Semantic Image Synthesis via Diffusion Models

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Figure 1. Semantic image synthesis results of our framework on four datasets. The left-top one is the input mask, the left three are the generated images from our framework, our framework generates realistic and diverse images under different scenes.

Abstract

Denoising Diffusion Probabilistic Models (DDPMs) have achieved remarkable success in various image generation tasks compared with Generative Adversarial Nets (GANs). Recent work on semantic image synthesis mainly follows the de facto GAN-based approaches, which may lead to unsatisfactory quality or diversity of generated images. In this paper, we propose a novel framework based on DDPM for semantic image synthesis. Unlike previous conditional diffusion model directly feeds the semantic layout and noisy image as input to a U-Net structure, which may not fully leverage the information in the input semantic mask, our framework processes semantic layout and noisy image differently. It feeds noisy image to the encoder of the U-Net structure while the semantic layout to the decoder by multi-layer spatially-adaptive normalization operators. To further improve the generation quality and semantic interpretability in semantic image synthesis, we introduce the classifier-free guidance sampling strategy, which acknowledge the scores of an unconditional model for sampling process. Extensive experiments on four benchmark datasets demonstrate the effectiveness of our proposed method, achieving state-of-the-art performance in terms of fidelity (FID) and diversity (LPIPS). The code and models are publicly available at https://github.com/WeilunWang/semantic-diffusion-model.

1. Introduction

Semantic image synthesis aims to generate photorealistic images based on semantic layouts, which is a reverse problem of semantic segmentation. This problem can be widely used in various applications, i.e., image editing, interactive painting and content generation. Recent work [24, 31, 41, 44, 46, 48] mainly follows the adversarial learning paradigm, where the network is trained with adversarial loss [9], along with a reconstruction loss. By exploring the model architectures, these methods gradually improve performance on the benchmark datasets. However, existing GAN-based approaches show limitations on some complex scenes in terms of generating high-fidelity and diverse results.

Denoising diffusion probabilistic models (DDPMs) [11] is a new class of generative model based on maximum likelihood learning. DDPMs generate samples from standard Gaussian distribution to samples of an empirical distribution by an iterative denoising process. With the help of progressive refinement of the generated results, they achieve state-of-the-art sample quality on a number of image generation benchmarks [8, 10, 11].

In this paper, we present the first attempt at exploring diffusion model for the problem of semantic image synthesis and design a novel framework named Semantic Diffusion Model (SDM). The framework follows the denoising diffusion paradigm, transforming the sampled Gaussian noise into a realistic image through an iterative denoising process (see Figure 2). The generation process is a parameterized Markov chain. In each step, the noise is estimated from the input noisy image by a denoising network conditioned on the semantic label map. According to the estimated noise, a less noisy image is generated by the posterior probability formulation. Through iteration, the denoising network progressively produces semantic-related content and injects it into the stream to generate realistic images.

We revisit the previous conditional DDPMs [35, 36]
that directly concatenate the condition information with the
noisy image as input of the denoising network. The ap-
proach does not fully leverage the information in the in-
put semantic mask, which leads to generated images in low
quality and semantic relevance as suggested in previous
work [31]. Motivated by this, we design a conditional de-
noising network which processes semantic layout and noisy
image independently. The noisy image is fed into the en-
coder of the denoising network while the semantic layout is
embedded into the the decoder of the denoising network by
multi-layer spatially-adaptive normalization operators. This
highly improves the quality and semantic correlation of gen-
erated images.

Furthermore, diffusion model are inherently capable of
generating diverse results. The sampling strategy plays an
important role in balancing quality and diversity of the gen-
erated results. The naive sampling procedure can generate
images that demonstrate high diversity but lack the realism
and strong correspondence with semantic label maps. In-
spired by [13], we adopt the classifier-free guidance strat-
 egy to boost image fidelity and semantic correspondence.
Specifically, we fine-tune the pre-trained diffusion model by
randomly removing the semantic mask input. Then the sam-
pling strategy is processed based on both the predictions
from diffusion model with and without semantic mask. By
interpolating the scores from these two situations, the sam-
pling results achieve a higher fidelity and stronger correla-
tion with the semantic mask input.

To demonstrate the superiority of our framework, we con-
duct experiments on four benchmark datasets, i.e.,
Cityscapes, ADE20K, CelebAMask-HQ and COCO-Stuff.
Both quantitative and qualitative results validates that our
framework can generate both high-fidelity and diverse re-
 sults, achieving superior performance compared with previ-
ous methods. Some example results are shown in Figure 1.

Overall, the contributions are summarized as follows:
• We propose a novel framework called Semantic Di-
fusion Model based on DDPMs, for high-fidelity and
diverse semantic image synthesis.
• We find the network structure of current conditional
diffusion models show limitation in handling the noisy
input and semantic masks. We propose a new structure
to handle noisy input and semantic mask separately
and precisely.
• To achieve better sampling results in diffusion process,
we introduce the classifier-free guidance, which yields
significantly higher quality and semantic input corre-
lated results.
• Extensive experiments on four benchmark datasets
demonstrate the effectiveness of the proposed frame-
work, achieving new state-of-the-art performance on
generation fidelity (FID) and diversity (LPIPS).

2. Related Work

In this section, we briefly review the related topics, in-
cluding denoising diffusion probabilistic models and se-
mantic image synthesis.

2.1. Denoising diffusion probabilistic models.

A diffusion probabilistic model [39] is a parameterized
Markov chain that optimizes the lower variational bound on
the likelihood function to generate samples matching the
data distribution. The diffusion probabilistic model is effi-
cient to define and train but is incapable of generating high-
quality samples before. Ho et. al. [11] first combine the
diffusion probabilistic model with the score-based model and
propose the denoising diffusion probabilistic model, which
achieves great success in image generation. After that, more
and more researchers [1,8,12,18,19,30,37,40] turn their at-
tention to DDPMs. Notably, Dhariwal and Nichol [8] show
the potential of DDPMs, achieving image sample quality
superior to GANs, on unconditional image generation.

Recently, conditional DDPMs [2,6,10,16,17,21,27,29,
35,36,38] are studied to develop the application on down-
stream tasks. Saharia et. al. [36] achieve success in su-
per resolution with DDPM. Pattle [35] explores DDPM on
four image-to-image translation problems, i.e., colorization,
inpainting, uncropping, and JPEG decompression. Bah-
 jat et. al. [16] propose an unsupervised posterior sampling
method, i.e., DDRM, to solve any linear inverse problem
with a pre-trained DDPM. Two concurrent works [10,29]
apply DDPMs for text-to-image generation. However, the
aforementioned methods mainly focus on low-level com-
puter vision tasks or work on single dimensional conditions.
Differently, we investigate conditional DDPM on genera-
tion problem with high-level dense semantic condition.

2.2. Semantic Image Synthesis.

Semantic image synthesis [5,14,15,22–26,31,32,41,43–
48,50,56,57] transforms semantic layouts into diverse re-
alistic images. Recent work on semantic image synthesis is
GAN-based and trained with the adversarial loss along with

![Figure 2. Conditional Diffusion Model for Semantic Image Synthesis.](image-url)

The framework transforms the noise from standard
Gaussian distribution to the realistic image through iterative de-
noising process. In each denoising step, we use a U-net-based
network to predict noise involved into the noisy images \( y_t \)
under the guidance of the semantic layouts \( x \).
the reconstruction loss. Pix2PixHD [48] utilizes a multi-scale generator to produce high-resolution images from semantic label maps. SPADE [31] proposes spatially-adaptive normalization to better embed the semantic layouts into the generator. CLADE [43] further improves the efficiency of SPADE by proposing a new class-adaptive normalization layer. SCGAN [50] introduces a dynamic weighted network for semantic relevance, structure and detail synthesis.

The aforementioned methods mainly focus on generating real and semantically-corresponding unimodal result. Paralleled with these methods, some other methods [14, 42, 55, 57] explore multimodal generation, which is also a core target for one-to-many problems like semantic image synthesis. To tackle this issue, BicycleGAN [55] encourages bidirectional mapping between the generated image and latent code, and DSCGAN [14] propose a simple regularization loss to penalize the generator from mode collapse. More recently, INADE [42] proposes a framework that supports diverse generation at the instance level by instance-adaptive stochastic sampling. However, these multimodal methods still fail to obtain satisfactory results on generation quality and learned correspondence. It is non-trivial for existing GAN-based methods to achieve high generation fidelity and diversity at the same time. To this end, we explore a new kind of approach to semantic image synthesis, i.e., conditional denoising diffusion probabilistic model, and achieve both better fidelity and diversity.

3. Methodology

In this paper, we present a novel framework named Semantic Diffusion Model (SDM) based on DDPMs to transform semantic layouts into realistic images (see Figure 2). With the iterative refinement, our framework generates high-quality images with fine-grained details. The multimodal generation is also supported and the generation results exhibit high diversity, which benefits from the randomness continuously involved by noise at each step. The rest of this section is organized as follows: We begin with reviewing previous conditional denoising diffusion probabilistic models. After that, we outline the architecture and objective functions of the semantic diffusion model. Finally, we present the classifier-free guidance adopted during inference.

3.1. Preliminaries

We first briefly review the theory of conditional denoising diffusion probabilistic models. Conditional diffusion models aims to maximize the likelihood $p_\theta(y_0|x)$ while the conditional data distribution follows $q(y_0|x)$. In conditional DDPM, two processes are defined, i.e. the reverse process and the forward process. The reverse process $p_\theta(y_{0:T}|x)$ is defined as a Markov chain with learned Gaussian transitions beginning with $p(y_T) \sim \mathcal{N}(0, I)$, which is formulated as follows,
\[ p_\theta(y_{0:T}|x) = p(y_T) \prod_{t=1}^{T} p_\theta(y_{t-1}|y_t, x), \]  
\[ p_\theta(y_{t-1}|y_t, x) = N(y_{t-1}; \mu_\theta(y_t, x, t), \Sigma_\theta(y_t, x, t)). \]

The forward process \( q(y_{1:T}|y_0) \) is defined as a process that progressively involves Gaussian noise into the data according to a variance schedule \( \beta_1, \ldots, \beta_T \), which is formulated as follows,

\[ q(y_t|y_{t-1}) = N(y_t; \sqrt{1 - \beta_t}y_{t-1}, \beta_t I). \]

With the notation \( \alpha_t := \prod_{s=1}^t (1 - \beta_s) \), we have

\[ q(y_t|y_0) = N(y_t; \sqrt{\alpha_t}y_0, (1 - \alpha_t)I). \]

The conditional DDPM is trained to optimize the upper variational bound on negative log likelihood. Assuming \( \Sigma_\theta(y_t, x, t) \) as \( \sigma_t I \), the optimization target is equivalent to a denoising process as follows,

\[ \mathcal{L}_{t-1} = \mathbb{E}_{y_0, \epsilon}[\gamma_t \| \epsilon - \epsilon_\theta(\sqrt{\alpha_t}y_0 + \sqrt{1 - \alpha_t} \epsilon, x, t) \|_2], \]

where \( \mathcal{L}_{t-1} \) is the loss function at the timestep \( t-1 \). \( \gamma_t \) is a constant about timestep \( t \).

### 3.2. Semantic Diffusion Model.

Figure 3 (a) gives an overview of the conditional denoising network in SDM, which is a U-Net-based network estimating the noise in the input noisy image. Unlike previous conditional diffusion models, our denoising network processes the semantic label map and noisy image independently. The noisy image is fed into the denoising network at the encoder part. To fully leverage the semantic information, the semantic label map is injected into the decoder of the denoising network by multi-layer spatially-adaptive normalization operators.

**Encoder.** We encode the feature of the noisy image with stacked semantic diffusion encoder resblocks (SDEResblocks) and attention blocks. We show the detailed structure of the SDEResblocks in Figure 3 (b), which consists of convolution, SiLU and group normalization. SiLU \([33]\), which is \( f(x) = x \cdot \text{sigmoid}(x) \) simply, is an activation function tending to work better than ReLU [28] on deeper models. To make the network estimate noise at different timestep \( t \), SDEResblock involves \( t \) by scaling and shifting the intermediate activation with learnable weight \( w(t) \in \mathbb{R}^{1 \times 1 \times C} \) and bias \( b(t) \in \mathbb{R}^{1 \times 1 \times C} \), which is formulated as follows,

\[ f^{t+1} = w(t) \cdot f^t + b(t), \]

where \( f^t, f^{t+1} \in \mathbb{R}^{H \times W \times C} \) are the input and output features, respectively. The attention block refer to a self-attention layer [49] with skip connection, which is formulated as follows,

\[ f(x) = W_f x, \quad g(x) = W_g x, \quad h(x) = W_h x, \]

\[ \mathcal{M}(u, v) = \frac{f(x_u)^\top g(x_v)}{\|f(x_u)\| \|g(x_v)\|}, \]

\[ y_u = x_u + W_v \sum_v \text{softmax}_{v}(\alpha_{\mathcal{M}(u, v)} \cdot h(x_v)), \]

where \( x \) and \( y \) are the input and output of the attention block. \( W_f, W_g, W_h \) and \( v \in \mathbb{R}^{C \times C} \) refer to \( 1 \times 1 \) convolution in the attention block, respectively. \( u \) and \( v \) is the index of spatial dimension, range from 1 to \( H \times W \). We adopt the attention block on the feature at a specific resolution, \( i.e., 32 \times 32, 16 \times 16 \) and \( 8 \times 8 \).

**Decoder.** We inject the semantic label map into the decoder of the denoising network to guide the denoising procedure. Revisiting the previous conditional diffusion models [35, 36] which directly concatenate the condition information with the noisy image as input, we find that this approach does not fully leverage the semantic information, which leads to the generated images in low quality and weak semantic relevance. To address this issue, we design the semantic diffusion decoder resblock (SDDResblock) (see Figure 3 (b)) to embed the semantic label map into the decoder of the denoising network in multi-layer spatially-adaptive manner. Different from SDEResblock, we introduce the spatially-adaptive normalization (SPADE) [31] instead of the group normalization. The SPADE injects the semantic label map into the denoising streams by regulating the feature in a spatially-adaptive, learnable transformation, which is formulated as follows,

\[ f^{t+1} = \gamma^t(x) \cdot \text{Norm}(f^t) + \beta^t(x), \]

where \( f^t \) and \( f^{t+1} \) are the input and output features of SPADE. \( \text{Norm}() \) refers to the parameter-free group normalization. \( \gamma^t(x), \beta^t(x) \) are the spatially-adaptive weight and bias learned from the semantic layout, respectively. It is worth mentioning that our framework is different from SPADE [31], since our SDM is specifically designed for diffusion process with attention block, skip-connection, and timestep embedding module while SPADE does not.

### 3.3. Loss functions.

We train our semantic diffusion model with two objective functions. The first objective function is the simple denoising loss. Given a reference output image \( y \) and a random timestep \( t \in \{0, 1, \ldots, T\} \), a noisy version of the reference image \( \tilde{y} \) is produced as follows,

\[ \tilde{y} = \sqrt{\alpha_t}y + \sqrt{1 - \alpha_t} \epsilon, \]

where \( \epsilon \) is a noise randomly sampled from the standard Gaussian distribution. \( \alpha_t \) is a noise scheduler at timestep.
t. We take $T$ as 1000 in our SDM. The conditional diffusion model is trained to reconstruct the reference image $y$ by predicting the involved noise $\epsilon$ under the guidance of the semantic layout $x$ and the timestep $t$, which is formulated as follows,

$$L_{\text{simple}} = \mathbb{E}_{t,y,\epsilon}||\epsilon - \epsilon_\theta(\sqrt{\alpha_t} y + \sqrt{1-\alpha_t} \epsilon, x, t)||_2^2. \quad (10)$$

Following the improved denoising diffusion model [30], we further train the network to predict variances $\Sigma_\theta(\tilde{y}, x, t)$ to improve the log-likelihood of generated images. The conditional diffusion model additionally outputs interpolation coefficient $\nu$ per dimension and turn the output into variances as follows,

$$\Sigma_\theta(\tilde{y}, x, t) = \exp(\nu \log \beta_t + (1 - \nu) \log \tilde{\beta}_t) \quad (11)$$

where $\beta_t$ and $\tilde{\beta}_t$ are the upper and lower bounds on the variance. The second objective function directly optimizes the KL divergence between the estimated distribution $p_\theta(y_{t-1}|y_t, x)$ and diffusion process posterior $q(y_{t-1}|y_t, y_0)$, which is formulated as follows,

$$L_{\text{vib}} = \text{KL}(p_\theta(y_{t-1}|y_t, x) || q(y_{t-1}|y_t, y_0)). \quad (12)$$

In summary, the overall loss is the weighted summation of two objective functions, which is formulated as follows,

$$L = L_{\text{simple}} + \lambda L_{\text{vib}}, \quad (13)$$

where $\lambda$ is the trade-off parameter to balance loss functions.

### 3.4. Classifier-free guidance.

Following the common sampling procedure in DDPM, it is noticed that the generated images are diverse but not photo-realistic and not strongly correlated with the semantic label maps. We hypothesize that the conditional diffusion model can not handle conditional input explicitly during the sampling process. Previous method [8] discovered that samples from conditional diffusion models can often be improved by the gradient of the log probability $\nabla_{y_t} \log p(x|y_t)$. Assuming a conditional diffusion model with estimated mean $\mu_\theta(y_t|x)$ and variance $\Sigma_\theta(y_t|x)$, the results can be improved by perturbing the mean, which is formulated as follows,

$$\hat{\mu}_\theta(y_t|x) = \mu_\theta(y_t|x) + s \cdot \Sigma_\theta(y_t|x) \cdot \nabla_{y_t} \log p(x|y_t) \quad (14)$$

where the hyper-parameter $s$ is named the guidance scale, which trades off the sample quality and diversity.

Previous work [8] applied an extra trained classifier $p_\phi(x|y_t)$ to provide the gradient during sampling process. Inspired by [13], we obtain from the guidance with the generative model itself instead of a classifier model that requires extra cost for training. The main idea is to replace the semantic label map $x$ with a null label $\emptyset$ to disentangle the noise estimated under the guidance of semantic label map $\epsilon_\theta(y_t|x)$ from unconditional situation $\epsilon_\theta(y_t|\emptyset)$. The disentangled component implicitly infers the gradient of the log probability, which is formulated as follows,

$$\epsilon_\theta(y_t|x) - \epsilon_\theta(y_t|\emptyset) \propto \nabla_{y_t} \log p(y_t|x) - \nabla_{y_t} \log p(y_t) \propto \nabla_{y_t} \log p(x|y_t). \quad (15)$$

During sampling procedure, the disentangled component is increased to improve the samples from conditional diffusion models, which is formulated as follows,

$$\hat{\epsilon}_\theta(y_t|x) = \epsilon_\theta(y_t|x) + s \cdot (\epsilon_\theta(y_t|x) - \epsilon_\theta(y_t|\emptyset)). \quad (16)$$

In our implementation, $\emptyset$ is defined as the all-zero vector. We show the detailed sampling procedure in Figure 3 (c).

### 4. Experiments

#### 4.1. Setup

**Datasets.** We conduct experiments on four benchmark datasets, i.e., Cityscapes [7], ADE20K [54], CelebAMask-HQ [20] and COCO-Stuff [3]. For Cityscapes dataset, we resize images to the resolution of 256 × 512 for training. For ADE20K, CelebAMask-HQ and COCO-Stuff dataset, we train our network on the resolution of 256 × 256.

**Evaluation.** We aim to assess visual quality, diversity and learned correspondence of generated images. For the visual quality, we adopt the widely-used Fréchet Inception Distance (FID) metrics. To evaluate the generation diversity of different methods, we compute the average distance measured by the LPIPS metrics [53] between multimodal generation results. For qualitative comparison, we try to compare all the methods but find some models are not publicly available and we also tried to email the author. We then choose the most recent and representative methods whose models are available for testing.

For the learned correspondence, we utilize an off-the-shelf network to evaluate the “semantic interpretability” of generated results. We use DRN-D-105 [52] for Cityscapes, UperNet101 [51] for ADE20K, Unet [20, 34] for CelebAMask-HQ and DeepLabV2 [4] for COCO-Stuff. With the off-the-shelf network, mean Intersection-over-Union (mIoU) is computed based on the generated images and semantic layouts. The mIoU metric refers to the semantic relevance of the generated images. However, mIoU highly depends on the capability of the off-the-shelf network. A strong segmentation network measures the semantic relevance of generated images more correctly. The reported mIoU is calculated by upsampling the generated images to the same resolution as default input resolution of the off-the-shelf segmentation models, which allows a more reasonable evaluation of the semantic interpretability.
Table 1. Quantitative comparison with existing methods on semantic image synthesis. ↑ indicates the higher the better, while ↓ indicates the lower the better. Notably, our method achieves state-of-the-art performance on FID and LPIPS.

Table 2. Paired user study on four benchmark datasets between our method and several challenging methods, i.e., SPADE [31], INADE [42] and OASIS [41]. The reported numbers refer to the percentage of user preferences in favor of our approach. It is observed that our method is clearly preferred over the competitors on four benchmark datasets.

4.2. Comparison with previous methods

We compare our method with several state-of-the-art methods on semantic image synthesis, i.e., SPADE [31], CC-FPSE [24], INADE [42] and OASIS [41], etc.

Key advantages. With the help of progressive refinement of the generated results, our methods achieve superior quality to previous GAN-based methods. Compared to the most recent methods, our method surpasses them by +2.2, +0.8, +2.0, +1.1 FID score on four datasets, respectively. Besides the quantitative results, we also conduct the qualitative results on four datasets. We show the results in Figure 15, 17 and 7, we observe that the images generated by our method have better visual performance compared with previous methods. Under the complex scenes, i.e., fences in front of the building, human faces in the side view and motorcycles with complex structure, our method can generate samples with more reasonable structure and content, which significantly outperforms previous methods. In Figure 6, we present zoomed-in results of the generated images. Notably, our model exhibits more fine-grained details, such as distant cars and traffic lights.

Furthermore, we conduct a user study to evaluate the visual performance of our method, and three previous methods, i.e., SPADE [31], INADE [42] and OASIS [41]. There are 20 volunteers participating in this study. In the study, we present each volunteer 10 pairs of generated results for each pair user study (100 pairs in total) and ask the volunteers to select more high-fidelity results. The voting results are reported in Table 2. It can be observed that our method is clearly preferred over the competitors in more than 75% of the time on four benchmark datasets.
We compare our method with several challenging methods, i.e., Pix2PixHD [48], SPADE [31], CC-FPSE [24], INADE [42] and OASIS [41]. We present zoomed-in results of the generated images. It is observed that our method generates more reasonable and distinct results on fine-grained objects, such as distant cars and traffic lights.

We compared our method with the several challenging methods, i.e., Pix2PixHD [48], SPADE [31], CC-FPSE [24], SCGAN [50] and OASIS [41]. By comparison, our method can better generate objects with complex structure, i.e., motorcycle.

### Table 3. mIoU comparison and analysis.

| Method          | CelebAMask | Cityscapes | ADE20K | COCO-Stuff |
|-----------------|------------|------------|--------|------------|
| Pix2PixHD [48]  | 76.1       | 63.0       | 28.8   | 26.6       |
| SPADE [31]      | 75.2       | 61.2       | 38.3   | 38.4       |
| DAGAN [44]      | 76.6       | 62.4       | 38.1   | n/a        |
| SCGAN [50]      | 75.5       | 55.9       | 41.5   | 44.3       |
| CLADE [43]      | 75.4       | 58.6       | 23.9   | 38.8       |
| CC-FPSE [24]    | n/a        | 65.2       | 40.5   | 22.3       |
| GroupDNet [57]  | 76.1       | 55.3       | 27.6   | n/a        |
| INADE [42]      | 74.1       | 57.7       | 33.0   | n/a        |
| OASIS [41]      | n/a        | 58.3       | 45.7   | 46.7       |
| SDM (Ours)      | 77.0       | 77.5       | 39.2   | 40.2       |

On the CelebAMask-HQ and Cityscapes dataset, we achieve 77.0 and 77.5 mIoU, surpassing previous sota by +0.4 and +12.3, indicating the superior performance of our methods for generating highly semantic correlated images. On the ADE20K and COCO-Stuff dataset, our method shows a weaker performance on mIoU compared with some existing methods. However, we observe that our generated images in Figure 17 and 7 have a strong semantic correlation with input mask visually, which are at least comparable with those of previous methods. One possible explanation is that the semantic segmentation model used for evaluating is not that strong, we checked that the segmentation model and find that this model only achieves 35.3 and 39.0 mIoU on the ground-truth images, which is much lower than the model we used on CelebAMask-HQ and Cityscapes dataset. We will show randomly selected 100 results in the supplementary material to further verify this issue.

### 4.3. Ablation Studies

We perform ablative experiments to verify the effectiveness of several important designs in our framework, i.e., the approach to embed the condition information and the
Table 4. Ablation studies on the approach to embed the condition information and the classifier-free guidance strategy. ↑ indicates the higher the better, while ↓ indicates the lower the better.

Condition Embedding. To evaluate the importance of embedding the condition information independent of the noisy image, we design a baseline variant as comparison. As an alternative, we directly apply the conditional DDPM in [35,36], which directly concatenates the semantic label map with the noisy image as input. The quantitative results are reported in Table 4. It is observed that our semantic diffusion model highly outperforms previous conditional DDPM on all the metrics. Additionally, we analyze the visual results between these two variants. In Figure 9, it can be seen, by embedding the semantic label map in a multi-layer spatially-adaptive manner, the generated image exhibits superior visual quality on fidelity and correspondence with the semantic label map.

Importance of classifier-free guidance. Furthermore, we study the effectiveness of the classifier-free guidance strategy. We take the variant without classifier-free guidance as a comparison. From Table 4, the classifier-free guidance highly improves the mIoU and FID metrics at the expense of little LPIPS. In Figure 9, we present the qualitative results on the classifier-free guidance strategy. The images generated with classifier-free guidance better exhibit semantic information and generates more structured content. This further improves the visual effects of generated images compared with those without classifier-free guidance.

4.4. Controlled Generation

We study our semantic diffusion model on the controlled image generation, i.e., semantic image editing. Considering a real image with corresponding semantic label map, we add or remove objects by modifying the semantic label map. After that, the edited region in the real image is erased, and our model inpaints it conditioned on the edited semantic label map. In this way, we can manipulate real images through user interaction. We show the semantic image editing results in Figure 10. It is observed that our model can produce a realistic completion matching both the semantic label map and surrounding context.

5. Conclusions

In this paper, we present the first attempt to explore diffusion model for the problem of semantic image synthesis and design a novel framework named Semantic Diffusion Model (SDM). Specifically, we propose a new network structure to handle noisy input and semantic mask separately and precisely to fully leverage the semantic information. Furthermore, we introduce classifier-free guidance during sampling process, significantly improve the generation quality and semantic interpretability in semantic image synthesis. Extensive experiments on four benchmark datasets demonstrate the effectiveness of our method. Our method achieves state-of-the-art performance in terms of FID and LPIPS metrics and shows better visual quality of generated images compared with previous methods.
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This supplementary material provides more details which are not included in the main paper due to space limitations. In the following, we first provide the implementation details. Then we will present more qualitative experiment results.

A. Implementation Details

In this section, we provide more implementation details on the semantic diffusion model, including details on data preprocessing, diffusion procedure, denoising network design, evaluation metrics, hyperparameter and optimization.

Data preprocessing. As mentioned in Section 4.1, we perform experiments on four benchmark datasets, i.e., Cityscapes [7], CelebA-Mask-HQ [20], ADE20K [54], COCO-Stuff [3]. For the Cityscapes dataset, we apply one-hot activation of 35 classes as the input semantic label map. Furthermore, inspired by SPADE [31], we produce an instance edge map from provided instance labels and concatenate it with a semantic label map as additional condition information. The CelebAMask-HQ dataset is processed similarly to the Cityscapes dataset, taking one-hot activation of 19 classes and instance edge map as input. For the ADE20K dataset, we apply one-hot activation of 151 classes (including an “unknown” object) as the input semantic label map. The instance edge map is not employed on ADE20K dataset since the instance labels are not available. On the COCO-Stuff dataset, we utilize one-hot activation of 183 classes (including an “unknown” class) and the instance labels.

Diffusion procedure. As mentioned in Section 3, we propose a semantic diffusion model to transform semantic layouts into realistic images. Following DDPM [11], we set the total diffusion timestep to 1000. In the forward process, the Gaussian noise is involved in the data according to a variance schedule $\beta_1, \ldots, \beta_T$. In our implementation, the variance schedule is arranged linearly with respect to the timestep $t$. During the sampling procedure, we utilize the classifier-free guidance strategy. The classifier-free guidance perturbs the mean as Equation (16) in the main paper. In addition to the mean value, the denoising network also estimates the variance at timestep $t$, $\Sigma(\tilde{y}, x, t)$. The variance $\Sigma(\tilde{y}, x, t)$ is not perturbed in classifier-free guidance.

Since different datasets have different complexity, we apply different guidance scales $s$ on four datasets. Guidance scale $s$ is set to 1.5, 2.0, 1.5 and 1.5 on the CelebAMask-HQ, Cityscapes, ADE20K and COCO-Stuff datasets, respectively. $s$ can affect the trade-off between quality and diversity of generated samples. The probability of dropping labels in classifier-free guidance strategy also affects the performance. We follow [31] and set the probability to 0.2 in the finetune stage by default. We further analyze the performance of different probability setting, i.e., 0.1 and 0.3, on ADE20K dataset. With probabilities set to 0.1 and 0.3, we achieved 29.1 FID and 37.8 mIOU, 30.0 FID and 37.5 mIOU, respectively. These results are slightly worse or comparable with probability set to 0.2.

Denoising network. In Section 3.2, we introduce the conditional denoising network in SDM, which is a U-Net-based network estimating the noise in the input noisy image. The encoder and decoder of the denoising network are 6 layers and the spatial resolution of the feature on each layer is 256 × 256, 128 × 128, 64 × 64, 32 × 32, 16 × 16 and 8 × 8, respectively. The channel of each layer is set to 256, 512, 512, 1024 and 1024, respectively. The attention block is applied on the last 3 layers, i.e., the resolution of 32 × 32, 16 × 16 and 8 × 8. We utilize the multi-head self-attention mechanism in our implementation and the number of channels in each head is set to 64. In addition, we use half-precision computation to accelerate training and reduce memory consumption.

Evaluation metrics. We adopt a more reasonable approach to measure the mIOU metric in the main paper. Unlike the results reported in [41] which directly adopt the off-the-shelf segmentation model and test the images on 256 × 256 resolution (that is inconsistent with the input resolution setting of the segmentation model in the training stage), our
reported mIOU is calculated by upsampling the generated images to the same resolution as the default input resolution of the off-the-shelf segmentation model. It is based on two important reasons. First, the segmentation model is trained on cropped patches from original images, which have different scales and aspect ratios from generated images. Second, [41] trained with a discriminative segmentation model on $256 \times 256$, which leads to a bias on $256 \times 256$ resolution.

**Hyperparameter and Optimization.** Following the [30], we set the trade-off parameter $\lambda$ as 0.001 to ensure training stability. We utilize AdamW optimizer to train the framework. During training, we adopt an exponential moving average (EMA) of the denoising network weights with 0.9999 decay. The whole framework is implemented by Pytorch and the experiments are performed on NVIDIA Tesla V100.

**B. Additional Experiment Results**

In this section, we first visualize the intermediate results of SDM during the diffusion process. Then we show more generation samples to further demonstrate the effectiveness of our method. Finally, we present more controlled generation results on different scenes to show the robustness of our method.

**B.1 Intermediate Results**

To help readers better understand the entire process of SDM, we visualize the intermediate results in both training and inference procedures. As shown in Figure 13, our method learns to produce noise-free images by predicting the noise involved during the training procedure and generate realistic images with iterative refinement during the inference procedure.

**B.2 Generation Samples**

Similar to Section 4.2 of the main paper, we visualize more generation results in Figure 14, 15 and 17. As shown in the figures, our method highly outperforms previous methods on the visual performance of generated images.

**B.3 Editing Samples**

In the main paper (Section 4.4), we study our semantic diffusion model on controlled image generation. In this section, we further present more semantic image editing results on different scenes in Figure 11 and Figure 12. It demonstrates the robustness of our method on controlled generation, which produces realistic completion matching the semantic label map under different scenes.
Figure 13. Visualization of the intermediate results in both training and inference procedure. During training, SDM learns to produce noise-free images by predicting the noise involved. In the inference process, SDM generates realistic images with iterative refinement.

Figure 14. More Qualitative results on the Cityscapes dataset. We compared our method with several challenging methods, i.e., Pix2PixHD [48], SPADE [31], CC-FPSE [24], INADE [42] and OASIS [41].
Figure 15. More Qualitative results on the CelebAMask-HQ dataset. We compared our method with several challenging methods, *i.e.*, *i.e.*, Pix2PixHD [48], SPADE [31], DAGAN [44], SCGAN [50] and INADE [42].
Figure 16. More Qualitative results on the ADE20K dataset. We compared our method with several challenging methods, i.e., SPADE [31], CC-FPSE [24], SCGAN [50], INADE [42] and OASIS [41].
Figure 17. More Qualitative results on the COCO-Stuff dataset. We compared our method with several challenging methods, i.e., Pix2PixHD [48], SPADE [31], CC-FPSE [24], SCGAN [50] and OASIS [41].