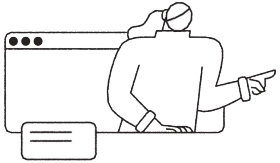
Introduction to Generative Modeling

Women Techmakers
Algiers
International Women's Day 2023

Terminology

- Artificial Intelligence : The Technology in General
- Machine Learning : Classical Statistical Models
- Deep learning : Emphasize on Neural Network Architectures
- ML/ DL Algorithm vs Model :
- Technique , tool , algorithm ...
- Learning : you take data , you input it into an ML technique ,that technique will output a model ,a model means a set of parameters ,
- A simple linear regression technique having the equation y=f(x)= ax+b in general .
- Training : model .fit : Learning parameters from training data : (a,b)
- Testing : model.predict : predicting on unseen data .

Machine & Deep Learning Basics



Raw data

Documents

Images

Numbers

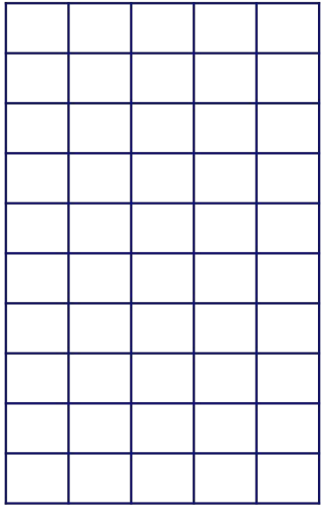
Sounds

●●●

Feature matrix (X)

n_features ⟶

n_samples ⟶



Target (y)

n_samples ⟶

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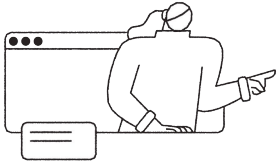
Supervised VS Unsupervised



Supervised Learning

X_1	X_2	X_3	X_p	Y

Target

Un-Supervised Learning

X_1	X_2	X_3	X_p	Y

No Target

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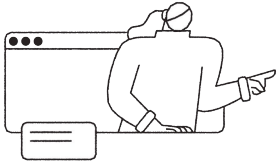
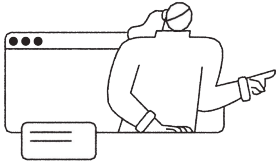
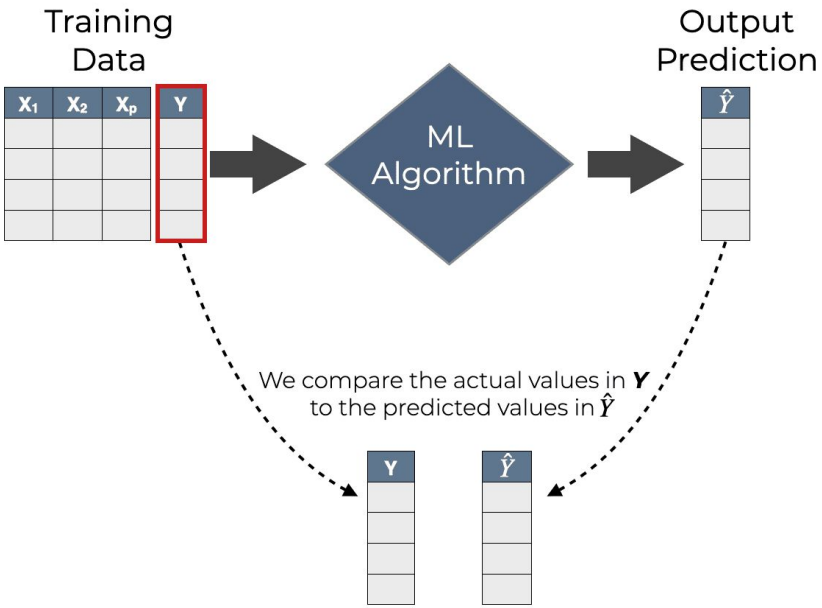


X_1	X_2	X_3	X_p	Y

Here, the target variable Y can "supervise" how the algorithm builds the model



IN SUPERVISED LEARNING, THE TARGET VARIABLE *Y* SUPERVISES THE MODELING PROCESS



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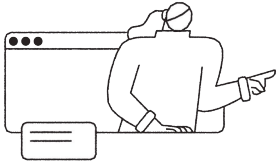
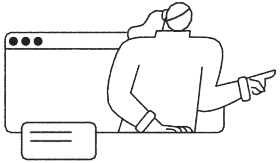


In unsupervised learning,
there *is* a set of input variables

X_1	X_2	X_3	X_p	Y

But, there's no target
variable, Y.

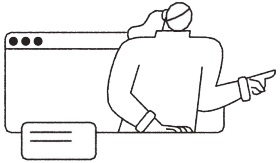
Semi-Supervised Learning



X_1	X_2	X_3	X_p	Y
				✓
				missing
				✓
				✓

Here, some of the values in the target variable Y are missing

Classification VS Regression



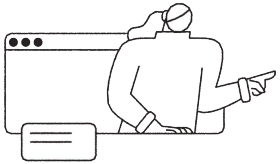
Regression Data

X_1	X_2	X_3	X_p	Y
				5.2
				1.3
				23.0
				7.4

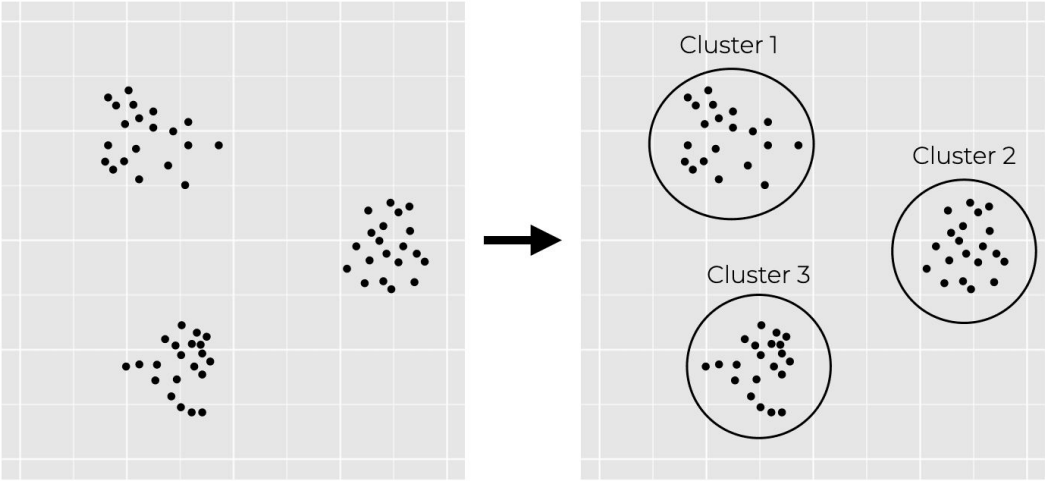
Classification Data

X_1	X_2	X_3	X_p	Y
				cat
				dog
				cat
				cat

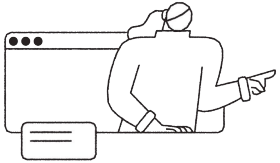
Clustering



Unsupervised Learning Is Often used to Find Structure in Data

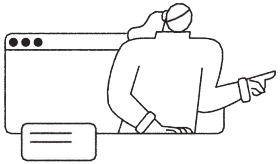


Dimensionality Reduction

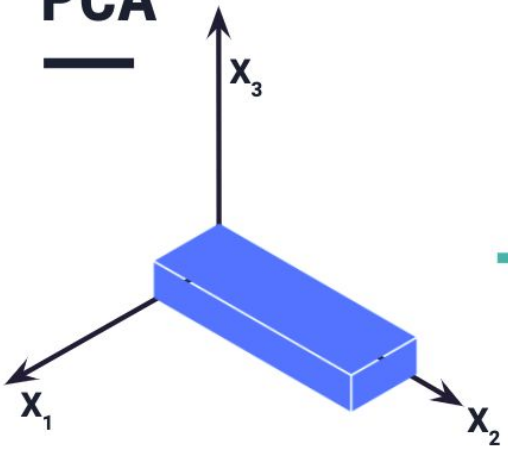


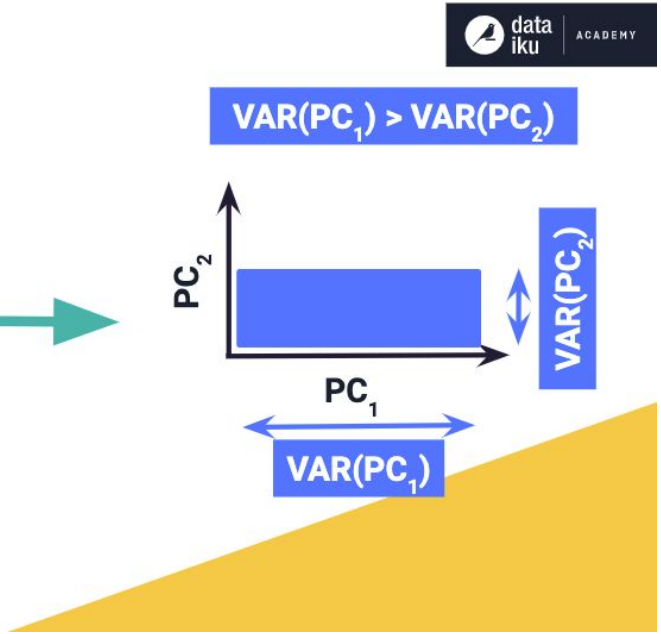
X_1	X_2	X_3	X_p

X_1	X_2



PCA





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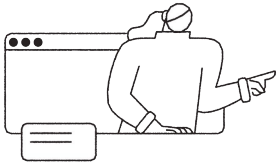
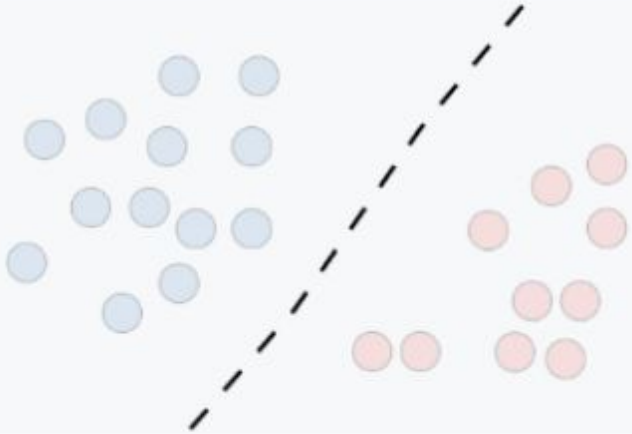
Let’s dive in!

Discriminative Models

- A class of models used in Statistical / ML Classification.



	Discriminative model
Goal	Directly estimate $P(y\|x)$
What's learned	Decision boundary
Illustration	
Examples	Regressions, SVMs

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- A type of Machine Learning / Deep Learning Model .
- Learns how to distinguish between groups or classes.
- They take a set of features and they learn or determine categories or classes .
- They Model the probability of Y knowing X : $P(Y|X)$

Examples of Discriminative Models

- Logistic regression
- Support vector machines(SVMs)
- Traditional neural networks
- Nearest neighbor
- Decision Trees and Random Forest

Generative Models

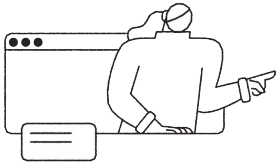
- Generative models are considered a class of statistical models that can generate new data instances.

- They try to make a realistic representation of some noisy input.
- Images can be generated, and text, and Numerical data.
- They try to capture the probability distribution of X, a set of features, knowing or not a Y class.P(X|Y)
- Example: A generative model that is trained on a collection of images to be able to generate similar images.

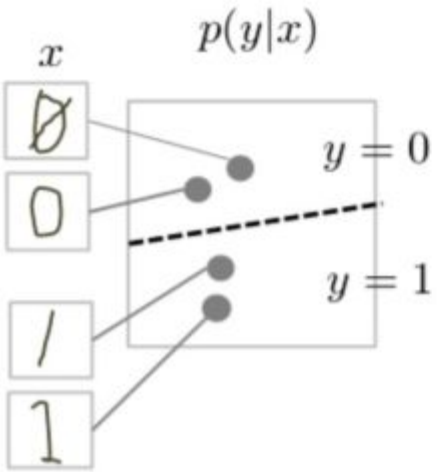
- A generative model can model a distribution ($P(X|Y)$) by producing convincing "fake" data that looks like it's drawn from that distribution.

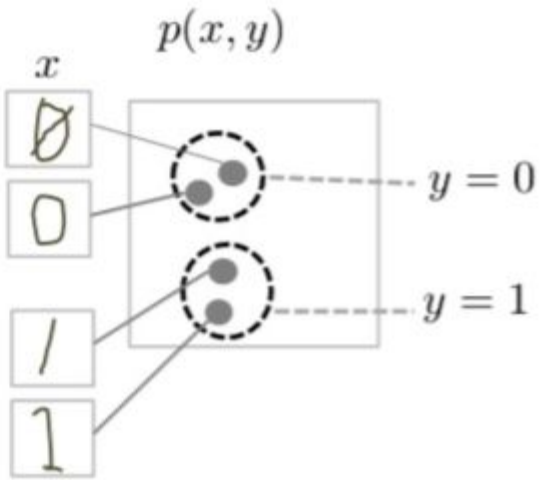
Examples of Generative Models

- Naïve Bayes
- Bayesian networks
- Markov random fields
- Hidden Markov Models (HMMs)
- Latent Dirichlet Allocation (LDA)
- Generative Adversarial Networks (GANs)
- Autoregressive Model



- Discriminative Model
- Generative Model

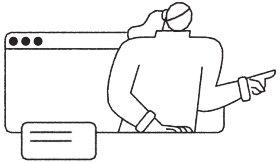




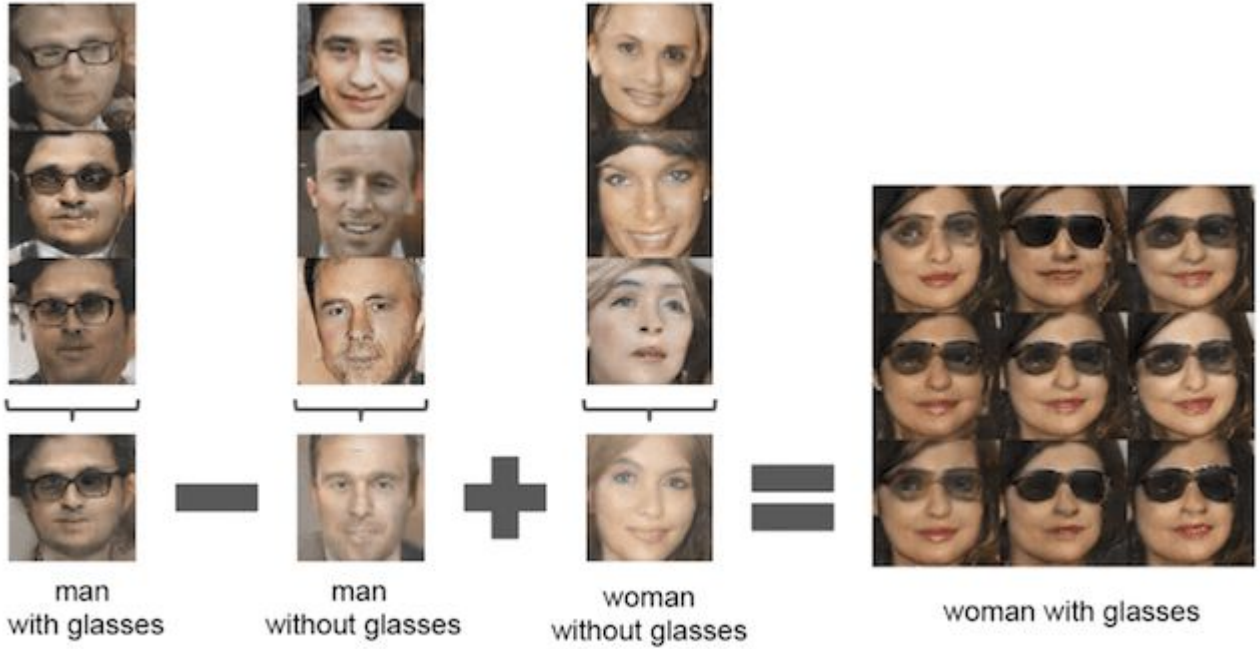
- The discriminative model tries to tell the difference between handwritten 0's and 1's by drawing a separating line in the data space.
- If it gets the line right, it can distinguish 0's from 1's without ever having to model exactly where the instances are placed in the data space on either side of the line.

- The generative model tries to produce convincing 1's and 0's by generating digits that fall close to their real counterparts in the data space.
- It has to model the distribution throughout the data space.

Why generative Models



Generate Examples for Image Datasets



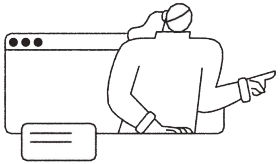
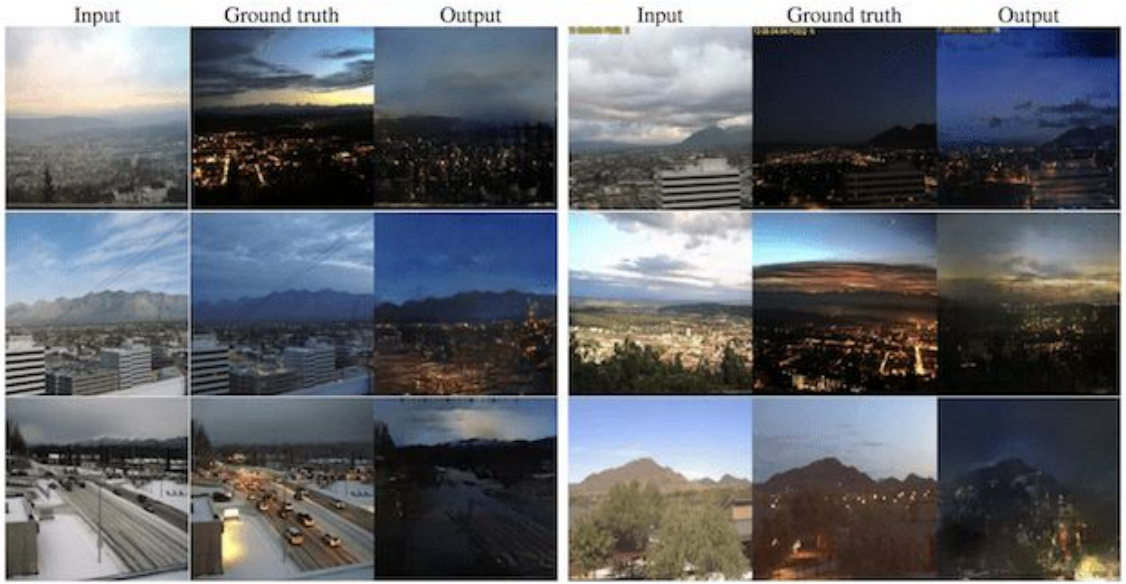
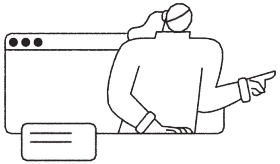
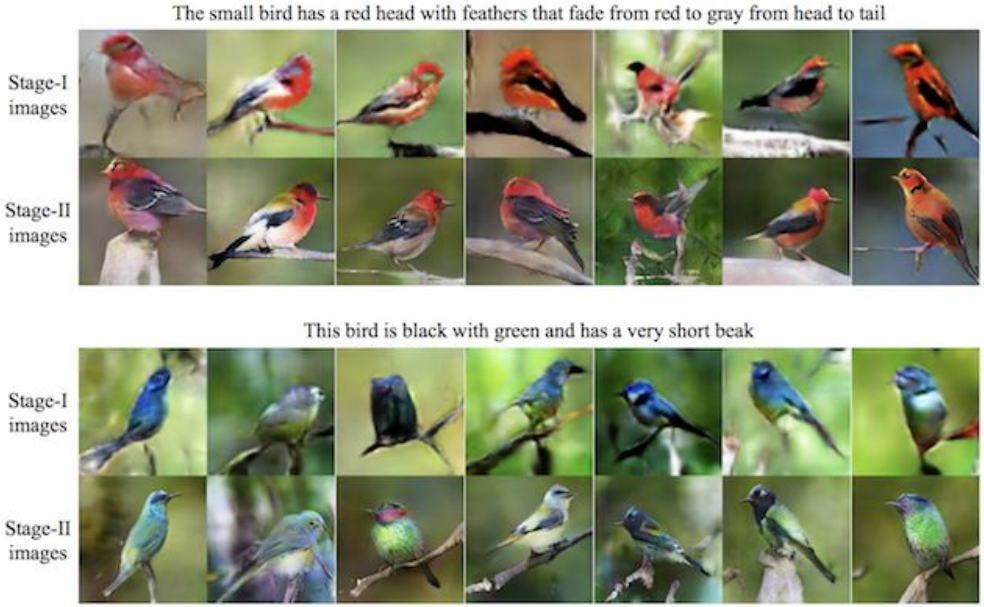


Image-to-Image Translation





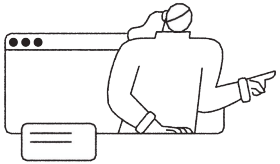
Text-to-Image Translation

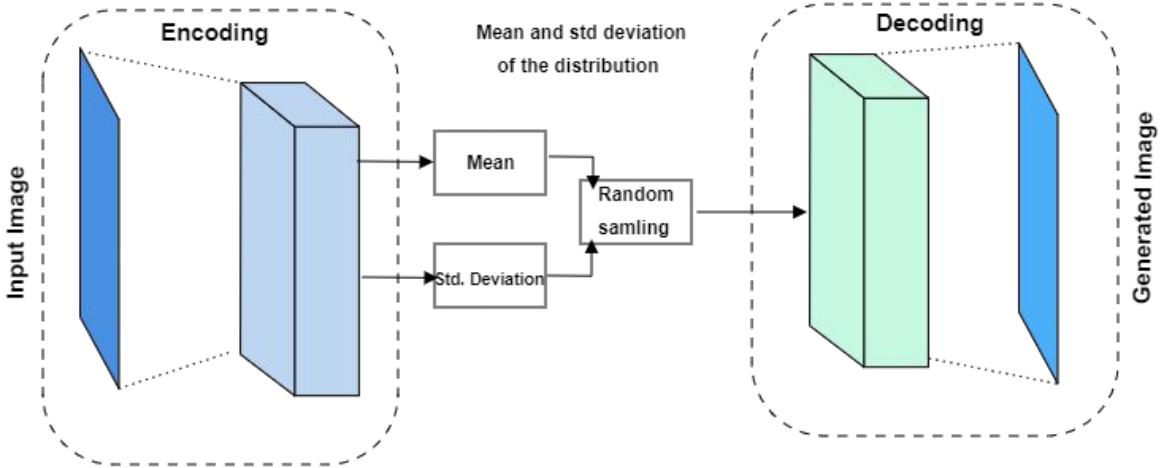


- Generate Synthetic and Tabular Data for imputation
- Generate Healthcare Data
- Generate New Drug Designs and Substances (Medicines).
- Generate Environments for Robot Perception
- ...

Architectures

AutoEncoders





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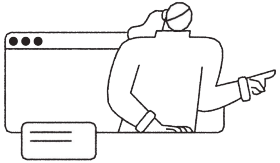
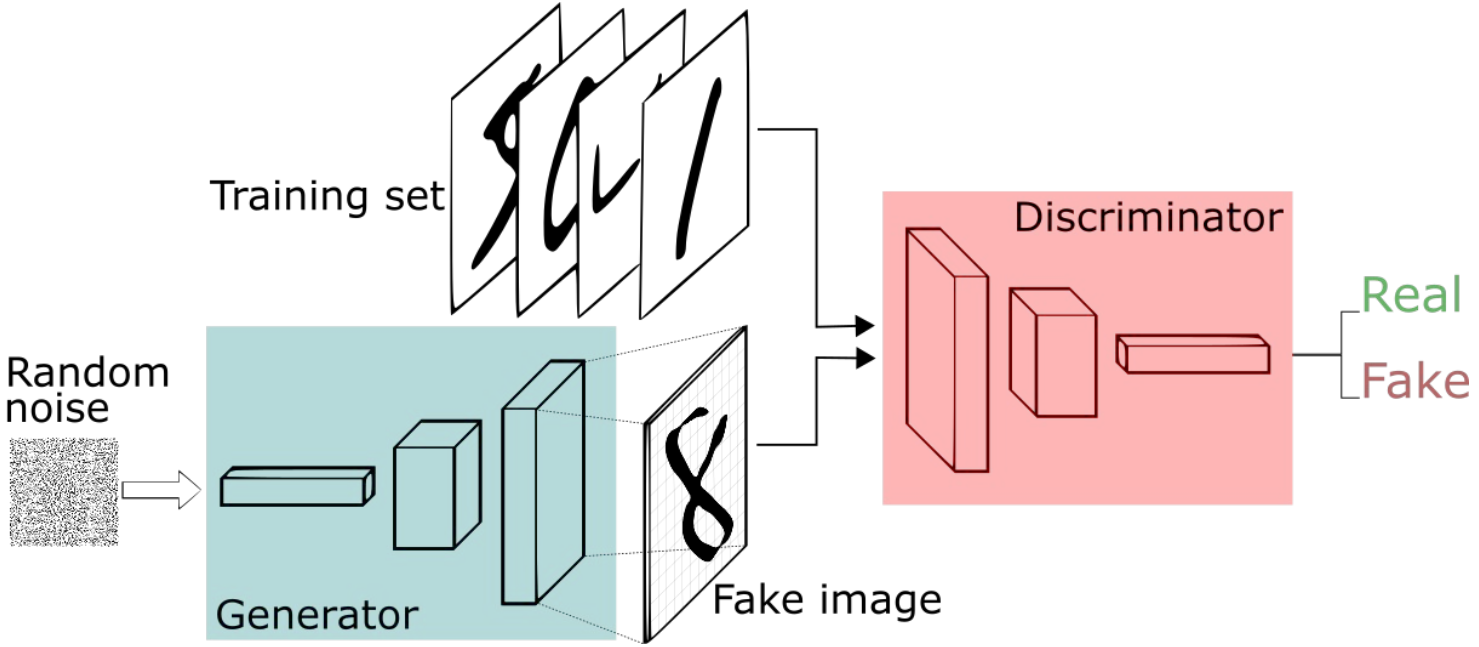
- VAE’s work with two models which are neural Networks.
- They learn by feeding realistic images to the encoder, then the encoder learns the best way to represent that image in a latent space.

- VAE takes a latent representation and puts it into a decoder.
- Decoder: tries to reconstruct the representation that was an output of the encoder.

- The encoder encodes the image into a distribution from which values are sampled to be fed into the decoder.
- After training, we log off the encoder, pick latent points from latent space and decode them into new images.
- This is done through the decoder which would have learned how to decode well.

Generative Adversarial Networks





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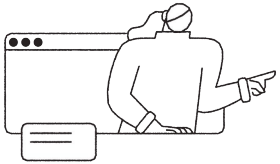
Intuition behind GANs

- GANs Learn to produce realistic objects that are hard to distinguish from real existing ones.
- They are composed of two models which learn by competing with each other Generator and Discriminator.
- Generator takes as input some random noise and produces a fake output (image for example).
- Discriminator learns to differentiate between real data and fake ones



Generator learns to make *fakes* that look **real**

Discriminator learns to distinguish **real** from *fake*

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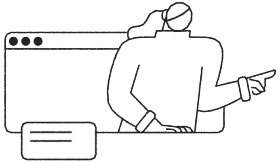

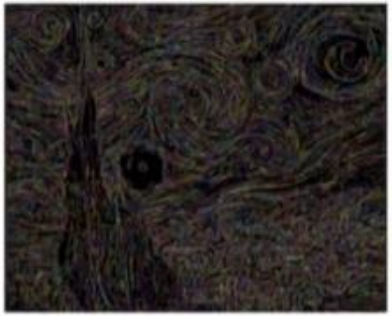

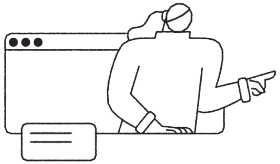

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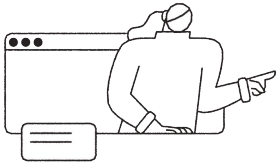
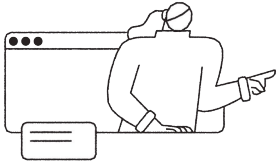


Generative Adversarial Network

Discriminator learns to distinguish real from *fake*

Fake

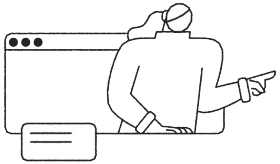
Real

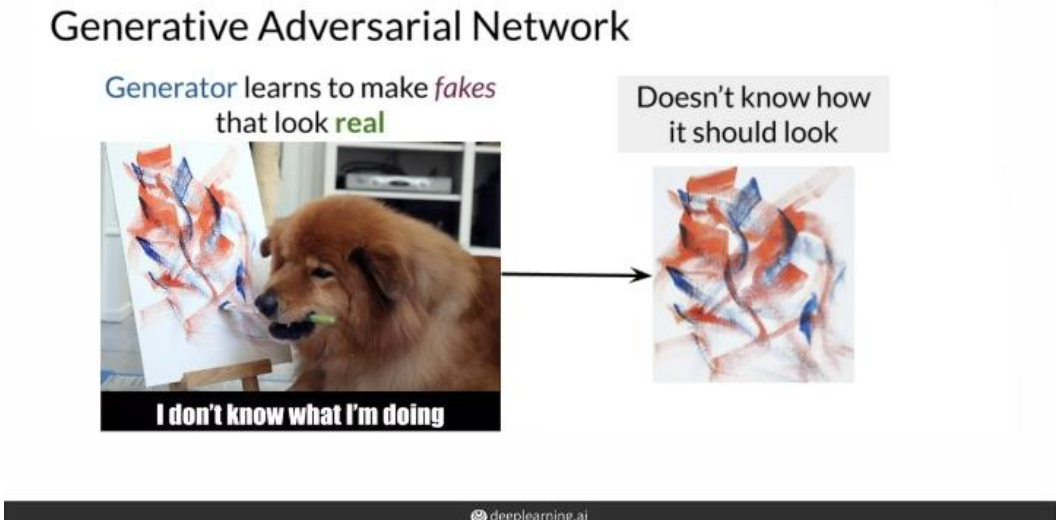


Generative Adversarial Network

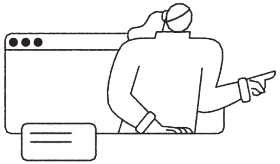
Generator learns to make *fakes* that look **real**

Discriminator learns to distinguish **real** from *fake*




Generative Adversarial Network
Generator learns to make *fakes* that look **real**
I don't know what I'm doing
Doesn't know how it should look
deeplearning.ai

Generative Adversarial Network
Discriminator learns to distinguish
real from fake
I don't know what I'm doing, either
deeplearning.ai



The Game Is On!

5% Real

40% Real

80% Real

deeplearning.ai

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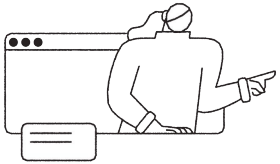
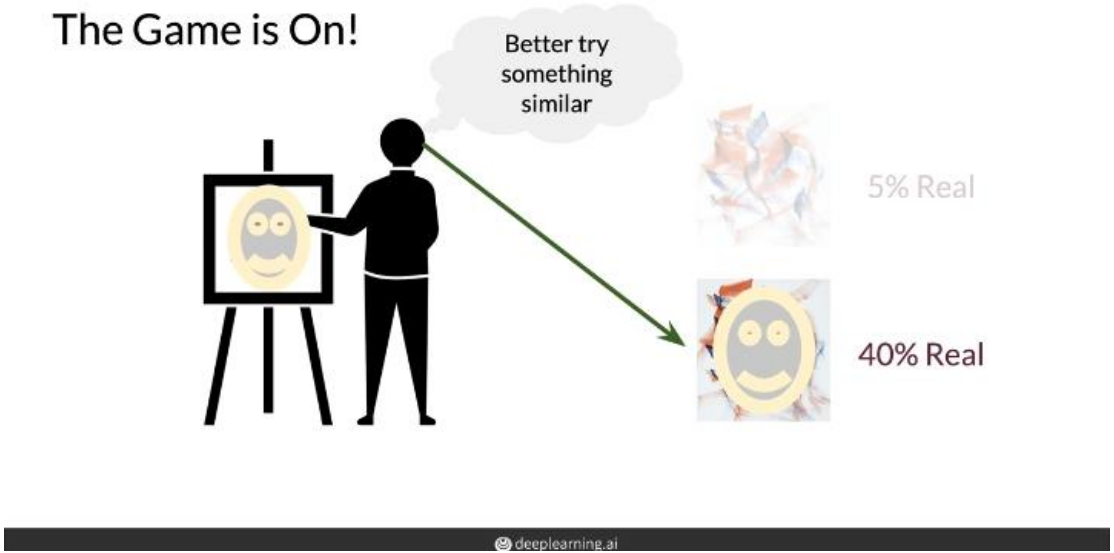
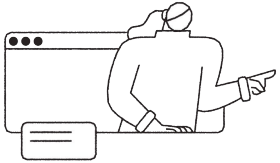
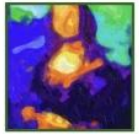



The Game is On!
Better try something similar
5% Real
40% Real
deeplearning.ai



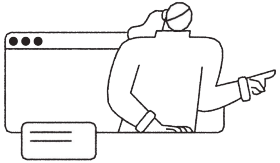
The Game Is On!

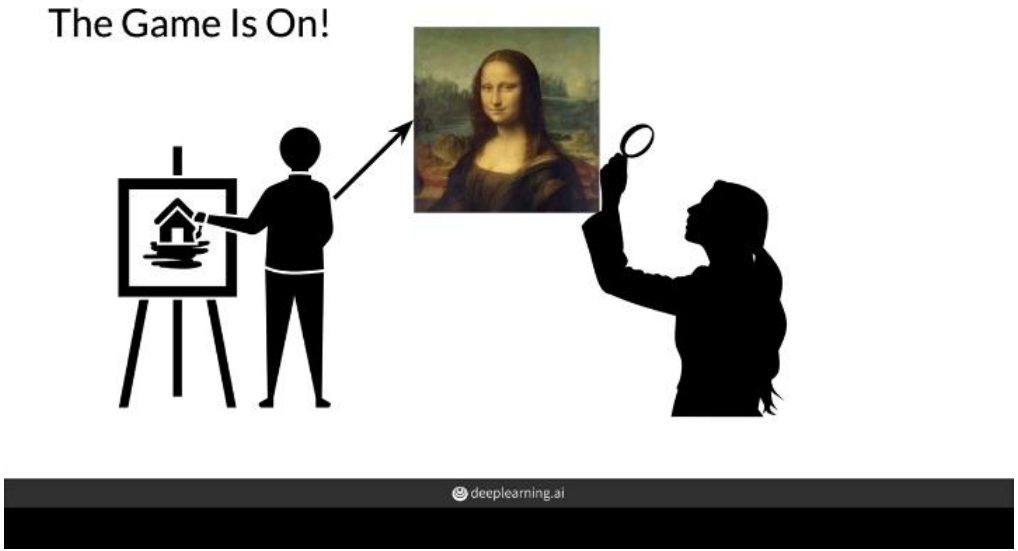
30% Real



60% Real

95% Real





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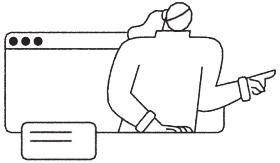
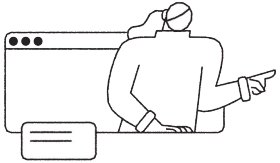


International Women's Day 2023

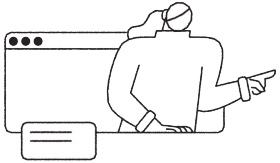


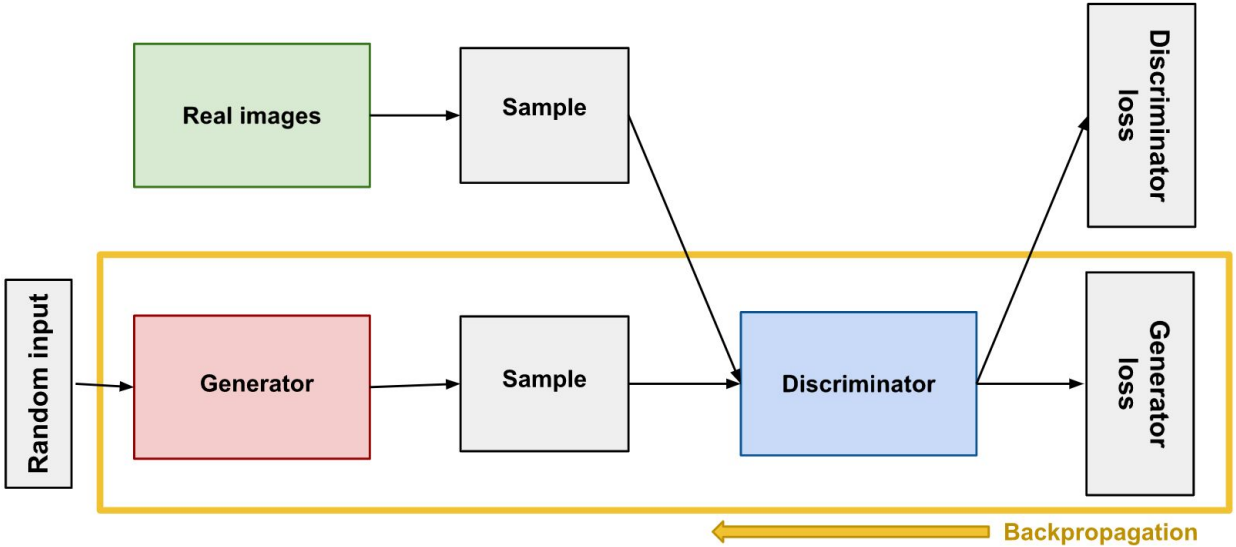
The Game Is On!

Adversaries ?

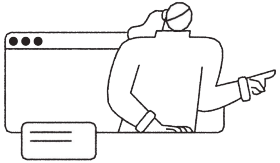
GANs learn by making a Discriminator and A Generator Compete with each other .

Training a GAN

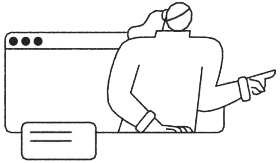




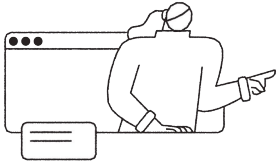
International Women's Day 2023



When training begins, the generator produces obviously fake data, and the discriminator quickly learns to tell that it's fake

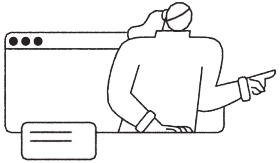


As training progresses, the generator gets closer to producing output that can fool the discriminator:



A good GAN is one in which the Generator is good enough at creating forged reals and the Discriminator is bad enough in classifying these generated images by a Generator .

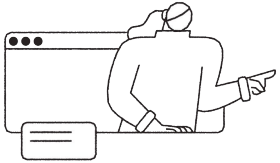
REAL REAL



As training progresses, the generator gets closer to producing output that can fool the discriminator:

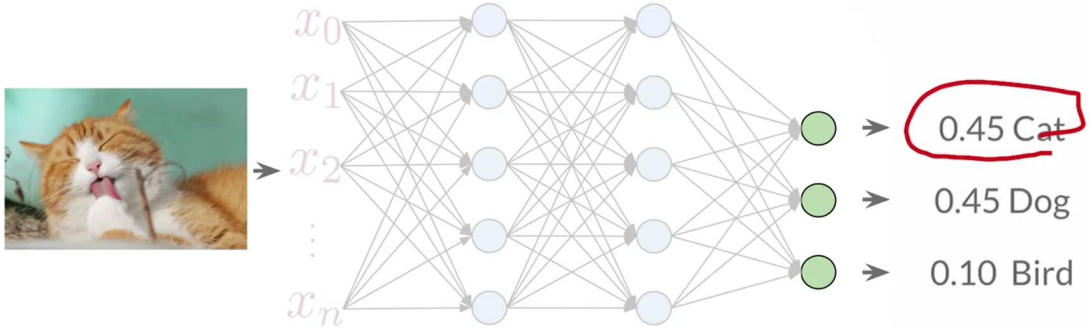
- Both the generator and the discriminator are neural networks.
- The generator output is connected directly to the discriminator input.
- Through backpropagation, the discriminator's classification provides a signal that the generator uses to update its weights.

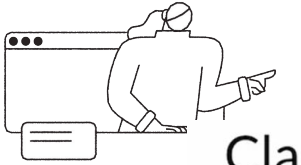
Training a Discriminator



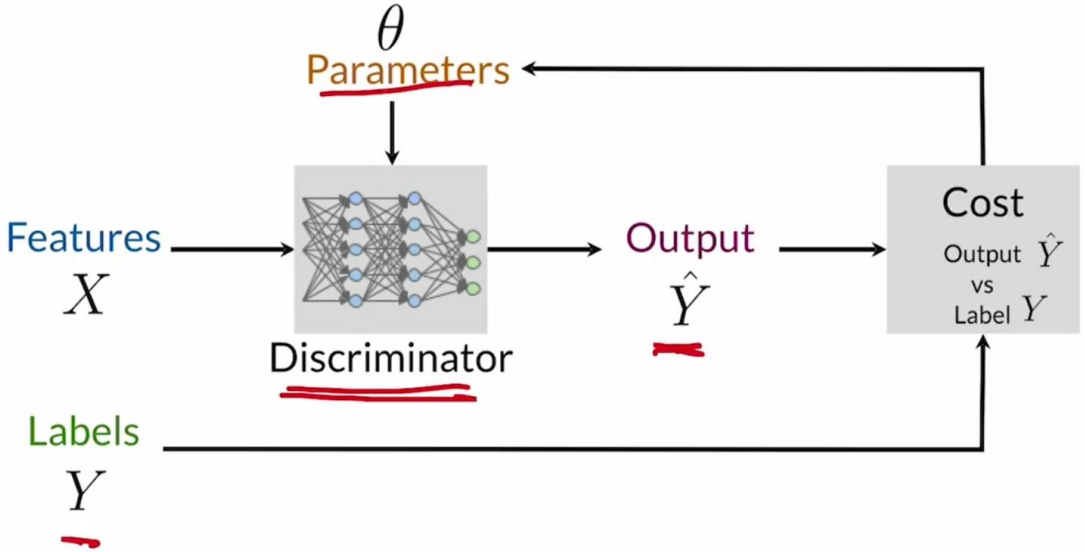
- Discriminators are Neural Net Classifiers.

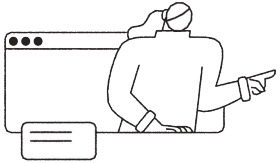
Neural Networks

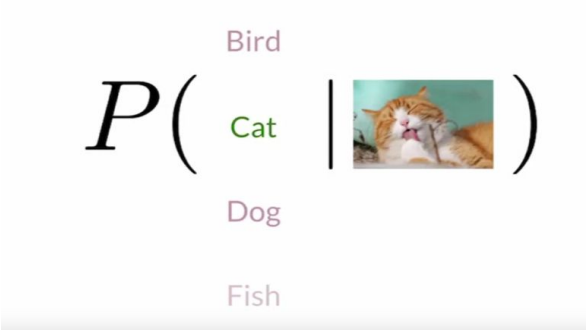




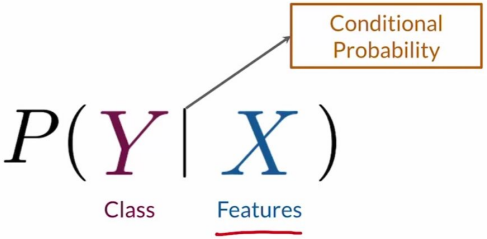
Classifiers (training)







Classifiers



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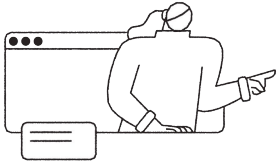
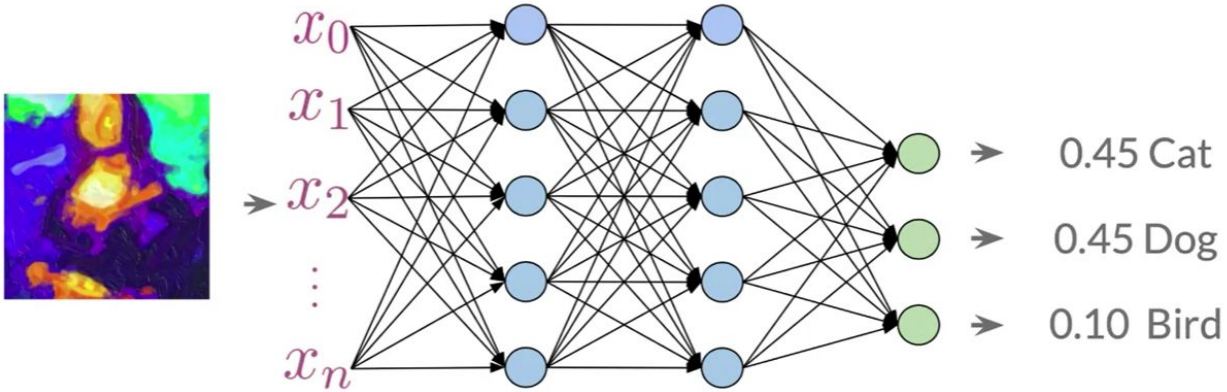
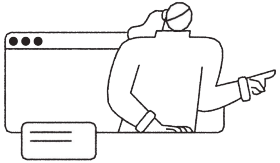


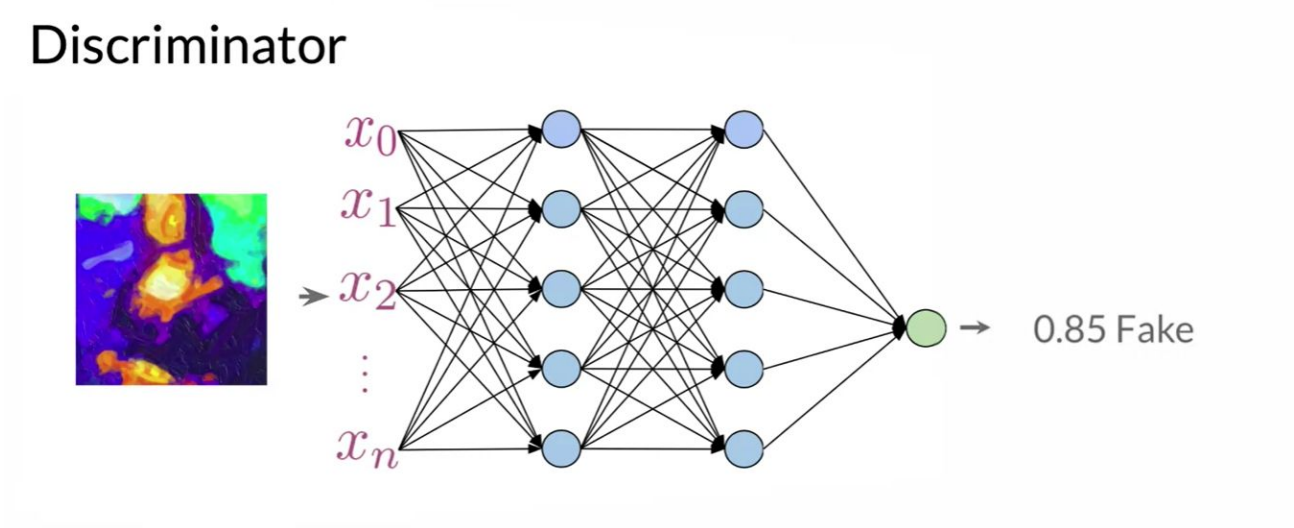
- Discriminators are Neural Net Classifiers.

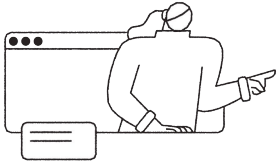
Discriminator





- Discriminators Classify to Real and Fake

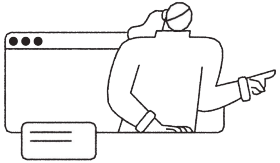




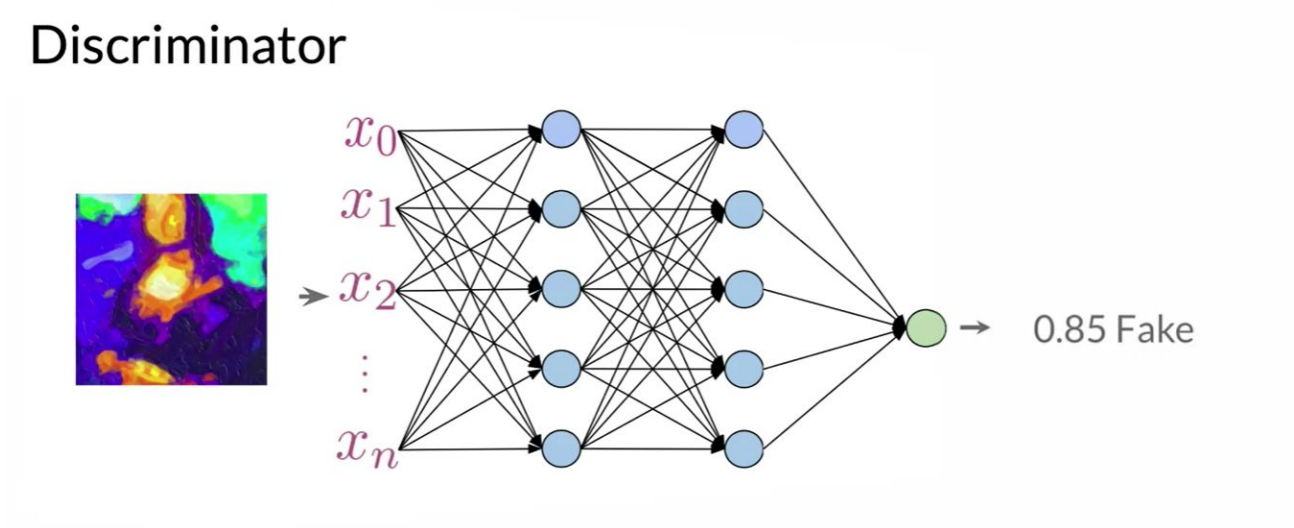
- Discriminators Classify to Real and Fake

Discriminator

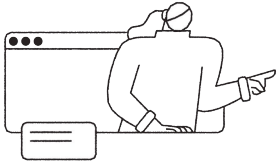
$$P(\underset{\text{Class}}{\text{Fake}} \mid \underset{\text{Features}}{\text{[image]}}) = 0.85 \longrightarrow \boxed{\text{Fake}}$$



- Discriminators Classify to Real and Fake



Training a Generator



Generator

Turtle

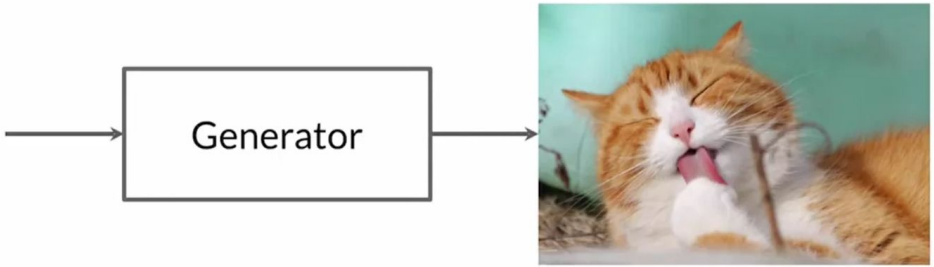
Generates examples of the class

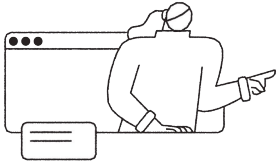
Bird

Cat

Dog

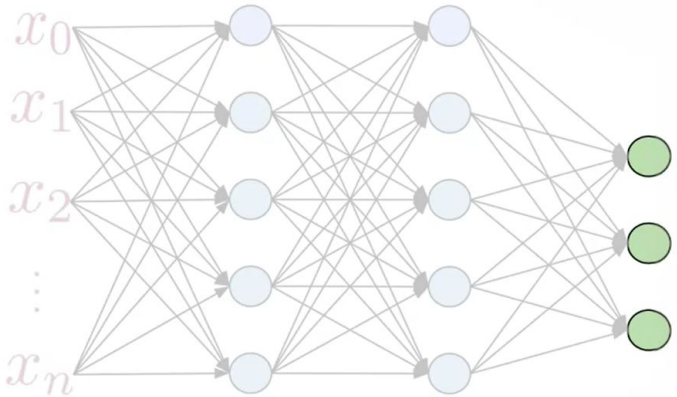
Fish

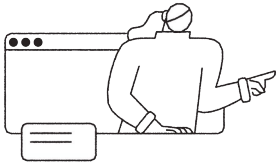


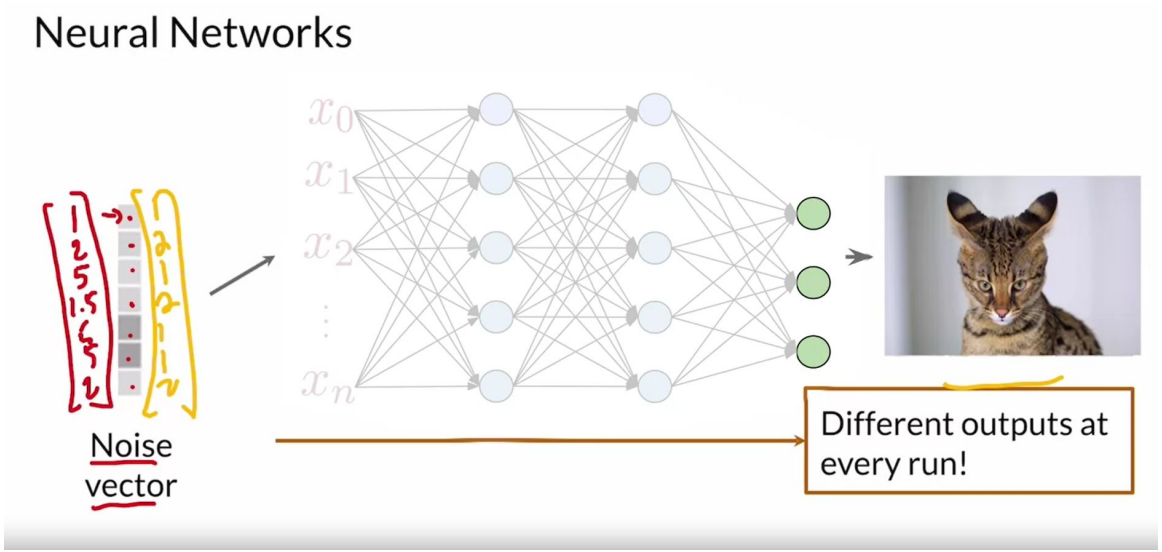


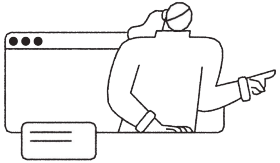
Neural Networks

Noise vector

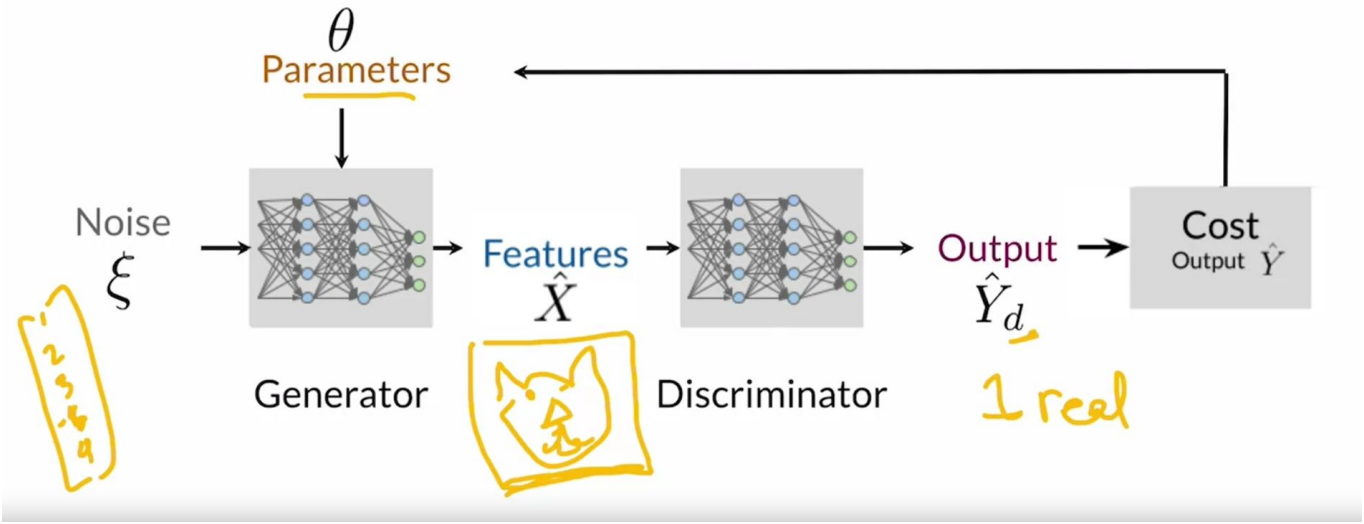


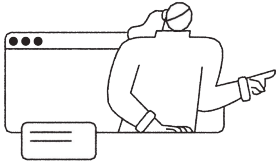


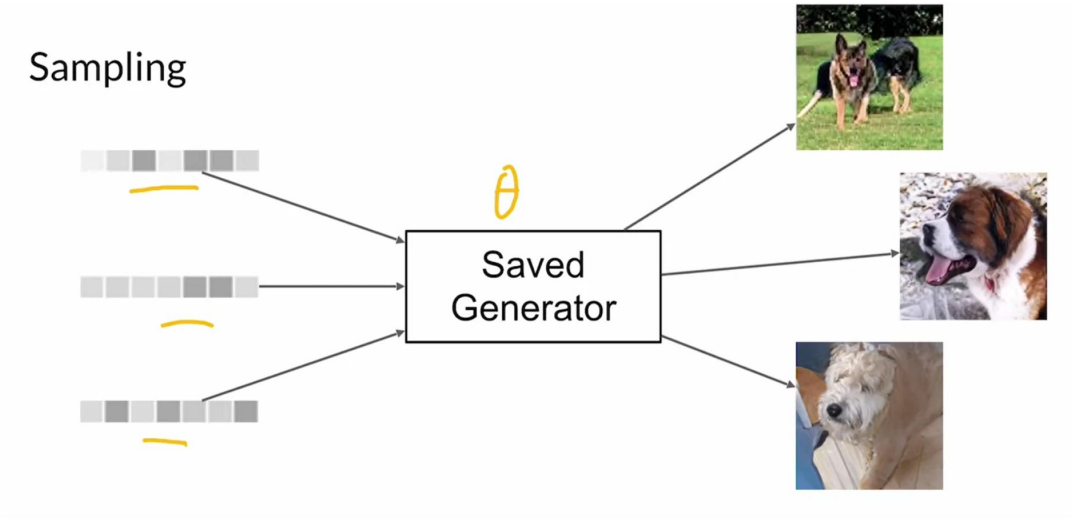

Neural Networks
x_0
x_1
x_2
x_n
Noise vector
Different outputs at every run!

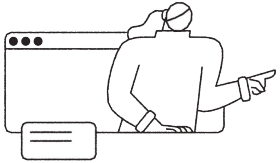


Generator: Learning






Sampling
θ
Saved
Generator



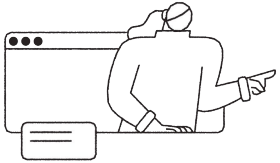
Generator

Conditional Probability

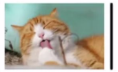
$$P(X \mid Y)$$

Features

Class



Generator

$P($  $|$ Turtle / Bird / Cat / Dog / Fish $)$

Generator

$P(X \mid$ Turtle / Bird / Cat / Dog / Fish $)$

Features

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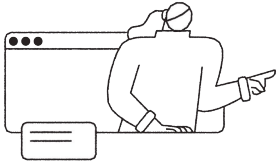
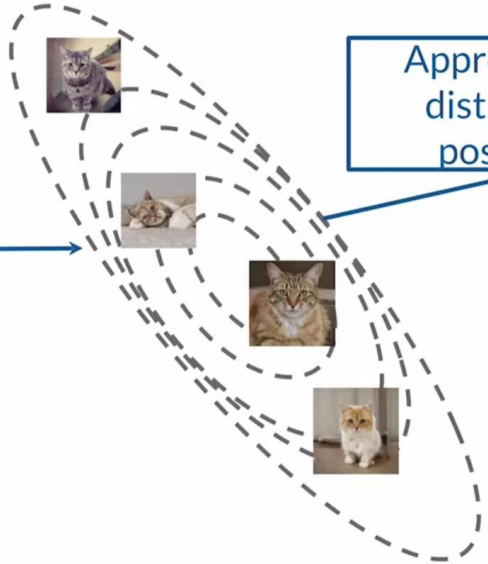


Generator

$$P(X)$$

Features



Approximate the distribution of possible cats

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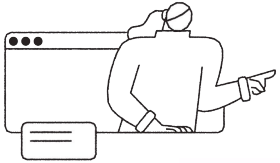
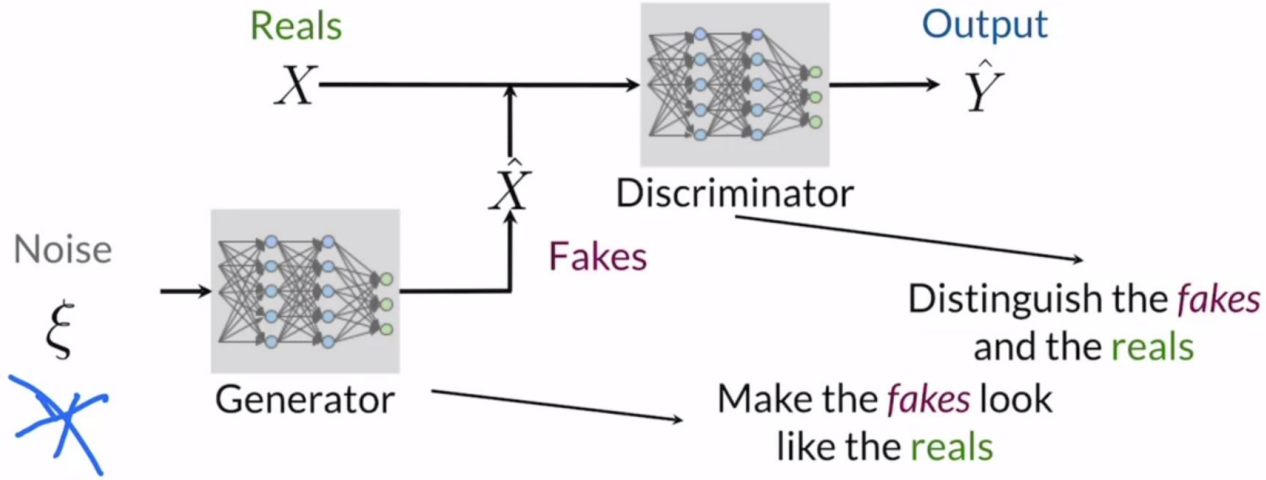
- The generator wants y-hat to be as close to one, meaning real as possible.
    - The discriminator is trying to get this to be zero, fake.
- He uses the difference between these two to then update the parameters of the generator, and that gets it to improve over time and know which direction to move it's parameters to generate something that looks more real and will fool the discriminator.
- So once you get a generator that looks pretty good, you can save the parameters theta of the generator.
- That typically means freezing those theta values and saving it somewhere and then you can load it back up and then sample from this safe generator.

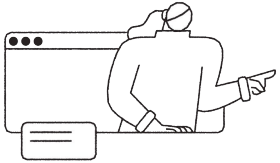
Back to the GAN

Whole Architecture

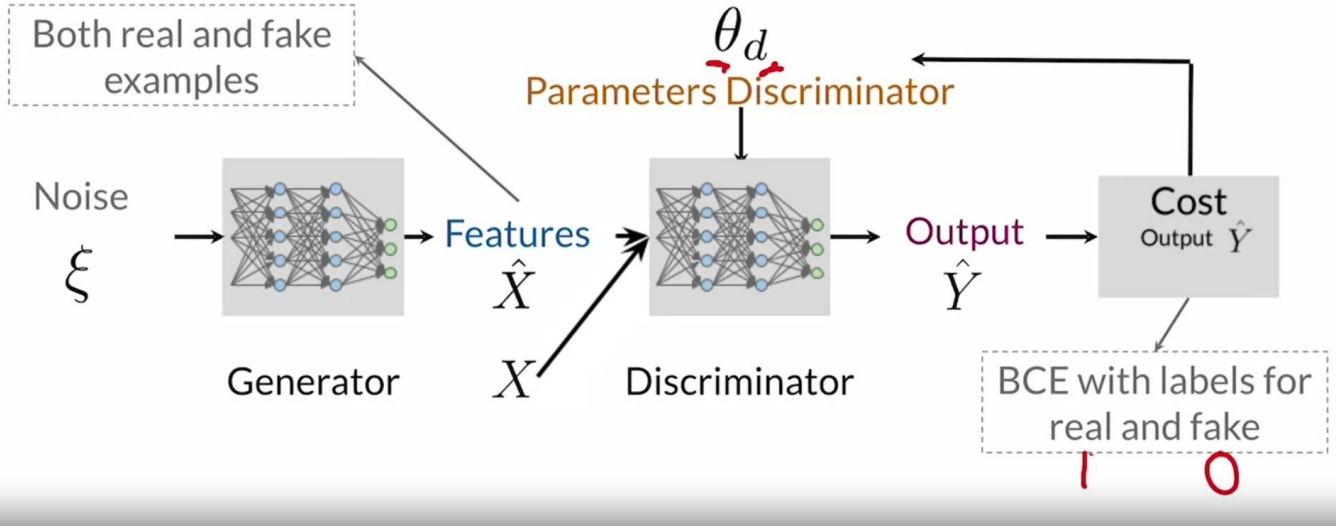


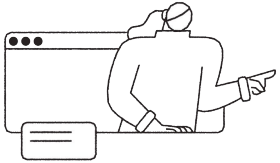
GANs Model

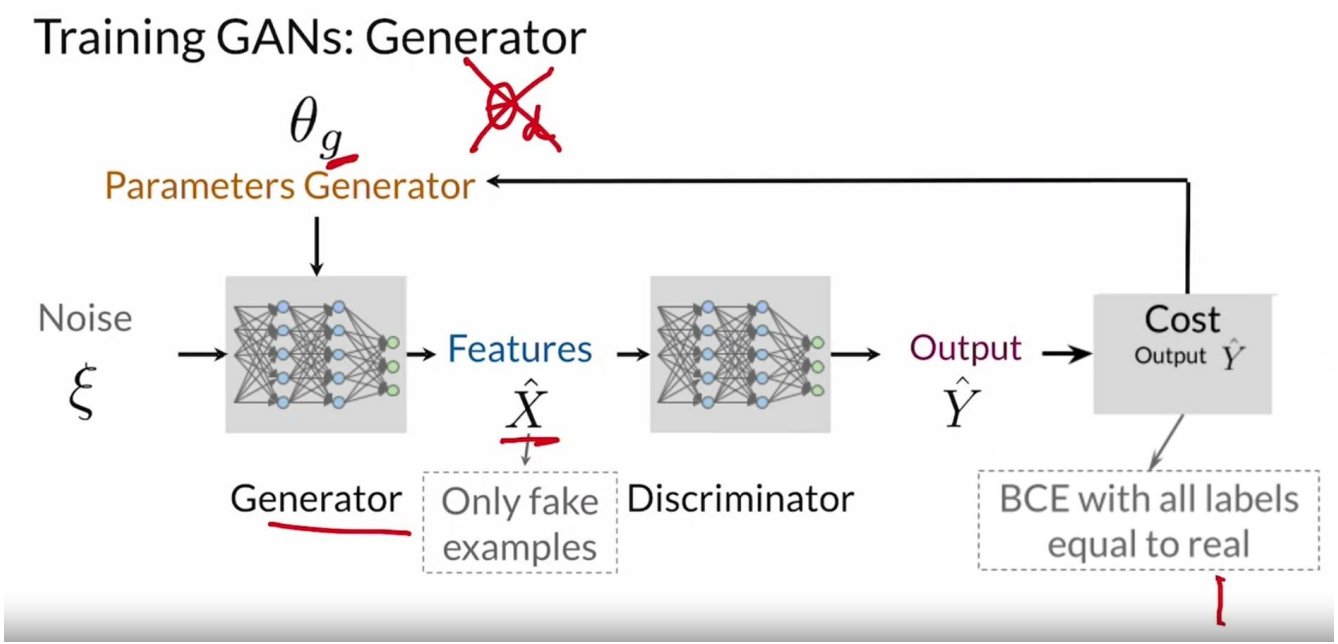

Reals
X
Output
$\hat{Y}$
$\hat{X}$
Discriminator
Noise
ξ
Fakes
Distinguish the *fakes* and the reals
Generator
Make the *fakes* look like the reals



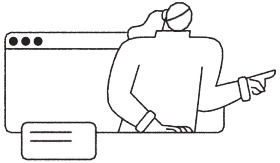
Training GANs: Discriminator






Training GANs: Generator
θ_g
Parameters Generator
Noise
ξ
Features
$\hat{X}$
Output
$\hat{Y}$
Cost
Output $\hat{Y}$
Generator
Only fake examples
Discriminator
BCE with all labels equal to real

- The training of a generator and discriminator are alternated.
- Both models should improve together and should be kept at a similar skill level. If u had a really skilled discriminator, it will be telling u that everything is fake, and doesn’t help the generator learn.
- If the Generator is super skilled; generated images will always seem too real to the discriminator.



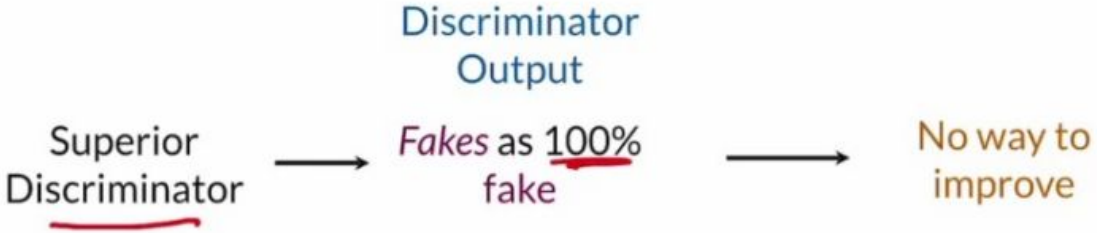
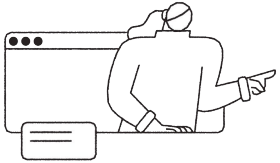
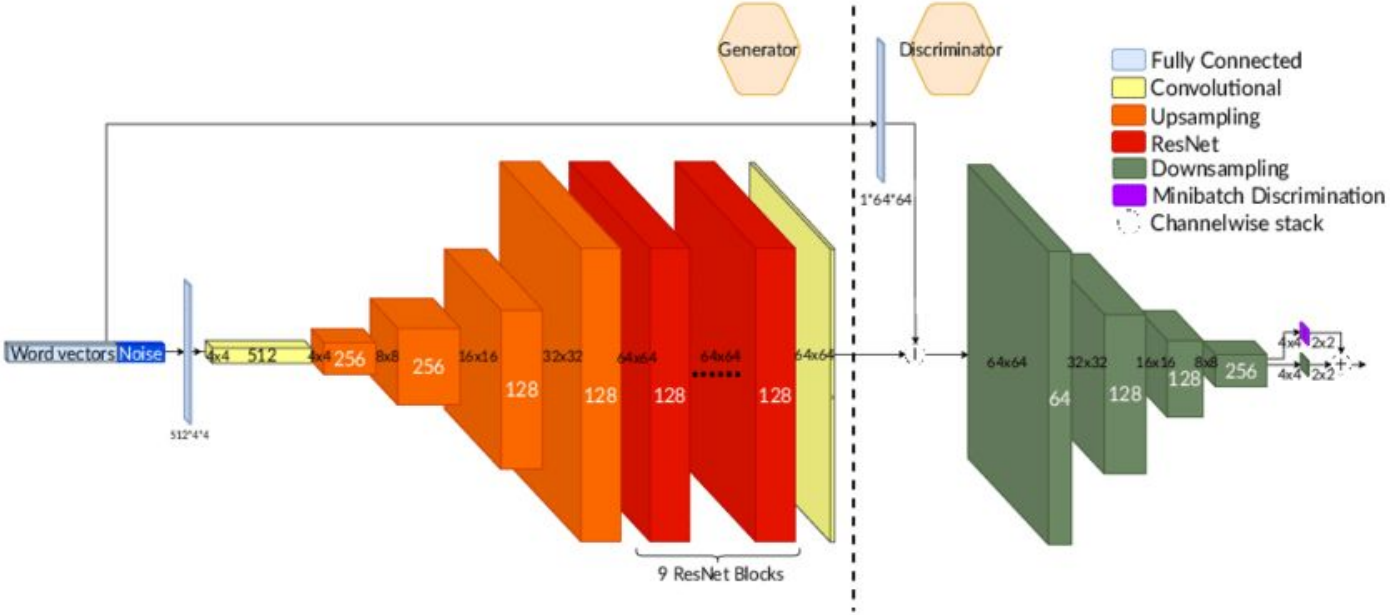


Figure 5: Case Generator is SuperSkilled

Back to Neural Networks Architectures





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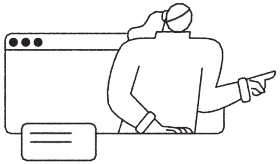

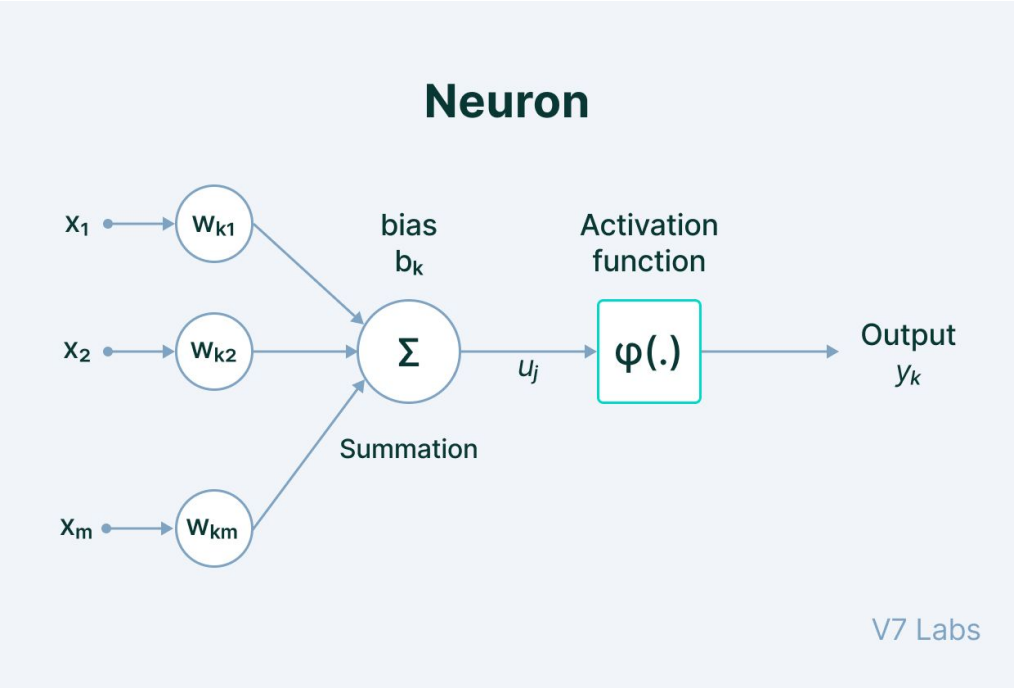

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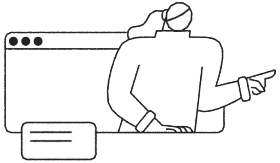
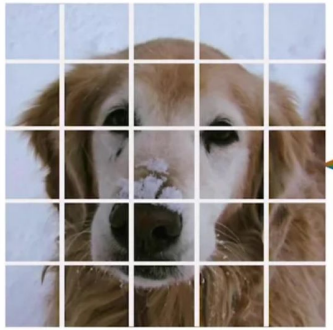
Layers in a GAN

Convolution

- Convo layer is sometimes called feature extractor layer because features of the image are extracted within this layer.



What is a convolution?



Eye Filter

5	3	1
10	23	1
1	42	4

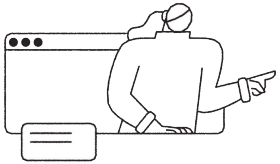
Nose filter

2	21	5
23	45	12
3	32	4

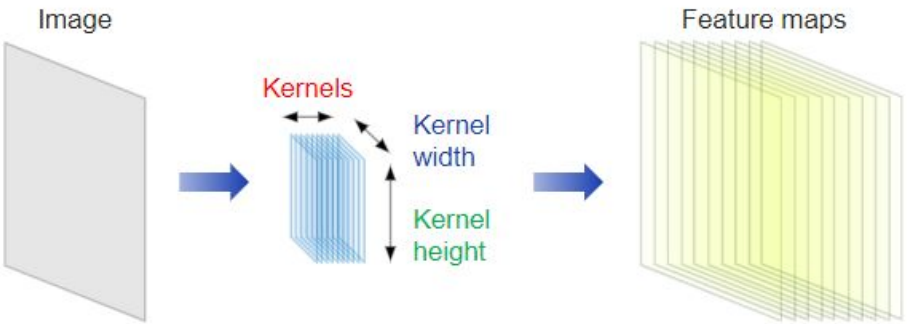
Ear filter

32	2	24
25	12	66
3	45	2

Activer Windows

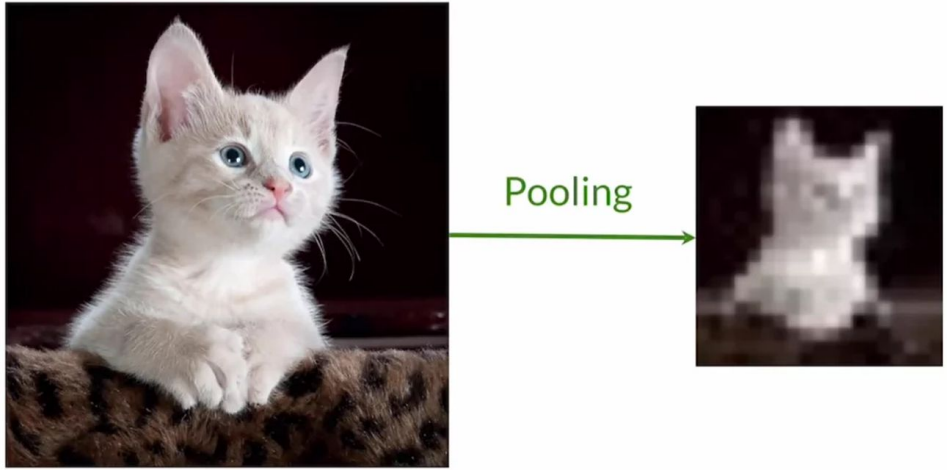


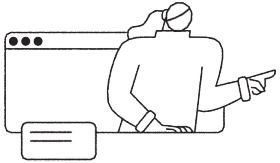
The image is scanned with a kernel and the next layer (feature map) is produced.



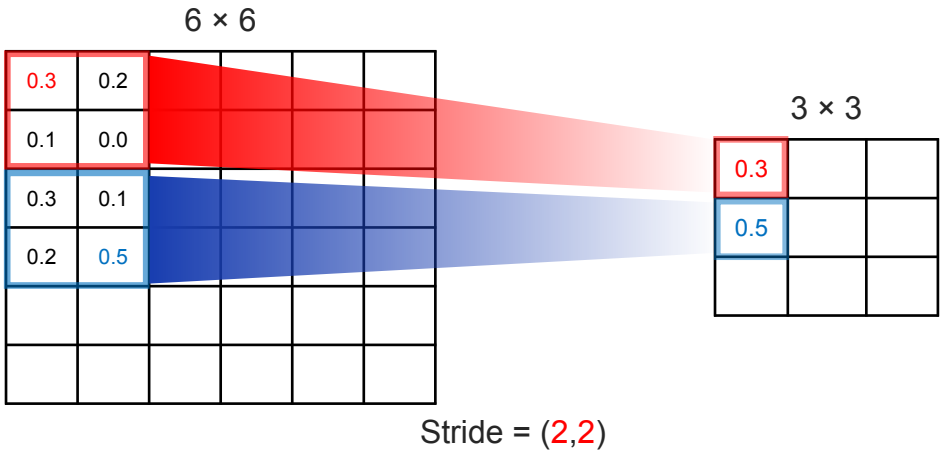
Pooling

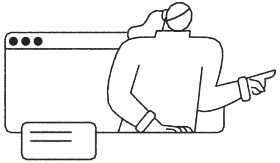
- Pooling is used to reduce the size of the input.


Pooling



In the pooling layer the size of the feature maps matrix is reduces





Max Pooling
Remember which element was max!

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

Input: 4 x 4

→

5	6
7	8

Output: 2 x 2

→ . . . →

Rest of the network

Max Unpooling
Use positions from pooling layer

1	2
3	4

Input: 2 x 2

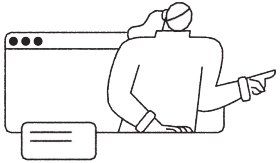
→

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

International Women's Day 2023

Upsampling : TransConv



Transposed Convolution

1	4
0	2

Input

*

2	2
1	1

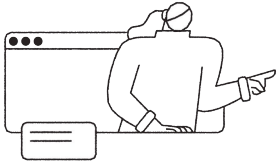
Filter

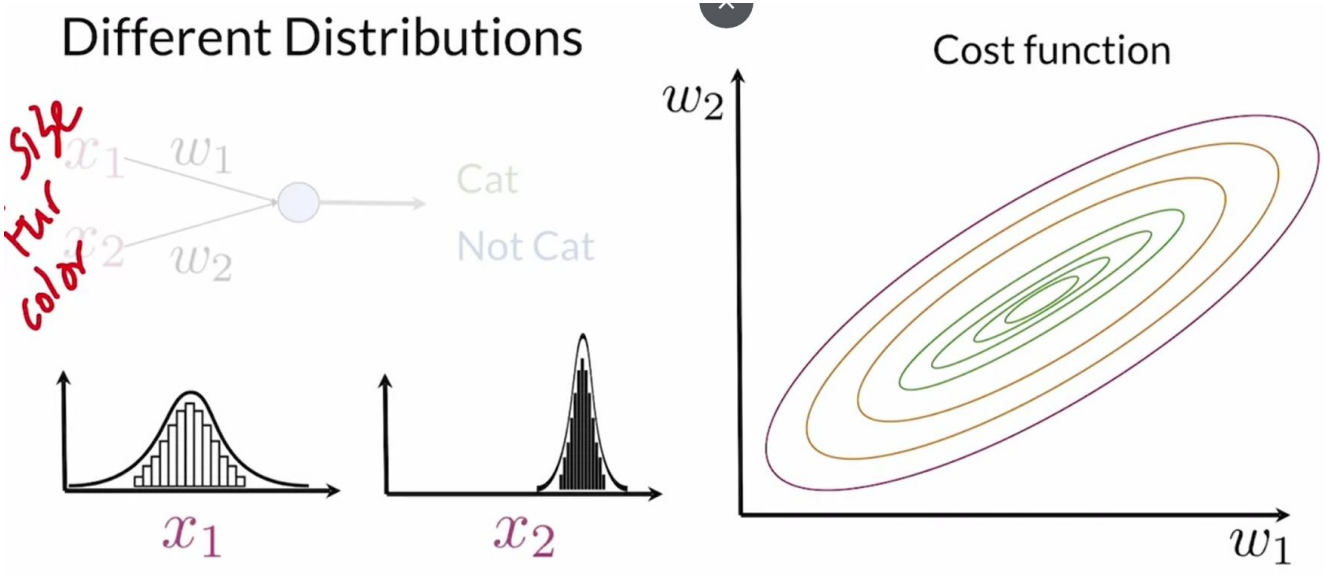
=

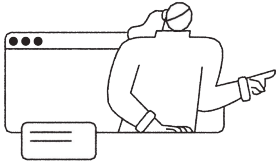
1*2	1*2	
1*1	1*1	

Stride = 1

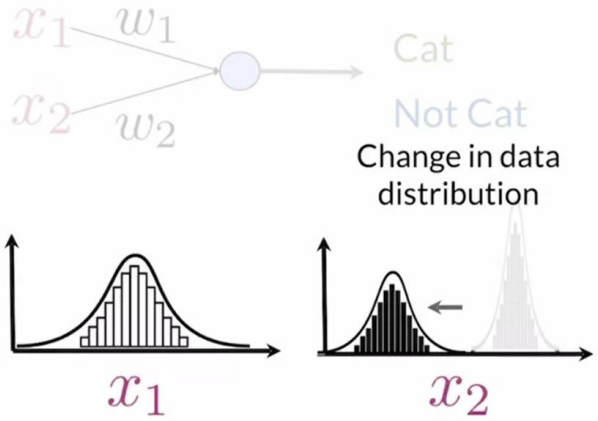
BatchNormalization

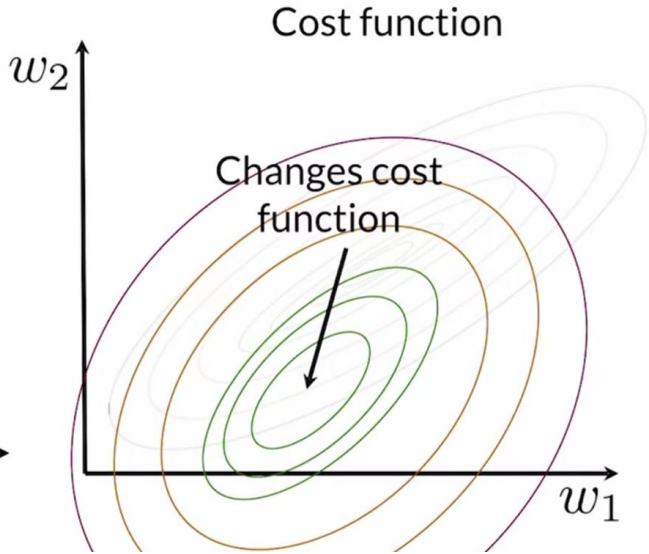



Different Distributions
size
fur
color
x_1
w_1
x_2
w_2
Cat
Not Cat
x_1
x_2
Cost function
w_2
w_1

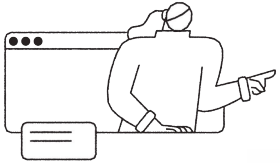


Covariate Shift

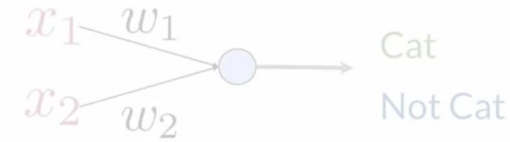


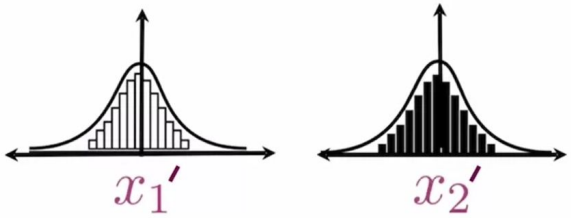


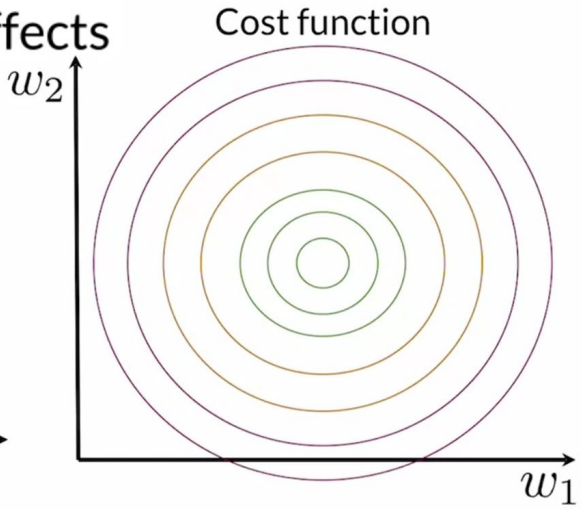
- In covariate shift , data values could change ,yet the features and what determines the output remains the same .



Normalization and Its Effects







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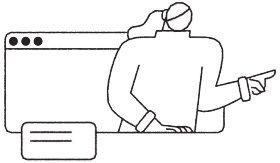
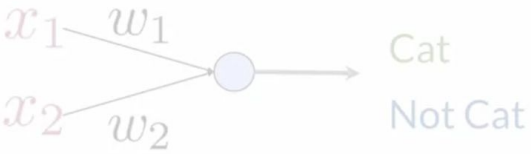
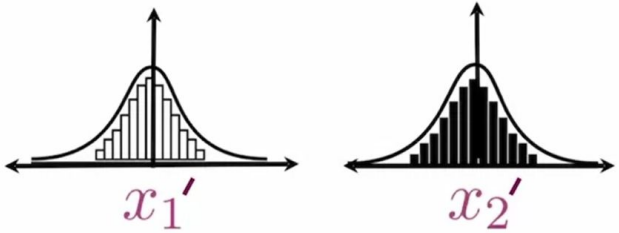


Normalization and Its Effects

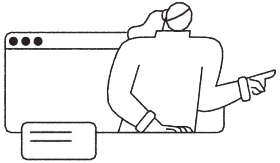




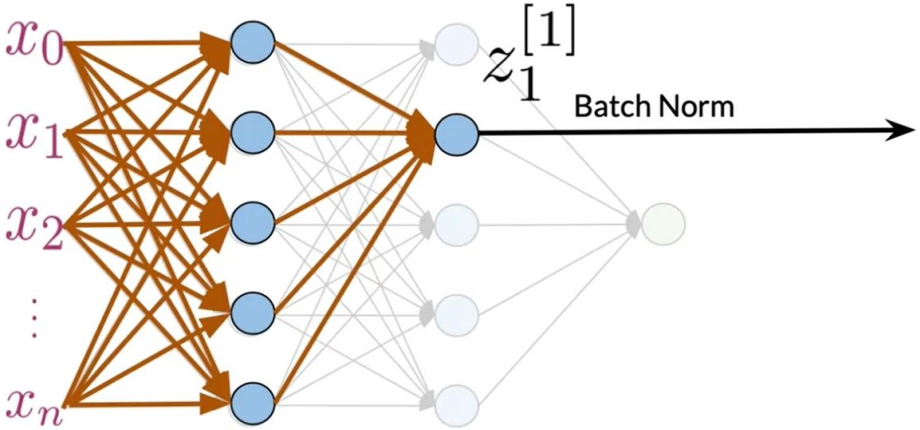
Around mean at 0 and std. at 1

Training data uses batch stats

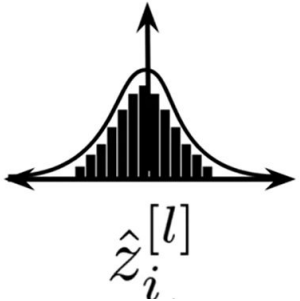
Test data uses training stats



Batch Normalization



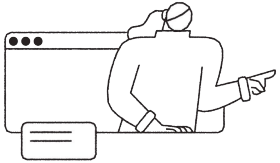
Normalizes the input for each neuron



- Different Distributions make training difficult , and dependent on initialization of weights .

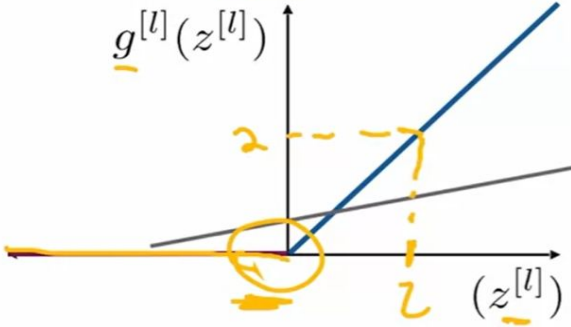
Transposed

Activation Functions



Activations: ReLU

ReLU = Rectified Linear Unit

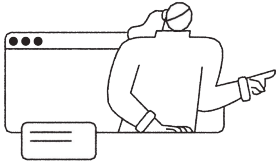


ReLU

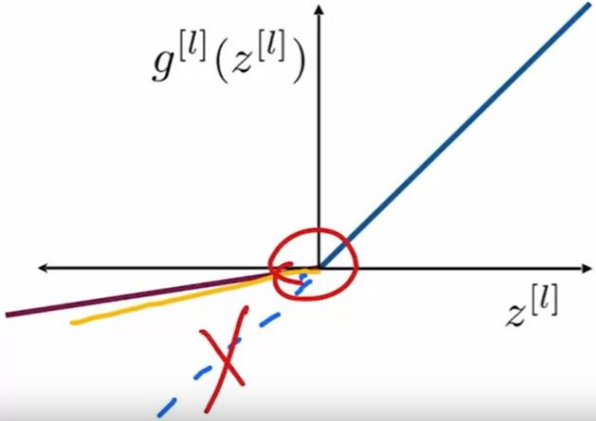
$$g^{[l]}(z^{[l]}) = \max(0, z^{[l]})$$

Dying ReLU problem

Activer Windows



Activations: Leaky ReLU

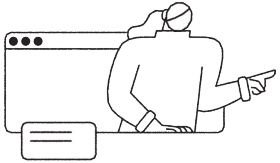


0.1

$$g^{[l]}(z^{[l]}) = max(az^{[l]}, z^{[l]})$$

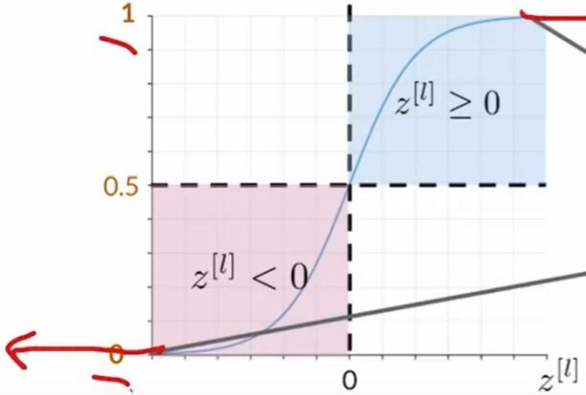
Solves the dying ReLU problem

Activer Windows



Activations: Sigmoid

$$g^{[l]}(z^{[l]}) = \frac{1}{1+e^{-z^{[l]}}}$$



Values between 0 and 1

Vanishing gradient and saturation problems

Build a Basic Generative Adversarial Network Model in TensorFlow

Women Techmakers
Algiers
International Women's Day 2023

Thank You !

LinkedIn : Samia BELHADDAD

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Github : Hypatchia