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STAR – State of The Art Report

The State of the Art in Map-Like Visualization

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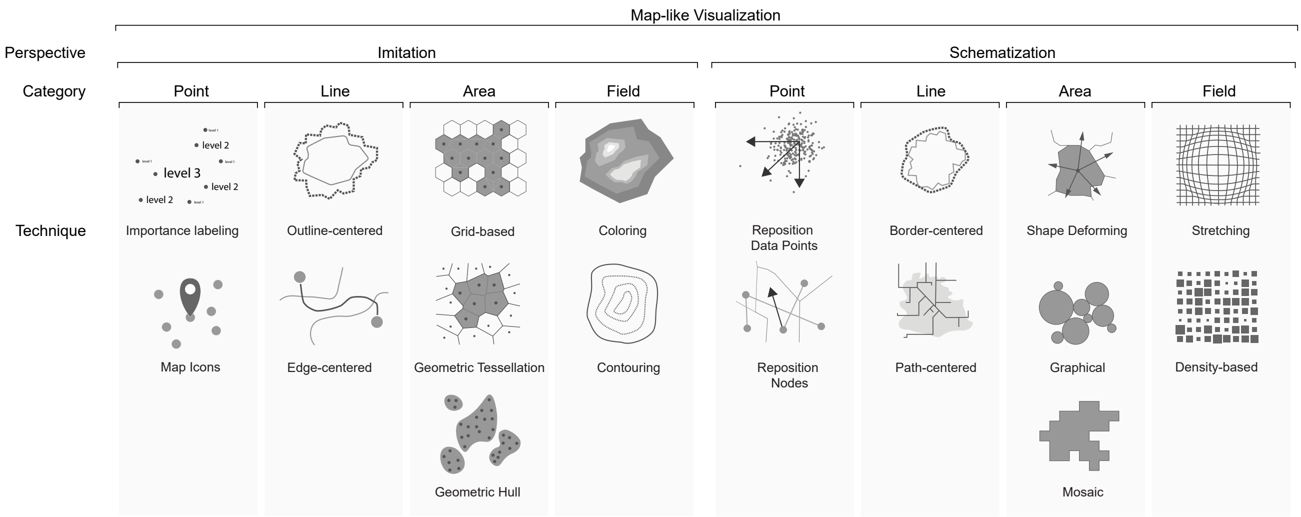


Figure 1: *The two perspectives of map-like visualization:* Imitation *transforms visualizations to make them look like a map.* Schematization *transforms cartographic maps to be more visualization-like, emphasizing the display of data over geographic accuracy.*

Abstract

Cartographic maps have been shown to provide cognitive benefits when interpreting data in relation to a geographic location. In visualization, the term map-like describes techniques that incorporate characteristics of cartographic maps in their representation of abstract data. However, the field of map-like visualization is vast and currently lacks a clear classification of the existing techniques. Moreover, choosing the right technique to support a particular visualization task is further complicated, as techniques are scattered across different domains, with each considering different characteristics as map-like. In this paper, we give an overview of the literature on map-like visualization and provide a hierarchical classification of existing techniques along two general perspectives: imitation and schematization of cartographic maps. Each perspective is further divided into four principal categories that group common map-like techniques along the visual primitives they affect. We further discuss this classification from a task-centered view and highlight open research questions.

1. Introduction

Cartographic maps have been a medium for centuries to represent spatial data in visual form. Research has shown the cognitive benefits of maps, such as our ability to read them from early ages [DeL04] or their benefits to recalling spatial information [Tve14]. Thus, visualization research has been investigating ways to leverage these properties for data visualization.

The term "map-like" is used in the literature to describe visualizations that incorporate features of cartographic maps into their representation of data [Sku02b, BLR00]. Visualizations are generally made to be map-like in order to leverage cognitive benefits of cartographic maps, such as people's ability to interpret spatial relations between map elements as a measure of similarity. However, the term map-like is used to describe rather different concepts

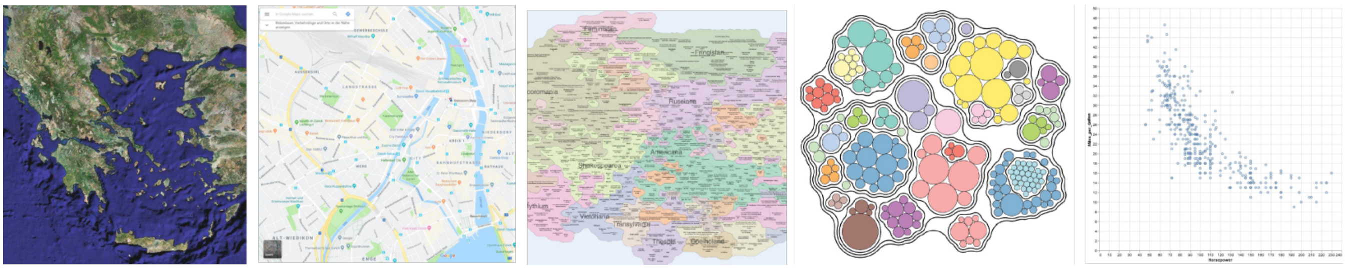


Figure 2: *Example images used during the interview study to assess the personal interpretations of HCI researchers and cartographers of the concept "map-like visualization", compared to abstract visualization and cartographic maps. Image sources from left to right: [NAS00], [Goo20], [HGK10], [GSWD18], [UW 20].*

throughout the literature, leading to an ambiguous and sometimes conflicting use of the term. Being unsure about the meaning of the term ourselves in the beginning, we conducted an interview study from which we determined two general perspectives on the idea of "map-likeness": imitation and schematization of cartographic maps. Where imitation tries to make a visualization more map-like, schematization aims to make a map more visualization-like.

Imitation and schematization both encompass mature research areas, for which some techniques have been surveyed before – e.g., cartograms [NK16], geographic network visualization [SKB20], or metro maps [Wol07]. However, to the best of our knowledge, these have never been put into the broader context of their map-like characteristics. We believe that such a broader view is useful for making informed decisions between these different approaches for creating map-like representations. After all, these approaches can be understood as lying on a continuum that reaches from the most realistic representations ("pure" maps) via map-like representations all the way to the most abstract representations ("pure" data visualizations). From this point of view, our two perspectives are merely different means to navigate this continuum of realism/abstractness: where schematization reduces the realism of a representation to make room for showing additional data in it (e.g., by using cartogram techniques), imitation reduces the abstractness of a representation and imitates a map for its visual familiarity and known affordances (e.g., by mimicking a road map). In that sense, schematization is a special case of *visual abstraction* [VI18] that reduces a visualization to its essentials by removing or de-emphasizing details and variation that are not needed and possibly distracting when conveying a dataset. Visual abstraction can be thought of as a maximization of Tufte's data-ink ratio [Tuf01]. Whereas imitation is a special case of *figurative visualization* [BAW16, BAW19] or *visual realism* [HVv05, AM02] that increase the likeness of a visualization to real-world scenes or objects through the use of visual metaphors or embellishments. From that overarching point of view, schematization and imitation are fulfilling complementary roles in generating map-like visualizations.

In this paper, we offer a top-down classification of the variety of existing techniques along these two perspectives (see Figure 1). We highlight the characteristics of each technique and present the relevant literature. Thereby, we give an overview of the disparate perspectives on map-like visualization and exemplify the ubiquity of map-like approaches in visualization. We found applications of map-like visualizations for example in geo-visualization (e.g., cartograms [HKPS05]), tree visualization (e.g., spatially-ordered treemaps [WD08]), graph visualization (e.g., [NPL*15]), visualization of document collections (e.g., strategic knowledge maps [PDJCRBBM12]), software visualization (e.g., software cartography [KELN10]), bibliometric analysis [Hoo07], and visualization of multi-variate data (e.g., using t-sne [SSL*19]).

The remainder of this paper is structured as follows: First, we derive the two perspectives on map-like visualization from the interview study we conducted. Then, we give an overview of the literature on map-like visualization along these two perspectives, listing landmark publications, approaches, and frameworks. Afterwards, we discuss interactions and tasks supported by map-like visualization and finally present open research questions in the field.

2. Perspectives on Map-Like Visualization

The term "map" might be one of the most overloaded terms in computer science. For instance, it is used to describe associative data structures, planar graphs, mathematical functions, scatter plots [Ito02], representations of geographic reality [KF17], hierarchical visual indices [Abe04], and the process of encoding information itself. Furthermore, it is also frequently added as a suffix to describe diverse techniques such as bit maps, color maps, heat maps, cognitive maps, treemaps [Shn92], science maps [BSBG18], or self-organizing maps [Koh90]. Hence, these different meanings make it difficult to compare objects described as a map.

Even when limiting the interpretations to a single domain, there is not always clarity as to how such a map is defined. In the cartographic domain, the definition of the term has been changing over time, adapting to the way maps are used or produced at a certain point in time [And96]. In recent years for example, the introduction of Geographic Information Systems (GIS) has lead to reinterpretations of maps in the community [Ito02, Car15, KF17]. In the visualization domain, the interpretation of what makes a visualization map-like is a subjective one as well [PBAY16]. The affix *-like* by itself indicates that the term describes a visualization that in some way resembles a map. However, visualization authors focus on different properties of maps for this resemblance, making it difficult to compare map-like techniques with each other.

To gain a better understanding of these diverse interpretations of the term map-like in the context of information visualization,

Figure 3: *Two perspectives on map-like visualization identified in our interview study: Either imitation is applied to abstract visualization to make the displayed information easier to understand or schematization is applied to a map in order to emphasize thematic attributes.*

we carried out a formative study in the form of structured interviews to determine what characterizes map-likeness. These interviews were conducted with three visualization and HCI researchers at Aarhus University and six cartographers at ETH Zurich, whose ages ranged between 26 and 65 years and who worked in their respective fields between 2 and 30 years. Each interview took on average around 40 minutes and was structured into three stages: First, we asked the participants' intuitive, personal definitions of the terms "map", "map-like visualization", and "visualization". Second, we presented the participants with 14 images from publications on map-like visualization, maps from atlases, scatter plots, and satellite images of the Earth (see Figure 2). For each image, we asked the participants to categorize them either as a map, as map-like, as a chart/visualization, or as something different altogether. The variety in the chosen images was intended to challenge participants to evaluate their own understanding of what distinguishes these three concepts. Third, we further asked for the reasoning behind the participants' decisions, in order to gauge what criteria were used in the process.

Only few participants were familiar with the term *map-likeness* and thus most of them needed to come up with an understanding of the term on the spot. This nevertheless gave us the opportunity to capture their first intuition of such a concept, which were rather subjective and dependent on the professional background of the participant. This reflects the results of a recent survey among cartographers [KF17], in which the authors found that the participants had quite different personal definitions for a map.

As for the categorization of the 14 images, participants based their decisions on a mix of the visual appearance, the utility, and the contents – with the most important aspect being the visual appearance. This is in line with the results of a user study by Pang *et al.* [PBAY16], who asked participants in relation to a set of map-like images "What makes you think this is a map?" Their participants also used mainly visual resemblance to decide whether a visualization was indeed map-like. Hence, it is not surprising that most of our participants classified an image of a road map and a screenshot from Google Maps as maps. A depiction of the fantasy world Middle Earth was likewise considered as a map by most participants, noting that it is useful for orientation in the fictional context. Yet a few categorized the fantasy world as map-like, noting that "it looks like a map but it does not show a real place." This example already points towards the aspects of utility and contents.

With respect to the utility of the representation, some participants argued that if it can be used like a map, it is a map. So, while the fantasy map was considered a map, cartograms and satellite images were only considered as map-like as they are difficult to use like a map. In our study, one participant specifically noted that being able to distinguish distance, direction, and absolute positions were necessary characteristics for map-likeness.

Regarding the image contents, it became clear from the study that maps were required to represent spatial, in most cases even geospatial data – i.e., data that is inherently linked to a place on the Earth and not to the fictional Middle Earth. Whenever the image used geographic space merely as a context for other information (i.e., an image of a cartogram), it was usually classified as map-like. Non-spatial representations like scatter plots and treemaps were considered as charts/visualizations by most of the participants.

In sum, our interviews revealed "map-likeness" not so much as a clear-cut concept, but as more of an umbrella term that subsumes all representations that somehow are neither maps, nor charts/plots, but that exhibit traits of both. The more aspects of map (appearance, utility, contents) an image exhibits, the more it is perceived as map-like – possibly even as a map if all of them come together. It is noteworthy that the participants' background plays a role in this distinction. For example, network/graph layouts and self-organizing maps were considered map-like by the visualization-inclined participants, but charts/visualizations by most of the cartographers. With "map-likeness" denoting this mix of maps and visualizations, we arrive at a dichotomous definition of the concept of map-likeness, which is also depicted in Figure 3:

Map-likeness denotes a **map schematization** that transforms cartographic maps to be more abstract like a visualization by emphasizing thematic data over the geospatial frame of reference. At the same time, map-likeness also denotes a **map imitation** that makes spatialized abstract data appear more like a cartographic map by emphasizing spatial context – even in cases where the data itself does not exhibit a spatial dimension.

3. Literature Overview

Based on the outcomes of our interview study, this section reviews the existing body of literature for both perspectives of map-like visualization. The concept of schematization is well-established in the cartographic literature as a transformation that abstracts geographic reality by modifying its map elements [BLR00]. The concept of imitation is also well-established, but usually referred to under the term of *metaphoric maps* [SF04]. These metaphoric maps aim to leverage cognitive benefits from cartography as an established body of knowledge for information visualization [Sku00]. The term metaphoric map is however overloaded and also used to describe schematized maps [CP12]. To avoid this ambiguity, we hence chose to refer to this concept as **imitation** instead.

Regardless which of the two perspectives is considered, both rely on transforming individual visual elements of a base representation – be it a map or a visualization – to create a map-like visualization. Following Bertin who introduced these elements as "classes of representation" [Ber10, p.44], these elements are point, line, and area. In addition to these discrete visual elements, cartographic literature commonly adds fields to this list for expressing continuous data features on maps [LGMR15, p. 64]. Our categorization of map-like techniques follows this distinction of four visual elements and classifies the different existing techniques for schematization and imitation into four categories each, depending on the kind of visual element it predominantly uses. Together with the different techniques in each category, this yields a three-level taxonomy of map-like visualization techniques, which is also shown in Figure 1:

1. The top level defines the overall **perspective** of an approach as either imitation or schematization.
2. The middle level differentiates each perspective into four **categories** (*point*, *line*, *area*, and *field*), based on the visual element that is affected.
3. The bottom level of the classification groups similar **techniques** for each category.

In the following, we present the literature on map-like visualization approaches along this three-level hierarchy. For each technique, we present its principal idea and its inherent challenge in a short paragraph, identified by an iconographic depiction of that technique. Then, we discuss individual solutions (e.g., the used algorithms) to these challenges. It is important to note that some of the discussed approaches actually combine multiple techniques to yield their map-like visualization. For instance, a technique affecting areas might in its course also apply a technique that changes the outlines of these areas. Therefore, the same visualization is potentially discussed in multiple sections, each highlighting the aspects of the particular technique relevant to that section.

3.1. Map-like Imitation: Using Features of Maps in Information Visualization

Imitation transforms a depiction of abstract data into a map-like visualization by adding map-like qualities. Its base visualization is thus a visualization of abstract data. Therein, abstract, non-spatial data is represented by visual primitives in a two-dimensional display. The data is thus spatialized, i.e., assigned a position on the plane. This position must necessarily implement a meaningful measure of distance between visual primitives in order to be considered map-like: Were item positions arbitrary, encoding densities or clusters by imitating cartographic maps would lead to inexpressive visualizations. This reflects the first law of geography, famously postulated by Tobler: "everything is related to everything else, but near things are more related than distant things" [Tob70]. Montello showed that the metaphor of similarity by proximity can be utilized in abstract visualization as well [MFRM03]. Fabrikant and Buttenfield describe spatialization to support "the viewer's intrinsic comfort with everyday concepts of human spatial orientation and wayfinding to guide the exploration and interpretation of the representation" [FB01]. Meaningful proximity can trivially be achieved by directly encoding two dimensions from the data in two axes of the visualization. In that case, similarity between data items is expressed

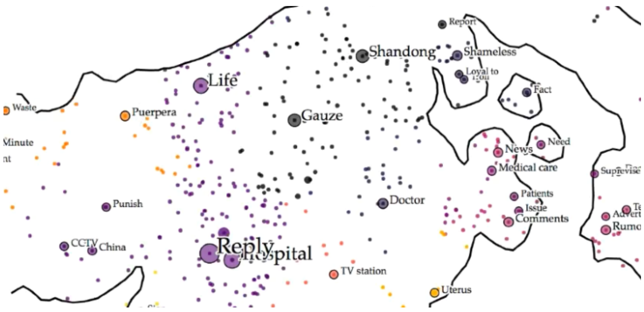


Figure 4: *Importance labeling technique in E-Map [CCL*17].*

regarding these two dimensions. Other spatialization algorithms aim to map n-dimensional data and their distances to 2D through dimensionality reduction. Skupin and Fabrikant [SF04, SF07] give an overview of spatialization methods for map-like techniques. Some of the most common spatializations are:

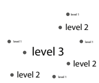
- Multi-dimensional scaling (MDS) [KW78, SDMT16]
- Principal component analysis (PCA) [WEG87, NH19]
- T-distributed stochastic neighbor embedding (t-SNE) [vdMH08, WVJ16]
- Self-organizing maps (SOM) [Koh90, Sch10, Sku02a]
- Force-directed layouts [Kob13]

The techniques discussed in the following assume such a spatialization has already been performed, in order to transform it into a map-like visualization.

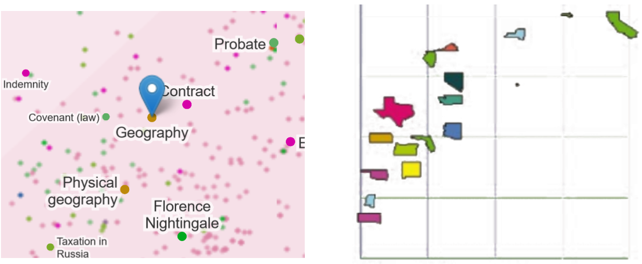
3.1.1. Point Imitation

The first category of imitation techniques is to use point map elements to imitate symbolism of cartographic maps. The general idea is that map symbols are recognizable for map users from early ages on [DeL04] and thus make it easier to get familiar with a visualization that applies them. The challenge for point-based techniques lies in utilizing established map symbolisms to encode abstract data without misleading the user about their meaning. We organize the literature in the following way:

- **Importance labeling techniques** that express an order of significance between items by adjusting their labels.
- **Map icon techniques** that use recognizable map iconography to encode the position of items.



Importance labeling techniques can be utilized to symbolize different levels of importance between elements on the map-like visualization (see Figure 4). A recent study on dot-label judgment concludes that cartographic placement guidelines cannot be applied to information visualization [RPHJ20]. Nevertheless, hierarchization of labels using different font sizes is a common sight in information visualization. This technique is often combined with semantic zoom interaction, in which elements of the data are hidden until the user reaches a specific zoom level, resembling a common behavior of digital maps [PBA11, MKH12, BAYP*15, BB17a]. The general challenge that this technique faces is computing expressive levels of importance on the data [Wol13].



(a) (b)

Figure 5: *Map icon technique used in (a) Cartograph [SSL*17] and (b) DataSplash [WOA*01].*

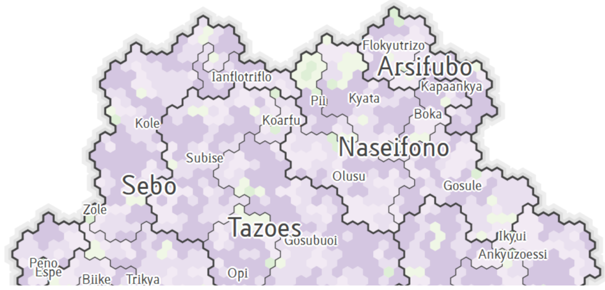


Figure 6: *Space-filling curve approach to the border-centered technique used by GosperMap [Abr14].*

One solution is to use the inherent structure of the data as a measure of importance. When visualizing hierarchical data for instance, the level of a node in that hierarchical structure can be used to determine its importance. Internal nodes that are closer to the root of the data are for example more visible than leaf nodes, which is commonly expressed through a larger [BAYP*15, WNSV19] or bolder [CSL*10] font. When visualizing multivariate data, another simple approach is to use a quantitative dimension of the data as an importance measure [CCA*18, CCL*17] (see Figure 4). The larger that dimension for a data item, the more important it is considered.

Other approaches compute an external measure of importance over the data to determine label size. In Cartograph [SSL*17] for example, labels of frequently referenced Wikipedia articles are shown when viewing the full dataset, while individual, less frequently referenced articles are labeled only after zooming in. This frequency of references is measured by the PageRank score of each article across the data, which was initially introduced to rank the importance of websites. At every zoom level, font size encodes the PageRank score of visible nodes, with larger labels indicating more frequently referenced articles. In a related approach, Tulip [Aub04] measures node importance by computing nodes' Strahler numbers – an approach adapted from hydrogeology where it is used to compute the importance of rivers [ADC04].

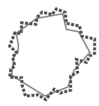
Another point-based imitation technique is using **map icons** to encode the location of items in the view (see Figure 5). Since map symbols are usually semiotically meaningful, the challenge for these techniques lies in using a symbol whose meaning is transferable to abstract data.

Cartograph [SSL*19] for example uses the pin symbol to indicate the location of a data item, similar to digital maps (see Figure 5a). While the symbol also resembles the signal poles used in American football, their wide-spread use to indicate locations in digital maps makes them recognizable as such for point-based imitation. In VideoMap [MGW16], multiple such location markers are placed on the map at the same time, with each identifying a different aspect about the data. DataSplash [WOA*01] uses the iconography of U.S. states when depicting quantitative data in a scatter plot (see Figure 5b). While some states such as California, Texas, and Florida are easily recognized by their shape, other states are less recognizable due to their regular, rectangular shape. In addition, using areas or shapes to indicate point positions makes reading off these positions problematic, as it remains unclear which point of the area was mapped to the respective position.

3.1.2. Line Imitation

This category of imitation encompasses techniques to generate irregular paths and borders to resemble those on cartographic maps. Techniques in this category are utilized to generate irregular, rugged lines, as these are generally perceived to be more map-like than long straight lines [PBAY16]. The techniques discussed here are related to the ones discussed in the next section on area imitation since algorithms that produce an irregular outline also generate an overall irregular area. We structure the approaches in this category along the following general techniques:

- **Outline-centered techniques** that generate a rugged border for areas in the visualization.
- **Edge-centered techniques** that change the routing of paths to adapt to surrounding virtual terrain.



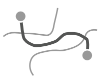
Outline-centered techniques are often applied to areas in the visualization to generate map-like borders (see Figure 6). The general idea is that borders of geometric maps are usually irregular. For this purpose, some techniques identify parts of the border that do not conform to a map-like heuristic and adjust it. Such heuristics detect for example sharp corners around the outline or long sections of the outline that do not contain any bends. Other techniques are applied when generating the areas to avoid regular outlines in the first place. The challenge for outline-centered techniques thus lies in providing algorithms that detect and correct or prevent regular outlines.

Some outline-centered imitation techniques create rugged outlines by introducing variety or randomness into their generation process. This variety is a way to introduce irregularity and to avoid straight lines, thus the outlines of areas appear map-like. For example, a space-filling curve is often used in combination with a regular grid to generate irregular outlines [Wat05, AHL*13, VMP16]. The general motivation for this is that coastlines on cartographic maps can also be described by fractal function, similar to space-filling curves [GgX96, Mul87]. Examples are fractal space-filling curves such as the Hilbert curve or the Gosper curve. By joining all cells encircled by such a curve into a border, the outline of a particular area on the regular grid appears rugged. Encircling nodes that are distributed with large variance across the drawing space [SNG*17]

Figure 7: *Terrain integration approach to the path-centered technique and geometric transformation approach to the outline-centered technique used by Gronemann and Jünger's visualization [GJ13].*

also yield irregular outlines. The GMap algorithm [HGK10] randomly places virtual points around the actual nodes of a graph, in order for the outlines of the resulting Voronoi mesh to appear less regular and to avoid long cell borders on the outskirts of a region.

Other approaches use geometric transformations as a post-processing step on existing borders (see Figure 7). In that case, regular segments around the outline of areas are detected by some map-likeness heuristic and are transformed by adding or removing vertices. Gronemann and Jünger [GJ13, GJKM13] for instance use the fat polygon partitioning algorithm [dBOS10] to identify sharp corners around the areas created by their partitioning strategy. Then, these corners are rounded by deleting the sharp edge and replacing it with a series of vertices that form a rounded bend. The E-Map technique [CCL*17] in contrast is computing a transformation on the full outline of each area. For this, the algorithm simulates water eroding the virtual coastline of all areas. Their technique fills low-density regions of the visualization with "landmass" by extending the outlines of adjacent regions [PD02].



Another approach to line imitation is the **edge-centered technique** that adapts the trajectory of paths routed between nodes (see Figure 7). Often, map-like visualizations of graph data do not use any distinctively map-like technique for paths but instead only draw them as thin, gray lines in the background or simply omit them. Hierarchical relationships are then indicated as a nesting of map-like areas. The general idea for the edge-centered technique is to instead imitate the curvature of streets and rivers on cartographic maps, which usually adapt their path to the surrounding topographic terrain. The challenge for these techniques is to route an edge through the "terrain" of map-like areas in a way that appears map-like while at the same time does not add distracting visual clutter.

One approach is to use edge bundling [ZPYQ13] to join edges that are routed along a similar path, similar to joining rivers and roads on topographic maps (see Figure 8). The general challenge with edge bundling is that while it reduces visual clutter, individual paths are harder to identify inside a bundle. GraphMaps [NPL*15, MN18] for this purpose perform local optimizations of each edge in order to minimize the total amount of "digital ink" used to draw edges. Starting from a rectangularized initial routing, edges are merged if they lie within a certain distance from one another. The

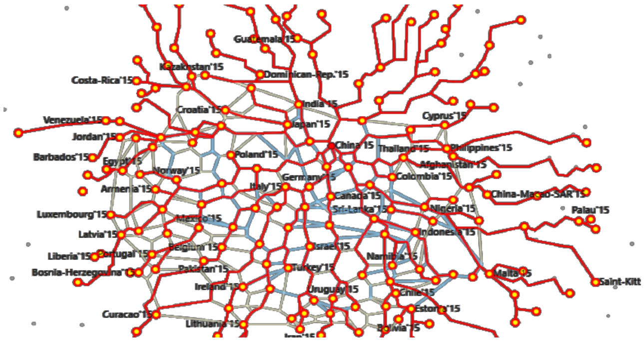


Figure 8: *Path-centered technique used in GraphMaps [NPL*15].*

resulting edges resemble road networks (see Figure 8). Edge junctions are moved towards the median location of connected nodes. In E-Map [CCL*17], crossing edges are smoothed out and merged along shared parts of their route to imitate the rivers on maps. In Metabopolis [WNSV19], edge-bundling is used to increase readability of long paths. For this purpose, a graph is divided into subgraphs, whose nodes are then represented by boxes in a rectangular partitioning. This places nodes with high interconnectivity next to each other, enclosing them with a rectangular outline. Then, edges between nodes from different subgraphs are routed along the rectangular outlines of each subgraph rectangle, leading to 'Manhattan'-style edges with only rectangular bends.

In combination with edge bundling, some approaches utilize the virtual terrain defined by map-like areas to route edges along a path similar to those of streets on cartographic maps (see Figure 7). In the work by Gronemann and Jünger [GJ13], edges are routed through virtual elevation terrain, following their "natural" pathways. To do this, they present a shortest path algorithm that takes the geometric "terrain" into account. As a result, paths follow the gradient of "mountains" and run between adjacent "coastlines" of clusters. At the same time, edges that connect similar regions are automatically edge bundled, as they follow the same path in the terrain. In a follow-up work, the authors presented an extension of the algorithm that also reduces the overall lengths of paths by optimizing the layout of the generated areas [GJKM13]. Preiner *et al.* [PSK*20] present another path-centered approach that use the virtual terrain. Therein, intersecting edges of a force-directed graph layout are rendered as tunnels of an underpass on road maps.

3.1.3. Area Imitation

The third category of imitation is related to the general appearance of visual primitives that make the visualization resemble cartographic maps. In cartographic maps, areas allow distinguishing landmasses from bodies of water and are responsible for iconic shapes of continents, countries, and states. Due to their enclosing nature, areas also allow to define the scope of a phenomenon, for instance the boundaries of a forest or a mountainous region. Thus, they are an important factor for effective imitation, as they can visually group similar regions of data. The main challenge for techniques in this category is to generate two-dimensional, irregular geometric shapes for representing data of similar value [PBAY16] (for a discussion on visualizations that are not two-dimensional, we

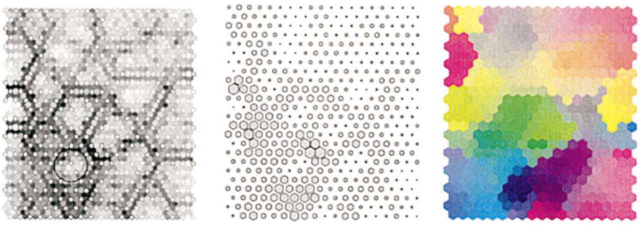
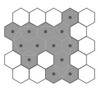


Figure 9: *Grid-based technique applied to a self-organizing map [Ves99].*

refer to Section 5.2). Different approaches exist to generate this irregularity. We structure the techniques in this category in the follow way:

- **Grid-based techniques** that produce irregular areas by filling adjacent cells of a regular grid.
- **Geometric tessellation techniques** that produce irregular areas from a cellular mesh computed over points in the view.
- **Geometric hull techniques** that produce irregular areas by generating a border through or around the outermost elements of a group of points.



Grid-based techniques generate ragged areas, for instance by placing the nodes of a graph along a regular grid (see Figure 9). The number of cells that represent each node encodes a quantitative attribute of the data. The more cells occupied by one node, the greater the value. Hexagonal grids are often used over squared and triangular grids, as they allow to express more adjacency relationships and appear inherently less regular. Adjacent cells represent nodes that are also similar in the data, for example because they share the same parent node. Another use case is the visualization of a SOM classification, where neurons are assigned cells on the grid. The main challenge for the grid-based technique thus lies in finding an encoding between data items and cells of the regular grid that produces irregular areas, representing a quantitative value by size and similarity by proximity of cells.

One approach to this is using space-filling curves, which we previously discussed as a way to produce irregular outlines in line-based imitation techniques. From an area imitation standpoint, these techniques produce closed, bordering shapes, similar to those of cartographic maps. In JigsawMaps [Wat05] for instance, the Hilbert Curve is used for this purpose, whereas the point-based tree layout [SHS11] uses a modified Z-curve to that end. Both approaches generate areas based on a rectangular grid. The GosperMap [AHL*13] makes use of the Gosper Curve to position the leaf nodes of hierarchical data in the cells of a hexagonal grid. In a related approach, Abrate [Abr14, p. 62] presents an approach to further encoding quantitative attributes into the size of cells. JASPER [VMP16] is an approach that visualizes nodes of large hierarchical data as pixels along a space-filling layout. The number of pixels that represent each node is decided by a quantitative attribute from the data. By coloring the cells belonging to each node in the same color, the graph is represented by map-like areas.

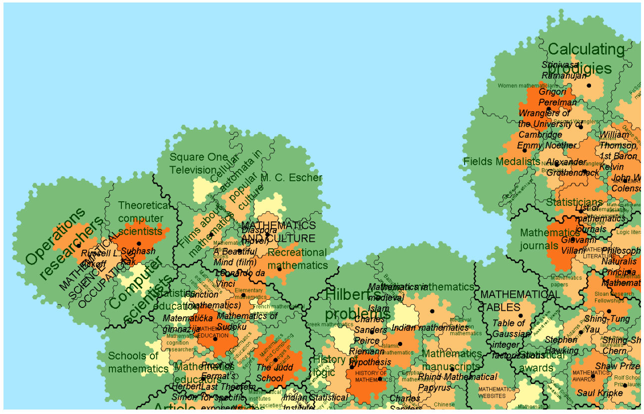
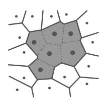


Figure 10: *Grid-based area technique in the Wikipedia World Map [PBA11].*

There are other approaches to the grid-based technique, which do not use space-filling curves. For instance, a force-directed layout can be used to generate a preliminary position for nodes, which are then placed approximately to that on the regular grid (see Figure 10). In the Wikipedia World Map [PBA11], grid cells are filled hierarchically by randomly picking an unoccupied cell that is neighboring an occupied cell. The initializing seed nodes are placed based on the preliminary layout. Yang and Biuk-Aghai [YBA15] extended this algorithm with a probabilistic model that prevents holes in the resulting areas and more accurately encodes values by the number of occupied cells. In D-Map [CCW*16, CCW*18], an algorithmic solution is presented to avoid holes in the areas produced on a hexagonal grid. First, disconnected areas are produced for subtrees of the graph that then are placed on the same grid. Afterwards all hexagons are shifted towards a center of gravity. A hexagonal grid is also often used without a space-filling curve when visualizing a SOM [Ves99, SF04, GGMZ05, Sch10]. For example, the activation intensity for a particular data value for a specific neuron can be visualized as a gradient color, similar to isopleth maps. Shapes result from neighboring nodes that have similar activation intensities, as their similar coloring gives them the look of a "region" (see Figure 9). The irregularly distributed training data in turn yields irregular areas similar to how they would appear on a map.



Another class of approaches that produce irregular areas is the application of **geometric tessellation techniques** on the spatialized data (see Figure 11). In these techniques, each point in the view is contained in a geometric cell. Cells are then grouped together if they represent similar points, for instance due to a common parent node or due to the output of a clustering algorithm. If the spatialized data is distributed irregularly, these techniques produce irregularly shaped areas. The main challenge for geometric tessellation techniques are to generate that geometric mesh.

The most common approach are Voronoi meshes. A Voronoi mesh partitions the view into cells by assigning all empty positions of the space to the data point closest to it. Therefore, if the spatialized data points are distributed irregularly, the area of the cells is

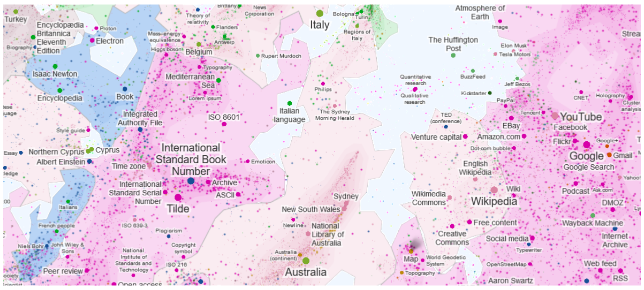


Figure 11: *Geometric tessellation technique used by Cartograph [SSL*17].*

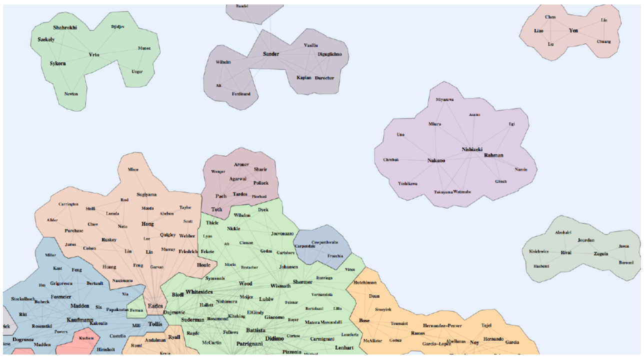
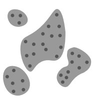


Figure 12: *Geometric tessellation technique used in GMap [HGK10].*

irregular, too. The approach was used for map-like visualization in VoroMap [PDOMA06]. The GMap algorithm [HGK10, HKV12, MKH12] further adapts the Voronoi mesh to visualize clustered data by coloring the cells of all nodes of the same cluster in the same color (see Figure 12).

Kobourov *et al.* [KPS14] extend the underlying algorithm to avoid discontinuous regions. Sen *et al.* [SSL*17, SSL*19] add virtual "water points" to the visualization for generating "water" regions not encircled by the Voronoi mesh for low-density parts on the spatialized data. In R-Map [CLCY20] and E-Map [CCL*17, CCA*18], an initial force-directed layout is used to compute a Voronoi mesh on graph data. The mesh is then visually subdivided into separate "islands", representing strongly connected components in the data.

There are also tessellation approaches that do not rely on the Voronoi mesh. One example is fat polygon partitioning [GJ13], which creates a nested structure of convex polygons for a clustered graph. The approach was further refined for graphs for which the cluster hierarchy does not reflect the natural clusters of the underlying graph [GJKM13]. Another tessellation technique was presented by Biuk-Aghai *et al.* [BAYP*15] for hierarchical data using the metaphor of liquid bubbles that push each other around the view. Forces are simulated that squeeze these bubbles together, which results in irregular areas.



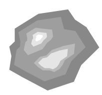
Geometric hull techniques generate areas around groups of points of the data in the view. Instead of generating map-like areas by joining cells of a grid or a tessellation, these techniques consider the grouping as a whole. This approach reflects users' intuition to use boundaries of clusters to isolate them visually [vR08]. The challenge for these techniques lies in finding a hull curve that captures all points in a group without overlapping with hulls of other groups.

Often, these hulls visualize density levels across spatialized data [CSL*10, XDC*13], for instance computed from a kernel-density estimator (KDE). Visually, such approaches resemble isopleth maps. Stahnke *et al.* [SDMT16] in contrast present an approach in which the hull represents a group of data items, generated either interactively by the user or automated by a clustering algorithm. These groupings are encapsulated by their convex hull, which passes through the outermost points of the group. Liu *et al.* [LJLH19] use the convex hull to encapsulate all points related to an attribute vector in a two-dimensional projection of high-dimensional data. Convex hulls thus visually group large numbers of points and serve as a visual guide when interpreting a complex machine learning model of high-dimensional data. Another related approach is used by Schulz *et al.* [SNG*17], in which the geometric hull encapsulates all places across the view that were occupied by a particular node during a simulation of a uncertain graph layout.

3.1.4. Field Imitation

The fourth category of techniques imitates continuous phenomena depicted on cartographic maps. By imitating continuity, techniques in this category give a more "natural" appearance to the spatialized data, as discrete data points are visually smoothed out. While techniques in this category thus affect both point- and area-based features of the visualization, they approach them from a continuous perspective, which is why we consider them in a separate section. We differentiate the literature into two principal techniques:

- **Coloring techniques** that use continuous color schemes that resemble distinct map types to encode values.
- **Contouring techniques** that indicate a value distribution across the visualization by adding isolines to group regions of similar value.



A common field imitation technique for map-like visualizations is using appropriate **coloring techniques** that make them appear map-like (see Figure 13). Using color allows for imitating the appearance of a particular map type that a user might already be familiar with. Colors can thus guide users in their interpretation of an unknown visualization. The general challenge for visualization techniques using color is to pick a color scheme that is both easily recognizable and still representative of the data.

A common use of this technique is assigning a specific color to each area in the view in order to mimic the use of color in maps. Similar to political maps for example, some approaches assign individual colors to each area in the visualization, for example visually differentiate clusters detected in the data [Ves99, PBA11, MKH12, AHL*13, GHK14, YBA15, VMP16]. Other approaches use the fill color of regions similar to choropleth maps, which encode quantitative attributes with colors from a continuous color scale [VMP16, XAA18, AXY*19]. Alternatively, color

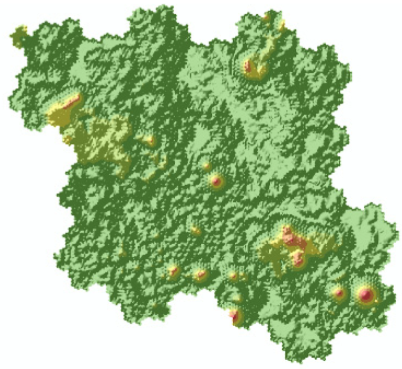
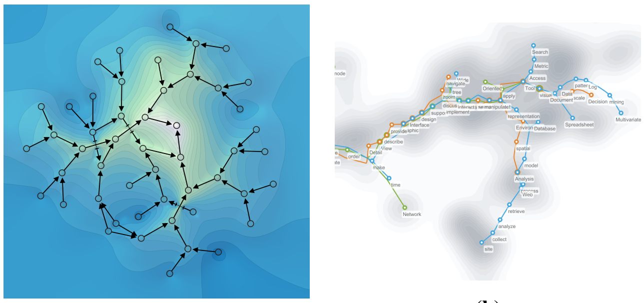


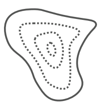
Figure 13: *Coloring technique applied to the GosperMap [XAA18].*



(a) (b)

Figure 14: *Contouring techniques used (a) by Preiner* et al. *[PSK*20] and (b) Xu* et al. *[XDC*13].*

can be used to symbolize a value distribution over a continuous area [Ves99, MSS01], which gives the impression of isopleth maps. These approaches thus support reading off the spatial distribution of a variable. Moreover, the terrain of topographic maps is imitated by encoding equal levels of hierarchy in an appropriate color scale that represents low-value regions as green fields and high-value regions as mountains in the landscape [GJ13, GJKM13, BAYP*15, SSL*17, XAA18, AXY*19, Big20]. Often, a blue color is used for the background [HGK10, PBA11, MKH12, HKV12, GJ13, BAYP*15, SSL*17], which lets areas appear like islands in an ocean. The topographic symbolization can help with finding a particular area of the map, as the virtual terrain supports visual recollection.



Another common field imitation is found in **contouring techniques**, in which regions of equal value are symbolized by an isoline that groups them visually (see Figure 14). Isolines make it easier to see the gradient of values across the view as they indicate the boundaries of a value range. Isolines that are close together indicate a steeper gradient in a certain region than isolines that are further apart.

Gronemann and Jünger [GJ13] use contouring in combination with a color scheme that resembles a topographic map. While the color scale supports identifying regions of higher importance globally, the contour lines simplify the interpretation of the color gradient on a local level. Kubota *et al.* [KNS07] discuss the use of different representations of contour lines to support different tasks by adjusting the shape of the contour lines. They present contouring techniques to visualize hierarchies, the number of leaf nodes in a subtree, and the distribution of a value across the visualization. Other approaches utilize contour lines to visualize the distribution of an "ambient" attribute along nodes of a force-directed graph layout [AHRH14, PSK*20] (see Figure 14a). Changing the ambient attribute maintains the graph layout, while the contour lines depicting the attribute are updated. This approach thus allows users to analyze a graph's topology in context of the distribution of other attributes. Other approaches [KELN10, XDC*13] use contour lines to visualize the data point density of a multivariate dataset spatialized with MDS (see Figure 14b). The regions defined by the contour lines thereby serve as a visual summary for large amounts of data. On top of this visualization, Xu *et al.* [XDC*13] visualize spanning trees across the data as linked graphs connecting individual points of the spatialized data. Thus, this solution allows comparing different spanning trees both pairwise and in regard to the global distribution of values. On data spatialized by a SOM, contour lines can serve as an alternative to cell-based visualization to indicate an agreement measure over the neurons. While neuron positions are static in a trained SOM, agreements are distributed differently for each concept. Contour lines can be used to interpret, which concepts are captured by the model across which neurons by comparing local value distributions [MSS01].

3.2. Schematization: Emphasizing Thematic Information in Geographic Maps

The second perspective on map-like visualization is schematization, which entails techniques that abstract the geospatial context on a cartographic map in order to emphasize a thematic attribute [BLR00, Wol13]. These schematizing transformations are sometimes also referred to as chorems [Bru84, Rei10, DCDFL*11]. We consider any attribute of the data that does not specify a location on a map as thematic. By schematizing a map, it emphasizes thematic information at the cost of accuracy of geospatial information. While all maps generalize reality by omitting information [Tve00], schematization is applied to further simplify the map for readability, to emphasize thematic data, or when representing geospatial information on a map of smaller scale [BLR00]. This process is opposite to imitation, where abstract visualizations were enriched with complex irregular areas and lines to make them map-like.

It may seem counterintuitive at first to reduce the accuracy of encoded positions – after all the most effective visual channel for displaying information [Mac86] – to emphasize information encoded in another channel. However, schematization does usually maintain geographic topology, which allows users to orient themselves in the data space based on the underlying geography. The availability of this geographical context is the defining difference between map-like visualization using schematization and imitation.

The base visualization for schematization is a cartographic map. Kraak *et al.* [KF17] define a map as "a visual representation of an environment". The authors purposely used a broad definition in order to capture the variety of particular interpretations of the term. It is influenced by how an individual makes use of maps, as

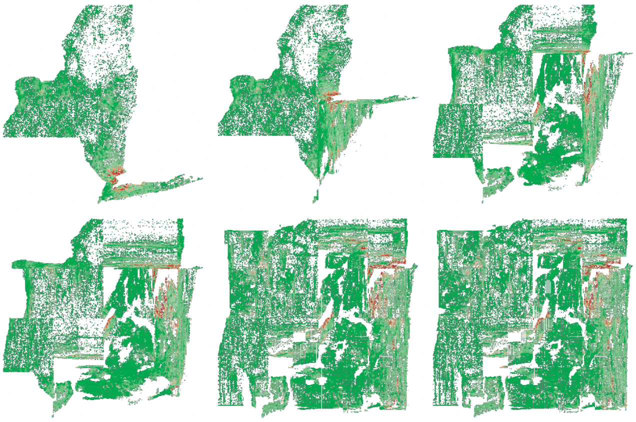


Figure 15: *Point repositioning technique used by PixelMaps [KPSN04].*

well as the technology that is used to create or interact with the map [And96]. Here, we consider visualizations of spatial, thematic data that is measured in connection to a location on the Earth as maps. Some of the most common map techniques are:

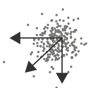
- Dot maps encode geospatial appearances [DTH08, ch. 7] [Tyn10, ch. 8].
- Flow maps encode geospatial movements or trajectories [PXY*05, JSM*18].
- Choropleth maps encode geospatial quantitative data [LGMR15, p. 46] [Tyn10, ch. 6].
- Topographic maps encode terrain and features of the earth's surface [KO13, p. 105].

Schematization techniques thus need to resolve an inherent trade-off: The more schematized the cartographic map, the more emphasis can be put on the visualization of data on top of the geography, which however at the same time becomes less recognizable. As shown in the following discussion of schematization techniques, this trade-off can be handled rather differently.

3.2.1. Point Schematization

The first category of schematization is applied to individual positions on a map, reducing their geographic accuracy by emphasizing other aspects of the data. In contrast to other techniques discussed later, point schematization techniques modify the position of individual points to move them along the view, rather than removing them entirely. The general challenge lies in first identifying points on the map that occlude important visual features and then finding an appropriate technique to resolve this occlusion. We organize the literature in the following way:

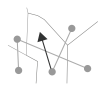
- **Techniques that reposition data points** to solve overplotting on symbol maps.
- **Techniques that reposition nodes** of geospatial graphs in order to fulfill aesthetic criteria from graph drawing.



One approach of point schematization includes **techniques that reposition data points** on dot maps to avoid overplotting (see Figure 15). These techniques are applied whenever large numbers of individual points are placed on the map, for instance when plotting the income of every household in a city as a colored dot per household. In that case, most data points are placed in major cities, with only few assigned to the countryside. The general challenge for these techniques lies in first identifying regions on the map with high and low density and then adjusting the positions of points plotted in these areas accordingly.

Figure 16: *Geo-restricted approach to node repositioning technique used by Brodkorb* et al. *[BKA*16].*

One approach to this is the GeoForce algorithm [LMR98], which uses a force-directed approach to spread nodes from dense regions on the map to less dense regions while restricting their movements to a geographical boundary. Point density is assessed based on the distribution of nodes relative to each other and the distance from each node to the borders of the view. GeoForce produces a set of evenly distributed points, in that it maximizes the minimum distance between any two points, while approximately retaining the shape of the original cluster. In PixelMaps [KPSN03, KPSN04], the underlying maps are schematized by representing sparsely populated regions of the map with a smaller scale, thus assigning more drawing space to densely populated regions. For this, PixelMaps recursively splits the view into areas containing equal amounts of data points and then scales the space occupied by the two halves to be equal as well. Brodkorb *et al.* [BKA*16] present a focus+context technique, in which densely populated areas of a geospatial graph are displayed as large-scale detail insets on an overview map. The geographic regions in this case are selected by the user. Insets are placed at the center of the geographic region they represent.



Another approach uses **techniques to reposition nodes** of a graph to fulfill aesthetic criteria (see Figure 16). Such criteria are usually applied in the non-spatial graph drawing context, where they serve to increase the readability of a graph layout by for example avoiding intersections between edges or by avoiding long edges. This gets challenging when drawing the edges of graph, for which the location of nodes is defined by a geographic location (i.e., *geospatial* graphs). In that case, traditional graph drawing algorithms would not consider the geographic context when reordering nodes. This would make it difficult to interpret geospatial graphs, as nodes are no longer positioned at the (approximate) position one would expect them at.

Abellanas *et al.* [AAP05] evaluate how traditional aesthetic criteria for graph drawing apply for cases where nodes represent geographical regions and introduce two criteria of their own: a node should be placed near the center of its region, and a node should not be placed near the borders of its region. They further introduce two algorithmic solutions to the problem, which extend es-

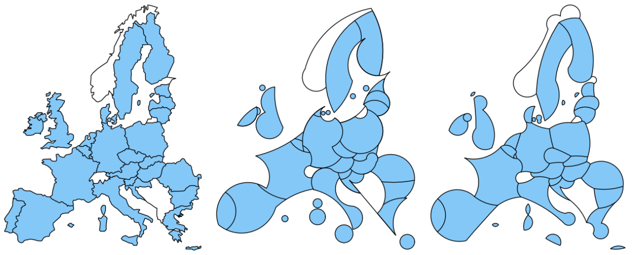


Figure 17: *Border-centered schematization technique used by van Dijk* et al. *[vDvGH*14].*

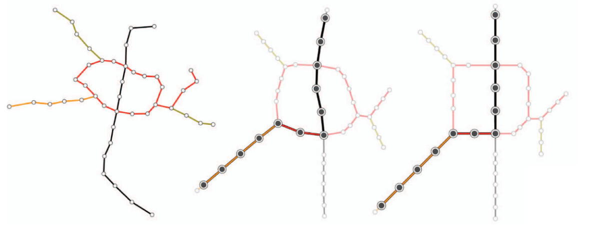


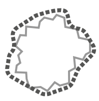
Figure 18: *Angular resolution reduction approach to the path-centered line schematization technique used by Focus+Context metro maps [WC11].*

tablished force-directed methods by restricting potential node locations to the represented geographical region, similar to anchored graph drawing [ADLDB*14, SSV18]. One application of this technique can be found in the inset-based visualization by Brodkorb *et al.* [BKA*16] discussed above. The geospatial graphs inside each inset can be distorted according to standard graph layouts to improve legibility. The authors present different techniques to indicate this distortion to the user. Others have investigated how the shapes of nodes in geospatial graphs reflect the shapes of the regions they represent to improve user orientation [FFMO07, DF10]. Instead of drawing nodes of geospatial graphs as abstract circles and the edges between them as straight lines, these techniques maintain the general shape of areas after the schematization. There are also more involved approaches that go beyond repositioning nodes of a graph. Zhou *et al.* [ZTXW17] for example lay out a graph, by assigning a cell from a regular grid to each node. Adjacency of cells on the grid indicate adjacency in the geospatial graph. The resulting schematization places far apart nodes close to one another, while at the same time resolving overplotting in dense regions, as each node is placed in its own cell. Then, thematic data is further mapped to each grid, using a color or size encoding. The authors also show the option of distorting the regular grid using a field schematization technique (see Section 3.2.4).

3.2.2. Line Schematization

The second category of schematization entails generalizing lines on a map. The general challenge for techniques in this category is to reduce the visual complexity of lines, while leaving them sufficiently recognizable and geographically accurate. Then, thematic information that is encoded in the visualization is easier to interpret while maintaining its geospatial context. We organize the remaining literature in the following way:

- **Border-centered techniques** that generalize the outline of regions, for example to emphasize a thematic attribute.
- **Path-centered techniques** that generalize paths, for example to simplify reading geospatial connections.



One approach to schematizing lines are **border-centered techniques** that simplify the outline of regions depicted on a map (see Figure 17). The general challenge for these techniques is to identify points along lines that can be removed or sections that can be modified, and then applying transformations to them that yield a reasonable degree of schematization.

Del Fatto *et al.* [DFLL*08] investigate the incremental application of so-called *chorems* to the outlines of geographic regions in order to generalize their shape. Chorems describe geometric transformations that can be applied to the outline of a shape in order to schematize it. As the border line of geographic regions remain recognizable, the map merely serves as a frame of reference for thematic data portrayed on it [WDS10]. As their approach incrementally applies transformations to the border line of shapes, the degree of distortion can be adjusted by using any intermediate result. Van Dijk *et al.* [vDvGH*14] discuss the different techniques that can be applied to schematize borders by gradually replacing path segments with circular arcs. Their algorithm reduces the geographic shape gradually by removing vertices along the outline while replacing straight lines with circular arcs (see Figure 17). The points along the outlines are picked based on how strongly their removal would influence the overall shape of the region. The authors suggest providing the user of a schematization with means to interactively explore the degree of schematization, as "the optimal number of arcs may not be clear a priori" [vDvGH*14]. There exist similar approaches to gradual schematization Barkowsky *et al.* [BLR00] reduce the number of bends on the outline in order to reduce the map's complexity for particular user tasks. Their method collapses the least relevant anchor points along the remaining lines on a map to reduce their complexity. This degree of relevance is measured by the contribution of an edge to the overall shape of an object, calculated by an approach named discrete curve evolution [LL99]. Fix points along border lines, which the algorithm will not remove, ensure that the outline of adjacent regions do not overlap after schematization.

Another approach is using **path-centered techniques** to schematize a map (see Figure 18). These techniques become particularly relevant when visualizing graph data on a cartographic map [Wol13]. The general motivation for these techniques is increasing the readability of paths on a map by reducing their complexity.

Possibly the most common path-centered approach is to reduce the angular resolution of the map. These approaches limit the possible bends of paths on the map to discrete steps, such as octolinear layouts (i.e. 45-degree steps), hexalinear layouts (i.e. 60-degree steps), or rectilinear layouts (i.e. 90-degree steps). Steiger *et al.* [SBMK14] discuss direction-preserving layout strategies for geo-referenced networks in detail, giving a user- and task-based perspective to the trade-off between realistic representation and

Figure 19: *Linear cartogram approach to path-centered line schematization technique used by travel time maps [BvGH*14].*

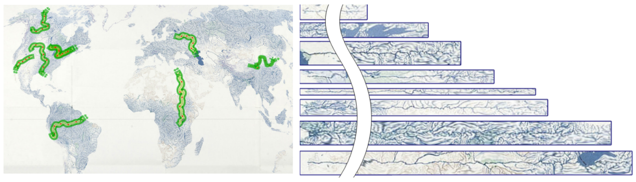


Figure 20: *Straightening approach to the path-centered technique used in transmogrification [BNP*13].*

readability. The general idea for these techniques is that the legibility of graph layout is increased when lines follow specific angles.

Often, these techniques are used to create metro maps (also named subway maps or tube maps). A metro map "is a schematic drawing of the underlying geographic network that represents the different stations and subway lines of a subway system" [Wol07]. To facilitate ease of navigating, metro maps schematize geographically accurate paths, for example by only relying on straight lines or restricting bends to a fixed set of angles. Locations of subway stops are therefore moved from their geospatial position. However, while fulfilling aesthetic criteria, the distance between two stops on a metro map often encodes the required travel time rather than travel distance, to make the map fit the needs of Subway travelers. Surveys on automated, parametrizable approaches to drawing metro maps were presented by Wolff [Wol07] and Nöllenburg [Nöl14]. Avelar and Hurni [AH06] discuss design criteria for the creation of metro maps by emphasizing the various choices that must be made consciously in the process. Here, we want to highlight some metro maps in the context of line-based schematization. Schwering *et al.* [SGL*19] for example propose using schematization along relevant landmarks and routes, in order to support "turn-by-turn" wayfinding on digital devices. Like metro maps, their approach schematizes paths and angles while retaining topological and spatial relations (see Figure 18). Focus+Context metro maps [WC11] are an interactive extension of the metro map approach, which highlights a selected route along the map on small displays by reducing the size of stops and lines not relevant to that particular route. In a related approach, the paths of the metro map are arranged in such a way that the stations along a user-selected route are rendered as a straight line [WTLY12]. Isenberg [Ise13] offers an aesthetic schematization technique that also limits the angular resolution of paths. Therein, angles of streets in a map are limited to only be 90 degrees. They also present a series of algorithms to schematize paths, including error optimization such that absolute edge lengths are kept within a threshold, rectangularization that yields right angles, a force-directed layout, replacing long chains of edges with simpler representations of these, and an approach that optimizes for the lowest displacement of areas.

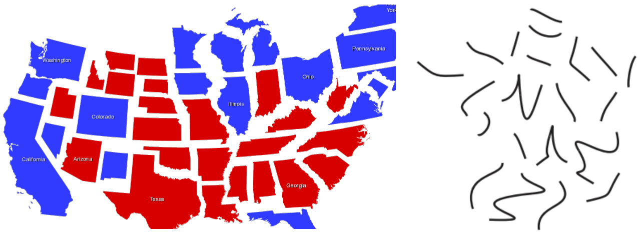
A related approach to path-centered schematization are linear cartograms (see Figure 19), which schematize distances on the map in relation to a thematic attribute, often the time it takes to reach a target from a starting point. For this reason, these approaches are also referred to as travel time maps. Some algorithms distort the position of the connected nodes on the underlying map in order to reflect the thematic attribute [AS01, CDR04, UK15]. The general idea is that target points on the map that can be reached faster along the road network are placed closer to a starting point. Other algorithms do not distort the space of the map itself, yet increase the length of paths by adding sinusoidal waves along them [BvGH*14].

Another path-centered approach is to straighten out lines in order to make them comparable with each other (see Figure 20). The general motivation for this approach is that curved paths in a hilly terrain are difficult to compare visually, compared to straight lines that are adjusted for topography. In turn, paths become comparable not only in terms of their absolute lengths, but can also be compared in terms of the environment surrounding them. The Snake Projection [IAP07] is a map projection method targeted towards railway construction projects, where long, but slightly bent paths must be measured. Their projection approximates the actual path of the construction with only a small error by taking into account the height of the terrain along the way. Transmogrification [BNP*13] is a transformation algorithm that allows arbitrarily shaped source areas on the map to be transformed into arbitrary destination regions. As a particular use case of Transmogrification, curved paths can thus be "straightened out" for visual comparison (see Figure 20). In contrast to the techniques discussed before, path-straightening techniques reduce the complexity of paths based on topographic features rather than geometric ones. Thus, they enhance the accuracy in depiction of topography, whereas the aforementioned techniques reduce it.

3.2.3. Area Schematization

The third category of schematization applies to discrete regions on the map, modifying their shape. The techniques presented in this section are partially related to those discussed in the previous section, as schematizing the outline of an area automatically generalizes its shape as well. However, here we focus on techniques that generalize an area on a map in order for its size to convey thematic information. In contrast to field schematization techniques that are presented in the following section, area schematization techniques utilize data that is defined per area or region, rather than continuously for every point on the map.

Area schematization techniques are also referred to as area cartograms. Area cartograms have a surprisingly long tradition, with manual techniques dating back to the 19th century [Bri39, NK16]. Nowadays, they are often used to encode geospatial, socioeconomic data in relation to population count for a certain region, for instance election results [NK16]. As population is typically distributed non-uniformly across the geographic area, this is partic-



(a) (b)

Figure 21: *Shape-deforming techniques for area schematization, using (a) non-contiguous scaling [Fie17] and StenoMaps [vMSW15].*

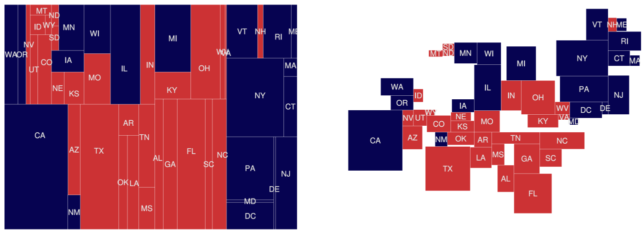


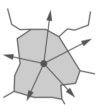
Figure 22: *Graphical techniques used by RecMap [HKPS05].*

ularly useful to counter perceptual bias towards larger geographic regions. Thus, cartograms are a well-researched field in cartography. Nusrat and Kobourov [NK16] give an in-depth overview of the state-of-the-art of cartograms, presenting three accuracy measures by which to characterize them:

1. *Statistical accuracy*, indicating how accurate the area of a cartogram represents the quantitative value. Minimizing this error is a common design goal in many cartogram algorithms.
2. *Geographical accuracy*, indicating the degree to which a cartogram offsets the geospatial positions of map regions.
3. *Topological accuracy*, indicating the degree to which regions in a cartogram maintain the adjacency of the input topology.

Any cartogram technique presents a particular trade-off between these three dimensions. The decision as to which cartogram technique to use in turn depends on the importance of these three measures for the task at hand. Here, we will briefly introduce the different techniques and discuss their respective trade-offs for the three measures of accuracy. In this section, we distinguish between three general types of area cartograms:

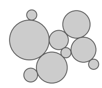
- **Shape-deforming techniques** that contort the overall form of geographical regions.
- **Graphical techniques** that create proportional symbols for the data values and then reorganize them.
- **Mosaic techniques** that represent the thematic data by filling cells on a regular grid.



Shape-deforming techniques modify the shape of area polygons, in order to represent thematic data, while aiming to stay recognizable (see Figure 21). This distinguishes them from other techniques, which do not directly interact with the area polygon, but instead generate new map elements. The principal challenge for these techniques is to find a transformation that correctly adapts the area of a region into topologically or geographically recognizable shapes.

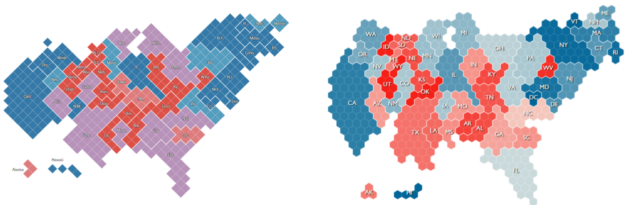
Arguably, the simplest solution to this problem is non-contiguous scaling, which deform geographic regions by scaling them in-place, disregarding any topological relations to adjacent regions (see Figure 21a). Thus, every region in the cartogram can be found at the exact place as in the unschematized map. Since all regions are treated without regarding topology, they can be deformed independently to accurately reflect the thematic attribute. In turn, the statistical and geographical accuracy of these techniques are generally high, while its topology is not maintained. A related approach are StenoMaps [vRSW14], which schematize areas into a single polyline that approximately follows the area's shape (see Figure 21b). This line is generated by relaxing the area's medial axis towards its borders, optimizing a trade-off between a line in the center of the country and its geographic outline.

More computationally involved solutions to the problem are contiguous algorithms [Fie17], which aim to maintain topological relationships between areas after deformation. In turn, the resizing of an area also influences its neighbors' deformation. This dependency between adjacent areas makes these shape-deformation algorithms generally computationally more expensive than non-contiguous algorithms. Another factor of complexity is retaining an approximate resemblance to the original shape. For this, the shape of the original region can be used as additional parameter in the error-minimization problem. Keim *et al.* [KNPS03, KNP04] for example measure the distance between border points along the outline of the area and scan-lines that are placed inside the area, following its general shape. Due to their distortion, however, contiguous algorithms generally yield moderate statistical accuracy, as well as moderate geographic accuracy. While shapes of regions are distorted, their location remains approximately at the position in space where they are located on the unschematized map. Their topological accuracy on the other hand is high, since bordering regions remain connected.



Graphical techniques do not directly manipulate the original area but use regular geometric shapes such as circles and rectangles to schematize them (see Figure 22). In turn, however, geographic accuracy in these techniques is generally moderate. In addition to that, topological accuracy is also usually moderate, since the regular shapes usually cannot convey the same adjacency relationships of the complex shapes of geographic regions. However, since they use regular shapes to convey the quantitative measure, graphical techniques have high statistical accuracy.

The general challenge for approaches to this technique is thus the placement of the representative shapes in relation to the original topology. Meirelles also refers to such techniques as *distance cartograms* [Mei13, p. 156]. The RecMap [HKPS05] generates rectangles for countries that represent quantitative values of geospatial data by their area. The algorithm allows defining visual constraints between the rectangles, such as *no area error*, *maintaining topology*, or *avoiding empty space* that are then resolved into a layout. Based on this parametrization, different visual outcomes can



(a) (b)

Figure 23: *Mosaic technique using squared and hexagonal grids [Fie17, vMSW15].*

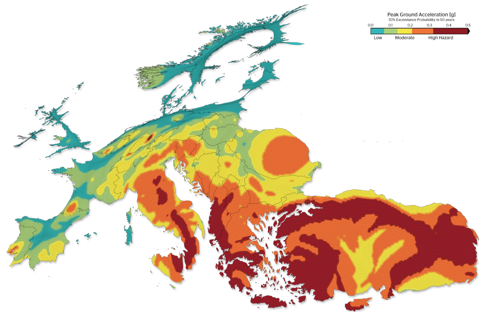
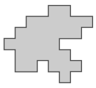


Figure 24: *A continuous stretching technique distorting a map of Europe based on the spatial variation of seismic hazard [Hen18].*

be generated (see Figure 22). Similar approaches exist for placing geographic constraints on the treemap algorithm [WD08, BEL*11], in which the location of nodes in a treemap of geospatial data approximately maintains their relative real-world location or topology. Buchin *et al.* [BSV12] present an approach that significantly improves rectangular layouts, achieving minimal statistical error while mostly preserving adjacencies between regions. *Rectilinear* layouts relax the constraint on strictly rectangular shapes and can thereby achieve good statistical accuracy while always preserving the adjacency between regions [dBMS10].



Mosaic techniques represent a quantitative value for a region through adjacent cells on a regular grid (see Figure 23). While these techniques thus also represent geographic regions with a set of regular shapes, these techniques can better maintain topologic accuracy than graphical techniques. Their statistical accuracy is generally good, due to the direct encoding of a variable by a number of cells in the schematization. Furthermore, they generally maintain geographically accurate shapes of the schematized regions.

Mosaic techniques can be distinguished by the type of polygon they use to fill the cells. Cano *et al.* [CBC*15] introduced the term "mosaic cartogram" and presented an algorithm for generating schematizations based on squared and hexagonal grids from an adjacency graph of the map. McNeill *et al.* [MH17] introduce an alternative algorithm to produce triangular, squared, hexagonal, and circular grids for geospatial visualization. Their algorithm uses heuristics that takes a particular user task and the depicted geography into account to propose the most suitable type of cell to the user. Brath and Banissi [BB17b] use quadratic cells to place labels representing individual countries in relation with each other. Field [Fie17] shows an approach using quadratic cells to schematizes a map, which rotates the regular grid by 45 degrees. In order to maintain the topology, other approaches to the mosaic technique utilize a hexagonal grid, as it provides more flexibility to express adjacency. At the same time, hexagons visually appear less uniform compared to squares, as they avoid right angles, making them suitable for the mosaic technique [PMaAaM16].

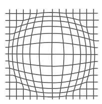
3.2.4. Field Schematization

The fourth category of schematization affects the display of scalar and vector field data on thematic maps. In contrast to the discrete techniques discussed in the previous sections, techniques in this section are concerned with the representation of continuous phenomena. The values of these phenomena vary continuously in space [Tyn10, p. 135]. This is in contrast to discrete phenomena, which represent entities with clearly delineated boundaries and whose values within these boundaries are constant. In practice, however, continuous phenomena are typically represented as (regular) grids where each cell holds the value of the underlying field at the respective location. This form of discretization is necessary, as the number of samples required to represent an entire continuous phenomenon would be infinitely large. Common examples for continuous phenomena are elevation, precipitation and temperature while less obvious examples are ocean current, air composition or natural hazard risk.

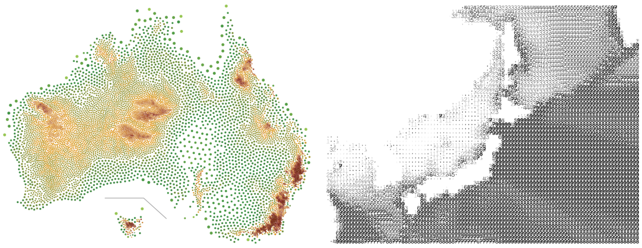
Field data inherently poses new challenges to the visual representation compared to other types of data. For one, the depiction of continuous phenomena on an inherently discrete display screen or paper printout requires some form of local aggregation. Depending on the resolution of the output visualization, this aggregation must be considered in the local context. The elevation relief of plains for example must be visualized differently from a relief of the Himalayas [FSH20]. Furthermore, continuous values cannot easily be encoded by discrete map elements like points, lines, or areas, but require consideration of the specific characteristics of the measured phenomenon and the degree to that it changes [LGMR15, p. 64]. Temperature for example is usually represented differently from the terrain heights, even though both are fields.

As a result of these particularities of field encoding, there exist specific schematization approaches for field data. Here, we distinguish between the following two techniques:

- **Continuous stretching techniques**, which distort local space based on a field data.
- **Density techniques**, which aggregate representatives for local regions based on field data.

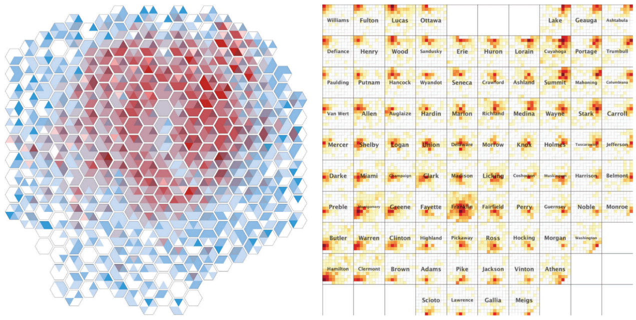


The first technique uses **continuous stretching** for schematization, which while visually similar to discrete, non-contiguous cartograms discussed in the previous section utilize field data in order to continuously distort the cartographic map (see Figure 24). There exist different solutions on how to compute this distortion. Usually, a regular grid is first virtually placed over the map, in which either each node or cell represents a field value. Then, this grid is distorted, assigning



(a) **(b)**

Figure 25: *Approaches to the density-based field schematization technique, using (a) stippling [GSS*19] and (b) Fat Fonts [NHC12].*



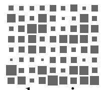
(a) **(b)**

Figure 26: *Direction-based approach to field schematization used by (a) direction-based pattern maps [YWZ*19] and (b) the origin-destination map [WDS10].*

more space to cells or vertices representing larger values, for instance using one of the algorithmic solutions discussed below. In the last step, the map is then fitted back onto the distorted grid. As a result, continuous stretching techniques also maintain topological relationships between all regions of a map when distorting them. The techniques are thus easily recognizable by the distorted images they create for well-known shapes of countries [Fie17].

In the context of cartogram metrics used by Nusrat and Kobourov [NK16] that were discussed for area schematization techniques in the previous section, continuous stretching techniques generally maintain moderate statistical accuracy, as well as moderate geographic accuracy. While shapes of regions are distorted, their location usually remains approximately at the position in space where they are located on the unschematized map. Their topological accuracy on the other hand is high, since bordering regions remain connected after distortion.

The general problem in generating a continuously stretched field is computing the local distortion of the virtual grid. As the selection of these approaches is vast, here we discuss a selection of common solutions to this problem. In diffusion-based solutions [GN04, Hen13] (see Figure 24) for example, the distortion is computed by equalizing the distribution of a virtual point cloud across the map space. For each value of the field, a set of points is placed in its particular cell from the grid. Then, the density of these points is equalized across the full grid, leading to cells containing more points to claim more space than cells with less. The general idea behind this solution thus resembles the diffusion process of gas concentrations in parts of a container that reach an equilibrium over time. A similar solution interprets the virtual grid as a rubber sheet [DCN85], where forces applied in one region affect the distortion of adjacent regions. There are different ways in which these distortions can be computed, for example, using angular and radial scaling in a polar coordinate system [BSS*09]. Dorling [Dor96] proposes the use of a cellular automaton to compute the distortion. However, rather than distorting the positions of nodes of the grid, his algorithm instead adapts the number of cells from the grid assigned to a region on the map. If two adjacent cells belonging to two adjacent map regions have a large difference in value, the cell with lower value is assigned to the same region as the cell with greater value. This process iterates, until all regions are assigned the correct number of cells. In Traffigrams [HKYA14], the field is distorted based on the temporal distance to a reference point, using so-called thin-plate spline warping, an algorithm commonly used in image matching.



The second technique for field schematization uses visual **density** to encode field values. For this purpose, a continuous variable is encoded by a glyph or discrete map element to convey a value distribution in a local region (see Figure 25). Different solutions exist on how visual density can be leveraged to schematize a map. The degree of density is usually achieved by rendering the map elements darker, larger, or closer to each other for regions with higher value, while rendering them brighter, smaller, or further-apart in regions with lower value.

The stippling method for instance is adapted from an artistic shading technique, where dots of the same size and color are placed with varying densities to convey brighter and darker regions in an image (see Figure 25a). Görtler *et al.* [GSS*19] adapted the technique for schematizing continuous data on a map. Their algorithm first creates a density encoding from the field data. Then, using the neighborhoods of a Voronoi mesh, points are either removed, added, or moved towards the local center of intensity. The resulting set of points form the visual encoding of the field data. Thus, higher-density regions are more visually salient than lower-density regions, as they are depicted by more dots. Nacenta *et al.* [NHC12] use the density technique to encode field data by the amount of ink that is used to render a certain value (see Figure 25b). In order to achieve this, they represent multi-digit numbers symbolically by placing each of its digits into the shape of a higher-order digit. Therefore, multi-digit numbers use more "virtual" ink than numbers with fewer digits. Additionally, the authors utilize a font face that increases "boldness" for larger digits, making "9" use more ink than a "0". By laying out the numbers in a regular grid over the map, high-valued regions can be distinguished based on how dark a region appears. A unique characteristic of this solution is that while the map can be interpreted from a distance based on the amount of ink used in a region, concrete values become readable when reading the schematization up-close. In a related approach, Ward [War02] uses star glyphs for density schematization. Therein, regions representing larger value automatically produce larger star glyphs, which occupy more space and thus use more "digital ink".

Visual density can also be utilized to schematize directed, vector field data (see Figure 26). In the hachuring technique for example, steeper gradients of terrain are encoded by thicker and shorter lines, resulting in greater visual density for those regions. Color can then be used instead of arrow heads to specify the orientation of the gradient [Sam14]). Viégas and Wattenberg [VW12] present a dynamic solution for visualizing wind measurements, using lines of varying width to encode wind power indicating the wind direction by the direction in which a line is "brushed" onto the screen in an animation. In the related approach named BristleMaps [KMM*13], so-called "bristles" – vertical lines that are added along the path of rectangularized road networks – encode a surrounding field attribute through their density along a road segment, length, or color. Kozik *et al.* [KTHE19] found such schematizing hachuring techniques to perform well in recognition and recollection tasks. Yao *et al.* [YWZ*19] use density to encode commuting patterns such as the direction, amount of people, and distance into cells on a hexagonal grid overlaying the Beijing metro region. Each hexagonal cell is subdivided into six wedges along the six major axes of the hexagon. Each wedge indicates the direction of travel for commuters from the particular region on the map. Regions with large amounts of commuters traveling from a certain cell are rendered as darker wedges, while regions with less commuters are rendered lighter. The border of the wedges further indicates the general distance of the commute with darker borders indicating longer distances. Origin-destination maps [WDS10] encode travel patterns over a map by overlaying each cell over which the data is measured with a smaller version of the field. Then, color is used to indicate the amounts of commuters traveling from the region of a cell on the inset map towards locations inside the cell in which it is placed.

4. Task-Based and Interactive Use of Map-Like Visualization

While the previous section offered an overview for map-like visualization based on the two perspectives identified in our interview study, in this section we present the literature from a usage-centered view. First, we present our task taxonomy for map-like visualization and then discuss effective techniques from both map-like imitation and schematization that lend themselves to individual tasks. Then, we present how common map interactions can be supported by map-like visualization techniques.

4.1. Tasks for Map-like Visualization

Task taxonomies and design-spaces are well-researched in the realm of abstract visualization [KK17]. We use the term *task* as defined by Schulz *et al.*, where tasks are defined as "activities to be carried out interactively on a visual data representation for a particular reason" [SNHS13]. However, the term is not used as commonly in the literature on cartographic maps. To particularly address the tasks carried out over cartographic maps, we have gathered tasks from teaching materials and relevant literature in cartography on how to use atlases [Cam98, Wie06, Hie11, KBM11, HOS16, Hur17, RHS*18], as the maps depicted in atlases are generally diverse and thus cover many scenarios. From that collection, we have distilled the following tasks for map-like visualization:

- **Identify locations** of an item in space
- **Retrieve values** of an item in space
- **Assess distances** between multiple points in space
- **Trace paths** between multiple points in space

These are low-level tasks, as they describe operations that are carried out directly on the map. As such, these tasks set the prerequisite for higher-level analysis tasks that are commonly executed on cartographic maps, such as identifying spatial patterns of a thematic attribute. In order to execute such higher-level tasks, the lower-level tasks mentioned here need to be accommodated for. This is because the higher-level tasks are composed of a series of lower-level task [GZ09]. Determining a distribution of a variable for example requires retrieving the values of that variable at different locations, assessing the distance between high-valued and low-valued regions, and tracing the gradient of these values across the terrain.

In the following, we discuss which imitation and schematization techniques presented in the literature overview lend themselves to a particular task. We present the techniques from both an imitation and a schematization perspective. Figure 27 gives an overview of this section.

4.1.1. Identifying Locations

A task often carried out on maps is finding an unknown position based on a known piece of information. It is thus the inverse operation to the value retrieving task. For example, one might need to locate the capitol city of Slovakia on a map or find the leaf node with the deepest level of hierarchy in a tree visualization. Maps and properly designed map-like visualizations have been recognized to facilitate rapid visual search for such information [FD01].

Different imitation techniques are applicable for this task. First, point imitation techniques using map symbols to mark locations in the visualization is frequently used for this exact purpose. Furthermore, using map-like areas can help identifying a cluster of elements that are similar to the one that is searched for. In large datasets, making clusters visually distinguishable from each other reduces the number of items that need to be looked at to find one specific item. Showing or hiding items according to their level of hierarchy during pan and zoom interaction reduces the number of items that are visible at all times, which can further simplify the process of navigating large datasets. Irregular outlines often produce unique, recognizable areas that help identify the same location in the future again based on visual recall [Tve81].

Generally, point-based schematization addresses the issue of locating items on a map. They aim to reduce visual clutter either produced by overplotted points on a dot map or densely-packed nodes on geospatial networks. By reducing visual clutter, locating points on the map becomes easier. Furthermore, some area-based techniques are particularly useful for this task as well. By reducing the visual complexity of shapes, schematization can be used to highlight regions in the map that are of interest. Regions of low interest can be schematized to a less recognizable shape than a region that is of high interest to the user.

4.1.2. Retrieving Values

Another common map task is retrieving a thematic value for any given position. For example, one might need to determine the number of votes for a particular party in a certain region, whereas in a

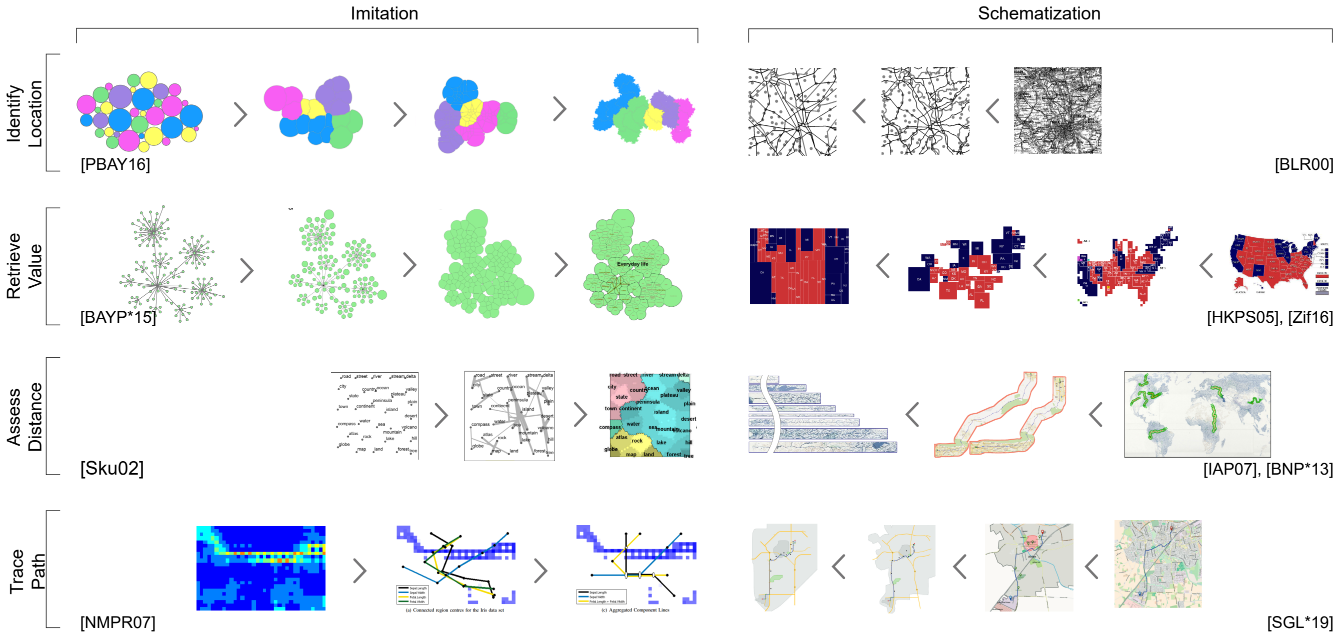


Figure 27: *Examples of map-like visualization techniques applied to representations of spatial and spatialized data, arranged by the map task they support: Imitation techniques produce visual similarity to make visualizations of spatialized data visually resemble maps. Schematization techniques abstract the representation of a geographic context, emphasizing task-related thematic attributes of the image. The depicted techniques are discussed in more detail in their respective section of the literature overview. Some images are the authors' recreations to illustrate a particular technique .*

spatialized visualization, the level of hierarchy for a particular node might be of interest.

Arguably, the most natural imitation technique for this task is mapping the thematic attribute to a map-like element. Color for example is often used to encode the level of hierarchy in a graph, imitating the symbolizations of topographic maps. Isolines can encode regions containing items of similar value; size can be applied to highlight individual items. Another approach is visualizing the result of a clustering computation as an irregular area around items with similar values. Clusters are often used to group items that share similar values for a set of dimensions of interest. In contrast to isolines and size, area can thus indicate similarity in high-dimensional space rather than just in a single attribute. To retrieve quantitative values from a map-like visualization, such values can be directly encoded in the size occupied by a map-like shape. Some techniques that use this explicitly are using regular grids to generate the areas. Here, the number of cells occupied by a node is representative of the quantitative value. Other techniques for example represent the measure by the size of simulated bubbles.

For geospatial data, the whole class of thematic maps includes diverse techniques to highlight different types of data on a map. Schematization can then be applied to further emphasize thematic data. Area cartograms are a good example for this. The area sizes of regions on the thematic map are schematized by distorting them to represent quantitative values. Cartograms thus lend themselves to represent election results, as they normalize the area of the total map that is occupied by the color assigned to a party.

4.1.3. Assessing Distances

Another task often carried out on cartographic maps is assessing distances between two points of a visualization. While schematized maps inherently implement Tobler's first law of geography [Tob70], imitation techniques utilize spatialization algorithms to fulfill it. Thus, the similarity between two points in a map-like visualization can generally be assessed based on their spatial proximity.

While some spatialization techniques such as MDS or SOM allow drawing such pairwise conclusions about similarity based on the proximity in the visualization, every technique introduces errors into the final image. To avoid false conclusions, one could for example support the interpretation of the spatialized image through imitation techniques. A general solution to this is that the distance in the data is explicitly encoded into a map-like symbol on the view, in addition to the spatial proximity between points in the visualization. Skupin for example presents an explicit encoding for the Euclidean distances in the view of a dimensionality reduction technique and its original data [Sku02b].

While unschematized maps inherently fulfill Tobler's first law except for errors introduced by non-distance preserving projection methods, depicted absolute distances can be misleading. The physical path that has to be traveled between two points may pass through mountainous terrain or along curvy paths, which makes it difficult to interpret the length of the travel path on an unschematized map. Here, path schematization techniques that straighten paths on a map can be beneficial, as they schematize the path to approximate a straight line, with some techniques also taking into account the topography. Thereby, multiple paths become visually comparable. As a benefit over just comparing paths lengths as numerical values, the schematizations also maintain context information such as nearby cities along the path, which can be of help when planning a travel.

4.1.4. Tracing Paths

Another task that is related to measuring the lengths of paths is finding such paths in the first place. For example, one might need to determine the shortest path between two nodes of a graph or find the quickest route from one city to another on a map.

Tracing paths on spatialized data can be simplified through different imitation techniques. Here, path-centered line imitation techniques are applicable. One example is to route paths through the virtual terrain, which integrates them visually with the areas drawn around clusters or virtual height profiles created by symbols, making them easier to follow.

There are already unschematized maps, which support tracing paths between two locations. Road maps for instance visually emphasize roads and cities over information about the terrain. However, when looking for a path that can be traveled quickest, geographic accuracy is not necessarily beneficial. For instance, the height traveled is often difficult to interpret from a two-dimensional map. Additionally, roads with bends can be difficult to compare visually as well. Some schematization techniques apply specific map projection techniques that straight out paths, respecting bends and topographic terrain. Moreover, the metro map technique can be applied to map the distance between these points to the overall travel time between them. Other schematization approaches aim to reduce the number of edge crossings on geospatial graphs by adapting the position of nodes within geographic boundaries. This simplifies tracing paths for geographic networks.

4.2. Interaction on Map-like Visualization

Interaction has been an invaluable extension to traditional cartography, enabling maps for use in visual analysis scenarios [EAAB09]. While traditional cartography can represent one static combination of a map with a set of thematic attributes, geographic information systems (GIS) can dynamically adapt the representation based on user input. This opens up a field of analysis tasks that can be carried out over interactive maps. In the following, we discuss how interactive methods for cartographic maps can be utilized in the context of map-like visualization.

Map-like visualization lends itself to spatial interaction techniques such as magic lenses [TGK*17] for visual analysis, as both imitation and schematization follow the first law of geography as discussed in Section 3. The undistort lens [BCN11] for example could be combined with most schematization techniques to "undo" the geospatial distortion in a local area of interest. Potential synergies between magic lens techniques and map-like visualization have however not been fully explored yet and thus offer a promising area of future research. Instead, interaction on map-like visualization in next to all cases is done by the traditional means of mouse and keyboard.

Interaction techniques in the geographic context have been classified by Roth [Rot13], describing map interaction along Norman's stages of interaction [Nor88]. While this interaction model has also been used to describe interaction on abstract visualization, Roth's classification distinguishes three map-specific "operands", on which the interaction is performed: space-alone, attributes-in-space, and space-in-time. These operands have a strict notion of spatiality and as such only apply to visualization, for which the position of items is representative of the data, i.e., visualization that follow Tobler's first law of geography [Tob70]. Thus, interaction on map-like visualization can be differentiated along Roth's interaction operands as well, which we discuss in the following.

Space-alone interaction Whenever the user draws conclusions about the data based on the spatial relationships of visual elements, this interaction is considered space-alone. Such interactions thus are not performed on attribute values but rely entirely on the visual mapping to display space. Map-like imitation relies on data to be spatialized in a way that allows the user to draw these exact conclusions. Therefore, any imitation technique inherently supports space-alone interaction. Point-based techniques for importance labeling from Section 3.1.1 in particular support pan+zoom techniques by guiding from overview to detail. Through schematization techniques, though, space-alone interaction is generally made more difficult, as these techniques abstract the geographic context and thus often distort geographic reality. However, some techniques also emphasize the "real" distance between points, usually using the line map element discussed in Section 3.2.2. Transmogrification for example stretches out paths on the map to better reflect terrain along the way, thus making it easier to gauge the actual distance between two points based on their spatial distance on the map.

Attributes-in-space interaction Interactions in which the user utilizes the spatial relation of attributes depicted in the visualization are considered attribute-in-space interactions. A common goal of schematization techniques is emphasizing thematic attributes by abstracting a cartographic map, which makes them generally applicable for this interaction class. Cartogram and distortion techniques discussed in Sections 3.2.3 and 3.2.4 for example distort the visual elements of a map in order to put emphasis on thematic or field data for this exact purpose. By applying visual transformations to spatialized data to encode attributes, imitation techniques are also generally applicable to attribute-in-space interaction. Field-based contouring techniques (see Section 3.1.4) for instance can be used to encode an attribute around data items. Therefore, this technique encodes the attribute value in the ambient space of spatialized data.

Space-in-time Interaction The third class of interaction discussed by Roth considers dynamic spatial developments. Map-like visualization techniques from the literature overview are usually static, in that they produce an expressive representation of the data in order to overcome shortcomings of the original representation. Thus, this spatial interaction operand is not directly supported by any map-like technique surveyed here. Broadening the view on this particular form of interaction to also include time-in-space interaction yields some imitation techniques suitable to support them. For example, some area-based imitation techniques discussed in Section 3.1.3 support analysis of user behavior over time. Others

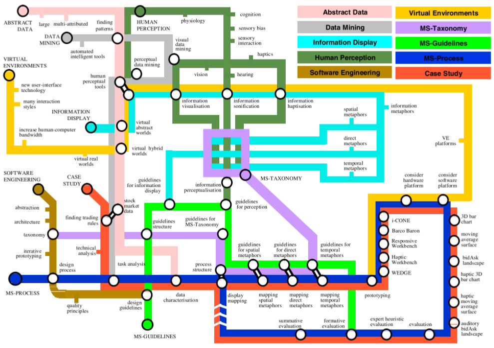


Figure 28: *A visualization of the writing process of a PhD thesis imitating the symbolism of a metro map [Nes04].*

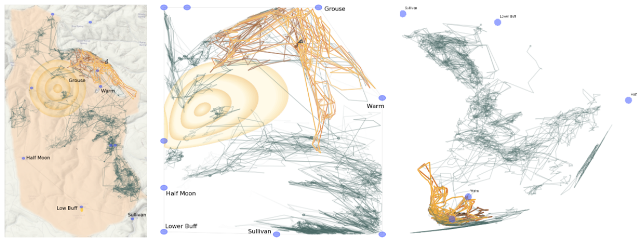


Figure 29: *A visualization of proximity of geospatial data [CMCM09], using the original position (left), proximity interpolation (center), and PCA dimensionality reduction (right).*

visualize the development of individual node locations throughout a force-directed simulation. Time is also used in various schematization techniques. Travel-time maps, linear cartograms, or traffigrams discussed in Section 3.2.2 for example distort map locations in order to encode temporal data in space.

5. Discussion and Research Questions

This section discusses our classification of map-likeness into different perspectives and categories. It looks at the classification's consistency by discussing corner cases, at its completeness by shining a light on literature it does not cover, as well as at its utility by pointing out what it can be used for. We further highlight open research questions at the end of each section.

5.1. Consistency

We have presented our classification of map-like visualization along the two perspectives of imitation and schematization. This binary view on the existing body of literature makes sense as a delimiter between the two principal ways in which most map-like visualization techniques work: they either schematize maps or they imitate maps. Nevertheless, there are a few map-like techniques that push the boundaries of this binary understanding of the field. This section highlights some of these corner cases, as they nicely illustrate how far the descriptive power of the proposed hierarchy reaches and at which points its delineation between the two perspectives starts to blur.

Schematization of Data Visualizations Schematization was defined as transforming a map to make it more like a visualization. Yet that has not stopped some researchers to apply schematization techniques to visualizations instead.

A prominent example is the use of the metro map metaphor (see Section 3.2.2) for the depiction of process diagrams and charts [Nes04, SRB*05], with an example depicted in Figure 28. Hence, these visualizations do not imitate maps, but actually the map-like symbolism of metro maps. So, one could argue that metro map techniques could actually be both: schematization and imitation of maps. The results of both could look strikingly similar, so that only knowledge about the generating algorithms can decide on which side a given metro map really is. Another example is the use of cartogram techniques (see Section 3.2.3) to distort other base visualizations than a map. This has been tried for SOMs to better reflect relevant structures in text corpora [BSF13], but also for such "mundane" visualizations as the periodic table of elements to reflect additional chemical or physical properties [Win11]. In these cases, the use of cartogram distortions is not so much intended to imitate the look&feel of cartograms, but rather to provide an additional visual channel to encode extra information.

Looking at these examples, the question arises why schematization techniques are not used more often to transform data visualizations? One can easily imagine the use of cartogram techniques for uncertainty visualization [PRJ12, BAL12] or the use of travel time maps for the computational steering in progressive visual analytics [ASSS18, MSA*19].

Which map schematizations can be used meaningfully and advantageously on data visualizations?

Attribute Space vs. Geo-Space One of the main distinctions between schematization and imitation is whether its transformation starts with a map or with an abstract visualization. Yet in particular for data measured in geo-space, this line often gets blurred, as its visualization could be seen both as a schematization of the geospatial data and as an imitation of the spatialized multivariate attributes.

Burns and Skupin [BS13] show such an example of a geospatial dataset visualized as a SOM on one hand, and as a choropleth map on the other hand. While in this case, both variants are unlikely to be mistaken for each other, techniques offering a more gradual transition between showing the data in attribute space and geo-space make this distinction increasingly hard. One such example is the movement trace visualization by Crnovrsanin *et al.* [CMCM09], where geospatial data is shown in geo-space. This space can be interactively stretched though using a technique called *proximity interpolation* to get a better view on dense data in small regions. The configuration of this "streching" can also be automatically determined using a PCA-based approach on the data attributes. All three of theses stages can be seen in Figure 29. So, what is this PCA-based data layout? A schematization, because it transforms a map into a distorted version of itself? Or an imitation, because it takes a PCA-based spatialization of the data attributes and adds a few landmarks to allow basic orientation?

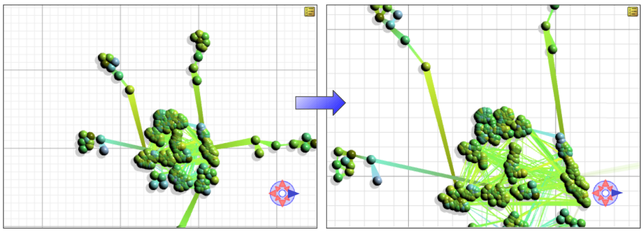


Figure 30: *Supplementary components in CGV (adapted from [TAS09]): A compass rose in the bottom right indicates the direction towards interesting clusters. An "infinite grid" in the background adapts to the current zoom level.*

Here, the classification cannot clearly distinguish between either of the two perspectives. Yet this example also shows that there are valuable intermediates and that it can make sense to allow the users to interactively tune the level of map-likeness. This way, they can determine themselves how much spatial context they want for an analysis task at hand and they can easily adjust this level once other tasks need to be carried out. While many, if not most schematization techniques allow for such a parametrizable level of map-likeness, imitation techniques usually do not offer this possibility.

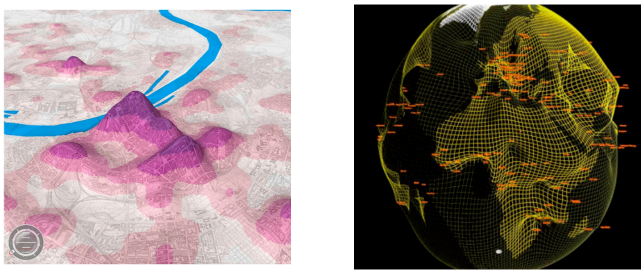
How can imitation techniques be used in a gradual manner that allows for tuning the degree of map-likeness they generate?

5.2. Completeness

To arrive at a reasonable classification and at a reasonably complete survey of the relevant literature, we had to limit the scope of this paper. This means that some highly related research directions could not be included in this state of the art report. Nevertheless, we believe it to be important to at least point them out to make their connection to this work known as possibly fruitful further avenues of research.

Imitation beyond Map Elements In our classification, we only look at techniques that transform the contents of a visualization – i.e., the actual data display – to make them more map-like. Yet, a map consists of more than just the visual representation of geography. There exist diverging lists of additional map components in cartographic literature [Tyn10, p. 31] [DTH08, p. 208] [CES13, ch. 9.1]. Common such components are scale indicators, graticule grids, legends, and North arrows. Other examples, which are also used in graphic design in general, are textual components like titles, labels, and descriptions, as well as map insets that show a region of a map at a different scale. Employing some of these supplementary components in abstract visualizations helps with its interpretation by utilizing people's familiarity with these components.

A graticule for example – the grid of (typically) longitudinal and latitudinal lines underlying many cartographic maps – can be used for zoomable visualizations to support orientation. Tominski *et al.* [TAS09] present an approach for exploring large graphs, where a grid is used to indicate zoom level magnitudes. The current zoom level is indicated as a primary grid, with the next lower magnitude indicated with a lighter color as a secondary grid (see Figure 30). The authors found this technique to help with judging distances during animated zoom level changes. Alper *et al.* [AHRH14] use grid cells with colored borders. The general idea of this approach is to help users navigate node-link diagrams by providing another frame of reference when zooming the visualization. However, their user study found no significant improvement in user performance compared to a node-link diagram without a grid symbolization. Another supplementary map component is used in CGV [TAS09], by adding a wind rose to support locating an element that is positioned outside the view. The wind rose points into the direction in which an element of interest is positioned relative to the currently focused region in the view.



(a) (b)

Figure 31: *Schematization of three-dimensional representations of geospatial data used (a) by Wolff [Wol10] and (b) by Alper* et al. *[ASB07].*

It has to be noted that the practice of using supplementary map components to enrich visualizations is not a one-way street. Maps can likewise benefit from using visualization as supplementary components – e.g., by using visualizations as map legends [Kum04, DWS10].

In which ways can we combine map imitation techniques with such supplementary map components to further enhance its map-like impression?

Map-like Visualization beyond two Dimensions Our classification of map-like techniques is furthermore confined to transformations of a two-dimensional input visualization that produce a two-dimensional output visualization. However, there also exist techniques that utilize the third dimension for "map"-like visualization.

For instance, there exist approaches that transform a two-dimensional input visualization into a three-dimensional output visualization by using height to encode thematic data (see Figure 31a). Wolff [Wol10] for example presents an approach that bulges regions of a two-dimensional, cartographic map outwards or upwards to encode an additional quantitative attribute (see Figure 31a). Kubota *et al.* [KNS07] place a graph layout on a sphere and then extrude that sphere along the placed graph to encode another attribute. As their approach is applied to graph layouts computed on abstract, non-spatial data, it thus visually imitates a globe with protruding mountains.

Other approaches distort three-dimensional representations of geospatial data (i.e, a globe) based on a thematic attribute, similar to the distorting techniques discussed in the area and field schematization sections (see Figure 31b). For example, geoides encode the measure of local gravity measured around Earth on the surface height of a globe, effectively deforming it into the well-known potato shape that reflects Earth's gravitational field [LGMR15, p. 86]. This approach is commonly used in geodesy to account for measuring errors that occur when considering Earth a perfect sphere. Alper *et al.* [ASB07] apply a force-directed layout algorithm to distort geospatial positions according to a thematic attribute. Their approach resembles two-dimensional cartograms, yet applied to three-dimensional data.

There also exist one-dimensional representations of geospatial data, often used in height profile visualization for hiking maps. Yet, we are not aware of algorithmic schematization techniques for this use case. It thus remains an open question, as to how schematization applies to one-dimensional depictions of geospatial data.

How can schematization techniques be extended to visualizations of one- and three-dimensional geographic data?

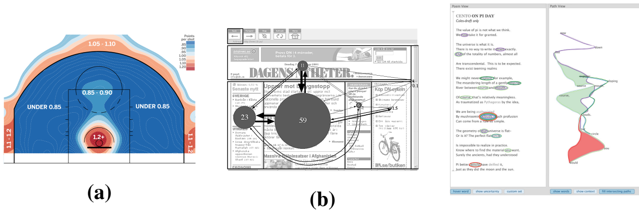
Schematization beyond Geospatial Data For the schematization perspective, we only considered geospatial data. Yet, visualizations of non-geographic, but nevertheless *spatial data* could potentially also benefit from map-like schematization techniques [HTWL19]. After all, their data items also have an inherent spatial position in regards to a particular frame of reference. In the following, we present three fields of such spatial visualization.

Sports visualizations [PVS*18] for example often use the playing field as a frame of reference for analysis of player behavior (see Figure 32a). While not located at a specific place on the Earth, playing fields are standardized across one sport, which makes them useful analysis contexts. Examples are plotting from where the most points where scored or which paths players took before scoring. In the latter case, players often only cover a certain partition of the playing field, which leaves other parts of the available drawing space empty. Point-based schematization techniques could reduce the visual clutter created in those instances and help with analyzing the movement patterns in these restricted regions.

Another field of visualizing spatial data is the visualization of eye tracking data [BKR*17]. These are collected for example to evaluate user interfaces or for behavior research in psychology (see Figure 32b). Here, the spatial frame of reference is the physical screen or the digital image that a participant has looked at. This allows for analyzing, which regions in that space the user has looked at a certain point in time. Area-based cartogram techniques which resize each interface element relative to the time the user has spent looking at them could potentially be a visualization method to emphasize small, but frequently looked at interface elements.

Another field that visualizing spatial data is text visualization [KK15]. Here, the words of books or manuscripts are analyzed based on the position of individual words in that document (see Figure 32c). The frame of reference is thus the page on which the text is displayed. When drawing edges between related words, for example to visualize semantic relationships across sentences, the pages can easily become cluttered. Here angle-reduction techniques along these paths could increase the readability of such connections.

How can the schematization techniques be utilized in the display of spatial, non-geographic data?



(a) (b) (c)

Figure 32: *Visualizations of non-geographic spatial data that also resemble maps: (a) Spatial visualization of a sports data [Gol19], (b) Spatial network visualization of eye-tracking measurements [HHBL03], (c) spatial visualization over a poem [MLCM16].*

5.3. Utility

A classification like ours is no end in itself. It is very much expected to be useful and to aid in practical tasks like constructing and evaluating a visualization in a given usage scenario. This section discusses two concrete ways in which we deem our classification to be or to become useful.

Evaluating Map-Like Visualization A general research problem for map-like visualization, in particular with regards to the task-perspective discussed in Section 4, is further evaluation. The literature on the cognitive benefits of using cartographic maps for geospatial analysis is well-established. Blades [BBD*04] and DeLoache [DeL04] for example found that children are able to read maps from early ages, regardless of their cultural background. Other research on cognitive aspects of map use has been discussed by Tversky. She for instance describes the cognitive role that maps play in making sense of an environment and the ability to abstract meaning in space [Tve14]. Furthermore, she showed how participants used subjective heuristics to remember the position of objects in space based on their relative position to each other [Tve81]. By noting that "maps depict conceptions of reality, not reality itself", she also notes the inherent social aspect of using maps [Tve00]. Stevens and Coupe [SC78] showed that participants remembered locations hierarchically, for example by recalling that a city was located in a country that was itself part of a larger continent.

There also exists some research on the applicability of the proximity-similarity metaphor. Montello and Fabrikant [MFRM03, FMRM04, FMM06] showed that Tobler's first law of geography indeed also applies to depictions of abstract data, with participants drawing conclusions on data similarity based on proximity. However, Tory *et al.* [TSW*07] showed that area-based imitation performed worse in finding area with most contained areas than just using points in small data samples. Furthermore, the authors found that 2D density plots do not aid the recollection of scatter plots, but in fact hinder it and do not significantly improve the accuracy [TSD09].

While authors of imitation techniques often refer to the benefits when motivating the use of map-like techniques, structured, generalizable evaluations of map-like visualizations are still lacking. It is so far unclear, to what degree the map-likeness of a visualization improves user performance and from what point it may in-fact be detrimental. We believe that the formal, hierarchical classification of map-like techniques finally allows for structured, quantitative evaluations of map-like visualization. This is because novel map-like visualization approaches can now be described along these three levels and be compared fairly to close alternatives.

Looking at Mackinlay's perceptual ranking of visual attributes for visualizing different data types [Mac86], we envision a similar ranking for map-like techniques. However, we are currently lacking the necessary quantitative evaluations for reasoning about such a ranking. Through systematic user evaluations comparing different map-like transformation techniques along the two perspectives and four categories, such a ranking could be constructed in order to suggest beneficial technique and highlight detrimental techniques for a given user task.

How do different map-like techniques from the classification compare with respect to their effectiveness for different visual analysis tasks?

Generating Map-like Visualization Visualization taxonomies have in the past also been used for constructive purposes. Bertin's Semiology of Graphics [Ber10] for example provided an initial structure for describing and thinking about information visualization. This structure was then picked up decades later in Wilkinson's Grammar of Graphics [Wil05], where it was adapted into series of formal transformation operators, applied to a dataset in order to generate a visualization. In recent years, declarative visualization grammars [SMWH17] have implemented Wilkinson's approach into usable libraries and thereby significantly simplified the construction of interactive information visualizations, reducing the required "coding" efforts to short specifications that are then interpreted and compiled into full-fledged visualizations.

We envision a similar development for map-like visualization. Our classification could serve as the first step towards this goal, in that it allows for descriptions of map-like techniques as either a schematization or imitation of cartographic maps in either of the four map elements. Therefore, the map-likeness of a visualization can be described by the particular technique it implements. With that as a starting point, it is plausible to define functional operators working on an input visualization that produce a map-like output visualization through a series of transformations. As map-like visualizations often employ a composite of multiple such operators on more than one map element, these functional "base operators" could then be further combined to describe more complex map-like transformations. The visualization proposed by Gronemann and Jünger [GJ13] for example could then be described by the operators for transformations applied by imitation techniques for the point (importance labelling), line (terrain routing and geometric transformation), area (geometric tessellation) and field (coloring and contouring) categories. A high-level description of these operators through a declarative grammar could later be implemented to provide an interface to them.

How can a declarative grammar for map-like visualization be constructed, which defines a high-level interface to generating map-like visualization?

6. Conclusion

In this paper, we have presented a classification and literature overview of map-like visualizations. What remains at this point is to ask "Is it worth it?" – i.e., does it actually pay off to go through the additional visualization step of, for example, imitating a map? While this question can be answered concretely and definitely only for specific techniques through comparative user studies, it seems that a lot speaks for map-like visualizations [Cou98].

Looking at the value of map-like visulizations using van Wijk's formula for knowledge generation [vW05], there are two parameters that govern how small or large this value is: the visual image that the users see and existing knowledge that they have about the world, including about visualization itself. A person with years of experience in a certain domain will gather different insights from a visualization than a novice. Similarly, it is usually easier for users to interpret a familiar visualization than a novel one, and from a cognitive perspective, there are efficient and inefficient ways to visualize the same data.

Applying this formula to map-like visualization, it is easy to argue for the benefit that map-like representations have. On one hand, map imitation builds on the user's prior knowledge of reading cartographic maps, thus using familiar symbolisms to present the data using a known system that is easy to decode and to use. On the other hand, map schematization fleshes out the thematic information from irrelevant geographic context when schematizing it, thus highlighting the relevant information making it easier to discern.

However, one could also argue for map-like visualization to be detrimental to the generation of knowledge. On one hand, excessive schematization may just as well confuse users when abstracting the geographic space beyond recognition. On the other hand, driving the map imitation too far when representing abstract data could also lead the user to draw false conclusions based on misinterpretations of the map symbolism. In that sense, finding the right degree of map-likeness that increases the effectiveness of a visualization without sacrificing its expressiveness remains as the ultimate challenge in map-like visualization research for the years to come.

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