

Unleashing Transformers: Parallel Token Prediction with Discrete Absorbing Diffusion for Fast High-Resolution Image Generation from Vector-Quantized Codes

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Abstract. Whilst diffusion probabilistic models can generate high quality image content, key limitations remain in terms of both generating high-resolution imagery and their associated high computational requirements. Recent Vector-Quantized image models have overcome this limitation of image resolution but are prohibitively slow and unidirectional as they generate tokens via element-wise autoregressive sampling from the prior. By contrast, in this paper we propose a novel discrete diffusion probabilistic model prior which enables parallel prediction of Vector-Quantized tokens by using an unconstrained Transformer architecture as the backbone. During training, tokens are randomly masked in an order-agnostic manner and the Transformer learns to predict the original tokens. This parallelism of Vector-Quantized token prediction in turn facilitates unconditional generation of globally consistent high-resolution and diverse imagery at a fraction of the computational expense. In this manner, we can generate image resolutions exceeding that of the original training set samples whilst additionally provisioning per-image likelihood estimates (in a departure from generative adversarial approaches). Our approach achieves state-of-the-art results in terms of the manifold overlap metrics Coverage (LSUN Bedroom: 0.83; LSUN Churches: 0.73; FFHQ: 0.80) and Density (LSUN Bedroom: 1.51; LSUN Churches: 1.12; FFHQ: 1.20), and performs competitively on FID (LSUN Bedroom: 3.64; LSUN Churches: 4.07; FFHQ: 6.11) whilst offering advantages in terms of both computation and reduced training set requirements.

Keywords: generative model, diffusion, high-resolution image synthesis

1 Introduction

Artificially generating plausible photo-realistic images, at ever higher resolutions, has long been a goal when designing deep generative models. Recent advance-

* Authors contributed equally. Source code for this work is available at <https://github.com/samb-t/unleashing-transformers>.



Fig. 1: Our approach uses a discrete diffusion to quickly generate high quality images optionally larger than the training data (right).

ments have benefited fields such as medical image synthesis [23], computer graphics [11, 91], image editing [52], image translation [77], and super-resolution [33].

These methods can be divided into five main classes [5], each making different trade-offs to scale to high resolutions. Techniques to scale Generative Adversarial Networks (GANs) [25] include progressive growing [42], large batches [8], and regularisation [53, 56]. Variational Autoencoders (VAEs) [49] can be scaled by building complex priors [12, 63, 84] and correcting samples [89]. Autoregressive approaches can make independence assumptions [69] or partition dimensions [55]. Normalizing Flows use multi-scale architectures [50], while diffusion models can be scaled using SDEs [81] and cascades [33]. Each of these have their own drawbacks, such as unstable training, slow sampling, and lack of global context.

Of particular interest to this work is the popular Transformer architecture [86] which models long distance relationships using a powerful parallelisable attention mechanism. By constraining the Transformer architecture to attend a fixed unidirectional ordering of tokens, they can be used to parameterise a generative autoregressive model [13, 64]. However, image data does not conform to such a structure and hence this bias limits the representation ability and unnecessarily restricts the sampling process to be sequential and slow.

Addressing these issues, our main contributions are:

- We propose a parallel token prediction approach for generating Vector-Quantized images allowing much faster sampling than autoregressive models.
- Our approach is able to generate globally consistent images at resolutions exceeding that of the original training data by aggregating multiple context windows, allowing for much larger context regions.
- Our approach demonstrates state-of-the art performance on three benchmark datasets in terms of Density (LSUN Bedroom: 1.51; LSUN Churches: 1.12; FFHQ: 1.20) and Coverage (Bedroom: 0.83; Churches: 0.73; FFHQ: 0.80), and is competitive on FID (Bedroom: 3.64; Churches: 4.07; FFHQ: 6.11).

2 Prior Work

Extensive work in deep generative modelling [5] and self-supervised learning [20] laid the foundations for this research, which we review here in terms of both existing models (Sections 2.1-2.4) and Transformer architectures (Section 2.5).

2.1 Autoregressive Models

Autoregressive models are a family of powerful generative models capable of directly maximising the likelihood of the data on which they are trained. These models have achieved impressive image generation results, however, their sequential nature limits them to relatively low dimensional data [14, 41, 62, 71, 76, 85].

The training and inference process for autoregressive models is based on the chain rule. By decomposing inputs into components $\mathbf{x} = \{x_1, \dots, x_n\}$, an autoregressive model with parameters θ can generate new latent samples sequentially:

$$p_\theta(\mathbf{x}) = p_\theta(x_1, x_2, \dots, x_n) = \prod_{i=1}^n p_\theta(x_i | x_1, \dots, x_{i-1}). \quad (1)$$

For many tasks, appropriate input orderings are not obvious; since the receptive field is limited to previous tokens, this can significantly affect sample quality.

2.2 Vector-Quantized Image Models

To scale autoregressive models to high-resolution data, Vector-Quantized image models can be used. These learn a highly compressed discrete representation taking advantage of an information rich codebook [63]. A convolutional encoder downsamples images \mathbf{x} to a smaller spatial resolution, $E(\mathbf{x}) = \{\mathbf{e}_1, \mathbf{e}_2, \dots, \mathbf{e}_L\} \in \mathbb{R}^{L \times D}$. A simple quantisation approach is to use the argmax operation which maps continuous encodings to their closest elements in a finite codebook of vectors [63]. Specifically, for a codebook $\mathcal{C} \in \mathbb{R}^{K \times D}$, where K is the number of discrete codes in the codebook and D is the dimension of each code, each \mathbf{e}_i is mapped via a nearest-neighbour lookup onto a discrete codebook value, $\mathbf{c}_j \in \mathcal{C}$:

$$\mathbf{z}_q = \{\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_L\}, \text{ where } \mathbf{q}_i = \min_{\mathbf{c}_j \in \mathcal{C}} \|\mathbf{e}_i - \mathbf{c}_j\|. \quad (2)$$

As this operation is non-differentiable, the straight-through gradient estimator [3] is used to approximate gradients resulting in bias. The quantized latents are fed through a decoder $\hat{\mathbf{x}} = G(\mathbf{z}_q)$ to reconstruct the input based on a perceptual reconstruction loss [22, 92]; this process is trained by minimising the loss \mathcal{L}_{VQ} ,

$$\mathcal{L}_{VQ} = \mathcal{L}_{\text{rec}} + \|\text{sg}[E(\mathbf{x})] - \mathbf{z}_q\|_2^2 + \beta \|\text{sg}[\mathbf{z}_q] - E(\mathbf{x})\|_2^2. \quad (3)$$

2.3 Discrete Energy-Based Models

Since the causal nature of autoregressive models limits their representation ability, other approaches with less constrained architectures have begun to outperform them even on likelihood [48]. Energy-based models (EBMs) are an enticing

method for representing discrete data as they permit unconstrained architectures with global context. Implicit EBMs define an unnormalised distribution over data that is typically learned through contrastive divergence [19, 31]. Unfortunately, sampling EBMs using Gibbs sampling is impractical for high dimensional discrete data. However, incorporating gradients can reduce mixing times [27].

Similar to autoregressive models, masked language models (MLMs) such as BERT [15] model the conditional probability of the data. However, these are trained bidirectionally by randomly masking a subset of tokens from the input sequence, allowing a much richer context than autoregressive approaches. Some attempts have been made to define an implicit energy function using the conditional probabilities [87], however, obtaining true samples leads to very long sample times and we found them to be ineffective at modelling longer sequences [26].

2.4 Discrete Denoising Diffusion Models

Diffusion models [32, 80] define a Markov chain $q(\mathbf{x}_{1:T}|\mathbf{x}_0) = \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1})$ that gradually destroys data \mathbf{x}_0 by adding noise over a fixed number of steps T so that \mathbf{x}_T contains little to no information about \mathbf{x}_0 and can be easily sampled. The reverse procedure is a generative model that gradually denoises towards the data distribution $p_\theta(\mathbf{x}_{0:T}) = p_\theta(\mathbf{x}_T) \prod_{t=1}^T p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)$, learned by optimising the variational upper bound on negative log-likelihood, with t^{th} term

$$\mathbb{E}_{q(\mathbf{x}_{t+1}|\mathbf{x}_0)} [D_{KL}(q(\mathbf{x}_t|\mathbf{x}_{t+1}, \mathbf{x}_0) \parallel p_\theta(\mathbf{x}_t|\mathbf{x}_{t+1}))], \quad (4)$$

where sampling from the reverse process is not required during training. In continuous spaces, distributions are typically parameterised as Normal distributions.

Discrete diffusion models [1, 36, 80] constrain the state space so that \mathbf{x}_t is a discrete random variable falling into one of K categories. As such, the forward process can be represented as categorical distributions $q(\mathbf{x}_t|\mathbf{x}_{t-1}) = \text{Cat}(\mathbf{x}_t; \mathbf{p} = \mathbf{x}_{t-1}\mathbf{Q}_t)$ for one-hot \mathbf{x}_{t-1} where \mathbf{Q}_t is a matrix denoting the probabilities of moving to each successive state. $q(\mathbf{x}_t|\mathbf{x}_0)$ can be expressed as $q(\mathbf{x}_t|\mathbf{x}_0) \equiv \text{Cat}(\mathbf{x}_t; \mathbf{p} = \overline{\mathbf{Q}}_t)$ where $\overline{\mathbf{Q}}_t = \mathbf{x}_0\mathbf{Q}_1\mathbf{Q}_2 \cdots \mathbf{Q}_t$, therefore scaling is simple if $\overline{\mathbf{Q}}_t$ can be expressed in closed form. Transition processes include moving states with some low uniform probability [36], moving to nearby states with some probability based on similarity or distance, and of particular interest to this work, masking inputs similar to generative MLMs.

2.5 Transformers

Transformers [86] have made a huge impact across many fields [30] due to their power and flexibility. They are based on self-attention, a function which allows interactions with strong gradients between all inputs, irrespective of their spatial relationships. This procedure (Eqn. 5) encodes inputs as key-value pairs, where values \mathbf{V} represent embedded inputs and keys \mathbf{K} act as an indexing method, subsequently, a set of queries \mathbf{Q} are used to select which values to observe:

$$\text{Attn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d_k}}\right)\mathbf{V}. \quad (5)$$

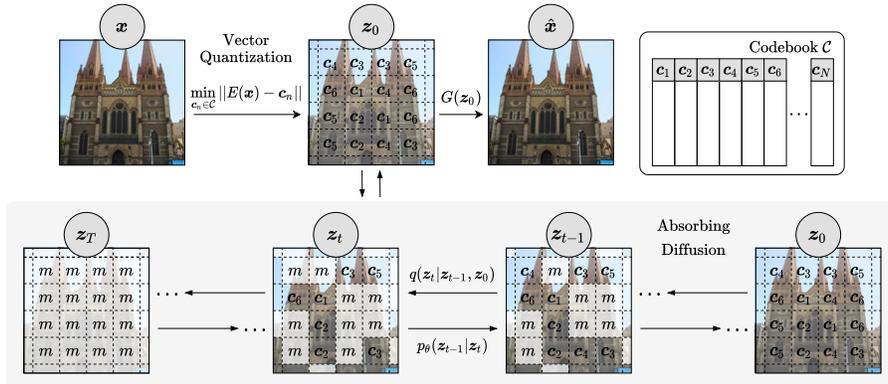


Fig. 2: Our approach uses a discrete absorbing diffusion model to represent Vector-Quantized images allowing fast high-resolution image generation. Specifically, after compressing images to an information-rich discrete space, elements are randomly masked and an unconstrained Transformer is trained to denoise the data, using global context to ensure samples are consistent and high quality.

While this allows long distance dependencies to be learned, complexity increases with sequence length quadratically, making scaling difficult. Approaches to mitigate this include independence assumptions [69], sparsity [13], and low rank [46].

3 Method

Modelling Vector-Quantized image representations with autoregressive models has a number of downsides, namely the slow sequential nature of sampling and the requirement to choose an input ordering which ignores the 2D structure of images thereby restricting modelling ability. To address these problems, we propose using a discrete diffusion model to represent Vector-Quantized image representations; this is visualised in Fig. 2. We hypothesise that by removing the autoregressive constraint, allowing bidirectional context when generating samples, not only will it be possible to speed up sampling, but an improved feature representation will be learned, enabling higher quality image generation.

3.1 Sampling Globally Coherent Latents

Once the training data is encoded as discrete, integer-valued latents $z \in \mathbb{Z}^D$, a discrete diffusion model can be used to learn the distribution over this highly compressed space. Specifically, we use the absorbing state diffusion [1] where in each forward time step t , each discrete latent at coordinate i , $[z]_i$, is independently either kept the same or masked out entirely with probability $\frac{1}{i}$; the reverse process gradually unveils these masks. In this formulation, the transition

matrix is defined as $\mathbf{Q}_t = (1 - \beta_t)I + \beta_t \mathbf{1}e_m^T$ where e_m is a vector with a one on mask states m and zeros elsewhere, and the beta schedule is $\beta_t = \frac{1}{T-t+1}$. Rather than directly approximating $p_\theta(\mathbf{z}_{t-1}|\mathbf{z}_t)$, training stochasticity is reduced by predicting $p_\theta(\mathbf{z}_0|\mathbf{z}_t)$ [32]. In this case, the variational bound reduces to

$$\mathbb{E}_{q(\mathbf{z}_0)} \left[\sum_{t=1}^T \frac{1}{t} \mathbb{E}_{q(\mathbf{z}_t|\mathbf{z}_0)} \left[\sum_{[\mathbf{z}_t]_i=m} \log p_\theta([\mathbf{z}_0]_i|\mathbf{z}_t) \right] \right]. \quad (6)$$

With p_θ modelled using multinomial distributions, a temperature $\tau < 1$ can be applied to the logits to improve sample quality at the expense of diversity.

Unlike, uniform diffusion, absorbing diffusion is an effective strategy for Vector-Quantized image modelling as noisy elements are removed entirely rather than being changed to a different value which in the discrete case may be unrelated but are much less easy to identify. Gaussian and token distance transitions which change states based on embedding distances are similarly ineffective as Vector-Quantized latents are not ordinal meaning that state changes can significantly change tokens’ semantics. This effectiveness is further evidenced by the success of BERT [15] which similarly learns to denoise randomly masked data.

Architecture Esser et al. [22] demonstrated that in the autoregressive case, Transformers [86] are better suited for modelling Vector-Quantized images than convolutional approaches due to the importance of long-distance relationships in this compressed form. As such, we use transformers to model the prior, but without the architectural restrictions imposed by autoregressive approaches.

Fast Sampling Because the diffusion model is trained to predict $p(\mathbf{z}_0|\mathbf{z}_t)$, it is possible to sample skipping an arbitrary number of time steps k , $p_\theta(\mathbf{z}_{t-k}|\mathbf{z}_t)$, allowing sampling in significantly fewer steps than autoregressive approaches.

3.2 Addressing Gradient Variance

When inputs are very noisy (at time steps close to T), denoising is difficult and the stochastic training results in gradients with high variance. As such, in practice continuous diffusion models are trained to estimate the noise rather than directly predict the denoised data, significantly reducing the variance. Unfortunately, no relevant reparameterisation currently exists for discrete distributions [36]. Instead, we address this problem by reweighting the ELBO based on the information available at time t , $\frac{T-t+1}{T}$ [1], so that components of the loss at time steps closer to T are weighted less than earlier steps. This effectively alters the learning rate based on gradient variance, improving convergence,

$$\mathbb{E}_{q(\mathbf{z}_0)} \left[\sum_{t=1}^T \frac{T-t+1}{T} \mathbb{E}_{q(\mathbf{z}_t|\mathbf{z}_0)} \left[\sum_{[\mathbf{z}_t]_i=m} \log p_\theta([\mathbf{z}_0]_i|\mathbf{z}_t) \right] \right]. \quad (7)$$

This is equivalent to the loss obtained by assuming the posterior does not have access to \mathbf{z}_t , i.e. if the $t-1^{\text{th}}$ loss term is $D_{KL}(q(\mathbf{z}_{t-1}|\mathbf{z}_0) \parallel p_\theta(\mathbf{z}_{t-1}|\mathbf{z}_t))$ (proof in Appendix B). Since we predict \mathbf{z}_0 this assumption does not harm the training.

3.3 Generating High-Resolution Images

Using convolutions to build Vector-Quantized image models encourages latents to be highly spatially correlated with generated images. It is therefore possible to construct essentially arbitrarily sized images by generating latents with the required shape. We propose an approach that allows globally consistent images substantially larger than those in the training data to be generated.

First, a large a by b array of mask tokens, $\mathbf{z}_T = m^{a \times b}$, is initialised that corresponds to the size of image we wish to generate. In order to capture the maximum context when approximating $\bar{\mathbf{z}}_0$ we apply the denoising network to all subsets of $\bar{\mathbf{z}}_t$ with the same spatial size as the usual inputs of the network, aggregating estimates at each location. Specifically, using $c_j(\bar{\mathbf{z}}_t)$ to represent local subsets, we approximate the denoising distribution as a mixture,

$$p([\bar{\mathbf{z}}_0]_i | \bar{\mathbf{z}}_t) \approx \frac{1}{Z} \sum_j p([\bar{\mathbf{z}}_0]_i | c_j(\bar{\mathbf{z}}_t)), \quad (8)$$

where the sum is over subsets c_j that contain the i^{th} latent and Z is the normalising constant. For extremely large images, this can require a very large number of function evaluations, however, the sum can be approximated by striding over latents with a step > 1 or by randomly selecting positions.

3.4 Improving Code Representations

There are various options to obtain high-quality image representations including using large numbers of latents and codes [67] or building a hierarchy of latent variables [68]. We use the adversarial framework proposed by Esser et al. [22] to achieve higher compression rates with high-quality codes using only a single GPU, without tying our approach to the characteristics typically associated with generative adversarial models. Additionally, we apply differentiable augmentations T , such as translations and colour jitter, to all discriminator inputs; this has proven to be effective at improving sample quality across methods [41, 93]. The overall loss \mathcal{L} is a linear combination of \mathcal{L}_{VQ} , the Vector-Quantized loss, and \mathcal{L}_{G} which uses a discriminator D to assess realism based on an adaptive weight λ . On some datasets, λ can grow to extremely large values hindering training. We find simply clamping λ at a maximum value $\lambda_{\text{max}} = 1$ an effective solution that stabilises training,

$$\mathcal{L} = \min_{E, G, C} \max_D \mathbb{E}_{p_d} [\mathcal{L}_{\text{VQ}} + \lambda \mathcal{L}_{\text{G}}], \quad (9a) \quad \lambda = \min \left(\frac{\nabla_{G_L} [\mathcal{L}_{\text{rec}}]}{\nabla_{G_L} [\mathcal{L}_{\text{G}}] + \delta}, \lambda_{\text{max}} \right), \quad (9b)$$

$$\mathcal{L}_{\text{G}} = \log D(T(\mathbf{x})) + \log(1 - D(T(\hat{\mathbf{x}}))). \quad (9c)$$

The argmax quantisation approach can result in codebook collapse, where some codes are never used; while other quantisation methods can reduce this [17, 40, 54, 67], we found argmax to yield the highest reconstruction quality.



Fig. 3: Samples from our models trained on 256x256 datasets: LSUN Churches, FFHQ, and LSUN Bedroom.

4 Evaluation

We evaluate our approach on three high-resolution 256x256 datasets: LSUN Bedroom, LSUN Churches [90], and FFHQ [44]. Sec. 4.1 evaluates the quality of samples from our proposed model. Sec. 4.2 demonstrates the representation abilities of absorbing diffusion models applied to the learned discrete latent spaces, including how sampling can be sped up, improvements over equivalent autoregressive models, and the effect of our reweighted ELBO. Finally, Sec. 4.3 evaluates our Vector-Quantized image model.

In all experiments, our absorbing diffusion model parameterised with an 80M parameter Transformer Encoder [86] is applied to 16×16 latents discretised to a codebook with 1024 entries and optimised using the Adam optimiser [47]. While, as noted by Esser et al. [22], a GPT2-medium [66] architecture (307M parameters) fits onto a GPU with 12GB of VRAM, in practice this requires small batch sizes and learning rates making training in reasonable times impractical. More details can be found in Appendix A. Source code is available [here](#).

4.1 Sample Quality

In this section we evaluate our model quantitatively and qualitatively. In contrast to other multi-step methods, our approach allows sampling in the fewest steps. Samples can be found in Figs. 3 and 5 which are high quality and diverse.

Limitations of the FID Metric FID is a popular choice for evaluating sample quality, it has been found to correlate well with image quality and is efficient to calculate. However, it unrealistically approximates the data distribution as Gaussian in embedding space and is insensitive to the global structure of the data distribution [83]. For likelihood models, calculating NLL is possible instead; by fine tuning our approach to model pixels as Gaussians, likelihood can be estimated as $p(\mathbf{x}) \geq p(\mathbf{x}|\mathbf{z})p(\mathbf{z})$ [63], giving 2.72BPD on 5-bit FFHQ. However, likelihood does not correlate well with quality [82]. Other approaches that address these issues [6] include PPL [44], which assesses sample consistency through

Model	LSUN Churches				LSUN Bedroom				FFHQ			
	P ↑	R ↑	D ↑	C ↑	P ↑	R ↑	D ↑	C ↑	P ↑	R ↑	D ↑	C ↑
DCT [58]	0.60	0.48	-	-	0.44	0.56	-	-	0.51	0.40	-	-
TT [22]	0.67	0.29	1.08	0.60	0.61	0.33	1.15	0.75	0.64	0.29	0.89	0.5
VDVAE [12]	-	-	-	-	-	-	-	-	0.59	0.20	0.80	0.50
PGGAN [42]	0.61	0.38	0.83	0.63	0.43	0.40	0.70	0.64	-	-	-	-
StyleGAN [44]	-	-	-	-	0.55	0.48	0.96	0.80	-	-	-	-
StyleGAN2 [45]	0.60	0.43	0.83	0.68	-	-	-	-	0.69	0.40	1.12	0.80
ProjGAN [78]	0.56	0.53	0.65	0.64	0.55	0.46	0.90	0.79	0.66	0.46	0.98	0.77
Ours ($\tau = 1.0$)	0.70	0.42	1.12	0.73	0.64	0.38	1.27	0.81	0.69	0.48	1.06	0.77
Ours ($\tau = 0.9$)	0.71	0.45	1.07	0.74	0.67	0.38	1.51	0.83	0.73	0.48	1.20	0.80

Table 1: Precision (P), Recall (R), Density (D), and Coverage (C) [51,57,75] for approaches trained on LSUN Churches, LSUN Bedroom, and FFHQ.

latent interpolations; IMD [83], which uses all moments making it sensitive to global structure; and MTD [2], which compares image manifolds.

PRDC In this work, we evaluate using Precision (P) and Recall (R) [75] approaches (Tab. 1) which, unlike FID, evaluate sample quality and diversity separately by quantifying the overlap between the data and sample distributions, and have been used in similar recent work assessing high-resolution image generation [38,45,58,68]. Precision is the expected likelihood of fake samples lying on the data manifold and recall vice versa. These metrics are computed by approximating the data and sample manifolds as hyper-spheres around data and sample points respectively; manifold $m(X_1, \dots, X_N) = \bigcup_{i=1}^N B(X_i, \text{NND}_k(X_i))$, where $B(x, r)$ is a hypersphere around x with radius r and NND_k is k^{th} nearest neighbour distance [51]. While modelling manifolds as hyperspheres is a flawed assumption, it is beneficial to evaluate on multiple metrics to obtain a more accurate representation of performance. We also calculate Density (D) and Coverage (C) which are modifications to Precision and Recall respectively that address manifold overestimation [57]. Formally, these metrics can be defined as,

$$P = \frac{1}{M} \sum_{j=1}^M 1_{Y_j \in m(X_1, \dots, X_N)}, \quad (10a) \quad D = \frac{1}{kM} \sum_{j=1}^M \sum_{i=1}^N 1_{Y_j \in B(X_i, \text{NND}_k(X_i))}, \quad (10b)$$

$$R = \frac{1}{N} \sum_{i=1}^N 1_{X_i \in m(Y_1, \dots, Y_M)}, \quad (10c) \quad C = \frac{1}{N} \sum_{i=1}^N 1_{\exists j \text{ s.t. } Y_j \in B(X_i, \text{NND}_k(X_i))}. \quad (10d)$$

Due to limited computing resources, we are unable to provide Density and Coverage scores for DCT [58] and PRDC scores for StyleGAN2 on LSUN Bedroom since training on a standard GPU would take more than 30 days, much more than the 10 days to train our models. On LSUN our approach achieves the highest Precision, Density, and Coverage; indicating that the data and sample manifolds



Fig. 4: Our method allows unconditional images larger than those seen during training to be generated by applying the denoising network to all subsets of the image, aggregating probabilities to encourage global continuity.

have the most overlap. On FFHQ our approach achieves the highest Precision and Recall. When sampling with lower temperatures to improve FID, generative models generally trade precision and recall [45, 68]; since we also calculate FID with $\tau=0.9$, we evaluate the effect on PRDC. In almost all cases this improves scores, indicating that more samples in data regions, increasing overlap.

FID In Tab. 2 we calculate the Fréchet Inception Distance (FID) of samples from our models using torch-fidelity [61]. Using a fraction of the parameters of other Vector-Quantized image models, our approach achieves much lower FID.

Higher Resolution Fig. 4 shows samples generated at higher resolutions (up to 768×256) than the observed training data using the method described in Sec. 3.3 with $\tau = 0.8$. Even at larger scales we observe high-quality, diverse, and consistent samples.

Method	Params	Bed	Church	FFHQ
DDPM [32]	114M	6.36	7.89	-
DCT [58]	448M	6.40	7.56	-
VDVAE [12]	115M	-	-	28.5
TT [21, 22]	600M	6.35	7.81	9.6
I-BART [21]	2.1B	5.51	7.32	9.57
PGGAN [42]	47M	8.34	6.42	-
SGAN2 [45]	60M	2.35	3.86	3.8
ADM [16]	552M	1.90	-	-
ProjGAN [78]	106M	1.52	1.59	3.39
Ours ($\tau=1.0$)	145M	5.07	5.58	7.12
Ours ($\tau=0.9$)	145M	3.27	4.07	6.11

Table 2: FID comparison on FFHQ, LSUN Bedroom and Churches (lower is better).

4.2 Absorbing Diffusion

In this section we analyse the usage of absorbing diffusion for high-resolution image generation, determining how many sampling steps are required to obtain high-quality samples and ablating the components of our approach.

Sampling Speed Our approach applies a diffusion process to a highly compressed image representation, meaning it is already $18\times$ faster to sample from

(a) Non-cherry picked, $\tau = 0.9$, 256×256 LSUN Churches samples.(b) Non-cherry picked, $\tau = 0.85$, 256×256 FFHQ samples.(c) Non-cherry picked, $\tau = 0.9$, 256×256 LSUN Bedroom samples.

Fig. 5: Samples from our approach are diverse and high quality.

than DDPM (ours: 3.8s, DDPM: 70s per image on a NVIDIA RTX 2080 Ti). However, since the absorbing diffusion model is trained to approximate $p(z_0|z_t)$ it is possible to speed the sampling process up further by skipping arbitrary numbers of time steps, unmasking multiple latents at once. In Tab. 3 we explore how sample quality is affected using a simple step skipping scheme: evenly skipping a constant number of steps so that the total number of steps meets some fixed computational budget. As expected, FID increases with fewer sampling steps. However, the increase in FID is minor relative to the improvement in sampling speed: our approach achieves similar FID to the equivalent autoregressive model using half the number of steps. With 50 sampling steps, our approach is $88\times$ faster than DDPMs. Using a more sophisticated step selection scheme such as dynamic programming [88], FID could potentially be reduced further.

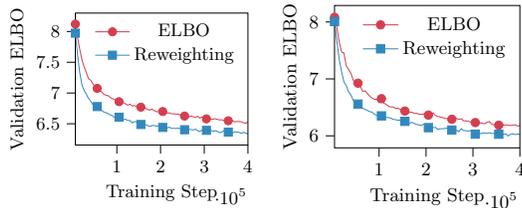
Autoregressive vs Absorbing DDPM Tab. 4 compares the representation ability of our absorbing diffusion model with an autoregressive model, both util-

Steps	50	100	150	200	256
Church	6.86	6.09	5.81	5.68	5.58
Church ($\tau=0.9$)	4.90	4.40	4.22	4.19	4.07
FFHQ	9.60	7.90	7.53	7.52	7.12
FFHQ ($\tau=0.9$)	6.87	6.24	6.16	6.14	6.11

Table 3: Our approach allows sampling in much fewer steps with only minor FID increase.

Method	Churches		FFHQ	
	FID ↓	NLL ↓	FID ↓	NLL ↓
*AR	13.23	6.67	9.47	6.65
*Absorbing	11.84	6.41	8.52	6.48
AR	5.93	6.24	8.15	6.18
Absorbing	5.58	6.01	7.12	5.96

Table 4: FID and validation latent NLL (in bpd) using the same Transformer. *=Default VQGAN



(a) LSUN Churches

(b) FFHQ

Fig. 6: Models trained with reweighting converge faster than models trained on ELBO.

Modifications	Churches	FFHQ
Default	5.25	3.37
$\lambda_{\max} = 1$	8.67	4.72
DiffAug	5.16	6.57
Both	2.70	3.12

Table 5: Effect of proposed VQGAN changes on FID.

using exactly the same Transformer architecture, but with the Transformer unconstrained in the diffusion case. On both datasets diffusion achieves lower FID, which is calculated in the image space. Validation NLL is evaluated in latent space (i.e. $-\log p(\mathbf{z})$) and again the diffusion model outperforms the autoregressive model despite being trained on a harder task with the same number of parameters, indicating that the diffusion models better approximate the prior distribution. Following previous works, early stopping was used to prevent autoregressive models from overfitting [21, 41]; increasing weight decay and dropout in some cases slightly improved validation NLL but caused FID to increase.

Rewighted ELBO In Sec. 3.2 we proposed using a reweighted ELBO when training the diffusion model to reduce gradient variance. We evaluate this in Fig. 6 by comparing validation ELBO (calculated with Eq. 6) during training for models trained directly on ELBO and our reweighting. The models trained on reweighted ELBO converge substantially faster, demonstrating that our reweighting is valid and simplifies optimisation.

4.3 Reconstruction Quality

In Tab. 5 we evaluate the effect of DiffAug [93] and λ limiting on Vector-Quantized image models. While each technique individually can lead to worse FID due to imbalance between the generator and discriminator, we found combining techniques offered the most stability and improved FID across all datasets.



(a) Impact of sampling temperature on diversity. For small temperature changes it is unclear how bias changes. (b) Our bidirectional approach allows local image editing by targeting regions to be changed (highlighted in grey).

Fig. 7: Evaluation of practical use cases of our proposed generative model.

4.4 Sample Diversity

To improve sample quality, many generative models are sampled using a reduced temperature or by truncating distributions. This is problematic, as these methods amplify any biases in the dataset. We visualise the impact of temperature on sampling from a model trained on FFHQ in Fig. 7a. For very low temperatures the bias is obvious: samples are mostly front-facing white men with brown hair on solid white/black backgrounds. Exactly how the bias changes for more subtle temperature changes is less clear, which is problematic. Practitioners should be aware of this effect and it emphasises the importance of dataset balancing.

4.5 Image Editing

An additional advantage of using a bidirectional diffusion model to model the latent space is that image inpainting is possible. Since autoregressive models are conditioned only on the upper left region of the image, they are unable to edit internal masked image regions in a consistent manner. Diffusion models, on the other hand, allow masked regions to be placed at arbitrary locations. After a region has been highlighted, we mask corresponding latents, identify the starting time step by counting the number of masked latents, then continue the denoising process from that point. Examples of this process can be found in Fig. 7b.

4.6 Limitations

In our experiments we only tested our approach on 256×256 datasets; directly scaling to higher resolutions would require more GPU resources. However, future work using more efficient Transformer architectures [39] may alleviate this. Our method outperforms all approaches tested on FID except StyleGAN2 [45]; we find that the primary bottleneck is the Vector-Quantized image model, therefore more research is necessary to improve these discrete representations. Whilst our approach is trained for significantly less time than other approaches such as

StyleGAN2, the stochastic training procedure means that more training steps are required compared to autoregressive approaches. Although when generating extra-large images the large context window made possible by the diffusion model encourages consistency, a reduced temperature is required, reducing diversity.

5 Discussion

While other classes of discrete generative model exist, they are less suitable for Vector-Quantized image modelling than discrete diffusion models: VAEs introduce prior assumptions about the latent space that can be limiting, in particular, continuous spaces may not be appropriate when modelling discrete data [7]; GAN training requires sampling from the generator meaning that gradients must be backpropagated through a discretisation procedure [60]; discrete normalising flows require functions to be invertible, significantly restricting function space [4, 37].

Another approach for modelling latent spaces using diffusion models is LS-GMs [84], which model continuous latents with SDEs. However, our approach trains more than $15\times$ faster thanks to the efficiency discrete approaches allow. There also exists a variety of different discrete diffusion methods [1, 35, 79]: ImageBART [21], developed concurrently with this work, models discrete latents using multinomial diffusion with separate autoregressive Transformers per diffusion step leading to slower training, inference, and substantially more parameters than our method. Other concurrent works [10, 29, 70] which apply diffusion processes to VQGANs are discussed in Appendix D. Also of interest are non-autoregressive discrete methods for translation [24, 28, 72] and alignment [9, 73].

There are a number of avenues that would make for interesting future work based upon the models proposed in this paper: methods that scale diffusion models such as momentum [18], noise schedules [59], cascaded models [34, 74] and classifier guidance [16] may yield improved performance. Or, to improve discrete image representations, networks invariant to translation and rotation [43] or other more powerful generative models could be used. Finally, by conditioning on both text and discrete image representations, absorbing diffusion models could allow text-to-image generation and image captioning to be accomplished using a single model with faster run-time than independent approaches [65, 67].

6 Conclusion

In this work we proposed a discrete diffusion probabilistic model prior capable of predicting Vector-Quantized image representations in parallel, overcoming the high sampling times, unidirectional nature and overfitting challenges associated with autoregressive priors. Our approach makes no assumptions about the inherent ordering of latents by utilising an unconstrained Transformer architecture. Experimental results demonstrate the ability of our approach to generate diverse, high-quality images, optionally at resolutions exceeding the training samples. Additional work is needed to reduce training times and to efficiently scale our approach to even higher resolutions.

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