



Deep Learning

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https://github.com/safayani/deep_learning_course

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Generative Adversarial Networks (GANs)

The slides are modified, based on original slides by
[Binglin, Shashnk & Bhargav]

GANS

- **Generative**

- Learn a generative model

- **Adversarial**

- Trained in an adversarial setting

- **Networks**

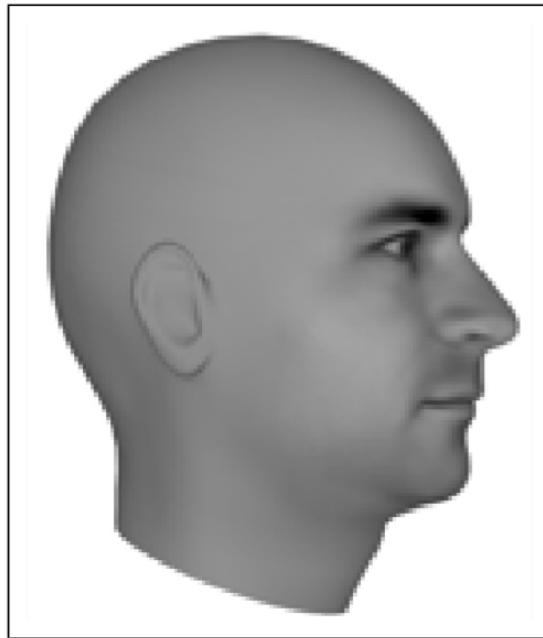
- Use Deep Neural Networks

Why Generative Models?

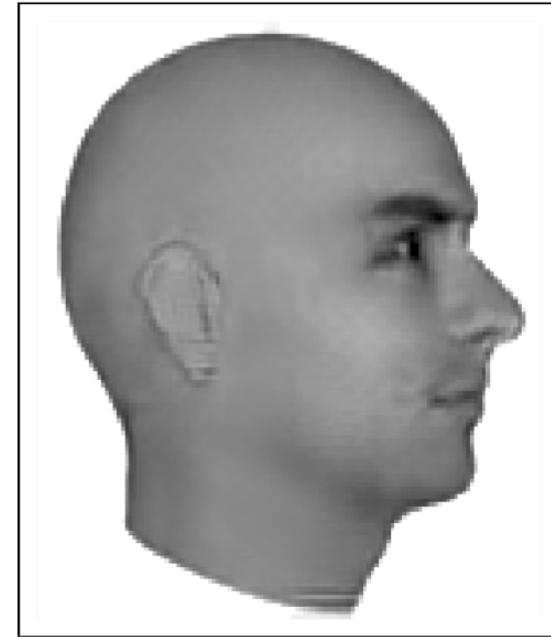
- We've only seen discriminative models so far
 - Given an image X , predict a label Y
 - Estimates $P(Y|X)$
- Discriminative models have several key limitations
 - Can't model $P(X)$, i.e. the probability of seeing a certain image
 - Thus, can't sample from $P(X)$, i.e. can't generate new images
- Generative 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...

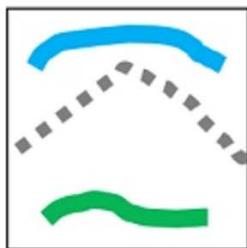
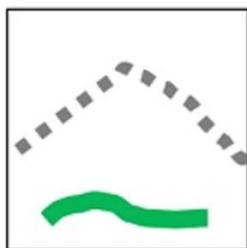
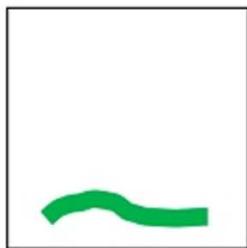
Which one is Computer generated?



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

Magic of GANs...

User edits



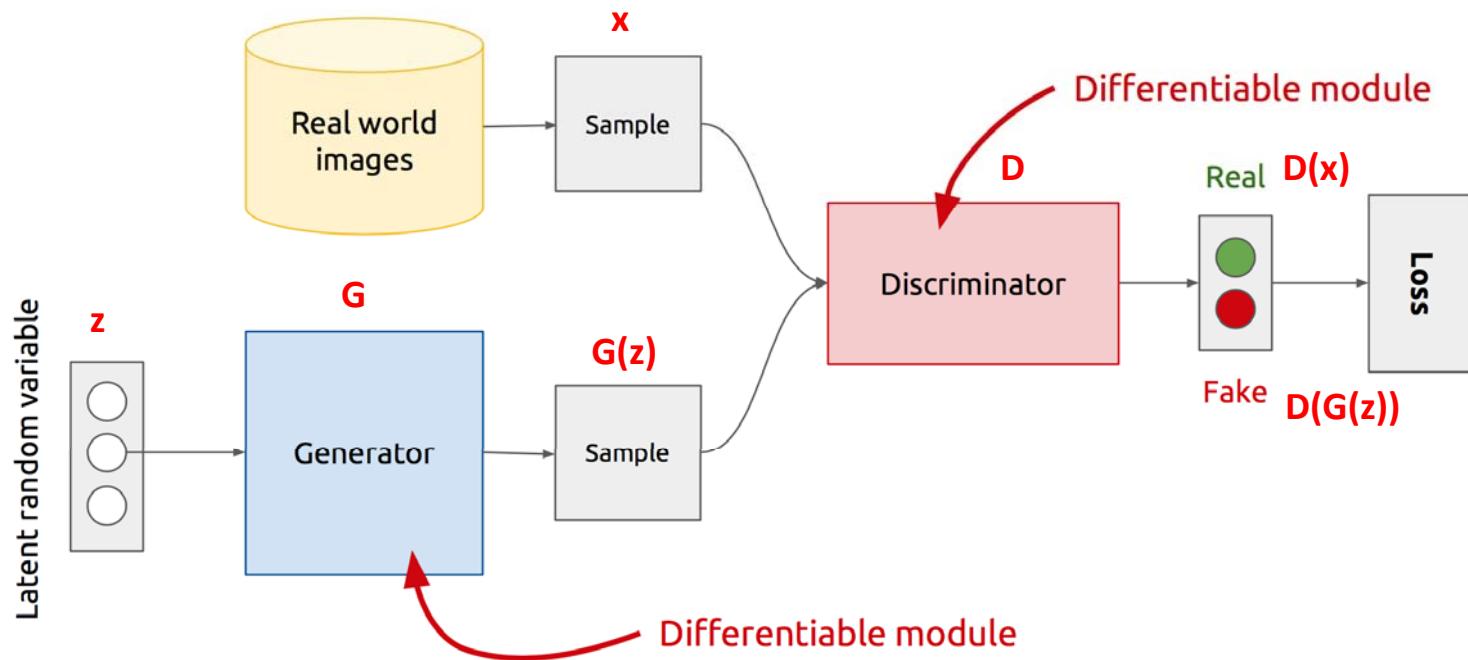
Generated images



Adversarial Training

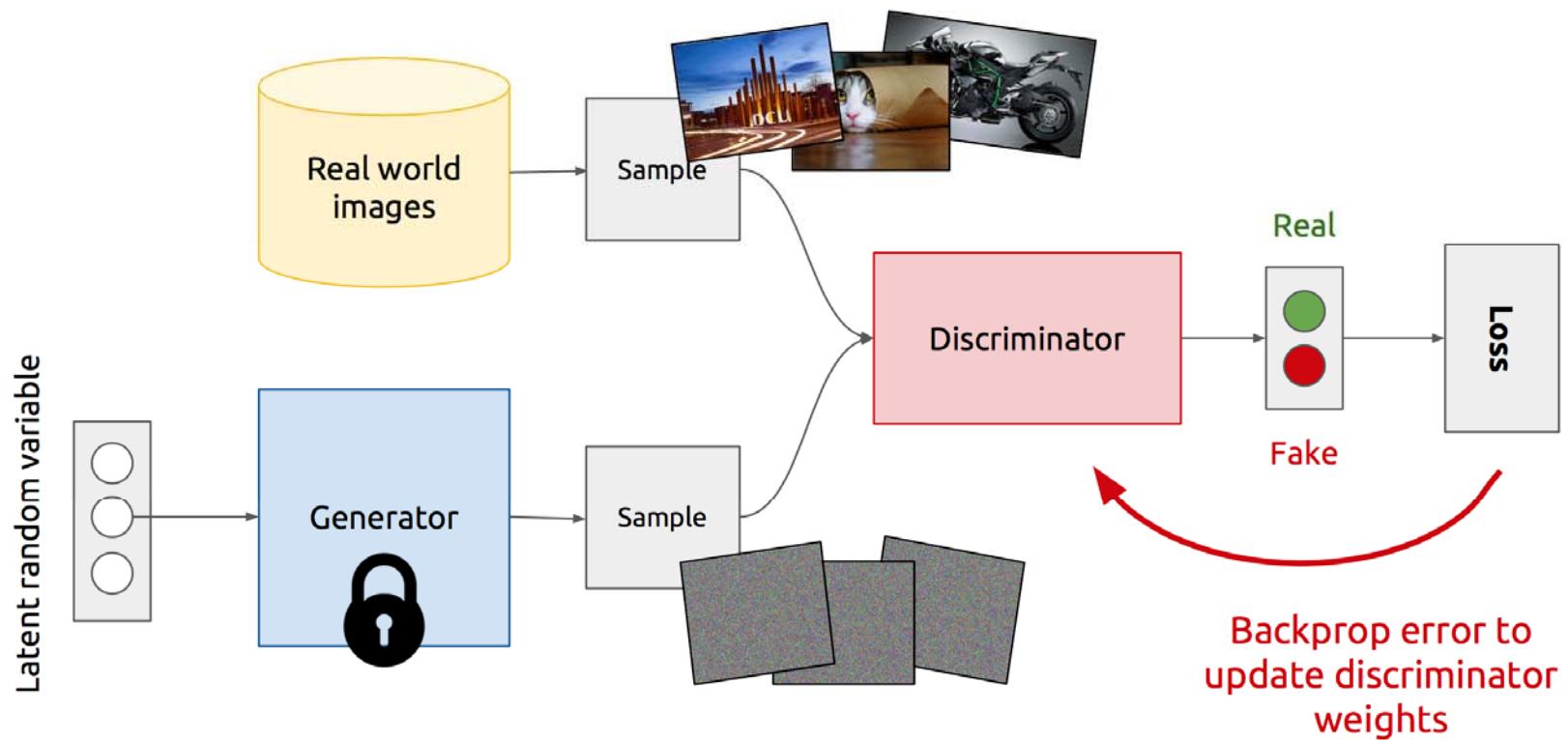
- Generator: generate fake samples, tries to fool the Discriminator
- Discriminator: tries to distinguish between real and fake samples
- Train them against each other
- Repeat this and we get better Generator and Discriminator

GAN's Architecture

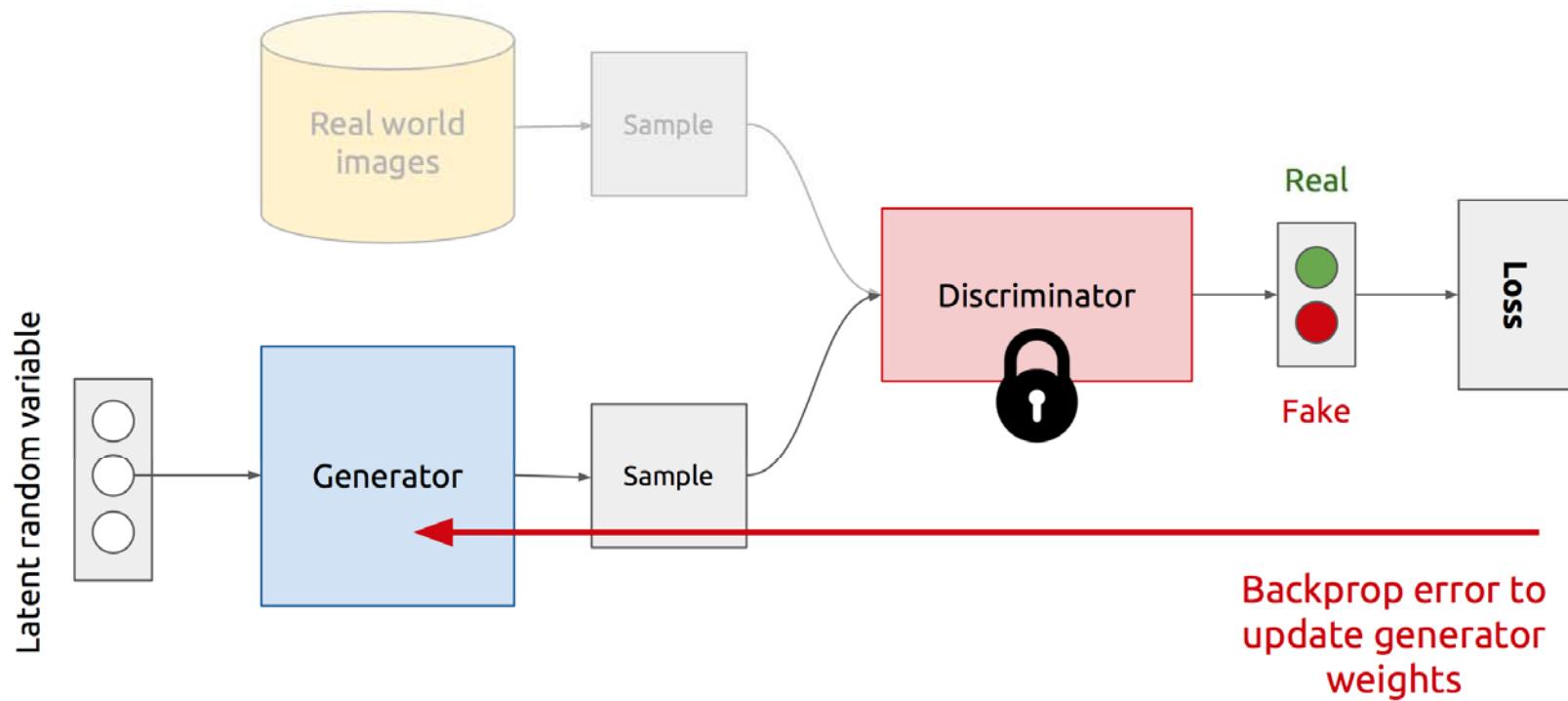


- z is some random noise (Gaussian/Uniform).
- z can be thought as the latent representation of the image.

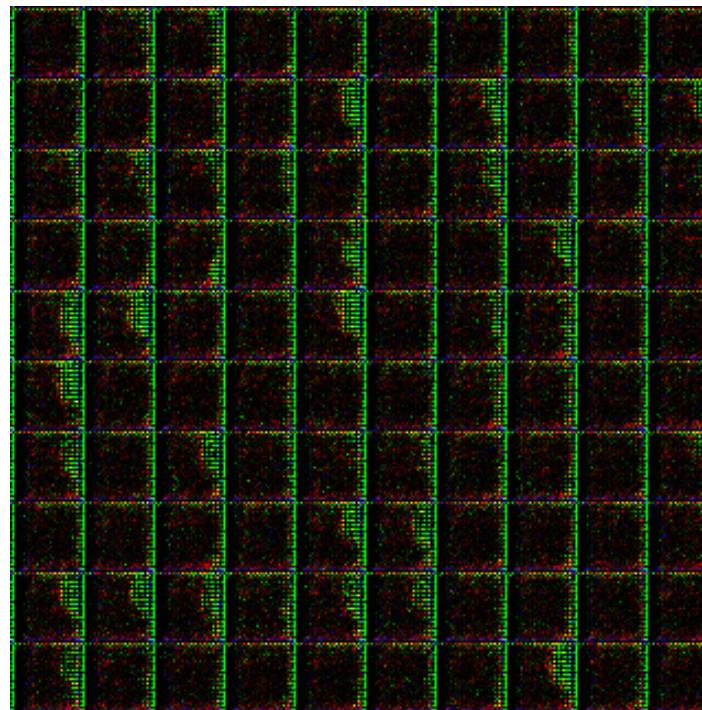
Training Discriminator



Training Generator



Generator in action



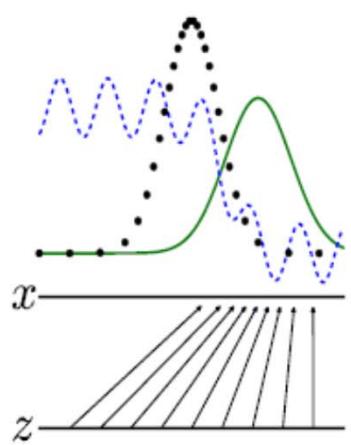
<https://openai.com/blog/generative-models/>

GAN's formulation

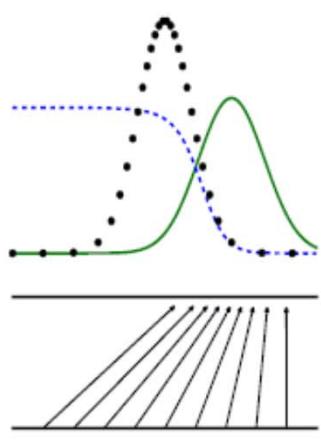
$$\min_G \max_D V(D, G)$$

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

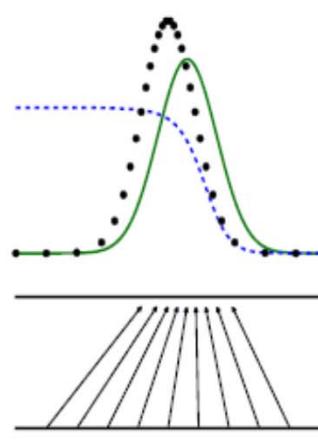
$$V(D, G) = \boxed{\mathbb{E}_{x \sim p(x)} [\log D(x)]} + \boxed{\mathbb{E}_{z \sim q(z)} [\log(1 - D(G(z)))]}$$



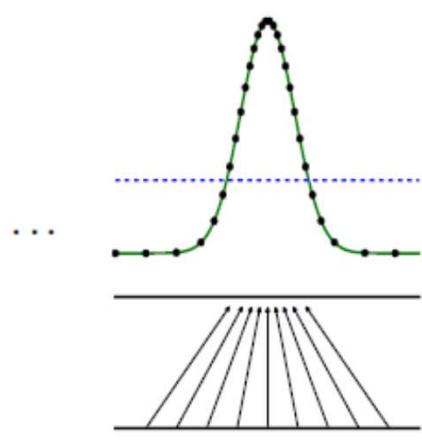
(a)



(b)



(c)



(d)

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

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

end for

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

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

end for

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

Discriminator
updates

Generator
updates

Vanishing gradient strikes back again...

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

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

- $\nabla_a \log(1 - \sigma(a)) = \frac{-\nabla_a \sigma(a)}{1 - \sigma(a)} = \frac{-\sigma(a)(1 - \sigma(a))}{1 - \sigma(a)} = -\sigma(a) = -D(G(z))$
- Gradient goes to 0 if D is confident, i.e. $D(G(z)) \rightarrow 0$
- Minimize $-\mathbb{E}_{z \sim q(z)}[\log D(G(z))]$ for **Generator** instead (keep Discriminator as it is)

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

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

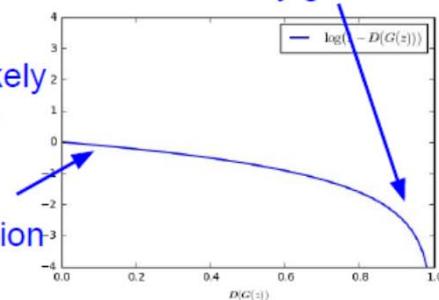
Gradient signal
dominated by region
where sample is
already good

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!



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

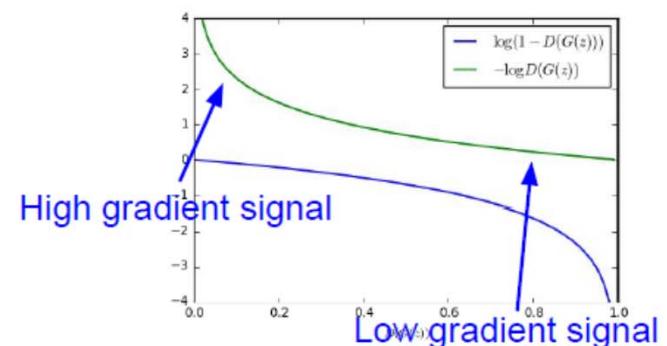
$$\max_{\theta_d} \left[\mathbb{E}_{x \sim p_{data}} \log D_{\theta_d}(x) + \mathbb{E}_{z \sim p(z)} \log(1 - D_{\theta_d}(G_{\theta_g}(z))) \right]$$

2. 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.



Training GANs: Two-player game

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

Putting it together: GAN training algorithm

```
for number of training iterations do
    for k steps do
        • Sample minibatch of m noise samples { $\mathbf{z}^{(1)}, \dots, \mathbf{z}^{(m)}$ } from noise prior  $p_g(\mathbf{z})$ .
        • Sample minibatch of m examples { $\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(m)}$ } from data generating distribution  $p_{\text{data}}(\mathbf{x})$ .
        • 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 { $\mathbf{z}^{(1)}, \dots, \mathbf{z}^{(m)}$ } from noise prior  $p_g(\mathbf{z})$ .
    • Update the generator by ascending its stochastic gradient (improved objective):
        
$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^m \log(D_{\theta_d}(G_{\theta_g}(z^{(i)})))$$

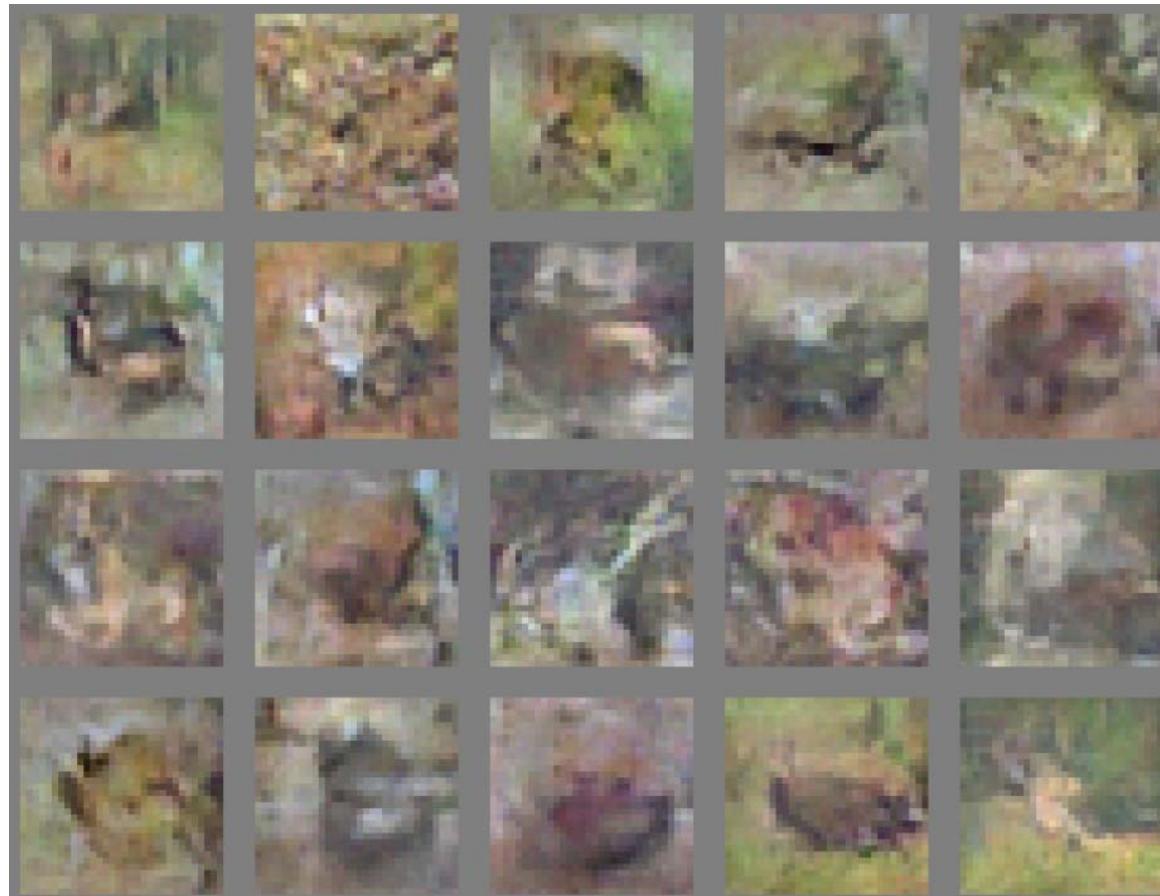
end for
```

Faces



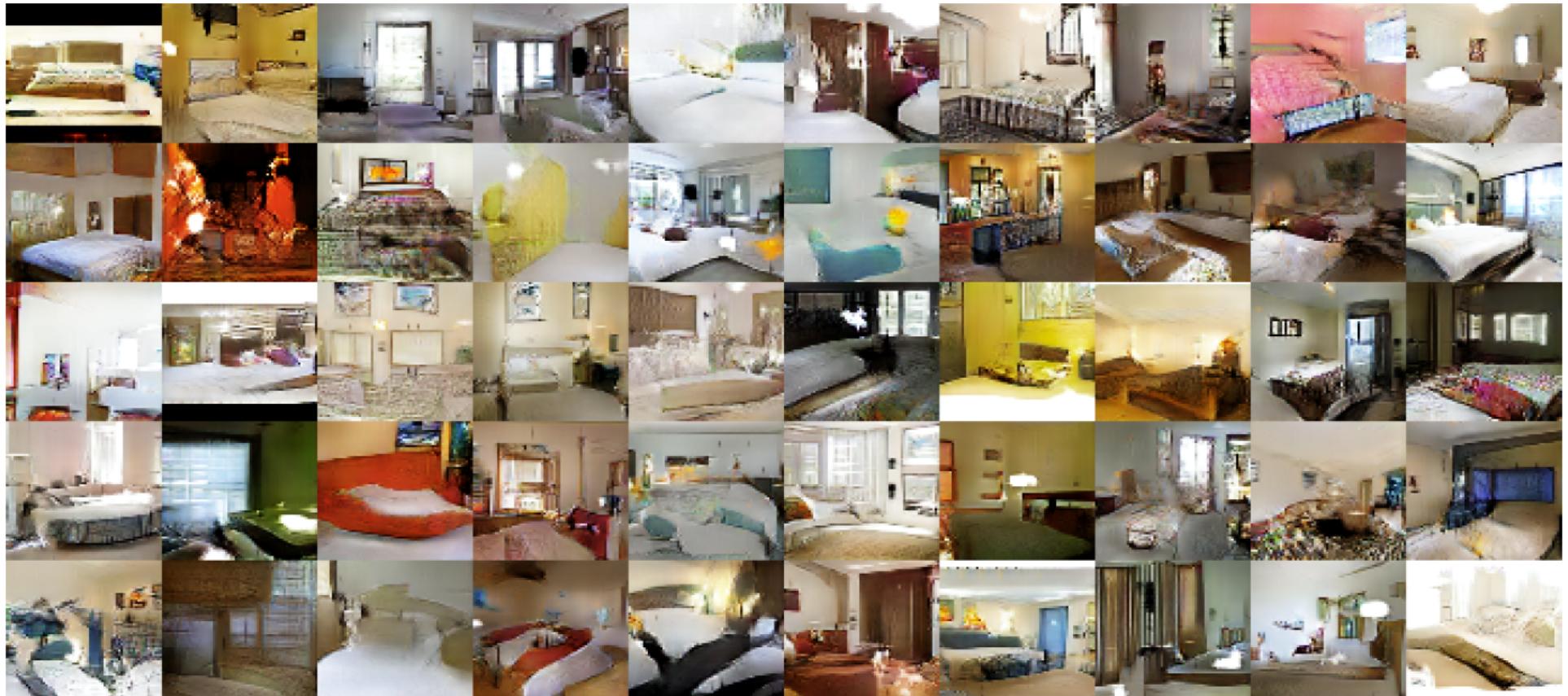
Goodfellow, Ian, et al. "Generative adversarial nets." *Advances in neural information processing systems*. 2014.

CIFAR



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

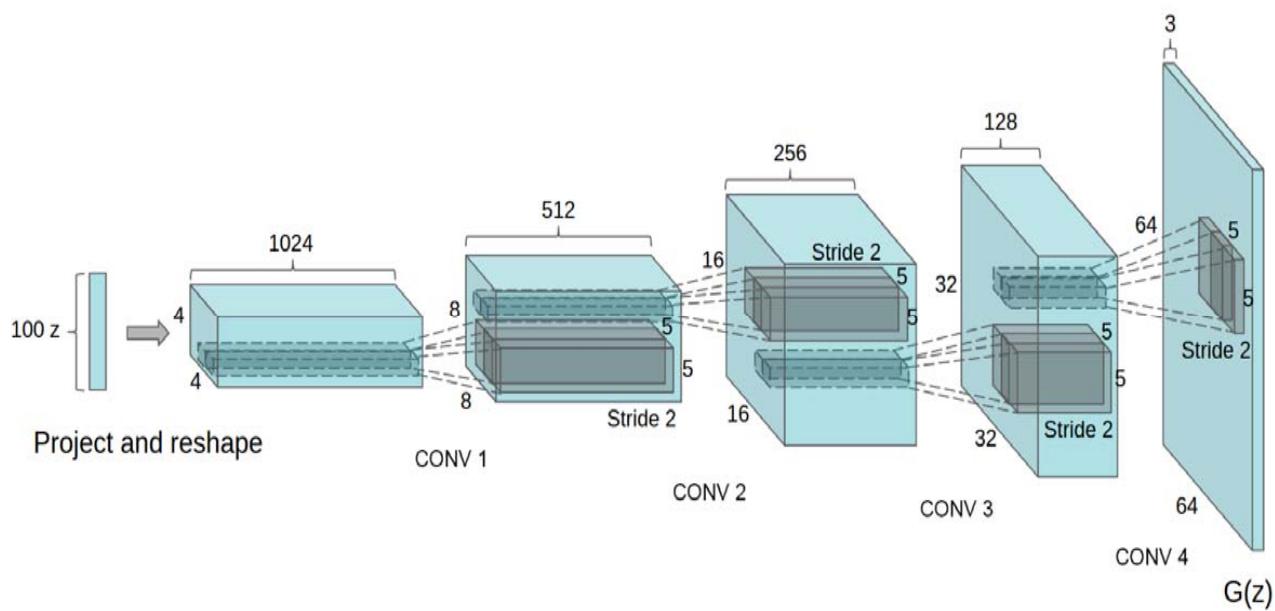
DCGAN: Bedroom images



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

Deep Convolutional GANs (DCGANs)

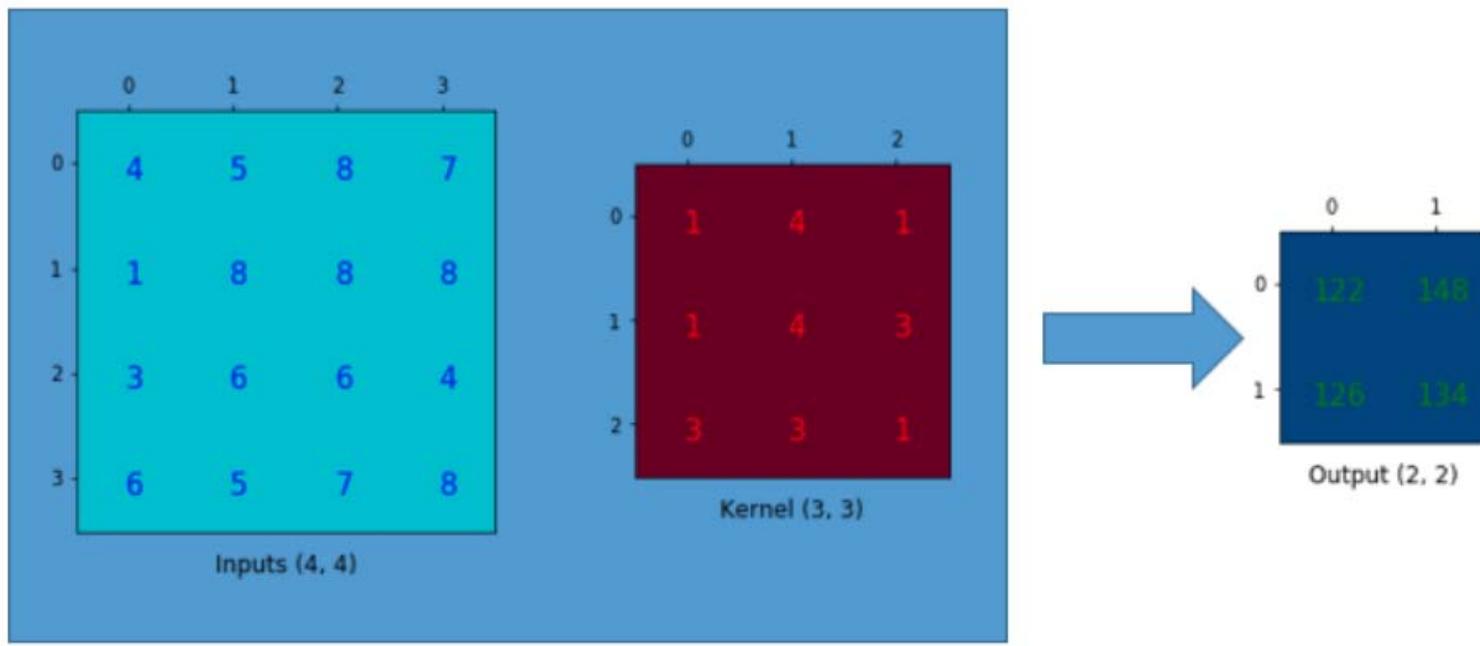
Generator Architecture



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).



<https://towardsdatascience.com/up-sampling-with-transposed-convolution-9ae4f2df52d0>

| | | | |
|---------|---|---|---|
| 1 | 4 | 1 | |
| 1 | 4 | 3 | |
| 3 | 3 | 1 | |
| 122 148 | | | |
| 126 134 | | | |
| 4 | 5 | 8 | 7 |
| 1 | 8 | 8 | 8 |
| 3 | 6 | 6 | 4 |
| 6 | 5 | 7 | 8 |

| | | | |
|---------|---|---|---|
| 1 | 4 | 1 | |
| 1 | 4 | 3 | |
| 3 | 3 | 1 | |
| 122 148 | | | |
| 126 134 | | | |
| 4 | 5 | 8 | 7 |
| 1 | 8 | 8 | 8 |
| 3 | 6 | 6 | 4 |
| 6 | 5 | 7 | 8 |

| | | | |
|---------|---|---|---|
| 1 | 4 | 1 | |
| 1 | 4 | 3 | |
| 3 | 3 | 1 | |
| 122 148 | | | |
| 126 134 | | | |
| 4 | 5 | 8 | 7 |
| 1 | 8 | 8 | 8 |
| 3 | 6 | 6 | 4 |
| 6 | 5 | 7 | 8 |

| | | | |
|---------|---|---|---|
| 1 | 4 | 1 | |
| 1 | 4 | 3 | |
| 3 | 3 | 1 | |
| 122 148 | | | |
| 126 134 | | | |
| 4 | 5 | 8 | 7 |
| 1 | 8 | 8 | 8 |
| 3 | 6 | 6 | 4 |
| 6 | 5 | 7 | 8 |

| | 0 | 1 | 2 |
|---|---|---|---|
| 0 | 1 | 4 | 1 |
| 1 | 1 | 4 | 3 |
| 2 | 3 | 3 | 1 |

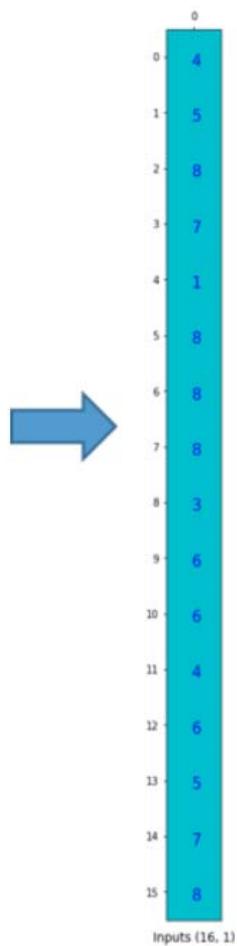
Kernal (3, 3)

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
|---|---|---|---|---|---|---|---|---|---|---|----|----|----|----|----|----|
| 0 | 1 | 4 | 1 | 0 | 1 | 4 | 3 | 0 | 3 | 3 | 1 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 1 | 4 | 1 | 0 | 1 | 4 | 3 | 0 | 3 | 3 | 1 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 1 | 4 | 1 | 0 | 1 | 4 | 3 | 0 | 3 | 3 | 1 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 1 | 4 | 1 | 0 | 1 | 4 | 3 | 0 | 3 | 3 | 1 |

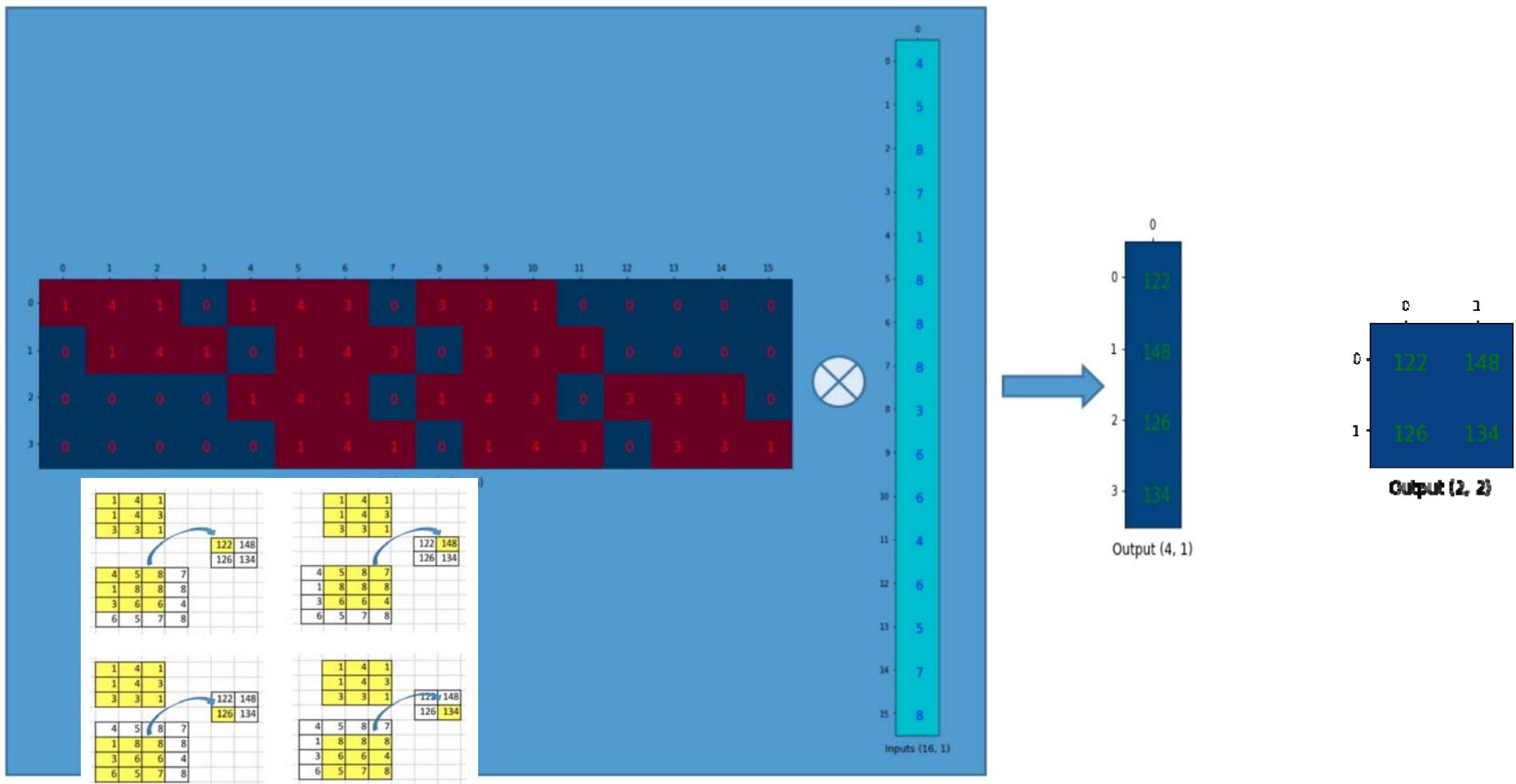
Convolution Matrix (4, 16)

| | 0 | 1 | 2 | 3 |
|---|---|---|---|---|
| 0 | 4 | 5 | 8 | 7 |
| 1 | 1 | 8 | 8 | 8 |
| 2 | 3 | 6 | 6 | 4 |
| 3 | 6 | 5 | 7 | 8 |

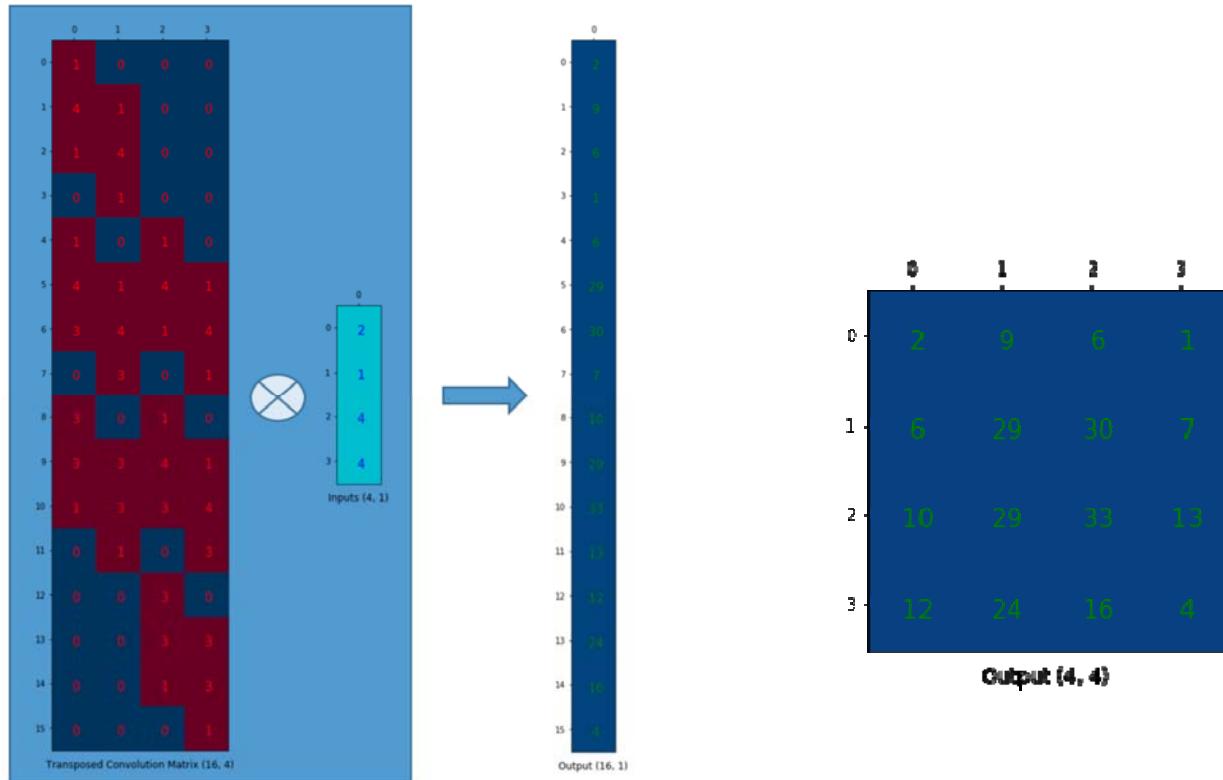
Inputs (4, 4)



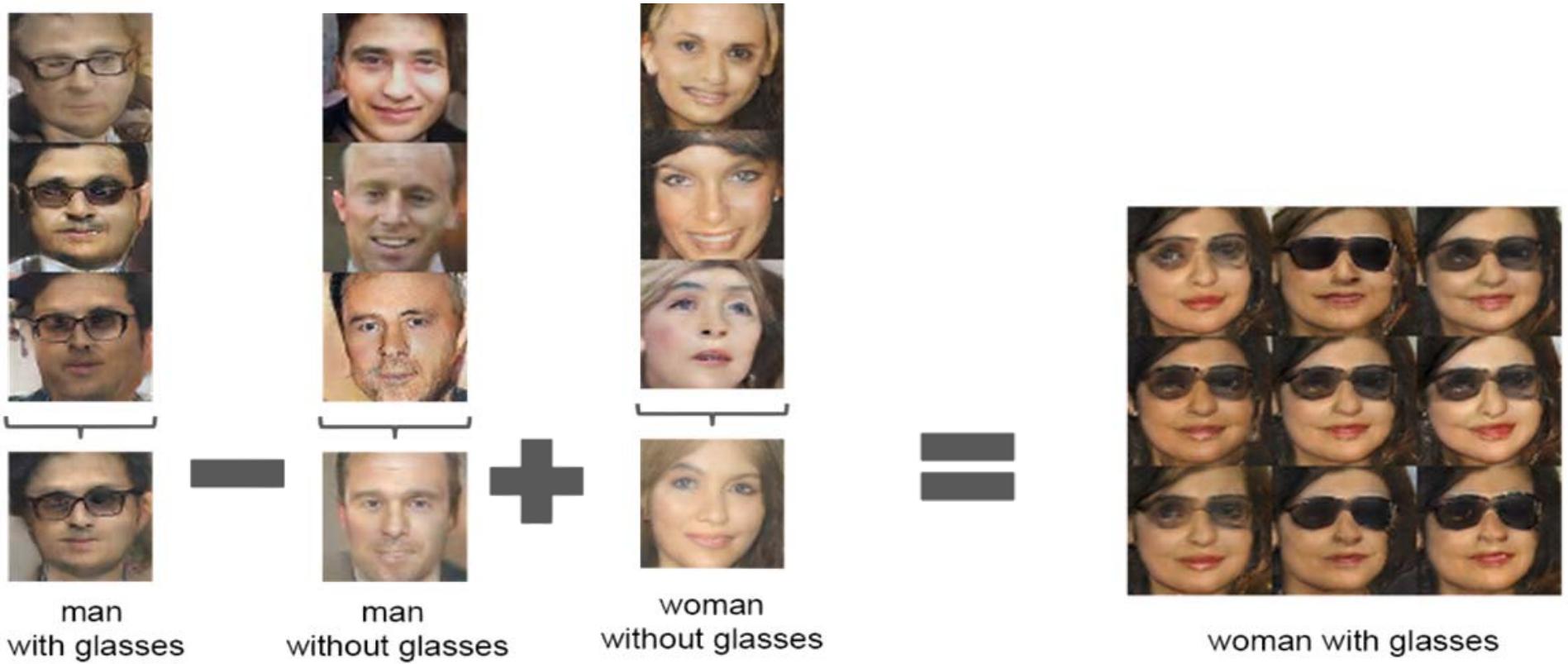
Inputs (16, 1)



Transposed Convolution Matrix



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).

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.

Conditional GANs

MNIST digits generated conditioned on their class label.

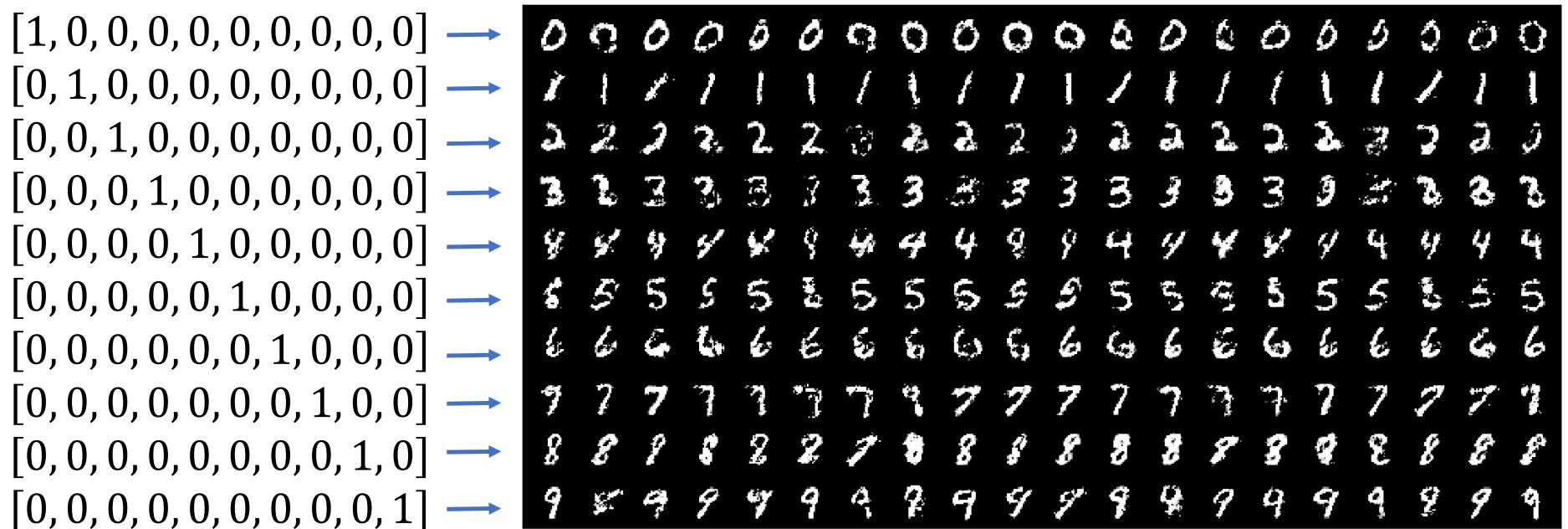
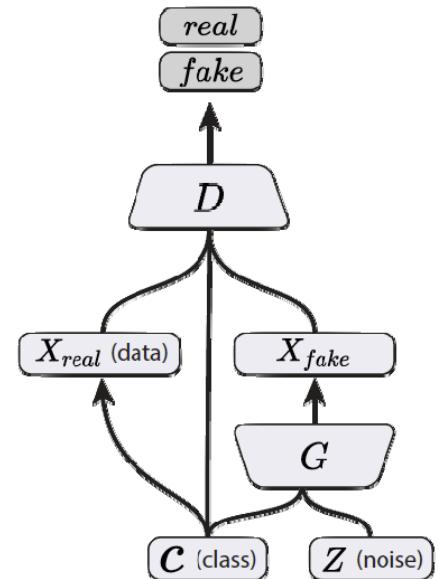


Figure 2 in the original paper.

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*.

Image-to-Image Translation

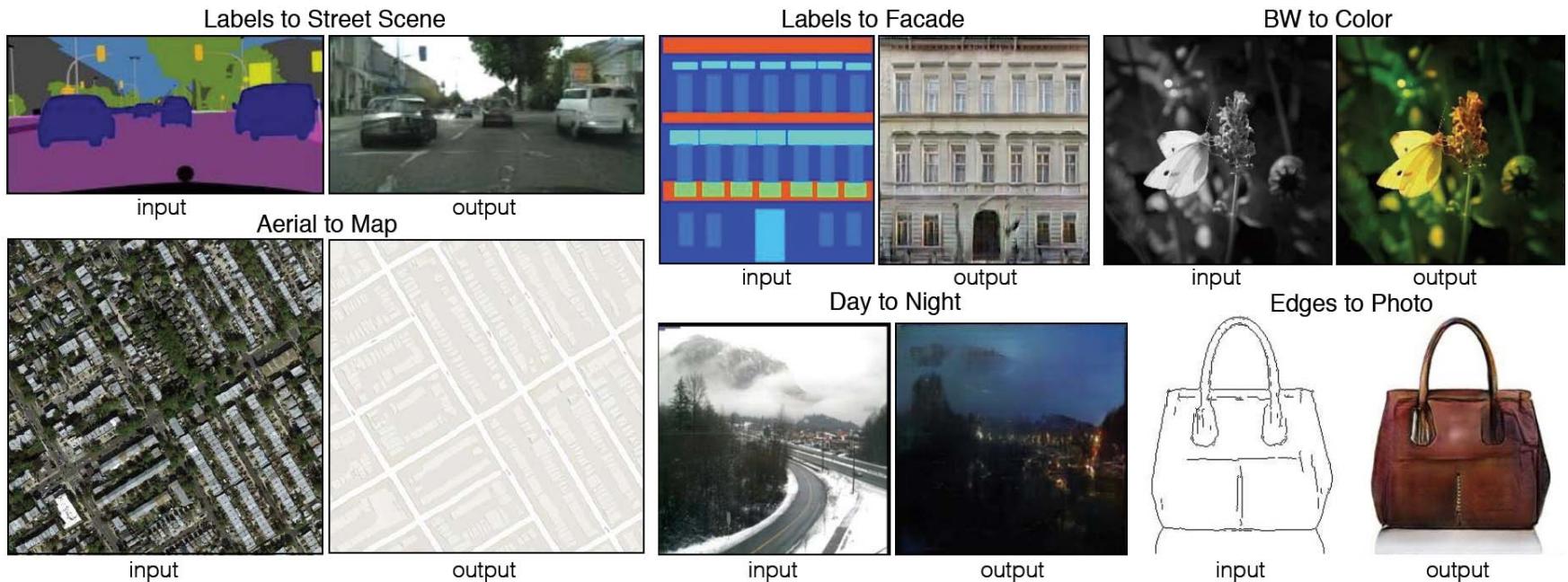


Figure 1 in the original paper.

[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.

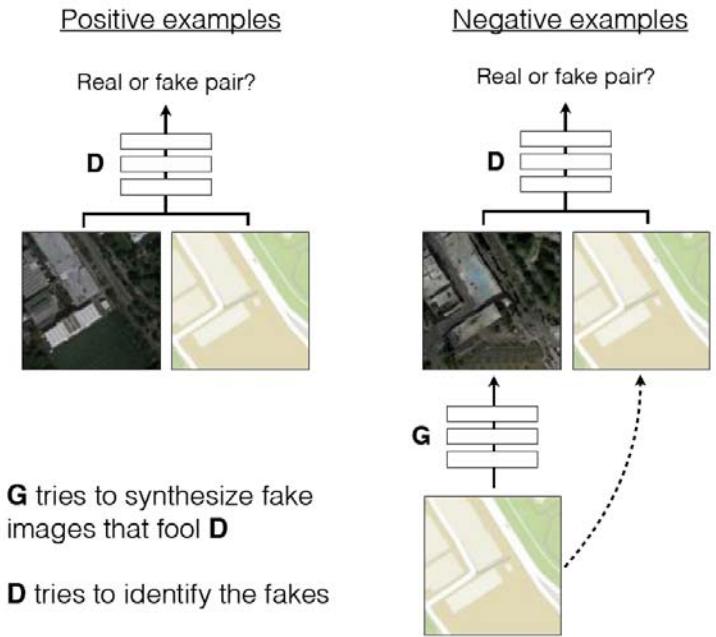


Figure 2 in the original paper.

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.

this small bird has a pink breast and crown, and black primaries and secondaries.



this magnificent fellow is almost all black with a red crest, and white cheek patch.



the flower has petals that are bright pinkish purple with white stigma



this white and yellow flower have thin white petals and a round yellow stamen

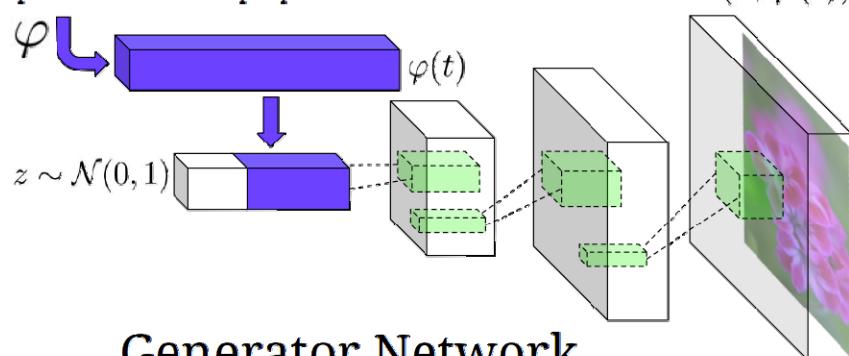


Figure 1 in the original paper.

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

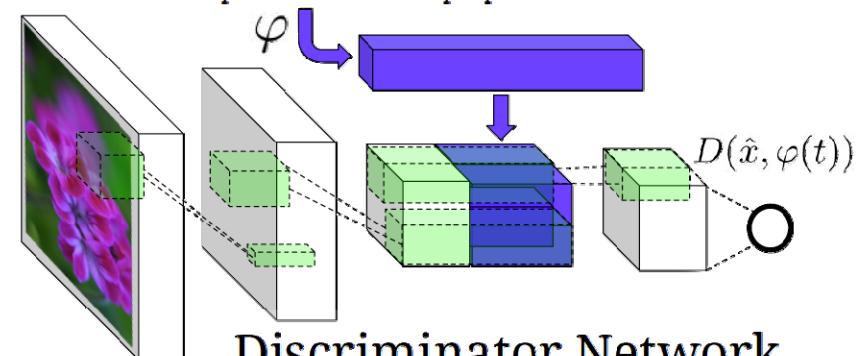
Text-to-Image Synthesis

This flower has small, round violet petals with a dark purple center



Generator Network

This flower has small, round violet petals with a dark purple center



Discriminator Network

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).

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

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.

Non-Convergence

$$\min_x \max_y V(x, y)$$

Let $V(x, y) = xy$

- State 1:

| | | |
|-------|-------|-------|
| x > 0 | y > 0 | V > 0 |
|-------|-------|-------|

| | |
|------------|------------|
| Increase y | Decrease x |
|------------|------------|
- State 2:

| | | |
|-------|-------|-------|
| x < 0 | y > 0 | V < 0 |
|-------|-------|-------|

| | |
|------------|------------|
| Decrease y | Decrease x |
|------------|------------|
- State 3:

| | | |
|-------|-------|-------|
| x < 0 | y < 0 | V > 0 |
|-------|-------|-------|

| | |
|------------|------------|
| Decrease y | Increase x |
|------------|------------|
- State 4 :

| | | |
|-------|-------|-------|
| x > 0 | y < 0 | V < 0 |
|-------|-------|-------|

| | |
|------------|------------|
| Increase y | Increase x |
|------------|------------|
- State 5:

| | | |
|-------|-------|-------|
| x > 0 | y > 0 | V > 0 |
|-------|-------|-------|

 == State 1

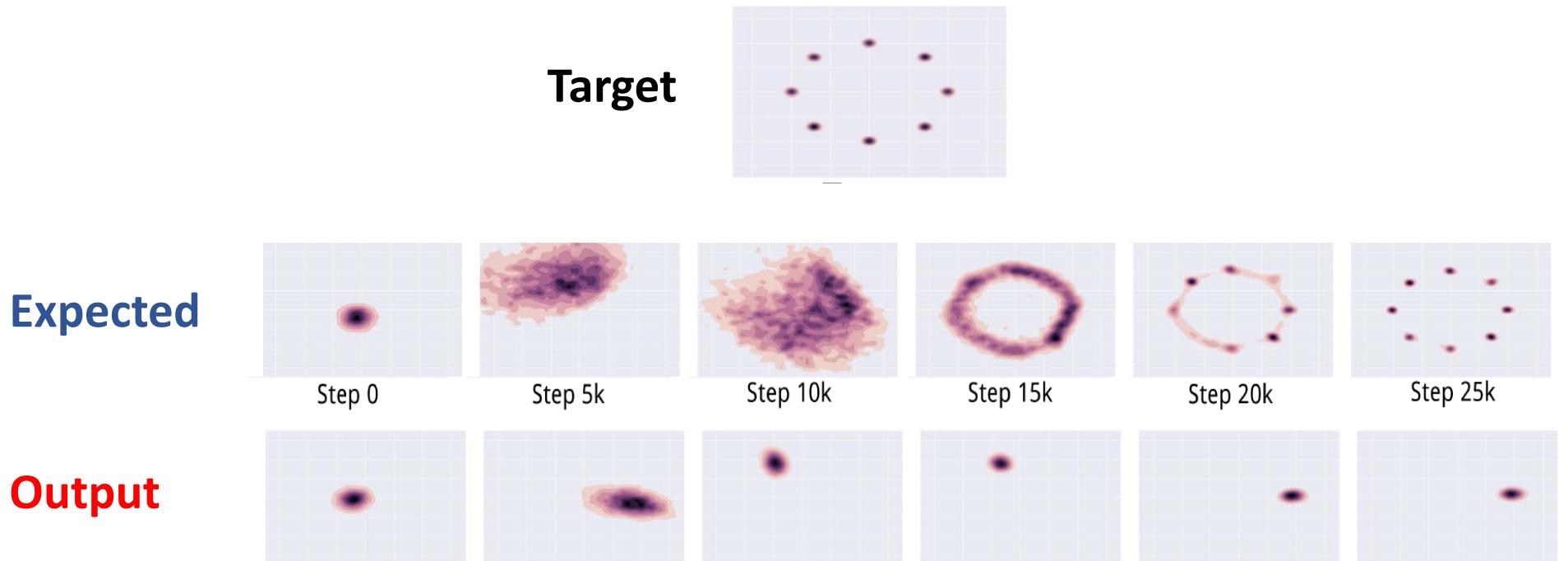
| | |
|------------|------------|
| Increase y | Decrease x |
|------------|------------|

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 real examples



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

Basic (Heuristic) Solutions

- Mini-Batch GANs

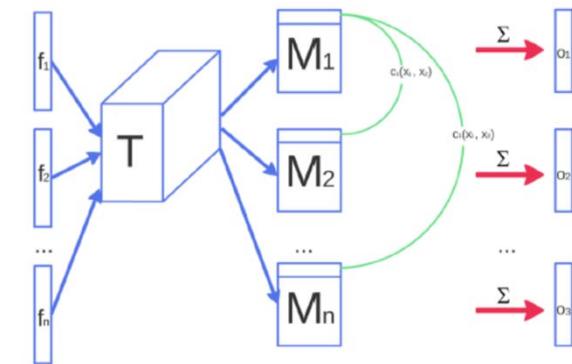
How to reward sample diversity?

- **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

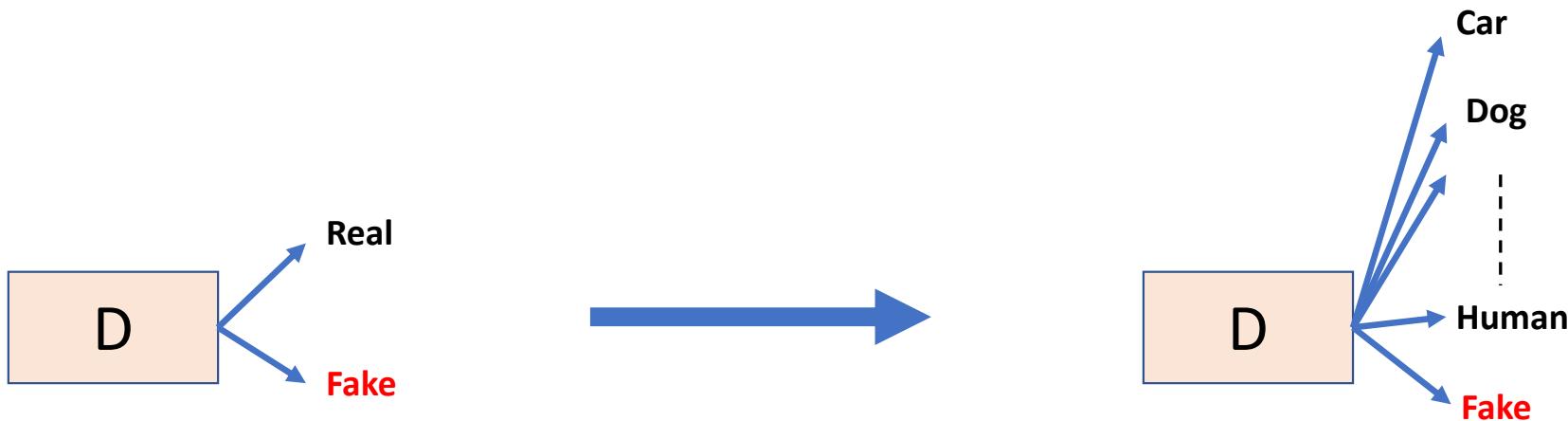


Basic (Heuristic) Solutions

- 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.

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.

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