Generative Adversarial Networks (GANs)

Adapted from material by Goodfellow, Binglin, Shashank, Bhargav

GANs

- **Generative**
  - Learn a generative model
- **Adversarial**
  - Trained in an adversarial setting
- **Networks**
  - Use Deep Neural Networks

Why Generative Models?

- **Discriminative models:**
  - Given an image **X**, predict a label **Y**
  - Estimates **P(Y|X)**

- **Discriminative models have several key limitations**
  - Can’t model **P(X)**, i.e. the probability of seeing a certain image
  - Thus, can’t sample from **P(X)**, i.e. **can’t generate new images**

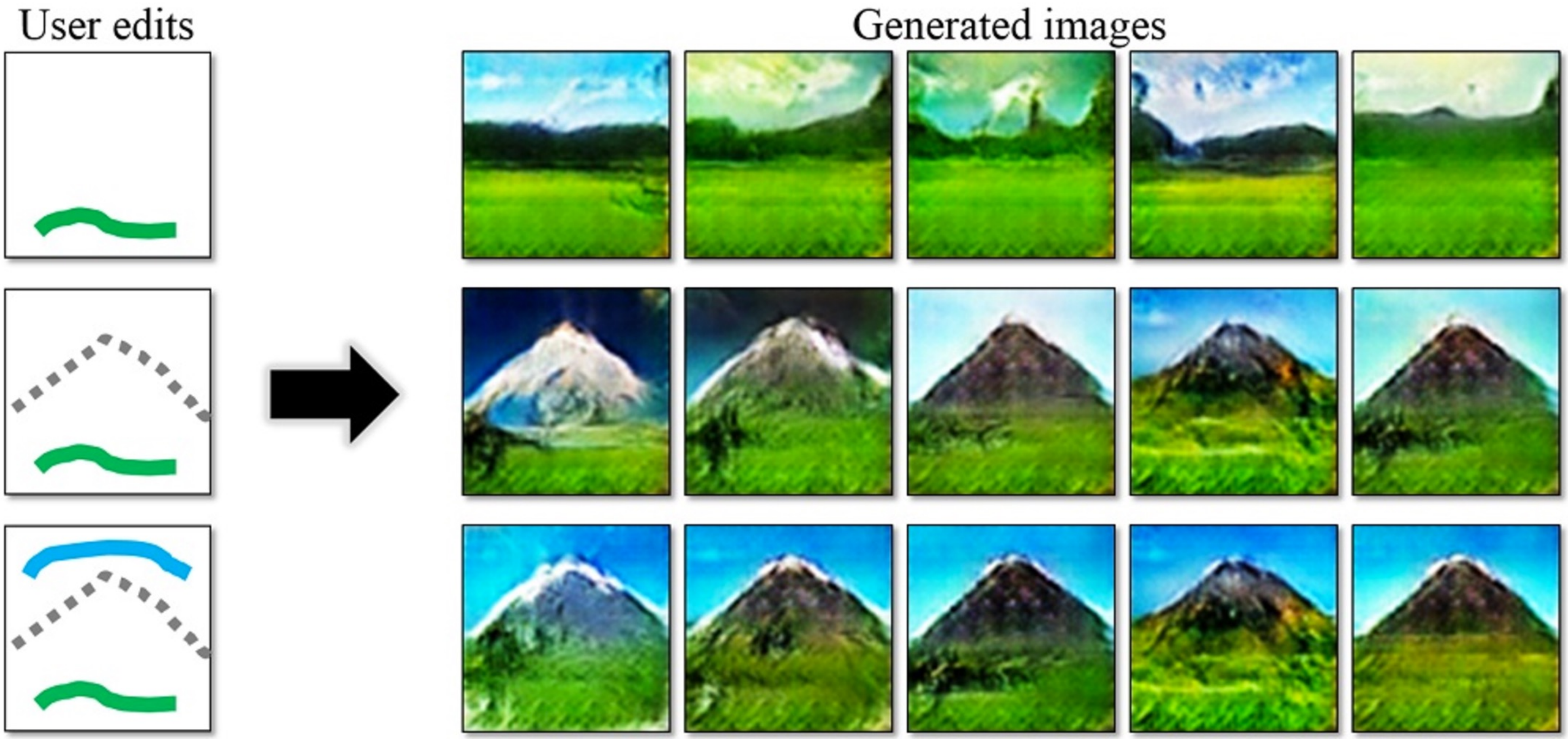
- **Generative models try to address these:**
  - model **P(X)**
  - generate new data (e.g. images)

Magic of GANs…

Which one is Computer generated?

Ledig, Christian, et al. "Photo-realistic single image super-resolution using a generative adversarial network." *arXiv preprint arXiv:1609.04802* (2016).

Magic of GANs…

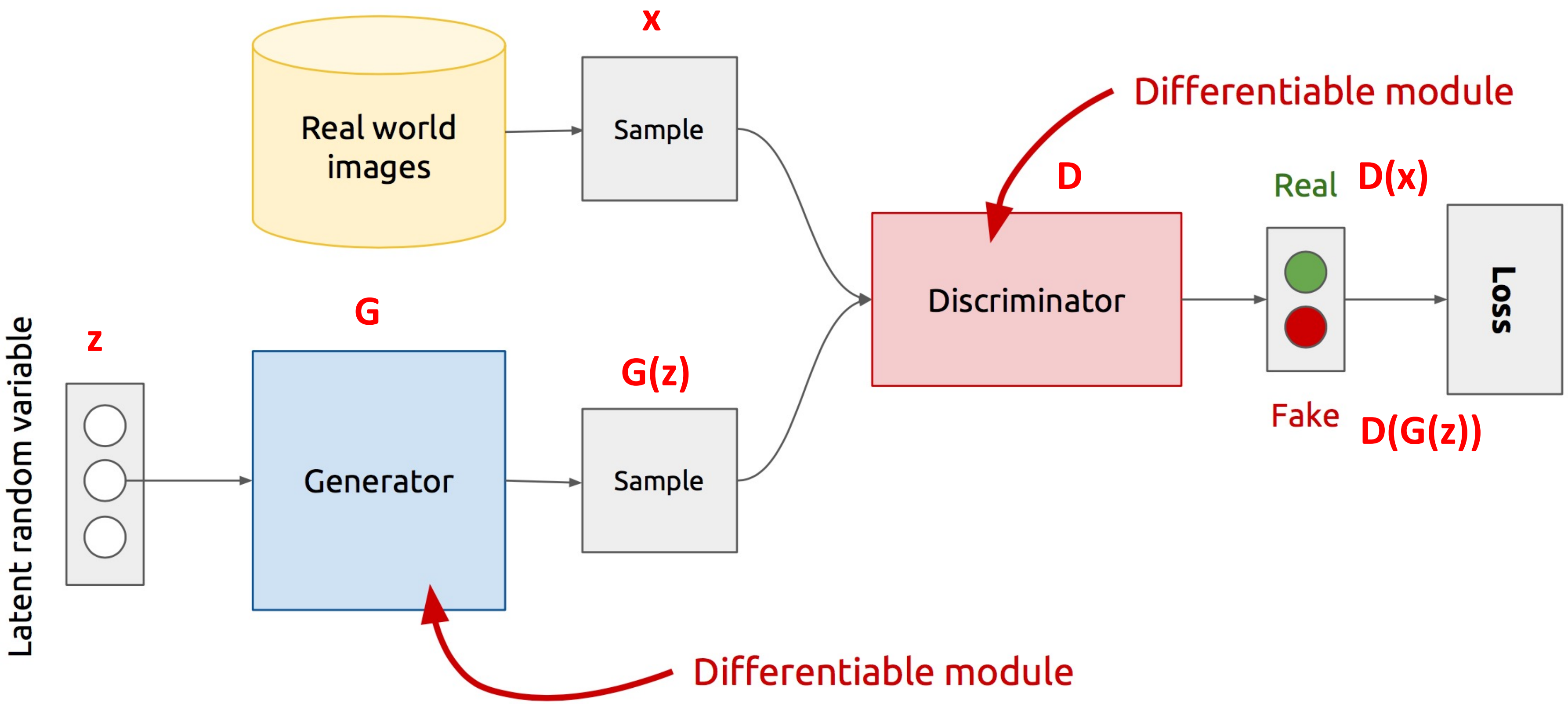


http://people.eecs.berkeley.edu/~junyanz/projects/gvm/

Adversarial Training

- Generator: generate fake samples, tries to fool the Discriminator
- Discriminator: tries to distinguish between real and fake samples
- Train them against each other
- Repeat this and we get better Generator and Discriminator

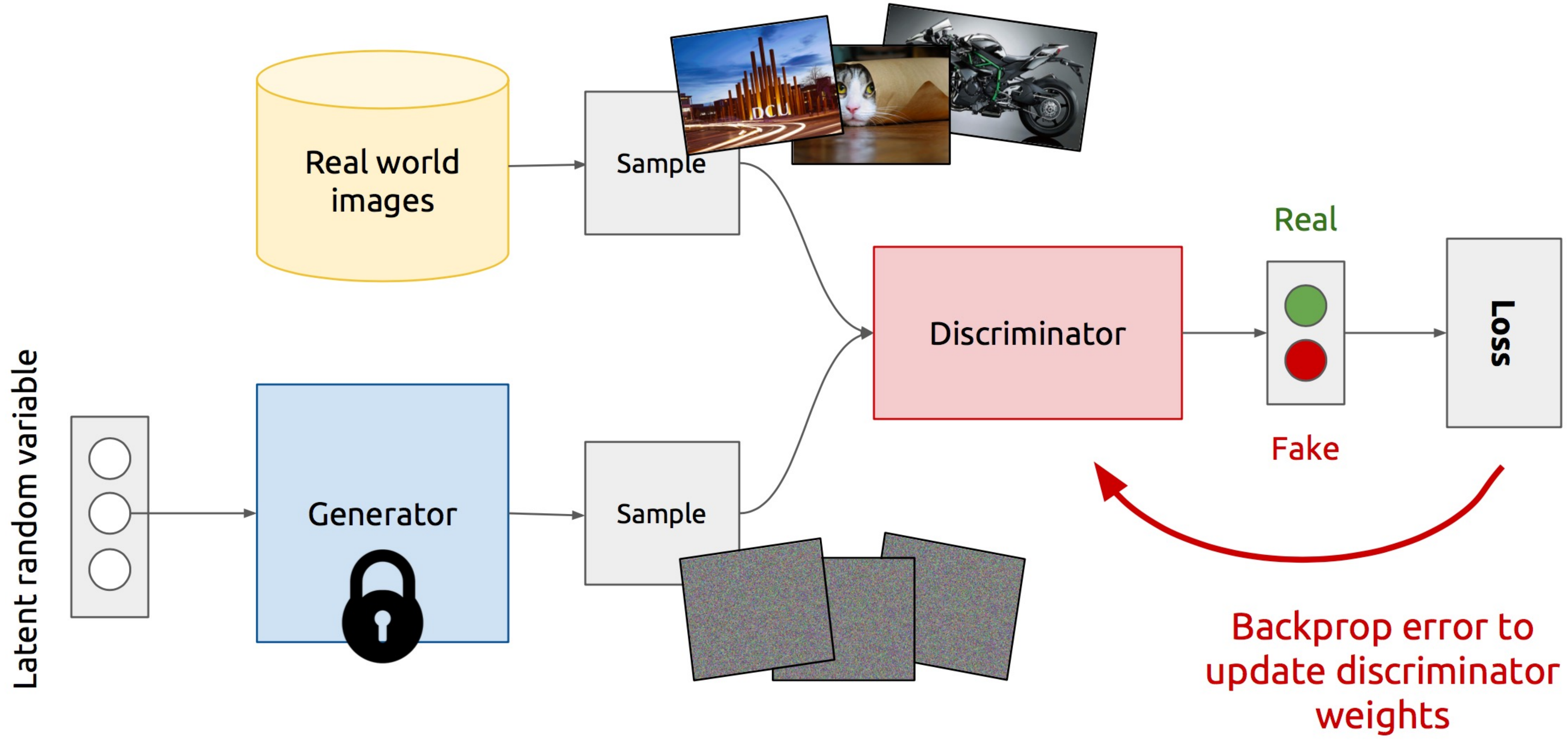
GAN’s Architecture



- **Z** is some random vector (Gaussian/Uniform).
- **Z** can be thought as the latent representation of the image.

https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

Training Discriminator



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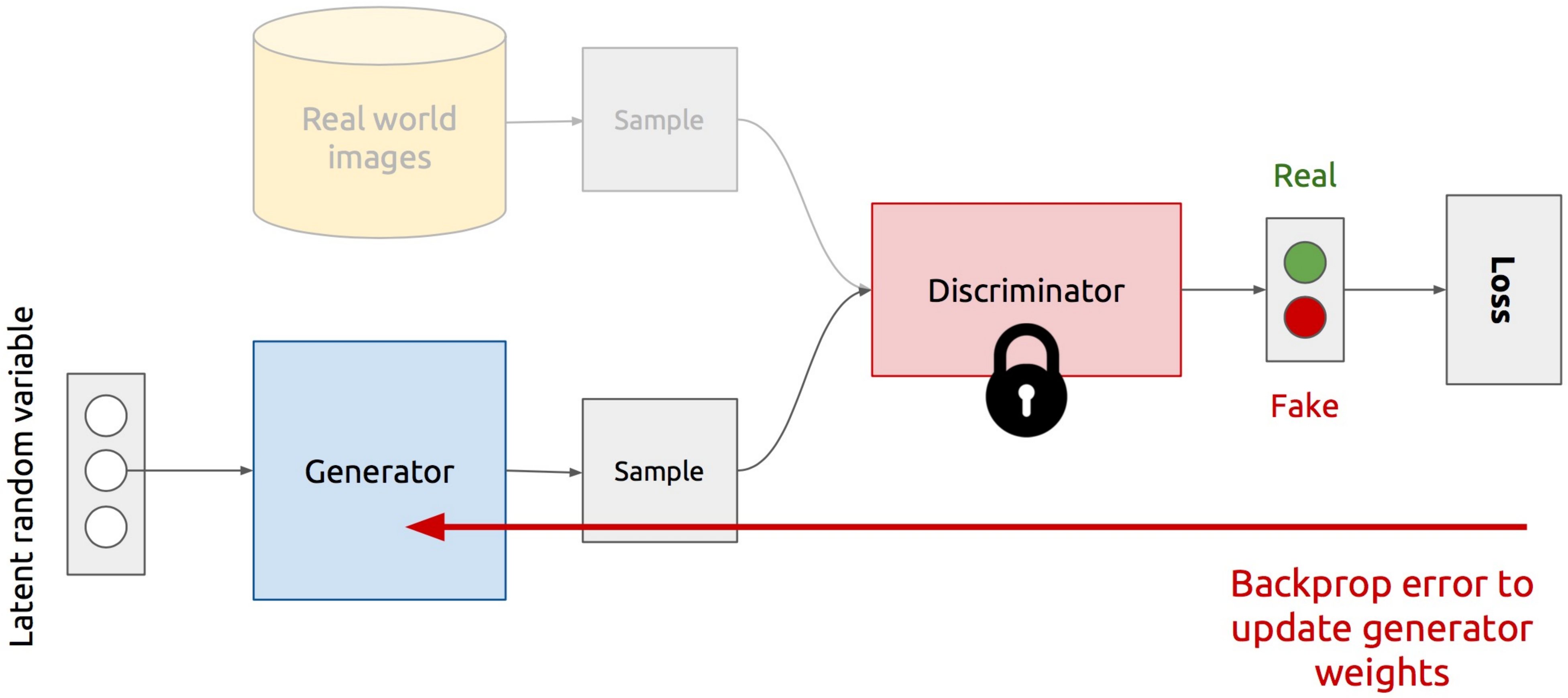
Training Generator



https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

GAN's formulation

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

- It is formulated as a **minimax game**, where:
  - The Discriminator is trying to maximize its reward $\boldsymbol{V(D, G)}$
  - The Generator is trying to minimize Discriminator's reward (or maximize its loss)

$$V(D, G) = \boxed{\mathbb{E}_{x \sim p(x)}[\log D(x)]} + \boxed{\mathbb{E}_{z \sim q(z)}\left[\log\left(1 - D(G(z))\right)\right]}$$

- The Nash equilibrium of this particular game is achieved at:
  - $P_{data}(x) = P_{gen}(x) \ \forall x$
  - $\mathrm{D}(x) = \frac{1}{2} \ \forall x$

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**

Discriminator updates

  for k steps **do**

  - Sample minibatch of m noise samples $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ from noise prior $p_g(\boldsymbol{z})$.
  - Sample minibatch of m examples $\{\boldsymbol{x}^{(1)}, \dots, \boldsymbol{x}^{(m)}\}$ 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

Generator updates

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

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

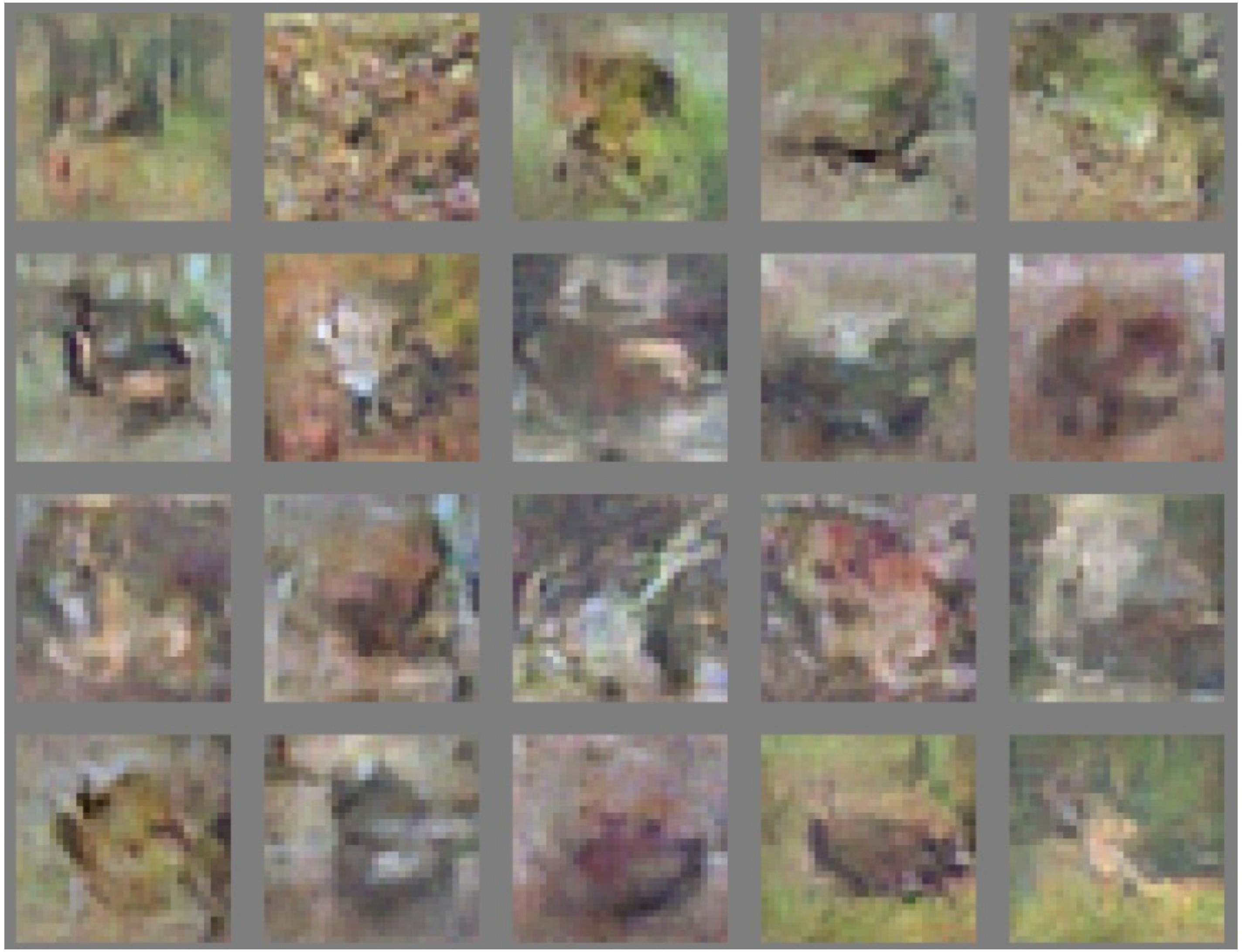
end for

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

Faces

Goodfellow, Ian, et al. **"Generative adversarial nets."** *Advances in neural information processing systems*. 2014.

CIFAR



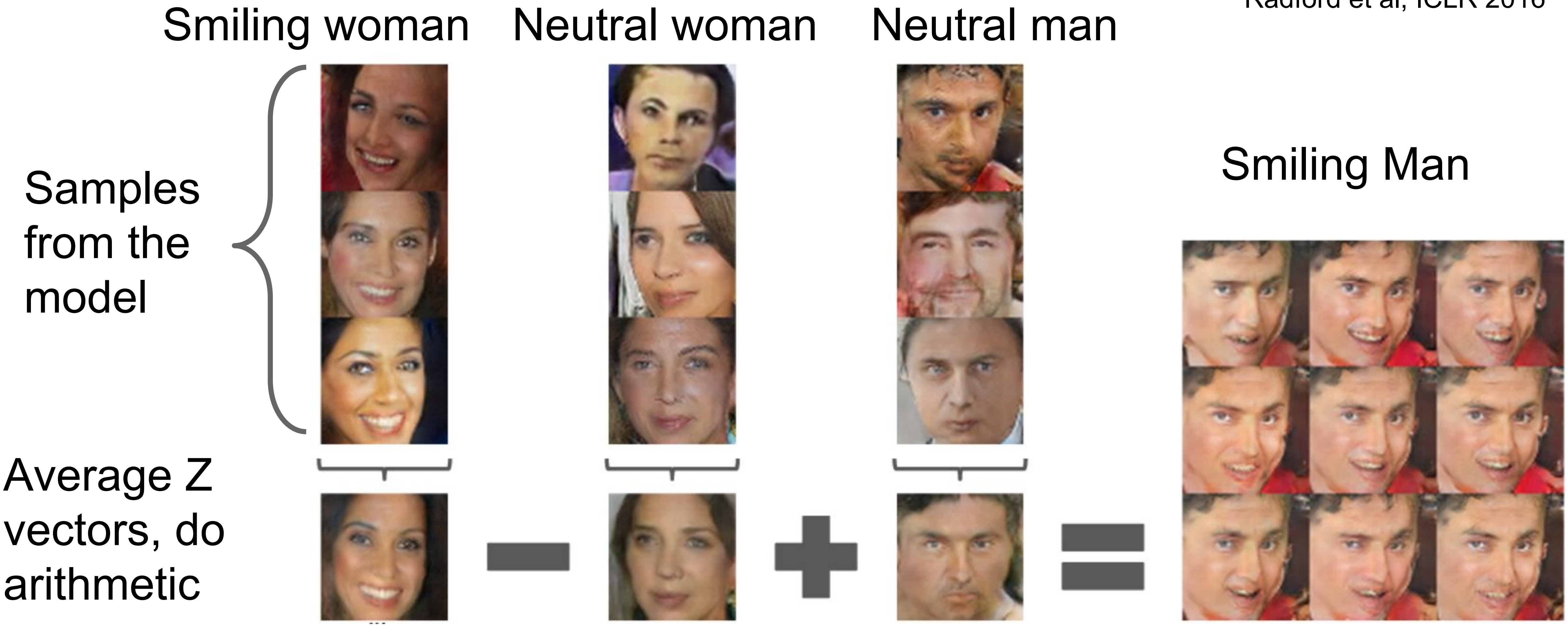
Goodfellow, Ian, et al. **"Generative adversarial nets."** *Advances in neural information processing systems*. 2014.

DCGAN: Bedroom images

Radford, Alec, Luke Metz, and Soumith Chintala. "Unsupervised representation learning with deep convolutional generative adversarial networks." arXiv:1511.06434 (2015).

Generative Adversarial Nets: Interpretable Vector Math

Radford et al, ICLR 2016



Generative Adversarial Nets: Interpretable Vector Math

Radford et al, ICLR 2016

Glasses man   No glasses man   No glasses woman

Woman with glasses