Introduction to Generative Models - Generative Adversarial Networks (GANs)

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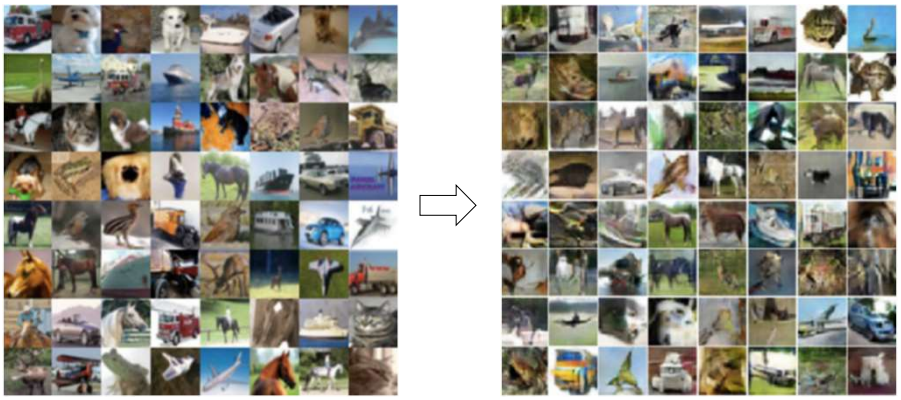
Generative Models

- The term "generative model" is used in many different ways
- We focus on generative models that generate new samples from the same distribution as given training data



Training data ~ $p_{\text{data}}(\mathbf{X})$ Generated samples~ $p_{\text{model}}(\mathbf{X})$

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Generative Models

- The term "generative model" is used in many different ways
- We focus on generative models that generate new samples from the same distribution as given training data
- Generative models take a training set, consisting of samples drawn from a distribution $p_{\text{data}}(\mathbf{X})$, and learns to represent an estimate of that distribution, $p_{\text{model}}(\mathbf{X})$
- In some cases, the model estimates $p_{\text{model}}(\mathbf{X})$ explicitly
  - Generative models explicitly model the joint probability distribution or conditional probability distribution
  - The abstraction and generation of sample happening on the explicitly computed distributions
  - Examples: PixelRNN, variational autoencoder (VAE), restricted Boltzmann machine (RBM) etc.

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Generative Models

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- Generative models take a training set, consisting of samples drawn from a distribution $p_{\text{data}}(\mathbf{X})$, and learns to represent an estimate of that distribution, $p_{\text{model}}(\mathbf{X})$
- In other cases, the model is only able to generate samples from $p_{\text{model}}(\mathbf{X})$
  - Learn model that can sample from $p_{\text{model}}(\mathbf{X})$ without explicitly computing it
  - Generative adversarial networks (GANs) focus primarily on sample generation without caring about the what $p_{\text{data}}(\mathbf{X})$ actually is

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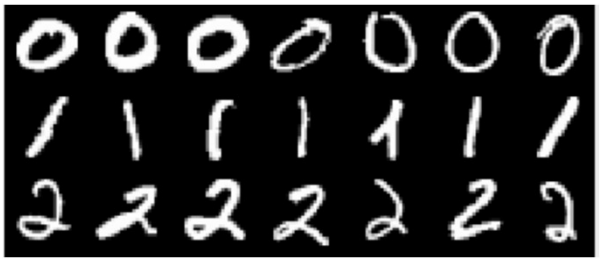
Introduction to GANs



- We are given some training data (say, MNIST images) which obviously comes from some underlying distribution
- Our goal is to generate more images from this distribution (i.e., create images which look similar to the images from the training data)
- In other words, we want to sample from a complex high dimensional distribution which is intractable
  - RBMs and VAE models deal with this intractability in their own way

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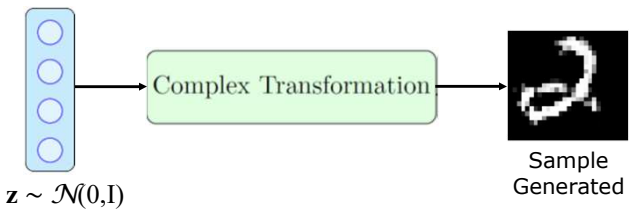
Introduction to GANs

- GANs take a different approach to this problem
- GAN completely bypass the process of learning $p(\mathbf{X})$ i.e. no explicit $p(\mathbf{X})$ is learnt
- The idea is to sample from a simple tractable distribution (say, $\mathbf{z} \sim \mathcal{N}(0,\mathrm{I})$) and then learn a complex transformation from this to the training distribution



- In other words, take a $\mathbf{z} \sim \mathcal{N}(0,\mathrm{I})$, learn to make a series of complex transformations on it so that the output looks as if it came from training distribution
- Neural networks is used to model that complex transformation

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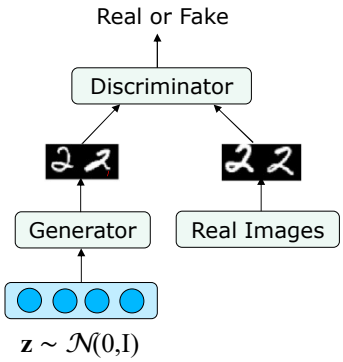
Introduction to GANs



- Neural networks is used to model that complex transformation
- Train the neural networks using two player game
- There are two players in the game:
  - Generator
  - Discriminator
- The job of the generator is to produce images which look so natural that the discriminator thinks that the images came from the real data distribution
- The job of the discriminator is to get better and better at distinguishing between true images and generated (fake) images

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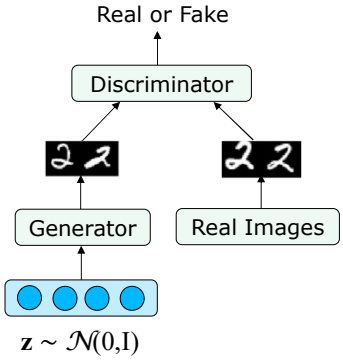
Introduction to GANs



- Let us define the problem formally
- Let $G_\varphi(.)$ be the generator and $D_\theta(.)$ be the discriminator
  - φ and θ are the parameters of $G_\varphi(.)$ and $D_\theta(.)$, respectively
- We have a neural network based generator which takes as input a noise vector $\mathbf{z} \sim \mathcal{N}(0,\mathrm{I})$ and produces $G_\varphi(\mathbf{z})$ [generated image]
- We have a neural network based discriminator which could take as input a real image $\mathbf{X}$ or a generated image $G_\varphi(\mathbf{z})$ and classify the input as real (1) or fake (0)

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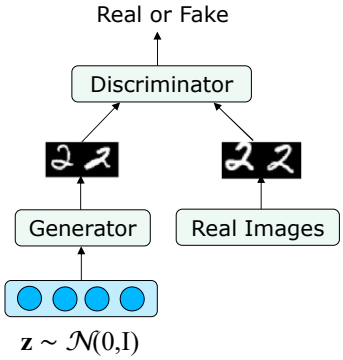
Introduction to GANs



- Let us define the objective function of overall network
- Generator and discriminator has contradicting objective functions
  - One is minimizing and other is maximizing

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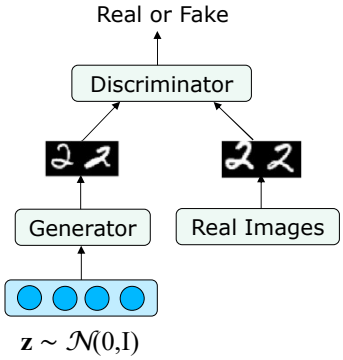
GANs: Objective Function of Generator



- Given an image generated by the generator as $G_\varphi(\mathbf{z})$ the discriminator assigns a score $D_\theta(G_\varphi(\mathbf{z}))$ to it
- This score will be between 0 and 1 and will tell us the probability of the image being real or fake
- Generator wishes $D_\theta(G_\varphi(\mathbf{z}))$ should be as high as possible (close to 1)
- For a given $\mathbf{z}$, the generator would want to maximize the log-likelihood of $D_\theta(G_\varphi(\mathbf{z}))$

$$\text{maximise } \log D_\theta(G_\varphi(\mathbf{z}))$$

- It is also same as minimize the log-likelihood of $(1\text{-}\, D_\theta(G_\varphi(\mathbf{z})))$

$$\text{minimise } \log\left(1 - D_\theta(G_\varphi(\mathbf{z}))\right)$$

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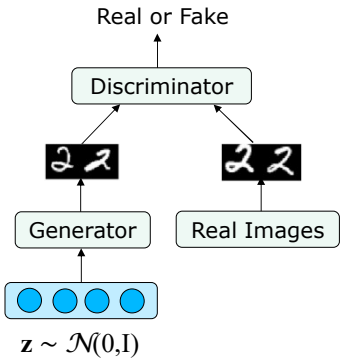
GANs: Objective Function of Generator



- This is just for a single $\mathbf{z}$ and the generator would like to do this for all possible values of $\mathbf{z}$
- For example, if $\mathbf{z}_n$ was discrete and drawn from a uniform distribution, i.e., $p(\mathbf{z}) = \frac{1}{N}$, then the generator's objective function would be

$$\underset{\varphi}{\text{minimise}} \sum_{n=1}^{N} \frac{1}{N} \log\left(1 - D_\theta(G_\varphi(\mathbf{z}_n))\right)$$

  - where N is the number of $\mathbf{z}$'s sampled from the distribution

- However, in our case, $\mathbf{z}$ is continuous and not uniform ($\mathbf{z} \sim \mathcal{N}(0,\mathrm{I})$) so the equivalent objective function would be

$$\underset{\varphi}{\text{minimise}} \int_{n=1}^{N} p(\mathbf{z}_n) \log\left(1 - D_\theta(G_\varphi(\mathbf{z}_n))\right)$$

$$\underset{\varphi}{\text{minimise}}\, \mathbb{E}_{\mathbf{z}\sim p(\mathbf{z})}\left[\log\left(1 - D_\theta(G_\varphi(\mathbf{z}))\right)\right]$$

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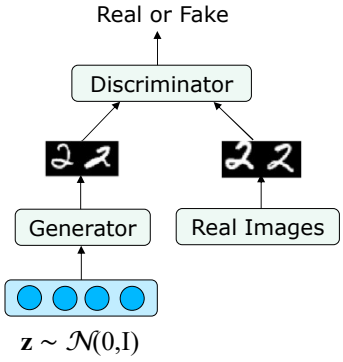
GANs: Objective Function of Discriminator



- The task of the discriminator is to assign a high score to real images and a low score to generated (fake) images
- And it should do this for all possible real images and all possible generated (fake) images
- For every possible $\mathbf{z}$ maximise the score assigned to real images ($D_\theta(\mathbf{X})$)

$$\text{maximise } \log D_\theta(\mathbf{X})$$

- For every possible $\mathbf{z}$ minimise the score assigned to generated (fake) images ($D_\theta(G_\varphi(\mathbf{z}))$)
- It is same as maximise one minus the score assigned to generated (fake) images ($D_\theta(G_\varphi(\mathbf{z}))$)

$$\text{maximise } \log(1 - D_\theta(G_\varphi(\mathbf{z})))$$

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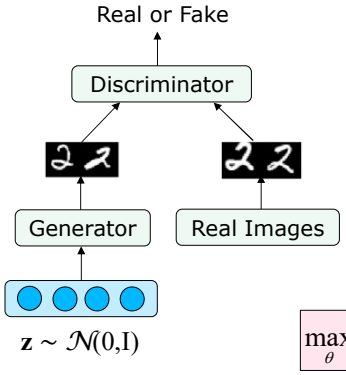
GANs: Objective Function of Discriminator



- The task of the discriminator is to assign a high score to real images and a low score to generated (fake) images
- And it should do this for all possible real images and all possible generated (fake) images
- Overall, it should maximize the following objective function

$$\max_{\theta} \mathbb{E}_{\mathbf{X}\sim p_{data}}\left[\log D_{\theta}(\mathbf{X})\right] + \mathbb{E}_{\mathbf{z}\sim p(\mathbf{z})}\left[\log\left(1 - D_{\theta}(G_{\varphi}(\mathbf{z}))\right)\right]$$

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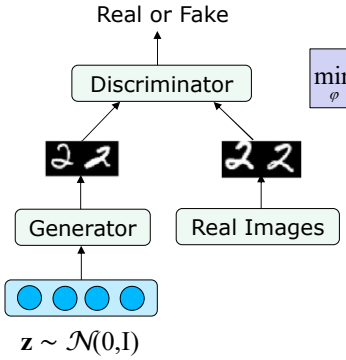
Objective Function of GAN



- If we put the objectives of the generator and discriminator together we get a minimax game

$$\min_{\varphi}\max_{\theta}\left(\mathbb{E}_{\mathbf{X}\sim p_{data}}\left[\log D_{\theta}(\mathbf{X})\right] + \mathbb{E}_{\mathbf{z}\sim p(\mathbf{z})}\left[\log\left(1 - D_{\theta}(G_{\varphi}(\mathbf{z}))\right)\right]\right)$$

- The first term in the objective is only w.r.t. the parameters of the discriminator (θ)
- The second term in the objective is w.r.t. the parameters of the generator (φ) as well as the discriminator (θ)
- The discriminator wants to maximize the second term whereas the generator wants to minimize it (hence it is a two-player game)

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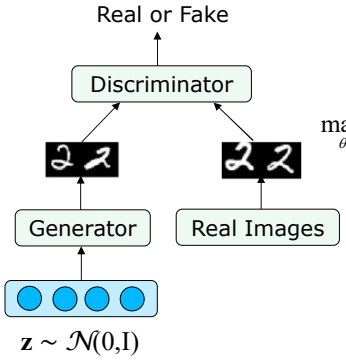
Training the GAN



- The overall training proceeds by alternating between these two step
- **Step1**
  - Gradient Ascent on Discriminator

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

- **Step2**
  - Gradient Descent on Generator

$$\min_{\varphi}\left(\mathbb{E}_{\mathbf{z}\sim p(\mathbf{z})}\left[\log\left(1-D_{\theta}(G_{\varphi}(\mathbf{z}))\right)\right]\right)$$

- In practice, the above generator objective does not work well and we use a slightly modified objective

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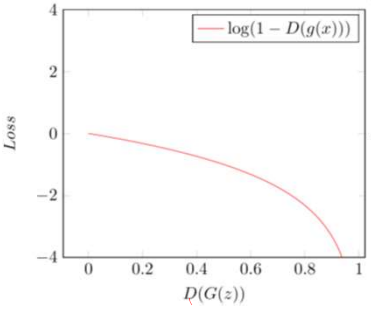
Training the GAN



- When the sample is likely fake (generated) image, we want to give a feedback to the generator (using gradients)
- However, in this region where $D_{\theta}(G_{\varphi}(\mathbf{z}))$ is close to 0,
  - the curve of the loss function is very flat and
  - the gradient would be close to 0
- Trick: Instead of minimizing the likelihood of the discriminator being correct, maximize the likelihood of the discriminator being wrong

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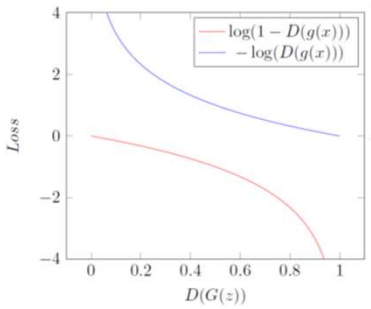
Training the GAN



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- However, in this region where $D_\theta(G_\varphi(\mathbf{z}))$ is close to 0,
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  - the gradient would be close to 0
- Trick: Instead of minimizing the likelihood of the discriminator being correct, maximize the likelihood of the discriminator being wrong
- In effect, the objective remains the same but the gradient signal becomes better

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Algorithm for Training GANs

1: **procedure** GAN TRAINING
2: **for** number of training iterations **do**
3: **for** k steps **do**
4: Sample minibatch of m noise vectors $\mathbf{z}_1, \mathbf{z}_2,\ldots,\mathbf{z}_m$ from $\mathcal{N}(0,I)$
5: Sample minibatch of m examples $\mathbf{X}_1, \mathbf{X}_2,\ldots,\mathbf{X}_m$ from data generating distribution $p_{\text{data}}(\mathbf{X})$
6: Update the discriminator by ascending its stochastic gradient:

$$\nabla_\theta \frac{1}{m}\sum_{i=1}^{m}\left[\log D_\theta(\mathbf{X}_i) + \log\left(1 - D_\theta(G_\varphi(\mathbf{z}_i))\right)\right]$$

7: **end for**
8: Sample minibatch of m noise vectors $\mathbf{z}_1, \mathbf{z}_2,\ldots,\mathbf{z}_m$ from $\mathcal{N}(0,I)$
9: Update the generator by ascending its stochastic gradient

$$\nabla_\varphi \frac{1}{m}\sum_{i=1}^{m}\left[\log\left(D_\theta(G_\varphi(\mathbf{z}_i))\right)\right]$$

10: **end for**
11: **end procedure**

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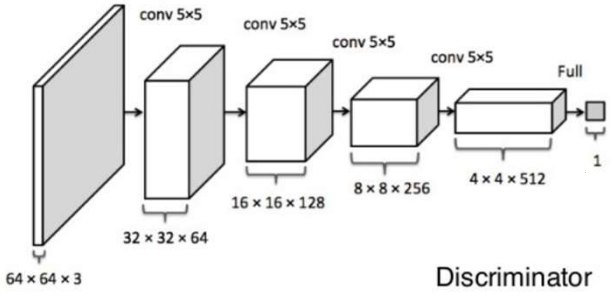
Deep Convolutional GANs (DCGAN)

- One of the popular architecture for GANs (i.e., neural networks used for the generator and discriminator)
- For discriminator, any CNN based classifier with 1 class (real) at the output can be used (e.g. VGG, ResNet, etc.)



[1]

[1] Raymond A. Yeh, Chen Chen, Teck Yian Lim, Alexander G. Schwing, Mark Hasegawa-Johnson and Minh N. Do, "Semantic Image Inpainting with Deep Generative Models", in *Proceedings of the Computer Vision and Pattern Recognition (CVPR-2017)*, pp. 6882-6890, 2017.

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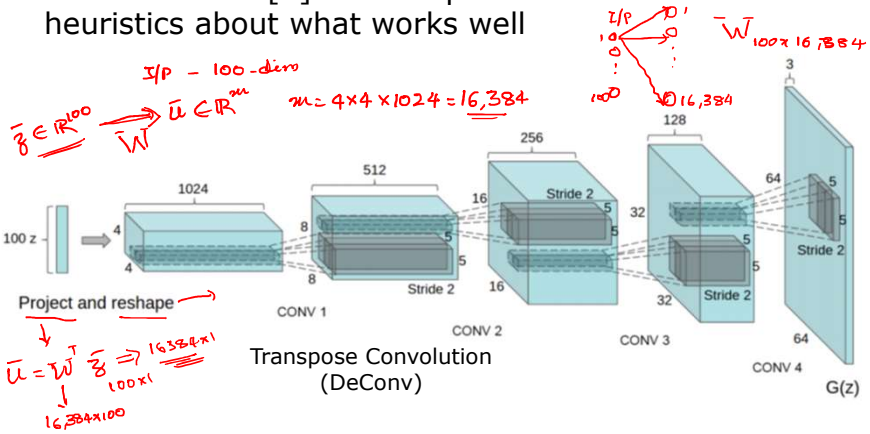
Deep Convolutional GANs (DCGAN)

- For generator, it is not straight forward
- Redford et al [2] came up with a architecture with heuristics about what works well



[2] Alec Radford, Luke Metz, Soumith Chintala, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", in *Proceedings of 4th International Conference on Learning Representations (ICLR 2016)*, San Juan, Puerto Rico, May 2-4, 2016

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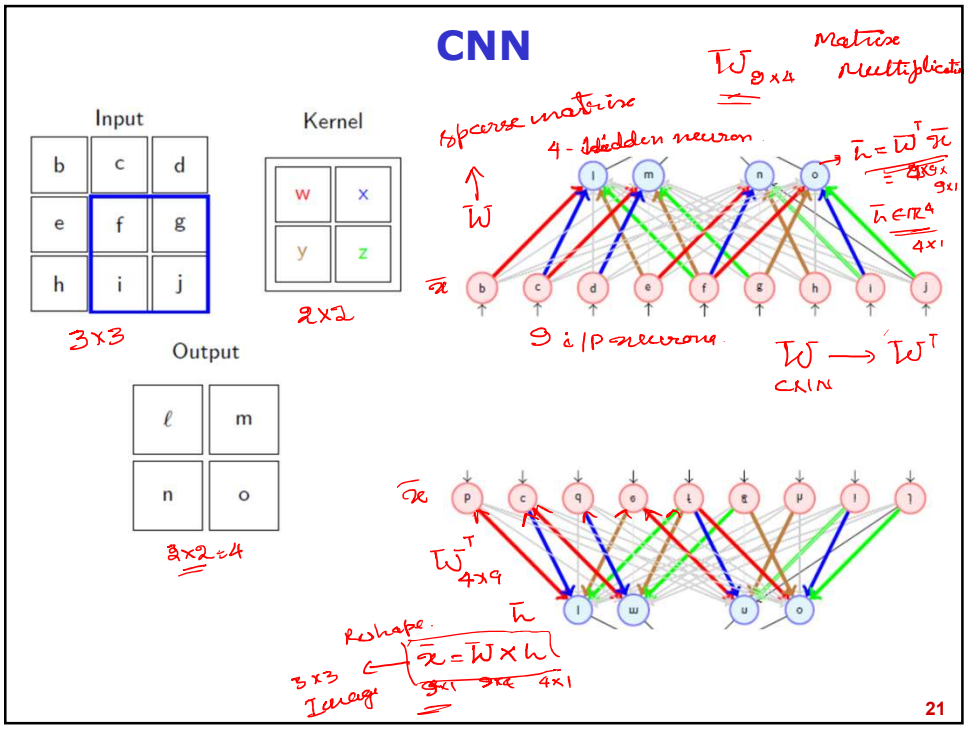

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Architecture Guidelines for Stable DCGANs

- Replace any pooling layers with strided convolutions in discriminator and fractional-strided convolutions (transpose convolution) in generator
- Use batchnorm in both the generator and the discriminator
- Remove fully connected hidden layers for deeper architectures
- Use ReLU activation in generator for all layers except for the output, which uses tanh
- Use LeakyReLU activation in the discriminator for all layers

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Illustrations: GANs

- Samples of images of bedrooms generated by a DCGAN trained on the LSUN dataset [2]

[2] Alec Radford, Luke Metz, Soumith Chintala, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", in *Proceedings of 4th International Conference on Learning Representations (ICLR 2016)*, San Juan, Puerto Rico, May 2-4, 2016

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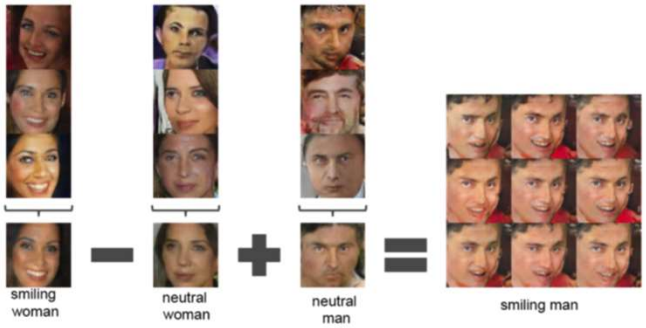
Illustrations: GANs



- The first 3 images in the first column were generated by feeding some $\mathbf{z}_{11}$, $\mathbf{z}_{12}$, $\mathbf{z}_{13}$ respectively as the input to the generator
- The fourth image, $\mathbf{z}_1$, was generated by taking an average of $\mathbf{z}_{11}$, $\mathbf{z}_{12}$, $\mathbf{z}_{13}$ and feeding it to the generator
- Similarly the average vectors $\mathbf{z}_2$ and $\mathbf{z}_3$ are obtained for the 2nd and 3rd columns
- If we do a simple vector arithmetic on these averaged vectors then we see the corresponding effect in the generated images

[2] Alec Radford, Luke Metz, Soumith Chintala, "Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks", in *Proceedings of 4th International Conference on Learning Representations (ICLR 2016)*, San Juan, Puerto Rico, May 2-4, 2016

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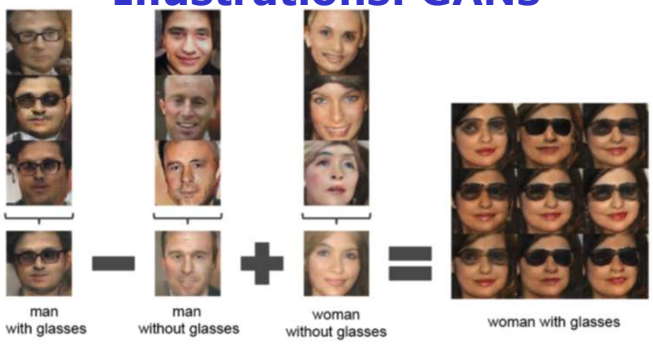

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Applications

- Image to image translation [3]
  - Encompassing many kinds of transformations of an image: converting a satellite photo into a map, converting a sketch into a photorealistic image, etc.

[3] Isola, P., Zhu, J.-Y., Zhou, T., and Efros, A. A., Image-to-image translation with conditional adversarial networks, arXiv preprint arXiv:1611.07004. 2016

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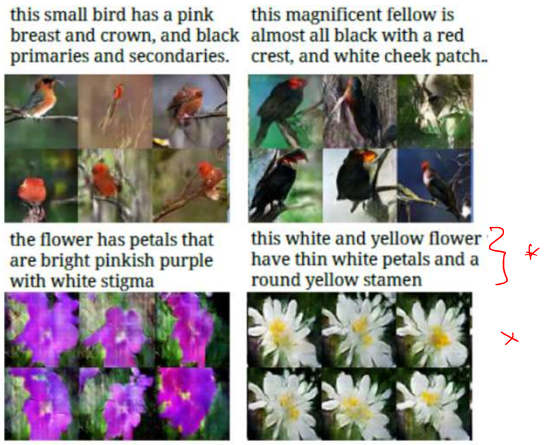
Applications

- Text-to-image synthesis with GANs [4]



[4] Reed, S., Akata, Z., Yan, X., Logeswaran, L., Schiele, B., and Lee, H., "Generative adversarial text to image synthesis", arXiv preprint, arXiv:1605.05396, 2016.

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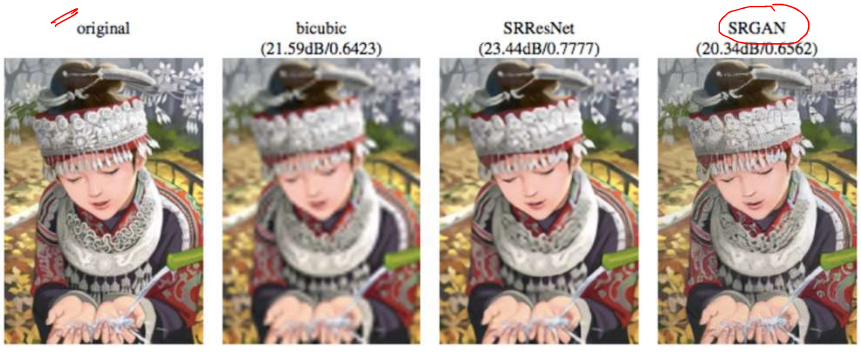
Applications

- Super-resolution [5]
  - The leftmost image is an original high-resolution image
  - It is then down sampled to make a low-resolution image, and different methods are used to attempt to recover the high-resolution image



[5] Ledig, C., Theis, L., Huszar, F., Caballero, J., Aitken, A. P., Tejani, A., Totz, J.,Wang, Z., and Shi, W. , Photo-realistic single image super-resolution using a generative adversarial network. CoRR, abs/1609.04802, 2016.

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Applications

- Generating art [6]
  - Generating art by looking at art and learning about styles

[6] Elgammal, A., Liu, B., Elhoseiny, M. and Mazzone, M., CAN: Creative adversarial networks, generating" art" by learning about styles and deviating from style norms. *arXiv preprint arXiv:1706.07068*, 2017.

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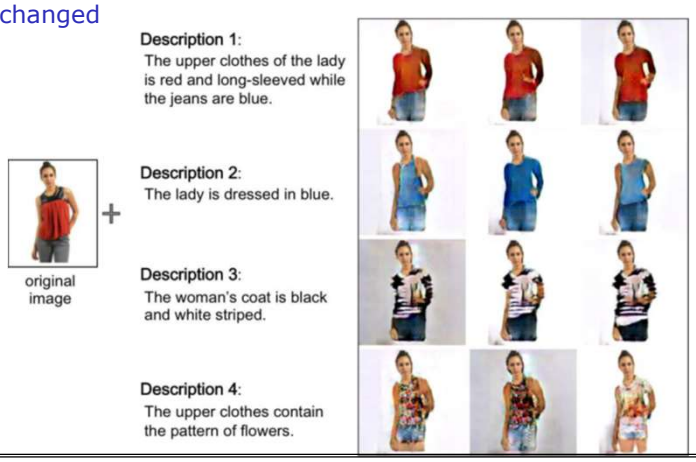
Applications

- Fashion Synthesis [7]
  - Given an input image of a person and a sentence describing a different outfit, the model "redresses" the person as desired, while at the same time keeping the wearer and her/his pose unchanged



[7] Zhu, S., Urtasun, R., Fidler, S., Lin, D. and Change Loy, C., Be your own prada: Fashion synthesis with structural coherence. In Proceedings of the IEEE international conference on computer vision, pp. 1680-1688, 2017

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Summary: GAN

- Generative adversarial network (GAN) is a generative model
- It generate the samples close to the training distribution without explicitly learning it
- In other words, take a $\mathbf{z} \sim \mathcal{N}(0,\mathrm{I})$, learn to make a series of complex transformations on it so that the output looks as if it came from training distribution
  - Neural networks is used to model that complex transformation
- Neural networks are trained using two player game
  - Two players in the game are a generator and a discriminator
- The job of the generator is to produce images which look so natural that the discriminator thinks that the images came from the real data distribution
- The job of the discriminator is to get better and better at distinguishing between true images and generated (fake) images

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Text Books

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