Dupo Ranking Measures

1 Introduction

Responsive visualization can be characterized as a trade-off between preserving takeaways and adjusting density [3]: Applying a set of responsive transformations to adjust graphical density (e.g., resizing, rescaling, aggregating, etc.) may cause changes to messages implied in the visualization. Thus, Dupo evaluates Exploration and Alteration suggestions in comparison with their source design in terms of "message" and density. To outline, we use the task-oriented loss measures for identification, comparison, and trend proposed by Kim et al. [4] to approximate changes to "message." In addition to them, we develop a text loss to approximate changes to explicit takeaways conveyed in text elements (title and annotation). Lastly, we use overplotting and occupied ratios to approximate changes to graphical density, inspired by Ellis and Dix [1]. An occupied ratio is how much space visual elements take in a visualization (i.e., the ratio of non-white space). We introduce the technical details of these measures for background. Our goal is to integrate those measures with the authoring interface, and the evaluation of each measure (except the text loss) can be found in the relevant prior work.

2 Message Loss Measures

Identification loss approximates the difference in support for identifying individual data points between two views [4]. Given a source design S and a target design T (i.e., a suggestion), the identification loss from S to T, $L(\text{identification}; S \rightarrow T)$, is:

$$L(\text{identification}; S \rightarrow T) = \sum_{e \in S, e' \in T} w_e |H(e) - H(e')|, \tag{1}$$

where e represents a set of the rendered values of each encoding channel (e.g., x positions in pixel) in S, and e' indicates the corresponding channel in T that encodes the same data field. H is Entropy measure. w_e and w'_e are the weight term for e and e', respectively.

Comparison loss estimates the difference in support for comparing each pair of data points between two views [4]. The comparison loss from S to T, $L(\text{comparison}; S \rightarrow T)$, is:

$$L(\text{comparison}; S \rightarrow T) = \sum_{e \in S, e' \in T} w_e \text{EMD}(D_e - D_{e'}), \tag{2}$$

where EMD is Earth Mover's Distance, and D_e is a set of pairwise distances of the rendered values in e.

Trend loss approximates the difference in support for recognizing implied trends of the underlying data between two views [4]. The trend loss from S to T, $L(\text{trend}; S \rightarrow T)$, is formalized as:

$$L(\text{trend}; S \rightarrow T) = \sum_{m \in S, m' \in T} w_m A(\text{LOESS}(m) - \text{LOESS}(m')), \tag{3}$$

where m is a trend model of rendered values (e.g., 2D models like $x \sim y$, 3D models like *color* $\sim x + y$) in S, and m' is the corresponding model in T. A refers to the area between curves approximated by LOESS regression for a 2D model (the volume between surfaces for 3D models). w_m is the weight term for m.

Lastly, the **text loss** estimates the changes to text contents in the visualization, such as annotations and titles, given their importance in narrative visualizations. Given a source design S and a target design T, the text loss from S to T, $L(\text{text}; S \rightarrow T)$, is formalized as:

$$L(\text{text}; S \rightarrow T) = \sum_{t \in S, t' \in T} I(t, t'), \tag{4}$$

where t and t' are corresponding text elements in the source and target designs, respectively. $I(t, t') = 0$ if they are same, $I(t, t') = 0.3$ if they are different, and $I(t, t') = 1$ if either one of them does not exist. We heuristically chose the value of 0.3 for inequality given that the pair of text elements are supposed to contain similar information.

3 Density Loss Measures

To approximate changes to graphical density, we use overplotted and occupied ratios as major sources of changes to graphical density under responsive transformation. The overplotted ratio of a visualization refers to the overplotted area (i.e., occupied by two or more elements) divided by the occupied area (i.e., containing one or more elements) [1]. An occupied ratio is defined as the occupied area (i.e., non-white space) divided by the entire visualization area. Dupo only considers the chart area for changes to overplotted

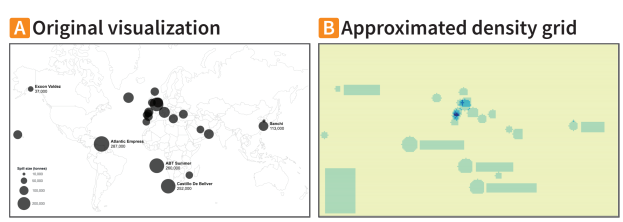

Figure 1: An example density grid (B) approximated for a map with circle marks (A). The color in the density grid indicates the number of occupying visualization elements in each grid cell. Geographic shapes are excluded when it has no encoding.

and occupied ratios because the ratios for out-chart text (e.g., title) are constant.

However, precisely measuring overplotted and occupied ratios lacks scalability, taking $O(n^2p^2)$ time (n: the number of elements, p: the size of the biggest element). Instead, we approximate a density grid, inspired by related work [1, 2]. In particular, Dupo divides a chart space by four-by-four (pixel) grid cells, as recommended by prior work [1]. Given a visualization V, we check the membership of the graphical and text elements in each grid cell, where $G_k(V)$ denotes the number of grid cells with k or more elements in V (G_0: entire cells, G_1: occupied cells, G_2: overplotted cells). Figure 1 shows an example density grid.

Using this approximation, the **occupied ratio** (C) and **overplotted ratio** (P), given a visualization V, are formalized as:

$$\begin{aligned} C(V) &= G_1(V)/G_0(V) \\ P(V) &= G_2(V)/G_1(V) \end{aligned} \tag{5}$$

Then, we formalize the changes to graphical density $L(\text{Density}, S \rightarrow T)$, from S to T, with the weight terms (w_C, w_P) as:

$$\begin{aligned} L(\text{Density}, S \rightarrow T) = \\ w_C|C(S) - C(T)| + w_P|P(S) - P(T)|, \end{aligned} \tag{6}$$

4 Combining Loss Measures

To combine these message and density loss measures, Dupo first normalizes them using their maximum value ($\hat{L}$) as each loss measures are in different scales but they evaluate each target design in comparison with the same source design. After normalization, the final loss value is the weighted sum of individual loss values. To formalize,

$$L(S \rightarrow T) = \sum_i w_i \hat{L}(i, S \rightarrow T) \tag{7}$$

where i is a loss type (identification, comparison, trend, text, density) and w_i is a weight term for each loss type. We initially decided the weight terms by heuristically testing them out, as shown in Table 1. Users can fine-tune weight terms to reflect their priorities in the preferences menu.

Loss type	**Channel/model**	**Wieght**
Identification/ Comparison	Total	1.5
	Position	3
	Length	2.5
	Color	2.2
	Size	2.2
	Shape	1.5
	Text	1.5
	Others	1
Trend	Total	5
	Y∼X	3
	Color∼x+y	2
	Size∼X+Y	2.3
	Color∼X	1
	Others	1
Text	Total	0.5
Density	Total	6
	Occupied ratio	3
	Overplotted ratio	5

Table 1: Initial weight terms

References

[1] G. Ellis and A. Dix. Enabling automatic clutter reduction in parallel coordinate plots. *IEEE Transactions on Visualization and Computer Graphics*, 12(5):717–724, 2006.

[2] E. Kandogan. Just-in-time annotation of clusters, outliers, and trends in point-based data visualizations. In *2012 IEEE Conference on Visual Analytics Science and Technology (VAST)*, pages 73–82, 2012.

[3] H. Kim, D. Mortiz, and J. Hullman. Design patterns and trade-offs in authoring communication-oriented responsive visualization. *Computer Graphics Forum (Proc. EuroVis)*, 40:00–00, 2021.

[4] H. Kim, R. Rossi, A. Sarma, D. Moritz, and J. Hullman. An automated approach to reasoning about task-oriented insights in responsive visualization. *IEEE Transactions on Visualization and Computer Graphics*, 28(1):129–139, 2022.