SESAME: Semantic Editing of Scenes by Adding, Manipulating or Erasing Objects

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Fig. 1. We assess SESAME on three tasks (a) image editing with free form semantic drawings (first row) (b) semantic layout driven semantic editing (second row) (c) layout to image generation with SESAME discriminator (third row)

Abstract. Recent advances in image generation gave rise to powerful tools for semantic image editing. However, existing approaches can either operate on a single image or require an abundance of additional information. They are not capable of handling the complete set of editing operations, that is addition, manipulation or removal of semantic concepts. To address these limitations, we propose SESAME, a novel generator-discriminator pair for Semantic Editing of Scenes by Adding, Manipulating or Erasing objects. In our setup, the user provides the semantic labels of the areas to be edited and the generator synthesizes the corresponding pixels. In contrast to previous methods that employ a discriminator that trivially concatenates semantics and image as an input, the SESAME discriminator is composed of two input streams that independently process the image and its semantics, using the latter to manipulate the results of the former. We evaluate our model on a diverse set of datasets and report state-of-the-art performance on two tasks: (a) image manipulation and (b) image generation conditioned on semantic labels.
Keywords: Generative Adversarial Networks, Interactive Image Editing, Image Synthesis

1 Introduction

Image editing is a challenging task that has received increasing attention in the media, movies and social networks. Since the early 90s, tools like Gimp [38] and Photoshop [36] have been extensively utilized for this task. Yet, both require high level expertise and are labour intensive. Generative Adversarial Networks (GANs) [10] provide a learning-based alternative able to assist non-experts to express their creativity when retouching photographs. GANs have been able to produce results of high photo-realistic quality [19][20]. Despite their success in image synthesis, their applicability on image editing is still not fully explored. Being able to manipulate images is a crucial task for many applications such as autonomous driving [15] and industrial imaging [4], where data augmentation boosts the generalization capabilities of neural networks [14][9].

Image manipulation has been used in the literature to refer to various tasks. In this paper, we follow the formulation of Bau et al. [3], and define the task of semantic image editing as the process of adding, altering and removing instances of certain classes or semantic concepts in a scene. Examples of such manipulations include but are not limited to: removing a car from a road scene, changing the size of the eyes of a person, adding clouds in the sky, etc. We use the term semantic concepts to refer to various class labels that can not be identified as objects, e.g., mountains, grass, etc.

Training neural networks for visual editing is not a trivial task. It requires a high level of understanding of the scene, the objects, and their interconnections [45]. Any region of an image added or removed should look realistic and should also fit harmoniously with the rest of the scene. In contrast to image generation, the co-existence of real and fake pixels make the fake pixels more detectable, as the network cannot take the ”easy route” of generating simple textures and shapes or even omit a whole class of objects [4]. Moreover, the lack of natural image datasets, where a scene is captured with and without an object, makes it impossible to train such models in a supervised manner.

One way to circumvent this problem is by inpainting the regions of an image we seek to edit. Following this scheme, we mask out and remove all the pixels we want to manipulate. Recent works [55][32][37][16] improve upon this approach by incorporating sketch and color inputs to further guide the generation of the missing areas and thus provide higher level control. However, inpainting can only tackle some aspects of semantic editing. To address this limitation, Hong et al. [12] manipulate the semantic layout of an image, and subsequently, they utilize it for inpainting the image. Yet, this approach requires access to the full semantic information of the image, which is costly to acquire.

To this end, we propose SESAME, a novel semantic editing architecture based on adversarial learning, able to manipulate images based on a semantic input. In particular, our method is able to edit images with pixel-level guidance of semantic
labels, permitting full control over the output. Note that our method requires the semantics only for regions to be edited. The generator seeks to synthesize an altered image such that the synthesized pixels comply with both the context and the user input. Moreover, we propose a new approach for semantics-conditioned discrimination, by utilizing two independent streams to process the input image and the corresponding semantics. We use the output of the semantics stream to manipulate the output of the image stream. We employ visual results along with quantitative analysis and a human study to validate the performance and flexibility of the proposed approach.

2 Related Work

Generative Adversarial Networks [10] have completely revolutionized a great variety of computer vision tasks such as image generation [20,19,30], super resolution [48,27], image attribute manipulation [28,40] and image editing [12,13]. While in their original formulation GANs were only capable of generating samples drawn from a random distribution [10], soon multiple models emerged able to perform conditional image synthesis [29,33]. This gave rise to approaches that employ a generative model for producing outputs conditioned on different types of information. There are many approaches targeting multiple levels of abstraction and locality of features that we seek to encapsulate in the output. For example, [29,31,57,5] focus on representing images characterized by a single label. In a different setting, [39,58,59,52] employ a text to image pipeline to provide a high-level description of the corresponding image. Recently, many methods utilize information of a scene graph [18,2] and sketches with color [42] to represent where objects should be positioned on the output image.

A more fine-grained approach aims to translate semantic maps, which carry pixel-wise information, to realistic-looking images [14,47,35,22]. For all the aforementioned models, the user can control the output image by altering the conditional information. Nonetheless, they are not suitable for manipulating an existing image, as they do not consider an image as an input.

User-guided semantic image editing is the task where the user is able to semantically edit an image by adding, manipulating or removing semantic concepts [3]. Both GANPaint [3] and SinGAN [43] are able to perform such operations. GANPaint [3] achieves this by manipulating the neuron activations and SinGAN [43] by learning the internal batch statistics of an image. However, both are trained on a single image and require retraining in order to be applied to another, while our model is able to handle manipulation of multiple images without retraining.

An other line of work is inpainting [13,56,25], where the user masks a region of the image for removal and the network fills it accordingly to the image context. This can been interpreted as a simple form of editing, but the user does not have control over the generated pixel. To address this, other research works guide the generation of the missing areas using edges [55,32] and/or color [37,16] information.
Recently, researchers shifted their attention to more semantic aware approaches for inpainting, by focusing on object addition and removal. Shetty et al. [44], for instance, propose a two stage architecture to address removal operations, by using an auxiliary network that predicts the masks of the objects during training, while, at inference, users provide their own masks. Note that their model cannot handle new objects generation. Another line of work is tackling object synthesis by utilizing semantic layout information, which provides a fine-grained guidance over the manipulation of an image. Yet, a subset of them is limited by generating objects from a single class [34,51] or placing prior fixed objects on the semantics plane [23]. Hong et al. [12] are able to handle both addition and removal, but require full semantic information of the scene to produce even the smallest change to an image. In contrast, our method requires only the semantics of the region to be edited.

The majority of the aforementioned works rely on adversarial learning to tackle the problem of image editing, by primarily focusing on adjusting the generator. Most recent models use a PatchGAN variant [14] which is able to discriminate on the high frequencies of the image. This is a desired attribute as conventional losses like Mean Squared Error and Mean Absolute Error can only convey information about the lower frequencies to the generator. PatchGAN can also be used for conditional generation of images on semantic maps, similar to our case study. Previous works targeting a similar problem concatenate the semantic information to the image and use it as an input to the discriminator. However, conventional conditional generation literature suggests that concatenation is not the optimal approach for conditional discrimination [39,33,31]. In this work, we extend PatchGAN to better incorporate conditional information by processing it separately from the image input. In a later stage of the network the two processed streams are merged to produce the final output of the discriminator.

3 SESAME

In this work we describe a deep learning pipeline for semantically editing images, using conditional Generative Adversarial Networks (cGANs). Given an image $I_{\text{real}}$ and a semantic guideline of the regions that should be altered by the network, denoted by $M_{\text{sem}}$, we want to produce a realistic output $I_{\text{out}}$. The real pixels values corresponding to $M_{\text{sem}}$ are removed from the input image. The generated pixels in their place should be both true to the semantics dictated by the mask and coherent with the rest of the pixels of $I_{\text{real}}$. In order to achieve this, our network is trained end-to-end in an adversarial manner. The generator is a Encoder-Decoder architecture, with dilated convolutions [53] and SPADE [35] layers, explained in section 3, and the discriminator is a two-stream patch discriminator, described in section 3.

SESAME Generator. Semantically editing a scene is an Image to Image translation problem. We want to transform an image where we substituted the RGB pixels of the regions with an one-hot semantics vector. From the generator’s
The SESAME Generator aims to generate the pixels designated by the semantic mask so they are both (1) true to their label and (2) fit naturally to the rest of the picture. It is an encoder-decoder architecture with dilated convolutions to increase the receptive field as well as SPADE layers in the decoder to guide in-class generation output, only the pixels on the masked out regions are retained, while the rest are retrieved from the original image:

\[
I_{\text{gen}} = G(I_m, M, M_{\text{sem}}),
\]

\[
I_{\text{out}} = I_{\text{gen}} \cdot M + I_{\text{real}} \cdot (1 - M).
\]

This architecture should accomplish two goals: generated pixels should 1) be coherent with their real neighboring ones as well as 2) be true to the semantic input. To achieve these goals we adapt our generator from the network proposed by Johnson et al. \[17\] to fill the gaps: two down-sampling layers, a semantic core made of multiple residual layers and two up-sampling ones.

We conceptually divide our architecture into two parts: the encoder and the decoder. In the encoder we aim to extract the contextual information of the pixels we want to synthesize. In the decoder part we combine the semantic information using Spatially Adaptive De-Normalization \[35\] blocks to every layer. As the area to be edited can span over a large region, we would like the receptive field of our network to be relatively large. Thus, we use dilated convolutions in the last and first layers of the encoder and the decoder respectively. A scheme of our SESAME generator can be seen in the Fig. 2, and for further details refer to the supplementary materials.

**SESAME Discriminator.** Layout to image editing can be seen as a sub-task of label to image translation. Inspired by Pix2Pix \[14\], more recent approaches \[47,35\] employ a variation of the PatchGAN discriminator. The Markovian discriminator, as it is also called, was a paradigm shift that made the discriminator focus on the higher frequencies by limiting the attention of the discriminator into local patches, producing a different fake/real prediction value for each of them. The subsequent methods added a multi-scale discrimination
Fig. 3. The SESAME discriminator, in contrast to the commonly used PatchGAN, is handling the RGB Image and its Semantics independently. Before the last convolutional layer the two streams, $D_{RGB}$ and $D_{Sem}$, are merged. The semantics stream is reduced via a *Sum Global Pooling* operation to a 2D matrix of spatial dimensions equal to the number of output patches. The feature vector of $D_{RGB}$ at each path is scaled by $D_{Sem}$ and a residual is added to product approach, the Feature Matching-Loss [17] and the use of Spectral Normalization [30] instead of Instance Normalization [35], which stabilized training and further improved the quality of the generated samples. However, the way the conditional information was provided to the discriminator remained unchanged.

Label to image generation is a sub-task of conditional image generation. In this more general category of methods, we can observe how the discriminator has evolved from the cGAN’s input concatenation [29], to concatenating the class information with a hidden layer [39], and lastly, to take the form of the projection discriminator [31]. In the latter approach, the inner product of the embedding of the conditional information and a feature extracted from the hidden layers of the discriminator are summed with the output of the discriminator to produce the final prediction. Each step of the conditional discriminator evolution improved the results over the naïve concatenation at its input [31]. On these methods the discriminator produces, nonetheless, a scalar output for the whole image.

We aim to design a discriminator for label to image generation that combines the aforementioned attributes. On the one hand, it should preserve the ability of PatchGAN to discriminate on high-frequencies. On the other hand, we want to enforce the semantic information guidance on the discriminator’s decision. If the pixels of the whole image shared semantic class, the projection discriminator would be easily extended to PatchGAN. In contrast, our case is characterized by fine-grained per pixel semantics: each output patch encompasses a variety of classes and different compositions of them.

Our proposed SESAME discriminator is comprised by two independent streams that handle the RGB and Semantic Labels inputs. As Fig. 3 depicts, the two
streams have identical architectures. Before the information is merged a *Sum Global Pooling* operation is applied on the outputs of the Semantics Stream. The output of the semantics stream is used to scale each output coming from the RGB stream. The resulted feature map is passed as input to a last $3 \times 3$ convolutional layer, which produces the final output. The process can be written as follows:

$$D(I, Sem) = Conv_{3\times3}(D_{RGB}(I_{out}) \cdot (1 + \sum_{\text{channels}} D_{sem}(Sem)))$$

where the $D_{RGB}$ is the output of the RGB stream and $D_{sem}$ of the semantics stream before the *Global Sum Pooling*. We also integrate the changes made to PatchGAN by Pix2PixHD [47] and SPADE [35]. We use a multi-scale discrimination scheme with squared patches and two different edge-sizes of 70 and 140 pixels, in order to provide also discrimination at a coarser level and Spectral Normalization. The input to the semantic stream is the same for both fake and real images discrimination, so we only need to calculate $D_{sem}$ once. Moreover, it makes sense to apply the Feature Matching Loss only to the Feature Maps produced by the RGB stream.

**Training Losses.** We train the Generator in an adversarial manner using the following losses: Perceptual Loss [17], Feature Matching Loss [41] and Hinge Loss [24,46,30] as the Adversarial Loss. Early experiments with Style Loss [17] did not improve the results. Accordingly:

$$L_G = \lambda_{\text{percept}} \cdot L_{\text{perc}} + \lambda_{\text{feat}} \cdot L_{\text{FM}} - E_{z \sim p(z)}[D_k(I_{out}, M, M_{sem})]].$$

(4)

For the discriminator at each scale the Hinge Loss takes the following form:

$$L_{D_k} = E_{z \sim q_{data}(x)}[\min(0, -1 + D_k(I_{real}, M, M_{sem}))] + E_{z \sim p(z)}[\min(1, -1 - D_k(I_{real}, M, M_{sem}))],$$

(5)

which is then combined to form the full discrimination loss,

$$L_D = L_{D_1} + L_{D_2}.$$  

(6)

### 4 Experiments

In Section 3 we described how the SESAME Generator can be used to semantic edit images for addition, manipulation and removal and how we designed the SESAME discriminator to tackle both image editing. To elucidate the merits of our approach we conducted a series of different experiments:

– In order to quantify the performance of our network we follow the data preparation and evaluation steps of Hong *et al.* [12], for generating and removing objects based on a given semantic layout.
Fig. 4. Visual results of addition on Cityscapes: (a) input image (b) edited semantics (c) SESAME (d) Hong et al. [12]. Note that Hong et al. [12] require the whole semantics while we use only the semantics of the box.

- We train our model to permit free form semantic input from users to manipulate scenes and show qualitative results.
- We train our SESAME discriminator along with SPADE Generator for Label to Image Generation.

Implementation Details. For training we are using the Two Time-Scale Update Rule [11] to determine the scale between the learning rate of the generator and the discriminators, with $lr_{gen} = 0.0001$ and $lr_{disc} = 0.0004$. We train for 200 epochs. After 100 we start to linearly decay the learning rates to 0. For our generator losses we multiplied the Feature Matching Loss and Perceptual loss by a factor of 10 before adding them to the adversarial loss. We use the Adam optimizer [21] with coefficient values of $b_1 = 0$ and $b_2 = 0.999$, similar to [35].

Datasets. In line with the literature we conduct experiments:

- Cityscapes [8]. The dataset contains 3,000 street-level view images of 50 different cities in Europe for the training set and 500 images for the validation set. The images are accompanied by fine grained information of the per-pixel semantics and instance segmentation with original resolution of the images is $2048 \times 1024$ pixels. For addition and removal we down-sample to $1024 \times 512$ pixels before patches of $256 \times 256$ pixels are extracted. Following Hong et al. [12], we choose 10 of the 30 available semantics classes as foreground objects, e.g., pedestrians, cars, bicycles, etc.. For generation we resize the image to $512 \times 256$ pixels.
- ADE20K [60,61] ADE20K has over 20,000 images together with their detailed semantics for 150 different semantic classes. In addition, 2,000 more images are offered for validation. We use this dataset for Image Generation.
Fig. 5. Visual results of addition on ADE20k: (a) input image (b) edited semantics (c) SESAME (d) Hong et al. [12]. In this setting we use the full semantic information to guide the editing

- **ADE20K-bedroom** Following Hong et al. [12] we experiment on a subset of the ADE20K dataset comprised of bedroom scenes. Similarly to Cityscapes, 31 objects are chosen as foreground objects. In total, we consider 49 semantic categories for training and evaluation.

- **Flickr-Landscapes Datasets** [35] Similar to SPADE [35], we first scrapped 200,000 images from Flickr with only landscape constraint. As our main purpose is to show image editing over significant areas within a landscape, we use a DeepLab-v2 [6] network trained on COCO-Stuff in order to extract images that contain at least 80% pixels of clouds, mountains, water, grass, etc. After post-processing, our curated dataset consists of 7367 training and 500 validation images with their corresponding segmentation for 17 different semantic classes.

**Data Pre-processing.** Free-form semantic editing is not trivial to achieve. The model can easily overfit on mask shapes used during training. In order to train our free-form semantic editing experiments, we randomly draw a box mask in conjunction with random strokes [55] with 70% chance, otherwise we drop all the pixels belonging to a semantic class of the training image.

For layout driven editing, we extend the data pre-processing scheme introduced by Hong et al. [12]. A rectangular area is removed from the input image and we try to inpaint it using the semantic labels. To train the addition operation, they extract the boundary boxes based on the instances of the foreground classes. For the removal sub-task, they randomly choose and remove blocks to train the network to inpaint background classes. While this makes sense for a dataset like ADE20k where the foreground objects can be found anywhere in the pictures, in Cityscapes the foreground objects placement follow certain dis-
Fig. 6. Free-form image manipulation. The user can select a semantic brush and paint over the image to adjust as they see fit

Table 1. Results for the Cityscapes dataset [8]. For the SSIM and mIoU higher is better, while for FID, lower is better. We follow [35] and use the DRN [53,54] for segmenting

| Method       | Addition | Removal |
|--------------|----------|---------|
|              | SSIM↑    | accu↑   | mIoU↑   | FID↓    | SSIM↑    | accu↑   | mIoU↑ | FID↓ |
| Hong et al. [12] | 0.377    | 83.8%   | 60.7%   | 12.11   | 0.584    | 83.9%   | 65.3% | 10.34 |
| SESAME       | 0.410    | 86.0%   | 65.3%   | 11.03   | 0.797    | 85.0%   | 67.6% | 7.43 |

tributions [23]. Thus we only extract a randomly chosen rectangular area if it contains at least a pixel of ground, road, sidewalk and parking.

Quantitative Results. For measuring the performance of our network we combine the evaluation approach of previous methods [12,35]. To assess the visual quality of our synthesis we use the Frechet Inception Distance (FID) [11]. Then we compare the mean Intersection over Union (mIoU) and the pixel-accuracy loss between the ground truth semantic layout and the inferred one. For all our experiments, we chose every time the same object in order to maintain consistency. Additionally, in our comparison with Hong et al. [12], we compute the Structural Similarity Index (SSIM) [50] between each \( \langle I_{real}, I_{out} \rangle \) pair, taking into account only the generated pixels. Naturally, as in the case of Editing only a small percentage of image pixels are changed we expect better results than in the Generation experiments, but also better methods yield larger performance gains when tackling the latter.
Table 2. Quantitative Results for the proposed SESAME in comparison to Hong et al. [12] on ADE20K dataset [61,60]. Note that the majority of the pixels used to calculate these metrics are real, thus reducing the actual numerical improvement of SESAME over our baseline.

| Method       | Addition | Removal |
|--------------|----------|---------|
|              | SSIM↑ | accu↑ | mIoU↑ | FID↓ | SSIM↑ | accu↑ | mIoU↑ | FID↓ |
| Hong et al. [12] | 0.236 | 92.5% | 33.9% | 27.53 | 0.456 | 91.7% | 40.0% | 24.98 |
| SESAME       | 0.267 | 93.4% | 36.7% | 24.88 | 0.491 | 92.3% | 41.6% | 23.30 |

Table 3. Comparison in number of parameters

| Method       | Parameters in millions |
|--------------|------------------------|
|              | Generator | Discriminator |
| Hong et al. [12] | 190m | 5.6m |
| SESAME       | 20.5m | 11.1m |

**Our Baselines.** For our semantic image editing baseline we are using the work of Hong et al. [12]. They introduced a hierarchical model to tackle the task of image editing. In the first stage, they inpaint the semantic classes of an image with a missing region. Then they combine the predicted output with the ground truth and after concatenating the real image with the missing pixels, they use their second stage model to fill the image. Similar to their work, we focus on the mask to image generation task and compare our model against their image generator trained on the ground truth labels. Their approach consists of an encoder and a decoder. The encoder has two input streams where the image and the semantics are processed separately and are then fused based on the mask of the object location. The result of the fusion is then passed to an image decoder which produces the end result. The generator is trained in conjunction with a PatchGAN discriminator. We use different architectures and largely decrease the number of parameters for the generator and have a larger discriminator as shown in Table 3. However, during inference time only the generator is used. Reduced number of parameters for the generator is clearly beneficial during execution. For Image Generation our Baseline is SPADE [35].

**Addition and Removal of Objects** To elucidate the ability of our network to perform well both on the addition and the removal part we compare on both tasks separately. The computed metrics for these cases can be found in Tables 1 and 2 for Cityscapes and ADE20k, respectively. For a fair comparison, we showcase a version of our model where a rectangular region of pixels is removed from the input image.

For Cityscapes and ADE20K we use the boundary box (BBox) semantics and the full semantics, respectively. In the visual results we can observe that objects look sharper and their features are more distinctive. Furthermore, as Figures 4
and illustrate, our method generates different patterns for different clothes, and cars in which the windows are not mixed with the rest of the car. Besides our better numerical results, our user study (see Section 4) further illustrates the superiority of our approach. In the case of removal, artifacts of the BBox are commonly left in picture by the method of Hong et al. [12], whilst in our case this effect is difficult to notice.

**Labels to Image Generation** The SESAME Discriminator is designed to tackle the shortcomings of the naive concatenation of an image and its semantics label when generating images. We measure the performance on Labels to Image Generation against SPADE [35] using the same generator. The results for Cityscapes and ADE20k datasets can be found on Table 6 and Fig. 7.

**Free-Form Semantic Image Editing** The user selects a brush of a semantic class and paints over the image. The pixels that are painted over are removed from the image and SESAME is filling the gaps based on the painted semantic guidance. Examples of hand painted masks and corresponding results can be seen on Fig. 6. We should note that snow is a different semantic label from mountain and we can observe when draw with the mountain brush the model learned to

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**Fig. 7.** Label to Image Generation results. For each triplet of images we are showing the semantic layout input (left), generation using PatchGAN (center) and SESAME (right) discriminator on top of SPADE generator.
Table 4. We ablate on the semantics availability, the generator architecture and the discriminator architecture for adding objects on street scenes from Cityscapes w.r.t. FID score (lower is better)

| Generator   | Discriminator | Full semantics | BBox semantics |
|-------------|---------------|----------------|----------------|
|             |               | Patch          | Ours           | Patch          | Ours           |
| SPADEPix2PixHD | 11.92         | 12.74          | 12.32          | 12.66          |
| Ours        | 11.95         | 11.64          | 11.13          | 11.03          |

differentiate this from snow. Additionally, the context is very important for the label we want to add: a patch of grass cannot be drawn in the middle of the sky. More results can be found in the supplementary materials.

Ablation Study  SESAME incorporates a Generation/Discrimination pair able to edit a scene by only considering the Semantics of regions in the image that the user seeks to edit. In order to showcase the benefits of our approach we ablate the performance of our architecture by varying (a) the generator architecture, (b) the discriminator architecture and (c) the available semantics, by utilizing either the Full semantic layout or the semantics of the rectangular region we want to edit, which we refer to as BBox Semantics. Regarding the generator architecture, we compare our generator against Pix2PixHD++ [47], with SPADE layers on the decoder part. Regarding discriminator architecture, we compare against the commonly used PatchGAN.

The performance assessment is reported in Table 4. The use of our discriminator over PatchGAN improved the results in almost all cases. However, we observe that while our generator-discriminator combination performs the best, the second combination is without any of our networks. We argue that our proposed method works better together as the large receptive field provided by the dilated convolutions in our generator synergizes well with the highly focused gradient flow coming from our discriminator.

In another series of experiments, we substituted our Semantics merging operation. Instead of applying Sum Global Pooling, we experiment with 1) concatenating the two streams of information and 2) calculating their element-wise product resulted in a lower FID score compared to the proposed approach, 11.96 and 12.02 respectively.

User Study  We employed Amazon Mechanical Turk[4] to conduct two experiments for the user study. For each of them, we sampled 100 images from our validation set and asked 20 Turkers: Which among the images looks more photorealistic?

The first experiment presented the Turkers with three options: our method with access to only the BBox information and both ours and Hong et al. [12]

[4] https://www.mturk.com
Table 5. User Study Results: Which image is the most photo-realistic? The first study invited the users to choose between Hong et al. [12] with full semantics information and ours with full and bbox semantics, respectively. The second study invited to choose between the results produced by our SESAME and the PatchGAN discriminator, for different availability of semantics.

| Setting       | Preference [%] |
|---------------|----------------|
| Hong et al. [12] | 22.50          |
| Ours w Full   | 35.83          |
| Ours w BBox   | 41.67          |

User Study II

| Discriminator | SESAME | PatchGAN |
|---------------|--------|----------|
| FullContext   | 56.67  | 43.33    |
| BBoxContext   | 61.04  | 38.96    |

Table 6. Layout to image generation results. For the SSIM, mIoU and accu, higher is better, while for FID, lower is better.

| Method      | Cityscapes | ADE20k |
|-------------|------------|--------|
|             | mIoU | accu | FID | mIoU | accu | FID |
| Pix2PixHD   | 58.3 | 81.4 | 95.0 | 22.4 | 68.38 | 81.8 |
| SPADE       | 62.3 | 81.9 | 71.8 | 38.5 | 81.9 | 33.9 |
| Ours        | 66.0 | 82.5 | 54.2 | 49.0 | 85.5 | 31.9 |

model using the Full Semantics. As shown in Table 5 the results of our SESAME approach were clearly preferred by the users over the results of our baseline. Moreover, in agreement with our quantitative analysis, the proposed scaling scheme in our discriminator benefits from less irrelevant semantic information. Another group of settings compared the results when the PatchGAN is used instead of our SESAME discriminator. The results consistently show that the independent processing of the semantic information leads to better perceptual quality of the results; they are picked more often by the human subjects.

5 Conclusion

In this work, we introduce SESAME a novel method for semantic image editing covering the complete spectrum of adding, manipulating and erasing operations. Our generator is capable of manipulating an image by only conditioning on the semantics of the regions the user seeks to edit, namely without requiring the information about the full layout. Our discriminator processes the semantic and image information in separate streams and overcomes the limitations of the concatenating approach inherent in PatchGAN. SESAME produces state-of-the-art results on the tasks of (a) semantic image manipulation and (b) layout to image generation and permits the user to edit an image by intuitively painting over it. As a future research direction, we plan to extend this work on image generation conditioned on other types of information, e.g., scene graphs, could also benefit from our two-stream discriminator. We refer to supplementary material for more
details. We will open-source the code and the models under the repository name OpenSESAME.

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A Supplementary Material

Model Architectures The detailed architectures of the SESAME generator and discriminator are depicted in Tables 7 and 8 respectively. Please note that for the discriminator we use this architecture twice, once for each scale.

| Layer | Normalization | Activation |
|-------|---------------|------------|
| ConvBlock $F = 64$, $K = 7$, $S = 1$, $D = 1$ | Instance | ReLU |
| ConvBlock $F = 128$, $K = 3$, $S = 2$, $D = 1$ | Instance | ReLU |
| ConvBlock $F = 256$, $K = 3$, $S = 2$, $D = 1$ | Instance | ReLU |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 1$ | Instance | ReLU |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 2$ | Instance | ReLU |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 2$ | Instance | ReLU |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 2$ | Instance | ReLU |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 2$ | SPADE | LeakyReLU(0.02) |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 2$ | SPADE | LeakyReLU(0.02) |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 2$ | SPADE | LeakyReLU(0.02) |
| ResBlock $F = 256$, $K = 3$, $S = 1$, $D = 2$ | SPADE | LeakyReLU(0.02) |
| Nearest Neighbour Upsampling $\times 2$ | - | - |
| ResBlock $F = 128$, $K = 3$, $S = 1$, $D = 1$ | SPADE | LeakyReLU(0.02) |
| Nearest Neighbour Upsampling $\times 2$ | - | - |
| ResBlock $F = 64$, $K = 3$, $S = 1$, $D = 1$ | SPADE | LeakyReLU(0.02) |
| ConvBlock $F = 3$, $K = 3$, $S = 1$, $D = 1$ | - | TanH |

Replacement of objects Apart from adding and removing objects, SESAME can also be used to replace an instance of an object, given that we know its class and its outline. SESAME can be utilized in this manner for dataset augmentation. We conduct experiments on replacing objects in street scenes of Cityscapes and we ablate on the usage of our SESAME discriminator against the PatchGAN. In Table 9 we measure the FID score of the image results, the SSIM of the generated regions and we also devoted a part of our user study, described in Section 4 of the main paper, to test which of the two discriminators produces the most photo-realistic results. Visual results can be found in Figure 8.

Visual Results We show more edited and generated images produced by our method:

- Figure 8 contains visual results of our ablation analysis on various access levels of semantics and different discriminators.
- Figure 9 contains visual results for removing objects under different configurations.
Table 8. SESAME discriminator architecture per scale. We depict the number of Filters, the Kernel size, the Stride and the Dilation factor

| Layer | Normalization | Activation          |
|-------|---------------|---------------------|
| Image Stream |                |                     |
| ConvBlock F = 64, K = 4, S = 2, D = 1 | - | LeakyReLU(0.02) |
| ConvBlock F = 128, K = 4, S = 2, D = 1 | SpectralInstance | LeakyReLU(0.02) |
| ConvBlock F = 256, K = 4, S = 2, D = 1 | SpectralInstance | LeakyReLU(0.02) |
| ConvBlock F = 512, K = 4, S = 1, D = 1 | SpectralInstance | LeakyReLU(0.02) |
| Semantics Stream |                |                     |
| ConvBlock F = 64, K = 4, S = 2, D = 1 | - | LeakyReLU(0.02) |
| ConvBlock F = 128, K = 4, S = 2, D = 1 | SpectralInstance | LeakyReLU(0.02) |
| ConvBlock F = 256, K = 4, S = 2, D = 1 | SpectralInstance | LeakyReLU(0.02) |
| ConvBlock F = 512, K = 4, S = 1, D = 1 | SpectralInstance | LeakyReLU(0.02) |
| Sum Global Pooling | - | - |
| Common Head |                |                     |
| ConvBlock F = 1, K = 4, S = 1, D = 1 | - | - |

Table 9. Object Replacement - Cityscapes. We show the performance of our SESAME model with our discriminator and the PatchGAN\[14,35\] discriminator as well as the percentage of user answers to the question: Which image looks more photo-realistic?

| Discriminator | SSIM↑ | FID↓ | User Preference(%) |
|---------------|-------|------|---------------------|
| PatchGAN      | 0.390 | 10.63| 45.03               |
| SESAME        | **0.433** | **9.3** | **54.97** |

- Figure 10 shows results for editing ADE20k-Bedroom scenes\[61,60\].
- Figure 11 showcases examples of free-from semantic editing.
- On Figures 12 and 13 we can observe layout to image generation results for Cityscapes and ADE20k.

Label to Image Generation: Comparison with CC-FPSE: Concurrently to our work, Liu et al.\[26\] developed an approach to tackle image generation conditioned on semantic layouts. They propose a generator architecture that learns to predict convolutional kernel weights conditioned on the semantic input. Moreover, they propose a feature pyramid semantics-embedding (FPSE) discriminator using a U-Net architecture. Each upsampling layer outputs two per-patch score maps, one trying to measure the realness and one to gauge the semantic matching with the labels; the later is derived after a patch-wise inner product operation with the down-sampled semantic embeddings.

Their FPSE discriminator, while it also addresses the shortcomings of previous models, follows a different approach to our SESAME discriminator. Although they similarly aim to short-circuit the guidance of the semantic labels to the discrimination, they choose to do so by embedding the patch with a 1 × 1 convolution and down-sampling via average pooling the semantic layout to match the size of their image processing pipeline. As we explained in the main paper, the
Fig. 8. Visual results for addition on Cityscapes [8]. We ablate on: (a) using the Full context, using only the labels of the rectangular areas to be edited and only replacing an object given its mask (b) generations due to training with the PatchGAN Discriminator and SESAME. Finally, we show the results produced by the method of Hong et al. [12], using the full semantics information.
Fig. 9. Visual results for removal on Cityscapes[8]. We ablate on: (a) using the Full context and using only the labels of the rectangular areas to be edited (b) generations due to training with the PatchGAN Discriminator and SESAME. In the first row we show the results produced by the method of Hong et al. [12], using the full semantics information.

Fig. 10. Visual results for editing Bedroom scenes from ADE20K dataset. Here we are using the Full semantic information to alter the gray area.
Fig. 11. Examples of free form editing using semantic brushes. Note that in the last, row instead of the mountain brush, we used rock and tree, on the left and right side respectively. The model fails to correctly depict a semantic concept out of context or with an unexpected shape.
Fig. 12. Cityscapes [8]: Visual results for image generation conditioned on Semantic Labels. We showcase the results using the generator from SPADE [35] with the PatchGAN Discriminator (SPADE) and ours (SESAME).
Fig. 13. Ade20k\textsuperscript{61,60}: Visual results for image generation conditioned on Semantic Labels. We showcase the results using the generator from SPADE\textsuperscript{35} with the Patch-GAN Discriminator(SPADE) and ours(SESAME)
Table 10. Layout to image generation results. For the mIoU and accu, higher is better, while for FID, lower is better.

| Method     | Cityscapes | ADE20k |
|------------|------------|--------|
|            | mIoU↑ | accu↑ | FID↓ | mIoU↑ | accu↑ | FID↓ |
| Pix2PixHD  | 58.3   | 81.4   | 95.0 | 20.3 | 69.2 | 81.8 |
| SPADE      | 62.3   | 81.9   | 71.8 | 38.5 | 79.9 | 33.9 |
| CC-FPSE    | 66.5   | 82.3   | 54.3 | 43.7 | 82.9 | 31.7 |
| SESAME     | 66.0   | 82.5   | 54.2 | 49.0 | 85.5 | 31.9 |

receptive field of a patch may contain a multitude of different semantic classes with a variety of compositions. Trivially down-sampling the semantic label can result into loss of information. Thus, we proposed a dedicated part of the discriminator to derive a meaningful representation for such an intricate semantic patch. Moreover, our model independently processes the semantic information for each scale.

In this work, we develop a solution to tackle the problem of semantic image editing and we apply our SESAME discriminator on top of SPADE’s generator to produce our label to image generation results. However, Liu et al. [26] focus solely on this task and achieve results similar to ours when incorporating all components to their model, as seen in Table 10. Note that their performance deteriorates when using SPADE’s generator, a setup comparable to our approach.

The values in italics of Table 10 are corrections of the ones reported on the main paper.