Low Distortion Block-Resampling with Spatially Stochastic Networks

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Abstract

We formalize and attack the problem of generating new images from old ones that are as diverse as possible, only allowing them to change without restrictions in certain parts of the image while remaining globally consistent. This encompasses the typical situation found in generative modelling, where we are happy with parts of the generated data, but would like to resample others ("I like this generated castle overall, but this tower looks unrealistic, I would like a new one"). In order to attack this problem we build from the best conditional and unconditional generative models to introduce a new network architecture, training procedure, and algorithm for resampling parts of the image as desired.

1 Introduction

Many computer vision problems can be phrased as conditional or unconditional image generation. This includes super-resolution, colorization, and semantic image synthesis among others. However, current techniques for these problems lack a mechanism for fine-grained control of the generation. More precisely, even if we like certain parts of a generated image but not others, we are forced to decide on either keeping the generated image as-is, or generating a complete new one from scratch. In this work we aim to obtain a generative model and an algorithm that allow for us to resample images while keeping selected parts as close as possible to the original one, but freely changing others in a diverse manner while keeping global consistency.

To make things more precise, let us consider the problem of conditional image generation, where the data follows an unknown distribution \( P(x, y) \) and we want to learn a fast mechanism for sampling \( y \in \mathcal{Y} \) given \( x \in \mathcal{X} \). The unconditional generation case can be instantiated by simply setting \( x = 0 \). The current state of the art algorithms for image generation usually employ generative adversarial networks (GANs) \( \text{[6, 13, 8]} \) when presented with a dataset of pairs \( (x, y) \). Conditional GANs learn a function \( g_\theta : Z \times \mathcal{X} \rightarrow \mathcal{Y} \), and afterwards images \( \hat{y} \) are generated from \( x \) by sampling \( z \sim P(z) \) and outputing \( \hat{y} := g_\theta(z, x) \). The distribution \( P(z) \) is usually a fixed Gaussian distribution, and the GAN procedure makes it so that \( g_\theta(z, x) \) when \( z \sim P(z) \) approximates \( P(y|x) \) in a very particular sense (see \( \text{[6, 8]} \) for more details). As such, GANs create a diverse set of outputs for any given \( x \) by transforming the \( z \)'s to different complex images.

One limitation of the above setup is that given a generated sample \( \hat{y} = g(z, x) \), we are restricted to accept it and use it as-is for whatever our downstream task is, or generate an entirely new sample by

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Figure 1: A diagram of Spatially Stochastic Networks. We decompose the latent code $z$ spatially into independent blocks, and regularize the model so that local changes in $z$ correspond to localized changes in the image. We then resample parts in the image by resampling their corresponding $z$’s.

Figure 2: Resampling a person’s hair. The top row consists of unmodified generations of our models, Spatially Stochastic Networks (SSNs), trained on FFHQ [7]. With SSNs, resampling two $z$’s near the top of each persons head makes spatially localized changes (middle row) while also allowing for minimal necessary changes in other parts of the image (third row), unlike in traditional inpainting.

resampling $z' \sim P(z)$ and obtaining $\hat{y}' = g(z', x)$. There is no in-between, which is not optimal for many use cases.

Consider however the case of Figure 2. Here, we have a GAN trained to do unconditional image generation, and the generations (top row) are of high-quality. However, we would like to provide the user with the ability to modify the hair in the picture while leaving the rest unchanged. In essence, instead of regenerating the entire image, we would like to keep some parts of the image we are happy with as much as possible, and only resample certain groups of pixels that correspond to parts we are unhappy with. The task here is image generation, but it could be super resolution, colorization, or any task where spatially disentangled resampling would be useful.

Our solution to this task is simple: we split the latent code $z$ into many independent blocks, and regularize the generator so that each block affects only a particular part of the image. In order to achieve good performance, we need to make architectural and algorithmic changes drawing from the best conditional and unconditional generative models. This solution, called Spatially Stochastic Networks (SSNs), is schematized in Figure 1. In the second row of Figure 2 we can see that we successfully achieve the resampling of the hair, while minimally affecting the rest of the image.

While much work has been done in inpainting, which consists of resampling parts of the image while leaving the rest exactly fixed, in problems with structured data this limits drastically the diversity of
the resampling. For instance, if we wanted to inpaint a set of pixels corresponding to the hair of a person, we would need to leave the rest of the face exactly fixed. It is unlikely that a resampling of the hair can be achieved without changing even minimally the facial structure and keeping a globally consistent image. We would also need a mask that tells us exactly where every single hair pixel is located, which is usually unavailable. However, with our new ideas, we can select a large block of pixels containing hair and the resample will change those pixels while minimally affecting the rest of the image. Another example of this is seen in Figure 1, where we only roughly select the blocks of pixels containing a tower and other pixels not in those blocks need to modified in order for changes to render a consistent resampling. Thus, in order to obtain diverse new resamplings that minimally change the rest of the image, we need to allow a small distortion in other parts of the image. This is what we understand as Low Distortion Block-Resampling, or LDBR.

The contributions of this paper are as follows:

- In section 2, we introduce a mathematical framework to study the low distortion block-resampling problem and showcase how it relates to other problems in computer vision such as inpainting.
- In section 3, we study why current techniques are unsuited to solve the LDBR problem. From this analysis, we construct Spatially Stochastic Networks (SSNs), an algorithm for image generation directly designed to attack this problem. In the process, we introduce several new developments for spatially-conditioned generative adversarial networks, which are of independent interest.
- In section 4, we perform both qualitative and quantitative experiments showing the workings and excellent performance of SSNs.
- In section 5 and section 6, we relate SSNs to other works, and conclude by posing open problems and new research directions that stem from this work.

2 Low Distortion Block-Resampling

Let \( y \in \mathbb{R}^{n_x \times n_y \times 3} \) be an RGB image. We define a block simply as a subimage of \( y \). More concretely, let \( I = \{1, \ldots, n_y\} \), and \( J_1, \ldots, J_{n_{\text{blocks}}} \subseteq I \times I \) be disjoint subsets of indices such that \( \bigcup_{a=1}^{n_{\text{blocks}}} J_a = I \). Then, the block with index \( a \) is defined as \( y_a := (y_{i,j,1}, y_{i,j,2}, y_{i,j,3})_{(i,j) \in J_a} \). To summarize, we want to construct a new plausible image such that only one block is allowed to change the rest of the image, we need to allow a small distortion in other parts of the image. This is what we understand as Low Distortion Block-Resampling, or LDBR.

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**Definition 1** Let \( \{P^a(y'|x,y)\}_{a=1,\ldots,n_{\text{blocks}}} \) be a set of conditional probability distributions over \( Y \), one for each block \( a = 1, \ldots, n_{\text{blocks}} \). We say that \( \{P^a\}_{a=1,\ldots,n_{\text{blocks}}} \) is a block-resampling of the probability distribution \( \mathbb{P}(y|x) \) if when \( y^{(n_{\text{blocks}})} \) is constructed by the sequential sampling process

\[
y^{(0)} \sim \mathbb{P}(\cdot|x)
y^{(1)} \sim P^{a_1} (\cdot|x, y^{(0)})
y^{(2)} \sim P^{a_2} (\cdot|x, y^{(1)})
\ldots
y^* := y^{(n_{\text{blocks}})} \sim P^{a_{n_{\text{blocks}}}} (\cdot|x, y^{(n_{\text{blocks}}-1)})
\]

we have that the distribution of \( y^* \) is \( \mathbb{P}(y|x) \).
In words, if we start from a sample \( y^{(0)} \) of \( \mathbb{P} \) and we resample every block in an arbitrary order, we obtain a new independent sample from \( \mathbb{P} \).

Note that simply setting \( P^n(\cdot|x, y) = \mathbb{P}(\cdot|x) \) gives a trivial resampling for \( \mathbb{P} \), which simply resamples the entire image every time. This, however, collides with our goal of each time resampling an individual block while leaving the other blocks as unchanged as possible. This is exactly why we need a low distortion block resampling, which we now define.

Let \( D : \mathbb{R}^{I_a \times 3} \times \mathbb{R}^{I_b \times 3} \rightarrow \mathbb{R}_{>0} \) be a notion of distortion between subimages such as the Euclidean distance between pixels or the Earth Mover’s distance[14]. Then, we define the problem of low distortion block resampling as the constrained optimization problem:

\[
\min_{P^n(y'|x, y)} \mathbb{E}_{(x, y) \sim \mathbb{P}} \left[ \sum_{a=1}^{n_{\text{blocks}}} \mathbb{E}_{y' \sim P^n(\cdot|x, y)} \left[ \sum_{b \neq a} D(y_b, y_b') \right] \right]
\]

subject to \( \{P^n\}_{a=1,\ldots,n_{\text{blocks}}} \) is a block-resampling of \( \mathbb{P} \)

At this point, it is important to clarify the distinction between resampling and inpainting (see for instance [4]). Inpainting constitutes the goal of sampling from the conditional probability distribution \( \mathbb{P}(y_a'|x, (y_b)_{b \neq a}) \), so resampling the block \( y_a \) conditioned on \( x \) and the other blocks \( y_b \), which are held exactly fixed[2] in LDBR we allow \( y_b' \) to differ from \( y_b \), but want to enforce that resampling all blocks constitutes a resampling of the entire image. However, sequentially inpainting all the different blocks in general does not constitute a resampling of the entire image. If it did, then inpainting would give a solution of (LDBR) with 0 distortion, which in general does not have to exist. Consider the simplistic example in which \( y \) has only two pixels \( y_0 \) and \( y_1 \), each of which is a separate 1 \times 1 block. If \( \mathbb{P}(y = (1, 1)|x) = \mathbb{P}(y = (0, 0)|x) = 1/2 \) for some \( x \), then sequentially inpainting starting on \( y = (1, 1), x \) would do nothing, since \( \mathbb{P}(y_0 = 1|y_1 = 1, x) = 1 = \mathbb{P}(y_1 = 1|y_0 = 1, x) \). In particular, one could never attain \( y'_1 = (0, 0) \) by this process starting with \( y = (1, 1) \). In fact, the only way that sequential inpainting can yield a block-resampling is if blocks are independent to each other conditioned on \( x \) (something virtually impossible for structured data). This is due to the fact that after sequential inpainting, \( y^{(1)} \) has distribution \( \mathbb{P}(y'|x, (y_b^{(0)})_{b \neq a_1}) \) which, unless blocks are independent conditioned on \( x \), is different to \( \mathbb{P}(y|x) \), and since \( y_{1,1} = y_{1,1}^{(n_{\text{blocks}})} \), we get that \( y^{(n_{\text{blocks}})} \) cannot have distribution \( \mathbb{P}(y|x) \), thus failing to be a block-resampling for \( \mathbb{P} \).

As mentioned, current generative adversarial networks are unsuited to solve the (LDBR) problem, since the only mechanism to generate new samples they have is to resample an entire image. In the next section we introduce Spatially Stochastic Networks, or SSNs, a particular kind of conditional GANs paired with a new loss function, both specifically designed to attack the (LDBR) problem.

3 Spatially Stochastic Networks

As mentioned, conditional GANs currently offer one sampling mechanism given an input \( x \): sample \( z \sim P_Z(z) \) and output \( y = g(x, z) \). Our idea to attack problem (LDBR) is simple in nature: split \( z \) into blocks, and regularize the generator so that each latent block \( z_a \) minimally affects all image blocks \( y_b \) for \( b \neq a \). Therefore, by consecutively resampling all individual latent blocks \( z_a \), we obtain an entire resampling of the image \( y \). In the case where blocks are just rectangular parts of the image, \( z \) becomes a 3D spatial tensor. We then need a generator architecture that performs well when conditioned on a spatial \( z \), and it needs to be regularized so for any given block \( z_a \), it affects as much as possible only the image block \( y_b \). We call the combination of these two approaches Spatially Stochastic Networks or SSNs, which we can see diagramed in Figure 3.

More formally, if we define \( P(y|x) \) is the distribution of \( g(x, z) \) with \( z \sim P_Z(z) \) and \( P_Z \) be such that \( z_a \) and \( z_b \) are independent for all \( a \neq b \) (such as \( P_Z = \mathcal{N}(0, I) \)). Then, given \( y = g(x, z) \), let \( P^n(y'|x, y) \) be defined as the distribution of \( y'_a = g(x, z_a) \) where \( z_a = z_a \), and \( z_b = z_b' \) for \( b \neq a \) and

\[ P^n(y'_a|x, y) \sim \mathbb{P}(\cdot|x) \]

\[ \mathbb{E}_{(x, y) \sim \mathbb{P}} \left[ \sum_{b \neq a} D(y_b, y_b') \right] \]

\[ \text{arg min}_{y'|x, (y_b)_{b \neq a}} \mathbb{E}_{(x, y) \sim \mathbb{P}} \left[ \sum_{b \neq a} D(y_b, y_b') \right] \]

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\]
Figure 3: Spatially Stochastic Networks. Each block $z_a$ is a vector $z_a \in \mathbb{R}^{n_z}$. If we have $n_{\text{blocks}} = n_w \times n_h$, then $z \in \mathbb{R}^{n_w \times n_h \times n_z}$. The generator is regularized so that each $z_a$ affects mostly $y_a$.

Let $z, z'$ independent samples of $P_Z$. It is trivial to see that $(P^a)_{a=1,...,n_{\text{blocks}}}$ is a resampling of $P(y|x)$, since applying $P^a$ consecutively just consists of taking a new independent $z \sim P(z)$. We can see this illustrated in Figure 3, if we resample $z_a$ for all $a$, this just amounts to sampling a new $z$, and hence a new independent sample from the generator.

As mentioned, for this approach to succeed we require two things: we need the generator distribution $P(\hat{y}|x)$ to be similar to the data distribution $P(y|x)$, and we need the resampling of $P(\hat{y}|x)$ described above to have low distortion. For the first objective, we need to come up with an architecture for the generator and training regime that achieves the best possible performance when conditioned on a spatial $z$. We achieve this goal in subsection 3.1. For the second objective of the resampling having low distortion, we need a regularization mechanism to penalize $z_a$ from affecting other blocks $y_b$ with $a \neq b$, which we study in subsection 3.3.

We begin with the design of a generator architecture that maximizes performance when conditioned on spatial $z$. To do so, we leverage ideas from the best conditional and unconditional generative models, as well as introduce new techniques.

3.1 Spatial conditioning revisited

The best current generator architecture and training regime for spatially conditioned generators is (to the best of our knowledge) SPADE [13]. While SPADE was a major improvement over previous methods for spatially conditioned generative modelling, its performance still lags behind from the best of unconditional generation methods like Improved Style-GAN (SGAN2) [8]. In addition to the performance and quality benefits, SGAN2 uses a simpler training process than SPADE. In particular, it doesn’t need the additional auxiliary losses of SPADE (which require training a separate VAE). In this section, we adapt the spatial conditioning elements of SPADE to work with the techniques of SGAN2, creating a new model for spatially conditioned GANs. When used with a spatial $z$, we will show this model performs on par with SGAN2, whose quality far surpasses that of SPADE.

One of the most important aspects of this contribution is the observation that SPADE’s conditioning has analogous downsides to those of the first Style-GAN (SGAN1) [7]. In particularly, both models exhibit prominent ‘droplet’ artifacts in their generations (see Figure 4 left). The reason for these artifacts in SGAN1 is the type of conditioning from $z$ the model employs [8], which shares important properties with SPADE’s conditioning. This problem of SGAN1 was solved in [8] by the introduction of normalizing based on expected statistics rather than concrete feature statistics for their conditioning layers. Following the same line of attack, we apply a similar analysis to the SPADE layers but whose normalization is based on expected statistics, thus eliminating the droplet artifacts from SPADE and yielding a new layer for spatial conditioning which we call Spatially Modulated Convolution.

$$\text{SpatiallyModulatedConv}_w(h, s) = \frac{w * (s \circ h)}{\sigma_E(w, s)}$$ (1)

with

$$\sigma_E(w, s)^2 := \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} (w^2 * s^2)_{c',i,j}$$
where $s \in \mathbb{R}^{1 \times C \times H \times W}$ is the conditioning and $h \in \mathbb{R}^{N \times C \times H \times W}$ is the input to the layer. Due to space constraints, we leave the full derivation of our new layer to Appendix A.

Now, the whole reason why we introduced spatially modulated convolutions is to avoid the droplet artifacts appearing in SPADE and thus get better quality generations when conditioning on spatial inputs. As can be seen in Figure 4, we successfully achieved the desired results: replacing SPADE layers with spatially modulated layers, we can see that droplet artifacts disappear.

Since the focus of our paper is on low distortion block resampling, we leave the application of spatially modulated convolutions for conditional image generation tasks like semantic image synthesis for future work. Given the drastic increase in performance from Style-GAN1 (which shares a lot of similarities with SPADE) to Style-GAN2 (of which one of the main changes is the adoption of modulated convolutions), we conjecture that there is a lot to be gained in that direction.

### 3.2 Leveraging unsupervised techniques

While our spatially modulated convolution got rid of bubble artifacts, there are a few other improvements introduced by Style-GAN2 that we can take advantage of to get the best possible performance and make the training process as simple as possible. First, we remove the VAE and the perceptual losses used in SPADE, thus reducing a lot of the complexity of the training process. Second, we utilize StyleGAN2’s idea of passing $z$ through a nonlinear transformation to another latent code (which we call $z_{\text{nonlin}}$) before passing it to the modulated convolutions. The way we do this is we apply the same MLP to each of the blocks $z_a$ to generate the blocks $z_{nonlin}^a$. We implement this efficiently with $1 \times 1$ convolutions applied to $z$ directly. We also utilize skip connections, the general architecture, and the $R_1$ and path length regularization (with weights of 1 and 2 respectively) of [8]. A diagram of the final architecture, which we call Spatially Stochastic Networks, can be seen in Figure 3.

### 3.3 Low distortion regularization

The current architecture is well suited to employ a spatial noise, and hence it is easy to resample individual blocks of $z$. However, nothing in the loss function is telling the model that this resampling should have low distortion. In particular, no part of the loss encourages the generator so that changing $z_a$ minimally changes $y_b$ for $b \neq a$. We attack this problem by regularizing distortion explicitly.

Let $\tilde{z}^a(z, z')$ be the noise vector with block $a$ equal to $z_a$, and block $b$ equal to $z'_b$ for all $b \neq a$ (see Figure 3). Then, we can regularize directly for the distortion of the resampling.

$$R_D(g) := \mathbb{E}_{(x,y) \sim P_{\text{train}}} \left[ \sum_a \sum_{b \neq a} \mathbb{E}_{z, z' \sim P_Z(z)} [D(g(x,z)_b, g(x, \tilde{z}^a(z,z'))_b)] \right]$$

Equation (2) is just the cost of equation (LDBR) rewritten employing the reparameterization trick over $P_{\text{train}}$. This way we explicitly encourage the model to induce a low distortion block resampling.

We also experimented with replacing the path length regularization term of [8] with one more explicitly designed for the LDBR setup without success. We leave these details to Appendix B.

### 3.4 Transfer learning for high resolution experiments

In order to experiment at high resolutions, we take advantage of pretrained SGAN2 models. The reason for this is simple: experimenting at high resolutions from scratch simply has a prohibitive cost.
Table 1: Comparison of SGAN2 and SSNs without distortion regularization. Lower scores are better for FID and PPL. Both models attain comparable quality, while SSN allows for block resampling.

| Configuration  | FFHQ (256x256 pixels) | LSUN Churches (256x256 pixels) |
|---------------|-----------------------|-------------------------------|
|               | FID       | PPL      | Resampling | FID       | PPL      | Resampling |
| A Baseline SGAN2B2 | 19.76 | 137.33 ✗ |           | 3.65 | 340.72 ✗ |           |
| B SSNs        | 12.24   | 151.01 ✓ |           | 8.68 | 282.75 ✓ |           |

for us, aside from being quite harmful to the environment. Before explaining our transfer protocol, it is good to justify its use with concrete numbers. All of the experiments in this paper used transfer. To give some perspective, training a single SGAN2 model from scratch on LSUN churches takes 781 GPU hours on V100s, which has a cost of about $2,343 USD, and 70.29 kilograms of CO$_2$ emitted into the atmosphere [10]. Using transfer, we only need 4 GPU hours, which translates to roughly $12 USD and only 0.36 kgs of CO$_2$. In total, all the experiments needed for this paper (including debugging runs and hyperparameter sweeps) had a cost of about $2,000 USD, and without transfer this would have required around $400,000 USD to run (incurring in almost 20,000 kgs of CO$_2$).

Our transfer protocol is as follows. First, we copy all the weights and biases directly from pretrained SGAN2 models (1 for LSUN and 2 for FFHQ) that correspond to analogous components: we map the weights from the 8-layer MLP from the original StyleGAN2 to an 8-layer set of 1x1 convolutions in SSNs, the weights from the StyleConvs from StyleGAN2 are mapped to the corresponding weights in the SpatialDemod blocks in SSNs, and finally, the ToRGB blocks in StyleGAN2 are mapped to the ToRGB coming out of spatial demod in SSNs. Our spatial encoder module has no direct analogy in StyleGAN2, so the layers in the spatial encoder are randomly initialized.

### 4 Experiments

We experiment with the FFHQ [8] faces and the LSUN churches [18] datasets at a resolution of 256x256 pixels. We provide both quantitative and qualitative experiments. The quantitative ones have as a purpose to study what is the tradeoff between quality of the generations and distortion, and also provide guidelines for selecting the hyperparameter that balances between these quantities. The qualitative ones are meant to show what these numbers mean visually. In particular, we will see that in both these datasets we can achieve close to optimal quality (in comparison to the best model available) and visually interesting resamplings, including those of the form “I like this generated church overall, but this tower looks unrealistic, I would like a new one”.

As a sanity check, we first compare the performance of unregularized SSNs with that of Style-GAN2, the current state of the art in unsupervised generative modelling. This is meant to verify that we don’t lose performance by introducing a spatial $z$ and the spatially modulated convolutions, which are necessary for our end goal of resampling. We can see these results in table [Table 1] where we indeed observe no noticeable loss in quality.

Second, we study the trade-off between quality and low distortion. This is determined by the regularization parameter for the term (2), which we call $\lambda_D$. To study this, we ablate different values of $\lambda_D$ for the FFHQ dataset, which can be seen in table [Table 2]. Based on these results, we chose the hyperparameter of $\lambda_D = 100$ for our qualitative experiments, since it gave a reduction in distortion of an entire order of magnitude while only incurring a minor loss in FID (note that the FID with $\lambda_D = 100$ is still marginally better than that of the original SGAN2). We also plot the corresponding Pareto curve in [Figure 7] in the Appendix. It is important to comment that these curves are arguably necessary for comparing different solutions to the (LDBR) problem, since different algorithms are likely to incur in different tradeoffs of quality and distortion.

#### 4.1 Qualitative Experiments

In [Figure 5] we show several resamples in LSUN churches. We can see that the images are of high quality, and the changes are mostly localized. We are able to see towers appearing, structural changes in the buildings, or even trees disappearing. Furthermore, in some of the cases the resampled area is of relatively poor quality while the resample is not (and vice versa), thus allowing for resampling to serve as a refining procedure. Similar changes in FFHQ can be seen in [Figure 6] with changes in glasses, eye color, hair style, among others. In most of the images, we also see small changes outside
Table 2: Ablation for different strengths of the low distortion regularization weight $\lambda_D$. Lower is better for both FID and PPL (quality metrics) and for distortion. The value of $\lambda_D = 100$ achieves a significant reduction in distortion without incurring a significant loss in quality (strictly better in both FID and PPL than the state of the art SGAN2 baseline). Surprisingly, the PPL metric decreases as the regularization strength increases.

Before we conclude and highlight the many avenues for future work, we first discuss how this relates to other works in the literature.

5 Related Work

Now that we have explored resampling in the context of LDBR, it is worth revisiting how related work has interpreted various forms of resampling. Some approaches have tackled this problem in cases where a more limited or hardcoded aspect of the image is being resampled. Several previous works use strong geometric conditioning via high resolution segmentation maps, and then effectively allow resampling over only the texture of a given map\[16, 19]. This contrasts SSNs in that our approach allows resampling of semantically higher level structures like towers, hair, and glasses.

In the conditional literature, there have been several improvements on leveraging stronger priors, whether temporal as in [15] or spatial [12], often using attention. One example of this family of approaches focuses on utilizing higher and higher resolution segmentation information as conditioning as in [11]. One disadvantage of this line of work is that it does not dramatically improve quality, and more importantly the network is even more constrained to textural changes. This makes it less applicable in cases applications where a high resolution segmentation map or other strong prior is not available. There are also perspectives on resampling that involve using an encoder while still supporting some form of resampling. Some of these like BigBiGAN [5] could be compatible with our method. As it stands, most of the encoder based methods involve changing the entire image, but there is nothing fundamentally blocking extending them to support LDBR.

6 Conclusions and future work

We have shown that generative model outputs can be modified in an incremental and well-defined way, with appropriate regularization. We also combine spatial conditioning with unconditional image generation using state-of-the-art architectures.

This reframing of the inpainting problem opens up a number of new lines of work. First, the use of MSE in pixel space as a distortion metric is a priori a terrible choice, with the Earth Mover’s distance or MSE on feature spaces being semantically more meaningful notions of distortion. Second, we have not explored the use of spatially modulated convolutions and SGAN2-like ideas in spatial conditioning tasks like semantic image synthesis. Given the vast quality difference from SPADE (the current state of the art on these tasks) to SGAN2, it is likely that there is still room for significant improvement. Third, while we have focused on resamplings at one resolution dominated by the dimensions of $z$, one could think of having multiple 3D $z$’s operating at different scales, thus providing finer control.

Finally, in this work we have focused on pre-specified rectangular blocks that come simply by putting a grid in the image. However, we could think of non-rectangular blocks that come from other parts of a computer vision pipeline itself. For instance, blocks could correspond to regions in a semantic
Figure 5: Generations of our SSN model and corresponding resamplings. The model was trained on 256 x 256 LSUN churches. The latent code has dimension $z \in \mathbb{R}^{4 \times 4 \times 512}$ and the new images were obtained by resampling the latent blocks $z_{(1,1)}$ and $z_{(1,2)}$. We can see that the new images change mostly locally, with elements like towers appearing or disappearing, or trees changing. However, some minor changes are present in other parts of the image in order to keep global consistency, something that inpainting wouldn’t be able to do. The quality is comparable to that of Style-GAN2 [8]

segmentation map of the image (created either by a human or by a machine learning algorithm), and hence resampling said blocks would constitute a resampling of objects in the picture. We are particularly excited in this direction, which could help open a vast amount of possibilities in terms of content creation and modification.

7 Broader Impact

The main goal of this paper is to give the user of a generative model finer control of its samples. This can have positive outcomes in the use case of creative applications of GANs, such as design, art, and gaming. Particularly, when the user is not the developer of the technology (for instance, it can be a player in a game who wishes to create a new level), we aim for him or her to be able create without being hindered by technical requirements.
Figure 6: Generations of our SSN model and corresponding resamplings. The model was trained on 256 x 256 FFHQ. The latent code has dimension $z \in \mathbb{R}^{4 \times 4 \times 512}$ and the new images were obtained by resampling the latent blocks $z_{(1,1)}$ and $z_{(1,2)}$. We can see that the new images change mostly locally, with changes corresponding to the hair, eye color, expressions, glasses, and other semantic elements. Some minor changes are present in non-resampled parts of the image in order to keep global consistency, something that inpainting wouldn’t be able to do. The quality is comparable to that of Style-GAN2 \cite{8}.

Currently, developers and artists need expensive skills, experience, and separate tools to produce content. This has a negative downstream impact on the diversity of content that is ultimately produced. Representation is not equal, as content skew towards representing those who can afford to become developers. We believe creativity is evenly distributed across location, race, and gender. Techniques like SSNs that make content creation more accessible can help bridge this gap in representation.

Furthermore, any technique that is based on learning from data is subject to the biases in the training distribution. We believe resampling approaches like SSNs can help to visualize and understand these biases.

As any technology that promises to give easier access, it has the potential for misuse. One could imagine cases where generative models are used to create things that may be harmful to society, and this can lower the technical entry barrier to misusers of this technology. For instance, SSNs could be
applied towards harmful DeepFakes. We thus believe that it’s our duty as researchers to participate in
the discussion of regulating these technologies so that they can be guided towards positive outcomes.

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A Spatial Conditioning without Bubble Artifacts

Let us begin by recalling how SPADE works, and study where its defects come from. SPADE is based on the utilization of Spatially Adaptive Normalization (SPADE) layers, which given an input \( h \in \mathbb{R}^{N \times C \times H \times W} \) and spatial conditioning ‘style’ \( s, b \in \mathbb{R}^{1 \times C \times H \times W} \)

\[
\text{SPADE}(h, s) = s \odot \frac{h - \mu_D(h)}{\sigma_D(h)} + s_b \tag{3}
\]

where \( \odot \) means pointwise multiplication and \( \mu_D(h), \sigma_D(h) \in \mathbb{R}^{1 \times C \times 1 \times 1} \) are per-channel statistics of \( h \):

\[
\mu_D(h)_c := \frac{1}{NHW} \sum_{n=1}^{N} \sum_{i=1}^{H} \sum_{j=1}^{W} h_{n,c,i,j} \tag{4}
\]

\[
\sigma_D(h)_c^2 := \frac{1}{NHW} \sum_{n=1}^{N} \sum_{i=1}^{H} \sum_{j=1}^{W} (h_{n,c,i,j} - \mu_D(h)_c)^2 \tag{5}
\]

These statistics are calculated via averages over examples and all spatial dimensions. To clarify, the substraction and division in (3) are broadcasted on non-channel dimensions, and the pointwise multiplication and addition are broadcasted over examples.

SPADE layers are remarkably similar to the Adaptive Instance Normalization (AdaIN) layers that are used in Style-GAN to condition on \( z \). In Style-GAN, the authors have \( z \sim P_z \), and first obtain \( s = (s_s, s_b) = F(z) \) with \( s_s, s_b \in \mathbb{R}^{1 \times C \times 1 \times 1} \) and \( F \) is a learned transformation from the noise vector \( z \). Finally, the conditioning of the generator’s output \( y = g(z) \) (Style-GAN is an unconditional generative model) is done via AdaIN layers conditioned on \( s(z) \). AdaIN layers are defined as

\[
\text{AdaIN}(h, s) = s_a \odot \frac{h - \mu(h)}{\sigma(h)} + s_b \tag{6}
\]

An important difference is that \( \mu(h), \sigma(h) \in \mathbb{R}^{N \times C \times 1 \times 1} \) are not averaged over the data

\[
\mu(h)_{n,c} := \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} h_{n,c,i,j} \tag{7}
\]

\[
\sigma(h)_{n,c}^2 := \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} (h_{n,c,i,j} - \mu(h)_{n,c})^2 \tag{8}
\]

and hence AdaIN is applied independently across examples.

AdaIN (6) and SPADE (3) are incredibly similar, with the only differences being the spatial conditioning and that SPADE averages over datapoints while AdaIN does not. As mentioned in [8], AdaIN is prominent to have droplet-like artifacts. In Figure 4 we can see that SPADE has these droplet artifacts as well. The solution presented in [8] was to take out the mean normalization, and replace the statistics \( \mu(h), \sigma(h) \) with expected statistics, assuming \( h \) are independent random variables with expectation 0 and standard deviation 1. When merging scaling conditioning with \( s = F(z) \in \mathbb{R}^{1 \times C \times 1 \times 1} \), convolution with a weight vector \( w \), and subsequent normalization, they arrive to the layer

\[
\text{ModulatedConv}_w(h, s) = \frac{w * (sh)}{\sigma_E(w, s)} \tag{9}
\]

where \( \sigma_E(w, s) \in \mathbb{R}^{1 \times C \times 1 \times 1} \) is the expected standard deviation of \( w * (sh) \) assuming \( h \) are independent variables with zero mean and unit variance

\[
\sigma_E(w, s)^2 = \mathbb{E}_h \left[ \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} \left( (w * (sh))_{c',i,j} - \mathbb{E}_h [(w * (sh))_{c',i,j}] \right)^2 \right] \tag{10}
\]

\[
= \frac{H}{i=1} \sum_{j=1}^{W} \sum_{c=1}^{C} w_{c', c, i,j}^2 \sigma^2 \tag{11}
\]
In the same way, we can derive a spatially modulated conv by merging spatial conditioning with convolution with a weight vector \( w \), and subsequent normalization based on expected statistics. Thus, we arrive to our Spatially Modulated Convolution layer

\[
\text{SpatiallyModulatedConv}_w(h, s) = \frac{w \ast (s \odot h)}{\sigma_E(w, s)}
\]

and in this case we have \( \sigma_E(w, s) \in \mathbb{R}^{1 \times C' \times H \times W} \) is the expected standard deviation of \( w \ast (s \odot h) \), which after some algebraic manipulations we can see equates

\[
\sigma_E^2(w, s) = E_h \left[ \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} \left( (w \ast (s \odot h))_{c', i, j} - E_h \left[ (w \ast (s \odot h))_{c', i, j} \right] \right)^2 \right] = \frac{1}{HW} \sum_{i=1}^{H} \sum_{j=1}^{W} \left( \sum_{c' = 1}^{C'} \sum_{i' = 1}^{i} \sum_{j' = 1}^{j} w_{c', i', j'}^2 \right) S_{c', i, j}^2
\]

where the squares in (14) are taken element-wise.

This new normalization layer has similarities and fundamental differences with that of SGAN2 [8]. An important difference between our spatially modulated convolution (1) and the modulated convolution of SGAN2 (9) is that (1) cannot be expressed as a convolution \( \tilde{w} \ast h \) with a new set of weights. While one can rewrite (9) as \( \left( \frac{c}{s}w \ast \sigma_E(w, s) \right) \ast h \), one cannot do the same thing with equation (1). This is due to the fact that one cannot commute the pointwise multiplication of (1) with the convolution. In essence, this means that when conditioning on spatial inputs, modulating the inputs is inherently different to modulating the weights, while in the non-spatial case these are equivalent.

## B  Negative Results

### B.1  Low Distortion Path Length Regularization

We identified one potential problem with the path length regularization technique introduced in [8]. Path length regularization drives the generator so that the Jacobian-vector product \( \frac{\partial g(z, y)_a}{\partial z_a}^T y \) has constant norm for all directions \( y \in \mathcal{Y} \) and all \( z \). In particular, this regularization term encourages all parts of \( z \) to affect all parts of \( y \) with equal strength, which directly contradicts the fact that we want \( z_a \) to minimally affect blocks \( y_b \) with \( a \neq b \). Therefore, we want to adapt the regularization technique so that \( \frac{\partial g(z, y)_a}{\partial z_a}^T y \) has large and constant norm for all \( z, y_a \), and \( \frac{\partial g(z, y)_b}{\partial z_a}^T y_b \) has small and constant norm for all \( z, y_b \). We tried to achieve this by replacing the path length regularization with

\[
E_{z, y \sim N(0, 1)} \left[ \sum_a \left( \left\| \frac{\partial g(z, y)_a}{\partial z_a}^T y_a \right\|^2 - \gamma_+ \right)^2 + \sum_{b \neq a} \left( \left\| \frac{\partial g(z, y)_b}{\partial z_a}^T y_b \right\|^2 - \gamma_- \right)^2 \right]
\]

where \( \gamma_+ \gg \gamma_- \). Note that if one had \( \gamma_+ = \gamma_- \) then this would be exactly the path length regularization of [8]. Taking \( \gamma_+ > \gamma_- \) allows us to keep the stability properties of this regularization, but driving \( g \) so that \( z_a \) minimally affects \( y_b \).

Despite the rationale behind this idea, we couldn’t find settings where we noticed a decrease in distortion that was not accompanied by a drastic decrease in quality. In particular, we could not observe any noticeable benefit by replacing the path length regularization term of [8] with (15). We experimented with \( \gamma_+ = 1, \gamma_- = 0.1 \), and regularization weights for (15) to one of the \{200000, 20000, 2000, 200, 20, 2\} without a perceived increase of quality for any given distortion value.

### C  Suplemental Figures
Figure 7: Pareto curve visualizing the trade-off between quality (measured by FID) and distortion for SSNs trained in FFHQ at 256 x 256 resolution. Based on these results we chose to use $\lambda_D = 100$ for the qualitative experiments since it incurred a negligible loss in FID while drastically decreasing distortion.