

Vector Quantized VAE for LArCV Images

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Neural Discrete Representation Learning: <https://arxiv.org/abs/1711.00937>

PixelCNN: <https://arxiv.org/abs/1606.05328>

Why Develop Generative Models?

- Fast simulation (NN's are parallelizable)
- Learn useful representations via compression (200 Mb in 80Kb)
- Conditional generation (“Give me a picture of a...”)
- Anomaly detection ***

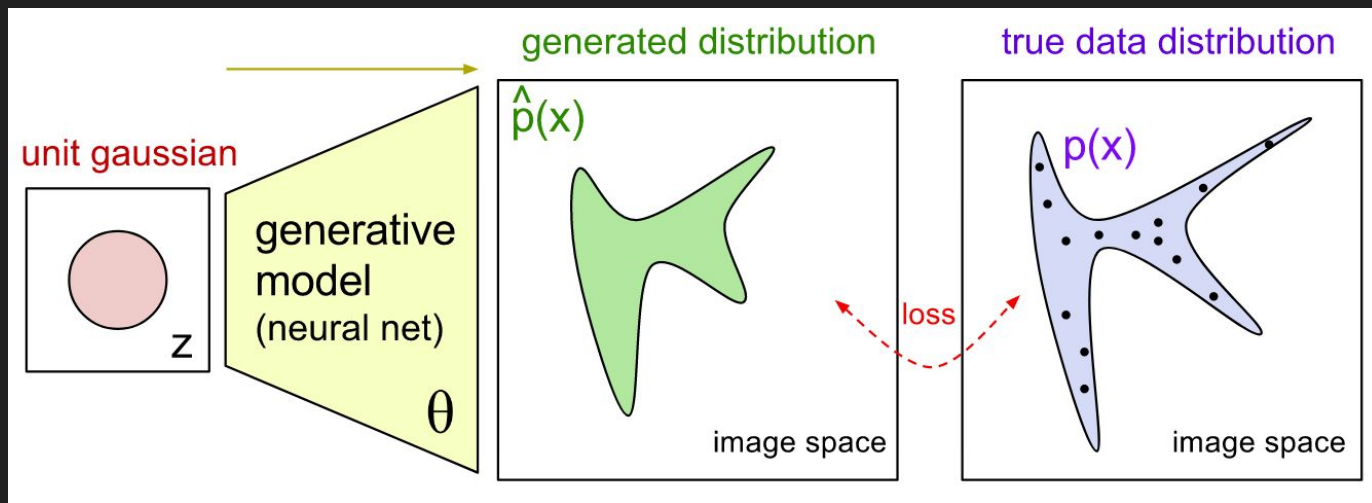


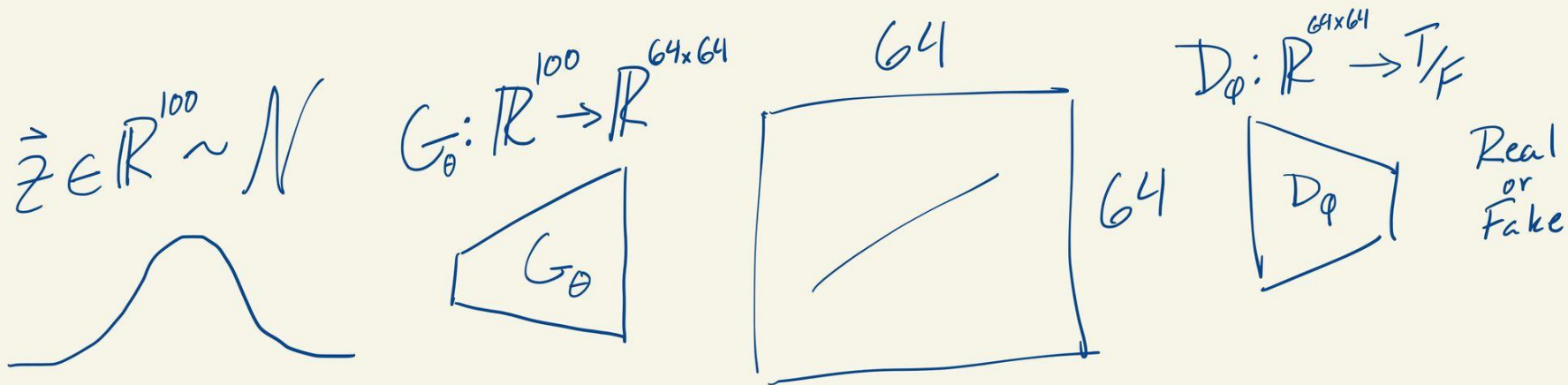
Figure:
[4] OpenAI

Generation Method: GAN

- Generative Adversarial Networks

Pros:
Discriminator training
encourages realism

Cons:
Training is
difficult



Generation Method: Autoregressive

$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_{i-1}, x_{i-2}, \dots, x_1)$$

Pros:
Can model more
complex dependencies

Cons:
Slow

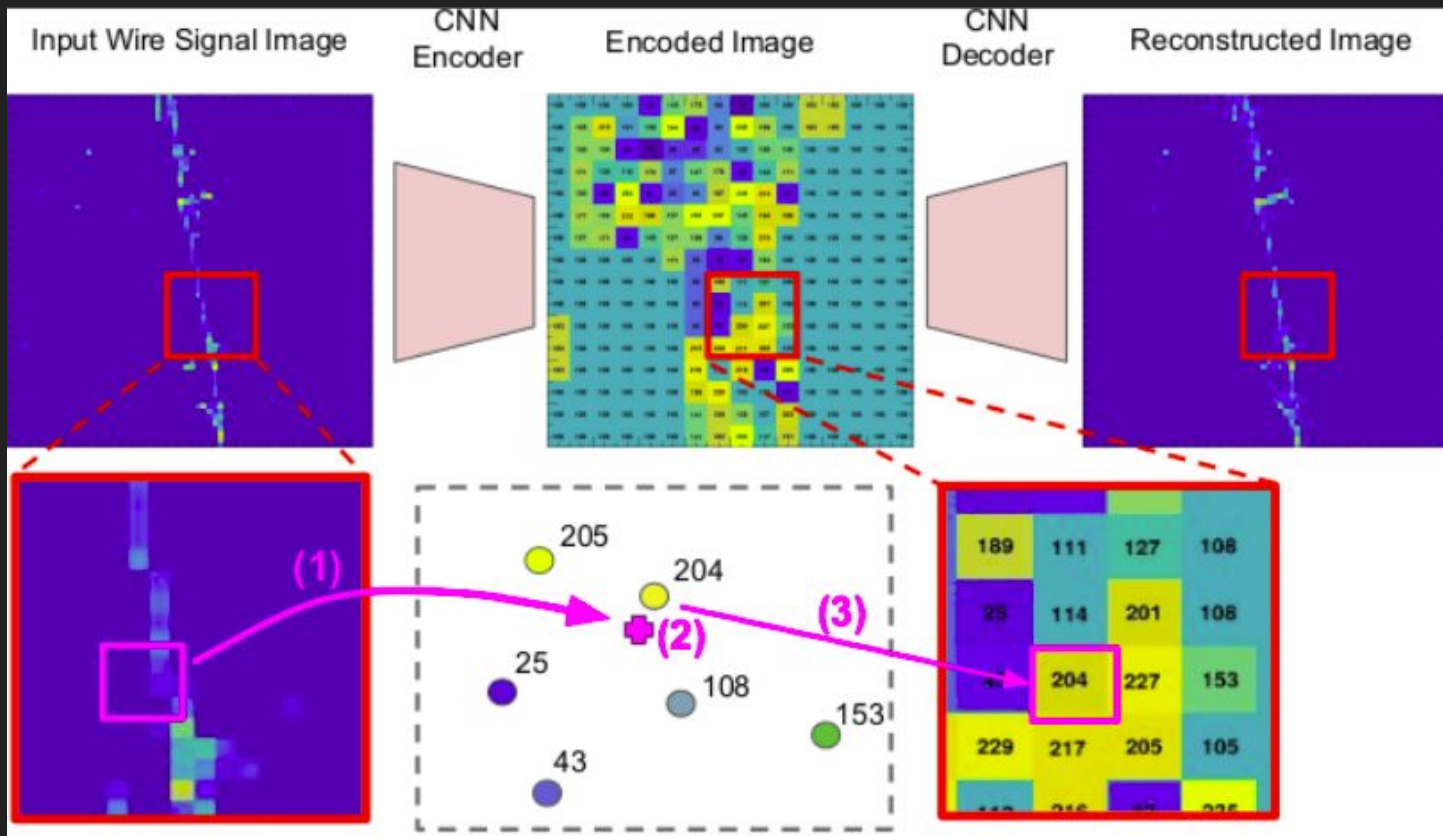
3-Pixel Image

$P(x_1)$	$P(x_2 x_1)P(x_1)$	$P(x_3 x_2)P(x_2 x_1)P(x_1)$
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Generation Method: VQVAE

- Pros:
- Feature selection
 - Recurrence in feature space

- Cons:
- Still recurrent



Vector Quantization

- Initialize code vectors randomly
- Cluster inputs around codes
- Average each cluster to get new codes

$$V_i = \{ \mathbf{x} : \|\mathbf{x} - \mathbf{y}_i\| \leq \|\mathbf{x} - \mathbf{y}_j\|, \forall j \neq i \}$$

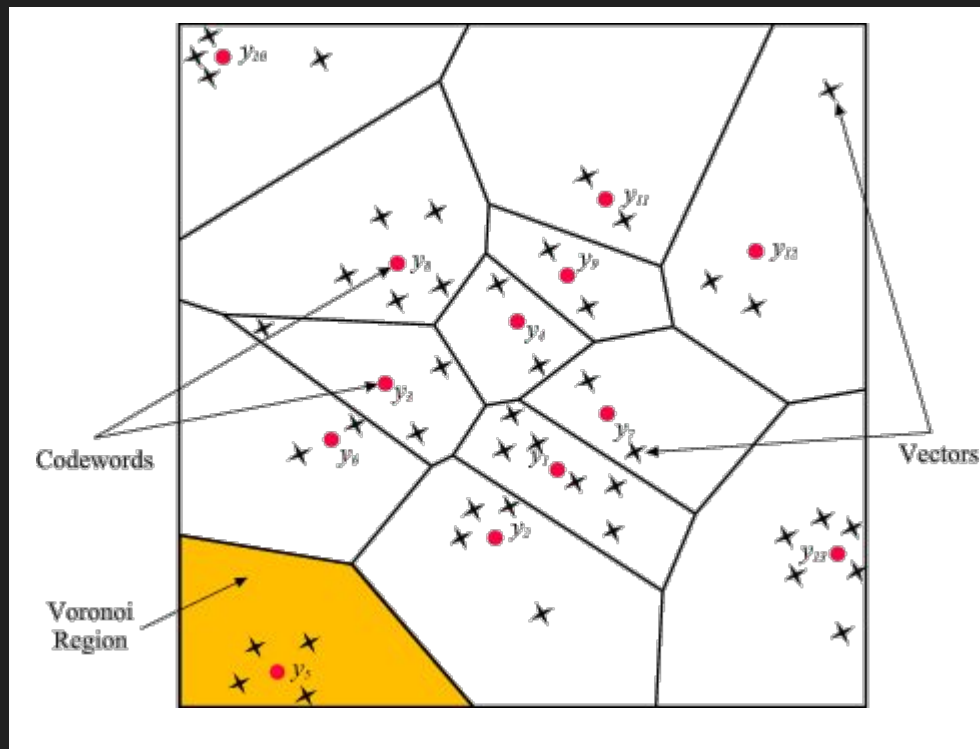


Figure: [3] Qasem M.

VQ for VQVAE

sg[] stops gradient flow

$$L_{\text{code}} = ||\text{sg}[z_e(\mathbf{x})] - z_q(\mathbf{x})||^2$$

$$L_{\text{commit}} = \beta ||z_e(\mathbf{x}) - \text{sg}[z_q(\mathbf{x})]||^2$$

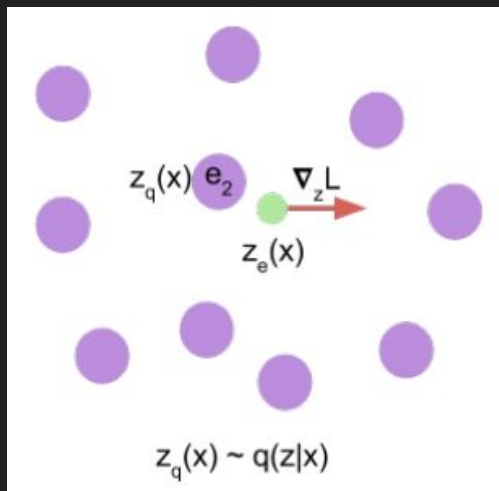
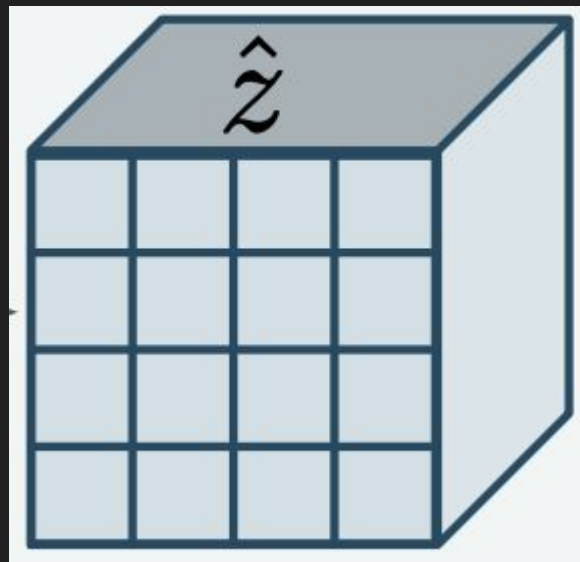


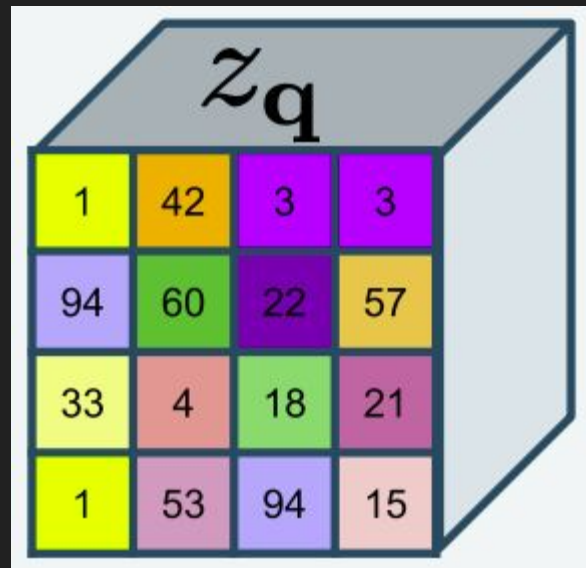
Figure: [1] Van der Oord et al.
(arXiv:arXiv:1606.05328)

Pixelwise Quantization

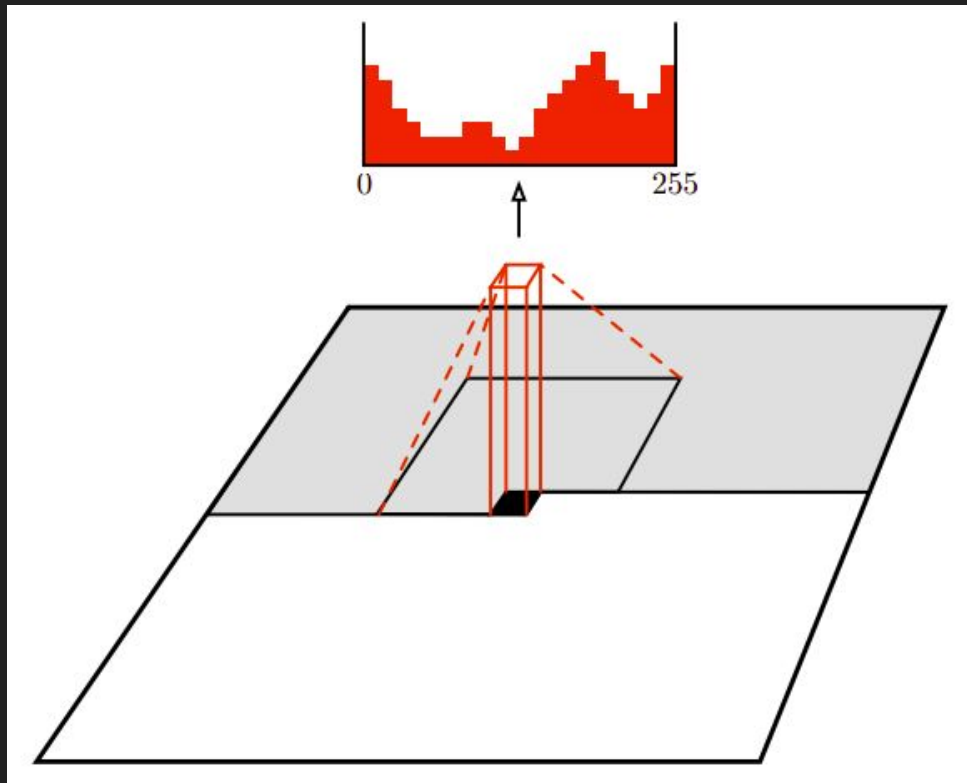


$$\arg \min_{z_i \in \mathcal{Z}} \|\hat{z} - z_i\|$$

quantization



PixelCNN

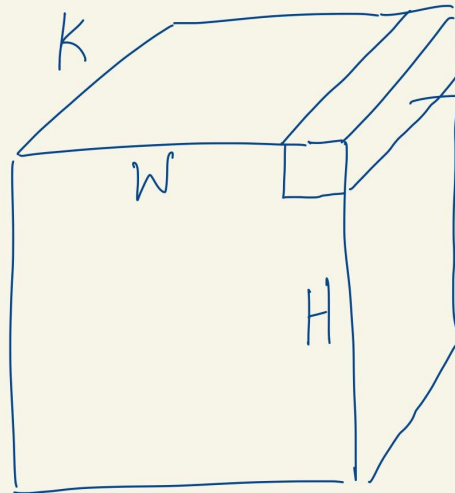


$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_{i-1}, x_{i-2}, \dots, x_1)$$

Figure: [1] Van der Oord et al.
(arXiv:arXiv:1606.05328)

Modeling the Distribution

	a	b	c	d	e
	f	g*	h	i	j
	k	l	m	n	o
	p	q	r	s	t
	u	v	w	x*	y



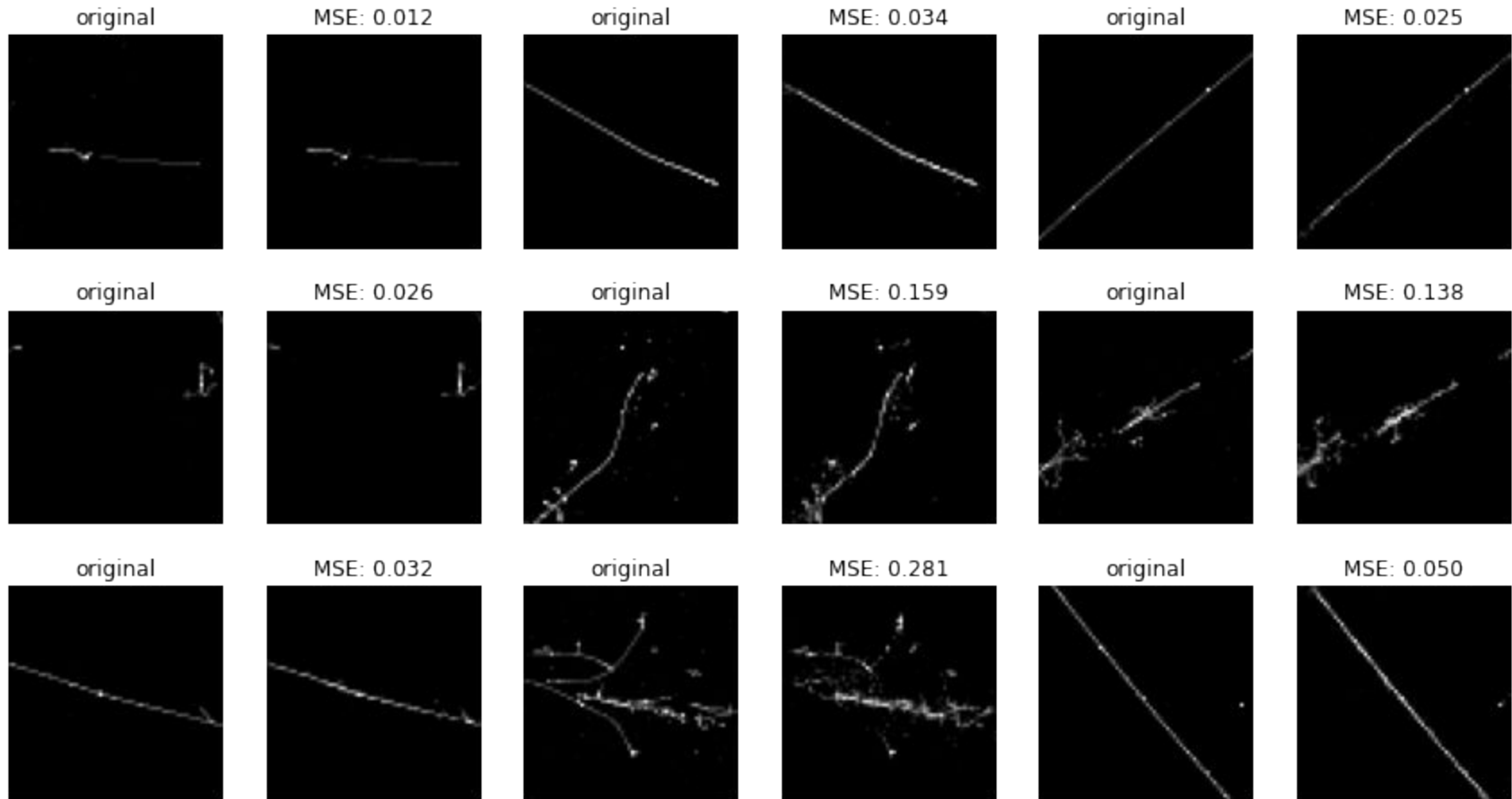
$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

$$i = 1, \dots, K$$

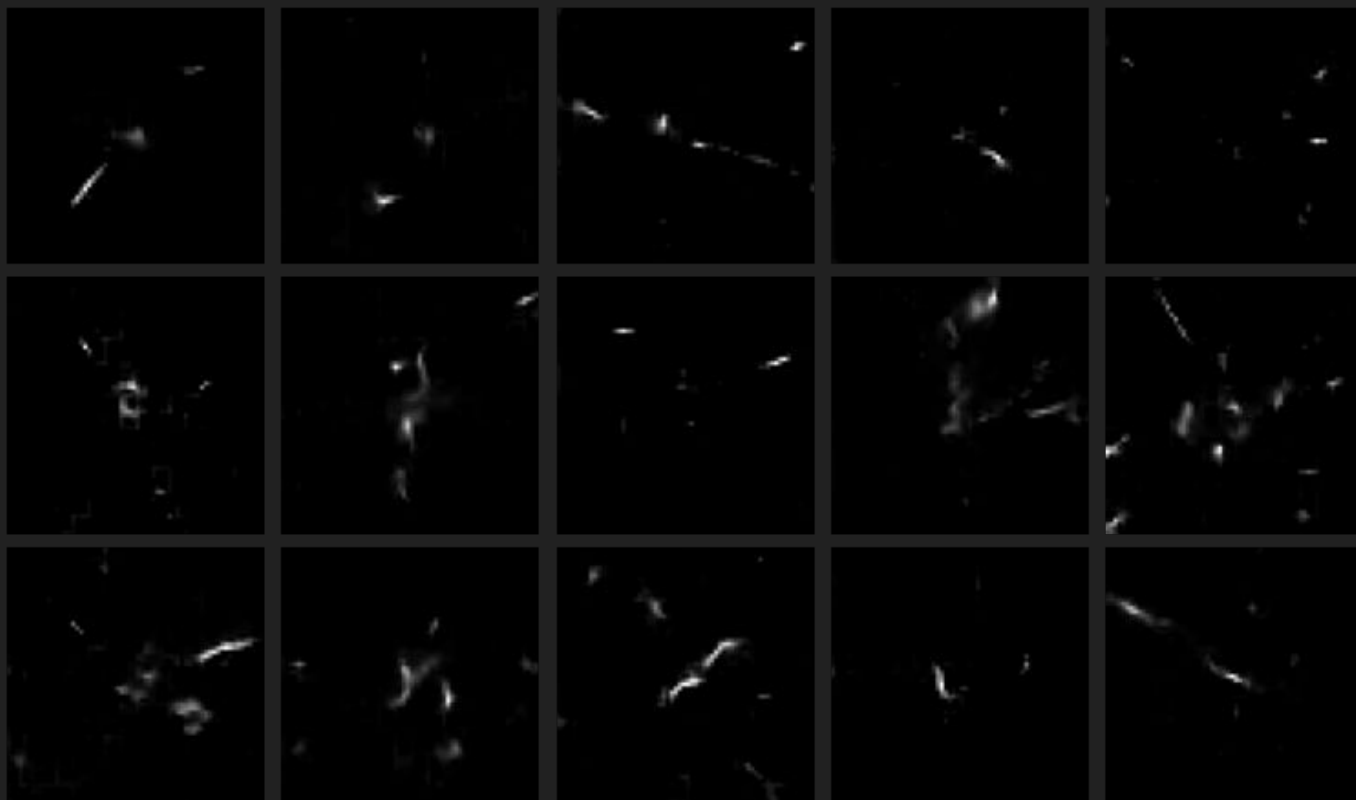
$$\vec{y} = \tanh(W_{k,f} * \vec{X}) \odot \sigma(W_{k,g} * \vec{X})$$

*: convolution, \odot : element-wise product

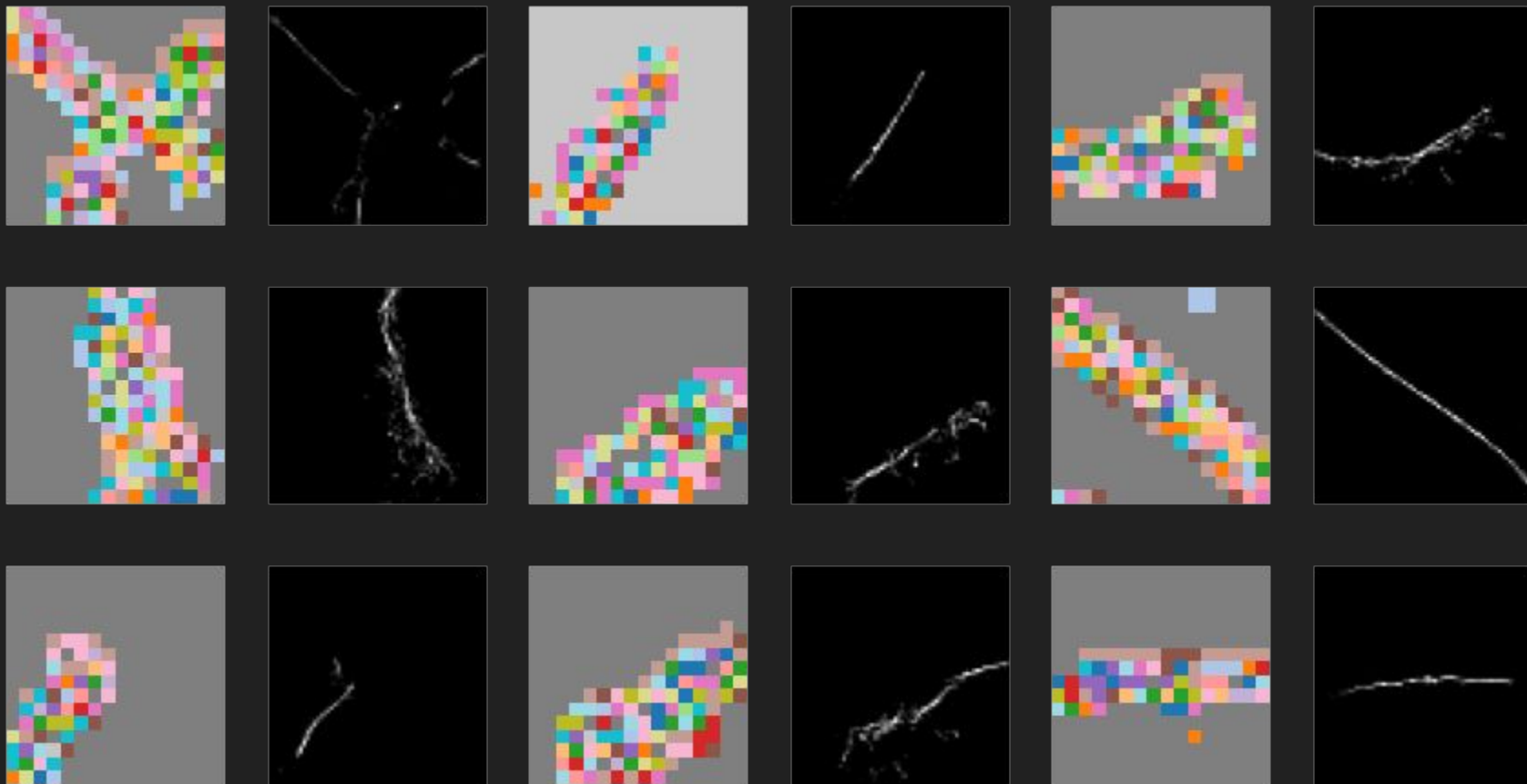
VQ-VAE Reconstructions | Avg. Test Loss: 0.071



VAE Samples

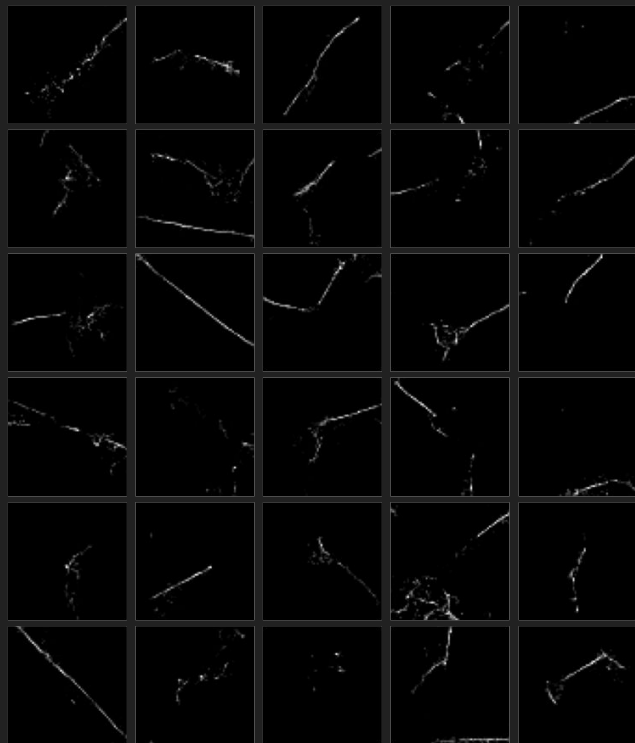


VQVAE Samples

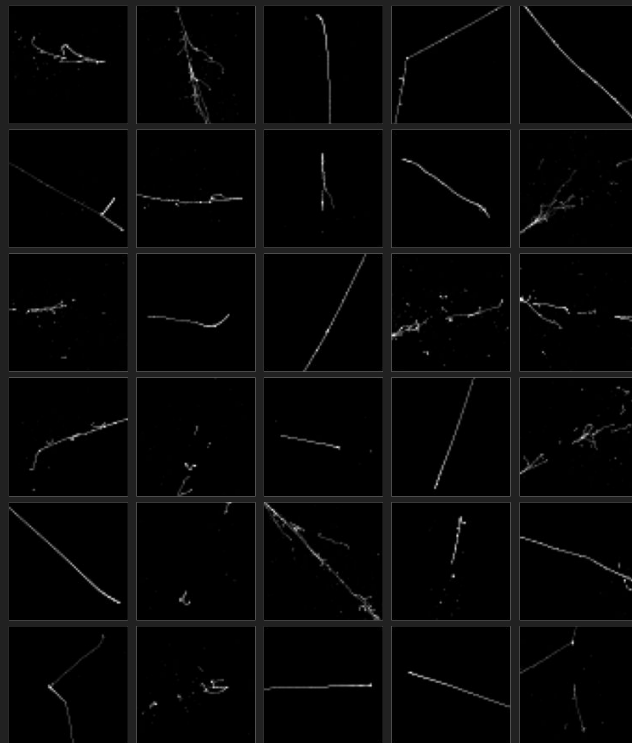


Generated vs Training

Generated Images



Training Images



Future Work

- Evaluation metrics
- Conditional generation
- VQVAE-2 and hierarchical representations
- PixelCNN -> Transformer
- Speed
- Discriminator

References

1. Conditional Image Generation with PixelCNN Decoders, Van der Oord et al. (arXiv:1606.05328)
2. Neural Discrete Representation Learning, Van der Oord et al. (arXiv:1711.00937)
3. Qasem, Mohamed. Vector Quantization.
<http://www.mqasem.net/vectorquantization/vq.html>.
4. “Generative Models.” OpenAI, 16 June 2016,
<https://openai.com/blog/generative-models/>.

Hyperparameters

VQ-VAE Hyperparameters (Decoder Filters are Reversed)

Batch Size	Epochs	Learning Rate (Adam)	Layer Filters (Enc.)	K	D	β
512	50	3e-4	[16, 32, 8]	256	8	1

PixelCNN Hyperparameters

Batch Size	Epochs	Learning Rate (Adam)	Gated Blocks	Block Width
512	50	1e-3	6	256

Blindspot

