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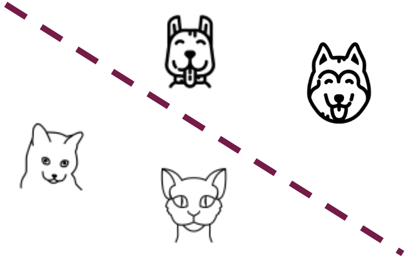
Generative Models

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

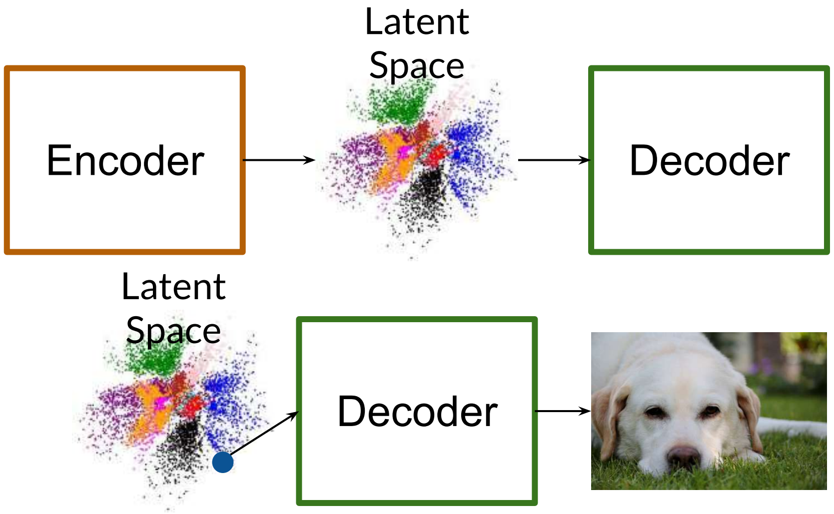
Noise Class Features

$$\xi, Y \rightarrow X$$

$$P(X|Y)$$

Generative Models

Variational Autoencoders



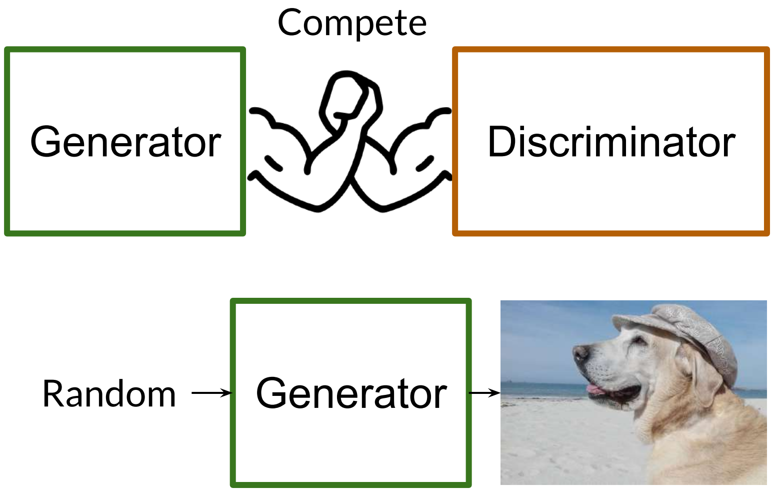
Generative Adversarial Networks

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

Generative Models

Variational Autoencoders

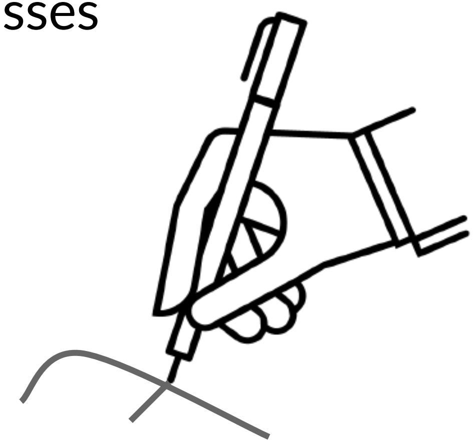
Generative Adversarial Networks



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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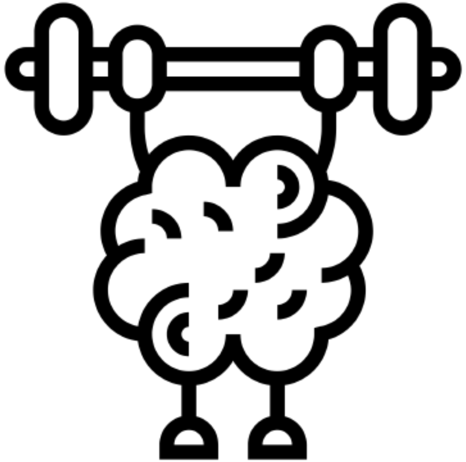
Real Life GANs

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

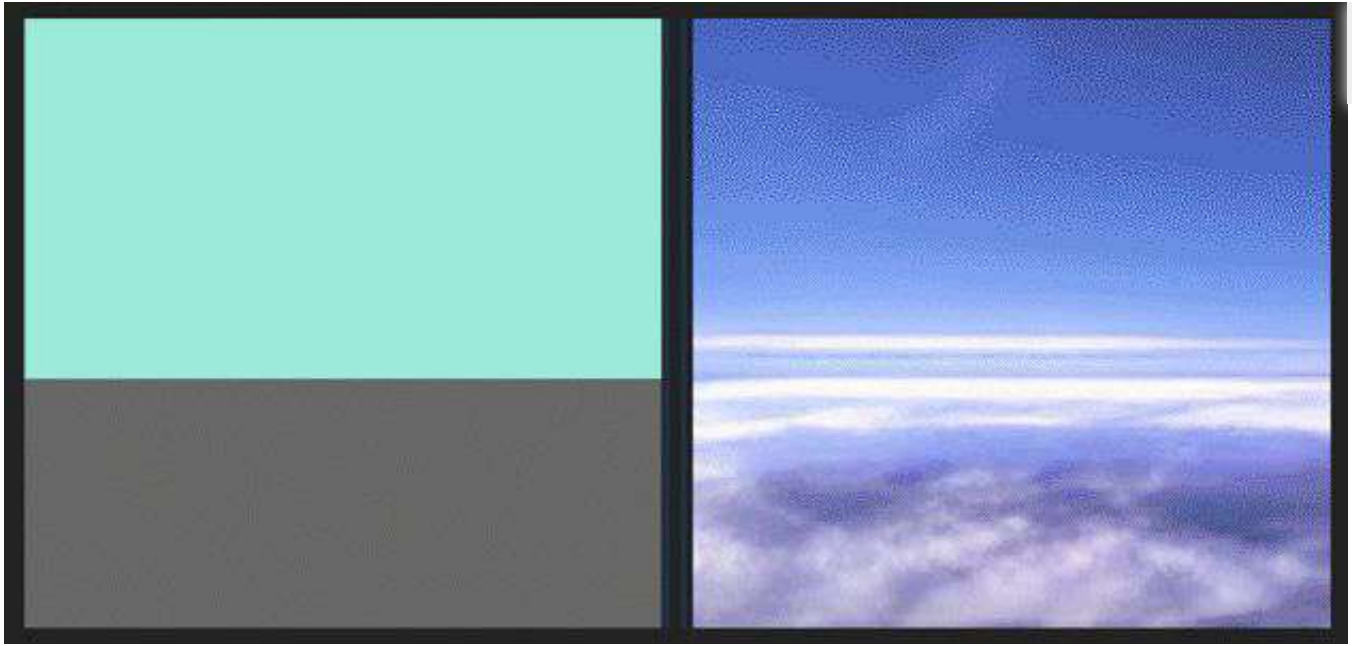
GANs for Image Translation

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



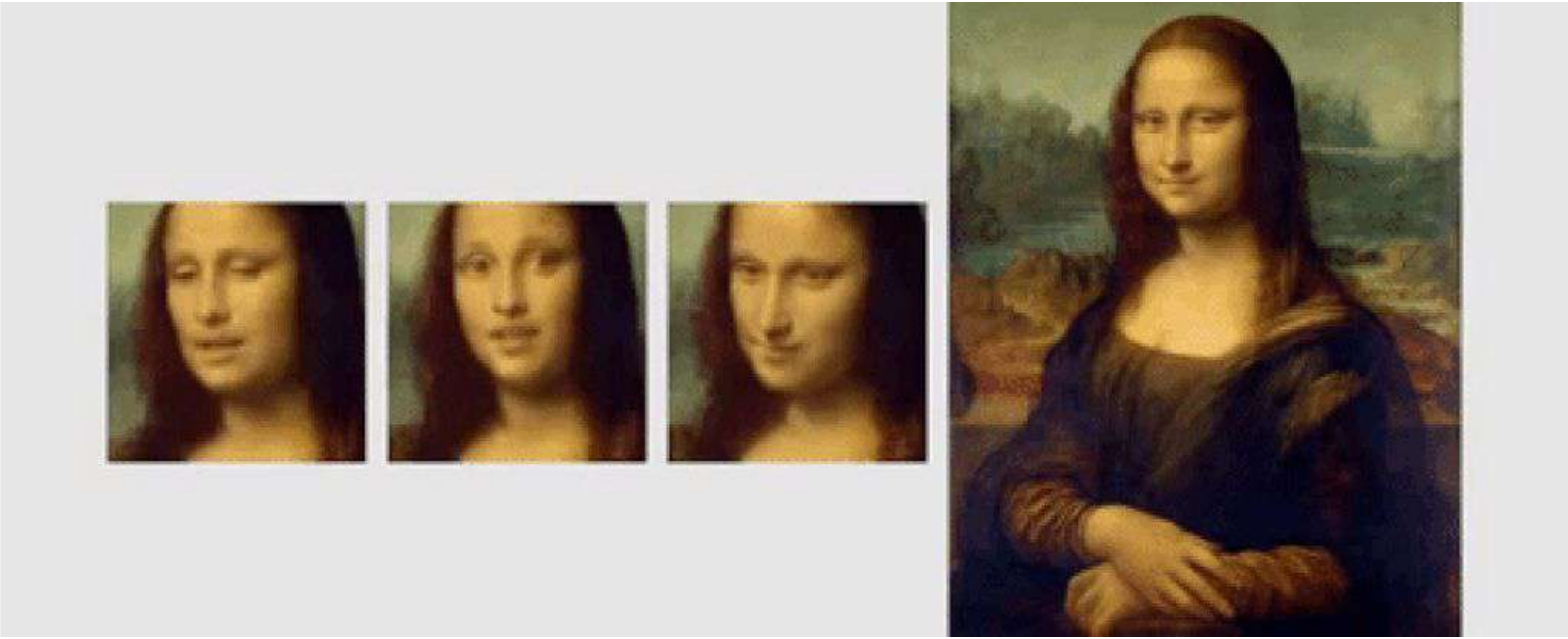
GauGAN

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

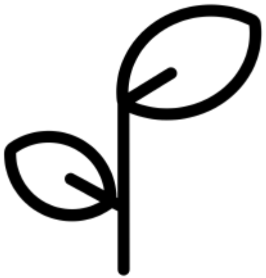
Wu, Jiajun, et al. "Learning a probabilistic latent space of object shapes via 3d generative-adversarial modeling." *Advances in neural information processing systems*. 2016.

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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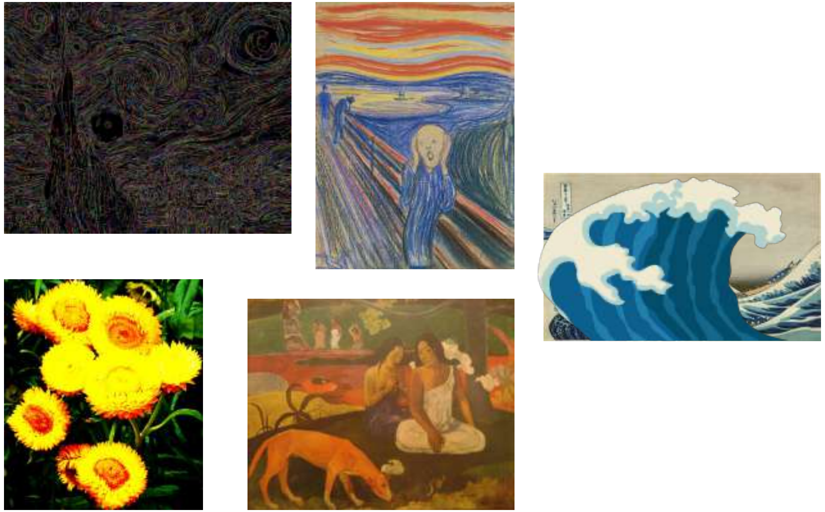
Intuition Behind GANs

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

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**

Doesn't know how it should look

Generative Adversarial Network

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

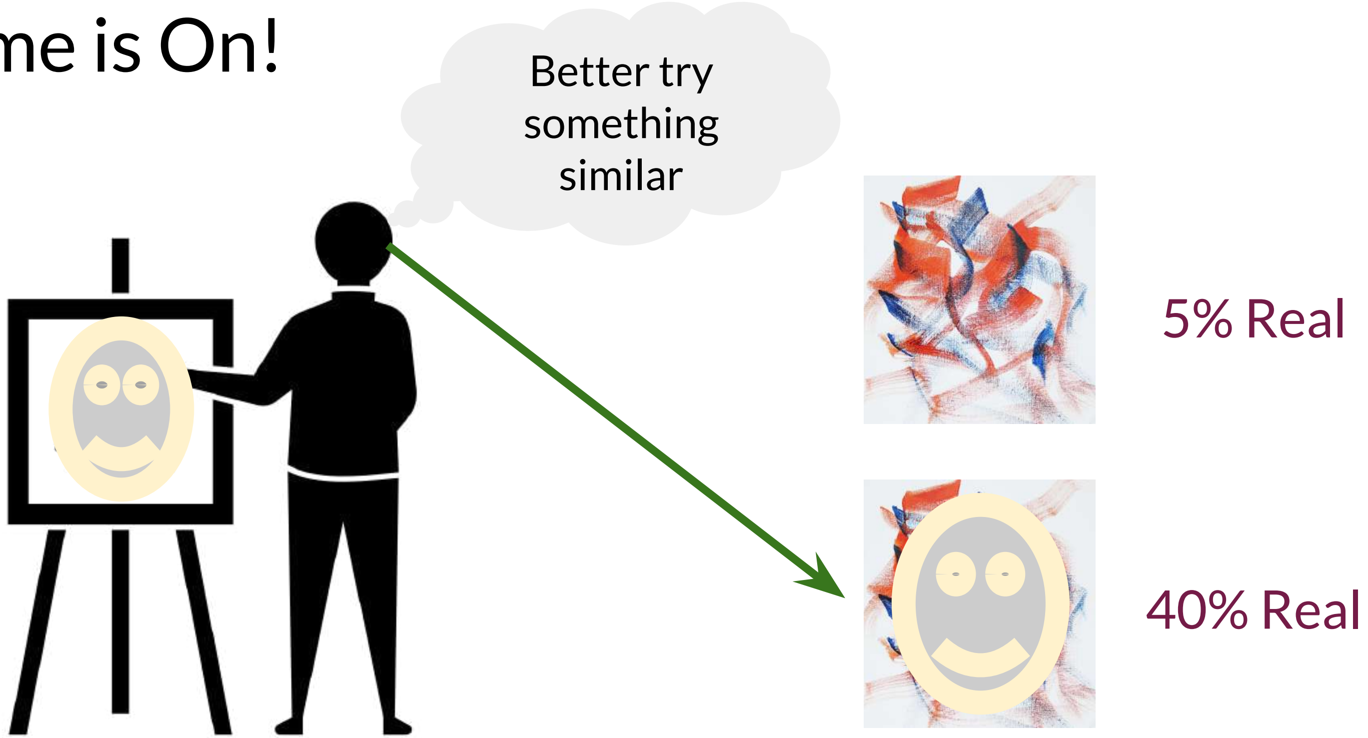
The Game Is On!

5% Real

40% Real

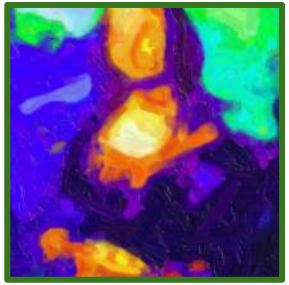
80% Real

The Game is On!



The Game Is On!

30% Real

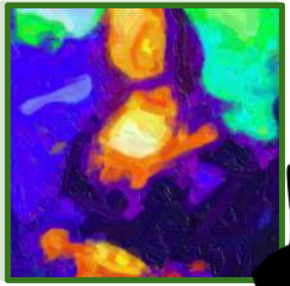


60% Real

95% Real

The Game Is On!

30% Real



60% Real

Wrong!

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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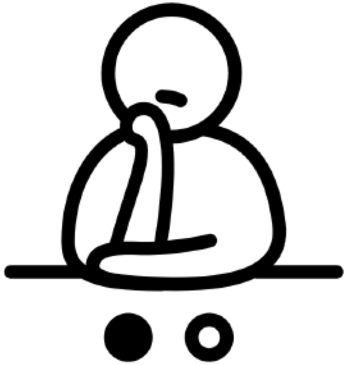
Discriminator

Outline

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



Classifiers

Distinguish between different classes

Classifier

Turtle

Bird

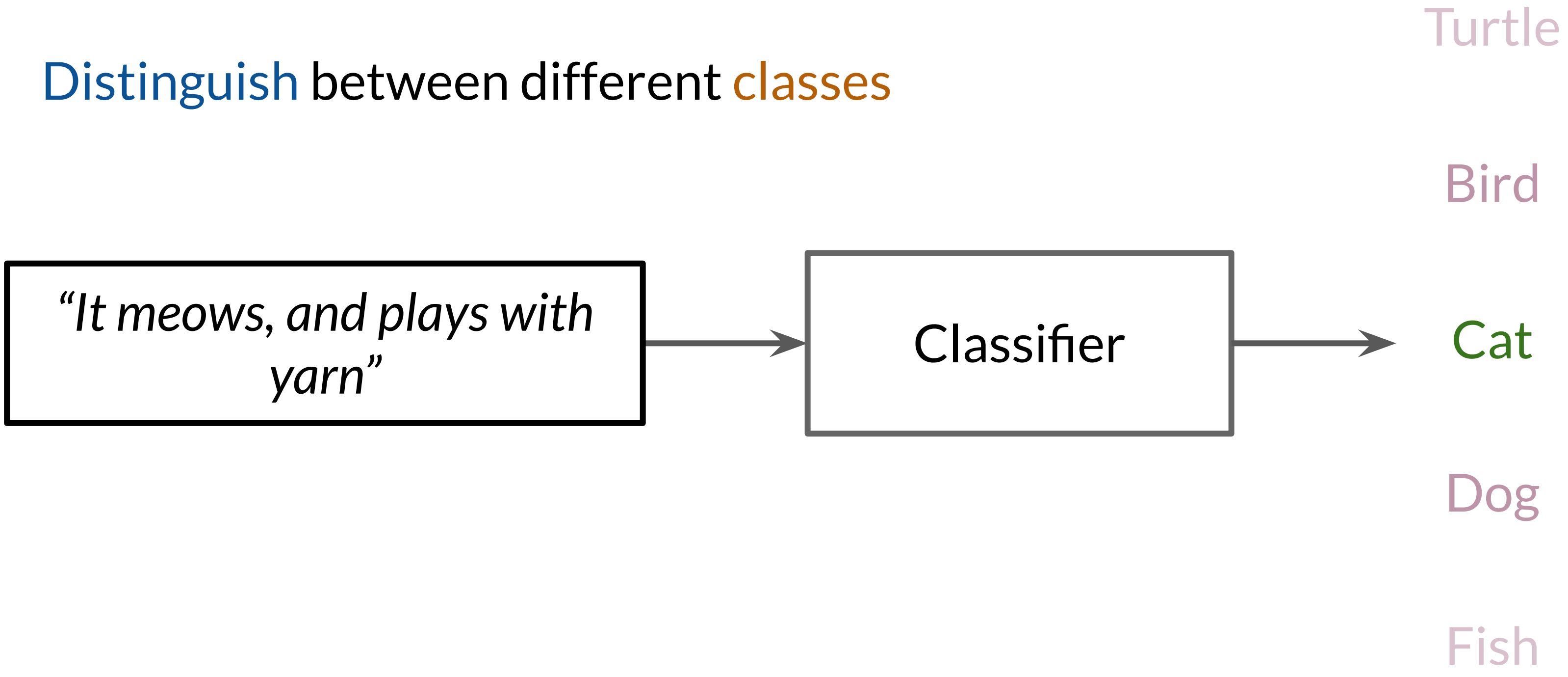
Cat

Dog

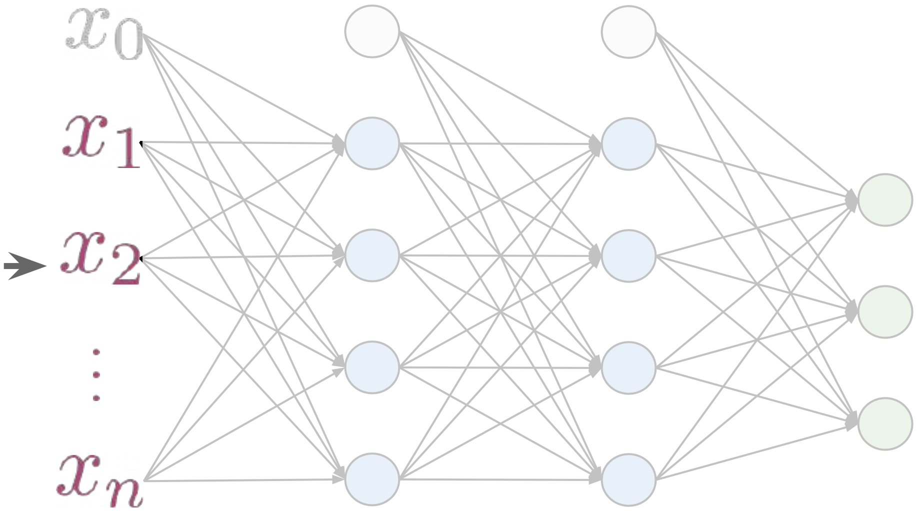
Fish

Classifiers

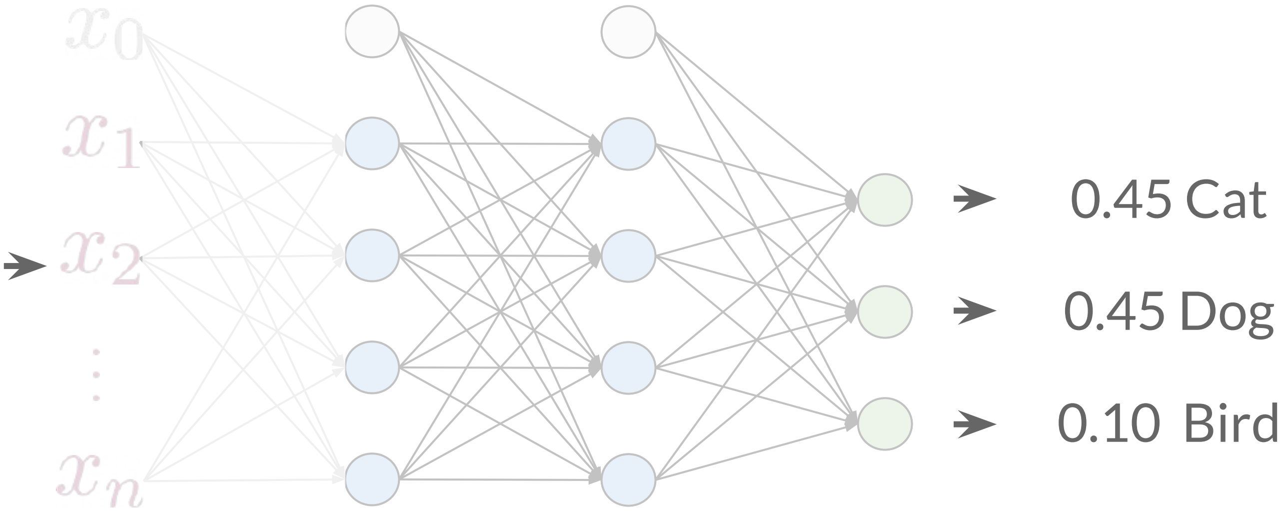
Distinguish between different classes



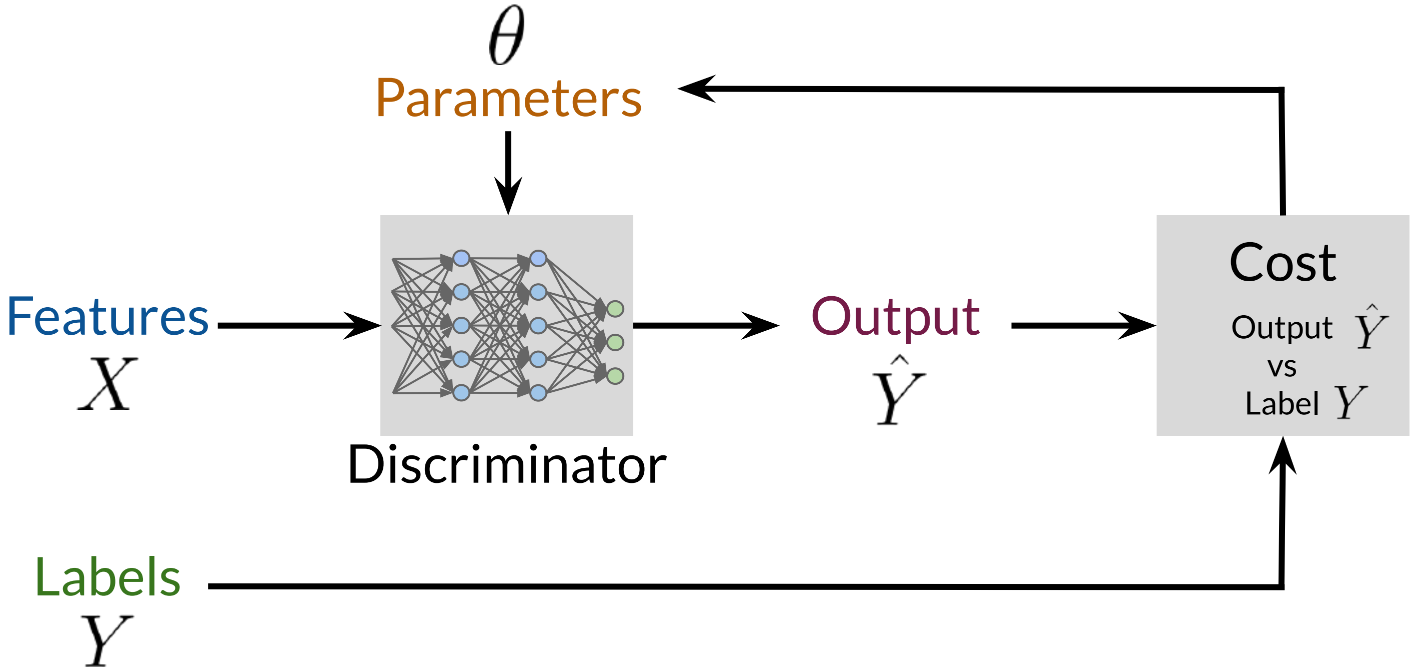
Neural Networks



Neural Networks



Classifiers (training)



Classifiers

Turtle

Bird

$P($ Cat $|$  $)$

Dog

Fish

Classifiers

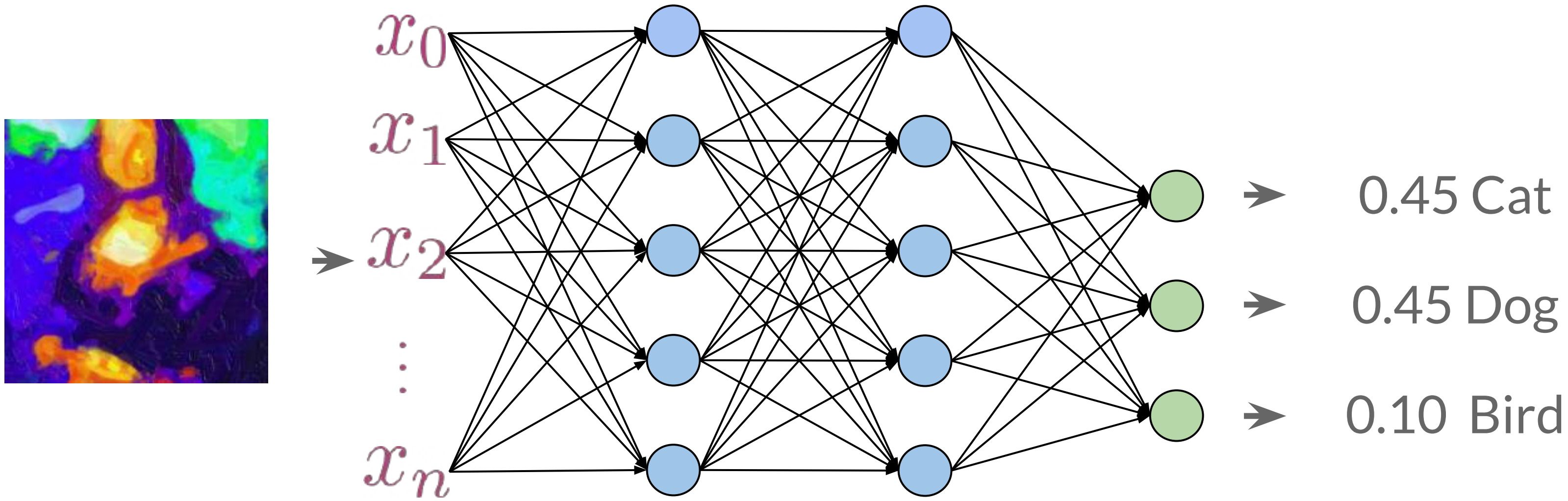
Conditional Probability

$$P(Y \mid X)$$

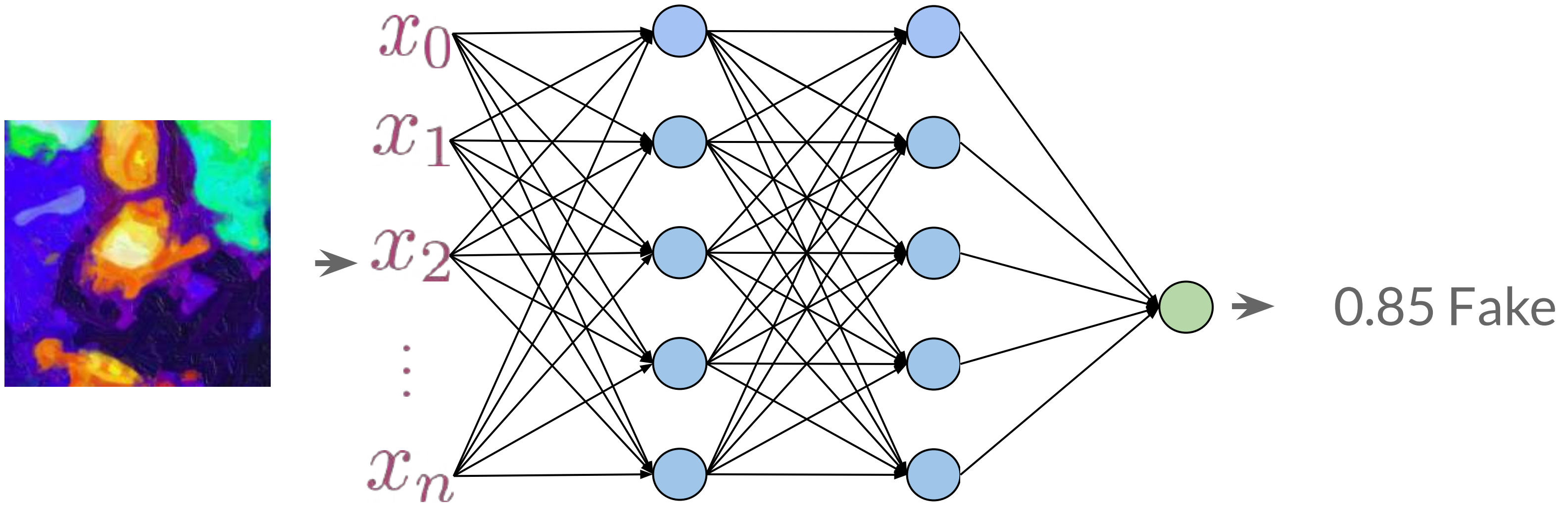
Class

Features

Discriminator



Discriminator

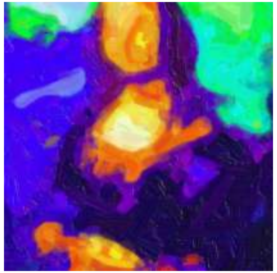


Discriminator

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

Class Features

Discriminator

$P($ Fake $\mid$  $) = 0.85 \rightarrow \boxed{\text{Fake}}$

Class

Features

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

Turtle

Generates examples of the class

Bird

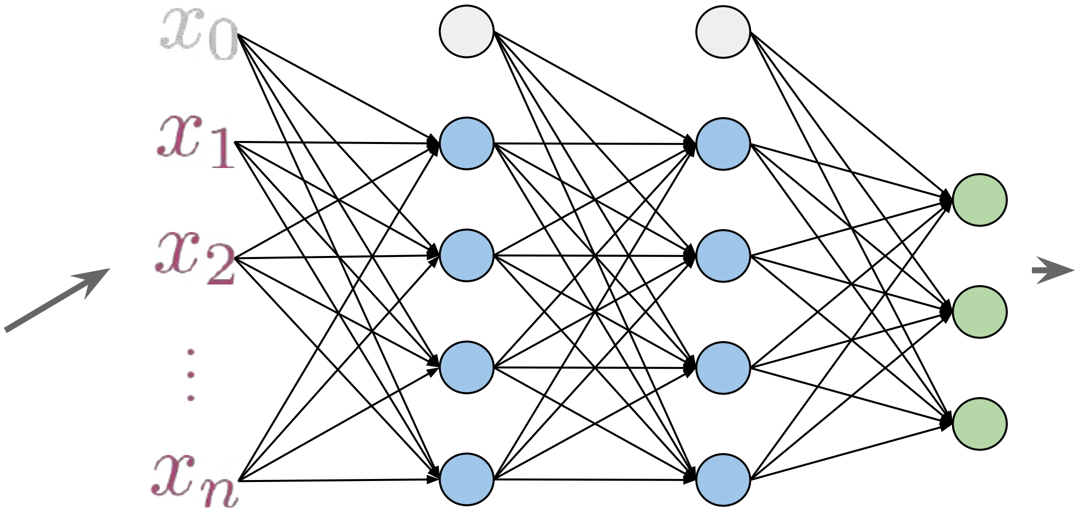
Cat → Generator →

Dog

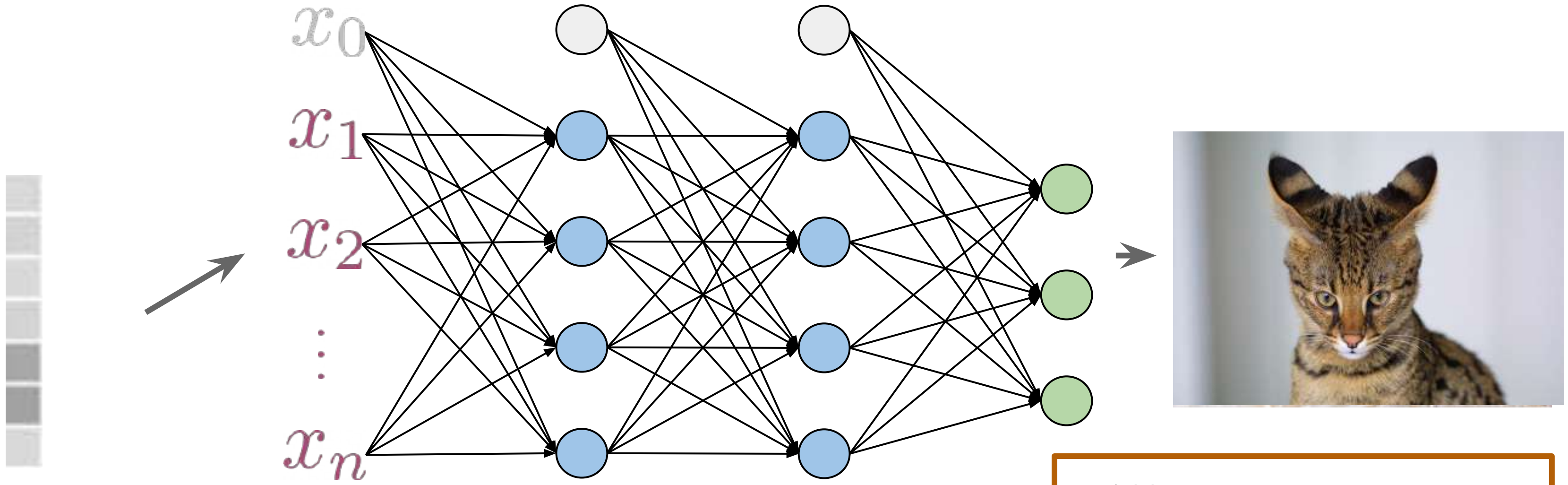
Fish

Neural Networks

Noise
(random features)



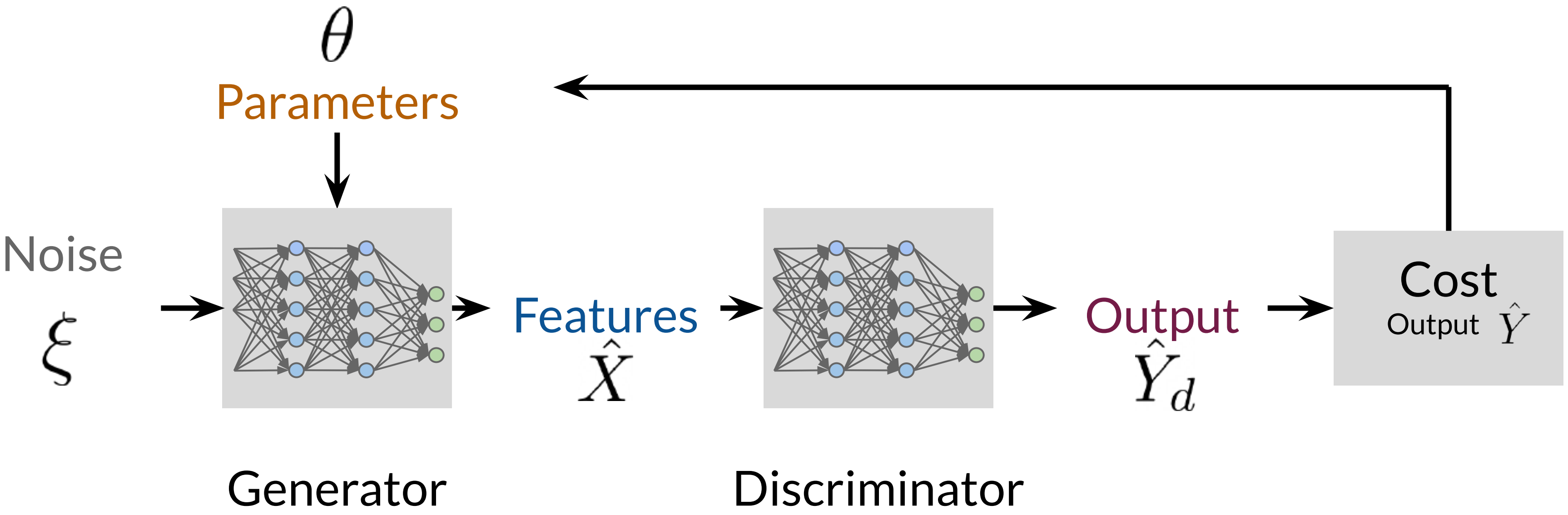
Neural Networks



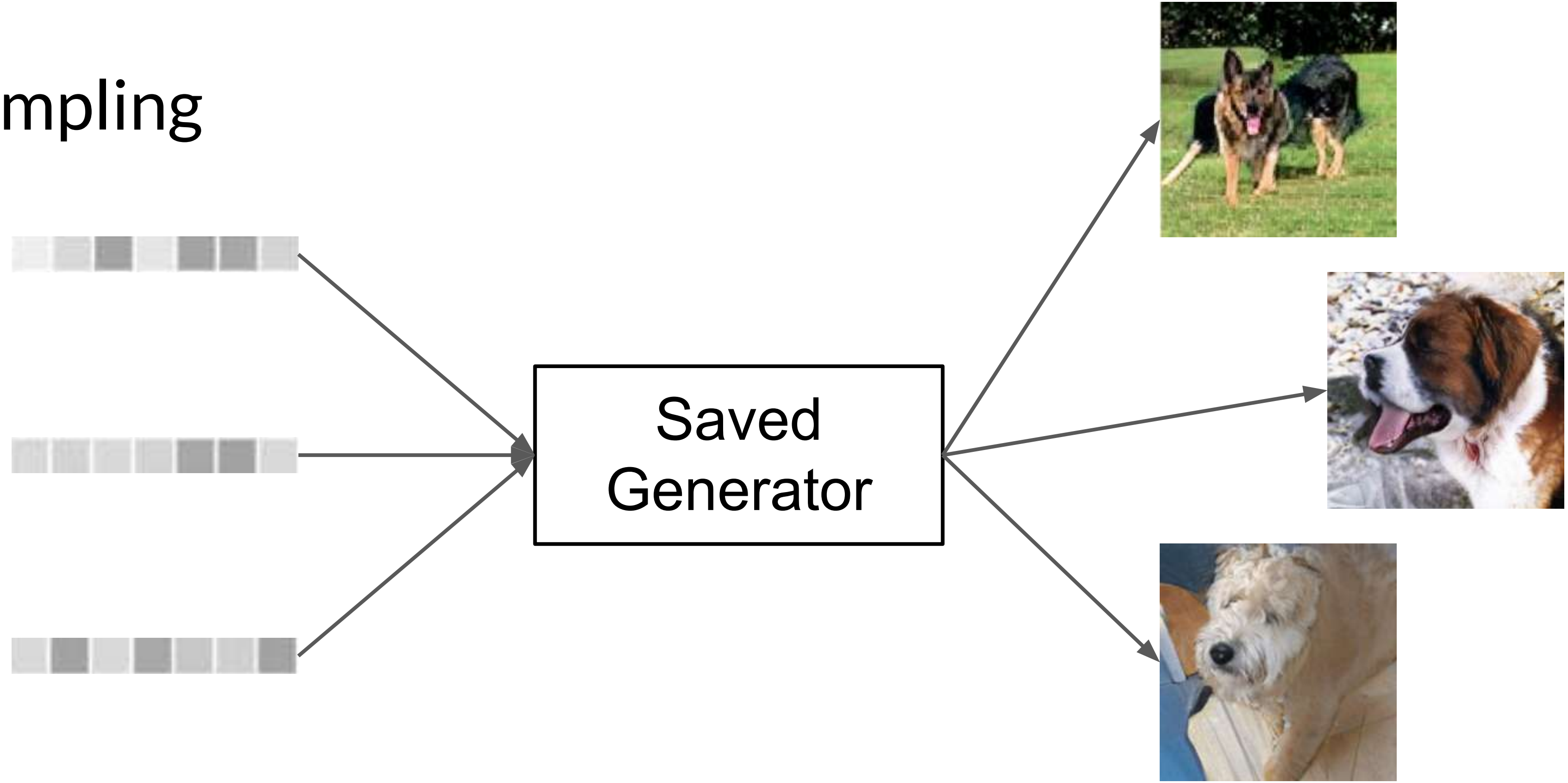
Noise
(random features)

Different outputs at every run!

Generator: Learning



Sampling



Generator

$P($  $|$

Turtle

Bird

Cat

Dog

Fish

$)$

Generator

Conditional Probability

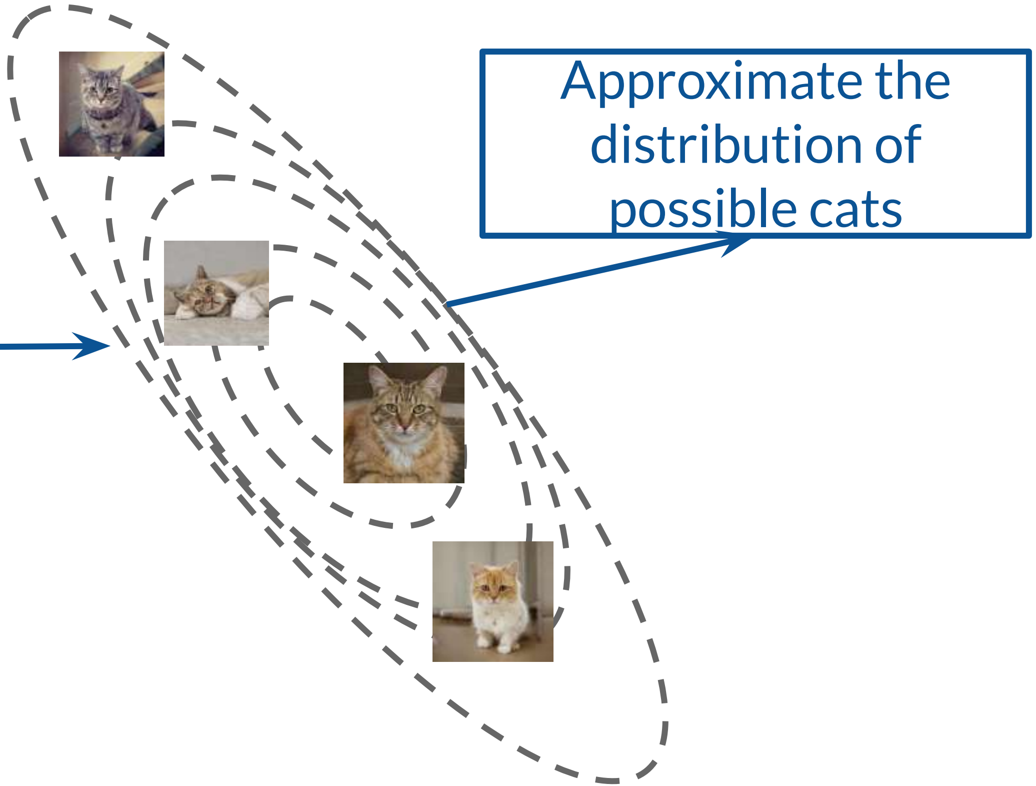
$$P(X \mid Y)$$

Features Class

Generator

$$P(X)$$

Features



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)

BCE Cost Function

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Outline

- Binary Cross Entropy (BCE) Loss equation by parts
- How it looks graphically

BCE Cost Function

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

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

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

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

Relevant when the label is 0

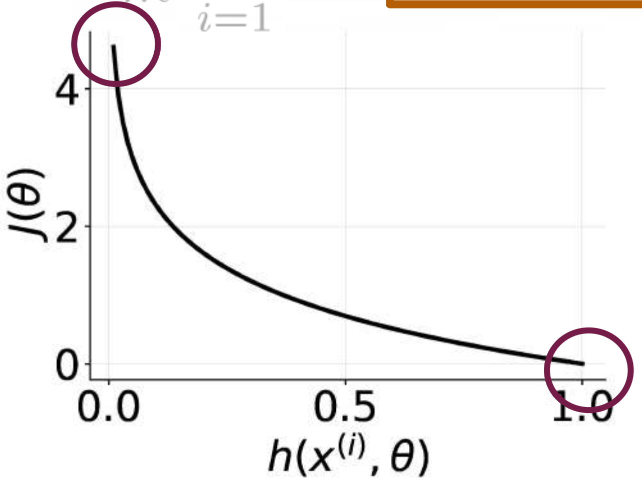
BCE Cost Function

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

Ensures that the cost is always greater or equal to 0

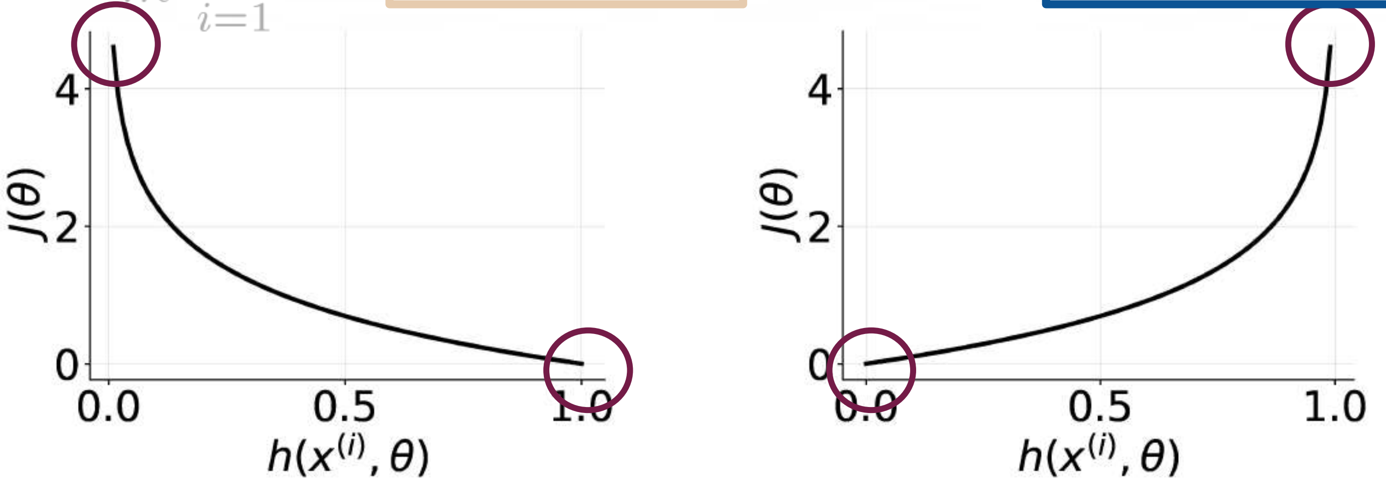
BCE Cost Function

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



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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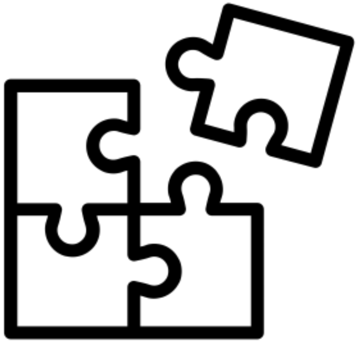
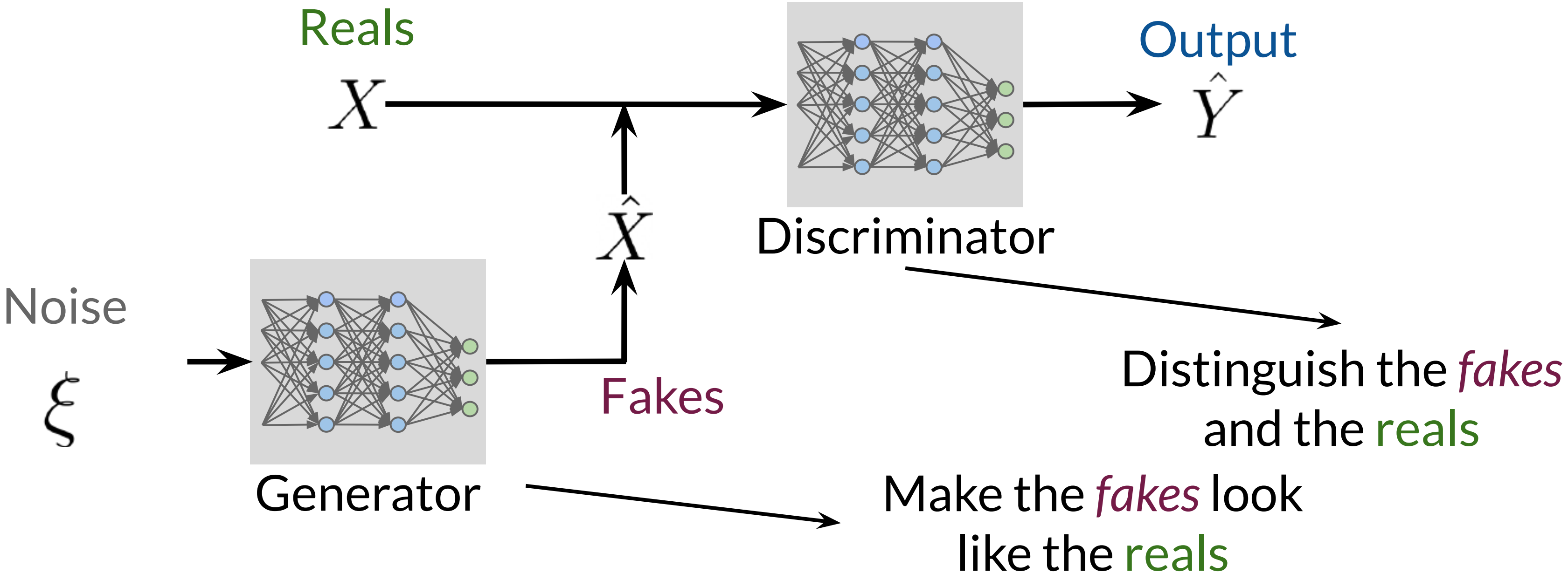
Putting It All Together

Outline

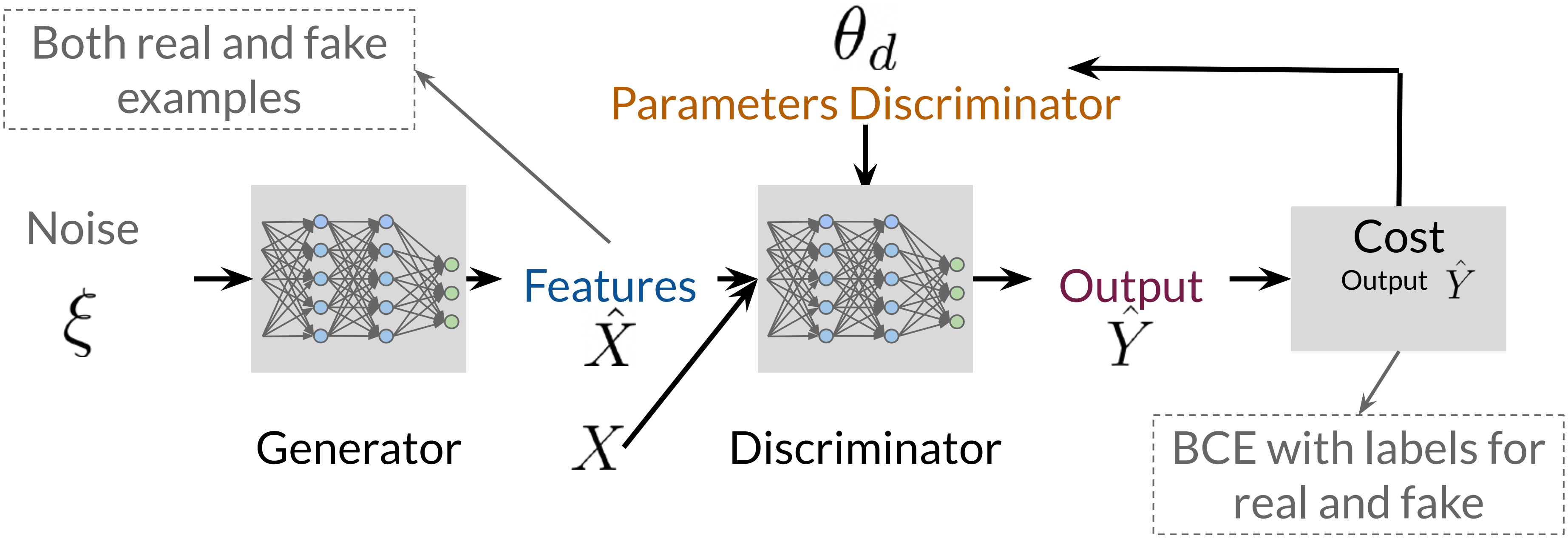
- How the whole architecture looks
- How to train GANs



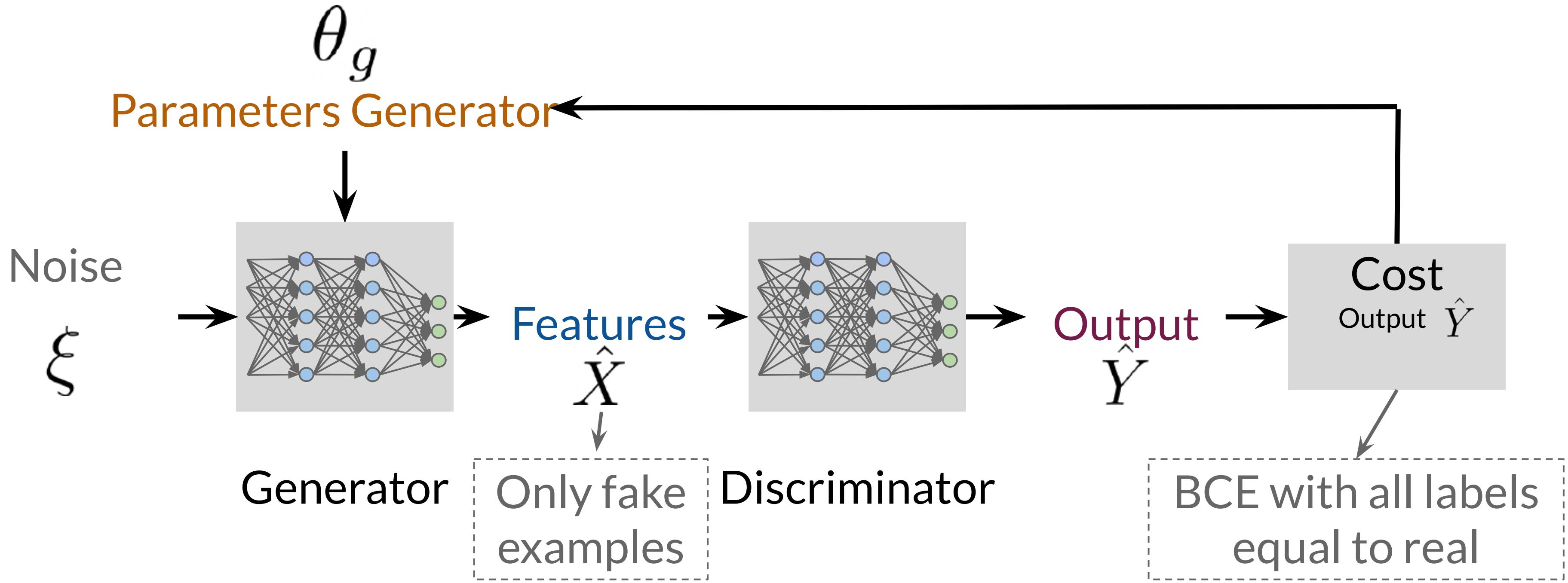
GANs Model


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



Training GANs: Generator



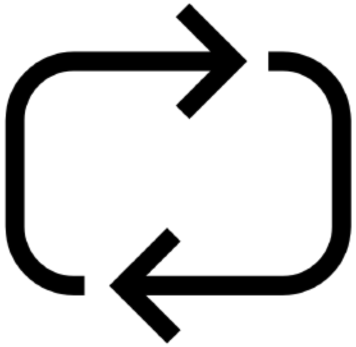
Training GANs

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

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

3

Dynamic Computational Graphs

TensorFlow

Symbolic, first define and then compile

```
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

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

Custom layers for DL

```
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!