Dashboard Vision: Using Eye-Tracking to Understand and Predict Dashboard Viewing Behaviors

Supplementary Material

Overview

In this supplementary material, we present detailed information on Dashboard Vision. The content is organized into the following sections:

1. DVSal Quantitative Evaluation Metrics (Table 1).
2. DVSal Qualitative Evaluation Cases (Fig.1).
3. DVElite Dashboards and Saliency Maps (Fig.2).
4. AOI Annotated Examples (Fig.3).
5. DVElite Statistic Results of Visual Objects (Fig.4).

Table 1: Evaluation of saliency models on the DVCrowd dataset (The best results are highlighted in **bold**). Compared to the prior state-of-the-art saliency models customized for single-view visualization, our model DVSal achieves better performance in all value, distribution, and location metrics. Results of ablation experiments also necessitates the AOI Detection and Layout Recognition modules in DVSal. The pair t-test results show that DVSal (row 15) significantly outperforms the best baseline model (row 9) in all metrics.

Model	DVCrowd Training	Value Metric	Distribution Metrics			Location Metrics		
		NSS↑	CC↑	SIM↑	KL↓	AUC-J↑	AUC-B↑	sAUC↑
VisImportance [1]	×	0.4412	0.3683	0.4224	1.3059	0.7494	0.6243	0.7480
DVS [4]	×	0.3917	0.4207	0.4459	1.0690	0.7517	0.6015	0.7486
UMSI [2]	×	0.2557	0.1240	0.3444	2.0024	0.6492	0.5692	0.6467
TranSalNet [3]	×	0.3634	0.2050	0.3718	1.8576	0.7047	0.5979	0.7017
Scanner Deeply [6]	×	0.3184	0.2174	0.3762	1.4416	0.7098	0.5905	0.7071
SimpleNet [5] (P)	×	0.2748	0.1357	0.3303	5.1469	0.6622	0.5510	0.6622
	✓	0.4727	0.4742	0.4750	1.4852	0.7924	0.6287	0.7915
SimpleNet [5] (D)	×	0.3468	0.1913	0.3616	1.7636	0.7032	0.5896	0.6979
	✓	0.4801	0.4878	0.4866	0.9383	0.8031	0.6250	0.8005
Ablation w/o LR (P)	✓	0.4858	0.4932	0.4859	0.9282	0.8035	0.6275	0.8014
Ablation w/o LR (D)	✓	0.4998	0.5198	0.4980	0.8884	0.8126	0.6269	0.8087
Ablation w/o AD (P)	✓	0.4854	0.4749	0.4769	0.9538	0.7972	0.6336	0.7950
Ablation w/o AD (D)	✓	0.4847	0.5110	0.4945	0.9043	0.8064	0.6226	0.8032
DVSal (ours) (P)	✓	0.4894	0.5074	0.4979	0.9025	0.8182	0.6283	0.8152
DVSal (ours) (D)	✓	**0.5283**	**0.5656**	**0.5225**	**0.7904**	**0.8395**	**0.6429**	**0.8379**

* P denotes the PNASNet-5 backbone, D denotes the DenseNet-161 backbone.
* LR denotes Layout Recognition, AD denotes AOI Detection.

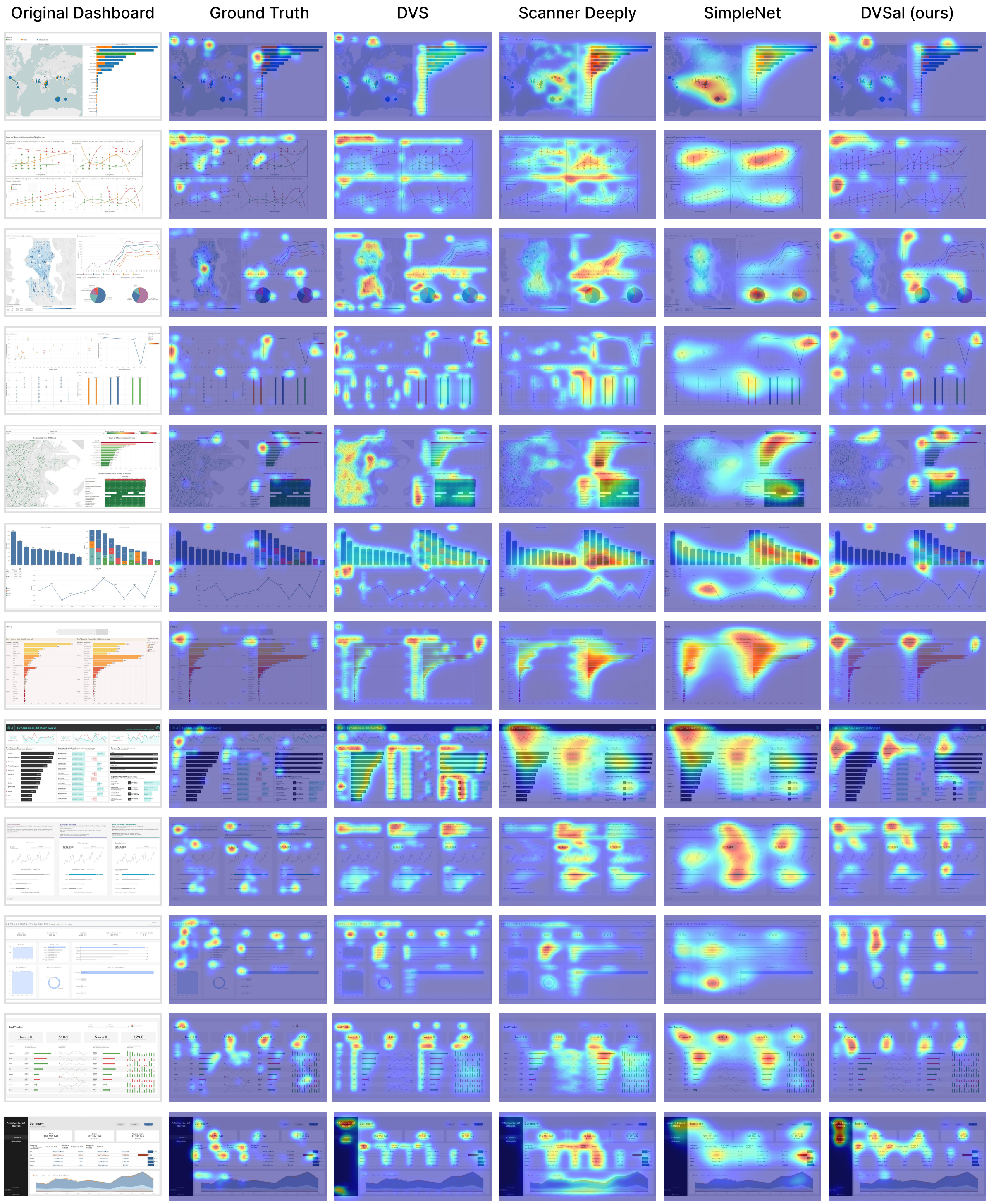

Figure 1: This figure presents more qualitative evaluation cases of DVSal in Fig.1 to show the effectiveness of DVSal in predicting dashboard viewing behaviors. The first row shows the original dashboards, the second row shows the ground truth of the eye-gaze recordings, and the third to fifth rows show the saliency maps predicted by baselines DVS[4], Scanner Deeply [6],SimpleNet [5]. The last row shows the saliency maps predicted by DVSal.

Figure 2: This figure shows the DVElite dashboards and saliency maps of 60 eye-gaze recordings. From these 16 dashboards, we can see different types of data visualizations, including bar charts, line charts, maps, tables, etc. According to the saliency map, we can intuitively see patterns about user viewing behaviors, such as subtitles and legends exhibit higher attraction levels than others, and the layout of the table layout shows grid-structured patterns. This information can provide design suggestions from the user's perspective for dashboard designers.

Figure 3: We provide more AOI annoted examples. The left-top of the rectangle labeling the type of AOI.

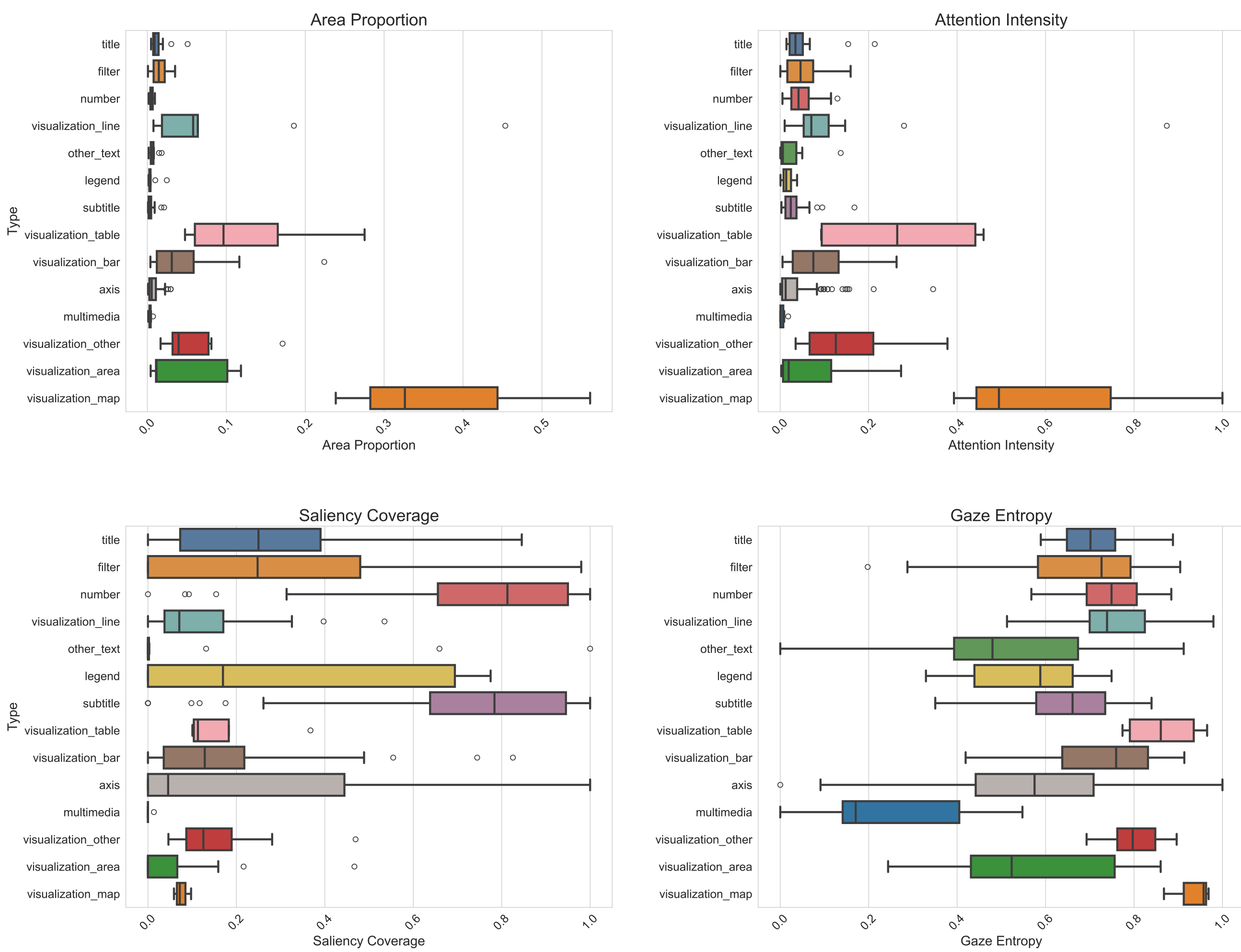

Figure 4: We provide detailed statistic results of visual objects in DVElite dashboards. We present box-plots of four metrics, including area proportion, attention intensity, salience coverage, and gaze entropy, to show the statistical characteristics of visual objects.

References

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