Controlling Style and Semantics in Weakly-Supervised Image Generation

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Abstract

We propose a weakly-supervised approach for conditional image generation of complex scenes where a user has fine control over objects appearing in the scene. We exploit sparse semantic maps to control object shapes and classes, as well as textual descriptions or attributes to control both local and global style. To further augment the controllability of the scene, we propose a two-step generation scheme that decomposes background and foreground. The label maps used to train our model are produced by a large-vocabulary object detector, which enables access to unlabeled sets of data and provides structured instance information. In such a setting, we report better FID scores compared to a fully-supervised setting where the model is trained on ground-truth semantic maps. We also showcase the ability of our model to manipulate a scene on complex datasets such as COCO and Visual Genome.

1. Introduction

Deep generative models such as VAEs [22] and GANs [9] have made it possible to learn complex distributions over various types of data, including images or text. For images, recent technical advances [13, 19, 27, 28, 45, 1] have enabled GANs to produce realistically-looking images for a large number of classes. However, these models often do not provide high-level control over image characteristics such as appearance, shape, texture, or color, and they fail to accurately model multiple (or compound) objects in a scene, thus limiting their practical applications.

A related line of research aims at disentangling factors of variation during the generation process [20]. While these approaches can produce images with varied styles by injecting noise at different levels, the style factors are learned without any oversight, leaving the user with a loose handle on the generation process. Furthermore, their applicability has only been demonstrated to single-domain images (e.g. faces, cars or birds). Some conditional approaches allow to control the style of an image using either attributes [42, 12]...
We propose weakly-supervised training using

- label and scalable to large unlabeled datasets.

fully-supervised counterparts, while being more control-
supervised setting can achieve better FID scores [13] than

2 and Visual Genome [24], and show that our weakly-
be frozen when manipulating the foreground objects.

conditioned on the former. The background image can also
background image

a multi-step generation process where we first generate a

sentations are useful to maximize scene coherence, they do not allow the user to modify a local part of a scene with-
without sacrificing visual quality, and which facilitates local manipulations.

An approach for controlling the style of the scene and its instances, either using high-level attributes or natural language with an attention mechanism.

• We will soon release our code.

2. Related work

The recent success of GAN models has triggered a lot of interest for conditional image synthesis where images are being generated from categorical labels [27, 28, 45, 1], text [31, 46, 47, 41], semantic maps [16, 40, 29], or conditioning images from other domains [49, 16].

Image generation from semantic maps. In this setting, a semantic segmentation map is translated into a natural image. Non-adversarial approaches are typically based on perceptual losses [4, 30], whereas GAN architectures are based on patch-based discriminators [16], progressive growing [40, 19], and conditional batch normalization where the semantic map is fed to the model at different resolutions [29]. Due to its stability and compelling results, we decided to base our architecture on [29]. Most approaches are trained on hand-labeled masks (limiting their application in the wild), but [29] shows one example where the model is weakly supervised on masks inferred using a semantic segmentation model [3]. Our model is also weakly supervised, but instead of a semantic segmentation model we use an object detector – which allows us to maintain instance information during manipulations, and results in sparse masks. While early work focused on class semantics, recent methods support some degree of style control. E.g. [40] trains an instance autoencoder and allows the user to choose a latent code from among a set of modes, whereas [29] trains a VAE to control the global style of a generated image by copying the style of a guide image. Both these methods, however,
do not provide fine-grained style control (e.g. changing the color of an object to red). Another recent trend consists in generating images from structured layouts, which are transformed into semantic maps as an intermediate step to facilitate the task. In this regard, there is work on generation from bounding-box layouts [48, 14] and scene graphs [17].

**Semantic control.** Existing approaches do not allow for easy manipulation of the semantic map because they present no interface for encoding existing images. In principle, it is possible to train a weakly-supervised model on maps inferred from a semantic segmentation model, as [29] does for landscapes. However, manipulations are still challenging because instance information is not available. Furthermore, since the label masks are *dense*, even simple transformations such as deleting or moving an object would create holes in the semantic map that need to be adjusted by the artist. *Dense* masks also make the task too constrained with respect to background aspects of the scene (e.g. sky, land, weather), which leaves less room for style control.

**Text-based generation.** Some recent models condition the generative process on text data. These are often based on autoregressive architectures [32] and GANs [31, 46, 47, 41]. Learning to generate images from text using GANs is known to be difficult due to the task being unconstrained. In order to ease the training process, [46, 47] propose a two-stage architecture named *StackGAN*. To avoid the instability associated with training a language model jointly with a GAN, they use a pretrained sentence encoder [23] that encodes a caption into a fixed-length vector which is then fed to the model. More advanced architectures such as *AttnGAN* [41] use an attention mechanism which we discuss in one of the next paragraphs. These approaches show interesting results on single-domain datasets (birds, flowers, etc.) but are less effective on complex datasets such as COCO [25] due to the intrinsic difficulty of generating coherent scenes from text alone. Some works [18, 44] have demonstrated that generative models can benefit from taking as input multiple diverse textual descriptions per image. Finally, we are not aware of any prior work that conditions the generative process on both text and semantic maps (our setting).

**Multi-step generation.** Approaches such as [43, 36] aim at disentangling background and foreground generation. While fully-unsupervised disentanglement is provably impossible [26], it is still achievable through some form of inductive bias – either in the model architecture or in the loss function. While [43] uses spatial transformers to achieve separation, [36] uses object bounding boxes. Both methods show compelling results on single-domain datasets that depict a centered object, but are not directly applicable to more challenging datasets. In our setting, we are not interested in full disentanglement (i.e. we do not assume independence between background and foreground), but merely in separating the two steps while keeping them interpretable. Our model still exploits correlations among classes to maximize visual quality, and is applied to datasets with complex scenes. Finally, there has also been work on interactive generation using dialogue [8, 6, 34].

**Attention models in GANs.** For unconditional models (or models conditioned on simple class labels), self-attention GANs [45, 1] use a visual-visual attention to improve spatial coherence. For generation from text, [41] employ sentence-visual attention coupled with an LSTM encoder, but only in the generator. Instead of adding attention in the discriminator, the caption is enforced through a supervised loss based on features extracted from a pretrained Inception [38] network. In our case, we use a new form of attention (*sentence-semantic*) which is applied to semantic maps instead of convolutional feature maps, and whose computational cost is independent of the image resolution. It is applied both to the generator and the discriminator, and on the sentence side it features a transformer-based [39] encoder.

### 3. Approach

#### 3.1. Framework

Our main interest is conditional image generation of complex scenes where a user has fine control over the objects appearing in the scene. Prior work has focused on generating objects from ground-truth masks [49, 16, 40, 29] or on generating outdoor scenes based on simple hand-drawn masks [29]. While the former approach requires a significant labeling effort, the latter is not directly suitable for complex datasets such as COCO-Stuff [2], whose images consist of a large number of classes with complex (hard to draw) shapes. We address these problems by introducing a new model that is conditioned on sparse masks – to control object shapes and classes – and on text/attributes to control style and textures. This gives the ability to a user to produce realistic scenes through a variety of image manipulations (such as moving, scaling or deleting an instance, adding an instance from another image or from a database of shapes) as well as style manipulations controlled using either high-level attributes on individual instances (e.g. *red, green, wet, shiny*) or using text that refers to objects as well as global context (e.g. “a red car at night”). In the latter case, visual-textual correlations are not explicitly defined but are learned in an unsupervised way.

**Sparse masks.** Instead of training a model on precise segmentation masks, as in [16, 40, 29], we use a mask generated automatically from a large-vocabulary object detector. Although this process introduces some noise, it also has the benefit of providing information about each instance (which may not always be available otherwise), including parts of objects which would require significant manual effort to label in a new dataset. In general, our set of classes comprises
countable objects (person, car, etc.), parts of objects (light, window, door, etc.), as well as uncountable classes (grass, water, snow), which are typically referred to as “stuff” in the COCO terminology [2]. For the latter category, an object detector can still provide useful sparse information about the background, while keeping the model autonomous to fill-in the gaps. We describe the details of our object detection setup in sec. 4.2.

**Two-step generation.** In the absence of constraints, conditional models learn class correlations observed in the training data. For instance, while dogs typically stand on green grass, zebras stand on yellow grass. While this feature is useful for maximizing scene coherence, it is undesirable when only a local change in the image is wanted. We observed similar global effects on other local transformations, such as moving an object or changing its attributes, and generally speaking, small perturbations of the input can result in large variations of the output. We show such an example in Fig. 2. To tackle this issue, we propose a variant of our architecture which we call two-step model and which consists of two concatenated generators (Fig. 3). The first step (generator $G_1$) is responsible for generating a background image, whereas the second step (generator $G_2$) generates a foreground image conditioned on the background image. The definition of what constitutes background and foreground is arbitrary: our choice is to separate by class: static/uncountable objects (e.g. buildings, roads, grass, and other surfaces) are assigned to background, and moving/uncountable objects are assigned to foreground. Some classes can switch roles depending on the parent class, e.g. window is background by default, but it becomes foreground if it is a child of a foreground object such as a car.

When applying a local transformation to a foreground object, the background can conveniently be frozen to avoid global changes. As a side benefit, this also results in a lower computational cost to regenerate an image. Unlike work on disentanglement [43, 36] which enforces that the background is independent of the foreground without necessarily optimizing for visual quality, our goal is to enforce separation while maximizing qualitative results. In our setting, $G_1$ is exposed to both background and foreground objects, but its architecture is designed in a way that foreground information is not rendered, but only used to induce a bias in the background (see sec. 3.2).

**Attributes and captions.** Our method allows the user to control the style of individual instances using high-level attributes. These attributes refer to appearance factors such as colors (e.g. white, black, red), materials (wood, glass), and even modifiers that are specific to classes (leafless, snowy), but not shape or size, since these two are determined by the mask. An object can also combine multiple attributes (e.g. black and white) or have none – in this case, the generator would pick a predefined mode. This setup gives the user a lot of flexibility to manipulate a scene, since the attributes do not need to be specified for every object.

Alternatively, one can consider conditioning style using natural language. This has the benefit of being more expressive, and allows the user to control global aspects of the scene (e.g. time of the day, weather, landscape) in addition to instance-specific aspects. While this kind of conditioning is harder to learn than plain attributes, in sec. 3.2 we introduce a new attention model that shows compelling results without excessively increasing the model complexity.

### 3.2. Architecture

We build our architecture upon SPADE [29], a conditional GAN architecture that has demonstrated stability in a wide range of scenarios. In the original formulation, the semantic map is fed to the generator at increasing spatial resolutions using conditional batch normalization. They use a multi-scale discriminator [40] where the semantic map is concatenated to the input. Additionally, they augment the adversarial loss with a perceptual loss using a pretrained VGG network [35] and a feature matching loss in the discriminator [40].

**One-step model.** Since this model (Fig. 3, left) serves as a baseline, we keep its architecture as close as possible to the reference model of [29]. We propose to insert the required information about attributes/captions in this architecture by modifying the input layer and the conditional batch normalization layers (SPADE blocks) of the generator, which is where semantic information is fed to the model. We name these augmented SPADE blocks. We apply the same change to the input layer of the discriminators.

**Augmented SPADE block.** In the original SPADE [29], the class mask (i.e. semantic map) is converted to a one-hot representation and convolved using $3 \times 3$ kernels with 128 output channels. The resulting feature map is passed through a ReLU non-linearity and convolved again to produce two feature maps $\gamma$ and $\beta$, respectively, the conditional batch normalization gain and bias. The normalization is then computed as $y = BN(x) \odot (1 + \gamma) + \beta$, where $BN(x)$ is the parameter-free batch normalization.

While $3 \times 3$ convolutions on one-hot masks are adequate when applied to a small set of classes, they result in too many parameters when applied to a large number of classes (our setting). Therefore, we replace the $3 \times 3$ convolutions on one-hot masks with a 64-dim. pixel-wise embedding layer followed by $3 \times 3$ convolutions. We apply the same principle to the first layer of the generator and discriminators. To add style information, we concatenate another 64-dim. representation to the class embedding (pixel-wise). We explain how we derive these representations in the next two paragraphs.

**Conditioning on attributes.** For attributes, we adopt a bag-
Conv3x3, nc
Beddings assigned to an instance are simply broadcast to bedding for each possible attribute, and all attribute embeddings are shared among classes and are not class-specific. This helps the model generalize better (e.g. colors such as “white” apply both to vehicles and animals), and unseen combinations (e.g. leafless person) are simply ignored by the generator without side effects.

**Conditioning on text.** While previous work has used fixed-length vector representations \([46, 47]\) or one-layer attention models coupled with RNNs \([41]\), the diversity of our scenes led us to use a more powerful encoder entirely based on self-attention \([39]\). We encode the image caption using a pretrained BERT\(_{base}\) model \([7]\), which consists of 12 attention layers and 110M parameters. It is unreasonable to attach such a model to a GAN and fine-tune it, both due to excessive memory requirements and due to potential instabilities. Instead, we freeze the pretrained model and encode the sentence, extract its hidden representation before the last layer (i.e. second-to-last), and train a custom multi-head attention layer for our task. This approach, which is also suggested by \([7]\), has proven successful on a variety of NLP downstream tasks, especially when these involve small datasets or limited vocabularies. Furthermore, instead of storing the language model in memory, we simply pre-compute the sentence representations and cache them.

Next, we describe the design of our trainable attention layer (Fig. 5). Our attention mechanism is different from sentence-visual attention \([41]\), where attention is directly compute the sentence, extract its hidden representation before the last layer (i.e. second-to-last), and train a custom multi-head attention layer for our task. This approach, which is also suggested by \([7]\), has proven successful on a variety of NLP downstream tasks, especially when these involve small datasets or limited vocabularies. Furthermore, instead of storing the language model in memory, we simply pre-compute the sentence representations and cache them.

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Figure 3: **Left:** One-step model (augmented SPADE). **Right:** two-step model. The background generator \(G_1\) takes as input a background mask (processed by \(S\) blocks) and the full mask (processed by \(S_{avg}\) blocks, where positional information is removed). The foreground generator takes as input the output of \(G_2\) and a foreground mask. Finally, the two outputs are alpha-blended. For convenience, we do not show attributes/text in this figure.
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Figure 4: Our SPADE block augmented with attributes. Class and attribute embeddings are concatenated and processed to generate the conditional batch normalization gain and bias. In the attribute mask, embeddings take the shape of the instance to which they refer. In \(G_1\) of the two-step model, where \(S\) and \(S_{avg}\) are both used, the embedding weights are shared.
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(e.g. length vector representations \([46, 47]\) or one-layer attention models coupled with RNNs \([41]\), the diversity of our scenes led us to use a more powerful encoder entirely based on self-attention \([39]\). We encode the image caption using a pretrained BERT\(_{base}\) model \([7]\), which consists of 12 attention layers and 110M parameters. It is unreasonable to attach such a model to a GAN and fine-tune it, both due to excessive memory requirements and due to potential instabilities. Instead, we freeze the pretrained model and encode the sentence, extract its hidden representation before the last layer (i.e. second-to-last), and train a custom multi-head attention layer for our task. This approach, which is also suggested by \([7]\), has proven successful on a variety of NLP downstream tasks, especially when these involve small datasets or limited vocabularies. Furthermore, instead of storing the language model in memory, we simply pre-compute the sentence representations and cache them.

Next, we describe the design of our trainable attention layer (Fig. 5). Our attention mechanism is different from sentence-visual attention \([41]\), where attention is directly applied to convolutional feature maps inside the generator. Instead, we propose a form of sentence-semantic attention which is computationally efficient, interpretable, and modular. It can be concatenated to existing SPADE layers in the same way as we concatenate attributes. Compared to sentence-visual attention, whose cost is \(O(nd^2)\) (where \(n\) is the sentence length and \(d \times d\) is the feature map resolution), our method has a cost of \(O(nc)\) (where \(c\) is the number of classes), i.e. it is independent of the image resolution. We construct a set of \(c\) queries (i.e. one for each class) of size \(h = 64\) (where \(h\) is the attention head size). We feed the hidden representations of each token of the sentence to two linear layers, one for the keys and one for the values. Finally, we compute a scaled dot-product attention \([39]\), which yields a set of \(c\) values. To allow the SPADE block to attend to multiple parts of the sentence, we use
Figure 5: Attention mechanism for conditioning style via text. The sentence (of length \( n = 7 \) including delimiters) is fed to a pretrained attention encoder, and each token is transformed into a key and a value using two trainable linear layers. The queries are learned for each class, and evaluating the attention function results in a set of contextualized class embeddings that are concatenated to the regular semantic embeddings.

12 attention heads, whose output values are concatenated and further transformed through a linear layer. This process can be thought of as generating contextualized class embeddings, i.e. class embeddings customized according to the sentence. For instance, given a semantic map that depicts a car and the caption “a red car and a person”, the query corresponding to the visual class car would most likely attend to “red car”, and the corresponding value will induce a bias in the model to add redness to the position of the car. Finally, the contextualized class embeddings are applied to the semantic mask via pixel-wise matrix multiplication with one-hot vectors, and concatenated to the class embeddings in the same way as attributes. In the current formulation, this approach is unable to differentiate between instances of the same class. We propose a possible mitigation in sec. 5.

Two-step model. This model consists of two concatenated generators. \( G_1 \) generates the background, i.e. it models \( p(x_{bg}) \), whereas \( G_2 \) generates the foreground conditioned on the background, i.e. \( p(x_{fg}|x_{bg}) \). One notable difficulty in training such a model is that background images are never observed in the training set (we only observe the final image), therefore we cannot use an intermediate discriminator for \( G_1 \). Instead, we use a single, final discriminator and design the architecture in a way that the gradient of the discriminator (plus auxiliary losses) is redirected to the correct generator. A natural choice is alpha blending, which is also used in [43, 36] for different reasons. Intuitively, \( G_2 \) generates an RGB foreground image plus a transparency mask (alpha channel), and the final image is obtained by pasting the foreground onto the background via linear blending:

\[
x_{\text{final}} = x_{bg} \cdot (1 - \alpha_{fg}) + x_{fg} \cdot \alpha_{fg},
\]

where \( x_{\text{final}} \), \( x_{bg} \), and \( x_{fg} \) are RGB images, and \( \alpha_{fg} \) is a 1-channel image bounded in \([0, 1]\). Readers familiar with highway networks [37] might notice a similarity to this approach in terms of gradients dynamics. If \( \alpha_{fg} = 1 \), the gradient is completely redirected to \( x_{fg} \) while if \( \alpha_{fg} = 0 \), the gradient is redirected to \( x_{bg} \). This scheme allows us to train both generators in an end-to-end fashion using a single discriminator, and we can also preserve auxiliary losses (VGG loss, feature matching loss) which [29] has shown to be very important for convergence. To incentivize separation between classes as defined in sec. 3.1, we provide supervision on \( \alpha_{fg} \) using a binary cross-entropy loss, and decay this term over time (see sec. 4.2).

In \( G_2 \) we use the same augmented SPADE blocks as the ones used in the one-step model (S block), which take the foreground mask as input. Since \( G_1 \) must exploit foreground information without rendering it, we devise a further variation of SPADE that consists of two branches: (i) the first branch (S block) takes the background mask as input and processes it as usual to produce the batch normalization gain \( \gamma \) and bias \( \beta \). (ii) the second branch (S_{avg} block, Fig. 4) takes the full mask as input (background plus foreground), processes it, and applies global average pooling to the feature map to remove information about localization. This way, the foreground information is only used to bias the generator and cannot be rendered at precise spatial locations. After pooling, it outputs \( \gamma_{avg} \) and \( \beta_{avg} \). (iii) The final conditional batch normalization is computed as

\[
y = \text{BN}(x) \odot (1 + \gamma_{avg} + \beta_{avg}) + \beta + \beta_{avg}
\]

Note that, if \( G_1 \) took the full mask as input without information reduction, it would render visible “holes” in the output image due to gradients never reaching the foreground zones of the mask, which is exactly what we are trying to avoid. Finally, the discriminator \( D \) takes the full mask as input (background plus foreground). In the App. A.1 we provide further low-level details about our architectures.

4. Experiments

4.1. Setup and datasets

For consistency with [29], we always evaluate our model on the COCO-Stuff validation set [2], but we train on a variety of training sets:

- **COCO-Stuff (COCO2017)** [25, 2] contains 118k training images with captions [5]. We train with and without captions. COCO-Stuff extends COCO2017 with ground-truth semantic maps, but for our purposes the two datasets are equivalent since we do not exploit ground-truth masks.
- **Visual Genome (VG)** [24] contains 108k images that partially overlap with COCO (≈50%). VG does not have a
default train/test split, therefore we leave out 10% of the dataset to use as a development set (IDs ending with 9), and use the rest as a training set from which we remove images that overlap with the COCO-Stuff validation set. We extract the attributes from the scene graphs.

**Visual Genome augmented (VG+)** VG augmented with the 123k images from the COCO unlabeled set. The total size is 217k images after removing exact duplicates. The goal is to evaluate how well our method scales to large unlabeled datasets. We train without attributes and captions.

For all experiments, we evaluate the Fréchet Inception Distance (FID) [13]. We report our results (qualitative and quantitative) in sec. 4.3. Furthermore, we provide precise implementation details of the FID in the Appendix A.2 as well as additional qualitative results in A.3.

### 4.2. Implementation details

**Semantic maps.** To construct the input semantic maps, we use the semi-supervised implementation of Mask R-CNN [11, 33] proposed by [15]. It is trained on bounding boxes from Visual Genome (3000 classes) and segmentation masks from COCO (80 classes), and learns to segment classes for which there are no ground-truth masks. We discard the least frequent classes, and, since some VG concepts overlap (e.g., car, vehicle) leading to spurious detections, we merge these classes and end up with a total of \(c = 280\) classes (plus a special class for “no class”). We set the threshold of the object detector to 0.2, and further refine the predictions by running a class-agnostic non-maximum-suppression (NMS) step on the detections whose mask intersection-over-union (IoU) is greater than 0.7. We also construct a transformation hierarchy to link children to their parents in the semantic map (e.g., headlight of a car), further details in Appendix A.1. We select the 256 most frequent attributes, manually excluding those that refer to shapes (e.g., short, square).

**Training.** Unless specified otherwise, our settings are the same as [29], including the image resolution which is \(256 \times 256\). In all experiments, we train on 8 Pascal GPUs for 100 epochs, and we start decaying the learning rate to 0 after the 50th epoch in a linear fashion. We use a batch size of 32 for the one-step model and 24 for the two-step model, which is the largest batch size that we can fit into memory, and we keep synchronized batch normalization enabled. Training takes approximately one week for the one-step model, and two weeks for the two-step model. In the two-step model, as introduced in sec. 3.2, we provide supervision on the alpha blending mask starting from a factor of 10 for this loss term, and decaying it exponentially with a factor of 0.9997 per weight update, down to 0.01. We observed that this term can be safely decayed without the model becoming unstable or diverging from the expected behavior (i.e., background and foreground separation). This gives \(G_2\) some extra flexibility in drawing details that are not represented by the mask (reflections, shadows).

For the experiments with captions, since COCO comprises five captions per image, we randomly select one caption at training time. In the evaluation phase, we concatenate the representations of all captions since our attention model can easily decide which ones to attend to.
Figure 7: Left: the larger set of labels in our sparse masks improves fine details. These masks are easy to obtain with a semi-supervised object detector, and would otherwise be too hard to hand-label. Right: some failure cases in our masks, mostly due to noisy detections.

| # | Training set | Type | Mask input | Style input | FID |
|---|--------------|------|------------|-------------|-----|
| 1 | COCO-Stuff   | 1 step [29] | Ground truth | –           | 22.54 |
| 2 | COCO-Stuff   | 1 step     | Sparse (ours) | –           | 20.02 |
| 3 | COCO-Stuff   | 1 step     | Sparse (ours) | Captions     | 20.63 |
| 4 | COCO-Stuff+  | 1 step     | Sparse (ours) | Captions+    | 20.44 |
| 5 | Visual Genome| 1 step     | Sparse (ours) | Attributes   | 21.13 |
| 6 | Visual Genome| 2 steps    | Sparse (ours) | Attributes   | 20.83 |
| 7 | Visual Genome+| 1 step | Sparse (ours) | –           | 18.93 |

Table 1: FID scores for different experiments, lower is better. The first line represents the SPADE baseline [29].

4.3. Results

We show the FID scores for various experiments in Table 1. While improving the FID scores is not the goal of our work, it is interesting to see that our weakly-supervised sparse mask setting yields slightly better scores than the supervised baseline (even with an equivalent architecture and training set as in model #2 in the table). We believe that is due to the masks better representing fine details (such as windows, doors, lights, wheels) in compound objects, which are not part of the COCO class set. In Fig. 7 (left) we show a small number of such examples. Furthermore, the experiment on the augmented Visual Genome dataset shows that our model benefits from extra unlabeled images (#7). In #4 (Captions+), the discriminator is augmented with attributes to provide a stronger supervision signal for the generator. We take the attributes from Visual Genome for the images that overlap between the two datasets. In Fig. 6 we show some qualitative results as well as examples of manipulations, either through attributes or text. Additional examples can be seen in the Appendix A.3, including visualizations of the attention mechanism (A.4).

As an ablation experiment, in the two-step model (#6) we remove foreground information from the $S_{avg}$ block of the first generator $G_1$ (we feed the background mask twice in $S$ and $S_{avg}$). We observe that the FID score increases to 25.16 (from 20.83), meaning that $G_1$ effectively exploits foreground information to bias the result.

Finally, we observe some failure cases in Fig. 7 (right). Some input masks can be noisy due to imprecise or spurious detections, leading to incoherent scenes. However, this can be easily tackled by using a better object detector and is not a limitation of our approach. In general, we also observe that our setup tends to work better on outdoor scenes and sometimes struggles with geometric details in indoor scenes or photographs shot from a close range.

5. Conclusion

We introduced a weakly-supervised approach for the conditional generation of complex images. The generated scenes can be controlled through various manipulations on the sparse semantic maps, as well as through textual descriptions or attribute labels. Our results are visually comparable to those of fully-supervised approaches, while enabling a higher level of semantic and style control. From a qualitative point-of-view, we have demonstrated a wide variety of manipulations that can be applied to an image. Furthermore, our weakly supervised setup opens up opportunities for large-scale training on unlabeled datasets, as well as mixed evaluations (training and testing different datasets).

There are several ways one could pursue to further enrich the set of tools used to manipulate the generation process. For instance, the current version of our attention mechanism cannot differentiate between instances belonging to the same class and it also does not have direct access to positional information. Incorporating such information is beyond the scope of this work, but we suggest that this can be achieved by generating queries and values based on instances instead of classes, and by appending a positional embedding to the query. In the NLP literature, the latter is often learned according to the position of the word in the sentence [39, 7], but images are 2D and therefore do not possess such natural order. Additionally, this would also require captions that are more descriptive than the ones in COCO, which typically focus on actions instead of style. Finally, in order to augment the quality of semantic maps, we would like to train the object detector on a high-quality, large-vocabulary dataset such as [10].
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A. Supplementary material

A.1. Detailed architecture

In this section, we provide additional implementation details about our architecture in order to consolidate the already-presented Fig. 3 (overview of the generators), Fig. 4 (S and $S_{avg}$ blocks), and Fig. 5 (attention mechanism for image captions).

One-step generator. In sec. 3.2 we mention that the backbone of the one-step model is the same as [29], and that we only modify the SPADE normalization blocks as well as the very first layer of the generator. In Fig. 8a we show the detailed architecture of this model. The implementation of an individual “SPADE ResBlock” is specified in [29], but for reference we mention that each residual block consists of two SPADE normalization blocks wrapped by a skip-connection. If the number of input and output channels does not match, the skip-connection is learned, i.e. we learn a third SPADE normalization block. In the models conditioned on captions, we never attach attention inputs to skip-connections (to avoid potential instabilities). Each normalization block learns its own set of weights, and in our case they correspond to the $S$ or $S_{avg}$ blocks specified in Fig. 4.

It is worth noting that, in the SPADE reference implementation, the input layer can either take a noise vector (for generation using a style image) or the semantic map as input. Since we control style deterministically, we are only interested in the latter case, so we simply concatenate style information to the semantic map in the same way as we do it in an $S$ block. This also applies to the two-step model.

Two-step generator. The architecture of the two-step generator is depicted in Fig. 9, and differs significantly from the aforementioned implementation. The background generator $G_1$ is a simplified version of the one-step generator with fewer residual blocks. The foreground generator $G_2$ implements a bottleneck architecture that takes as input the generated background image and compresses it through a series of non-SPADE residual blocks. The low-resolution feature-map is then expanded again through a series of SPADE residual blocks. Interestingly, for foreground manipulations it is possible to preprocess the feature maps up to the last downsampling block in $G_2$ (8 × 8 resolution) and greatly speed up regeneration.

Discriminator. We use the multi-scale discriminator from [40, 29] and change its input layer to add information about attributes or captions. The architecture is shown in Fig. 8b. As usual with multi-scale discriminators, we train two instances: one which takes as input an image with full resolution, and one which takes as input a downsampled version (by a factor of two). They learn a different set of embeddings, and a different set of attention heads if the style is conditioned on a sentence.

Model complexity. Table 2 presents the number of parameters for all variants of our approach. The SPADE baseline trained on the 182 COCO-Stuff classes requires 97.5M parameters. Our 1-step baseline trained without style information (neither attributes nor captions) on our set of 280 classes requires a slightly lower number of parameters (94.2M). As explained in sec. 3.2, this is due to replacing 3 × 3 convolutions over one-hot vectors with point-wise 64-dim embeddings followed by 3 × 3 convolutions. In the version with attributes, the added cost (+2.3M parameters) is only due to the learned attribute embeddings (256 64-dim embeddings per SPADE normalization block). In the version with captions, the custom attention modules add a significant cost (+23.3M parameters), but this can be easily reduced by training fewer attention heads (e.g. 6 instead of
Figure 9: Two-step generator. The left side of the figure depicts $G_1$ (background generator), while the right side depicts $G_2$ (foreground generator). Orange arrows indicate that the input information is fed to $S$ blocks, whereas green arrows denote inputs to $S_{\text{avg}}$ blocks.

We conduct a similar analysis for the two-step model. In this case, the background generator is slightly more powerful than the foreground generator.

**Semantic map generation.** In this paragraph we provide further details in addition to those presented in sec. 4.2. Specifically, we describe how we construct and maintain the data structure that enables instance manipulation and rasterization. Since a scene may consist of objects that partially overlap, the order in which they are drawn on the semantic map is important, e.g. given a car and its headlight, we want to render the headlight semantic mask on top of the car and not the opposite. Therefore, we sort all instances by mask area and draw them from the largest to the smallest. Additionally, we construct a hierarchical structure to facilitate manipulation: if 70% of the area of an instance is contained within another instance, it becomes a child of the latter. With regard to the previous example, moving the car would also move the headlights attached to it. This hierarchy is only used for manipulation purposes, and has no effect on the model. Finally, in our experiments on Visual Genome, we link attributes to an instance if the IoU between the ground-truth region and the detected bounding box is greater than 0.5.

### A.2. FID evaluation

The FID metric is very sensitive to aspects such as image resolution, number of images (where a low number results in worse FID scores), and the weights of the pretrained Inception network. To be consistent with [29], we try to follow their methodology as closely as possible. We resize the ground-truth images to the same resolution as the generated ones (256 × 256), and we keep the two sets aligned, i.e. one generated image per test image. We use the weights of the pretrained InceptionV3 network provided by PyTorch. To make the results in Table 1 comparable, we retrained the baseline from [29] and evaluated the results using our methodology.

### A.3. Additional results

Fig. 11 and Fig. 12 show examples of semantic manipulation and style manipulation (either using attributes or text). The last row of Fig. 12 suggests that our attention mechanism can correctly exploit the contextualized token embeddings produced by BERT. For instance, the caption “a black and white cat” affects only the cat, while “a black and white picture of a cat” affects the entire scene by generating a black-and-white image.

| Approach   | Style input | # params  |
|------------|-------------|-----------|
| Baseline [29] | None        | 97.5M     |
| 1-step     | None        | 94.2M     |
| 1-step     | Attributes  | 96.5M     |
| 1-step     | Captions   | 117.5M    |
| 2-step     | None        | 74.5M + 50.6M |
| 2-step     | Attributes  | 78.3M + 51.9M |
| 2-step     | Captions   | 90.7M + 65.8M |

Table 2: Number of parameters for different variations of our approach. For the two-step models we specify the numbers for both generators (respectively $G_1$ and $G_2$).

- Table 2
A man in a blue coat skiing through a snowy field

A man in a red coat walking in the forest

Figure 10: Visualization of the attention mechanism in the discriminator for two images generated from the same semantic map, but different captions. An attention map is produced for each class in the semantic map, and each of these consists of 12 independent attention heads. In this illustration we only show those corresponding to person and no class (i.e. blank space). [CLS] and [SEP] are special delimiters indicating respectively the start and end of a sentence. A head paying attention to these can be interpreted as not being triggered by the sentence. In the attention maps, a darker color indicates a higher weight.

Fig. 13 shows additional demos generated by our two-step model on the Visual Genome development set. In particular, we highlight the decomposition of the background and foreground, and the inputs taken by $G_1$ and $G_2$. Since $G_2$ outputs a soft transparency channel for the alpha blending, it can slightly violate the constraints imposed by the foreground mask. This allows it to draw reflections and shadows underneath foreground objects.

A.4. Attention visualization

The behavior underlying our attention model can be easily visualized. Our formulation (sentence-semantic attention) is particularly suited for visualization tasks because it is tied to the semantic map, and not to feature maps in inner convolutional layers. Therefore, for each class in the semantic map (e.g. person, tree, empty space), we can observe how the sentence conditions that particular class.

Considering that the attention modules have multiple entry points in the generator (one for each SPADE normalization block), it is easier to carry out this analysis in the discriminator, where there are only two entry points (in the input layer of each discriminator, since we adopt a multi-scale discriminator). We select the first discriminator for illustration purposes, and show the resulting attention maps in Fig. 10. The figure shows what parts of the sentence the discriminator is attending to in order to discriminate whether the caption is suitable for the input image.

A.5. Demo video and interpolation

The accompanying video in the supplementary material shows some examples of interactive manipulations. Among other things, we show that our approach can smoothly interpolate between masks, attributes, and text. While attention models usually preclude interpolation (whereas models based on fixed-length sentence embeddings such as [46] easily allow it), our sentence-semantic attention mechanism enables interpolation over the contextualized class embeddings, i.e. over the pooled attention values. For all cases (masks, attributes, text), we respectively interpolate between class embeddings, attribute embeddings, and contextualized class embeddings using spherical interpolation (slerp), which traverses regions with a higher probability mass [21]. Unlike [46], we found it unnecessary to enforce a prior on the embeddings via a KL divergence term in the loss.
Figure 11: Examples of semantic and attribute manipulations (Visual Genome dataset). The images are generated by our two-step model. In the first row, the background is frozen to encourage locality.

Figure 12: Further examples of style manipulation using text (COCO2017 validation set). It is possible to control the style of individual instances (albeit in a less targeted fashion than attributes) as well as the global style of the image.
Figure 13: Demos generated by our two-step model. In addition to the full input mask, we show its decomposition into background mask and foreground mask (taken as input in $S$ blocks respectively by $G_1$ and $G_2$). Note that $G_1$ also takes as input the full mask in $S_{avg}$ blocks.