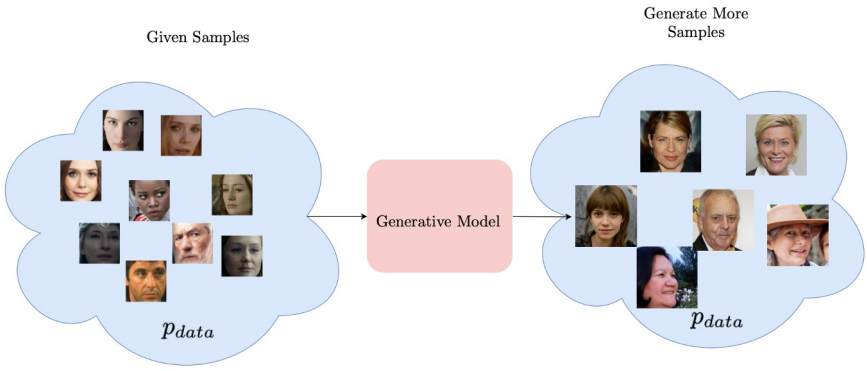
Generative Models

1

1

Generative Modelling

How does one sample from a distribution given only its samples?



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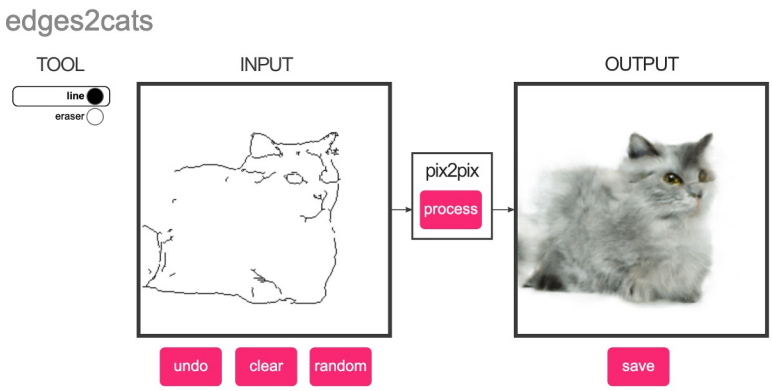
Generative Modelling: Why?

We can do some cool stuff! Like generate images from line drawings



Demo: https://affinelayer.com/pixsrv/

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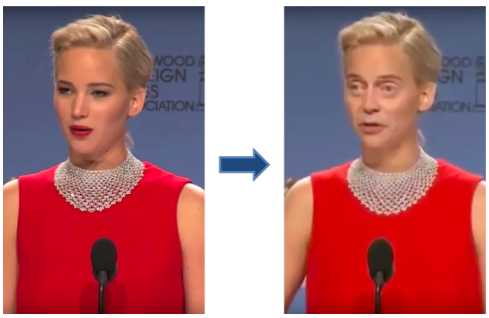
Generative Modelling: Why?

Change faces!



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Generative Modelling: Why?

Or edit faces!

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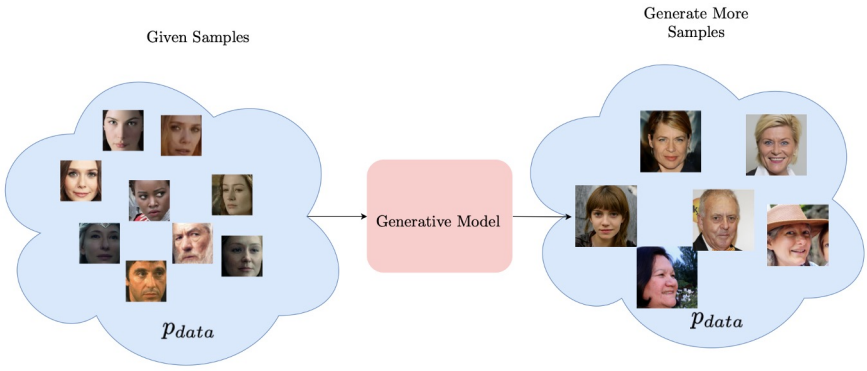
Generative Modelling

Right, so how does one sample from a distribution given only its samples?



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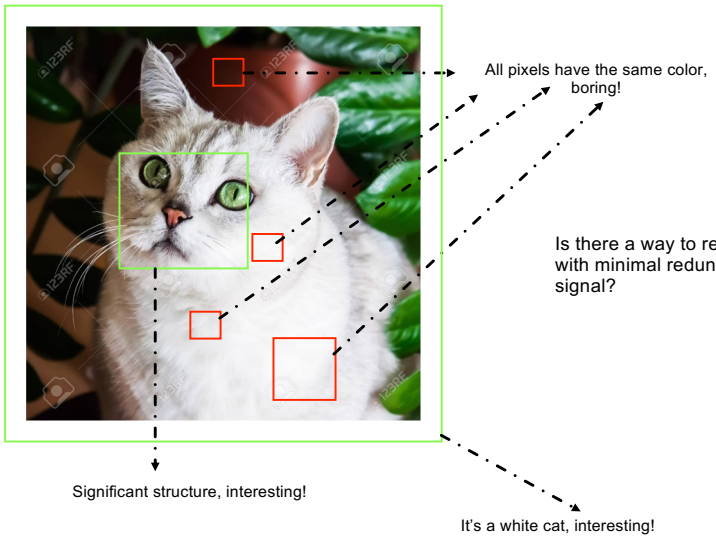
Generative Modeling: A Closer look at images

They're redundant, like very redundant



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Generative Modeling: A Closer look at images

More realistically, is there a way to represent this image with minimal redundancy and a "good amount" of signal?

Yes! we do it all the time! Language!

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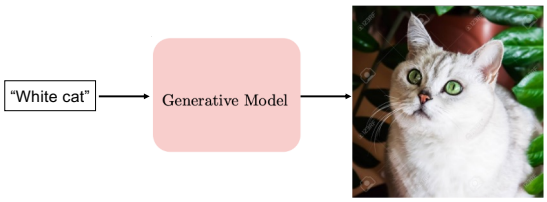
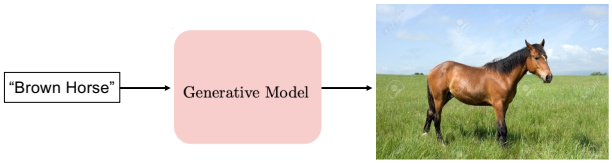
Generative Modeling: An ideal generative model

Say what you want the model to generate, and it generates it!





We can generate whatever we want!

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Generative Modeling – From CSE527, 2020

"Unfortunately, life ain't that good and training such a model is hard. Especially because, text is quite a lossy representation" – Me, 2020

"White cat"

Eye Color? Head Shape? Number of whiskers?
Background?……

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Generative Modeling – From CSE527, 2020

"Unfortunately, life ain't that good and training such a model is hard. Especially because, text is quite a lossy representation" – Me, 2020

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Generative Modeling – From CSE527, 2020

"Unfortunately, life ain't that good and training such a model is hard. Especially because, text is quite a lossy representation" – Me, 2020

Right……

"A photorealistic image of a white cat on a garden ledge"

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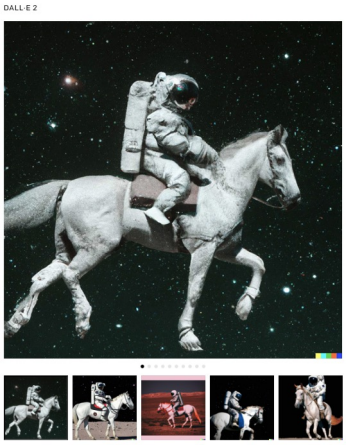
Generative Modeling

So, how do we get to DALL-E or Imagen? Lets start out journey…



"An astronaut riding a horse in a photorealistic style"

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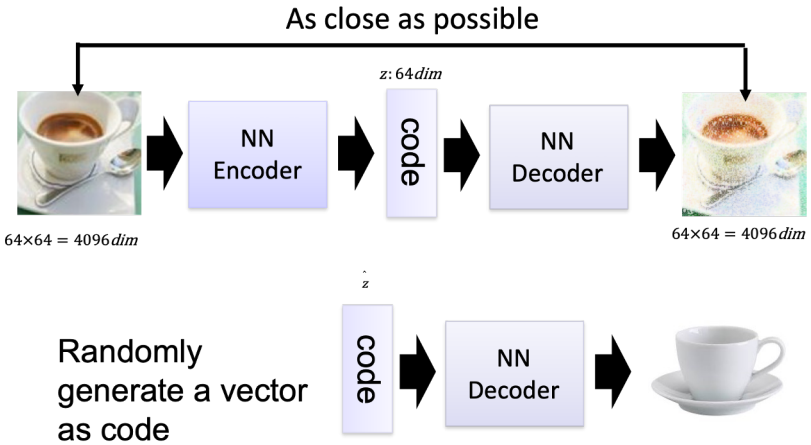
Generative Modeling: Autoencoders

Learn a representation by compressing an image as much as possible and then reconstructing it.



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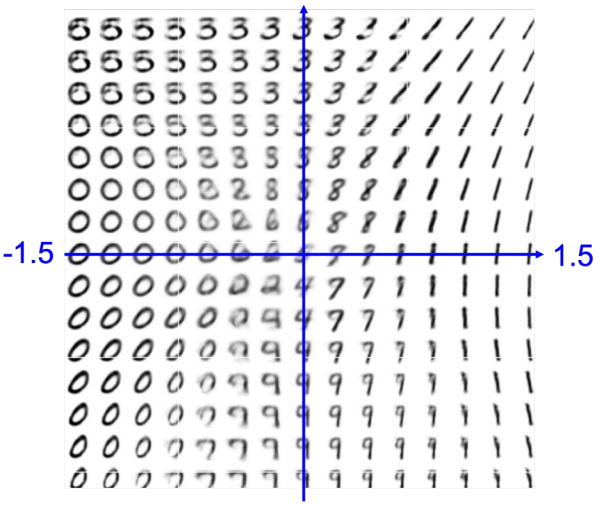
Generative Modeling: Autoencoders

But where do we sample from? A random vector may not produce a realistic image



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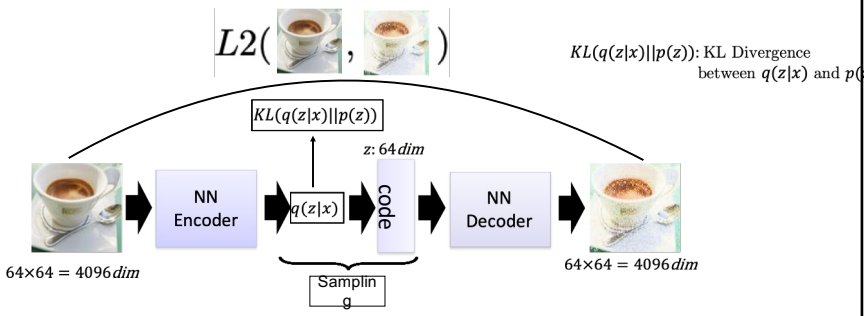
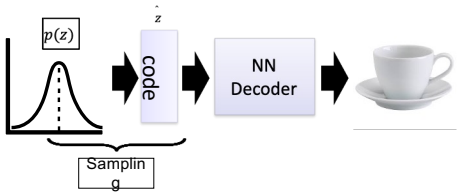
Generative Modeling: Variational Autoencoders

Learn a representation by compressing an image as much as possible and then reconstructing it, and push the distribution of the latent representation (i.e z) to a known prior $p(z) \sim N(0, I)$



Images can now be generated from a known prior distribution $p(z)$!



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Generative Modeling: A diversion into divergences

A divergence allows one to measure the "distance" between two distributions $p(x)$ and $q(x)$. It is not a true distance measure because it may not be symmetric nor satisfy the triangle inequality. They satisfy the following properties:

- $D(p(x)||q(x)) \geq 0 \; \forall \; p(x), q(x)$
- $D(p(x)||q(x)) = 0 \textit{ if and only if } p(x) = q(x)$

Therefore, even if not a true distance, a divergence can allow us to measure how similar or dissimilar two distributions $p(x)$ and $q(x)$ are!

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Generative Modeling: The KL and Jenson-Shanon Divergence

A divergence we've already seen is the KL-Divergence or Kullback-Leibler divergence which is defined as follows:

$$KL(p(x)||q(x)) = \int_{-\infty}^{\infty} p(x) log\left(\frac{p(x)}{q(x)}\right) dx$$

Notice $KL(p(x)||q(x)) \neq KL(q(x)||p(x))$!

This animation should give you some intuition about how the KL-Divergence works!

The Jenson-Shanon Divergence (JSD) is a symmetric version of the KL-Divergence and is defined as follows

$$JSD(p(x)||q(x)) = \frac{1}{2} KL\left(p(x)||\frac{p(x)+q(x)}{2}\right) + \frac{1}{2} KL\left(q(x)||\frac{p(x)+q(x)}{2}\right)$$

We'll be running into JSD when discussing GANs 🙂

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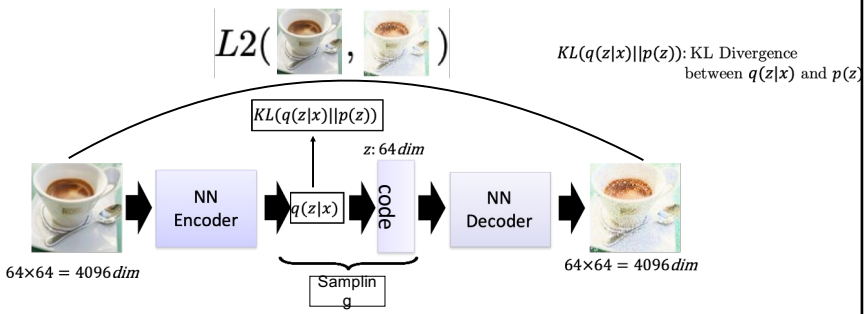
Generative Modeling: Variational Autoencoders

Learn a representation by compressing an image as much as possible and then reconstructing it, and push the distribution of the latent representation (i.e z) to a known prior $p(z) \sim N(0, I)$



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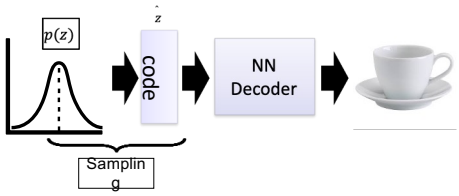

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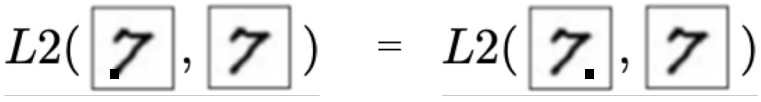
Generative Modeling: Variational Autoencoders

Unfortunately, the L2 loss does not capture realism



More realistic

Less realistic

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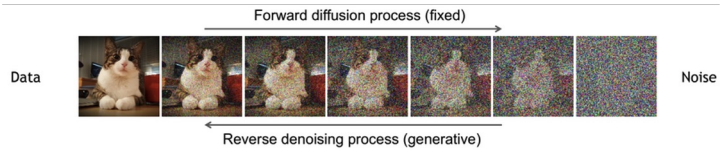
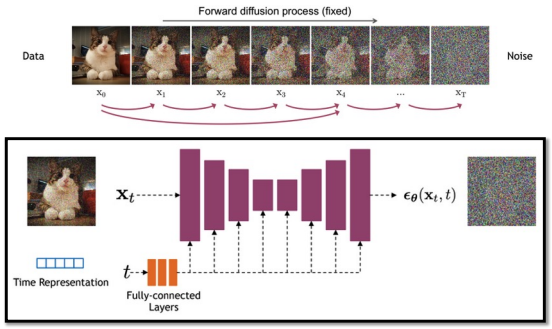
Generative Modeling: Denoising Diffusion models

A Denoising Diffusion model consists of two processes:
- A Forward diffusion process that gradually adds noise to the input
- A Reverse diffusion process that learns to generate data by denoising
- The objective this minimizes is very similar to that of a VAE i.e a variational lower bound



Slides are mostly from the workshop on Denoising Diffusion models, CVPR2022: https://drive.google.com/file/d/1DYHDbt1tSl9oqm3O333biRYzSCOIdtmn/view

Generative Modeling: Denoising Diffusion models, The forward process



Use a U-Net to predict the noise at each step
- Push the noise to be as close to gaussian as possible

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\epsilon$$

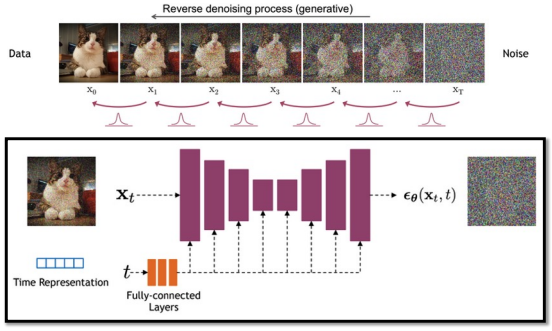
$$\epsilon \sim N(0, \mathbf{I})$$

Algorithm 1 Training

1: **repeat**
2: $\mathbf{x}_0 \sim q(\mathbf{x}_0)$
3: $t \sim \text{Uniform}(\{1, \dots, T\})$
4: $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
5: Take gradient descent step on
$\nabla_\theta \left\| \boldsymbol{\epsilon} - \boldsymbol{\epsilon}_\theta(\sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\boldsymbol{\epsilon}, t) \right\|^2$
6: **until** converged

Slides are mostly from the workshop on Denoising Diffusion models, CVPR2022: https://drive.google.com/file/d/1DYHDbt1tSl9oqm3O333biRYzSCOIdtmn/view

Generative Modeling: Denoising Diffusion models, The forward process



Use the predicted noise by U-Net to invert the image

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t}\mathbf{x}_0 + \sqrt{1-\bar{\alpha}_t}\epsilon$$

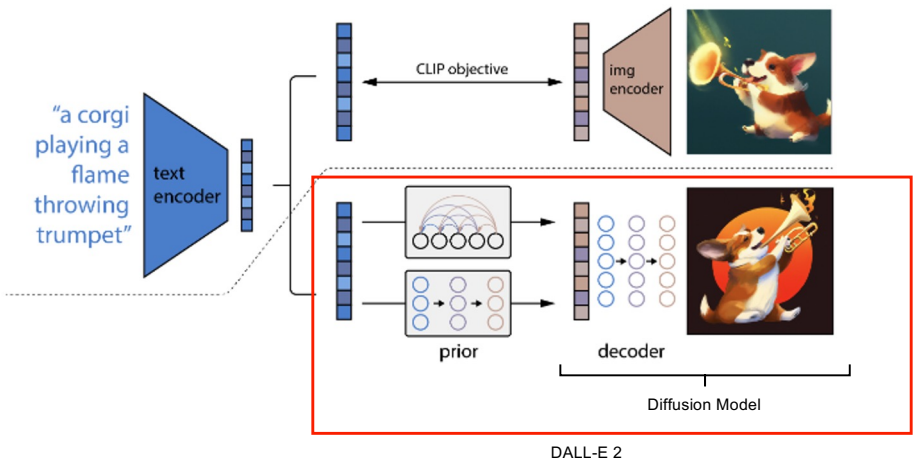
$$\epsilon \sim N(0, \mathbf{I})$$

Algorithm 2 Sampling

1: $\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
2: **for** $t = T, \ldots, 1$ **do**
3: $\quad \mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$
4: $\quad \mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}}\left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}}\boldsymbol{\epsilon}_\theta(\mathbf{x}_t, t)\right) + \sigma_t \mathbf{z}$
5: **end for**
6: **return** $\mathbf{x}_0$

Slides are mostly from the workshop on Denoising Diffusion models, CVPR2022: https://drive.google.com/file/d/1DYHDbt1tSl9oqm3O333biRYzSCOIdtmn/view

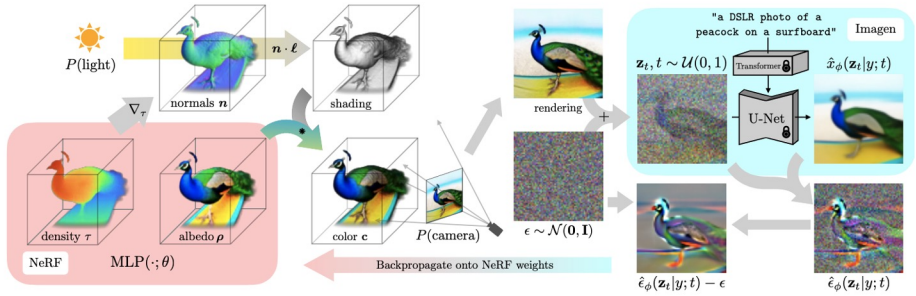
Generative Modeling: DALL-E 2



DALL-E 2

Slides are mostly from the workshop on Denoising Diffusion models, CVPR2022: https://drive.google.com/file/d/1DYHDbt1tSl9oqm3O333biRYzSCOIdtmn/view

Generative Modeling: Text to 3D, DreamFusion



Slides are mostly from the workshop on Denoising Diffusion models, CVPR2022: https://drive.google.com/file/d/1DYHDbt1tSl9oqm3O333biRYzSCOIdtmn/view

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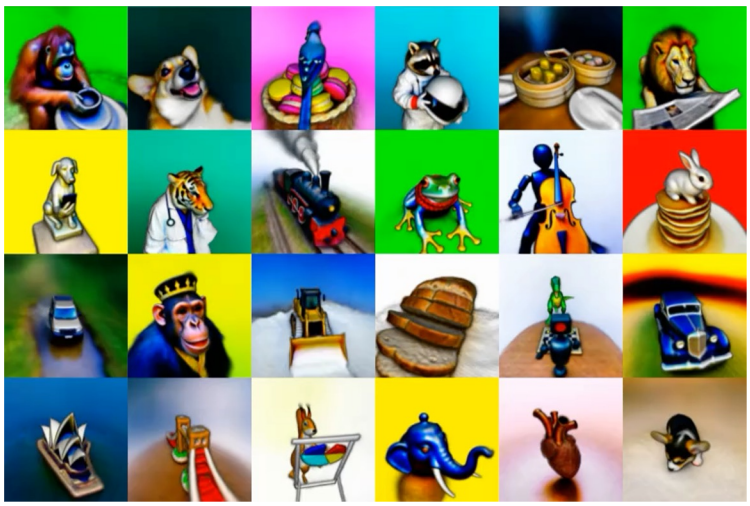
Generative Modeling: Text to 3D, DreamFusion



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Generative Modeling: Some Resources

- The Deep Learning Book discusses Autoencoders along with many other generative models: https://www.deeplearningbook.org/
- Durk Kingma's thesis is a great read for probabilistic generative models and VAEs: https://pure.uva.nl/ws/files/17891313/Thesis.pdf
- Lilian Weng's blog post on the VAE is great! https://lilianweng.github.io/lil-log/2018/08/12/from-autoencoder-to-beta-vae.html
- Diffusion models: https://lilianweng.github.io/posts/2021-07-11-diffusion-models/
- Diffusion Models: https://cvpr2022-tutorial-diffusion-models.github.io/

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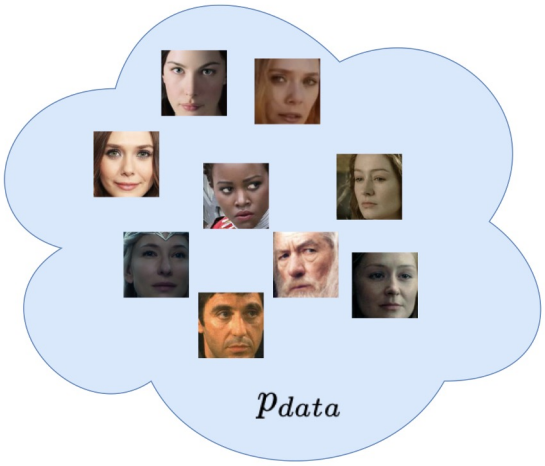
Generative Adversarial Networks (Goodfellow et al. NIPS2014)

How does one sample from a distribution given only its samples?



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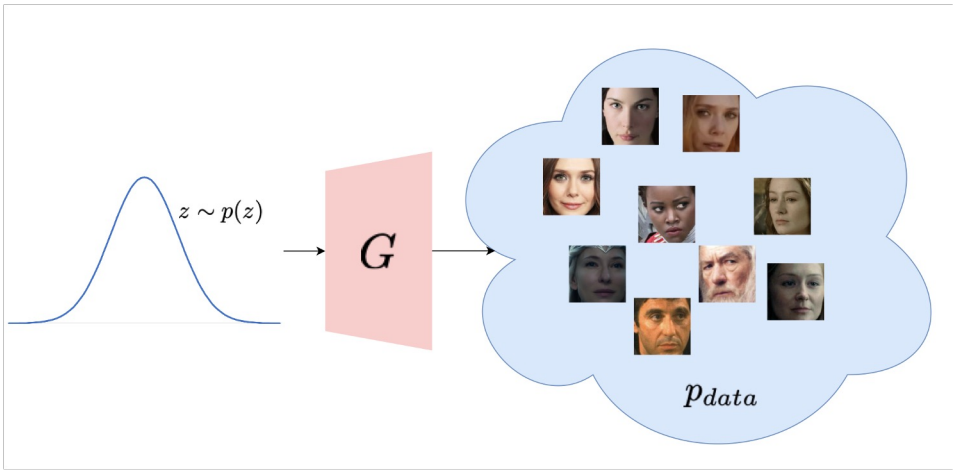
Generative Adversarial Networks

Train a “Generator” to transform samples from a gaussian to the image space!



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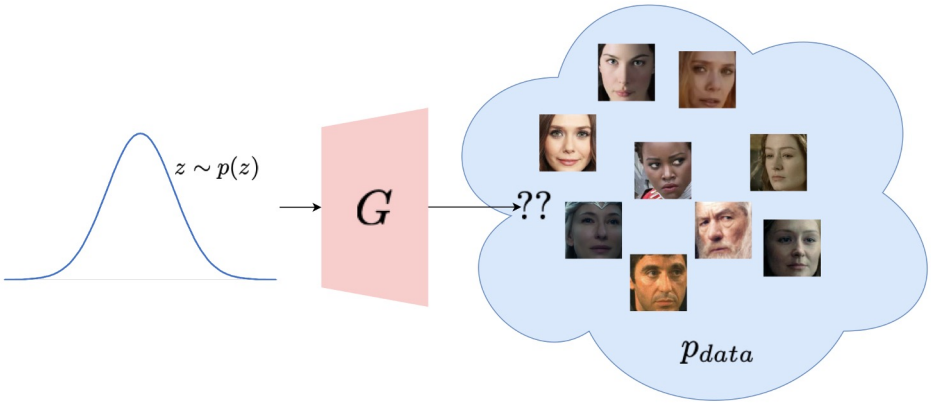
Generative Adversarial Networks

- But we don’t know what a random z maps to in the Image space, in other words we do not have $(z, Image)$ pairs.
- Supervised losses (L2, L1 etc) cannot be used!



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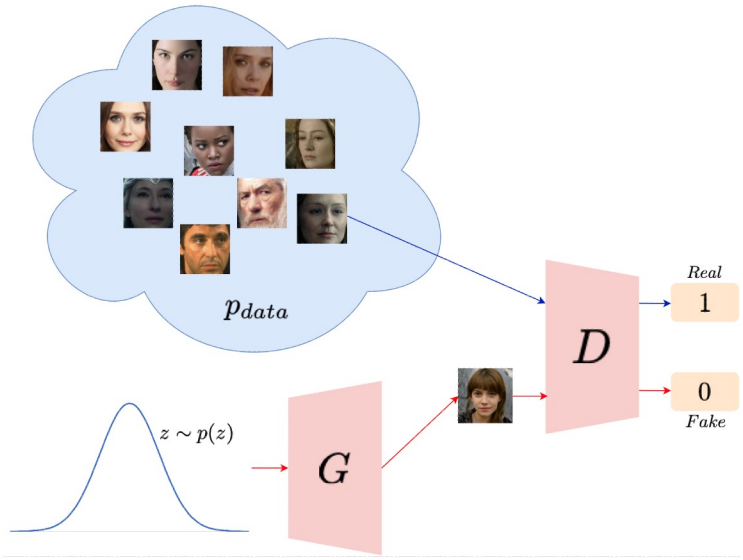
Generative Adversarial Networks

Use a "Discriminator" to distinguish between samples generated by G and the real samples.



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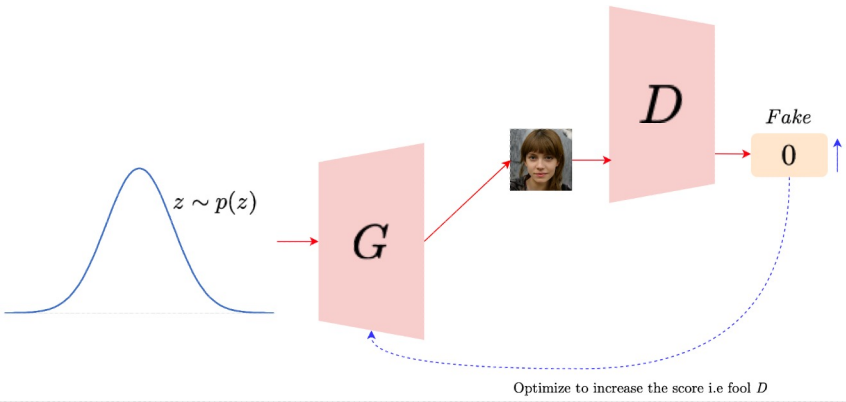
Generative Adversarial Networks

Train G to maximize D's score. Use the gradient as a "guide" to generate realistic images.



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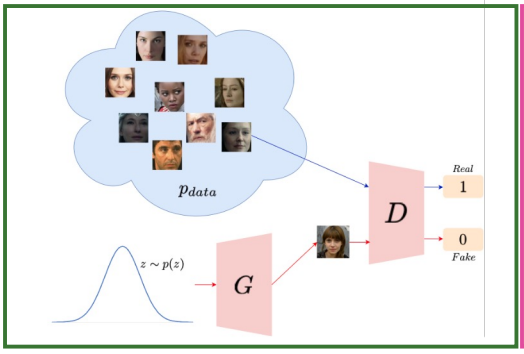
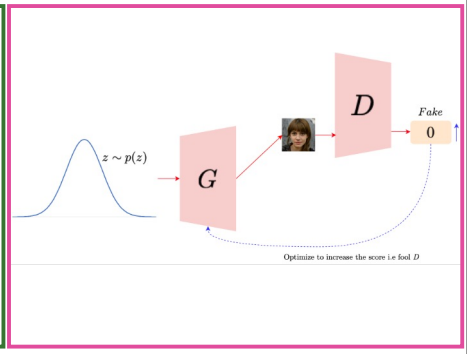
Generative Adversarial Networks

More formally





$$\max_D \mathbb{E}_{x \sim p_{data}} [\log D(x)] + \mathbb{E}_{z \sim p(z)} [\log (1 - D(G(z)))]$$

Train D to discriminate

$$\min_G \mathbb{E}_{z \sim p(z)} [\log (1 - D(G(z)))]$$

Train G to fool D

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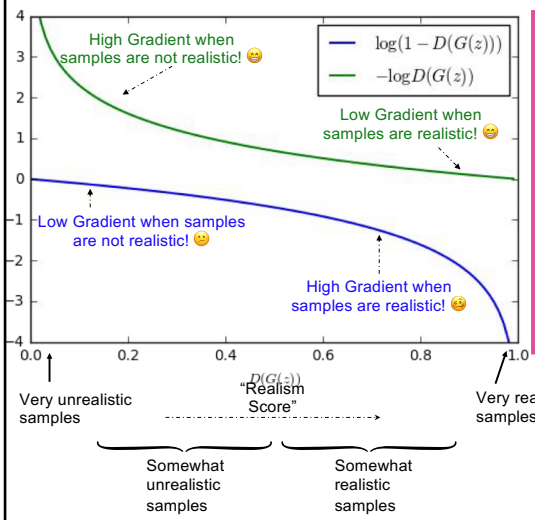
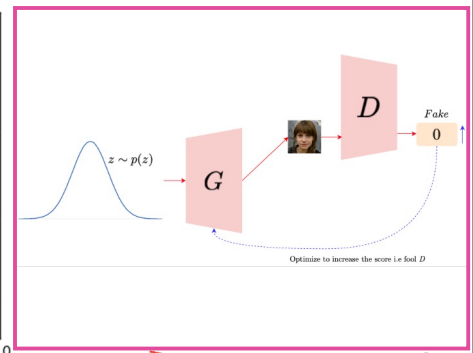
Generative Adversarial Networks

Fixing the gradient





$$\min_G \mathbb{E}_{z \sim p(z)} [\log (1 - D(G(z)))]$$

Bad Gradients!

$$\max_G \mathbb{E}_{z \sim p(z)} [\log D(G(z))]$$

Better Gradients!

Train G to fool D

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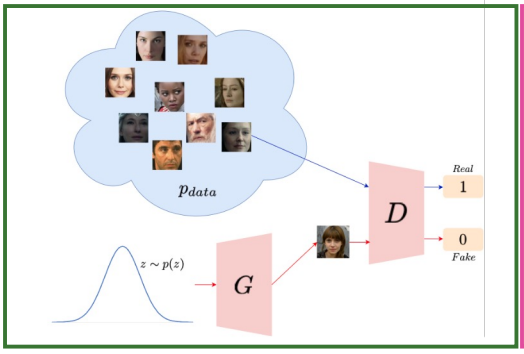
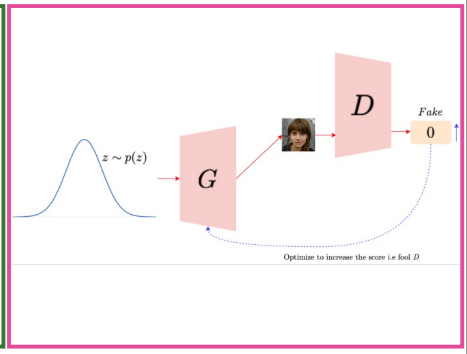
Generative Adversarial Networks

Finally, the "Non-Saturating" GAN-loss





Train G to fool D

$\max_G \mathbb{E}_{z \sim p(z)} [\log D(G(z))]$

Train D to discriminate

Train G to fool D

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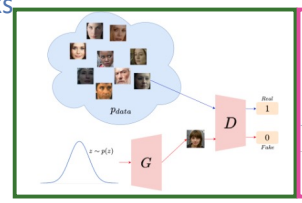
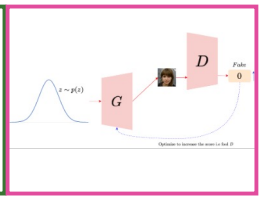
Generative Adversarial Networks

What's really happening



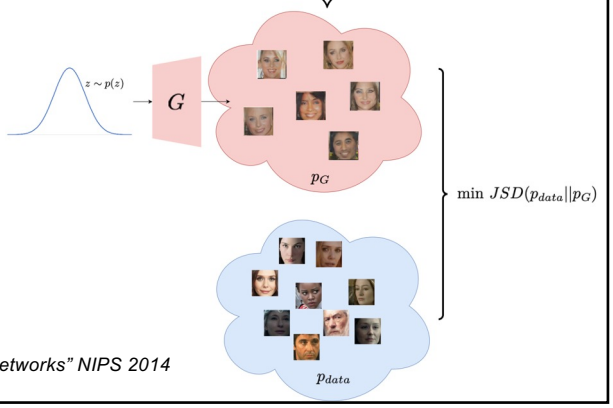


$\max_D \mathbb{E}_{x \sim p_{data}} [\log D(x)] + \mathbb{E}_{z \sim p(z)} [\log (1 - D(G(z)))]$

$\max_G \mathbb{E}_{z \sim p(z)} [\log D(G(z))]$

$JSD(p_{data} || p_G)$ = JSD between p_{data} and p_G.

GAN training minimizes it.



Goodfellow et al. "Generative Adversarial Networks" NIPS 2014

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Generative Adversarial Networks

GAN samples have become really good. Samples from StyleGAN V2 (Karras et al. CVPR2020)

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Generative Adversarial Networks

GAN samples have become really good. Samples from StyleGAN V2 (Karras et al. CVPR2020)

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Generative Adversarial Networks

GAN samples have become really good. Samples from BigGAN (Brock et al. ICLR2019)

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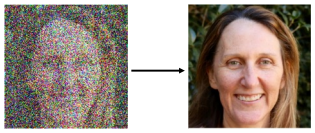
Generative Adversarial Networks: What can they be used for?

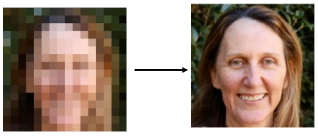
Let's see how GANs can help us for two standard CV problems: *Denoising* and *Super-Resolution*

Denoising



Noisy Image *Real Image*

Super-Resolution : 4×



Low-Res Image 32×32 *Real Image* 128×128

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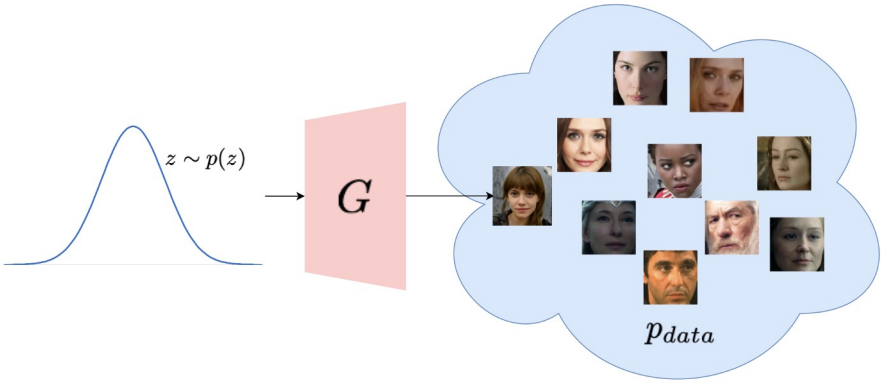
Generative Adversarial Networks

GANs allow us to go from one space to another without using paired data! Here, we're going from vectors to Images!



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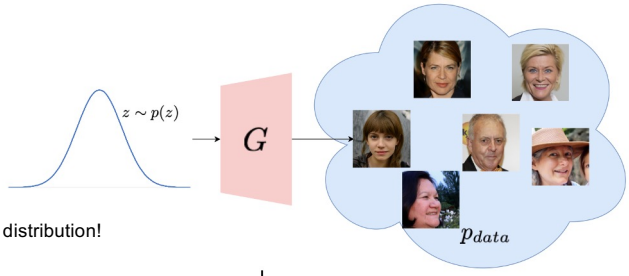
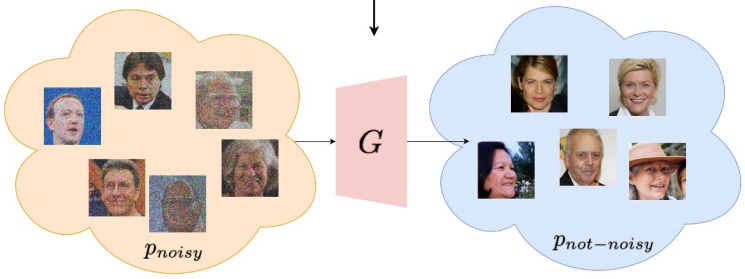
GANs for X: X = "Denoising"

Consider the task of going from ***Noisy Images*** → ***Denoised Images***. How can GANs help?



Change the sampling distribution!



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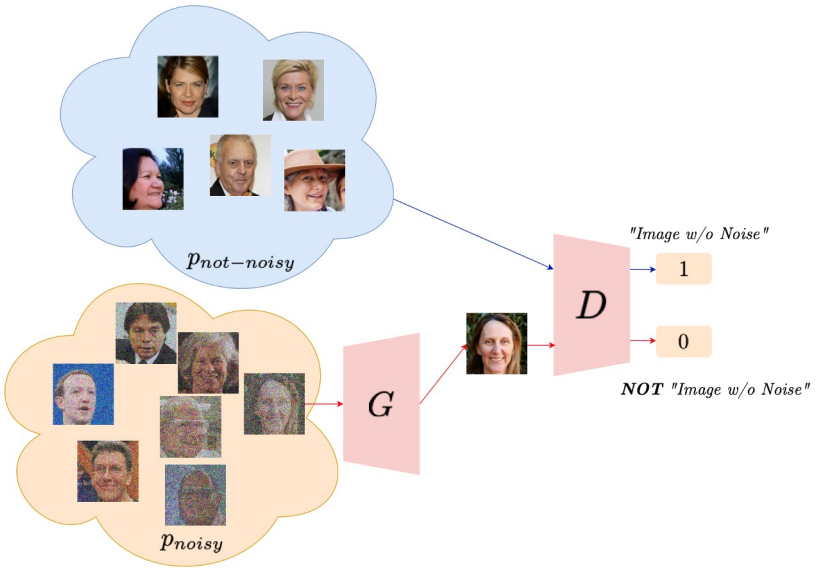
GANs for X: X = "Denoising"

Train with the adversarial loss! We don't need pairs!



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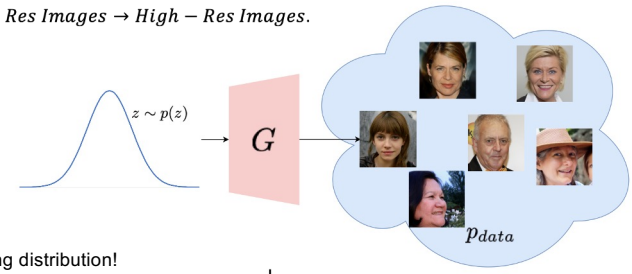
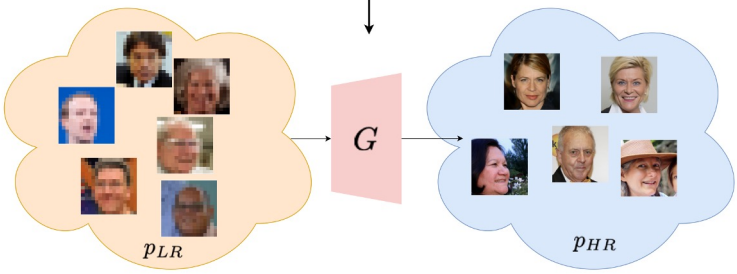
GANs for X: X = "Super-Resolution"

Similarly for $Low - Res\ Images \rightarrow High - Res\ Images$.



Change the sampling distribution!



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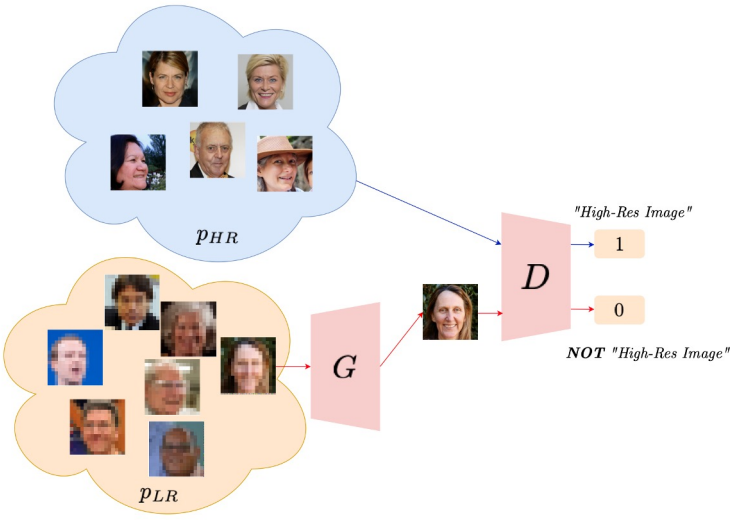
GANs for X: X = "Super-Resolution"

Train with the adversarial loss! We don't need pairs!



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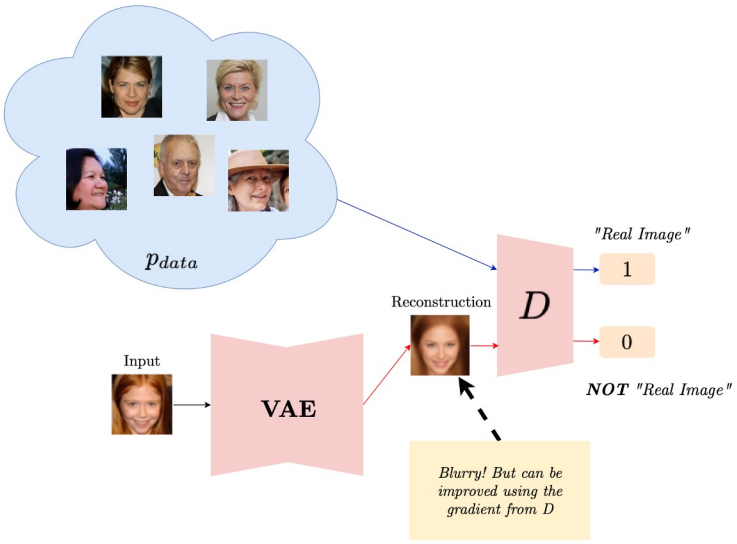
The Adversarial Loss

Use a discriminator to push VAE reconstructions to be sharper!



Larsen et al. "Autoencoding beyond pixels using a learned similarity metric" PMLR 2016

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The Adversarial Loss

Use a discriminator to push VAE reconstructions to be sharper!

Larsen et al. "Autoencoding beyond pixels using a learned similarity metric" PMLR 2016

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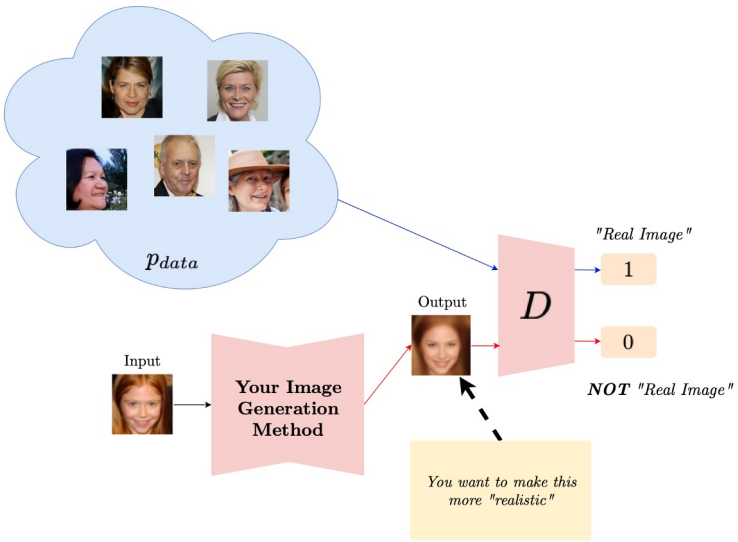
The Adversarial Loss

A discriminator can be used to improve to results of any image generation method!



You et al. "Your Paper Tilte" WhereverYouSubmit 2XXX

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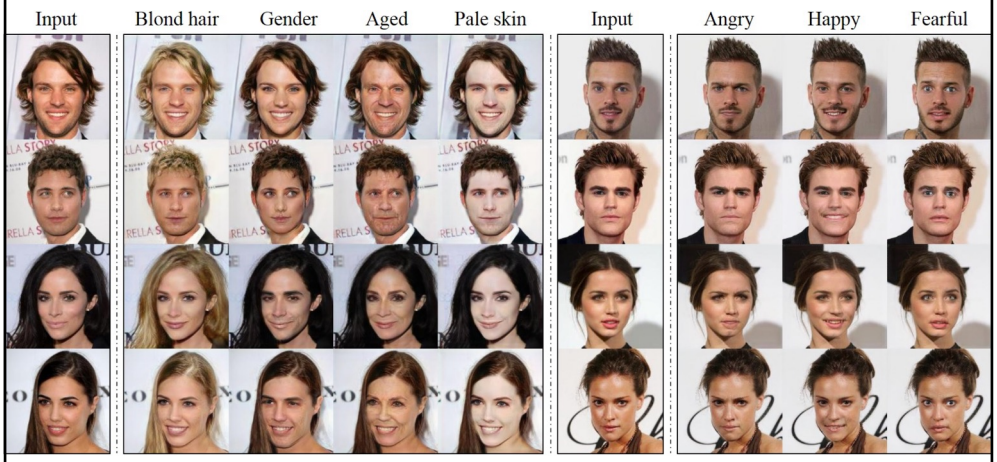
StarGAN: GAN for domain translation



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Generative Adversarial Networks: Losses Galore!

The Standard GAN Loss can be pretty unstable to train with. Consequently, multiple losses and regularizers have been proposed

- WGAN-GP (Gulrajani et al. 2017)

$$\underbrace{\mathop{\mathbb{E}}_{\tilde{\boldsymbol{x}}\sim\mathbb{P}_g}[D(\tilde{\boldsymbol{x}})] - \mathop{\mathbb{E}}_{\boldsymbol{x}\sim\mathbb{P}_r}[D(\boldsymbol{x})]}_{\text{Original critic loss}} + \underbrace{\lambda \mathop{\mathbb{E}}_{\hat{\boldsymbol{x}}\sim\mathbb{P}_{\hat{\boldsymbol{x}}}}\left[(\|\nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}})\|_2 - 1)^2\right]}_{\text{Our gradient penalty}}.$$

- Least-Squares GAN (Mao et al. 2016)

$$\min_D V_{\text{LSGAN}}(D) = \frac{1}{2}\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}\left[(D(\boldsymbol{x})-1)^2\right] + \frac{1}{2}\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}\left[(D(G(\boldsymbol{z})))^2\right]$$
$$\min_G V_{\text{LSGAN}}(G) = \frac{1}{2}\mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}\left[(D(G(\boldsymbol{z}))-1)^2\right].$$

- Spectral Normalization (Miyato et al. 2018)
- R1 Regularization (Mescheder et al. 2018)

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Generative Adversarial Networks: Architectures

Architectures (including activations, normalizations etc) of both the Generator and the Discriminator are also crucial to generate good samples. Some important work is given below

- DCGAN (Radford et al. 2016): First Convolutional Generator
- Pix2pix (Isola et al. 2017): Introduced a patch-based discriminator that discriminated on overlapping patches of the input image.
- Progressive GAN (Karras et al. 2017): First Mega-Pixel level image generation using GANs. Proposed Progressive Training
- CycleGAN (Zhu et al 2017): GANs for image-to-image translation from one domain to another
- StarGAN (Choi et al. 2017): GANs for image-to-image translation between *multiple* domains
- Spectral Normalization (Miyato et al. 2018): First good results on ImageNet classes
- StyleGAN (Karras et al. 2018): High Quality Mega-Pixel level image generation using GANs. Doesn't require progressive training. Introduced a much richer "style" latent space.
- BigGAN (Brock et al. 2019): HQ results in ImageNet Classes

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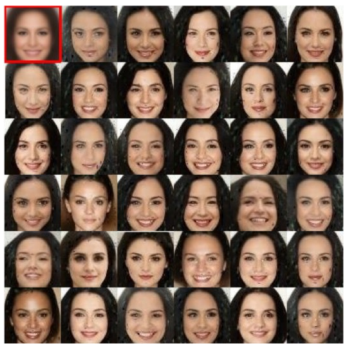
Generative Adversarial Networks: The problems

- As alluded to earlier, training can be unstable
- Mode Collapse can occur (example from Richardson et al, "On GANs and GMMs", 2018). Faces are very similar!



- Given a sample x, GANs can't tell you how likely (realistic) it is i.e it cannot give you $p_{data}(x)$. The discriminator score cannot be used for this, check out *Goodfellow et al 2014* (the original GAN paper) for why.

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Generative Modeling: Some Resources

- The Deep Learning Book discusses GANs along with many other generative models: Link
- The original GAN paper is a great read!
- Scott Rome's blog digs into the details the the proofs in the GAN paper
- Lilian Weng's blog post on GANs is great too!

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Other Methods are catching up

VQ-VAE-2 (Razavi et al. 2019): Uses a autoregressive prior on the VAE latent space and a much deeper encoder and decoder.

1024×1024

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Other Methods are catching up

GLOW (Kingma et al. 2018): Based on Normalizing Flows (Dinh et al, *NICE: Non-linear Independent Components Estimation*, 2015). Methods based on Normalizing Flows give exact likelihoods $p_{data}(x)$!

256×256

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