InfoColorizer: Interactive Recommendation of Color Palettes for Infographics

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Appendix A
Feature Explanation

As mentioned in Sec. 5.1, we distill a list of features to characterize an infographic at multiple levels. Below we give a detailed explanation of each non-color feature and illustrate them with the infographic shown in Fig. 1.

Infographic Level. We use the following features:

- *VIF Type* is the underlying narrative structure (visual information flow) of an infographic [4], where there are 12 types of VIF, such as *Landscape*, *Portrait*, *Clock*, *Up-ladder*. The VIF type of Fig. 1 is *portrait*.
- *Visual Group Number* is the number of visual groups on the VIF backbone. There are two visual groups (the first A1 and the second B2 row) in Fig. 1.
- *Visual Group Distance* is the average distance between the centroids of two adjacent visual groups on the VIF backbone. The distance between the two groups in Fig. 1 can be calculated as the distance between centers of two circles (Element 3 and 8).

Visual Group Level. We consider the following features:

- *Visual Group Element Number* is the number of (artistic and graphical data) elements within a visual group. In Fig. 1, each group has eight elements.
- *Relative Visual Group Size* is the width and height of the bounding box of a visual group divided by the width and height of the infographic image, respectively.

Element Level. We extract the following features for each artistic and graphical data element:

- *Element Type* classifies the appearance of an element, where for an artistic element, it can be *triangle*, *square*, *rectangle*, *pentagon*, *circle* or *others*, and for a graphical data element, it can be *index*, *text*, *icons* or *arrows* [4]. In Fig. 1, A1 and B2 are text, and their background shapes are pentagons.

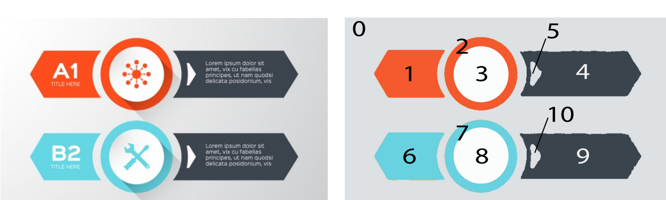

Fig. 1. An example for illustrating features.

- *Relative Element Size* is the width and height of its bounding box divided by the width and height of the infographic, respectively.
- *Relative Element Pixel Area* is the pixel area of an element divided by the total pixel area of the infographic. Note that the pixel area of an element is not necessary the same as its bounding box (e.g., text, icons, index, and non-convex shapes).

To represent spatial arrangement within an infographic, we adopt the nested set model [2] to traverse its corresponding tree structure described in Sec. 4.2. In particular, we store the following information of each node:

- *Left Index Number and Right Index Number* of a node are the visiting sequence numbers generated in a pre-order traversal where each node is visited twice and thus two indices are assigned. Every tree structure is then uniquely associated with these left and right node index numbers.

Appendix B
Model Training and Evaluation

B.1 VAEAC Training

We trained a VAEAC (Variational AutoEncoder with Arbitrary Conditioning) [3] model based on feature vectors $[\mathbf{F}, \mathbf{C}]$ extracted from a large expert-designed infographic collection (Sec. 5.2). To obtain a fixed-length vector based on the flattened tree, we limited the maximum number of nodes as 19 based on our observation of the infographics in InfoVIF [1]. Zeros were filled in the feature vector if there were not enough nodes. The final dataset contained 2,278 infographics after removing those with more than 19 nodes. We split the data into 80% for training and 20% for testing. We further used 10% of the training data as the validation set to select the best model during training.

The resulting VAEAC model can handle infographics with up to 19 elements. However, it can be easily generalized to handle infographics with more elements by training it on vectors with more nodes.

B.2 Model Alternatives and Evaluation

In developing InfoColorizer, we considered two alternative models solving the same problem as VAEAC including GAIN (Generative Adversarial Imputation Nets) [6] and MICE (Multivariate Imputation by Chained Equations) [5].

TABLE 1
Comparison of model performances with NRMSE (lower is better), Color Relevance Score (CRS, lower is better), and Color Variance Score (CVS, higher is better).

	NRMSE	CRS	CVS
VAEAC	**0.6543**	**2.4826**	5.6748
GAIN	2.4574	4.1742	4.1075
MICE	15.6098	16.5096	**27.6199**
VAEAC (non-spatial)	1.1536	3.6874	6.429

We trained a GAIN and MICE model on the same set of feature vectors $[\mathbf{F}, \mathbf{C}]$ as VAEAC model. We also investigated whether the spatial features would influence the effectiveness of the VAEAC. To do so, we obtained new feature vectors $[\mathbf{F}', \mathbf{C}]$ from $[\mathbf{F}, \mathbf{C}]$ by removing spatial features, encoded by *Left Index Number* and *Right Index Number*. We then trained a non-spatial VAEAC model based on $[\mathbf{F}', \mathbf{C}]$ with the same network architecture and hyperparameters as the VAEAC model.

To evaluate the models, we adopted a similar approach as in [3]. For each infographic in the test set, we randomly dropped 50% of the color features $\mathbf{C}$ as the "missing" features; therefore, we had the ground truth information that is the original $\mathbf{C}$. We replaced each infographic by five different ones with random unobserved color features; thus, the test data size increased by five times. In the experiments, for each model, we generated five full color features $\mathbf{C}$ for each test infographic.

We considered three metrics for assessing the model performance: *NRMSE*, *Color Relevance Score* (CRS), and *Color Variance Score* (CVS). NRMSE is Root Mean Square Error (RMSE) normalized by the standard deviation of each feature. For each test case, we computed this measure via $\frac{1}{n}\sum_{i=1}^{n} NRMSE(\mathbf{C}_o, \mathbf{C}_i)$, where $n = 5$, $\mathbf{C}_o$ is the original feature, and $\mathbf{C}_i$ is the imputed one. CRS measures the degree of relevance between the ground truth and the generated color features: $\sum_{i=1}^{n} d(\mathbf{C}_o, \mathbf{C}_i)$, where $d = \frac{1}{m}\sum_{k=1}^{m} CIEDE(\mathbf{C}_o^k, \mathbf{C}_i^k)$. $CIEDE(\cdot)$ is the CIEDE2000 difference between the corresponding m pairs of colors, $\mathbf{C}_o^k$ and $\mathbf{C}_i^k$, in the feature vectors. CVS measures the degree of variance among the generated color features, which is computed by the pairwise color differences: $\sum_{i=1}^{n}\sum_{j=i+1}^{n} d(\mathbf{C}_i, \mathbf{C}_j)$. The above measures were computed for each test case, and we report the averages across the test set in Table 1. We can see that VAEAC had the lowest NRMSE and CRS while having higher CVS than GAIN. While MICE had the highest CVS, its other two metrics were the lowest. We also note that the spatial features had a positive influence. Compared to non-spatial VAEAC, VAEAC had lower NRMSE and CRS. This indicates that VAEAC successfully captured the relationships between the colors and the spatial features.

Therefore, we chose VAEAC trained with spatial features as the basis of InfoColorizer's recommendation engine.

Appendix C
More Examples

Here, we present some examples designed by InfoColorizer users of the controlled user study (Sec. 6.2). Fig. 3 shows some results of Task 1, in which participants were asked to design palettes for an infographic under specific color preferences (e.g., exact colors, color names, and semantic or affective words). Fig. 2 shows the four experimental infographics along with the preferences. Fig. 4 shows some examples generated during Task 2, in which users were given general contextual information rather than concrete preferences. The complete results are available at https://github.com/yuanlinping/InfoColorizer.

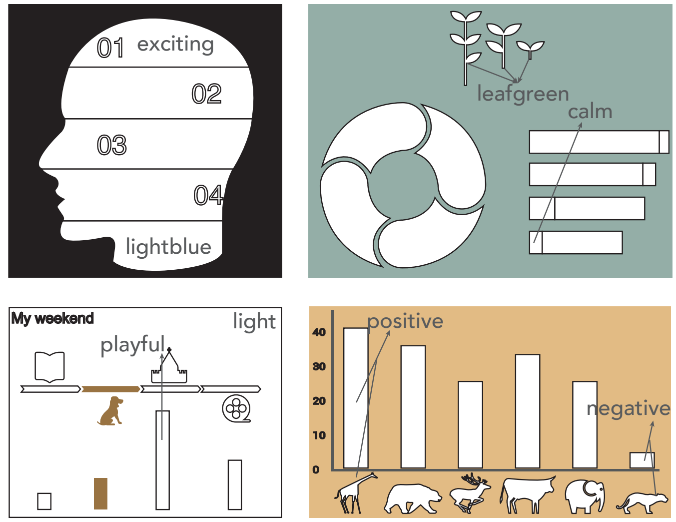

Fig. 2. Experimental infographics along with color preferences in Task 1 of the controlled user study. The preferences are either annotated (color names and semantic words) or directly colored (exact colors) on the corresponding elements.

References

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Fig. 3. Examples generated by InfoColorizer users during Task 1 of the controlled user study.

Fig. 4. Examples generated by InfoColorizer users during Task 2 of the controlled user study.