Deep Learning

9.1 Generative Adversarial Networks (GANs)

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Let's see something cool

GANs

1. Popular framework for learning high-dimensional densities

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3. Non-parametric (implicit) density modeling

GANs

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2. Discriminator D classifies samples: real versus fake
3. Generator G produces samples (maps a simple, fixed distribution to generated samples)

GANs

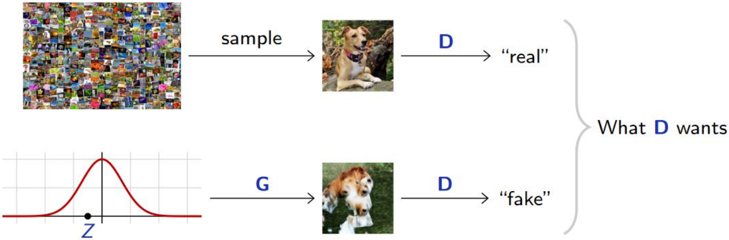
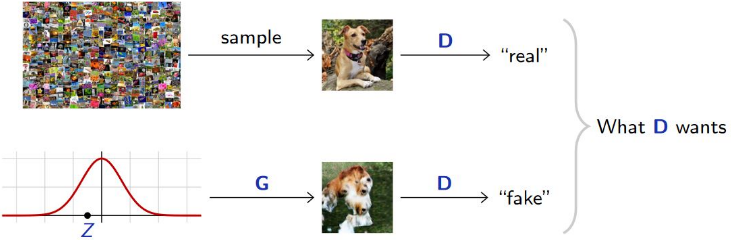


Figure credits: Francois Fleuret

GANs



Framework is adversarial: Both the modules have conflicting objectives.

Figure credits: Francois Fleuret

GANs

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1. Generator $G : \mathbb{R}^D \to \mathcal{X}$
2. Maps a random normal sample to data distribution
3. Discriminator $D : \mathcal{X} \to [0, 1]$
4. Takes a sample as input and predicts if it comes from G or the actual data distribution

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   - Two class classification dataset $\mathcal{D} =$
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2. Minimize the binary cross entropy loss

$$\mathcal{L}(D) = -\frac{1}{2N}\left(\sum_{1}^{N} log(D(x_n)) + \sum_{1}^{N} log(1 - D(G(z_n)))\right)$$

$$= -\frac{1}{2}\left(\mathbb{E}_{X\sim\mu}\left[log(D(X))\right] + \mathbb{E}_{X\sim\mu_G}\left[log(1 - D(X))\right]\right)$$

GANs

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GANs

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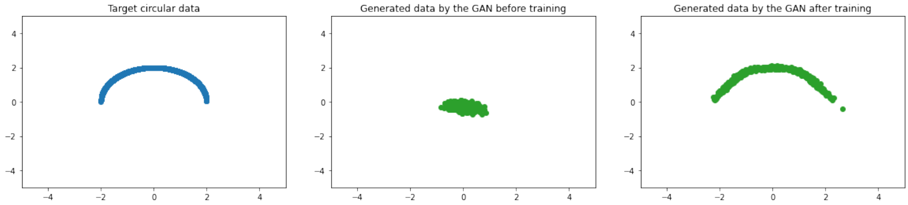
$$\begin{aligned}\mathcal{L}(G) =& \frac{1}{2}\left(\mathbb{E}_{X\sim\mu}\left[log(D(X))\right] + \mathbb{E}_{X\sim\mu_G}\left[log(1 - D(X))\right]\right)\\ =& \frac{1}{2}\mathbb{E}_{X\sim\mu_G}\left[log(1 - D(X))\right]\end{aligned}$$

2. In practice, initial fake samples are very poor that D response is saturated and $log(1 - D(X))$ generates zero gradients $\rightarrow$ Goodfellow *et al.* suggest to use $-log(D(X))$

GANs


Target circular data
Generated data by the GAN before training
Generated data by the GAN after training
4
2
0
−2
−4
−4
−2
0
2
4

Deep Convolutional GANs

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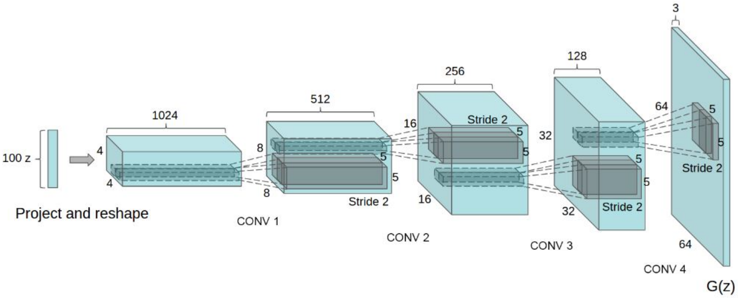
2. Scales GANs to generating realistic images
3. Uses convolution and transposed convolution layers

Deep Convolutional GANs

1. Architecture of Generator (G) (Radford *et al.* 2015)



Deep Convolutional GANs

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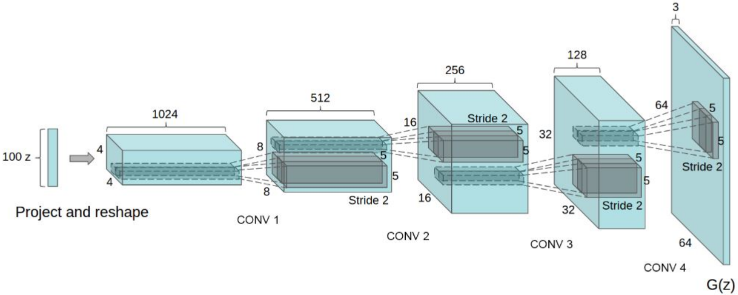
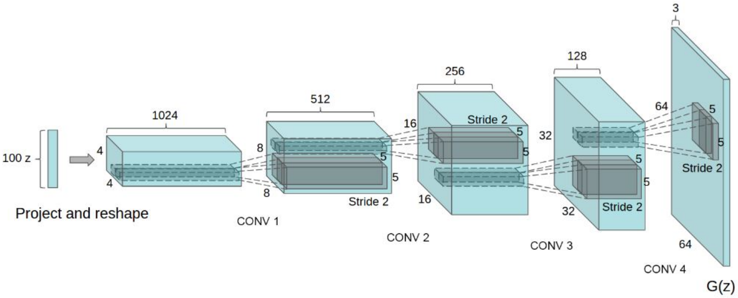
2. D is a binary CNN classifier (typically doesn't use fc layers and pooling layers)

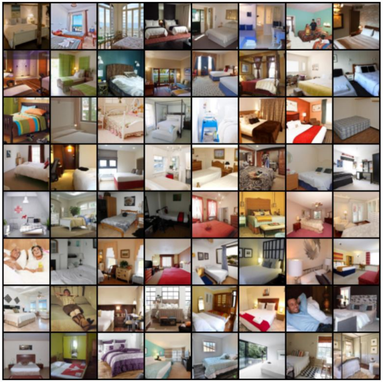


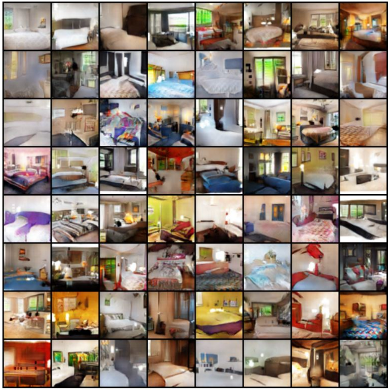
Deep Convolutional GANs

1. Architecture of Generator (G) (Radford *et al.* 2015)
2. D is a binary CNN classifier (typically doesn't use fc layers and pooling layers)
3. Batch Normalization layers are used, ReLU for G, leakyReLU for D



Deep Convolutional GANs





GAN training pathologies

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2. Mode collapse: G learns models only a portion of real data distribution

Quality assessment of GANs

1. Inception score (Salimans *et al.* 2016) $\rightarrow$ verifies the posterior distribution of fake images is similar to that of real data (penalizes missing classes)

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3. Assessment is often deals aesthetic evaluation of the generated samples

References

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