Extracting Sunbeams From Cucumbers

Richard A. FEINBERG and Howard WAINER[1]

In this article we survey the display formats used in the *Journal of Computational and Graphical Statistics* during the period 2005–2010 and discover that the most dominant format was the table. We then examine the actual tables used and find that most could have been made more comprehensible had they utilized one or more of three simple rules for table construction. We illustrate these rules on tables drawn from the *Journal* and elsewhere.

Key Words: Ordering; Rounding; Spacing; Table formatting.

1. INTRODUCTION

There is a time of life, Sir,
When a man requires the repair of a table.

Samuel Johnson (1709–1784)

In the March, 2011 issue of this *Journal*, Columbia's famous polymath, Andrew Gelman (2011a), spent some time providing a tongue-in-cheek argument supporting improperly constructed tabular displays over statistical graphics. After subsequent discussion Gelman (2011b) rejoined with the question "If graphs are so great (a sentiment with which we all evidently agree) why are they not more popular?"

This question immediately raises two others:

1. How popular are graphs?

2. How popular should they be?

It seems worthwhile to try to answer the first of these and perhaps to illuminate the path toward an answer for the second. Of course such an answer must be conditional, depending on the audience and the goals of the communication. So let us narrow the discussion to a level that allows an answer, as well as one of likely interest to the readers of this *Journal*.

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[1]This work is collaborative in all regards, and the order of authorship is alphabetical.

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Let us begin by looking carefully through the pages of the last six years of this journal (2005–2010) and see what kinds of displays authors opt to use. This being a journal focused on computational statistics and graphics, we would assume that we would see an abundance of graphical displays. We were (modestly) surprised to discover that the most popular display format used was the table. This surprise was diminished after we tallied the number of articles that were dedicated to each of the journal's topics. Of the 263 articles we examined, 237 (90%) were on computational statistics and but 26 (10%) were on graphics. This led us to conclude that in the spirit of graphical clarity, some consideration should be given to presenting the name of the journal as:

Journal of Computational *and Graphical* *Statistics*

Now it should be clear why we should not have been surprised that there were not a greater proportion of graphical displays; but first a word about our priors. In an earlier survey of graphic utilization in scientific journals we found that tables dominated. For example, in the *Journal of the American Medical Association* (see Figure 1) and an almost identical picture emerged from a similar survey of the *New England Journal of Medicine* (Figure 2). A longer-term survey of *Psychological Bulletin* told an identical story (Figure 3). The story of the popularity of display formats within the pages of this journal is similar, although it varies in emphasis; see Figure 4. Tables remain the most popular format, but they are not the runaway favorite. Tables combined with Line Graphs and Scatterplots (both the ordinary and enhanced kind) account for fully 75% of all data displays found in this journal

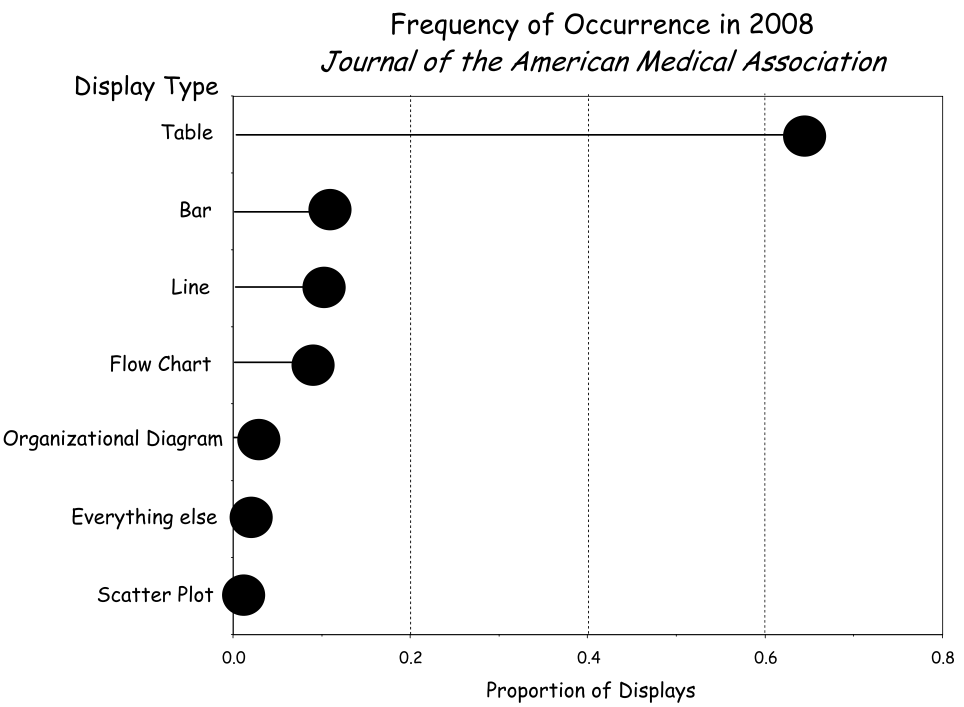

Figure 1. Summarizing display formats for the *Journal of the American Medical Association* in 2008.

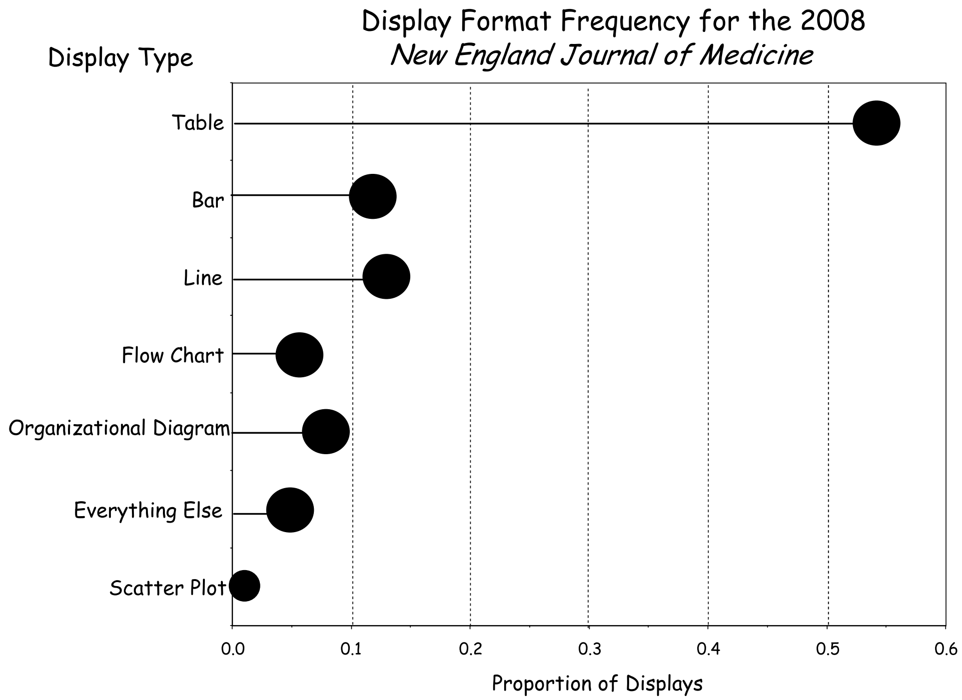

Figure 2. Summarizing display formats for the *New England Journal of Medicine* in 2008.

over the six years surveyed. From this historical perspective, it seems clear that we could do the most good by focusing our attention on the tabular format with the goal of improving its use.

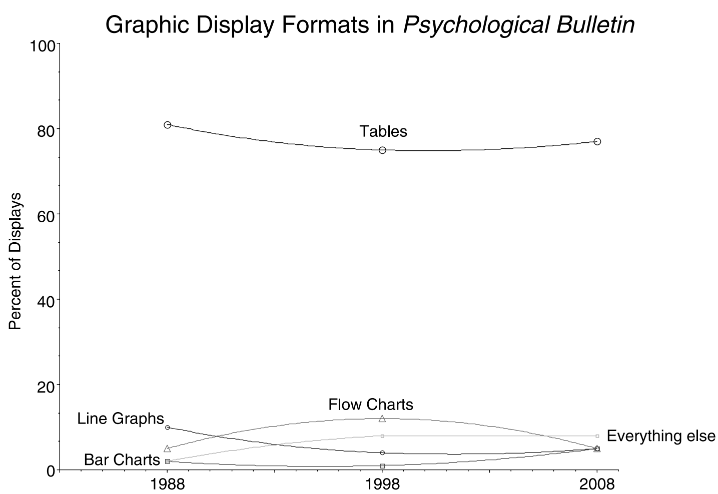

Figure 3. Summarizing display formats for the journal *Psychological Bulletin* from 1988 until 2008.

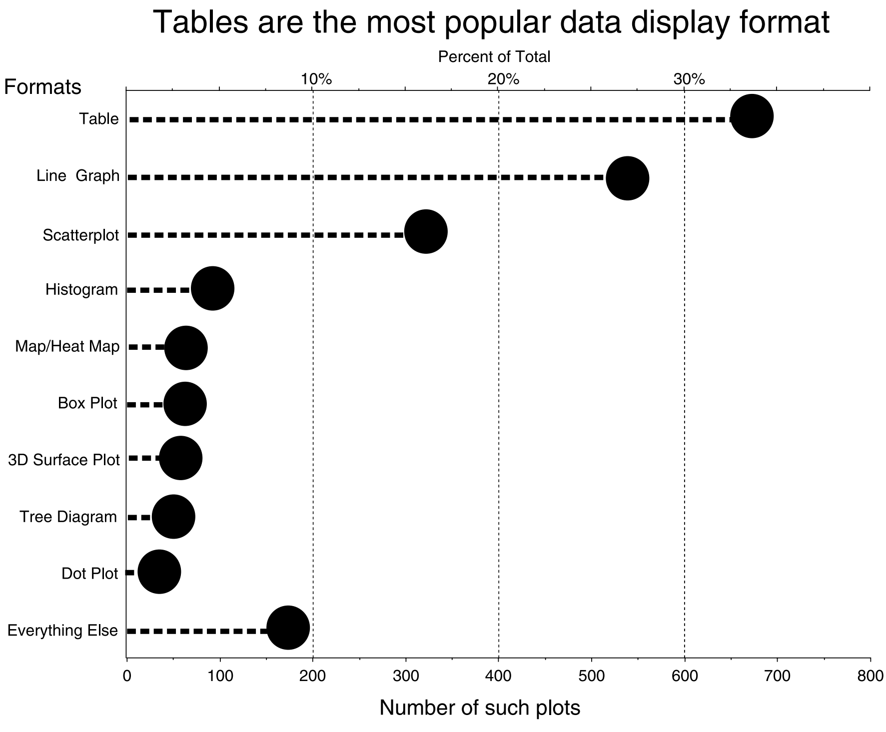

Figure 4. Summarizing display formats for the *Journal of Computational and Graphical Statistics* from 2005 until 2010.

2. WHAT'S THE PROBLEM?

> *"The graphical method has considerable superiority for the exposition of statistical facts over the tabular. A heavy bank of figures is grievously wearisome to the eye, and the popular mind is as incapable of drawing any useful lessons from it as of extracting sunbeams from cucumbers."*
>
> Farquhar and Farquhar (1891, p. 55)

It is hard to refute the conclusion of the brothers Farquhar; it is harder to draw inferences from tables than from graphs. But this brings us back to Gelman's question that instigated this article: "If graphs are so great why are they not more popular?" The irony of this comment is made greater through our discovery that even in a journal dedicated, at least in part, to graphical statistics, tables are preferred to any single graphical format.

It seems clear that tables will still be the format of choice for many datasets. This will be true for a collection of reasons; three among them are:

(i) Data are usually recorded initially as a table.

(ii) Tables are easy to prepare; just use EXCEL or any other spreadsheet program.

(iii) Tables make the extraction of specific entries easy.

This is not likely to change any time soon, so it seems worthwhile to think a bit about how to improve the tabular format, so that it is less susceptible to the scorn expressed by the Farquhars.

Before going forward with some guidelines it will surely be helpful to have an orienting attitude. In the past, an important role for tables was for data storage. In the modern world this role is better served by some electronic format. Instead the table is used for human eyes and human minds, and so many of the various elements critical for an accurate archive may no longer be suitable.

To make a table more compatible with the strengths and weaknesses of the human mind we should make it more graphical. What does this mean? The very heart of a graphic display is that it uses space to convey information, whereas a table uses icons (numbers) to do it. A number is an icon that we must read; an effective graphic we can just see. Happily, numbers are often a little graphic: 100 looks bigger than 10, and 10 in its turn looks bigger than 1. Sadly, we lose this little bit of help if we insist on printing out all numbers in the same way, for example, 9.977324 and 1.443357.[2] Note if we had rounded to integers we would have had 10 and 1 and been able to see the difference without reading.

Using the metaphoric, rather than the iconic, character of numbers to convey information is but one way to make tables more like a graph, and hence more comprehensible. The general idea of making a table more like a graph means using space, the location of data representation in the xy plane, to convey information.

2.1 THE FIRST STEP TOWARD TABULAR IMPROVEMENT: ROUNDING

Let us consider table 5 from the article by Nelson et al. (2006), an excerpt of which is shown as Table 1.[3]

The conclusion they drew from the simulations summarized in this table was that when the data come from the same distribution as was assumed the method yielded unbiased estimates, but when there was a mismatch a bias resulted. But if we round the entries in the table (see Table 2), these inferences are hard to miss. Note that we also eliminated the

Table 1. An extract of Nelson et al.'s (2006, table 5).

			Random effects distribution		
Parameter	n_i	N	Gamma($\frac{1}{\theta_1}, \theta_1$)	Normal(0, θ_1)	Gamma*($\frac{1}{\theta_1}, \theta_1$)
$\theta_1 = 1$	5	10	0.981 (0.548)	1.042 (0.730)	1.763 (1.397)
		50	0.995 (0.231)	1.018 (0.298)	1.644 (0.522)
		100	1.000 (0.163)	1.008 (0.203)	1.646 (0.365)
		250	1.000 (0.098)	1.001 (0.114)	1.635 (0.219)
	10	10	0.967 (0.479)	0.994 (0.536)	1.888 (1.434)
		50	1.000 (0.201)	0.986 (0.228)	1.747 (0.522)
		100	0.993 (0.136)	0.990 (0.157)	1.721 (0.352)
		250	1.010 (0.098)	1.000 (0.101)	1.729 (0.226)

[2]We suspect that results like these, seen in the output of virtually all statistics software, are the unfortunately anachronistic result of fifty-year-old FORTRAN F12.6 format statements. How long gone are such notions!

[3]This is a long way from the only case in which the use of an unrounded tabular format hides what the author wanted to show (e.g., Park, Vannucci, and Hart 2005; Loader and Pilla 2007; Chen, Variyath, and Abraham 2008).

Table 2. A revision of Table 1 with entries rounded to one decimal place and headings changed to be more evocative. Source: Nelson et al. (2006).

			Random effects distribution		
Parameter	n_i	N	Gamma assumed Gamma	Normal assumed Normal	Gamma assumed Normal
$\theta = 1$	5	10	1	1	1.8
		50	1	1	1.6
		100	1	1	1.6
		250	1	1	1.6
	10	10	1	1	1.9
		50	1	1	1.7
		100	1	1	1.7
		250	1	1	1.7

standard errors which had little to do with the principal point of the display and added visual clutter. This result illustrates why the first step in improving tables is to round, a lot. This for three reasons:

a. Humans cannot comprehend more than three digits[4] very easily.

b. We almost never care about accuracy of more than three digits.

c. We can only rarely justify more than three digits of accuracy statistically.

Let us consider these one at a time.

First, comprehension. Consider standing in front of a large audience to which you are describing the annual corporate budget. On the screen is a list of the budgetary components, which sum to $128,322,114,357. What do you say as you describe the total? What does the audience remember? The answer to both questions is surely "$128 billion." One can imagine performing a variety of psychophysical experiments, akin to those reported by Cleveland and McGill (1984) to confirm this, but they hardly seem necessary.

Moving on to point (b), we often hear complaints that with such violent rounding we are compromising accuracy. Perhaps, but by how much? In this case it is about 0.1%.[5] In Table 3 we show a list of the revenues of ten large corporations as well as the error introduced by rounding. Who would believe the $212 appended to Wal-Mart's figure? One suspects that this was included to show that accountants have a sense of humor as well. Mark Twain (1989) weighed in on this when he pointed out (in *Following the Equator*, chapter 59) that, "*Often the surest way to convey misinformation is to tell the strict truth.*"

[4]Actually, we prefer just two digits, but have been persuaded that we must move toward this goal in steps: first, three digits, then later, two. In fact, we have found that one-digit correlation matrices are useful surprisingly often. But that may be a bridge too far—at least now.

[5]The American economist Edgar Russell Fiedler made this point clearly when he pointed out that "Economists state their GNP growth projections to the nearest tenth of a percentage point to prove they have a sense of humor."

Table 3. Corporate Revenues for ten largest corporations in full and rounded.

Corporation	Corporation Revenue ($) in 2003	Billions ($)	Percent error
1. Wal-Mart Stores (U.S.A.)	256,317,134,212	256	0.1
2. BP (U.K.)	232,645,976,455	233	0.2
3. ExxonMobil (U.S.A.)	222,879,200,000	223	0.1
4. General Motors (U.S.A.)	185,500,000,000	186	0.3
5. Ford Motor (U.S.A.)	164,211,100,000	164	0.1
6. DaimlerChrysler (Germany)	157,100,000,000	157	0.1
7. Toyota Motor (Japan)	135,788,000,000	136	0.2
8. General Electric (U.S.A.)	134,200,125,874	134	0.1
9. Royal Dutch/Shell Group (Netherlands/U.K.)	133,590,667,000	134	0.3
10. Total Fina Elf (France)	131,600,000,000	132	0.3

And, finally, point (c), a statistical argument. Suppose we have a correlation that we calculate to be equal to 0.7654. What is the sample size that would justify reproducing this number to this level of precision? We would want a standard error to be less than 0.00005, for it is only in this situation that we have a reasonable chance for the last digit to be a 4 and not a 3 or 5. We note that the standard error is proportional to one over the square root of the sample size ($1/\sqrt{n}$). And so, doing the algebra yields

$$\text{standard error} = 0.00005 = 1/\sqrt{n}, \qquad \text{or}$$

$$\sqrt{n} = 1/0.00005 = 20{,}000, \qquad \text{or}$$

$$n = (20{,}000)^2 = 400 \text{ million}.$$

We leave as an exercise for the reader to calculate the sample size necessary to justify reproducing a correlation to more than one decimal place (hint: $n > 400$).

2.2 THE SECOND STEP—ALL IS DIFFERENT AND IMPORTANT

In most tables it is usually useful, and often critical, to surround the table with some kind of summary statistics. Sometimes these are sums, sometimes means, but most often medians have proven to be the summary of choice. The characteristic that makes medians especially useful is their insensitivity to unusual data points. Thus the median can represent the mass of points and when we look at deviations from medians unusual points will have large residuals. In addition to computing row or column (or both) summaries, we should also separate them perceptually from other entries: make them bold and perhaps space them apart and/or separate them with a ruled line.

As one example of how such practice can help, consider Table 4, which is drawn directly from the article by Vivar and Ferreira (2009). One of the authors' aims is to compare the performance of the various models shown in the table. Such comparisons are usually more easily done if they are made across columns rather than down rows. In Table 5 we have transposed the table, rounded the entries to integers, and calculated the median value for each column. These medians are shown, suitably labeled, in bold at the bottom of the table separated from the other entries by a solid line. Now that we have a standard of comparison

Table 4. Originally table 1 in Vivar and Ferreira (2009, p. 668).

SDI	Criterion	Model I	II	III	IV	V	VI	VII	CML
Yes	BF	0	**26**	−500	−230	−142	−214	−138	–
	DIC	3658.2	3653.0	3659.4	3645.8	3671.2	3647.7	3665.4	–
	pD	489.3	505.9	565.4	541.2	535.2	541.3	552.4	–
No	BF	−27	−24	−449	−449	−333	−445	−331	NA
	DIC	3637.7	3635.6	3655.5	3655.5	3664.7	3657.2	3663.0	4057.4
	pD	582.9	587.0	605.3	605.3	594.5	604.6	595.9	1081.4

Table 5. Vivar and Ferreira's (2009) table transposed, rounded, and column medians computed.

	SDI = Yes Criterion			SDI = No Criterion		
Model	BF	DIC	pD	BF	DIC	pD
I	0	3658	489	−27	3638	583
II	26	3653	506	−24	3636	587
III	−500	3659	565	−449	3656	605
IV	−230	3646	541	−449	3656	605
V	−142	3671	535	−333	3665	595
VI	−214	3648	541	−445	3657	605
VII	−138	3665	552	−331	3663	596
CML	–	–	–	–	4057	1081
Medians	**−142**	**3658**	**541**	**−333**	**3656**	**600**

Table 6. Table 5 re-expressed as the ratio of each entry to its column median.

	SDI = Yes Criterion			SDI = No Criterion		
Model	BF	DIC	pD	BF	DIC	pD
I	0	1	1	0	1	1
II	0	1	1	0	1	1
III	4	1	1	1	1	1
IV	2	1	1	1	1	1
V	1	1	1	1	1	1
VI	2	1	1	1	1	1
VII	1	1	1	1	1	1
CML	–	–	–	–	1	2

we can see that there is only modest variation from the median within each column. Indeed we can make the constancy within columns, BF columns excepted, abundantly clear by simply dividing each entry in a column by its median (see Table 6). For those who fear that the rounding to the nearest integer has lost some important precision we could easily present these ratios to one or even two decimal places, but doing so emphasizes the small differences within the column rather than the overwhelming similarity.

2.3 THE THIRD STEP: ORDERING

We are almost never interested in "Anaheim First."

The order of the rows and columns of a table should be based on the data within it, almost never on the alphabet, nor on any other arbitrary label. One often useful order is based on the size of the row (or column) effects. This is why we recommended calculating these effects in Step 2. Ordering by the data relates the location of a data point on the page to the point's value on an aspect of the data important to us, thus making the table more graphic.

Ordering sensibly yields many benefits, some surprising. Quite often the order reflects the location of each row (column) on some latent dimension. It also helps us pick out groupings and unusual points. It accomplishes these things effortlessly.

Let us consider an example from within the pages of JC&GS. Table 1 from the article by Daniels, Zhou, and Zou (2006, p. 167), shown here as Table 7, carries in it information about pollution in various parts of the Los Angeles area. The top panel is for particulate matter (PM), the bottom panel is for ozone. The order of the rows is arbitrary, determined by the code numbers that indicate the location where the measurements were taken. We can clarify matters by reordering both the rows and the columns of the table. The columns can be reordered to graphically show the mean value of the pollutant as resting between its minimum and maximum values, while making the mean value (our primary concern) visibly larger. If we reorder the rows of each panel by the mean amounts (Table 8), two things become evident. First, in the top panel there is a clear gap (Wainer 1983) between sites 3 and 4 (Roubidoux and Fontana), and the remaining three sites (1, 2, and 5—Los Angeles, Diamond Bar, and Anaheim). In the bottom panel Long Beach (site 6) seems unusually low in ozone, perhaps because of its proximity to the ocean and its cleansing breezes.

We also indicated, by boxing it in, Crestline (site 11), which in addition to being high in ozone also shows unusual variability (its standard deviation is almost twice that of other sites).

Last, we also included the names of each of the sites. It would be hard to imagine any use for these results that would not need that information.[6]

An interpretation was suggested by one long-term Los Angeles resident who explained,

> "*Rialto/Rubidoux/Fontana are part of the inland empire. From Eagle Rock you take I-210 East 30 miles to Claremont (Harvey Mudd College) + 20 miles more along the 210 East and you're in Fontana. The wind also blows east and takes all of the smog from Los Angeles and the San Gabriel Valley to Rialto/Rubidoux/Fontana. The smog pretty much just settles in Rialto/Rubidoux/Fontana.*

[6]We are grateful to Michael Daniels for generously sharing the identification information for his dataset.

Table 7. From Daniels, Zhou, and Zou's (2006) table 2 of Los Angeles pollution data.

Pollutant	Site no.	Mean	Variance	Min	Max
Particulate matter	1	3.93	0.077	3.42	5.27
	2	3.70	0.056	3.13	4.76
	3	4.38	0.059	3.75	4.81
	4	4.21	0.112	3.36	5.35
	5	3.79	0.040	3.47	4.34
Ozone	1	3.22	0.042	2.73	3.61
	2	3.15	0.073	2.65	3.65
	3	3.78	0.059	3.35	4.25
	4	3.68	0.082	3.21	4.27
	5	3.38	0.082	2.73	3.85
	6	2.67	0.094	1.72	3.24
	7	3.66	0.046	3.30	4.10
	8	3.73	0.121	2.83	4.55
	9	3.46	0.051	2.96	4.05
	10	3.57	0.118	3.14	4.60
	11	4.00	0.282	1.97	4.59
	12	3.28	0.089	2.48	3.88
	13	3.13	0.092	2.45	3.71
	14	3.83	0.061	3.41	4.38
	15	3.30	0.044	2.59	3.71
	16	3.79	0.043	3.23	4.19
	17	3.96	0.054	3.39	4.45
	18	3.24	0.067	2.64	3.73
	19	3.81	0.058	3.17	4.32
	20	3.92	0.075	3.36	4.35
	21	3.63	0.095	3.05	4.28
	22	3.66	0.053	3.29	4.11
	23	3.54	0.047	3.04	4.01
	24	3.86	0.058	3.34	4.41
	25	3.43	0.038	3.02	3.84
	26	3.53	0.040	3.13	3.96
	27	3.53	0.068	3.08	4.03
	28	4.04	0.083	3.37	4.54
	29	3.48	0.062	2.82	4.04
	30	3.95	0.065	3.53	4.41
	31	3.80	0.062	3.35	4.60
	32	3.59	0.051	3.03	4.60
	33	3.75	0.074	3.33	4.28
	34	3.84	0.139	2.57	4.60
	35	3.31	0.046	2.62	3.73

Lastly, the 210 freeway was only recently extended to Rialto and was accompanied by a burst of new housing construction."

But for those of us without intimate knowledge of the local geography, plotting these locations on a map of Los Angeles might help us see if their pollution had an obvious explanation (e.g., lower near the ocean, higher along freeways, etc.). Better still is a map of this region connecting areas that share common ozone levels (see Figure 5). This instantly provides us with a better understanding of these results.

Table 8. Table 7 revised by reordering, spacing, and adding identification information.

Pollutant	Site Name	Site No.	Min	Mean	Max	Std. dev.
Particulate matter	*RUBIDOUX*	3	3.8	4.4	4.8	0.2
	FONTANA	4	3.4	4.2	5.4	0.3
	LOS ANGELES	1	3.4	3.9	5.3	0.3
	DIAMOND BAR	5	3.5	3.8	4.3	0.2
	ANAHEIM	2	3.1	3.7	4.8	0.2
	Medians		**3.4**	**3.9**	**4.8**	**0.2**
Ozone	*CRESTLINE*	11	2.0	4.0	4.6	0.5
	HESPERIA	28	3.4	4.0	4.5	0.2
	REDLANDS	17	3.4	4.0	4.5	0.3
	SAN BERNARDINO	30	3.5	4.0	4.4	0.3
	LANCASTER	20	3.4	3.9	4.4	0.3
	PERRIS	24	3.3	3.9	4.4	0.2
	UPLAND	34	3.4	3.8	4.3	0.2
	GLENDORA	14	3.4	3.8	4.4	0.2
	HEMET	19	3.2	3.8	4.2	0.2
	LAKE ELSINORE	31	3.2	3.8	4.3	0.2
	SIMI VALLEY	16	3.4	3.8	4.6	0.2
	RUBIDOUX	3	3.3	3.8	4.3	0.3
	VICTORVILLE	33	2.6	3.8	4.6	0.4
	AZUSA	8	3.2	3.7	4.3	0.3
	FONTANA	4	3.3	3.7	4.1	0.2
	BANNING	7	2.8	3.7	4.6	0.3
	NORCO	22	3.3	3.7	4.1	0.2
	COSTA MESA	21	3.1	3.6	4.6	0.3
	NEWHALL	32	3.1	3.6	4.3	0.3
	THOUSAND OAKS	10	3.0	3.6	4.6	0.2
	BURBANK	23	3.0	3.5	4.1	0.2
	PASADENA	26	3.0	3.5	4.0	0.2
	PIRU	27	3.1	3.5	4.0	0.2
	POMONA	29	3.1	3.5	4.0	0.3
	RESEDA	9	2.8	3.5	4.0	0.2
	DIAMOND BAR	5	2.7	3.4	3.9	0.3
	PICO RIVERA	25	3.0	3.4	3.8	0.2
	EL RIO	35	2.5	3.3	3.9	0.3
	HAWTHORNE	15	2.6	3.3	3.7	0.2
	WEST LOS ANGELES	12	2.6	3.3	3.7	0.2
	LA HABRA	18	2.7	3.2	3.6	0.2
	LOS ANGELES	1	2.7	3.2	3.7	0.3
	ANAHEIM	2	2.6	3.2	3.7	0.3
	EL TORO	13	2.5	3.1	3.7	0.3
	LONG BEACH	6	1.7	2.7	3.2	0.3
	Medians		**3.1**	**3.6**	**4.2**	**0.2**

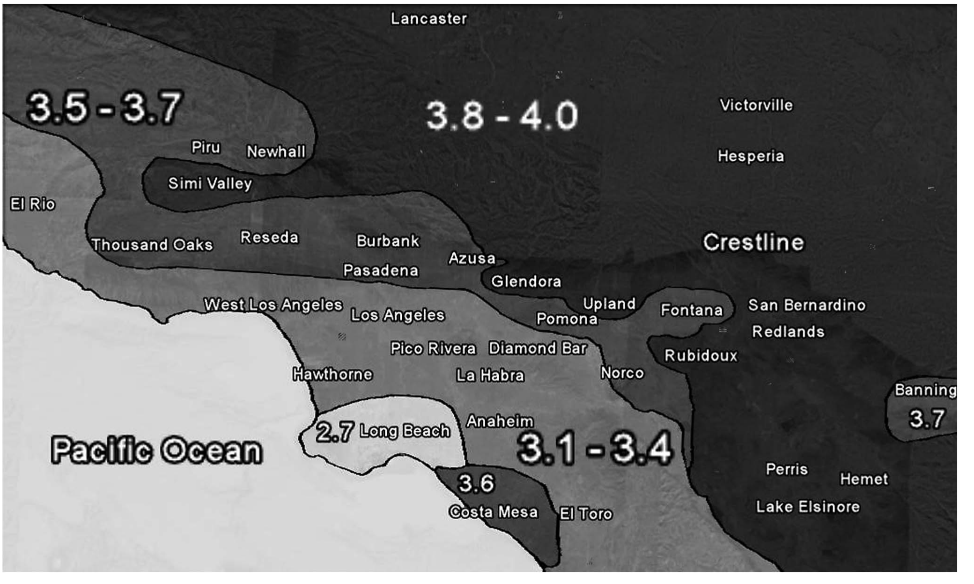

Figure 5. Ozone concentrations in the Los Angeles Area increase with distance from the Pacific Ocean (data from Daniels, Zhou, and Zou 2006).

3. MANY OF THE GRAPHS COULD USE SOME WORK, TOO

The focus of this essay was on tables, but we did not want to leave the false impression that none of the graphs that grace the pages of JC&GS would profit from any further attention. They could, but we will leave a more extensive review to other accounts. A quick taste of the kinds of treasures that such a review could mine might start with “How to display data badly” (Wainer 2000, chapter 1). We note Rule 1: Show as few data as possible, which was illustrated with a figure from a *Journal of the American Statistical Association* article by Friedman and Rafsky (1981). Their figure showed but four data points in 8 square inches for a data density of 0.5 (see Figure 6). This is a mark for limiting information that is not easily beaten. But coming close is a figure from an article by Lazar (2005) with a great deal of open space (see Figure 7). It has ten data points in 12 square inches, for a density of 0.8; close but no cigar.

4. CONCLUSION AND DISCUSSION

In this essay we have shown how applying three simple rules when you prepare tables can often yield dramatic improvements in the comprehensibility of the display. Reviewing, those rules are:

1. Round entries to no more than three digits. Often two or even one digit will be even better.

2. Calculate some kind of summary statistic for both rows and columns. Sometimes a total, sometimes a mean, but most often a median because of its resistance to the

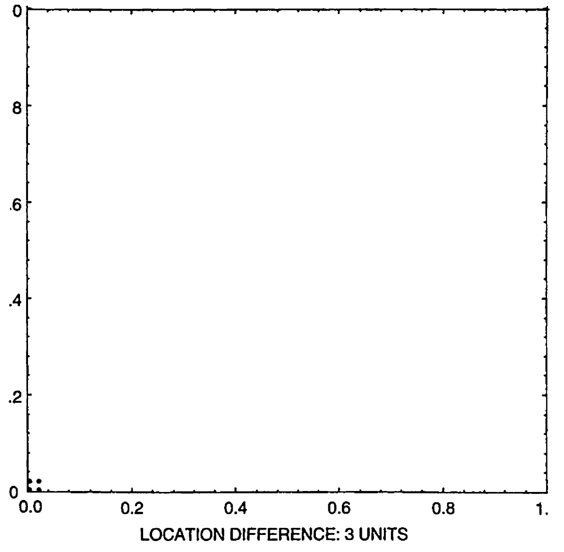

Figure 6. From Freedman and Rafsky (1981).

effects of long tails is the summary of choice. These summaries are different than the rest of the table's components and so should be set apart visually; perhaps in **bold face**, perhaps spaced apart, perhaps separated with a thin line. Most often using all of these is the best choice.

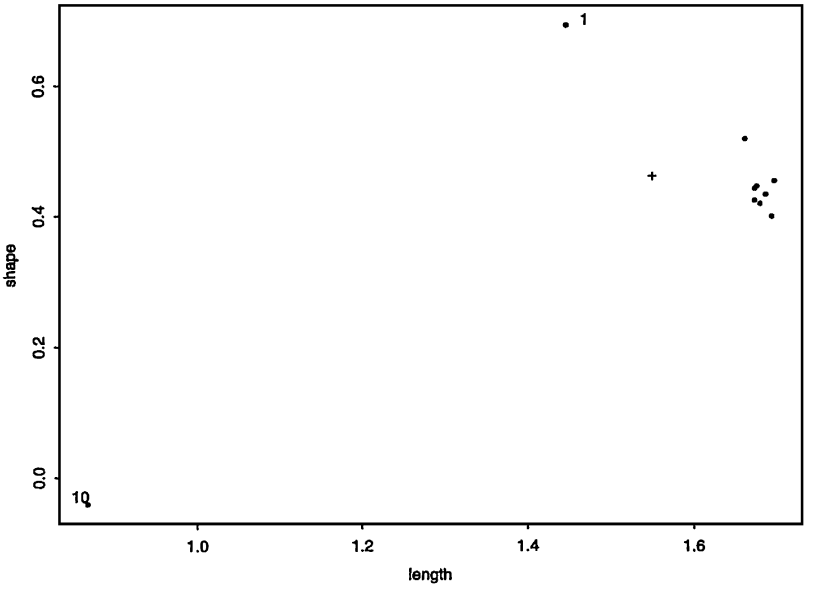

Figure 7. From Lazar (2005).

3. Order the rows and the columns in a way that is not arbitrary. Alphabetical order is rarely the most useful option, whereas ordering by the size of the effect (calculated in Step 2) yields greatest dividends.

Is this all that can be done? No, but just these three steps often take us 90% of the way there. Two other steps that are often helpful, because they use space to convey information, are:

4. Insert extra space between rows (columns) when the data seem to indicate a gap. Remember that a gap in the middle of a distribution has greater meaning than the same size gap in a tail. To determine the likelihood that an observed gap is not epiphenomenal they need to be somehow equalized. One approach that uses inverse Gaussian weights on the gaps, based on the gap's order statistics, has worked very well since its initial development more than 30 years ago (Wainer and Schacht 1978; Wainer 1983).

5. Indicate unusual entries (e.g., interactions). The row and column summaries typically will show the main effects, but there may be unusual individual entries that warrant attention. One approach is to simply encircle the unusual entry with a box. This works well if there are not too many. When an additive model is appropriate we can uncover which entries deserve highlighting by removing the row and column effects and then highlighting especially large residuals.

A fully worked example that uses all of these techniques is found in chapter 10 of the book by Wainer (2000).

Let us conclude with a dramatic illustration of how thoughtfully following these rules can transform what is an otherwise unremarkable table into one that reveals deep truths about the topic of the data (taken from chapter 11 of Wainer 2005). Consider the table shown as Table 9 in which the rows are countries that receive arms shipments from the countries that are the columns during the years 1975–1979. The entries are the dollar values of the arms received by the indicated buying country from the indicated selling country. The order of the rows is alphabetical; the columns were ordered by the dollar value of their total exports. This table already has been surrounded by the row and column totals, and they are emphasized to set them apart from ordinary entries. But if we reorder the rows of the table first by the value of the arms each country imports from the Soviet Union and then by the value of what they import from the United States (see Table 10), we immediately see several things, previously hidden:

1. There are only two major arms exporters: the USSR and the US.

2. Importing countries typically buy arms from one or the other, rarely both. These buying patterns reflect political alignments.

3. A few arms exporting countries (mostly France) will sell to anyone.

We began this essay with Samuel Johnson's observation that sometimes we need to repair a table. We hope that the procedures we have advocated aid in this reparation and

Table 9. Value of arms transfers, cumulative 1975–1979, by major supplier and recipient country (in millions of current dollars).

		Suppliers										
Recipient	Total	Soviet Union	United States	France	United Kingdom	West Germany	Czecho-slovakia	Italy	Poland	China	Canada	Others
Afghanistan	465	450	–	–	–	–	10	–	–	–	–	5
Algeria	1940	1500	–	10	–	350	–	10	–	–	–	70
Angola	845	500	–	5	10	10	10	–	20	–	–	290
Argentina	970	–	90	270	60	110	–	80	–	–	–	360
Australia	690	–	420	–	130	130	–	–	–	–	–	10
Belgium	615	–	270	40	120	140	–	–	–	–	5	40
Brazil	740	–	160	50	400	20	–	80		–	–	30
Bulgaria	1230	1200	–	–	–	–	20	–	10	–	–	–
Canada	1035	–	825	–	10	190	–	–	–	–	–	10
China	630	210	–	50	350	–	–	–	–	–	10	10
Cuba	875	875	–	–	–	–	–	–	–	–	–	–
Czechoslovakia	1250	1200	–	–	–	–	–	–	–	–	–	50
Ecuador	575	–	40	280	70	110	–	5	–	–	10	60
Egypt	1500	250	250	490	110	180	20	60	–	60	–	80
Ethiopia	1830	1500	90	10	–	5	30	20	10	5	–	160
Germany, East	2005	1700	–	–	–	–	230	–	70	–	–	5
Germany, West	2230	–	1600	140	10	–	–	10	–	–	10	460
Greece	1990	–	1200	390	20	230	–	60	–	–	10	80
Hungary	1035	975	–	–	–	–	50	–	10	–	–	–
India	2150	1800	40	40	100	10	50	20	40	–	–	50
Iran	8770	650	6600	200	310	430	–	340	–	–	–	240
Iraq	6780	4900	–	410	20	160	80	70	30	10	–	1100
Israel	4300	–	4200	10	60	–	–	30	–	–	–	–
Italy	620	–	550	–	–	10	–	–	–	–	–	60
Japan	745	–	725	–	20	–	–	–	–	–	–	–
Jordan	590	–	500	–	20	5	–	–	–	–	5	60
Korea, North	580	280	–	–	–	10	–	–	10	170	–	110
Korea, South	1925	–	1700	10	5	80	–	50	–	–	40	40
Kuwait	790	50	350	150	210	20	–	–	–	–	–	10
Libya	6910	5000	–	310	10	160	270	450	250	–	–	460
Morocco	1415	20	310	725	5	50	5	50	–	–	–	250
Netherlands	690	–	370	–	120	80	–	10	–	–	10	100
Pakistan	895	20	180	320	20	–	5	–	–	240	–	110
Peru	1090	650	100	110	10	40	–	80	–	–	–	100
Poland	1420	1200	–	–	–	–	210	–	–	–	–	10
Romania	875	675	–	70	–	–	30		70	10	–	20
Saudi Arabia	3590	–	1800	290	900	20	–	130	–	–	–	450
South Africa	535	–	20	310	–	–	–	50	–	–	5	150
Soviet Union	2850	–	–	–	–	–	1900	–	800	–	–	150
Spain	1020	–	550	170	–	90	–	20	–	–	10	180
Switzerland	580	–	460	–	10	–	–	–	–	–	10	100
Syria	4500	3600		190	30	100	310	–	10	–	–	260
Turkey	1110	–	550	–	–	290	–	240	–	–	–	30
United Kingdom	915	–	825	30	–	–	–	–	–	–	–	60
United States	790	–	–	5	230	70	–	5	–	–	250	230
Viet Nam, North	1320	1300	–	–	–	–	–	–	–	10	–	10
Viet Nam, South	850	–	850	–	–	–	–	–	–	–	–	–
Yemen (Aden)	580	575	–	–	–	–	–	–	–	–	–	5
Yemen (Sanaa)	620	210	110	80	–	5	–	5	100	–	–	110
Yugoslavia	630	525	10	20	10	–	–	10	5	–	20	30
TOTAL	82,885	31,815	25,745	5185	3380	3105	3230	1885	1435	505	395	6205

Table 10. Value of arms transfers, cumulative 1975–1979, by major supplier and recipient country sorted to show structure, some Middle Eastern recipients shaded for emphasis (in millions of current dollars).

	Suppliers								
Recipients	**Soviet Union**	Czecho-slovakia	Poland	**United States**	United Kingdom	France	West Germany	Italy	Others
Libya	5000	270	250			**310**	**160**	**450**	**460**
Iraq	4900					**410**	**160**		**1110**
Syria	3600	310				**190**	**100**		**260**
India	1800				100				
Germany, East	1700	230							
Ethiopia	1500								165
Algeria	1500						350		
Viet Nam (North)	1300								
Bulgaria	1200								
Czechoslovakia	1200								
Poland	1200	210							
Hungary	975								
Cuba	875								
Romania	675								
Peru	650			100		110			100
Yemen (Aden)	575								
Yugoslavia	525								
Angola	500								290
Afghanistan	450								
Korea, North	280								280
South Africa						310			155
Ecuador						280	110		
Argentina						270	110		360
China	210				350				
Yemen (Sanaa)	210		100	110					110
Brazil				160	400				
Pakistan				180		320			350
Egypt	250			250	110	490	180		140
Belgium				270	120		140		
Morocco				310		725			250
Kuwait				350	210	150			
Netherlands				370	120				110
Australia				420	130		130		
Switzerland				460					110
Jordan				500					
Turkey				550			290	240	
Spain				550		170			190
Italy				550					
Japan				725					
Canada				825			190		
United Kingdom				825					
Viet Nam, South				850					
Greece				1200		390	230		
Germany, West				1600		140			470
Korea, South				1700					
Saudi Arabia				1800	900	290		130	450
Israel				4200					
Iran	650			6600	310	200	430	340	240
TOTAL	**31,725**	**1020**	**350**	**25,455**	**2750**	**4755**	**2580**	**1160**	**5600**

help to make real the demand expressed by the Hebrew prophet Habakkak almost three thousand years ago:

Write the vision,
and make it plain upon tables,
That he may run that readeth it.

Habakkak was clearly concerned with utilitarian purposes, a view with which we certainly resonate. We believe that the suggestions we have made, if followed, would satisfy him. But sometimes, when the data support it and we are very lucky, what emerges from proper design is so much more. This same vision of a transcendent table was described by the poet William Blake (1757–1827):

Wondrous the gods, more wondrous the men,
More wondrous, wondrous still the cock and hen,
More wondrous still the table.

and is what we all strive for. We hope that this essay pushes practice a bit in that direction. But, to return briefly to Gelman's comment that motivated this research, we must point out that while there is a great deal that can be done to make tables better, and that sometimes they can, indeed, be wondrous, tables have limitations that cannot easily be surmounted. No matter how clever we were in revising Daniels, Zhou, and Zou's table of Los Angeles air pollution, no table could ever communicate as much as a quick glance at the map in Figure 5.

We fully expect that tables will continue to dominate in the scientific literature, if for no other reason than they are so much easier to prepare than a graph. Perhaps our rules for good table preparation will have a double benefit: (i) following them will result in clearer tables, but doing such revisions takes a little extra time and care, thus diminishing the marginal difference in effort required to prepare a graphical representation and as a result might then (ii) increase the likelihood that a suitable graph will be prepared and used.

We can only hope.

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