

# VASCAR: Content-Aware Layout Generation via Visual-Aware Self-Correction



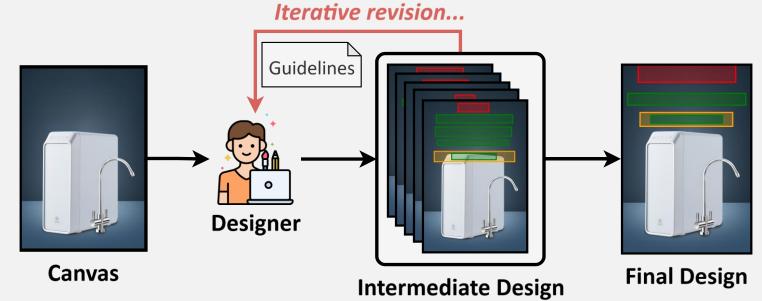
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**OS3A-09** 

# **Motivation**



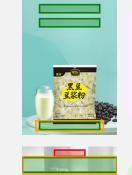
(a) The iterative revision workflow of designers.



Q. This image is an idea of layout design rendered on a poster, where green boxes show texts, yellow underlays, and red logos. Please comment on the design in terms of alignment, content occlusion, and utilization of spaces and score them in [1--5], higher is better.

Score: 2/5. The space is not utilized effectively, and the design feels

unbalanced with too much empty space at the top. The placement of



\*\*Content Occlusion: 2/5\*\*

the text boxes feels arbitrary...

**Utilization of Spaces:** 

- There is some occlusion of the background elements by the text boxes, which could potentially distract from the product focus. Improved transparency or repositioning could enhance clarity.

**ChatGPT** 

Gemini

(b) Inspiring conversations with Gemini/ChatGPT.

#### Introduction

#### What is the Content-aware layout generation task?

• Content-aware layout generation aims to automatically arrange visual elements (e.g., text, logo, underlay) on a canvas based on its visual content — a task essential in applications such as poster and magazine design.

While recent large language models (LLMs) can generate structured layouts via HTML or JSON, they lack the ability to see, limiting their effectiveness when visual cues are crucial.

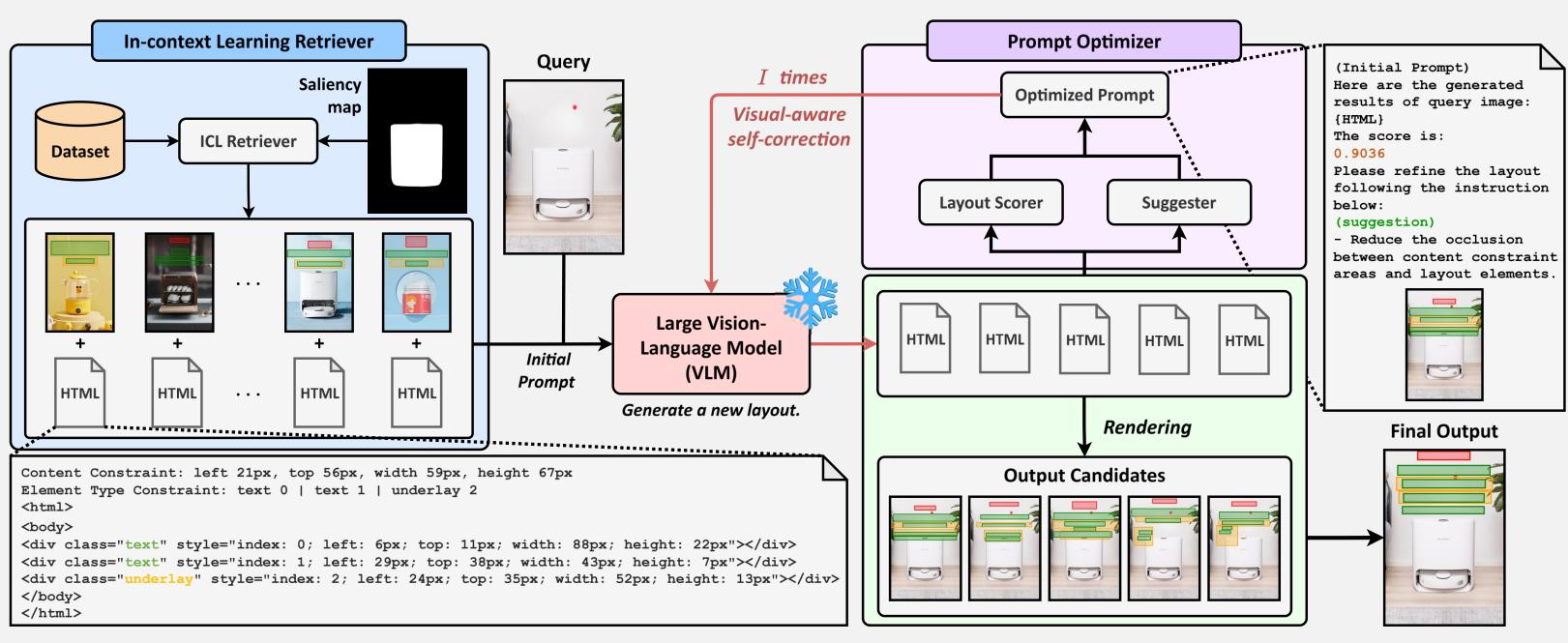
#### **Key Challenges**

- Lack of visual understanding in LLMs hinders layout quality.
- High cost of training generative models on layout data.
- Absence of iterative refinement, which is common in human design workflows.

#### **Our Solution: VASCAR**

- We introduce VASCAR, a training-free framework for content-aware layout generation using large vision-Language models (VLMs) such as GPT-40 and Gemini.
- Inspired by how human designers work, VASCAR:
  - Generates layout candidates via few-shot in-context learning (ICL).
  - Evaluates layout quality using automatic multi-criteria scoring.
  - **Refines outputs iteratively** based on visual feedback and textual suggestions.

#### Method



#### The overview of proposed **VASCAR**.

# ICL Retriever:

Retrieves a small set of in-context learning (ICL) examples similar to the Query canvas, using saliency map similarity.

$$s(x_{test}, x_j) \triangleq IoU(m_{test}, m_j) = \frac{m_{test} \cap m_j}{m_{test} \cup m_j}$$

 $x_{test}, x_i$  are **Query** and ICL samples,  $m_{test}, m_i$  are corresponding saliency maps.

- **Each exemplar includes:**
- HTML format layout description
- Rendered layout (colored bounding boxes)

# **Layout Generator:**

Generates initial layout candidates using a frozen VLM given the query canvas and ICL examples.

$$Y_q^0 = G(x_q, \emptyset; p_0)$$

- $x_a$ : Query canvas
- $p_0$ : Initial prompt
- $G(\cdot)$ : VLM generator (GPT-40 & Gemini)  $Y_q^0$ : Set of initial layout candidates

Output is in HTML format, describing bounding box coordinates and element types.

# Visual-Aware Self-Correction:

Performs iterative layout refinement using visual feedback from rendered images and evaluation scores.

# Refinement formula (iteration i):

- $Y_q^i = G(x_q, Y_q^{i-1}; p(Y_q^{i-1}))$
- Renders previous layouts onto canvas
- Scores each candidate
- Adds suggestions as text prompt
- Feeds it back to the VLM

# **Prompt Optimizer:**

Constructs the next-step multi-modal prompt for the VLM.

# Input:

- **Query** canvas image
- Top-k previous rendered layouts
- ICL examples
- Suggestions + scores

# **Layout Scorer:**

Assigns a fused quality score to each layout candidate based on multiple normalized criteria.

$$v(y_q) = \sum_{m \in \mathcal{M}} \lambda_m \cdot f_m(y_q)$$

- $\mathcal{M}$ : Set of evaluation metrics
- $f_m(y_q)$ : Normalized score for metric m
- $\lambda_m$ : Weight for each metric

# Suggester:

Provides **natural language suggestions** to refine the layout, based on low-scoring metrics, threshold  $\theta_m$  is calculated by ICL examples:

$$\theta_m = \frac{1}{|S(x_q)|} \sum_{y \in S(x_q)} f_m(y)$$

• If  $f_m(y_a) < \theta_m$ , add a suggestion related to that score, such as:

"Reduce the overlap between the text and image."

w/o Occ

w/o Rea

w/o Ove

w/o Und

# Results

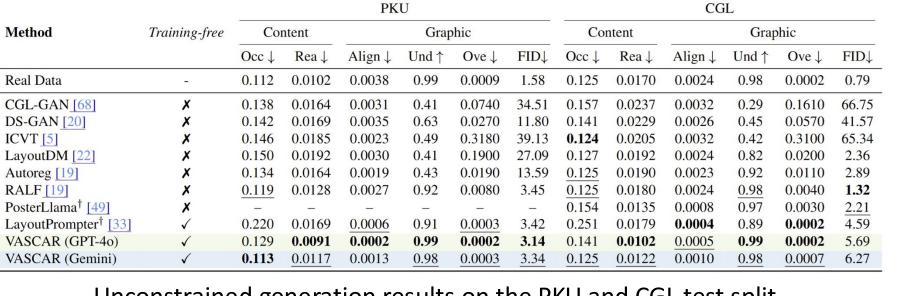
#### Experimental Setup:

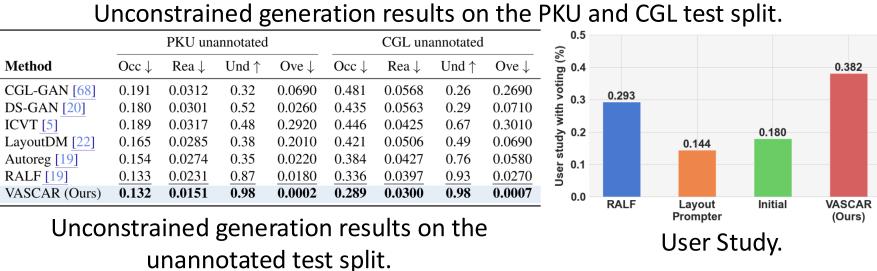
#### ■ Datasets:

We conducted our experiments on two opensource datasets: PKU and CGL, both of which contain e-commerce posters featuring shopping product images.

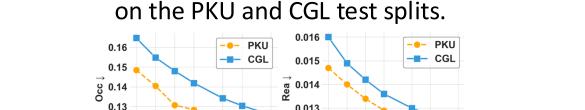
# **■** Compared Methods:

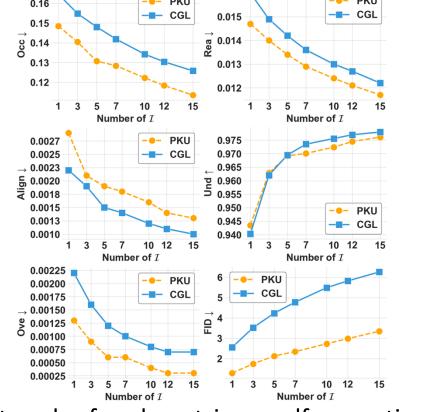
- LLM-based:
- LayoutPrompter, PosterLlama **Generative baselines (trained):**
- CGL-GAN, DS-GAN, ICVT, LayoutDM, Autoreg, RALF **Evaluation Metrics:**
- Content metrics: Occusion, Unreadability Graphic metrics: Overlay, Non-alignment, Underlay Effectiveness, FID
- Implementation Details. gemini-1.5-flash and gpt-40 are used as VLMs.
- ICL examples: 10. Self-correction: 15 for Gemini, 5 for GPT-40



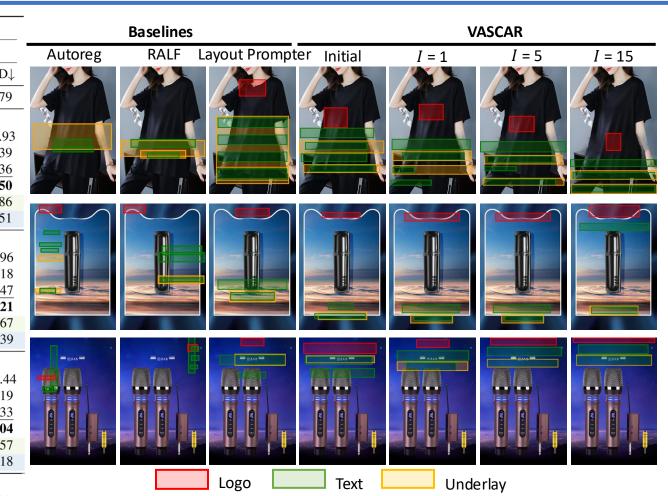


#### PKU CGL Graphic Content Method Ove ↓ $FID\downarrow Occ \downarrow Rea \downarrow$ Real Data $\mathbf{C} \to \mathbf{S} + \mathbf{P}$ CGL-GAN LayoutDM Autoreg 0.00020.139 **0.0099** VASCAR (GPT-40) VASCAR (Gemini) $\mathbf{C} + \mathbf{S} \rightarrow \mathbf{P}$ CGL-GAN VASCAR (GPT-4o) 0.123 0.0117 **0.90 0.0009** 1.11 0.140 0.0132 0.88 $\overline{\mathbf{0.0107}}$ 0.88 0.0018 $\overline{\mathbf{2.21}}$ **0.122** $\overline{\mathbf{0.0123}}$ $\overline{\mathbf{0.85}}$ CGL-GAN LayoutDM Autoreg VASCAR (GPT-40) 0.1200.0063 6.19 0.1370.0068VASCAR (Gemini) Refinement CGL-GAN LayoutDM 0.127 Autoreg VASCAR (GPT-40) 0.125 0.0072 0.99 VASCAR (Gemini) Relationship Autoreg 2.23 0.126 VASCAR (GPT-4o) 0.151 0.0139 0.92 **1.94** 0.153 VASCAR (Gemini) **0.119 0.0117** 2.00 0.132 **0.0123** 0.96 0.0008Quantitative result of five constrained generation tasks on the PKU and CGL test splits.





The trends of each metric on self-correction I.



Visual comparison of baselines and VASCAR with different values of *I*.

	Cor	ntent	Graphic							
Setting	Occ ↓	Rea↓	Align↓	Und ↑	Ove ↓	FID↓				
Rendered Image (Ours)	0.1304	0.0134	0.0017	0.97	0.0012	2.13				
Text-only	0.1529	0.0153	0.0024	0.97	0.0009	1.91				
Saliency Map	0.1356	0.0140	0.0023	0.97	0.0009	1.69				
Inpainting Image	0.1312	0.0137	0.0022	0.98	0.0004	2.37				
Original Poster	0.1315	0.0134	0.0023	0.98	0.0006	2.34				
Multi-modal analysis for VASCAR on the PKU test spl										

# Content Graphic

Setting	Occ↓	Rea↓	Align↓	Und ↑	Ove ↓	FID↓				
Number of ICL Examples $(M)$										
1	0.2014	0.0184	0.0026	0.84	0.0017	1.45				
3	0.1617	0.0160	0.0020	0.90	0.0016	2.27				
5	0.1466	0.0150	0.0018	0.95	0.0006	2.25				
10 (Ours)	0.1304	0.0134	0.0017	0.97	0.0012	2.13				
Number of Output Candidates $( Y_q )$										
1	0.1659	0.0180	0.0023	0.89	0.0011	2.29				
3	0.1393	0.0150	0.0017	0.96	0.0010	2.24				
5 (Ours)	0.1304	0.0134	0.0017	0.97	0.0012	2.13				
10	0.1225	0.0127	0.0025	0.97	0.0008	2.04				
Ablation Study on $\lambda$										
VASCAR (Ours)	0.1304	0.0134	0.0017	0.97	0.0012	2.13				
Initial	0.2080	0.0218	0.0040	0.97	0.0013	1.05				

0.00400.0013 0.20800.0218 0.0022 1.95 0.0114 0.97 0.0002 0.1709 0.0024 2.03 0.0162 0.97 0.00080.12842.23 2.14 0.1301 0.0137 0.0018 0.97 0.0030 0.1237 0.0130 0.0023 0.0007

Comparison of results across various settings on PKU.