
Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks

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Abstract

In this paper we introduce a generative parametric model capable of producing high quality samples of natural images. Our approach uses a cascade of convolutional networks within a Laplacian pyramid framework to generate images in a coarse-to-fine fashion. At each level of the pyramid, a separate generative convnet model is trained using the Generative Adversarial Nets (GAN) approach [10]. Samples drawn from our model are of significantly higher quality than alternate approaches. In a quantitative assessment by human evaluators, our CIFAR10 samples were mistaken for real images around 40% of the time, compared to 10% for samples drawn from a GAN baseline model. We also show samples from models trained on the higher resolution images of the LSUN scene dataset.

1 Introduction

Building a good generative model of natural images has been a fundamental problem within computer vision. However, images are complex and high dimensional, making them hard to model well, despite extensive efforts. Given the difficulties of modeling entire scene at high-resolution, most existing approaches instead generate image patches. In contrast, in this work, we propose an approach that is able to generate plausible looking scenes at 32×32 and 64×64 . To do this, we exploit the multi-scale structure of natural images, building a series of generative models, each of which captures image structure at a particular scale of a Laplacian pyramid [1]. This strategy breaks the original problem into a sequence of more manageable stages. At each scale we train a convolutional network-based generative model using the Generative Adversarial Networks (GAN) approach of Goodfellow *et al.* [10]. Samples are drawn in a coarse-to-fine fashion, commencing with a low-frequency residual image. The second stage samples the band-pass structure at the next level, conditioned on the sampled residual. Subsequent levels continue this process, always conditioning on the output from the previous scale, until the final level is reached. Thus drawing samples is an efficient and straightforward procedure: taking random vectors as input and running forward through a cascade of deep convolutional networks (convnets) to produce an image.

Deep learning approaches have proven highly effective at discriminative tasks in vision, such as object classification [3]. However, the same level of success has not been obtained for generative tasks, despite numerous efforts [13, 24, 28]. Against this background, our proposed approach makes a significant advance in that it is straightforward to train and sample from, with the resulting samples showing a surprising level of visual fidelity, indicating a better density model than prior methods.

1.1 Related Work

Generative image models are well studied, falling into two main approaches: **non-parametric** and **parametric**. The former copy patches from training images to perform, for example, texture synthesis [6] or super-resolution [8]. More ambitiously, entire portions of an image can be in-painted, given a sufficiently large training dataset [12]. Early parametric models addressed the easier problem of tex-

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ture synthesis [2, 31, 20], with Portilla & Simoncelli [20] making use of a steerable pyramid wavelet representation [25], similar to our use of a Laplacian pyramid. For image processing tasks, models based on marginal distributions of image gradients are effective [18, 23], but are only designed for image restoration rather than being true density models (so cannot sample an actual image). Very large Gaussian mixture models [32] and sparse coding models of image patches [29] can also be used but suffer the same problem.

A wide variety of deep learning approaches involve generative parametric models. Restricted Boltzmann machines [13, 16, 19, 21], Deep Boltzmann machines [24, 7], Denoising auto-encoders [28] all have a generative decoder that reconstructs the image from the latent representation. Variational auto-encoders [15, 22] provide probabilistic interpretation which facilitates sampling. However, for all these methods convincing samples have only been shown on simple datasets such as MNIST and NORB, possibly due to training complexities which limit their applicability to larger and more realistic images.

Several recent papers have proposed novel generative models. Dosovitskiy *et al.* [5] showed how a convnet can draw chairs with different shapes and viewpoints. While our model also makes use of convnets, it is able to sample general scenes and objects. The DRAW model of Gregor *et al.* [11] used an attentional mechanism with an RNN to generate images via a trajectory of patches, showing samples of MNIST and CIFAR10 images. Sohl-Dickstein *et al.* [26] use a diffusion-based process for deep unsupervised learning and the resulting model is able to produce reasonable CIFAR10 samples. Theis and Bethge [27] employ LSTMs to capture spatial dependencies and show convincing inpainting results of natural textures.

Our work builds on the GAN approach of Goodfellow *et al.* [10] which works well for smaller images (e.g. MNIST) but cannot directly handle large ones, unlike our method. Most relevant to our approach is the preliminary work of Mirza and Osindero [17] and Gauthier [9] who both propose conditional versions of the GAN model. The former shows MNIST samples, while the latter focuses solely on frontal face images. Our approach also uses several forms of conditional GAN model but is much more ambitious in its scope.

2 Approach

The basic building block of our approach is the generative adversarial network (GAN) of Goodfellow *et al.* [10]. After reviewing this, we introduce our LAPGAN model which integrates a conditional form of GAN model into the framework of a Laplacian pyramid.

2.1 Generative Adversarial Networks

The GAN approach [10] is a framework for training generative models, which we briefly explain in the context of image data. The method pits two networks against one another: a generative model G that captures the data distribution and a discriminative model D that distinguishes between samples drawn from G and images drawn from the training data. In our approach, both G and D are convolutional networks. The former takes as input a noise vector z drawn from a distribution $p_{\text{Noise}}(\mathbf{z})$ and outputs an image \tilde{h} . The discriminative network D takes an image as input stochastically chosen (with equal probability) to be either \tilde{h} – as generated from G , or h – a real image drawn from the training data $p_{\text{Data}}(\mathbf{h})$. D outputs a scalar probability, which is trained to be high if the input was real and low if generated from G . A minimax objective is used to train both models together:

$$\min_G \max_D \mathbb{E}_{h \sim p_{\text{Data}}(\mathbf{h})} [\log D(h)] + \mathbb{E}_{z \sim p_{\text{Noise}}(\mathbf{z})} [\log(1 - D(G(z)))] \quad (1)$$

This encourages G to fit $p_{\text{Data}}(\mathbf{h})$ so as to fool D with its generated samples \tilde{h} . Both G and D are trained by backpropagating the loss in Eqn. 1 through their respective models to update the parameters.

The conditional generative adversarial net (CGAN) is an extension of the GAN where both networks G and D receive an additional vector of information l as input. This might contain, say, information about the class of the training example h . The loss function thus becomes

$$\min_G \max_D \mathbb{E}_{h, l \sim p_{\text{Data}}(\mathbf{h}, \mathbf{l})} [\log D(h, l)] + \mathbb{E}_{z \sim p_{\text{Noise}}(\mathbf{z}), l \sim p_l(\mathbf{l})} [\log(1 - D(G(z, l), l))] \quad (2)$$

where $p_l(\mathbf{l})$ is, for example, the prior distribution over classes. This model allows the output of the generative model to be controlled by the conditioning variable l . Mirza and Osindero [17] and

Gauthier [9] both explore this model with experiments on MNIST and faces, using l as a class indicator. In our approach, l will be another image, generated from another CGAN model.

2.2 Laplacian Pyramid

The Laplacian pyramid [1] is a linear invertible image representation consisting of a set of band-pass images, spaced an octave apart, plus a low-frequency residual. Formally, let $d(\cdot)$ be a downsampling operation which blurs and decimates a $j \times j$ image I , so that $d(I)$ is a new image of size $j/2 \times j/2$. Also, let $u(\cdot)$ be an upsampling operator which smooths and expands I to be twice the size, so $u(I)$ is a new image of size $2j \times 2j$. We first build a Gaussian pyramid $\mathcal{G}(I) = [I_0, I_1, \dots, I_K]$, where $I_0 = I$ and I_k is k repeated applications* of $d(\cdot)$ to I . K is the number of levels in the pyramid, selected so that the final level has very small spatial extent ($\leq 8 \times 8$ pixels).

The coefficients h_k at each level k of the Laplacian pyramid $\mathcal{L}(I)$ are constructed by taking the difference between adjacent levels in the Gaussian pyramid, upsampling the smaller one with $u(\cdot)$ so that the sizes are compatible:

$$h_k = \mathcal{L}_k(I) = \mathcal{G}_k(I) - u(\mathcal{G}_{k+1}(I)) = I_k - u(I_{k+1}) \quad (3)$$

Intuitively, each level captures image structure present at a particular scale. The final level of the Laplacian pyramid h_K is not a difference image, but a low-frequency residual equal to the final Gaussian pyramid level, i.e. $h_K = I_K$. Reconstruction from a Laplacian pyramid coefficients $[h_1, \dots, h_K]$ is performed using the backward recurrence:

$$I_k = u(I_{k+1}) + h_k \quad (4)$$

which is started with $I_K = h_K$ and the reconstructed image being $I = I_o$. In other words, starting at the coarsest level, we repeatedly upsample and add the difference image h at the next finer level until we get back to the full resolution image.

2.3 Laplacian Generative Adversarial Networks (LAPGAN)

Our proposed approach combines the conditional GAN model with a Laplacian pyramid representation. The model is best explained by first considering the sampling procedure. Following training (explained below), we have a set of generative convnet models $\{G_0, \dots, G_K\}$, each of which captures the distribution of coefficients h_k for natural images at a different level of the Laplacian pyramid. Sampling an image is akin to the reconstruction procedure in Eqn. 4, except that the generative models are used to produce the h_k 's:

$$\tilde{I}_k = u(\tilde{I}_{k+1}) + \tilde{h}_k = u(\tilde{I}_{k+1}) + G_k(z_k, u(\tilde{I}_{k+1})) \quad (5)$$

The recurrence starts by setting $\tilde{I}_{K+1} = 0$ and using the model at the final level G_K to generate a residual image \tilde{I}_K using noise vector z_K : $\tilde{I}_K = G_K(z_K)$. Note that models at all levels except the final are conditional generative models that take an upsampled version of the current image \tilde{I}_{k+1} as a conditioning variable, in addition to the noise vector z_k . Fig. 1 shows this procedure in action for a pyramid with $K = 3$ using 4 generative models to sample a 64×64 image.

The generative models $\{G_0, \dots, G_K\}$ are trained using the CGAN approach at each level of the pyramid. Specifically, we construct a Laplacian pyramid from each training image I . At each level

*i.e. $I_2 = d(d(I))$.

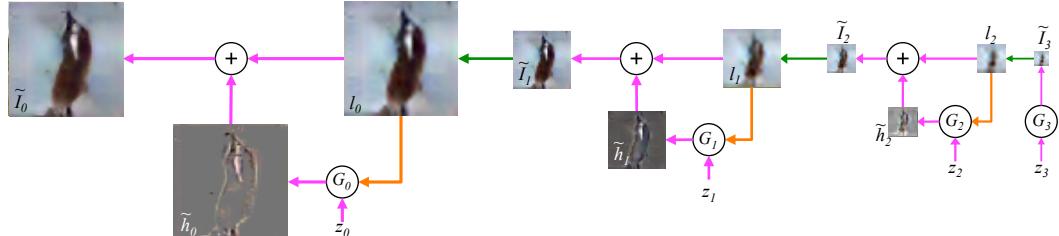


Figure 1: The sampling procedure for our LAPGAN model. We start with a noise sample z_3 (right side) and use a generative model G_3 to generate \tilde{I}_3 . This is upsampled (green arrow) and then used as the conditioning variable (orange arrow) l_2 for the generative model at the next level, G_2 . Together with another noise sample z_2 , G_2 generates a difference image \tilde{h}_2 which is added to l_2 to create \tilde{I}_2 . This process repeats across two subsequent levels to yield a final full resolution sample I_0 .

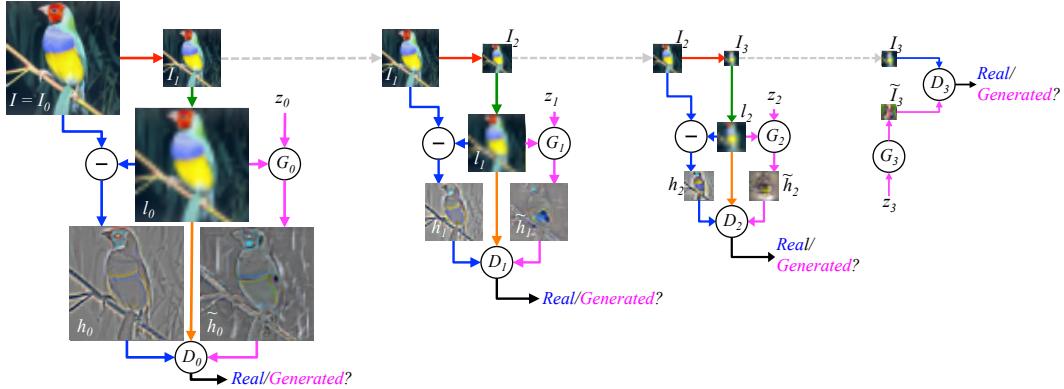


Figure 2: The training procedure for our LAPGAN model. Starting with a 64×64 input image I from our training set (top left): (i) we take $I_0 = I$ and blur and downsample it by a factor of two (red arrow) to produce I_1 ; (ii) we upsample I_1 by a factor of two (green arrow), giving a low-pass version l_0 of I_0 ; (iii) with equal probability we use l_0 to create either a real or a generated example for the discriminative model D_0 . In the real case (blue arrows), we compute high-pass $h_0 = I_0 - l_0$ which is input to D_0 that computes the probability of it being real vs generated. In the generated case (magenta arrows), the generative network G_0 receives as input a random noise vector z_0 and l_0 . It outputs a generated high-pass image $\tilde{h}_0 = G_0(z_0, l_0)$, which is input to D_0 . In both the real/generated cases, D_0 also receives l_0 (orange arrow). Optimizing Eqn. 2, G_0 thus learns to generate realistic high-frequency structure \tilde{h}_0 consistent with the low-pass image l_0 . The same procedure is repeated at scales 1 and 2, using I_1 and I_2 . Note that the models at each level are trained independently. At level 3, I_3 is an 8×8 image, simple enough to be modeled directly with a standard GANs G_3 & D_3 .

we make a stochastic choice (with equal probability) to either (i) construct the coefficients h_k either using the standard procedure from Eqn. 3, or (ii) generate them using G_k :

$$\tilde{h}_k = G_k(z_k, u(I_{k+1})) \quad (6)$$

Note that G_k is a convnet which uses a coarse scale version of the image $l_k = u(I_{k+1})$ as an input, as well as noise vector z_k . D_k takes as input h_k or \tilde{h}_k , along with the low-pass image l_k (which is explicitly added to h_k or \tilde{h}_k before the first convolution layer), and predicts if the image was real or generated. At the final scale of the pyramid, the low frequency residual is sufficiently small that it can be directly modeled with a standard GAN: $\tilde{h}_K = G_K(z_K)$ and D_K only has h_K or \tilde{h}_K as input. The framework is illustrated in Fig. 2.

Breaking the generation into successive refinements is the key idea in this work. Note that we give up any “global” notion of fidelity; we never make any attempt to train a network to discriminate between the output of a cascade and a real image and instead focus on making each step plausible. Furthermore, the independent training of each pyramid level has the advantage that it is far more difficult for the model to memorize training examples – a hazard when high capacity deep networks are used.

As described, our model is trained in an unsupervised manner. However, we also explore variants that utilize class labels. This is done by add a 1-hot vector c , indicating class identity, as another conditioning variable for G_k and D_k .

3 Model Architecture & Training

We apply our approach to three datasets: (i) **CIFAR10** – 32×32 pixel color images of 10 different classes, 100k training samples with tight crops of objects; (ii) **STL** – 96×96 pixel color images of 10 different classes, 100k training samples (we use the unlabeled portion of data); and (iii) **LSUN** [30] – $\sim 10M$ images of 10 different natural scene types, downsampled to 64×64 pixels.

For each dataset, we explored a variety of architectures for $\{G_k, D_k\}$. We now detail the best performing models, selected using a combination of log-likelihood and visual appearance of the samples. Complete `Torch` specification files for all models are provided in supplementary material [4]. For all models, the noise vector z_k is drawn from a uniform $[-1, 1]$ distribution.

3.1 CIFAR10 and STL

Initial scale: This operates at 8×8 resolution, using densely connected nets for both G_K & D_K with 2 hidden layers and ReLU non-linearities. D_K uses Dropout and has 600 units/layer vs 1200 for G_K . z_K is a 100-d vector.

Subsequent scales: For CIFAR10, we boost the training set size by taking four 28×28 crops from the original images. Thus the two subsequent levels of the pyramid are $8 \rightarrow 14$ and $14 \rightarrow 28$. For STL, we have 4 levels going from $8 \rightarrow 16 \rightarrow 32 \rightarrow 64 \rightarrow 96$. For both datasets, G_k & D_k are convnets with 3 and 2 layers, respectively (see [4]). The noise input z_k to G_k is presented as a 4th “color plane” to low-pass l_k , hence its dimensionality varies with the pyramid level. For CIFAR10, we also explore a class conditional version of the model, where a vector c encodes the label. This is integrated into G_k & D_k by passing it through a linear layer whose output is reshaped into a single plane feature map which is then concatenated with the 1st layer maps. The loss in Eqn. 2 is trained using SGD with an initial learning rate of 0.02, decreased by a factor of $(1 + 4 \times 10^{-5})$ at each epoch. Momentum starts at 0.5, increasing by 0.0008 at epoch up to a maximum of 0.8. During training, we monitor log-likelihood using a Parzen-window estimator and retain the best performing model. Training time depends on the models size and pyramid level, with smaller models taking hours to train and larger models taking several days.

3.2 LSUN

The larger size of this dataset allows us to train a separate LAPGAN model for each the 10 different scene classes. During evaluation, so that we may understand the variation captured by our models, we commence the sampling process with validation set images[†], downsampled to 4×4 resolution.

The four subsequent scales $4 \rightarrow 8 \rightarrow 16 \rightarrow 32 \rightarrow 64$ use a common architecture for G_k & D_k at each level. G_k is a 5-layer convnet with $\{64, 368, 128, 224\}$ feature maps and a linear output layer. 7×7 filters, ReLUs, batch normalization [14] and Dropout are used at each hidden layer. D_k has 3 hidden layers with $\{48, 448, 416\}$ maps plus a sigmoid output. See [4] for full details. Note that G_k and D_k are substantially larger than those used for CIFAR10 and STL, as afforded by the larger training set.

4 Experiments

We evaluate our approach using 3 different methods: (i) computation of log-likelihood on a held out image set; (ii) drawing sample images from the model and (iii) a human subject experiment that compares (a) our samples, (b) those of baseline methods and (c) real images.

4.1 Evaluation of Log-Likelihood

A traditional method for evaluating generative models is to measure their log-likelihood on a held out set of images. But, like the original GAN method [10], our approach does not have a direct way of computing the probability of an image. Goodfellow *et al.* [10] propose using a Gaussian Parzen window estimate to compute log-likelihoods. Despite showing poor performance in high dimensional spaces, this approach is the best one available for estimating likelihoods of models lacking an explicitly represented density function.

Our LAPGAN model allows for an alternative method of estimating log-likelihood that exploits the multi-scale structure of the model. This new approach uses a Gaussian Parzen window estimate to compute a probability at each scale of the Laplacian pyramid. We use this procedure, described in detail in Appendix A, to compute the log-likelihoods for CIFAR10 and STL images (both at 32×32 resolution). The parameter σ (controlling the Parzen window size) was chosen using the validation set. We also compute the Parzen window based log-likelihood estimates of the standard GAN [10] model, using 50k samples for both the CIFAR10 and STL estimates. Table 1 shows our model achieving a significantly higher log-likelihood on both datasets. Comparisons to further approaches, notably [26], are problematic due to different normalizations used on the data.

4.2 Model Samples

We show samples from models trained on CIFAR10, STL and LSUN datasets. Additional samples can be found in the supplementary material [4].

[†]These were not used in any way during training.

Model	CIFAR10	STL (@32×32)
GAN [10]	-3617 ± 353	-3661 ± 347
LAPGAN	-1799 ± 826	-2906 ± 728

Table 1: Parzen window based log-likelihood estimates for a standard GAN, our proposed LAPGAN model on CIFAR10 and STL datasets.

Fig. 3 shows samples from our models trained on CIFAR10. Samples from the class conditional LAPGAN are organized by class. Our reimplementations of the standard GAN model [10] produces slightly sharper images than those shown in the original paper. We attribute this improvement to the introduction of data augmentation. The LAPGAN samples improve upon the standard GAN samples. They appear more object-like and have more clearly defined edges. Conditioning on a class label improves the generations as evidenced by the clear object structure in the conditional LAPGAN samples. The quality of these samples compares favorably with those from the DRAW model of Gregor *et al.* [11] and also Sohl-Dickstein *et al.* [26]. The rightmost column of each image shows the nearest training example to the neighboring sample (in L2 pixel-space). This demonstrates that our model is not simply copying the input examples.

Fig. 4(a) shows samples from our LAPGAN model trained on STL. Here, we lose clear object shape but the samples remain sharp. Fig. 4(b) shows the generation chain for random STL samples.

Fig. 5 shows samples from LAPGAN models trained on three LSUN categories (tower, bedroom, church front). The 4×4 validation image used to start the generation process is shown in the first column, along with 10 different 64×64 samples, which illustrate the inherent variation captured by the model. Collectively, these show the models capturing long-range structure within the scenes, being able to recompose scene elements into credible looking images. To the best of our knowledge, no other generative model has been able to produce samples of this complexity. The substantial gain in quality over the CIFAR10 and STL samples is likely due to the much larger training LSUN training set which allowed us to train bigger and deeper models.

4.3 Human Evaluation of Samples

To obtain a quantitative measure of quality of our samples, we asked 15 volunteers to participate in an experiment to see if they could distinguish our samples from real images. The subjects were presented with the user interface shown in Fig. 6(right) and shown at random four different types of image: samples drawn from three different GAN models trained on CIFAR10 ((i) LAPGAN, (ii) class conditional LAPGAN and (iii) standard GAN [10]) and also real CIFAR10 images. After being presented with the image, the subject clicked the appropriate button to indicate if they believed the image was real or generated. Since accuracy is a function of viewing time, we also randomly pick the presentation time from one of 11 durations ranging from 50ms to 2000ms, after which a gray mask image is displayed. Before the experiment commenced, they were shown examples of real images from CIFAR10. After collecting $\sim 10k$ samples from the volunteers, we plot in Fig. 6 the fraction of images believed to be real for the four different data sources, as a function of presentation time. The curves show our models produce samples that are far more realistic than those from standard GAN [10].

5 Discussion

By modifying the approach in [10] to better respect the structure of images, we have proposed a conceptually simple generative model that is able to produce high-quality sample images that are both qualitatively and quantitatively better than other deep generative modeling approaches. A key point in our work is giving up any “global” notion of fidelity, and instead breaking the generation into plausible successive refinements. We note that many other signal modalities have a multiscale structure that may benefit from a similar approach.

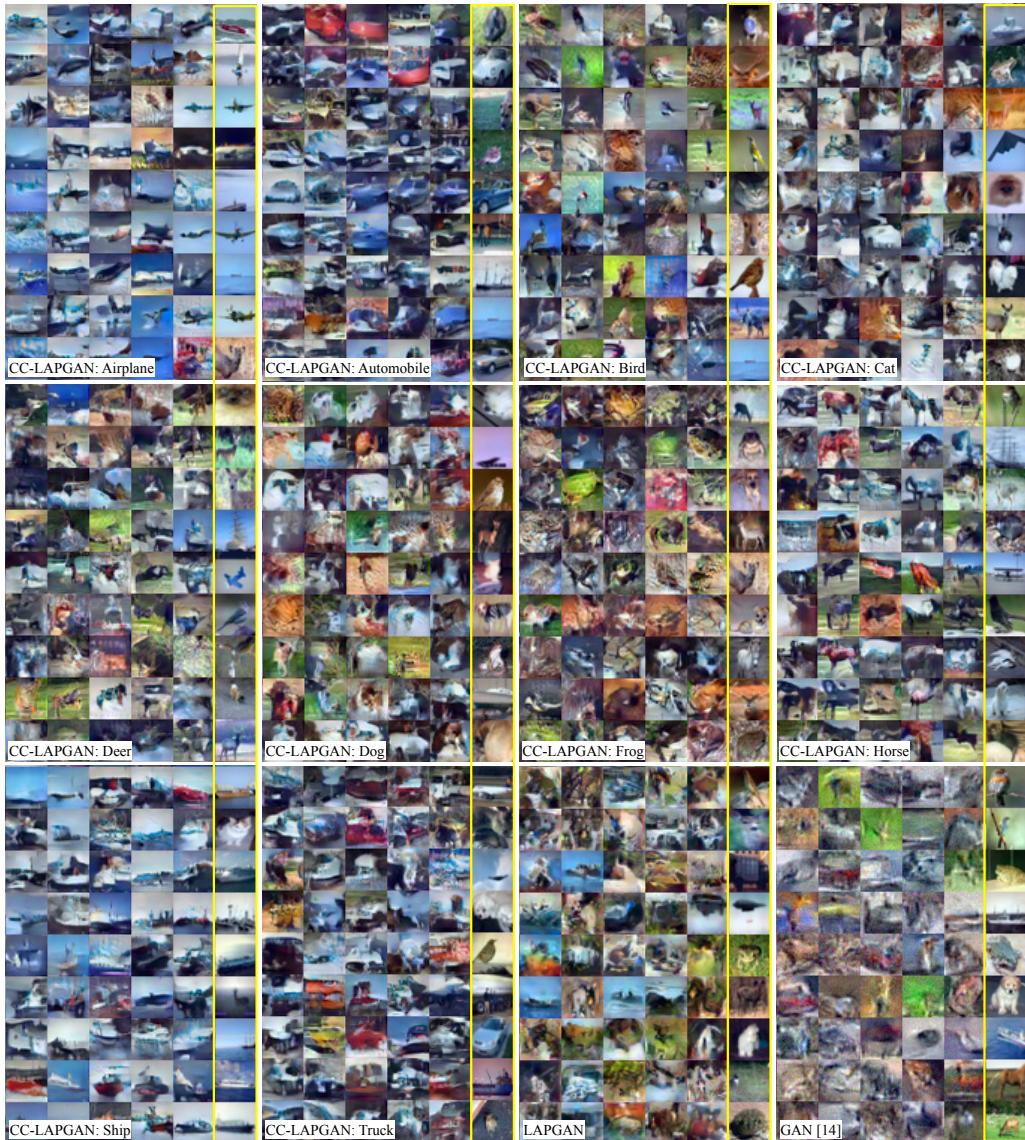


Figure 3: CIFAR10 samples: our class conditional CC-LAPGAN model, our LAPGAN model and the standard GAN model of Goodfellow [10]. The yellow column shows the training set nearest neighbors of the samples in the adjacent column.



Figure 4: STL samples: **(a)** Random 96x96 samples from our LAPGAN model. **(b)** Coarse-to-fine generation chain.

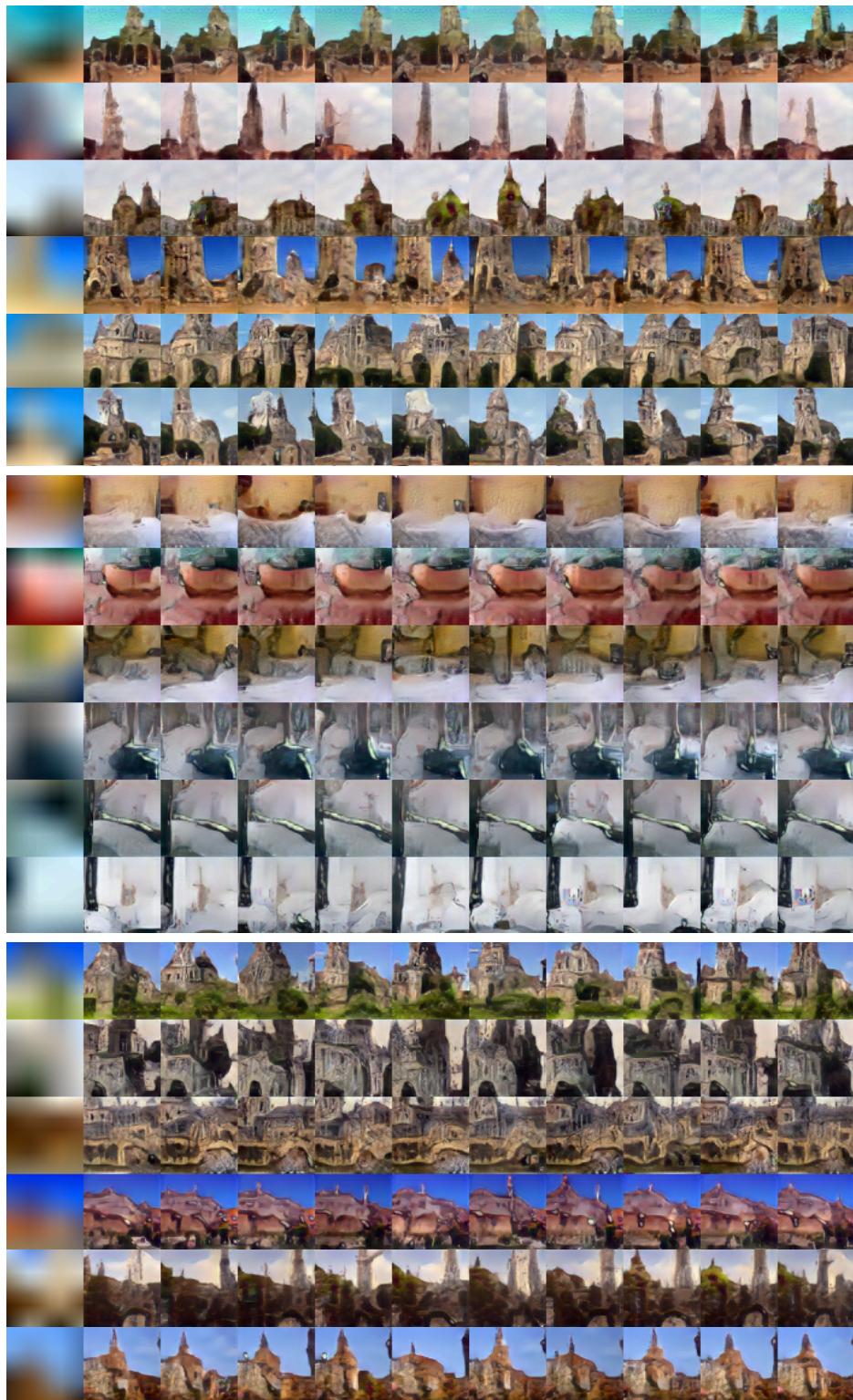


Figure 5: 64×64 samples from three different LSUN LAPGAN models (top: tower, middle: bedroom, bottom: church front). The first column shows the 4×4 validation set image used to start the generation process, with subsequent columns showing different draws from the model.

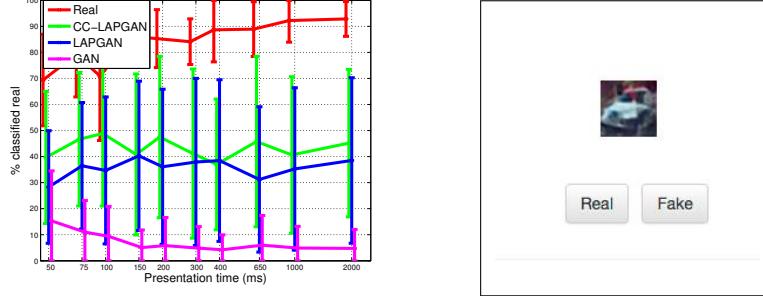


Figure 6: Left: Human evaluation of real CIFAR10 images (red) and samples from Goodfellow *et al.* [10] (magenta), our LAPGAN (blue) and a class conditional LAPGAN (green). The error bars show $\pm 1\sigma$ of the inter-subject variability. Around 40% of the samples generated by our class conditional LAPGAN model are realistic enough to fool a human into thinking they are real images. This compares with $\leq 10\%$ of images from the standard GAN model [10], but is still a lot lower than the $> 90\%$ rate for real images. Right: The user-interface presented to the subjects.

Appendix A

To describe the log-likelihood computation in our model, let us consider a two scale pyramid for the moment. Given a (vectorized) $j \times j$ image I , denote by $l = d(I)$ the coarsened image, and $h = I - u(d(I))$ to be the high pass. In this section, to simplify the computations, we use a slightly different u operator than the one used to generate the images displayed in Fig. 3. Namely, here we take $d(I)$ to be the mean over each disjoint block of 2×2 pixels, and take u to be the operator that removes the mean from each 2×2 block. Since u has rank $3d^2/4$, in this section, we write h in an orthonormal basis of the range of u , then the (linear) mapping from I to (l, h) is unitary. We now build a probability density p on \mathbb{R}^{d^2} by

$$p(I) = q_0(l, h)q_1(l) = q_0(d(I), h(I))q_1(d(I));$$

in a moment we will carefully define the functions q_i . For now, suppose that $q_i \geq 0$, $\int q_1(l) dl = 1$, and for each fixed l , $\int q_0(l, h) dh = 1$. Then we can check that p has unit integral:

$$\int p dI = \int q_0(d(I), h(I))q_1(d(I))dI = \int \int q_0(l, h)q_1(l) dl dh = 1.$$

Now we define the q_i with Parzen window approximations to the densities of each of the scales. For q_1 , we take a set of training samples l_1, \dots, l_{N_0} , and construct the density function $q_1(l) \sim \sum_{i=1}^{N_1} e^{-||l-l_i||^2/\sigma_1}$. We fix $l = d(I)$ to define $q_0(I) = q_0(l, h) \sim \sum_{i=1}^{N_0} e^{-||h-h_i||^2/\sigma_0}$. For pyramids with more levels, we continue in the same way for each of the finer scales. Note we always use the true low pass at each scale, and measure the true high pass against the high pass samples generated from the model. Thus for a pyramid with K levels, the final log likelihood will be: $\log(q_K(l_K)) + \sum_{k=0}^{K-1} \log(q_k(l_k, h_k))$.

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