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Information Visualization in Computing and Related Sciences: Evidence from Top Journals

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Abstract:

Information visualization provides a ready and potentially powerful mechanism for communicating research results. Understanding how visualizations are used in scientific discourse is one way to characterize this discourse, as well as to identify opportunities for expanding or refining it.

This article proposes a systematic framework for classifying visualizations in published journal articles with respect to the data used to construct them, the processes they seek to explain, and the research goals they serve. The framework is applied to top journals in the computing and related sciences, revealing two main findings: while visualizations appear frequently in the surveyed articles, they serve a narrow band of uses relative to those encompassed by the framework. An implication of this finding is that discourse based on information visualization may be enriched by expanding the range of information visualizations found in this research, and by developing new classes of visualizations to illuminate a broader range of research results.

Keywords: information visualization, taxonomy

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INTRODUCTION

Scientists draw on the ability of different visualization techniques to help communicate their results within and across diverse research communities. In doing so, they take advantage of visualizations' potential for high information content coupled with high comprehensibility. Given the wide range of tools now available for producing information visualizations—together with ongoing expansion of topics covered by researchers—it is appropriate to assess how information visualizations have been used in scholarly publications and to identify opportunities for extending scientific discourse through their expanded use.

A number of prior studies suggest how different types of visualizations are used in communicating the results of scientific investigations (e.g., Card 1996; Herman et al. 2000). A novel contribution of this work is that it proposes a systematic framework for classifying information visualizations and applies this framework to visualizations found in recent articles published in top journals in computing and related sciences. Application of the framework results in a classification of each visualization with respect to the data used to construct it, the process it seeks to explain, and the research goal it serves. Both visual and statistical methods are used to analyze the results of this classification. One conclusion of this work is that, while visualizations appear frequently in these articles, they serve a narrow band of uses relative to those encompassed by the framework. The main implication of this result is that the discourse based on information visualization may be enriched by exploring other uses of visualization and, indeed, by developing new classes of visualizations to illuminate a broader range of research results.

STUDY FRAMEWORK

To understand the use of visualization in communicating scientific results, visualizations are here examined using a framework of four interrelated activities associated with the conduct of scientific research: the *goals* of the work, the *processes* under investigation, the *data* associated with these processes, and the *visualizations* used to communicate the results. As discussed more fully below, this framework provides a mechanism for classifying visualizations in relation to the nature of the research they are intended to support.

A taxonomy of *goals* of research activities in the computing sciences is given by Leigh (1992) in the context of systems theory. In this taxonomy, a system is defined as a set of elements interconnected by information links in a boundary surrounded by the environment. Leigh offers three *goals* of research on systems: *system understanding*, which pertains to understanding the elements and information links within the boundary, or the whole system in the context of its environment; *influencing systems behavior*, which pertains to manipulating the properties or characteristics of the system; and *system design*, which is the task of replacing either the whole system or at least one of its components so that the system exhibits particular behaviors.

Meeting any of these research goals can involve the investigation of system states and/or transitions between those states (i.e., *system processes*) (Widmeyer 2003). A *transactional* process represents the transitions between states and how reliably the transitions occur independent of any other process. A *relational* process represents the relationship of one process with another or the case in which a relationship is a process in and of itself. An *informational* process is a mediating process that captures the strength of a relationship between two other processes.

CONTRIBUTION

This article reviews the state of the art in the use of information visualizations to communicate the results of research published in top journals in computing and related sciences. A total of 570 separate visualizations—taken from a total of 119 articles published in twenty different journals—are classified using a framework developed for this research. The framework enables classification of each visualization by type, underlying data, process under examination, and primary research goal. The results show that visualizations are used in close to 80 percent of the articles examined, and that they help address a range of research goals via examination of transactional, relational, and informational processes. On the other hand, this use is confined to a relatively narrow band of specific types of visualizations (e.g., dimensional and network), using mainly nominal and ratio data. A number of opportunities for extending visualization-based communication of findings are identified, including development of temporal visualizations, as well as visualizations based on absolute and ordinal data types.

Data may be collected in order to support the investigation of system processes. A discussed by Roberts (1979), data may be classified into any of the following four types. *Absolute* data is the simplest form of measurement, where there is only one way to measure the data (e.g., numerical count). *Ratio* data is represented in comparison to a fixed point, is transformed by a known operation, and gives the data as a measure relative to the point. Ratio data includes interval data that is ratio data marked off by two end points on a range. *Ordinal* data provide only an ordering, where scores or measurements are transformed to a monotonically increasing scale where each point describes the order of the data in the given scale. In *nominal* data, all functions define one to one transformations, as in a simple labeling.

A *visualization* may be understood as a function that maps on or more of these data types to a shape and/or color. Shneiderman's (2002) taxonomy describes a range of information visualizations, presented here in somewhat simplified form. *Dimensional* visualizations include one-dimensional, two-dimensional, and three-dimensional visualizations. One-dimensional visualization is a line of text containing strings or characters organized in a sequential manner. Two-dimensional visualization is a representation in terms of part of a total area (e.g., a pie chart). Three-dimensional visualization is a representation of a volume. *Multidimensional* visualization consists of items with n attributes becoming points in n-dimensional space, with $n > 3$. *Temporal* visualization places data in relation to a timeline having a distinct start and finish. *Network* visualizations include items linked to any number of other items. Trees are special cases of networks having a link only to a parent item. Items and links can have multiple attributes and can be represented either as a node and link diagram or a square matrix of the items with the value of a link attribute in the row and link in the column.

Examples of each possible combination of the above data types and visualization types may be found in Bertin's (1983) comprehensive inventory of visualizations. To illustrate this point, Table 1 provides the page number and figure number for each data/visualization combination in Bertin's work, thus offering at least face validity for the claim that all combinations are possible and, therefore, possibly useful. Other sources of examples include examples given by Geisler (1998) of visualizations in terms of Shneiderman's (2002) taxonomy and by Herman et al. (2000) of visualizations of networks.

Table 1: Data/Visualization Combinations Found in Bertin (1983), by page(figure number)

Visualization / *Data*	Dimensional	Multi-dimensional	Temporal	Network
Absolute	102(1)	103(2)	380(2)	109(4)
Ratio	110 (1)	103(3)	398-399(1)	281(2)
Ordinal	353(3)	123(4)	182(4)	274(6)
Nominal	352(2)	307(8)	354(1)	282(1)

The above framework, therefore, provides considerably more context to the use of information visualization in scientific research than would be provided simply by classifying the visualizations themselves. To the extent that each of the above typologies is salient in research in computing and related sciences, a reasonable null hypothesis is that there will be no particular tendency toward one distribution of visualizations across the typologies. We address this hypothesis in two ways. First, we examine the distribution of visualizations across each two adjacent levels in the framework (i.e., goal vs. process, process vs. data, data vs. visualization). This is accomplished by examining visualizations of the study data, and by conducting more formal statistical testing. Second, we visually examine the distribution of visualizations across all possible values in the framework, and conduct a multivariate test that is analogous to the bivariate test conducted in the first part of the study.

STUDY DESIGN

Twenty highly-ranked journals in computing and associated sciences were first identified using the results of a recent ranking (Rainer and Miller 2005). A list was first compiled of all 147 issues published in these journals during the study period (2004–2005). A target sample size of approximately 500 visualizations was determined and an estimate made of the approximate number of articles that would need to be surveyed to furnish a sample of this size. A random sample of 119 articles was, therefore, selected from those published in these journals during the study period. Each visualization in a given article was first identified, then classified using Shneiderman's (2002) typology. Next, the type of data used in the visualization was determined using Roberts's (1979) typology, followed by the *system process* (Widmeyer 2003) pertaining to it and the corresponding research *goal* (Leigh 1992).

This coding procedure was undertaken by two independent human coders using written instructions that defined the framework, the elements in it, and how to record the results of the coding. To assess reliability of the coding instructions, Cohen's κ (Cohen 1960) was computed and found to be at an acceptable level (above 0.87 for all typologies). A description of the data set is provided in Table 2, which shows the name, ranking, volume (issue) range over the study period, the total number of issues in the study period, the number of articles sampled, and the total number of visualizations for the articles sampled from a given journal.

Table 2: Description of Study Sample

	Journal	Ranking	Vol. (Issue)	Issues	Articles	Visualizations
1	*Academy of Management Journal*	17	47(3)–48(2)	6	2	2
2	*Academy of Management Review*	22	29(3)–30(2)	4	6	3
3	*ACM Tr. on Database Systems*	13	29(2)–30(1)	4	4	47
4	*Communications of the ACM*	2	47(6)–48(5)	12	14	28
5	*Decision Sciences*	8	35(3)–36(2)	4	1	1
6	*Decision Support Systems*	9	37(4)–40(2)	4	10	42
7	*European Journal of Information Systems*	11	13(2)–14(1)	3	2	0
8	*Harvard Business Review*	7	82(7)–83(6)	4	5	8
9	*IEEE Tr. on Engineering Management*	6	51(3)–52(2)	12	6	10
10	*IEEE Tr. on Knowledge and Data Engineering*	6	16(8)–17(7)	4	12	111
11	*IEEE Tr. on Software Engineering*	6	30(6)–31(5)	12	6	31
12	*IEEE Tr. on Systems, Man and Cybernetics (A, B, C)*	6	34(4)–35(3)	12	17	179
13	*Information and Management*	10	41(7)–42(6)	16	7	24
14	*Information Systems Journal*	16	29(7)–30(6)	11	2	25
15	*Information Systems Research*	3	15(2)–16(1)	8	4	13
16	*Journal of Management Information Systems*	4	21(1)–21(4)	4	2	6
17	*Management Science*	5	50(6)–51(5)	4	11	28
18	*MIS Quarterly*	1	28(2)–29(1)	13	3	4
19	*Organization Science*	15	15(3)–16(2)	4	1	4
20	*Sloan Management Review*	12	45(3)–46(2)	6	4	4
	Total			*147*	*119*	*570*

RESULTS

The 119 articles in the sample contained a total of 570 visualizations (an average of 4.8 visualizations per article), with 95 articles (79.8 percent) containing at least one visualization. Therefore, visualizations may be said to be in widespread use within this sample. Further detail on this use is obtained by examining how visualizations are distributed across each level of the hierarchy implied by the framework (i.e., **goal**→ **process**→ **data**→ **visualization**). A summary of the data for this study is given in Tables 3 through 5. The data may be illustrated using the top panel of the figure, which shows the distribution of visualizations between *goal* and *process* levels. A total of 340 visualizations are associated with the goal of system understanding, and eighty-five of them concern relational processes. Also provided in Tables 3 through 5 are normalized scores, which are used below to enable comparisons across any two levels in the framework. The normalized score is computed as $a(count/max)+b$, where *count* is the number of visualizations in the combination of typology values of interest, and *max* is the highest count value among all combinations of typology values of interest (a and b are simply scale parameters, and are set arbitrarily to $a = 0.9$ and $b = 0.1$). For the example above, the levels are *goal* and *process*, with *count* = 85 and *max* = 195, resulting in a normalized score of 0.49. The implications of the normalized scores across levels in the framework are presented below.

As shown in Tables 3 through 5, most of the visualizations are associated with the goal of *system understanding (340)*, followed by *influencing system behavior* (198) and *system design (32).* A total of 278 visualizations are associated with *transactional* processes, 176 with *informational* processes, and 116 with *relational* processes. As may be seen in the second panel, most (312) of the visualizations are based on *nominal* data, with 235 for *ratio*, 16 for *absolute* and 7 for *ordinal*. The visualizations themselves are mainly *dimensional* (227) or *network* (213), with 121 *multidimensional*, and 9 *temporal*.

Table 3: Count and (Normal Score) for Goal→Process

Process / *Goal*	Transactional	Relational	Informational	Total
System Understanding	195 (1.0)	85 (0.49)	60 (0.37)	**340**
System Design	17 (0.18)	13 (0.16)	2 (0.11)	**32**
Influencing System Behavior	66 (0.40)	18 (0.18)	114 (0.63)	**198**
Total	**278**	**116**	**176**	**570**

Table 4: Count and (Normal Score) for Process→Data

Data / *Process*	Absolute	Ratio	Ordinal	Nominal	Total
Transactional	9 (0.14)	82 (0.50)	5 (0.12)	182 (1.0)	**278**
Relational	2 (0.11)	22 (0.21)	0 (0.1)	92 (0.55)	**116**
Informational	5 (0.12)	131 (0.75)	2 (0.11)	38 (0.29)	**176**
Total	**16**	**235**	**7**	**312**	**570**

Table 5: Count and (Normal Score) for Data→Visualization

Visualization / *Data*	Dimensional	Multi-dimensional	Temporal	Network	Total
Absolute	14 (0.16)	0 (0.1)	0 (0.1)	2 (0.11)	**16**
Ratio	108 (0.58)	120 (0.63)	2 (0.11)	5 (0.12)	**235**
Ordinal	2 (0.11)	0 (0.1)	3 (0.11)	2 (0.11)	**7**
Nominal	103 (0.55)	1 (0.1)	4 (0.12)	204 (1.0)	**312**
Total	**227**	**121**	**9**	**213**	**570**

The first objective of this work is to compare the distribution of visualizations between levels in the hierarchy. This is done in two parts. First, star plots of the normalized scores (given in Figures 1 to 3) are examined. A star plot is a visualization used in representing multivariate observations, where one ray is assigned to each single variable, with the length of a ray proportional to the value of the variable (Chambers et al. 1983). In Figures 1 to 3, the maximum value with respect to a given axis is unity, corresponding to the case where *max* = *count*, as may be seen for the combination *goal* = system understanding and *process* = transactional shown in Figure 1. The second part of work toward the first objective of the study is testing of a null hypothesis of independence between adjacent levels in the hierarchy. The null hypotheses reflect an *a priori* assumption that the distribution of visualizations will not depend on the values in the typologies of the levels. (It should be noted, under the null hypothesis, each ray would have a length of unity, so that all polygons would be overlapping,)

Figure 1 depicts the results for the **goal→process** levels, where each value for *goal* is indicated by a different line type. The axes correspond to the values of *process* (where *rel* = *relational*, *tran* = *transactional* and *inf* = *informational*). The relative frequency of appearance of visualizations for each type of goal is reflected in the size of the corresponding polygon in Figure 1 (e.g., far more visualizations are used to support the goal of system understanding rather than the goal of system design). The distances from the origin of points on a given polygon indicate the relative frequency of appearance of those visualizations within a given category. For example, when the goal is *system understanding* or *system designing*, visualizations are most often used to explain *transactional* processes. When the goal is *influencing system behavior*, visualization are most often used to explain *informational* processes. Figure 1 strongly suggests that the proportion of visualizations used to explain a given type of process varies by goal. More formally, a null hypothesis of independence between **goal** and **process** is rejected: visualizations tend not to be distributed at random across the various combinations of *goal* and *process* ($\chi^2 = 108.6$, $p < 0.0001$).

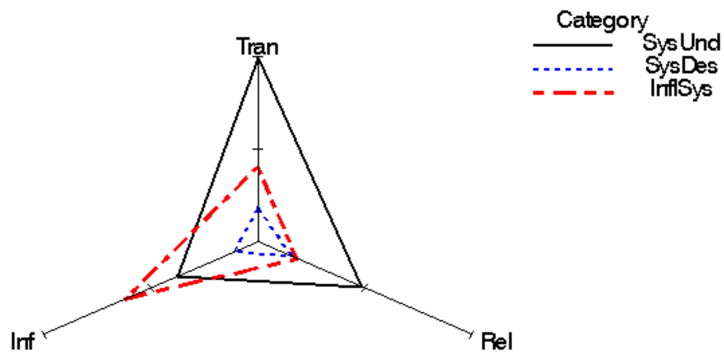

Figure 1: Goal→process levels.

Considering the **process→data** levels, the results are considerably more uniform. Most strongly associated with *transactional* and *relational* processes are visualizations of *nominal* data, while for *informational* processes the use of visualizations based on *ratio* data predominates. As shown in Table 4 and the corresponding star diagram in Figure 2, some **process→data** combinations (e.g., *transitional-ordinal*) are not found in the sample. The hypothesis of independence between **process** and **data** is rejected ($\chi^2 = 127.1$, $p < 0.0001$).

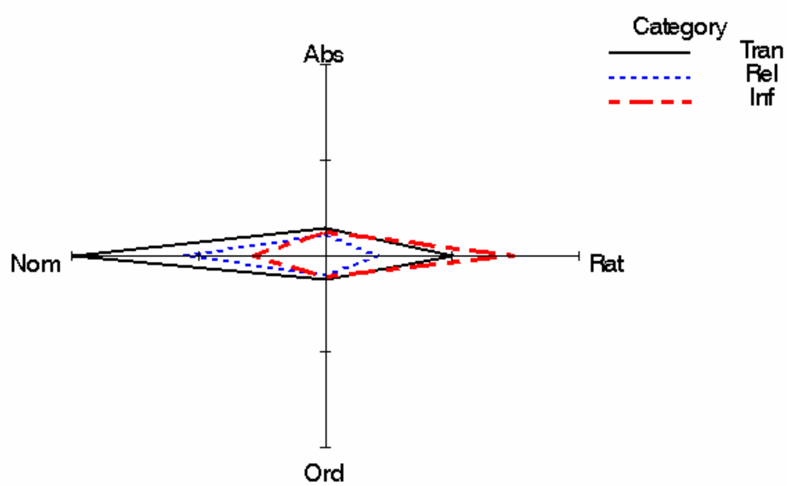

Figure 2: Process→data levels.

Finally, considering the **data→visualization** levels, *absolute* data tend to be represented in a *dimensional* visualization, *ratio* data in *multidimensional* visualization, *ordinal* data in *temporal* visualization, and *nominal* data in *network* visualization. As shown in Figure 3, there are no observations for a number of combinations of data and visualization, including (i) *abs* and *multi-d*, (ii) *ord* and *multi-d* and (iii) *abs* and *temp*. The hypothesis of independence between **data** and **visualization** is rejected ($\chi^2 = 406.1$, $p < 0.0001$).

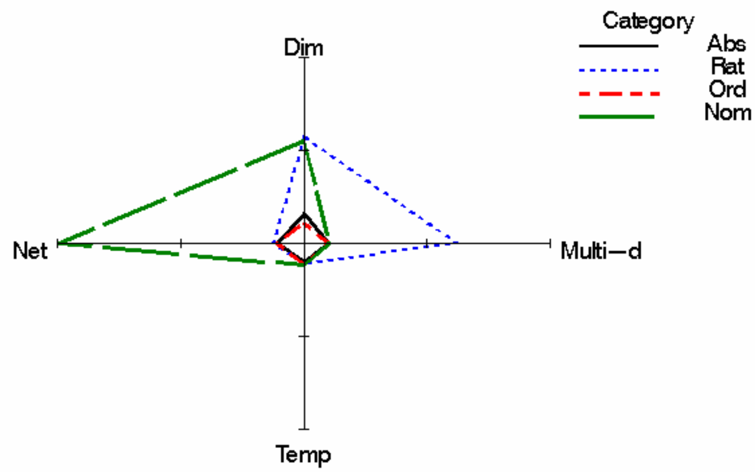

Figure 3: Data→visualization levels.

The second stated objective of this work is to examine the distribution of visualizations across all levels of the hierarchy. This is done by identifying combinations of **goal**-**process**-**data**-**visualization** that are infrequently observed or not observed at all. Tables 3 through 5 suggest that there is a high degree of variability—sometimes two orders of magnitude—in the distribution of visualizations across the framework. One example is the combination *goal* = system design and *process* = informational (two visualizations) versus *goal* = system understanding and *process* = transactional (195 visualizations). This high degree of variability is also found within a given level (e.g., *goal* = system understanding versus *goal* = system design). It is immediately obvious, then, that certain combinations of values within individual levels and between adjacent levels are more predominant than others. We now examine these gaps graphically and statistically.

The distribution of visualizations throughout the framework may be represented visually in a tree diagram. Figure 4 shows all combinations of **goal**–**process**–**data**–**visualization** as either present or absent in the data set. It, therefore, provides an expanded view of the data in Tables 3 through 5 (albeit one where all nonzero values are visually equally weighted). Since the focus is on identifying gaps, combinations that are *not* found in the data set are highlighted. One example is the combination where *goal* = system understanding, *process* = transformational, *data* = absolute and *visualization* = multidimensional. (A hypothetical example would be a three-dimensional visualization of count data showing a transformative process in order to explain how a system functions. A practical situation calling for this combination could be in showing the difference in the final versus initial number of operational, managerial, and strategic users of a given system over some time period.) The lighter paths show observed combinations (e.g, *goal* = system understanding, *process* = transformational, *data* = absolute and *visualization* = dimensional).

As shown in Figure 4, visualizations are found for all nine *goal*/*process* combinations of the framework, as are most (i.e., twenty-six of thirty-six possible) *process*/*data* combinations. Gaps at the *process*/*data* level may be found exclusively for visualizations employing data of type absolute and ordinal. At the *data/visualization* level, gaps are frequently found for temporal and network visualizations—regardless of the type of data. It may also be noted that, of the 144 possible combinations of *goal*, *process*, *data,* and *visualization* (represented as the lowest set nodes in the figure), forty-eight (i.e., ⅓) are found (recall that the total sample includes 570 visualizations). These results suggest that visualizations are used to support all goals via consideration of all process types. But on the other hand, absolute and ordinal data are under-observed, as are temporal visualizations (see Tables 3 through 5).

A more formal and holistic method may be used to investigate whether there is systematic departure from uniformity in the distribution of visualizations across all the combinations of *goal*, *process*, *data,* and *visualization*. The null hypothesis in the simultaneous test of proportions (Johnson and Wichern 1992) is one of independence between all levels. The result is strong rejection of the null ($p < 0.0001$), suggesting that the at least two of the levels are dependent. This result—which mirrors that of the qualitative assessment above—may be interpreted to mean that visualizations tend to be found with certain combinations of *goal*, *process*, *data,* and *visualization* but not others.

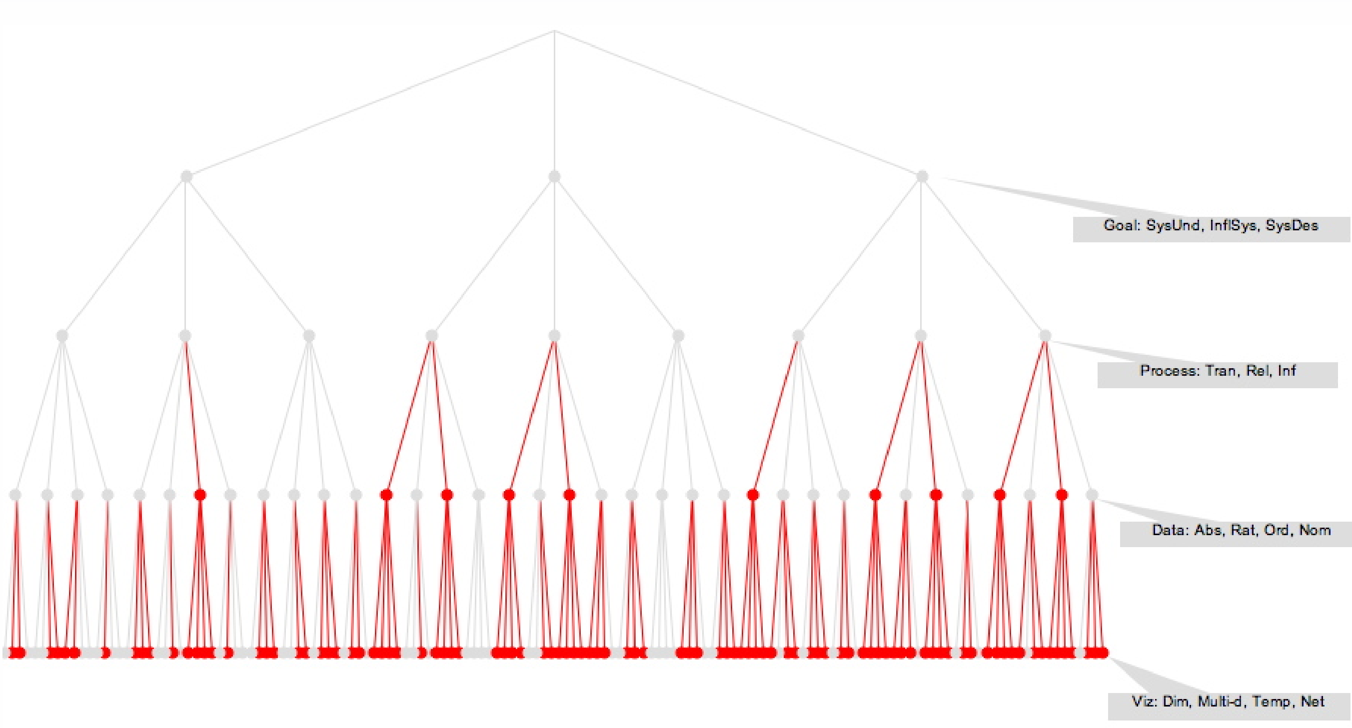

Figure 4: Unobserved goal–process–data–visualization combinations.

DISCUSSION AND CONCLUSIONS

The results of the application of the study framework show clearly that visualizations are in widespread use in top journals in the computing and related sciences. The first objective of this work is to compare the distribution of visualizations between adjacent levels in the hierarchy. At the **goal→process** level, visualizations are used predominantly to support the goals of system understanding (through examination of transactional processes) and influencing system design (through examination of informational processes). An implication, then, is that results concerning system design are seldom communicated through visualizations.

A striking feature of the results at the **process→data** level is the relatively infrequent use of visualizations employing absolute and ordinal data to explain *any* type of process. The lack of visualizations based on absolute data is perhaps not surprising: many performance and psychometric measures are typically expressed using ratio data (e.g., percent of maximum throughput or attitude toward particular technology). The lack of visualizations of ordinal data to explain system processes is more surprising, but perhaps may in part be due to the lack of statistical methods for treating ordinal data, as well as to the ready availability of more precise (i.e., ratio) data.

At the **data→visualization** level, ratio and nominal data are most predominantly used, but chiefly for multidimensional and network visualizations, respectively. One obvious gap here is in the visualization of time series data (typically based on ordinal or ratio data). Given the well documented advantages of visualizations in explaining time series, it may be that this gap is reflective of a larger gap—and hence an opportunity—in examining time-based processes in computing and related sciences (Avital 2000). The need for further work in developing “time-dependent visualizations” has been emphasized by Johnson (2004), which would include interacting with time-dependent data as it unfolds.

Taking this first set of results as a whole, there are clear and significant departures from uniformity in the distribution of visualizations across adjacent levels in the framework. The results may be evidence simply of preference among researchers for different (pairwise) combinations of goal, process, visualization, and data. A possibly fruitful direction of inquiry for future research, then, is to investigate these preferences more closely, perhaps in terms of assessing perceived cognitive fit between, say, temporal visualizations using ratio versus ordinal data in relation to a given process and research goal (for additional perspective on this issue, see [van Wijk 2006]).

The second stated objective of this work is to examine the distribution of visualizations across all levels of the framework. Visual inspection of a tree diagram showing the distribution of visualizations throughout the framework reveals many unexplored branches at the *process*, *data,* and *visualization* levels. The result is reinforced via statistical testing, which shows that there are systematic departures from independence across the framework. Consequently, we conclude that the use of visualization is less expansive than it could be, perhaps impoverishing scientific discourse. Two distinct but related research paths may lead to further insight on these issues. First, additional work may be devoted to examining the expressive possibilities of existing visualizations (Bertin 1983; Tufte 1983) in light of particular values of *goal*, *process,* and *data*. Second, research may be directed toward developing new visualizations with the intention of providing a good fit with particular combinations of values of *goal*, *process,* and *data*. Johnson (2004) has argued for applying the scientific method to the task of visualization development. Guidelines for visualization development range widely, from Tufte's (1983) principles of graph design, to Card and Mackinlay's (1997) demarcation of an information visualization design space. In seeking to understand the actual genesis of visualizations, it may be useful to examine cognition during initial design. Evaluation with respect to efficacy of the resulting visualization has an important role here, a point emphasized in studies on task/visualization fit (Shneiderman 2002), as well as methods for evaluation of visualizations (North 2006; Shneiderman and Plaisant 2006).

In conclusion, use of visualization is widespread in top journals in the computing and related sciences, but this use is focused on a comparatively narrow range of **goal→process→data** combinations. A more systematic approach to developing and evaluating visualizations in the underexplored regions of the study framework may help enrich scientific discourse, while contributing to our understanding of the circumstances under which certain visualizations lead to better understanding than others.

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