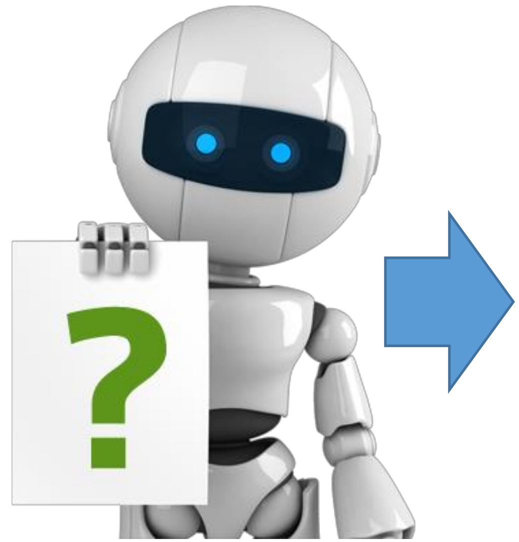
Unsupervised Learning: Generation

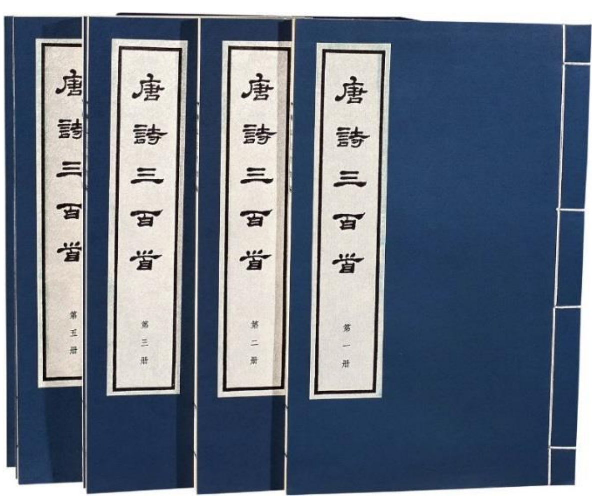
從無到有產生（無中生有）

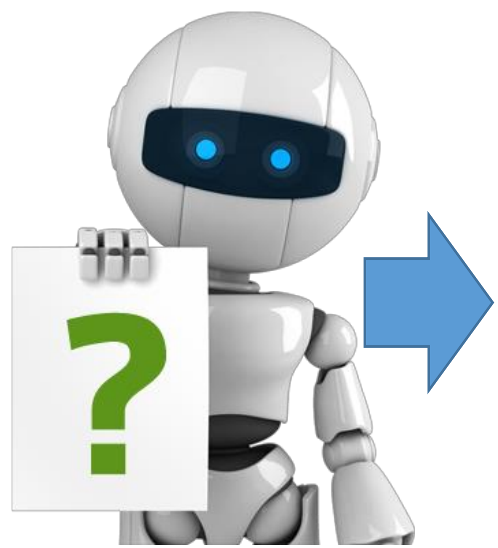
http://www.rb139.com/index.php?s=/Lot/44547

Creation



Drawing?

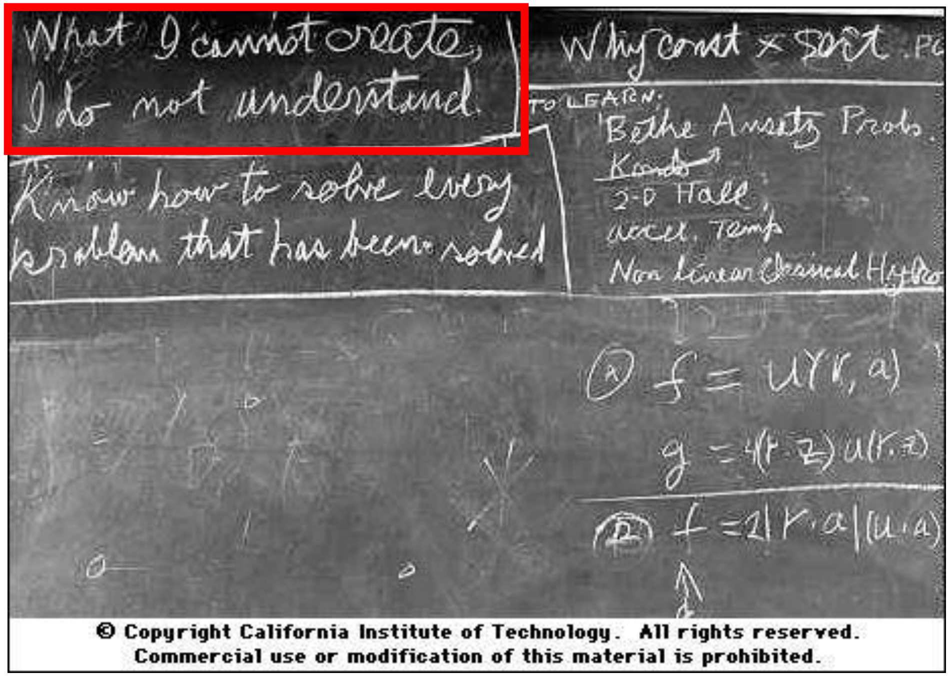




Writing Poems?

Creation

- Generative Models: https://openai.com/blog/generative-models/

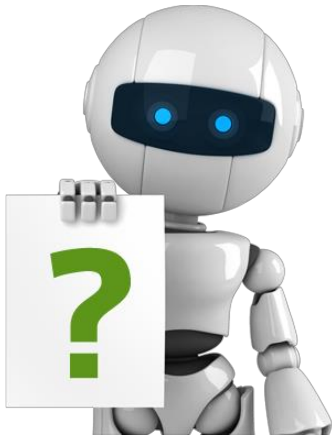


What I cannot create,
I do not understand.

Richard Feynman

https://www.quora.com/What-did-Richard-Feynman-mean-when-he-said-What-I-cannot-create-I-do-not-understand

Creation



Now

v.s.

In the future

Machine
draws a cat

http://www.wikihow.com/Draw-a-Cat-Face

Generative Models

假設現在要產生一個複雜的物件，改讓machine一次產生一部分component，最後再將所有component組合起來

Component-by-component

Autoencoder

Generative Adversarial Network (GAN)

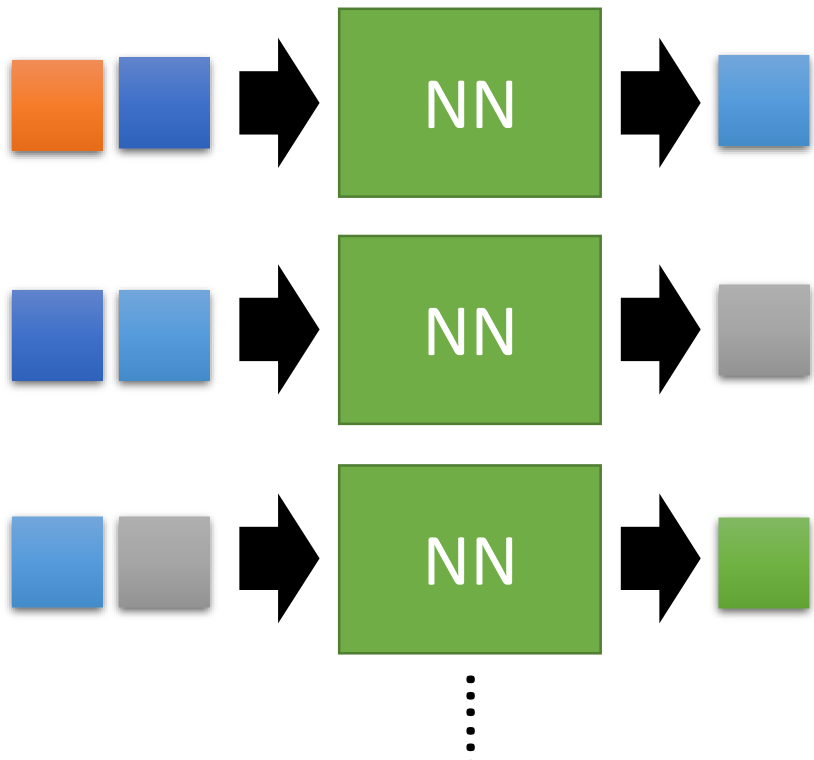
Component-by-component

un–supervise: 不需要label data

- Image generation

透過前兩個pixel畫出下一個pixel顏色

E.g. 3 x 3 images



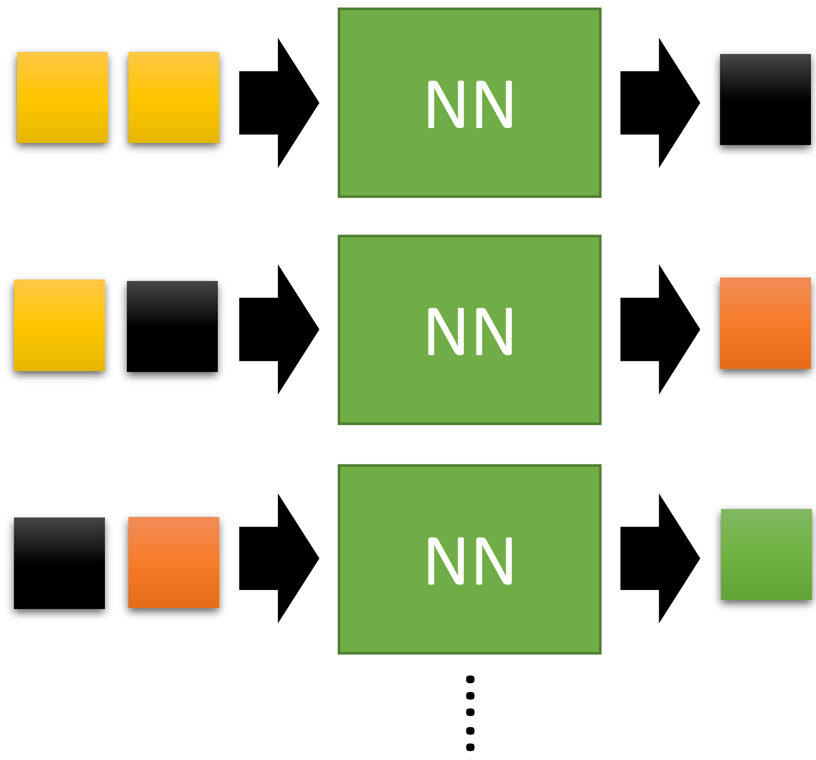
Can be trained just with a large collection of images without any annotation

Component-by-component

初始化前兩個pixel，接下來就是透過前兩個pixel預測下一個pixel

- Image generation

E.g. 3 x 3 images



Can be trained just with a large collection of images without any annotation

Practicing Generation Models: Pokémon Creation

- Small images of 792 Pokémon's
  - Can machine learn to create new Pokémons?

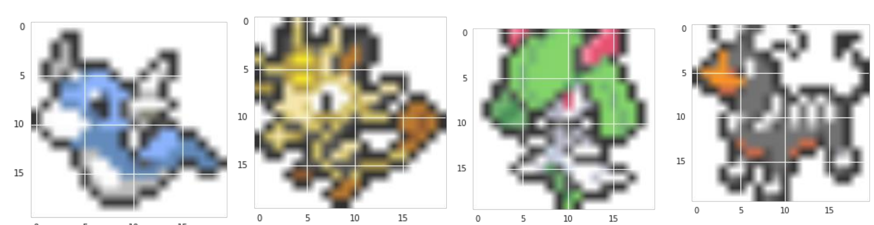
<u>Don't catch them! Create them!</u>

老師上網對所有神奇寶貝各抓一張照片，並做一個model根據這些寶可夢產生一張新的寶可夢

- Source of image: http://bulbapedia.bulbagarden.net/wiki/List_of_Pok%C3%A9mon_by_base_stats_(Generation_VI)

Original image is 40 x 40

Making them into 20 x 20



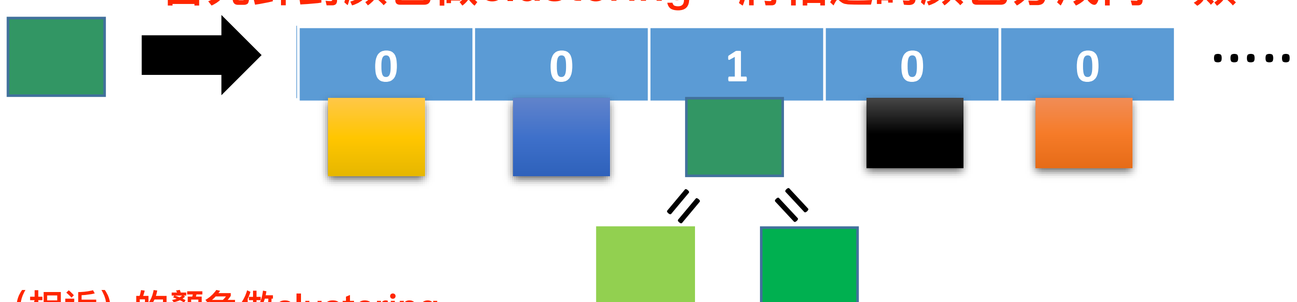
Practicing Generation Models: Pokémon Creation

- Tips (?) 對data做一點process
  - ➢ Each pixel is represented by 3 numbers (corresponding to RGB)

R=50, G=150, B=100

  - ➢ Each pixel is represented by a 1-of-N encoding feature

首先針對顏色做clustering，將相近的顏色分成同一類



先將類似（相近）的顏色做clustering

Clustering the similar color → 167 colors in total

Practicing Generation Models: Pokémon Creation 實作的data

- Original image (40 x 40): http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2016/Pokemon_creation/image.rar
- Pixels (20 x 20): http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2016/Pokemon_creation/pixel_color.txt
  - Each line corresponds to an image, and each number corresponds to a pixel
    - http://speech.ee.ntu.edu.tw/~tlkagk/courses/ML_2016/Pokemon_creation/colormap.txt

```
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 19 41 34 0 0 19 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 1 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 1 44 74 44 51 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 1 21 80 80 81 0 0 0 0 0 0 0 0
0 0 0 0 0 1 2 3 18 35 22 0 5 2 0 0 0 0 0 0
93 94 93 93 85 95 38 96 97 98 99 99 67 99 9
0 0 0 0 0 0 1 106 106 106 106 106 61 107 0
```

……

0, 1, 2

```
255 255 255
53 53 53
49 49 49
186 186 186
51 51 51
54 54 54
187 187 187
83 83 83
50 51 52
251 251 251
52 52 52
⋮
```

- Following experiment: 1-layer LSTM, 512 cells

Real Pokémon

Never seen by machine!

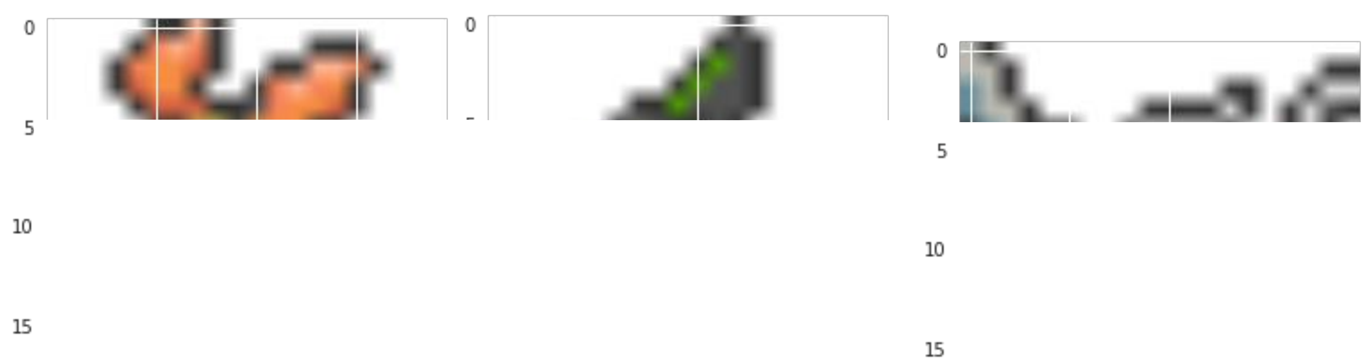
保留三隻machine沒看過，並將下半身遮住讓機器畫出結果

Cover 50%

It is difficult to evaluate generation.

不容易衡量到底好不好

Cover 75%



結果發現machine描黑邊還不錯

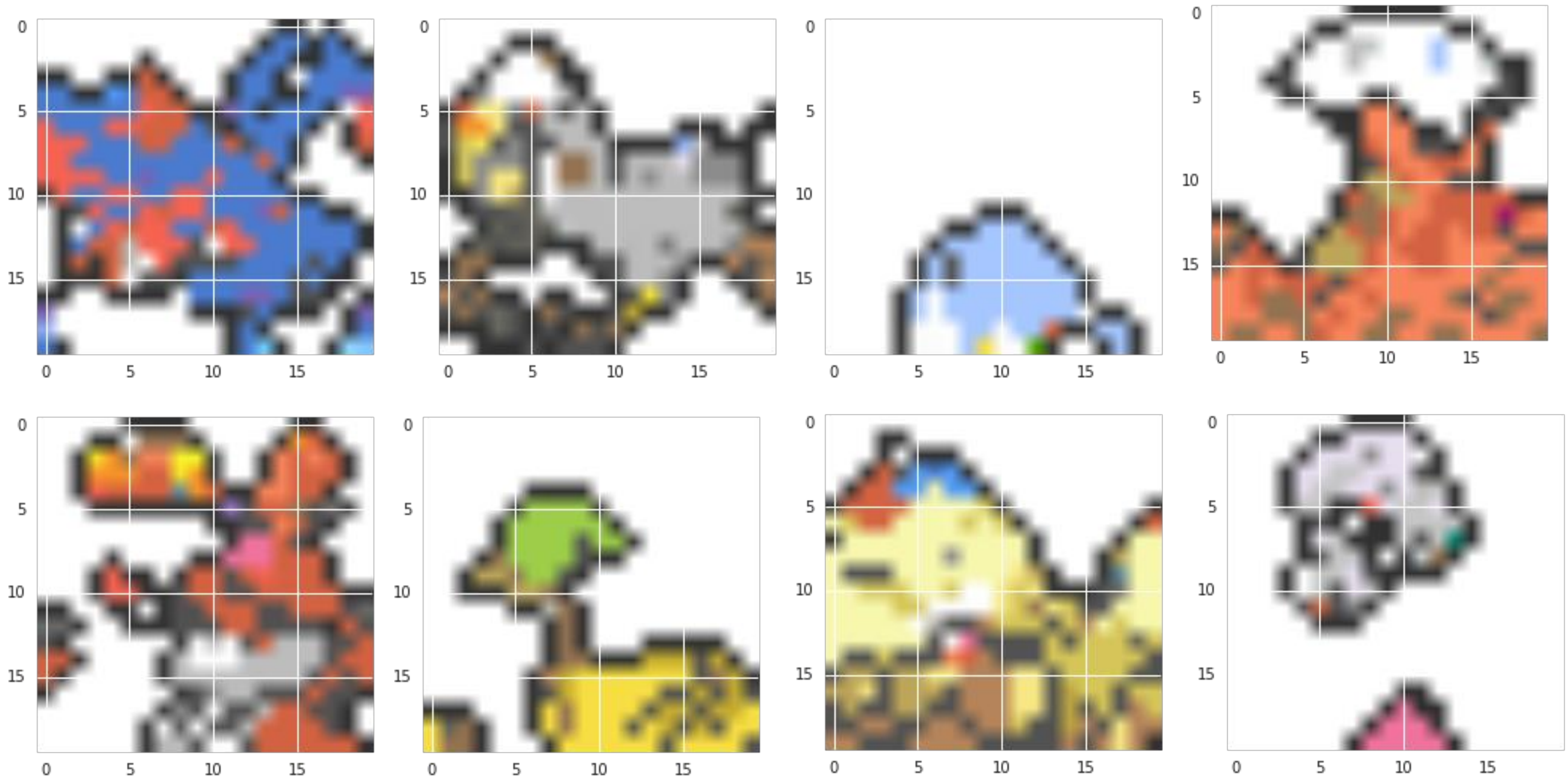
讓machine從頭開始產生一隻寶可夢

Pokémon Creation

加入一點random，將network output隨機置換成別的顏色才會有色彩繽紛性

Drawing from scratch

Need some randomness

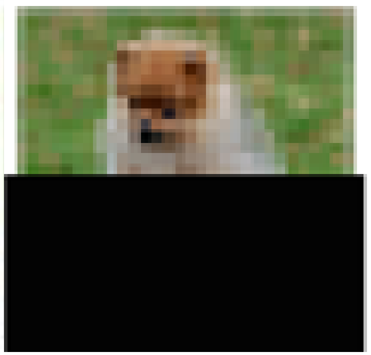


Google Model

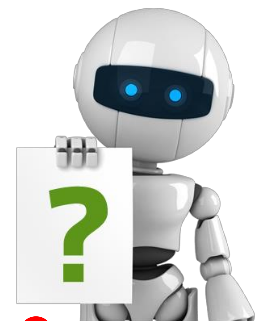
PixelRNN

Ref: Aaron van den Oord, Nal Kalchbrenner, Koray Kavukcuoglu, Pixel Recurrent Neural Networks, arXiv preprint, 2016

將狗的下半身遮住後給machine預測

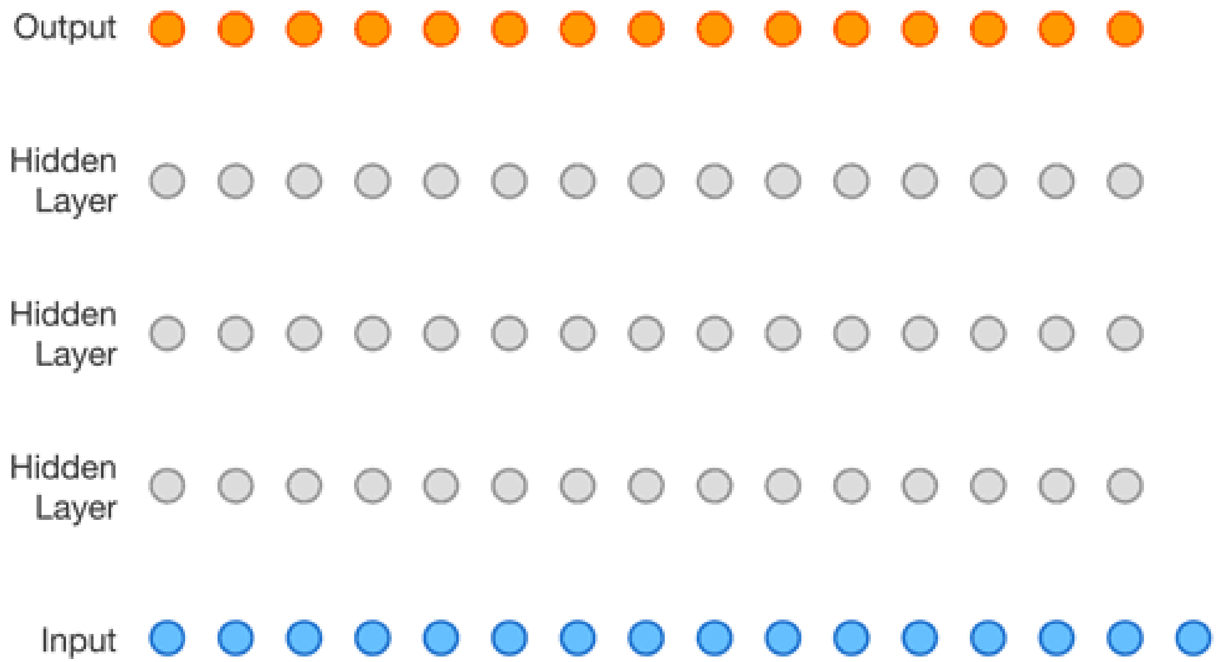


Real World



語音合成，產生wave form。每次都利用k個input產生下一個input

More than images ......



Audio: Aaron van den Oord, Sander Dieleman, Heiga Zen, Karen Simonyan, Oriol Vinyals, Alex Graves, Nal Kalchbrenner, Andrew Senior, Koray Kavukcuoglu, WaveNet: A Generative Model for Raw Audio, arXiv preprint, 2016

將wave 改成frame，可產生影片

Video: Nal Kalchbrenner, Aaron van den Oord, Karen Simonyan, Ivo Danihelka, Oriol Vinyals, Alex Graves, Koray Kavukcuoglu, Video Pixel Networks , arXiv preprint, 2016

Generative Models

一次產生一個component會失去大局觀

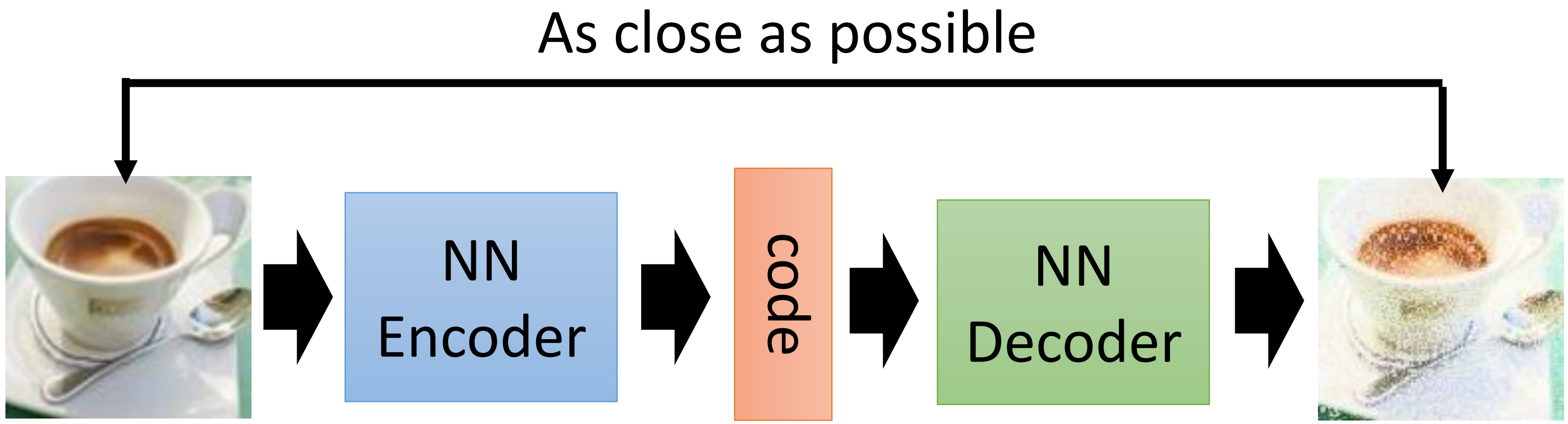
Component-by-component

一次產生整張image，而不是一個一個pixel產生，讓整個result是有大局觀的

Autoencoder

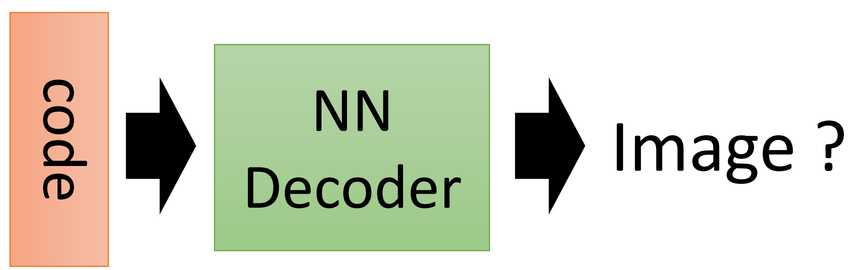
Generative Adversarial Network (GAN)

Auto-encoder

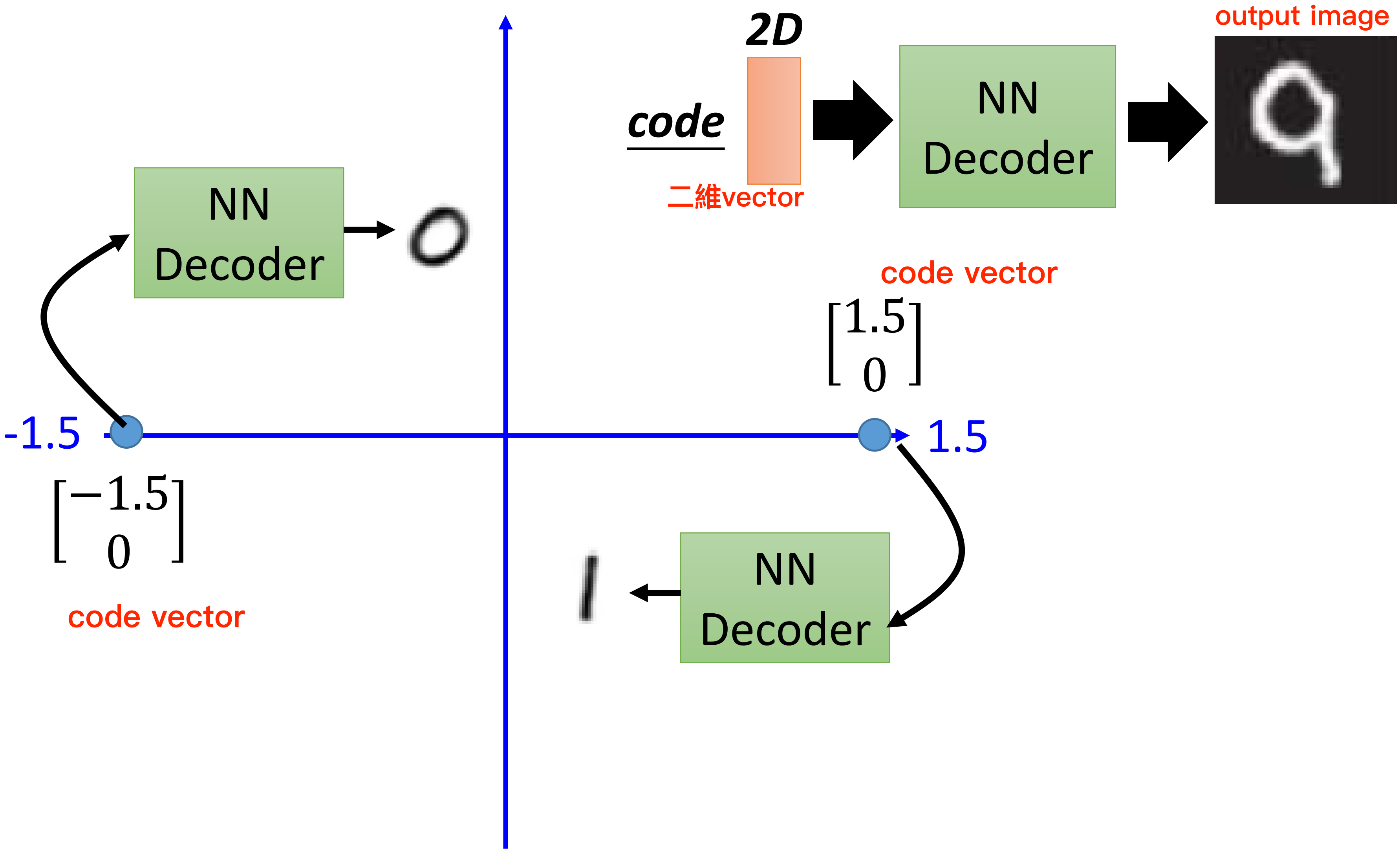


Random產生一個code vector餵進去給
Decoder，即可讓他產生一張新的image

Randomly generate
a vector as code

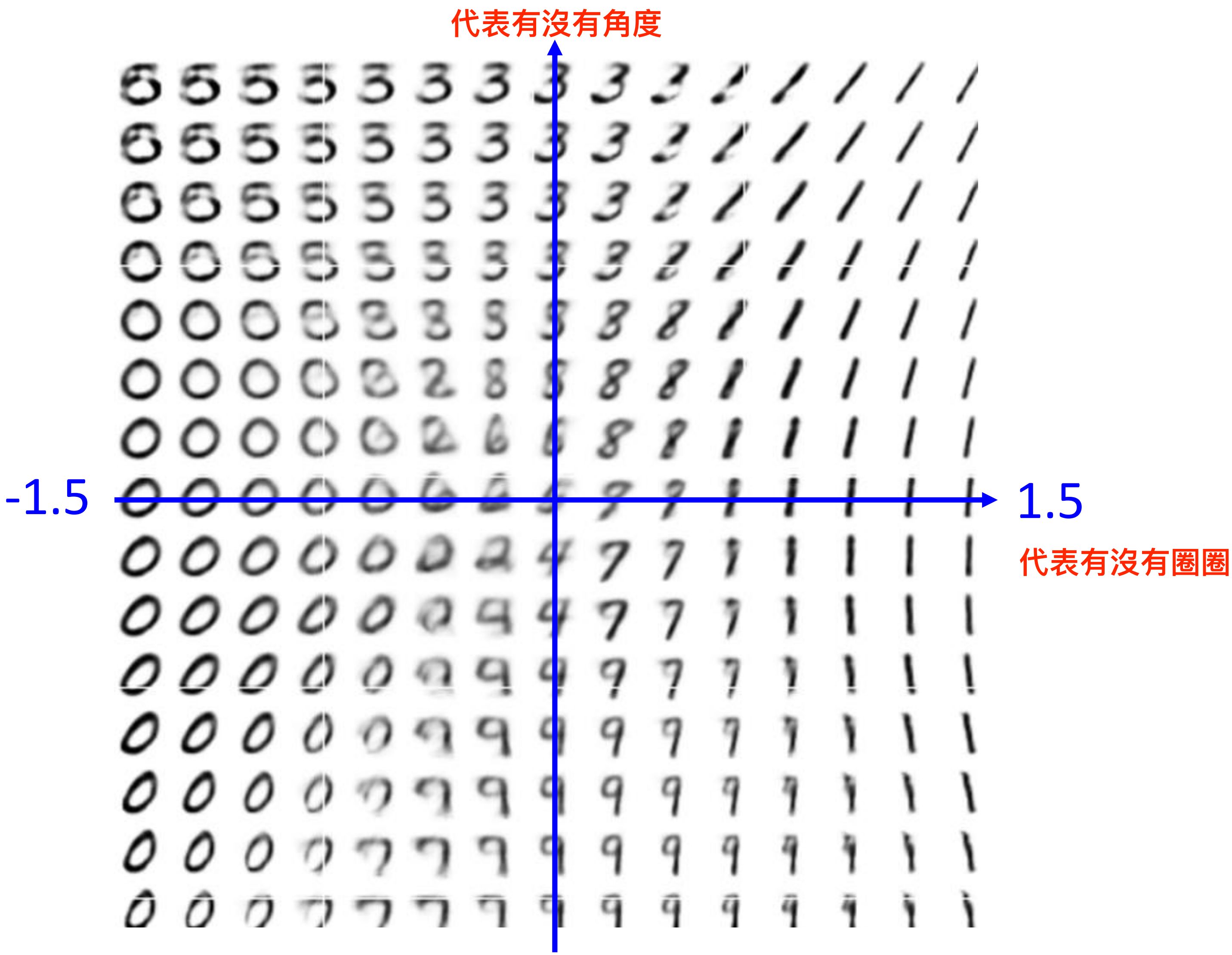


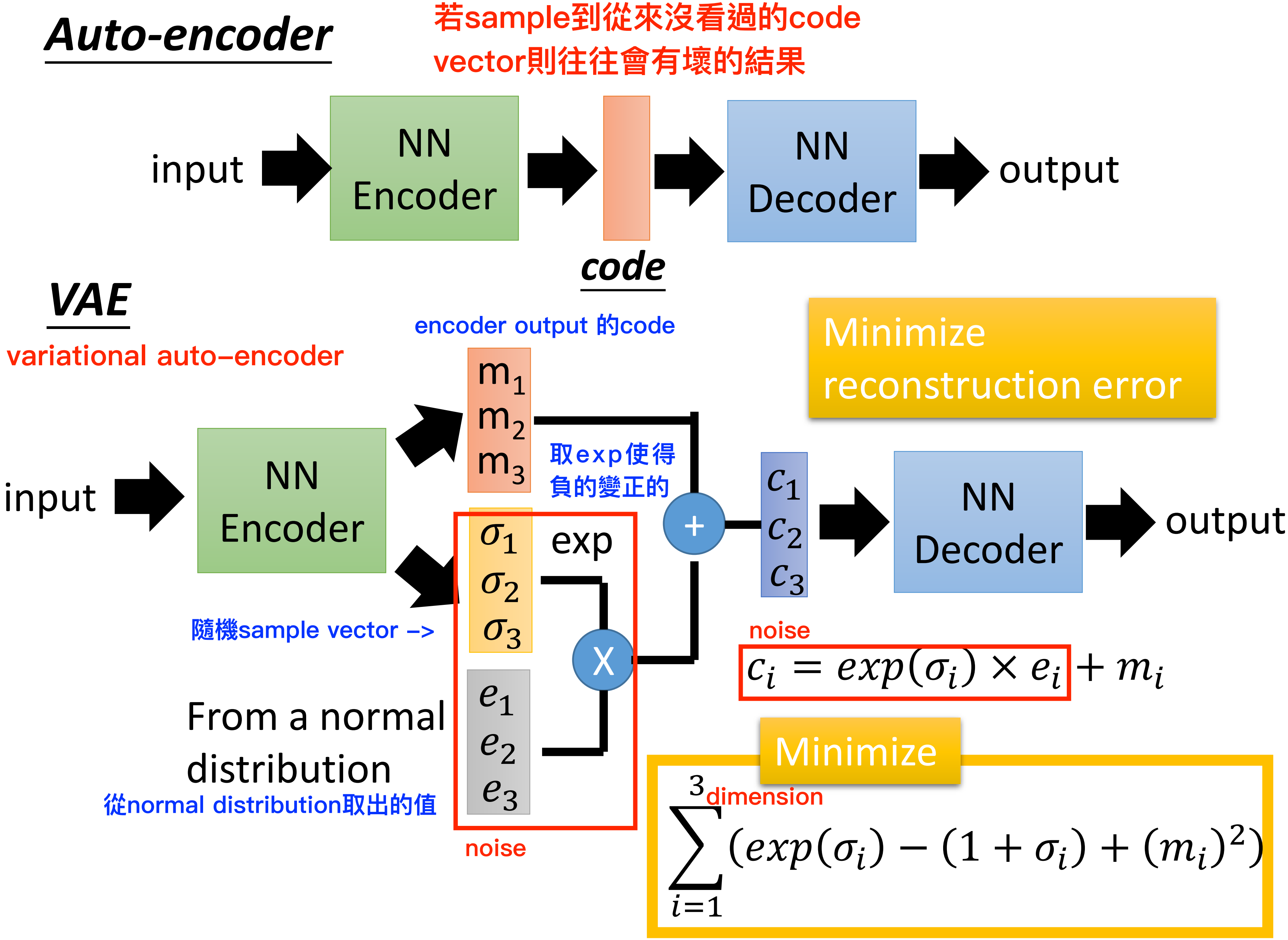
Review: Auto-encoder



sample這些code vector丟進去decoder後得到的結果

Review: Auto-encoder



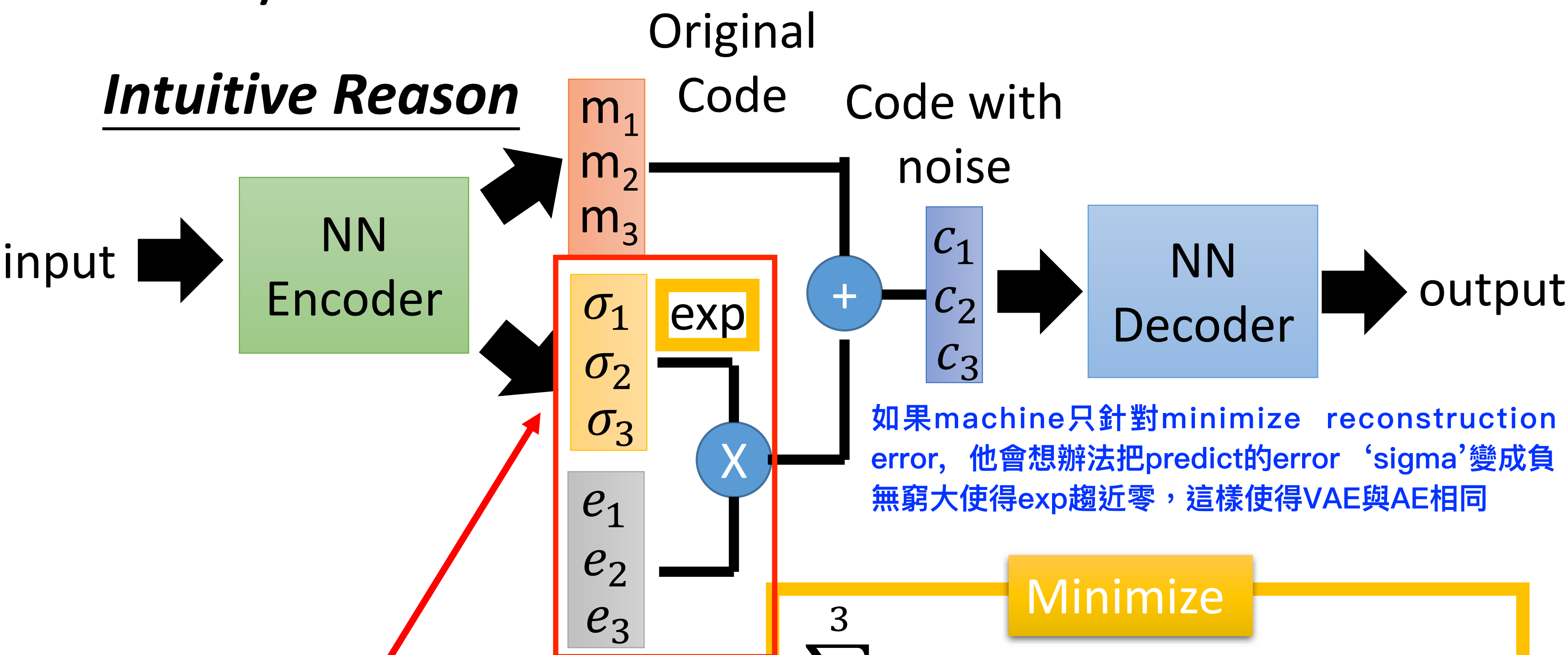


Auto-encoder
若sample到從來沒看過的code
vector則往往會有壞的結果
input
NN
Encoder
code
NN
Decoder
output
VAE
variational auto–encoder
encoder output 的code
m_1
m_2
m_3
Minimize
reconstruction error
取exp使得
負的變正的
input
NN
Encoder
σ_1
σ_2
σ_3
exp
+
c_1
c_2
c_3
NN
Decoder
output
隨機sample vector –>
X
noise
$c_i = exp(\sigma_i) \times e_i + m_i$
e_1
e_2
e_3
From a normal
distribution
從normal distribution取出的值
noise
Minimize
dimension
$\sum_{i=1}^{3} (exp(\sigma_i) - (1 + \sigma_i) + (m_i)^2)$

Why VAE?

What will happen if we only minimize reconstruction error?

Intuitive Reason



如果machine只針對minimize reconstruction error，他會想辦法把predict的error 'sigma'變成負無窮大使得exp趨近零，這樣使得VAE與AE相同

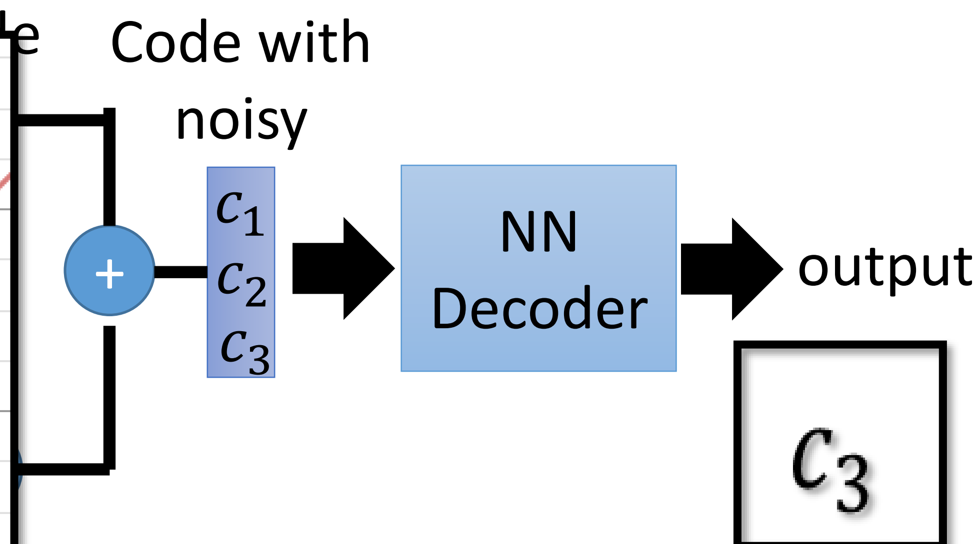
Minimize

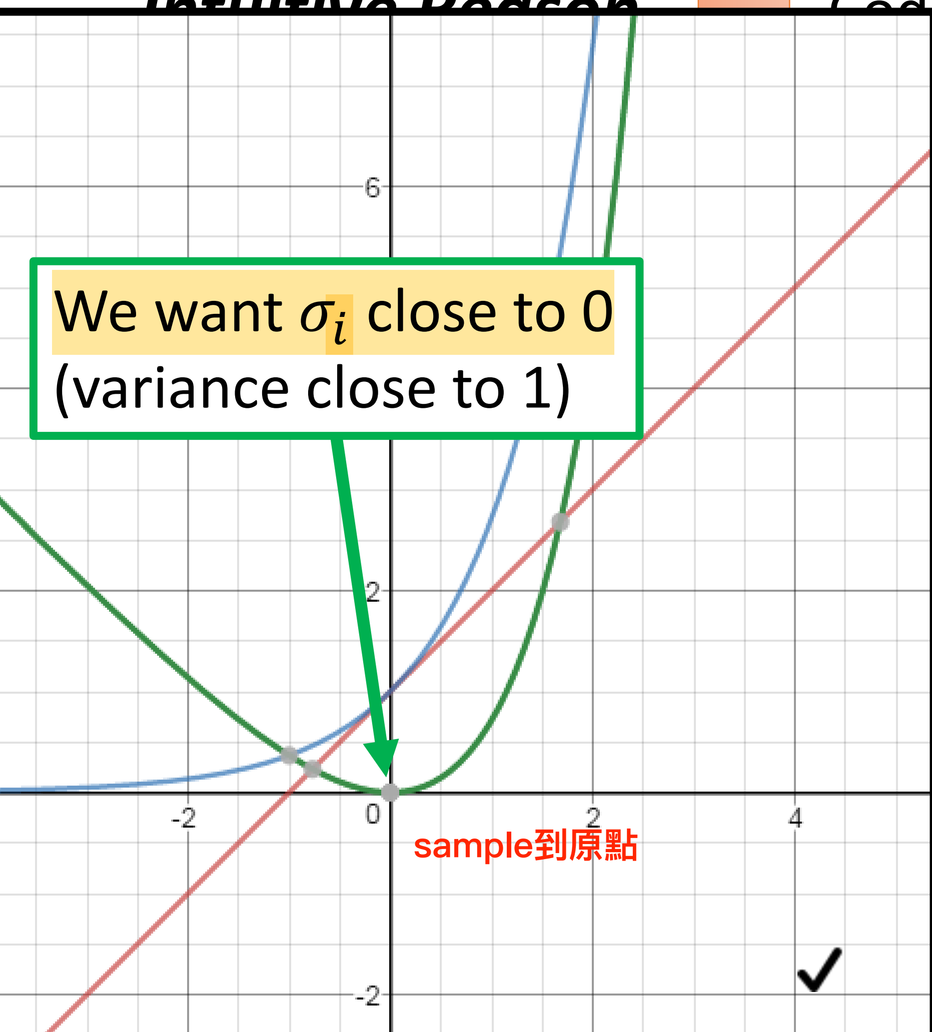
$$\sum_{i=1}^{3}\left(exp(\sigma_i)-(1+\sigma_i)+(m_i)^2\right)$$

The variance of noise is automatically learned

Why VAE?

What will happen if we only minimize reconstruction error?





其min值為，因此sigma最多逼近到0，不會到負無窮大

Minimize

$$\sum_{i=1}^{3}\left(\underline{exp(\sigma_i)} - \underline{(1+\sigma_i)} + \underline{(m_i)^2}\right)$$

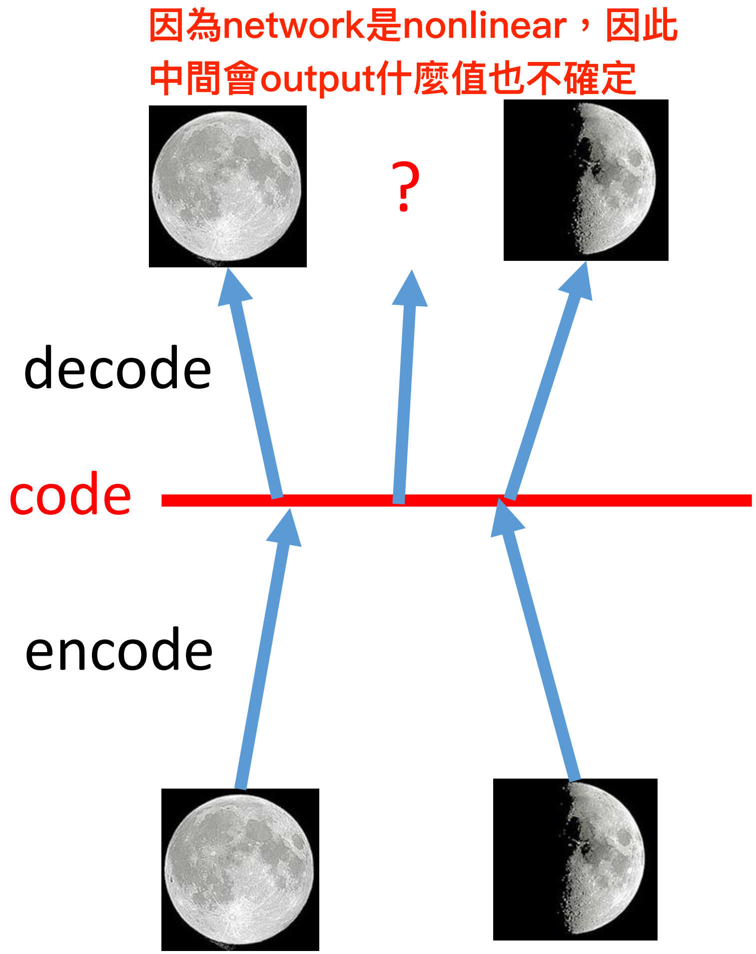
綠色的線為藍色減掉紅色

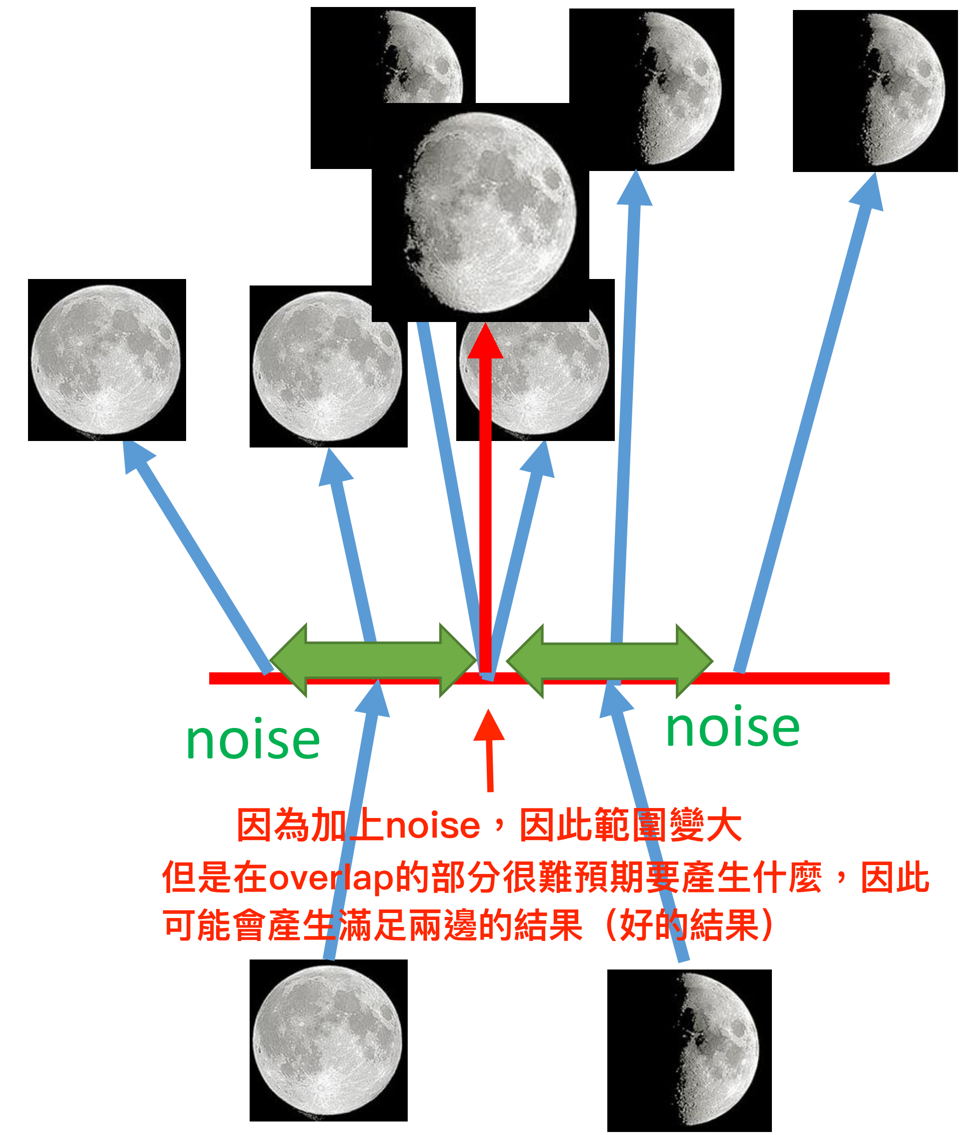
L2 regularization

其實在實作上多加上這一項是不太夠的（太強或太弱）

Why VAE?

Intuitive Reason





Warning of Math

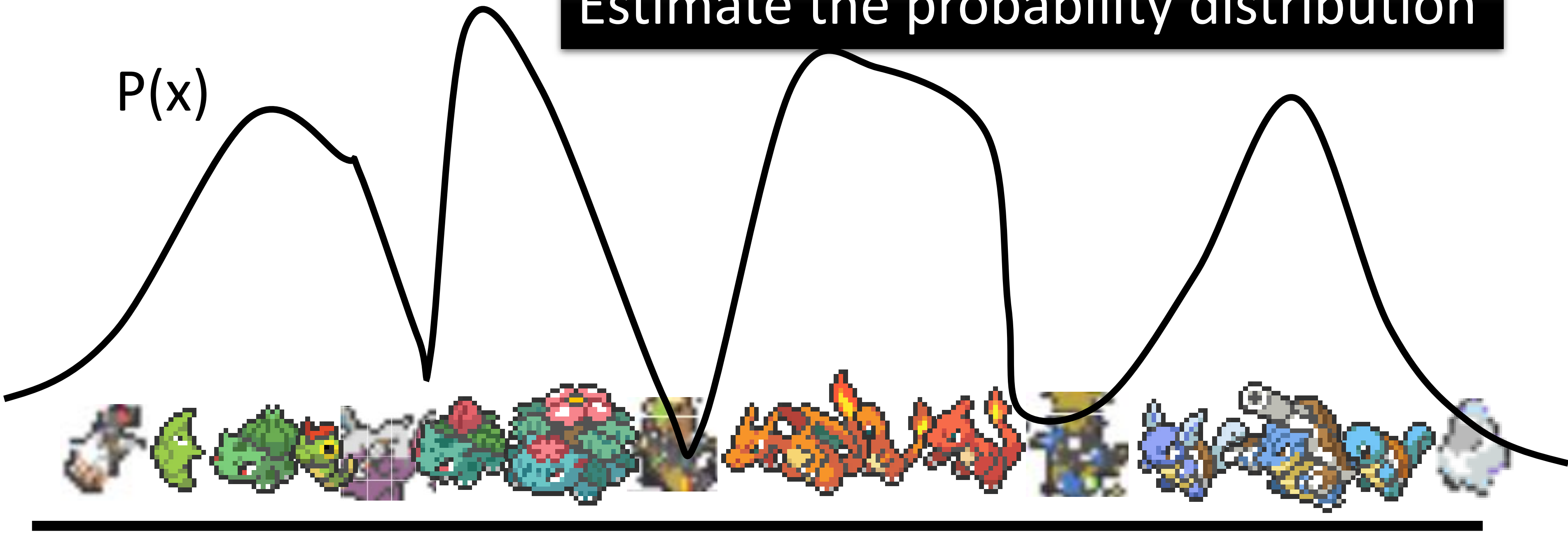
找neural network的參數去maximize likelihood

Why VAE?

- Back to what we want to do

Estimate the probability distribution

P(x)



Each Pokémon is a point x in the space

可estimate probability distribution

Gaussian Mixture Model

corelation

$$P(x) = \sum_m P(m)P(x|m)$$

m代表一個gaussian

How to sample?

$m \sim P(m)$ (multinomial)

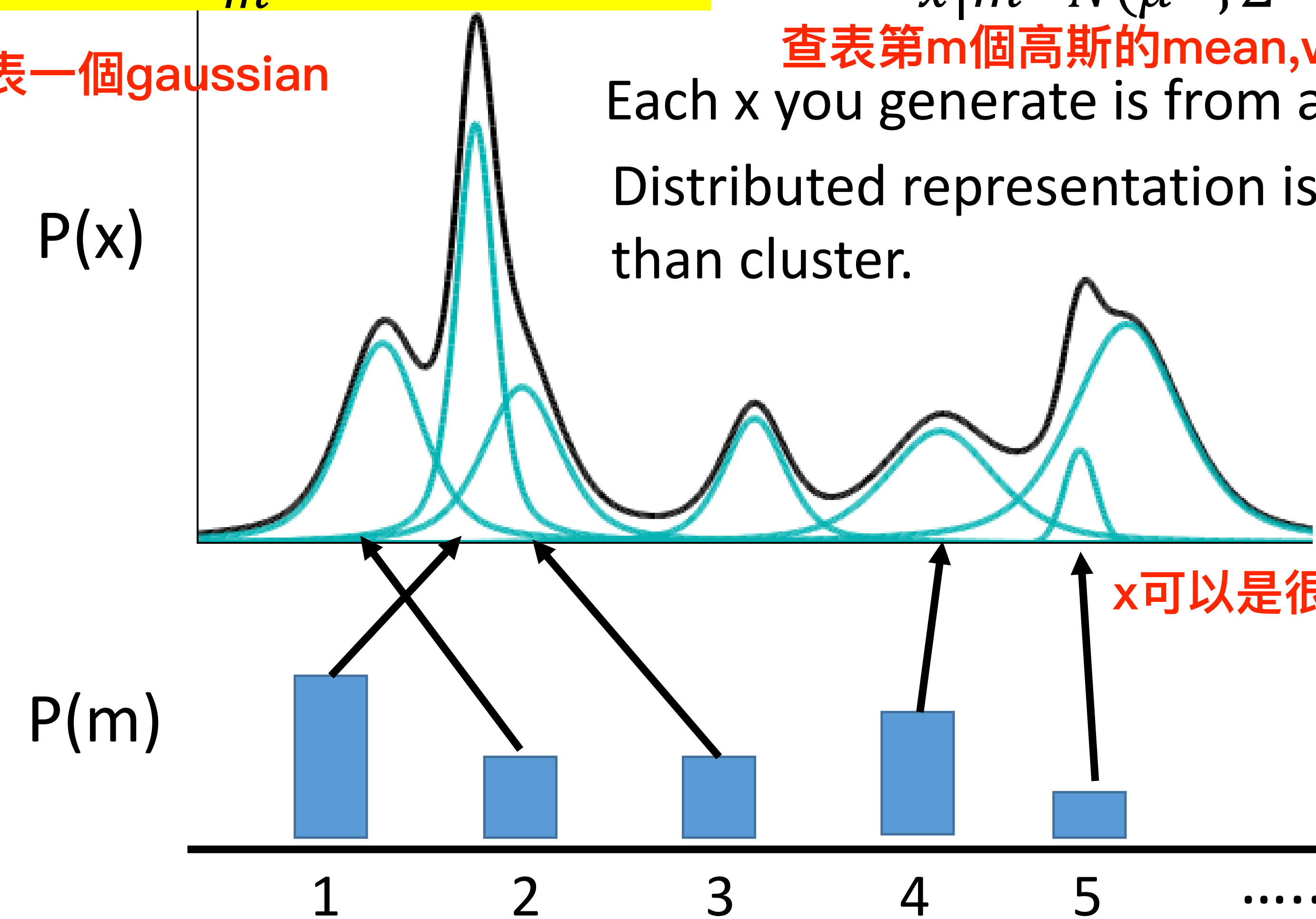
m is an integer

$x|m \sim N(\mu^m, \Sigma^m)$

查表第m個高斯的mean,variance

Each x you generate is from a mixture

Distributed representation is better than cluster.



x可以是很高維的vector

problem: 到底要幾個gaussian

無窮無盡個gaussian

VAE

$$z \sim N(0, I)$$

z is a vector from normal distribution

Each dimension of z represents an attribute

$$x|z \sim N\big(\mu(z), \sigma(z)\big)$$

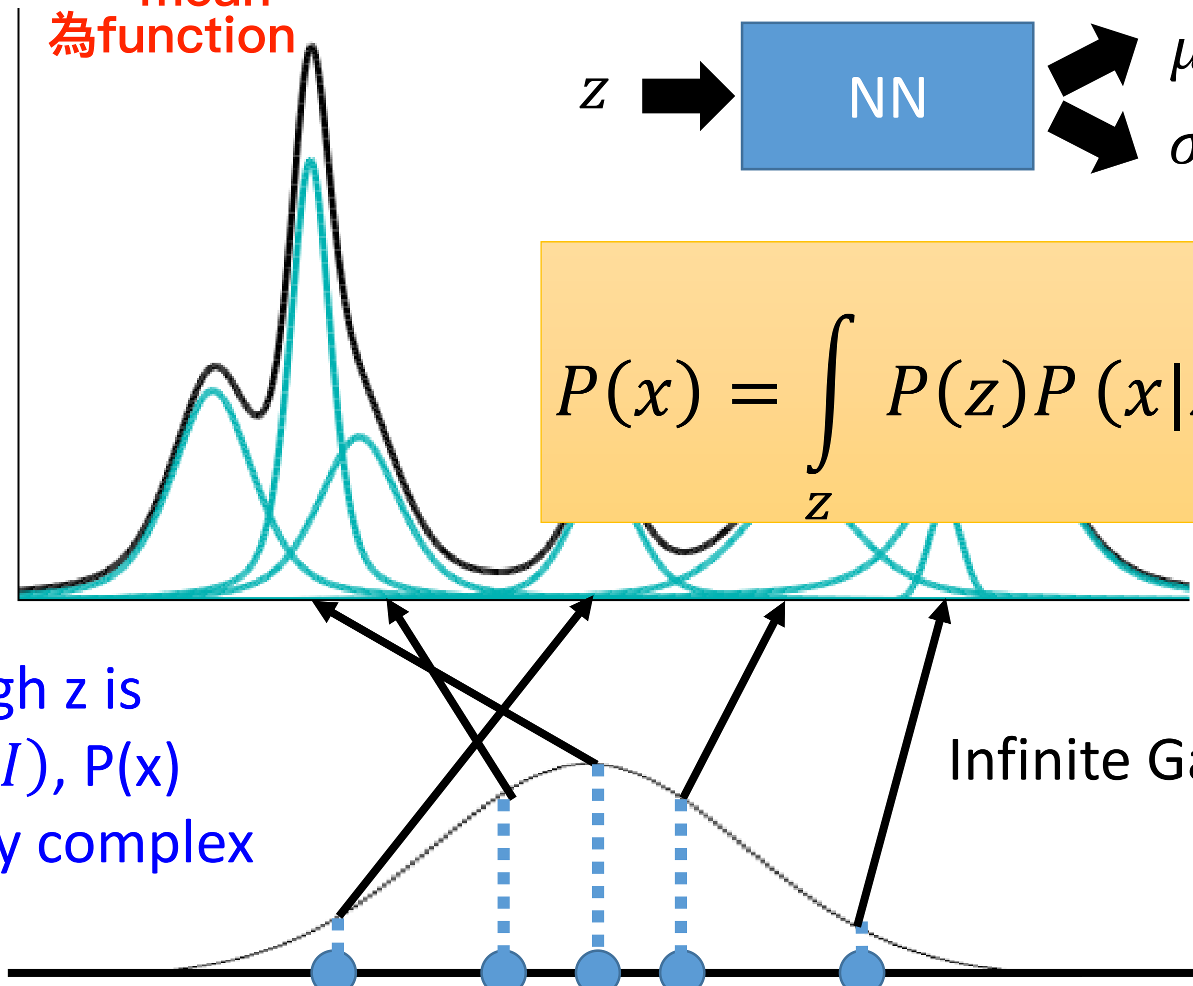
mean var，假設
mean
為function

x: high dim
z: low dim

z → NN → $\mu(z)$, $\sigma(z)$

P(x)

$$P(x) = \int_z P(z)P\left(x|z\right)dz$$



Even though z is from $N(0, I)$, P(x) can be very complex

Infinite Gaussian

Normal Distribution
variance = 1

z上面每一個點是一個Gaussian的分佈，z是無窮無盡的

Maximizing Likelihood

P(z) is normal distribution

$$x|z \sim N\big(\mu(z), \sigma(z)\big)$$

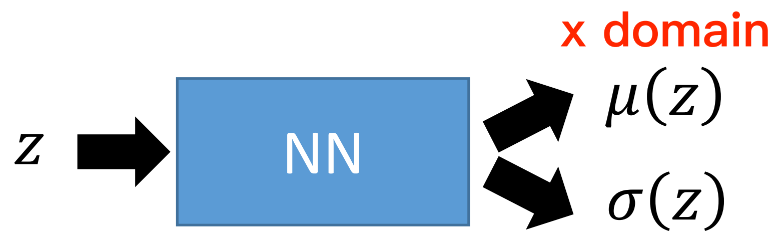
$\mu(z), \sigma(z)$ is going to be estimated

$$P(x) = \int_z P(z) P\,(x|z) dz$$

$$L = \sum_x log P(x)$$

Maximizing the likelihood of the observed x

Tuning the parameters to maximize likelihood L



Decoder

We need another distribution q(z|x)

$$z|x \sim N\big(\mu'(x), \sigma'(x)\big)$$

Encoder

Maximizing Likelihood

P(z) is normal distribution

$$P(x) = \int_z P(z)P(x|z)dz$$

$x|z \sim N(\mu(z), \sigma(z))$

$\mu(z), \sigma(z)$ is going to be estimated

$$L = \sum_x logP(x)$$

Maximizing the likelihood of the observed x

logP(x)可提出來剩下的積分為1

$$logP(x) = \int_z q(z|x)logP(x)dz$$

因為q(z|x)的積分一定為1

q(z|x) can be any distribution

$$= \int_z q(z|x)log\left(\frac{P(z,x)}{P(z|x)}\right)dz = \int_z q(z|x)log\left(\frac{P(z,x)}{q(z|x)}\frac{q(z|x)}{P(z|x)}\right)dz$$

lower bound

$$= \int_z q(z|x)log\left(\frac{P(z,x)}{q(z|x)}\right)dz + \underline{\int_z q(z|x)log\left(\frac{q(z|x)}{P(z|x)}\right)dz}$$

上下相等

$KL(q(z|x)||P(z|x))$

p,q的相異程度

≥ 0

2個distribution的距離

$$\geq \int_z q(z|x)log\left(\frac{P(x|z)P(z)}{q(z|x)}\right)dz$$

$lower\ bound\ L_b$

Maximizing Likelihood

likelihood
likelihodd

$$logP(x) = L_b + KL\big(q(z|x)||P(z|x)\big)$$

norm distribution

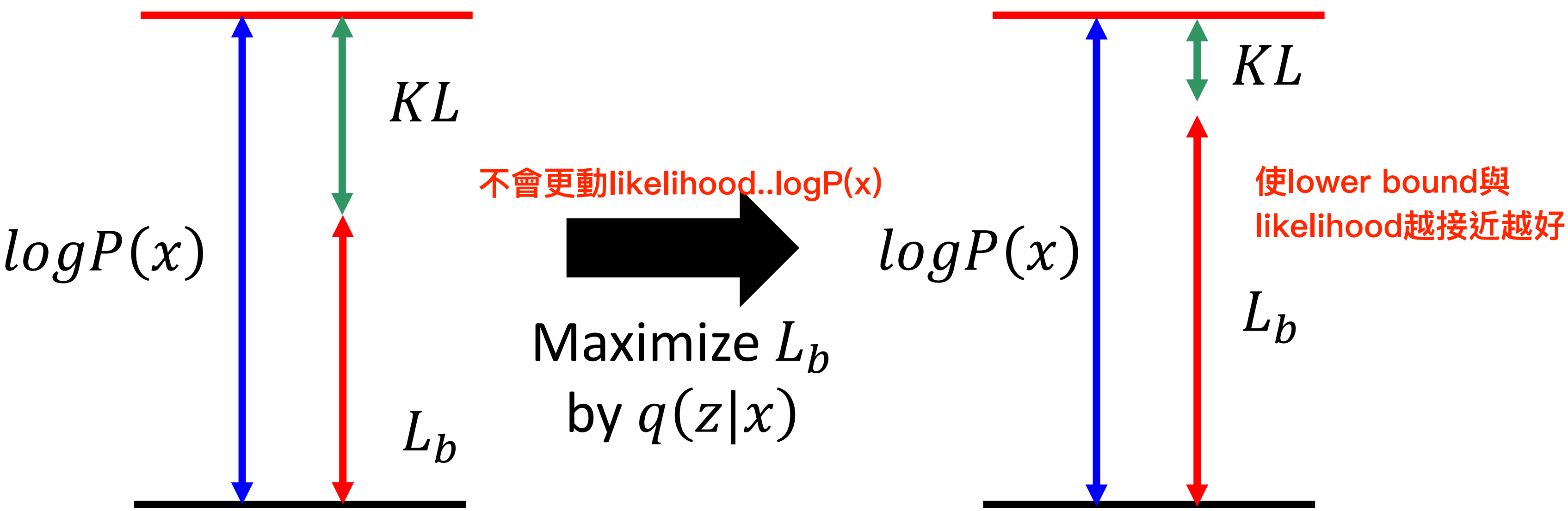
$$L_b = \int_z q(z|x) log\left(\frac{P(x|z)P(z)}{q(z|x)}\right) dz$$

maximize lower bound

Find $P(x|z)$ and $q(z|x)$

maximizing L_b

max lower bound 不一定等同於max likelihood



$q(z|x)$ will be an approximation of $p(z|x)$ in the end

之後就可以拿lower bound來估測P(z|x)

Maximizing Likelihood

P(z) is normal distribution

$$x|z \sim N(\mu(z), \sigma(z))$$

$\mu(z), \sigma(z)$ is going to be estimated

$$P(x) = \int_z P(z)P(x|z)dz$$

$$L = \sum_x logP(x)$$

maximize

Maximizing the likelihood of the observed x

$$L_b = \int_z q(z|x)log\left(\frac{P(z,x)}{q(z|x)}\right)dz = \int_z q(z|x)log\left(\frac{P(x|z)P(z)}{q(z|x)}\right)dz$$

$$= \underbrace{\int_z \boxed{q(z|x)}log\left(\frac{P(z)}{\boxed{q(z|x)}}\right)dz}_{-KL(q(z|x)||P(z))} + \int_z q(z|x)logP(x|z)dz$$

max lower bound希望q(z|x) and P(x)越接近，KL divergence越小越好

$$z|x \sim N(\mu'(x), \sigma'(x))$$

$x \rightarrow$ NN' $\rightarrow \mu'(x)$, $\sigma'(x)$

Connection with Network

這些式子只有在P(z)是normal distribution才能推倒且有好的結果

minimize KL divergence

Minimize

$$\sum_{i=1}^{3}\left(exp(\sigma_i) - (1+\sigma_i) + (m_i)^2\right)$$

Minimizing $KL\big(q(z|x)||P(z)\big)$

(Refer to the Appendix B of the original VAE paper)

Maximizing

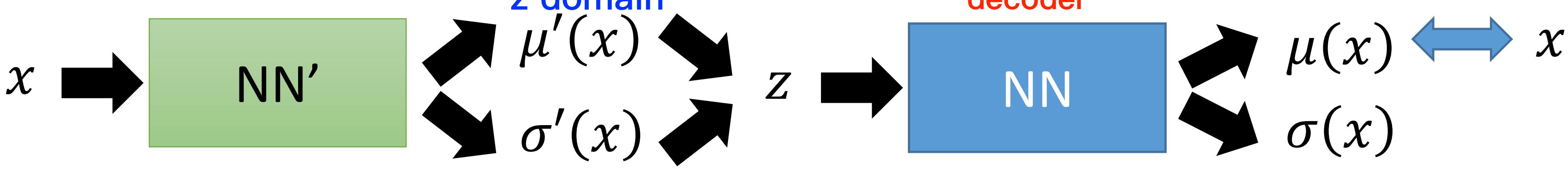
期望值

$$\int_z q(z|x)logP(x|z)dz \;= E_{q(z|x)}[logP(x|z)]$$

與mean越接近，likelihood越大越好close

z domain

decoder



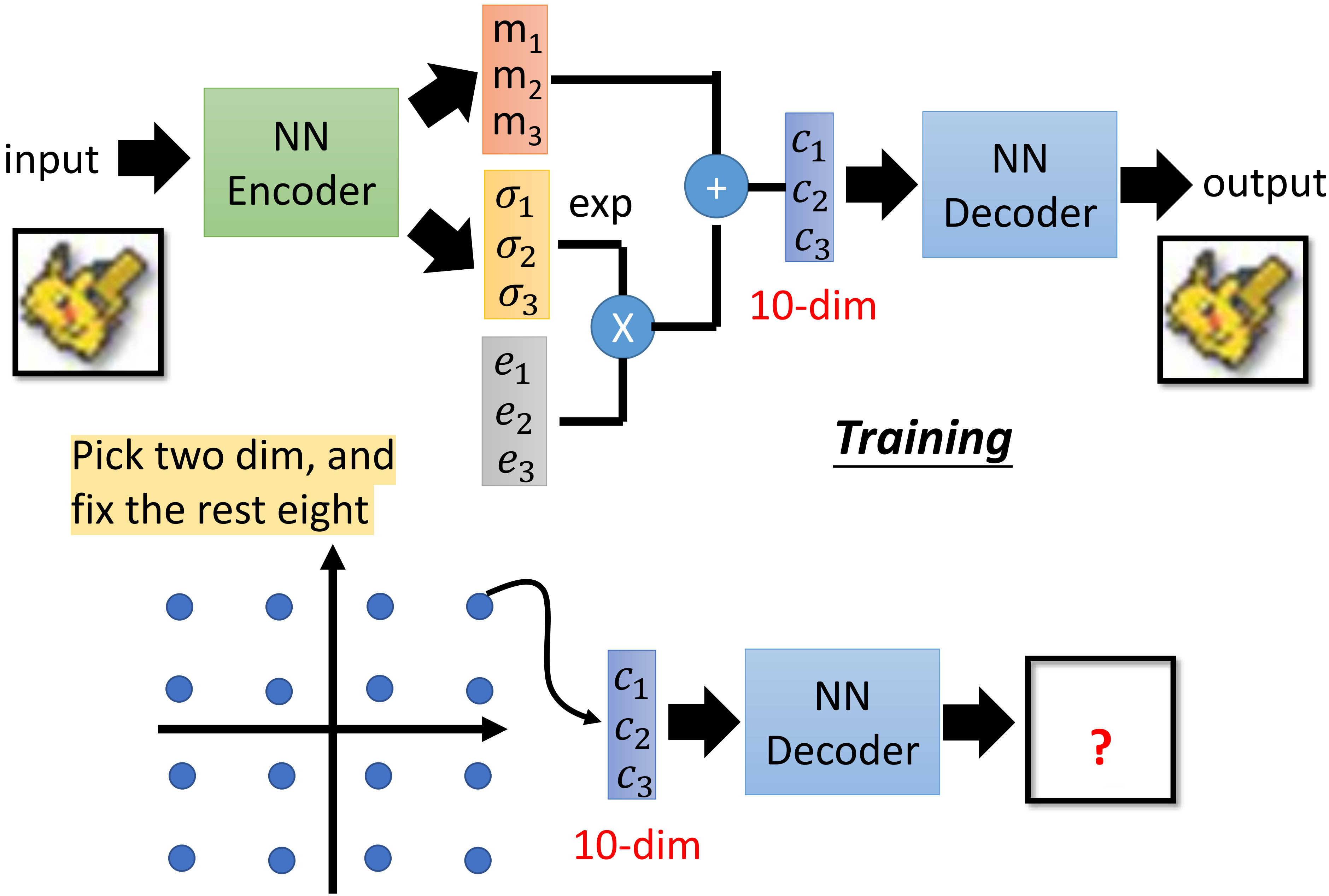
假設為identity，無視

sample時VAE加noise

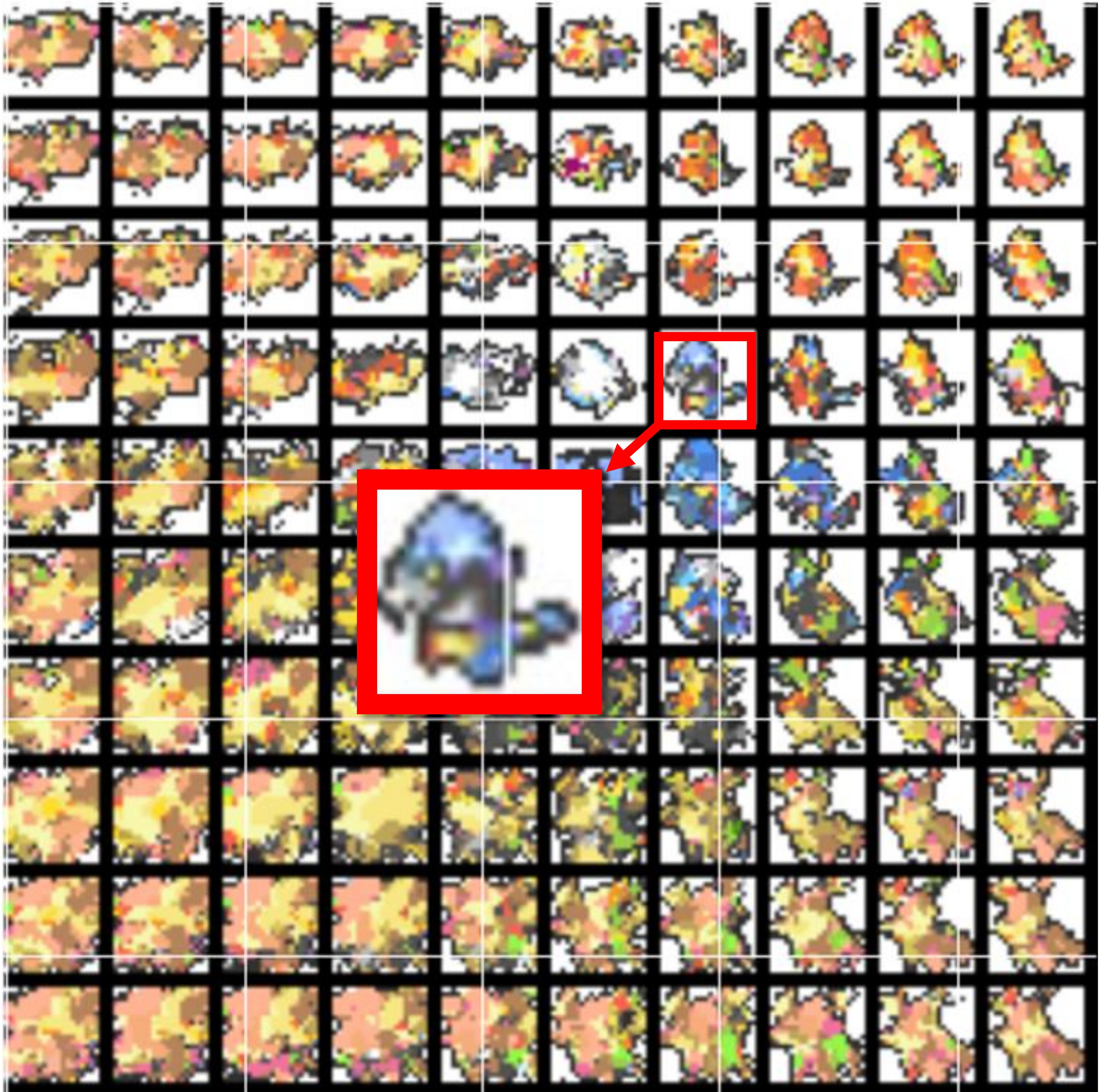
This is the auto-encoder

End of Warning

Pokémon Creation

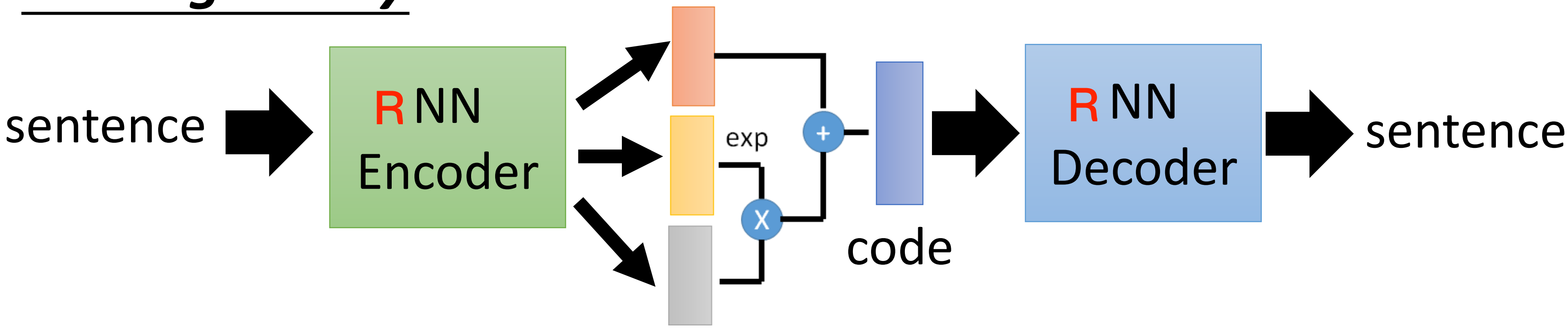


匡邊的效
果不錯



Writing Poetry

Reconstruct Sentence



Code Space

VAE好處是大部分的點sample出來會是一個句子

以往的autodecoder無法達到

Ref: http://www.wired.co.uk/article/google-artificial-intelligence-poetry

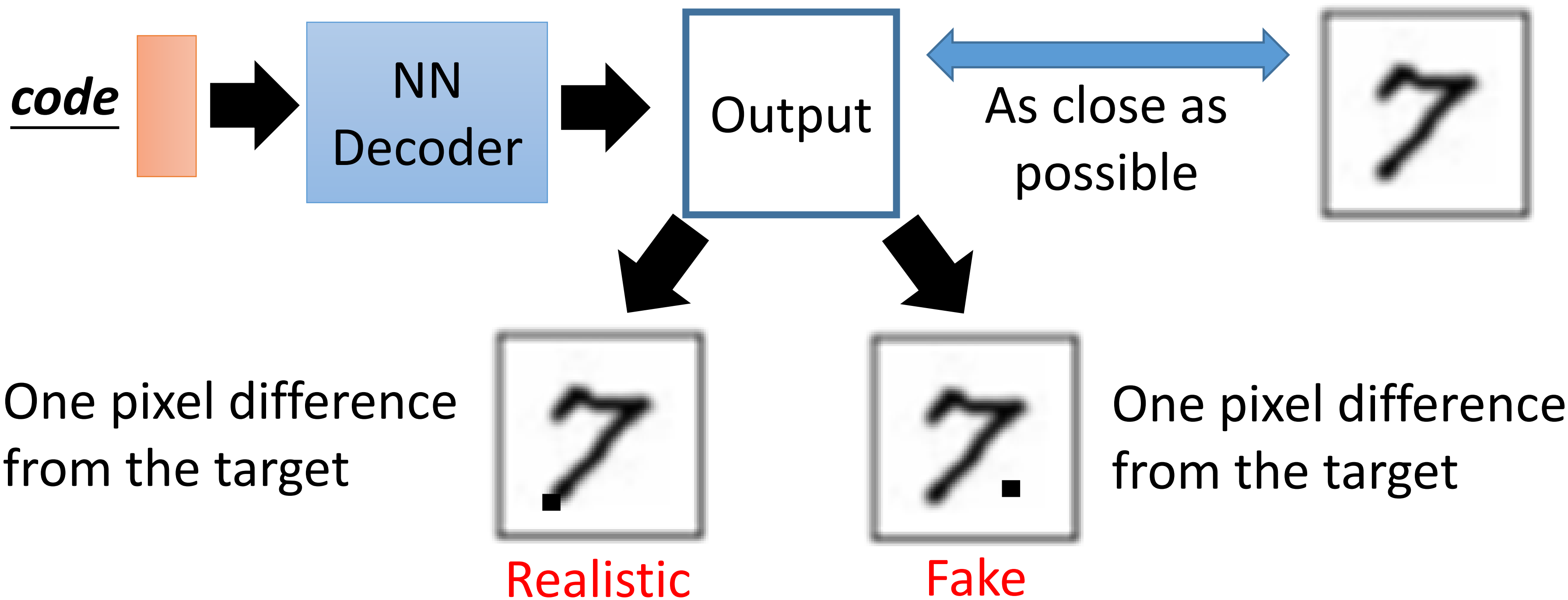
Samuel R. Bowman, Luke Vilnis, Oriol Vinyals, Andrew M. Dai, Rafal Jozefowicz, Samy Bengio, Generating Sentences from a Continuous Space, arXiv prepring, 2015

V A E 的缺點

Problems of VAE

VAE訓練的時候就是希望跟data base中的image越像越好

- It does not really try to simulate real images



兩張image對machine來說loss value皆為一個pixel，然而第一張圖人類比較能接受但VAE(AE)無法判斷

VAE may just memorize the existing images, instead of generating new images

Generative Models

Component-by-component

Autoencoder

Generative Adversarial Network (GAN)

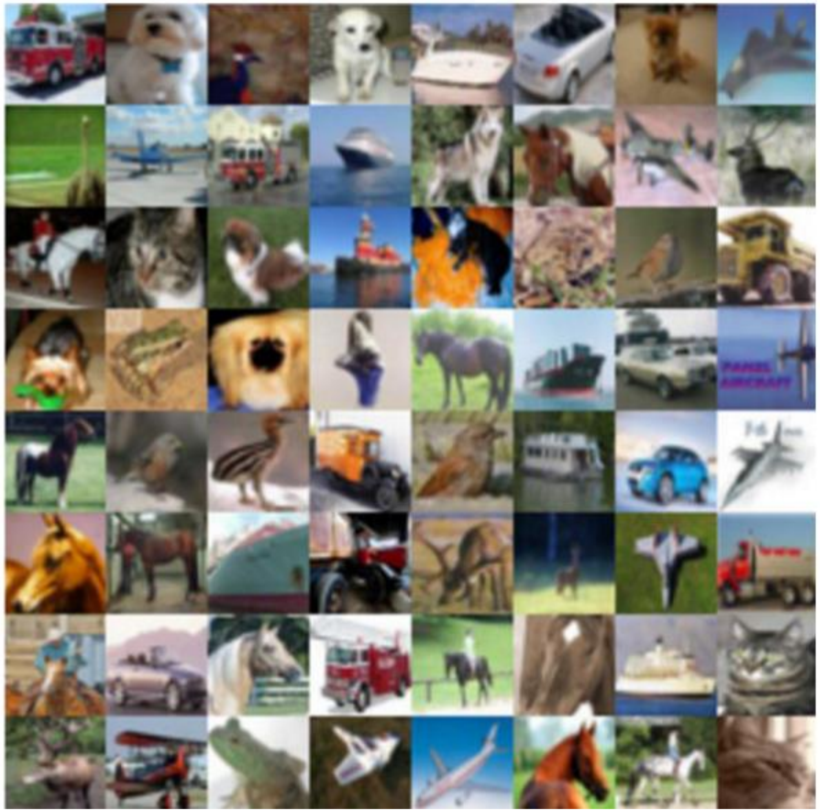
Ian J. Good fellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio, Generative Adversarial Networks, arXiv preprint 2014

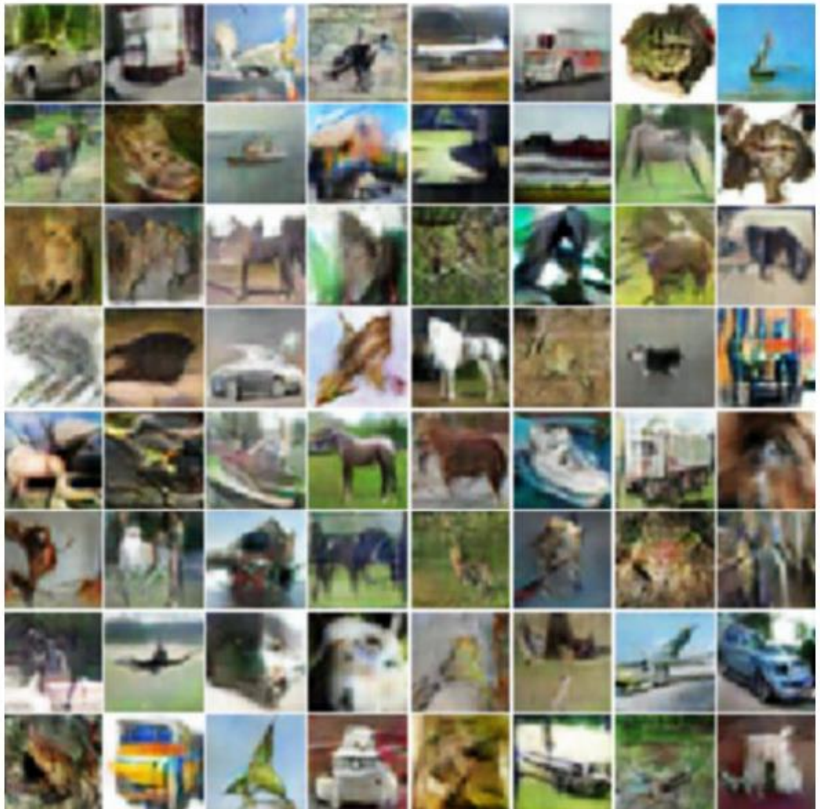
可合出真實且以假轉真的結果

Cifar-10

- Which one is machine-generated?

ＧＡＮ產生





Ref: https://openai.com/blog/generative-models/

Yann LeCun’s comment

What are some recent and potentially upcoming breakthroughs in unsupervised learning?

Yann LeCun, Director of AI Research at Facebook and Professor at NYU

Written Jul 29 · Upvoted by Joaquin Quiñonero Candela, Director Applied Machine Learning at Facebook and Huang Xiao

有史以來

Adversarial training is the coolest thing since sliced bread.

I’ve listed a bunch of relevant papers in a previous answer.

Expect more impressive results with this technique in the coming years.

What’s missing at the moment is a good understanding of it so we can make it work reliably. It’s very finicky. Sort of like ConvNet were in the 1990s, when I had the reputation of being the only person who could make them work (which wasn’t true).

https://www.quora.com/What-are-some-recent-and-potentially-upcoming-breakthroughs-in-unsupervised-learning

Yann LeCun's comment

What are some recent and potentially upcoming breakthroughs in deep learning?

Yann LeCun, Director of AI Research at Facebook and Professor at NYU

Written Jul 29 · Upvoted by Joaquin Quiñonero Candela, Director Applied Machine Learning at Facebook and Nikhil Garg, I lead a team of Quora engineers working on ML/NLP problems

……

The most important one, in my opinion, is adversarial training (also called GAN for Generative Adversarial Networks). This is an idea that was originally proposed by Ian Goodfellow when he was a student with Yoshua Bengio at the University of Montreal (he since moved to Google Brain and recently to OpenAI).

This, and the variations that are now being proposed is the most interesting idea in the last 10 years in ML, in my opinion.

https://www.quora.com/What-are-some-recent-and-potentially-upcoming-breakthroughs-in-deep-learning

Evolution

演化過程

http://peellden.pixnet.net/blog/post/40406899-2013-%E7%AC%AC%E5%9B%9B%E5%AD%A3%EF%BC%8C%E5%86%AC%E8%9D%B6%E5%AF%82%E5%AF%A5

Brown

Kallima inachus

veins

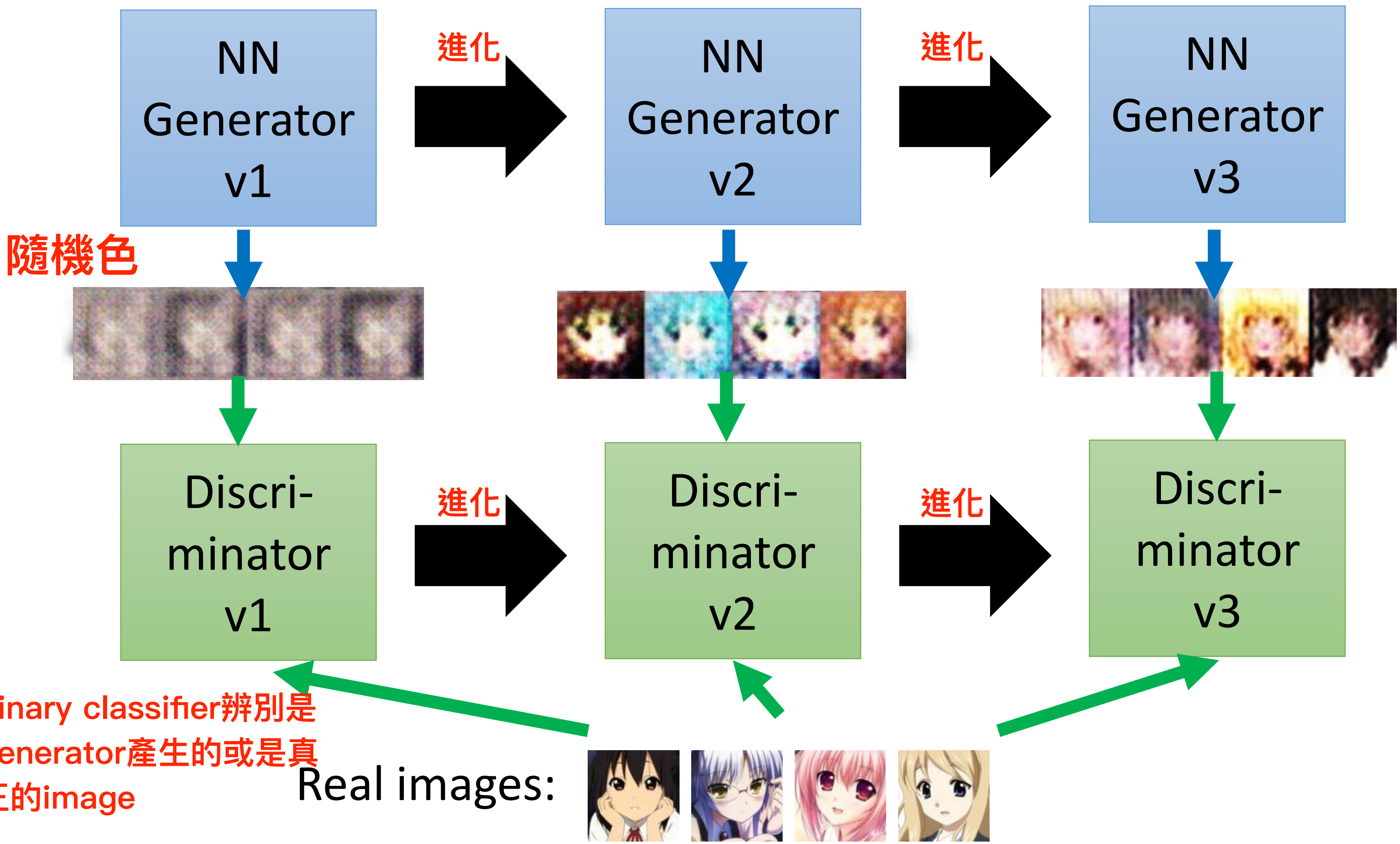
Butterflies are not brown

Butterflies do not have veins

……..

GAN就像演化過程

The evolution of generation



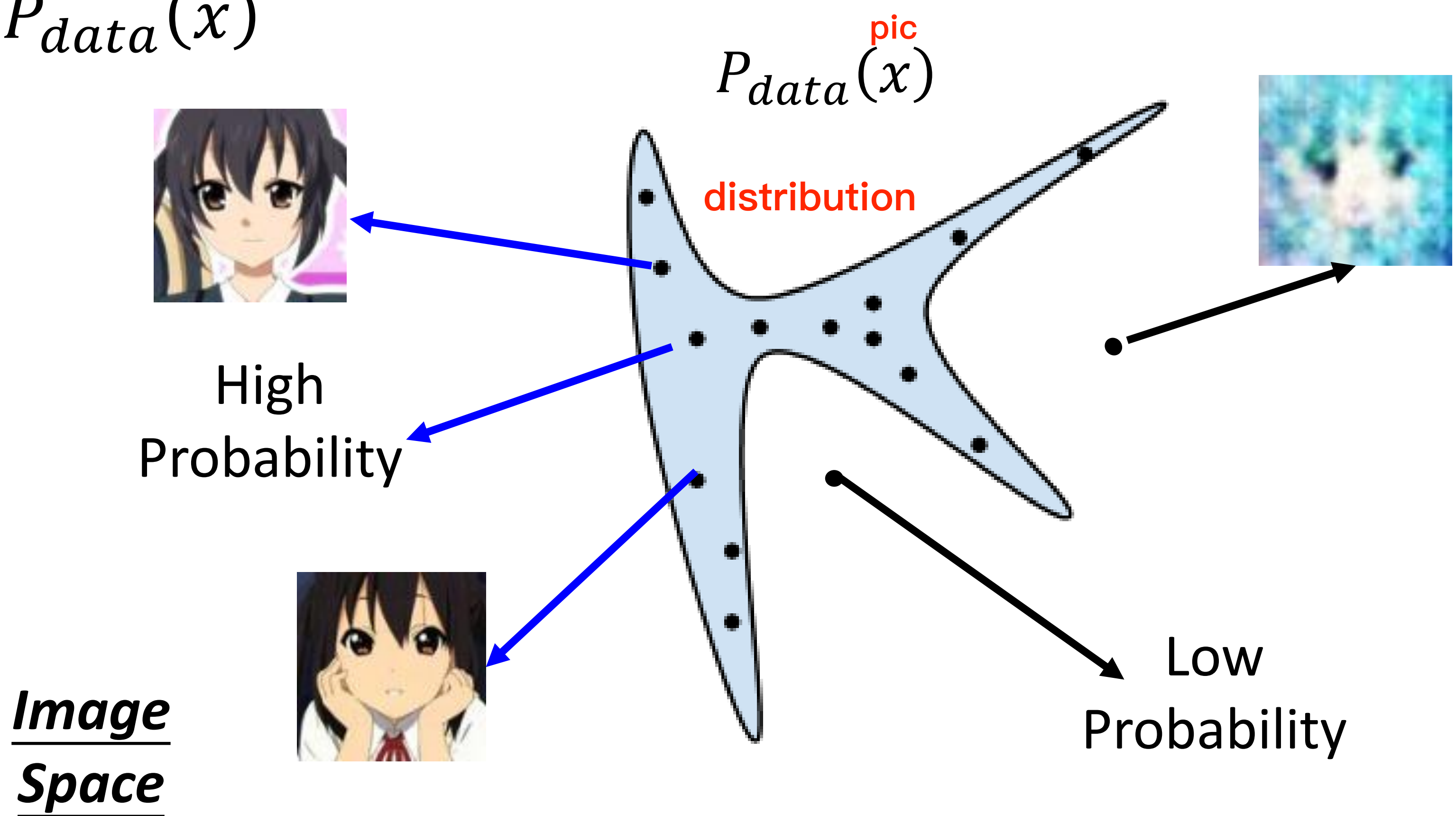
binary classifier辨別是generator產生的或是真正的image

Basic Idea of GAN

每個點是高維空間中的一個vector

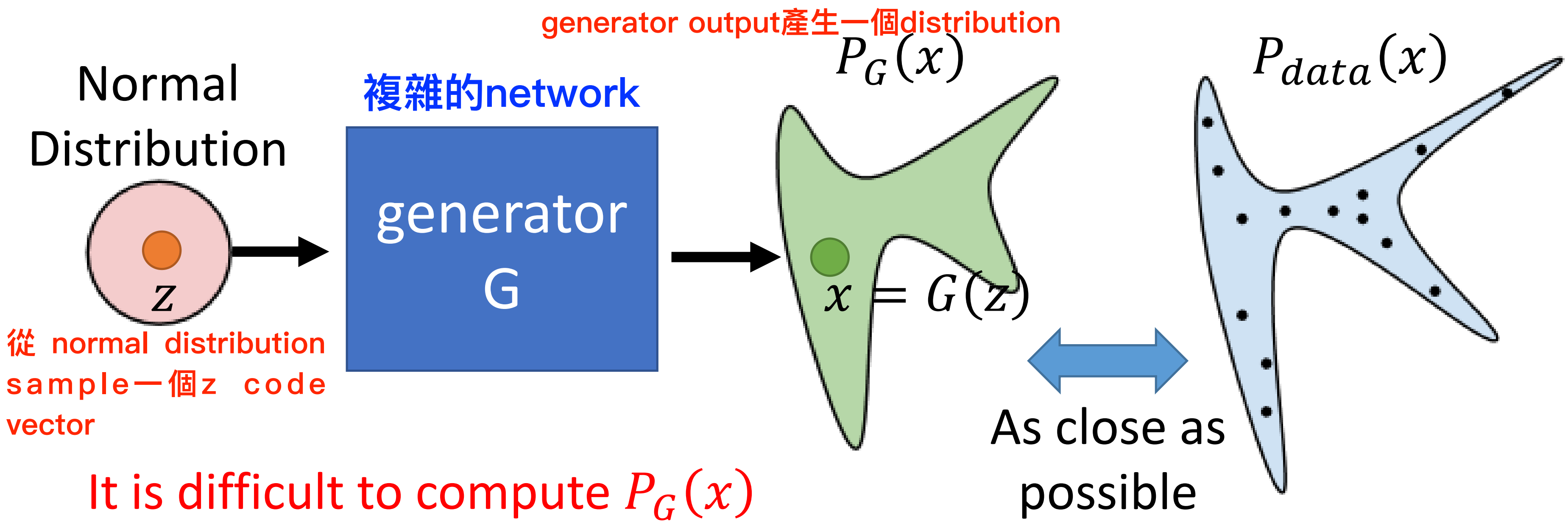
因此只要找到一個好的distribution即可sample出一個正常的model

- The data we want to generate has a distribution $P_{data}(x)$



Basic Idea of GAN

- A generator G is a network. The network defines a probability distribution.



It is difficult to compute $P_G(x)$

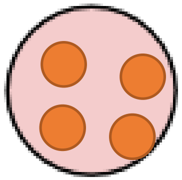
We do not know what the distribution looks like. 無法計算maximum likelihood，因此無法衡量到底接不接近

https://blog.openai.com/generative-models/

ＧＡＮ提出一個有趣的方法比較generator產生的distribution與真實data的distribution相似度

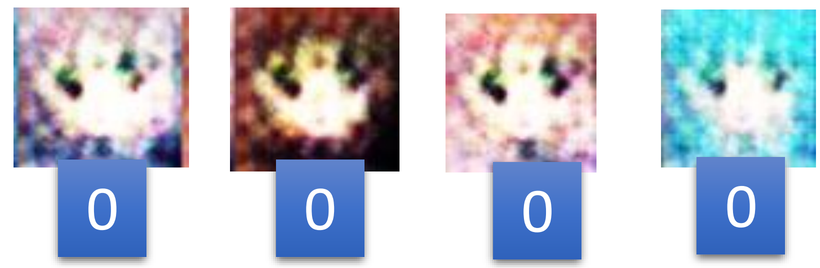
Basic Idea of GAN

Normal Distribution



NN Generator v1

$P_G(x)$



不知道distribution，無法計算相近程度

$P_{data}(x)$

ＧＡＮ利用discriminator比較相近

discriminator: binary classifier/ sigmoid/ min cross entropy

image → Discri-minator v1 → 1/0

It can be proofed that the ***loss the discriminator*** related to ***JS divergence***.

KL divergence...等

train一個discriminator，其loss即代表其JS divergence

Basic Idea of GAN

更新generator參數讓discriminator的loss變大，代表讓JS divergence變小

- ***Next step***:
  - Updating the parameters of generator
  - To minimize the JS divergence

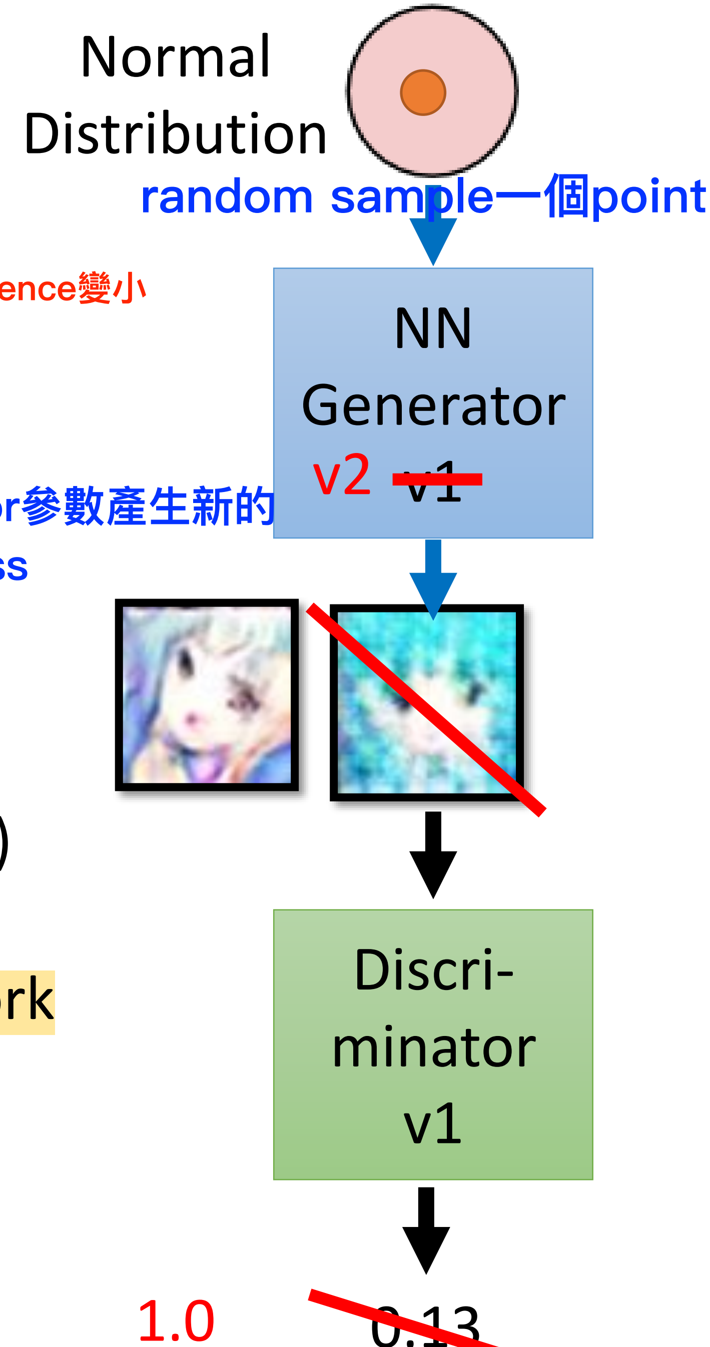
調整generator參數產生新的 image提高loss

➡ The output be classified as "real" (as close to 1 as possible)

1: realistic，0: generative

Generator + Discriminator = a network

Using gradient descent to update the parameters in the generator, but fix the discriminator



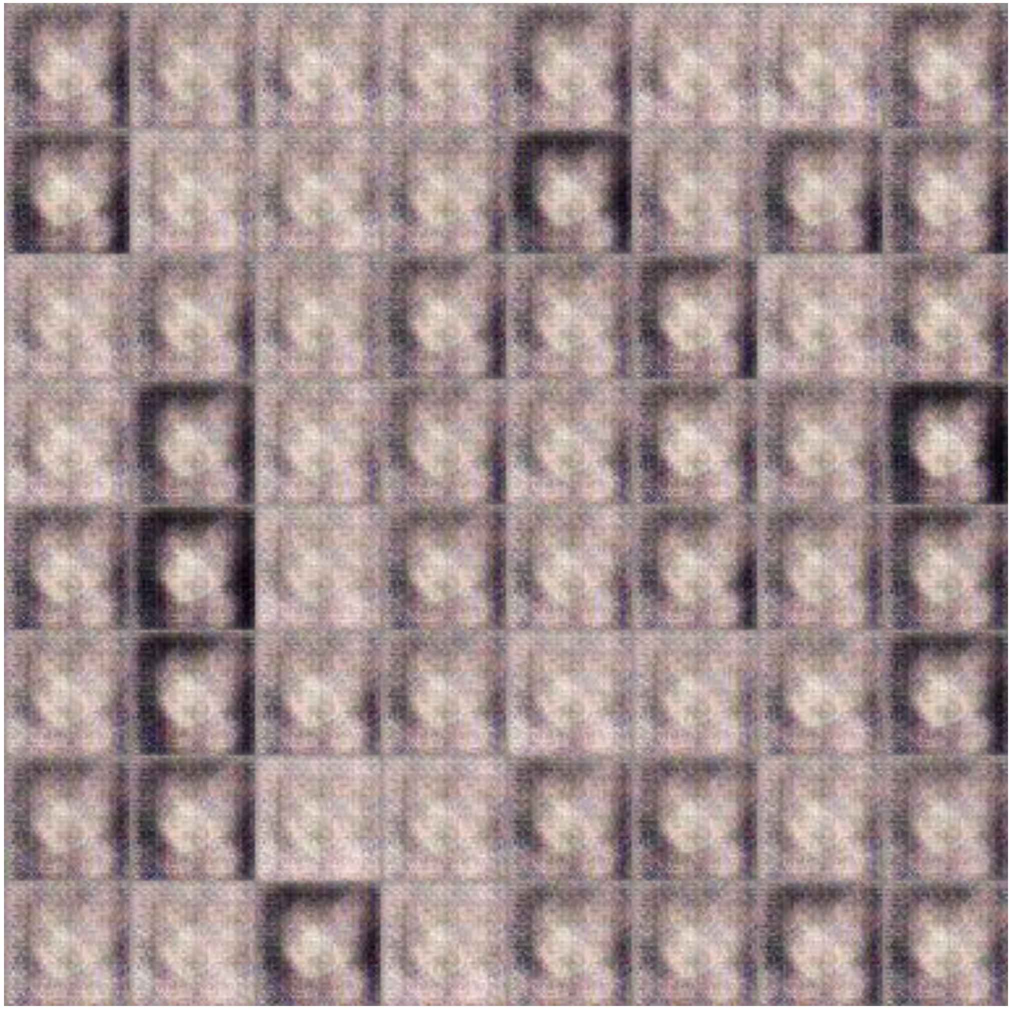
讓機器將generator產生的圖誤判成真實的圖

GAN – 二次元人物頭像鍊成

Source of images: https://zhuanlan.zhihu.com/p/24767059

DCGAN: https://github.com/carpedm20/DCGAN-tensorflow

GAN – 二次元人物頭像鍊成



update 100次參數

100 rounds

GAN – 二次元人物頭像鍊成

update 1000次參數

1000 rounds

GAN – 二次元人物頭像鍊成

update 2000次參數

2000 rounds

GAN – 二次元人物頭像鍊成

update 5000次參數

5000 rounds

GAN – 二次元人物頭像鍊成

update 10000次參數

10,000 rounds

GAN – 二次元人物頭像鍊成

update 20000次參數

20,000 rounds

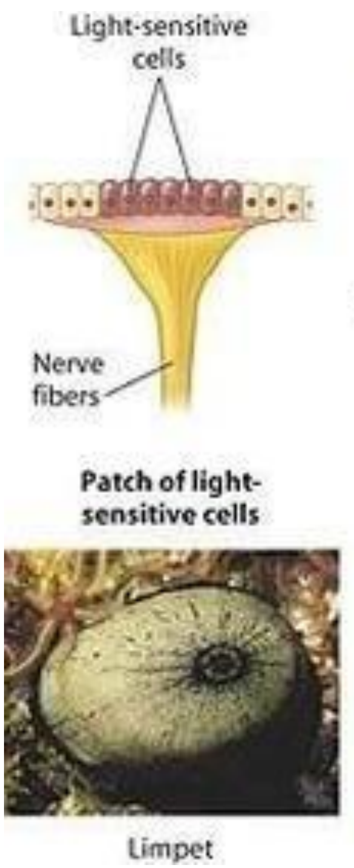
GAN – 二次元人物頭像鍊成

update 50000次參數

50,000 rounds

Why GAN is hard to train?

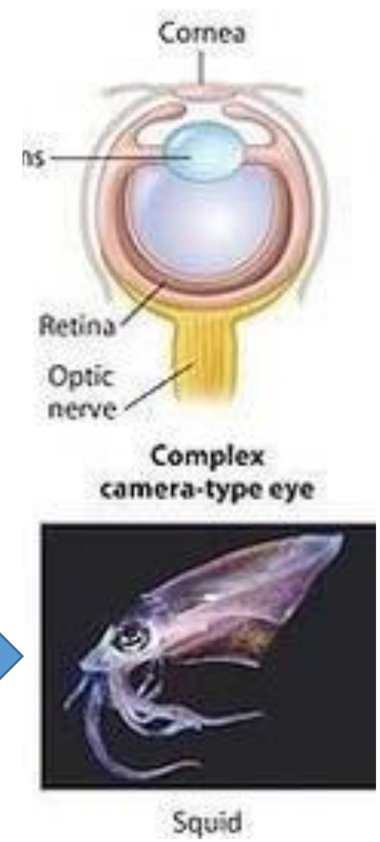
回到演化的比喻 ……



每個階段要比前一個階段好

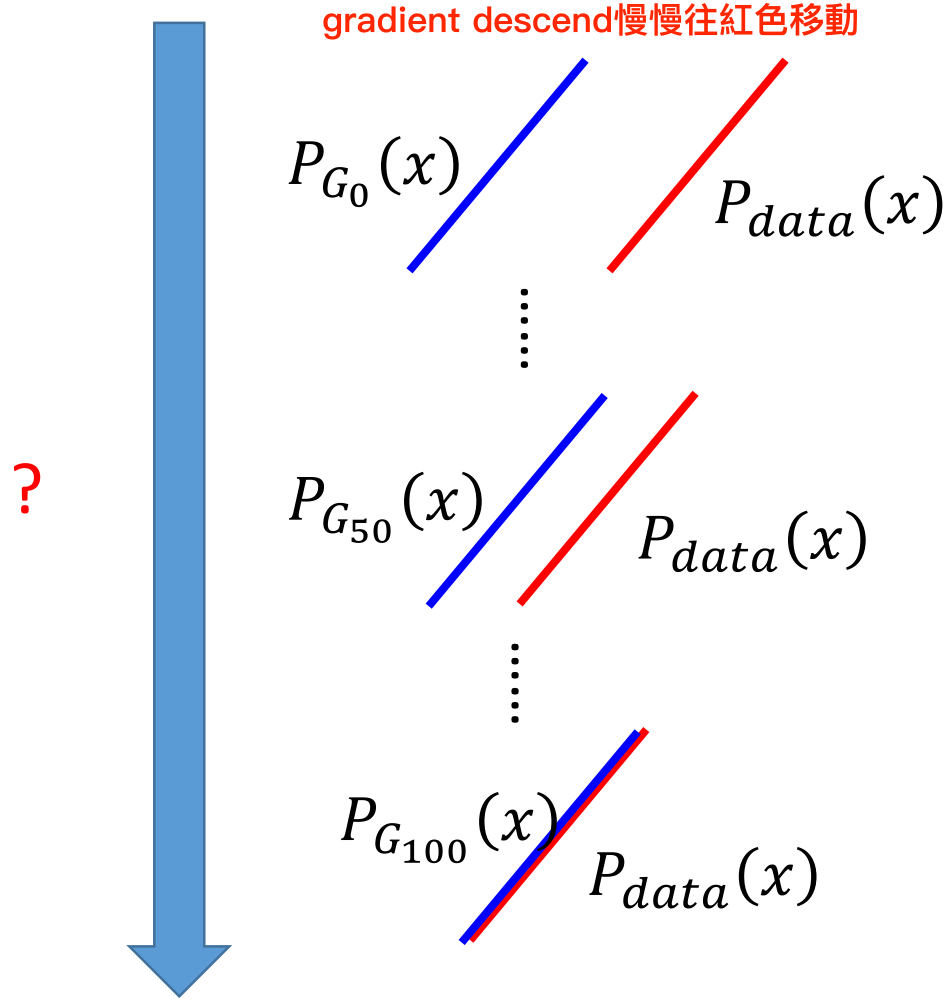
眼球的演化階段 X D

Better



Why GAN is hard to train?

gradient descend慢慢往紅色移動



$JS(P_{G_1}||P_{data}) = log2$

JS divergence 在沒有overlap的情況下value皆固定為log2，因此不知道要往哪裡移動

$JS(P_{G_2}||P_{data}) = log2$

Not really better ……

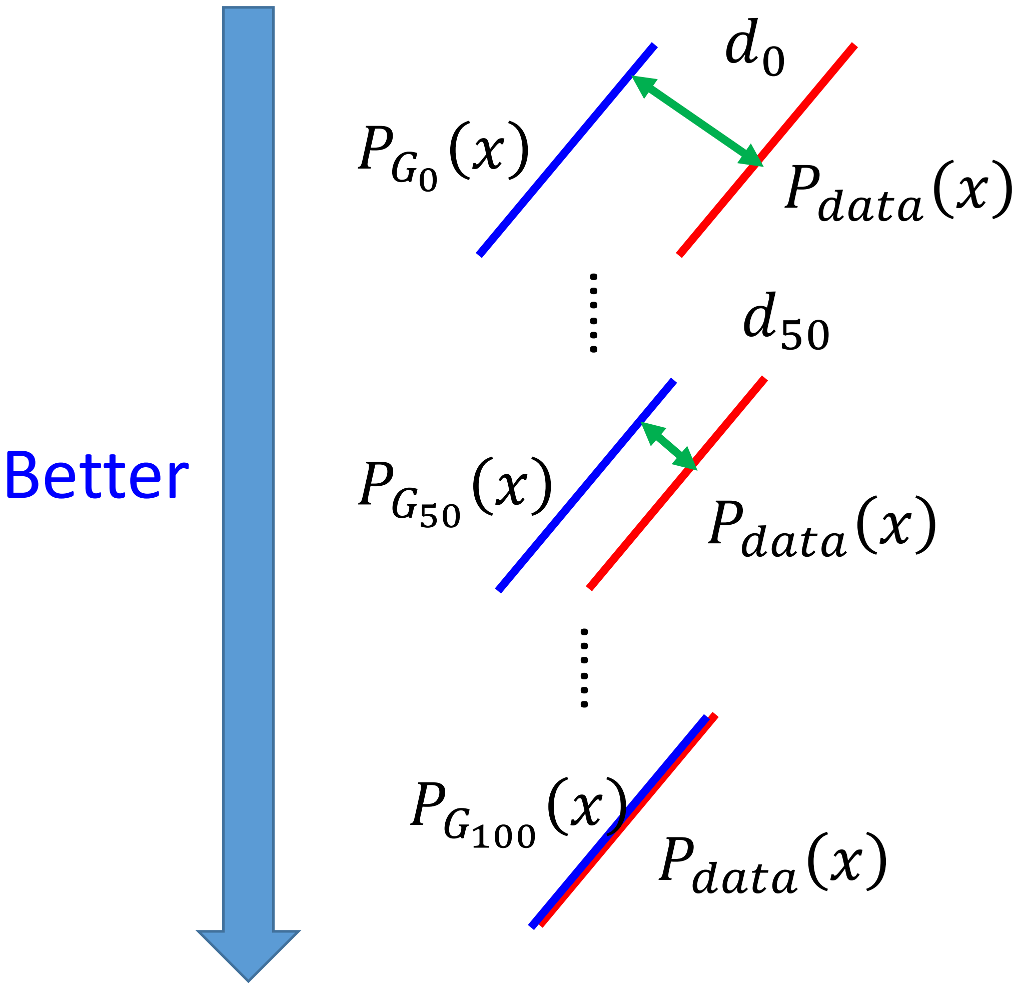
$JS(P_{G_2}||P_{data}) = 0$

WGAN解決GAN的JS divergence難train的問題，因為利用Wasserstein distance

WGAN

v'

Using Wasserstein distance instead of JS divergence



距離

$$W\left(P_{G_1}||P_{data}\right) = d_0$$

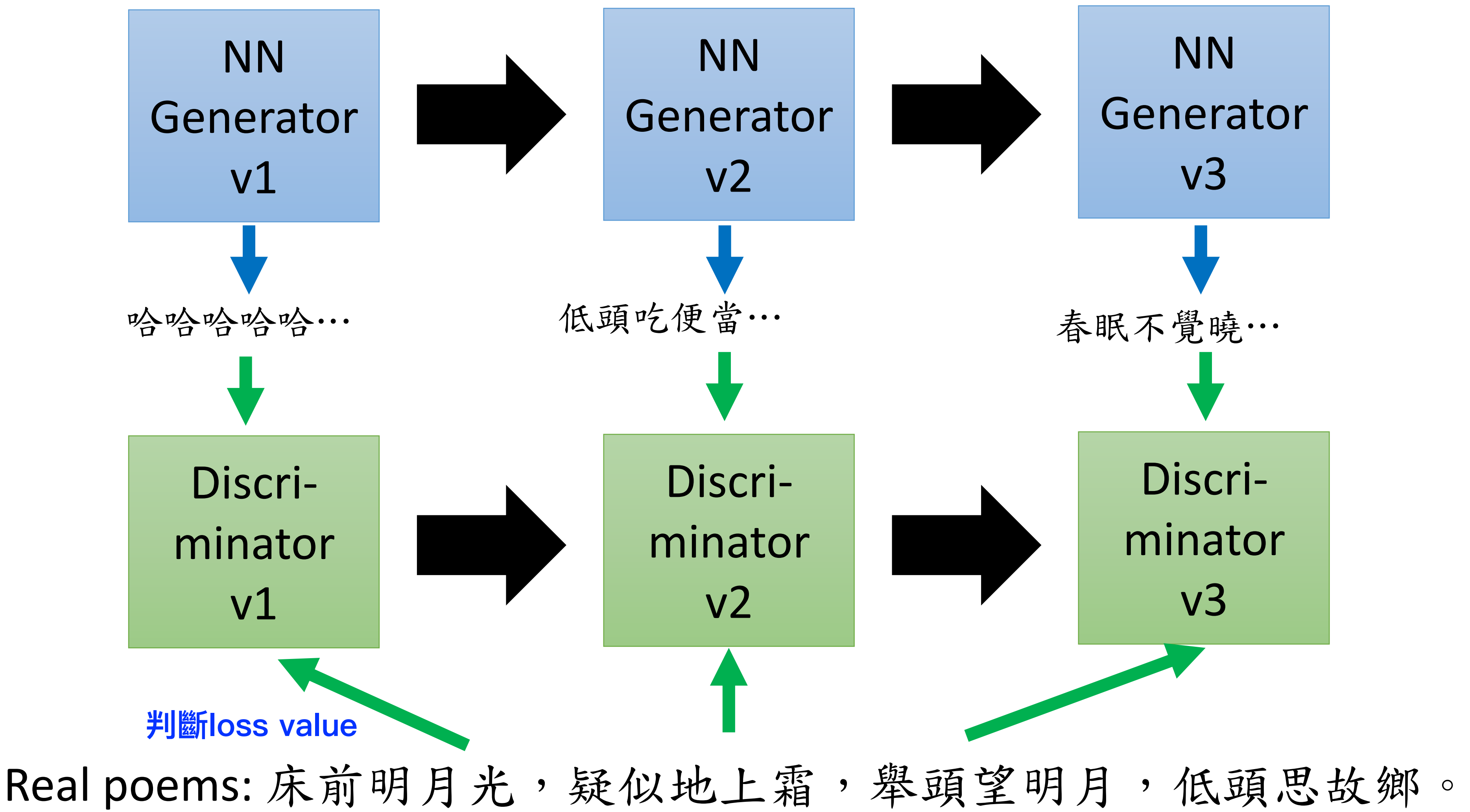
距離

$$W\left(P_{G_2}||P_{data}\right) = d_{50}$$

距離

$$W\left(P_{G_2}||P_{data}\right) = 0$$

WGAN – 唐詩鍊成



NN Generator v1
NN Generator v2
NN Generator v3
哈哈哈哈哈…
低頭吃便當…
春眠不覺曉…
Discri-minator v1
Discri-minator v2
Discri-minator v3
判斷loss value
Real poems: 床前明月光，疑似地上霜，舉頭望明月，低頭思故鄉。

WGAN – 唐詩鍊成

由 李仲翊 同學提供實驗結果

Random generated

- 升雲白遲丹齋取，此酒新巷市入頭。黃道故海歸中後，不驚入得韻子門。
- 據口容章蓄翎翎，邦貸無遊隔將毬。外蕭曾臺遶出畧，此計推上呂天夢。
- 新來寶伎泉，手雪泓臺蓑。曾子花路魏，不謀散薦船。
- 功持牧度機邈爭，不躚官嬉牧涼散。不迎白旅今掩冬，盡蘸金祇可停。
- 玉十洪沄爭春風，溪子風佛挺橫鞋。盤盤稅焰先花齋，誰過飄鶴一丞幢。
- 海人依野庇，為阻例沉迴。座花不佐樹，弟闌十名儂。
- 入維當興日世瀕，不評皺。頭醉空其杯，駸園凋送頭。
- 鉢笙動春枝，寶粢潔長知。官爲窸爛去，絆粒薛一靜。
- 吾涼腕不楚，縱先待旅知。楚人縱酒待，一蔓飄聖猜。
- 折幕故癘應韻子，徑頭霜瓊老徑徑。尚錯春鏘熊悽梅，去吹依能九將香。
- 通可矯目鷚須浄，丹迤挈花一抵嫖。外子當目中前醒，迎日幽筆鈎弧前。
- 庭愛四樹人庭好，無衣服仍繡秋州。更怯風流欲鴆雲，帛陽舊據畆婷儻。

Moving on the code space

database中的一張圖 <–interpolation後丟進去DCGAN產生圖–> database中的一張圖

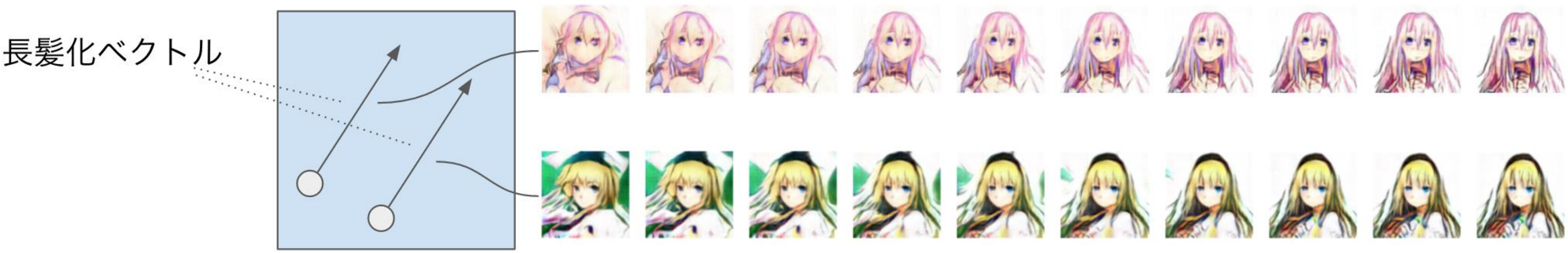
Alec Radford, Luke Metz, Soumith Chintala, Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks, ICLR, 2016

DC GAN

Moving on the code space

如果知道每個dimension的含義就可以自由調整

- Ref: http://qiita.com/mattya/items/e5bfe5e04b9d2f0bbd47

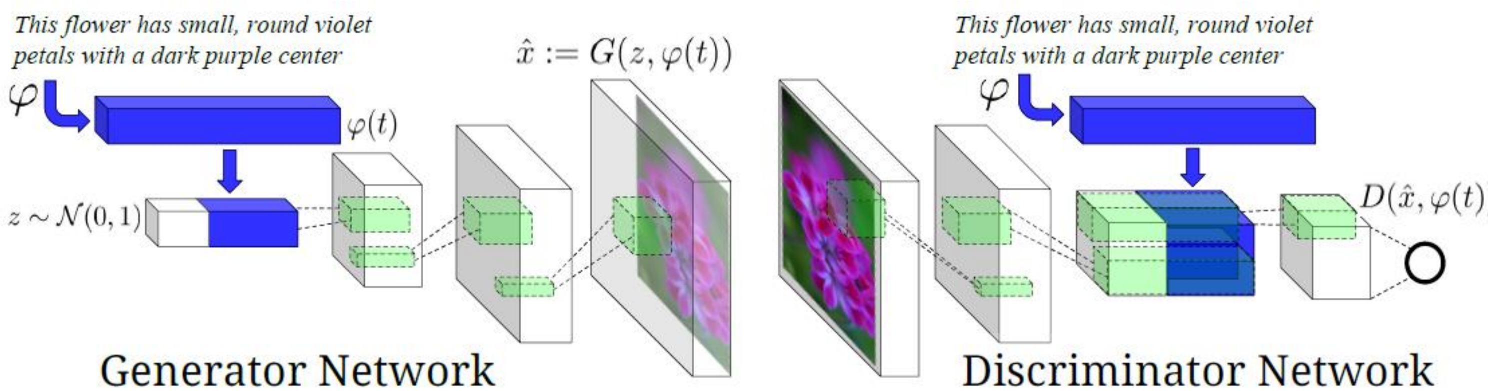


一番左のキャラクターが元画像で、
右に行くほど長髪化ベクトルを強く足している

元画像　－赤髪＋金髪　－赤目＋青目　＋制服＋セーラー　＋笑顔＋口開き　＋青背景

Text to Image

Text → Generator → Image



Scott Reed, Zeynep Akata, Xinchen Yan, Lajanugen Logeswaran, Bernt Schiele, Honglak Lee, "Generative Adversarial Text-to-Image Synthesis", ICML 2016

Han Zhang, Tao Xu, Hongsheng Li, Shaoting Zhang, Xiaolei Huang, Xiaogang Wang, Dimitris Metaxas, "StackGAN: Text to Photo-realistic Image Synthesis with Stacked Generative Adversarial Networks", arXiv prepring, 2016

Scott Reed, Zeynep Akata, Santosh Mohan, Samuel Tenka, Bernt Schiele, Honglak Lee, "Learning What and Where to Draw", NIPS 2016

Text to Image

"red flower with black center"

Caption	Image
this flower has white petals and a yellow stamen	
the center is yellow surrounded by wavy dark purple petals	
this flower has lots of small round pink petals	

Text to Image

由 曾柏翔 同學
提供實驗結果

- E.g. 根據文字敘述畫出動漫人物頭像

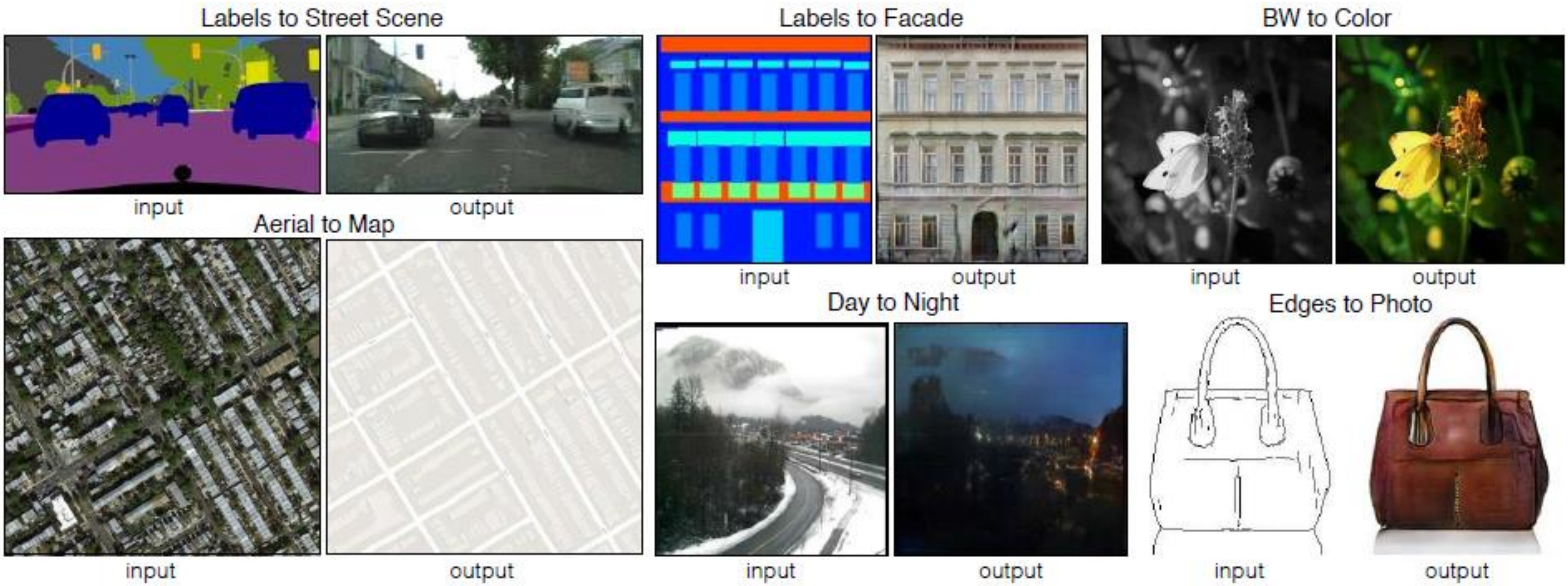
Red hair, long hair

Black hair, **blue** eyes

Blue hair, **green** eyes

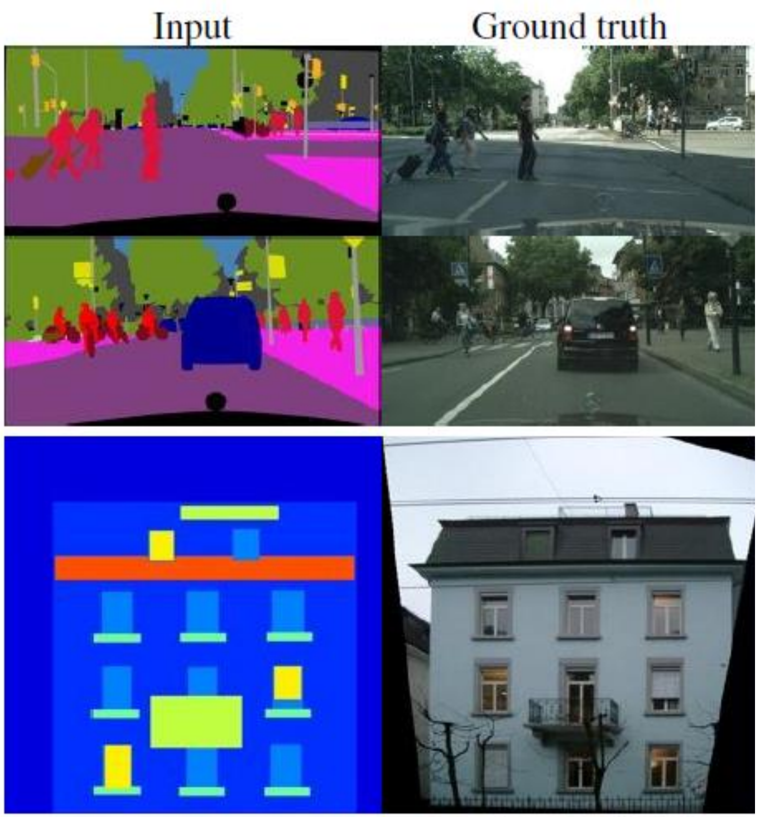
Image-to-image Translation

image input image output



Phillip Isola, Jun-Yan Zhu, Tinghui Zhou, Alexei A. Efros, “Image-to-Image Translation with Conditional Adversarial Networks”, arXiv preprint, 2016

Image-to-image Translation - Results



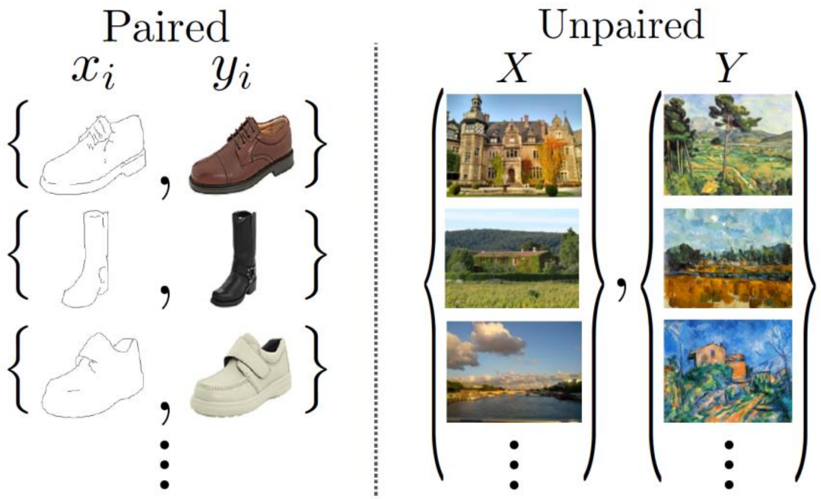
2017.03

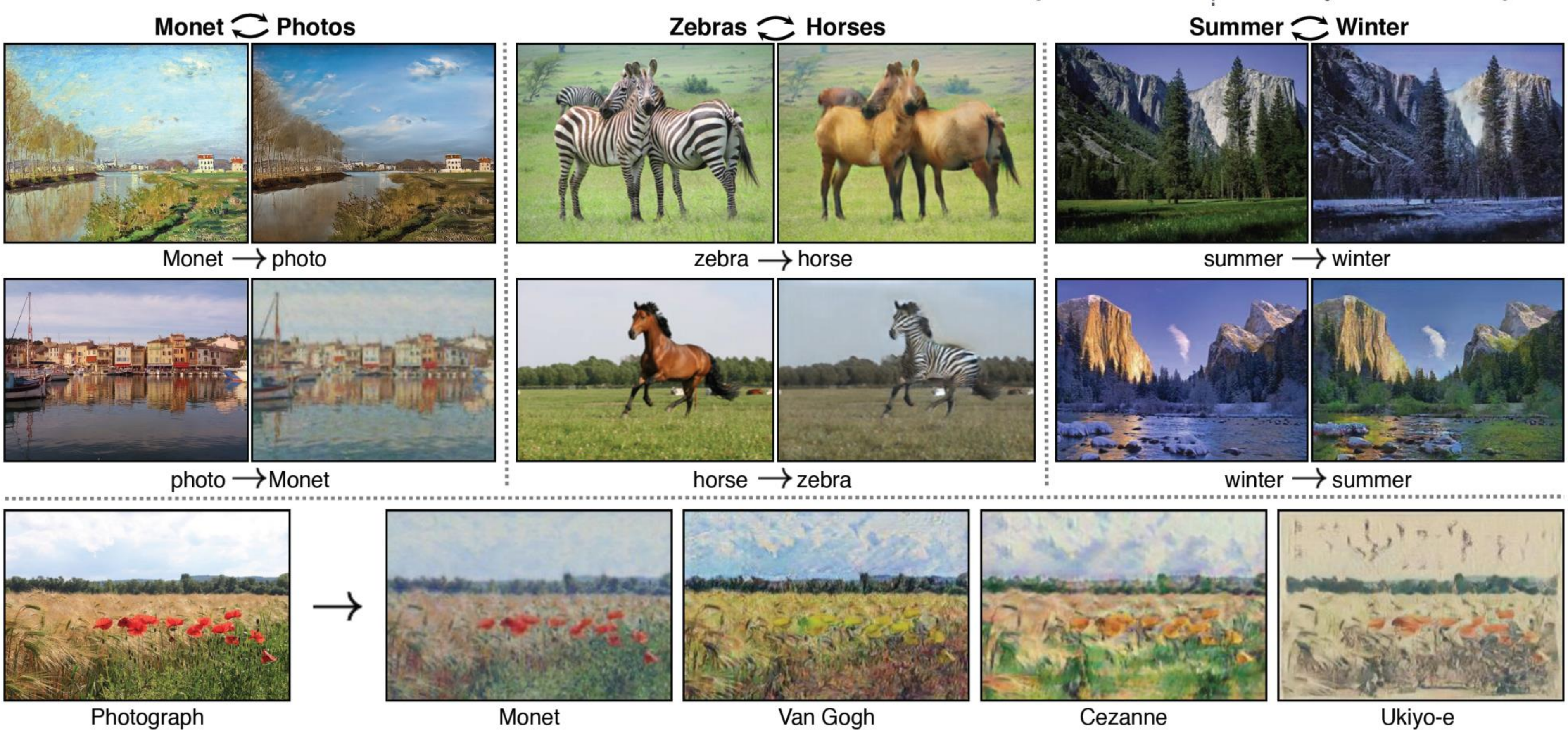
Cycle GAN

https://arxiv.org/abs/1703.10593

training data是unpaired的，結果很棒！

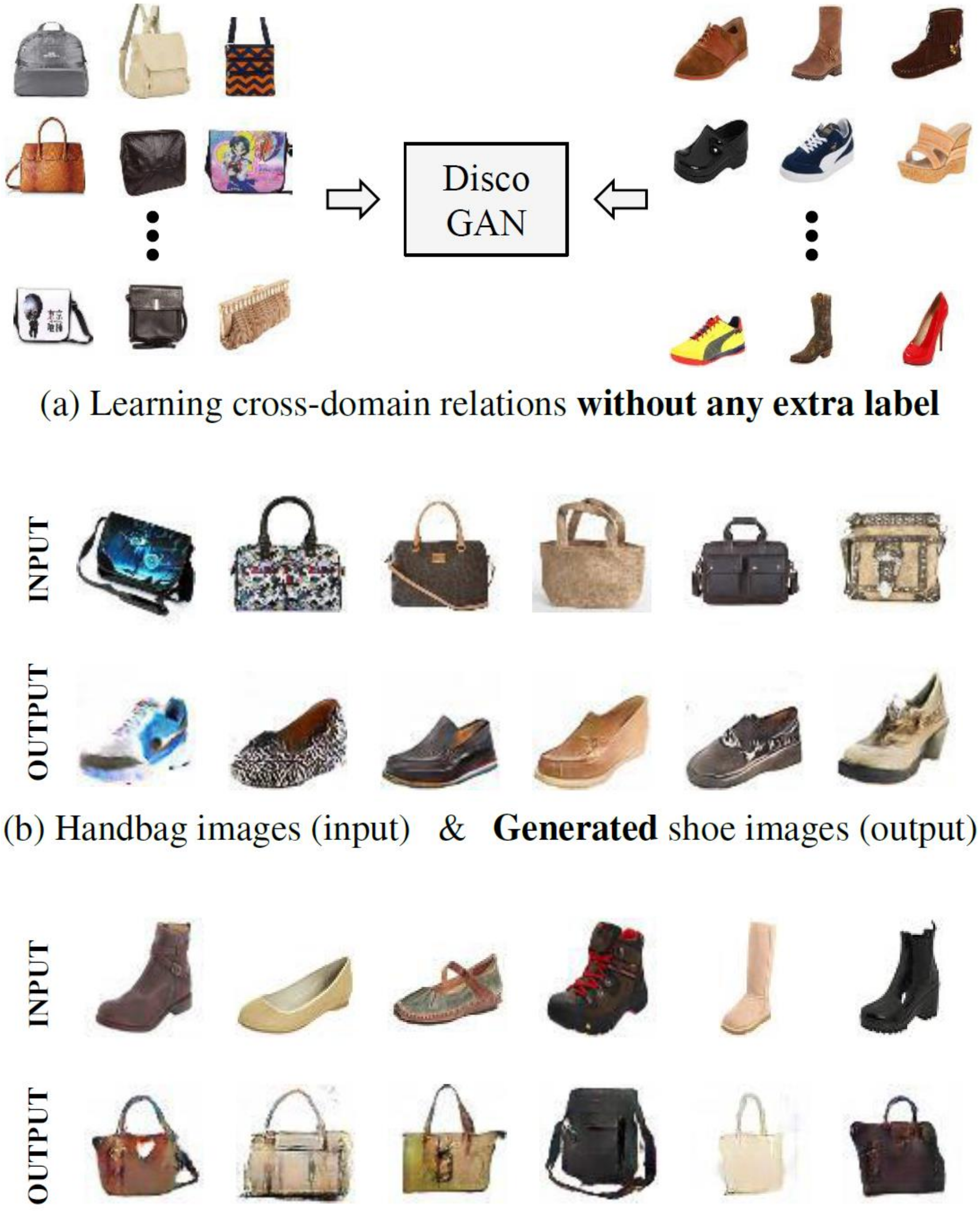
可以互相轉換結果





Disco GAN

2017.03



(a) Learning cross-domain relations **without any extra label**

(b) Handbag images (input) & **Generated** shoe images (output)

(c) Shoe images (input) & **Generated** handbag images (output)

https://arxiv.org/abs/1703.05192

機械学習で美少女化~あるいはNEW GAME! の世界

- http://qiita.com/Hi-king/items/8d36d9029ad1203aac55

理論上搜集一堆真人的圖跟動漫的圖，透過disco/cycle GAN可以互相轉換

So many GANs
…… Just name a few

Modifying the Optimization of GAN
fGAN
WGAN
Least-square GAN
Loss Sensitive GAN
Energy-based GAN
Boundary-seeking GAN
Unroll GAN
……

Different Structure from the Original GAN
Conditional GAN
Semi-supervised GAN
InfoGAN
BiGAN
Cycle GAN
Disco GAN
VAE-GAN
……

Acknowledgement

- 感謝 Ryan Sun 來信指出投影片上的錯字