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Perceptual psychology research
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Ensemble encoding

To extract and combine information in parallel from large number of objects at once
Four types of ensemble coding in data visualizations

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Ensemble coding supports rapid extraction of visual statistics about distributed visual information. Researchers typically study this ability with the goal of drawing conclusions about how such coding extracts information from natural scenes. Here we argue that a second domain can serve as another strong inspiration for understanding ensemble coding: graphs, maps, and other visual presentations of data. Data visualizations allow observers to leverage their ability to perform visual ensemble statistics on distributions of spatial or feature visual information to estimate actual statistics on data. We survey the types of visual statistical tasks that occur within data visualizations across everyday examples, such as scatterplots, and more specialized images, such as weather maps or depictions of patterns in text. We divide these tasks into four categories: identification of sets of values, summation across those values, segmentation of collections, and estimation of structure. We point to unanswered questions for each category and give examples of such cross-pollination in the current literature. Increased collaboration between the data visualization and perceptual psychology research communities can inspire new solutions to challenges in visualization while simultaneously exposing unsolved problems in perception research.

Introduction

Some types of visual information must be extracted from small numbers of objects at a time, such as complex object identity (Wolfe, 1994) or spatial relationships (Franconeri, Scimeca, Roth, Helmsley, & Kahn, 2012). Other types of information can be extracted and combined in parallel from large numbers of objects at once, such as the average object size (Ariely, 2001). A growing body of work seeks to understand such ensemble coding of spatially distributed visual information (for surveys, see Alvarez, 2013; Whitney, Flaherman, & Swartz, 2014). Researchers typically study this ability in order to draw conclusions about how ensemble coding helps extract information from natural scenes. For example, one might want to estimate the number of books on a shelf (Rous & Baren, 2010) or gauge the average emotional expression within a crowd of people (Flaherman & Whitney, 2007).

Here we argue for another domain that should serve as an equally exciting inspiration for understanding ensemble coding: visual presentations of data (e.g., maps, charts, and graphs). Data visualizations are ubiquitous to students, scientists, and any broader audience that reads graphs, uses maps, or reads a newspaper. Visualizations communicate patterns in data by mapping data dimensions to visual features (for an overview, see Bertin, 1983; Hae, Boiack, & Owejovsky, 2010). To illustrate, consider a scatterplot, which maps data values to spatial positions. For some types of inspection, such as mapping symbols to a legend or knowing whether a particular data value is lower or higher than another, we must serially inspect small numbers of data values at a time. But other types of information can be extracted in parallel, such as the approximate mean position, or size, of an entire cloud of points (Figure 1a) or the portion of a line graph with the highest variability (Figure 1b).

These judgments are ensemble judgments, and they merit more intense study both for their value as a case

Ensemble encoding

To extract and combine information in parallel from large number of objects at once

In perceptual psychology, ensemble encoding is typically studied in natural scenes, like:
- the numbers of books on a shelf, or
- the average emotional expression within a crowd of people

Here, the authors apply it to the field of data visualisation

Sara Sprinkhuizen – Data visualisatie spreekuur @ H&W – 2022
Example plot

Some information needs to be extracted **serially** (e.g. mapping symbols to a legend)

Some information can be extracted **in parallel** (e.g. mean position or mean size of all points) ← ensemble encoding

Goal: identify a broader set of visualization tasks that benefit from ensemble encoding
Tasks divided in 4 categories

1. Identification
2. Summarization
3. Segmentation
4. Structure estimation
Identification

Figure 6. Identification tasks require a viewer to locate a specific set of data points, such as (a) the class of points in a scatterplot that are labeled as red or blue or (b) the minimum and maximum values that constitute the value range in a bar graph.
2 Summarization

Figure 7. Summary tasks require viewers to estimate a value that summarizes a collection, such as its (b) mean and (c) numerosity.
Figure 9. Segmentation tasks, such as (b) spatially or (c) featurally clustering data elements, require the viewer to visually segment the data set into discrete clusters.
Figure 12. Trend and motif detection are two examples of structure-recognition tasks in visualization.
Findings

- Color better supports summary tasks, while position better supports identification tasks.

- If both color and shape are used to encode different properties, segmentation based on shape is more difficult for shapes of different color, whereas viewers can segment different colors regardless of shape.
Findings

The ranking of effectiveness of precise extraction of individual values (Cleveland & McGill) is not identical when it comes to ensemble encoding.

For example: color depictions can beat spatial position depictions when a viewer needs to analyze average values from subset of raw data.
### Visual Aggregation Task

<table>
<thead>
<tr>
<th>Visual Feature</th>
<th>Summary (Mean)</th>
<th>Identification (Outlier)</th>
<th>Pattern Recognition (Trends)</th>
<th>Segmentation (Clustering)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position</td>
<td><img src="image1" alt="Position Summary" /></td>
<td><img src="image2" alt="Position Identification" /></td>
<td><img src="image3" alt="Position Pattern Recognition" /></td>
<td><img src="image4" alt="Position Segmentation" /></td>
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<tr>
<td>Size</td>
<td><img src="image5" alt="Size Summary" /></td>
<td><img src="image6" alt="Size Identification" /></td>
<td><img src="image7" alt="Size Pattern Recognition" /></td>
<td><img src="image8" alt="Size Segmentation" /></td>
</tr>
<tr>
<td>Orientation</td>
<td><img src="image9" alt="Orientation Summary" /></td>
<td><img src="image10" alt="Orientation Identification" /></td>
<td><img src="image11" alt="Orientation Pattern Recognition" /></td>
<td><img src="image12" alt="Orientation Segmentation" /></td>
</tr>
<tr>
<td>Color &amp; Luminance</td>
<td><img src="image13" alt="Color &amp; Luminance Summary" /></td>
<td><img src="image14" alt="Color &amp; Luminance Identification" /></td>
<td><img src="image15" alt="Color &amp; Luminance Pattern Recognition" /></td>
<td><img src="image16" alt="Color &amp; Luminance Segmentation" /></td>
</tr>
</tbody>
</table>

Figure 4. We identify four categories of visualization tasks (top) that require ensemble coding of information spread throughout the visual field. The tasks can be performed on multiple visual features, but not necessarily with equal speed or efficiency. In visualizations, choosing which visual feature is mapped to each dimension of the data set affects which tasks are most easily performed on which data dimensions (e.g., perhaps it is best to map size to the data dimension that will likely require a summary judgement, and position to the data dimension that will likely be segmented).
(a) Tagged text visualization uses color and position to allow users to identify linguistic patterns in a document (Alexander, Kohinan, Valenza, Witmore, & Gleicher, 2014).

(b) Weather maps use color and orientation to visualize information about wind speeds, temperatures, and other meteorological data (Ware & Plume, 2013).

(c) GapMinder uses size, position and color to reveal patterns in global demographics (Rosling, 2009).

(d) Inspired by work on ensemble encoding, Sequence Surveyor depicts changes in the use of 170,000 words across 34 decades, locally permuting color to help the visual system construct ensemble summaries of noisy information (Albers, Dewey, & Gleicher, 2011).
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