Style-Content Disentanglement in Language-Image Pretraining Representations for Zero-Shot Sketch-to-Image Synthesis

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Abstract

In this work, we propose and validate a framework to leverage language-image pretraining representations for training-free zero-shot sketch-to-image synthesis. We show that disentangled content and style representations can be utilized to guide image generators to employ them as sketch-to-image generators without (re-)training any parameters. Our approach for disentangling style and content entails a simple method consisting of elementary arithmetic assuming compositionality of information in representations of input sketches. Our results demonstrate that this approach is competitive with state-of-the-art instance-level open-domain sketch-to-image models, while only depending on pretrained off-the-shelf models and a fraction of the data.

1. Introduction

The power and promise of deep generative models such as GANs (Goodfellow et al., 2014) lie in their ability to synthesize endless realistic, diverse, and novel content with minimal user effort. The potential utility of these models continues to grow thanks to the increased quality and resolution of large-scale generative models in recent years. Conditional image synthesis allows users to use inputs to control the output of image synthesis methods. A variety of input modalities have been studied, mostly based on conditional GANs (Mirza & Osindero, 2014). Several methods exist that allow generative models to be guided by conditioning variables, e.g. text, sketches or segmentation maps. Sketch conditioning finds a practical middle ground within the characteristics of these methods. It allows significantly more control over output structure than text conditioning, while not requiring labels as segmentation conditioning does.

However, current sketch conditioned models are trained on a relatively narrow set of visual concepts. This restricts the space of possible inputs that result in desired output images, impeding the general usability of these models. An important cause of this is the fact that paired image datasets are labor intensive and costly to create. Approaches that circumvent this requirement exist, including CycleGAN based architectures (Liu et al., 2020; Xiang et al., 2021) and the usage of image-to-sketch models for synthesizing paired data. But as of yet, no work has been published applying sketch-to-image synthesis on large, highly diverse datasets.

Recently, the idea of learning visual concepts from supervision contained in natural language has gained a lot of attention. Language-Image Pre-training models learn unified visual- and natural language representations from the supervision contained in the vast amount of text and associated images on the internet, resulting in very rich visual representations and strong zero-shot classification performance.

In this work, we adopt a framework to leverage classifier representations for sketch-to-image generation. A simple method consisting of elementary arithmetic assuming compositionality of information in the representations is used to disentangle spatial and conceptual information from stylistic information in representations of input sketches. We show that these disentangled representations can then be utilized to guide image generators to employ them as sketch-to-image generators without (re-)training any parameters.

Our results demonstrate that this approach, when used with sufficiently flexible image generators and informative representations, is competitive with state-of-the-art instance-level open-domain sketch-to-image models evaluated on in-domain inputs. Current state-of-the-art models feature complex architectures and require large datasets, while our proposed framework depends on pretrained off-the-shelf models, requires no training, and is evaluated in a zero-shot fashion. Figure 1 shows several selected sketch-to-image translations by our approach.

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1 Our code and additional samples will be made publicly available at [retracted for anonymity].
Our approach is simple to implement while also requiring minimal tuning. To emphasize the potential of the core methodology itself, we report results with default hyperparameters and no additional optimizations. The effectiveness of our method indicates that representations learned by language-image pretraining exhibit strong compositionality, something that has not been harnessed for disentanglement in earlier research.

2. Related Work

2.1. Sketch to Image Synthesis

The goal of sketch-based image synthesis is to output a target image from a given sketch. Early works (Chen et al., 2009; 2012; Eitz et al., 2011) regard freehand sketches as queries or constraints to retrieve each composition and stitch them into a picture, requiring availability of close image matches in the queried database for reasonable results. In recent years, an increasing number of works adopt GAN-based models to learn sketch-to-image synthesis directly.

Several works (Zhu et al., 2017a; Li et al., 2019; Chen et al., 2020) train Conditional GANs with photos and corresponding edge maps to make up for the lack of real sketch data, but only report results trained on single class datasets. However, sketches differ from edge maps in several ways, resulting in inferior results when applying these models to sketches. The authors of SketchyGAN (Chen & Hays, 2018) extended the largest currently available paired dataset of sketches and pictures (75k sketches across 125 categories), extended it and trained a conditional GAN on these. Contextual-GAN (Lu et al., 2018) turns the image generation problem into an image completion problem: the network learns the joint distribution of sketch and image pairs and acquires the result by iteratively traversing the manifold. PoE-GAN (Huang et al., 2021) is a multimodal conditional GAN that is trained on images with paired text, sketch and segmentation maps, achieving state-of-the-art scene-level sketch-to-image synthesis. Xiang et al. (Xiang et al., 2021) propose a framework that jointly learns sketch-to-photo and photo-to-sketch generation to help in generalizing to open-domain classes, and achieve state-of-the-art instance-level sketch-to-image synthesis.

All of these previously proposed architectures are trained on datasets with a limited amount of classes. To the best of our knowledge, there is no published research reporting training any kind of image-to-image translation architectures on large-scale, diverse datasets for zero-shot image-to-image, or sketch-to-image synthesis.
2.2. Language-Image Pre-training

Multiple recent works learn cross-modal vision and language representations (Lu et al., 2019; Xu et al., 2018) for a variety of tasks. Following the success of Transformers (Vaswani et al., 2017) in various language tasks, recent vision and joint vision language methods typically use transformers as their backbone. A recent model, based on Contrastive Language-Image Pre-training (CLIP) (Radford et al., 2021), consisting of a transformer- language encoder and image encoder is trained to learn a multi-modal representation space. which can be used to estimate the semantic similarity between a given text and an image by evaluating embeddings’ cosine similarity.

CLIP was trained on 400 million text-image pairs, collected from a variety of publicly available sources on the Internet. The representations learned by CLIP have been shown to be extremely powerful, enabling state-of-the-art zero-shot image classification on a variety of datasets.

2.3. Classifier Guidance Based Image Synthesis

GANs for conditional image synthesis make heavy use of class labels. This often takes the form of class-conditional normalization statistics (De Vries et al., 2017) as well as discriminator heads that are explicitly designed to behave like classifiers (Miyato & Koyama, 2018), indicating that class information is crucial to the success of these models. The general idea of optimizing latent representations or parameters of an image generator using a separately trained classifier has been widely used as a powerful framework for generating, editing and recovering images (Dhariwal & Nichol, 2021; Abdal et al., 2019; Härkönen et al., 2020). Santurkar et al. (Santurkar et al., 2019) show that adversarial robustness of the classifier is a crucial aspect for optimal execution of such tasks.

Several projects use CLIP as a classifier to guide text-to-image generation through optimization. Examples include optimizing the weights of implicit neural representation networks (Stanley, 2007), the latent space of StyleGAN2 (Karras et al., 2020) and VQGAN (Esser et al., 2021), and guiding diffusion architectures (Nichol et al., 2021).

3. Methodology

Much current research in unsupervised image-to-image translation relies on learning content and style representations. In these approaches, the content $c_i$ of input images $X_i$ and the style of target images $s_j$ together condition a generator $G$ that synthesizes translated images $X_i = G(c_i, s_j)$.

Instead of learning content and style representations from scratch, we propose a simple method for disentangling style and content in representations of a pretrained image encoder $E$ under the assumptions of in-distribution input and compositionality of representations. We use obtained representations to guide $G$. We apply this framework to zero-shot sketch-to-image synthesis. To emphasize the potential of the core methodology itself, we report results with default hyperparameters and no additional optimizations. See Figure 2 for a general overview.

3.1. Problem Formulation

Let us model the formation of an image $X$ as a function of style $s \in \mathcal{S}$ and content $c \in \mathcal{C}$, $X = G(s, c)$. Let $\mathcal{P}$ denote the set of possible “parts” of an image, these parts be any feature of the input, e.g. the presence and location of an object, features of this object such as its size and color, or global style of an image. Let $\mathcal{X}$ denote the input space. For each $X \in \mathcal{X}$, we assume the existence of a function $D$ mapping $X$ to $\mathcal{P} \subseteq \mathcal{P}$, the set of its parts. Style $s$ describes all parts $p^s \in D(X)$ that are invariant within the stylistic domain of $X$, while content $c$ describes all residual parts $p^c \in D(X)$ that are not described by style $s$.

Given an input dataset $D_j$ of $N$ images $X_i$, all sampled from stylistic domain $s_j$ with normally distributed content $c_i$,

$$D_j = \{X_i\}_{i=1}^N, \quad X_i = G(s_j, c_i), \quad c_i \sim \mathcal{N}(0, \sigma^2 I),$$

we use image encoder $E$: $\mathcal{X} \rightarrow \mathcal{R}$ to obtain representations $r_i = E(X_i)$, where $\mathcal{R}$ denotes the representation space. We assume $r_i$ to be compositional, meaning it can be expressed as a weighted sum of simpler parts. Let $h: \mathcal{P} \rightarrow \mathcal{R}$ denote a function that maps parts to representations. Formally, we define a function $f(X) \in \mathcal{R}$ as compositional if it can be expressed as a weighted sum of the elements of $\{h(p) | p \in D(X)\}$

Then, we can decompose $r_i$ as a sum of content representation $r^c_i$ and style representation $r^s_i$, $r_i = r^c_i + r^s_i$. We assume $X_i$ to be in-distribution for $E(X)$, and note that $r^c_i$ follows the distribution of $c_i$. We can then obtain $r^s_i$ by taking the arithmetic mean over all $r_i$,

$$r^s_i = \frac{1}{N} \sum_{i=1}^N r_i = \frac{1}{N} \sum_{i=1}^N r^c_i + \frac{1}{N} \sum_{i=1}^N r^s_i = 0 + \frac{N}{N} r^s_i.$$

Finally, to obtain $r^c_i$ we subtract $r^s_i$ from $r_i$,

$$r^c_i = r_i - r^s_i = r^c_i + r^s_i - r^s_i.$$

Using these operations we obtain $r^s_i$ describing the content of input images $X_i$ from stylistic domain $s_j$, and $r^c_i$ describing target stylistic domain $s_j$ of dataset $D_j$ of $M$ images. We use these to create target representations for guiding image synthesis: $r_i = r^c_i + r^s_i$.

Specifically, given image generator $G(z)$, and image encoder $E$, we solve the following optimization problem to
iteratively update $X_t$, a translation of $X_i$ in style $s_t$:

$$\arg \min_{z \in Z} \left( \langle E(G(z)), r_t \rangle \right) \| E(G(z)) \| \cdot \| r_t \|,$$

where $\langle \cdot, \cdot \rangle$ computes the cosine similarity between its arguments.

### 3.2. Improving Adversarial Robustness

Most off-the-shelf classifiers are not trained for exhibiting adversarial robustness. Since we are directly optimizing images using such classifiers, this process is prone to induce non-semantic perturbations in $X_t$ that increase classification scores (Liu et al., 2021). Inspired by self-supervised learning methods, we use augmentation pipeline $a$ when feeding input $X_t$ to image encoder $E$:

$$a(X_t) = E(X'_t \sim \pi(\cdot | X_t))$$

where $X'_t$ is a random perturbation of the input image $X_t$, drawn from distribution $\pi(\cdot | X_t)$ of candidate data augmentations, including random colorization, translation, and cutout. This generates new samples $X'_t$ that should average out adversarial gradients while preserving content and style information in $X_t$.

### 4. Experimental setup

#### 4.1. Image Encoder $E$

To evaluate the adopted framework we report experiments with CLIP (Radford et al., 2021) as the image encoder $E$. CLIP is well-suited for our framework as the large-scale dataset it has been trained on ensures that a wide range of styles $s$ are in-distribution. And, more importantly, the excellent zero-shot performance of CLIP indicates its representations exhibit a significant amount of compositionality, making it well-suited for our style-content disentanglement method.

The notion that zero-shot classification performance strongly correlates with compositionality in learned representations is demonstrated by Sylvain et al. (Sylvain et al., 2019). This is very intuitive: we expect compositionality to be an advantage in zero-shot learning: if a model has a good understanding of how parts map to representations, it can learn to combine known concepts to describe new classes.

Since CLIP also includes a natural language encoder which maps text to the same embedding space as its image encoder, we also experiment with target styles $s_t$ obtained through directly encoding text.

#### 4.2. Image Generator $G$

The space of images our approach is able to synthesize is limited by the representational power of the image generator we use. Our method is prone to inherit biases of the used generator, either induced by its training data e.g. center, spatial or color bias, or by inductive biases present in its architecture.

Since we aim to achieve zero-shot sketch-to-image synthesis, the image generator needs to be relatively flexible. However, very flexible image generators such as differentiable image parameterizations, e.g. implicit neural representations (Stanley, 2007) or direct pixel optimization, facilitate adversarial attacks.

Based on preliminary experiments we use VQGAN (Esser et al., 2021) as $G$ for our main experiments. VQGAN exhibits flexible image synthesis, arguably due to its latent embedding structure. We initialize $z$ by using VQGAN’s image encoder to encode input sketch $X_i$.

In 5.1.2 we report results of using GLIDE (Dhariwal & Nichol, 2021) as $G$, a recently proposed diffusion model trained on a similar dataset as CLIP. We use a small version of this model, trained with filtered data, since the weights of the full model have not been released. In these experiments
Figure 3. Zero-shot sketch-to-image results $X_t$ for several random source images $X_i$ and target styles $s_t$. 
the model is guided by representations obtained by a smaller CLIP model trained on this same filtered dataset, with noise augmentations.

### 4.3. Datasets

For obtaining sketch style representations $s_j$, we use sketches of the sketchy dataset (Sangkloy et al., 2016), a collection of 75,471 sketch-photo pairs sampled from 125 categories. When evaluating our framework we sample 10k images from the sketchy dataset to determine $s_j$, excluding the class of the input sketch. Thus, all reported image translations can be considered zero-shot outputs. In section 5.1.1 we report results of using 2, 10, 100, 1k or 70k samples from the sketchy dataset for determining $s_j$. For obtaining target style $s_t$, we use 10k randomly sampled items of ImageNet (Deng et al., 2009), unless specified otherwise.

### 5. Results

Figure 3 shows sketch-to-image results $X_t$ for several random source images $X_i$ and target styles $s_t$ obtained from ImageNet and several text prompts.

To better illustrate the effectiveness of our proposed solution, we show some quick and dirty comparisons to state-of-the-art open domain sketch-to-image synthesis by Xiang et al. (Xiang et al., 2021). In their work, Xiang et al. report qualitative comparisons of their results with CycleGAN (Zhu et al., 2017b), conditional CycleGAN, and EdgeGAN (Gao et al., 2020). We fed all compared input sketches in their work to our proposed framework and added the outputs to their comparison, see Figure 4. Entries not marked with a star are conditioned on their respective class. Our framework shows competitive results without making use of class information, and while being the only method evaluated in a zero-shot fashion.

### 5.1. Ablations

#### 5.1.1. VARYING DATASET SIZE FOR OBTAINING $s_j$

To shed light on the required dataset size we report results of varying the amount of used samples (2, 10, 100, 1k, 70k) for calculating $s_j$, see Figure 5. Remarkably, 10 samples are enough to get decent results, and after using more than 100 samples gains are minimal.

#### 5.1.2. USING GLIDE AS $G$

In Figure 6 we show a handful of random results of employing GLIDE (Dhariwal & Nichol, 2021) as $G$ instead of VQGAN (Esser et al., 2021). We tried guiding GLIDE with different target styles $s_t$, but this was not effective. A possible reason for this could be the fact that representations learned by the smaller, noised CLIP model used in GLIDE show less compositionality and/or contain less information than the regular CLIP model released by OpenAI.

### 6. Conclusion

We show that simple arithmetic can be an effective tool for intuitively editing language-image pretraining architectures’ learned representations, and prove this to be a computationally cheap method for disentangling style and content.
Our method applies this idea to achieve zero-shot instance-level sketch-to-image synthesis competitive with state-of-the-art instance-level open-domain sketch-to-image models, while only depending on pretrained off-the-shelf architectures and a sketch dataset as small as 100 items.

Additionally, these results suggest that large language-image pretraining architectures’ learned representations show a significant amount of compositionality, similar to what is generally observed in word-embeddings (Gittens et al., 2017; Allen & Hospedales, 2019).

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