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Features vs Prototypes: amplifying cognition with common data graphics

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Abstract

The most common and important data visualizations, such as barcharts or scatterplots are typically feature-based. In this paper we question whether feature-based representations are favorable from the cognition point of view. We show through the examples how the notion of prototypes can be introduced and discuss based on Card's taxonomy how feature- and prototype-based representations amplify cognition.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Visual Analytics]: prototypes visualizations—features visualization

1. Introduction

We all say that the aim of the visualization is to enhance the understanding of the data. But how often do we explicitly think about the strengths of the human perceptual and cognitive abilities when designing visualizations? There are plenty of studies from which we can learn how to design visualization so that they are effective [CM86, CC12]. Effective visualizations of information support cognition in numerous ways. They offload cognitive load onto the external world, schematize and reduce complexity, aid in problem solving, and promote discovery, to name a few. So which characteristics of good design do we employ the provide better understanding?

Two important aspects that contribute to the effectiveness of the visualization are the choice of the data representation and the choice of the graphical representation. We know which graphical representations are most suitable for certain visual encodings and which data types correspond to those [Car03]. How about the data representation? The common way to represent data is with feature measurements. Should thus the data also be visualized using features? Are features always the best, also when datasets are high-dimensional and heterogeneous? Could we replace them with a different representation and when is it better to use features next to other representations? What would be the recipe for choosing the best representation for both data and graphics?

An alternative to feature-based representations are prototype-based representations. There is plenty of evidence from cognitive science that prototypes support well the cognitive abilities of humans [Ros78, Lak87, Pri08, Ede98, KT84]. Also there are many prototype-based visualization techniques, from simple reference curves in lineplots to more advanced organizational techniques, as [EHM*11, JPC*11, vdM14, MvGW11], that organize points by allowing the user to place landmarks, and positioning other points based on these. Only a limited number of prototypes can already represent a high-dimensional dataset well [PDP06]. Here, we let human cognitive understanding take the center stage and analyze from a theoretical point of view the cognitive benefits of using features versus prototypes in data visualization.

According to Card [TC05] humans can transform data to offload cognition into easier perceptual processes in six ways: (1) *increased resources*: e.g. using resources to expand human working memory; (2) *reduced search*: e.g. representing large amount of data in a small space; (3) *enhanced recognition of patterns*: e.g. organizing information in space by its relationships; (4) *perceptual inference*: e.g. supporting easy perceptual inference of relationships; (5) *perceptual monitoring*: e.g. perceptual monitoring of a large number of potential events; (6) *manipulable medium*: e.g. enable dynamic exploration of a space of parameters values. In this paper we take common feature-based data visualizations: barchart, lineplot, radarplot and scatterplot and transform them into prototype-based visualizations. We then use Card's taxonomy to discuss how those visualizations compare for cognitive understanding in terms of the six transformations.

2. From features to prototypes

Common spatial position encoding visualizations techniques can be transformed from a feature-based to a prototype-based representation.

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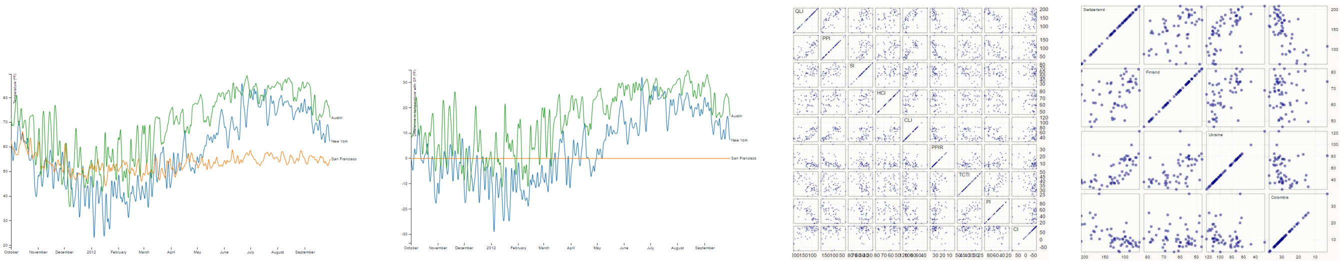

(i) (ii) (iii) (iv)

Figure 1: *The lineplot and scatterplot matrix showing two different approaches of converting visualizations from feature-based to prototype-based. (i) Multi-series line plot using features; (ii) Multi-series line plot using reference to prototype. (iii) Scatterplot matrix using features; (iv) Scatterplot matrix using similarities to prototypes.*

Table 1: *How feature-based and prototype-based visualizations amplify (✔) and diminish (✘) cognition according to Card's taxonomy: (1)increased resources, (2) reduced search,(3) enhanced recognition of patterns, (4) perceptual inference, (5) perceptual monitoring, (6) manipulable medium.*

Transformation approach	Property	Features	Prototypes
Reference to prototype e.g. lineplot & barchart	individual feature patterns visible	✔ (3)	✘ (1)(2)
	easy comparison between data instances	✘ (4)	✔ (2)(3)(4)
	scales to many dimensions	✘ (1)(2)	✘ (1)(2)
	interactive selection	✘ (6)	✔ (3)(6)
Similarity to prototype e.g. scatterplot & radarplot	individual feature patterns visible	✔ (3)	✘ (4)
	easy comparison between data instances	✘ (3)(4)	✔ (1)(3)(4)
	scales to many dimensions	✘ (1)(2)	✔ (1)(2)
	interactive selection	✘ (6)	✔ (3)(6)

2.1. Reference to prototype transformation

Visualizations that excel in heterogeneous or continues data such as a lineplot, heatmap, or barchart reveal individual feature dimensions. Such visualizations can be transformed to a prototype-representation by comparing each individual feature value to the reference feature value of the prototype. The reference prototype can be interactively selected by the user. In figure 1(i) we show the feature-based lineplot and figure 1(ii) shows the reference lineplot.

2.2. Similarity to prototype transformation

Several visualizations are suitable for uniform feature measurements including a scatterplot, parallel coordinates, radarplot, etc. A transformation to a prototype-based representation uses prototypes instead of features and visualize the rest of the data in terms of similarities to those prototypes. In figure 1(iii) we show an example of a feature-based scatterplot-matrix and figure 1(iv) shows the prototype-based scatterplot-matrix with data points in terms of similarities to the prototypes.

3. How features and prototypes amplify cognition?

For both types of transformations we specify the properties which we then compare for feature-based and prototype-based representations and map to the six concepts according to the taxonomy of Card. In table 1 we present our results.

We see that the combination of the choice of data representation and the choice of the visualization technique have influence on our cognitive abilities. Carefully choosing the right representation for the task at hand can amplify cognition. For example, consciously using the reference bars could be particularly useful in a grouped barchart, where multiple values are to be compared. Feature-based representation amplifies cognition when the comparison of feature values is required. In general, the high-dimensional datasets are from cognitive point of view better visualized with prototype-based representation, as those scale better. We think that the prototype representation has especially a lot of potential for visualizations that use linked views, since we can use the homogeneous prototype-based representations for all the building block of a system.

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