Understanding Deep Neural Networks

Chapter Seven

Sequence Learning

Zhang Yi, IEEE Fellow Autumn 2020

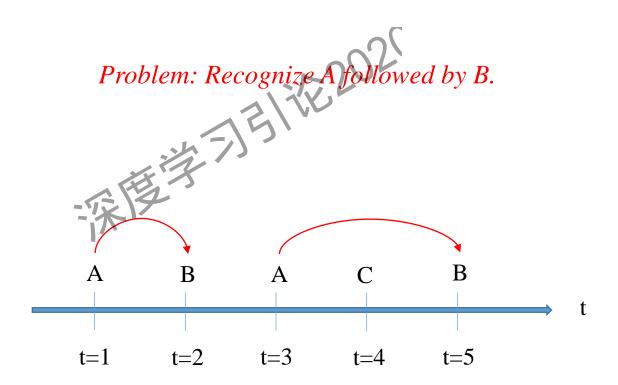
Outline

- A Sequence Recognizing Example
- Review of BP for Mono-target Output NNs
- ■BP Method for Multi-target Outputs NNs
- ■BP Algorithm for Multi-target Outputs NNs
- ■Illustrative Examples
- Assignment

Generated Sequences

- 1. ABACB
- 2. CCBBA
- 3. CACCB
- 4. ACCCB
- 5. CACBC
- 6. AAACB
- 7. BAACB
- 8. CCBAB
- 9. BCCAB
- 10. CABAC

.

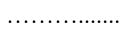


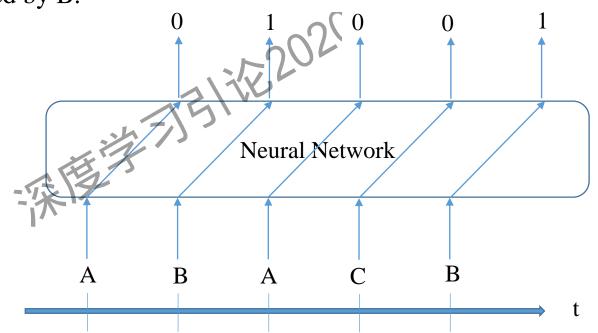
Recognize A followed by B Problem

The task is to recognize A followed by B.

Generated Sequences

- 1. ABCAB
- 2. CCBBA
- 3. CACCB
- 4. ACCCB
- 5. CACBC
- 6. AAACB
- 7. BAACB
- 8. CCBAB
- 9. BCCAB
- 10. CABAC





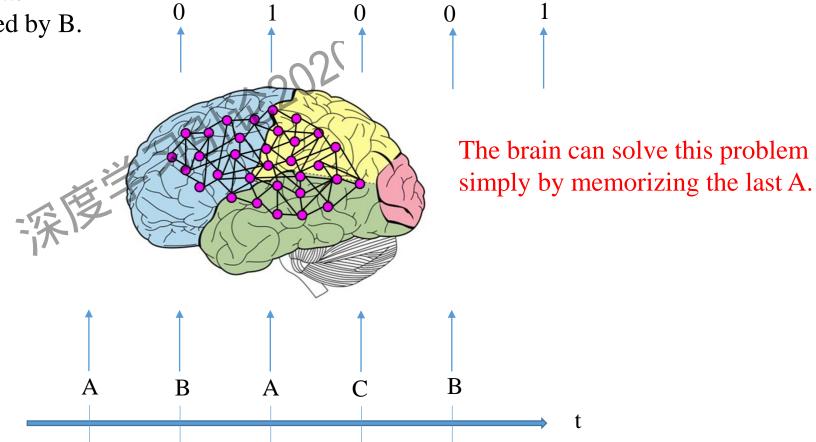
Problem: Can we use neural network to solve this problem?

Recognize A followed by B Problem

The task is to recognize A followed by B.

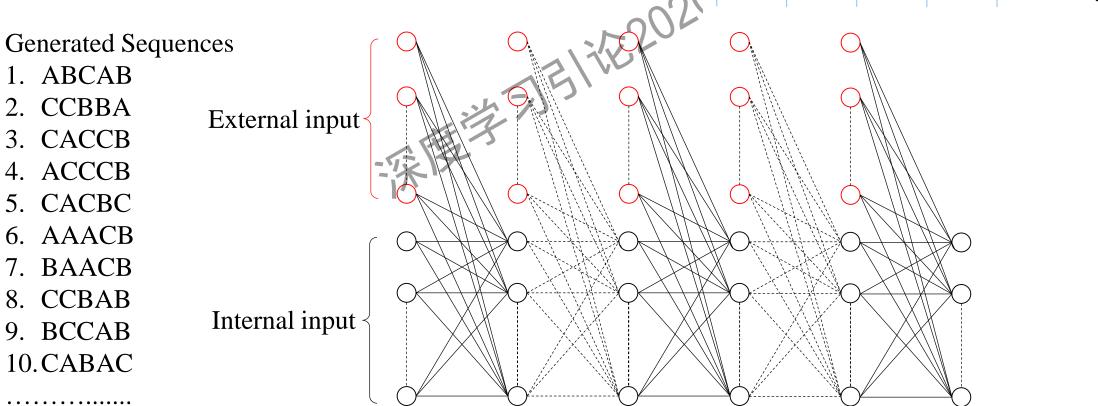
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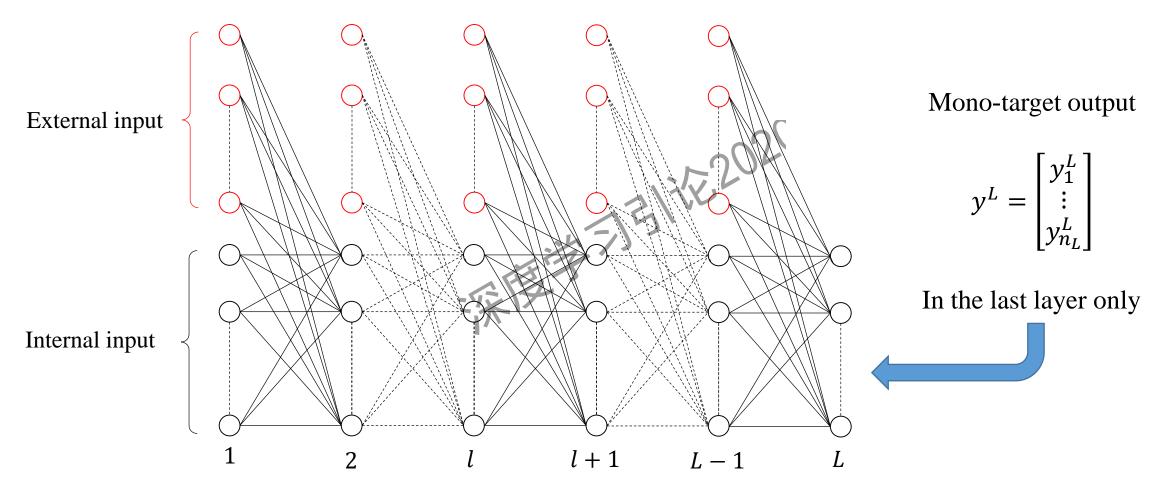


Recognize A followed by B Problem

The task is to recognize A followed by B.



Neural Network



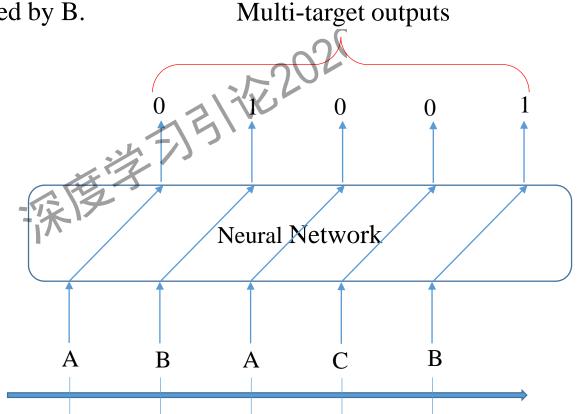
Mono-target output network cannot solve the sequence recognizing problem.

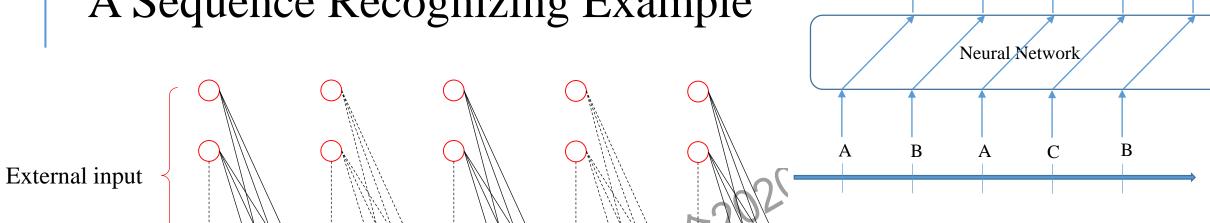
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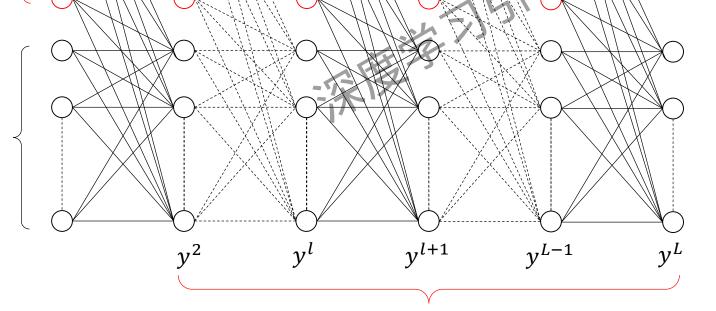
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Internal input

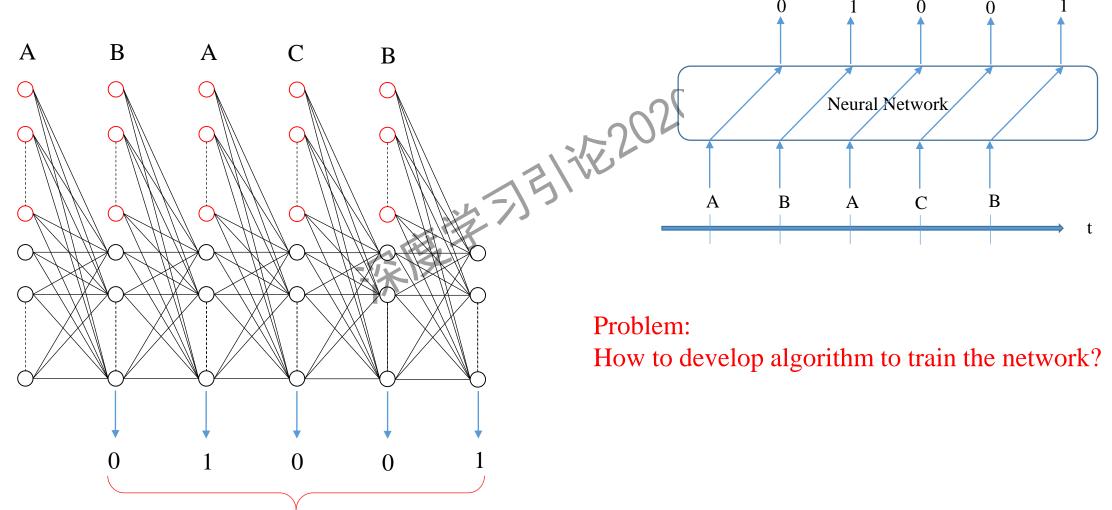


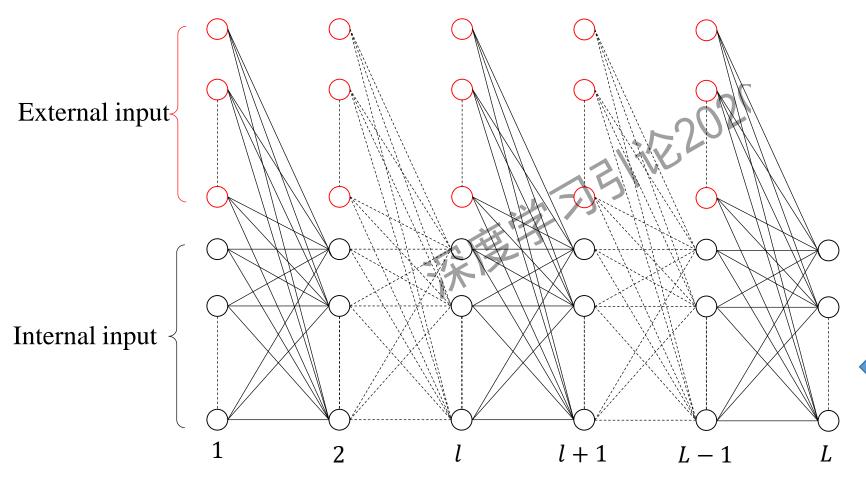
Multi-target outputs

$$y^l = \begin{bmatrix} y_1^l \\ \vdots \\ y_{n_L}^l \end{bmatrix}$$

$$(l=2,\cdots,L)$$

Multi-target outputs

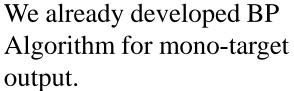


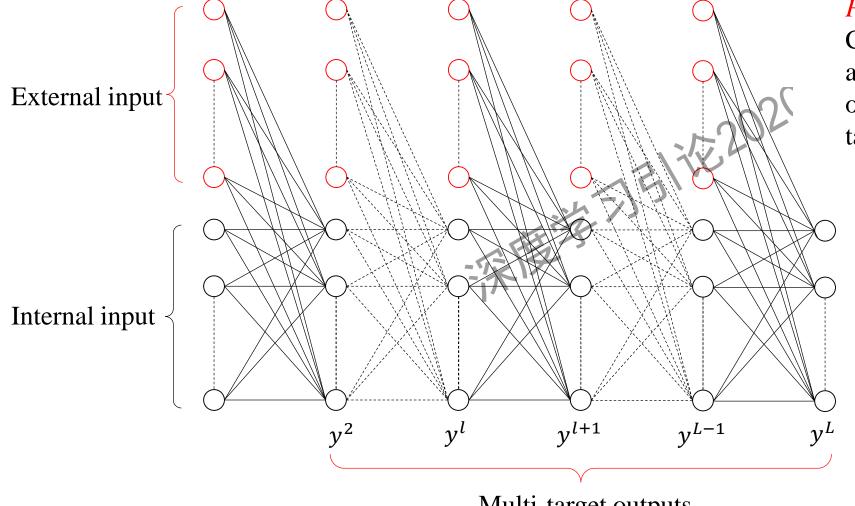


Mono-target output

$$y^L = \begin{bmatrix} y_1^L \\ \vdots \\ y_{n_L}^L \end{bmatrix}$$

In the last layer only





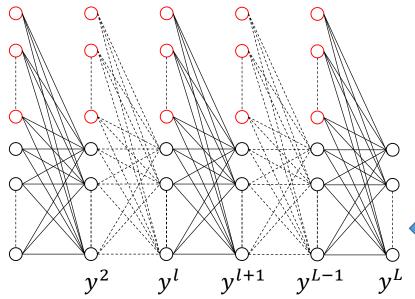
Problem:

Can we develop learning algorithms for multi-target output similar to BP for monotarget output?

Multi-target outputs

$$y^l = \begin{bmatrix} y_1^l \\ \vdots \\ y_{n_L}^l \end{bmatrix}$$

$$(l=2,\cdots,L)$$



Combine the external and internal inputs in first layer

Equivalent

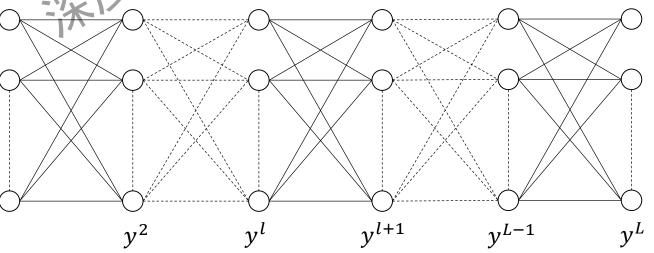
Multiple Target Outputs

$$y^l = \begin{bmatrix} y_1^l \\ \vdots \\ y_{n_L}^l \end{bmatrix}$$

$$(l=2,\cdots,L)$$

Problem:

Can we develop learning algorithms similar to BP?

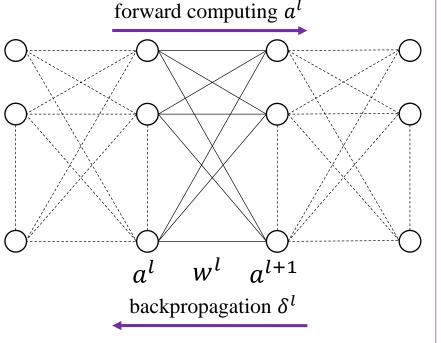


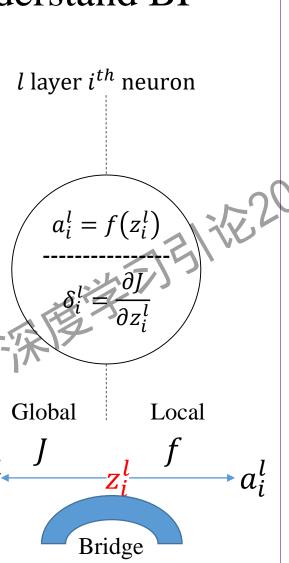
Outline

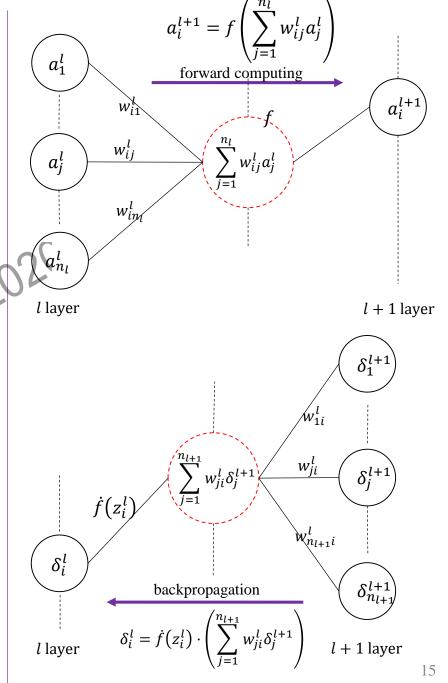
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Only One Page to Understand BP

Cost function: $J(w^1, \dots, w^{L-1})$ Updating rule: $w_{ji}^l \leftarrow w_{ji}^l - \alpha \cdot \frac{\partial J}{\partial w_{ji}^l}$ Relationship: $\frac{\partial J}{\partial w_{ji}^l} = \delta_j^{l+1} \cdot a_i^l$



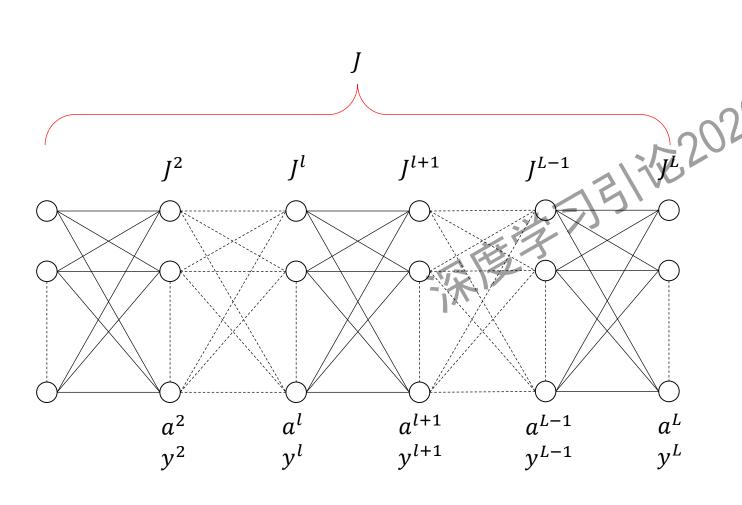




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BP Method for Multi-target Outputs NNs



Cost function

$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}, (l = 2, \dots, L)$$

$$J = \sum_{l=2}^{L} J^{l} = \frac{1}{2} \sum_{l=2}^{L} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}$$

Network Outputs Multi-target outputs

$$a^{l} = \begin{bmatrix} a_{1}^{l} \\ \vdots \\ a_{n_{l}}^{l} \end{bmatrix} \qquad y^{l} = \begin{bmatrix} y_{1}^{l} \\ \vdots \\ y_{n_{l}}^{l} \end{bmatrix}$$
$$(l = 2, \dots, L) \qquad (l = 2, \dots, L)$$

BP Method for Multi-target Outputs NNs

Steepest Descent Method

$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}, (l = 2, \dots, L)$$

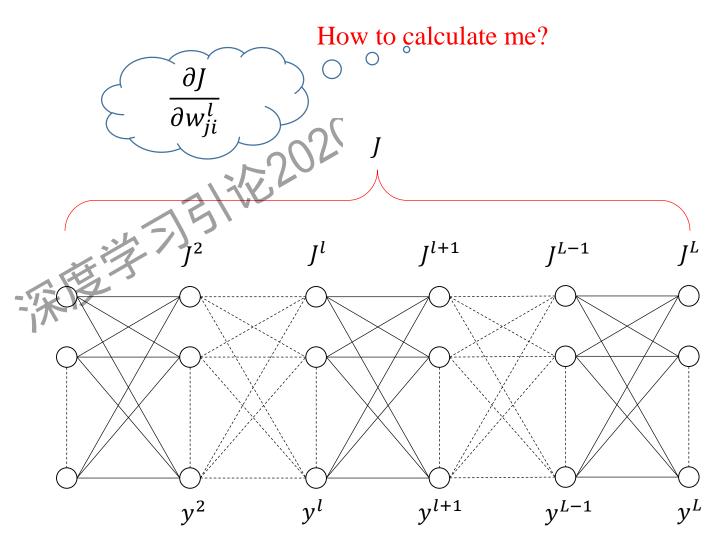
$$J = \sum_{l=2}^{L} J^{l} = \frac{1}{2} \sum_{l=2}^{L} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}$$

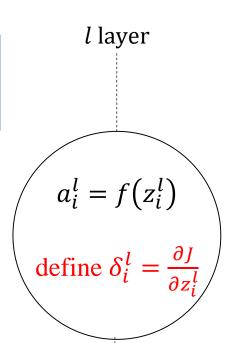
1. Computing

$$\frac{\partial J}{\partial w_{ji}^l}$$

2. Iterating

$$w_{ji}^l \leftarrow w_{ji}^l - \alpha \cdot \frac{\partial J}{\partial w_{ji}^l}$$





Relation between
$$\delta_i^l$$
 and $\frac{\partial J}{\partial w_{ji}^l}$

$$\frac{\partial J}{\partial w_{ji}^l} = \delta_j^{l+1} \cdot a_i^l$$

Why?

Why?
$$\frac{\partial J}{\partial w_{ji}^{l}} = \frac{\partial J}{\partial z_{j}^{l+1}} \cdot \frac{\partial z_{j}^{l+1}}{\partial w_{ji}^{l}} = \delta_{j}^{l+1} \cdot a_{i}^{l}$$

$$a_{i}^{l} = f(z_{i}^{l})$$

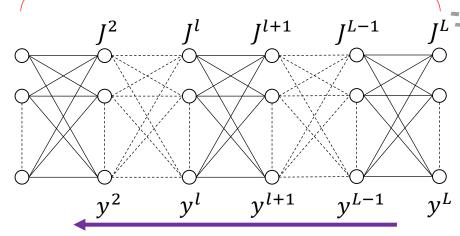
$$w_{ji}^{l}$$

$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}$$
, $(l = 2, \dots, L)$

$$J = \sum_{l=2}^{L} J^{l} = \frac{1}{2} \sum_{l=2}^{L} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}$$

l+1 layer

Llayer
$$\frac{\partial J}{\partial w_{ji}^l} = \delta_j^{l+1} \cdot a$$



$$a_i^l = f(z_i^l)$$

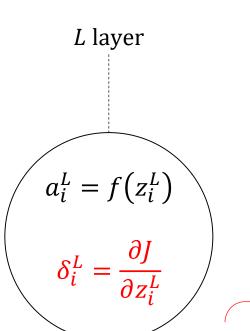
$$\delta_i^l = \frac{\partial J}{\partial z_i^l}$$

$$\delta_i^l = \frac{\partial J}{\partial z_i^l}$$

$$\delta_j^{l+1} = \frac{\partial J}{\partial z_j^{l+1}}$$

$$z_j^{l+1} = \sum_{i=1}^l w_{ji}^l a_i^l$$

Step 1: Calculating δ^L in Last Layer

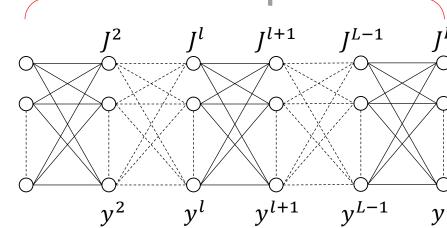


$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} \left(a_{i}^{l} - y_{i}^{l} \right)^{2}, (l = 2, \dots, L)$$

$$J = \sum_{l=2}^{L} J^{l} = \frac{1}{2} \sum_{l=2}^{L} \sum_{i=1}^{n_{l}} \left(a_{i}^{l} - y_{i}^{l} \right)^{2}$$

$$It holds that,$$

$$\delta_{i}^{L} = \frac{\partial J}{\partial z_{i}^{L}} = \frac{\partial J^{L}}{\partial z_{i}^{L}} = \frac{1}{2} \cdot \frac{\partial \left(a_{i}^{l} - y_{i}^{l} \right)^{2}}{\partial z_{i}^{L}} = \left(a_{i}^{L} - y_{i}^{L} \right) \cdot \frac{\partial a_{i}^{L}}{\partial z_{i}^{L}} = \left(a_{i}^{L} - y_{i}^{L} \right) \cdot \dot{f}(z_{i}^{L})$$



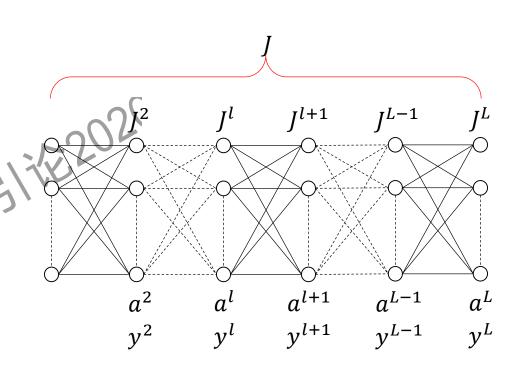
Step 2: Relation Between δ^l and δ^{l+1}

$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}, (l = 2, \dots, L)$$

$$J = \sum_{l=2}^{L} J^{l} = \frac{1}{2} \sum_{l=2}^{L} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}$$

J may have an explicit dependence on z_i^l , it may also have an implicit dependence on z_i^l through later output values. To avoid ambiguity in interpreting partial derivatives, define $z_i^l(*) = z_i^l$.

$$\delta_{i}^{l} = \frac{\partial J}{\partial z_{i}^{l}} = \frac{\partial J}{\partial z_{i}^{l}(*)} \cdot \frac{\partial z_{i}^{l}(*)}{\partial z_{i}^{l}} + \sum_{j=1}^{n_{l+1}} \frac{\partial J}{\partial z_{j}^{l+1}} \cdot \frac{\partial z_{j}^{l+1}}{\partial z_{i}^{l}}$$



Step 2: Relation Between δ^l and δ^{l+1}

$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}, (l = 2, \dots, L)$$

$$J = \sum_{l=2}^{L} J^{l} = \frac{1}{2} \sum_{l=2}^{L} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}$$

An Illustrate Example $J = x + y, y = \exp(x)$ I may have an explicit dependence on z_i^l , it may also have an implicit dependence on z_i^l through later output values. To avoid mbiguity in interpreting particles define $z_i^l(*) = z_i^l$.

$$\delta_{i}^{l} = \frac{\partial J}{\partial z_{i}^{l}} = \frac{\partial J}{\partial z_{i}^{l}(*)} \cdot \frac{\partial z_{i}^{l}(*)}{\partial z_{i}^{l}} + \sum_{j=1}^{n_{l+1}} \frac{\partial J}{\partial z_{j}^{l+1}} \cdot \frac{\partial z_{j}^{l+1}}{\partial z_{i}^{l}}$$

$$J = x + y, y = \exp(x)$$

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial x} + \frac{\partial J}{\partial y} \cdot \frac{\partial y}{\partial x}$$

$$x^* = x$$

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial x^*} \cdot \frac{\partial x^*}{\partial x} + \frac{\partial J}{\partial y} \cdot \frac{\partial y}{\partial x}$$

Step 2: Relation Between δ^l and δ^{l+1}

$$\delta_{i}^{l} = \frac{\partial J}{\partial z_{i}^{l}} = \frac{\partial J}{\partial z_{i}^{l}(*)} \cdot \frac{\partial z_{i}^{l}(*)}{\partial z_{i}^{l}} + \sum_{j=1}^{n_{l+1}} \frac{\partial J}{\partial z_{j}^{l+1}} \cdot \frac{\partial z_{j}^{l+1}}{\partial z_{i}^{l}}$$

$$\frac{\partial J}{\partial z_i^l(*)} \cdot \frac{\partial z_i^l(*)}{\partial z_i^l} = \frac{\partial J^l}{\partial z_i^l} = \frac{1}{2} \cdot \frac{\partial \left(a_i^l - y_i^l\right)^2}{\partial z_i^l} = \left(a_i^l - y_i^l\right) \cdot \frac{\partial a_i^l}{\partial z_i^l} =$$

$$\frac{\partial J}{\partial z_{i}^{l}(*)} \cdot \frac{\partial z_{i}^{l}(*)}{\partial z_{i}^{l}} = \frac{\partial J^{l}}{\partial z_{i}^{l}} = \frac{1}{2} \cdot \frac{\partial \left(a_{i}^{l} - y_{i}^{l}\right)^{2}}{\partial z_{i}^{l}} = \left(a_{i}^{l} - y_{i}^{l}\right) \cdot \frac{\partial a_{i}^{l}}{\partial z_{i}^{l}} = \left(a_{i}^{l} - y_{i}^{l}\right) \cdot \frac{\partial \left(z_{i}^{l}\right)}{\partial z_{i}^{l}} = \left(a_{i}^{l} - y_{i}^{l}\right) \cdot \frac{\partial \left(z_{i}^{l}$$

$$z_{j}^{l+1} = \sum_{i=1}^{n_{l}} w_{ji}^{l} a_{j}^{l}$$

$$a_{i}^{l+1} = f(z_{i}^{l+1})$$

$$z_{j}^{l+1} = \sum_{i=1}^{n_{l}} w_{ji}^{l} a_{j}^{l}$$

$$a_{i}^{l+1} = f(z_{i}^{l+1})$$

$$\frac{\partial z_{j}^{l+1}}{\partial z_{i}^{l}} = w_{ji}^{l} \cdot \frac{\partial a_{j}^{l}}{\partial z_{i}^{l}} = w_{ji}^{l} \cdot \dot{f}(z_{i}^{l})$$

$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}, (l = 2, \dots, L)$$

$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}, (l = 2, \dots, L)$$

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$$J^{l} = \frac{1}{2} \sum_{i=1}^{n_{l}} (a_{i}^{l} - y_{i}^{l})^{2}$$

$$\delta_i^l = \dot{f}(z_i^l) \cdot \left[\left(a_i^l - y_i^l \right) + \left(\sum_{j=1}^{n_{l+1}} \delta_j^{l+1} \cdot w_{ji}^l \right) \right]$$

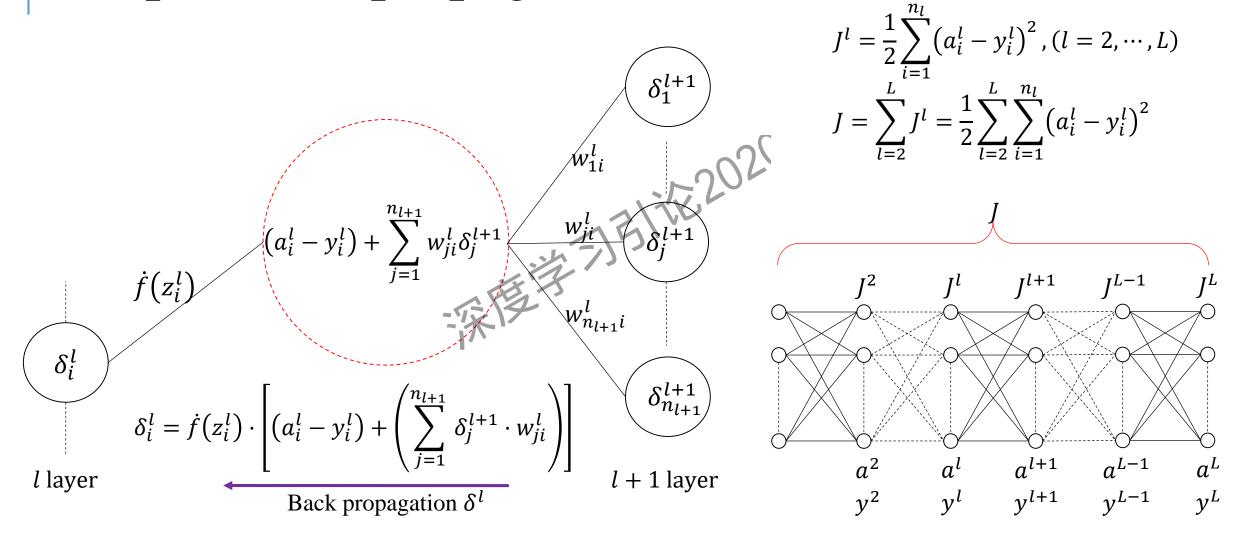
$$\delta_i^l = f(z_i^l)$$

$$\delta_i^l = \frac{\partial J}{\partial z_i^l}$$

$$a_{n_{l+1}}^{l+1} = f(z_{n_{l+1}}^{l+1})$$

$$\delta_{n_{l+1}}^{l+1} = \frac{\partial J}{\partial z_{n_{l+1}}^{l+1}}$$

Step 3: Backpropagation δ^l



Only One Page to Understand BP

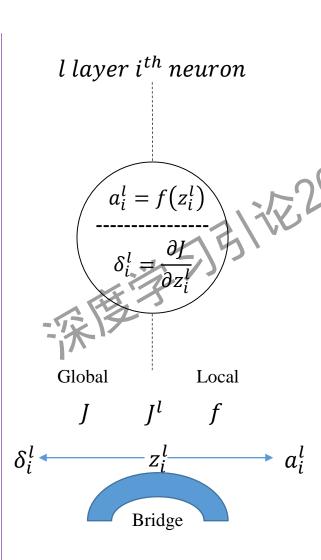
Cost function: $J(w^1, \dots, w^{L-1})$

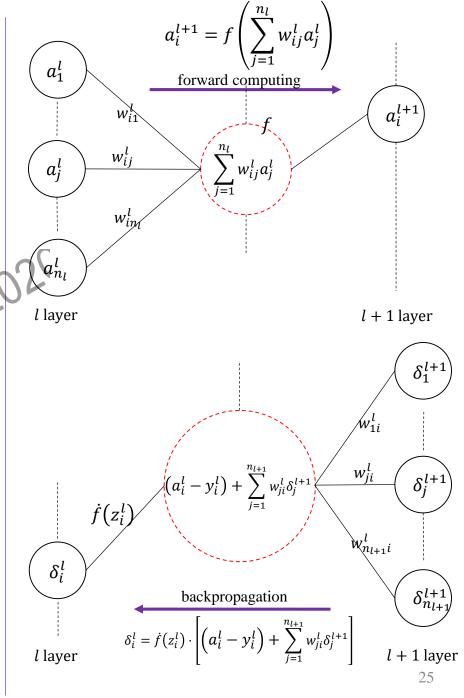
Updating rule: $w_{ji}^l \leftarrow w_{ji}^l - \alpha \cdot \frac{\partial J}{\partial w_{ji}^l}$

Relationship: $\frac{\partial J}{\partial w_{ii}^l} = \delta_j^{l+1} \cdot a_i^l$

forward computing a^l

 $a^{l} \qquad a^{l+1}$ $y^{l} \qquad y^{l+1}$ $backpropagation <math>\delta^{l}$





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The BP Algorithm

Step 1. Input the training data set $D = \{(x, y)\}$

Step 2. Initial each w_{ij}^l , and choose a learning rate α .

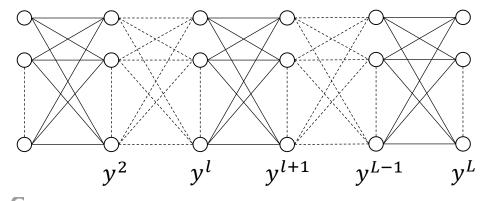
Step 3. For each mini-batch sample
$$D_m \subseteq D$$

for each
$$x \in D_m$$
 $a^1 \leftarrow x$;
for $l = 2$: L
 $a^l \leftarrow fc(w^l, a^l)$;
end
 $\delta^L = \frac{\partial J}{\partial z^L}$;
for $l = L - 1$: 2
 $\delta^l \leftarrow bc(w^l, \delta^{l+1})$;
end
 $\frac{\partial J}{\partial w^l_{ji}} \leftarrow \frac{\partial J}{\partial w^l_{ji}} + \delta^{l+1}_j \cdot a^l_i$;
end

Step 4. Updating

$$w_{ji}^l \leftarrow w_{ji}^l - \alpha \cdot \frac{\partial J}{\partial w_{ji}^l};$$

Step 5. Return to Step 3 until each w^l converge.



function
$$fc(w^l, a^l)$$

 $for i = 1: n_{l+1}$
 $z_i^{l+1} = \sum_{j=1}^{n_l} w_{ij}^l a_j^l$
 $a_i^{l+1} = f(z_i^{l+1})$
 end

end

Relationship:
$$\frac{\partial J}{\partial w_{ii}^l} = \delta_j^{l+1} \cdot a_i^l$$

function
$$bc(w^l, \delta^{l+1})$$

$$for \ i = 1: n_l$$

$$\delta_i^l = \dot{f}(z_i^l) \cdot \left[(a_i^l - y_i^l) + \left(\sum_{j=1}^{n_{l+1}} \delta_j^{l+1} \cdot w_{ji}^l \right) \right]$$

Outline

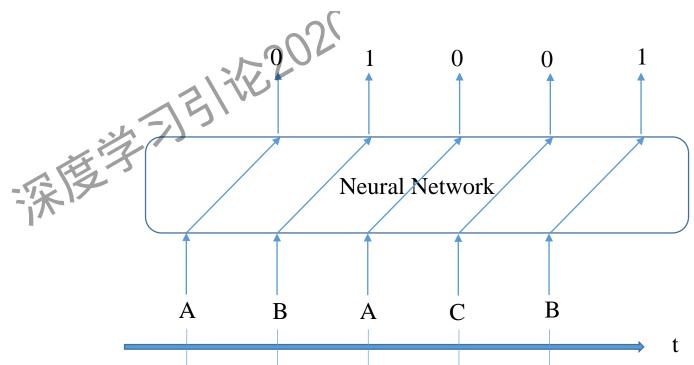
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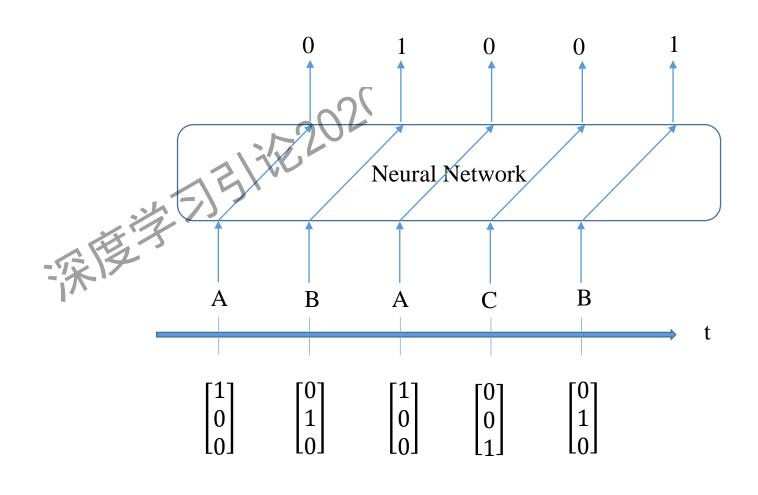
Coding the Inputs:

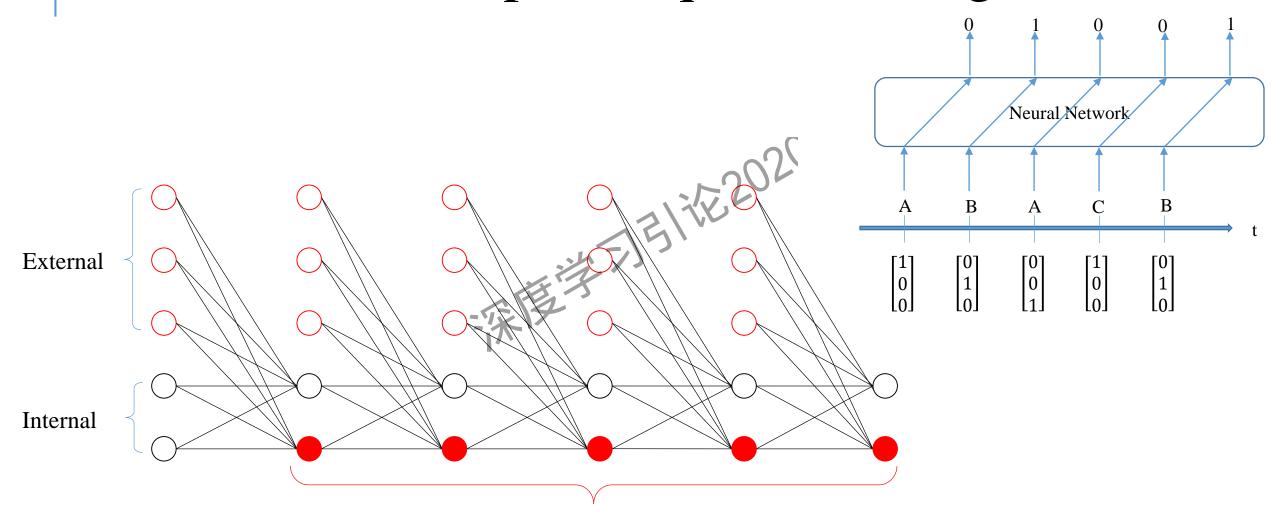
$$A = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \qquad B = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \qquad C = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

Generated Sequences

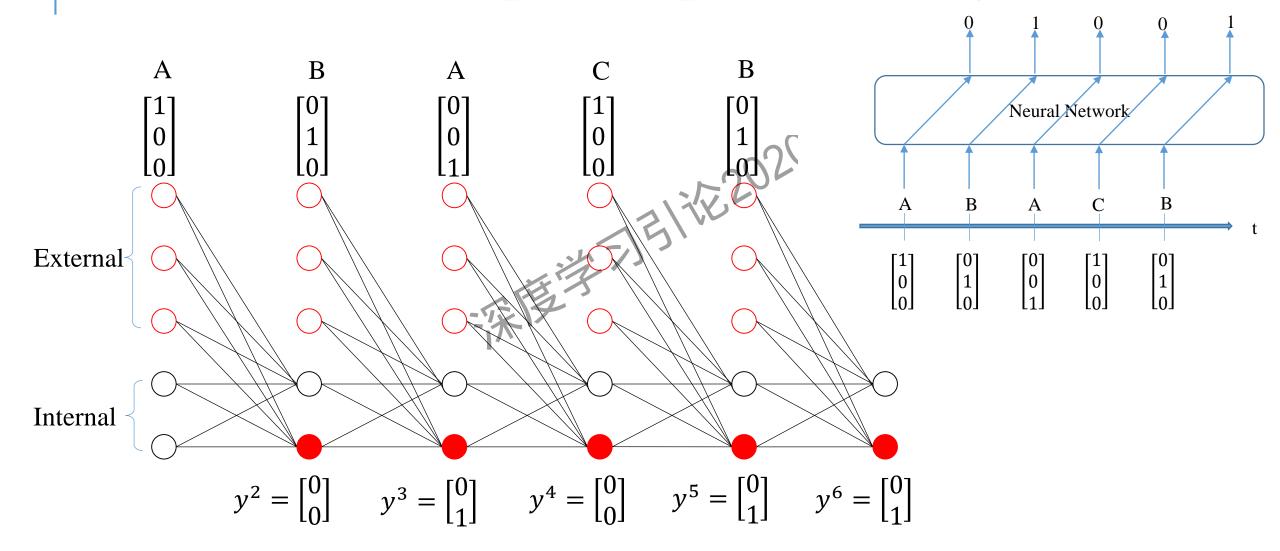
1. A B C A B
$$\begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$

2. C A C C B
$$\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$$



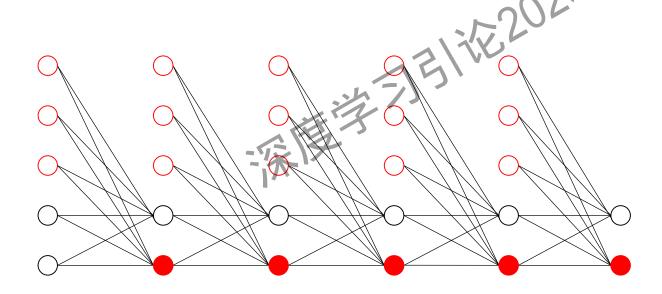


Target outputs



Generated Training Sequences

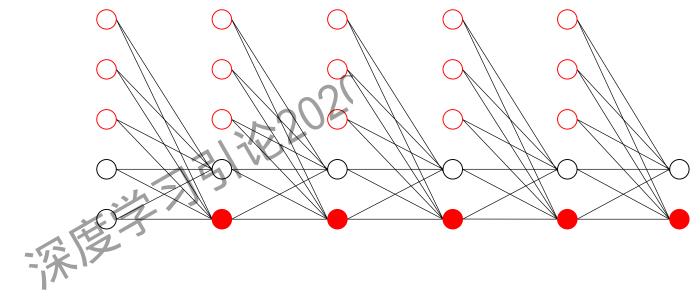
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- 10. CABAC



Generated Testing Sequences

- 1. CBCAC
- 2. ACBBA
- 3. BACCB
- 4. ACBCB
- 5. AACBC
- 6. BAACB
- 7. AAACB
- 8. CCBAB
- 9. BBCAB
- 10. AABAC

$$A = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \qquad B = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \qquad C = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$



Example outputs:

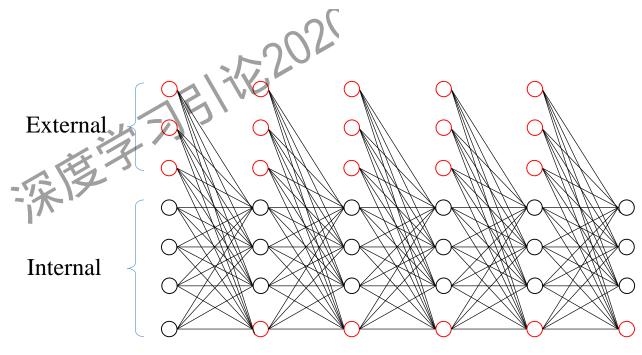
CAACB	\rightarrow	0.0184	0.0001	0.0211	0.0801	0.9928
ABBCA	\rightarrow	0.0179	0.9375	0.0267	0.0012	0.0000
AACBA	\rightarrow	0.0179	0.0336	0.0286	0.8722	0.0000
CACBB	\rightarrow	0.0184	0.0001	0.0170	0.8494	0.0013
BCAAA	\longrightarrow	0.0182	0.0001	0.0001	0.0622	0.0018

Recognize A followed by B Problem

The task is to recognize A followed by B.

Generated Sequences

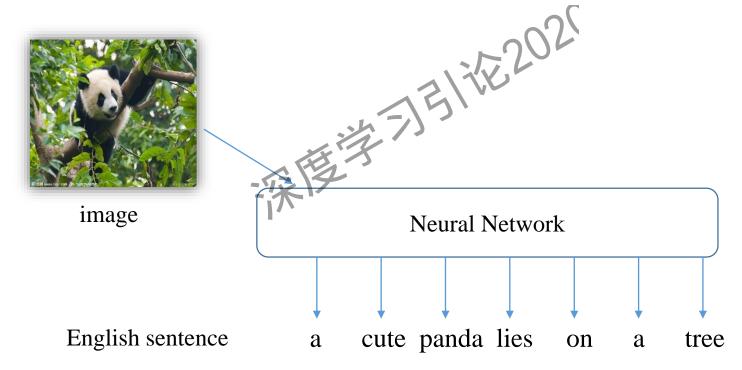
- 1. ABCAB
- 2. CCBBA
- 3. CACCB
- 4. ACCCB
- 5. CACBC
- 6. AAACB
- 7. BAACB
- 8. CCBAB
- 9. BCCAB
- 10. CABAC



Illustrative Example: Image Caption

Image Caption:

The task is to describe the content of an image using properly formed English sentence.



Dataset: COCO

COCO is a new image recognition, segmentation, and captioning dataset sponsored by Microsoft.

http://mscoco.org/dataset/#download

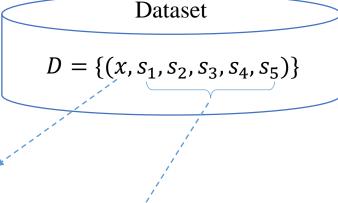
There are:

80,000 training samples 40,000 validation samples

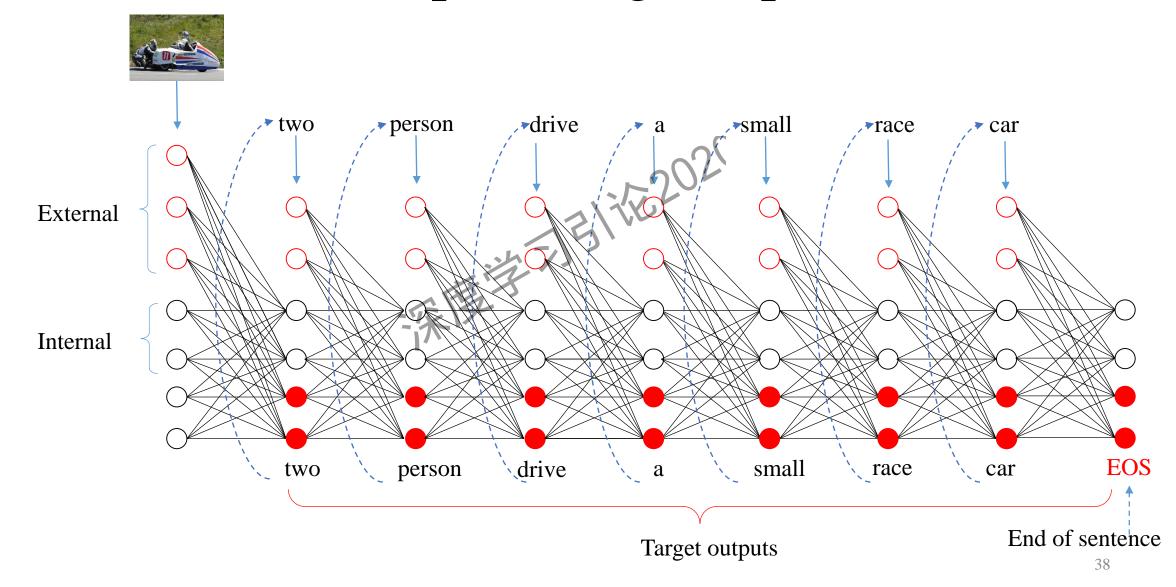
40,000 test samples

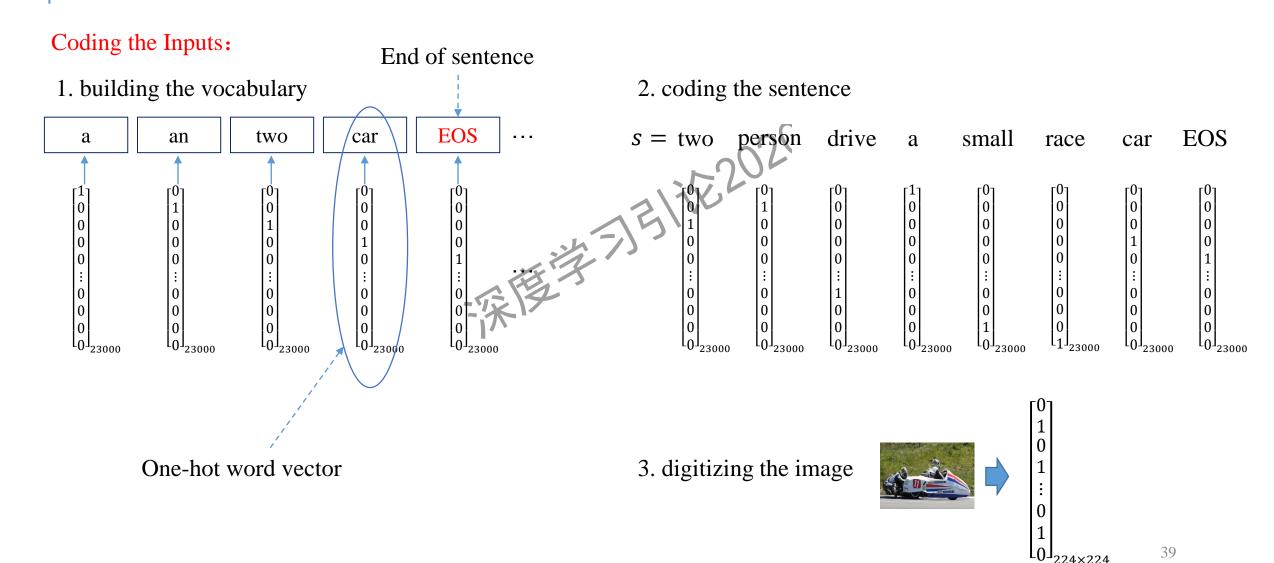


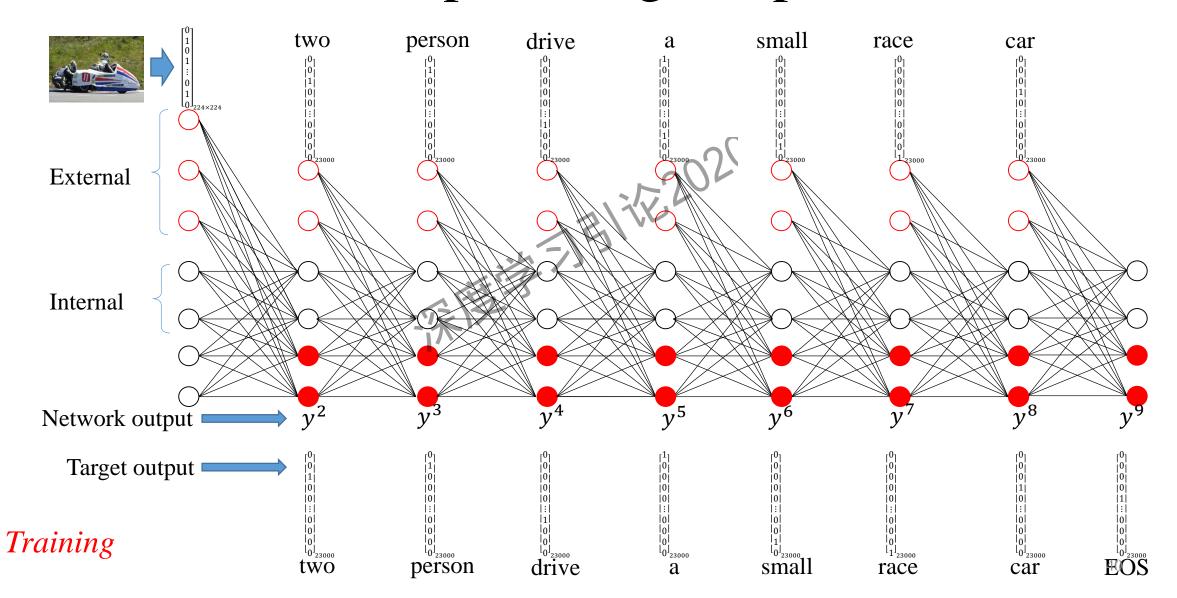


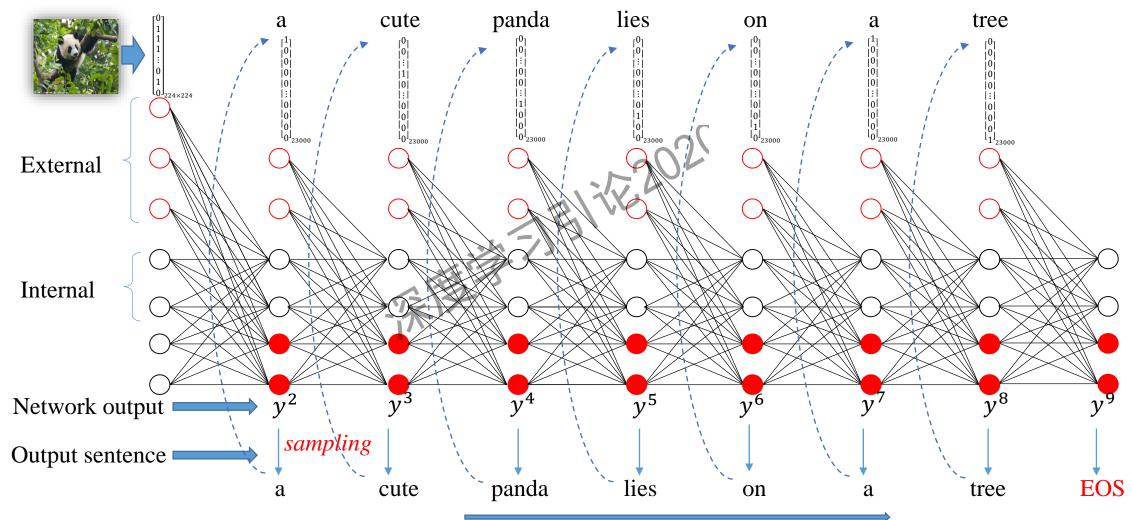


- 1. Two person drive a small race car .
- 2. Two racer drive a white bike down a road.
- 3. Two motorist be ride along on their vehicle that be oddly design and color.
- 4. Two person be in a small race car drive by a green hill.
- 5. Two person in race uniform in a street car .







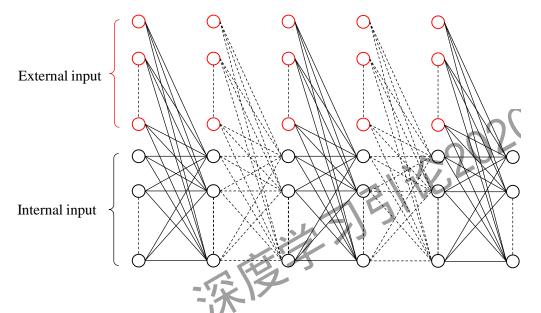


Illustrative Example: Poem Creating



陆游 ト算子・咏梅

驿外断桥边, 寂寞开无主。 已是黄昏独自愁, 更著风和雨。 无意苦争春, 一任群芳妒。 零落成泥碾作尘, 只有香如故。



Can artificial neural networks create poem?

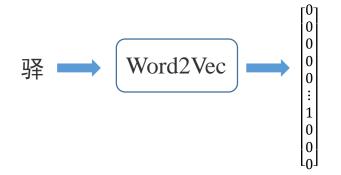




毛泽东 卜算子·咏梅

风雨送春归, 飞雪迎春到。 已是悬崖百丈冰, 犹有花枝俏。 俏也不争春, 只把春来报。 待到山花烂漫时, 她在丛中笑。

Illustrative Example: Poem Creating

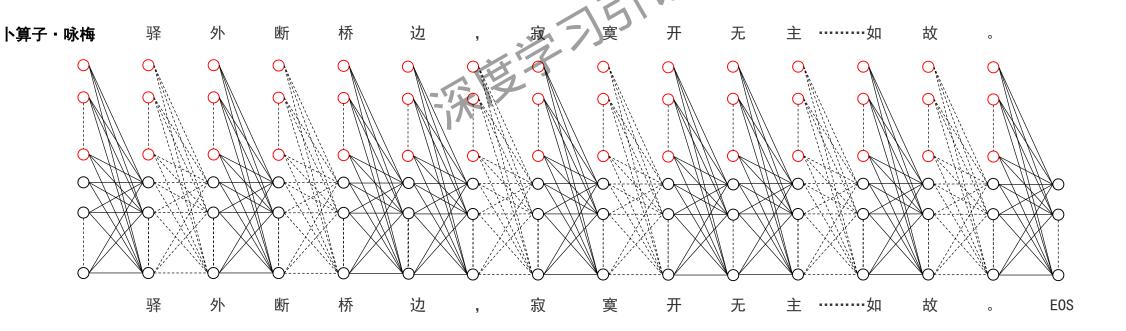


卜算子・咏梅

卜算子・咏梅

驿外断桥边, 寂寞开无主。 已是黄昏和雨。 无意苦争春, 一任群芳妒。 零落成泥碾作尘, 只有香如故。

风雨送春归, 飞雪迎春到。 已是悬崖百丈冰, 犹有花枝俏。 俏也不争春, 只把春来报。 待到山花烂漫时, 她在丛中笑。



Illustrative Example: Poem Creating



卜算子·咏梅

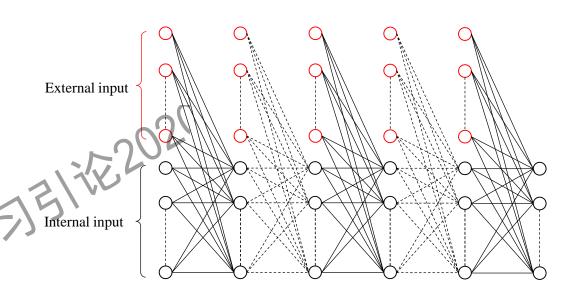
花谢早疏篱, 几度陶潜里。 永日梅花昔底寒, 比向梅花妒。 荣悴幻非凡, 谓是娇芳伴。 后著金陵几日时, 中酒争先理。

卜算子· 咏梅

朱阁见幽芳, 露叶梅花里。 玉屑琼台地屑琼, 玉屑琼飞尾。 便倚彩毫归, 使上簪盐谱。 别作千秋一笑随, 好趁伊家笑。

ト算子・咏梅

小试买梅花, 并蒂栖香粉。 肯向红蕖似竹姿, 一叶清风许。 心思寺炉高, 深院松间曲。 万纸参差故与黎, 效我何知道。



Outline

- A Sequence Recognizing Example
- Review of BP for Single Target Output NNs
- ■BP Method for Multiple Target Outputs NNs
- ■BP Algorithm for Multiple Target Outputs NNs
- ■Illustrative Examples
- Assignment

Assignment

Assignment:

Design a multi-target outputs neural network to learn to complete sequence. The first two items of a sequence uniquely determine the remaining four.

Training Dataset

111010	AC1231	AD1001	AE1019	
AA1212	AC1231	AD1221	AE1213	
BA2312	BB2323	BC2331	BE2313	
CB3123	CC3131	CD3121	CE3113	
DA2112	DB2123	DC2131	DD2121	
EA1312	EB1323	ED1321	EE1313	

Testing Dataset

The End

A Sequence Recognizing Example

