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Automatic synthesis of advertising images according to a specified style

Key words: Image dataset; Data-driven method; Automatic advertisement synthesis

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Introduction

1. Images in advertising play an important role in helping companies spread awareness of their products or services. A considerable amount of time and money is spent on the creation of advertisements (ads) every year.
2. To automate the process of designing multi-format ads, most researchers have used data-driven methods to learn the design attributes in advertising images. However, acquiring an adequate number of ads with element-level labels is challenging and time-consuming.
3. Most previous studies have focused on a particular design problem related to ad synthesis, such as the generation of pleasing colors or understanding the content of an ad.

Contributions

1. We develop and introduce probabilistic models that capture the stylistic design attributes of training images, which incorporate the features of the graphic element's role to predict the design performance in the target context.
2. We propose functions and algorithms that are flexible enough to represent the unique features of Chinese characters, and encode various types of advertising image layouts to efficiently produce a layout from the input elements and texts.
3. We demonstrate how our dataset can be applied in the automatic synthesis of advertising images according to user-preference constraints to produce high-quality layout and color designs with a specified style.

Dataset

Fig. 1 shows the workflow for constructing our dataset, with an example of the results at the bottom of each step. Finally, we obtain 13 280 ads.

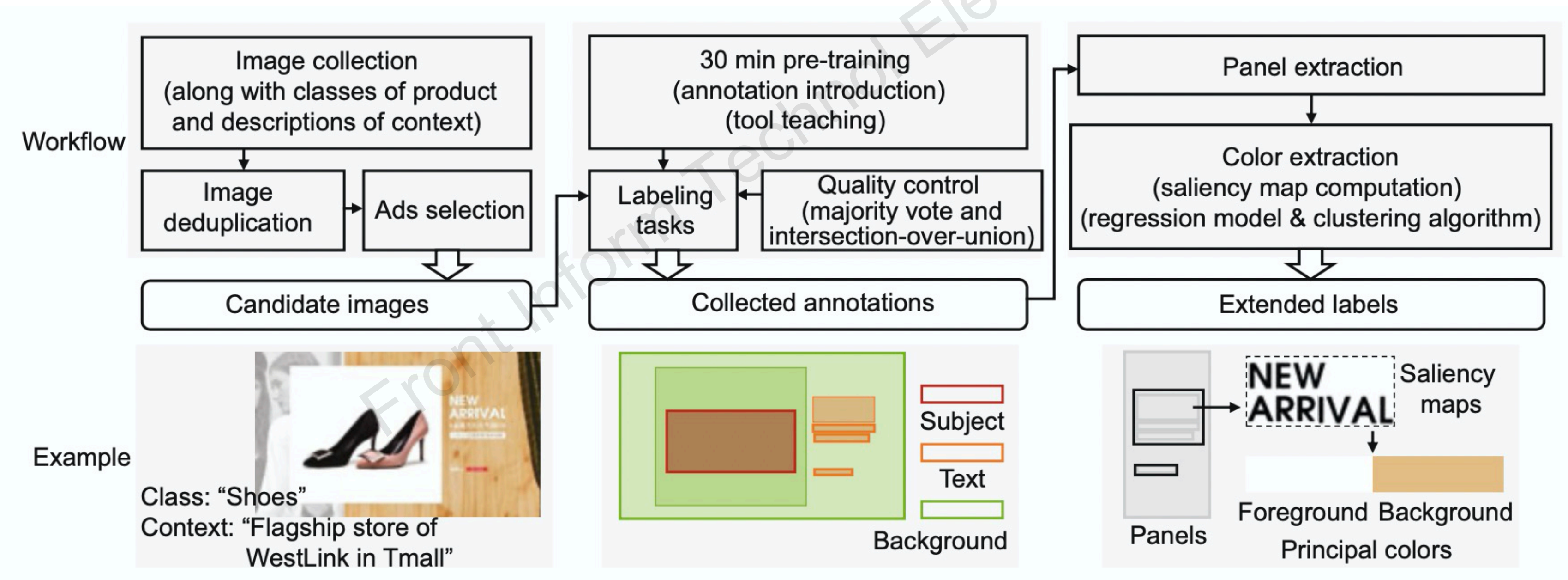


Fig. 1 Flow diagram for the construction of our dataset

Method

1. Probabilistic graphical model

- Local graphical model:

$$\hat{f}(\boldsymbol{x}) = \frac{1}{n}\sum_{i=1}^{n} K_{\boldsymbol{H}}(\boldsymbol{x}-\boldsymbol{x}_e^i) = \frac{1}{n\,|\boldsymbol{H}|^{1/2}}\sum_{i=1}^{n} K\left(\frac{\boldsymbol{x}-\boldsymbol{x}_e^i}{\boldsymbol{H}^{1/2}}\right),$$

$$K\left(\frac{\boldsymbol{x}-\boldsymbol{x}_e^i}{\boldsymbol{H}^{1/2}}\right) = \frac{\exp\left(-\frac{1}{2}(\boldsymbol{x}-\boldsymbol{x}_e^i)'\boldsymbol{H}^{-1}(\boldsymbol{x}-\boldsymbol{x}_e^i)\right)}{(2\pi)^{d/2}}.$$

- Conditional graphical model:

$$P(\boldsymbol{x}|\boldsymbol{C}_e) = \sum_{i=1}^{10} \exp\left(\frac{-\left\|\boldsymbol{x}-\boldsymbol{n}_e^i\right\|^2}{2\sigma^2}\right)\cdot p(\boldsymbol{n}_e^i|\boldsymbol{C}_e).$$

Method

2. Layout synthesis

- Fig. 4 shows the layout synthesis process.
- Fig. 5 shows an example of layout synthesis.

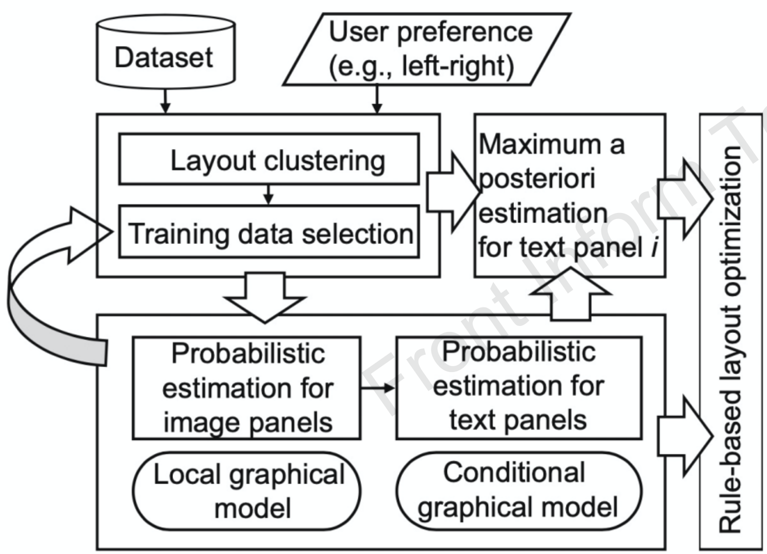


Fig. 4 Framework of the layout synthesis method

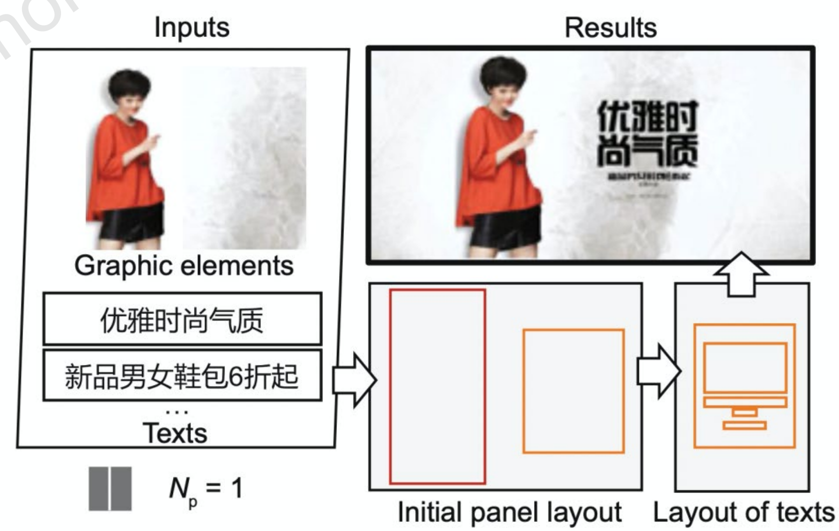


Fig. 5 Workflow of automatic layout synthesis

Method

3. Image recoloring

- To achieve a good color combination among the input text and graphic elements, we recolor each element automatically.
- Fig. 6 shows an example of image recoloring.

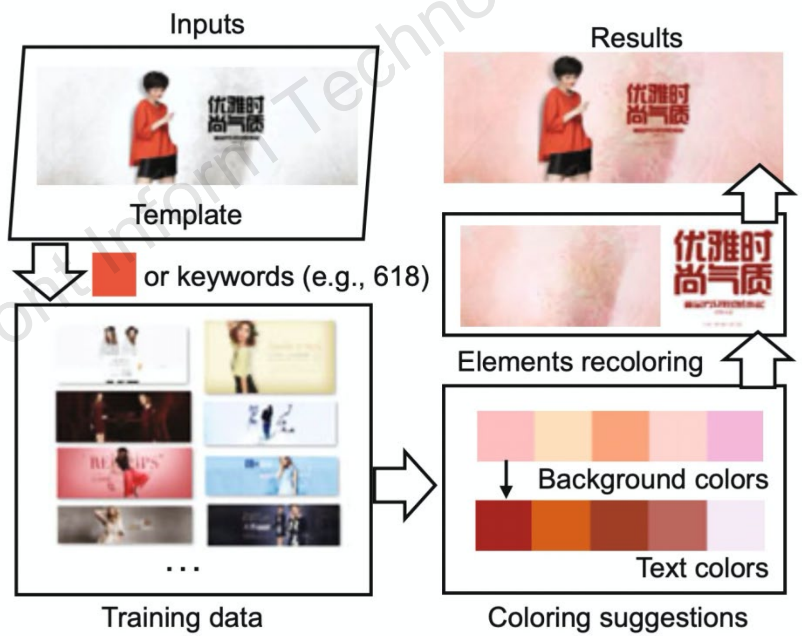
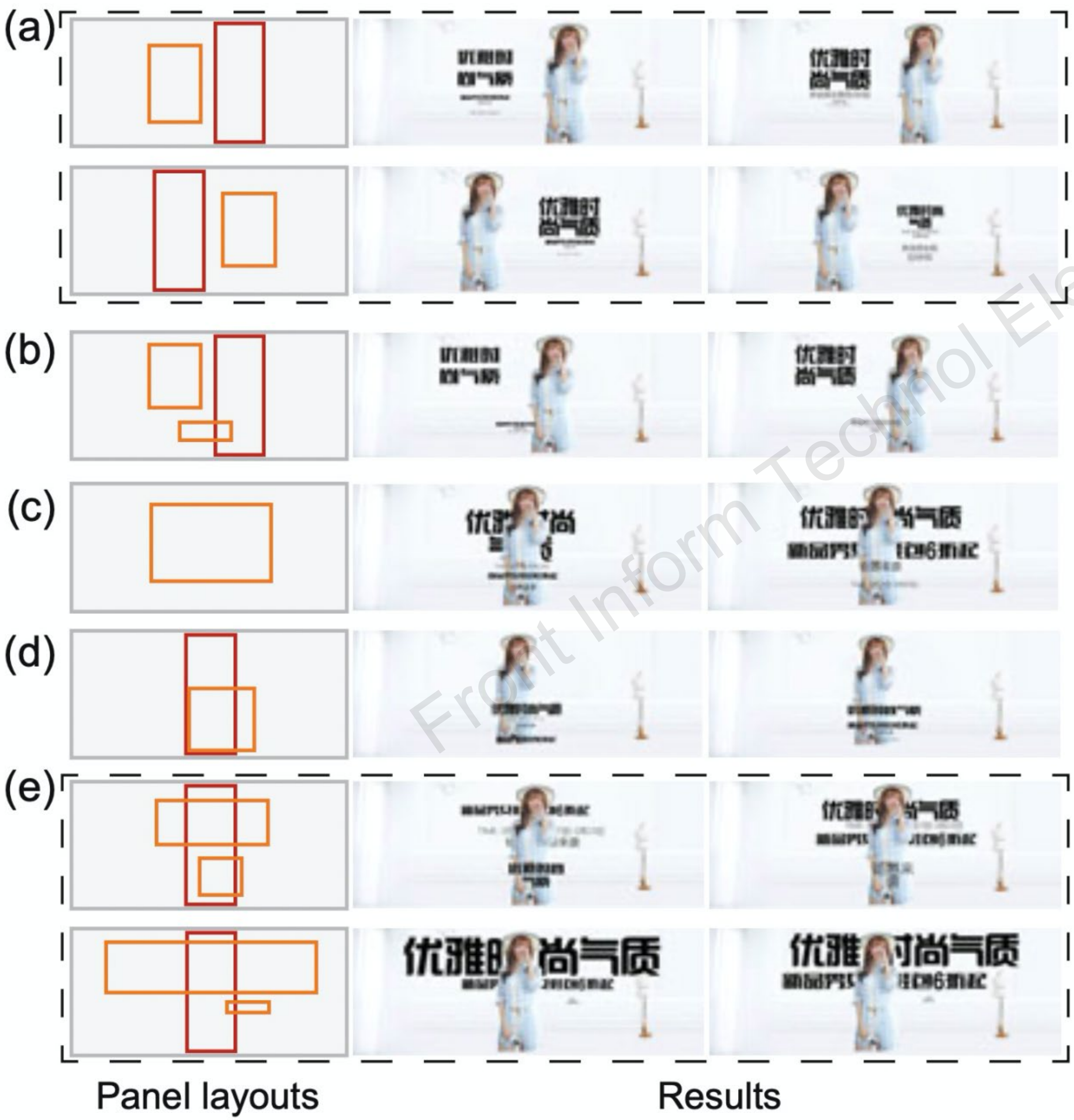


Fig. 6 Workflow for automatic image recoloring

Major results



Results with different types of layout and numbers of text panels:

(a) left-right;

(b) left-right and $N_p = 2$;

(c) center and $N_p = 1$;

(d) top-down and $N_p = 1$;

(e) top-down and $N_p = 2$.

Major results

Input product Results Input product Results

Advertising images generated with different product colors

Evaluation

1. We run a multivariate analysis of variance test using the creator of the ads and type of layout as dependent variables.

2. The analysis reveals a significant difference among the professional, nonprofessional, and synthesized ads ($F = 4.874$, $p = 0.017$), but the type of layout shows no significant difference ($F = 0.214$, $p = 0.886$).

3. The average score of our results is 3.208, which is higher than 2.996 for the nonprofessional students with $p = 0.069$; as such, our average score has an improvement of 7.1%.

Evaluation

4. A chi-squared test shows that the source of a coloring suggestion significantly affects its ranking in terms of preference by the subjects ($\chi^2 = 154.18$, $p < 0.01$).

5. The coloring results learned from our dataset contain more "like" and fewer "dislike" images.

6. The percentage of "top" images is 51%, which is improved by 22% and 31% compared with those obtained by the color harmony model and Colormind, respectively.

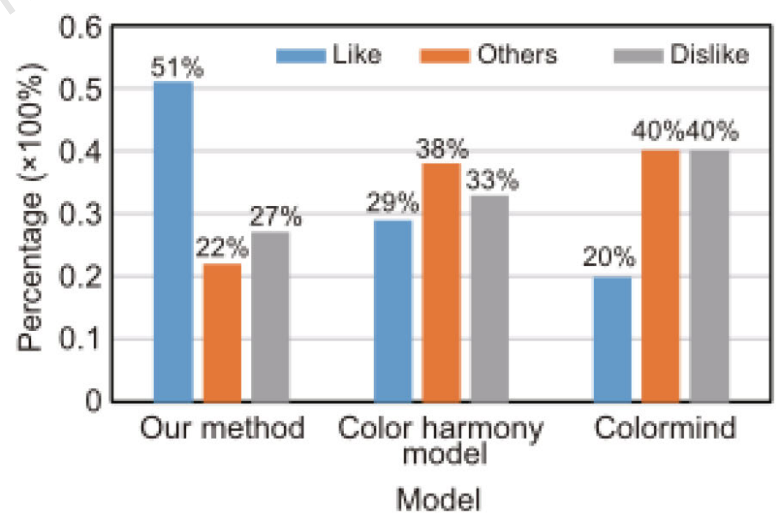


Fig. 11 Percentage of images selected from different models