Lab 14-2
GANs

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Outline

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

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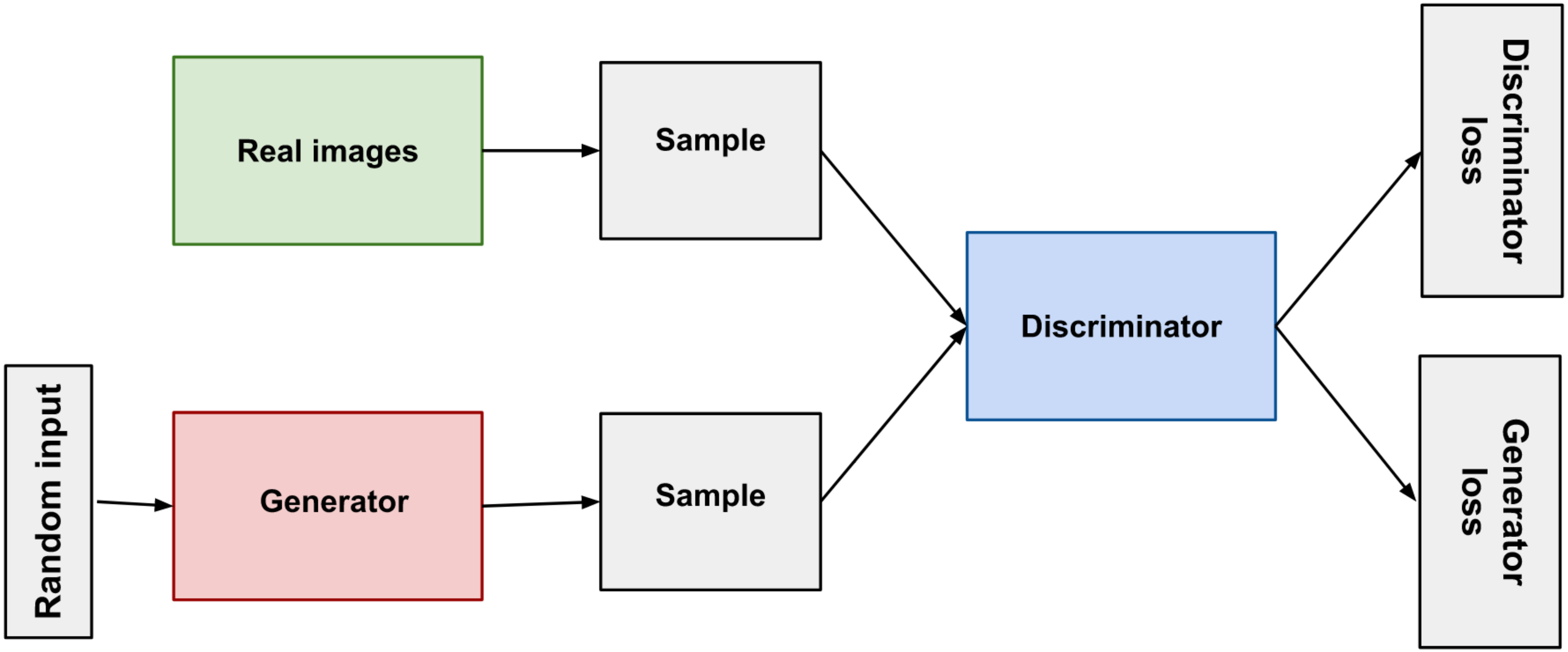
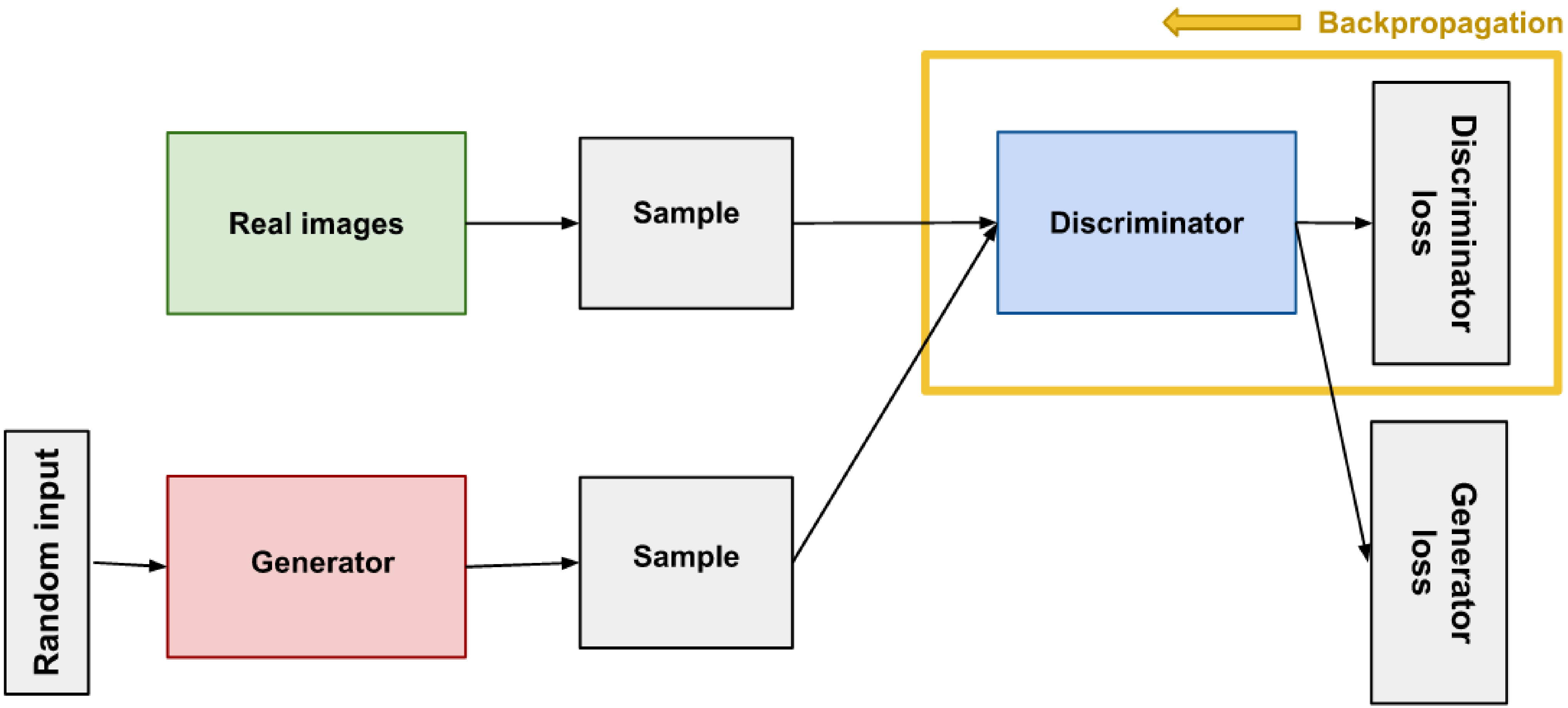
Review - GAN

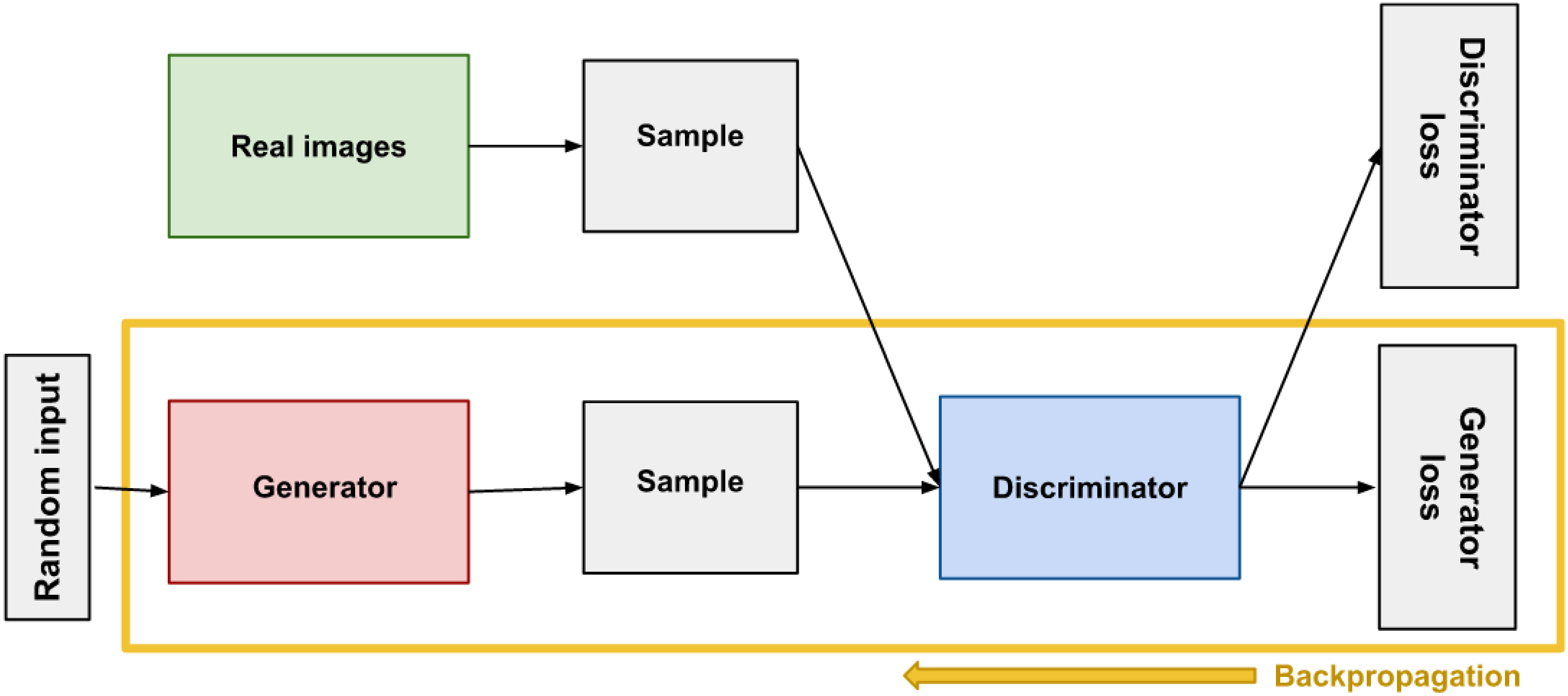


Real images
Sample
Random input
Generator
Sample
Discriminator
Discriminator loss
Generator loss

Review - GAN


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

Review - GAN


Real images
Sample
Discriminator loss
Random input
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Generator loss
Backpropagation

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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 $E_{x\sim P_x}[f_w(x)] - E_{z\sim P_z}[f_w(G(z))]$

$f_w \in K - Lipschitz\ functions$ 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

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- 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

$$\text{Sample } \{x^{(i)}\}_{i=1}^{m} \sim \mathbb{P}_r \text{ a batch from the real data.}$$

$$\text{Sample } \{z^{(i)}\}_{i=1}^{m} \sim p(z) \text{ a batch of prior samples.}$$

$$g_w \leftarrow \nabla_w \left[\frac{1}{m}\sum_{i=1}^{m} f_w(x^{(i)}) - \frac{1}{m}\sum_{i=1}^{m} f_w(g_\theta(z^{(i)}))\right]$$

$$w \leftarrow w + \alpha \cdot \text{RMSProp}(w, g_w)$$

$$w \leftarrow \boxed{\text{clip}(w, -c, c)}$$

Make sure critic is 1-Lipchitz

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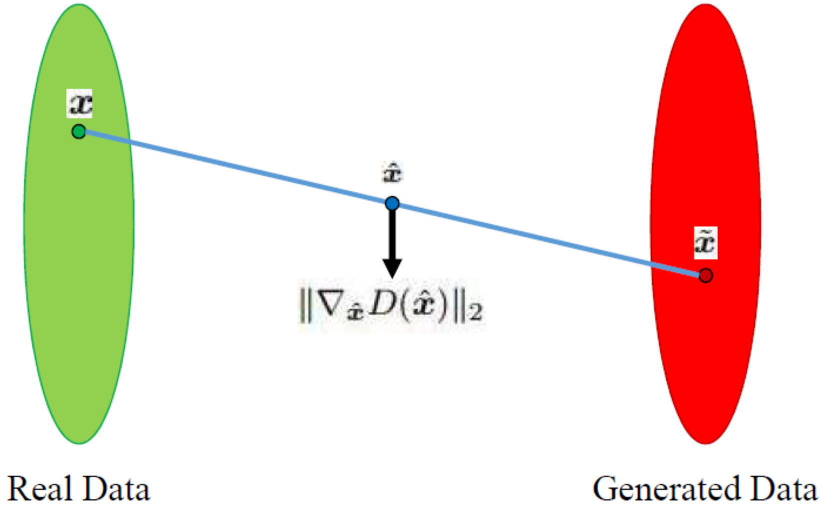
WGAN-GP

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

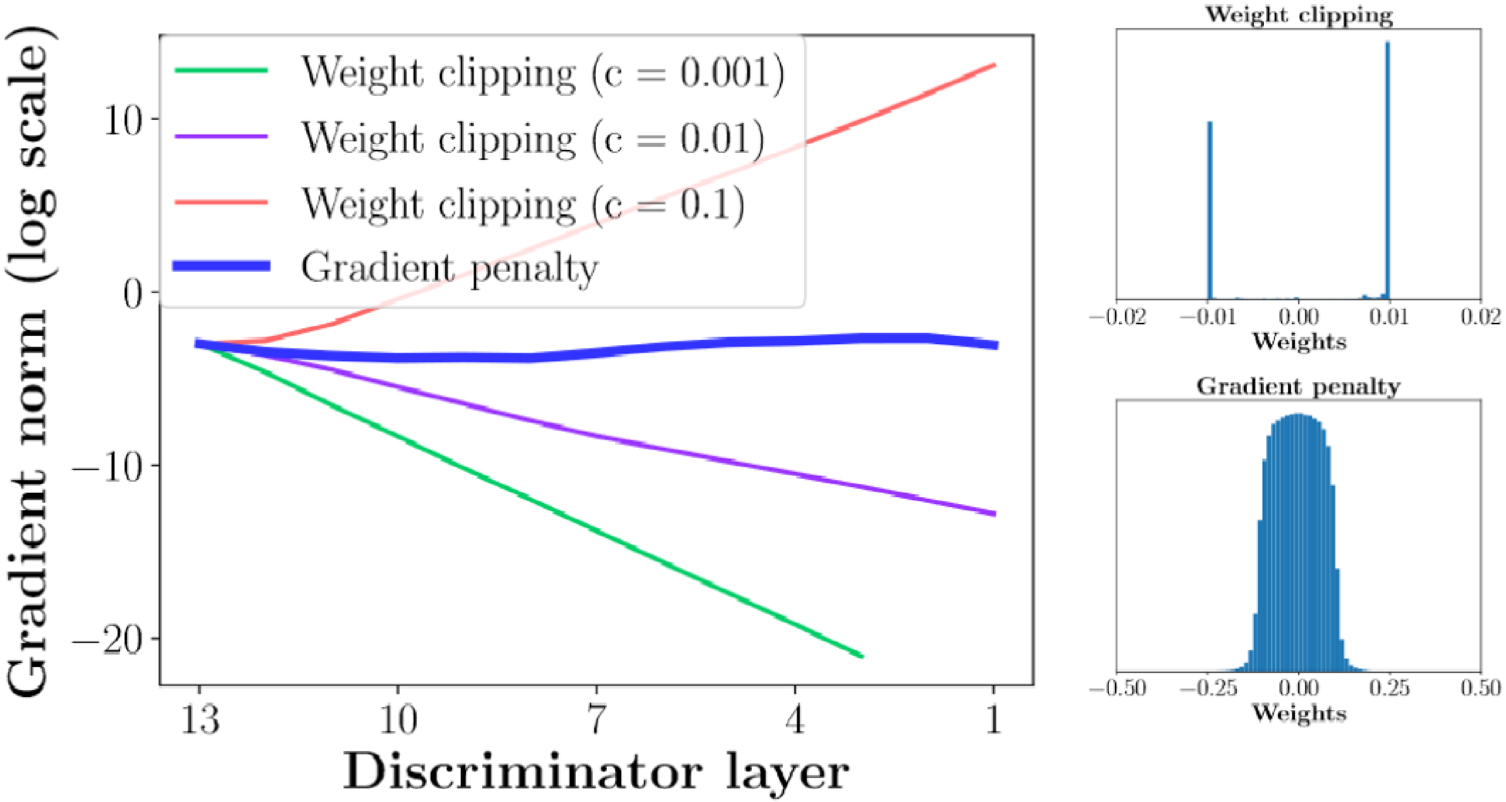
$$E_{x\sim P_x}[f_w(x)] - E_{z\sim P_z}[f_w(G(z))] - \boxed{\lambda E_{\tilde{x}\sim P_{\tilde{x}}}[(||\nabla_{\tilde{x}} f_w(\tilde{x})||_2 - 1)]}$$

Gradient Penalty



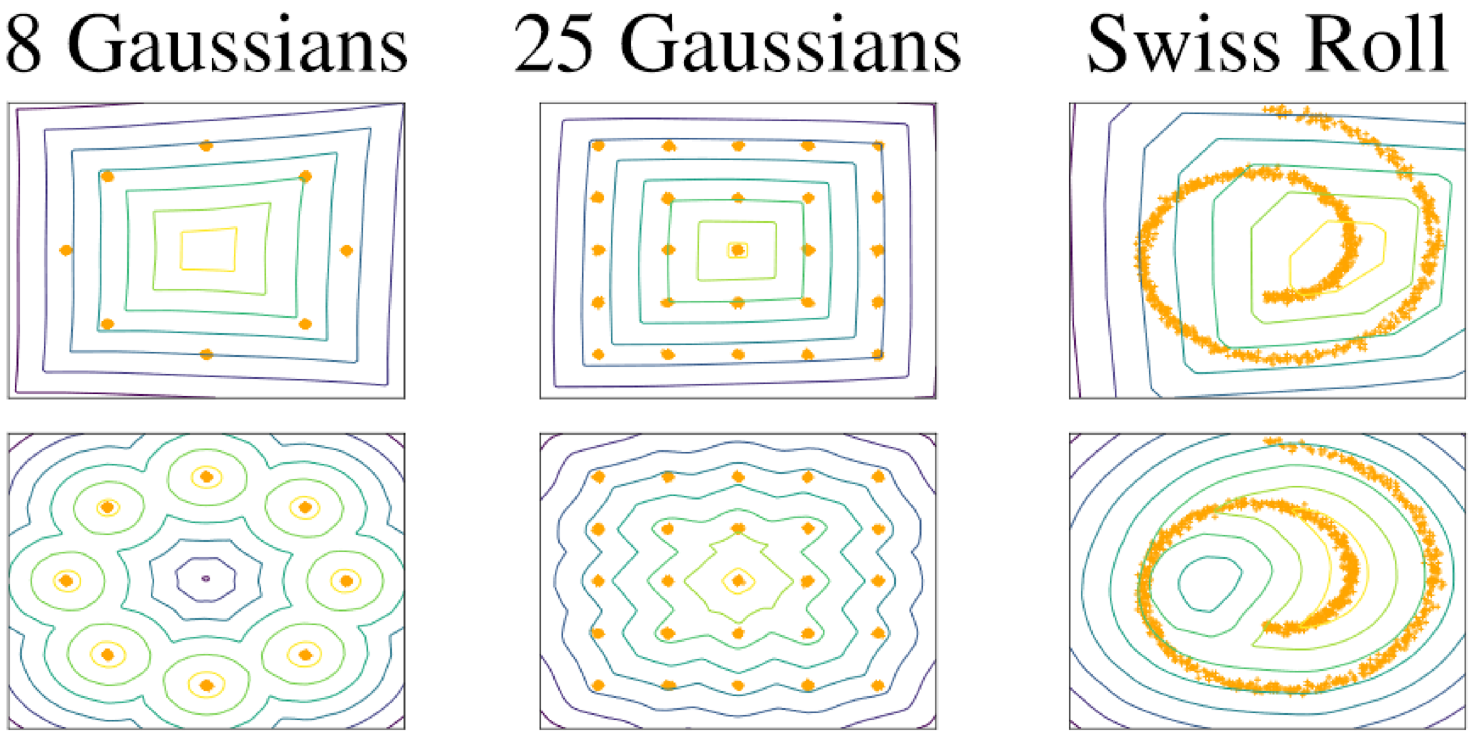
WGAN-GP

- In comparison with WGAN



WGAN-GP

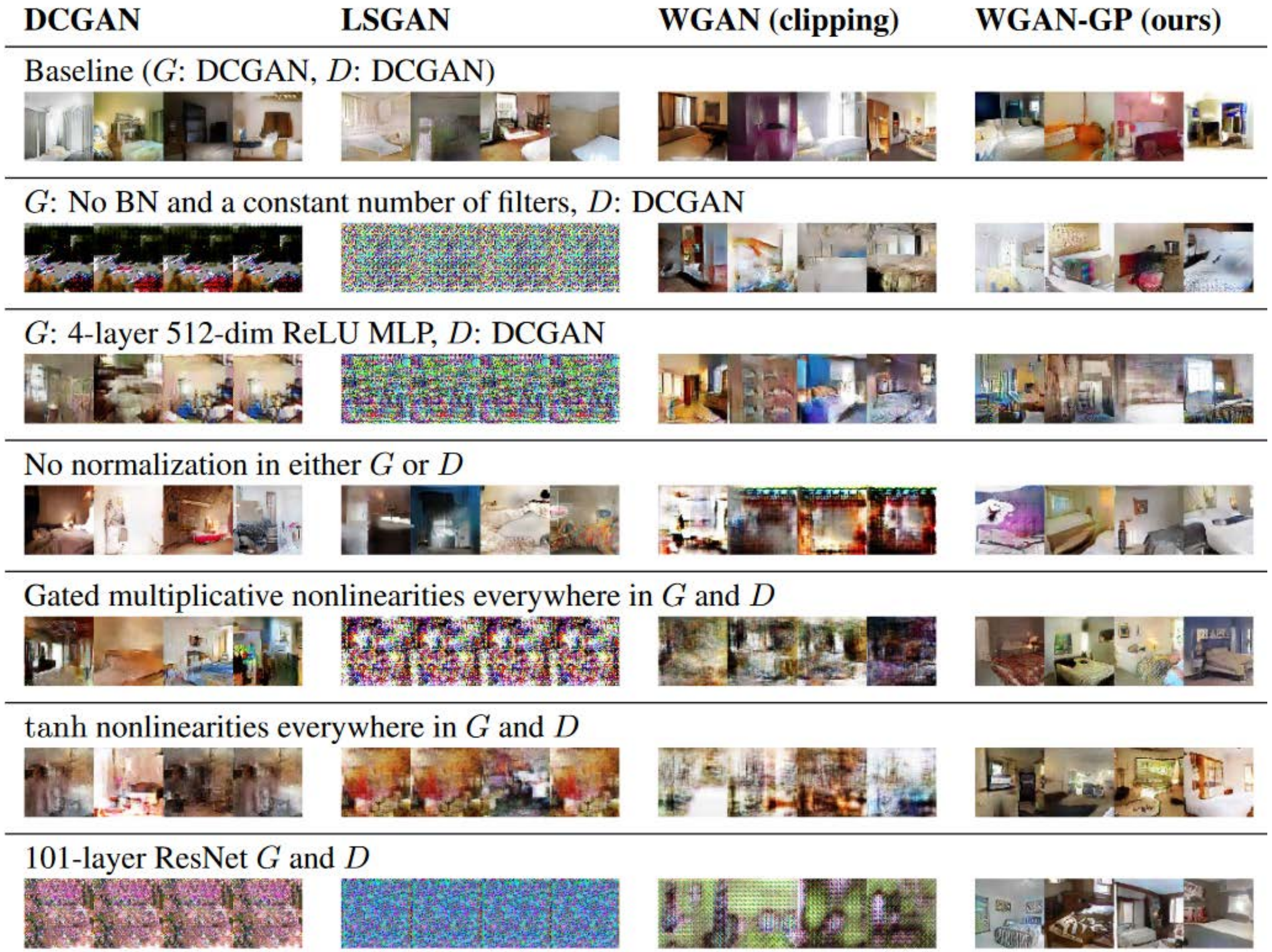
- In comparison with WGAN



WGAN

WGAN-GP

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

WGAN-GP

- Example

Assignment

- Assignment 1 requirements
  - Implementation of Improved WGAN (WGAN-GP) and train on CelebA.
  - Build dataset to read and resize image to 64×64 for training
  - Training loop(s) / routine(s) for GAN. Pre-trained models are not allowed.
  - Show at least 8×8 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

- Assignment 1 submission
    - Upload notebook and attachments to google drive and submit the link to iLMS.
    - Your notebook should be named after “Lab14-2_{student id}.ipynb”.
    - Deadline : 2020/12/15 23:59

Assignment

- Assignment 2
  - Read the Lab notebook of the autoencoder.