Generative Models p.2

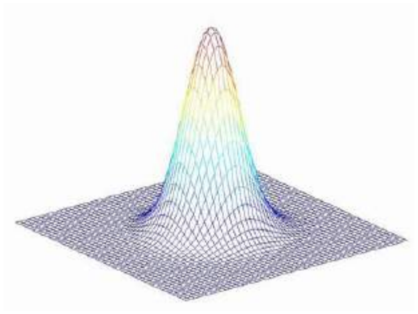
Outline

- Generative Latent Optimization Model (GLO)
- Autoencoders + DeepFake
- Variational Autoencoders (VAE)
- Genarative Adversarial Networks (GAN)

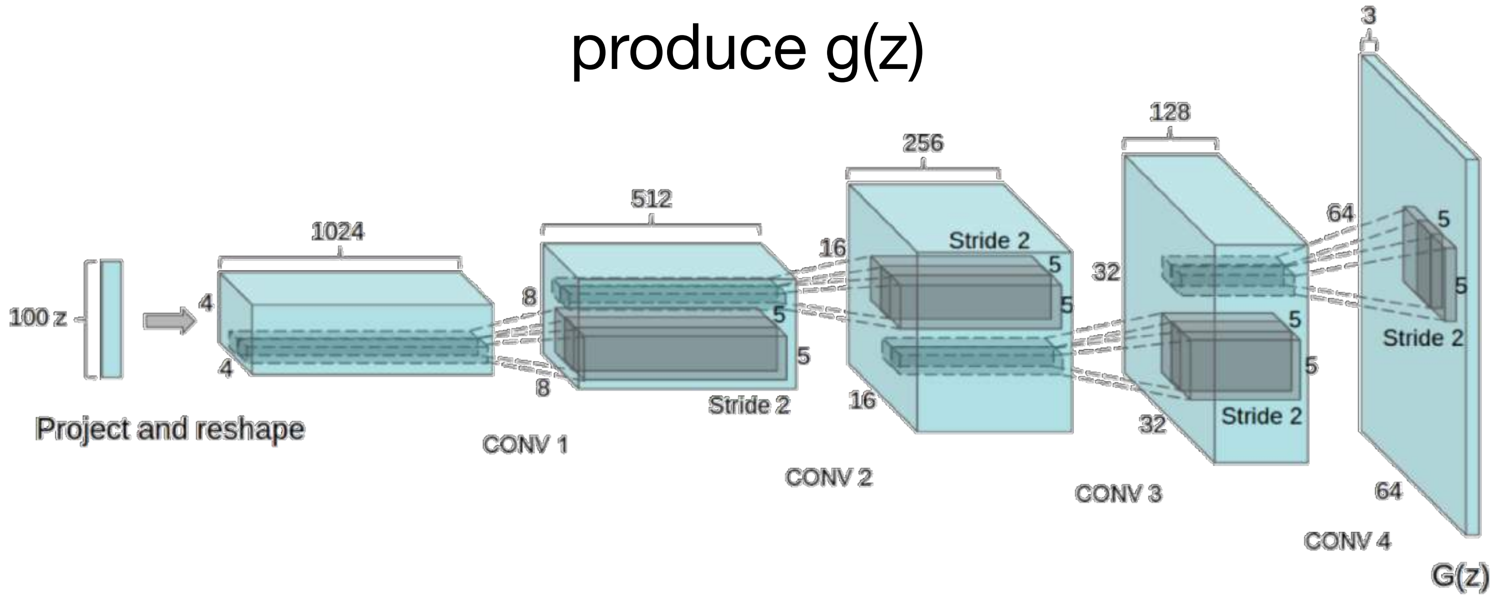
Generative Latent Optimization Model (GLO)

Generative Latent Optimization Model (GLO)

sample z



produce g(z)



backpropagate

both on z and θ

$$\min_{\theta \in \Theta} \frac{1}{N} \sum_{i=1}^{N} \left[\min_{z_i \in \mathcal{Z}} \ell\left(g_\theta(z_i), x_i\right) \right]$$

calculate loss

Source: Bojanovski et al. 2017

Generative Latent Optimization Model (GLO)

Source: Bojanovski et al. 2017

Generative Latent Optimization Model (GLO)

Source: Bojanovski et al. 2017

Generative Latent Optimization Model (GLO)

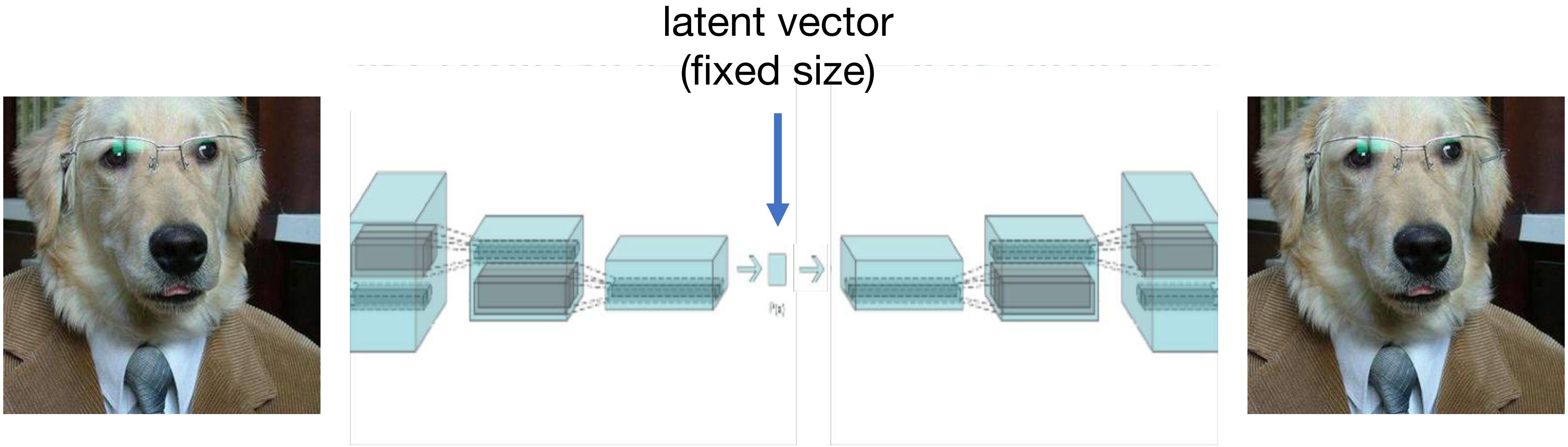
Какие проблемы есть у такого подхода?

Чтобы получить вектора для новых картинок нам
понадобится оптимизация (долго).

Нет гарантии, что распределение останется
таким же, как было вначале
(не получится качественной генерации).

Autoencoders

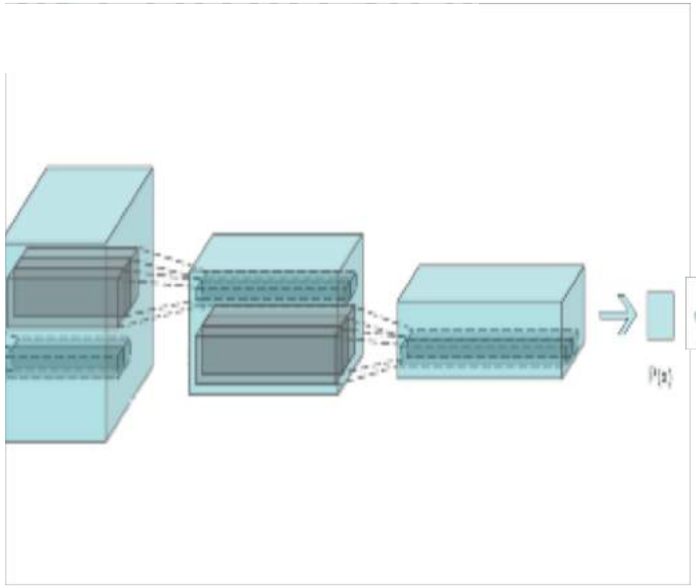
Autoencoder

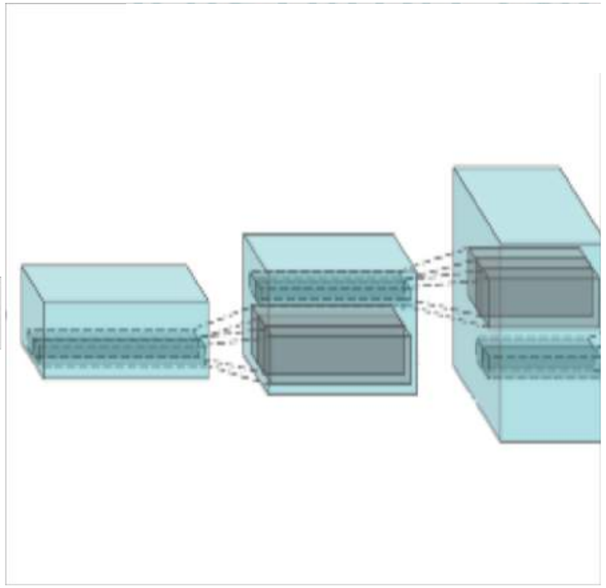


Получить вектора для новых картинок стало просто.

Мы заменили процедуру оптимизации нейронной сетью.

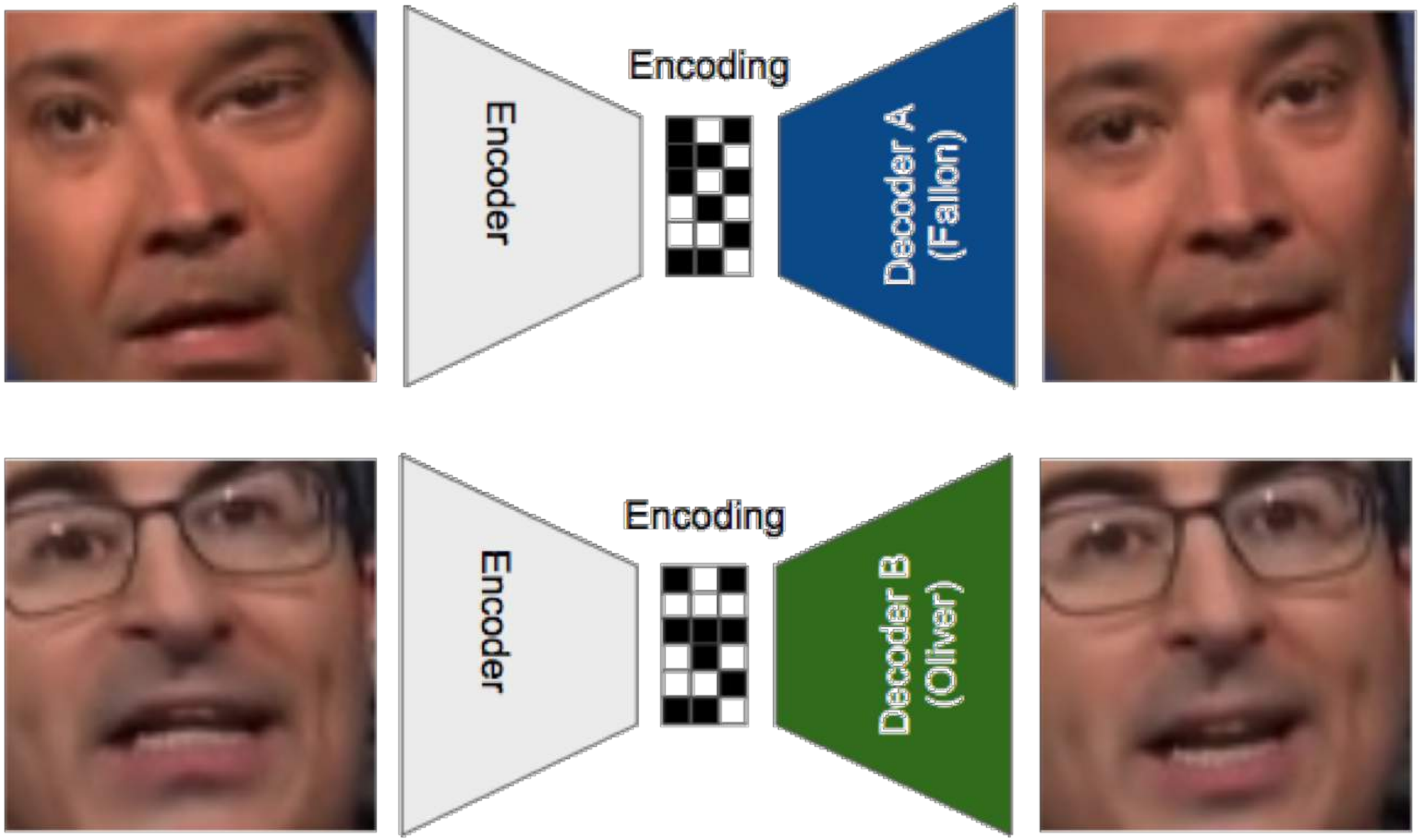
Autoencoder





MSE
MAE
Perceptual Loss
...

DeepFake

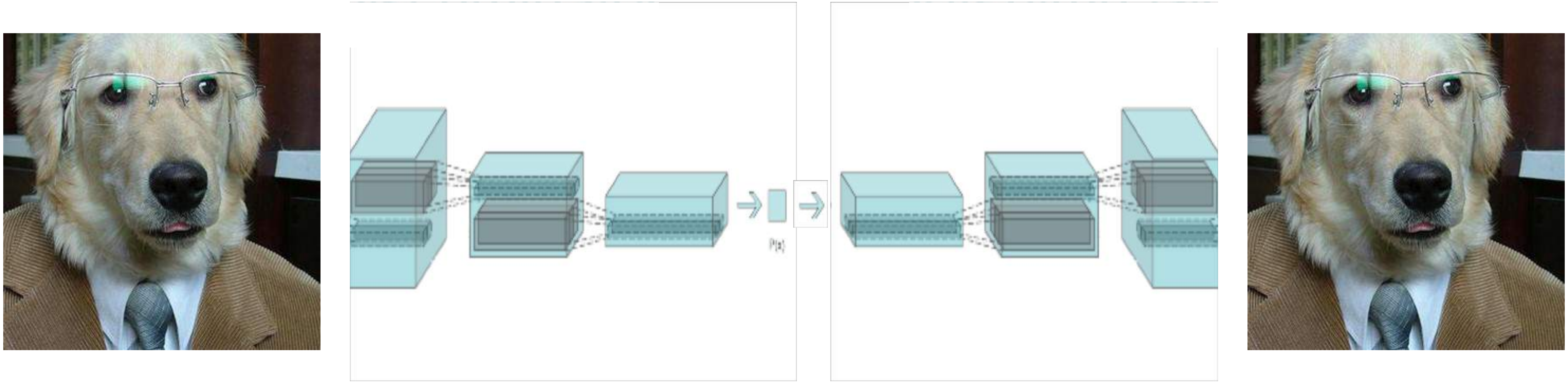


Source: Gaurav Oberoi blog

DeepFake

DeepFake

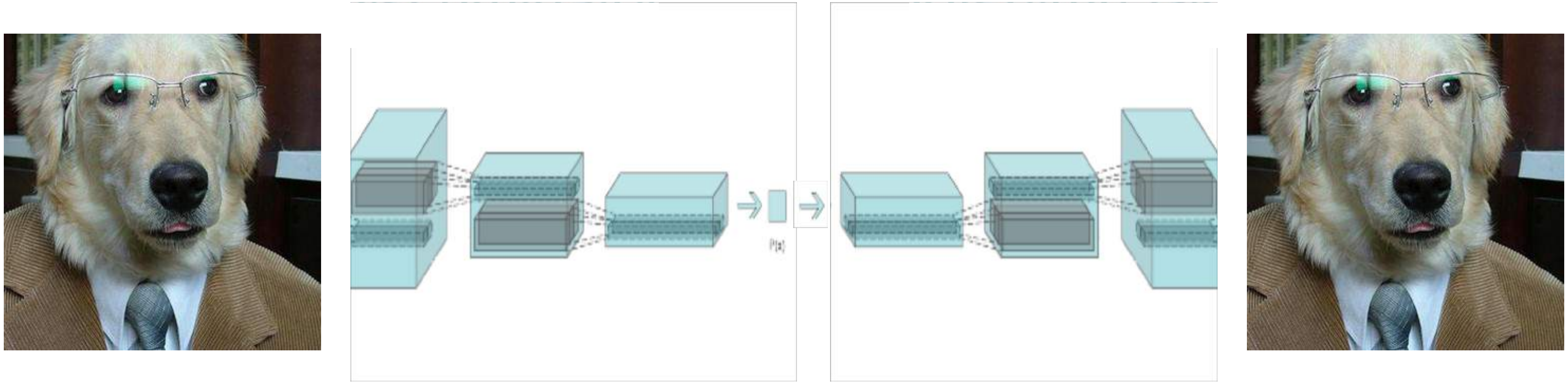
Autoencoder



Причем тут underfitting?

Причем тут overfitting?

Autoencoder



Мы смогли избавиться от процесса поиска (оптимизации) правильного вектора для картинки.

Каким образом мы будем брать новые вектора для того, чтобы генерировать новые изображения?

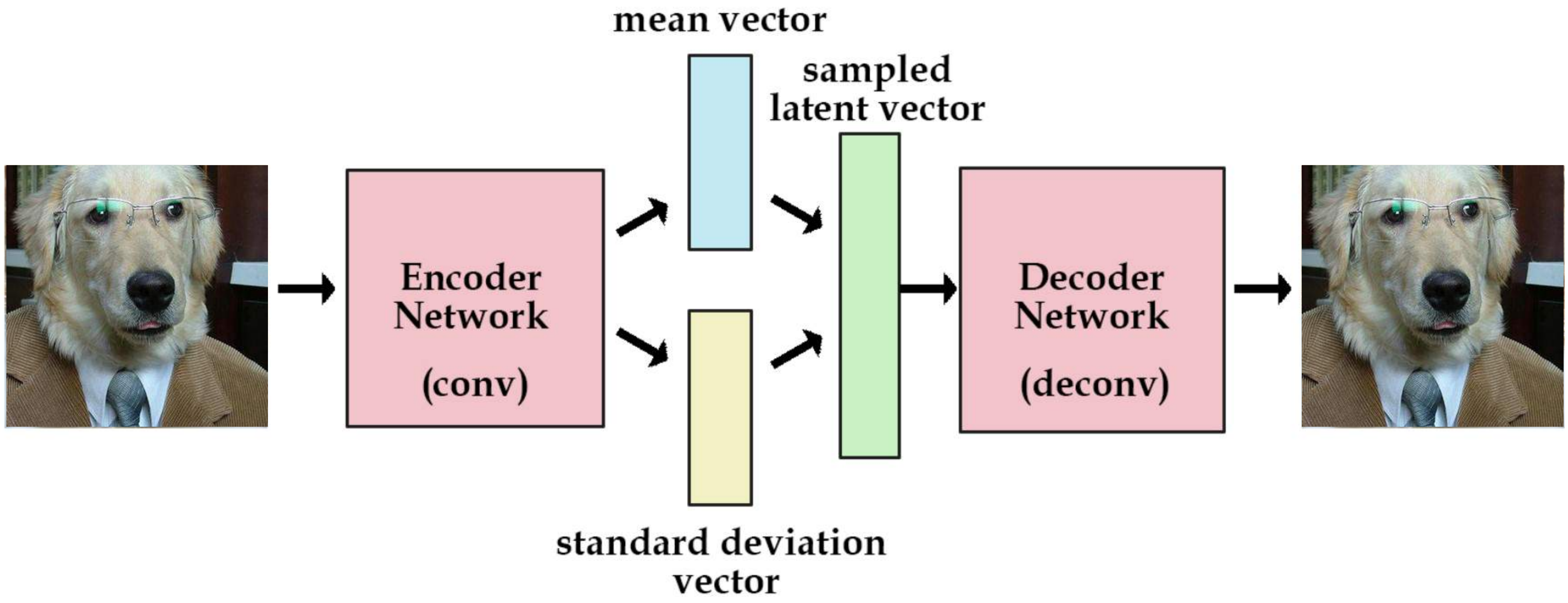
Autoencoder

Мы можем попытаться вручную подобрать новые вектора для генерации новых картинок. Но хотелось бы иметь распределение, из которого их можно сэмплировать.

Как гарантированно получить распределение из которого можно будет сэмплировать вектора?

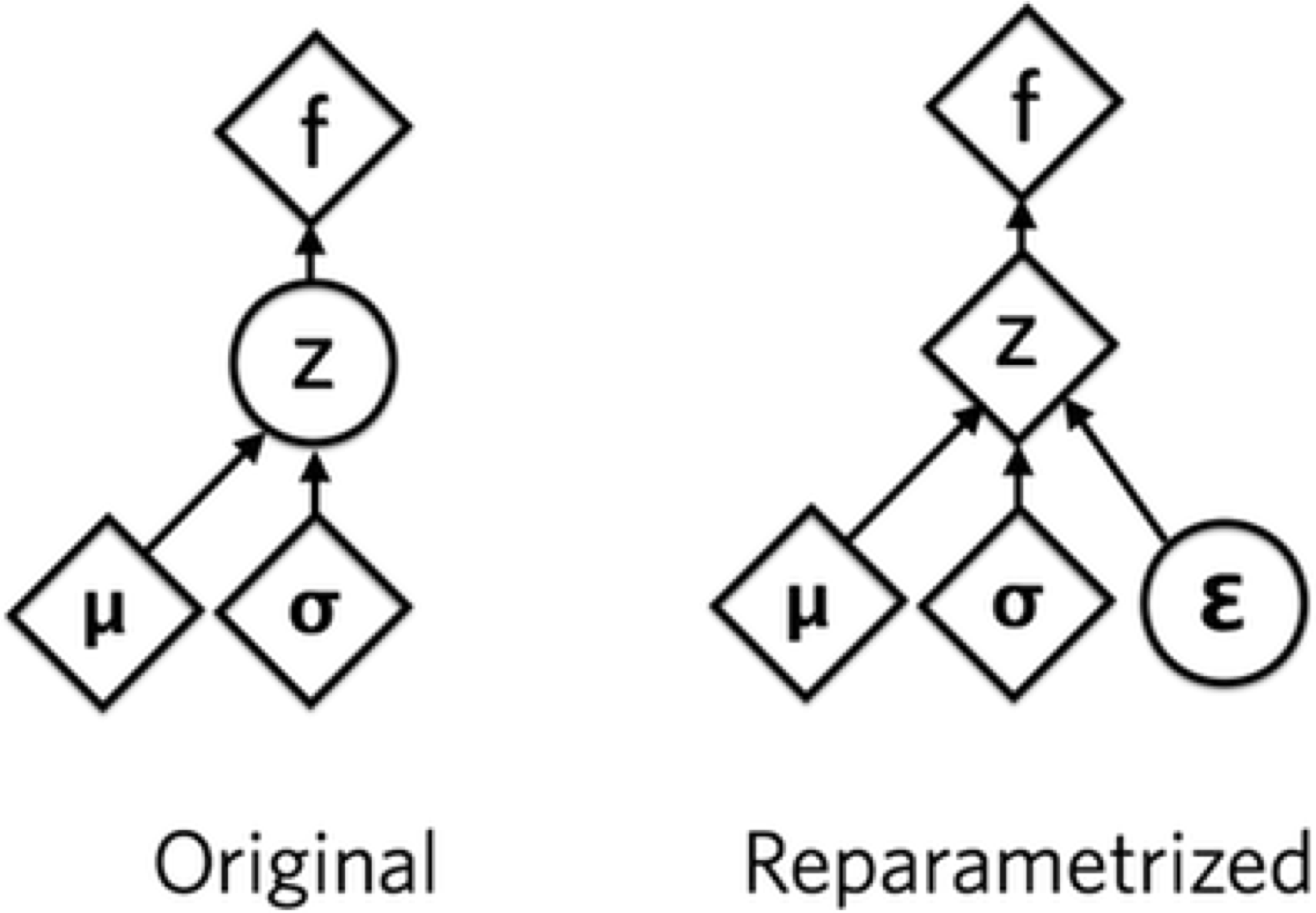
Variational Autoencoders (VAE)

Variational Autoencoder (VAE)

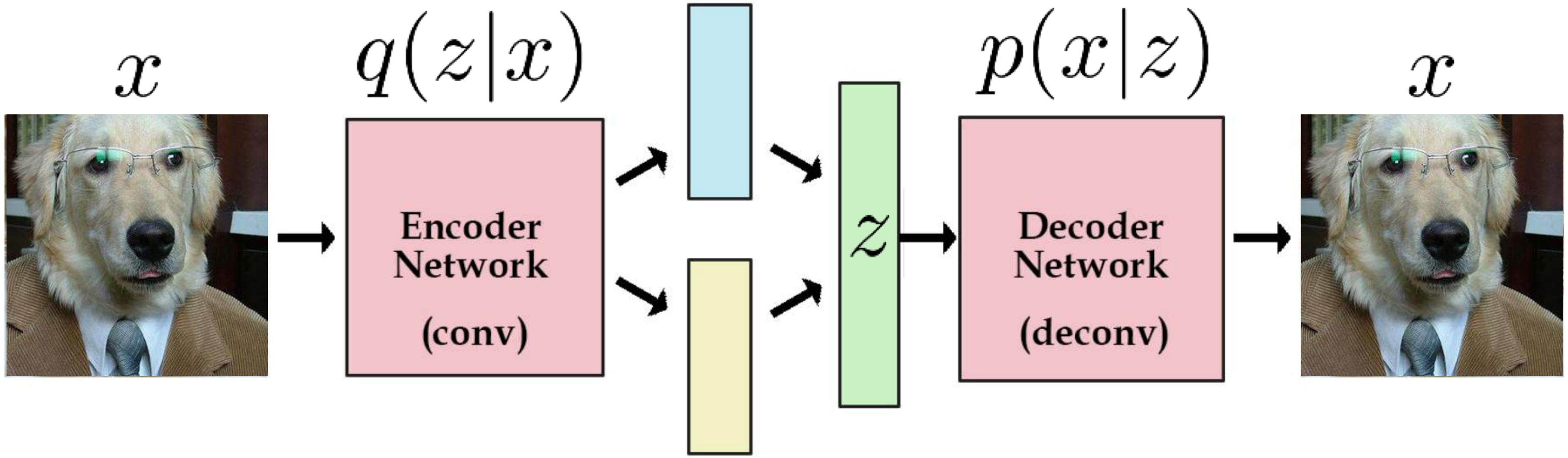


Source: http://kvfrans.com/variational-autoencoders-explained/ (slightly modified)

Variational Autoencoder (VAE)



Variational Autoencoder (VAE)



$$\mathbb{E}_{q(z|x)} \log p(x|z) - \mathrm{KL}\big(q(z|x) \,\|\, p(z)\big)$$

Variational Autoencoder (VAE)

$$\mathbb{E}_{q(z|x)} \log p(x|z) - \mathrm{KL}\big(q(z|x) \,\|\, p(z)\big)$$

$$\mathbb{E}_{q_\phi(z|x)} \|d_\theta(z) - x\|^2$$

objective

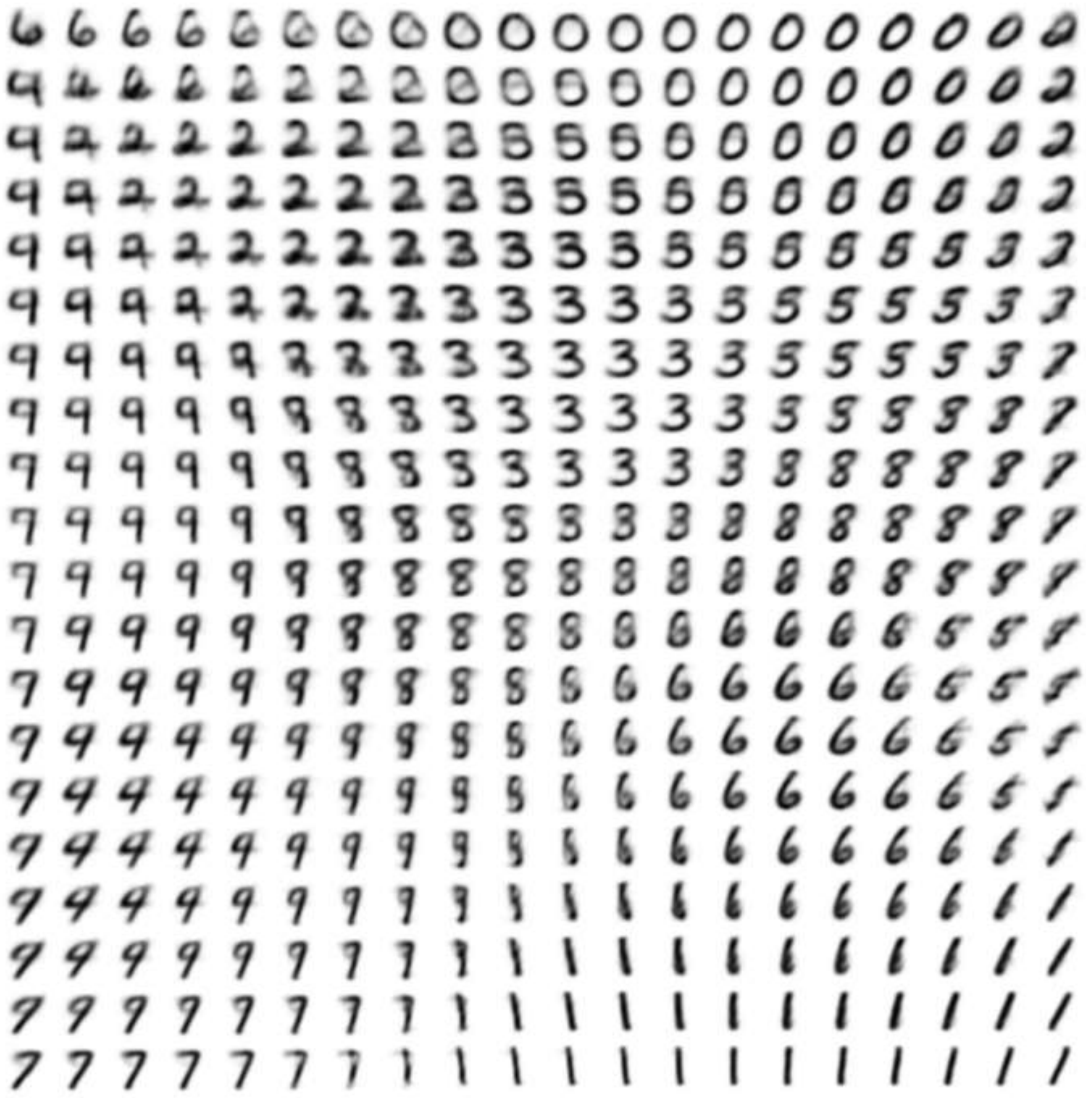
$$\frac{1}{2}\sum_i (\mu_i^2 + \sigma_j^2 - 1 - \log \sigma_j^2)$$

regularization

Variational Autoencoder (VAE)

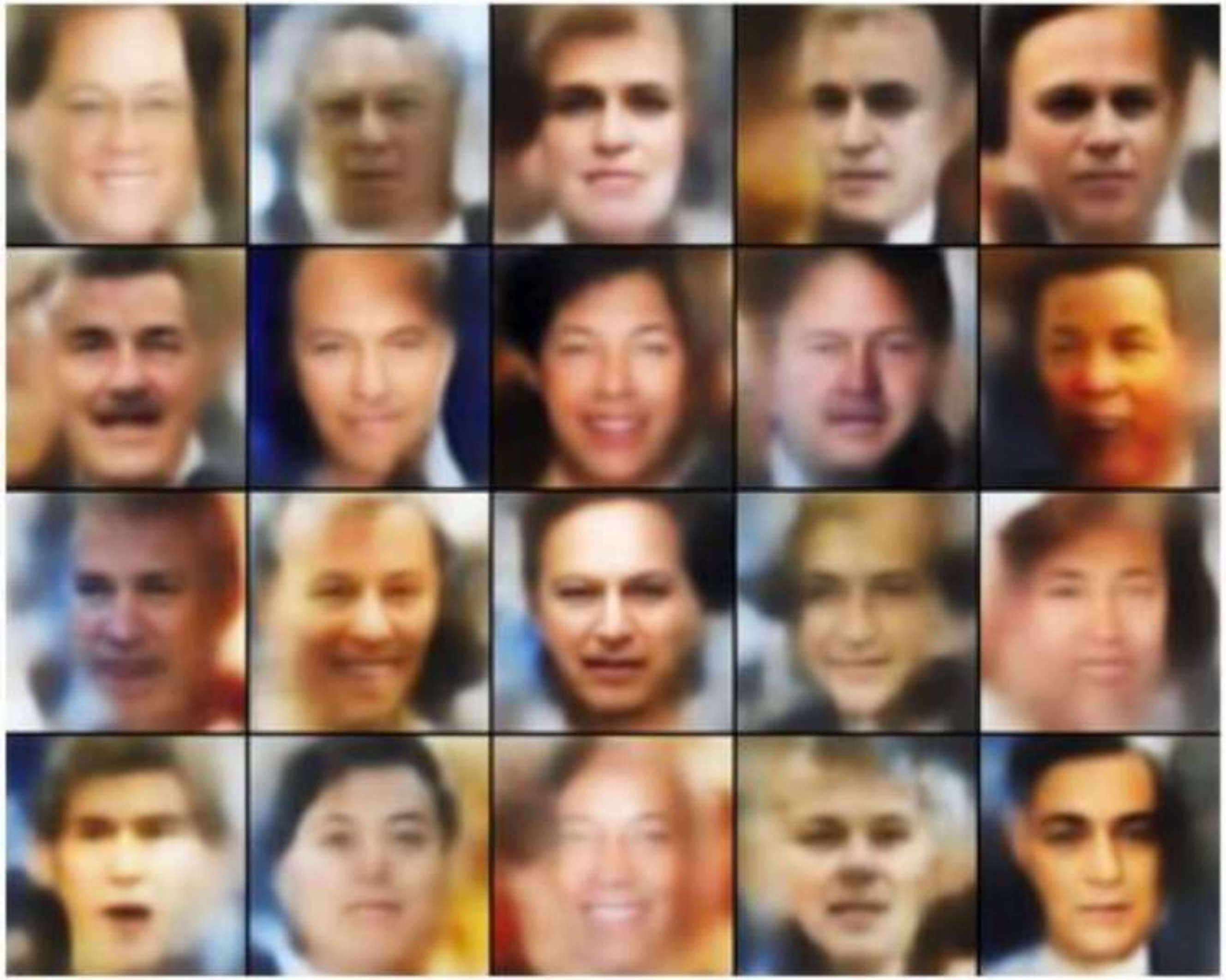
$$\min_{\theta,\phi} \left(\mathbb{E}_{q_\phi(z|x)} \|d_\theta(z) - x\|^2 + \frac{1}{2}\sum_i (\mu_i^2 + \sigma_j^2 - 1 - \log \sigma_j^2) \right)$$

Variational Autoencoder (VAE)



Source: cs231n Lecture 13 2017

Variational Autoencoder (VAE)



Source: cs231n Lecture 13 2017

Variational Autoencoder (VAE)

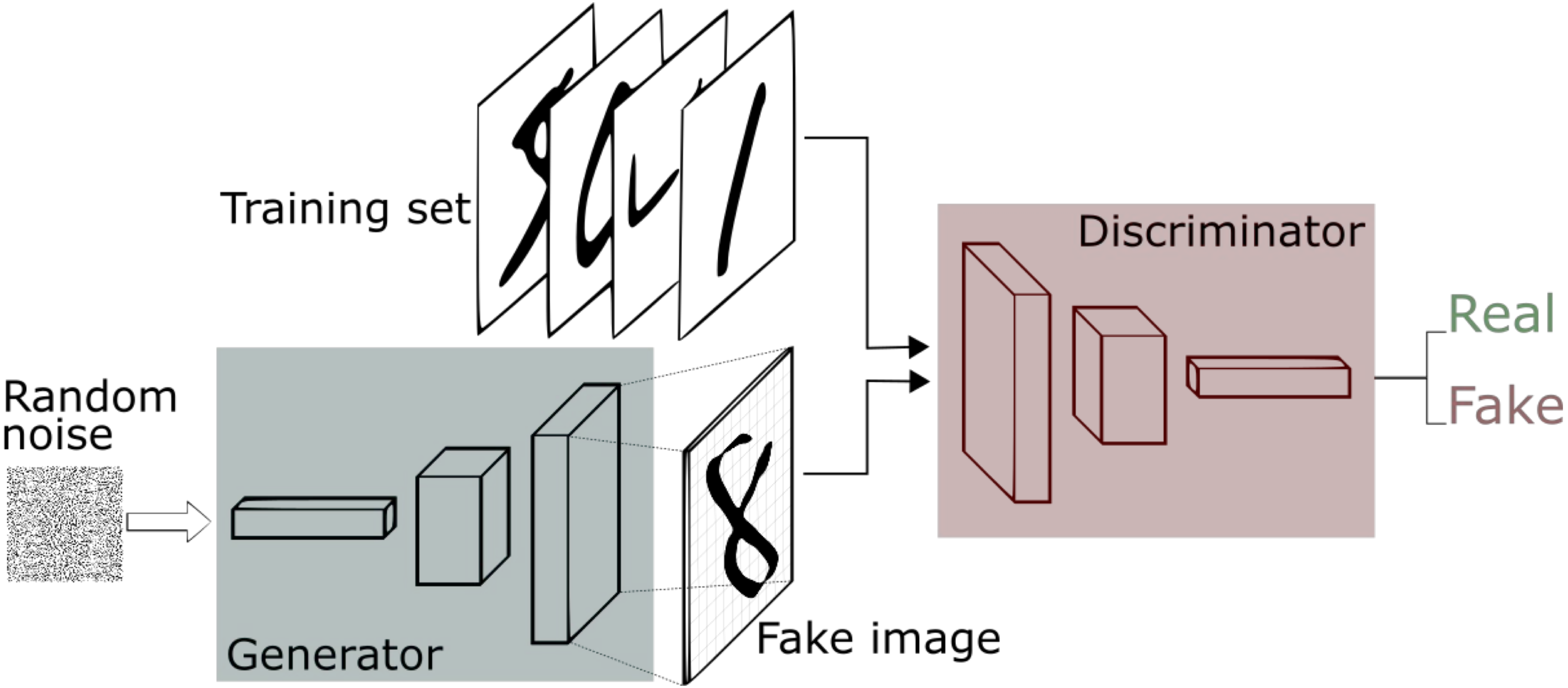
Нам по прежнему не нужно искать вектор для каждой картинки путем оптимизации.

Теперь, чтобы генерировать картинки мы можем просто сэмплировать вектора из нашего априорного распределения p(z).

Что, если мы попробуем решить задачу не напрямую, а опосредованно?

Generative Adversarial Networks

Generative Adversarial Network



Source: GAN: A Beginner's Guide to Generative Adversarial Networks by deeplearning4j

Generative Adversarial Network

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\substack{\text{Решение}\\ \text{дискриминатора для}\\ \text{реальной картинки}}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z)))}_{\substack{\text{Решение}\\ \text{дискриминатора для}\\ \text{картинки, которую}\\ \text{сделал генератор}}} \right]$$

Проблема: если дискриминатор сильный, то генератор ничему не учится.

Source: cs231n Lecture 13 2017

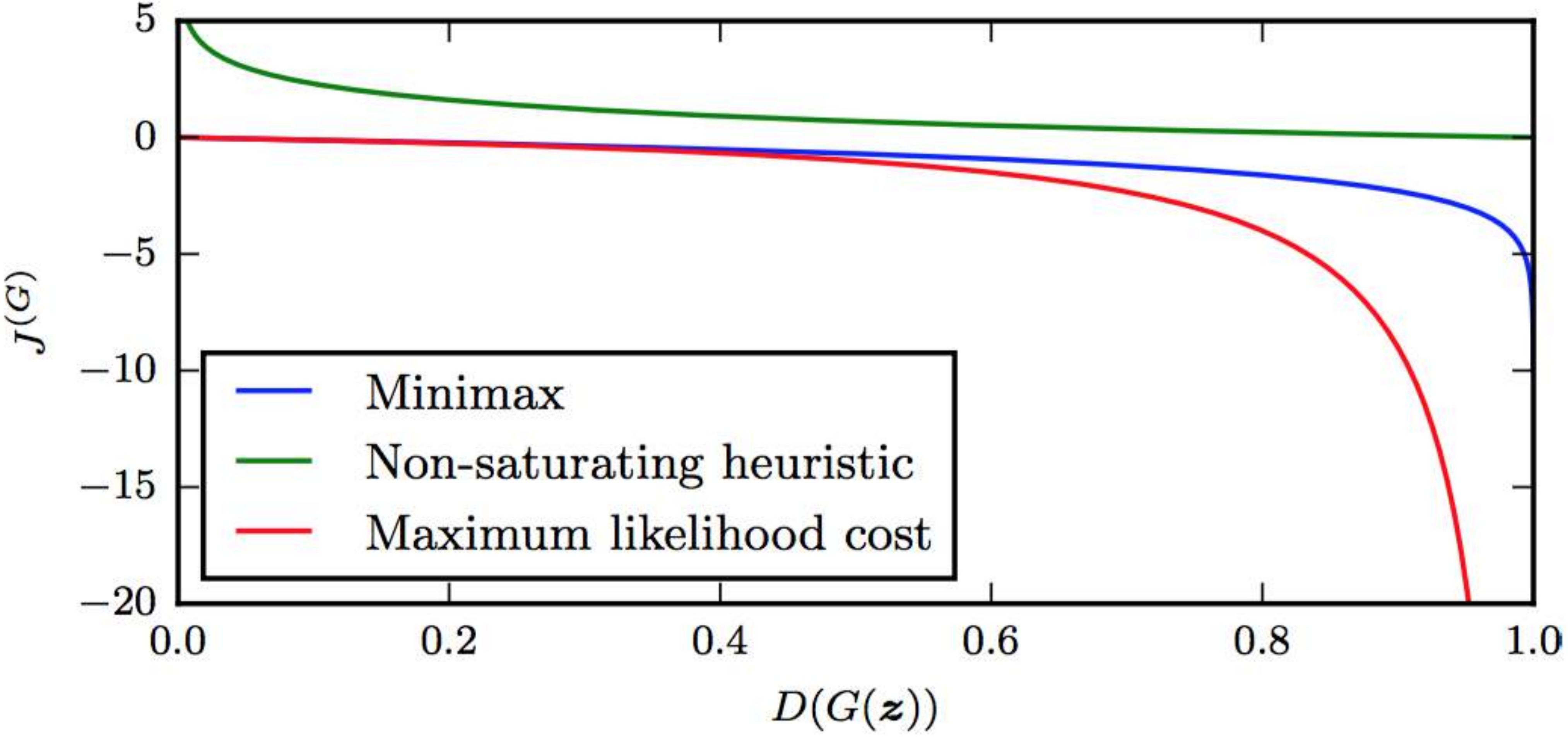
Generative Adversarial Network

$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

$$\min_{\theta_g} \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z)))$$

Source: cs231n Lecture 13 2017

Generative Adversarial Network



Generative Adversarial Network

$$\max_{\theta_d}\left[\mathbb{E}_{x\sim p_{data}}\log D_{\theta_d}(x)+\mathbb{E}_{z\sim p(z)}\log(1-D_{\theta_d}(G_{\theta_g}(z)))\right]$$

$$\max_{\theta_g}\mathbb{E}_{z\sim p(z)}\log(D_{\theta_d}(G_{\theta_g}(z)))$$

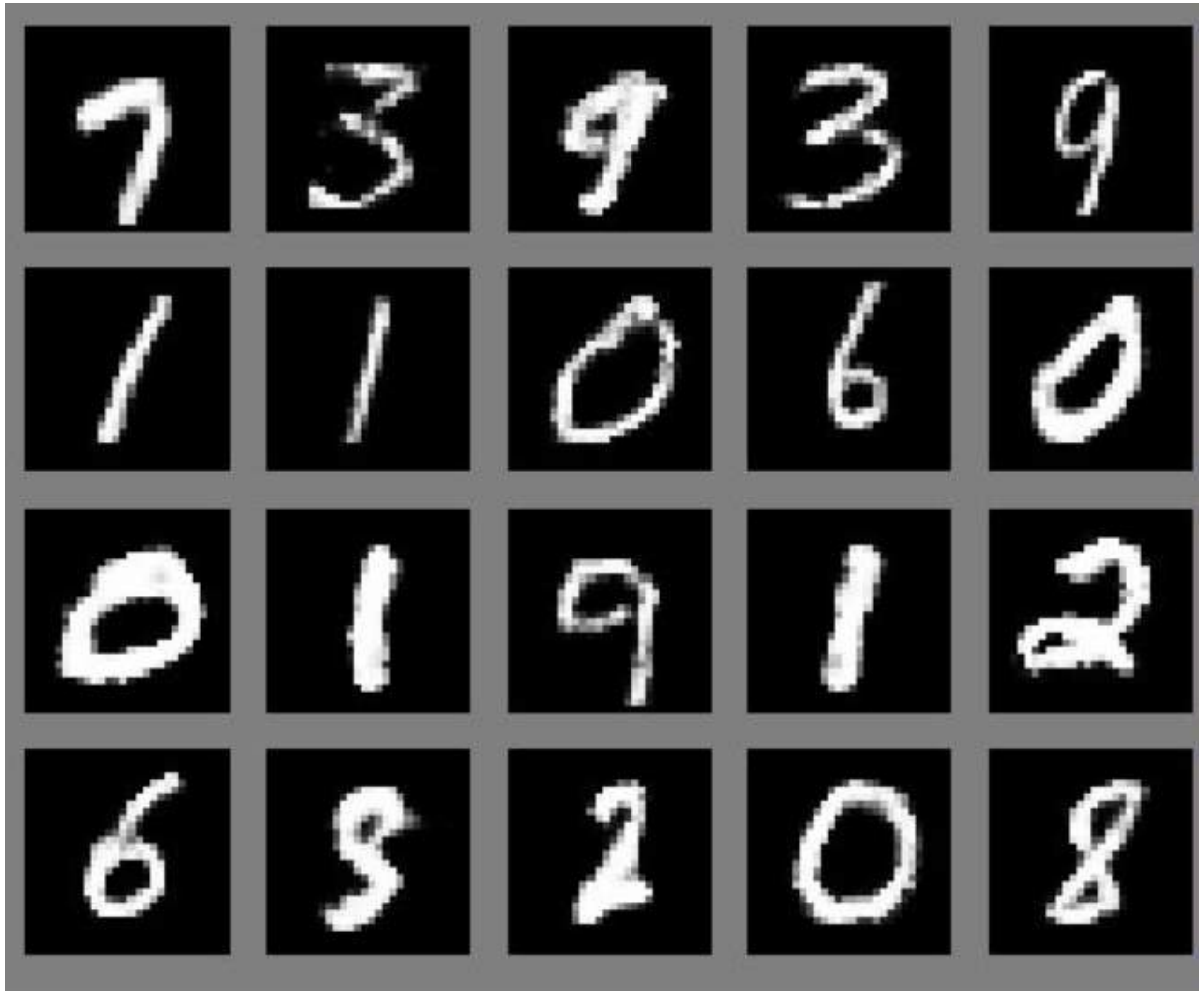
Более стабильный вариант обучения.

Source: cs231n Lecture 13 2017

Generative Adversarial Network

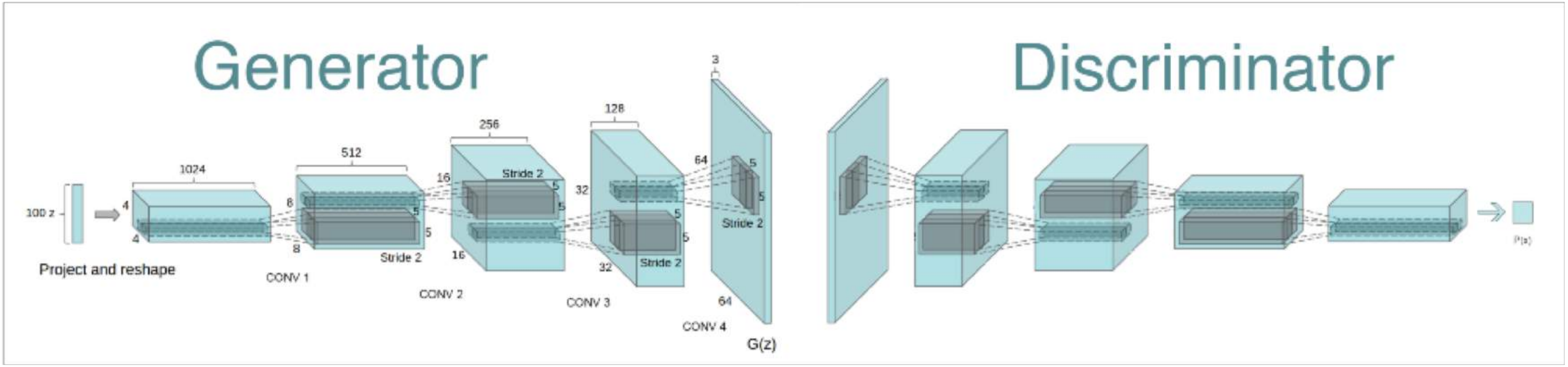
Source: cs231n Lecture 13 2017

Generative Adversarial Network



Source: cs231n Lecture 13 2017

DCGAN



Source: Radford et al 2015

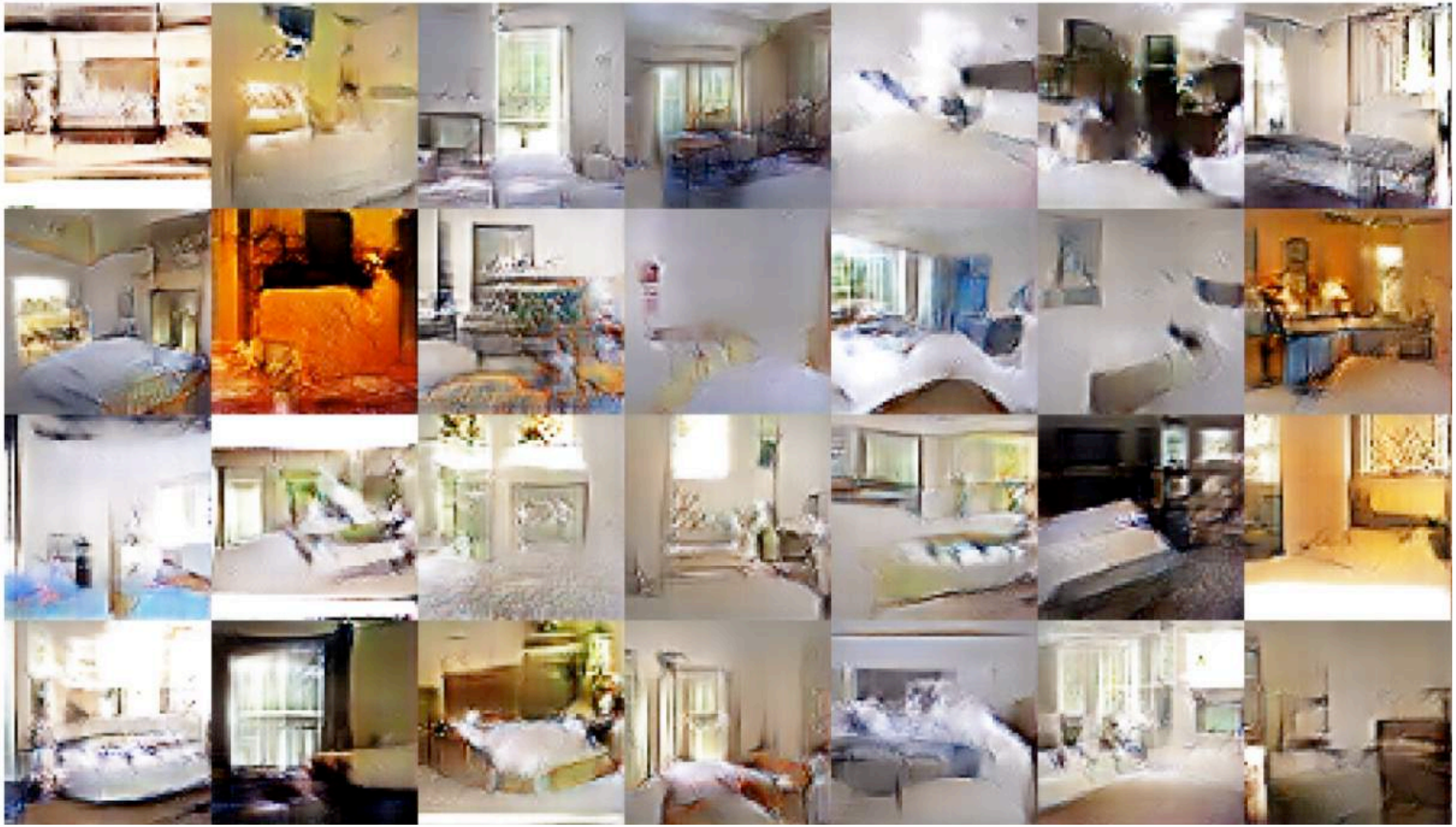
DCGAN

Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

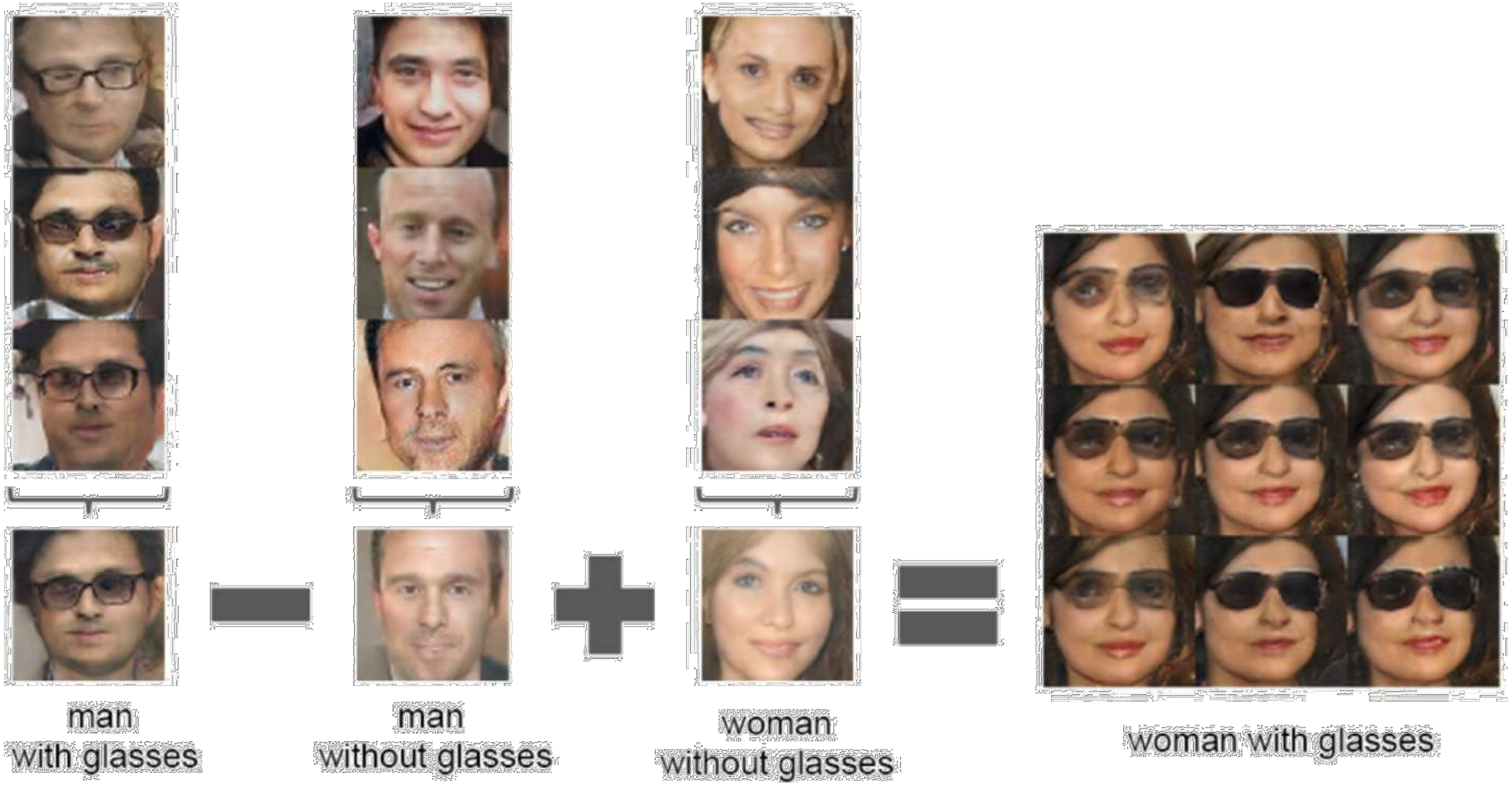
Source: Radford et al 2015

DCGAN



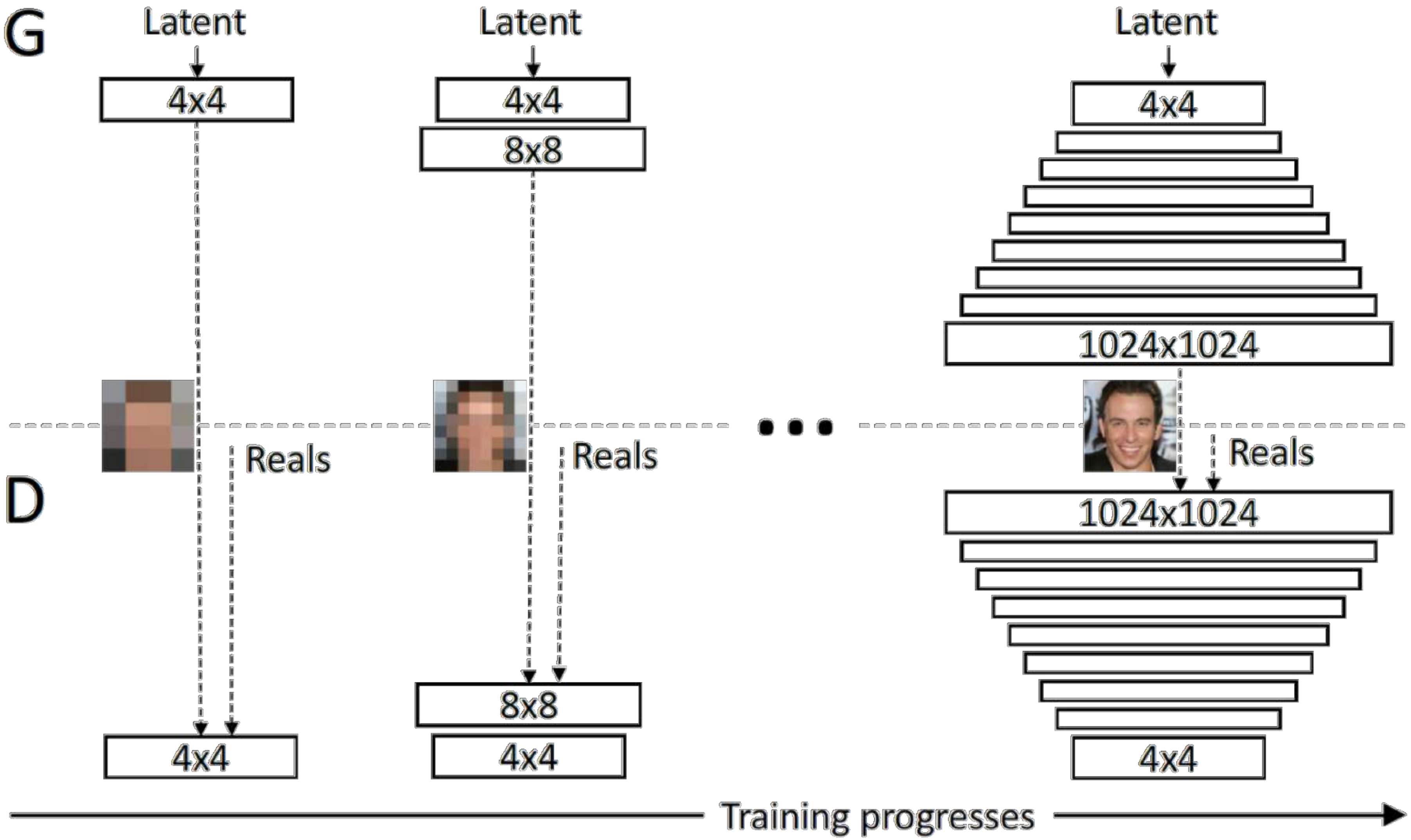
Source: Radford et al 2015

DCGAN



Source: Radford et al 2015

Progressive Growing of GANs



Source: Karras et al. 2017

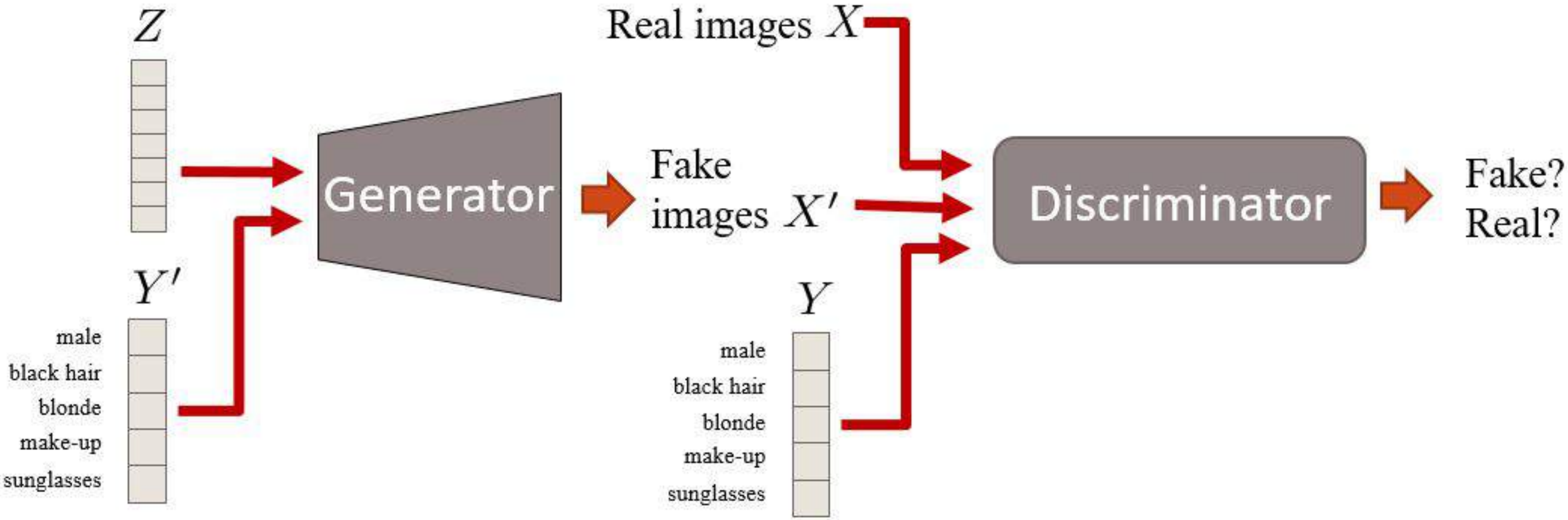
Progressive Growing of GANs

Source: Karras et al. 2017

StyleGAN

Source: Karras et al. 2017

Conditional GAN



Source: Guim Perarnau blog

Conditional GAN: pix2pix

Source: Isola et al. 2017

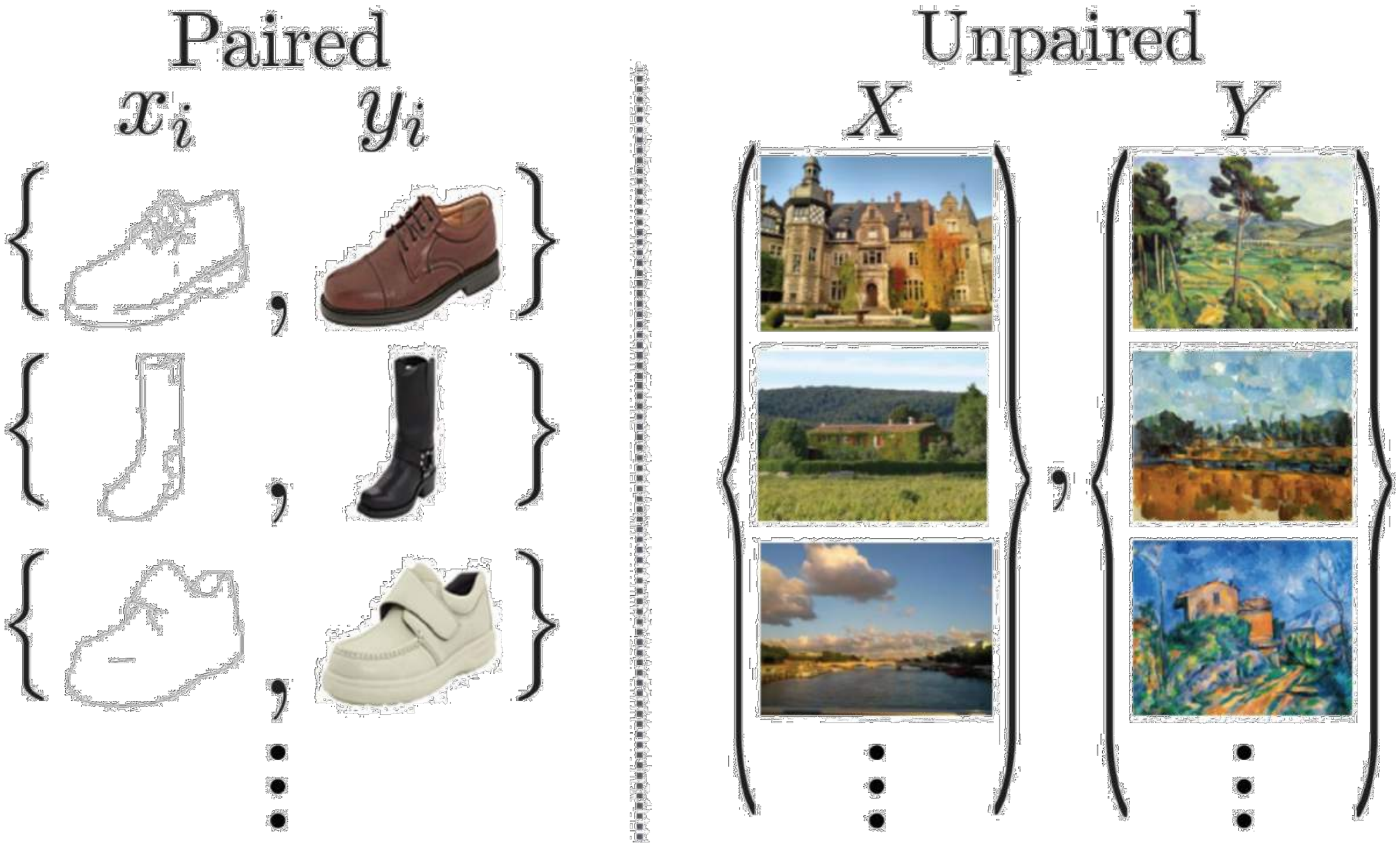
Conditional GAN: pix2pix

Source: Isola et al. 2017

Conditional GAN: pix2pix

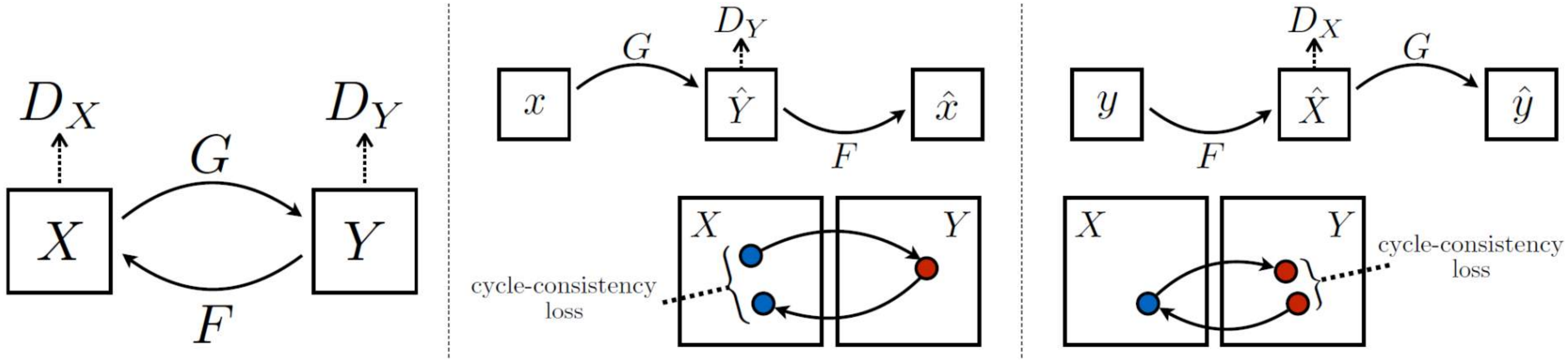
Source: Isola et al. 2017

Paired vs Unpaired Data



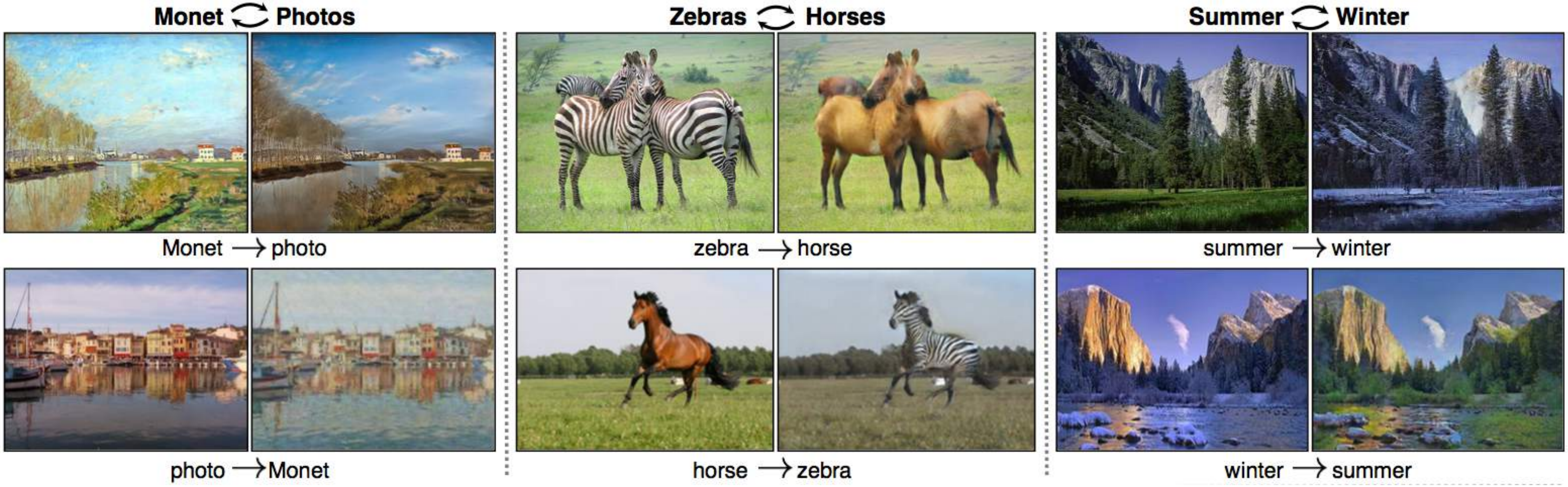
Source: Zhu et al. 2017

CycleGAN



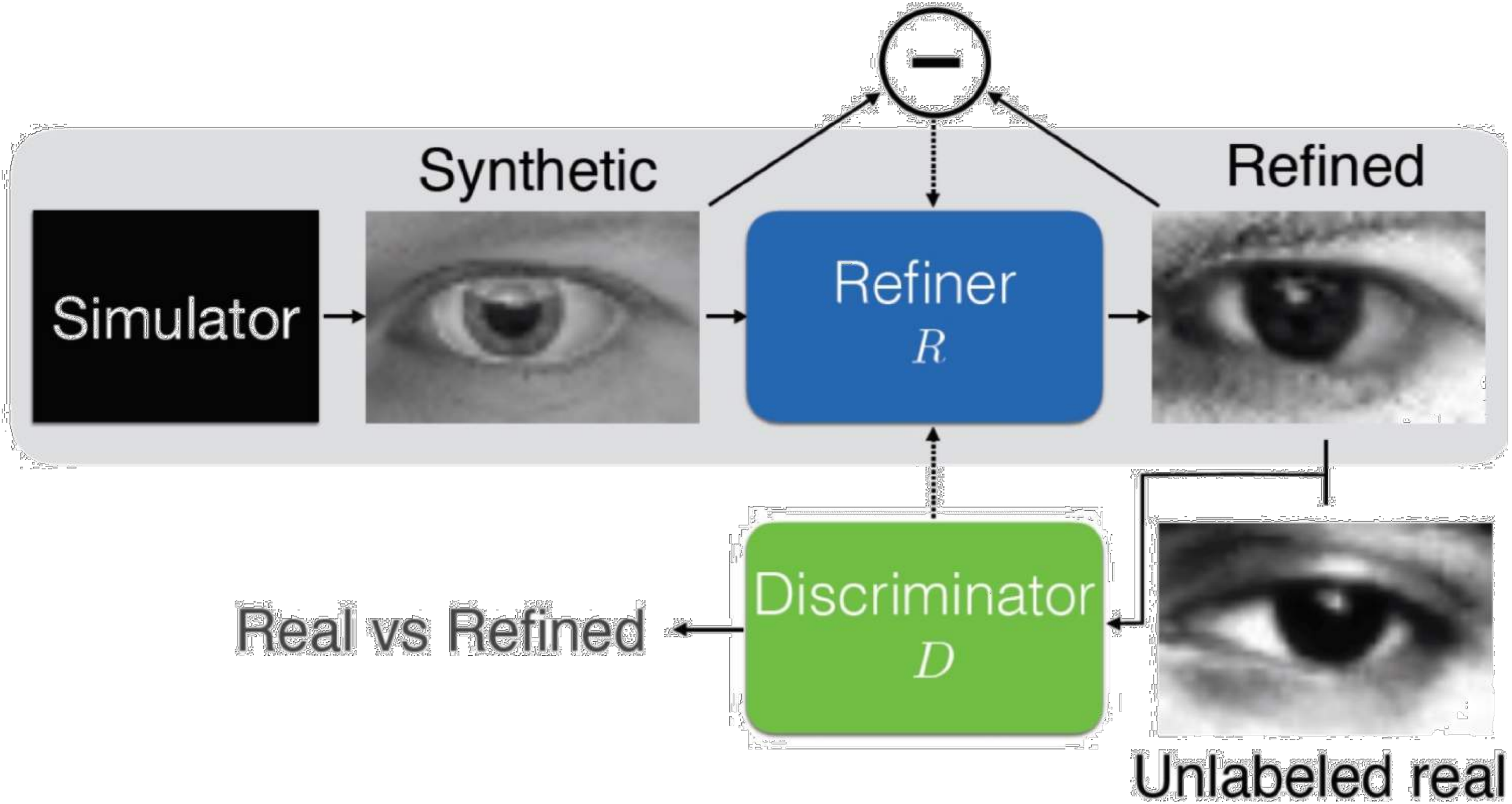
Source: Zhu et al. 2017

CycleGAN



Source: Zhu et al. 2017

GANs for Synthetic Data Generation



Source: Srivastava et al. 2017

GAN Zoo

- GAN - Generative Adversarial Networks
- 3D-GAN - Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling
- acGAN - Face Aging With Conditional Generative Adversarial Networks
- AC-GAN - Conditional Image Synthesis With Auxiliary Classifier GANs
- AdaGAN - AdaGAN: Boosting Generative Models
- AEGAN - Learning Inverse Mapping by Autoencoder based Generative Adversarial Nets
- AffGAN - Amortised MAP Inference for Image Super-resolution
- AL-CGAN - Learning to Generate Images of Outdoor Scenes from Attributes and Semantic Layouts
- ALI - Adversarially Learned Inference
- AM-GAN - Generative Adversarial Nets with Labeled Data by Activation Maximization
- AnoGAN - Unsupervised Anomaly Detection with Generative Adversarial Networks to Guide Marker Discovery
- ArtGAN - ArtGAN: Artwork Synthesis with Conditional Categorial GANs
- b-GAN - b-GAN: Unified Framework of Generative Adversarial Networks
- Bayesian GAN - Deep and Hierarchical Implicit Models
- BEGAN - BEGAN: Boundary Equilibrium Generative Adversarial Networks
- BiGAN - Adversarial Feature Learning
- BS-GAN - Boundary-Seeking Generative Adversarial Networks
- CGAN - Conditional Generative Adversarial Nets
- CaloGAN - CaloGAN: Simulating 3D High Energy Particle Showers in Multi-Layer Electromagnetic Calorimeters with Generative Adversarial Networks
- CCGAN - Semi-Supervised Learning with Context-Conditional Generative Adversarial Networks
- CatGAN - Unsupervised and Semi-supervised Learning with Categorical Generative Adversarial Networks
- CoGAN - Coupled Generative Adversarial Networks
- Context-RNN-GAN - Contextual RNN-GANs for Abstract Reasoning Diagram Generation
- C-RNN-GAN - C-RNN-GAN: Continuous recurrent neural networks with adversarial training
- CS-GAN - Improving Neural Machine Translation with Conditional Sequence Generative Adversarial Nets
- CVAE-GAN - CVAE-GAN: Fine-Grained Image Generation through Asymmetric Training
- CycleGAN - Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks
- DTN - Unsupervised Cross-Domain Image Generation
- DCGAN - Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks
- DiscoGAN - Learning to Discover Cross-Domain Relations with Generative Adversarial Networks
- DR-GAN - Disentangled Representation Learning GAN for Pose-Invariant Face Recognition
- DualGAN - DualGAN: Unsupervised Dual Learning for Image-to-Image Translation
- EBGAN - Energy-based Generative Adversarial Network
- f-GAN - f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization
- FF-GAN - Towards Large-Pose Face Frontalization in the Wild
- GAWWN - Learning What and Where to Draw
- GeneGAN - GeneGAN: Learning Object Transfiguration and Attribute Subspace from Unpaired Data
- Geometric GAN - Geometric GAN
- GoGAN - Gang of GANs: Generative Adversarial Networks with Maximum Margin Ranking
- GP-GAN - GP-GAN: Towards Realistic High-Resolution Image Blending
- IAN - Neural Photo Editing with Introspective Adversarial Networks
- iGAN - Generative Visual Manipulation on the Natural Image Manifold
- IcGAN - Invertible Conditional GANs for image editing
- ID-CGAN - Image De-raining Using a Conditional Generative Adversarial Network
- Improved GAN - Improved Techniques for Training GANs
- InfoGAN - InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets
- LAGAN - Learning Particle Physics by Example: Location-Aware Generative Adversarial Networks for Physics Synthesis
- LAPGAN - Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks

Source: cs231n Lecture 13 2017

Final Remarks

- GAN и VAE – до сих пор очень горячие темы в глубоком обучении.

- VAE – очень красивая с теоретической точки зрения идея, которую можно использовать не только в качестве генеративной модели.

- GAN – не менее красивая идея, но менее теоретически обоснованная. GAN тоже можно использовать не только для целей генерации примеров.

Useful Materials

Advances in Generative Adversarial Networks (GANs) (Medium):
https://medium.com/beyondminds/advances-in-generative-adversarial-networks-7bad57028032

ProGAN: How NVIDIA Generated Images of Unprecedented Quality (Medium):
https://towardsdatascience.com/progan-how-nvidia-generated-images-of-unprecedented-quality-51c98ec2cbd2

Explained: A Style-Based Generator Architecture for GANs - Generating and Tuning Realistic Artificial Faces (Medium):
https://towardsdatascience.com/explained-a-style-based-generator-architecture-for-gans-generating-and-tuning-realistic-6cb2be0f431