LANGUAGE MODELING FOR SPEECH RECOGNITION

HUNG-YI LEE 李宏毅

Why Language Model?

- Language model (LM): Estimated the probability of token sequence
  - Token sequence: $Y = y_1, y_2, \dots \dots, y_n$
  - $P(y_1, y_2, \dots \dots, y_n)$

HMM $\quad \mathrm{Y}^* = arg \max_{\mathrm{Y}} P(X|\mathrm{Y})P(\mathrm{Y})$

LM is usually helpful when your model outputs text

LAS $\quad \mathrm{Y}^* = arg \max_{\mathrm{Y}} \underbrace{P(\mathrm{Y}|X)}_{\text{Need paired data}} \underbrace{P(Y)}_{\text{Easy to collect}}$

https://numberofwords.com/faq/how-many-words-are-in-a-1-minute-speech/

Why we need LM?

$$Y^* = arg \max_{Y} \underbrace{P(Y|X)}_{\text{Need paired data}} \; \underbrace{P(Y)}_{\text{Easy to collect}}$$

Words in Transcribed Audio

12,500 hours transcribed audio

= 12,500 x 60 x 130 ≈ 一億!

(哈利波特全套約 100 萬個詞)

Moschitta had been credited in The Guinness Book of World Records as the World's Fastest Talker

Source of video: https://youtu.be/ExKCcndqK5c https://numberofwords.com/faq/how-many-words-are-in-a-1-minute-speech/

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BERT:
https://youtu.be/UYPa347-DdE

Just Words …

BERT (一個巨大的 LM) 用了 30 億個以上的詞

N-gram

P("wreck a nice beach")
=P(wreck|START)P(a|wreck)
P(nice|a)P(beach|nice)

- How to estimate $P(y_1, y_2, \ldots \ldots, y_n)$
- Collect a large amount of text data as training data
  - However, the token sequence $y_1, y_2, \ldots \ldots, y_n$ may not appear in the training data
- *N-gram language model*: $P(y_1, y_2, \ldots \ldots, y_n) = P(y_1|BOS)P(y_2|y_1) \ \ldots \ P(y_n|y_{n-1})$ ← 2-gram
  - E.g. Estimate P(beach|nice) from training data

$$P(\text{beach}|\text{nice}) = \frac{C(nice\ beach)}{C(nice)}$$

Count of "nice beach"

Count of "nice"

  - It is easy to generalize to 3-gram, 4-gram ……

Challenge of N-gram

- The estimated probability is not accurate.
  - Especially when we consider n-gram with large n
  - Because of data sparsity (many n-grams never appear in training data)

Training Data:

The dog ran ……
The cat jumped ……

P(jumped | the, dog) = ~~0~~ 0.0001

P(ran | the, cat) = ~~0~~ 0.0001

Give some small probability

This is called **language model smoothing**.

Continuous LM

- Recommendation system

				
A	5	5		1
B	5	5?	1	
C	5	5		2
D	1		4	4
E		1	5	4

Matrix Factorization

Ref: https://youtu.be/iwh5o_M4BNU?t=4673

Continuous LM

Borrowing the idea from recommendation system

	dog h^1	cat h^2	……	child
ran v^1	2 n_{11}	3		1
jumped v^2	0	2 n_{22}		1
cried v^3	0	0		3
laughed v^4	0	0		3
……				

history

Vocabulary

Not observed

Count of "cat jumped"

v^i, h^j are vectors to be learned

$$n_{12} = v^1 \cdot h^2$$
$$n_{21} = v^2 \cdot h^1 \ \ldots$$

Minimizing

$$L = \sum_{(i,j)} \left(v^i \cdot h^j - n_{ij} \right)^2$$

v^i, h^j found by gradient descent

Borrowing the idea from recommendation system

Continuous LM

history

Vocabulary

	dog h^1	cat h^2	……	child
ran v^1	2 n_{11}	3		1
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cried v^3	0	0		3
laughed v^4	0	0		3
……				

Not observed

Count of “cat jumped”

History “dog” and “cat” can have similar vector h^{dog} and h^{cat}

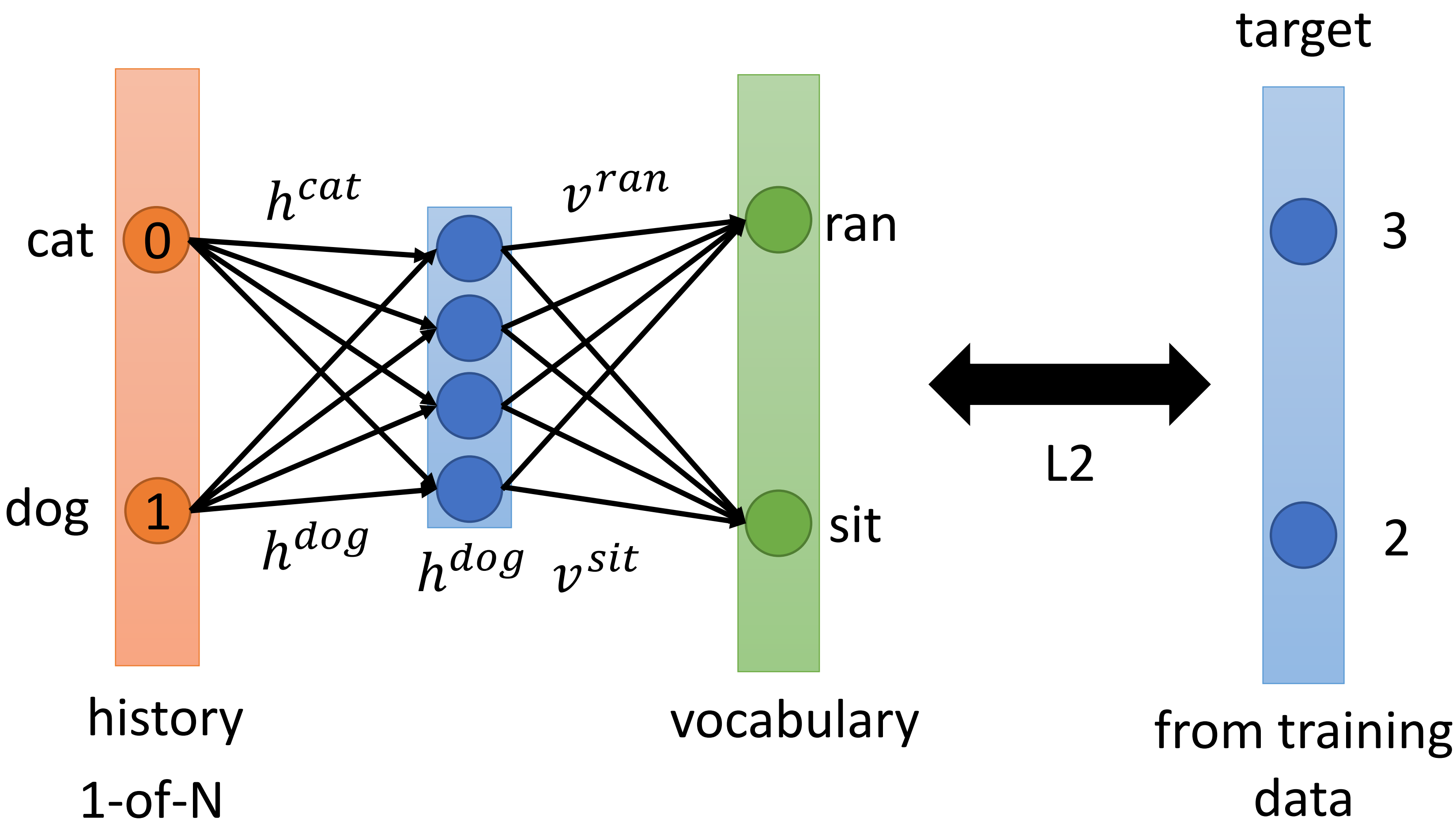
If $v^{jumped} \cdot h^{cat}$ is large, $v^{jumped} \cdot h^{dog}$ would be large accordingly.

Even if we have never seen “dog jumped …”

Smoothing is automatically done.

$$L = \sum_{(i,j)} \left(v^i \cdot h^j - n_{ij}\right)^2$$

Continuous LM



Consider it as a NN ……

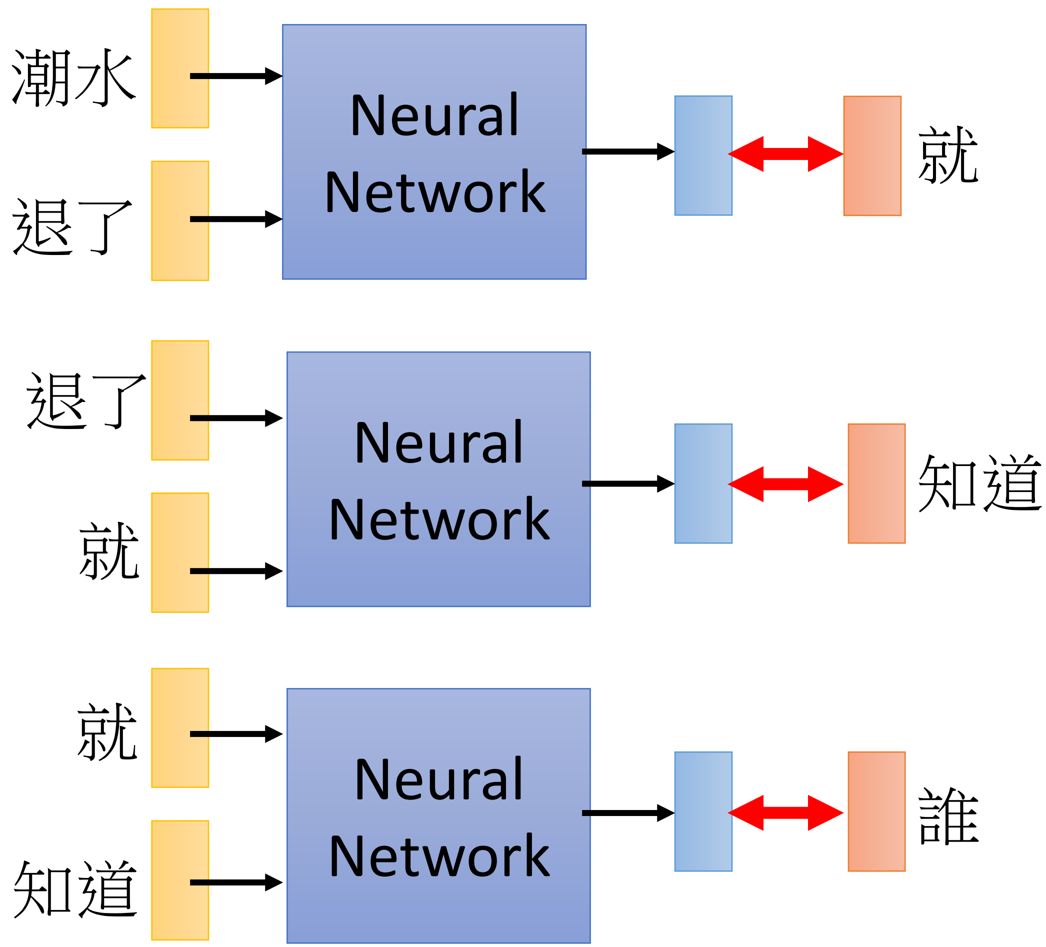
NN-based LM

- Training:

Collect data:

潮水 退了 就 知道 誰 …
不爽 不要 買 …
公道價 八萬 一 …
………

Learn to predict the next word

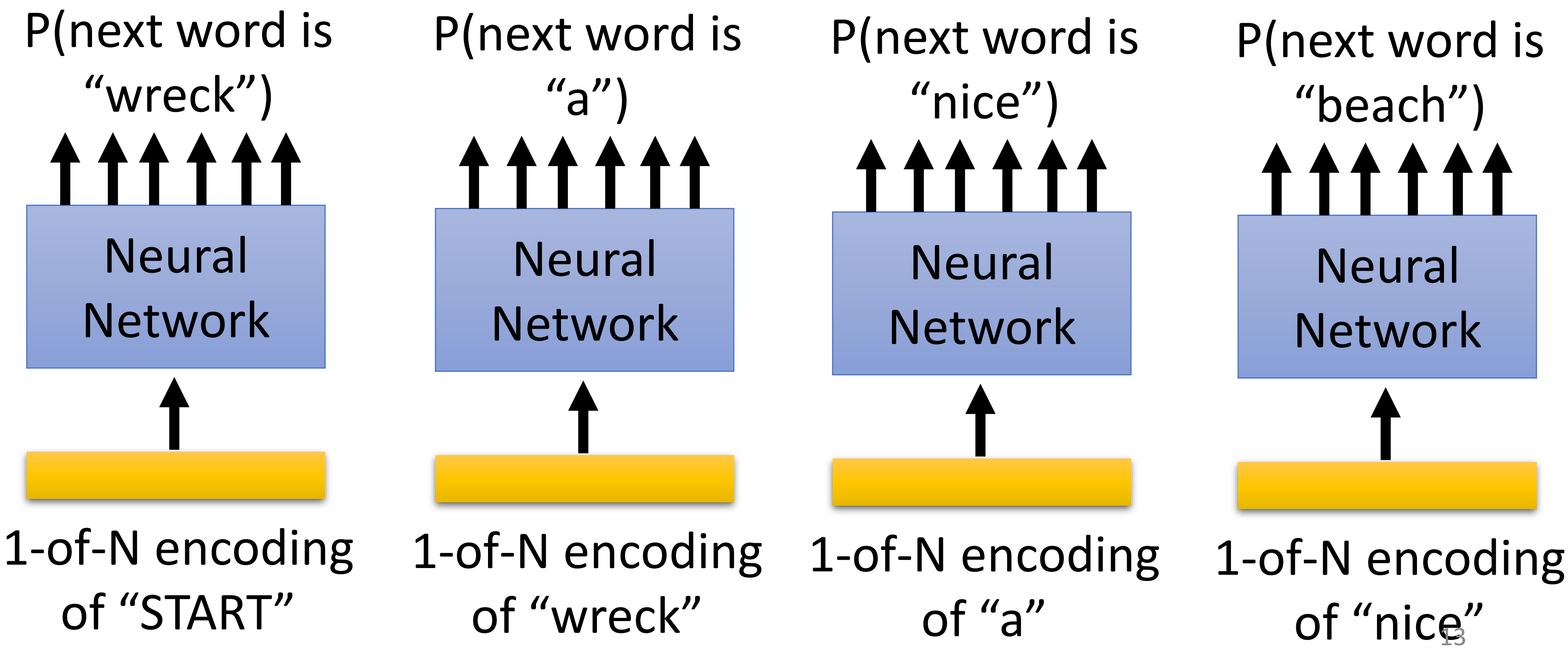


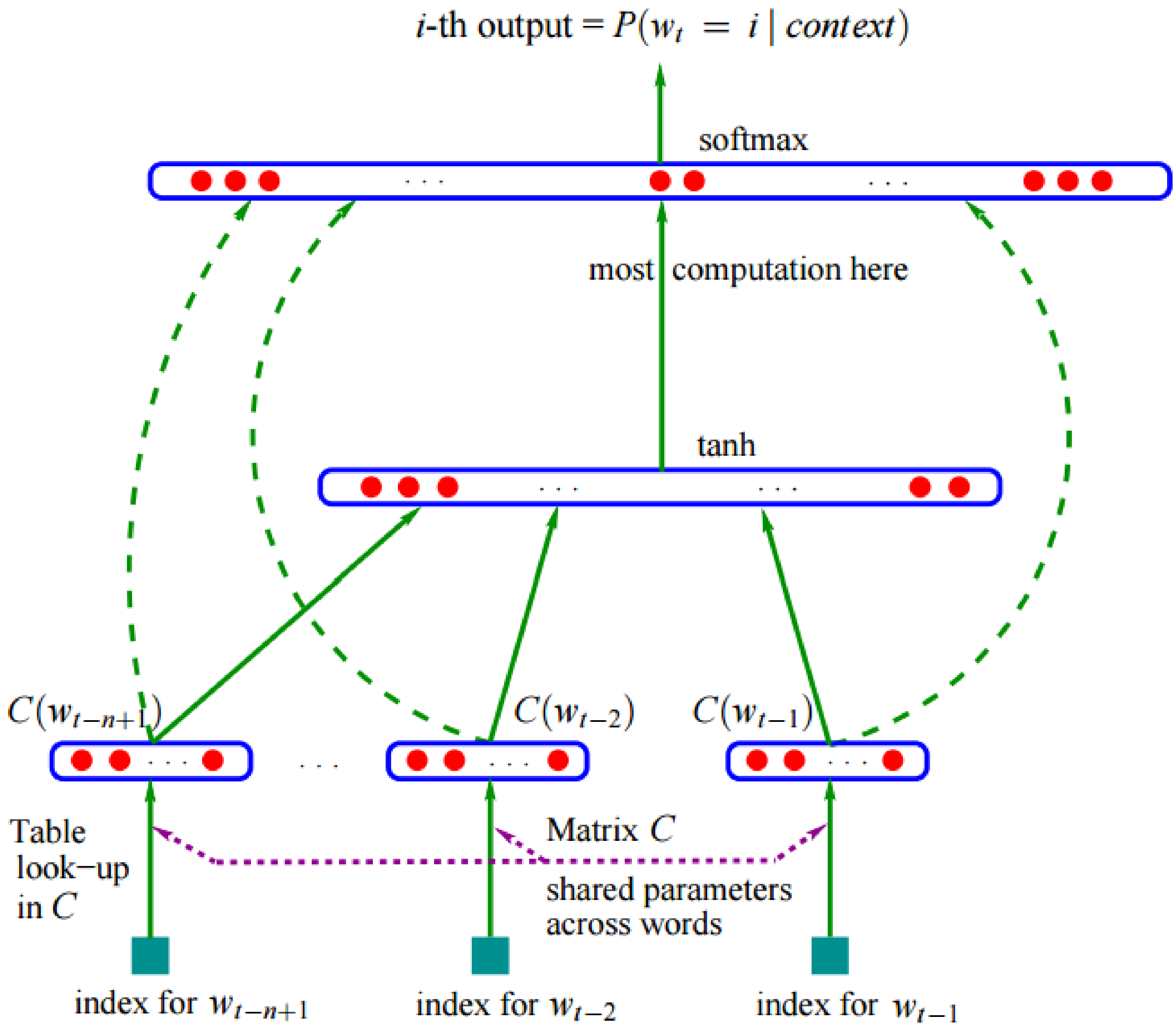
NN-based LM

P("wreck a nice beach")

=P(wreck|START)P(a|wreck)P(nice|a)P(beach|nice)

P(b|a): the probability of NN predicting the next word.



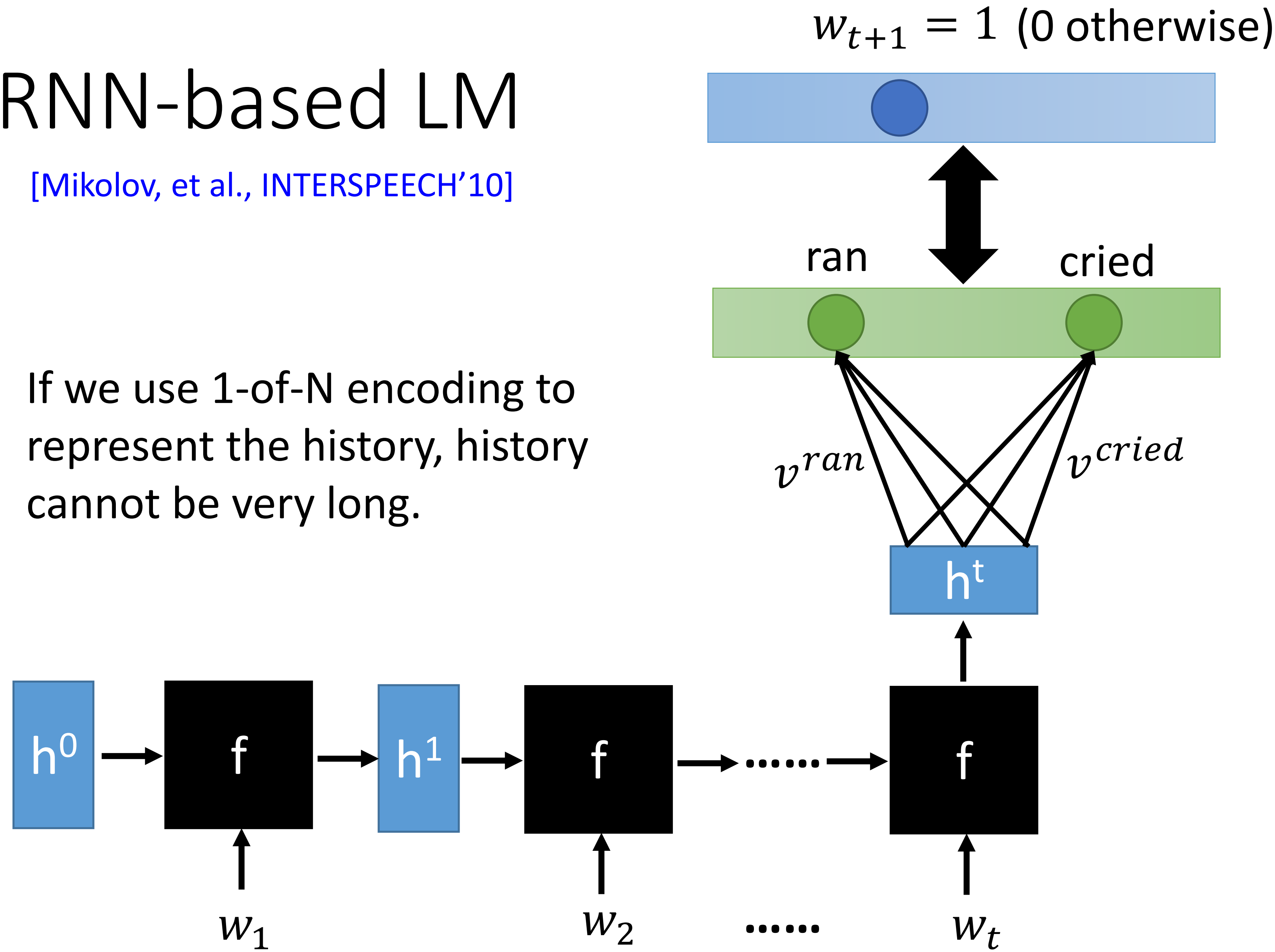


[Bengio, et al., JMLR'03]

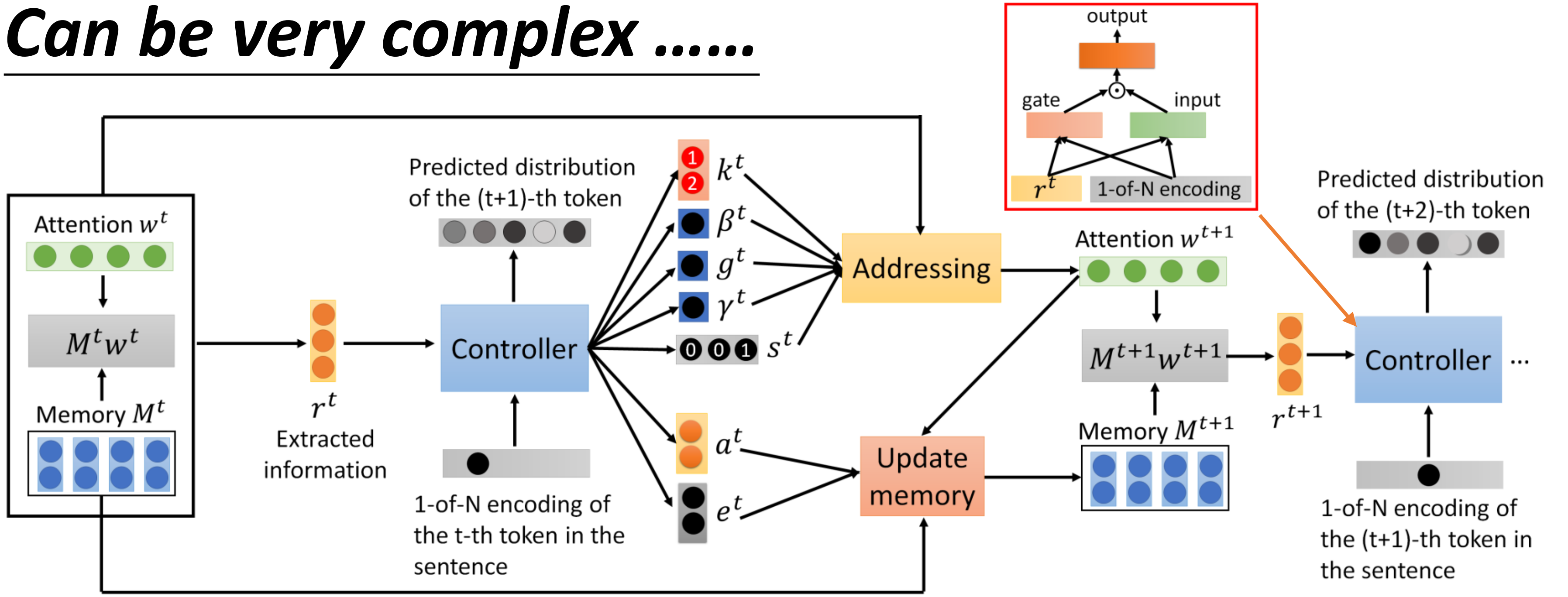
RNN-based LM

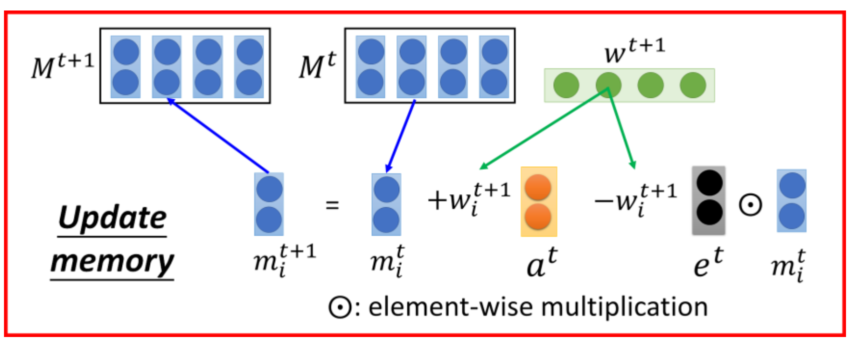
[Mikolov, et al., INTERSPEECH'10]

If we use 1-of-N encoding to represent the history, history cannot be very long.

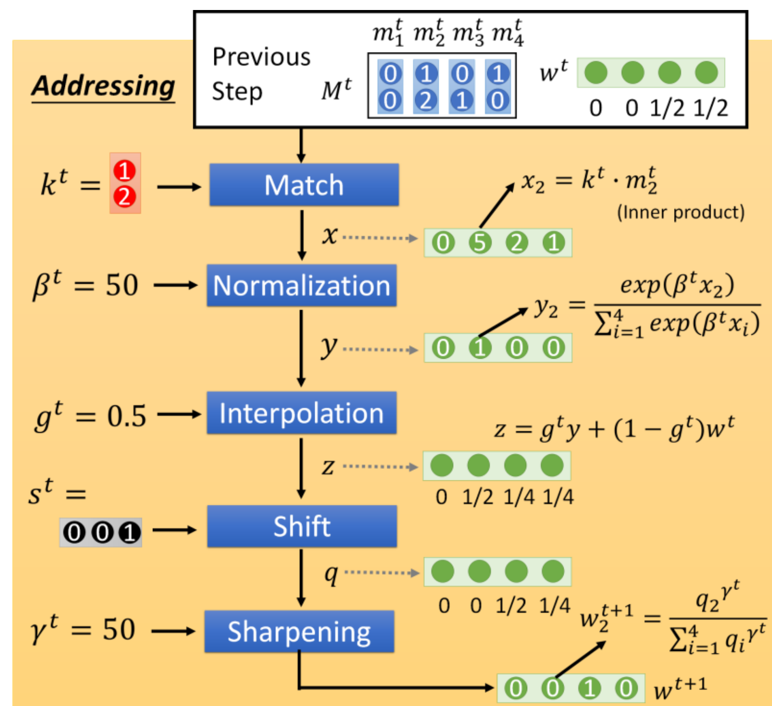


Can be very complex ……





[Ko, et al., ICASSP'17]



LSTM with proper optimization and regularization can be good.

[Merity, et al., ICLR'18]

How to use LM to improve LAS?

how to integrate

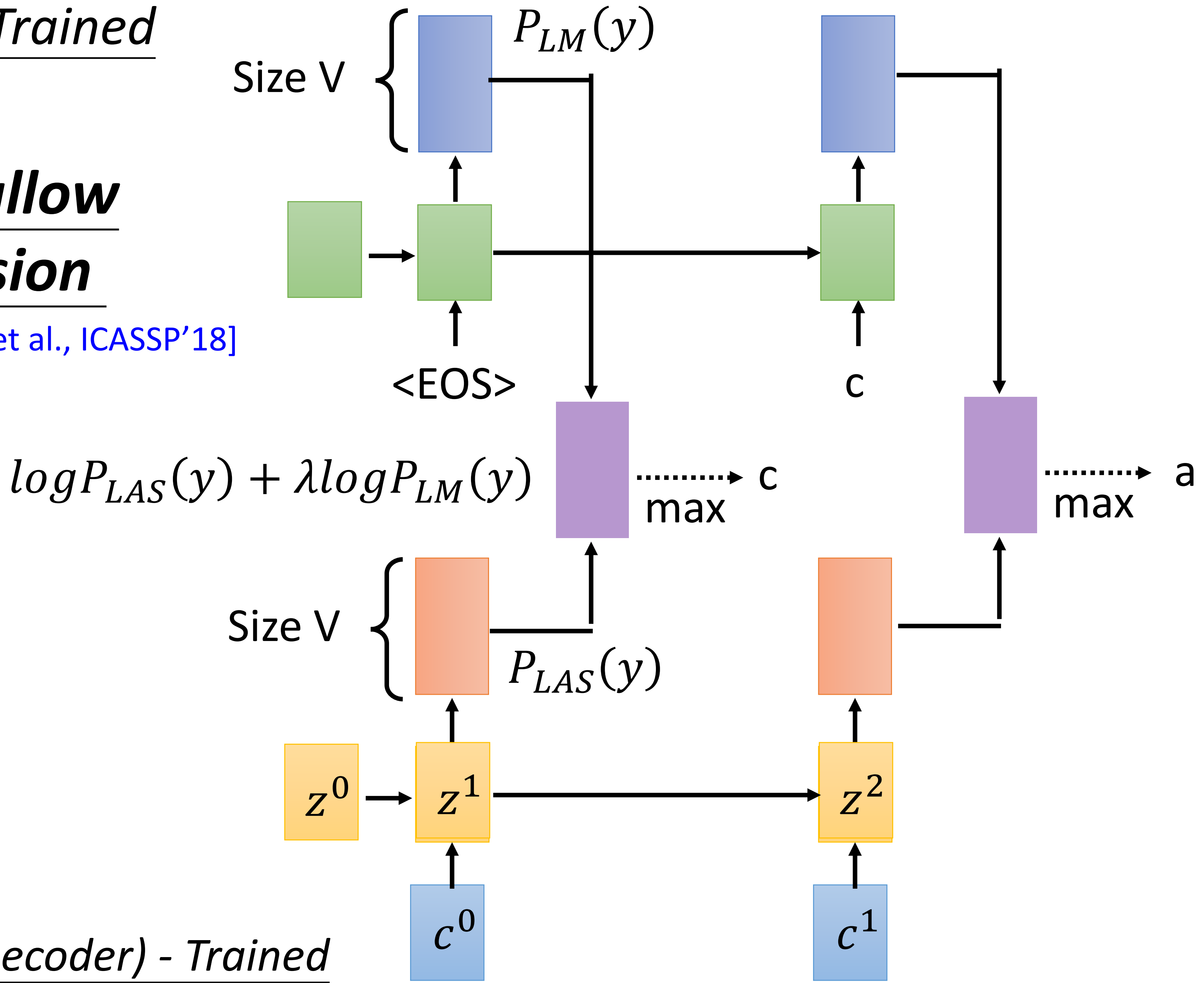
when to integrate

	Output	Hidden
After Training	Shallow Fusion	Deep Fusion
Before Training		Cold Fusion

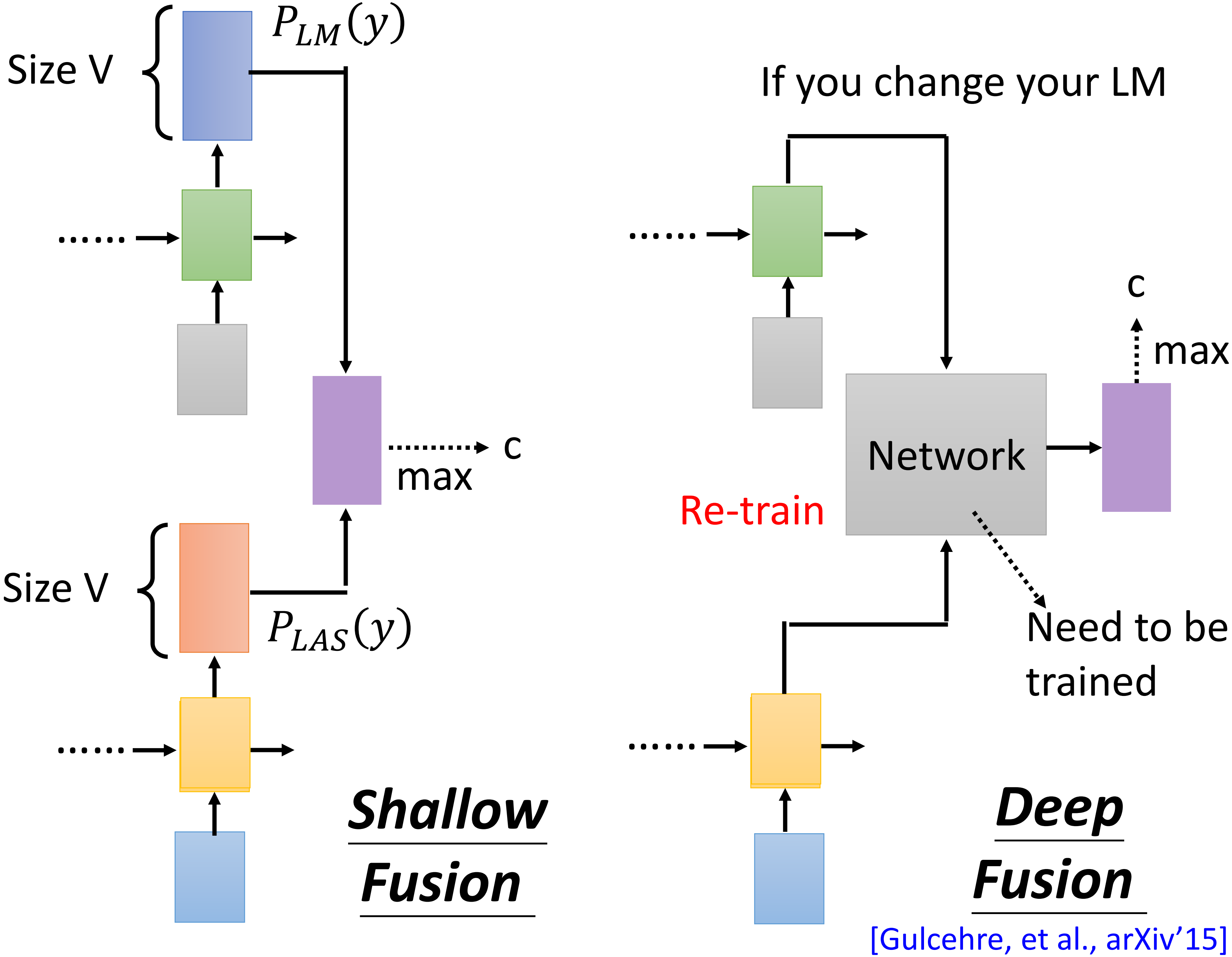
LM - Trained

Shallow Fusion

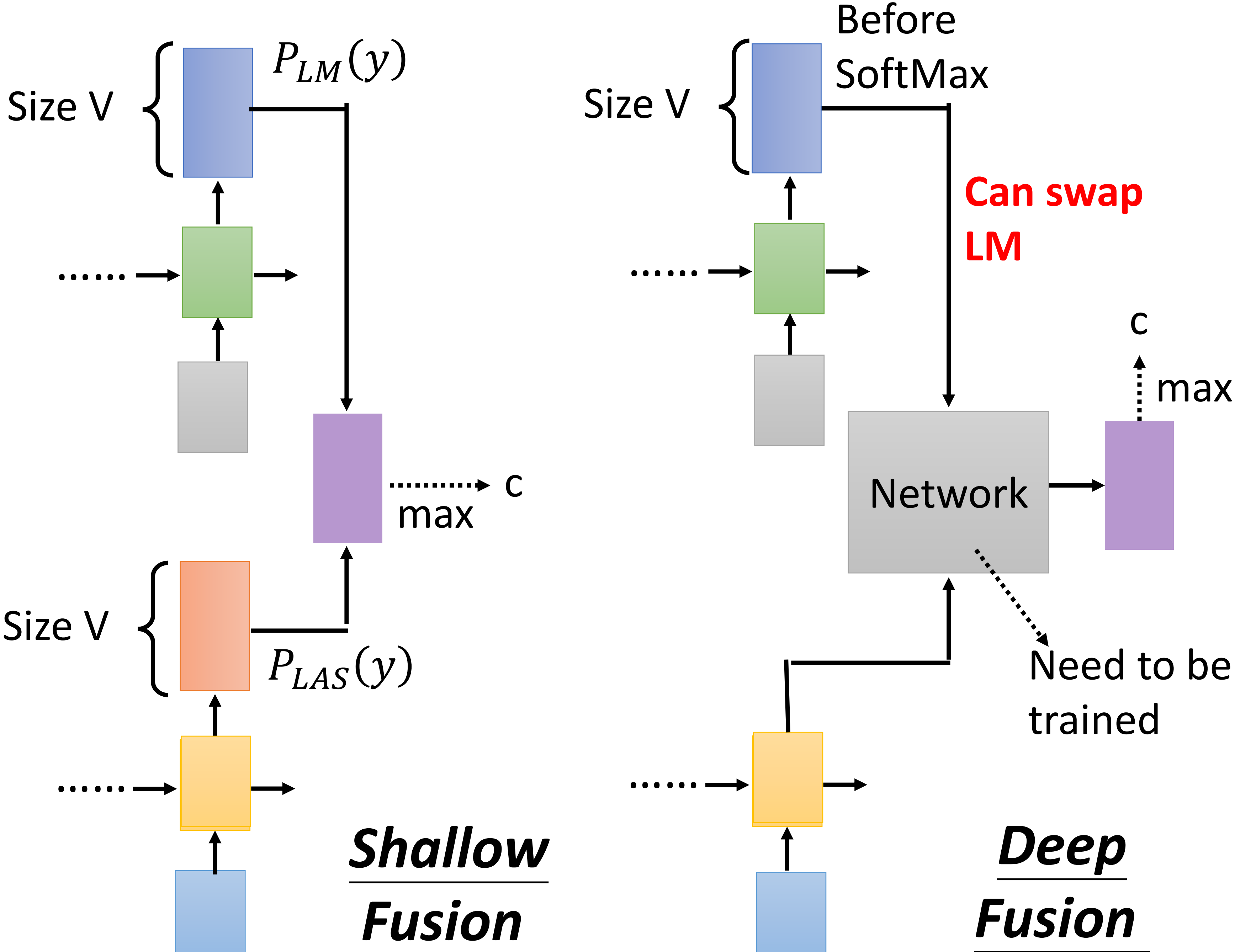
[Kannan, et al., ICASSP'18]



LAS (Decoder) - Trained



Size V
$P_{LM}(y)$
max
c
Size V
$P_{LAS}(y)$
Shallow Fusion
If you change your LM
c
max
Network
Re-train
Need to be trained
Deep Fusion
[Gulcehre, et al., arXiv'15]

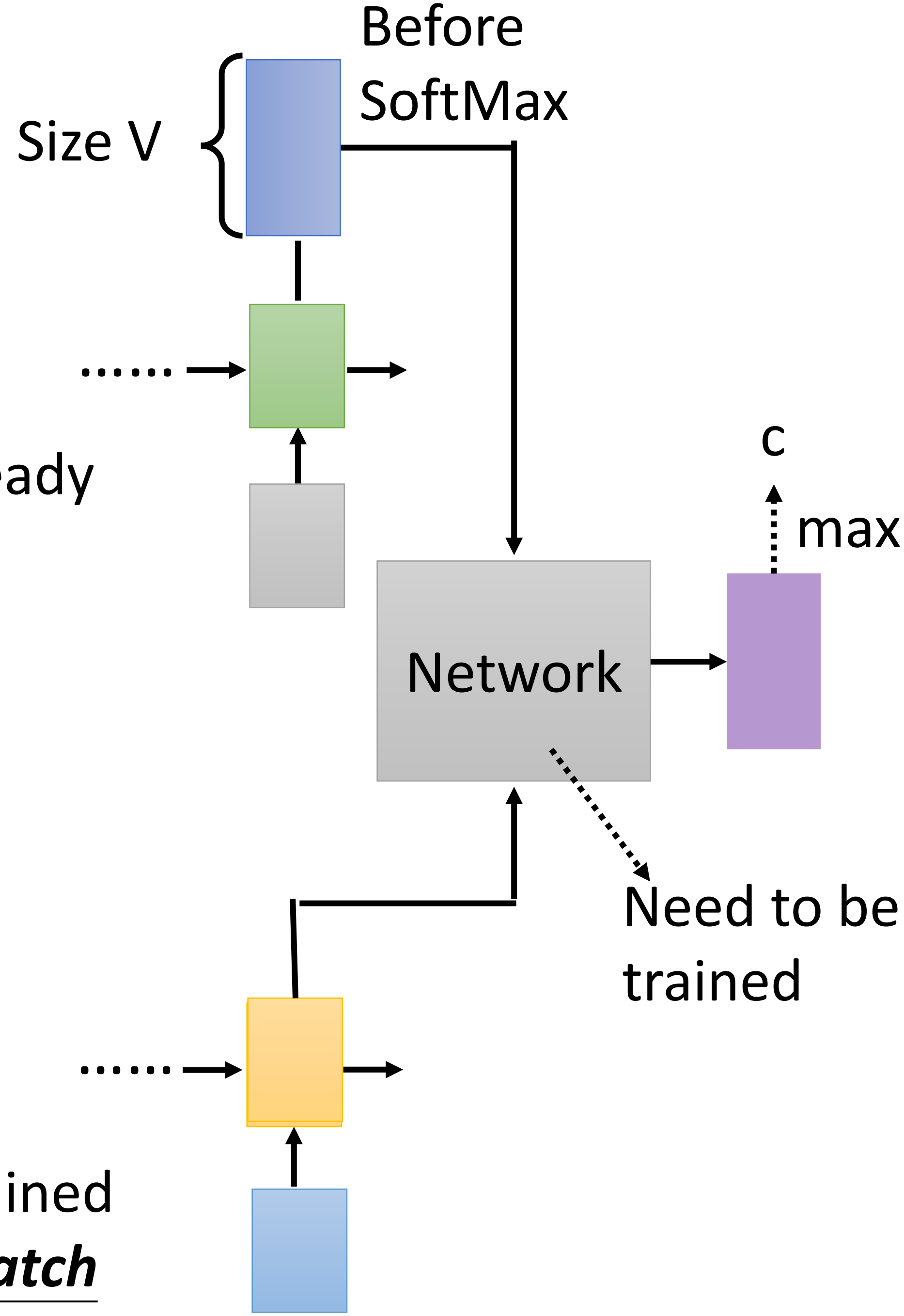


Size V
$P_{LM}(y)$
c
max
Size V
$P_{LAS}(y)$
Shallow Fusion
Before SoftMax
Size V
Can swap LM
c
max
Network
Need to be trained
Deep Fusion

Cold Fusion

[Sriram, et al., INTERSPEECH'18]

LM is already trained



- LAS converges faster during training
- LAS has to be trained again if you have a new LM.

LAS is trained ***from scratch***

Concluding Remarks

how to integrate

when to integrate

	Output	Hidden
After Training	Shallow Fusion	Deep Fusion
Before Training		Cold Fusion

Reference

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