The Introduction To Artificial Intelligence

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The Introduction to Artificial Intelligence

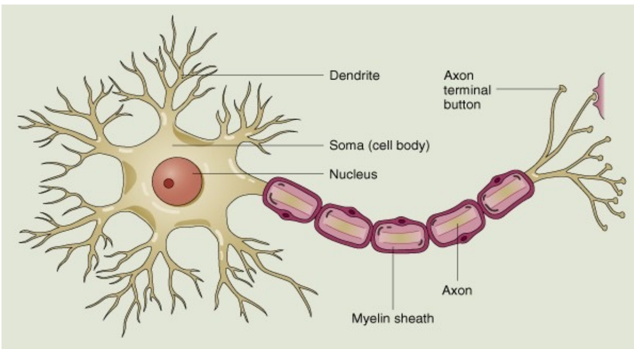
- Part I Brief Introduction to AI & Different AI tribes
- Part II Knowledge Representation & Reasoning
- Part III AI GAMES and Searching
- Part IV Model Evaluation and Selection
- Part V Machine Learning
- Part VI Neural Networks

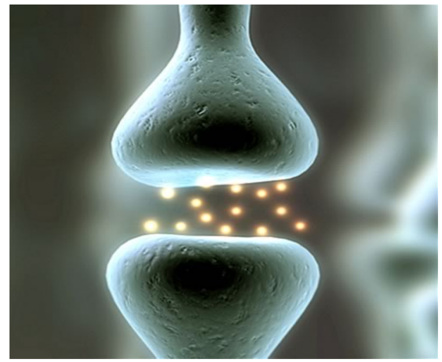
Neural Networks

- *Brief review*
- Sequence Learning

Brief review

Artificial Neuron





Neuron output

a

z

$a = f(z)$

Neuron input

x_1

Connection weights

w_1

x_i

w_i

w_n

x_n

$z = \sum_{i=1}^{n} w_i x_i$ | f

Activation function

$a = f(z)$

$$y = f\left(\sum_{i=1}^{n} w_i x_i\right)$$

Total input

inputs

Neuron output

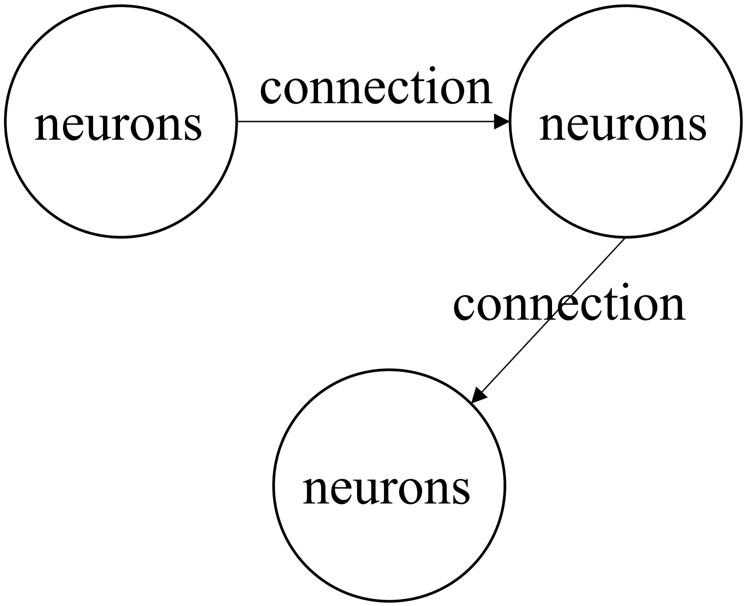
Computational Model of Neural Network

Neural Networks

Feedforward neural network

=

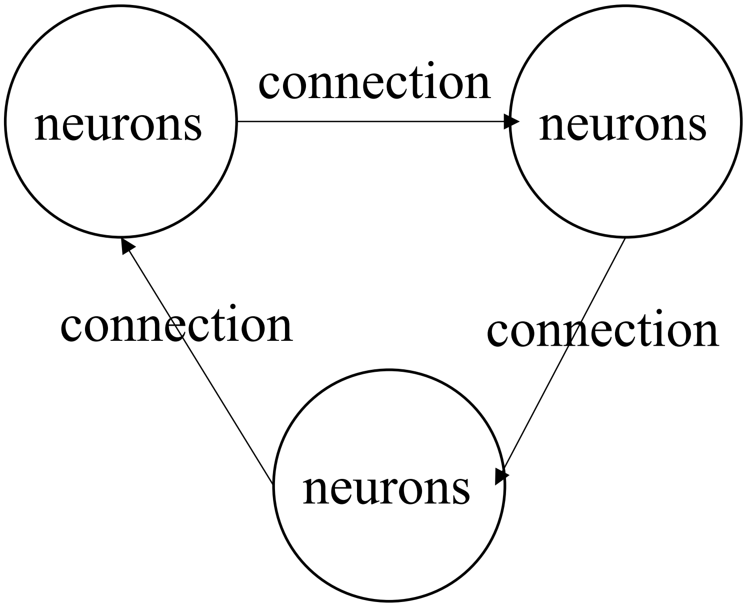
neurons + feedforward connections



Recurrent neural network

=

neurons + recurrent connections

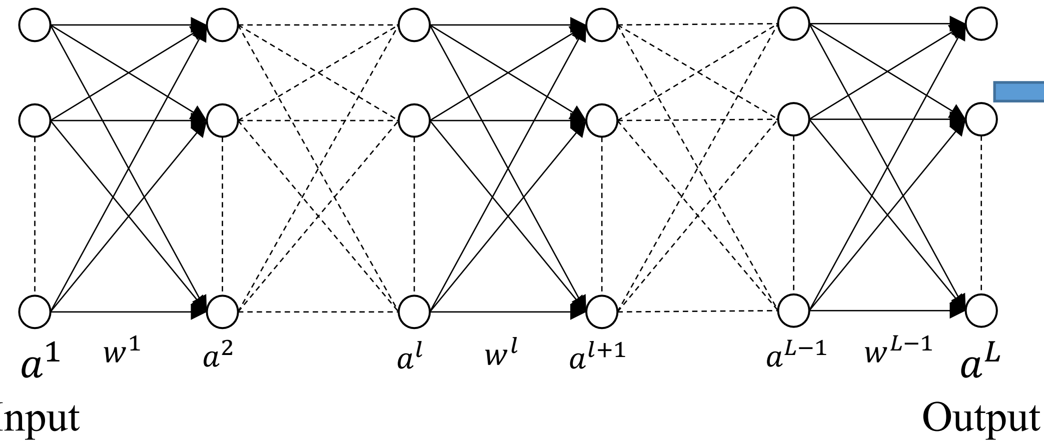


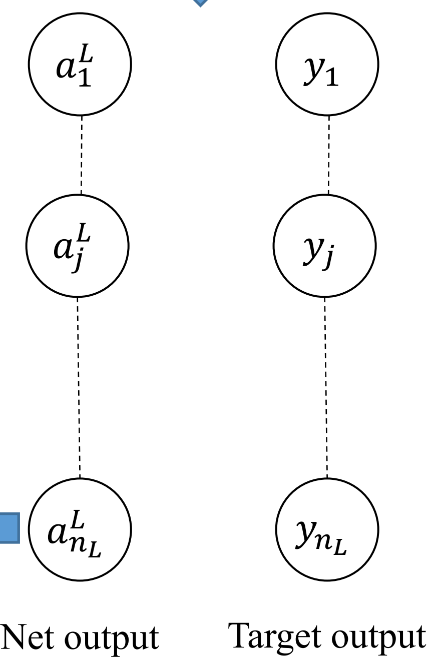
Steepest Descent Method

- Deep learning

Steepest Descent Algorithm:

$$w^{k+1} = w^k - \alpha_k \cdot \left.\frac{\partial F}{\partial w}\right|_{w^k}$$





Construct cost function

$$J = \frac{1}{2}\sum_{j=1}^{n_L}\left(y_j - a_j^L\right)^2$$

Computing gradient

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

Updating weights

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

Backpropagation

Conclusion: BP for FNN

Forward computing: $y = f\left(\sum_{i=1}^{n} w_i x_i\right)$

Define cost function: $J = J(w^1, \cdots, w^{L-1})$

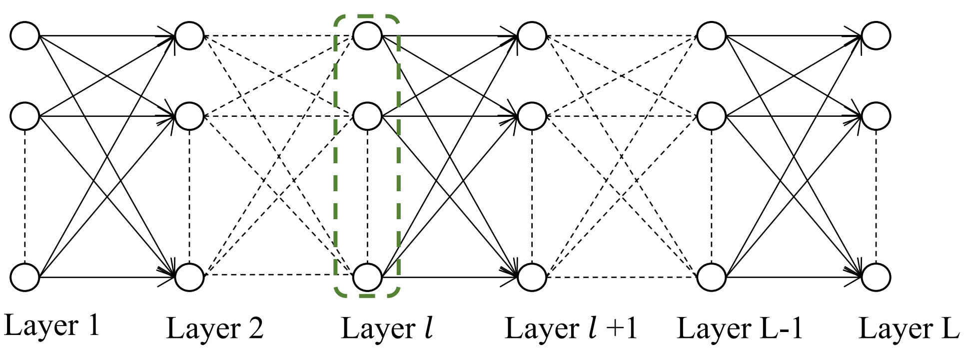
Updating rule: $w_{ji}^l \leftarrow w_{ji}^l - \alpha \cdot \dfrac{\partial J}{\partial w_{ji}^l}$

Define δ: $\delta_i^l = \dfrac{\partial J}{\partial z_i^l}$

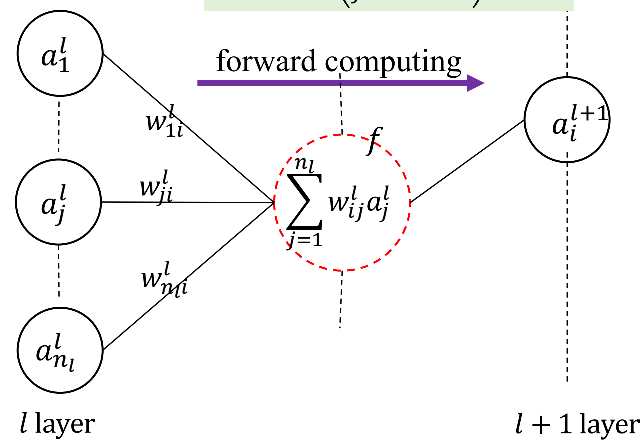
Find the relation: $\dfrac{\partial J}{\partial w_{ji}^l} = \delta_j^{l+1} \cdot a_i^l$

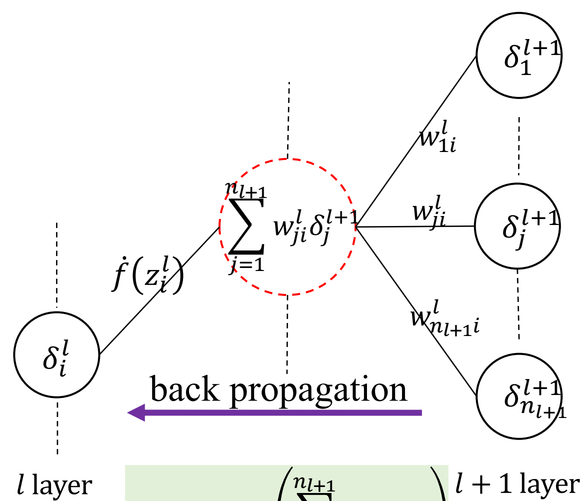
Back propagation: $\delta_i^L = \dfrac{\partial J}{\partial z_i^L} = (a_i^L - y_i^L) \cdot \dot{f}(z_i^L)$

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



$$a_i^{l+1} = f\left(\sum_{j=1}^{n_l} w_{ij}^l a_j^l \right)$$





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

Neural Networks

- Brief review
- Sequence Learning

Sequence Learning

A Sequence Recognizing Example

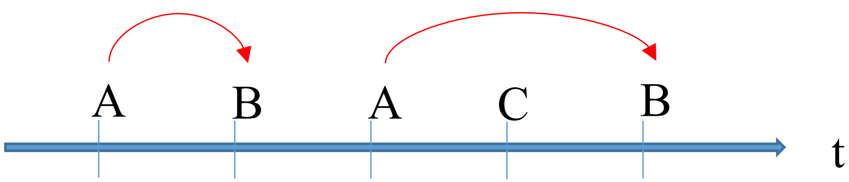
Recognize A followed by B Problem

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

………………



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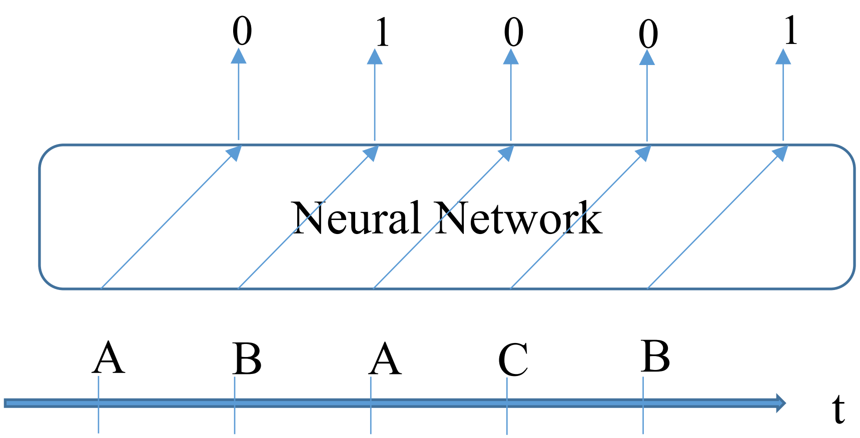

Problem: Can we use neural network to solve this problem?

Sequence Learning

A Sequence Recognizing Example

The brain can solve this problem simply by memorizing the last A.

Recognize A followed by B Problem

The task is to recognize A followed by B.

Generated Sequences

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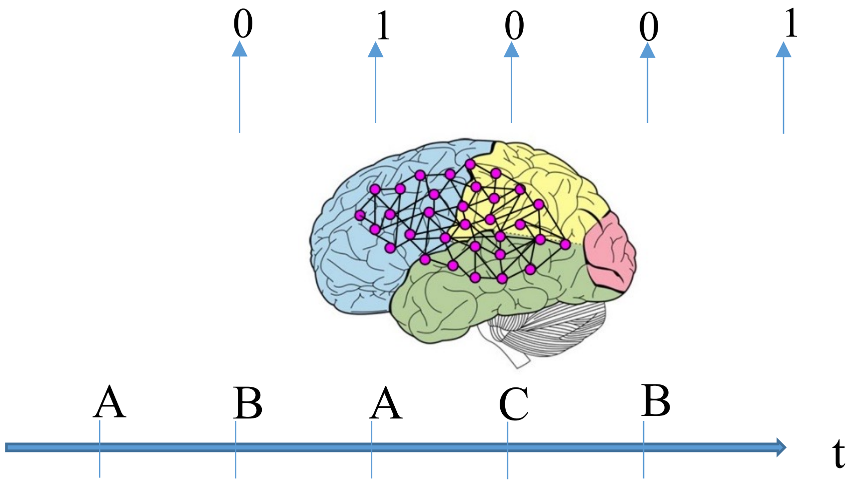

Problem: Can we use neural network to solve this problem?

Sequence Learning

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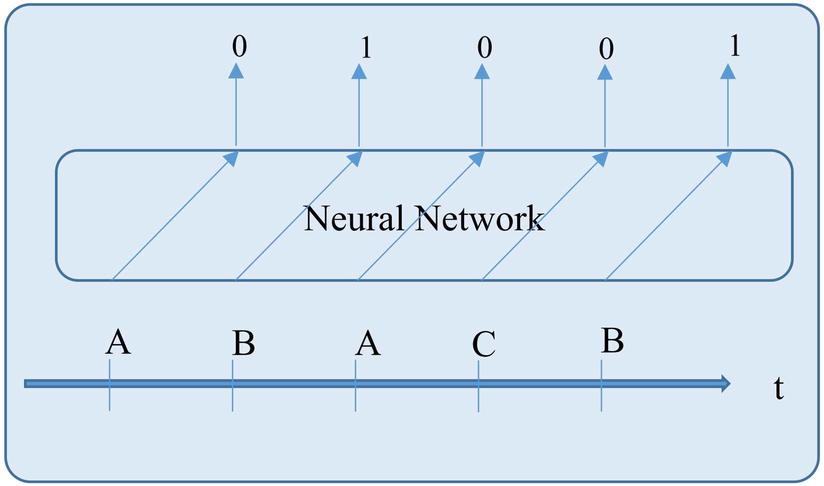

Generated Sequences

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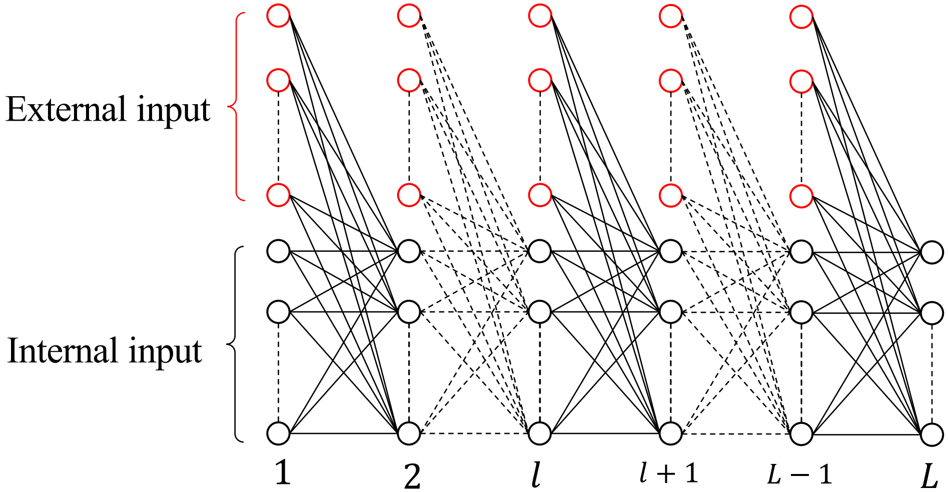
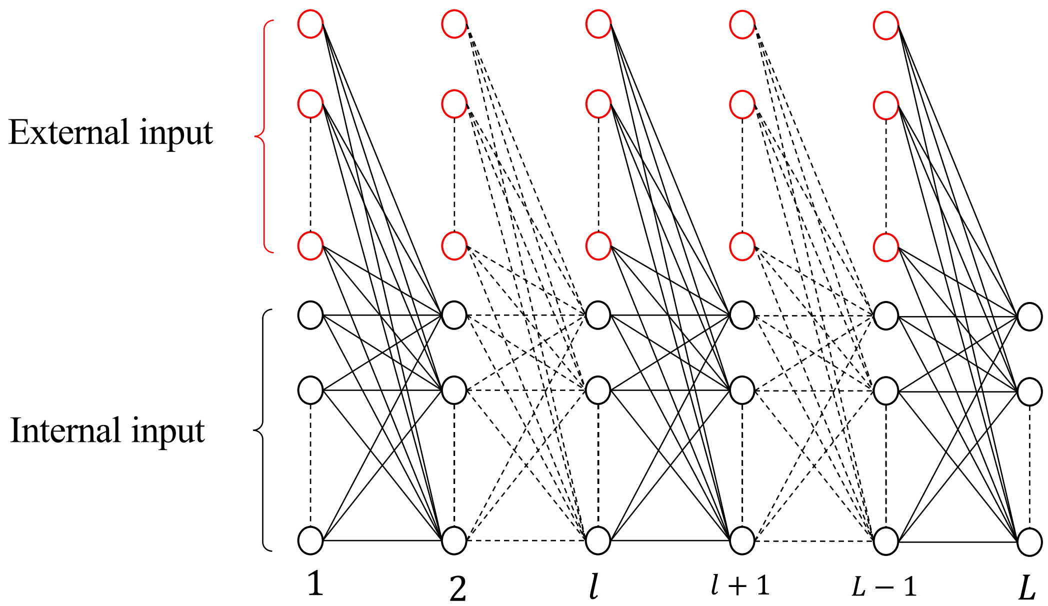


Sequence Learning

A Sequence Recognizing Example



Mono-target output

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

In the last layer only

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

Sequence Learning

A Sequence Recognizing Example

Recognize A followed by B Problem

The task is to recognize A followed by B.

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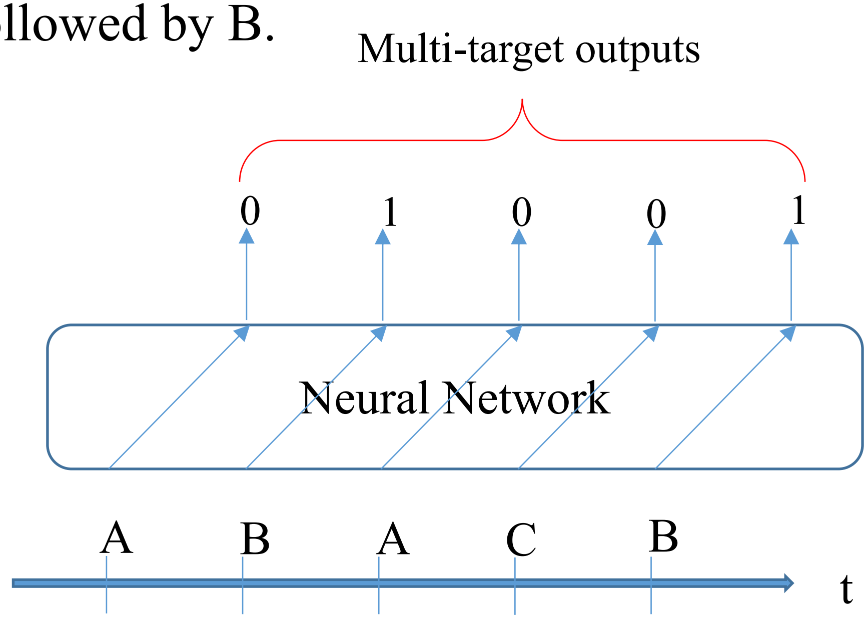
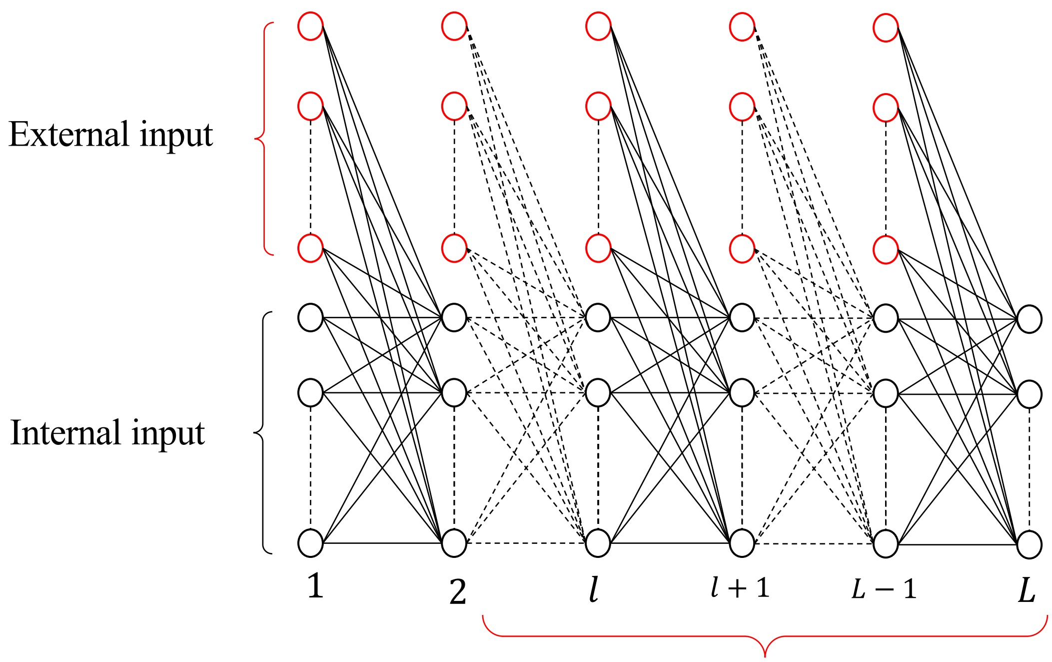


Problem: Can we use neural network to solve this problem?

Sequence Learning

A Sequence Recognizing Example



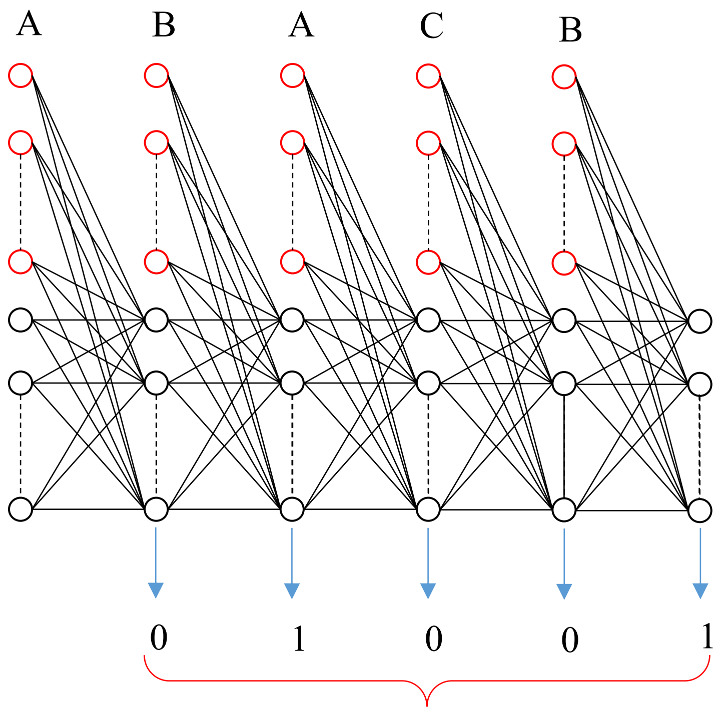
Multi-target outputs

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

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

Sequence Learning

A Sequence Recognizing Example



Multi-target outputs

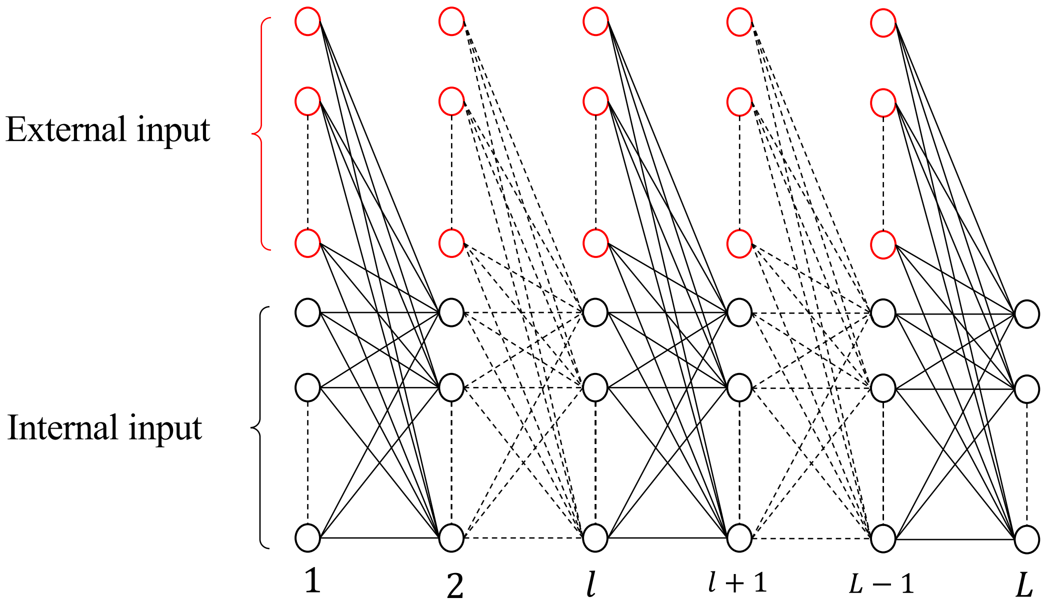
$$y^l = \begin{bmatrix} y_1^l \\ \vdots \\ y_{n_L}^l \end{bmatrix}$$

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

Problem:
How to develop algorithm to train the network?

Sequence Learning

A Sequence Recognizing Example



Mono-target output

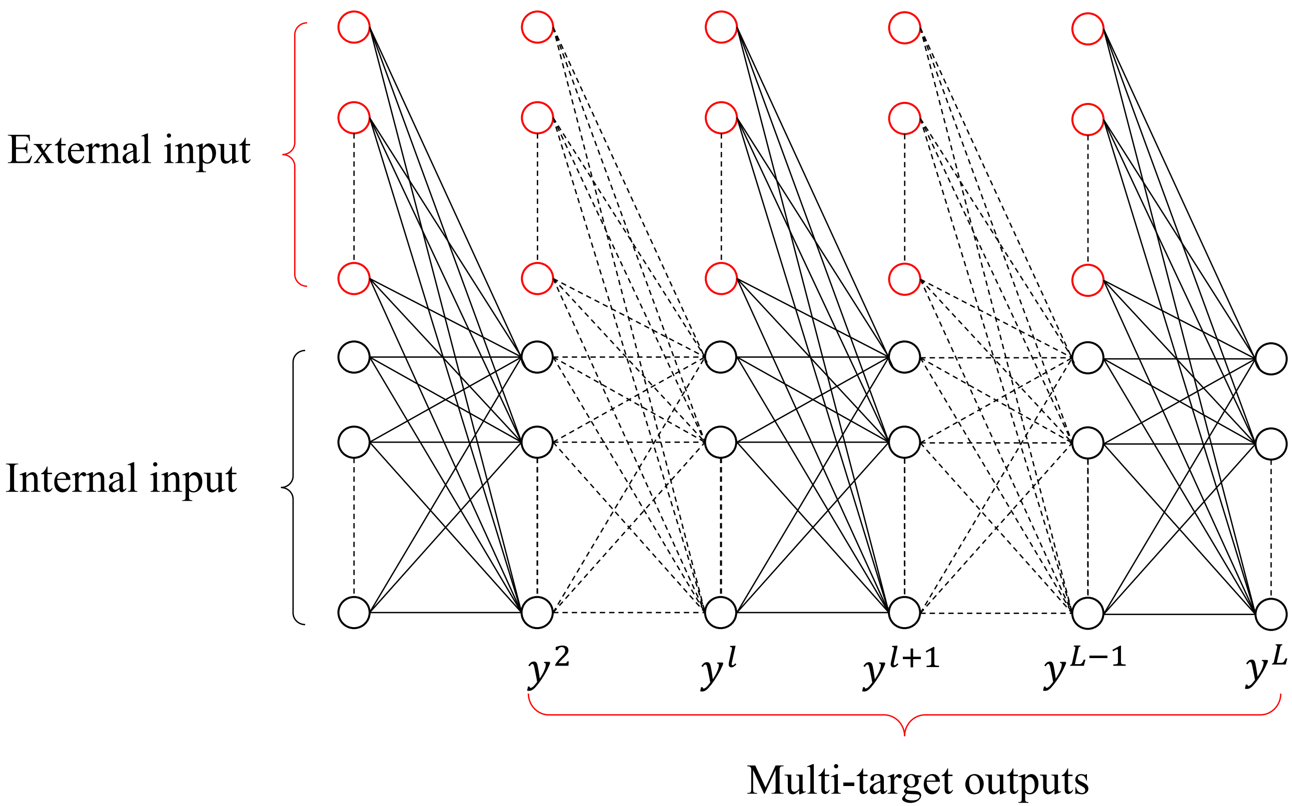
$$y^L = \begin{bmatrix} y_1^L \\ \vdots \\ y_{n_L}^L \end{bmatrix}$$

In the last layer only

We already developed BP Algorithm for mono-target output.

Sequence Learning

A Sequence Recognizing Example



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

Multi-target outputs

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

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

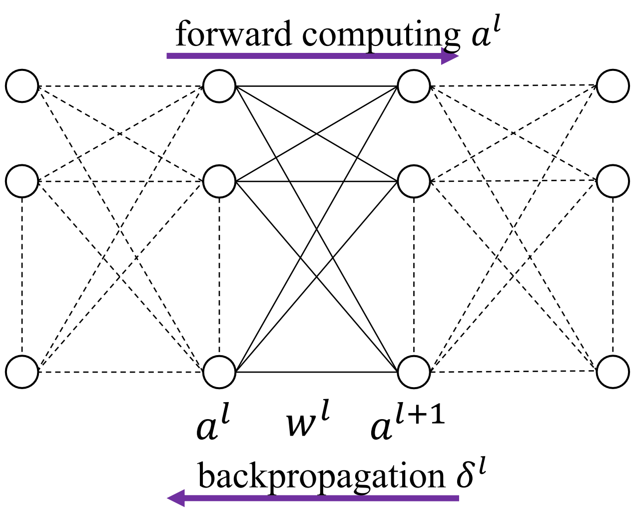
Sequence Learning

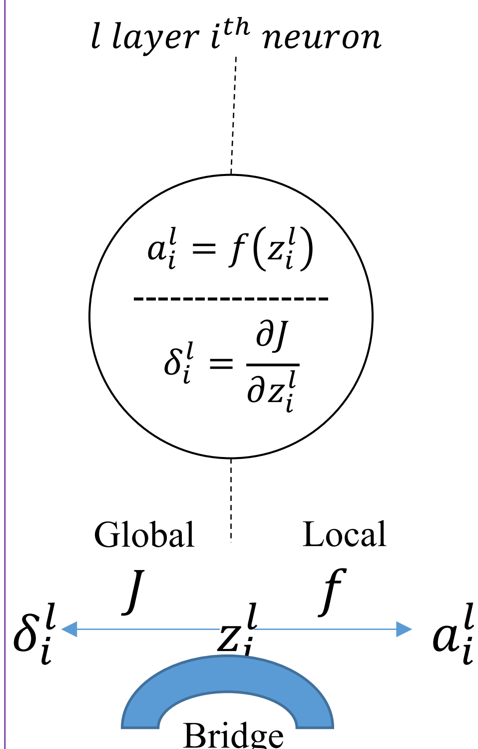
Review of BP algorithm for mono-output NNs

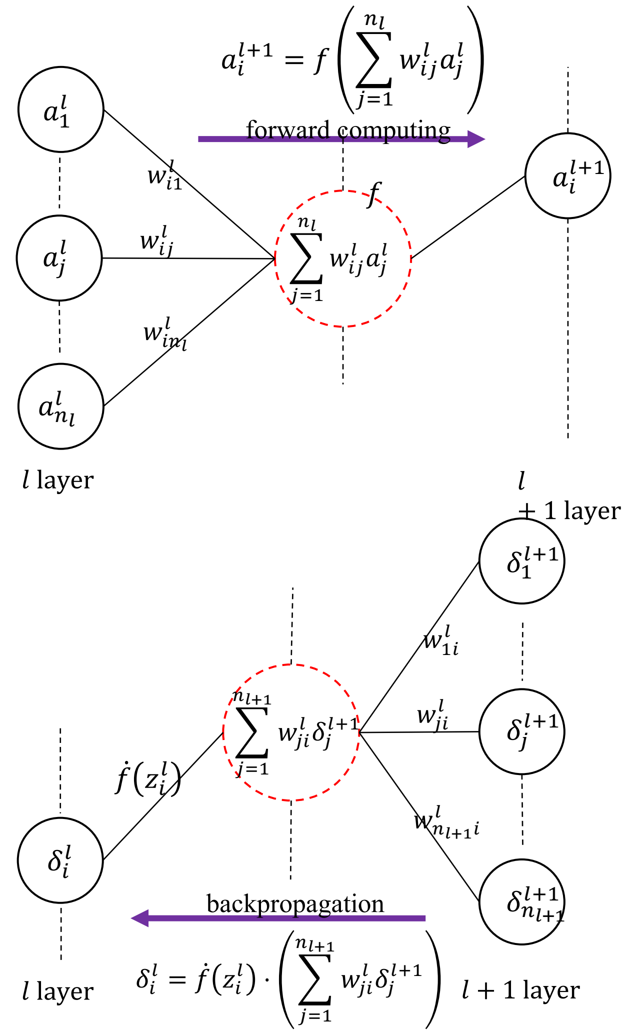
Cost function: $J(w^1, \cdots, w^{L-1})$

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

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

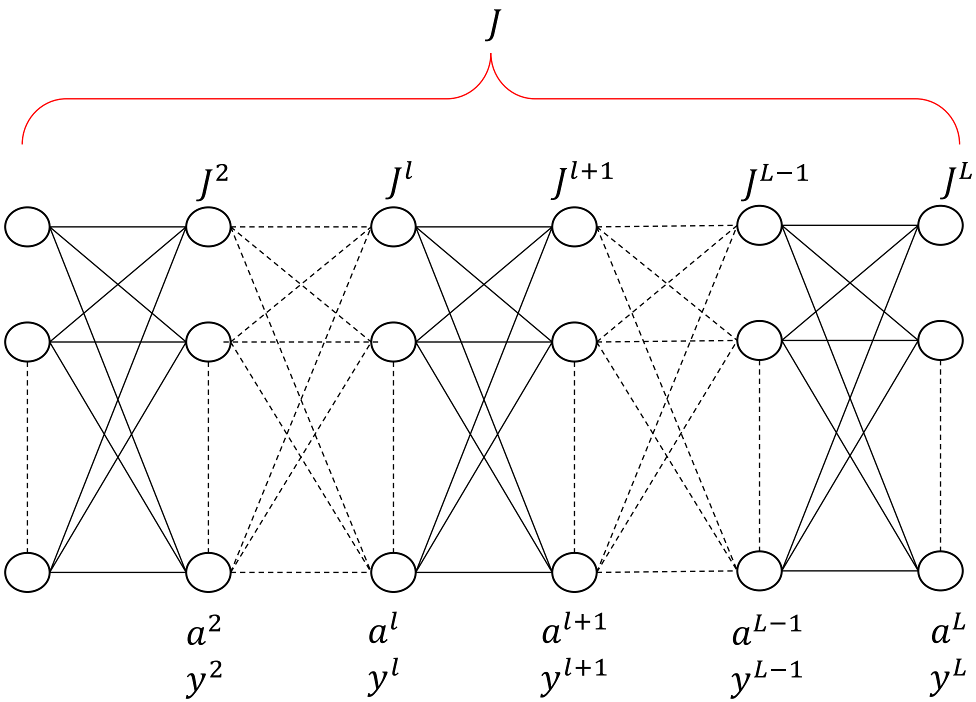






Sequence Learning

Review of BP algorithm for mono-output NNs



Cost function

$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2, (l = 2, \cdots, L)$$

$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2$$

Network Outputs

$$a^l = \begin{bmatrix} a_1^l \\ \vdots \\ a_{n_l}^l \end{bmatrix}$$

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

Multi-target outputs

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

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

Sequence Learning

Review of BP algorithm for mono-output NNs

Steepest Descent Method

$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2, (l = 2, \cdots, L)$$

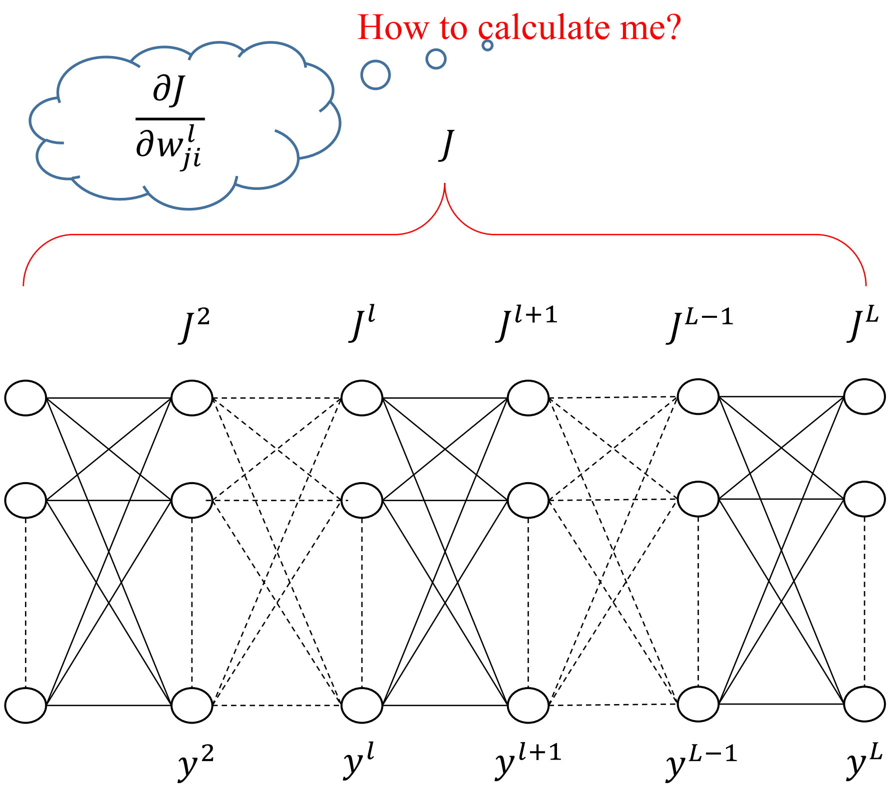
$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2$$

1. Computing

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

2. Iterating

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



Sequence Learning

Review of BP algorithm for mono-output NNs

l layer

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

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

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

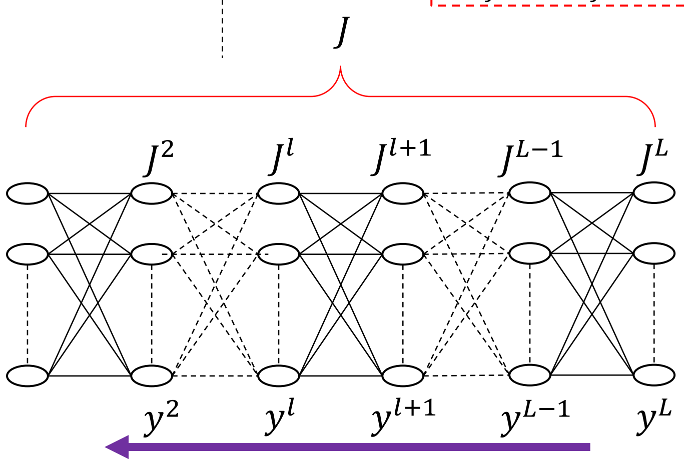
$$\frac{\partial J}{\partial w_{ji}^l} = \delta_j^{l+1} \cdot a_i^l$$

Why?

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

$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}(a_i^l - y_i^l)^2, (l = 2, \cdots, L)$$

$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}(a_i^l - y_i^l)^2$$



Problem: Can we back propagate δ^l?

l layer

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

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

w_{ji}^l

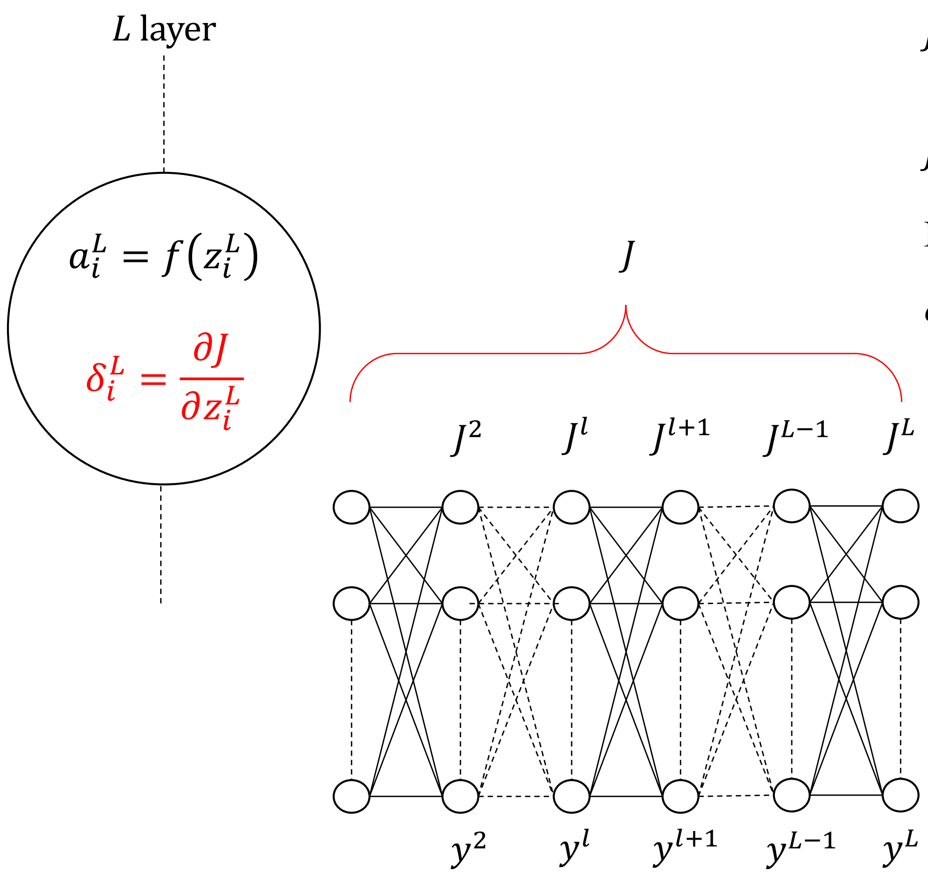
$l+1$ layer

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

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

Sequence Learning

Step 1: Calculating δ^L in Last Layer



$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2, (l = 2, \cdots, L)$$

$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2$$

It holds that,

$$\delta_i^L = \frac{\partial J}{\partial z_i^L} = \frac{\partial J^L}{\partial z_i^L} = \left(a_i^L - y_i^L\right) \cdot \frac{\partial a_j^L}{\partial z_i^L} = \left(a_i^L - y_i^L\right) \cdot \dot{f}\left(z_i^L\right)$$

Sequence Learning

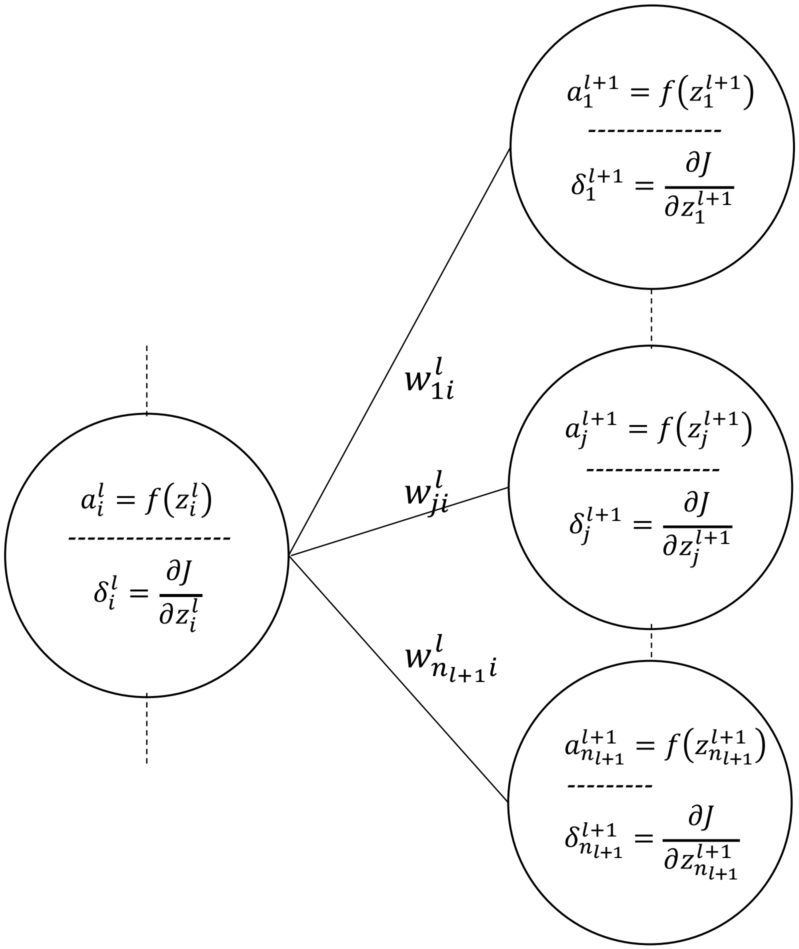
Step 2: Relation Between δ^l and δ^(l+1)

$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2, (l = 2, \cdots, L)$$

$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2$$

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

$$\delta_i^l = \frac{\partial J}{\partial z_i^l} = \frac{\partial J}{\partial z_i^l(*)} \cdot \frac{\partial z_i^l(*)}{\partial z_i^l} + \sum_{j=1}^{n_{l+1}} \frac{\partial J}{\partial z_j^{l+1}} \cdot \frac{\partial z_j^{l+1}}{\partial z_i^l}$$



Sequence Learning

Step 2: Relation Between δ^*l* and δ^(*l*+1)

$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2, (l = 2, \cdots, L)$$

$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2$$

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

$$\delta_i^l = \frac{\partial J}{\partial z_i^l} = \frac{\partial J}{\partial z_i^l(*)} \cdot \frac{\partial z_i^l(*)}{\partial z_i^l} + \sum_{j=1}^{n_{l+1}} \frac{\partial J}{\partial z_j^{l+1}} \cdot \frac{\partial z_j^{l+1}}{\partial z_i^l}$$

An Illustrate Example

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

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

$$x^* = x$$

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

Sequence Learning

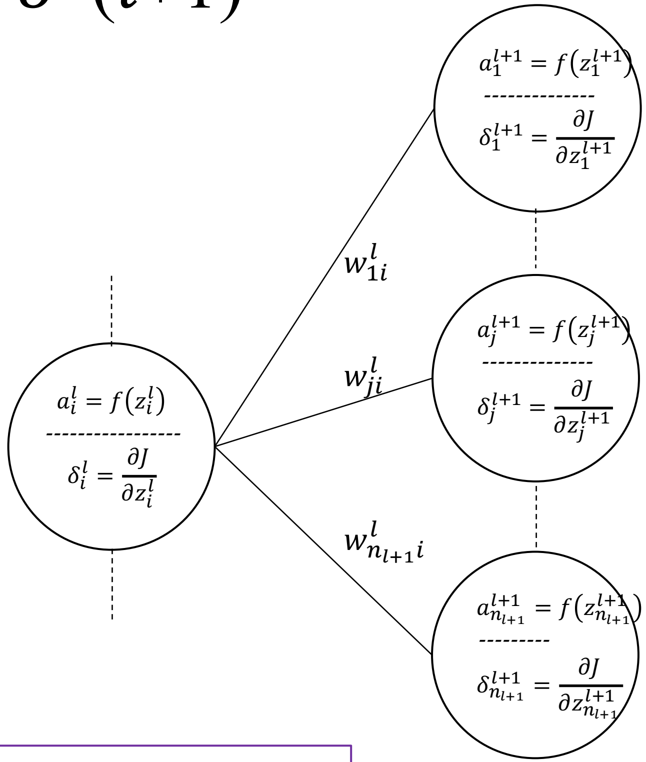
Step 2: Relation Between δ^l and δ^(l+1)

$$\delta_i^l = \frac{\partial J}{\partial z_i^l} = \frac{\partial J}{\partial z_i^l(*)} \cdot \frac{\partial z_i^l(*)}{\partial z_i^l} + \sum_{j=1}^{n_{l+1}} \frac{\partial J}{\partial z_j^{l+1}} \cdot \frac{\partial z_j^{l+1}}{\partial z_i^l}$$

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

$$\sum_{j=1}^{n_{l+1}} \frac{\partial J}{\partial z_j^{l+1}} \cdot \frac{\partial z_j^{l+1}}{\partial z_i^l} = \sum_{j=1}^{n_{l+1}} \delta_j^{l+1} \cdot \frac{\partial z_j^{l+1}}{\partial z_i^l} = \dot{f}\left(z_i^l\right) \cdot \left(\sum_{j=1}^{n_{l+1}} \delta_j^{l+1} \cdot w_{ji}^l\right)$$

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



$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2, (l = 2, \cdots, L)$$

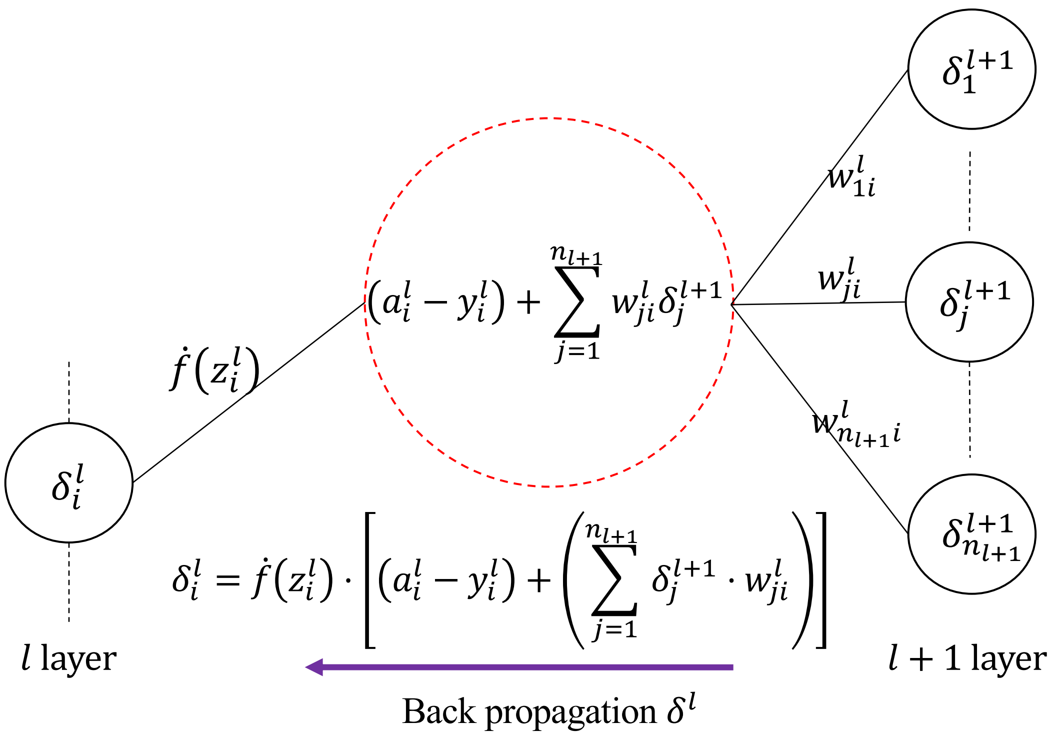
$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2$$

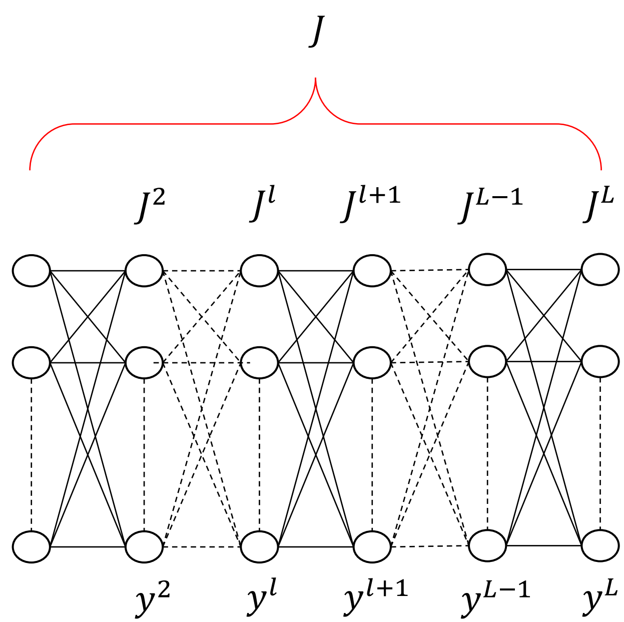
Sequence Learning

Step 3: Backpropagation δ

$$J^l = \frac{1}{2}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2, (l = 2, \cdots, L)$$

$$J = \sum_{l=2}^{L} J^l = \frac{1}{2}\sum_{l=2}^{L}\sum_{i=1}^{n_l}\left(a_i^l - y_i^l\right)^2$$





Sequence Learning

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 $D_m \subseteq D$

$$a^1 \leftarrow x \in D_m;$$

for $l = 1: L-1$

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

end

$$\delta^L = \frac{\partial J}{\partial z^L};$$

for $l = L-1: 2$

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

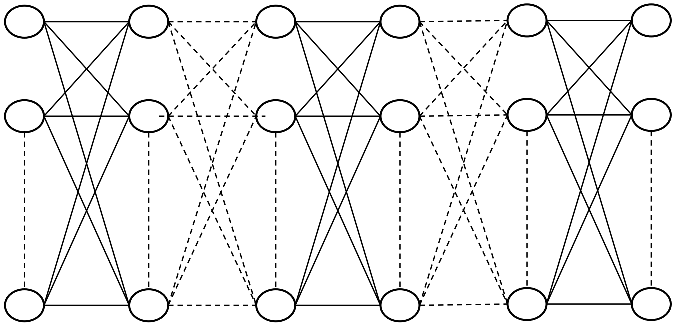
end

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

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

Relationship:

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

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

for $i = 1: n_l$

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

end

Sequence Learning

Illustrative Example

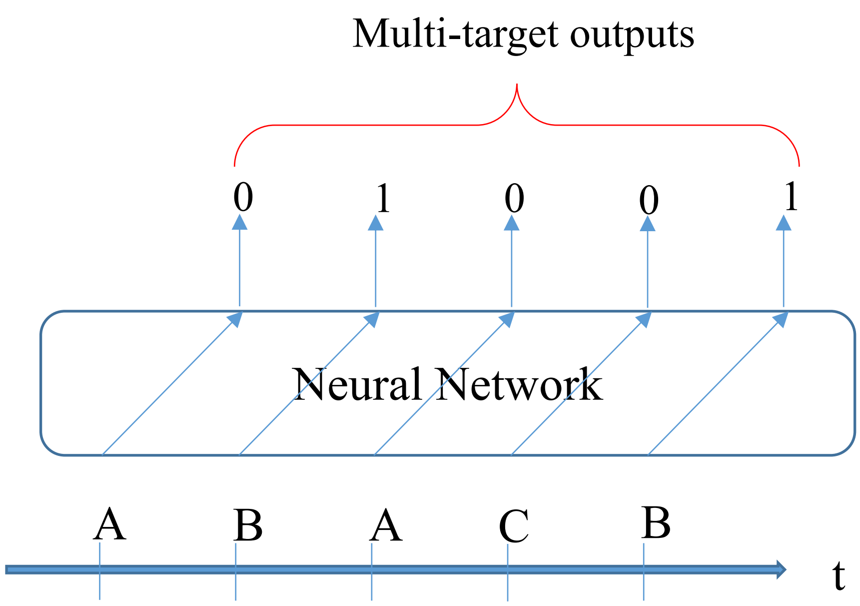
Recognize A followed by B Problem

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

……………..



Sequence Learning

Illustrative Example

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

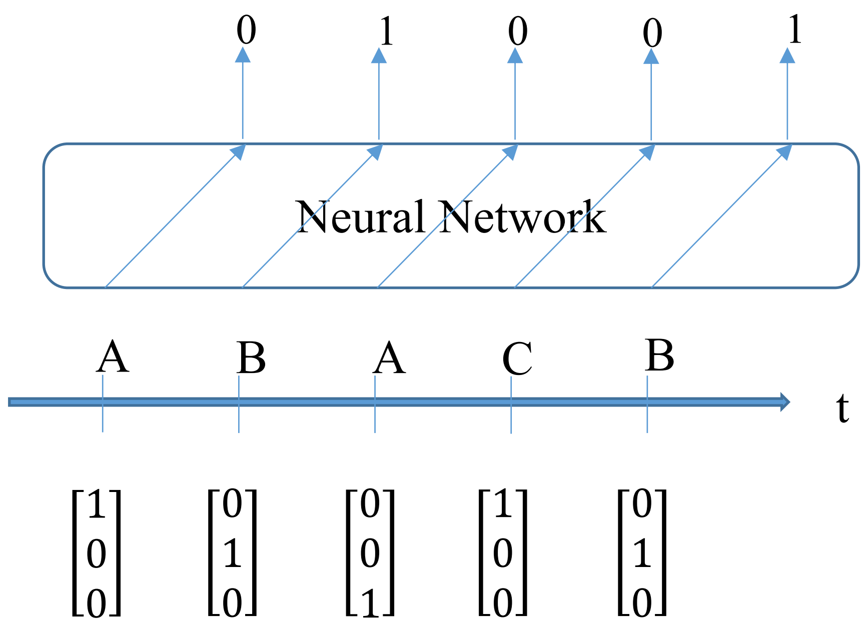
Generated Sequences

1. A B C A B

$$\begin{bmatrix}1\\0\\0\end{bmatrix}\begin{bmatrix}0\\1\\0\end{bmatrix}\begin{bmatrix}0\\0\\1\end{bmatrix}\begin{bmatrix}1\\0\\0\end{bmatrix}\begin{bmatrix}0\\1\\0\end{bmatrix}$$

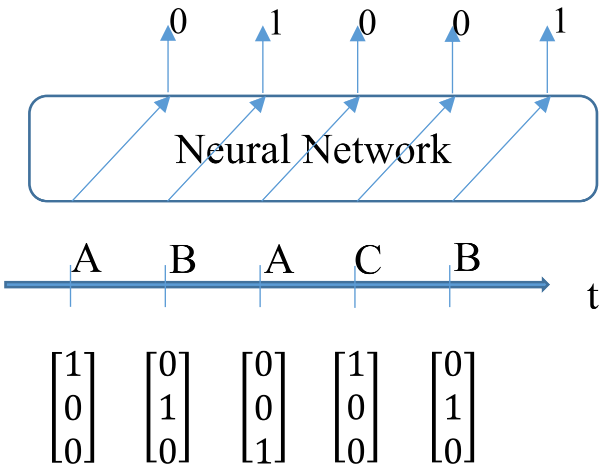
2. C A C C B

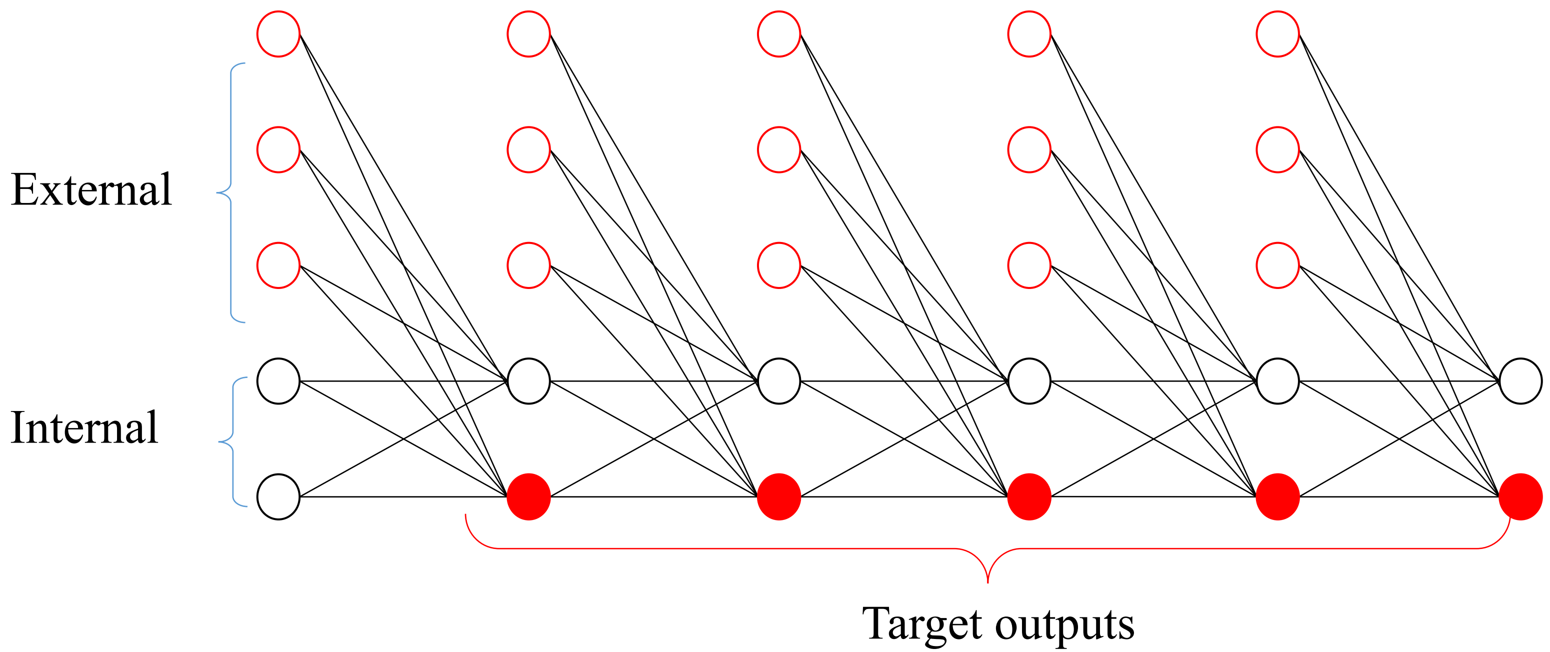
$$\begin{bmatrix}0\\0\\1\end{bmatrix}\begin{bmatrix}1\\0\\0\end{bmatrix}\begin{bmatrix}0\\0\\1\end{bmatrix}\begin{bmatrix}0\\0\\1\end{bmatrix}\begin{bmatrix}0\\1\\0\end{bmatrix}$$



Sequence Learning

Illustrative Example





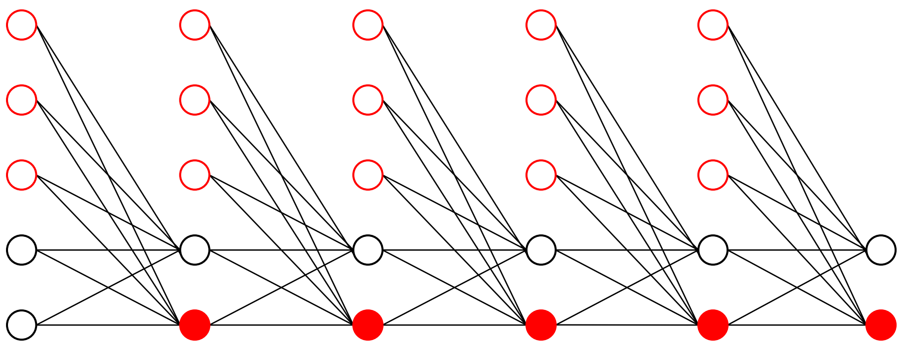
Sequence Learning

Illustrative Example

Generated Training Sequences

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

……….......



Generated Testing Sequences

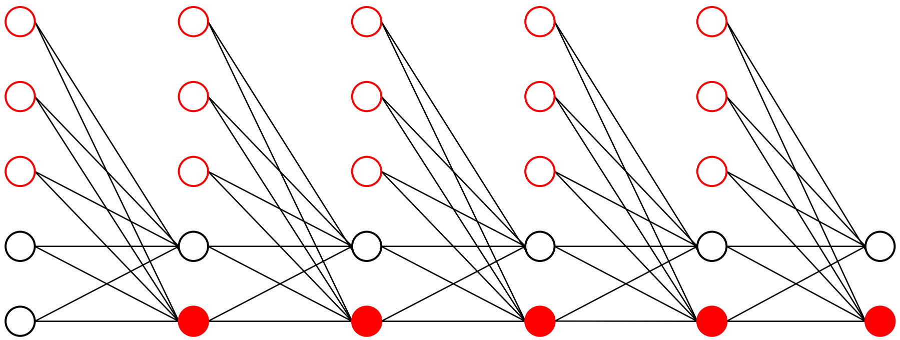
1. CBCAC
2. ACBBA
3. BACCB
4. ACBCB
5. AACBC
6. BAACB
7. AAACB
8. CCBAB
9. BBCAB
10. AABAC

……….......

Sequence Learning

Illustrative Example

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



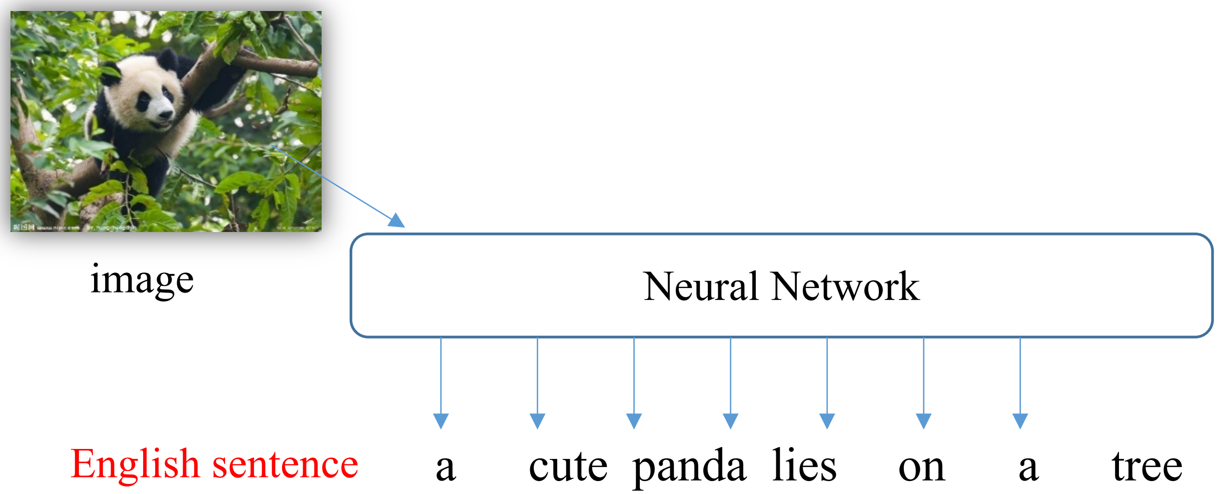
Example outputs:

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

Sequence Learning

Another Example: Image Caption

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



Sequence Learning

Another Example: Image Caption

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

Microsoft

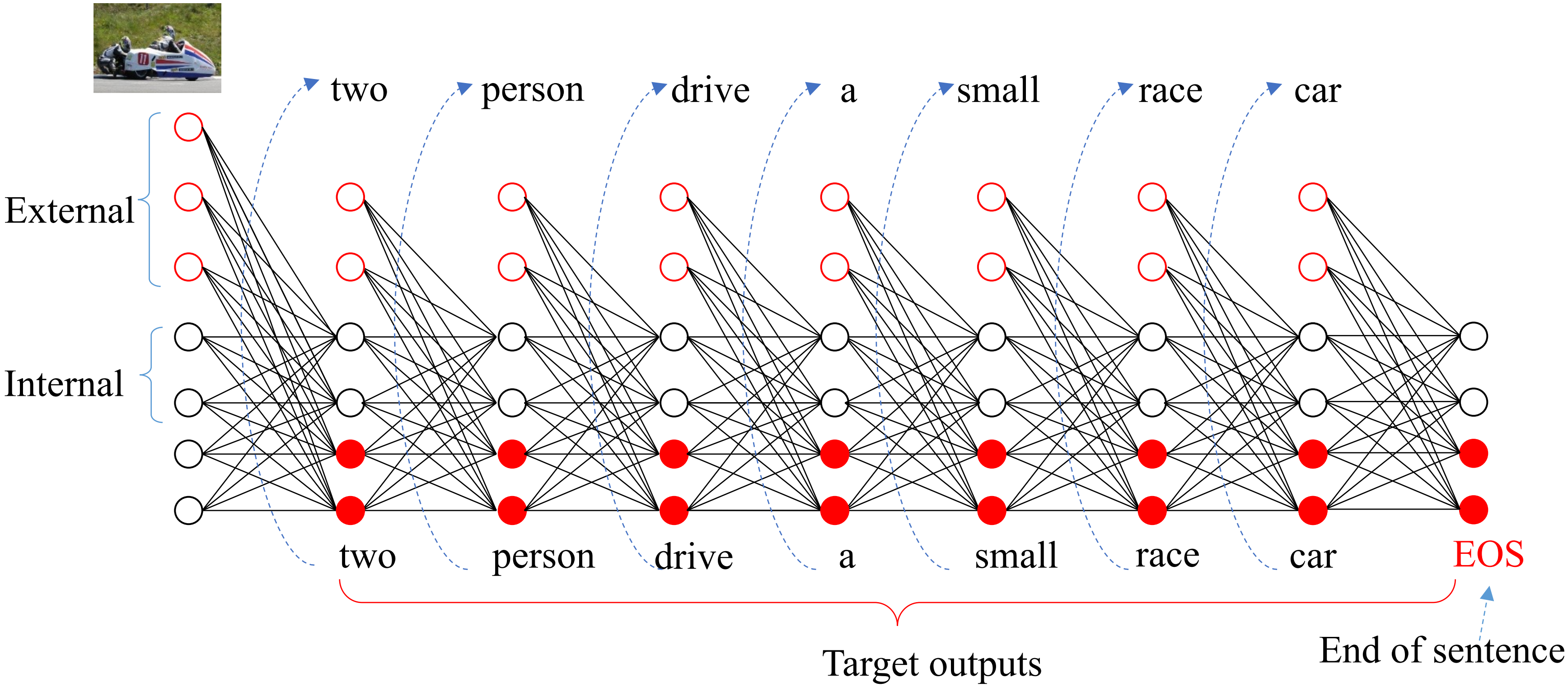
Dataset

$$D = \{(x, \underbrace{s_1, s_2, s_3, s_4, s_5})\}$$

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 .

Sequence Learning

- Another Example: Image Caption



Sequence Learning

Another Example: Image Caption

Coding the Inputs：

1. building the vocabulary

End of sentence

a	an	two	car	EOS	…

$$\begin{bmatrix}1\\0\\0\\0\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\1\\0\\0\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\1\\0\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\0\\1\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\0\\0\\1\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\cdots$$

One-hot word vector

2. coding the sentence

$s =$ two person drive a small race car EOS

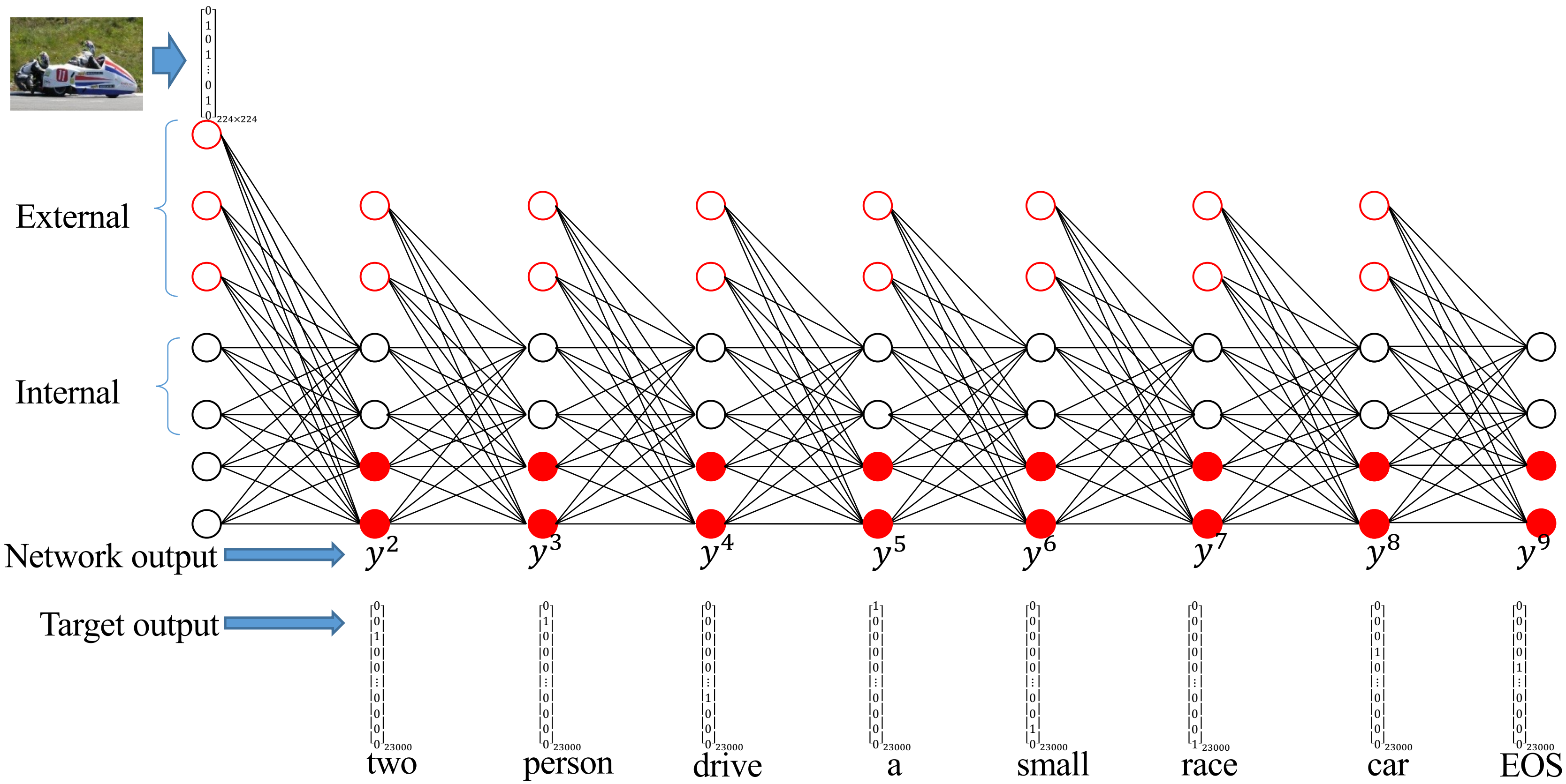
$$\begin{bmatrix}0\\0\\1\\0\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\1\\0\\0\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\0\\0\\0\\\vdots\\1\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}1\\0\\0\\0\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\0\\0\\0\\\vdots\\0\\0\\1\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\0\\0\\0\\\vdots\\0\\0\\0\\1\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\0\\1\\0\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}\quad\begin{bmatrix}0\\0\\0\\0\\1\\\vdots\\0\\0\\0\\0\end{bmatrix}_{23000}$$

3. digitizing the image

$$\Rightarrow \begin{bmatrix}0\\1\\0\\1\\\vdots\\0\\1\\0\end{bmatrix}_{224\times224}$$

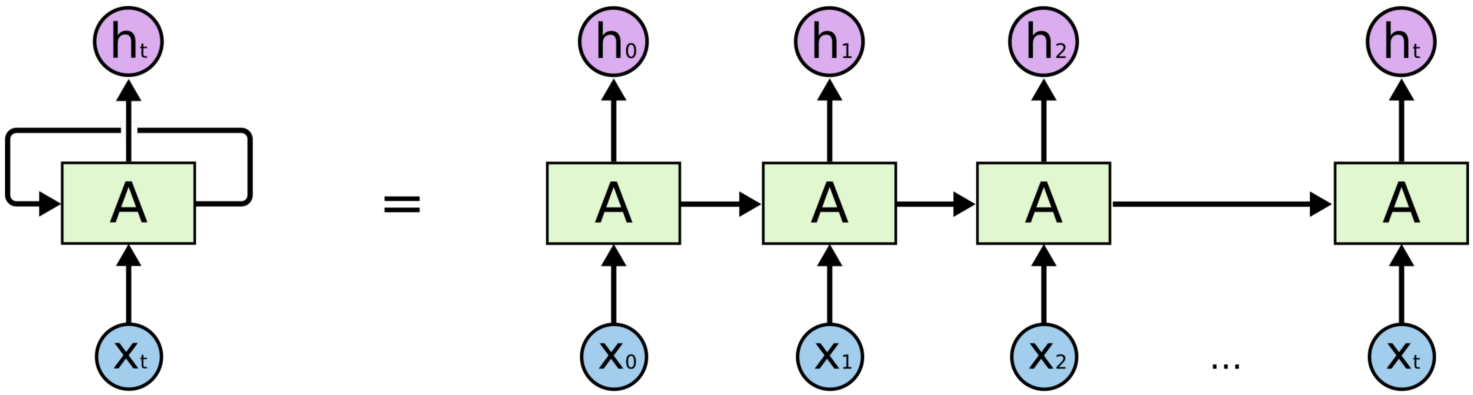
Sequence Learning

Another Example: Image Caption



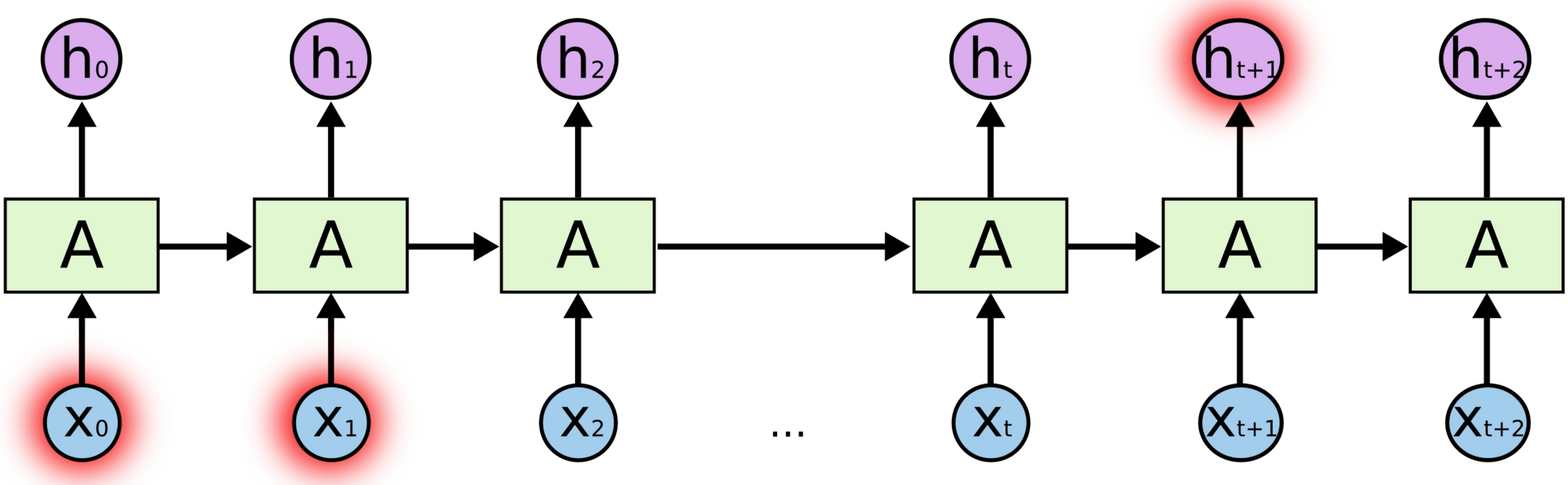
Sequence Learning

Other RNN



Sequence Learning

Other RNN



长期依赖(Long Term Dependencies)

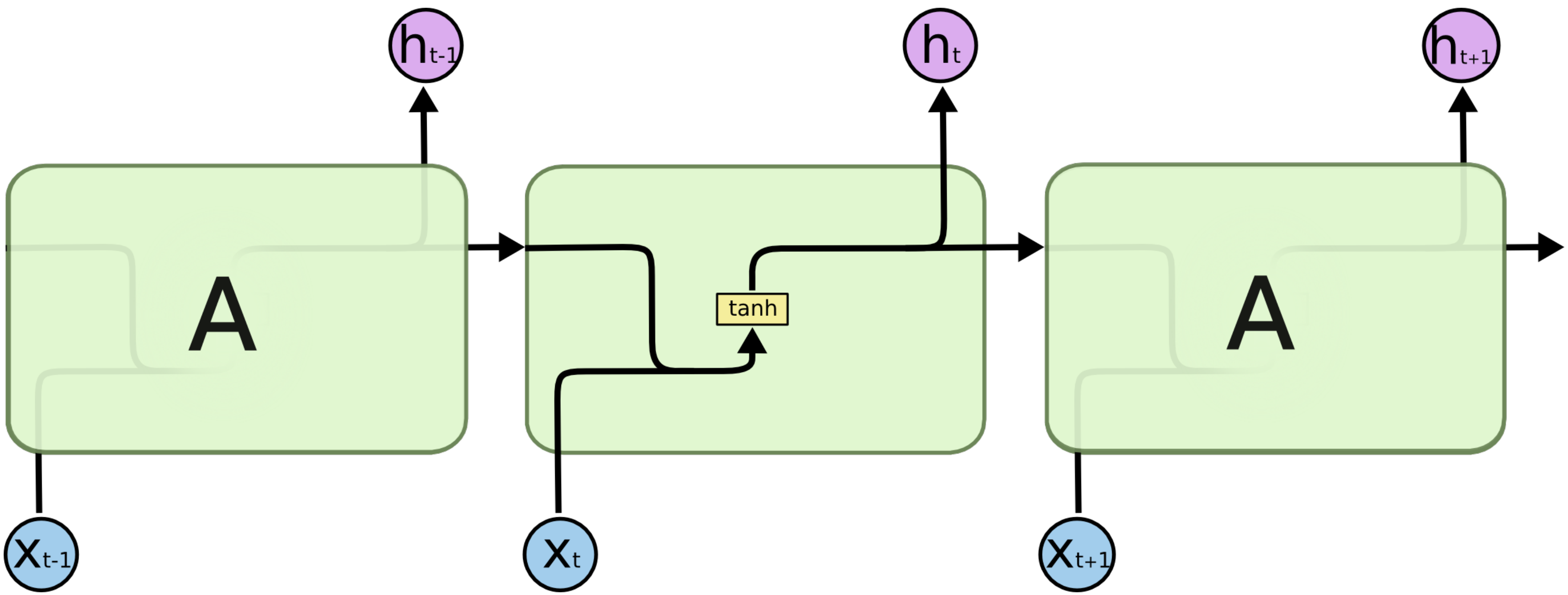
eg1: The cat, which already ate a bunch of food, was full.

eg2: The cats, which already ate a bunch of food, were full.

Sequence Learning

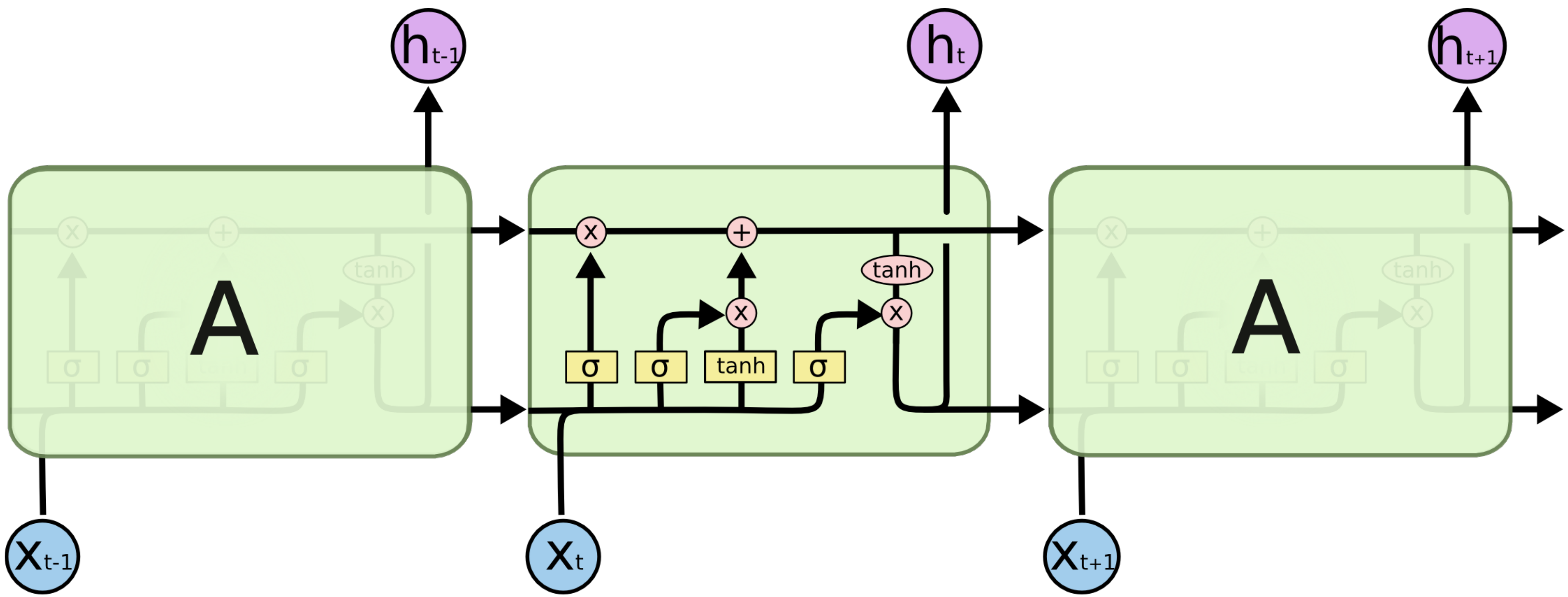
Other RNN - LSTM

LSTM: Long Short Term Memory，顾名思义，它具有记忆长短期信息的能力的神经网络



Sequence Learning

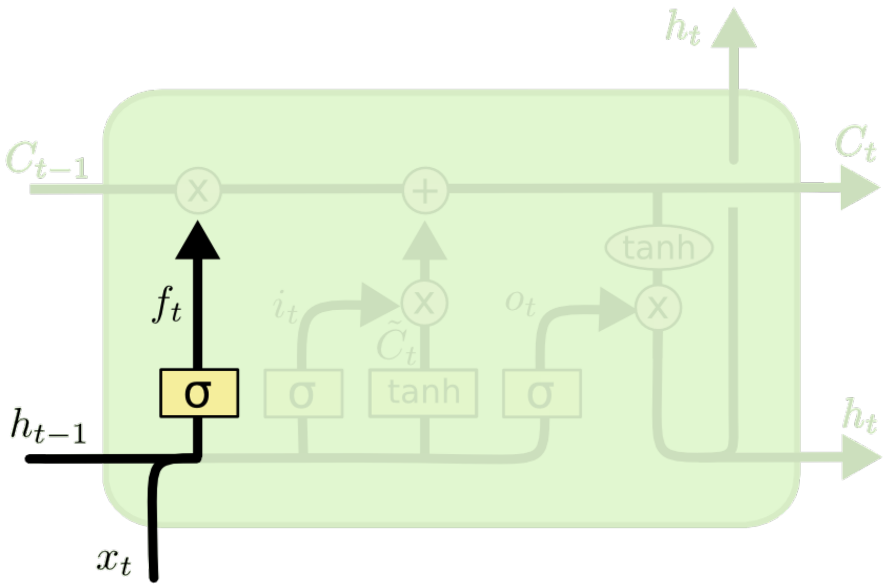
Other RNN - LSTM



LSTM解决RNN的长期依赖问题:LSTM引入了门（gate）机制用于控制特征的流通和损失

Sequence Learning

Other RNN - LSTM

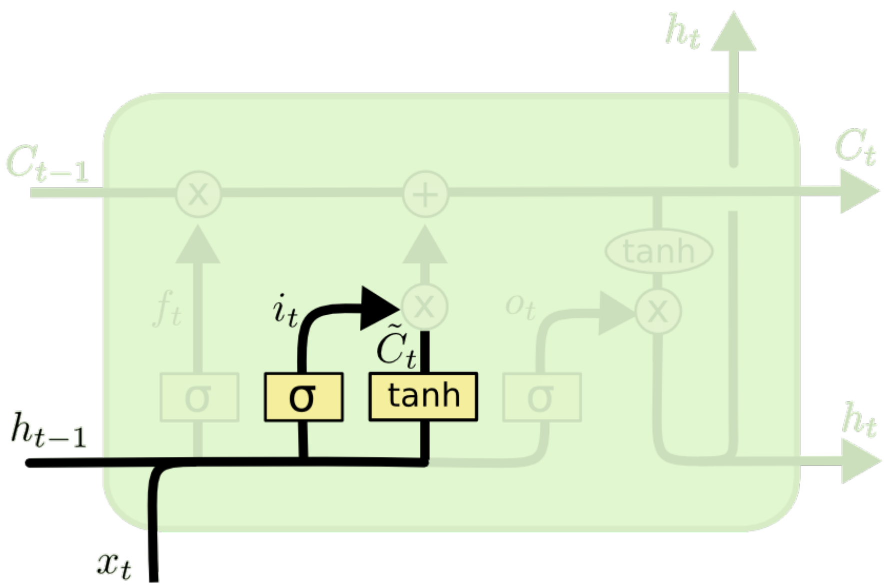


$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \ + \ b_f\right)$$

f_t 遗忘门

Sequence Learning

Other RNN - LSTM

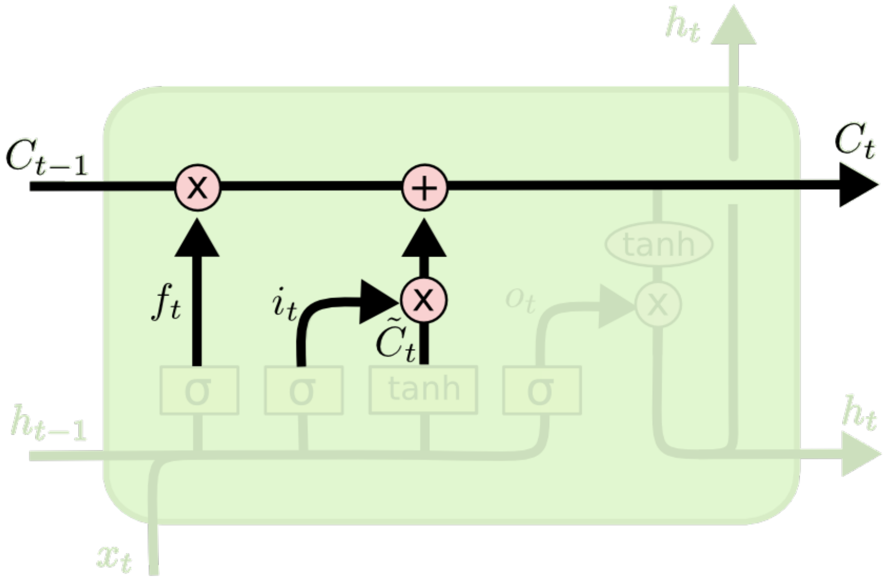


$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

Sequence Learning

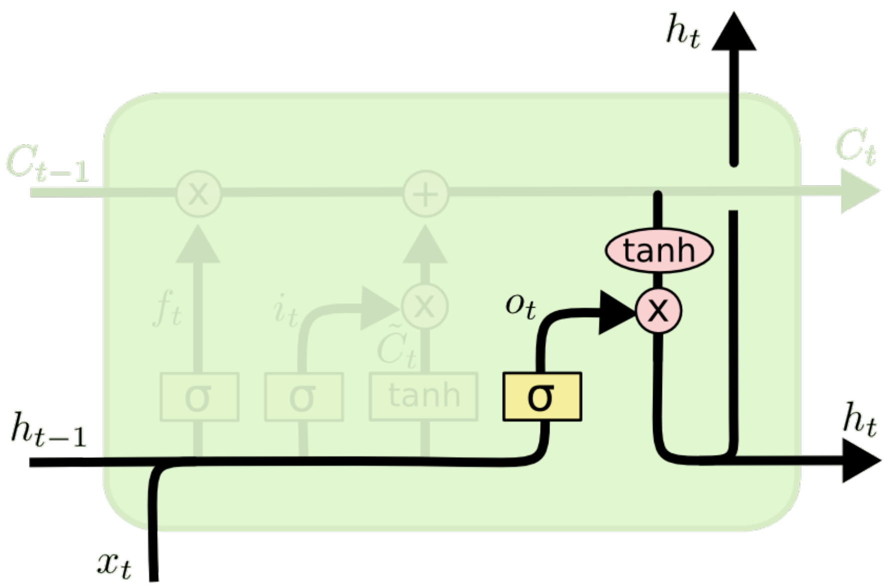
Other RNN - LSTM



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

Sequence Learning

Other RNN - LSTM

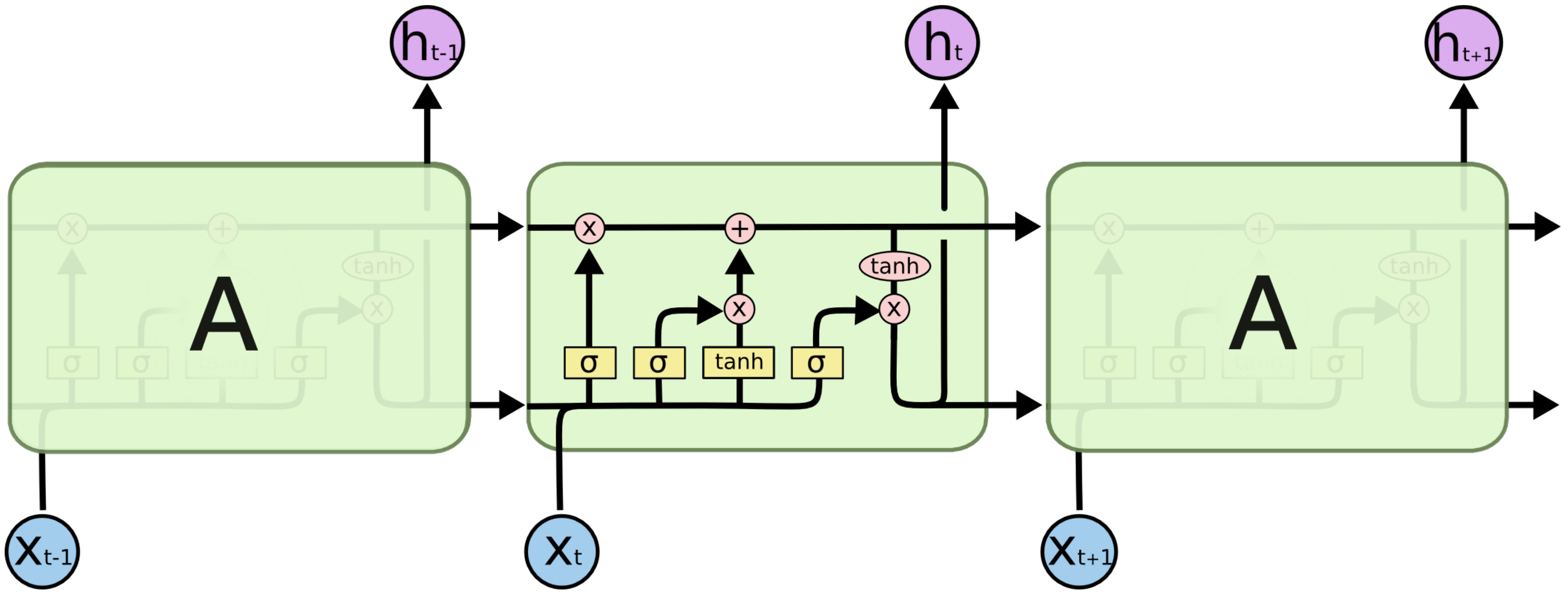


$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$

$$h_t = o_t * \tanh\left(C_t\right)$$

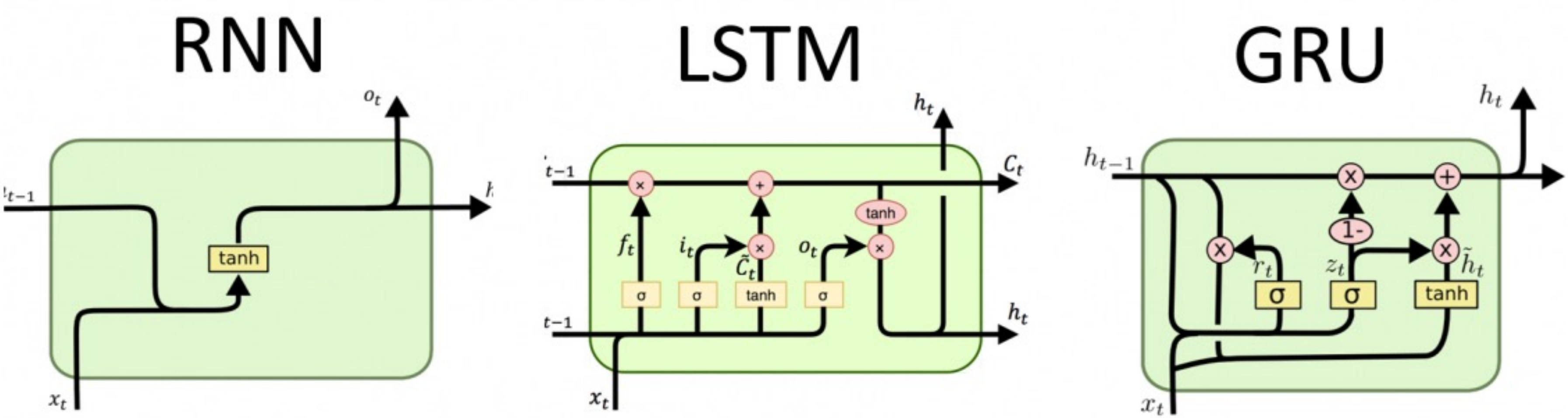
Sequence Learning

Other RNN - LSTM



Sequence Learning

Other RNNs

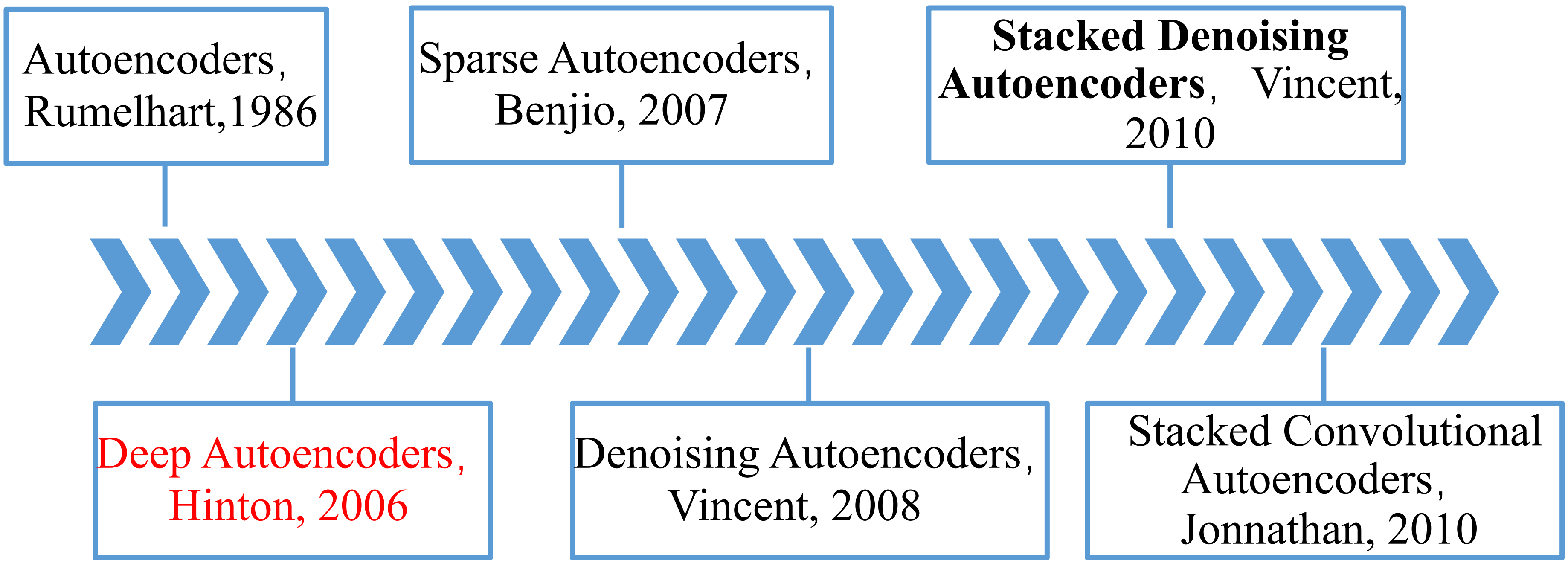


Neural Networks

- Brief review
- Sequence Learning
- *Representation learning*

Representation learning

- Autoencoders



Representation learning

- Autoencoders

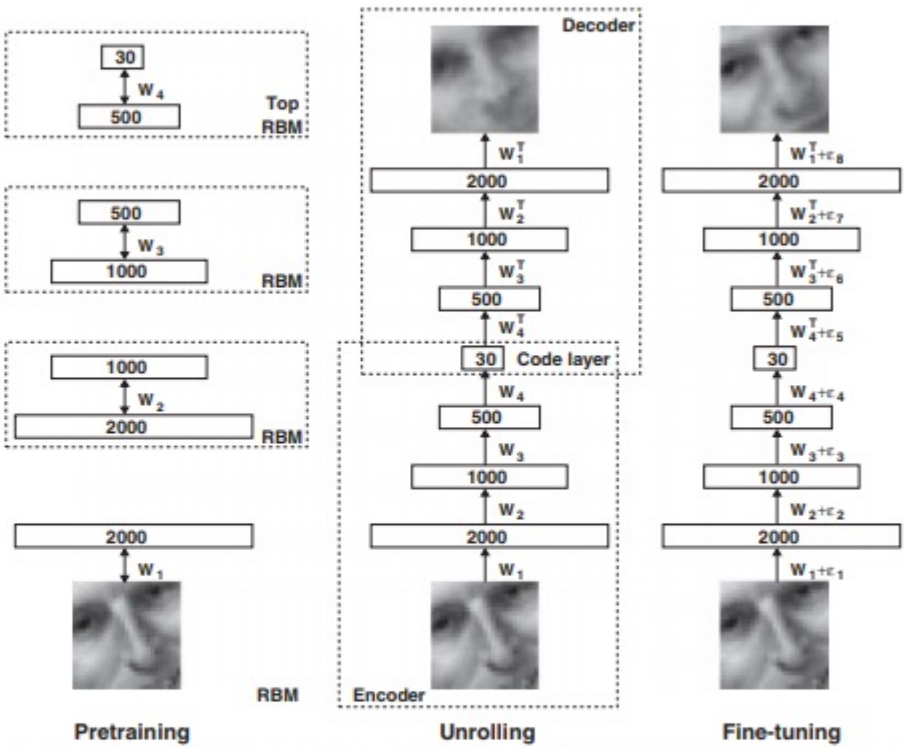


Fig. 1. Pretraining consists of learning a stack of restricted Boltzmann machines (RBMs), each having only one layer of feature detectors. The learned feature activations of one RBM are used as the "data" for training the next RBM in the stack. After the pretraining, the RBMs are "unrolled" to create a deep autoencoder, which is then fine-tuned using backpropagation of error derivatives.

Reducing the Dimensionality of Data with Neural Networks

G. E. Hinton* and R. R. Salakhutdinov

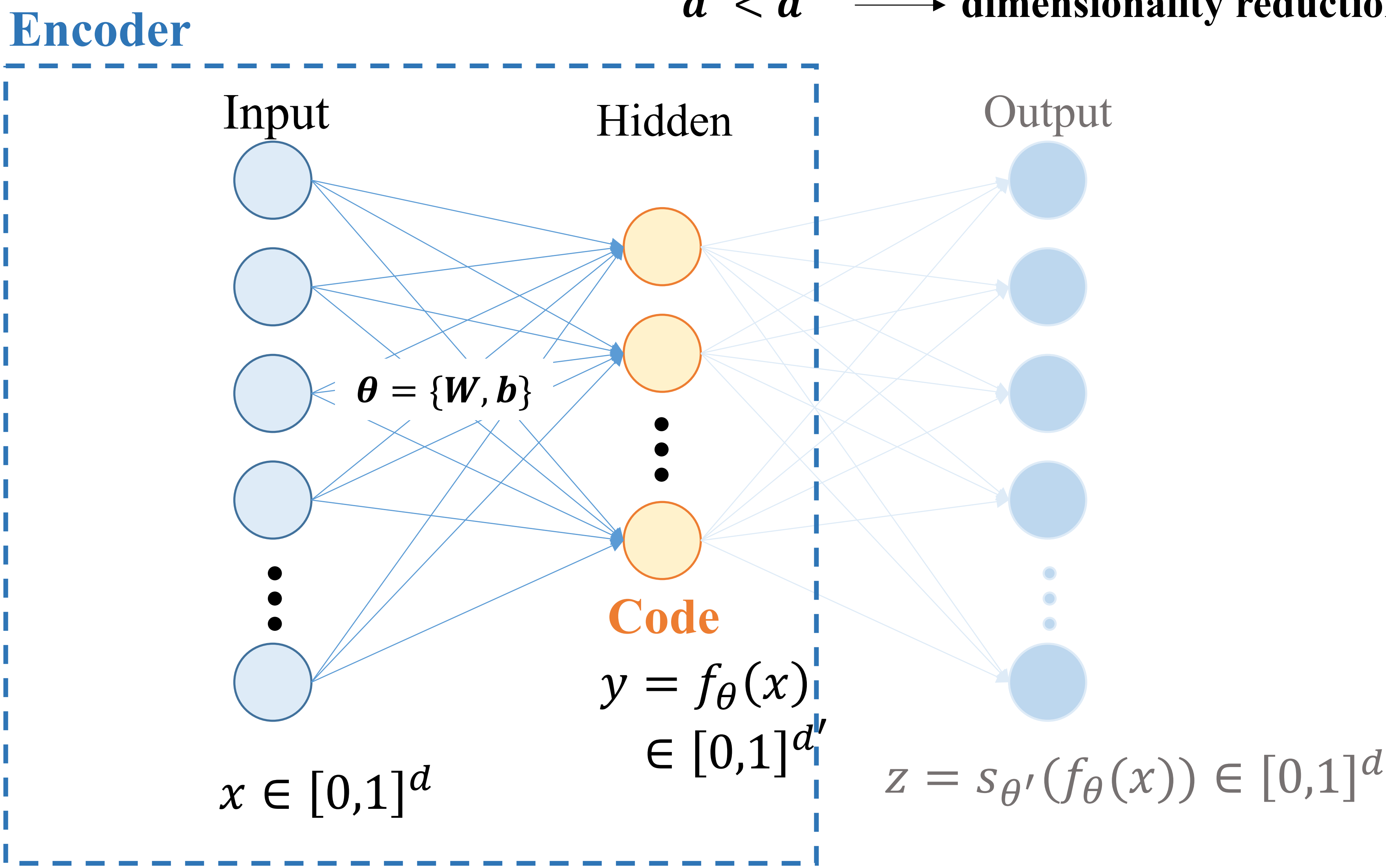
High-dimensional data can be converted to low-dimensional codes by training a multilayer neural network with a small central layer to reconstruct high-dimensional input vectors. Gradient descent can be used for fine-tuning the weights in such "autoencoder" networks, but this works well only if the initial weights are close to a good solution. We describe an effective way of initializing the weights that allows deep autoencoder networks to learn low-dimensional codes that work much better than principal components analysis as a tool to reduce the dimensionality of data.

Dimensionality reduction facilitates the classification, visualization, communication, and storage of high-dimensional data. A simple and widely used method is principal components analysis (PCA), which finds the directions of greatest variance in the data set and represents each data point by its coordinates along each of these directions. We describe a nonlinear generalization of PCA that uses an adaptive, multilayer "encoder" network

Representation learning

Autoencoders

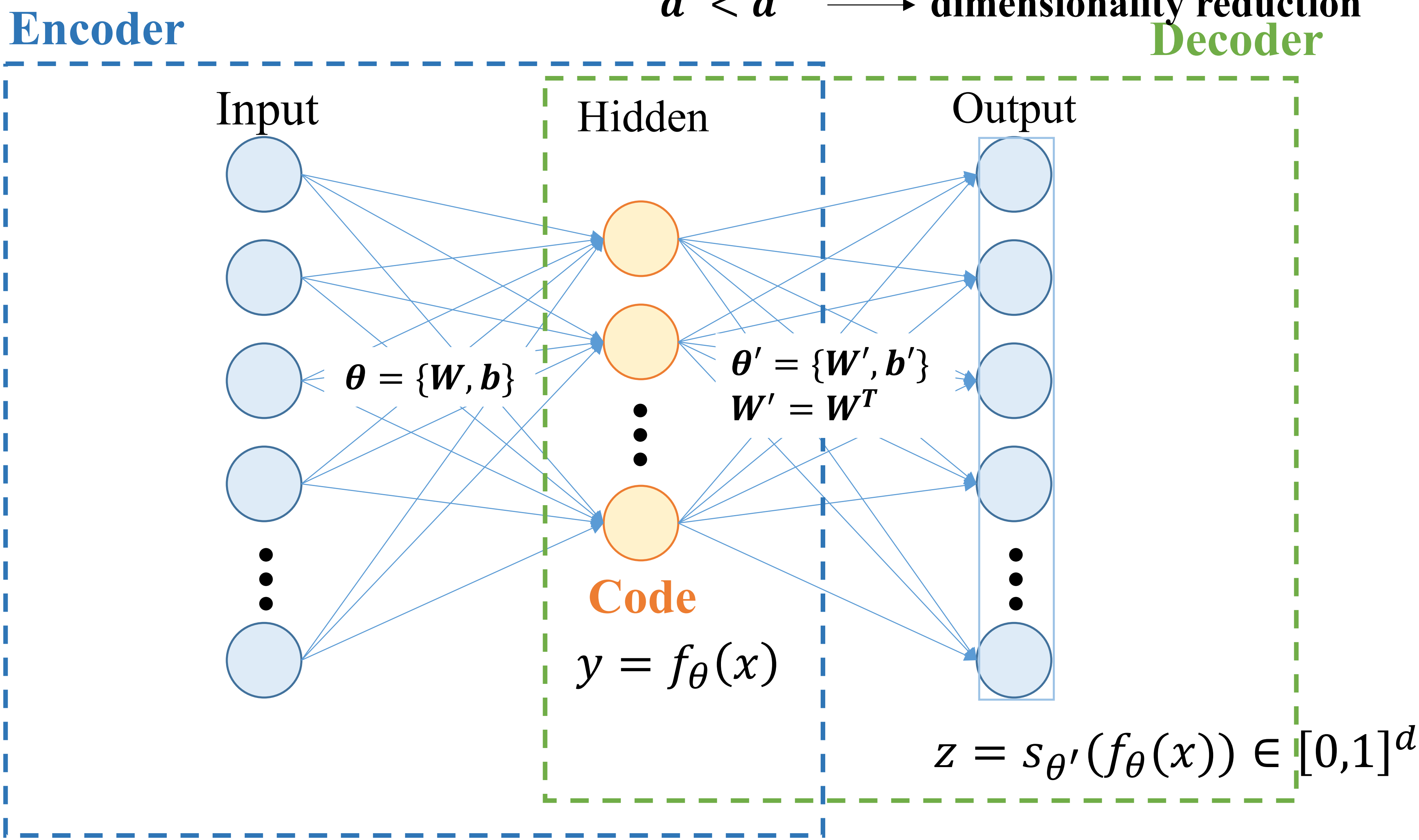
$d' < d$ → **dimensionality reduction**



Representation learning

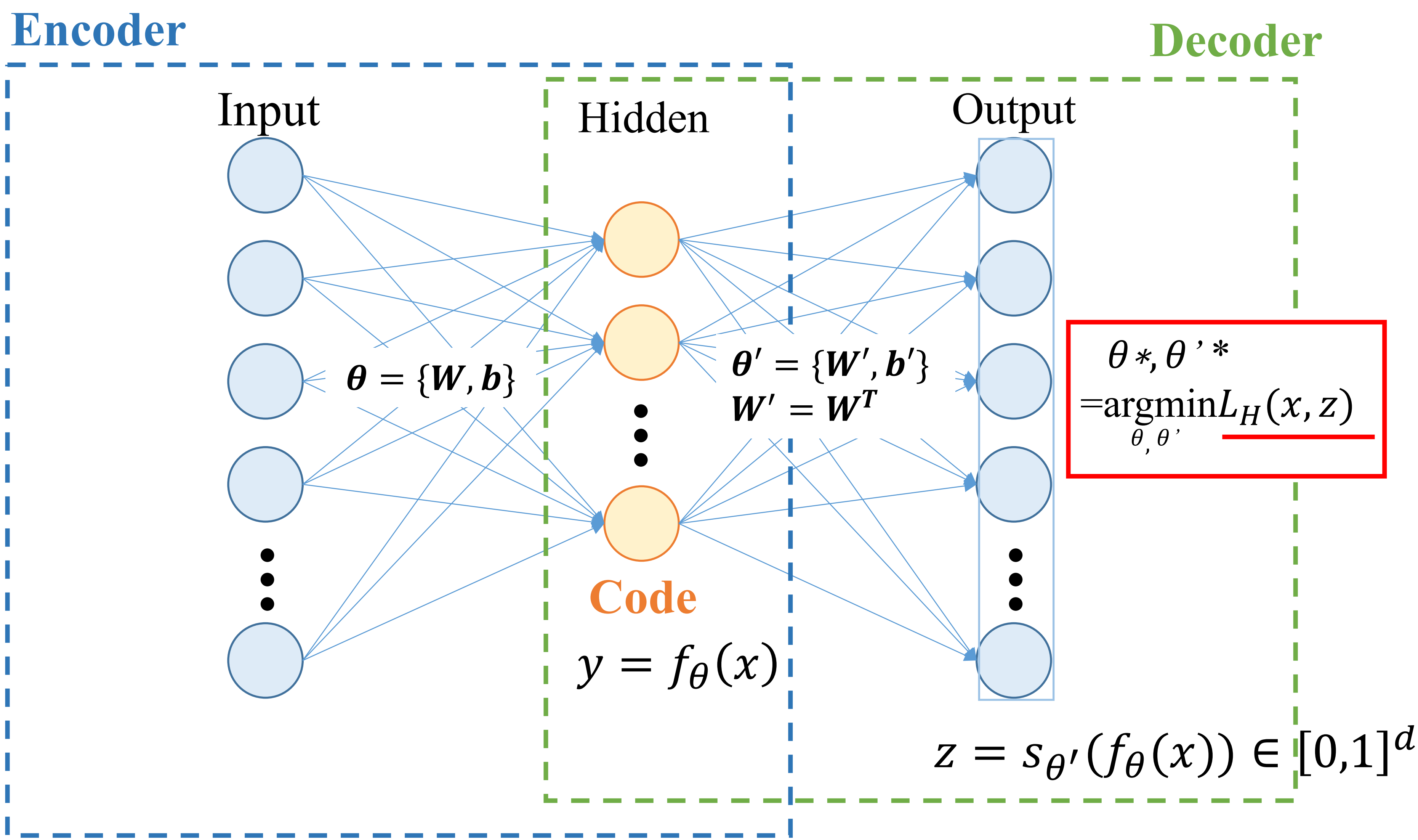
Autoencoders

$d' < d$ → **dimensionality reduction**



Representation learning

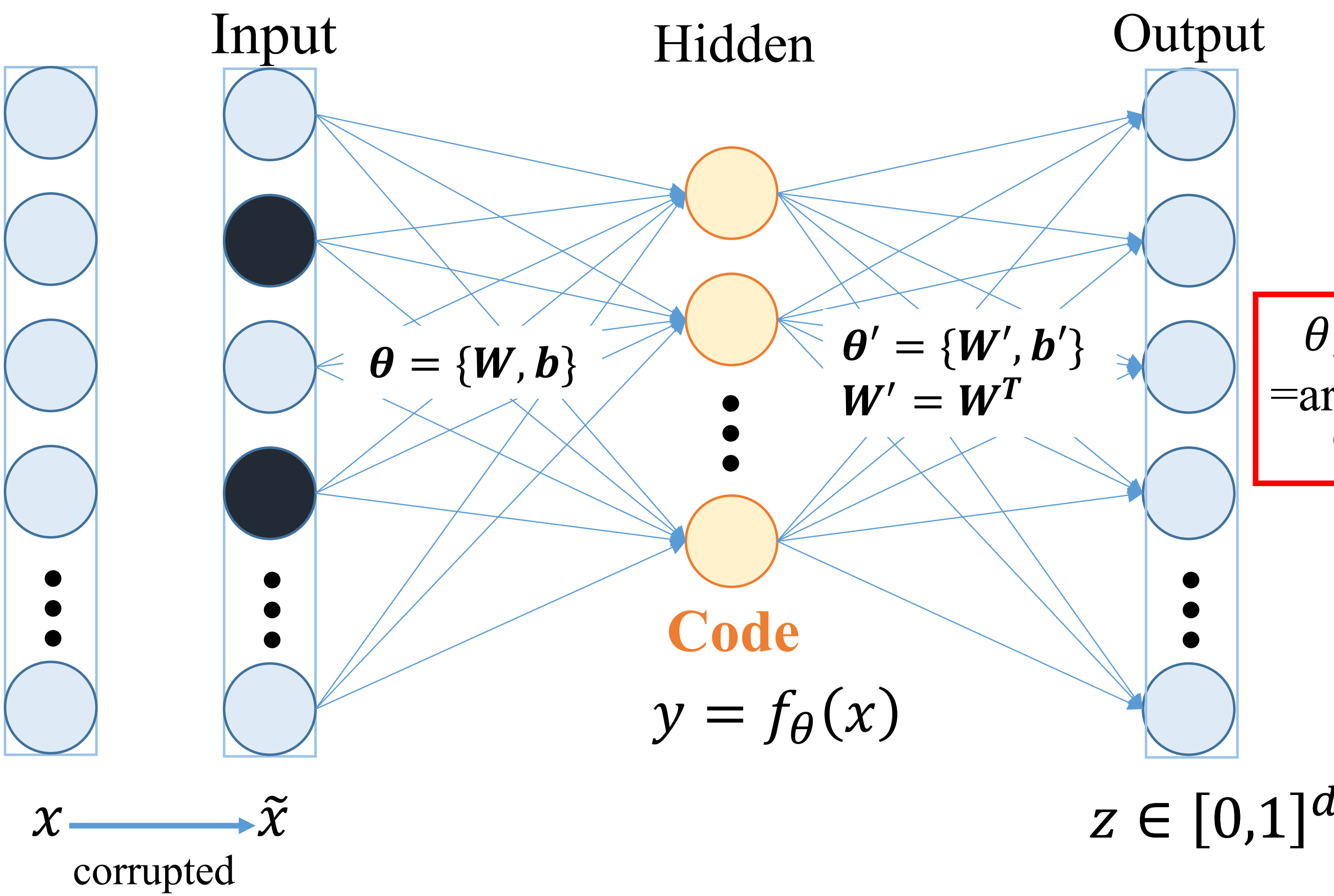
Autoencoders



Representation learning

A **good** representation is one that be obtained **robustly** from a **corrupted** input.

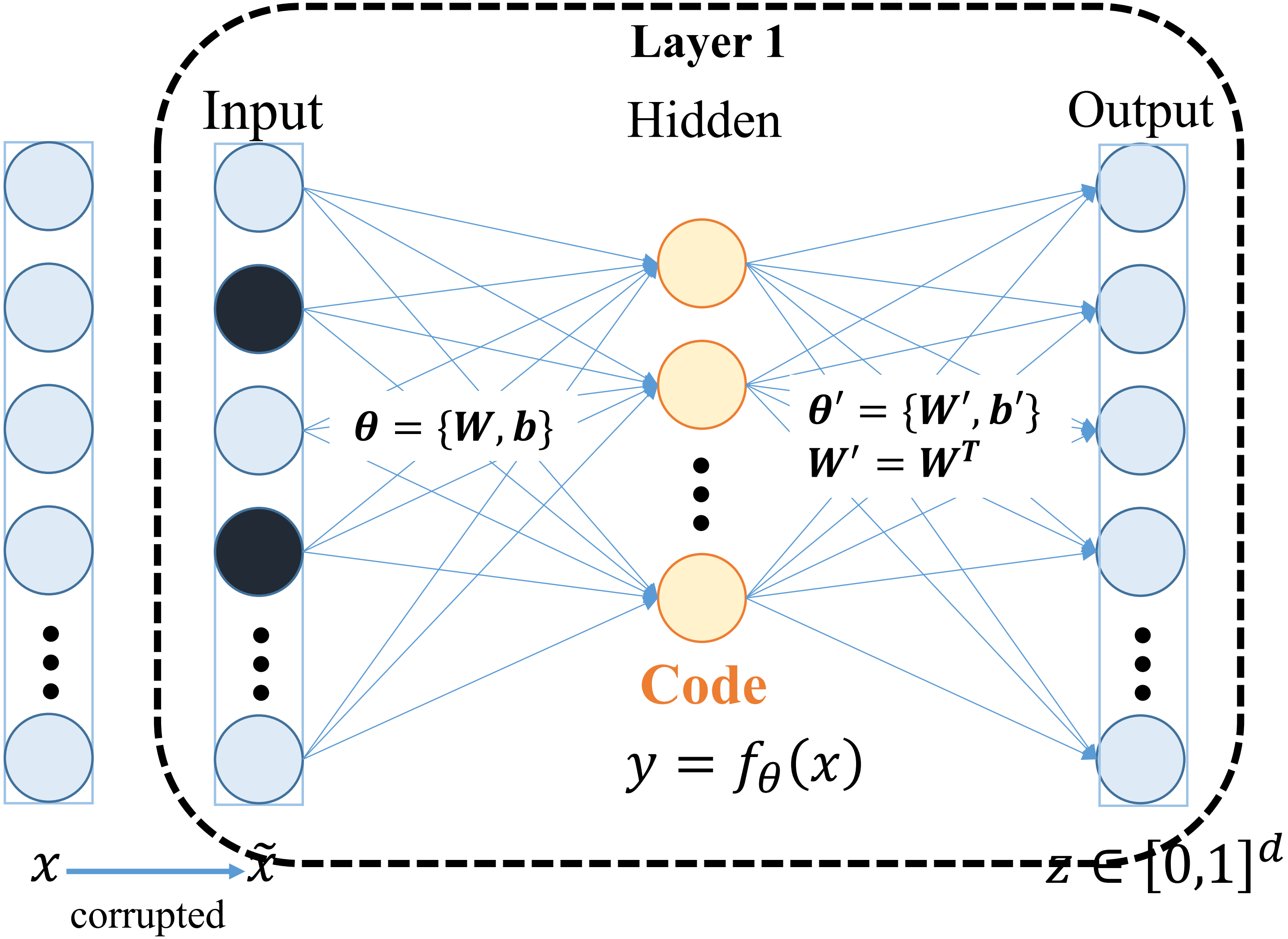
- Denoising Autoencoders



$$\theta, \theta'^{*} = \underset{\theta, \theta'}{\operatorname{argmin}} L_H(x, z)$$

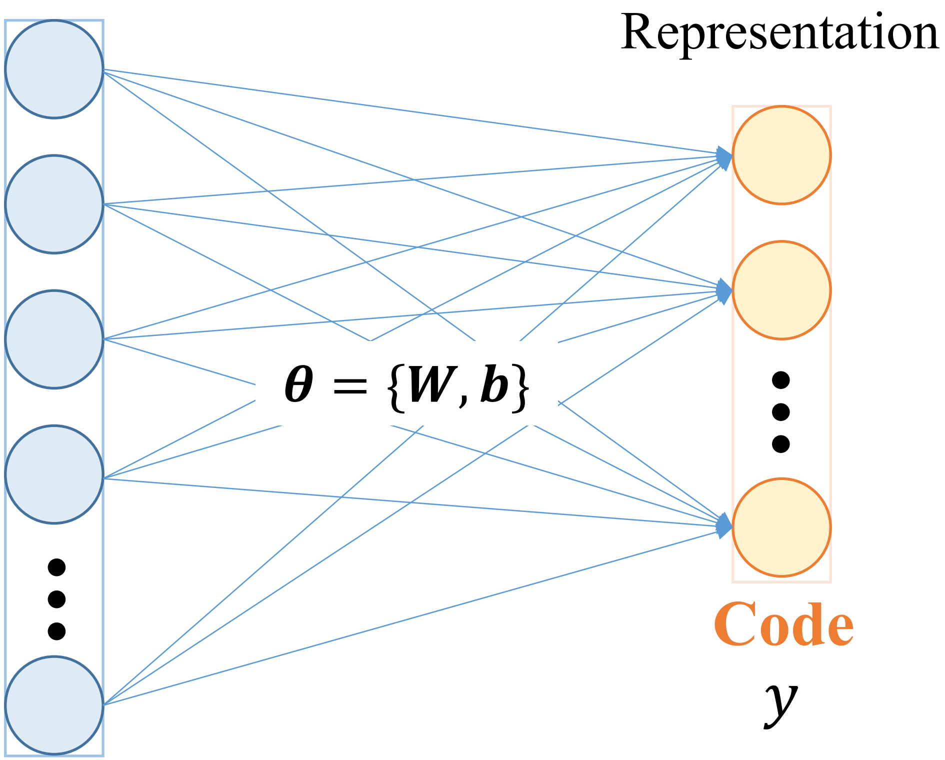
Representation learning

- Denoising Autoencoders



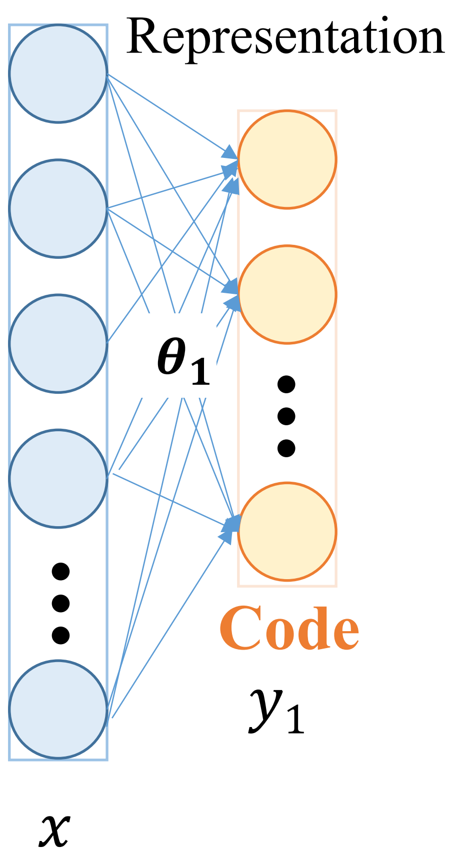
Representation learning

Denoising Autoencoders



Representation learning

Denoising Autoencoders

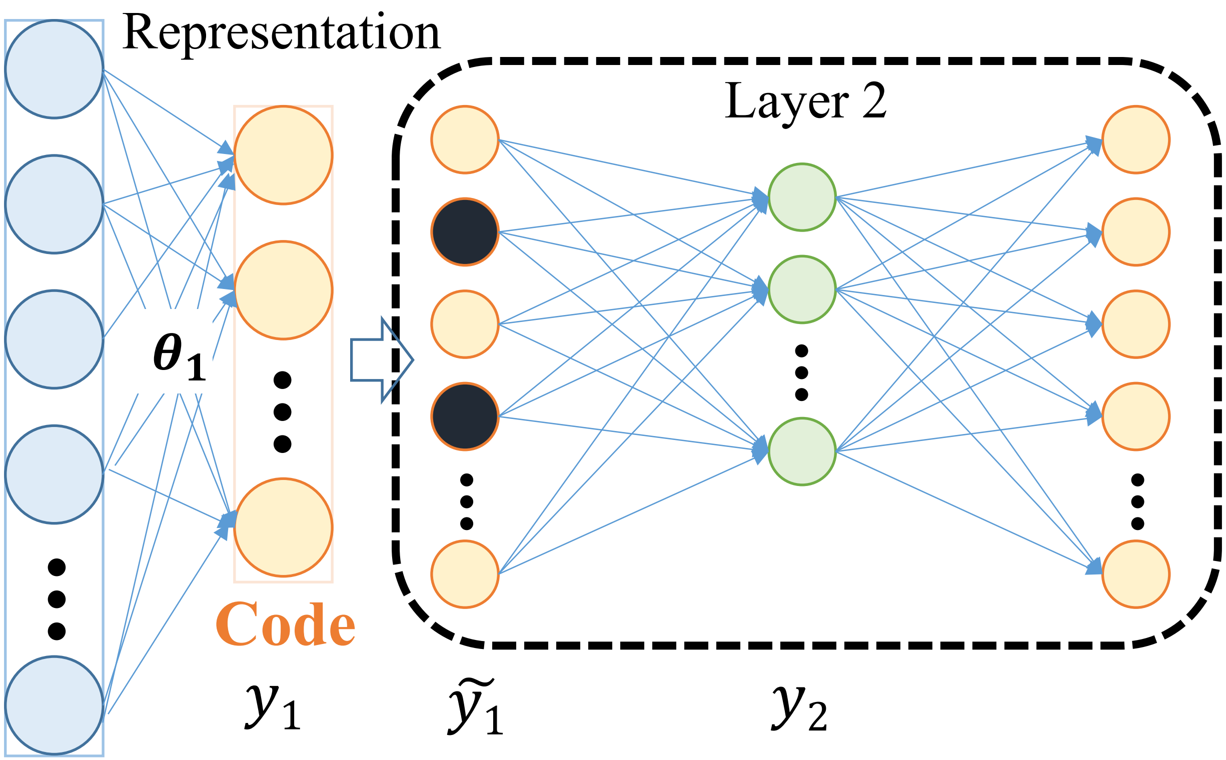


Advantages of deep architectures:

- Re-use of features
- More abstract features

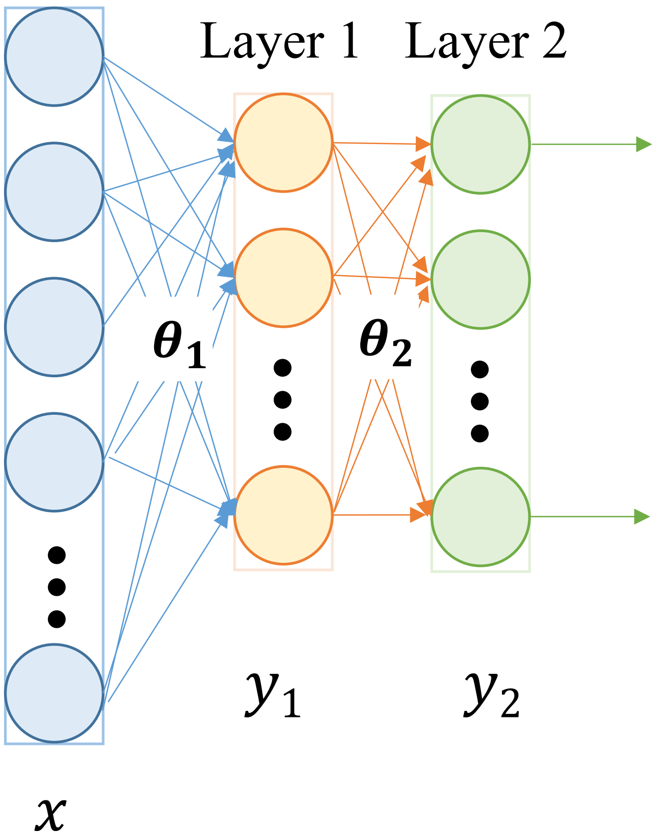
Representation learning

Stacked Denoising Autoencoders



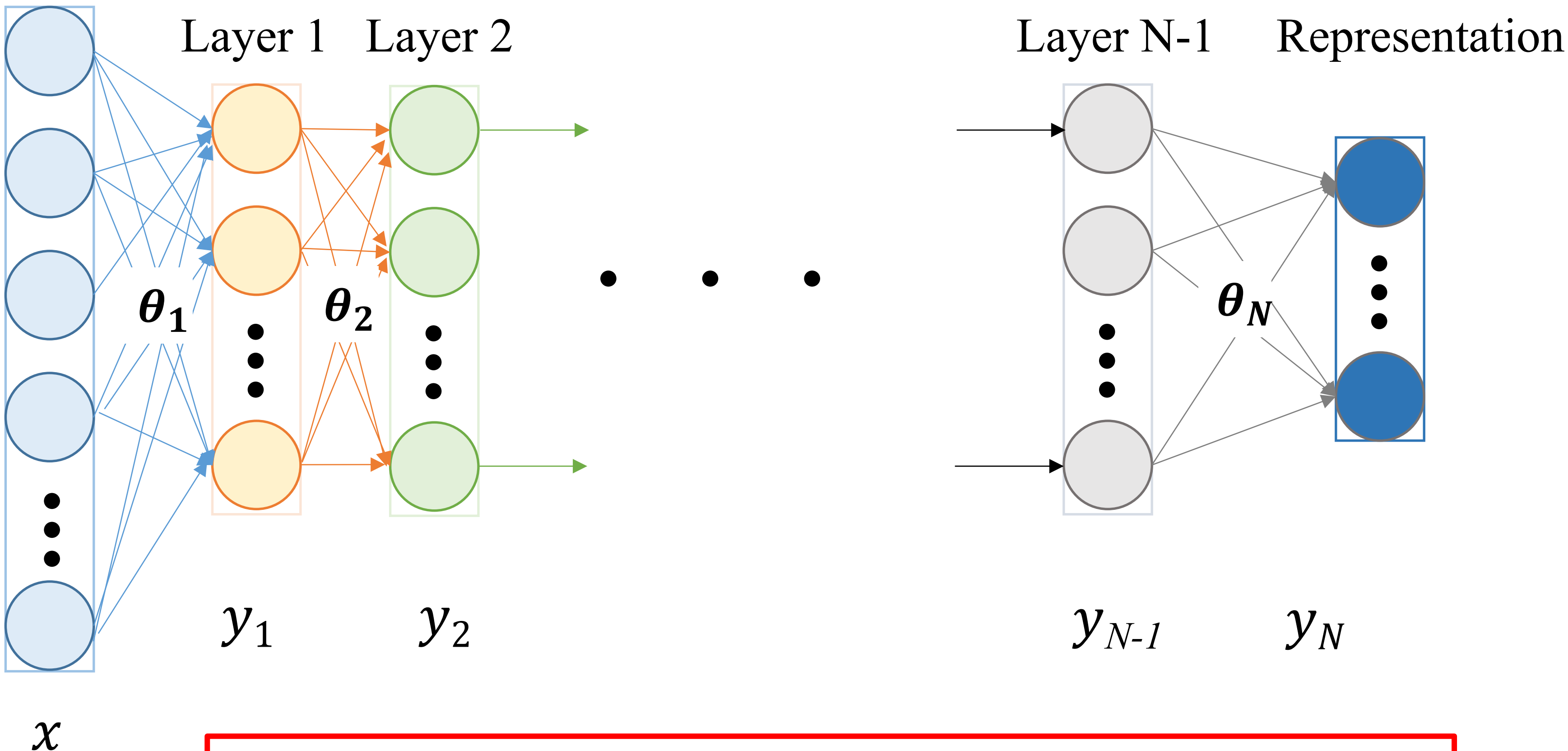
Representation learning

- Stacked Denoising Autoencoders



Representation learning

Stacked Denoising Autoencoders



Each layer of the network is trained to produce a higher- level representation of the observed patterns.