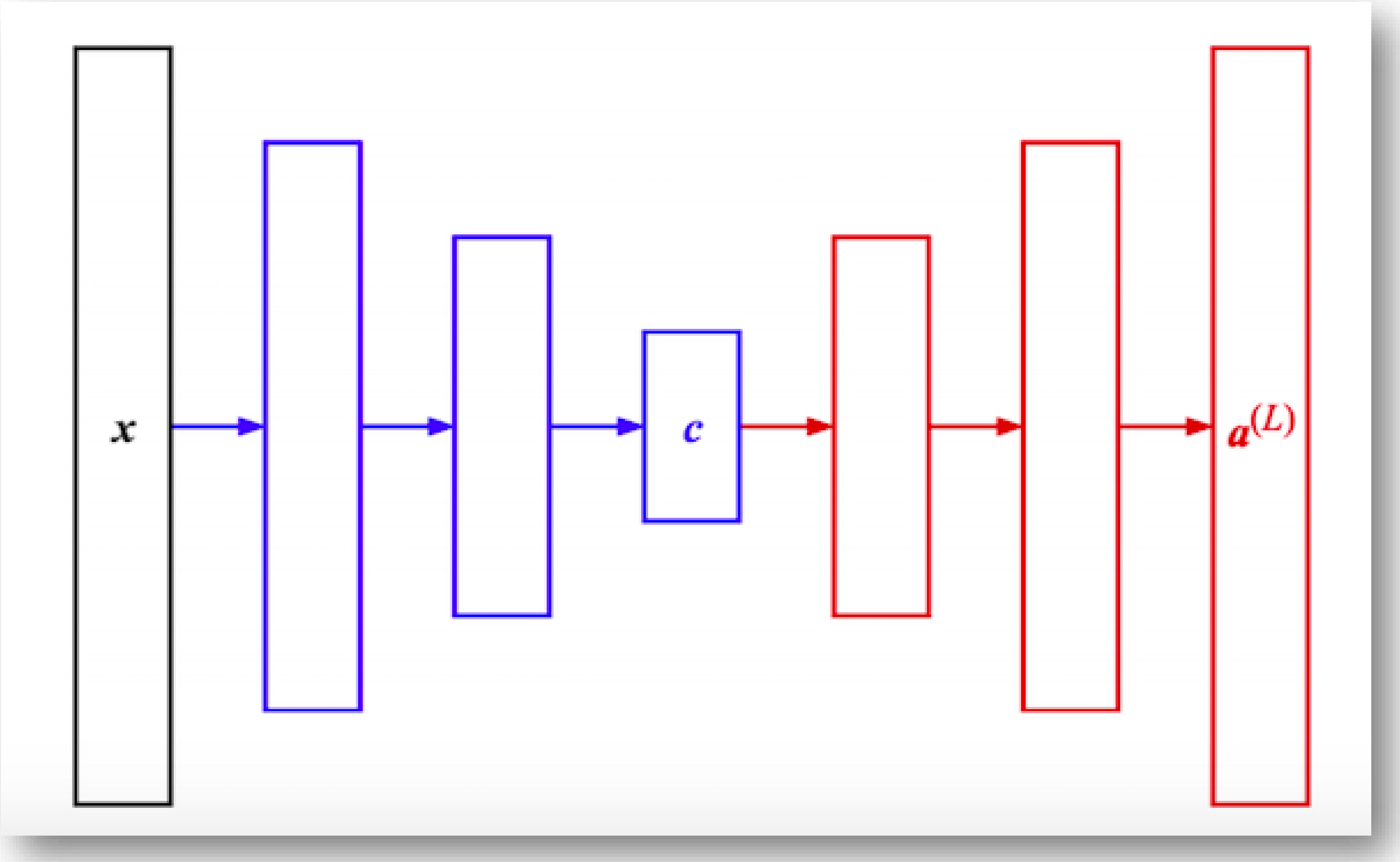
# Lab 13
# Autoencoder & GANs

DataLab

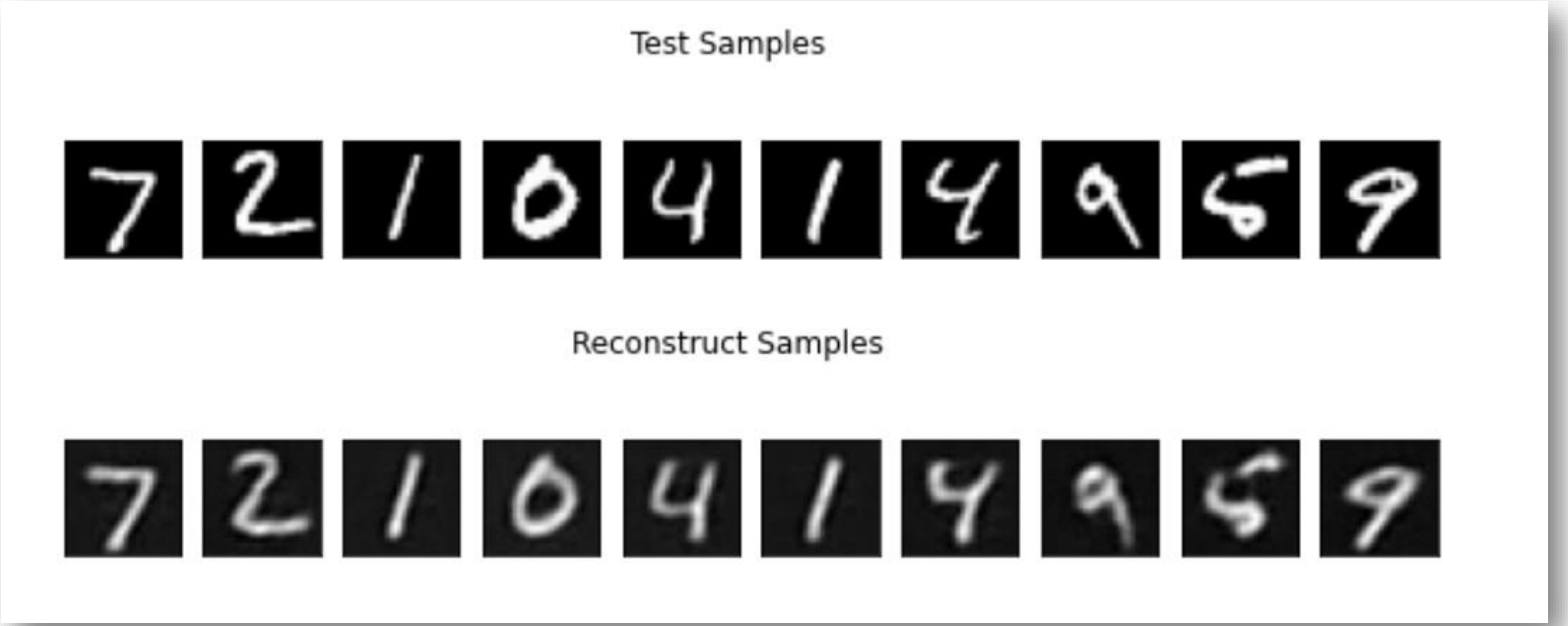
Department of Computer Science,
National Tsing Hua University, Taiwan

# 13-1 Autoencoder



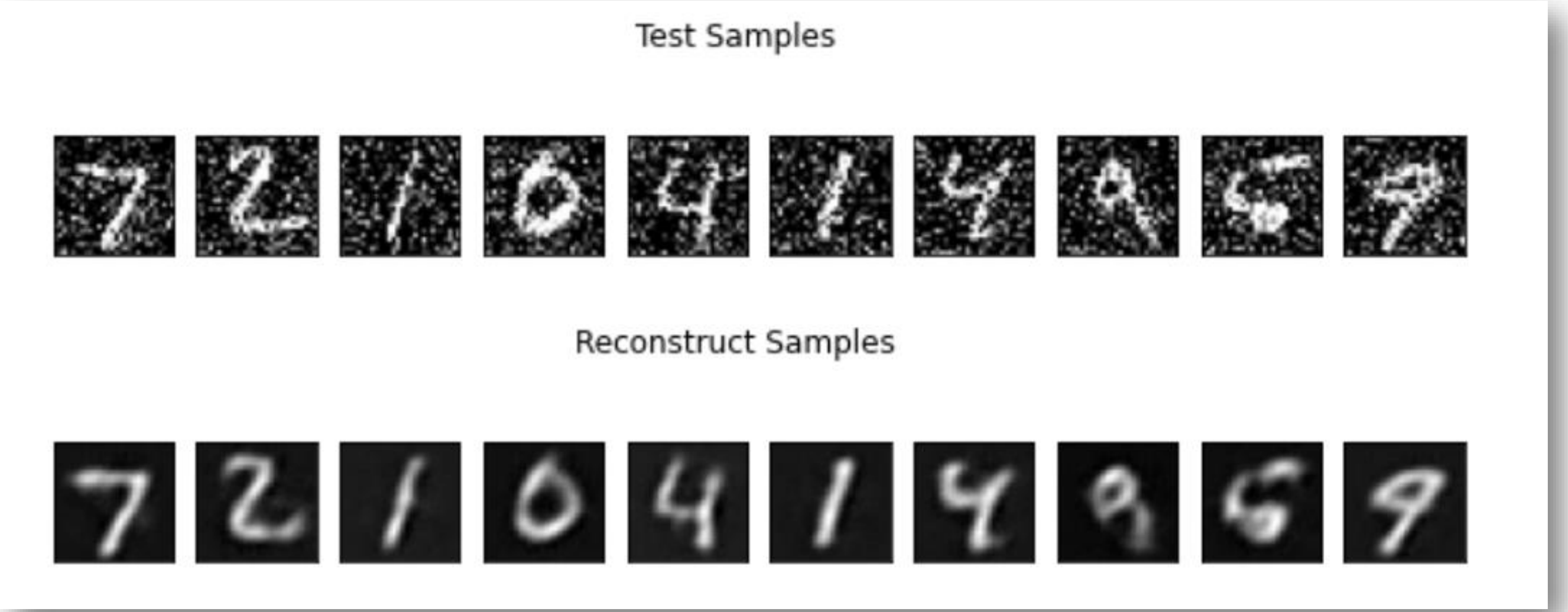
# Autoencoder

- Autoencoder without noise



# Autoencoder

- Autoencoder with noise



# 13-2 GAN Outline

- Reviewing GAN Structure
- Loss Functions
- WGAN
- WGAN-GP (improved WGAN)

# Outline

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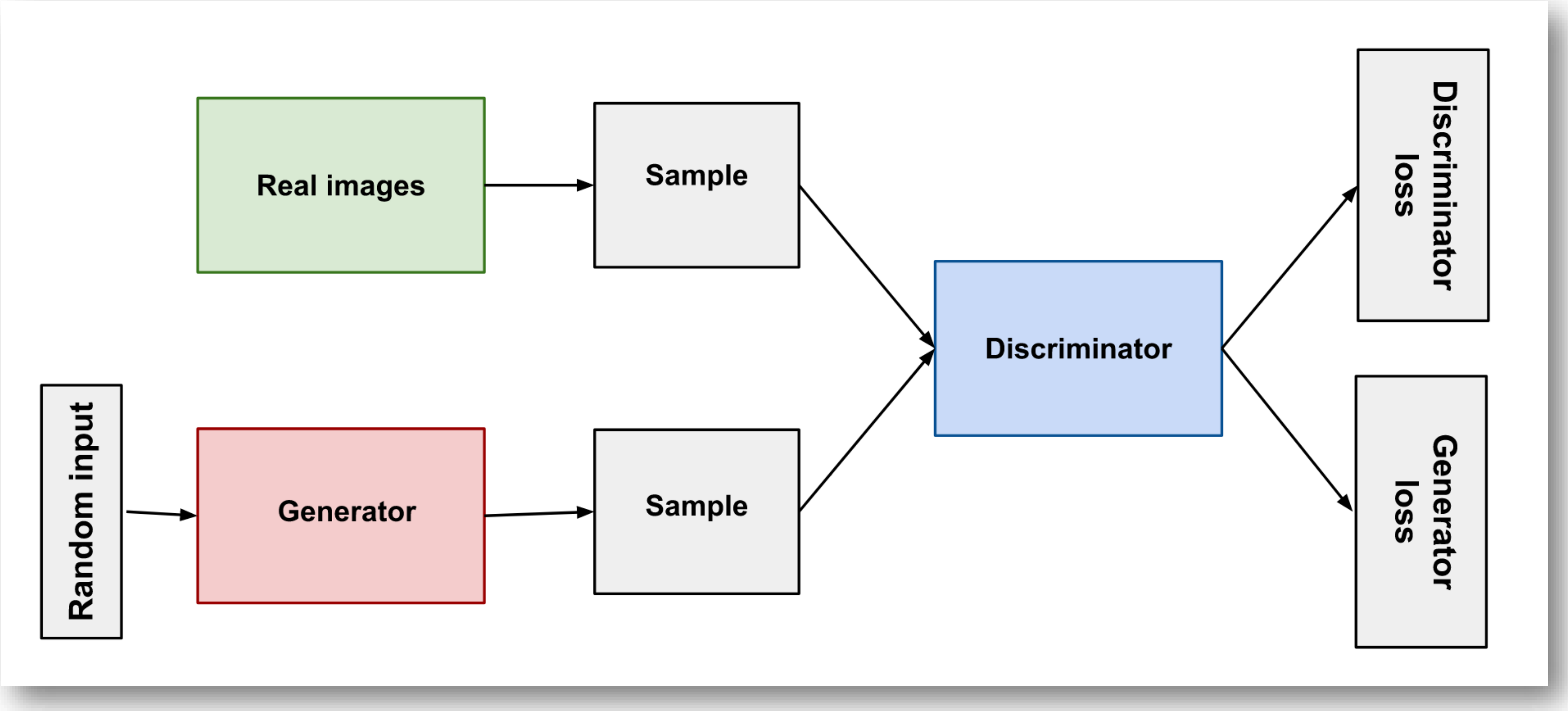
# Review - GAN



Real images
Sample
Random input
Generator
Sample
Discriminator
Discriminator loss
Generator loss

# Outline

- Reviewing GAN Structure
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# Loss Functions

- Minimax Loss:
  - For D: maximize $E_x[\log(D(x))] + E_z[\log(1 - D(G(z)))]$
  - For G: minimize $E_x[\log(D(x))] + E_z[\log(1 - D(G(z)))]$
- Wasserstein Loss:
  - For D: maximize $E_{x \sim P_x}[f_w(x)] - E_{z \sim P_z}[f_w(G(z))]$
  - For G: minimize $E_{x \sim P_x}[f_w(x)] - E_{z \sim P_z}[f_w(G(z))]$

# Loss Functions

- Minimax Loss:
  - For D: maximize $E_x[\log(\boxed{D(x)})] + E_z[\log(1 - D(G(z)))]$
  - For G: minimize $E_x[\log(D(x))] + E_z[\log(1 - D(G(z)))]$
- Wasserstein Loss:
  - For D: maximize $E_{x\sim P_x}[\boxed{f_w(x)}] - E_{z\sim P_z}[f_w(G(z))]$
  - For G: minimize $E_{x\sim P_x}[f_w(x)] - E_{z\sim P_z}[f_w(G(z))]$

$f_w \in K - \mathit{Lipschitz\ functions}$ for some $K$

# Loss Functions

- Lipschitz continuity: a function $f : X \to Y$ is called **Lipschitz continuous** if there exists a real constant $K \geqq 0$ such that, for all $x_1$ and $x_2$ in $X$

$$d_Y(f(x_1), f(x_2)) \leq K d_X(x_1, x_2)$$

# Loss Functions

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- How to make the discriminator Lipschitz continuous?

# Loss Functions

- Lipschitz continuity: a function $f : X \rightarrow Y$ is called **Lipschitz continuous** if there exists a real constant $K \geqq 0$ such that, for all $x_1$ and $x_2$ in $X$

$$d_Y(f(x_1), f(x_2)) \leq K d_X(x_1, x_2)$$

- How to make the discriminator Lipschitz continuous?
  - Weight clipping – clip all weights in $f_w$ into a certain range.

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# WGAN

## Discriminator Training

Sample $\{x^{(i)}\}_{i=1}^{m} \sim \mathbb{P}_r$ a batch from the real data.
Sample $\{z^{(i)}\}_{i=1}^{m} \sim p(z)$ a batch of prior samples.
$g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^{m} f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^{m} f_w(g_\theta(z^{(i)}))\right]$
$w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w)$
$w \leftarrow \boxed{\text{clip}(w, -c, c)}$

Make sure critic is 1-Lipchitz

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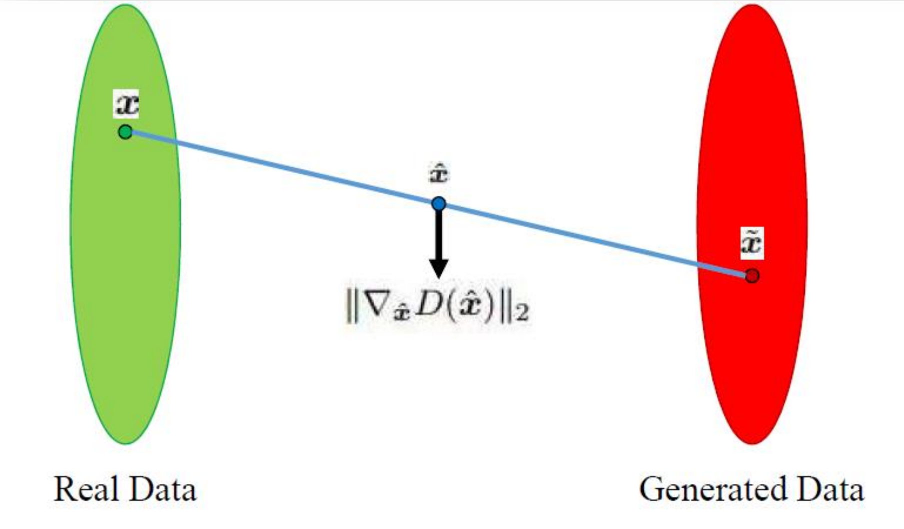
# WGAN-GP

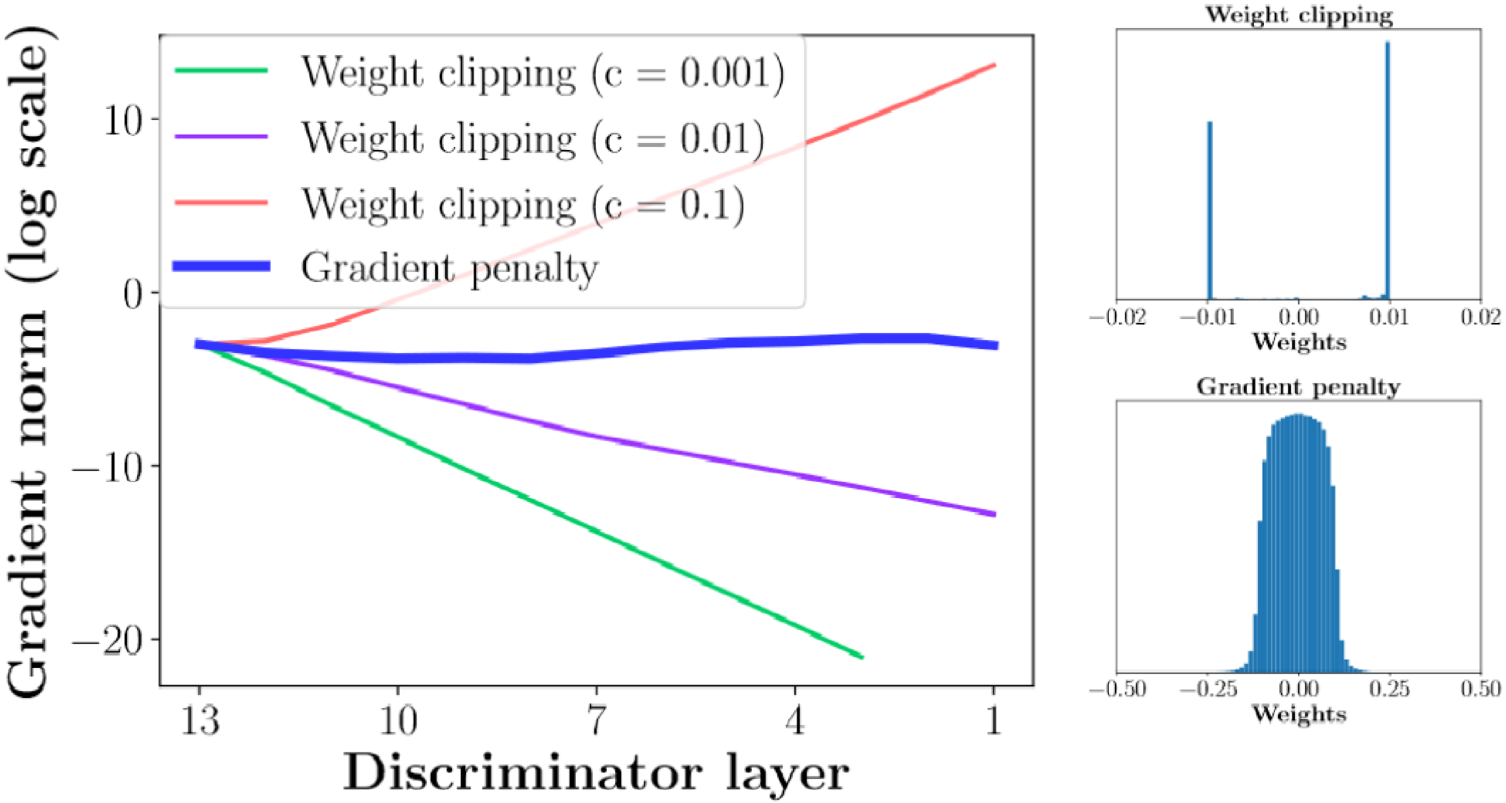
- Instead of weight clipping, adding gradient penalty can also achieve Lipchitz continuity.

$$L = \underbrace{\mathop{\mathbb{E}}_{\tilde{\boldsymbol{x}} \sim \mathbb{P}_g} \left[ D(\tilde{\boldsymbol{x}}) \right] - \mathop{\mathbb{E}}_{\boldsymbol{x} \sim \mathbb{P}_r} \left[ D(\boldsymbol{x}) \right]}_{\text{Original critic loss}} + \underbrace{\lambda \mathop{\mathbb{E}}_{\hat{\boldsymbol{x}} \sim \mathbb{P}_{\hat{\boldsymbol{x}}}} \left[ (\| \nabla_{\hat{\boldsymbol{x}}} D(\hat{\boldsymbol{x}}) \|_2 - 1)^2 \right]}_{\text{Our gradient penalty}} .$$



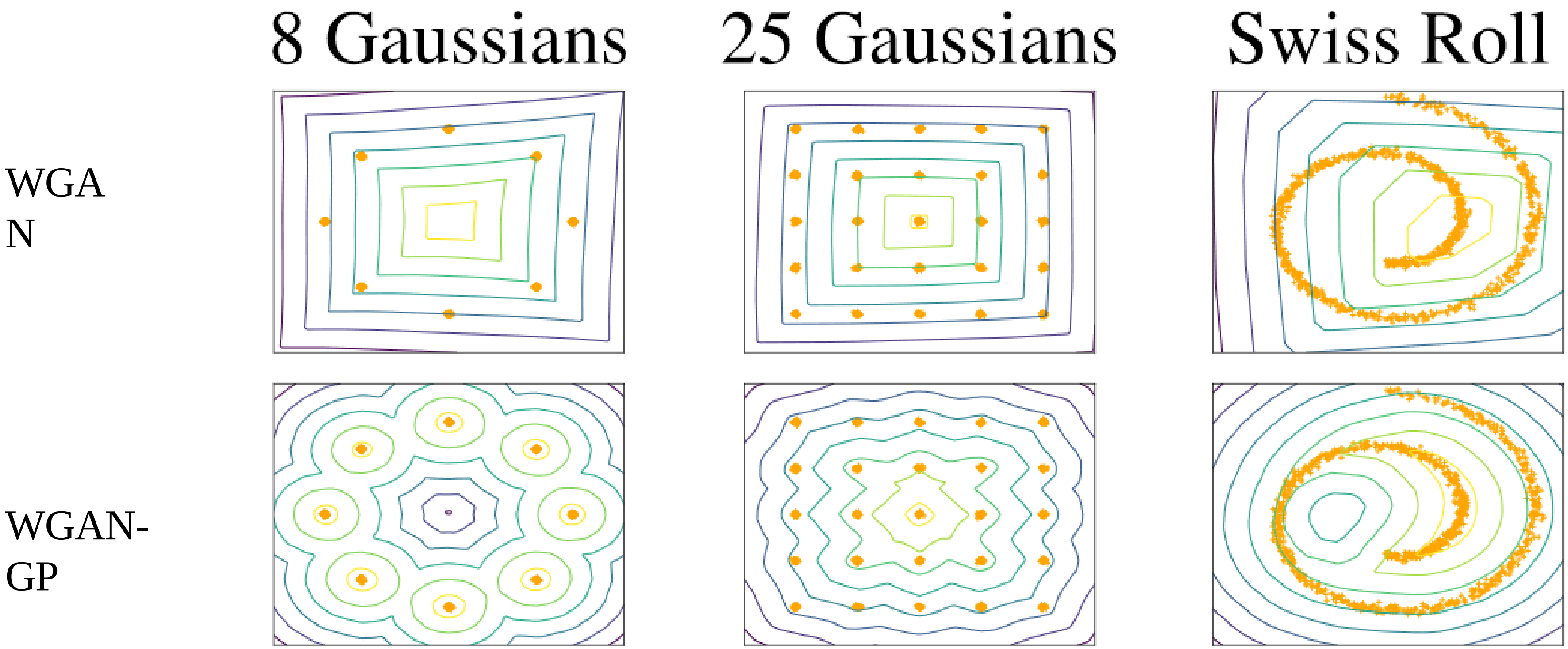
# WGAN-GP

- In comparison with WGAN

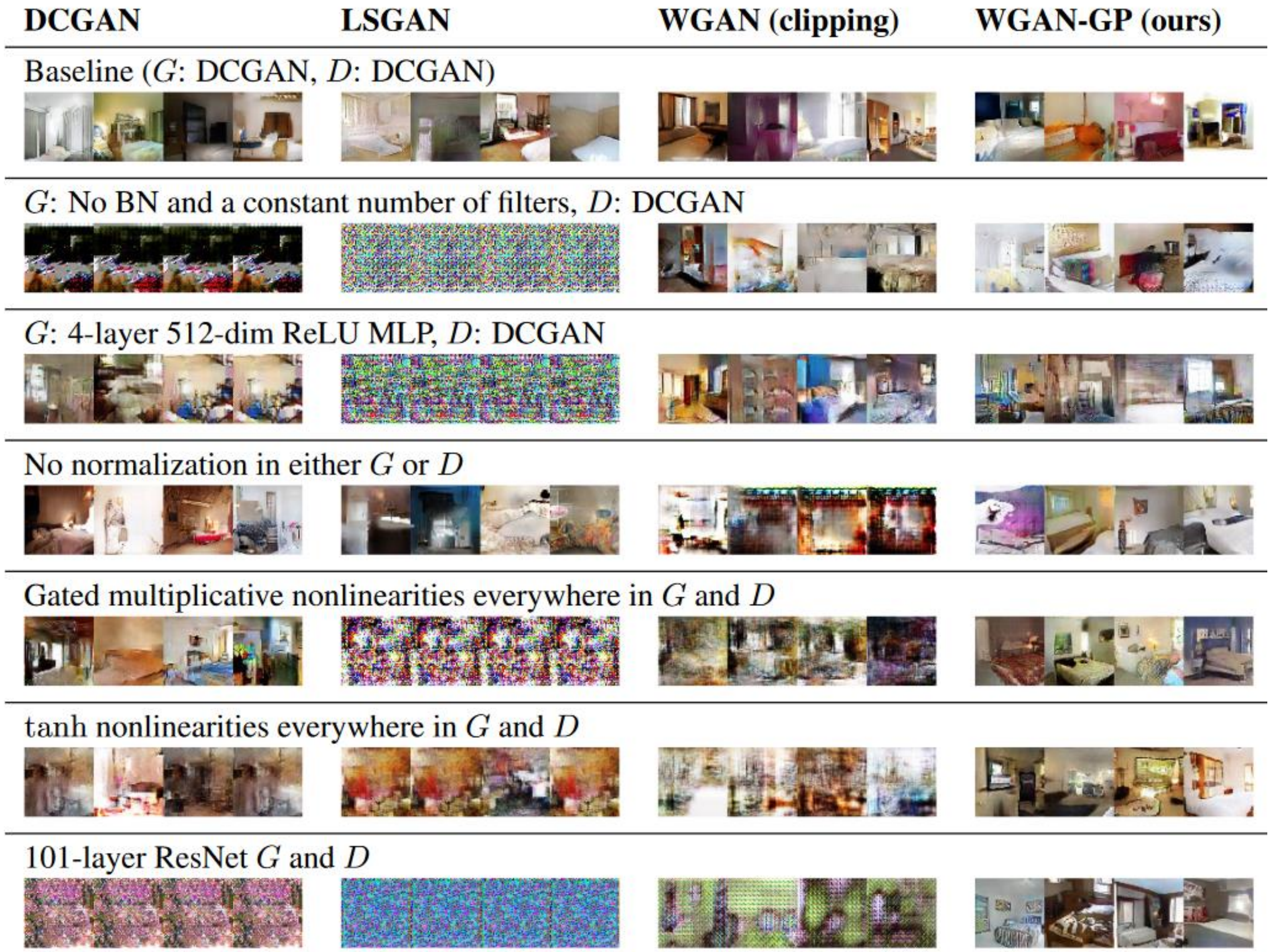


# WGAN-GP

- In comparison with WGAN



# WGAN-GP


DCGAN
LSGAN
WGAN (clipping)
WGAN-GP (ours)
Baseline ($G$: DCGAN, $D$: DCGAN)
$G$: No BN and a constant number of filters, $D$: DCGAN
$G$: 4-layer 512-dim ReLU MLP, $D$: DCGAN
No normalization in either $G$ or $D$
Gated multiplicative nonlinearities everywhere in $G$ and $D$
tanh nonlinearities everywhere in $G$ and $D$
101-layer ResNet $G$ and $D$

# Assignment

- Assignment requirements
  - Implementation of Improved WGAN (WGAN-GP) and train on CelebA.
  - Build dataset to read and resize image to $64 \times 64$ for training
  - Training loop(s) / routine(s) for GAN. Pre-trained models are not allowed.
  - Show at least $8 \times 8$ animated image of training and some best generated samples.
  - Draw the curve of discriminator loss and generator loss during training process in a single image.
  - Brief report about what you have done.

# Assignment

- Submission
  - Upload notebook and attachments to google drive and submit the link to eeclass.
  - Your notebook should be named after “Lab13-2_{student id}.ipynb”.
  - Deadline : 2022/12/08 23:59