Tips for Improving GAN

Martin Arjovsky, Soumith Chintala, Léon Bottou, Wasserstein GAN, arXiv prepring, 2017

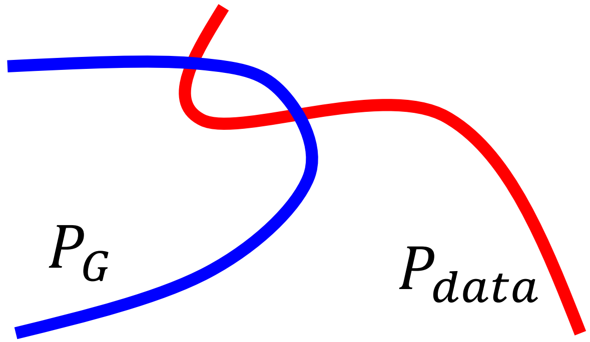
Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, Aaron Courville, “Improved Training of Wasserstein GANs”, arXiv prepring, 2017

JS divergence is not suitable

- In most cases, P_G and P_{data} are not overlapped.
- 1. The nature of data

  Both P_{data} and P_G are low-dim manifold in high-dim space.

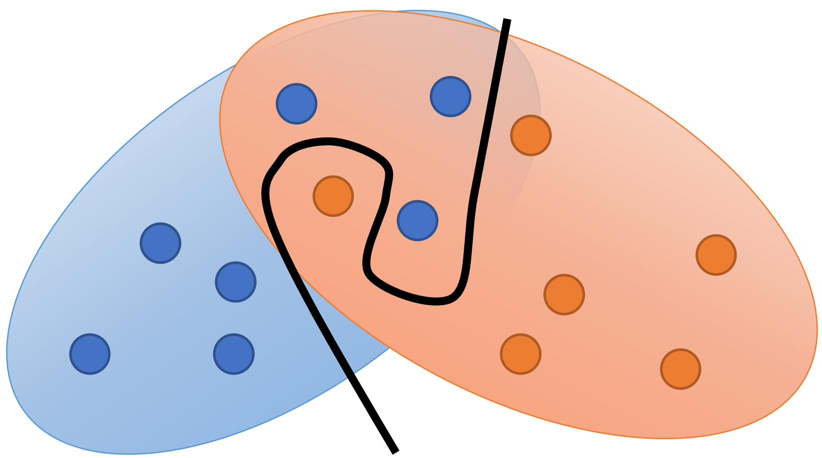
  The overlap can be ignored.



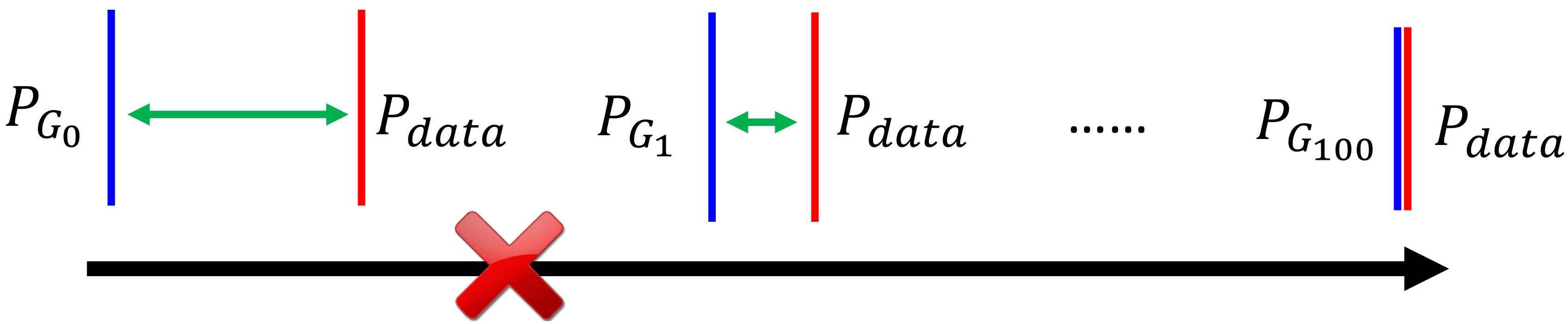
- 2. Sampling

  Even though P_{data} and P_G have overlap.

  If you do not have enough sampling ……



What is the problem of JS divergence?



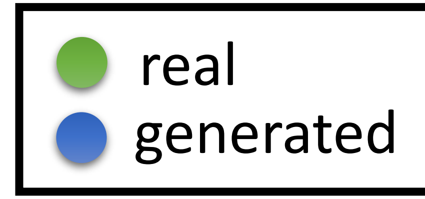
Equally bad

$JS(P_{G_0}, P_{data}) = log2$ $JS(P_{G_1}, P_{data}) = log2$ …… $JS(P_{G_{100}}, P_{data}) = 0$

JS divergence is log2 if two distributions do not overlap.

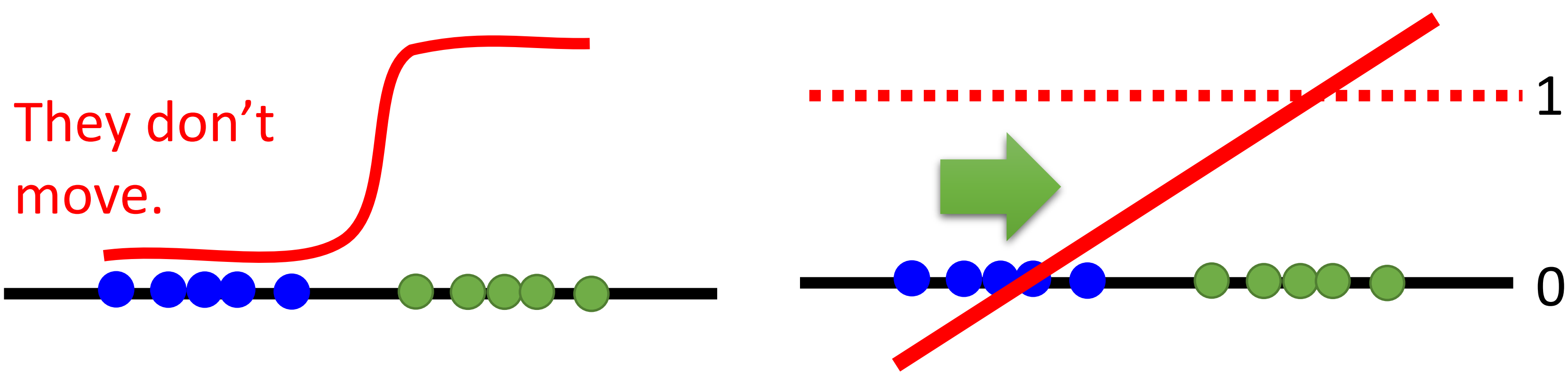
Intuition: If two distributions do not overlap, binary classifier achieves 100% accuracy

Same objective value is obtained. Same divergence



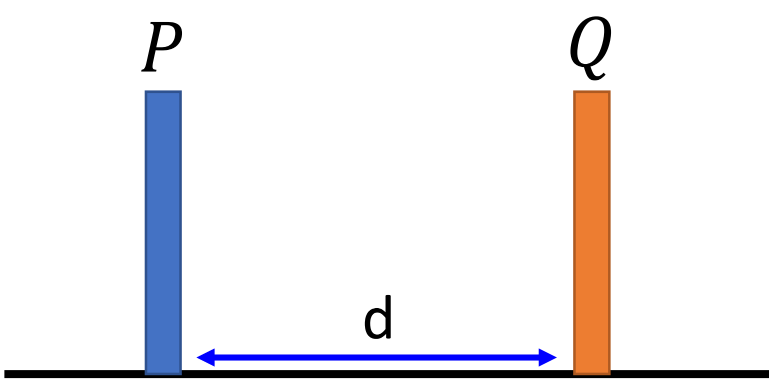
Least Square GAN (LSGAN)

- Replace sigmoid with linear (replace classification with regression)



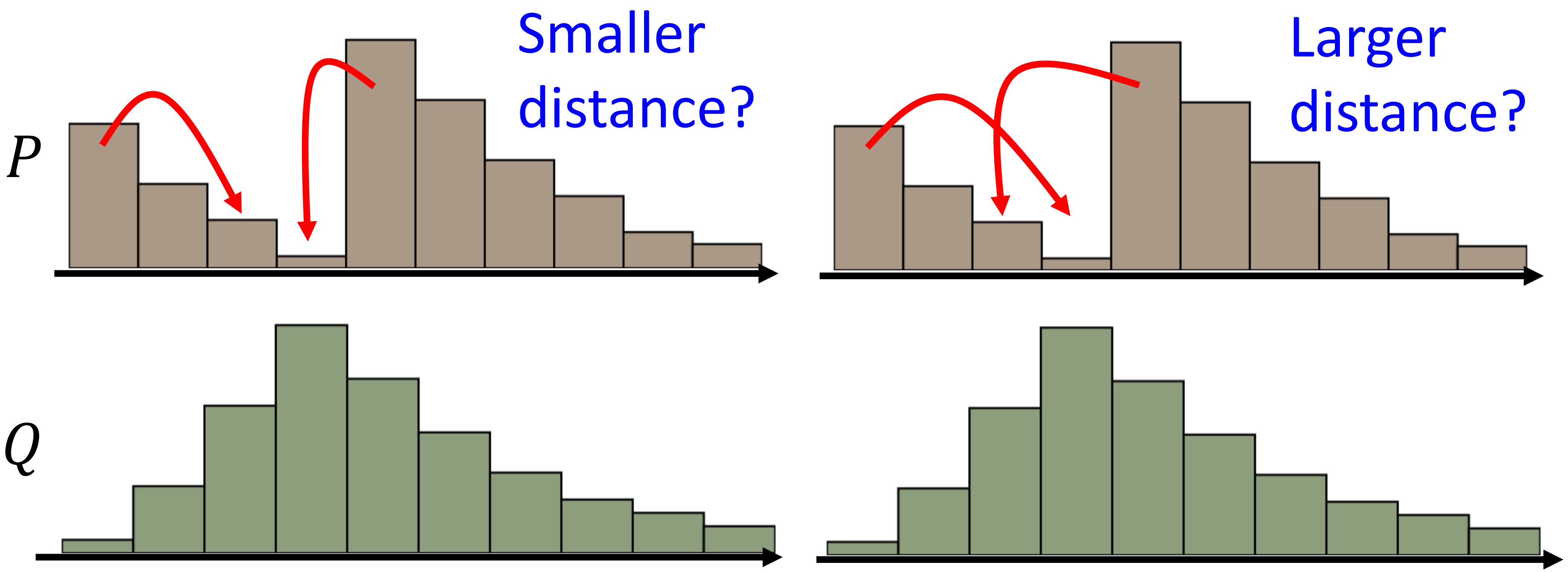
Wasserstein GAN (WGAN): Earth Mover’s Distance

- Considering one distribution P as a pile of earth, and another distribution Q as the target
- The average distance the earth mover has to move the earth.



$$W(P, Q) = d$$

WGAN: Earth Mover’s Distance



There many possible “moving plans”.

Using the “moving plan” with the smallest average distance to define the earth mover’s distance.

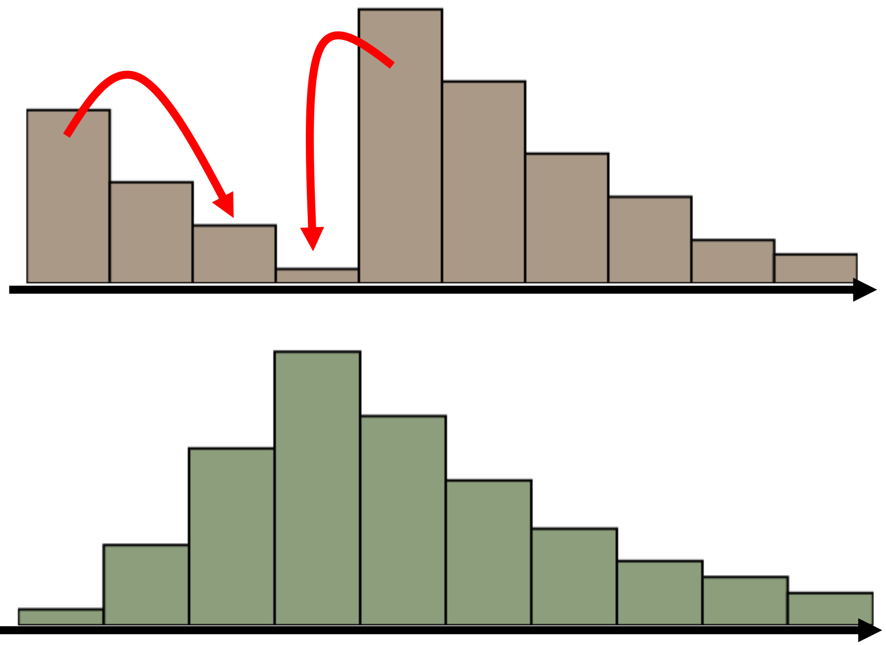
Source of image: https://vincentherrmann.github.io/blog/wasserstein/

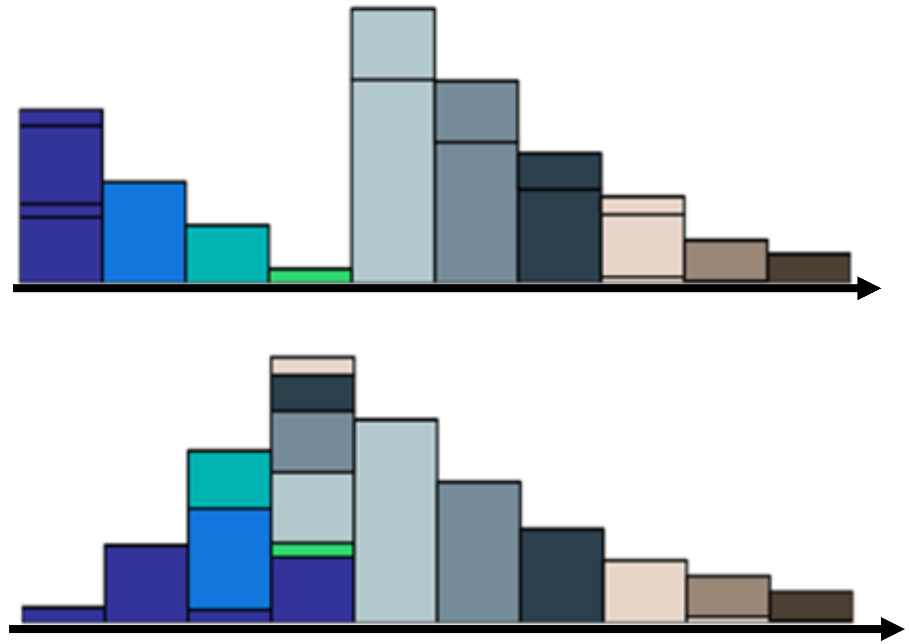
WGAN: Earth Mover’s Distance

Best “moving plans” of this example

P

Q

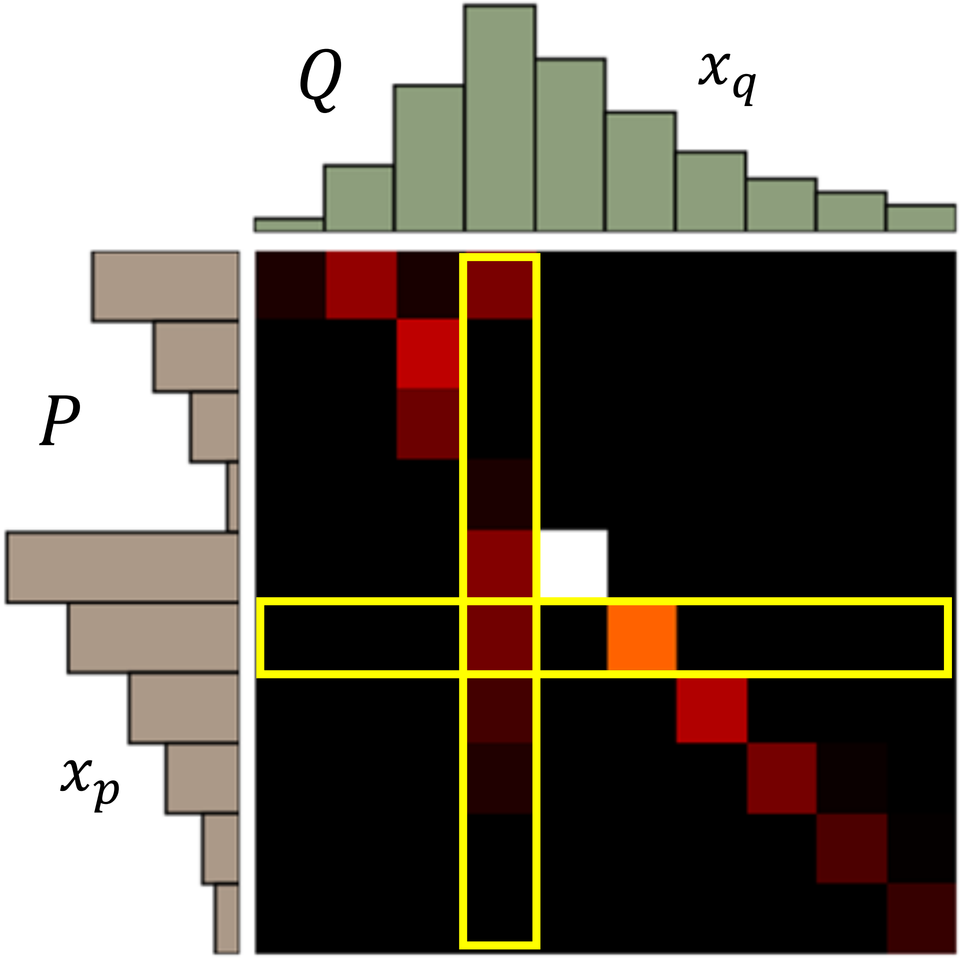




There many possible “moving plans”.

Using the “moving plan” with the smallest average distance to define the earth mover’s distance.

Source of image: https://vincentherrmann.github.io/blog/wasserstein/



A "moving plan" is a matrix

The value of the element is the amount of earth from one position to another.

Average distance of a plan γ:

$$B(\gamma) = \sum_{x_p, x_q} \gamma(x_p, x_q) \|x_p - x_q\|$$

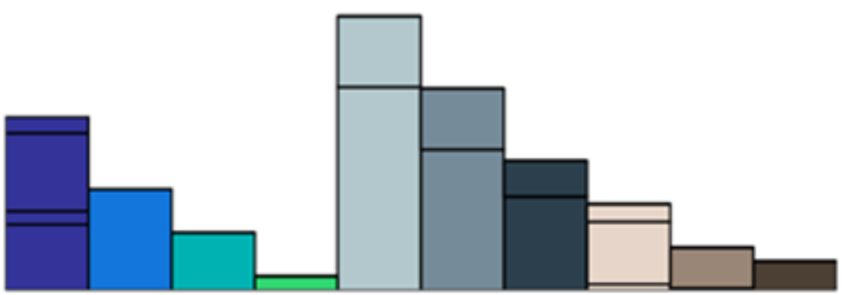
moving plan γ

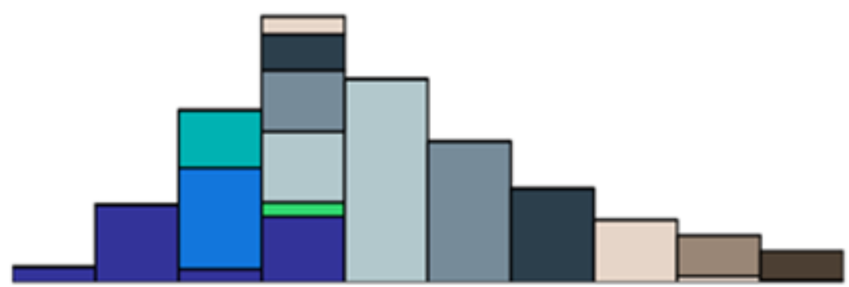
All possible plan Π

Earth Mover's Distance:

$$W(P, Q) = \min_{\gamma \in \Pi} B(\gamma)$$

The best plan

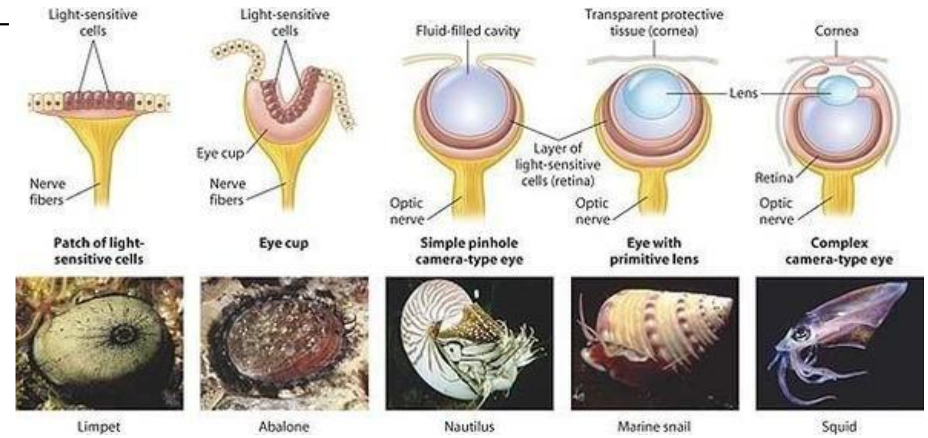


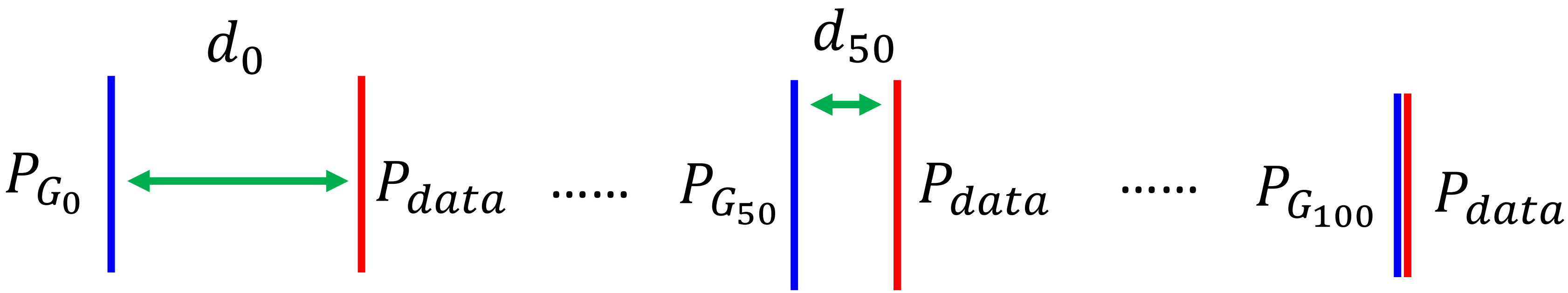


Why Earth Mover's Distance?

$$D_f(P_{data}||P_G)$$

$$W(P_{data}, P_G)$$





$$JS(P_{G_0}, P_{data}) = log2$$

$$JS(P_{G_{50}}, P_{data}) = log2$$

$$JS(P_{G_{100}}, P_{data}) = 0$$

$$W(P_{G_0}, P_{data}) = d_0$$

$$W(P_{G_{50}}, P_{data}) = d_{50}$$

$$W(P_{G_{100}}, P_{data}) = 0$$

[Martin Arjovsky, et al., arXiv, 2017]

WGAN

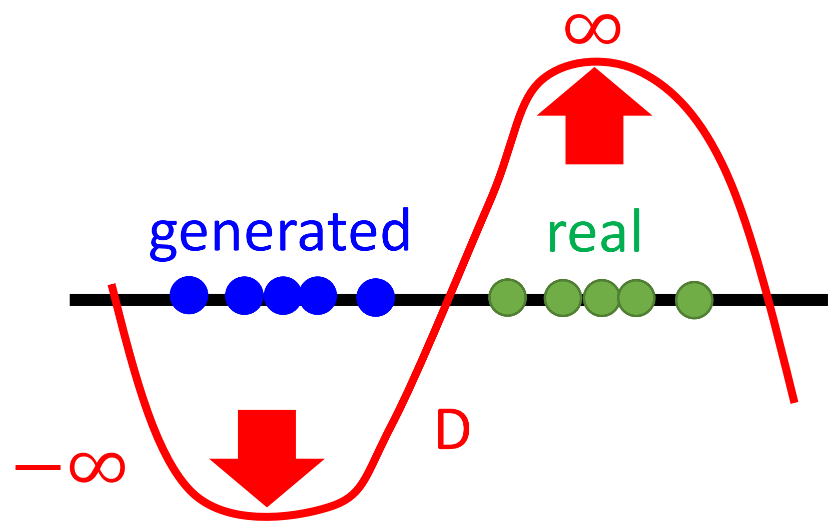
Evaluate wasserstein distance between P_{data} and P_G

$$V(G,D) = \max_{D \in 1-\underline{Lipschitz}} \left\{ E_{x \sim P_{data}}[D(x)] - E_{x \sim P_G}[D(x)] \right\}$$

D has to be smooth enough.

Without the constraint, the training of D will not converge.

Keeping the D smooth forces D(x) become ∞ and $-\infty$



Weight Clipping

[Martin Arjovsky, et al., arXiv, 2017]

Force the parameters w between c and -c

After parameter update, if w > c, w = c;

if w < -c, w = -c

WGAN

Evaluate wasserstein distance between P_{data} and P_G

$$V(G,D) = \max_{D \in 1-Lipschitz} \{E_{x \sim P_{data}}[D(x)] - E_{x \sim P_G}[D(x)]\}$$

D has to be smooth enough. How to fulfill this constraint?

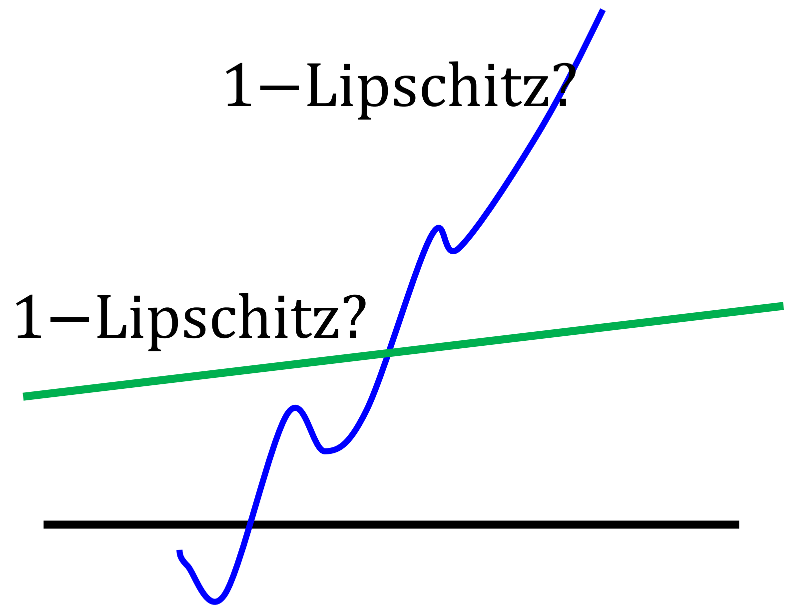
Lipschitz Function

$$\|f(x_1) - f(x_2)\| \le K\|x_1 - x_2\|$$

Output change Input change

K=1 for "$1 - Lipschitz$"

Do not change fast



Improved WGAN (WGAN-GP)

$$V(G,D) = \max_{D \in 1-Lipschitz} \{E_{x\sim P_{data}}[D(x)] - E_{x\sim P_G}[D(x)]\}$$

A differentiable function is 1-Lipschitz if and only if it has gradients with norm less than or equal to 1 everywhere.

$$D \in 1 - Lipschitz \Longleftrightarrow \|\nabla_x D(x)\| \le 1 \text{ for all x}$$

$$V(G,D) \approx \max_{D}\{E_{x\sim P_{data}}[D(x)] - E_{x\sim P_G}[D(x)]$$

$$\cancel{-\lambda \int_x max(0, \|\nabla_x D(x)\| - 1)dx\}}$$

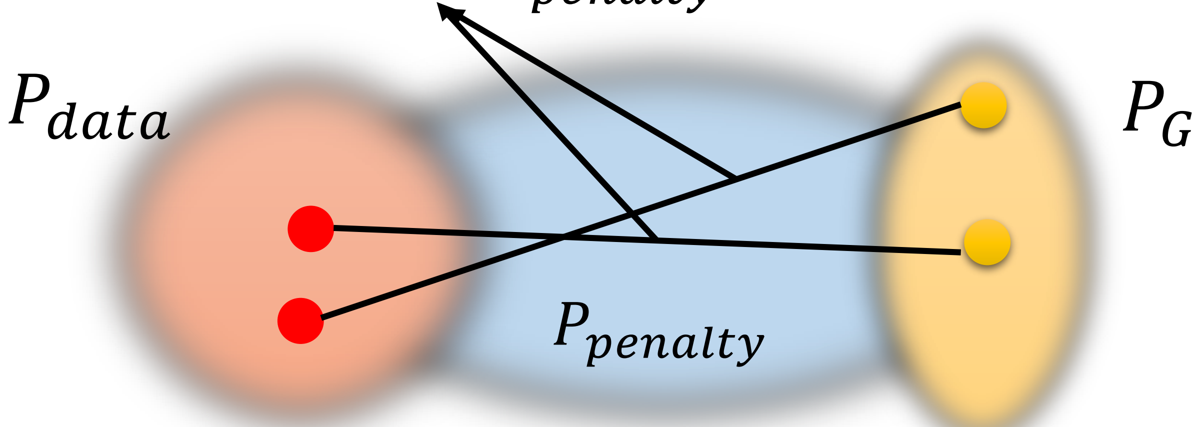
Prefer $\|\nabla_x D(x)\| \le 1$ for all x

$$-\lambda E_{x\sim P_{penalty}}[max(0, \|\nabla_x D(x)\| - 1)]\}$$

Prefer $\|\nabla_x D(x)\| \le 1$ for x sampling from $x \sim P_{penalty}$

Improved WGAN (WGAN-GP)

$$V(G,D) \approx \max_{D}\{E_{x\sim P_{data}}[D(x)] - E_{x\sim P_G}[D(x)]$$
$$-\lambda E_{x\sim P_{penalty}}[max(0, \|\nabla_x D(x)\| - 1)]\}$$



"Given that enforcing the Lipschitz constraint everywhere is intractable, enforcing it ***only along these straight lines*** seems sufficient and experimentally results in good performance."

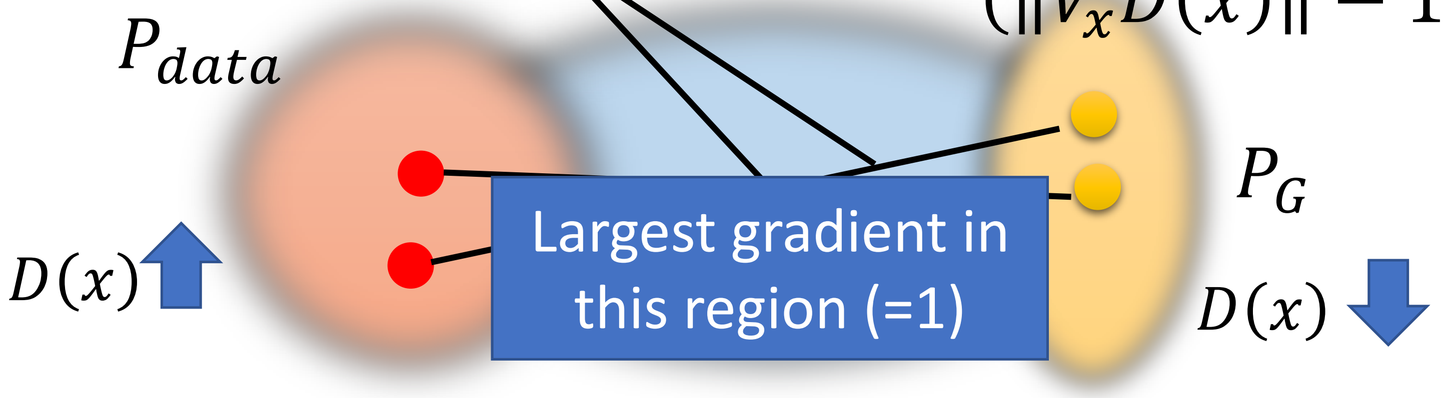
Only give gradient constraint to the region between P_{data} and P_G because they influence how P_G moves to P_{data}

Improved WGAN (WGAN-GP)

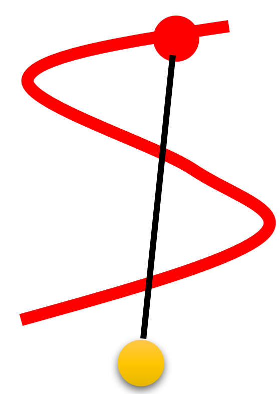
$$V(G,D) \approx \max_D \{ E_{x\sim P_{data}}[D(x)] - E_{x\sim P_G}[D(x)]$$

$$-\lambda E_{x\sim P_{penalty}}[\cancel{max(0, \|\nabla_x D(x)\| - 1)}]\}$$

$$(\|\nabla_x D(x)\| - 1)^2$$



"Simply penalizing overly large gradients also works in theory, but experimentally we found that this approach converged faster and to better optima."



Spectrum Norm

Spectral Normalization → Keep gradient norm smaller than 1 everywhere [Miyato, et al., ICLR, 2018]

Algorithm of WGAN

- In each training iteration:

No sigmoid for the output of D

Learning D

Repeat k times

- Sample m examples $\{x^1, x^2, \dots, x^m\}$ from data distribution $P_{data}(x)$
- Sample m noise samples $\{z^1, z^2, \dots, z^m\}$ from the prior $P_{prior}(z)$
- Obtaining generated data $\{\tilde{x}^1, \tilde{x}^2, \dots, \tilde{x}^m\}$, $\tilde{x}^i = G(z^i)$
- Update discriminator parameters θ_d to maximize
  - $\tilde{V} = \frac{1}{m}\sum_{i=1}^{m} D(x^i) - \frac{1}{m}\sum_{i=1}^{m} D(\tilde{x}^i)$
  - $\theta_d \leftarrow \theta_d + \eta \nabla \tilde{V}(\theta_d)$

Weight clipping / Gradient Penalty …

Learning G

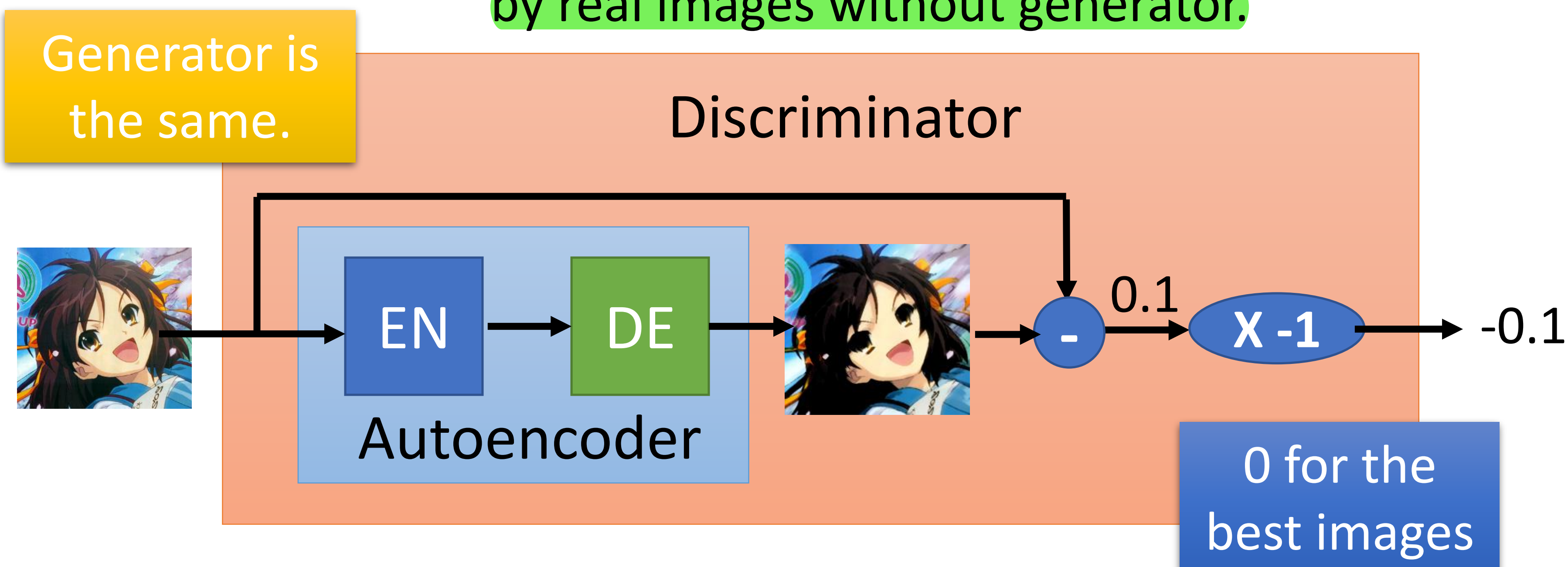
Only Once

- Sample another m noise s } from the prior $P_{prior}(z)$
- Update generator parameters θ_g to minimize
  - $\tilde{V} = \cancel{\frac{1}{m}\sum_{i=1}^{m} log D(x^i)} - \frac{1}{m}\sum_{i=1}^{m} D\left(G(z^i)\right)$
  - $\theta_g \leftarrow \theta_g - \eta \nabla \tilde{V}(\theta_g)$

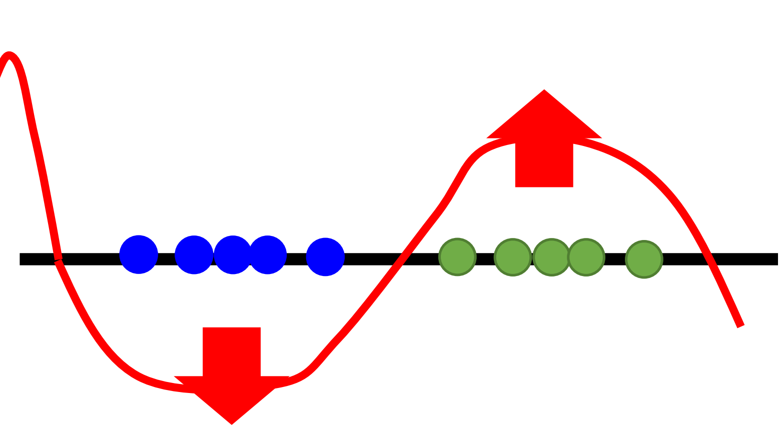
[Junbo Zhao, et al., arXiv, 2016]

Energy-based GAN (EBGAN)

- Using an autoencoder as discriminator D
  - ➢ Using the negative reconstruction error of auto-encoder to determine the goodness
  - ➢ **Benefit**: The auto-encoder can be pre-train by real images without generator.

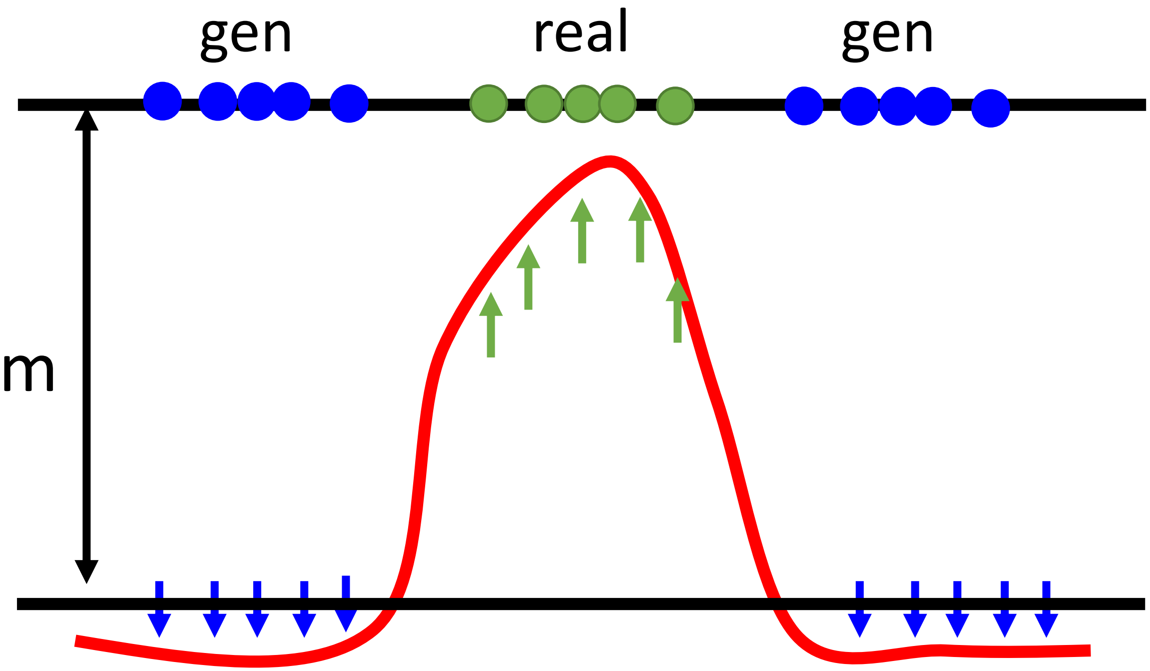


EBGAN



Auto-encoder based discriminator only gives limited region large value.

0 is for the best.

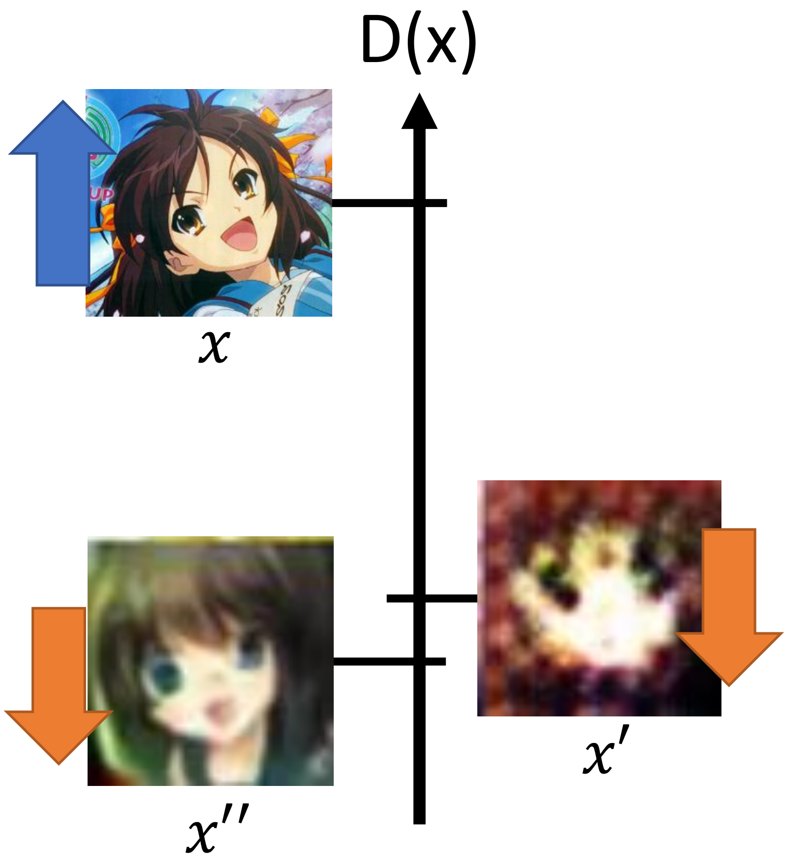


Do not have to be very negative

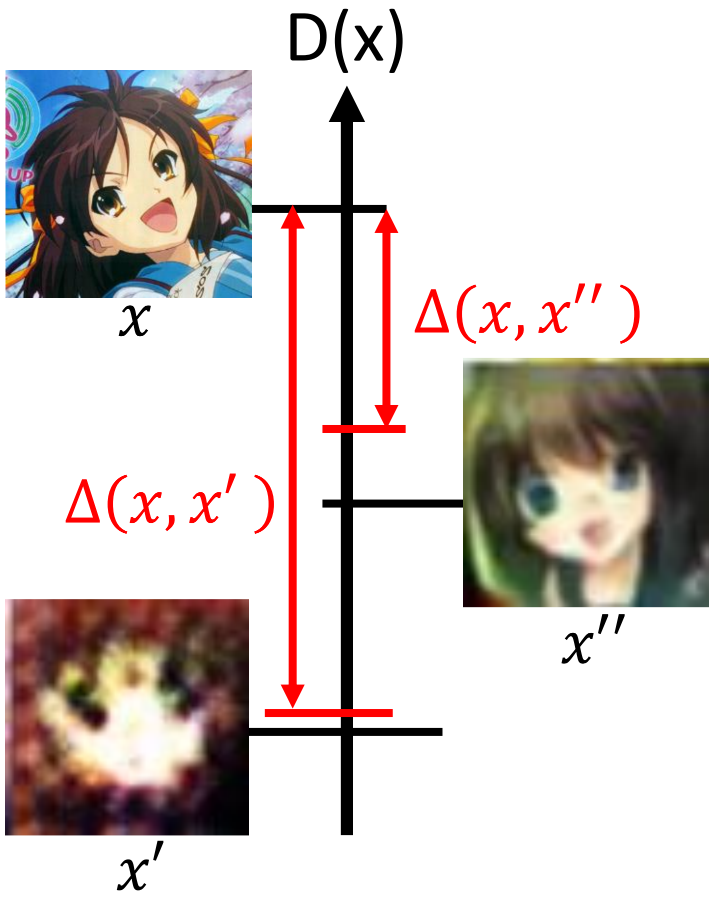
Hard to reconstruct, easy to destroy

Outlook:
Loss-sensitive GAN (LSGAN)

WGAN



LSGAN



Reference

- Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, Generative Adversarial Networks, NIPS, 2014
- Sebastian Nowozin, Botond Cseke, Ryota Tomioka, “f-GAN: Training Generative Neural Samplers using Variational Divergence Minimization”, NIPS, 2016
- Martin Arjovsky, Soumith Chintala, Léon Bottou, Wasserstein GAN, arXiv, 2017
- Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, Aaron Courville, Improved Training of Wasserstein GANs, NIPS, 2017
- Junbo Zhao, Michael Mathieu, Yann LeCun, Energy-based Generative Adversarial Network, arXiv, 2016
- Mario Lucic, Karol Kurach, Marcin Michalski, Sylvain Gelly, Olivier Bousquet, “Are GANs Created Equal? A Large-Scale Study”, arXiv, 2017
- Tim Salimans, Ian Goodfellow, Wojciech Zaremba, Vicki Cheung, Alec Radford, Xi Chen Improved Techniques for Training GANs, NIPS, 2016

Reference

- Martin Heusel, Hubert Ramsauer, Thomas Unterthiner, Bernhard Nessler, Sepp Hochreiter, GANs Trained by a Two Time-Scale Update Rule Converge to a Local Nash Equilibrium, NIPS, 2017
- Naveen Kodali, Jacob Abernethy, James Hays, Zsolt Kira, "On Convergence and Stability of GANs", arXiv, 2017
- Xiang Wei, Boqing Gong, Zixia Liu, Wei Lu, Liqiang Wang, Improving the Improved Training of Wasserstein GANs: A Consistency Term and Its Dual Effect, ICLR, 2018
- Takeru Miyato, Toshiki Kataoka, Masanori Koyama, Yuichi Yoshida, Spectral Normalization for Generative Adversarial Networks, ICLR, 2018