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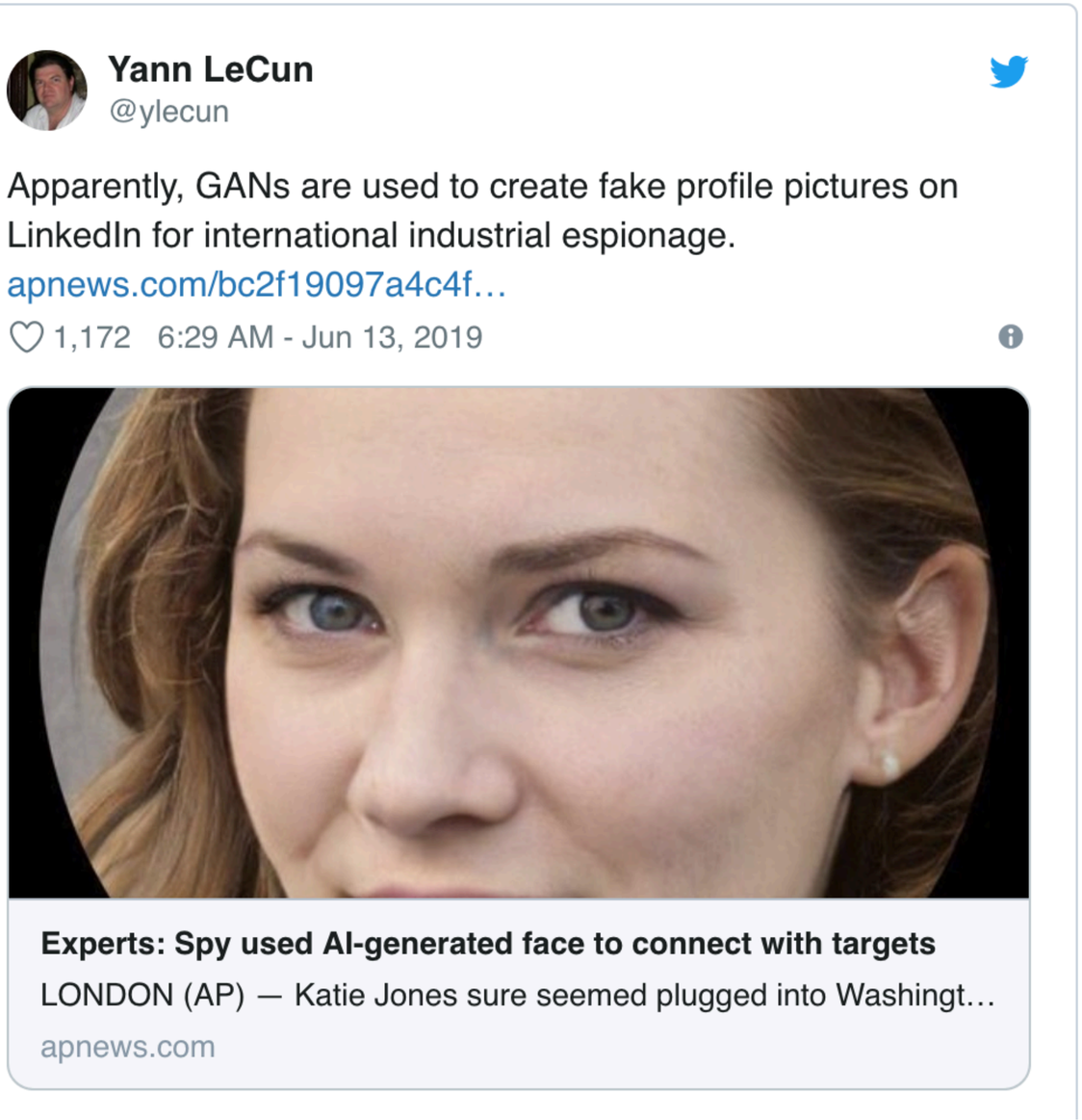
Pattern Analysis & Machine Intelligence
Praktikum: MLPR-WS19

Week 11: Generative Adversarial Networks (GANs)

We have already seen VAEs, why should we look at GANs?



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All images created by BigGAN

Image taken from: https://cdn-images-1.medium.com/max/2600/1*Yw2KxjmIkj8yqS-ykLCQCQ.png

How do GANs work?

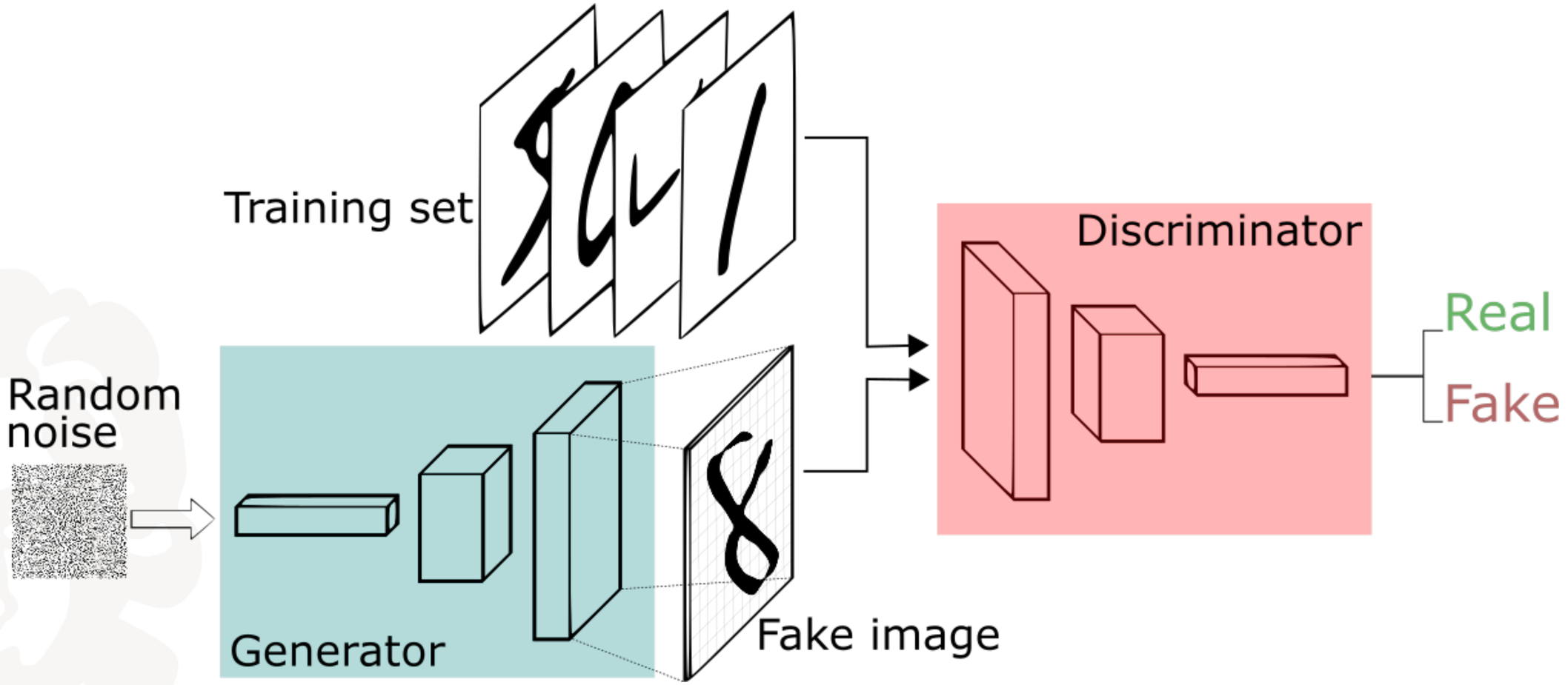


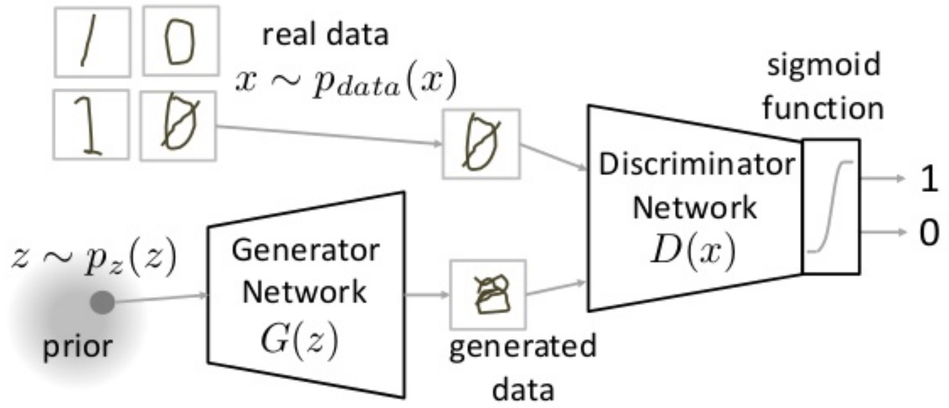
Image taken from: https://skymind.ai/images/wiki/GANs.png

How do GANs work? Alternating training

Generative Adversarial Networks

$$\min_G \max_D V(D,G)$$

$$V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1-D(G(z))]$$



Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k, is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(m)}\}$ from data generating distribution $p_{\text{data}}(\boldsymbol{x})$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D\left(\boldsymbol{x}^{(i)}\right) + \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right)\right].$$

end for

- Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \ldots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log\left(1 - D\left(G\left(\boldsymbol{z}^{(i)}\right)\right)\right).$$

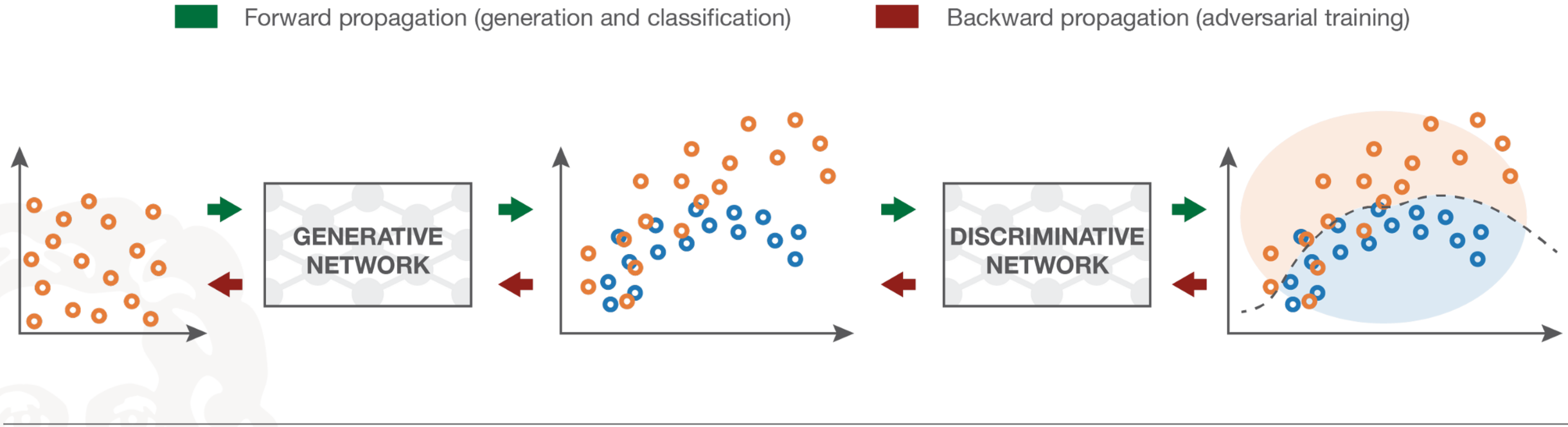
end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Taken from: https://image.slidesharecdn.com/generativeadversarialnetworks-161121164827/95/generative-adversarial-networks-11-638.jpg?cb=1480242452

From original 2014 NeurIPS paper by Goodfellow et. Al.
https://arxiv.org/pdf/1406.2661.pdf

How do GANs work? Alternating training



Taken from: https://towardsdatascience.com/understanding-generative-adversarial-networks-gans-cd6e4651a29

Variants of GANs

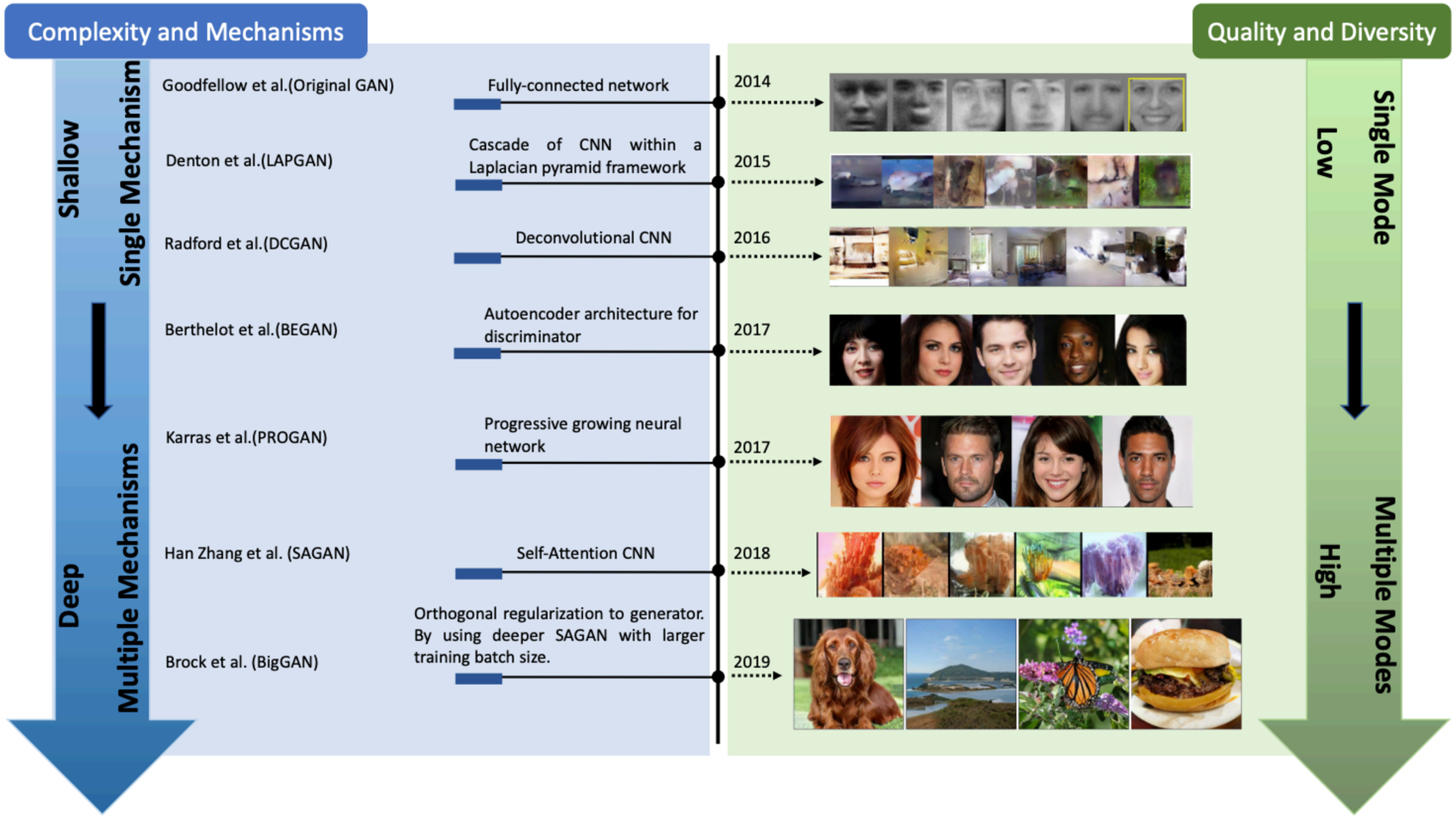
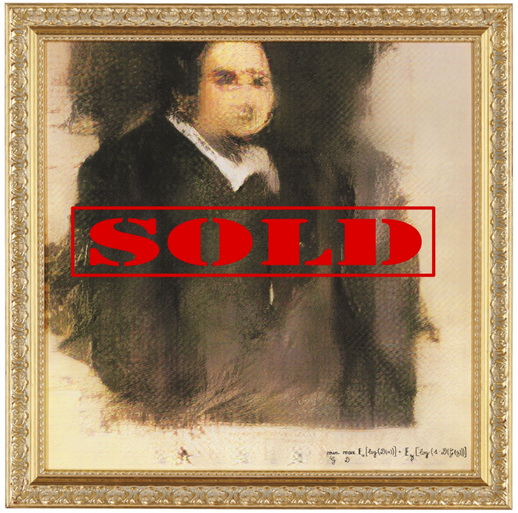


Fig. 2. Timeline of architecture-variant GANs. Complexity in blue stream refers to size of the architecture and computational cost such as batch size. Mechanisms refer to the number of types of models used in the architecture (e.g., BEGAN uses an autoencoder architecture for its discriminator while a deconvolutional neural network is used for the generator. In this case, two mechanisms are used).

Taken from Wang et. al 2019 “Generative Adversarial Networks: A Survey and Taxonomy“: https://arxiv.org/pdf/1906.01529.pdf

GAN examples



Taken from: https://medium.com/datadriveninvestor/432-000-painting-by-ai-sold-at-christies-my-thoughts-4a33cd94f782

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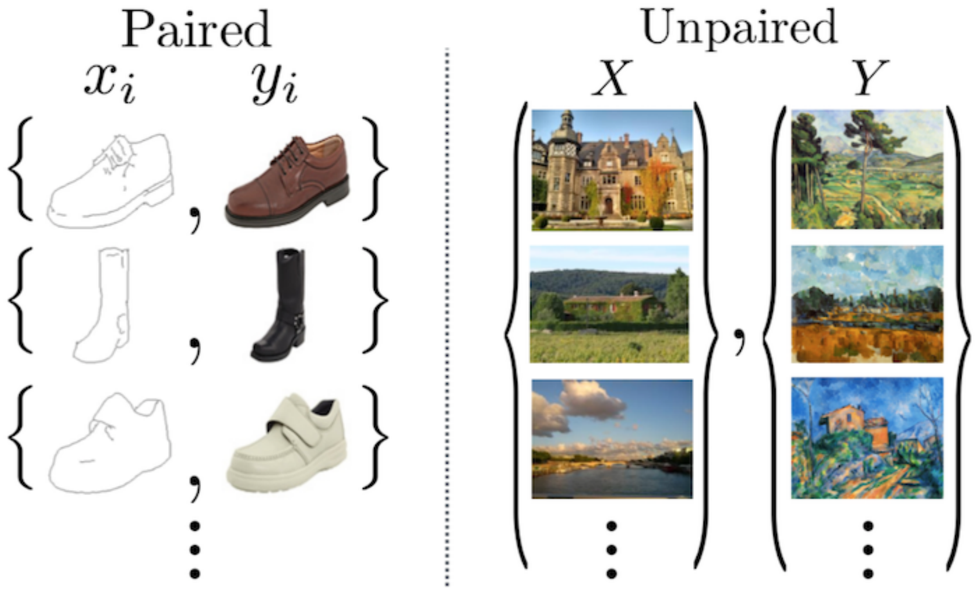

Taken from: https://cdn-images-1.medium.com/max/1200/1*oZsw1JaGkKPxWKKvVUWlyg.png

Taken from: https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/