Fit, Bias and Enacted Sensemaking in Data Visualization: Frameworks for Continuous Development in Operations and Supply Chain Management Analytics

Journal of Business Logistics, forthcoming 2016
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Abstract

Data visualization has a critical role in the advancement of modern data analytics. Visualization lends assurances to data validity and completeness, as well as to the effectiveness of cleaning and aggregation tactics. It provides the means by which to explore and discover relationships otherwise hidden from default assumptions in statistical modeling. Strong visualization is also fundamental to end-result conveyance and audience interpretation. But how can one ensure that strength? How can one avoid developing representations that are marginal in value, or worse misleading? In this paper, I will discuss theory, evidence and practical approaches to managing data visualization development, viewing data visualization not simply as an outcome but as a continuous process and facet of organizational culture.

1. Introduction

"Use a picture. It's worth a thousand words." – Arthur Brisbane

This quote – along with its various permutations – has been thrown around for more than a century now. And there's good reason: It's often true. In the realm of data analysis, we now use the term *data visualization* to describe a specific genre of informational "picture" that allows for the effective depiction of data and the relationships it can suggest. Some of these visualizations are what we might more simply term *graphs* (control charts, scatter plots, best fit lines within such scatters, surface plots, confidence intervals, population ellipsoids, network diagrams, chloropleths, etc.). By themselves these choices of individual graphical depictions are also often referred to as *idioms*. However, data visualization efforts often extend beyond the use of any single graphic, and the results are often deliberately non-static and interactive creations.

Well-integrated *systems of idioms* (i.e., the most effective of dashboards used in practice) are similarly the result of deliberate efforts by designers to convey more complex data stories. Indeed, these systems can be just as critical to research as they are to practice, given the often highly complex, non-monotonic, feedback-inclusive and nominally-constrained relationships scholars are increasingly attempting to capture (Bendoly 2014; Bendoly 2013a). In the words of Edward Tufte (2003): "There are many true statements about complex topics that are too long to fit on a PowerPoint slide." Imagine for example the task of describing how even a single supply chain disruption reverberates across a network. Rather than attempt to describe the dynamics in the form of bullet points, how much more powerful and insightful would be annotations accompanying a dynamic visual of supply chain activity? Perhaps a visual rendering with snapshots of time controlled by individual viewers, denoting fulfillment failures along geographically mapped nodes and arcs? Throwing in the additional ability to see the disruption unfold visually from one time point to another with simulated automation?

Despite the existence of a wide range of ubiquitous tools available for developing data visuals, the process by which a strong visual representation of data, or particularly meaningful systems of such visuals is selected, is far from a simple one. To complicate matters, the demands on data and visualization are increasingly multi-disciplinary (Meyer et al. 2013). Indeed, in many instances, these demands are best viewed as interdisciplinary, requiring not just simultaneous parallel use but truly joint utilization and team-wise sensemaking for effective decisions. As with verbal communication, differences in disciplinary biases and terminology create barriers over which interdisciplinary discourse often cannot maneuver. Franco (2013) discusses these as syntactic, semantic and pragmatic boundaries (citing Bechky 2003; Carlile 2004). Breaking down these barriers, or at least figuring out how to work around them, requires leveraging standard nomenclature for describing visualization and identifying where the greatest gulf between disciplines exist.

The process further relies on the use of meaningful frameworks for the selection of appropriate visualization tactics for tasks at hand and, moreover, organizational cultures in which data visualization as an aspect of analytics is thought of as a continuous development process, not simply an artifact but a representation that is the foundation for further critical inquiry. In other words, purchasing a large high resolution screen to install in a managerial 'war room' to show a map with long-term warehouse capacity depicted by 3-D bars protruding out of a geographic plane or curved rendering of the Earth… Not indicative of an effective organizational approach to visualization (even if dynamic and/or interactive). Why? Apart from the fact that 3-D bar charts are notoriously easy to misread (masking data, perspective confounds, etc.), organizational reach and customization are both constrained in such a set-up. Creating dynamic interactive interfaces for multiple stakeholders, accessible at their desktops, focusing not on how many superfluous frills can be added but rather on practical storytelling… This is what will tend to support the organizational use of visualization. Consider how much more impactful would be simple heat map showing how warehouse capacity utilization varies seasonally, or as a function of SKU diversity, or whatever relationship the stakeholder in question actually needs to see?

The intent of this paper is multifold. Foremost, the aim is to present frameworks to assist scholars in the development of effective data visualizations based on established and contemporary theoretical notions of fit and the sensemaking process, appreciating the pitfalls that can arise due to the presence of prior experience bias and self-reinforcement traps, but also capitalizing on the distinct biases that others may have in their visual preferences in order to ensure robust interpretability across levels and stages of use. The discussion of these frameworks is accompanied by the results of a survey conducted across a wide range of practitioners and academics, identifying where similarities and some of the most salient differences in data visual biases exist across disciplines.

2. Applied Theory

Currently, academic discussion of modern data visualization tactics as an effective art and science is relatively nascent. In fact, the academy is somewhat overwhelmed by a wealth of diverse approaches and only a handful of well-adopted guidelines; while intelligently developed, they can in themselves prove limiting (cf. Tufte 2006; Few 2009). Unfortunately, it's one thing to be able to say "I know what I like" when it comes to visual depictions, and an entirely different thing to actually have a best practice for developing what's meaningful for varied audiences and purposes on a regular basis. This is despite the existence of novel texts that provide descriptions of the variety of options available (Bendoly 2013b; Munzner 2014; Ward et al. 2015). Put plainly, practitioners are still largely in the dark about how they can best approach data visualization as an integrated aspect of their analytical capabilities.

Given this general state of understanding, let us begin a discussion with the purpose of shoring up this ambiguity and creating a foundation for more targeted planning in visualization efforts. As a first step, we must accept the presence of a wide variety of contexts in which visualization efforts may take place. Many contextual factors certainly will – and in many cases should – impact the nature in which data is visualized, not the least being the nature of the data itself and the task being addressed through visualization. Aligned with a discussion of analytics in general (see Cantor 2016), some visualization efforts may be focused on assurances of acquired data completeness and quality, while others focus on the effectiveness of operations to clean and aggregate data into meaningful forms. These efforts largely fall into what is typically termed the *descriptive stage* in analytical efforts (Think geographic depictions of current or projected customer demographics; raw material availability maps; vehicle packing or delivery time distributions, or historical deviations of such from times expected). Alternate visualization approaches are applied to the exploration of relationships in data, prior to or in confirmatory/exploratory iteration with more targeted statistical modeling. These efforts are typically indicative of the *predictive stage* of analytics, though they will also spill into prescription. Perhaps most indicative of analytical *prescriptive stages* are efforts in visualization focused on the critical communication of discovered intelligence to the end audience (prescriptive conveyance).

Each of these potential applications can imply both (a) ostensibly identifiable, objectively appropriate visualization techniques based on the target audience, task context and stage, as well as (b) the risk of subjective biases towards less appropriate techniques driven by the backgrounds of the individuals leveraging them (or those they work under). These biases can, in fact, be apparent regardless of the nature of the data itself, and these biases make the prospect of valuable interdisciplinary consideration fairly daunting, as is the case in verbal interdisciplinary communication – common to supply chain execution. Consider for example an attempt by a shipping manager to convey fulfillment failures as a percentage based on product category, summarizing these rates as slices in a piece chart. Although possibly emphasizing the relative severity of some of these rates in the mind of that manager, this particular use of a pie chart depiction (not indicating relative volume, cost, value or other issues, for example; hence making implied relative comparisons spurious) is extremely prone to misinterpretation by others such as purchasing managers that might be in the position to help resolve these issues. In other words, once the fundamental contextual nature of the visualization effort is taken into consideration, it is likely that – in the absence of well-structured cultural norms on visualization – disciplinary biases will be observable.

Because of the negative implications that such forced and misaligned visual enactments can yield, it is these biases to which the academic community and the community in practice should be cognizant (Shneiderman 2014; Frankel 2013). In an associated sense, it is these biases that well-structured cultural norms on visualization can in fact both mitigate and potentially take advantage of, provided those norms are built around the appreciation of the form these biases might otherwise take on. To accomplish this goal, we require some insights from theory and practice, and must look for a rationale for why the fit between visual techniques and contextual needs matter, and why context itself can introduce biases that complicate the pursuit of this fit.

2.1. Data Visualization in the Lens of Semiotics

Semiotics, or the study of how signs and symbols convey meaning, provides a nice foundation for approaching a wide range of questions regarding visualization in management. Which characteristics of data might be the best focus for visualization efforts, depending on contextual need? Is it most critical to depict the changes experienced in a single measurement dimension over time? Is it sufficient to depict a general static distinction between the distributions of two discernable sub-populations? Does this distinction require the depiction of multiple dimensions characterizing these sub-populations? Are we less interested in drawing lines in the sand, and more interested in why such distinctions come into being in the first place? Do we need to examine the potential existence of complex non-linear multi-dimensional associations over time? Do we need to go a step further and argue visually for evidence that supports a more causal relationship that we can act on?

Depending on the answer to these questions, ones that the reader can likely apply to any application domain they happen to be interested in, the choice of visual representation should significantly differ. Figure 1 outlines a common taxonomy of visualization characteristics, or traits, known as the "Standard Convention." Any one of these, or a handful in combination, can be used on the design of a visual idiom – a single representation of data. However, a system of such representational idioms (e.g., a management dashboard) can leverage a wider collection of these traits, with the effectiveness of the visual system dependent on the meaningful connections between the idioms as well as their individual effectiveness. The best dashboards are more than the sum of their parts.

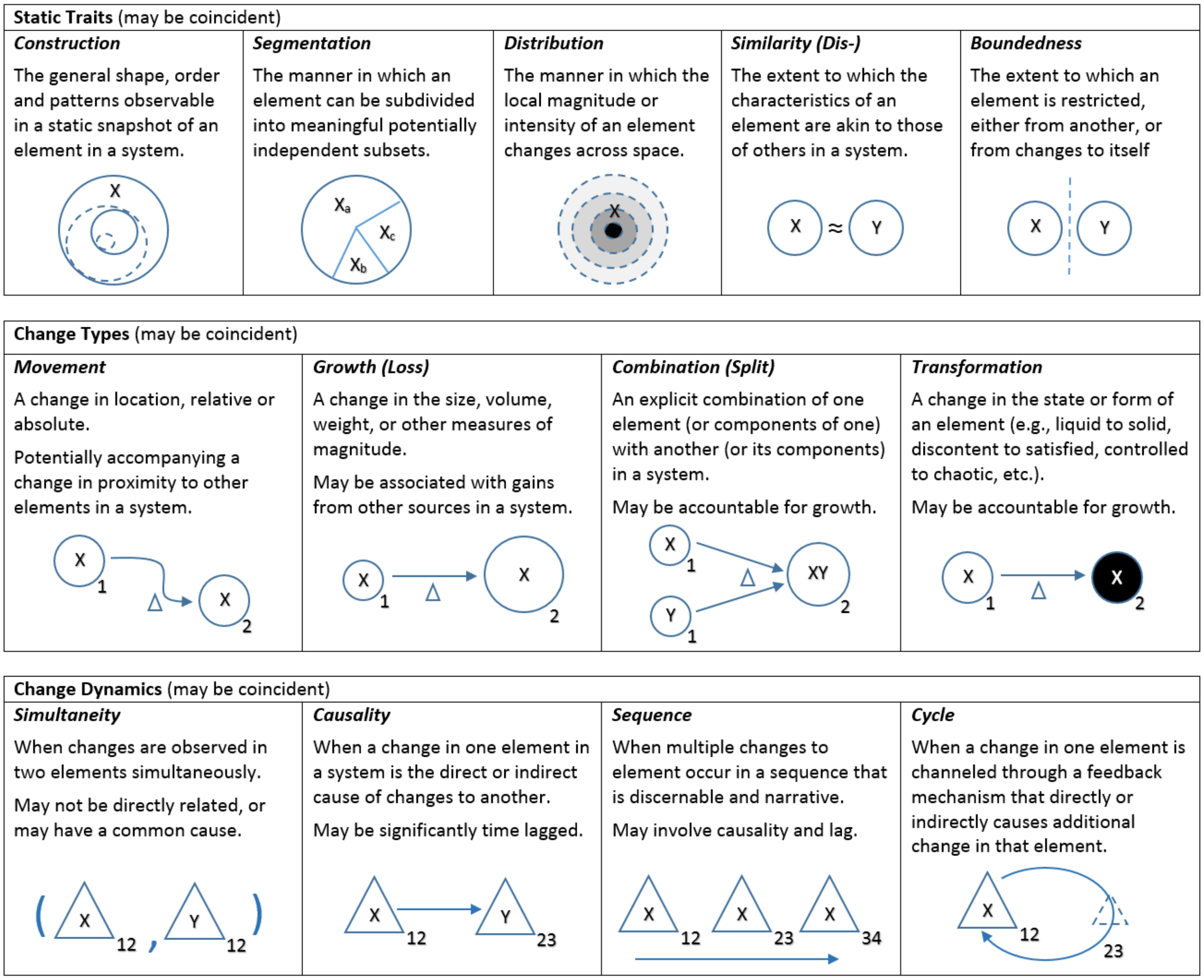


Figure 1. Representational Foci in the Functional Design of Data Visual Representations

There are many obvious examples in which these traits can become relevant in management. Construction as a static trait, for example, is relevant not only in depictions of the assembled nature of goods but also in discussions of how goods are packaged in pallets, or how they are accommodated within vehicles and warehouses. Supply networks as a whole are often described and ultimately visualized by structure as well, along with other static traits such as distribution, boundedness, etc.

They are also commonly and relevantly discussed in terms of 'change type' traits. In what way do goods and services move? Are aspects of the network growing? In what manner have combinations occurred (e.g. pooling)? Has technology or a natural disaster transformed the network structure? And of course most interesting often are the questions that get to the driving forces behind these changes (change dynamic traits); Can we attribute and depict cause in a meaningful way, or at least raise awareness of correlated activity in the event of mergers, outages, politically sparked shifts in demand or supply? These higher level traits ostensible capture richer stories, and are hence worth some distinction from those that are more static.

The use of effective symbolic representations is, of course, not new. The study of signs and symbols as representations go as far back as Plato and Aristotle. As the field of semiotics began to become more fully established in the 19th century, the theories of Pierce attempt to rationalize the use of signs and symbols, the issue of “fit” between need and design being discussed (Pierce, reprinted 1958). Still more recently, management researchers and practitioners have been well-familiarized with the value of “fit” considerations in a broad set of managerial choice scenarios, many of which have been scrutinized in contemporary academic literature (cf. Goodhue and Thompson 1995; Bendoly and Cotteleer 2008). Authors have even leveraged the task-technology fit framework to consider the value to matching the attention given to strategically-aligned operational data, and conversely the cost of focusing on enterprise data not critical to strategic gains (Bendoly et al. 2009). However, the consideration of which visual representation of data is best suited to data analytic tasks is somewhat novel.

According to recent applications of Pierce’s semiotic framework (as depicted in Figure 2) and, again, much reflective of the gestalt of task-technology fit discussions, the objectives of the task at hand are paramount in the development of effective signs and symbols in representation (Amare and Manning 2008). Pierce’s framework has three dimensions, each subsequently representing choices based on the earlier. The first choice involves determining the intent of the representation: What is the derived meaning that the representation (e.g., a solitary visual idiom or a system of idioms) should be conveying? The answer may be seemingly simple; i.e., “We need to show the difference between the earnings distributions of these two sets of firms over the last ten years.” On the other hand, the answer may be rather complicated; i.e., “We need to show how increased dependencies on suppliers active in radical innovation appear to pave the wave for increasingly radical patents that capture greater market share in years following such patents.”

Derived Meaning Targeted	**Connection to the Object-Referent**	**Sign's Representational Characteristics**
What are the properties and connections of the message you intend to convey?	In what way are the properties of this message and their connections best represented?	*What are the properties of depiction that capture these message properties*
		1. Single attribute / Binning / Frequency / Density
	1.Analogy / Summary of central tendency / expected value	2. Multiple dimensions jointly depicted / rich-static snapshot
1. Demonstrating properties without association	2. Emblematic multidimensional subset / facsimile of multiple rich observations	3.Comprehensive system depiction demonstrating dynamics of associations
2. Demonstrating association among properties	3. Replication of reality / Comprehensive facsimile connecting properties over time	
3. Supporting causal arguments explaining associations		

Figure 2. Pierce's Classic Semiotic Framework Applied to Management Data Visualization

Objectives that are more ambitious require data visuals that are more sophisticated. Pierce's second dimension in Figure 2, the connection to the object-referent, describes the properties of the real-world object or scenario that needs to be captured in order to accomplish the chosen objective (derived meaning targeted). Pierce's last column (sign's representational characteristics) involves the choice of specific visual traits of focus (as per the taxonomy of Figure 1) that can be used as a structure for depicting the needed properties outlined in column 2. Pierce's suggested use of this framework is hierarchical in the sense that an earlier column choice (e.g., choice 1, 2 or 3 in column 1) must be followed by a choice no smaller in subsequent columns. As a result, combinations of choices such as 1-1-1 or 2-2-3 are deemed effective, where choice sets such as 3-1-1 would be deemed ineffective; Attempting to capture a complex systematic phenomenon with piece-wise non-integrated representations.

It's useful to consider some examples here, especially where they pertain to visualizations practice is familiar with. Control charts, for example are and continue to be highly effective visuals in supply chain practice. Why? They measure things that are very defined in scope, without overcomplicating their intention. They inspire investigations of causality but don't attempt to explain it in and of themselves. In Pierce's framework, most control charts would be viewed predominantly as 1-1-1 schema idioms (See Figure 3, parts a-c respectively). Even cause-selecting control charts still remain limited in their dimensionality, representing “cleaner” variance rather than the specific form of multivariate associations – which are determined somewhat “behind the scenes” and thus ostensibly hidden from view.

Scatter plots (and the best fit lines often graphed along with them) similarly are well suited to their task, capturing the relationship between two or three dimensions of an object or scenario, regardless of temporal anchoring. These are largely 2-2-2 schema idioms in Pierce’s framework. The addition of confidence intervals further enriches potential value by emphasizing the robust/non-robust ability of the relationship to serve in a predictive (if not prescriptive) capacity. That is, features of lower dimensionality (e.g., capturing the distribution of a given fit parameter) continue to add value, provided they do not distract from achieving the goal of the targeted interpretation, a point we will return to in a moment.

Far more ambitious intentions regarding the depiction of causality in a system require still more sophisticated visual approaches, however, and these tend to be the most challenging for practice as well as academic research. Many take critical steps in the right direction but fall short of being effective. For example, causal loop diagrams (CLDs) alone typically do not capture dynamics of assumed causality sufficiently. Why? They do not reveal in and of themselves the mathematical assumptions regarding flow rates, feedback rules, constraints, etc. that give life to their conceptual form – a form that is not static but rather one that holds value in its very dynamics. CLDs therefore set the stage for visual representation but must be paired with rich summary depictions of associated data (plots of the dynamics of multiple system dimensions over time, yielding 3-3-3 schemas). Indeed, the objective of depicting dynamics often benefits from non-static depictions; i.e., graphic interactivity in the idioms and systems of idioms developed.

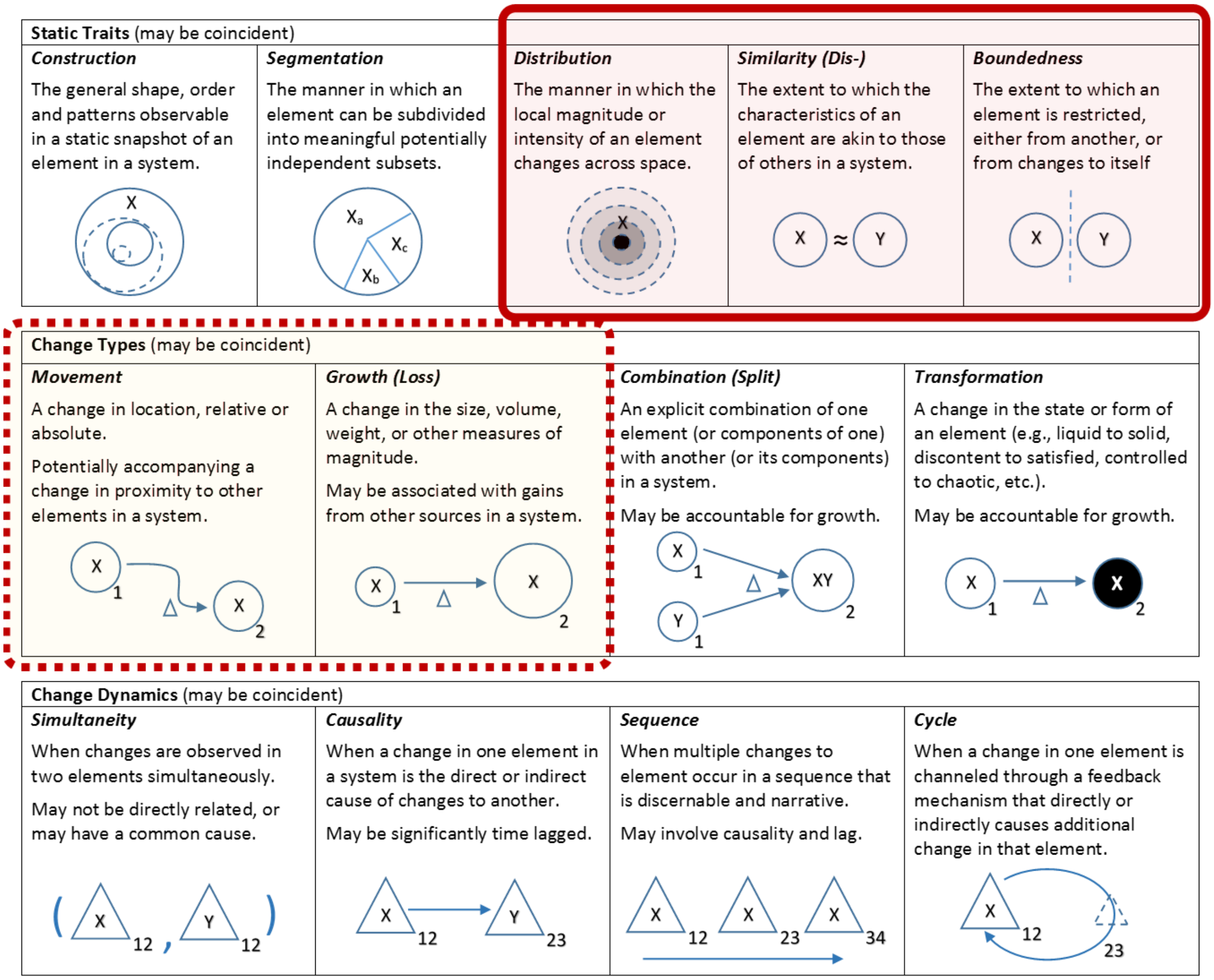


Figure 3-a. Control Chart Characteristics Supporting 1-1-1 in Pierce's Framework

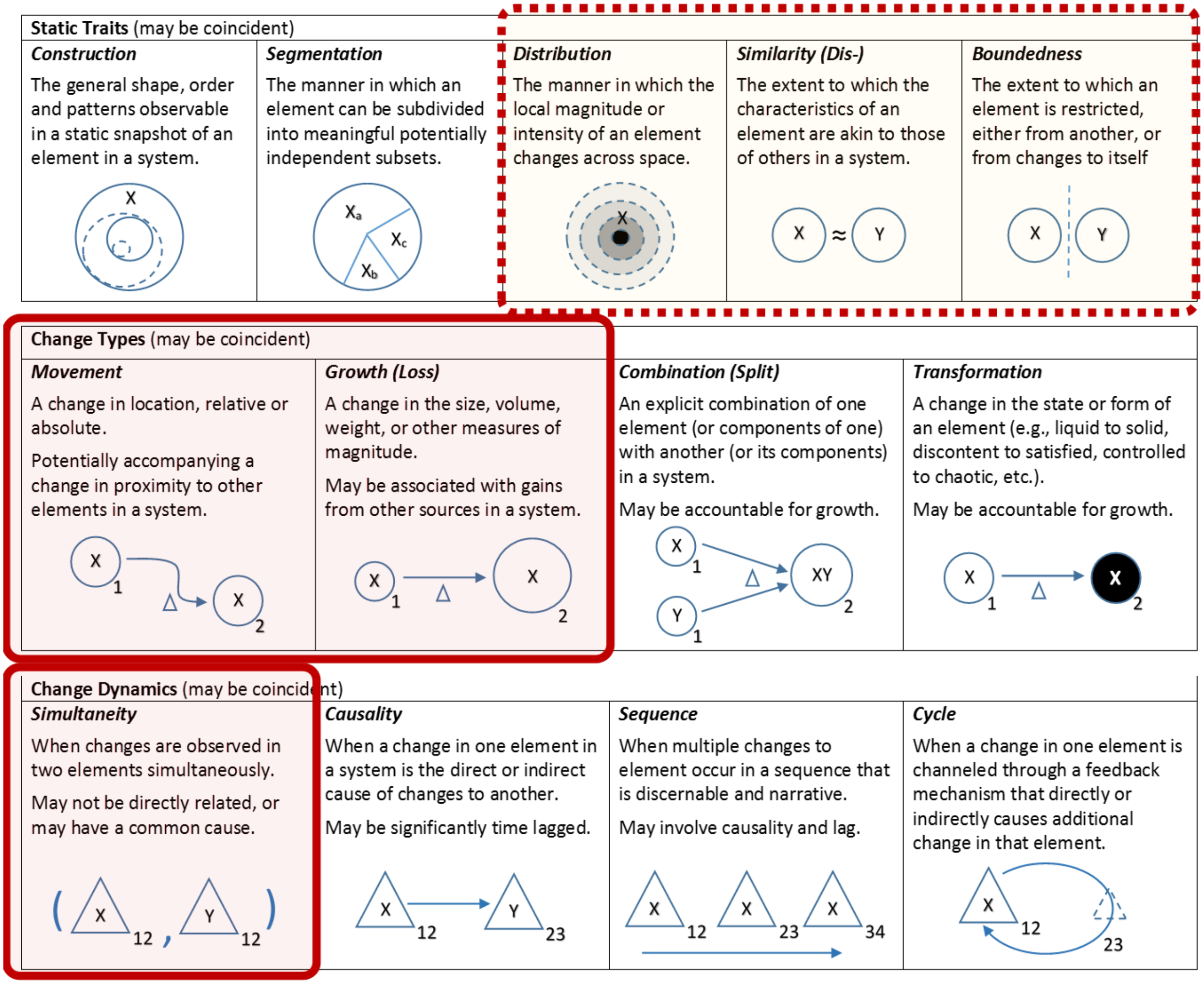


Figure 3-b. Best-fit Scatter-plot Characteristics Supporting 2-2-2 in Pierce's Framework

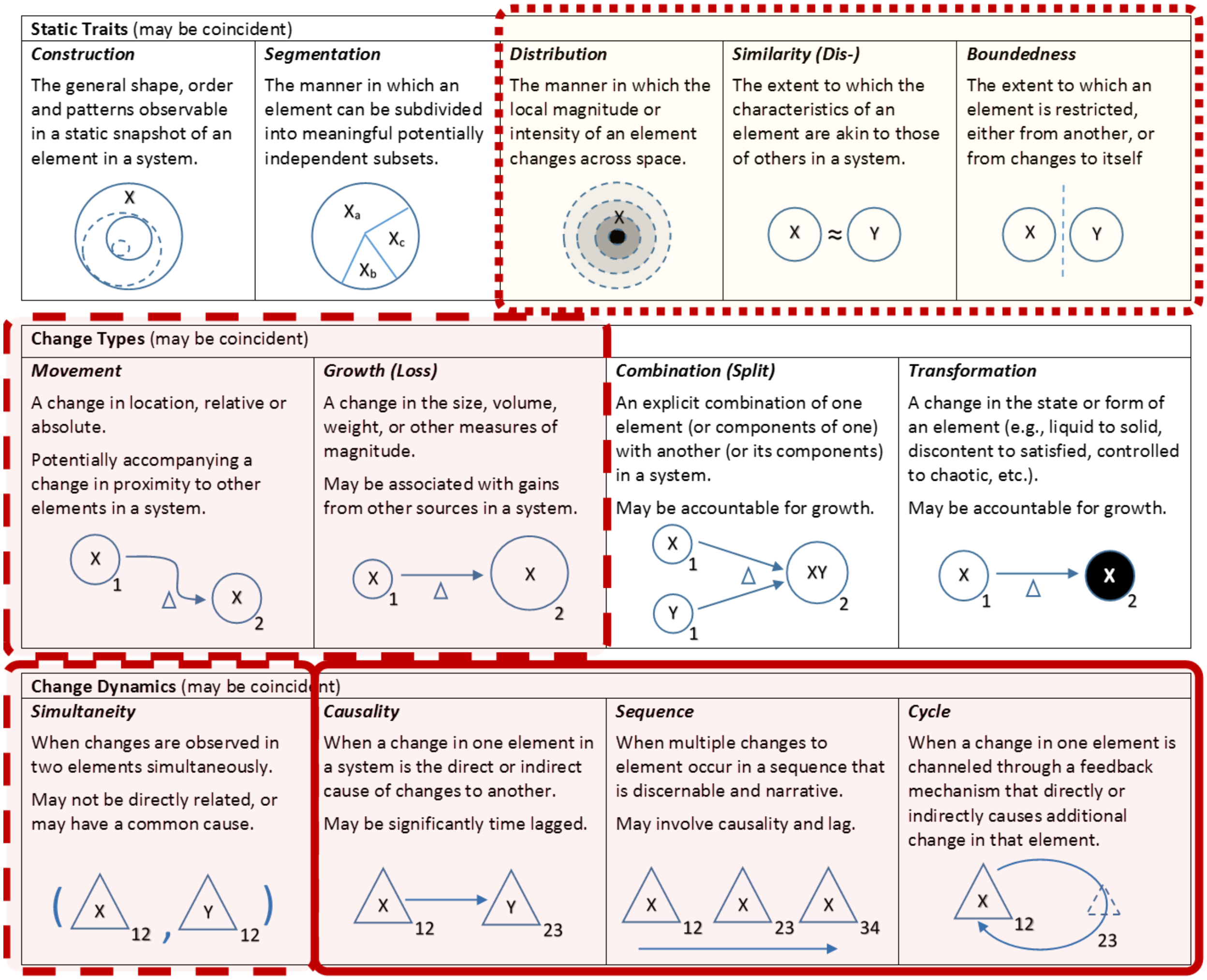


Figure 3-c. CLD/Dynamic Plot Characteristics Supporting 3-3-3 in Pierce's Framework

However, Pierce's semiotic prescriptions are somewhat unidirectional, both generally and with regard to data visualization choices. Specifically, Pierce suggests that it would be acceptable to pair the goal (meaning targeted) of demonstrating the disconnected properties of the represented object or scenario with a full, multi-dimensional, longitudinal explication of the data in hand, using causal loop diagrams and system dynamic time-series snapshots. If accurate, such highly rich presentations would pose no difficulty in the absence of information-processing constraints. Unfortunately, human beings do function in the presence of such constraints. We have difficulty identifying key signals when they are obscured or even marginally accompanied by noise. Occasionally, we are prone to lose the forest for the trees (Dervin 2003b). Certainly, the extent to which information overload can diminish targeted meaning is dependent on the individual interpreting the material data representation – including their own familiarity with the issues depicted – as well as the strength of the systematic integration of idioms incorporated by the designer of the visual representation (Yang et al. 2003). The richness of data visualization therefore offers both critical economies as well as diseconomies.

2.2 Data Visualization in Enacted Sensemaking

Given the potential for data visualizations to provide highly appropriate renderings for a given objective, as well as their potential for missing the mark considerably – in the worst cases inspiring counter-productive and highly costly decisions – it is critical to consider in some greater depth *the process* through which individuals and organizations may actually go about constructing and leveraging these representations. To ensure messaging, an individuals tasked with conveyance can always attempt to make strategic selections of visual forms that a given audience is familiar with interpreting (Gantt charts for PMs, chloropleths for sales managers, network diagrams for fleet managers, etc.). However it is also worth appreciating that the outcomes derived by individuals, even in contexts in which they are highly familiar with the depiction's form, may only be the start of what they and those they work with ultimately get out of these depictions. To consider the possible 'extended lives' of visual renderings in more depth we can draw upon the rich literature on individual (cf. Dervin 1983, 2003a) and organizational (cf. Weick 1988, 2010) sensemaking as a foundation for considering both the nature of the design process as well as the interpretations that follows.

To begin, consider Weick's perspective on what is referred to as enacted sensemaking. Weick's theoretical proposition is that individuals give meaning to experiences by retrospectively considering the actions they have taken (enactment) and the consequent material artifacts of those actions. That is, putting visual renderings and interfaces for visual exploration into the hands of supply chain managers, for example, changes their behavior; But it also has the potential to lead to the creation of new artifacts that may be shared, perpetuating knowledge creation and the development of future exploratory renderings (limited by the flexibility and usability of each subsequent artifact). Consider for example a purchasing manager viewing a scatterplot comparing product quality variation to price; seeing a relationship only after filtering by specific product categories; mapping the filtered data to distinguish possible regional moderation effects; using these artifacts to lay a new foundation for discussions of criteria in contract development. The act of engaging in analysis creates artifacts along the way that support further sensemaking.

This stance regarding the material byproducts of analysis and their intermediating role in sensemaking systems has been reiterated by numerous contemporary scholars considering the role of data visualization (Sandberg and Tsoukas 2015; Stigliani and Ravasi 2012; Dadzie et al. 2009; Dastani

2002; Baron and Misovich 1999). These actions taken and material outcomes are in part driven by contextual factors outside of their control, but are also highly influenced by the prior experiences and pre-existing beliefs of the actors. Hence, the "evidence" represented in the material results of their action can, in fact, represent something of a self-fulfilling prophesy, with confirmation bias feeding a reinforcing loop in the structuring of mental models of cause-and-effect (Nickerson 1998). These same potentially self-reinforced mental models then provide the pre-existing belief structure for future action and sensemaking (see Figure 4).

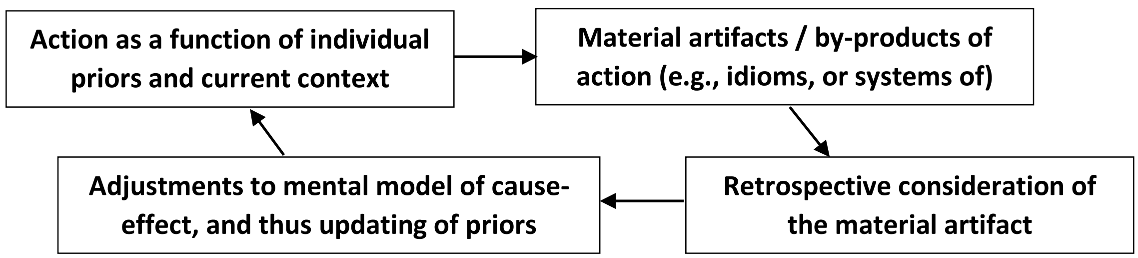


Figure 4. Data Visualization in an Enacted Sensemaking Cycle

Paroutis et al. (2015) has an interesting take on the manner in which the material artifacts of enactment can, in fact, influence subsequent sensemaking. Using Gibson's theory of affordance (1986), these authors suggest that the traits of a visual representation of data as material artifacts of enactment enable or constrain (i.e., afford) its ability to be leveraged. Specifically the choice of which traits to depict – the sign's representational characteristics, as per column 3 in Pierce's framework – influence the setting in which with retrospective consideration and mental model adjustment takes place and thus only afford certain kinds of consideration and adjustment. If prior biases influence the choices made in visualization – choices that may not be aligned with the conveyance of the most relevant meaning – the resulting visuals may provide very limited value added moving forward. If the purchasing manager in the prior example felt that there was no reason to see differences across certain product categories, the artifacts emerging from her examination would have been different; perhaps less informative to those considering contract modification opportunities. Biases therefore and importantly can influence not only future actions by the designer, but also others expected to leverage or simply casually encountering the visual design (Bendoly 2014; Bendoly and Swink 2006).

This is sadly far too common a scenario today. Individual practitioners, researchers, and entire organizations regularly put the cart before the horse in data visualization, first selecting the tools (software and methods) to fill their toolboxes, and only afterward trying to apply them to problems. The result of these overly constrained perspectives can be overly constrained learning, which can, in turn, self-perpetuate, reinforcing the perceived relevance of the "hammer in hand" and forcing future problems to be viewed as yet additional – albeit occasionally uncooperative – "nails." Individuals and organizations seldom come to terms with the fact that one of the greatest obstacles to leveraging data may be in fact the constrained infrastructure and culture of use that they have themselves enacted in their quest to be data-savvy.

Avoiding an enacted sensemaking trap in data visualization requires doing something that is often viewed negatively in organizational process management: embracing the prospect of variation. Specifically, the battle against natural internal bias necessitates the incorporation of alternative viewpoints relevant to a range of possible extensions to the visual artifact's use. Figure 5 provides a rough representation of the stages in analytical work that data visualization can be applied to (as listed in the introduction of this section), crossed with one very simplified but prototypical organizational hierarchy. If exploratory analytics tend to be the domain of strategic planning and tactical management in descriptive and predictive stages, would the visual artifact developed serve all such purposes and audiences as well as it serves the task at hand? Would a rather different alternative depiction prove more useful in some of these stage-level settings? Would it serve well in conveying prescriptions on work execution? Here again we return to the point made earlier regarding audience-specific considerations. Planning managers may benefit from a tool that allows them to explain various modifications to supplier ties across their network. Warehouse managers may not, but they might benefit from visuals of RFID granularity and accuracy across the floor plan they manage.

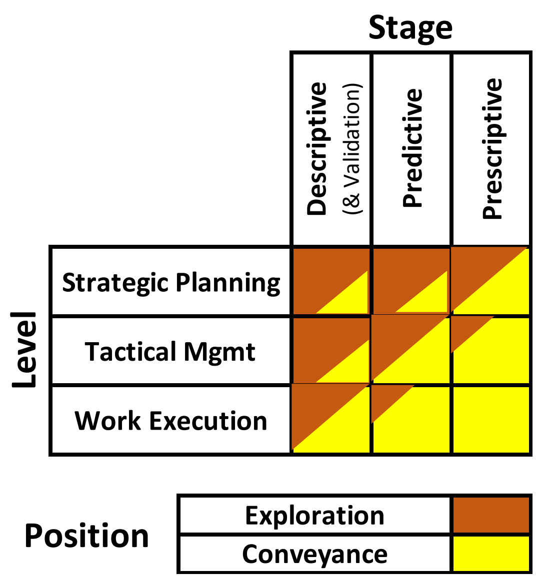


Figure 5. Analytical Purpose Specifications: Level and Stage of Design/Use

By no means should a single visual representation or system of idioms be expected to serve all such settings effectively. However, the mere act of considering how the visual representation might be interpreted and used in alternate settings – attempting to shift one's internal anchoring or to put oneself in the shoes of others – can help identify deficiencies in its design as well as opportunities for improvement. The most effective data visual developers share a willingness to re-examine and iterate across levels of application and stages of development and evaluation. They proceed in development with an understanding that a strict linear approach may not possible, and perhaps most critically that the work may not have a fixed endpoint but rather should be viewed as a process in continuous development.

2.3 Data Visualization Biases in Design and Interpretation

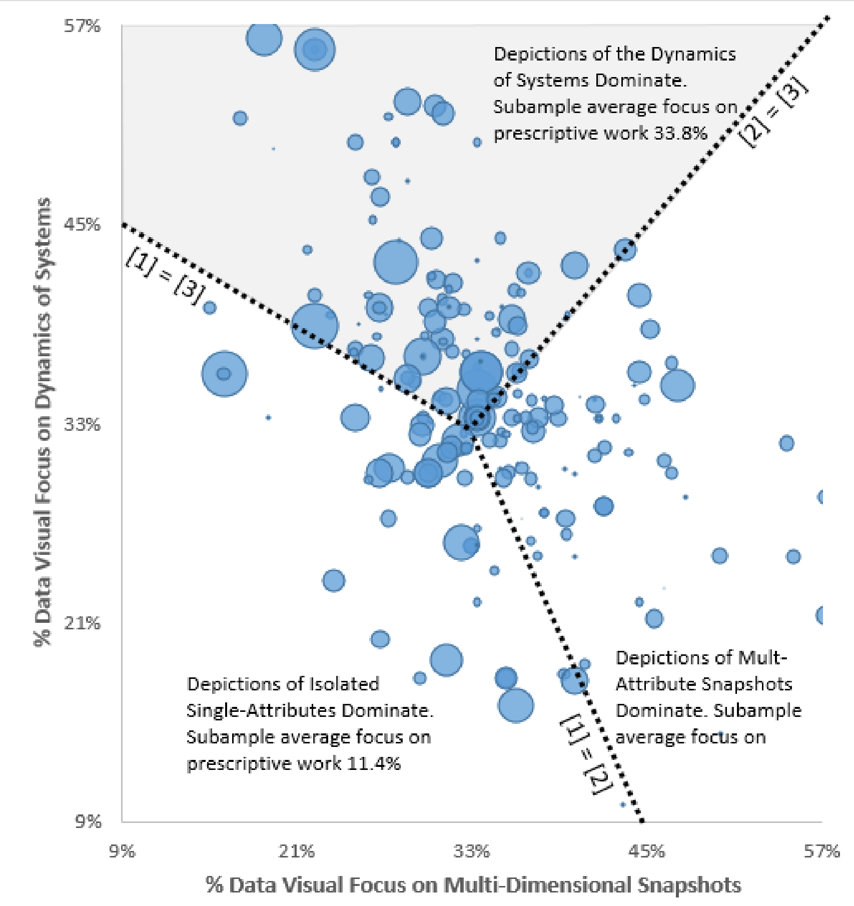
Are there shortcuts to this iterative process? Yes and no. Debiasing efforts remain critical; however, these can be intelligently and efficiently targeted. In other words, given that we can anticipate the existence of biases based on prior experience, organizations and individuals should both be cautious of and take advantage of the variety of perspectives they may interact with. Those using data visuals to help in their own sensemaking, as well as those developing data representations for others, would do well to conduct both fit and robustness analysis on their work. They must certainly check to make sure the meaning they are attempting to capture is sufficiently represented, with obfuscation minimized. However, the robust interpretability of the resulting idiom, or system of idioms, may be best carried out by focusing on the specific visual biases held by those in stage-level settings considered (Figure 5).

And here we face the billion-dollar question: How can we anticipate the nature of individual visual biases so that such focus can be achieved and used to test the robustness of a design? Apart from knowing that a range of individual backgrounds may describe potential interpreters of the visuals, how can we guess regarding their tendencies to click with or balk at certain design features? To begin to approach this intelligently, and fitting to this general discussion, we need some data.

3. Exploring Extent Biases

A practitioner survey was developed to include purposeful-use questions (questions relating to analytical stage targeting of data visual design) as well as questions regarding characteristic reliance on the traits of the 'Standard Convention' (Figure 1). The survey was distributed to a target sample population consisting of 24,000 management professionals and academics. Only those considered to have had sufficient experience in the development of data visualizations were asked to complete the study. A total of 374 responses have been collected to date. The majority of respondents hail from backgrounds in internal process operations such as quality management, supply chain management, finance, corporate accounting and software development, with smaller subsets representing engineering, medicine, marketing and general management/HRM.

Before we take a look at the distinctions that may exist by virtue of field expertise, let us examine the tendency for a focus on specific representational characteristics to be associated with targeted use – in other words, the general tendency for the sample population to design visuals in line with the adaptation of Pierce's framework (Figure2). Figure 6 provides a depiction of higher-level design tendencies in relation to the use of data visualization in prescriptive messaging. In this graphic, the greater the width of the data point, the greater the intent to use data visualization prescriptively.



* Bubble size depicts % of the analyst's work focusing on Prescriptive, versus Predictive or Descriptive/Cleaning/Aggregating data work

** Diagonals (eg. [1]=[2]) show cutoffs in the dominance of methodological tendencies (eg. the area below the [1]=[2]-[1]=[3] frontier shows respondants with a tendency towards single-attribute depictions such as standard control charting.

Figure 6. Data Visual Focus on the Prescriptive Analytics Stage Depicted by Point Width

Looking at the top sector, where we focus on capturing the dynamics of systems dominates, we see that those who tend to afford greater attention to attempting to capture these features tend to, in fact, be targeting greater prescriptive use. While that is not, in itself, surprising, what is interesting is that this sort of a relationship isn't apparent across more of the cases examined. Specifically, there are many instances where designers seem interested in depicting the dynamics of systems without a strong interest in using such visual prescriptively (indicated by the several smaller circles in the upper sector). Perhaps more critically is the large number of respondents who do, indeed, suggest an interest in prescriptive depictions but show relatively marginal interest in any visual traits outside of the unidimensional or static (indicated by the several large circles below the top section, and particularly where single-attribute idiom use is the focus).

Where do these mismatches come from? Does the tendency to focus a more seemingly appropriate graphical representation to match messaging needs have anything to do with biases specific to a discipline? Are the biases driven by the nature of training, or the basis of their incentive structure?

Let's take a different approach to examining these data. Figure 7 provides 75% confidence ellipses for the survey subpopulations of operations, supply chain management, finance and software/IT. Each graph shows subpopulation tendencies to design using representative characteristics along with tendencies to use data visualization to support theoretically-fitting targeted meaning. The ellipses emphasize distinctions among the groups of respondents, bivariate association within the groups (the slope of the ellipses), and proximity to the theoretical 45-degree fit line. Such graphics can be created using any variety of freeware such as, in this case, the Blackbelt Ribbon (excel-blackbelt.com). OM and SCM practitioners may be pleased to find the general intuition of their fields, although not perfect, follows design theory more closely than finance/accounting and software/IT field representation. Apart from serving as an additional warning against placing blind faith in third-party software offerings ahead of actual needs, these early results also suggest the value that operations and SCM practitioners and research may enjoy in conferring with finance and accounting professionals, who likely have different visual tendencies in the design of idioms and dashboards.

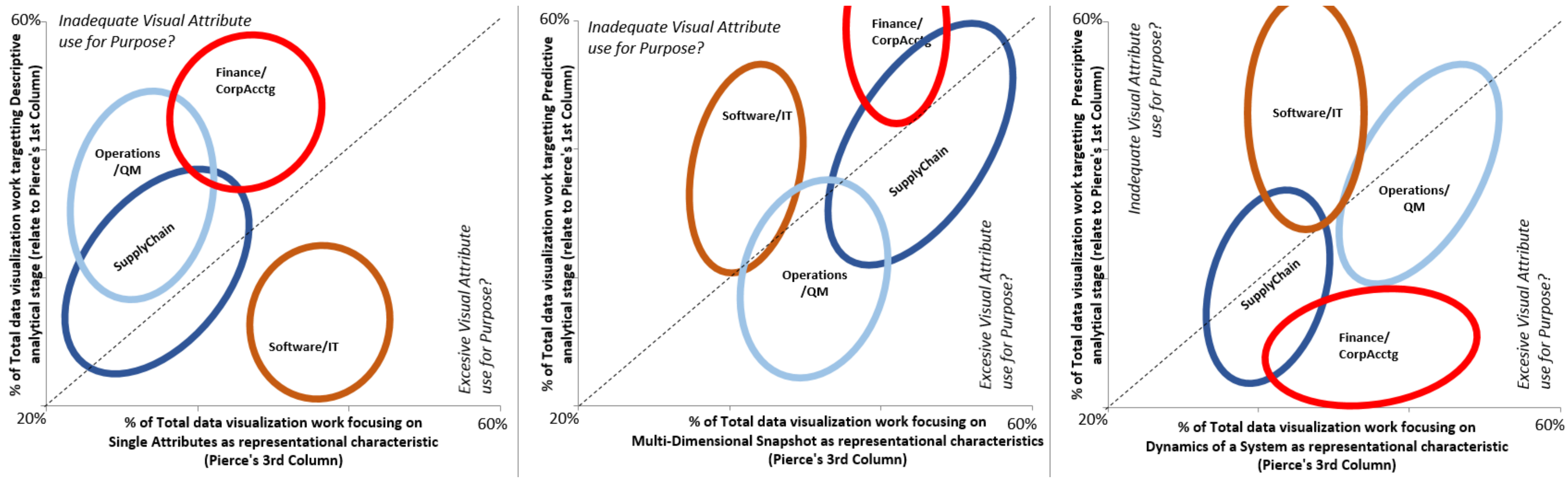


Figure 7. 75% Confidence Ellipses: Tendencies towards Functional Traits of Data Visuals, and Their Targeted Use in Analytical Stages

What do we not see in these graphical examinations? Specific cause. Figure 6 is a multi-attribute static depiction focusing on distribution, similarity and boundedness. Figure 7 is a multi-attribute idiom capturing related traits as well as association (the slant of the ellipse representing correlation, their proximity to a central diagonal capturing theoretical fit). But in neither case do we see anything that would suggest why the associations and differences between fields exist, and certainly it would be inappropriate to claim such meaning could be extracted from such visuals, nor was it the original intent of this first survey. At this point the issue is left to speculation. What we do have is the foundation for asking additional questions at this point that subsequent data collection, visualization and statistical analysis might shed light on. For example, is the apparent mismatch between data visualization design and intended messaging among software/IT professionals an artifact of industry incentives? Or perhaps some other inducement driven by corporate or national culture?

4. Conclusions

Through this discussion, the hope has been to increase the awareness of terminology, applied theory and frameworks for consideration in the use of data visualization as a critical process in the analytical work of supply chain management and operations researchers and practitioners. As a field, we are certainly not playing catch-up, but we are also not without our own biases; we need to be aware of how those might lead us to premature designs and ultimately misdirected conclusions upon which critical decision-failures made are based.

Although multiple theoretical perspectives are reviewed here, the general guidelines for developing strong visuals draw from core principles that resonate across all these viewpoints. Table 1 highlights the fundamentals of these guidelines in a 'rules of thumb' format.

Intended Message Focus	**Rules of Thumb**
Static Traits in the 'Standard Convention' (Fig. 1) and Level-1 points in Pierce's adapted semiotic framework (Fig. 3)	For those variables that benefit from a descriptive depiction in order to better understand their static traits, ensure that their depiction is crisp and non-ambiguous, fully leverage their dimensional attributes but do not impose additional false attributes on their depictions. Avoid superfluous graphic effects such as 3-D renderings of bars emerging from a geographic plane (or simply in a bar chart), when a 2-D heat map can do the job more clearly. Strive for linear representations of magnitude, rather than radial, area or volumetric.
Change Type Traits in the 'Standard Convention' (Fig. 1) and Level-2 points in	For variables that benefit from a depiction of the changes that have occurred and are likely to occur in the future, higher dimensional renderings are critical. Time will often be an instrumental dimension in

Pierce's adapted semiotic framework (Fig. 3)	such visuals however this does not mandate its presence along an X-axis in a plot. Time can also be depicted by changes to iconography in a scatterplot (e.g. color scale or fading) or by arc/arrow connections to extend visual dimensionality. Such depictions of change also benefit from dynamic and/or interactive designs, providing users for example the ability to dial-back (using sliders for example) depictions across time or permit controlled animation of the progression of change.
Change Dynamic Traits in the 'Standard Convention' (Fig. 1) and Level-3 points in Pierce's adapted semiotic framework (Fig. 3)	For those variables whose association with other variable (causal or simply coincident) is critical to convey/explore, the effective use of the above two rules of thumb must be extended to support formal arguments. Controlled time depictions therefore find significant relevance here. In these cases in particular, the existence of multiple depictions of change in a single visual idiom is essential (e.g. scatterplots showing points over time that demonstrate how fulfillment may be constrained variously by capacity in some cases and by ordering errors in others; i.e. floating bottlenecks). Succinctly stated: System visualizations require systems of visuals.

Table 1. Fundamental Rules of Thumb Design Principles for Data Visual Design

Data visualization must be approached methodically, starting – as with any good method – from the objectives regarding meaning to be developed and conveyed. It must be viewed as part of an ongoing process of sensemaking, and as such must be viewed as both representative of extant biases as well as the foundation on which future mental model development can be honed. It must move forward not only with the appreciation of biases that may be inherently discipline specific, but also be willing to embrace other viewpoints in an effort to debias and avoid self-confirming reinforcement traps. Shared use of terminology and cross-cutting disciplinary guidelines for strong visualization practice will be essential, both within organizations and among research units, to facilitate the kinds of collaborative sensemaking efforts that are increasingly critical.

I hope that in providing this dialogue, it will facilitate further collaborative discussions finding commonality as well as a solid foundation for debating differences in data representation. Further special topic forum efforts spearheaded by JBL will be targeted with discussions such as this in mind, and will provide critical opportunities for a variety of perspectives to be applied. I look forward to seeing how these collaborative discussions can advance the science of what we do. These are exciting times for our research and practitioner communities… the view from here is amazing.

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