Analog Bits: Generating Discrete Data using Diffusion Models with Self-Conditioning [1]

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MVA: Generative modeling

Introduction

- State-of-the-art generative models for discrete data have limitations in terms of computation and slow generation.
- Diffusion models offer a solution to these limitations by enabling modeling of higher-dimensional data with parallel sampling steps.
- However, current diffusion models struggle to generate discrete/categorical data effectively.
- The proposed approach introduces analog bits and additional techniques to enable continuous-state diffusion models to generate high-quality discrete data.

Method - context

Introduction to Diffusion Models:

- Diffusion models learn state transitions from noise to data distribution.
- Forward transition equation: $x_t = \sqrt{\gamma(t)} \cdot x_0 + \sqrt{1 - \gamma(t)} \cdot \epsilon$.
- Diffusion models cannot directly handle discrete/categorical data.

Learning Process of Diffusion Models:

- Instead of modeling x_t to $x_{t-\Delta}$, learn $f(x_t, t)$ to predict x_0.
- Estimate $x_{t-\Delta}$ using x_t and estimated $\tilde{x}_0$.
- Training based on denoising with regression loss.

Sample Generation in Diffusion Models:

- Perform reverse state transitions from x_T to x_0.
- Apply denoising function f iteratively to estimate x_0 at each state x_t.
- Transition rules specified in DDPM [2] or DDIM [3].

Method - Analog Bits

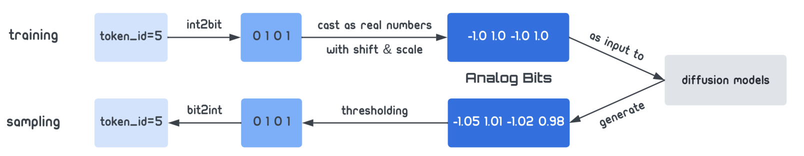

Figure 1: Bit Diffusion

- Novel approach: Representing discrete data variables using a continuous representation.
- Analog bits: Introducing real numbers trained to capture bimodal characteristics.
- Bridging the gap between continuous and discrete data representation.

- Real number values are mapped to their digit-wise binary representations in $[0,1]^d$.
- The approach of the authors : example in $\mathbb{R}^3$ of analog bits representation :

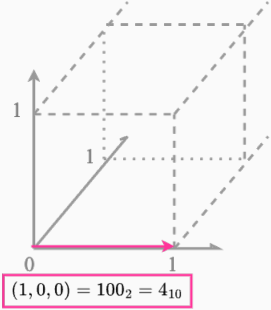

Figure 2: Representation of 4 in analog bits, values of $[0,1]^d$

Method - Analog bits

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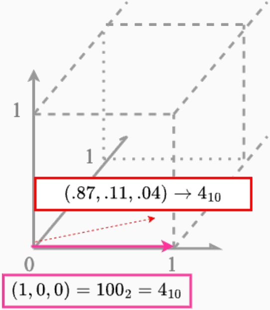

Figure 3: Representation of 4 in analog bits, values of $[0, 1]^d$

Quantization and continuous models

- Goal is for model to learn to output bimodal representation.

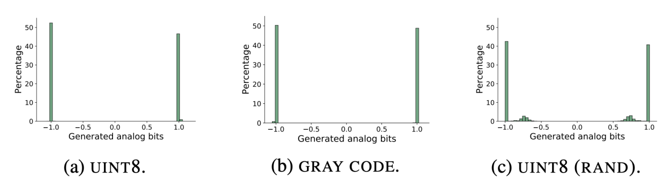

Figure 4: Histogram of the model's output before quantization

- Their continuous model behaves in an almost discrete manner.
- Otherwise, their continuous model would hardly learn due to stochastic loss feedback.

Quantization and continuous models

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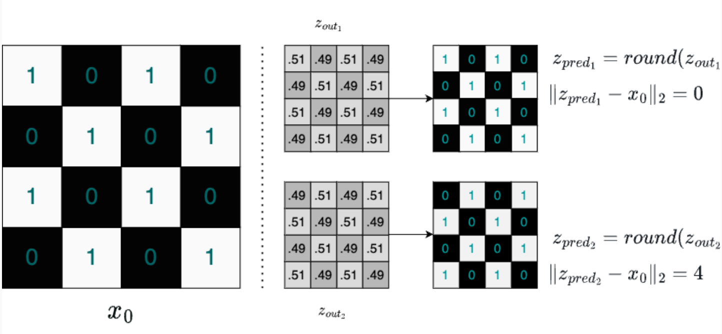


Figure 5: Opposite L_2 loss for near-indistinguishable outputs

Quantization and continuous models, other possible limits

- Loss of the semantic property of pixel space :
  - close pixels have close appearances
  - images are continuous by nature

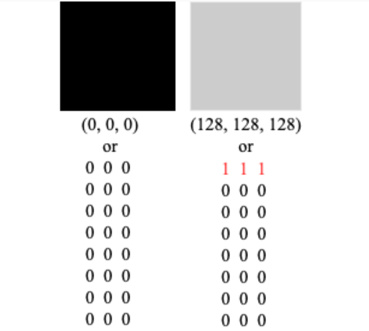


Figure 6: Example of two pixels distant in RGB space, close in analog bits space

Quantization and continuous models, other possible limits

- Loss of the semantic property of pixel space :
  - close pixels have close appearances
  - images are continuous by nature
- All dimensions of analog bits space are not equivalent in importance :

$$00000001_2 - 00000000_2 << 10000000_2 - 00000000_2$$

$$1 << 128$$

Quantization and continuous models, other possible limits

- Adressed in the paper: study of Random assignation of analog bits to the powers of 2 of the number.

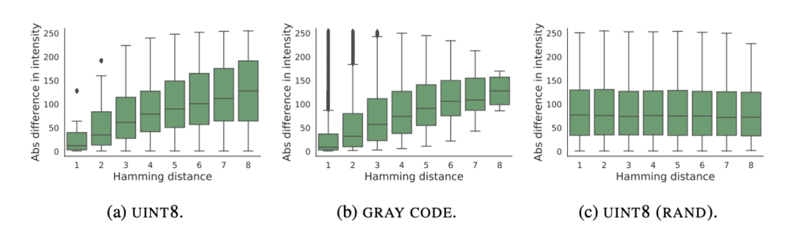
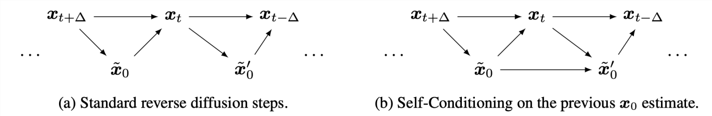


Figure 7: Study of correlation of bit values to pixel intensity

Method - Self-conditioning



- Improves diffusion models by directly conditioning the model on previously generated samples during the iterative sampling process, leading to enhanced sample quality.
- In the typical diffusion sampling process, the previous estimate of x_0 is discarded when estimating x_0 for a new time step. The implementation involves concatenating x_t with the previously estimated $\tilde{x}_0$. This incurs a negligible additional cost during sampling.
- Training the denoising function $f(x_t, \tilde{x}_0, t)$ involves making some changes to the training process. $\tilde{x}_0$ is set to 0 with a certain probability, while at other times, it is estimated as $f(x_t, 0, t)$ and used for Self-Conditioning. The estimated $\tilde{x}_0$ is not backpropagated, resulting in a minimal increase in training time (less than 25%).

Asymmetric Time Intervals

Impact of Time Step Parameter:

- Traditional symmetric time intervals used in Bit Diffusion models.
- Authors propose asymmetric time intervals to enhance sampling quality.

Asymmetric Time Intervals for Improved Sampling:

- Sampling process with $f(x_t, t_0)$, where $t_0 = t + \xi$ and ξ is a small non-negative time difference parameter.
- Demonstrated improvement in sampling quality without changing the training process.

Experiments conducted in the paper

- Datasets: CIFAR-10 [4] and IMAGENET 64x64 [5]
- Evaluation metric: Fréchet Inception Distance (FID) [**?**]
- Discrete image generation: we consider three discrete encoding for sub-pixels: UINT8, GRAY CODE, and UINT8 (RAND).
  Architecture: U-Net [6]
  - CIFAR-10 [4]: Single channel dimension of 256, 3 stages (with 3 residual blocks). 51M parameters. Dropout of 0.3
  - IMAGENET [5]: base channel dimension of 192, multiplied by 1,2,3,4 in 4 stages and 3 residual blocks per stage. 240M parameters
- Image Captioning: Tokenisation using a vocabulary of size 32K. And then encode each token using 15 analog bits. Architecture:
  - Pre-trained image encoder using the object detection task.
  - Randomly initialized 6-layer Transformer decoder with 512 dimension per layer.
- Adam Optimizer [7]

Fréchet Inception Distance

- **Fréchet Distance** measure the **discrepancy** or **dissimilarity**
- Use of **InceptionV3** hidden features as **content** and **style** extractor
- **FID**: Fréchet Distance with the use of hidden features extracted
- Lower FID values indicate better image quality and similarity

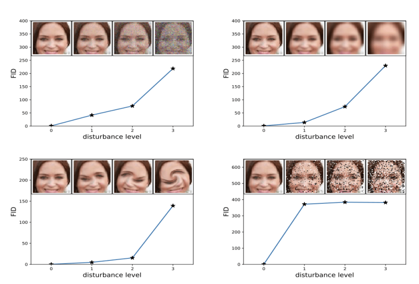


Figure 8: Example of How Increased Distortion of an Image Correlates with High FID Score.

Related work and importance of the paper

- **Autoregressive Models** work well on discrete image generation for small image resolution but very challenging to scale these approaches to data with large dimensions.
- Advantages of Continuous **Diffusion Models** (for discrete data) over 'standard' diffusion models using discrete state space: they are more flexible. There is also the benefit of Binary Encoding with Analog Bits (decoding easier and more robust).
- Limitations of **Normalizing Flows** [8] for Categorical Data: strict invertible restrictions on network architecture, thus limiting their capacity.
- Performance Comparison with **VAE** [9] and **GAN** [10]: not explored yet in the paper
- self-conditioning shares similarities with Self-Modulation in **GANs** [10] and **SUNDAE** [11] Techniques
- **Basically, unique work that incorporates Self-Conditioning and Asymmetric Time Intervals**

Our reproduction of the experiments - settings

- CIFAR-10 dataset: for its small size
- U-Net: 4 stages, 3 residual blocks, and 32 channels dimension for 9.1M params
- Training set up:
  - Adam optimizer with Exponential Moving Average
  - Learning rate: 10^{-4}
  - 100K steps (24 hours)
  - 64 batch size
  - 16-mixed precision
- FID score on CIFAR training set and 5K generated samples

Our reproduction of the experiments - results

Figure 9: Two samples generated with a U-Net BitDiffusion trained using self-conditioning on Cifar-10 after 70,000+ epochs

- Good visual results while training only 100K steps
- Classes like frogs, dogs and horses can be guessed sometimes.
- Not too much diversity in generated samples

Our reproduction of the experiments - results

- Training of BitDiffusion with self-conditionning and without

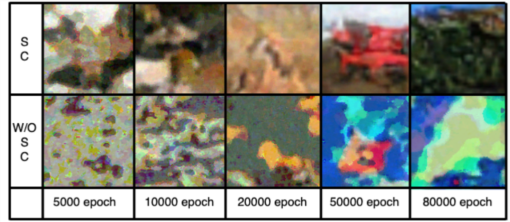


Figure 10: Comparison between images generated by our model with and without Self-Conditioning (SC), after respectively 5,000, 10,000, 20,000, 50,000 and 70,000 epochs.

Our reproduction of the experiments - results

Model type	SC	No SC
FID score	186.3	394.9

Table 1: FID score on Cifar-10 test set using BitDiffusion with and without self-conditionning

Training setup comparison with the paper:

- **Hyperparameters and training setup:** 100K vs 1.5M steps
- **Sample size to evaluate FID:** 5K vs 50K
- **Model complexity:** 9.1M vs 51M parameters

Conclusion

- Multiple concurrent contributions in this paper:
  - **Analog bits**: a technique to cast discrete data to higher-dimensional continuous space.
  - **Self-conditioning**: a technique to better guide generation at training and inference time.
  - **Asymmetric time intervals**: a technique impacting the t time parameters at sampling time, reducing the amount of artefacts.

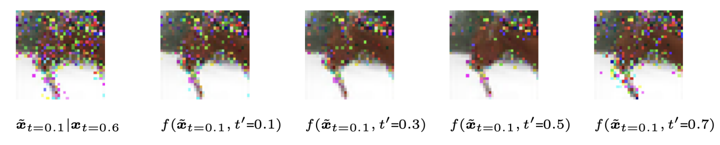


Figure 11: Improvement of their intermediate generation results using asymmetric time intervals at sampling time

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