POINTS OF VIEW

Unentangling complex plots

Carefully designed subplots scaled to the data are often superior to a single complex overview plot.

Factorial experiments are frequently used to investigate different combinations of independent variables (e.g., dose, strain, temperature or gender) on a response variable. Plotting their outputs can present a variety of challenges—the interaction plots or time-course response curves for each factor combination may vary in range, noise level and trend. Let's look at how we can mitigate these issues by organizing the data into small multiples, each cropped and scaled to a different range to emphasize relative changes while preserving the context of the full data range to show absolute changes. These strategies can be used with nonlinear scaling (e.g., logarithmic, probit, logit or reciprocal) to increase the dynamic range and resolution and to linearize Gaussian and sigmoidally shaped data.

A single plot scaled to show all the data is likely to be a jumble of lines—patterns will be difficult to discern owing to overplotting, data occlusion, inadequate separation of the visual channels for each variable combination, and compression of detail in data traces with a small range (**Fig. 1a**). If traces can be grouped by nonoverlapping ranges, axis breaks can help separate them, but this will affect the perception of absolute differences. Variable combinations can be distinguished using colors, dashed lines and symbols, but in a tight space it can be difficult to find encodings that are easily distinguishable. An even greater challenge is to include uncertainty (e.g., error bars) without complicating the graphic further. As a result, figures of this type are confusing because many features are battling for emphasis, hindering our perception of categories, patterns and relationships. The design is being unduly influenced by the dimensions and constraints of a single plot rather than structure of the data.

When categories have similar ranges, small multiples may solve the problem[1] (**Fig. 1b**). When data ranges differ, we may need to crop or truncate an axis to account for different maxima or minima between categories. However, truncated scales may be deceptive and create different interpretations of a graphic[2]. Therefore, any adjustment to scale ranges needs to be clearly presented.

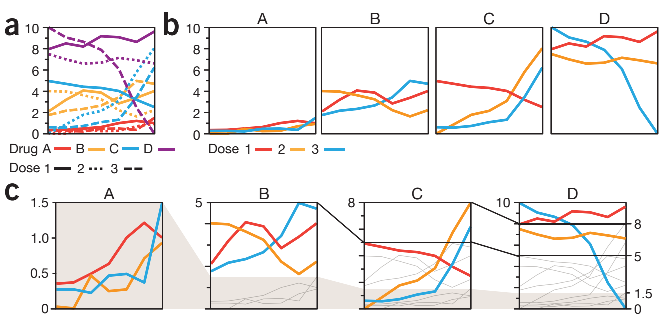

Figure 1 | Small multiples and progressive cropping helps to compare data traces across various *y*-axis ranges. (**a**) Categories and patterns can be difficult to distinguish when all the time-course response data are in a single plot. (**b**) Small-multiple plots isolate and untangle the categories but lose context as categories are separated. (**c**) Subtle scale annotations provide context while maintaining clarity.

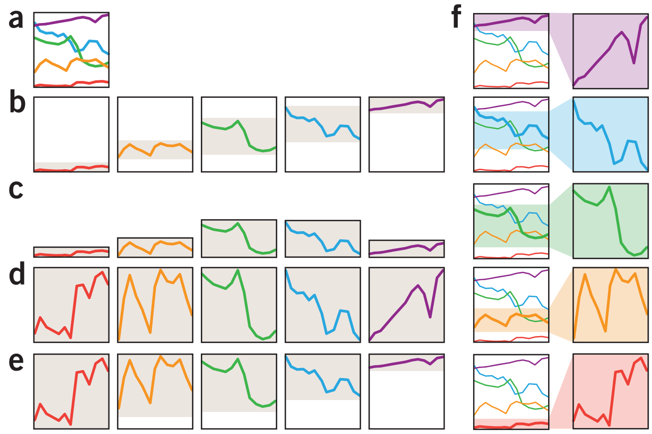

Figure 2 | Make design choices that show trends in context. (**a**) In a single panel, categories with the widest ranges are often the most prominent. (**b**) Small multiples help navigation and simplify encodings. (**c**) Perception of differences is compromised across multiples for which minima, maxima or range vary. (**d**) Relative changes within categories are emphasized when panels are scaled within each category, but those between categories are difficult to judge. (**e**) Scaling to each category's maximum while using a global minimum contextualizes variation between categories. (**f**) Use an overview and scaled detail to contextualize, highlight and examine each category. Colored backgrounds emphasize differences in scale expansion. A vertical layout helps in identifying common changes in patterns.

One approach is to apply progressively decreasing axis truncation relative to the whole data range across the small multiples and emphasize the changes in scales using reference lines and background highlights (**Fig. 1c**). Simpler visual encodings are required because each panel subsequently contains fewer categories; context can be maintained by subtly displaying remaining data in the background. Care must be taken to avoid too much embellishment, which can complicate the plot and shift emphasis away from the data.

When data categories differ in both minima and maxima, a single plot will illustrate differences in scale but obscure patterns (**Fig. 2a**). Small multiples of the data (**Fig. 2b**) can be individually scaled by various schemes to emphasize patterns and metrics of interest (**Fig. 2c–e**). The choice of aspect ratio of the plots affects how slopes are perceived and compared—choosing one that orients the average trace to 45 degrees is a useful rule of thumb[3]. Small-multiple pairs showing the full and cropped ranges can highlight differences in absolute values, illustrate patterns and correlations across the range of each category and even unveil a storyline[4] (**Fig. 2f**).

Making important features and patterns salient in each small multiple requires consistency in design elements. The result may require more page space but should be worth it.

COMPETING FINANCIAL INTERESTS
The authors declare no competing financial interests.

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