Text *Style* Transfer

Hung-yi Lee 李宏毅

Image Style

Audio Style

male

female

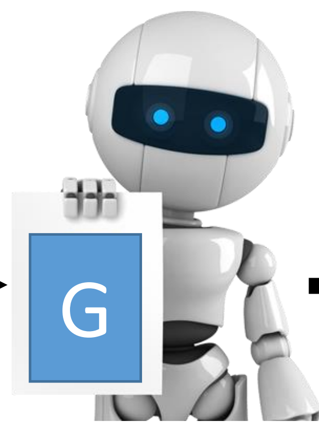
positive sentences

negative sentences

Text Style Transfer

Text Style Transfer

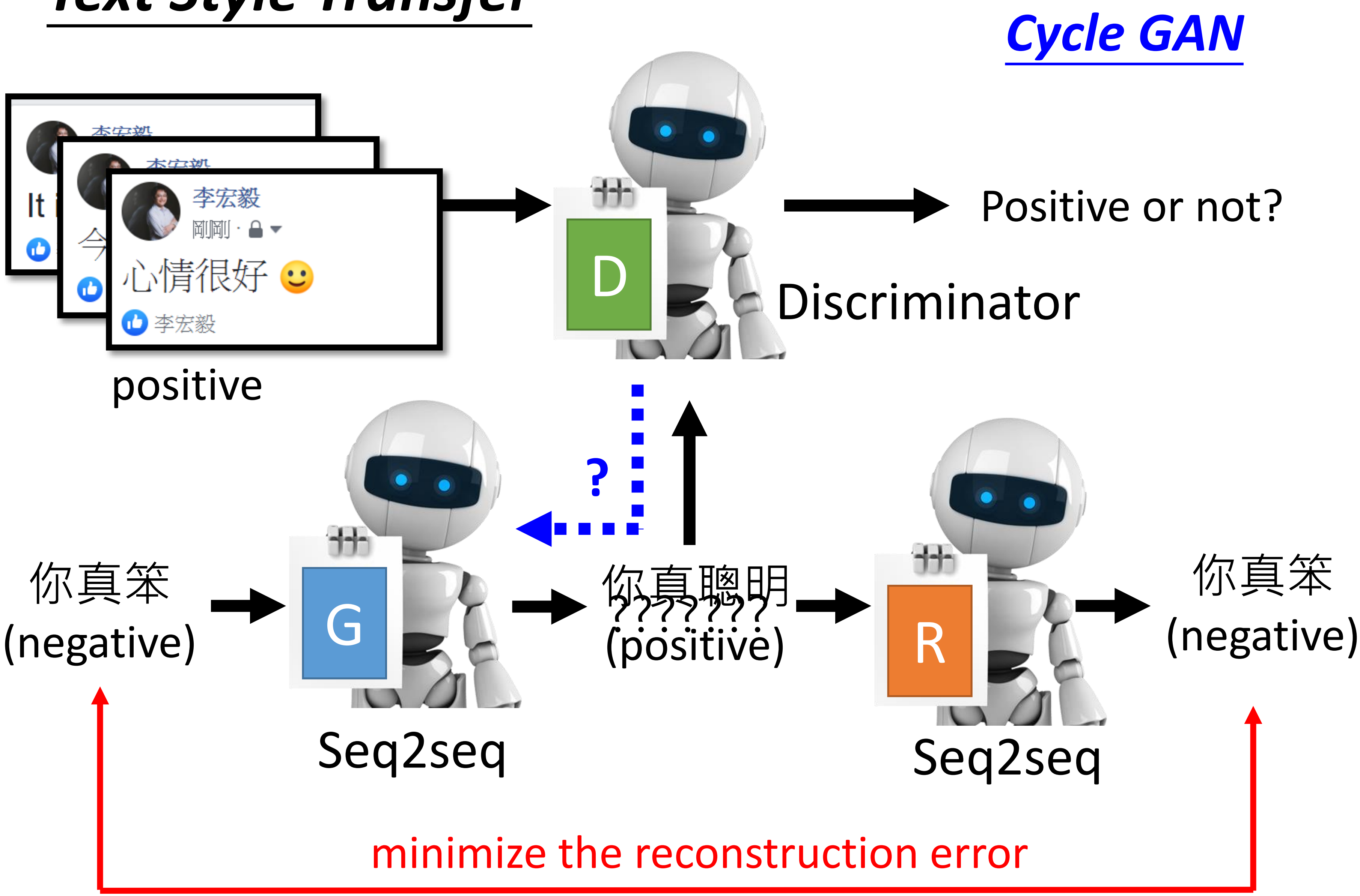
你真笨
(negative)



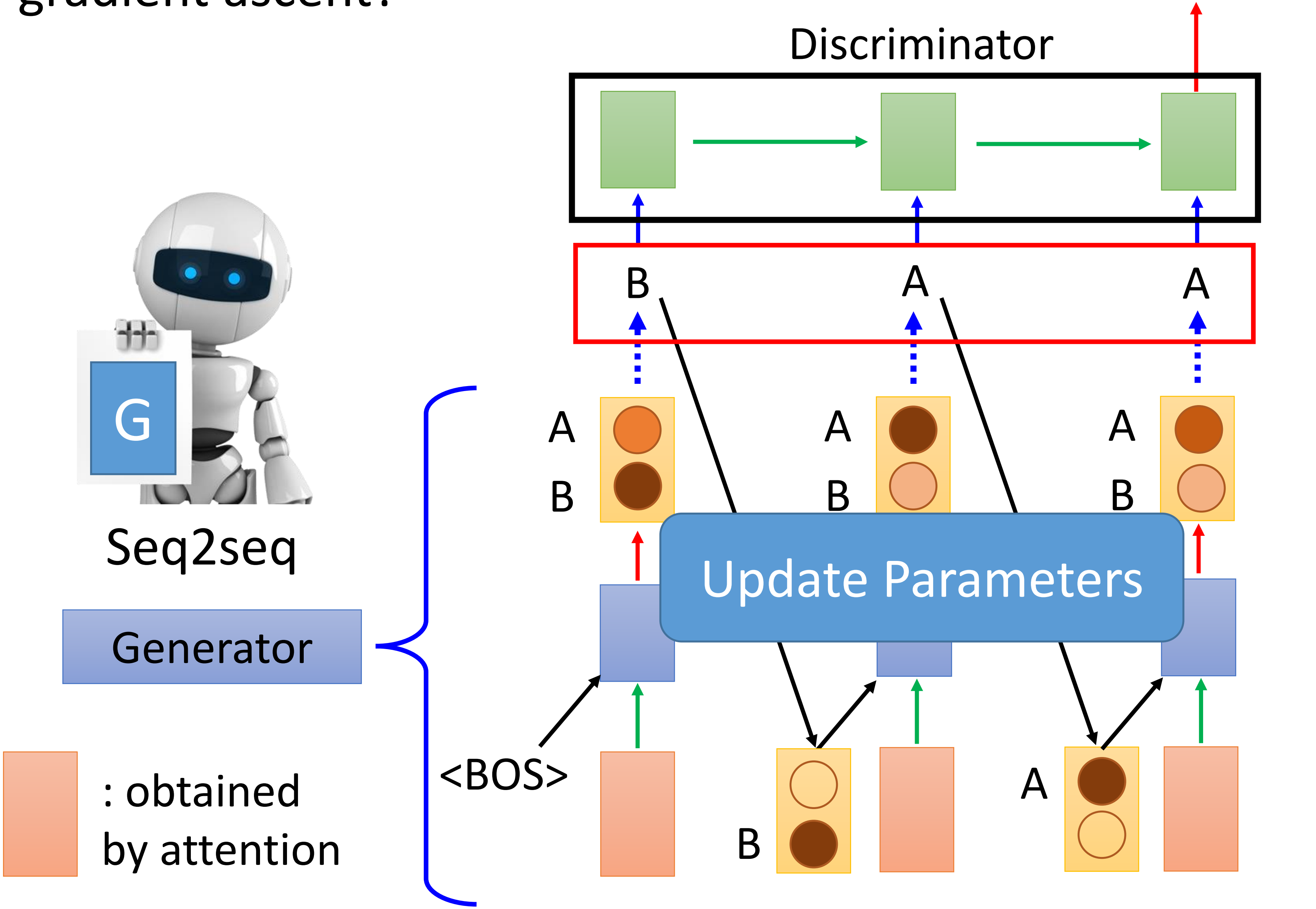
你真聰明
???????
(positive)

Seq2seq

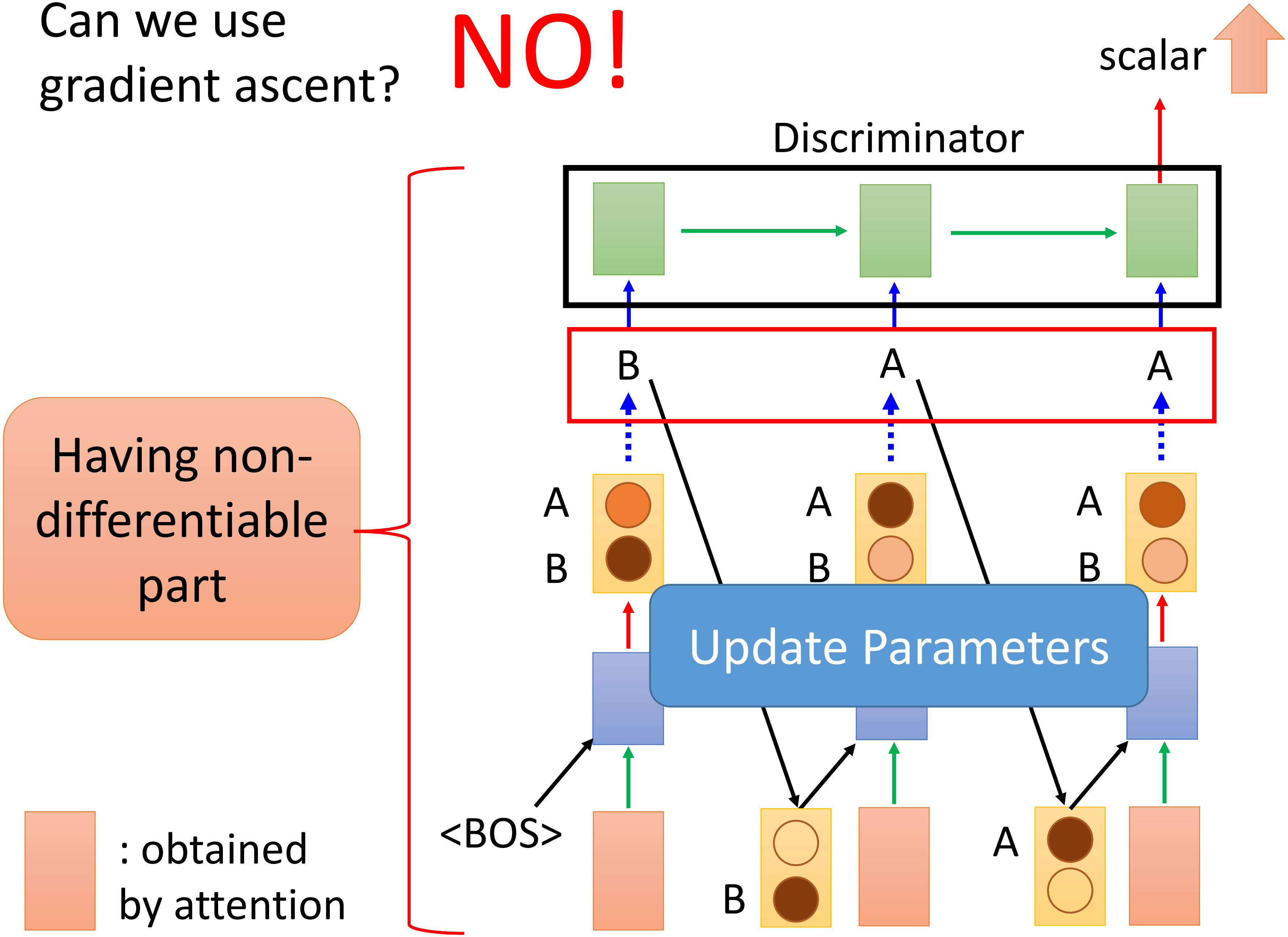
Text Style Transfer



Can we use gradient ascent? NO!



Can we use gradient ascent? **NO!**



Three Categories of Solutions

Gumbel-softmax

- [Matt J. Kusner, et al., arXiv, 2016][Weili Nie, et al. ICLR, 2019]

Continuous Input for Discriminator

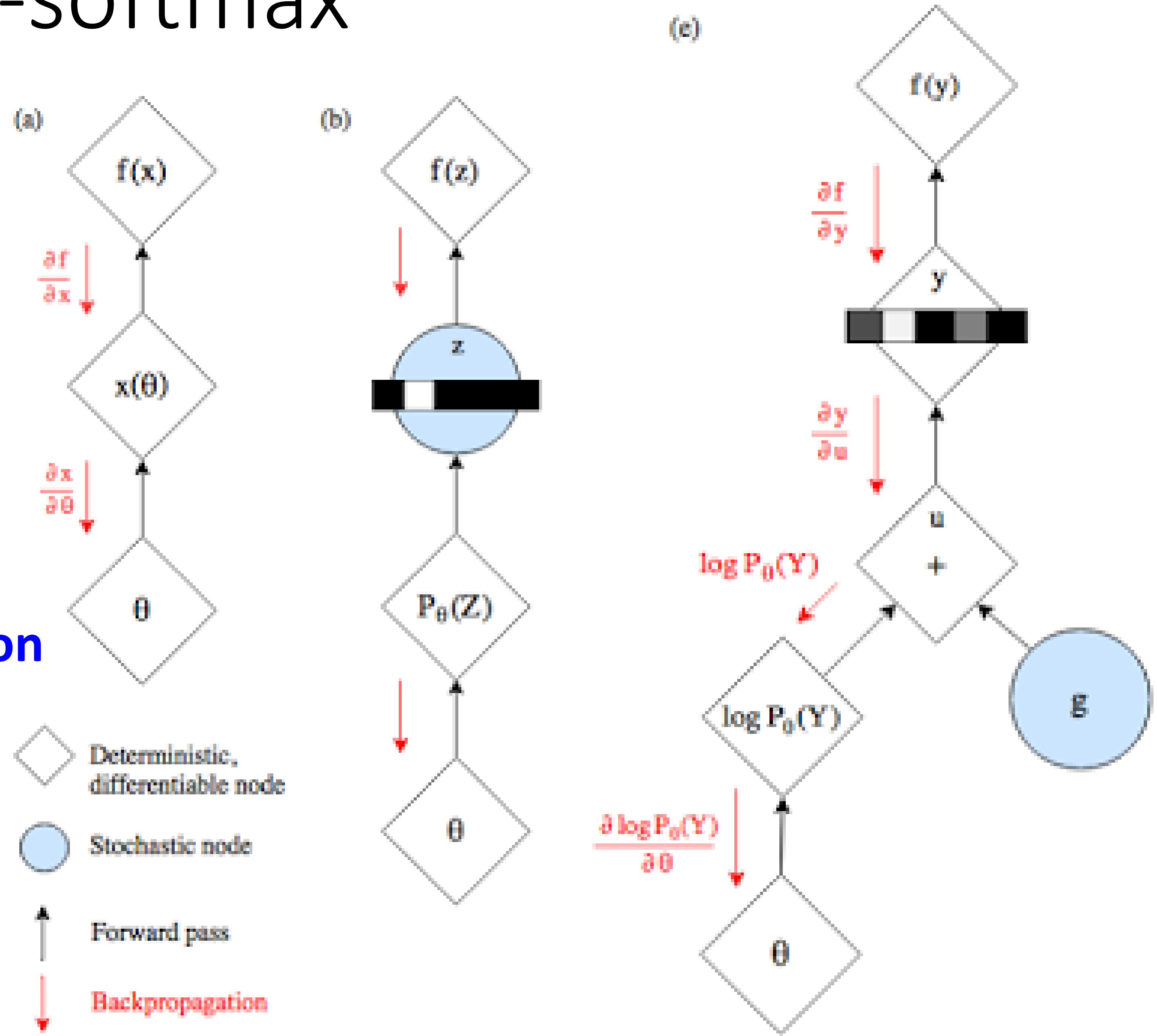
- [Sai Rajeswar, et al., arXiv, 2017][Ofir Press, et al., ICML workshop, 2017][Zhen Xu, et al., EMNLP, 2017][Alex Lamb, et al., NIPS, 2016][Yizhe Zhang, et al., ICML, 2017]

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]

Source of image: https://blog.evjang.com/2016/11/tutorial-categorical-variational.html

Gumbel-softmax



Using the **reparameterization** trick

As what people do for training **VAE**

Three Categories of Solutions

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Reinforcement Learning

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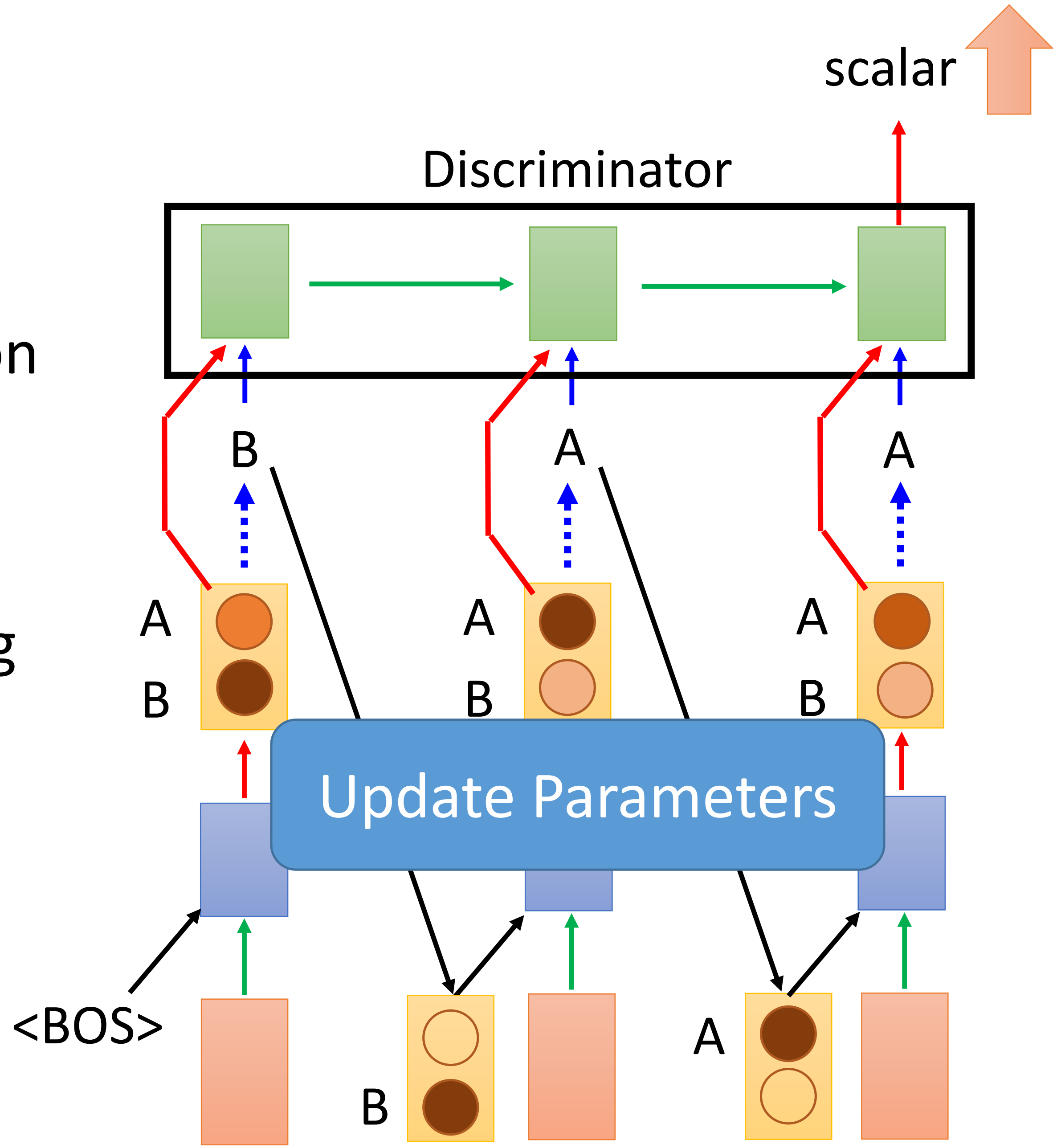
Use the distribution as the input of discriminator

Avoid the sampling process

We can do backpropagation now.



What is the problem?

Discriminator with constraint (e.g. WGAN) can be helpful.

- Real sentence

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

- Generated

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-hot

Discriminator can immediately find the difference.

Three Categories of Solutions

Gumbel-softmax

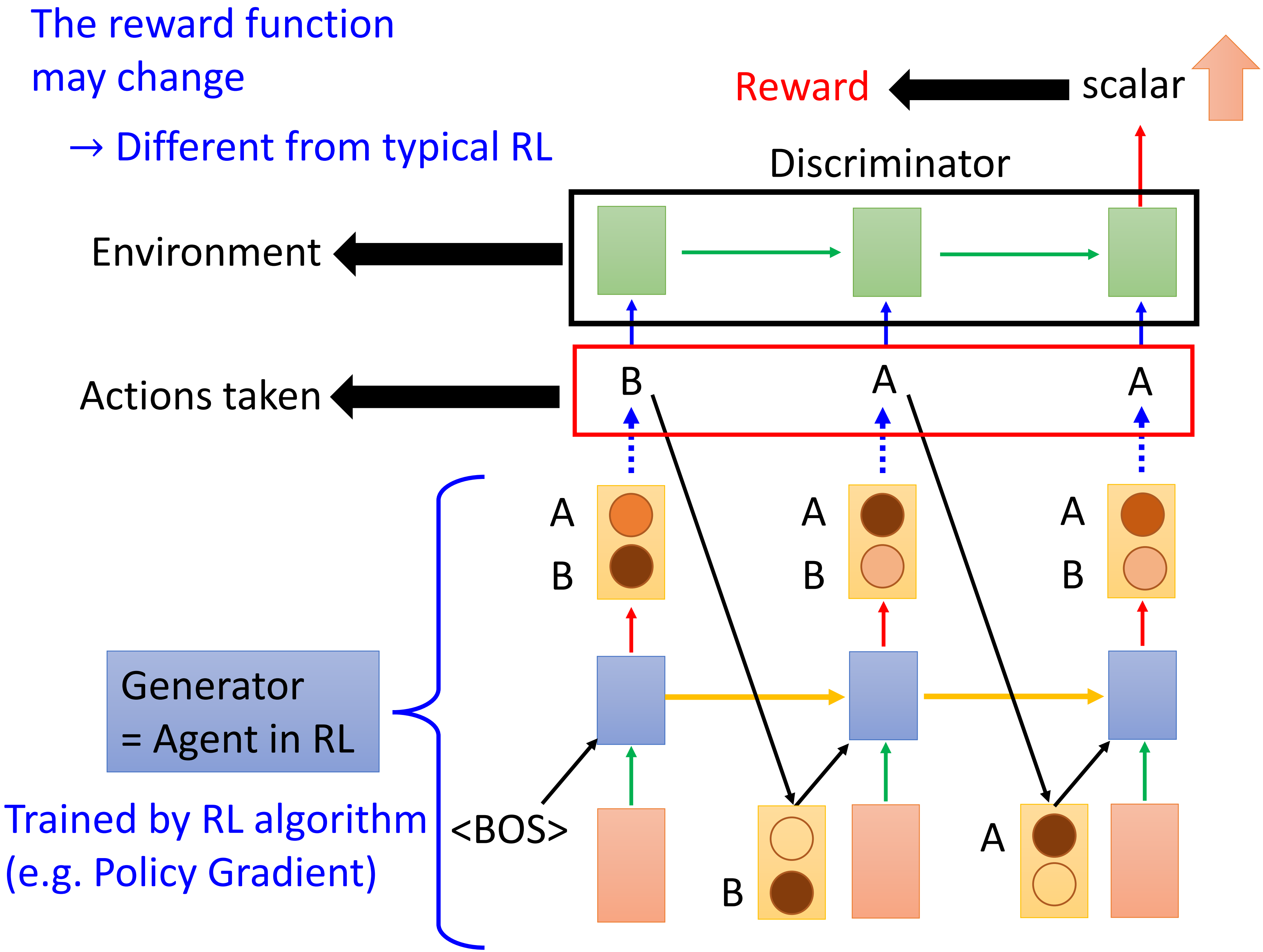
- [Matt J. Kusner, et al., arXiv, 2016][Weili Nie, et al. ICLR, 2019]

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]

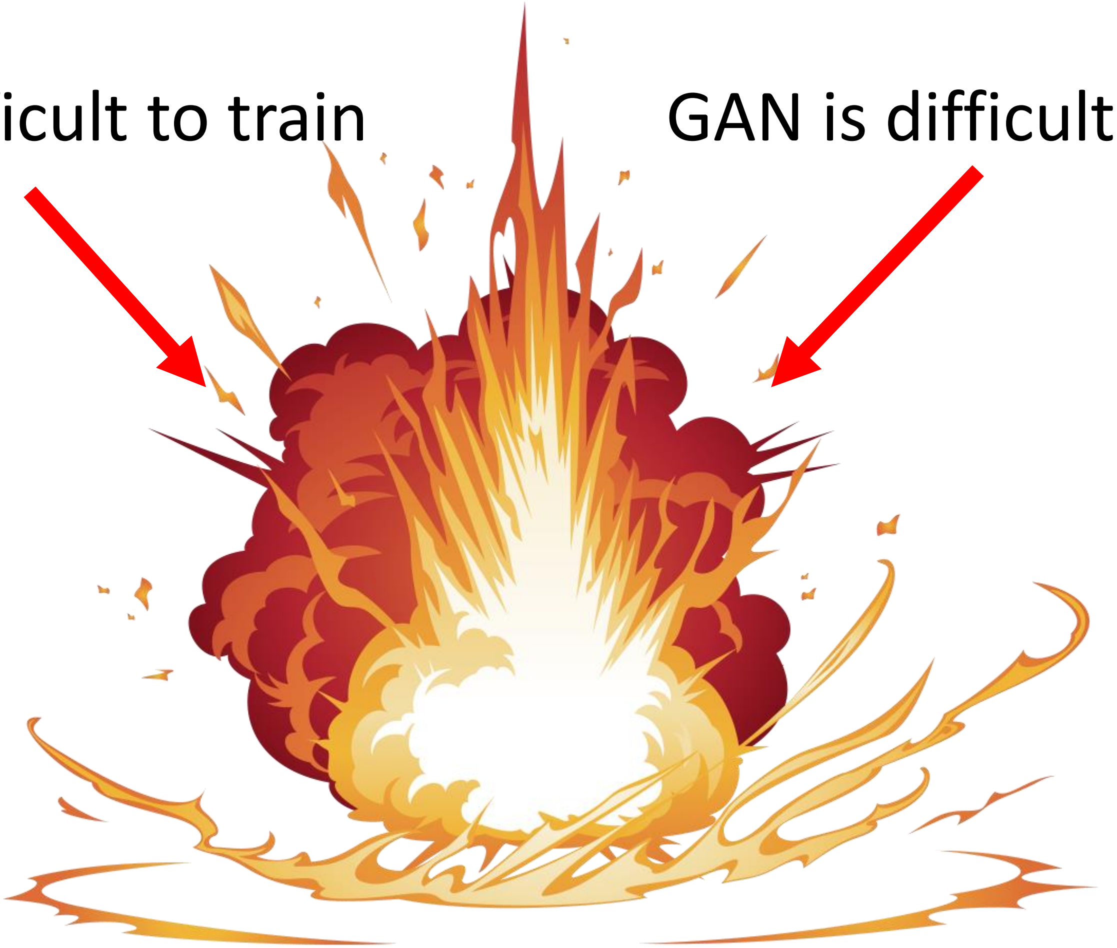


The reward function
may change
→ Different from typical RL
Reward
scalar
Discriminator
Environment
Actions taken
B
A
A
A
B
A
B
A
B
Generator
= Agent in RL
Trained by RL algorithm
(e.g. Policy Gradient)
<BOS>
B
A

Disaster ……

RL is difficult to train

GAN is difficult to train

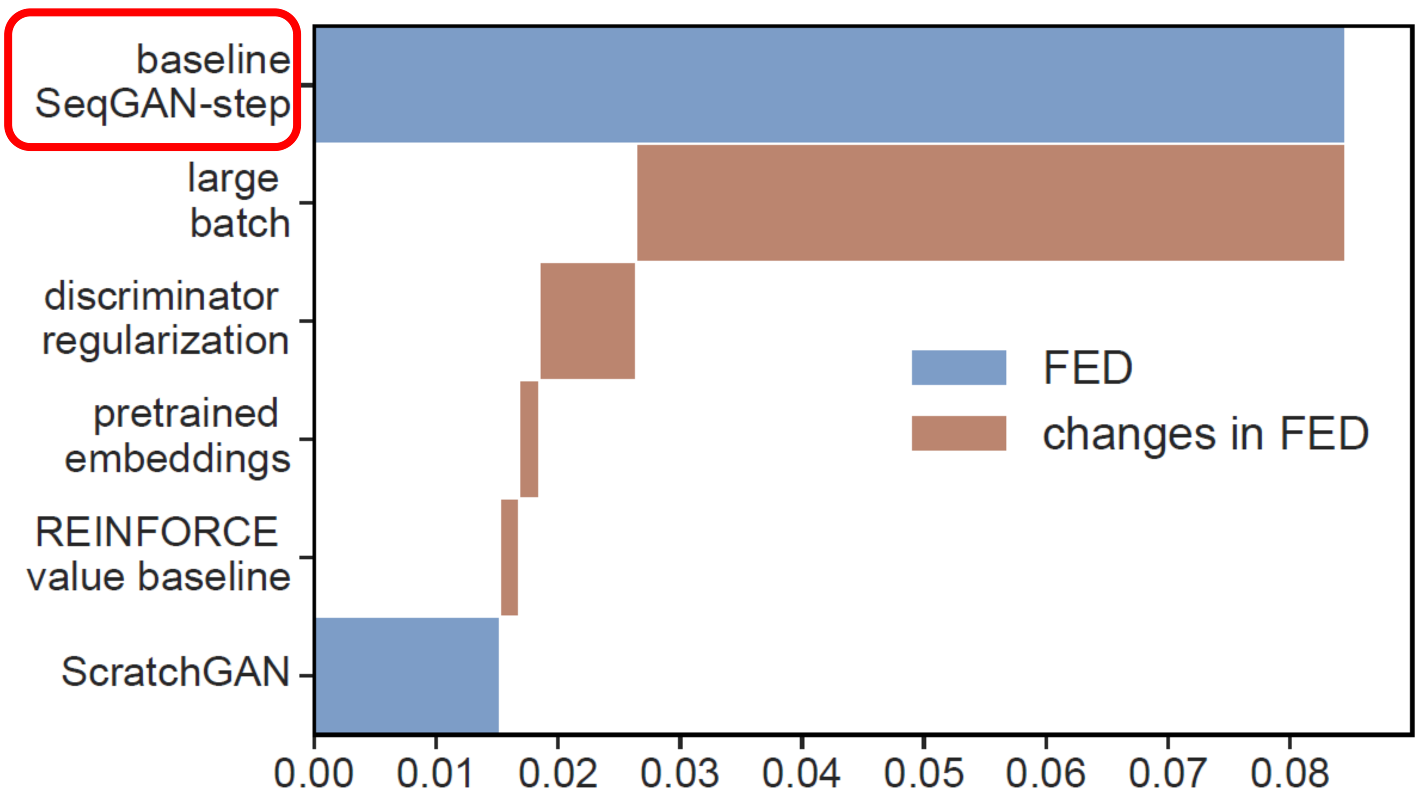


RL+GAN

Tips?

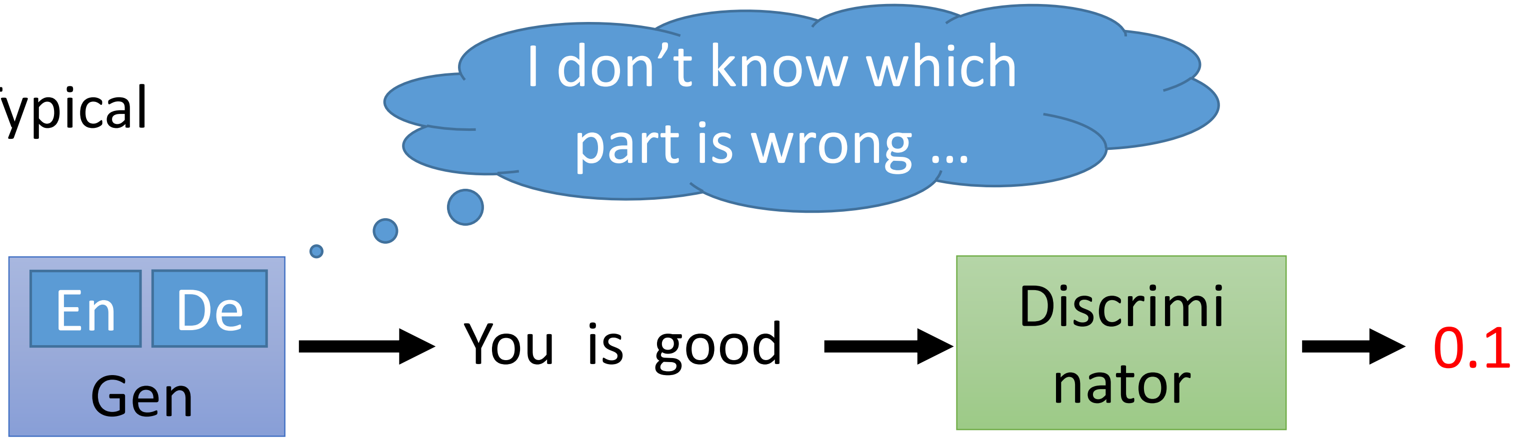
[Cyprien de Masson d'Autume, et al., arXiv 2019]

- ScratchGAN

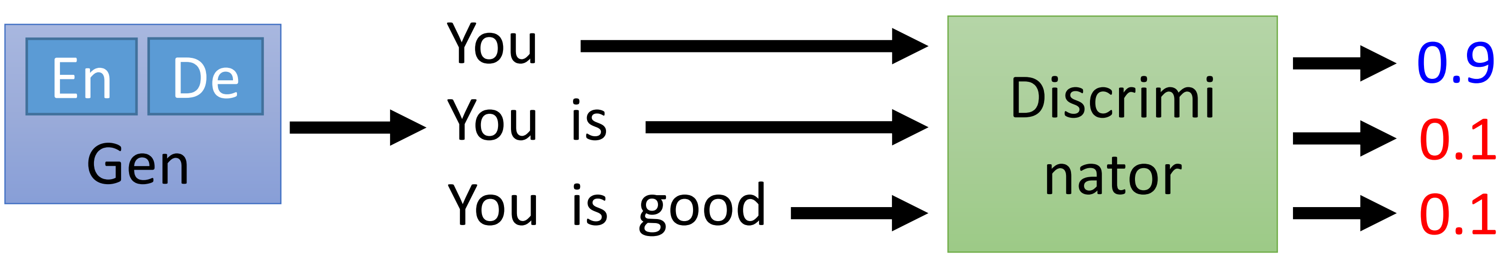


Tips?

- Typical

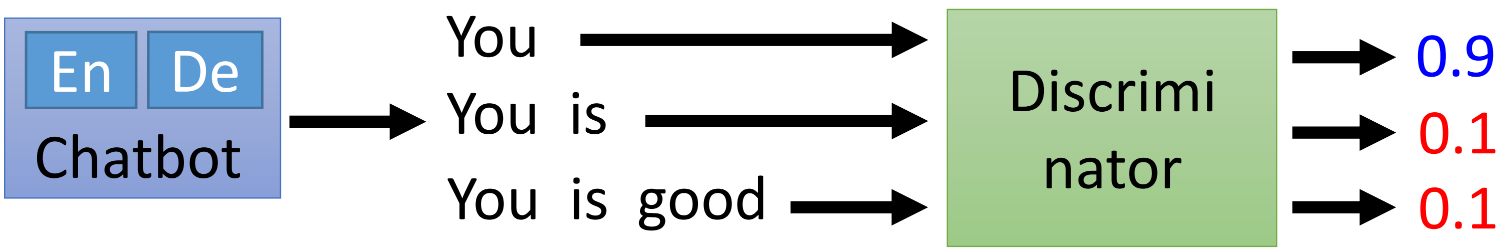


- Reward for Every Generation Step



Tips?

- Reward for Every Generation Step

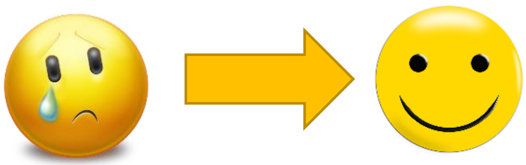


Method 1. Monte Carlo (MC) Search [Yu, et al., AAAI, 2017]

Method 2. Discriminator For Partially Decoded Sequences [Li, et al., EMNLP, 2017]

Method 3. Step-wise evaluation [Tual, Lee, TASLP, 2019][Xu, et al., EMNLP, 2018][William Fedus, et al., ICLR, 2018]

感謝 張瓊之 同學提供實驗結果



Text Style Transfer

[Lee, et al., ICASSP’18]

- From negative sentence to positive one

胃疼 , 沒睡醒 , 各種不舒服

我都想去上班了, 真夠賤的!

暈死了, 吃燒烤、竟然遇到個變態狂

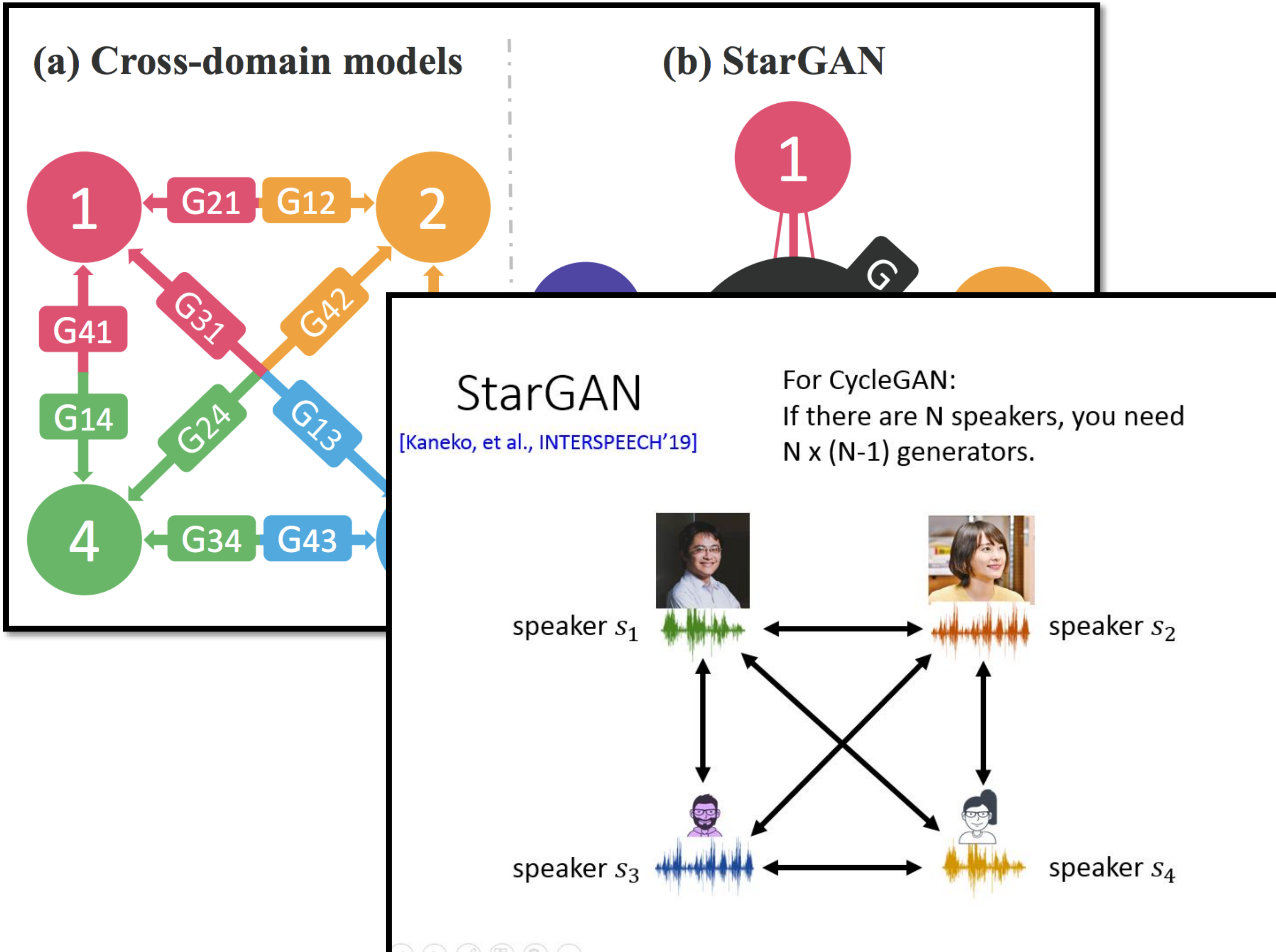
我肚子痛的厲害

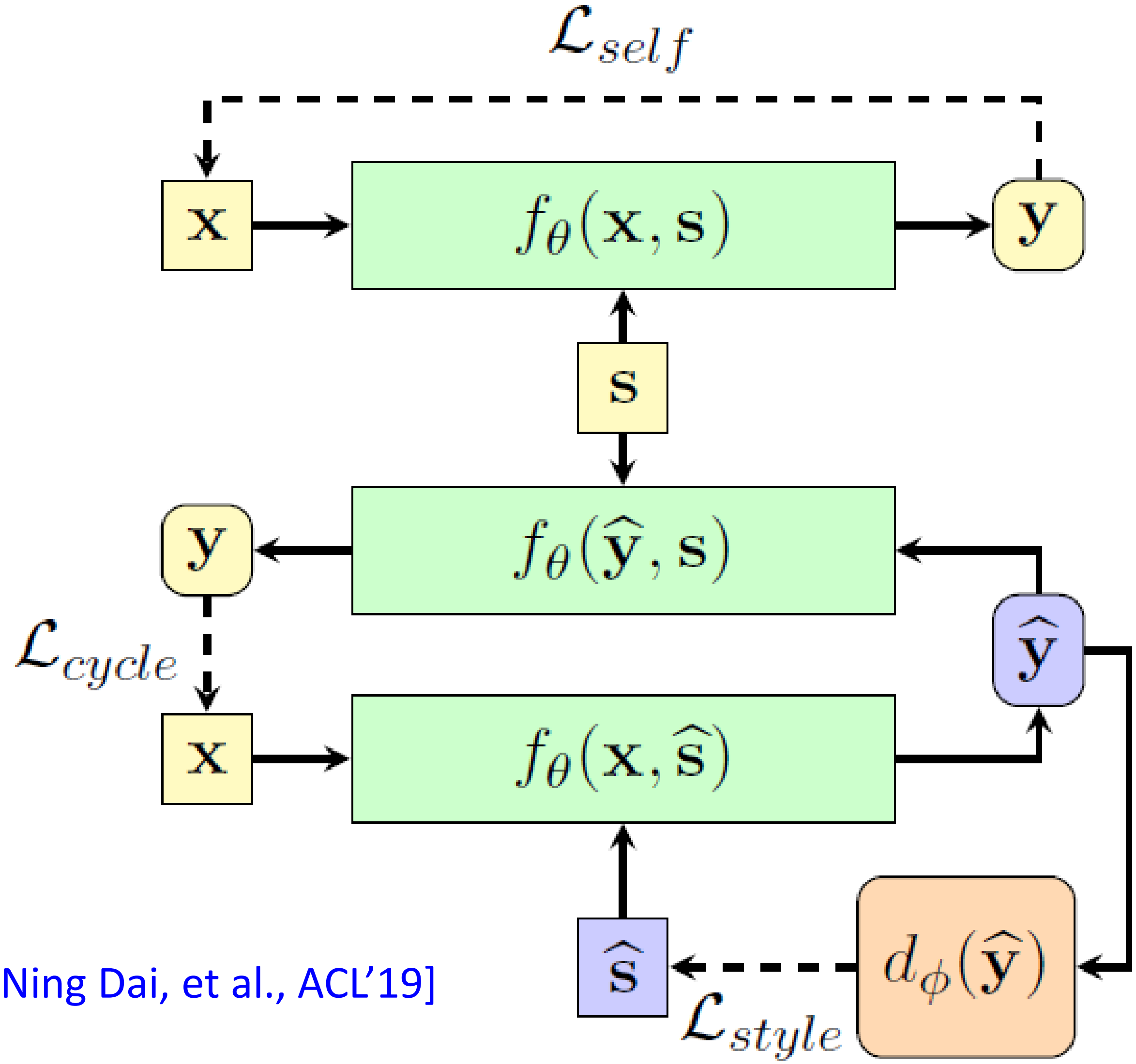
Relaxed ↔ Annoyed	
Relaxed	Sitting by the Christmas tree and watching Star Wars after cooking dinner. What a nice night 💗 🎄 ✨
Annoyed	Sitting by the computer and watching The Voice for the second time tonight. What a horrible way to start the weekend 😡 😡 😡
Annoyed	Getting a speeding ticket 50 feet in front of work is not how I wanted to start this month 😒
Relaxed	Getting a haircut followed by a cold foot massage in the morning is how I wanted to start this month 😊
Male ↔ Female	
Male	Gotta say that beard makes you look like a Viking...
Female	Gotta say that hair makes you look like a Mermaid...
Female	Awww he's so gorgeous 😍 can't wait for a cuddle. Well done 😘 xxx
Male	Bro he's so f***ing dope can't wait for a cuddle. Well done bro
Age 18-24 ↔ 65+	
18-24	You cheated on me but now I know nothing about loyalty 😂 ok
65+	You cheated on America but now I know nothing about patriotism. So ok.
65+	Ah! Sweet photo of the sisters. So happy to see them together today .
18-24	Ah 😂 Thankyou 💞 #sisters ❤️ happy to see them together today

[1]Note that using "gender" (or any other attribute for that matter) as a differentiating attribute between several bodies of text implies that there are indeed signatures of gender in the data. These signatures could be as innocuous as some first names like Mary being usually associated with women, or disheartening like biases and stereotypes exposed by statistical methods, (e.g., "man is to computer programmer as woman is to homemaker" (Bolukbasi et al., 2016)). We certainly do not condone those stereotypes, and on the contrary, we hope that showing that our models can uncover these biases might down the line turn them into powerful tools for researchers who study fairness and debiasing (Reddy & Knight, 2016).

Source of image: https://openreview.net/forum?id=H1g2NhC5KQ

[Lample, et al., ICLR'19]


(a) Cross-domain models
(b) StarGAN
1
2
4
G21
G12
G41
G14
G31
G42
G24
G13
G34
G43
G
StarGAN
[Kaneko, et al., INTERSPEECH'19]
For CycleGAN:
If there are N speakers, you need
N x (N-1) generators.
speaker s_1
speaker s_2
speaker s_3
speaker s_4

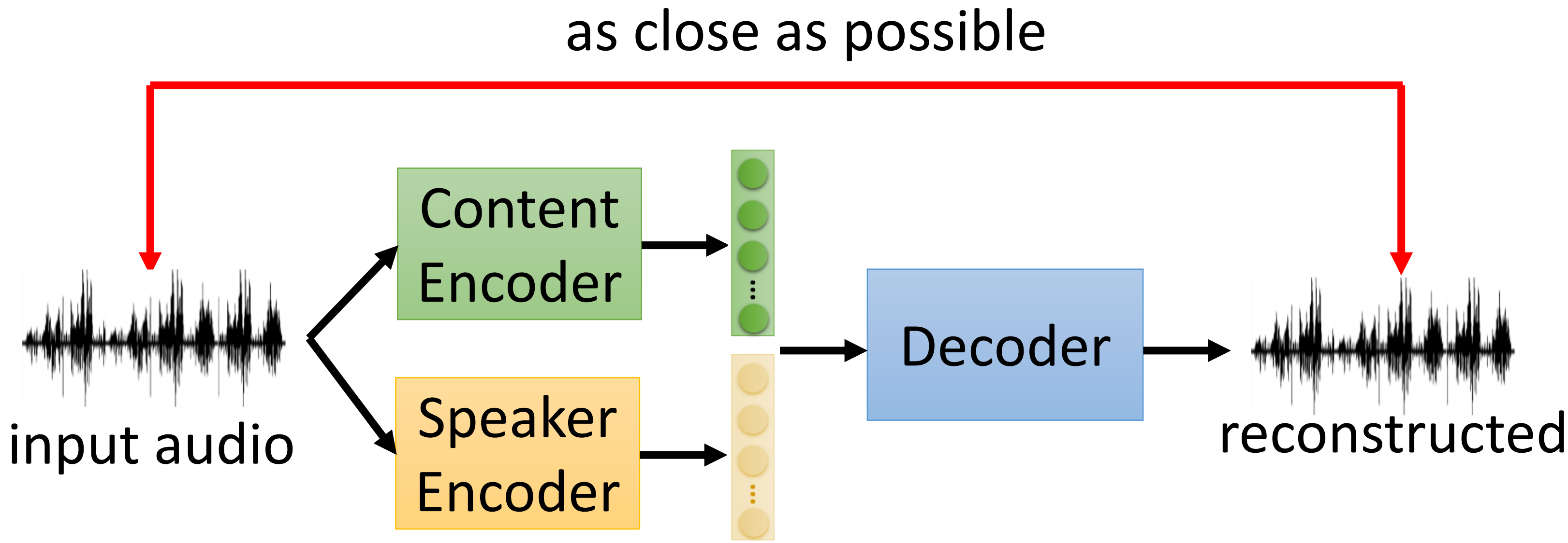


[Ning Dai, et al., ACL'19]

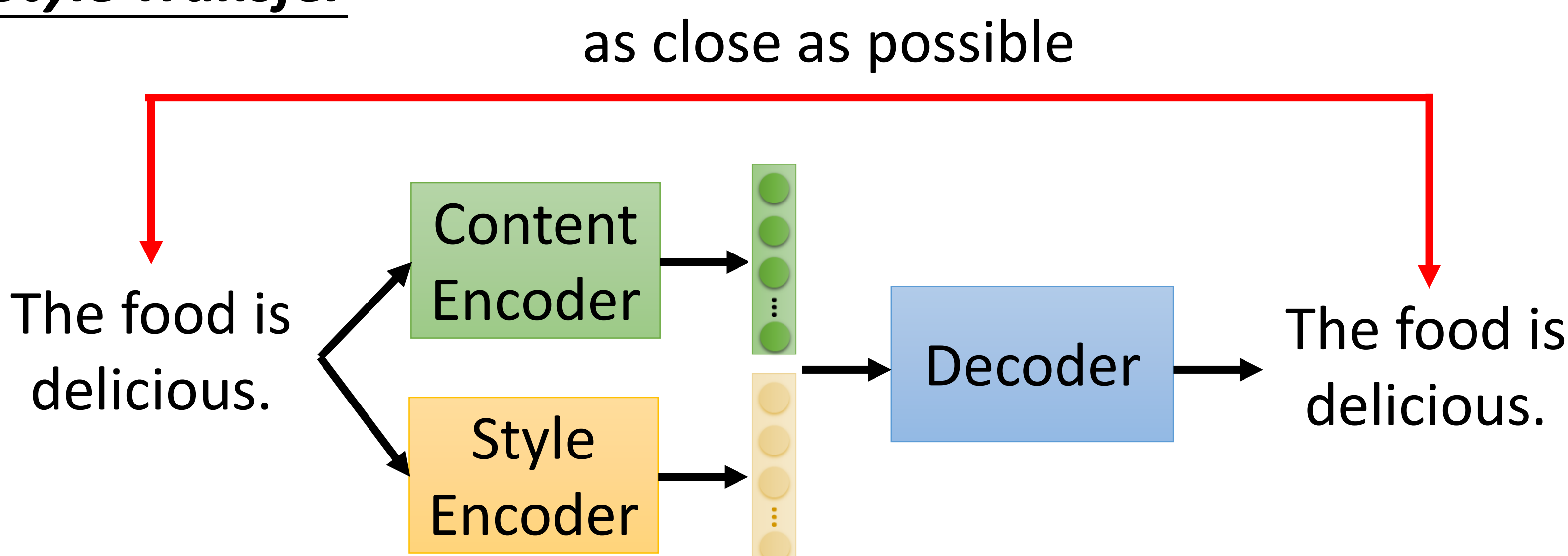
Style Transformer (Text version of StarGAN)

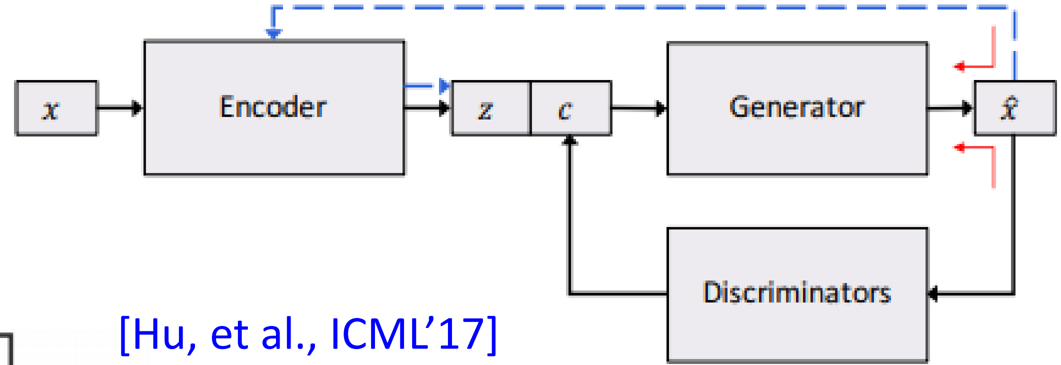
Source of image: https://arxiv.org/abs/1905.05621

Voice Conversion



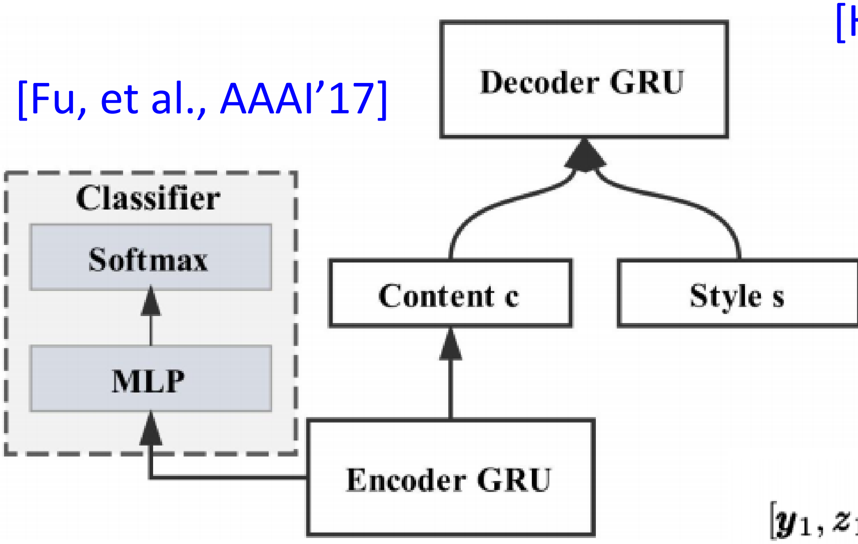
Text Style Transfer



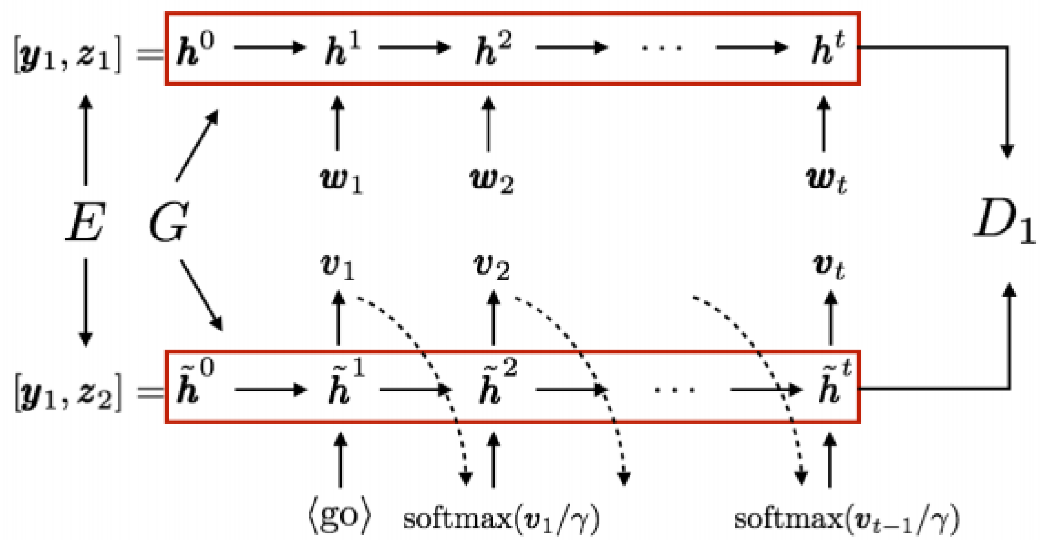


[Hu, et al., ICML'17]

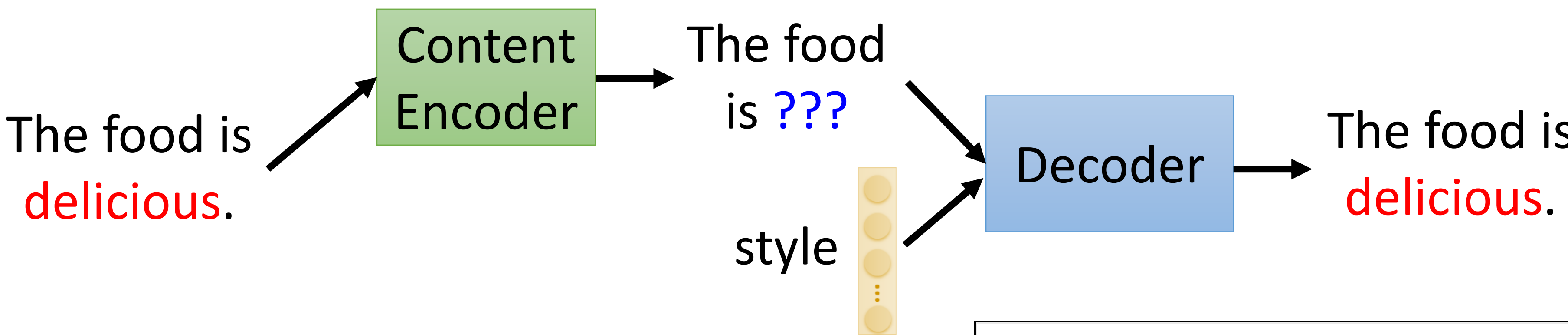
[Fu, et al., AAAI'17]

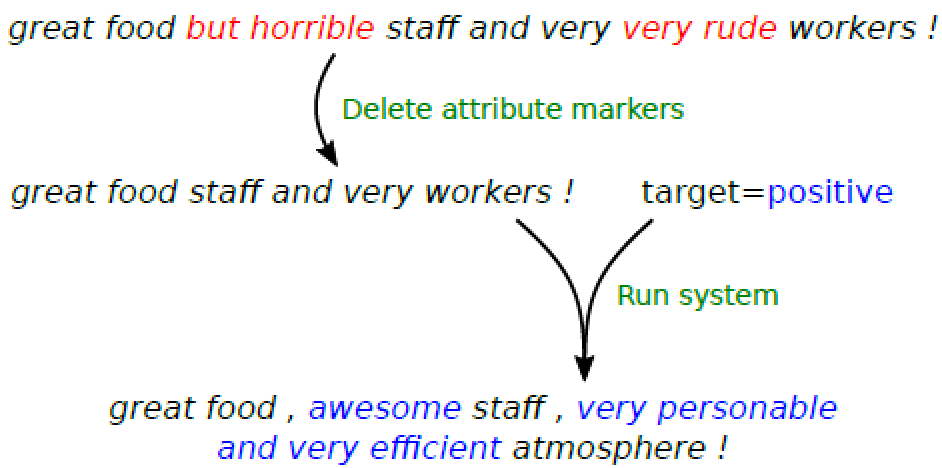


[Shen, et al., NIPS'17]

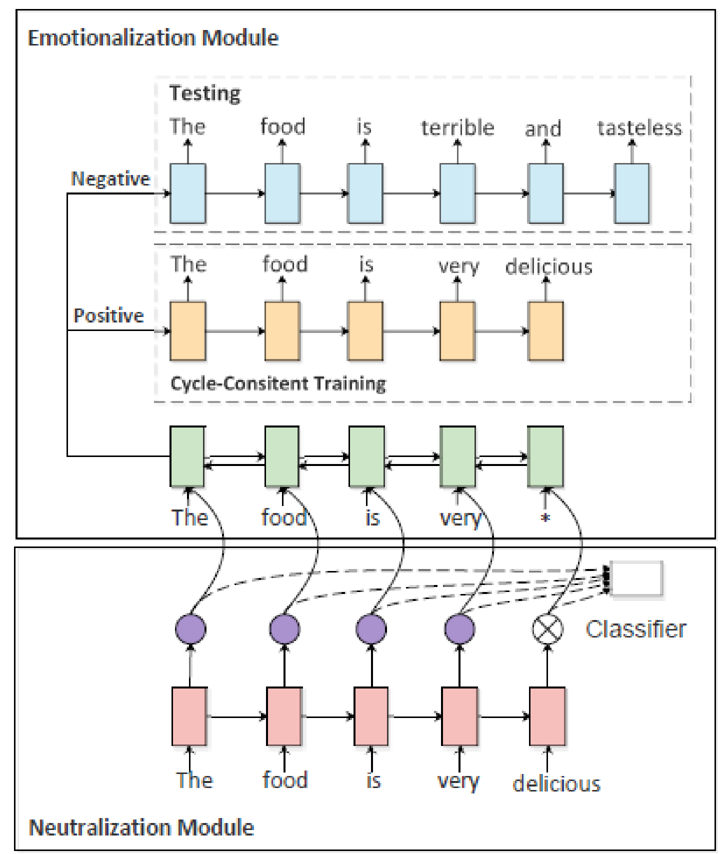


Text Style Transfer





[Li, et al., NAACL’18]



[Xu, et al., ACL’18]

Image Style

Audio Style

male

female

positive sentences

negative sentences

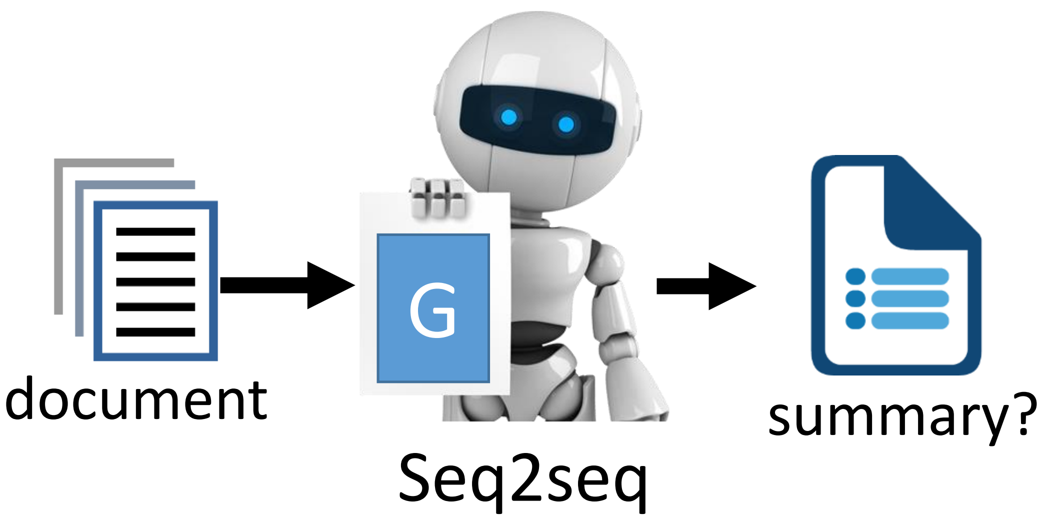
Text Style Transfer

document

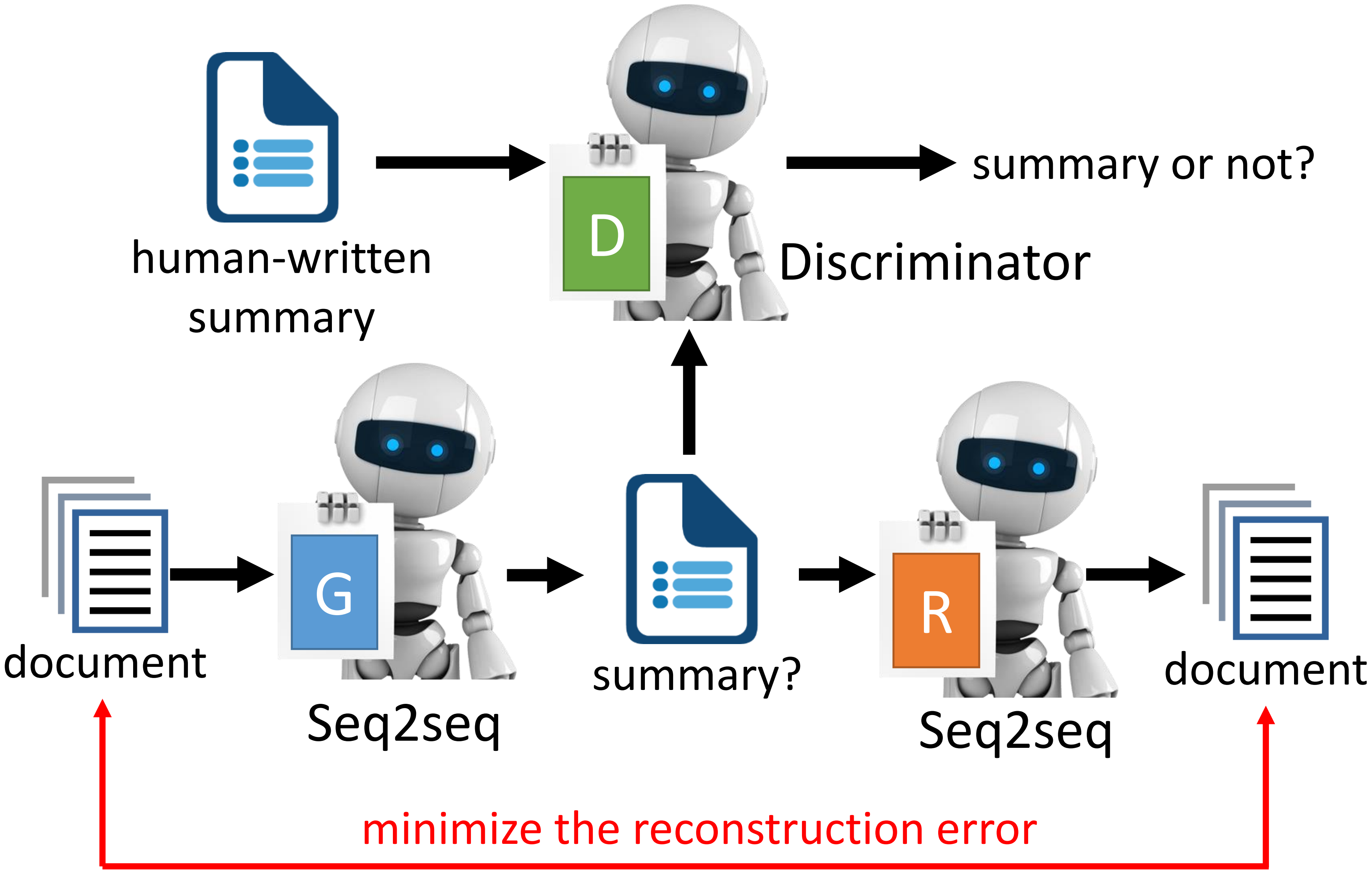
summary

Unsupervised Abstractive Summarization

Unsupervised Abstractive Summarization



Unsupervised Abstractive Summarization



Summarization

[Wang, Lee, EMNLP 2018]

English Gigaword (Document title as summary)

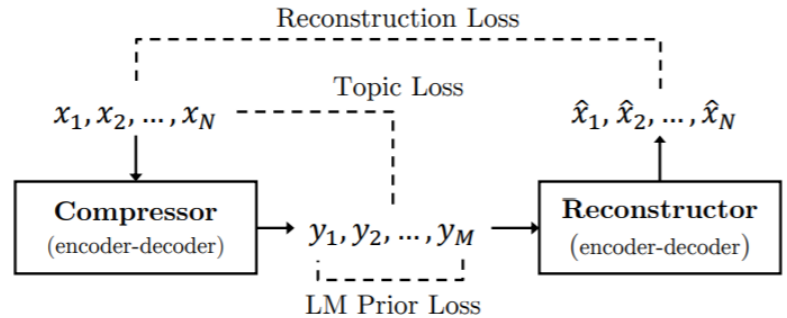
	ROUGE-1	ROUGE-2	ROUGE-L
Supervised	33.2	14.2	30.5
Trivial	21.9	7.7	20.5
Unsupervised (matched data)	28.1	10.0	25.4
Unsupervised (no matched data)	27.2	9.1	24.1

- Matched data: using the title of English Gigaword to train Discriminator
- No matched data: using the title of CNN/Diary Mail to train Discriminator

More Unsupervised Summarization

- Unsupervised summarization with language prior

[Baziotis, et al., NAACL 2019]



- Unsupervised multi-document summarization

[Chu, et al., ICML 2019]

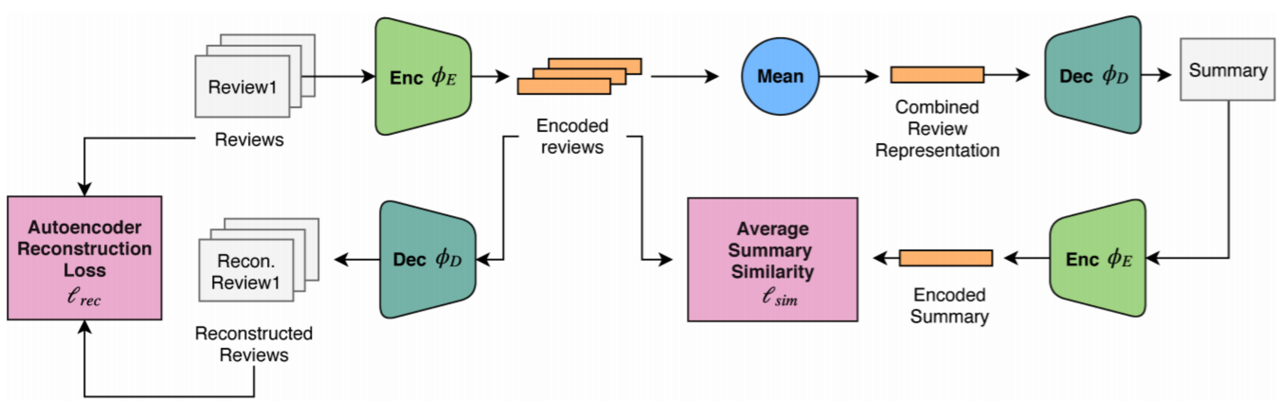


Image Style

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male

female

positive sentences

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Text Style Transfer

document

summary

Unsupervised Abstractive Summarization

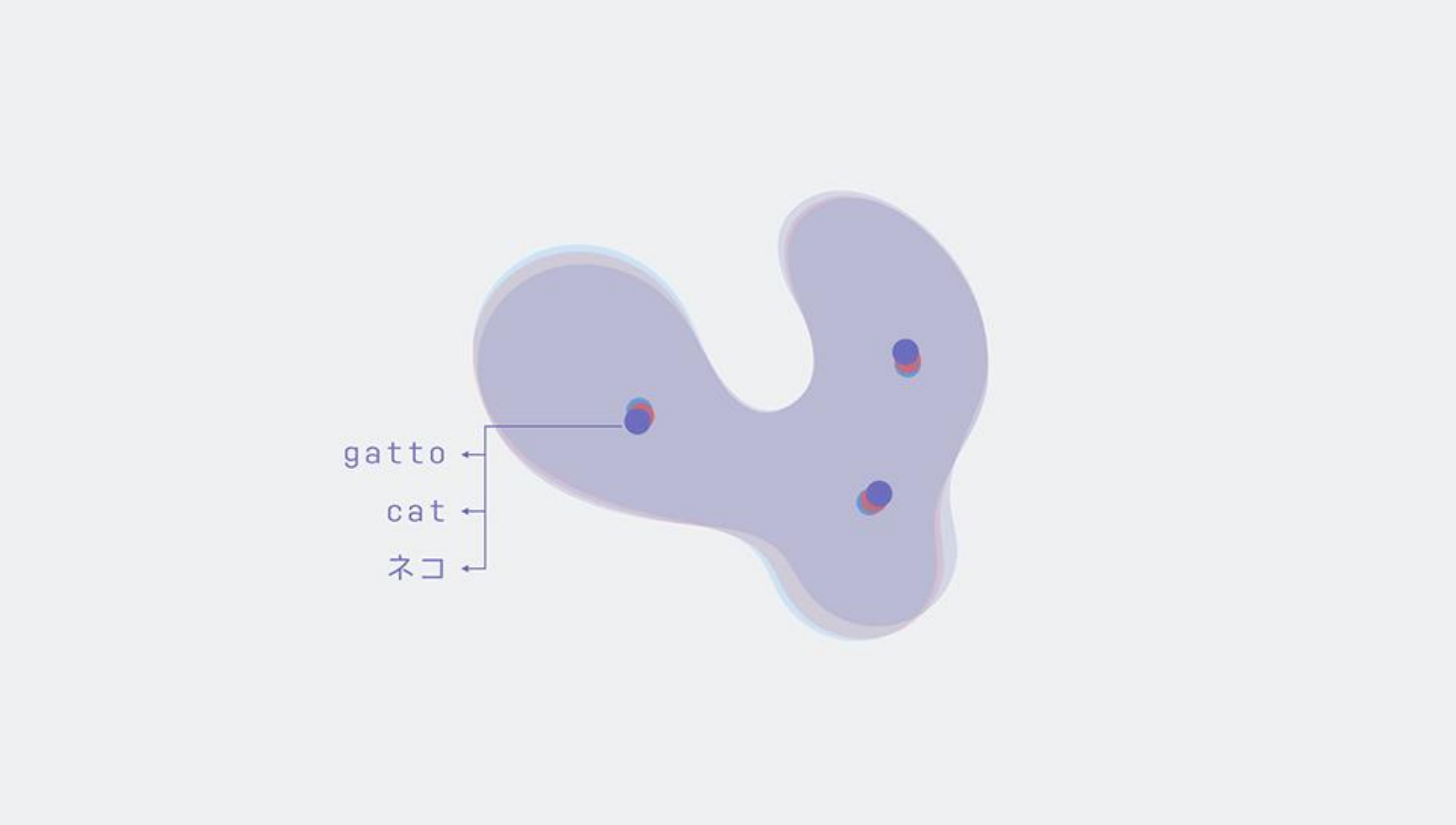
Language 1

Language 2

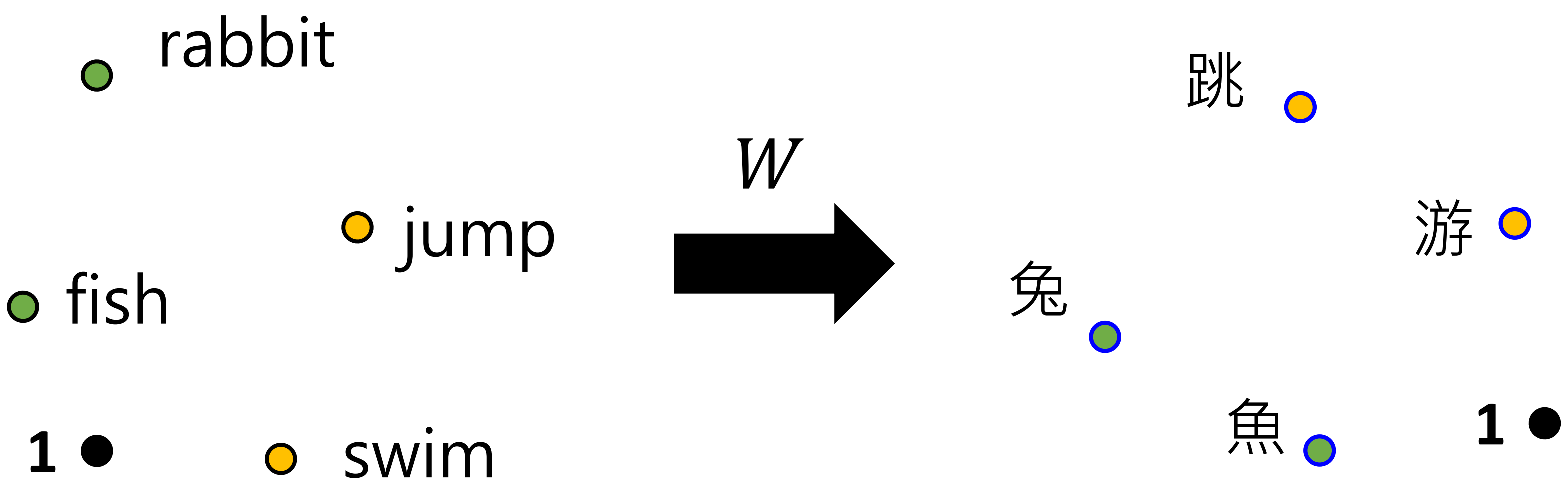
Unsupervised Translation

https://engineering.fb.com/ai-research/unsupervised-machine-translation-a-novel-approach-to-provide-fast-accurate-translations-for-more-languages/

Mapping of Word Embedding



Mapping of Word Embedding



Authors	Unsupervised step	Supervised step	Extras
Barone (2016)	GAN	None	
Zhang et al. (2017)	Wasserstein GAN	Procrustes	
Conneau et al. (2018)	GAN	Procrustes	
Hoshen and Wolf (2018)	ICP	Procrustes	Restarts
Alvarez-Melis and Jaakkola (2018)	Gromov-Wasserstein	Procrustes	
Artetxe et al. (2018)	Gromov-Wasserstein	Stochastic	
Yang et al. (2018)	Gromov-Wasserstein	MMD	
Xu et al. (2018)	GAN	Sinkhorn	Back-translation
Grave et al. (2018)	Gold-Rangarajan	Sinkhorn	

[Hartmann, et al., NeurIPS'19]

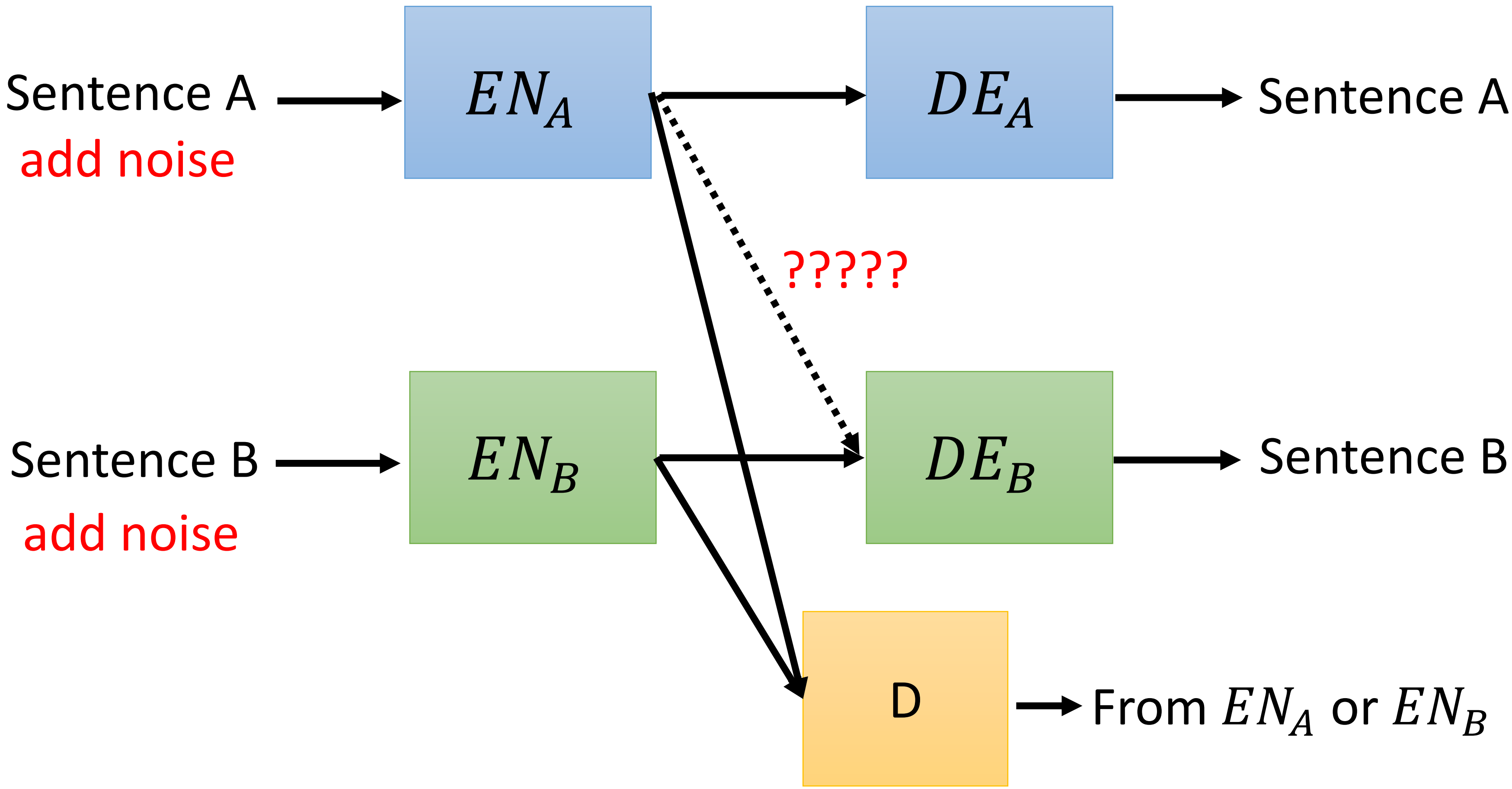
VecMap

[Artetxe, et al., ACL'18]

Supervision	Method	EN-IT	EN-DE	EN-FI	EN-ES
5k dict.	Mikolov et al. (2013)	34.93†	35.00†	25.91†	27.73†
	Faruqui and Dyer (2014)	38.40*	37.13*	27.60*	26.80*
	Shigeto et al. (2015)	41.53†	43.07†	31.04†	33.73†
	Dinu et al. (2015)	37.7	38.93*	29.14*	30.40*
	Lazaridou et al. (2015)	40.2	-	-	-
	Xing et al. (2015)	36.87†	41.27†	28.23†	31.20†
	Zhang et al. (2016)	36.73†	40.80†	28.16†	31.07†
	Artetxe et al. (2016)	39.27	41.87*	30.62*	31.40*
	Artetxe et al. (2017)	39.67	40.87	28.72	-
	Smith et al. (2017)	43.1	43.33†	29.42†	35.13†
	Artetxe et al. (2018a)	45.27	44.13	**32.94**	36.60
25 dict.	Artetxe et al. (2017)	37.27	39.60	28.16	-
Init. heurist.	Smith et al. (2017), cognates	39.9	-	-	-
	Artetxe et al. (2017), num.	39.40	40.27	26.47	-
None	Zhang et al. (2017a), $\lambda = 1$	0.00*	0.00*	0.00*	0.00*
	Zhang et al. (2017a), $\lambda = 10$	0.00*	0.00*	0.01*	0.01*
	Conneau et al. (2018), code‡	45.15*	46.83*	0.38*	35.38*
	Conneau et al. (2018), paper‡	45.1	0.01*	0.01*	35.44*
	Proposed method	**48.13**	**48.19**	32.63	**37.33**

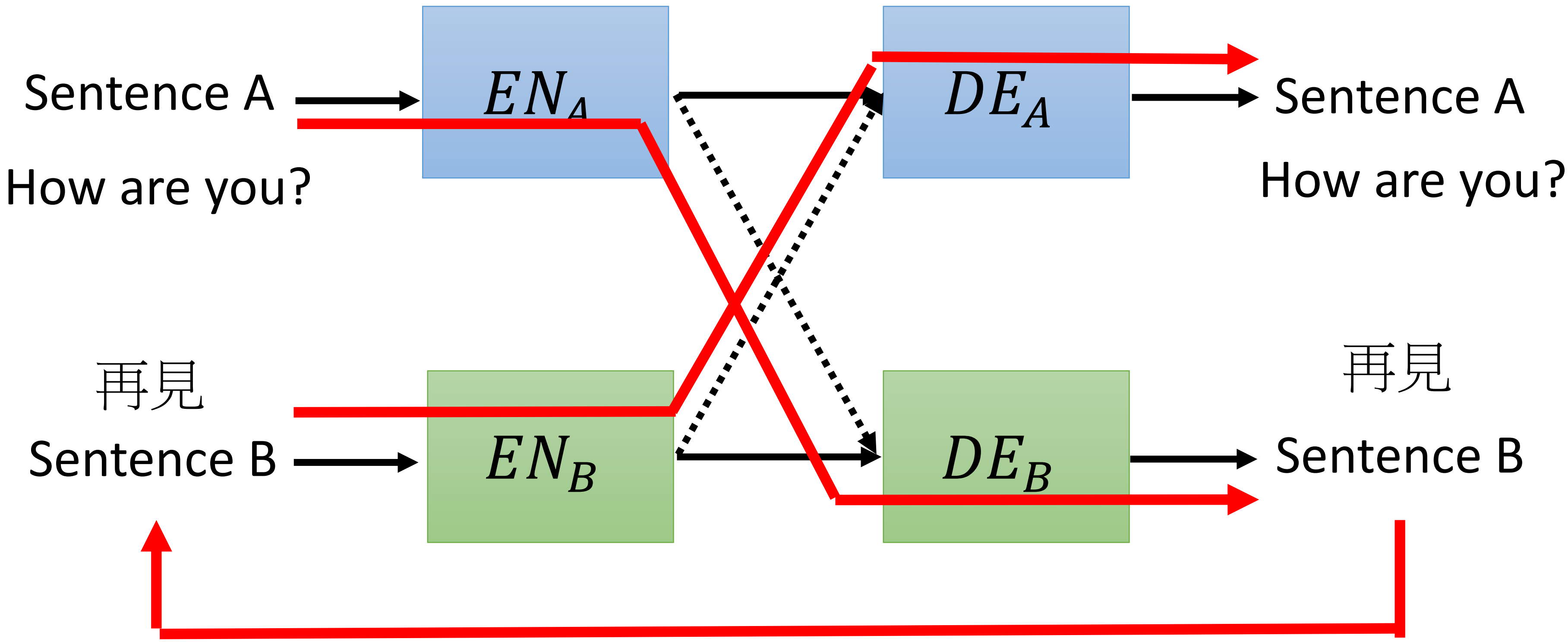
[Lample, et al., ICLR, 2018]

Unsupervised Translation

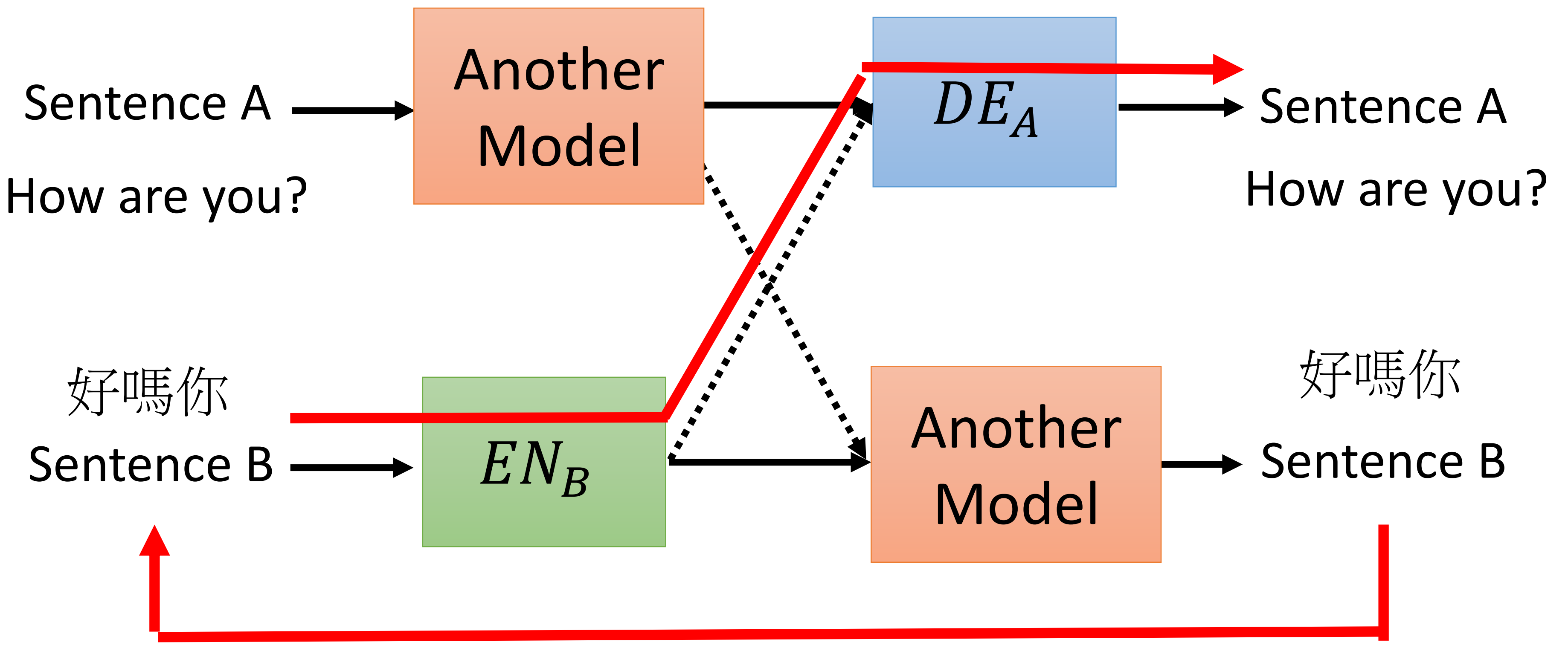


[Lample, et al., ICLR, 2018]

Unsupervised Translation

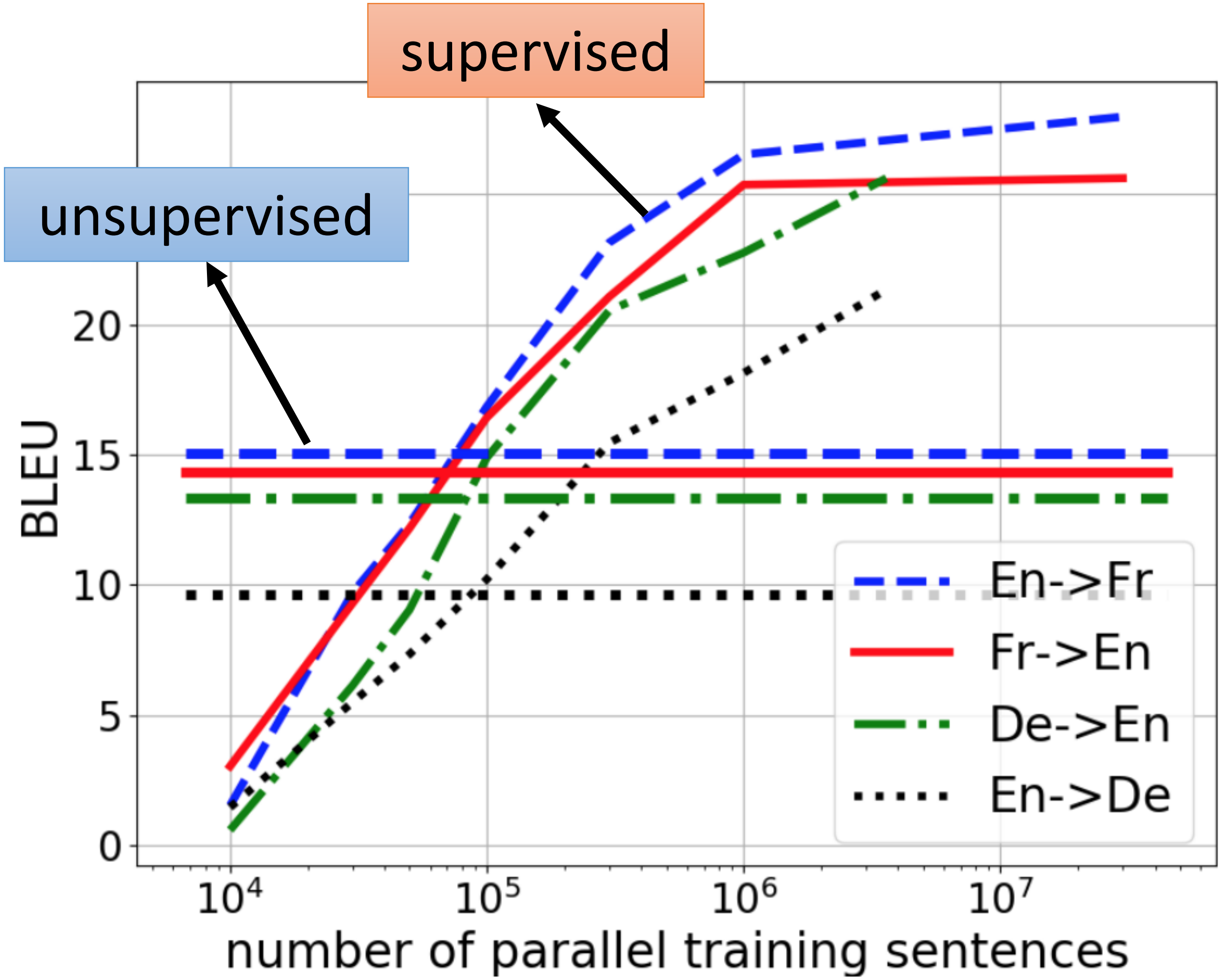


Unsupervised Translation



Start from another unsupervised translation model
(word embedding translation model)

[Lample, et al., ICLR, 2018]



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

	en → fr	fr → en	en → de	de → en	en → ro	ro → en	en → ru	ru → en
Unsupervised PBSMT								
Unsupervised phrase table	-	17.50	-	15.63	-	14.10	-	8.08
Back-translation - Iter. 1	24.79	26.16	15.92	22.43	18.21	21.49	11.04	15.16
Back-translation - Iter. 2	27.32	26.80	17.65	22.85	20.61	22.52	12.87	16.42
Back-translation - Iter. 3	27.77	26.93	17.94	22.87	21.18	22.99	13.13	16.52
Back-translation - Iter. 4	27.84	27.20	17.77	22.68	21.33	23.01	13.37	**16.62**
Back-translation - Iter. 5	**28.11**	27.16	-	-	-	-	-	-
Unsupervised NMT								
LSTM	24.48	23.74						
Transformer	25.14	24.18						
Phrase-based + Neural network								
NMT + PBSMT	27.12	26.29						
PBSMT + NMT	27.60	**27.68**						

[Lample, et al., EMNLP'18]

		en-fr	fr-en	en-de	de-en	en-ro	ro-en
Previous state-of-the-art - Lample et al. (2018b)							
NMT		25.1	24.2	17.2	21.0	21.2	19.4
PBSMT		28.1	27.2	17.8	22.7	21.3	23.0
PBSMT + NMT		27.6	27.7	20.2	25.2	25.1	23.9
Our results for different encoder and decoder initializations							
EMB	EMB	29.4	29.4	21.3	27.3	27.5	26.6
-	-	13.0	15.8	6.7	15.3	18.9	18.3
-	CLM	25.3	26.4	19.2	26.0	25.7	24.6
-	MLM	29.2	29.1	21.6	28.6	28.2	27.3
CLM	-	28.7	28.2	24.4	30.3	29.2	28.0
CLM	CLM	30.4	30.0	22.7	30.5	29.0	27.8
CLM	MLM	32.3	31.6	24.3	32.5	31.6	29.8
MLM	-	31.6	32.1	**27.0**	33.2	31.8	30.5
MLM	CLM	**33.4**	32.3	24.9	32.9	31.7	30.4
MLM	MLM	**33.4**	**33.3**	26.4	**34.3**	**33.3**	**31.8**

[Lample, et al., NeurIPS'19]

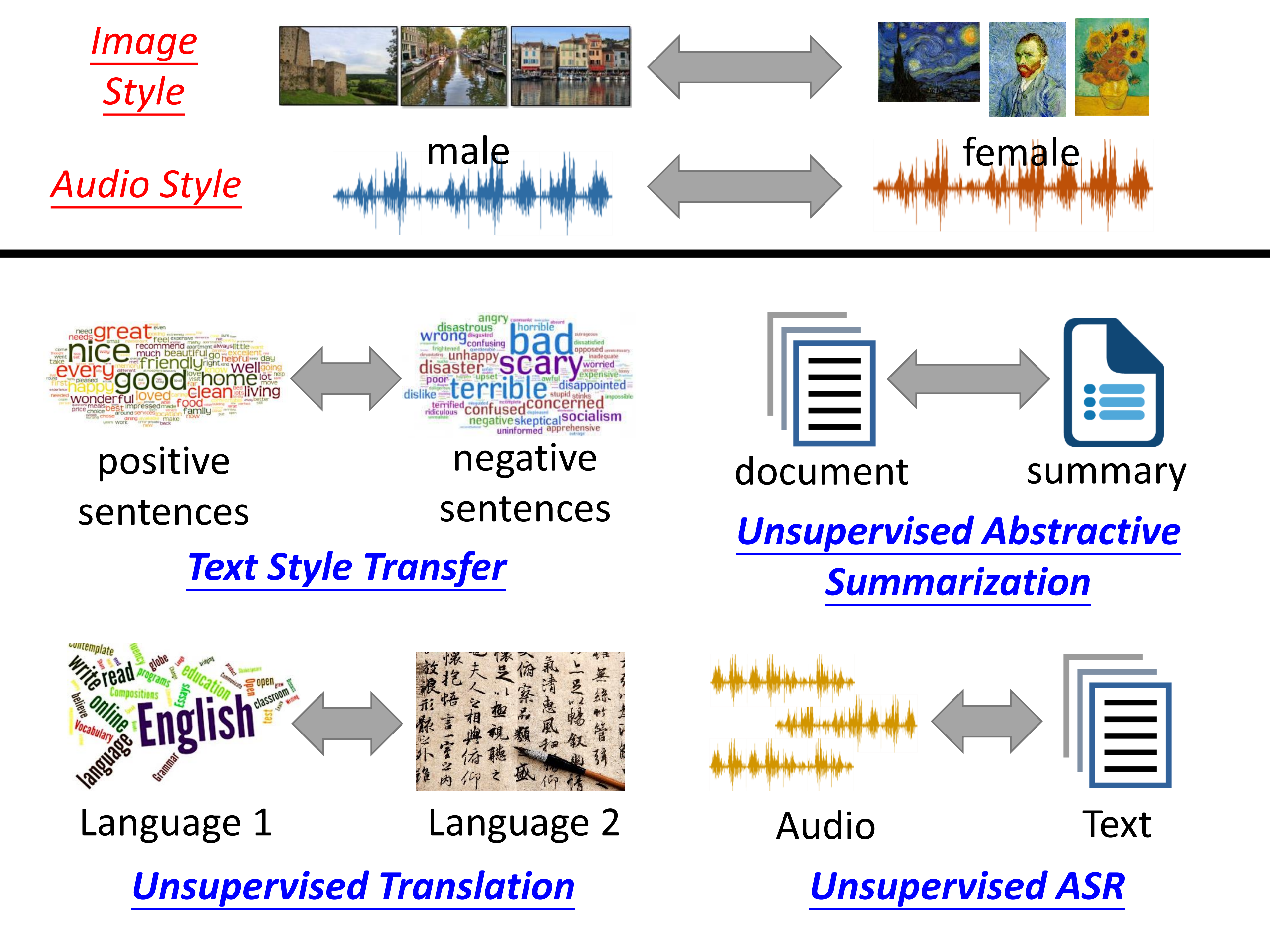


Image Style
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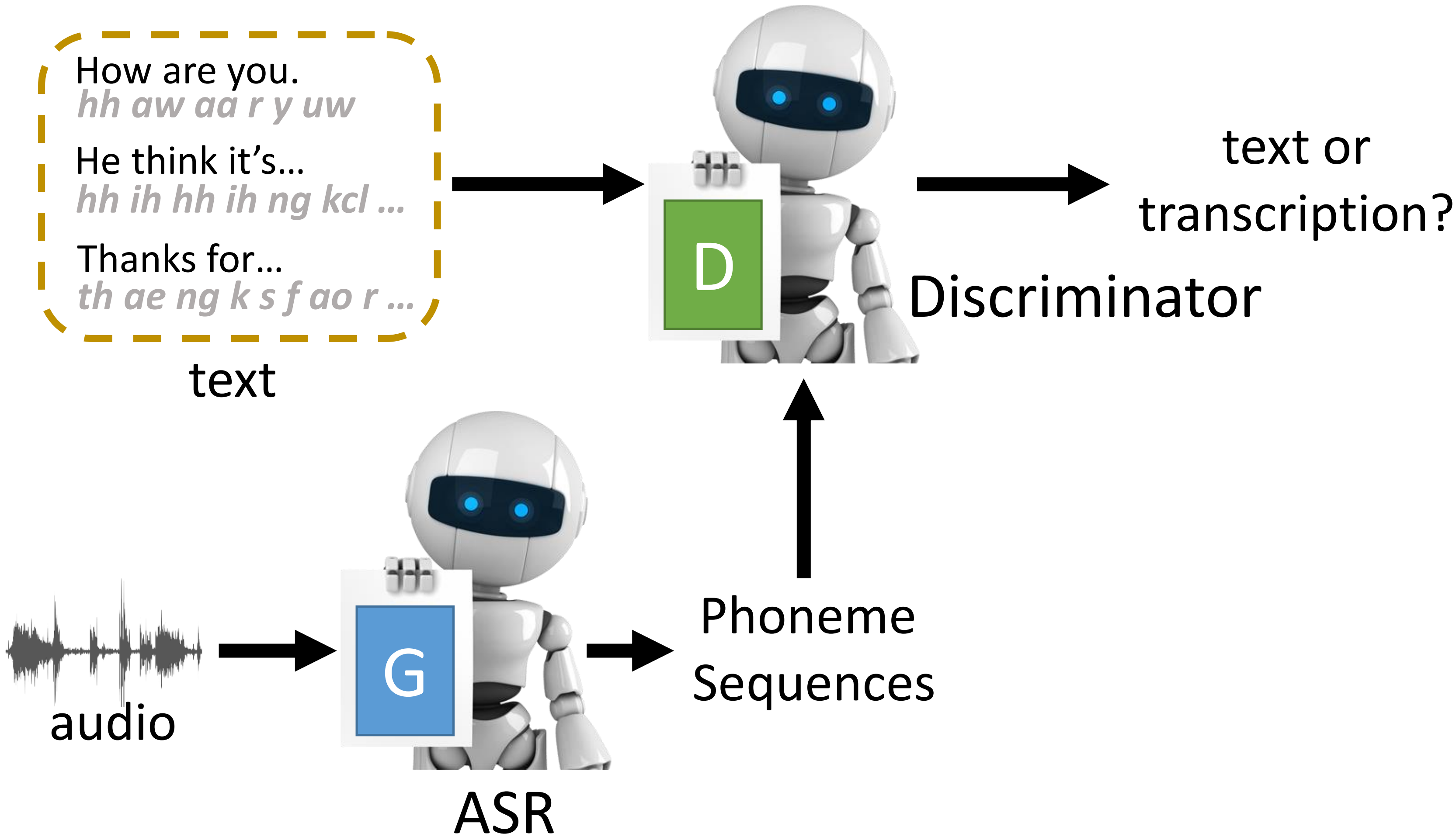
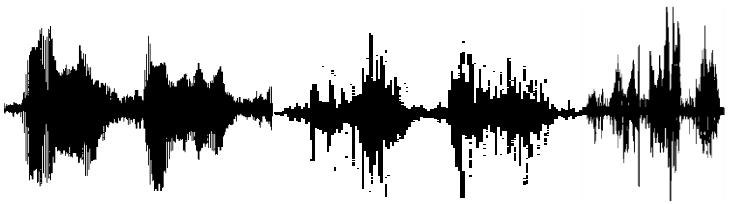
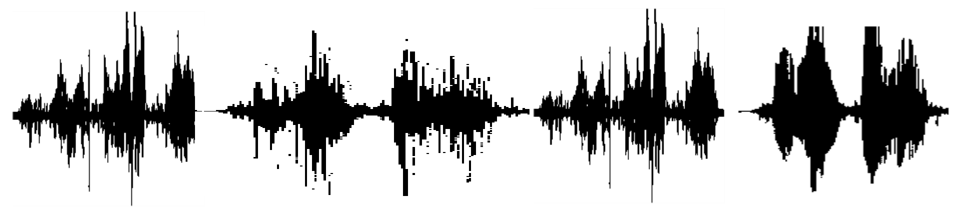
Unsupervised Abstractive Summarization
Language 1
Language 2
Unsupervised Translation
Audio
Text
Unsupervised ASR

Unsupervised Speech Recognition

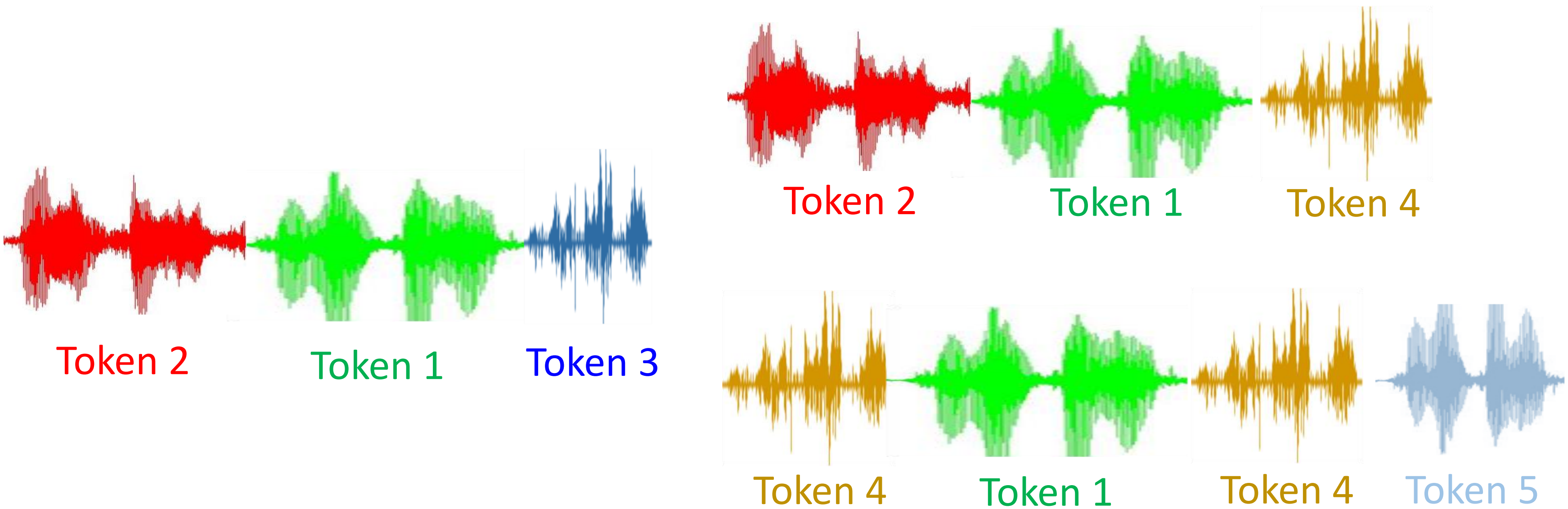


Acoustic Token Discovery





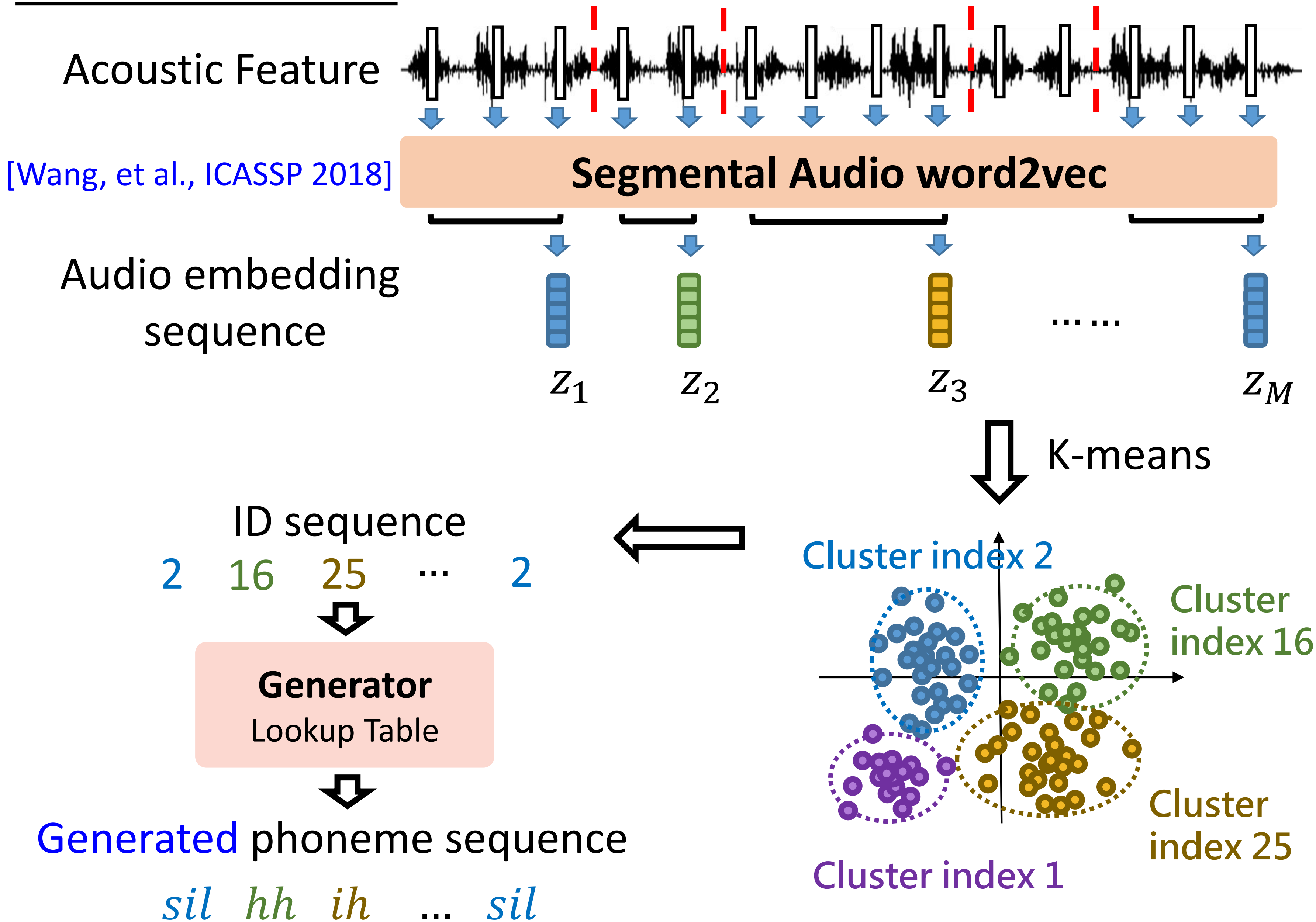
Acoustic Token Discovery



Acoustic tokens can be discovered from audio collection without text annotation.

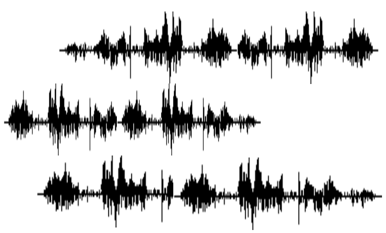
Acoustic tokens: chunks of acoustically similar audio segments with token IDs

Generator (v1)



Experiment

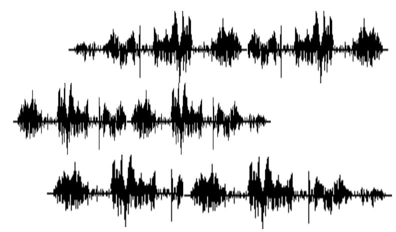
Matched Case
(Oracle)



4620
(TIMIT)

4620
(TIMIT)

Nonmatched
Case



3620
(TIMIT)

1000
(TIMIT)

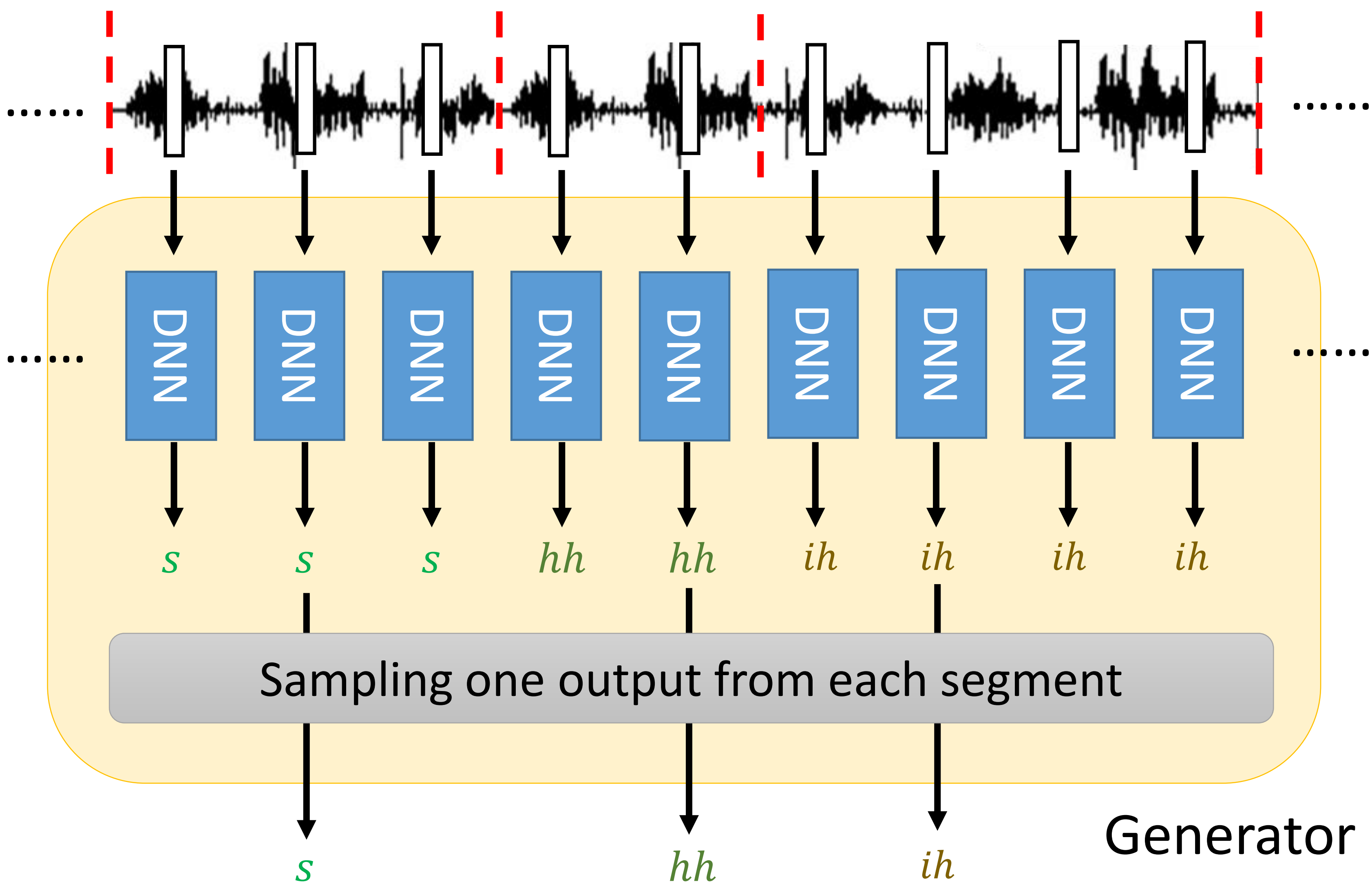
Experimental Results [Liu, et al., INTERSPEECH, 2018]

Approaches	PER	
	Matched	Nonmatched
Supervised		
RNN Transducer	17.7	-
Standard HMMs	21.5	-

Generator (v2)

Phoneme boundaries obtained by Gate Activation Signals (GAS)

[Wang, et al., INTERSPEECH 2017]

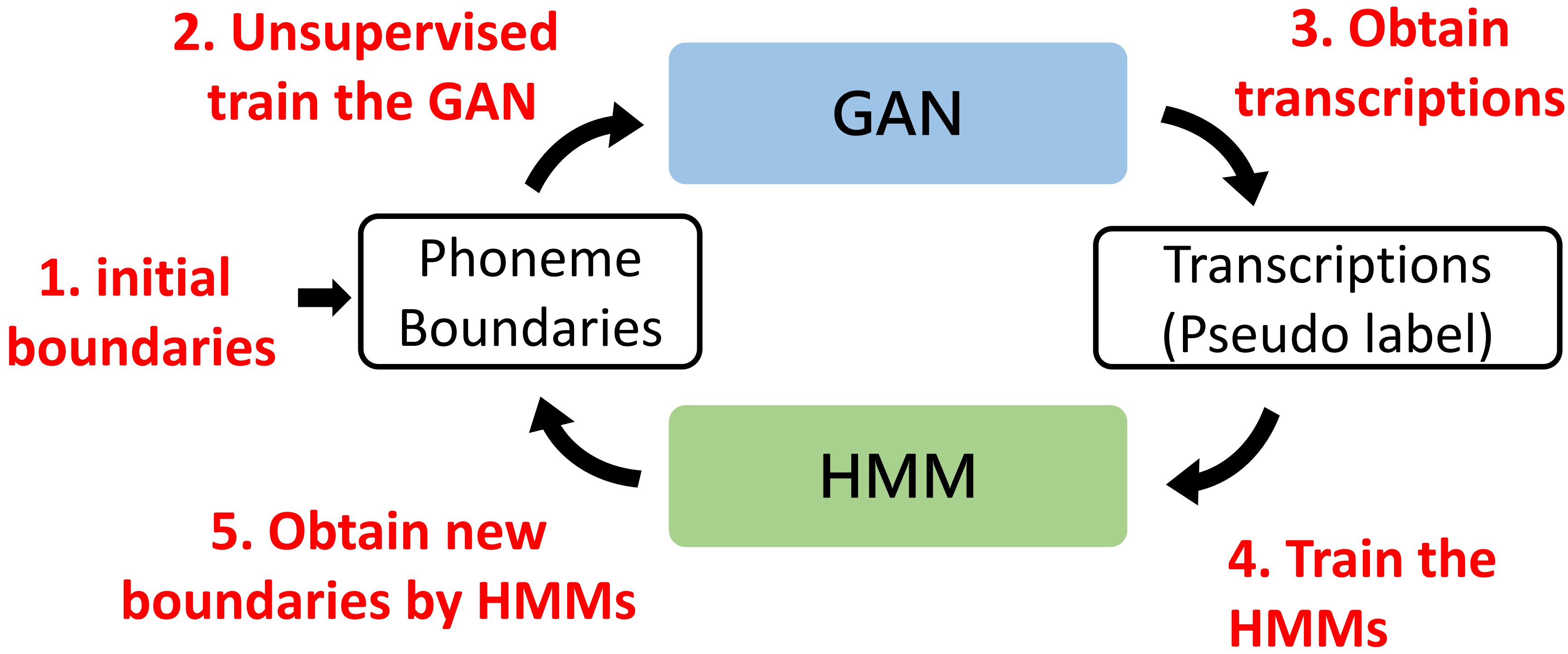


Inspired From [Yeh, et al., ICLR 2019]

Experimental Results [Chen, et al., INTERSPEECH, 2019]

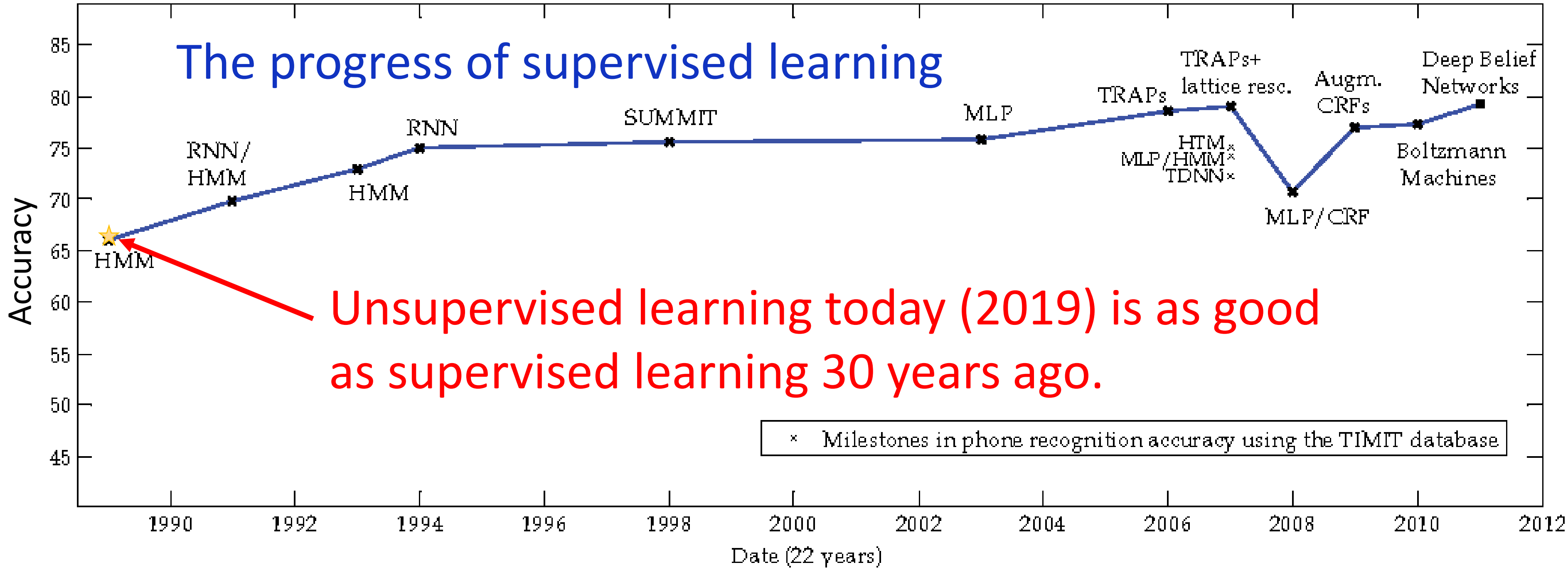
Approaches			PER	
			Matched	Nonmatched
Supervised				
RNN Transducer			17.7	-
Standard HMMs			21.5	-
Completely unsupervised (no label at all)				
Generator (v1)			76.0	-
Generator (v2)	Iteration 1	GAN	48.6	50.0

Refining Boundaries



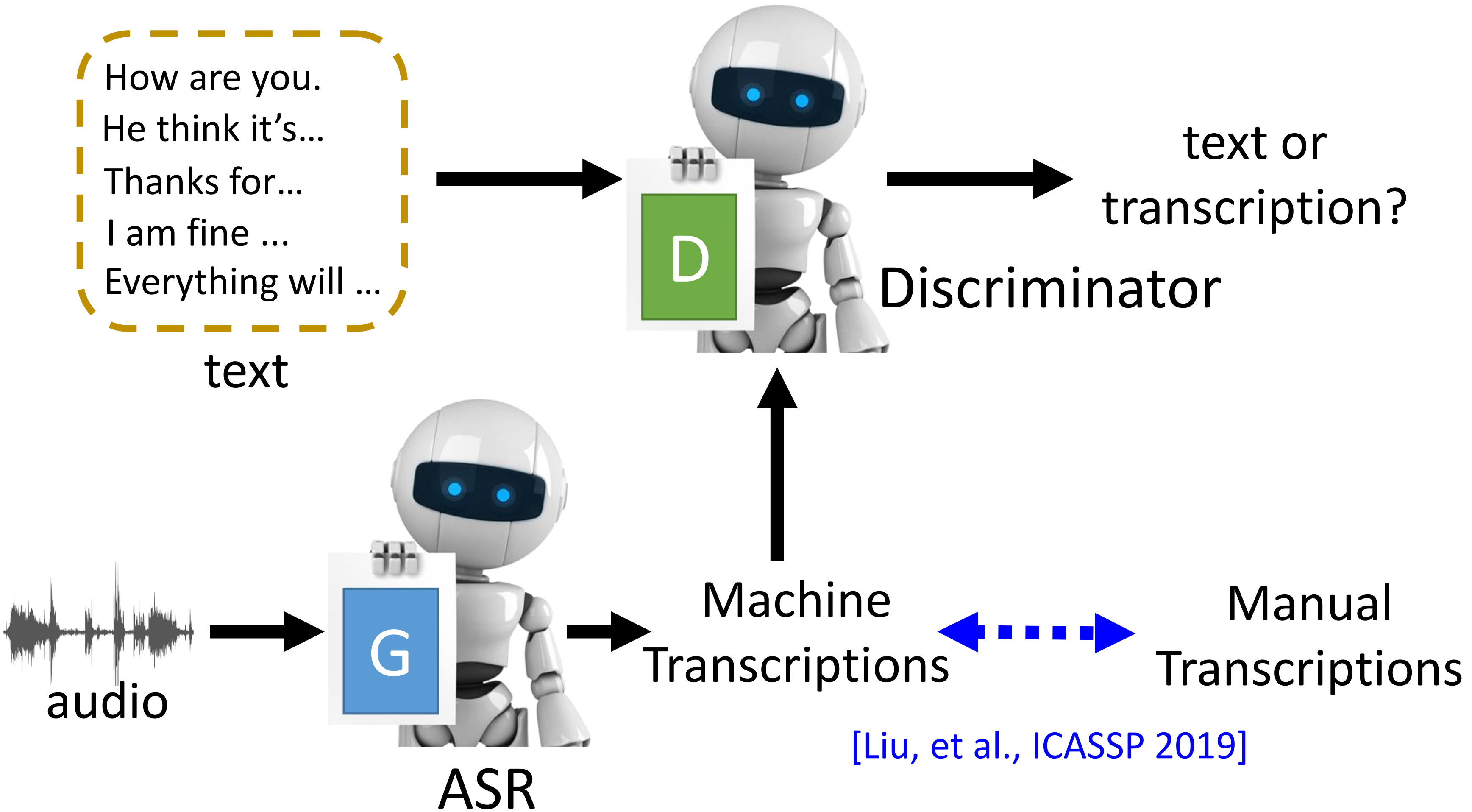
Experimental Results [Chen, et al., INTERSPEECH, 2019]

Approaches			PER	
			Matched	Nonmatched
Supervised				
RNN Transducer			17.7	-
Standard HMMs			21.5	-
Completely unsupervised (no label at all)				
Generator (v1)			76.0	-
Generator (v2)	Iteration 1	GAN	48.6	50.0
		HMM	30.7	39.5
	Iteration 2	GAN	41.0	44.3
		HMM	27.0	35.5
	Iteration 3	GAN	38.4	44.2
		HMM	26.1	33.1



The image is modified from: Phone recognition on the TIMIT database Lopes, C. and Perdigão, F., 2011. Speech Technologies, Vol 1, pp. 285--302.

Semi-supervised Speech Recognition

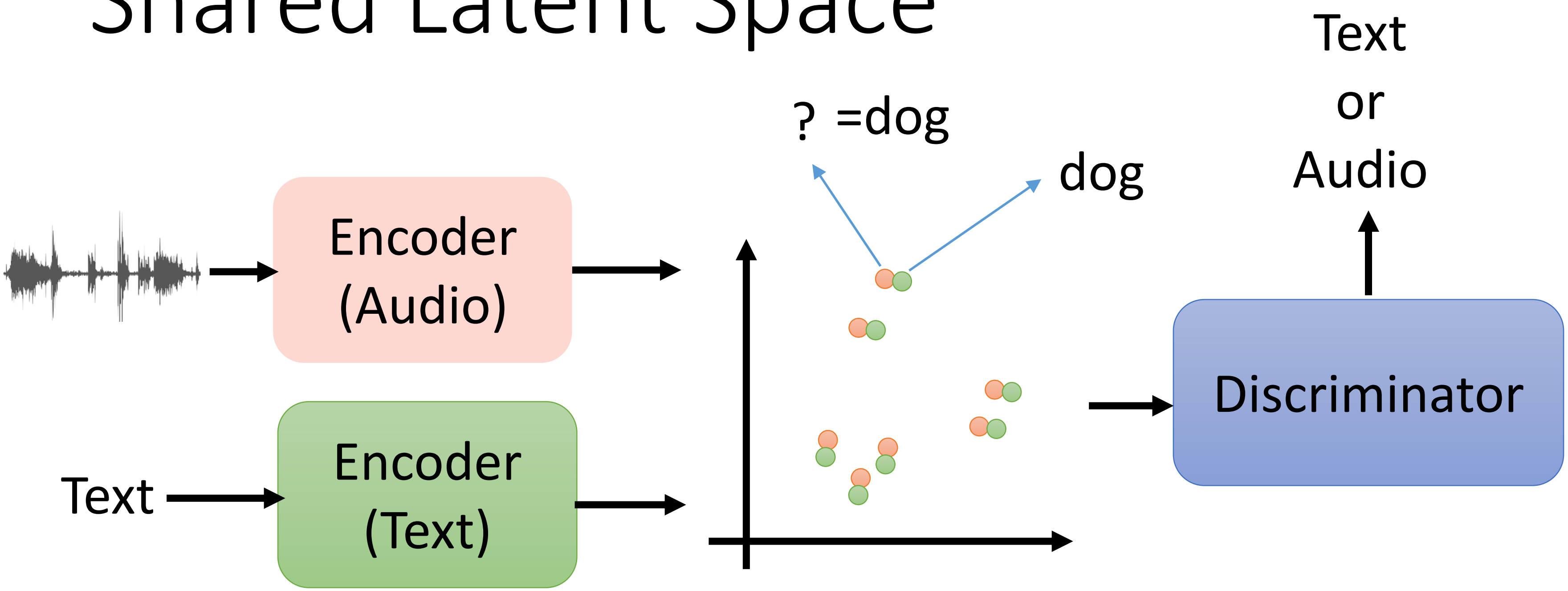


[Liu, et al., ICASSP 2019]

Using ***100 hours pairs annotated audio*** from Librispeech, and ***text without audio***

21.7% WER → 18.7% WER

Shared Latent Space



- Initial attempt [Chen, et al., SLT, 2018]
- 76.3% WER on Librispeech [Chung, et al., NIPS 2018]
- WSJ with 2.5 hours paired data: 64.6% WER
  [Jennifer Drexler, et al., SLT 2018]
- LJ speech with 20 mins paired data: 11.7% PER [Ren, et al., ICML 2019]
- Unsupervised speech translation is possible [Chung, et al., ICASSP 2019]

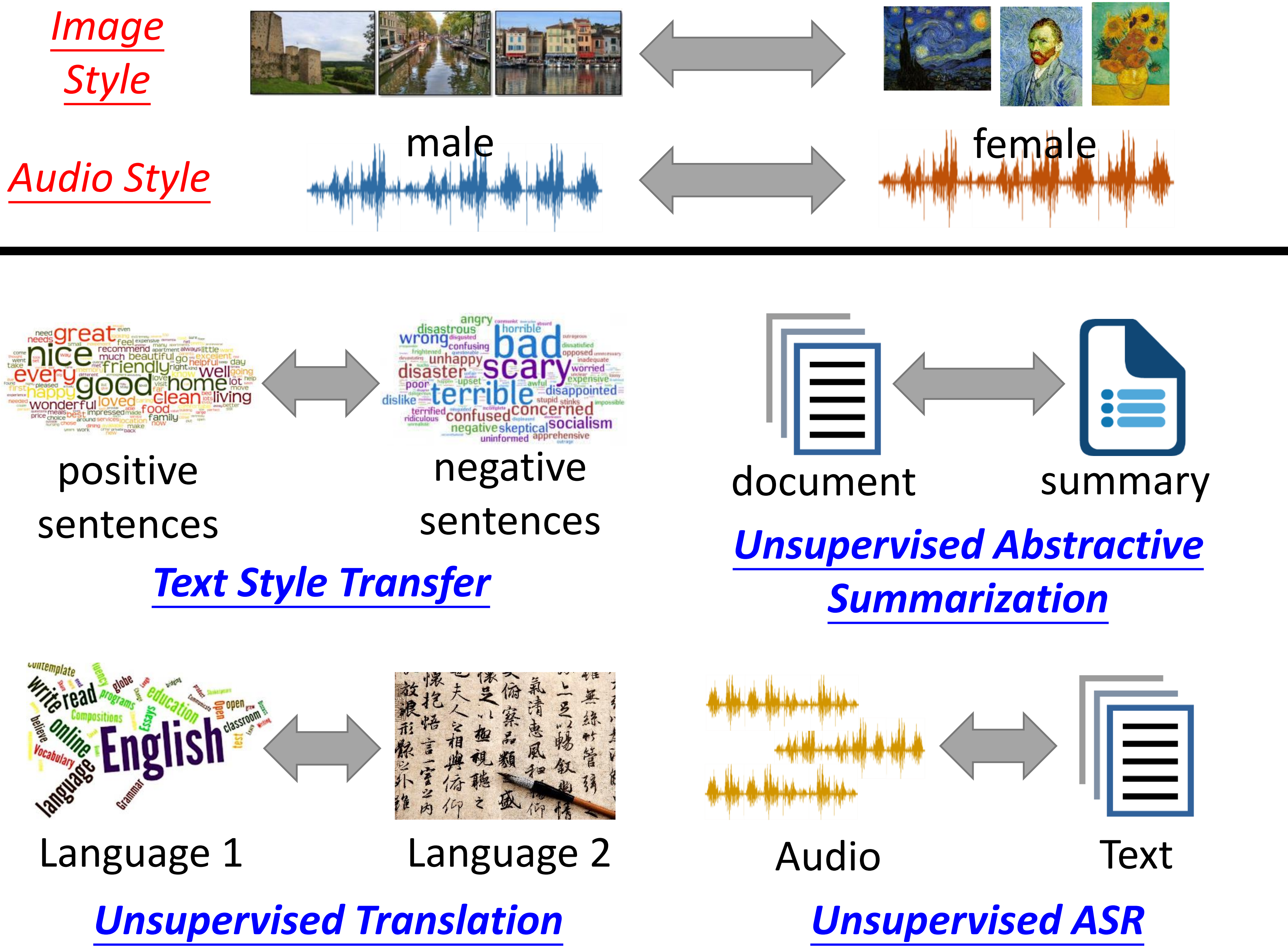


Image Style
male
female
Audio Style
positive sentences
negative sentences
Text Style Transfer
document
summary
Unsupervised Abstractive Summarization
Language 1
Language 2
Unsupervised Translation
Audio
Text
Unsupervised ASR

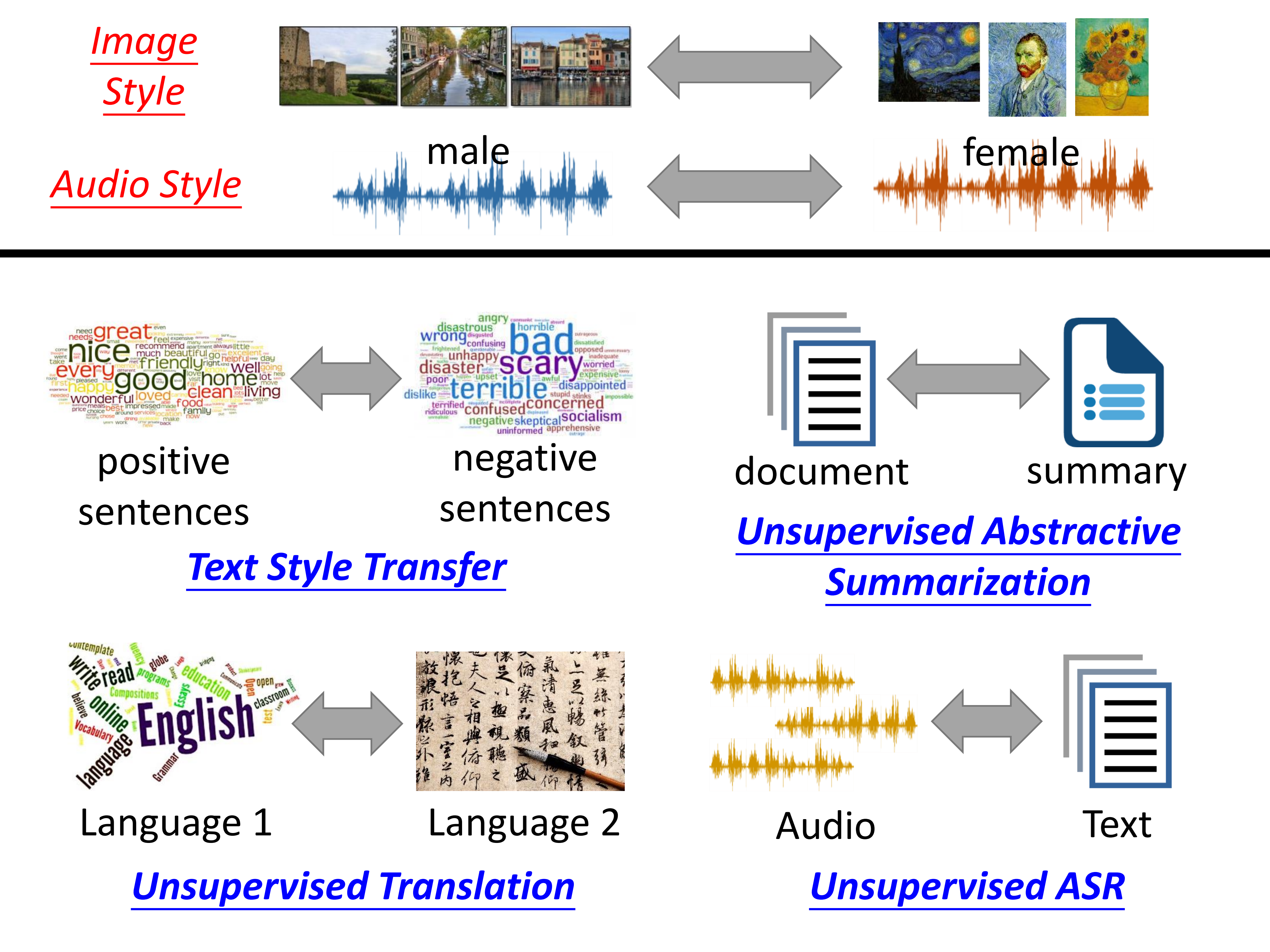


Image Style
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