Generative Adversarial Networks (GANs)

From **Ian Goodfellow et al.**

A short tutorial by :-

Binglin, Shashank & Bhargav

Outline

- **Part 1: Introduction to GANs**
- **Part 2: Some challenges with GANs**
- **Part 3: Applications of GANs**

Part 1

- **Motivation for Generative Models**
- **From Adversarial Training to GANs**
- **GAN’s Architecture**
- **GAN’s objective**
- **DCGANs**

GANs

- **Generative**
  - Learn a generative model

- **Adversarial**
  - Trained in an adversarial setting

- **Networks**
  - Use Deep Neural Networks

Why Generative Models?

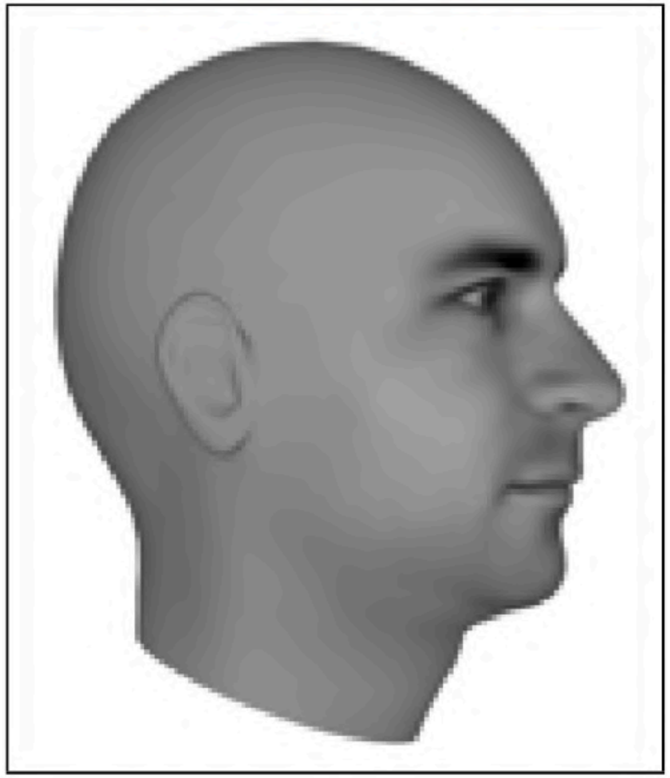
- **We've only seen discriminative models so far**
  - Given an image **X**, predict a label **Y**
  - Estimates **P(Y|X)**

- **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**

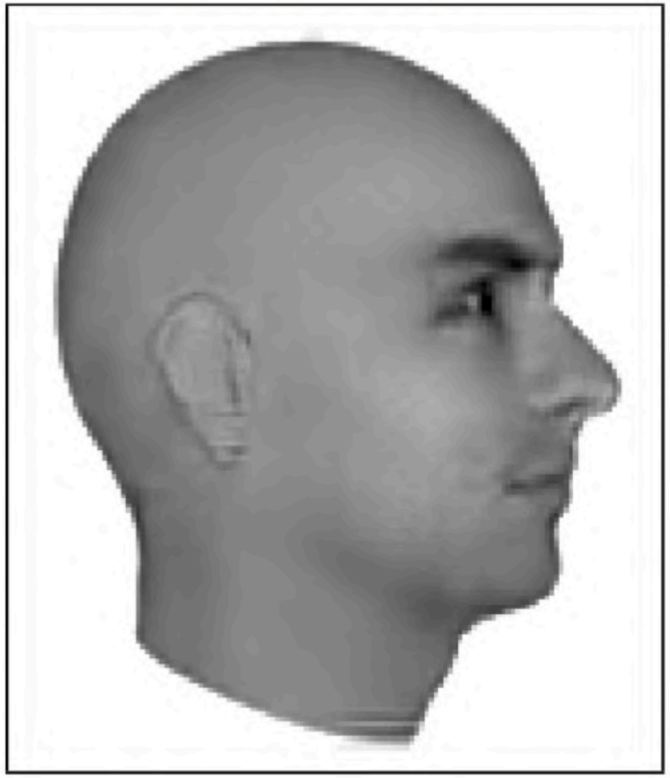
- **Generative models (in general) cope with all of above**
  - Can model **P(X)**
  - Can generate new images

Magic of GANs…

Ground Truth



Adversarial



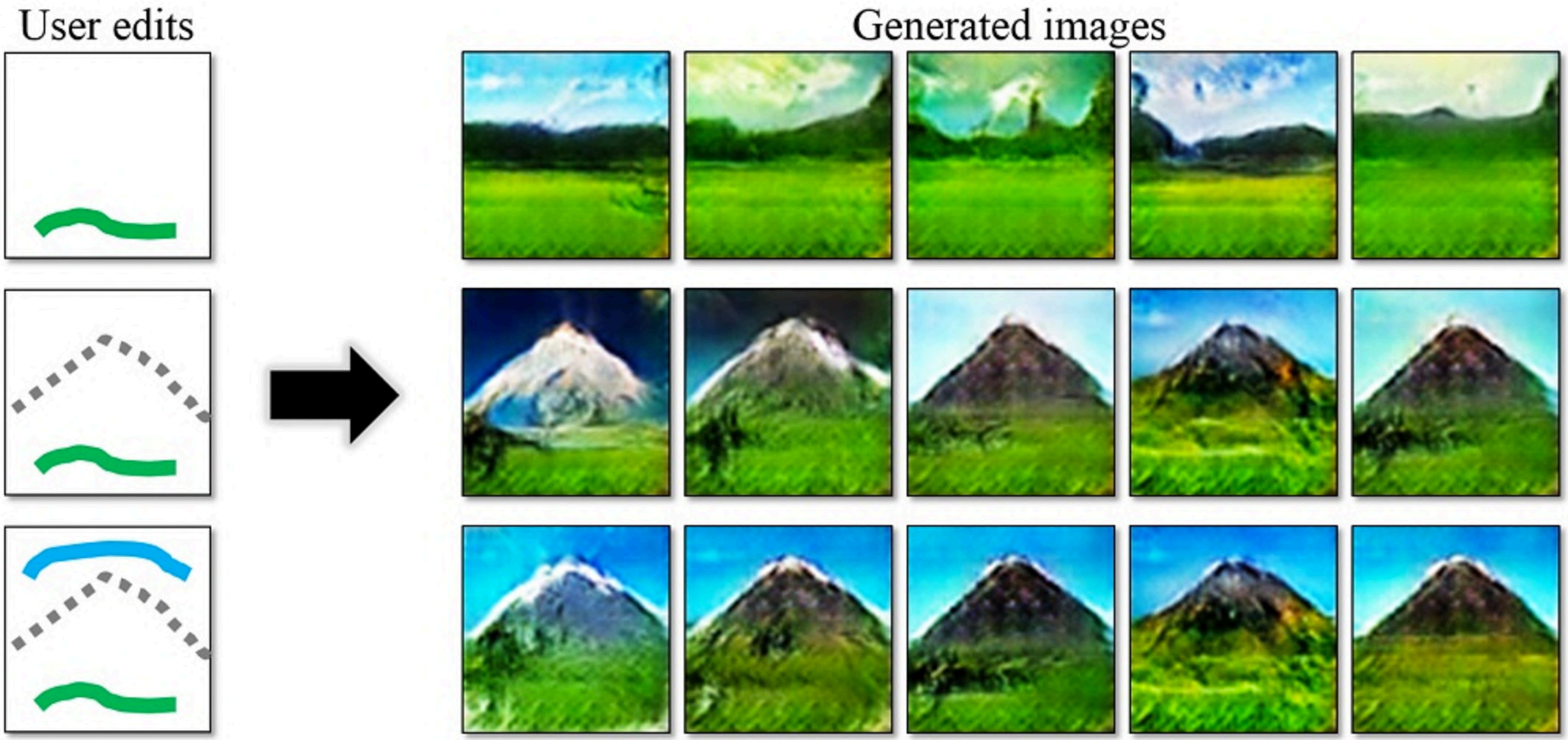
Lotter, William, Gabriel Kreiman, and David Cox. "Unsupervised learning of visual structure using predictive generative networks." *arXiv preprint arXiv:1511.06380* (2015).

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...

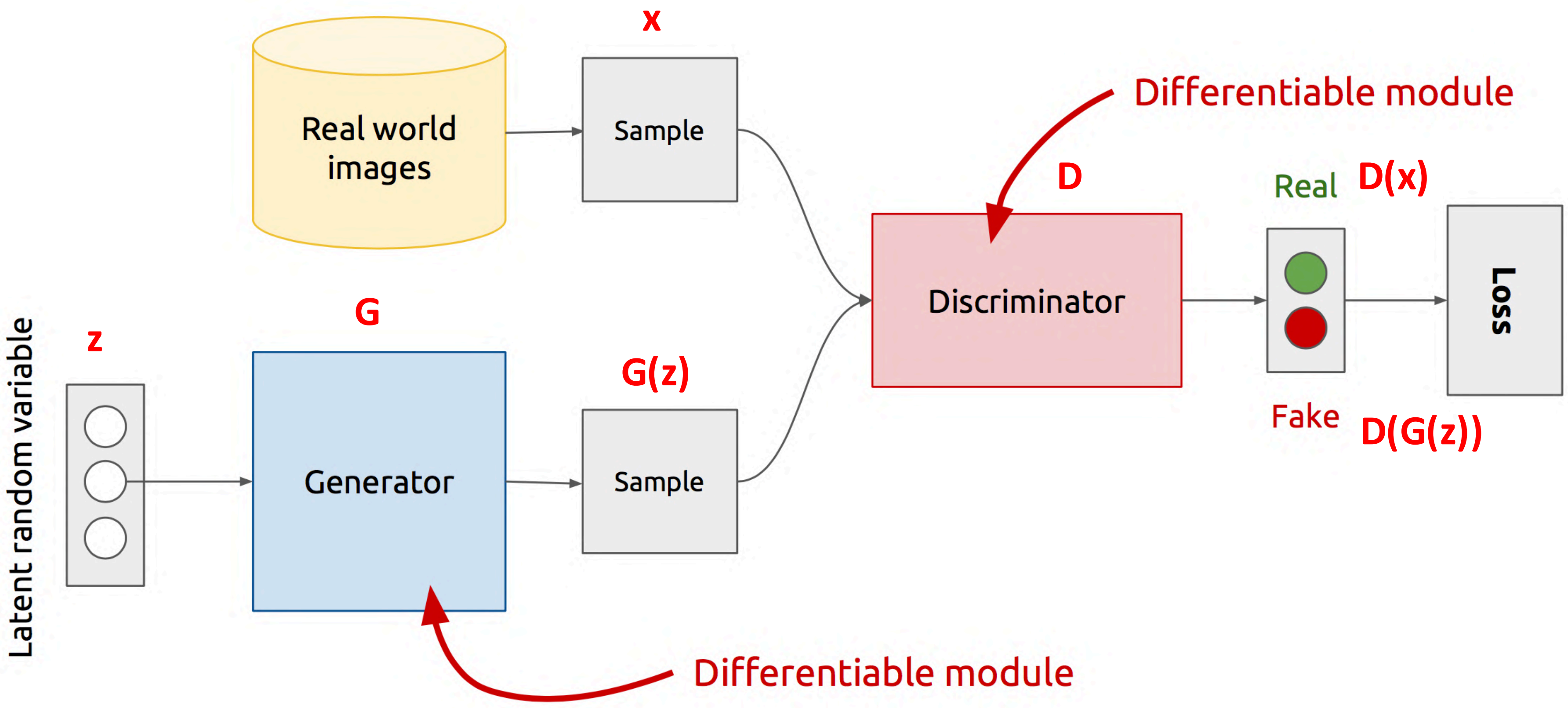


http://people.eecs.berkeley.edu/~junyanz/projects/gvm/

Adversarial Training

- **In the last lecture, we saw:**
  - We can generate adversarial samples to fool a discriminative model
  - We can use those adversarial samples to make models robust
  - We then require more effort to generate adversarial samples
  - Repeat this and we get better discriminative model
- **GANs extend that idea to generative models:**
  - 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

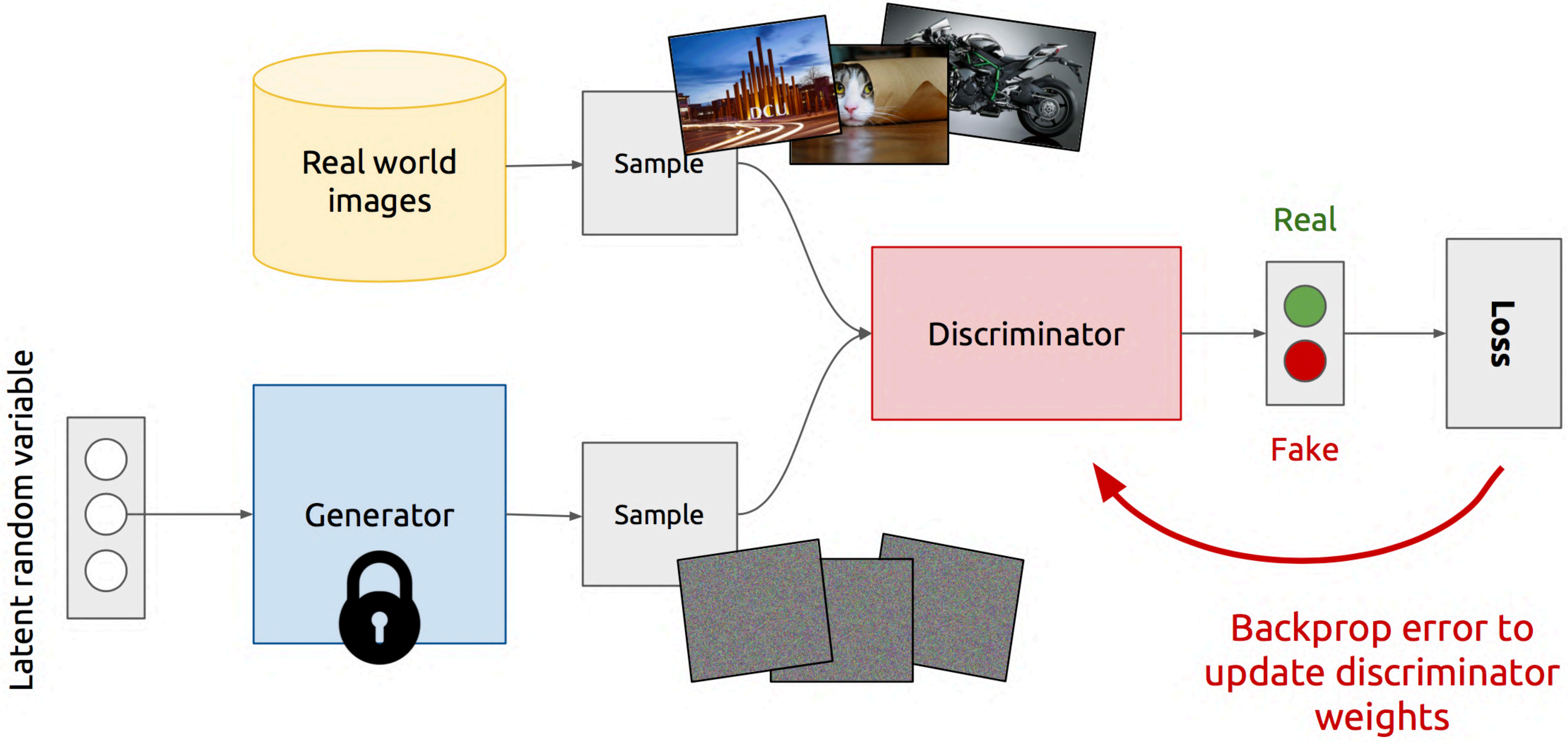
GAN’s Architecture



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

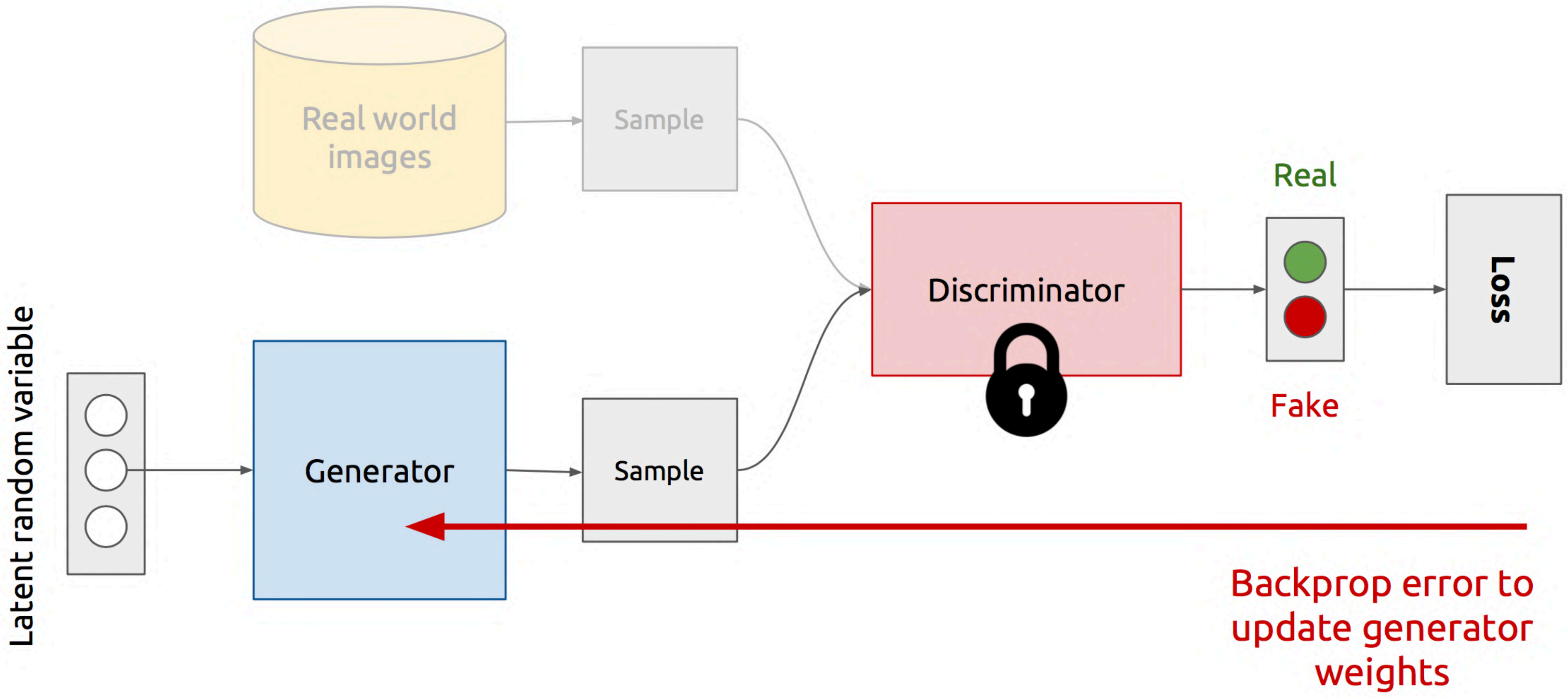
https://www.slideshare.net/xavigiro/deep-learning-for-computer-vision-generative-models-and-adversarial-training-upc-2016

Training Discriminator



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

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:
  - $P_{data}(x) = P_{gen}(x) \;\; \forall x$
  - $\mathrm{D}(x) = \frac{1}{2} \;\; \forall x$

Discriminator updates

Generator updates

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 $\{\boldsymbol{z}^{(1)}, \dots, \boldsymbol{z}^{(m)}\}$ 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

- 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:

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

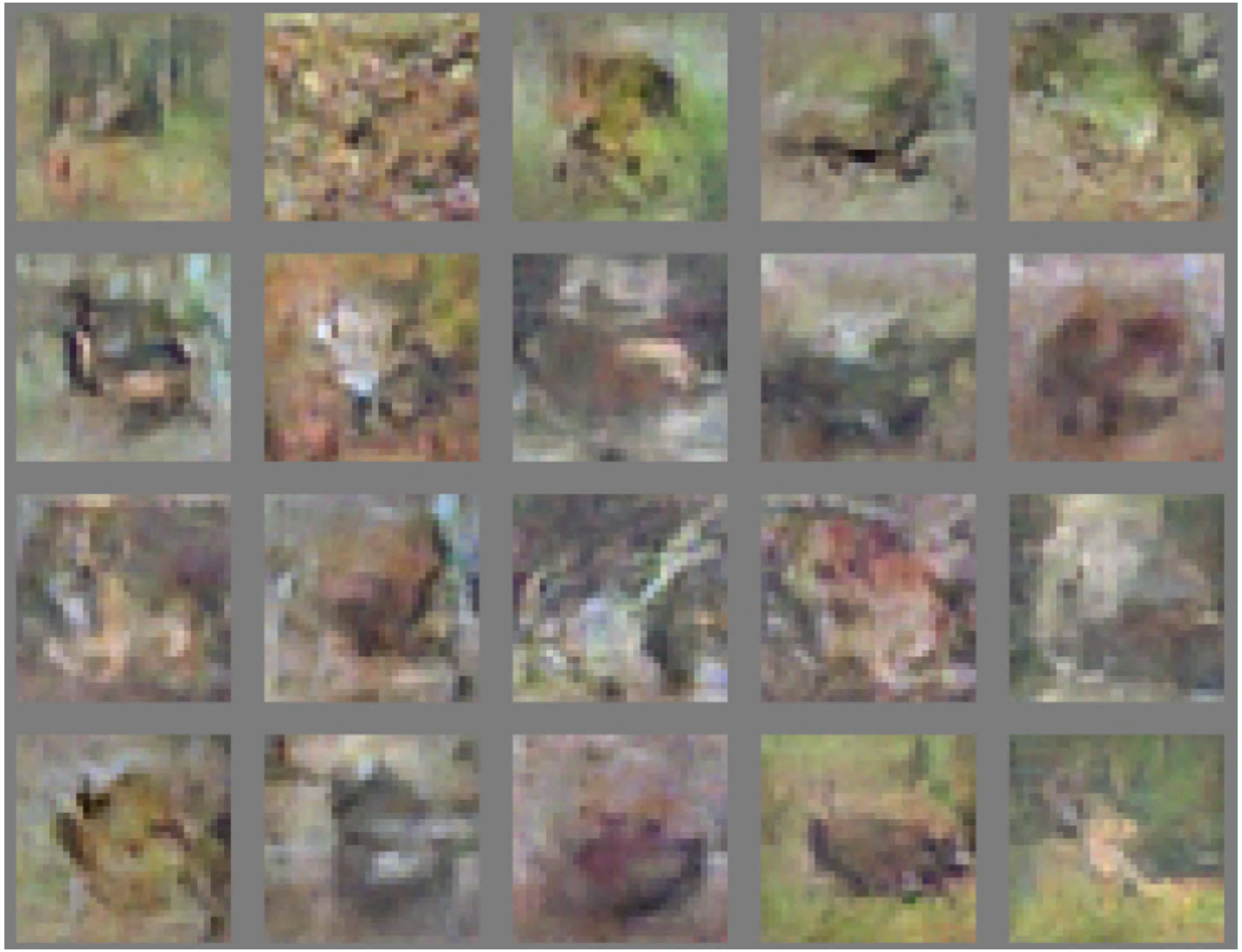
end for

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



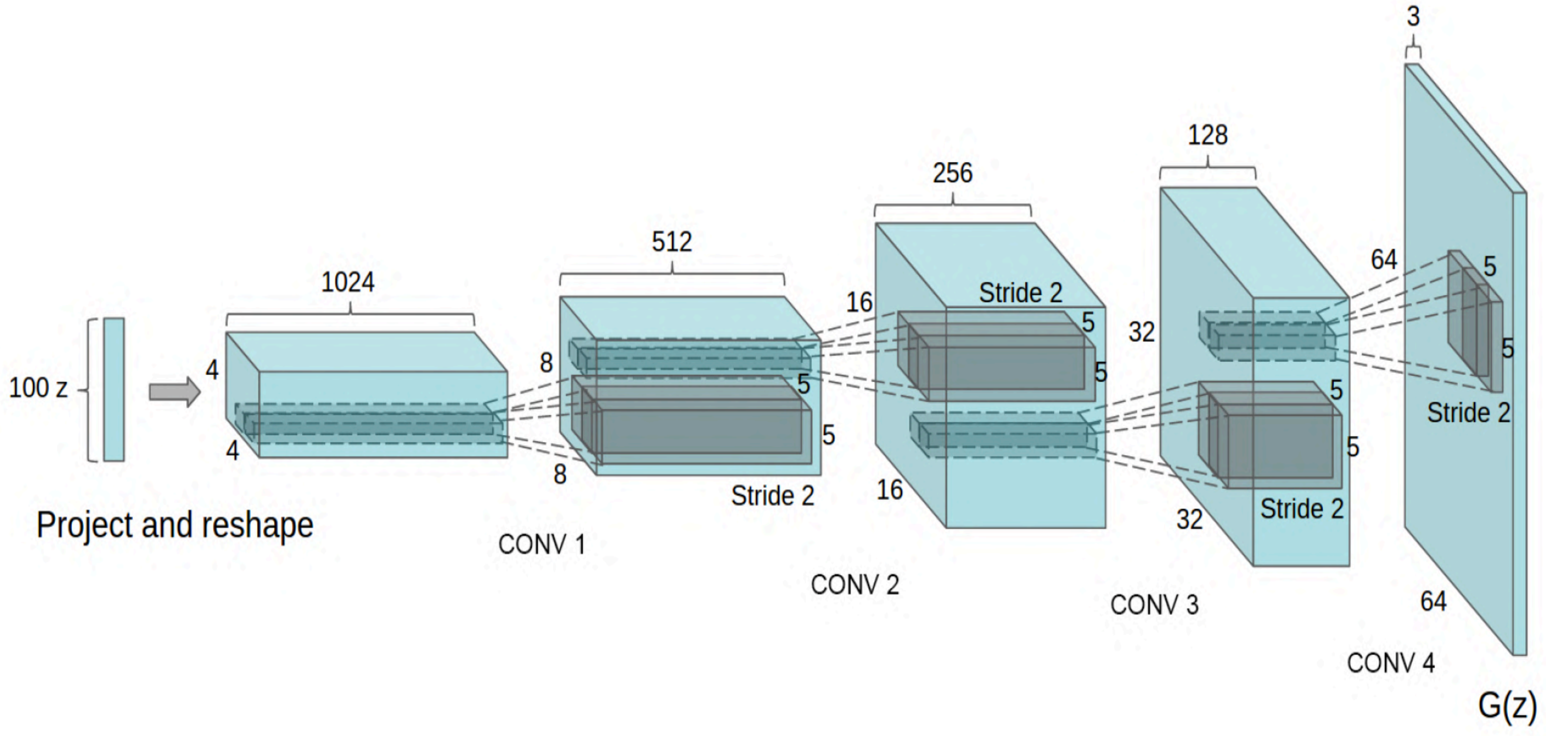
Goodfellow, Ian, et al. **"Generative adversarial nets."** *Advances in neural information processing systems*. 2014.

DCGAN: Bedroom images

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

Deep Convolutional GANs (DCGANs)

Generator Architecture

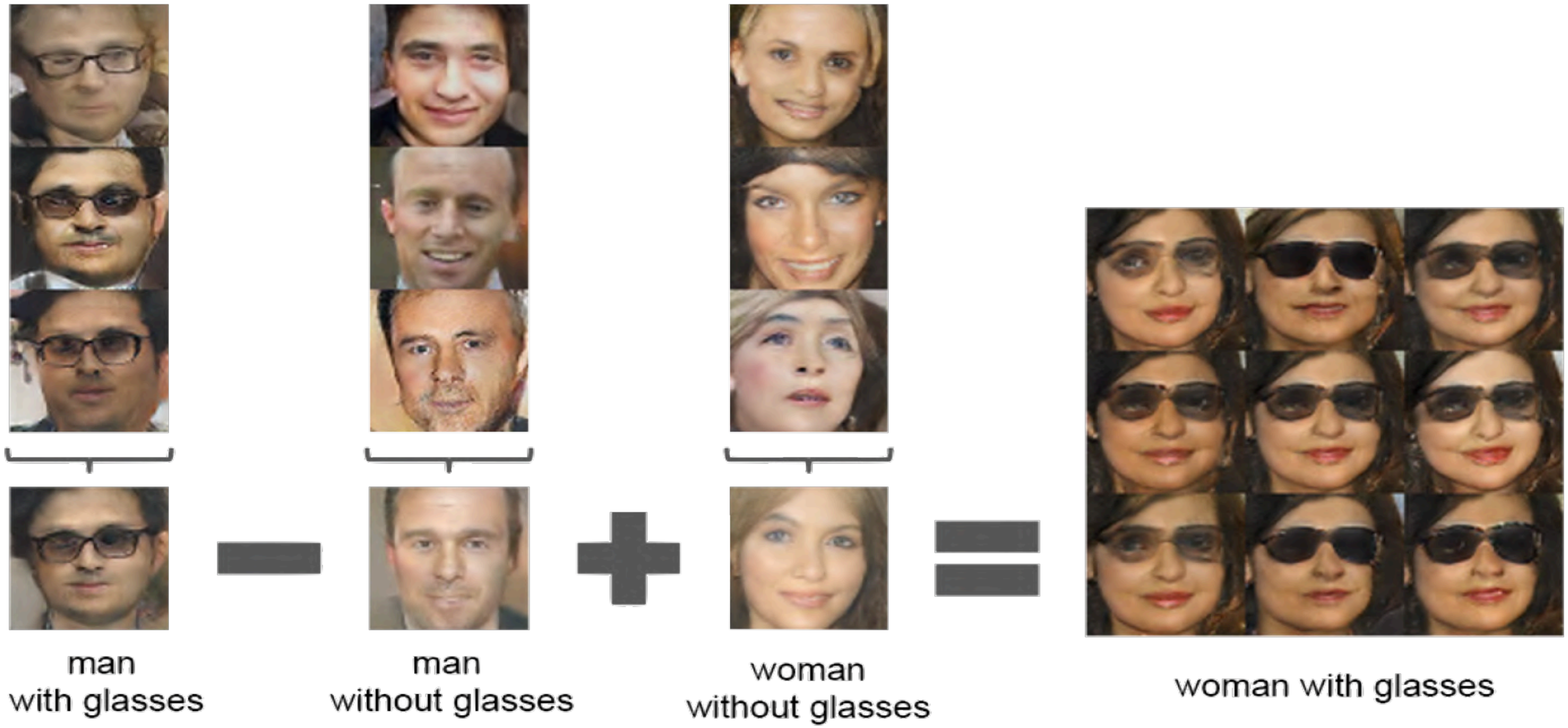


Key ideas:

- Replace FC hidden layers with Convolutions
  - **Generator:** Fractional-Strided convolutions
- Use Batch Normalization after each layer
- **Inside Generator**
  - Use ReLU for hidden layers
  - Use Tanh for the output layer

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

Latent vectors capture interesting patterns…



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

Part 2

- **Advantages of GANs**
- **Training Challenges**
  - Non-Convergence
  - Mode-Collapse
- **Proposed Solutions**
  - Supervision with Labels
  - Mini-Batch GANs
- **Modification of GAN's losses**
  - Discriminator **(EB-GAN)**
  - Generator **(InfoGAN)**

Advantages of GANs

- **Plenty of existing work on Deep Generative Models**
  - Boltzmann Machine
  - Deep Belief Nets
  - Variational AutoEncoders (VAE)

- **Why GANs?**
  - Sampling (or generation) is straightforward.
  - Training doesn't involve Maximum Likelihood estimation.
  - Robust to Overfitting since Generator never sees the training data.
  - Empirically, GANs are good at capturing the modes of the distribution.

Goodfellow, Ian. **"NIPS 2016 Tutorial: Generative Adversarial Networks."** arXiv preprint arXiv:1701.00160 (2016).

Problems with GANs

- **Probability Distribution is Implicit**
  - Not straightforward to compute P(X).
  - Thus **Vanilla GANs** are only good for Sampling/Generation.

- **Training is Hard**
  - Non-Convergence
  - Mode-Collapse

Goodfellow, Ian. **"NIPS 2016 Tutorial: Generative Adversarial Networks."** arXiv preprint arXiv:1701.00160 (2016).

Training Problems

- **Non-Convergence**
- Mode-Collapse

- **Deep Learning models (in general) involve a single player**
  - The player tries to maximize its reward (minimize its loss).
  - Use SGD (with Backpropagation) to find the optimal parameters.
  - SGD has convergence guarantees (under certain conditions).
  - **Problem:** With non-convexity, we might converge to local optima.

$$\min_{G} L(G)$$

- **GANs instead involve two (or more) players**
  - Discriminator is trying to maximize its reward.
  - Generator is trying to minimize Discriminator's reward.

$$\min_{G} \max_{D} V(D, G)$$

  - SGD was not designed to find the Nash equilibrium of a game.
  - **Problem:** We might not converge to the Nash equilibrium at all.

Salimans, Tim, et al. "Improved techniques for training gans." *Advances in Neural Information Processing Systems*. 2016.

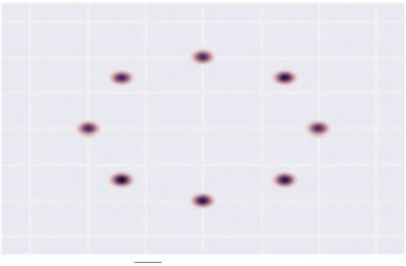
Problems with GANs

- Non-Convergence
- **Mode-Collapse**

Mode-Collapse

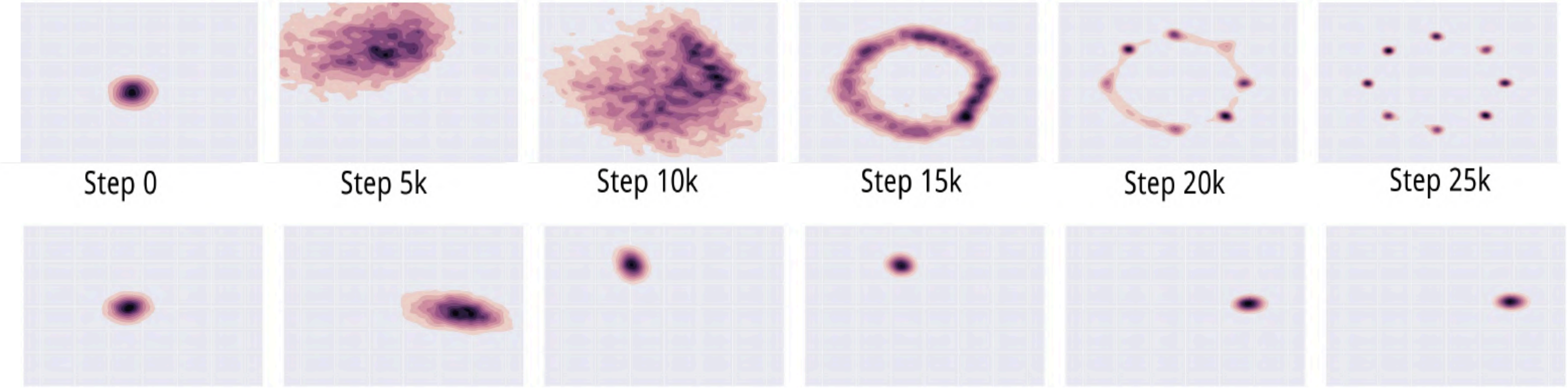
- **Generator fails to output diverse samples**

Target



Expected

Output



Metz, Luke, et al. **"Unrolled Generative Adversarial Networks."** arXiv preprint arXiv:1611.02163 (2016).

Some real examples

Reed, S., et al. ***Generating interpretable images with controllable structure.*** Technical report, 2016. 2, 2016.

Part 3

- **Conditional GANs**
- **Applications**
  - Image-to-Image Translation
  - Text-to-Image Synthesis
  - Face Aging
- **Advanced GAN Extensions**
  - Coupled GAN
  - LAPGAN – Laplacian Pyramid of Adversarial Networks
  - Adversarially Learned Inference
- **Summary**

Conditional GANs

MNIST digits generated conditioned on their class label.

$[1,0,0,0,0,0,0,0,0,0]$

$[0,1,0,0,0,0,0,0,0,0]$

$[0,0,1,0,0,0,0,0,0,0]$

$[0,0,0,1,0,0,0,0,0,0]$

$[0,0,0,0,1,0,0,0,0,0]$

$[0,0,0,0,0,1,0,0,0,0]$

$[0,0,0,0,0,0,1,0,0,0]$

$[0,0,0,0,0,0,0,1,0,0]$

$[0,0,0,0,0,0,0,0,1,0]$

$[0,0,0,0,0,0,0,0,0,1]$

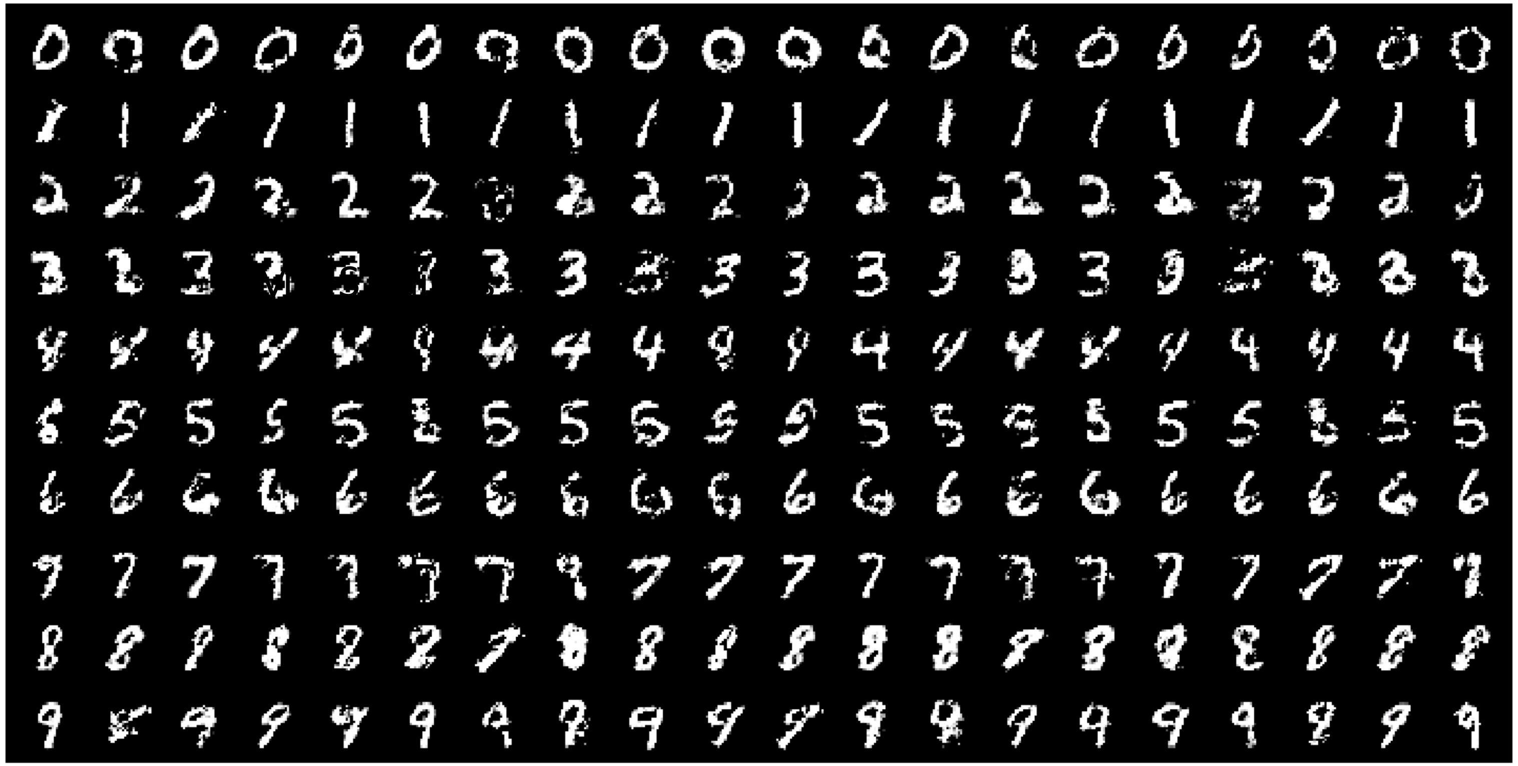


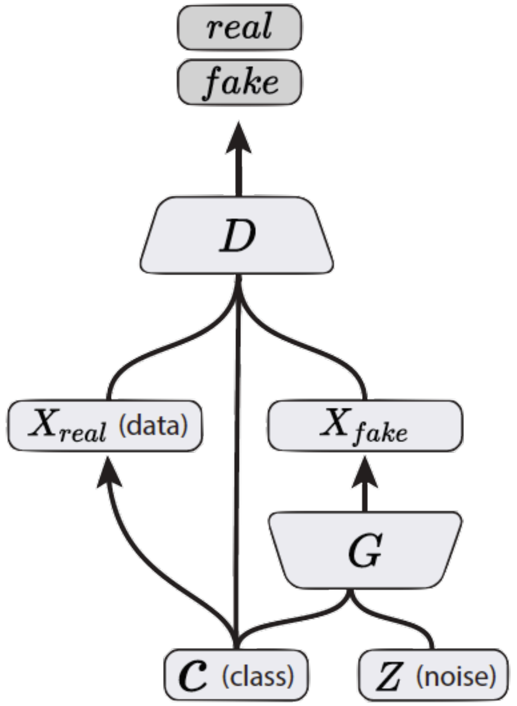
Figure 2 in the original paper.

Mirza, Mehdi, and Simon Osindero. Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784 (2014).

Conditional GANs

- Simple modification to the original GAN framework that conditions the model on *additional information* for better multi-modal learning.

- Lends to many practical applications of GANs when we have explicit *supervision* available.



Conditional GAN
(Mirza & Osindero, 2014)

Image Credit: Figure 2 in Odena, A., Olah, C. and Shlens, J., 2016. Conditional image synthesis with auxiliary classifier GANs. *arXiv preprint arXiv:1610.09585*.

Mirza, Mehdi, and Simon Osindero. "**Conditional generative adversarial nets**". arXiv preprint arXiv:1411.1784 (2014).

Part 3

- Conditional GANs
- **Applications**
    - Image-to-Image Translation
    - Text-to-Image Synthesis
    - Face Aging
- Advanced GAN Extensions
    - Coupled GAN
    - LAPGAN – Laplacian Pyramid of Adversarial Networks
    - Adversarially Learned Inference
- Summary

Image-to-Image Translation

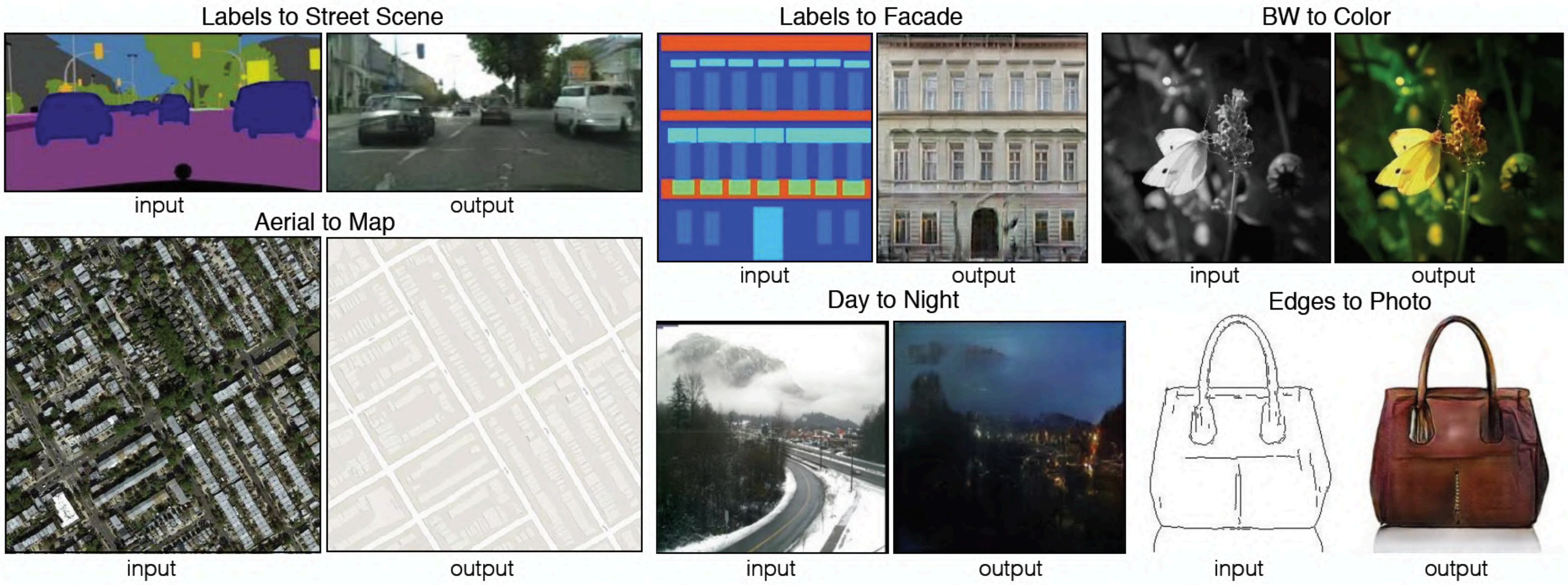


Figure 1 in the original paper.

Link to an interactive demo of this paper

Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. "**Image-to-image translation with conditional adversarial networks**". arXiv preprint arXiv:1611.07004. (2016).

Image-to-Image Translation

- Architecture: *DCGAN*-based architecture

- Training is conditioned on the images from the source domain.

- Conditional GANs provide an effective way to handle many complex domains without worrying about designing *structured loss* functions explicitly.

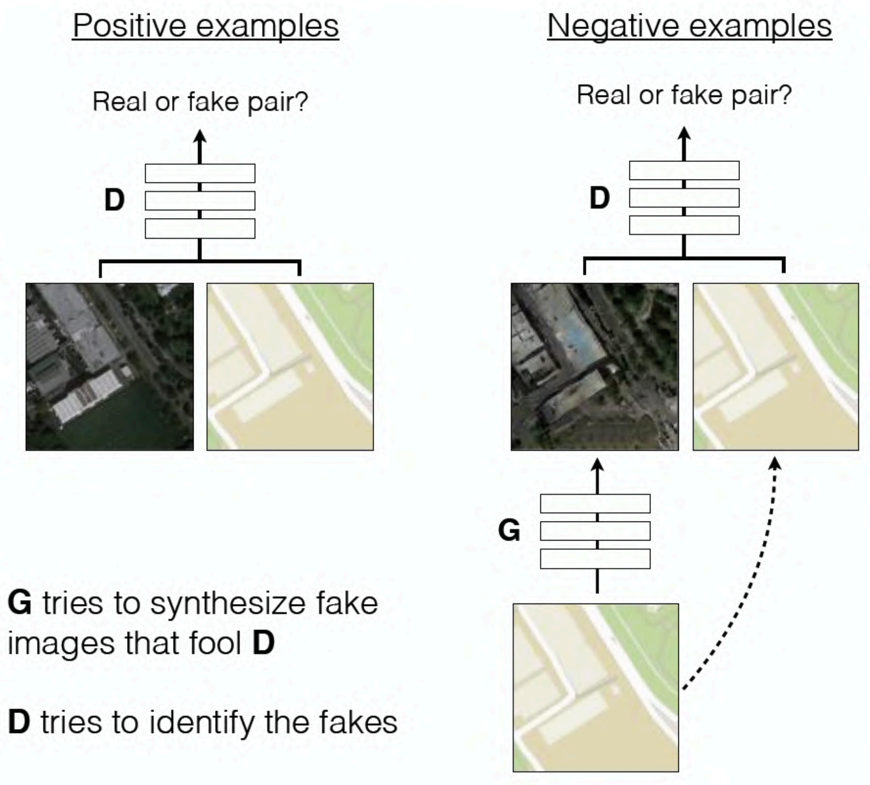


Figure 2 in the original paper.

Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. "**Image-to-image translation with conditional adversarial networks**". arXiv preprint arXiv:1611.07004. (2016).

Text-to-Image Synthesis

Motivation

Given a text description, generate images closely associated.

Uses a conditional GAN with the generator and discriminator being condition on “dense” text embedding.

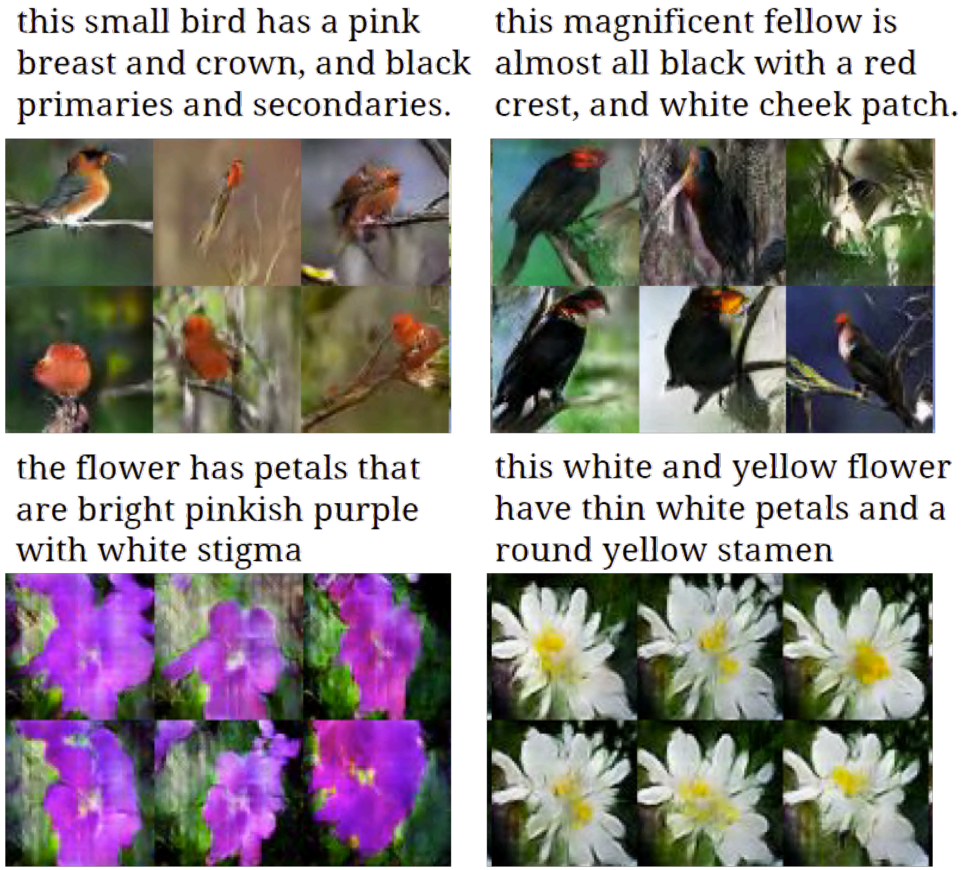


Figure 1 in the original paper.

Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., & Lee, H. “**Generative adversarial text to image synthesis**”. ICML (2016).

Text-to-Image Synthesis

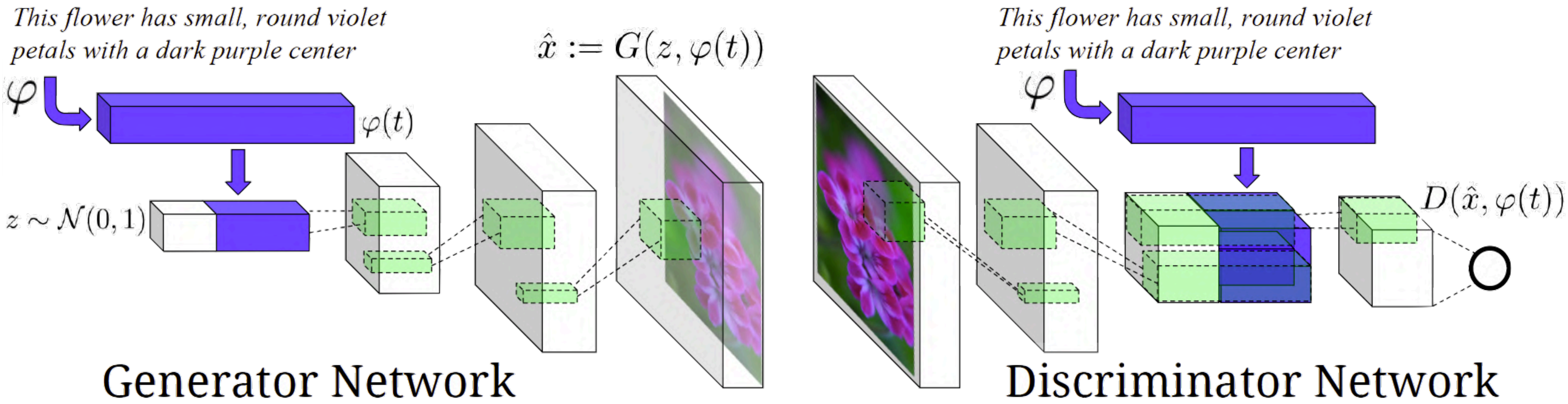


Figure 2 in the original paper.

Positive Example:

Real Image, Right Text

Negative Examples:

Real Image, Wrong Text

Fake Image, Right Text

Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., & Lee, H. "**Generative adversarial text to image synthesis**". ICML (2016).

Face Aging with Conditional GANs

- Differentiating Feature: Uses an *Identity Preservation Optimization* using an auxiliary network to get a better approximation of the latent code (z*) for an input image.
- Latent code is then conditioned on a discrete (one-hot) embedding of age categories.

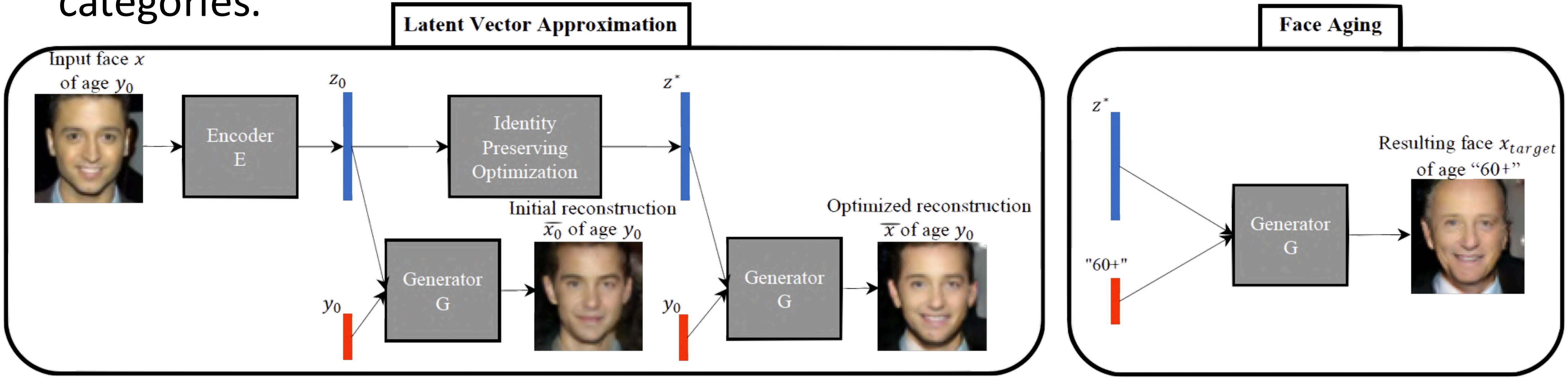


Figure 1 in the original paper.

Antipov, G., Baccouche, M., & Dugelay, J. L. (2017). “**Face Aging With Conditional Generative Adversarial Networks**”. arXiv preprint arXiv:1702.01983.

Face Aging with Conditional GANs

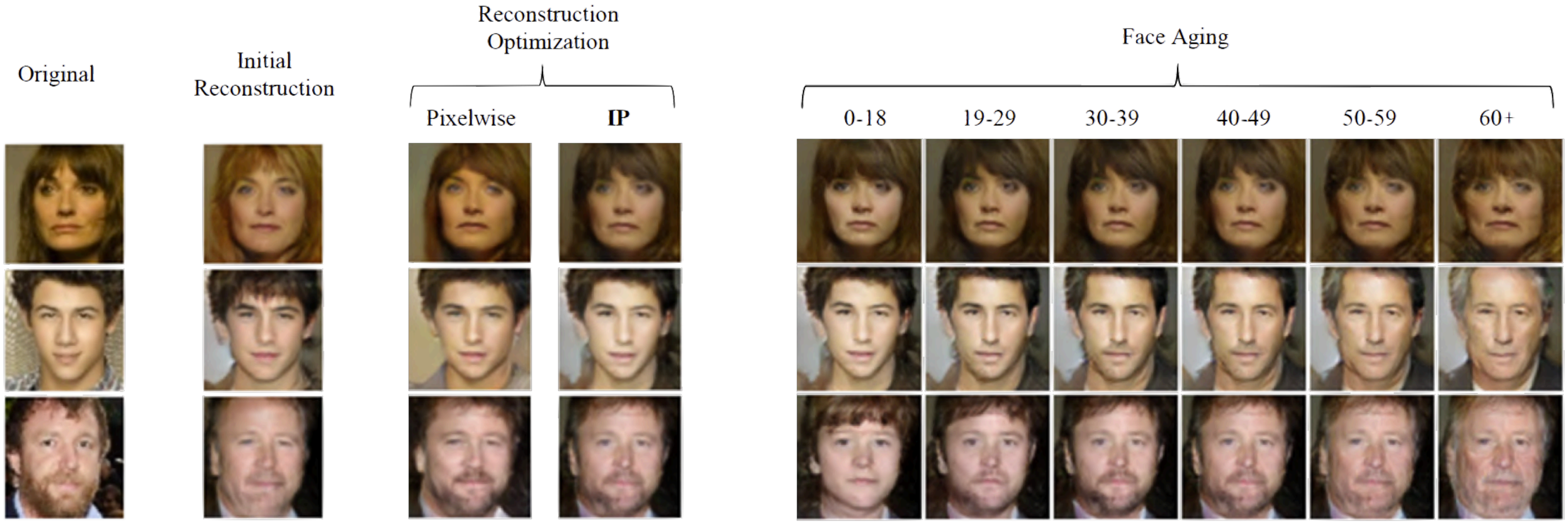


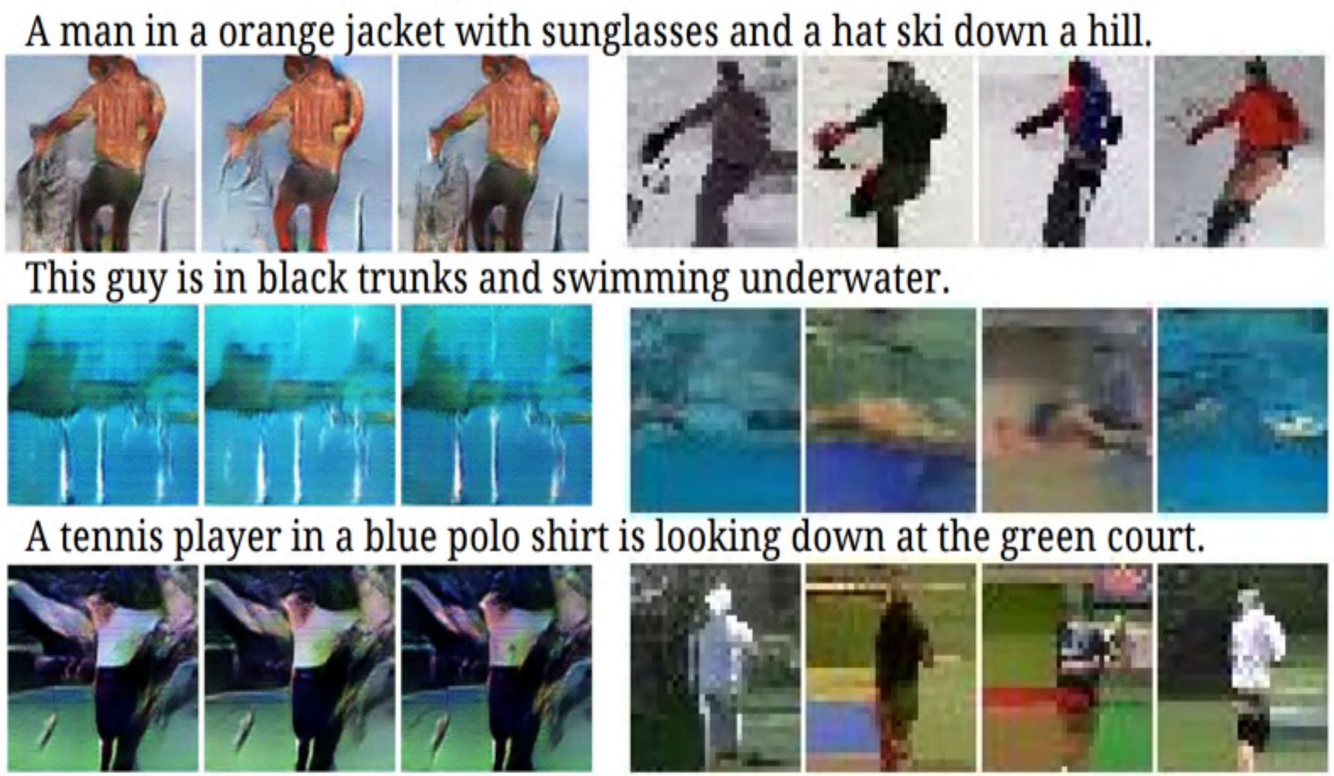
Figure 3 in the original paper.

Antipov, G., Baccouche, M., & Dugelay, J. L. (2017). "**Face Aging With Conditional Generative Adversarial Networks**". arXiv preprint arXiv:1702.01983.

Conditional GANs

Conditional Model Collapse

- Scenario observed when the Conditional GAN starts *ignoring* either the code (c) or the noise variables (z).
- This limits the diversity of images generated.



Credit?

Mirza, Mehdi, and Simon Osindero. Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784 (2014).

Summary

- GANs are generative models that are implemented using two stochastic neural network modules: **Generator** and **Discriminator**.
- **Generator** tries to generate samples from random noise as input
- **Discriminator** tries to distinguish the samples from Generator and samples from the real data distribution.
- Both networks are trained adversarially (in tandem) to fool the other component. In this process, both models become better at their respective tasks.

Why use GANs for Generation?

- Can be trained using back-propagation for Neural Network based Generator/Discriminator functions.
- Sharper images can be generated.
- Faster to sample from the model distribution: *single* forward pass generates a *single* sample.

Reading List

- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y. Generative adversarial nets, NIPS (2014).
- Goodfellow, Ian NIPS 2016 Tutorial: Generative Adversarial Networks, NIPS (2016).
- Radford, A., Metz, L. and Chintala, S., Unsupervised representation learning with deep convolutional generative adversarial networks. arXiv preprint arXiv:1511.06434. (2015).
- Salimans, T., Goodfellow, I., Zaremba, W., Cheung, V., Radford, A., & Chen, X. Improved techniques for training gans. NIPS (2016).
- Chen, X., Duan, Y., Houthooft, R., Schulman, J., Sutskever, I., & Abbeel, P. InfoGAN: Interpretable Representation Learning by Information Maximization Generative Adversarial Nets, NIPS (2016).
- Zhao, Junbo, Michael Mathieu, and Yann LeCun. Energy-based generative adversarial network. arXiv preprint arXiv:1609.03126 (2016).
- Mirza, Mehdi, and Simon Osindero. Conditional generative adversarial nets. arXiv preprint arXiv:1411.1784 (2014).
- Liu, Ming-Yu, and Oncel Tuzel. Coupled generative adversarial networks. NIPS (2016).
- Denton, E.L., Chintala, S. and Fergus, R., 2015. Deep Generative Image Models using a Laplacian Pyramid of Adversarial Networks. NIPS (2015)
- Dumoulin, V., Belghazi, I., Poole, B., Lamb, A., Arjovsky, M., Mastropietro, O., & Courville, A. Adversarially learned inference. arXiv preprint arXiv:1606.00704 (2016).

Applications:

- Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. Image-to-image translation with conditional adversarial networks. arXiv preprint arXiv:1611.07004. (2016).
- Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., & Lee, H. Generative adversarial text to image synthesis. JMLR (2016).
- Antipov, G., Baccouche, M., & Dugelay, J. L. (2017). Face Aging With Conditional Generative Adversarial Networks. arXiv preprint arXiv:1702.01983.

Questions?