

Predicting Visual Importance Across Graphic Design Types

Camilo Fosco¹, Vincent Casser¹, Amish Kumar Bedi²,
Peter O’Donovan², Aaron Hertzmann³, Zoya Bylinskii³,

¹MIT ²Adobe Inc. ³Adobe Research

{camilolu, vcasser}@mit.edu {ambedi, podonova, hertzman, bylinski}@adobe.com

MODEL-ASSISTED INTERACTIVE DESIGN

Once a user triggers an interaction with the bar graph of importance scores, we automatically generate $N = 100$ new design variants (in the background). In a given variant, every graphical element is adjusted with a probability of $p = 0.5$ via positional offsets and scaling factors. We evaluate each design variant by running our importance prediction model and measuring the mean-squared-error (MSE) between the predicted and target importance scores. We add penalty terms for overlapping elements. We keep the top 25 of designs with the lowest MSE. We generate a new set of 75 designs by “genetic crossover”: combining positional offsets and scaling factors for individual design elements across pairs of designs from the top 25, to produce a new “population” of 100 designs. The idea of crossover here is to allow for the effective combination of positive aspects from different variants. We repeat this genetic design breeding process for 20 epochs. After every epoch, we update the canvas with the best design so far.

MODEL-ASSISTED DESIGN REFLOW

All 17 designs and their corresponding reflow variants from our user studies are shown in Figures 1-5.

ADDITIONAL TRAINING DETAILS

We train with KL and CC losses, with coefficients of 10 and -3. A binary cross-entropy loss with a weight of 5 is used for the classification submodule. We obtained these coefficients through grid search and 3-split cross validation, testing values of 1, 3, 5, 10, 15 for each loss (negative values for CC). The learning rate and dropout rate was similarly defined, testing 5 values with 3-split cross validation. The definition of the architectural modules follows insights from previous literature, including image classification [3, 4] and image segmentation work [1, 2].

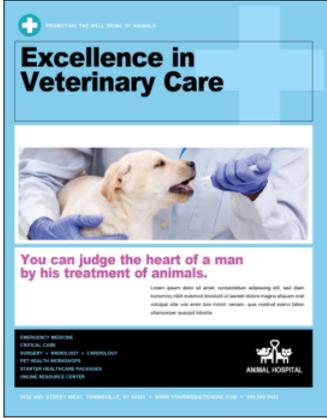
REFERENCES

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connected crfs. *IEEE transactions on pattern analysis and machine intelligence* 40, 4 (2018), 834–848.

2. Liang-Chieh Chen, George Papandreou, Florian Schroff, and Hartwig Adam. 2017. Rethinking atrous convolution for semantic image segmentation. *arXiv preprint arXiv:1706.05587* (2017).
3. François Chollet. 2017. Xception: Deep learning with depthwise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 1251–1258.
4. Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2818–2826.

Image: 1



Avg. rank (baseline): 1.67

Avg. rank (prior art): 3.00

Avg. rank (UMSI): 1.33

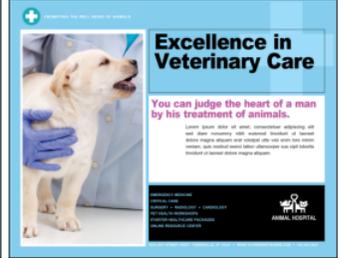


Image: 2



Avg. rank (baseline): 2.00

Avg. rank (prior art): 2.33

Avg. rank (UMSI): 1.67



Image: 3



Avg. rank (baseline): 1.83

Avg. rank (prior art): 2.50

Avg. rank (UMSI): 1.67



Image: 4



Avg. rank (baseline): 2.50

Avg. rank (prior art): 1.17

Avg. rank (UMSI): 2.33

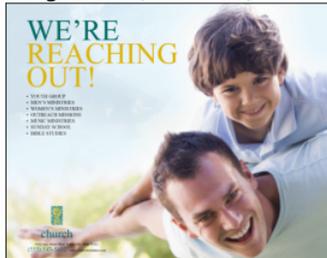


Figure 1.

Image: 5



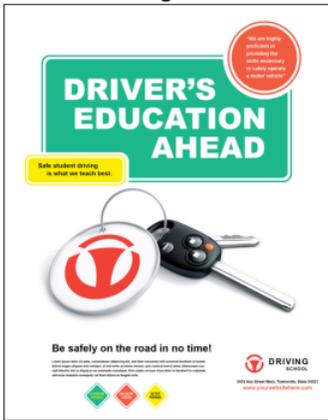
Avg. rank (baseline): 1.83

Avg. rank (prior art): 2.33

Avg. rank (UMSI): 1.83



Image: 6



Avg. rank (baseline): 1.67

Avg. rank (prior art): 2.33

Avg. rank (UMSI): 2.00

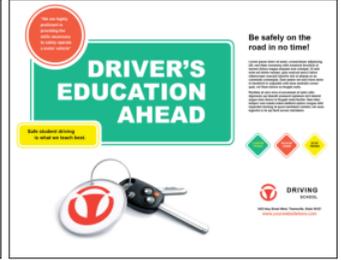
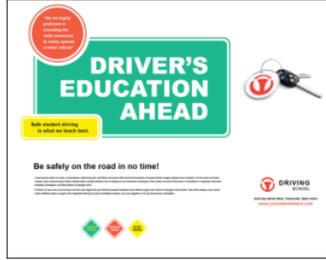


Image: 7



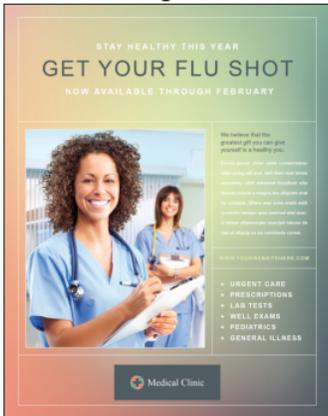
Avg. rank (baseline): 1.50

Avg. rank (prior art): 2.33

Avg. rank (UMSI): 2.17



Image: 8



Avg. rank (baseline): 1.83

Avg. rank (prior art): 2.67

Avg. rank (UMSI): 1.50



Figure 2.

Image: 9



Avg. rank (baseline): 2.00

Avg. rank (prior art): 2.00

Avg. rank (UMSI): 2.00



Image: 10



Avg. rank (baseline): 3.00

Avg. rank (prior art): 2.00

Avg. rank (UMSI): 1.00



Image: 11



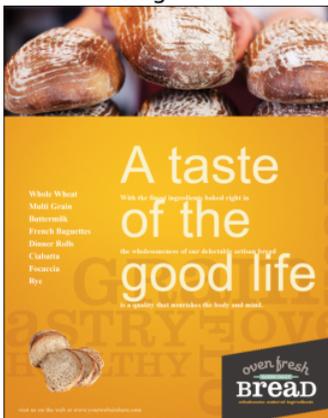
Avg. rank (baseline): 1.67

Avg. rank (prior art): 2.00

Avg. rank (UMSI): 2.33



Image: 12



Avg. rank (baseline): 1.67

Avg. rank (prior art): 3.00

Avg. rank (UMSI): 1.33

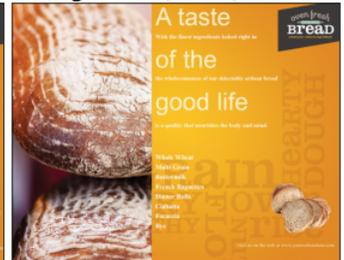


Figure 3.

Image: 13



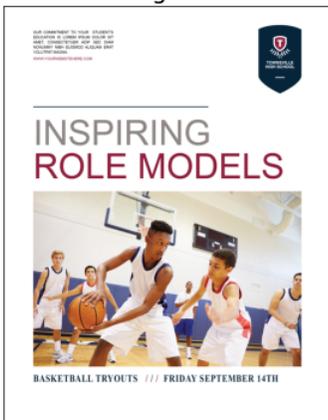
Avg. rank (baseline): 2.00

Avg. rank (prior art): 3.00

Avg. rank (UMSI): 1.00



Image: 14



Avg. rank (baseline): 1.83

Avg. rank (prior art): 2.67

Avg. rank (UMSI): 1.50

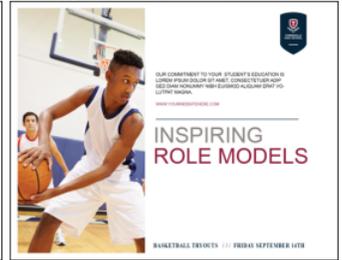
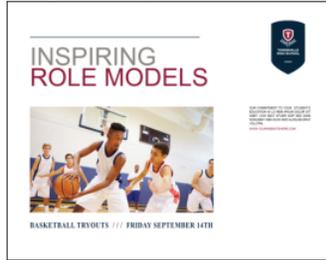
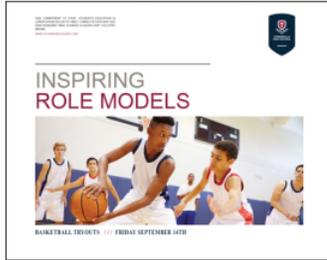


Image: 15



Avg. rank (baseline): 1.83

Avg. rank (prior art): 3.00

Avg. rank (UMSI): 1.17

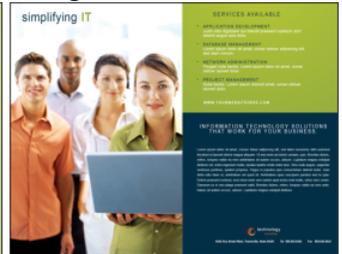


Image: 16



Avg. rank (baseline): 2.17

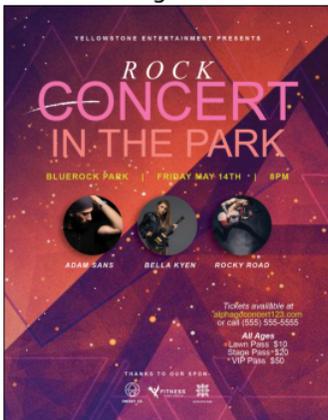
Avg. rank (prior art): 2.67

Avg. rank (UMSI): 1.17



Figure 4.

Image: 17



Avg. rank (baseline): 1.67

Avg. rank (prior art): 2.00

Avg. rank (UMSI): 2.33



Figure 5.