

PixelSynth: Generating a 3D-Consistent Experience from a Single Image

Chris Rockwell

David F. Fouhey
University of Michigan

Justin Johnson

Abstract

Recent advancements in differentiable rendering and 3D reasoning have driven exciting results in novel view synthesis from a single image. Despite realistic results, methods are limited to relatively small view change. In order to synthesize immersive scenes, models must also be able to extrapolate. We present an approach that fuses 3D reasoning with autoregressive modeling to outpaint large view changes in a 3D-consistent manner, enabling scene synthesis. We demonstrate considerable improvement in single-image large-angle view synthesis results compared to a variety of methods and possible variants across simulated and real datasets. In addition, we show increased 3D consistency compared to alternative accumulation methods.

1. Introduction

Imagine that you walk into the office shown in Figure 1. What will you see if you turn right? Is there a door onto a patio? What if you step backward then look left? While the image itself does not contain this information, you can imagine a rich world behind the image due to your experience of other rooms. This task of *single-image scene synthesis* promises to bring arbitrary photos to life, but requires solving several key challenges. First, handling large view changes involves *extrapolation* far beyond the input pixels. Second, generating multiple outputs from the same input requires *consistency*: turning left by 10° or 20° should reveal progressively more of a single underlying world. Finally, modeling view changes requires *3D-awareness* to properly capture perspective changes.

Prior methods for view synthesis fall short of these goals. There has been great progress at *interpolating* between many input views of a single scene [29, 28, 43, 44, 48, 50]; while these 3D-aware methods generate consistent outputs, they do not attempt to extrapolate beyond their input views. Prior approaches to single-image view synthesis [15, 47, 53] can extrapolate to small rotations and translations, but fail to model viewpoint changes at this scale. For example, we show that naively retraining SynSin [53]

Figure 1: Single-Image Scene Synthesis. Our framework fuses the complementary strengths of 3D reasoning and autoregressive modeling to create an immersive scene from a single image.

for larger angles leads to collapse.

In parallel, autoregressive models have shown impressive results for image generation and completion [4, 30, 35, 40, 49]. These methods are very successful at extrapolating far beyond the boundaries of an input image; however they make no attempt to explicitly model a consistent 3D world behind their generated images.

In this paper we present an approach for single-image scene synthesis that addresses these challenges by fusing the complementary strengths of 3D reasoning and autoregressive modeling. We achieve *extrapolation* using an autoregressive model to complete images when faced with large view changes. Generating all output views independently would give inconsistent outputs. Instead, we identify a *support set* at the extremes of views to be generated (shown at the boundaries of Figure 1). Generated images for the support set are then lifted to 3D and added to a consistent scene representation. Intermediate views can then be re-rendered from the scene representation instead of generated from scratch, ensuring *consistency* among all outputs.

Producing a system that can both do extreme view syn-

thesis and lift the results to 3D without requiring auxiliary data poses a challenge. Our approach, described in Section 3, builds upon insights from both the view synthesis and autoregressive modeling communities. Each image and new viewpoint yields a large and custom region to be filled in, which we approach by adapting VQVAE2 [35] and expanding Locally Masked Convolutions [18] to learn image-specific orderings for outpainting. Once filled, we obtain 3D using techniques from SynSin [53]. This system can outpaint large and diverse regions, accumulate outpainting in 3D, and can be trained without any supervision beyond images and 6DOF relative pose.

We evaluate our approach as well as a variety of alternative methods and competing approaches on standard datasets, Matterport 3D+Habitat [3, 41] and RealEstate10K [63], using substantially larger angle changes (6° larger than [53]). Throughout the experiments in Section 4, we evaluate with the standard metrics of human judgments, PSNR, Perceptual Similarity, and FID. Our experimental results suggest that: (1) Our proposed approach produces meaningfully better results compared to training existing methods on our larger viewpoints. In particular, users select our approach 73% of the time vs. the best variant of multiple SynSin ablations. (2) Our approach of re-rendering support sets outperforms alternate iterative approaches, being more consistent an average of 72% of images.

2. Related Work

Both novel view synthesis and image completion have recently seen rapid progress. While novel view synthesis work has approached large view change, it typically uses multiple input images. Given only a single input image, completion becomes highly relevant for outpainting.

Novel view synthesis. If multiple views are available as input, 3D information can be inferred to synthesize new viewpoints. Classical methods often use multi-view geometry [6, 9, 11, 22, 42, 65]. Deep networks use a learned approach, and have shown impressive results with fewer input views and less additional information. They represent 3D in a variety of ways including depth images [1, 28, 37, 56], multi-plane images [47, 63], point clouds [53], voxels [25, 44], meshes [15, 20, 26], multi-layer meshes [13, 43], and radiance fields [29, 50, 60]. We use a point cloud representation.

Given only a single input image, CNNs have also achieved success [8, 23, 48, 57], owing largely to progress in generative modeling [2, 5, 17, 19, 21, 32, 51, 59]. Nevertheless, single-image work has been limited to small angle change [45, 47, 64]. Methods such as SynSin [53] treat outpainting the same as inpainting, which struggles beyond a margin. Our goal is to synthesize a scene from an image, which requires large outpainting. We thus outpaint explicitly using a completion-based approach.

Concurrent work approaches similar, though distinct, problems. Liu *et al.* [23] move forward on camera trajectories through nature scenes. In contrast, our focus is on indoor scenes and we handle outpainting. We show in this setting, a completion-based approach produces better results than a similar approach to [23]. Hu and Pathak [15] use a mesh representation which undertakes twice the rotation of SynSin, but still treats outpainting as interpolation. In contrast, our completion-based approach outpaints explicitly, which we show beats inpainting-based methods in large angles. Rombach *et al.* [38] approach large angle change on images, but do not learn a 3D representation. On scenes, we show our approach of accumulating 3D information across views is critical for consistency.

Image Completion and Outpainting. Recent work in inpainting takes an adversarial approach [16, 24, 54, 58], and has been used in novel view synthesis refinement [23, 44, 47, 53]. However, inpainting is not suitable for synthesizing large angle change, which yields large missing regions. Methods targeting outpainting [46, 52, 55] improve extrapolation, but are not flexible to arbitrary missing regions that may occur in view synthesis.

Our work adopts techniques from the literature on deep autoregressive models. These works use masking with RNNs [30], CNNs [27, 30, 36, 40, 49], and Transformers [4] to predict individual pixels sequentially. While sequential generation is slower than feed-forward methods, it enables flexible ordering and state-of-the-art performance [4, 7, 27, 31, 35]. Yet, autoregressive methods by themselves do not enable 3D consistent outpainting. Thus, we build upon this literature in conjunction with 3D view synthesis to produce a set of *3D consistent* views. Making this 3D fusion work requires building upon several recent developments: we adapt the masked convolution approach of Jain *et al.* [18] to handle custom, per-image, regions to outpaint; also, like VQVAE2 [35] and Dall-E [33], we find that selecting from a set of completions aids realism.

3. Approach

Our goal is to input a single image and synthesize a consistent set of images showing the surrounding scene. This requires generating high-quality images even under large transformations, and ensuring 3D consistency in the results. We propose an approach to this task which uses deep autoregressive modeling to facilitate high-quality extrapolations in conjunction with 3D modeling to ensure consistency.

The two critical insights of the method are the order in which image data is produced and the 3D nature of the approach. As illustrated in Figure 2, our system generates data on extremal *support views* first and operates on point clouds. We outpaint these support views with an autoregressive outpainting module that handles most of the generation. As we

Figure 2: Consistent Scene Synthesis. The model first generates extremal support views, from which intermediate views can be generated. This allows the model to outpaint once and re-render many times, which improves 3D consistency.

reproject intermediate views, we touch up the results with a refinement module. Throughout, we translate from images to point clouds with a self-supervised depth module and back with a differentiable renderer.

3.1. 3D and Synthesis Modules

We begin by introducing each of the modules used by our system, which are pictured on the right of Figure 3. We first describe the two modules that map to and from point clouds, followed by the models that generate and refine pixels. With the exception of the projection module, all are learnable functions that are represented by deep neural networks. Full descriptions of each are in the supplement.

Depth Module D : Given an image I , we can convert it into a colored point cloud $C = D(I)$ using a learned depth prediction system. Specifically, the per-pixel depth is inferred using a U-Net [39] and the pixel is mapped to 3D using known intrinsics. In our work, we learn D via end-to-end training on reprojection losses.

Projector : Given a colored point cloud C , and 6DOF pose \mathbf{p} , we can project it to an image $I = (C; \mathbf{p})$ using Pytorch3D [34]’s differentiable renderer. This renderer uses a soft z-buffer which blends nearby points.

Outpainter O : When the viewpoint changes dramatically, large missing regions come into the field of view and must be outpainted. The specific regions depend on both the viewpoint shift and the image content. We perform per-image outpainting on the latent space of a VQ-VAE [31, 35]. Our particular model autoencodes $256 \times 256 \times 3$ inputs through a discrete $32 \times 32 \times 1$ -dimensional embedding space $fZg, Z_{i,j,1} \in Z_1^{512}$. Using discrete values encourages the model to choose more divergent completions.

We outpaint in this 32×32 latent space using an autoregressive model [31, 33, 10]. In our particular case we predict pixel embeddings with a PixelCNN++ [40] architecture, using a 512-way classification head to predict a distri-

bution over embeddings. We use Locally Masked Convolution [18] blocks to implement image-specific custom-pixel orderings. We show examples of the orders used in Figure 4, which outpaint pixels close to the visible region, followed by those farther away.

Refinement Module R : Outpainting returns images that are sensible, but often lack details or have inconsistencies due to imperfect depth. We therefore use an adversarially-trained refinement module to correct local errors. This module blends the reprojection of the original and outpainted pixels and predicts a residual to its input. Our generator architecture is similar to [53] and uses 8 ResNet [12] blocks containing Batch Normalization injected with noise like [2]. We adopt the discriminator from [51].

3.2. Inference

At inference time, we compose the modules to generate the full set of images in two phases: support view outpainting, followed by intermediate view rendering. The process overview is shown on the left of Figure 3, and can be reused to synthesize multiple viewing directions.

Support View Outpainting and Refinement: Given a single input image and support view \mathbf{p}_1 , our goal is to create an updated point cloud that includes a set of pixels that might be seen in view \mathbf{p}_1 . We achieve this by outpainting in the support view: first, we estimate what can be seen in the support view by projecting the point cloud inferred from the input, or $I^0 = (D(I); \mathbf{p}_1)$. This projection usually has a large and image-specific gap (Figure 4). Our second step composes the outpainting and refinement module, or $I_1 = R(O(I^0))$. Finally, the resulting large-view synthesis itself is lifted to a point cloud by applying D , or $C_1 = D(I_1)$.

Intermediate View Rendering and Refinement: Once the input and outpainted support views have converted to point clouds, we can quickly render any intermediate view \mathbf{p}_i by applying the projection and refinement modules. Specifically, if $C = D(I)$ is the input point cloud and C_1 is the support view point cloud, we simply apply the refinement to their combined projection, or $R((C; C_1); \mathbf{p}_i)$.

3.3. Training and Implementation Details

End-to-end training of the model is difficult because the Outpainter requires ground truth input and output, which breaks gradient flow. We therefore perform training of the Depth and Refinement Modules, the Outpainter VQ-VAE, and Outpainter autoregressive model separately. In all cases, batch size is chosen to maximize GPU space, and training stops when validation loss plateaus.

We first train the latent VQ-VAE space of the Outpainter O , which is then frozen and used by the other modules during training. Training takes $\sim 30k$ iterations with batch size

Figure 3: Approach Overview. At inference, the model first outpaints an extremal support view, then renders intermediate views (left). Both steps rely on the Depth Module to lift images to point clouds, the Projector to render in a novel view, and the Refinement Module to smooth outputs (right). The Outpainter fills in missing information in the target view during outpainting.

Figure 4: Autoregressive Outpainting. We outpaint using image-specific orderings, which begin with pixels adjacent to the visible region and move outward. Our model outpaints a vector-quantized embedding space.

of 120 and uses the losses from [35]: an L_2 reprojection loss and an embedding commitment loss.

Next, we train the Depth and Refinement Modules jointly. Ground truth is used in place of missing pixels to be outpainted to avoid having to sample from the Outpainter during training. The composition of Depth and Refinement is trained with an L_1 pixel loss, a content loss [61], and a multi-scale discriminator loss [51]. The discriminator in the Refinement Module is trained at multiple scales with a feature-matching loss. In the process, the Depth Module is implicitly learned. We train for 125k iterations (200k on Matterport) with batch size 12.

Finally, the autoregressive model in O is trained. It is trained upon the learned VQ-VAE latent space using custom outpainting orderings. Orders move outward from reprojections (Figure 4); reprojections are a function of depths

predicted by the Depth Module. Training takes 75k iterations using a batch size of 60 and cross-entropy loss.

Curriculum Learning. The Depth and Refinement Modules are trained via a curriculum. They first learn to synthesize small view changes, then generalize to larger angles. For the first 25k iterations, we train at the same rotation as [53]. For Matterport, this is 20 in each Euclidean direction, for RealEstate10K it is 5 total. Next, we increase maximum rotation by this amount, and repeat this increase every 25k iterations until reaching our target rotation.

Outpainting Inference Details: Outpainting produces diverse completions, which is a dual-edged sword: some are good, but many will be inconsistent with the input. We thus produce multiple samples and select the best. Selection uses the complementary signals of classifier entropy and discriminator losses – samples that are consistent with inputs usually have less entropy over model classes (we use a Places [62] classifier), and detailed images usually have higher discriminator loss. Full details are in supplement.

Computational Reduction. We perform aggressive yet efficient pruning to the aggregate model, which becomes heavy otherwise. The Outpainter is most critical to speed. We reduce the depth of the autoregressive model by 60% and reduce width by 50%, and use 32×32 completions compared to VQVAE2’s of both 32×32 and 64×64 completions. We find that detail from 64×64 completions can instead be generated by pairing a 32×32 completions with the refinement module.

In total, our changes improve our inference speed by 10 for 50 completions (500 for one completion), compared to using a full VQVAE2 and PixelCNN++ setup. One completion takes 1 minute using 50 samples, or 1 second with 1 sample. Training takes 5 days on 4 2080 Ti GPUs.

Figure 5: Consistent, High Quality Scenes. Given a single image, the proposed method generates images across large viewpoint changes. It both continues content (e.g. wall, bottom right) and invents consistent content (e.g. door, top left). Results shown on RealEstate10K.

4. Experiments

The goal of our experiments is to identify how well our proposed method can synthesize new *scenes* from a single image. We do this on standard datasets and compare with the state of the art (Sec. 4.1). Our task requires not only creating plausible new content, but also ensuring the created content is 3D consistent. We evaluate these two goals separately. We test the generated views for quality by independently evaluating each generated view (Sec. 4.2); we measure consistency by evaluating consistency across a *set* of overlapping views (Sec. 4.3).

4.1. Experimental setup

We evaluate throughout on standard datasets, using standard metrics. We compare our approach with baselines from the state of the art, as well as ablations that test alternate scene generation or view synthesis strategies.

Datasets. Following [53], we evaluate on Matterport3D [3] and RealEstate10K [63]. These enable the generation of pairs of views for training and evaluation. For consistency with past work, we follow a similar selection setup as [53], except we increase rotations; making corresponding changes in sampling to do so. Full details appear in the supplement.

Matterport: Image selection is done by an embodied agent doing randomized navigation in Habitat [41]. We increase the limits of [53] angle selection from 20° in each direction to 120° .

RealEstate10K: RealEstate10K is a collection of videos and image collection consists of selecting frames from a clip. SynSin selects pairs with angle changes of 5° with maximum frame difference of 30. Increasing the angle change is not straightforward since 30° changes are infrequent and can correspond to far away frames from different rooms.

We therefore select pairs of between 20° and 60° apart and 1m away. The average angle is 30° , roughly 8° larger than SynSin. SynSin average angle is less than 5° because it sometimes re-samples; see [53] for details.

Evaluation Metrics. We evaluate content quality and consistency using human judgments as well as a set of automated metrics.

Human A/B Judgments: We evaluate image quality by asking annotators to compare generated images and consistency by asking annotators to compare image pairs. In both cases, we ask humans to make pairwise comparisons and report average preference rate compared to the proposed method: a method is worse than the proposed method if it is below 50%. Automatic evaluation of synthesis is known to be difficult, and we find that human judgments correlate with our own judgments more than automated systems.

Fréchet Inception Distance (FID) [14]: We evaluate how well generation images match on a distribution level using FID, which measures similarity by comparing distributions of activations from an Inception network. It has been shown to correlate well with human judgments [14], and we find it is the best automated measure of image quality.

PSNR and Perceptual Similarity [61]: PSNR and Perc Sim are standard metrics for comparing images. They are excellent measures of *consistency*, which is a unimodal task. Prior work [46, 52, 54] suggests that they are poor measures for conditional image generation since there are many modes of the output. We report them only for consistency with past work.

Baselines. We compare with existing work in the space of synthesizing unseen parts of rooms, as well as ablations that test components of our system (which are introduced when used). Our primary point of comparison is SynSin [53] since it is state of the art, although we evaluate other stan-

Figure 6: View Synthesis Ablations. Prior work is not capable of synthesizing large angle change, even with additional training and sequential generation. This typically leads to collapse. Explicit outpainting instead creates realistic and consistent content.

dard baselines [45, 47, 64]. In addition to standard SynSin, we evaluate many approaches to extending SynSin to handle the large rotations in our dataset.

SynSin [53]: One primary baseline is SynSin as described in [53] with no adaptation for extreme view change. We also evaluate the following extensions: (*SynSin - Sequential*) an autoregressive SynSin that breaks the transformation into 6 smaller transforms, accumulating 3D information; (*SynSin - 6X*) a SynSin model trained on larger view change; (*SynSin - 6X, Sequential*) a SynSin model trained on larger view changes and evaluated sequentially.

Other Baselines: We compare with a number of other view synthesis approaches, which tests whether any difficulties are specific to SynSin. In particular, we use: *Appearance Flow [64]*; *Tatarchenko et al. (Multi-View 3D from Single Image) [45]*; and *Single-View MPI [47]*, which is only available on RealEstate10K.

4.2. Evaluating Quality

We begin by measuring the generated image quality. Being able to synthesize realistic images well beyond inputs is critical to generate an immersive scene.

Qualitative Results. Figure 5 shows that the proposed method can produce high-quality, 3D-consistent images across large angle changes. The images suggest the method is capable of continuing visible scene information realistically, including an entirely new door that is consistent with the original image content on top left and the continuation of the textured wall on bottom right.

Comparisons with prior work in Figure 6 show that the baselines struggle with large angle changes. Straightforward solutions like sequential generation or training on large angle changes do not succeed. While SynSin - 6X generates some results, it mainly repeats visible pixels. Our approach can extend visible information where appropriate, but also creates new objects like desks, windows, and tables.

Table 1: Image Quality as measured by A/B testing (preference frequency for a method compared to ours) as well as FID. In A/B tests, workers select the synthesized image better matching image reprojections choosing from the alternate method and ours. All baselines are preferred less often than our approach, and our approach better matches the true distribution as measured by FID. Single-View MPI [47] is not available on Matterport.

Method	Matterport		RealEstate	
	A/B	" FID #	A/B	" FID #
Tatarchenko <i>et al.</i> [45]	0.0%	427.0	0.0%	256.6
Appearance Flow [64]	19.8%	95.8	1.9%	248.3
Single-View MPI [47]	-	-	2.7%	74.8
SynSin [53]	14.8%	72.0	5.8%	34.7
SynSin - Sequential	19.5%	77.8	11.5%	34.9
SynSin - 6X	27.3%	70.4	22.0%	27.9
SynSin - 6X, Sequential	21.2%	79.3	14.4%	33.1
Ours	-	56.4	-	25.5

Quantitative Results. Quantitative results in Table 1 are largely consistent with qualitative results from Figures 6. On Matterport, our explicit outpainting does substantially better across metrics compared to baselines including SynSin. Alternative baselines to SynSin perform worse, showing this is not a failing specific to SynSin. Training on larger rotation and applying sequential generation to SynSin help, but do not close the gap to our method.

On RealEstate10K, the gap is even larger for human judgment. Interestingly, SynSin - 6X does well on FID on RealEstate10K despite often producing repeated and mean colors. This is in part because RealEstate10K contains a high frequency of images looking through doorways. In these cases, the target view often includes the wall next to the doorway, which typically consists of bland and repeated colors. Thus, repeated colors become reasonable at a distribution level, even if the difference is clear to humans.

To follow past work, we report PSNR and Perceptual

Table 2: Traditional metrics such as PSNR are poor measures for extrapolation tasks [46, 52, 54], but are reported for reference.

Method	Matterport		RealEstate10K	
	PSNR	" Perc Sim #	PSNR	" Perc Sim #
Tatarchenko <i>et al.</i> [45]	13.72	3.82	10.63	3.98
Appearance Flow [64]	13.16	3.68	11.95	3.95
Single-View MPI [47]	-	-	12.73	3.45
SynSin - 6X, Sequential	15.61	3.17	14.21	2.73
Ours	14.60	3.17	13.10	2.88

Figure 7: Consistency Ablations. The proposed method generates a consistent scene across views. Without 3D accumulation, outpainted regions are completely inconsistent. Sequential outpainting yields artifacts, due to using autoregressive completions in multiple views.

Similarity metrics in Table 2 for best performing methods (see supplement for all). These automated metrics, especially PSNR, are poor measures for extrapolation tasks [46, 52, 54], so A/B testing is the primary measure of success. The results of Appearance Flow in Figure 6 is evidence of this phenomenon. This method often produces entirely gray images in RealEstate10K, and loses to our method 98.1% of the time in A/B testing. Yet, its PSNR is competitive with other methods.

4.3. Evaluating Consistency

Having evaluated the quality of individual images, we next evaluate consistency. We note that consistency only matters if results are of high quality – producing a constant value is consistent. We therefore focus only on our approach and alternate accumulation strategies for our method. We evaluate consistency between a pair of generated results, one extreme view and an intermediate view. The setup follows view synthesis, with two exceptions: we

Table 3: Scene Consistency. A/B comparison of consistency. Workers select the most consistent pair of overlapping synthesized images (e.g. right two full images in Figure 7). All scores below 50 indicate the proposed method beats all ablations, on average. Consistency is lowest without 3D accumulation. Sequential order generation is less consistent than ours due to repeated outpainting.

Method	A/B vs. Ours "	
	Matterport	RealEstate10K
No 3D Accumulation	22.6%	7.5%
Sequential Generation	44.0%	36.2%
Ours	-	-

pick a large view change (35 horizontal, 17.5 vertical) to ensure enough change to check consistency, and we use only horizontal and vertical rotation since camera roll makes judging consistency difficult. Full details are in supplement.

Alternate Strategies For Scene Synthesis. Throughout, we use our base model but compare with alternate strategies for scene synthesis. Specifically, we try:

Ours - No 3D Accumulation: We apply the method without accumulating the point cloud across generated images. This means outpainting takes place for each synthesized view, and outpainting is independent across views.

Ours - Sequential Generation: We apply the proposed 3D accumulation using the reverse order: this outpaints the missing region for the nearest image, then repeats outward. This results in outpainting in each new view, compared to our method which outpaints only one extremal view.

Qualitative Results. We show two outputs for an image in Figure 7. Without accumulation, one gets two wildly different results for each of the views (top row). Adding the accumulation helps resolve this, but doing it sequentially in two stages (middle row) produces visible artifacts. By generating a single large change first, our approach (bottom row) produces more consistent results.

Quantitative Results. A/B testing shown in Table 3 supports the qualitative findings: On RealEstate10K, independent generation is chosen only 7.5% of the time. Sequential generation accumulates a 3D representation, and performs better than the naïve method, but is less consistent than the proposed method.

We quantitatively validate these results using PSNR and Perceptual Similarity in a controlled setting. We use the same setup, but apply pure rotations to images, which means the resulting images are related by a homography. We apply this on RealEstate10K and use homographies to warp extreme to intermediate views and to warp intermediate to extreme views. We then calculate consistency using

Figure 8: Improving Sample Selection. Selection is crucial since the Outpainter creates a diversity of completions. Using classifier entropy yields completions consistent with inputs, while the trained discriminator provides more detail. Combined selection produces both consistent and detailed generations.

PSNR on overlapping regions and Perc Sim on warped images with non-overlapping regions masked. Without 3D accumulation does poorly, with Perc Sim/PSNR 0.606/13.6; sequential generation with 3D accumulation improves results tremendously to 0.456/17.9. The full method improves further to 0.419/18.6.

4.4. Ablations

Finally, we report some ablations of the method. These test the contribution of our latent space, the use of multiple samples, and the mechanism used to select the samples.

Ablations. We compare the proposed Outpainting Module and Sampling to alternatives.

Ours - RGB Autoregressive: We compare with using a RGB space to test the value of our latent space. Similar to prior work [40], we only consider a single completion for RGB. As opposed to VQ-VAE-based models, multiple completions is less helpful empirically.

Ours - 1 Completion: We evaluate effectiveness of our method with just one completion, which is more efficient but often less effective.

Ours - Classifier Selection: We apply our proposed method without using a discriminator for selection.

Ours - Discriminator Selection: We apply our proposed method without classifier included for selection.

Qualitative Results. An autoregressive approach alone does not fully explain our success. As we examine in Figure 8, the variety of autoregressive completions means sample selection is critical. While classifier entropy [35] selects sensible completions, they tend to lack detailed texture (left). In contrast, a discriminator selects completions with realistic textures, but they may not make sense with the entire scene (middle). We find the selection methods are complimentary. Combined they select sensible completions with realistic detail (right).

Quantitative Results. Table 4 confirms the qualitative results. On RealEstate10K, the baseline classifier and trained discriminator perform about as good or better than a single

Table 4: Synthesis Ablations. Comparison of autoregressive model and selection criteria. Our method beats all ablations on RealEstate10K. On Matterport, the same selection trends are true. However, Matterport’s scanned environments exhibit homogeneous lighting, so a single completion is sufficient to maximize autoregressive performance.

Method	Matterport		RealEstate10K	
	A/B vs. Ours	FID #	A/B vs. Ours	FID #
RGB Autoregressive	41.3%	60.73	29.6%	31.90
1 Completion	52.3%	55.46	38.4%	28.04
Classifier Selection	47.7%	59.78	44.9%	28.71
Discriminator Selection	47.9%	56.49	47.7%	26.30
Ours	-	56.36	-	25.53

Figure 9: Two Input Synthesis. The proposed method can readily generalize to two input images due to building on point clouds.

completion. Again, combining the discriminator and classifier yields the best selections. Combining is also helpful on Matterport. However, its scanned environments tend to result in more homogeneous lighting, in comparison with the reflection effects of light in real images. As a result, a single completion is typically sufficient to maximize autoregressive performance. Finally, in the table, we confirm outpainting in a VQ-VAE space is superior to using RGB.

5. Discussion

We see synthesizing a rich, full world from a single image as a steep new challenge. Requiring only a single input opens up new experiences, but even with a single image, we see 3D awareness as important for good results and generality. For instance, our model’s 3D awareness enables the application of our system to two views as shown in Figure 9 by ingesting two point clouds.

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