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

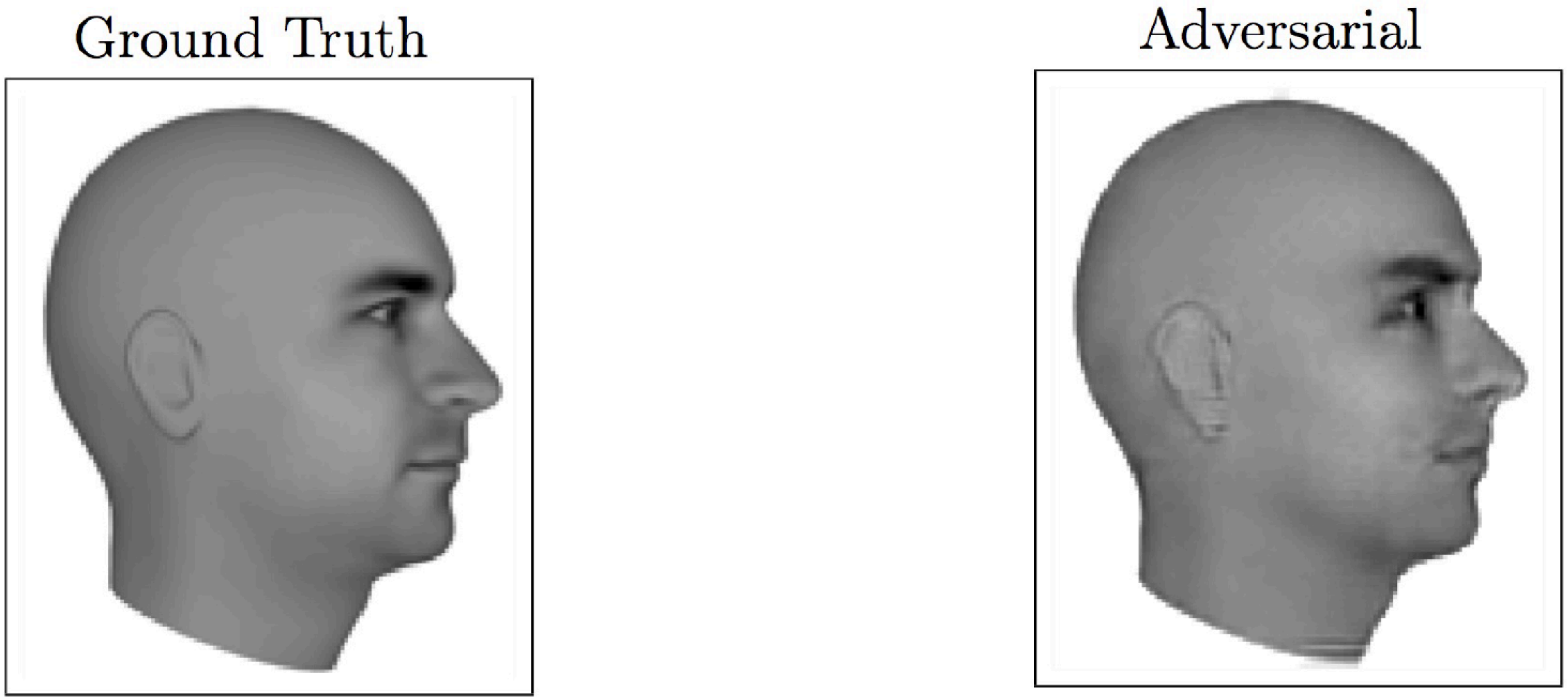
Why Generative Models?

- **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…



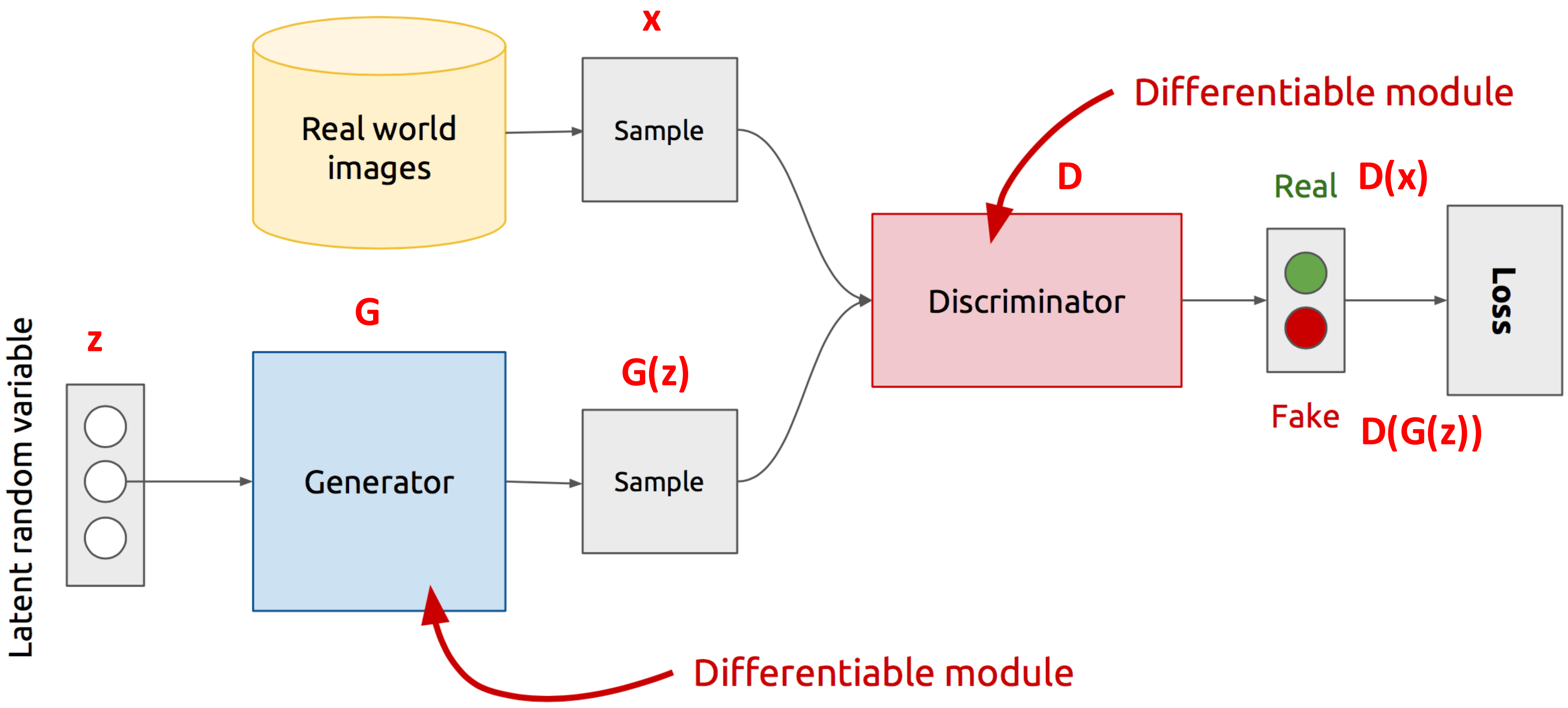
Lotter, William, Gabriel Kreiman, and David Cox. "Unsupervised learning of visual structure using predictive generative networks." *arXiv preprint arXiv:1511.06380* (2015).

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).

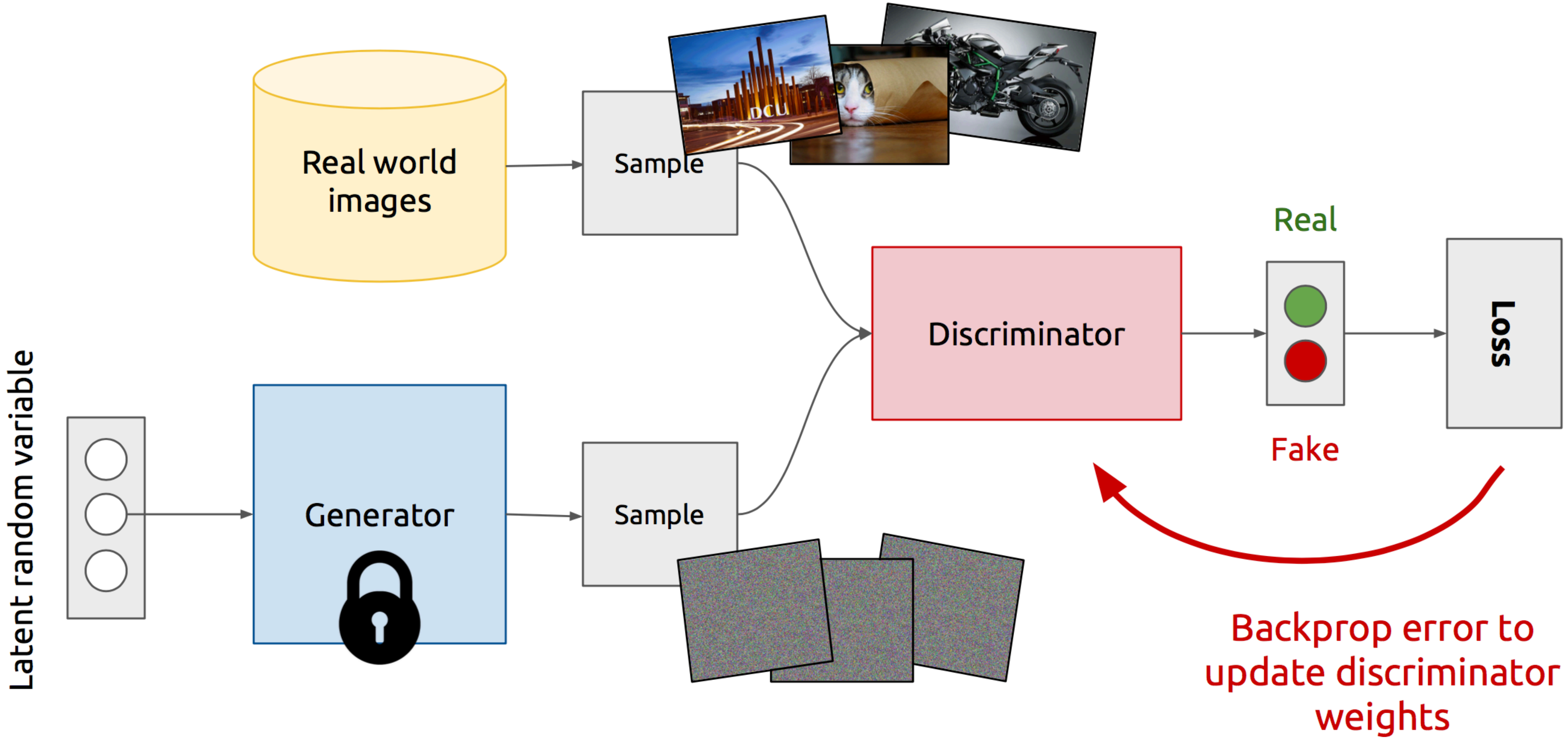
GAN's Architecture



- **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



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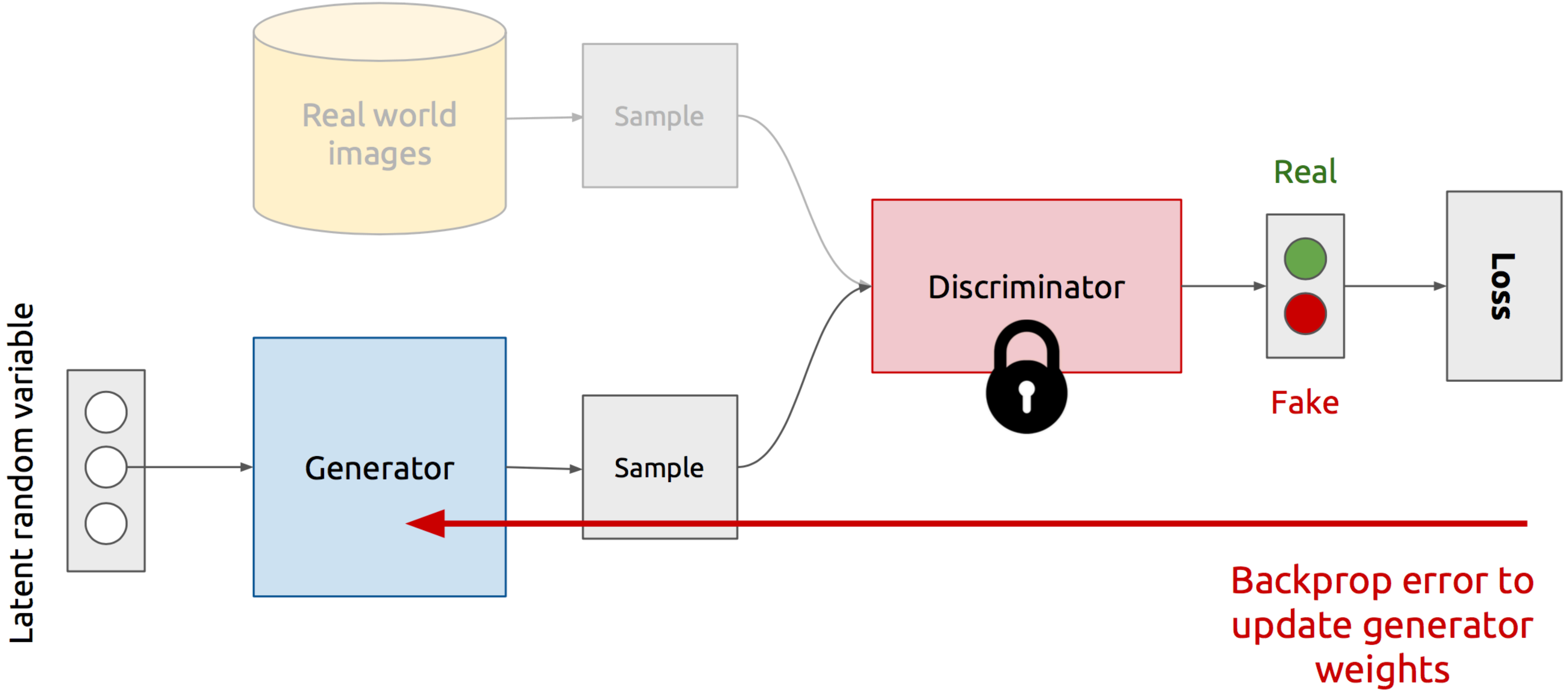
Training Generator



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.

Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Putting it together: GAN training algorithm

Some find k=1 more stable, others use k > 1, no best rule.

Recent work (e.g. Wasserstein GAN) alleviates this problem, better stability!

for number of training iterations **do**

  for $\boxed{k \text{ steps}}$ **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:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^{m} \left[\log D_{\theta_d}(x^{(i)}) + \log(1 - D_{\theta_d}(G_{\theta_g}(z^{(i)}))) \right]$$

  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 ascending its stochastic gradient (improved objective):

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^{m} \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

end for

Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Generator network: try to fool the discriminator by generating real-looking images
Discriminator network: try to distinguish between real and fake images

Train jointly in **minimax game**

Minimax objective function:

Discriminator outputs likelihood in (0,1) of real image

$$\min_{\theta_g} \max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log \underbrace{D_{\theta_d}(x)}_{\text{Discriminator output for real data x}} + \mathbb{E}_{z \sim p(z)} \log(1 - \underbrace{D_{\theta_d}(G_{\theta_g}(z))}_{\text{Discriminator output for generated fake data G(z)}}) \right]$$

- Discriminator (θ_d) wants to **maximize objective** such that D(x) is close to 1 (real) and D(G(z)) is close to 0 (fake)
- Generator (θ_g) wants to **minimize objective** such that D(G(z)) is close to 1 (discriminator is fooled into thinking generated G(z) is real)

Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Minimax objective function:

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

Alternate between:

1. **Gradient ascent** on discriminator

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

2. **Gradient descent** on generator

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

Training GANs: Two-player game

Ian Goodfellow et al., "Generative Adversarial Nets", NIPS 2014

Minimax objective function:

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

Alternate between:

1. **Gradient ascent** on discriminator

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

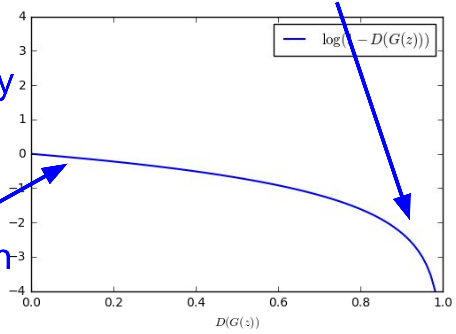
2. **Gradient descent** on generator

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

In practice, optimizing this generator objective does not work well!

When sample is likely fake, want to learn from it to improve generator. But gradient in this region is relatively flat!

Gradient signal dominated by region where sample is already good



Training GANs: Two-player game

Ian Goodfellow et al., “Generative Adversarial Nets”, NIPS 2014

Minimax objective function:

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Alternate between:

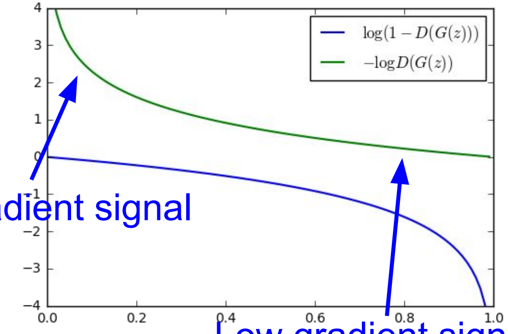
1. **Gradient ascent** on discriminator

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

2. **Instead: Gradient ascent** on generator, different objective

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

Instead of minimizing likelihood of discriminator being correct, now maximize likelihood of discriminator being wrong.
Same objective of fooling discriminator, but now higher gradient signal for bad samples => works much better! Standard in practice.



Vanishing gradient strikes back again…

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

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

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

- $\nabla_a \log(1 - \sigma(a)) = \frac{-\nabla_a \sigma(a)}{1 - \sigma(a)} = \frac{-\sigma(a)\left(1 - \sigma(a)\right)}{1 - \sigma(a)} = -\sigma(a) = -D\left(G(z)\right)$

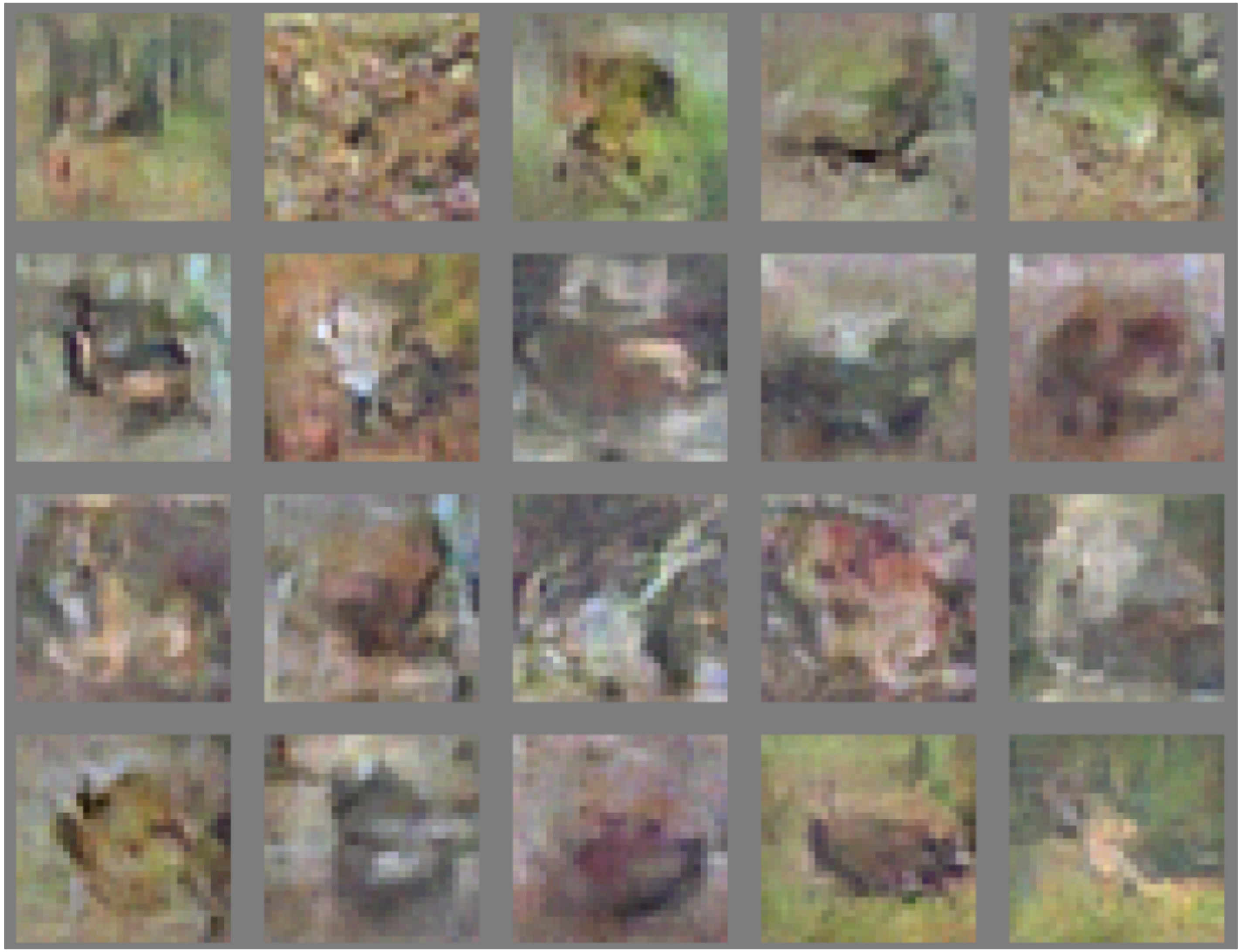
- Gradient goes to 0 if D is confident, i.e. $D\left(G(z)\right) \rightarrow 0$

- Minimize $\boxed{-\mathbb{E}_{z \sim q(z)}[\log D\left(G(z)\right)]}$ for **Generator** instead (keep Discriminator as it is)

Faces

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

CIFAR



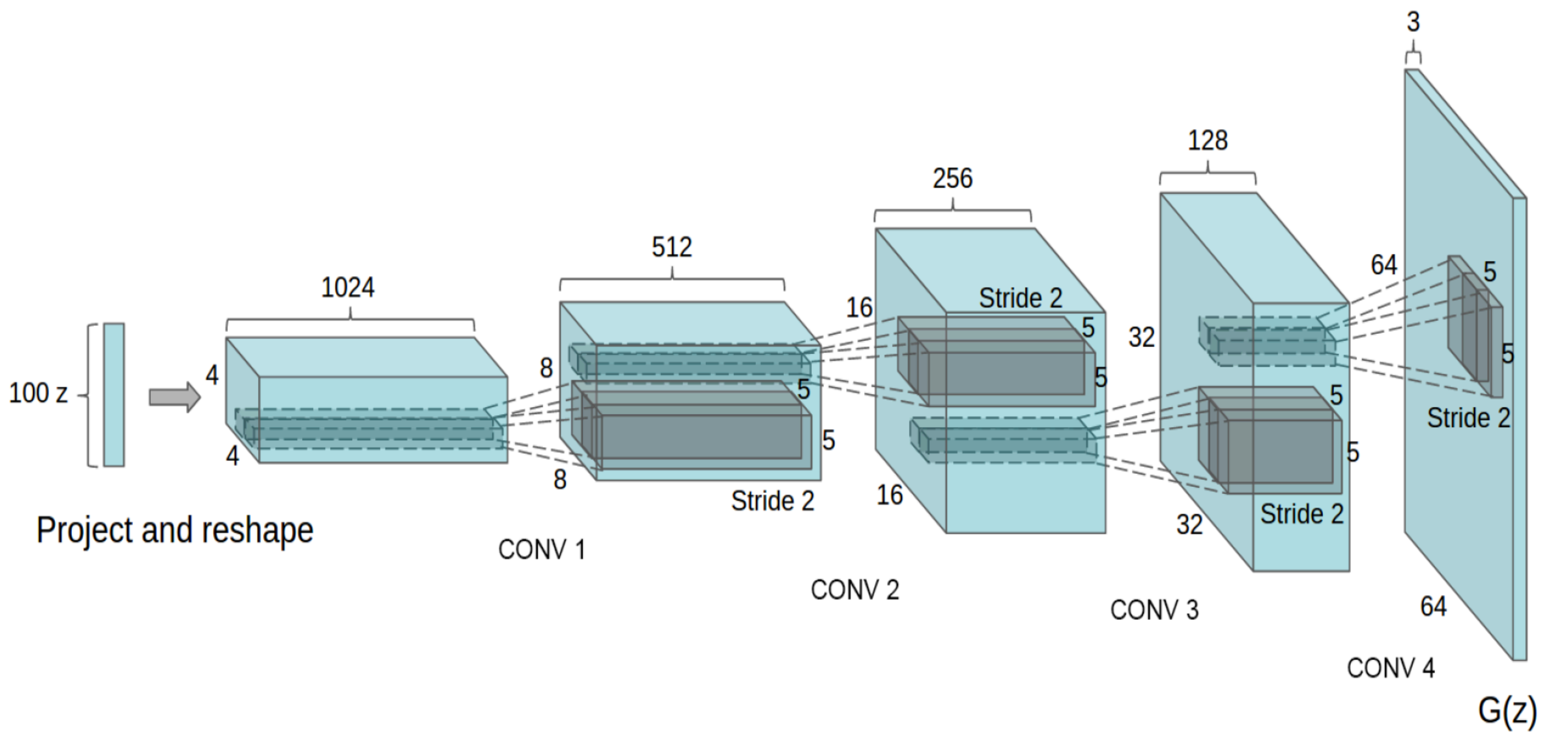
Goodfellow, Ian, et al. **"Generative adversarial nets."** *Advances in neural information processing systems*. 2014.

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).

Generative Adversarial Nets: Interpretable Vector Math

Radford et al, ICLR 2016

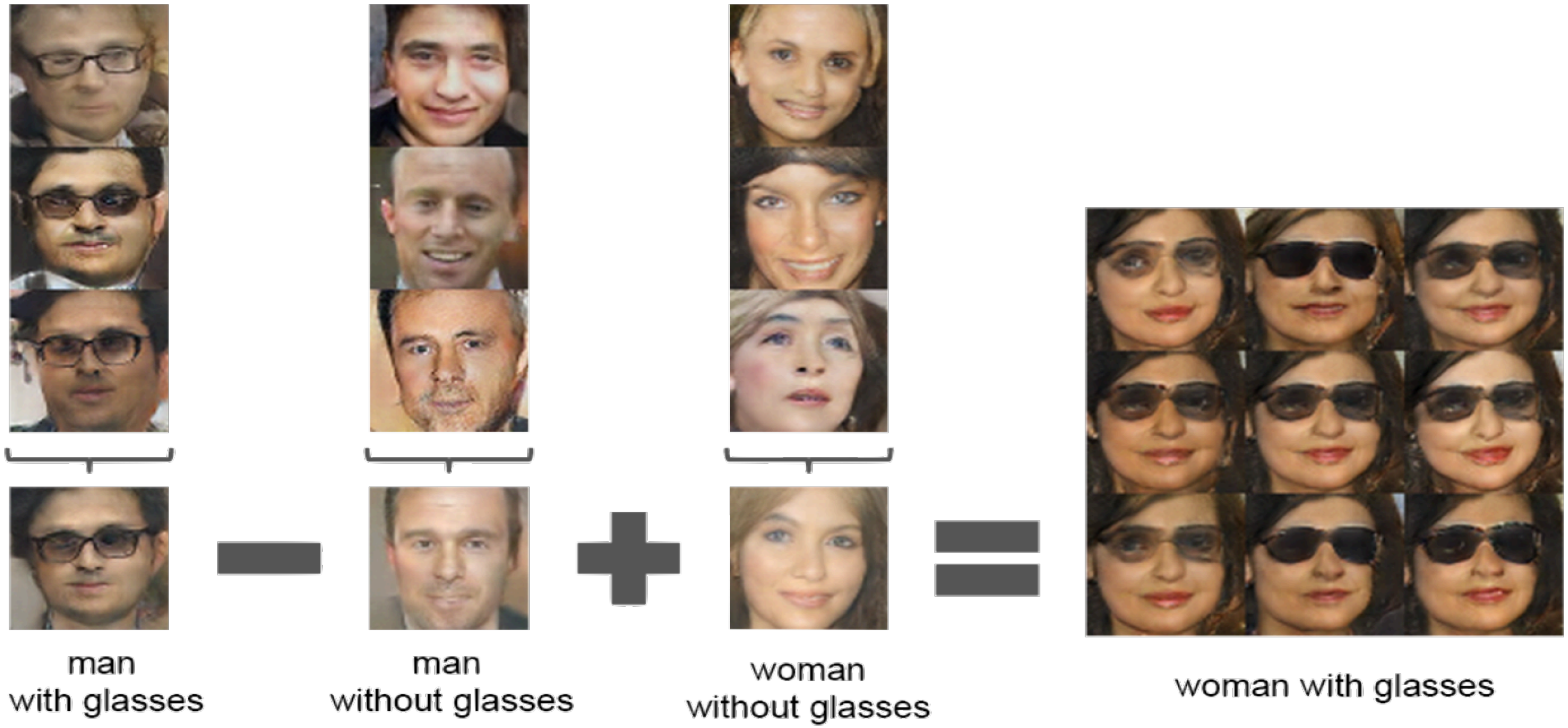
Smiling woman | Neutral woman | Neutral man

Samples from the model

Average Z vectors, do arithmetic

Smiling Man

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)**

Training Problems

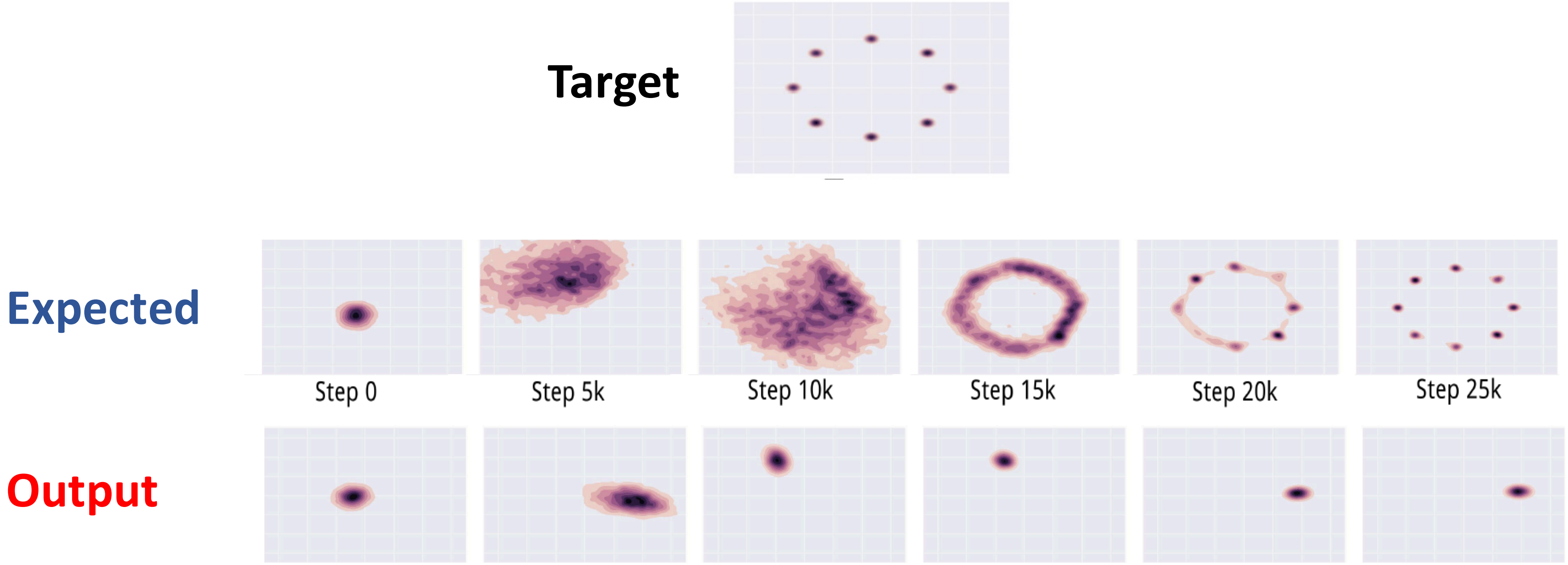
- **Non-Convergence**
- Mode-Collapse

Problems with GANs

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

Mode-Collapse

- **Generator fails to output diverse samples**



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

Some Solutions

- **Mini-Batch GANs**
- **Supervision with labels**

- **Some recent attempts :-**
  - [Unrolled GANs]
  - [W-GANs]

Basic (Heuristic) Solutions

- **Mini-Batch GANs**
- Supervision with labels

How to reward **sample diversity**?

- **At Mode Collapse,**
  - Generator produces good samples, but a very few of them.
  - Thus, Discriminator can’t tag them as fake.
- **To address this problem,**
  - Let the Discriminator know about this edge-case.
- **More formally,**
  - Let the Discriminator look at the entire batch instead of single examples
  - If there is lack of diversity, it will mark the examples as fake
- **Thus,**
  - Generator will be forced to produce diverse samples.

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

Mini-Batch GANs

- **Extract features that capture diversity in the mini-batch**
  - For e.g. L2 norm of the difference between all pairs from the batch
- **Feed those features to the discriminator along with the image**
- **Feature values will differ b/w diverse and non-diverse batches**
  - Thus, Discriminator will rely on those features for classification
- **This in turn,**
  - Will force the Generator to match those feature values with the real data
  - Will generate diverse batches

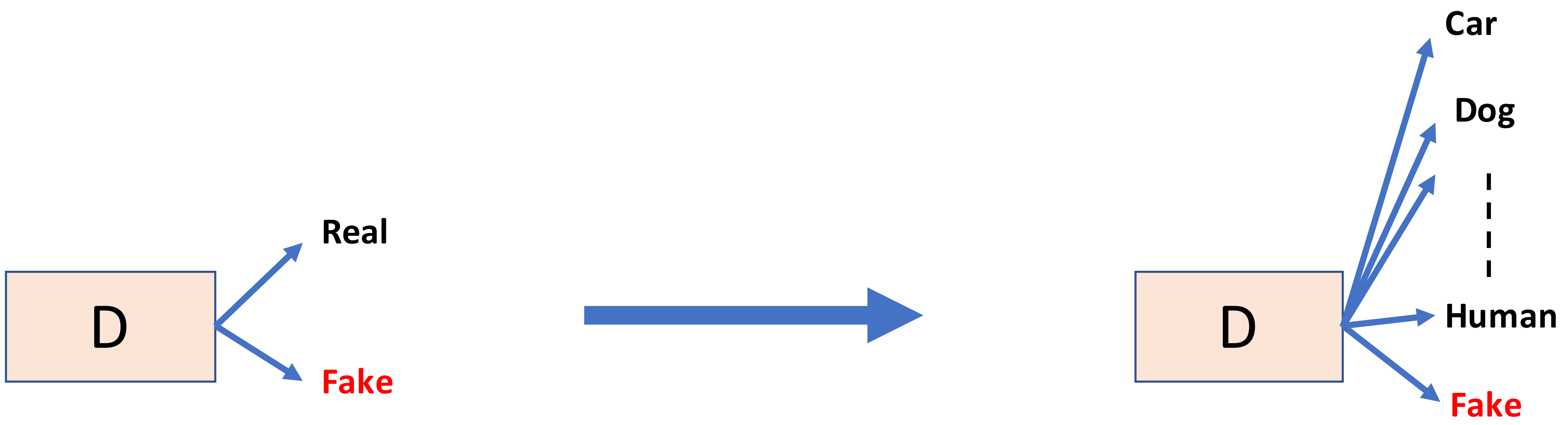
Salimans, Tim, et al. "Improved techniques for training gans." *Advances in Neural Information Processing Systems*. 2016.

Basic (Heuristic) Solutions

- Mini-Batch GANs
- **Supervision with labels**

Supervision with Labels

- Label information of the real data might help



- Empirically generates much better samples

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

Alternate view of GANs

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

$$D^* = \arg\max_D V(D,G)$$ $$G^* = \arg\min_G V(D,G)$$

- In this formulation, Discriminator's strategy was $D(x) \rightarrow 1,\ \ D\big(G(z)\big) \rightarrow 0$

- Alternatively, we can flip the binary classification labels i.e. **Fake = 1**, **Real = 0**

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

- In this new formulation, Discriminator's strategy will be $D(x) \rightarrow 0,\ \ D\big(G(z)\big) \rightarrow 1$

Zhao, Junbo, Michael Mathieu, and Yann LeCun. **"Energy-based generative adversarial network."** arXiv preprint arXiv:1609.03126 (2016)

Alternate view of GANs (Contd.)

- If all we want to encode is $D(x) \rightarrow 0, \quad D\big(G(z)\big) \rightarrow 1$

$$D^* = argmax_D\ \mathbb{E}_{x\sim p(x)}\big[\log\big(1 - D(x)\big)\big] + \mathbb{E}_{z\sim q(z)}\big[\log\big(D(G(z))\big)\big]$$

We can use this

$$D^* = argmin_D\ \mathbb{E}_{x\sim p(x)} \log\big(D(x)\big) + \mathbb{E}_{z\sim q(z)} \Big[\log\Big(1 - D\big(G(z)\big)\Big)\Big]$$

- Now, we can replace cross-entropy with any loss function **(Hinge Loss)**

$$D^* = argmin_D\ \mathbb{E}_{x\sim p(x)} D(x) + \mathbb{E}_{z\sim q(z)} \max\Big(0, m - D\big(G(z)\big)\Big)$$

- And thus, instead of outputting probabilities, Discriminator just has to output :-
  - High values for fake samples
  - Low values for real samples

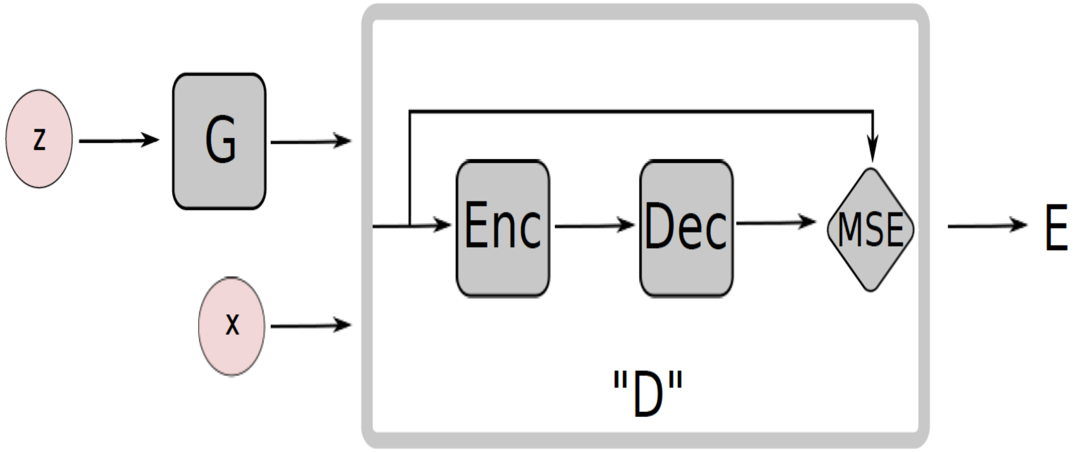
Zhao, Junbo, Michael Mathieu, and Yann LeCun. **"Energy-based generative adversarial network."** arXiv preprint arXiv:1609.03126 (2016)

Energy-Based GANs

- Modified game plans
  - **Generator** will try to generate samples with low values
  - **Discriminator** will try to assign high scores to fake values

$$D(x) = \ ||Dec\big(Enc(x)\big) \ - x||_{MSE}$$

- **Use AutoEncoder inside the Discriminator**
- **Use Mean-Squared Reconstruction error as $D(x)$**
  - High Reconstruction Error for Fake samples
  - Low Reconstruction Error for Real samples



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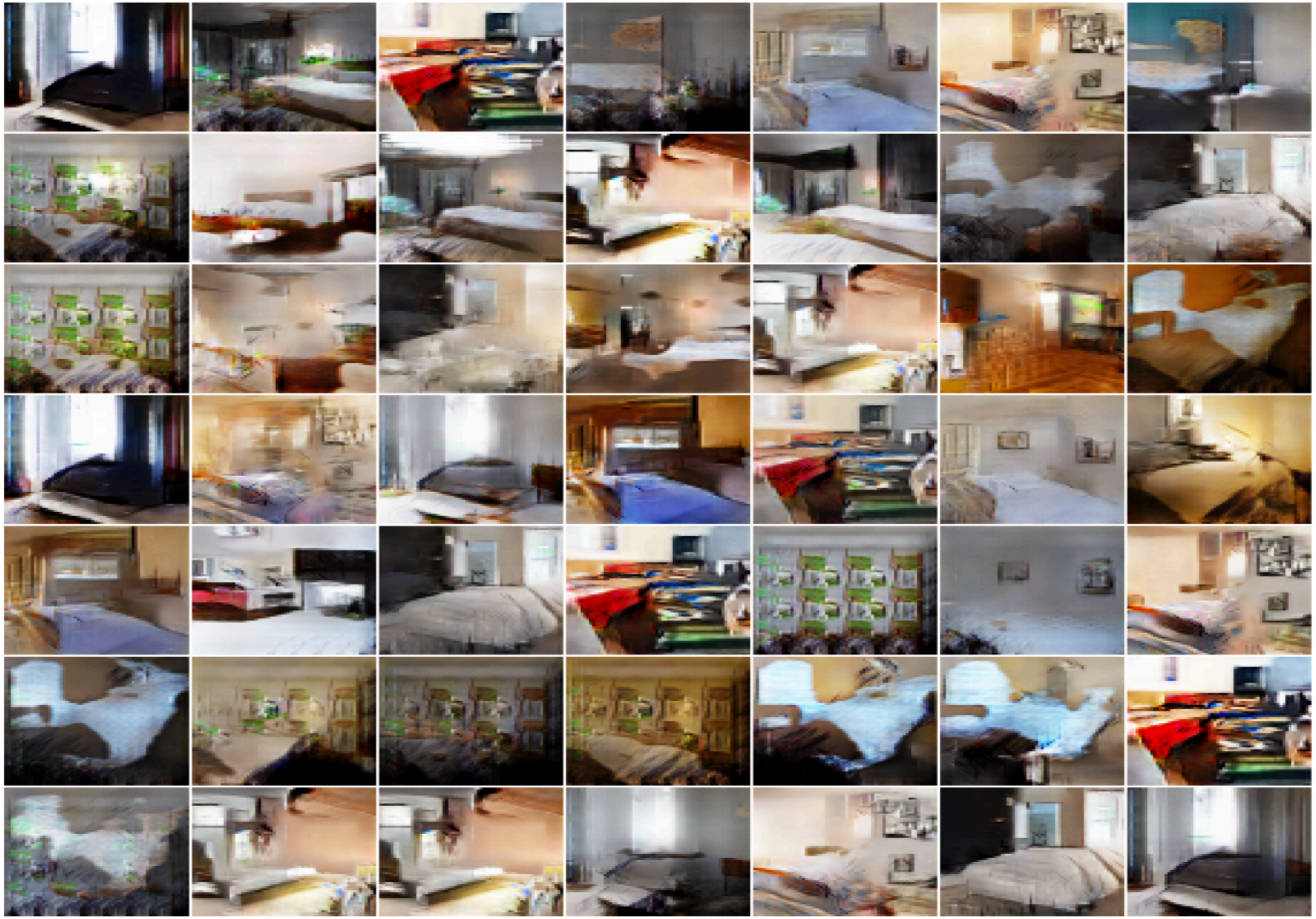
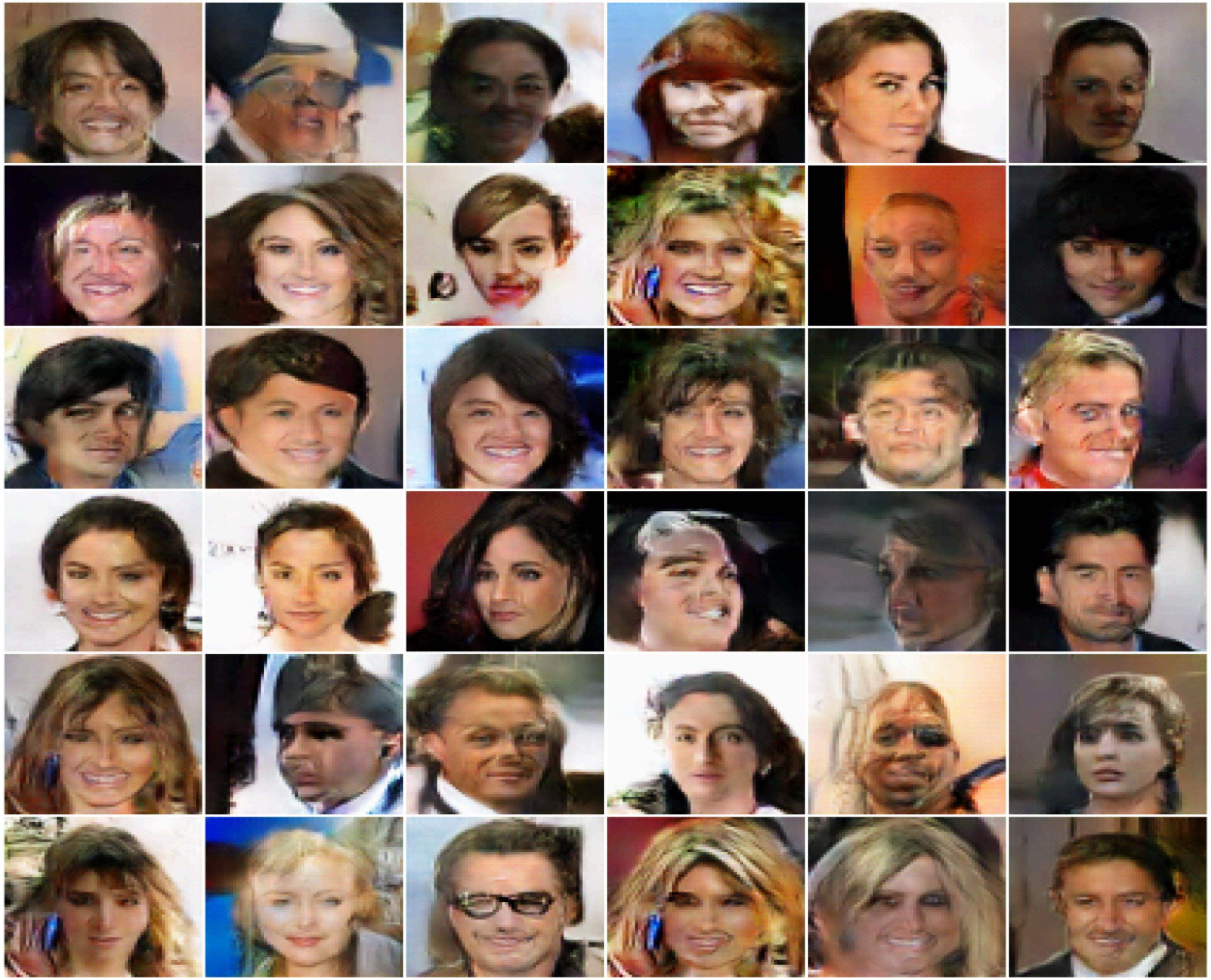
More Bedrooms…



Zhao, Junbo, Michael Mathieu, and Yann LeCun. **"Energy-based generative adversarial network."** arXiv preprint arXiv:1609.03126 (2016)

Celebs...



2017: Explosion of GANs

"The 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

https://github.com/hindupuravinash/the-gan-zoo

2017: Explosion of GANs

See also: https://github.com/soumith/ganhacks for tips and tricks for trainings GANs

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- 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

https://github.com/hindupuravinash/the-gan-zoo

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?