Megapixel Image Generation with Step-unrolled Denoising Autoencoders

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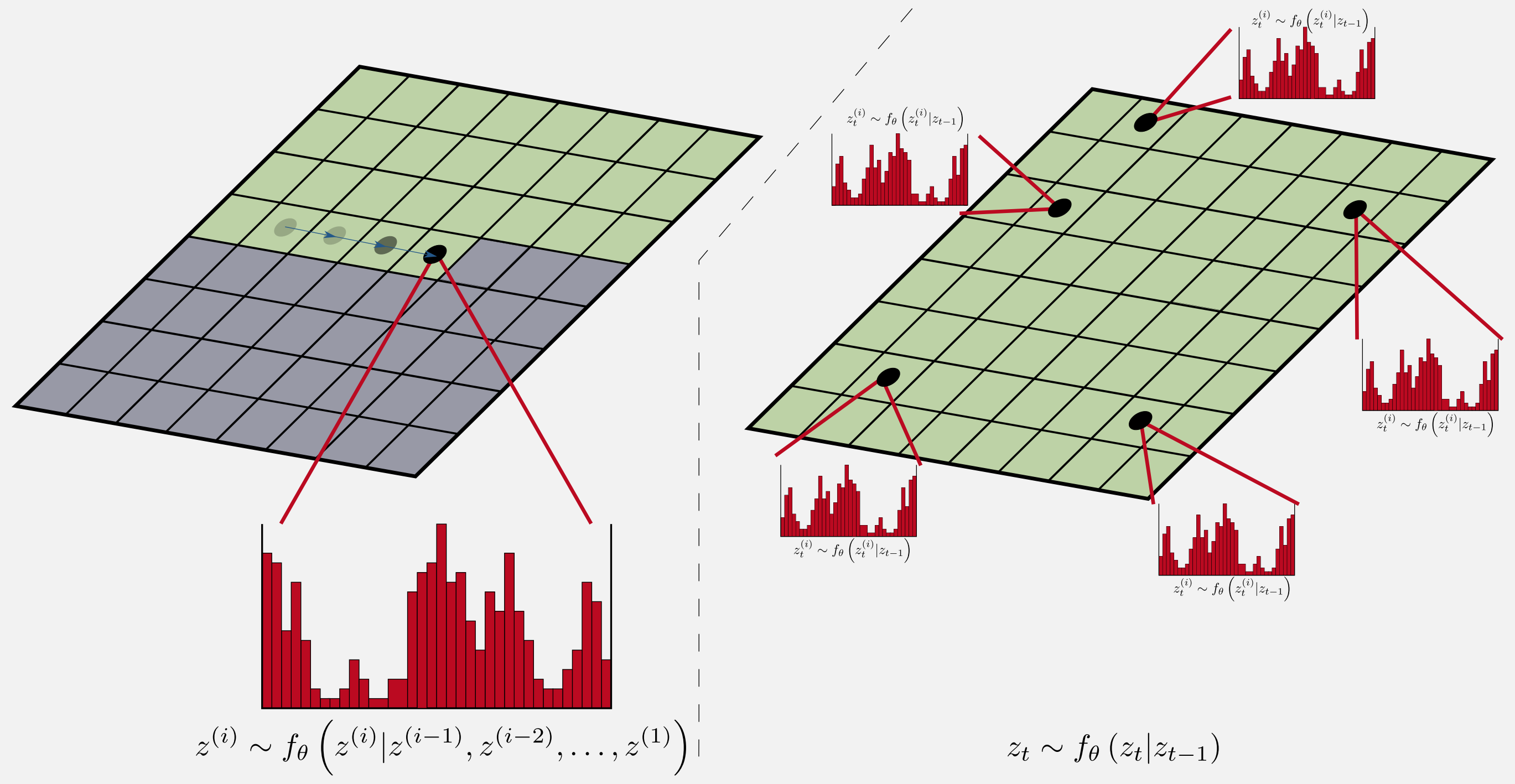
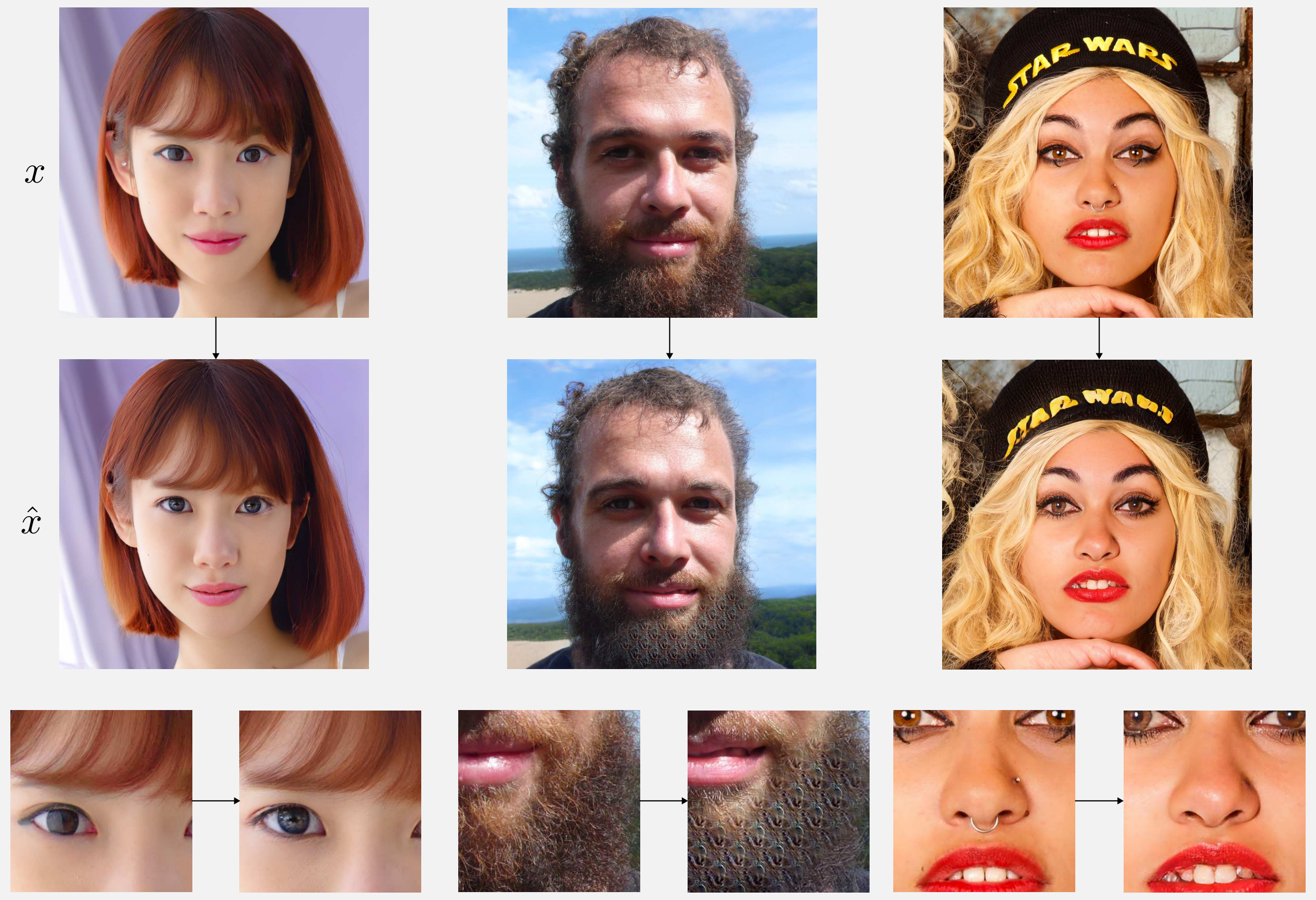
Figure 1: Samples from our FFHQ1024 model. Resulting samples are diverse and of high-fidelity. **Each 1024×1024 sample was generated in two seconds** on a consumer-grade GPU (GTX 1080Ti), in contrast to existing approaches at this resolution, which take minutes to generate. To our knowledge, this is the fastest sampling, non-adversarial generative framework at this resolution.

Background

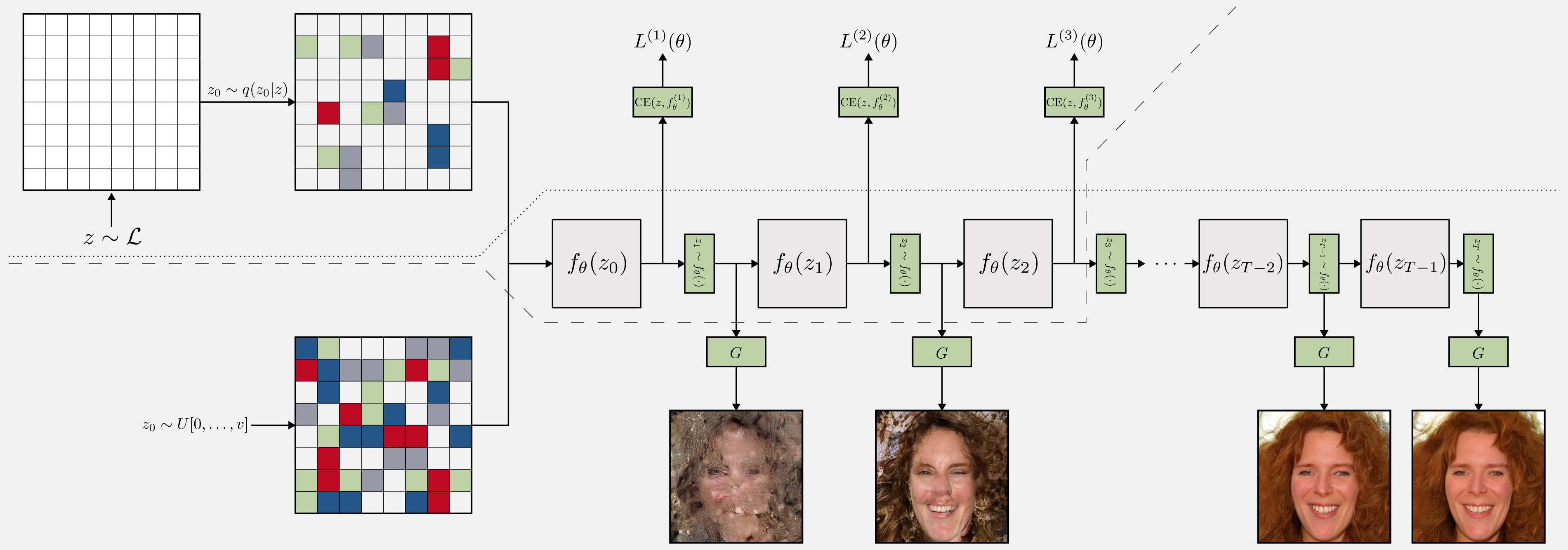

$z^{(i)} \sim f_\theta\left(z^{(i)}|z^{(i-1)}, z^{(i-2)}, \dots, z^{(1)}\right)$
$z_t \sim f_\theta\left(z_t|z_{t-1}\right)$

- **Autoregressive (AR)** sampling (left) is defined by the probabilistic chain rule. This means sampling is done iteratively with complexity $\mathcal{O}(n)$.
- **Non-autoregressive (NAR)** sampling (right) samples an arbitrary number of elements in parallel and does not scale with input size n, but may still require thousands of iterations ($\mathcal{O}(1)$ with potentially a large constant).
- AR sampling is **limited to using past context**, whereas NAR uses **all context available to it**.



- **VQ-GAN** is used to reduce computational requirements in generative models by compressing the input into a **discrete space**.
- It offers a higher compression rate than prior work, but does not always faithfully reconstruct the input, for example the left has eye colour changed, and the right has piercings removed.

Proposed Method


$z \sim \mathcal{L}$
$z_0 \sim q(z_0|z)$
$z_0 \sim U[0, \dots, v]$
$L^{(1)}(\theta)$
$L^{(2)}(\theta)$
$L^{(3)}(\theta)$
$\mathrm{CE}(z, f_\theta^{(1)})$
$\mathrm{CE}(z, f_\theta^{(2)})$
$\mathrm{CE}(z, f_\theta^{(3)})$
$f_\theta(z_0)$
$z_1 \sim f_\theta(\cdot)$
$f_\theta(z_1)$
$z_2 \sim f_\theta(\cdot)$
$f_\theta(z_2)$
$z_3 \sim f_\theta(\cdot)$
$f_\theta(z_{T-2})$
$z_{T-1} \sim f_\theta(\cdot)$
$f_\theta(z_{T-1})$
$z_T \sim f_\theta(\cdot)$
G
G
G
G

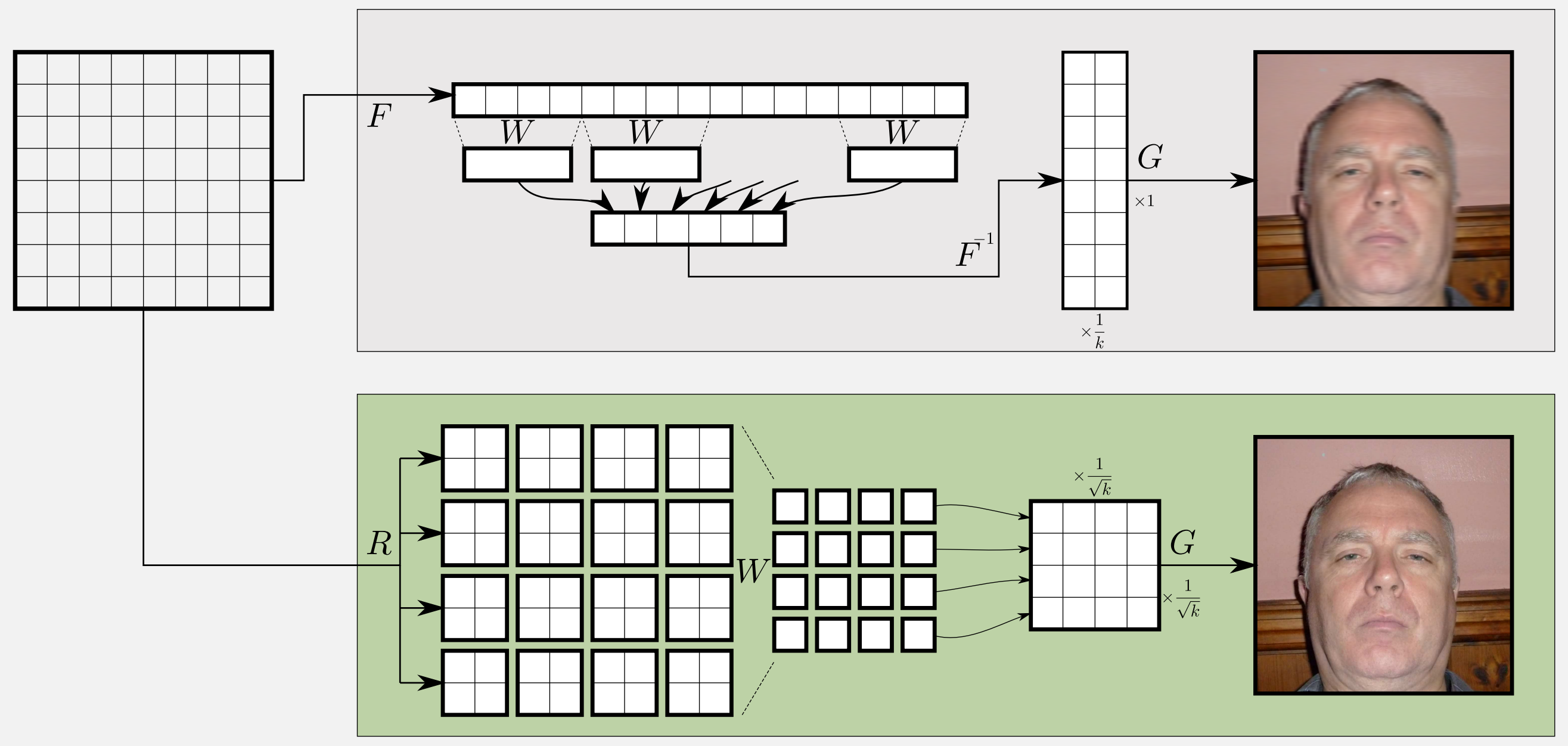
An overview of our proposed training and sampling method:

- Above the dashed line shows the training process, beginning by sampling a corrupted sample $\mathbf{z}_0 \sim q(\cdot|\mathbf{z})$. SUNDAE denoises for 2 to 3 steps and averages the cross entropy losses across all steps in the Markov chain.
- Below the dotted line shows the sampling process, beginning by sampling $\mathbf{z}_0$ from a uniform prior distribution. SUNDAE denoises for $T \gg 3$ steps to produce $\mathbf{z}_T$ before using VQ-GAN to decode the final sample.
- To demonstrate the scalability of our approach, we trained a VQ-GAN model from scratch on megapixel images – **considerably larger than prior work**. The loss function is:

$$\begin{aligned} L_{\mathsf{VQ}} &= \alpha_{\mathsf{VQ}} \cdot (||\hat{\mathbf{z}} - \mathbf{z}||^2 \\ &\quad + ||sg[E(\mathbf{x})] - \mathbf{z}||_2^2 + ||E(\mathbf{x}) - sg[\mathbf{z}]||_2^2) \\ L_{\mathsf{PIX}} &= \alpha_{\mathsf{PIX}} \cdot |\mathbf{x} - \hat{\mathbf{x}}| \cdot \\ L_{\mathsf{GAN}} &= \alpha_{\mathsf{GAN}} \cdot (\log D(\mathbf{x}) + \log(1 - D(\hat{\mathbf{x}}))) \\ L &= L_{\mathsf{VQ}} + \lambda \cdot L_{\mathsf{GAN}} \end{aligned}$$

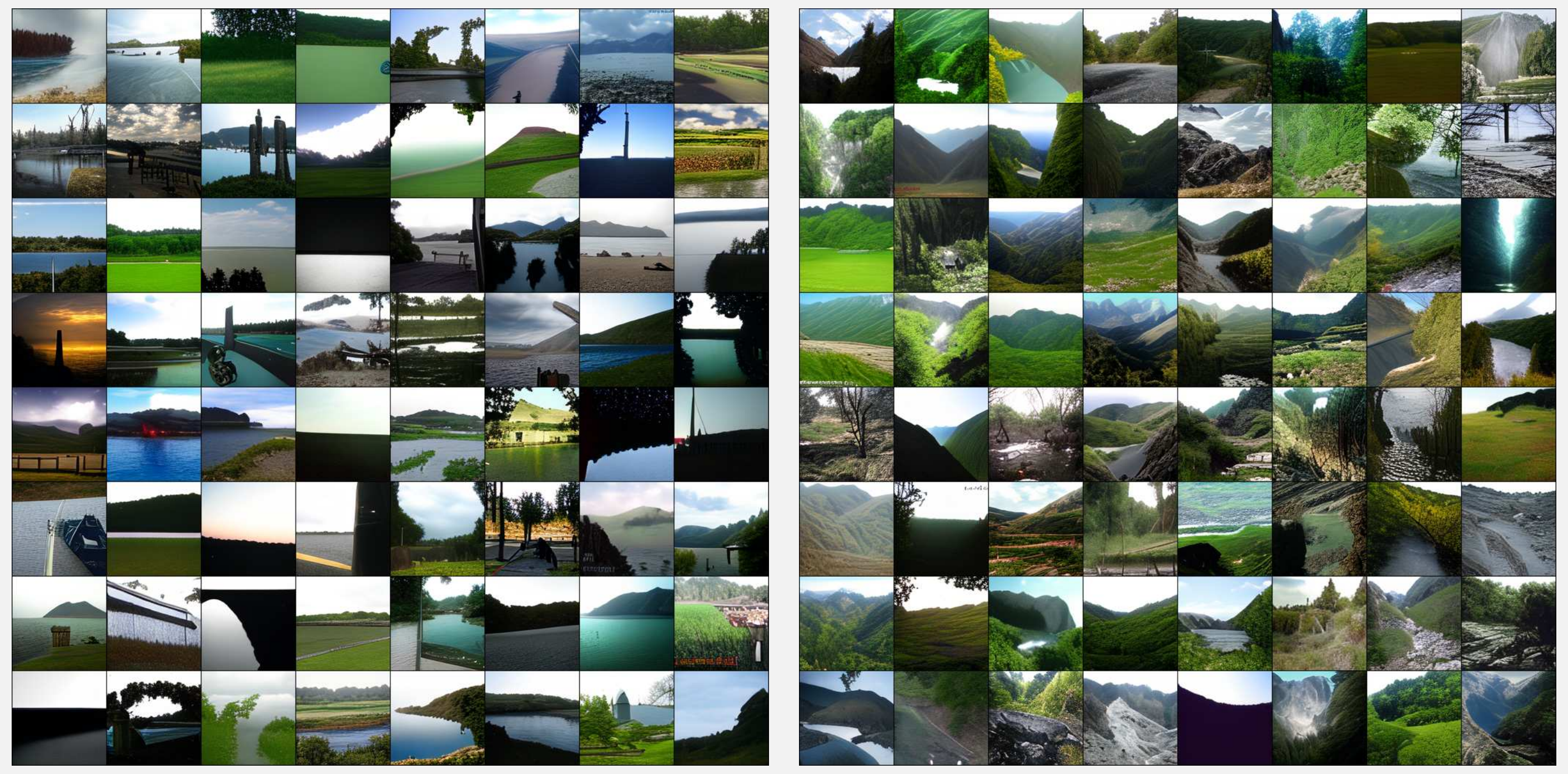
$$\begin{aligned} \lambda &= \frac{\nabla_{G_{-1}}[L_{\mathsf{PIX}} + L_{\mathsf{PER}}]}{\nabla_{G_{-1}}[L_{\mathsf{GAN}}] + \epsilon} \\ \alpha_{\mathsf{PIX}} &= 1.0,\ \alpha_{\mathsf{VQ}} = 1.0, \\ \alpha_{\mathsf{GAN}} &= 0.5,\ \alpha_{\mathsf{PER}} = 1.0 \end{aligned}$$

- By applying our framework to discrete latent representations, we obtained a **fast and scaleable generative model on megapixel images**.
- Our method generates 1024×1024 samples in only **two seconds** – a wide margin faster than prior non-adversarial methods which take **minutes** to generate at this resolution.



- As a result of our work, we also found flaws in the original formulation of hourglass transformers when applied to multi-dimensional data.
- Our modifications have **applications in a wider context**, outside of generative modelling.

Results



- 256×256 **class-conditioned** samples from our ImageNet model.
- Left and right batches are from classes “Lakeside” and “Valley” respectively.
- Our approach is easily extendable to use text prompts, **yielding a fast text-to-image generator**.

- Example inpainting results using our FFHQ1024 model. We show multiple results given the same image-mask pair to **demonstrate diversity in the outputs**.
- NAR methods allow for **arbitrary inpainting patterns** to be easily used. In contrast, AR models cannot easily handle all patterns, nor can they use all context when inpainting.

References

[1] Patrick Esser, Robin Rombach, and Björn Ommer. *Taming Transformers for High-Resolution Image Synthesis*. 2021. arXiv: `2012.09841 [cs.CV]`.

[2] Piotr Nawrot et al. *Hierarchical Transformers Are More Efficient Language Models*. 2021. arXiv: `2110.13711 [cs.LG]`.

[3] Nikolay Savinov et al. *Step-unrolled Denoising Autoencoders for Text Generation*. 2022. arXiv: `2112.06749 [cs.CL]`.