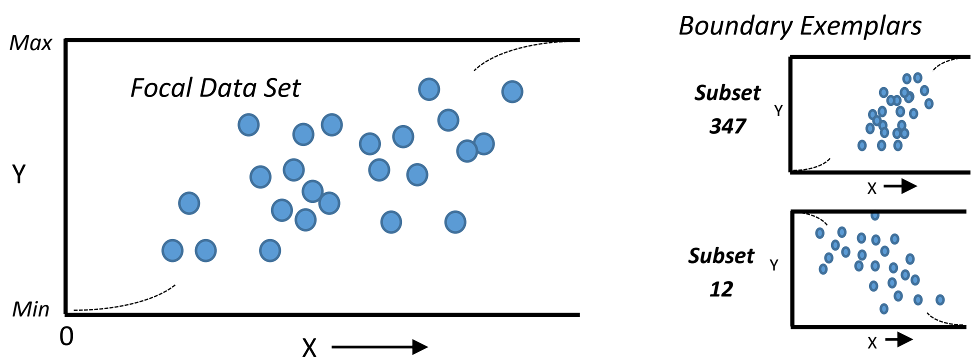


Figure 2.4 Deterring Trend and Causal Biases through Limit and Variance Awareness

And what about the first Gestalt law of groups we discussed: Past experience? How can we counter that in a visual design? One approach would be to actually enabling users to engage in new experiences with the data. Guide intelligence and meaningful examinations of aspects of the data that are of the most interest to the audience. This suggests a certain level of dynamism in the design of visual artifacts and brings us to our closing discussion for this chapter.

2.3 Bifocals in the Forest

Ockham's Razor is often cited using the following phrase: "The simplest explanation is usually the correct one." Sadly much like many statement and claims attributed to people like Deming and Tufte, William of Ockham (c. 1287–1347) probably never said these specific words. At least we don't have any historical record of him doing so. What historians do have him on record for is: "Non sunt multiplicanda entia sine necessitate", or…

"Entities must not be multiplied beyond necessity"

This suggestion applies equally well to data visualization design as it does to theoretical and empirical arguments. It implies that given the choice between functionally equivalent designs, the simplest design will tend to yield the best results in interpretation. It reiterates the Law of Prägnanz and the Gestalt principles of psychology, although predating these appreciably. Yet regardless of who's claim of "simple is beautiful" we chose to adopt, we must adopt with some precautions. Specifically we must adopt with a caveat referring back to the first chapter, remaining cautious regarding the threat of over simplification. The best visual designs reside in a middle ground. Design decisions must intelligently consider key features of audience and problem context, as well as required guidance and flexibility, towards effective use and understanding. They must include the "necessary" as well as the "sufficient" (to reference Goldratt 2000)… just not the "excessive".

Accepting the fact that you as a designer can never fully anticipate the level of detail an audience might want along a specific data dimension can also lead to other health design practices: namely the enablement of drilling and satelliting mechanisms in visual data and decision support designs.

The idea of a "drill down" is well established. When there is a need for greater detail, strong visual representations permit such investigations. When broader perspectives are needed audiences are not forced to assemble a forest for the trees. The forest is already concisely presented. Users of even the most pervasive data manipulation systems are familiar with drilling down to better understand why anomalies in the broader picture exist (think Pivot and PowerPivot table drilldowns as outlined in Bendoly 2013). The efficient availability of these details on an as-needed basis help audiences intelligently fill in the gaps in their mental models without being swamped in similar details that they may already understand well.

The opposite of the drill down – satelliting – is an equally valuable mechanism. It allows decision makers that are otherwise regularly tasked with work as a much more granular level to ask “what is the broader impact”, the “system impact”, of the action or event or property being studied. Satelliting is notably less common in modern data visual designs, in part because these broader holistic system-wide pictures are what they imply – extremely complex and often inclusive of issues beyond the knowledge base of the designers. Designs typically focus around what the user needs to know to maximize their effectiveness in their role, rather than what a user “should know” given that their actions are only part of a much larger system. Because of that, design requirements typically follow a drill-down path of a sort and seldom work their way up to higher levels of external impact.

This does not need to be the case. Although time and resource constraints on the development process do mandate some limits to scope, there is a growing understanding that a silo-oriented philosophy to a wide range of work and research settings is generally detrimental. What we do impacts others across both space and time; what we study is connected through space and time to the performance and actions of others as well. If we are to provide strong intelligence to guide actions through visualization techniques, we need to think at least about the most immediate recipients of the outcomes of these intelligently guided actions… otherwise the term “intelligent” won’t be very meaningful. In short we should certainly focus on principal audience and their needs in data visualization design, but we should also consider and enable them to consider at least a glimpse of the broader universe in which they are set. This requires a bit more sophistication than a single static monolithic depiction. Once again:

System visualizations require systems of visuals.

In the next chapter we will provide some concrete frameworks for managing this balancing act between providing efficient perspectives on the most critical data attributes for our audiences and providing them with sufficient (albeit non-blinding) richness for building deeper more intelligent understanding.

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