Supplementary Material SceneGenie: Scene Graph Guided Diffusion Models for Image Synthesis

1. Architecture Details

1.1. Denoising UNet

The denoising UNet of latent diffusion model [5] takes latent code of image compressed by KL-regularized autoencoder as input. Table 1 shows our denoising UNet model hyperparameters.

Table 1:	Model	hyperparameters
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z-shape	(32,32,4)
Diffusion steps	1000
Noise Schedule	linear
Channels	320
Channel Multiplier	1,2,4,4
Number of Heads	8
Conditioning	CA
Cross-Attention Resolutions	32,16,8
Transformers Depth	1
Context dimension	1280

1.2. SG2SEG

B.BoxNet Architecture The B.Box Net predicts bounding box for each object embeddings from the GCN. Specifically, it predicts the 2D coordinates of the bottom-left vertex (x_l, y_l) and upper-right vertex (x_r, y_r) of the bounding box. The B.Box Net contains two layers of MLP with ReLU activation function. The architecture is shown in Table 2.

Block	Operation	Output Shape	
-	Objecrt embedding	[128]	
MLP	Linear	[512]	
	ReLU	[512]	
	Linear	[4]	

MaskNet Architecture The MaskNet for semantic segmentation prediction in the SG2SEG network consists of a set of convolutional blocks that upsample input embeddings to the desired resolution in a cascaded manner. Each convolutional block contains an Upsample layer with ratio 2, a BatchNorm layer, a Convolution layer with kernel size 3 and padding 1, and a ReLU activation function. We stack the convolutional blocks to generate 64×64 segmentation maps. The architecture is shown in Table 3.

Table 3: MaskNet Architecture

Block	Block Operation	
Reshane	Objecrt embedding	[128]
Keshape	Reshape	[128, 1, 1]
	Upsample	[128, 2, 2]
Conv Block 1	BatchNorm	[128, 2, 2]
COIN BIOCK I	Conv 3x3	[128, 2, 2]
	ReLU	[128, 2, 2]
	Upsample	[128, 4, 4]
Conv Block 2	BatchNorm	[128, 4, 4]
COIN DIOCK 2	Conv 3x3	[128, 4, 4]
	ReLU	[128, 4, 4]
	Upsample	[128, 64, 64]
Conv Block 6	BatchNorm	[128, 64, 64]
COIN DIOCK O	Conv 3x3	[128, 64, 64]
	ReLU	[128, 64, 64]
Output	Conv 1x1	[1, 64, 64]
Output	Sigmoid	[1, 64, 64]

2. Additional Qualitative Results on COCO

Figure 1 shows additional qualitative results of our method, compared against SG2Im [2] and LDM [5] on COCO [1] dataset.



Prompt	GT	SG2Im [2]	LDM [5]	SceneGenie (Ours)
A man stands beside a bus in a snowy forest at night.	- 4 KEWISTR			
A bride and groom cutting a wedding cake				
A tennis player is serving his ball to his opponents.				
A woman riding a horse jumps over an obstacle.				
A unique car sitting beside an airplane				

Figure 1: Additional qualitative results on the comparison of SceneGenie against related work on the COCO stuff [1] test set. As it can be seen, the images generated by SceneGenie represent the given prompt more accurately compared to previous work. SceneGenie, in addition to high quality image generation, correctly generates the number of given instances in the image and represents the scene more accurately overall.

3. Additional Qualitative Results on VG

Figure 2 shows additional qualitative results of our method, compared against SG2Im [2] and LDM [4] on VG [3] dataset.





Figure 2: Additional qualitative results on the comparison of SceneGenie against related work on the VG [3] test set.

References

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