

Zero-shot Text-guided Infinite Image Synthesis with LLM guidance

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Abstract. Text-guided image editing and generation methods have diverse real-world applications. However, text-guided infinite image synthesis faces several challenges. First, there is a lack of text-image paired datasets with high-resolution and contextual diversity. Second, expanding images based on text requires global coherence and rich local context understanding. Previous studies have mainly focused on limited categories, such as natural landscapes, and also required to train on high-resolution images with paired text. To address these challenges, we propose a novel approach utilizing Large Language Models (LLMs) for both global coherence and local context understanding, without any high-resolution text-image paired training dataset. We train the diffusion model to expand an image conditioned on global and local captions generated from the LLM and visual feature. At the inference stage, given an image and a global caption, we use the LLM to generate a next local caption to expand the input image. Then, we expand the image using the global caption, generated local caption and the visual feature to consider global consistency and spatial local context. In experiments, our model outperforms the baselines both quantitatively and qualitatively. Furthermore, our model demonstrates the capability of text-guided arbitrary-sized image generation in zero-shot manner with LLM guidance.

Keywords: Image outpainting · Large language models(LLMs) · Diffusion models

1 Introduction

Recently the field of image generation has witnessed a significant advancement in synthesizing high-resolution images from text inputs. However, the existing studies [6, 13, 14, 19] face difficulties in generating arbitrary-size image from text with diverse context because of the following challenges. Firstly, there is a lack of high-resolution text-image paired datasets with diverse contexts. Several high-resolution images [24] may not include rich context since most of them are online shopping product photos or individual portraits. Secondly, it is not just about repetitive expansion; it is essential to expand image depicting rich content based on given text description, while maintaining visual consistency [14]. Most prior

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research [4, 13, 14] has focused on datasets [4, 30] within limited categories, such as natural landscapes. Nevertheless, in the real world, it is desirable to depict the detailed surroundings beyond a given image, guided by textual descriptions, while ensuring visual consistency with the overall context. Therefore, unlike prior image outpainting models [4, 7, 11–14, 25] that focus on limited datasets or unconditional image outpainting, we address this issue in a zero-shot manner by shifting the image autoregressively based on diverse contexts utilizing Large Language Models (LLMs).

Recent research [1, 9, 26, 28] has demonstrated that LLMs can perform multi-modal tasks, while understanding the visual content as text descriptions. Furthermore, as illustrated in Figure 1, we empirically find that LLMs are able to describe (and thus *imagine*) the scene beyond the image in text, using only the image captions. This shows that, with the LLMs, image captioning datasets can encompass diverse contexts extending beyond its resolution.

By leveraging the capabilities of the LLMs, we propose a novel approach that can expand an image to arbitrary size without the need for high-resolution, text-image paired datasets. Our model leverages the LLMs to incorporate global contextual information and uses a diffusion model to generate high-quality and coherent images across various contexts.

To address the lack of high-resolution text-image paired datasets with rich contexts, we utilize the LLMs to generate the captions that describe scenes beyond the image from the existing datasets [10, 15, 21]. We take a two-step process. As depicted in Figure 1 (a), first, we generate imaginary local captions outside of the image from the annotated caption of existing text-image paired datasets. Each of the generated captions describes details about individual unfolding scenes. Next, as shown in Figure 1 (b), we summarize the annotated caption and the generated local captions to create a global caption that describes the surroundings of the image for global and local context consistency.

The global image caption describes the entire image beyond the local image, while the local captions provide semantic details for filling in the local masked image. We input these captions into our proposed diffusion model [22] as a textual condition to fill in the local masked image while maintaining the global context consistency as illustrated in Figure 2.

In order to expand images guided by text while considering both global and local contexts, as illustrated in Figure 2, we train our model using global and local captions as textual conditions and CLIP [20] visual features as visual condition, with the local masked image serving as input. We make four local masked images by masking the top, bottom, left, and right sections. During inference, we expand the image gradually, by shifting patch by patch with LLM guidance. We input a generated local image into the LLM and it generates a next local caption in an autoregressive manner for expanding the image.

Experimental results show that our model outperforms the baselines, demonstrating the ability to arbitrarily expand images in a zero-shot manner with text and generate realistic high-resolution images with rich context.

In summary, our contributions are as follows:

- To the best of our knowledge, we are first to propose zero-shot text-guided infinite image synthesis without training on high resolution image. We introduce a novel approach with LLM guidance for zero-shot text-guided image outpainting.
- We can expand images preserving visual consistency by shifting local masked images in an autoregressive manner. Additionally, we can generate arbitrary-sized images that incorporate diverse contexts with global consistency by conditioning on the global caption and the local caption generated with LLM effectively.
- In experimental results, our model outperforms baselines in both quantitative and qualitative evaluations. These results show the potential of our model for real-world applications.

2 Related Work

Image Inpainting. Text-guided image inpainting, which involves filling in a portion of an image based on input text, is closely related to text-guided image outpainting [4]. Existing image inpainting methods [2, 5, 17, 18, 22, 29] include models based on GANs and diffusion-based methods. Recently, various works [2, 8, 18, 22] have focused on enhancing inpainting capabilities across general domains with diffusion models. Stable Diffusion Inpainting [22], Blended-Latent Diffusion [2] and PowerPaint [31] involve taking an image and a mask as input and then filling in the image based on the text. These studies effectively edit the masked portions of given images from text, understanding the content well.

Image Outpainting. There are various studies [4, 7, 11, 14, 25, 27] aimed at infinitely expanding images. InfinityGAN [14], a GAN-based model, proposes a method for generating arbitrarily sized images unconditionally. This approach is trained on landscape image dataset aiming to capture both local and global consistency while generate realistic arbitrarily sized images without repetitive patterns. Additionally, InOut [4], which uses GAN inversion for image outpainting, avoids the need of sequential outpainting. While previous models [4, 12–14] have attempted to address the challenging task of image outpainting, the lack of high-resolution text-image paired dataset still leads these methods to focus on limited categories, such as natural landscapes.

Text-guided Image Outpainting. The task of arbitrarily extending images from text is more challenging than unconditional image outpainting due to the scarcity of datasets and the difficulty of maintaining global and local consistency. Nuwa-Infinity [13] successfully performs text-guided image outpainting in an autoregressive manner. However, due to the lack of high-resolution datasets containing rich content, Nuwa-Infinity, like previous studies [4, 12, 14], performs text-guided image outpainting on limited datasets [4, 30] such as nature landscapes. To the best of our knowledge, we are the first to arbitrarily expand images from general text using LLM and diffusion model in a zero-shot manner.

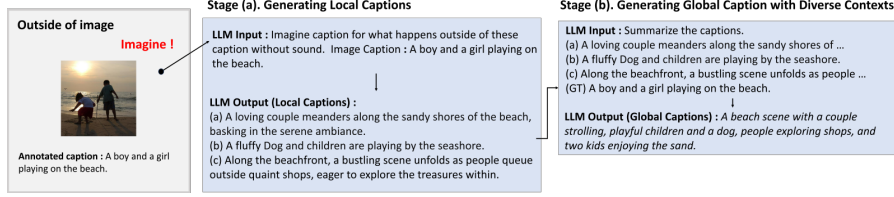


Fig. 1: Global caption generation with LLM for training. To address the lack of text-image paired datasets with high resolution images that have rich context, we generate our global caption from local image captions using the LLM.

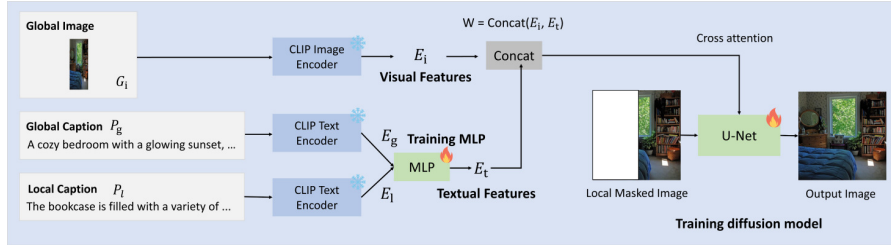


Fig. 2: Model architecture. We fine-tune the diffusion model [22] using local masked image as input, conditioned on the W vector. Green boxes are trainable networks. Blue boxes are frozen networks.

3 Method

In the training stage, we train our model conditioned on a global caption, local caption, and visual features. In the inference stage, we expand the given image conditioned on the global caption, generated local caption and the visual feature. Through this approach, our model is able to perform the text-guided image outpainting task without high-resolution text-image paired datasets.

3.1 Global Caption Generation for Training

To train the model without a high-resolution text-image paired dataset, we generate imaginary global captions describing the expanded image based on the local captions using the LLM in training step. We consider a 512×512 resolution image as a local image, and an annotated caption of the image as a local caption. We generate a global caption that depicts diverse contexts from the annotated caption by leveraging the LLM. To generate a global caption, we follow two steps. Firstly, using an annotated caption as a local caption, we create imaginary *local captions* that describe the surroundings of the given image by using the LLM. As seen in Figure 1, in the stage (a), we input an annotated caption, “A boy and a girl playing on the beach.”, to the LLM with the instruction, “*Imagine caption for what happen outside of these caption without sound.*”. Then the LLM generates several local captions following the content of the given caption, such as “A loving couple meanders along the sandy shores of the beach, basking in the serene

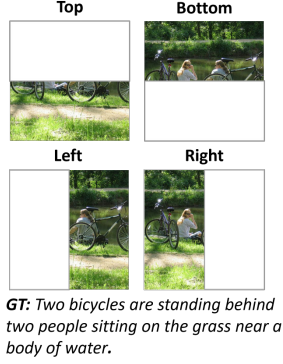


Fig. 3: Masked image generation. We mask the images in four directions: top, bottom, left, and right.

ambiance.”. These generated local captions depict various local contexts within the expanded image by imagining the scene outside of the given local image. Next, in the stage (b), we create a *global caption* by summarizing the annotated caption and the generated local captions. Using the instruction, “*Summarize the captions*”, we generate a global caption, “A beach scene with a couple strolling, playful children and a dog, people exploring shops, and two kids enjoying the sand.”.

The global caption summarizes an annotated caption and a variety of imaginary local captions, thereby acquiring the global context of the image that is expanded from the local image. Also we empirically found that this two-step process can generate a global caption with more rich contents for the given local image by leveraging the LLM.

3.2 Training Pipeline

To expand images from general text, we fine-tune a pre-trained Stable Diffusion model [22]. As shown in Figure 3, first, we take local masked images M_l , each masked on the top, bottom, left, and right.

To maintain spatial information and global visual consistency of the images generated thus far, we input a generated global image G_i to the CLIP [20] vision encoder to extract visual feature E_i . Since there is no high-resolution image available in the training step, we use an unmasked area of the local masked image M_l as the generated global image G_i . Also, as shown in Figure 2 and Equation 1, we concatenate the embeddings E_g of global caption P_g with embeddings E_l of local captions P_l . Then we extract the fused textual feature by compressing the concatenated vector through a Multi-Layer Perceptron (MLP) composed of two linear layers. As we fine-tune our model conditioned on the compressed textual feature, our model can reflect both global and local contexts when generating images.

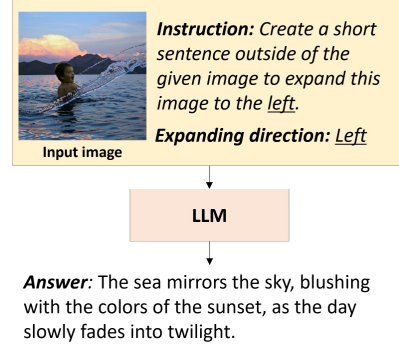


Fig. 4: Local caption generation during inference. Using the input image and the instruction, the LLM generates an imaginary local caption.



Fig. 5: Inference Pipeline. We expand the local image autoregressively by conditioning on the global caption, local caption generated by the LLM and the visual feature. The figure image is generated with a 16-step process (4608×512). The red box is a local masked image, and the blue box is an expanded global image that is input into the CLIP image encoder.

$$E_t = MLP(E_g, E_l), \quad W = \text{Concat}(E_i, E_t) \quad (1)$$

To consider both textual and visual information effectively, we expand the cross-attention dimension of the U-Net in the pre-trained Stable Diffusion model [22]. After matching the dimension of the visual feature E_i (77×768) with the textual feature E_t (77×768), we concatenate them to create the W vector (154×768). Then we apply it as cross-attention to the U-Net. We train our model end-to-end using MSE loss, following Stable Diffusion [22]. We provide detail in the supplementary material.

Through this method, we train our model to expand the given local image to represent various contexts while maintaining visual consistency, by conditioning on the global caption, local caption, and visual features.

3.3 Inference Pipeline

We perform inference as shown in Figure 5. First, a local image and a global caption are inputted. We then apply a mask to the image in the direction of the

desired expansion to expand this image. And then, we generate an imaginary local caption with the LLM to fill in the local masked image. Figure 4 illustrates the process of generating an imaginary local caption. We input a local image and the instruction “*Create a short sentence outside of the given image to expand this image to the left.*” into the LLM to generate the local caption. By providing the expanding direction with the instruction, the LLM can effectively imagine the local caption which describes the scene surrounding the given local image.

Next, we shift the local masked image autoregressively. To expand a local image that incorporates the details of the local caption while considering the global semantic context, we use both the global and local captions as text condition. After extracting the embeddings of these captions, we concatenate the vectors. Then we input the vector into the MLP layer. By compressing the vector, we extract the textual feature from global and local captions, E_t (77×768). Additionally, to maintain visual consistency and understand the spatial information of the previously generated image, we use the CLIP image embedding of the generated global image as the visual feature, E_i (77×768). Then we create a conditioning vector, W (154×768) by concatenating both textual and visual features. Our model expands an image with each step conditioning on the vector, W , with an expanded cross-attention dimension (154×768). This enables us to generate an output image by considering on the textual and visual features. Also we can arbitrarily extend the input local image in an autoregressive manner while maintaining global coherence and local consistency.

4 Experiment

4.1 Experimental Setup

Implementation detail. We use 100,000 text-image pairs from the MS-COCO [15] dataset. We construct global captions on MS-COCO [15] using GPT 3.5 [3] following the Section 3.1. We fine-tune Stable Diffusion 1.5 [22] for 25 epochs with a batch size of 20, using two NVIDIA A100 GPUs. We use LLAVA 1.6 [16] to generate the local captions during the inference. We provide the training dataset examples to the supplementary material.

Baselines. Since we focus on text-guided infinite image synthesis in zero-shot manner, it is challenging to select the baseline models. For example, previous models [4, 12–14], such as InfinityGAN [14] performs the unconditional image outpainting and NuWA-Infinity [13] is mainly focused on the limited categories such as natural landscapes. Also as NuWA-Infinity [13] require high resolution training dataset and do not provide the official code, we cannot compare with it. Therefore, we compare our model with the text-guided inpainting models such as SD Inpainting model [22], Blended Latent Diffusion [2] and PowerPaint [31] which can be applied to text-guided image outpainting, and for which pre-trained models are available. We use only global caption as the text condition for the baselines with the same masking setting as ours.

Evaluation Datasets. To evaluate the text-guided image outpainting performance, we utilize image captioning datasets, MS-COCO [15], Flickr 8k [10] and

Table 1: Quantitative evaluations with baselines. $\times 4$ corresponds to the image being expanded four times, and $\times 8$ corresponds to the image being expanded eight times.

Method	Expand $\times 4$						Expand $\times 8$					
	MS-COCO		Flickr		Pascal		MS-COCO		Flickr		Pascal	
	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP
SD Inp [22]	14.31	27.41	11.03	28.37	14.53	27.62	8.55	27.41	6.25	28.37	8.88	27.62
BLD [2]	11.88	27.73	10.78	28.82	12.79	27.96	6.39	27.73	6.86	28.82	8.11	27.96
PP [31]	12.91	27.42	9.75	28.37	9.88	27.63	7.37	27.42	6.01	28.37	7.15	27.63
Ours	16.05	27.94	11.04	28.83	15.07	28.07	9.97	27.94	7.25	28.83	9.36	28.07

UIUC Pascal [21], which are text-image paired datasets with various context. We randomly use 1,000 text-image pair samples for our evaluation on each datasets. We divided dataset into four equal parts, each comprising 25% of the data, and applied masking as shown in Figure 3: top, bottom, left, and right. To generate a global caption, we use GPT-3.5 [3] based on the annotated caption, as described in Section 3.1.

Evaluation Metrics. We compare our model with the baselines using CLIP-SIM [20] (average CLIP similarity between entire expanded image and global caption), and Inception score (IS) [23] as evaluation metrics. We are unable to use FID and KID evaluation metrics because we do not have the ground truth images for the extended images.

4.2 Quantitative Result

To evaluate the performance of our model, we compare our model with SD Inpainting model (SD Inp) [22], Blended Latent Diffusion (BLD) [2] and Power-Paint (PP) [31] on three datasets [10, 15, 21].

Image Extension $\times 4$ experiment. We expand the image four times, and the resolution of the expanded image is 1536×512 or 512×1536 . As shown in Table 1, our model outperforms the baselines [2, 22, 31] in terms of IS [23] and CLIPSIM [20]. Since our model expands an image conditioned on a local caption generated by LLM, which represents the details within a global caption, the expanded image is faithful to the global caption while preserving its contextual coherence. However, the baseline models repetitively expand images and do not contain the rich context beyond the global caption.

Image Extension $\times 8$ experiment. We expand the image eight times, and the resolution of the expanded image is 2560×512 or 512×2560 . As shown in Table 1, our model shows better performance than the baseline models in IS [23] and CLIPSIM [20]. These results show that our model can maintain visual quality and global coherence while generating images with a more diverse context as it extends more images.

4.3 Qualitative Analysis

We qualitatively analyze the generated results of our model and baselines, specifically focusing on the aspects, “text matching”, “image quality”, and “global coherence”. Also we provide more generated samples with larger resolutions in the supplementary material.

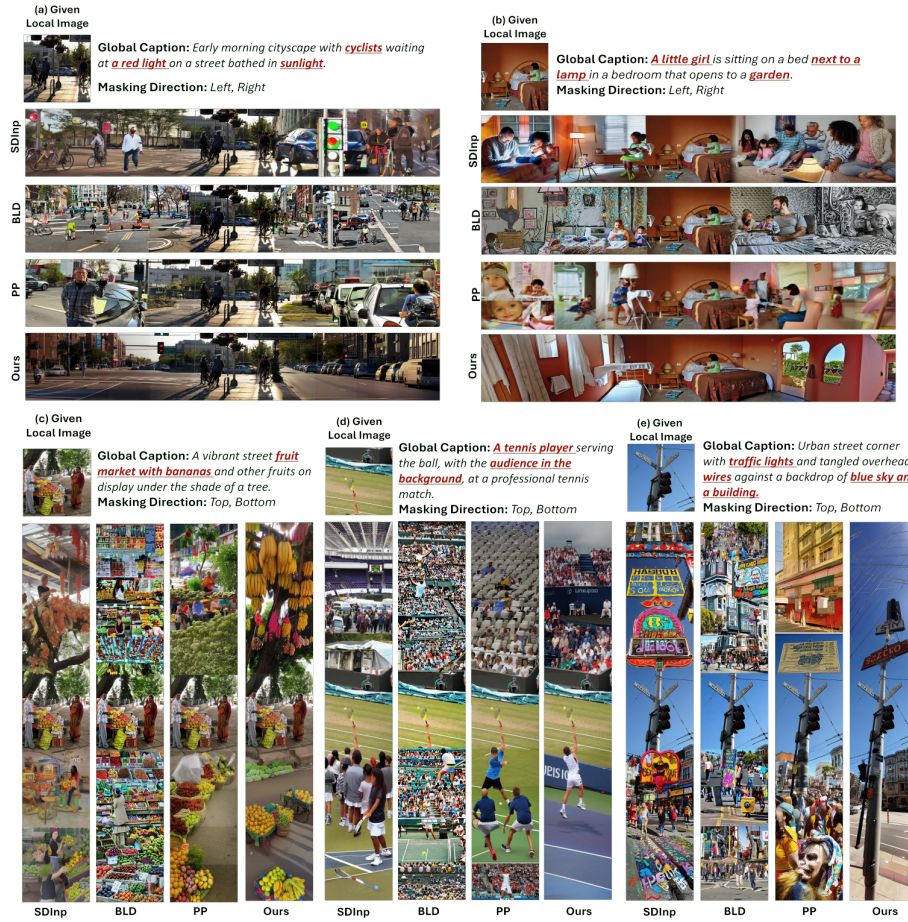


Fig. 6: Comparison of generated image results. We expand the image eight times. The expanded image has a resolution of 512×2560 or 2560×512 . The red box is the given local image. **We provide more samples in the supplementary material.**

(i) Text Matching. It is important for the expanded image to follow the context of the given global caption without repetitive patterns. According to Figure 6 (e), our model generates objects that match the content of the global caption, such as “traffic lights”, “wires” and “building” in a harmonious manner. It extends into one consistent image that matches the global caption. However, the baselines either reflect only partial objects mentioned in the global caption or fail to match the expanded overall image with the global caption by generating repetitive images. These results show that our model can generate an expanded image maintaining global visual consistency while successfully capturing the textual context of the global caption, compared to our baselines.

(ii) Image Quality. As shown in Figure 6, when expanding the image, our model shows the ability to generate clear objects in the intended direction of expansion. In contrast, the baselines [2, 22, 31] often generate blurred or indis-

Table 2: Human evaluation with baselines. Each cell lists the winning percentage of our model versus baselines. TM is “text matching”. IQ is “image quality”. GC is “global coherence”. We report only our winning percentages and omit LOSS and TIE due to space.

Expand $\times$ 4									
Method	MS-COCO			Flickr			Pascal		
	TM	IQ	GC	TM	IQ	GC	TM	IQ	GC
SD Inp [22]	65.00	71.20	75.40	63.00	63.40	75.20	63.40	62.20	74.20
BLD [2]	71.60	73.00	78.40	71.40	70.80	77.00	73.20	69.80	76.40
PP [31]	71.20	74.40	75.00	78.10	73.90	73.00	73.80	68.00	70.20
Expand $\times$ 8									
Method	MS-COCO			Flickr			Pascal		
	TM	IQ	GC	TM	IQ	GC	TM	IQ	GC
SD Inp [22]	70.40	75.20	77.80	69.20	69.40	78.40	68.20	68.80	76.20
BLD [2]	74.60	77.00	80.20	76.10	77.30	80.90	75.90	73.40	79.10
PP [31]	76.40	76.20	74.00	78.40	75.00	72.00	75.80	76.20	75.20

tinct objects. For instance, as depicted in Figure 6 (a), the image expanded by SD Inp [22] shows variations in the human form with each expansion, and the shapes of objects are not clear. Also, in the case of BLD [2], the objects of expanded image have distinct colors, but shapes such as bicycles and human in the image remain indistinct. These results show that our model exhibits better image quality compared to existing models when expanding images.

(iii) Global Coherence. When expanding images, it is crucial to maintain the overall visual consistency of the entire image and avoid the repetitive patterns. According to Figure 6, our model expands the images exhibiting overall harmony while encompassing a variety of content. However, in the case of the baselines, repetitive patterns are present, and it fails to maintain the overall positioning or global consistency of the image. In the Figure 6 (d), our model maintains overall harmony and generates objects reflecting the expansion of the image. However, the baselines repetitively generate “tennis players” or “audiences” without maintaining the positioning or global consistency of the expanded image. These results demonstrate that our model better reflects global consistency and overall harmony compared to the baselines when expanding images.

4.4 Human Evaluation

Because the evaluation metrics may not perfectly measure the performance of our model, we conduct a human evaluation on Amazon Mechanical Turk (AMT). For human evaluation, we randomly sample 100 generated images from each of MS-COCO [15], Flickr 8k [10], and Pascal [21] test sets, in total 300 samples. We conduct three surveys with 5 participants to compare our model with the baselines in the aspect of the text matching (TM), image quality (IQ) and global coherence (GC).

Image Extension $\times 4$ experiment. Table 2 shows the results of human evaluation on image expansion $\times 4$. participants significantly preferred our model in terms of text matching and image quality. From a global coherence aspect, our model outperformed the baselines by a large margin. These results demonstrate

Table 3: Quantitative evaluations with ablation models. $\times 4$ corresponds to the image being expanded four times, and $\times 8$ corresponds to the image being expanded eight times.

Method	Expand $\times 4$						Expand $\times 8$					
	MS-COCO		Flickr		Pascal		MS-COCO		Flickr		Pascal	
	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP
w/o All	14.67	27.40	10.90	28.37	10.66	27.62	8.37	27.42	6.04	28.37	7.14	27.62
w/o CLIP	14.26	27.53	10.80	28.70	13.55	27.74	8.03	27.53	7.06	28.70	8.37	27.74
w/o LLM	14.83	27.43	10.44	28.39	13.82	27.63	9.04	27.43	6.59	28.39	8.84	27.63
w/o GC	15.52	27.42	11.02	28.37	10.51	27.62	9.47	27.42	6.50	28.37	7.27	27.62
Ours	16.05	27.94	11.04	28.83	15.07	28.07	9.97	27.94	7.25	28.83	9.36	28.07

Table 4: Quantitative evaluations with baselines with the LLM. We compare with baselines with local captions generated by the LLM instead of global captions.

Method	Expand $\times 4$						Expand $\times 8$					
	MS-COCO		Flickr		Pascal		MS-COCO		Flickr		Pascal	
	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP	IS	CLIP
SDInp w/ LLM [22]	13.74	27.70	11.01	28.77	13.68	27.88	8.59	27.70	7.19	28.77	8.79	27.88
BLD w/ LLM [2]	15.72	27.41	8.83	28.61	10.06	27.64	9.47	27.41	4.99	28.61	6.75	27.64
PP w/ LLM [31]	12.65	27.42	8.70	28.37	8.50	27.63	7.47	27.42	4.98	28.37	5.66	27.63
Ours	16.05	27.94	11.04	28.83	15.07	28.07	9.97	27.94	7.25	28.83	9.36	28.07

that our model reflects text alignment, image quality and visual consistency much better than the baselines.

Image Extension $\times 8$ experiment. Table 2 shows the results of human evaluation on image expansion $\times 8$: similar to the human evaluation of image extension $\times 4$, participants significantly preferred our model by a substantial margin. Furthermore, the number of participants who preferred our model was higher in extension $\times 8$ than in extension $\times 4$. These results indicate that as images are expanded, our model show better performance than the baseline in all aspects.

4.5 Ablation Study

To explore the impact of the proposed components, we conduct an ablation study with different models. Also we provide the human evaluation results in the supplementary material, which show that our model is preferred than ablated models. All experimental settings are the same as in Section 4.1 and Section 4.4.

Effect of the LLM guidance and CLIP visual feature. To see the effect of the LLM guidance and CLIP visual feature, we compare our model with the w/o all model which generates an image with only a global caption. In Figure 7, the w/o all model simply reflects the keywords of the global caption, while failing to maintain global consistency and diverse context. This indicates that the w/o all model expands an image repetitively that depicts the same content without considering the overall structure. As shown in Table 3, our model outperforms the w/o all model in both IS [23] and CLIPSIM [20]. This indicates that our model can expand image better than the w/o all model in aspect of image quality and text faithfulness.

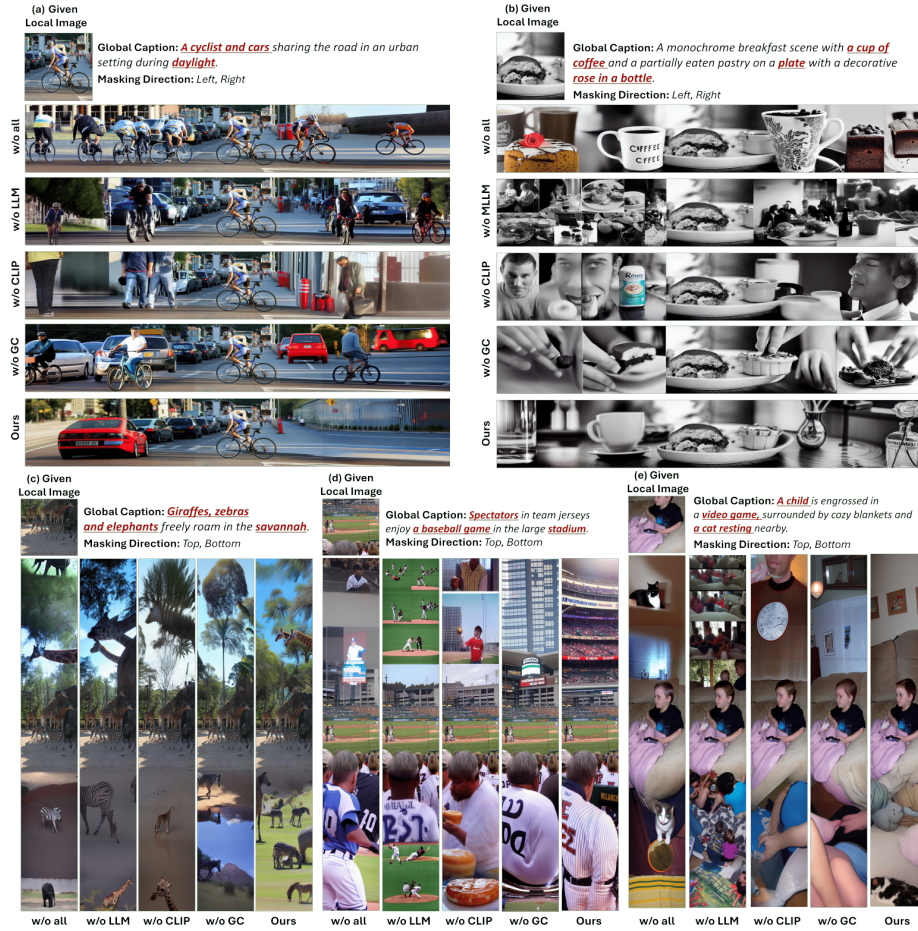


Fig. 7: Comparison of generated image results between our ablation models. We expand the image eight times. The expanded image has a resolution of 512×2560 or 2560×512 . The red box is the given local image.

Effect of the local caption with LLM guidance. We compare our model with the w/o LLM model which generates an image with a global caption and the CLIP visual feature. In Figure 7, the w/o LLM model fails to incorporate content beyond the global caption since it is conditioned only on the global caption as a textual condition. Also, the extended image does not appear as a single image but rather as a collage of the images. For example, in Figure 7 (d), our model expands the image by imagining the full view of the “baseball stadium with spectators” whereas the w/o LLM model extends the image by repeating the “baseball game” image. In Table 3, our model outperforms the w/o LLM model in both IS [23] and CLIPSIM [20]. This shows that our model can expand image with better quality and text faithfulness comparing to the w/o LLM model.

Table 5: Quantitative evaluations with different architectures on MS-COCO dataset. The All in MLP model gets all conditions through cross-attention using a compressed vector by the MLP (77×768). The All in cross-attention model gets all conditions directly through cross-attention (231×768). Our model gets the textual condition, a vector compressed by the MLP, and the visual condition through cross-attention (154×768).

	Expand $\times$ 4		Expand $\times$ 8	
	IS	CLIP	IS	CLIP
All in MLP	15.57	27.51	9.11	27.51
All in cross attention	15.02	27.42	9.75	27.42
Ours	16.05	27.94	9.97	27.94



Fig. 8: Qualitative evaluations with different architectures The red box is the given local image.

Effect of the CLIP visual feature. We compare our model with the w/o CLIP model which generates an image with a global caption and a local caption generated with the LLM. In Figure 7, comparing with our model, the w/o CLIP model often generates images with slightly lower image quality and global consistency, as it does not consider the visual feature of the overall expanded image. Figure 7 shows that the w/o CLIP model is unable to enhance the image while maintaining visual coherence. In Table 3, our model outperforms the w/o CLIP model in terms of the IS. This demonstrates that the CLIP visual feature helps the model to generate an image with better image quality. Also for CLIPSIM [20], even though the w/o CLIP model is conditioned on both global and local captions, our model generates an image that closely matches with the global caption.

Effect of the global caption. We compare our model with the w/o GC model which generates an image with a local caption generated with the LLM and CLIP visual feature. Figure 7 shows that, in comparison to our model, the w/o GC model generates images that do not maintain global consistency well. Also, since it does not consider the global context of the expanded image, the expanded images fail to maintain overall harmony. In Table 3, our model outperforms the w/o GC model in terms of IS and CLIPSIM. This demonstrates that the our model can generate images that maintain global consistency by effectively reflecting the global caption.

Effect of mask ratio. To explore various masking behaviors, we train our model on the dataset with a masking ratio of 3:1. As shown in Figure 8 (c), we found that although we can generate more content at once, it becomes more challenging to maintain global consistency when the provided(unmasked) input content gets smaller. This result demonstrates that our mask ratio is effective.

Effect of LLM guidance for baselines. Our proposed method can effectively expand an image using both the LLM and the diffusion model. To explore its effectiveness, we compare our model with the baselines using local captions generated by the LLM instead of global captions. Table 4 shows that our model outperforms the baselines with the LLM. These results demonstrate the effectiveness of our architecture for this task, enhanced by the guidance of the LLM.

4.6 Exploring Other Model Architectures

We explore the effect of our model architecture by comparing with two alternative model architectures: 1) In the all-in MLP model, we compress the global caption, local caption and CLIP visual feature by the MLP layer, as a compressed vector (77×768) then the model generates an image conditioned on the vector. 2) In the all-in cross attention model, we concatenate the global caption, local caption and CLIP visual feature (231×768) then the model generates an image conditioned on the concatenated vector through the expanded U-Net.

In Figure 8 (a), the all-in MLP model produces images with blurred edges and indistinct objects, likely due to difficulty in representing both textual and visual features. Figure 8 (b) shows the all-in cross-attention model generating repetitive "berry" images, possibly influenced by textual content. In Figure 8 (c), our model achieves semantic and visual consistency with both global and local captions.

In Table 5, our model performs better than the all-in MLP and all-in cross-attention model in both IS [23] and CLIPSIM [20]. This shows that our model architecture can reflect the content of text and visual features effectively.

5 Conclusion and Limitation

In this work, we propose a novel zero-shot text-guided image outpainting model by addressing the two main challenges: 1) the lack of high-resolution text-image paired datasets that have rich context; 2) preserving global coherence and understanding the context. In contrast to prior research, which generates images in limited categories, we leverage the LLMs to imagine the outside scene of the given image. During inference, we utilize LLMs to generate imaginary prompts to expand images. This allows us to expand the image to arbitrary size with diverse contexts. Additionally, by conditioning on the visual context, we can maintain global consistency and spatial local context. The experimental results demonstrate that our model can extend images arbitrarily in a zero-shot manner, and it offers promising opportunities for text-guided image outpainting approaches. Our model has a limitation as it relies on a pre-trained text-to-image model, but the generated images can contain rich visual contents. For future work, we will expand to image outpainting through stories or other modalities, such as sound.

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