

Versatile Diffusion: Text, Images and Variations All in One Diffusion Model

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<https://github.com/SHI-Labs/Versatile-Diffusion>

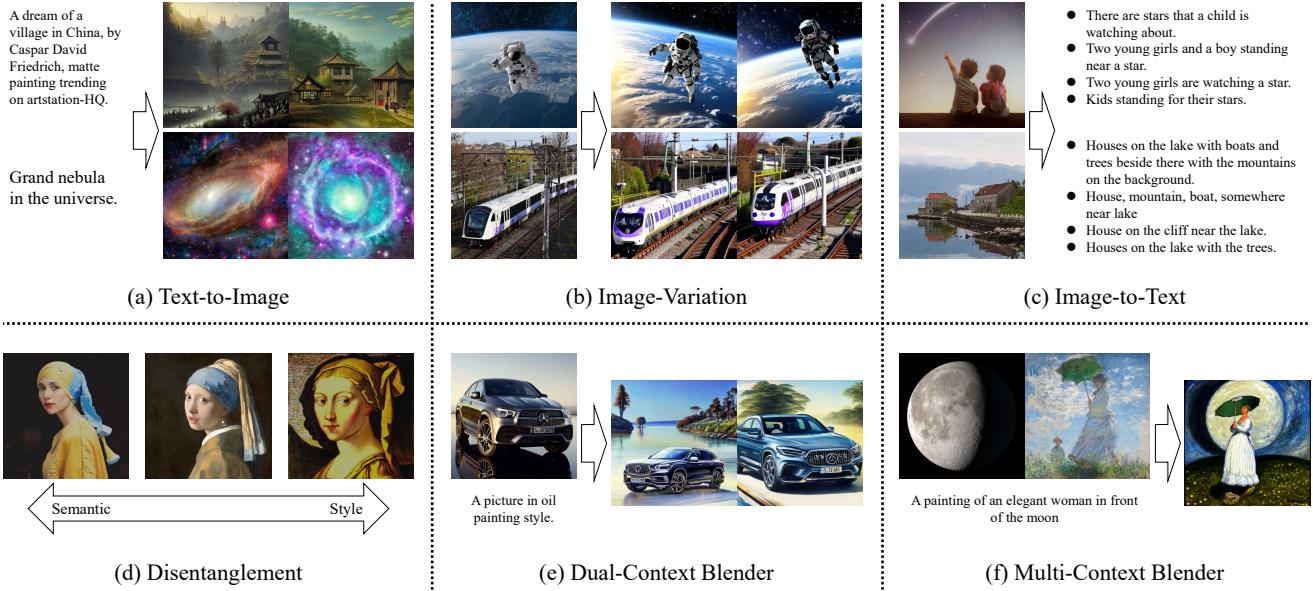


Figure 1: Demo results of our Versatile Diffusion (VD) framework on three out of all primary tasks (*i.e.* Figures **a**, **b**, and **c**) and three derived tasks (*i.e.* Figure **d**, **e**, and **f**). As shown in the captions, the three primary tasks are text-to-image, image-variation, and image-to-text. Figure **d** demonstrates the disentanglement between image semantics and style. Figure **e** shows the demo of dual-context blender using one image and one text. Figure **f** shows the demo of the multi-context blender using multiple images and one text.

Abstract

Recent advances in diffusion models have set an impressive milestone in many generation tasks, and trending works such as DALL-E2, Imagen, and Stable Diffusion have attracted great interest. Despite the rapid landscape changes, recent new approaches focus on extensions and performance rather than capacity, thus requiring separate models for separate tasks. In this work, we expand the existing single-flow diffusion pipeline into a **multi-task multimodal** network, dubbed **Versatile Diffusion** (VD), that handles multiple flows of text-to-image, image-to-text, and variations in one unified model. The pipeline design of VD instantiates a **unified multi-flow diffusion framework**, consisting of sharable and swappable layer modules that enable the crossmodal generality beyond images and text.

Through extensive experiments, we demonstrate that VD successfully achieves the following: a) VD outperforms the baseline approaches and handles all its base tasks with competitive quality; b) VD enables novel extensions such as disentanglement of style and semantics, dual- and multi-context blending, etc.; c) The success of our multi-flow multimodal framework over images and text may inspire further diffusion-based universal AI research. Our code and models are open-sourced at <https://github.com/SHI-Labs/Versatile-Diffusion>.

1. Introduction

Multi-modality is the “crown jewel” for achieving universal AI. With the attributes of deep learning, methods designed for traditional tasks such as classification, detection, segmentation, etc., have reached near-human level

accuracy. On top of them, multimodal research such as [19, 37, 3, 31] primarily focused on discriminative tasks of jointly recognizing, matching, or understanding multimodal data. Nevertheless, research on multimodal generative models remains scarce. Previously, the best-performing generative vision models, generative adversarial networks (GAN) [34, 7, 35] merely focus on specific domains (*i.e.* faces [35, 10, 94], fonts [99, 45], natural scenes [75, 51], *etc.*); and on specific tasks (inpainting [84, 103, 98], super-resolution [48], image-to-image translation [30, 105], *etc.*).

The recent success of diffusion models [28, 78, 63, 70, 67] has brought new horizons. Diffusion models are likelihood-based models that gradually restore image contents from Gaussian corruptions. It has proved to be effective in bridging modalities and tasks, for instance, unconditional generation [28, 78, 16], density estimation [39], super-resolution [71], and text-to-image generation [56, 63, 70, 67]. The success of diffusion models can be attributed to several aspects. Firstly, their training objectives lead to a more robust training procedure than other approaches like GANs. The iterative refinement inference procedure also expands the model capability at the cost of more running time. Besides, the competitive performance of recent diffusion models such as DALL-E2 [63],Imagen [70], and Stable Diffusion [67] benefits from the remarkable data collection such as LAION [74], CC12M [11], COYO [9], etc. The disadvantages of earlier diffusion models, such as the data hunger and high inference costs, are gradually alleviated by more efficient structures and schedulers [78, 43, 73, 29, 67]. Diffusion-based text-to-image methods [63, 70, 67] arguably set new state-of-the-art for multi-modal generative AI. However, those works by far almost exclusively hinge on single-flow diffusion pipelines (illustrated in Section 3); and meanwhile, most of them are trained and evaluated on a single specialized generation task (*e.g.*, text to image) despite being cross-modality.

What is the next move forward, then? We believe in the central role of multimodal, multi-task models in universal AI, and we consider diffusion models to be a promising workhorse to enable so. To fulfill our goal, we proposed *Versatile Diffusion (VD)* that comprehensively solves text, images, and variations within one unified generative model. The *key underlying technique* is a novel multi-flow diffusion framework, that generalizes existing single-flow diffusion pipelines to *handle multiple modalities and tasks simultaneously* while effectively sharing information across them. Thanks to the *larger capacity* as well as capturing crossmodal semantics, VD not only performs well on the aforementioned supported tasks but notably derives many new capabilities including semantic-style disentanglement, cross-modal dual context or multi-context generation (blending), leading to remarkable advances of *empirical performance* for multi-modal generative AI. Our main

contributions are summarized in the following:

- We introduce *Versatile Diffusion (VD)*, a multimodal, multi-task diffusion network that adopts a novel generalized multi-flow pipeline, unlike existing single-flow diffusion models.
- VD solves multiple modalities and tasks in one unified model, including image generation (text-to-image, image-variation), and text generation (image-to-text, text-variation). Through comprehensive experiments, we show that VD outperforms the baselines via scores and quality. For example, VD’s high-quality text-to-image and image-variation results demonstrate that it indeed better captures the context semantics.
- The unique multi-flow multimodal property of VD enables more novel derivative tasks, that may further facilitate downstream users engaged in this technology, including the semantic-style disentanglement, dual-context and multi-context blending, *etc.*

2. Related Works

Multi-modalities are unions of information with different forms, including but not limited to vision, text, audio, *etc.* [83, 4]. Early deep learning work led by Ngiam *et al.* [55] learned a fused representation for audio and video. The similar idea was also adopted across vision and text label [55], and across vision and language [42]. A part of multimodal approaches focused on zero-shot learning, for instance, DiViSE [19] targeted mapping images on semantic space from which unseen category labels can be predicted. Socher *et al.* [76] trained a recognition model with similar ideas in which images were projected on the space of text corpus. [47] shared the same design as DiViSE but was upgraded for a large and noisy dataset. Another set of works [59, 37, 3, 38], focused on increasing classification accuracy via multimodal training: in which [59] and [37] did a simple concatenation on multimodal embeddings; [3] proposed a gated unit to control the multimodal information flow in the network; [38] surveyed FastText [32] with multiple fusion methods on text classification. Meanwhile, multimodal training was also widely adopted in detection and segmentation [22, 25, 31] in one shot. Another topic, VQA [2, 20], conducted cross-modal reasoning that transferred visual concepts into linguistic answers. Methods such as [100, 54] extracted visual concepts into neural symbolics, and [101, 95] learned additional concept structures and hierarchies.

Multimodal generative tasks involve simultaneous representation learning and generation/synthesis [85], in which representation networks [93, 41, 23, 90, 58, 89] with contrastive loss [60, 14, 1, 87, 88] played an essential role. Specifically, our model VD adopts VAEs [41] and CLIP [60] as the latent and context encoders, which are

two critical modules for the network. VD also shares the common cross-modal concepts such as domain transfer [30, 105] and joint representation learning [82, 96, 86].

Diffusion models (DM) [77, 28] consolidate large family of methods including VAEs [41, 90, 65], Markov chains [6, 77, 72, 79], and score matching models [80, 81], *etc.* Differ from GAN-based [23, 7, 35] and flow-based models [66, 40], DM minimizes the lower-bounded likelihoods [28, 80] in backward diffusion passes, rather than exact inverse in flow [66] or conduct adversarial training [23]. Among the recent works, DDPM [28] prompted ϵ -prediction that established a connection between diffusion and score matching models via annealed Langevin dynamics sampling [92, 80]. DDPM also shows promising results on par with GANs in unconditional generation tasks. Another work, DDIM [78], proposed an implicit generative model that yields deterministic samples from latent variables. Compared with DDPM, DDIM reduces the cost of sampling without losing quality. Regarding efficiency, FastDDPM [43] investigated continuous diffusion steps and generalized DDPM and DDIM with faster sampling schedules. Another work, [73], replaced the original fixed sampling scheme with a learnable noise estimation that boosted both speed and quality. [29] introduced a hierarchical structure with progressive increasing dimensions that expedite image generations for DM. Regarding quality, [16] compared GANs with DMs with exhaustive experiments and concluded that DMs outperformed GANs on many image generation tasks. Another work, VDM [39], introduced a family of DM models that reaches state-of-the-art performance on density estimation benchmarks. Diffwave [44] and WaveGrad [13] show that DM also works well on audio. [57] improved DDPM with learnable noise scheduling and hybrid objective, achieving even better sampling quality. [53] introduced semantic diffusion guidance to allow image or language-conditioned synthesis with DDPM.

Text-to-image generation, nowadays a joint effort of multimodal and diffusion research, has drawn lots of attention. Among these recent works, GLIDE [56] adopted pretrained language models and the cascaded diffusion structure for text-to-image generation. DALL-E2 [63], a progressive version from DALL-E [64], utilized CLIP model [60] to generate text embedding and adopted the similar hierarchical structure that made 256 text-guided images and then upscaled to 1024. Similarly, Imagen [70] explored multiple text encoders [15, 62, 60] with conditional diffusion models and explores the trade-offs between content alignment and fidelity via various weight samplers. LDM [67] introduced a novel direction in which the model diffuses on VAE latent spaces instead of pixel spaces. Such design reduced the resource needed during inference time, and its latter version, SD, has proven to be equally effective in text-to-image generation.

3. Method

In this section, we will first revisit the fundamentals of diffusion models [77, 28], including the forward-backward processes and training objectives. We will then highlight the multi-flow multimodal framework of Versatile Diffusion (VD), which is a key contribution that makes VD a unified model of multiple tasks. Finally, we will reveal all details of VD, including the choice of VAEs, context encoders, loss functions, *etc.*

3.1. Diffusion basics

The forward diffusion process $p(x_T|x_0)$ is a Markov Chain [28] with T steps that gradually degrade x_0 to x_T with random Gaussian noises (Equation 1).

$$\begin{aligned} q(x_T|x_0) &= \prod_{t=1}^T q(x_t|x_{t-1}) = \prod_{t=1}^T \mathcal{N}(\sqrt{1-\beta_t}x_{t-1}; \beta_t \mathbf{I}) \\ &= \mathcal{N}(\sqrt{\bar{\alpha}_T}x_0; (1-\bar{\alpha}_T)\mathbf{I}); \\ \bar{\alpha}_t &= \prod_{t=1}^T \alpha_t; \quad \alpha_t = 1 - \beta_t \end{aligned} \quad (1)$$

Given the forward diffusion process as prior, diffusion models are trained to reverse the process and recover signal x_0 back from x_T by removing the added Gaussian noises. This is known as the backward diffusion process, and each step $p_\theta(x_{t-1}|x_t)$ is sampled from the Gaussian distribution with network predicted mean $\mu_\theta(x_t, t)$ and variance $\Sigma_\theta(x_t, t)$, shown as Equation 2.

$$p_\theta(x_{t-1}|x_t) = \mathcal{N}(\mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \quad (2)$$

The objective function to train a diffusion model is to minimize the variational bound for negative log-likelihood [28] shown in Equation 3. In practice, many works assume deterministic α_t and β_t for step t in Equation 1. Given that both forward and backward processes are Gaussian processes, the objective can then be simplified as the variational weighted l_2 loss between the ground truth and predicted mean.

$$L = \mathbb{E}[-\log p_\theta(x_0)] \leq \mathbb{E}\left[-\log \frac{p_\theta(x_{0:T})}{q(x_{1:T}|x_0)}\right] \quad (3)$$

3.2. Multi-flow multimodal diffusion framework

The core part of Versatile Diffusion (VD) is the multi-flow multimodal diffusion framework capable of generating various forms of outputs (*e.g.* image, text, 3D, *etc.*) conditioned on various crossmodal contexts (*e.g.* image, text, audio *etc.*). A formal definition of a single flow in VD is to synthesize features of modality n using contexts of modality m . One may notice that the well-explored text-to-image

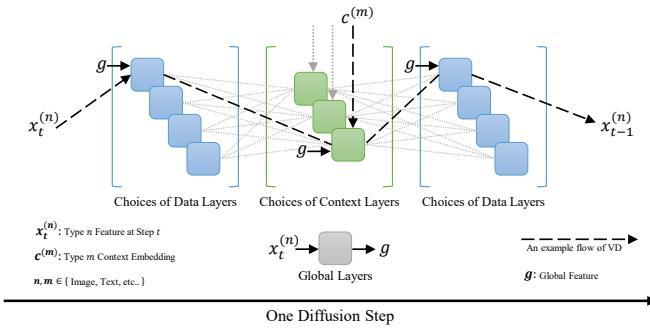


Figure 2: Graphic illustration of one diffusion step of VD’s multi-flow multimodal diffusion framework, in which multiple choices of data layers (blue), context layers (green), and fixed global layers (gray) are involved. The black dash line shows one flow of the model that handles one crossmodal task (*i.e.* text-to-image), in which the top data blocks, the bottom context blocks, and the shared global layers are activated. Other data and context blocks stay silent but will be activated when performing other tasks.

task [21, 63, 70, 67], *i.e.* synthesizing images based on text prompts, matches the definition of a single flow in VD. But the scope of VD goes beyond one single task; particularly in this work, VD is set up to fulfill numerous tasks: text-to-image, image-to-text, and variations, and may further extend to cover more modalities such as 3D, audio, music, *etc.*

Speaking with details, VD handles groups of crossmodal tasks due to its multi-flow framework, in which layers can be activated or muted based on the modalities of the input contexts and output results. As shown in Figure 2, we categorize all diffuser layers into three groups: global layers, data layers, and context layers. The global layers are flow-independent layers that will always be activated. Data layers are output-dependent layers that will be activated when the network generates the corresponding output type. Lastly, context layers are context-dependent layers that will be activated when the corresponding context type is input. Using SD [67] as a reference, the global layers are time-embedding layers; the data layers are residual blocks; and the context layers are cross-attentions. One flow of VD routes the feed-forward pass through the shared global layers and the chosen data and context layers, while other irrelevant layers will stay silent (see Figure 2). Use text-to-image as an example. The t -step intermediate result x_t will be fed to image data blocks and text context blocks to generate the next step result x_{t-1} . Similarly, if our goal is to perform image-variation, we need to use image data blocks and image context blocks.

One may notice that such a multi-flow multimodal framework highly promotes parameter sharing. In this work, our default VD setting is a four-flow model. In order to replicate such four-flow VD, one would require a total of four diffusion models (*i.e.* four times the size of an

SD [67]), while VD reduces the number of parameters by half via its shared layers in the framework. A more generalized version of VD handles $N \times M$ crossmodal tasks with N types of output and M types of context. The size of the model would then become $\mathcal{O}(\max(N, M))$, which is significantly smaller than a vanilla model ensembling that requires an accumulated size of $\mathcal{O}(N \times M)$.

3.3. Versatile Diffusion

Tasks: As mentioned earlier, Versatile Diffusion (VD) is a unified diffusion model for text-to-image, image-to-text, and variations. Text-to-image and image-to-text are two well-known tasks in which the former generates images from text prompts, and the latter generates image captioning. Image-variation (IV) is a fairly new task in which users generate new images that are semantically similar to the reference images. IV differs from SD’s image-to-image (I2I) [67] by two points a) IV diffuses from pure noise while I2I diffuses from images half-mixed with noise; b) IV maintains high-level semantics but relaxes the low-level structures, while I2I only replicates low-level structures and has no guarantee on high-level semantics. Lastly, VD can also generate variations in text due to its multi-flow nature, whose goal is to generate similar expressions from reference text.

Network: The full model of VD includes three components: a) A diffuser that follows our multi-flow multimodal framework described in Sec 3.2; b) VAEs that convert data samples to latent representations; c) Context encoders that encode contexts into embeddings. The overall network diagram is also shown in Figure 3. **Diffuser:** We use the well-adopted UNet [68] with cross attentions [91] as the main structure of our diffuser network. Part of the UNet follows SD [67], where we adopt residual blocks [26] as image data layers and cross-attention as text and image context layers. For text data layers, we propose the fully connected residual blocks (FCResBlock) that expand 768-dimensional text latent vectors into a 320-by-4 hidden feature and follow a similar residual block paradigm with GroupNorms [97], SiLU [18], and skip connections (see Figure 4). **VAE:** We adopt the same Autoencoder-KL [67] like SD as our image VAE. Parallelly, we adopt Optimus [49] as our text VAE. Optimus consists of a Bert [15] text encoder and a GPT2 [61] text decoder, by which it can bidirectionally transform sentences into 768-dimensional normally-distributed latent vectors. **Context encoder:** We use both CLIP [60] text and image encoders as VD’s context encoders. Unlike SD, which uses raw text embeddings as context inputs, we use normalized and projected embeddings that minimize the CLIP text-image contrastive loss. In our experiments, we noticed that closer embedding spaces between contexts (*i.e.* image and text) help converge fast and perform better.

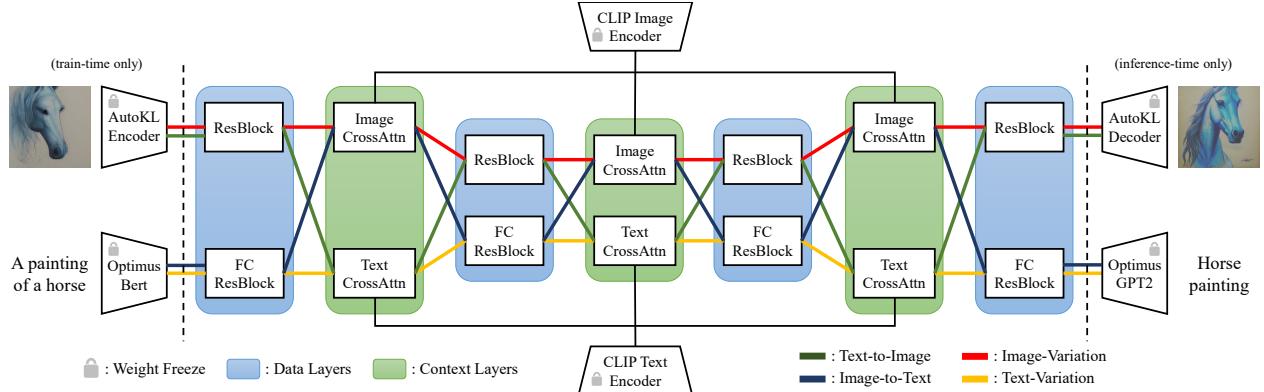


Figure 3: The overall structure of four-flow Versatile Diffusion (VD). Each color line depicts a single flow of VD that represents one supported task (*i.e.* green line for text-to-image). The VAE encoders at the far left are only used in training and are replaced with Gaussian noise inputs during inference. Oppositely, the VAE decoders at the far right are only used in inference for output generation, not train-time loss computation. For simplicity, we hide global layers in this figure. Better viewed in color.

Algorithm 1: Backpropagation of VD

```

 $X = \{x^{(1)} \dots x^{(N)}\}; // N$  types data
 $C = \{c^{(1)} \dots c^{(M)}\}; // M$  types context
 $L_\theta(x^{(\cdot)}, c^{(\cdot)})$ ; // Loss with params  $\theta$ 
 $\delta_\theta = 0$ ; // Param gradients
for  $x^{(i)} \in X$  do
    for  $c^{(j)} \in C$  do
         $\delta'_\theta = \nabla_\theta L_\theta(x^{(i)}, c^{(j)})$ ; // One flow
         $\delta_\theta = \delta_\theta + \delta'_\theta$ ;
    end
end
Update network with  $\delta_\theta$ ;

```

Loss: Training VD is surprisingly simple. For each of the flows, we compute the variational weighted l_2 losses described in Equation 3 and do regular backpropagation (see Algorithm 1). Model weights will be updated when the gradients in all flows are accumulated. Besides, when updating the weights, we manually set gradient scales for parameters in data and context layers to better adapt our multi-flow model settings. More information can be found in the Experiments session.

4. Experiments

In this session, we will describe VD’s data and settings, show the performance of VD on primary tasks, and introduce several derived applications empowered by the multi-flow multimodal property of VD.

4.1. Dataset

We used Laion2B-en [74] and COYO-700M [9] as VD’s train data. Both Laion2B and COYO are collections of image-text pairs in English, in which images are collected

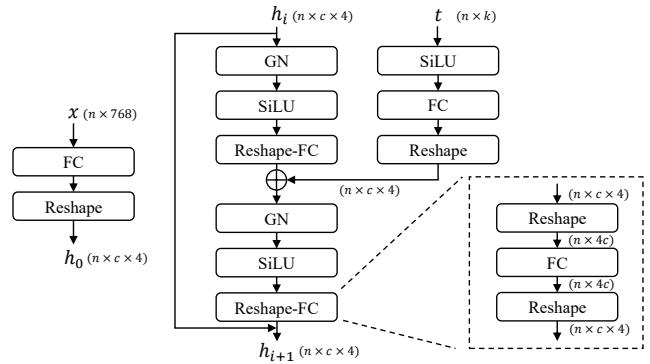
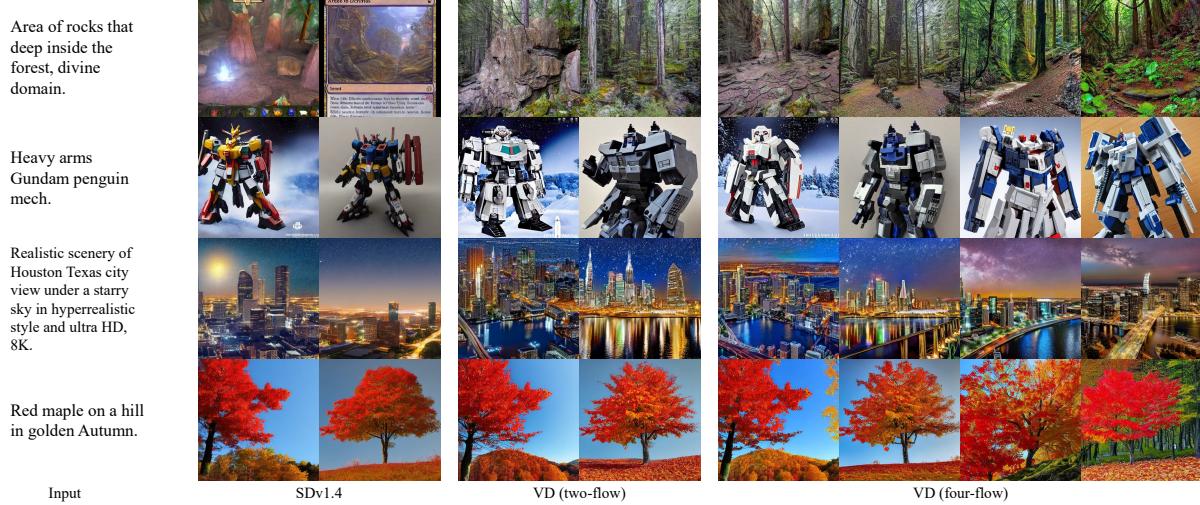


Figure 4: FCResBlock contains two sets of fully connected layers (FC), group normalizations (GN) [97], and sigmoid linear units (SiLU) [18]. x is the input text latent code, t is the input time embedding, and h_i are the intermediate features.

from websites, and the corresponding captions are excerpted from HTML pages. We further filtered all data with the following criteria: a) image-text CLIP similarity scores above 0.3; b) safety scores (*i.e.* NSWF) below 0.3; c) the probability containing watermark below 0.3; d) image aspect ratios within 0.6 to 1.6667; e) image area above $256^2 \times 0.75$. These filtered samples served as the train data for all our VD experiments. Besides, we noticed that the web crawling captions tend to be noisy, so we cleaned them with a customized algorithm described in Supplementary.

4.2. Training

We trained VD progressively with three settings: single-flow, dual-flow, and four-flow, among which the single-flow is an image-variation model; the dual-flow is a text-to-image and image-variation model; and the four-flow is the main VD model with four tasks we majorly described in this work. During training, we kept diffusion settings close



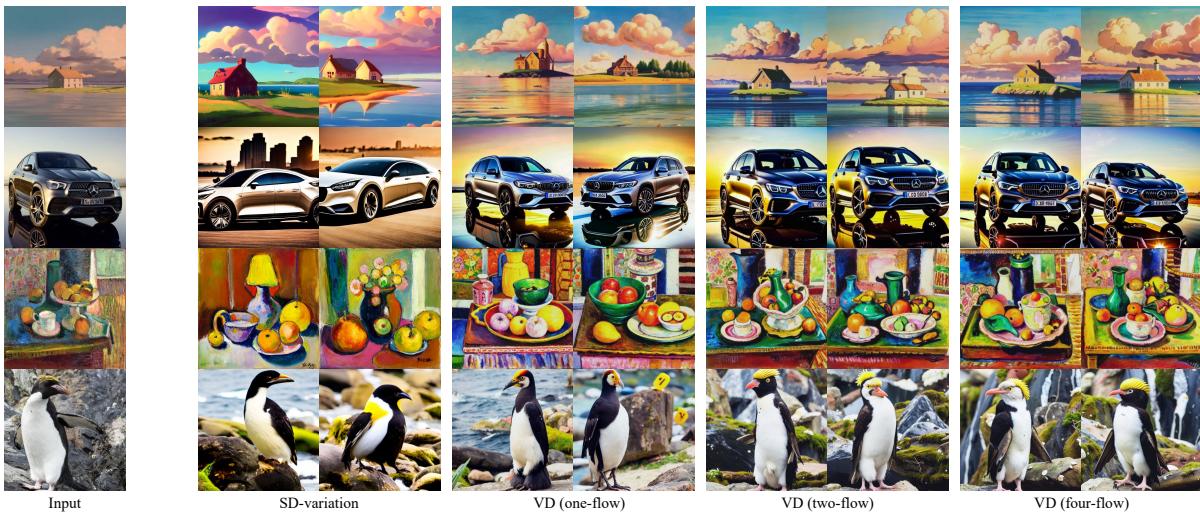
Input

SDv1.4

VD (two-flow)

VD (four-flow)

(a) Text-to-Image performance.



Input

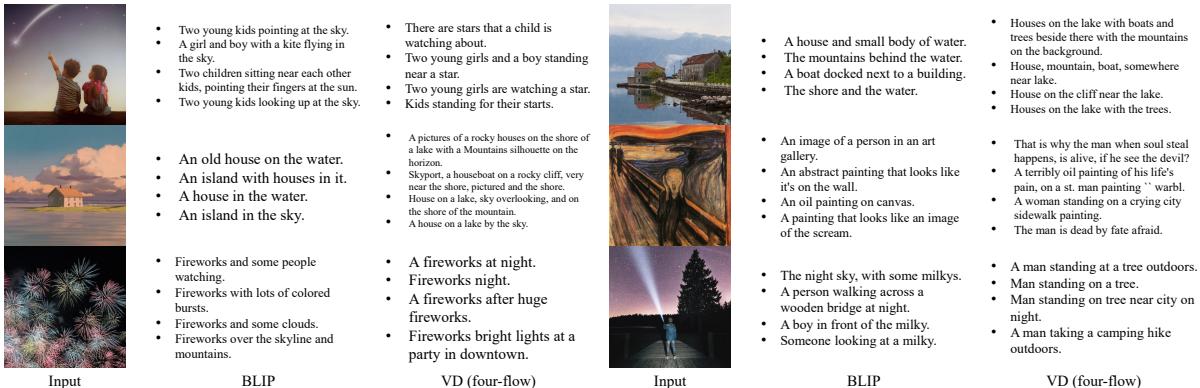
SD-varying

VD (one-flow)

VD (two-flow)

VD (four-flow)

(b) Image-Variation performance.



Input

BLIP

VD (four-flow)

Input

BLIP

VD (four-flow)

(c) Image-to-Text performance.

Figure 5: These figures show the qualitative comparison between our VD models and prior works, from which we conclude that VD performs well on all three tasks. In text-to-image and image-variation, VD captures semantics from the input context more accurately. In image-to-text, VD generates more creative sentences and has a better chance to describe images with more details.

to DDPM [28] and SD [67], *i.e.*, 1000 diffusion steps and linearly increasing β from $8.5e - 5$ to $1.2e - 2$ according to steps. The learning rates were set to $1.e - 4$ for single-flow and dual-flow, and were set to $5.e - 5$ for four-flow. The single-flow model used SD checkpoint v1.4 [67] as its initial weights, and others continued finetuning the latest checkpoint from the previous models. During training, we set different gradient scales for different layers to best cooperate with the initial weights. One can find these details in Table 1. The effective batch size was 2048 for single-flow, 1024 for dual-flow, and 512 for four-flow. The logic behind the learning rates, batch sizes, and gradient scales is to roughly balance each gradient step while training. All models were trained with 30 million samples on resolution 256, followed by 6.4 million samples on resolution 512. Compared with SDv1.4, which was trained on 500 plus 230 million samples on resolutions 256 and 512, VD’s training cost is more affordable, benefiting researchers in the long run.

	Data(I)	Data(T)	Ctx(I)	Ctx(T)	Global
VD (1-flow)	0.1	–	1.0	–	0.1
VD (2-flow)	0.1	–	1.0	1.0	0.1
VD (4-flow)	0.2	1.0	1.0	1.0	0.1

Table 1: This table shows the gradient scales used by different layers when training various settings of VD. Data(I) means the image data layer, so on and so forth.

4.3. Performance

To the best of our knowledge, VD is the first image-text multi-flow multimodal model that can be evaluated across different tasks. Thus, we chose single-task-focused prior works as our baselines when comparing the performance. Explicitly speaking: we chose SDv1.4 [67] as our text-to-image baseline; SD-variation [33] (*i.e.* a finetuned SD for image-variation) as our image-variation baseline; and BLIP [50] as our image-to-text baseline. We conducted both qualitative and quantitative comparisons between baselines and various versions of VD, *i.e.*, dual-flow and four-flow for text-to-image, and all three models for image-variation. Although DALLE2 [63] and Imagen [70] also achieved SOTA on text-to-image, they were not compared because of no publicly available code and model. For image-to-text (*i.e.* image captioning), we only compare BLIP [50] with our four-flow VD since other settings do not support this task.

Figure 5 compares VD’s qualitative performance with its baseline, in which images in each row are created with the same random seeds for better quality checks. We also compute text-to-image and image-variation FID scores by comparing 30000 randomly generated samples with the validation set of COCO-caption [52]. In Figure 6, we list VD’s performance along with other related works. We

Method	FID ↓
(A) Text-to-Image Synthesis	
CogView [17]	27.10
LAFITE [104]	26.94
GLIDE [56]	12.24
Make-a-Scene [21]	11.84
LDM [67]	12.63
SD (baseline)	11.21 ± 0.03
VD (four-flow)	11.10 ± 0.09
(B) Image-Variation Synthesis	
SD (baseline)	18.81 ± 0.06
VD (four-flow)	4.57 ± 0.02

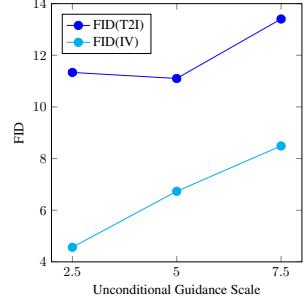


Figure 6: FID scores of VD comparing with baseline and prior approaches, and under various unconditional (classifier-free) guidance scales.

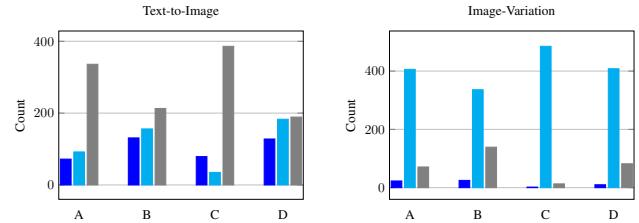


Figure 7: User studies on text-to-image and image-variation in which we count the votes from 4 individual moderators on SD (blue), VD (cyan), or equally good (gray).

also plot the changes in VD’s FID according to the unconditional guidance scale (*i.e.* the classifier-free guidance scale). Lastly, we carried out user studies on 2000 samples from COCO-Caption [52] split by four moderators, in which moderators were asked to vote for better quality or “equally good” (see Figure 7).

Through all results, we not only demonstrated that VD outperforms its baseline on these primary tasks, but reveals the effectiveness of our multi-flow multimodal diffusion framework in which context and data with distinct modalities can be analyzed and generated in one unified model.

4.4. Disentanglement of style and semantic

One exciting discovery of our VD is that it can enhance or reduce image styles from semantics without further supervision. Such a phenomenon inspires us to explore a novel area where disentanglement between styles and semantics can happen on images with arbitrary contents in arbitrary styles. Recall that prior works such as [5, 24] explored similar properties in GAN latent spaces, but their domain of study was restricted to well-aligned data such as faces or churches. To our best knowledge, we are the first group exploring: a) unsupervised semantic and style disentanglement on natural images without domain specifications; b) semantic and style disentanglement on diffusion models’ latent space.

Figure 8 shows the disentanglement results of VD. In practice, we notice that both two-flow and four-flow mod-



Figure 8: Our VD can disentangle image semantics from styles and vice versa. In this figure, we first generate variations of the input images and then manipulate them focused on either semantics (to the left) or styles (to the right).

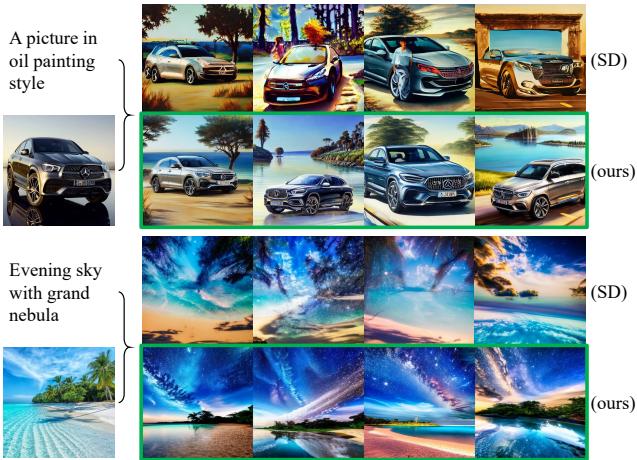


Figure 9: This figure shows images generated from dual-context blender (one image and one prompt). Images without borders are baseline results generated by ensembling SDv1.4 [67] with SD-variation [33]. Images with green borders are VD’s outputs (ours) with a deeper level of mixing. To fairly compare the performance, samples in the same columns use the same random seed and initial noise inputs.

els serve similar performance, while single-flow has slightly lower performance. This may be due to the caption-agnostic and insufficient training that reduced the model’s capacity. More details and analysis can be found in Supplementary.

4.5. Dual- and multi-context blender

Since VD is a unified model for multiple tasks, generation from multi-context becomes a natural extension for VD. Recall that a baseline multi-context generation can be achieved by mixing up diffusion steps from distinct models [53]. However, in practice, we notice such a baseline cannot reach satisfactory results despite doubling the model usage. Figure 9 compares the dual-context results using one text and one image, in which we use the mixing of

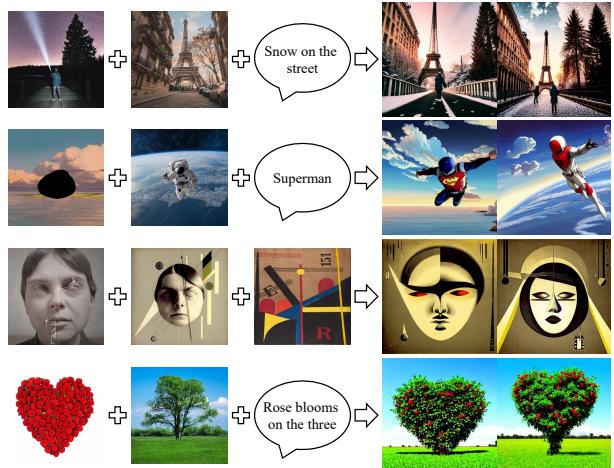


Figure 10: This figure shows images created with VD’s multi-context blender in which multiple images with optional text and masks are applied as contexts. One can notice that VD can smoothly transfer and reconstruct semantic from contexts to outputs.

SDv1.4 [67] (text-to-image) and SD-variation [33] (image-variation) as our baseline (labeled as SD). One may easily notice that VD generates more natural-looking results with fewer distortions. We believe that the good performance of VD is largely attributed to its multi-flow structure, through which intermediate features generated from different contexts can be merged on a much deeper level (*i.e.* layer-level or attention-level), instead of merged on the shallow model-level between diffusion steps. More details regarding mixing levels can be found in Supplementary.

We further expand this task to a more generalized form with multi-context, resulting in the multi-context blender application. The multi-context blender for VD supports an optional text context, several image contexts, and optional image masks in order to guide the generation process with more detail controls. Figure 10 shows the performance of our multi-context blender. Notice that there are other recent works such as [27, 8, 102, 12, 69, 46, 36] focused on the broader image editing topic. We encourage readers to check our Supplementary for more details and comparisons.

5. Conclusion

In this article, we proposed Versatile Diffusion that handles text, image, and variations all in one, from which we generalized a multi-flow multimodal framework that can further extend to new tasks and domains. Through inclusive experiments, we demonstrate that such a multi-flow multimodal diffusion method can perform well on both primary tasks and applications. Moreover, VD can be a heuristic step toward universal AI research.

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