Chapter 3
Grables: Visual Displays That Combine the Best Attributes of Graphs and Tables

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Abstract A grable combines the emergent features of a graph with the precise quantities of a table into a single display. Its purpose is to accommodate a wider variety of visual tasks and a possibly wider audience, than either a graph or a table can address alone. The best principles of visual perception from both graph and table design and construction should be considered when designing and constructing grables. We present some proposed visual and cognitive strengths and weaknesses of graphs and tables, the visual tasks that each is best suited for, and some specific guidelines for their design and construction. We use these guidelines and principles of perception to design and construct a variety of grables. We also provide some general guidelines for software selection.

3.1 Introduction

A grable combines the emergent features of a graph with the precise quantities of a table into a single display. Its purpose is to accommodate a wider variety of visual tasks and a possibly wider audience, than either a graph or a table can address alone (Hink et al. 1996, 1998). We present two introductory examples.

3.1.1 Example 1: Oral Contraceptive Interaction Study: Pharmacokinetic Data

A well-known grable often used for exploratory data analysis is the stem-and-leaf display (Tukey 1977). This display not only provides a histogram of the sample

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A. Krause and M. O'Connell (eds.), *A Picture is Worth a Thousand Tables: Graphics in Life Sciences,* DOI 10.1007/978-1-4614-5329-1_3,

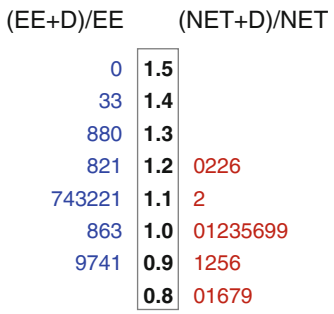

Fig. 3.1 Individual AUC ratios. Individual ratios of AUCs comparing Drug D administered with an oral contraceptive (OC + D) versus the oral contraceptive alone (OC) in 22 female subjects. The oral contraceptive is comprised of two components, ethinyl estradiol (EE) and norethindrone (NET). Ratios shown are (EE + D)/EE and (NET + D)/NET

distribution, but it also documents the data values. In Fig. 3.1, the back-to-back stem-and-leaf plot displays the ratios of areas under the plasma-concentration-versus-time-curves (AUCs) for 22 female subjects who completed a 2-treatment, 2-period, complete crossover oral contraceptive interaction trial. The objective of the trial was to determine if the concomitant administration of Drug D with an oral contraceptive (OC + D) perturbs the usual pharmacokinetic profile of the oral contraceptive alone (OC). The oral contraceptive is comprised of two components, ethinyl estradiol (EE) and norethindrone (NET).

In Fig. 3.1, the ratios correspond to each component of the oral contraceptive, (EE + D)/EE and (NET + D)/NET. The stem (vertical rectangular box) contains the *bolded black stem* values **0.8** to **1.5**, which are the observed ratios accurate to one decimal place. The leaves are shown for EE and NET hanging to the left and to the right of the *stem values*, respectively, and they provide additional accuracy to two decimal places. For example, the smallest ratio is **0.8**0, (NET + D)/NET, and the largest ratio is **1.5**0, (EE + D)/EE. At each *stem value*, the leaves are sorted from smallest to largest, starting from the stem.

Figure 3.1 immediately provides information about the sample distributions of the ratios for EE and NET. Both distributions appear to be truncated on the left as does NET on the right, but EE is somewhat skewed right. All of the ratios for NET are contained in the narrower and lower range, **0.8**0 to **1.2**6, versus **0.9**1 to **1.5**0, for EE. The sample median for NET is (**1.0**1 + **1.0**2)/2 = **1.0**15, smaller than the corresponding value, (**1.1**3 + **1.1**4)/2 = **1.1**35 for EE. Both distributions have their modal value on the stem, **1.0** for NET, which is lower than **1.1** for EE. However, the modal values for NET are **1.0**9 and **1.2**2, for EE they are **1.1**2, **1.3**8, and **1.4**3. Neither distribution contains an outlier. A detailed analysis of the original data can be found in Bradstreet and Panebianco (2004). A further generalization of the stem-and-leaf display to multi-way tables can be found in Schenker et al. (2007).

3.1.2 Example 2: Iontophoresis Induced Pain: Pharmacodynamic Data

Sixteen subjects completed an 8-treatment, 8-period, complete crossover trial investigating whether or not a proposed iontophoresis induced pain model is valid.

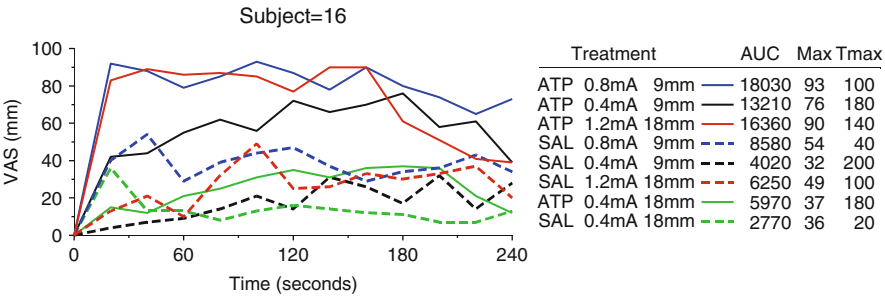

Fig. 3.2 VAS Pain Scores for Subject 16. The pain responses over time for ATP treatments are shown with *solid lines* (—), and saline treatments are shown with *dashed lines* (– – – –). Matching pairs of ATP and saline treatments are shown with the same color. Tabled along side each line are the treatment label and the corresponding summary statistics. The treatment labels are ordered from top to bottom according to the last VAS score reported at 240 s for each treatment

Each iontophoresis treatment comprised a combination of either ATP solution or saline solution (SAL), paired with one of 3 electrical currents (0.4, 0.8, 1.2 mA), using either a 9 or 18 mm iontophoresis chamber. Eight of 12 possible factorial combinations were evaluated. Given the same current and chamber size, ATP should cause more pain than saline.

Subjects scored pain on a 100 mm visual analogue scale (VAS). The VAS is a horizontal line 10 cm in length labeled with a 0 at the left end and the number 100 at the right end. Every 20 s for 4 min in each treatment period, the subjects scored their pain level by marking a vertical line on the VAS. Among the objectives of the study were to identify electrical current level and iontophoresis chamber size combinations that induce sufficient pain; to identify a range in time over the 240 s iontophoresis period where the results look most promising; and to identify within-subject summary measures computed over the individual time points that are the most sensitive and clinically meaningful.

Figure 3.2 presents the results for Subject 16. The graph portion of the grable displays the subject's VAS response for each of the eight factorial treatments. The pain responses over time for ATP treatments are shown with solid lines (—), and saline treatments are shown with dashed lines (– – – –). Matching pairs of ATP and saline treatments are shown with the same color. For example, the 1.2 mA current and 18 mm chamber size combination is shown in red. Tabled along side each VAS line is the treatment label and the corresponding summary statistics: AUC (area under the curve), Max (maximum VAS), and Tmax (time in seconds that Max was observed). The treatment labels are ordered from top to bottom according to the last VAS score reported at 240 s for each treatment.

For Subject 16 we see that in general, each ATP treatment induces more pain than its corresponding saline treatment. The difference between ATP and saline is notable in three treatments: ATP, 0.8 mA, 9 mm (solid blue); ATP, 1.2 mA, 18 mm (solid red); and ATP, 0.4 mA, 9 mm (solid black). A similarly designed grable can be used to display information summarized across the 16 subjects.

In Sect. 3.2 we present some proposed visual and cognitive strengths and weaknesses of graphs and tables, including comparisons between the two groups of displays regarding the visual tasks that each is best suited for when presenting information. Specific guidelines for their design and construction follow. We provide additional references containing additional principles of visual perception and construction of graphs and tables. In Sect. 3.3 we present some ideas on designing and constructing grables. In Sect. 3.4 we present four more examples of grables. Some of the examples are more graph than table, some are as much table as graph, and one shows a grable that is more like a text table than a graph. In Sect. 3.5 we provide some guidance on selecting software for constructing and displaying grables. In Sect. 3.6 we close with a discussion.

3.2 Graphs Versus Tables

Before focusing on grables, it is important to become familiar with proposed visual and cognitive strengths and weaknesses of graphs and tables as these should be considered when designing and constructing grables. The literature comparing graphs to tables spans a wide range of disciplines including statistics, computer science, management information systems, industrial engineering, business, management science, information science, psychology, education, and political science. Many competing theories exist as to which display formats are better than others. These theories include, but are not limited to, analytic models (e.g., Tufte 1983, 2001; Kosslyn 1989, 1994), compatibility models (e.g., Vessey 1991, 1994), and cognitive process models (e.g., Cleveland and McGill 1984, 1986, 1987; Cleveland 1985, 1994; Meyer et al. 1997; Meyer 2000).

Several visual task experiments were conducted under a wide range of experimental designs, conditions, limitations, and restrictions. Many evaluated the simplest graphs and tables under relatively simple conditions. A large portion of the results are either inconsistent or inconclusive which is not surprising given the wide range of experimental designs, endpoints, and statistical analyses performed. There are also several surveys and meta-analyses comparing graphs to tables. For example, see Carter (1947), Powers et al. (1984), Lalomia and Coovert (1987), Coll (1992), Hwang (1995), Harvey and Bolger (1996), Meyer et al. (1997, 1999), Meyer (2000), and Porat et al. (2009).

Professional opinions vary as to exactly when and why a graph is better to use than a table (Ehrenberg 1978; Gelman et al. 2002; Scott 2003; Kastellec and Leoni 2007) or a table better than a graph (Ehrenberg 1978). Sometimes neither display is deemed as appropriate and a description using only text is best as for small data sets (Carswell and Ramzy 1997), or in larger data sets when only limited results are of interest (Ehrenberg 1978). This debate is far from over (e.g., Gelman 2011). Researchers continue to conduct experiments (e.g., Porat et al. 2009). Useful observations and guidelines are emerging. We highlight some of these.

Visual tasks are divided into two categories. They are:

1. *Spatial tasks*: require making associations between values or perceiving relations in the data
2. *Symbolic tasks*: involve the extraction of individual data values

Cognitive fit exists when both the visual representation of the data and the visual task are both spatial or both symbolic. For lower level visual tasks, cognitive fit produces increased speed and accuracy in problem solving, decision making, and information retrieval (Vessey 1991; Meyer 2000).

Graphs efficiently present spatially related information identifying associations, trends, relationships, deviations, minima, maxima, and orders of magnitude in the data, facilitating a mostly qualitative view at a glance without addressing the individual elements separately or analytically. Tables efficiently present symbolic information quantitatively representing individual data values and facilitating tasks such as locating, reading, extracting individual data values, and performing exact computations such as differences and ratios on the selected values (Ehrenberg 1977c, 1978; Lalomia and Coovert 1987; Vessey 1991; Coll 1992; Harvey and Bolger 1996; Meyer 2000; Kastellec and Leoni 2007; Porat et al. 2009). Tables can also simultaneously display multiple variants of the data such as the original data, transformed data, means, proportions, differences, ratios, and percentages, in a compact area, but this must be done with care (Bradstreet et al. 2008).

The visual effectiveness of both tables and graphs can be improved by sorting the data according to purpose. For look-up and documentation capabilities in tables, sorting by patient number, alphabetically, or by one or more demographics can be productive. For understanding what the data have to say, sorting the data by the magnitude of a desired effect or trend can be insightful (Friendly and Kwan 2003; Bradstreet and Palcza 2012).

When time pressure on the viewer is low, the effectiveness of graphs and tables depends upon the type and complexity of the visual task. But with increasing time pressure, graphs generally are favored (Hwang 1995), and graphs can improve visual task performance with increased complexity.

The observers' prior and accumulating knowledge and experience with a particular graph or table format can favor that format over others (Powers et al. 1984; Meyer 2000). Rightly or wrongly, the most familiar form of data presentation is often perceived as the easiest to comprehend, even among pairs of competing table designs, or similarly among pairs of competing graph designs. Indeed we observed such familiarity bias when introducing box-and-whisker plots, schematic plots, dot charts, and several other visual displays to collaborators as alternatives to those which were their standard at the time such as pie charts and segmented bar charts. The new displays were initially met with resistance. But once the users understood the advantages of the new graphs, with use, the new graphs became familiar friends. Then the new graphs were requested routinely, even in some cases where not appropriate. People will also choose one display format over another if it requires the least effort to perform the visual task (Porat et al. 2009) regardless of its ability to correctly communicate information.

The relative efficiency of competing displays depends on one or more variables. Meyer et al. (1997) identified and summarized seven categories of variables for considering the relative efficiency of competing displays. They are:

1. Type of display (graph vs. table)
2. Variations within display type (e.g., line graph versus bar graph)
3. Conditions of presentation (e.g., visual angle, room illumination, display-background contrast, time pressure)
4. Complexity of displayed data (number of points in the display, configuration of the points in the display, regularity or order in the data displayed)
5. Information sought by the user (e.g., evaluation of trend versus extraction of specific numerical values)
6. Characteristics of the user population (e.g., users' experience with competing displays)
7. Criterion for choosing a display (e.g., speed of extraction, accuracy of information obtained, quality of decisions, understanding of complex relations between variables, aesthetic appeal, users' subjective preferences)

3.2.1 Guidelines for Graphs

Effective graphs exhibit combinations of the following qualities (Chambers et al. 1983; Cleveland 1985, 1994; Tukey 1990, 1993; Wainer 1997; Bradstreet et al. 2008). Effective graphs:

1. Serve a defined purpose: exploration, understanding, or communication
2. Show the data
3. Tell the truth
4. Encourage comparison of different pieces of data
5. Reveal a large amount of quantitative information in a small area
6. Reveal the data at several levels of detail; effectiveness increases with the complexity of the data
7. Are only as complex as required by the task that they are designed to perform; they avoid pomposity
8. Provide impact: communication with clarity, precision, and efficiency
9. Are a visual metaphor for the data
10. Are closely integrated with statistical and verbal descriptions of the data

When designing and constructing graphs, quantitative and categorical information is encoded by symbols, geometry, and color. Graphical perception is the visual decoding of this encoded information. Ten graphical-perception tasks can be ranked from best to worst on how accurately we perform those tasks in decoding quantitative information from graphs (Cleveland 1985, 1994). They are:

1. Position along a common scale
2. Position along identical, nonaligned scales

3. Length
4. Angle
5. Slope
6. Area
7. Volume
8. Color hue
9. Color saturation
10. Density of information

In addition, we must be able to detect all intended graphical elements (as is not the case with either coincident points or superimposed curves), and we must be able to judge distance accurately. These 10 elementary graphical-perception tasks along with detection of graphical elements and judging distance accurately, should be considered when designing and constructing a graph. Data should be encoded in the graph so that visual decoding involves tasks as high as possible in the ordering of the graphical-perception tasks (Cleveland 1985, 1994).

A large share of the ink in a graph should present data-information, with the ink changing as the data change. Data ink is the non-erasable core of the graph, the non-redundant ink arranged in response to variation in the numbers represented. The data ink ratio is the ratio of the data ink to the total ink used to print the graph. For a clear and efficient graph, the data ink ratio should be maximized by erasing both non-data ink and redundant data ink, within reason. This includes eliminating chartjunk. Chartjunk is the unnecessary, often default, but as often intended, graphical decorations found in conventional graphical design and software which clouds and stagnates the flow of important quantitative messages from the graph, and does not tell the viewer anything new. A particularly prolific form is moiré vibration, the undisciplined and distracting appearance of vibration and movement due to cross hatchings and visually distracting patterns injected into graphical elements. Graphs should be information rich in that the amount of data is large relative to the area that the graph covers with high data density. Many graphs are comparative, often constructed from a series of small multiples, i.e., many shrunken plots per page that show shifts in variable relationships as the index variable changes (Tufte 1983, 1990, 2001).

Other guidelines for graph construction and principles of visual perception will be pointed out as required for each of the examples later in the chapter.

3.2.2 Guidelines for Tables

Each table should have a specific purpose (Ehrenberg 1975). We posit that generally there are 3 reasons to construct a table of data. They are:

1. To communicate key findings
2. To organize summaries of statistical analyses to facilitate interpretation
3. To document and store detailed information such as the original data

The amount, type, arrangement, and degree of accuracy of data displayed in tables vary according to purpose. For example, a table that presents key results generally should be constructed from only three of four columns and rows, contain a dozen or fewer highly rounded data values, and the information in the rows and columns should be arranged comparatively, ordered either by addressing a hierarchy of questions of interest or by effects observed in the data. These types of tables should follow Ehrenberg's (1977a, c) strong criteria for a good table in that patterns and exceptions in the data should be obvious at a glance or, at least meet his weak criterion that the patterns and exceptions should be obvious at a glance once the viewer has been informed as to what they are, perhaps with a caption. Conversely, a documentation table would contain most or all of the raw data, perhaps accompanied by some descriptive summary statistics, with only selected rounding, if any, presenting exact data values. A documentation table would be organized by combinations of clerical aspects of the data such as patient numbers and time, making for an easy look-up and extraction of one or more individual datum.

Some of the many guidelines for constructing tables are listed below (Ehrenberg 1975, 1977a, b, c, 1982). The guidelines should be considered as is appropriate for the table attributes of the grable.

1. Place or order the data to compliment the graph part of the grable (Bradstreet et al. 2008)
2. Make it easy to compare relevant numbers. Put numbers that have to be compared close to together. Arrange row order so that if mental arithmetic needs to be performed vertically, it is easy to do so. Consider ordering columns and rows based upon prior knowledge about the table content. Or, rows and columns can be ordered qualitatively by the magnitude of some aspect of the data such as means
3. Numbers are easier to read down a column than across a row, especially for a large quantity of numbers
4. Align the data values vertically according to decimal points or other features common to the data that are meaningful
5. Unless exact values are needed for documentation, generally round numbers to two effective digits. Round to a variable number of digits when necessary
6. The parallel concept to chartjunk (Tufte 1983, 2001) is tablejunk (Bradstreet et al. 2008). Labels should be clear, brief, and have meaning independent of the text. There is no need to rule off every column (or row) with a separate line. Too many or incorrectly placed vertical grid lines can interrupt eye movements. Irregular spacing of rows and columns can be particularly distracting. Too much space between rows or columns can force the eye to move too much making patterns more difficult to see and remember
7. Horizontal and vertical lines, and also gaps of white space, should be used sparingly, to parse major divisions in a table. Occasional regular gaps can help guide the eye and emphasize patterns. Single spacing with occasional gaps is an easy rule to adopt

8. *Bold* and *light* typeface can help distinguish between data falling into two categories. They can also be used to visually separate column and row headings from the data (Wright 1973)
9. A brief written summary should be given for every table to bring out the main qualitative features

Other guidelines for table construction and principles of visual perception will be pointed out as required for the examples later in the chapter.

3.2.3 More Guidelines and Examples: Recommended Reading

The guidelines for construction of graphs and tables and principles of visual perception highlighted above and illustrated in the examples, are not meant to be exhaustive. But instead we hope to provide readers with some initial display tools, and stimulate readers to learn more. Additional information on the proper and improper design and construction of graphs and tables, and principles of visual perception, can be found in Ehrenberg (1975, 1982), Tufte (1983, 1990, 1997, 2001, 2006), Schmid (1983), Cleveland (1985, 1993, 1994), Kosslyn (1994), Henry (1995), Wainer (1997, 2005, 2009), Harris (1999), Gelman et al. (2002), Few (2004, 2006, 2009), Wilkinson (2005), Robbins (2005), Chen et al. (2008), Freeman et al. (2008), and Wong (2010). These references are rich with principles, guidelines, and examples, and they present a diversity of authors' opinions and areas of interest.

3.3 Grables

The challenge at hand is to design and construct data displays that in meaningful ways best deliver the messages that the data contain, while simultaneously addressing the viewers' needs for a clear understanding. In some cases the viewers' needs may suggest constructing either a graph or a table, both, or a combination of both. For example, in the assessment of average bioequivalence, the viewer needs to know how the values of the geometric mean ratio and confidence interval from the statistical analysis relate relative to the values of the regulatory limits for establishing average bioequivalence. Further, there is an interest in individual subjects' responses, especially those subjects with extreme data who demonstrate a large subject-by-formulation interaction. Another example is graphing individual subject safety data, and simultaneously tabling and graphing the corresponding group summary statistics. Again, even if the average results look favorable, there is an interest in identifying those individual patients whose data are extreme suggesting a potential safety issue.

Tullis (1981) found that combinations of graphs and tables produce faster but an equally accurate level of understanding as tables constructed in either a narrative or a structured format. Lucas (1981) found that subjects receiving both graph-

ical and tabular output had a higher level of understanding than subjects receiving only graphs, and the subjects found the combined information more useful to them. Powers et al. (1984) found slower but more accurate performance by subjects when given both a graph and a table as compared to either graphs or tables alone. Also, presenting both a graph and a table provides the viewer and the presenter with the option of focusing on the format that they are most familiar with (Powers et al. 1984).

A strategy that takes the simultaneous presentation of the information in a graph and table a step further is to construct a grable. A grable combines the emergent features of a graph with the precise quantities of a table into a single display (Hink et al. 1996, 1998). A grable accommodates a wider variety of visual tasks and a possibly wider audience, than either a graph or a table can address alone. Hink et al. (1998) showed when considering both accuracy and time simultaneously, that grables and tables were favored over conventional graphs alone. Subsequently, Calcaterra and Bennett (2003) showed improved performance in subjects when specific data values were added to configural displays (displays that map multiple individual variables into a single graphical format). Tufte's (2006) sparklines are a successful implementation of the grable strategy.

Given the combination of ink from both a graph and a table, a grable must be designed and constructed with even greater care so as not to clutter up the display and hinder the clarity and accessibility of important information contained in the data. The best principles of visual perception from both graph and table design and construction should be considered.

3.4 More Grables

The following examples continue to present a variety of grables. Some are more graph than table, some are as much table as graph, and one is more like a text table than a graph. For each example, the grable characteristics are discussed followed by principles of good (and bad) graph and table design and construction. The examples work cumulatively in that characteristics and principles pointed out in an earlier example may not be highlighted again in a subsequent example, but they may be implicit in their use in the subsequent example. Electronic versions of the data used in Examples 1 (Bradstreet and Liss 1995), 4 (Bradstreet 1994), and 6 (Bradstreet and Short 2001) can be found at a website continuously maintained by Short (2006).

3.4.1 Example 3: Evaluating Dosing Regimens: Reflux in GERD Patients

This example provides some foundations for the others which follow. It demonstrates a transition from a table to several grables in a step-by-step fashion, pointing

Table 3.1 Anti-Rankit mean percent reflux time

Placebo	40 mg h.s.	20 mg b.i.d.	40 mg b.i.d.
11.3%	7.4%	5.9%	2.5%

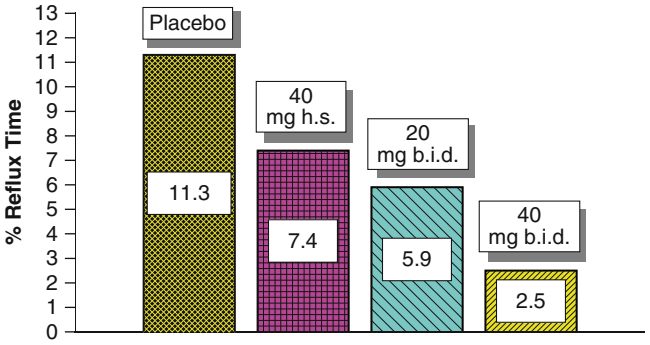

Fig. 3.3 Mean percent reflux time. First attempt at constructing a grable

out some favorable, and some not so favorable, principles of graph construction and visual perception. It also emphasizes that constructing effective grables (or graphs or tables) can be an iterative process with the final grable constructed dependent upon a combination of visual tasks, visual perception, the structure of the data, human preferences, and software capabilities. But once the serious work of communicating effectively is completed, the final grable can become a standard display for similar studies to follow.

Twelve gastroesophageal reflux disease (GERD) patients completed a 4-treatment, 4-period, complete crossover trial to evaluate 20 mg b.i.d. (twice daily), 40 mg b.i.d., and 40 mg h.s. (at bed time) doses of a drug targeted at the reduction of GERD symptoms as compared to placebo, and as compared to each other. The percent reflux time was measured for each of the three doses and placebo when each patient was in the upright position. For more information on the design and statistical analysis of data from higher order crossover studies see Ratkowsky et al. (1993), Jones and Kenward (2003), Brown and Prescott (2006), and Bradstreet et al. (2010). Table 3.1 documents the results of the study.

A first attempt at constructing a grable might look like the data labeled bar chart in Fig. 3.3.

Some major design, construction, and visual perception maladies are worth noting. In general, use of bar charts is tricky when differences are of interest since viewers tend to visually place shorter bars on top of taller bars and estimate proportional differences rather then additive differences. As scaled, the visual slope does not equal the algebraic slope among the placebo and the b.i.d. dosing regimens and this is not communicated. If the b.i.d. dose response evaluation is of key importance, then it can be argued that the 40 mg h.s. results should be visually detached from the b.i.d. results. There is a plethora of non-data ink, redundant data ink, and chartjunk

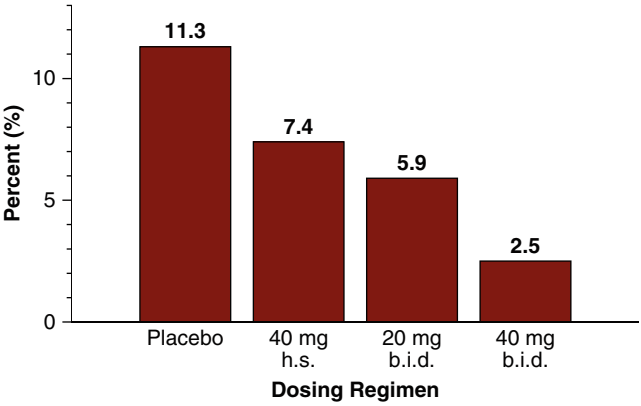

Fig. 3.4 Mean percent reflux time. Second (improved) attempt at constructing a grable

wrapped around just four bivariate data points—only eight data values. Examples of wasted ink include the shadow boxed dosing regimen labels, the moiré vibration in the cross hatching patterns inset into each bar, and there are too many tick marks and tick mark labels, with misguided emphasis on the tick marks. The data density in Fig. 3.3 is unacceptably low. Colors could be selected to visually group and compare the dosing regimens in a more meaningful fashion, and for many scientific publications there are other colors which might be viewed as more appropriate.

Figure 3.4 improves upon Fig. 3.3. The shadow boxes were removed, the dosing regimen labels were moved to the *x*-axis, and the corresponding *x*-axis label was added. The cross hatchings were removed and replaced, for now, with a uniform color. The *y*-axis is marked by regularly spaced major and minor tick marks, only the major tick marks have labels, and the tick marks are no longer visually distracting. The *y*-axis label has been shortened to just the key information. The data labels were moved from the middle of the bars, to the top of the bars, nearer to their value on the *y*-axis.

Figure 3.5 incorporates further improvements. The data values were removed from just above the bars and used as tick mark labels for tick marks at irregular intervals corresponding only to the most important data values. Bar colors were changed to visually link the two b.i.d. dosing regimens for comparison to each other, while setting apart both the 40 mg h.s. dosing regimen and the placebo for comparisons among themselves and to the b.i.d. dosing regimens. The tick mark labels were color coded to match the corresponding bar.

From here, there are several directions in which we might proceed including a dot chart, but we illustrate a dot chart in Example 5. The two strategies we chose both concentrate on removing most of the redundant data ink and non-data ink in the bars. The first strategy in Fig. 3.6 emphasizes the vertical distances between the dosing regimens as ordered in this case, by the response, mean percent reflux time. Colors again emphasize the four dosing regimens, and the corresponding vertical differences as visualized by the bolded, two sided, tick marks. This grable might be considered as more a text table than a graphic—a tablic.

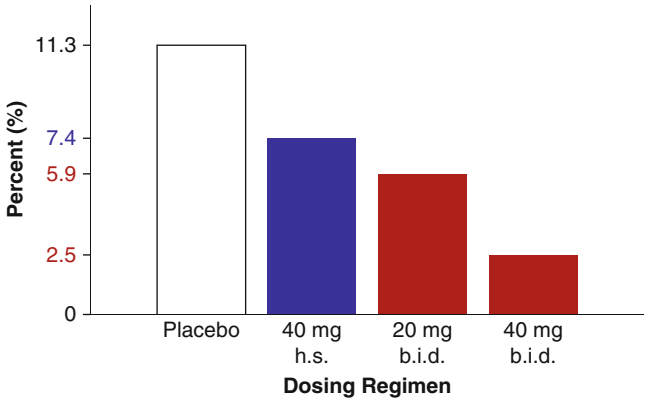

Fig. 3.5 Mean percent reflux time. Third (improved) attempt at constructing a grable

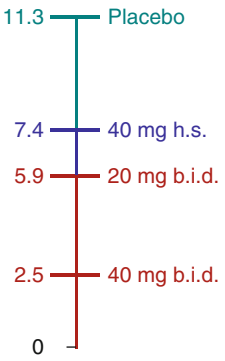

Fig. 3.6 Mean percent reflux time. A tablic—a grable that is more a like a text table than a graphic. Vertical distances between the responses of the dosing regimens are emphasized and ordered by response

The second strategy shown in Fig. 3.7 emphasizes the b.i.d. dose response aspect of the study while providing a pairwise comparison between the 40 mg h.s. and 40 mg b.i.d. dosing regimens. To demonstrate the second strategy, we choose an arithmetic scaling on the *x*-axis for the placebo and two b.i.d. doses so that the distance between adjacent doses is 20 mg. We also insert a full axis break between the 40 mg h.s. dose and the other doses to indicate that the 40 mg h.s. dose is not part of the dose response analysis, but is still part of pairwise comparisons.

The slope portrayed in Fig. 3.7 is still too steep. Most software packages automatically default to, or give the user an easy choice among either landscape, portrait, or square orientations, which do not except by coincidence, ensure that the graph portion of the grable is proportionally correct. To make our point, we arbitrarily chose the square orientation taken over the entire *y*-axis and over the entire *x*-axis including the 40 mg h.s. dose, since it is a common default and it is intermediate between landscape and portrait.

When possible given the physical dimensions of the hardcopy page or computer screen, and when reasonable given the story that the data are telling, the physical slope on the graph portion of the grable should match the algebraic slope given by

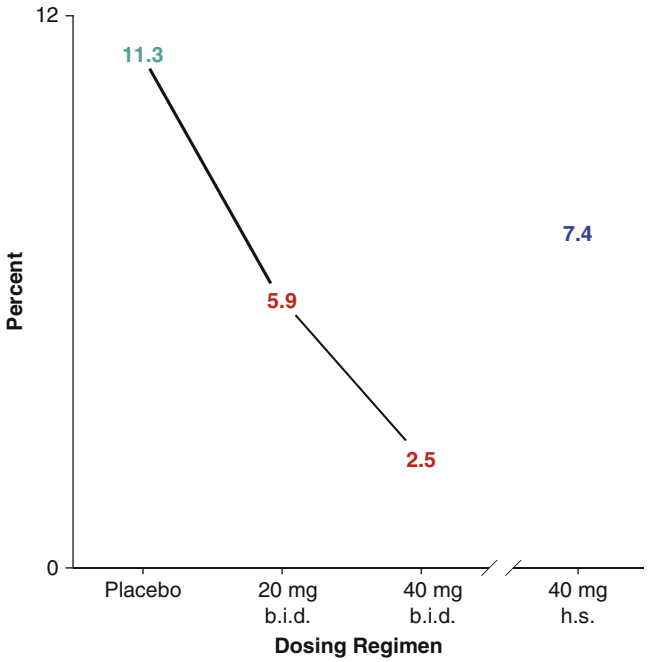

Fig. 3.7 Mean percent reflux time. A grable emphasizing the dose response between the placebo, 20 mg b.i.d., and 40 mg b.i.d. doses, and visualizing pairwise comparisons with the 40 mg h.s. dose. The slope of the dose response is too steep

the data (Bradstreet et al. 2006, 2008). Consider on each axis the ratio of the distance traveled in units (e.g., %) to the physical distance traveled (e.g., inches). The general idea is that the ratio must be the same on both the *x*- and *y*-axes. The implementation of this seemingly simple idea is highly dependent upon the specific details of a given grable.

In our example, suppose the placebo, 20 mg b.i.d., and 40 mg b.i.d. doses were spaced along 10 in. of the *x*-axis, from the placebo tick mark to the 40 mg b.i.d. tick mark. Then for the correct physical slope, the physical length of the *y*-axis from the 0 tick mark to the 12 percentage point tick mark, is the solution for *d* in the equality, $(40–0)/10 = (12–0)/d$. Solving for *d* gives $d = 3$ in. Similarly, if the 40 mg difference between the placebo and 40 mg b.i.d dose spanned 5 in. on the *x*-axis, then solving for *d* in $(40–0)/5 = (12–0)/d$, the 12 percentage points from zero to 12 should span 1.5 in. on the *y*-axis.

In some cases, the proportionally correct grable will not be as scientifically revealing as other combinations of dimensions with different aspect ratios (Cleveland 1985, 1994) or when banking to 45° (Cleveland 1994). It may not be physically possible to construct a proportionally correct grable given available space. Or the software being used either is not be able to do this or it may be extremely difficult to get the software to perform accordingly. In these cases, additional information should be provided as to what a grable with proportionally correct visual slope

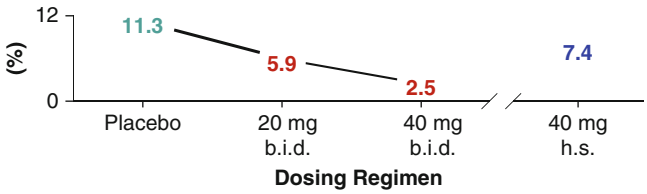

Fig. 3.8 Mean percent reflux time. A proportionally correct grable visualizing the correct dose response between the placebo, 20 mg b.i.d., and 40 mg b.i.d. doses

would look like relative to the one shown (Bradstreet et al. 2006, 2008). This information can take several forms. One is to provide an additional miniature grable which shows the correct slope, either nearby or possibly inset into the original grable. Another visual indicator sources from geometry and non-digital clock faces. Proximal to, or inset into the original grable, provide a visual representation of a pair of rays originating from a common point like the hands on a clock. One ray represents the physical slope, the other represents the algebraic slope, with each ray labeled accordingly. Or, instead, but preferably in addition to visual cues, provide a written notification as how to adjust the slope in your visual mind. A grable with proportionally correct slope is shown in Fig. 3.8. Figure 3.8 leaves a much different impression and interpretation of dose response than Fig. 3.7.

If in Fig. 3.7 we had originally chosen the portrait orientation instead of the square orientation, then the change in the physical slope from Fig. 3.7 to Fig. 3.8 would have been even more dramatic.

Whatever scaling is chosen for statistical analysis (e.g., arithmetic, ordinal, logarithmic), the observed mean results for the placebo, 20 mg b.i.d., and 40 mg b.i.d. doses should be connected with line segments only if the statistical analysis estimates or describes dose response directly incorporating the observed sample means. An example is partitioning the sums of squares due to treatments in the corresponding ANOVA into single degree-of-freedom contrasts for linear and quadratic curvature using orthogonal polynomial coefficients. However, for linear and polynomial regression, the best fitting function is obtained by least squares minimization of the vertical distances from the individual data points. The estimated function may or may not pass through one or more sample means. In this case, plot the estimated function, possibly with a confidence band, and the individual data points (Bradstreet et al. 2006, 2008).

Quite often the most important information to display is the relative difference between some or all of the treatments. In this situation, it is important to construct a grable where mental calculations are either minimized or eliminated (Bradstreet et al. 2006, 2008). In the current example, the primary interest is in the responses of the 3 active treatment regimens relative to the placebo, and secondarily relative to each other in either a pairwise or dose response fashion. A common strategy is to create 2 grables, one showing the observed data and one showing the differences from placebo. These would be arranged either spatially side-by-side (preferred), or shown temporally in time one after the other (less desirable). However, a single grable which effectively displays both the observed data, and the differences from

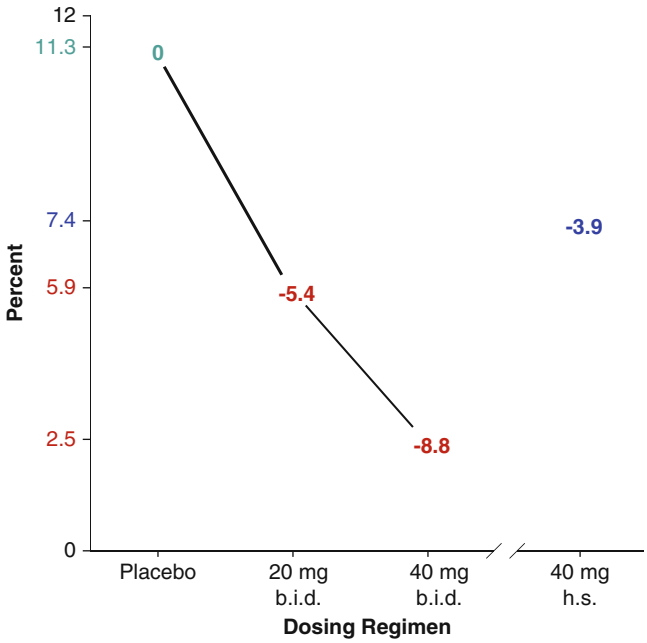

Fig. 3.9 Mean percent reflux time vs. placebo. A *line plot* which displays both the observed data and the difference from placebo

placebo, can be the best approach. Figures 3.9 and 3.10, illustrate strategies for showing both the observed levels of response and the differences from placebo.

Depending on the target audience and the amount of previous use, various hybrids of Fig. 3.9 can be reasonable. For example, it may be effective to plot the observed values in the plotting area and the corresponding differences from placebo on the *y*-axis, labeling the tick marks with the differences. A bit more advanced hybrid of Fig. 3.7, but possibly confusing to a naïve audience, would be to remove the tick mark and the tick mark label at 11.3, and replace the zero difference, 0, with 11.3, the observed value for placebo. Although not technically correct given the title and the scale, this gives the impression of starting at the 11.3 value and sliding downward to the right by the stated differences. The selection of the best suited version requires the careful consideration of technical accuracy versus the combination of an informative figure caption and the familiarity of the audience with the different versions.

3.4.2 Example 4: Evaluating Bioequivalence: Pharmacokinetic Data

Twenty-six healthy male subjects completed a 2-treatment, 2-period crossover bioequivalence trial to determine if the pharmacokinetic characteristics of one 40 mg

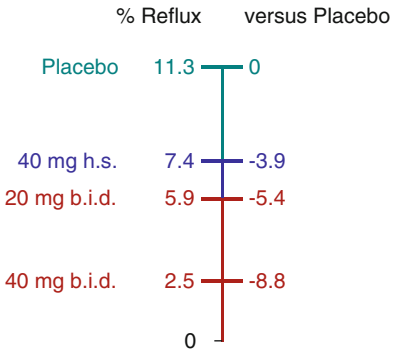

Fig. 3.10 Mean percent reflux time vs. placebo. A tablic which displays both the observed data and the differences from placebo

capsule of a drug made by Company A are the same as the concurrent administration of two 20 mg capsules of the same drug made by Company B. The pharmacokinetic variable, area under the plasma-concentration-versus-time-curve (AUC), was calculated (ng×h/mL) for each subject for each formulation from drug levels (ng/mL) assayed from plasma samples taken over time. For more information on the design, conduct, statistical analysis, and the display of results from a 2-treatment, 2-period crossover bioequivalence studies, see Bradstreet and Dobbins (1996), Pikounis et al. (2001), Food and Drug Administration (2001, 2003), Jones and Kenward (2003), Bradstreet and Panebianco (2004), and European Medicines Agency (2009).

In Fig. 3.11 the open circles (**O**) represent the ratio (Company A, 1×40 mg/ Company B, 2×20 mg) of AUCs for each subject. The solid dot (•) indicates the estimated geometric mean ratio and the vertical bar with horizontal endpoints (I) represents the corresponding 90% confidence interval. On the *y*-axis the Food and Drug Administration's regulatory limits for average bioequivalence of (**0.80**, **1.25**) are labeled as is the ratio of **1.00**.

Visually, it is immediately clear that average bioequivalence was not concluded since the upper confidence limit of the 90% confidence interval (I) lies above the upper bioequivalence limit (−−−).

The exact numerical results are also of interest, particularly so in cases like this indicating a notable degree of subject-by-formulation interaction, which is further magnified by two extreme AUC ratios, and with the upper confidence limit close to the upper bioequivalence limit. Therefore, the geometric mean symbol (•) is labeled with its value, 1.12, as are the limits of the 90% confidence interval (0.98, 1.27). The 2 up arrows (↑↑) signal that there are 2 subjects with AUC ratios lying above the upper end of the *y*-axis with values of 2.32 and 2.70. These arrow indicators for outliers were first suggested to us by John W. Tukey (personal communication). Importantly, the arrow indicators allow a detailed view of the behavior of the majority of the data. Graphing the data to scale including the two outliers would condense much of the data into a series of blue ink blobs that would not provide much useful information.

Other principles for graph and table design, and visual perception, were used in constructing Fig. 3.11. They include:

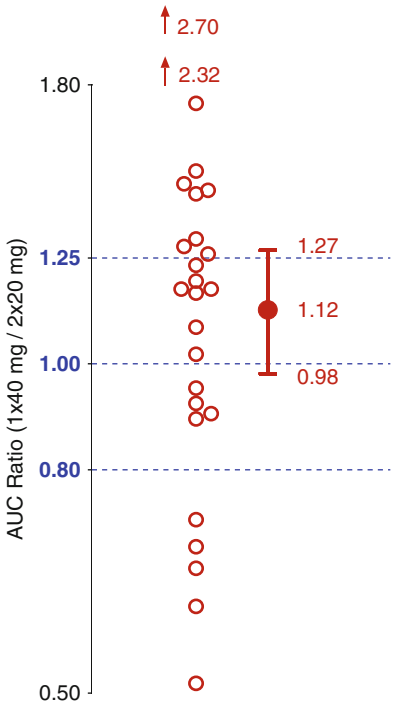

Fig. 3.11 Average bioequivalence analysis. The *open circles* (**O**) represent the ratio (1 × 40 mg/2 × 20 mg) of AUCs for each subject. The *solid dot* (•) indicates the estimated geometric mean ratio and the vertical bar with horizontal endpoints (I) represents the corresponding 90% confidence interval. On the *y*-axis, the Food and Drug Administration's regulatory limits for average bioequivalence of (**0.80**, **1.25**) are labeled as is the ratio of **1.00**

1. Spending data ink wisely; minimal non-data ink and redundant data ink
2. Plotting data on the log scale to align correctly with the statistical analyses
3. Labeling tick marks, summary statistics, and individual ratios with antilog values which are more easily accessible to a wider audience
4. Using an open plotting symbol (**O**) to lessen confusion due to overplotting
5. Jittering plotting symbols horizontally to lessen confusion due to overplotting
6. Clearly indicating in the caption that error bars represent a 90% confidence interval and not another interval measure such as standard deviation or standard error
7. Assigning thicker lines to more important graphing elements (e.g., 90% CI) and thinner lines to less important ones (e.g., *y*-axis)
8. Using reference lines to indicate important values across the entire graph
9. Constructing the reference lines with texture and width so as not to distract from the data, and placing the lines behind the data
10. Placing and labeling only those tick marks, critical to understanding the data and making a decision on bioequivalence
11. Choosing distinct color combinations either for emphasis (red, blue) or without emphasis (black), that are not problematic for some viewers (e.g., red, green), and not relying solely on color to transmit information
12. Heavily, but intelligently, rounding exact data values. Note that in this example, there is no need to display the 90% confidence limits to 3 decimal places as neither is close enough to the regulatory limits for average bioequivalence for rounding to matter in the decision
13. Using relatively simple sans serif fonts

3.4.3 *Example 5: First in Man Evaluation: Clinical Lab Safety Data*

Two panels of 6 male subjects enrolled in an alternating panel, fixed-rising-dose, safety study. Each subject received placebo and three of six possible doses of a drug. Panel A (**O**) received 0.2 mg, 1 mg, and 5 mg, and Panel B (**Δ**) received 0.5 mg, 2 mg, and 10 mg. For more information on the design and analysis of alternating panel fixed-rising-dose studies, see Rodda et al. (1988), Bolognese (1991), and Jin and Sun (2008).

Figure 3.12 combines a dot chart (Cleveland 1985, 1993, 1994) of individual subject values with a table of the corresponding summary statistics. Each line in the dot chart portion of the grable displays each subject's percent change from baseline in basophils at 24 h (**O Δ**) with the mean value (**X**) for that group of subjects. Open circles (**O**) represent subjects in Panel A, and in Panel B subjects are represented by open triangles (**Δ**). Tabled to-the-right on the same line are the corresponding number of subjects, mean, standard deviation, minimum value, and maximum value.

Other principles of graph and table design, and visual perception, were used in constructing Fig. 3.12. They include:

1. The dot chart takes advantage of the higher level, more accurate, visual decoding of information positioned along a common scale
2. Spending data ink wisely; minimal non-data ink and minimal redundant data ink
3. Using open and clearly distinct plotting symbols (**O Δ X**) to lessen confusion due to overplotting
4. Jittering plotting symbols vertically to lessen confusion due to overplotting
5. Using prominent graphing elements to represent the data values (**O Δ**) and summary statistics (**X**) while downplaying less important non-data structure such as the *x*- and *y*-axes
6. Positioning a reference line (*y*-axis) to indicate an important value (zero) that applies across the entire graph, but placing it in the background with texture, width, and color chosen so as not to interfere with the data
7. Encoding categorical information (Panel A and Panel B) with combinations of symbols and colors (**O Δ**), not relying solely on color to transmit information
8. Choosing distinct color combinations either to emphasize (blue, cyan, red) or deemphasize (black, gray) components of a grable, that are not problematic for color challenged viewers (e.g., red, green)
9. Placing and labeling only the necessary tick marks
10. Ordering rows monotonically, from bottom to top, by dose
11. Placing the data values according to the graph part of the grable
12. Heavily, but intelligently, rounding exact data values
13. Decimal aligning data values in columns
14. Using white space, not vertical grid lines, to separate columns of data values
15. Removing unnecessary leading digits in data values
16. Providing a brief, insightful, verbal summary of the grable in the caption
17. Using relatively simple sans serif fonts

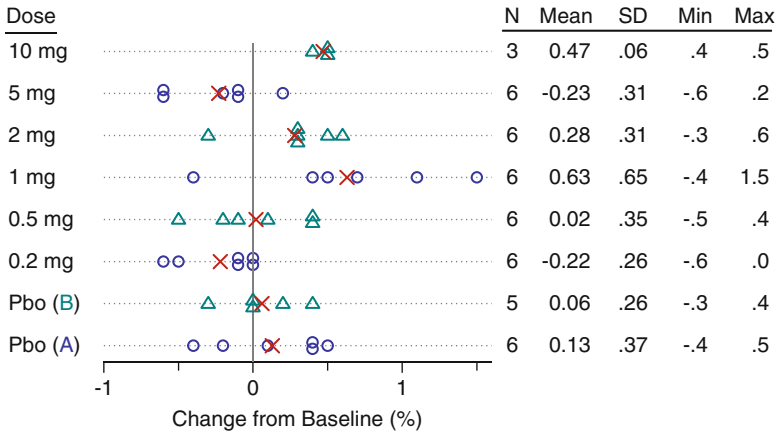

Fig. 3.12 Clinical laboratory data: Basophils. Each line of the *dot chart* displays each subject's change from baseline (%) in basophils at 24 h (**O Δ**) with the mean value (**X**) for that group of subjects. Panel A is represented by *open circles* (**O**), Panel B by *open triangles* (**Δ**). Tabled on the same line are the corresponding summary statistics: the number of subjects (*N*), the mean, the standard deviation, the minimum value, and the maximum value

In a similar fashion, Fig. 3.13 shows lengths of PQ intervals (ms) at 3 time points post dose (baseline, 2 h, 24 h) incorporating the comparative small multiples strategy.

3.4.4 Example 6: Evaluating Dose Proportionality: Pharmacokinetic Data

A total of 12 healthy male and 12 healthy female subjects completed a 4-treatment, 4-period crossover dose proportionality trial to determine if the pharmacokinetic characteristics of four oral doses (2.5, 5, 10 and 15 mg) of a drug are dose proportional. The pharmacokinetic variable, area under the plasma-concentration-versus-time-curve (AUC), was calculated (ng × h/mL) for each subject for each dose of drug calculated from drug levels (ng/mL) assayed from plasma samples taken over time. For more information on the design, conduct, and statistical analysis of dose proportionality studies, see Haynes and Weiss (1989), Yuh et al. (1990), Gough et al. (1995), Smith (1997), Smith et al. (2000), and Sethuraman et al. (2007).

There are at least 3 general strategies for visualizing and assessing dose proportionality at the individual subject level (Bradstreet et al. 1999, 2008). In the first, arithmetic AUC (*y*-axis) is plotted versus arithmetic dose (*x*-axis), with the AUC values connected by line segments. Dose proportionality is indicated for a subject if the line segments form a straight line with a positive slope which also passes through the origin (0, 0). In the second strategy, log-transformed AUC (*y*-axis) is plotted versus log transformed dose (*x*-axis), again connecting the log AUC values with line

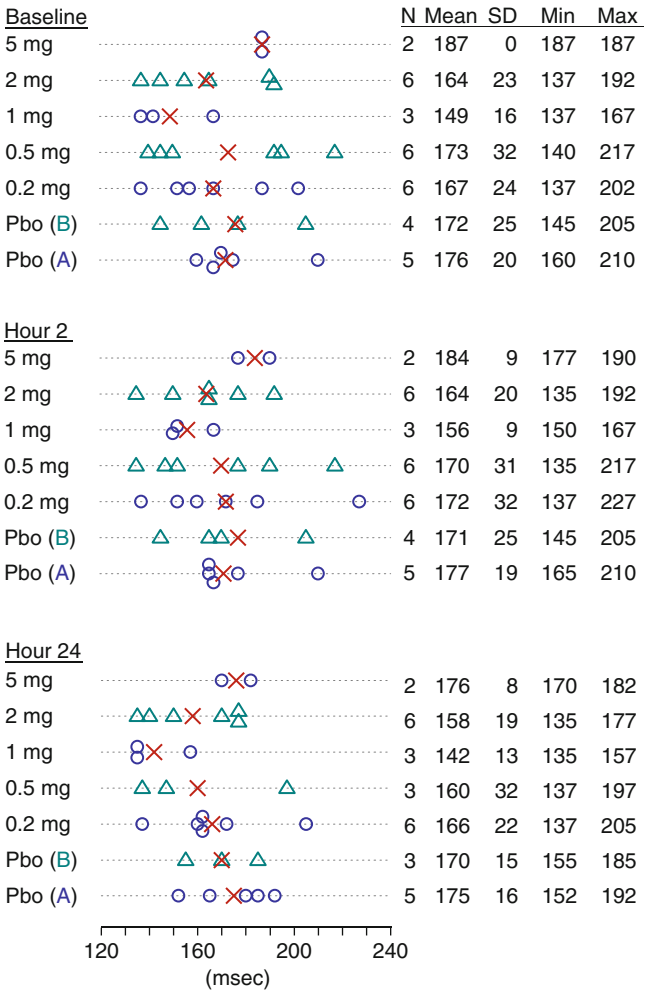

Fig. 3.13 Clinical laboratory data: PQ intervals. Data are arranged in small multiples sorted by time and then by dose within time. Each line of the dot chart displays each subject's individual value (**O Δ**) with the mean value (**X**) for that group of subjects. Panel A is represented by *open circles* (**O**), Panel B by *open triangles* (**Δ**). Tabled on the same line are the corresponding summary statistics: the number of subjects (*N*), the mean, the standard deviation, the minimum value, and the maximum value

segments. Dose proportionality is indicated for a subject if the line segments form a straight line with slope equal to 1. The intercept is not of immediate interest but it provides useful subject specific information. In the third strategy, each arithmetic AUC value is divided by the corresponding arithmetic dose which standardizes the AUC values to 1 mg, or the AUCs can be standardized to a particular dose such as 10 mg. Then the AUC/dose values (*y*-axis) are plotted versus the arithmetic dose values (*x*-axis), connecting the AUC/dose values with line segments. Dose proportionality

Table 3.2 AUC standardized to 1 mg of drug—males ($n = 12$)

Subject	2.5 mg	5 mg	10 mg	15 mg
1	9.8	6.5	8.6	10.5
2	10.7	6.4	7.7	10.5
3	8.3	8.5	7.2	7.5
4	3.3	4.4	5.2	4.9
5	4.4	6.6	6.2	8.4
6	2.0	3.5	4.1	4.1
7	8.7	9.2	9.3	11.9
8	3.4	4.4	3.4	4.2
9	7.2	7.2	8.1	7.9
10	6.2	8.6	9.3	10.9
11	7.8	7.5	10.8	13.3
12	4.9	6.0	6.6	7.8

is indicated for a subject if the line segments form a straight line with slope equal to 0. Again, the intercept is not of immediate interest but it provides useful subject specific information.

We use the third strategy, AUC/dose versus dose, to demonstrate the construction of a grable from the corresponding table of individual subject data. The dose adjusted to 1 mg AUC data for the males are documented in Table 3.2. The original AUC/dose values were rounded to one decimal place to be more easily read.

Table 3.2 is sorted by subject number and dose, facilitating the documentation and look-up of individual values. The grable in Fig. 3.14 not only documents the individual values, but importantly provides an initial assessment of dose proportionality for each subject, and compares responses among the subjects. For clarity, the data were sorted vertically, from bottom to top, by the AUC/dose values for the 2.5 mg dose (Friendly and Kwan 2003; Tufte 2006; Bradstreet and Palcza 2012). Since there are only 10 subjects, this arrangement should not increase look-up speed, especially when considering the additional information provided on dose proportionality.

The data values in Fig. 3.14 were rounded to the first decimal place to retain enough accuracy for documentation and look-up. But the trailing decimals to some degree, inhibit readability and they slow down even simple mental arithmetic. To address this, exact values could be plotted but labeled instead with AUC/dose values which are rounded excluding the decimal. However, this would generate line segments with non-zero slope visually connecting the same rounded data label, an awkward position to be in. Alternatively, the rounded data labels could be plotted, but this is too much rounding for the accuracy desired given the range of the data is from 2.0 to 13.3. A possible solution is to standardize the data values to another dose, say to the 10 mg dose. Figure 3.15 displays this arrangement. The desired accuracy is achieved, readability is increased, and mental arithmetic is simplified. We remind ourselves that if either differences or ratios among the doses were of primary interest, these could be plotted avoiding the mental arithmetic.

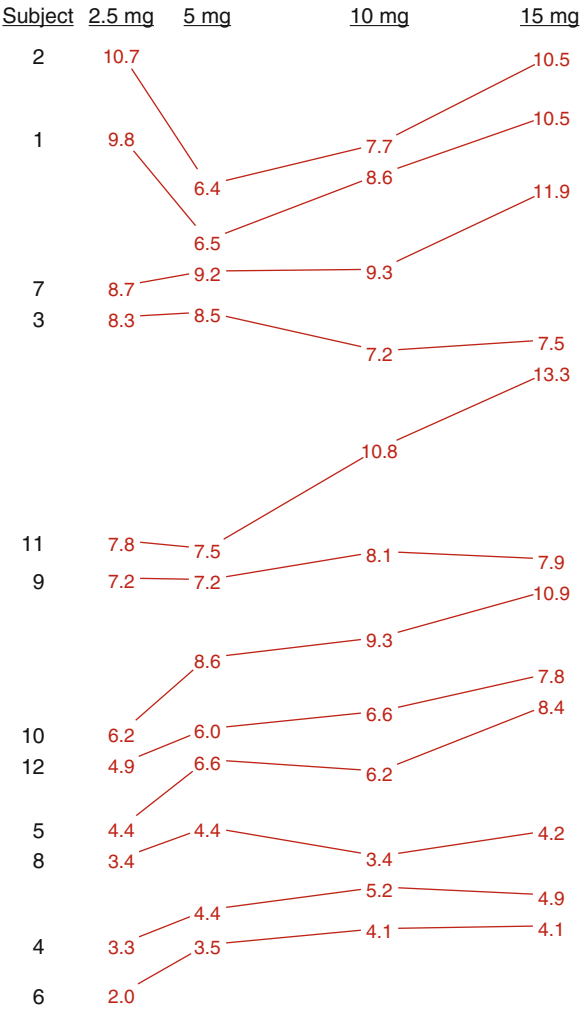

Fig. 3.14 AUC standardized to 1 mg of drug. Males, sorted vertically from bottom to top, by value of AUC/dose for 2.5 mg dose

3.5 Software

To construct a well-designed grable, or as equally important a well-designed graph or table, requires software with the prerequisite capabilities, which some software packages may not possess. In addition, the default settings of many software packages are not conducive to producing effective visual displays immediately. However, an initial investment of time will pay off for the visual task at hand as well as for subsequent runs of the same or similar displays.

It is not our intention to condemn or promote particular software packages, but instead to provide a list of qualities to consider when selecting software. These considerations should be framed within your particular needs and local computing environment. Some desired software characteristics include (Bradstreet et al. 2008):

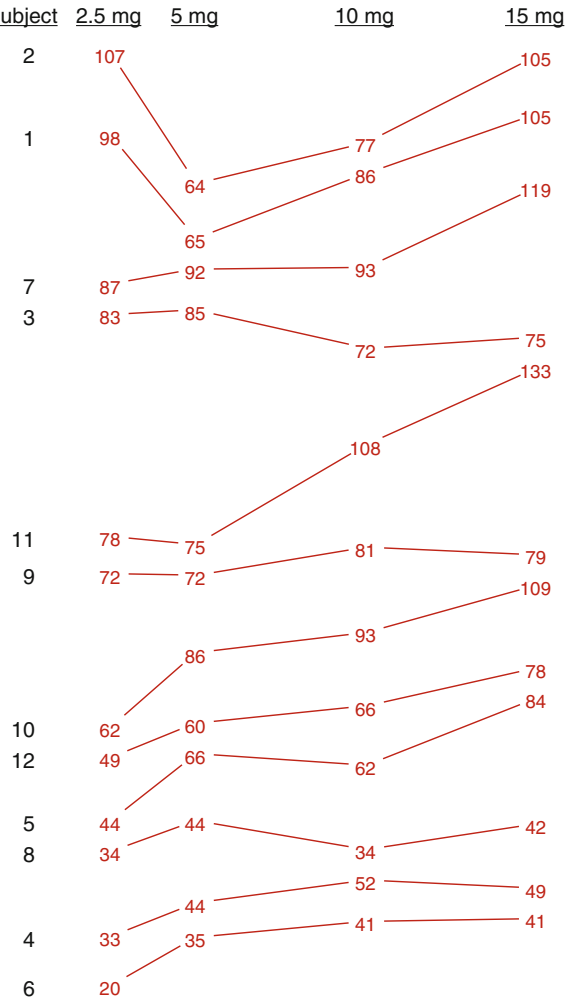

Fig. 3.15 AUC standardized to 10 mg of drug. Males, sorted vertically from bottom to top, by value of AUC/dose for 2.5 mg dose

1. Capable and flexible enough to construct grables correctly
2. Relatively easy to learn and program
3. Modest complexity to run
4. A GUI (*G*raphics *U*ser *I*nterface) may be helpful for users with lesser programming skills, provided it allows for virtually the same capabilities and flexibility as constructing code from first programming principles
5. Highly portable, both electronically and physically
6. Amenable to automation to support production as well as one-off environments
7. Must integrate well with other graphics, statistical, and word processing software
8. Satisfies data analysis as well as presentation and publication requirements

Traditionally, no one software package will meet all of your needs. Consider choosing one that meets most of your needs while sacrificing on lower priorities, or shop for

a complimentary set that meets all of your needs. It is also useful to organize a local group of software users who are similarly dedicated to implementing the principles of visual perception in the design and construction of effective grables.

3.6 Discussion

When presenting patient data, many situations require showing spatial relationships and also displaying, highlighting, or extracting individual data values. Spatial relationships like trends, associations, and other visual patterns typically are best displayed with a graph. Displaying, highlighting, or extracting one or more data values typically is best accomplished with a table. Because of personal familiarity, or a path of least effort, presenters and viewers may arbitrarily favor one display format over the other.

This dual display dilemma can often be solved with a grable. A grable combines the emergent features of a graph with the precise quantities of a table into a single display. Its purpose is to simultaneously accommodate a wider variety of visual tasks and a possibly wider audience, than either a graph or a table can address alone.

Proposed visual and cognitive strengths and weaknesses of graphs and tables should be considered when designing grables, as should proposed guidelines for their construction. Designing and constructing a grable can be more challenging than for either a graph or a table alone. The best practices selected from each visual format must be complimentary when used in combination, which is not guaranteed.

We provided examples of grables highlighting principles of design, construction, and perception. Although rather simple, these grables and the guidelines for graph and table construction provide initial guidance on how to get started. Additional guidance and examples can be found in the recommended readings.

Careful consideration should be given to software selection. It can be productive and rewarding to collaborate with users who have a similar desire to efficiently produce high-quality grables.

Grables are not automatic visual panaceas for perception. Like well-constructed graphs and tables, they require careful thought in design and construction. Several iterations may be required before the final design is achieved. Once completed, the final display or variations of it, can be used for future clinical studies.

Acknowledgments The author thanks Christine Stocklin for her indispensible help in creating the grables using an S-PLUS GUI.

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