Energy-based GAN

Hung-yi Lee

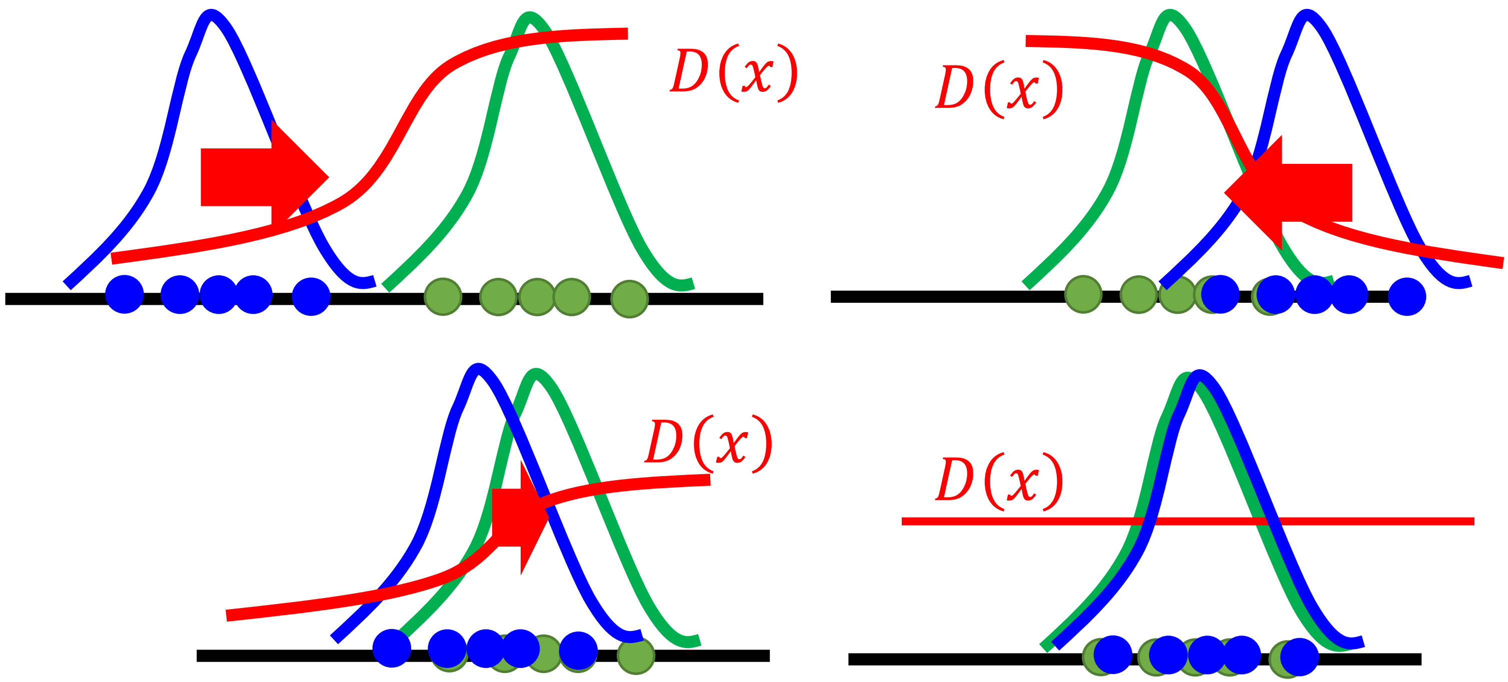
Original Idea

Discriminator

Data (target) distribution

Generated distribution

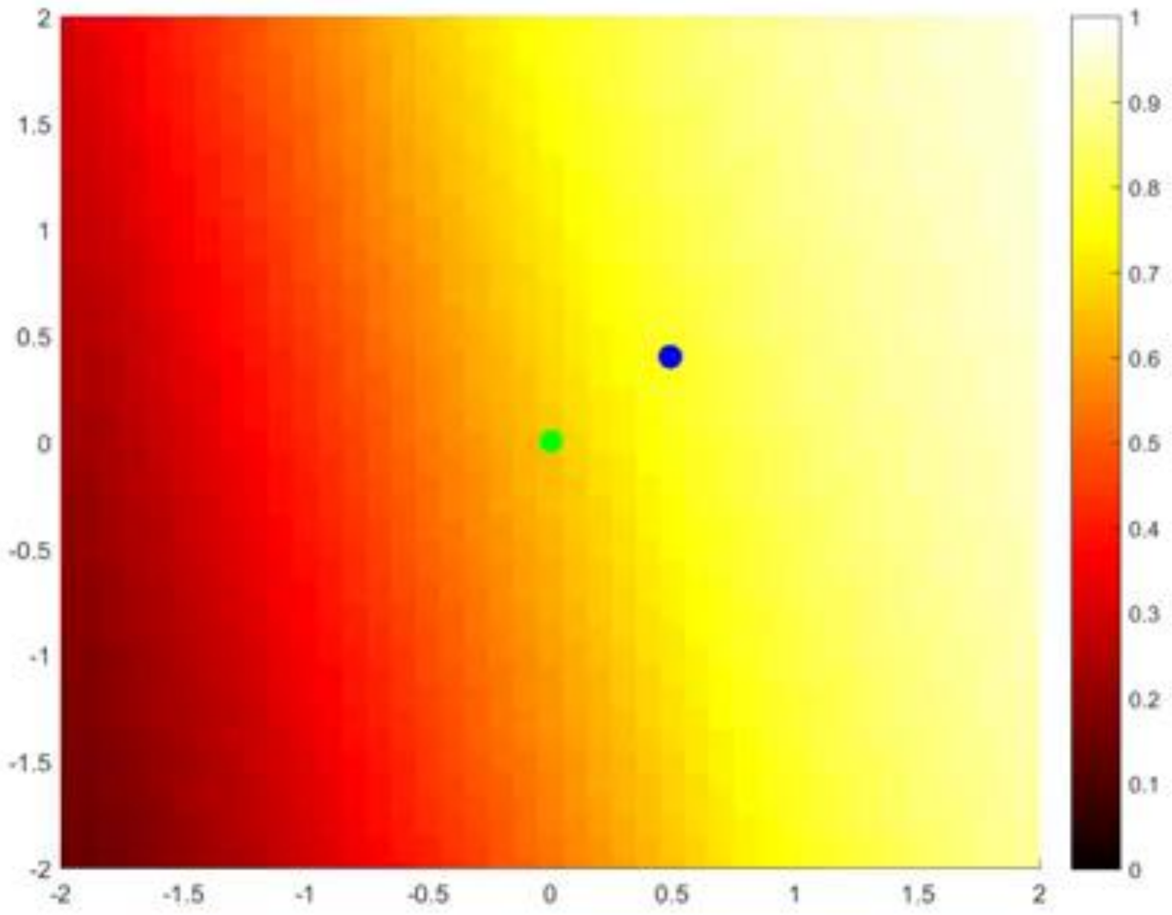
- Discriminator leads the generator



Is it the only explanation of GAN?

Original GAN

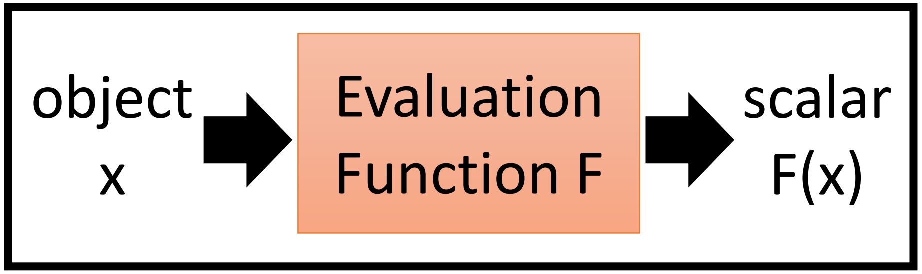
The discriminator is flat in the end.



Source: https://www.youtube.com/watch?v=ebMei6bYeWw (credit: Benjamin Striner)

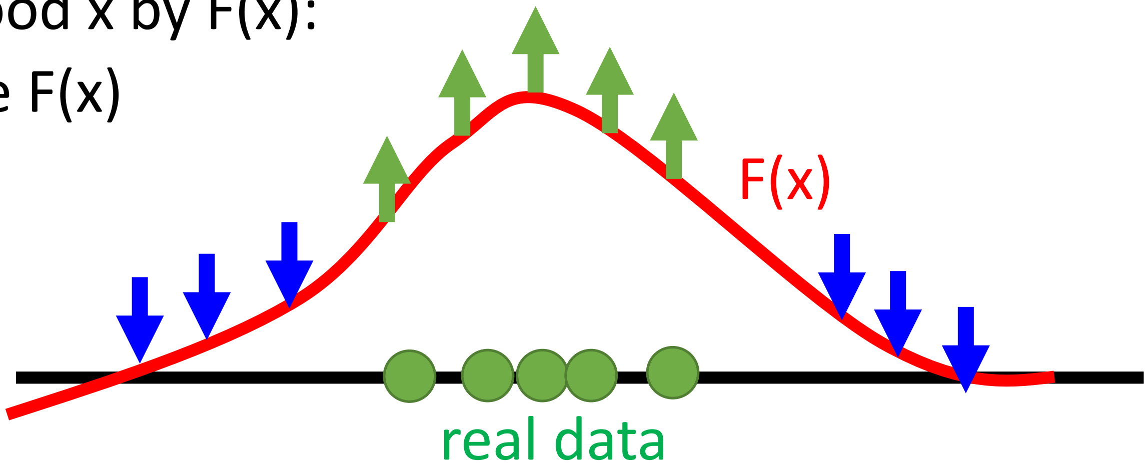
Evaluation Function

- We want to find an evaluation function F(x)
  - Input: object x, output: scalar F(x) (how "good" the object is)
  - E.g. x are images
    - Real x has high F(x)
  - F(x) can be a network



- We can generate good x by F(x):
  - Find x with large F(x)
- How to find F(x)?

In practice, you cannot decrease all the x other than real data.



Evaluation Function
- Structured Perceptron

- **Input**: training data set $\left\{\left(x^1, \hat{y}^1\right), \left(x^2, \hat{y}^2\right), \ldots, \left(x^r, \hat{y}^r\right), \ldots\right\}$
- **Output**: weight vector w
- **Algorithm**: Initialize w = 0
  - do
    - For each pair of training example $\left(x^r, \hat{y}^r\right)$
      - Find the label $\tilde{y}^r$ maximizing F(x^r, y)
      - If $\tilde{y}^r \neq \hat{y}^r$, update w
  - until w is not updated

$$F(x, y) = w \cdot \phi(x, y)$$

Can be an issue

$$\tilde{y}^r = \arg\max_{y \in Y} F\left(x^r, y\right)$$

Increase $F(x^r, \hat{y}^r)$, decrease $F(x^r, \tilde{y}^r)$

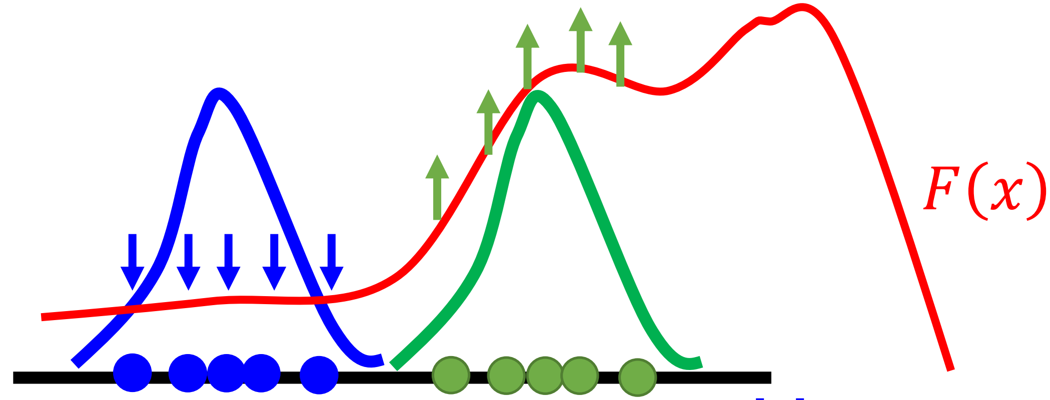
$$w \to w + \phi\left(x^r, \hat{y}^r\right) - \phi\left(x^r, \tilde{y}^r\right)$$

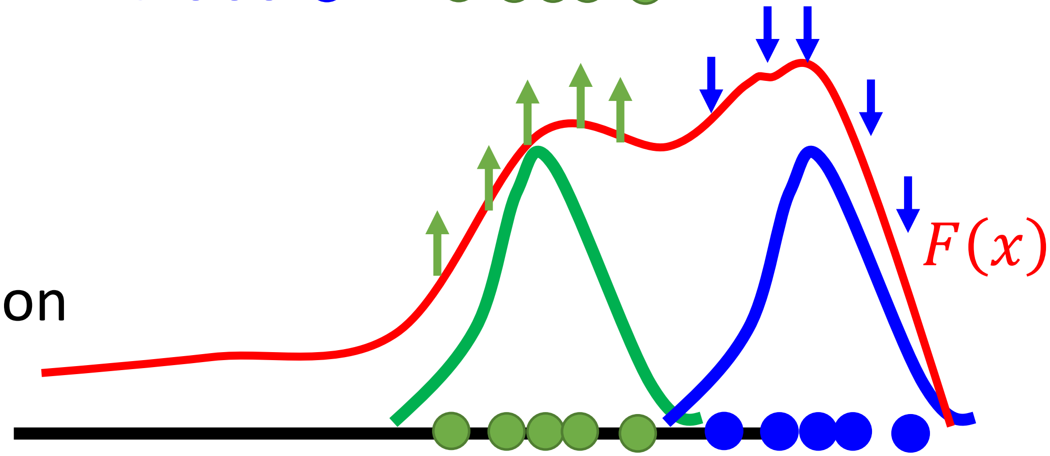
We are done!

How about GAN?

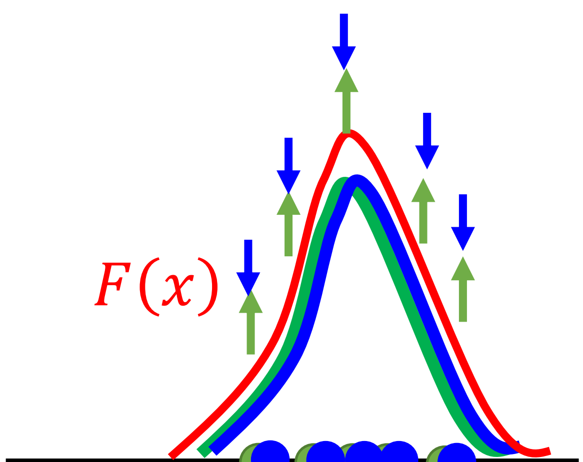
- Generator is an intelligent way to find the negative examples.

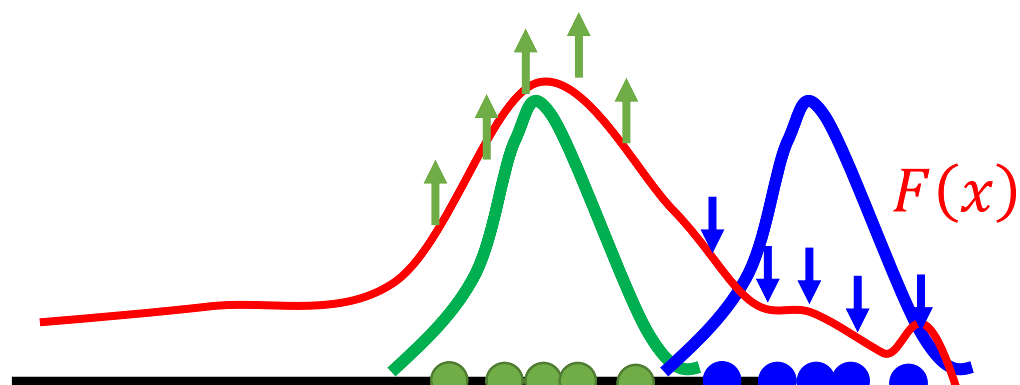
“Experience replay”, parameters from last iteration

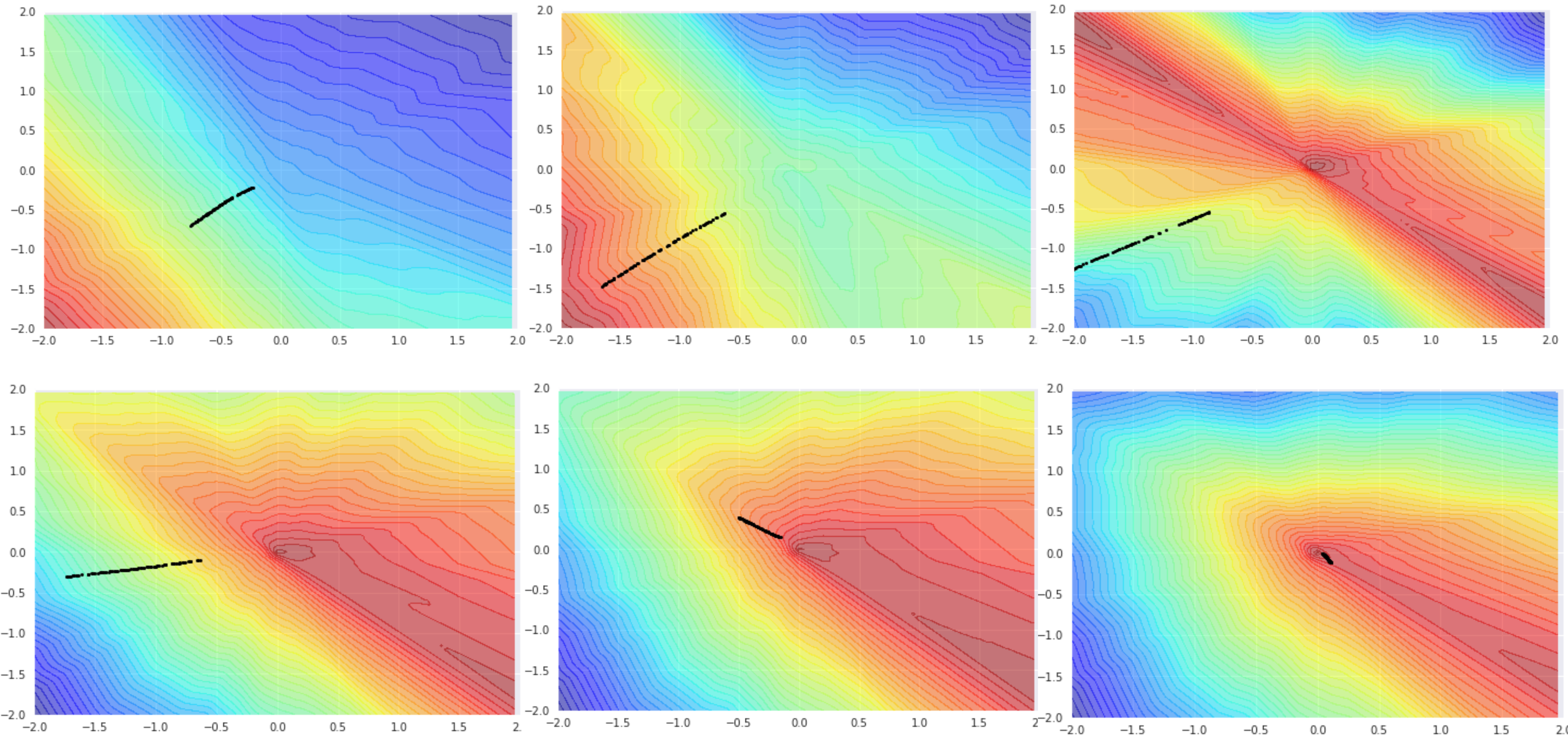


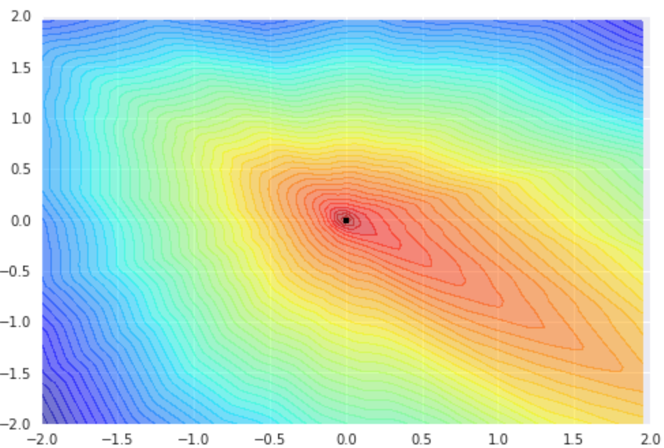


In the end ……





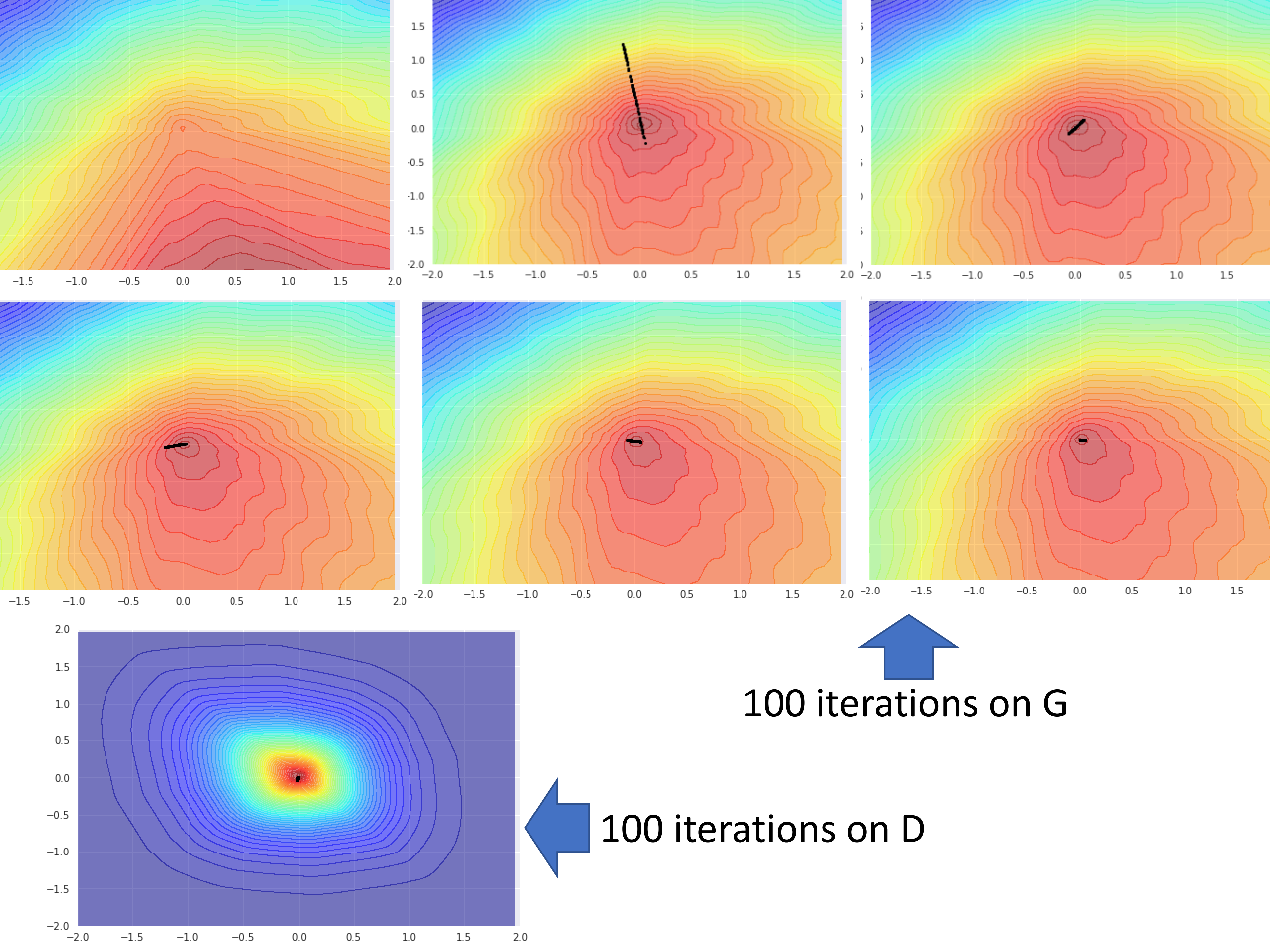




P_{data} = “origin”

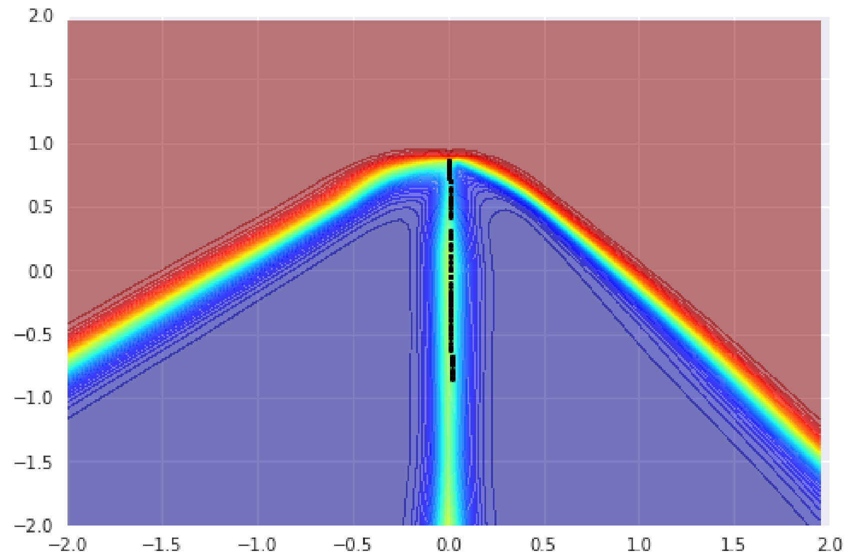
G = 1 hidden layer (100)

D = 1 hidden layer (100)

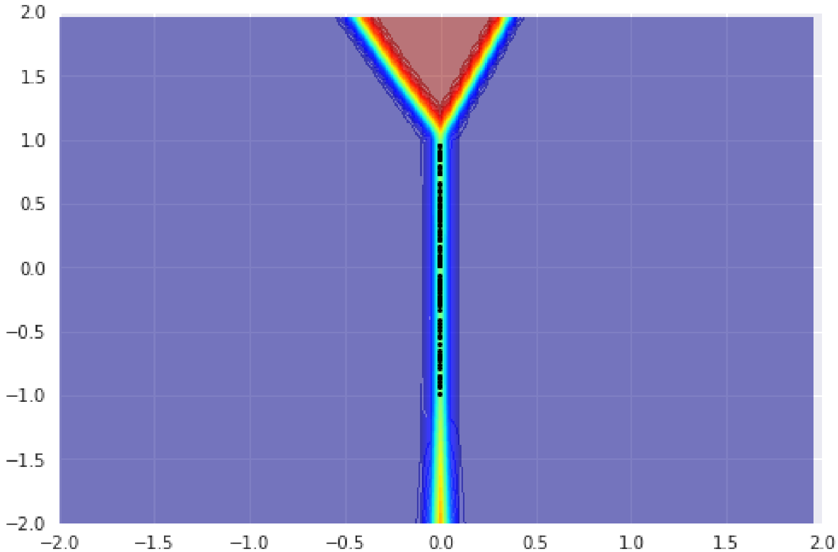

100 iterations on G
100 iterations on D

P_{data} = "line"

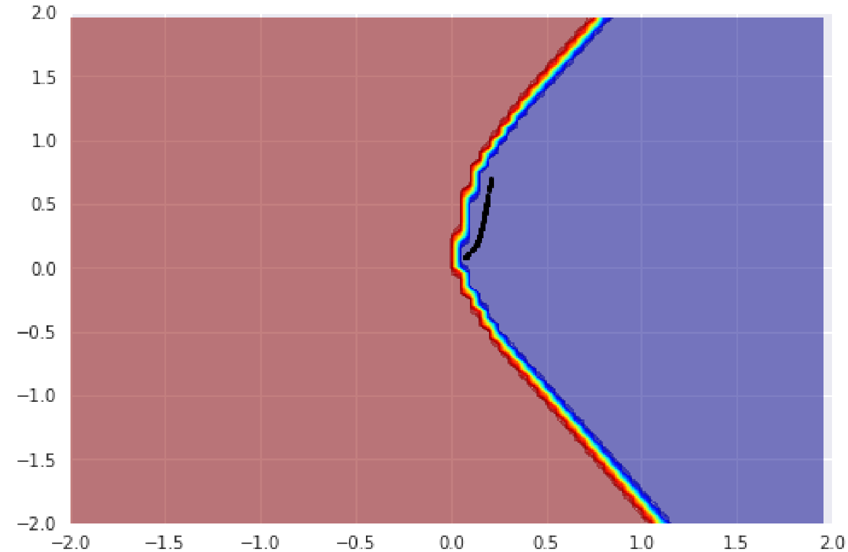
100 iterations on D



G = 1 hidden layer (100)
D = 1 hidden layer (100)



G = 2 hidden layer (100)
D = 1 hidden layer (100)



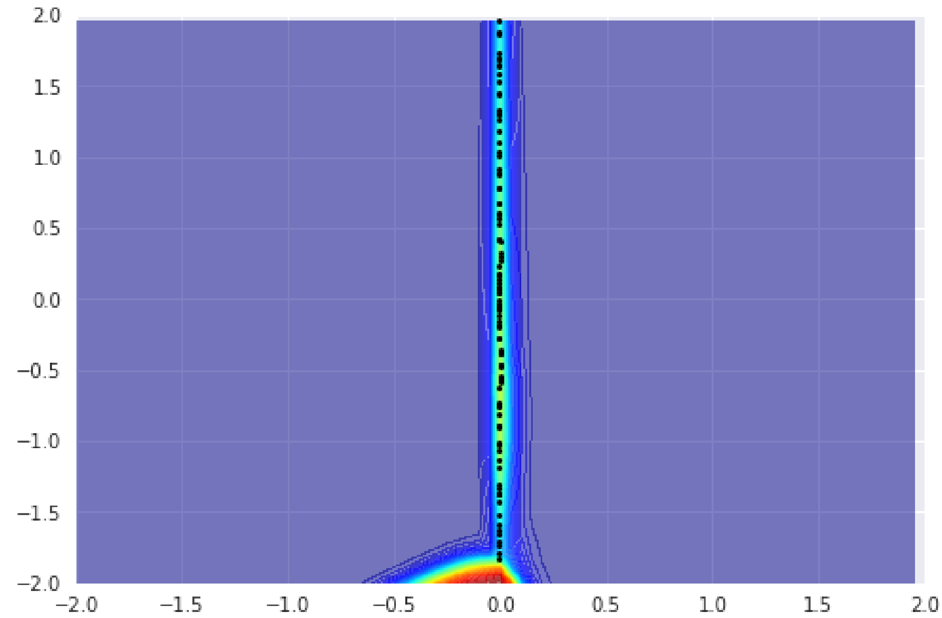
G = 1 hidden layer (100)
D = 2 hidden layer (100)

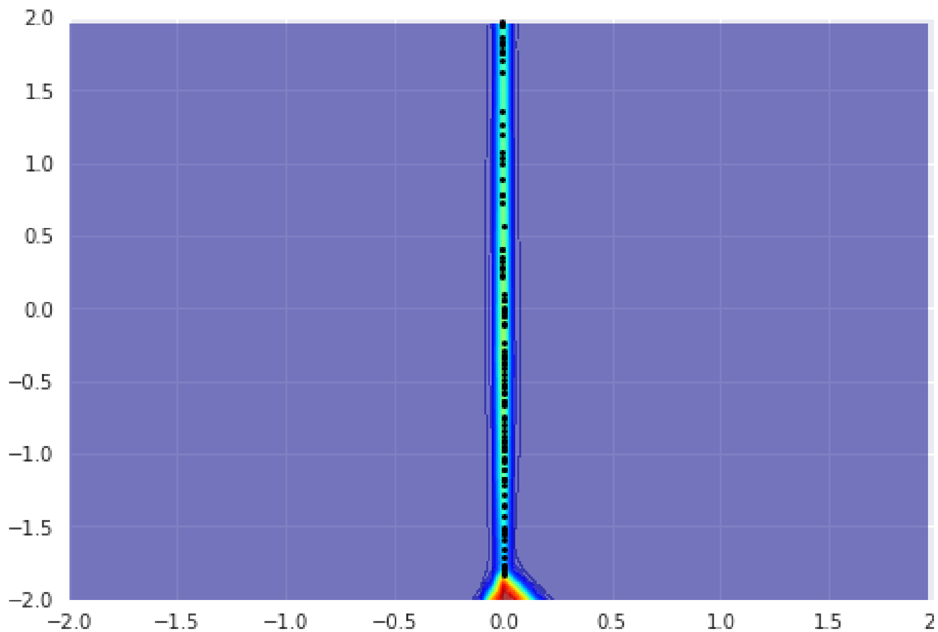
P_{data} = 1-D Gaussian

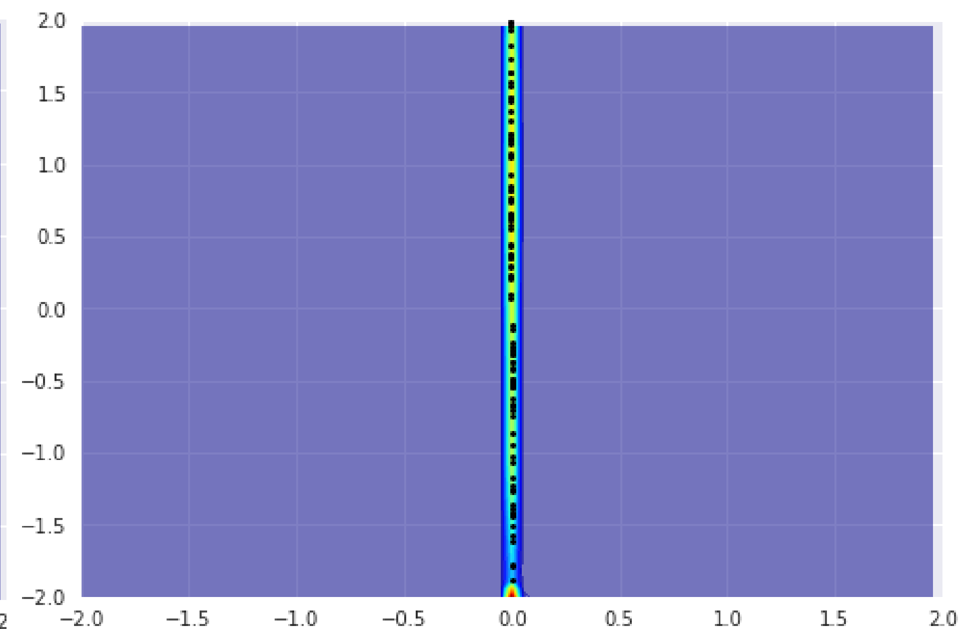
100 iterations on D

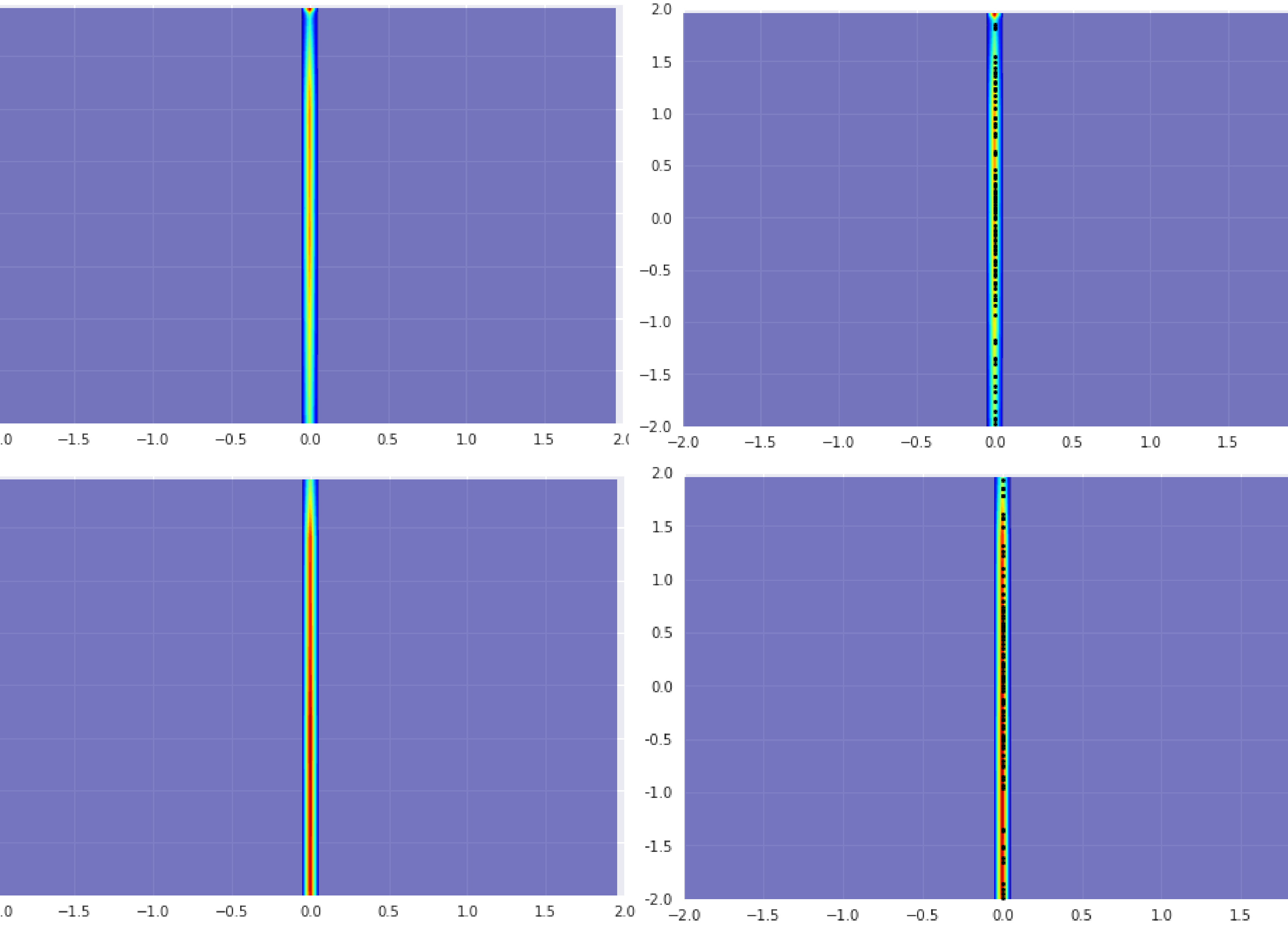
G = 2 hidden layer (100)

D = 1 hidden layer (100)









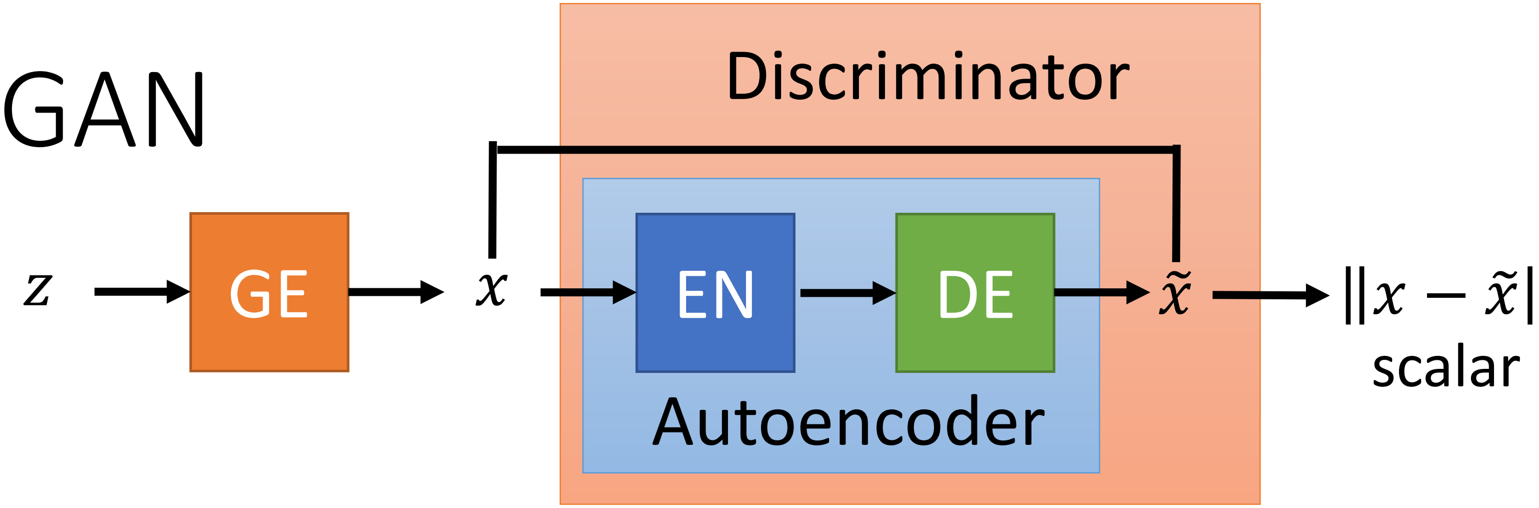
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
−1.5
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5

Energy-based GAN (EBGAN)

- Viewing the discriminator as an energy function (negative evaluation function)
- Auto-encoder as discriminator (energy function)
- Loss function with margin for discriminator training
- Generate reasonable-looking images from the ImageNet dataset at 256 x 256 pixel resolution
  - without a multiscale approach

Junbo Zhao, Michael Mathieu, Yann LeCun, “Energy-based Generative Adversarial Network”, arXiv preprint, 2016

EBGAN



Sample real example x

Sample code z from prior distribution

Update discriminator D to minimize

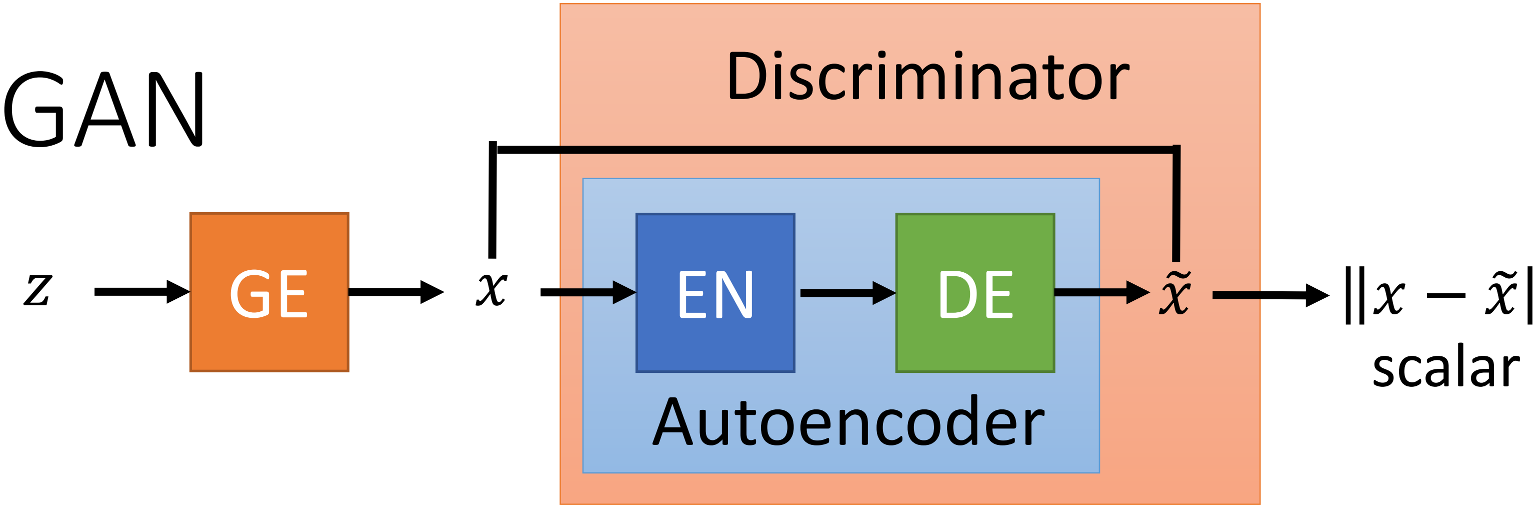
$$L_D(x,z) = D(x) + max\left(0, m - D\big(G(z)\big)\right)$$

Sample code z from prior distribution

Update generator G to minimize

$$L_G(z) = D\big(G(z)\big)$$

EBGAN

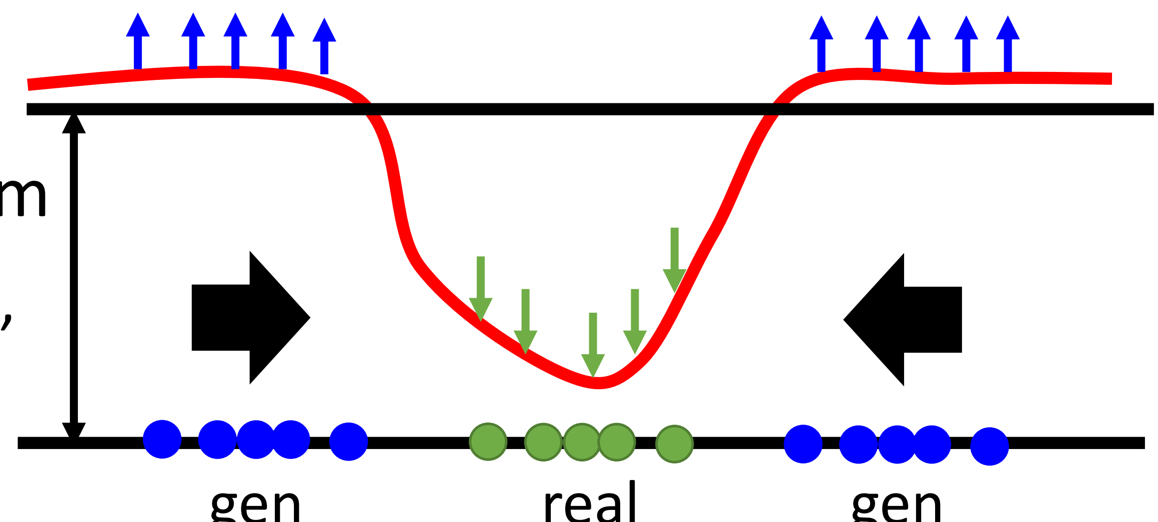


Discriminator D: $L_D(x,z) = D(x) + \cancel{max\left(0, m - D\left(G(z)\right)\right)}$

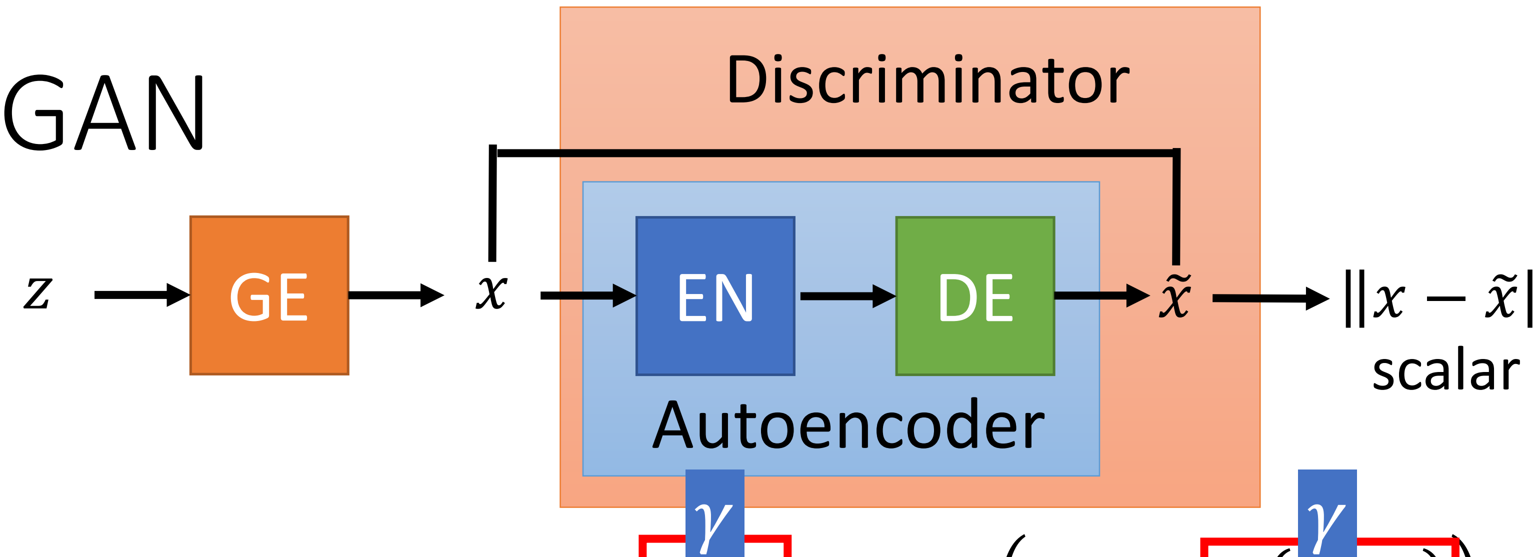
$-D\left(G(z)\right)$

Generator G: $L_G(z) = D\left(G(z)\right)$

Hard to reconstruct, easy to destroy



EBGAN



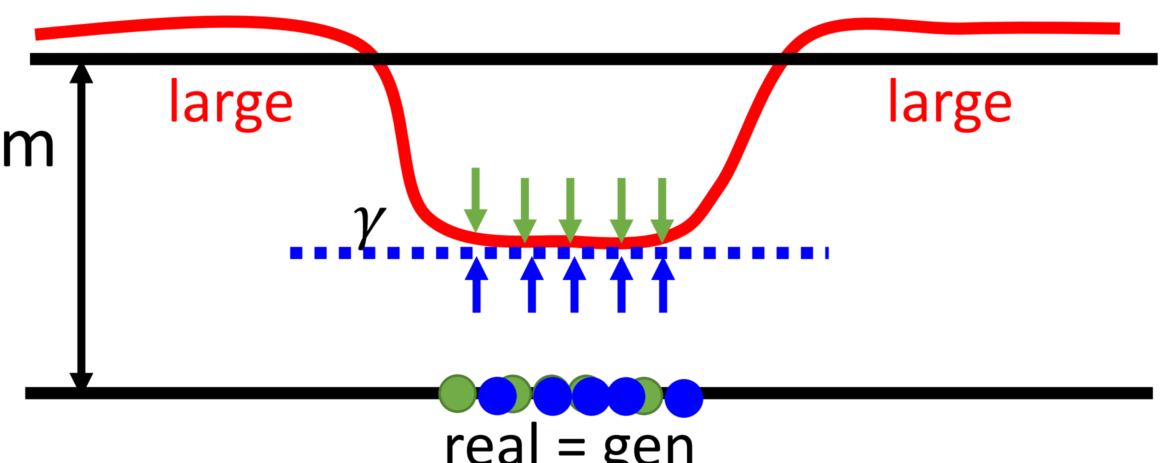
Discriminator D: $L_D(x,z) = \boxed{D(x)} + max\left(0, m - \boxed{D\left(G(z)\right)}\right)$

Generator G: $L_G(z) = D\left(G(z)\right)$

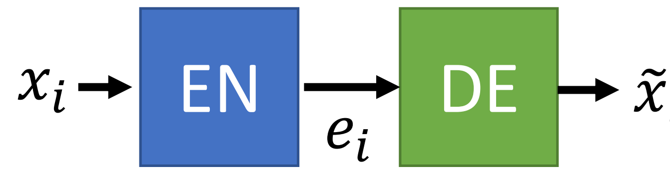
For auto-encoder, the region for low value is limited.

What would happen if x and $G(z)$ have the same distribution?

γ is a value between 0 and m



More about EBGAN



- Pulling-away term for training generator

  Given a batch $S = \{\cdots x_i \cdots x_j \cdots\}$ from generator

$$f_{PT}(S) = \sum_{i,j,i\neq j} cos(e_i, e_j)$$

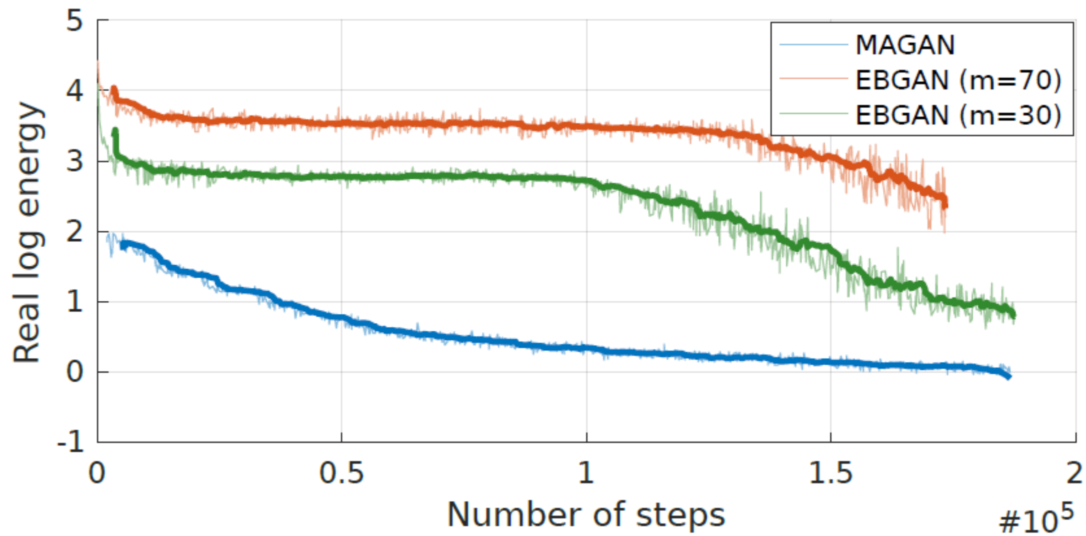
To increase diversity

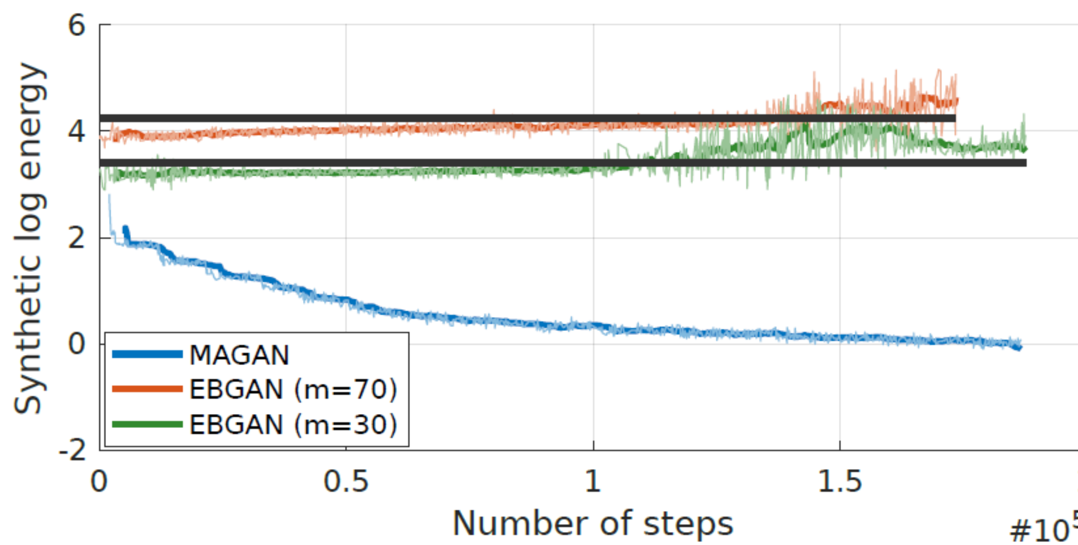
- Better way to learn auto-encoder?
  - If auto-encoder only learns to minimize the reconstruction error of real images
    - Can obtain nearly identity function (not properly designed structure)
  - Giving larger reconstruction error for fake images regularized auto-encoder

Margin Adaptation GAN (MAGAN)

$$L_D(x,z) = D(x) + max\left(0, m - D\big(G(z)\big)\right)$$

- ***Dynamic margin m***
  - As the generator generates better images
  - The margin becomes smaller and smaller





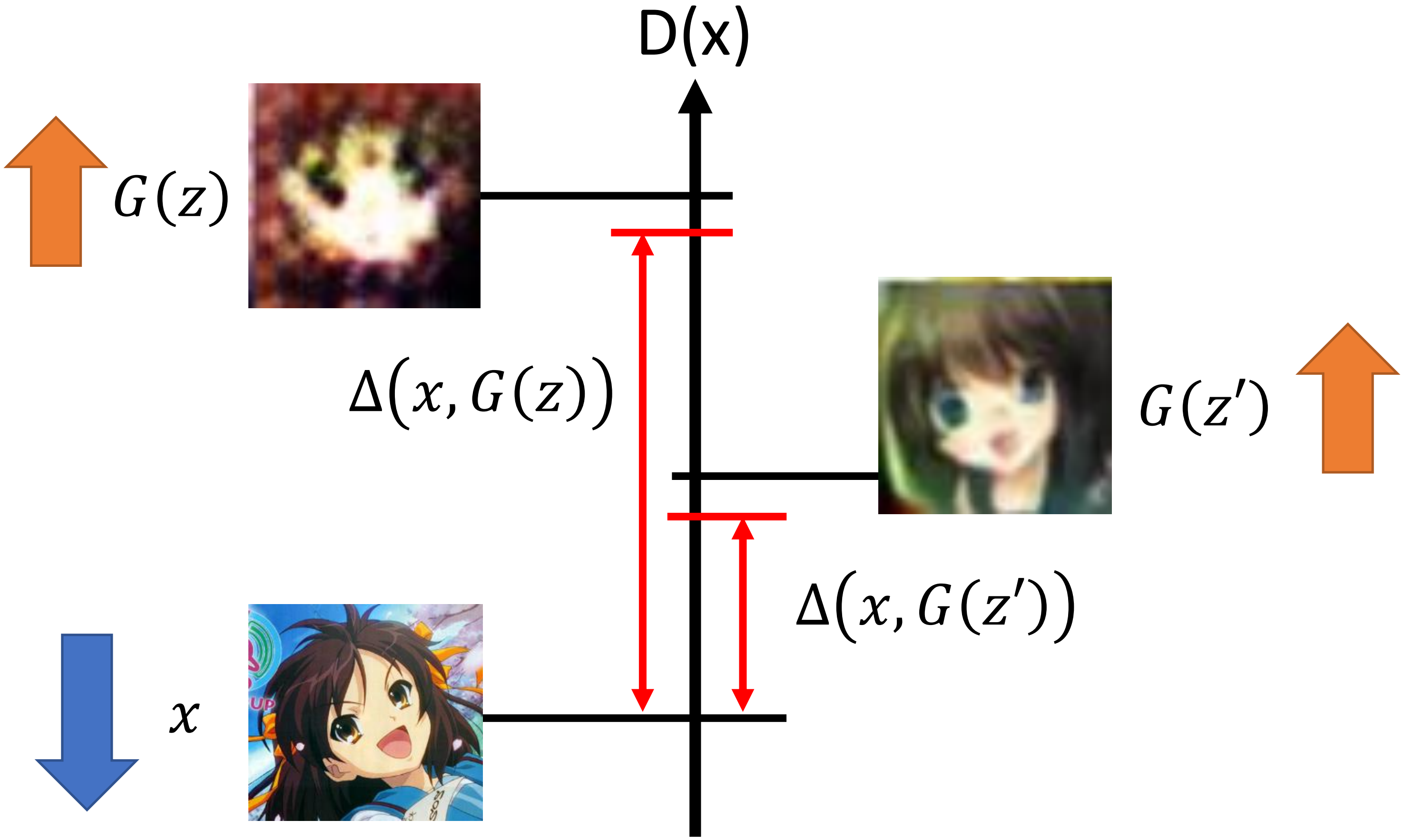
Loss-sensitive GAN (LSGAN)

- Reference: Guo-Jun Qi, “Loss-Sensitive Generative Adversarial Networks on Lipschitz Densities”, arXiv preprint, 2017
- LSGAN allows the generator to focus on improving poor data points that are far apart from real examples.
- Connecting LSGAN with WGAN

LSGAN Assuming D(x) is the ***energy function***

Discriminator minimizing:

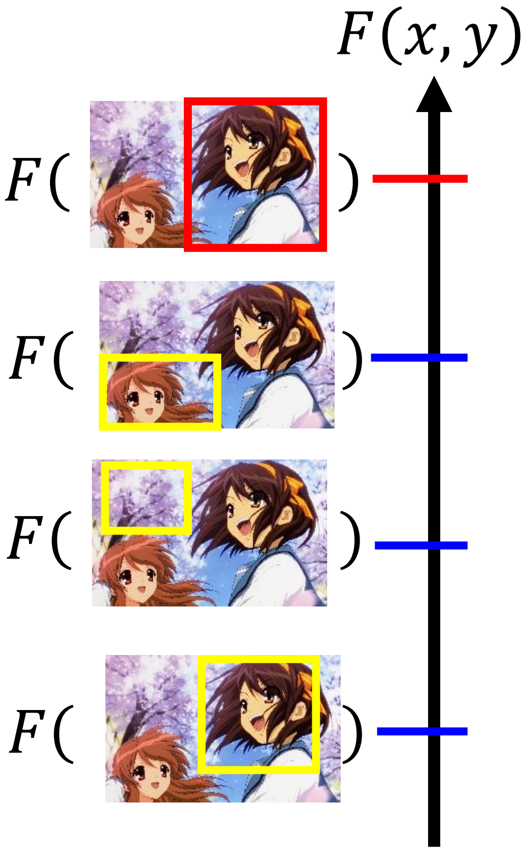
$$D(x) + max\left(0, \Delta\big(x, G(z)\big) + D(x) - D\big(G(z)\big)\right)$$



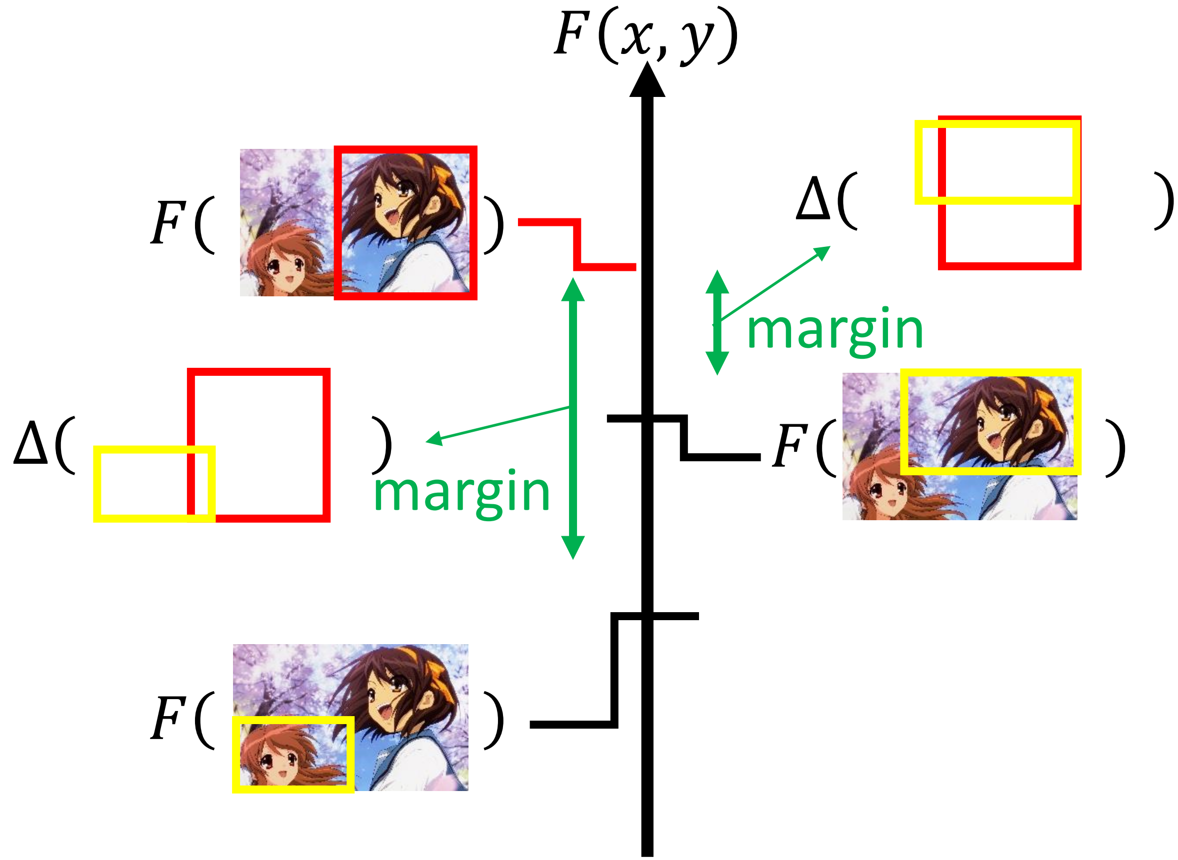
LSGAN Assuming D(x) is the ***energy function***

Discriminator minimizing:

$$D(x) + max\left(0, \Delta\left(x, G(z)\right) + D(x) - D\left(G(z)\right)\right)$$



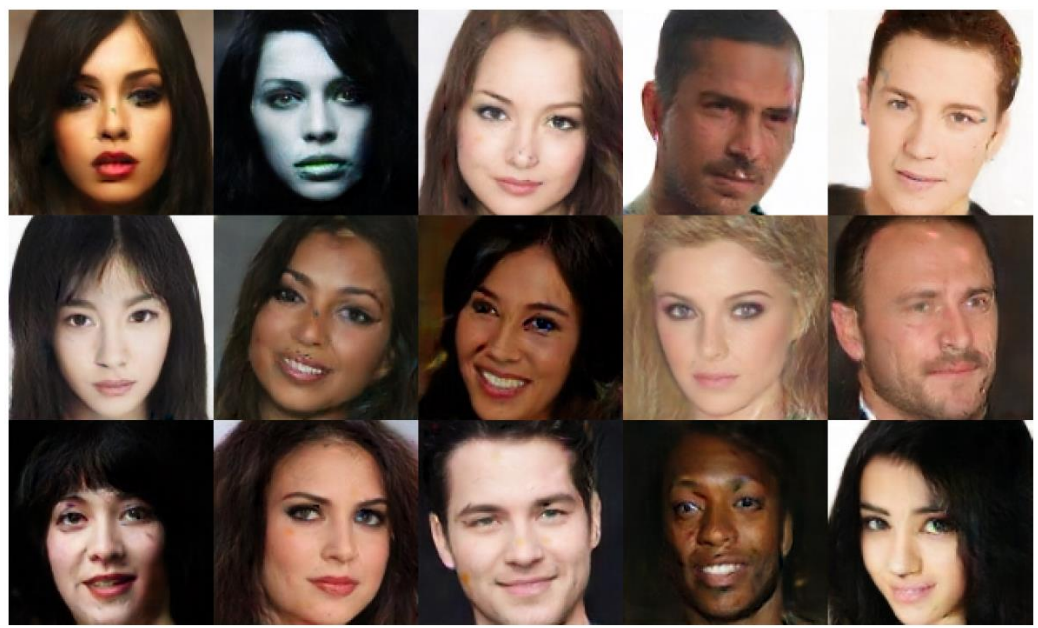
$$F(x^n, \hat{y}^n) \geq F(x^n, y)$$



$$F(x^n, \hat{y}^n) - F(x^n, y) \geq \Delta(\hat{y}^n, y)$$

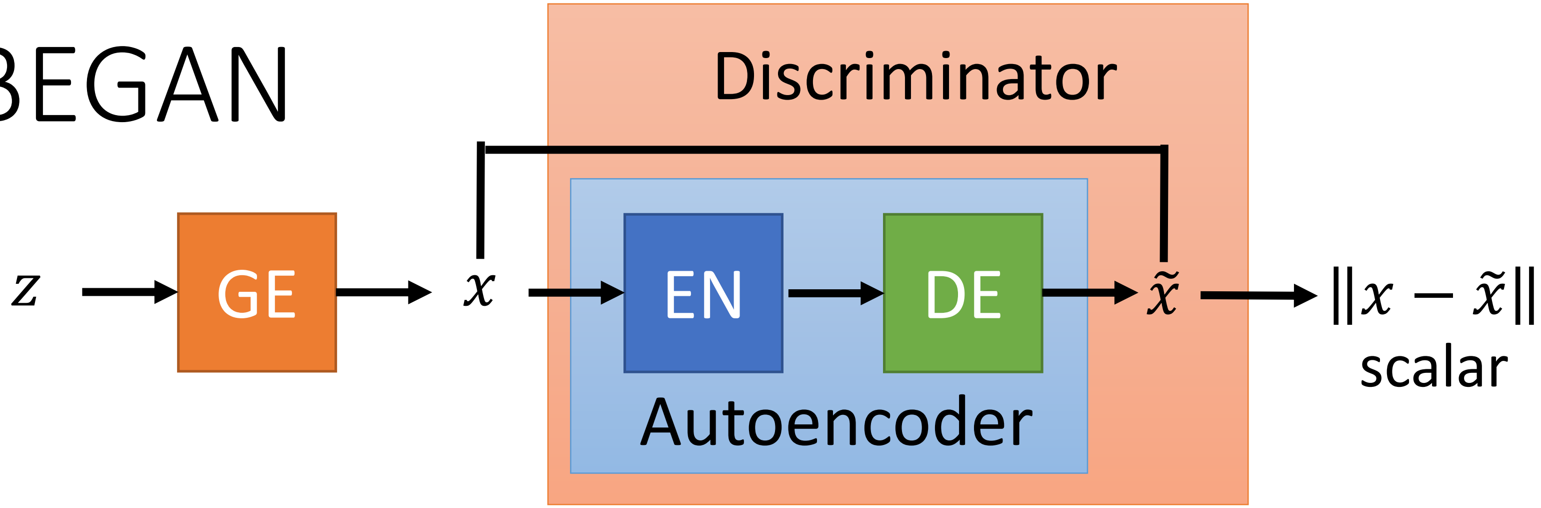
Boundary Equilibrium Generative Adversarial Networks (BEGAN)

- Ref: David Berthelot, Thomas Schumm, Luke Metz, “BEGAN: Boundary Equilibrium Generative Adversarial Networks”, arXiv preprint, 2017
- Auto-encoder based GAN



Not from celebA

BEGAN



For discriminator: $L_D = D(x) - k_t D\big(G(z)\big)$

For generator: $L_G = D\big(G(z)\big)$

For each training step t:

$$k_{t+1} = k_t + \lambda\Big(\gamma D(x) - D\big(G(z)\big)\Big)$$

k_t increase

If $\gamma D(x) > D\big(G(z)\big)$ $\qquad \dfrac{D\big(G(z)\big)}{D(x)} < \gamma$

BEGAN

$$\frac{D\big(G(z)\big)}{D(x)} < \gamma$$

For discriminator: $L_D = D(x) - k_t D\big(G(z)\big)$

For generator: $L_G = D\big(G(z)\big)$

For each training step t:

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陳柏文 (大四) 提供實驗結果 (using CelebA)