

BlobGAN: Spatially Disentangled Scene Representations

Dave Epstein¹ Taesung Park² Richard Zhang²
Eli Shechtman² Alexei A. Efros¹

¹UC Berkeley ²Adobe Research

Abstract. We propose an unsupervised, mid-level representation for a generative model of scenes. The representation is mid-level in that it is neither per-pixel nor per-image; rather, scenes are modeled as a collection of spatial, depth-ordered “blobs” of features. Blobs are differentially placed onto a feature grid that is decoded into an image by a generative adversarial network. Due to the spatial uniformity of blobs and the locality inherent to convolution, our network learns to associate different blobs with different entities in a scene and to arrange these blobs to capture scene layout. We demonstrate this emergent behavior by showing that, despite training without any supervision, our method enables applications such as easy manipulation of objects within a scene (*e.g.* moving, removing, and restyling furniture), creation of feasible scenes given constraints (*e.g.* plausible rooms with drawers at a particular location), and parsing of real-world images into constituent parts. On a challenging multi-category dataset of indoor scenes, BlobGAN outperforms StyleGAN2 in image quality as measured by FID. See our project page for video results and interactive demo: <http://www.dave.ml/blobgan>.

Keywords: scenes, generative models, mid-level representations

1 Introduction

The visual world is incredibly rich. It is so much more than the typical ImageNet-style photos of solitary, centered objects (cars, cats, birds, faces, *etc.*), which are the mainstays of most current paper result sections. Indeed, it was long clear, both in human vision [9,27] and in computer vision [91,56,58,28,19], that understanding and modeling objects within the context of a *scene* is of the utmost importance. Visual artists have understood this for centuries, first by discovering and following the rules of scene formation during the Renaissance, and then by expertly breaking such rules in the 20th century (cf. the surrealists including Magritte, Ernst, and Dalí).

However, in the current deep learning era, scene modeling for both analysis and synthesis tasks has largely taken a back seat. Images of scenes are either represented in a top-down fashion, no different from objects – *i.e.* for GANs or image classifiers, scene classes such as “bedrooms” or “kitchens” are represented

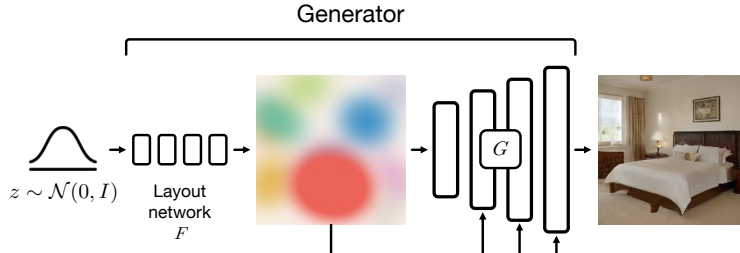


Fig. 1: In our generator, random noise is mapped by the layout network F to blob parameters. Blobs output by F are *splatted* spatially onto corresponding locations in the feature grid, used both as initial input and as spatially-adaptive modulation for the convolutional decoder G . Our blob representation automatically serves as a strong mid-level generative representation for scenes, discovering objects and their layouts.

the same way as object classes, such as “beds” or “chairs”. Or, scenes are modeled in a bottom-up way by semantic labeling of each image pixel, *e.g.*, semantic segmentation, pix2pix [31], SPADE [59], *etc.* Both paths seem unsatisfactory because neither can provide easy ways of reasoning about parts of the scene as *entities*. The scene parts are either baked into a single entangled latent vector (top-down), or need to be grouped together from individual pixel labels (bottom-up).

In this paper, we propose an *unsupervised mid-level representation* for a generative model of scenes. The representation is mid-level in that it is neither per-pixel nor per-image; rather, scenes are modeled as a collection of spatial, depth-ordered Gaussian “blobs”. This collection of blobs provides a bottleneck in the generative architecture, as shown in Figure 1, forcing each blob to correspond to a specific object in the scene and thus causing a spatially disentangled representation to emerge. This representation allows us to perform a number of scene editing tasks (see Figure 3) previously only achievable with extensive semantic supervision, if at all.

2 Related Work

Mid-level scene representations. Work on mid-level scene representations can be traced back to the 1970s, to the seminal papers of Yakimovsky and Feldman [91] and Ohta et al [56], which already contained many key ideas including joint bottom-up segmentation and top-down reasoning. Other important developments were the line of work on normalized-cuts segmentation [78,96,20] and qualitative 3D scene interpretation [28,24,81,19] in the early 2000s. But most relevant to the present manuscript is the classic *Blobworld* work of Carson et al. [12], a region-based image retrieval system, with each image represented by a mixture-of-Gaussian blobs. Our model could be considered a generative version of this representation, except we also encode the depth ordering of the blobs.

Scene analysis by synthesis. The idea of modeling a complex visual scene by trying to generate it has been attempted a number of times in the past.

Early methods, such as [87,84,85], introduced key ideas but were limited by the generative models of the time. To address this, several approaches tried non-parametric generation [47,73,30], with Scene Collaging [30] the most valiant attempt, showing layered scene representations despite very heavy computational burden. With the advancement of deep generative models, parametric analysis-by-synthesis techniques are having a renaissance, with some top-down [93,57,95] as well as bottom-up [62,22] techniques.

Conditional image generation. Conditional GANs [103,29,89], such as image-to-image translation setups [31], predict an image from a predefined representation, *e.g.* semantic segmentation maps [59,45], object-attribute graphs [33,8], text [99,68,53,66,71,67], pose [43,75,3], and keypoints [11]. Other setups include using perceptual losses [14], implicit likelihood estimation [44], and more recently, diffusion models [50,74]. [80,49,48,79,88,23] explore related intermediate representations to help generation (mostly of humans or objects) but none provide the ability to generate and manipulate high-quality scene images of our method.

Unconditional generation and disentanglement. Rather than use explicit conditioning, it is possible to learn an image “manifold” with a generative model such as a VAE [41,26] or GAN [18] and explore emergent capabilities. GANs have improved in image quality [65,16,98,10,35,37,38,36] and are our focus. Directions of variation naturally emerge in the latent space and can be discovered when guided by geometry/color changes [32], language or attributes [61,65,76,2,90], cognitive signals [17], or in an unsupervised manner [21,77,63]. Discovering disentangled representations remains a challenging open problem [46]. To date, most successful applications have been on data of objects, *e.g.* faces and cars, or changing textures for scenes [60]. Similar to us, an active line of work explores adding 3D inductive biases [54,51,52], but individual object manipulation has largely focused on simple diagnostic scenes [34]. Alternatively, the internal units of a pretrained GAN offer finer spatial control, with certain units naturally correlating with object classes [6,5,92]. The internal compositionality of GANs can be leveraged to harmonize images [15,13] or perform a limited set of edits on objects in a scene [6,97,101]. Crucially, while these works require semantic supervision to identify units and regions, our work uses a representation where these factors naturally emerge.

3 Method

Our method aims to learn a representation of scenes as spatial maps of blobs through the generative process. As shown in Figure 1, a layout network maps from random noise to a set of blob parameters. Then, blobs are differentially splatted onto a spatial grid – a “blob map” – which a StyleGAN2-like decoder [39] converts into an image. Finally, the blob map is used to modulate the decoder. We train our model in an adversarial framework with an unmodified discriminator [38]. Interestingly, even without explicit labels, our model learns to decompose scenes into entities and their layouts.

Our generator model is largely divided into two parts. First, we apply an 8-layer MLP F to map random noise $z \in \mathbb{R}^{d_{\text{noise}}} \sim \mathcal{N}(0, I_d)$ to a collection of blobs parameterized by $\beta = \{\beta_i\}_{i=1}^k$ which are splatted onto a spatial $H \times W \times d$ feature grid in a differentiable manner. This process is visualized in Figure 2. The feature grid is then passed to a convolutional decoder G to produce final output images. In the remainder of this section, we describe the design of our representation as well as its implementation in detail.

3.1 From noise to blobs as layout

We map from random Gaussian noise to distributions of blobs with an MLP F with dimension d_{hidden} . The last layer of F is decoded into a sequence of blob properties β . We opt for a simple yet effective parametrization of blobs, representing them as ellipses by their center coordinates $x \in [0, 1]^2$, scale $s \in \mathbb{R}$, aspect ratio $a \in \mathbb{R}$, and rotation angle $\theta \in [-\pi, \pi]$. Each blob is also associated with a structure feature $\phi \in \mathbb{R}^{d_{\text{in}}}$ and a style feature $\psi \in \mathbb{R}^{d_{\text{style}}}$. Altogether, our blob representation is:

$$\beta \in \mathbb{R}^{2+1+1+1+d_{\text{in}}+d_{\text{style}}} \triangleq (x, s, a, \theta, \phi, \psi)$$

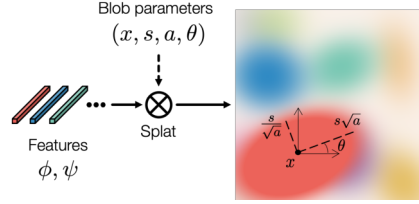


Fig. 2: Our elliptical blobs β are parametrized by centroid x , scale s , aspect ratio a , and angle θ . We composite multiple blobs with alpha values that smoothly decay from blob centers. The features ϕ or ψ are splatted on their corresponding blobs and passed to the decoder.

Next, we transform the blob parameters to a 2D feature grid by populating the ellipse specified by β with the feature vectors ϕ and ψ . We do this differentially by assigning an opacity and spatial falloff to each blob. Specifically, we calculate a grid $\alpha \in [0, 1]^{H \times W \times k}$ which indicates each blob’s opacity value at each location. We then use these opacity maps to *splat* the features ϕ, ψ at various resolutions, using a single broadcasted matrix multiplication operation.

In more detail, we begin by computing per-blob opacity maps $o \in [0, 1]^{H \times W}$. For each grid location $x_{\text{grid}} \in \left\{ \left(\frac{w}{W}, \frac{h}{H} \right) \right\}_{w=1, h=1}^{W, H}$ we find the squared Mahalanobis distance to the blob center x :

$$d(x_{\text{grid}}, x) = (x_{\text{grid}} - x)^T (R \Sigma R^T)^{-1} (x_{\text{grid}} - x), \quad (1)$$

where $\Sigma = c \begin{bmatrix} a & 0 \\ 0 & \frac{1}{a} \end{bmatrix}$, R is a 2D rotation matrix by angle θ , and $c = 0.02$ controls blob edge sharpness. The opacity of a blob at a given grid location is then:

$$o(x_{\text{grid}}) = \sigma(s - d(x_{\text{grid}}, x)), \quad (2)$$

where s acts as a control of blob size by shifting inputs to the sigmoid. Intuitively, this can be thought of as taking a soft thresholding operation on a Gaussian to define an in-region and an out-region. For example, our model can output a large negative $s < 0$ to effectively “turn off” a blob. Rather than taking the softmax to

normalize values at each location, we use the alpha-compositing operation [64], which allows us to model occlusions and object relationships more naturally by imposing a 2.1-D z-ordering [55]:

$$\alpha_i(x_{\text{grid}}) = o_i(x_{\text{grid}}) \prod_{j=i+1}^k (1 - o_j(x_{\text{grid}})). \quad (3)$$

Lastly, our blob mapping network also outputs background vectors ϕ_0, ψ_0 , with a fixed opacity $o_0 = 1$. Final features at each grid location are the convex combination of blob feature vectors, given by the $(k+1)$ α_i scores.

3.2 From blob layouts to scene images

We now describe a function G that converts the representation of scenes as blobs β described in Section 3.1 into realistic, harmonized images. To do so, we build on the architecture of StyleGAN2 [38]. We modify it to take in a spatially-varying input tensor based on blob structure features rather than a single, global vector, and perform spatially-varying style modulation.

As opposed to standard StyleGAN, where the single style vector w must capture information about all aspects of the scene, our representation separates layout (blob locations and sizes) and appearance (per-blob feature vectors) by construction, naturally providing a foundation for a disentangled representation.

Concretely, we compute a feature grid Φ at 16×16 resolution using blob structure vectors ϕ_i and use Φ as input to G , removing the first two convolutional blocks of the base architecture to accommodate the increased resolution. We also apply spatial style-based modulation [59] at each convolution using feature grids $\Psi_{l \times l}$ for $l \in \{16, 32, \dots, 256\}$ computed from blob style vectors ψ_i .

3.3 Encouraging disentanglement

Intuitively, all activations within a blob are governed by the same feature vector, encouraging blobs to yield image regions of self-similar properties, *i.e.* entities in a scene. Further, due to the locality of convolution, the layout of blobs in the input must strongly inform the final arrangement of image regions. Finally, our latent space separates layout (blob location, shape, and size) from appearance (blob features) by construction. All the above help our model learn to bind individual blobs to different objects and arrange these blobs into a coherent layout, disentangling scenes spatially into their component parts.

To further nudge our network in this direction, we stochastically perturb blob representations β before inputting them to G , enforcing our model to be robust under these perturbations. We implement this by corrupting blob parameters with uniform noise δx , δs , and $\delta \theta$. This requires that blobs be independent of each other, promoting object discovery and discouraging degenerate solutions which rely on precise blob placement or shape.

We also experiment with style mixing, where with probability 0.2 we uniformly sample between 0 and k blobs to swap, and permute style vectors for

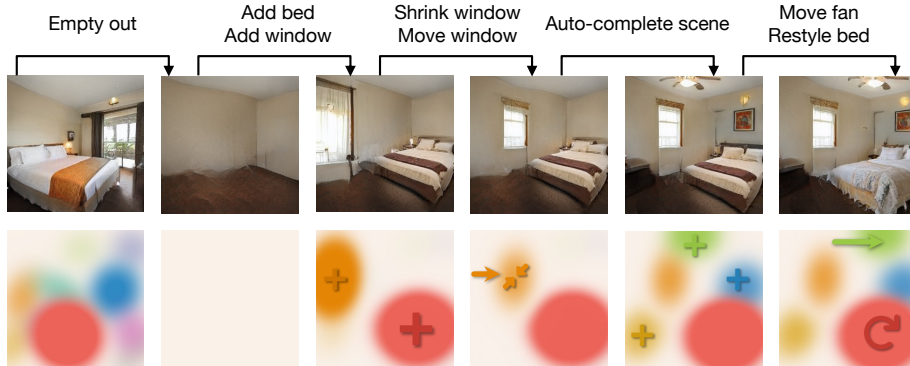


Fig. 3: **Blobs allow extensive image manipulation:** We apply a sequence of modifications to the blob map of an image generated by our model and show the resulting images outputs at each stage of the editing process, demonstrating the strength of our learned representation.

these blobs among different batch samples. We find that this intervention harms our training process since it requires that all styles match all layouts, an assumption we show does not hold in Section 4.3. We also try randomly removing blobs from the forward process with some probability, but found this hurts training, since certain objects must always be present in certain kinds of scenes (*e.g.* kitchens are unlikely to have no refrigerator). This constraint led to a more distributed, and therefore less controllable, representation of scene entities.

4 Experiments

We evaluate our learned representation quantitatively and qualitatively and demonstrate that a spatially disentangled representation of scenes emerges. We begin by showing that our model learns to associate individual blobs with objects in scenes, and then show that our representation captures the distribution of scene layouts. We highlight some applications of our model in Figure 3. Finally, we use our model to parse the layouts of real scene images via inversion. For more results, including on additional datasets and ablations, please see Appendix.

4.1 Training and implementation

We largely follow the training procedure set forth in StyleGAN2 [38], with non-saturating loss [18], R1 regularization every 16 steps with $\gamma = 100$ but no path length regularization, and exponential moving average of model weights [35]. We use the Adam optimizer [40] with learning rate 0.002 and implement equalized learning rate for stability purposes as recommended by [38,35].

We set $d_{\text{noise}} = 512$. Our layout generator F is an 8-layer MLP with $d_{\text{hidden}} = 1024$ and leaky ReLU activations. We L2-normalize ϕ and ψ vectors output by the layout generator before splatting. Altogether, the dimension of the last layer



Fig. 4: **Moving blobs to rearrange objects:** By modifying coordinates x_i of certain blobs as shown in the middle row, we can perform operations such as rearranging furniture in bedrooms. Note that since our representation is layered, we can model occlusions, such as the bed and the dresser in the leftmost and rightmost images.

is $d_{\text{out}} = k(d_{\text{in}} + d_{\text{style}} + 5) + d_{\text{in}} + d_{\text{style}}$. To compensate for the removal of the first two convolutional blocks in the generator G , we increase channel widths at all remaining layers by 50%. We set d_{in} and d_{style} depending on the number of blobs k , and values range between 256 and 768. We experiment with $k \in [5, 50]$ depending on the data considered. We set the blob sigmoid temperature $c = 0.02$ by visual inspection of blob edge hardness. Model performance is relatively insensitive to jittering parameters. We perturb blob parameters with uniform noise as $\delta x \in [-0.04, 0.04]$ (around 10px at 256px resolution), $\delta \theta \in [-0.1, 0.1]$ rad (around 6°), and $\delta s \in [-0.5, 0.5]$ (varying radii of blobs by around 5px).

We train our model on categories from the LSUN scenes dataset [94]. In particular, we train models on bedrooms; conference rooms; and the union of kitchens, living rooms, and dining rooms. In the following section, we show results of models trained on bedroom data with $k = 10$ blobs. Please see Appendix for results on more data (§A), further details on our blob parametrization and its implementation (§C), and ablations (§E).

4.2 Discovering entities with blobs

The ideal representation is able to disentangle complex images of scenes into the objects that comprise them. Here, we demonstrate through various image manipulation applications that this ability emerges in our model. Our unsupervised representation allows effortless rearrangement, removal, cloning, and restyling of objects in scenes. We also measure correlation between blob presence and semantic categories as predicted by an off-the-shelf network and thus empirically verify the associations discovered by our model.

Figure 4 shows the result of intervening to manipulate the center coordinates x_i of blobs output by our model, and thus **rearranging furniture configu-**



Fig. 5: **Removing blobs:** Despite the extreme rarity of bedless bedrooms in the training data, the ability to remove beds from scenes by removing corresponding blobs emerges. We can also remove windows, lamps and fans, paintings, dressers, and nightstands in the same manner.

rations. We are able to arbitrarily alter the position of objects in the scene by shifting their corresponding blobs without affecting their appearance. This interaction is related to traditional “image reshuffling” where rearrangement of image content is done in pixel space [82,4,72]. Our model’s notion of depth ordering also allows us to easily de-occlude objects – *e.g.* curtains, dressers, or nightstands – that were hidden in the original images, while also enabling the introduction of new occlusions by moving one blob behind another.

In Figure 5, we show the effect of **removing entirely certain blobs** from the representation. Specifically, we remove all blobs but the one responsible for beds, and show that our model is able to clear out the room accordingly. We also remove the bed blob but leave the rest of the room intact, showing a remarkable ability to create bedless bedrooms, despite training on a dataset of rooms with beds. Figure 3 shows the effect of resizing blobs to change window size; see Appendix A for further results on changing blob size and shape. In Fig. 6, we remove a blob that our model – trained on a challenging multi-category union of scene datasets – has learned to associate with tables across scene categories.

Our edits are not constrained to the set of blobs present in a layout generated by our model; we can also introduce new blobs. Figure 8 demonstrates the impact of **copying and pasting the same blob** in a new location. Our model is able to faithfully duplicate objects in scenes even when the duplication yields an image that is out of distribution, such as a room with two ceiling fans.

Our representation also allows performing edits across images. Figure 7 shows the **highly granular redecorating** enabled by swapping blob style vectors; we are able to copy objects such as bedsheets, windows, and artwork from one room to another without otherwise affecting the rendered scene.

Quantitative blob analysis. Next, we quantitatively study the strong associations between blobs and semantic object classes. We do so by randomly

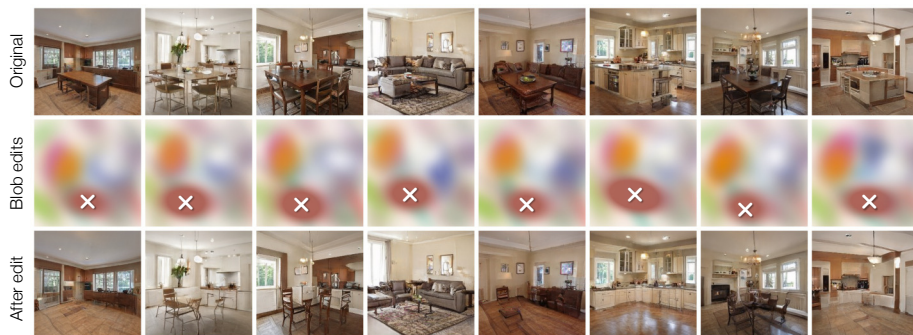


Fig. 6: **Removing all sorts of tables:** We train BlobGAN on a multi-category dataset of kitchens, living rooms, and dining rooms. We find that a particular blob specializes in generating tables across scene types, and feature vectors dictate whether it becomes a coffee table, kitchen island, or dining table. For many more editing operations on this dataset and others, please see Appendix.

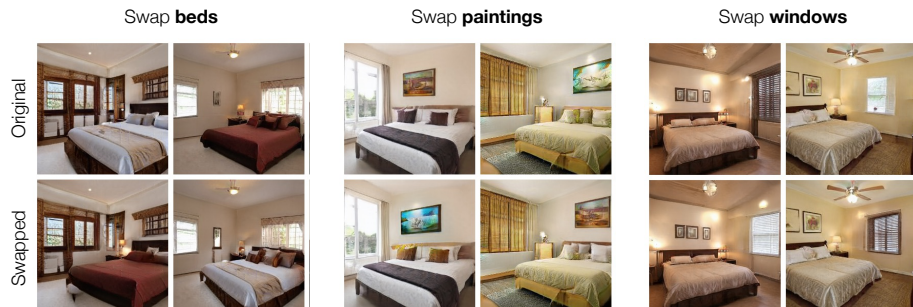


Fig. 7: **Swapping blob styles:** Interchanging ψ_i vectors without modifying layout leads to localized edits which change the appearance of individual objects in the scene.

setting the size parameter s of a blob to a large negative number to effectively remove it. We then use an off-the-shelf segmentation model to measure which semantic class has disappeared. We visualize the correlation between classes and blobs in Figure 9 (left); the sparsity of this matrix shows that blobs learn to specialize into distinct scene entities. We also visualize the distribution of blob centroids in Figure 9 (right), computed by sampling many different random vectors z . The resultant heatmaps provide a glimpse into the distribution of objects in training data – our model learns to locate blobs at specific image regions and control the objects they represent by varying feature vectors.

4.3 Composing blobs into layouts

The ideal representation of scenes must go beyond simply disentangling images into their component parts, and capture the rich contextual relationships between these parts that dictate the process of scene formation [9, 27]. In contrast to previous work in generative modeling of realistic images, our representation explicitly discovers the layout (*i.e.*, the joint distribution) of objects in scenes.



Fig. 8: **Cloning blobs:** We clone blobs in scenes, arrange them to form a new layout, and show corresponding model outputs. Added blobs are marked with a +.

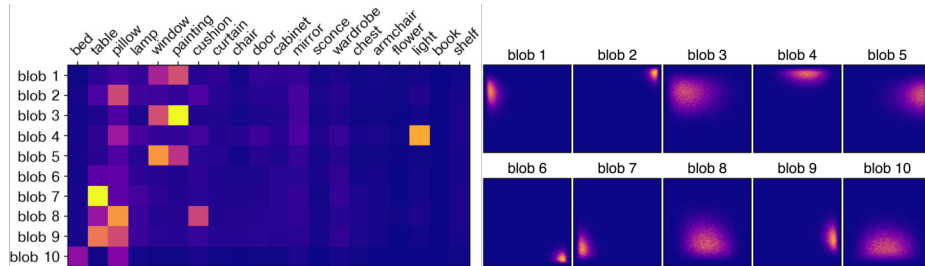


Fig. 9: **Blob spatial preferences:** Our model allocates each blob to a certain region of the image canvas, revealing patterns in the training distribution of objects. We visualize each blob’s correlation with classes predicted by a segmentation model [83] (*left*) as well as the spatial distribution of blob centroids (*right*).

By solving a simple constrained optimization problem at test-time, we are able to sample realistic images that satisfy constraints about the underlying scene, a functionality we call “scene auto-complete”. This auto-complete allows applications such as filling empty rooms with items, plausibly populating rooms given a bed or window at a certain location, and finding layouts that are compatible with certain sets of furniture.

We ground this ability quantitatively by demonstrating that “not everything goes with everything” [11] in real-world scenes – for example, not every room’s style can be combined with any room’s layout. We show that our scene auto-complete yields images that are significantly more photorealistic than naïvely combining scene properties at random, and outperforms regular StyleGAN in image quality, diversity as well as in fidelity of edits.

Conditionally sampling scenes: We can construct an ad-hoc conditional distribution by optimizing random inputs to match a set of constraints in the

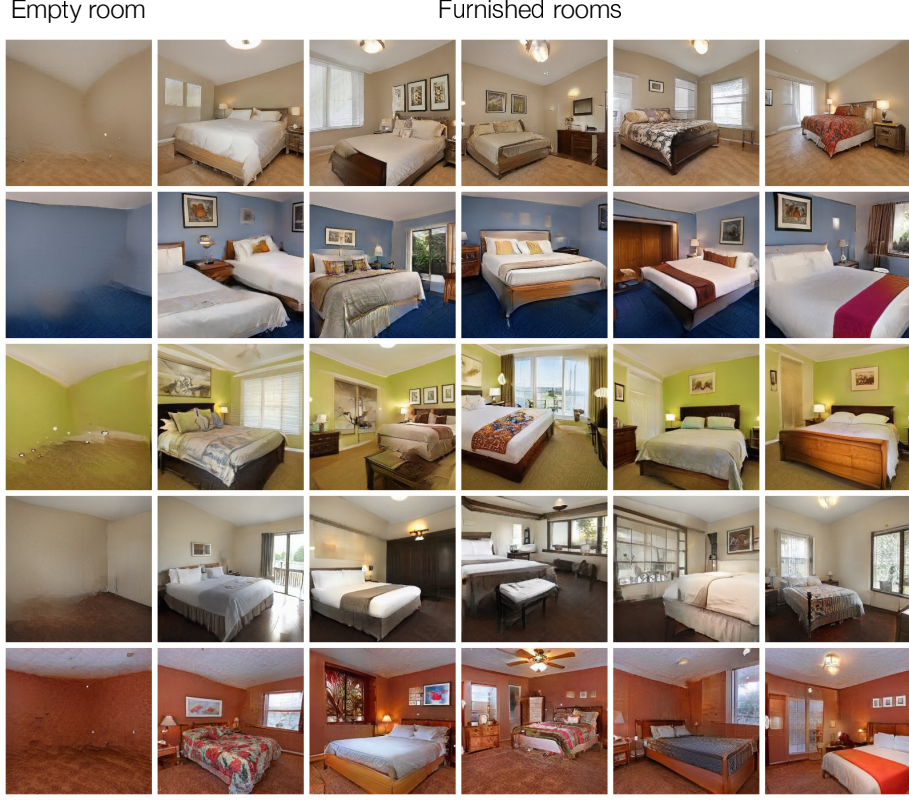


Fig. 10: **Generating and populating empty rooms:** We show different empty rooms, each with their own background vector ψ_0 , as well as furnished rooms given by latents z optimized to match these background vectors. This simple sampling procedure yields a diverse range of layouts to fill the scenes. Note that while empty rooms do not appear in training data, our model is reasonably capable of generating them.

form of properties c of a source image’s blob map β :

$$c \subset \bigcup_{i=0}^k \{x_i^{\text{src}}, s_i^{\text{src}}, a_i^{\text{src}}, \theta_i^{\text{src}}, \phi_i^{\text{src}}, \psi_i^{\text{src}}\} \quad (4)$$

For example, $c = \{\phi_0^{\text{src}}, \psi_0^{\text{src}}\}$ constrains the background of an output image to match that of a source image, and $c = \{x_i^{\text{src}}, s_i^{\text{src}}, a_i^{\text{src}}\}$ constrains the shape (but not the appearance) of the i -th blob to match the source.

We obtain conditional samples by drawing initial noise vectors $z^{\text{init}} \sim \mathcal{N}(0, I_d)$ and optimizing $F(z^{\text{init}})$ to match the constraint set c with an L2 loss, leaving other parameters free. We use the Adam optimizer with learning rate 0.01 and find that between 50 and 300 iterations, which complete in around a second on an NVIDIA RTX 3090, give z^{optim} vectors that sufficiently match constraints. We then set the final layout to be $c \cup \{\beta^{\text{optim}} \setminus c\}$, *i.e.* the initial constraints combined with the free parameters given by the optimized noise vectors, and de-

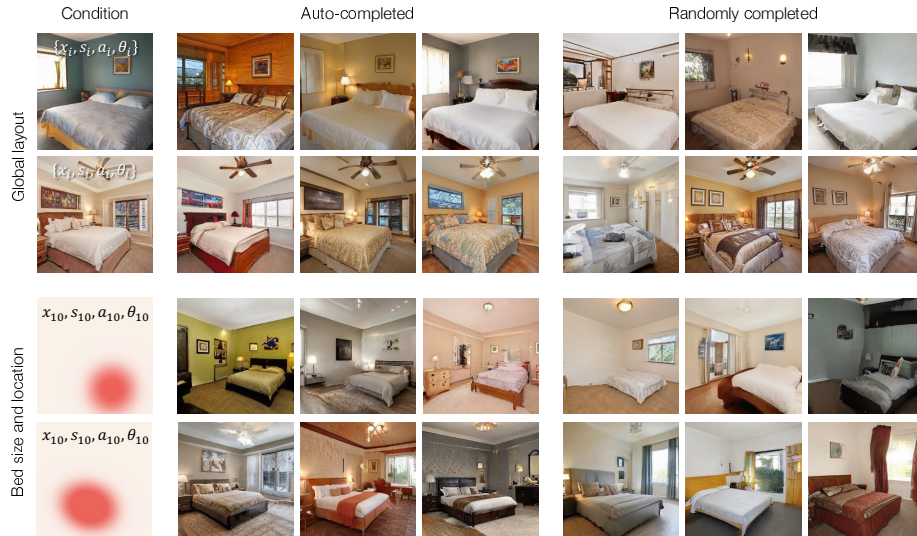


Fig. 11: **Scene auto-complete**: Various conditional generation problems fall under the umbrella of “scene auto-complete”, *i.e.* using our layout network F to sample different scenes satisfying constraints on a subset of blob parameters. We show layout-conditioned style generation as well as prediction of plausible scenes given the location and size (but not style) of beds. Rather than using F to plausibly auto-complete scenes, we can also generate a random scene and simply override parameters of interest to match desired values. As shown on the right, such scenes have objects inserted, removed, reoriented, or otherwise disfigured due to incompatibility.

code layouts into images as described in Section 3.2. In effect, this process finds new scenes known by our model to be compatible with the specified constraints, as opposed to randomly drawn from an unconditional distribution.

We examine applications of our scene auto-complete and compare it to scenes generated by baseline approaches in Figures 10 and 11. Scene auto-complete yields images that are both more realistic and more faithful to the desired image operations. We quantitatively demonstrate this in Table 1, where we show that using auto-complete to find target images whose properties to apply for conducting edits significantly outperforms the use of randomly sampled targets and/or models such as StyleGAN not trained with compositionality in mind.

To evaluate image photorealism after an edit, we calculate FID [25] on automatically edited images. We must also ensure that image quality does not come at the expense of sample diversity; to this end, we measure the average LPIPS [100] distance between images before and after the edit and refer to this as Paired Distance (**PD**). We also measure the expected distance between pairs of edited images to gauge whether edits cause perceptual mode collapse, and call this Global Diversity (**GD**). Finally, we confirm that our editing operations stay faithful to the conditioning provided. For predicting style from layout, we simply report the fraction of image pixels whose predicted class label as output by a segmentation network [83] remains the same. For localized object edits, we

		Layout \rightarrow Styles				Window \rightarrow Room				Bed \rightarrow Room				Painting \rightarrow Room			
		FID \downarrow	PD \uparrow	GD \uparrow	C \uparrow	FID	PD	GD	C	FID	PD	GD	C	FID	PD	GD	C
StyleGAN	2 coarse	4.23	0.75	0.77	46.5	-	-	-	-	-	-	-	-	-	-	-	-
	3 coarse	5.04	0.73	0.76	55.3	-	-	-	-	-	-	-	-	-	-	-	-
	4 coarse	5.58	0.71	0.76	62.9	-	-	-	-	-	-	-	-	-	-	-	-
BlobGAN	Random	8.10	0.72	0.74	47.9	6.41	0.72	0.73	17.4	10.88	0.67	0.73	52.6	6.31	0.72	0.73	7.7
	Conditional	4.59	0.70	0.74	55.2	4.75	0.67	0.72	27.2	7.12	0.64	0.72	60.0	4.58	0.69	0.73	13.0
	+ source Φ	5.06	0.68	0.74	63.6	-	-	-	-	-	-	-	-	-	-	-	-

Table 1: **Not everything goes with everything:** We edit images by overriding properties in target images either generated at random or conditionally sampled using our model. By varying the network depth at which we begin to swap styles in StyleGAN, we tune a knob between image quality and edit consistency. To further preserve global layout and improve consistency, our model can also use structure grids Φ from the source image. **PD** = paired distance, **GD** = global diversity, **C** = consistency. In all cases, scene auto-complete outperforms baselines. Metrics are defined in the main text.

report the intersection-over-union of the set of pixels whose prediction was the target class before and after edit. We refer to this metric as Consistency (**C**).

Our results verify the intuition that, *e.g.*, not every configuration of furniture can fit a bed at a given location. Please see Appendix D for more results.

4.4 Evaluating visual quality and diversity

Our model achieves perceptual realism competitive with previous work. In Table 2, we report FID [25] as well as improved precision and recall [42], which capture realism and diversity of samples. Bedroom images generated by our model appear more realistic than StyleGAN’s [37], but less diverse. We hypothesize this is due to the design of our representation, which rejects strange scene configurations that cannot be modeled by blobs. When trained on the challenging union of multiple LSUN indoor scene categories, *BlobGAN outperforms StyleGAN2*, indicating an ability to scale to harder data. See Appendix A for details.

	FID \downarrow	Precision \uparrow	Recall \uparrow
StyleGAN2	3.85	0.5932	0.4492
BlobGAN	3.43	0.5974	0.4463

Table 2: BlobGAN achieves visual quality competitive with StyleGAN2 [39] on LSUN Bedrooms. Our samples are more realistic but capture less of the data distribution [42], perhaps by rejecting unconventional or malformed scenes in the training data.

4.5 Parsing images into regions

Though our representation is learned on generated (*i.e.* fake) images, in Figure 12 we show that it can represent real images via inversion. We follow best practices [102, 1, 69, 86, 7] for inversion: We train an encoder to predict blob parameters, reconstructing both real and fake images, and then optimize encoder predictions to better reconstruct specific inputs. While this method leads to uneditable, off-manifold latents in previous work [70], we find our blob representation to be more robust in this sense and amenable to naïve optimization. Importantly, we find that the same manipulations described above can be readily applied to real images after inversion. See Appendix B for more information.

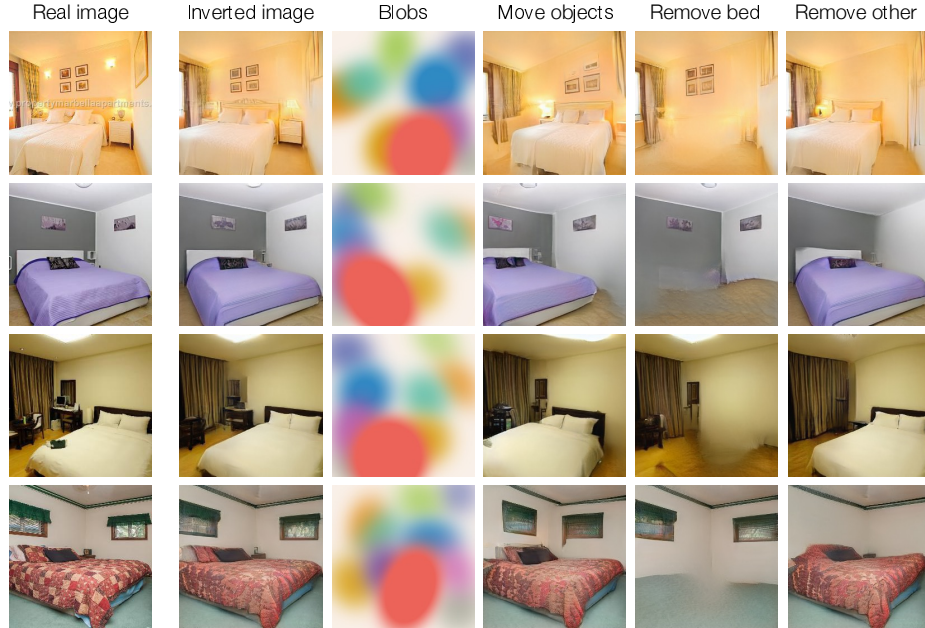


Fig. 12: **Parsing real images via inversion:** Our representation can also parse real images by inverting them into blob space. We can remove and reposition objects in real images – spot the differences from the original!

5 Conclusion

We present BlobGAN, a mid-level representation for generative modeling and parsing of scenes. Taking random noise as input, our model first outputs a set of spatial, depth-ordered blobs, and then splats these blobs onto a feature grid. This feature grid is used as input to a convolutional decoder which outputs images. While conceptually simple, this approach leads to the emergence of a disentangled representation that discovers entities in scenes and their layout. We demonstrate a set of edits enabled by our approach, including rearranging layouts by moving blobs and editing styles of individual objects. By removing or cloning blobs, we are even able to generate empty or densely populated rooms, though none exist in the training set. Our model can also parse and manipulate the layout of real images via inversion.

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References

1. Abdal, R., Qin, Y., Wonka, P.: Image2stylegan: How to embed images into the stylegan latent space? In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 4432–4441 (2019) [13](#)
2. Abdal, R., Zhu, P., Mitra, N.J., Wonka, P.: Styleflow: Attribute-conditioned exploration of stylegan-generated images using conditional continuous normalizing flows. *ACM Transactions on Graphics (TOG)* **40**(3), 1–21 (2021) [3](#)
3. AlBahar, B., Lu, J., Yang, J., Shu, Z., Shechtman, E., Huang, J.B.: Pose with Style: Detail-preserving pose-guided image synthesis with conditional stylegan. *ACM Transactions on Graphics* (2021) [3](#)
4. Barnes, C., Shechtman, E., Finkelstein, A., Goldman, D.B.: Patchmatch: a randomized correspondence algorithm for structural image editing. *ACM Trans. Graph.* **28**(3), 24 (2009) [8](#)
5. Bau, D., Liu, S., Wang, T., Zhu, J.Y., Torralba, A.: Rewriting a deep generative model. In: European Conference on Computer Vision. pp. 351–369. Springer (2020) [3](#)
6. Bau, D., Zhu, J.Y., Strobel, H., Zhou, B., Tenenbaum, J.B., Freeman, W.T., Torralba, A.: Gan dissection: Visualizing and understanding generative adversarial networks. *arXiv preprint arXiv:1811.10597* (2018) [3](#)
7. Bau, D., Zhu, J.Y., Wulff, J., Peebles, W., Strobel, H., Zhou, B., Torralba, A.: Seeing what a gan cannot generate. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 4502–4511 (2019) [13](#)
8. Bear, D., Fan, C., Mrowca, D., Li, Y., Alter, S., Nayebi, A., Schwartz, J., Fei-Fei, L.F., Wu, J., Tenenbaum, J., et al.: Learning physical graph representations from visual scenes. *Advances in Neural Information Processing Systems* **33**, 6027–6039 (2020) [3](#)
9. Biederman, I.: On the semantics of a glance at a scene (1981) [1](#), [9](#)
10. Brock, A., Donahue, J., Simonyan, K.: Large scale gan training for high fidelity natural image synthesis (2018) [3](#)
11. Brooks, T., Efros, A.A.: Hallucinating pose-compatible scenes. *arXiv preprint arXiv:2112.06909* (2021) [3](#), [10](#)
12. Carson, C., Thomas, M., Belongie, S., Hellerstein, J.M., Malik, J.: Blobworld: A system for region-based image indexing and retrieval. In: International conference on advances in visual information systems. pp. 509–517. Springer (1999) [2](#)
13. Chai, L., Wulff, J., Isola, P.: Using latent space regression to analyze and leverage compositionality in gans. *arXiv preprint arXiv:2103.10426* (2021) [3](#)
14. Chen, Q., Koltun, V.: Photographic image synthesis with cascaded refinement networks. In: Proceedings of the IEEE international conference on computer vision. pp. 1511–1520 (2017) [3](#)
15. Collins, E., Bala, R., Price, B., Susstrunk, S.: Editing in style: Uncovering the local semantics of gans. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 5771–5780 (2020) [3](#)
16. Denton, E.L., Chintala, S., Fergus, R., et al.: Deep generative image models using a laplacian pyramid of adversarial networks. *Advances in neural information processing systems* **28** (2015) [3](#)
17. Goetschalckx, L., Andonian, A., Oliva, A., Isola, P.: Ganalyze: Toward visual definitions of cognitive image properties. In: Proceedings of the IEEE/CVF international conference on computer vision. pp. 5744–5753 (2019) [3](#)

18. Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y.: Generative adversarial nets. *Advances in neural information processing systems* **27** (2014) [3](#), [6](#)
19. Gupta, A., Efros, A.A., Hebert, M.: Blocks world revisited: Image understanding using qualitative geometry and mechanics. In: *European Conference on Computer Vision*. pp. 482–496. Springer (2010) [1](#), [2](#)
20. Hariharan, B., Arbeláez, P., Girshick, R., Malik, J.: Simultaneous detection and segmentation. In: *European conference on computer vision*. pp. 297–312. Springer (2014) [2](#)
21. Härkönen, E., Hertzmann, A., Lehtinen, J., Paris, S.: Ganspace: Discovering interpretable gan controls. *Advances in Neural Information Processing Systems* **33**, 9841–9850 (2020) [3](#)
22. He, K., Chen, X., Xie, S., Li, Y., Dollár, P., Girshick, R.: Masked autoencoders are scalable vision learners. *arXiv preprint arXiv:2111.06377* (2021) [3](#)
23. He, X., Wandt, B., Rhodin, H.: Latentkeypointgan: Controlling gans via latent keypoints. *arXiv preprint arXiv:2103.15812* (2021) [3](#)
24. Hedau, V., Hoiem, D., Forsyth, D.: Recovering the spatial layout of cluttered rooms. In: *2009 IEEE 12th international conference on computer vision*. pp. 1849–1856. IEEE [2](#)
25. Heusel, M., Ramsauer, H., Unterthiner, T., Nessler, B., Hochreiter, S.: Gans trained by a two time-scale update rule converge to a local nash equilibrium. *Advances in neural information processing systems* **30** (2017) [12](#), [13](#)
26. Higgins, I., Matthey, L., Pal, A., Burgess, C., Glorot, X., Botvinick, M., Mohamed, S., Lerchner, A.: beta-vae: Learning basic visual concepts with a constrained variational framework (2016) [3](#)
27. Hock, H.S., Romanski, L., Galie, A., Williams, C.S.: Real-world schemata and scene recognition in adults and children. *Memory & Cognition* **6**(4), 423–431 (1978) [1](#), [9](#)
28. Hoiem, D., Efros, A.A., Hebert, M.: Recovering surface layout from an image. *IJCV* **75**(1), 151–172 (Oct 2007) [1](#), [2](#)
29. Huang, X., Liu, M.Y., Belongie, S., Kautz, J.: Multimodal unsupervised image-to-image translation. In: *Proceedings of the European conference on computer vision (ECCV)*. pp. 172–189 (2018) [3](#)
30. Isola, P., Liu, C.: Scene collaging: Analysis and synthesis of natural images with semantic layers. In: *ICCV* (2013) [3](#)
31. Isola, P., Zhu, J.Y., Zhou, T., Efros, A.A.: Image-to-image translation with conditional adversarial networks. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. pp. 1125–1134 (2017) [2](#), [3](#)
32. Jahanian, A., Chai, L., Isola, P.: On the” steerability” of generative adversarial networks. *arXiv preprint arXiv:1907.07171* (2019) [3](#)
33. Johnson, J., Gupta, A., Fei-Fei, L.: Image generation from scene graphs. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. pp. 1219–1228 (2018) [3](#)
34. Johnson, J., Hariharan, B., Van Der Maaten, L., Fei-Fei, L., Lawrence Zitnick, C., Girshick, R.: Clevr: A diagnostic dataset for compositional language and elementary visual reasoning. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. pp. 2901–2910 (2017) [3](#)
35. Karras, T., Aila, T., Laine, S., Lehtinen, J.: Progressive growing of gans for improved quality, stability, and variation (2018) [3](#), [6](#)

36. Karras, T., Aittala, M., Laine, S., Härkönen, E., Hellsten, J., Lehtinen, J., Aila, T.: Alias-free generative adversarial networks. *Advances in Neural Information Processing Systems* **34** (2021) [3](#)
37. Karras, T., Laine, S., Aila, T.: A style-based generator architecture for generative adversarial networks. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. pp. 4401–4410 (2019) [3](#), [13](#)
38. Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., Aila, T.: Analyzing and improving the image quality of stylegan. In: *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. pp. 8110–8119 (2020) [3](#), [5](#), [6](#)
39. Karras, T., Laine, S., Aittala, M., Hellsten, J., Lehtinen, J., Aila, T.: Analyzing and improving the image quality of stylegan (2020) [3](#), [13](#)
40. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014) [6](#)
41. Kingma, D.P., Welling, M.: Auto-encoding variational bayes. *arXiv preprint arXiv:1312.6114* (2013) [3](#)
42. Kynkäänniemi, T., Karras, T., Laine, S., Lehtinen, J., Aila, T.: Improved precision and recall metric for assessing generative models. *Advances in Neural Information Processing Systems* **32** (2019) [13](#)
43. Lewis, K.M., Varadharajan, S., Kemelmacher-Shlizerman, I.: Tryongan: Body-aware try-on via layered interpolation. *ACM Transactions on Graphics (Proceedings of ACM SIGGRAPH 2021)* **40**(4) (2021) [3](#)
44. Li, K., Zhang, T., Malik, J.: Diverse image synthesis from semantic layouts via conditional imle. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. pp. 4220–4229 (2019) [3](#)
45. Li, Y., Li, Y., Lu, J., Shechtman, E., Lee, Y.J., Singh, K.K.: Collaging class-specific gans for semantic image synthesis. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. pp. 14418–14427 (2021) [3](#)
46. Locatello, F., Bauer, S., Lucic, M., Raetsch, G., Gelly, S., Schölkopf, B., Bachem, O.: Challenging common assumptions in the unsupervised learning of disentangled representations. In: *international conference on machine learning*. pp. 4114–4124. PMLR (2019) [3](#)
47. Malisiewicz, T., Efros, A.: Beyond categories: The visual memex model for reasoning about object relationships. *Advances in neural information processing systems* **22** (2009) [3](#)
48. Mejjati, Y.A., Milefchik, I., Gokaslan, A., Wang, O., Kim, K.I., Tompkin, J.: Gaussigan: Controllable image synthesis with 3d gaussians from unposed silhouettes. *arXiv preprint arXiv:2106.13215* (2021) [3](#)
49. Mejjati, Y.A., Shen, Z., Snower, M., Gokaslan, A., Wang, O., Tompkin, J., Kim, K.I.: Generating object stamps. In: *Computer Vision and Pattern Recognition Workshop on AI for Content Creation (CVPRW)* (June 2020) [3](#)
50. Meng, C., Song, Y., Song, J., Wu, J., Zhu, J.Y., Ermon, S.: Sdedit: Image synthesis and editing with stochastic differential equations. *arXiv preprint arXiv:2108.01073* (2021) [3](#)
51. Nguyen-Phuoc, T., Li, C., Theis, L., Richardt, C., Yang, Y.L.: Hologan: Unsupervised learning of 3d representations from natural images. In: *Proceedings of the IEEE/CVF International Conference on Computer Vision*. pp. 7588–7597 (2019) [3](#)
52. Nguyen-Phuoc, T.H., Richardt, C., Mai, L., Yang, Y., Mitra, N.: Blockgan: Learning 3d object-aware scene representations from unlabelled images. *Advances in Neural Information Processing Systems* **33**, 6767–6778 (2020) [3](#)

53. Nichol, A., Dhariwal, P., Ramesh, A., Shyam, P., Mishkin, P., McGrew, B., Sutskever, I., Chen, M.: Glide: Towards photorealistic image generation and editing with text-guided diffusion models. arXiv preprint arXiv:2112.10741 (2021) **3**
54. Niemeyer, M., Geiger, A.: Giraffe: Representing scenes as compositional generative neural feature fields. In: Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR) (2021) **3**
55. Nitzberg, M., Mumford, D.B.: The 2.1-D sketch. IEEE Computer Society Press (1990) **5**
56. Ohta, Y., Kanade, T., Sakai, T.: An analysis system for scenes containing objects with substructures. In: Proceedings of 4th International Joint Conference on Pattern Recognition (IJCPR '78). pp. 752 – 754 (November 1978) **1, 2**
57. Oktay, D., Vondrick, C., Torralba, A.: Counterfactual image networks (2018), <https://openreview.net/forum?id=SyYYPdg0-> **3**
58. Oliva, A., Torralba, A.: The role of context in object recognition. Trends in cognitive sciences **11**(12), 520–527 (2007) **1**
59. Park, T., Liu, M.Y., Wang, T.C., Zhu, J.Y.: Semantic image synthesis with spatially-adaptive normalization. In: Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. pp. 2337–2346 (2019) **2, 3, 5**
60. Park, T., Zhu, J.Y., Wang, O., Lu, J., Shechtman, E., Efros, A., Zhang, R.: Swapping autoencoder for deep image manipulation. Advances in Neural Information Processing Systems **33**, 7198–7211 (2020) **3**
61. Patashnik, O., Wu, Z., Shechtman, E., Cohen-Or, D., Lischinski, D.: Styleclip: Text-driven manipulation of stylegan imagery. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 2085–2094 (2021) **3**
62. Pathak, D., Krähenbühl, P., Donahue, J., Darrell, T., Efros, A.: Context encoders: Feature learning by inpainting (2016) **3**
63. Peebles, W., Peebles, J., Zhu, J.Y., Efros, A., Torralba, A.: The hessian penalty: A weak prior for unsupervised disentanglement. In: European Conference on Computer Vision. pp. 581–597. Springer (2020) **3**
64. Porter, T., Duff, T.: Compositing digital images. In: Proceedings of the 11th annual conference on Computer graphics and interactive techniques. pp. 253–259 (1984) **5**
65. Radford, A., Metz, L., Chintala, S.: Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434 (2015) **3**
66. Ramesh, A., Dhariwal, P., Nichol, A., Chu, C., Chen, M.: Hierarchical text-conditional image generation with clip latents. arXiv preprint arXiv:2204.06125 (2022) **3**
67. Ramesh, A., Pavlov, M., Goh, G., Gray, S., Voss, C., Radford, A., Chen, M., Sutskever, I.: Zero-shot text-to-image generation. In: International Conference on Machine Learning. pp. 8821–8831. PMLR (2021) **3**
68. Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., Lee, H.: Generative adversarial text to image synthesis. In: International conference on machine learning. pp. 1060–1069. PMLR (2016) **3**
69. Richardson, E., Alaluf, Y., Patashnik, O., Nitzan, Y., Azar, Y., Shapiro, S., Cohen-Or, D.: Encoding in style: a stylegan encoder for image-to-image translation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 2287–2296 (2021) **13**
70. Roich, D., Mokady, R., Bermano, A.H., Cohen-Or, D.: Pivotal tuning for latent-based editing of real images. arXiv preprint arXiv:2106.05744 (2021) **13**

71. Rombach, R., Blattmann, A., Lorenz, D., Esser, P., Ommer, B.: High-resolution image synthesis with latent diffusion models. arXiv preprint arXiv:2112.10752 (2021) [3](#)
72. Rott Shaham, T., Dekel, T., Michaeli, T.: Singan: Learning a generative model from a single natural image. In: Computer Vision (ICCV), IEEE International Conference on (2019) [8](#)
73. Russell, B., Efros, A., Sivic, J., Freeman, B., Zisserman, A.: Segmenting scenes by matching image composites. *Advances in Neural Information Processing Systems* **22** (2009) [3](#)
74. Saharia, C., Chan, W., Chang, H., Lee, C.A., Ho, J., Salimans, T., Fleet, D.J., Norouzi, M.: Palette: Image-to-image diffusion models. arXiv preprint arXiv:2111.05826 (2021) [3](#)
75. Sarkar, K., Golyanik, V., Liu, L., Theobalt, C.: Style and pose control for image synthesis of humans from a single monocular view (2021) [3](#)
76. Shen, Y., Yang, C., Tang, X., Zhou, B.: Interfacegan: Interpreting the disentangled face representation learned by gans. *IEEE transactions on pattern analysis and machine intelligence* (2020) [3](#)
77. Shen, Y., Zhou, B.: Closed-form factorization of latent semantics in gans. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 1532–1540 (2021) [3](#)
78. Shi, J., Malik, J.: Normalized cuts and image segmentation. *IEEE Transactions on pattern analysis and machine intelligence* **22**(8), 888–905 (2000) [2](#)
79. Siarohin, A., Lathuilière, S., Tulyakov, S., Ricci, E., Sebe, N.: First order motion model for image animation. In: Conference on Neural Information Processing Systems (NeurIPS) (December 2019) [3](#)
80. Siarohin, A., Woodford, O., Ren, J., Chai, M., Tulyakov, S.: Motion representations for articulated animation. In: CVPR (2021) [3](#)
81. Silberman, N., Hoiem, D., Kohli, P., Fergus, R.: Indoor segmentation and support inference from rgb-d images. In: European conference on computer vision. pp. 746–760. Springer (2012) [2](#)
82. Simakov, D., Caspi, Y., Shechtman, E., Irani, M.: Summarizing visual data using bidirectional similarity. In: CVPR. IEEE Computer Society (2008) [8](#)
83. Strudel, R., Garcia, R., Laptev, I., Schmid, C.: Segmenter: Transformer for semantic segmentation. In: Proceedings of the IEEE/CVF International Conference on Computer Vision. pp. 7262–7272 (2021) [10](#), [12](#)
84. Sudderth, E.B., Torralba, A., Freeman, W.T., Willsky, A.S.: Learning hierarchical models of scenes, objects, and parts. In: Tenth IEEE International Conference on Computer Vision (ICCV’05) Volume 1. vol. 2, pp. 1331–1338. IEEE (2005) [3](#)
85. Torralba, A., Willsky, A., Sudderth, E., Freeman, W.: Describing visual scenes using transformed dirichlet processes. *Advances in neural information processing systems* **18** (2005) [3](#)
86. Tov, O., Alaluf, Y., Nitzan, Y., Patashnik, O., Cohen-Or, D.: Designing an encoder for stylegan image manipulation. *ACM Transactions on Graphics (TOG)* **40**(4), 1–14 (2021) [13](#)
87. Tu, Z., Chen, X., Yuille, A.L., Zhu, S.C.: Image parsing: Unifying segmentation, detection, and recognition. *International Journal of computer vision* **63**(2), 113–140 (2005) [3](#)
88. Wang, J., Yang, C., Xu, Y., Shen, Y., Li, H., Zhou, B.: Improving gan equilibrium by raising spatial awareness. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 11285–11293 (2022) [3](#)

89. Wang, T.C., Liu, M.Y., Zhu, J.Y., Tao, A., Kautz, J., Catanzaro, B.: High-resolution image synthesis and semantic manipulation with conditional gans. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 8798–8807 (2018) [3](#)
90. Wu, Z., Lischinski, D., Shechtman, E.: Stylespace analysis: Disentangled controls for stylegan image generation. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp. 12863–12872 (2021) [3](#)
91. Yakimovsky, Y., Feldman, J.A.: A semantics-based decision theory region analyser. In: IJCAI. pp. 580–588. William Kaufmann (1973) [1](#), [2](#)
92. Yang, C., Shen, Y., Zhou, B.: Semantic hierarchy emerges in deep generative representations for scene synthesis. *International Journal of Computer Vision* **129**(5), 1451–1466 (2021) [3](#)
93. Yao, S., Hsu, T.M., Zhu, J.Y., Wu, J., Torralba, A., Freeman, B., Tenenbaum, J.: 3d-aware scene manipulation via inverse graphics. *Advances in neural information processing systems* **31** (2018) [3](#)
94. Yu, F., Seff, A., Zhang, Y., Song, S., Funkhouser, T., Xiao, J.: Lsun: Construction of a large-scale image dataset using deep learning with humans in the loop. *arXiv preprint arXiv:1506.03365* (2015) [7](#)
95. Yu, H.X., Guibas, L.J., Wu, J.: Unsupervised discovery of object radiance fields. *arXiv preprint arXiv:2107.07905* (2021) [3](#)
96. Yu, S.X., Gross, R., Shi, J.: Concurrent object recognition and segmentation by graph partitioning. *Advances in neural information processing systems* **15** (2002) [2](#)
97. Zhang, C., Xu, Y., Shen, Y.: Decorating your own bedroom: Locally controlling image generation with generative adversarial networks. *arXiv preprint arXiv:2105.08222* (2021) [3](#)
98. Zhang, H., Goodfellow, I., Metaxas, D., Odena, A.: Self-attention generative adversarial networks. In: International conference on machine learning. pp. 7354–7363. PMLR (2019) [3](#)
99. Zhang, H., Xu, T., Li, H., Zhang, S., Wang, X., Huang, X., Metaxas, D.N.: Stackgan: Text to photo-realistic image synthesis with stacked generative adversarial networks. In: Proceedings of the IEEE international conference on computer vision. pp. 5907–5915 (2017) [3](#)
100. Zhang, R., Isola, P., Efros, A.A., Shechtman, E., Wang, O.: The unreasonable effectiveness of deep features as a perceptual metric. In: Proceedings of the IEEE conference on computer vision and pattern recognition. pp. 586–595 (2018) [12](#)
101. Zhu, J., Shen, Y., Xu, Y., Zhao, D., Chen, Q.: Region-based semantic factorization in gans. *arXiv preprint arXiv:2202.09649* (2022) [3](#)
102. Zhu, J.Y., Krähenbühl, P., Shechtman, E., Efros, A.A.: Generative visual manipulation on the natural image manifold. In: European conference on computer vision. pp. 597–613. Springer (2016) [13](#)
103. Zhu, J.Y., Zhang, R., Pathak, D., Darrell, T., Efros, A.A., Wang, O., Shechtman, E.: Toward multimodal image-to-image translation. *Advances in neural information processing systems* **30** (2017) [3](#)