Deep Learning

Lecture 6: Adversarial models

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Lecture overview

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- properties
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- Lipschitz continuity
- spectral normalisation
- conditional GANs
- information maximizing GANs
- adversarial autoencoders

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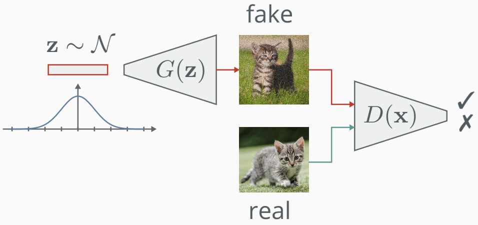
Definition: generative adversarial networks

A generative adversarial network (GAN) is a non-coorporative zero-sum game where two networks compete against each other [1].

One network $G(\mathbf{z})$ generates new samples, whereas D estimates the probability the sample was from the training data rather than G:

$$\min_G \max_D V(D,G) = \mathbb{E}_{\mathbf{x}\sim p_{\text{data}}(\mathbf{x})}[\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(1 - D(G(\mathbf{z})))].$$

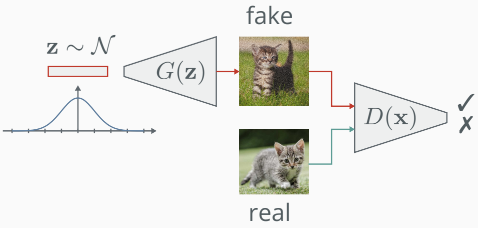


GAN **properties**

GANs benefit from differentiable data augmentation [2] for both reals and fakes, but are otherwise notoriously difficult to train:

- Non-convergence
- Diminishing gradient
- Difficult to balance
- Mode collapse (next slide)

Link to Colab example



Generative adversarial networks mode collapse

Definition: mode collapse

This is where the generator rotates through a small subset of outputs, and the discriminator is unable to get out of the trap. Mode collapse is arguably the main limitation of GANs.

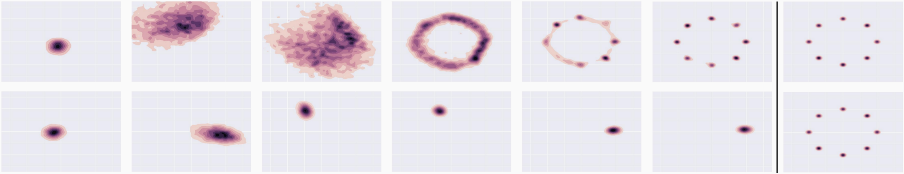


Figure from [3]. The final column shows the target data distribution and the bottom row shows a GAN rotating through the modes.

Definition: Lipschitz function

A function f is Lipschitz continous if it is bounded by how fast it can change. Specifically if there exists a positive real constant k where:

$$|f(x) - f(y)| \leq k|x - y|,$$

for all y sufficiently near x. For example, any function with a bounded first derivative is a Lipschitz function.

Wasserstein GANs [4, 5] were the first to reduce mode collapse in GANs by lowering the Lipschitz constant for the descriminator function.

Distance functions are 1-Lipschitz

Definition: spectral normalisation

The matrix (spectral) norm defines how much a matrix can stretch a vector $\mathbf{x}$:

$$\|\boldsymbol{A}\| = \max_{\mathbf{x}\neq 0} \frac{\|\boldsymbol{A}\mathbf{x}\|}{\|\mathbf{x}\|}$$

Spectral norm [6] normalises the weights for each layer using the spectral norm $\sigma(\boldsymbol{W})$ such that the Lipschitz constant for every layer and the whole network is 1:

$$\hat{\boldsymbol{W}}_{\text{SN}} = \boldsymbol{W}/\sigma(\boldsymbol{W})$$
$$\sigma(\hat{\boldsymbol{W}}_{\text{SN}}(\boldsymbol{W})) = 1$$
$$\|f\|_{\text{Lip}} = 1$$

Pseudocode: 1-Lipschitz discriminator

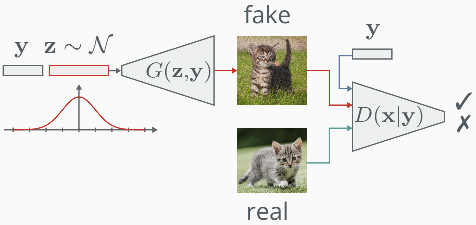
```
class Discriminator(nn.Module):
  def __init__(self, f=64):
    super().__init__()
    self.discriminate = nn.Sequential(
      spectral_norm(Conv2d(1, f, 3, 1, 1)),
      nn.LeakyReLU(0.1, inplace=True),
      nn.MaxPool2d(kernel_size=(2,2)),
      spectral_norm(Conv2d(f, f*2, 3, 1, 1)),
      nn.LeakyReLU(0.1, inplace=True),
      nn.MaxPool2d(kernel_size=(2,2)),
      spectral_norm(Conv2d(f*2, f*4, 3, 1, 1)),
      nn.LeakyReLU(0.1, inplace=True),
      nn.MaxPool2d(kernel_size=(2,2)),
      spectral_norm(Conv2d(f*4, f*8, 3, 1, 1)),
      nn.LeakyReLU(0.1, inplace=True),
      nn.MaxPool2d(kernel_size=(2,2)),
      spectral_norm(Conv2d(f*8, 1, 3, 1, 1)),
      nn.Sigmoid()
    )
```

Definition: conditional GAN

GANs can be conditioned with labels $\mathbf{y}$ if available [7] by feeding the label information into both the generator and the discriminator:

$$\min_G \max_D V(D,G) = \mathbb{E}_{\mathbf{x},\mathbf{y}\sim p_{\text{data}}(\mathbf{x})}[\log D(\mathbf{x}|\mathbf{y})] + \mathbb{E}_{\mathbf{z}\sim p_{\mathbf{z}}(\mathbf{z})}[\log(1 - D(G(\mathbf{z},\mathbf{y})|\mathbf{y}))].$$

Link to Colab example



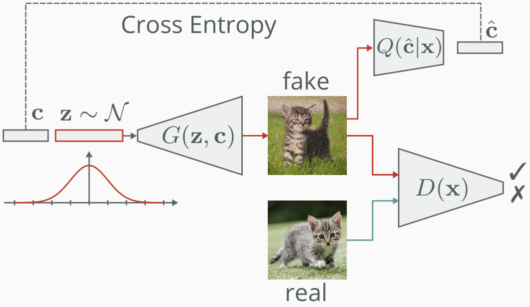
Definition: information maximizing GANs

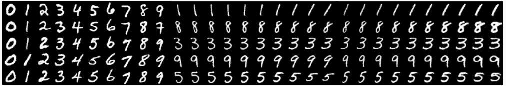
GANs can be trained to learn disentangled latent representations in a completely unsupervised manner. InfoGAN [8] popularised this by maximizing mutual information between the observation and a subset of the latents:

$$\min_{G,Q} \max_{D} V_{\text{InfoGAN}}(D, G, Q) = V(D, G) - \lambda L_I(G, Q)$$

where $L_I(G, Q)$ is a variational lower bound of the mutual information.

Link to Colab example

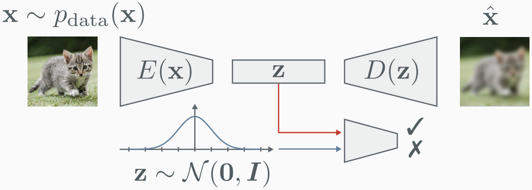




Definition: adversarial autoencoders

Adversarial autoencoders [9] are generative models that permit sampling.

In addition to the reconstruction loss, such $\|\mathbf{x} - \hat{\mathbf{x}}\|^2$, they use adversarial training to match the aggregated posterior of the hidden code vector $\mathbf{z}$ of the autoencoder with an arbitrary prior distribution, such as $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \boldsymbol{I})$.

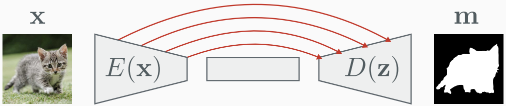


Definition: skip connections (U-Net)

Skip connections (U-Net) is a popular residual approach used for paired image translation tasks [10]. For example for images $\mathbf{x}$ and paired masks $\mathbf{m}$, where: $\mathcal{L} = \mathbb{E}_{\mathbf{x},\mathbf{m}\sim p_{\text{data}}}\left[\|U(\mathbf{x}) - \mathbf{m}\|^2\right]$

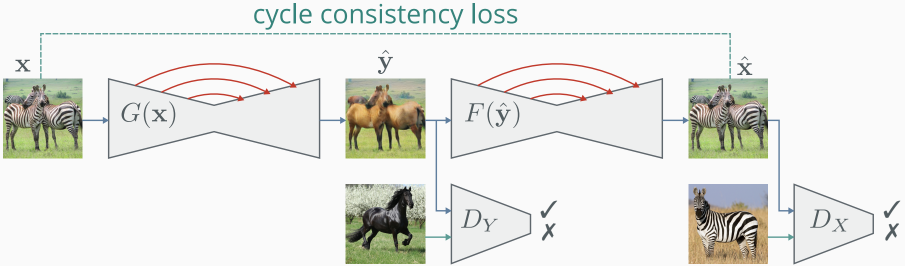
Link to Colab example

Note: U-Net is not an adversarial method, but the use of skip connections is popular in many papers, so now is a good time to introduce it.



Definition: unpaired translation (CycleGAN)

CycleGAN [11] propose an adversarial architecture that enables unpaired image translation. It has twin residual generators and two discriminators, which translate between the domains, alongside a cycle consistency loss (an L1 norm) which ensures the mapping can recover the original image.

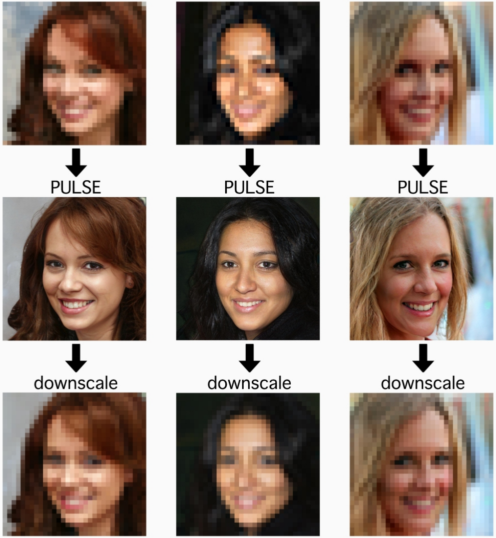


Definition: super-resolution

Adversarial models are popular in super-resolution approaches. The challenge is that a single low-resolution (LR) input can map to a distribution of high-resolution (HR) outputs.

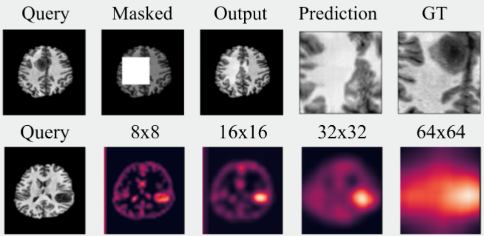
PULSE [12] investigates this by projecting points in the search of the latent space of StyleGAN (a large conditional GAN) onto a hypersphere, which ensures probable outputs in the high-dimensional latent space.

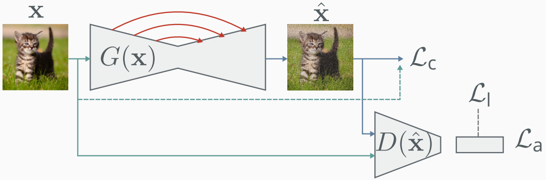
Online example



Definition: anomaly detection

Unsupervised anomaly detectors [13] learn a normal distribution over (healthy) observations. Then, when they observe something not observed in training (unhealthy/dangerous), they fail to reconstruct - detecting it as an anomaly. Region-based anomaly detectors [14] learn a distribution over inpainted (erased) regions.





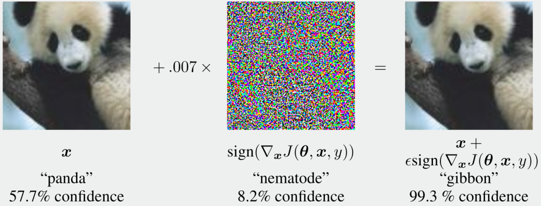
Adversarial examples attacks

Definition: adversarial examples

These are small but intentionally worst-case perturbations that fool the model to output incorrect answers with high confidence [15]. It is possible to generate examples that also fool the human visual system [16]. Cat or dog?

Example: adversarial examples

Example adding an imperceptibly small vector by the sign of the elements of the gradient of the cost function with respect to the input [15]:



Adversarial examples defences

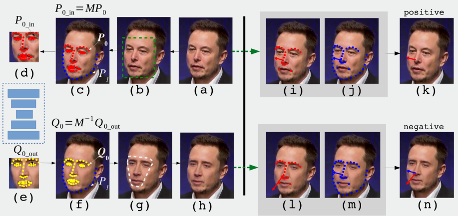
Definition: adversarial defence

There are several defence strategies that introduce the adversarial examples into training [15]. A popular approach uses U-Net to denoise and reduce the amplification of the adversarial perturbations [17].

Black-box adversarial defence is where an adversary can only monitor the outputs of the model. White-box methods are more difficult, as an adversary has access to the model allowing for specific attacks. White-box defence generally overfits to the attack used during training.

Example: adversarial defences

Question: What is the behaviour at the limit of the adversarial generative model arms-race? Who wins at convergence?



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