Bidirectional
Generative
Adversarial
Networks

BiGAN

SMARCLE 신도현

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ADVERSARIAL FEATURE LEARNING

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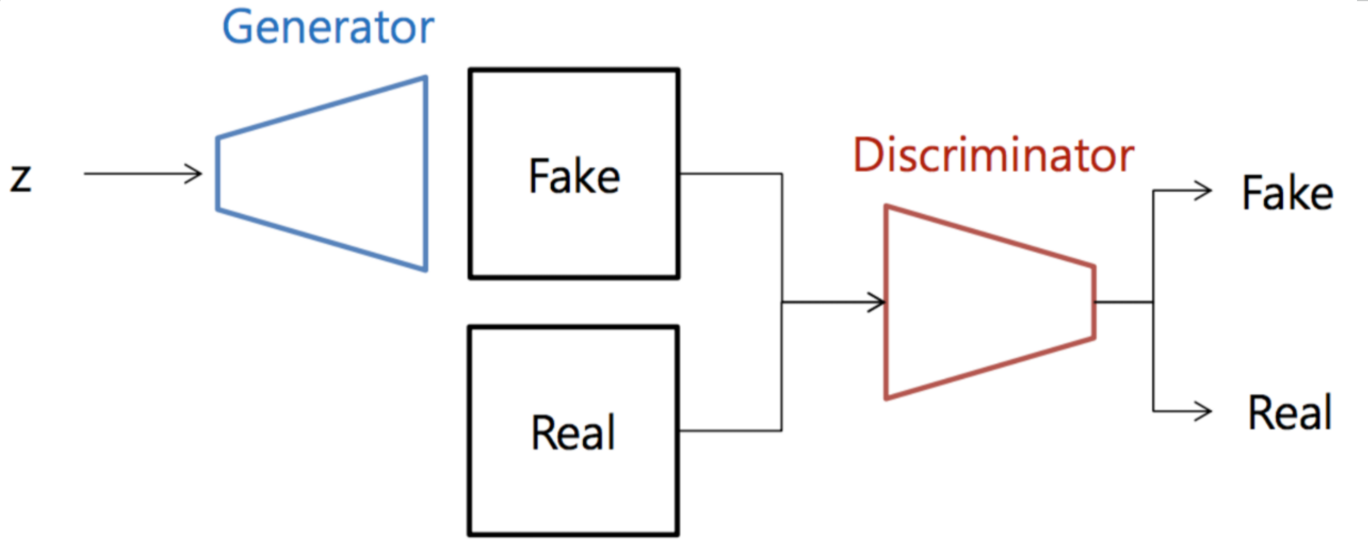
1. BiGAN ?

ABSTRACT

The ability of the Generative Adversarial Networks (GANs) framework to learn generative models mapping from simple latent distributions to arbitrarily complex data distributions has been demonstrated empirically, with compelling results showing that the latent space of such generators captures semantic variation in the data distribution. Intuitively, models trained to predict these semantic latent representations given data may serve as useful feature representations for auxiliary problems where semantics are relevant. However, in their existing form, GANs have no means of learning the inverse mapping – projecting data back into the latent space. We propose Bidirectional Generative Adversarial Networks (BiGANs) as a means of learning this inverse mapping, and demonstrate that the resulting learned feature representation is useful for auxiliary supervised discrimination tasks, competitive with contemporary approaches to unsupervised and self-supervised feature learning.

2. GAN vs BiGAN



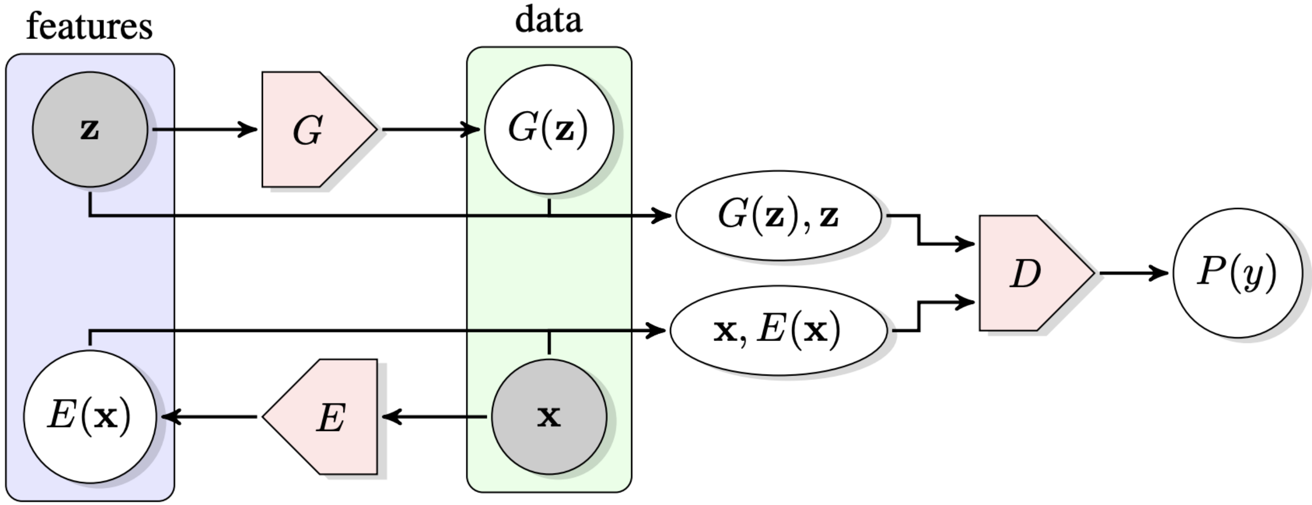
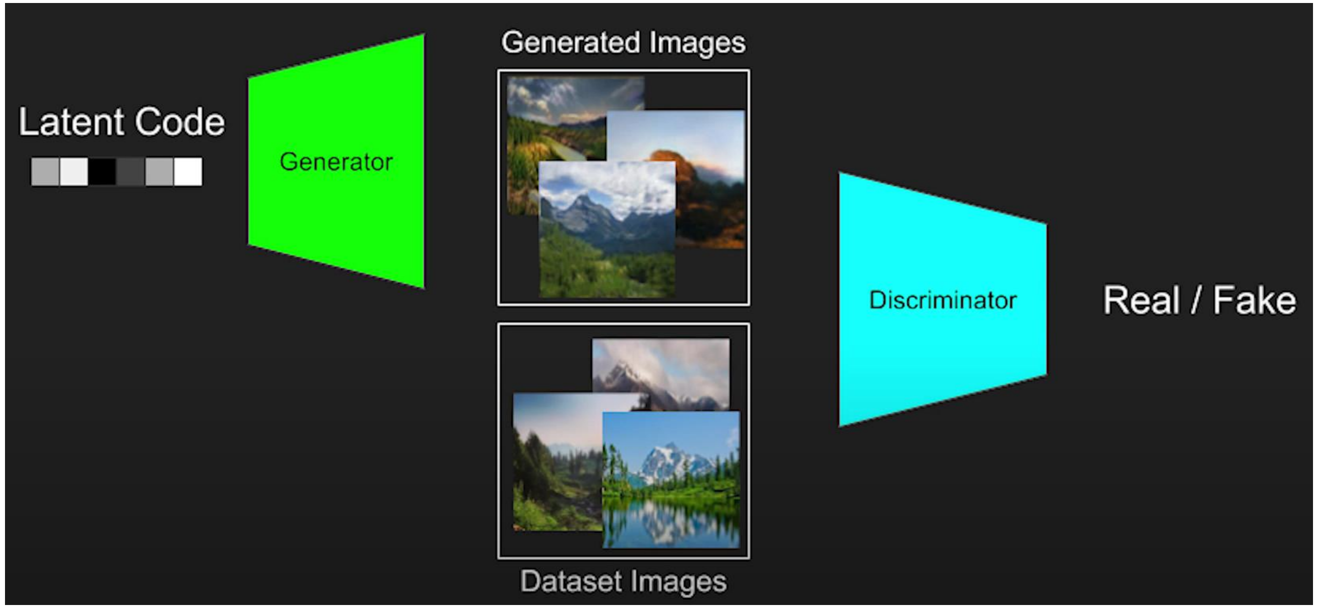


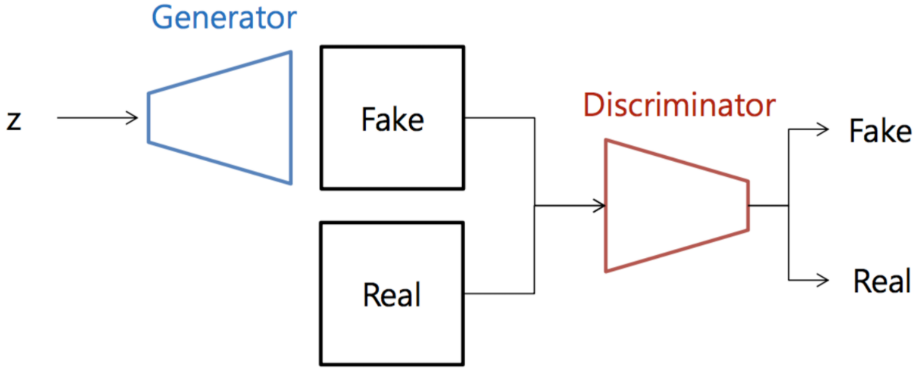
Figure 1: The structure of Bidirectional Generative Adversarial Networks (BiGAN).

Which is more similar to the middle photo?

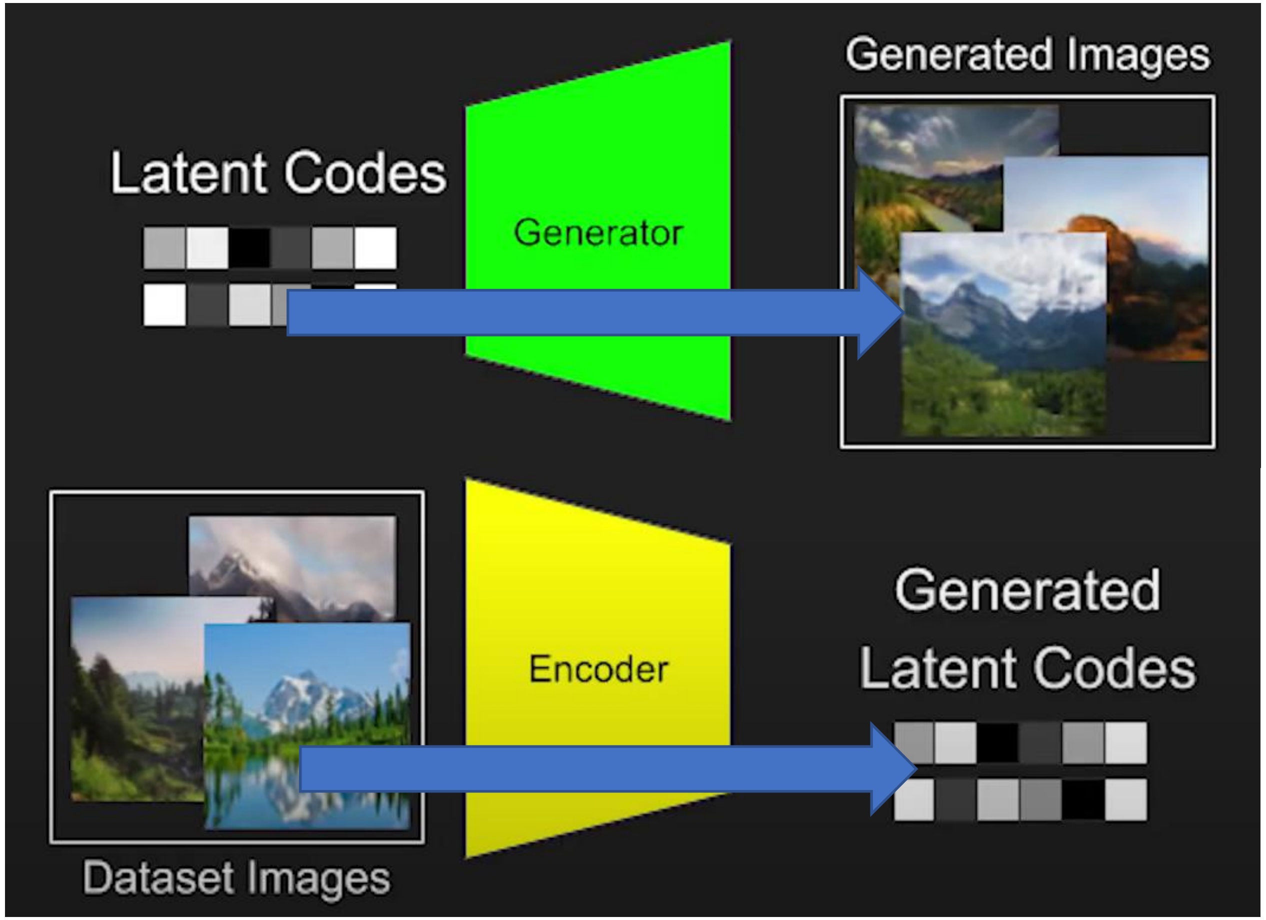
Which is more similar to the middle photo?

GAN


Latent Code
Generator
Generated Images
Discriminator
Real / Fake
Dataset Images


Generator
z
Fake
Real
Discriminator
Fake
Real

BiGAN



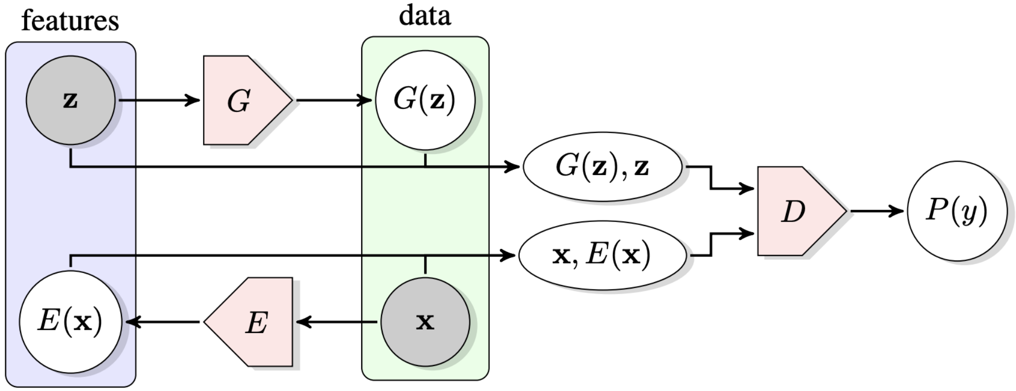
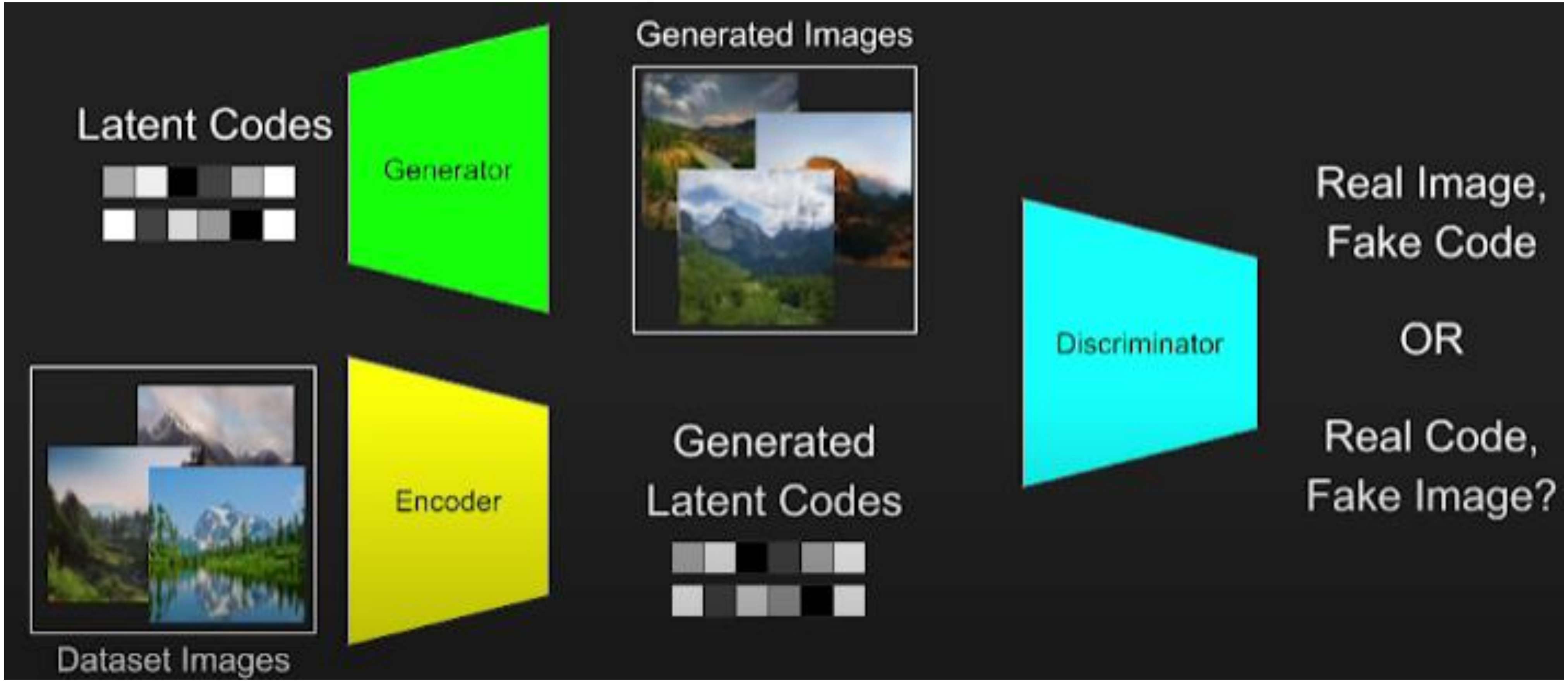


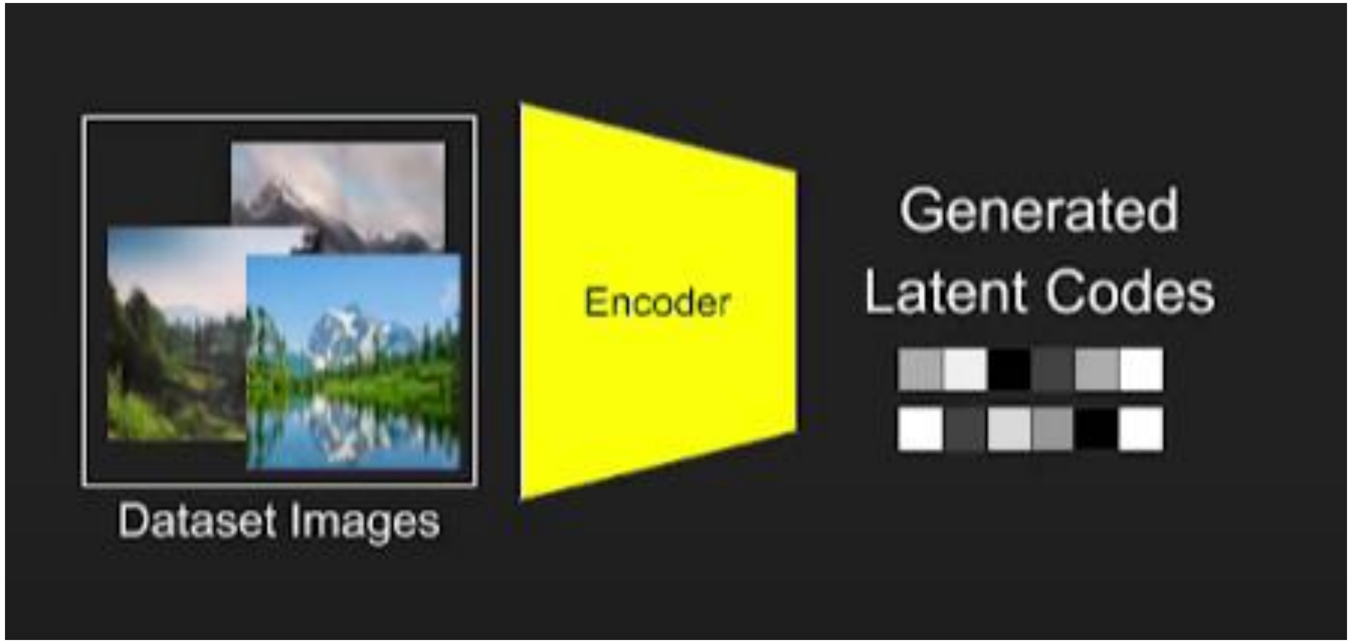
Figure 1: The structure of Bidirectional Generative Adversarial Networks (BiGAN).

BiGAN



Latent Codes
Generator
Generated Images
Dataset Images
Encoder
Generated
Latent Codes
Discriminator
Real Image,
Fake Code
OR
Real Code,
Fake Image?

Feature learning Achieve



BiGANs are a robust and highly generic approach to unsupervised feature learning, making no assumptions about the structure or type of data to which they are applied, as our theoretical results will demonstrate. Our empirical studies will show that despite their generality, BiGANs are competitive with contemporary approaches to self-supervised and weakly supervised feature learning designed specifically for a notoriously complex data distribution – natural images.

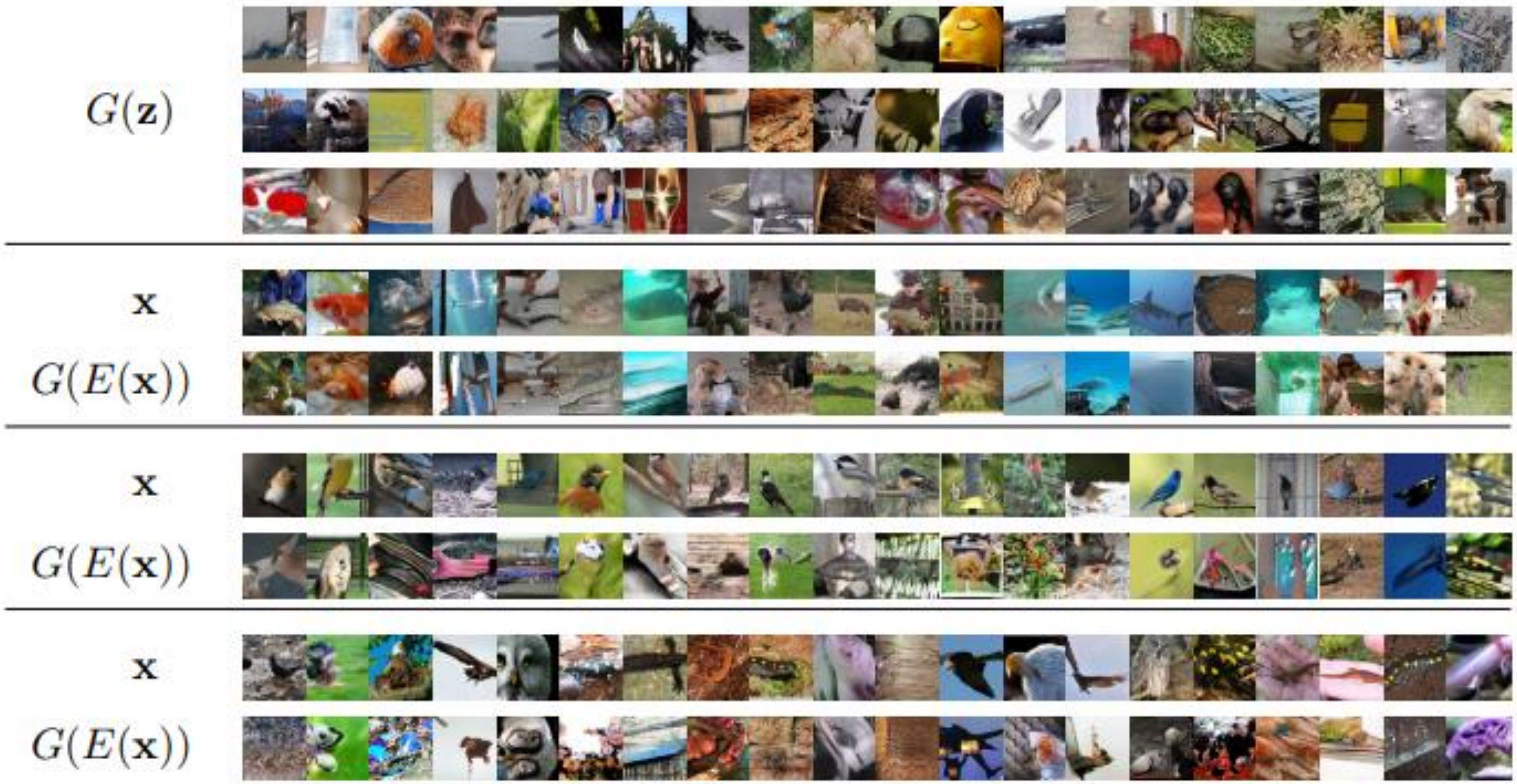


Figure 4: Qualitative results for ImageNet BiGAN training, including generator samples $G(\mathbf{z})$, real data $\mathbf{x}$, and corresponding reconstructions $G(E(\mathbf{x}))$.

Accuracy

	conv1	conv2	conv3	conv4	conv5
Random (Noroozi & Favaro, 2016)	48.5	41.0	34.8	27.1	12.0
Wang & Gupta (2015)	51.8	46.9	42.8	38.8	29.8
Doersch et al. (2015)	53.1	47.6	48.7	**45.6**	30.4
Noroozi & Favaro (2016)*	57.1	56.0	52.4	48.3	38.1
BiGAN (ours)	**56.2**	**54.4**	**49.4**	43.9	33.3
BiGAN, 112 $\times$ 112 E (ours)	55.3	53.2	49.3	44.4	**34.8**

- ImageNet LSVRC(Russakovsky et al., 2015) 검증 세트의 분류 정확도(%)

Thank you