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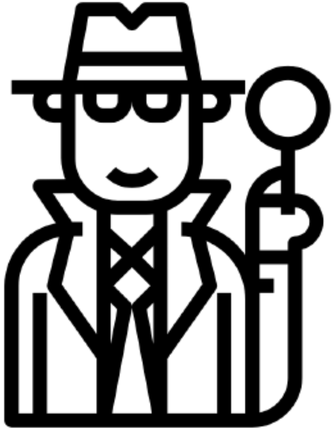
Generative Models

Outline

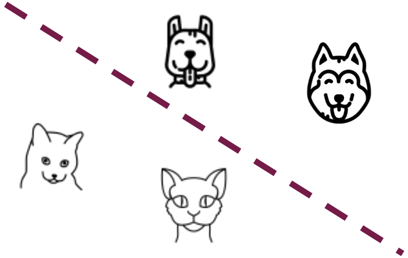
- What are generative models

- Types of generative models



Generative Models vs. Discriminative Models

Discriminative models



Features Class

$$X \rightarrow Y$$

$$P(Y|X)$$

Generative models

Noise Class Features

$$\xi, Y \rightarrow X$$

$$P(X|Y)$$

Generative Models vs. Discriminative Models

Generative models

Noise Class Features

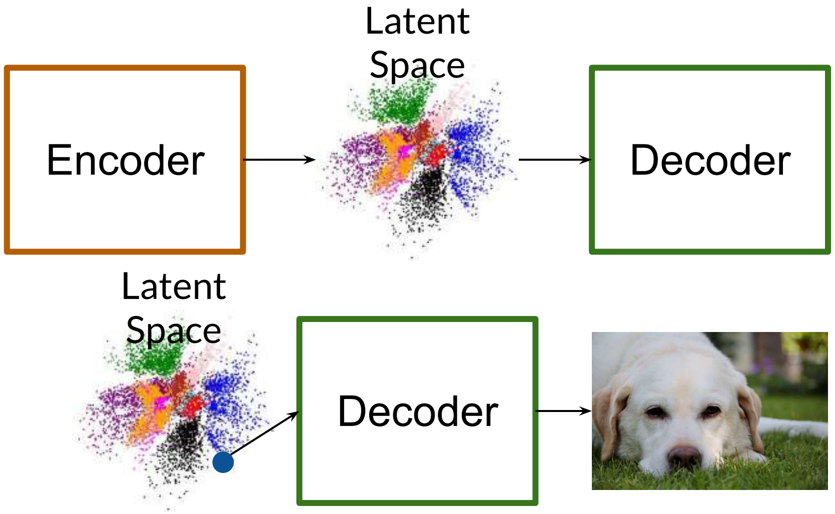
$$\xi, Y \to X$$

$$P(X|Y)$$

Generative Models

Variational Autoencoders

Generative Adversarial Networks



Latent Space

Encoder

Decoder

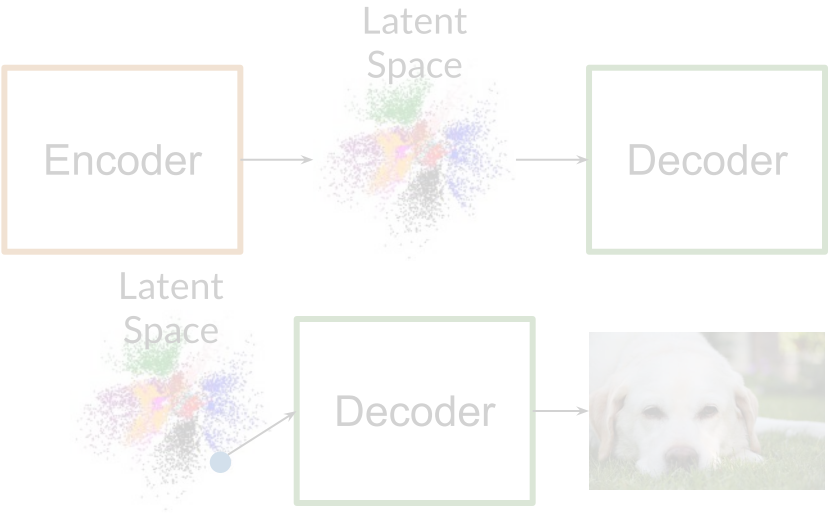
Latent Space

Decoder

Available from: https://arxiv.org/abs/1804.00891

Generative Models

Variational Autoencoders



Latent Space

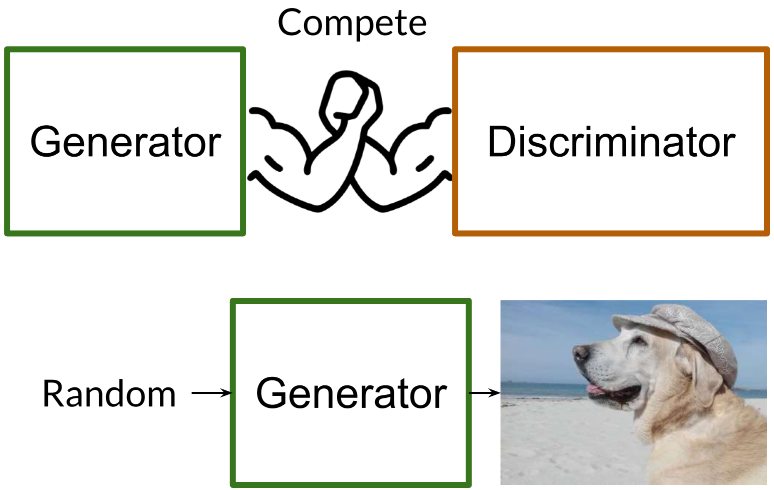
Encoder

Decoder

Latent Space

Decoder

Generative Adversarial Networks



Compete

Generator

Discriminator

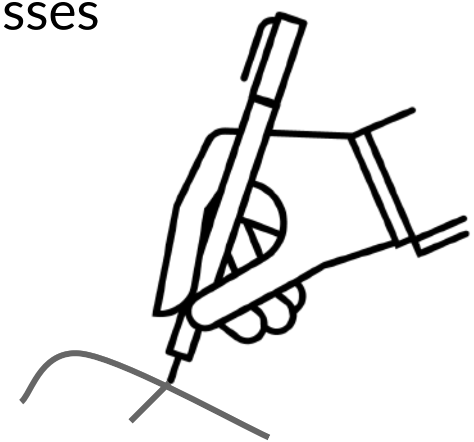
Random

Generator

Available from: https://arxiv.org/abs/1804.00891

Summary

- Generative models learn to produce examples
- Discriminative models distinguish between classes
- Up next, GANs!



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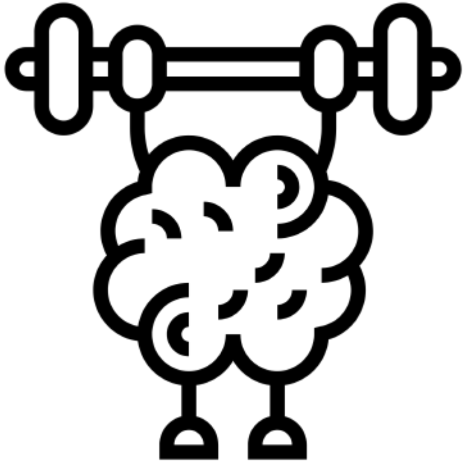
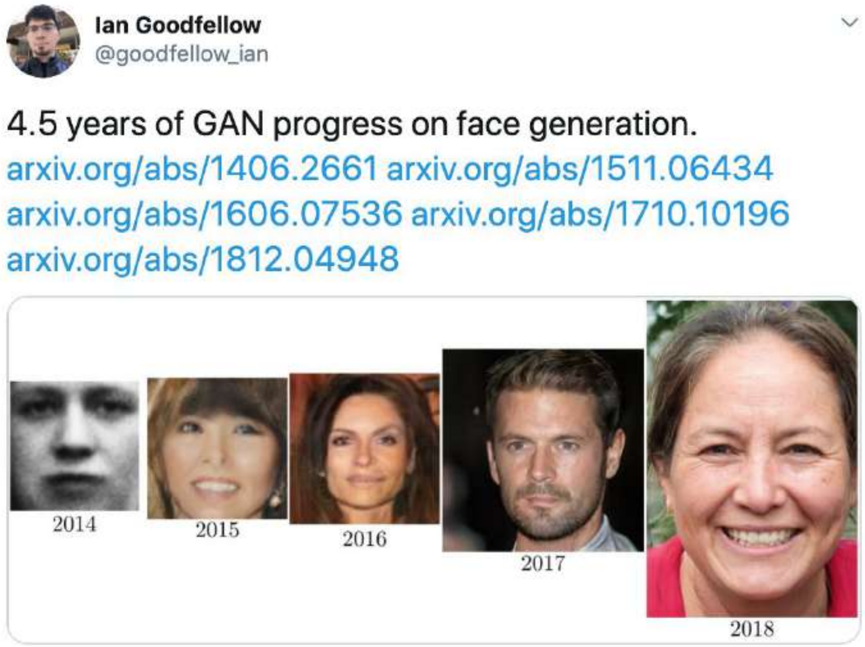
Real Life GANs

Outline

- Cool applications of GANs
- Major companies using them

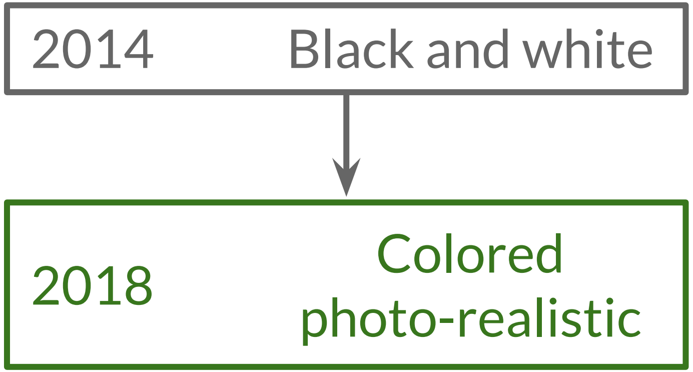


GANs Over Time



Ian Goodfellow
@goodfellow_ian

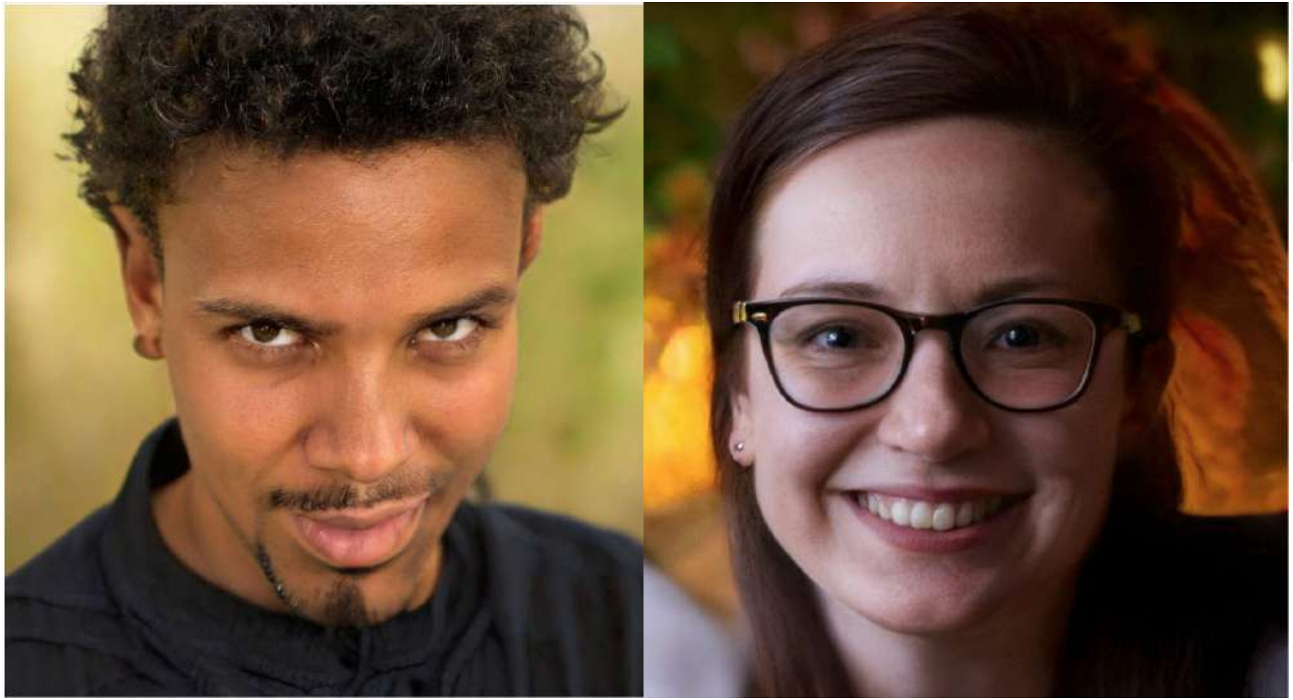
4.5 years of GAN progress on face generation. arxiv.org/abs/1406.2661 arxiv.org/abs/1511.06434 arxiv.org/abs/1606.07536 arxiv.org/abs/1710.10196 arxiv.org/abs/1812.04948



2014 Black and white

2018 Colored photo-realistic

GANs Over Time

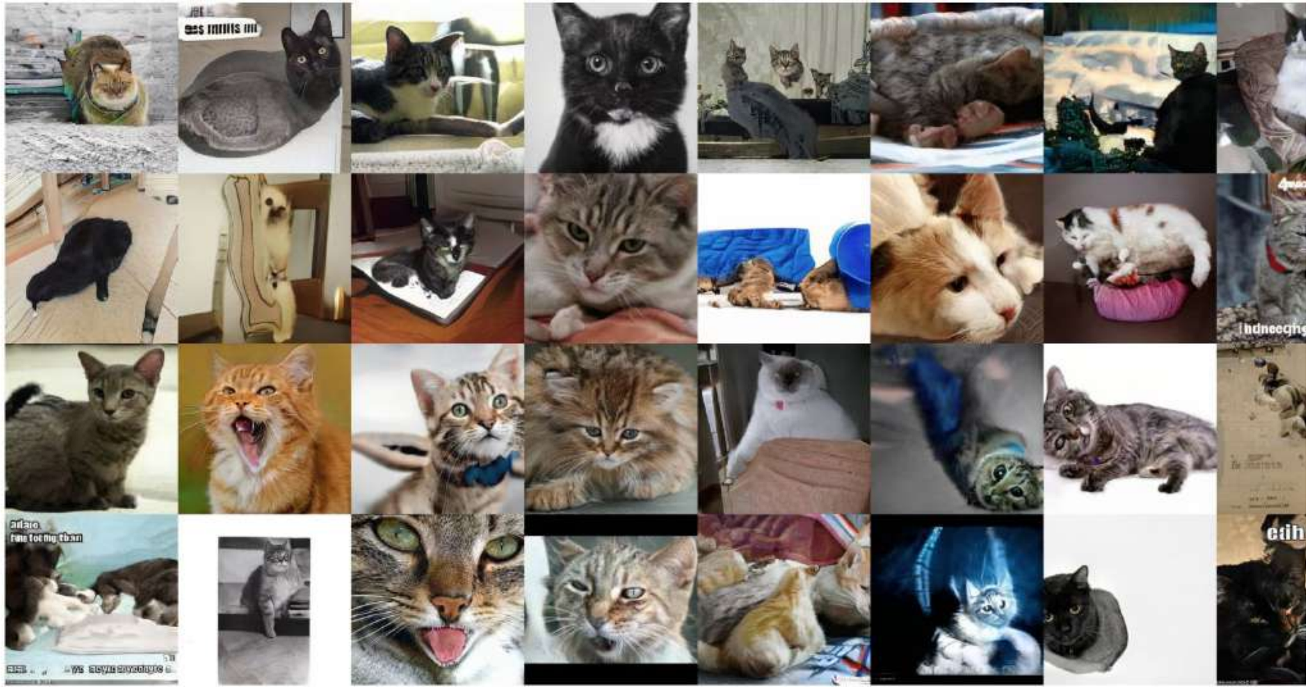


Face Generation
StyleGAN2

These people do not exist!

Karras, Tero, et al. "Analyzing and improving the image quality of stylegan." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020.

GANs Over Time



StyleGAN2

Mimics the distribution of the training data

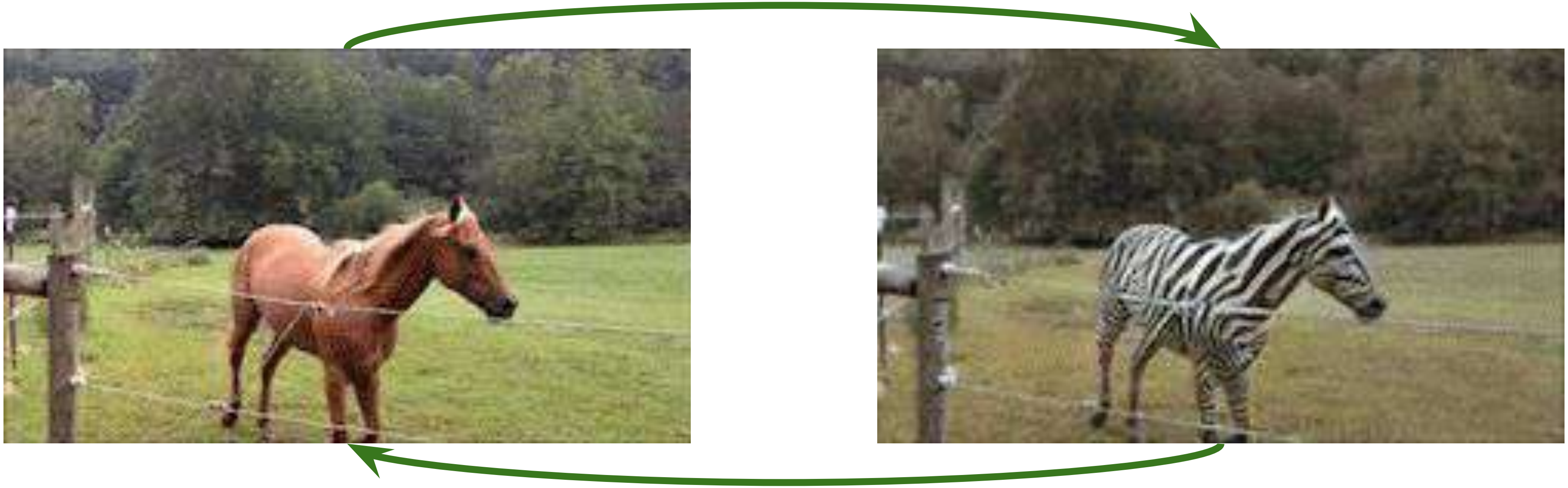
Karras, Tero, et al. "Analyzing and improving the image quality of stylegan." *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*. 2020.

https://9gag.com/gag/aWYZKWx

GANs for Image Translation

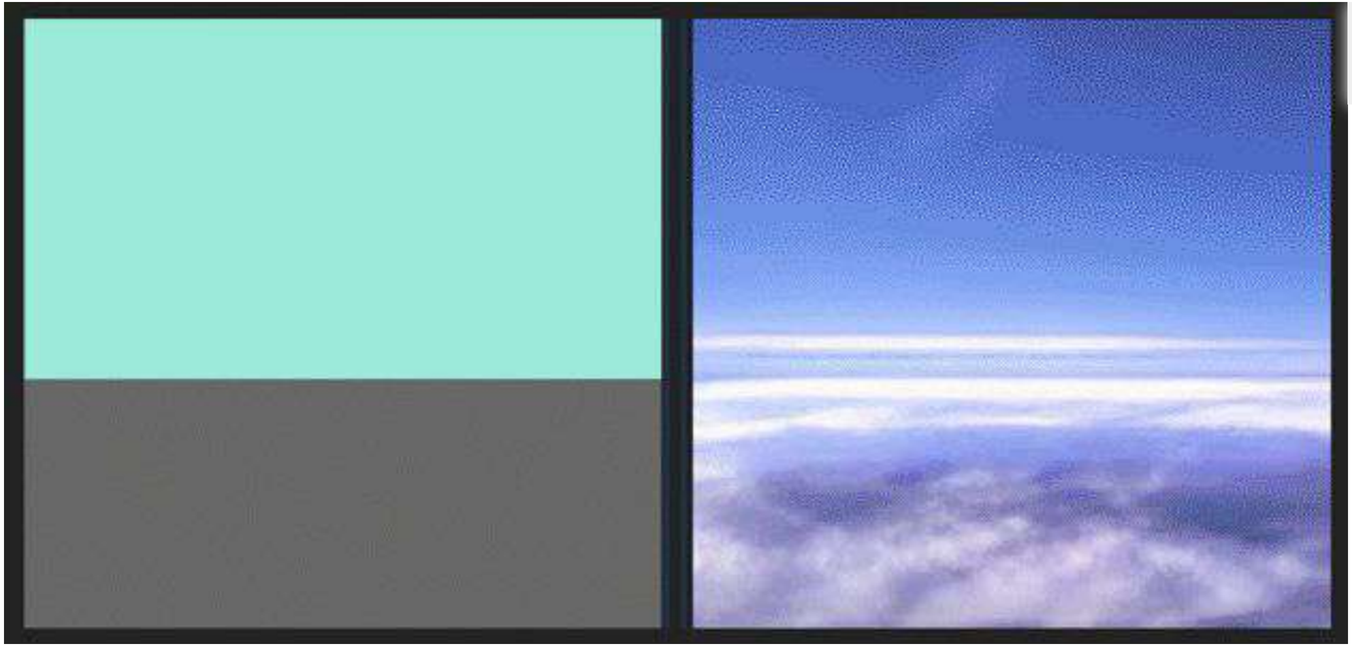
From one domain to another

CycleGAN



Park, Taesung, et al. "Semantic image synthesis with spatially-adaptive normalization." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019.

GANs for Image Translation



GauGAN

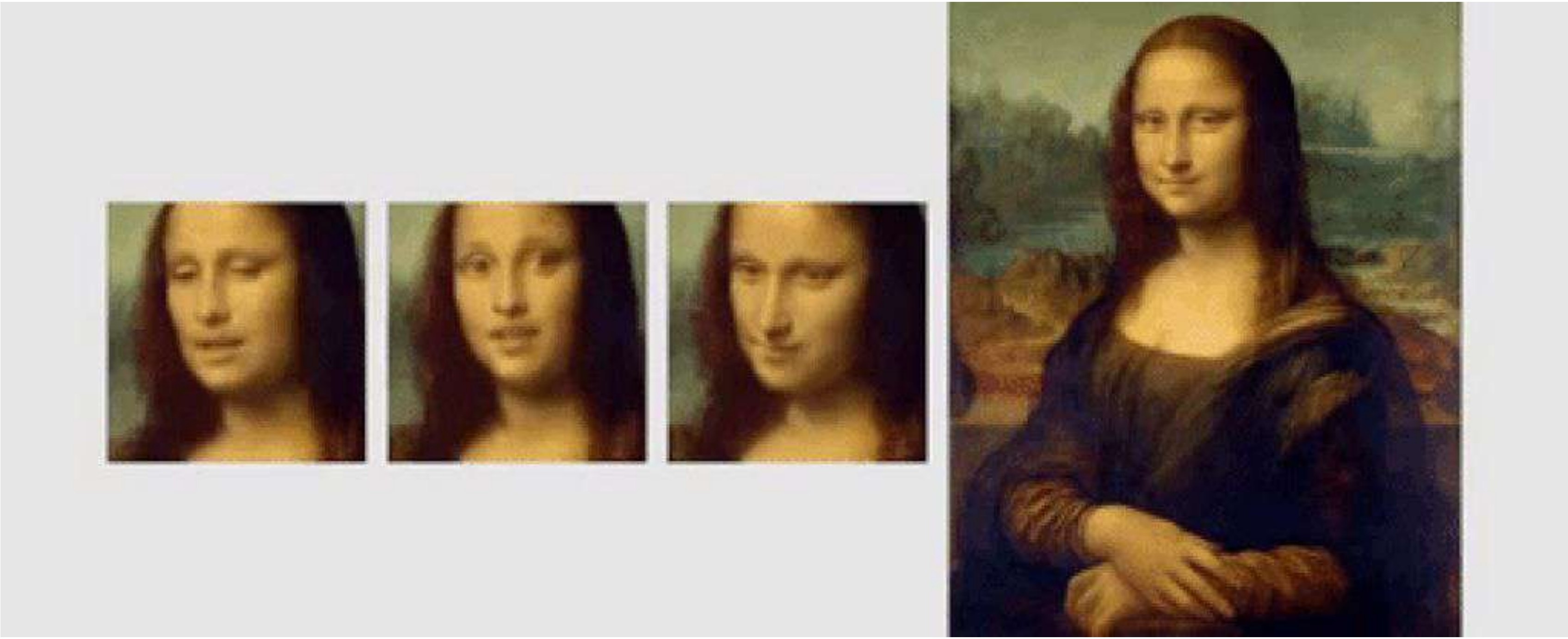
Doodles

↓

Pictures

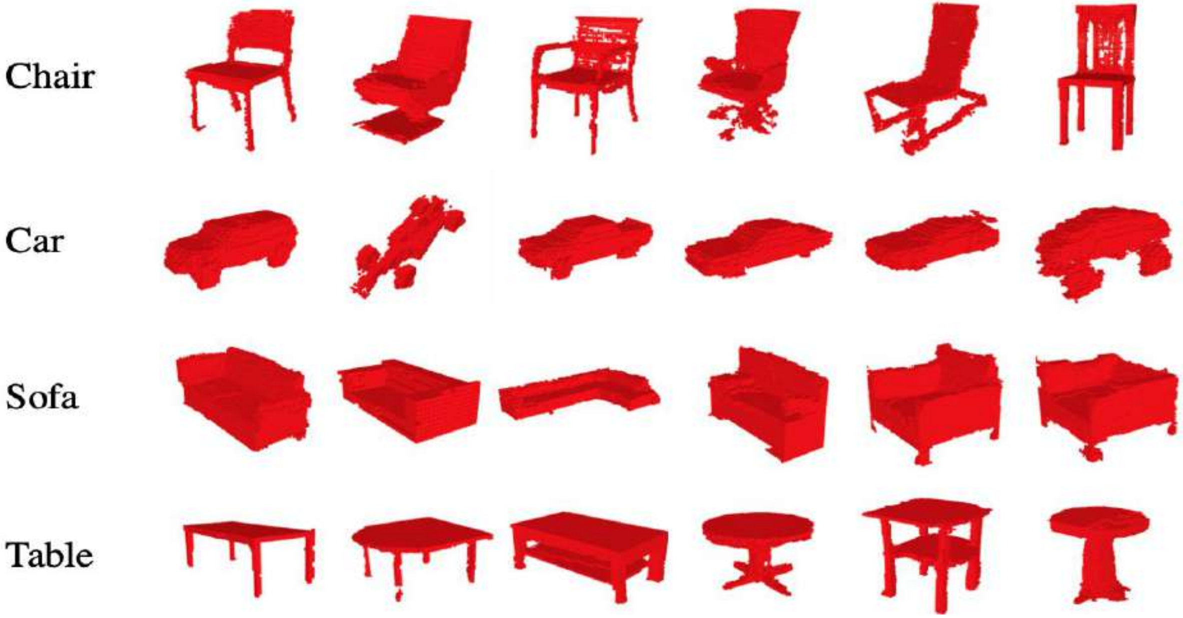
Park, Taesung, et al. "Semantic image synthesis with spatially-adaptive normalization." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2019.

GANs are Magic!



Zakharov, Egor, et al. "Few-shot adversarial learning of realistic neural talking head models." *Proceedings of the IEEE International Conference on Computer Vision*. 2019.

GANs for 3D Objects



3D-GAN

Generative Design

Wu, Jiajun, et al. "Learning a probabilistic latent space of object shapes via 3d generative-adversarial modeling." *Advances in neural information processing systems*. 2016.

Companies Using GANs

Adobe	Next-gen Photoshop	Google	Text Generation
IBM	Data Augmentation		Image Filters
Disney	Super-resolution		

Summary

- GANs' performance is rapidly improving
- Huge opportunity to work in this space!
- Major companies are using them

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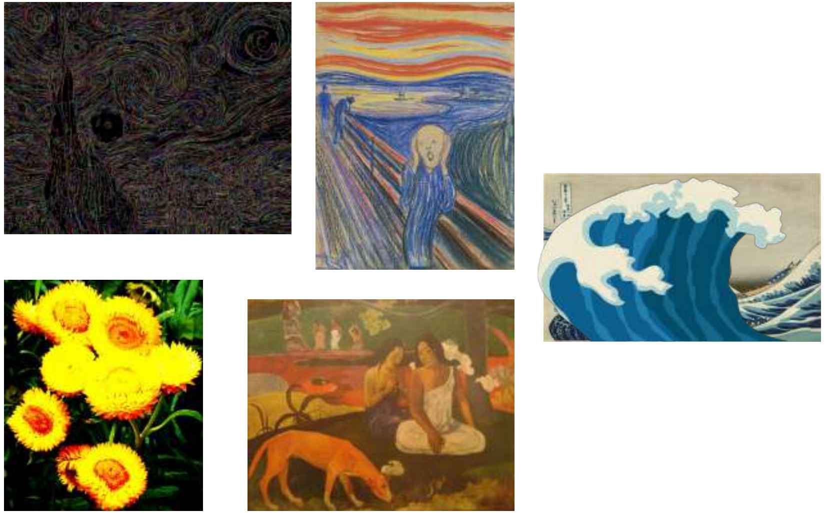
Intuition Behind GANs

Outline

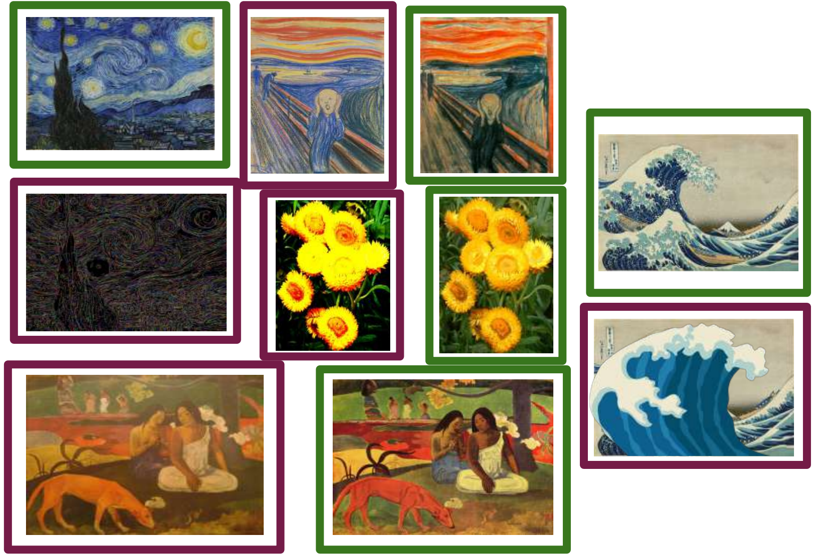
- The goal of the generator and the discriminator
- The competition between them

Generative Adversarial Network

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



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



Generative Adversarial Network

Fake

Real

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

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**

Doesn't know how it should look

Generative Adversarial Network

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

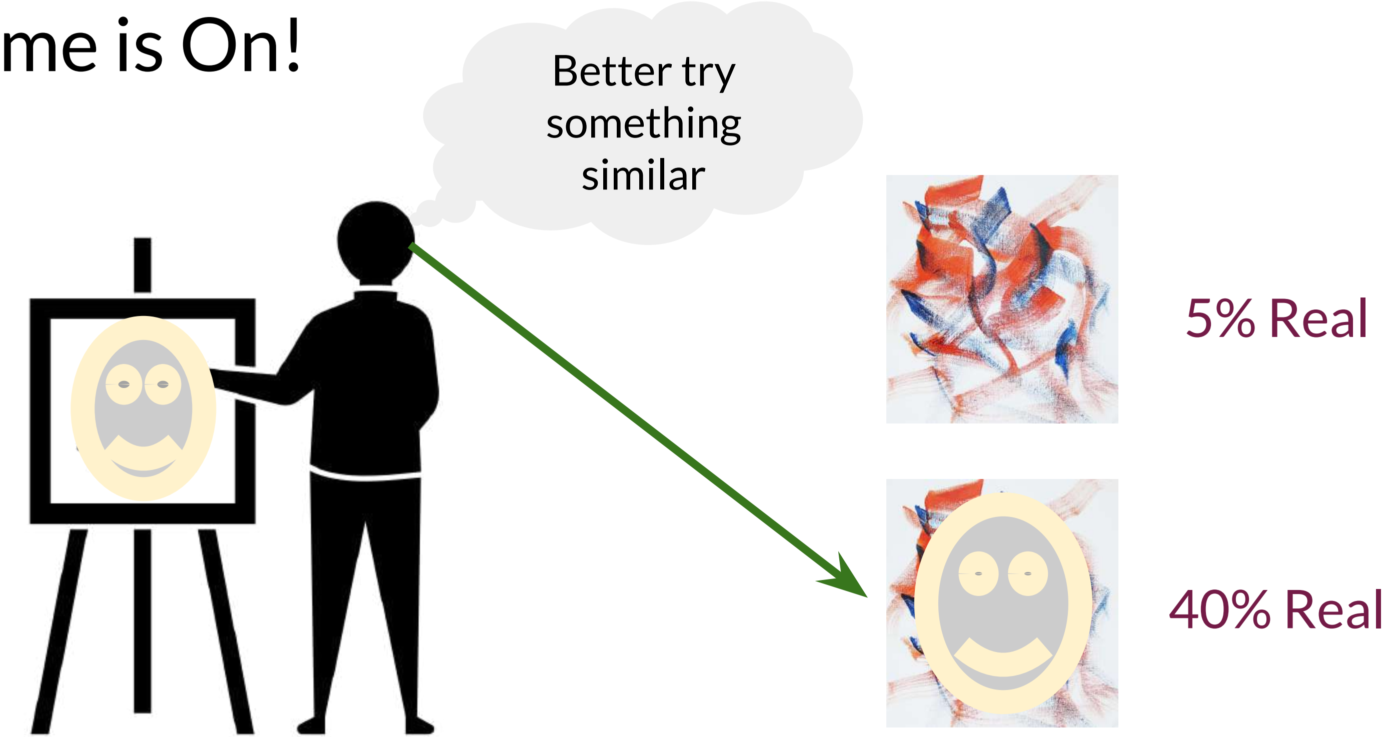
The Game Is On!

5% Real

40% Real

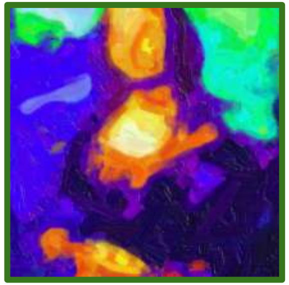
80% Real

The Game is On!



The Game Is On!

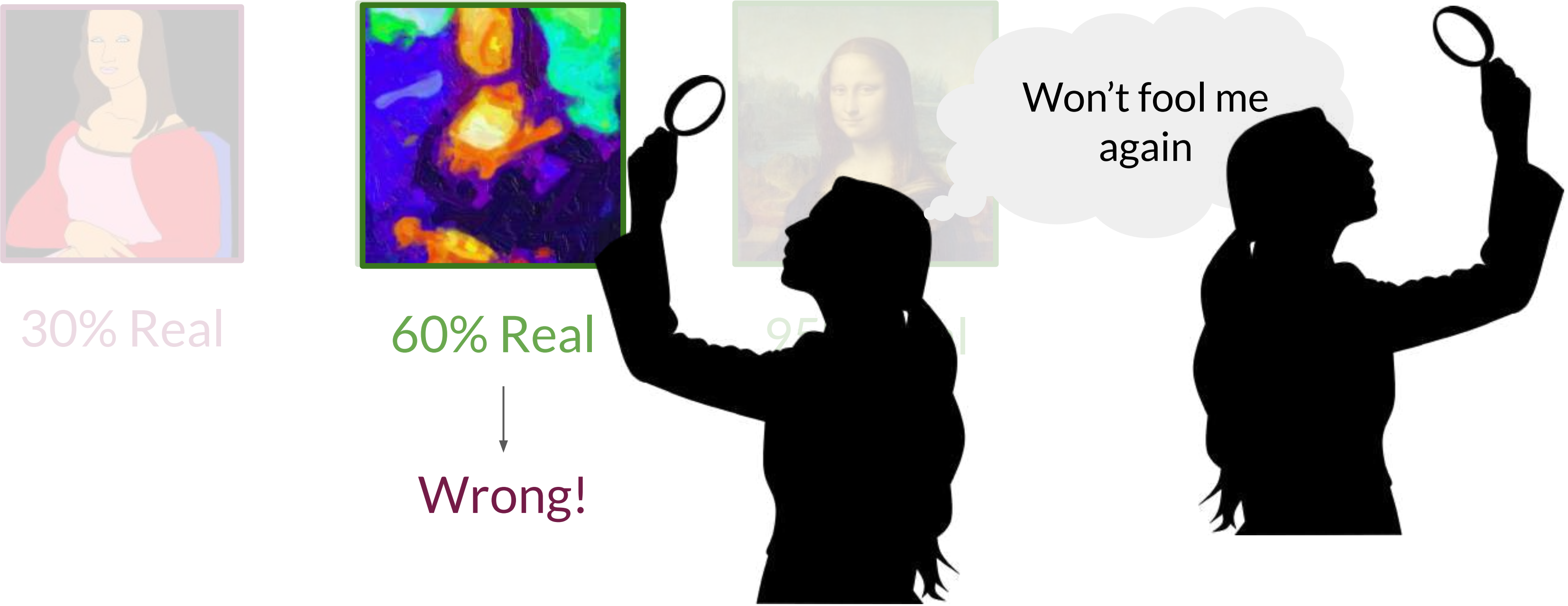
30% Real



60% Real

95% Real

The Game Is On!



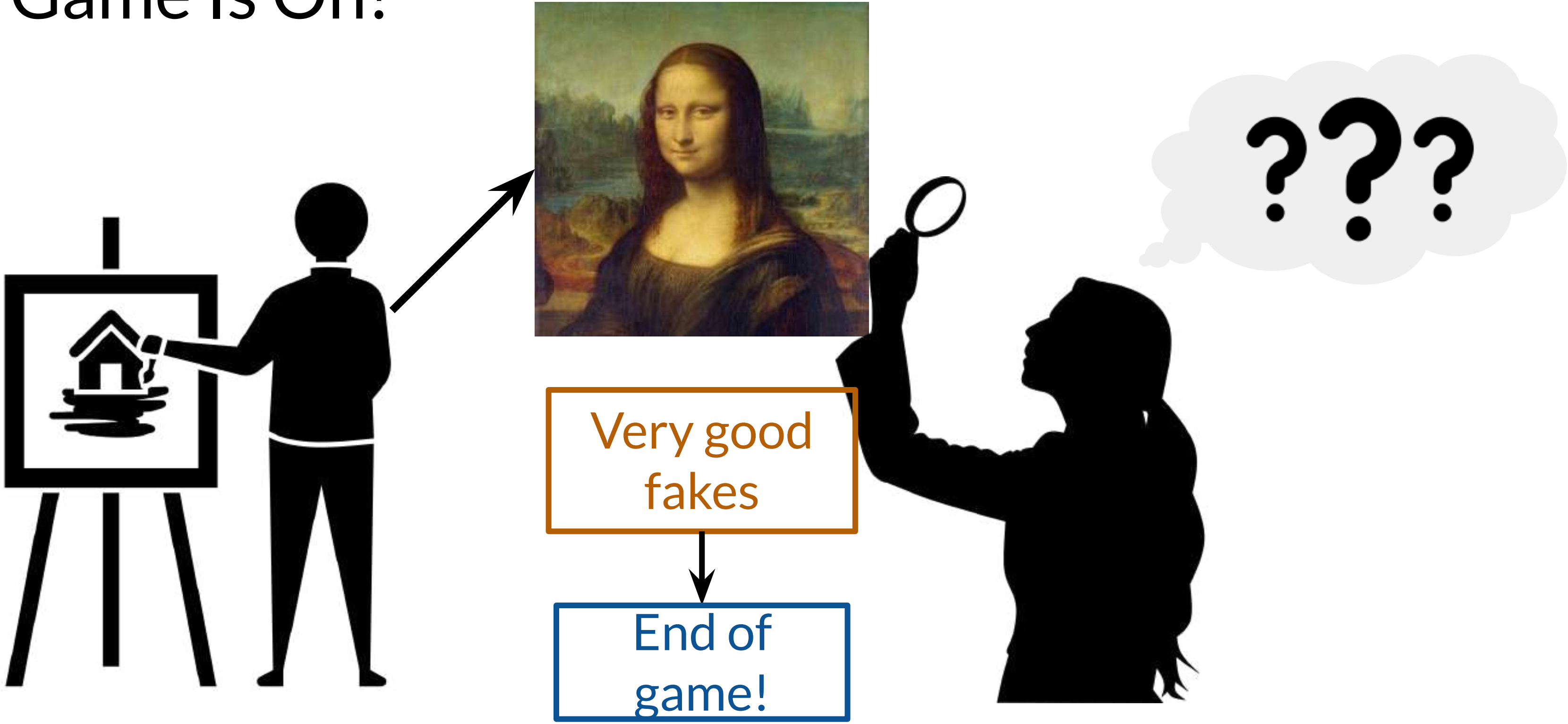
30% Real

60% Real

Wrong!

Won’t fool me again

The Game Is On!



Very good fakes

End of game!

Summary

- The generator's goal is to fool the discriminator
- The discriminator's goal is to distinguish between real and fake
- They learn from the competition with each other
- At the end, *fakes* look real

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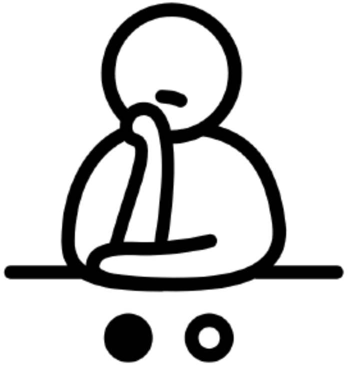
Discriminator

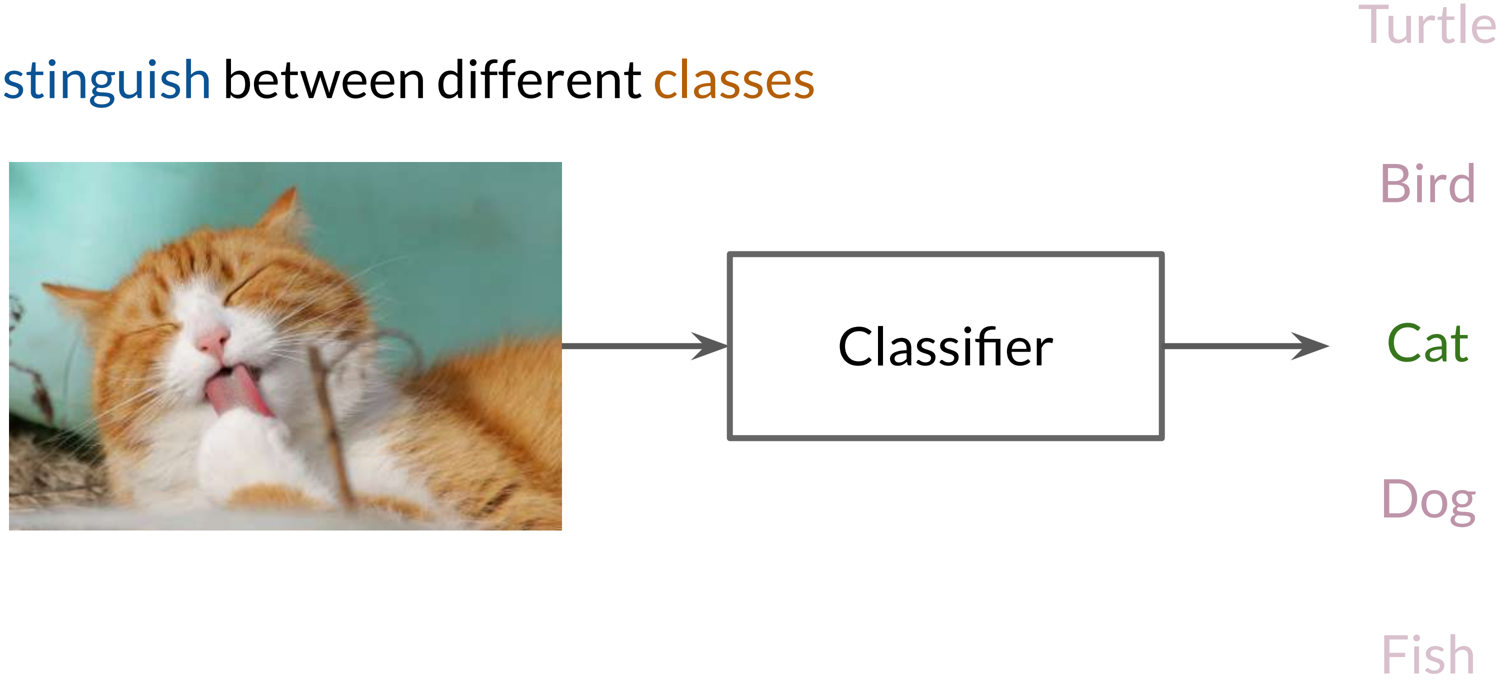
Outline

- Review of classifiers
- The role of classifiers in terms of probability
- Discriminator



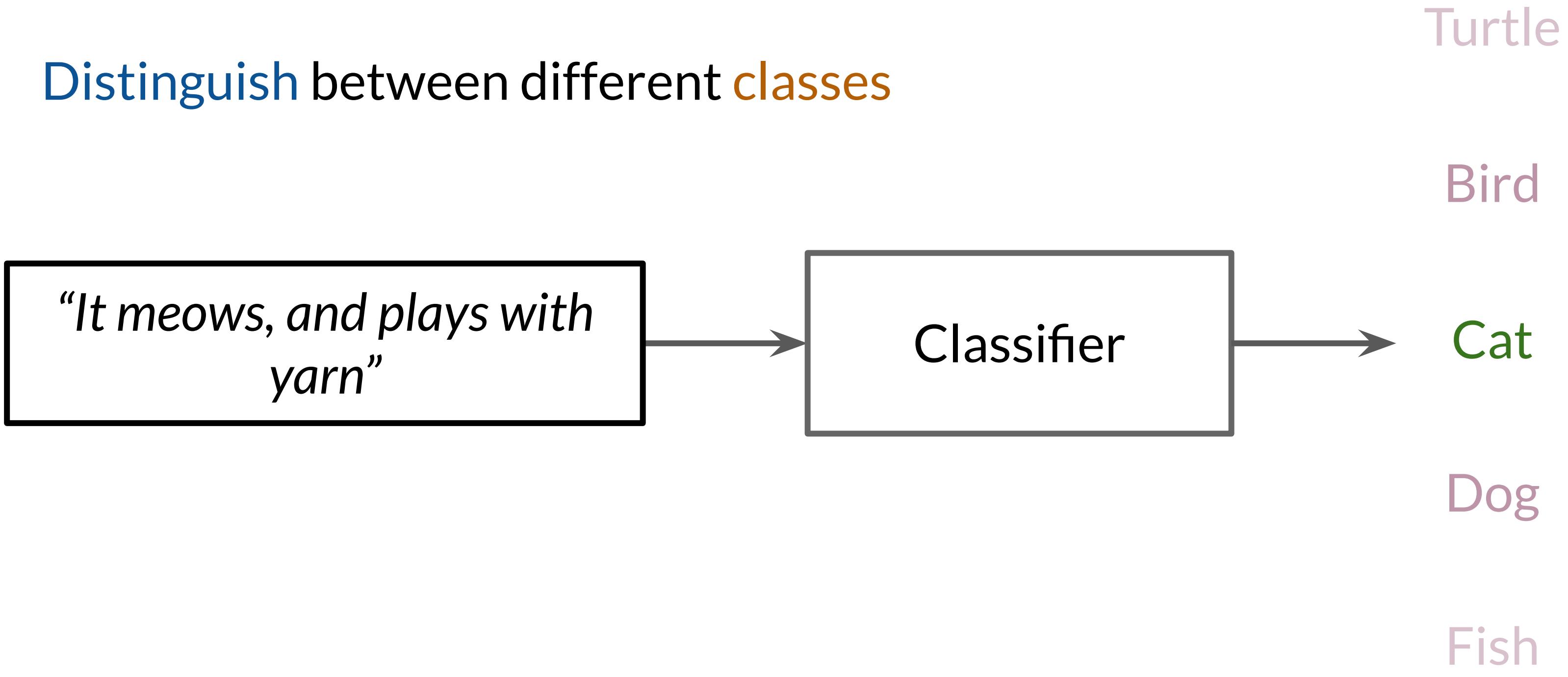
Classifiers

Distinguish between different classes

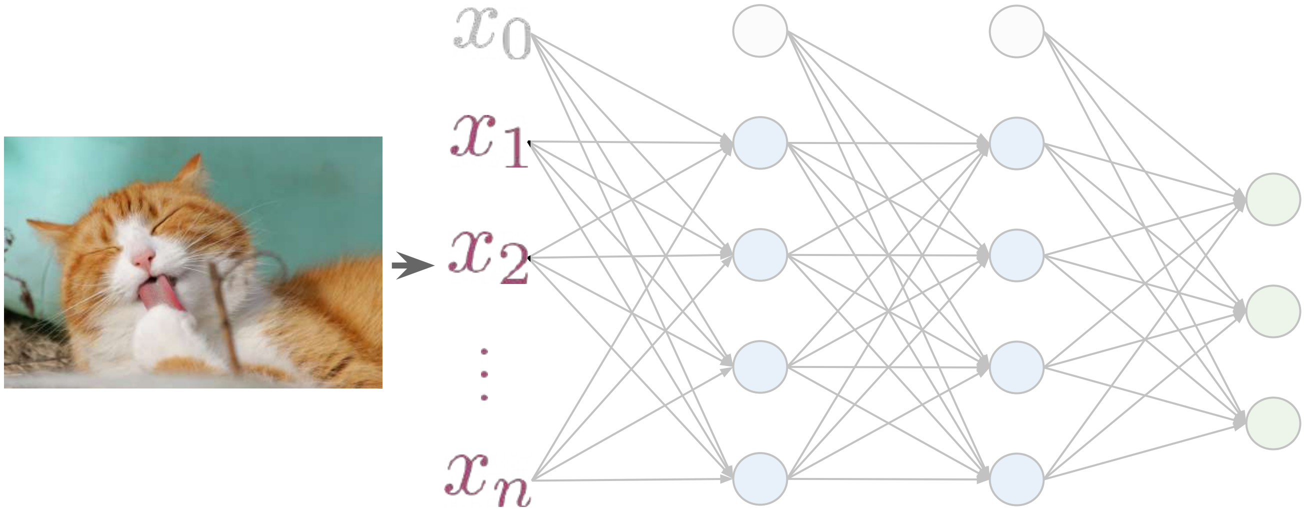


Classifiers

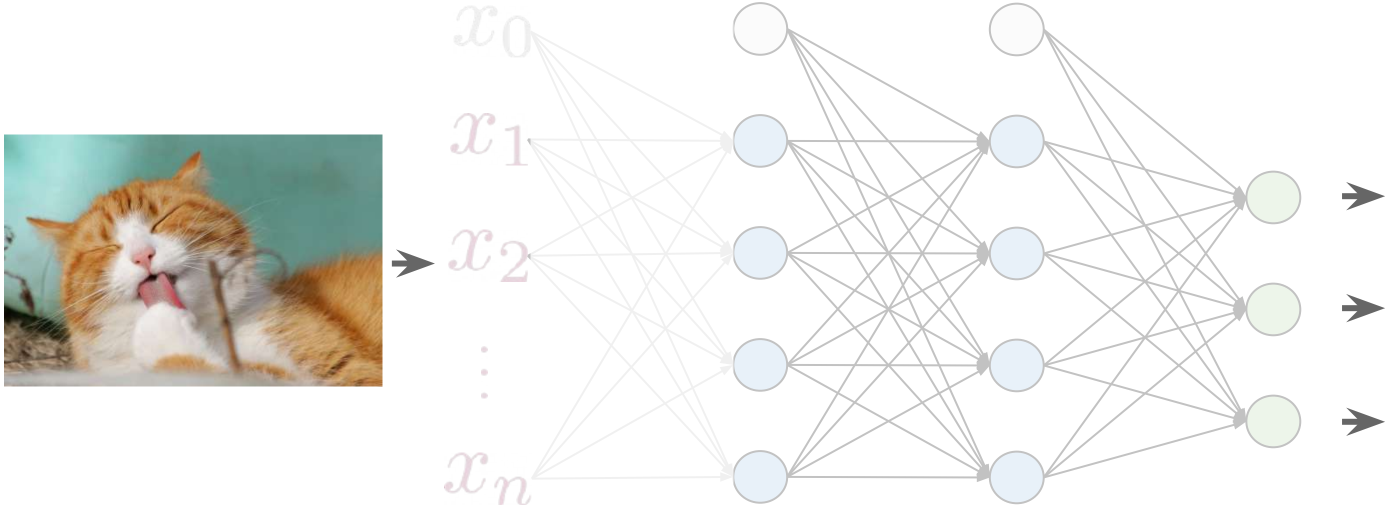
Distinguish between different classes



Neural Networks



Neural Networks

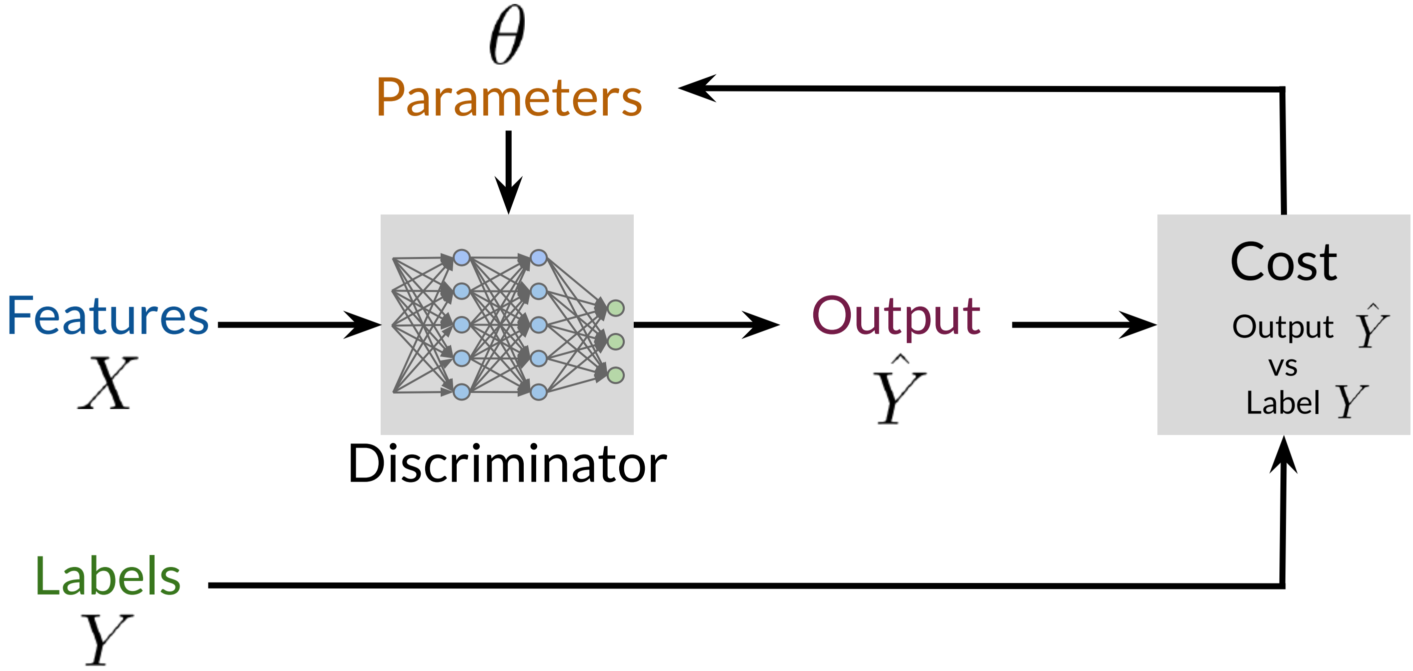


0.45 Cat

0.45 Dog

0.10 Bird

Classifiers (training)



θ

Parameters

Features

X

Discriminator

Output

$\hat{Y}$

Cost

Output $\hat{Y}$

vs

Label Y

Labels

Y

Classifiers

Turtle

Bird

$P($ Cat $|$ $)$

Dog

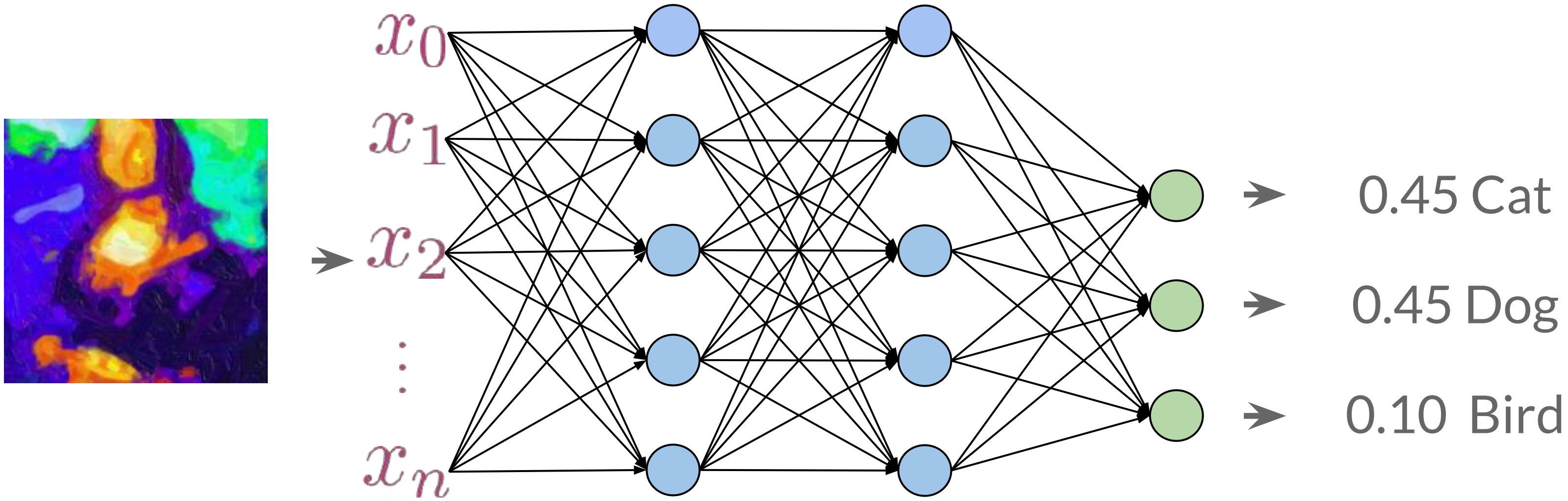
Fish

Classifiers

Conditional Probability

$$P(\underset{\text{Class}}{Y} \mid \underset{\text{Features}}{X})$$

Discriminator

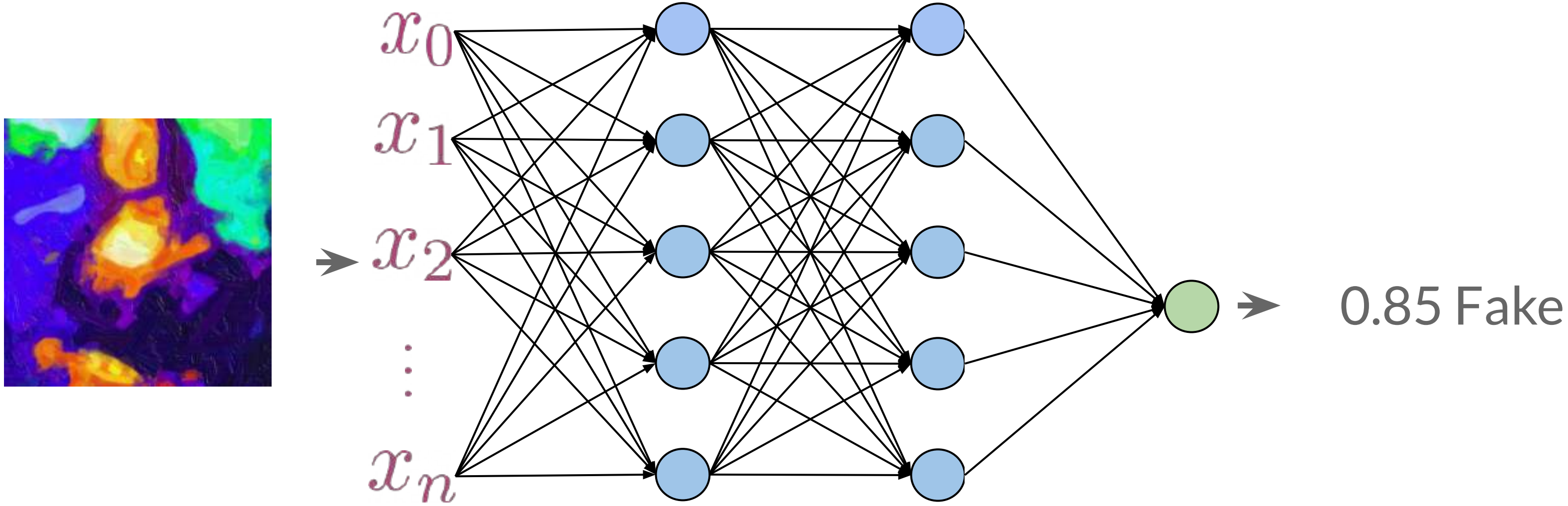


0.45 Cat

0.45 Dog

0.10 Bird

Discriminator



Discriminator

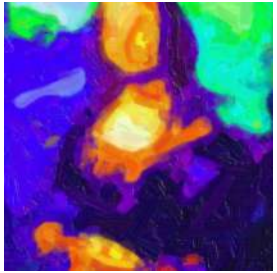
$$P(\text{Fake} \mid X)$$

Class

Features

Discriminator

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



Summary

- The discriminator is a classifier
- It learns the probability of class Y (**real** or *fake*) given features X
- The probabilities are the feedback for the generator

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Generator

Outline

- What the generator does
- How it improves its performance
- Generator in terms of probability

Generator

Generates examples of the class

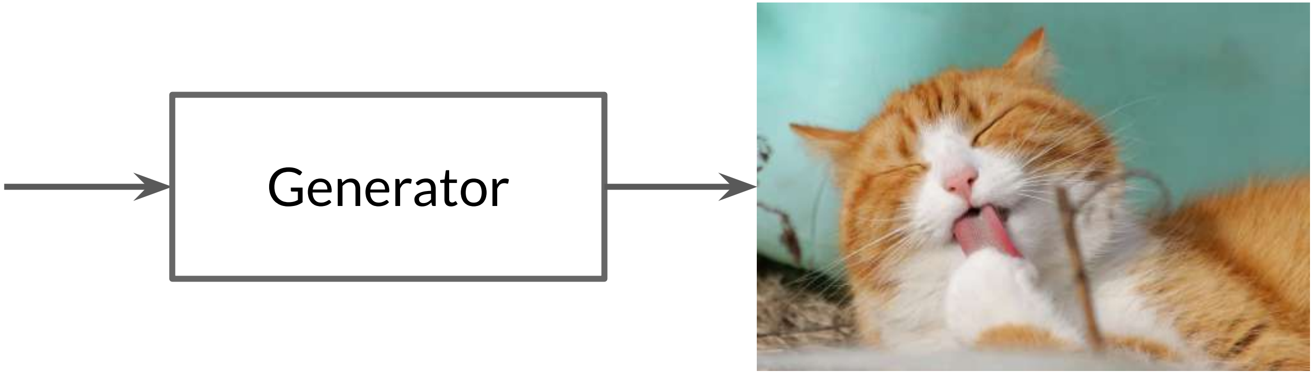
Turtle

Bird

Cat

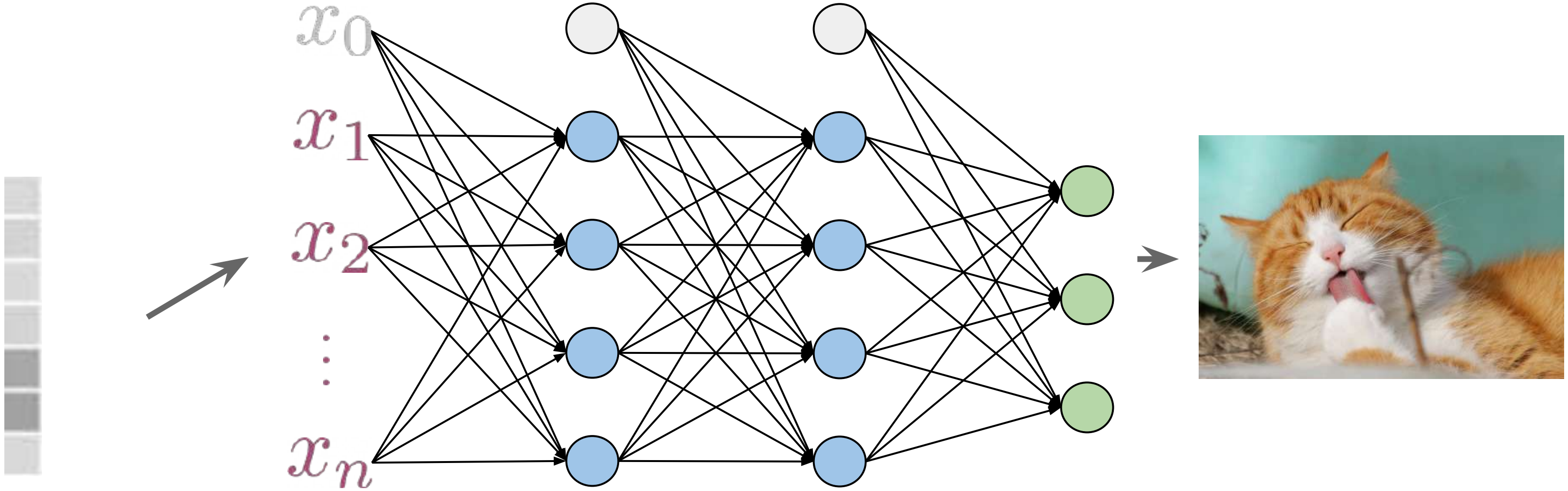
Dog

Fish



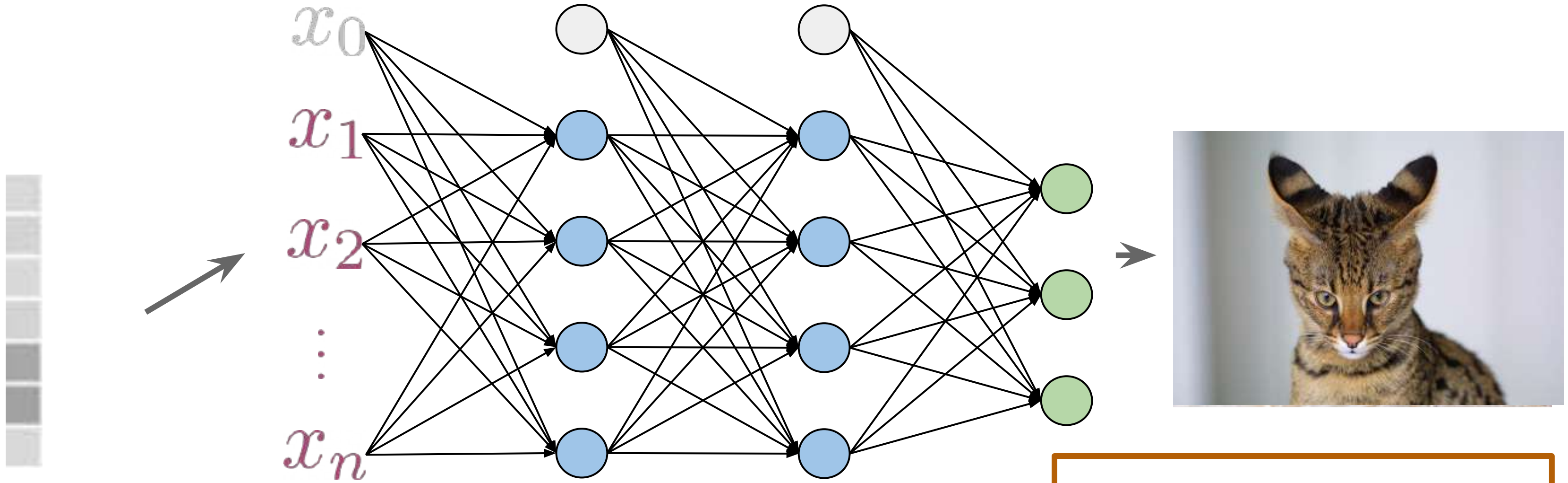
Generator

Neural Networks



Noise
(random features)

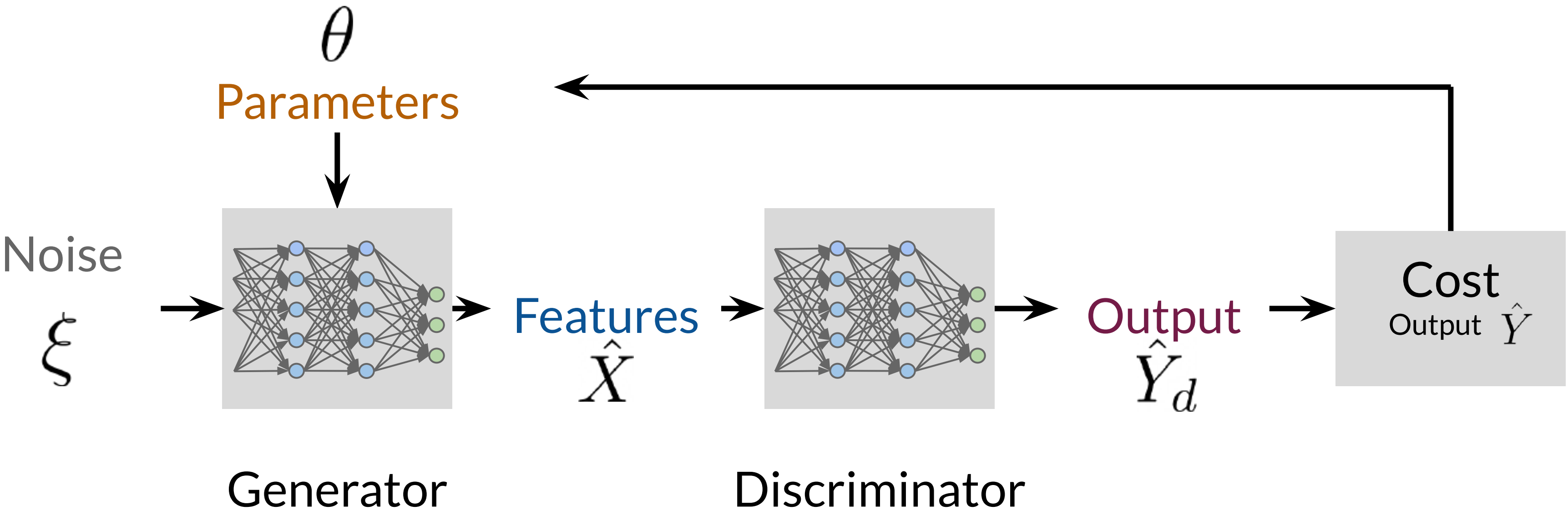
Neural Networks



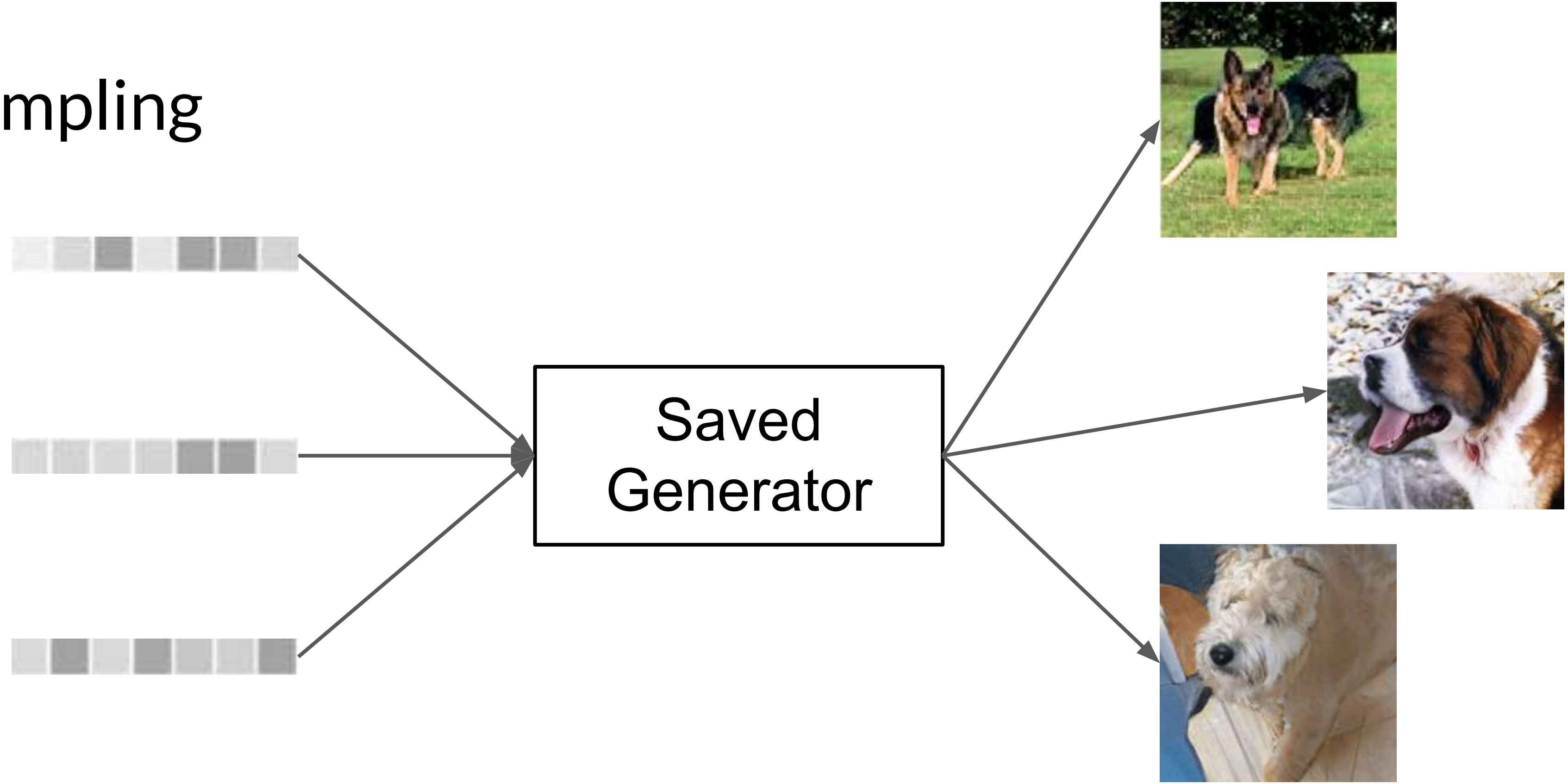
Noise
(random features)

Different outputs at every run!

Generator: Learning



Sampling



Generator

$P($ $|$

Turtle

Bird

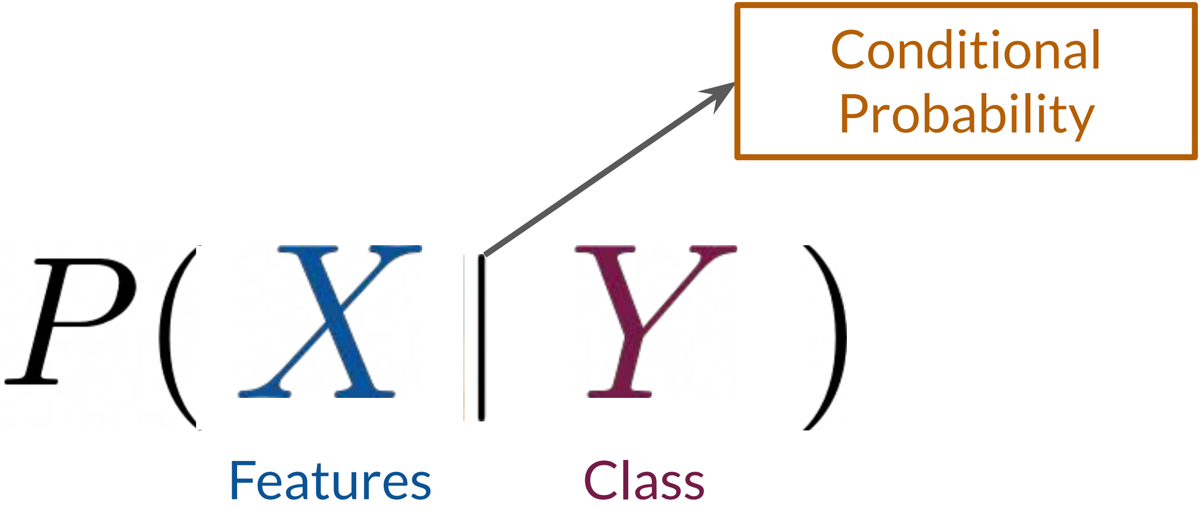
Cat

Dog

Fish

$)$

Generator



$$P(X \mid Y)$$

Conditional Probability

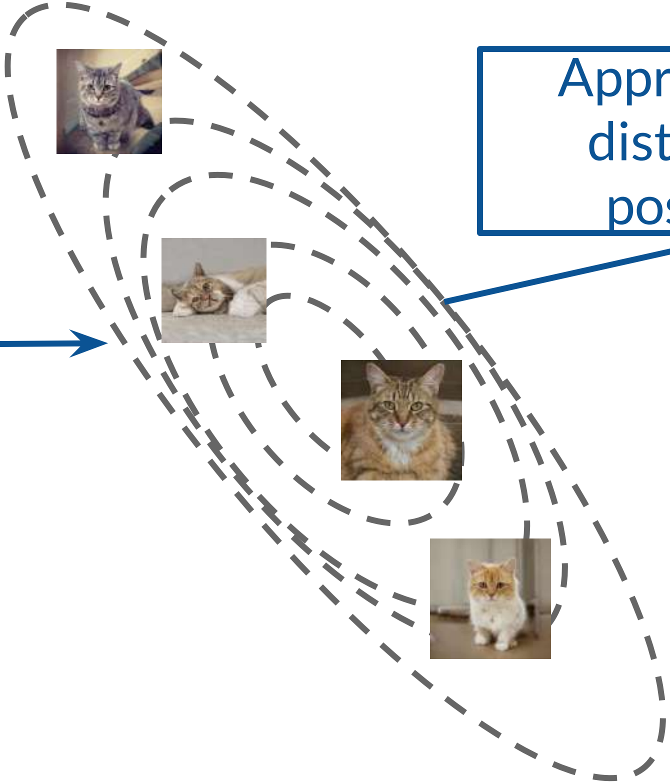
Features

Class

Generator

$$P(X)$$

Features



Approximate the distribution of possible cats

Images available from: http://thesecatsdonotexist.com/

Summary

- The generator produces fake data
- It learns the probability of features X
- The generator takes as input noise (random features)

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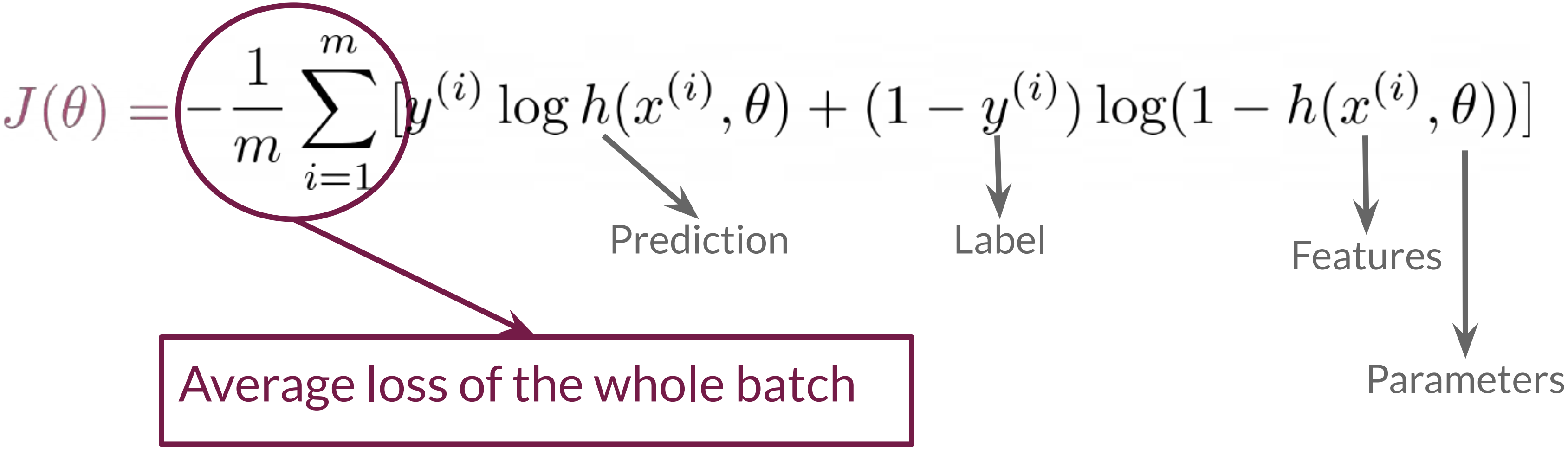
BCE Cost Function

Outline

- Binary Cross Entropy (BCE) Loss equation by parts

- How it looks graphically

BCE Cost Function



$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\log h(x^{(i)},\theta) + (1-y^{(i)})\log(1-h(x^{(i)},\theta))\right]$$

Prediction

Label

Features

Parameters

Average loss of the whole batch

BCE Cost Function

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[\boxed{y^{(i)}\log h(x^{(i)},\theta)} + \boxed{(1-y^{(i)})\log(1-h(x^{(i)},\theta))}\right]$$

BCE Cost Function

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[\boxed{y^{(i)} \log h(x^{(i)}, \theta)} + \boxed{(1 - y^{(i)}) \log(1 - h(x^{(i)}, \theta))}\right]$$

$y^{(i)}$	$h(x^{(i)}, \theta)$	$y^{(i)} \log h(x^{(i)}, \theta)$
0	any	0
1	0.99	~0
1	~0	-inf

Relevant when the label is 1

BCE Cost Function

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[\boxed{y^{(i)}\log h(x^{(i)},\theta)} + \boxed{(1-y^{(i)})\log(1-h(x^{(i)},\theta))}\right]$$

$y^{(i)}$	$h(x^{(i)},\theta)$	$(1-y^{(i)})\log\left(1-h(x^{(i)},\theta)\right)$
1	any	0
0	0.01	~0
0	~1	-inf

Relevant when the label is 0

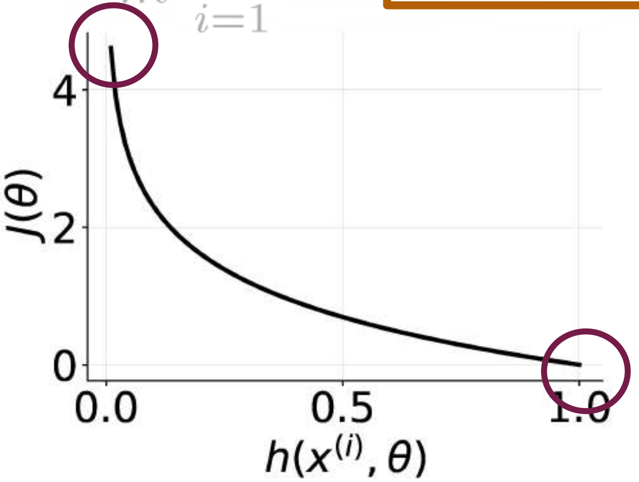
BCE Cost Function

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[\boxed{y^{(i)}\log h(x^{(i)},\theta)} + \boxed{(1-y^{(i)})\log(1-h(x^{(i)},\theta))}\right]$$

Ensures that the cost is always greater or equal to 0

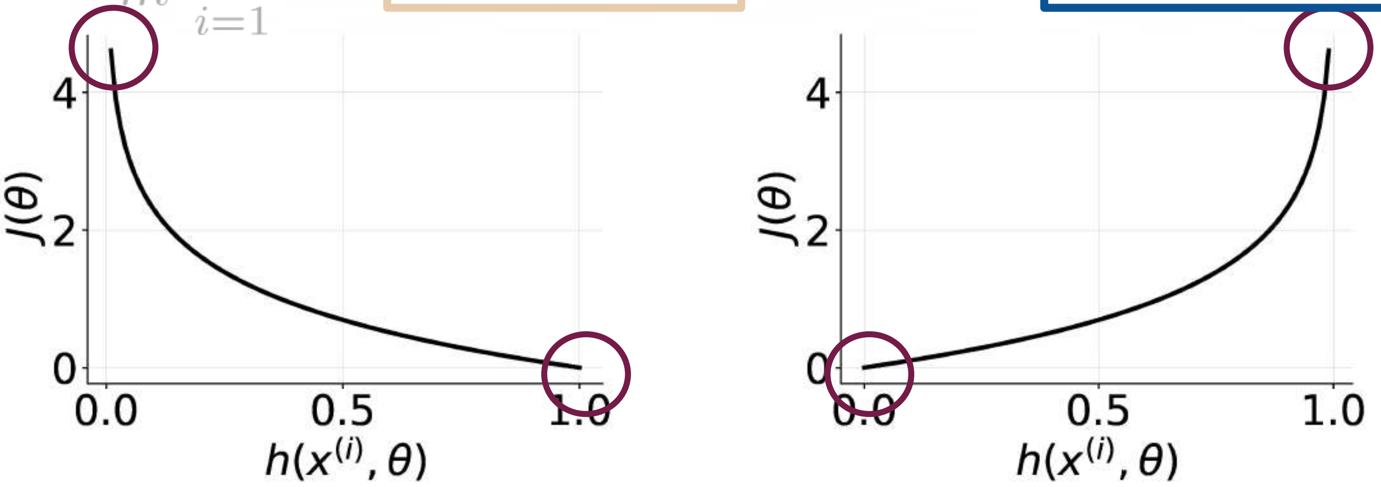
BCE Cost Function

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\boxed{\log h(x^{(i)},\theta)} + (1-y^{(i)})\boxed{\log(1-h(x^{(i)},\theta))}\right]$$



BCE Cost Function

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}\left[y^{(i)}\boxed{\log h(x^{(i)},\theta)} + (1-y^{(i)})\boxed{\log(1-h(x^{(i)},\theta))}\right]$$



Summary

- The BCE cost function has two parts (one relevant for each class)
- Close to zero when the label and the prediction are similar
- Approaches infinity when the label and the prediction are different

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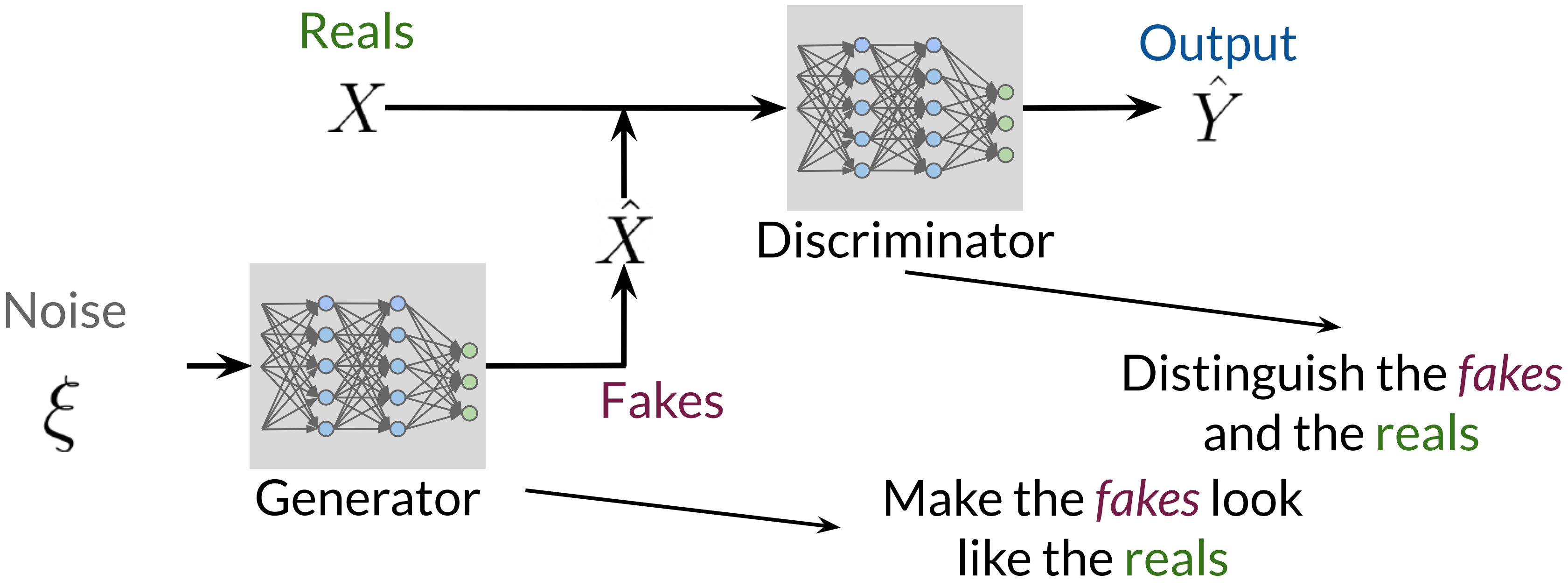
Putting It All Together

Outline

- How the whole architecture looks
- How to train GANs

GANs Model



Reals

X

Output

$\hat{Y}$

Discriminator

$\hat{X}$

Noise

ξ

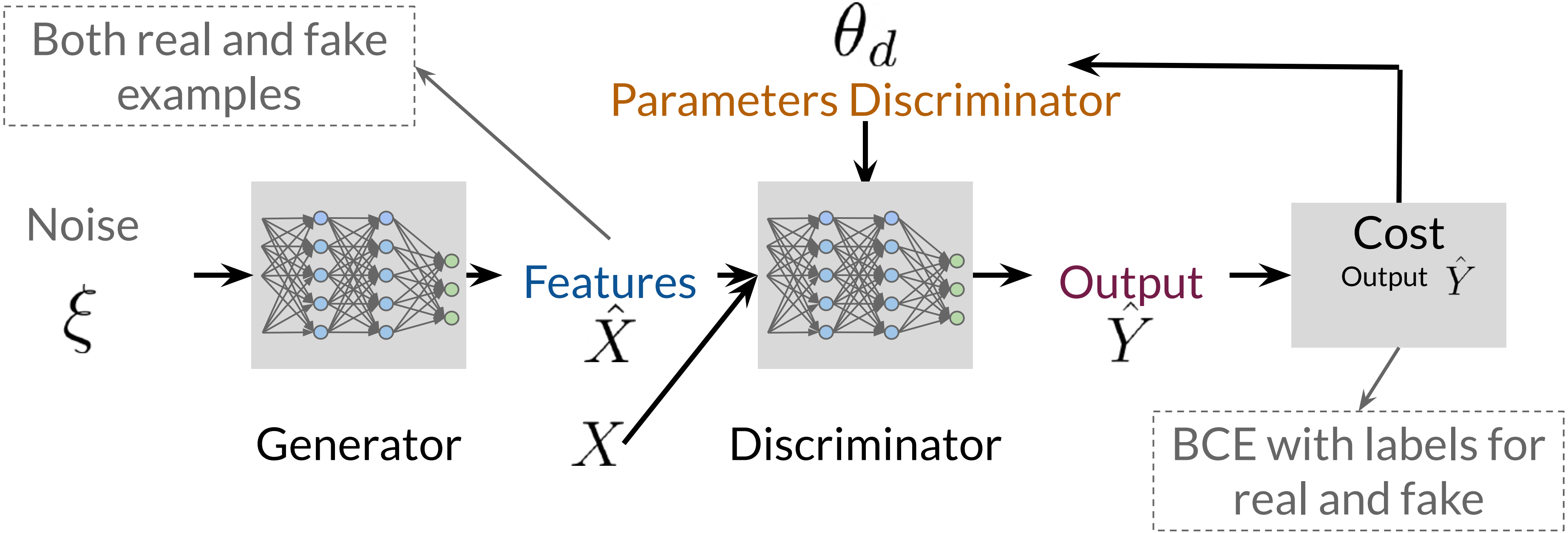
Generator

Fakes

Distinguish the *fakes* and the reals

Make the *fakes* look like the reals

Training GANs: Discriminator



Both real and fake examples

θ_d

Parameters Discriminator

Noise

ξ

Generator

Features

$\hat{X}$

X

Discriminator

Output

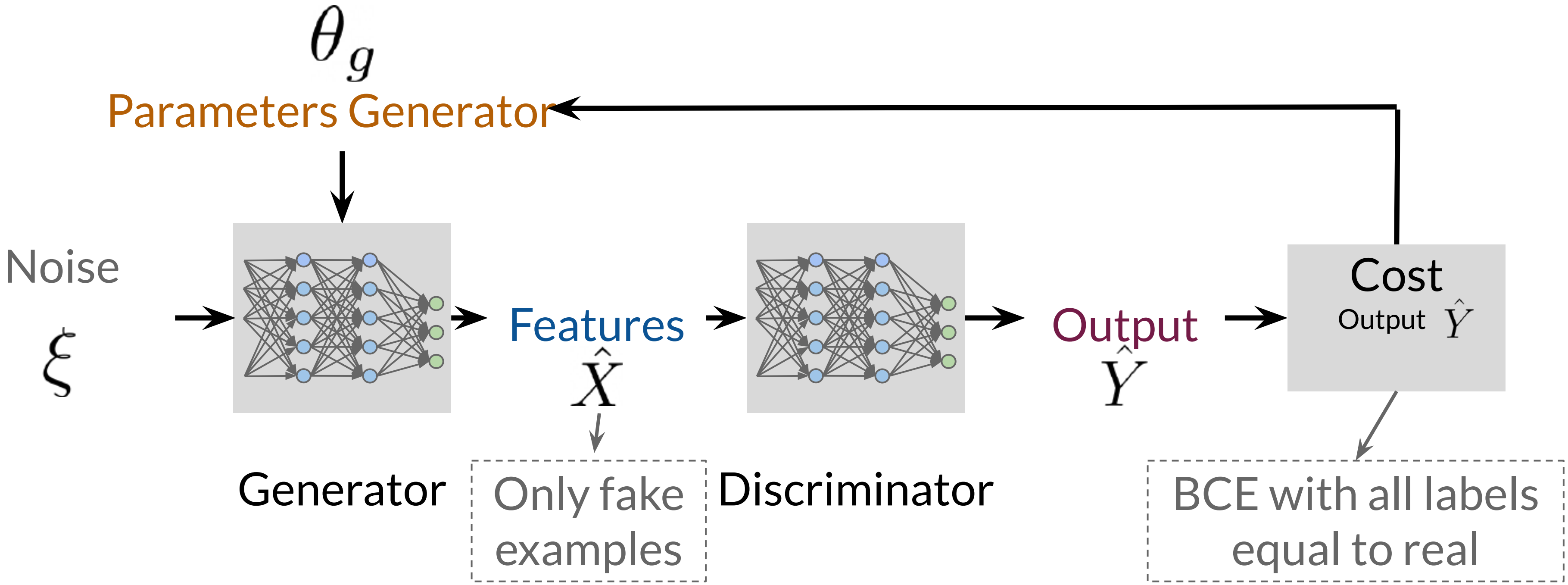
$\hat{Y}$

Cost

Output $\hat{Y}$

BCE with labels for real and fake

Training GANs: Generator



Training GANs

Discriminator Output

Superior Discriminator → *Fakes* as 100% fake → No way to improve

Summary

- GANs train in an alternating fashion
- The two models should always be at a similar “skill” level

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Intro to PyTorch (Optional)

Outline

- Comparison with TensorFlow
- Defining Models
- Training

PyTorch vs TensorFlow

PyTorch

Imperative, computations on the go

```python
A, B = 1, 2
C = A + B
print(C)
```

```
3
```

Dynamic Computational Graphs

TensorFlow

Symbolic, first define and then compile

```python
C = A + B
f = compile(C)
print(f(A = 1, B = 2))
```

```
3
```

Static Computational Graphs

Tensorflow > 2.0 moves toward PyTorch by including Eager Execution

PyTorch vs TensorFlow

PyTorch | TensorFlow

Currently very similar frameworks!

Tensorflow > 2.0 moves toward PyTorch by including Eager Execution

Defining Models in PyTorch

```python
import torch
from torch import nn
```

Custom layers for DL

```python
class LogisticRegression(nn.Module):
     def __init__(self, in):
          super().__init__()
          self.log_reg = nn.Sequential(
              nn.Linear(in,  1),
              nn.Sigmoid()
          )
     def forward(self, x):
          return self.log_reg(x)
```

Define the model as a class

Initialization method with parameters

Definition of the architecture

Forward computation of the model with inputs x

Training Models In PyTorch

```
model = LogisticRegression(16)
```

Initialization of the model

```
criterion = nn.BCELoss()
```

Cost function

```
optimizer = torch.optim.SGD(model.parameters(), lr=0.01)
```

Optimizer

```
for t in range(n_epochs):

    y_pred = model(x)
    loss = criterion(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Training loop for number of epochs

Forward propagation

Optimization step

Summary

- PyTorch makes computations on the run
- Dynamic computational graphs in Pytorch
- Just another framework, and similar to Tensorflow!