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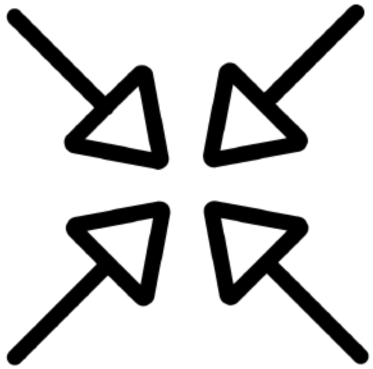
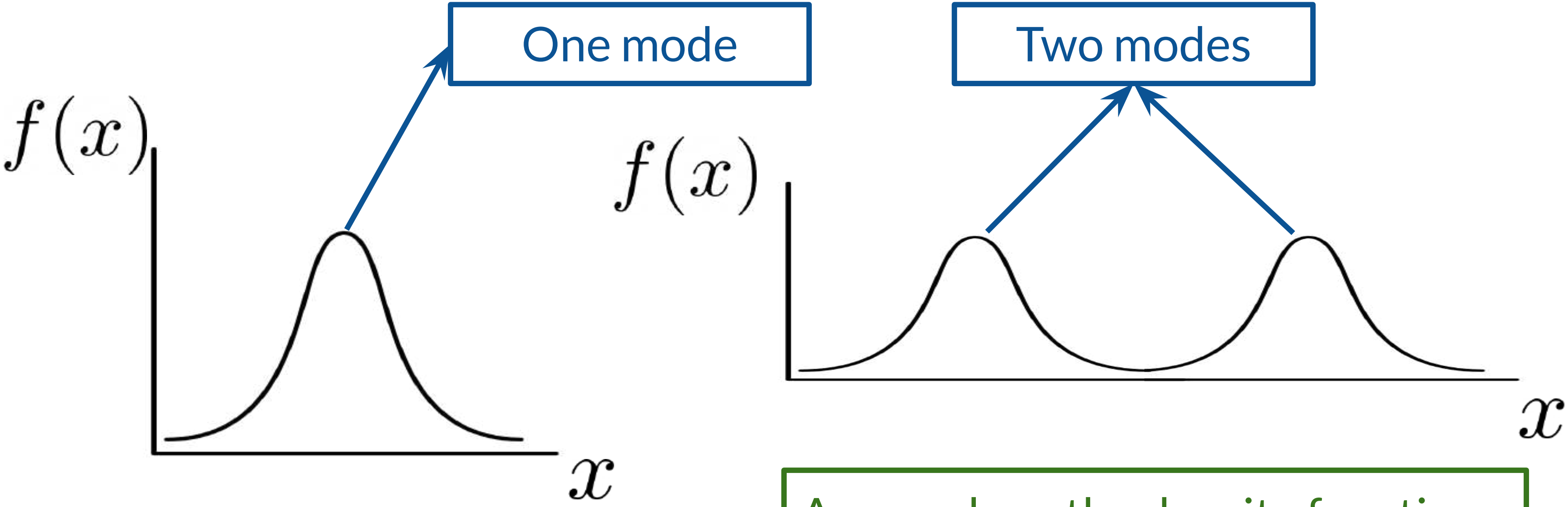
Mode Collapse

Outline

- Modes in distributions
- Mode collapse in GANs
- Intuition behind it during training

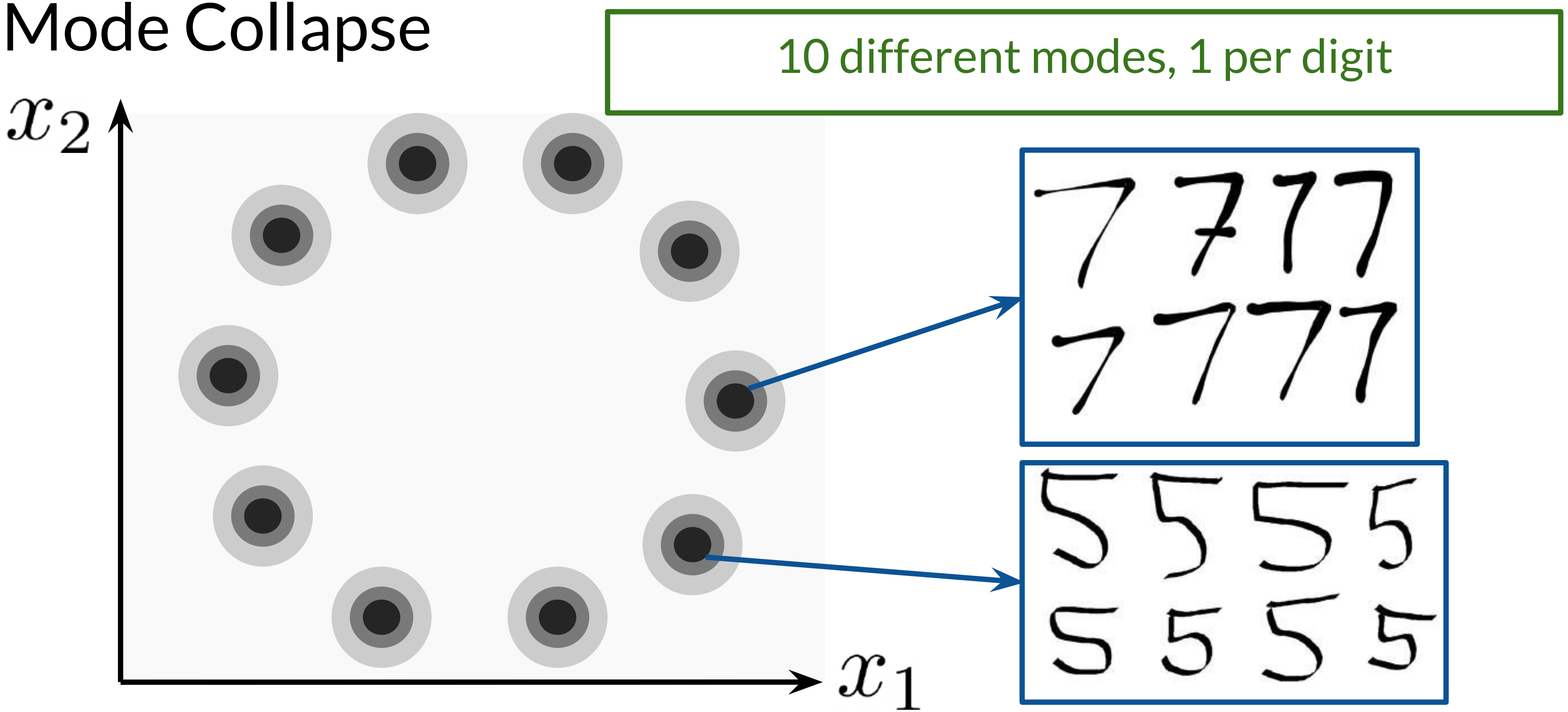


Mode Collapse



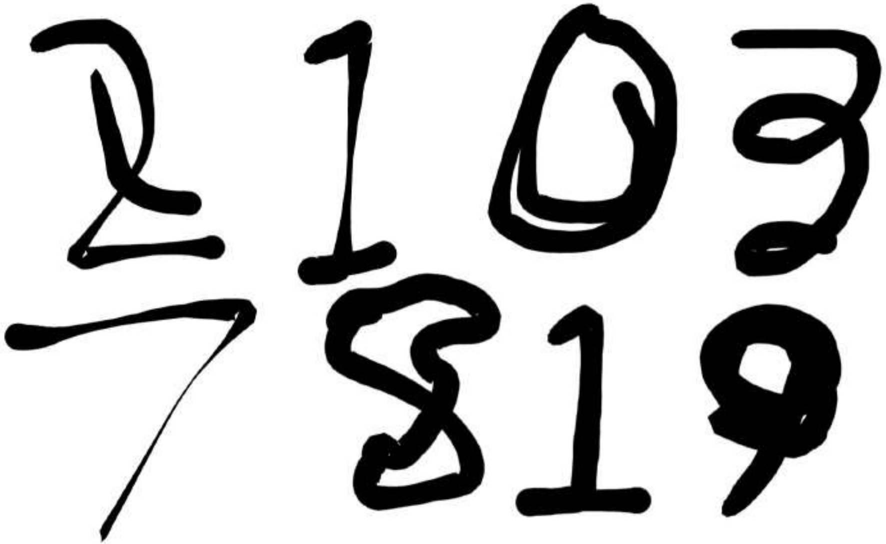
Any peak on the density function is a mode!

Mode Collapse

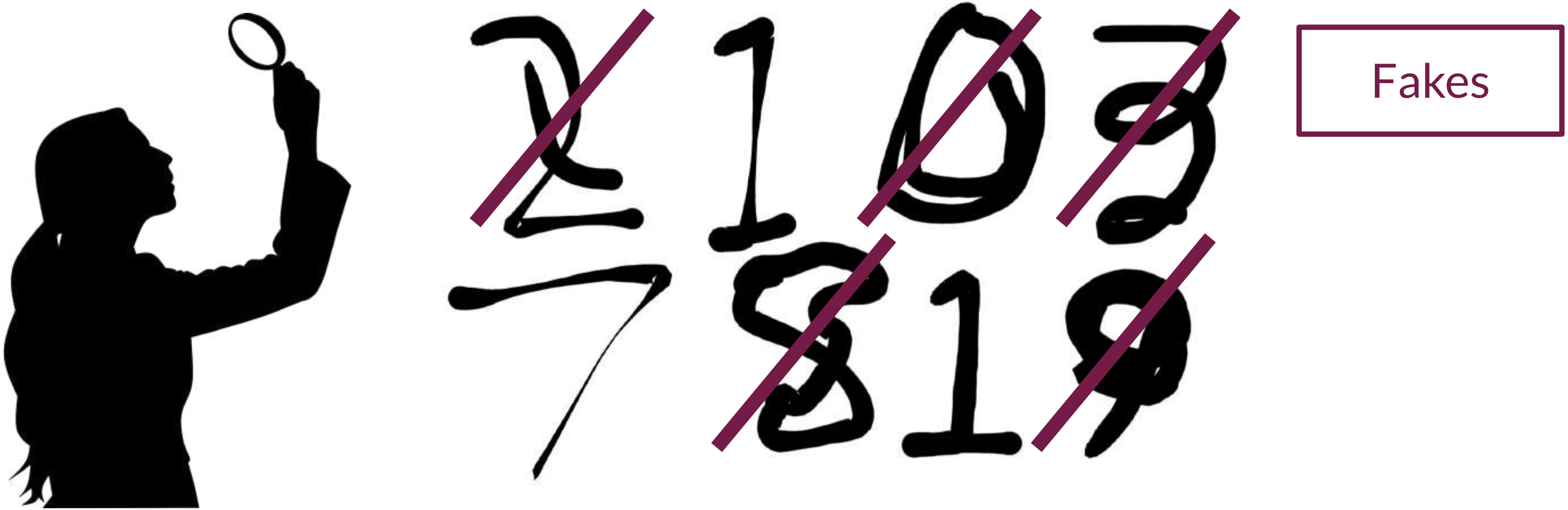


Mode Collapse

Discriminator

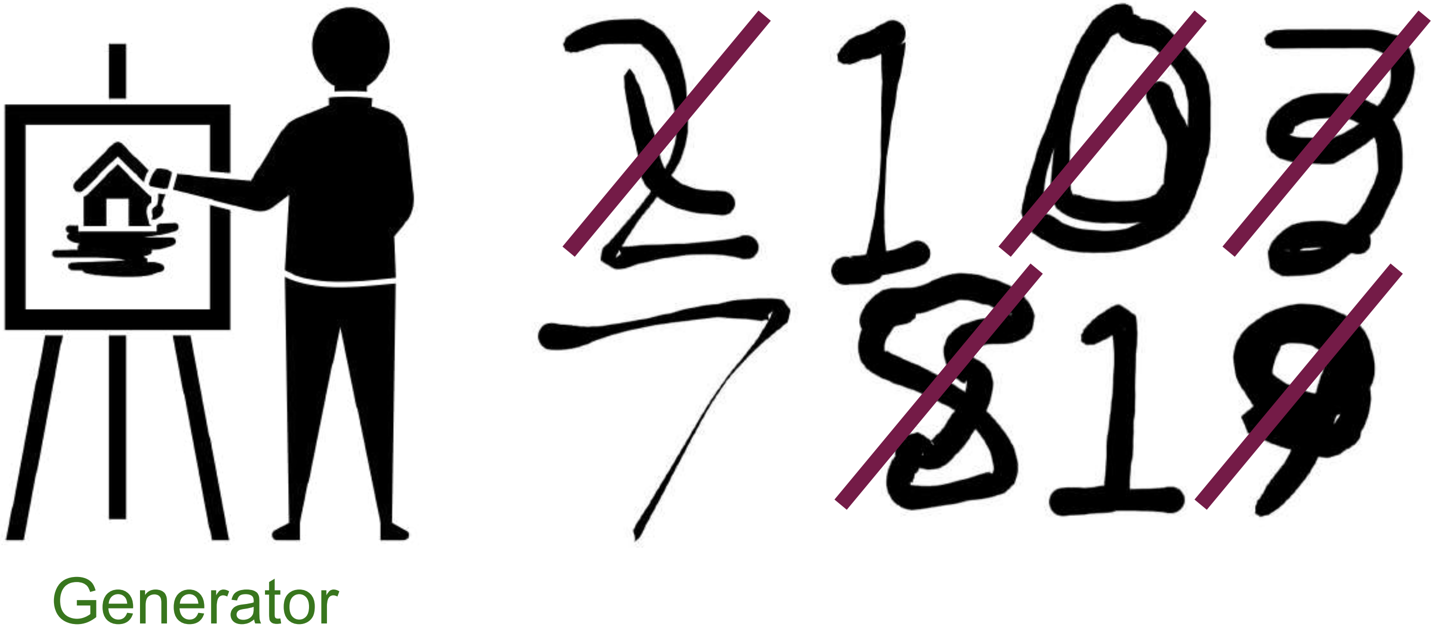


Mode Collapse

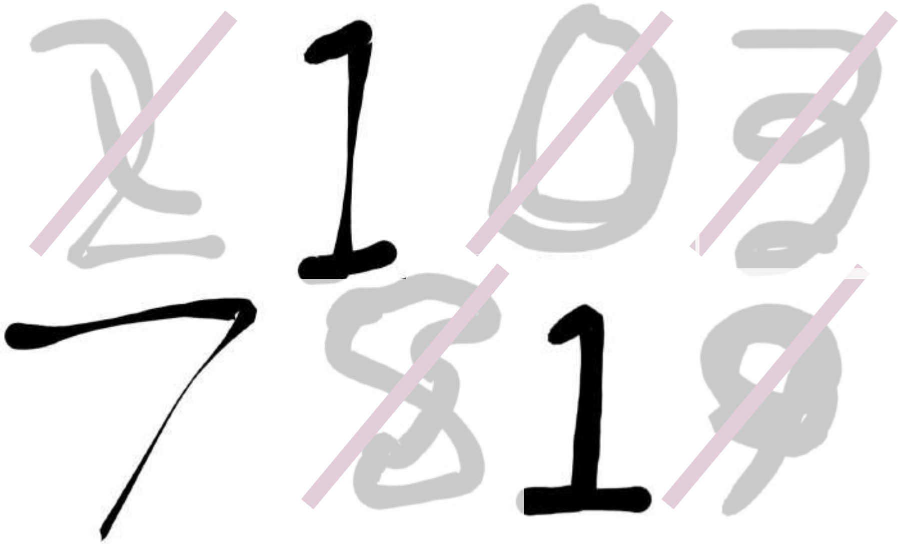


Discriminator

Mode Collapse



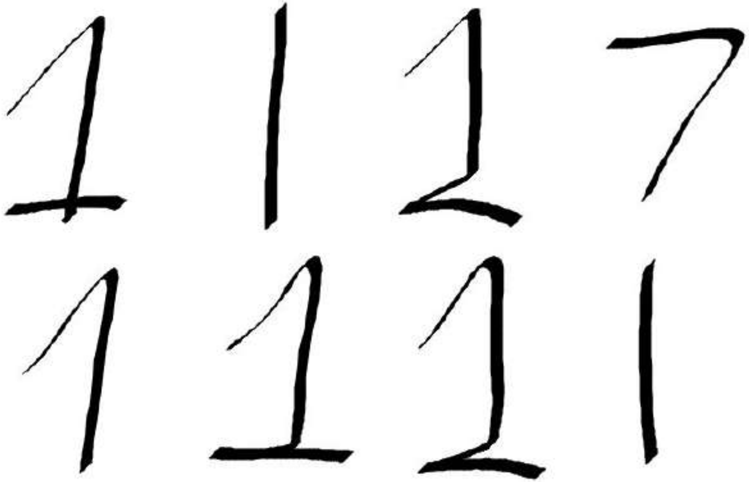
Mode Collapse



Fakes that fooled the discriminator

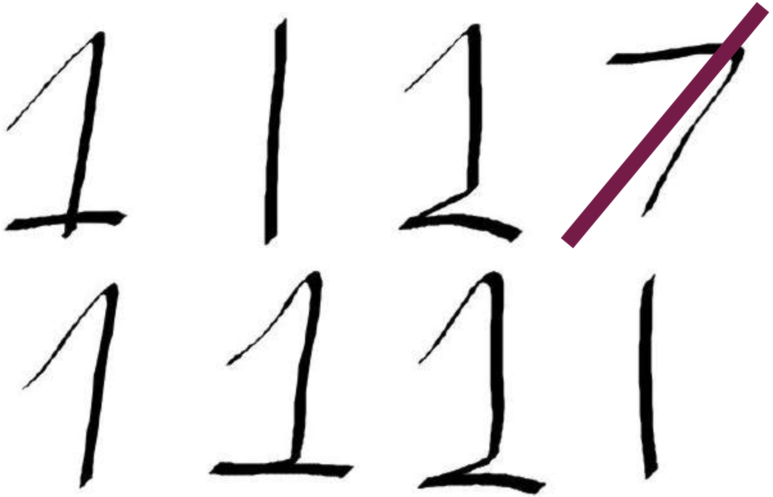
Mode Collapse

Generator



Mode Collapse

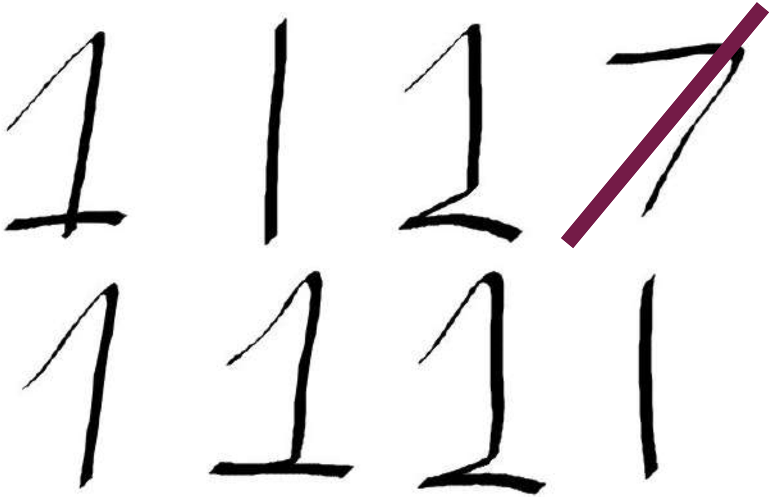
Discriminator



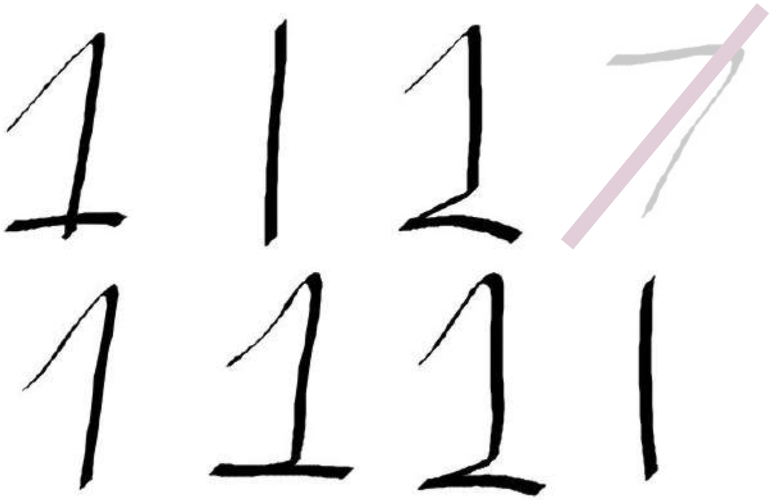
Fakes

Mode Collapse

Generator



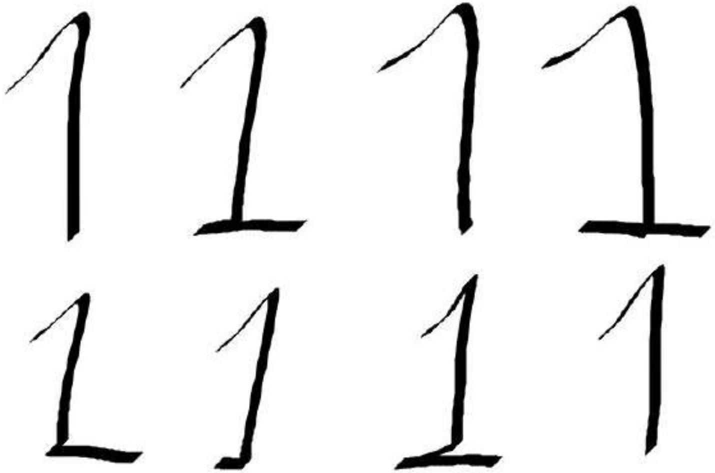
Mode Collapse



Fakes that fooled the discriminator

Mode Collapse

Generator



Summary

- Modes are peaks in the distribution of features
- Typical with real-world datasets
- Mode collapse happens when the generator gets stuck in one mode

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Problem with BCE Loss

Outline

- BCE Loss and the end objective in GANs
- Problem with BCE Loss

BCE Loss in GANs

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

Prediction

Label

Features

Parameters

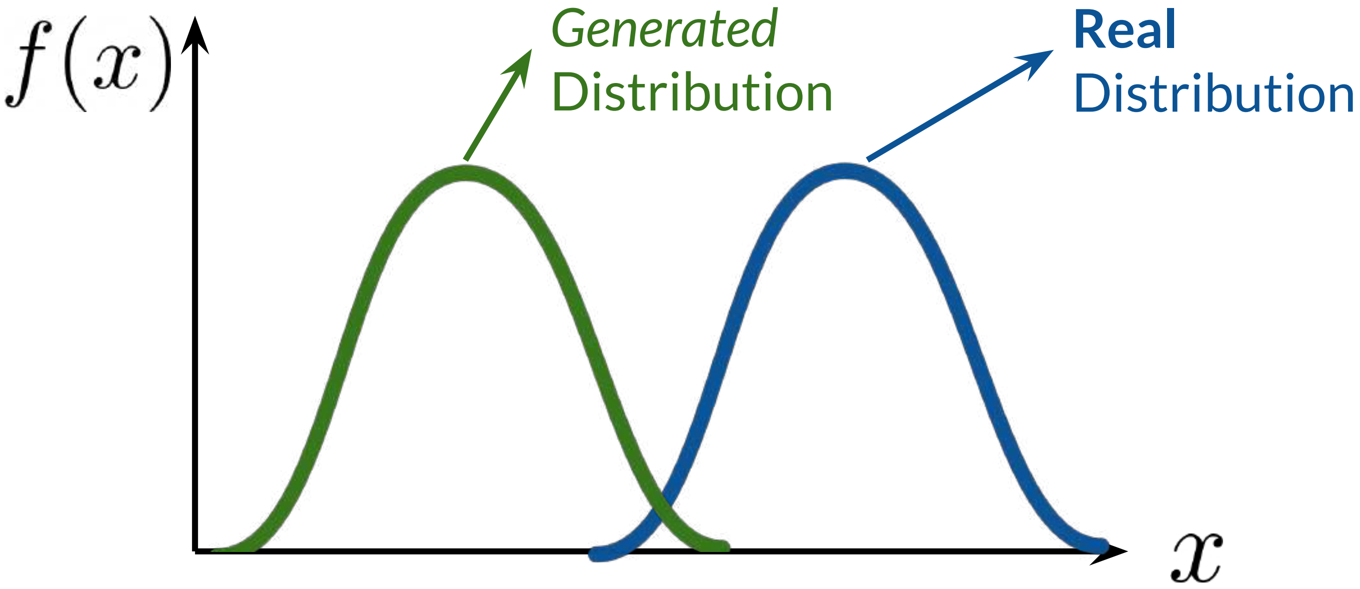
Generator

Maximize cost

Discriminator

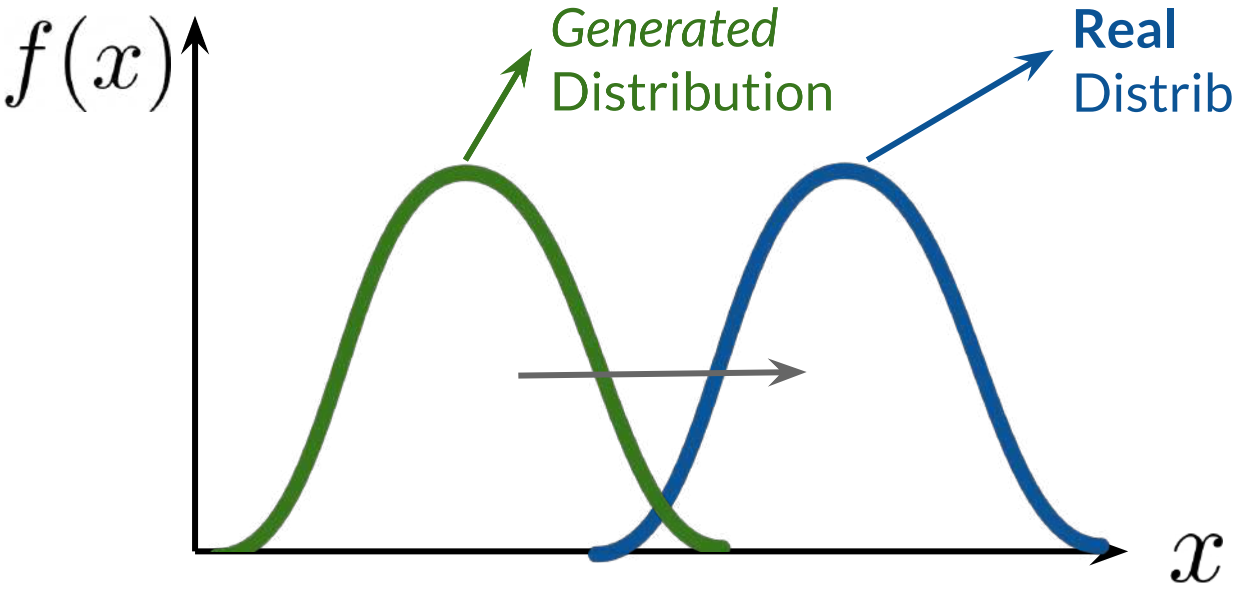
Minimize cost

Objective in GANs



Objective in GANs

Make the generated and real distributions look similar



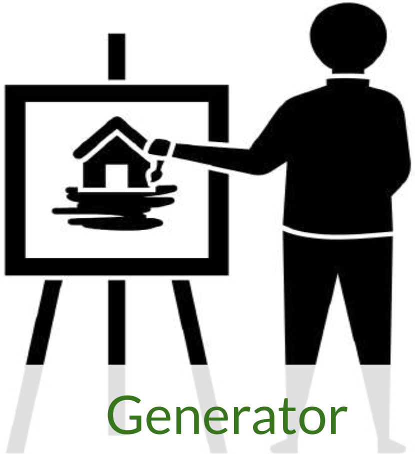
BCE Loss in GANs

Criticizing is more straightforward

Discriminator

Single output

Easier to train than the generator



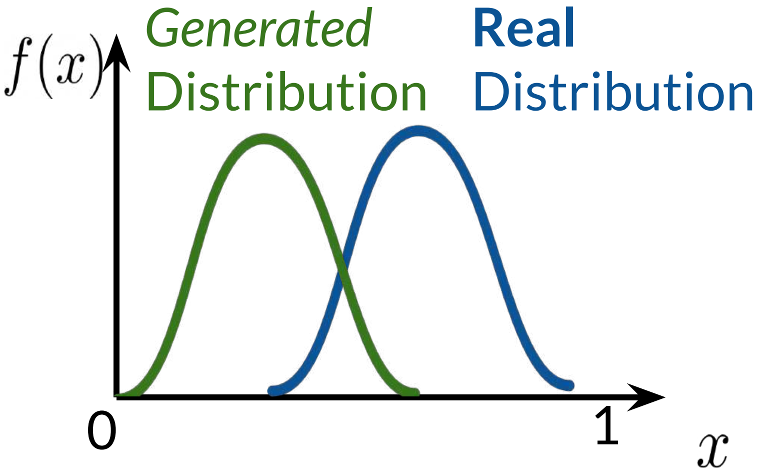
Generator

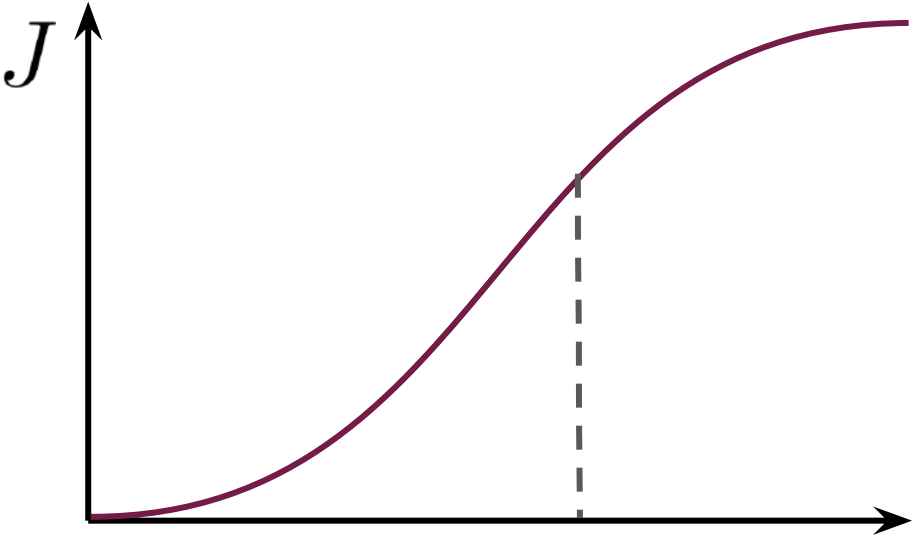
Complex output

Difficult to train

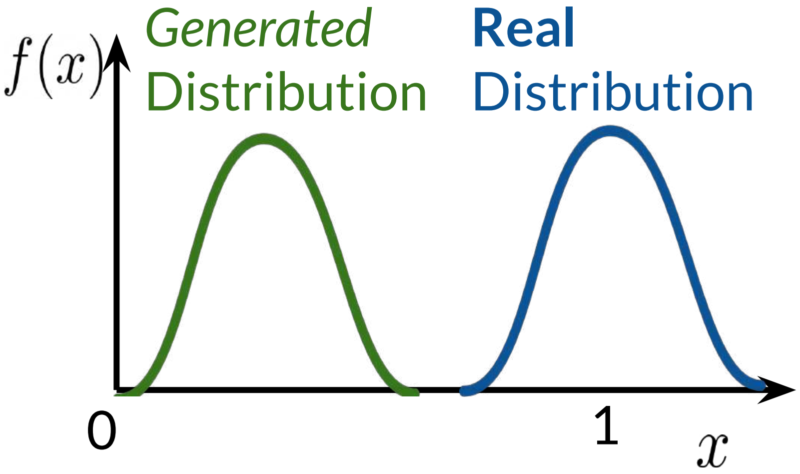
Often, the discriminator gets better than the generator

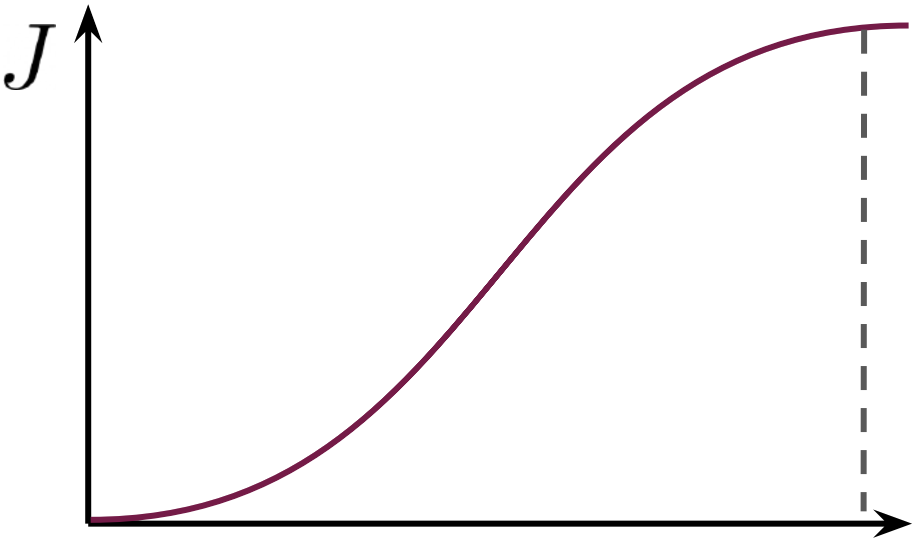
Problems with BCE Loss



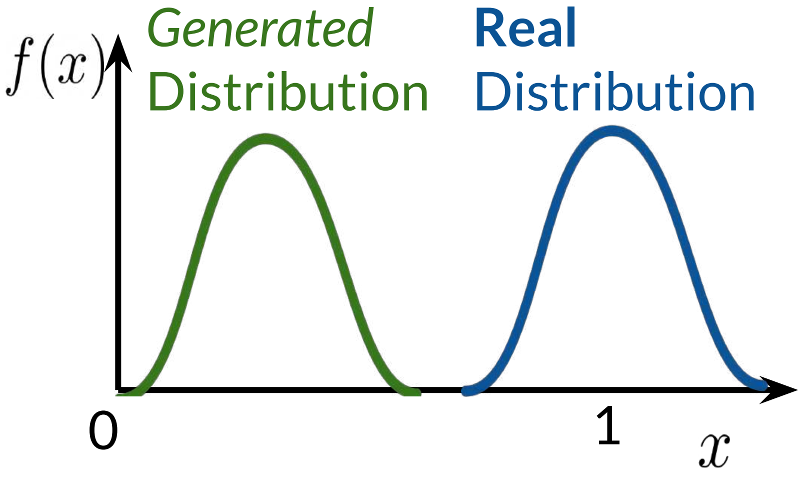


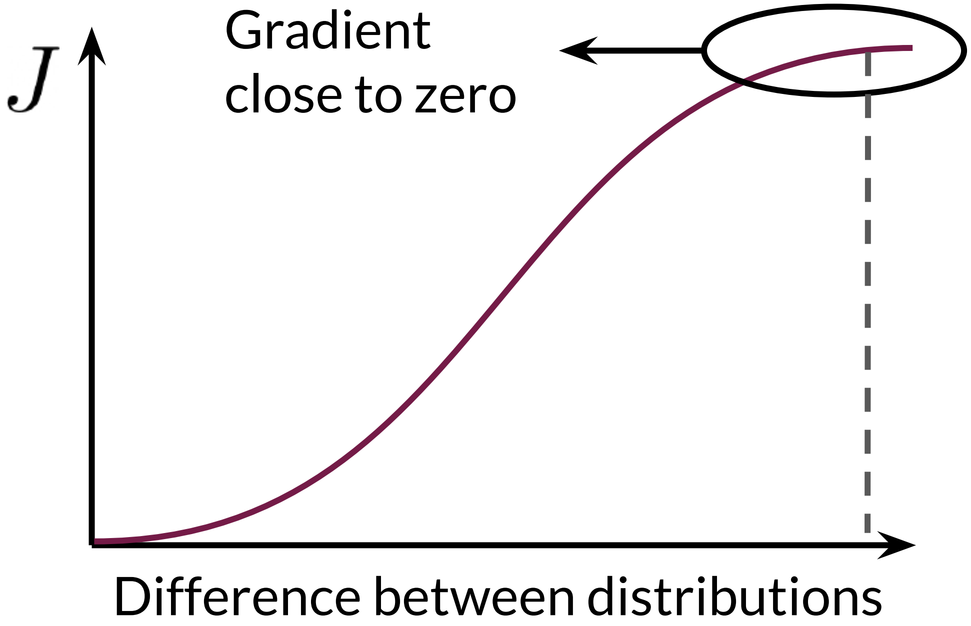
Problems with BCE Loss





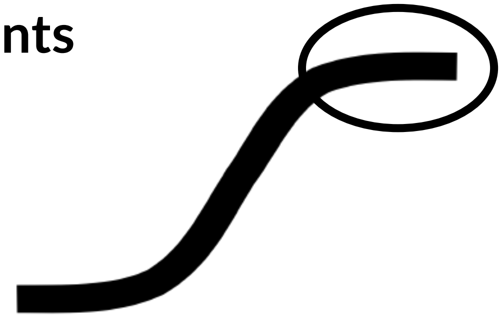
Problems with BCE Loss





Summary

- GANs try to make the real and generated distributions look similar
- When the discriminator improves too much, the function approximated by BCE Loss will contain flat regions
- Flat regions on the cost function = **vanishing gradients**



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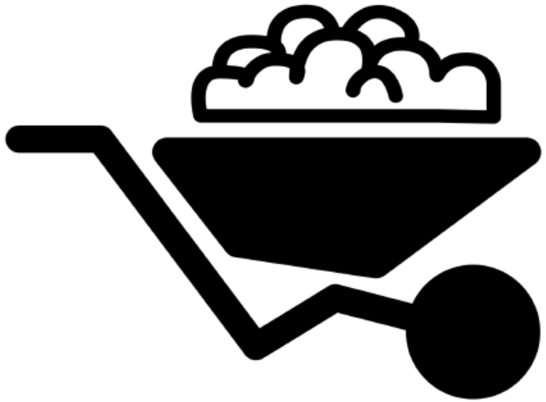
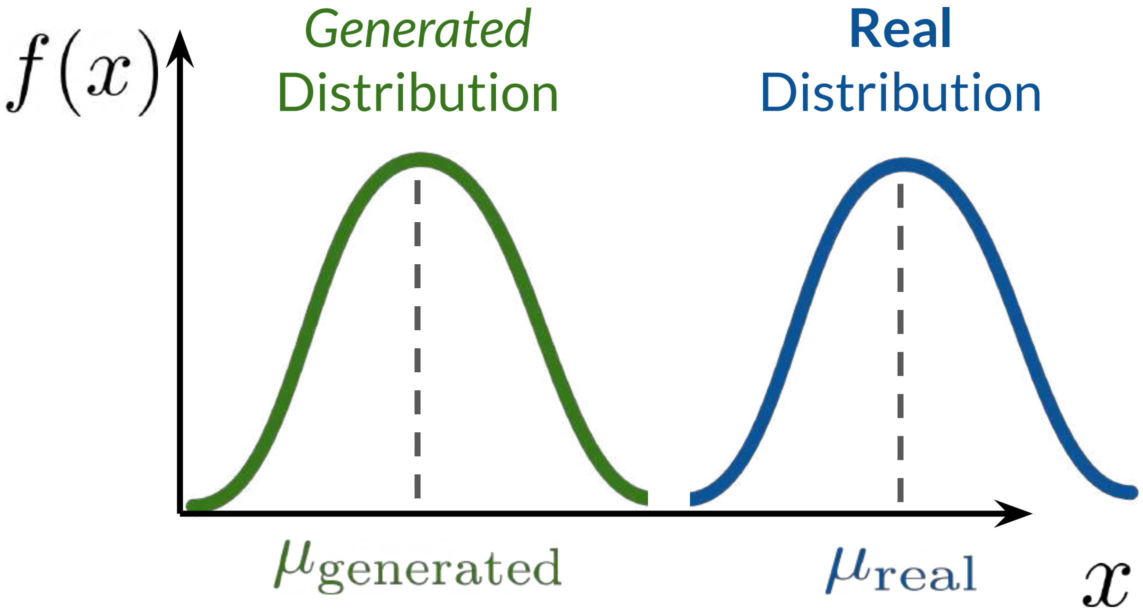
Earth Mover's Distance

Outline

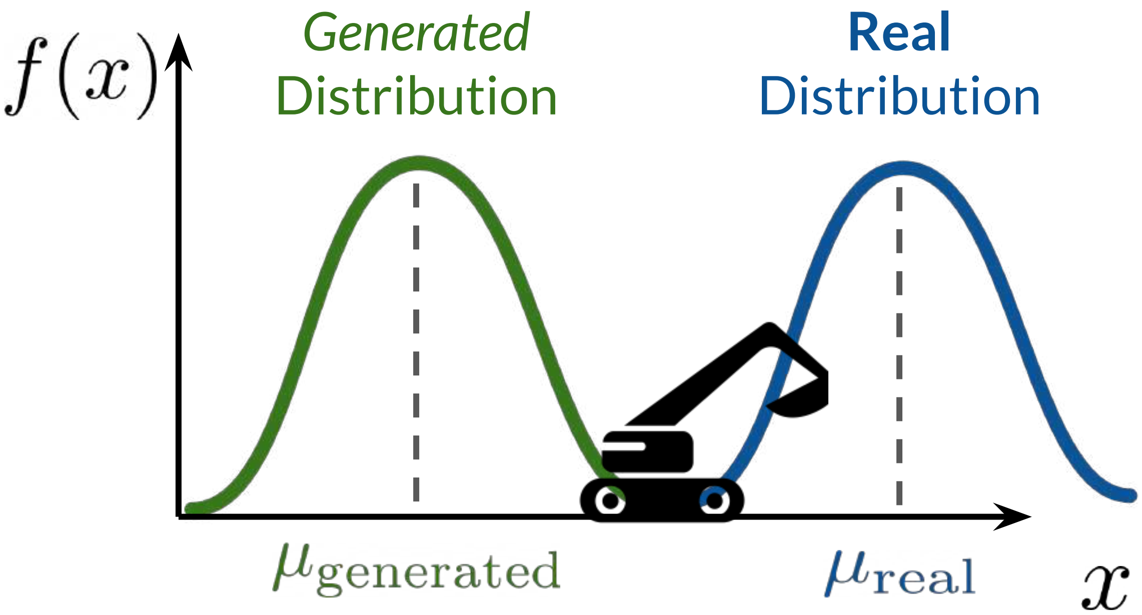
- Earth Mover’s Distance (EMD)
- Why it solves the vanishing gradient problem of BCE Loss



Earth Mover's Distance



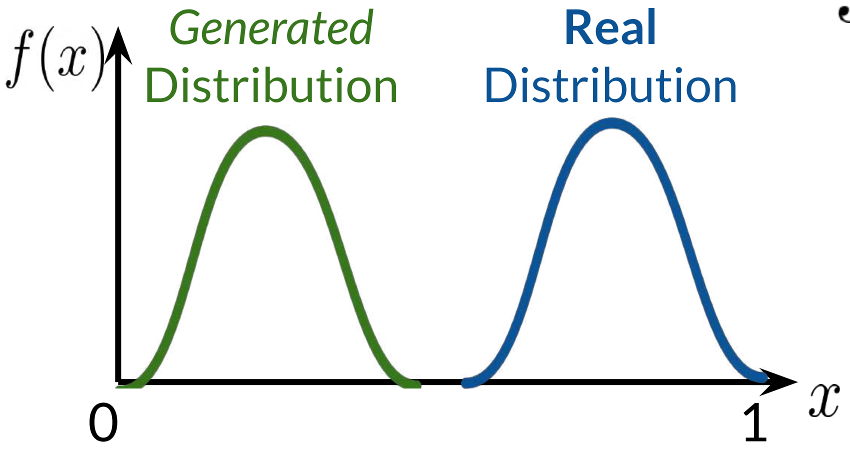
Earth Mover's Distance



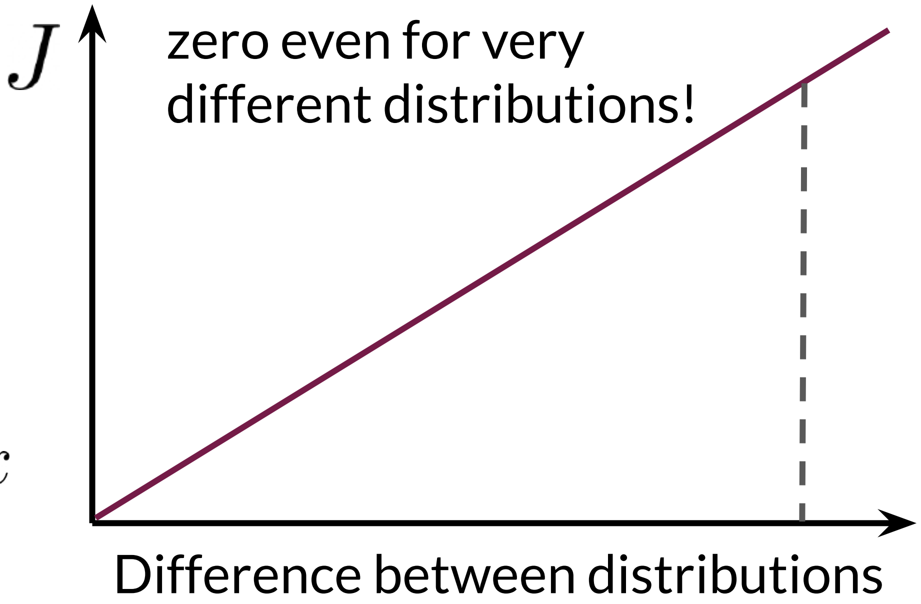
Effort to make the *generated* distribution equal to the **real** distribution

Depends on the distance and amount moved

Earth Mover's Distance



Gradient not close to zero even for very different distributions!



Summary

- Earth mover's distance (EMD) is a function of amount and distance
- Doesn't have flat regions when the distributions are very different
- Approximating EMD solves the problems associated with BCE

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Wasserstein Loss

Outline

- BCE Loss Simplified
- W-Loss and its comparison with BCE Loss

BCE Loss Simplified

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

$$\min_{d} \max_{g}$$

Discriminator

Minimize cost

Generator

Maximize cost

BCE Loss Simplified

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

$$\min_{d} \max_{g} -[\mathbb{E}(\log(d(x))) + \mathbb{E}(\qquad)]$$

Minimize cost

Maximize cost

BCE Loss Simplified

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

$$\min_{d} \max_{g} -[\mathbb{E}(\log(d(x))) + \mathbb{E}(1 - \log(d(g(z))))]$$

Minimize cost

Maximize cost

W-Loss

W-Loss approximates the Earth Mover's Distance

W-Loss

W-Loss approximates the Earth Mover's Distance

$$\min_{g} \max_{c} \; \mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))$$

W-Loss

W-Loss approximates the Earth Mover's Distance

$$\min_g \max_c \; \mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))$$

Maximize the distance

W-Loss

W-Loss approximates the Earth Mover's Distance

$$\min_{g} \max_{c} \; \mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))$$

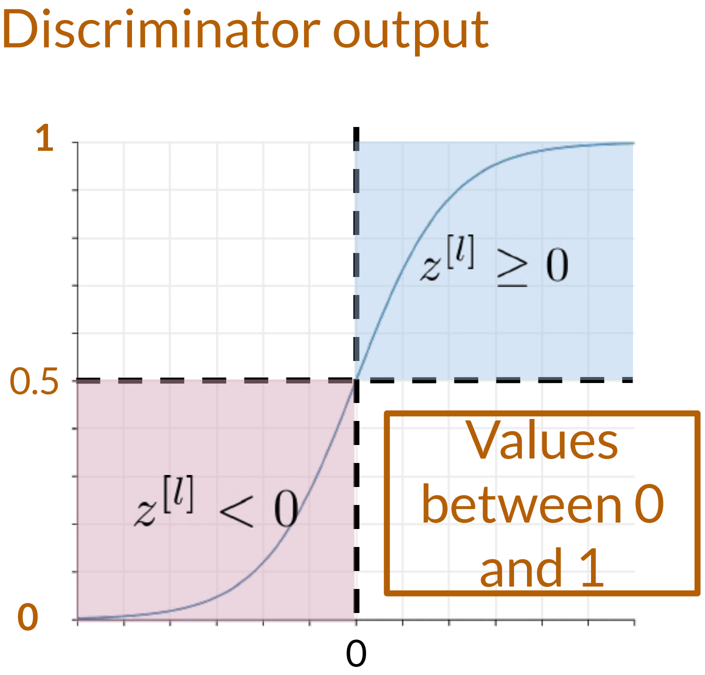
Generator

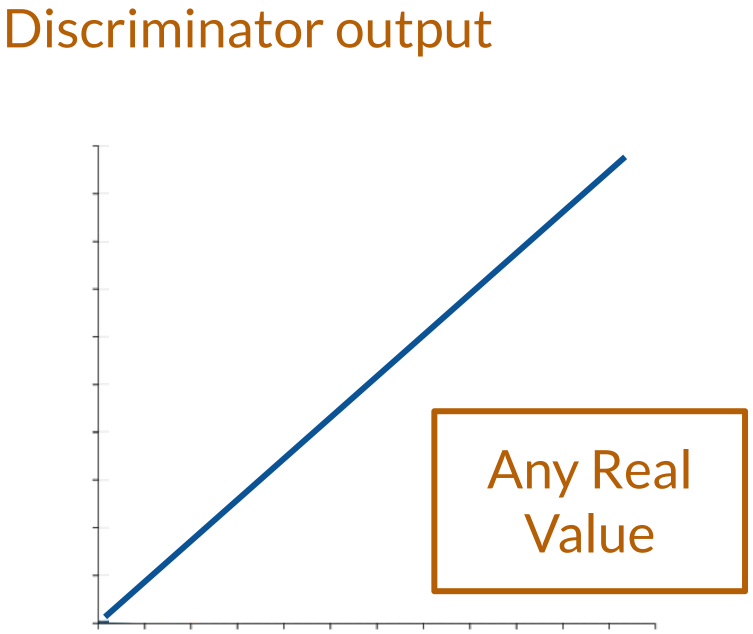
Minimize the distance

Critic

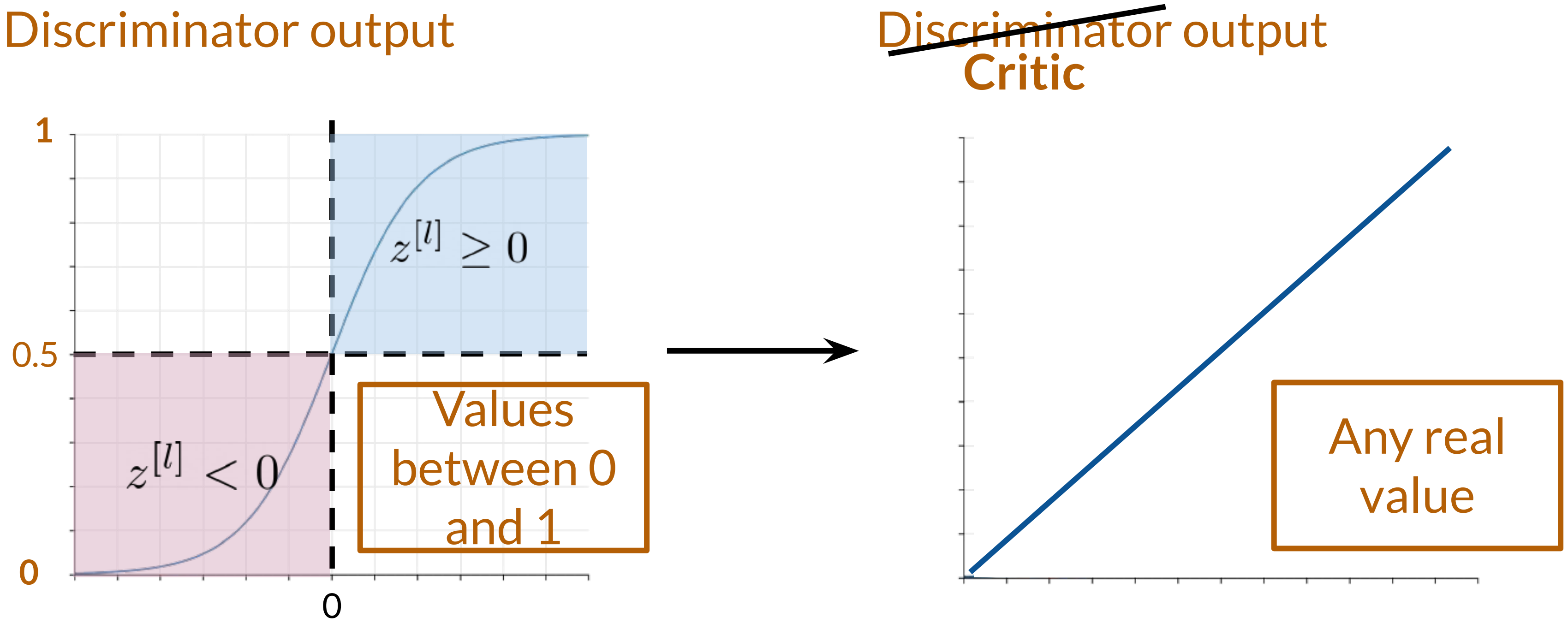
Maximize the distance

Discriminator Output





Discriminator Output



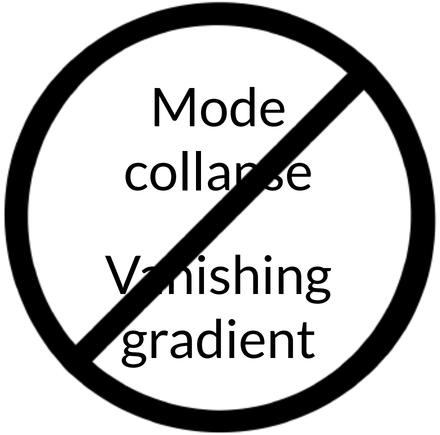
W-Loss vs BCE Loss

BCE Loss	W-Loss
Discriminator outputs between 0 and 1	Critic outputs any number
$-[\mathbb{E}(\log(d(x))) + \mathbb{E}(1 - \log(d(g(z))))]$	$\mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))$

W-Loss helps with mode collapse and vanishing gradient problems

Summary

- W-Loss looks very similar to BCE Loss
- W-Loss prevents mode collapse and vanishing gradient problems



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Condition on Wasserstein Critic

Outline

- Continuity condition on the critic's neural network
- Why this condition matters

Condition on W-Loss

$$\min_{g} \max_{c} \; \mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))$$

Condition on W-Loss

$$\min_{g} \max_{c} \ \mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))$$

Condition on W-Loss

$$\min_{g} \max_{c} \; \mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))$$

Condition on W-Loss

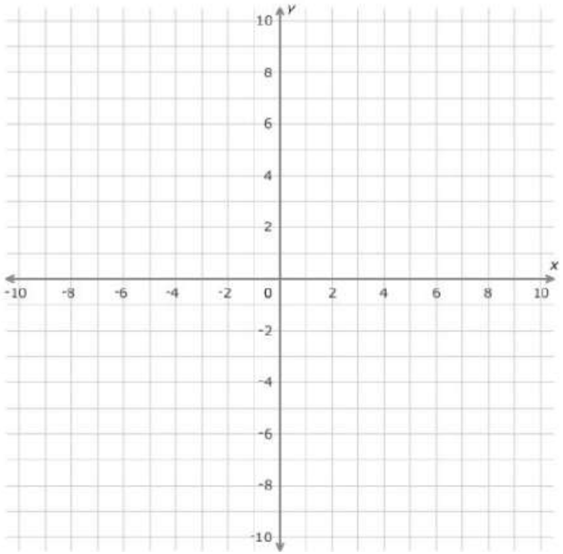
$$\min_{g} \max_{\boxed{c}} \mathbb{E}(\boxed{c}(x)) - \mathbb{E}(\boxed{c}(g(z)))$$

Needs to be 1-Lipschitz Continuous

Condition on W-Loss

Critic needs to be **1**-L Continuous

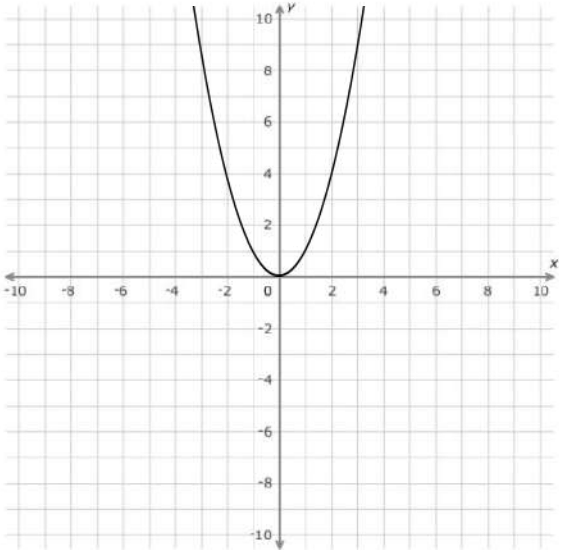
The norm of the gradient should be at most **1** for *every point*



Condition on W-Loss

Critic needs to be **1**-L Continuous

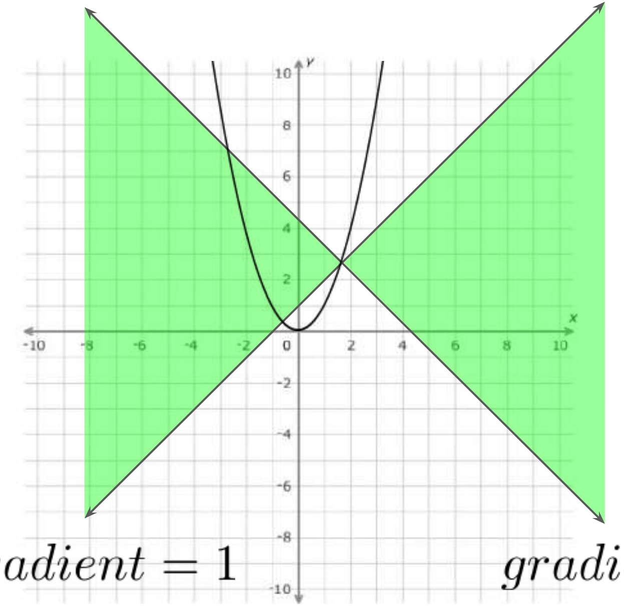
The norm of the gradient should be at most **1** for *every point*



Condition on W-Loss

Critic needs to be **1**-L Continuous

The norm of the gradient should be at most **1** for *every point*



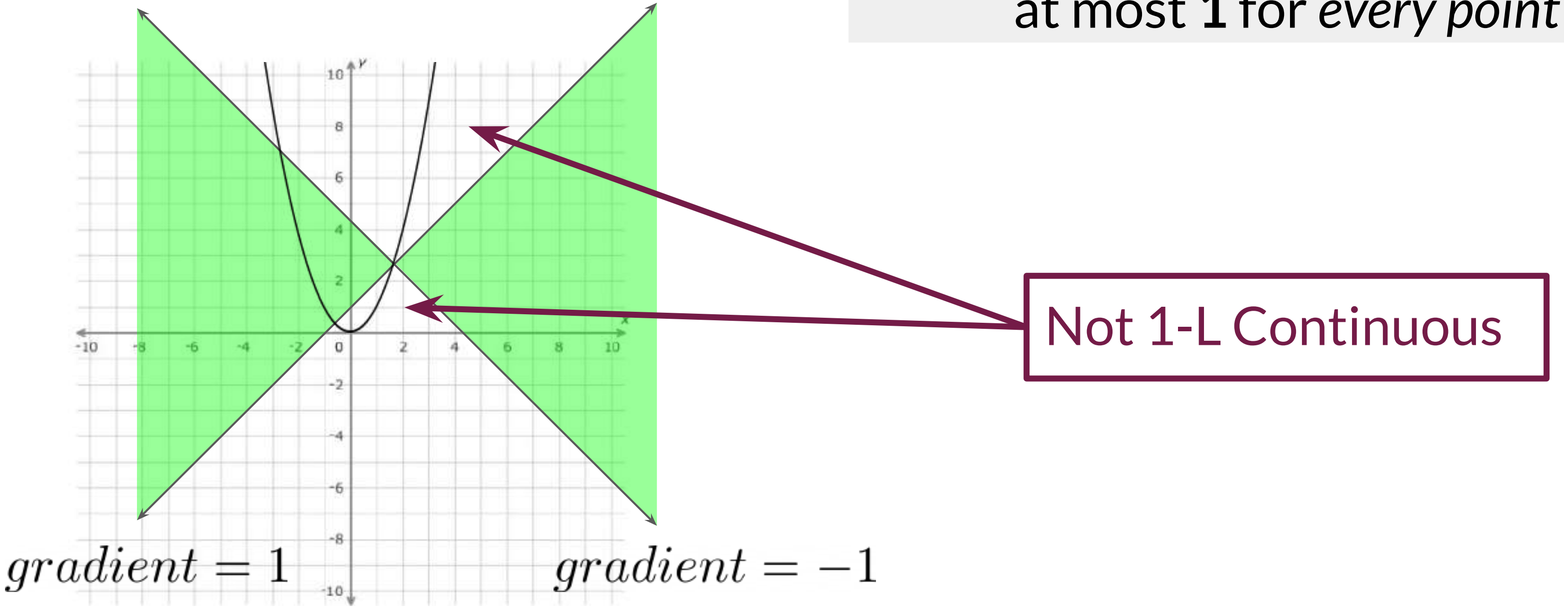
$gradient = 1$

$gradient = -1$

Condition on W-Loss

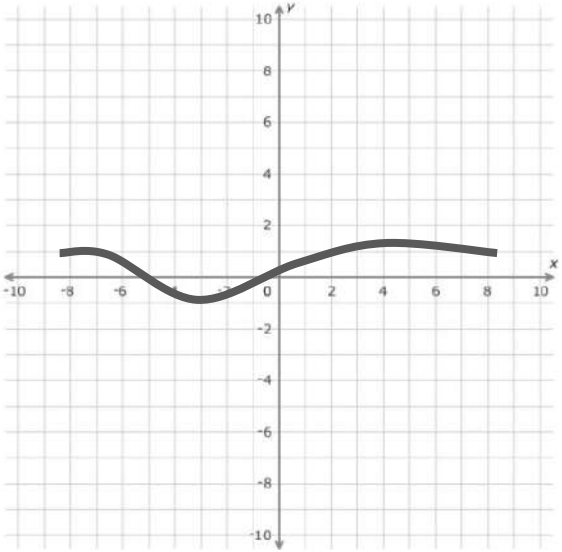
Critic needs to be **1**-L Continuous

The norm of the gradient should be at most **1** for *every point*



Condition on W-Loss

Critic needs to be **1**-L Continuous

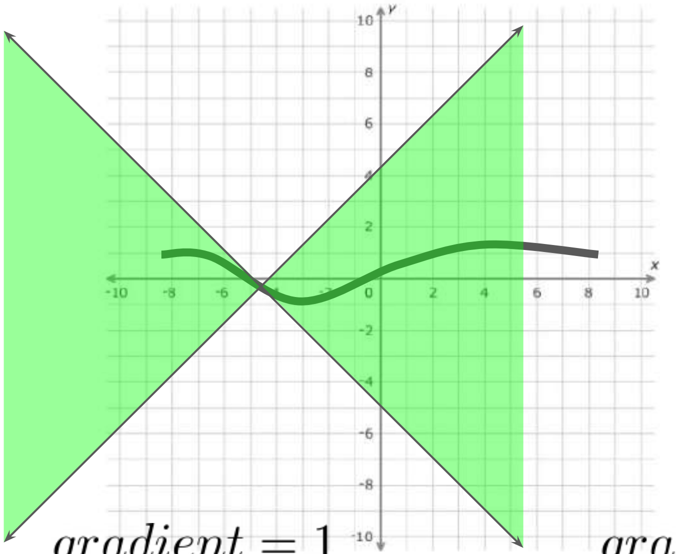


The norm of the gradient should be at most **1** for *every point*

Condition on W-Loss

Critic needs to be **1**-L Continuous

The norm of the gradient should be at most **1** for *every point*

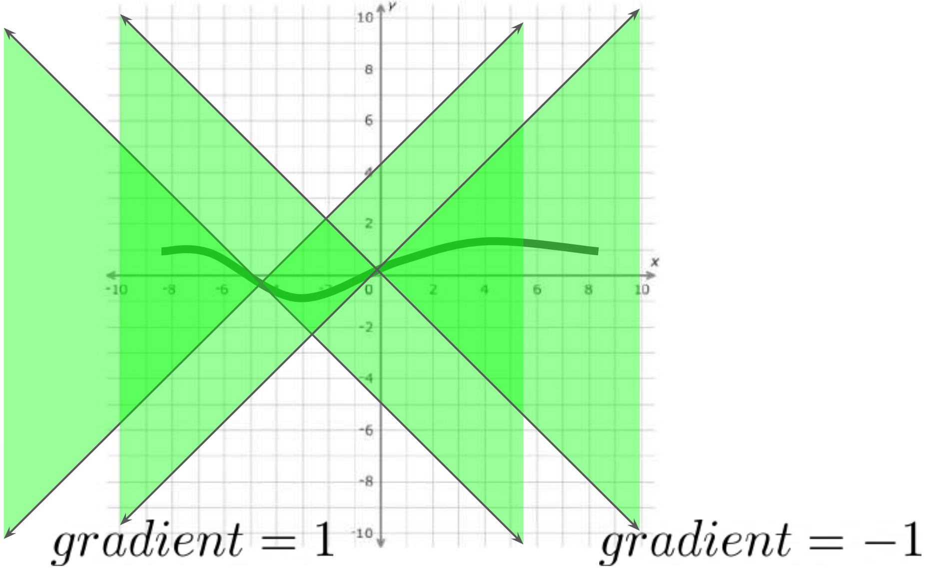


$gradient = 1$ $gradient = -1$

Condition on W-Loss

Critic needs to be **1**-L Continuous

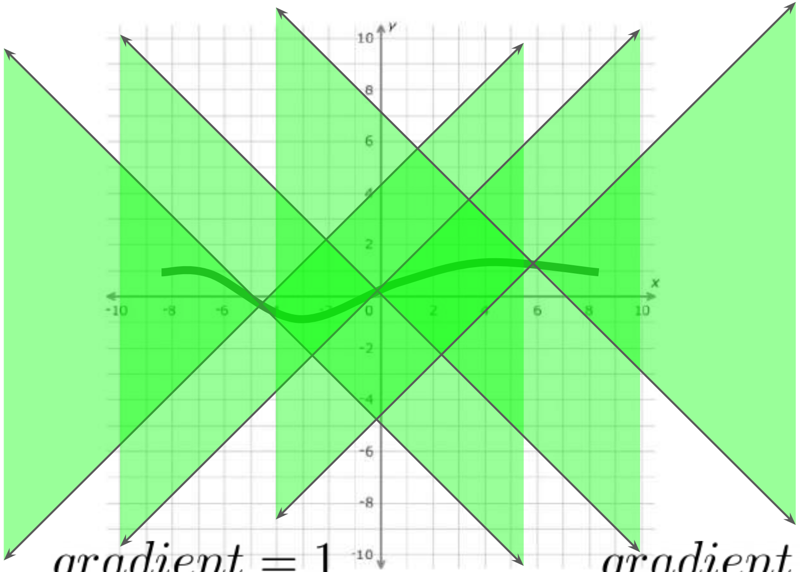
The norm of the gradient should be at most **1** for *every point*



Condition on W-Loss

Critic needs to be **1**-L Continuous

The norm of the gradient should be at most **1** for *every point*

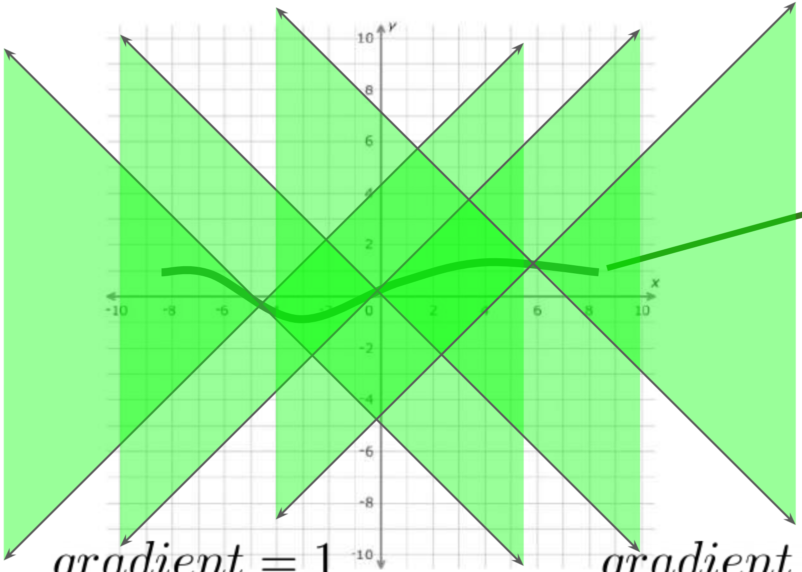


$gradient = 1$

$gradient = -1$

Condition on W-Loss

Critic needs to be **1**-L Continuous



$gradient = 1$ $gradient = -1$

The norm of the gradient should be at most **1** for *every point*

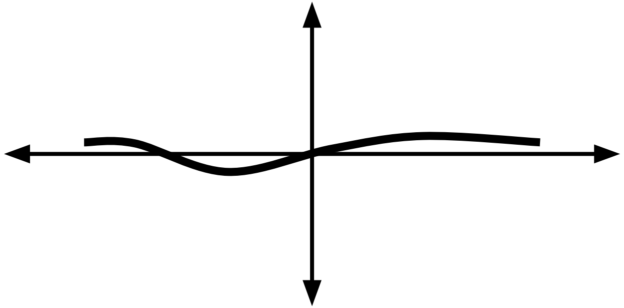
1-L Continuous

W-Loss is valid

Needed for training stable neural networks with W-Loss

Summary

- Critic's neural network needs to be 1-L Continuous when using W-Loss
- This condition ensures that W-Loss is validly approximating Earth Mover's Distance



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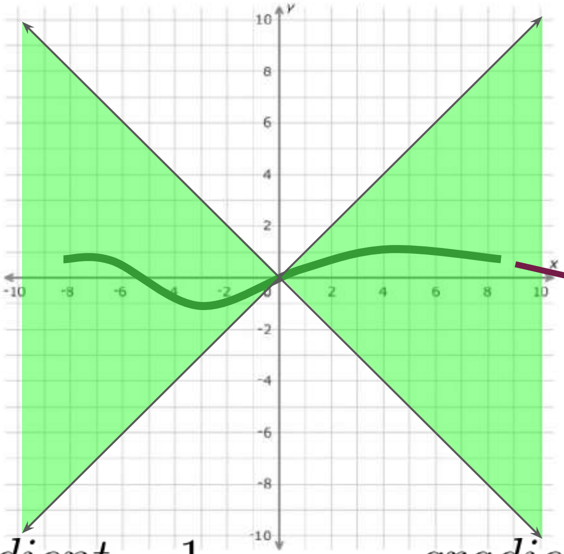
1-Lipschitz Continuity Enforcement

Outline

- Weight clipping and gradient penalty
- Advantages of gradient penalty

1-L Enforcement

Critic needs to be 1-L Continuous



$gradient = 1$ $\qquad$ $gradient = -1$

Norm of the gradient at most 1

$$||\nabla f(x)||_2 \leq 1$$

Slope of the function at most 1

1-L Enforcement: Weight Clipping

Weight clipping forces the weights of the critic to a fixed interval

Gradient descent to update weights

↓

Clip the critic's weights

Limits the learning ability of the critic

1-L Enforcement: Gradient Penalty

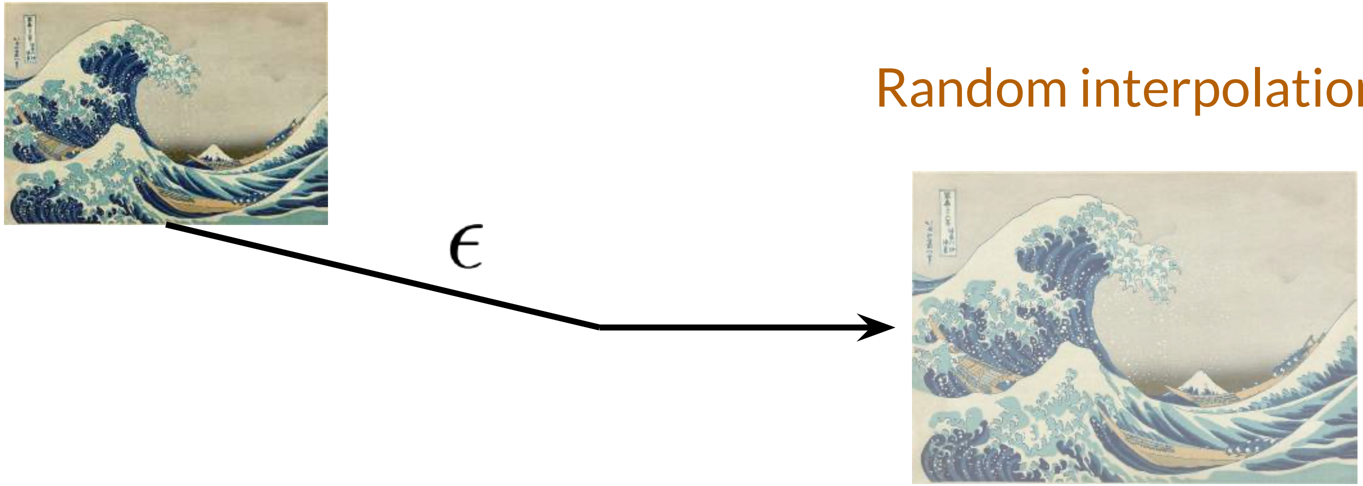
$$\min_g \max_c \; \mathbb{E}(c(x)) - \mathbb{E}(c(g(z))) + \lambda \text{reg}$$

Regularization of the critic's gradient

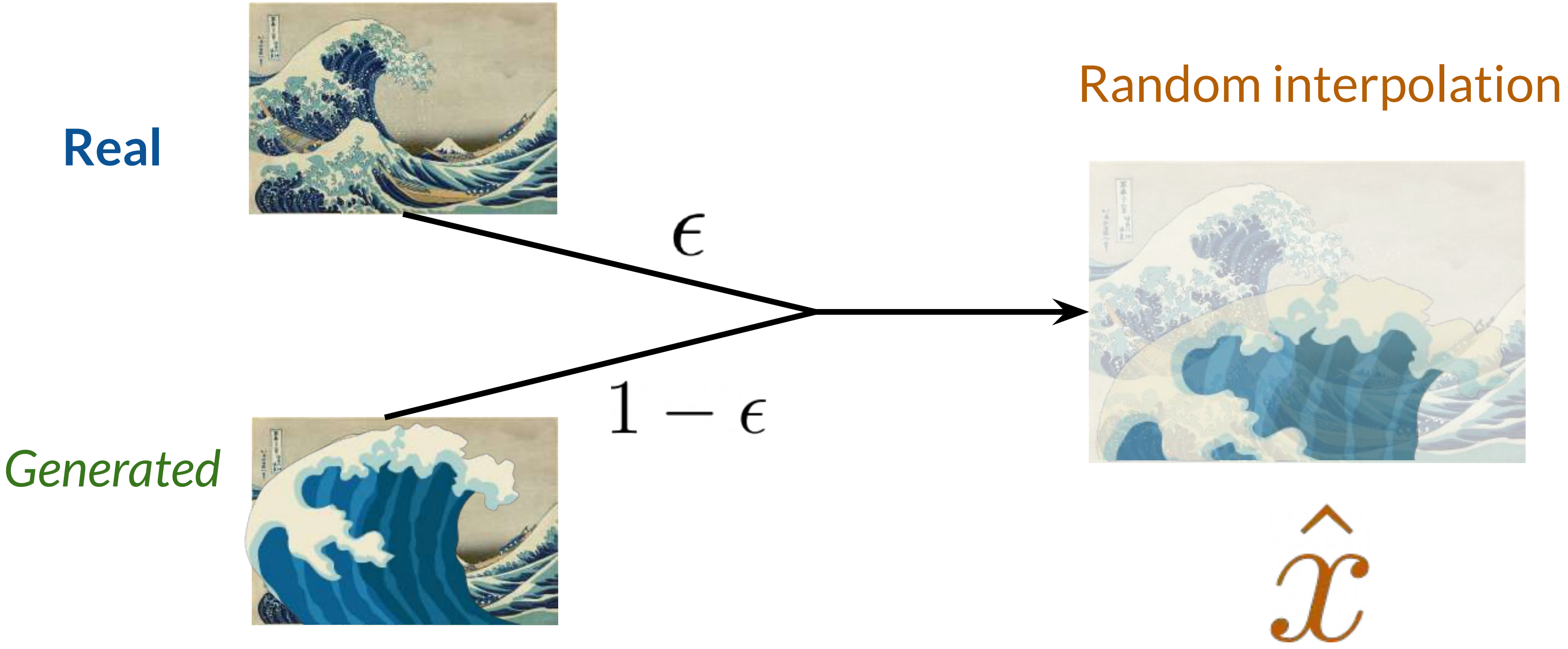
1-L Enforcement: Gradient Penalty

Real

Random interpolation



1-L Enforcement: Gradient Penalty



1-L Enforcement: Gradient Penalty

$$\mathbb{E}(||\nabla c(\hat{x})||_2 - 1)^2$$

Regularization term

1-L Enforcement: Gradient Penalty

$$\mathbb{E}(||\nabla c(\boxed{\hat{x}})||_2 - 1)^2$$

Regularization term

1-L Enforcement: Gradient Penalty

$$\mathbb{E}(||\nabla c(\boxed{\hat{x}})||_2 - 1)^2$$

Regularization term

$$\epsilon x + (1 - \epsilon) g(z)$$

Interpolation

1-L Enforcement: Gradient Penalty

$$\mathbb{E}(||\nabla c(\boxed{\hat{x}})||_2 - 1)^2$$

Regularization term

$$\epsilon \boxed{x} + (1 - \epsilon) g(z)$$

Real

Interpolation

1-L Enforcement: Gradient Penalty

$$\mathbb{E}(||\nabla c(\boxed{\hat{x}})||_2 - 1)^2$$

Regularization term

$$\epsilon \boxed{x} + (1 - \epsilon) \boxed{g(z)}$$

Interpolation

Real

Generated

Putting It All Together

$$\min_{g} \max_{c} \mathbb{E}(c(x)) - \mathbb{E}(c(g(z))) + \lambda \mathbb{E}(||\nabla c(\hat{x})||_2 - 1)^2$$

Putting It All Together

$$\min_{g} \max_{c} \boxed{\mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))} + \lambda \mathbb{E}(||\nabla c(\hat{x})||_2 - 1)^2$$

Makes the GAN less prone to **mode collapse** and **vanishing gradient**

Putting It All Together

$$\min_{g} \max_{c} \boxed{\mathbb{E}(c(x)) - \mathbb{E}(c(g(z)))} \boxed{+\lambda\mathbb{E}(||\nabla c(\hat{x})||_2 - 1)^2}$$

Makes the GAN less prone to **mode collapse** and **vanishing gradient**

Tries to make the critic be 1-L Continuous, for the loss function to be **continuous and differentiable**

Summary

- Weight clipping and gradient penalty are ways to enforce 1-L continuity
- Gradient penalty tends to work better