

PosterLLaVa: Constructing a Unified Multi-modal Layout Generator with LLM

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ABSTRACT

Layout generation is the keystone in achieving automated graphic design, requiring arranging the position and size of various multi-modal design elements in a visually pleasing and constraint-following manner. Previous approaches are either inefficient for large-scale applications or lack flexibility for varying design requirements. Our research introduces a unified framework for automated graphic layout generation, leveraging the multi-modal large language model (MLLM) to accommodate diverse design tasks. In contrast, our data-driven method employs structured text (JSON format) and visual instruction tuning to generate layouts under specific visual and textual constraints, including user-defined natural language specifications. We conducted extensive experiments and achieved state-of-the-art (SOTA) performance on public multi-modal layout generation benchmarks, demonstrating the effectiveness of our method. Moreover, recognizing existing datasets' limitations in capturing the complexity of real-world graphic designs, we propose two new datasets for much more challenging tasks (user-constrained generation and complicated poster), further validating our model's utility in real-life settings. Marking by its superior accessibility and adaptability, this approach further automates large-scale graphic design tasks. The code and datasets will be publicly available on <https://github.com/posterllava/PosterLLaVA>.

CCS CONCEPTS

- Human-centered computing → Visualization design and evaluation methods; • Applied computing → Media arts.

KEYWORDS

Layout Generation, Multi-modal LLM, User-constrained, Real-world Poster

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1 INTRODUCTION

For diverse sorts of graphic design (commercial posters, mobile app UIs, webpages, video thumbnails, etc.), layout plays a critical role in structuring visual and textual elements to captivate audiences and communicate intended messages. This task has required designers to create layouts manually, demanding their extensive expertise and experience. For large-scale designing tasks, the efficiency of this strategy is far from expected.

The most naive idea for massive graphic design generation is to utilize pre-design templates and replace content according to requirements. However, the production and selection of templates still involve human labor, and mechanically applying the inappropriate layout can lead to obtrusive designs. Previous researchers attempted to frame layout generation as an optimization problem, tackling it with heuristic algorithms like genetic algorithms [30] and simulated annealing [3]. However, these methods hinge on crafting well-designed energy functions, a task that still depends heavily on design expertise and lacks generality across different applications.

With the advance in deep learning, researchers are glad to embrace data-driven methods [2, 12, 15, 17–19] in layout generation. Most of these works focus on adopting the latest generative architecture but overlook the necessary conditional requirements for layout. This limits their applicability in real-world scenarios, which frequently demand the integration of complex multi-modal conditions. Recently, more and more researchers have recognized the importance of multi-modal conditions and started to explore *content-aware layout generation*. For visual conditions, CGL-GAN [47] and DS-GAN [13] take an innovative step to incorporate the semantic information on background images into layout generation, and some later works also [40, 43] consider the content of foreground elements as conditions. For textual conditions, some preliminary attempts [16, 18, 22] generate layouts under given graphic conditions. However, the introduced constrained optimization processes or specific intermediate representations strengthen

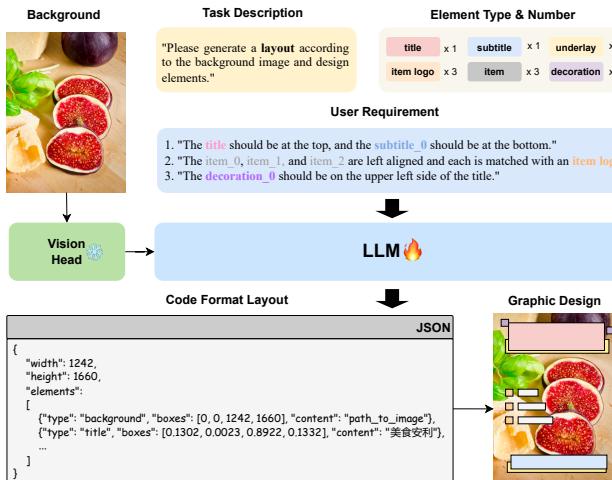


Figure 1: The overall framework of our proposed content-aware layout generation method. Adopting the multi-modal LLM [25] as the central processing unit, we embed information from both visual and textual domains to generate a reasonable and visually pleasing graphic layout. The result is encoded in JSON format and can be rendered into a real-world poster.

the training or labeling complexity. An efficient end-to-end framework that can directly translate natural language instructions into desired layouts is still needed.

Although previous approaches have demonstrated progress on certain datasets, most of them rely on highly customized network architectures lack universality. Such specificity necessitates substantial modifications or complete redesigns to accommodate new or varied layout design challenges. Recognizing this limitation, we develop a unified framework named PosterLLaVa (see Fig. 1) for layout generation task, inspired by the simplicity and effectiveness of the recently published multi-modal instruction tuning [20, 25, 36, 41, 45, 48] method. Pre-trained with numerous amounts of unlabelled corpora and fine-tuned with instruction-following data, MLLMs (Multi-modal Large Language Models) are capable of handling multiple vision-language tasks (e.g., VQA [25, 48], visual grounding [36, 41], etc.) according to the given instructions and their background knowledge. For layout generation, we first show how layout information can be naturally represented by structured text content in JSON format. With this representation, we can measure the performance of PosterLLaVa on established content-aware generation datasets and compare it with previous benchmarks. To tackle the multi-modal condition inputs, we utilize the pre-trained visual head of LLaVa[24] to convert visual representation into textual domain and fine-tuning the LLM[35] to interpret and generate layout data. With the LLM as the central processing unit, our model can manage a wide range of layout generation tasks through simple modifications of the input instructions, eliminating any need for changes in model architecture. Moreover, textual user requirements can be seamlessly integrated into the generation instructions, enhancing the model's responsiveness to specific design needs.

The main contribution of our work can be summarized as follows.

- (1) **A Unified Layout Generation Tool** We propose a unified content-aware layout generation method utilizing multi-modal LLMs, adaptable across various design scenarios through simple modifications of input instructions. Our approach is validated across multiple public datasets (See Tab. 2) and two newly proposed datasets, showcasing its superior performance and versatility.
- (2) **Natural Language User Requirements** Our framework's ability to process natural language inputs significantly enhances the intuitiveness and efficiency of the design process. With the inherited support of LLMs for natural language inputs, our method eliminates any additional network modules or loss functions, achieving this purpose end-to-end manner. We generate large-scale instruction-following data from a small amount of high-quality human-annotated data with the aid of GPT [5] and contribute to the field's largest constrained layout generation dataset of 84,200 samples, far more than the previous efforts.
- (3) **Real-world Complicated Posters** We collect a challenging graphic layout dataset named QB-Poster (QQ Browser Poster), composed of 5,188 samples designed with a prevalent in Chinese social media. This dataset is characterized by its intricate geometric relationships between sufficient kinds of content. Through comparative analysis with the latest comparable method, our method demonstrates remarkable adaptability and effectiveness in capturing the distribution of complicated real-world layouts.

2 RELATED WORK

2.1 Automatic Graphic Layout Generation

Rule-based Methods Before the appearance of deep learning, layout generation has been studied for decades [3, 26, 30, 42]. Typically, Yin et al. [42] proposed a series of principles according to widely accepted aesthetic or information-conveying rules and a heuristic algorithm to minimize the overall energy function. These methods do not require training. Instead, they perform a runtime searching process during every inference. The true complexity of these methods lies in the design of the energy function, which requires a lot of design experience and expertise. Moreover, these functions must be manually re-designed when encountering a new design element or applied to a different styled layout (e.g., from UI to commercial poster).

Content-agnostic Layout Generation Neural networks offer researchers a way to formulate designing principles implicitly from numerous data, saving human efforts. Most early works [2, 12, 17, 21, 44, 46] focus on generating visually reasonable layouts for mobile UIs, documents, and magazine pages. LayoutGAN [21] employs the GAN (Generative Adversarial Network) paradigm and designs a differentiable rendering process for connecting the visual and graphic domains. LayoutVAE [17] and CanvasVAE[39] adopt the VAE (Variational Auto-Encoder) paradigm, while more recent works adopt the auto-regressive architecture [2, 12, 19] or the diffusion architecture [14, 15, 44]. Despite their achievement on unconditioned layout generation tasks, they are hard to use in real-world scenarios.

Content-aware Layout Generation Recently, some other works [13, 38, 40, 43, 47] have paid their attention to commercial-style posters, in which case the graphic designs are usually based on a non-empty background image. CGL-GAN [47] contributes a large dataset with around 60k Chinese commercial posters and proposes to learn with a transformer-based GAN network receiving a saliency map and the inpainted background as input. Similarly, PosterLayout [13] tackles the problem with a CNN-LSTM network with saliency map as input. [6] adopts a C-VAE (Conditional Variational Auto-Encoder) to predict the layout. LayoutDETR [43] design a DETR-like[7] to utilize the pre-trained objects detection model and integrate both GAN and VAE for layout generation. They also include pre-trained ViT [10] and BETR [9] as visual and textual encoders to get embedded features of the design elements.

Interestingly, some work [16, 18, 22] also attempted to generate layouts following specific constraints. Primitively, LayoutGAN++ [18] introduces an additional constrained optimization process based on the Lagrangian multiplier method to get the desired layout. Then, LayoutFormer++ [16] and Parse-then-place [22] design a specific intermediate representation to handle various constraints. The latter also studies the text-to-layout problem, which includes implicitly expressed user requirements and is very similar to ours.

2.2 Multi-modal Large Language Models and Application

LLMs (Large Language Models) [1, 5, 35] have achieved remarkable success across a wide range of natural language processing (NLP) tasks. With billions of parameters, these models derive extensive knowledge from pre-training on vast unlabeled text corpora. Various instruction-tuning methods have been investigated to enhance the ability of LLMs to comprehend and execute natural language instructions [27, 37]. While LLMs have proven adept at understanding and generating text, multi-modal LLMs have been facilitated by incorporating additional modalities like visual and auditory data [20, 25, 48]. A prevalent approach involves injecting LLMs with multi-modal information and leveraging their robust reasoning capabilities.

LLMs-assisted Layout Generation Layouts, which can be encoded in formats such as XML or JSON, are ideally suited to be processed by pre-trained Large Language Models (LLMs). Previous works have used domain-specific data to strengthen their code generation ability. LayoutNUWA [33] fine-tunes the LLaMa [34] and CodeLLaMa [31] to the content-agnostic layout generation task, achieving the SOTA performance in multiple content-agnostic layout datasets. LayoutPrompter [23] introduces an interesting training-free approach, leveraging RAG (Retrieval-Augmented Generation) to strengthen the in-context learning ability of GPT [5], dynamically sourcing examples from a dataset. However, this retrieval-centric strategy is limited to open-domain generation. These works overlook the visual domain feature or translate it into hard tokens before feeding into LLM, potentially resulting in severe information loss. To tackle this weakness, we include the latest proposed multi-modal technique - visual instruct tuning [25] to fine-tune a pre-trained large model, which accepts the visual information with a pre-trained and aligned visual adaptation head [29]. For the

layout-to-image generation, interestingly, some contemporaneous work like LayoutGPT[11] and TextDiffuser-2[8] also adopt LLMs, showing a promising production pipeline for LLM-based graphic design.

2.3 Methodology

2.3.1 Multi-modal Layout Tokenization. Assuming that all complicated attributes and art styles have their default values, we can explicitly represent the information of a graphic design L_j by defining the position (x_i, y_i) , size (h_i, w_i) , and content I_i of every element. The position and size can be further expressed as bounding box format if rotation and irregular shapes are not involved. The class labels c_i of elements are explicitly given to excavate the relationship between different kinds of elements. We got the following representation of a poster:

$$L_j = \{(x_i, y_i, h_i, w_i), c_i, I_i\}_{i=0}^N \quad (1)$$

in which N represents the number of elements. For previous papers, most consider L_j as a numeric form, which means solving the problem in a continuous space. We, however, design the following process to tokenize L_j and feed it into LLMs to predict the next token. First, we normalized the bounding box coordinates with the background width and height to facilitate multi-resolution generation. Each coordinate data value of the bounding box vector is truncated to K decimal places to avoid redundancy. For class label c_i , we use the corresponding text label instead, for example {text, logo, underlay} regarding the PosterLayout [13] dataset. Finally, for image elements, I_i^{img} is encoded by a pre-trained vision header, which is composed of a ViT [10] encoder and a linear projection head, namely

$$h(I_i^{\text{img}}) = \mathbf{W}^T \text{CLIP}(I_i^{\text{img}}). \quad (2)$$

and the content I_i^{txt} of the text element is inherently in a text format.

2.3.2 Training Scheme. To facilitate the learning of tokenized layout data, we adopt the training scheme proposed by Liu et al. [25], i.e., the visual instruction tuning. The original paper, focusing on general visual-language tasks, recommends fine-tuning a pre-trained LLM [34] by two phrases: 1. pre-training for feature alignment, and 2. end-to-end fine-tuning. The alignment phase usually requires numerous image-text pairs to adapt visual information into language space, and the fine-tuning phase requires relatively less data to acquire instruction-following outputs. Recognizing that the primary challenge in layout generation resides in decoding the semantic and geometric relationship between graphic elements, we streamline the training process by using the pre-trained linear projection layer to skip the feature alignment phase. This allows us to reduce training expenditure while maintaining comparable performance with the full-trained model.

2.3.3 Prompt Template. We introduce the following prompt template for the adopting end-to-end fine-tuning phase of visual instruction tuning in various content-aware layout generation tasks. The template is described in Tab. 1. The pre-trained vision head converts the background image into soft tokens (as Eq. 2 shows) to get **<image>**. **<N>** is replaced with the exact number of design elements, and **<resolution>** is replaced with the canvas resolution. We use a domain indicator **<domain_name>** to distinguish

USER:**<image>**

Please help me to place **<N>** foreground elements over the background of **<resolution>** to craft a **<domain_name>**. Remember to avoid unbalance, overlap, misalignment, and occlusion of semantic-meaningful objects on the background image. Return the result by filling in the following JSON file while keeping the number and types of elements unchanged. The initial JSON is defined as: **<masked_json>**, in which each design element is represented by a bounding box described as [left, top, right, bottom], and each coordinate is a contiguous number in 0-1. The user constraints are defined as: **<constraints>**, which should be adopted as compulsory design requirements.

ASSISTANT:

Sure! Here is the design result: **<json>**.

Table 1: Prompt template for applying visual instruction tuning on content-aware generation task. The placeholder tokens in bold type are replaced with specific information during training or inference.

different tasks and datasets. For example, "commercial poster" for CGL dataset and "ad banner" for ad banner dataset. The ground-truth layout information is expressed by textual representation through the process introduced in Sec. 2.3.1 and arranged in JSON format (as Fig. 1) to replace **<json>**. For human instruction, we delete bounding boxes and preserve the category labels to get the **<masked_json>**. As for user-constrained generation tasks, the constraints are given as **<constraints>**.

3 EXPERIMENT

Implementation Details Most experiments are conducted on 8 NVIDIA A10 GPUs and can be finished within 12 hours. The MLLM checkpoint adopted is the full-tuning 7B version of LLaVa-v1.5 [24], which is trained with LLaMa-2 [35] 7B as base model with visual instruction tuning. For most of the following layout datasets, we fine-tune the MLLM with one epoch, but for the banners dataset, we employ the 3rd epoch model considering its tiny scale. For the adaptation into the QB-Poster dataset, we adopt the pre-trained model on all training sets of Ad Banner, CGL, and PosterLayout as a starting point to enhance its performance. We increase the max token from 2048 to 4096 as the token length grows with the element number. For other training or inference hyper-parameters, we apply the default recipe recommended by LLaVa [25].

3.1 Result on Public Content-aware Layout Dataset

Dataset Description As mentioned in Section 2.1, content-aware layout generation, as a new task, has only received attention since around 2020, and related research is still in its early stages. We extensively investigated datasets published in the past literature to verify the model's performance on the general content-aware layout generation task. Available public datasets and baselines are listed in Tab. 2.

CGL dataset [47], one of the pioneering content-aware collections, comprises 60548 training samples and 1000 test samples collected from e-commerce platforms. The design elements are divided into 4 categories: logo, text, underlay, and embellishment. The class labels and bounding boxes of elements for each poster in the training set are annotated manually, while the test set includes only the background image. Techniques like image inpainting [32] and

Table 2: An overall description of the content-aware layout generation datasets. QB-Poster is the complicated real-world poster dataset proposed in this paper, which outperforms previous datasets in both annotation categories and numbers per poster.

Dataset	Train	Test	Classes	Boxes/img	Total Boxes
CGL dataset	60548	1000	4	4.87	265818
PosterLayout	9974	905	3	4.73	47024
Ad Banner	7672	1000	8	2.23	16593
YouTube	10000	1000	3	5.88	67223
QB-Poster	4675	513	10	15.17	78723

saliency detection [4] are needed to get additional visual information. Recognizing the limitations of the CGL dataset, particularly its repetitive content and scarcity of complex layouts featuring over ten elements, Hsu et al. [13] introduces PosterLayout, offering 9974 poster-layout pairs for training and 905 background images for testing. LayoutDETR [43] contributes an ad banner dataset with multi-modal information, containing 7,672 samples divided into training and testing subsets in a 9:1 ratio. The background images are either from the Pitt Image Ads Dataset or Google Image, and the bounding boxes, categories, and text contents are extracted by OCR automatically. But different from CGL and PosterLayout, this dataset contains banners of multi-resolutions. The YouTube [40] dataset is another newly proposed dataset focusing on video thumbnail generation. Compared with the former poster dataset, it incorporates foreground images with rotation angles, thus demanding a more advanced level of multi-modal understanding.

Evaluation Metrics For a convenient comparison of different datasets, we adopt the original evaluation measurements without change. The metrics used are similar for CGL-dataset [47] and PosterLayout [13] dataset. The calculation of content-aware metrics is related to background or saliency image: the R_{com} and Rea represent the readability of text elements; R_{shm} , R_{sub} , Occ represent the occlusion of semantic meaningful or saliency region on the background, while Uti indicates the utility of non-saliency region. The geometric metrics are only related to the predicted bounding boxes: R_{ove} , and Ove represents the overlap ratio; R_{und} , Und_l and Und_s indicates whether the underlays are correctly placed under texts;

Table 3: Results comparison on PosterLayout dataset. Evaluations are conducted under PosterLayout’s [13] settings. Previous results are copied for comparison.

Methods	Content-aware			Geometric				
	Uti \downarrow	Occ \downarrow	Rea \downarrow	Val \uparrow	Ove \downarrow	Ali \downarrow	Und $_l \uparrow$	Und $_s \uparrow$
Ground-Truth	0.2222	0.1900	0.1522	0.9999	0.0001	0.0002	0.9965	0.9912
Content-aware Methods								
CGL-GAN	0.2257	0.1546	0.1715	0.7066	0.0605	0.0062	0.8624	0.4043
DS-GAN[13]	0.2541	0.2088	0.1874	0.8788	0.0220	0.0046	0.8315	0.4320
LayoutPrompter[23]	0.2597	0.0992	0.1723	0.9992	0.0036	0.0036	0.8986	0.8802
PosterLLaVa(Ours)	0.2628	0.1649	0.1142	1.0000	7.7e-5	0.0002	1.0000	1.0000

Table 4: Results comparison on CGL-GAN dataset. Evaluations are conducted under CGL-GAN’s [47] settings. Previous results are copied for comparison. \dagger indicates that we apply BASNet [28] for saliency detection rather than PFPN [4] since the pre-trained link of the latter one expires.

Methods	Content-aware			Geometric			
	R _{com} \downarrow	R _{shm} \downarrow	R _{sub} \downarrow	R _{ove} \uparrow	R _{und} \uparrow	R _{ali} \uparrow	R _{occ} \uparrow
Content-unaware Methods							
LayoutTransformer [12]	40.92	21.08	1.310	0.0156	0.9516	0.0049	-
VTN [2]	41.77	22.21	1.323	0.0130	0.9628	0.0047	-
Content-aware Methods							
ContentGAN [46]	45.59	17.08	1.143	0.0397	0.8626	0.0071	93.4
CGL-GAN [47]	35.77	15.47	0.805	0.0233	0.9359	0.0098	99.6
PDA-GAN [38]	33.55	12.77	0.688	0.0290	0.9481	0.0105	99.7
PosterLLaVa(Ours)	34.80	8.214	0.277\dagger	2.4e-10	1.0000	0.0008	100

R_{ali} and R_{ali} represent the alignment; R_{occ} and Val indicates the valid (e.g., non-empty) layout ratio. For Ad Banner [43] and YouTube [40] dataset, similarity metrics are included since the ground-truth layouts are available. VB in the YouTube dataset represents Visual Balance, which represents whether the overall placement is balanced. To avoid redundancy, please refer to the original papers for detailed explanations of metrics.

Result Comparison The results presented in Tab. 3, 4, 5, and 6 demonstrate that our method outperforms existing approaches, both content-unaware and content-aware, by a significant margin. In the Ad Banner dataset, our model exhibits improvements across all metrics except Misalign. For the PosterLayout dataset, our method markedly enhances geometric metrics, whereas LayoutPrompter [23] achieves a better trade-off between utility and occlusion. This is understandable because all previous methods incorporate additional input (i.e., pre-processed saliency maps), while our method relies solely on the original background image. Similarly, in the CGL dataset, our method outperforms other approaches, particularly in geometric measurements. These results confirm the effectiveness of our method across various datasets and metrics.

3.2 Towards Real-world Poster Design - Two New Content-aware Layout Dataset

User-constrained Layout Generation Although content-aware layout generation has been a valuable step toward real-world applications, realistic graphic design problems often involve more

Table 5: Results comparison on the ad banner dataset under LayoutDETR’s [43] settings. Results of previous methods are copied for comparison, among which PosterLLaVa achieves SOTA performance in all metrics except misalignment.

Methods	Similarity			Geometric		
	Layout FID \downarrow	Image FID \downarrow	IoU \uparrow	DocSim \uparrow	Overlap \uparrow	Misalign $(\times 10^{-2}) \downarrow$
Ground-Truth	-	-	-	-	0.035	1.889
Content-unaware Methods						
LayoutGAN++ [18]	4.25	28.40	0.163	0.130	0.104	0.759
READ	4.45	32.10	0.177	0.141	0.093	2.867
Vinci	38.97	58.12	0.104	0.143	0.243	0.271
LayoutTransformer [12]	5.47	39.70	0.080	0.115	0.127	3.632
Content-aware Methods						
CGL-GAN [47]	4.69	30.50	0.154	0.127	0.116	1.191
HPCVTG [6]	12.54	30.11	0.163	0.137	0.423	0.682
LayoutDETR-VAE [43]	3.25	27.47	0.216	0.152	0.119	1.737
PosterLLaVa(Ours)	2.37	24.87	0.242	0.158	0.029	1.161

Table 6: Results comparison on the YouTube dataset under HPCVTG’s [40] settings. Previous results are copied for comparison. PosterLLaVa shows promising performance in reducing overlap and saliency occlusion.

Methods	Similarity			Geometric		
	mIoU \uparrow	FID \downarrow	VB \downarrow	Overlap \downarrow	Misalign \downarrow	Occlusion \downarrow
Ground-Truth	-	-	0.93	6.29	1.55	5.88
Content-unaware Methods						
LayoutGAN++ [18]	4.06	145.7	6.01	151.02	1.52	21.23
LayoutTransformer [12]	11.42	59.89	6.53	76.15	0.06	18.38
Content-aware Methods						
HPCVTG [40]	14.16	18.50	2.13	47.51	3.25	14.41
PosterLLaVa(Ours)	27.50	12.14	3.10	8.17	0.49	7.24

conditionality. User constraint is one of them, usually including optional suggestions or mandatory opinions for graphic design products. These constraints, typically articulated in natural language, introduce even more complexity due to their potential ambiguity. As Section 2.1 mentioned, several previous works [16, 18, 22] have explored similar topics. Yet a comprehensive end-to-end solution that seamlessly integrates visual content with natural language constraints is still required. Our methodology, leveraging large multi-modal models, is inherently equipped to bridge this gap.

To this end, we propose a new dataset to validate the constrained generation ability of our approach. Firstly, we ask human annotators to write 3 user constraints according to the original poster layout in the CGL [47] validation set (6,006 samples), which are later used as test samples in this experiment. Then, with these high-quality human-annotated constraints serving as in-context learning examples, we utilize ChatGPT to generate constraints automatically. This approach enables us to expand our constraint dataset to include the entire training corpus of the CGL dataset (54,546 samples) and the PosterLayout dataset (9,974 samples), thereby assembling a

Table 7: Results comparison on the user-constrained poster dataset (up) and the QB-Poster dataset (down). In both datasets, PosterLLaVa outperforms LayoutPrompter significantly.

Methods	Similarity		Content-aware			Geometric					Constraint	
	Image FID \downarrow	IoU \uparrow	Uti \uparrow	Occ \downarrow	Rea \downarrow	Val \uparrow	Ove \downarrow	Ali \downarrow	Und $_l$ \uparrow	Und $_s$ \uparrow	VB \downarrow	Vio \downarrow
User-constrained Poster dataset												
LayoutPrompter [23]	20.29	0.0961	0.2024	0.2846	0.1038	0.8512	0.0014	0.0018	0.3916	0.2906	0.0781	0.4130
PosterLLaVa(Ours)	3.823	0.1996	0.1751	0.0924	0.1000	0.9432	0.0014	0.0003	0.9962	0.9944	0.0662	0.1156
QB-Poster dataset												
LayoutPrompter [23]	96.86	0.0195	0.2467	0.4504	0.1956	0.9509	0.0233	0.0004	0.2686	0.1501	0.2784	-
PosterLLaVa(Ours)	35.97	0.1996	0.2656	0.3377	0.1659	0.9949	0.0117	4.75e-5	0.9418	0.9141	0.1221	-

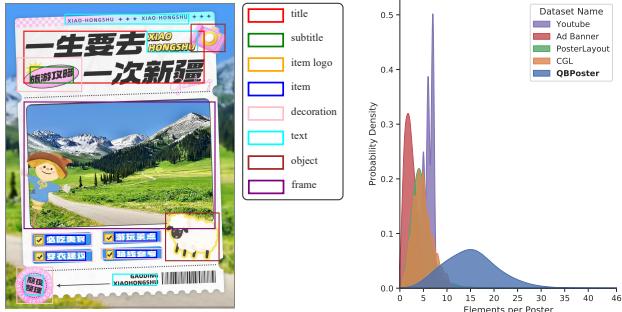


Figure 2: The left figure shows a sample of the poster and the corresponding annotation information in the proposed QB-Poster dataset. The right shows the distribution of element numbers estimated by KDE (Kernel Density Estimation) across all included datasets, in which QB-Poster significantly surpasses other datasets.

enormous training dataset to mirror the diverse demands of real-world graphic design tasks.

A New Real-world Poster Dataset A notable limitation of existing content-aware datasets is their oversimplification. Typically, these datasets feature layouts with no more than 15 design elements, categorized into fewer than 5 types. Such simplicity falls short of conveying sufficient semantic information and mirroring the complexity of designs employed in real-world graphic designs.

To better align with the demands of real-life scenarios, we collect a new dataset named QB-Poster with a much more complicated style. As shown in Fig. 2, the elements per poster and geometric complexity of QB-Poster surpasses other datasets significantly. This includes 5,188 poster-layout pairs, with 4,675 for training and 513 for testing. The dataset categorizes design elements into 10 categories: title, subtitle, item logo, item, item title, object, text background, decoration, frame, and text. These fine-grained class labels reveal the design pattern of elements and provide the algorithm with additional semantic information. Text elements are organized using a hierarchical classification to indicate their levels of importance. Meanwhile, visual elements are categorized as decoration, text background, object, and frame, which respectively identify decorative icons, underlays, semantically significant objects within background images, and the canvas area.

Baseline and Evaluation Metrics To be fair in model scale, we choose LayoutPrompter [23] for comparison, which also employs LLM as its central component. We use *gpt-3.5-turbo-instruct* instead of *text-davinci-003* since OpenAI has abandoned the latter model. Unlike our method, which uses a visual encoder, LayoutPrompter only accepts textual input. Thus, for user-constrained content-aware generation task, we extend the original method by concatenating the pre-extracted saliency bounding box and the constraint texts. Other methods are omitted since they cannot support multi-modal input, and LayoutPrompter already surpasses other methods by a clear margin in the PosterLayout dataset. For evaluation metrics, since the metrics used in PosterLayout [13] and CGL-GAN [47] are very similar to each other. We chose the PosterLayout style for our evaluation as it relies less on additional data and pre-trained models. But different from the original paper, our definition (which uses validation split) includes the ground truth layout for the testing, which enables the computation of similarity metrics. We cut the patches in the original poster with a ground-truth bounding box and resize it with the predicted bounding box to form the predicted poster image for computing image FID. The IoU is also introduced as a measurement of similarity. For geometric measurements, we adopt the VB (Visual Balance) used in HPCVTG [40] as an important supplement, reflecting whether the elements' placement is spatially balanced. Most importantly, to measure to what degree the model follows the input constraints, we sample a subset (50 layouts) of the test set and ask human annotators to verify the average constraint violation ratio, noted as vio. The overall result shown in Tab 7.

Result Comparison As shown in Tab.7, PosterLLaVa significantly surpasses LayoutPrompter in all metrics, no matter similarity or geometry, showing the power of utilizing visual instruction tuning in layout generation. This result differs from the PosterLayout dataset shown in Tab. 3, but it is still within expectation once recognizing the difference between RAG and fine-tuning. This shows that despite the efficiency of the learning-free method, it may fail to fit target distribution when dealing with complicated and highly customized data. Besides, the RAG doesn't use the training set for tuning the model directly, whereas it still requires a large database size to ensure the retrieval of high-quality and low-variance exemplars, which worsens the performance of this method under data scarcity.

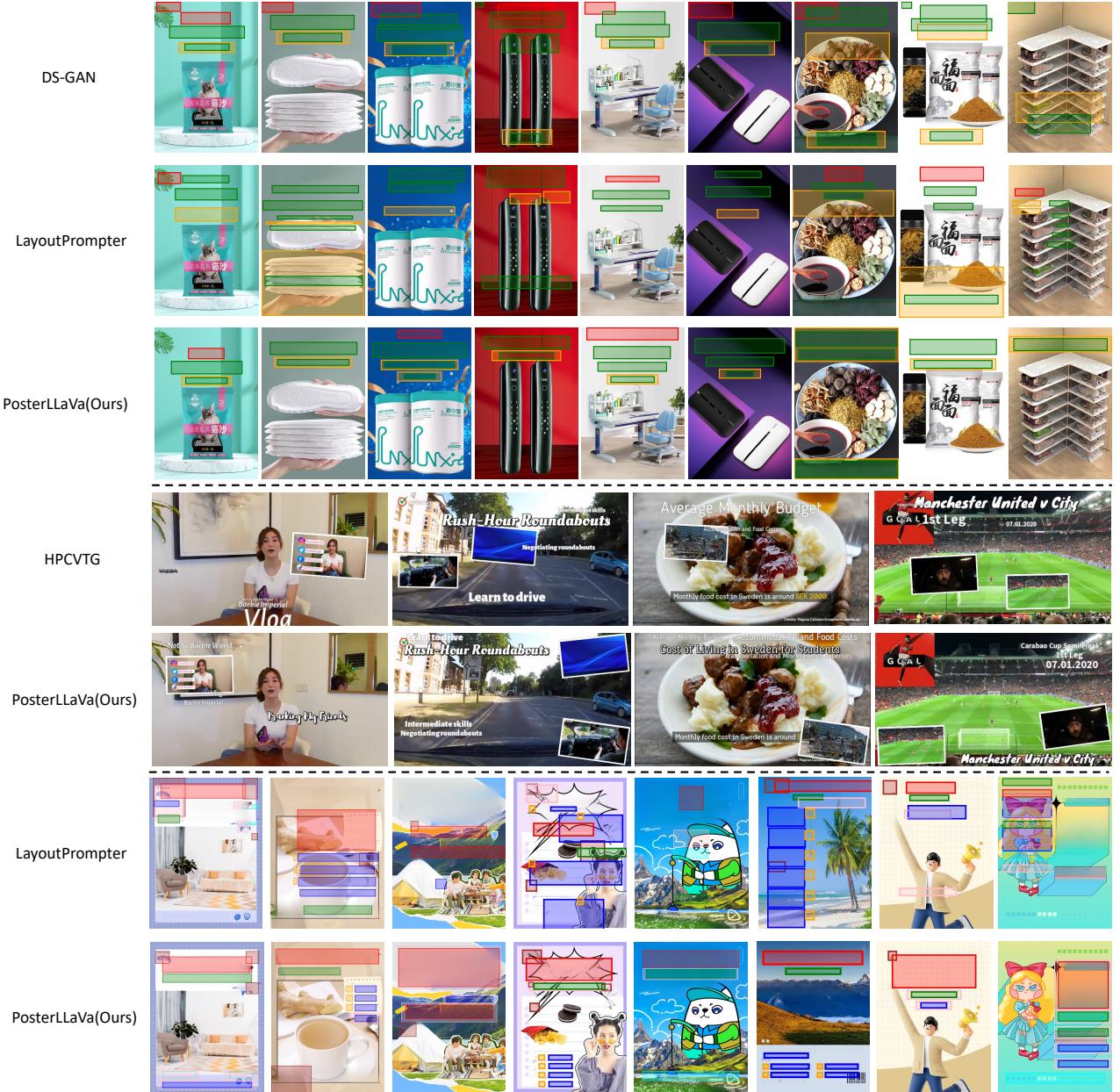


Figure 3: Qualitative results on the PosterLayout (top), Youtube (middle), and QB-Poster (bottom) dataset. PosterLLaVa achieves the highest overall generation quality on all three datasets.

4 ABLATION

We design several ablation experiments to verify the necessity of our proposed method on the following dimensions. We assume that 1. Considering the small scale of the existing content-aware dataset (<100,000 samples), the generation performance of the model is positively correlated to the number of training samples and model size; 2. the multi-modal information used should contribute to the generated layout quality. The ad banner dataset is selected for ablation because it is the most lightweight but still contains

sufficient multi-modal information, and the metrics used are stable (in contrast, the reliability of utility and occlusion scores highly depends on the quality of saliency detection).

Result The result shown in Tab. 8 demonstrates the assumption proposed above. For extra training data, we apply the whole training set of CGL, PosterLayout, and ad banner datasets (78,194 samples in total) for fine-tuning, which improves all geometric measurements. Surprisingly, it also improves the similarity metrics except for Layout FID, which reveals the generality in content-aware generation datasets. Furthermore, the similarity measurement continues to



Figure 4: Qualitative results on the User-constrained Poster dataset. The user requirement texts are shown on the left side, and the bolden requirement means it was violated by either method.

Table 8: Ablation Studies conducted on ad banner dataset [43]. Results demonstrate the necessity of applying large models, large datasets, and multi-modal information in content-aware layout generation.

Methods	Similarity			Geometric		
	Layout	Image	IoU	DocSim	Overlap	Misalign
	FID \downarrow	FID \downarrow	\uparrow	\uparrow	\downarrow	($\times 10^{-2}$) \downarrow
PosterLLaVa(Ours)	2.37	24.87	0.242	0.158	0.029	1.161
+ extra training data	3.91	24.40	0.251	0.160	0.027	0.949
+ 7B \rightarrow 13B LLM	2.78	23.86	0.262	0.156	0.026	1.676
- textual info	2.98	25.14	0.225	0.115	0.021	1.522
- visual info	8.27	40.59	0.092	0.115	0.020	2.193

increase by upgrading the pre-trained LLaVa model from 7B to 13B. For multi-modal information, we reduce the visual input (i.e., background image) and textual input (i.e., text element content), respectively, and both of these degrade the overall performance (with a slight improvement in overlap metric, probably because the reduction of information has lower the learning difficulty). These results together demonstrate the effectiveness of utilizing **multi-modal large models** in content-aware layout generation tasks, and with whose enormous learning capacity, the corresponding demand for **more high-quality layout data**.

5 CONCLUSION

Content-aware layout generation is a highly multi-modal problem. Utilizing the latest multi-modal large model instruction fine-tuning techniques, we propose a method named PoserLLaVa that represents multi-modal layout information as tokens, which are then processed by a Large Language Model (LLM). The proposed method achieves SOTA performance across multiple content-aware layout generation datasets. Additionally, by surveying existing content-aware layout generation datasets, we identify significant shortcomings in the current public datasets, namely the lack of user-constrained data and complicated data, both of which are crucial in real-world applications. We further collect two new datasets to bridge this gap, the user-constrained poster dataset and the QB-Poster, based on which we verify the extended ability of our method. In summary, to achieve large-scale automated production, high-quality multi-modal layout data and a unified learning approach are still under demand, for which our method paves the way.

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6 APPENDICES

6.1 More Comparisons

In Section 3.2 we only included the state-of-the-art method, LayoutPrompter [23], for comparison on the two proposed datasets, since it serves as a strong representative (another reason is other methods did not release their code). We reproduced several previous methods to ensure a comprehensive comparison and included these results in the Appendix. We still found that most previous methods could not converge well on our proposed QB-Poster dataset since it contains more complicated element categories and spatial layouts. Tab. 9 presents a preliminary reproduction result, demonstrating that our method outperforms in most metrics. Although some traditional methods excel in one or two specific metrics, our model achieves the best overall trade-offs.

We also included other instruction-tuning techniques for comparison. MiniGPT-4 [48] is an instruction-tuning method based on Q-Former[20], while mPLUG [41] is a more recent method that tunes both the large language model (LLM) and the visual encoder simultaneously. The results indicate that the visual tuning scheme adopted by LLaVa [25] generally performs the best. This is understandable because the primary task for layout generation is to adapt the input and output format, making the LLM the central component for tuning. Additionally, the existing layout data is still limited in both quality and quantity, and aligning the visual encoder using such data would weaken its general feature extraction ability.

6.2 Efficiency Tests

The utilization of LLMs brings better performance but also a larger computational burden. In this section, we present training time experiments to demonstrate that the increased complexity introduced

Table 9: Additional comparison on the QB-Poster dataset.

Methods	Similarity		Content-ware				Geometric				
	Image FID \downarrow	IoU \uparrow	Uti \uparrow	Occ \downarrow	Rea \downarrow	Val \uparrow	Ove \downarrow	Ali \downarrow	Und $_l \uparrow$	Und $_s \uparrow$	VB \downarrow
QB-Poster dataset											
DS-GAN [13]	85.19	0.0558	0.5048	0.4146	0.1995	1.0000	0.1541	0.0034	0.3094	0.1627	0.0287
CGL-GAN [47]	67.10	0.0373	0.2908	0.3904	0.1800	0.9959	0.1375	0.0040	0.3726	0.0600	0.0956
ICVT [6]	97.59	0.0231	0.1121	0.3629	0.1442	0.9599	0.4666	0.0018	0.4673	0.3617	0.2903
LayoutDM [15]	159.3	0.0144	0.2218	0.4096	0.1850	0.9980	0.2240	0.0003	0.4736	0.3618	0.1223
LayoutPrompter [23]	96.86	0.0195	0.2467	0.4504	0.1956	0.9509	0.0233	0.0004	0.2686	0.1501	0.2784
PosterLLaVa(Ours)	35.97	0.1996	0.2656	0.3377	0.1659	0.9949	0.0117	4.75e-5	0.9418	0.9141	0.1221

Table 10: Training efficiency test.

Methods	Training Device	Training Time (sec)	Training Epochs
DS-GAN [13]	16 X NVIDIA A10 (24GB)	9030	300
CGL-GAN [47]	16 X NVIDIA A10 (24GB)	21667	300
ICVT [6]	16 X NVIDIA A10 (24GB)	12030	300
LayoutDM [15]	16 X NVIDIA A10 (24GB)	19740	300
PosterLLaVa (LLaVa-v1.5)	8 X NVIDIA A10 (24GB)	4186	2
PosterLLaVa (LLaVa-v1.5 LoRA)	8 X NVIDIA A10 (24GB)	2093	2
PosterLLaVa (mPLUG-owl2)	16 X NVIDIA A10 (24GB)	1628	2
PosterLLaVa (miniGPT4)	8 X NVIDIA A100 (40GB)	3414	20

by LLMs is manageable. Results are shown in Table 10. Interestingly, our method, despite incorporating a much larger model (LLaVa-7B or 13B), requires significantly fewer epochs to converge compared to previous methods (2 epochs vs. 300 epochs) and can thus save 50% time (4186 sec v.s. 9030 sec). This improvement is likely due to the spatial arranging knowledge implicitly encoded in the pre-trained LLM models. Additionally, by using the zero3_offload script for DeepSpeed, the LLM can be tuned on constrained GPU devices,

such as 8 x NVIDIA A10 GPUs with only 24 GB of memory each, which is the same as the previous method required. Furthermore, the LoRA scheme can further reduce training time and memory requirements, making it a better alternative than full-tuning when adopting larger models (>13B). In summary, using LLM for layout generation is promising for achieving both better effectiveness and improved efficiency.

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