A Unified Framework for Multi-class Scatterplot Colorization

KECHENG LU* and G.K.M. TOBIN*, Institute for Clarity in Documentation, USA
LARS THØRVÄLD, The Thørväld Group, Iceland
VALERIE BÉRANGER, Inria Paris-Rocquencourt, France
APARNA PATEL, Rajiv Gandhi University, India
HUIFEN CHAN, Tsinghua University, China
CHARLES PALMER, Palmer Research Laboratories, USA
JOHN SMITH, The Thørväld Group, Iceland
JULIUS P. KUMQUAT, The Kumquat Consortium, USA

Fig. 1. Results for different conditions of two categorical scatterplots comparison: (left top) Random Assignment; (left bottom) C3-Palette Assignment; (center top) Optimized Assignment [54]; (center bottom) Applying Alpha-Blending on Optimized Assignment, all the classes' alpha are set to 0.5 except the changed class; (right top) Palettailor [37]; (right bottom) C3-Palette Generation. Our system unifies the palette assignment and palette generation to single or multiple scatterplots in a data-aware manner.

A clear and well-documented LaTeX document is presented as an article formatted for publication by ACM in a conference proceedings or journal publication. Based on the "acmart" document class, this article presents and explains many of the common variations, as well as many of the formatting elements an author may use in the preparation of the documentation of their work.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: datasets, neural networks, gaze detection, text tagging

*Both authors contributed equally to this research.

Manuscript submitted to ACM

ACM Reference Format:
Kecheng Lu, G.K.M. Tobin, Lars Thørväld, Valerie Béranger, Aparna Patel, Huifen Chan, Charles Palmer, John Smith, and Julius P. Kumquat. 2018. A Unified Framework for Multi-class Scatterplot Colorization. In *Woodstock '18: ACM Symposium on Neural Gaze Detection, June 03–05, 2018, Woodstock, NY*. ACM, New York, NY, USA, 22 pages. https://doi.org/10.1145/1122445.1122456

1 INTRODUCTION

ACM's consolidated article template, introduced in 2017, provides a consistent LaTeX style for use across ACM publications, and incorporates accessibility and metadata-extraction functionality necessary for future Digital Library endeavors. Numerous ACM and SIG-specific LaTeX templates have been examined, and their unique features incorporated into this single new template.

If you are new to publishing with ACM, this document is a valuable guide to the process of preparing your work for publication. If you have published with ACM before, this document provides insight and instruction into more recent changes to the article template.

The "`acmart`" document class can be used to prepare articles for any ACM publication — conference or journal, and for any stage of publication, from review to final "camera-ready" copy, to the author's own version, with *very* few changes to the source.

2 CO-SALIENCY BASED COLOR DESIGN

Given multiple labeled scatterplots with the same class labels (or a subset thereof), each scatterplot $\mathbf{X}^j$ has M classes and n_j data items $\{\mathbf{x}_1^j, \cdots, \mathbf{x}_{n_j}^j\}$, where each $\mathbf{x}_t^j$ has a label $l(\mathbf{x}_t^j)$ and the i-th class (with n_i^j data points) consists of $\{\mathbf{x}_{i,1}^j, \cdots, \mathbf{x}_{i,n_i^j}^j\}, i \in \{1, \cdots, m\}$. All visualizations use the same background color $\mathbf{c}_b$ and the same color mapping scheme $\tau : L \mapsto c$. Our goal is to find the best mapping τ that supports effective comparison of multiple categorical scatterplots.

In line with the design requirements of natural image comparison and categorial data visualization [19, 30, 37], our problem is formulated based on the following three design requirements:

(i) **DR1:** highlighting the most concerned classes between visualizations as much as possible for an efficient comparison;
(ii) **DR2:** maximizing the visual discrimination between classes in individual visualizations for an efficient exploration of multi-class data; and
(iii) **DR3:** providing flexible interactions for the exploration of relationships among the compared datasets.

Although visual comparison is an essential part of interactive data analysis, most of the existing colorization techniques [20, 37] attempt to meet DR2. The key challenge in meeting DR1 is that we need a proper model to characterize the most salient features in multiple visualizations. To address this issue, we propose a categorical visualization co-saliency model that calculates the saliency of each data item in the context of other similar visualizations. Integrating this model into the objective of state-of-the-art color mapping selection or generation frameworks [37, 54], we can generate proper color mappings to highlight salient differences between juxtaposed categorical visualizations.

2.1 Co-saliency for Multi-class Scatterplots

Following the definition of image co-saliency [30], we model the class co-saliency with two factors: class importance between scatterplots and class contrast within scatterplots. The class importance describes how much each class should stand out from the visualizatioin. While the class contrast measures the distinctness from neighboring classes and the background, which is similar to perceptual class separability [8, 54]. Hence, we define two types of class contrasts: contrast with neighboring classes and contrast to the background. Analogous to bottom-up image co-saliency models [17, 30], the co-saliency of the ith class is defined as the product between class importance and class contrast score to emphasize the target class, and the co-saliency for M classes:

$$E_{CoS} = \sum_i \left(\sum_j \frac{1}{n_i^j} (\lambda \alpha_i^j + (1 - \lambda) \beta_i^j) \right) \exp(\theta_i) \tag{1}$$

where θ_i is the importance of the ith class, α_i^j is the contrast with neighboring classes of the ith class in the jth scatterplot, β_i^j is the contrast to the background, and λ is a weight between them. To better support DR1, we apply an exponential function to enlarge the weight of class importance, thus makes the target class easy to get a discriminable color from the optimization process.

Class Contrast. Given the jth scatterplot, we define the local class contrast with both point distinctness and point contrast with background [54] based on the neighbors calculated by α-Shape [37]. For each data point $\mathbf{x}_t^j$, we define its point distinctness as:

$$\gamma(\mathbf{x}_t^j) = \frac{1}{|\Omega_t^j|} \sum_{\mathbf{x}_p^j \in \Omega_t^j} \frac{\Delta\epsilon(\tau(l(\mathbf{x}_t^j)), \tau(l(\mathbf{x}_p^j)))}{d(\mathbf{x}_t^j, \mathbf{x}_p^j)}, \tag{2}$$

where Ω_t^j is set of nearest neighbors of $\mathbf{x}_t^j$, $\tau(l(\mathbf{x}_p^j))$ is the color of $\mathbf{x}_p^j$, $\Delta\epsilon$ is the CIELAB color distance [48] and d is the Euclidean distance. For the ith class, its point distinctness is the sum of all points with the same class label in the scatterplot:

$$\alpha_i^j = \frac{1}{n_i^j} \sum_p^{n_j} \gamma(\mathbf{x}_p^j) \delta(l(\mathbf{x}_p^j), i) \tag{3}$$

where $\delta(l(\mathbf{x}_p^j), i)$ is one if the class label $l(\mathbf{x}_p^j)$ is i and else zero. Similar to [54], we define non-separability as the difference value between $\mathbf{x}_t^j$ with data points belonging to the different classes and same class, thus the contrast to the background can be defined as:

$$\rho(\mathbf{x}_t^j) = \frac{1}{|\Omega_t^j|} \sum_{\mathbf{x}_p^j \in \Omega_t^j} \frac{(1 - 2\delta(l(\mathbf{x}_t^j), l(\mathbf{x}_p^j))) \Delta\epsilon(\tau(l(\mathbf{x}_t^j)), \mathbf{c}_b)}{d(\mathbf{x}_t^j, \mathbf{x}_p^j)}, \tag{4}$$

the contrast to the background of the ith class is defined as follows:

$$\beta_i^j = \frac{f(\theta_i)}{n_i^j} \sum_p^{n_j} \exp(\rho(\mathbf{x}_p^j)) \delta(l(\mathbf{x}_p^j), i) \tag{5}$$

where we use a piecewise function to weight the background contrast:

$$f(\theta_i) = \begin{cases} 1 & \text{if } \theta_i > \kappa \\ -1 & \text{else} \end{cases} \tag{6}$$

κ is a user-specified threshold with the default zero. The reason for the two different weighting schemes is that classes with less or no importance might be treated as the background by viewers [55]. To suppress the saliency of such classes, we introduce a negative importance for them. Since $\rho(\mathbf{x}_t^j)$ might be a negative value, we apply an exponential function to transfer it to positive.

Class Importance. Class importance reflects whether a class should be highlight or not. It can be specified by user or by some measures. In our paper, we use class change degree to represent the importance of each class as default.

To quantify how users perceive class structure changes, we measure the difference between class distributions in two scatterplots with the Earth Mover's Distance (EMD) [44], a perceptual metric. Suppose the ith class with two sets of points $\mathbf{X}_i^1 = \{\mathbf{x}_{i,1}^1, \cdots, \mathbf{x}_{i,n_i^1}^1\}$ and $\mathbf{X}_i^2 = \{\mathbf{x}_{i,1}^2, \cdots, \mathbf{x}_{i,n_i^2}^2\}$. Taking the Euclidian distance between two points as the cost, we need to minimize the total matching cost

$$H(\mathbf{X}_i^1, \mathbf{X}_i^2) = \min_{\chi} \sum_t d(\mathbf{x}_{i,t}^1, \mathbf{x}_{i,\chi(t)}^2), \tag{7}$$

which constrains an one-to-one mapping χ between points (see an illustration in Fig. 2). This is the classic bipartite matching problem, which can be solved by the Hungarian method [34]. When the number of points of two sets is not equal, we further take the difference between the number of points into account. In doing so, the class change degree is defined as:

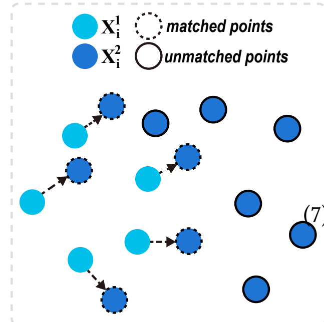

Fig. 2. An one-to-one mapping for computing the changes between two classes.

$$\theta_i = \frac{H(\mathbf{X}_i^1, \mathbf{X}_i^2)}{\min\{n_i^1, n_i^2\}} + \nu \frac{||n_i^1 - n_i^2||}{\max\{n_i^1, n_i^2\}} \tag{8}$$

where both terms range within [0,1] and ν is 1.0 as the default.

2.2 Co-Saliency based Color Mapping

On the basis of the co-saliency model, we meet DR1 and DR2 in two ways: co-saliency based color assignment and co-saliency based palette generation.

Co-saliency based Color Assignment. Given a good color palette with P colors ($P \geq M$), the optimal color mapping can be obtained by taking the co-saliency model in Eq. 1 as the objective of the state-of-the-art color assignment method [54]. Starting from a random permutation of P colors, we use the simulated annealing algorithm [1] to find the optimal permutation with two randomized strategies to improve the solution. One is randomly exchanging two colors from the selected m colors and the other is replacing one color from the m selected colors with the one chosen from the unselected $P - M$ colors. With a few iterations, we can obtain a reasonable color mapping as shown in Fig. 1 bottom left.

However, this method has two major limitations: i) requiring users to try many palettes for selecting a good one; and ii) the design of most existing palettes is not oriented towards visual comparison so that even the best color assignment cannot provide prominent cues for this task. For example, all colors in the ColorBrewer 8-class Set1 [25] palette are highly discriminable, but it is hard to find a satisfactory solution. Fig. 3 shows an example, where the change of the red class is hard to identify at once even it is very distinctive. Thus, we prompt users to use our co-saliency based palette generation method.

Co-saliency based Palette Generation. The recently proposed data-aware palette generation method [37] automatically generates discriminable and preferable palettes by maximizing the combination of three palette quality measures: point distinctness, name difference, and color discrimination. By replacing the first measure with our co-saliency model, the palette generation is formulated as an optimization problem:

$$\arg\max_{\tau} E(\tau) = \omega_0 E_{CoS} + \omega_1 E_{ND} + \omega_2 E_{CD}. \tag{9}$$

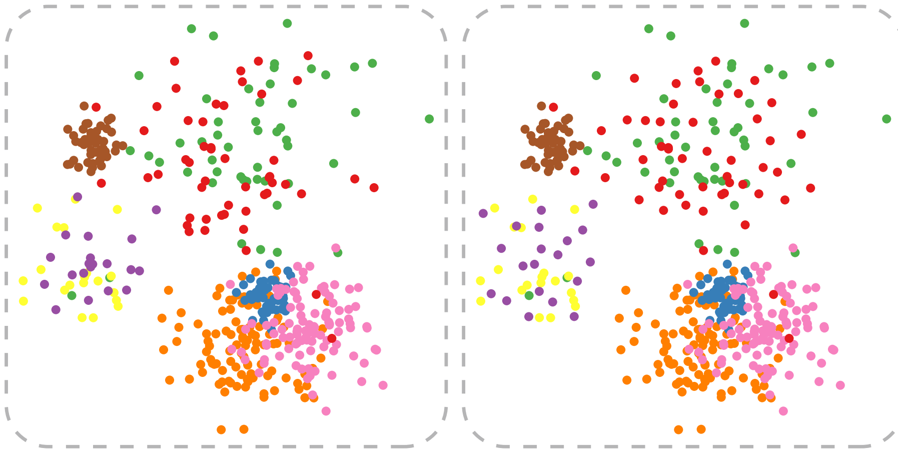

Fig. 3. Visualizing the same data sets as shown in Fig. 4 with the ColorBrewer palette and our assignment method.

which consists of a co-saliency term E_{CoS} (see Eq. 1), a name difference term E_{ND} and a color discrimination term E_{CD}, balanced by ω_0, ω_1 and ω_2. For more detail about E_{ND} and E_{CD}, we refer readers to [37]. By using the same optimization method as Lu et al. [37], we can generate desired colors in real time.

2.3 Parameter Effect

Besides different weights for different terms in palette generation [37], our co-saliency model involves three parameters: the weight λ between two contrasts, the threshold for the class importance κ, and ν that is related to the definition of the class change degree which is used as our default class importance. Since ν is fixed in our experiments and the class importance can be specified by user, we mainly discuss the effects of λ and κ.

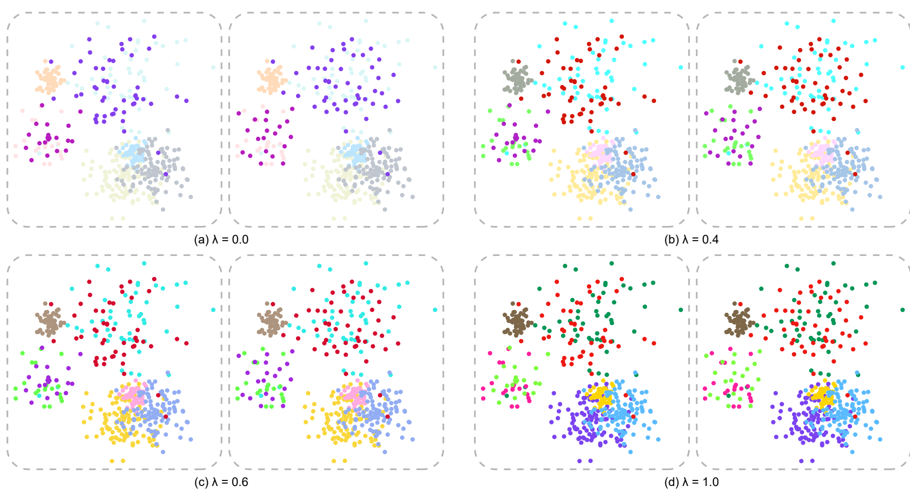

Fig. 4. Effect of λ: (a) result generated by only considering contrast to the background; (b) result generated by setting λ to 0.4; (c) result generated by setting λ to 0.6; (d) result generated by only considering contrast with nearest classes.

Balancing Weight λ. Although this parameter modulates the influence between the class contrast with neighbors and background, it offers a compromise between DR1 and DR2. As shown in Fig. 4(a), considering only the contrast to the background would have a good 'pop out' effect but other classes are hard to discriminate. While considering only the contrast with nearest neighbors, such as Fig. 4(d), all the classes are each to distinguish but the changed classes are hard to find out. This is reasonable, because pre-attentive vision lets a bright saturated color region within regions of de-saturated colors "pop-out" to the viewer [26]. In our experiments, we found that setting $\lambda = 0.4$ as the default allows to simultaneously emphasize changes and preserve the discriminability between classes, see an example in Fig. 4(b).

Importance Threshold κ. The threshold κ selects the classes with large importance to be highlighted. With a default value of zero, all classes with importance value larger than zero are ensured to be highlighted. Likewise, a large κ will de-emphasize classes with a small importance. We further allow users to specify κ by interaction through the control panel (see Sec. 3).

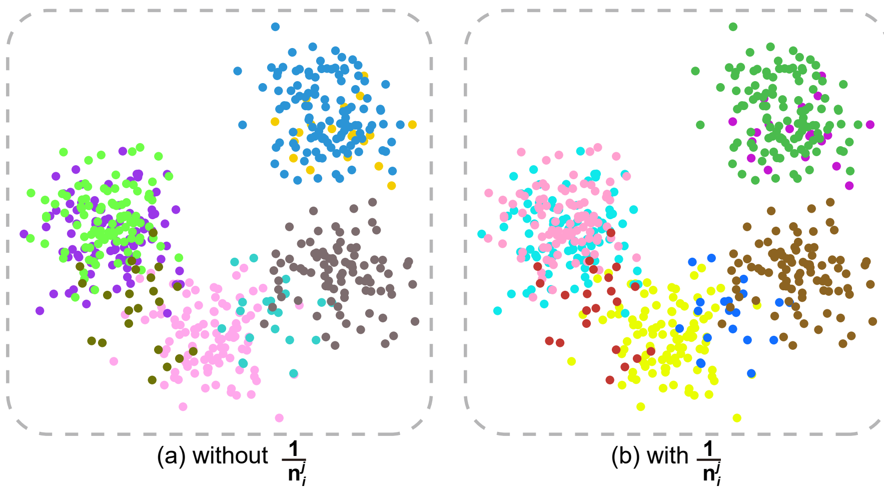

Fig. 5. Effect of $\frac{1}{n_i^j}$: (a) without this term the small classes are hard to catch user's attention; (b) with this term, small classes are easy to find. Palettes are generated with same scatterplot.

We can observe that when there's only one scatterplot and θ_i of each class is zero, then Equation. 1 is very similar to the objective function of [54]. Our method extends Wang et.al's work to multiple scatterplots with a carefully designed co-saliency model. Besides, we add $\frac{1}{n_i^j}$ to emphasize the class with less points. As shown in Fig. 5(b), with this new term, the little classes, like red, blue and purple classes, become more discriminable.

3 INTERACTIVE SYSTEM

To help users interactively design colors for comparing multi-class scatterplots, we developed a web-based multi-view visualization tool [1] (see Fig. 6). It consists of four coordinated views: (a) a settings panel, (b) a control panel for adjusting importance threshold κ and even importance value of each class, (c) the juxtaposed visualizations, and (d) a history view. The control panel shows the decision which classes are highlighted, and the history view allows to quickly explore and access previous color mappings.

[1] https://c3-palette.github.io/

Fig. 6. Screenshot of the interactive system. (a) Settings Panel; (b) Control Panel; (c) Visualization Panel; (d) History Panel.

After uploading multiple labeled scatterplots, the user can either choose a default color palette or use our system to automatically generate color palettes. In this case, the system automatically finds an optimal color mapping scheme to colorize the input data, while each class is encoded as a circle where the x-axis represents class label and the y-axis indicates the importance of each class. By default, the importance is represented by the change degree and κ is set to zero. User can drag the circle to modify the corresponding importance value. The κ is controlled by a black circle on the y-axis which can also be dragged to modify. Our system finds a color mapping scheme to highlight the classes with large importance and renders the classes in ascending order of the corresponding importance. If users like the color mapping scheme, they can save it to the history view.

Using θ_i defined in Eq. 1, the classes whose importance values are larger than the threshold κ will be highlighted. Figs. 6(b,c) show an example, where the three classes with the adjusted importance values larger than κ are emphasized with salient *red*, *blue* and *purple* colors, respectively. This control panel allows users to select arbitrary classes of interest to highhlight by simply adjust circle position and κ value.

4 EVALUATION

We evaluated the effectiveness of our method on supporting juxtaposed visual comparisons and the discriminability for reading scatterplots.We conducted two online controlled experiments through Amazon Mechanical Turk (AMT) with 160 participants in total, to evaluate how well our method can support people in *observing changes* and *visual separability* for juxtaposed categorical scatterplots:

(i) *Spotting the Difference task*. To evaluate how well our method can support people in *observing changes* for juxtaposed categorical scatterplots;

(ii) *Counting class number task*. To evaluate whether our method can support the *visual separability* of classes in each individual scatterplot, which is considered fundamental to juxtaposed comparison.

Independent Variables. In each of our studies, we investigated three independent variables: colorization method, change magnitude and change type.

Colorization method: We used six different ways to colorize scatterplots: four benchmark methods (*Random Assignment*, *Optimized Assignment*, *Alpha Blending* and *Palettailor*) and two experimental methods based on our approach (*C3-Palette Assignment*, *C3-Palette Generation*):

- C1: *Random Assignment* is randomly selecting and assigning colors from Tableau-20 palette to the classes.
- C2: *Optimized Assignment* uses the optimized assignment approach [54] for one of the two scatterplots with an input of Tableau-20 color palette.
- C3: *Alpha Blending* is changing the alpha of each unchanged class to 0.5 while the changed classes are stay to 1.0 based on *Optimized Assignment* result. We choose 0.5 since we also have the discrimination task.
- C4: *Palettailor* uses the method proposed by Lu et.al [37] for single scatterplot palette generation. The palette is generated for one of the two scatterplots with the default settings.
- C5: *C3-Palette Assignment* uses the color assignment optimization solution of Eq. 1 based on Tableau-20.
- C6: *C3-Palette Generation* uses the unified color generation and assignment optimization method, and produced the results with the parameters $\omega_0 = 1.0$, $\omega_1 = 1.0$ and $\omega_2 = 1.0$.

Our approach are all using the default parameters $\lambda = 0.4$ and $\kappa = 0$.

Change magnitude and *Change type*: While the colorization method is the primary independent variable to be investigated, we are also interested in how the effect of our methods would vary based on the level of change and the different change type between the two scatterplots. Thus we first define two types of changes that a class would have across multiple scatterplots: *point number* and *point position*. Then for each change type, we define three levels of change magnitude calculated using Eq. 8: *small*, *medium*, and *large*. (See the next paragraph for the detailed calculation.)

Scatterplot Dataset Generation. The paired scatterplot datasets used in our studies were generated as follows. First, we designed a set of multi-class scatterplots, each containing 8 classes. Each class was generated using Gaussian random sampling and placed randomly in a 600×600 area. Similar to [37], these classes belong to one of the four settings of varying size and density: small & dense ($n = 50, \sigma = 20$), small & sparse ($n = 20, \sigma = 50$), large & dense ($n = 100, \sigma = 50$), and large & sparse (($n = 50, \sigma = 100$).

Then, for each scatterplot generated above, we produced its paired scatterplot by randomly choosing one or more classes and changing the positions or number of their data points. To systematically compute the changes, we defined two variables: *change ratio* and *number of changed classes*. *Change ratio* defines how large the change of a type is, ranging from 0 to 1; and number of changed classes defines the number of classes that are changed, ranging from 1 to 3. We summarize our basic idea of data generation for each change type as below.

- *Point number*: For each class in the original scatterplot, we calculated the new point number by multiplying the original number by (1± *change ratio*). An addition means to increase the point number, which was implemented by generating the new points with the same distribution as the original class. Subtraction was achieved by randomly deleting data points from the original class.
- *Point position*: Point position contains many types, such as class center position change and shape change. In our experiment, we use the two different position changes mentioned above. For center position change, the center of a class can be moved in a certain *direction* with a specific *distance*. We moved the center towards a random direction by a distance calculated by multiplying a maximal change distance (400 by default) by the *change ratio*. For shape change, we define the shape of a class as the bounding box of its data points. We simulated a shape change of a class by modifying the density parameter of its Gaussian distribution to the opposite direction. For example, a small & dense class ($n = 50, \sigma = 20$) would be changed into a small & sparse ($n = 50, \sigma = 50$) class. In

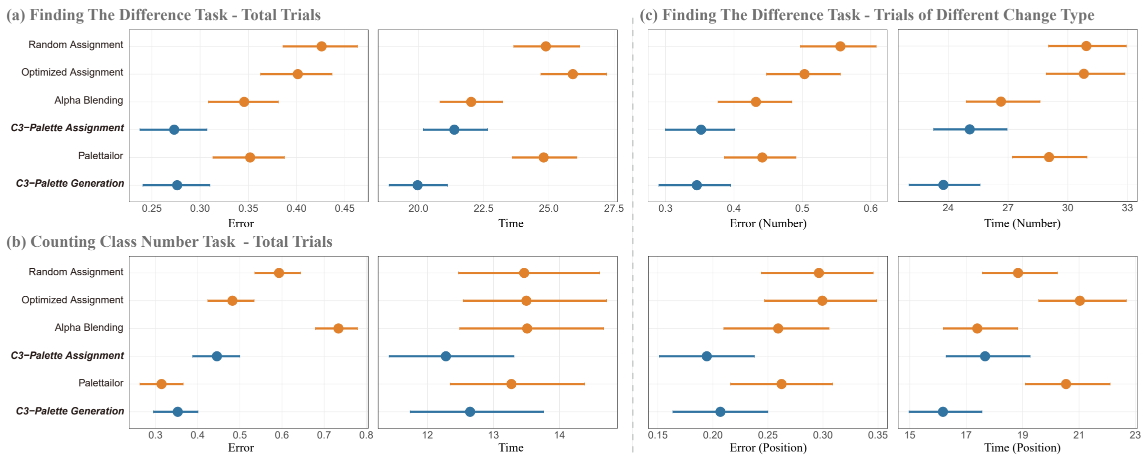

Fig. 7. Confidence interval plots and statistical tables for the two online controlled experiments. Error bars represent 95% confidence intervals. Each table shows the statistical test results of C3-Palette Generation condition with other conditions, including the mean with 95% confidence interval (μ ~95%CI), the W-value and p-value from the Mann-Whitney test, and the effect size (d ~95%CI).

order to produce a new shape for a class, we first calculate the one-to-one mapping between the newly-generated class and the original class using [34] and then linearly interpolated the new point between each two points based on the *change ratio* parameter. We randomly choose one change type when disturbing the class to be changed.

For each change type, we produced 300 candidate scatterplot pairs and then calculated the *change magnitude* for each pair, and split all pairs into three levels: *small*, *medium*, and *large*. Next, we randomly selected 2 pairs from each change magnitude level for each change type and each number of changed classes. Thus in total we used 36 paired scatterplot in each of the two studies. The detailed dataset is showed in Table. 1

Table 1. Grouping of Datasets: 36 datasets × 6 conditions. C: condition; G: participant group; Position Small 1: point position change with small change magnitude for 1 changed class.

	C1	C2	C3	C4	C5	C6
Dataset 1: Position Small 1	**G1**	G2	G3	G4	G5	G6
Dataset 2: Position Small 1	G6	**G1**	G2	G3	G4	G5
Dataset 3: Position Small 2	G5	G6	**G1**	G2	G3	G4
Dataset 4: Position Small 2	G4	G5	G6	**G1**	G2	G3
Dataset 5: Position Small 3	G3	G4	G5	G6	**G1**	G2
Dataset 6: Position Small 3	G2	G3	G4	G5	G6	**G1**
Dataset 7: Position Medium 1	**G1**	G2	G3	G4	G5	G6
Dataset 8: Position Medium 1	G6	**G1**	G2	G3	G4	G5
...						
Dataset 35: Number Large 3	G3	G4	G5	G6	**G1**	G2
Dataset 36: Number Large 3	G2	G3	G4	G5	G6	**G1**

4.1 Experiment 1: Spotting the Difference

To evaluate how well our approach can assist observing changes between juxtaposed categorical scatterplots, we conduct an online "spot-the-difference" experiment through Amazon Mechanical Turk (AMT) with 136 participants.

Hypotheses. We hypothesized that our approach would generally be more effective than the benchmark methods on the juxtaposed comparison tasks, and that this effect would vary based on *change magnitude*.

- **H1.** Our color generation method (*C3-Palette Generation*) outperforms the benchmark conditions (*Random Assignment*, *Optimized Assignment*, *Alpha Blending* and *Palettailor*) on the task performance.
- **H2.** Our color assignment method (*C3-Palette Assignment*) using a color palette with a larger range of brightness and saturation (*Tableau-20*) outperforms the benchmark conditions (*Random Assignment*, *Optimized Assignment*, *Alpha Blending* and *Palettailor*) on the task performance.
- **H3.** There would be an interaction effect between colorization methods and change magnitude. Specifically, the difference between the effect of our methods (*C3-Palette Generation* and *C3-Palette Assignment*) and that of the benchmark methods (*Random Assignment*, *Optimized Assignment*, *Alpha Blending* and *Palettailor*) would change based on the *change magnitude* between the two scatterplots.
- **H4.** There would be an interaction effect between colorization methods and change type. Specifically, the difference between the effect of our methods (*C3-Palette Generation* and *C3-Palette Assignment*) and that of the benchmark methods (*Random Assignment*, *Optimized Assignment*, *Alpha Blending* and *Palettailor*) would change based on the *change type* between the two scatterplots.

4.1.1 Experimental Design.

Task & Measures. In this experiment, each participant was asked to perform a *spot-the-difference* task. Inspired by the Spot the Difference game where one needs to compare a pair of similar pictures to detect their differences [18], we asked participants to identify all the classes that have been changed in two scatterplots. At the beginning of each trial, the number of changed classes was provided. Each participant was asked to select all the changed classes by clicking the points belonging to these class in either of the scatterplots.

For each participant, we measured the *time* taken for each trial, and counted the errors (0/1) indicating whether the actual changed classes are aligned with the participant's response. Note that if any of the changed classes was mistakenly identified, the trial would be considered as "wrong" (1).

While the participant was instructed to do the task "*as accurately as possible*", we set a 60-second time limit for each trial. If the participant could not find all the changed classes during the time limit, they were directed to the next trial. There also will appear a "*Can't Find it*" button after 30 seconds. This was done since we observed from the pilot study that when participants spent too much time on a single trial, they may decide to quit (which will lead to an incorrect answer) or to spend more time till they get the correct answer (which will lead to increasing time spent on the trial). This subject decision would add noise to our measurements. Thus we added a 30-second time limit, which was informed by our pilot study, where over 85% correct trials were completed within 30 seconds. More details can be found in the supplementary material.

Experiment Organization. We tested the effects of the 6 method conditions across 36 paired multi-class scatterplot datasets using a *between-subject* experiment design. To avoid ordering effects, where the participant would get familiar with a dataset after seeing it several times, each participant was assigned to a group and saw a specific subset of datasets under different conditions. We used a Latin Square grouping (see Table. 1) to organize the trials for each participant.

In addition, some participants might apply a "shortcut" strategy when seeing a class that is obviously more salient than the others, especially under the *C3-Palette Assignment* and *C3-Palette Generation* conditions. Thus, for quality control, we added 4 sentinels which were very simple trials with only one changed class and a large change magnitude, and we assigned a de-saturated color to the changed class that made it less salient. We add these 4 distractor trials to each group to identify whether the participants is doing the task seriously and reject the results with more than two wrong trials.

Finally, there were 6 participant groups and each of them had 40 trials in total. To further avoid learning effects between trials, we randomly shuffled the display orders of all scatterplot pairs, and randomly placed the two scatterplots in each pair on the left or right side.

Table 2. Participants details for each task.

Task & Group	Spotting the Difference		Counting class number	
	Pilot(28)	Formal(108)	Pilot(29)	formal(52)
Group 1	5	18	5	9
Group 2	5	17	5	8
Group 3	5	19	4	8
Group 4	3	17	5	9
Group 5	5	19	5	9
Group 6	5	18	5	9

Pilot Study & Power Analysis. We conducted a pilot study involving 28 participants to check the experimental setup and determine the parameters, such as the time limit for a trial. Harnessing by the pilot study, we also obtained our expected effect sizes, which were in further fed into a power analysis. With an effect size Cohen's d of 0.4, alpha level of 0.05 and beta level of 0.8, the power analysis suggested a minimum number of 100 participants for the spot-the-difference task. See the supplementary material for more details.

Participants. We recruited 108 participants(as shown in Table. 2) for the experiment on Amazon Mechanical Turk. According to the completion time in the pilot study, we paid each participant $1.5 for the task based on the US minimum hourly wage. No participant claimed color vision deficiency on their informed consent.

Procedure. Each participant went through the following steps in our experiment: (i) viewing a user guide of the task and completing three training trials; (ii) completing each trial as accurately as possible; (iii) providing demographic information.

4.1.2 Results.

Following previous studies, we analyzed the results using 95% confidence intervals, and also conducted Mann-Whitney tests to compare the differences between conditions. The non-parametric test was used due to observations of non-normally distributed data from our pilot study. In addition, we computed the effect size using *Cohen's d*, i.e., the difference in means of the conditions divided by the pooled standard deviation. We used ANOVA to examine the interaction effect between variables.

Results of the online experiment are shown in Fig.7 (a). First, we found that our approach(*C3-Palette Assignment* and *C3-Palette Generation*) leads to a significantly lower error rate than all benchmark conditions ($p < 0.001$). For consuming time, *C3-Palette Generation* has significantly less time ($p = 0.0025$) than *Alpha Blending* condition while *C3-Palette Assignment* has no significant difference, and our approach has significantly less time than all other benchmark conditions($p < 0.001$). The result indicates that our palette generation method(*C3-Palette Generation*) has a better performance than benchmark conditions in the "spot-the-difference" task (**H1** confirmed). As for color palette with a larger range of brightness and saturation, our approach(*C3-Palette Assignment*) is better than most conditions and is at least comparable to *Alpha Blending* condition(**H2** confirmed).

Second, we compared our approach to other conditions based on two different change types(*Point Number Change* and *Point Position Change*). For *Point Number Change*, as shown in the top row of Fig.7 (c), our approach(*C3-Palette Assignment* and *C3-Palette Generation*) leads to a significantly lower error rate than all benchmark conditions, including *Random Assignment* and *Optimized Assignment*($p < 0.001$), *Alpha Blending* and *Palettailor*($p < 0.05$). *C3-Palette Generation* condition has a better performance on consuming time than all other benchmark conditions($p < 0.001$), while *C3-Palette Assignment* is just comparable to *Alpha Blending* condition. For *Point Position Change*, we observed that our approach has significant lower error rate than *Random Assignment* and *Optimized Assignment*($p < 0.01$), while there's no significant difference with *Alpha Blending* and *Palettailor*. *C3-Palette Generation*) leads to a significantly lower consuming time than all benchmark conditions except *Alpha Blending*($p = 0.044$).

Finally, we did not find significant interaction effect between *colorization methods* and *change magnitude*, meaning that the effect of our method is not necessarily influenced by the magnitude of change between the two scatterplots (**H3** not confirmed).

4.2 Experiment 2: Counting Class Number

To evaluate whether our approach can fundamentally support the visual separability of the classes in each scatterplot, we conduct an online "counting class number" experiment through Amazon Mechanical Turk (AMT) with 81 participants. The experimental design was similar to the first study, but we set up with different task during the experiment. We expected to see different patterns of the discriminability across different conditions. Specifically, our methods would lead to a shorter error and time than *Random Assignment* and *Alpha Blending* conditions.

Hypotheses. We hypothesized that our approach would generally be more effective than the benchmark methods on the discrimination tasks, and that this effect would not vary based on *change magnitude* or *change type*.

- **H1.** Our color generation method (*C3-Palette Generation*) outperforms the benchmark conditions (*Random Assignment*, *Optimized Assignment*, *Alpha Blending*), while is comparable to *Palettailor* on the task performance.
- **H2.** Our color assignment method (*C3-Palette Assignment*) based on *Tableau-20* outperforms the benchmark conditions (*Random Assignment*, *Alpha Blending*), while is comparable to *Optimized Assignment* condition on the task performance.
- **H3.** *Change magnitude* or *change type* would have no effect on discrimination task between different conditions.

4.2.1 Experimental Design. **Task & Measures.** Following previous methodologies [37, 54], each participant was asked to perform a *counting class number* task. We asked participants to identify how many classes(colors) are there in the given two scatterplots and then choose an answer among several options below the two scatterplots. We recorded the participant's answer and response time for each trial, while *error* is 0 if the participant's response not equal to the actual class number, else 1.

Pilot Study & Power Analysis. We conducted a pilot study involving 29 participants to check the experimental setup and determine the parameters, such as the time limit for a trial. Harnessing by the pilot study, we also obtained our expected effect sizes, which were in further fed into a power analysis. With an effect size Cohen's d of 0.6, alpha level of 0.05 and beta level of 0.8, the power analysis suggested a minimum number of 50 participants for the spot-the-difference task. See the supplementary material for more details.

Participants. We recruited 52 participants(as shown in Table. 2) for the experiment on Amazon Mechanical Turk. According to the completion time in the pilot study, we paid each participant \$1.5 for the task based on the US minimum hourly wage. No participant claimed color vision deficiency on their informed consent.

4.2.2 Results. Through this study we found that first the task performance results (time and error) are aligned with those in our online experiment (see supplemental materials for more details). Second, as shown in Figure **??** (a), we found a slight trend that our methods (*Ours Generation*, *Ours Tableau 20* and *Ours Tableau 10*) leads to a shorter scanpath on average than the benchmark conditions (*Random Tableau-10* and *Random Tableau-20*) and *Optimized Tableau*). From Figure **??** (b,c), where we plot the participant's scanpaths of two example trials, we can see that the participant had longer gazes and more eye movements across the two scatterplots under *Random Tableau-20*, compared to *Ours Tableau 20*. This indicates that our approach might reduce people's cognitive load needed when performing the task.

4.3 Discussion

In summary, we evaluated the effectiveness of our approach against the benchmark conditions through a series of studies. We found that first, our experimental methods (*Ours Generation*, *Ours Tableau-20* and *Ours Tableau-10*) generally support the fundamental visual separability of the classes. Second, our methods outperform the benchmark methods on juxtaposed comparison tasks, and their effects are influenced by the color variety of the input palettes, yet not necessarily influenced by the change magnitude of the two scatterplots. Third, we observed some evidences indicating that our methods might help alleviate eye movement distance when doing the comparison tasks.

Some limitations exist in our evaluation. First, our experiment focuses on scatterplots, a single visualization type. While scatterplots are commonly used in juxtaposed comparison (e.g., correlation matrix), the effectiveness of our approach might be different for other types of visualizations such as line charts or bar charts. Second, our experiment focuses on identifying the differences between two scatterplots, which is a simplified situation, since in real-world cases often more than two visualizations are compared. Third, we cannot further analyze the effect of *change type*, given the current study design, though we did observe some trends that for certain types of change, our methods are more effective. That brings us to a series of more fundamental questions: how can we properly define the types of changes? What is the just noticeable change magnitude for each change type? Further research is needed to answer these questions so that our approach can be thoroughly evaluated.

5 CONCLUSION

We presented an interactive color design approach for the effective juxtaposed comparison of multiple labeled datasets. It is built upon a novel co-saliency model, which characterizes the most co-salient features between juxtaposed labeled data visualizations while maintaining class discrimination in the individual visualizations. We evaluated this approach in three ways: a numeric study for the class separability in each view, an online study for its usability of detecting changes between multiple views, and a lab study with eye tracking to learn if our approach can alleviate eye movements.

The results demonstrate that our produced color mapping schemes are well suited for efficient visual comparison. We further demonstrated the effectiveness of our approach for visually comparing juxtaposed line charts with a case study.

Our work concentrated on juxtaposed comparisons to detect changes between multiple datasets. Although detecting changes is a fundamental visual comparison task, its optimal color palette might not be appropriate for understanding other analytical comparison tasks (such as max delta and correlation tasks [40]. Future work needs to investigate the effectiveness and extensions of our approach for such comparison tasks. Furthermore, our approach produces colors with salient hue to highlight classes with large changes, but those colors do not visually indicate the ranking of class changes. It would be helpful to associate the color ordering constraint [10] with the degree of changes, so that the ranking of class changes can be shown clearly. Last, while we only studied the interaction effect between change magnitude and different colorization methods, we plan to investigate how this effect is influenced by different types of changes, such as point number, center position and shape.

6 TEMPLATE OVERVIEW

As noted in the introduction, the "`acmart`" document class can be used to prepare many different kinds of documentation — a double-blind initial submission of a full-length technical paper, a two-page SIGGRAPH Emerging Technologies abstract, a "camera-ready" journal article, a SIGCHI Extended Abstract, and more — all by selecting the appropriate *template style* and *template parameters*.

This document will explain the major features of the document class. For further information, the *LaTeX User's Guide* is available from https://www.acm.org/publications/proceedings-template.

6.1 Template Styles

The primary parameter given to the "`acmart`" document class is the *template style* which corresponds to the kind of publication or SIG publishing the work. This parameter is enclosed in square brackets and is a part of the `documentclass` command:

```
\documentclass[STYLE]{acmart}
```

Journals use one of three template styles. All but three ACM journals use the `acmsmall` template style:

- `acmsmall`: The default journal template style.
- `acmlarge`: Used by JOCCH and TAP.
- `acmtog`: Used by TOG.

The majority of conference proceedings documentation will use the `acmconf` template style.

- `acmconf`: The default proceedings template style.
- `sigchi`: Used for SIGCHI conference articles.
- `sigchi-a`: Used for SIGCHI "Extended Abstract" articles.
- `sigplan`: Used for SIGPLAN conference articles.

6.2 Template Parameters

In addition to specifying the *template style* to be used in formatting your work, there are a number of *template parameters* which modify some part of the applied template style. A complete list of these parameters can be found in the *LaTeX User's Guide*.

Frequently-used parameters, or combinations of parameters, include:

- `anonymous,review`: Suitable for a "double-blind" conference submission. Anonymizes the work and includes line numbers. Use with the `\acmSubmissionID` command to print the submission's unique ID on each page of the work.
- `authorversion`: Produces a version of the work suitable for posting by the author.
- `screen`: Produces colored hyperlinks.

This document uses the following string as the first command in the source file:

```
\documentclass[sigconf,authordraft]{acmart}
```

7 MODIFICATIONS

Modifying the template — including but not limited to: adjusting margins, typeface sizes, line spacing, paragraph and list definitions, and the use of the `\vspace` command to manually adjust the vertical spacing between elements of your work — is not allowed.

Your document will be returned to you for revision if modifications are discovered.

8 TYPEFACES

The "`acmart`" document class requires the use of the "Libertine" typeface family. Your TEX installation should include this set of packages. Please do not substitute other typefaces. The "`lmodern`" and "`ltimes`" packages should not be used, as they will override the built-in typeface families.

9 TITLE INFORMATION

The title of your work should use capital letters appropriately - https://capitalizemytitle.com/ has useful rules for capitalization. Use the `title` command to define the title of your work. If your work has a subtitle, define it with the `subtitle` command. Do not insert line breaks in your title.

If your title is lengthy, you must define a short version to be used in the page headers, to prevent overlapping text. The `title` command has a "short title" parameter:

```
\title[short title]{full title}
```

10 AUTHORS AND AFFILIATIONS

Each author must be defined separately for accurate metadata identification. Multiple authors may share one affiliation. Authors' names should not be abbreviated; use full first names wherever possible. Include authors' e-mail addresses whenever possible.

Grouping authors' names or e-mail addresses, or providing an "e-mail alias," as shown below, is not acceptable:

```
\author{Brooke Aster, David Mehldau}
\email{dave,judy,steve@university.edu}
\email{firstname.lastname@phillips.org}
```

The `authornote` and `authornotemark` commands allow a note to apply to multiple authors — for example, if the first two authors of an article contributed equally to the work.

If your author list is lengthy, you must define a shortened version of the list of authors to be used in the page headers, to prevent overlapping text. The following command should be placed just after the last `\author{}` definition:

```
\renewcommand{\shortauthors}{McCartney, et al.}
```

Omitting this command will force the use of a concatenated list of all of the authors' names, which may result in overlapping text in the page headers.

The article template's documentation, available at https://www.acm.org/publications/proceedings-template, has a complete explanation of these commands and tips for their effective use.

Note that authors' addresses are mandatory for journal articles.

11 RIGHTS INFORMATION

Authors of any work published by ACM will need to complete a rights form. Depending on the kind of work, and the rights management choice made by the author, this may be copyright transfer, permission, license, or an OA (open access) agreement.

Regardless of the rights management choice, the author will receive a copy of the completed rights form once it has been submitted. This form contains LaTeX commands that must be copied into the source document. When the document source is compiled, these commands and their parameters add formatted text to several areas of the final document:

- the "ACM Reference Format" text on the first page.
- the "rights management" text on the first page.
- the conference information in the page header(s).

Rights information is unique to the work; if you are preparing several works for an event, make sure to use the correct set of commands with each of the works.

The ACM Reference Format text is required for all articles over one page in length, and is optional for one-page articles (abstracts).

12 CCS CONCEPTS AND USER-DEFINED KEYWORDS

Two elements of the "acmart" document class provide powerful taxonomic tools for you to help readers find your work in an online search.

The ACM Computing Classification System — https://www.acm.org/publications/class-2012 — is a set of classifiers and concepts that describe the computing discipline. Authors can select entries from this classification system, via https://dl.acm.org/ccs/ccs.cfm, and generate the commands to be included in the LaTeX source.

User-defined keywords are a comma-separated list of words and phrases of the authors' choosing, providing a more flexible way of describing the research being presented.

CCS concepts and user-defined keywords are required for for all articles over two pages in length, and are optional for one- and two-page articles (or abstracts).

13 SECTIONING COMMANDS

Your work should use standard LaTeX sectioning commands: `section`, `subsection`, `subsubsection`, and `paragraph`. They should be numbered; do not remove the numbering from the commands.

Simulating a sectioning command by setting the first word or words of a paragraph in boldface or italicized text is **not allowed.**

Table 3. Frequency of Special Characters

Non-English or Math	Frequency	Comments
Ø	1 in 1,000	For Swedish names
π	1 in 5	Common in math
$	4 in 5	Used in business
Ψ_1^2	1 in 40,000	Unexplained usage

Table 4. Some Typical Commands

Command	A Number	Comments
`\author`	100	Author
`\table`	300	For tables
`\table*`	400	For wider tables

14 TABLES

The "`acmart`" document class includes the "`booktabs`" package — https://ctan.org/pkg/booktabs — for preparing high-quality tables.

Table captions are placed *above* the table.

Because tables cannot be split across pages, the best placement for them is typically the top of the page nearest their initial cite. To ensure this proper "floating" placement of tables, use the environment **table** to enclose the table's contents and the table caption. The contents of the table itself must go in the **tabular** environment, to be aligned properly in rows and columns, with the desired horizontal and vertical rules. Again, detailed instructions on **tabular** material are found in the *LaTeX User's Guide*.

Immediately following this sentence is the point at which Table 3 is included in the input file; compare the placement of the table here with the table in the printed output of this document.

To set a wider table, which takes up the whole width of the page's live area, use the environment **table*** to enclose the table's contents and the table caption. As with a single-column table, this wide table will "float" to a location deemed more desirable. Immediately following this sentence is the point at which Table 4 is included in the input file; again, it is instructive to compare the placement of the table here with the table in the printed output of this document.

Always use midrule to separate table header rows from data rows, and use it only for this purpose. This enables assistive technologies to recognise table headers and support their users in navigating tables more easily.

15 MATH EQUATIONS

You may want to display math equations in three distinct styles: inline, numbered or non-numbered display. Each of the three are discussed in the next sections.

15.1 Inline (In-text) Equations

A formula that appears in the running text is called an inline or in-text formula. It is produced by the **math** environment, which can be invoked with the usual `\begin . . . \end` construction or with the short form `$ . . . $`. You can use any of the symbols and structures, from α to ω, available in LaTeX [35]; this section will simply show a few examples of in-text equations in context. Notice how this equation: $\lim_{n\rightarrow \infty} x = 0$, set here in in-line math style, looks slightly different when set in display style. (See next section).

15.2 Display Equations

A numbered display equation—one set off by vertical space from the text and centered horizontally—is produced by the **equation** environment. An unnumbered display equation is produced by the **displaymath** environment.

Again, in either environment, you can use any of the symbols and structures available in LaTeX; this section will just give a couple of examples of display equations in context. First, consider the equation, shown as an inline equation above:

$$\lim_{n\rightarrow \infty} x = 0 \tag{10}$$

Notice how it is formatted somewhat differently in the **displaymath** environment. Now, we'll enter an unnumbered equation:

$$\sum_{i=0}^{\infty} x + 1$$

and follow it with another numbered equation:

$$\sum_{i=0}^{\infty} x_i = \int_{0}^{\pi+2} f \tag{11}$$

just to demonstrate LaTeX's able handling of numbering.

16 FIGURES

The "`figure`" environment should be used for figures. One or more images can be placed within a figure. If your figure contains third-party material, you must clearly identify it as such, as shown in the example below.

Your figures should contain a caption which describes the figure to the reader.

Figure captions are placed *below* the figure.

Every figure should also have a figure description unless it is purely decorative. These descriptions convey whatâĂŹs in the image to someone who cannot see it. They are also used by search engine crawlers for indexing images, and when images cannot be loaded.

A figure description must be unformatted plain text less than 2000 characters long (including spaces). **Figure descriptions should not repeat the figure caption âĂŞ their purpose is to capture important information that is not already provided in the caption or the main text of the paper.** For figures that convey important and complex new information, a short text description may not be adequate. More complex alternative descriptions can be placed in an appendix and referenced in a short figure description. For example, provide a data table capturing the information in a bar chart, or a structured list representing a graph. For additional information regarding how best to write figure descriptions and why doing this is so important, please see https://www.acm.org/publications/taps/describing-figures/.

16.1 The "Teaser Figure"

A "teaser figure" is an image, or set of images in one figure, that are placed after all author and affiliation information, and before the body of the article, spanning the page. If you wish to have such a figure in your article, place the command immediately before the `\maketitle` command:

```
\begin{teaserfigure}
  \includegraphics[width=\textwidth]{sampleteaser}
  \caption{figure caption}
  \Description{figure description}
\end{teaserfigure}
```

17 CITATIONS AND BIBLIOGRAPHIES

The use of BibTeX for the preparation and formatting of one's references is strongly recommended. Authors' names should be complete — use full first names ("Donald E. Knuth") not initials ("D. E. Knuth") — and the salient identifying features of a reference should be included: title, year, volume, number, pages, article DOI, etc.

The bibliography is included in your source document with these two commands, placed just before the `\end{document}` command:

```
\bibliographystyle{ACM-Reference-Format}
\bibliography{bibfile}
```

where "`bibfile`" is the name, without the "`.bib`" suffix, of the BibTeX file.

Citations and references are numbered by default. A small number of ACM publications have citations and references formatted in the "author year" style; for these exceptions, please include this command in the **preamble** (before the command "`\begin{document}`") of your LaTeX source:

```
\citestyle{acmauthoryear}
```

Some examples. A paginated journal article [3], an enumerated journal article [13], a reference to an entire issue [12], a monograph (whole book) [33], a monograph/whole book in a series (see 2a in spec. document) [24], a divisible-book such as an anthology or compilation [15] followed by the same example, however we only output the series if the volume number is given [16] (so Editor00a's series should NOT be present since it has no vol. no.), a chapter in a divisible book [50], a chapter in a divisible book in a series [14], a multi-volume work as book [32], a couple of articles in a proceedings (of a conference, symposium, workshop for example) (paginated proceedings article) [4, 22], a proceedings article with all possible elements [49], an example of an enumerated proceedings article [21], an informally published work [23], a couple of preprints [7, 9], a doctoral dissertation [11], a master's thesis: [5], an online document / world wide web resource [2, 41, 51], a video game (Case 1) [39] and (Case 2) [38] and [36] and (Case 3) a patent [47], work accepted for publication [43], 'YYYYb'-test for prolific author [45] and [46]. Other cites might contain 'duplicate' DOI and URLs (some SIAM articles) [31]. Boris / Barbara Beeton: multi-volume works as books [28] and [27]. A couple of citations with DOIs: [29, 31]. Online citations: [51–53]. Artifacts: [42] and [6].

18 ACKNOWLEDGMENTS

Identification of funding sources and other support, and thanks to individuals and groups that assisted in the research and the preparation of the work should be included in an acknowledgment section, which is placed just before the reference section in your document.

This section has a special environment:

```
\begin{acks}
...
\end{acks}
```

so that the information contained therein can be more easily collected during the article metadata extraction phase, and to ensure consistency in the spelling of the section heading.

Authors should not prepare this section as a numbered or unnumbered `\section`; please use the "`acks`" environment.

19 APPENDICES

If your work needs an appendix, add it before the "`\end{document}`" command at the conclusion of your source document.

Start the appendix with the "`appendix`" command:

```
\appendix
```

and note that in the appendix, sections are lettered, not numbered. This document has two appendices, demonstrating the section and subsection identification method.

20 SIGCHI EXTENDED ABSTRACTS

The "`sigchi-a`" template style (available only in LaTeX and not in Word) produces a landscape-orientation formatted article, with a wide left margin. Three environments are available for use with the "`sigchi-a`" template style, and produce formatted output in the margin:

- `sidebar`: Place formatted text in the margin.
- `marginfigure`: Place a figure in the margin.
- `margintable`: Place a table in the margin.

ACKNOWLEDGMENTS

To Robert, for the bagels and explaining CMYK and color spaces.

REFERENCES

[1] EHL Aarts. 1989. A stochastic approach to combinatorial optimization and neural computing. *Simulated Annealing and Boltzmann Machines* (1989).

[2] Rafal Ablamowicz and Bertfried Fauser. 2007. *CLIFFORD: a Maple 11 Package for Clifford Algebra Computations, version 11.* Retrieved February 28, 2008 from http://math.tntech.edu/rafal/cliff11/index.html

[3] Patricia S. Abril and Robert Plant. 2007. The patent holder's dilemma: Buy, sell, or troll? *Commun. ACM* 50, 1 (Jan. 2007), 36–44. https://doi.org/10.1145/1188913.1188915

[4] Sten Andler. 1979. Predicate Path expressions. In *Proceedings of the 6th. ACM SIGACT-SIGPLAN symposium on Principles of Programming Languages (POPL '79)*. ACM Press, New York, NY, 226–236. https://doi.org/10.1145/567752.567774

[5] David A. Anisi. 2003. *Optimal Motion Control of a Ground Vehicle.* Master's thesis. Royal Institute of Technology (KTH), Stockholm, Sweden.

[6] Sam Anzaroot and Andrew McCallum. 2013. *UMass Citation Field Extraction Dataset.* Retrieved May 27, 2019 from http://www.iesl.cs.umass.edu/data/data-umasscitationfield

[7] Sam Anzaroot, Alexandre Passos, David Belanger, and Andrew McCallum. 2014. Learning Soft Linear Constraints with Application to Citation Field Extraction. arXiv:1403.1349

[8] M. Aupetit and M. Sedlmair. 2016. SepMe: 2002 New visual separation measures. In *2016 IEEE Pacific Visualization Symposium*. 1–8. https://doi.org/10.1109/PACIFICVIS.2016.7465244

[9] Lutz Bornmann, K. Brad Wray, and Robin Haunschild. 2019. Citation concept analysis (CCA)—A new form of citation analysis revealing the usefulness of concepts for other researchers illustrated by two exemplary case studies including classic books by Thomas S. Kuhn and Karl R. Popper. arXiv:1905.12410 [cs.DL]

[10] R. Bujack, T. L. Turton, F. Samsel, C. Ware, D. H. Rogers, and J. Ahrens. 2018. The Good, the Bad, and the Ugly: a Theoretical Framework for the Assessment of Continuous Colormaps. *IEEE Transactions on Visualization and Computer Graphics* 24, 1 (2018), 923–933. https://doi.org/10.1109/TVCG.2017.2743978

[11] Kenneth L. Clarkson. 1985. *Algorithms for Closest-Point Problems (Computational Geometry).* Ph.D. Dissertation. Stanford University, Palo Alto, CA. UMI Order Number: AAT 8506171.

[12] Jacques Cohen (Ed.). 1996. Special issue: Digital Libraries. *Commun. ACM* 39, 11 (Nov. 1996).

[13] Sarah Cohen, Werner Nutt, and Yehoshua Sagic. 2007. Deciding equivalances among conjunctive aggregate queries. *J. ACM* 54, 2, Article 5 (April 2007), 50 pages. https://doi.org/10.1145/1219092.1219093

[14] Bruce P. Douglass, David Harel, and Mark B. Trakhtenbrot. 1998. Statecarts in use: structured analysis and object-orientation. In *Lectures on Embedded Systems*, Grzegorz Rozenberg and Frits W. Vaandrager (Eds.). Lecture Notes in Computer Science, Vol. 1494. Springer-Verlag, London, 368–394. https://doi.org/10.1007/3-540-65193-4_29

[15] Ian Editor (Ed.). 2007. *The title of book one* (1st. ed.). The name of the series one, Vol. 9. University of Chicago Press, Chicago. https://doi.org/10.1007/3-540-09237-4

[16] Ian Editor (Ed.). 2008. *The title of book two* (2nd. ed.). University of Chicago Press, Chicago, Chapter 100. https://doi.org/10.1007/3-540-09237-4

[17] H. Fu, X. Cao, and Z. Tu. 2013. Cluster-Based Co-Saliency Detection. *IEEE Transactions on Image Processing* 22, 10 (2013), 3766–3778. https://doi.org/10.1109/TIP.2013.2260166

[18] Eiji Fukuba, Hajime Kitagaki, Akihiko Wada, Kouji Uchida, Shinji Hara, Takafumi Hayashi, Kazushige Oda, and Nobue Uchida. 2009. Brain Activation during the Spot the Differences Game. *Magnetic Resonance in Medical Sciences* 8, 1 (2009), 23–32. https://doi.org/10.2463/mrms.8.23

[19] M. Gleicher. 2018. Considerations for Visualizing Comparison. *IEEE Transactions on Visualization and Computer Graphics* 24, 1 (2018), 413–423. https://doi.org/10.1109/TVCG.2017.2744199

[20] C. C. Gramazio, D. H. Laidlaw, and K. B. Schloss. 2017. Colorgorical: creating discriminable and preferable color palettes for information visualization. *IEEE Transactions on Visualization and Computer Graphics* 23, 1 (2017), 521–530. https://doi.org/10.1109/TVCG.2016.2598918

[21] Matthew Van Gundy, Davide Balzarotti, and Giovanni Vigna. 2007. Catch me, if you can: Evading network signatures with web-based polymorphic worms. In *Proceedings of the first USENIX workshop on Offensive Technologies (WOOT '07)*. USENIX Association, Berkley, CA, Article 7, 9 pages.

[22] Torben Hagerup, Kurt Mehlhorn, and J. Ian Munro. 1993. Maintaining Discrete Probability Distributions Optimally. In *Proceedings of the 20th International Colloquium on Automata, Languages and Programming (Lecture Notes in Computer Science, Vol. 700)*. Springer-Verlag, Berlin, 253–264.

[23] David Harel. 1978. *LOGICS of Programs: AXIOMATICS and DESCRIPTIVE POWER*. MIT Research Lab Technical Report TR-200. Massachusetts Institute of Technology, Cambridge, MA.

[24] David Harel. 1979. *First-Order Dynamic Logic*. Lecture Notes in Computer Science, Vol. 68. Springer-Verlag, New York, NY. https://doi.org/10.1007/3-540-09237-4

[25] Mark Harrower and Cynthia A. Brewer. 2003. ColorBrewer.org: an online tool for selecting colour schemes for maps. *The Cartographic Journal* 40, 1 (2003), 27–37. https://doi.org/10.1179/000870403235002042

[26] Christopher G Healey, Kellogg S Booth, and James T Enns. 1995. Visualizing real-time multivariate data using preattentive processing. *ACM Transactions on Modeling and Computer Simulation* 5, 3 (1995), 190–221. https://doi.org/10.1145/217853.217855

[27] Lars Hörmander. 1985. *The analysis of linear partial differential operators. III*. Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences], Vol. 275. Springer-Verlag, Berlin, Germany. viii+525 pages. Pseudodifferential operators.

[28] Lars Hörmander. 1985. *The analysis of linear partial differential operators. IV*. Grundlehren der Mathematischen Wissenschaften [Fundamental Principles of Mathematical Sciences], Vol. 275. Springer-Verlag, Berlin, Germany. vii+352 pages. Fourier integral operators.

[29] IEEE 2004. IEEE TCSC Executive Committee. In *Proceedings of the IEEE International Conference on Web Services (ICWS '04)*. IEEE Computer Society, Washington, DC, USA, 21–22. https://doi.org/10.1109/ICWS.2004.64

[30] David E. Jacobs, Dan B. Goldman, and Eli Shechtman. 2010. Cosaliency: where People Look When Comparing Images. In *Proceedings of the 23nd Annual ACM Symposium on User Interface Software and Technology*. 219–228. https://doi.org/10.1145/1866029.1866066

[31] Markus Kirschmer and John Voight. 2010. Algorithmic Enumeration of Ideal Classes for Quaternion Orders. *SIAM J. Comput.* 39, 5 (Jan. 2010), 1714–1747. https://doi.org/10.1137/080734467

[32] Donald E. Knuth. 1997. *The Art of Computer Programming, Vol. 1: Fundamental Algorithms (3rd. ed.)*. Addison Wesley Longman Publishing Co., Inc.

[33] David Kosiur. 2001. *Understanding Policy-Based Networking* (2nd. ed.). Wiley, New York, NY.

[34] Harold W Kuhn. 1955. The Hungarian method for the assignment problem. *Naval Research Logistics Quarterly* 2, 1-2 (1955), 83–97. https://doi.org/10.1007/978-3-540-68279-0_2

[35] Leslie Lamport. 1986. *LaTeX: A Document Preparation System*. Addison-Wesley, Reading, MA.

[36] Newton Lee. 2005. Interview with Bill Kinder: January 13, 2005. Video. *Comput. Entertain.* 3, 1, Article 4 (Jan.-March 2005). https://doi.org/10.1145/1057270.1057278

[37] K. Lu, M. Feng, X. Chen, M. Sedlmair, O. Deussen, D. Lischinski, Z. Cheng, and Y. Wang. 2021. Palettailor: discriminable colorization for categorical data. *IEEE Transactions on Visualization and Computer Graphics* 27, 2 (2021), 475–484. https://doi.org/10.1109/TVCG.2020.3030406

[38] Dave Novak. 2003. Solder man. Video. In *ACM SIGGRAPH 2003 Video Review on Animation theater Program: Part I - Vol. 145 (July 27–27, 2003)*. ACM Press, New York, NY, 4. https://doi.org/99.9999/woot07-S422

[39] Barack Obama. 2008. A more perfect union. Video. Retrieved March 21, 2008 from http://video.google.com/videoplay?docid=6528042696351994555

[40] B. Ondov, N. Jardine, N. Elmqvist, and S. Franconeri. 2019. Face to face: evaluating visual comparison. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (2019), 861–871. https://doi.org/10.1109/TVCG.2018.2864884

[41] Poker-Edge.Com. 2006. Stats and Analysis. Retrieved June 7, 2006 from http://www.poker-edge.com/stats.php

[42] R Core Team. 2019. *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/

[43] Bernard Rous. 2008. The Enabling of Digital Libraries. *Digital Libraries* 12, 3, Article 5 (July 2008). To appear.

[44] Yossi Rubner, Carlo Tomasi, and Leonidas J. Guibas. 2000. The Earth Mover's Distance as a Metric for Image Retrieval. *International Journal of Computer Vision* 40, 2 (2000), 99–121. https://doi.org/10.1023/A:1026543900054

[45] Mehdi Saeedi, Morteza Saheb Zamani, and Mehdi Sedighi. 2010. A library-based synthesis methodology for reversible logic. *Microelectron. J.* 41, 4 (April 2010), 185–194.

[46] Mehdi Saeedi, Morteza Saheb Zamani, Mehdi Sedighi, and Zahra Sasanian. 2010. Synthesis of Reversible Circuit Using Cycle-Based Approach. *J. Emerg. Technol. Comput. Syst.* 6, 4 (Dec. 2010).

[47] Joseph Scientist. 2009. The fountain of youth. Patent No. 12345, Filed July 1st., 2008, Issued Aug. 9th., 2009.

[48] Gaurav Sharma, Wencheng Wu, and Edul N Dalal. 2005. The CIEDE2000 color-difference formula: implementation notes, supplementary test data, and mathematical observations. *Color Research & Application* 30, 1 (2005), 21–30. https://doi.org/10.1002/col.20070

[49] Stan W. Smith. 2010. An experiment in bibliographic mark-up: Parsing metadata for XML export. In *Proceedings of the 3rd. annual workshop on Librarians and Computers (LAC '10, Vol. 3)*, Reginald N. Smythe and Alexander Noble (Eds.). Paparazzi Press, Milan Italy, 422–431. https://doi.org/99.9999/woot07-S422

[50] Asad Z. Spector. 1990. Achieving application requirements. In *Distributed Systems* (2nd. ed.), Sape Mullender (Ed.). ACM Press, New York, NY, 19–33. https://doi.org/10.1145/90417.90738

[51] Harry Thornburg. 2001. *Introduction to Bayesian Statistics*. Retrieved March 2, 2005 from http://ccrma.stanford.edu/~jos/bayes/bayes.html

[52] TUG 2017. *Institutional members of the TEX Users Group*. Retrieved May 27, 2017 from http://wwtug.org/instmem.html

[53] Boris Veytsman. [n.d.]. *acmart—Class for typesetting publications of ACM*. Retrieved May 27, 2017 from http://www.ctan.org/pkg/acmart

[54] Yunhai Wang, Xin Chen, Tong Ge, Chen Bao, Michael Sedlmair, Chi-Wing Fu, Oliver Deussen, and Baoquan Chen. 2019. Optimizing color assignment for perception of class separability in multiclass scatterplots. *IEEE Transactions on Visualization and Computer Graphics* 25, 1 (2019), 820–829. https://doi.org/10.1109/TVCG.2018.2864912

[55] Dingwen Zhang, Huazhu Fu, Junwei Han, Ali Borji, and Xuelong Li. 2018. A review of co-saliency detection algorithms: fundamentals, applications, and challenges. *ACM Transactions on Intelligent Systems and Technology* 9, 4 (2018), 1–31. https://doi.org/10.1145/3158674

A RESEARCH METHODS

A.1 Part One

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Morbi malesuada, quam in pulvinar varius, metus nunc fermentum urna, id sollicitudin purus odio sit amet enim. Aliquam ullamcorper eu ipsum vel mollis. Curabitur quis dictum nisl. Phasellus vel semper risus, et lacinia dolor. Integer ultricies commodo sem nec semper.

A.2 Part Two

Etiam commodo feugiat nisl pulvinar pellentesque. Etiam auctor sodales ligula, non varius nibh pulvinar semper. Suspendisse nec lectus non ipsum convallis congue hendrerit vitae sapien. Donec at laoreet eros. Vivamus non purus placerat, scelerisque diam eu, cursus ante. Etiam aliquam tortor auctor efficitur mattis.

B ONLINE RESOURCES

Nam id fermentum dui. Suspendisse sagittis tortor a nulla mollis, in pulvinar ex pretium. Sed interdum orci quis metus euismod, et sagittis enim maximus. Vestibulum gravida massa ut felis suscipit congue. Quisque mattis elit a risus ultrices commodo venenatis eget dui. Etiam sagittis eleifend elementum.

Nam interdum magna at lectus dignissim, ac dignissim lorem rhoncus. Maecenas eu arcu ac neque placerat aliquam. Nunc pulvinar massa et mattis lacinia.