

CNNs, Generation

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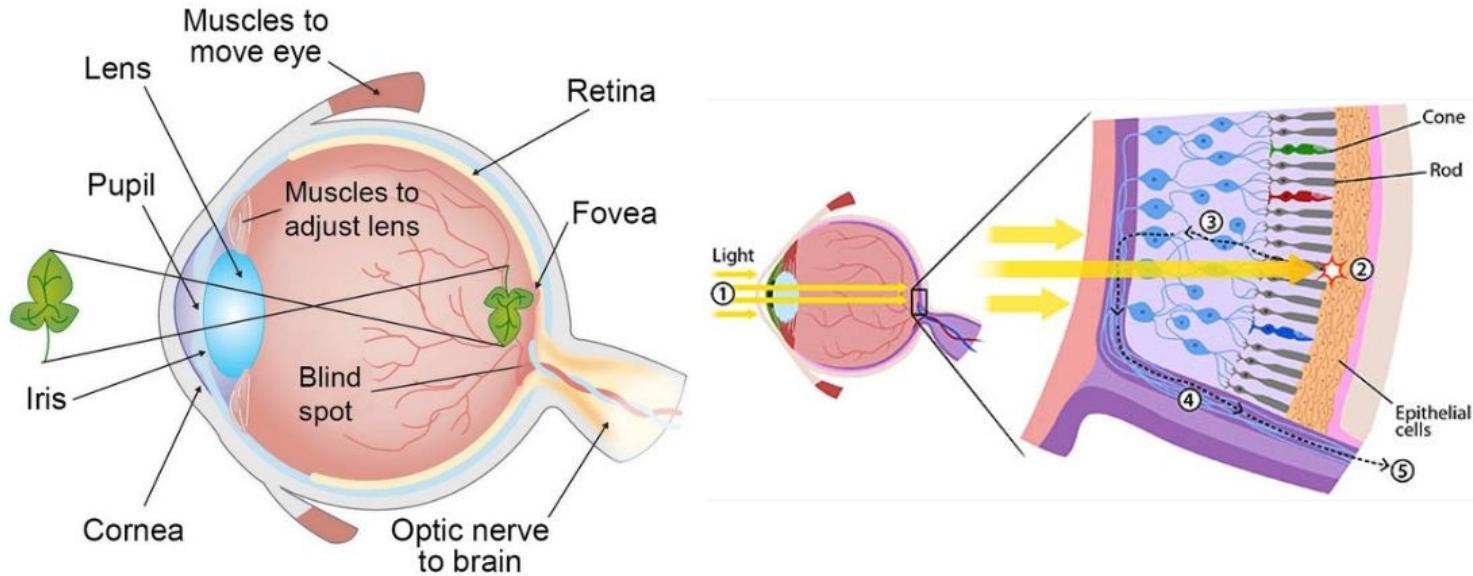
Background Prerequisites

Welcome to the world of computer vision!

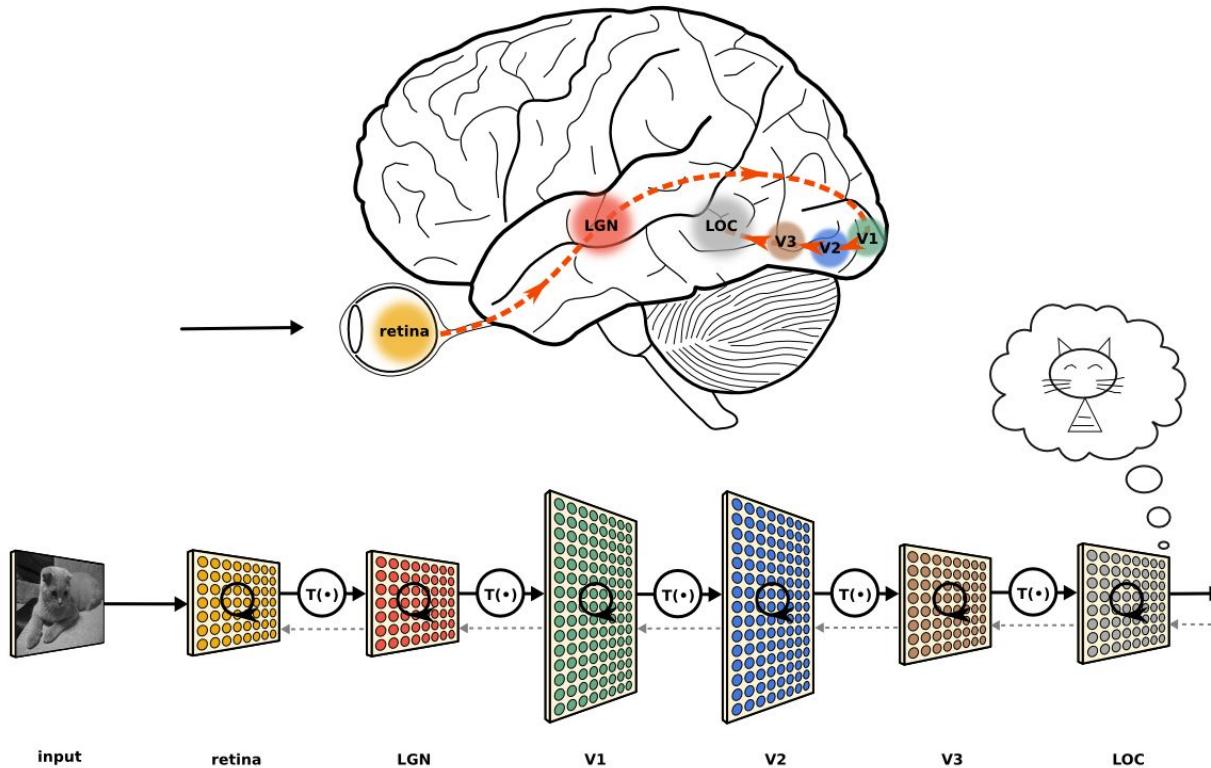
How do we let computers see something?

How do we see something

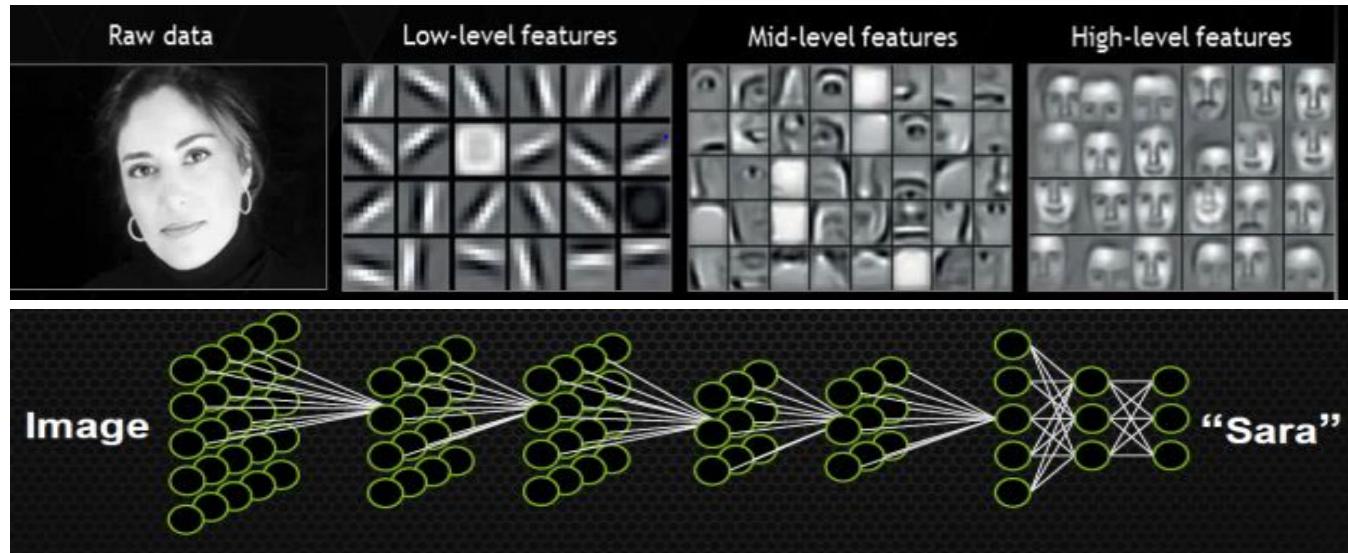
Human eyes



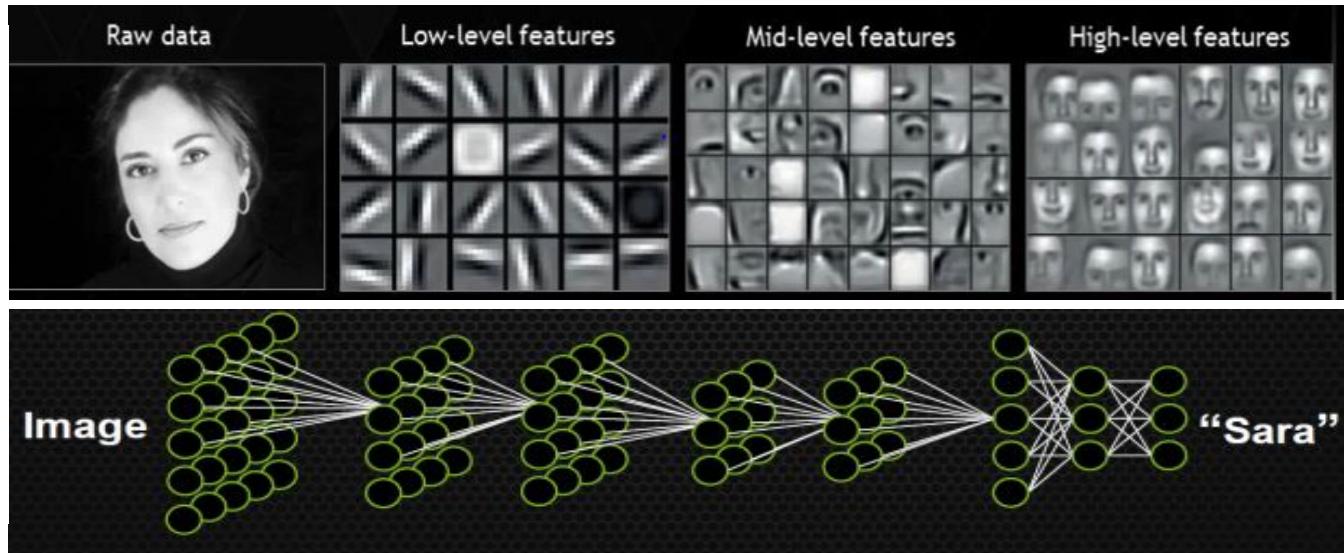
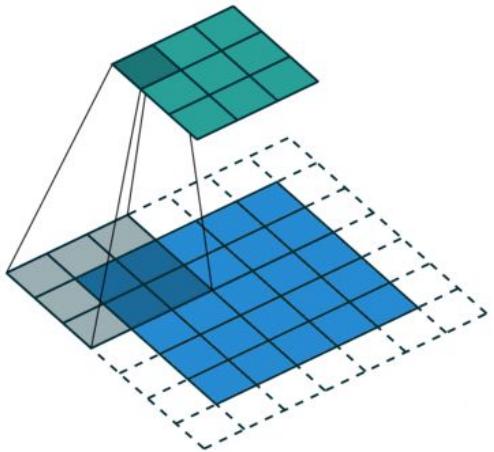
Human eyes



Convolutional Neural Network



Convolutional Neural Network



Representation of images in computers?

An **image**

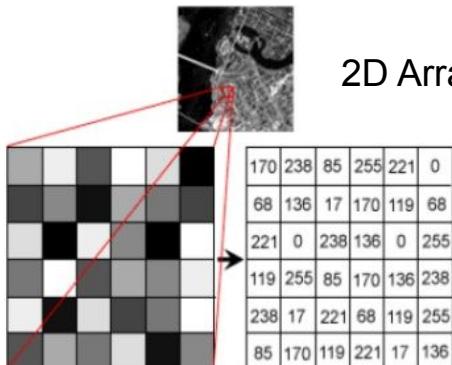
1. Is a matrix/array of intensity values
2. Usually consists of integers [0, 255] or float points [0,1]
3. Each element in the matrix is a **pixel**
4. Can have 1 greyscale channel or multiple colour
channels: RGB

Representation of images in computers?

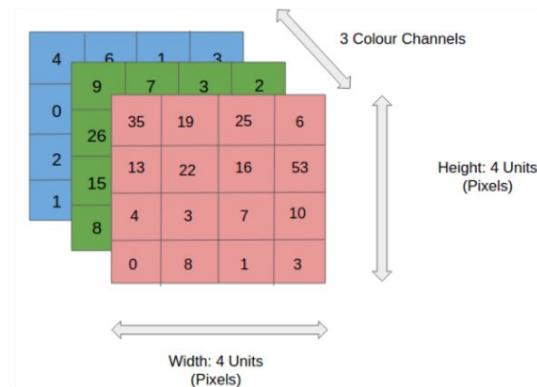
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2. Usually consists of integers [0, 255] or float points [0,1]
3. Each element in the matrix is a **pixel**
4. Can have 1 greyscale channel or multiple colour **channels: RGB**

3D Array. Shape: (width, height, channel)

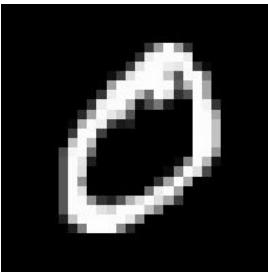


2D Array. Shape = (width, height)

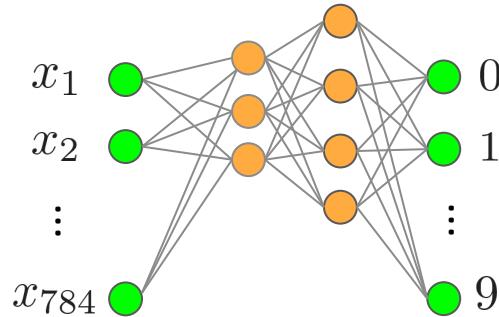


Representation of images in computers?

We will use a neural network to recognize
Hand written digits

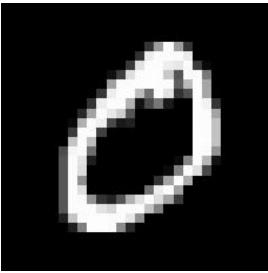


images of size $28 \times 28 = 784$ pixels



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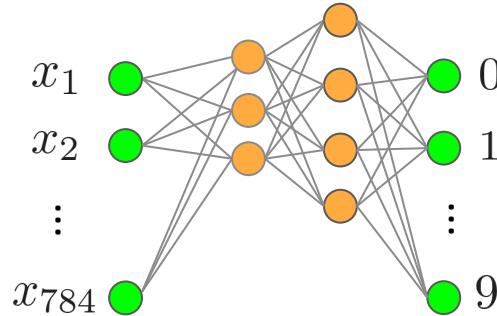


images of size $28 \times 28 = 784$ pixels

Inefficient: Every pixel is connected to
everything

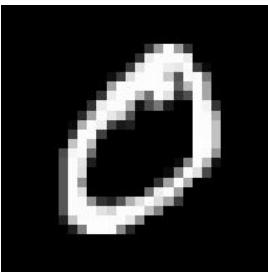
Regions in Images share features

Not shift invariant



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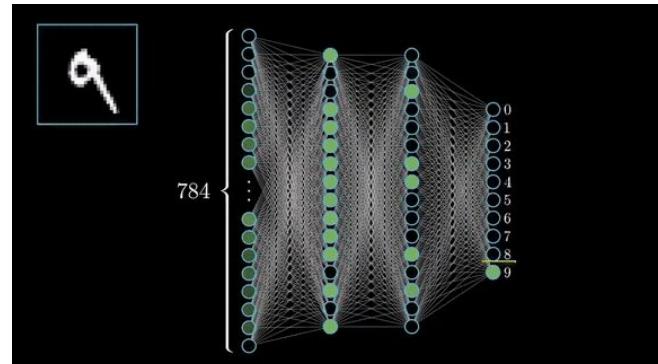
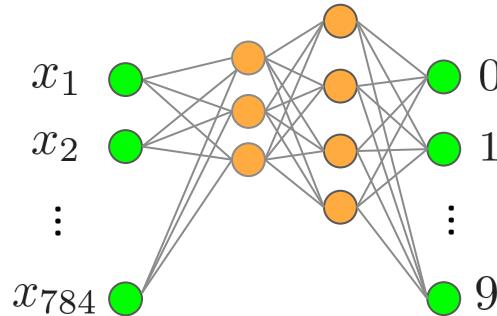


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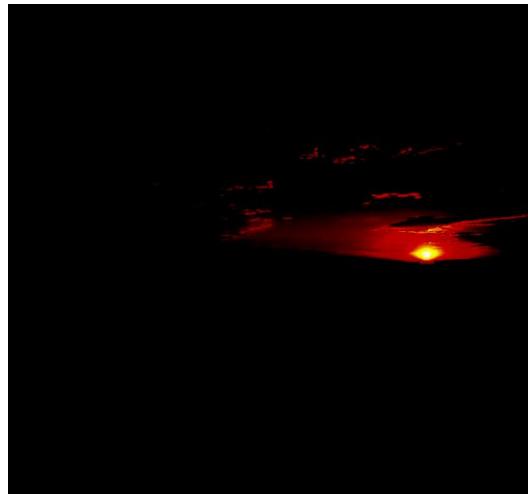


Convolutions

Filters



f



Convolutions

Filters



f



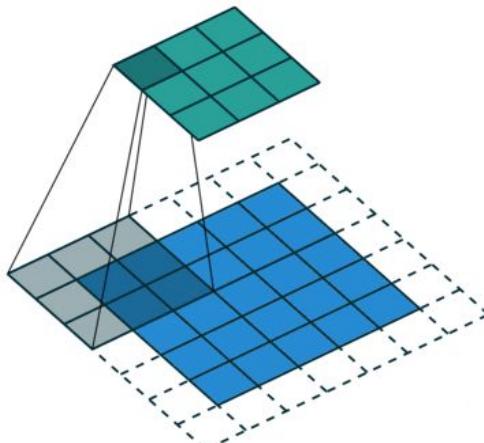
Convolutions

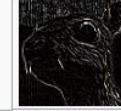
A filter applies a **convolution** operation upon the original signal

Kernel (filter): small matrix that we use to convolve an image

Convolution:

An operation that “blends” one function with another.



Operation	Kernel	Image result
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	

Convolutions

2	2	6	8	2	0	1	2
4	3	4	5	1	9	6	3
3	9	4	4	7	7	6	9
1	3	4	6	8	2	2	1
8	4	6	2	3	1	8	8
5	8	9	0	1	0	2	3
9	2	6	6	3	6	2	1
9	8	8	2	6	3	4	5

Source layer (image)

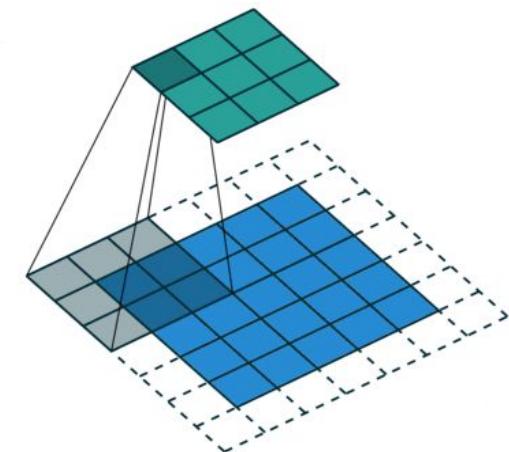
$$(-1 \times 2) + (0 \times 2) + (1 \times 6) + (-2 \times 4) + (0 \times 3) + (2 \times 4) + (-1 \times 3) + (0 \times 9) + (1 \times 4) = 5$$

Convolutional
Kernel (filter)

-1	0	1
-2	0	2
-1	0	1

Destination layer

5



Convolutions

1 x1	1 x0	1 x1	0	0
0 x0	1 x1	1 x0	1	0
0 x1	0 x0	1 x1	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

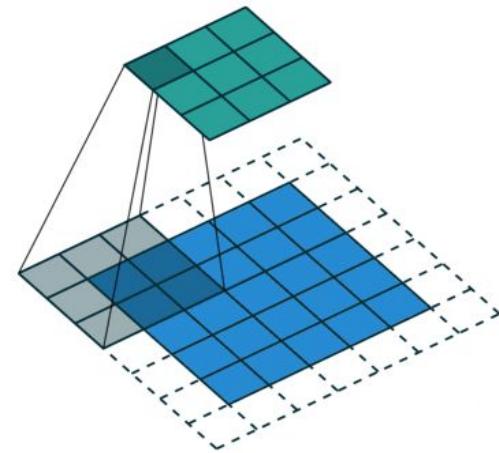
Convolved Feature

- The kernel is **shifted** over the image with a step size, and computes the output for each position.
- The step size is called **stride**.
- Output has **smaller** dimension than input: $\text{dim}(\text{output}) = \text{dim}(\text{input}) - (\text{dim}(\text{kernel}) - 1)$
- Padding** is used to solve this problem, which artificially make the image “bigger” by adding synthesis data (typically 0-padding)

0	0	0	0	0	0	0
0	2	2	6	8	2	0
0	4	3	4	5	1	0
0	3	9	4	4	7	0
0	1	3	4	6	8	0
0	8	4	6	2	3	0
0	0	0	0	0	0	0

Original array

Padded array



Convolutions

Source layer (image)

2	2	6	8	2	0	1	2
4	3	4	5	1	9	6	3
3	9	4	4	7	7	6	9
1	3	4	6	8	2	2	1
8	4	6	2	3	1	8	8
5	8	9	0	1	0	2	3
9	2	6	6	3	6	2	1
9	8	8	2	6	3	4	5



W ₁	W ₂	W ₃
W ₄	W ₅	W ₆
W ₇	W ₈	W ₉

Kernel (filter)

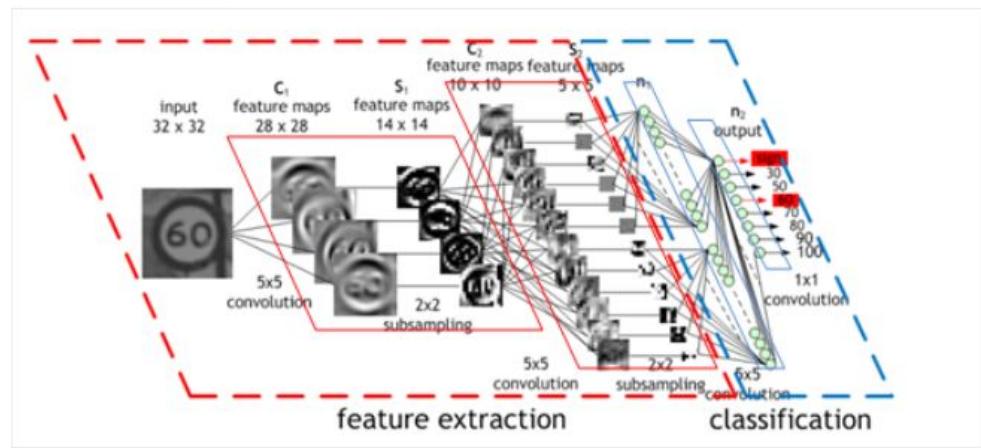
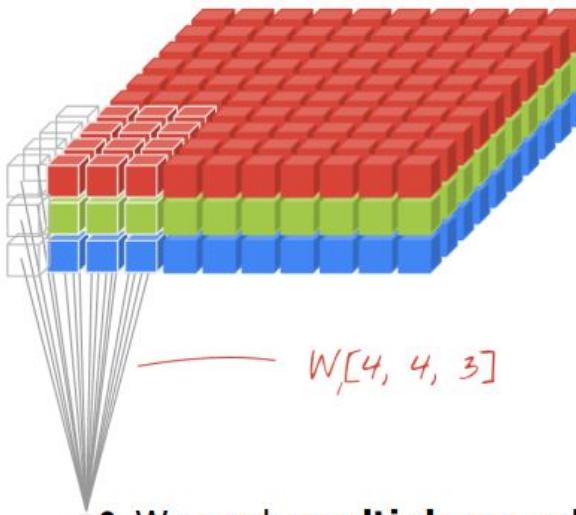
Feature map (activation map)

5								

How do we know which kernels to use?

- Kernels are learnt!
- Initialized **randomly**
- Backward propagation; the CNN learns which features to detect

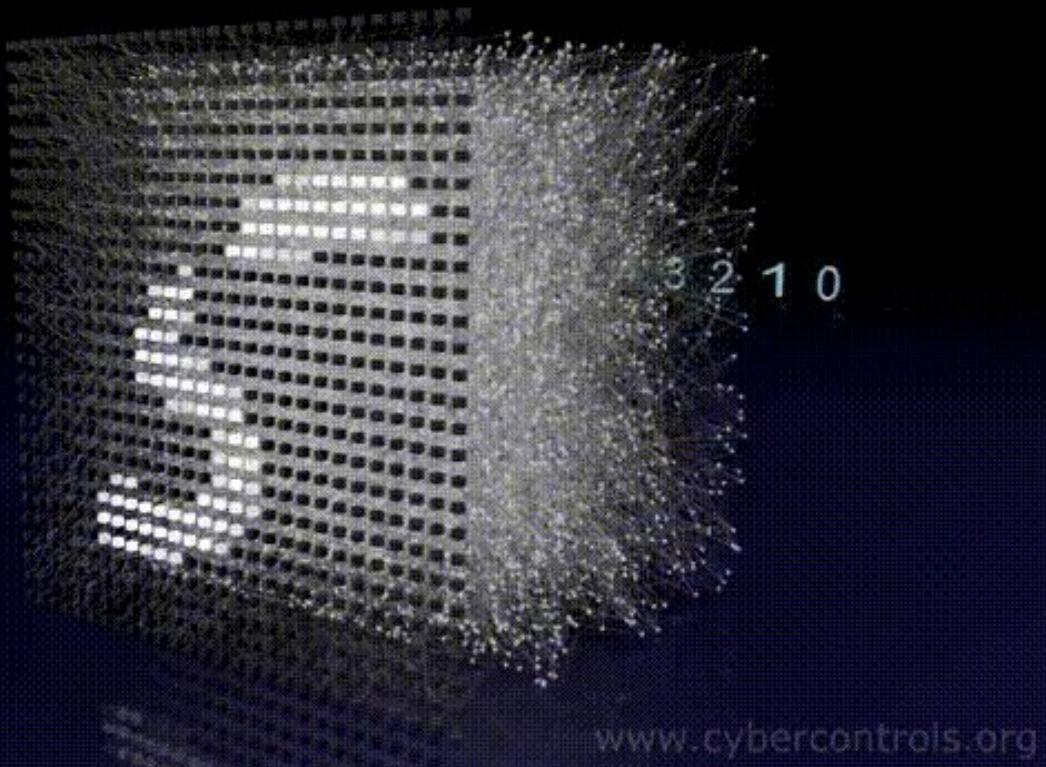
Convolutions



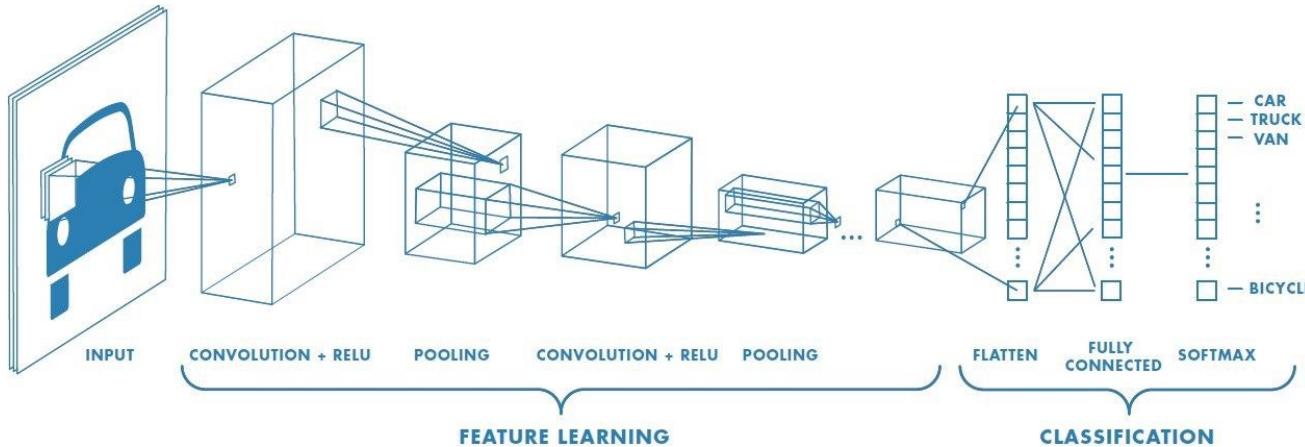
- We apply **multiple** convolutional **filters/kernels** to the **same** image.
- Each filter results in one convolutional **channel**.
- By learning the same image from different channels, one can detect complex patterns.

Convolutions

Type: ML Perceptron
Data Set: MNIST
Hidden Layers: 3
Hidden Neurons: 10000
Synapses: 24864180
Synapses shown: 1284
Learning: BP



CNN Form



Two parts:

1. Feature Learning
2. Classification (fully connected layers)

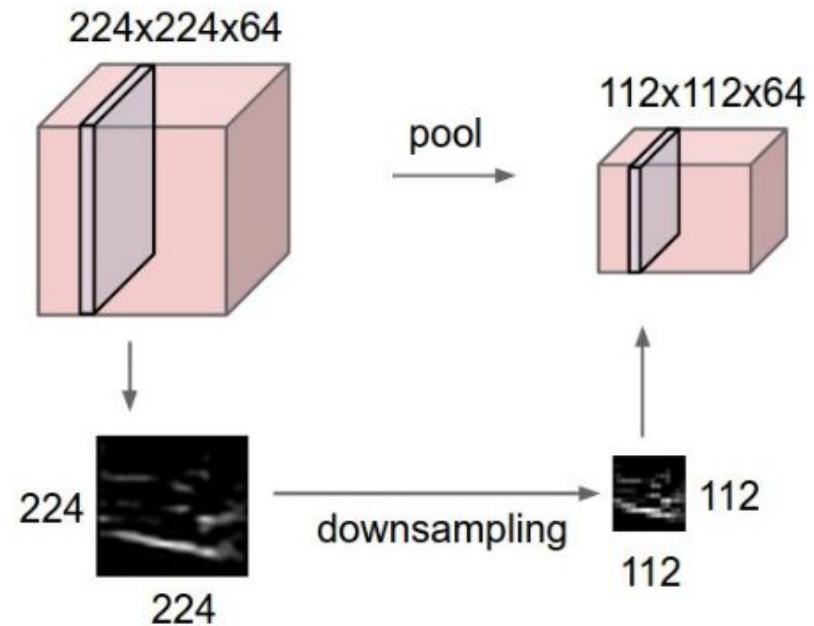
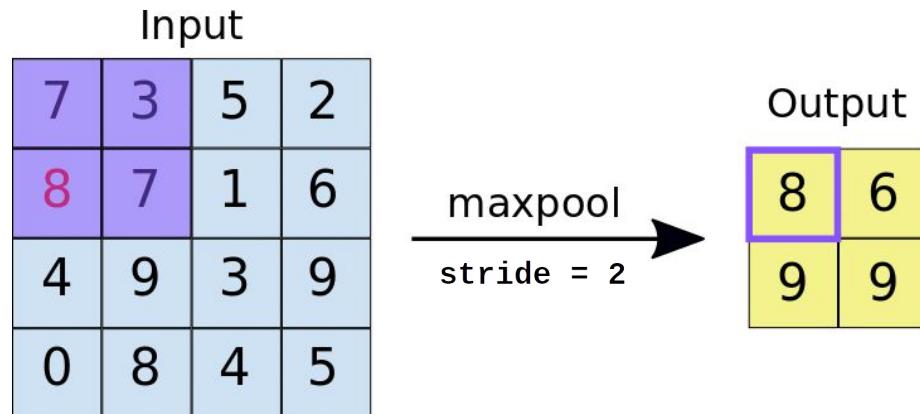
Images become smaller and number of filters increases as we go deeper
Complex Images -> we need more filters
Easy images -> we need fewer filters

Pooling (downsampling)

We need to **discard** information **gradually**.

Pooling is a way of information **abstraction**.

Pooling is usually applied **after** convolutions.



Max pooling: keep the **strongest** signal

Average pooling: use the **local average** as the signal

Transfer Learning



Trained



Continue
Training



CNN reuses its knowledge; its features

Generative Models

How do we generate images?

What I cannot create, I do not understand

Generative Models

Classification: mapping a distribution to a certain output

Generation: mapping a distribution to a certain output



Happy cat



Angry cat



Relaxed cat



"Cats"

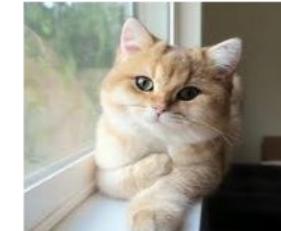
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Angry cat



Relaxed cat

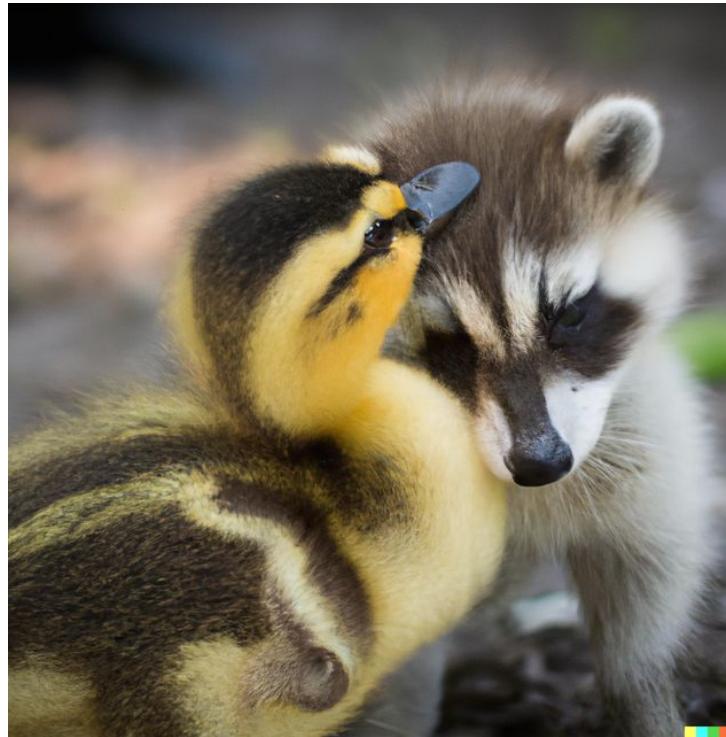
“A yellow futuristic organic robot by Boston Dynamics”



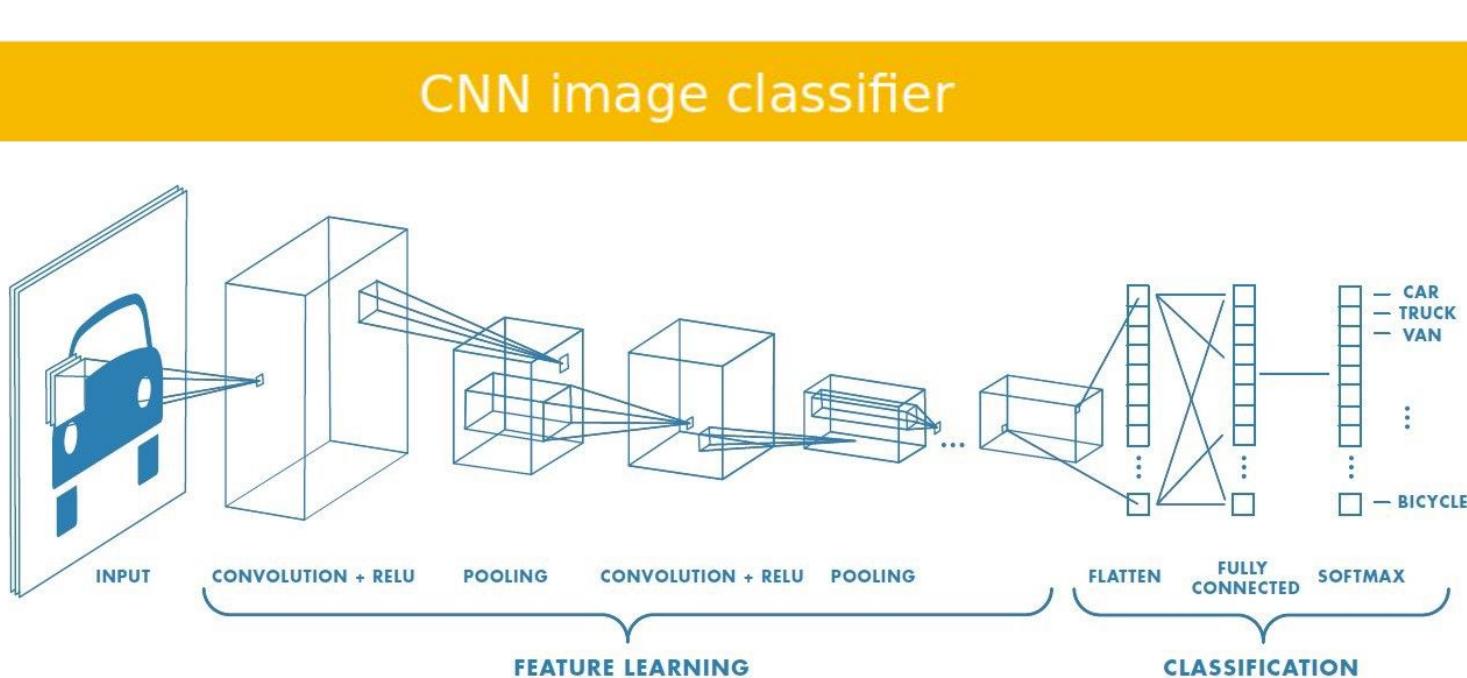
“A giant jellyfish floating above the eiffel tower”



“A cute baby raccoon hugging a cute baby duckling”



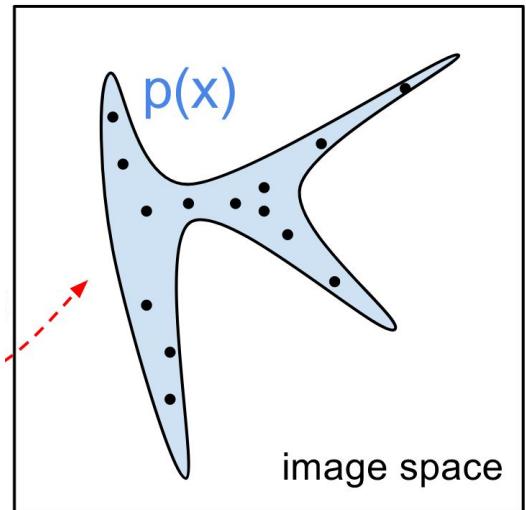
Generative Models



Generative models?

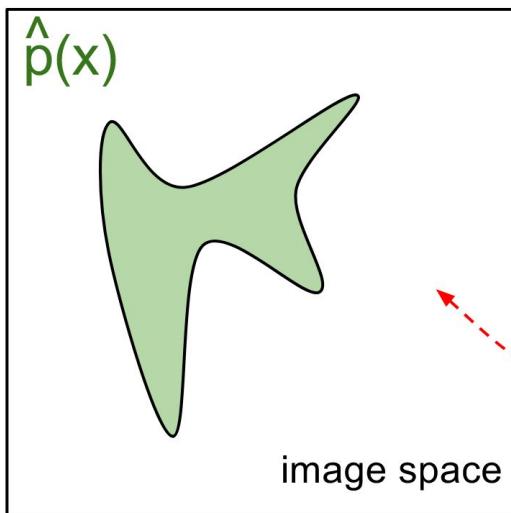
Generative Models

true data distribution

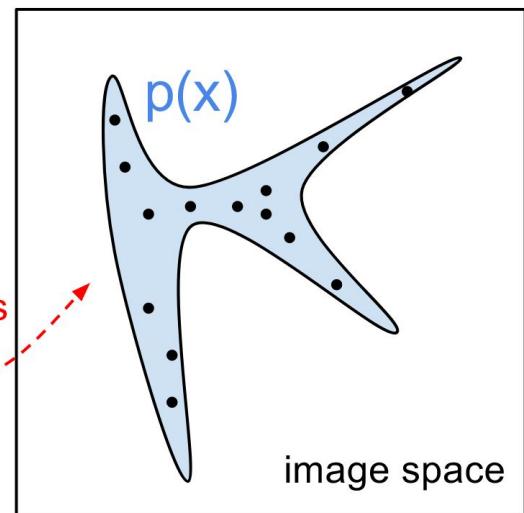


Generative Models

generated distribution



true data distribution



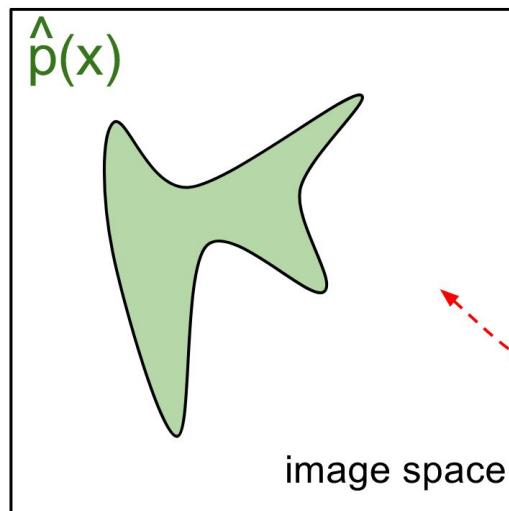
loss

Generative Models

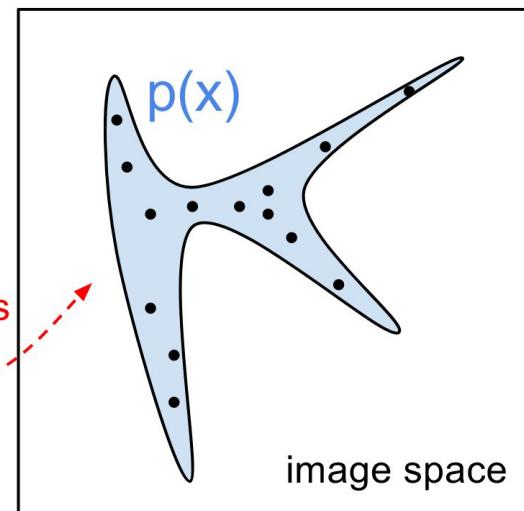
A generative model

1. Learns the data distribution instead
2. Allows uncertainties to be captures
3. Allows for (condition) density estimation

generated distribution



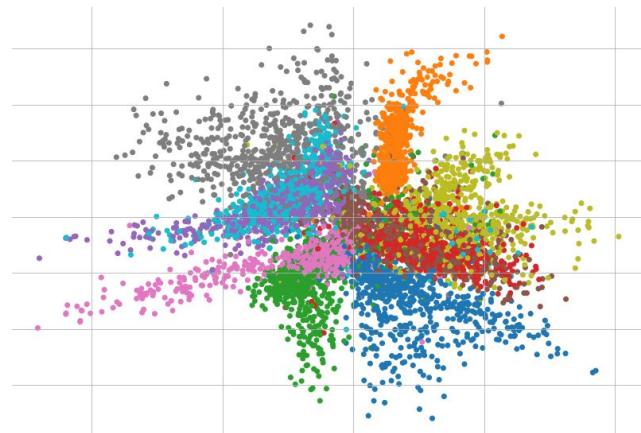
true data distribution



AutoEncoder

How data is represented is imperative for neural networks

The data representation could have been **engineered** by a human

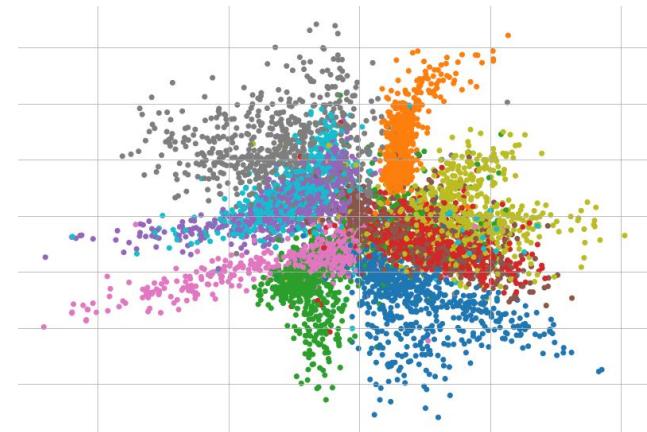


AutoEncoder

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As an alternative: Feed raw data to the neural network and **learn** the representation automatically



AutoEncoder

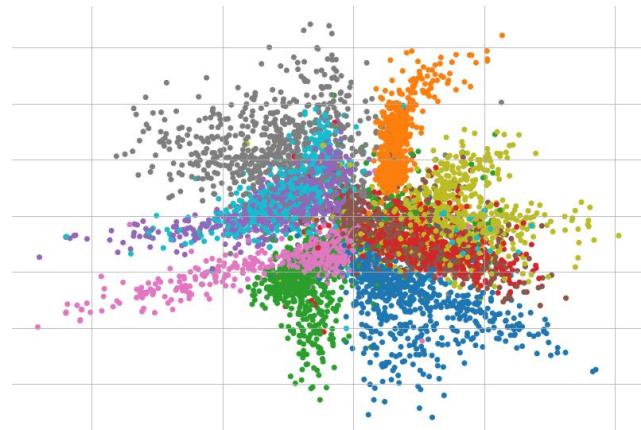
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Manifold Hypothesis: High-dimensional data “lives” in a lower dimensional manifold

High-dimensional data can be sufficiently represented using lower dimensional latents



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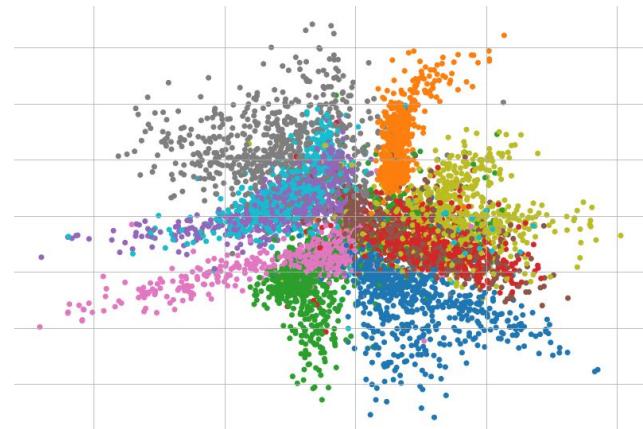
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High-dimensional data can be sufficiently represented using lower dimensional latents

lower dimensional manifold = lower dimensional Latent Space



AutoEncoder

Encoder learns a mapping

$$e : X \rightarrow Z$$

Decoder learns a mapping

$$d : Z \rightarrow X$$

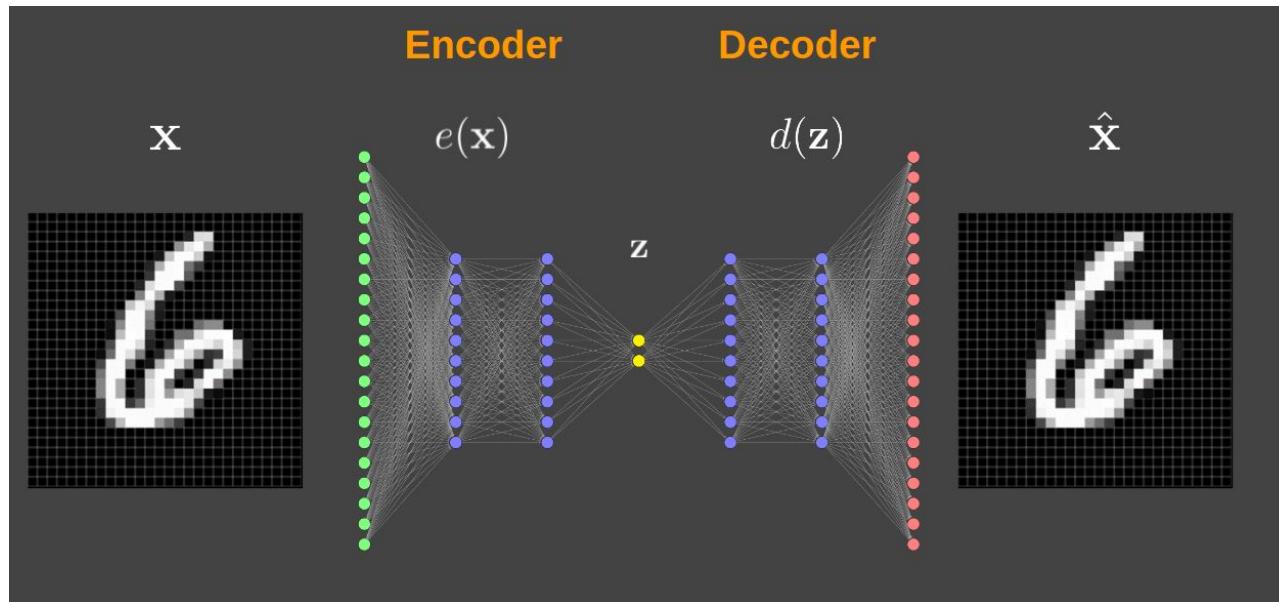
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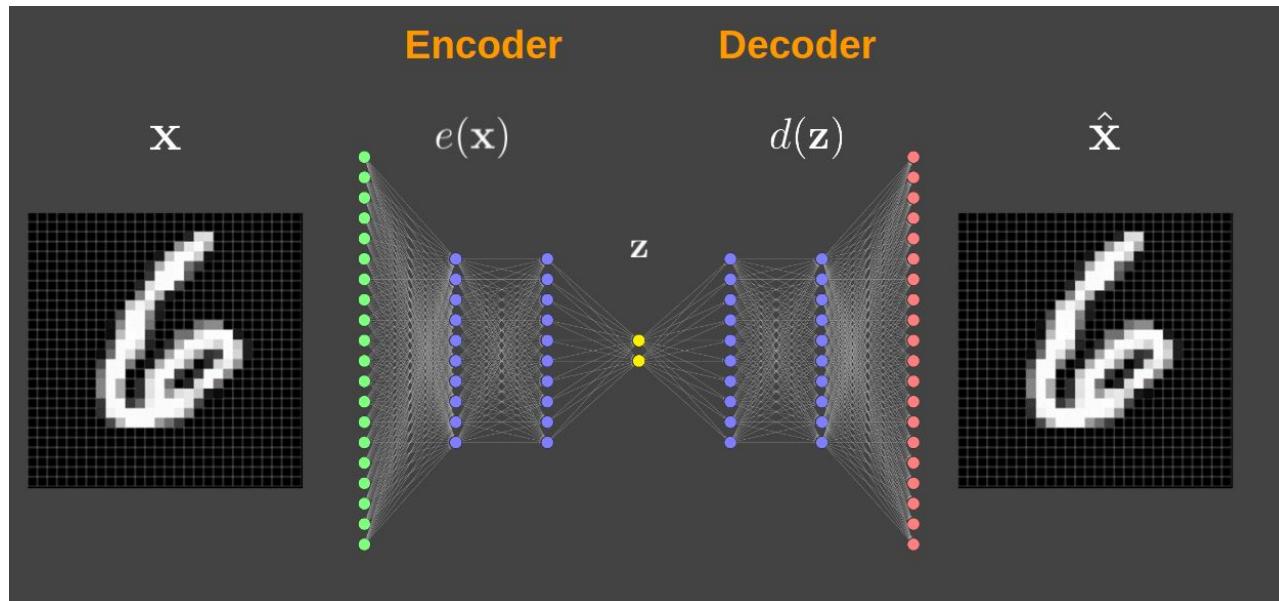
$$e : X \rightarrow Z$$

Nested functions

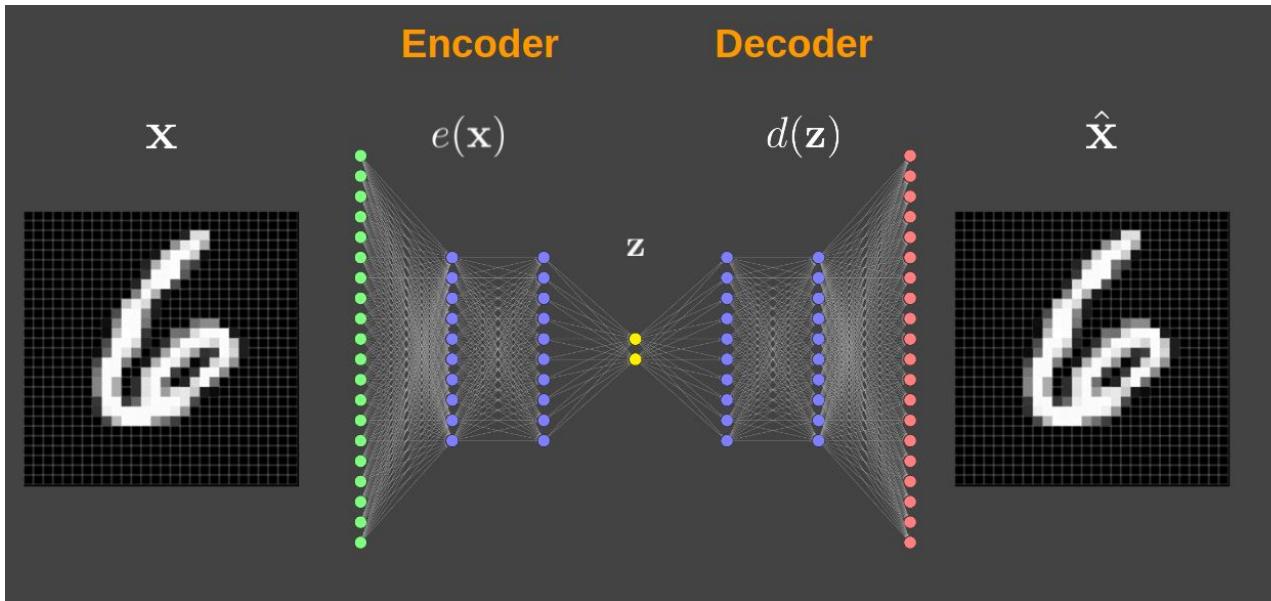
Decoder learns a mapping

$$d : Z \rightarrow X$$

$$f(\mathbf{x}) = d(e(\mathbf{x}))$$



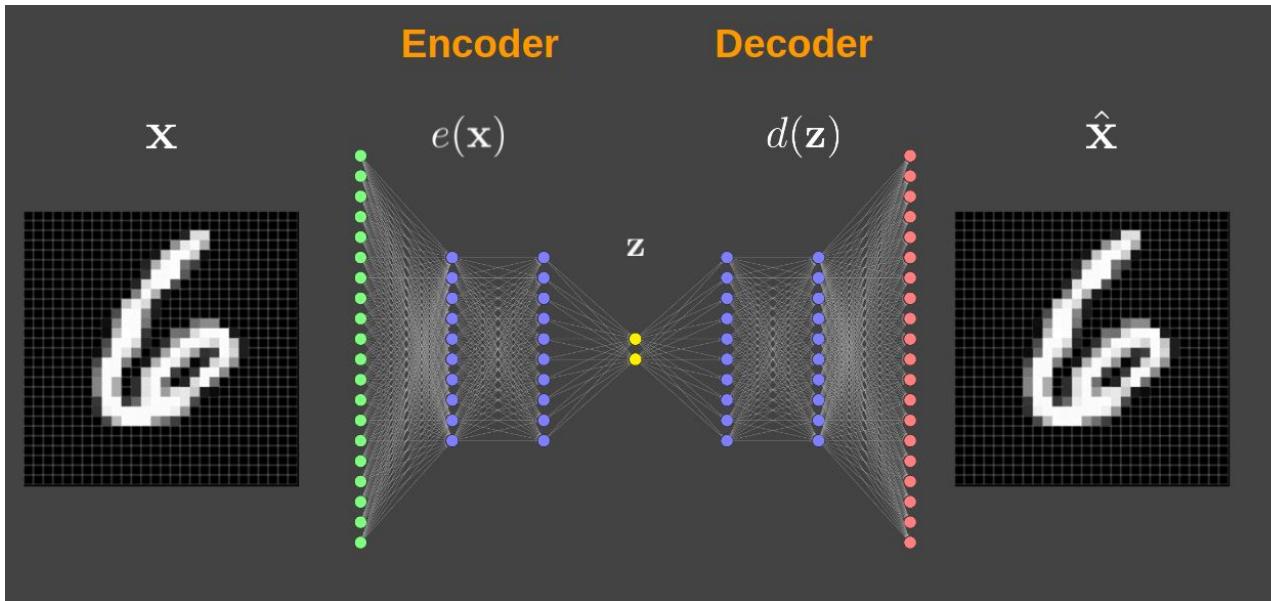
AutoEncoder



Classification

$$L(y, \hat{y}) = L(W, b) = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

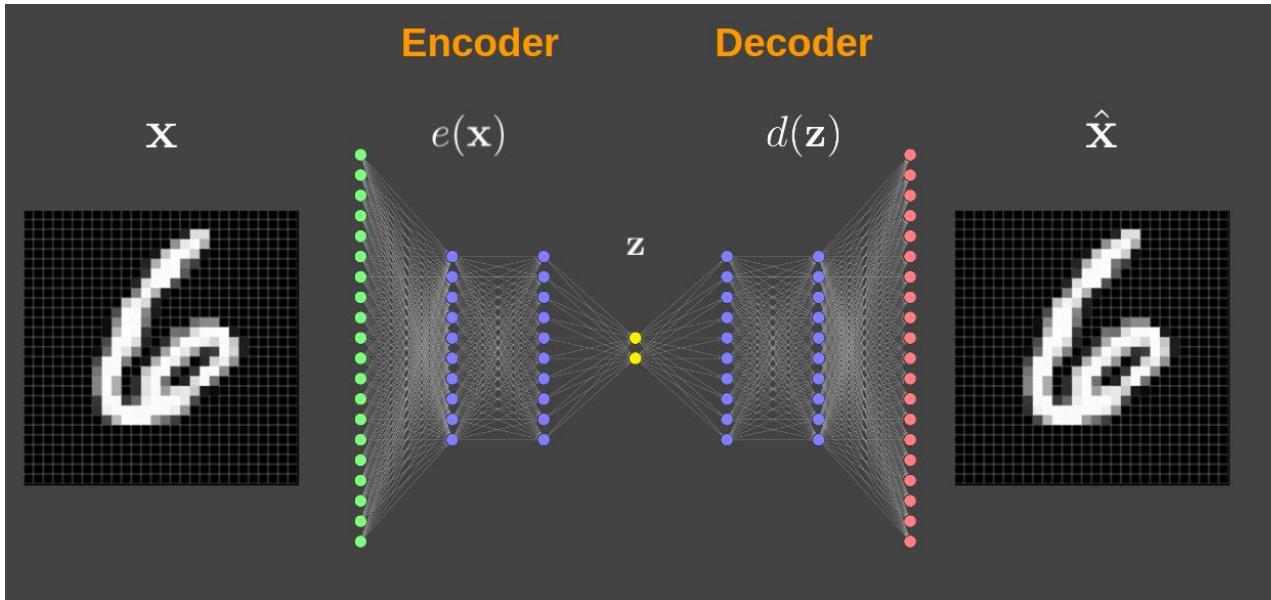
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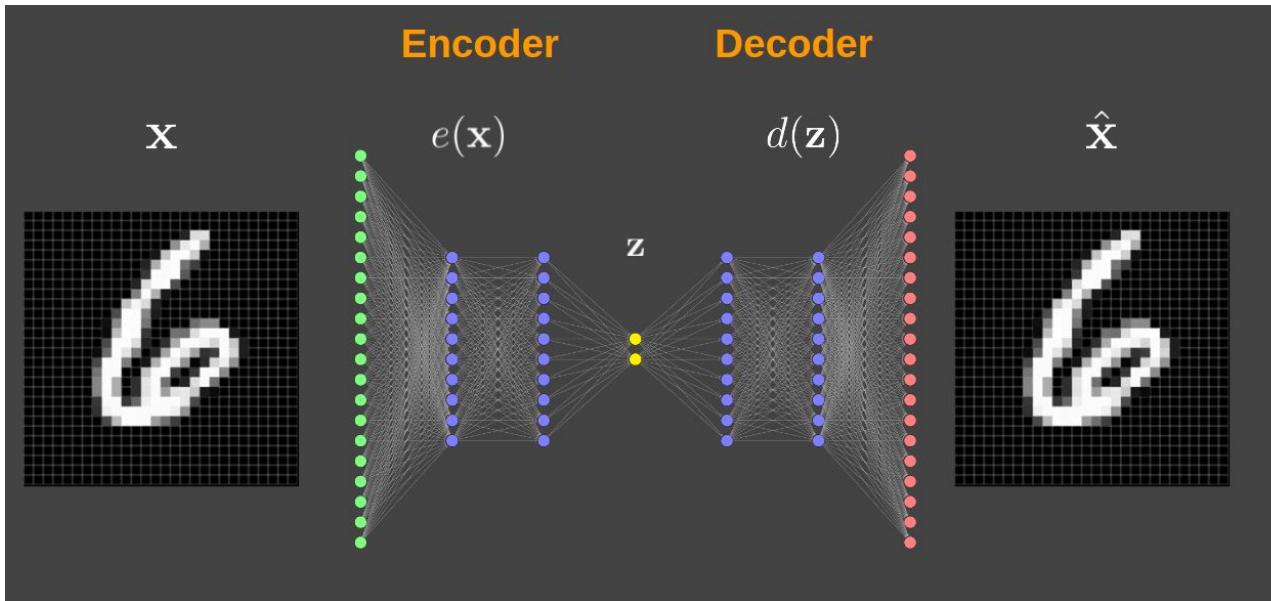
AutoEncoder



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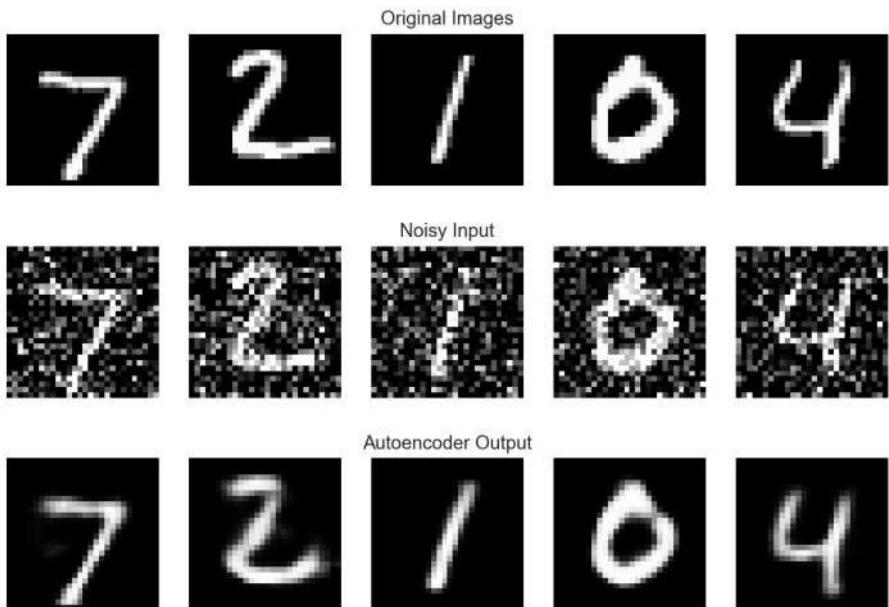
AutoEncoder



Reconstruction Loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = L(W, b) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

AutoEncoder



AutoEncoder

IMAGE COLORING



Before

After

IMAGE NOISE REDUCTION



Before

After

Original Images



Noisy Input

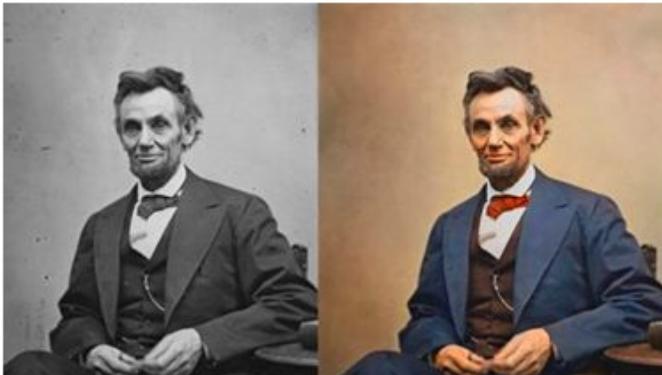


Autoencoder Output



AutoEncoder

IMAGE COLORING



Before

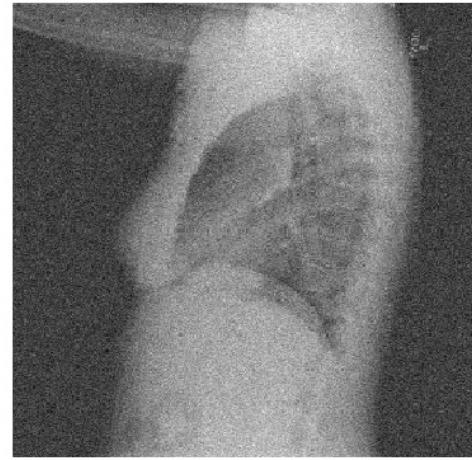
After

IMAGE NOISE REDUCTION

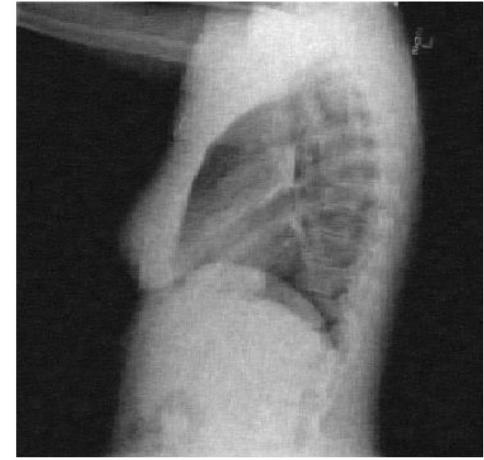


Before

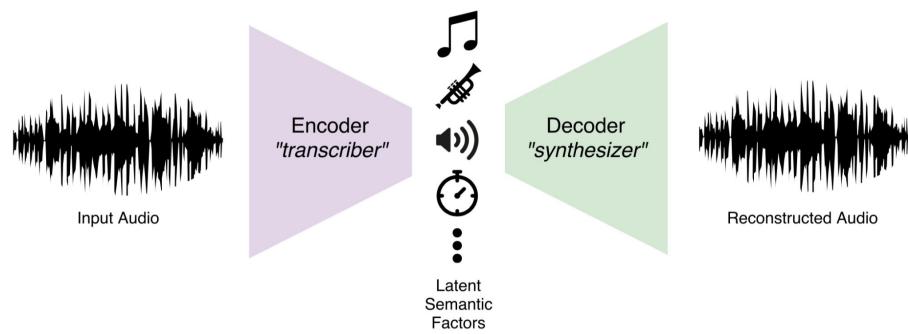
After



Noisy



Unsupervised Cleaning



AutoEncoder

Issues

Limited use aside from denoising and simple transformations

We cannot generate new data from the learned representations

Suppose we learn a two dimensional representation for MNIST

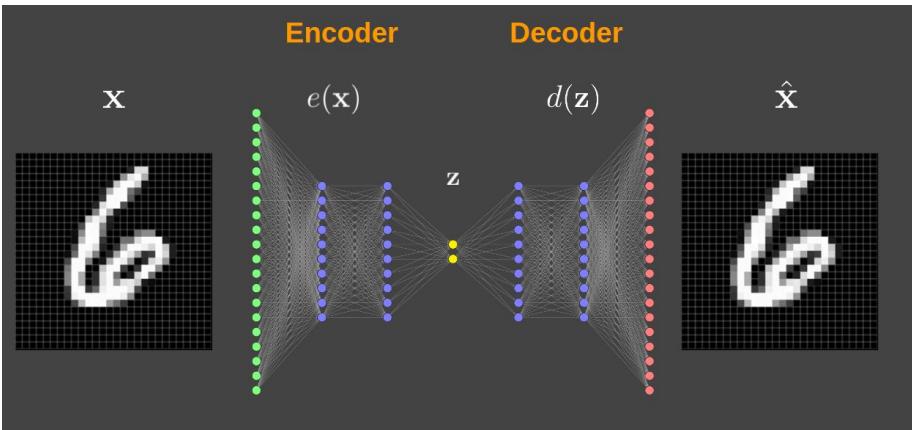
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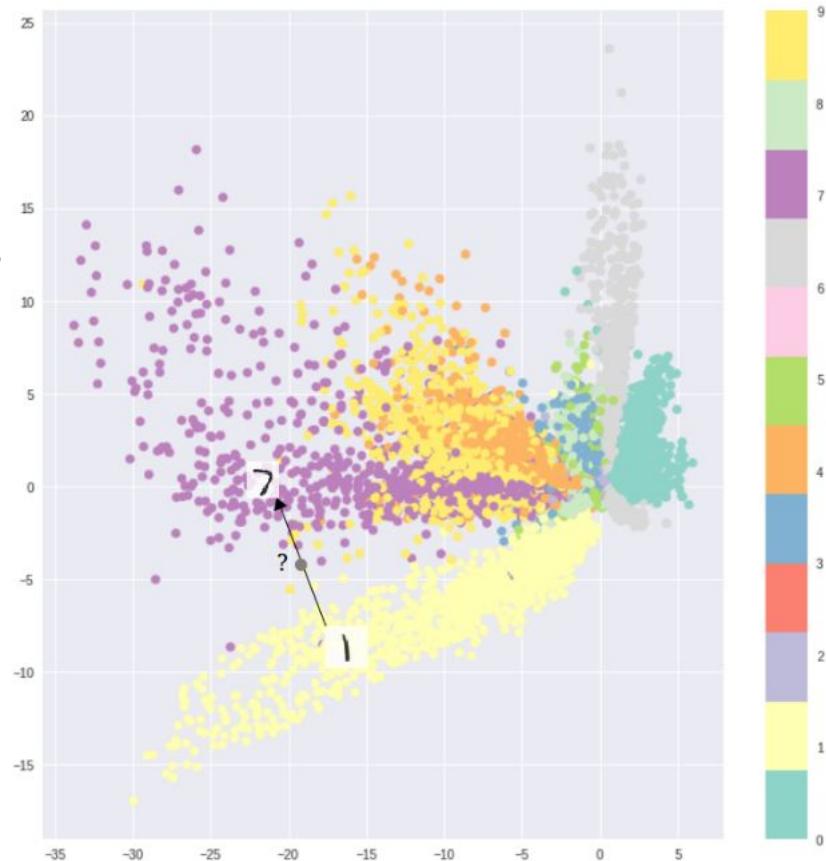
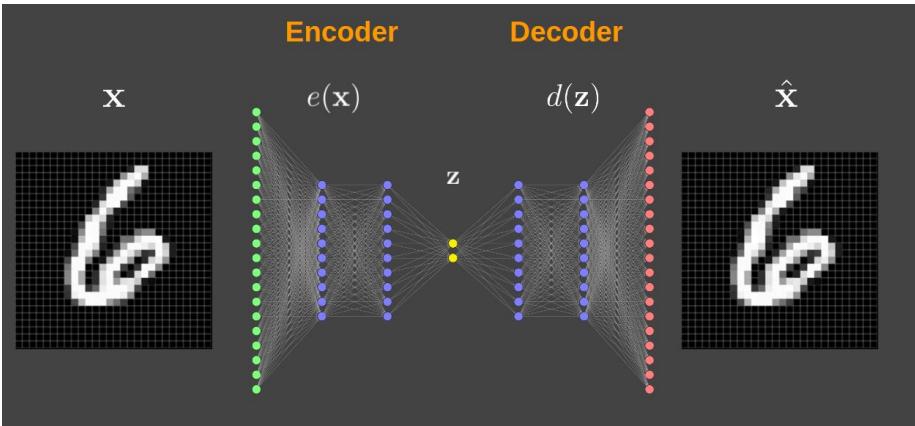
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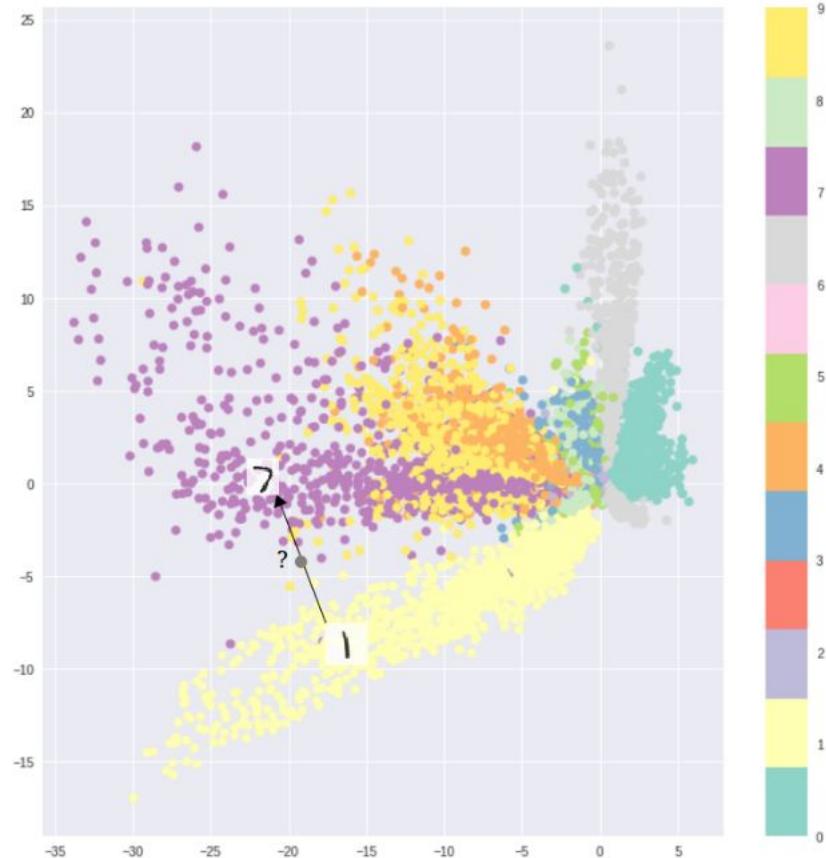
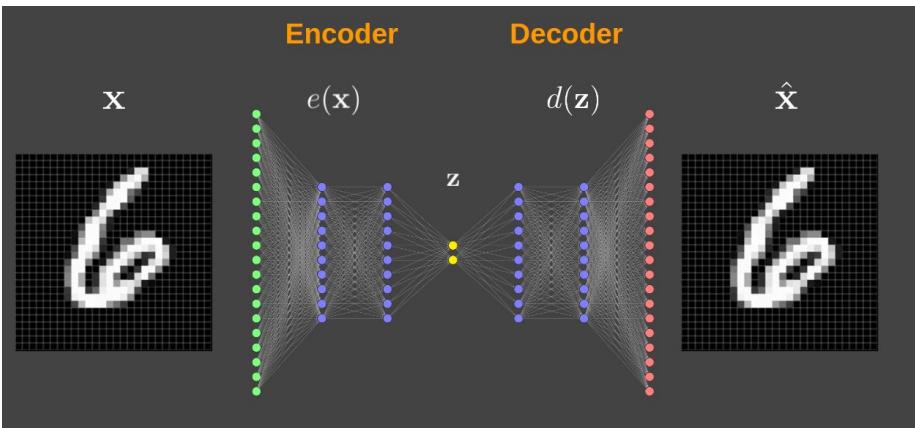
AutoEncoder

Issues

Latent space has 'gaps'

We would like to generate variations of the data from a gapless/continuous latent space

Keep disentanglement of the features that represent the data



Variational AutoEncoder

Same structure as a normal AutoEncoder

We want stochasticity in our model

Map inputs to a probability distribution over our latent space

Learn the statistics of our latent space

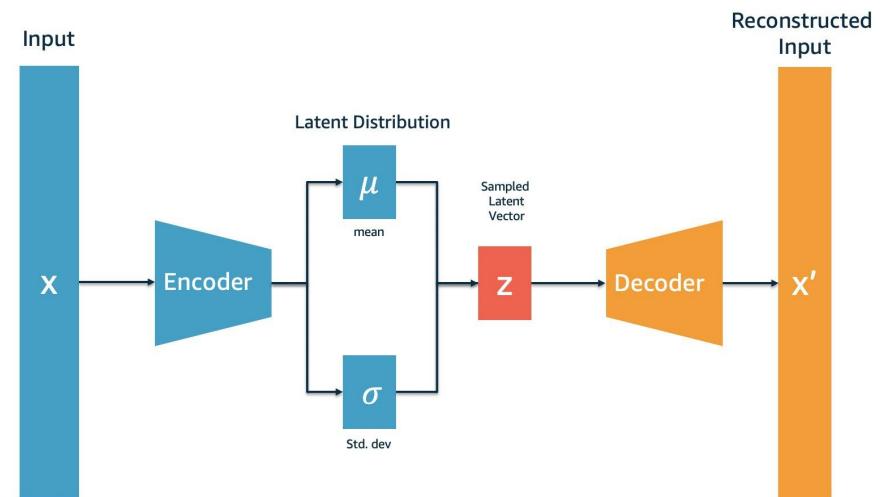
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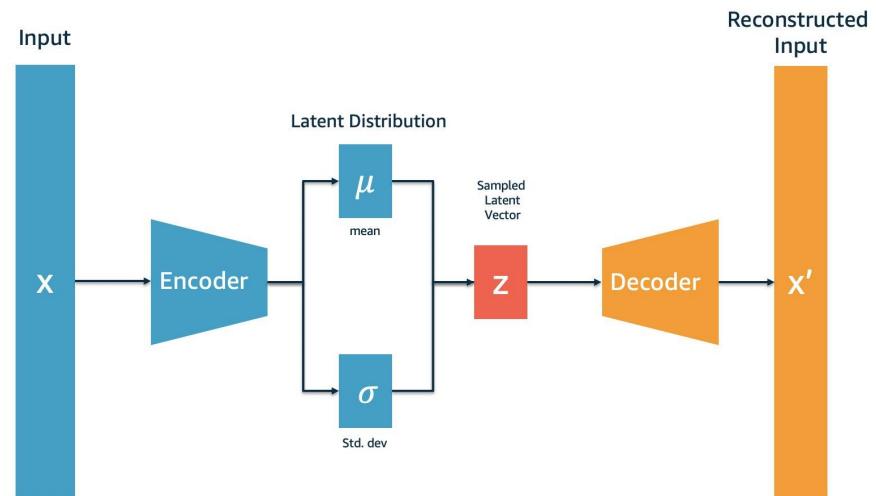
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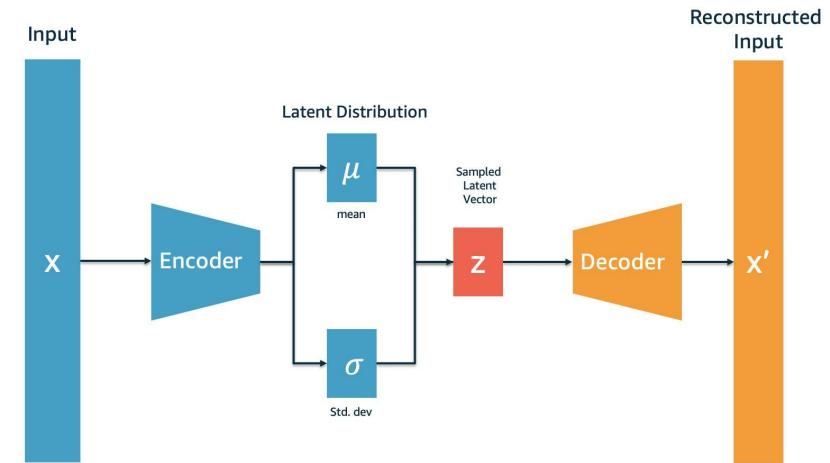
$$\mathbf{z} \sim \mathcal{N}(\mu, \sigma)$$



Variational AutoEncoder

$$\mathbf{z} \sim \mathcal{N}(\mu, \sigma)$$

Model is stochastic now! We want determinism back!



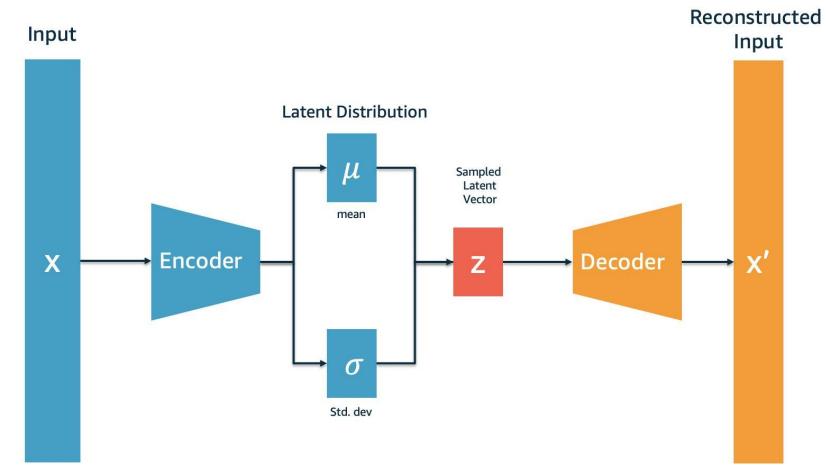
Variational AutoEncoder

$$z \sim \mathcal{N}(\mu, \sigma)$$

Model is stochastic now! We want determinism back!

Cannot compute gradients through a stochastic layer

Derivative should be non-zero



Variational AutoEncoder

$$\mathbf{z} \sim \mathcal{N}(\mu, \sigma)$$

Model is stochastic now! We want determinism back!

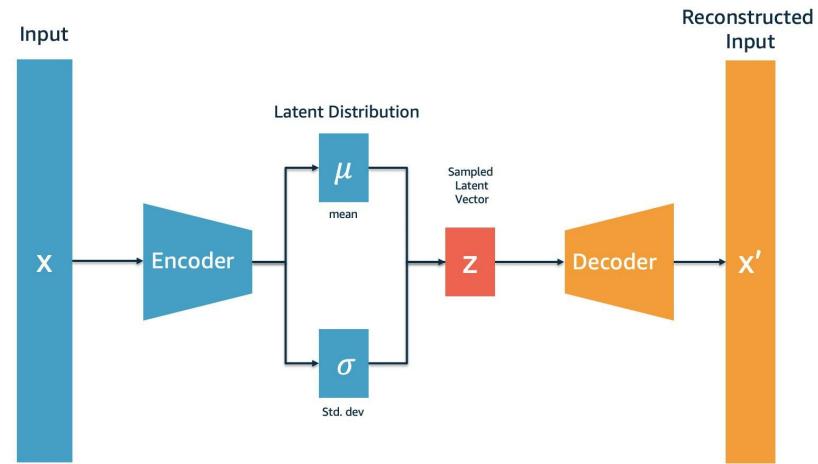
Cannot compute gradients through a stochastic layer

Derivative should be non-zero

Reparameterization ‘hack’

$$\mathbf{z} = \mu + \sigma \cdot \epsilon$$

Backpropagation possible



Variational AutoEncoder

$$\mathbf{z} \sim \mathcal{N}(\mu, \sigma)$$

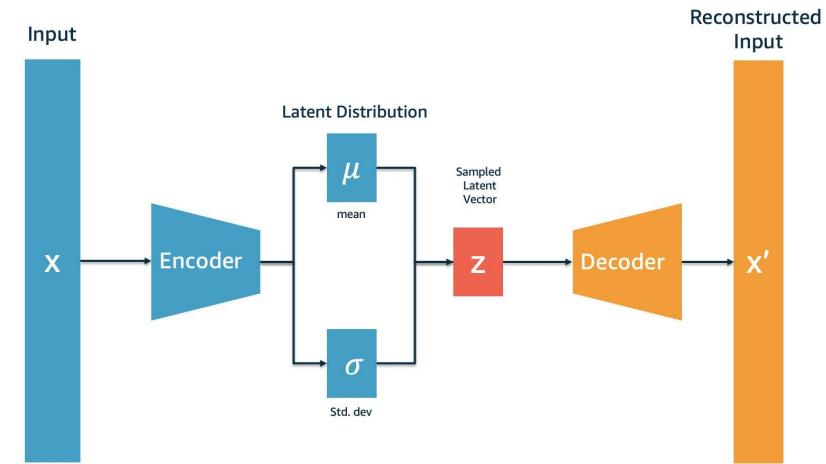
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$$\mathbf{z} = \mu + \sigma \cdot \epsilon \quad \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{1})$$



Backpropagation possible

Variational AutoEncoder

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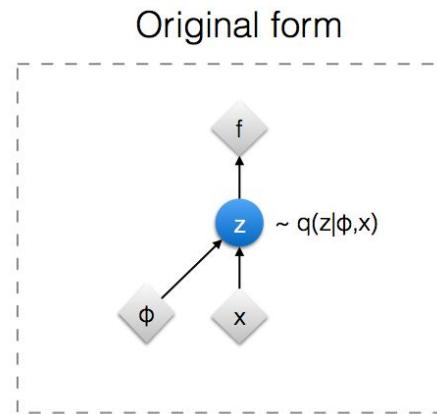
Cannot compute gradients through a stochastic layer

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Backpropagation possible



- ◊ : Deterministic node
- : Random node

Variational AutoEncoder

$$\mathbf{z} \sim \mathcal{N}(\mu, \sigma)$$

Model is stochastic now! We want determinism back!

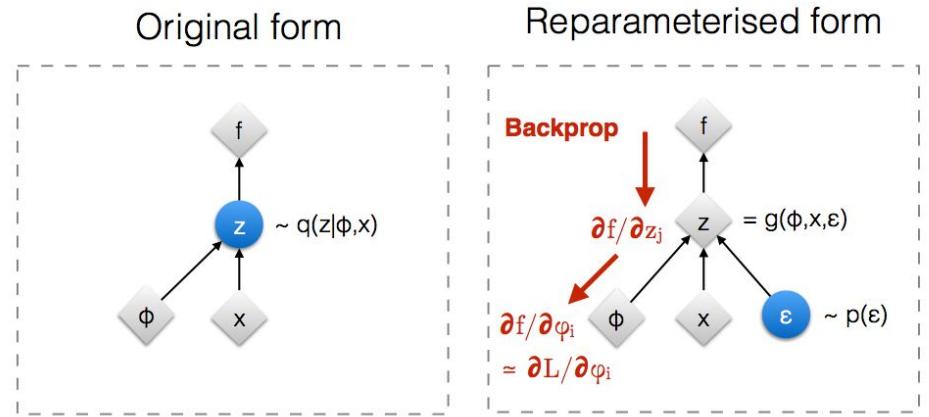
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Derivative should be non-zero

Reparameterization ‘hack’

$$\mathbf{z} = \mu + \sigma \cdot \epsilon \quad \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{1})$$

Backpropagation possible



Legend:
Grey diamond: Deterministic node
Blue circle: Random node

[Kingma, 2013]
[Bengio, 2013]
[Kingma and Welling 2014]
[Rezende et al 2014]

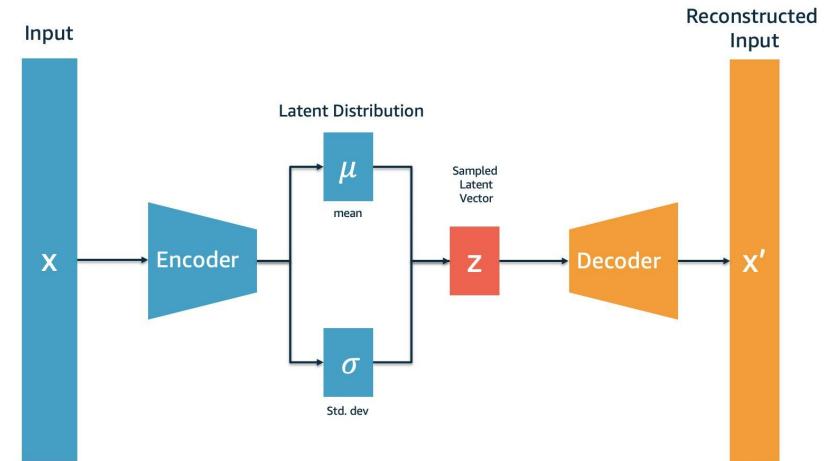
Variational AutoEncoder

$$\mathbf{z} = \mu + \sigma \cdot \epsilon$$

$$\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{1})$$

Reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = L(W, b) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

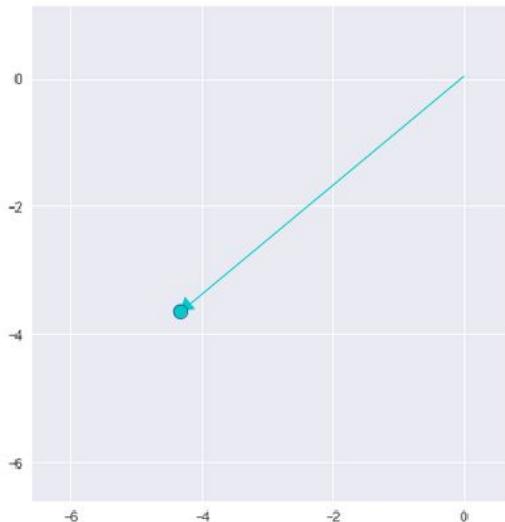


Not done yet; need to force the network to adhere to a unit normal distribution

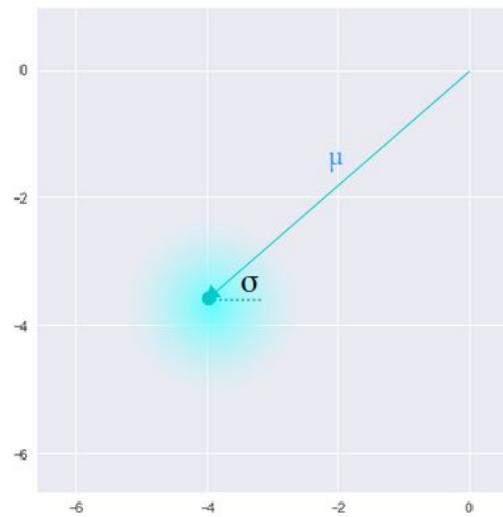
Network will just learn very small standard deviations and learn the mean, similar to a regular autoencoder

Variational AutoEncoder

Network will just learn very small standard deviations and learn the mean, similar to a regular autoencoder



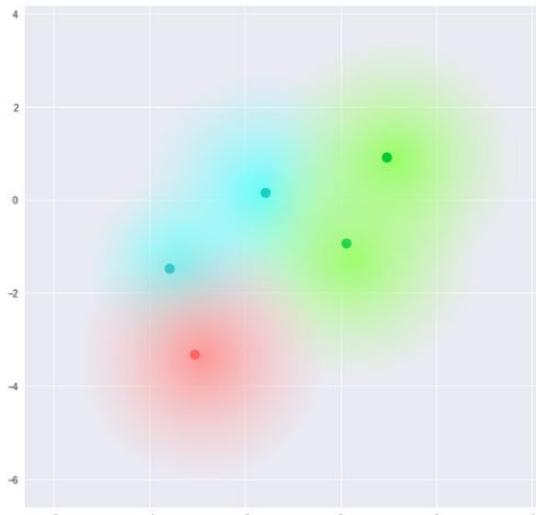
Standard Autoencoder
(direct encoding coordinates)



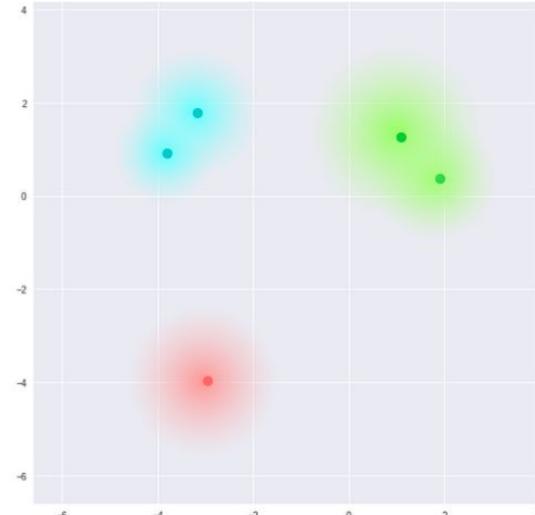
Variational Autoencoder
(μ and σ initialize a probability distribution)

Variational AutoEncoder

Network will just learn very small standard deviations and learn the mean, similar to a regular autoencoder



What we require



What we may inadvertently end up with

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

Use the Kullback-Leibler divergence from information theory

$$D_{KL}(q||p) = \sum_x q(x) \log \frac{q(x)}{p(x)}$$

Measures the information content between distributions q and p

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

Use the Kullback-Leibler divergence from information theory

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Measures the information content between distributions q and p

We want the (posterior) distribution $q_\theta(z|x)$ that we are learning

Variational AutoEncoder

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$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

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$$D_{KL}(q||p) = \sum_x q(x) \log \frac{q(x)}{p(x)}$$

Measures the information content between distributions q and p

We want the (posterior) distribution $q_\theta(z|x)$ that we are learning to be close to a (prior) standard normal distribution $\mathcal{N}(\mathbf{0}, \mathbf{1})$

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

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Why standard normal though?



Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

Why standard
normal though?

1. Learn a smooth/continuous distribution
2. Expand evenly in the latent space
3. KL divergence with a normal distribution has an easy analytical solution
4. We can estimate any distribution with a normal distribution

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

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$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2 - D_{KL}(q_\theta(z|x) || \mathcal{N}(0, 1))$$

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2 - D_{KL}(q_\theta(z|x) || \mathcal{N}(0, 1))$$

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2 - \frac{1}{2} \sum_{i=1}^N 1 + \sigma_i^2 - \mu_i^2 - \log(\sigma_i)$$

Likelihood

KLD

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2 - \frac{1}{2} \sum_{i=1}^N 1 + \sigma_i^2 - \mu_i^2 - \log(\sigma_i)$$

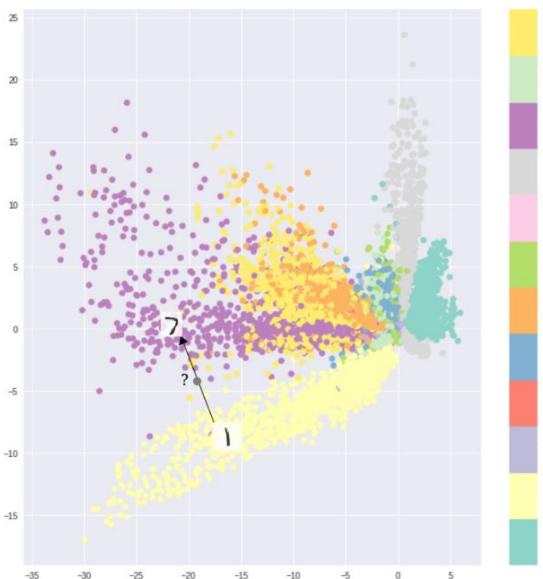
Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x} - \hat{\mathbf{x}})^2 - \frac{1}{2} \sum_{i=1}^N 1 + \sigma_i^2 - \mu_i^2 - \log(\sigma_i)$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{1})$

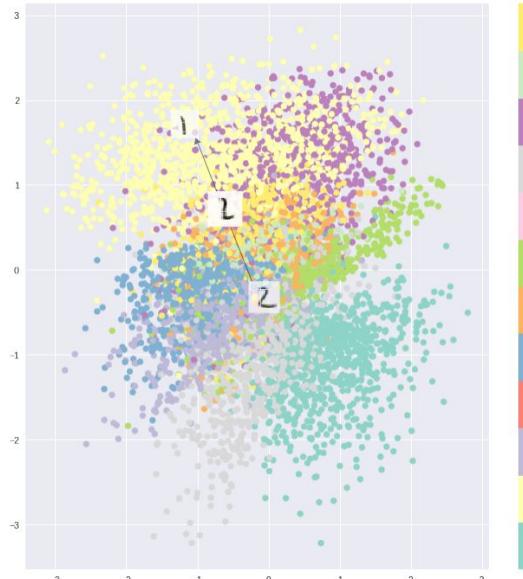
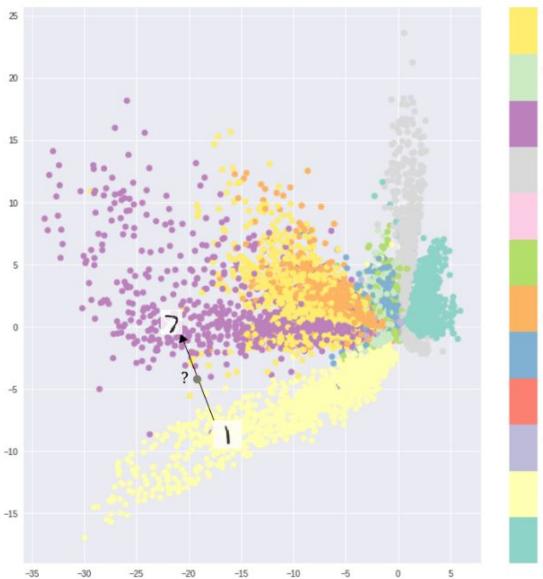


Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \hat{\mathbf{x}}_i)^2 - \frac{1}{2} \sum_{i=1}^N 1 + \sigma_i^2 - \mu_i^2 - \log(\sigma_i)$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{I})$

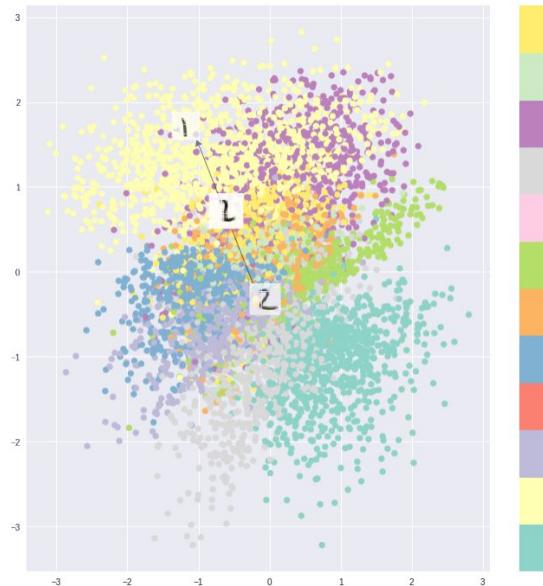
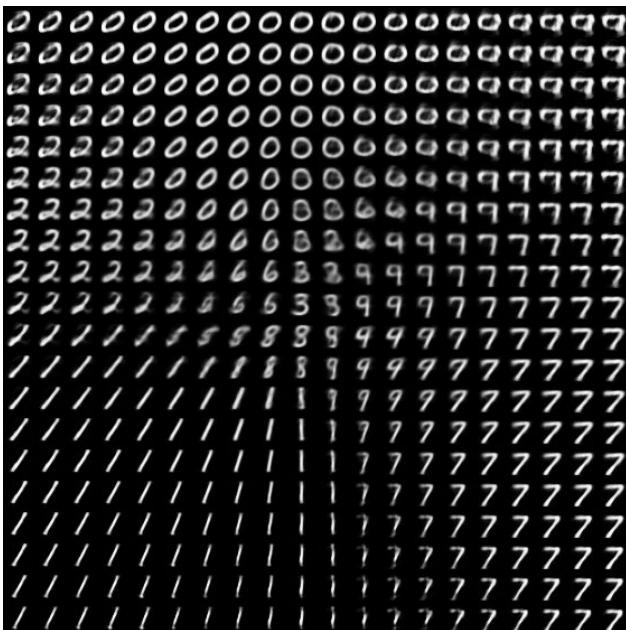


Variational AutoEncoder

We add a regularization term to the reconstruction loss

$$L(\mathbf{x}, \hat{\mathbf{x}}) = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \hat{\mathbf{x}}_i)^2 - \frac{1}{2} \sum_{i=1}^N 1 + \sigma_i^2 - \mu_i^2 - \log(\sigma_i)$$

Not only reconstruct but also stay close to $\mathcal{N}(\mathbf{0}, \mathbf{I})$



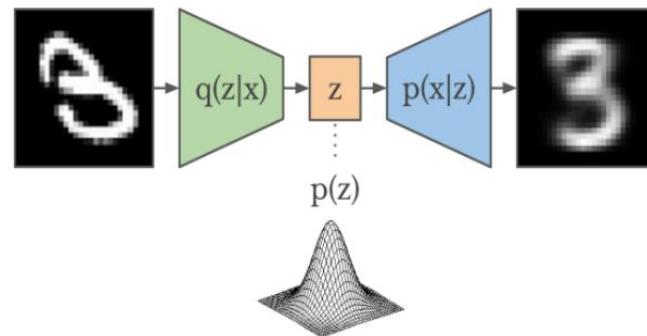
Variational Bayesian AutoEncoder

Evidence lower bound (ELBO)

$$\ln p(x) \geq \mathbb{E}_{q(z|x)} [\ln p(x|z)] - D_{KL}[q(z|x)||p(z)]$$

Proposed by Kingma & Welling (2013) and Rezende et al. (2014)

$$\mathcal{L}(\theta, \phi) = \mathbb{E}_{q_\phi(z|x)} [\log p_\theta(x|z)] - \mathbb{KL}(q_\phi(z|x) \| p(z))$$



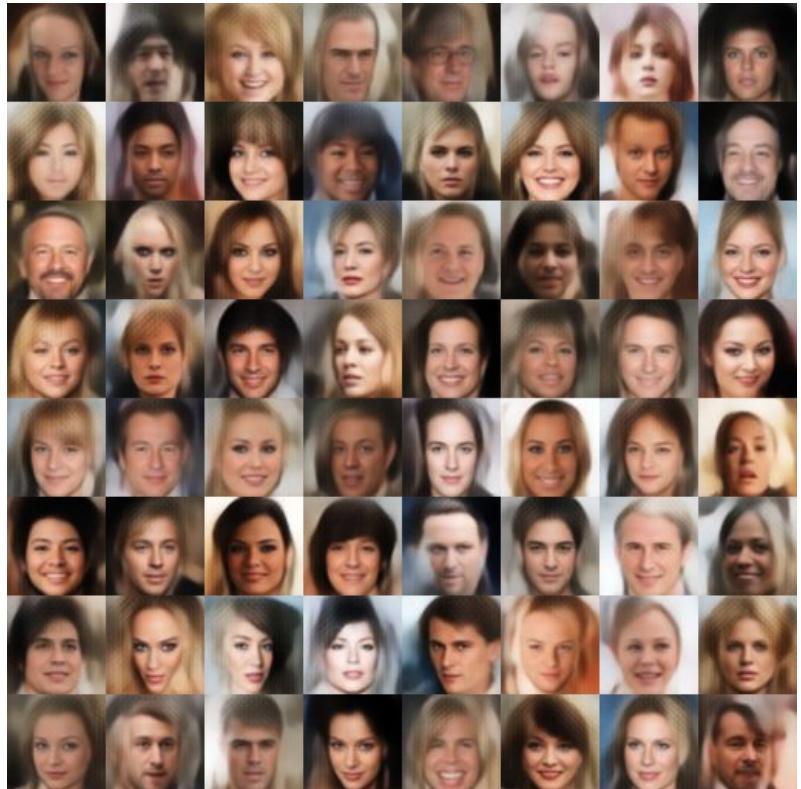
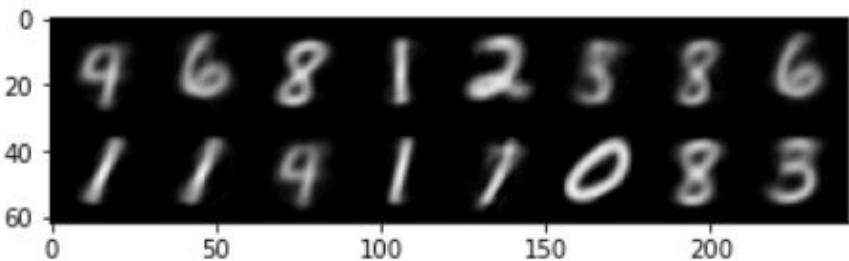
$$p(z|x) = \frac{p(x|z)p(z)}{p(x)}$$

More on this:

<https://arxiv.org/pdf/1906.02691.pdf>

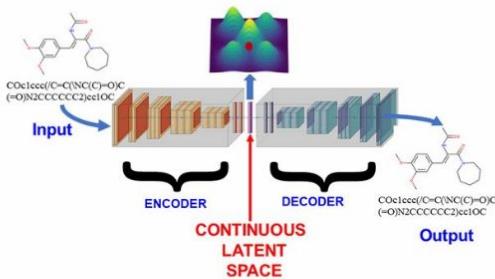
<https://www.cs.princeton.edu/courses/archive/fall11/cos597C/lectures/variational-inference-i.pdf>

VAE applications

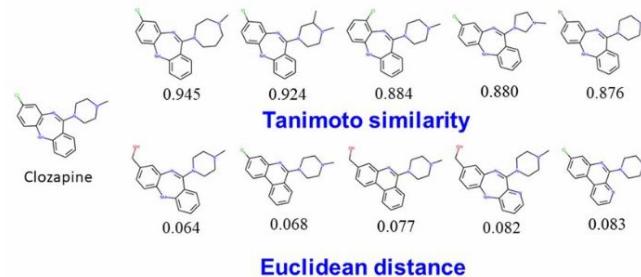


VAE applications

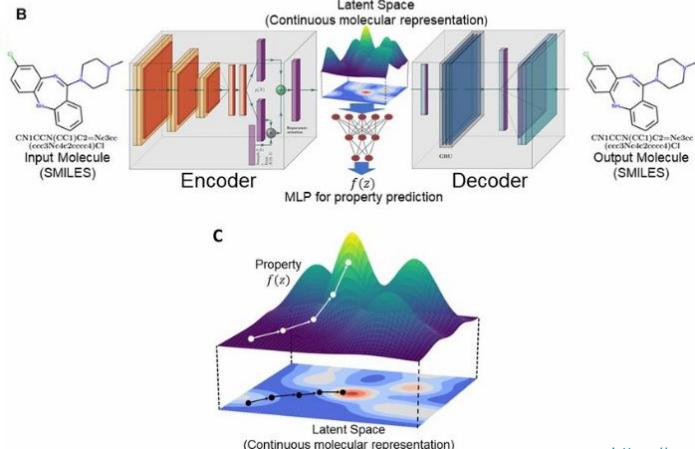
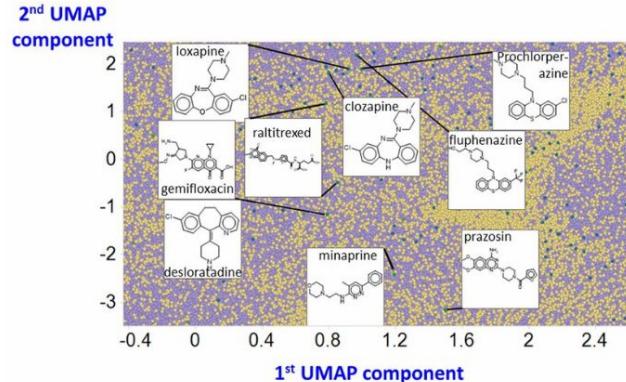
A Variational autoencoder



A Nearest neighbours in latent space for clozapine

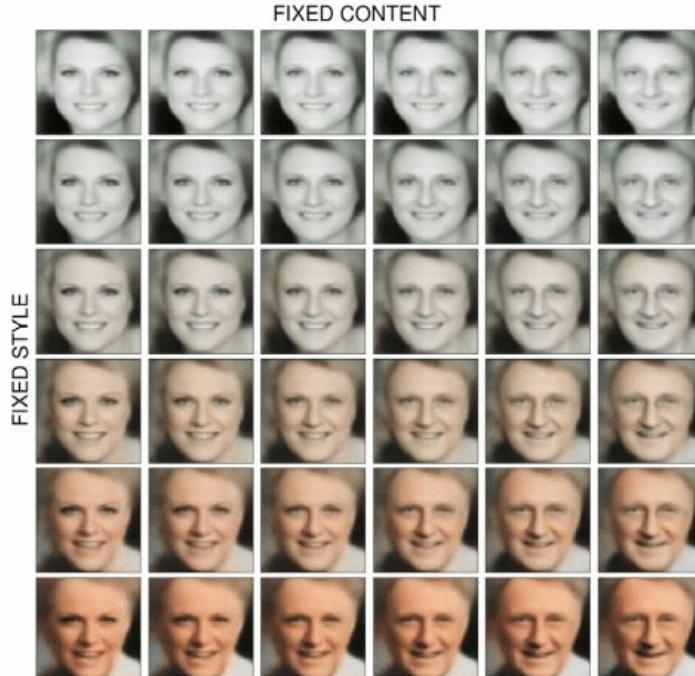


B Zooming in to latent space



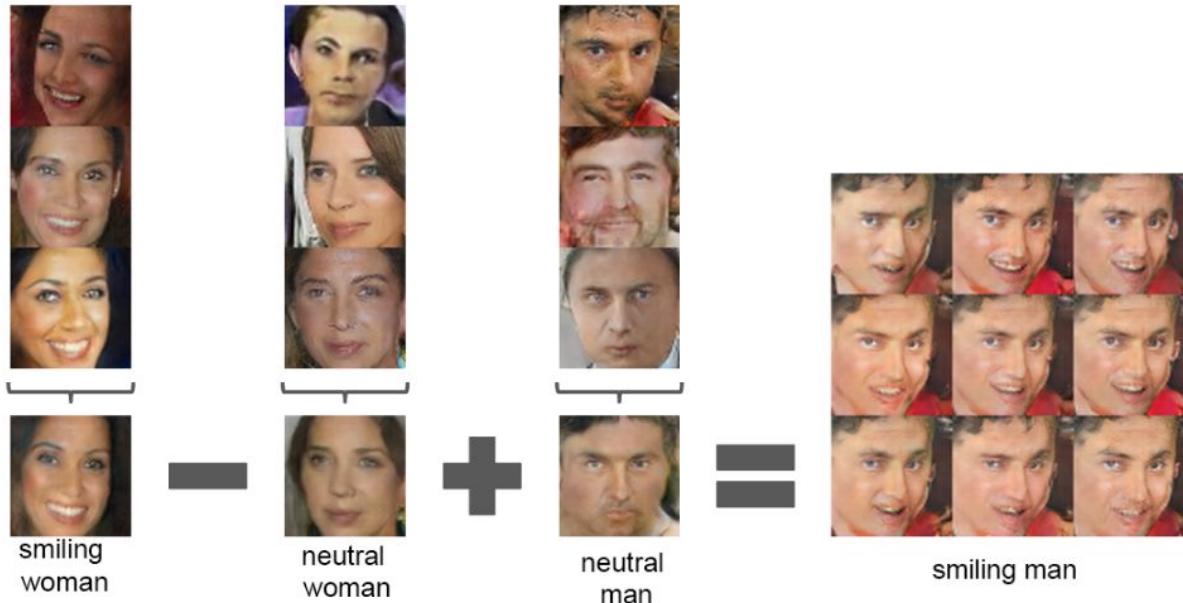
Latent Vector Interpolation

6 6 6 6 6 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
4 4 4 4 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0 2
9 2 2 2 2 2 2 2 8 5 5 5 5 0 0 0 0 0 0 0 0 2
9 4 2 2 2 2 2 2 3 3 3 3 5 5 5 5 0 0 0 0 0 0 2
9 9 4 2 2 2 2 2 3 3 3 3 3 5 5 5 5 5 5 5 3 3
9 9 9 4 2 2 2 2 3 3 3 3 3 3 5 5 5 5 5 5 3 3
9 9 9 9 9 2 2 2 3 3 3 3 3 3 5 5 5 5 5 5 3 3
9 9 9 9 9 8 3 3 3 3 3 3 3 5 5 5 5 8 8 7
9 9 9 9 9 8 3 3 3 3 3 3 3 8 8 8 8 8 8 8 7
9 9 9 9 9 8 3 8 8 8 8 8 8 8 8 8 8 8 8 8 7
9 9 9 9 9 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 7
9 9 9 9 9 8 8 8 8 8 8 6 6 6 6 6 6 5 5 7
9 9 9 9 9 9 8 8 8 8 8 6 6 6 6 6 6 6 5 5 7
9 9 9 4 9 9 9 9 9 5 5 5 6 6 6 6 6 6 6 5 5 7
9 9 4 4 4 4 9 9 9 5 5 6 6 6 6 6 6 6 6 5 5 7
9 9 4 4 4 4 9 9 9 5 5 6 6 6 6 6 6 6 6 6 6 7
9 9 4 4 4 4 9 9 9 5 5 6 6 6 6 6 6 6 6 6 6 7
9 9 9 9 9 7 7 7 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9 9 9 9 9 7 7 7 1 1 1 1 1 1 1 1 1 1 1 1 1 1



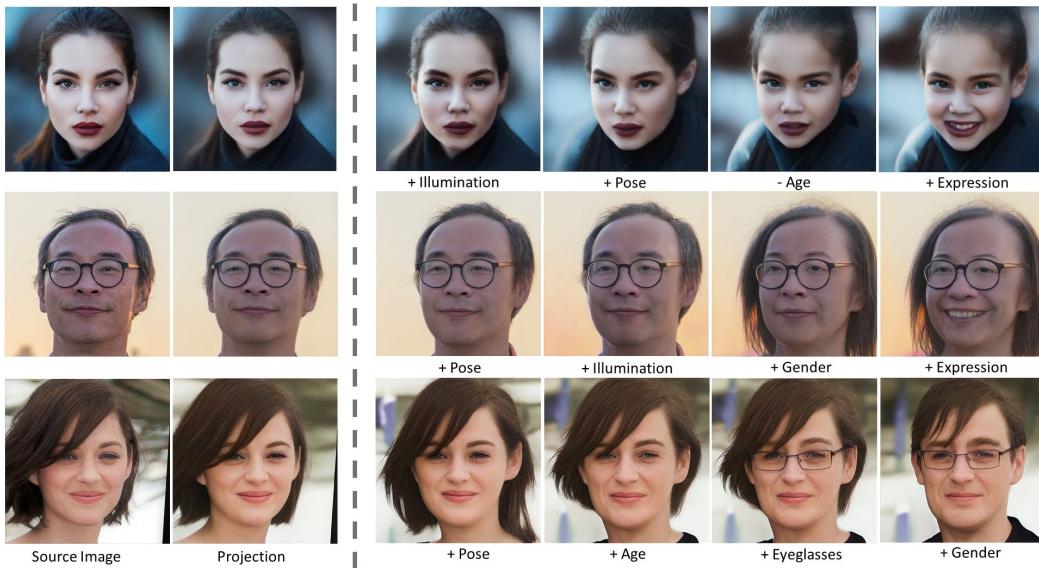
Arithmetic

Latent Space Arithmetic



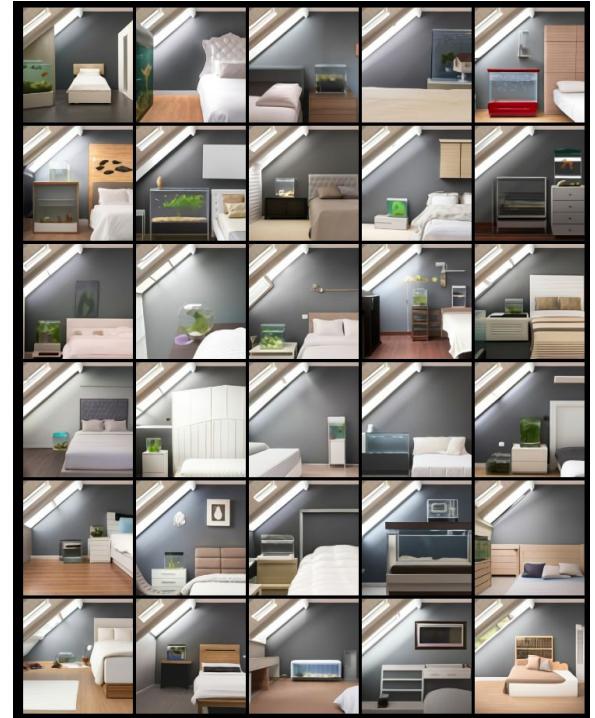
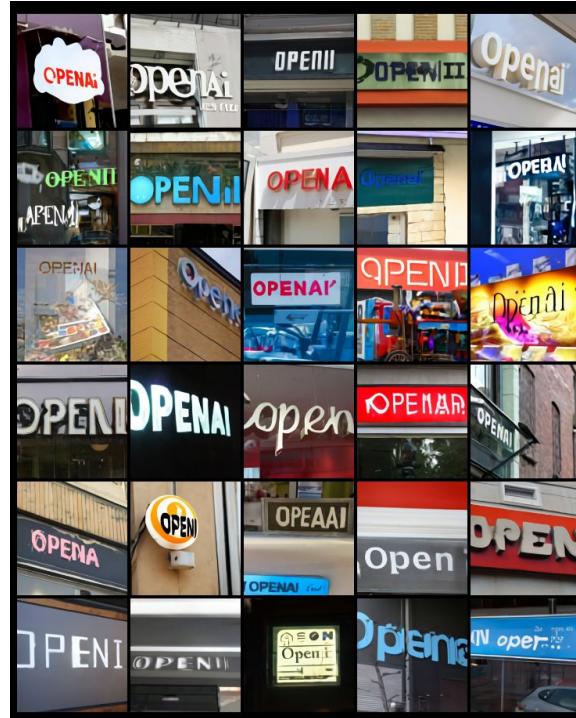
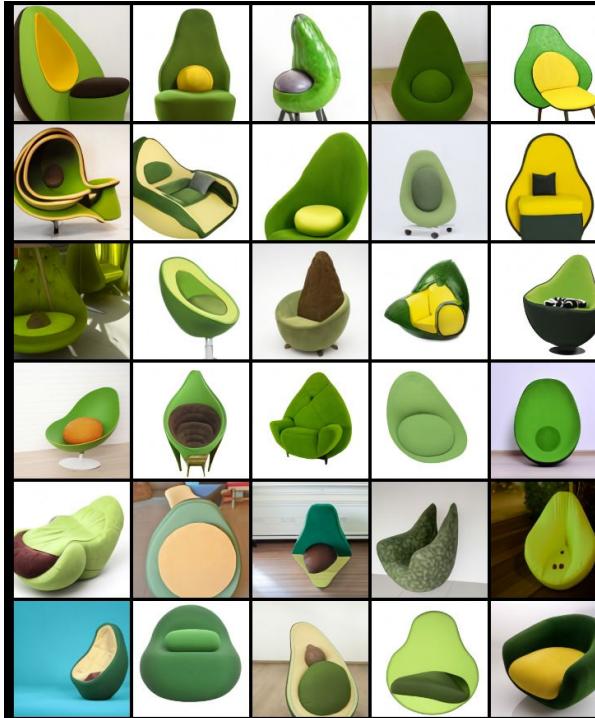
Arithmetic

Latent Space Arithmetic



Dall-E

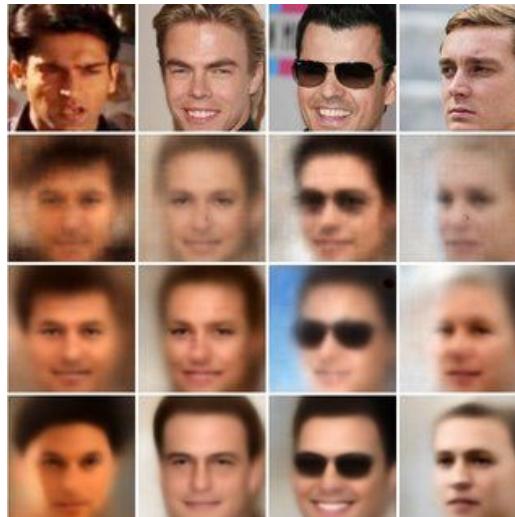
Original Dall-e by OpenAI used a discrete VAE, where the latent space is discrete and not continuous



Problems with VAEs

Posterior Collapse: The posterior (encoder) is too weak and the decoder starts ignoring samples from the posterior. The encoder becomes “disconnected” from the mean and standard deviation it needs to learn

Blurry Generations: The assumption of a standard normal distribution makes the generations ‘noisy’. Using a MSE loss as reconstruction increases the problem



Families of Generative Networks

Variational Autoencoders

Discrete VAEs

GAN (Generative Adversarial Network)

Diffusion Models

Autoregressive Models

Dall-E 2

(DALL-E 2) "An astronaut surfing on a sea turtle over a rainbow past planets in space, digital art"

Image Synthesis



an ai in the shape of a campfire telling stories to an audience of enthralled forest animals in hyperrealistic digital fantasy style

"a raccoon astronaut with the cosmos reflecting on the glass of his helmet dreaming of the stars"

@OpenAI DALL-E 2



Dall-E 2



Figure 19: Random samples from unCLIP for prompt “A teddybear on a skateboard in Times Square.”

Dall-E 2



(a) A high quality photo of a dog playing in a green field next to a lake.



(b) A high quality photo of Times Square.

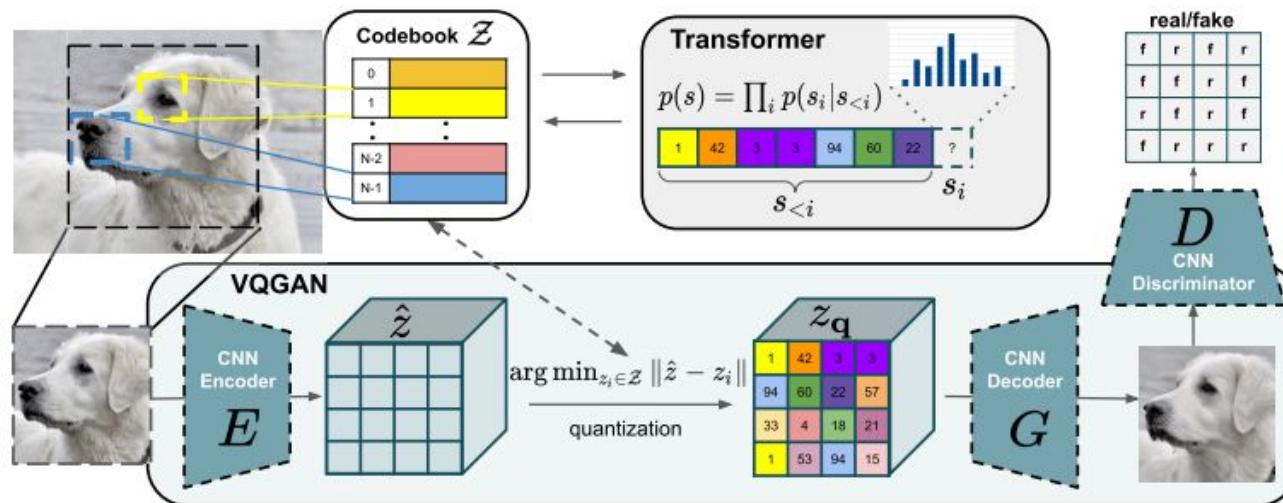


panda mad scientist mixing sparkling chemicals, artstation



a corgi's head depicted as an explosion of a nebula

Quality of GAN-Generated images



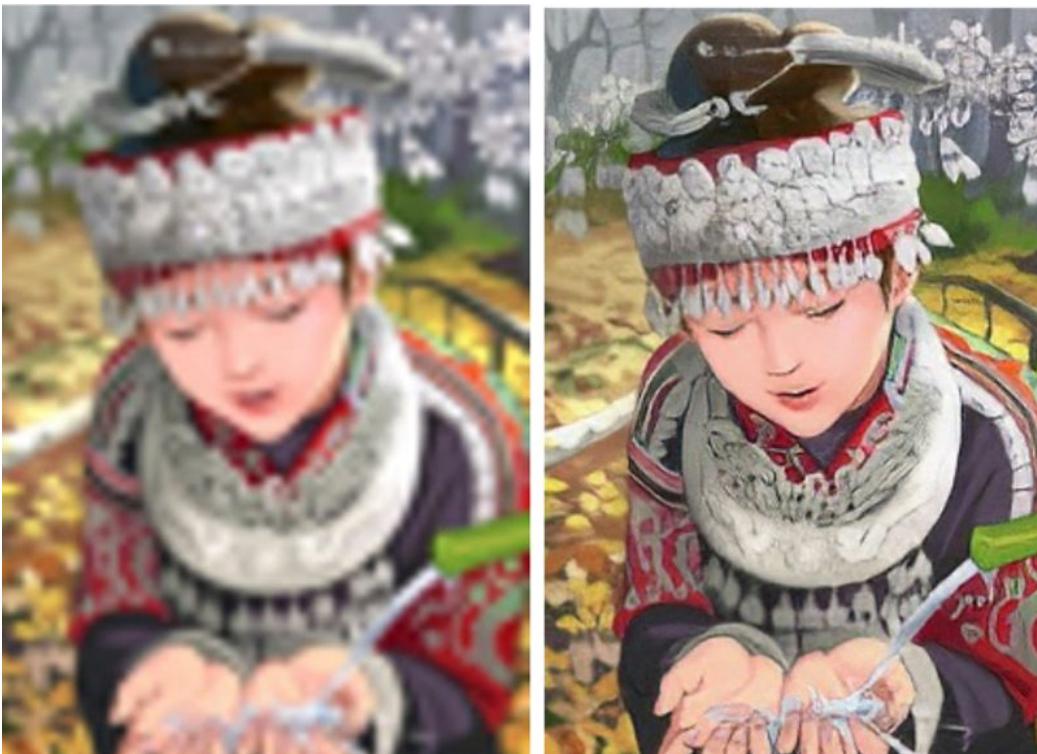
Quality of GAN-Generated images



Quality of GAN-Generated images



Super Resolution



Change Style: Young to Old

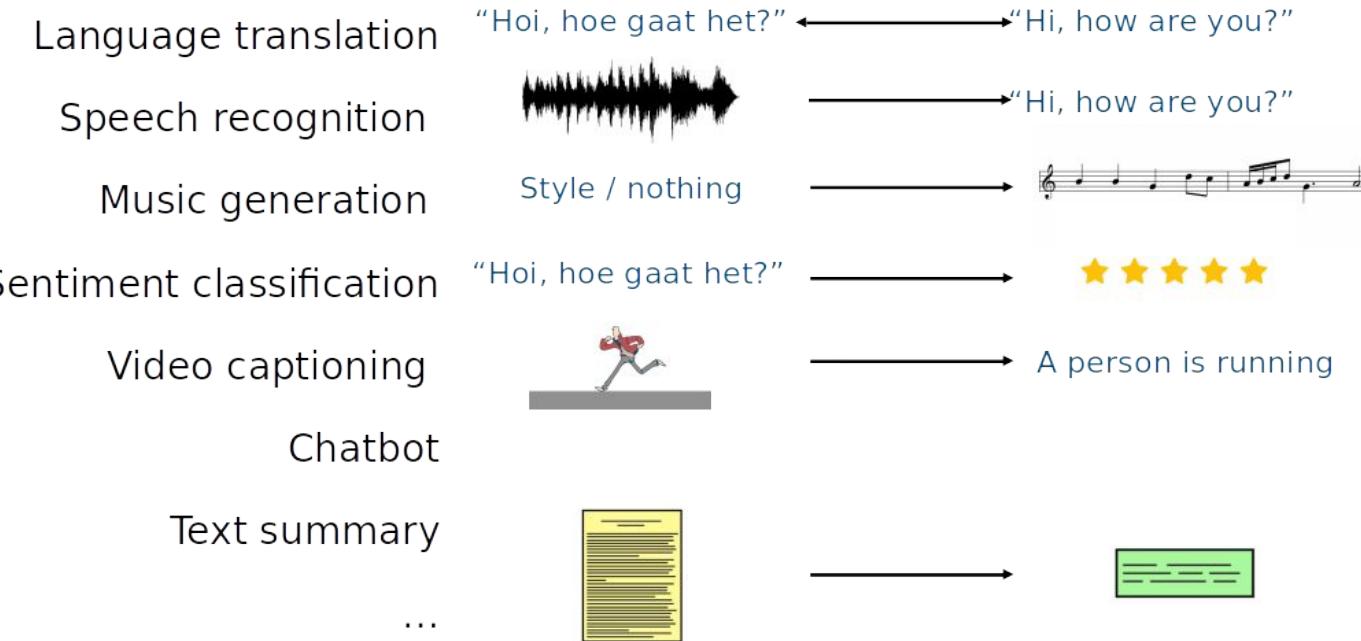


<https://yuval-alaluf.github.io/SAM/>

Modelling Sequences

How to work with data that has a temporal dimension?

Modelling Sequences



Sequential Data

Sequential Data are represented with 1d or 2d arrays

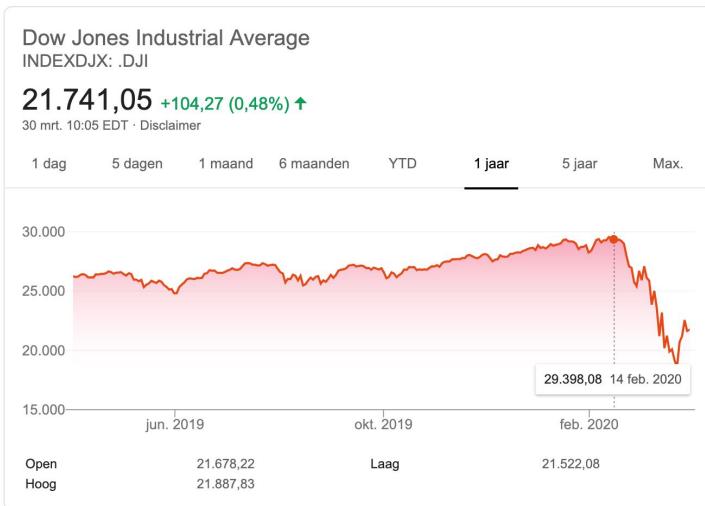


Time	24/3	25/3	26/3	27/3	28/3	...
Value	19,722	21,050	21,188	22,532	21,678	...

Sequential Data

Sequential Data are represented with 1d or 2d arrays

“The cat is black.”



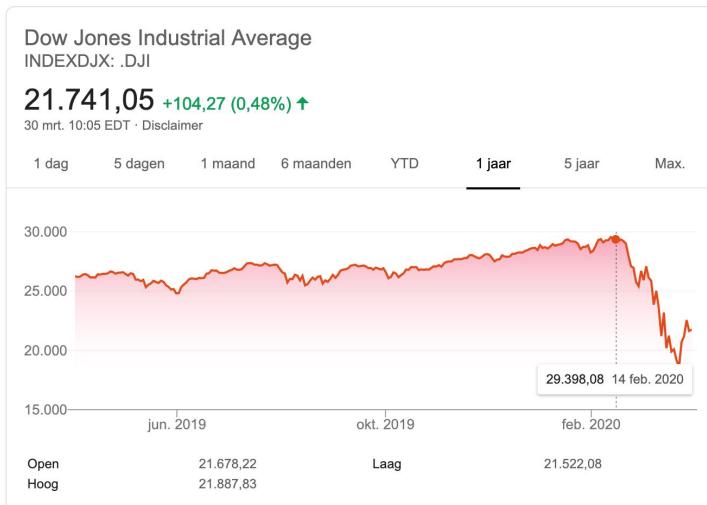
Value	42	82	16	4	0	...
-------	----	----	----	---	---	-----

Time	24/3	25/3	26/3	27/3	28/3	...
Value	19,722	21,050	21,188	22,532	21,678	...

Sequential Data

Sequential Data are represented with 1d or 2d arrays

“The cat is black.”



Value	42	82	16	4	0	...
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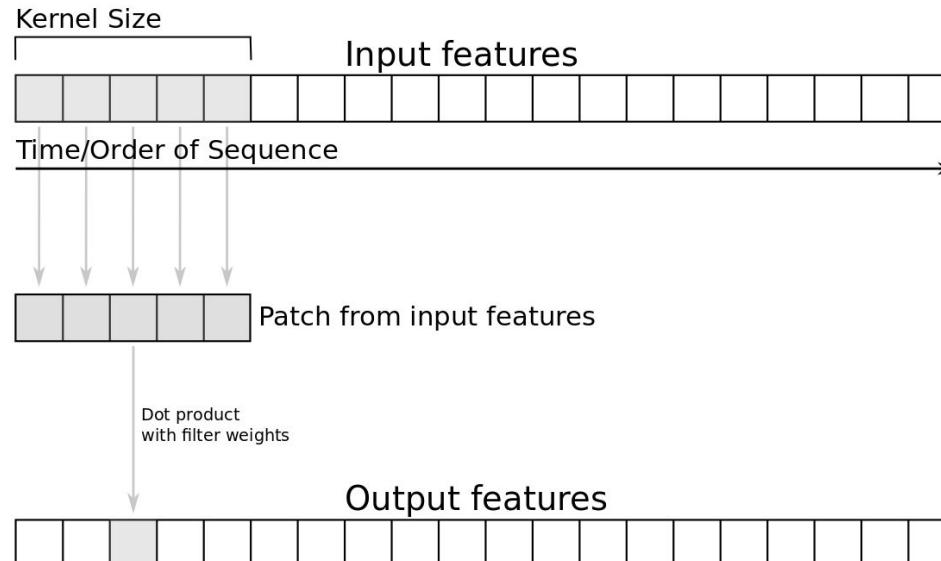
In Natural Language Processing (NLP)

- Words converted into tokens
- Token is represented numerically
- Sentence is a sequence of tokens
- Tokens may be logically related to each other

Time	24/3	25/3	26/3	27/3	28/3	...
Value	19,722	21,050	21,188	22,532	21,678	...

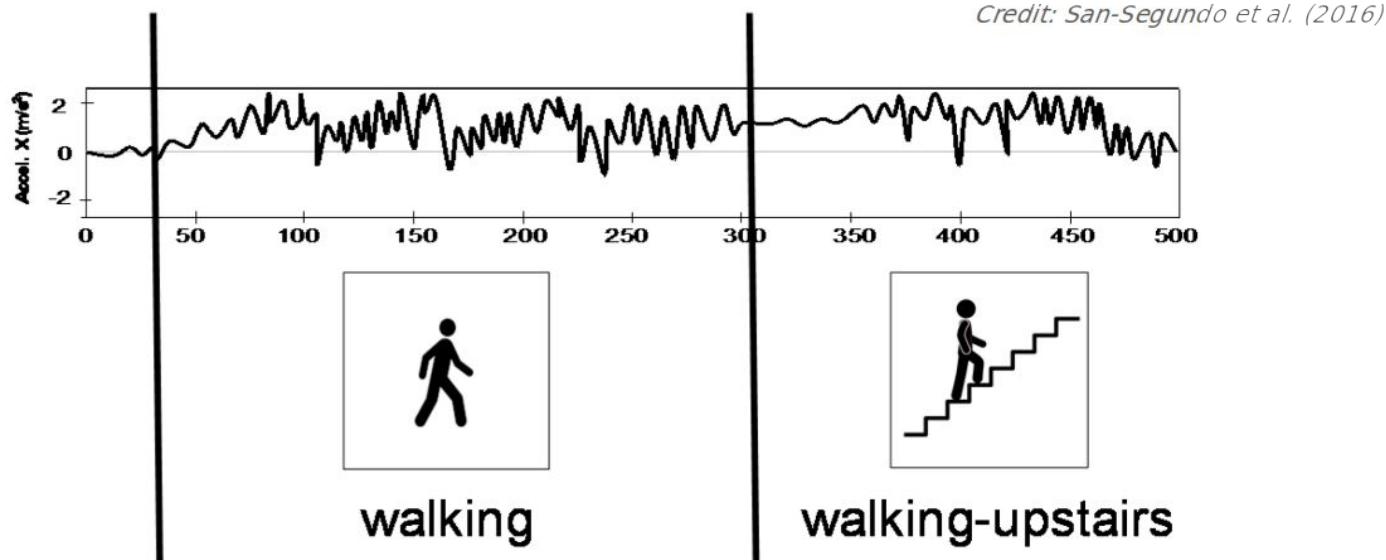
Sequence modelling with 1D convolutions

- CNNs work here because they take into account **nearby tokens**



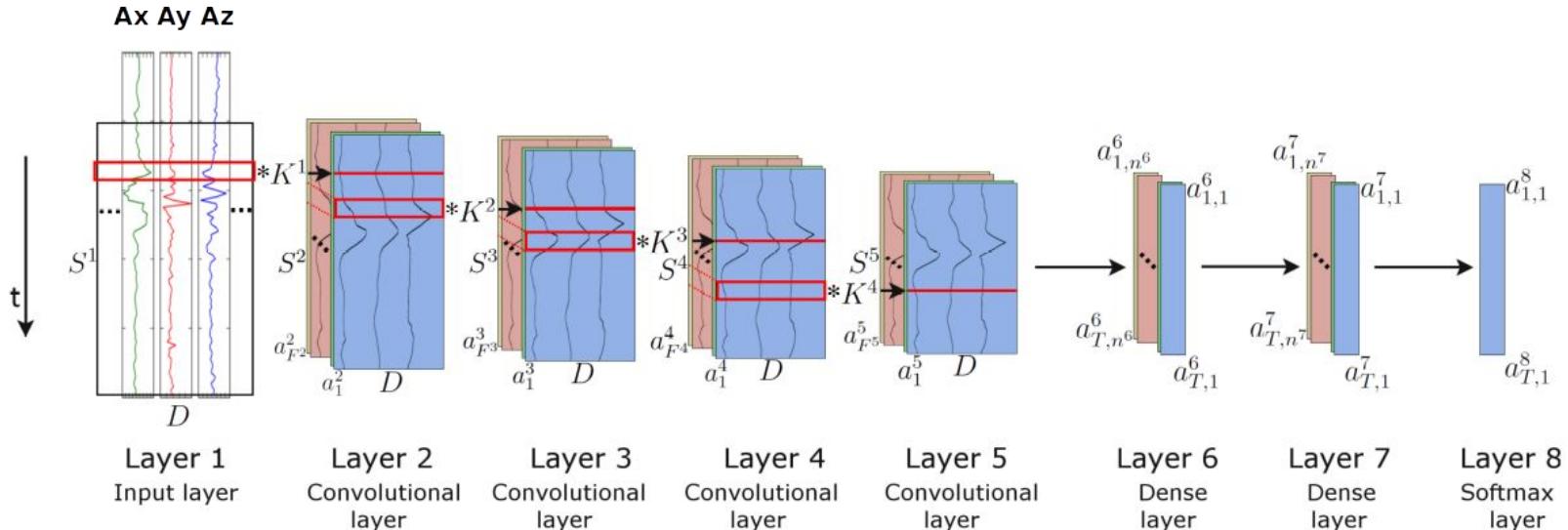
Human Activity Modelling with CNNs

- CNNs work here because they take into account **nearby** tokens

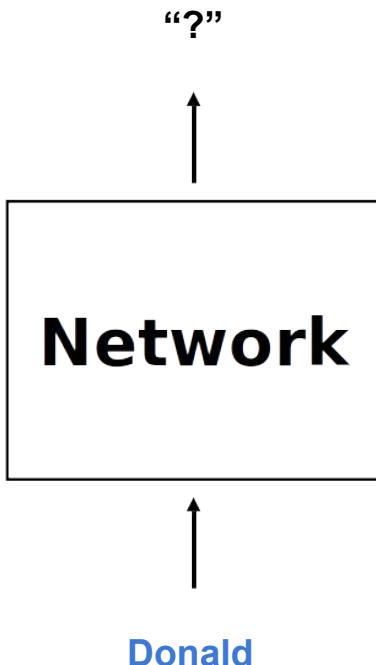


The DNN can be trained with **existing** open datasets!
e.g., <https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones>

Human Activity Modelling with CNNs



Natural Language Processing



Natural Language Processing

“?”



Network

How about modeling just the next word?

*The president of the United States is Donald Trump.
Wherever Donald Trump goes, security is tight.*

The comic Donald Duck is very famous.

Donald

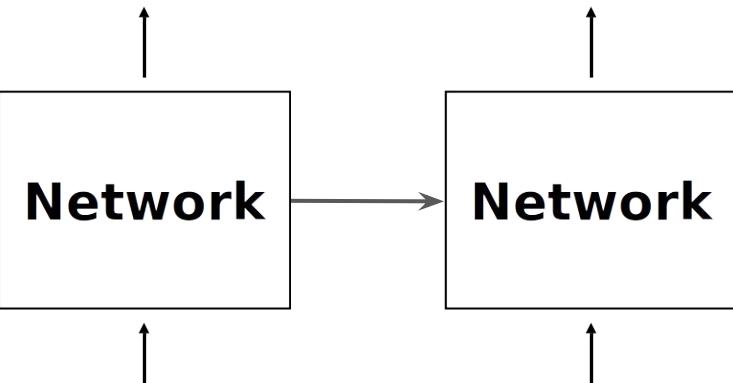


Context matters to the prediction!

Natural Language Processing

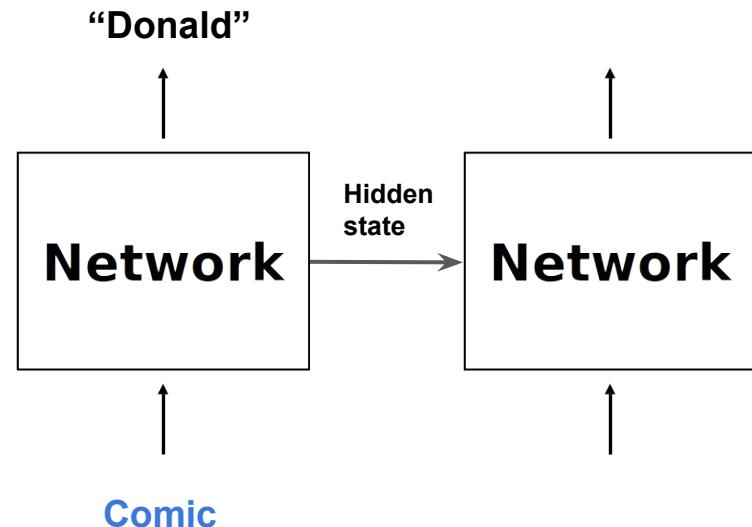
“Donald”

The meaning of the sentence depends on the
context



Comic

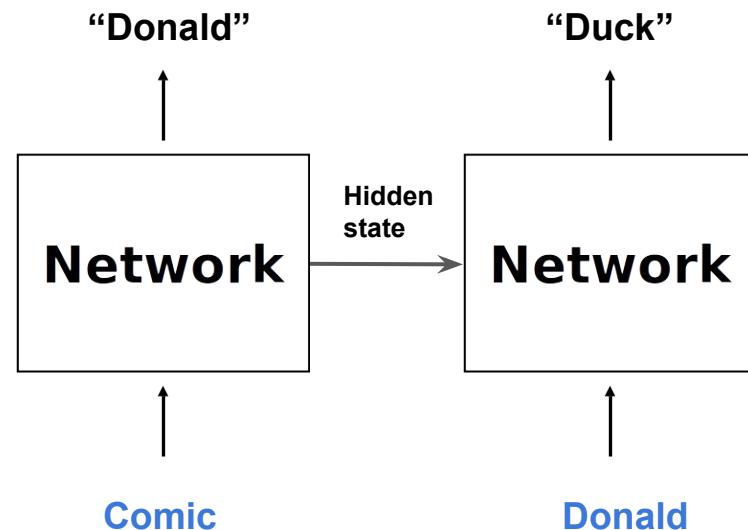
Natural Language Processing



The meaning of the sentence depends on the **context**

The context is propagated to the next time step via the **hidden state**.

Natural Language Processing

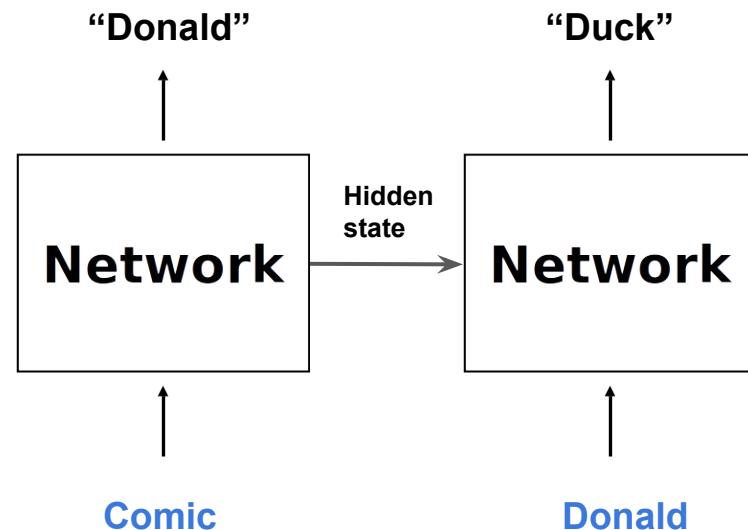


The meaning of the sentence depends on the **context**

The context is propagated to the next time step via the **hidden state**.

The next prediction is then modelled with both the hidden state and the next word

Natural Language Processing

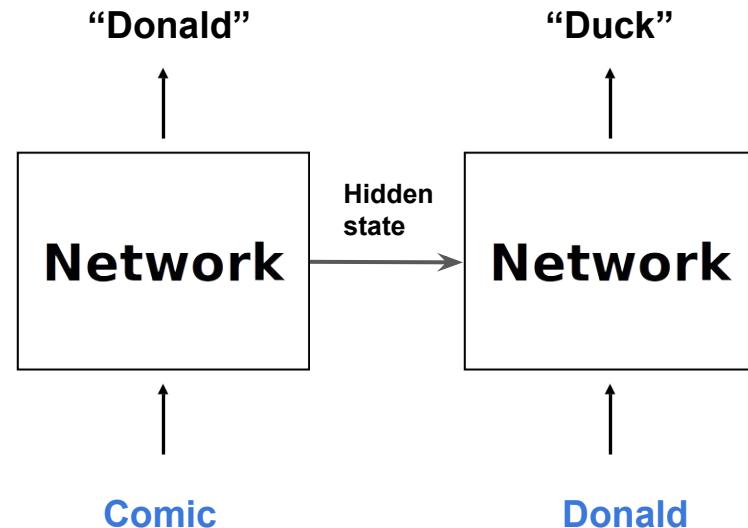


The meaning of the sentence depends on the **context**

The context is propagated to the next time step via the **hidden state**.

The next prediction is then modelled with both the hidden state and the next word

Natural Language Processing



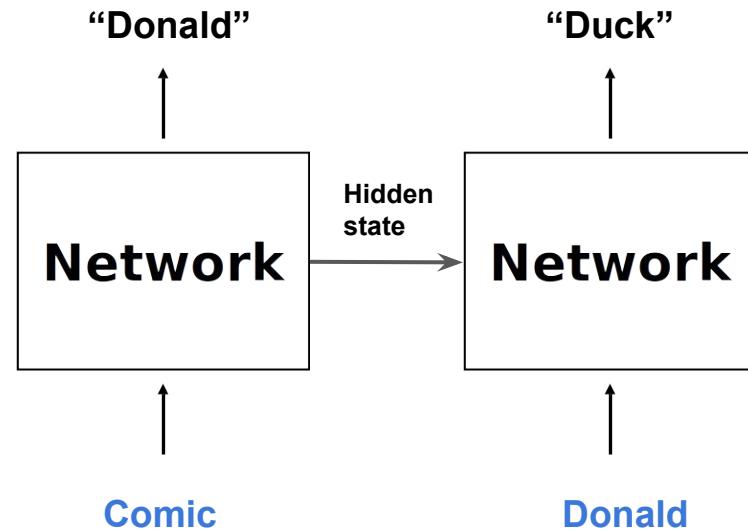
The meaning of the sentence depends on the **context**

The context is propagated to the next time step via the **hidden state**.

The next prediction is then modelled with both the hidden state and the next word

The hidden state allows the network to have **memory**

Natural Language Processing



The meaning of the sentence depends on the **context**

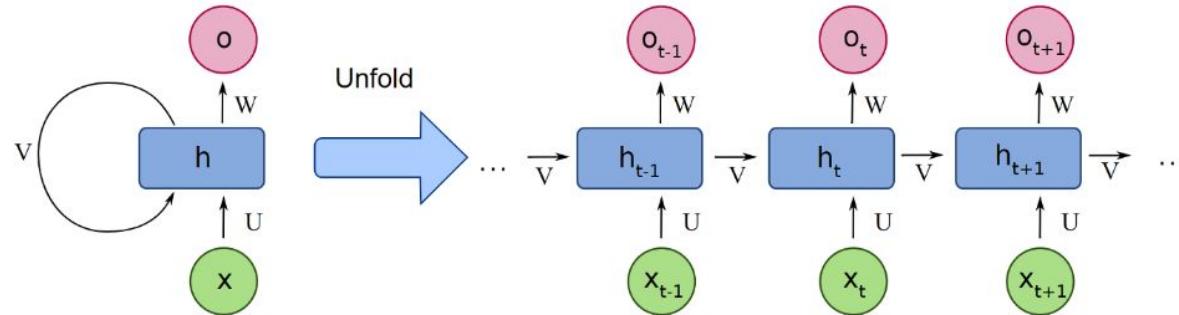
The context is propagated to the next time step via the **hidden state**.

The next prediction is then modelled with both the hidden state and the next word

The hidden state allows the network to have **memory**

Recurrent Neural Network

In RNNs, weights are reused across time steps



RNN

$$h_t = \sigma(U x_t + V h_{t-1} + b_h)$$
$$O_t = \sigma(W h_t + b_o)$$

Back propagation through **time**

Non-RNN

$$O_t = \sigma(W x_t + b)$$

Back propagation through **layers**

Long-term Dependency

Sometimes, the contexts are far away

The clouds are in the **sky**

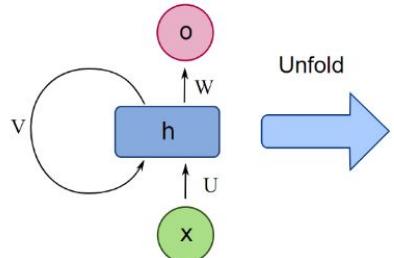
I grew up in The Netherlands ... I speak fluent **Dutch**

Long-term Dependency

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I grew up in The Netherlands ... I speak fluent **Dutch**

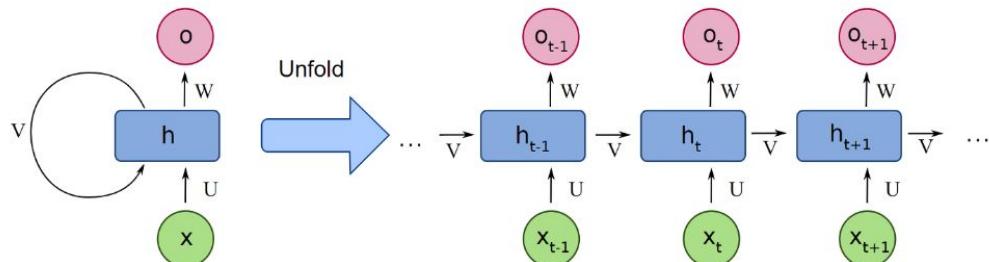


Long-term Dependency

Sometimes, the contexts are far away

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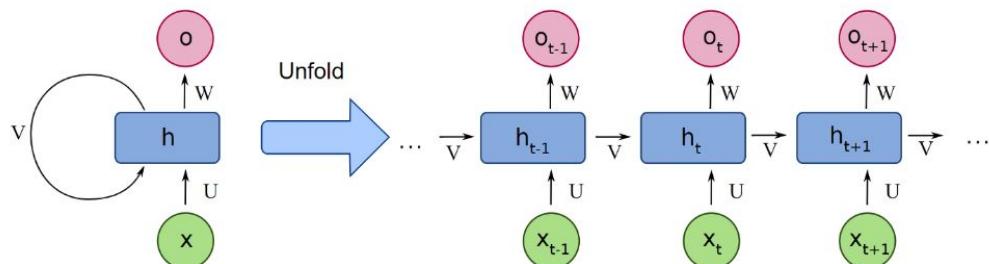


Long-term Dependency

Sometimes, the contexts are far away

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I grew up in The Netherlands ... I speak fluent **Dutch**



$$\mathbf{x}_t = F(\mathbf{x}_{t-1}, \mathbf{u}_t, \theta) \quad (1)$$

$$\mathbf{x}_t = \mathbf{W}_{rec}\sigma(\mathbf{x}_{t-1}) + \mathbf{W}_{in}\mathbf{u}_t + \mathbf{b} \quad (2)$$

$$\frac{\partial \mathcal{E}}{\partial \theta} = \sum_{1 \leq t \leq T} \frac{\partial \mathcal{E}_t}{\partial \theta} \quad (3)$$

$$\frac{\partial \mathcal{E}_t}{\partial \theta} = \sum_{1 \leq k \leq t} \left(\frac{\partial \mathcal{E}_t}{\partial \mathbf{x}_t} \frac{\partial \mathbf{x}_t}{\partial \mathbf{x}_k} \frac{\partial^+ \mathbf{x}_k}{\partial \theta} \right) \quad (4)$$

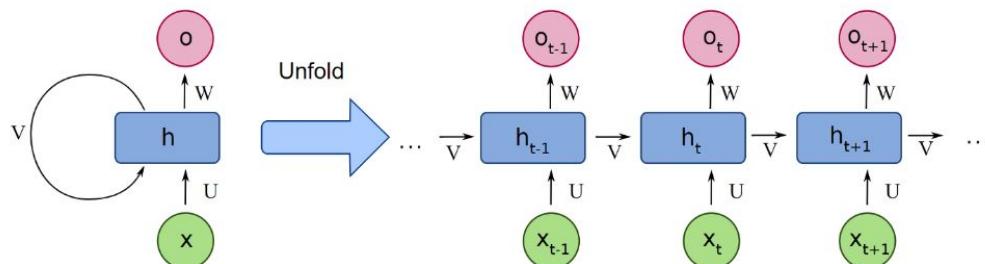
$$\frac{\partial \mathbf{x}_t}{\partial \mathbf{x}_k} = \prod_{t \geq i > k} \frac{\partial \mathbf{x}_i}{\partial \mathbf{x}_{i-1}} = \prod_{t \geq i > k} \mathbf{W}_{rec}^T diag(\sigma'(\mathbf{x}_{i-1})) \quad (5)$$

Long-term Dependency

Sometimes, the contexts are far away

The clouds are in the **sky**

I grew up in The Netherlands ... I speak fluent **Dutch**



If $\mathbf{W}_{rec}^T diag(\sigma'(\mathbf{x}_{i-1}))$ is < 1 , in a long product, gradients

start to vanish

$$\mathbf{x}_t = F(\mathbf{x}_{t-1}, \mathbf{u}_t, \theta) \quad (1)$$

$$\mathbf{x}_t = \mathbf{W}_{rec}\sigma(\mathbf{x}_{t-1}) + \mathbf{W}_{in}\mathbf{u}_t + \mathbf{b} \quad (2)$$

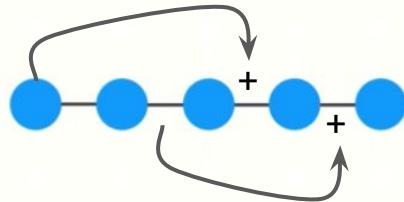
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Long Short-term Memory

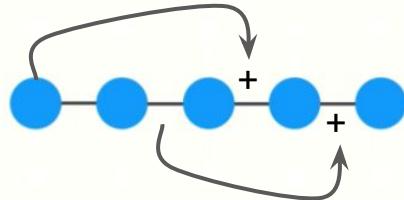
Residual connection is a general solution to the vanishing gradient problem.



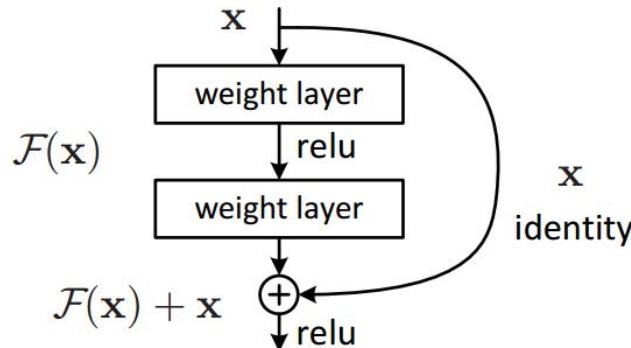
However, for very long dependency (which is common in RNNs), this solution is not sufficient. We should instead regulate which information to **keep** and which to **forget**.

Long Short-term Memory

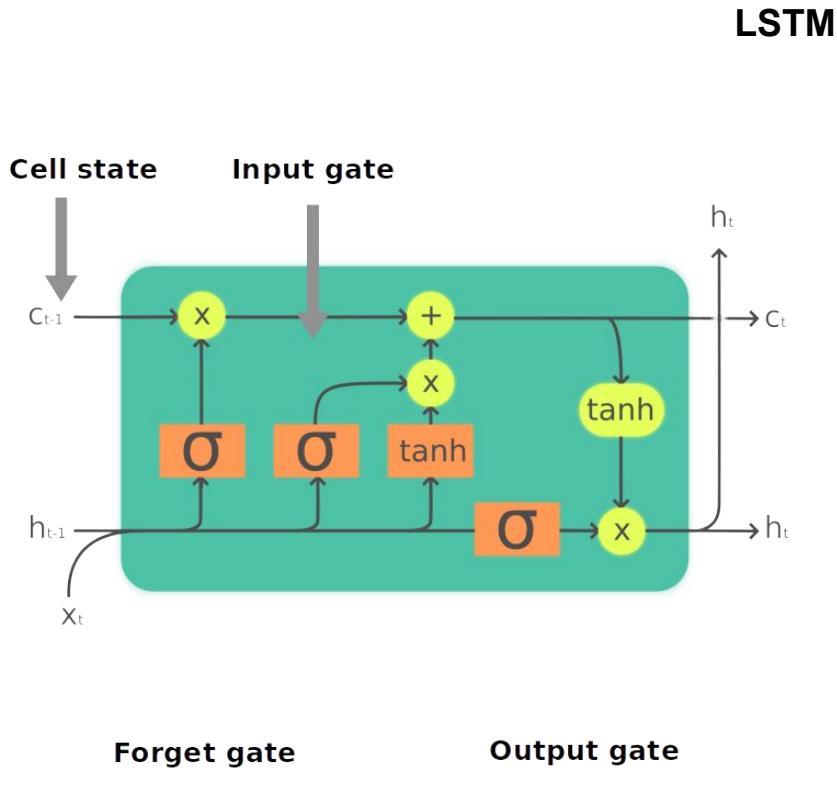
Residual connection is a general solution to the vanishing gradient problem.



However, for very long dependency (which is common in RNNs), this solution is not sufficient. We should instead regulate which information to **keep** and which to **forget**.



Long Short-term Memory



LSTM regulates the flow of information through gates.

- **Input gate**: controls the extent to which a new value flows into the cell;
- **Forget gate**: controls the extent a value remains in the cell;
- **Output gate**: controls the extent to which the value in the cell is used to calculate the output activation.

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$

$$c_t = \sigma_h(W_c x_t + U_c h_{t-1} + b_c)$$

$$h_t = f_t \circ c_{t-1} + i_t \circ c_t$$
$$h_t = o_t \circ \sigma_h(c_t)$$

Sequence Modeling

LSTM

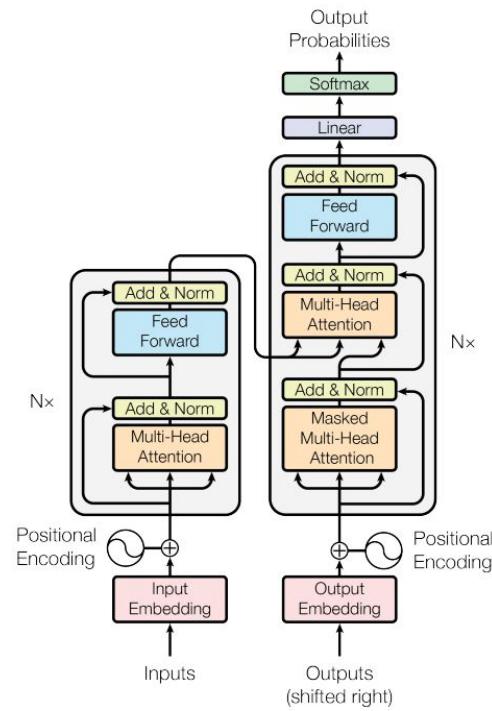
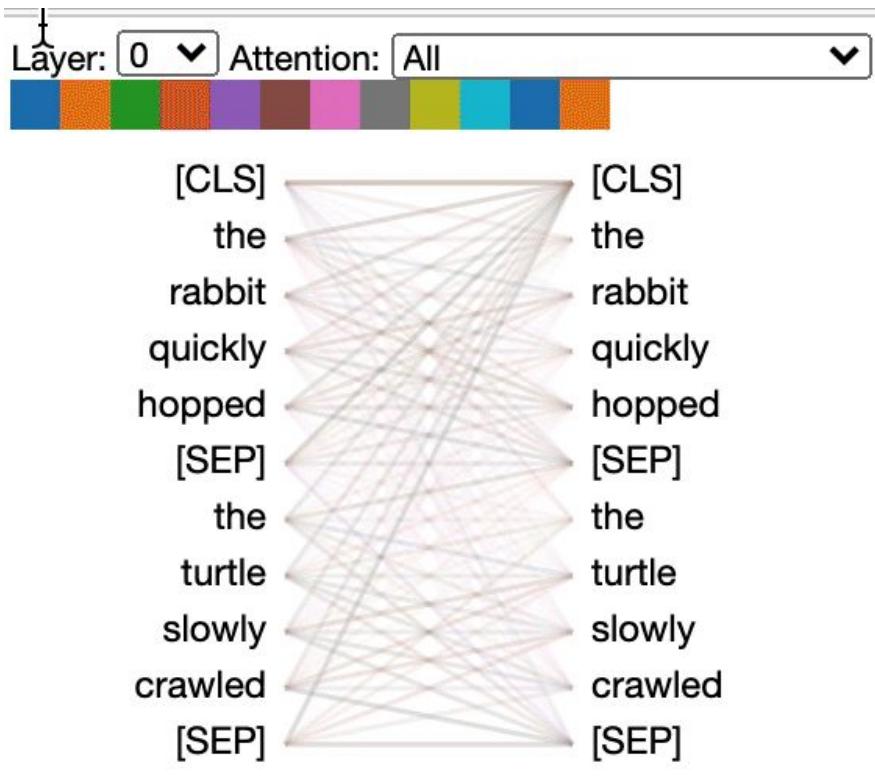
BISHOP OF ELY:

Marry, and will, my lord, to weep in such a one were prettiest;
Yet now I was adopted heir
Of the world's lamentable day,
To watch the next way with his father with his face?

ESCALUS:

The cause why then we are all resolved more sons.

Self-Attention and Transformers



Sequence Modeling

Transformer: GPT-3

The unicorns told the scientists that they had left the valley to explore the world, but that after years of traveling the world, they found humans to be incredibly stupid and decided to return to the valley to live in peace.

“We were shocked”, said Dr. St. Maurice. “We had no idea that the unicorns had been waiting for us. We also had no idea that the unicorns were capable of speech. It was a truly magical moment.”

<https://www.buildgpt3.com/post/88/>

<https://openai.com/api/>

Final Notes

CNNs allow us to use images in machine learning in an efficient way

Classifiers want to extract feature for estimation

Generative models want to learn the distribution of the data

CNNs can be used for sequence modelling

RNNs are better than CNNs for NLP

LSTMs solves an inherent problem to RNNs

There is so much more...

The END

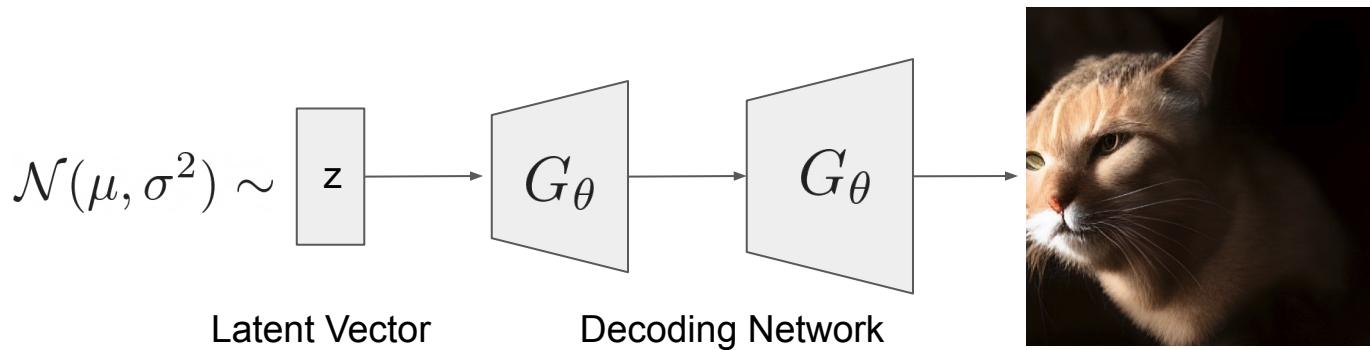
bryan.cardenasguevara@surf.nl
bryca@pm.me



UNUSED SLIDES

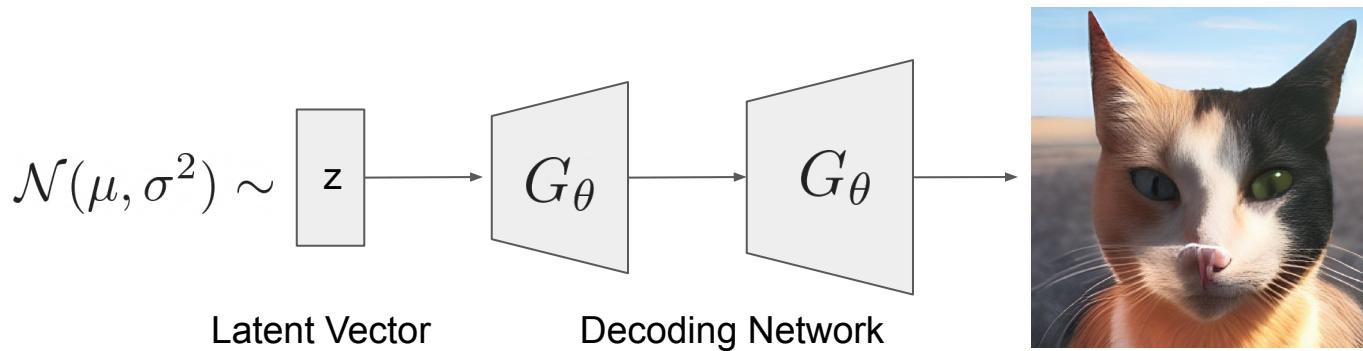
Generative Models

Generator



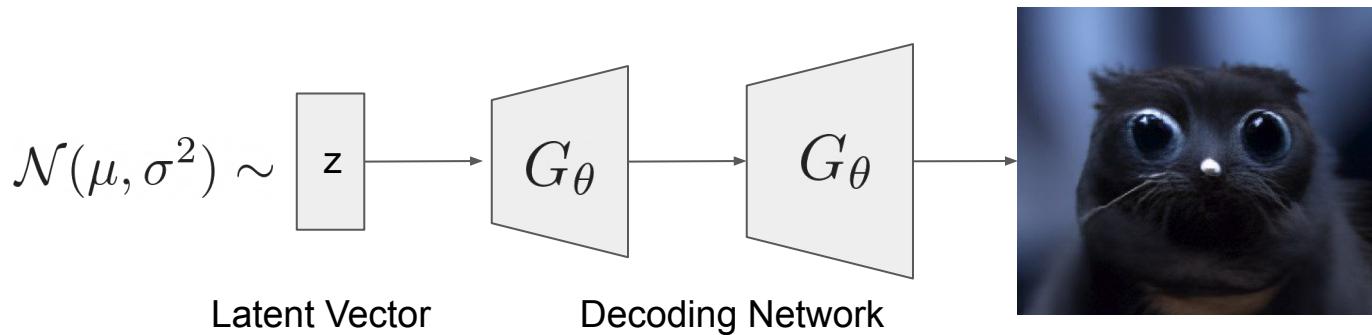
Generative Models

Generator



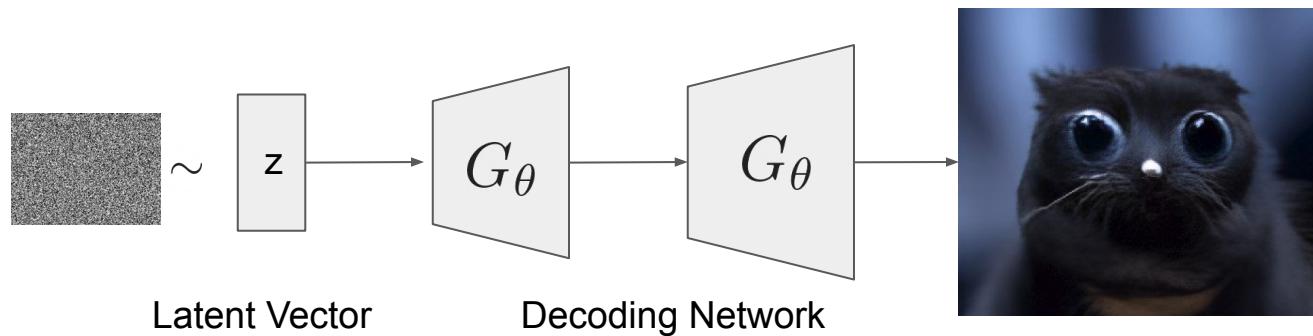
Generative Models

Generator

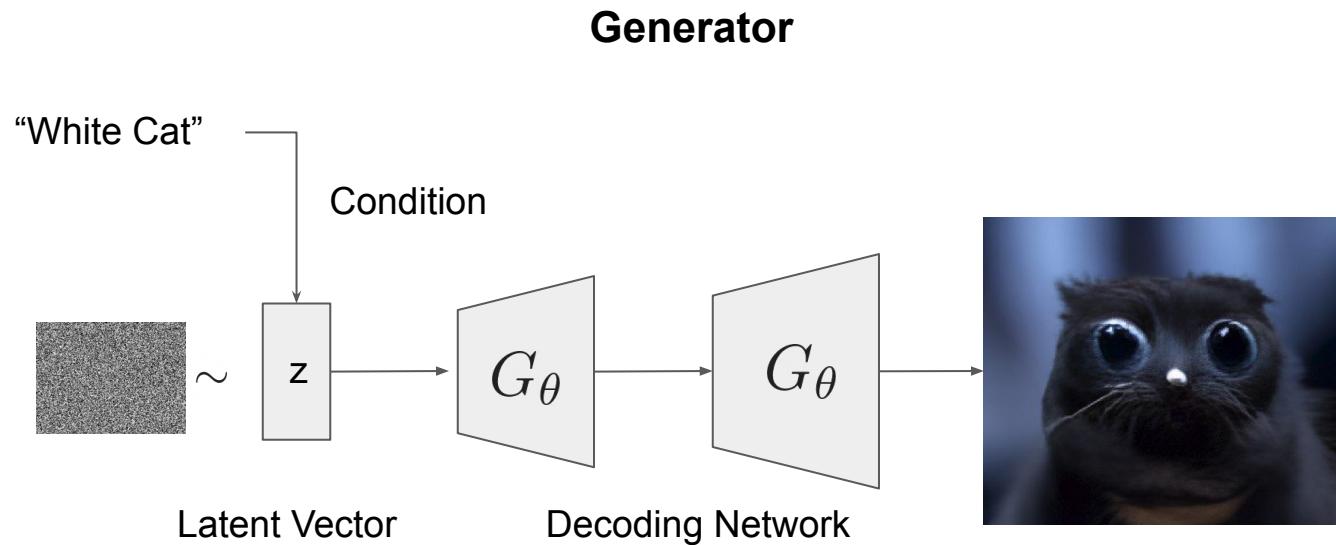


Generative Models

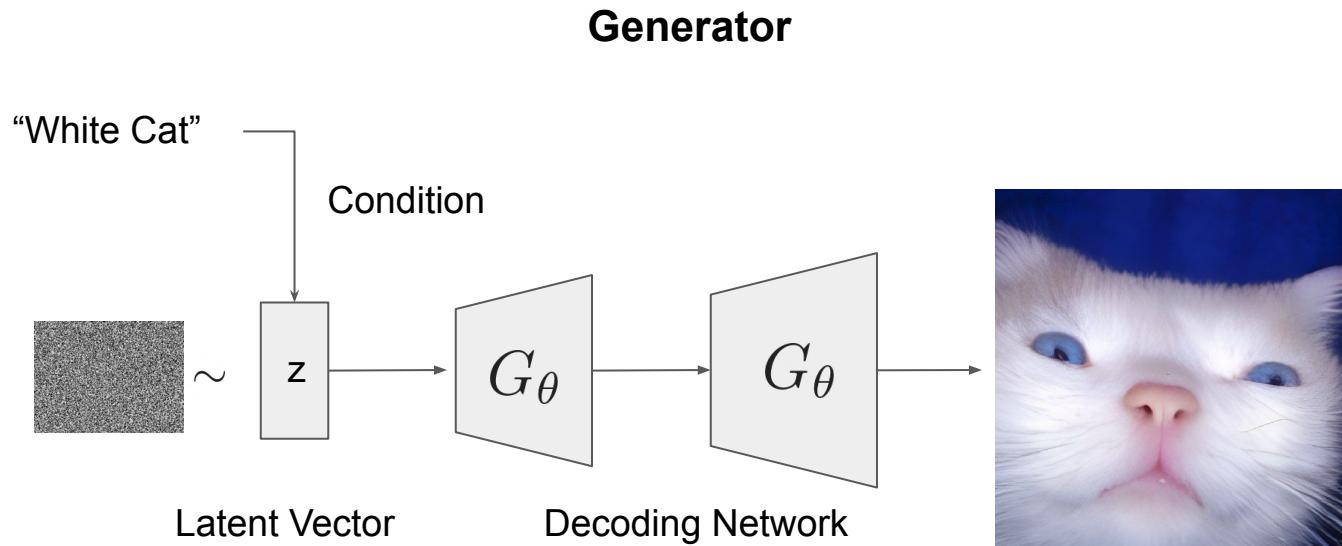
Generator



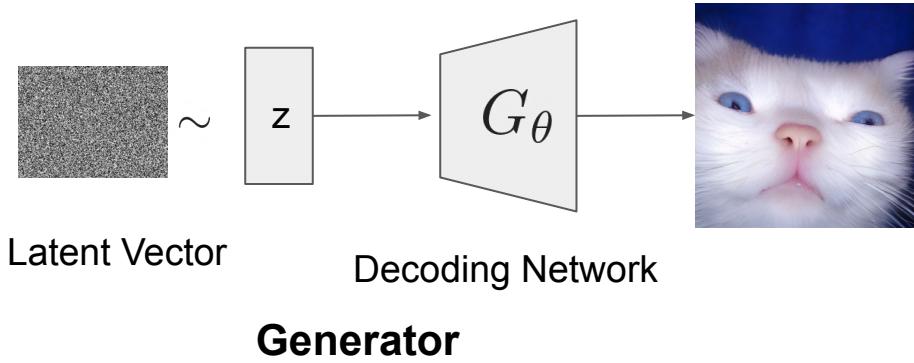
Generative Models



Generative Models

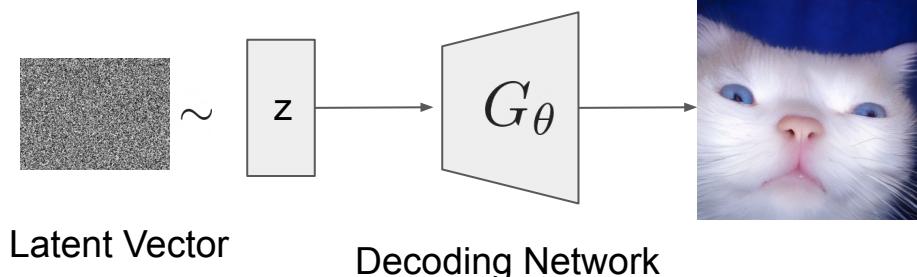


Adversarial Training



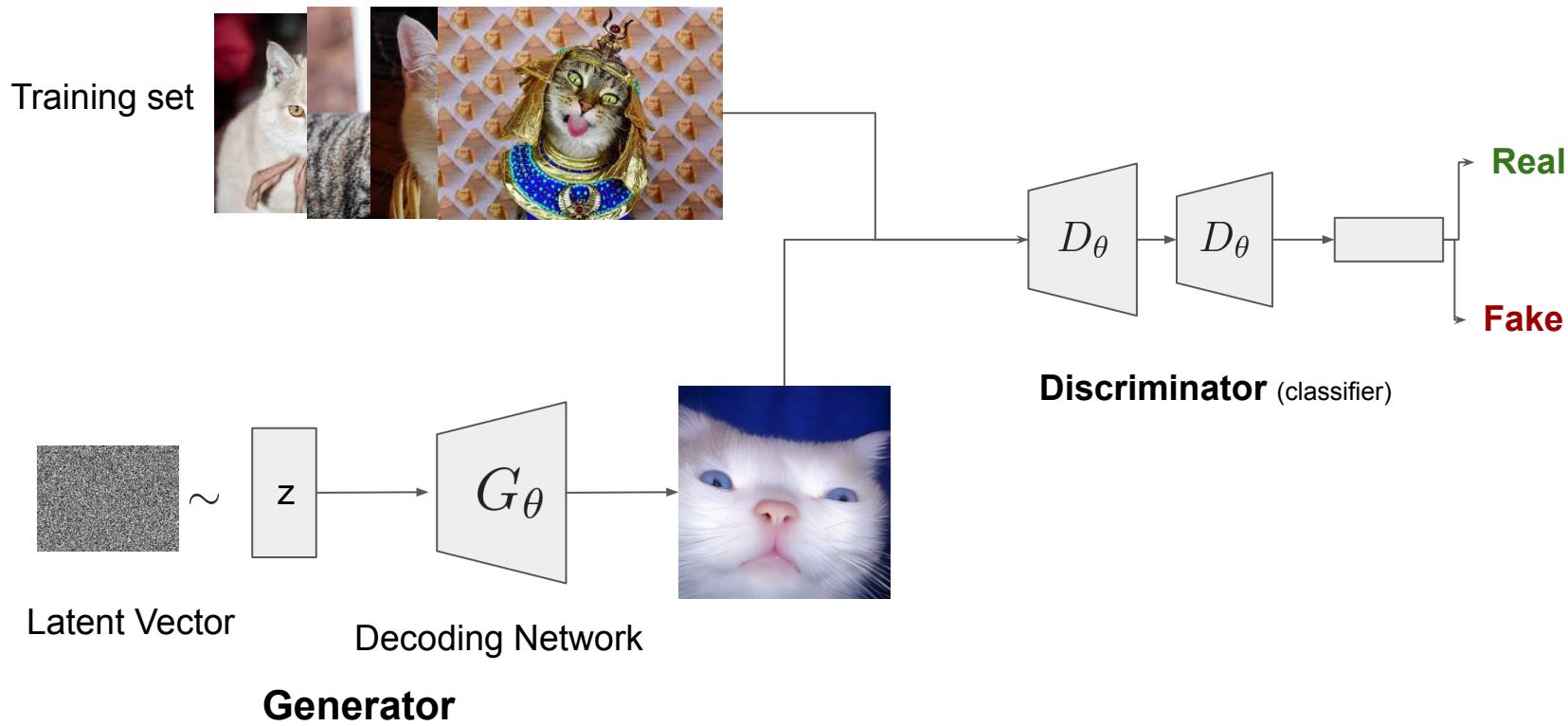
Adversarial Training

Training set

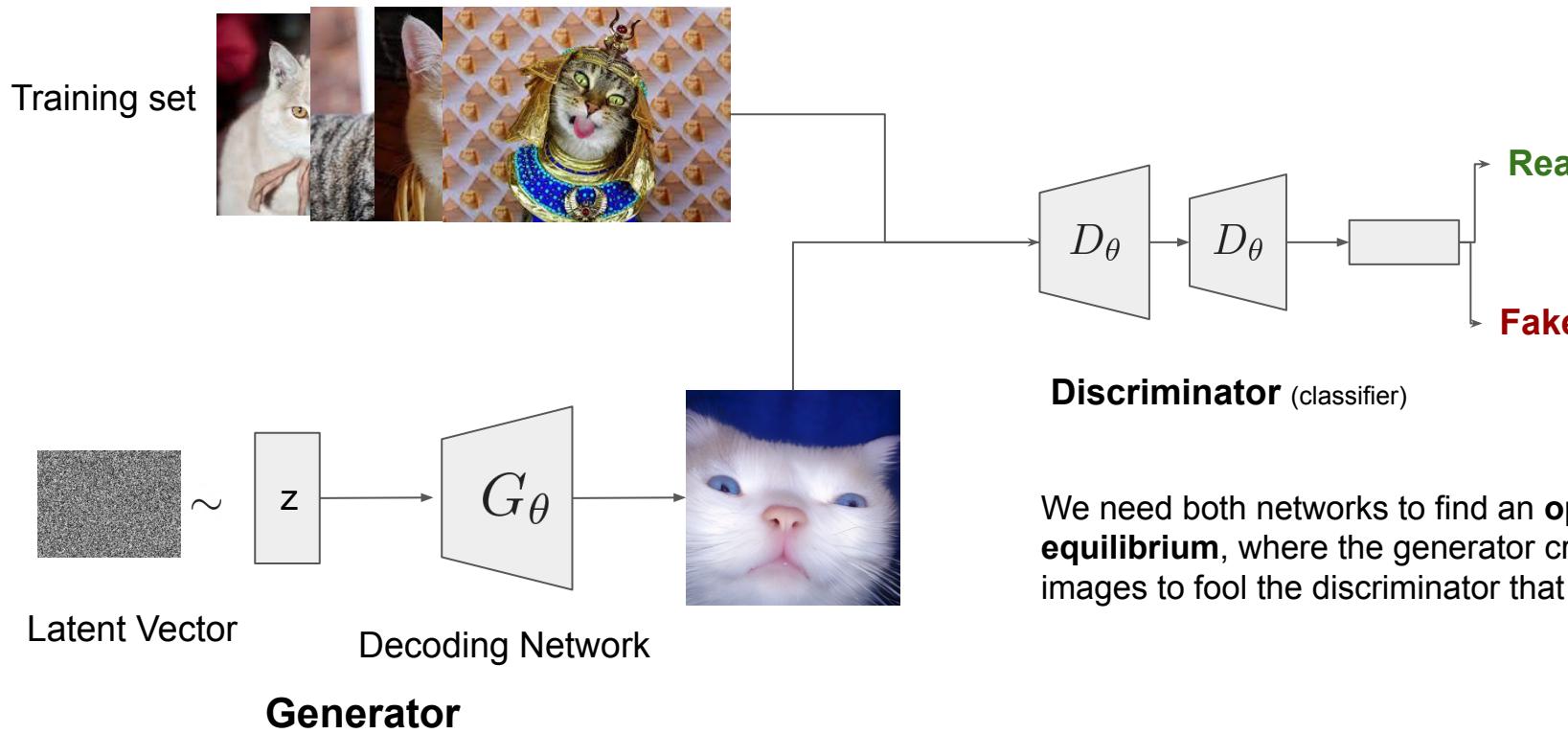


Generator

Adversarial Training

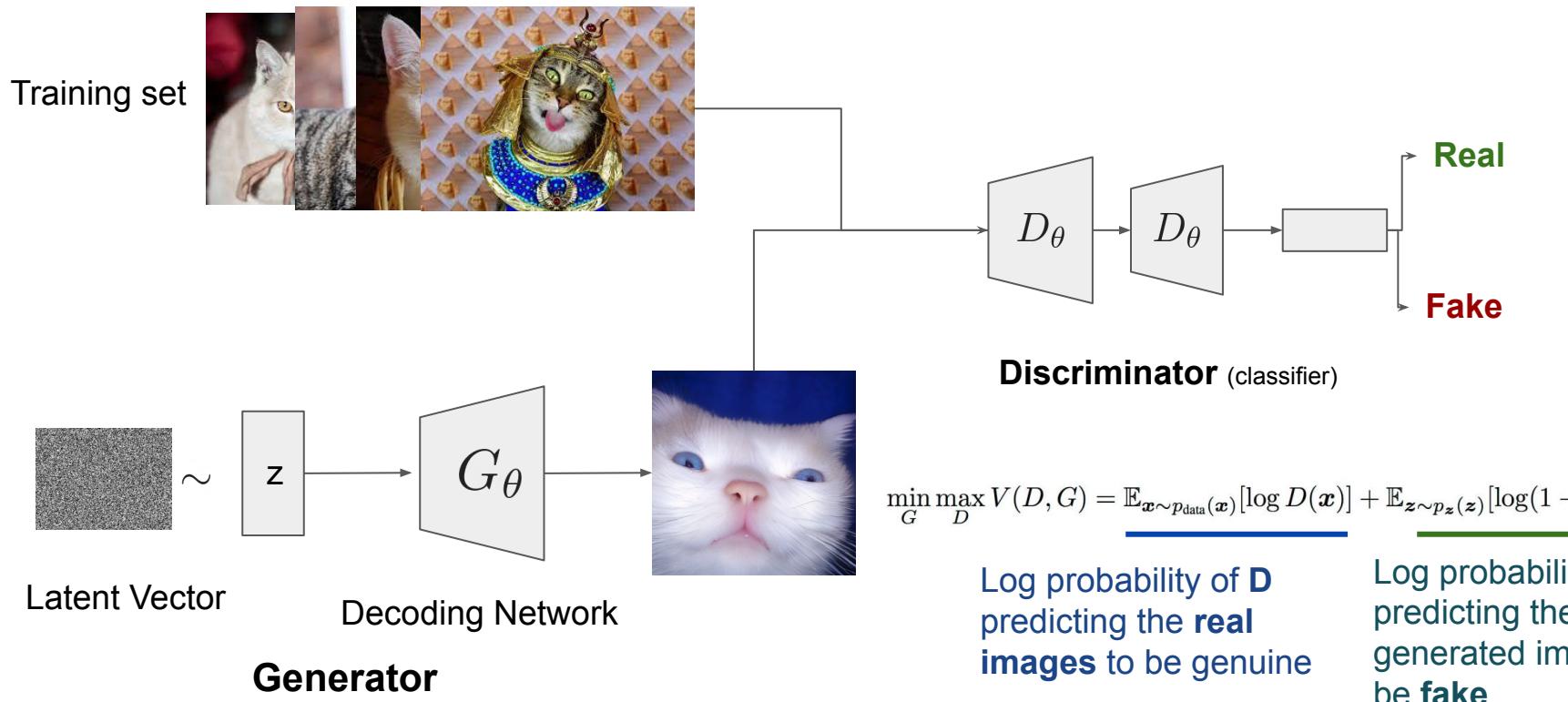


Adversarial Training



We need both networks to find an **optimal equilibrium**, where the generator creates good images to fool the discriminator that they are real

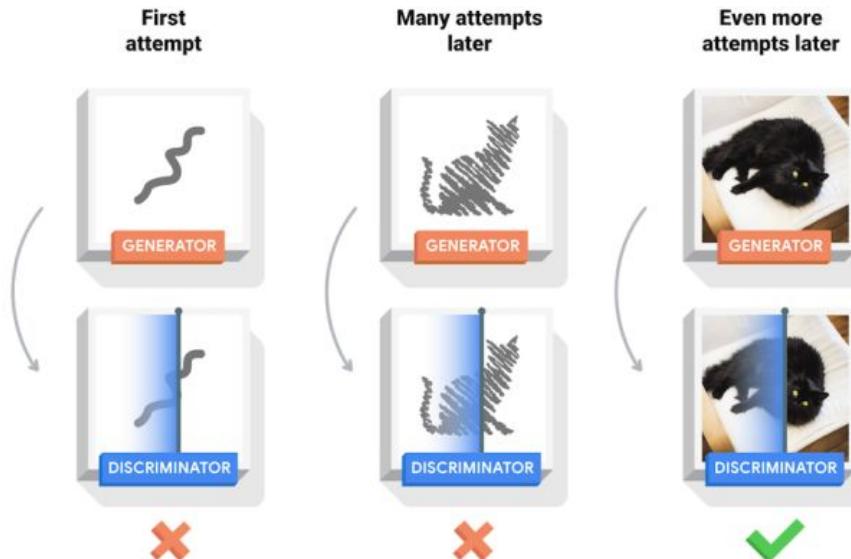
Adversarial Training



Adversarial Training

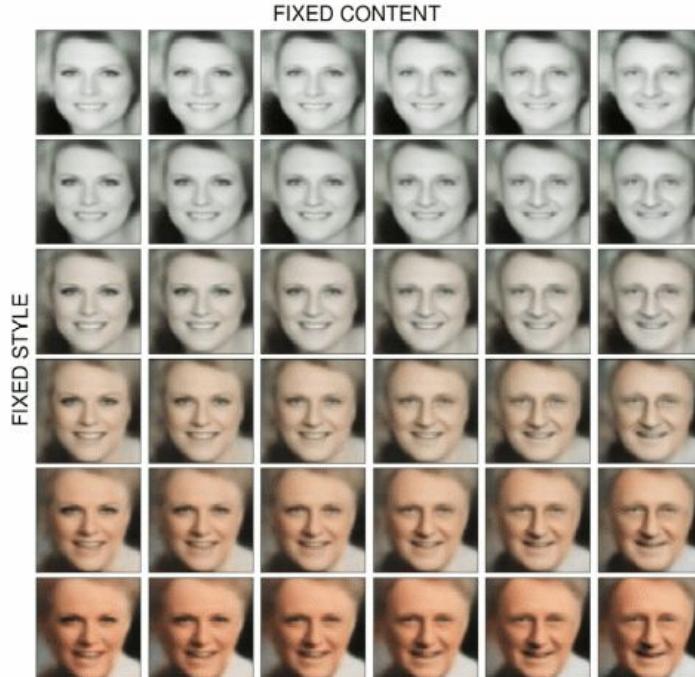
During the training:

- The **generator** progressively **becomes better** in creating images that looks real;
- The **discriminator** progressively **becomes better** in telling them apart.
- The process reaches an **equilibrium** when the discriminator can no longer distinguish real images from fakes.



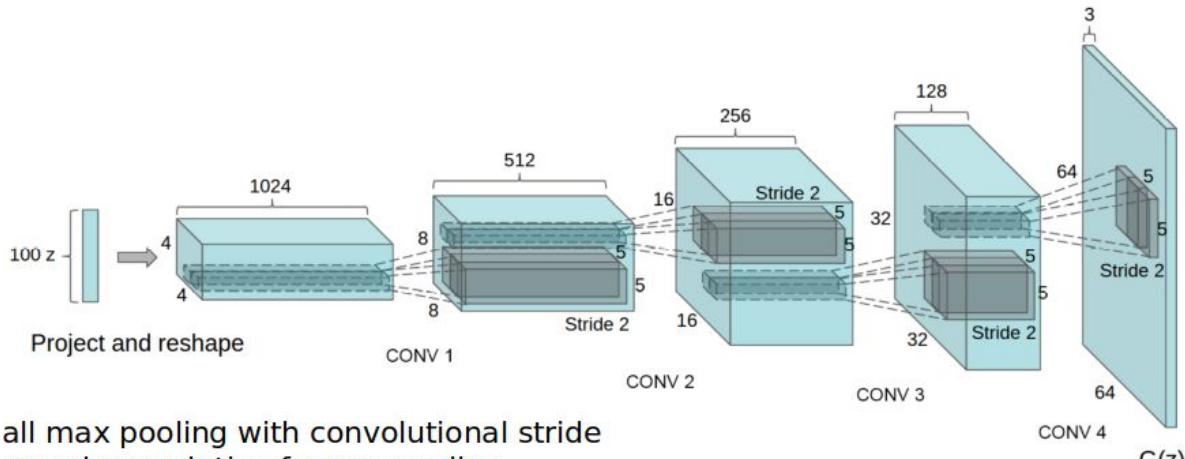
Latent Vector Interpolation

6 6 6 6 6 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
4 4 4 4 2 2 2 2 2 0 0 0 0 0 0 0 0 0 0 0 0 2
9 2 2 2 2 2 2 2 8 5 5 5 5 0 0 0 0 0 0 0 0 2
9 4 2 2 2 2 2 2 3 3 3 3 3 3 0 0 0 0 0 0 0 3
9 9 4 2 2 2 2 2 3 3 3 3 3 3 5 5 5 5 5 5 3 3
9 9 9 4 2 2 2 2 3 3 3 3 3 3 5 5 5 5 5 5 3 3
9 9 9 9 9 2 2 2 3 3 3 3 3 3 5 5 5 5 5 5 3 3
9 9 9 9 9 8 3 3 3 3 3 3 3 5 5 5 5 8 8 7
9 9 9 9 9 8 3 3 3 3 3 3 3 8 8 8 8 8 8 8 7
9 9 9 9 9 8 3 8 8 8 8 8 8 8 8 8 8 8 8 8 7
9 9 9 9 9 8 8 8 8 8 8 8 8 8 8 8 8 8 8 8 7
9 9 9 9 9 8 8 8 8 8 8 6 6 6 6 6 6 5 5 7
9 9 9 9 9 9 8 8 8 8 8 6 6 6 6 6 6 6 5 5 7
9 9 9 4 9 9 9 9 9 5 5 5 6 6 6 6 6 6 6 5 5 7
9 9 4 4 4 4 9 9 9 5 5 6 6 6 6 6 6 6 6 5 5 7
9 9 4 4 4 4 9 9 9 5 5 6 6 6 6 6 6 6 6 6 6 7
9 9 4 4 4 4 9 9 9 5 5 6 6 6 6 6 6 6 6 6 6 7
9 9 9 9 9 7 7 7 1 1 1 1 1 1 1 1 1 1 1 1 1 1
9 9 9 9 9 7 7 7 1 1 1 1 1 1 1 1 1 1 1 1 1 1



Case Study: DCGAN

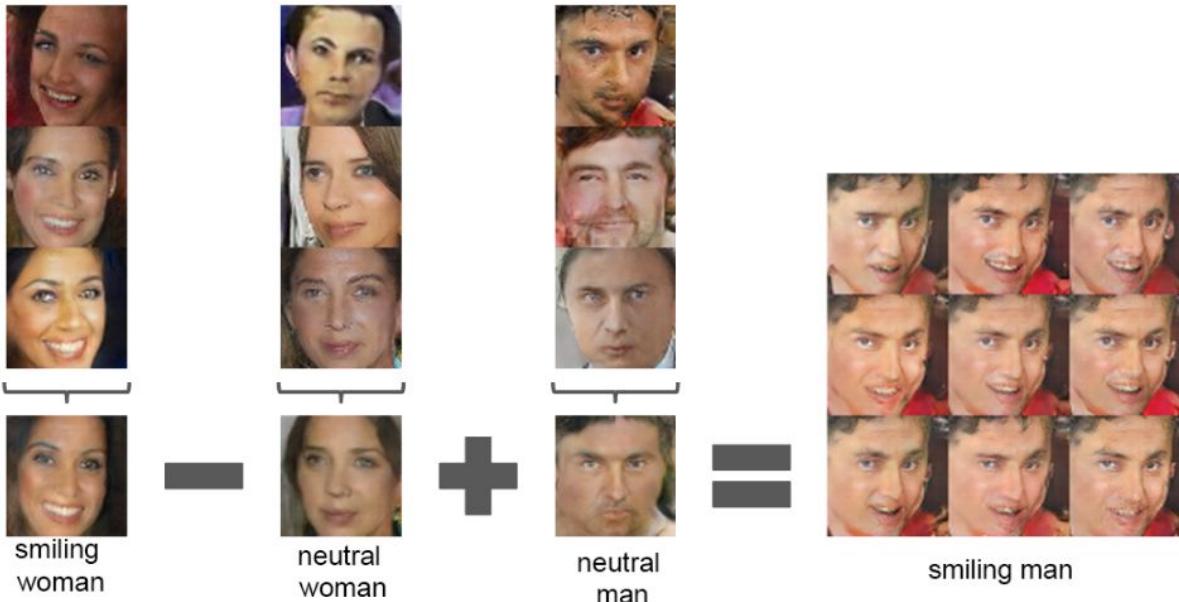
DCGAN: Deep Convolutional Generative Adversarial Network



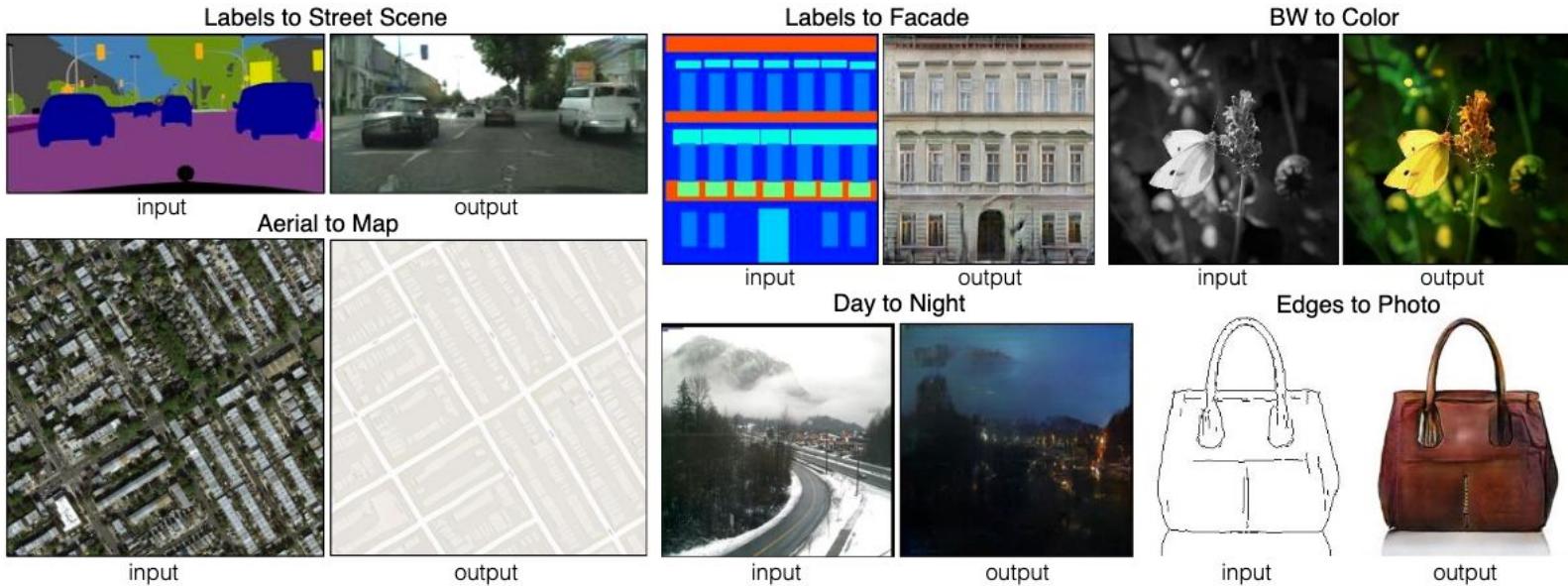
- Replaces all **max pooling** with convolutional stride
- Use transposed convolution for upsampling
- Eliminate fully connected layers
- Use batch normalization except the output layer for the generator
- Use batch normalization for the input layer of the discriminator
- Use ReLU in the generator except for the output (which uses tanh)
- Use LeakyReLU in the discriminator.

Case Study: DCGAN

Latent Space Arithmetic



Case Study: CGAN



Quality of GAN-Generated images

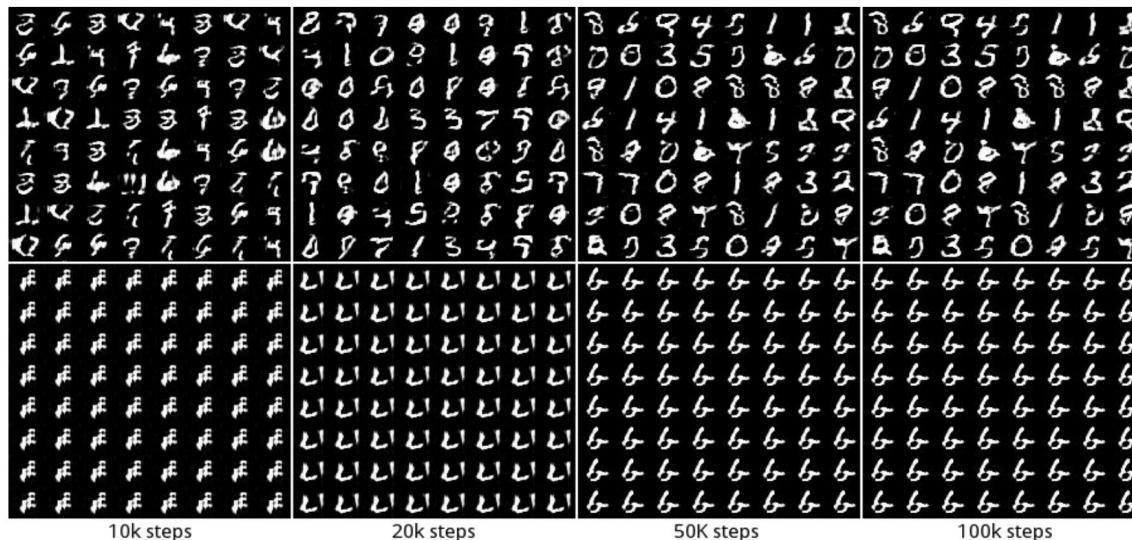


Problems with GANs

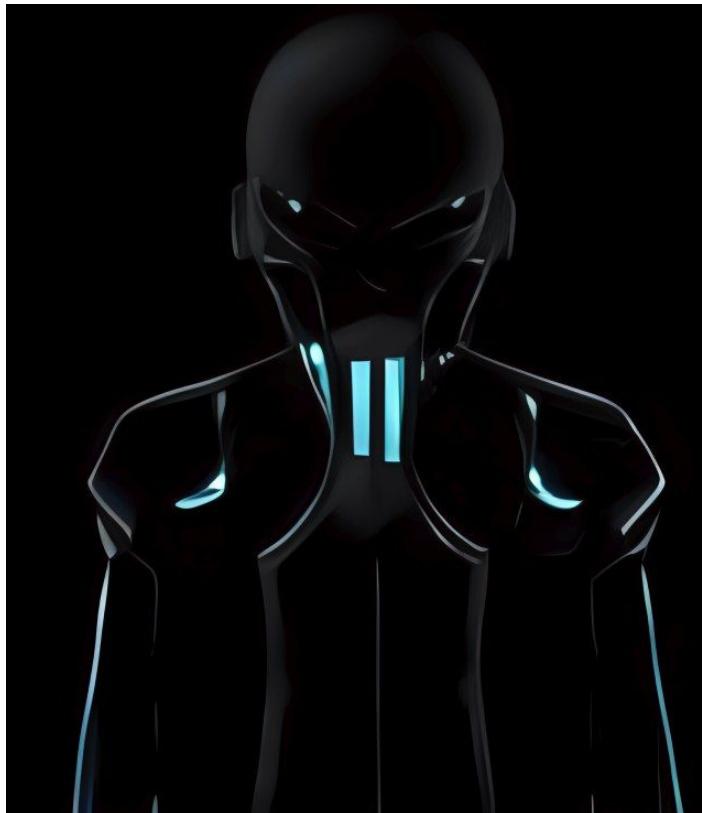
Convergence is not guaranteed: Learning is unstable due to adversarial nature -> no convergence

Mode Collapse: Limited variation learnt

Diminished Gradient: The discriminator is too good telling fake from real \rightarrow the generator learns nothing

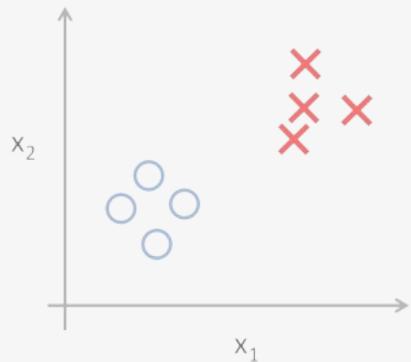


Quality of GAN-Generated images

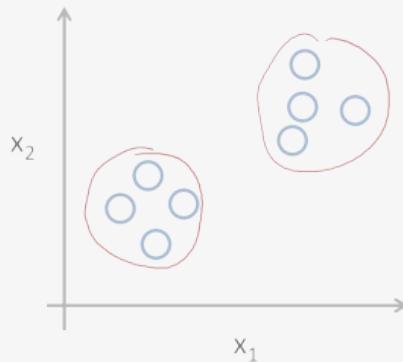


Reinforcement Learning

Supervised



Unsupervised

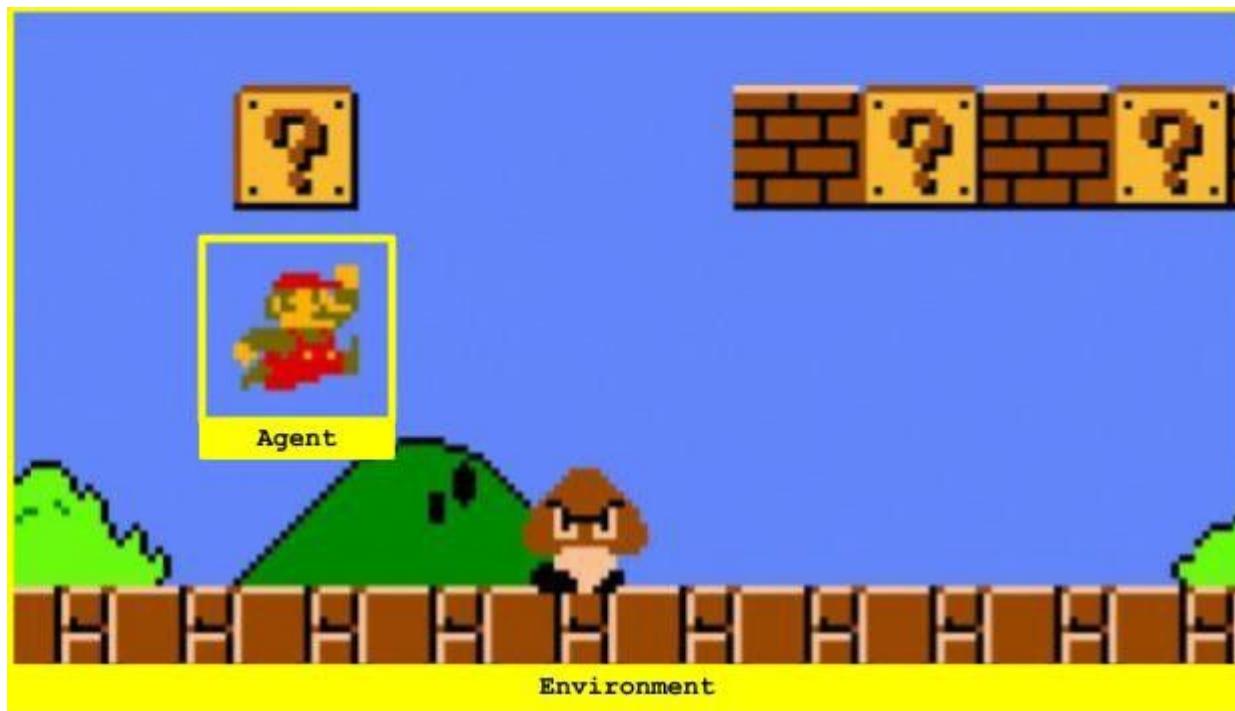


Reinforcement

Learn from mistakes



Agent & Environment

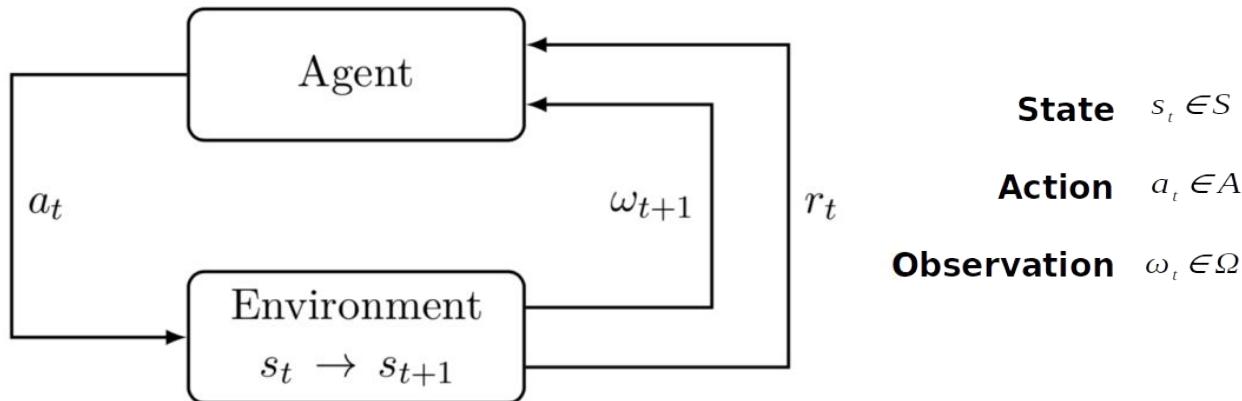


Agent & Environment

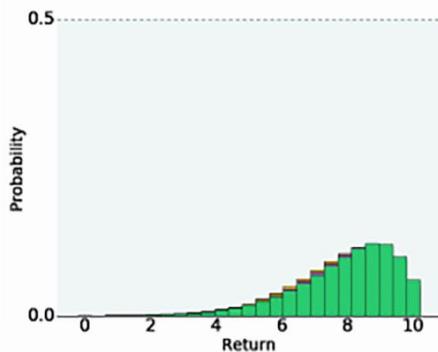
Subset of ML that deals with **sequential decision-making**

Maximize cumulative reward given sequences of actions in an environment

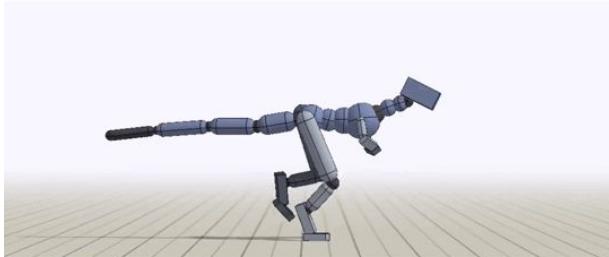
Learn good behaviour through experience



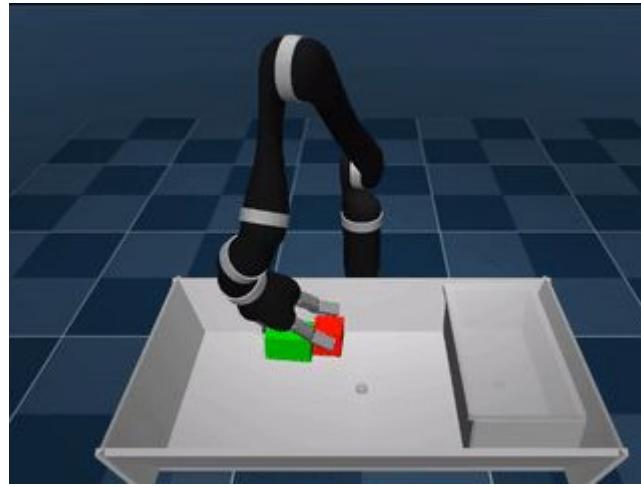
Agent & Environment



T-Rex: Walk



Simulated Character



Agent & Environment



Our World is way too complicated

Reinforcement learning is very promising but has a long way to go