Structuring Visualization Mock-ups at the Graphical Level by Dividing the Display Space

Romain Vuillemot and Jeremy Boy

Abstract— Mock-ups are rapid, low fidelity prototypes, that are used in many design-related fields to generate and share ideas. While their creation is supported by many mature methods and tools, surprisingly few are suited for the needs of information visualization. In this article, we introduce a novel approach to creating visualizations mock-ups, based on a dialogue between graphic design and parametric toolkit explorations. Our approach consists in iteratively subdividing the display space, while progressively informing each division with realistic data. We show that a wealth of mock-ups can easily be created using only temporary data attributes, as we wait for more realistic data to become available. We describe the implementation of this approach in a D3-based toolkit, which we use to highlight its generative power, and we discuss the potential for transitioning towards higher fidelity prototypes.

Index Terms—Design Methodologies, Rapid Prototyping, Graphic Design, Mock-Ups, Toolkit Design.

1 Introduction

We present a principled design approach for creating visualization mock-ups that are informed by only little, or no data. Our approach is inspired by a dialogue between *graphic design* theory, and *parametric toolkit* explorations. We propose that mock-ups can be created at the graphical level, by iteratively subdividing the display space, and progressively informing each division with realistic data, as they become known or available.

The information visualization (InfoVis) pipeline [9, 25] (Fig. 1) indicates that the first step in visualizing data should be to structure the data, before moving on to projecting them in visual form, and rendering them on a display. For the purpose of this article, we refer to this as a *data-to-display* approach to visualization, upstreaming from the data to the final graphic, or interface. While this is the most commonly accepted approach in InfoVis, designers sometimes have to create visualizations without having access to the data they will eventually be displaying. This can happen for a number of reasons, for example when an interface needs to be open and welcome different types of data, when the data are too sensitive to be shared with the designer, or when the data have simply not yet been collected [42]. In other cases, where the data are available, cleaning, structuring, and processing them can require large amounts of time and effort. This greatly complicates the ideation process for designers who may want to try out different concepts—each of which may require reprocessing the data—while attempting to meet organizational requirements, like iterating with users and other stakeholders, and reporting progress with visual mock-ups.

Adopting the data-to-display approach also tends to imply that the interesting properties and trends in the data are unknown—they should be discovered using visualization. However, when a graphic is created to communicate a message, the designer should have an initial idea of what trends to put forward, in order to develop an intent, or a *parti pris* [42]. The first step is to think about how to convey the message appropriately, before diving deep into the specific properties of the data. Even for more exploratory interfaces, information architects, user-interface, and user-experience designers can develop an idea of what visual and interactive features they want to include for the user, before actually loading data to the interface.

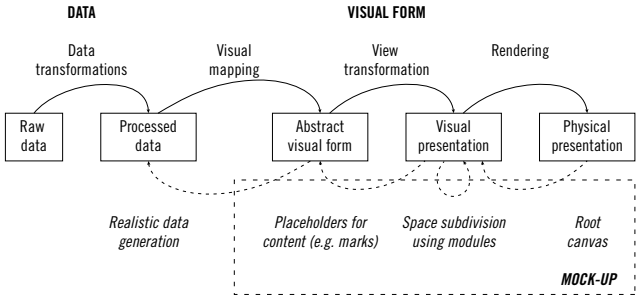

Fig. 1: Visualizations mock-ups are progressively structured starting from the end of the visualization pipeline; with only little, or no data.

Inspired by these situations, we propose an alternative approach to visualization, based on the progressive division of space. We refer to this as a *display-to-data* approach, starting with the configuration of the display space, and moving down to the data (Fig. 1, bottom right). While there are many tools available for creating visualizations, most assume the data-to-display approach. They require an understanding and availability of data, which needs to be cleaned and processed to meet very specific formats; and arriving at a convincing and well-structured final graphic or interface can be very time-consuming—especially if several iterations are required. We argue that our display-to-data approach can alleviate this issue, by helping visualization designers create rapid, low-fidelity mock-ups that can progressively be informed by realistic data, as they become available. We explore this approach from two different perspectives. First, from a *graphic design* perspective, we analyze how the use of grid systems for structuring the display space, and the progressive segmentation of inlaid modules, can inform the design of visualizations. Second, from a *parametric toolkit* perspective, we explore how different patterns of space partitioning, in combination with the progressive inclusion of data attributes (whether only anticipated or actually known), can help generate a variety of visualization mock-ups. We detail the creation of several of these mock-ups, highlighting the generative power of our approach. We then discuss how it can facilitate rapid explorations of design alternatives. Ultimately, we hope this work will pave the way for higher-level prototyping tools, useful for InfoVis designers, developers, and teachers.

2 Background

As visualization designers, we have learned to appreciate the need for quickly creating mock-ups that can progressively be informed by realistic data. One of the authors is an InfoVis practitioner, whose background is in graphic design. The other is a computer scientist by

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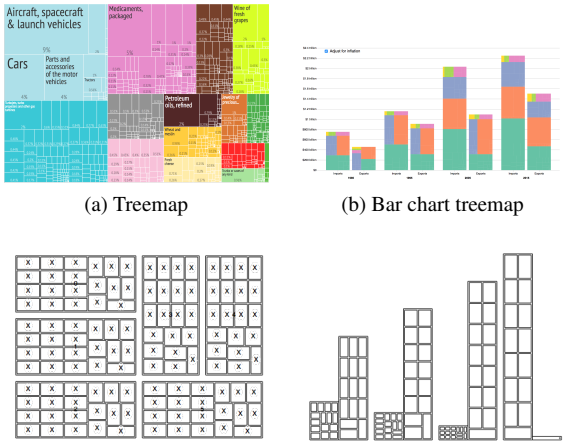


(a) Treemap (b) Bar chart treemap

(c) Mock-up of (a) (d) Mock-up of (b)

Fig. 2: Examples of Treemaps mock-ups created in the graphical space, informed by representative data (but not the full dataset).

training, who also has experience as an InfoVis practitioner, having worked for several years with a team of economists. We see this work as a dialogue between our disciplines. In this section, we first provide a motivating scenario inspired by our experience. We then discuss the use of sketching in visualization design, and finish by reviewing existing tools that facilitate the creation of visualizations.

2.1 Motivating Scenario

Economists are often interested in characterizing world economies using trade data. These data essentially capture the goods and services countries import and export over time; they are commonly represented using Treemaps [21] (Fig. 2) that show individual trade profiles of specific countries, at specific times. We have encountered great interest from economists in exploring treemap variations, like "double" treemaps that show both imports and exports simultaneously, with their respective breakdowns, while showing the overall balance of trade; or "temporal" treemaps that show the evolution of trade over time. While these are not entirely novel representations, they are not common, and are hard to produce—they are not directly supported by most popular visualization tools. Preparing the data (e. g., transforming the data-structure, modifying the format, etc.) is time consuming, and the range of design possibilities is wide. Different solutions must rapidly be explored and prototyped to inform discussions on design choices and potential challenges [59]. According to [11], it takes two days for a D3 developer to generate a "double", "temporal" treemap (or "treemap barchart"). This is a major investment for a visualization that might be immediately abandoned if it does not fit the needs of economists.

To address this issue, we need a principled method for producing rapid mock-ups at the graphical level that can be progressively informed by realistic data. This should allow to collect important feedback from interlocutors (e. g., economists) early on. The final data should not be immediately necessary, although knowing certain aspects like their most salient attributes might. The visual output should not need to be greatly detailed, but capturing the general structure of the visualization is crucial, so interlocutors may estimate whether it will be useful to them or not. This echoes the findings in [5], which indicate that designers tend to create visualizations in a "top-down, graphical process," in which they try to understand the overall appearance of a visualization, before including more realistic data.

2.2 Sketching

A simple solution to creating visualization mock-ups is sketching. Sketching is a commonly used technique in design, architecture, engineering, and more generally in innovation processes, by which designers lay out, clarify, store, reflect on, and share their ideas with others [29, 52, 53]. Sketches generally appear to be made quickly; they contain minimal detail, and are intended to suggest, rather than tell [8]. Low-fidelity, "sketchy" prototypes have indeed been found to be more effective at facilitating ideation, and encouraging feedback in the early stages of design processes, than more polished mock-ups [31, 41, 60].

Roberts et al. [42] advocate for the use of sketching in their Five Design-Sheet methodology for InfoVis, in which they provide grounded support for generating, iterating over, and refining visualization mock-ups, from ideation to realization.

Walny et al. [54] have studied the lifecycle of sketches in software development. They have found that sketches are created, iterated upon, copied, archived, and finally discarded. Much of this lifecycle is influenced by changing communication needs. People draw, redraw, annotate, and transform sketches to share different aspects of a design with others. In our experience, this is typically influenced by the progressive inclusion of realistic data attributes, as they become known or available. This resonates with Walny et al.'s call for visualization tools that can help designers transition through various levels of formality, from sketches to more accomplished "diagram" visualizations.

Walny et al. [55] have also studied how sketching can inform InfoVis design. They have explored the diversity of representations people draw when asked to sketch out a dataset, and have studied the relationship between the types of sketches people produce, and their understanding of the data. They have found that most sketches follow a visual continuum from numeracy to abstraction, and a data continuum from simple statements to conjectures and hypotheses about the data.

Overall, sketching has the advantage of being entirely freeform, and does not depend on specialized equipment: a pencil and paper suffice. It also requires little practice or skill [55] to arrive at satisfying and useful results. However, sketches are not dynamic, i. e. they (generally) cannot be updated, and it is usually difficult to capture the subtleties of certain data attributes (e. g., the specific numbers of entries, dimensions, etc.) as the sketch lifecycle progresses—this is often necessary when moving towards high(er)-fidelity prototypes. More importantly, sketches are only renderings of ideas: in of themselves, they do not provide a principled way of mapping data to visual elements (and *vice versa*) that can be systematically explored.

2.3 Visualization Design Tools

There are many visualization design tools that aim at facilitating the mapping of data attributes to visual marks and variables. Some offer programmatic APIs, like D3 [6] and Vega [44], while others offer GUIs with more or less advanced mapping capabilities, ranging form simple chart templates in Excel, to more expressive data-binding options in Tableau/Polaris [48], Lyra [43], iVisDesigner [40], or Voyager [61]—the latter even provides mapping recommendations to support exploration. Meanwhile, Sketchstories [32] offers a sketching interface that allows users to invoke chart schema using simple gestures.

Despite their diversity, these tools scarcely allow the design process to start at the graphical level. Whether they first require processing data, or placing graphical primitives on a canvas, they are based on the assumption that visualizations should be 'built up' from the data (data-to-display approach), rather than 'structured down' from the display space (display-to-data). For example, few of these tools offer quick, high level visualization specifications without the constraint of having an initial dataset. Data-driven grids [28], and to some extent Sketchstories, are an exception (and are probably closest to our approach), as they allow designers to first create freeform graphics, before binding data to them.

3 A Graphic Design Perspective

We first explore the creation of visualization mock-ups at the graphical level from a graphic design perspective. We examine how the use of *grids* and *modules* can help *lay out* the different elements that compose a visualization, with little, or no use of data. We begin by introducing the concepts of modularity and grid systems, and we clarify the basic structural lexicon we use. We then illustrate our approach by creating mock-ups of the "double" and "temporal" treemaps, as well as of the treemap barchart, discussed in our motivating scenario. We detail how we progressively divide the display space to create placeholders for

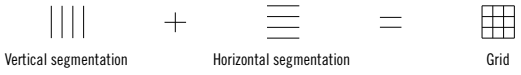
all the visual marks that build up the different visualizations. We also highlight opportunities for including more realistic data along the way. We start with divisions at the *canvas level*, where we organize the different elements that complement each chart (e. g., titles, legends, labels, chart-space, etc.), before moving down to the *chart level*, where we organize the different marks that compose the visualizations.

3.1 Modularity and Grid Systems

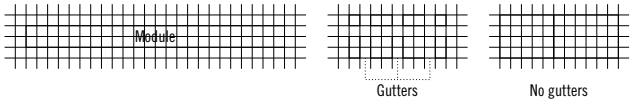
Modularity is a principle shared by many design disciplines, as well as architecture [1,12]. It is based on the idea that everything should be built using a strict set of rules, which are defined by a *system* (e. g., a *grid system*). In graphic design, *grids* [2, 22, 37] are essentially vertical and horizontal *segmentations* of a page; they are the "skeleton" upon which all content is laid out. *Modules* can be placed at the intersections of these segmentations, which determine *placeholders* for future content. Vertical segments typically control the inner and outer margins of the page, define the columns, as well as the space separating them; while horizontal segments determine the head and foot margins, the depths of columns, and the location of headlines and visual material [22].

Grids and modular layouts can vary in almost an infinite number of ways, and they are useful throughout the whole design process—from initial low-fidelity mock-ups, to higher-fidelity ones, and even to final designs[1]. They enable designers to rapidly try out different ideas, even before the final content is available. As per our motivating scenario, this is often essential for facilitating necessary discussions among a variety of interlocutors—for example, in the case of magazine design, between the designer, the editor, the production director, the advertisement director, and sometimes the journalist(s).

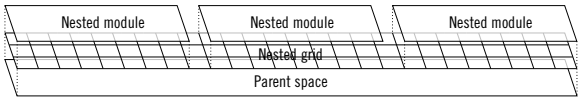
3.2 Basic Structural Lexicon



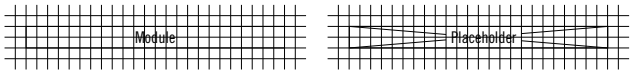
The basis of our approach is the iterative subdivision of the display space. From a graphic design perspective, this translates into a progressive *segmentation* of that space, which can be *vertical*, and/or *horizontal*, the combination of which results in a *grid*.



Grids are used to place *modules*. Modules can range from one to any number of cells, both horizontally, and vertically. Grids can contain several modules, and adjacent modules may, or may not be separated by a single column: the *gutter*.



In turn, each module has its own inner-space, which can be segmented to create *nested* segmentations, grids, and modules. Reciprocally, any nested segmentation, grid, or module has a *parent space*. If a module is not segmented, and is used to place content (e. g., visual marks, text, etc.), it becomes a *placeholder*.



The resulting combination of grids, modules, and placeholders creates a simple black and white visualization mock-up, which complies with the general look and feel of *wireframes* in other disciplines. This enables discussions to stay focused on the main design issues, rather than on any superfluous embellishments.

[1] An interesting collection of grid system examples can be found at: `http://www.thinkingwithtype.com/misc/Experimental_Typography.pdf`

3.3 Segmenting the Canvas Space

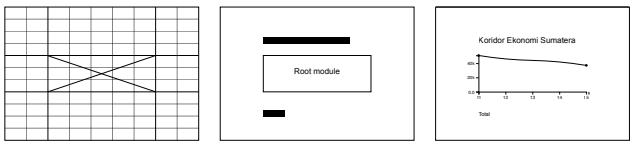


Fig. 3: *Root* canvas module: laying out the canvas space for a simple line graph, based on proportions of the canvas width and height. Note that here, the visualization is simply considered an element of content, which is why the root module is represented as a placeholder (left).

We begin by segmenting the canvas space to set up the general layout. This will help place the chart, and the different elements that complement it. Layouts usually start at the edges of the page, and progressively move inwards [34]. The proportions of the page determine the grid, and its ratio is repeated in the inlaid modules. This creates a sense of balance, connectedness, and aesthetic appeal [50]. Although it can be argued that screen-based design, like web design, is progressively moving away from this standard, because webpages have no "edges" (content can flow beyond the page fold, both vertically and horizontally), visualizations are still generally set within a fixed canvas. This unlikely to change, as the "overview first" mantra [46] demands that the whole visualization be visible in a single frame of reference.

Fig. 3 shows the layout of a simple linegraph. The vertical and horizontal segmentations of the canvas space are respectively proportional to the canvas width and height—with the slight specificity here that the horizontal segmentation is also co-defined by the line-height of the typesetting. This is why there are more horizontal segments than vertical ones. The resulting grid is used to place the *root module* in the center, which determines the placeholder for the *chart space*; and the different elements that complement the chart, i. e. the tile and subtitle. The chart space is a single *proportional module*, since it is defined by the proportional segmentation of its *parent* space, i. e. the canvas. It is used to render the linegraph.

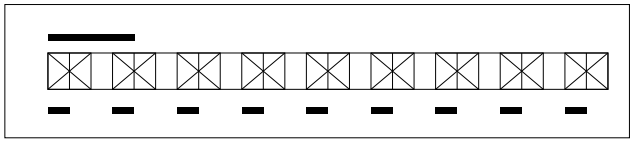


Fig. 4: *Nested* canvas modules within the root module: setting up nine charts in the same canvas space.

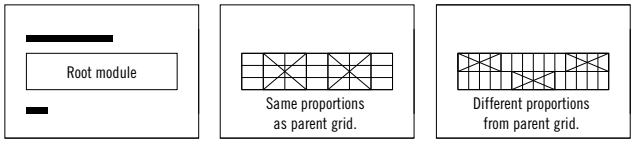


Fig. 5: Nested canvas grids: relative or not to the *parent* grid.

In some cases, the root module may need to contain several charts—typically for small multiples. As for every module, its inner-space can be segmented, using *nested segmentations*, resulting in a *nested grid*. Fig. 4 shows a nested, proportional, vertical segmentation of the root module, used to create nine *nested modules* that each determine a placeholder for a unique chart space. Note that the canvas and root module have been extended horizontally in this figure to welcome these nine modules. Fig. 5 further illustrates how nested segmentations may, or may not be identical to those of the module's parent space.

Finally, Fig. 6 shows how nested segmentations, grids, and modules can be informed by other values than proportions of their parent space,

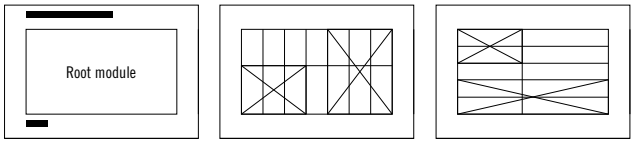


Fig. 6: Nested canvas grids and modules based on random values—instead of proportions of the root module.

like *random values*, or more *realistic data*. The central mock-up in Fig. 6 typically illustrates the placeholders for the two chart spaces needed to create a "double" treemap: their different sizes helps convey the idea that the overall volume of trade will likely be different.

3.4 Segmenting the Chart Space(s)

When the chart placeholder(s) have been laid out, we can segment the chart space(s) to simulate where the different visual marks in the visualization(s) might fit, and how they might relate to each-other. Here, we present a series of examples that lead to a mock-up of a treemap barchart. We begin by prototyping a "double" treemap, following up on the layout in the central mock-up in Fig. 6. We then create a simple barchart, which we use to prototype a "temporal" treemap. Finally, we create a grouped barchart, which we use to combine the "double" and "temporal" treemaps into a treemap barchart.

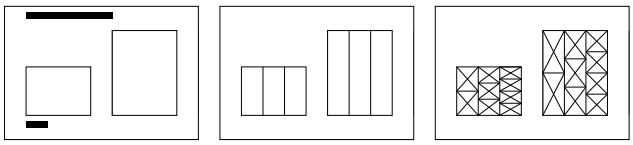


Fig. 7: Successive vertical and horizontal segmentations of the two chart spaces created in Fig. 6: creating a mock-up of a "double" treemap.

Fig. 7 shows the construction of a "double" treemap, based on the segmentation of the two chart spaces determined in Fig. 6. Each space is first segmented vertically, proportionally to the chart width. The resulting modules are then segmented horizontally, proportionally to the chart height (nested, proportional, horizontal segmentations). The subsequent nested modules determine the placeholders for each rectangular mark in the treemaps. Note that we could have equally started with horizontal segmentations, followed by nested vertical segmentations (as done in Fig. 9). In addition, while we only apply these operations once to get a rough mock-up of the treemaps, they can both be repeated as many times as there are expected levels in the hierarchical data. This can easily be iterated on, as realistic data become available.

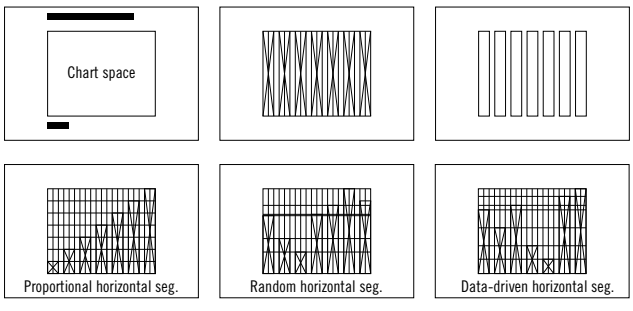


Fig. 8: Three horizontal segmentations of the canvas space: creating three barcharts, informed by more or less realistic data.

Fig. 8 shows the construction of three simple barcharts, based on the segmentation of a single chart space, and the progressive mapping of data. The space is first segmented vertically, proportionally to the chart width, to create the *bar modules*. The space is then segmented horizontally to determine the height of each module. The bottom-left mock-up in Fig. 8 uses a proportional segmentation; the bottom-center mock-up uses a random segmentation; and the bottom-right mock-up uses more realistic data. Note that in this case, the proportional segmentation is sufficient to communicate the type of visualization.

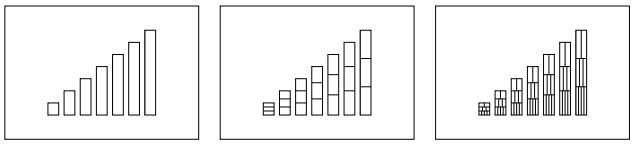


Fig. 9: Nested the segmentations for a treemap in those for a barchart: creating a "temporal" treemap. Note that we do not represent the final modules as placeholders here, because a) each module could be further subdivided, and b) adding the "X" pattern to each of them would result in very high visual clutter.

Fig. 9 continues Fig. 8. It shows the construction of a "temporal" treemap. Each bar module is first segmented horizontally, proportionally to its own height. Each resulting nested module is then segmented vertically, proportionally to its width (nested, proportional, vertical segmentation). As mentioned for Fig. 7, these operations can be repeated any number of times.

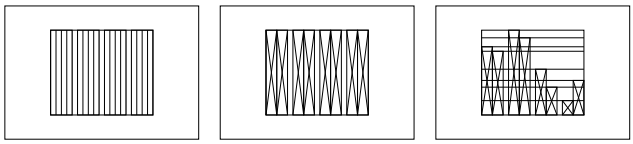


Fig. 10: Two successive vertical segmentations: creating a grouped barchart.

Fig. 10 is similar to Fig. 8, except it includes an extra nested, proportional, vertical segmentation with no gutters for each bar module, to create a grouped barchart.

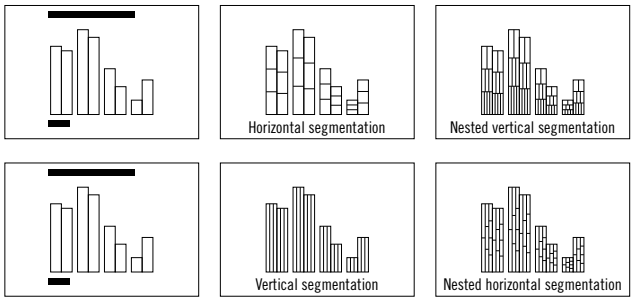


Fig. 11: Two combinations of the "double" and "temporal" treemaps: creating two barchart treemaps.

Fig. 11 illustrates the combination of the "double" and "temporal" treemaps (Figs. 7 and 9) using the grouped barchart (Fig. 10). It shows two variations of a barchart treemap, one starting the treemaps with a horizontal segmentation (top row), the other with a vertical segmentation (bottom row). This simple comparison immediately reveals that starting with a horizontal segmentation is likely to be more legible, as the alternative makes it harder to distinguish between grouped bars. Seeing this early on can help save time later in the design process.

Finally, Fig. 12 shows an overview the whole mock-up creation process, from the segmentations at the canvas level, down to the those at the chart level.

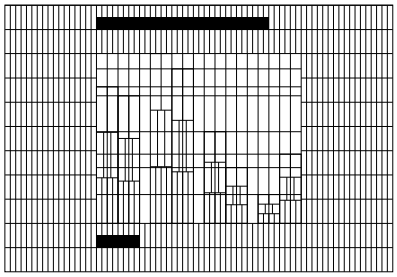


Fig. 12: Overview of all the segmentations, grids, and modules used to create a mock-up of a barchart treemap.

Overall, this graphic design perspective illustrates how using grids and modules, and more generally iterative subdivisions of the display space, can help create balanced, effective visualization mock-ups, with little, or no use of data. It also indicates how mock-ups can help identify a number of possible design challenges early on, while allowing to rapidly test different alternatives. For example, we immediately see in Fig. 12 that the number of items a treemap barchart can support is quite low: the number of bars must remain small to preserve the legibility of the nested treemaps. Similarly, the treemaps are likely to be easier to read if they are first segmented horizontally (Fig. 11), and they likely cannot support a great number of categories, i. e. further nested modules. As such, this approach complies with Munzner's nested model for visualization design [36], in that it allows designers to rapidly test encodings (without relying on real data), enabling them to identify and correct potential upstream misunderstandings—typically by discussing the mock-ups with their interlocutors.

However, while this perspective is informative, it is not entirely practical. All the examples provided in this section were created using a popular graphics editor (Adobe Illustrator). We believe this sets two important drawbacks. The first is that setting up grids does require time, effort, and a good understanding of the graphics editor; and the automation of this process is complicated. This results in an incompressible initial time cost, and the necessity to collaborate with a skilled graphic designer, which prevents an immediate exploration of different visualization ideas. The second is that, when these ideas begin to crystallize, the mock-ups created with graphics editors do not truly afford the progressive inclusion of data. These software generally do not support the binding of data with visual marks [28, 49], which prevents from moving on to higher-fidelity mock-ups.

4 A Parametric Toolkit Perspective

We now turn to exploring the creation of visualization mock-ups at the graphical level from a parametric toolkit perspective. We begin by highlighting the lexical differences between this perspective and the previous one, and we introduce a simple visual grammar we use to describe visualization mock-up variations. We then detail the implementation and API of the D3-based toolkit we developed to explore the generative power of our approach.

4.1 Lexicon Abstraction

All examples created from the graphic design perspective systematically started with segmentations of the main space, i. e. the canvas or chart space, to create grids, which determined the size and placement of modules. Here, we use an abstracted operation we call *partitioning*. A *partition* automatically lays out a defined number of modules, according to a defined layout *pattern*. This helps simplify the lengthy process of manually setting up a grid, and laying out modules.

As the resulting modules do not strictly follow an underlying grid, we provide them with individual *width*, *height*, and *padding* parameters

(instead of gutters). This complies with standard web design practice, where CSS widths, heights, margins and padding are used to determine the size of, and space between elements.

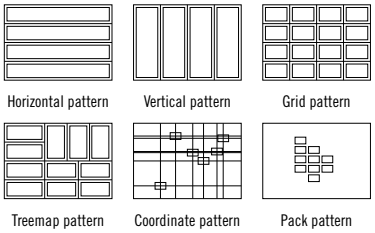


Fig. 13: Six predefined *partition patterns*.

Partitions follow predefined *patterns* of space segmentations. Basic patterns are *horizontal*, *vertical*, and *grid*. These follow the simple, orthogonal segmentations we used previously. However, grids can also be triangular, diamond-shaped, or hexagonal [35]. While these layout patterns are not particularly common in InfoVis (save perhaps hexagonal patterns), others like *treemap*, *coordinate system*, and *pack* layouts are [45]. We add these to our lexicon to complement our basic rectangular patterns, and to extend our design space. Note that the partitioning operations for *coordinate system* and *pack* patterns are different from others, as they focus more on module placement than on space segmentation (as discussed in [45]).

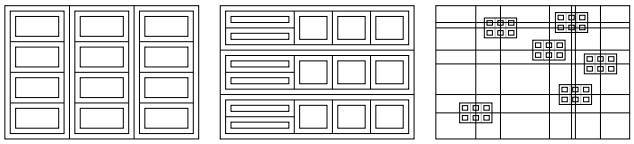
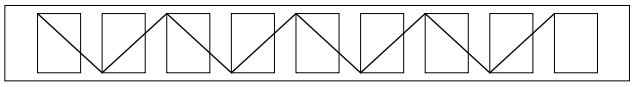


Fig. 14: Three examples of *nested partitions*.

Partitions can be repeated any number of times, creating *nested partitions* within each module of the mock-up.



Finally, to add expressiveness, and to cater for line-based charts, we created a visual *linking* operation that connects each module in a partition with an overlaid line.

4.2 Visual Grammar

In addition to our abstracted lexicon, we propose a visual grammar to describe the visualization mock-up variations we create. A basic vocabulary captures the main operations in our approach, as well as the (expected) data attributes they can be applied to. We believe this vocabulary is necessary, as many mock-ups are composite, and can be difficult to name; we also expect it will help highlight parameter patterns across charts. Our vocabulary consists of:

- six *partition patterns*[2] (based on Fig 13):
  - vertical ▥,
  - horizontal ▤,

[2]Each partitioning operation has a set of parameters, which we describe in the following subsection.

  - grid ▦,
  - treemap ▤,
  - coordinate ❁,
  - pack ⁂;
- a *nesting operation*: ⋈;
- an *overlay operation* [30]: +;
- a *linking operation*: ξ; and
- two *data transformations* [48, 58]:
  - *data attributes*:
    * items (e. g., entries, transactions) (I),
    * dimensions or categories (D),
    * time points (T).
  - *data operators*: Value, Bin, Filter, Frequency, Stack, Rank, Permutation.

Our grammar then simply consists in sequentially combining operations with data attributes and operators. For example, consider the first mock-up in Fig. 14 (left). Imagine we are expecting to receive an extremely simple dataset, which we have been asked to visualize. We know that this dataset should have no more than four items (I), and three dimensions (D). We decide to first partition the chart space vertically (▥) according to the different dimension. We then nest each item horizontally (▤) within the resulting modules. This simple succession of operations can be summarized using our grammar as follows: ▥(D) ⋈ ▤(I).

4.3 Toolkit Implementation

We implemented our basic vocabulary in a parametric toolkit, using D3 data transformation (e. g., `d3.nest`), and visual presentation (e. g., `d3.scale`, `d3.layout`) functions. To facilitate writing these functions, we developed an application programming interface (API), through which we simply pass a set of parameters in the form of a JavaScript object (see Listing 1). The code is available at `https://github.com/romsson/d3-gridding/`; it furthers the effort to serialize chart parameters [23, 44]. This toolkit enabled us to easily explore various computation-based designs, using a parametric approach. We used it to generate all the remaining figures in this article, which are also available at a higher resolution in the code repository (e. g., `https://romsson.github.io/d3-gridding/example/capture/display.html`).

```
1  // Canvas properties
2  var width = 400, height = 300;
3
4  // Realistic data generation
5  var data = [], nb_year = 4, nb_flow = 2,
       nb_product = 10;
6  d3.range(nb_year).map(function(y) {
7    d3.range(nb_flow).map(function(f) {
8      d3.range(nb_product).map(function(p) {
9        data.push({"year": y, "flow": f, "product":
             p});
10     });
11   });
12 });
13 var nesting = ["year", "flow", "product"];
14
15 // Partition parameters
16 var params = [{
17   "size": function() { return [width, height]; },
18   "offset": function(d) { return [0, 0]; },
19   "mode": "vertical",
20   "valueHeight": "__agg_sum",
21   "orient": "up",
22   "padding": 2
23 }, {
24   "size": function() { return [width, height]; },
25   "offset": function(d) { return [0, 0]; },
26   "mode": "treemap",
27   ...}]
28
29 // Subdivisions drawing
30 draw(data, params, nesting);
```

Listing 1: Our toolkit parameters to generate a treemap bar chart

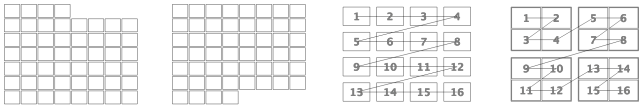


Fig. 15: Two different orientations (left figures) and orderings (right figures) of modules.

Listing 1 illustrates the code required to generate a treemap bar chart mock-up (similar to Fig. 12) using our API. The *partition parameters* are those passed to the underlying D3 functions for each partition; these can be noted as (▥(I) ⋈ ▤(Value(D))). The main parameter is the `mode`, which determines the partition pattern. It is associated with a `size` parameter, which determines the dimensions of the partition; and an `offset` parameter, which determines the position of the partition, relative to its parent space. Other, secondary parameters, include `orient`, which determines the direction in which the modules are laid out (see Fig. 15, left figures); `order` (not shown here), which determines their logical ordering (see Fig. 15, right figures); `padding`, which determines the spacing between modules; and `valueHeight` (and `valueWidth`, not shown here), which determines the data operator to use for the height of each module. Note that these parameters are not necessary for all partitioning operations.

By default, our toolkit renders all nested partitions in a space-filling manner using individual, *local* scales, which are based on the dimensions of their parent space (similarly to proportional segmenting—see Fig. 18, center). In specific cases, where nested partitions must share a common, *global* scale (independent from their parents' dimensions—see Fig. 18, right), we assign the `size` parameter absolute values (as done on line 24 in Listing 1), and note the operation using absolute signs (||). Thus, Fig. 18 (right) can be summarized as: ▦(I) ⋈ |▦|.

5 Explorations of Parameter Variations

In this section, we describe the creation of a series of example mock-ups using our parametric toolkit. Unfortunately, due to space limitations, we do not discuss all parameter settings for each design. Note however, that most required only small tweaks of the `params` array of objects in Listing 1. We start by exploring the creation of basic visualization mock-ups that require partitioning only the chart level. We then move to more complex mock-ups that require partitioning both the canvas and chart levels, and we finish with advanced mock-ups of multi-view visualization.

5.1 Basic Chart Space Subdivisions

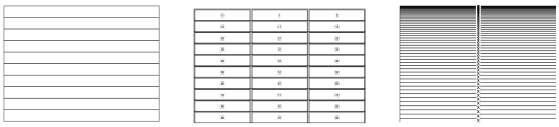


Fig. 16: Tables result from horizontal grids, with nested vertical grids.

Tables To create a table mock-up (▤(I) ⋈ ▥(D)) (Fig. 16), we first partition the chart space horizontally, according to the expected number of items in the data (▤(I)). Each resulting *row module* is given the same height (similarly to a proportional segmentation in the graphic design perspective), and is then partitioned vertically, according to the expected number of dimensions (▥(D)). The final *cell modules*

determine the placeholders for each value in the data. Variations can be explored either by further partitioning the cell modules (see *grid-based* charts below) or by compressing rows and columns (see *stack-based* charts below).

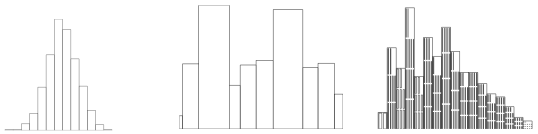


Fig. 17: Bars histogram, with variable width and with a nested grid

Bars To create a simple barchart mock-up (▥(I) ⋈ ▥(Value(D))) (Fig. 17), we first partition the chart space vertically, according to the expected number of items in the data (▥(I)). We then nest a second vertical partition in each resulting *bar module* using the value data operator (▥(Value(D))), which determines the height of each bar. This operation can be based on random values, or more realistic data. Horizontal barchart variations can be obtained by simply changing the partition pattern from ▥, to ▤. Histogram variations (▥Bin(I) ⋈ ▥Freq(I)) can be achieved by adding a bin operator to the first vertical segmentation (▥Bin(I)), and a frequency operator to the second (▥Freq(I)). Finally, grouped barchart variations (▥(Group(I)) ⋈▥(I) ⋈ ▥(Value(D))) (see Fig. 2) only require an extra initial vertical partition (or *parent* partition) using a group operator (▥(Group(I))). Further variations can be explored by varying the width of each bar module (Fig. 17, center), for example to reflect non-equal bin sizes; or by nesting a grid partition in a histogram, to reflect the number of individual binned values (▦(I)) (Fig. 17, right).

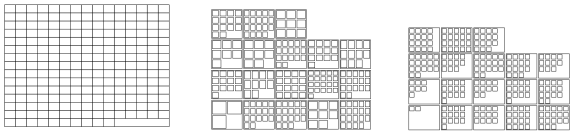


Fig. 18: Square data modules with grouped squares

Grids Simple grids ▦(I) may, or may not be entirely filled with modules. For example, a 10×10 grid will be entirely filled. However, the same grid with $|I| < 100$ will not (see Fig. 18, left). We then use the orientation parameter to determine whether the empty space is located at the top of the grid, or at the bottom. The resulting *cell modules* can either nest other partitions, or determine placeholders for visual marks. For example, they can nest further grids (▦(I) ⋈ ▦), using either an individual *local* scale (Fig. 18, center), or a shared *global* scale (Fig. 18, right). By extension, they can also become small multiple chart variations [51] (▦(I) ⋈ (chart)). Cell modules can also be used to place units, like Anthropographics [7] and other Isotypes [38], in a unit visualization [14]. Variations can be explored by repeating nested partitioning operations all the way down to the pixel level, for example to create mock-ups for VisDB-like visualizations [27].

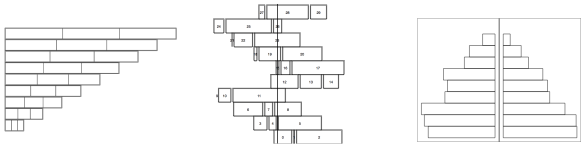


Fig. 19: Horizontal grids (left) divide space in lines, that can subsequently be divided to create a table and a stacked chart.

Stacks Typical stack layouts break the uniform vertical and horizontal separations (see Fig. 19) by compressing certain subdivisions, and changing their alignment. This way, a regular data table can have rows compressed on the left to reflect a cumulative perspective (using the stack operator) on each of the columns. This follows seminal work on Table Lens [39], which gives more space to rows or columns of interest, by squeezing in the others. If accumulation is performed on the first column of the table, it results in a vertical ranking of rows that sum up all the columns values, as done in Lineup [19] (▤(I) ⋈ ▥Stack(D)) (Fig. 19, left). Changing the stacking baseline to an intermediate value (see Fig. 19, middle) can provide another form of comparison. Side-by-side comparisons [18] can also be done (see Fig. 19) with different stacking orientations to mock-up for example, a population pyramid, where groups are gender (▥(Group(I)) ⋈▤(I) ⋈ ▥(Stack(D))) Fig. 19, right).

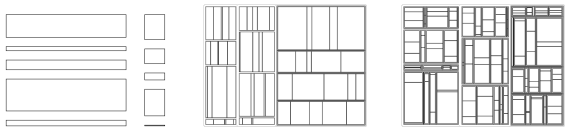


Fig. 20: Mosaic plots encoding 2, 5 and 7 dimensions

Stacks (continued) Variations can be explored by recursively nesting partitions to create for example, Mosaic Plot mock-ups [20] (▤(D) ⋈ ▥(D) ⋈ ▤(D) ⋈ (etc.)) (see Fig. 20). Mosaic plots suggest encoding dimensions at every recursion, alternating between horizontal, then vertical partitions (or *vice-versa*). This mechanism is somewhat similar to *slicing and dicing* a treemap layout [26] (▤), although treemaps are generally better at space optimization, and they focus on encoding a single quantity per shape. To include more data, treemap partitions can be nested within each other (▤ ⋈ ▤), or in a vertical partition (▥ ⋈ ▤) to create for example, a treemap barchart.

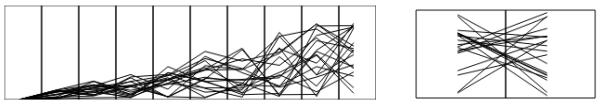


Fig. 21: Line chart and slope graph.

Lines To create a linegraph mock-up (▥(T) ⋈ |▤(I)| + ξ(I)) (Fig. 21, left), we first need to partition the chart space vertically, according to the number of expected timesteps in the data (▥(T)). We then partition each resulting *timestep module* according to the number of expected items (▤(I)). The height of each of these nested modules is determined either by a proportion of the parent module's (the timestep module) height, a random value, or more realistic data. We also assign each module a global scale, as the y scale at each timestep should be the same. Finally, we link each module. Slope graph [51] variations (▥(I) ⋈ ▥Filter(T) + ξ(I)) (Fig. 21, right) can be obtained by simply replacing the nested horizontal partition with a vertical partition, to which we apply a filter operator (▥Filter(T)), thus limiting the number of timesteps to two.

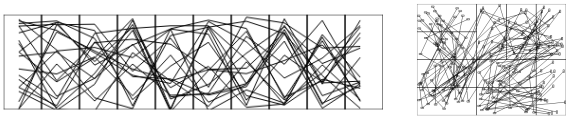


Fig. 22: Parallel coordinates and treemap overlays.

Lines (continued) Parallel coordinate variations are also very similar: they only require changing the data attribute of the initial vertical partition to the expected number of dimensions (D)), and assigning the resulting nested modules local scales. Further variations can be explored by changing the partition patterns, for example to create semantic substrates [47] (D) ⋈ + ξ(I)), or treemap overlays [16] (D,D) ⋈ + ξ(T)) and (IxD) + ξ(I)).

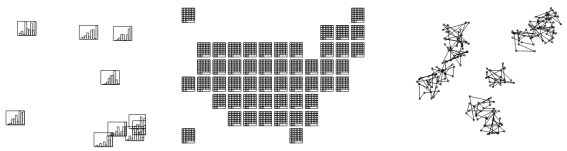


Fig. 23: Coordinate systems with nested histograms and a U.S. geo-grid map with nested ordered grids, and connected modules.

Coordinate systems Simple coordinate partitions ((D, D)) can be used to place modules according to (x, y) values. These can nest other partitions, or determine placeholders for visual marks (e. g., in a scatterplot). Fig. 23 (left and center) typically illustrates nested partitions in a coordinate partition ((D, D) ⋈(histogram)). Connected coordinate system variations ((D, D) + ξ(T)) can be obtained by simply linking each module to show for example, the temporal evolution of items. By extension, we can easily create node-link diagram variations ((ø, ø) + ξLink(I, I)) (Fig. 23, right) by connecting items with an additional link operator.

5.2 Canvas and Chart Space Subdivisions

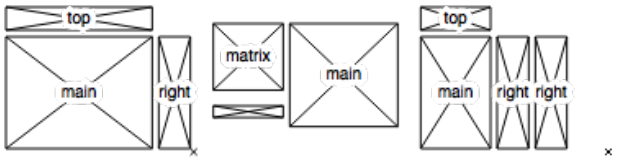


Fig. 24: Example of page grid layouts.

We extended our language with canvas subdivisions (Fig. 24), and their corresponding parameters. Note that the coordinate values of those parameters (`x`, `y`, `width`, `height`) are proportions of the page within which the canvas is drawn.

```
{"name": "chartTwoMargins", "values": [
  {"name": "container", "x": 0, "y": 0,
                        "height": 10, "width": 10},
  {"name": "main", "x": 0, "y": 2,
                        "height": 8, "width": 8},
  {"name": "right", "x": 8, "y": 2,
                        "height": 8, "width": 2},
  {"name": "top", "x": 0, "y": 0,
                        "height": 2, "width": 8}]}
```

Listing 2: Code for a marginal chart layout

We also augment our pictograms with an operator ∨ that denotes multiple nesting on the same grid layout.

Permutation matrices A permutation matrix (Permutation(D,D) ⋈ (D,D) ∨ (histogram))) is a pairwise combination of dimensions using coordinate systems nested in a grid layout (Fig. 25). The diagonal nests histograms that show each dimension's distribution. Generalized plot matrices [24] follow the same principle, but embed different graphics according to the row/column dimension type (e. g., quantitative, nominal, or ordinal).

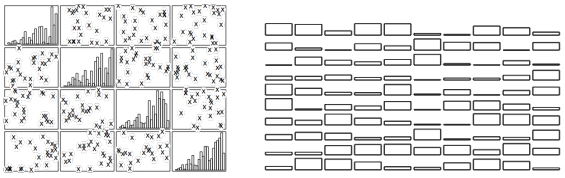


Fig. 25: Permutation matrix and heatmap chart mock-ups.

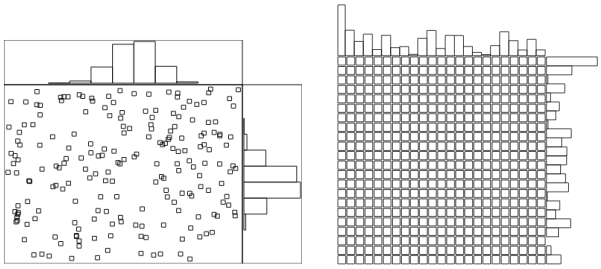


Fig. 26: Marginal distribution and adjacency matrix charts mock-ups.

Marginal distribution A canvas' margins can be used to nest vertical and horizontal histograms that show each axes' distribution (Fig. 26, left) ((D, D)) ∨ (Bin(I) ⋈ Freq(I)) and provide context. Adjacency matrices (Permutation(I,I)) use the same layout, but their main content is a permutation matrix—on items this time—and marginal bar charts encoding quantitative values, and not distribution (Fig. 26, right).

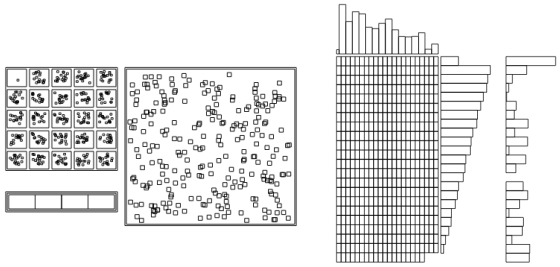


Fig. 27: ScatterDice and UpSet mock-ups using our toolkit.

5.3 Advanced Multi-View Visualization Mock-ups

We now describe two advanced multi-view visualization mock-ups, inspired by InfoVis tools that were originally implemented (or re-implemented) in part by one of the authors of this article. Each original implementation took at least two months to build. These mock-ups took less than one hour.

ScatterDice [15] (D,D) ⋈ ((D,D) ∨ ((D,D)))) is a multi-dimensional data exploration technique, which main component is a standard scatterplot, combined with a permutation matrix as a top-left inset. Fig. 27–left illustrates the main appearance of the tool re-created by composing modules (despite missing key features such as the 3D extrusion/rotation, query, history and labelling mechanisms). However, this prototype is handy to asses some limitations ScatterDice may face, by only tweaking a couple of the toolkit parameters: with more than 20 dimensions, the permutation matrix does not render very well; if dimensions are not quantitative (e. g., binary) scatterplots are not well suited any more; and one might also want to test improvements of the matrix such as using a GPLOM instead of the scatterplot matrix.

UpSet [33] (▦(D,D) ⋈ ∨ (▤bar chart)) is a recent technique to visually explore all possible set intersection permutations, and their quantification. Fig. 27 (right) shows UpSet's main feature, which is the vertical matrix that is the permutation of all sets intersections. The matrix has a bar chart as header showing set distributions for each column; the horizontal bar charts show the quantities for each intersection. Additional bar charts are added to the rightmost part of the canvas to display more set properties.

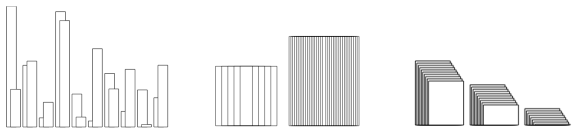


Fig. 28: Negative padding parameters allow compact charts creation.

As a known limit of UpSet is the vertical length of the matrix, we tested adding little vertical overlaps between grids, as our toolkit allows negative padding and margin values. Fig. 28 shows how bars can overlap slightly to create a bit of visual clutter, but acceptable as the trade off will be vertical compactness improvements. We also tested bar-piling, which is featured in small multipiles [3] Fig. 28. More stacking strategies could be further explored as they are known to be an efficient way to pack more information on screen [13].

6 Discussion and Design Implications

We have explored how iteratively subdividing the display space can help create visualization mock-ups at the graphical level, through a dialogue between graphic design, and parametric toolkit explorations. The graphic design perspective informed the viability of our display-to-data approach, and highlighted how the main operations needed to create mock-ups can be executed with little, or no data input. The parametric toolkit perspective illustrated how simple, iterative partitions of the display space, combined with light-weight data operations applied to expected data attributes (whether actually known or not), can help create a wide variety of more or less advanced visualization mock-ups.

We believe the main benefit of our display-to-data approach is that it allows designers to focus primarily on the visual form segment of the InfoVis pipeline (see Fig. 1). While our approach is not entirely data agnostic, it should prevent designers from having to worry about upstream data-related constraints. This suggests they should be able spend more time iterating over the output visualization—which can be shared with interlocutors—than on the input data in the early stages of the design process. For example, multiple parameters can easily be tweaked using our API to quickly assess how a visualization might fit on a screen [17]; whether partitions can be distinguished from each other; or whether a chart is likely to be overplotted. Therefore, it seems our approach could easily be integrated to broader visualization ideation methodologies, like Roberts et al's Five Design-Sheets [42], where our toolkit would provide a more principled way of exploring both data, and visual design spaces than traditional sketching. Indeed, design explorations can also go beyond the simple recreation of existing visualizations. Fig. 29 shows a naive attempt to nest all partition patterns within each other (e. g., ▦ ⋈ ▥, ⁂ ⋈ ▥), a method of benchmarking parameters that is in line with data-driven charts like scatterplot matrices, and other seminal work on spreadsheet structures [10, 57] that use grid-based layouts to visualize data using different charts, and different properties.

The main limit we see in our approach (and in mock-ups in general) is that it does not support high density charts, continuous charts (e. g., spark-line, streamgraph, curve links on graphs), and more complex data structures (e. g., hierarchical data, etc.). Also metadata (e. g., countries shapes), annotations, labelling, transitions, and interaction are not supported. We acknowledge that this currently makes it complicated to transition directly from the mock-up produced using our toolkit to final designs. That said, we argue that some marks and properties can be achieved by simply adding partition patterns to our toolkit, particularly non-standard patterns, like hexagonal and triangular patterns,

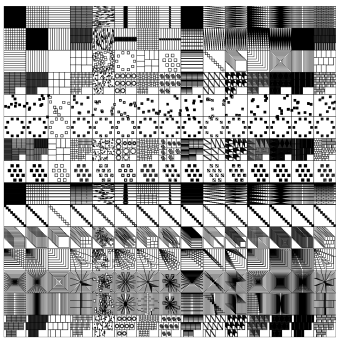


Fig. 29: Computation-based generation of nested canvas.

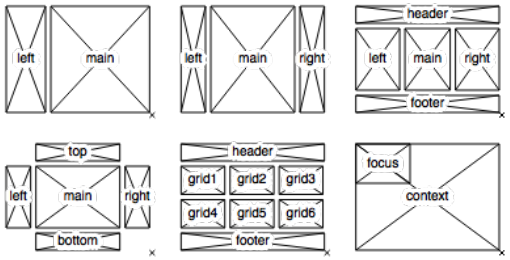


Fig. 30: Additional canvas configurations.

and pie chart wedges; and by using other coordinate systems like polar coordinates. Some retinal properties like color could also be supported, although they do not comply with the look and feel of wireframes. An alternative would be to use *textures* [4], as they are a reasonable alternative to color, and can be generated using further partitions patterns [56]. Other graphic design elements could also be added to the mock-ups (see Figures in section 3), such as *reference structures* [30] (like map graticules), as they can facilitate both construction, and comparison.

However, adding more expressiveness to mock-ups could also add visual complexity, as well as API complexity. This could make our toolkit less usable, and could impair the creative process.

7 Conclusion and Perspectives

In this article, we have presented a principled design approach for creating visualization mock-ups from the graphical level downwards. It relies mainly on the iterative subdivision of the display space, and the progressive inclusion of data. It is highly modular, and can help rapidly iterate over design ideas for both basic charts, and more advanced visualization interfaces. We hope this work will motivate and inform the development of future high-level prototyping tools for InfoVis.

Nevertheless, we acknowledge our approach is bound to a number of constraints (e. g., *grid systems* from the graphic design perspective, and *partition patterns* from the parametric toolkit perspective), which may be limiting. Therefore, we would like conclude by echoing the words of famous graphic designer Muller-Brockmann, and of famous architect Le Corbusier. The former stated that the "grid system is an aid, not a guarantee. It permits a number of possible uses, and each designer can look for a solution appropriate to his personal style. But one must learn how to use the grid; it is an art that requires practice." While the later mentioned "I still reserve the right, at any time, to doubt the solutions furnished by the Modulor [3], keeping intact my freedom, which must depend on my feeling rather than my reason" (in [22]).

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