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

Sam Bond-Taylor*, Peter Hessey*, Hiroshi Sasaki, Toby P. Breckon, and Chris G. Willcocks

Durham University

Project Page

Introduction

A parallel prediction approach that allows **fast generation** of high-res Vector-Quantized images:

- SOTA quantitative sample quality scores.
- Sample resolutions higher than training data.
- Global context allows samples to be edited.

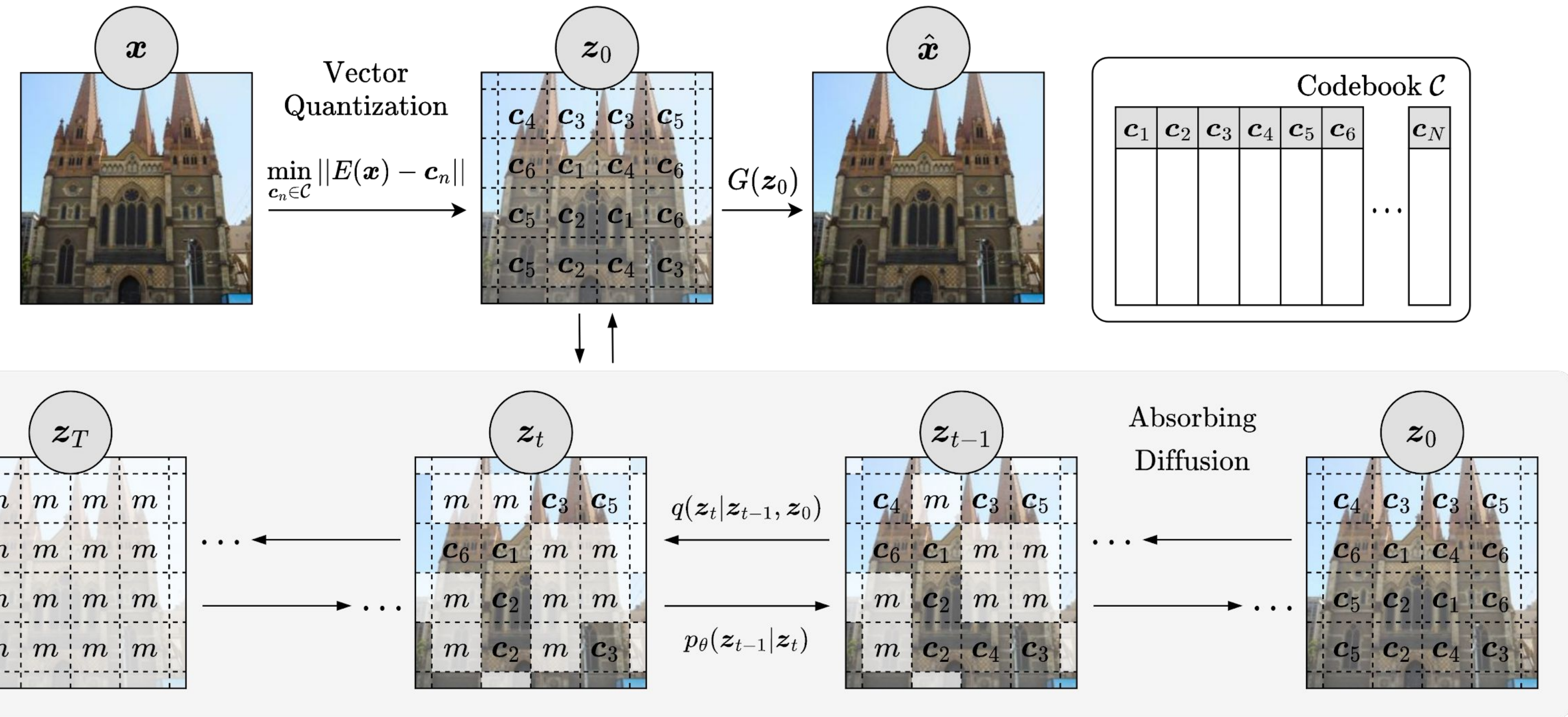
Method

Discrete latents **z** obtained using a VQ-VAE are modelled with discrete **absorbing diffusion**:

$$p_\theta(\boldsymbol{z}_{0:T}) = p_\theta(\boldsymbol{z}_T)\prod_{t=1}^{T} p_\theta(\boldsymbol{z}_{t-1}|\boldsymbol{z}_t)$$

Elements of **z** are randomly masked and an **unconstrained Transformer** learns to denoise the data by optimising a carefully reweighted ELBO designed to improve convergence rates:

$$\sum_{t=1}^{T}\frac{T-t+1}{T}\mathbb{E}_{q(\boldsymbol{z}_t|\boldsymbol{z}_0)}\Big[\sum_{[\boldsymbol{z}_t]_i=m}\log p_\theta([\boldsymbol{z}_0]_i|\boldsymbol{z}_t)\Big]$$



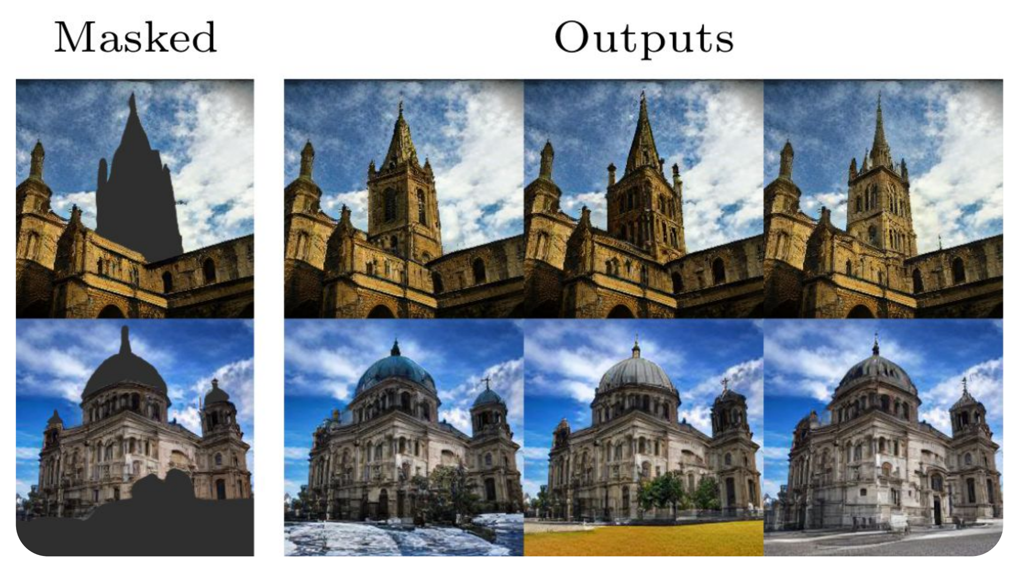
A discrete absorbing diffusion process destroys latents by slowly masking out tokens over many steps, similar to masked language models like BERT.

Sampling at Higher Resolutions

Globally consistent images at **higher resolutions** than the training data can be generated by aggregating multiple context windows:

Image Editing

Our bidirectional approach with **global context** allows internal image regions to be edited by masking those areas (highlighted in grey).



Quantitative Results

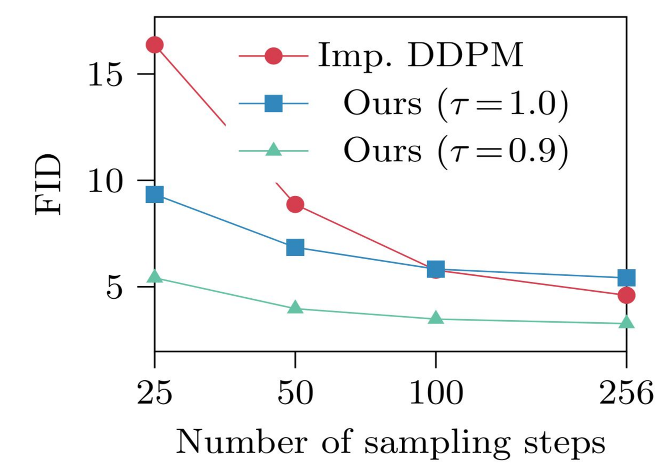
Our models achieve competitive FID scores on LSUN and FFHQ. Evaluating our models using Precision, Recall, Density and Coverage (PRDC) metrics further demonstrates **SOTA** results:

	Churches			Bedroom			FFHQ		
Model	FID ↓	D ↑	C ↑	FID ↓	D ↑	C ↑	FID ↓	D ↑	C ↑
TT	7.81	**1.08**	0.60	6.35	1.15	0.75	9.6	0.89	0.50
ImageBART	7.32	-	-	5.51	-	-	9.57	-	-
StyleGAN2	3.85	0.83	0.68	2.35	-	-	3.80	1.12	0.80
ProjGAN	**1.59**	0.65	0.64	**1.52**	0.90	0.79	**3.39**	0.98	0.77
Ours	4.07	1.07	**0.74**	3.27	**1.51**	**0.83**	6.11	**1.20**	**0.80**

Sampling Speed

Faster sampling can be achieved by predicting tokens in parallel with only small FID change:

Steps	Church	FFHQ
50	4.90	6.87
100	4.40	6.24
150	4.22	6.16
200	4.19	6.14
256	4.07	6.11



Summary

Using a discrete absorbing diffusion model parameterised by an unconstrained Transformer to model VQ-VAE representations we achieve faster sampling with higher visual quality.

Github repository with trained models at *https://samb-t.github.io/unleashing-transformers*

*Authors contributed equally