

Flow++: Improving Flow-Based Generative Models with Variational Dequantization and Architecture Design

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Overview

- Goal: likelihood-based model with
 - Fast sampling and training
 - Good samples and density estimation performance
- Our strategy: improve flow models
 - Uniform dequantization -> variational dequantization
 - Affine coupling -> mixture of logistics coupling
 - Convolutions -> convolutions + self-attention

Continuous flows for discrete data

- A problem arises when fitting continuous density models to discrete data: degeneracy
 - When the data are 3-bit pixel values, $\mathbf{x} \in \{0, 1, 2, \dots, 255\}$
 - What density does a model assign to values between bins like 0.4, 0.42...?
- Correct semantics: we want the integral of probability density within a discrete interval to approximate discrete probability mass

$$P_{\text{model}}(\mathbf{x}) := \int_{[0,1)^D} p_{\text{model}}(\mathbf{x} + \mathbf{u}) d\mathbf{u}$$

Continuous flows for discrete data

- Solution: **Dequantization**. Add noise to data.
 - $\mathbf{x} \in \{0, 1, 2, \dots, 255\}$
 - We draw noise \mathbf{u} uniformly from $[0, 1)^D$

$$\begin{aligned}\mathbb{E}_{\mathbf{y} \sim p_{\text{data}}} [\log p_{\text{model}}(\mathbf{y})] &= \sum_{\mathbf{x}} P_{\text{data}}(\mathbf{x}) \int_{[0,1)^D} \log p_{\text{model}}(\mathbf{x} + \mathbf{u}) d\mathbf{u} \\ &\leq \sum_{\mathbf{x}} P_{\text{data}}(\mathbf{x}) \log \int_{[0,1)^D} p_{\text{model}}(\mathbf{x} + \mathbf{u}) d\mathbf{u} \\ &= \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} [\log P_{\text{model}}(\mathbf{x})]\end{aligned}$$

[Theis, Oord, Bethge, 2016]

Variational Dequantization

- **Variational Dequantization.** Add a learnable noise q to data.

$$\begin{aligned}\mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} [\log P_{\text{model}}(\mathbf{x})] &= \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} \left[\log \int_{[0,1]^D} q(\mathbf{u}|\mathbf{x}) \frac{p_{\text{model}}(\mathbf{x} + \mathbf{u})}{q(\mathbf{u}|\mathbf{x})} d\mathbf{u} \right] \\ &\geq \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} \left[\int_{[0,1]^D} q(\mathbf{u}|\mathbf{x}) \log \frac{p_{\text{model}}(\mathbf{x} + \mathbf{u})}{q(\mathbf{u}|\mathbf{x})} d\mathbf{u} \right] \\ &= \mathbb{E}_{\mathbf{x} \sim P_{\text{data}}} \mathbb{E}_{\mathbf{u} \sim q(\cdot|\mathbf{x})} \left[\log \frac{p_{\text{model}}(\mathbf{x} + \mathbf{u})}{q(\mathbf{u}|\mathbf{x})} \right]\end{aligned}$$

[Ho et al., 2019]

Coupling layers

RealNVP

$$\mathbf{y}_1 = \mathbf{x}_1$$

$$\mathbf{y}_2 = \mathbf{x}_2 \cdot \exp(\mathbf{a}_\theta(\mathbf{x}_1)) + \mathbf{b}_\theta(\mathbf{x}_1)$$

convolutions

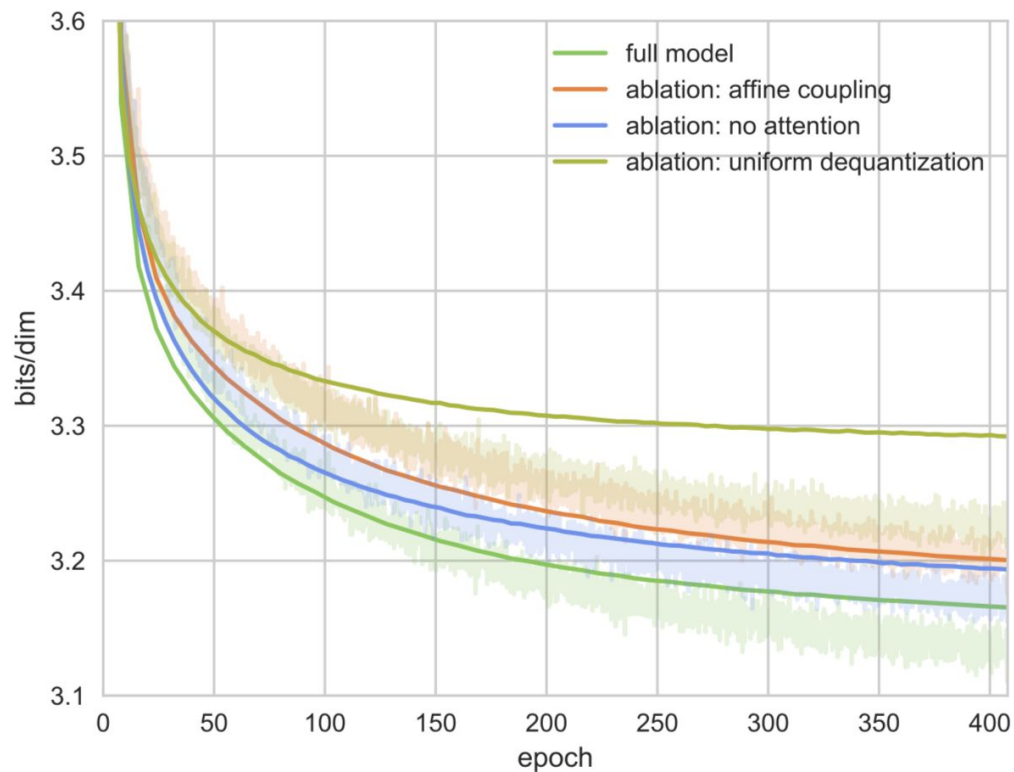
Ours: logistic mixture CDF

$$\mathbf{y}_1 = \mathbf{x}_1$$

$$\mathbf{y}_2 = \sigma^{-1}(\text{MixLogCDF}(\mathbf{x}_2; \pi_\theta(\mathbf{x}_1), \mu_\theta(\mathbf{x}_1), \mathbf{s}_\theta(\mathbf{x}_1))) \cdot \exp(\mathbf{a}_\theta(\mathbf{x}_1)) + \mathbf{b}_\theta(\mathbf{x}_1)$$

convolutions & self-attention

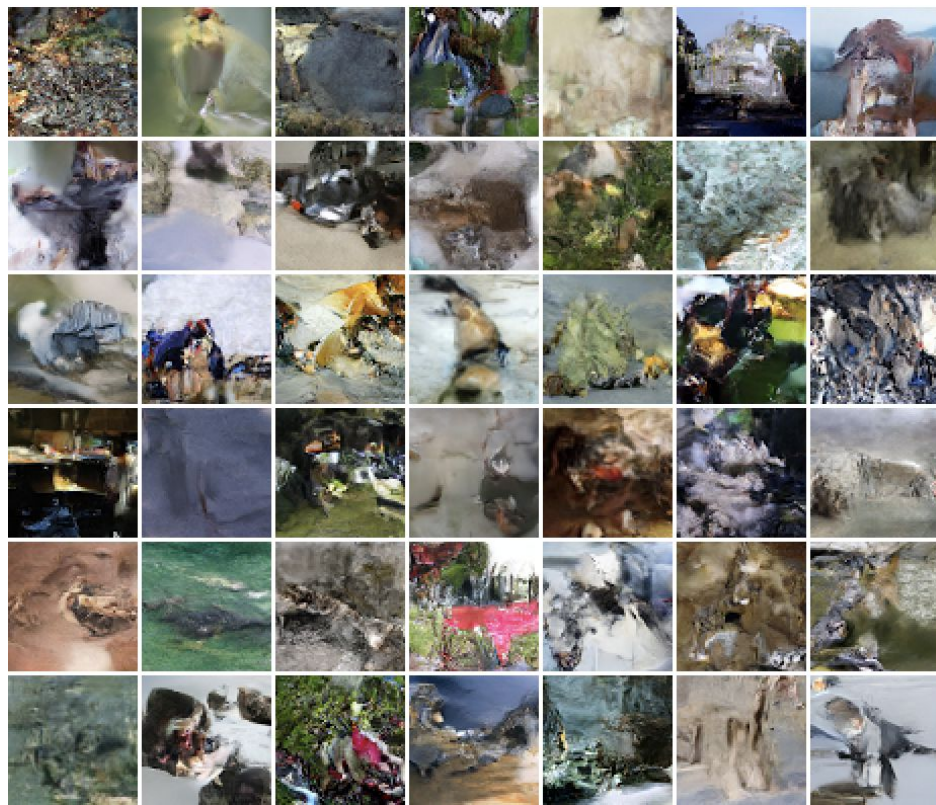
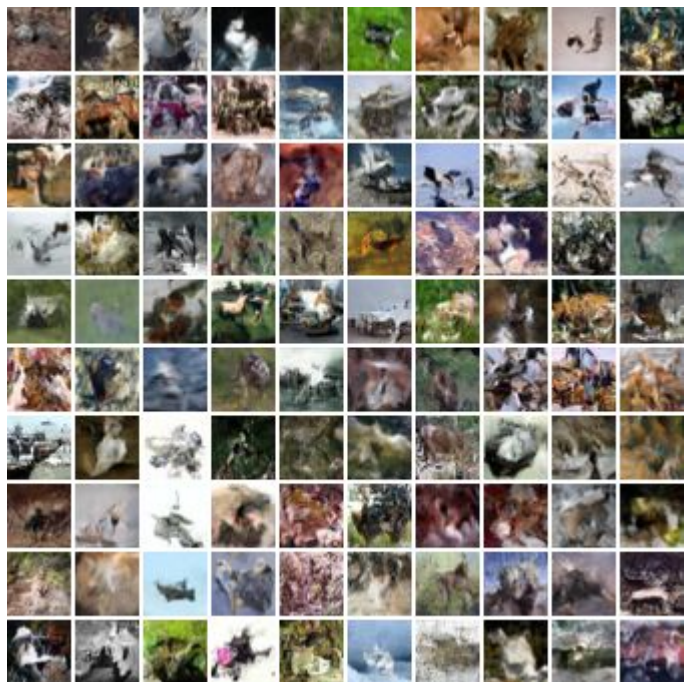
Ablation on CIFAR



Results

Model family	Model	CIFAR10	ImageNet 32x32	ImageNet 64x64
Non-autoregressive	RealNVP (Dinh et al., 2016)	3.49	4.28	–
	Glow (Kingma & Dhariwal, 2018)	3.35	4.09	3.81
	IAF-VAE (Kingma et al., 2016)	3.11	–	–
	Flow++ (ours)	3.08	3.86	3.69
Autoregressive	Multiscale PixelCNN (Reed et al., 2017)	–	3.95	3.70
	PixelCNN (van den Oord et al., 2016b)	3.14	–	–
	PixelRNN (van den Oord et al., 2016b)	3.00	3.86	3.63
	Gated PixelCNN (van den Oord et al., 2016c)	3.03	3.83	3.57
	PixelCNN++ (Salimans et al., 2017)	2.92	–	–
	Image Transformer (Parmar et al., 2018)	2.90	3.77	–
	PixelSNAIL (Chen et al., 2017)	2.85	3.80	3.52

Samples (CIFAR10, ImageNet 64x64)



Samples (CelebA 5-bit)



- Slides adapted from Berkeley CS294-158 Deep Unsupervised Learning class:

<https://sites.google.com/view/berkeley-cs294-158-sp19/home>

- Want to learn more about foundation of Deep Generative Models & Self-Supervised learning methods?
- All lecture videos are available on youtube, featuring guest speakers: Ilya Sutskever, Alyosha Efros, Alec Radford, Aaron van den Oord