Boundary Attention Constrained Zero-Shot Layout-To-Image Generation

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Abstract

Recent text-to-image diffusion models excel at generating high-resolution images from text but struggle with precise control over spatial composition and object counting. To address these challenges, several studies developed layout-to-image (L2I) approaches that incorporate layout instructions into text-to-image models. However, existing L2I methods typically require either fine-tuning pretrained parameters or training additional control modules for the diffusion models. In this work, we propose a novel zero-shot L2I approach, BACON (Boundary Attention Constrained generation), which eliminates the need for additional modules or fine-tuning. Specifically, we use text-visual cross-attention feature maps to quantify inconsistencies between the layout of the generated images and the provided instructions, and then compute loss functions to optimize latent features during the diffusion reverse process. To enhance spatial controllability and mitigate semantic failures in complex layout instructions, we leverage pixel-to-pixel correlations in the self-attention feature maps to align cross-attention maps and combine three loss functions constrained by boundary attention to update latent features. Comprehensive experimental results on both L2I and non-L2I pretrained diffusion models demonstrate that our method outperforms existing zero-shot L2I techniques both quantitatively and qualitatively in terms of image composition on the DrawBench and HRS benchmarks.

1. Introduction

In recent years, text-to-image (T2I) diffusion models such as DALL-E [19], Imagen [22], and Stable Diffusion [20] have demonstrated an impressive ability to generate high-resolution images from textual input. These models derive their ability to unify textual and visual latent spaces from supervised training on large-scale datasets [18, 24] of text-image pairs sourced from the internet. While such generative models achieve remarkable success in various downstream tasks, textual input alone cannot accurately specify spatial composition or the precise location of different concepts within generated images.

To tackle this deficiency, numerous studies [3, 11, 29, 30, 32] have explored layout-to-image (L2I) generation approaches that enable localization of concept positions in prompts using various forms of layout instructions such as semantic masks, bounding boxes, or sketches. By incorporating additional layout information, text-to-image (T2I) models can achieve more precise spatial controllability and generate datasets with specific ground-truth labels for data augmentation in supervised training [11, 29]. However, these L2I approaches require adapting the pretrained T2I models with additional control modules that need to be fine-tuned on large datasets containing paired images and layout annotations such as COCO [12].

The significant data and computational requirements for model fine-tuning restrict the use of such approaches in many data-scarce or resource-constrained scenarios. To this end, a line of methods for layout-to-image generation in a zero-shot manner that require no additional supervised training has been proposed [4, 16, 27, 28, 31]. These techniques leverage the cross-attention maps extracted from U-Net [21] in the diffusion model to quantify the discrepancy between a synthetic image, sampled from the initialized latent feature z_t based on the input text prompt, and the target layout instructions; the subsequent iterative update of the latent feature z_t helps reduce the discrepancy. However, it has been observed that cross-attention maps typically exhibit high scores in the central regions of the concepts while assigning negligible scores to their edges [16, 27, 31]. Consequently, the generated concepts often appear larger than or misaligned with the specified bounding boxes, which diminishes the accuracy of layout control and leads to unsatisfactory image generation. Additionally, the existing ap-

Figure 1. An illustration of zero-shot layout-to-image (L2I) generation using various diffusion models. Text prompts and layout information, where specific concepts are localized within corresponding bounding boxes, are provided as input to the pretrained diffusion models to generate images that align with the instructions. Our method, Bacon, is capable of guiding non-L2I diffusion models such as SD [20] and SDXL [17] to generate images based on layout instructions, while also enhancing L2I models such as Gligen [11] to achieve improved spatial control.

proaches often face overlapping cross-attention maps when the bounding boxes for multiple objects within the same concept are closely spaced with minimal gaps, leading to inaccuracies in object counts relative to the input prompt.

To improve spatial controllability and address semantic failures, we propose BACON, which stands for Boundary Attention Constrained generation, a novel zero-shot L2I approach. Specifically, we introduce two key design principles: (1) leveraging pixel-to-pixel correlations from visual self-attention maps to align the coarse-grained cross-attention maps, and (2) proposing a boundary attention constraint to address the previously discussed challenges of size misalignment and inaccurate counting. Self-attention maps capture pixel-to-pixel correlations in the visual features which can be used to filter noisy cross-attention maps and enhance the edges of concepts with low attention scores. Meanwhile, the boundary attention constraint ensures that cross-attention for each single object remains within the boundaries of the boxes, while promoting separation of the cross-attention maps of multiple objects within the same concept. Our comprehensive experimental results demonstrate that the proposed method outperforms existing zero-shot L2I methods both quantitatively and qualitatively in term of image compositions (*spatial relationship*, *size*, *color*, *object counting*) on the **DrawBench** [23] and **HRS** [1] benchmarks.

The main contribution of this paper can be summarized as follows:

- We investigate semantic failures in zero-shot L2I generation with complex layout inputs, focusing on the issue of overlapping cross-attention maps which leads to inaccurate object counting.
- We propose a novel method, BACON, that advances the L2I generation performance by incorporating self-attention enhancement to filter noisy cross-attention maps, and boundary attention constraints to prevent overlapping cross-attention maps.
- We perform comprehensive experiments comparing our method with the existing L2I approaches. The quantitative and qualitative experimental results demonstrate that our method achieves state-of-the-art performance as compared to the existing L2I techniques.

2. Related Work

2.1. Text-To-Image Diffusion Models

Recently, diffusion models [7, 25, 26] have achieved remarkable success in image generation, demonstrating greater stability and controllability compared to GANs [5]. Essentially, a diffusion model learns the dynamics of mapping natural image-like data to a prior (e.g., Gaussian) distribution. The seminal work LDM [20] facilitates high-resolution image synthesis by performing forward and reverse processes in the latent space rather than the pixel space, thereby addressing issues of low inference speed and high training costs. In this framework, a U-net [21] is trained as the denoiser $\boldsymbol{\epsilon}_\theta$ to approximate the noise $\boldsymbol{\epsilon}_t$ based on the perturbed latent variable $\mathbf{z}_t$ and the condition $\mathbf{c}$ with the loss function

$$L(\theta) = \mathbb{E}_{\mathbf{z}_0, \epsilon\sim\mathcal{N}(0,1),t}\left[\left\|\boldsymbol{\epsilon}_t - \boldsymbol{\epsilon}_\theta(\mathbf{z}_t, \mathbf{c}, t)\right\|^2\right]. \quad (1)$$

Building on the foundations of conditional generation with diffusion models, DALL-E [19] advances text-to-image (T2I) generation by utilizing the powerful image-language encoder CLIP [18] to transform text prompts into condition embeddings $\mathbf{c}$ for guiding the reverse process of diffusion models. Imagen [22] and Stable Diffusion [20] extend this work by enhancing the diffusion sampling technique, thus enabling more photorealistic and detailed image generation. However, relying solely on text prompts limits the ability to precisely control spatial composition, necessitating additional input in the form of layout instructions.

2.2. Layout-To-Image Generation

In addition to text prompts, layout-to-image (L2I) models require auxiliary layout instructions as input, *i.e.*, semantic masks or bounding boxes. Several approaches aim to map layout instructions into the condition embedding space of diffusion models through supervised fine-tuning on datasets consisting of paired layout and image data. These approaches either integrate bounding boxes into the text prompts [3, 29, 32] and fine-tune the text encoder, or incorporate additional modules or adapters alongside the text encoder to enhance the understanding of layout instructions [11, 30]. Another line of zero-shot approaches aims to address the computational and data challenges associated with supervised L2I methods. Inspired by the connection between spatial layouts of generated images and the cross-attention maps observed in [6], DenseDiff [10] guides the placement of objects in targeted positions by manipulating the cross-attention maps of the text encoder. Follow-up studies such as A&E [2] and BoxDiff [28] propose optimizing the latent variable z_t by maximizing the supremum of cross-attention scores located in specific regions during the reverse process of diffusion models. A&R [16] incorporates self-attention maps into the objective function to penalize objects that appear outside the designated boxes.

In contrast to previous studies that utilized the supremum, layout-guidance [32] uses the average of cross-attention scores in the objective function to update the latent variable z_t. Due to the typically coarse-grained and noisy nature of raw cross-attention maps, R&B [27] employs the Sobel Operator [8] to detect edges within these maps and select candidate boxes that encompass all edges for loss calculation. To address the additional computation and slower inference speed introduced by edge detection, concurrent work LoCo [31] directly leverages start-of-text tokens (SoT), end-of-text tokens (EoT), and self-attention maps to enhance cross-attention maps. However, none of the aforementioned approaches incorporate boundary attention constraints, leading to failures in object counting and precise spatial controllability.

3. Methodology

3.1. Zero-shot Layout-To-Image Generation

Zero-shot layout-to-image generation aims to generate images based on input text prompts and corresponding layout instructions using a pretrained diffusion model, without the need for additional parameter training or extra modules. Let us consider a text prompt $\mathbf{p} = \{\mathbf{p}_1, \ldots, \mathbf{p}_n\}$ and a set of bounding boxes $\mathcal{B} = \{\mathcal{B}_i \text{ for } \forall i \in \mathcal{I}, \text{where } \mathcal{I} \subset [n]\}$; here $\mathcal{B}_i = \{\mathbf{b}_1^{(i)}, \ldots, \mathbf{b}_{N_i}^{(i)}\}$ denotes the corresponding bounding boxes for phrase $\mathbf{p}_i$ consisting of N_i pairs of top-left and bottom-right points (x_1, y_1, x_2, y_2) that specify locations of N_i objects described by $\mathbf{p}_i$. The generated images should closely align with the text prompts while being consistent with the layout instructions defined by the set of bounding boxes $\mathcal{B}$. An illustration of zero-shot layout-to-image generation using bounding boxes as layout instruction is given in Figure 1.

3.2. Cross-Attention and Self-Attention Maps

In the T2I diffusion models, text prompt $\mathbf{p}$ is encoded via text tokens $\mathbf{e} = f_{\text{CLIP}}(\mathbf{p}) \in \mathbb{R}^{n \times d_e}$ using a pretrained CLIP encoder. These tokens are then input into the cross-attention layers where they are fused with the visual embedding characterized by $\mathbf{z}_t$. Specifically, in layer l, the visual and text embeddings are projected into the *query* $\mathbf{Q}_z^l \in \mathbb{R}^{hw \times d}$ and *key* $\mathbf{K}_e^l \in \mathbb{R}^{n \times d}$, respectively, allowing the cross-attention maps to be computed as

$$\mathbf{A}_c^l = \text{softmax}\left(\frac{\mathbf{Q}_z^l (\mathbf{K}_e^l)^\top}{\sqrt{d}}\right) \in [0,1]^{hw \times n}, \quad (2)$$

where n denotes the length of the text prompt (including SoT and EoT); d_e and d denote the dimensions of the text and visual embeddings, respectively; and h and w represent the height and width of the visual feature maps, respectively. Similarly, the image embeddings are projected into the *key* matrix $\mathbf{K}_z^l \in \mathbb{R}^{hw \times d}$, enabling computation of self-attention maps

$$\mathbf{A}_s^l = \text{softmax}\left(\frac{\mathbf{Q}_z^l (\mathbf{K}_z^l)^\top}{\sqrt{d}}\right) \in [0,1]^{hw \times hw} \quad (3)$$

which measure the pixel-to-pixel similarity in the visual features. These cross-attention and self-attention maps obtained from L different cross-attention layers are aggregated as

$$\mathbf{A}_c = \frac{1}{L}\sum_{l=1}^{L} \mathbf{A}_c^l, \quad \mathbf{A}_s = \frac{1}{L}\sum_{l=1}^{L} \mathbf{A}_s^l. \quad (4)$$

3.3. Boundary Attention Constrained Guidance

While prior studies [4, 27] demonstrated effectiveness of backward guidance, a procedure where cross-attention scores are used to form the loss utilized for optimizing

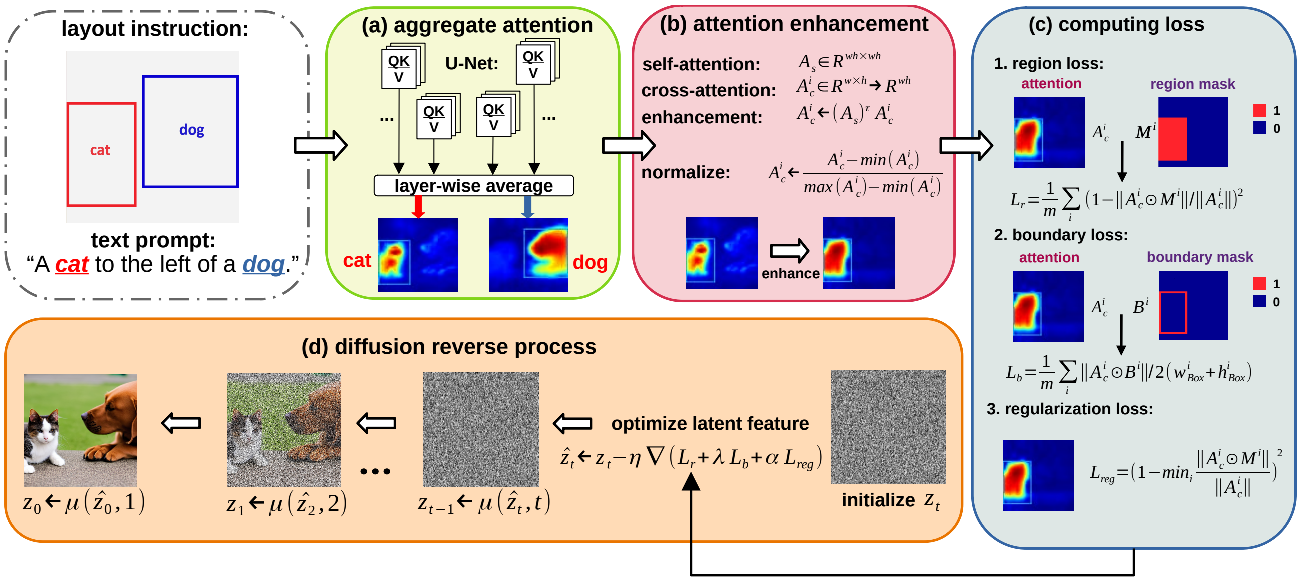


Figure 2. The overall framework of BACON for zero-shot L2I generation consists of four steps: (a) aggregating cross-attention and self-attention maps obtained from the language-vision fusion blocks by layer-wise averaging; (b) enhancing cross-attention maps with self-attention maps; (c) computing three losses and combining them with coefficients; (d) optimizing z_t by gradient descent in diffusion reverse process.

the latent feature z_t during the diffusion reverse process, the designed loss functions fail to address issues related to counting and semantic failures arising due to the coarse-grained nature of the cross-attention maps. In this section, we discuss the effect of attention enhancement and present three loss functions designed to address the problems encountered by previous schemes.

Attention enhancement. As depicted in the pink block in Figure 2, the raw cross-attention map for "cat" is coarse-grained, with attention dispersed across multiple parts of the object. It also shows notable scores for "dog" in the the cross-attention map for the "cat", likely due to the high correlation between "cat" and "dog" within the pretrained model, which causes inconsistency in the loss computation. Inspired by the previous studies [14, 15] that aim to build synthetic datasets by generating grounded labels using cross-attention, we leverage the global information contained in self-attention maps to enhance the cross-attention maps,

$$\mathbf{A}_c^{(i)} = (\mathbf{A}_s)^\tau \cdot \mathbf{A}_c^{(i)} \in [0,1]^{wh}, \tag{5}$$

where i denotes the index of the phrase $\mathbf{p}_i$, and τ is a power coefficient for adjusting the magnitude of enhancement (set to 1 by default). For dimensional consistency, we normalize and reshape $\mathbf{A}_c^{(i)}$ according to

$$\mathbf{A}_c^{(i)} = \textbf{reshape}\left(\frac{\mathbf{A}_c^{(i)} - \min(\mathbf{A}_c^{(i)})}{\max(\mathbf{A}_c^{(i)}) - \min(\mathbf{A}_c^{(i)})}\right) \in [0,1]^{w\times h}. \tag{6}$$

Essentially, the self-attention map $\mathbf{A}_s$ captures the pairwise correlations between pixels, allowing salient parts in the raw cross-attention maps to propagate to the most relevant regions. Using these enhanced cross-attention maps, we compute three losses that are then utilized for improving the L2I generation.

Region-attention loss. Similar to the prior studies [4, 16, 27], the key idea of region-attention loss is to measure the proportion of cross-attention map $\mathbf{A}_c^{(i)}$ outside bounding boxes $\mathcal{B}_i \in \mathcal{B}$ and compute the average of these proportions for normalization as

$$\mathbf{M}^{(i)}[x,y] = \begin{cases} 1, & \text{if } (x,y) \text{ inside } \mathcal{B}_i \\ 0, & \text{if } (x,y) \text{ outside } \mathcal{B}_i \end{cases}, \tag{7}$$

$$L_r = \frac{1}{|\mathcal{B}|}\sum_{i\in\mathcal{I}}\left(1 - \frac{\mathbf{A}_c^{(i)} \odot \mathbf{M}^{(i)}}{\sum_{x,y}\mathbf{A}_c^{(i)}[x,y]}\right)^2, \tag{8}$$

where $\mathbf{A}_c^{(i)}[x,y]$ and $\mathbf{M}^{(i)}[x,y]$ are the (x,y)-th element in $\mathbf{A}_c^{(i)}$ and $\mathbf{M}^{(i)}$, respectively. However, relying solely on region-attention loss L_r cannot ensure high-quality generation in the scenarios where multiple objects constrained

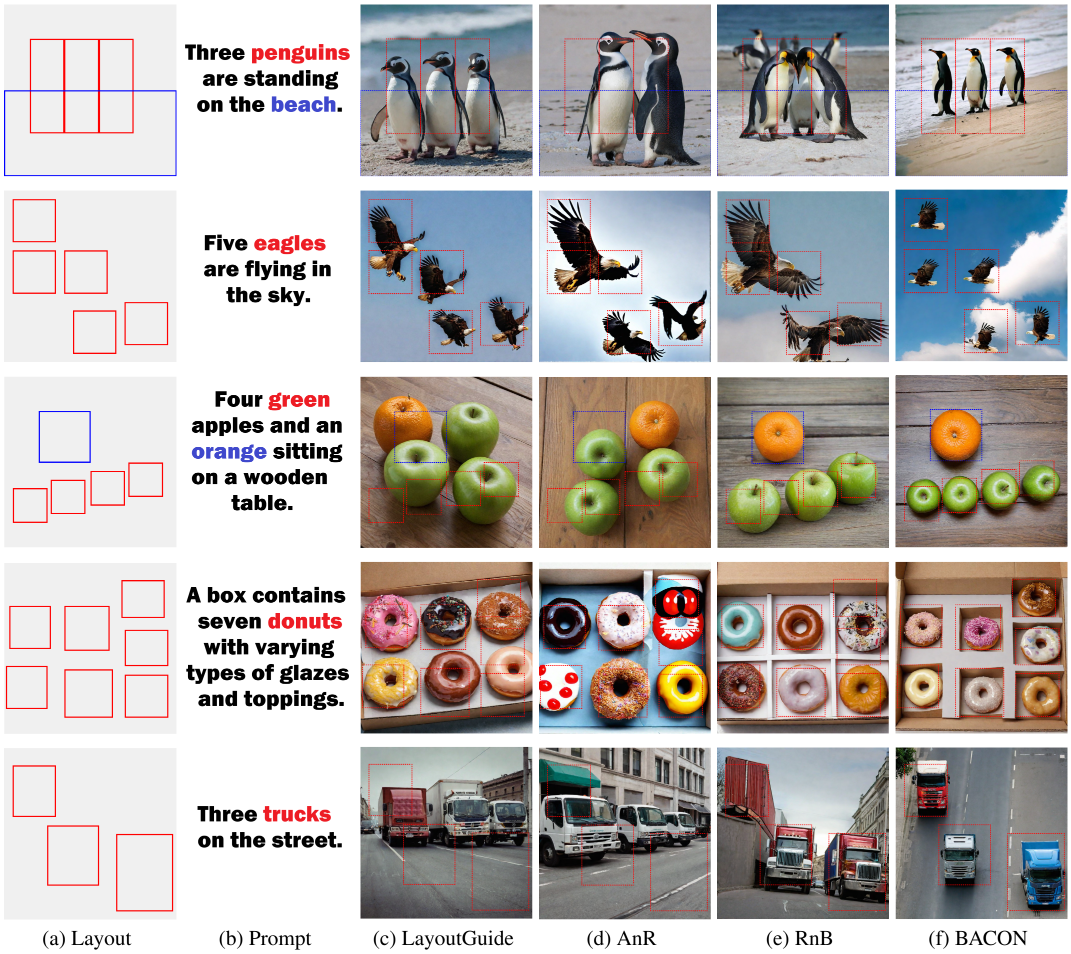


Figure 3. Visual comparison with different zero-shot L2I schemes based on Stable Diffusion XL [17]. The layout input and text prompt are shown in the first and second columns, respectively. The layout instructions are also annotated on the generated images with dashed boxes. Our method, BACON, significantly outperforms prior schemes in terms of spatial control and counting accuracy.

by the same $\mathcal{B}_i$ have overlapping cross-attention scores, resulting in incorrect counting in the generated image.

Boundary-attention loss. As previously mentioned, adjacent bounding boxes for multiple objects described by the same phrase often lead to incorrect counting in the L2I generation due to the interference between cross-attention scores. However, the region-attention loss may remain small as long as these cross-attention scores are inside the target bounding boxes. We propose a boundary-attention loss that aims to isolate adjacent cross-attention maps corresponding to different objects,

$$\mathbf{B}^{(i)}[x,y] = \begin{cases} 1, \text{ if } (x,y) \text{ on } \mathcal{B}_i \\ 0, \text{ if } (x,y) \text{ not on } \mathcal{B}_i \end{cases}, \tag{9}$$

$$L_r = \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{I}} \frac{\mathbf{A}_c^{(i)} \odot \mathbf{B}^{(i)}}{2(w_{\text{Box}} + h_{\text{Box}})}, \tag{10}$$

where $w_{\text{Box}} = \sum_{k=1}^{N_i} w_k^{(i)}$, $h_{\text{Box}} = \sum_{k=1}^{N_i} h_k^{(i)}$, and $w_k^{(i)}$ and $h_k^{(i)}$ denote the width and height of the bounding box $\mathbf{b}_k^{(i)}$, respectively. With the proposed boundary-attention loss, we are able to force z_t to generate cross-attention maps without overlap between multiple objects and thus help improve the accuracy of counting.

Regularization loss. While the region-attention and boundary-attention losses generally help localize generated objects within the target bounding boxes, these losses may be minimal when an incorrect number of objects has cross-attention scores completely contained within the bounding boxes (i.e., experiencing no boundary crossing). To prevent bad generation in such scenarios, we propose a regularized loss that ensures the assigned objects do not have void cross-attention map,

$$L_{\text{reg}} = \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{I}} \left(1 - \min_k \frac{\mathbf{A}_c^{(i)} \odot \mathbf{M}^{(i,k)}}{\sum_{x,y} \mathbf{A}_c^{(i)}[x,y]}\right)^2, \quad (11)$$

where $\mathbf{M}^{(i,k)}$ is a subset of $\mathbf{M}^{(i)}$ indicating the location of the k-th object in $\mathcal{B}_i$.

Latent Feature Optimization. At each sampling time step in the reverse process, L_{bacon} can be computed as the weighted summation of L_{r}, L_{b} and L_{reg},

$$L_{\text{bacon}} = L_{\text{r}} + \lambda L_{\text{b}} + \alpha L_{\text{reg}}, \quad (12)$$

where λ and α control the intervention strength of L_b and L_{reg}, respectively. We compute and use the gradient of L_{bacon} to update z_t as

$$\hat{z}_t \leftarrow z_t - \eta \nabla L_{\text{bacon}}, \quad (13)$$

where parameter η controls the size of the updates. After t_{optim} iterations or an early stop that happens when L_{bacon} becomes smaller than a predetermined threshold, the optimized latent feature $\hat{z}_t$ is forwarded to the U-Net for predicting the latent feature z_{t-1} at the previous time step.

4. Experiments

4.1. Experimental Setup

Datasets and base models. Following the strategy in the prior studies [16, 27], we perform experiments on a subset of two widely used benchmarks **HRS** [1] and **Drawbench** [23]. Specifically, we use four tracks from the HRS benchmark – **spatial relationship**, **size**, **color**, and **object counting** – which include 1002, 501, 501, and 3000 text prompts, respectively. These prompts, along with the corresponding layout instructions generated by Chat-4 in [16], are used to evaluate the performance of our method and baseline approaches both quantitatively and qualitatively. Similarly, 39 text prompts from Drawbench involving **spatial** and **counting** specifications are also used in the evaluation. We conduct experiments with the widely-used Stable Diffusion (SD) 1.5 [20] as the base model and perform an ablation study with SD-XL [17] and the fine-tuned L2I model, Gligen [11]. The sampling time step is set to 50, with the classifier-free guidance weight set to 7.5. Optimization is applied only to the latent feature z_t during the first 10 sampling steps, and η is set to 70. Unless specified otherwise, the hyper-parameters λ and α are both set to 0.5.

Baselines and metrics. We compare our proposed scheme, BACON, to six state-of-the-art methods: A&E [2], BoxDiff [28], Layout-Guidance [4], A&R [16], R&B [27], and LoCo [31]. To quantitatively assess our method against these baselines, we use the state-of-the-art object detector, Ground-DINO [13], to detect objects in the synthetic images and predict bounding boxes. These predicted boxes are then compared with the ground truth. We compute precision, recall, and F1 metrics to comprehensively evaluate BACON's performance in object counting. By comparing the area and centroid of the predicted and ground-truth boxes, we compute the accuracy of object size and spatial relationships. Additionally, Ground-DINO predicts the color of detected objects, which we use to compute color accuracy. The details of the metric computations can be found in the Appendix.

4.2. Visual Comparisons

In Figure 3, we present visual comparisons between BACON and several competing L2I schemes – Layout, A&R, and R&B – deployed on SD-XL [17]. To thoroughly evaluate the performance of these schemes, we use several complex inputs featuring multiple objects distributed in random positions, which makes it more challenging to generate images with precise object counts. As shown in the figure, BACON demonstrates significant improvement over the baselines in terms of (1) better alignment within the bounding boxes, and (2) more precise object counting. Although the prior works typically generate objects within the corresponding bounding boxes, most of these objects are only partially inside the boxes or even appear in the bounding boxes of other objects due to coarse-grained cross-attention maps, as we discussed earlier. For example, Layout [32] and A&R [16] fail to generate penguins (1st row) within the red bounding boxes and an orange (3rd row) within the blue bounding box. Additionally, none of these prior schemes can generate the correct number of objects according to the prompts and bounding boxes specifications.

To better understand the miscounting failures, we visualize the cross-attention maps obtained from these schemes as shown in Figure 4. Since the cross-attention maps for objects described by the same phrase in the prompt are not independent, existing zero-shot L2I schemes, which aim to encourage cross-attention within the corresponding boxes, often produce overlapping cross-attention maps. For instance, in the RnB scheme, the cross-attention scores are concentrated within three boxes, representing a single eagle, even though three eagles are meant to be depicted. However, boundary-attention loss proposed in BACON can isolate these cross-attention scores to ensure they depict independent objects in the generated images.

4.3. Quantitative Results

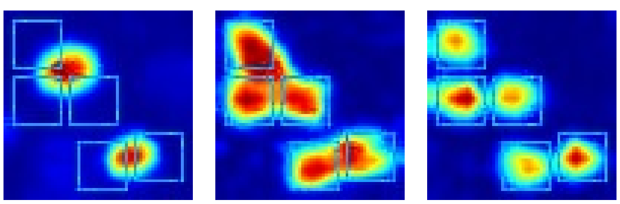
We validate the improvement in spatial controllability and object counting of the proposed BACON framework as

Table 1. Quantitative comparisons with baseline schemes. The precision (%), recall (%) and F1 score (%) with respect to object counting are reported in the table. The reported average inference time for generating one image is for a single NVIDIA A100 GPU.

Method	DrawBench			HRS-Bench			Inference (s)
	Precision	Recall	F1	Precision	Recall	F1	
SD1.5	76.51	70.58	71.35	71.86	52.19	58.31	14
+ A&E	75.52	66.17	76.27	73.10	54.79	60.47	42
+ BoxDiff	86.36	77.94	86.17	73.57	63.33	68.07	42
+ LoCo	86.04	54.41	66.66	85.61	59.55	71.23	39
+ Layout	85.93	80.88	83.33	87.25	63.10	73.24	**37**
+ A&R	86.00	63.23	72.88	87.93	56.69	68.94	45
+ R&B	87.50	82.35	84.84	85.73	68.53	76.17	84
+ **BACON**	**93.84**	**89.71**	**91.72**	**89.51**	**68.92**	**77.88**	41

Table 2. Quantitative comparisons with baseline schemes. The evaluated accuracy (%) with respect to spatial relationship, size relationship and color are reported in the table.

Benchmarks	Metrics	SD	A&E	BoxDiff	LoCo	Layout	A&R	R&B	**BACON**
DrawBench	Spatial	12.50	15.00	25.00	40.00	45.00	40.00	55.00	**60.00**
HRS-Bench	Size	11.23	14.77	12.77	14.56	14.37	12.17	16.17	**16.96**
	Color	13.01	18.27	34.69	37.88	31.18	30.15	36.36	**39.74**
	Spatial	10.80	17.56	19.76	37.42	33.73	25.94	47.80	**50.39**



(a) AnR (b) RnB (c) BACON

Figure 4. Visualization of cross-attention maps with the prompt: *Five eagles are flying in the sky.*

compared to existing state-of-the-art zero-shot L2I approaches through quantitative experiments. As shown in Tables 1 and 2, BACON outperforms state-of-the-art baselines on both DrawBench and HRS benchmarks. Notably, BACON demonstrates significant improvements in object counting across three metrics: precision, recall, and F1 score. On DrawBench, BACON outperforms the best baseline, R&B, by 6.34%, 7.36%, and 6.88% in precision, recall, and F1 score, respectively. On the larger HRS benchmark, BACON consistently achieves the best performance among all L2I schemes, with improvements of 3.78%, 0.39%, and 1.71% in precision, recall, and F1 score, respectively. Furthermore, BACON surpasses R&B in the spatial relationship metric on both DrawBench and HRS benchmark, with improvement of 5% and 2.59%. Additionally, BACON achieves the best performance in color and size metrics, though its advantage over R&B in these areas is relatively small.

Nevertheless, R&B requires to apply Sobel operator [9] to detect edge of cross-attention map for creating minimum bounding rectangle (MBR) which is then used to compute region-aware loss. Therefore, R&B needs more computation in the process of optimizing latent feature z_t which leads to longer inference time. As shown in Table. 1, R&B needs more than double time in average for generating one image compared to BACON even though R&B has comparable performance to BACON.

4.4. Plug and Play with BACON

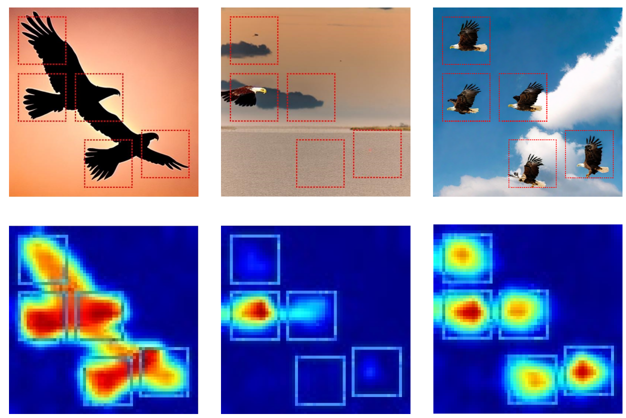
Although we mainly conduct experiments based on SD 1.5, BACON as well as these prior zero-shot L2I schemes do not assume specific model architecture and can be plugged into arbitrary pre-trained Text-to-Image models using cross-attention blocks. We further evaluate performance of BACON by deploying it on another L2I model, GLIGEN [11], trained by supervised learning with labeled datasets. As shown in Table 3, all zero-shot L2I schemes demonstrate improved performance across nearly all metrics quantifying controllability. Compared to SD 1.5, GLIGEN has the ability to perceive input bounding boxes and incorporate layout information into the prior conditions for sampling the initial noise z_0. With the initial latent feature z_0 generated by GLIGEN, the reverse sampler can synthesize an image with a layout that more closely aligns with the given instructions than when using z_0 produced by SD 1.5. According to Table 3, BACON consistently delivers the best performance in object counting, spatial relationships, and

Table 3. Zero-shot schemes can be integrated into existing fully-supervised layout-to-image schemes, *e.g.*, GLIGEN [11]. We compare the improvement of GLIGEN augmented with BACON vs. the competing schemes.

Method	DrawBench		HRS-Bench			
	Counting (F1)	Spatial	Counting (F1)	Spatial	Size	Color
GLIGEN	77.03	40.00	68.32	44.81	35.31	30.55
+ LoCo	76.61	40.00	71.89	49.48	38.33	37.97
+ Layout	80.59	55.00	81.85	50.68	29.64	35.05
+ A&R	76.27	55.00	77.66	52.17	30.72	38.74
+ R&B	87.59	**65.00**	79.10	53.88	39.72	40.59
+ **BACON**	**93.22**	**65.00**	**83.34**	**55.76**	**43.31**	**42.48**

Table 4. The results of experiments on BACON under three settings: (1) L_{bacon} only includes the region-aware loss (setting R); (2) L_{bacon} includes both the region-aware loss and boundary-aware loss (setting $R + B$); (3) using the complete loss proposed in Eq. 12 (setting $R + B + Reg$).

Method	HRS-Bench			
	Counting	Spatial	Size	Color
SD1.5	71.35	10.80	11.23	13.01
+ R	73.48	30.57	14.15	30.67
+ $R + B$	76.03	43.61	15.63	32.53
+ $R + B + Reg$	**77.88**	**50.39**	**16.96**	**39.74**
SD-XL	76.99	34.23	19.96	25.20
+ R	76.71	33.34	30.34	27.42
+ $R + B$	78.09	38.82	27.34	28.42
+ $R + B + Reg$	**80.43**	**42.31**	**38.12**	**32.12**
GLIGEN	68.32	44.81	35.31	30.55
+ R	79.94	49.43	30.87	35.46
+ $R + B$	82.63	53.08	38.12	40.44
+ $R + B + Reg$	**83.34**	**55.76**	**43.31**	**42.28**



(a) R (b) $R + B$ (c) $R + B + Reg$

Figure 5. Visualization of cross-attention maps of targeting objects generated in three settings: (1) R; (2) $R + B$; (3) $R + B + Reg$.

color. While R&B outperforms BACON in the size metric, BACON achieves the second-best performance. In experiments with SD 1.5, plain SD 1.5 generates initial noise z_0 corresponding to undesirable cross-attention maps that are minimally modified through optimization, resulting in limited improvement of BACON on the size metric. In contrast, GLIGEN generates improved initial noise z_0 that facilitates BACON's enhancement.

4.5. Ablation Study

To investigate the effect of L_{r}, L_{b} and L_{reg}, the components of BACON's loss / objective function, we conduct additional experiments using SD 1.5, SD-XL, and GLIGEN under three settings: (1) only the region-attention loss L_{r} is used (setting R) (2) L_{r} is combined with the boundary-attention loss L_{b} (setting $R + B$); (3) using the complete loss objective as described in Eq. 12 (setting $R + B + Reg$).

When using only the region-attention loss, BACON synthesizes images similar to those produced by R&B, with the cross-attention map exhibiting the same overlapping issue discussed earlier – see the illustration in Figure 5(a). Adding the boundary-attention loss to the objective resolves the overlapping problem but may cause attention vanishing, as shown in Figure 5(b). This issue does not occur when there is only one bounding box per phrase, due to the constraint imposed by L_{r}. Moreover, the regularization loss L_{reg} addresses the attention vanishing problem, ensuring that each bounding box corresponds to exactly one object in the generated images, as shown in Figure 5(c).

The quantitative results in Table 4, obtained in experiments on three distinct pretrained diffusion models, further demonstrate the improvement achieved by including L_{b} and L_{reg} in the objective function. However, the attention vanishing problem typically arises in settings where multiple objects are assigned adjacent bounding boxes. The text prompts in HRS are relatively simple, so there is minimal difference between $R + B$ and $R + B + Reg$ settings.

5. Conclusion

We proposed BACON, a novel zero-shot layout-to-image (L2I) generation scheme utilizing pre-trained diffusion models. We identify two inherent issues that lead to semantic errors and incorrect object counts in generation: (1) coarse-grained cross-attention maps, and (2) overlapping cross-attention. To address these issues, we leverage self-attention maps to refine cross-attention maps and design an objective that combines three distinct loss functions. Comprehensive quantitative and visual results demonstrate that BACON outperforms state-of-the-art L2I schemes and consistently adapts well across varying model architectures.

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