

Introduction

When evaluating the quality of synthetic data, it might be reasonable to speculate whether one could

- Train a NN to distinguish between real and synthetic data

We will call a NN designed for that purpose a *Discriminator*.

We will call the NN designed to *generate* synthetic data the *Generator*.

It's easy to train a weak Discriminator

- one that distinguishes between real data and noise (random data)

We can train a stronger Discriminator if we have access to higher quality (than noise) synthetic data.

The higher the quality of the synthetic data, the stronger the Discriminator.

But how do we construct a Generator that might be able to create synthetic data good enough to fool the Discriminator ?

Using the NN for the Discriminator

- given an input \mathbf{x} created by the Generator
- we can compute the Gradient
 - of the logit (the Discriminator output indicating Real or Not Real)
 - with respect to \mathbf{x}
- the Generator can modify \mathbf{x} using the Gradient in the direction that moves the logit toward "Real"

One can imagine an iterative process in which

- feedback from the Discriminator improves the Generator
- the resulting higher quality synthetic data from the Generator can be used to train a stronger Discriminator

This "adversarial" training is the basis for a *Generative Adversarial Network (GAN)*

Aside

The GAN (<https://arxiv.org/pdf/1406.2661.pdf>) was invented by Ian Goodfellow in one night, following a party at a bar (<https://www.technologyreview.com/2018/02/21/145289/the-ganfater-the-man-whos-given-machines-the-gift-of-imagination/>). !

Details

Notation summary

text	meaning
p_{data}	Distribution of real data
$\mathbf{x} \in p_{\text{data}}$	Real sample
p_{model}	Distribution of fake data
$\hat{\mathbf{x}}$	Fake sample
	$\hat{\mathbf{x}} \notin p_{\text{data}}$
	$\text{shape}(\hat{\mathbf{x}}) = \text{shape}(\mathbf{x})$
$\tilde{\mathbf{x}}$	Sample (real or fake)
	$\text{shape}(\tilde{\mathbf{x}}) = \text{shape}(\mathbf{x})$
D_{Θ_D}	Discriminator NN, parameterized by Θ_D
	Binary classifier: $\tilde{\mathbf{x}} \mapsto \{\text{Real}, \text{Fake}\}$
	$D_{\Theta_D}(\tilde{x}) \in \{\text{Real}, \text{Fake}\}$ for $\text{shape}(\tilde{\mathbf{x}}) = \text{shape}(\mathbf{x})$
\mathbf{z}	vector or randoms with distribution $p_{\mathbf{z}}$
G_{Θ_G}	Generator NN, parameterized by Θ_G
	$\mathbf{z} \mapsto \hat{\mathbf{x}}$
	$\text{shape}(G(\mathbf{z})) = \text{shape}(\mathbf{x})$
	$G(\mathbf{z}) \in p_{\text{model}}$

Our goal is to generate new *synthetic* examples.

Let

- \mathbf{x} denote a *real* example
 - vector of length n
- p_{data} be the distribution of real examples
 - $\mathbf{x} \in p_{\text{data}}$

We will create a Neural Network called the *Generator*

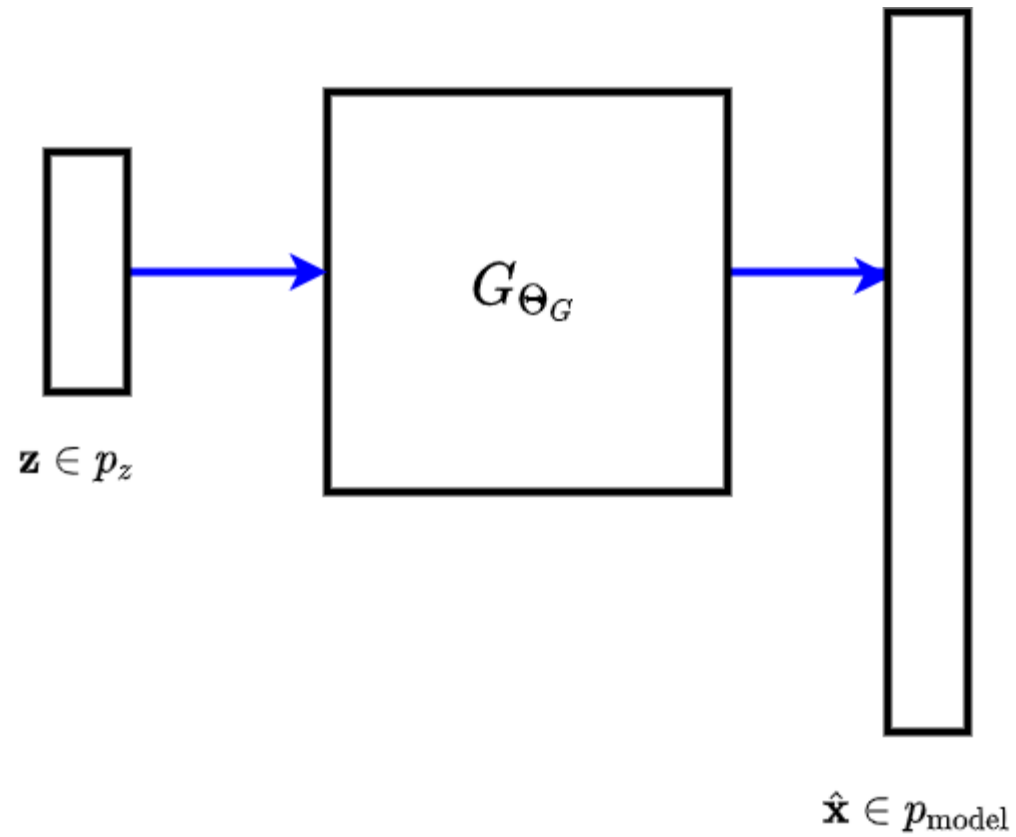
Generator G_{Θ_G} (parameterized by Θ_G) will

- take a vector \mathbf{z} of random numbers from distribution $p_{\mathbf{z}}$ as input
- and outputs $\hat{\mathbf{x}}$
- a *synthetic/fake* example
 - vector of length n

Let

- p_{model} be the distribution of fake examples

GAN Generator



The Generator will be paired with another Neural Network called the *Discriminator*.

The Discriminator D_{Θ_D} (parameterized by Θ_D) is a binary Classifier

- takes a vector $\tilde{\mathbf{x}} \in p_{\text{data}} \cup p_{\text{model}}$

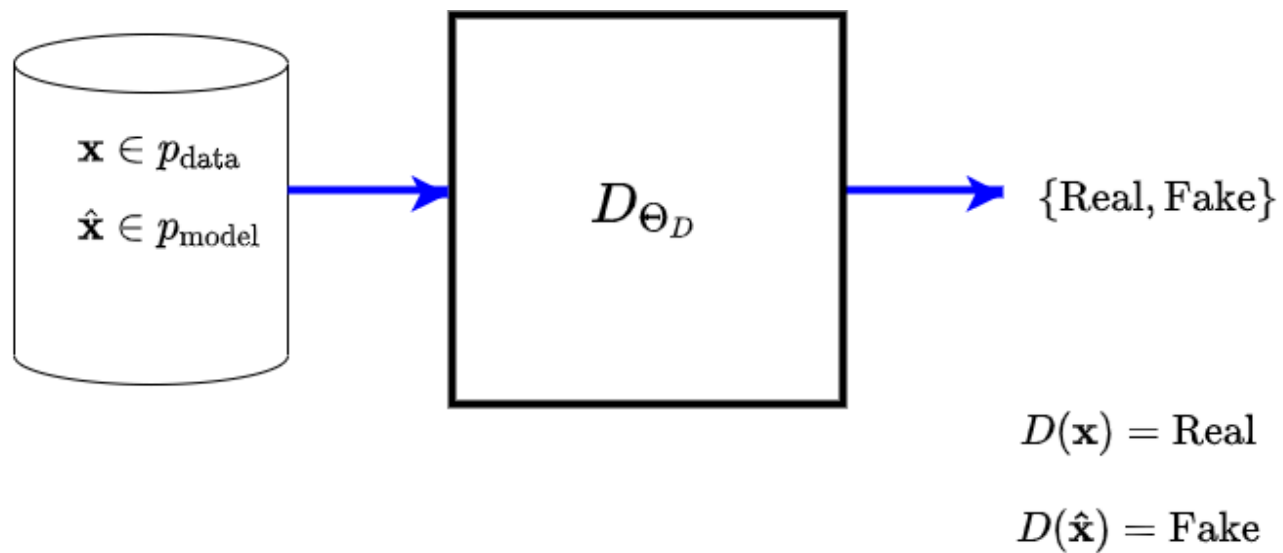
Goal of Discriminator

$$\begin{aligned} D(\tilde{\mathbf{x}}) &= \text{Real} && \text{for } \tilde{\mathbf{x}} \in p_{\text{data}} \\ D(\tilde{\mathbf{x}}) &= \text{Fake} && \text{for } \tilde{\mathbf{x}} \in p_{\text{model}} \end{aligned}$$

That is

- the Discriminator tries to distinguish between Real and Fake examples

GAN Discriminator



In contrast, the goal of the Generator

Goal of Generator

$$D(\hat{\mathbf{x}}) = \text{Real} \quad \text{for } \hat{\mathbf{x}} = G_{\Theta_G}(\mathbf{z}) \in p_{\text{model}}$$

That is

- the Generator tries to create fake examples that can fool the Discriminator into classifying as Real

How is this possible ?

We describe a training process (that updates Θ_G and Θ_D)

- That follows an *iterative* game
- Train the Discriminator to distinguish between
 - Real examples
 - and the Fake examples produced by the Generator on the prior iteration
- Train the Generator to produce examples better able to fool the updated Discriminator

Sounds reasonable, but how do we get the Generator to improve its fakes?

It is all through the Loss functions that we will define:

- \mathcal{L}_G for the Generator
- \mathcal{L}_D for the Discriminator
 - technically: the Discriminator is *maximizing*: $-1 * \mathcal{L}_D$

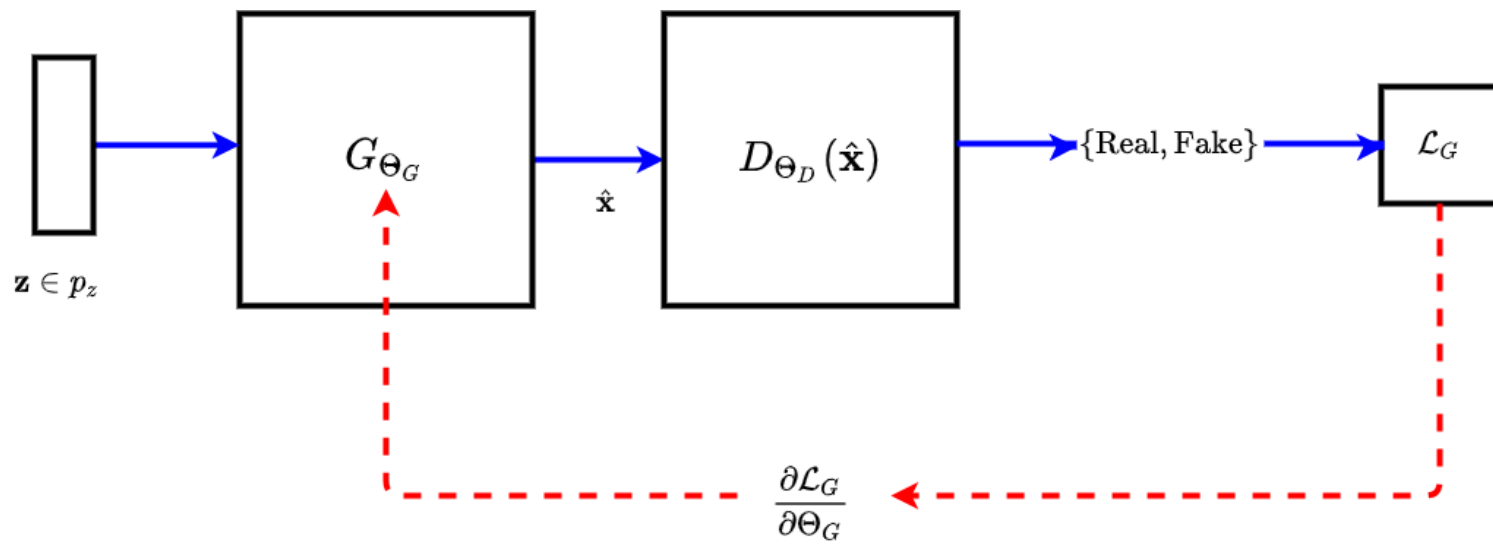
As we will see, the Loss function for the Generator will

- be based on how confidently the Discriminator detected the fake
- updating Θ_G
 - by $-\frac{\partial \mathcal{L}_G}{\partial \Theta_G}$
 - to reduce loss
- means we make the Discriminator less confident that this example is fake

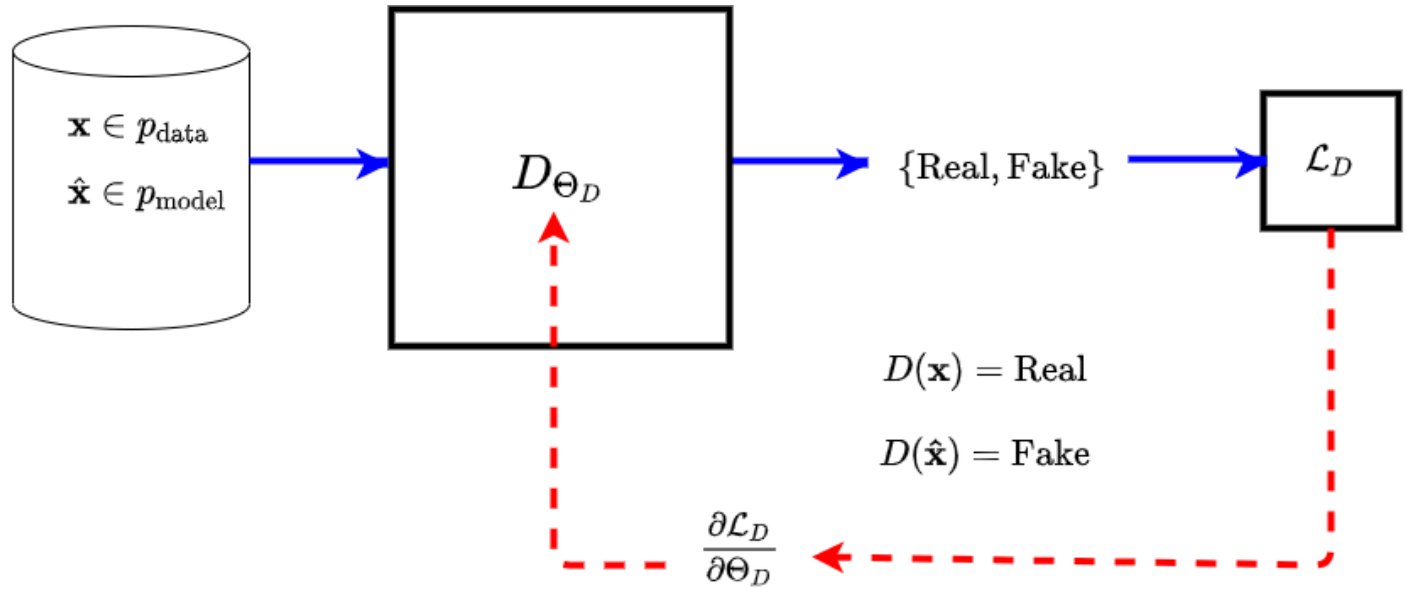
In essence

- The Discriminator will indirectly give "hints" to the Generator as to why a fake example failed to fool

GAN Generator training



GAN Discriminator training



After enough rounds of the iterative "game" we hope that the Generator and Discriminator battle to a stand-off

- the Generator produces realistic fakes
- the Discriminator has only a 50% chance of correctly labeling a fake as Fake

Loss functions

The goal of the generator can be stated as

- Creating p_{model} such that
- $p_{\text{model}} \approx p_{\text{data}}$

There are a number of ways to measure the dis-similarity of two distributions

- KL divergence
 - equivalent to Maximum Likelihood estimation
- Jensen Shannon Divergence (JSD)
- Earth Mover Distance (Wasserstein GAN)

The original paper choose the minimization of the KL divergence, so we illustrate with that measure.

To be concrete, let the Discriminator use labels

- 1 for Real
- 0 for Fake

The Discriminator tries to maximize per example \mathcal{L}_D (by minimizing the $-\mathcal{L}_D$)

$$-\mathcal{L}_D = \begin{cases} \log D(\tilde{\mathbf{x}}) & \text{when } \tilde{\mathbf{x}} \in p_{\text{data}} \\ 1 - \log D(\tilde{\mathbf{x}}) & \text{when } \tilde{\mathbf{x}} \in p_{\text{model}} \end{cases}$$

That is

- Classify real \mathbf{x} as Real
- Classify fake $\hat{\mathbf{x}}$ as Fake

In training the Discriminator, we present it with batches of examples

- half real, half fake

The Discriminator tries to maximize (over the batch) the negative of the loss over the batch

$$\begin{aligned}\mathcal{L}_D &= - \left(\frac{1}{2} \mathbb{E}_{\mathbf{x}^{(i)} \in p_{\text{data}}} \log D(\mathbf{x}^{(i)}) + \frac{1}{2} \mathbb{E}_{z \in P_z} \log(1 - D(G(\mathbf{z}))) \right) \\ &= - \left(\frac{1}{2} \mathbb{E}_{\mathbf{x}^{(i)} \in p_{\text{data}}} \log D(\mathbf{x}^{(i)}) + \frac{1}{2} \mathbb{E}_{\mathbf{x}^{(i)} \in p_{\text{model}}} \log(1 - D(\mathbf{x}^{(i)})) \right) \\ &= - \frac{1}{2} \sum_{\mathbf{x}^{(i)} \in p_{\text{data}}} p_{\text{data}}(\mathbf{x}^{(i)}) \log D(\mathbf{x}^{(i)}) - \frac{1}{2} \sum_{\mathbf{x}^{(i)} \in p_{\text{model}}} p_{\text{model}}(\mathbf{x}^{(i)}) \log(1 -\end{aligned}$$

You will recognize this term as Binary Cross Entropy (BCE)

- hence, you will see BCE used as the Loss Function in the code
-

The per-example Loss for the Generator is

$$\mathcal{L}_G = 1 - \log D(G(\mathbf{z}))$$

which is minimized when the fake example

$$D(G(\mathbf{z})) = 1$$

That is

- the Discriminator mis-classifies the fake example as Real

This is the "hint" from the Discriminator

- that enables the Generator to improve the quality of its fakes

The Generator takes batches of \mathbf{z} (and hence sees only fake examples, not an even mix of real and fake as does the Discriminator).

Since the game is zero sum

$$\mathcal{L}_G = -\mathcal{L}_D$$

and you will similarly see BCE as the Loss for the Generator

- except the "true" labels passed to BCE will be an array of "Real"
- as opposed to a mix of "Real" and "Fake" labels in the BCE of the Discriminator

Note

- all the examples passed by the Generator to the Discriminator are synthetic
- so the "true labels" passed to the Loss Function
 - are not accurate
 - but are meant to achieve the goal of fooling the Discriminator into classifying examples as "Real"

That is: the objective of the Generator is to produce examples that the Discriminator labels as "Real".

So the iterative game seeks to solve a minimax problem

$$\min_G \max_D (\mathbb{E}_{\mathbf{x} \in p_{\text{data}}} \log D(\mathbf{x}) + \mathbb{E}_{\mathbf{z} \in p_z} (1 - \log D(G(\mathbf{z})))$$

- D tries to
 - make $D(\mathbf{x})$ big: correctly classify (with high probability) real \mathbf{x}
 - and $D(G(\mathbf{z}))$ small: correctly classify (with low probability) fake $G(\mathbf{z})$
- G tries to
 - make $D(G(\mathbf{z}))$ high: fool D into a high probability for a fake

Note that the Generator improves

- by updating Θ_G
- so as to increase $D(G(\mathbf{z}))$
 - the mis-classification of the fake as Real

Optimal Discriminator Loss

Can minimize per example \mathcal{L}_D wrt $D(\mathbf{x})$ by taking the derivative and setting to 0

$$\begin{aligned}
 \frac{\partial \mathcal{L}_D}{\partial D(\mathbf{x})} &= -\frac{1}{2} \left(p_{\text{data}}(\mathbf{x}) * \frac{1}{\log_e 10} \frac{1}{D(\mathbf{x})} + p_{\text{model}}(\mathbf{x}) * \frac{1}{\log_e 10} \frac{1}{1-D(\mathbf{x})} * -1 \right) && \text{Def: } \log_e \\
 &= -\frac{1}{2 * \log_e 10} \frac{p_{\text{data}}(\mathbf{x}) * (1-D(\mathbf{x})) - p_{\text{model}}(\mathbf{x}) * D(\mathbf{x})}{D(\mathbf{x}) * (1-D(\mathbf{x}))} && \text{Der: } \frac{d}{dx} \frac{1}{x} = -\frac{1}{x^2} \\
 &= \frac{1}{c} \frac{p_{\text{data}}(\mathbf{x}) - D(\mathbf{x})(p_{\text{model}}(\mathbf{x}) + p_{\text{data}}(\mathbf{x}))}{D(\mathbf{x}) * (1-D(\mathbf{x}))} \\
 \frac{\partial \mathcal{L}_D}{\partial D(\mathbf{x})} = 0 &\mapsto D^*(\mathbf{x}) = \frac{p_{\text{data}}(\mathbf{x})}{p_{\text{model}}(\mathbf{x}) + p_{\text{data}}(\mathbf{x})}
 \end{aligned}$$

So the optimal Discriminator succeeds with probability

$$\frac{p_{\text{data}}(\mathbf{x})}{p_{\text{model}}(\mathbf{x}) + p_{\text{data}}(\mathbf{x})}$$

The optimal Generator results in

$$p_{\text{model}}(\mathbf{x}) = p_{\text{data}}(\mathbf{x})$$

Thus, if the minimax optimization succeeds

$$D^*(\mathbf{x}) = \frac{1}{2}$$

Nothing better than a coin toss !

Training

We will train Generator G_{Θ_G} Discriminator D_{Θ_D} by turns

- creating sequence of updated parameters
 - $\Theta_{G,(1)} \dots \Theta_{G,(T)}$
 - $\Theta_{D,(1)} \dots \Theta_{D,(T)}$
- Trained *competitively*

Competitive training

Iteration t

- Train $D_{\Theta_{D,(t-1)}}$ on samples
 - $\tilde{\mathbf{x}} \in p_{\text{data}} \cup p_{\text{model},(t-1)}$
 - where $G_{\Theta_{G,(t-1)}}(\mathbf{z}) \in p_{\text{model},(t-1)}$
 - Update $\Theta_{D,(t-1)}$ to $\Theta_{D,(t)}$ via gradient $\frac{\partial \mathcal{L}_D}{\partial \Theta_{D,(t-1)}}$
 - D is a maximizer of $\int_{\mathbf{x} \in p_{\text{data}}} \log D(\mathbf{x}) + \int_{\mathbf{z} \in p_{\mathbf{z}}} \log (1 - D(G(\mathbf{z})))$
- Train $G_{\Theta_{G,(t-1)}}$ on random samples \mathbf{z}
 - Create samples $\hat{\mathbf{x}}_{(t)} \in G_{\Theta_{G,(t-1)}}(\mathbf{z}) \in p_{\text{model}}$
 - Have Discriminator $D_{\Theta_{D,(t)}}$ evaluate $D_{\Theta_{D,(t)}}(\hat{\mathbf{x}}_{(t)})$
 - Update $\Theta_{G,(t-1)}$ to $\Theta_{G,(t)}$ via gradient $\frac{\partial \mathcal{L}_G}{\partial \Theta_{G,(t-1)}}$
 - G is a minimizer of $\int_{\mathbf{z} \in p_{\mathbf{z}}} \log (1 - D(G(\mathbf{z})))$
 - i.e., want $D(G(\mathbf{z}))$ to be high
 - May update G multiple times per update of D

Training code for a simple GAN: Highlights

The key to implementing a GAN

- is a custom training step
- that trains *both* the Discriminator and the Generator

Here is the detailed [custom training step](http://keras.io/examples/generative/dcgan_overriding_train_step/#override-trainstep)
(http://keras.io/examples/generative/dcgan_overriding_train_step/#override-trainstep).

We break down this step in our [module on Advanced Keras](#)
([Keras_Advanced.ipynb#GAN](#)).

Issues

Although the description of GAN training as an adversarial game is appealing, actually getting training to find a stable equilibrium is difficult in practice.

Vanishing Gradient

Early in training, the Discriminator has the advantage

- it has been trained to distinguish real input from noise
- the parameters of the Generator are uninitialized
 - Generator needs feedback from Discriminator in order to learn direction for improvement

What happens if the Discriminator is "too good" ?

- $D(\hat{\mathbf{x}})$ for all $\hat{\mathbf{x}} \in p_{\text{model}}$
 $= 0$

With absolute certainty that every $\hat{\mathbf{x}}$ from the Generator is Fake, the gradient is zero (or near zero)

- Generator can't learn (weight updates near zero)

So we don't want the Discriminator to be too good, too early in training.

Mode Collapse

We condition the Generator on random \mathbf{z} so that it will produce diverse $\hat{\mathbf{x}}$.

Sometimes, the Generator is only able to create a single (or small number) $\hat{\mathbf{x}}'$ that is good enough to fool the Discriminator.

In this case: the Generator may learn to ignore input \mathbf{z} and *only* produce $\hat{\mathbf{x}}'$.

Hard to achieve equilibrium

The optimal solution is the Nash equilibrium of the minimax problem

$$\min_G \max_D (\mathbb{E}_{\mathbf{x} \in p_{\text{data}}} \log D(\mathbf{x}) + \mathbb{E}_{\mathbf{z} \in p_z} (1 - \log D(G(\mathbf{z})))$$

However: the objective of Neural Network training is minimization of a Loss.

There is no guarantee that Gradient Descent will always converge to the Nash equilibrium

- [See this paper, section 3 \(https://arxiv.org/pdf/1412.6515.pdf\)](https://arxiv.org/pdf/1412.6515.pdf)
- [Also, see this paper, section 3 \(https://arxiv.org/pdf/1606.03498.pdf\)](https://arxiv.org/pdf/1606.03498.pdf)

The gradients are partials with respect to the denominator, *holding everything else constant*.

But everything is *not* constant: the Generator and Discriminator are each modifying their weights.

- So the weight update of the Generator may not result in improvement if the simultaneous weight update of the Discriminator moves in the opposite direction.

An often cited example 2 player game illustrates the point

- Player 1 seeks to minimize product $x * y$ by manipulating x

$$\frac{\partial x*y}{\partial x} = y$$

$x \rightarrow (x - y)$ update x by negative of gradient

- Player 2 seeks to minimize product $-x * y$ by manipulating y

$$\frac{\partial (-x*y)}{\partial y} = -x$$

$y \rightarrow (y + x)$ update y by negative of gradient

If x, y have opposite signs, then the update causes them to either both increase or both decreases.

- one can show by experiment that each update causes x, y to oscillate in increasing magnitude.

Code

- [GAN on Colab](https://colab.research.google.com/github/keras-io/examples/blob/master/generative/dcgan_override_train_step.ipynb)
(https://keras.io/examples/generative/dcgan_override_train_step/)
- [Wasserstein GAN with Gradient Penalty](https://colab.research.google.com/github/keras-io/examples/blob/master/generative/wgan_gp_create_model.ipynb)
(https://keras.io/examples/generative/wgan_gp/#create-the-wgangp-model)

References

- Goodfellow (<https://arxiv.org/pdf/1406.2661.pdf>).
- Huszar (<https://arxiv.org/pdf/1511.05101.pdf>).
- Wasserstein GAN paper (<https://arxiv.org/pdf/1701.07875.pdf>).

Good blog, submitted as paper

- Weng blog (<https://arxiv.org/pdf/1904.08994.pdf>).

In [2]: `print("Done")`

Done

