# Tips for Improving GAN

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

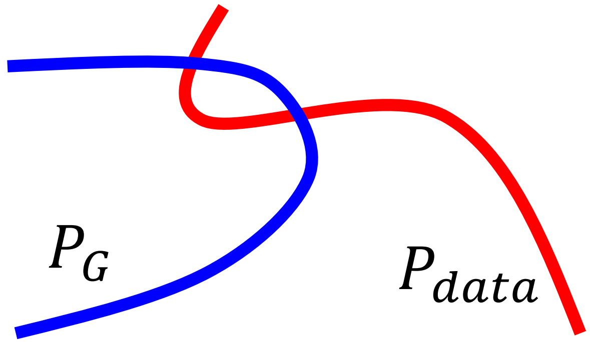
Ishaan Gulrajani, Faruk Ahmed, Martin Arjovsky, Vincent Dumoulin, Aaron Courville, “Improved Training of Wasserstein GANs”, arXiv prepring, 2017

# 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.

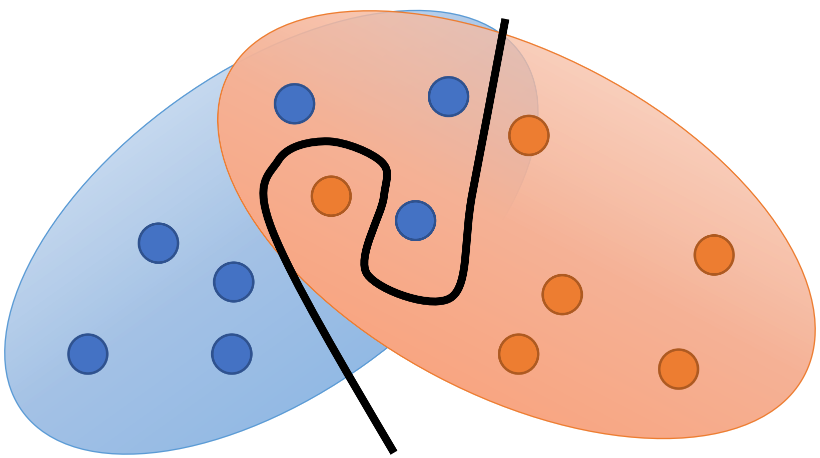
The overlap can be ignored.



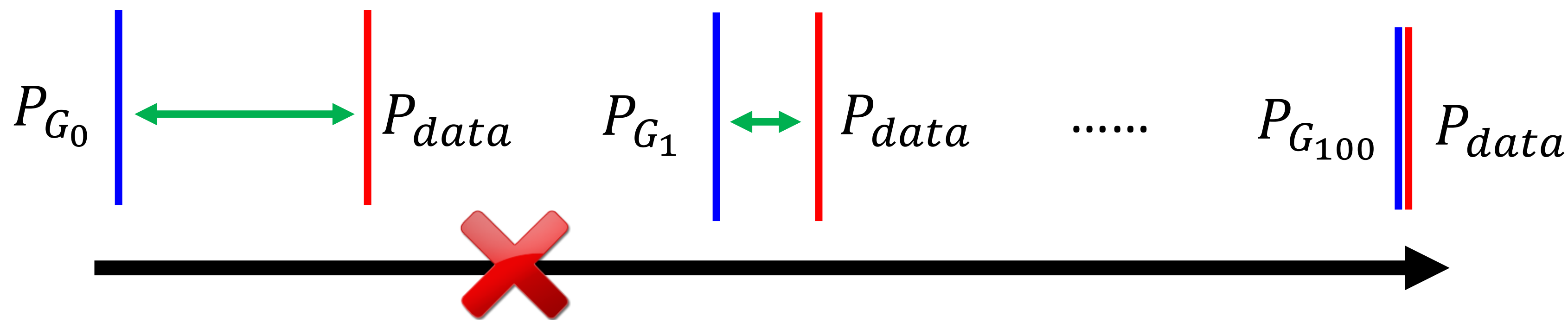

- 2. Sampling

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

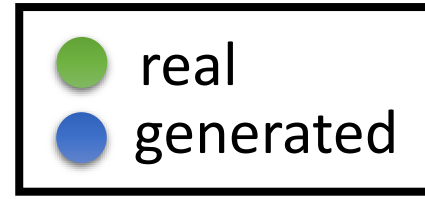
$JS(P_{G_0}, P_{data}) = log2$ $JS(P_{G_1}, P_{data}) = log2$ …… $JS(P_{G_{100}}, P_{data}) = 0$

JS divergence is log2 if two distributions do not overlap.

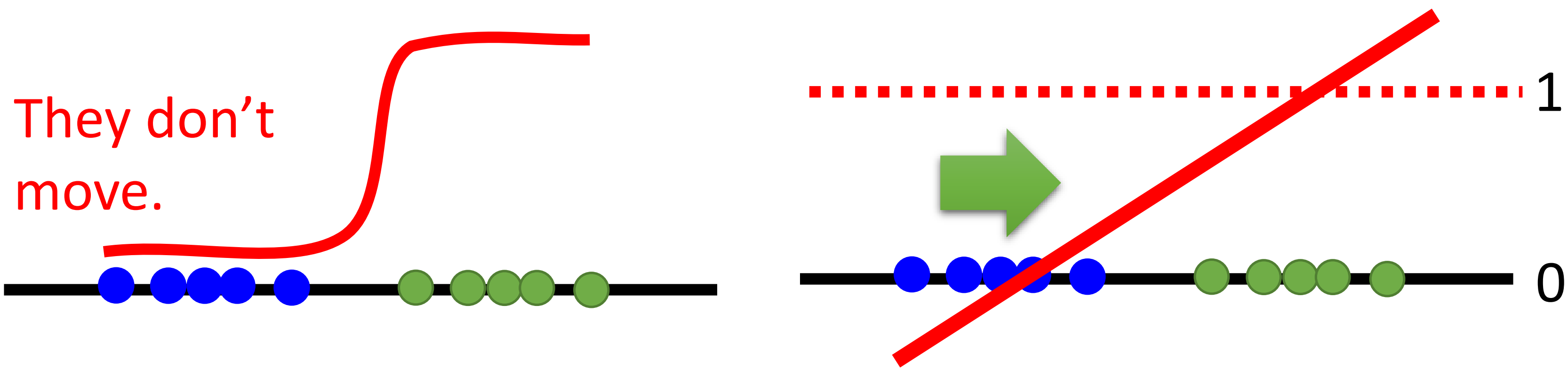
Intuition: If two distributions do not overlap, binary classifier achieves 100% accuracy

➡ Same objective value is obtained. ➡ Same divergence

# Least Square GAN (LSGAN)

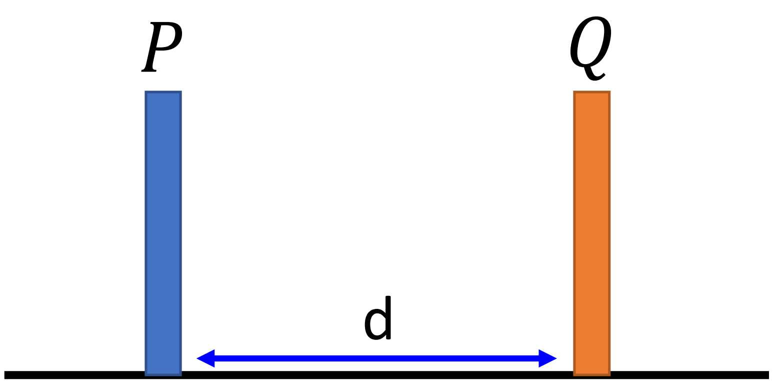



- Replace sigmoid with linear (replace classification with regression)

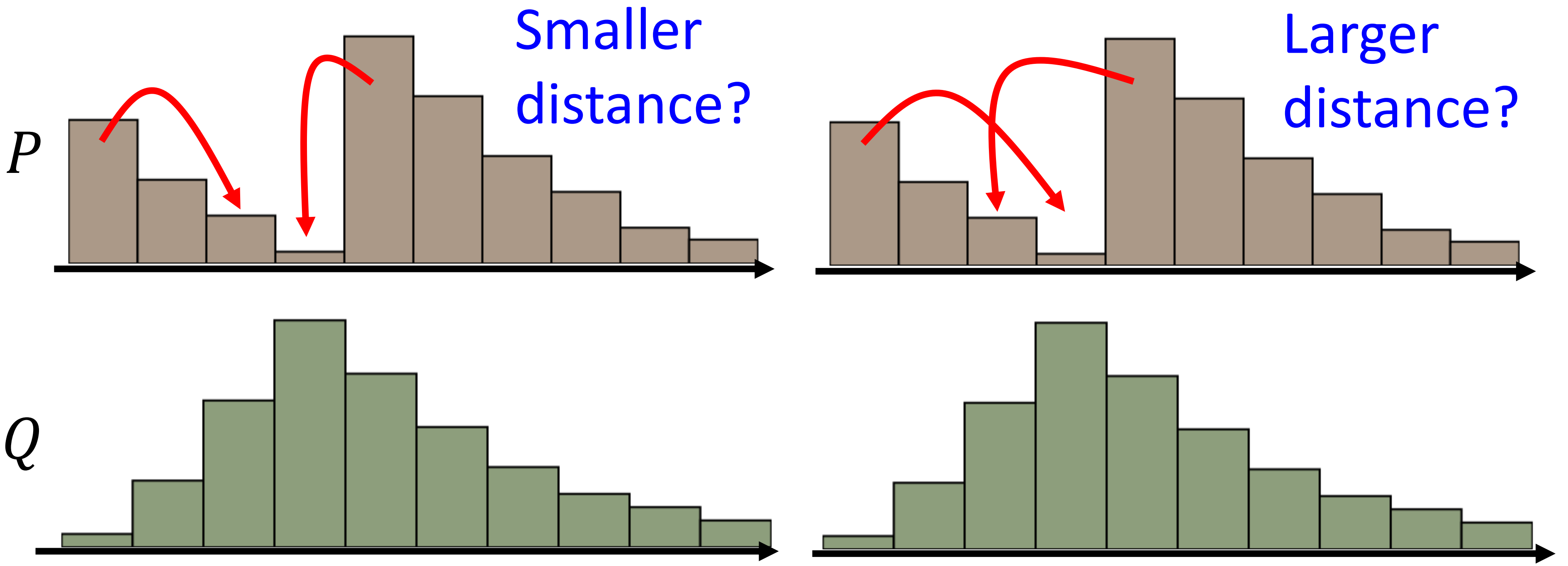
# Wasserstein GAN (WGAN): Earth Mover's Distance

- 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



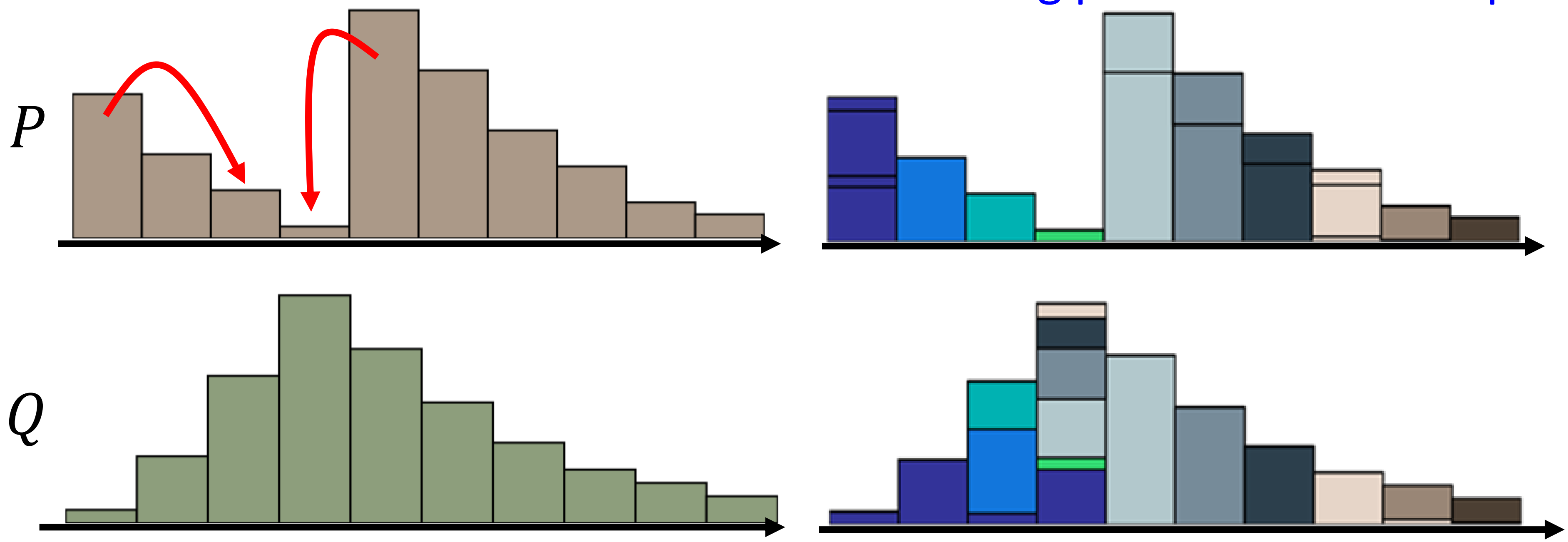

There many possible "moving plans".

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

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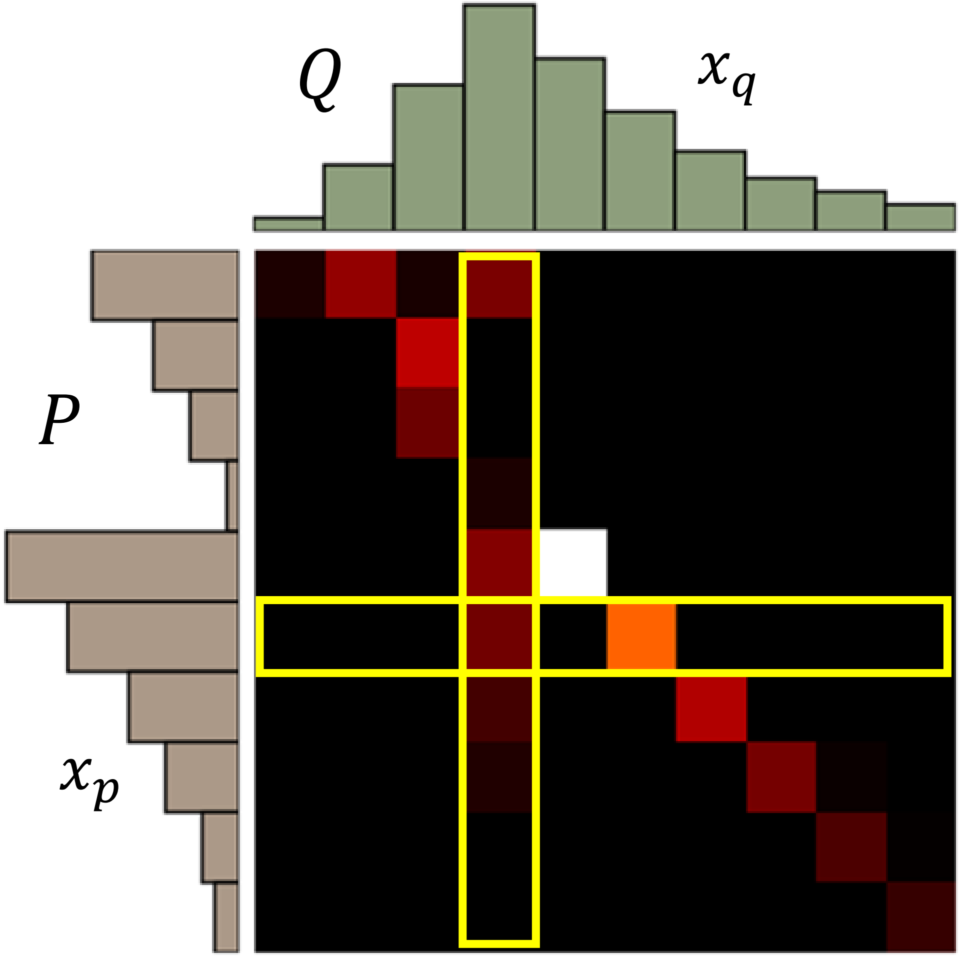



moving plan $\gamma$

All possible plan $\Pi$

A “moving plan” is a matrix

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

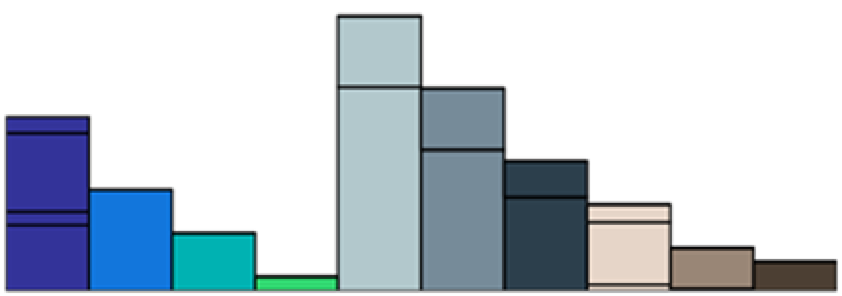
Average distance of a plan $\gamma$:

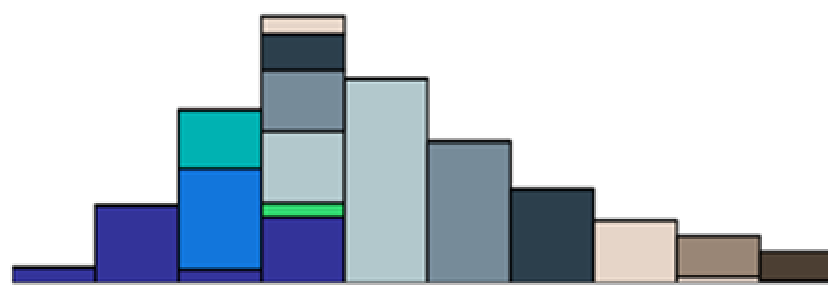
$$B(\gamma) = \sum_{x_p, x_q} \gamma(x_p, x_q) \|x_p - x_q\|$$

Earth Mover’s Distance:

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

The best plan

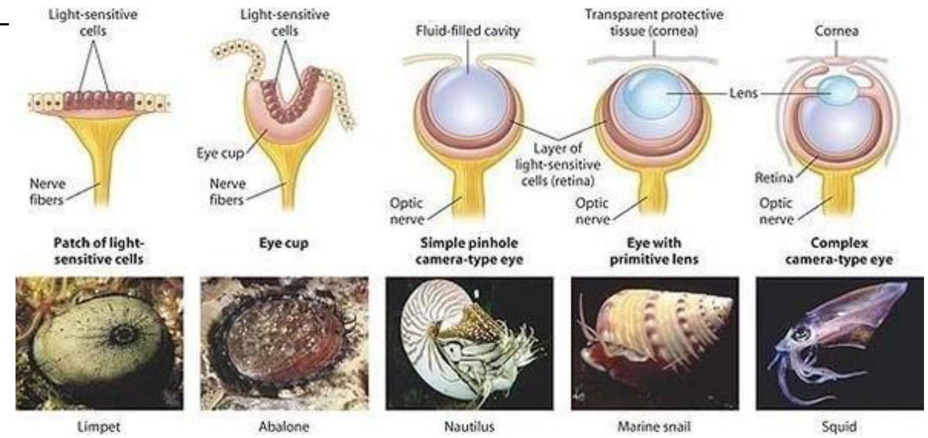


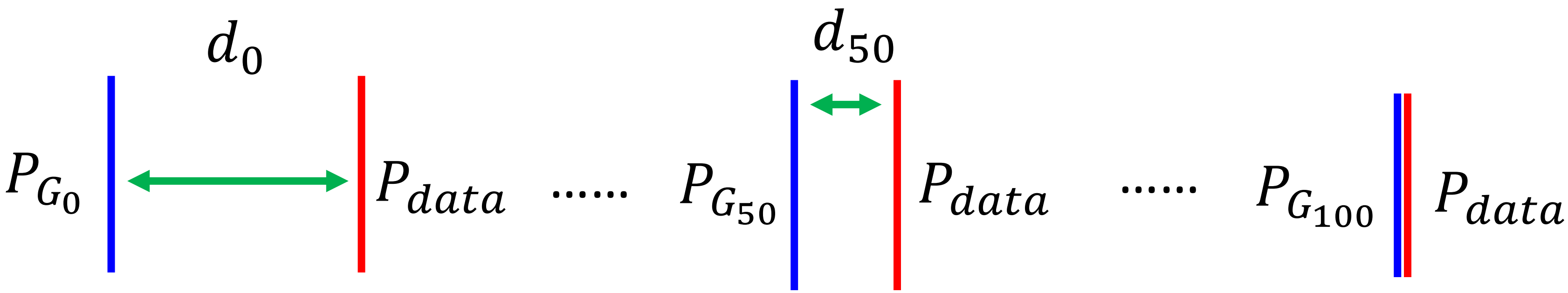


# Why Earth Mover's Distance?

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

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




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

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

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

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

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

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

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

# WGAN

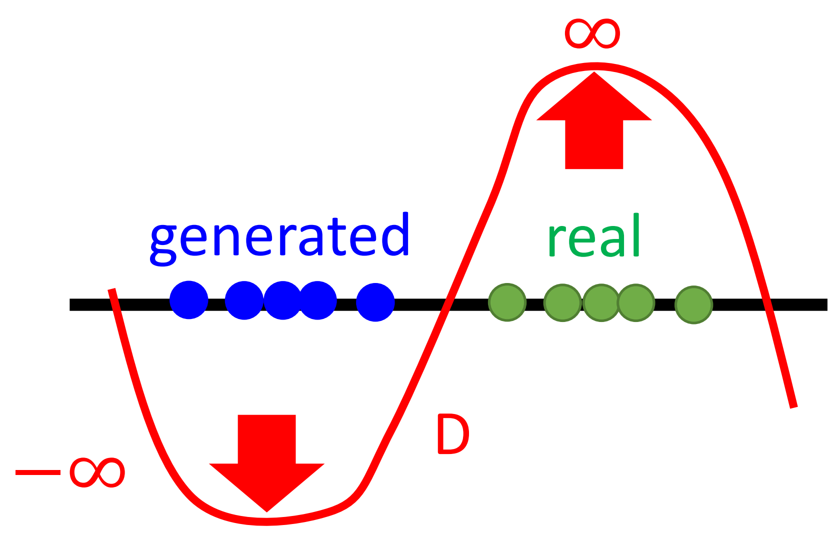
Evaluate wasserstein distance between $P_{data}$ and $P_G$

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

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 −∞



# WGAN

## ***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

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?

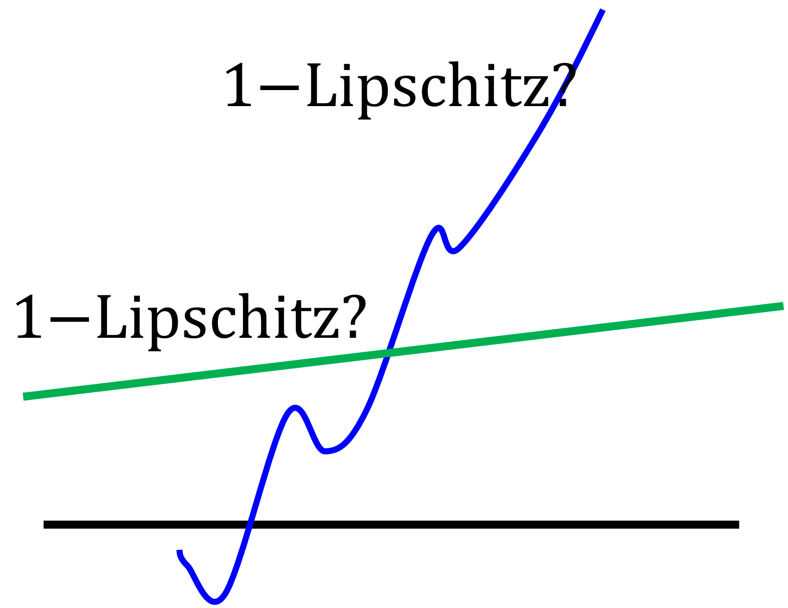
### ***Lipschitz Function***

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

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.

$D \in 1 - Lipschitz$ ⟺ $\|\nabla_x D(x)\| \leq 1$ for all x

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

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

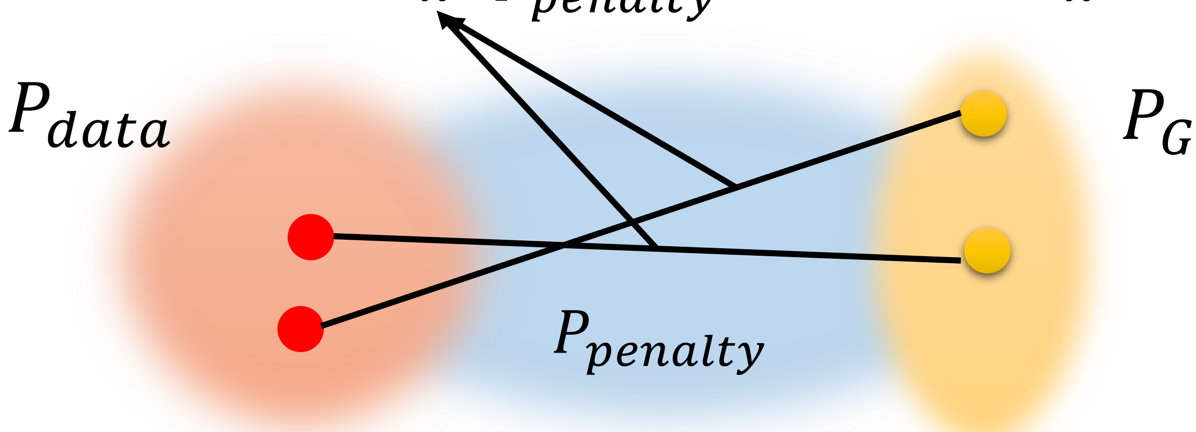
Prefer $\|\nabla_x D(x)\| \leq 1$ for all x

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

Prefer $\|\nabla_x D(x)\| \leq 1$ 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."

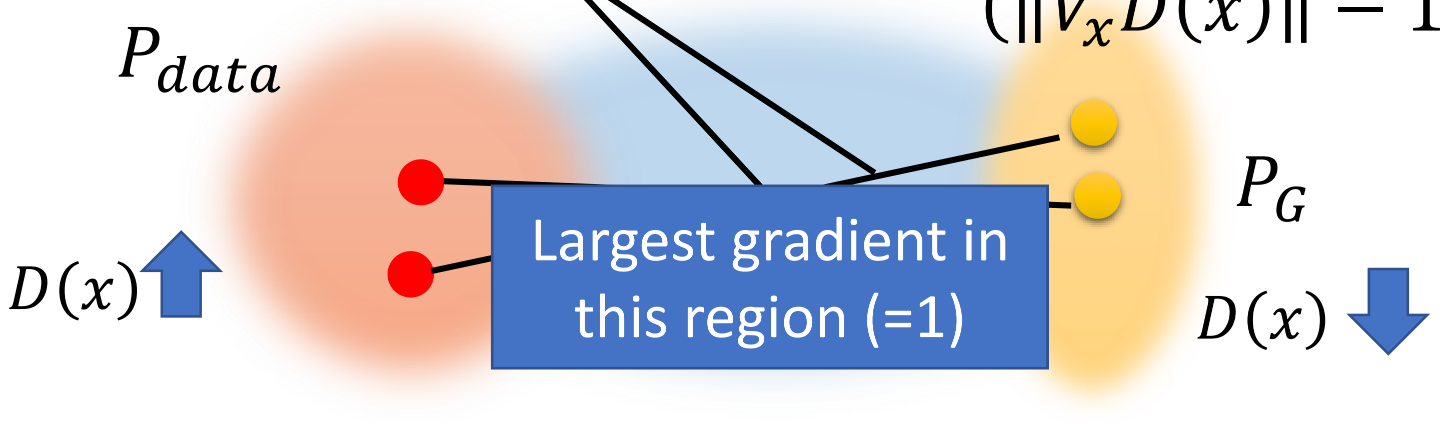
Only give gradient constraint to the region between $P_{data}$ and $P_G$ because they influence how $P_G$ moves to $P_{data}$

# ***Improved WGAN (WGAN-GP)***

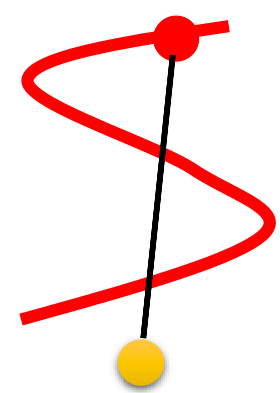
$$V(G,D) \approx \max_D \{E_{x\sim P_{data}}[D(x)] - E_{x\sim P_G}[D(x)]$$

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

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




"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 $\theta_d$ 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

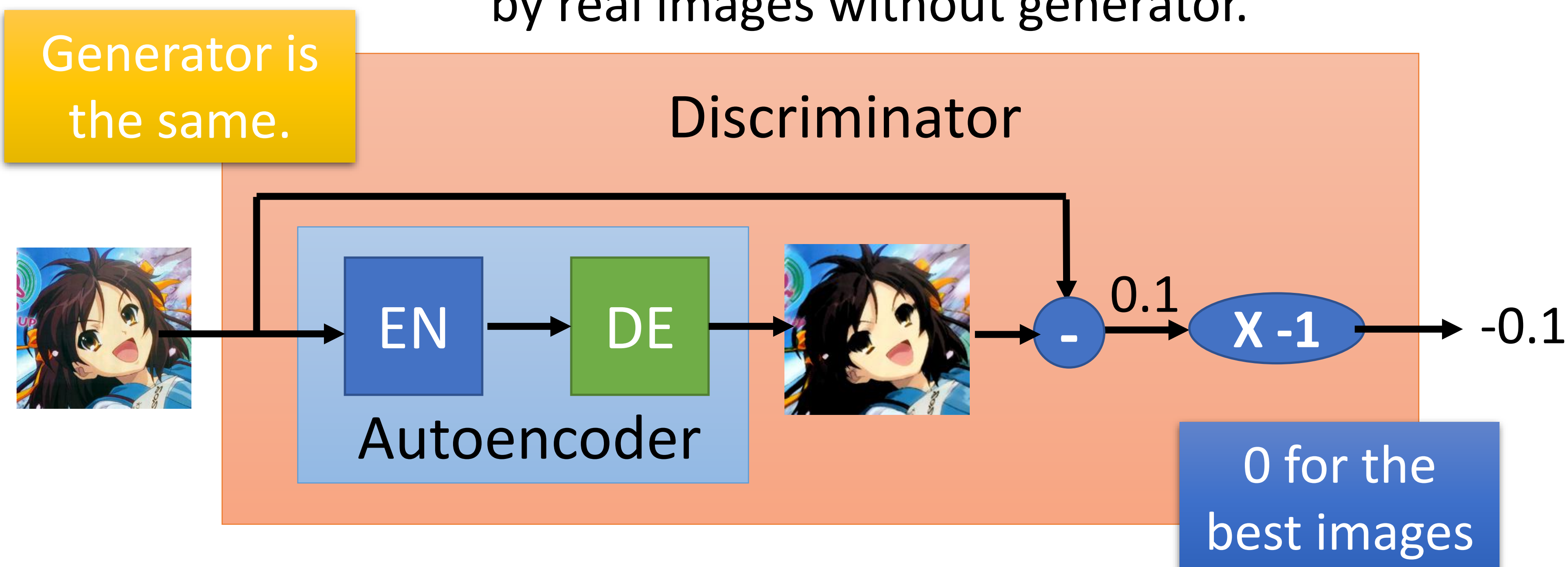
Only Once

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

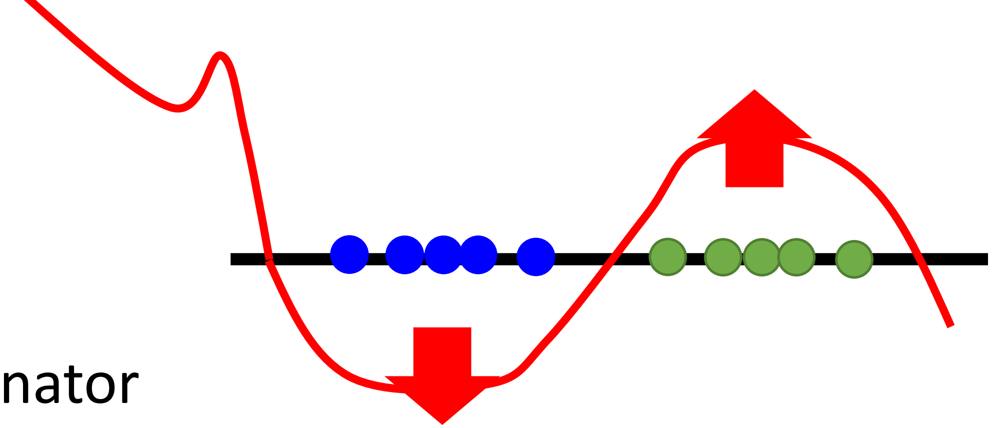
[Junbo Zhao, et al., arXiv, 2016]

# 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.

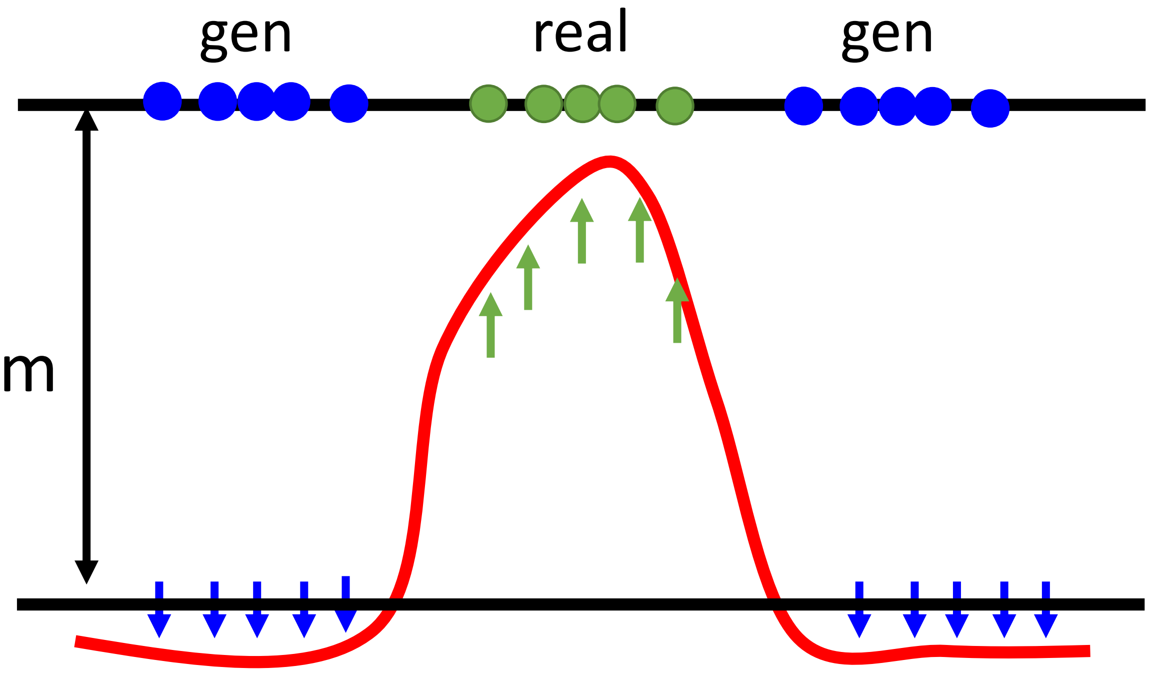


# EBGAN



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

0 is for the best.

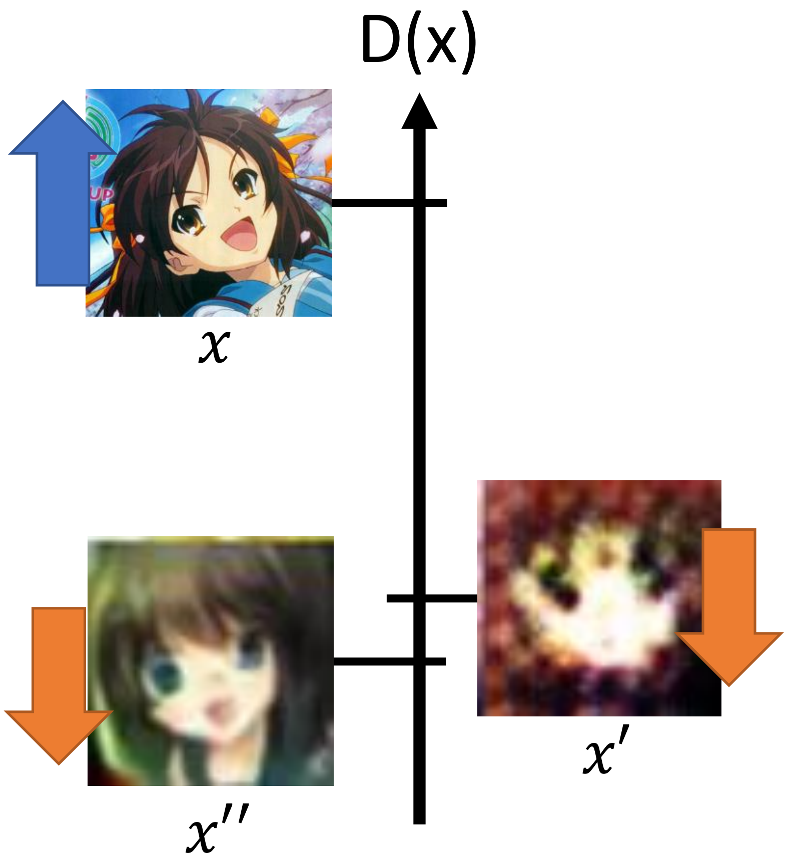



Do not have to be very negative

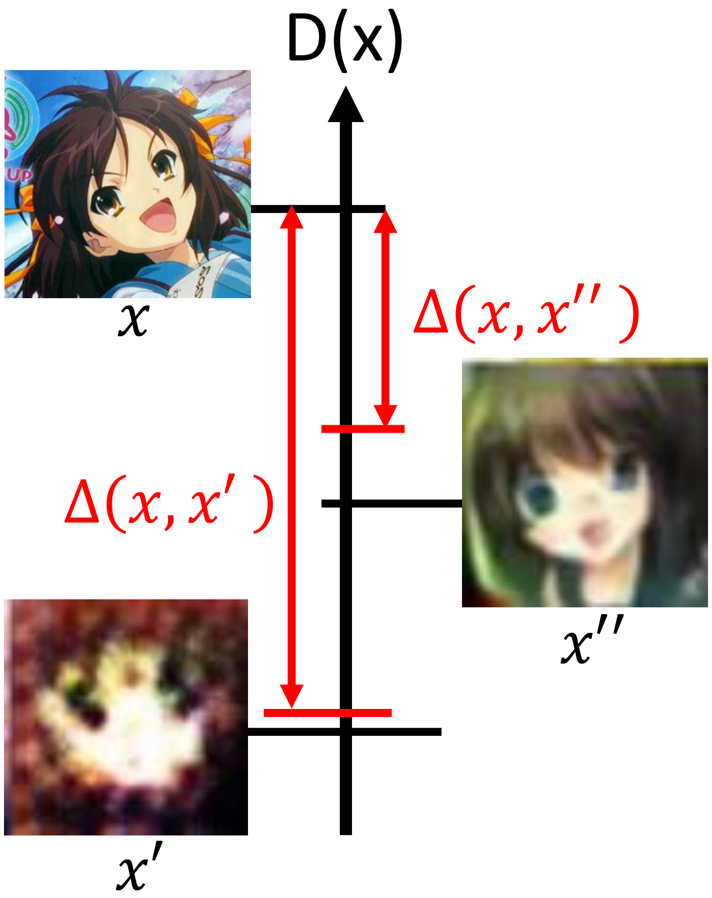
Hard to reconstruct, easy to destroy

# Outlook:
# Loss-sensitive GAN (LSGAN)

***WGAN***




***LSGAN***



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