Speech Recognition

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Speech Recognition is Difficult?

Whither Speech Recognition?

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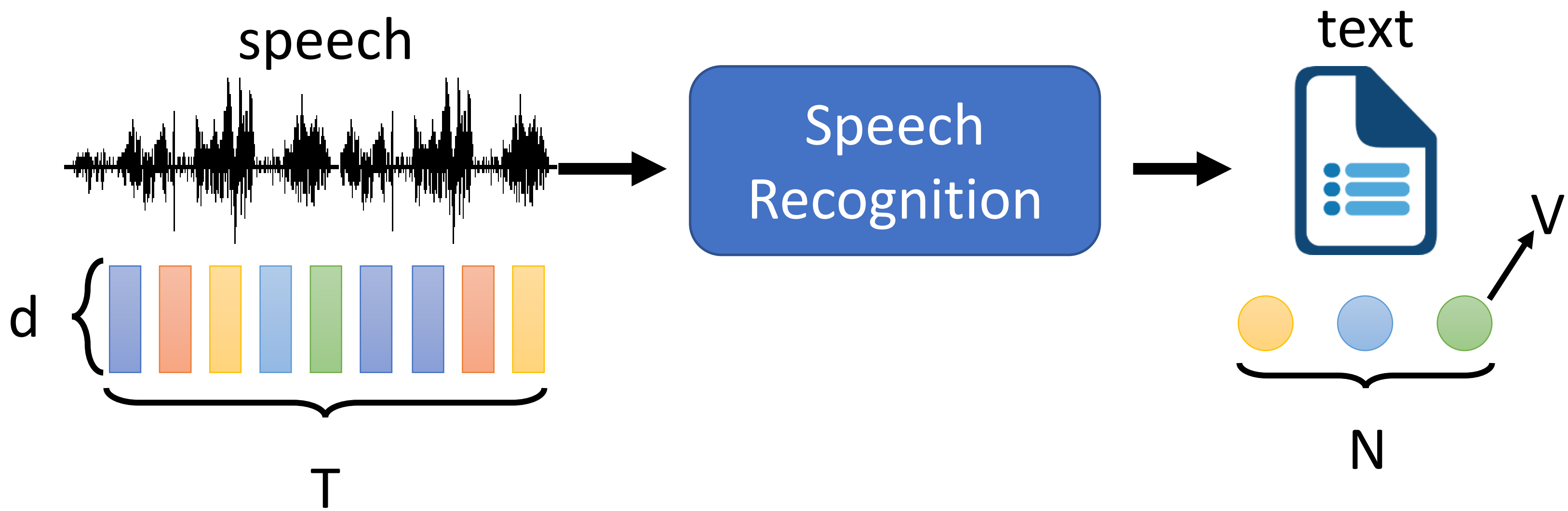
necessary but not a sufficient condition. We are safe in asserting that speech recognition is attractive to money. The attraction is perhaps similar to the attraction of schemes for turning water into gasoline, extracting gold from the sea, curing cancer, or going to the moon. One doesn't attract thoughtlessly given dollars by

I heard the story from Prof Haizhou Li.

Speech Recognition



Speech: a sequence of vector (length T, dimension d)

Text: a sequence of token (length N, V different tokens)

Usually T > N

Token

Phoneme: a unit of sound

W AH N P AH N CH M AE N

one punch man

Lexicon: word to phonemes

cat ⟶ K AE T

good ⟶ G UH D

man ⟶ M AE N

one ⟶ W AH N

punch ⟶ P AH N CH

Grapheme: smallest unit of a writing system

Lexicon free!

one_punch_man

N=13, V=26+?

"一"，"拳"，"超"，"人"

N=4, V≈4000

26 English alphabet

+ { _ } (space)

+ {punctuation marks}

Chinese does not need "space"

Token

Word:

one punch man → N=3, usually V>100K

“一拳” “超人” → N=2, V=???

For some languages, V can be too large!

Token

Turkish: Agglutinative language

Source of information: http://tkturkey.com/ (土女時代)

「Muvaffak」是成功的

「Muvaffakiyet」則轉為名詞

「Muvaffakiyet**siz**」變成是不成功

「Muvaffakiyet**sizleş**」是變得不成功

「Muvaffakiyet**sizleştir**」是使變得不成功

70 characters?!

Muvaffakiyetsizleştiricileştiriveremeyebileceklerimizdenmişsinizcesine

如果你是我們當中不容易變成不成功者的其中一個

Token

Word: one punch man → N=3, usually V>100K

"一拳" "超人" → N=2, V=???

For some languages, V can be too large!

Morpheme: the smallest meaningful unit (< word, > grapheme)

unbreakable → "un" "break" "able"

rekillable → "re" "kill" "able"

What are the morphemes in a language?

linguistic or statistic

Token

Bytes (!): The system can be **language independent**!

UTF-8

	Binary
$	00100100
¢	11000010 10100010
ह	11100000 10100100 10111001
€	11100010 10000010 10101100
한	11101101 10010101 10011100
𐍈	11110000 10010000 10001101 10001000

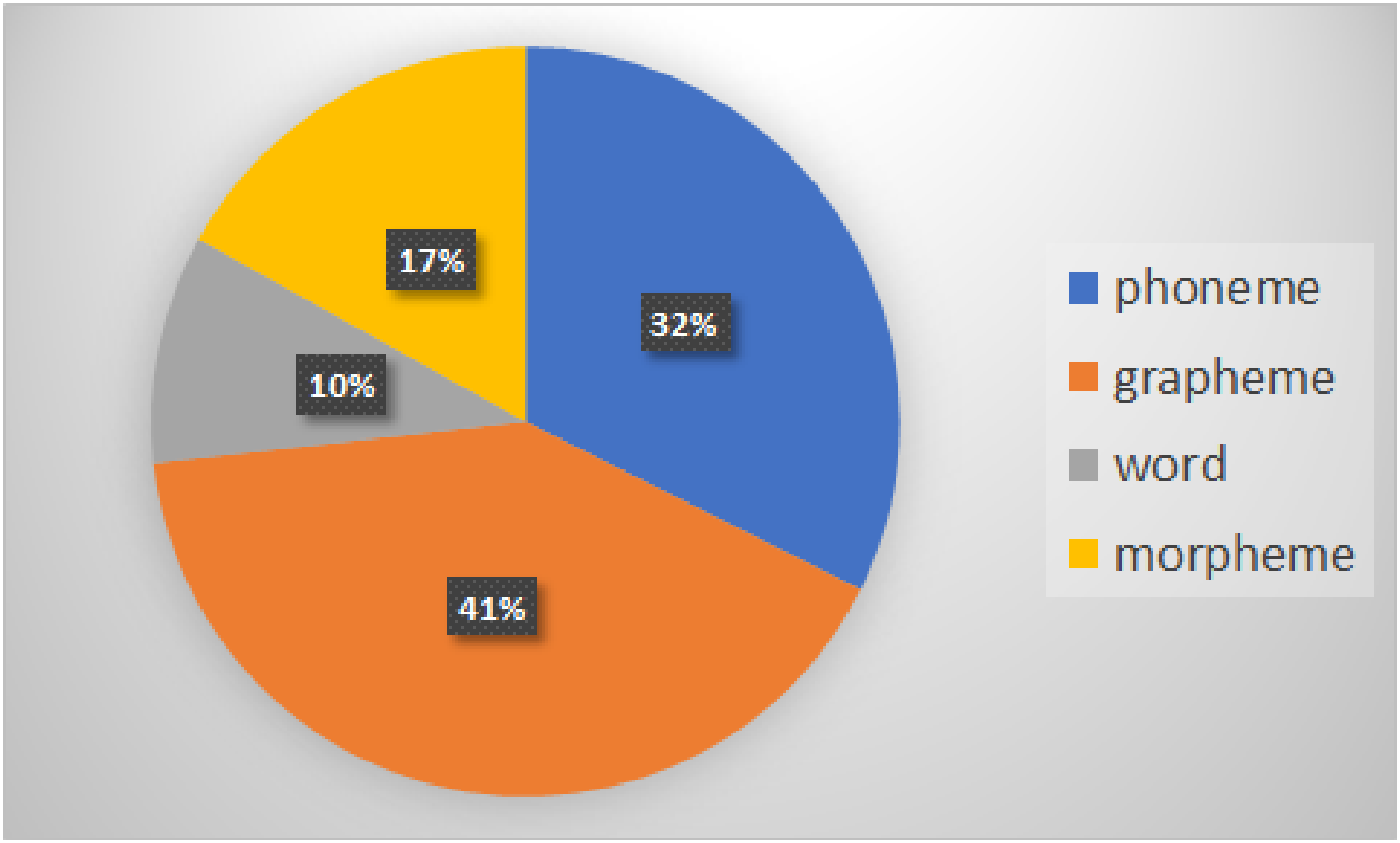
V is always 256

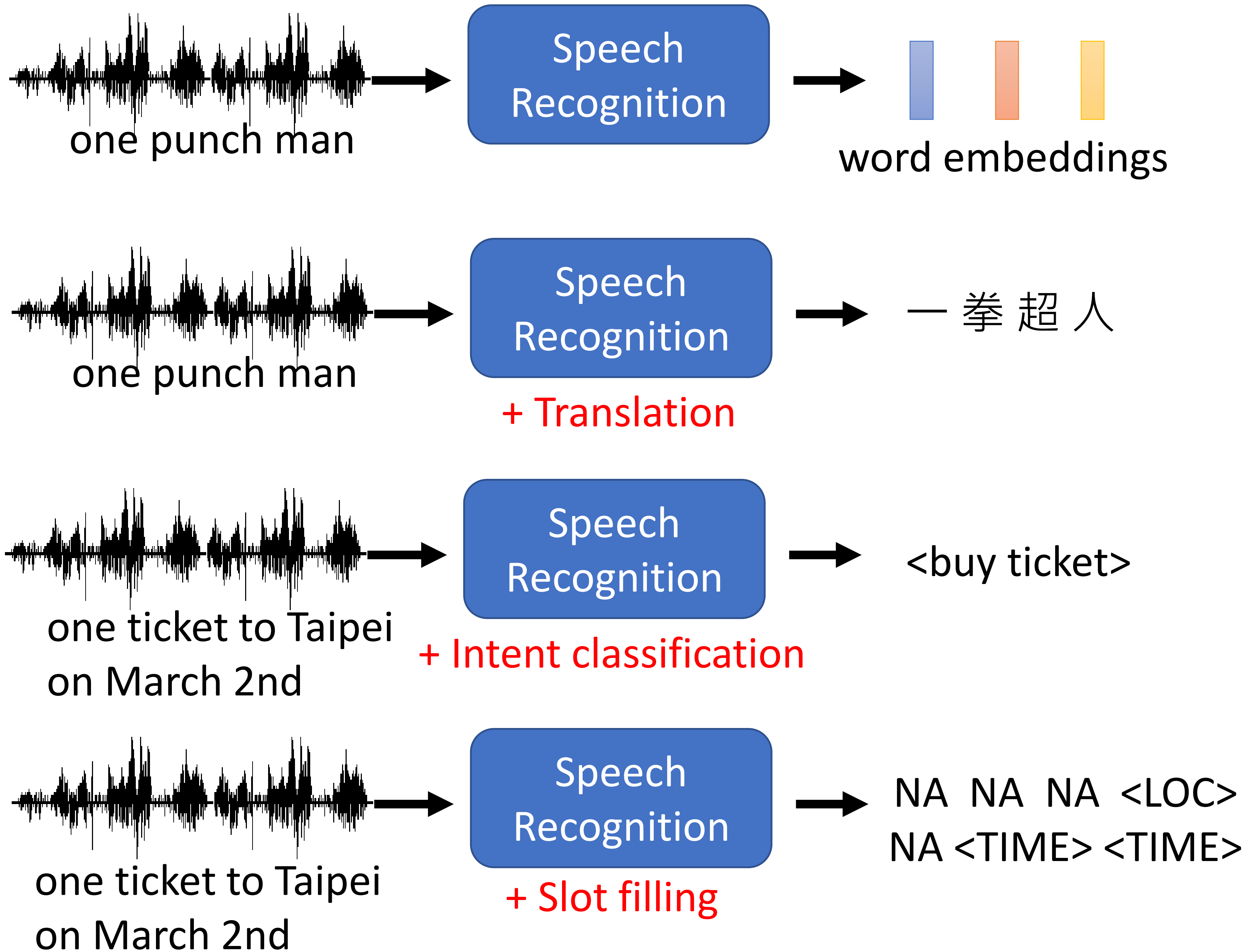
[Li, et al., ICASSP'19]

Token

Go through more than 100 papers in INTERSPEECH'19, ICASSP'19, ASRU'19

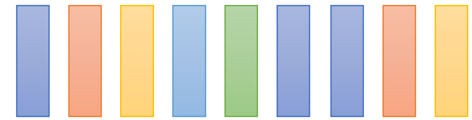
感謝助教群的辛勞





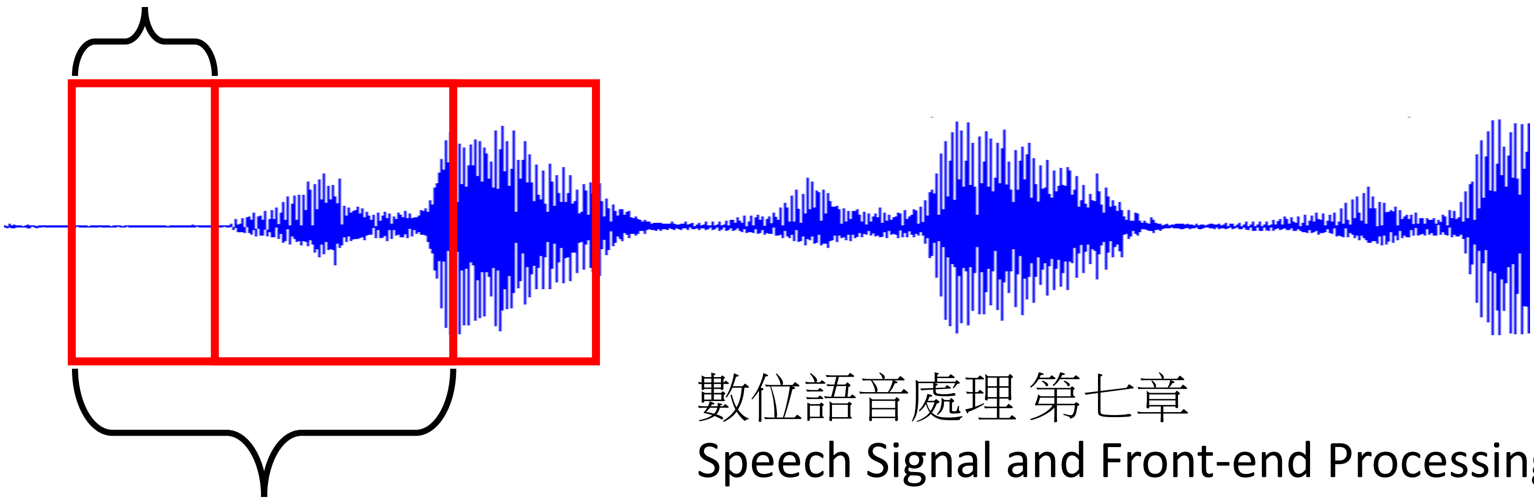
Speech Recognition
one punch man
word embeddings
Speech Recognition
+ Translation
one punch man
一 拳 超 人
Speech Recognition
+ Intent classification
one ticket to Taipei on March 2nd
<buy ticket>
Speech Recognition
+ Slot filling
one ticket to Taipei on March 2nd
NA NA NA <LOC> NA <TIME> <TIME>

Acoustic Feature



length T, dimension d

1s → 100 frames

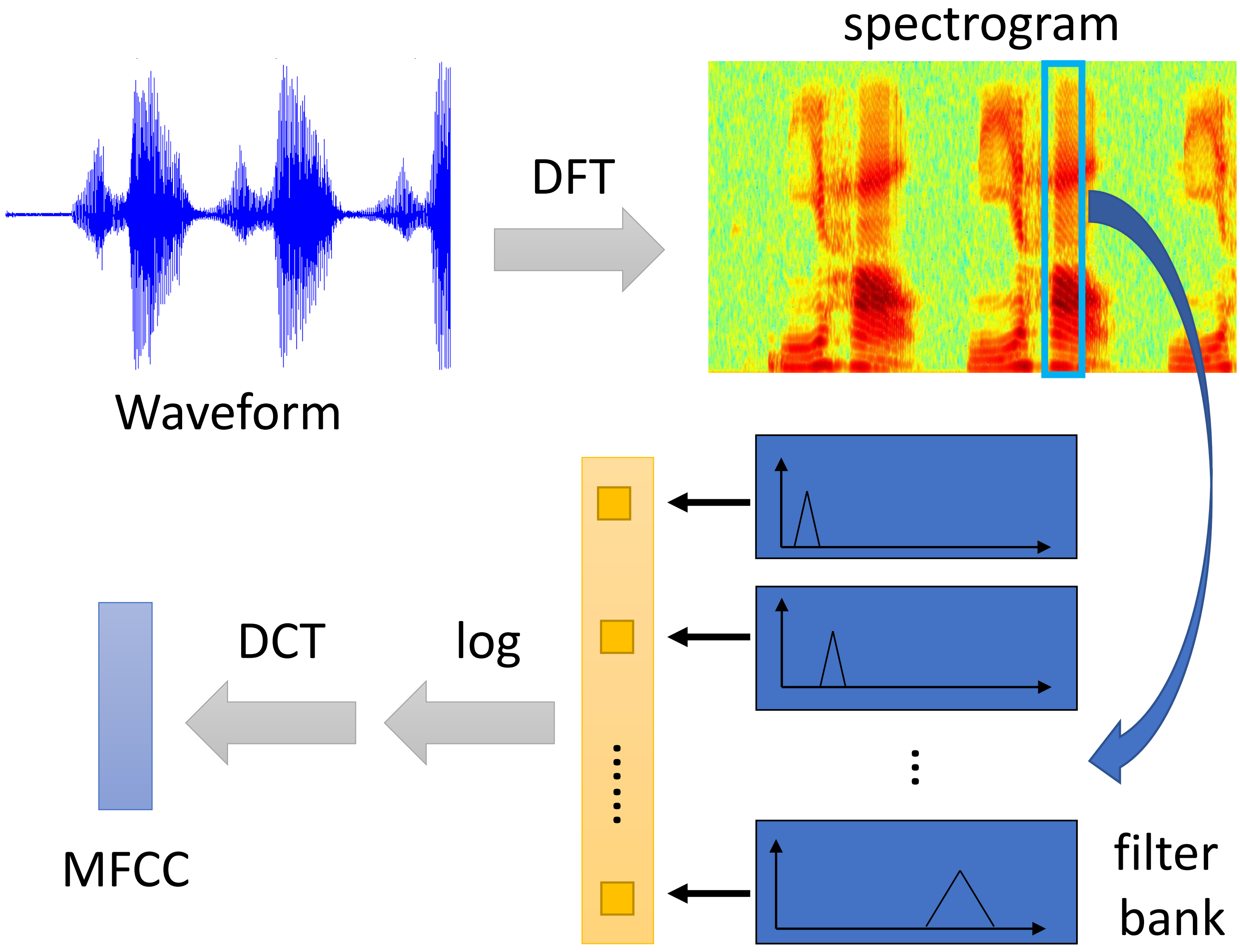


數位語音處理 第七章
Speech Signal and Front-end Processing
http://ocw.aca.ntu.edu.tw/ntu-ocw/ocw/cou/104S204/7

frame

400 sample points (16KHz)
39-dim MFCC
80-dim filter bank output

Acoustic Feature



Acoustic Feature

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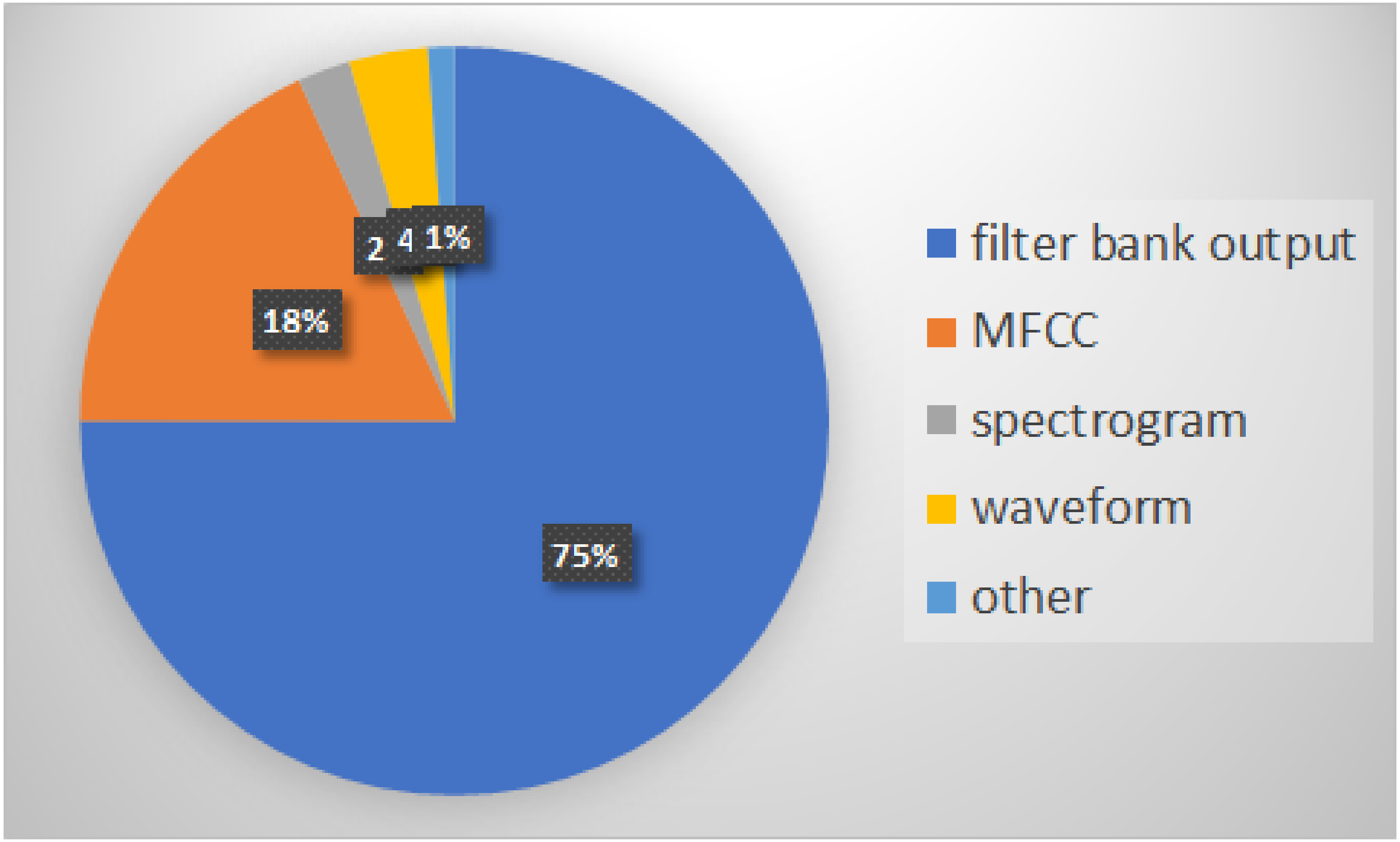


How much data do we need?

(English corpora)

MNIST: 28 x 28 x 1 x 60000

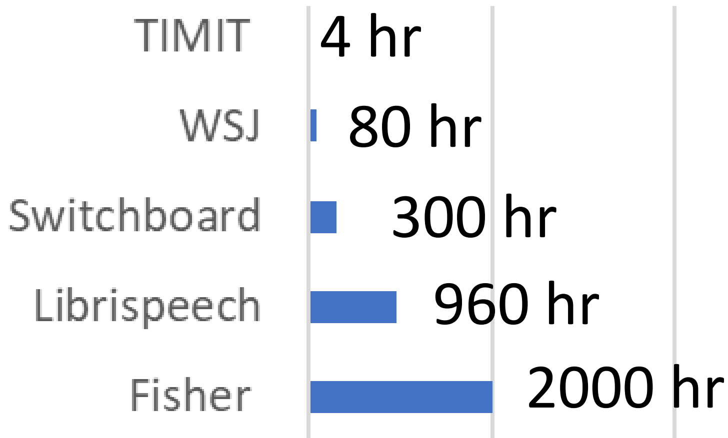
= 47,040,000

= 49 minutes (16kHz)

CIFAR-10: 32 x 32 x 3 x 50000

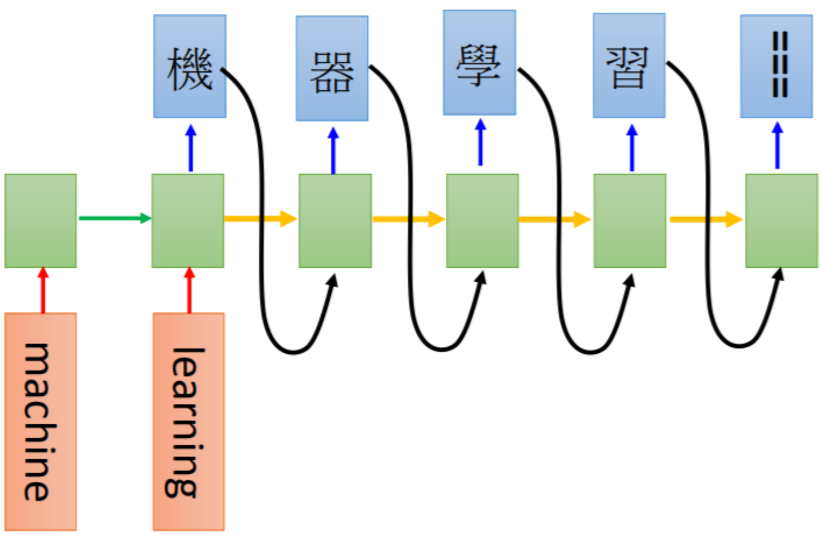
= 153,600,000

= 2 hours 40 minutes

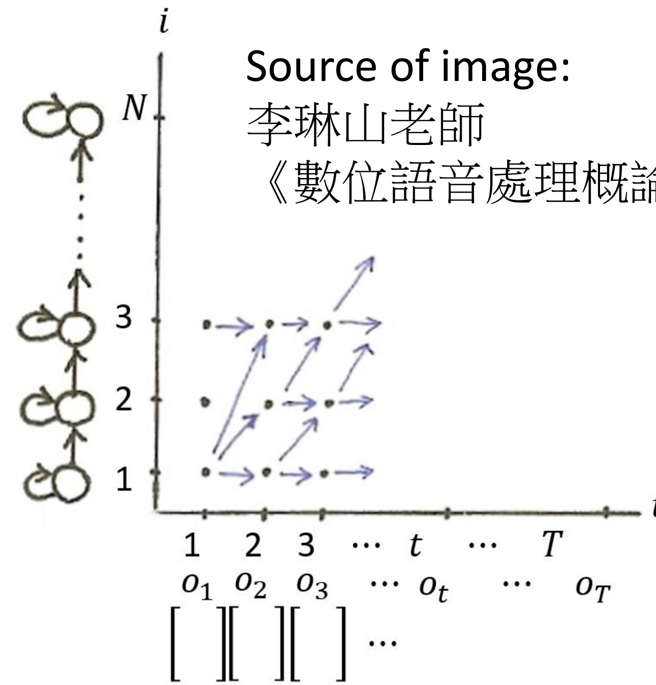


The commercial systems use more than that ……

Two Points of Views



Seq-to-seq



Source of image:
李琳山老師
《數位語音處理概論》

HMM

Models to be introduced

- Listen, Attend, and Spell (LAS) [Chorowski. et al., NIPS'15]
- Connectionist Temporal Classification (CTC) [Graves, et al., ICML'06]
- RNN Transducer (RNN-T) [Graves, ICML workshop'12]
- Neural Transducer [Jaitly, et al., NIPS'16]
- Monotonic Chunkwise Attention (MoChA) [Chiu, et al., ICLR'18]

Models

Go through more than 100 papers in INTERSPEECH'19, ICASSP'19, ASRU'19

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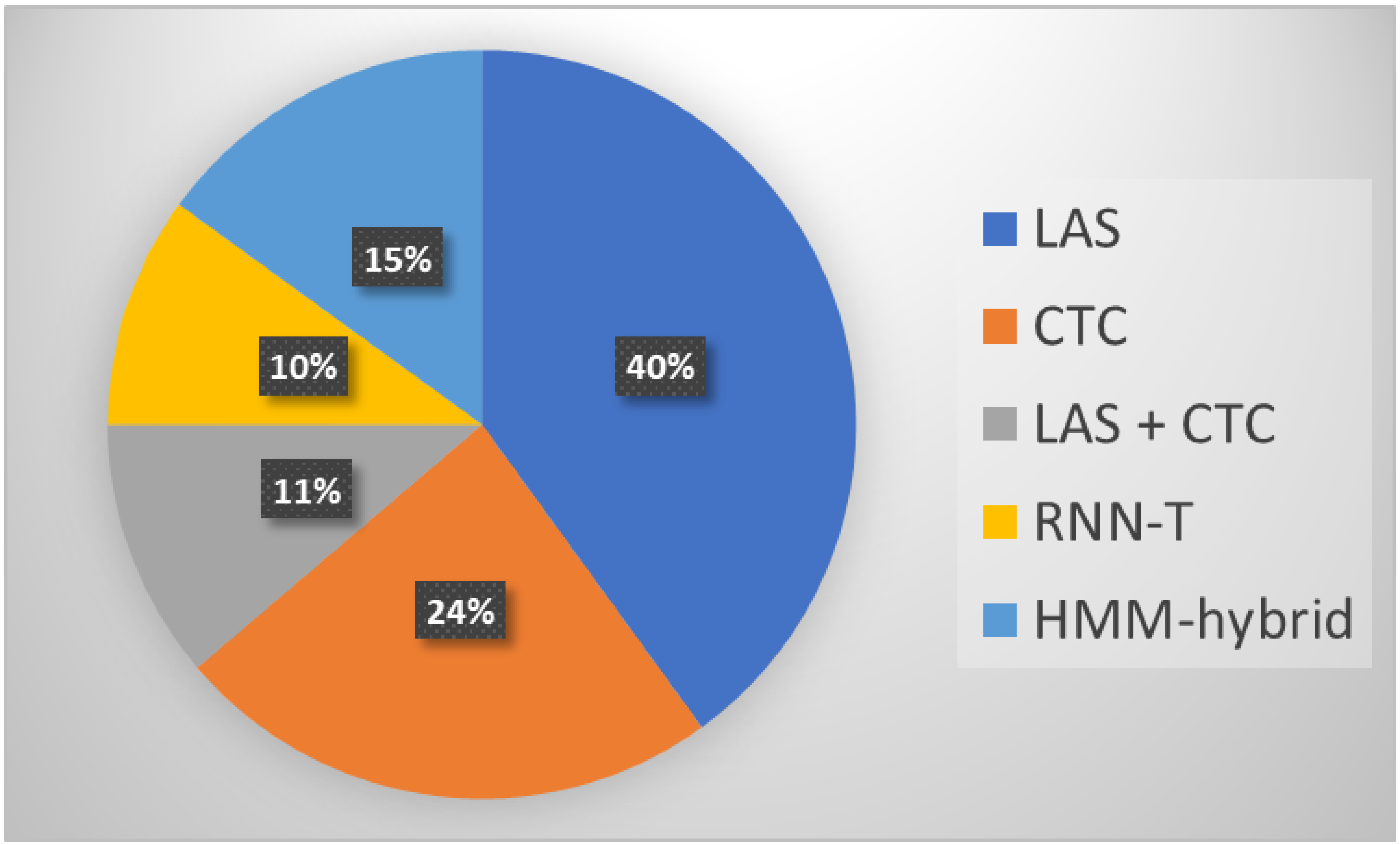

Models to be introduced

Encoder Decoder

- Listen, Attend, and Spell (LAS) [Chorowski. et al., NIPS'15]

It is the typical seq2seq with attention.

- Connectionist Temporal Classification (CTC) [Graves, et al., ICML'06]
- RNN Transducer (RNN-T) [Graves, ICML workshop'12]
- Neural Transducer [Jaitly, et al., NIPS'16]
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Listen

- Extract content information
- Remove speaker variance, remove noises

output:

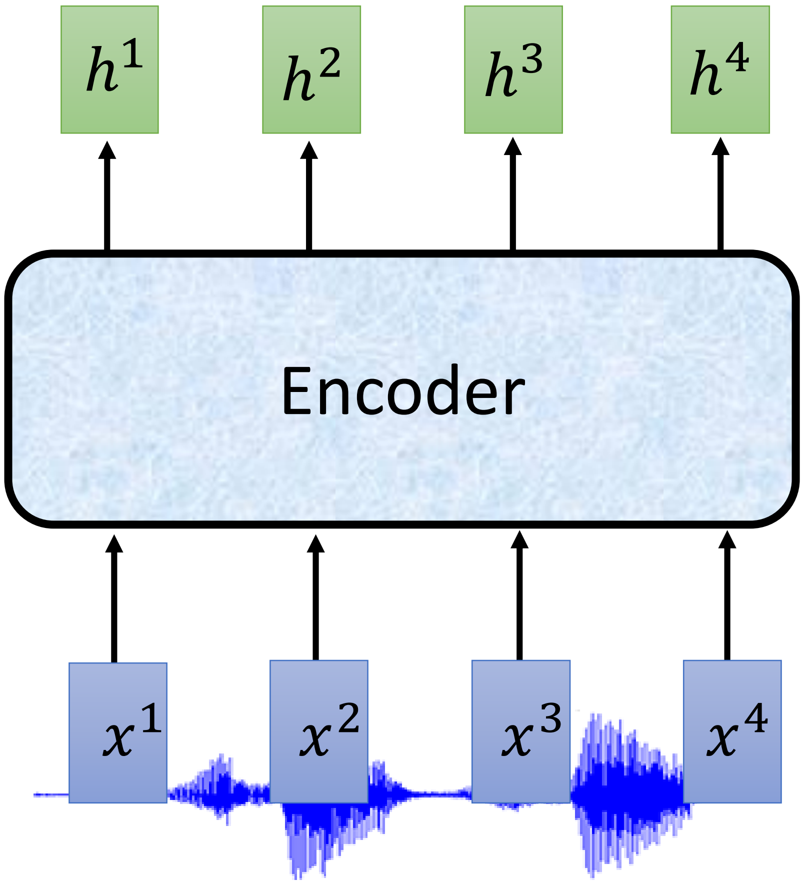
$\{h^1, h^2, \cdots, h^T\}$

high-level representations

Input:

$\{x^1, x^2, \cdots, x^T\}$

acoustic features



Listen

output:

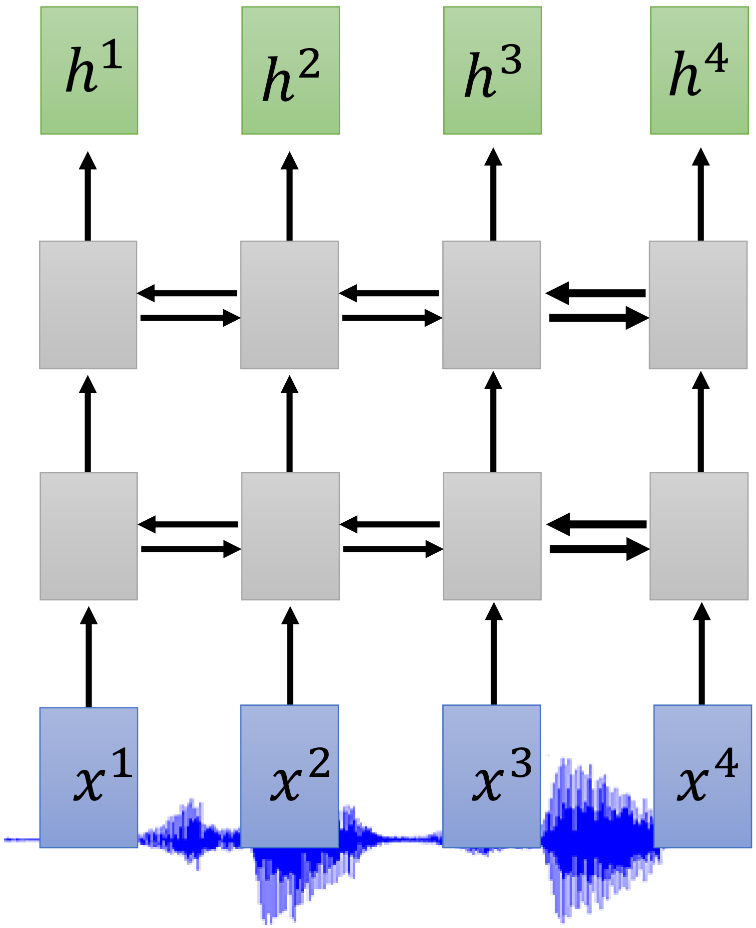
$\{h^1, h^2, \cdots, h^T\}$

high-level representations

Input:

$\{x^1, x^2, \cdots, x^T\}$

acoustic features



RNN

Listen

output:

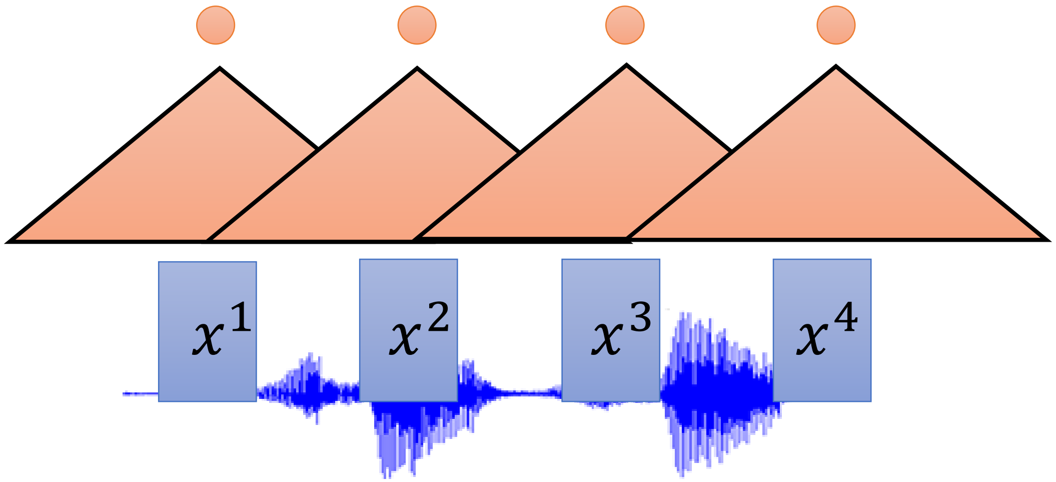
$\{h^1, h^2, \cdots, h^T\}$

high-level representations

Input:

$\{x^1, x^2, \cdots, x^T\}$

acoustic features



1-D CNN

Listen

- Filters in higher layer can consider longer sequence
- CNN+RNN is common

output:

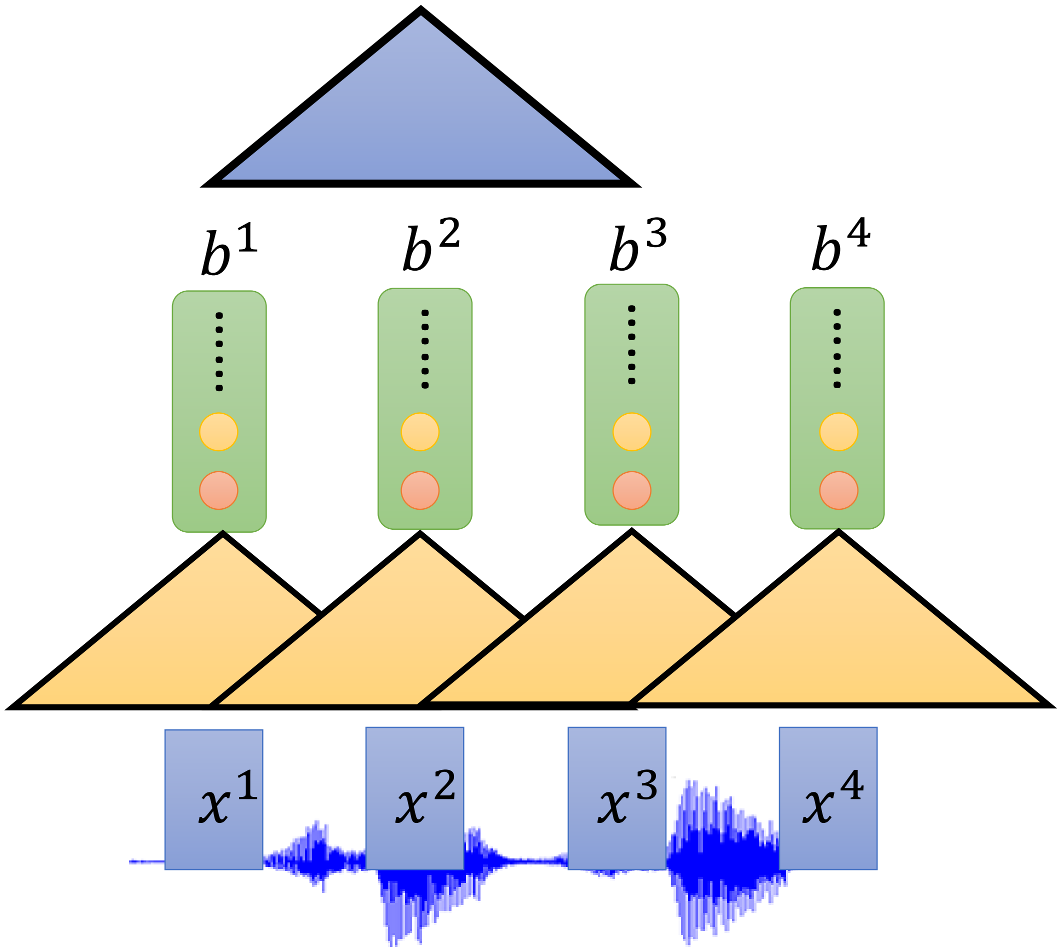
$\{h^1, h^2, \cdots, h^T\}$

high-level representations

Input:

$\{x^1, x^2, \cdots, x^T\}$

acoustic features



1-D CNN

Listen

Please refer to ML video recording: https://www.youtube.com/watch?v=ugWDIIOHtPA

[Zeyer, et al., ASRU'19]

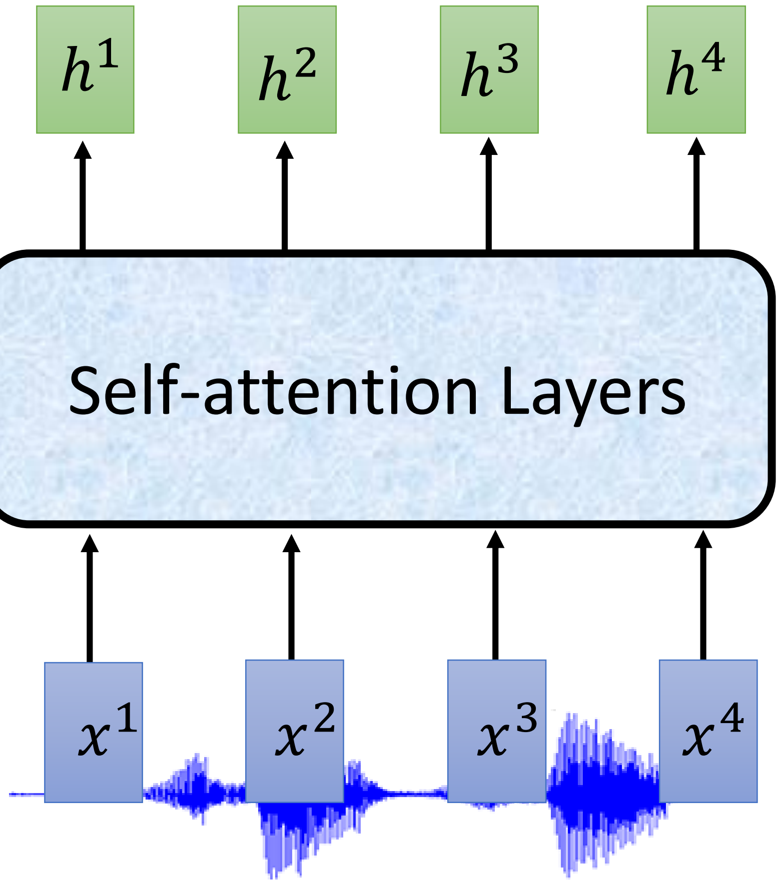
[Karita, et al., ASRU'19]

output:
$\{h^1, h^2, \cdots, h^T\}$

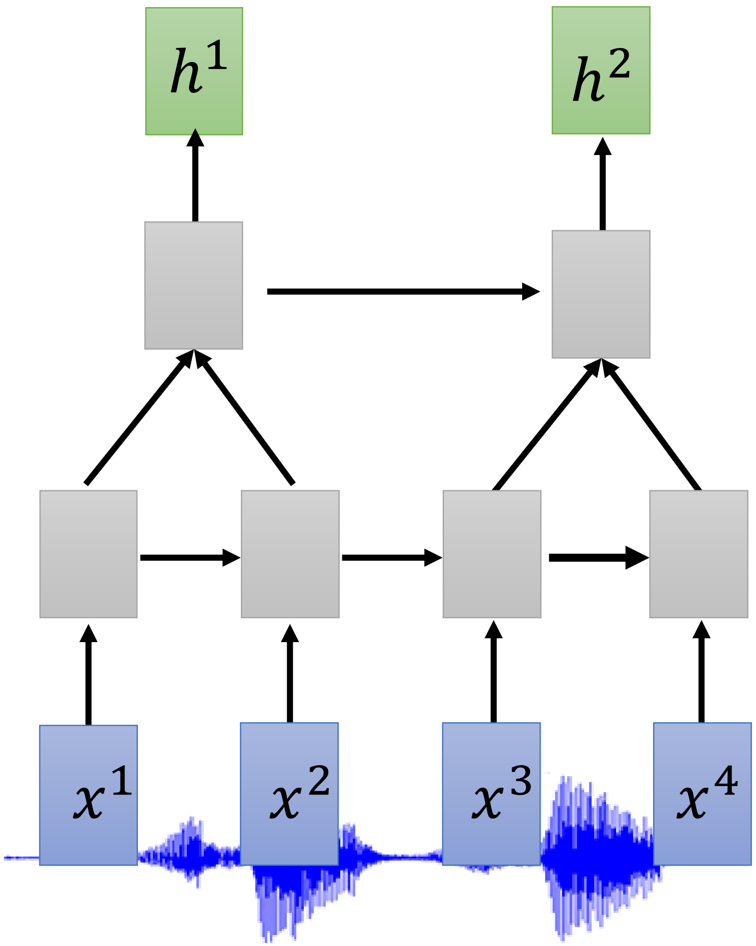
high-level representations

Input:
$\{x^1, x^2, \cdots, x^T\}$

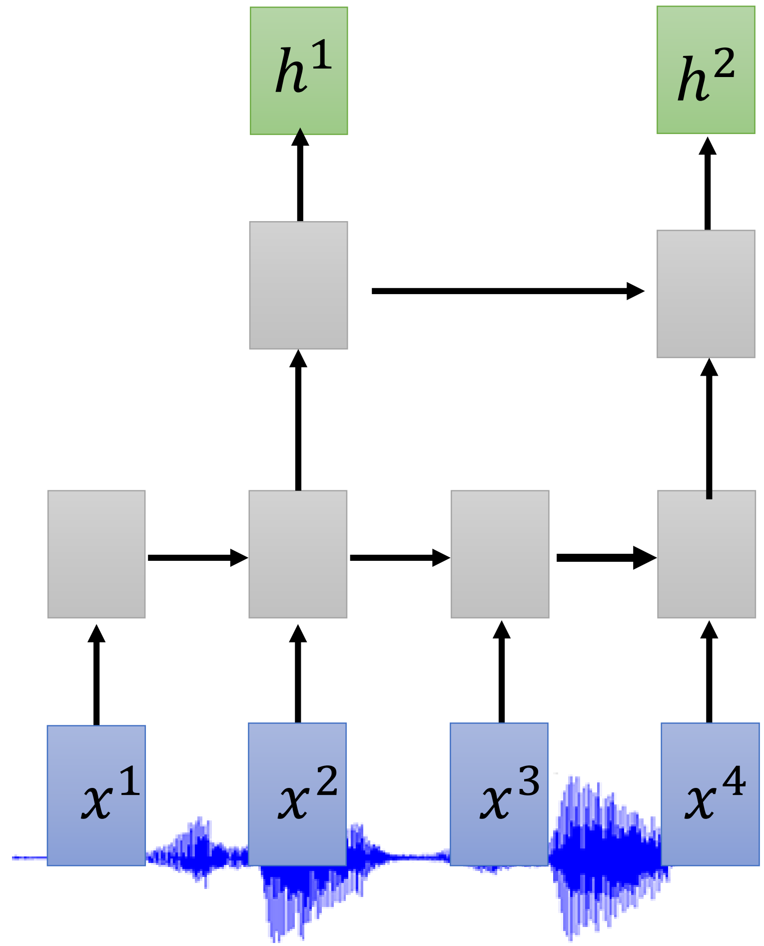
acoustic features



Listen – Down Sampling



Pyramid RNN [Chan, et al., ICASSP'16]



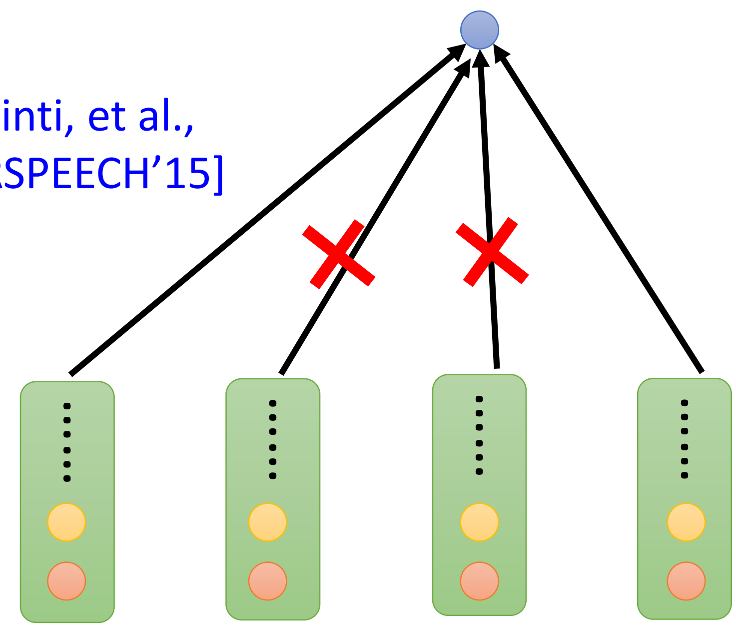
Pooling over time [Bahdanau. et al., ICASSP'16]

Listen – Down Sampling

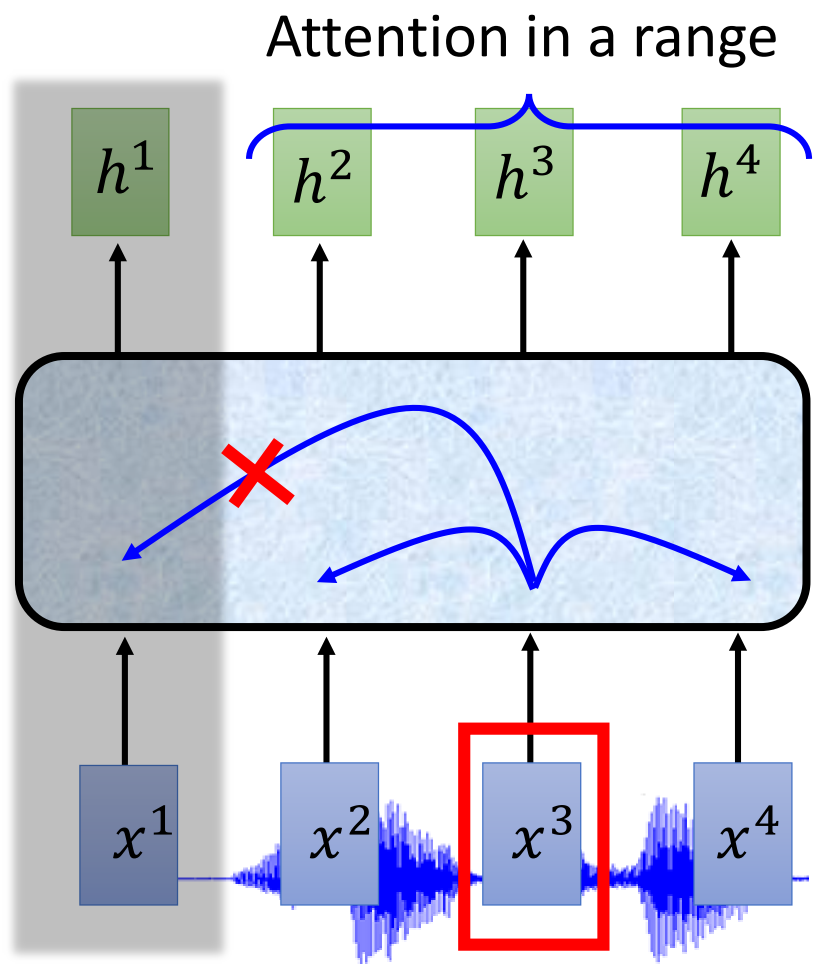
[Yeh, et al., arXiv'19]

Dilated CNN has the same concept

[Peddinti, et al., INTERSPEECH'15]



Time-delay DNN (TDNN)

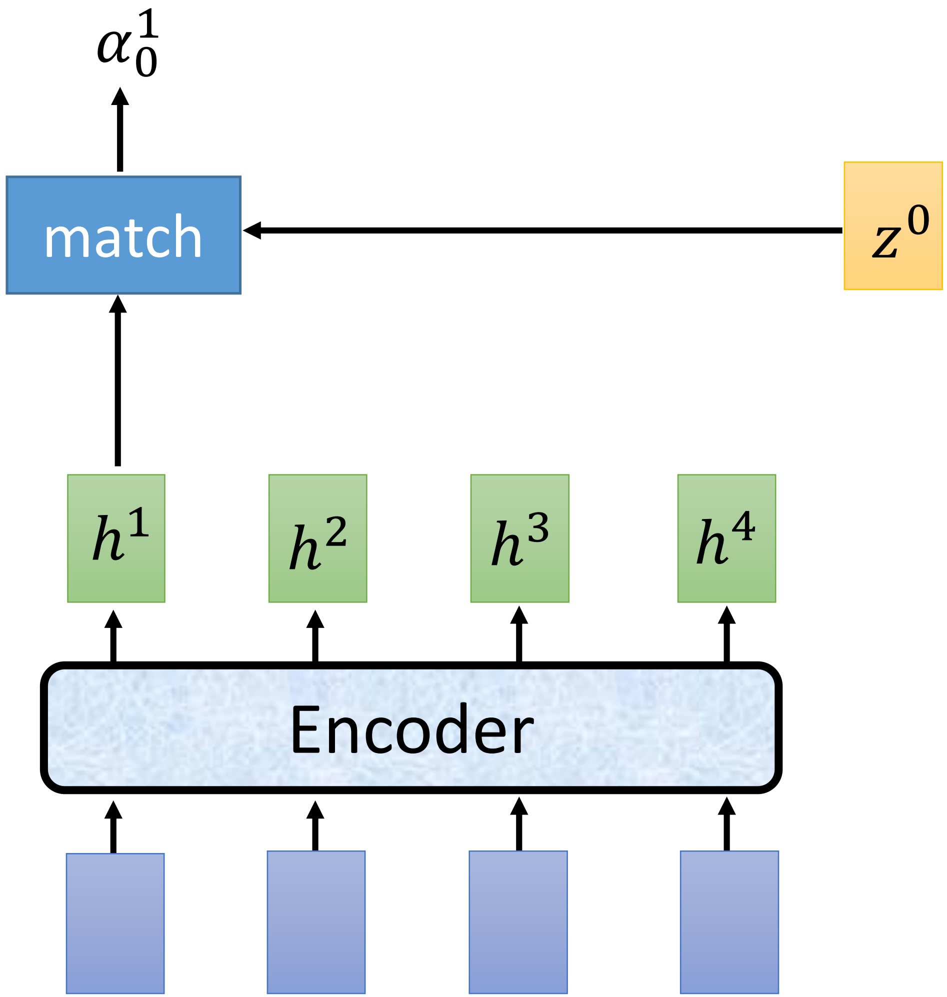


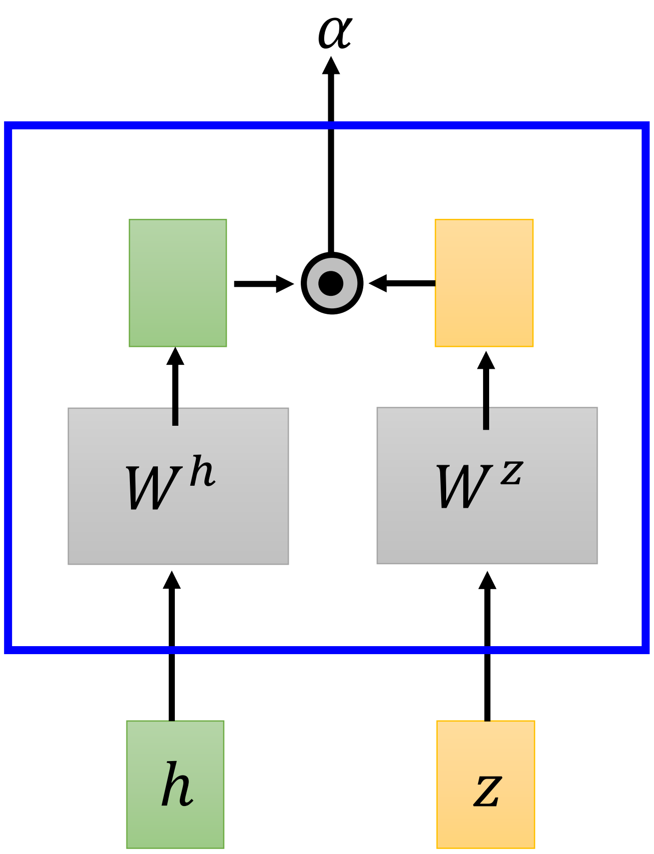
Truncated Self-attention

Attention

Dot-product Attention

[Chan, et al., ICASSP'16]

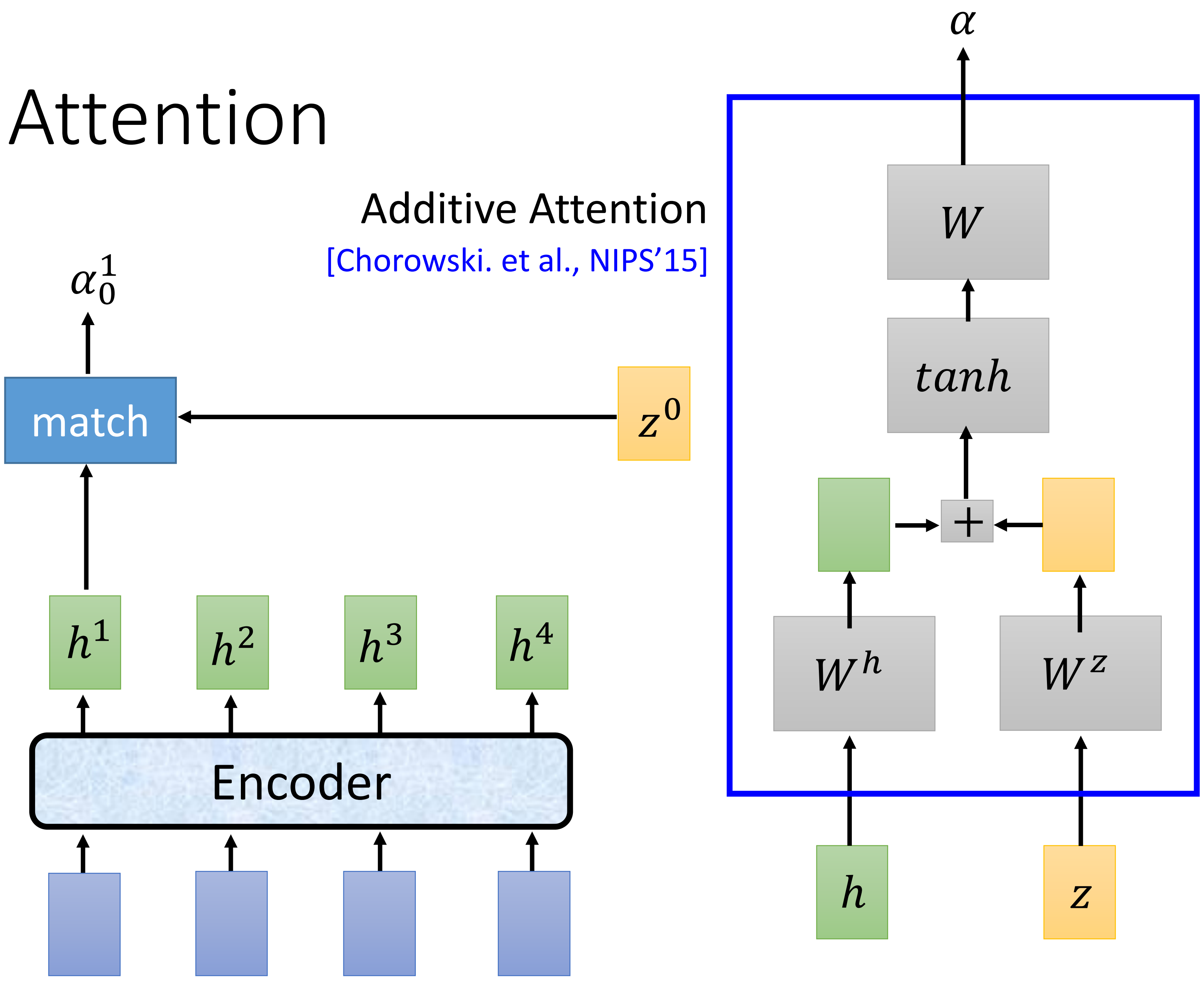




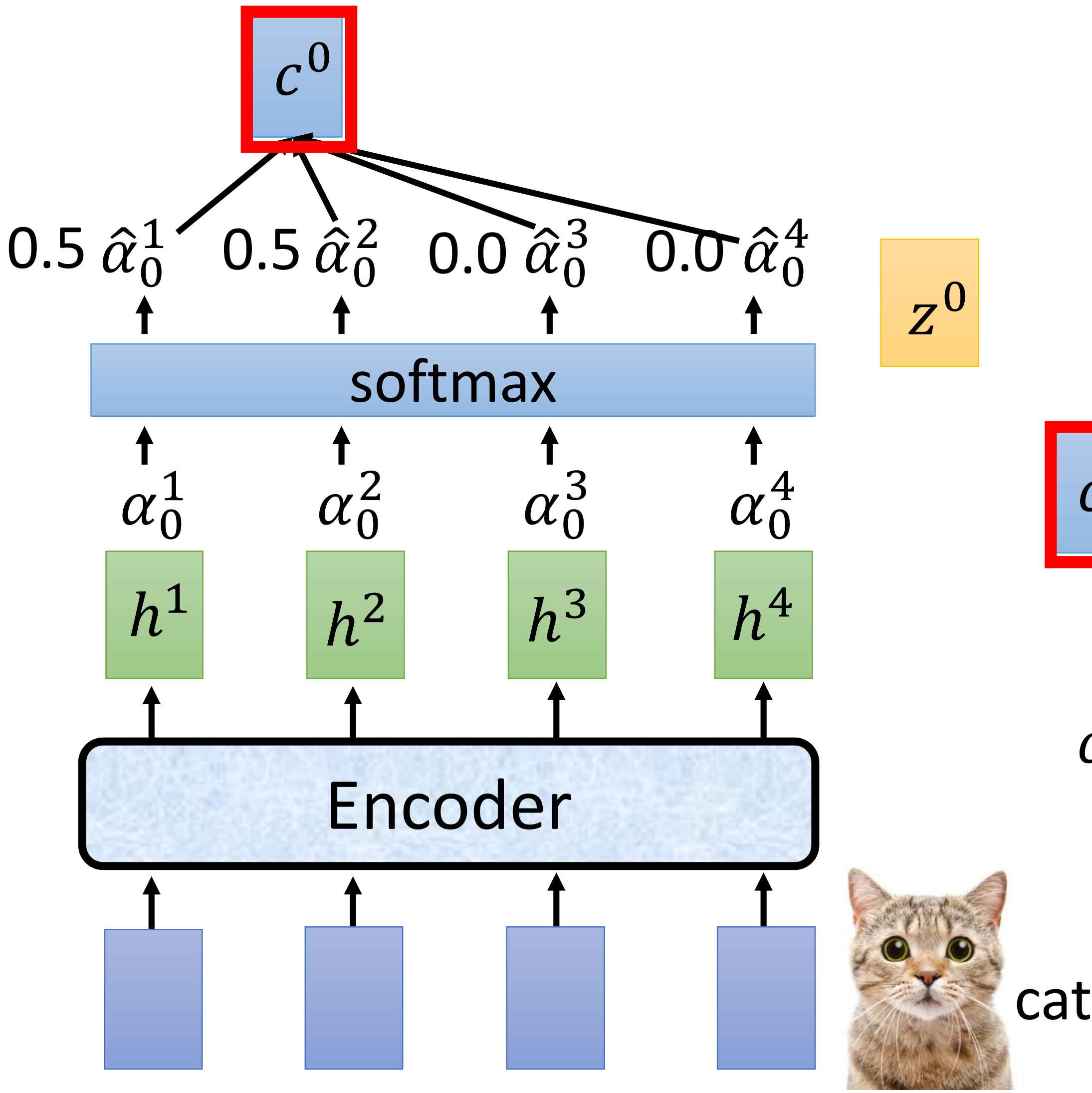
Attention

Additive Attention

[Chorowski. et al., NIPS'15]



Attention

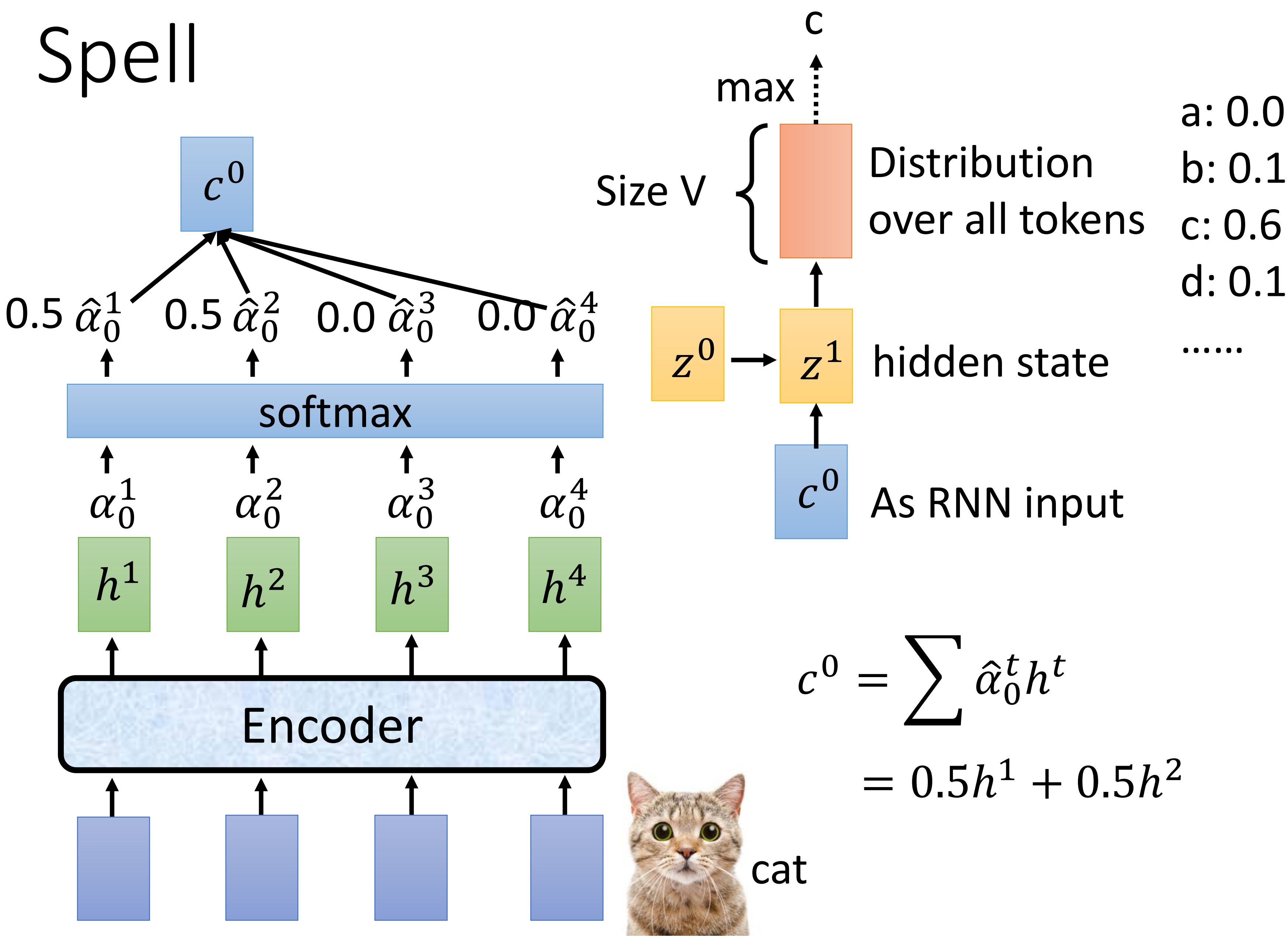


$\boxed{c^0}$ As RNN input

$$c^0 = \sum \hat{\alpha}_0^i h^i$$

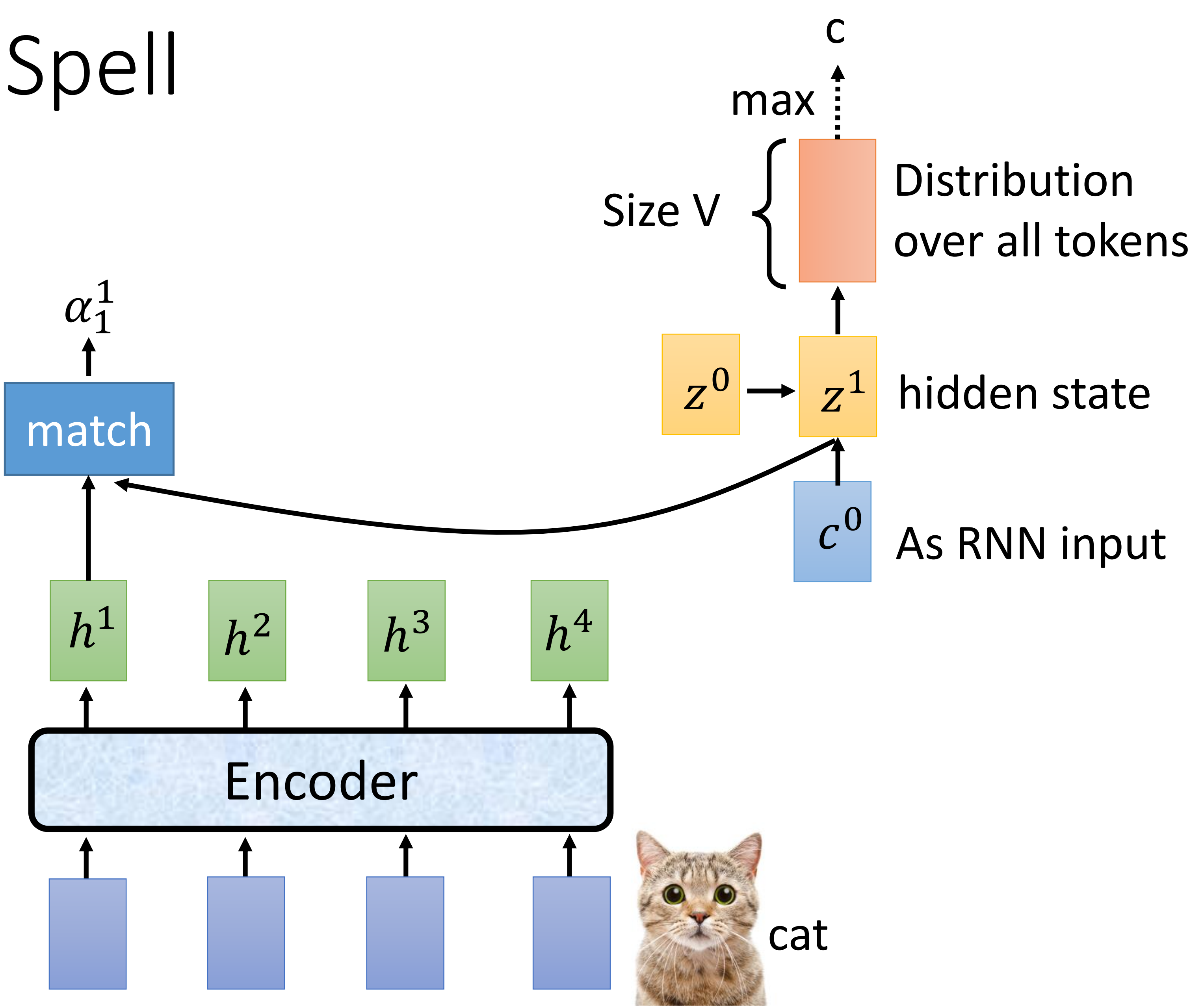
$$= 0.5h^1 + 0.5h^2$$

Spell



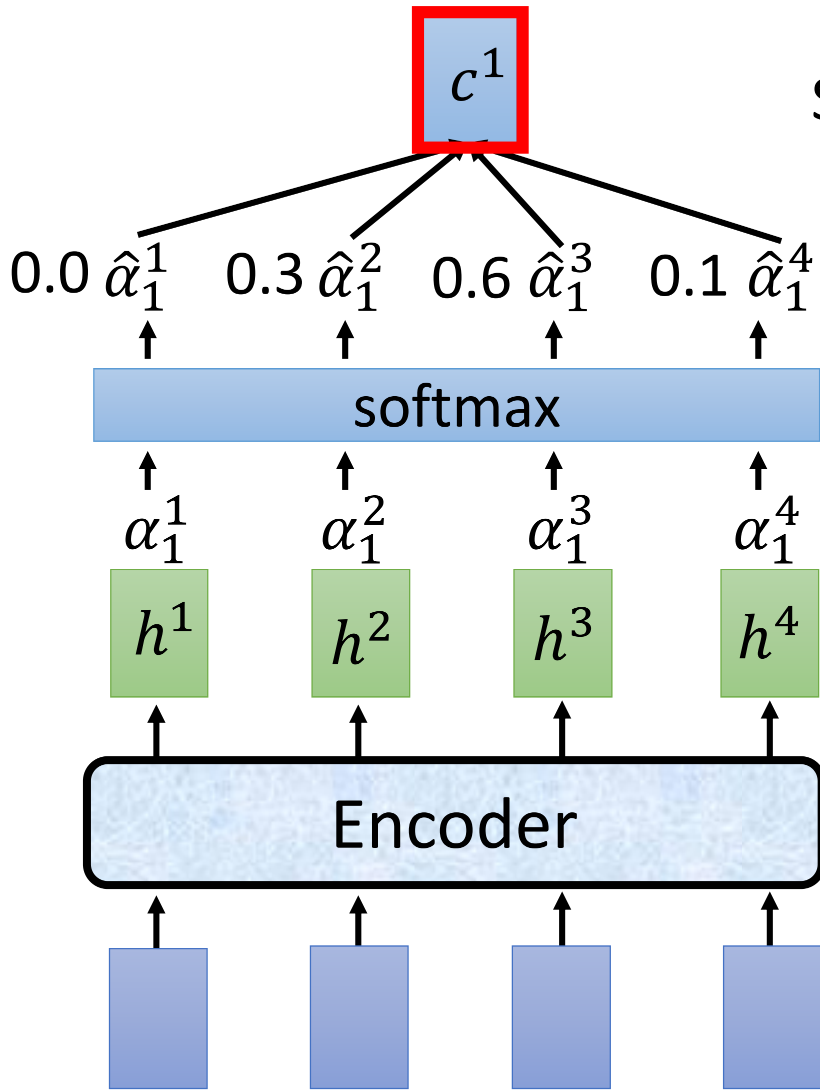
c
max
Size V
Distribution over all tokens
a: 0.0
b: 0.1
c: 0.6
d: 0.1
……
z^0
z^1
hidden state
c^0
As RNN input
c^0
0.5 $\hat{\alpha}_0^1$
0.5 $\hat{\alpha}_0^2$
0.0 $\hat{\alpha}_0^3$
0.0 $\hat{\alpha}_0^4$
softmax
α_0^1
α_0^2
α_0^3
α_0^4
h^1
h^2
h^3
h^4
Encoder
cat
$c^0 = \sum \hat{\alpha}_0^t h^t$
$= 0.5h^1 + 0.5h^2$

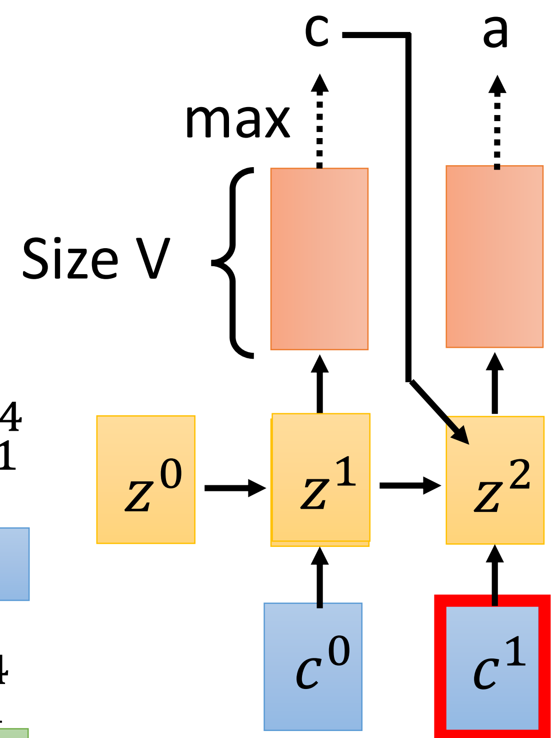
Spell



c
max
Size V
Distribution
over all tokens
α_1^1
match
z^0
z^1
hidden state
c^0
As RNN input
h^1
h^2
h^3
h^4
Encoder
cat

Spell





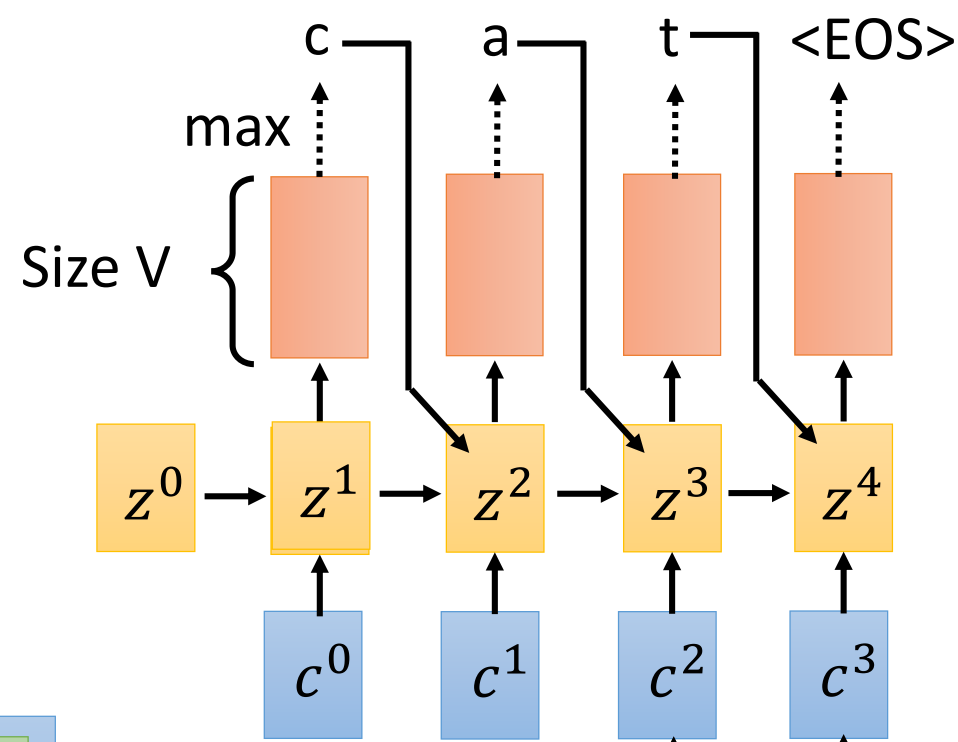
$$c^1 = \sum \hat{\alpha}_1^t h^t$$

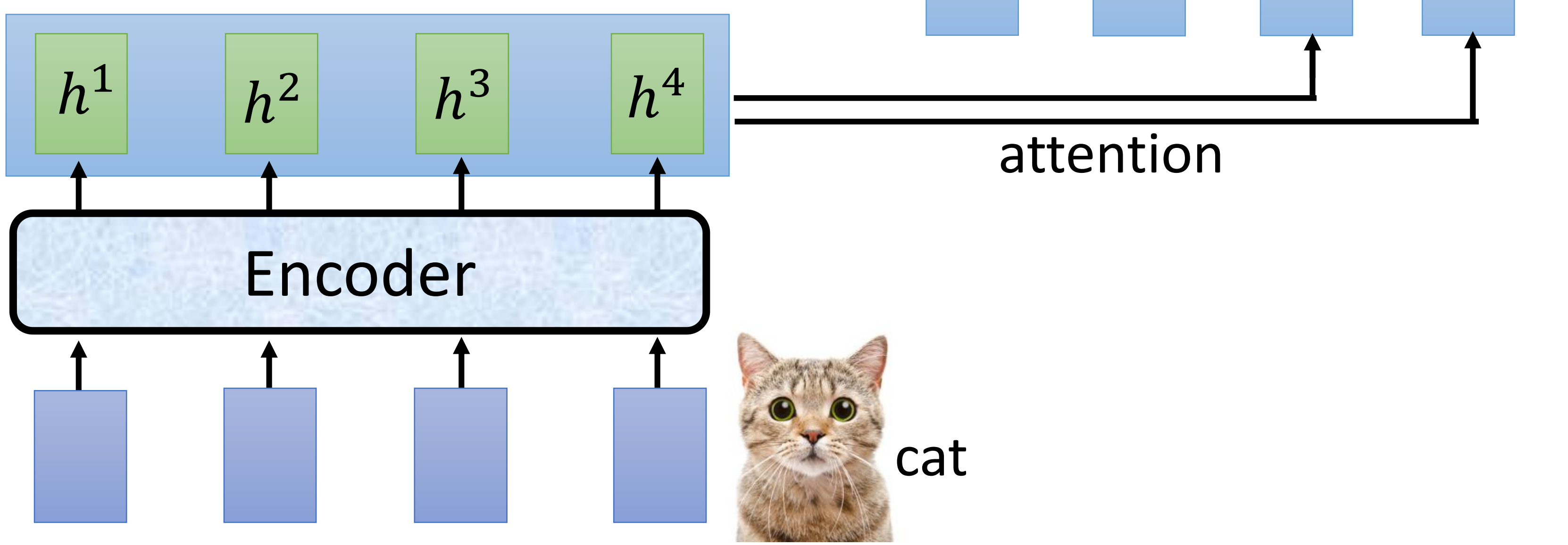
$$= 0.3h^2 + 0.6h^3 + 0.1h^4$$

cat

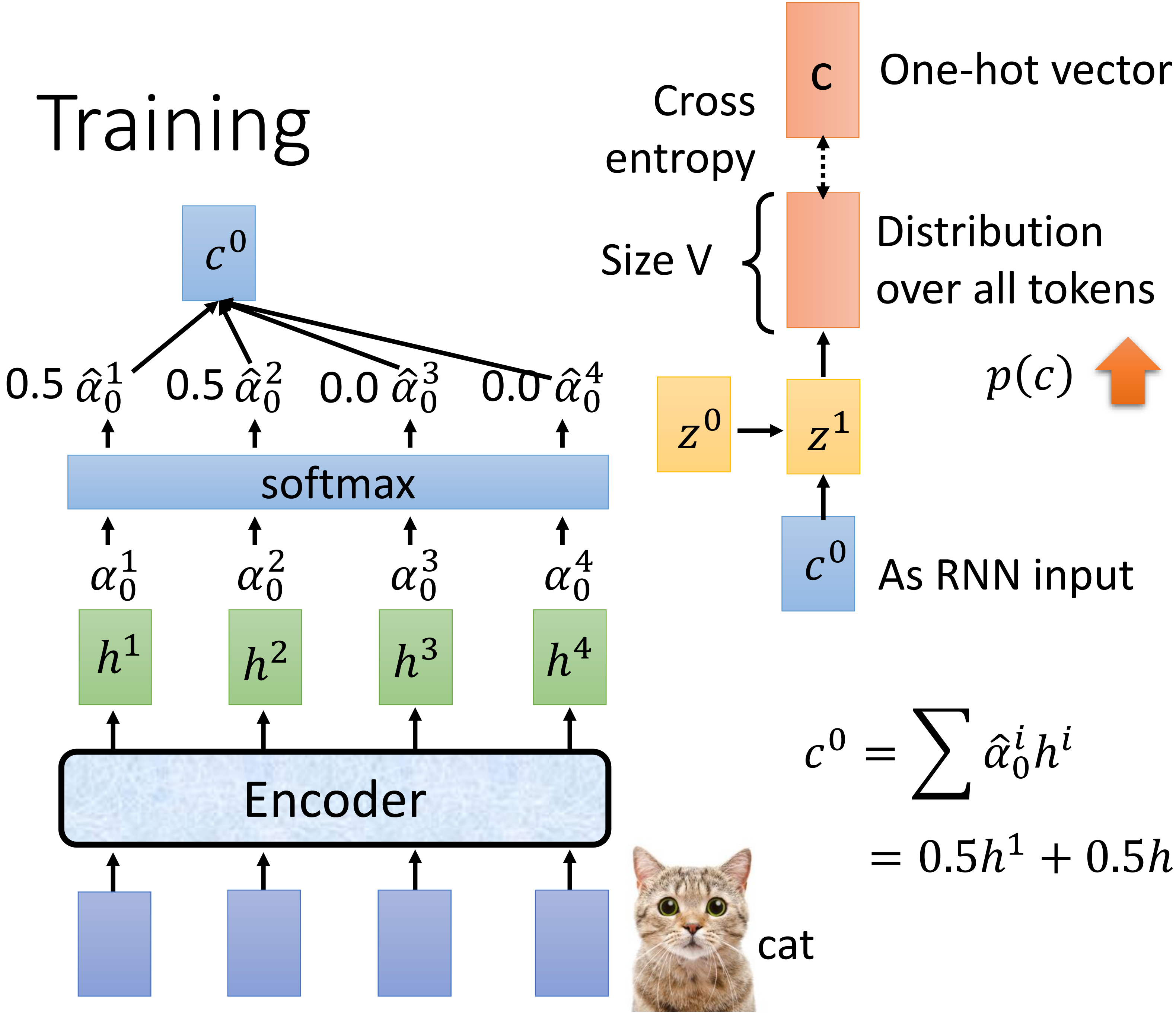
Spell

Beam Search is usually used (not today)



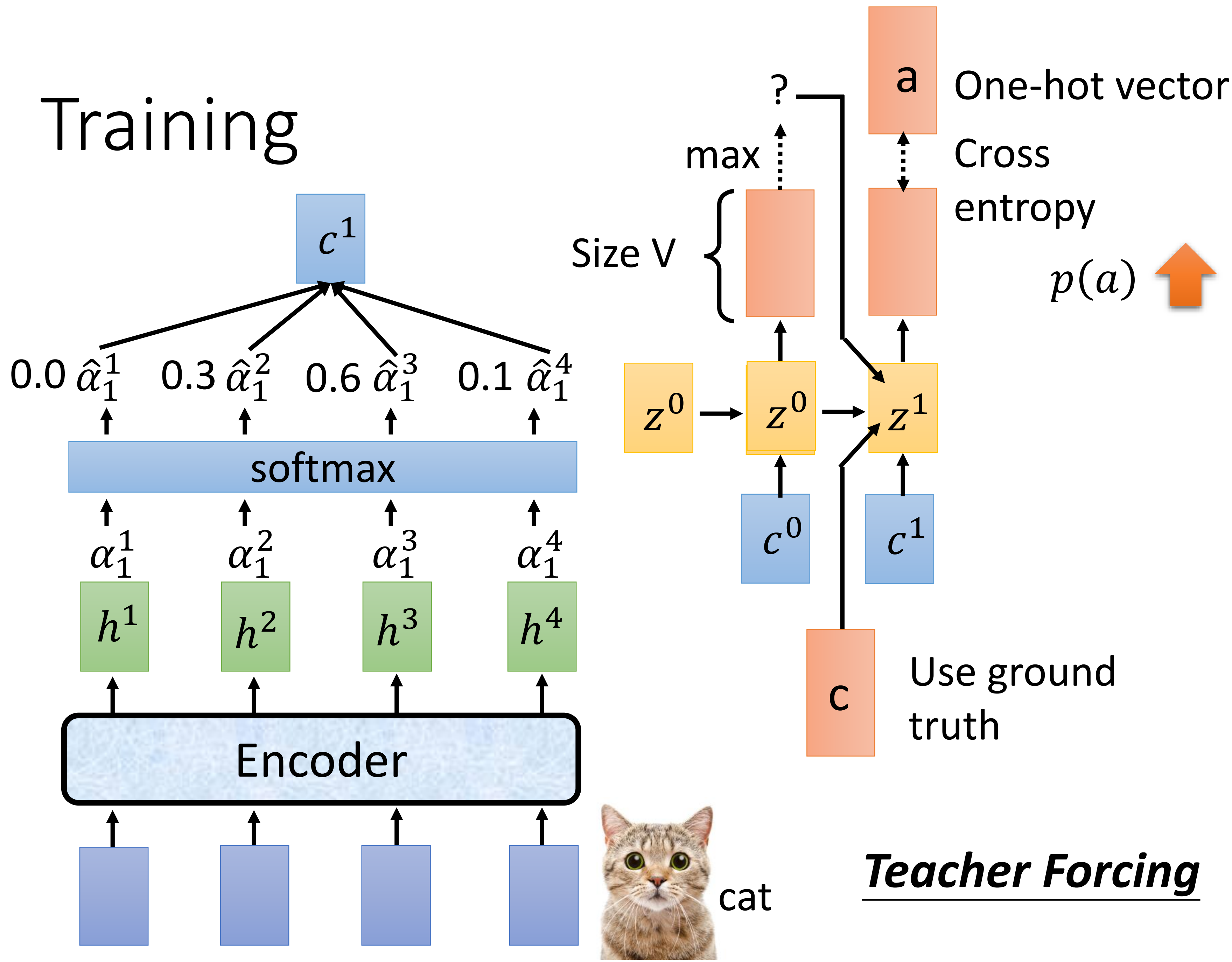


Training

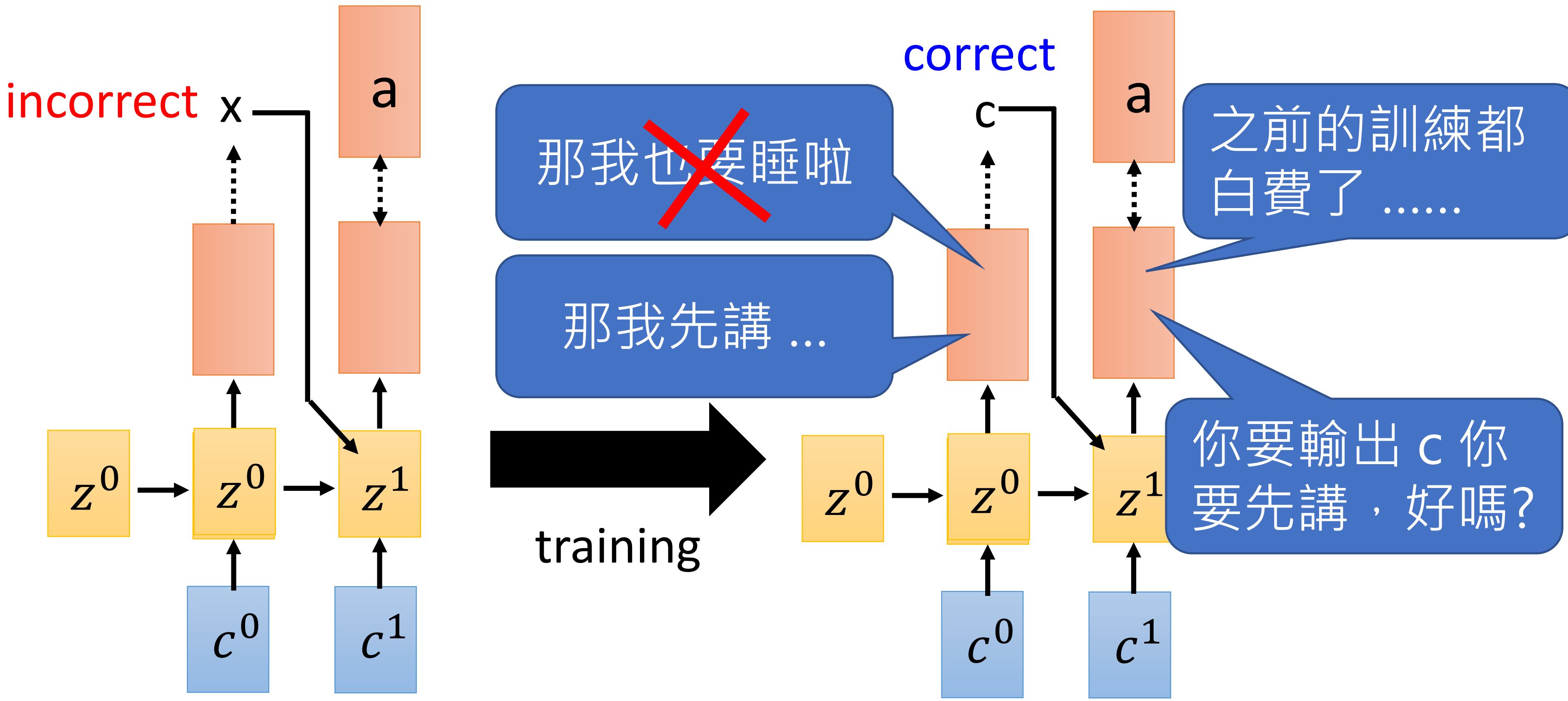


$$c^0 = \sum \hat{\alpha}_0^i h^i$$

$$= 0.5h^1 + 0.5h^2$$

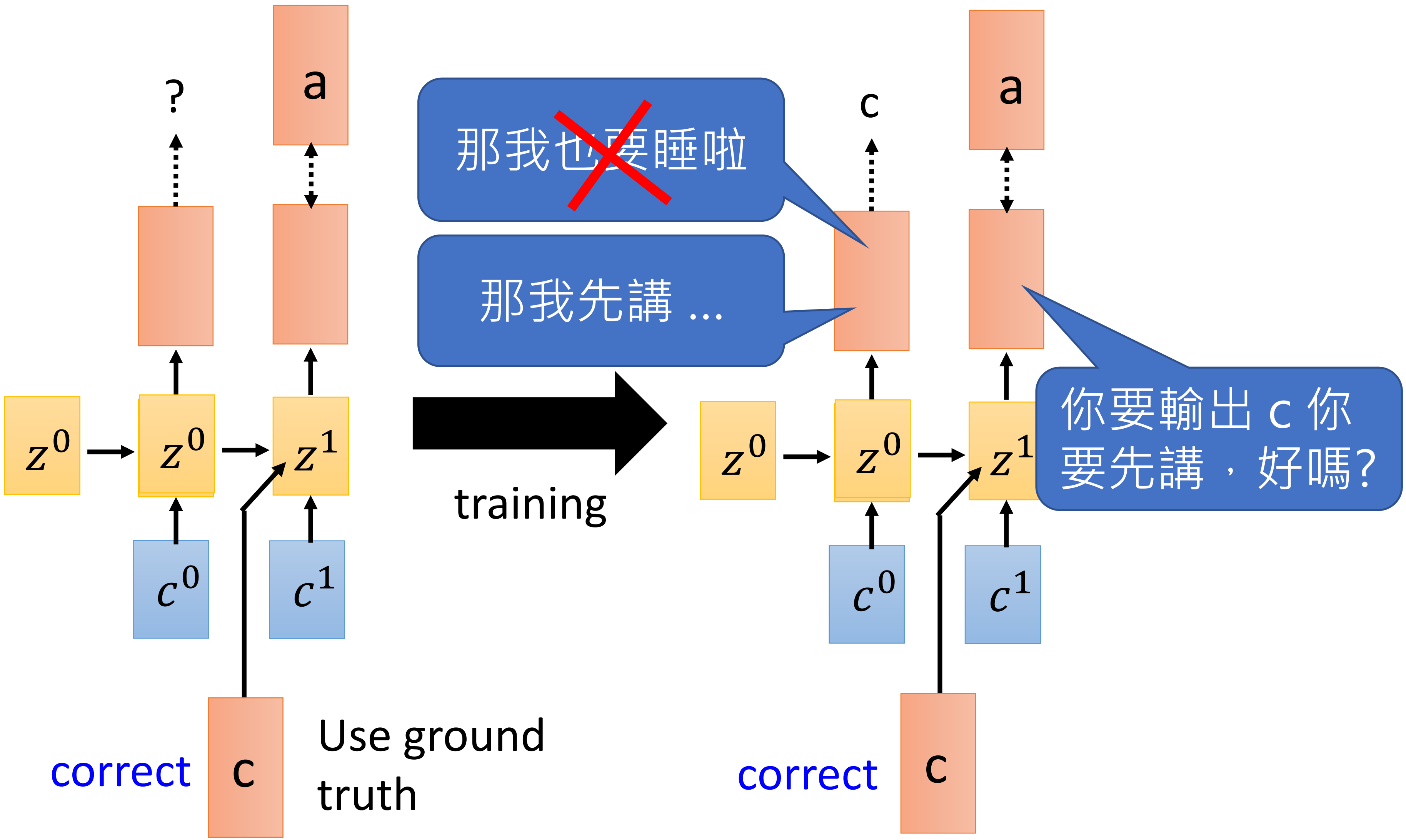

Training
c^1
0.0 $\hat{\alpha}_1^1$
0.3 $\hat{\alpha}_1^2$
0.6 $\hat{\alpha}_1^3$
0.1 $\hat{\alpha}_1^4$
softmax
α_1^1
α_1^2
α_1^3
α_1^4
h^1
h^2
h^3
h^4
Encoder
cat
?
max
a
One-hot vector
Cross entropy
Size V
$p(a)$
z^0
z^0
z^1
c^0
c^1
c
Use ground truth
Teacher Forcing

Why Teacher Forcing?

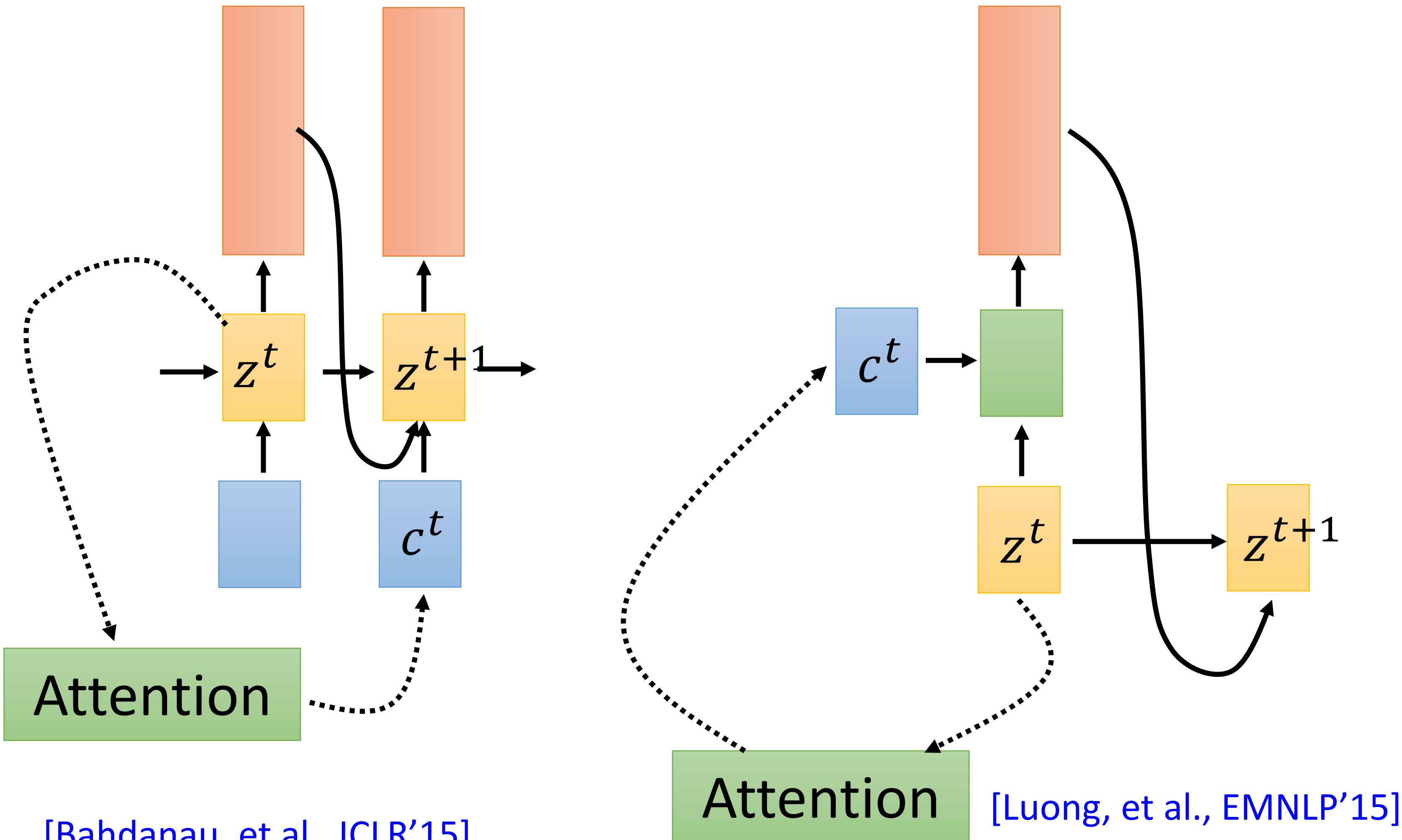


Use previous output

Why Teacher Forcing?

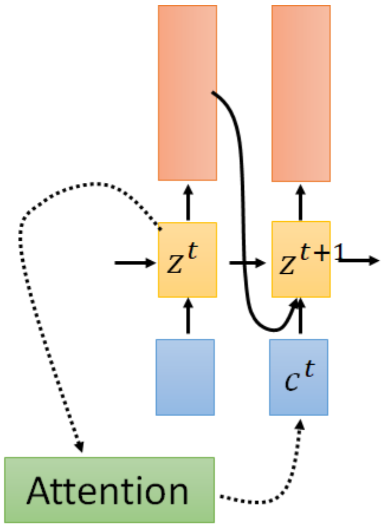


Back to Attention

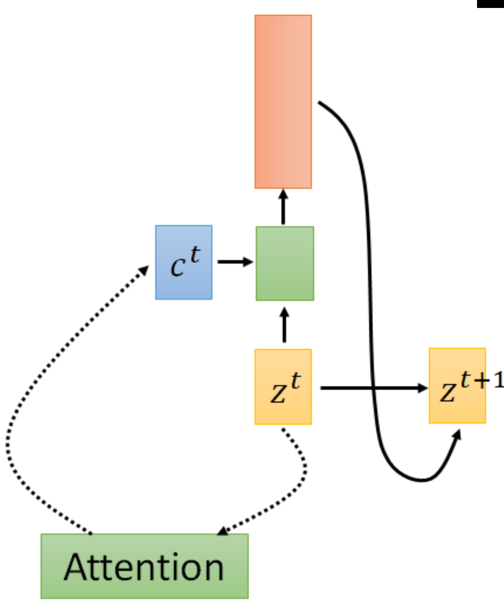


[Bahdanau. et al., ICLR'15]

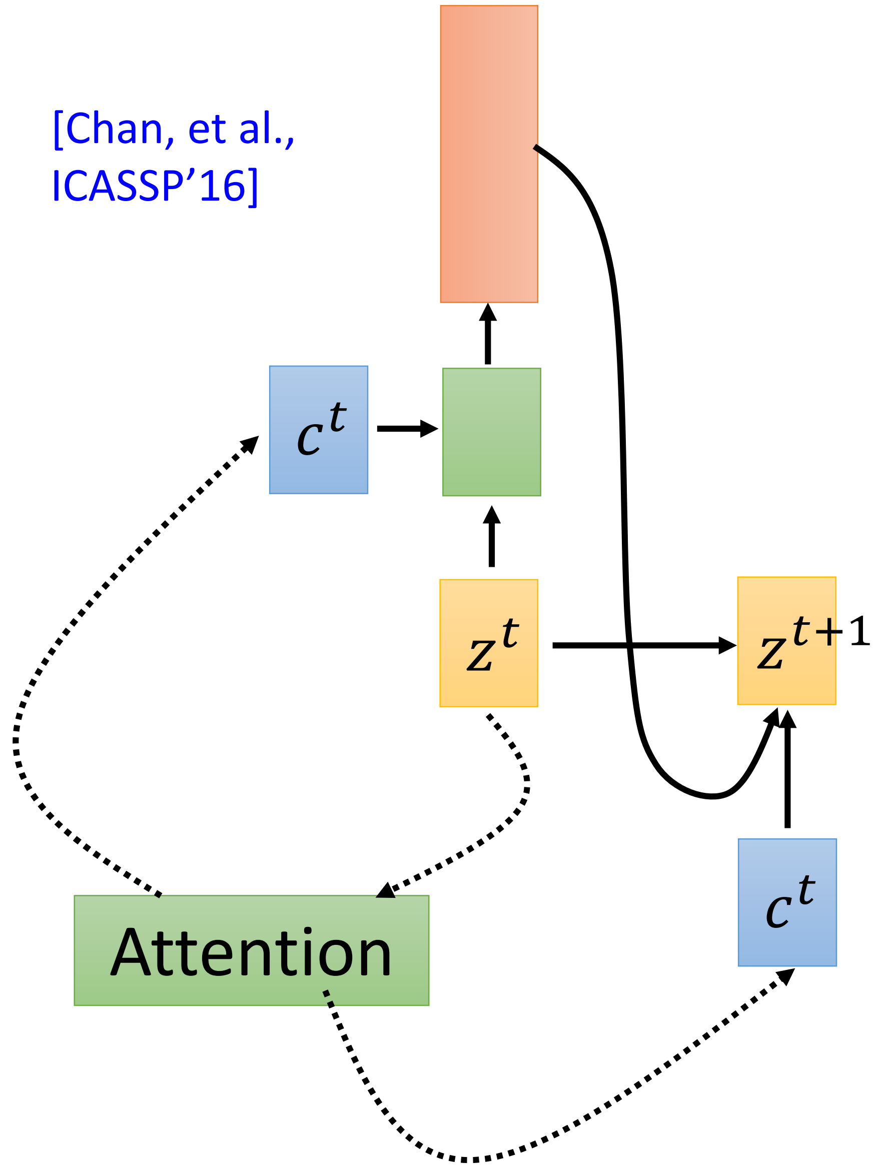
[Luong, et al., EMNLP'15]



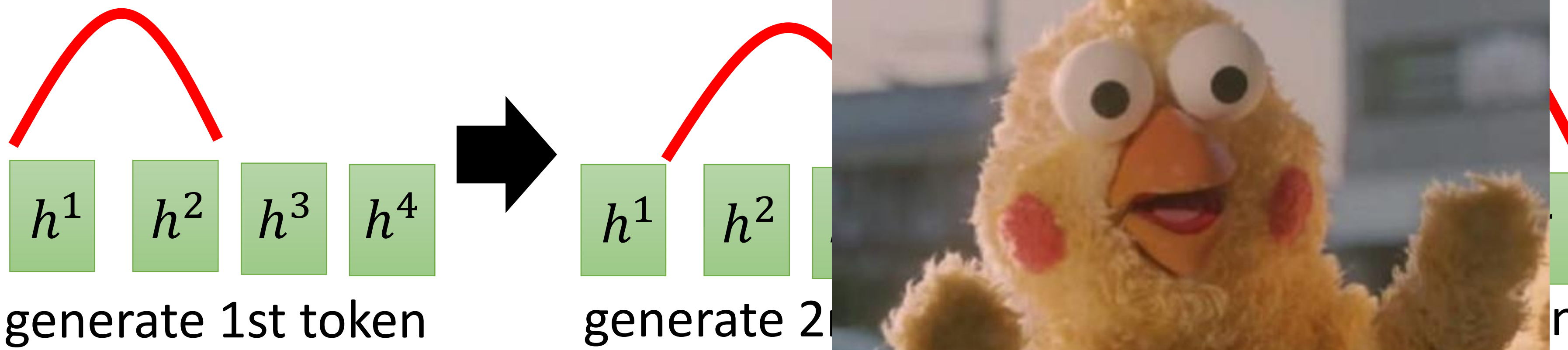
+

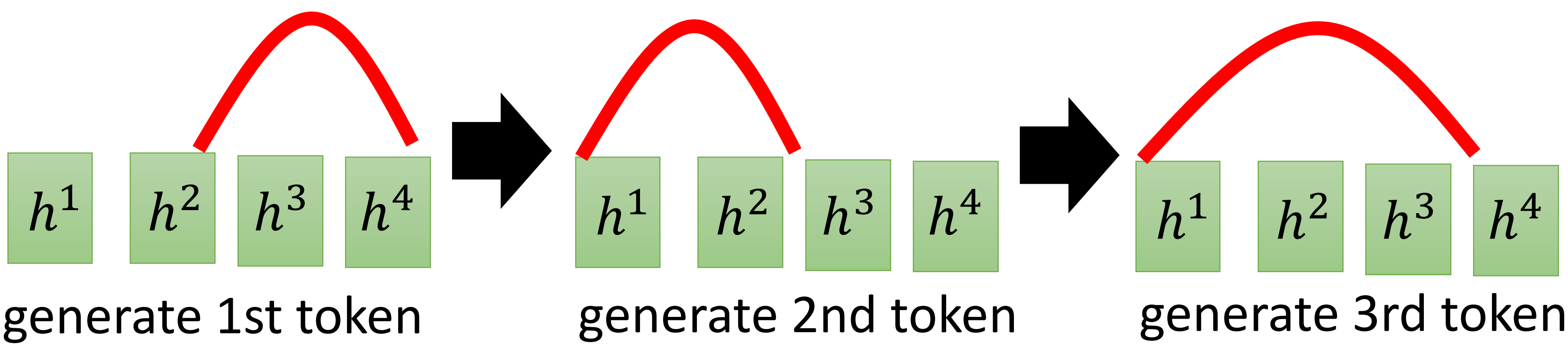


[Chan, et al., ICASSP'16]



Back to Attention

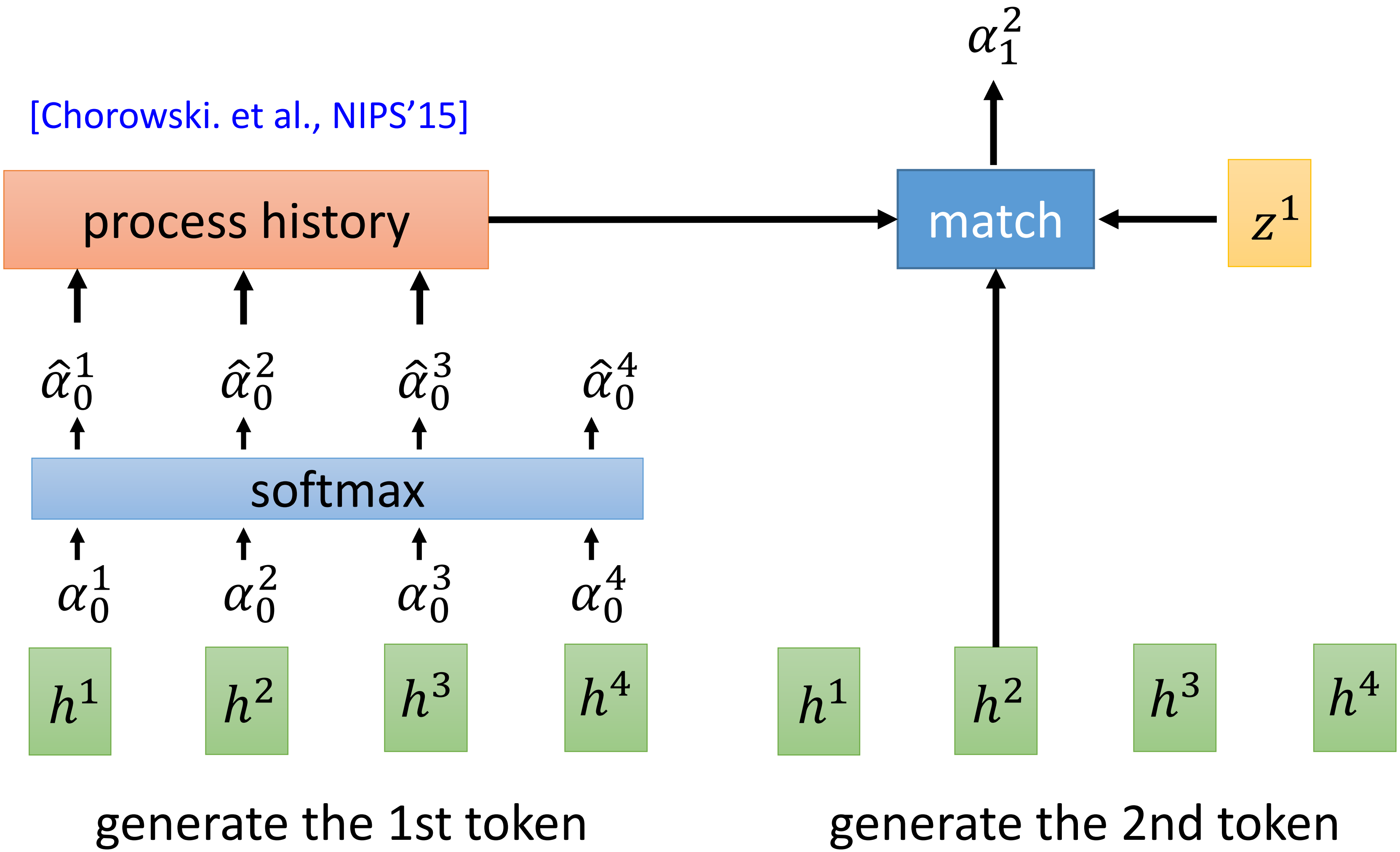




原始論文難以理解，感謝劉浩然同學指點

Location-aware attention

[Chorowski. et al., NIPS'15]



LAS – Does it work?

Model	Dev	Test
Baseline Model	15.9%	18.7%
Baseline + Conv. Features	16.1%	18.0%
Baseline + Conv. Features + Smooth Focus	15.8%	**17.6%**
RNN Transducer [16]	N/A	17.7%
HMM over Time and Frequency Convolutional Net [25]	13.9%	16.7%

TIMIT

[Chorowski. Et al., NIPS'15]

10.4% on SWB …

[Soltau, et al., ICASSP'14]

300 hours

[Lu, et al., INTERSPEECH'15]

Step	Splicing	Space	CHM	SWB	Avg
1	± 5	feature	62.7	47.6	55.2
2	± 5	feature	61.3	40.8	51.1
3	± 5	feature	59.9	**38.8**	**49.4**
4	± 5	feature	60.2	41.7	51.0
1	± 7	feature	65.5	47.6	56.6
2	± 7	feature	59.9	41.7	50.9
3	± 7	feature	59.8	40.3	50.1
4	± 7	feature	60.0	43.0	51.6
2	± 5	hidden	60.7	42.3	51.5
3	± 5	hidden	**58.9**	41.7	50.3

LAS – Yes, it works!

Model	Clean WER	Noisy WER
CLDNN-HMM [22]	8.0	8.9
LAS	14.1	16.5
LAS + LM Rescoring	10.3	12.0

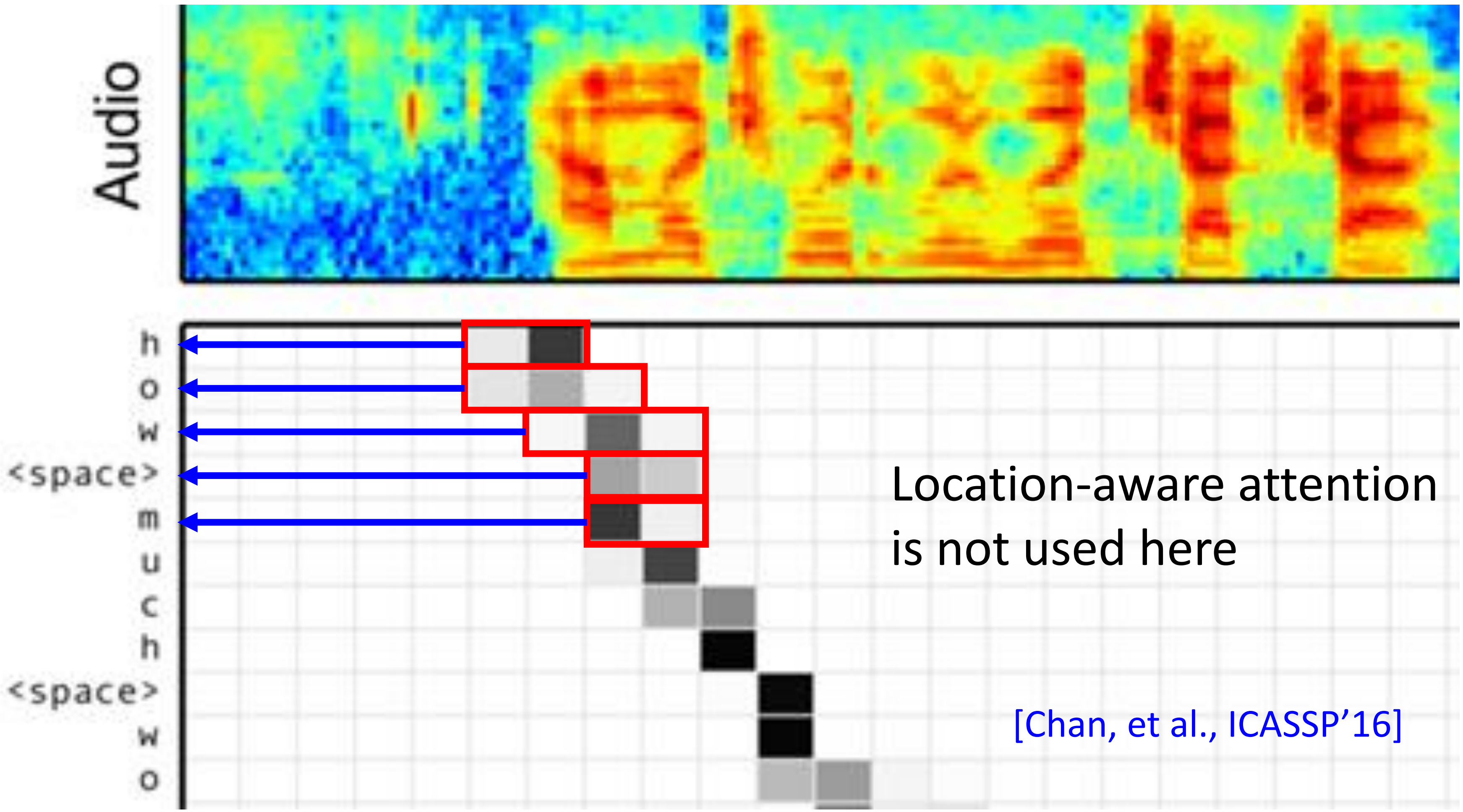
2000 hours

[Chan, et al., ICASSP'16]

Exp-ID	Model	VS/D	1st pass Model Size
E8	Proposed	**5.6/4.1**	**0.4 GB**
E9	Conventional LFR system	6.7/5.0	0.1 GB (AM) + 2.2 GB (PM) + 4.9 GB (LM) = 7.2GB

12500 hours

[Chiu, et al., ICASSP, 2018]

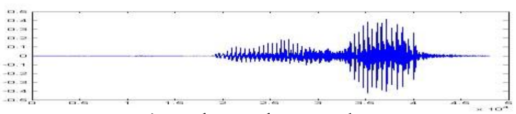


Beam	Text	Log Probability	WER
Truth	call aaa roadside assistance	-	-
1	call aaa roadside assistance	-0.5740	0.00
2	call triple a roadside assistance	-1.5399	50.00
3	call trip way roadside assistance	-3.5012	50.00
4	call xxx roadside assistance	-4.4375	25.00

[Chan, et al., ICASSP'16]

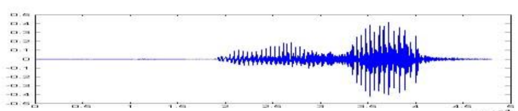
感謝 李仲翊 同學提供實驗結果

Hokkien (閩南語、台語)

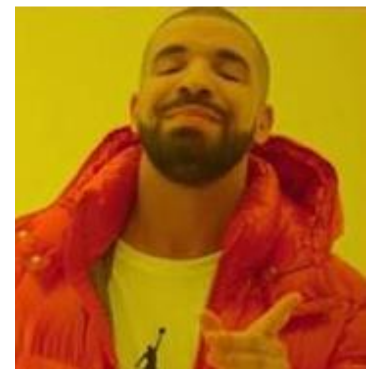


(台語語音) → 台語語音辨識 → “母湯”

看不懂 ...



(台語語音) → 台語語音辨識+中文翻譯 → “不行”

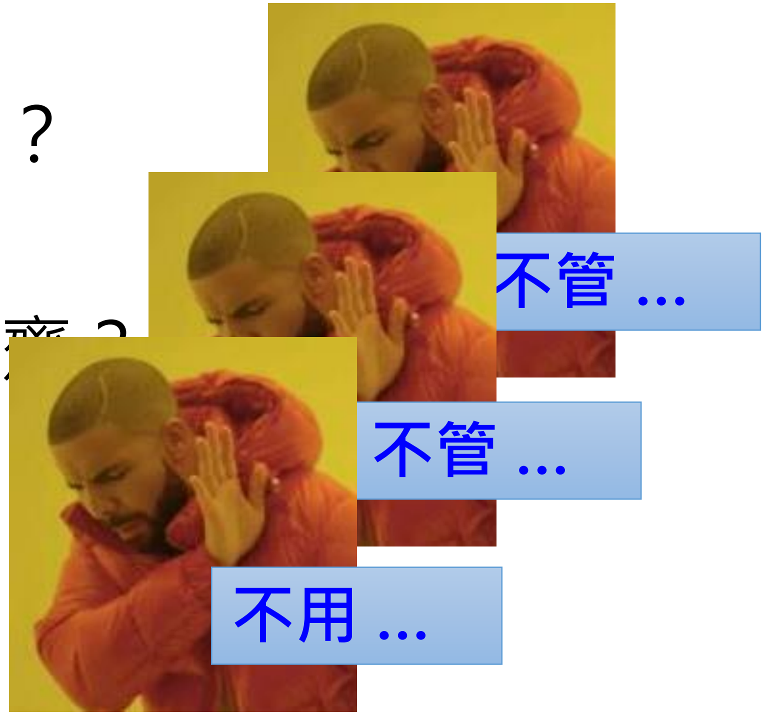


訓練資料: YouTube 上的鄉土劇 (台語語音、中文字幕)，約 1500 小時

然後就直接用 LAS 訓練下去

Hokkien (閩南語、台語)

- 有背景音樂、音效？
- 語音和字幕沒有對齊？
- 台羅拼音？



只有用深度學習
"硬train一發"

Results

Accuracy = 62.1%

你 的 身 體 撐 不 住

沒 事 你 為 什 麼 要 請 假

要 生 了 嗎

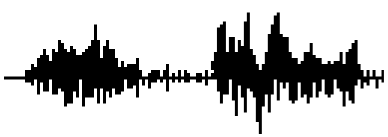
正解:不 會 膩 嗎

我 有 幫 廠 長 拜 託

正解: 我 拜 託 廠 長 了

Limitation of LAS

- LAS outputs the first token after listening the whole input.
- Users expect on-line speech recognition.



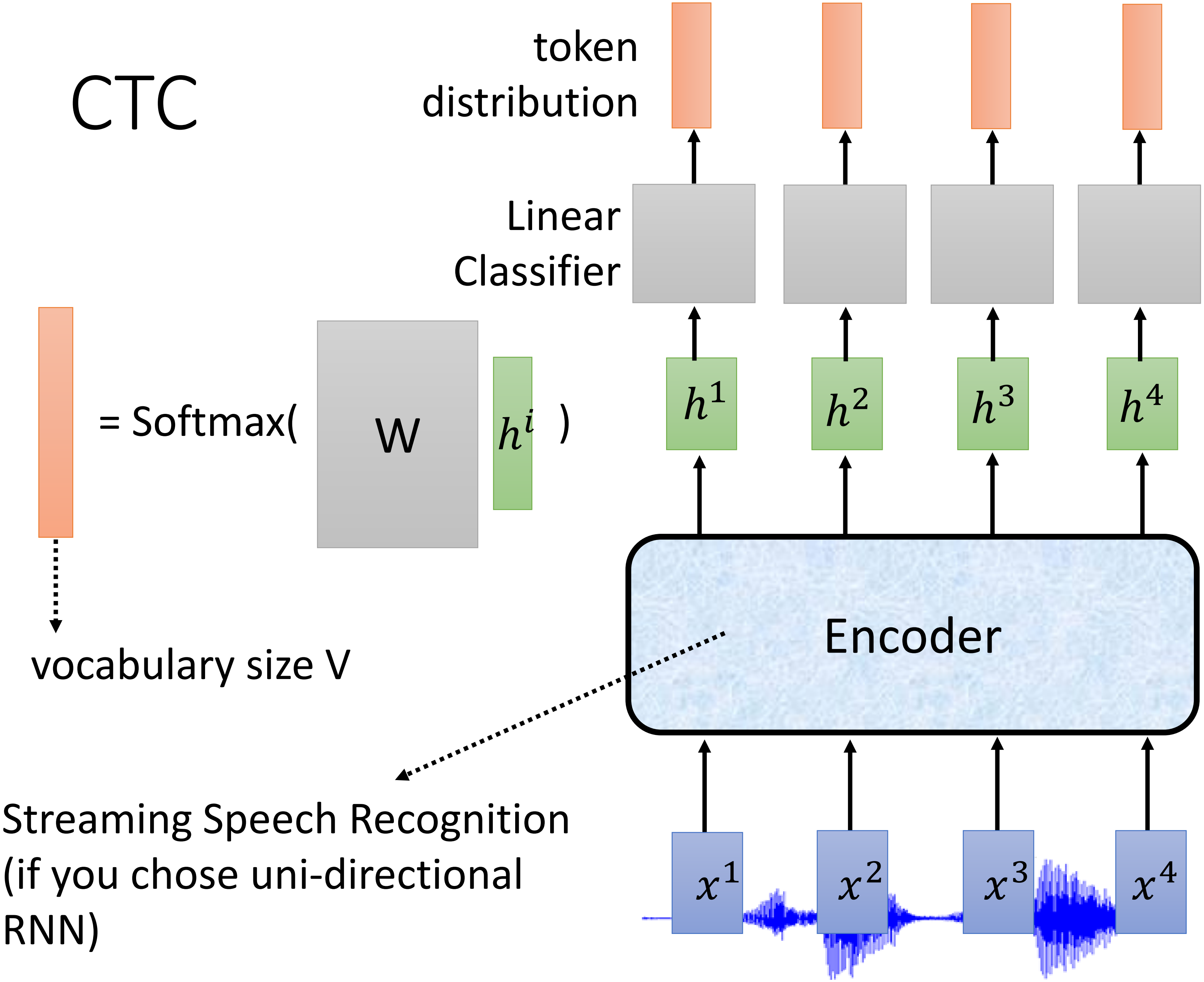
今 天 的 天 氣 非 常 好

LAS is not the final solution of ASR!

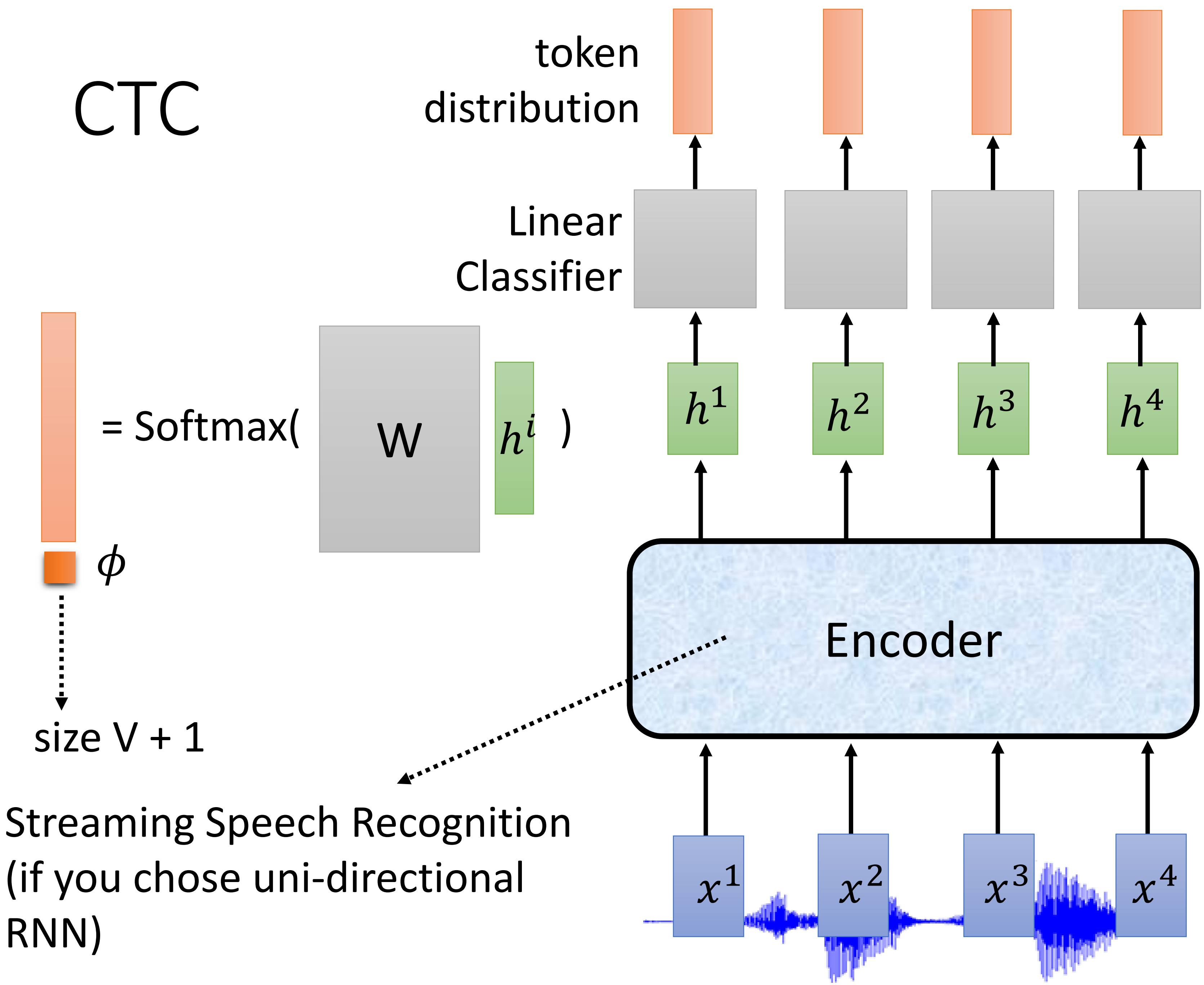
Models to be introduced

- Listen, Attend, and Spell (LAS) [Chorowski. et al., NIPS'15]
- Connectionist Temporal Classification (CTC) [Graves, et al., ICML'06]
- RNN Transducer (RNN-T) [Graves, ICML workshop'12]
- Neural Transducer [Jaitly, et al., NIPS'16]
- Monotonic Chunkwise Attention (MoChA) [Chiu, et al., ICLR'18]

CTC



token distribution
Linear Classifier
= Softmax(W h^i)
vocabulary size V
h^1
h^2
h^3
h^4
Encoder
x^1
x^2
x^3
x^4
Streaming Speech Recognition (if you chose uni-directional RNN)


CTC
token
distribution
Linear
Classifier
= Softmax(
W
h^i
)
ϕ
size V + 1
h^1
h^2
h^3
h^4
Encoder
x^1
x^2
x^3
x^4
Streaming Speech Recognition
(if you chose uni-directional
RNN)

CTC

- Input T acoustic features, output T tokens (ignoring down sampling)
- Output tokens including ϕ, merging duplicate tokens, removing ϕ

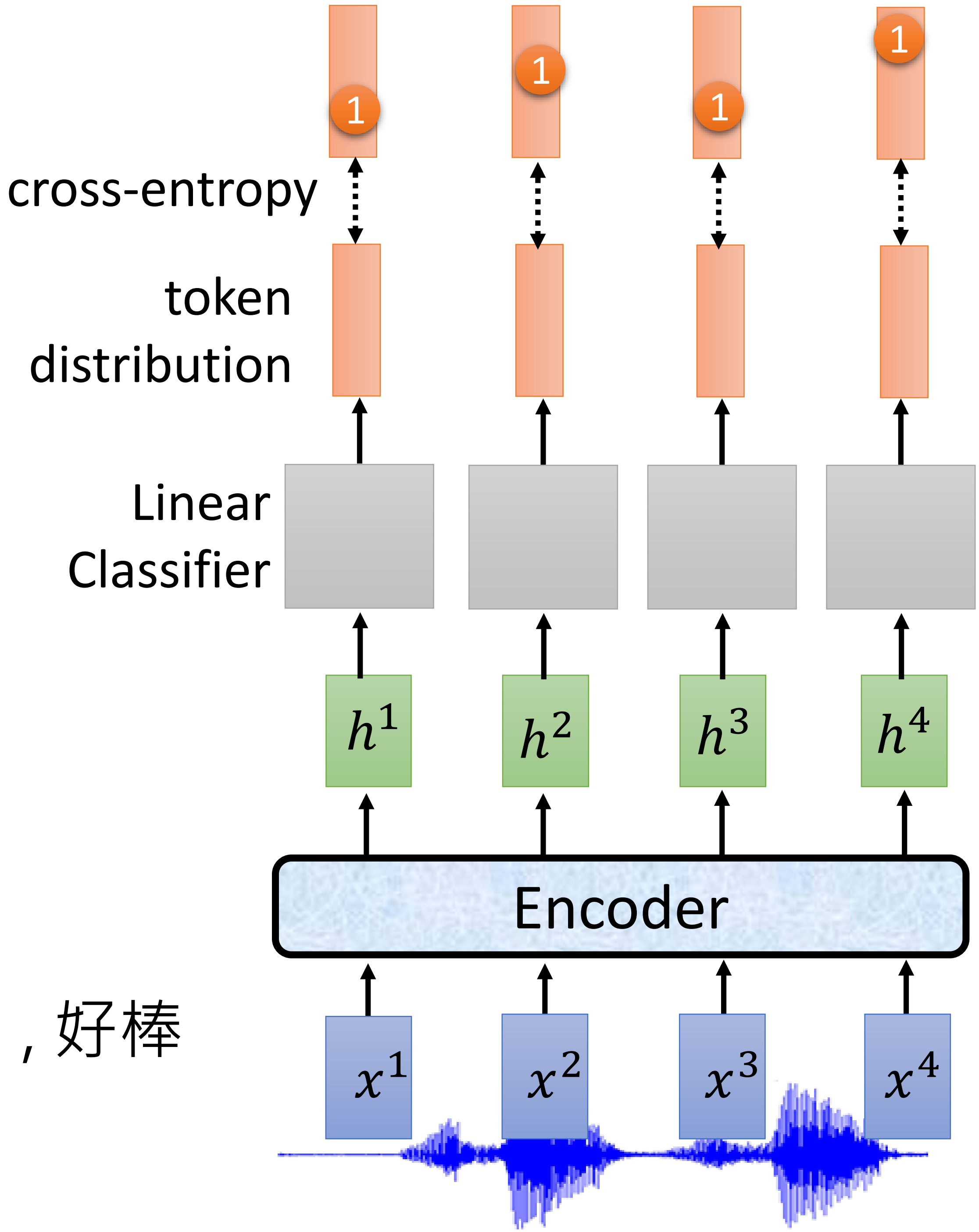
ϕ ϕ d d ϕ e ϕ e ϕ p p → d e e p

ϕ ϕ d d ϕ e e e ϕ p p → d e p

好 好 棒 棒 棒 棒 棒 → 好 棒

好 ϕ 棒 ϕ 棒 ϕ ϕ → 好 棒 棒

CTC



paired training data:

x^1 x^2 x^3 x^4 , 好棒

CTC – Training

paired training data:

x^1 x^2 x^3 x^4 , 好棒

How to enumerate all
possible alignment?

x^1 x^2 x^3 x^4 ,好好棒ϕ

x^1 x^2 x^3 x^4 ,ϕ好棒棒

x^1 x^2 x^3 x^4 ,好棒棒棒

x^1 x^2 x^3 x^4 , 好棒$\phi\phi$

x^1 x^2 x^3 x^4 , 好ϕ棒ϕ

x^1 x^2 x^3 x^4 , 好$\phi\phi$棒

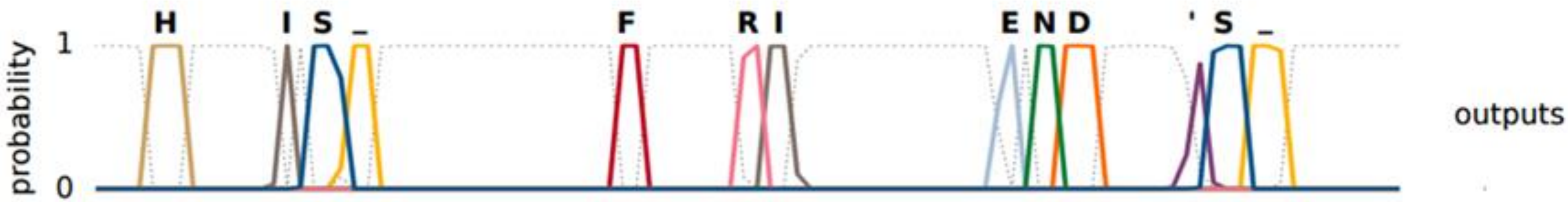
x^1 x^2 x^3 x^4 ,ϕ好棒ϕ

x^1 x^2 x^3 x^4 ,ϕ好ϕ棒

x^1 x^2 x^3 x^4 ,$\phi\phi$好棒

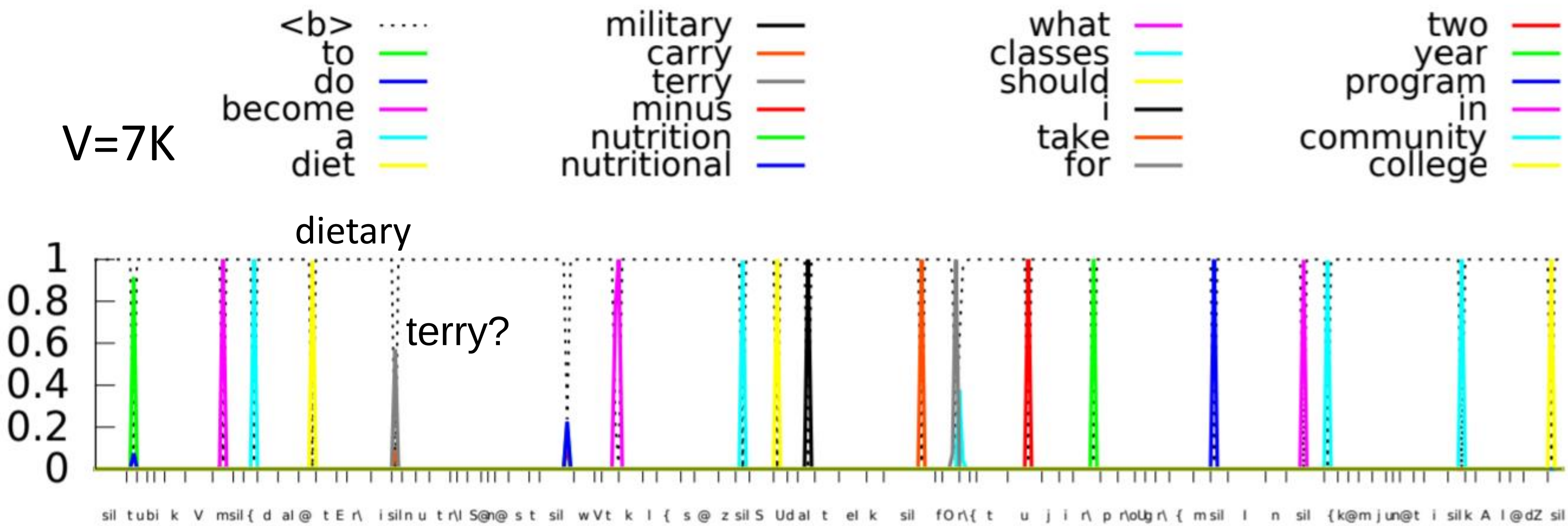
x^1 x^2 x^3 x^4 , 好棒ϕ棒

Does CTC work?



[Graves, et al., ICML’14]

V=7K



One can increase V to obtain better performance

[Sak, et al., INTERSPEECH’15]

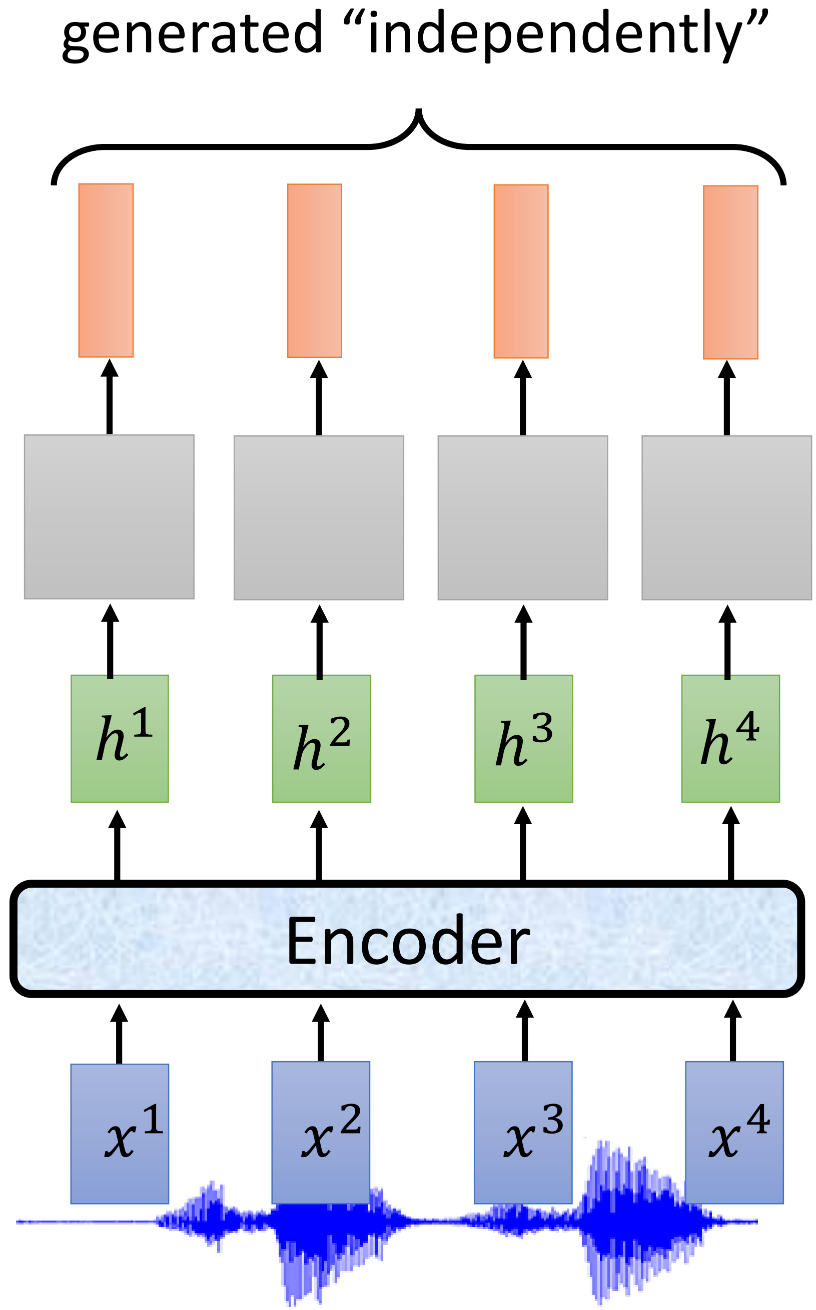
Does CTC work?

Model	CER	WER
Encoder-Decoder	6.4	18.6
Encoder-Decoder + bigram LM	5.3	11.7
Encoder-Decoder + trigram LM	4.8	10.8
Encoder-Decoder + extended trigram LM	3.9	9.3
Graves and Jaitly (2014)		
CTC	9.2	30.1
CTC, expected transcription loss	8.4	27.3
Hannun et al. (2014)		
CTC	10.0	35.8
CTC + bigram LM	5.7	14.1
Miao et al. (2015),		
CTC for phonemes + lexicon	-	26.9
CTC for phonemes + trigram LM	-	7.3
CTC + trigram LM	-	9.0

80 hours

[Bahdanau. et al., ICASSP'16]

Issue



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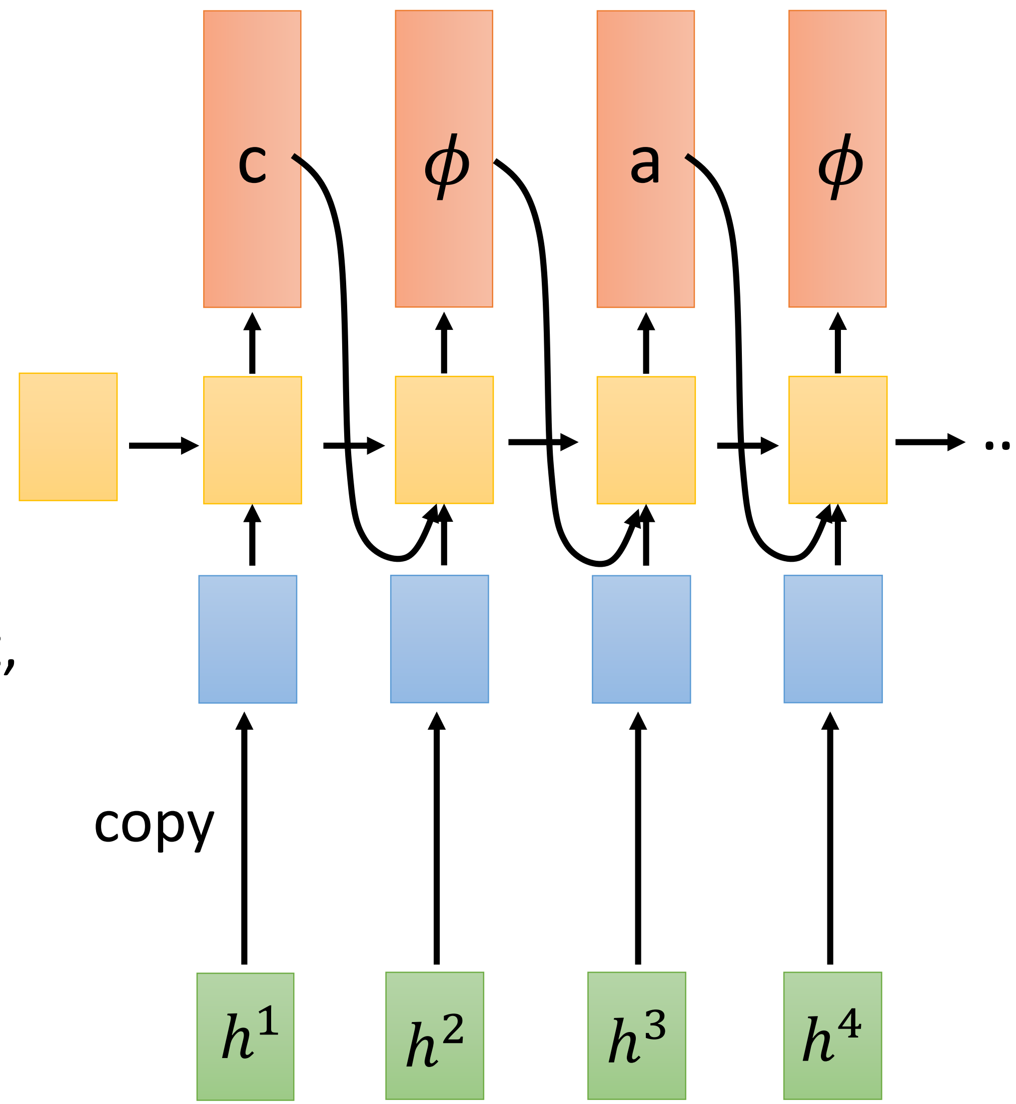
RNA

[Sak, et al., INTERSPEECH'17]

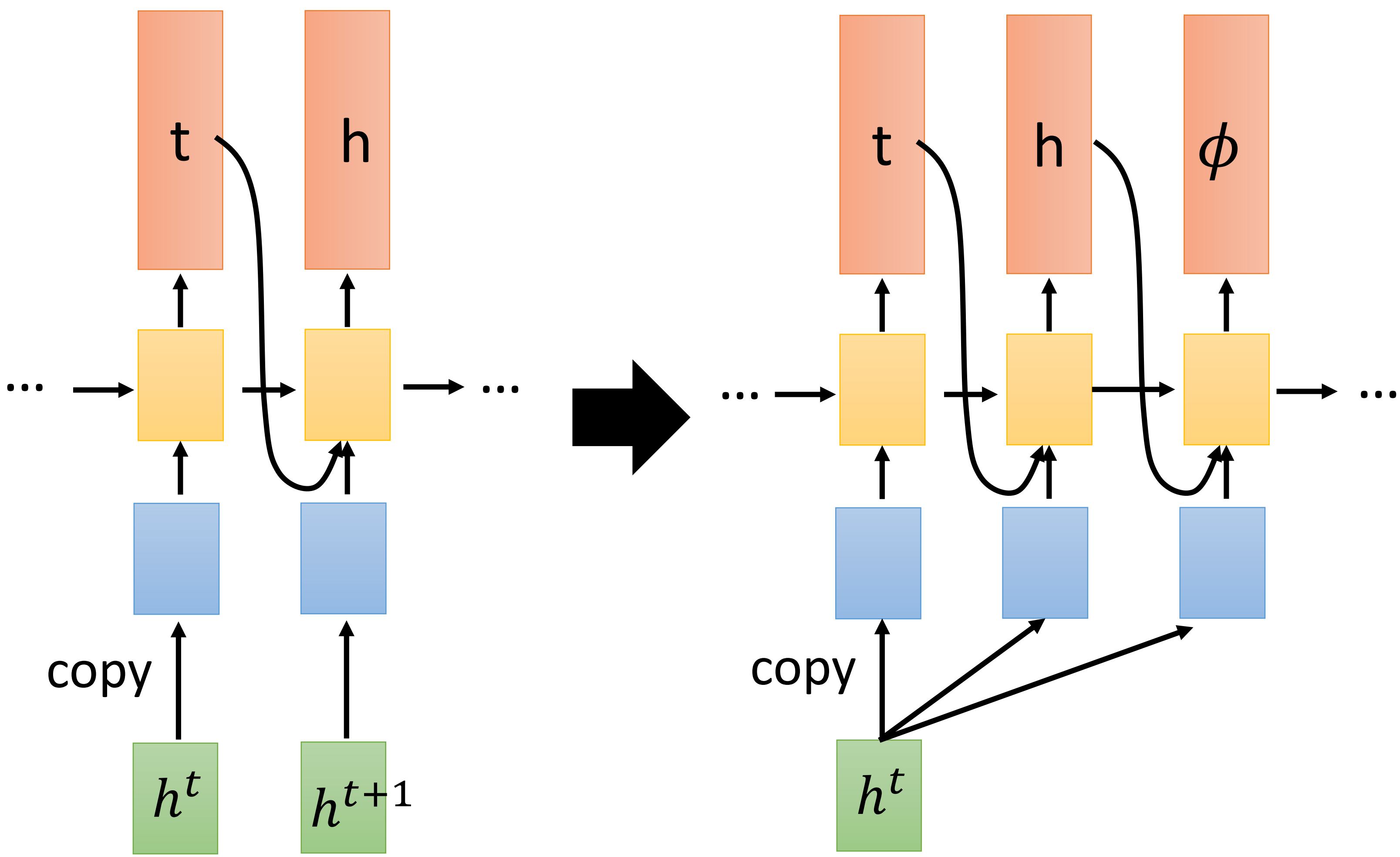


Decoder:
take one vector as input,
Output one token

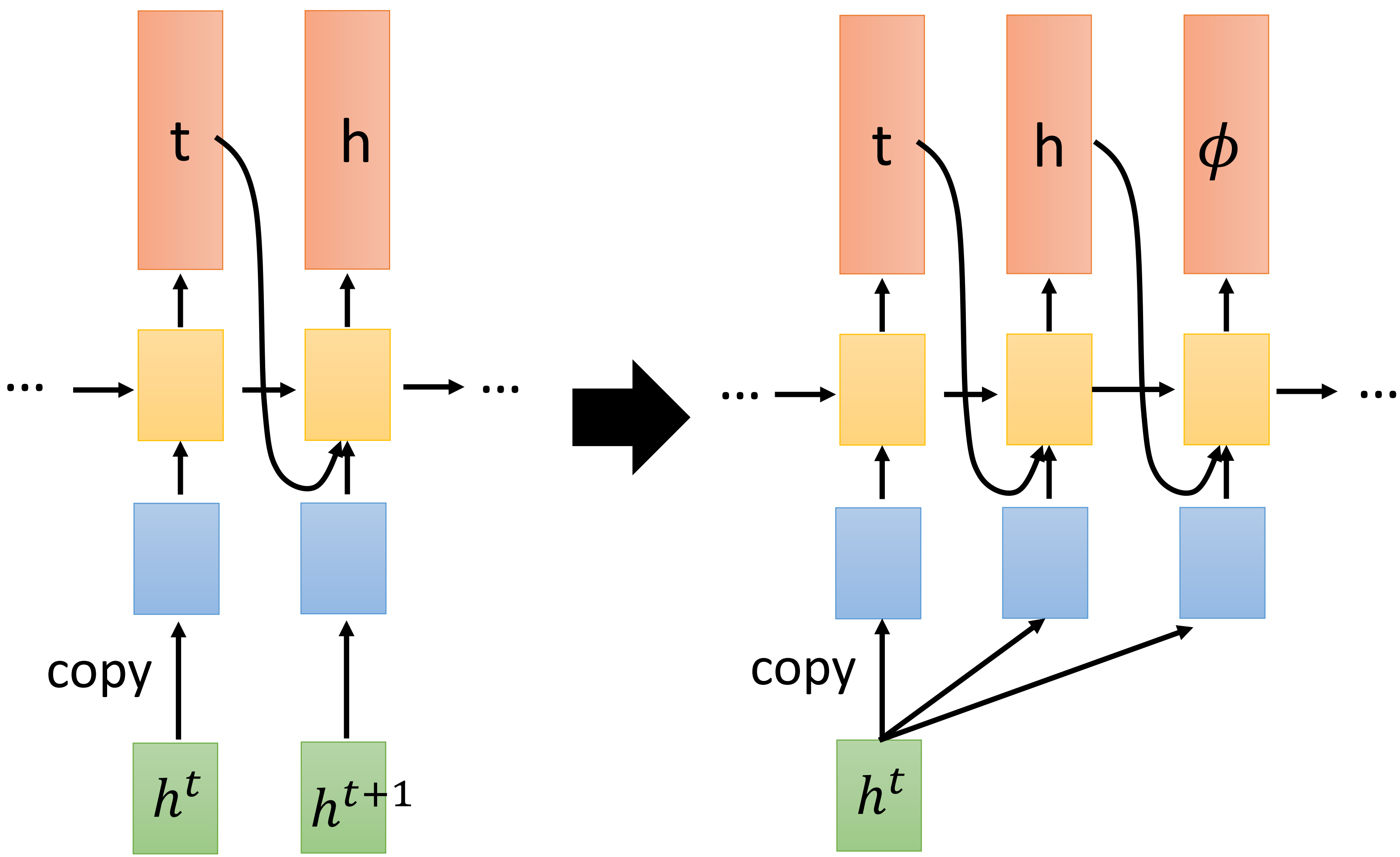
Can one vector map to
multiple tokens?

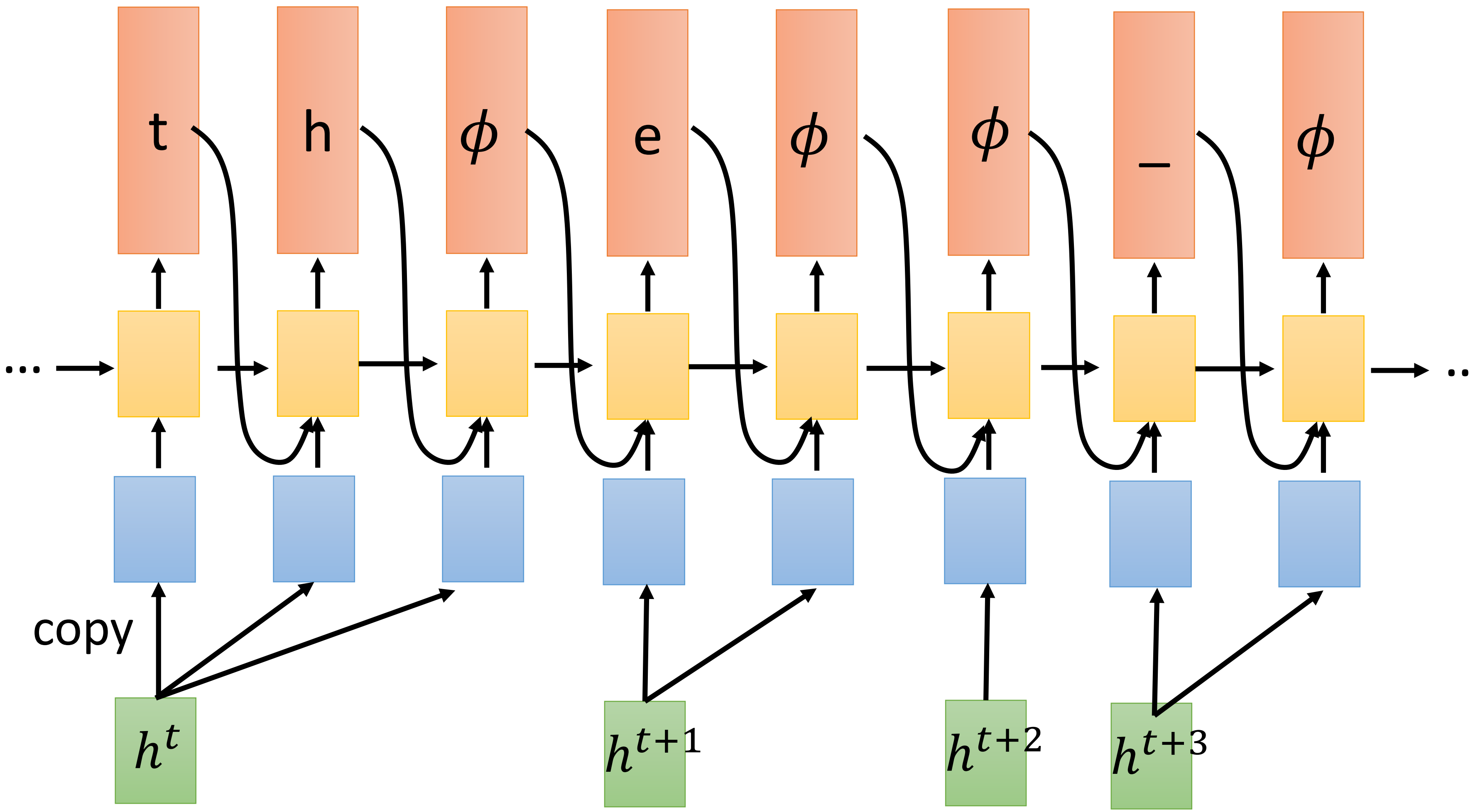
for example, "th"

RNN-T



RNN-T




t
h
ϕ
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ϕ
ϕ
_
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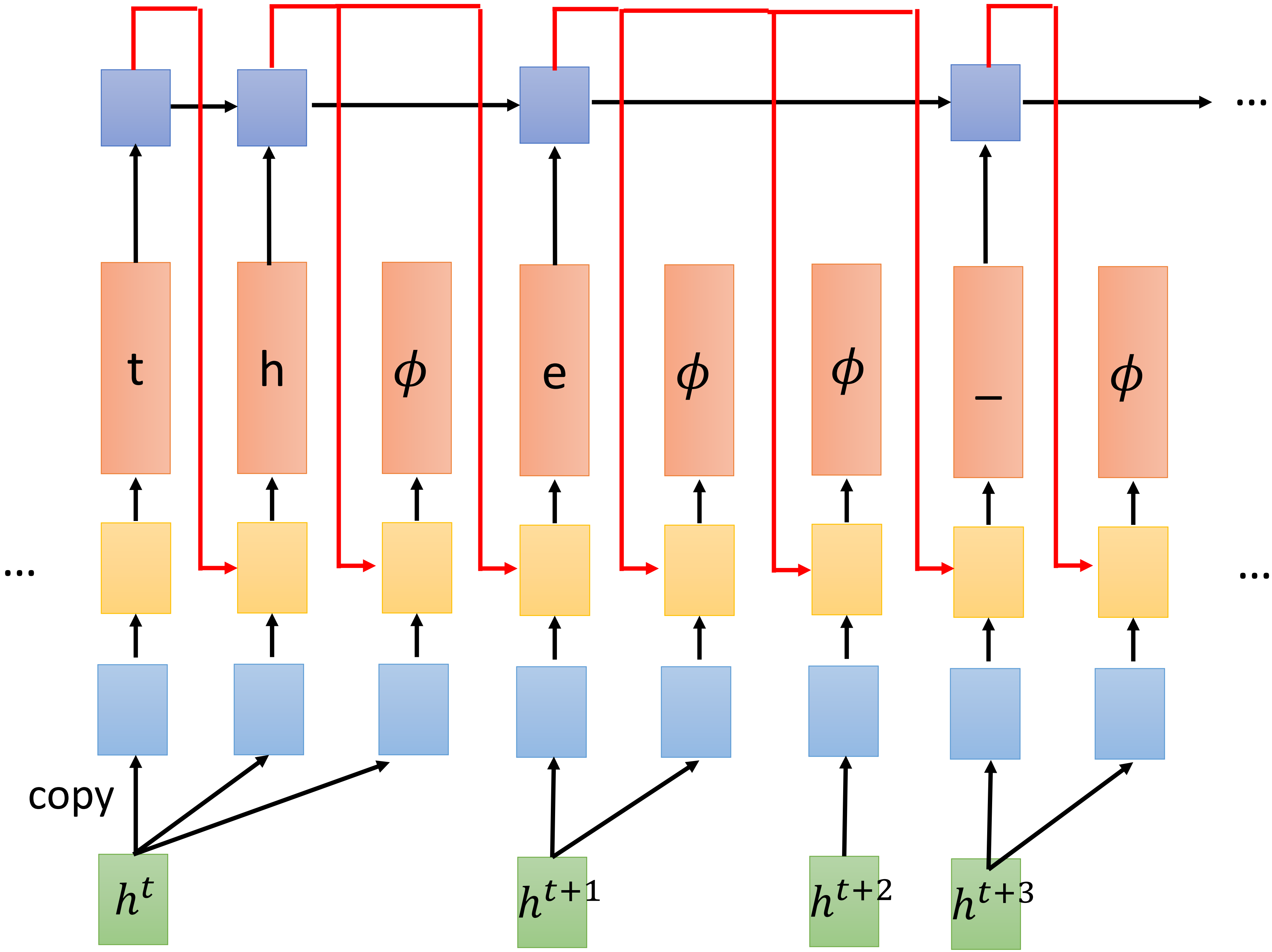
...
copy
h^t
h^{t+1}
h^{t+2}
h^{t+3}



t
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copy
h^t
h^{t+1}
h^{t+2}
h^{t+3}

RNN-T

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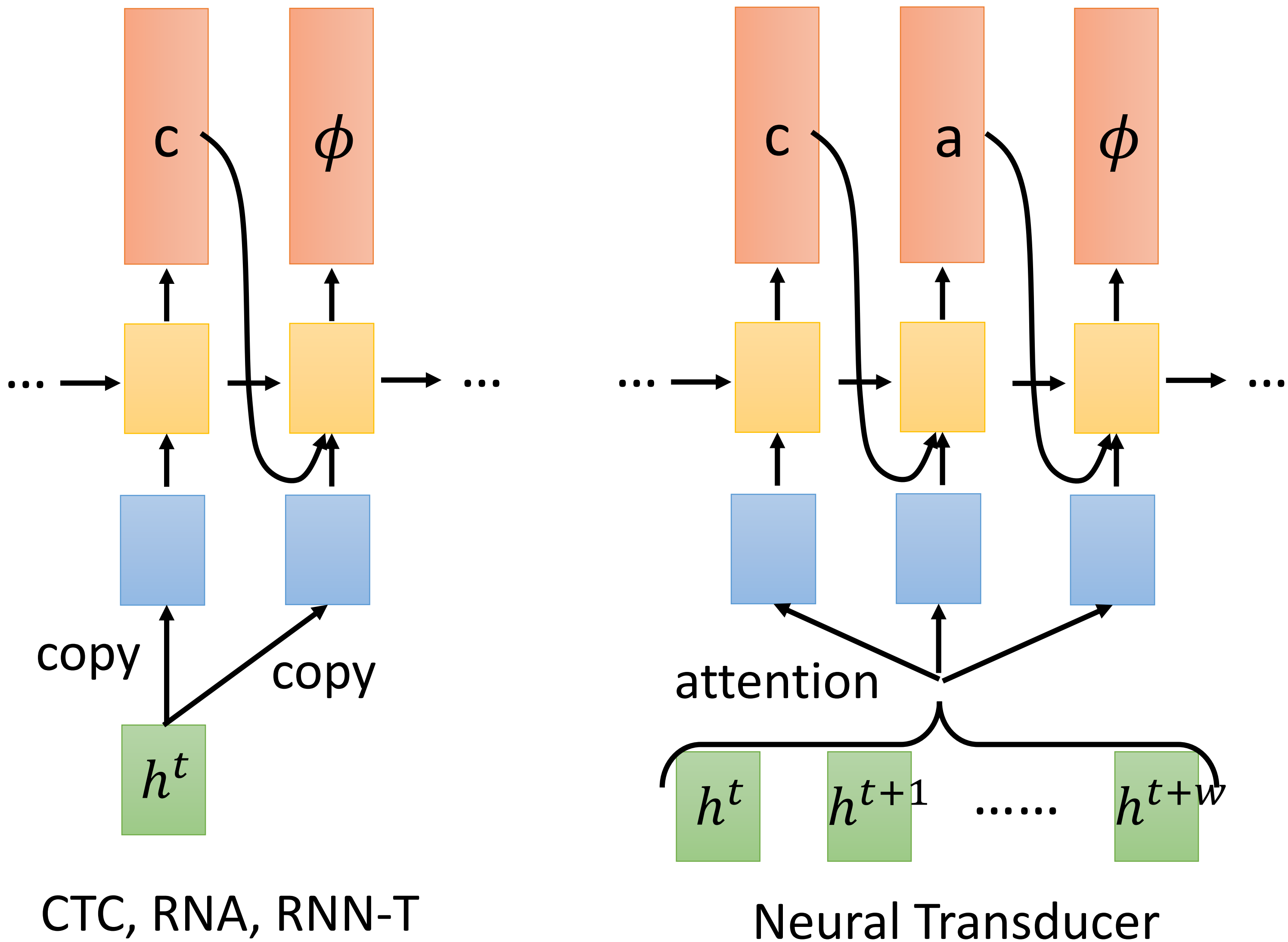
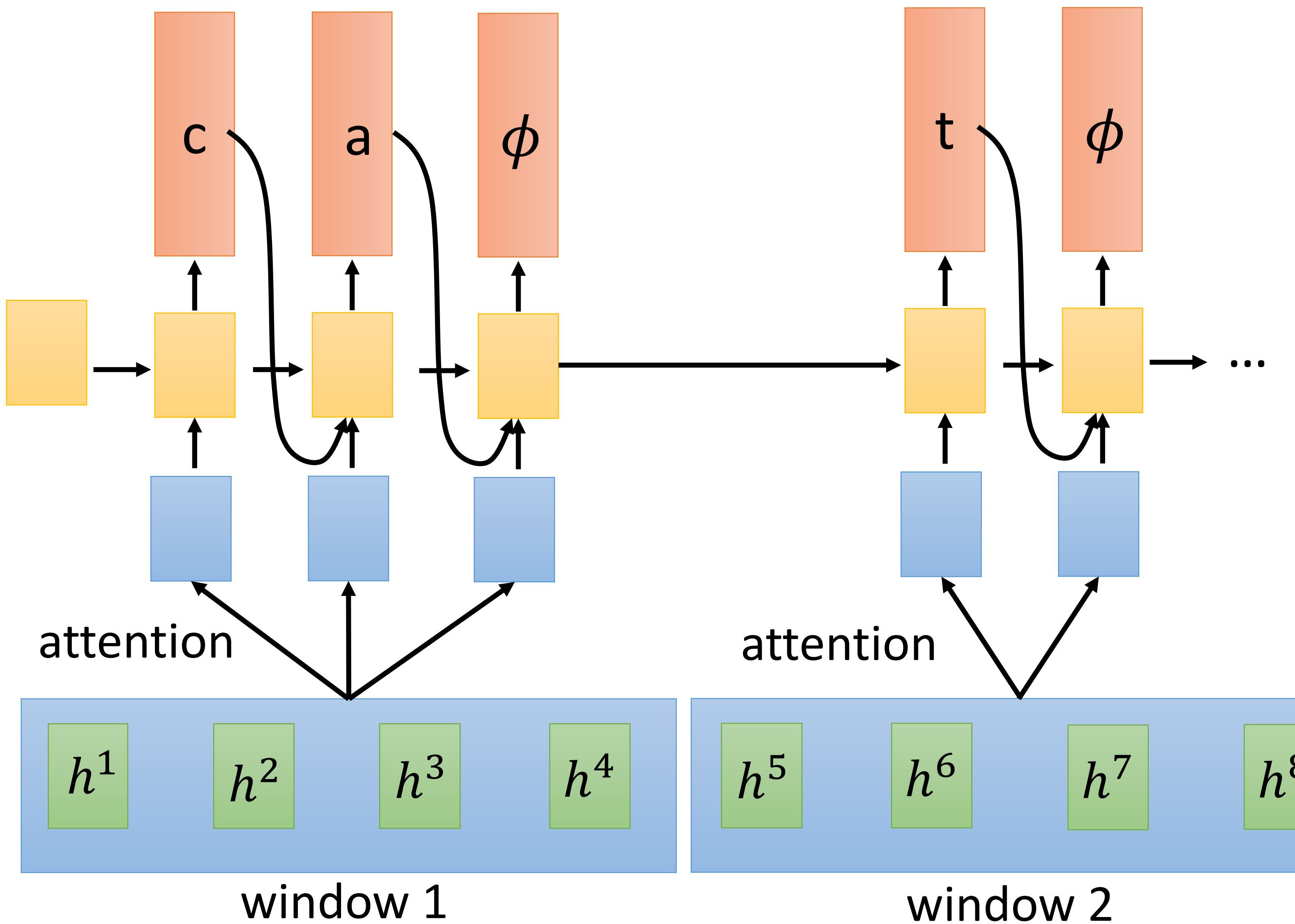
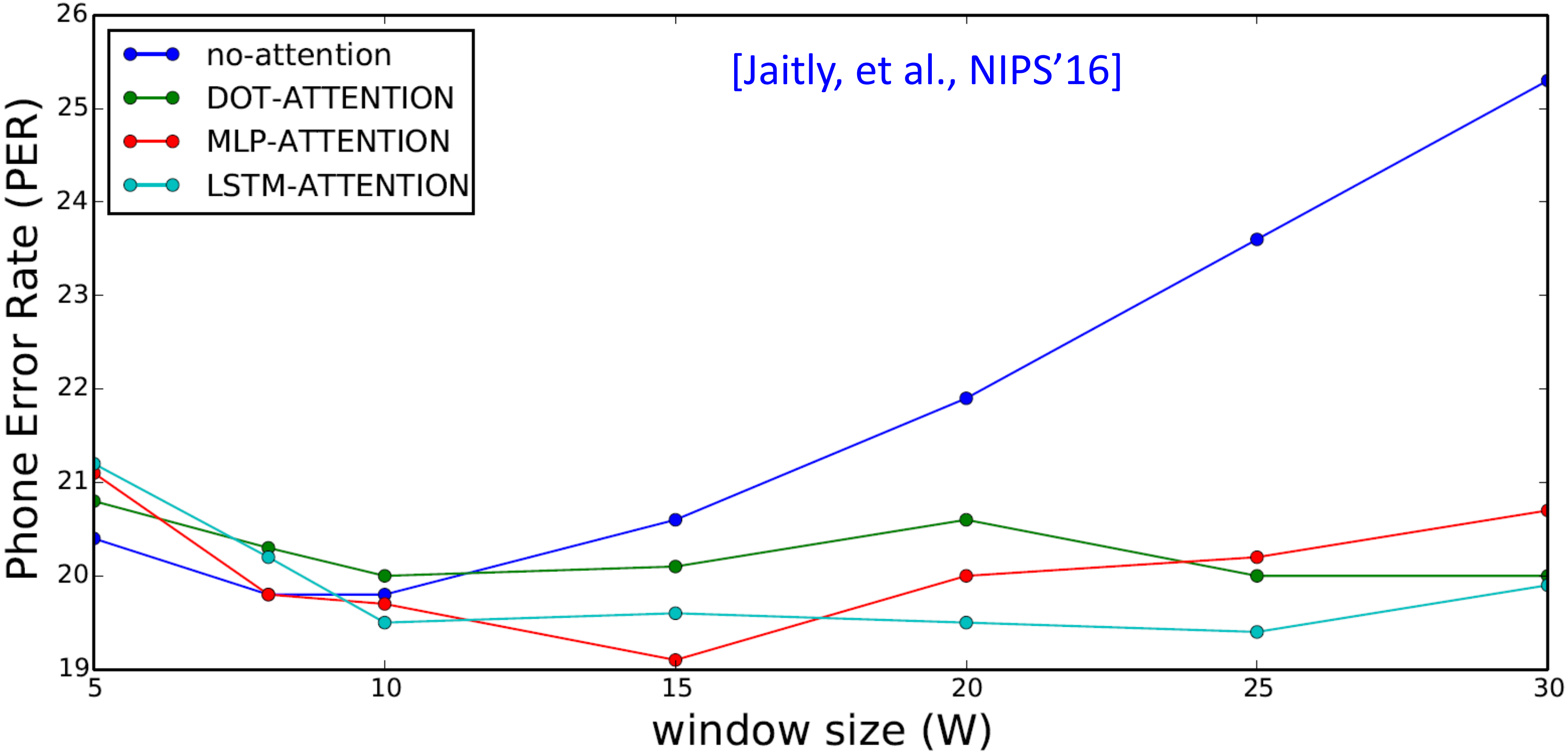
Neural Transducer



Neural Transducer



Neural Transducer



Models to be introduced

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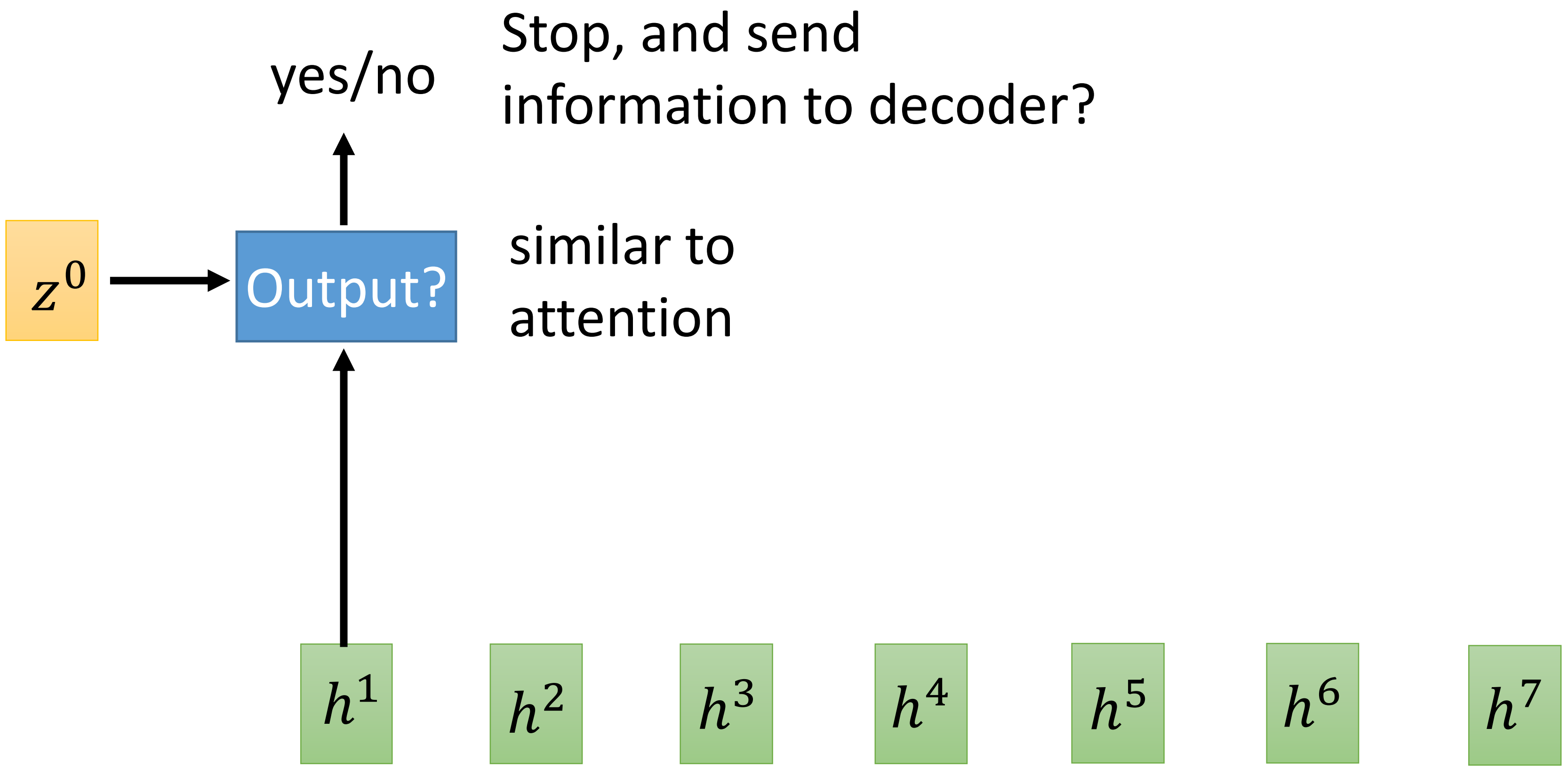
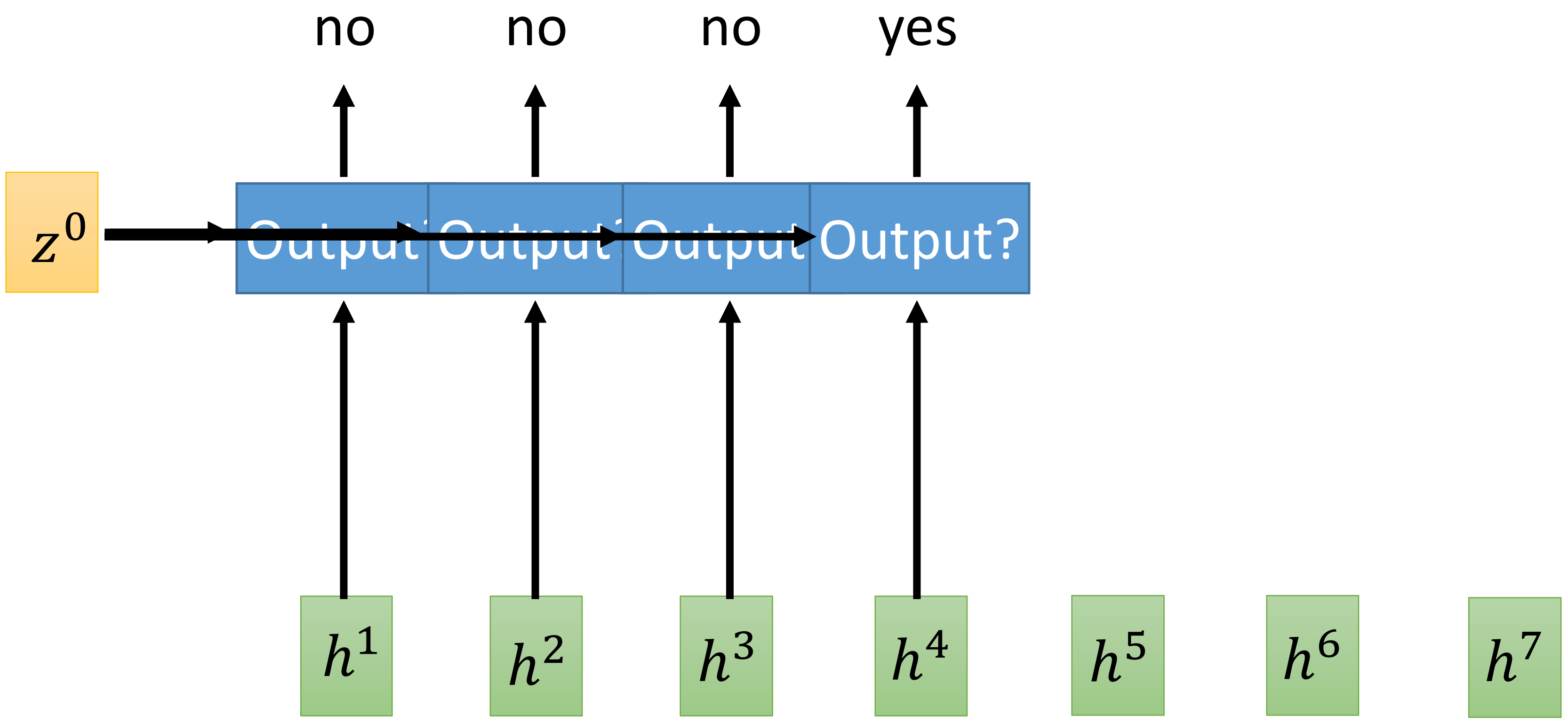
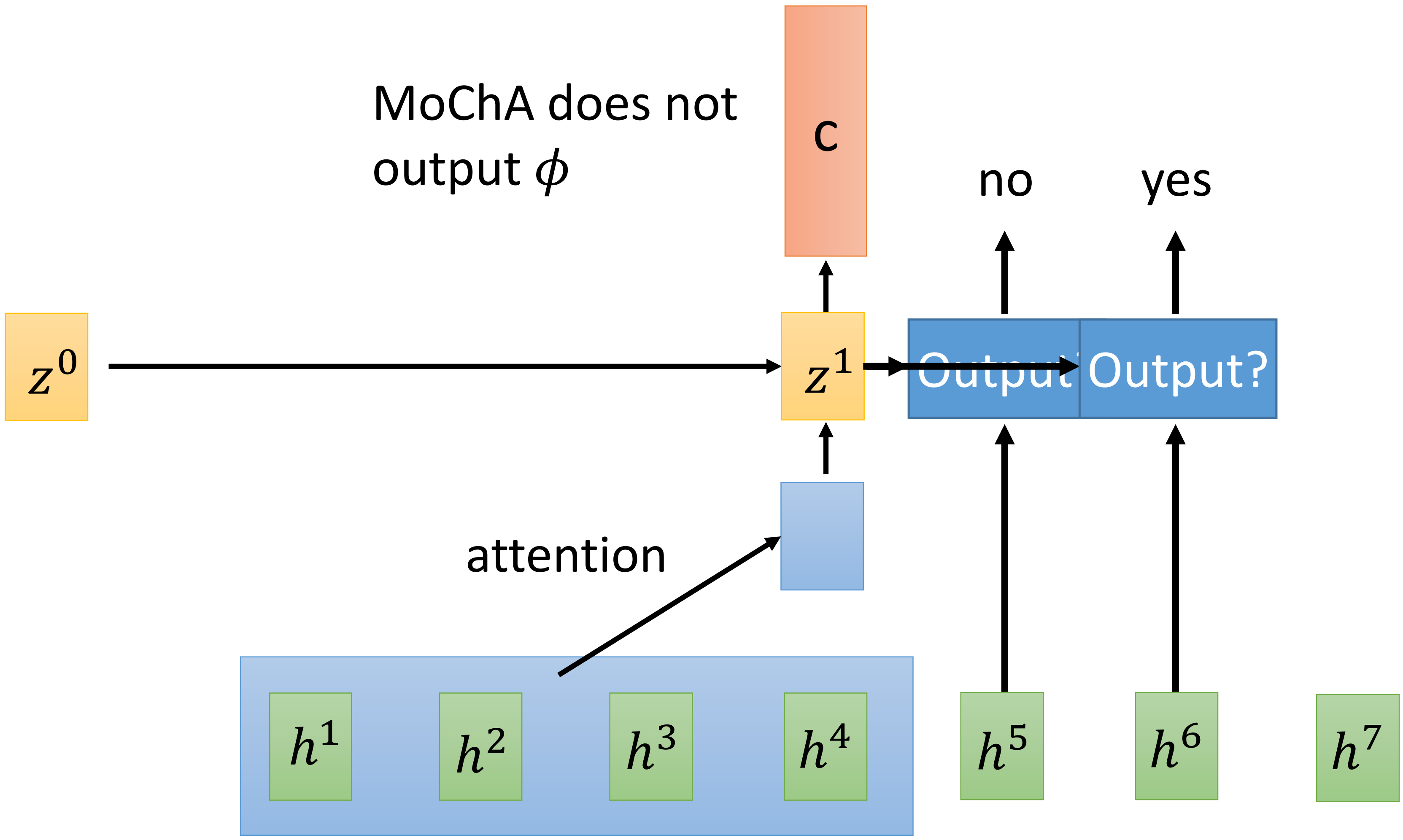
MoChA: Monotonic Chunkwise Attention



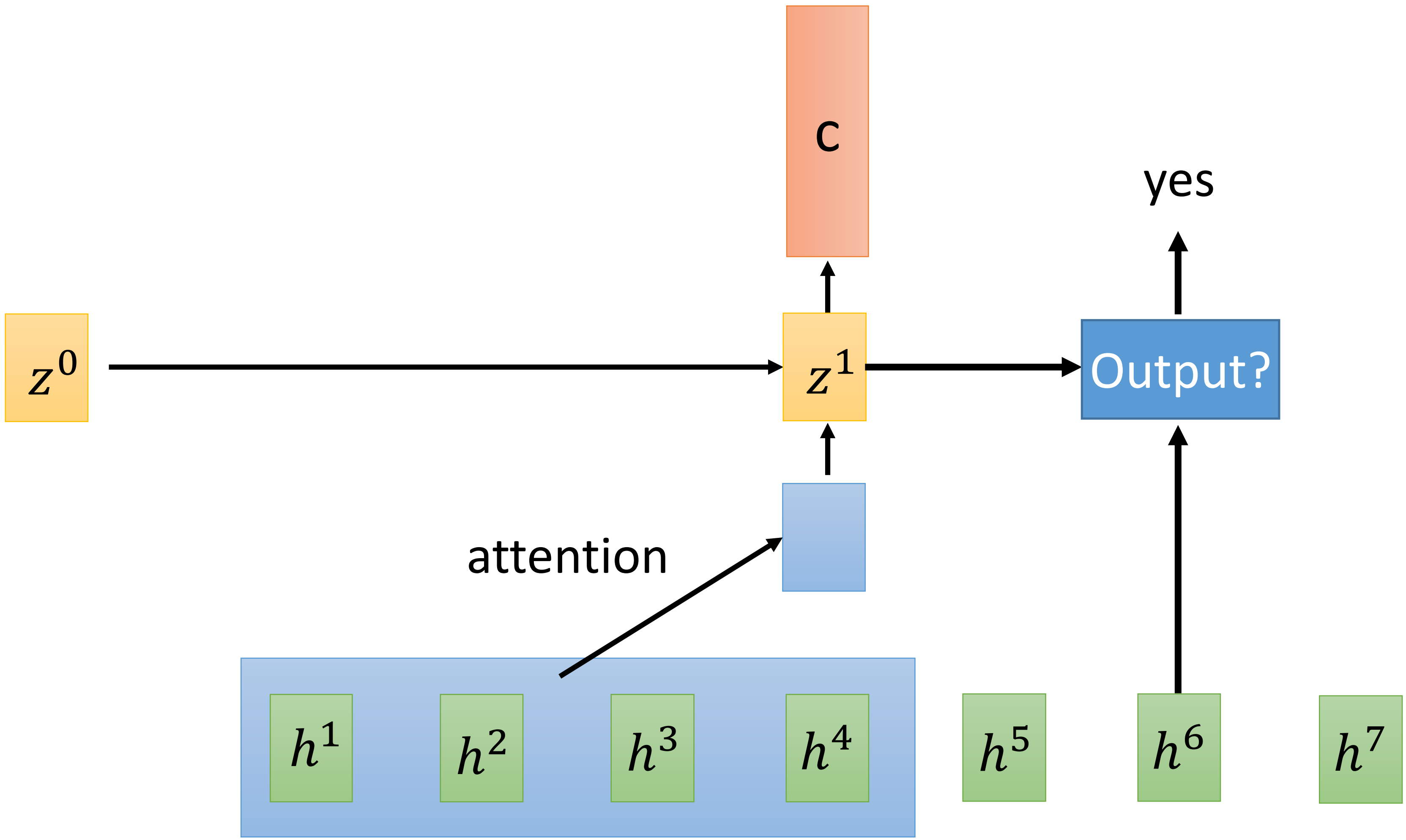
MoChA



MoChA


MoChA does not
output ϕ
c
no
yes
z^0
z^1
Output?
Output?
attention
h^1
h^2
h^3
h^4
h^5
h^6
h^7

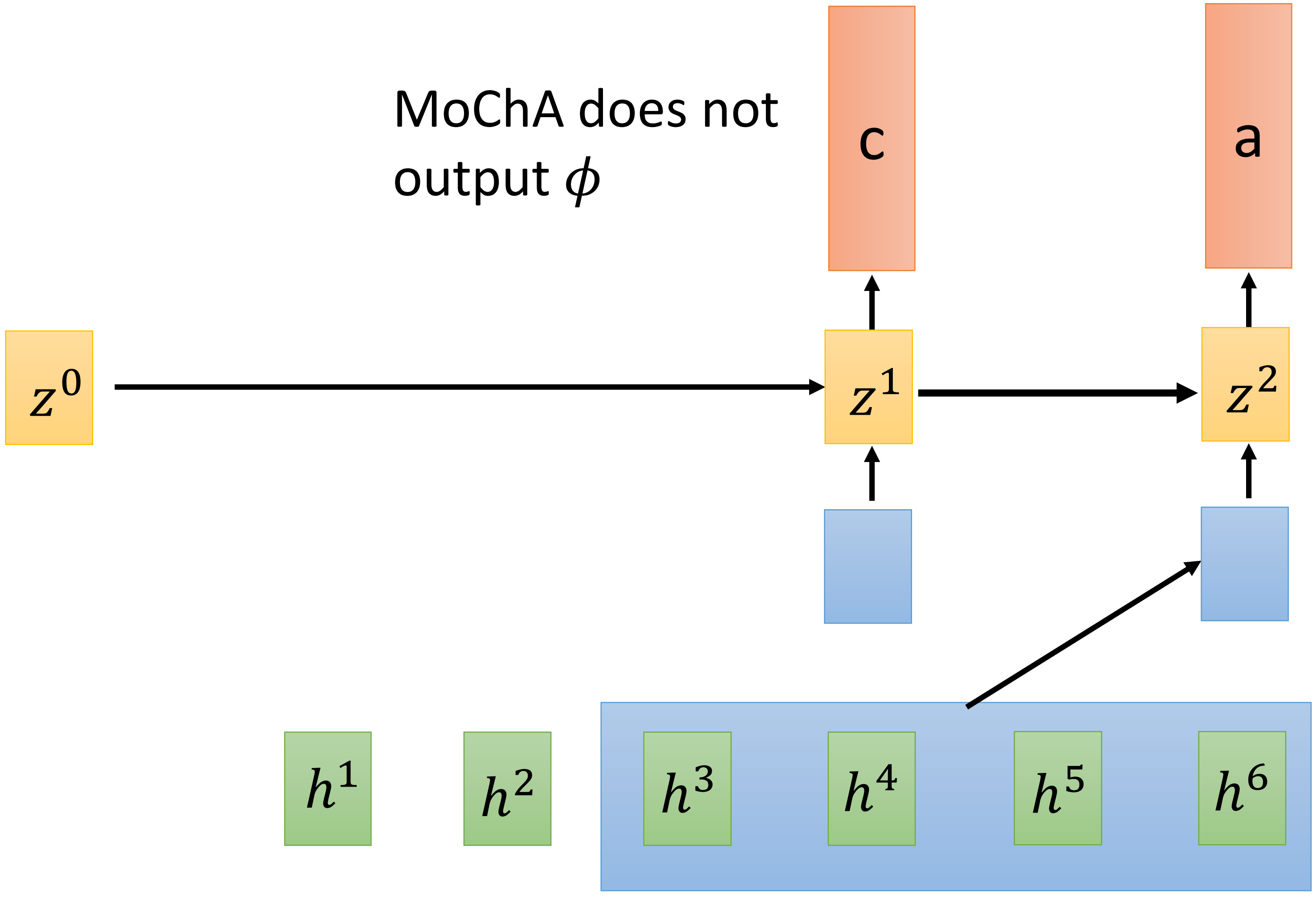
MoChA



MoChA

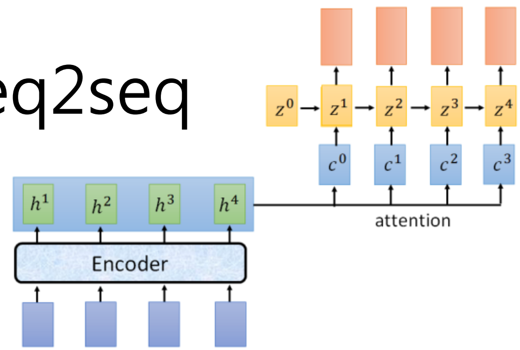
Please refer to the original paper for model training [Chiu, et al., ICLR'18]

MoChA does not output ϕ

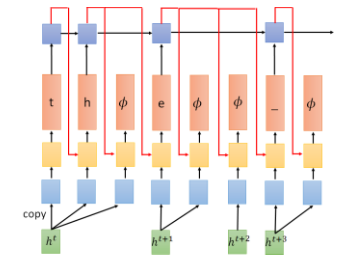


Summary

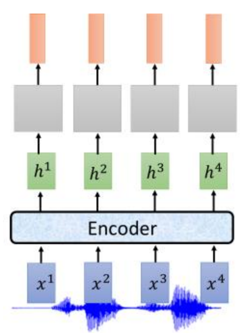
LAS: 就是 seq2seq



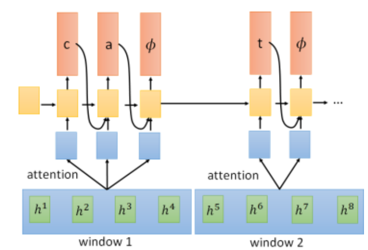
RNN-T: 輸入一個東西可以輸出多個東西的 seq2seq



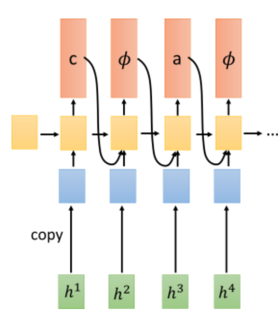
CTC: decoder 是 linear classifier 的 seq2seq



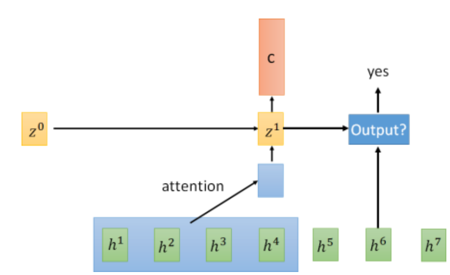
Neural Transducer: 每次輸入一個 window 的 RNN-T



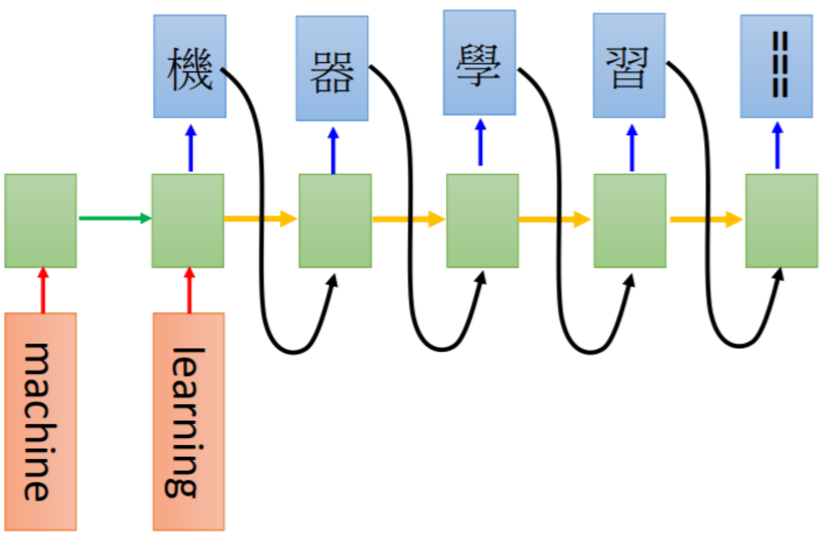
RNA: 輸入一個東西就要輸出一個東西的 seq2seq



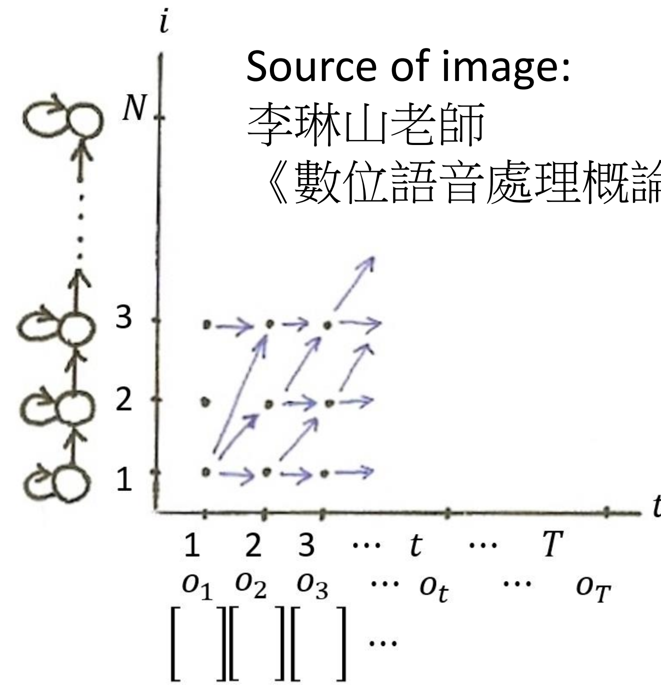
MoCha: window 移動伸縮自如的 Neural Transducer



Two Points of Views



Seq-to-seq



Source of image:
李琳山老師
《數位語音處理概論》

HMM

Reference

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