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Walt Disney ANIMATION STUDIOS

JUNE 2020 WEBINAR

Hands-on Workshop: Machine Learning and Neural Networks

SIGGRAPHNOW

RAJESH SHARMA
SOFTWARE ENGINEER
Walt Disney Animation Studios

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Machine Learning

Rajesh Sharma

Today

- Recap
  - Transfer Learning
    - Homework - celebrity match
- Variational Autoencoder
- Generative Adversarial Network

Questions

How can we tweak the weights in the MT-CNN model?

Ganesh Belgur Ramachandra

MT-cnn seems to have problems where the face is rotated. Is that a structured problem with the network or a training problem with the dataset?

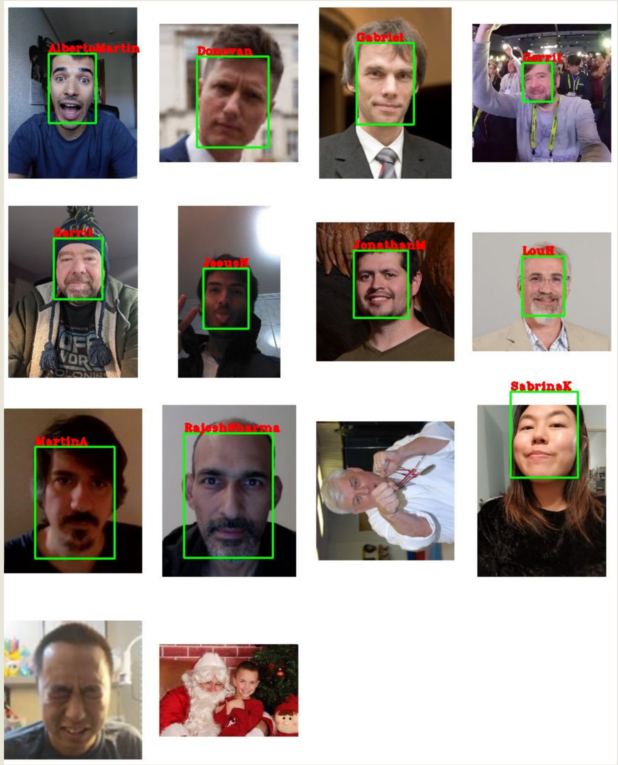
Bobby Bodenheimer

"If your database of faces you can recognize is larger, does that mean you need to do more comparisons? Or can you somehow reduce the amount of faces to compare to?"

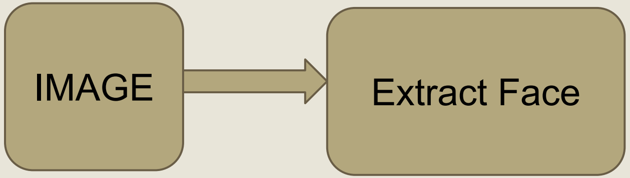
Marijn Eken

Recap: Transfer Learning

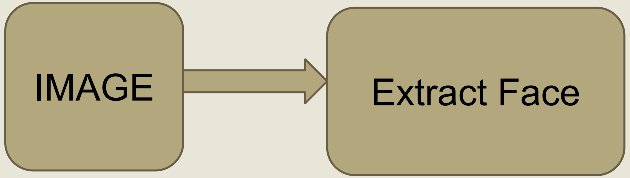
Built a Facial Recognition System

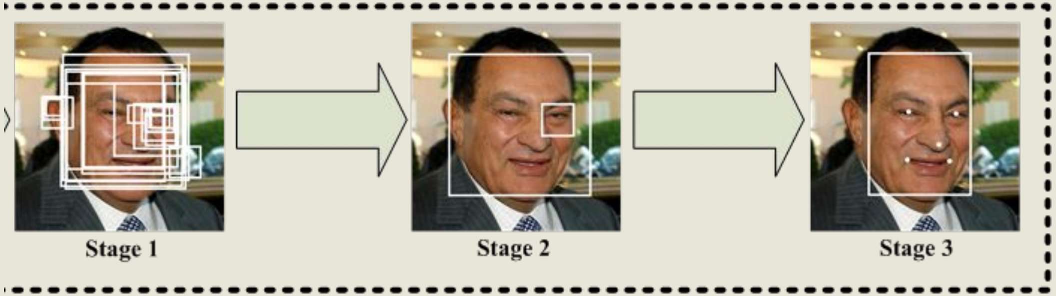


Extracting Faces -- Haar Cascades



Extracting Faces -- Haar Cascades



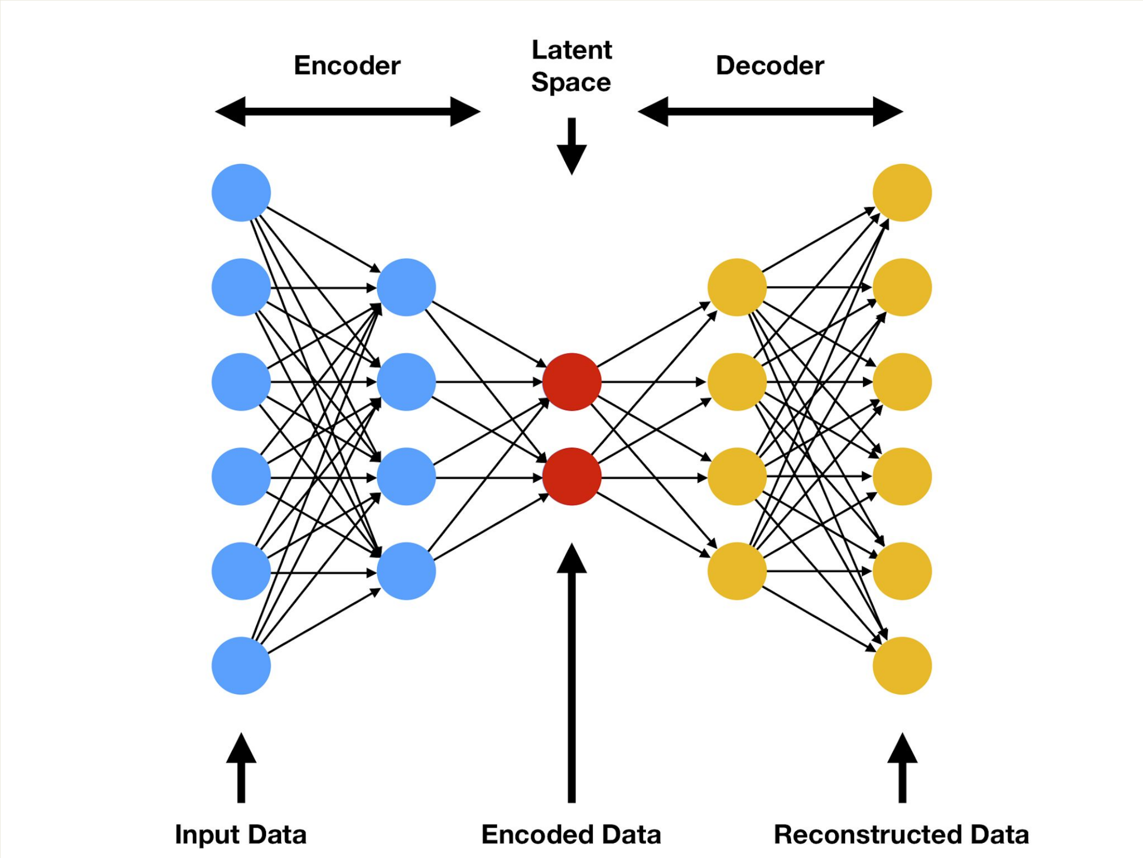


https://arxiv.org/abs/1604.02878, *Zhang et.al mt-cnn*

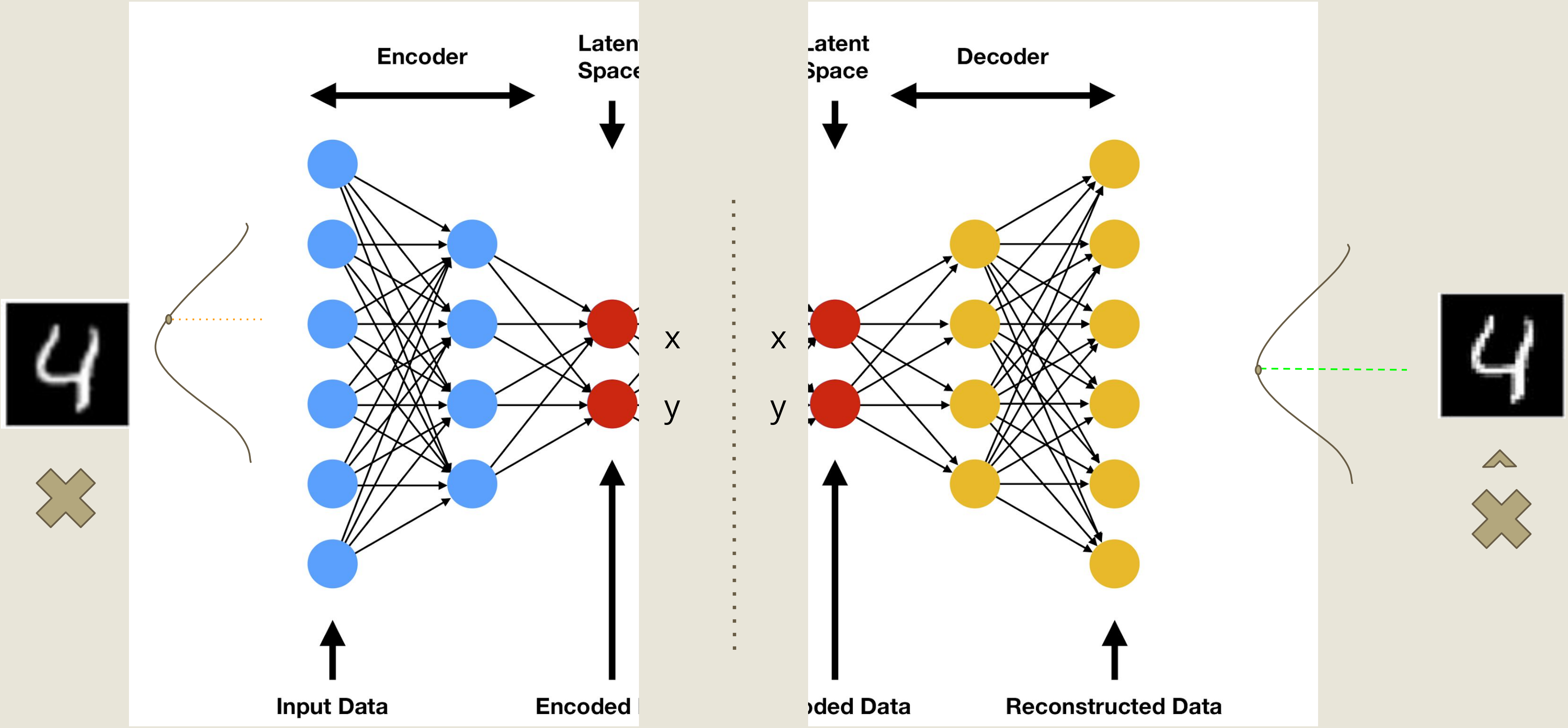
Homework (facialRecognition03Celeb.ipynb)

```
AlbertoMartin
b' Luca_Marin': 59.564%
b' Rodrigo_Santoro': 4.248%
b' Darian_Alvarez': 4.104%

Donovan
b' Maciej_Stuhr': 20.821%
b' Steve_Windolf': 9.195%
b' Dietrich_Bruggemann': 8.932%

Gabriel
b' Cliff_Richards': 6.434%
b' Uday_Chopra': 5.626%
b' Daniel_Gimeno-Traver': 4.730%

ThanhP
b' Teofisto_Guingona_III': 5.069%
b' Hayden_Kho': 3.328%
b' Giorgia_Meloni': 3.065%

Gerrit
b' Toby_Keith': 29.544%
b' Guillaume_de_Tonquedec': 12.076%
b' Jurgen_von_der_Lippe': 4.295%

JesusH
b' Sami_Yusuf': 9.901%
b' Egbert_Jan_Weeber': 6.369%
b' Ismail_YK': 5.618%

JonathanM
b' Clifton_Collins_Jr.': 5.461%
b' Pooja_Bhatt': 4.759%
b' Danny_Gokey': 4.721%

Rajesh
b' Keegan-Michael_Key': 6.683%
b' Stomy_Bugsy': 6.621%
b' Mark_Medlock': 6.309%

LouH
b' Yona_Metzger': 24.793%
b' Ali_Akbar_Salehi': 13.760%
b' Ben_Bernanke': 8.014%

MartinA
b' Vedran_Corluka': 15.950%
b' Alexandre_Pato': 4.681%
b' Brian_Harman': 3.689%

Randi
b' David_Alward': 32.692%
b' Charlie_Weis': 11.711%
b' Les_Dennis': 8.377%

SabrinaK
b' Angelica_Panganiban': 15.201%
b' Gretchen_Barretto': 6.866%
b' Alana_Nichols': 5.128%
```

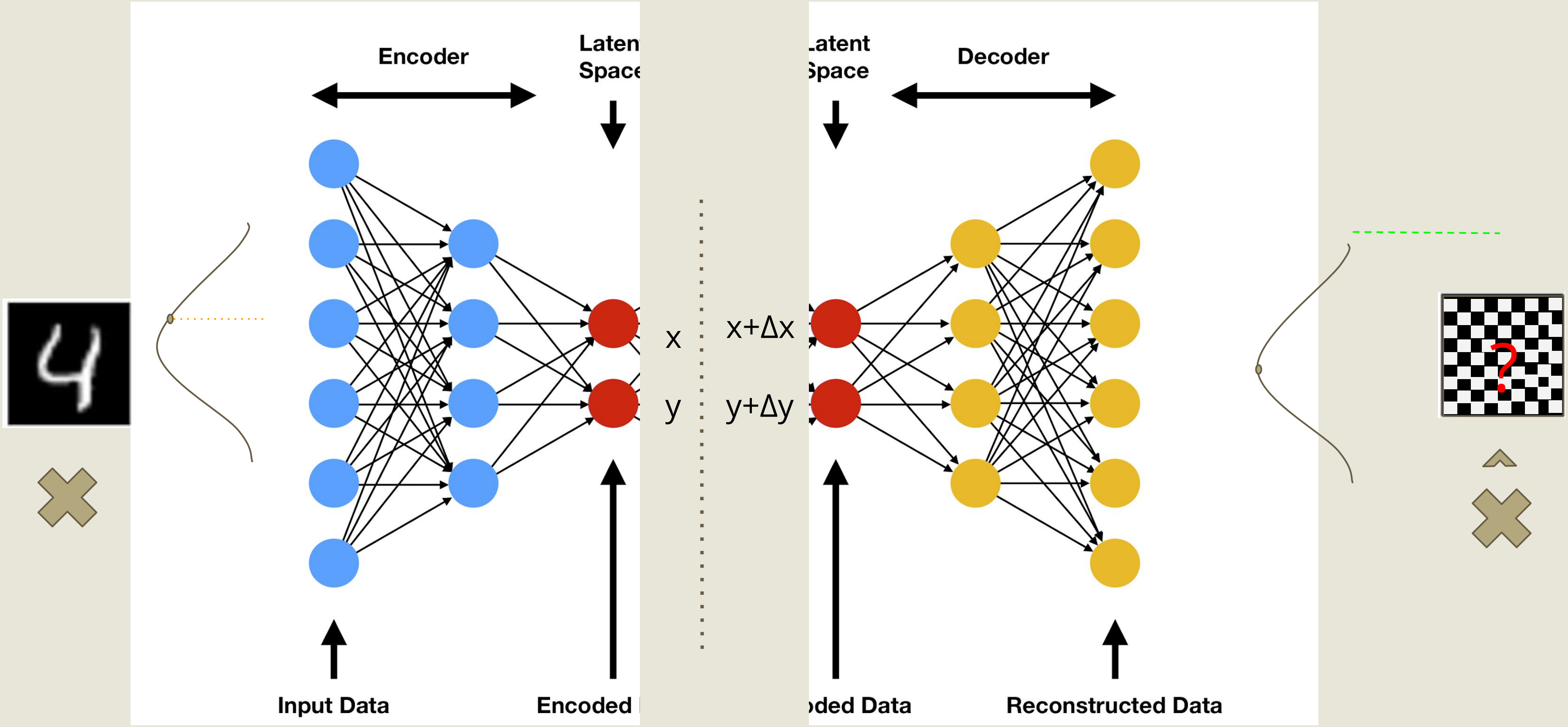
Autoencoder



Autoencoder



Autoencoder - A variation



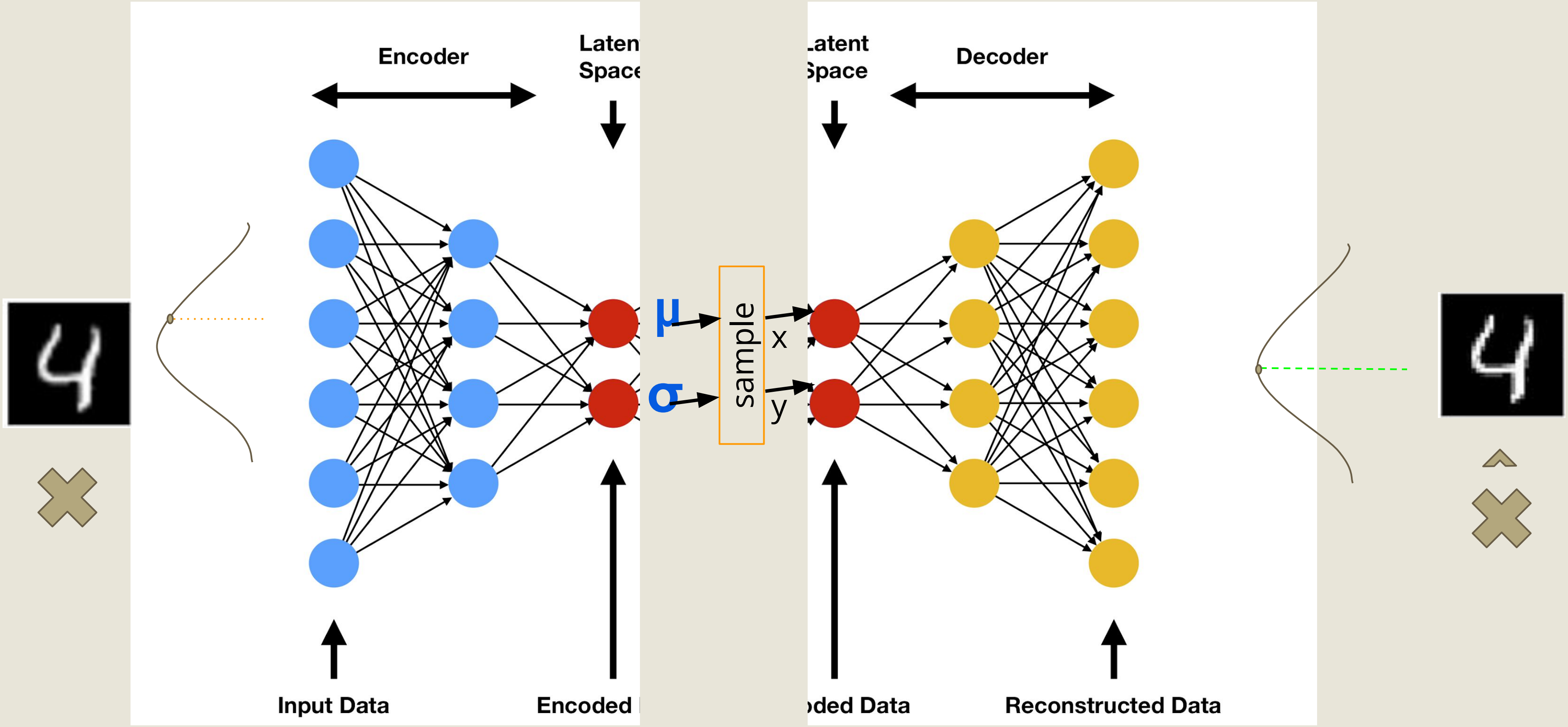
You don't because...

The latent space and the input distributions are *different*!

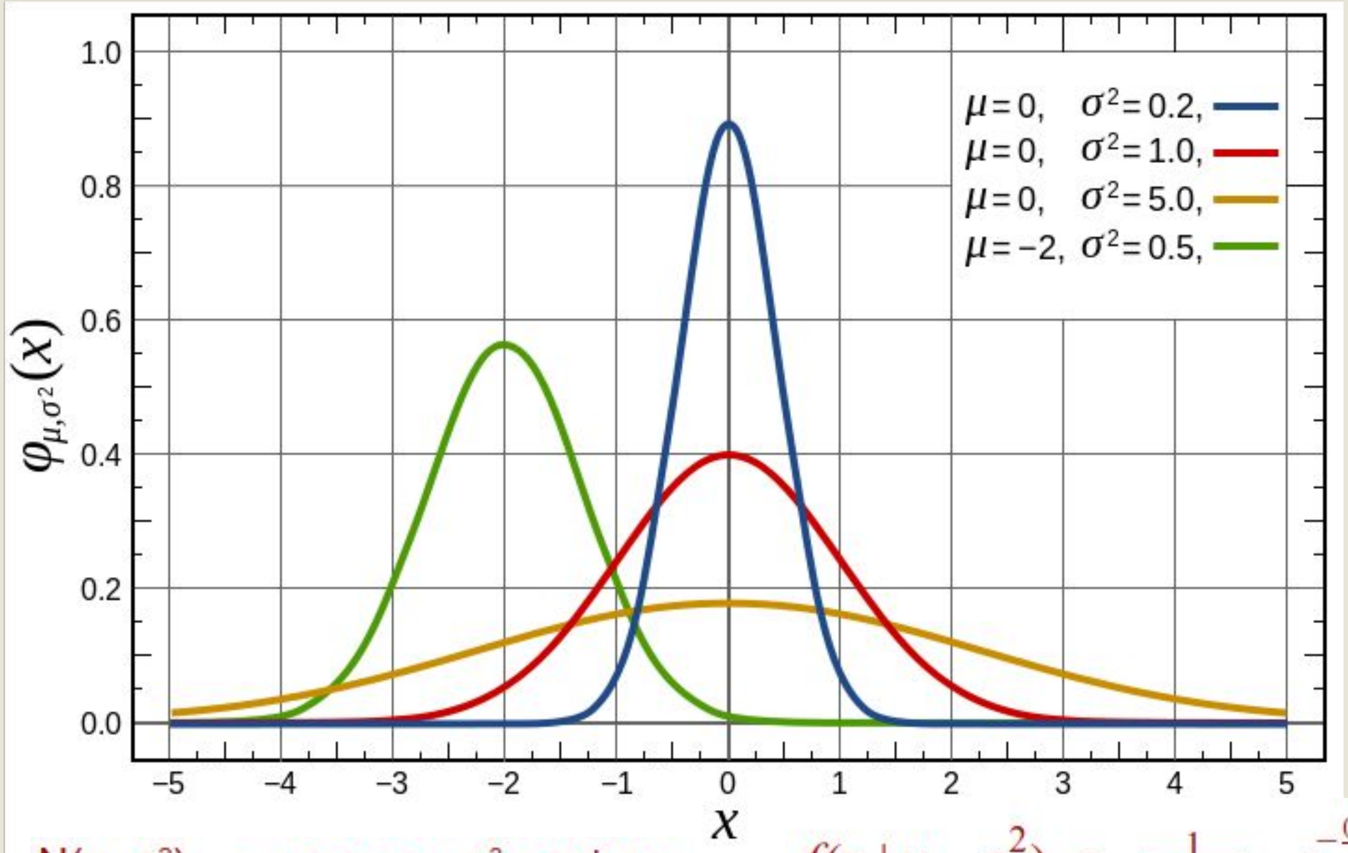
But there is a way:

Treat encoder output as μ and $\boldsymbol{\sigma}$ of a distribution

Variational Autoencoder



You get nice continuous distribution for each input



N(μ, σ²) ; μ - mean , σ² - variance

$$f(x \mid \mu, \ \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Latent Spaces and Embeddings

https://projector.tensorflow.org

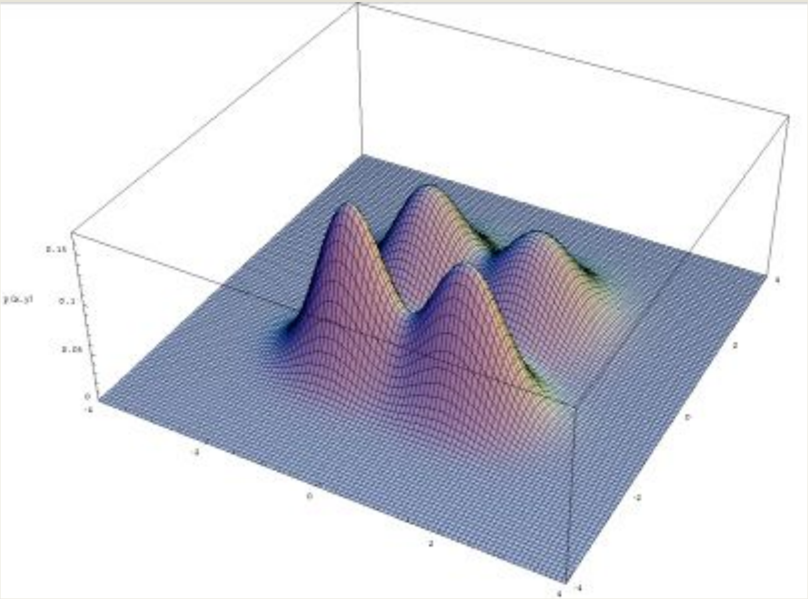
For each input we can generate new 'fake' output!

Moreover, we can interpolate!

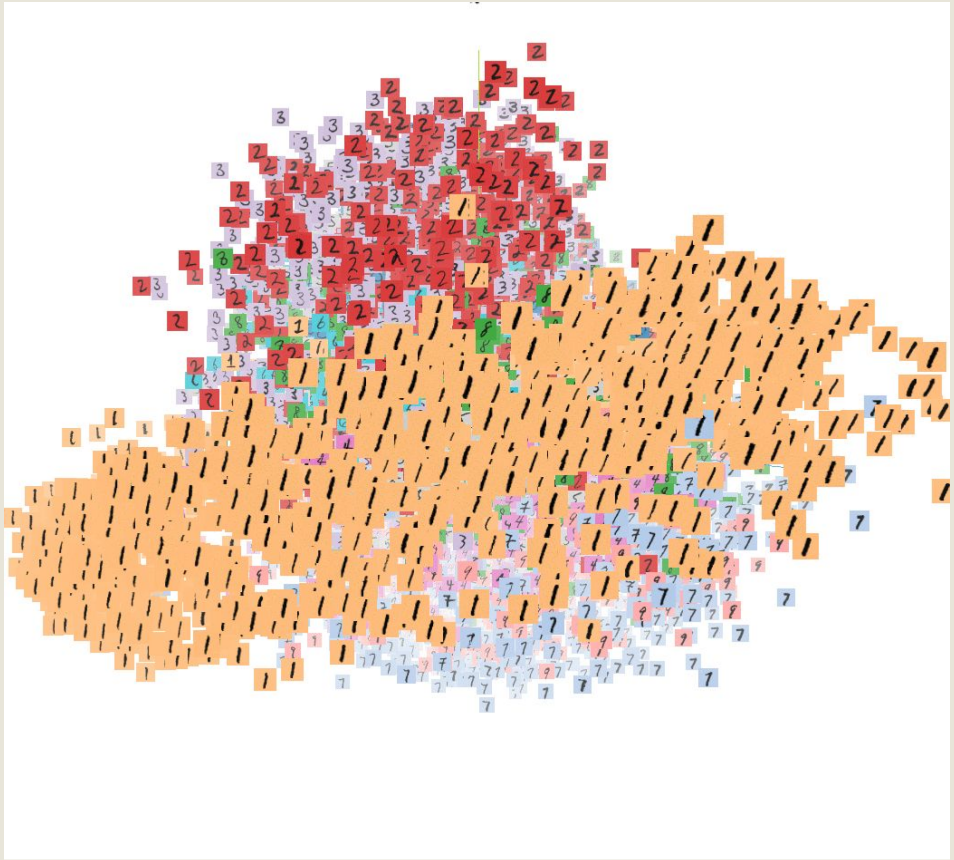
but, we can do even better!

What about the distributions for other inputs?

We can interpolate between distributions



We can interpolate between two (or more) inputs

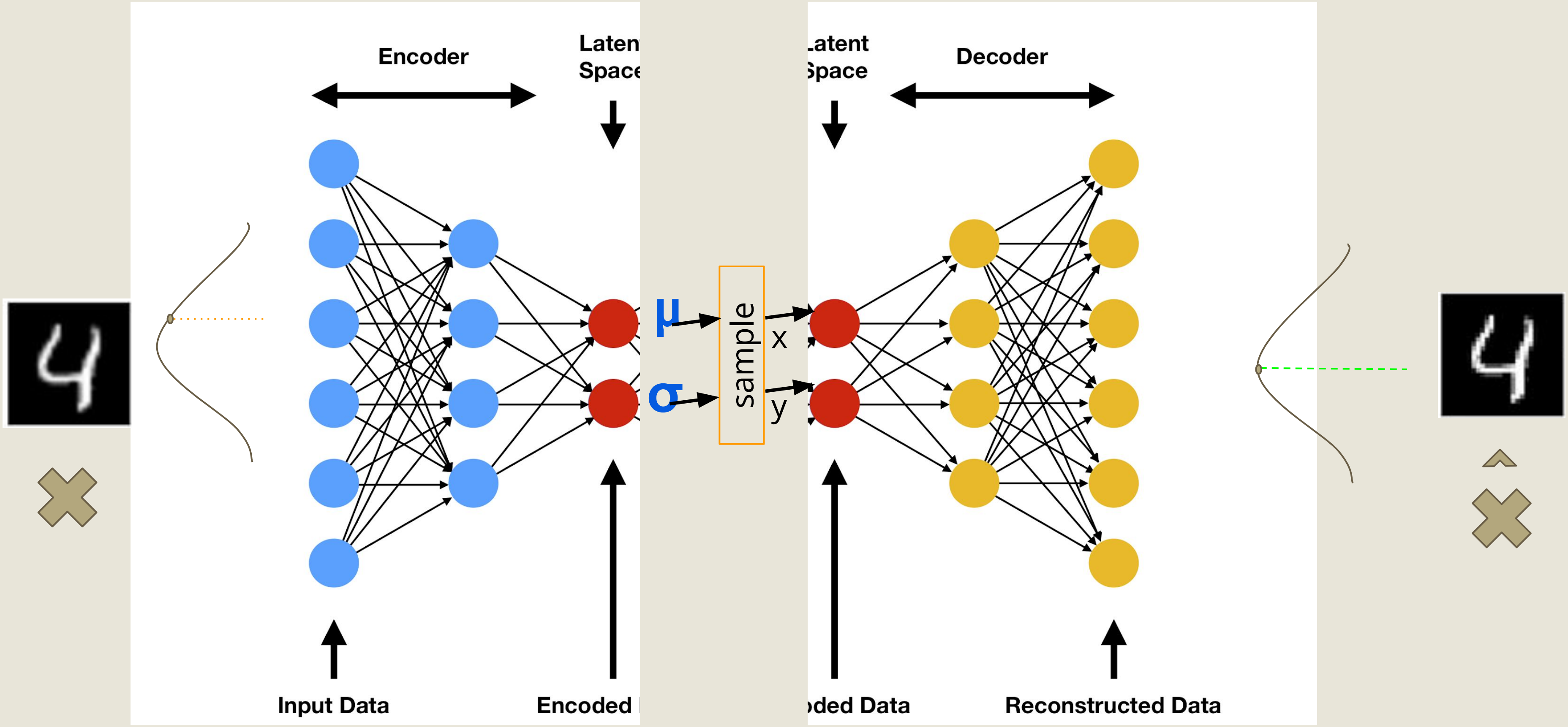


https://projector.tensorflow.org

What are GANs?

..a look back at the Variational Autoencoder

Variational Autoencoder



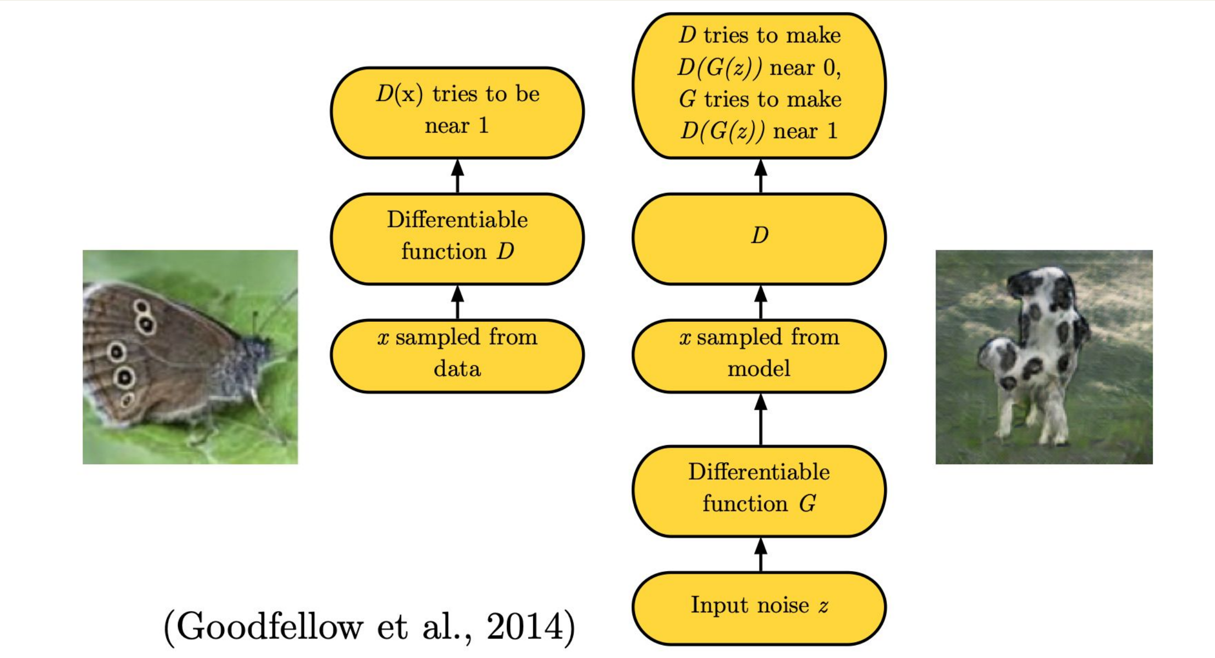
What are GANs?

GANs are similar to variational Autoencoder

Instead of estimating the distribution (var, mean)

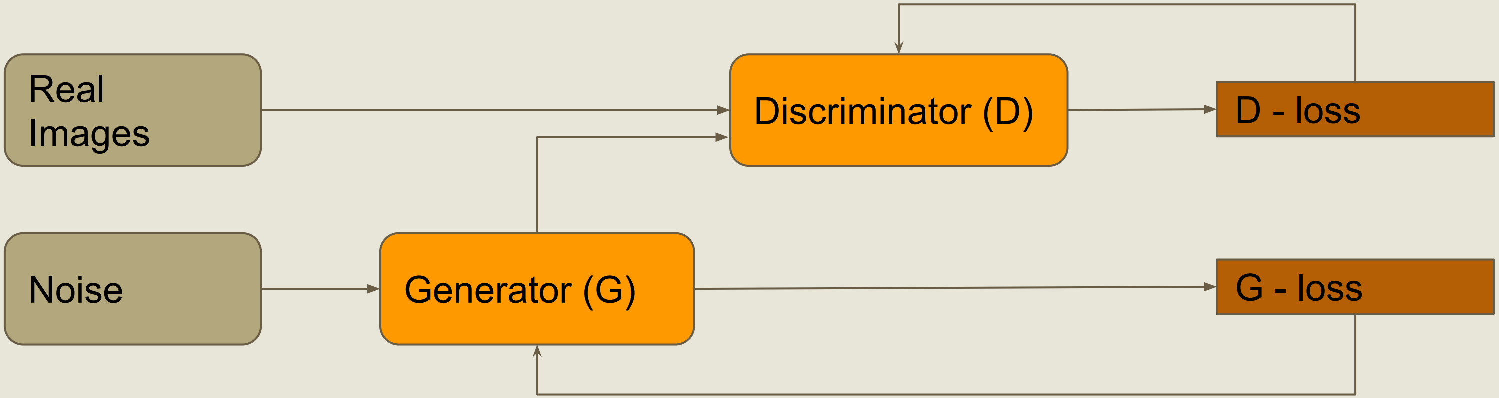
They try to sample from the distribution directly
by generating the sample from noise

• GAN - Generative Adversarial Networks



(Goodfellow et al., 2014)

GAN - Generative Adversarial Networks



GAN training proceeds in alternating periods:

1. The discriminator trains for one or more epochs.
2. The generator trains for one or more epochs.
3. Repeat steps 1 and 2 to continue to train the generator and discriminator networks.
4. Both the generator and the discriminator are neural networks.
5. The generator output is connected directly to the discriminator input.
6. Through backpropagation, the discriminator's classification is used by the generator to update its weights.

Easier to explain by building up an example

Goal: Generate random unseen cat images

Step1: Need a classifier: cat or not

Input: labeled images of cat and not cats

(we did this with iris flowers)

GAN...

Goal: Generate random unseen cat images

Step2: Random image generator

Input: Noise

GAN...

Goal: Generate random unseen cat images

Step3: Hook them up together!

Hands on...

Find and open:

`mnistGAN.ipynb`

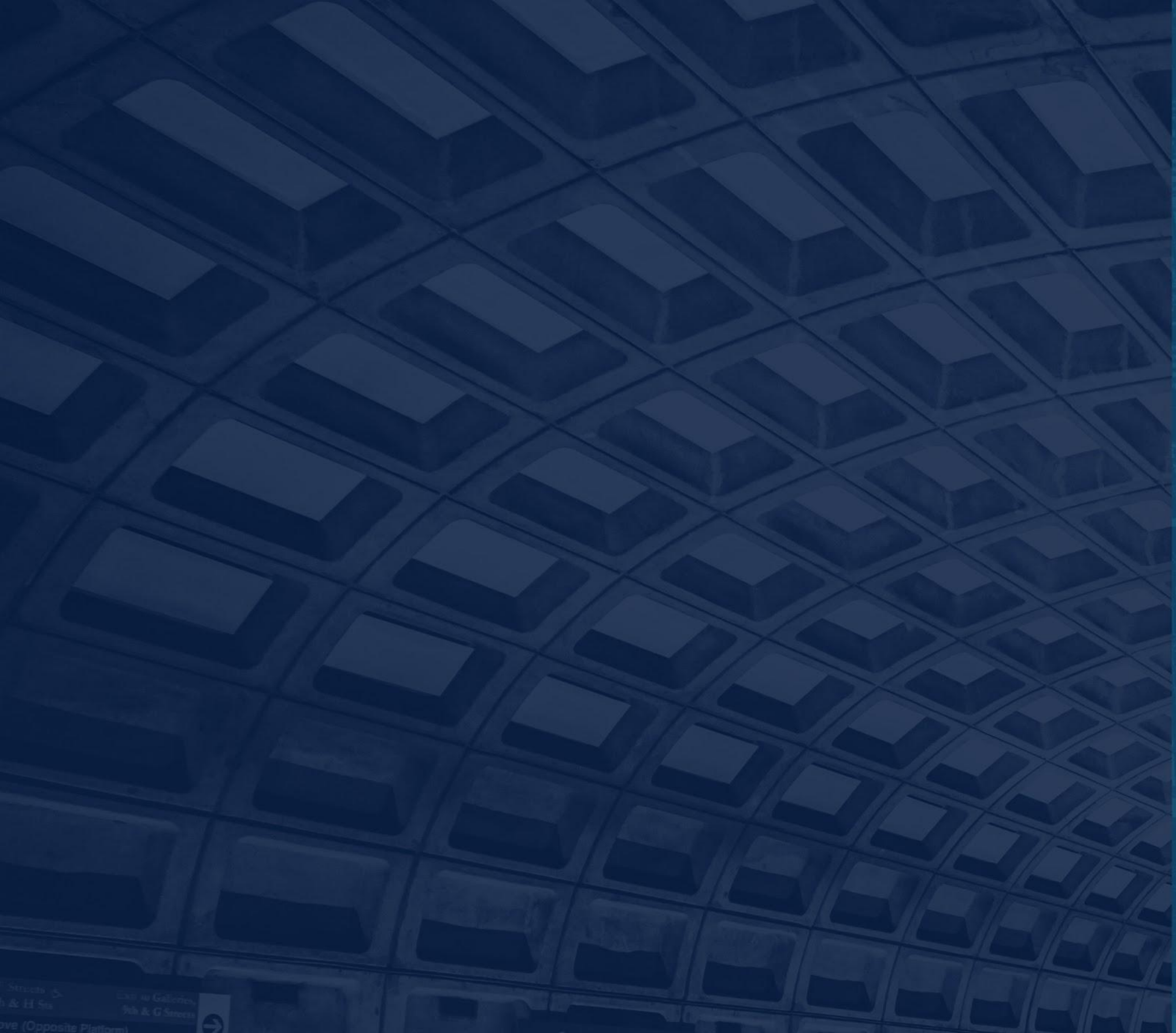
Advanced Examples

GANimals

GauGAN

Next Class

- Exploring Latent Spaces
- Recurrent Neural Networks
- Homework:
  - Take one of the classes of satellite images
  - Using GAN generate images of that class
- @xarmalarma, #siggraphNOW



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QUESTIONS?

Submit now!

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