Discriminative Diffusion Models as Few-shot Vision and Language Learners

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Abstract

Diffusion models, such as Stable Diffusion (Rombach et al., 2022a), have shown incredible performance on text-to-image generation. Since text-to-image generation often requires models to generate visual concepts with fine-grained details and attributes specified in text prompts, can we leverage the powerful representations learned by pre-trained diffusion models for discriminative tasks such as image-text matching? To answer this question, we propose a novel approach, Discriminative Stable Diffusion (DSD), which turns pre-trained text-to-image diffusion models into few-shot discriminative learners. Our approach uses the cross-attention score of a Stable Diffusion model to capture the mutual influence between visual and textual information and fine-tune the model via attention-based prompt learning to perform image-text matching. By comparing DSD with state-of-the-art methods on several benchmark datasets, we demonstrate the potential of using pre-trained diffusion models for discriminative tasks with superior results on few-shot image-text matching.

1 Introduction

"What I Cannot Create, I Do Not Understand."

Richard Feynman

This quote by Richard Feynman perfectly captures the essence of human learning techniques. In the context of machine learning, it can be interpreted as the ability to generate images given text prompts is a strong indicator of understanding and matching between visual and textual information. Despite the success of various methods in the image-text matching task (Karpathy and Fei-Fei, 2015; Lee et al., 2018), there is still a need for more advanced models that can better capture the fine-grained details, spatial relationships, and compositionality. Meanwhile, diffusion models (Sohl-Dickstein et al., 2015a; Rombach et al., 2022a) have been shown to produce high-quality and diverse images from text descriptions. Therefore, in this paper, we investigate the idea of leveraging the power of pre-trained Diffusion Models, specifically the state-of-the-art text-to-image generative model—Stable Diffusion (Rombach et al., 2022a), for the discriminative image-text matching task, as shown in Figure 1. The success of Stable Diffusion in generative tasks suggests that it has a strong understanding of the relationship between visual and textual information, and we aim to harness this understanding for image-text matching tasks.

The key advantages of using Stable Diffusion for text-image alignment are two folds: <u>first</u>, Stable Diffusion uses a pre-trained Variational Autoencoder (VAE) (Kingma and Welling, 2013) and cross-



Figure 1: The upper subfigure in the teaser image illustrates the ability of Stable Diffusion to generate realistic images given a text prompt. The bottom subfigure illustrates the process of our proposed method, Discriminative Stable Diffusion (DSD), for utilizing Stable Diffusion for the image-text matching task. DSD can output a matching score for a given text prompt and image, with a higher score indicating a stronger match.

attention layers in its architecture, which provides strong compressed representations and shed information about the alignment of the data from different modalities. <u>Second</u>, Stable Diffusion has the ability to understand spatial relations and fine-grained disentangled concepts, so as to generate images per text prompts' requests, while traditional vision and language model pre-trained on discriminative tasks such as CLIP (Radford et al., 2021) only allows to model image-text contextual alignment at coarse-grained contextual (global) level but ignores the compositional matching of disentangled concepts (i.e., finer-grained cross-modal alignment at region-word level) (Jiang et al., 2022).

However, to efficiently adapt Stable Diffusion, a pre-trained text-to-image generation model, to the image-text matching task, two key challenges need to be addressed: (1) how to disentangle the degree of alignment between the image and text from the latent space of Stable Diffusion? In text-to-image generation, the model is trained to generate an image that is semantically consistent with a given text prompt. However, in image-text matching, the task is to determine the degree of alignment between the image and text. Therefore, it is important to disentangle the degree of alignment between the image and text in the latent space of Stable Diffusion, to effectively use it for image-text matching; (2) how to efficiently adapt the model in the few-shot setting. Fine-tuning a text-to-image generation model like Stable Diffusion for image-text matching requires adapting the model from a generative task to a discriminative task, which can be challenging.

To address these challenges, we propose the Discriminative Stable Diffusion (DSD) method, which includes two key ideas: (1) identifying and leveraging attention scores from the selected cross-attention maps as the matching score and (2) using attention-based prompt learning to fine-tune the attention matrices. DSD can outperform the CLIP-based methods by 2.09% on the Compositional Visual Genome and 3.19% on the RefCOCOg datasets in terms of accuracy under the few-shot setting. Our approach reveals the potential of diffusion models that can broaden their scope of use to discriminative tasks.

Our contributions in this paper are threefold:

- We do a pioneer study using latent text-to-image generation diffusion models which are initially proposed for generative tasks to address discriminative tasks such as image-text matching.
- We propose a new method based on exploiting the use of cross-attention maps of Stable Diffusion across layers and attention-based prompt learning for solving the image-text matching task.
- We demonstrate the effectiveness of our approach through experimental evaluation under the few-shot setting on both the Compositional Visual Genome (Jiang et al., 2022) and the RefCOCOg (Yu et al., 2016) datasets for image-text matching. We also extend our method to the visual question answering task, demonstrating its potency on the VQAv2 (Antol et al., 2015) dataset.

2 Related Work

Diffusion Probabilistic Models (DPMs) Diffusion probabilistic models (DPMs) have been widely used as generative models for images in recent years. These models, which include diffusion (Sohl-

Dickstein et al., 2015b) and score-based generative models (Song and Ermon, 2019), have been shown to outperform generative adversarial networks (GANs) (Goodfellow et al., 2014) in many cases. In the past two years, significant progress has been made in the development of DPMs, with a focus on improving sampling techniques such as classifier-free guidance (Ho and Salimans, 2021). DPMs are typically implemented using convolutional U-Net architectures (Ronneberger et al., 2015a) which contain cross-attention layers. Hertz et al. (2022) finds that replacing attention maps in the cross-attention module of text-to-image generation diffusion models can edit image attributes. Just scaling the attention maps of the respective word can adjust the effect of a particular word in the prompt. Feng et al. (2022) demonstrates that one can retain the compositional semantics in the generated image by manipulating the cross-attention. Kumari et al. (2022) proposes to fine-tune the key and value mapping from text to latent features in the cross-attention layers of text-to-image diffusion model to compose multiple new concepts in the image. In the context of image-text matching, the attention scores between the text and image representations in the DPMs can reflect the degree of alignment between them.

Few-shot Learning for Vision and language Tasks Vision and Language discriminative models pretrained on large-scale image-text pairs have demonstrated great potential in multimodal representation learning (Jia et al., 2021; Yao et al., 2021; Yuan et al., 2021; Radford et al., 2021; He et al., 2022a). Among them, CLIP (Radford et al., 2021) benefits from 400M curated data and defines various prompt templates to carry out zero-shot image classification. Like CLIP, several different few-shot learners were proposed. GPT (Brown et al., 2020), as a strong few-shot learner, is capable of performing a new language task by learning from only a few training instances. Frozen (Tsimpoukelli et al., 2021) is developed based on GPT and made into a multimodal few-shot learner by expanding the soft prompting to include a collection of images and text. The concept of prompt learning (Schick and Schütze, 2020) has been widely explored in natural language processing (NLP) and computer vision. It allows pre-trained models to adapt to various downstream tasks with minimal data by introducing a small prompt layer (Schick and Schütze, 2020; Liu et al., 2021). In the context of image-text matching, prompt learning has been used to fine-tune pre-trained models for the task (He et al., 2022b). In our work, instead of adding learnable prompts over the inputs or between transformer layers (Jia et al., 2022), we introduce learnable prompts over the attention layers.

Generative Models for Discriminative Tasks There has been a significant amount of research on using generative models for discriminative tasks in natural language processing and machine learning. One approach is to fine-tune the model on a discriminative task. Dai et al. (2021) finetunes a large transformer-based language model on several discriminative tasks, including named entity recognition and machine translation, and show that fine-tuning the model leads to improved performance compared to using the model in a generative only setting. Yang et al. (2019) proposes a model that combines a generative model for text generation with a discriminative model for sentiment analysis. Wang et al. (2018) proposes a method for adapting a generative model for language translation to perform the discriminative task of language classification, and shows that the adapted model outperforms strong baselines on the language classification task. Other examples of using generative models for discriminative tasks include using a generative model to initialize a discriminative model for improved performance (Mao et al., 2019), and using a generative model to pre-train a discriminative model for domain adaptation (Chen et al., 2020b). For diffusion models, recently, Li et al. (2023); Clark and Jaini (2023) propose to use pre-trained diffusion models for zero-shot classification. Wei et al. (2023) formulates diffusion models as masked autoencoders and achieves state-of-the-art classification accuracy on video tasks.

3 Preliminaries on Diffusion Models

In this section, we provide a brief overview of the concepts and techniques in denoising diffusion models that are necessary to understand our proposed method. Diffusion models are a class of generative models that are particularly effective at generating high-quality images (Sohl-Dickstein et al., 2015b; Nichol et al., 2021; Ramesh et al., 2022; Saharia et al., 2022; Rombach et al., 2022b). They aim to model a distribution $p_{\theta}(x_0)$ that approximates the data distribution $q(x_0)$ and is easy to sample from. DPMs model a "forward process" in the space of x_0 from data to noise by adding noise to real data, and a reverse process that tries to reconstruct the original data from the noisy version. The forward process is described by the equation

$$q(x_t|x_0) = \mathcal{N}(x_t; \sqrt{\bar{\alpha}_t} x_0, (1 - \bar{\alpha}_t)\mathbf{I}), \tag{1}$$



Figure 2: Overview of our Discriminative Stable Diffusion framework, which measures how much the given images and texts matched use the cross-attention mechanism in the Stable Diffusion. Discriminative Stable Diffusion added input-dependent prompt embeddings over attention matrices (red boxes). We then fine-tune the prompt under the few-shoot setting.

where $x_{1:T}$ defines a set of noisy images and x_0 is the initial image. \mathcal{N} denotes a Gaussian distribution, and $\bar{\alpha}_t$ are hyperparameters. The reverse process is modeled by a Gaussian distribution

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

where neural networks are used to predict the mean and covariance of the distribution. The parameters of the model, θ , are learned by optimizing a variational lower bound on the log-likelihood of the real data. Once trained, new images can be generated by starting from a noise sample and iteratively sampling from the reverse process distribution until reaching the final time step. In latent diffusion probabilistic models such as Stable Diffusion, this two process are similar, while they proceeds in the latent space: x_0 is encoded into z_0 in an efficient, low-dimensional latent space first and then do the diffusion process. And in the case where a DPM is conditioned on additional information, such as text information c, the reverse process becomes $p_{\theta}(z_{t-1}|z_t, y)$, where y is the input text.

4 Discriminative Latent Diffusion Models

4.1 **Problem Formulation**

The problem of image-text matching is formalized as follows: given a text prompt $y \in \mathcal{Y}$ and a set of images \mathcal{X} , we aim to find the image $x^* \in \mathcal{X}$ that is most semantically aligned with the given text prompt y. Formally, we define the image-text matching problem as finding the function $f : \mathcal{Y} \times \mathcal{X} \to [0, 1]$ that assigns a score to each image-text pair (y, x) indicating the degree of semantic alignment between the text and image. The goal is to find the image x that maximizes the score for a given text prompt y, i.e., $x^* = \arg \max_{x \in \mathcal{X}} f(y, x)$.

4.2 Method Overview

To learn the function f, the main idea is to leverage the powerful representations learned by a pre-trained Stable Diffusion model to perform image-text matching. There are three key modules in DSD, cross-attention score computation, LogSumExp pooling, and attention-based prompt learning, as shown in Figure 2. The cross-attention score computation module extracts the mutual influence between visual and textual information by computing the attention scores from the cross-attention matrix in U-Nets of the Stable Diffusion model. The LogSumExp pooling module pools these attention scores over all tokens in the text description to obtain a single matching score. Finally, the attention-based prompt learning module fine-tunes the model by updating the key and value mappings from text to latent features in the cross-attention layers under a few-shot setting. This allows the model to learn new image-text concepts while retaining the ability to capture complex and nuanced relationships between images and text. The model outputs a score that measures the

alignment between the image and text, which can be used to adapt the model from a text-to-image generation task to an image-text matching task.

4.3 Cross-attention Score Computation

Cross-attention scores are a measure of the relevance of an image and a text to each other (Chen et al., 2020a; Li et al., 2019). They are calculated by taking the dot product of the representations of the image and text in a latent space, and normalizing by the product of their norms. We propose to adapt cross-attention scores as a way to better capture the complex relationships between images and text in the image-text matching task. In the sequel, we elaborate on our strategy in depth.

Stable Diffusion (Jaegle et al., 2021) is trained to generate images from text prompts, and as such, it has learned strong compressed representations of both text and images. We can make use of these representations to learn the function f for image-text matching.

More specifically, given a text prompt y, we first encode it into a intermediate text representation $r_y = \tau_{\theta}(y) \in \mathbb{R}^{M \times d_{\tau}}$ using the domain specific encoder τ_{θ} . We then encode each image $x \in \mathcal{X}$ where $x \in \mathbb{R}^{H \times W \times 3}$ in RGB space into a latent image representation $z = \mathcal{E}(x)$, where $\mathcal{E}(x)$ is the encoder. The encoder ϵ_{θ} in the U-Net (Ronneberger et al., 2015b) of the pre-trained text-to-image generation model then encode z into $r_x = \varphi_i(z_t)$, where $\varphi_i(z_t) \in \mathbb{R}^{N \times d_{\epsilon}^i}$ denotes a (flattened) intermediate representation of the UNet implementing ϵ_{θ} , which are then mapped to intermediate layers of the UNet via a cross-attention layer implementing $A = \operatorname{softmax}\left(\frac{QK^T}{\sqrt{d}}\right) \cdot V$, with $Q = W^{q^{(i)}} \cdot r_x$, $K = W^{k^{(i)}} \cdot r_y$, $V = W^{v^{(i)}} \cdot r_y$. Here, $W^{v^{(i)}} \in \mathbb{R}^{d \times d_{\epsilon}^i}$, $W^{q^{(i)}} \in \mathbb{R}^{d \times d_{\tau}}$, $W^{k^{(i)}} \in \mathbb{R}^{d \times d_{\tau}}$ are learnable projection matrices (Jaegle et al., 2021; Vaswani et al., 2017), mapping the inputs to a query, key, and value feature, respectively, and d' is the output dimension of key and query features.

4.4 LogSumExp Pooling (LSE)

To compute the function g and quantitatively evaluate the degree of semantic alignment between an image and a text prompt, we leverage LogSumExp (LSE) pooling (Blanchard et al., 2021) as a means of aggregating the attention maps generated by the cross-attention mechanism in our model. By using LSE pooling, we are able to take into account the relative importance of different image and text tokens in the attention map, rather than simply averaging or summing all elements in the map. This has several benefits. Firstly, LSE pooling is able to handle large values and outliers in the attention map more robustly than other pooling methods, such as average or sum pooling. Secondly, LSE pooling is able to better preserve the ordering of values in the attention map, allowing for more interpretable and accurate matching scores.

The attention map matrix is denoted as $A \in \mathbb{R}^{n \times m}$, where n and m are the number of image and text tokens, respectively. The LSE pooling operator is defined as:

$$S(A) = \frac{1}{\lambda} \log \left(\sum_{i=1}^{n} \exp\left(\lambda A_{i,:}\right) \right)$$
(3)

Where $A_{i,:}$ represents the *i*-th row of the matrix A. λ is a factor that determines how much to magnify the importance of the most relevant pairs of image region features and attended text sentence vectors. The LSE pooling operator computes the log sum of the exponentiated values in each row of the matrix, resulting in a vector of length m.

The score for the image-text pair (y, x) is then computed by averaging across-attention maps, denoted by

$$f(y,x) = \operatorname{Ave}(S(A)) = g(A) \tag{4}$$

where $g : \mathbb{R}^{M \times d} \times \mathbb{R}^{N \times d} \to [0, 1]$ is a scoring function that measures the degree of semantic alignment between the text and image representations.

Overall, our method combines the strengths of the U-Net architecture and the attention mechanism of the Stable Diffusion model. We resort to attention-based prompt learning (Lester et al., 2021) to efficiently adapt the model to perform image-text matching.

Alg	Algorithm 1 Image-Text Matching with Discriminative Stable Diffusion					
1:	I: Image space					
2:	\mathbb{T} : Text space					
3:	x: Image					
4:	y: Text					
5:	z: Latent representation					
6:	E: Encoder					
7:	τ : Domain-specific encoder					
8:	φ : Intermediate representation of the U-Net					
9:	function $\mathcal{DSD}(\mathbb{I},\mathbb{T})$					
10:	for (i, t) in the batch do					
11:	Image latent representation $z_i \leftarrow \mathcal{E}(x)$					
12:	Text latent representation $r_y \leftarrow \tau(y)$					
13:	Intermediate representation $r_x \leftarrow \varphi(z_t)$					
14:	Add prompts $W^{k'} \leftarrow W^k, W^{v'} \leftarrow W^v$	⊳ Eq. 5				
15:	Compute attention maps $A \leftarrow r^y, r^x$					
16:	Compute LSE score $S(A) \leftarrow A$	⊳ Eq. 3				
17:	Compute matching score $g(A) \leftarrow A$	⊳ Eq. 4				
18:	Compute loss $L \leftarrow \hat{y}_n$	⊳ Eq. 6				
19:	Update $p_k(x), p_v(x)$					
20:	end for					
21:	end function					

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4.5 Attention-based Prompt Learning for Stable Diffusion

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We aim to adapt the latent diffusion probabilistic model to the image-text matching task leveraging only a few examples, that is, under the few-shot setting. The task of fine-tuning aims at updating the mapping from the given text to the aligned image distribution, and the text features are only input to W^k and W^v projection matrix in the cross-attention block. Therefore, we propose the use of learnable prompts, which are added to the attention matrices in our model. Specifically, as shown in Figure 2, we introduce learnable prompt embedding matrices, which are added element-wise to the key and value attention matrices at the identified layer of the Stable Diffusion model. Let $m_{\theta}(\cdot)$ denote the mapping network parameterized by θ , each prompt token is now obtained by $p(x) = p + \pi$ where $\pi = m_{\theta}(x)$ so that the prompt will be conditional on the input image. As our prompt addition operation applies to all layers and sampled time-steps, we will omit superscripts t and layer l for notational clarity and obtains:

$$W^{k'} = W^k + p_k(x), W^{v'} = W^v + p_v(x).$$
(5)

Both $p_k(x)$ and $p_v(x)$ are updated during training. This allows the model to adapt to new instances by attending to relevant information in the intermediate representation of the text inputs, $\tau_{\theta}(y)$. With the learned prompt embeddings in the few-shot scenario, we can effectively adapt the Stable Diffusion to image-text matching performance. The overall algorithm is shown in Algorithm 1. For optimization, we use the cross-entropy loss function between the predicted match score and the true match score. Let L be the cross-entropy loss, we have:

$$L = -\frac{1}{N} \sum_{n=1}^{N} \left(y_n \log \hat{y}_n + (1 - y_n) \log(1 - \hat{y}_n) \right)$$
(6)

where N is the number of samples in the training dataset and y_n and \hat{y}_n are the true and predicted match scores for the *n*-th sample, respectively.

Dynamic Attention Head Weighting We propose a method for adjusting the weights of different heads in the cross-attention of our model. The classifier-free guidance (Ho and Salimans, 2022) is a technique that encourages the DPM to sample images that are likely to belong to a certain class by using the gradient of the log probability of the class given the image. This is done by adding a term to the loss function that is proportional to the gradient of the log probability of the class given the image. Inspired by them, where they use classifier-free guidance for diffusion models and demonstrate that it is possible to guide the learning of diffusion models by using a representation that is learned to maximize the mutual information between the input and the output, we compute the gradient of the

output of each attention head with respect to the input, and use this gradient to weight the contribution of each head to the final output of the model as follows:

$$\operatorname{Attr}_{h}(A) = A_{h} \odot \sum_{k=1}^{H} \frac{\partial f(A)}{\partial A_{h}},$$
(7)

where \odot is element-wise multiplication, $A_h \in \mathbb{R}^{n \times m}$ denotes the *h*-th head's attention weight matrix, and $\frac{\partial f(A)}{\partial A_h}$ computes the gradient of model $F(\cdot)$ along A_h . The (i, j)-th element of $Attr_h(A)$ is computed for the interaction between input token x_i and x_j in terms of the *h*-th attention head. By adjusting these weights during training, we are able to estimate the gradient flow, keep the most essential token alignment, guide the matching process between text and image and achieve better performance in our task.

5 Experiments

5.1 Datasets

We use the Compositional Visual Genome (ComVG) (Krishna et al., 2017) and RefCOCOg (Yu et al., 2016) datasets to do image-text matching, which requires model's ability to understand fine-grained details, spatial relationships, and compositionality of image and text pairs, that are more challenging for traditional vison-language models.

Compositional Visual Genome (ComVG) (Krishna et al., 2017) is a reconstructed dataset of the Visual Genome (Krishna et al., 2017) dataset, which contains 108,007 images annotated with 2.3 million relationships. These relationships are represented as subject-predicate-object triplets and include both action and spatial relationships. ComVG was created by selecting a subset of 542 images from Visual Genome that contain clear relationships, and generating mutated images by changing a single value in the subject, predicate, or object of each image. These mutated images were then used as negative examples, while the original images were used as positive examples, resulting in a total of 5400 data points.

RefCOCOg (Yu et al., 2016) is a reconstructed dataset of the MSCOCO (Lin et al., 2014) dataset. The dataset was created in a non-interactive setting, using Amazon Mechanical Turk workers. The process consisted of two stages: first, workers were asked to write referring expressions for objects in the images, and then, another set of workers were asked to indicate the referred object in the image by clicking on it. The final dataset includes 85,474 referring expressions for 54,822 objects in 26,711 images, with a focus on images containing between 2 and 4 objects of the same category.

VQAv2 (Goyal et al., 2017) The VQAv2 dataset (Goyal et al., 2017) is commonly converted to a classification task with 3,129 answer classes with frequency large than 9. In the context of a few-shot learning scenario, we ramdomly sample 3000 images from VQAv2 training set for training, while reserving 1,000 images from the validation set for the testing. We modify the candidate text to be the concatenation of question and answer pair for each question and perform matching with images.

5.2 Experimental Setup

We use the Stable Diffusion v2 with the xFormer (Lefaudeux et al., 2022) and flash attention (Dao et al., 2022) implementation. The Stable Diffusion utilizes a subset of the LAION-5B (Schuhmann et al., 2022) dataset during pre-training, specifically 170 million examples, along with LAION-2B-en and LAION-aesthetics v2 datasets for pre-training. On the RefCOCOg dataset, we sample 10 text prompts from the pool each time, and the model is asked to do the correct matching given the image and the 10 sampled text prompts. We first evaluate our method under the zero-shot setting and select the variant with the best performance (using attention maps with dynamic attention head weighting, averaged across all U-Net layers, and using the LogSumExp, see the ablation studies section for details). We then test our Discriminative Stable Diffusion under the few-shot setting using the best variant where we use 5% data to train the model.

Method	Compositional Visual Genome				RefCOCOg	
	Subjects	Objects	Predicate	Average	Top-1 Acc.	Top-5 Acc.
CLIP (Fine-tuning)	80.77	82.49	60.50	76.10	69.88	84.57
CLIP (Prompt Learning)	78.88	79.51	60.41	74.24	69.40	84.48
DSD	80.81	83.17	63.51	78.11	73.07	84.91

Table 1: Comparison of accuracy (%) on Compositional Visual Genome (ComVG) and Top-1 and Top-5 accuracy (%) on RefCOCOg using CLIP and Discriminative Stable Diffusion (DSD) under the few-shot setting. Our method outperforms CLIP based baselines, demonstrating the superiority of our approach compared with traditional vision and language pre-trained models such as CLIP pre-trained for discriminative tasks.

5.3 Baselines

In order to provide a comprehensive evaluation of our Discriminative Stable Diffusion method, we establish two baselines for comparison.

- Fine-tuning (Radford et al., 2021): The first baseline involves fine-tuning the CLIP model, with the last linear head being the only component subject to tuning.
- Prompt learning: The second baseline is based on the prompt learning strategy applied to CLIP, incorporating learnable prompts to the textual inputs that are conditioned on individual input images, as described in Zhou et al. (2022).

5.4 Results

To compare the performance of our method to other approaches, we conducted fine-tuning on CLIP and prompting on CLIP, in addition to our method. The results of these experiments are summarized in Table 1 on the Compositional Visual Genome dataset and RefCOCOg dataset. In order to facilitate a fair comparison, we adapt the use of the DSD model to two distinct settings on ComVG, given the different resolution of Stable Diffusion and CLIP. The first setting involves resizing all images in the dataset to a resolution of 224x224 first, and then upsampling and resizing to 512x512 for the use of DSD, so that DSD will not take advantage of its higher input resolution. The results are shown in Table 1. The other setting involves directly resizing all images to 224x224 and 512x512 base resolution, which is employed by CLIP and Stable Diffusion, with the results shown in the Supplements.

From the results, it is clear that our method outperforms both fine-tuning on CLIP and prompt learning on CLIP on both Compositional Visual Genome across the three different problem types and RefCOCOg.

We also show the results on the VQAv2 dataset in Table 2. These results demonstrate the extentiveness of our method to other vision and language tasks.

Method	Binary	Other	All
CLIP (Fine-tuning)	66.94	5.10	17.86
CLIP (Prompt Learning)	67.32	5.16	18.03
DSD	70.59	6.77	20.43

Table 2: Comparison of accuracy (%) on the VQAv2 dataset under the few-shot setting. Our method outperforms CLIP, demonstrating the superiority of our approach compared with traditional vision and language pre-trained models pretrained on other vision and language tasks.

5.5 Ablation Studies

Effect of Attention Maps from Dif-

ferent Sets of U-Net Layers We investigate the effect of using different numbers of layers in the U-Net of Stable Diffusion to compute the attention map. We use two variants of Stable Diffusion v2 and take the average of the attention maps from different layers of U-Net. Specifically, we consider the last one, the last two, the last eight, and all layers. The later layers in the U-Net may contain similar task-specific information, which can be found from observing that using only the last two layers also provides a close performance with that of one. The results, shown in Figure 3, indicate



Figure 3: Ablation study on the number of attention maps used from layers of the U-Net (x-axis). Tests on two variants of Stable-Diffusion v2: trained as a standard noise-prediction model on 512x512 images and 768x768 images.



Figure 5: Ablation study on using cosine similarity, maximum value from each column of the attention map, and the smoothed maximum (LogSumExp pooling).



Figure 4: Ablation study on the number of attention heads (five in total within the Stable Diffusion) in the U-Net (x-axis) with few-shot performance (y-axis) under the two scenarios: using the average of all attention maps and using our dynamic attention head weighting method. The results illustrate the superiority of our weighting method.



Figure 6: Ablation study on the amount of noise added during the diffusion process: using consistent noise levels of 0.4, 0.8 and using ensembling.

that using all layers in the U-Net gives the best performance in terms of accuracy, suggesting that the information from all layers can make use of both the high-level and low-level features when making predictions and preserve both coarse and fine image details for the image-text matching task.

Cosine Similarity vs. Maximum vs. LogSumExp Pooling for Score Computation We compare the overall accuracy of using Cosine Similarity, Maximum value from the attention map, and LogSumExp Pooling for score computation in Figure 5. As can be seen, using LogSumExp performs the best, followed by the maximum value, and finally the cosine similarity. This suggests that LogSumExp can effectively capture the overall importance of each element in the attention map, rather than just relying on the maximum value. Additionally, LogSumExp can smooth out the influence of individual noisy elements, resulting in more robust and accurate matching scores. As the dimensions of the image feature and text feature vectors in Stable Diffusion are not the same, we implement the cosine similarity by only comparing the shared dimensions of the image and text feature vectors. Overall, these results highlight the effectiveness of LogSumExp as a method for computing the matching score in image-text matching tasks.

Effect of Dynamic Attention Head Weighting We investigate the effect of using varying numbers of attention heads in Stable Diffusion on image-text matching performance. To do this, we randomly sample a subset of heads and leave the rest unused. The results, as shown in Figure 4, indicate that using all heads (five in total in Stable Diffusion v2) from the Spatial Transformer (Jaderberg et al., 2015) located in the U-Net of Stable Diffusion performs the best. Additionally, we compare the results of using dynamic attention head weighting versus averaging across selected heads (few-shot) to evaluate the impact of attention head selection on performance, and dynamic attention head weighting performs better.

Ensembling over Noise Levels In diffusion models, the level of noise controls the variance of the Gaussian noise added during the diffusion process, which can affect the degree of change in the generated image. To further improve the performance of our method, we use an ensemble technique inspired by Wolleb et al. (2022) by averaging the scores over four different noise levels: $\{0.2, 0.4, 0.6, 0.8\}$. This is done by first obtaining the score under each noise level scenario and then averaging them. The results of this comparison are shown in Figure 6. Our experimental results demonstrate that this ensemble technique leads to a noticeable improvement in performance.

6 Conclusion

In this paper, we proposed a method for aligning text and images in the latent space of Stable Diffusion. During experiments, we found that VAE determines the quality of the pixel space, while U-Net and CLIP determine the quality of the semantic space. Therefore, we fine-tuned the U-Net part of the model by focusing on the cross-attention between CLIP embeddings and encoder embeddings, which reflects the alignment between text and image. Our results show that this fine-tuning approach improves the alignment between text and image, leading to better performance in image-text matching tasks. Overall, our proposed method demonstrates a promising approach for aligning text and images in the latent space of Stable Diffusion, and has the potential to be widely adopted in these areas. Our results motivate research on simpler alternatives to adapt Stable Diffusion models, as well as on future methods for better utilization of them.

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