Improving Sequence Generation by GAN

李宏毅
Hung-yi Lee

Outline

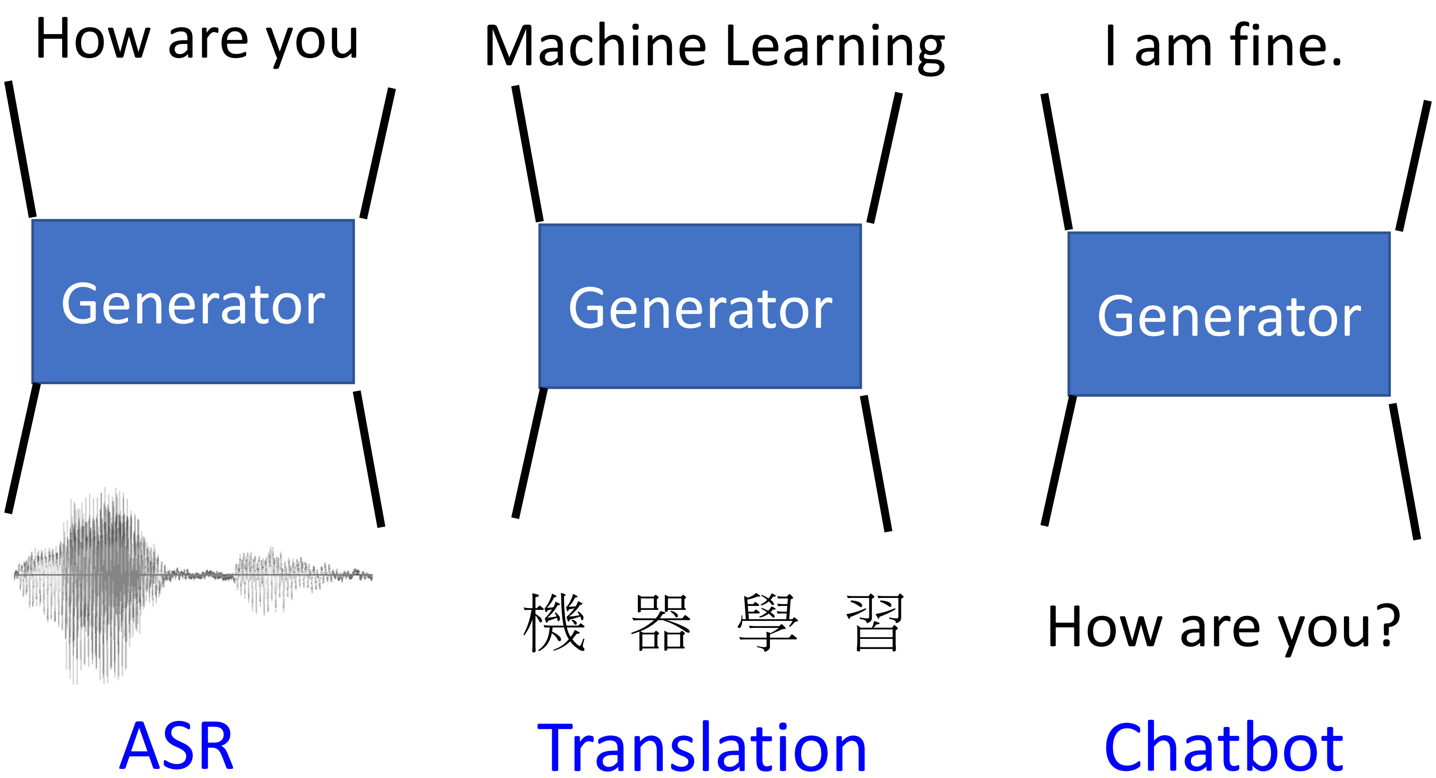
Conditional Sequence Generation

- RL (human feedback)
- GAN (discriminator feedback)

Unsupervised Conditional Sequence Generation

- Text Style Transfer
- Unsupervised Abstractive Summarization
- Unsupervised Translation

Conditional Sequence Generation



The generator is a typical seq2seq model.

With GAN, you can train seq2seq model in another way.

Review: Sequence-to-sequence

- Chat-bot as example

Output:	Not bad	I'm John.
Human	better	
Training Criterion		better

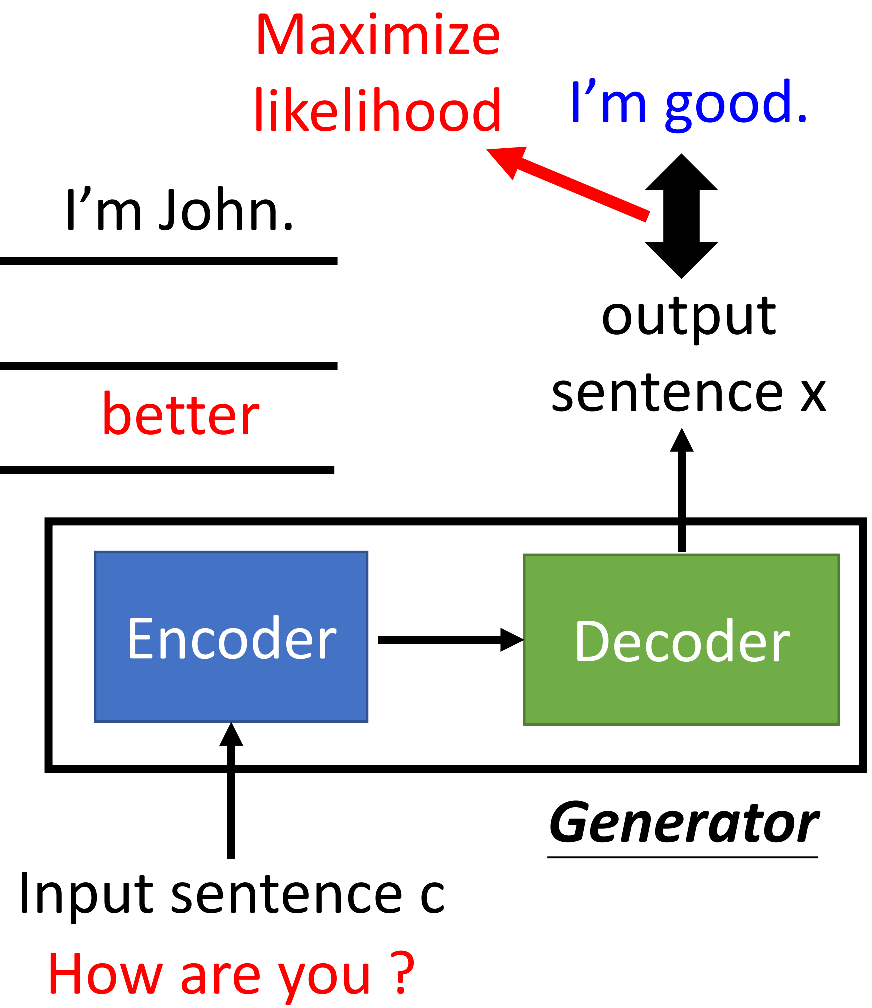
Training data:

⋮

A: How are you ?

B: I'm good.

⋮



Outline of Part III

Improving Supervised Seq-to-seq Model

- RL (human feedback)
- GAN (discriminator feedback)

Unsupervised Seq-to-seq Model

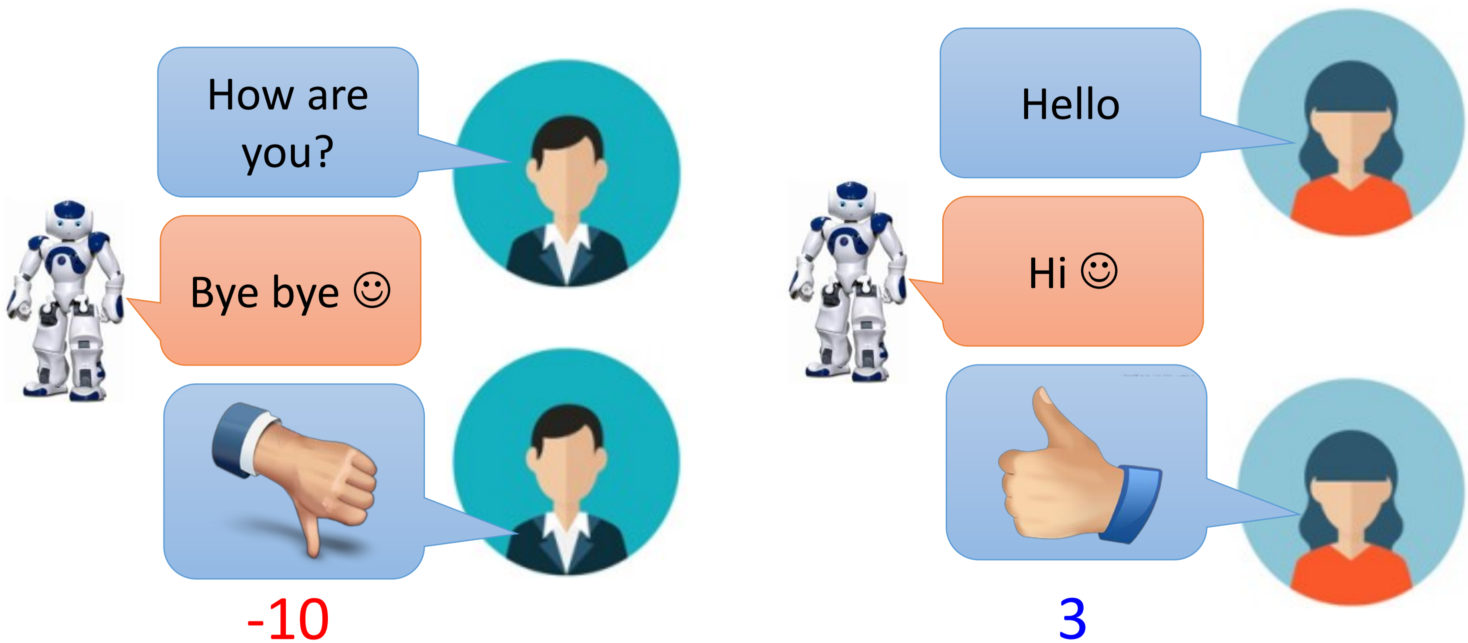
- Text Style Transfer
- Unsupervised Abstractive Summarization
- Unsupervised Translation

Introduction

https://image.freepik.com/free-vector/variety-of-human-avatars_23-2147506285.jpg

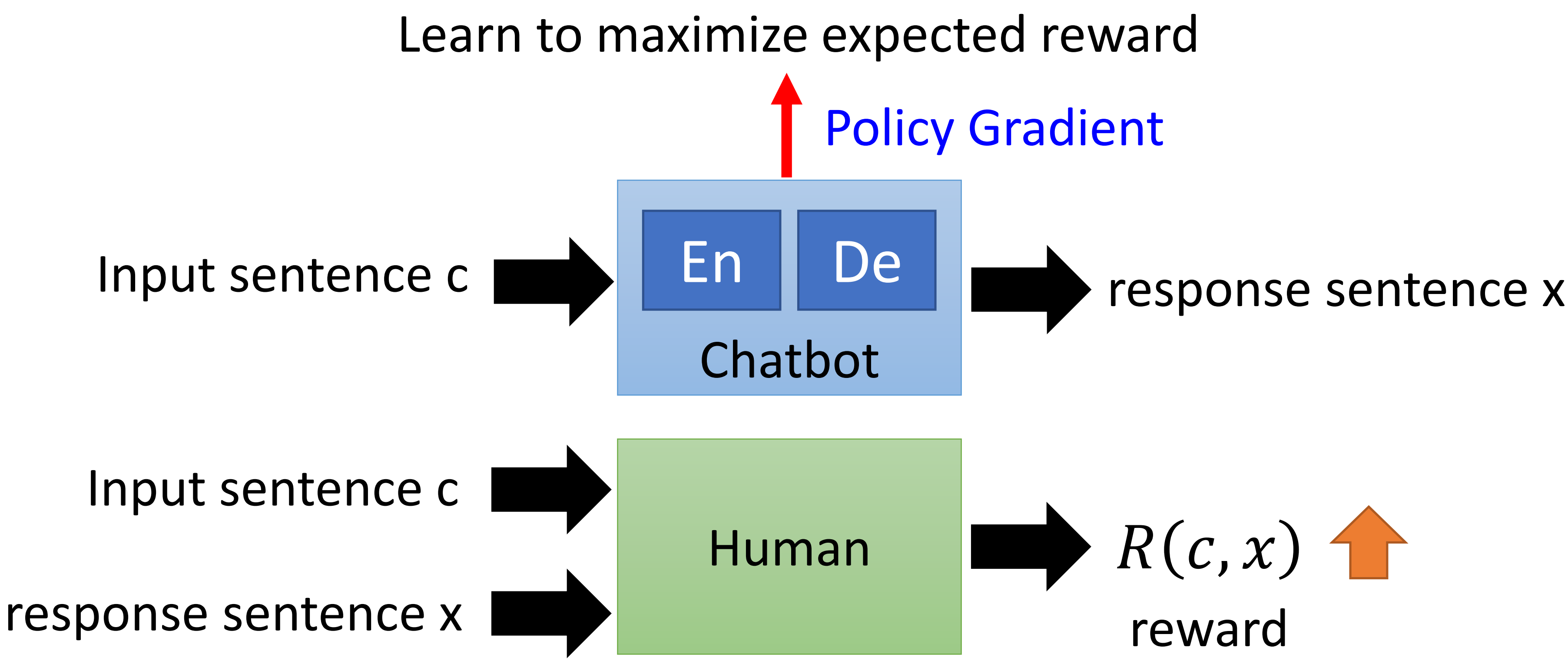
http://www.freepik.com/free-vector/variety-of-human-avatars_766615.htm

- Machine obtains feedback from user



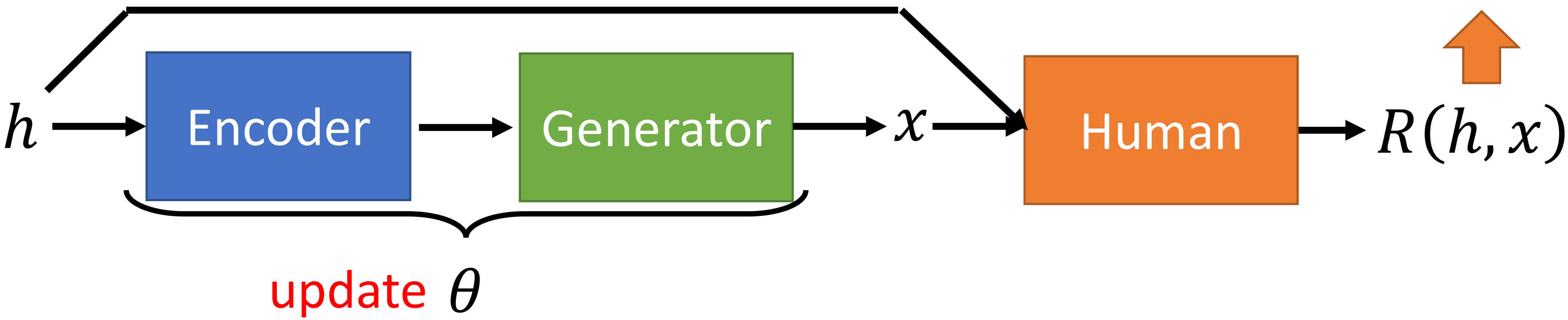
- Chat-bot learns to maximize the ***expected reward***

Maximizing Expected Reward



[Li, et al., EMNLP, 2016]

Maximizing Expected Reward



調整theta使得reward期望值越大越好

$$\theta^* = arg \max_{\theta} \bar{R}_\theta$$

Maximizing expected reward

窮舉所有可能的

output sentence

$$\bar{R}_\theta = \sum_h P(h) \sum_x R(h,x) \, P_\theta(x|h)$$

reward的期望值

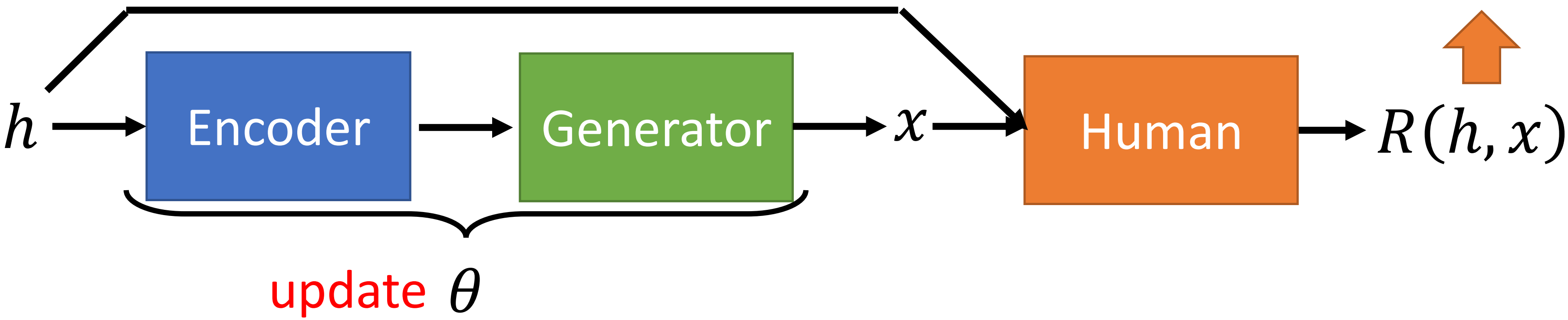
窮舉所有可能的

input sentence

Randomness in generator

Probability that the input/history is h

Maximizing Expected Reward



$$\theta^* = arg\max_{\theta} \bar{R}_{\theta}$$ Maximizing expected reward

照理來說應該要對R 算theta之gradient找maxima

$$\bar{R}_{\theta} = \sum_{h} P(h) \sum_{x} R(h,x)\, P_{\theta}(x|h) = E_{h\sim P(h)}\left[E_{x\sim P_{\theta}(x|h)}[R(h,x)]\right]$$

$$= E_{h\sim P(h),x\sim P_{\theta}(x|h)}[R(h,x)] \approx \frac{1}{N}\sum_{i=1}^{N} R\left(h^i, x^i\right)$$

但是這裡沒有包含theta，無法算gradient

無法算期望值，改成sample N 筆來逼近

Sample: $(h^1, x^1), (h^2, x^2), \cdots, (h^N, x^N)$

Where is θ?

Policy Gradient

$$\boxed{\frac{dlog\big(f(x)\big)}{dx} = \frac{1}{f(x)}\frac{df(x)}{dx}}$$

提前在sampling時就先算gradient

因為這一步無法對theta算gradient

$$\bar{R}_\theta = \sum_h P(h) \sum_x R(h,x)\, P_\theta(x|h) \approx \frac{1}{N}\sum_{i=1}^{N} R\big(h^i, x^i\big)$$

$$\nabla \bar{R}_\theta = \sum_h P(h) \sum_x R(h,x) \nabla P_\theta(x|h) \approx \frac{1}{N}\sum_{i=1}^{N} R\big(h^i, x^i\big) \nabla log P_\theta(x_i|h_i)$$

Sampling

$$= \sum_h P(h) \sum_x R(h,x) P_\theta(x|h) \boxed{\frac{\nabla P_\theta(x|h)}{P_\theta(x|h)}}$$

這兩項是等價的

$$= \sum_h P(h) \sum_x R(h,x) P_\theta(x|h) \boxed{\nabla log P_\theta(x|h)}$$

$$= E_{h\sim P(h), x\sim P_\theta(x|h)}\big[R(h,x) \nabla log P_\theta(x|h)\big]$$

Policy Gradient

- Gradient Ascent

$$\theta^{new} \leftarrow \theta^{old} + \eta \nabla \bar{R}_{\theta^{old}}$$

$$\nabla \bar{R}_{\theta} \approx \frac{1}{N} \sum_{i=1}^{N} R\left(h^i, x^i\right) \nabla log P_{\theta}\left(x^i | h^i\right)$$

$R\left(h^i, x^i\right)$ is positive given hi, output xi是好的，則放大這機率

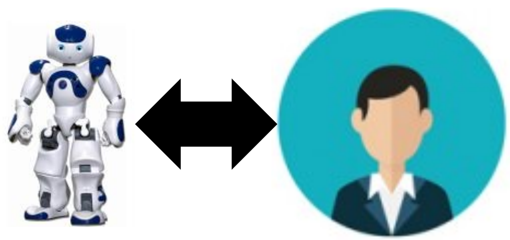
After updating θ, $P_{\theta}\left(x^i | h^i\right)$ will increase

$R\left(h^i, x^i\right)$ is negative 反之

After updating θ, $P_{\theta}\left(x^i | h^i\right)$ will decrease

Policy Gradient - Implemenation

θ^t



(c^1, x^1) $R(c^1, x^1)$

(c^2, x^2) $R(c^2, x^2)$

$\vdots$ $\vdots$

(c^N, x^N) $R(c^N, x^N)$

$$\theta^{t+1} \leftarrow \theta^t + \eta \boxed{\nabla \bar{R}_{\theta^t}}$$

$$\frac{1}{N}\sum_{i=1}^{N} R(c^i, x^i) \nabla log P_{\theta^t}(x^i | c^i)$$

$R(c^i, x^i)$ is positive

Updating θ to increase $P_\theta(x^i | c^i)$

$R(c^i, x^i)$ is negative

Updating θ to decrease $P_\theta(x^i | c^i)$

update完後要回去重新sample data!

理論上R是沒有限制的，因為都是機率（和為1），因此雖然都是正的但是有大有小，因此還是可以提高positive example
但是我們再實作上的時候希望reward function是有正有負的（同減去threshold）
因為我們再sample的時候不一定所有data都會被找到，這樣造成反而沒sample到的機率會下降

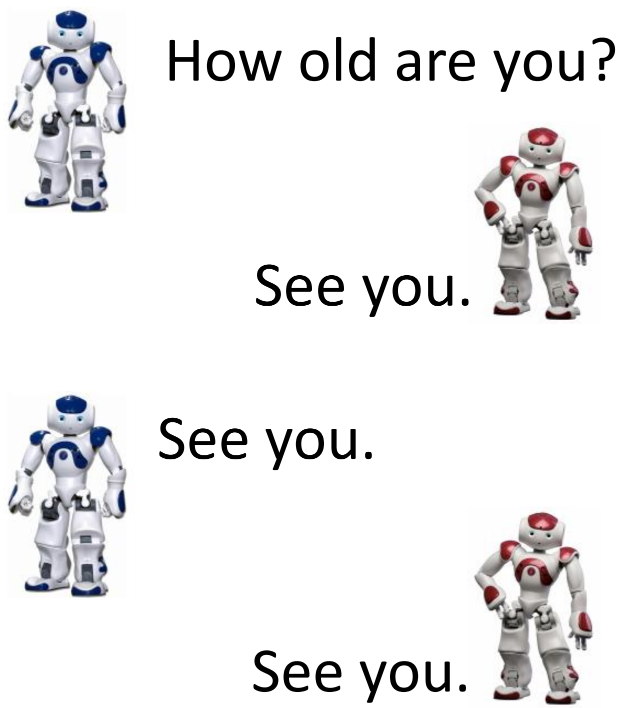
Comparison

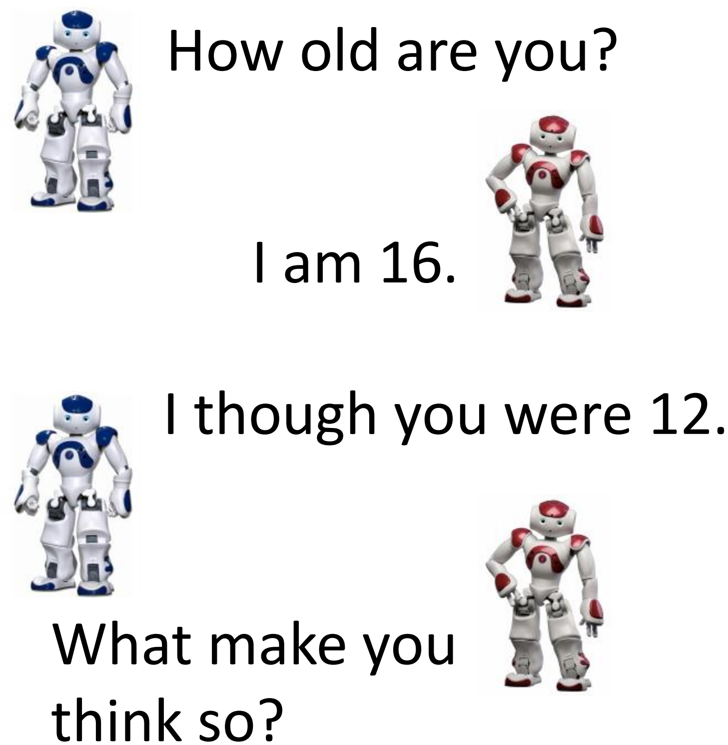
	每一筆data都有相同weight Maximum Likelihood	每一筆data都是有不同weight Reinforcement Learning
Objective Function	$\frac{1}{N}\sum_{i=1}^{N} logP_\theta(\hat{x}^i\vert c^i)$	$\frac{1}{N}\sum_{i=1}^{N} R(c^i,x^i)logP_\theta(x^i\vert c^i)$
Gradient	$\frac{1}{N}\sum_{i=1}^{N} \nabla logP_\theta(\hat{x}^i\vert c^i)$	$\frac{1}{N}\sum_{i=1}^{N} R(c^i,x^i)\nabla logP_\theta(x^i\vert c^i)$
Training Data	人標記的ground truth $\{(c^1,\hat{x}^1),\ldots,(c^N,\hat{x}^N)\}$ $R(c^i,\hat{x}^i)=1$	machine自己產生的，因此有些x是錯的 $\{(c^1,x^1),\ldots,(c^N,x^N)\}$ obtained from interaction weighted by $R(c^i,x^i)$

Alpha GO style training !

用兩個bot互相聊天，但是reward不能太複雜，只能設計很簡單的
譬如說陷入infinite loop就給負的reward

- Let two agents talk to each other





Using a pre-defined evaluation function to compute R(h,x)

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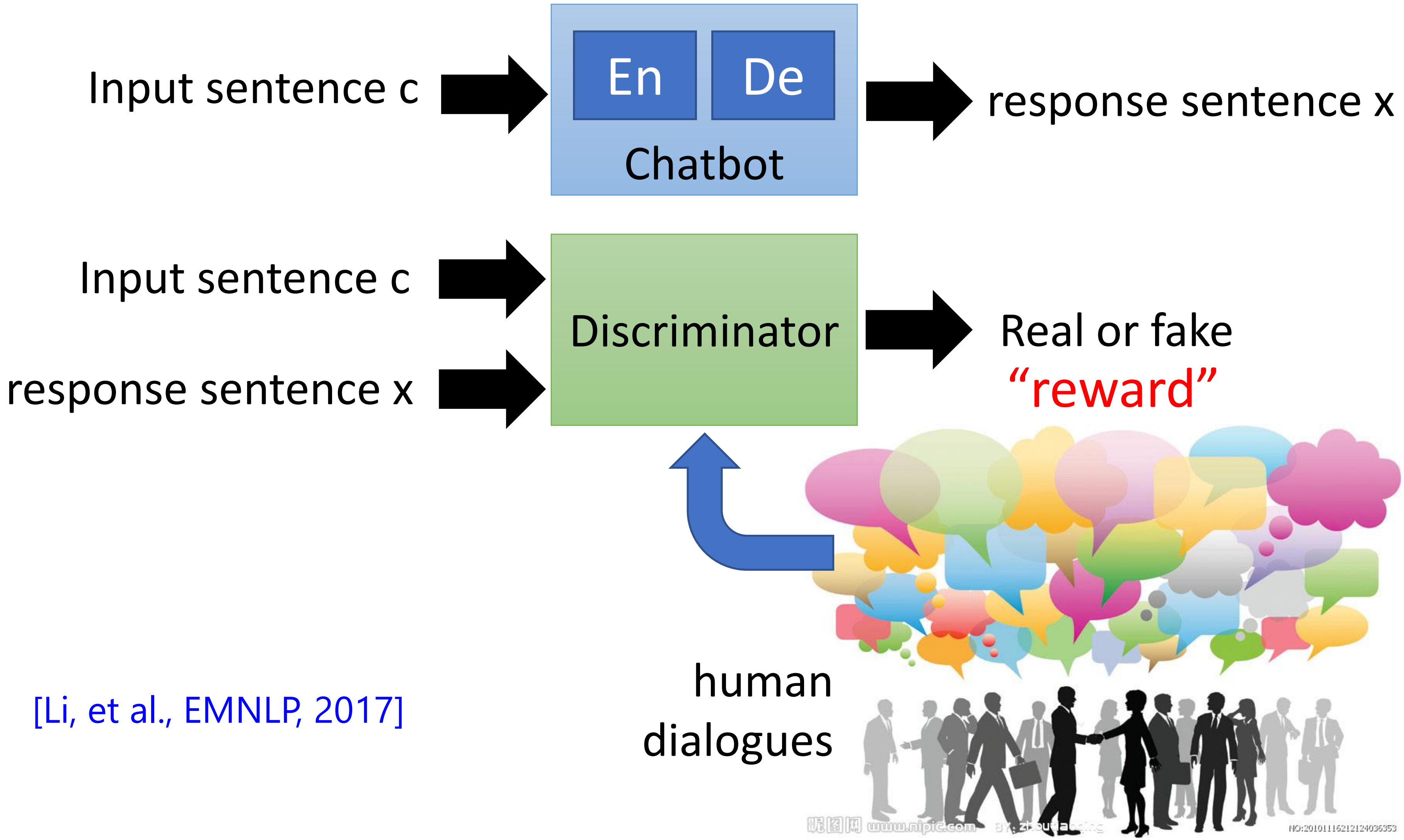
http://www.nipic.com/show/3/83/3936650kd7476069.html

為了解reward不能太複雜的問題，引入GAN

Conditional GAN

以前的reward是人類定義的，現在改成用discriminator來給定reward



[Li, et al., EMNLP, 2017]

Algorithm

Training data: 正確的pair

Pairs of conditional input c and response x

- Initialize generator G (chatbot) and discriminator D
- In each iteration:

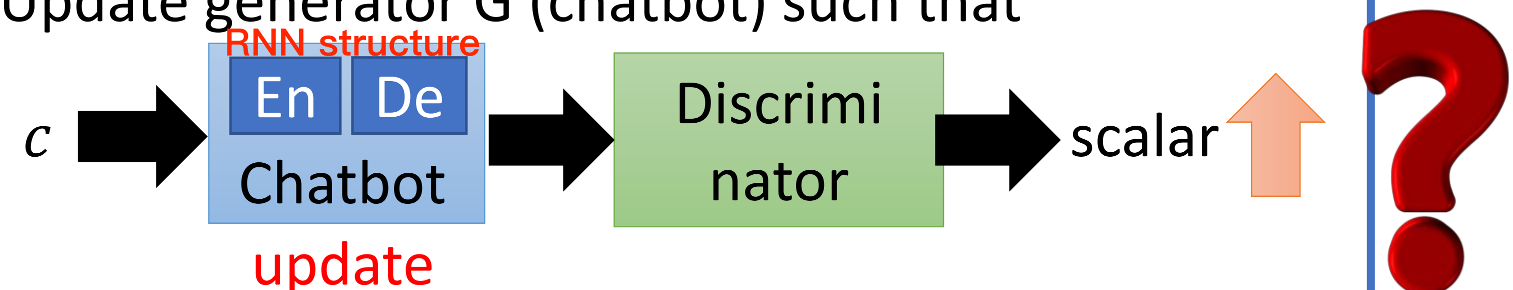
learn D

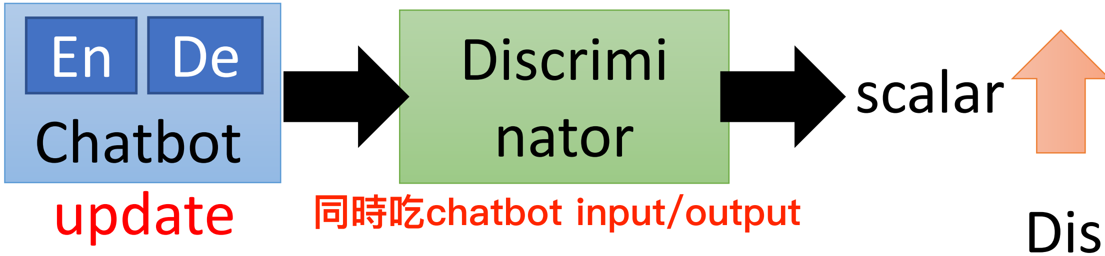
- Sample input c and response x from training set
- Sample input c' from training set, and generate response $\tilde{x}$ by G(c')
- Update D to increase $D(c, x)$ and decrease $D(c', \tilde{x})$

正確的 錯誤的

learn G

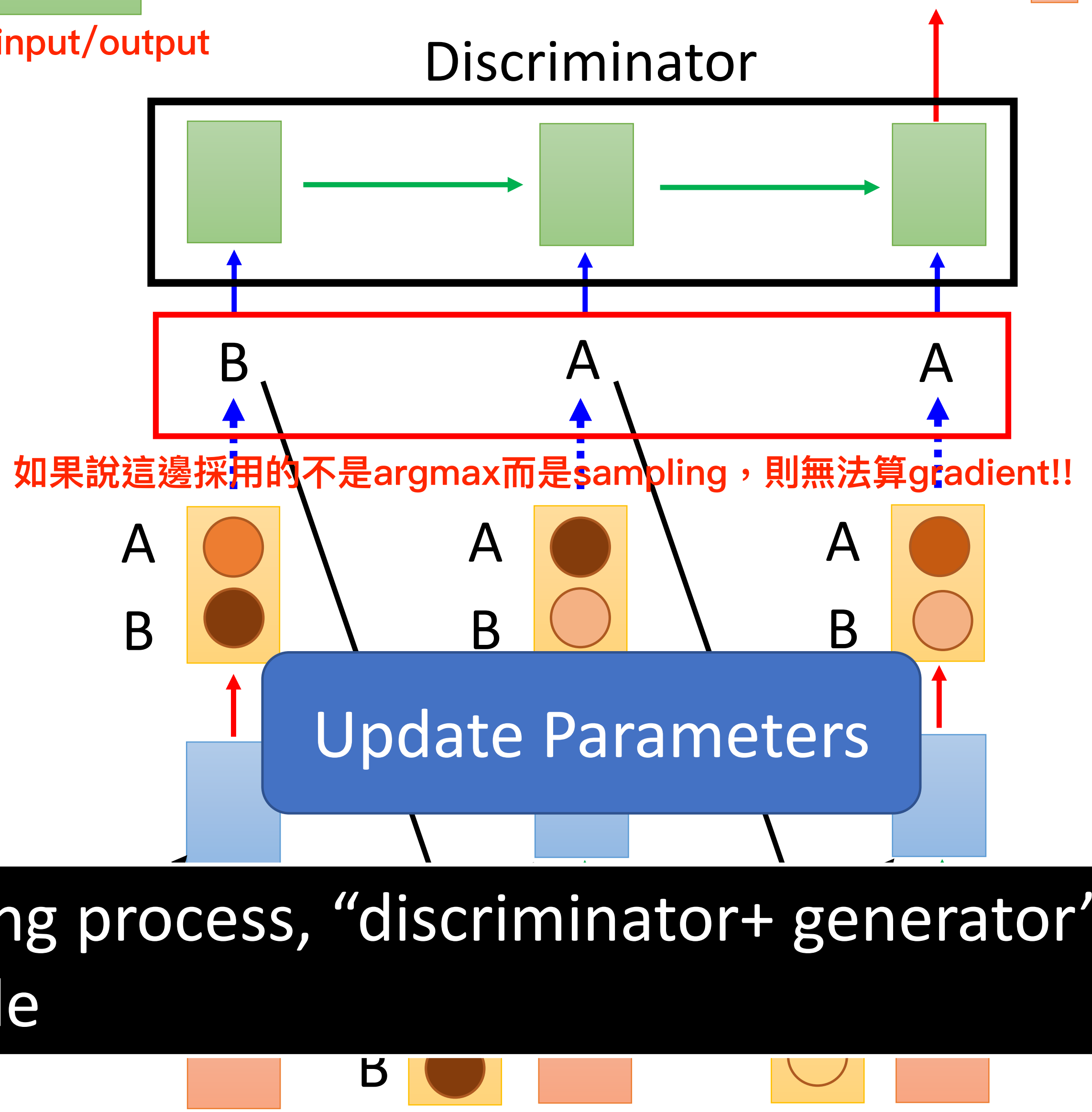
- Update generator G (chatbot) such that





Can we use gradient ascent?

NO!



Due to the sampling process, “discriminator+ generator” is not differentiable

Three Categories of Solutions

如何解這問題（在有sampling process的net算gradient）？

Gumbel-softmax

- [Matt J. Kusner, et al, arXiv, 2016]

想了一個trick讓本來不能算微分的東西變成可以算

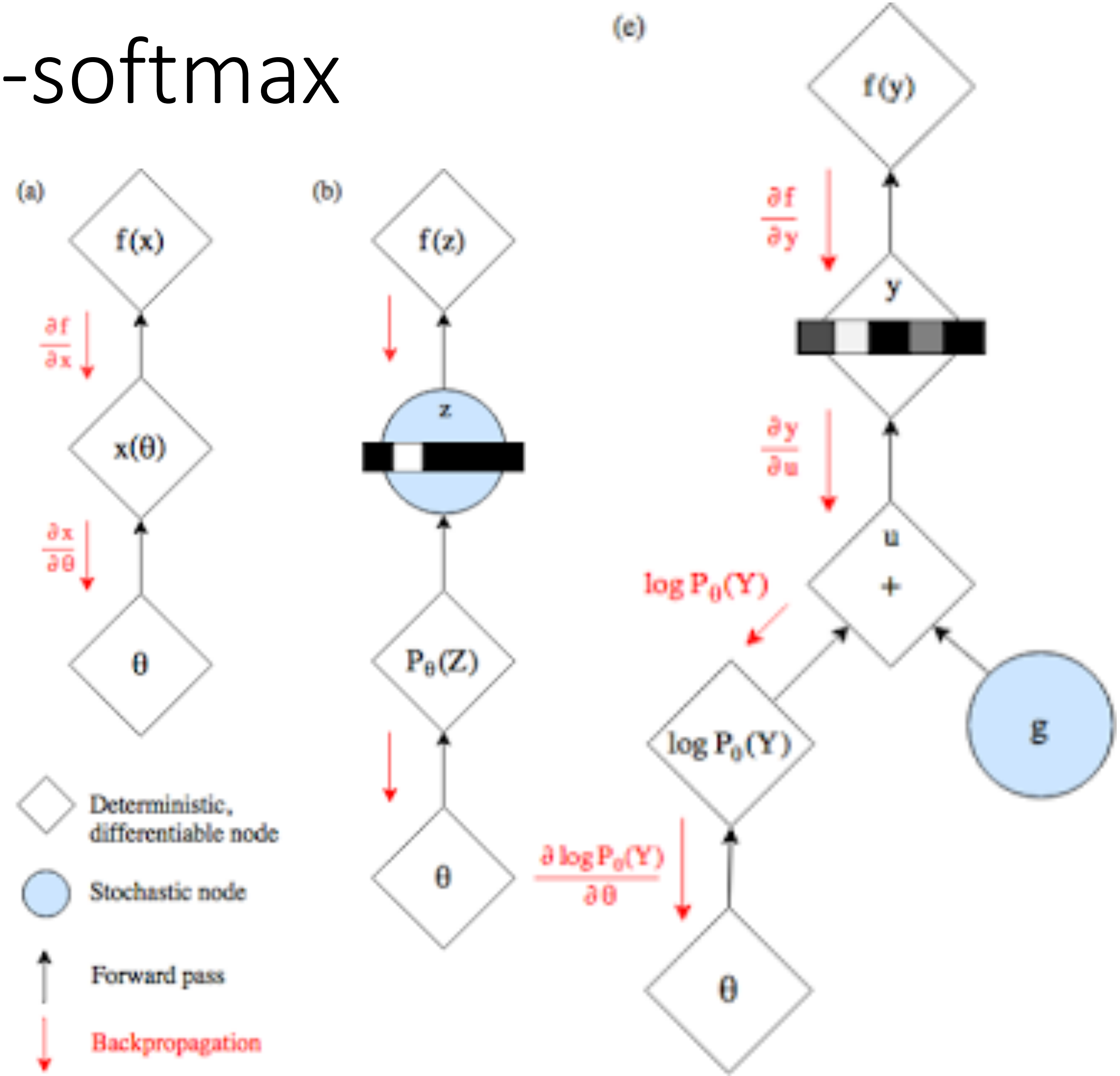
Continuous Input for Discriminator

- [Sai Rajeswar, et al., arXiv, 2017][Ofir Press, et al., ICML workshop, 2017][Zhen Xu, et al., EMNLP, 2017][Alex Lamb, et al., NIPS, 2016][Yizhe Zhang, et al., ICML, 2017]

“Reinforcement Learning”

- [Yu, et al., AAAI, 2017][Li, et al., EMNLP, 2017][Tong Che, et al, arXiv, 2017][Jiaxian Guo, et al., AAAI, 2018][Kevin Lin, et al, NIPS, 2017][William Fedus, et al., ICLR, 2018]

Gumbel-softmax



https://gabrielhuang.gitbooks.io/machine-learning/reparametrization-trick.html

https://casmls.github.io/general/2017/02/01/GumbelSoftmax.html

http://blog.evjang.com/2016/11/tutorial-categorical-variational.html

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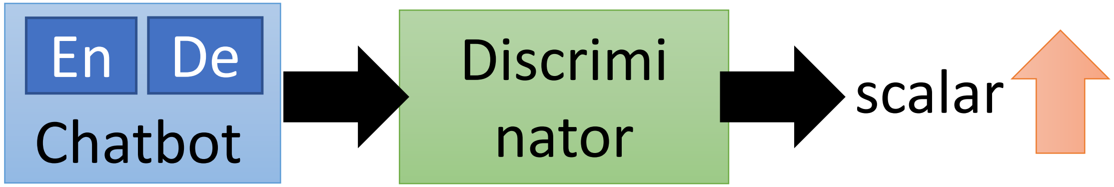
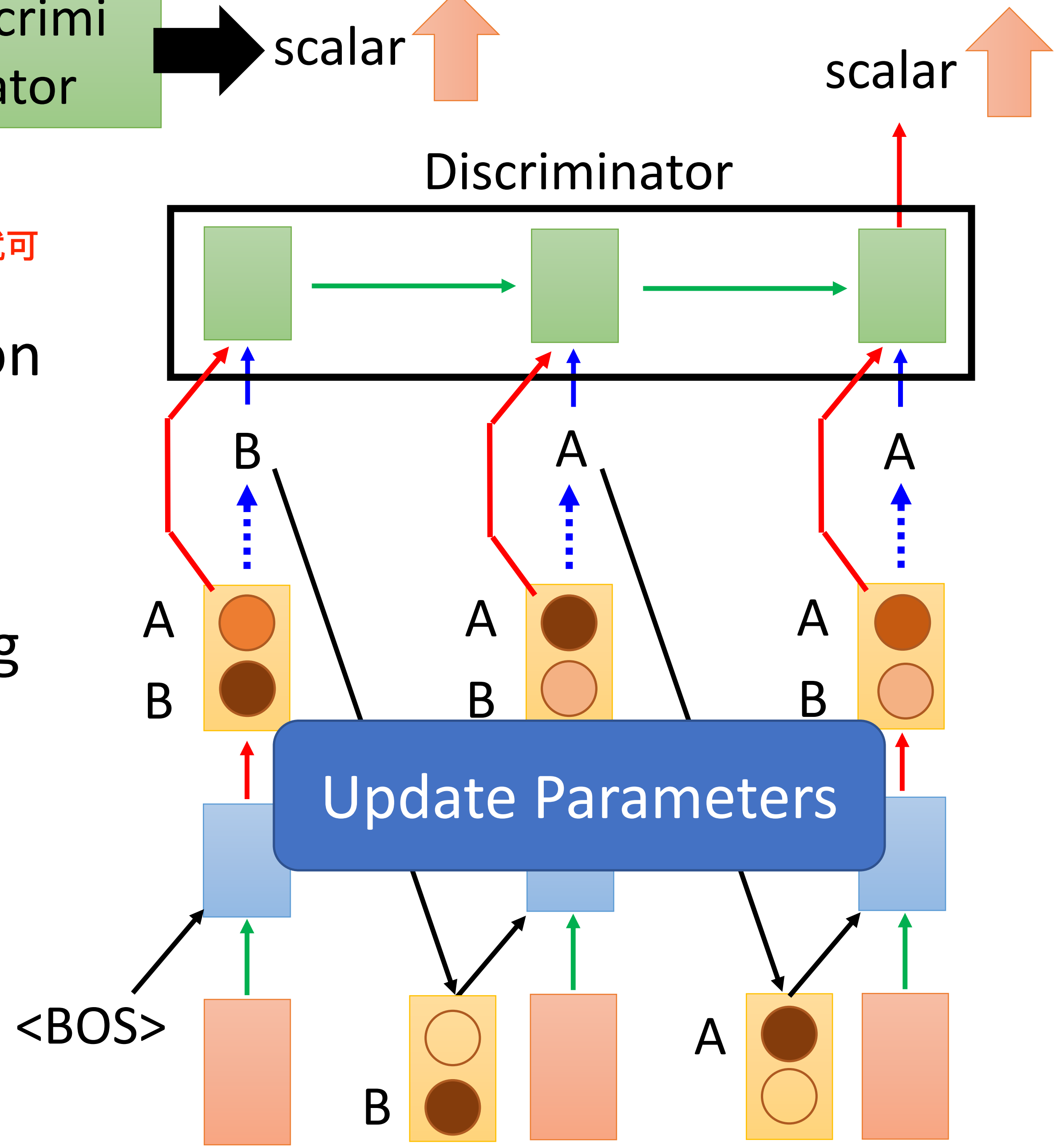


Discriminator如果改成不要吃sampling結果而是distribution，就可以微分了

Use the distribution as the input of discriminator

Avoid the sampling process

We can do backpropagation now.



What is the problem?

對Discriminator來說辨別真假太容易，只要辨別是不是one hot即可！

造成Generator只要學會產生one hot即可！

- Real sentence

real data

1	0	0	0	0
0	1	0	0	0
0	0	1	0	0
0	0	0	1	0
0	0	0	0	1

Discriminator can immediately find the difference.

- Generated

fake data

0.9	0.1	0.1	0	0
0.1	0.9	0.1	0	0
0	0	0.7	0.1	0
0	0	0.1	0.8	0.1
0	0	0	0.1	0.9

Can never be 1-of-N

WGAN is helpful

constrain: D必須是1–lipsitz function，造成他是比較fuzzy的，所以比較不容易分辨one hot

Three Categories of Solutions

Gumbel-softmax

- [Matt J. Kusner, et al, arXiv, 2016]

Continuous Input for Discriminator

- [Sai Rajeswar, et al., arXiv, 2017][Ofir Press, et al., ICML workshop, 2017][Zhen Xu, et al., EMNLP, 2017][Alex Lamb, et al., NIPS, 2016][Yizhe Zhang, et al., ICML, 2017]

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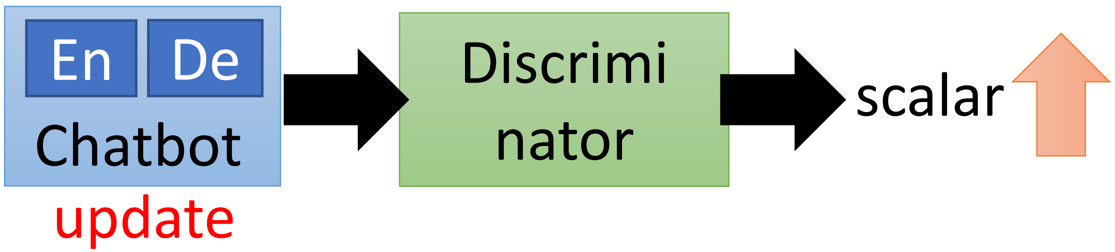
Reinforcement Learning?



- Consider the output of discriminator as reward
  - Update generator to increase discriminator = to get maximum reward
  - Using the formulation of policy gradient, replace reward $R(c, x)$ with discriminator output $\mathrm{D}(c, x)$
- Different from typical RL
  - The discriminator would update

d-step

iterative train

g-step

c

x

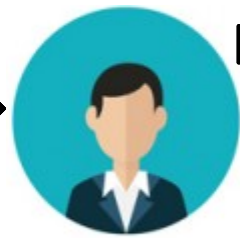
fake

discriminator

real

把人(reward)換成機器（discriminator）

θ^t



D

(c^1, x^1)	$D(c^1, x^1)$
(c^2, x^2)	$D(c^2, x^2)$
$\vdots$	$\vdots$
(c^N, x^N)	$D(c^N, x^N)$

$$\theta^{t+1} \leftarrow \theta^t + \eta \boxed{\nabla \bar{R}_{\theta^t}}$$

$$\frac{1}{N}\sum_{i=1}^{N} D(c^i, x^i) \nabla log P_{\theta^t}(x^i | c^i)$$

$D(c^i, x^i)$ is positive

Updating θ to increase $P_\theta(x^i | c^i)$

$D(c^i, x^i)$ is negative

Updating θ to decrease $P_\theta(x^i | c^i)$

Reward for Every Generation Step

把R換成D

$$\nabla \bar{R}_\theta \approx \frac{1}{N}\sum_{i=1}^{N} D(c^i, x^i) \nabla log P_\theta(x^i|c^i)$$

c^i = "What is your name?"

x^i = "I don't know"

$D(c^i, x^i)$ is negative

Update θ to decrease $\log P_\theta(x^i|c^i)$

$$log P_\theta(x^i|c^i) = log P(x_1^i|c^i) + log P(x_2^i|c^i, x_1^i) + log P(x_3^i|c^i, x_{1:2}^i)$$

一大堆term的連乘

$P("I"|c^i)$?

雖然希望這項減小，但開頭是 I 應該是好的不需要下降呀

雖然sample夠多，positive可以拉回來I的機率，但是實作上不一定sample夠多

c^i = "What is your name?"

x^i = "I am John"

$D(c^i, x^i)$ is positive

Update θ to increase $\log P_\theta(x^i|c^i)$

$$log P_\theta(x^i|c^i) = log P(x_1^i|c^i) + log P(x_2^i|c^i, x_1^i) + log P(x_3^i|c^i, x_{1:2}^i)$$

$P("I"|c^i)$

Reward for Every Generation Step

h^i = "What is your name?" x^i = "I don't know"

$$logP_\theta(x^i|h^i) = \underline{logP(x_1^i|c^i)} + \underline{logP(x_2^i|c^i,x_1^i)} + \underline{logP(x_3^i|c^i,x_{1:2}^i)}$$

$$P("I"|c^i) \quad P("don't"|c^i,"I") \quad P("know"|c^i,"I\ don't")$$

$$\nabla\bar{R}_\theta \approx \frac{1}{N}\sum_{i=1}^{N} \underline{D(c^i,x^i)}\,\underline{\nabla logP_\theta(x^i|c^i)}$$

換成Q作為reward，對"每一個timestamp"都給訂一個reward

$$\nabla\bar{R}_\theta \approx \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\underline{Q(c^i,x_{1:t}^i) - b}\right)\underline{\nabla logP_\theta(x_t^i|c^i,x_{1:t-1}^i)}$$

Method 1. Monte Carlo (MC) Search [Yu, et al., AAAI, 2017] 運算量太大

Method 2. Discriminator For Partially Decoded Sequences

效果不如蒙地卡羅

[Li, et al., EMNLP, 2017]

Tips: RankGAN

Kevin Lin, Dianqi Li, Xiaodong He, Zhengyou Zhang, Ming-Ting Sun, “Adversarial Ranking for Language Generation”, NIPS 2017

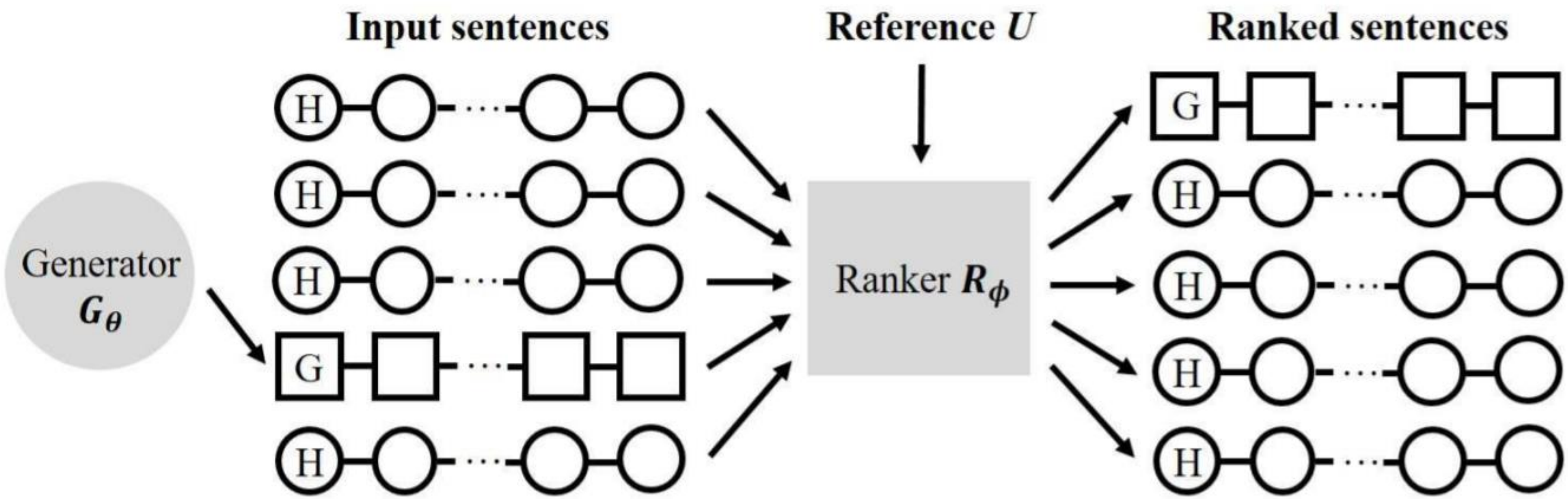


Image caption generation:

Method	BLEU-2	BLEU-3	BLEU-4
MLE	0.781	0.624	0.589
SeqGAN	0.815	0.636	0.587
RankGAN	**0.845**	**0.668**	**0.614**

Method	Human score
SeqGAN	3.44
RankGAN	4.61
Human-written	**6.42**

Experimental Results

實驗發現chatbot有1/10都在說模糊的句子譬如說i'm sorry...
對應到image就像是模糊的火車

Input	We've got to look for another route.
MLE	I'm sorry.
GAN	You're not going to be here for a while.

Input	You can save him by talking.
MLE	I don't know.
GAN	You know what's going on in there, you know what I mean?

- MLE frequently generates "I'm sorry", "I don't know", etc. (corresponding to fuzzy images?)
- GAN generates longer and more complex responses (however, no strong evidence shows that they are better)

Find more comparison in the survey papers.

[Lu, et al., arXiv, 2018][Zhu, et al., arXiv, 2018]

More Applications

- Supervised machine translation [Wu, et al., arXiv 2017][Yang, et al., arXiv 2017]
- Supervised abstractive summarization [Liu, et al., AAAI 2018]
- Image/video caption generation [Rakshith Shetty, et al., ICCV 2017][Liang, et al., arXiv 2017]

If you are using seq2seq models, consider to improve them by GAN.

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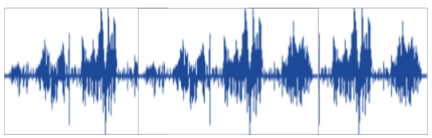
Text Style Transfer

正面的句子當作一種style

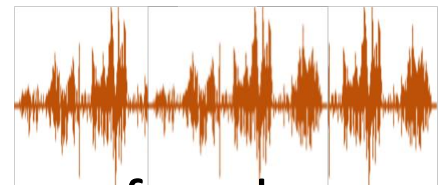
負面的句子當作一種style

Domain X



male

Domain Y



female

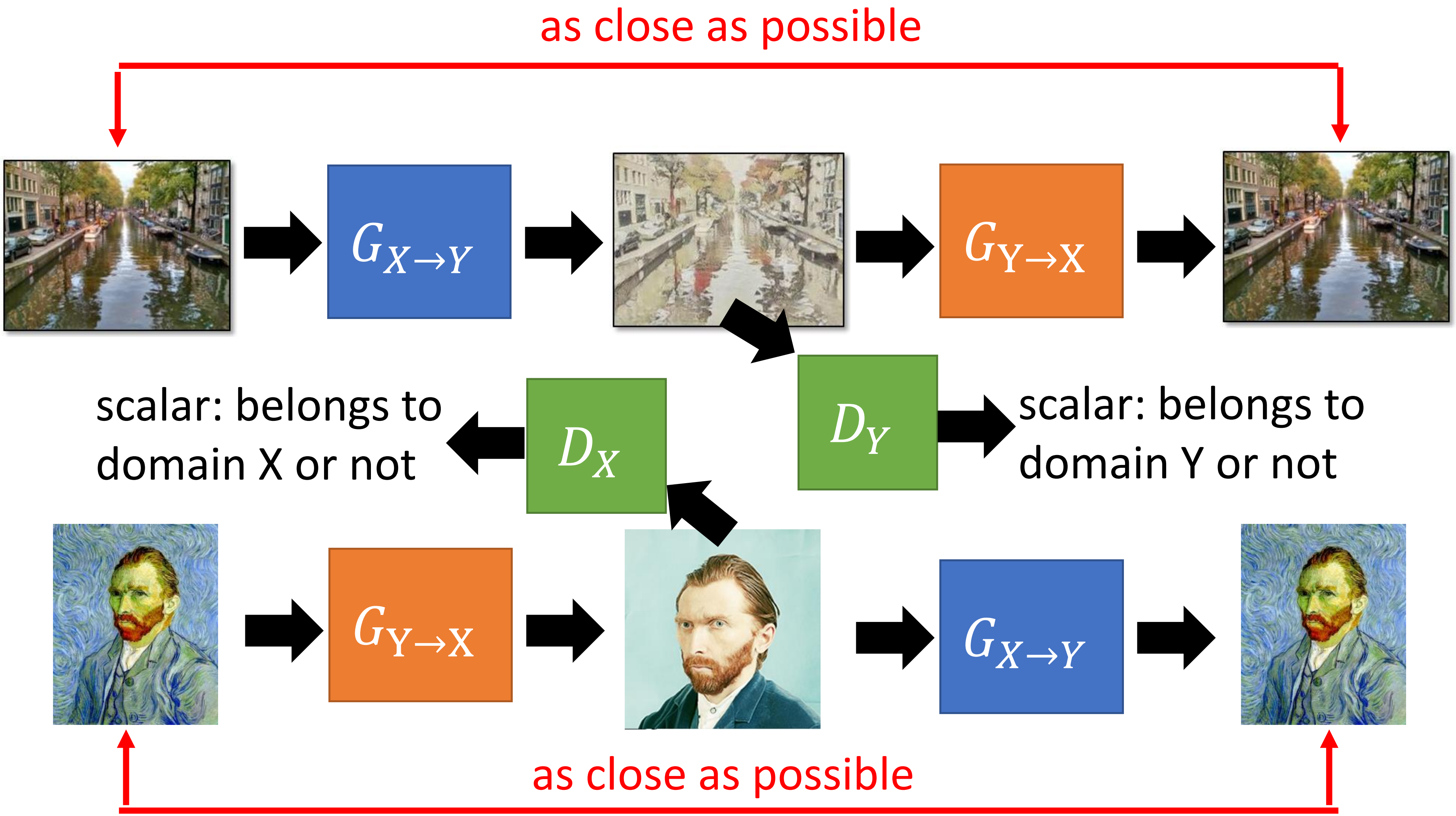
It is good.
It’s a good day.
I love you.

positive sentences

It is bad.
It’s a bad day.
I don’t love you.

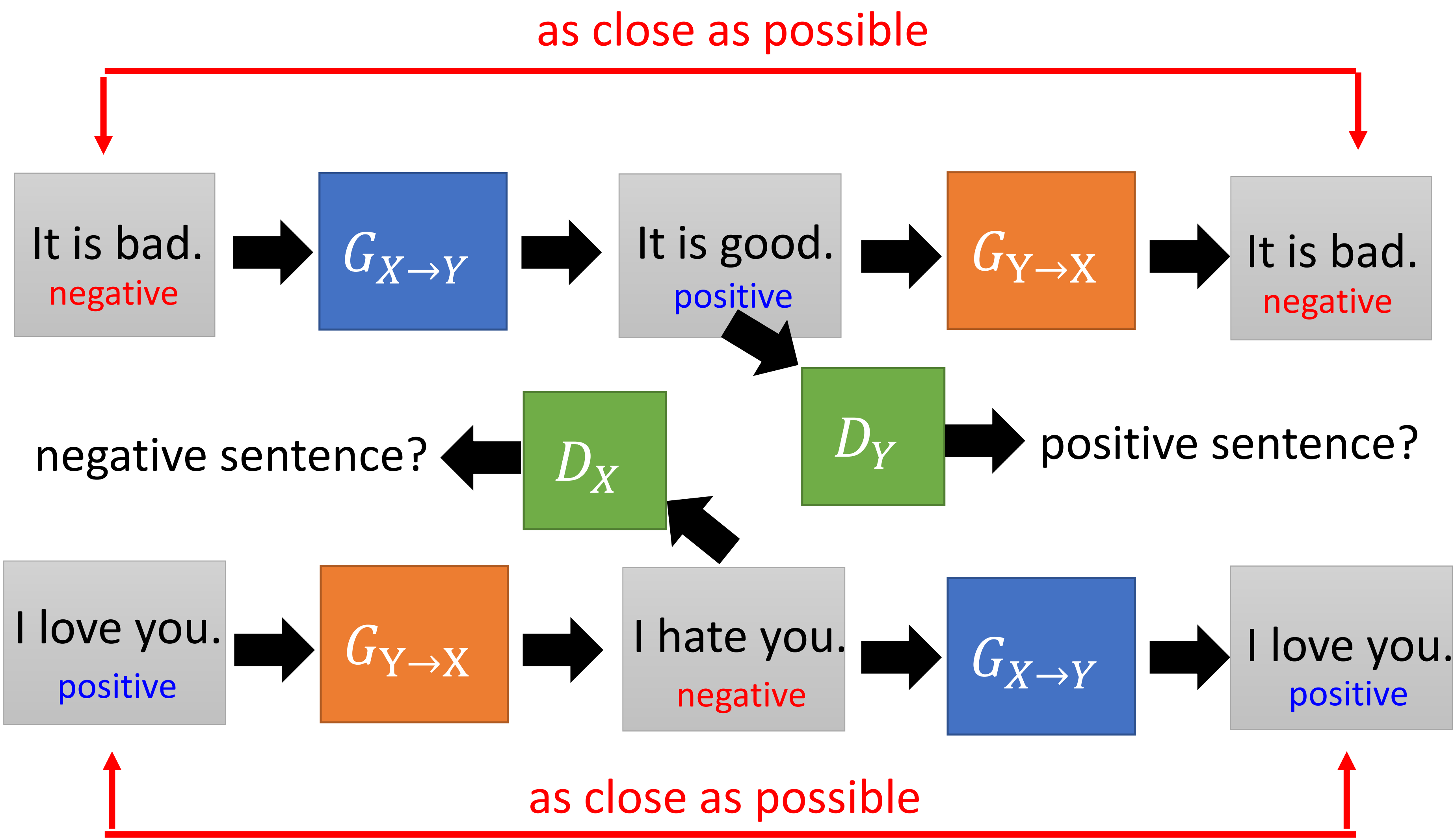
negative sentences

Direct Transformation



把影像換成文字

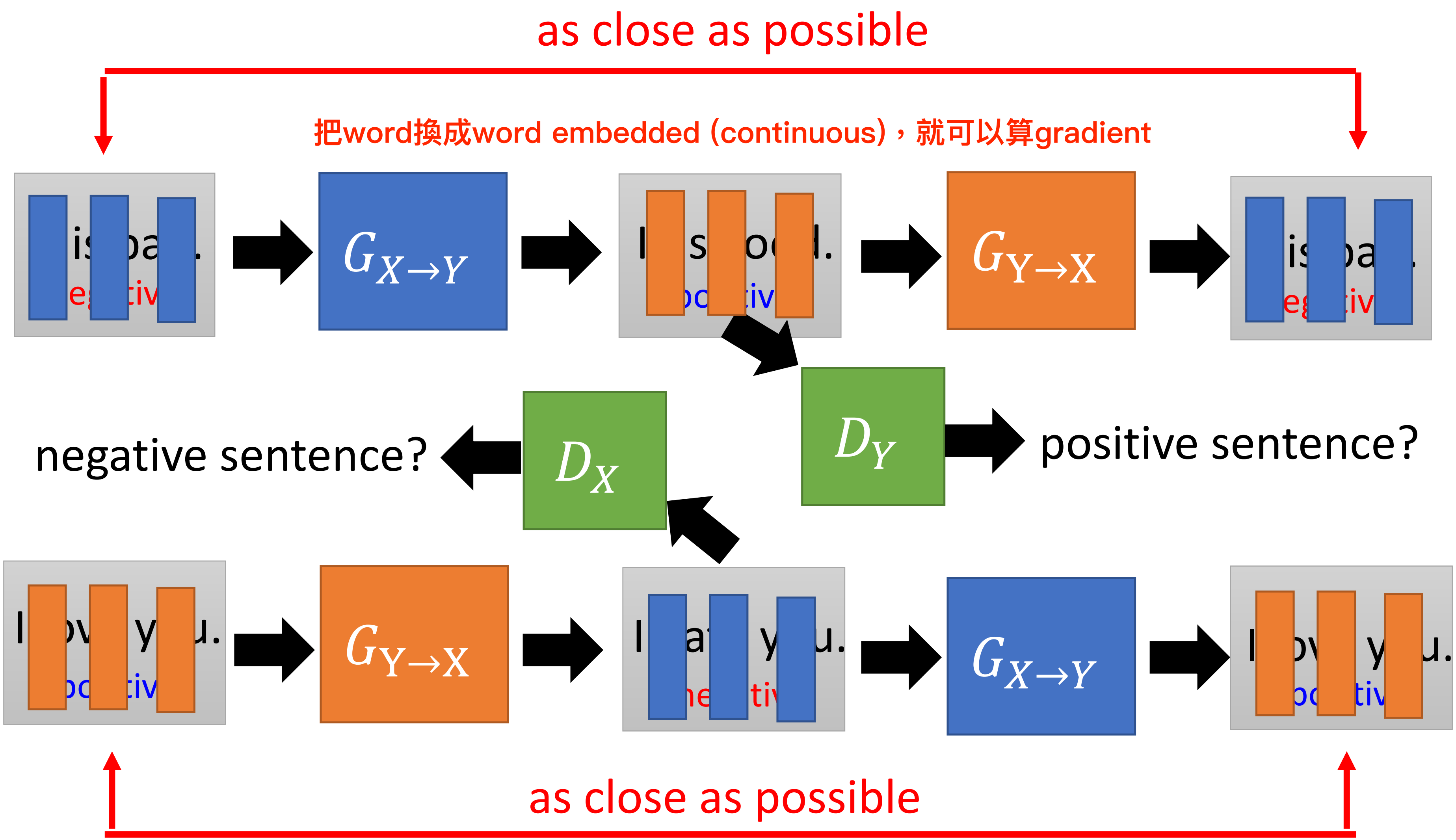
Direct Transformation



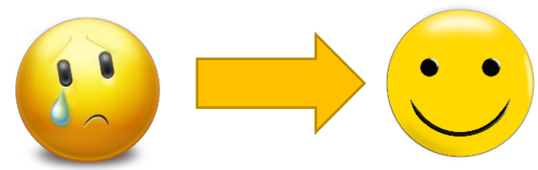
Direct Transformation

Discrete?

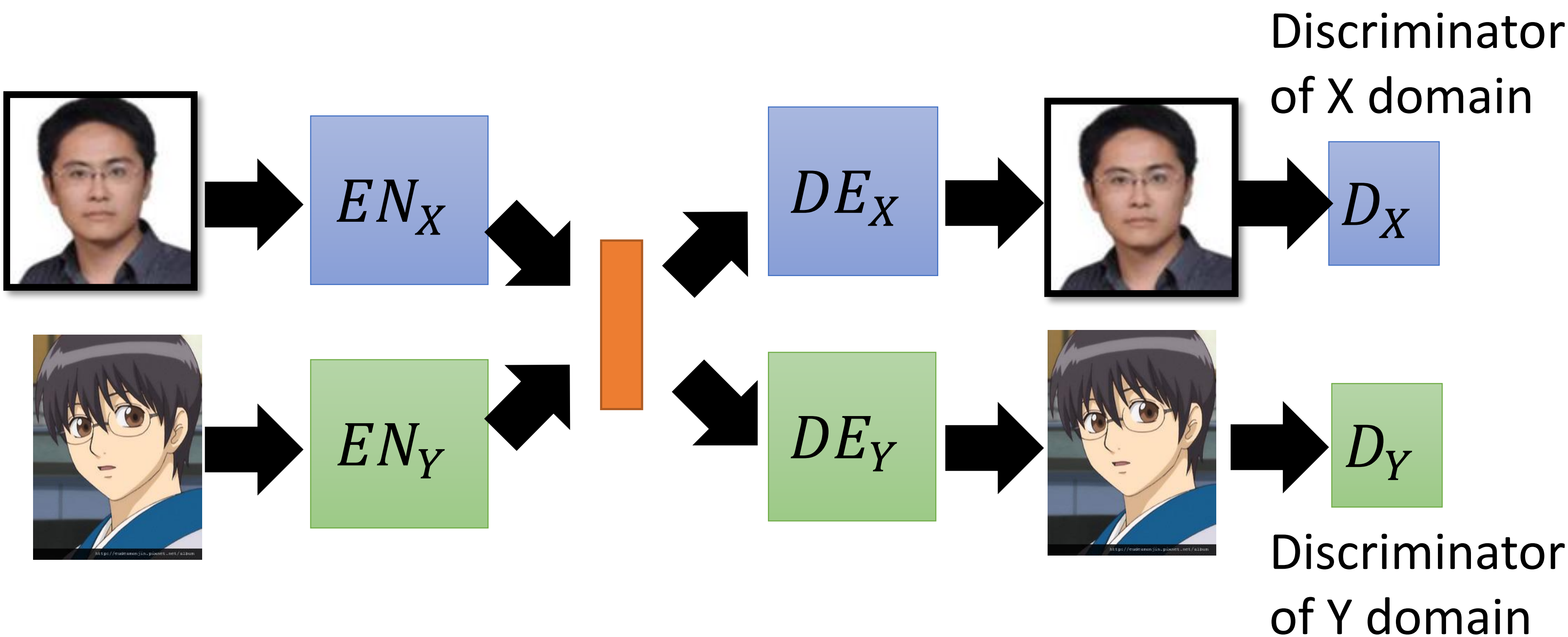
Word embedding
[Lee, et al., ICASSP, 2018]



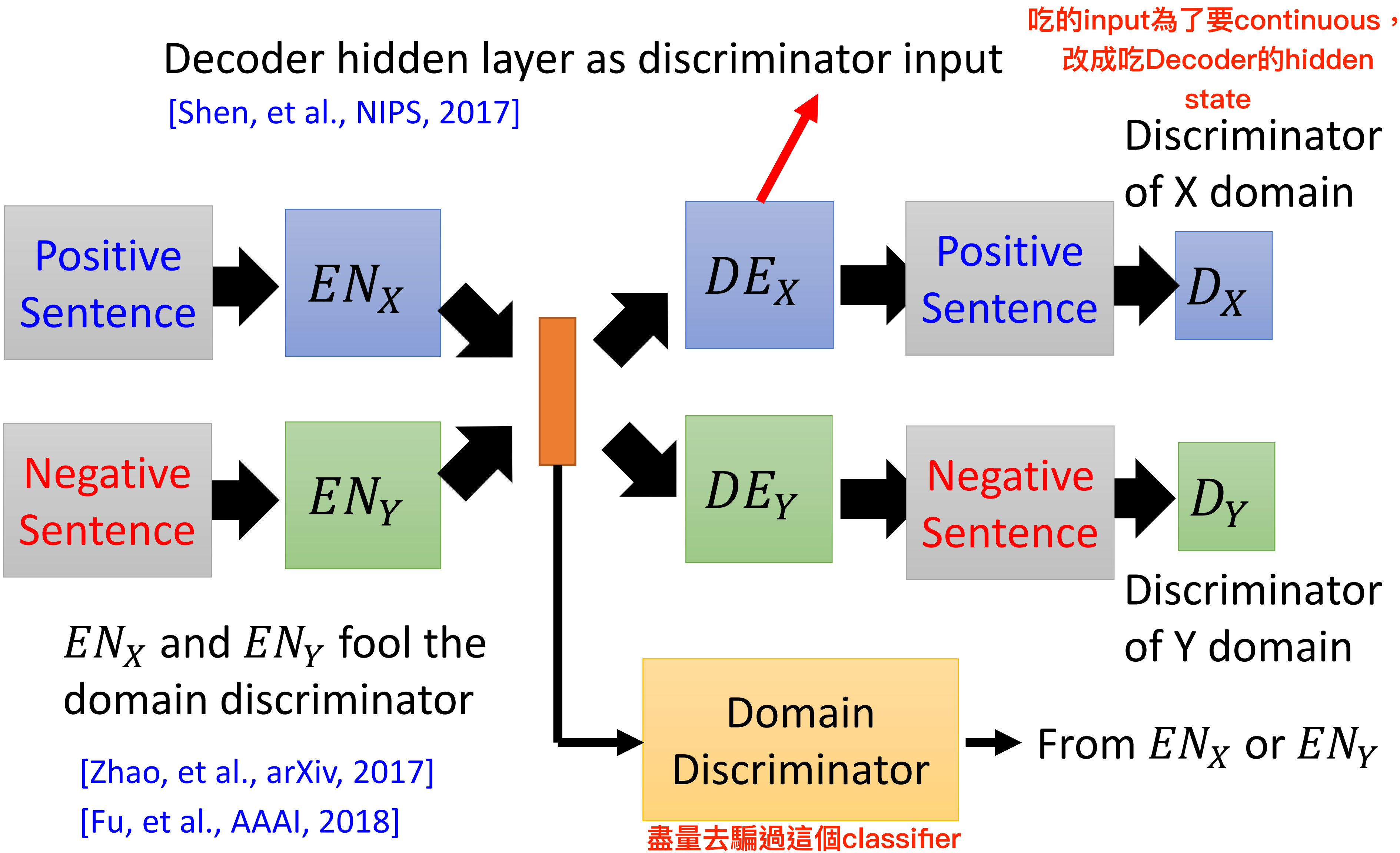
- Negative sentence to positive sentence:
  it's a crappy day → it's a great day
  i wish you could be here → you could be here
  it's not a good idea → it's good idea
  i miss you → i love you
  i don't love you → i love you
  i can't do that → i can do that
  i feel so sad → i happy
  it's a bad day → it's a good day
  it's a dummy day → it's a great day
  sorry for doing such a horrible thing → thanks for doing a great thing
  my doggy is sick → my doggy is my doggy
  my little doggy is sick → my little doggy is my little doggy



Projection to Common Space



Projection to Common Space



Outline of Part III

Improving Supervised Seq-to-seq Model

- RL (human feedback)
- GAN (discriminator feedback)

Unsupervised Seq-to-seq Model

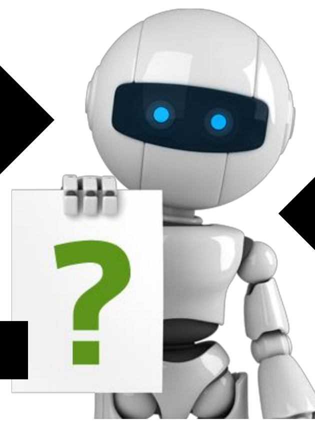
- Text Style Transfer
- Unsupervised Abstractive Summarization
- Unsupervised Translation

通常要上百萬的paired training data

Abstractive Summarization

判斷input句子是不是重要的，並且把所有重要的句子拼成摘要

- Now machine can do **abstractive summary** by seq2seq (write summaries in its own words)



summary
(in its own words)

seq2seq

summary 1

summary 2

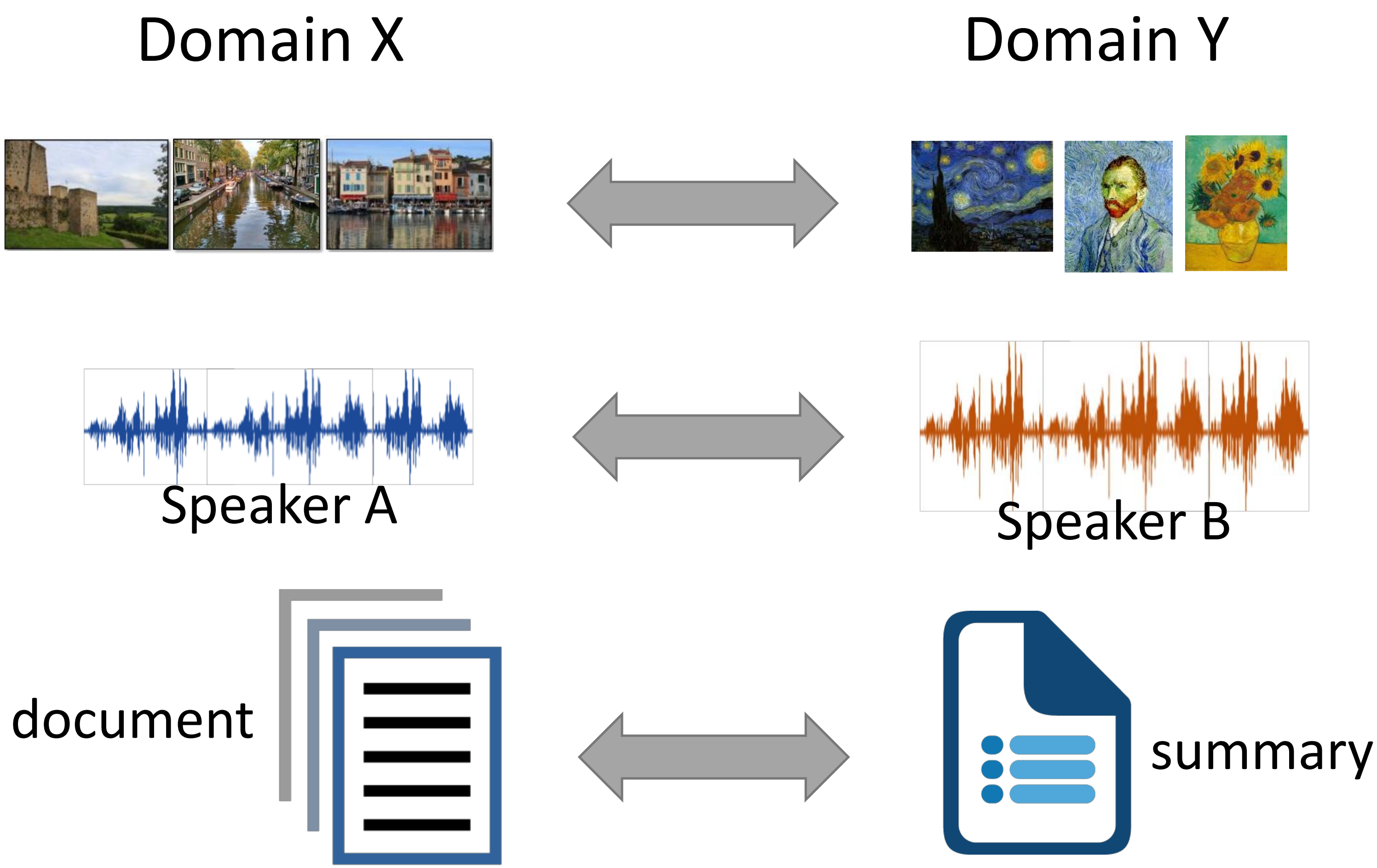
summary 3

Supervised: We need lots of labelled training data.

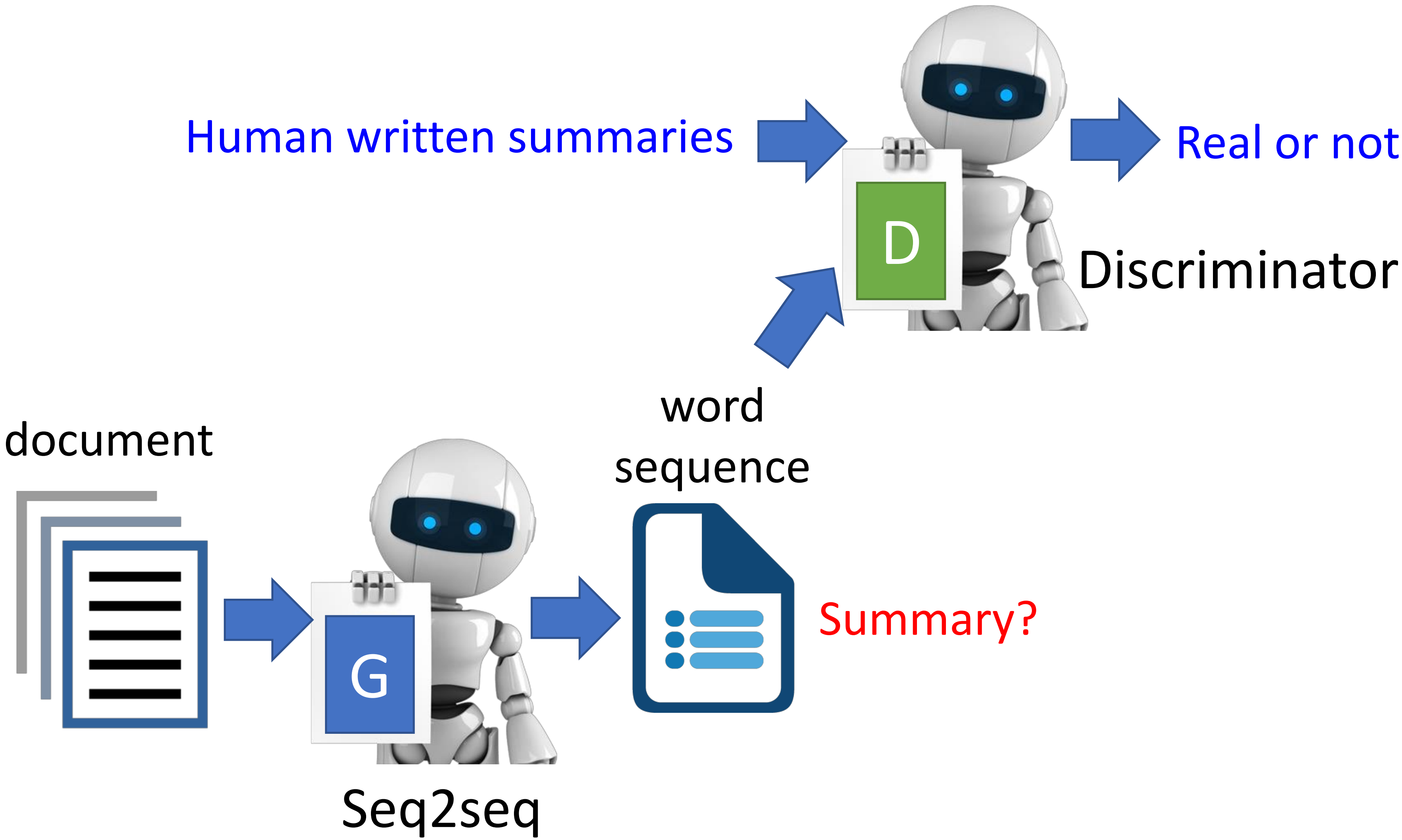
Training Data

Review: Unsupervised Conditional Generation

把文章跟摘要是為兩種domain，並且利用cycleGAN即可

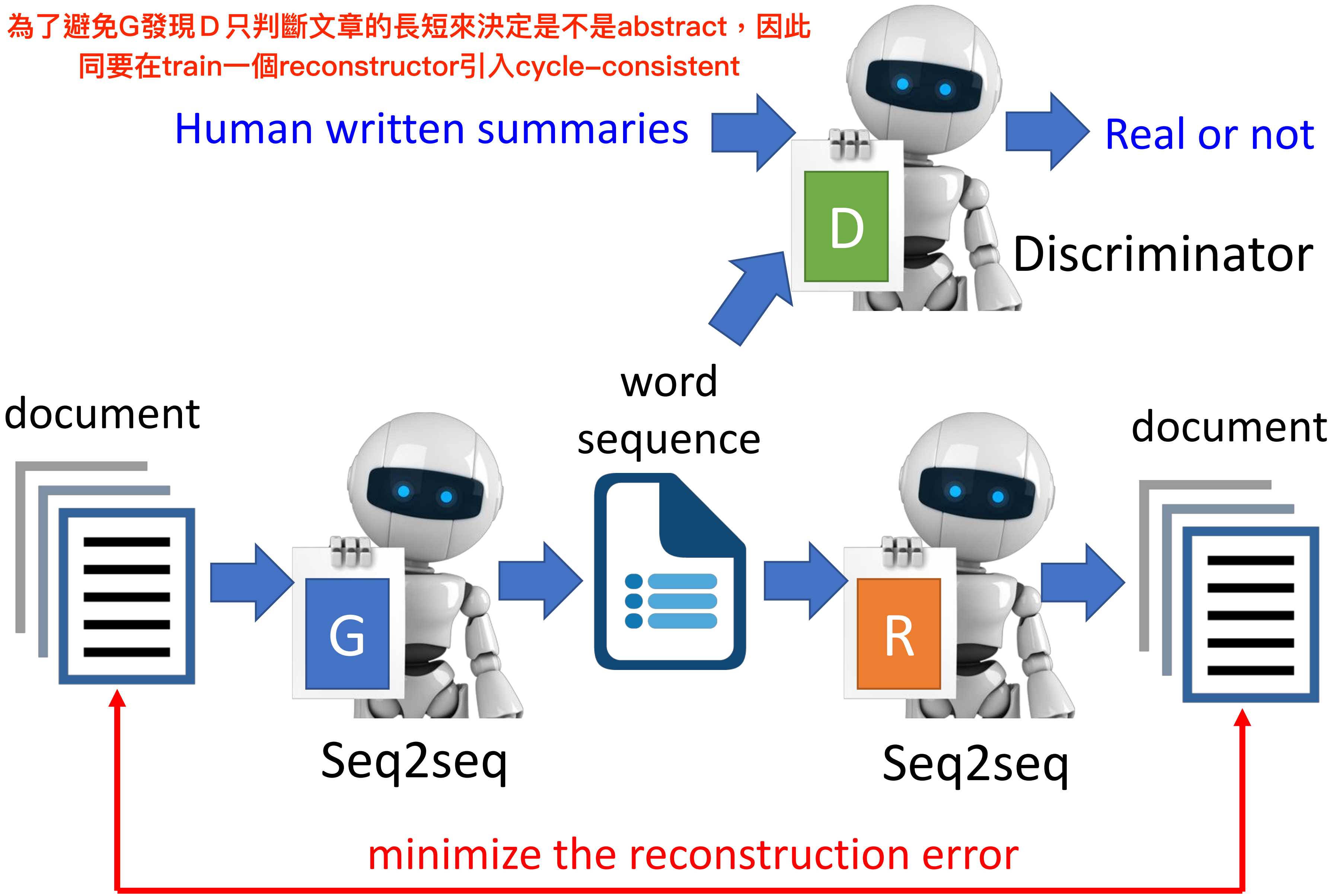


Unsupervised Abstractive Summarization



Unsupervised Abstractive Summarization

為了避免G發現D只判斷文章的長短來決定是不是abstract，因此
同要在train一個reconstructor引入cycle-consistent



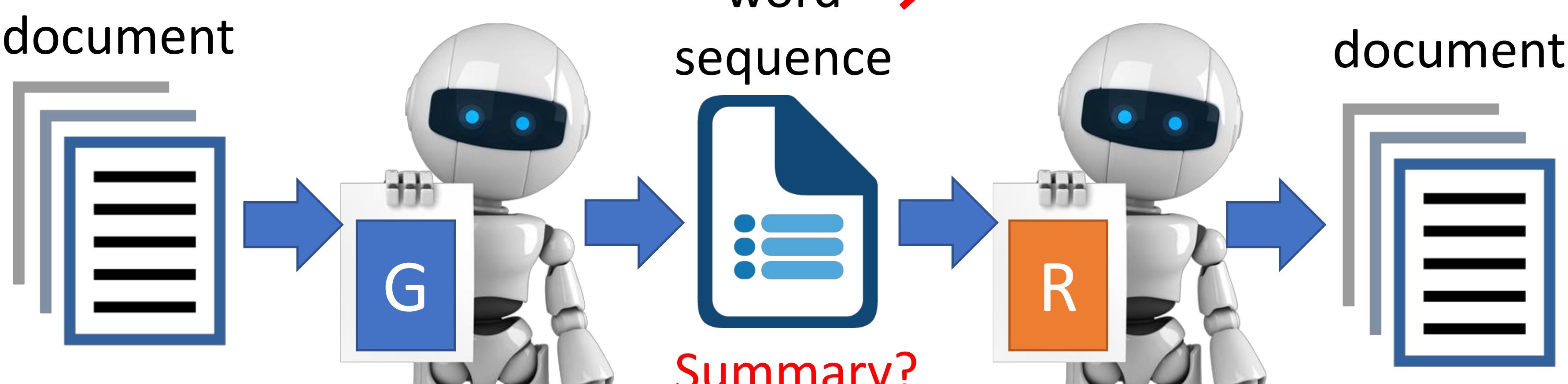
Unsupervised Abstractive Summarization

Only need a lot of documents to train the model

This is a ***seq2seq2seq auto-encoder***.

Using a sequence of words as latent representation.

not readable …



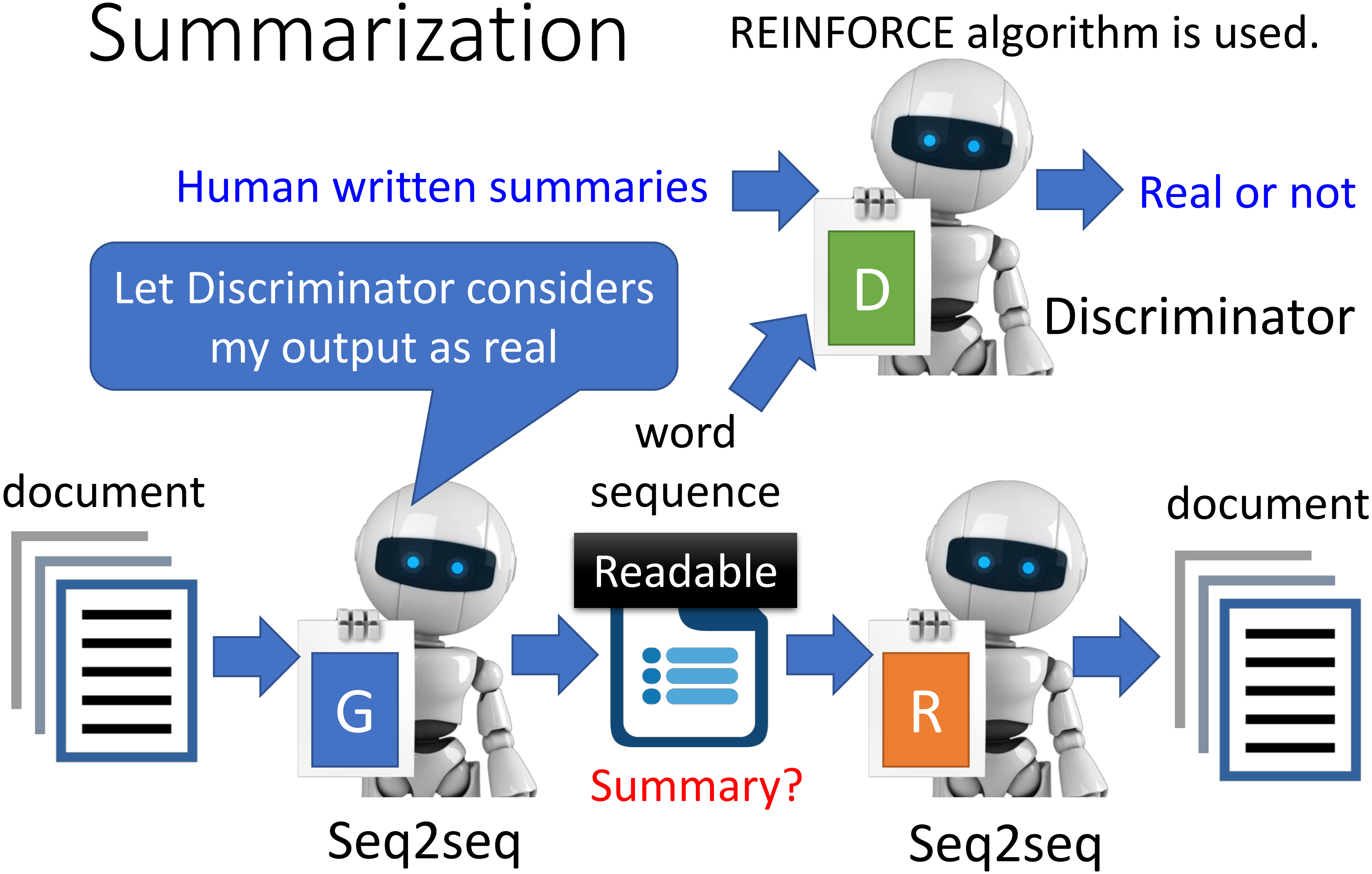
Summary?

Seq2seq

Seq2seq

discrete problem用reinforcement技術解決

Unsupervised Abstractive Summarization



感謝 王耀賢 同學提供實驗結果

Unsupervised Abstractive Summarization

- ***Document***:澳大利亞今天與13個國家簽署了反興奮劑雙邊協議,旨在加強體育競賽之外的藥品檢查並共享研究成果 ……
- ***Summary***:
  - Human:澳大利亞與13國簽署反興奮劑協議
  - Unsupervised:澳大利亞加強體育競賽之外的藥品檢查
- ***Document***:中華民國奧林匹克委員會今天接到一九九二年冬季奧運會邀請函,由於主席張豐緒目前正在中南美洲進行友好訪問,因此尚未決定是否派隊赴賽 ……
- ***Summary***:
  - Human:一九九二年冬季奧運會函邀我參加
  - Unsupervised:奧委會接獲冬季奧運會邀請函

感謝 王耀賢 同學提供實驗結果

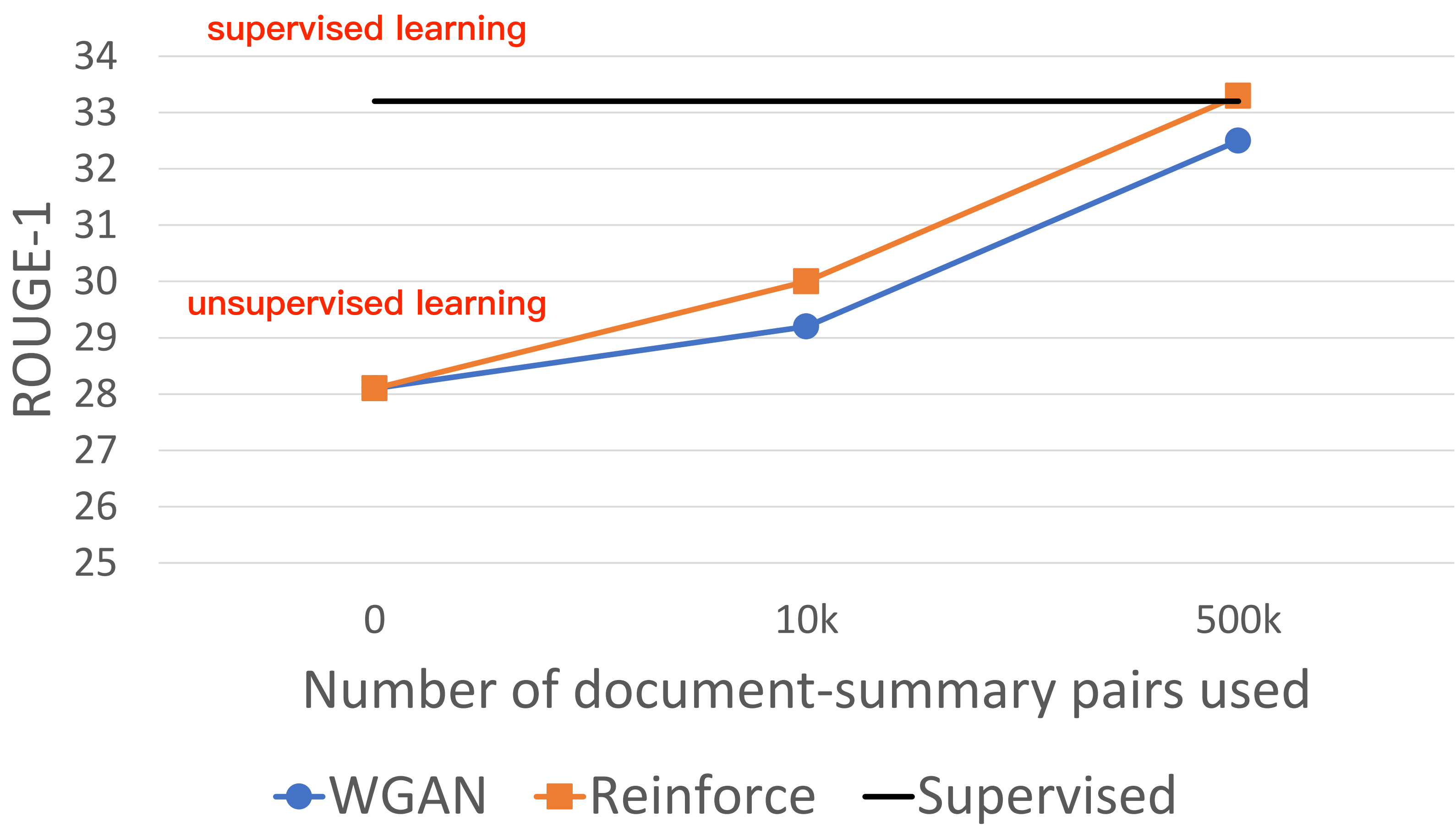
Unsupervised Abstractive Summarization

- ***Document***:據此間媒體27日報道,印度尼西亞蘇門答臘島的兩個省近日來連降暴雨,洪水泛濫導致塌方,到26日為止至少已有60人喪生,100多人失蹤 ……
- ***Summary***:
  - Human:印尼水災造成60人死亡
  - Unsupervised:印尼門洪水泛濫導致塌雨
- ***Document***:安徽省合肥市最近為領導幹部下基層做了新規定:一律輕車簡從,不準搞迎來送往、不準搞層層陪同 ……
- ***Summary***:
  - Human:合肥規定領導幹部下基層活動從簡
  - Unsupervised:合肥領導幹部下基層做搞迎來送往規定:一律簡

note: 先supervised再unsupervised, 還是先unsupervised再supervised？ (unpublished result)

Semi-supervised Learning

Using matched data



(3.8M pairs are used)

Outline of Part III

Improving Supervised Seq-to-seq Model

- RL (human feedback)
- GAN (discriminator feedback)

Unsupervised Seq-to-seq Model

- Text Style Transfer
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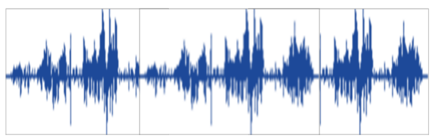
- Unsupervised Translation

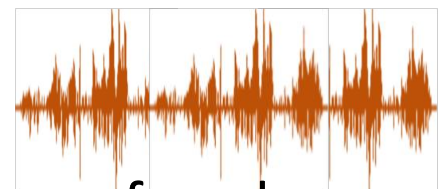
Unsupervised Machine Translation

Domain X

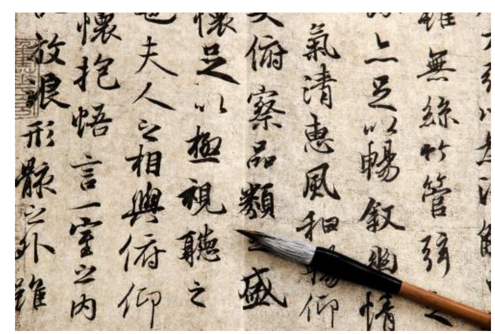
Domain Y



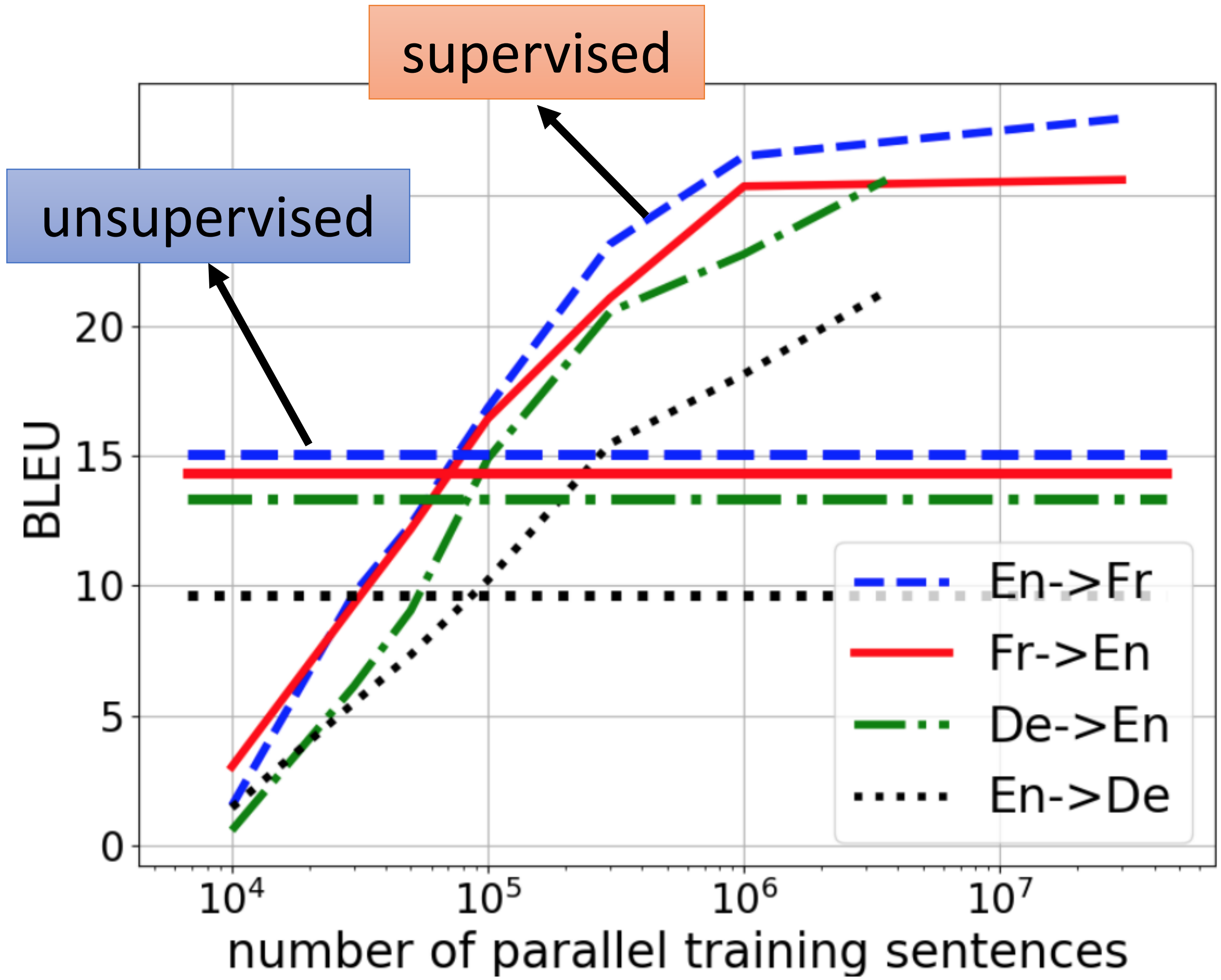
male



female

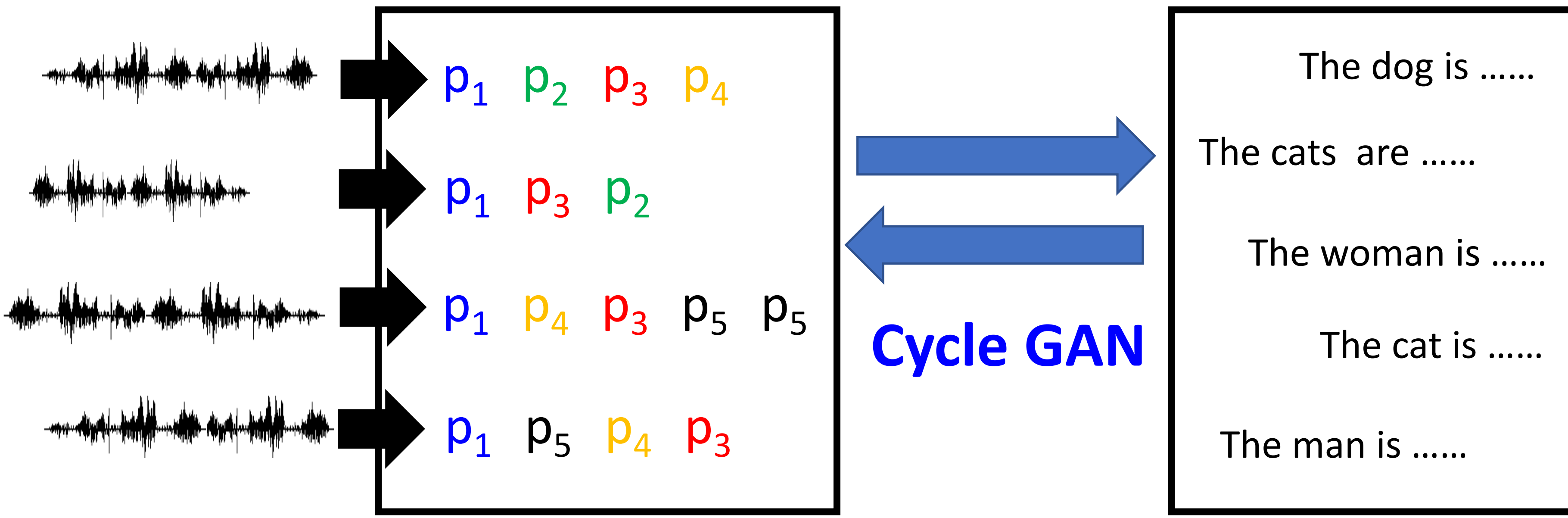


[Alexis Conneau, et al., ICLR, 2018]
[Guillaume Lample, et al., ICLR, 2018]



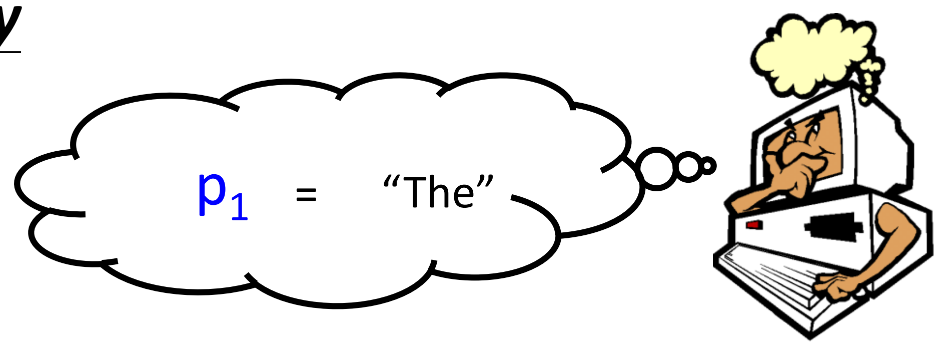
Unsupervised learning with 10M sentences = **Supervised** learning with 100K sentence pairs

Unsupervised Speech Recognition



Acoustic Pattern Discovery

Can we achieve unsupervised speech recognition?

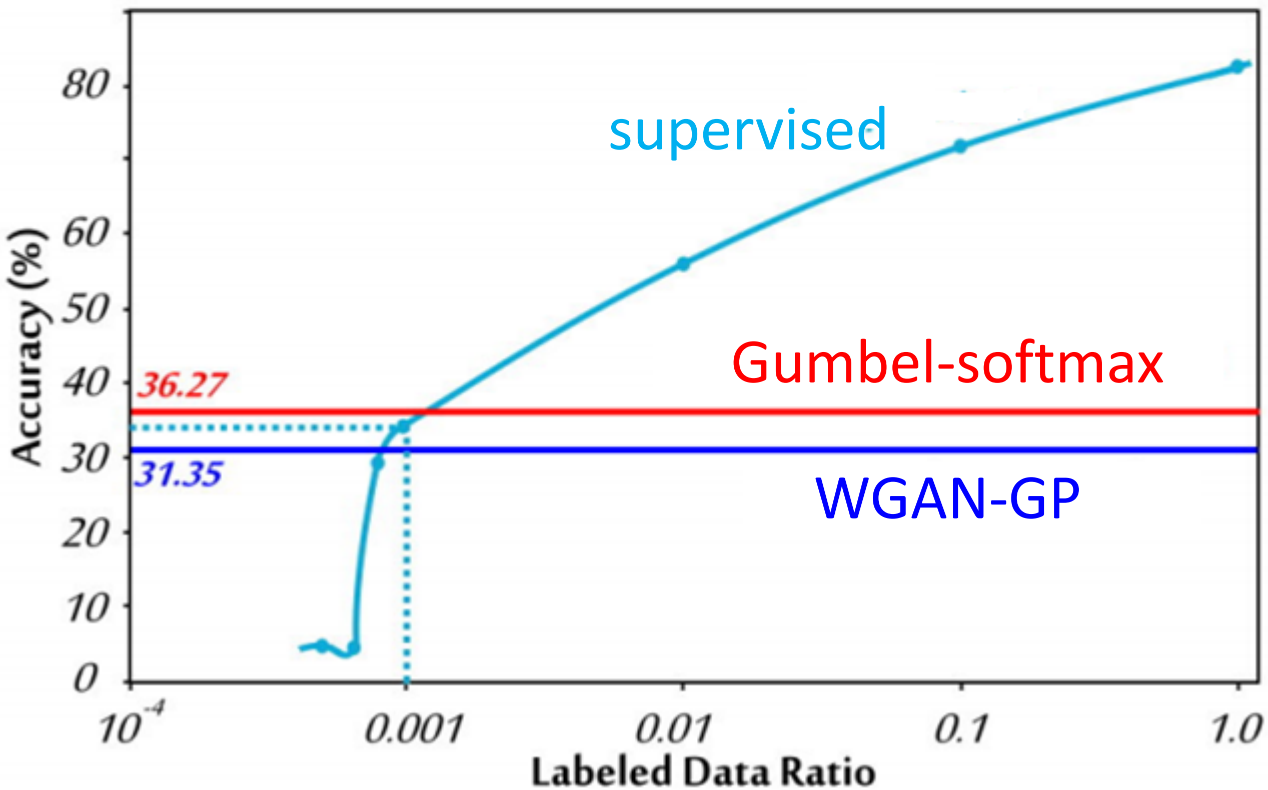


[Liu, et al., arXiv, 2018] [Chen, et al., arXiv, 2018]

Unsupervised Speech Recognition

- Phoneme recognition

Audio: TIMIT
Text: WMT



Concluding Remarks

Conditional Sequence Generation

- RL (human feedback)
- GAN (discriminator feedback)

Unsupervised Conditional Sequence Generation

- Text Style Transfer
- Unsupervised Abstractive Summarization
- Unsupervised Translation

Concluding Remarks

from A to Z

A	B	C	D	E	F
ACGAN HW 3-2	BiGAN	CycleGAN	DCGAN DuelGAN	EBGAN	fGAN

G	H	I	J	K	L
GAN	?	InfoGAN	?	?	LSGAN

(only list those mentioned in class)

M	N	O	P	Q	R
MMGAN	NSGAN	?	Progressive GAN	?	Rank GAN

S	T	U	V	W	X
StackGAN StarGAN SeqGAN	Triple GAN	Unroll GAN	VAEGAN	WGAN	XGAN

Y ?

Z ?

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