# Feature Extraction

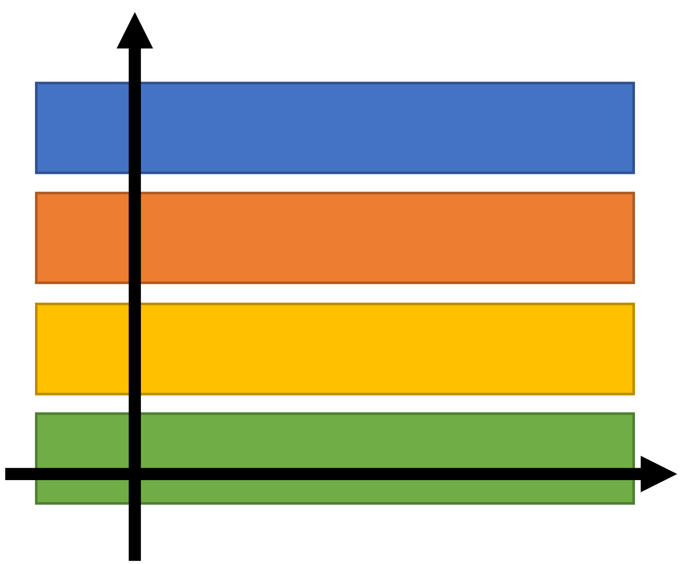
# InfoGAN

(The colors represents the characteristics.)

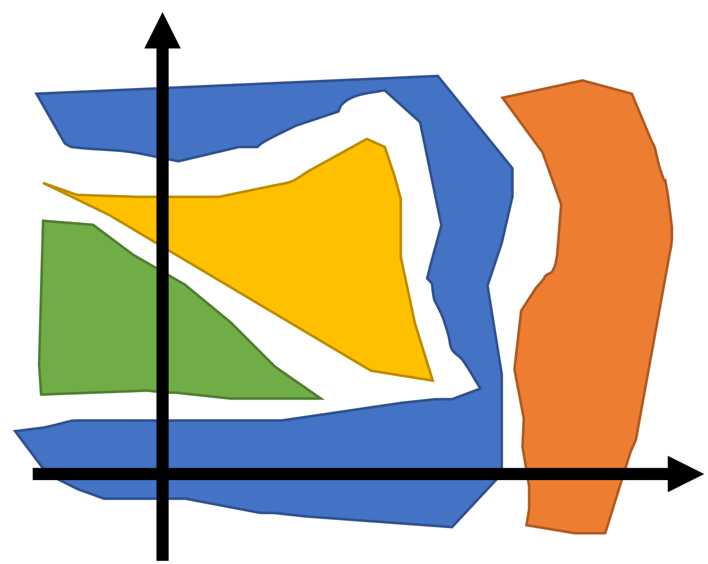
Regular GAN

Modifying a specific dimension, no clear meaning

What we expect



Actually …

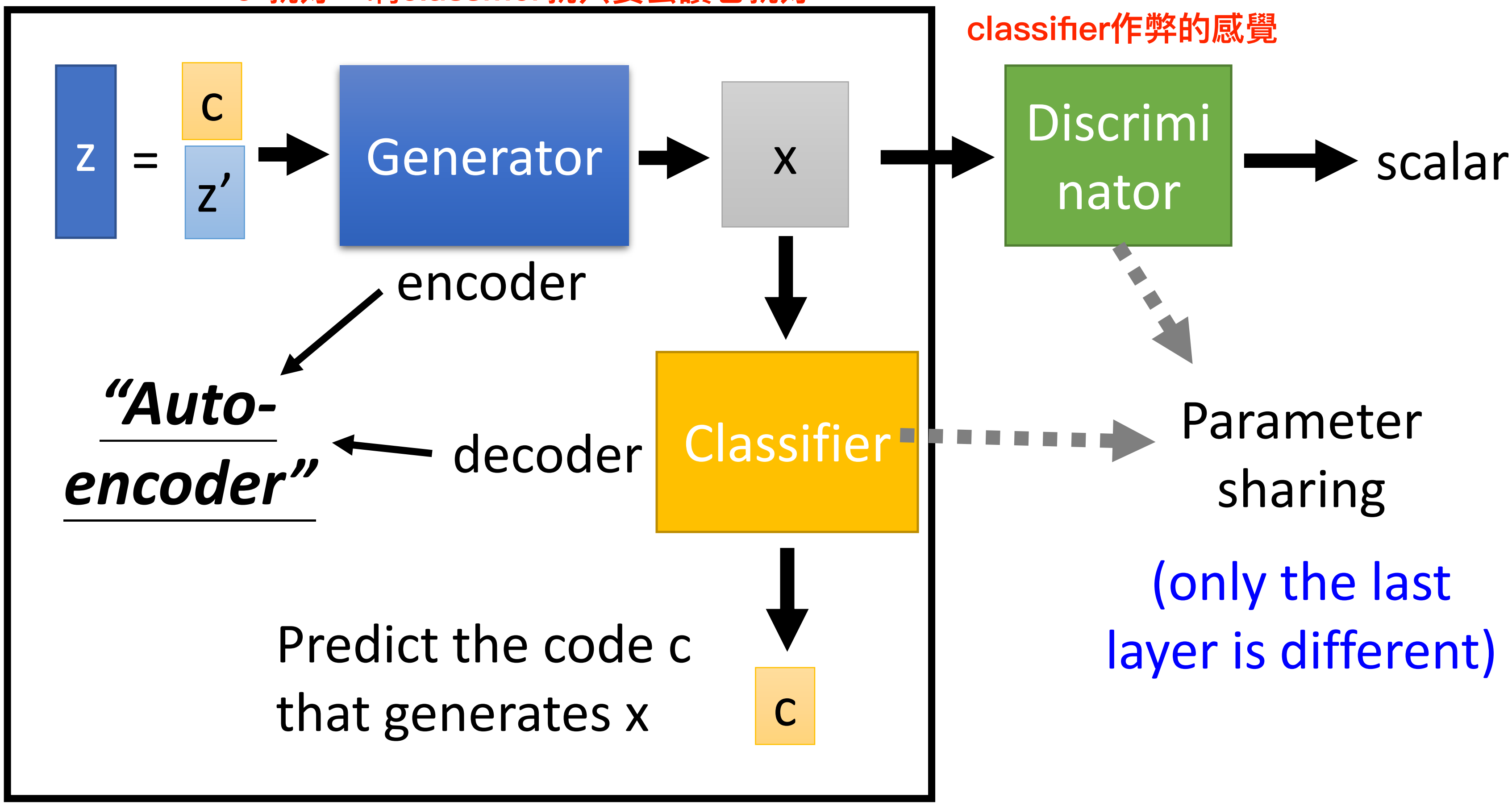


input vector characteristics

# What is InfoGAN?

一定要discriminator，不然的話最簡單的方法G只要在imageX中間貼一個‘c’就好，啊classifier就只要去讀它就好

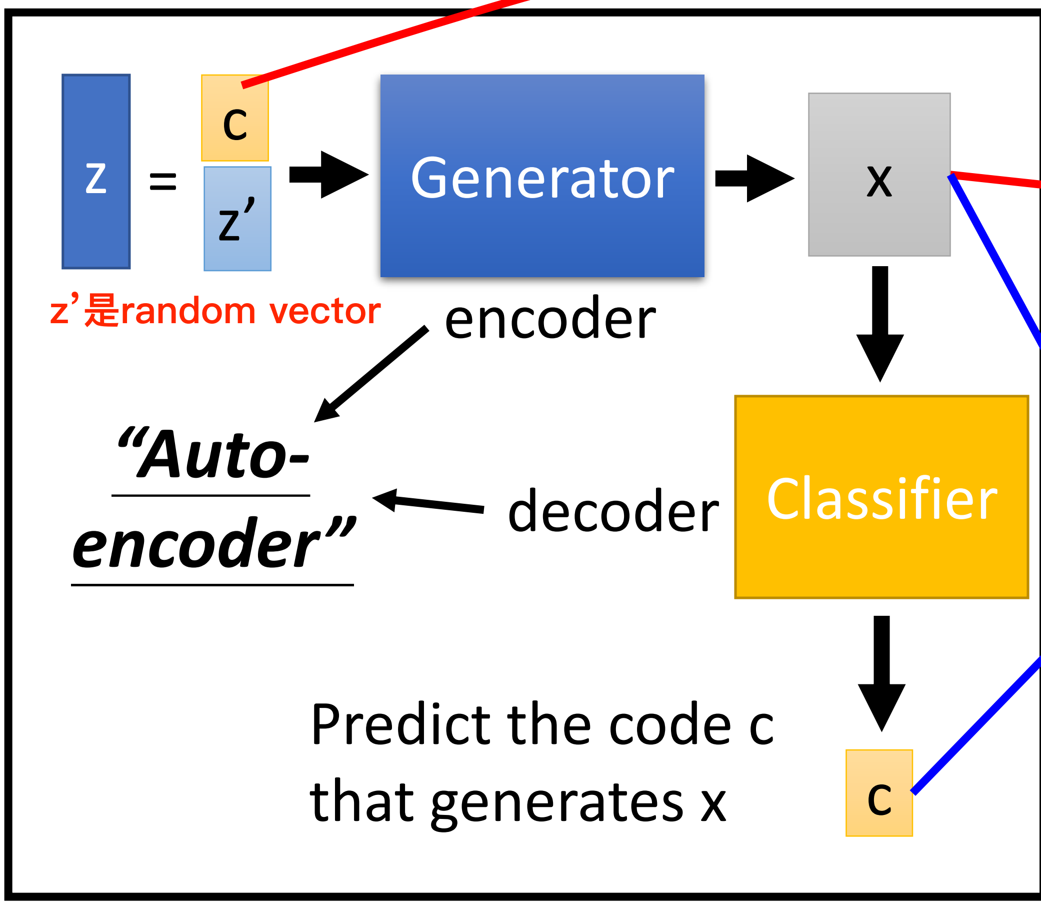
有點像防止G跟classifier作弊的感覺




根據image X判斷他的類別c

# What is InfoGAN?

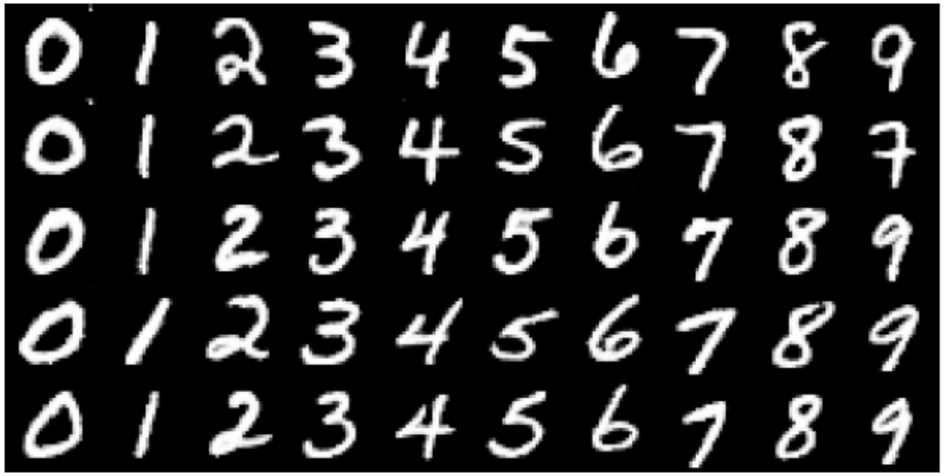
G要學會對c的每一個維度變化造成x的影響



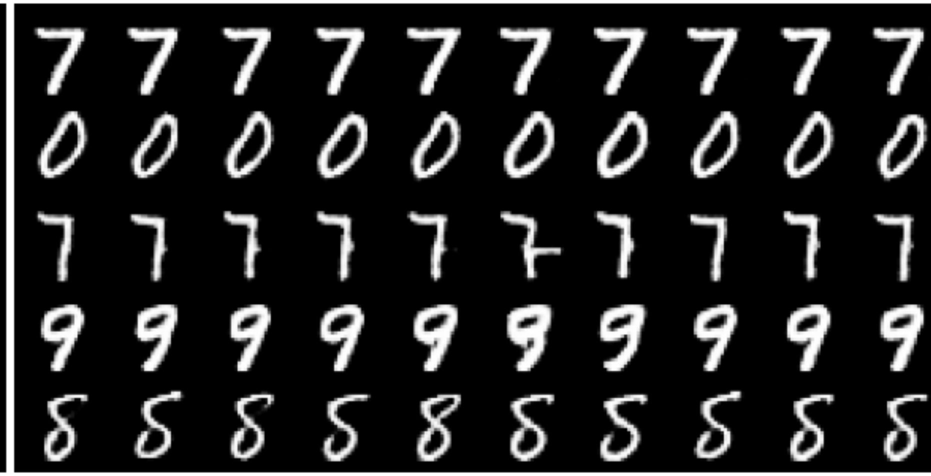

c must have clear influence on x

The classifier can recover c from x.

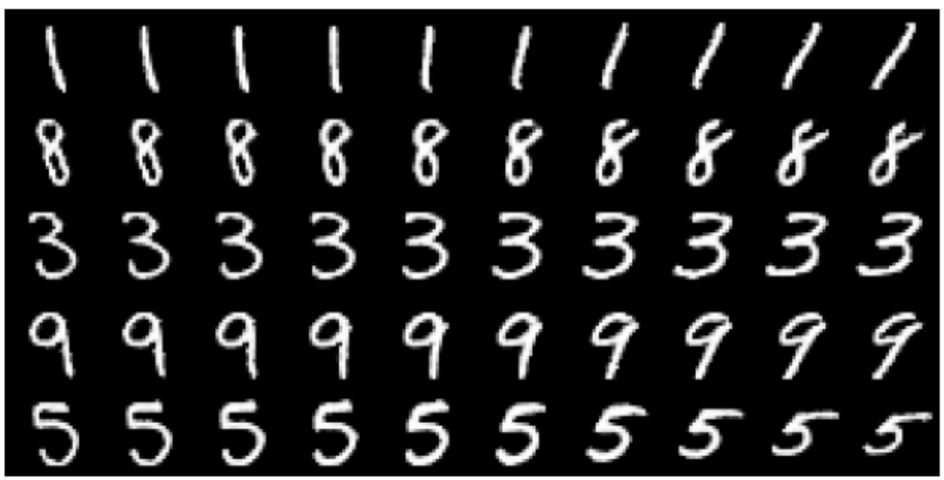
因為他被設為'c'，經過infoGAN的訓練後使得這些c被代表某些意義



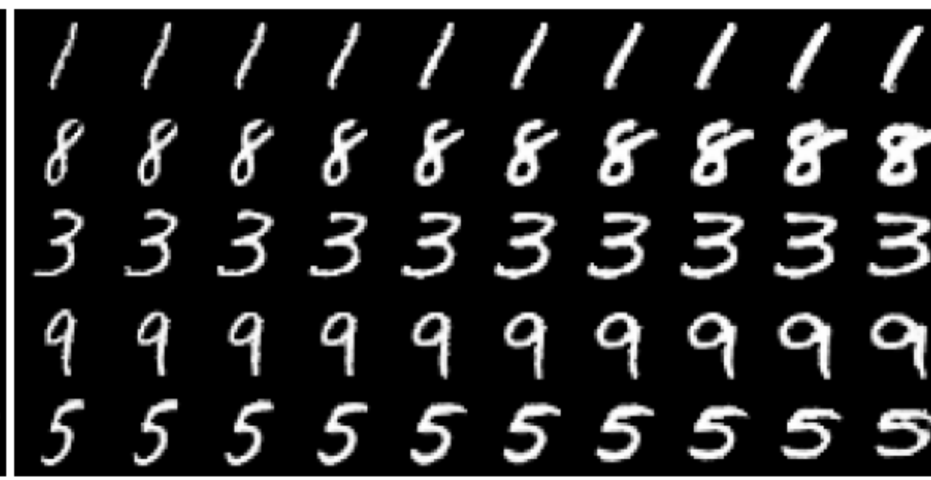
(a) Varying $c_1$ on InfoGAN (Digit type)



(b) Varying $c_1$ on regular GAN (No clear meaning)



(c) Varying $c_2$ from $-2$ to $2$ on InfoGAN (Rotation)



(d) Varying $c_3$ from $-2$ to $2$ on InfoGAN (Width)

https://arxiv.org/abs/1606.03657

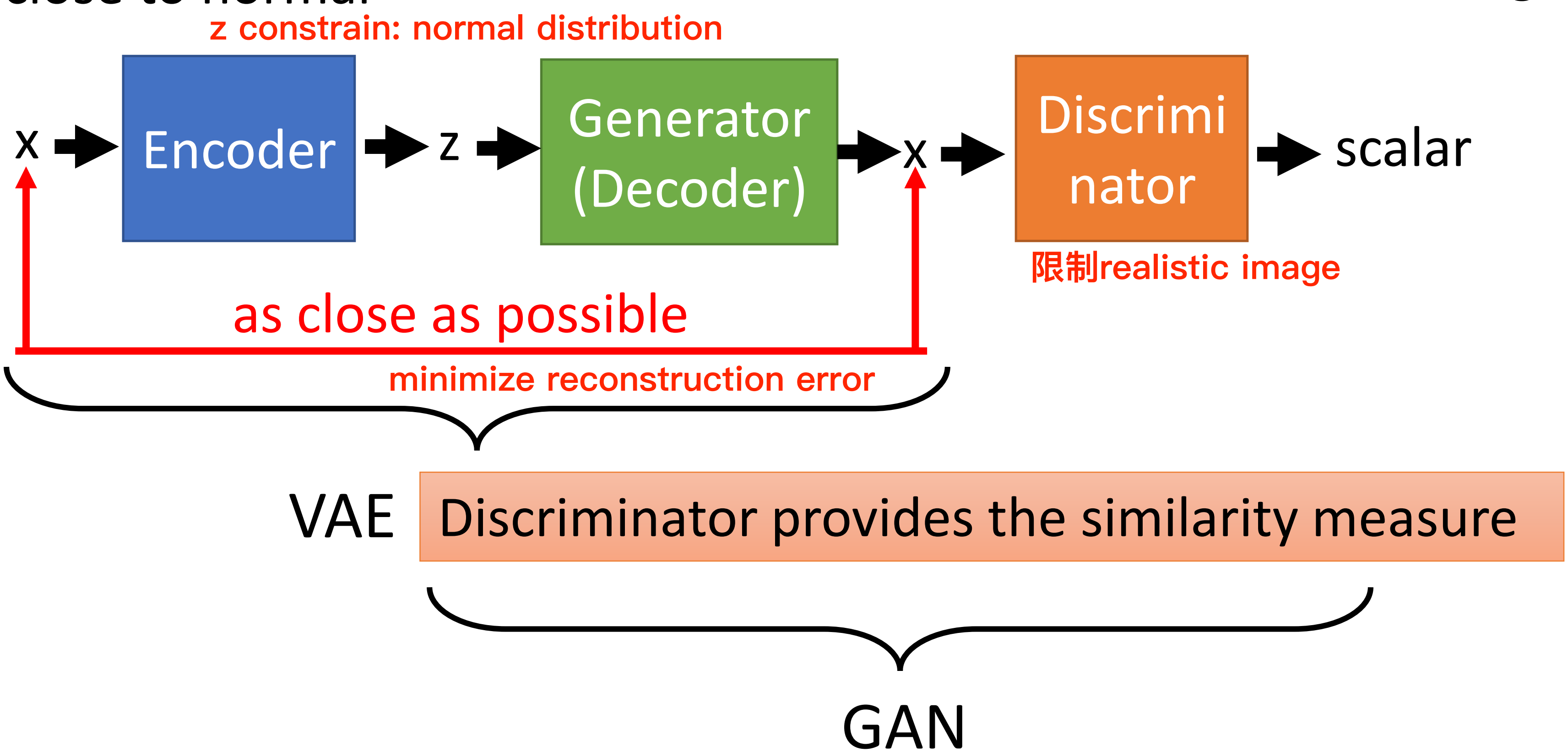
# VAE-GAN

Anders Boesen, Lindbo Larsen, Søren Kaae Sønderby, Hugo Larochelle, Ole Winther, “Autoencoding beyond pixels using a learned similarity metric”, ICML. 2016

- ➢ Minimize reconstruction error
- ➢ z close to normal

- ➢ Minimize reconstruction error
- ➢ Cheat discriminator

- ➢ Discriminate real, generated and reconstructed images



# ***Algorithm***

- Initialize En, De, Dis
- In each iteration:
  - Sample M images $x^1, x^2, \cdots, x^M$ from database
  - Generate M codes $\tilde{z}^1, \tilde{z}^2, \cdots, \tilde{z}^M$ from encoder
    - $\tilde{z}^i = En\left(x^i\right)$
  - Generate M images $\tilde{x}^1, \tilde{x}^2, \cdots, \tilde{x}^M$ from decoder
    - $\tilde{x}^i = De\left(\tilde{z}^i\right)$

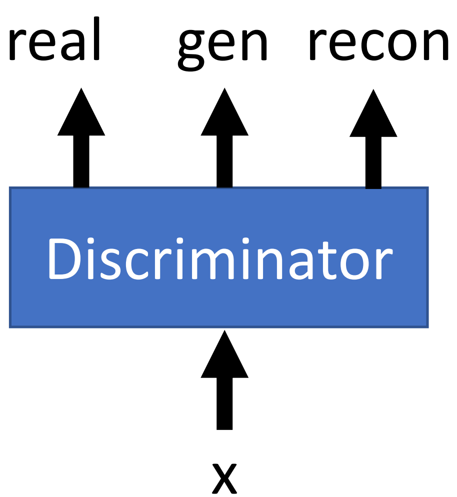
sample from normal distribution

  - Sample M codes $z^1, z^2, \cdots, z^M$ from prior P(z)
  - Generate M images $\hat{x}^1, \hat{x}^2, \cdots, \hat{x}^M$ from decoder
    - $\hat{x}^i =$ De$\left(z^i\right)$
  - Update En to decrease $\left\|\tilde{x}^i - x^i\right\|$, decrease KL(P($\tilde{z}^i$|x$^i$)||P(z)) 希望code z越接近normal distribution越好
  - Update De to decrease $\left\|\tilde{x}^i - x^i\right\|$, increase $Dis\left(\tilde{x}^i\right)$ and $Dis\left(\hat{x}^i\right)$

reconstruct image real image

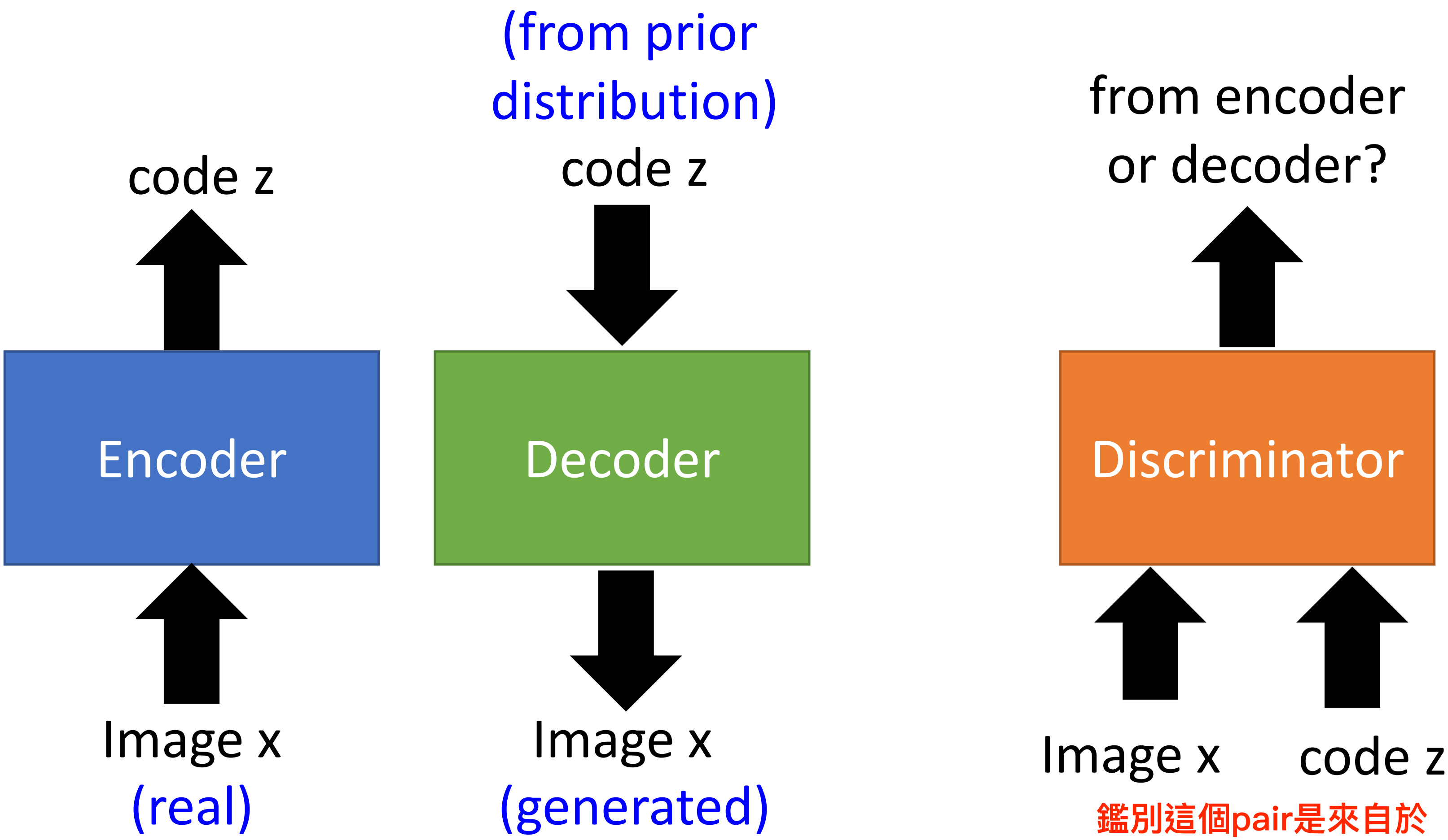
  - Update Dis to increase $Dis\left(x^i\right)$, decrease $Dis\left(\tilde{x}^i\right)$ and $Dis\left(\hat{x}^i\right)$

Another kind of discriminator:



# BiGAN

input/output並沒有接在一起




鑑別這個pair是來自於
encoder還是decoder

# Algorithm

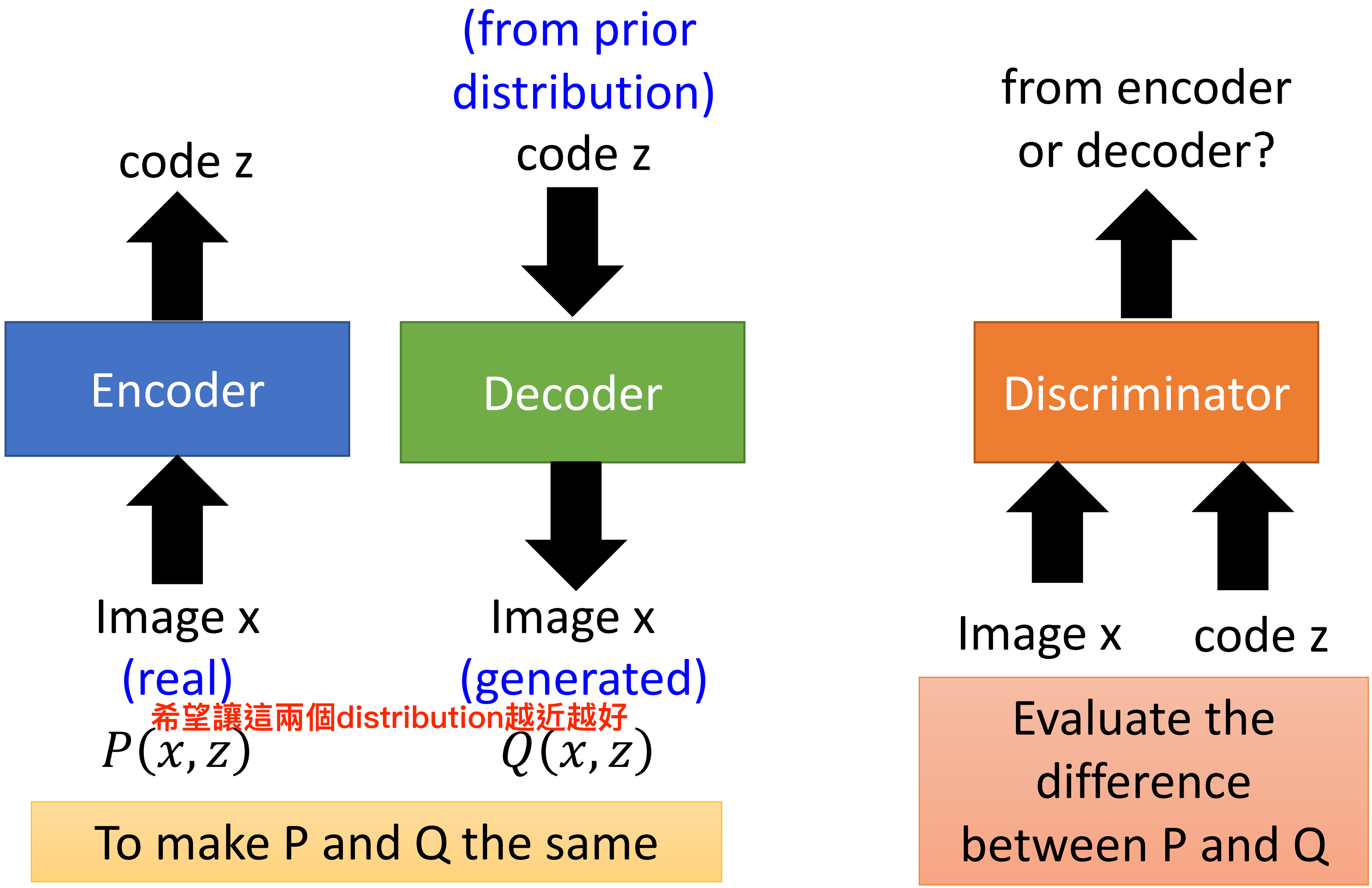
迫使encoder跟decoder合作一起騙過discriminator

- Initialize encoder En, decoder De, discriminator Dis
- In each iteration:
  - Sample M images $x^1, x^2, \cdots, x^M$ from database
  - Generate M codes $\tilde{z}^1, \tilde{z}^2, \cdots, \tilde{z}^M$ from encoder
    - $\tilde{z}^i = En(x^i)$

    encoder
  - Sample M codes $z^1, z^2, \cdots, z^M$ from prior P(z)
  - Generate M codes $\tilde{x}^1, \tilde{x}^2, \cdots, \tilde{x}^M$ from decoder
    - $\tilde{x}^i = De(z^i)$

    decoder
  - Update Dis to increase $Dis(x^i, \tilde{z}^i)$, decrease $Dis(\tilde{x}^i, z^i)$

    不管給誰高分給誰低分都是一樣的意思 encoder decoder
  - Update En and De to decrease $Dis(x^i, \tilde{z}^i)$, increase $Dis(\tilde{x}^i, z^i)$




Optimal encoder and decoder:

En(x’) = z’ ⇒ De(z’) = x’ For all x’

De(z’’) = x’’ ⇒ En(x’’) = z’’ For all z’’

# BiGAN

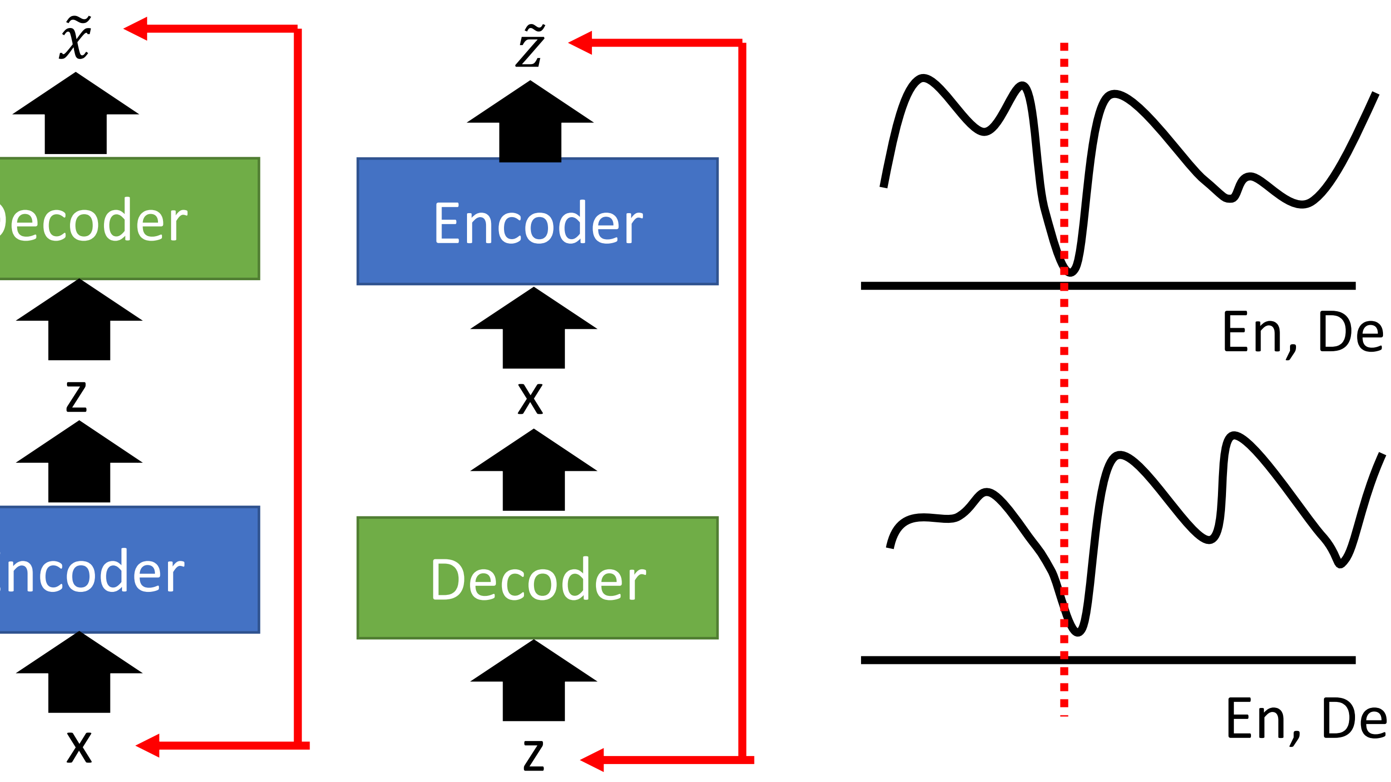
auto encoder產生的圖會模糊

biGAN可以產生較清晰的圖片，但是可能input是一隻鳥，output是另外一隻鳥（清晰的圖片）

optimal solution是一樣的，但是兩個都無法達到optimal，且兩個的error surface是不一樣的

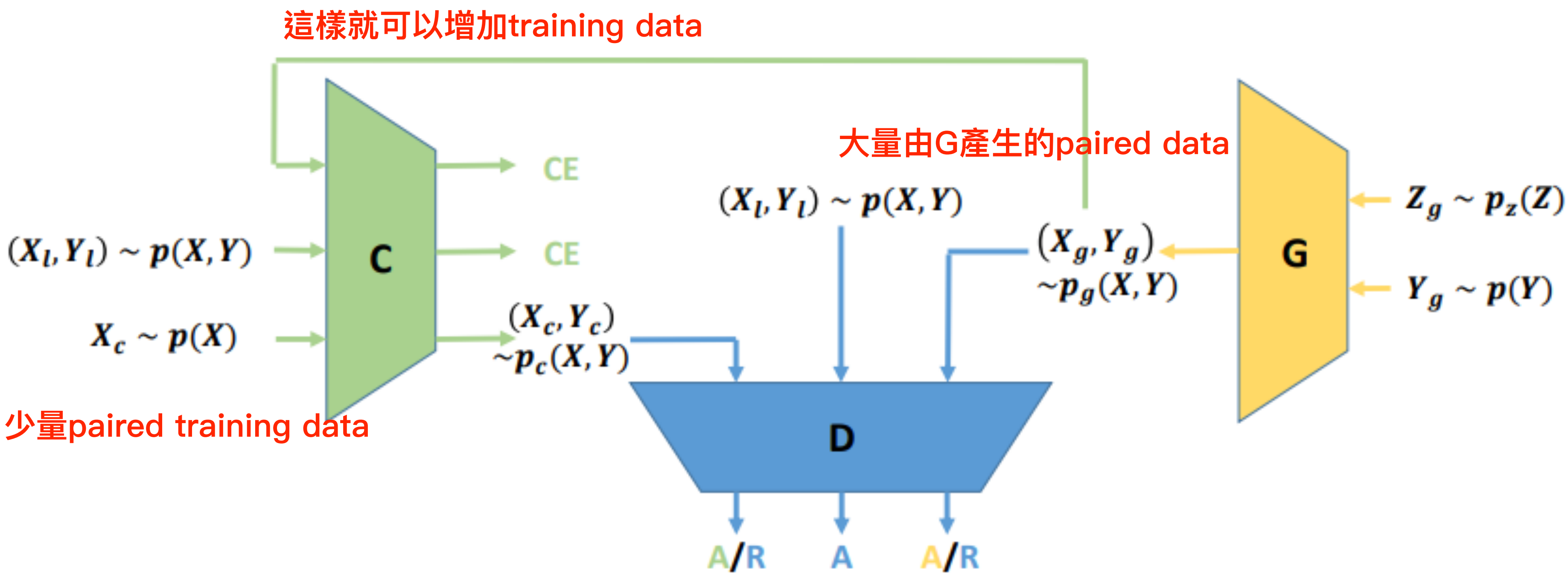
| | | | |
|---|---|---|---|
| Optimal encoder and decoder: | $En(x') = z'$ | $\Rightarrow De(z') = x'$ | For all $x'$ |
| | $De(z'') = x''$ | $\Rightarrow En(x'') = z''$ | For all $z''$ |

How about?



# Triple GAN

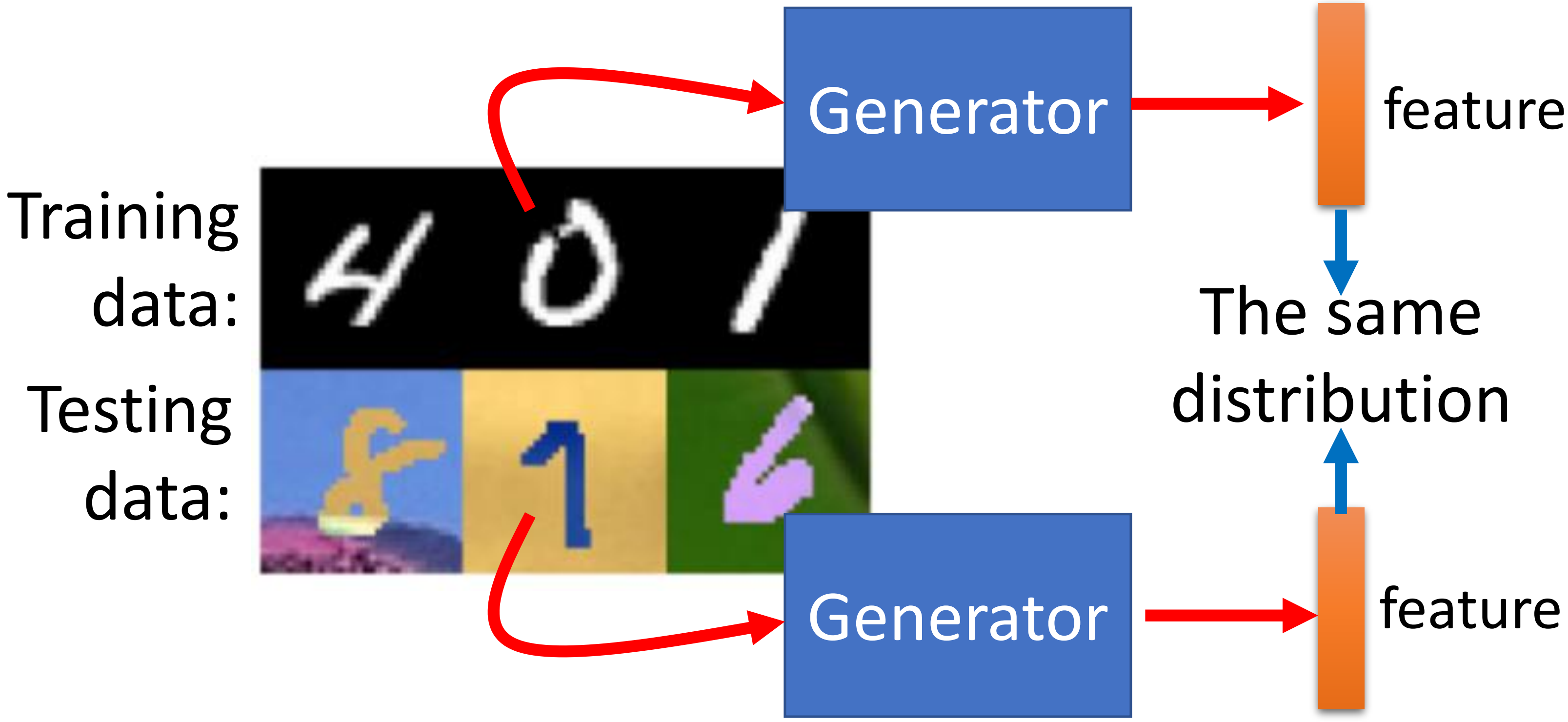
semi-supervised learning




Chongxuan Li, Kun Xu, Jun Zhu, Bo Zhang, “Triple Generative Adversarial Nets”, arXiv 2017

# Domain-adversarial training

- Training and testing data are in different domains



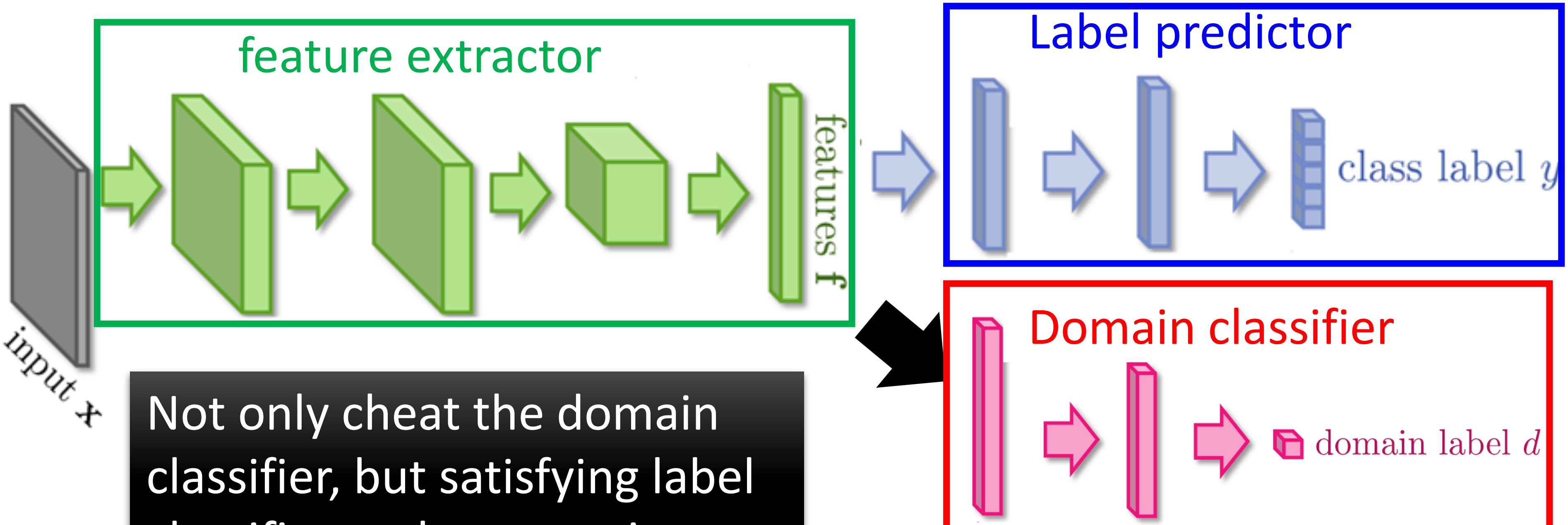

Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, Domain-Adversarial Training of Neural Networks, JMLR, 2016

# Domain-adversarial training

原始是一起learn的

Maximize label classification accuracy + minimize domain classification accuracy

Maximize label classification accuracy



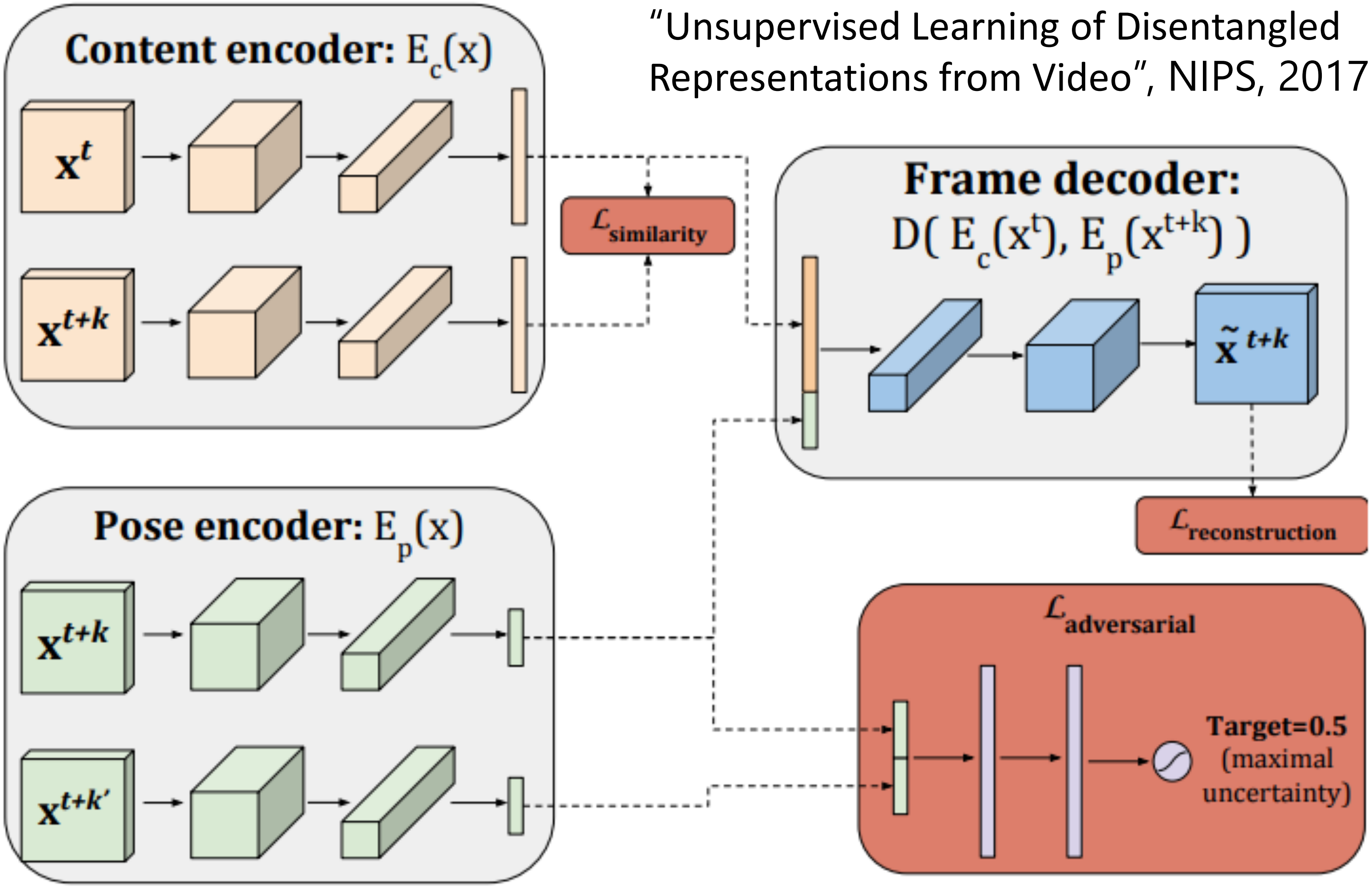

Not only cheat the domain classifier, but satisfying label classifier at the same time

Maximize domain classification accuracy

This is a big network, but different parts have different goals.

# Feature Disentangle

Emily Denton, Vighnesh Birodkar, “Unsupervised Learning of Disentangled Representations from Video”, NIPS, 2017



# ***Experimental Results***

https://arxiv.org/pdf/1705.10915.pdf