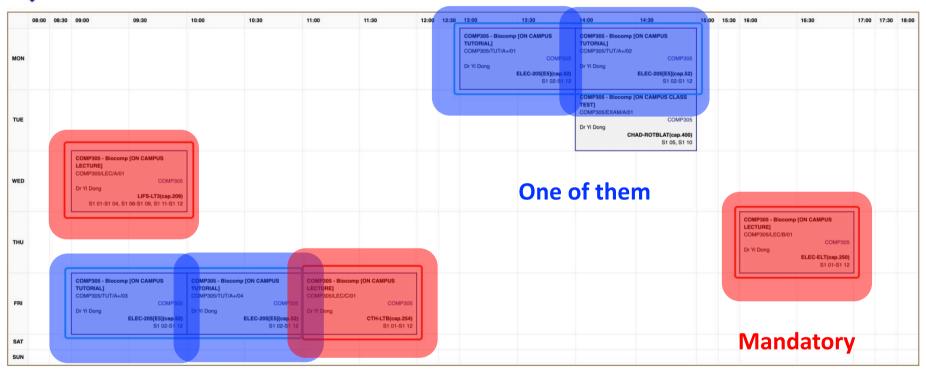
Comp305

Biocomputation

Lecturer: Yi Dong

Comp305 Module Timetable





There will be 26-30 lectures, thee per week. The lecture slides will appear on Canvas. Please use Canvas to access the lecture information. There will be 9 tutorials, one per week.

Lecture/Tutorial Rules

Questions are welcome as soon as they arise, because

- Questions give feedback to the lecturer;
- 2. Questions help your understanding;
- 3. Your questions help your classmates, who might experience difficulties with formulating the same problems/doubts in the form of a question.

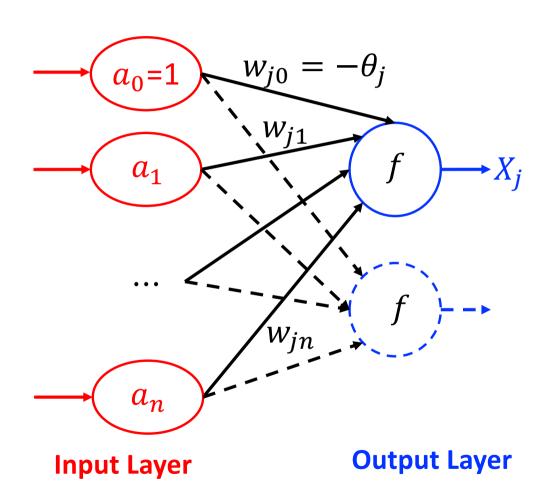
Comp305 Part I.

Artificial Neural Networks

Topic 6.

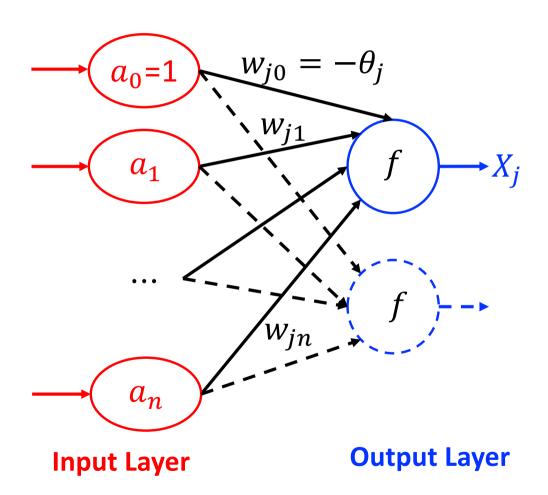
Perceptron

Perceptron (1958)



Weights w_{ji} of connections between two layers are changed according to perceptron learning rule, so the network is more likely to produce the <u>desired</u> output in response to certain inputs.

Weight Update



1. Compute "error" of very connection for every output neuron:

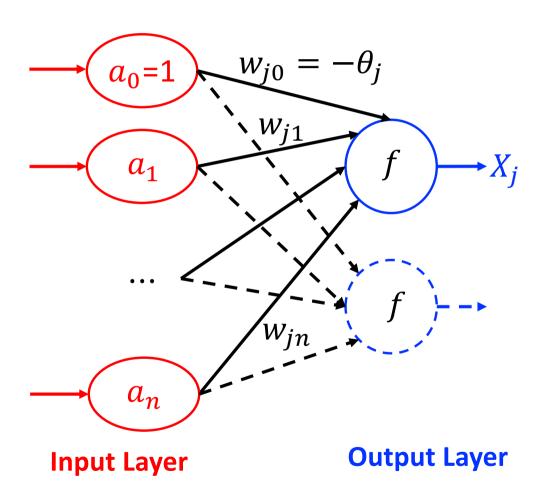
$$e_j^k = \left(t_j^k - X_j^k\right)$$

where

 t_j^k : the target value for the j-th output neuron for the k-th input pattern in the data set,

 X_j^k : the instant value for the j-th output neuron for the k-th input pattern.

Weight Update



2. Update the weights:

$$w_{ji}^k = w_{ji}^k + \Delta w_{ji}^k$$

where

$$\Delta w_{ii}^k = C e_i^k a_i^k$$

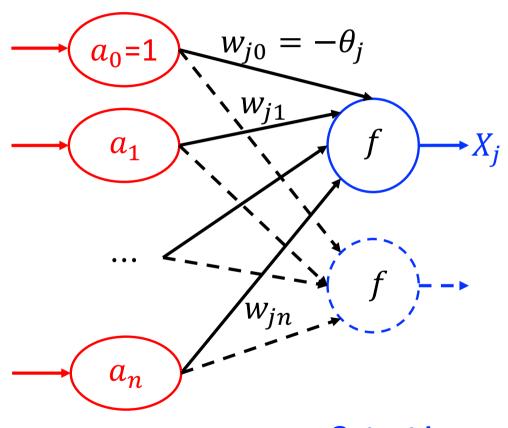
Perceptron Learning Rule!

According to the learning rule, a weight of connection changes

If and only if both the input value and the error of the output are not equal to 0.

Q: Difference with Hebb's rule?

Network Performance



Input Layer

Output Layer

RMS =
$$\sqrt{\frac{\sum_{k=1}^{r} \sum_{j=1}^{m} (e_{j}^{k})^{2}}{rm}}$$

= $\sqrt{\frac{\sum_{k=1}^{r} \sum_{j=1}^{m} (t_{j}^{k} - X_{j}^{k})^{2}}{rm}}$

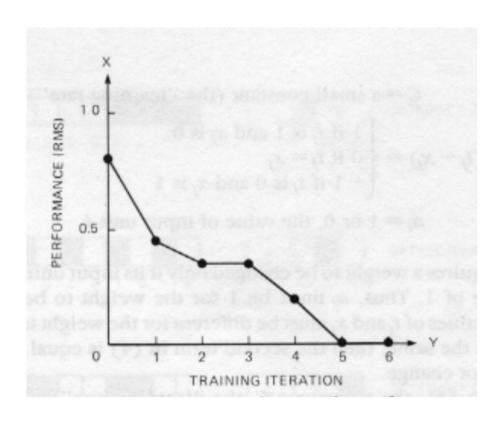
where

r: the number of patterns in the data set,

m: the number of output neurons.

The **network performance** during training session is measured by a root-mean-square (RMS) error value.

Network Performance



Thus, RMS error can be represented as: $RMS = F_D(w)$ where w is network weight, D is data set.

Learning curve: dependency of the RMS error on the number of iterations.

- Initially, the adaptable weights are all set to small random values, and the network does not perform very well;
- Performance improves during training;
- Finally, the error gets close to zero, training stops. We say the network has converged.

Perceptron Learning Algorithm

Algorithm 1: Perceptron Learning Algorithm

```
Data: Labelled data set D: r n-dimensional input points, each of which has m labels. Small positive real \delta. Learning rate C.

Result: Weight matrix w = [w_1, \cdots, w_m]

1 Initialize weights w randomly;

2 while !convergence (RMS \le \delta) do

3 | Pick random a' \in D;

4 | a \leftarrow [1, a'];

5 | for j = 1, \cdots, m do

| /* We represent the learning rule in the vector form */

6 | w_j = w_j + C(t_j - X_j)a;

7 return w;
```

Perceptron Learning Algorithm

Algorithm 1: Perceptron Learning Algorithm

Data: Labelled data set D: r n-dimensional input points, each of which has m labels. Small positive real δ . Learning rate C.

```
Result: Weight matrix w = [w_1, \dots, w_m]
```

1 Initialize weights w randomly;

```
2 while !convergence (RMS \leq \delta) do
```

```
Pick random a' \in D;
a \longleftarrow [1, a'];
for j = 1, \dots, m do
```

A common way is to enumerate all the patterns in *D* sequentially. An epoch means training the neural network with all the training data for one cycle.

```
/* We represent the learning rule in the vector form */w_j = w_j + C(t_j - X_j)a;
```

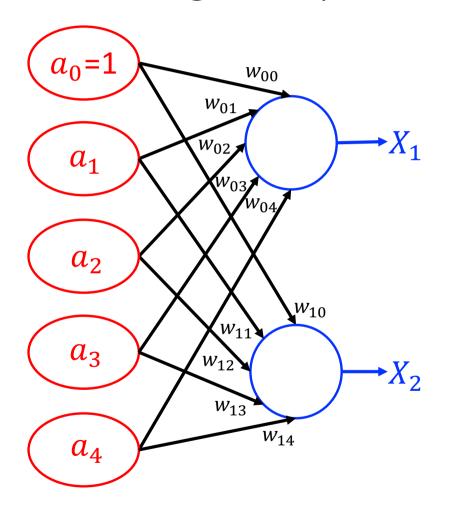
7 return w;

Perceptron Learning Algorithm

Algorithm 1: Perceptron Learning Algorithm

Data: Labelled data set D: r n-dimensional input points, each of which has m labels. Small positive real δ . Learning rate C.

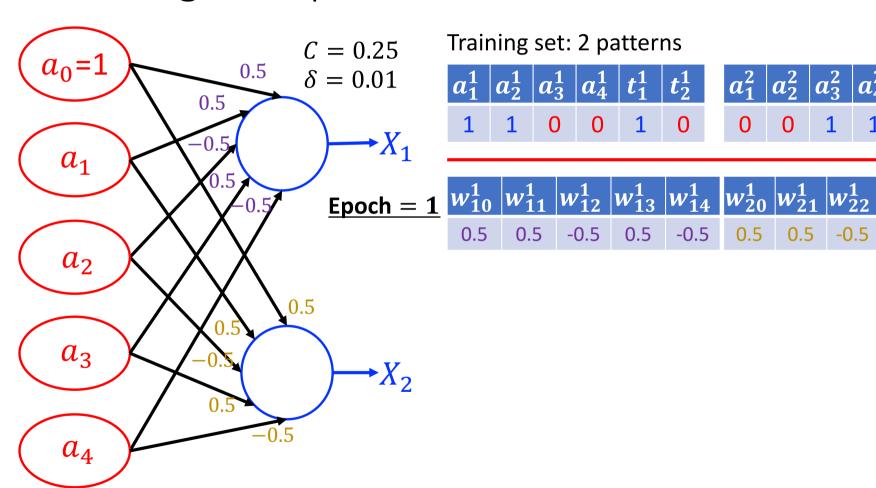
```
Result: Weight matrix w = [w_1, \dots, w_m]
                                                       Then the convergence checking
  Initialize weights w randomly;
                                                       is only done after one epoch.
2 while !convergence (RMS \leq \delta) do
                                              A common way is to enumerate all the patterns in
       Pick random a' \in D;
3
                                              D sequentially. An epoch means training the neural
      a \leftarrow [1, a'];
4
                                              network with all the training data for one cycle.
       for j=1,\cdots,m do
5
          /* We represent the learning rule in the vector form w_j = w_j + C(t_j - X_j)a;
                                                                                            */
7 return w;
```



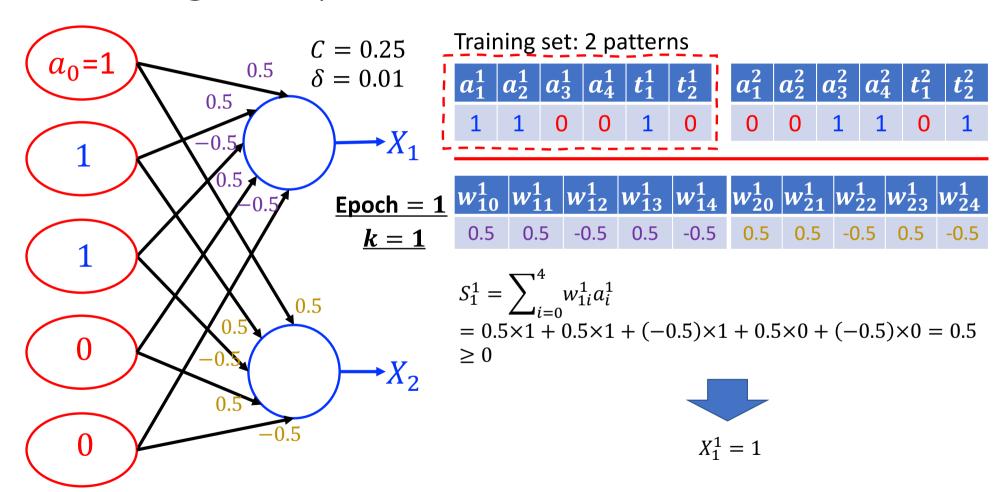
Training set: 2 patterns

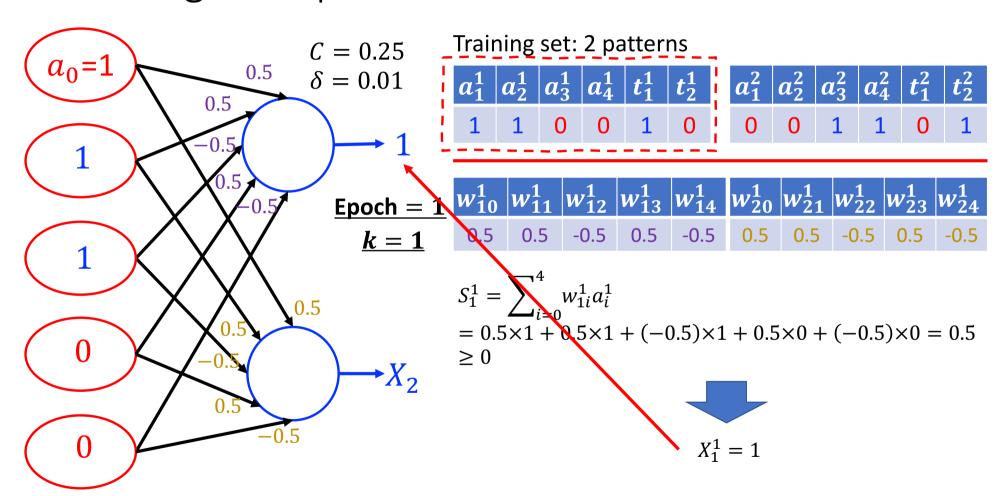
a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

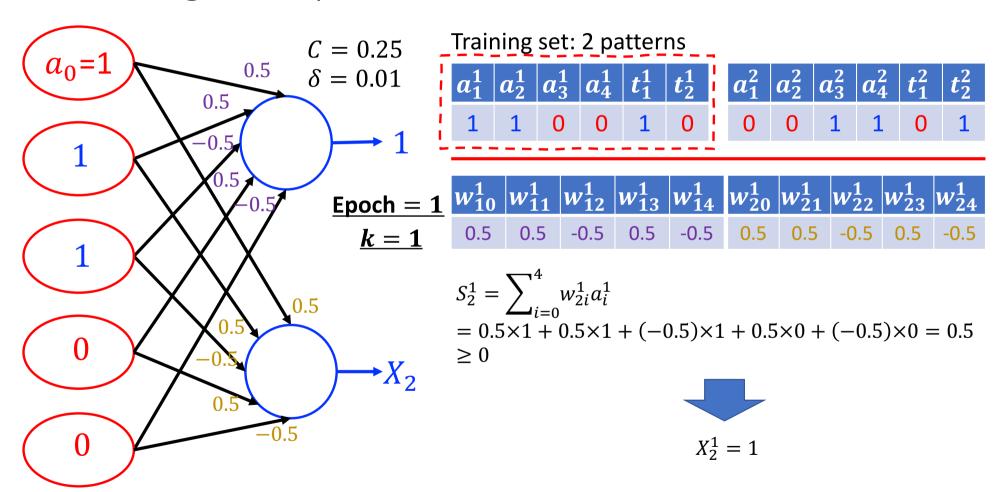
a_1^2	a_2^2	a_3^2	a_4^2	t_1^2	t_2^2
0	0	1	1	0	1

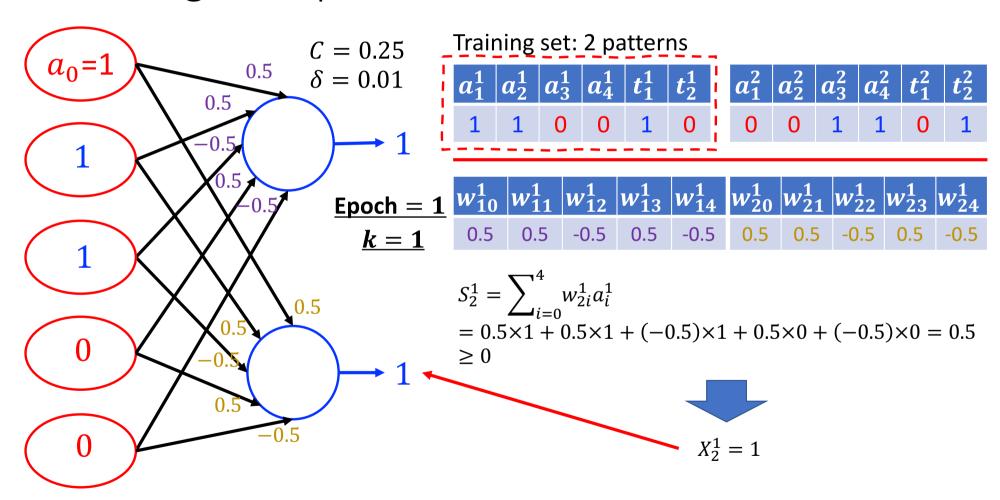


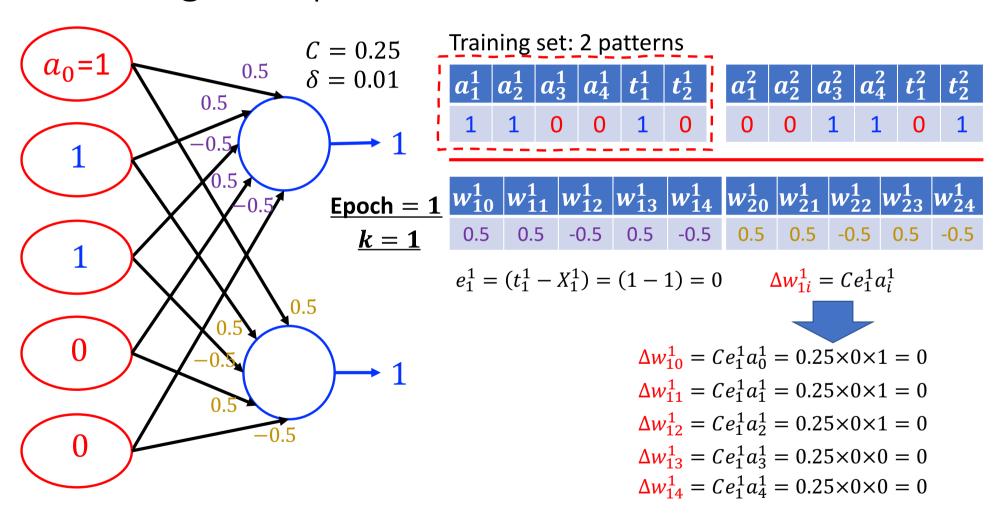
 t_2^2

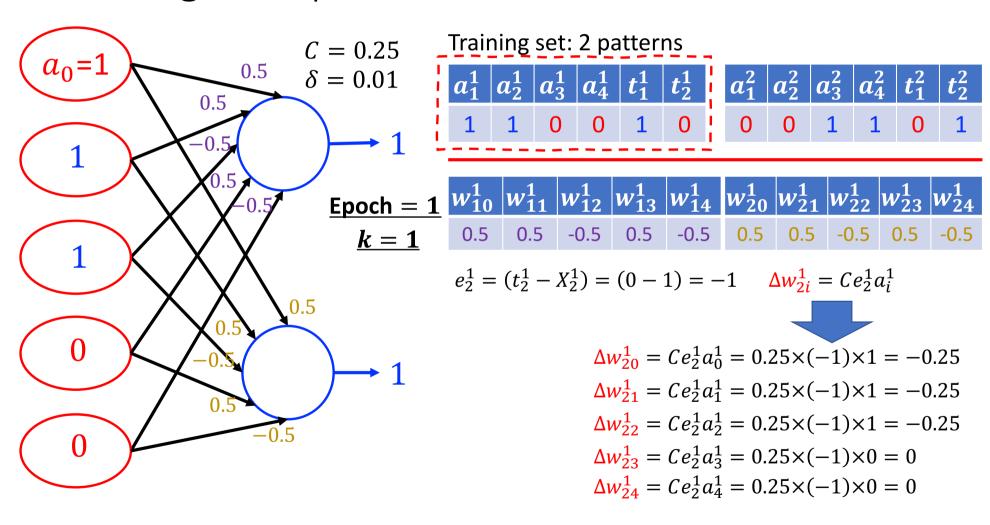


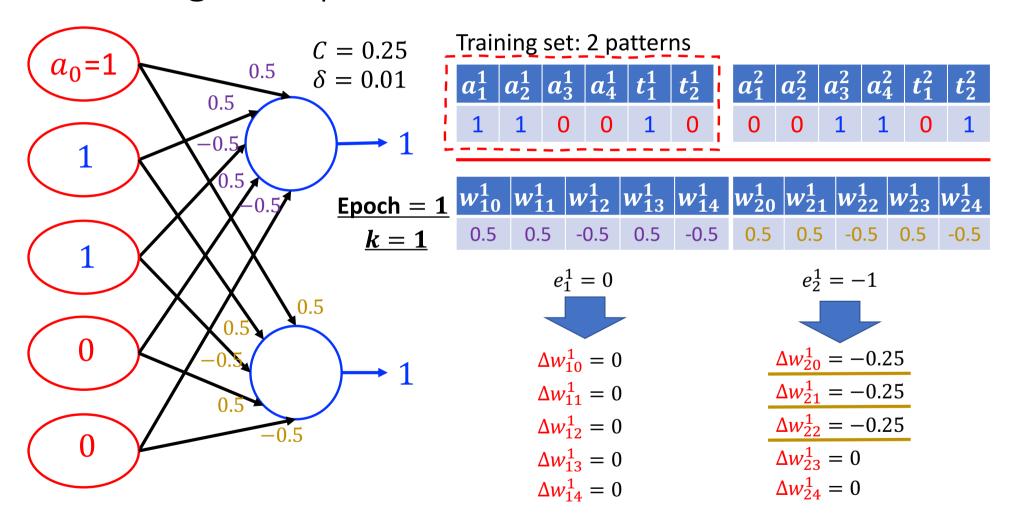


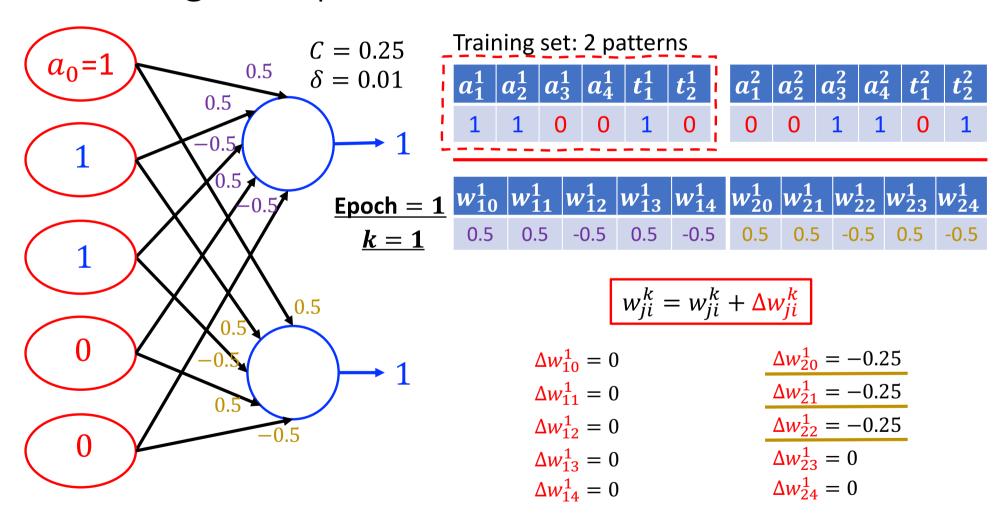


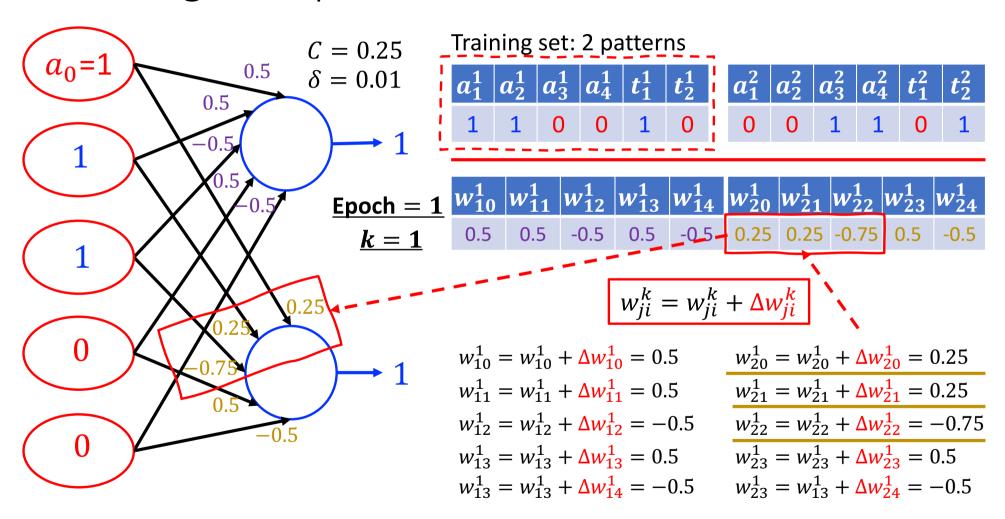


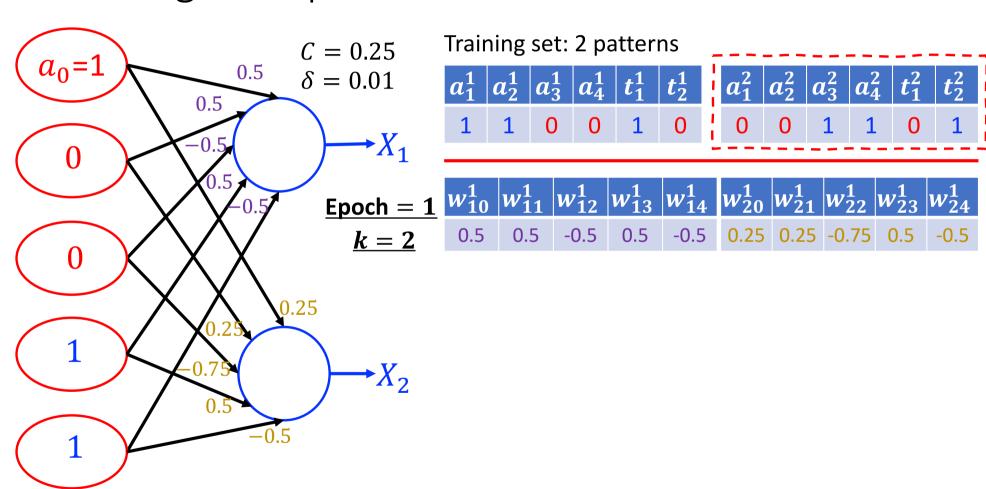


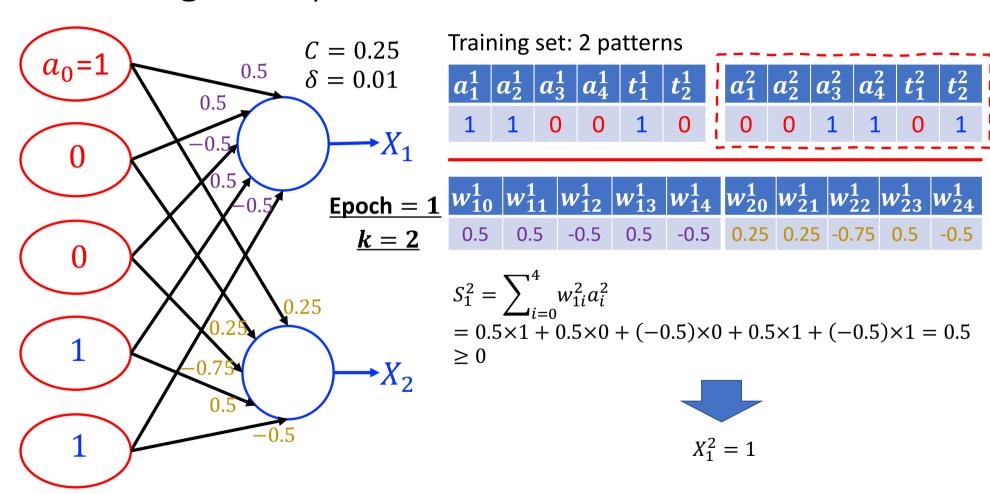


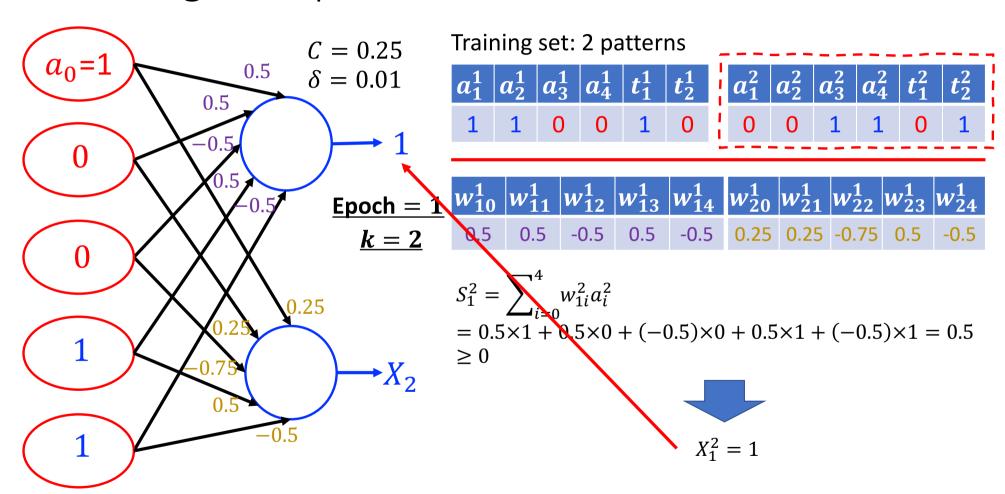


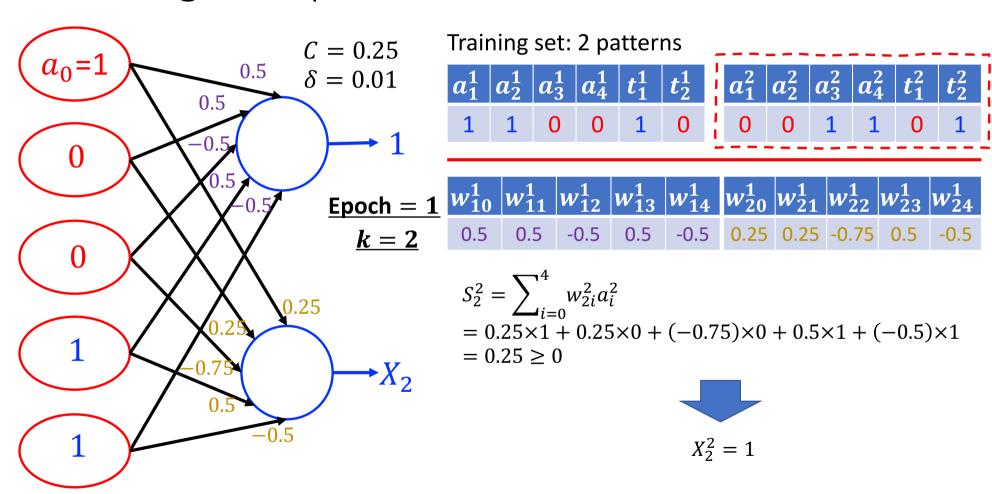


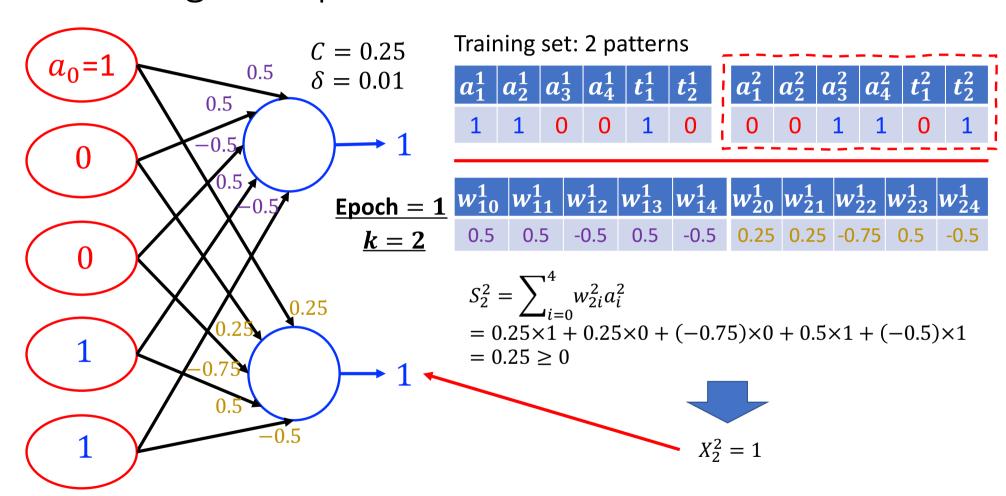


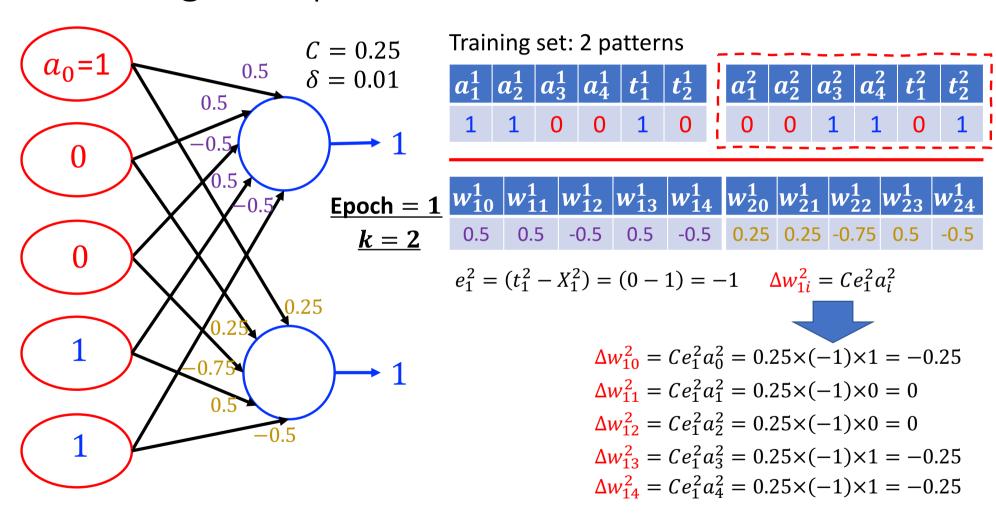


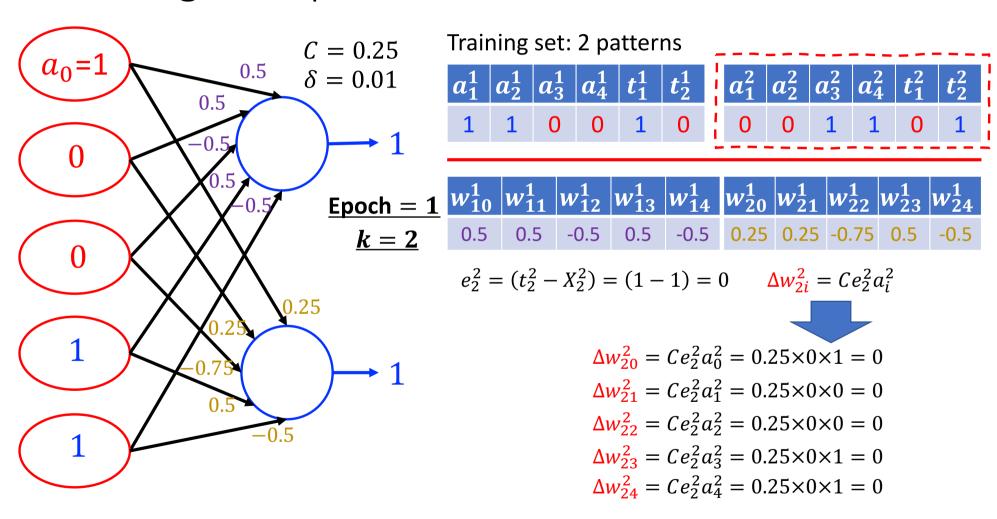


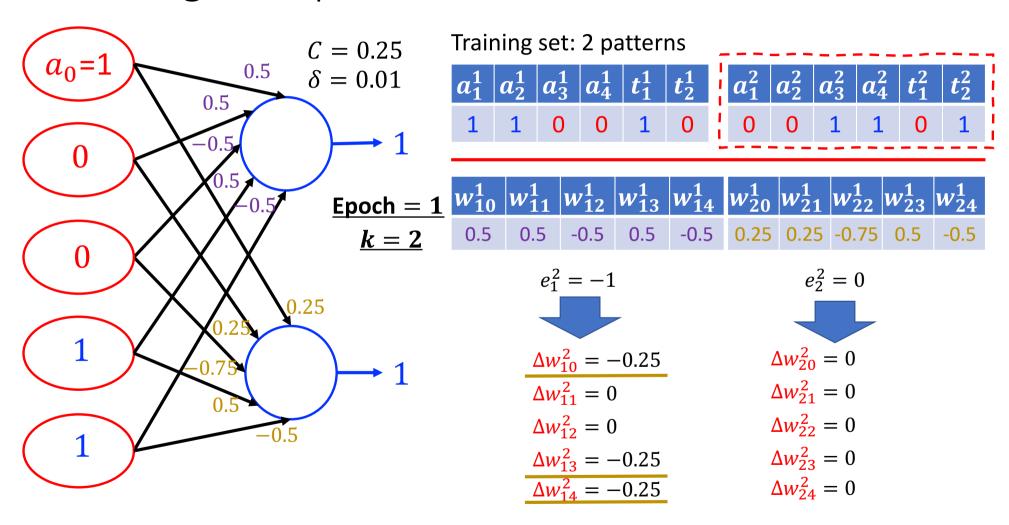


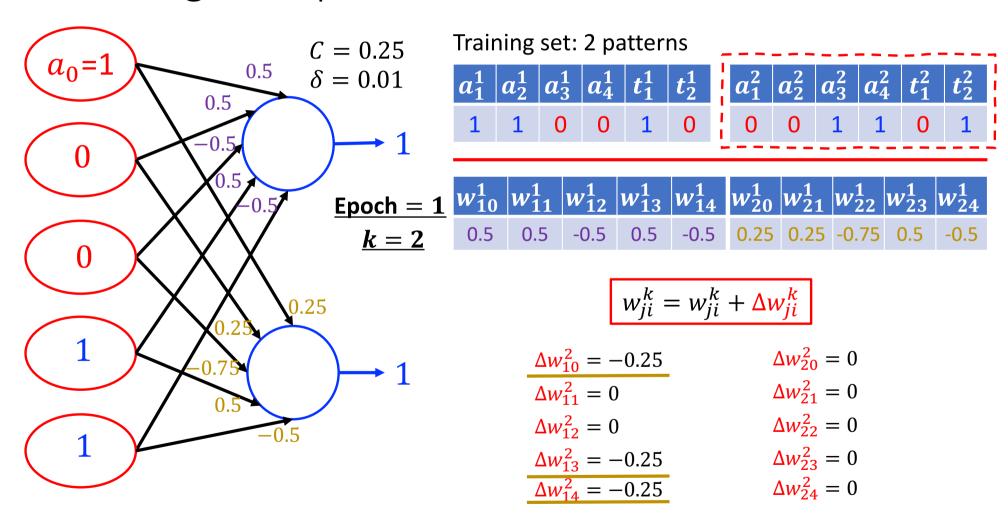


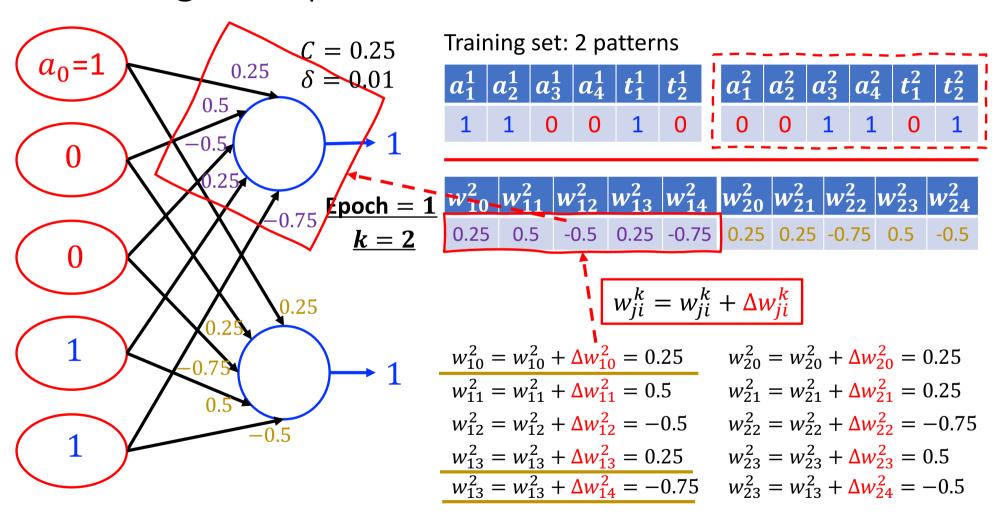


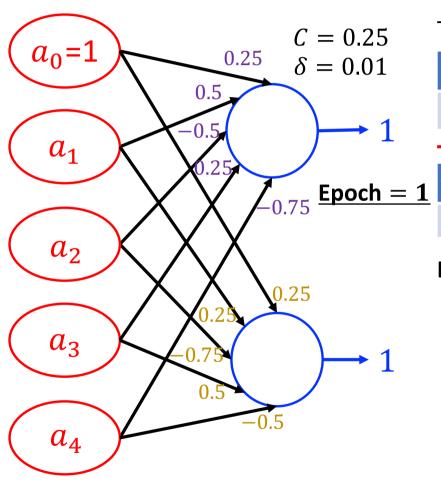












Training set: 2 patterns

a_1^1	a_2^1	$a_3^1 a_4^1$		t_1^1	t_2^1	
1	1	0	0	1	0	

a_1^2	a_2^2	a_3^2	a_4^2	t_1^2	t_2^2
0	0	1	1	0	1

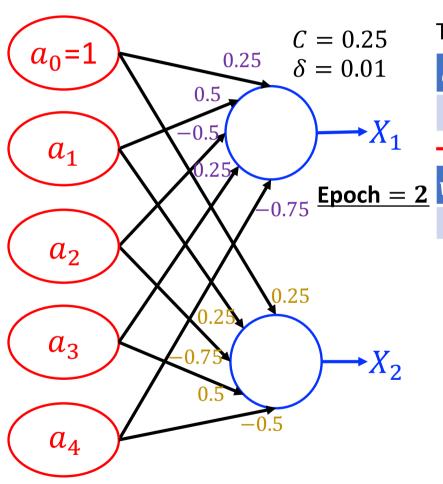
_	w_{10}^{2}	w_{11}^{2}	w_{12}^{2}	w_{13}^{2}	w_{14}^{2}	w_{20}^{2}	w_{21}^{2}	w_{22}^{2}	w_{23}^{2}	w_{24}^{2}
	0.25	0.5	-0.5	0.25	-0.75	0.25	0.25	-0.75	0.5	-0.5

Epoch 1 finishes. Evaluate performance.

RMS =
$$\sqrt{\frac{\sum_{k=1}^{r} \sum_{j=1}^{m} (e_j^k)^2}{rm}} = \sqrt{\frac{\sum_{k=1}^{2} \sum_{j=1}^{2} (e_j^k)^2}{2 \times 2}}$$

= $\sqrt{\frac{(e_1^1)^2 + (e_2^1)^2 + (e_1^2)^2 + (e_2^2)^2}{2 \times 2}} = \frac{\sqrt{2}}{2} > \delta = 0.01$

Not good. Continue.

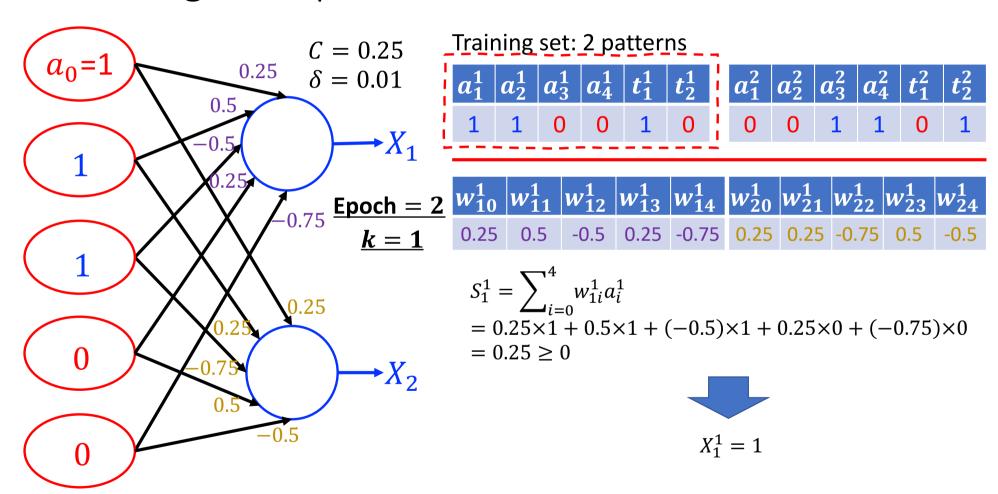


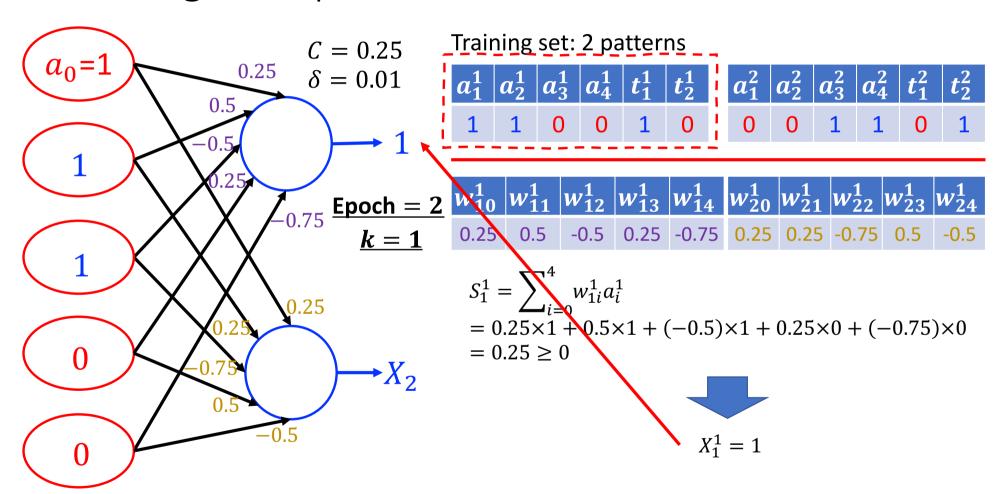
Training set: 2 patterns

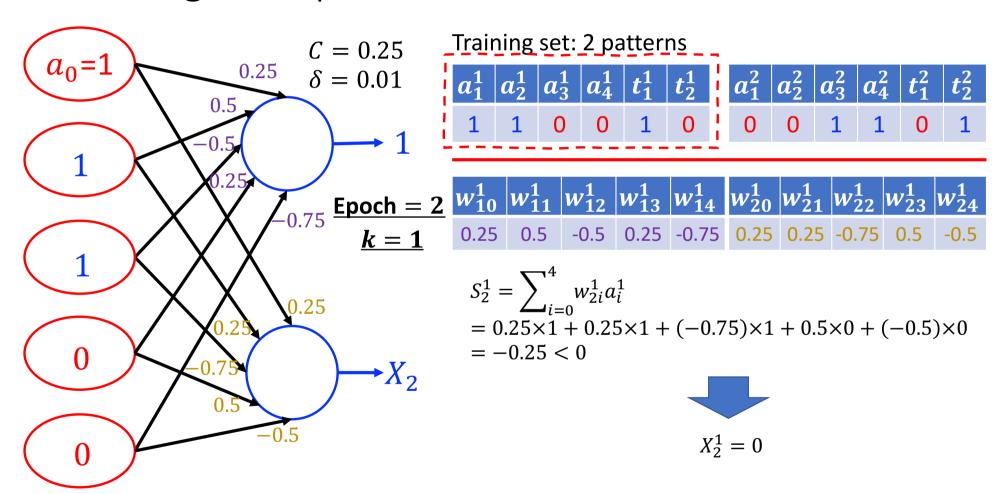
a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

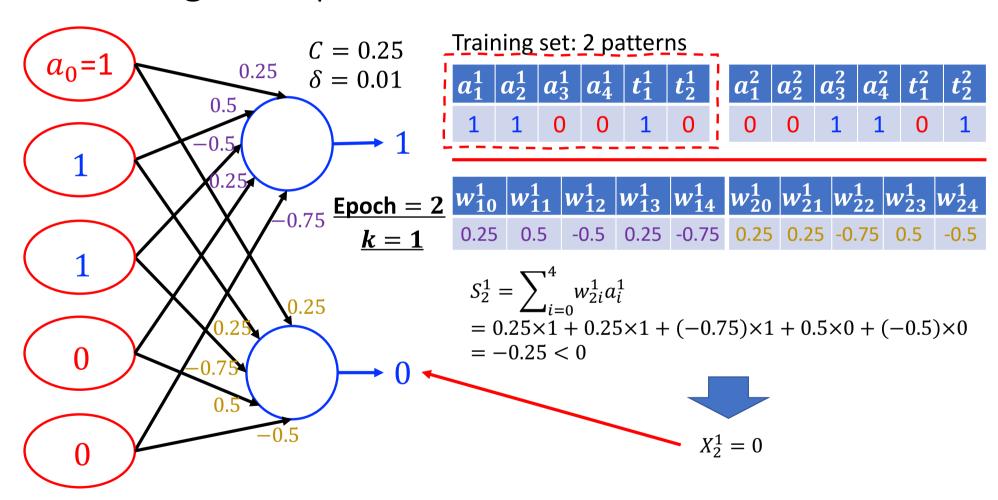
a_1^2	a_2^2	a_3^2	a_4^2	t_{1}^{2}	t_2^2
0	0	1	1	0	1

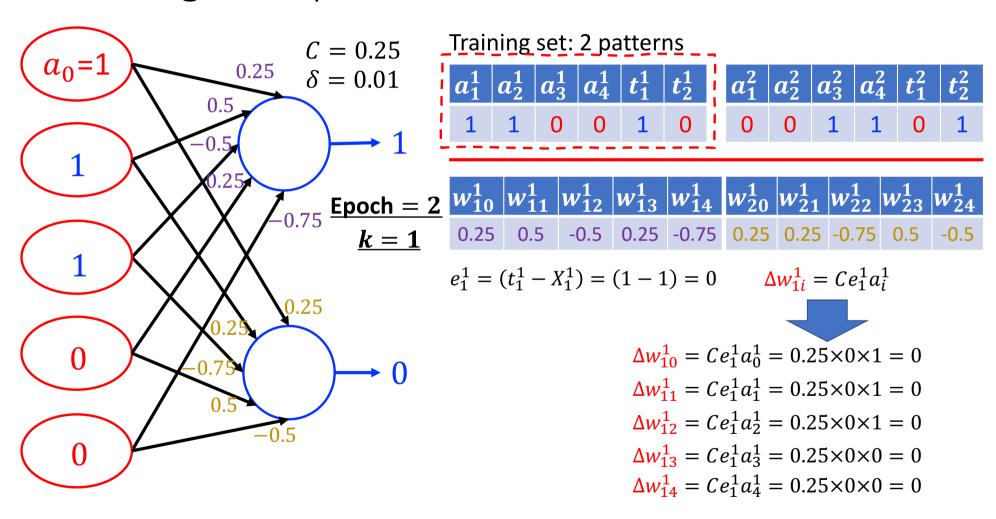
w_{10}^{1}	w_{11}^{1}	w_{12}^{1}	w_{13}^{1}	w_{14}^{1}	w_{20}^{1}	w_{21}^{1}	w_{22}^{1}	w_{23}^{1}	w_{24}^{1}
0.25	0.5	-0.5	0.25	-0.75	0.25	0.25	-0.75	0.5	-0.5

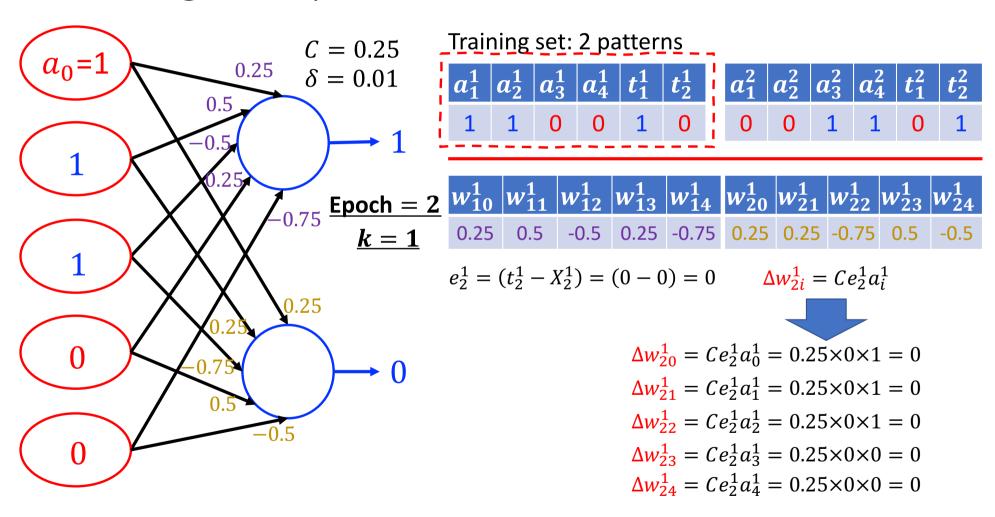


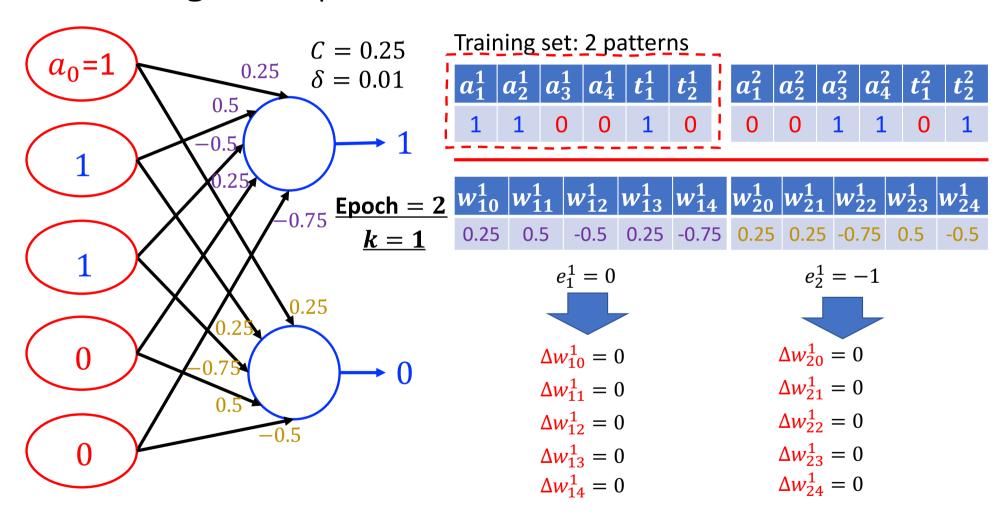


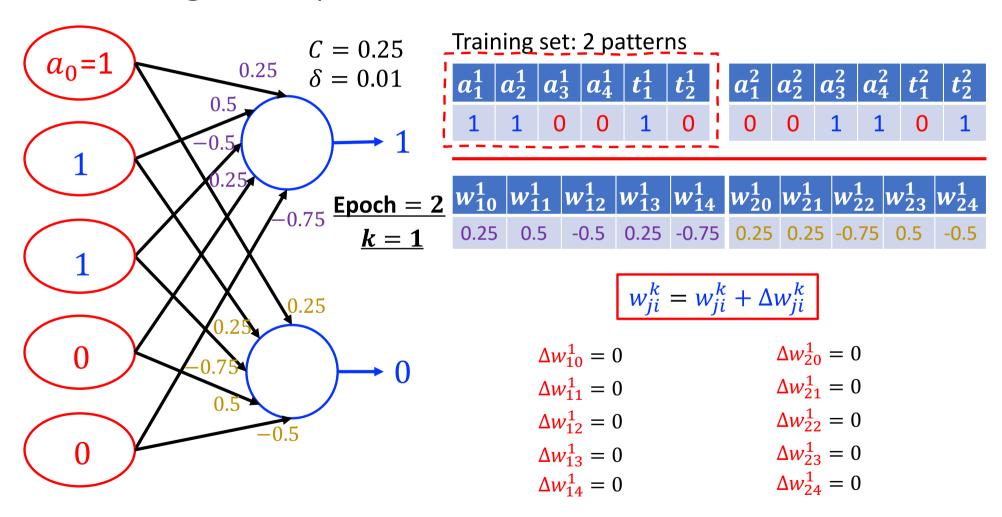


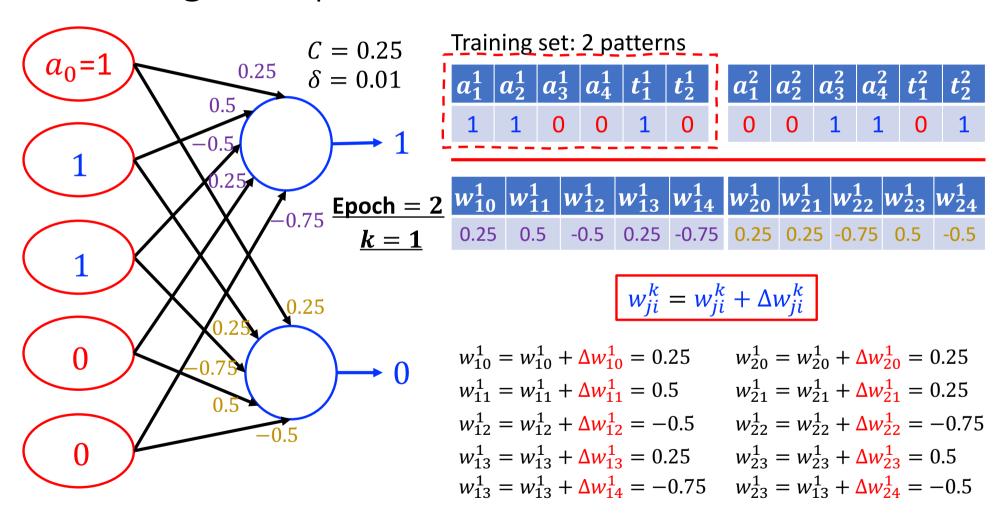


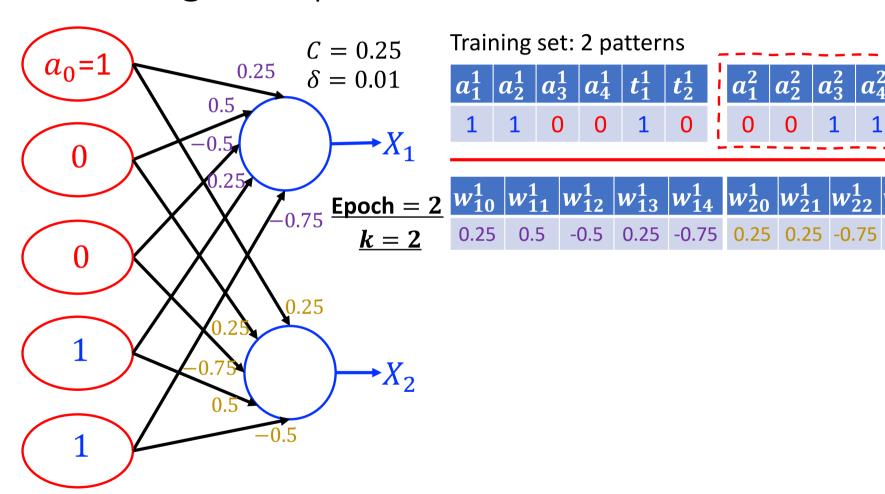


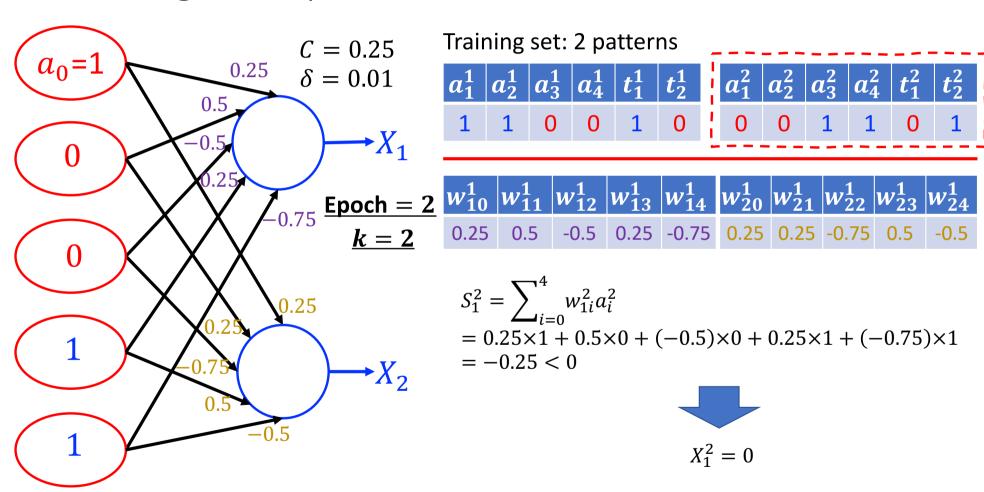


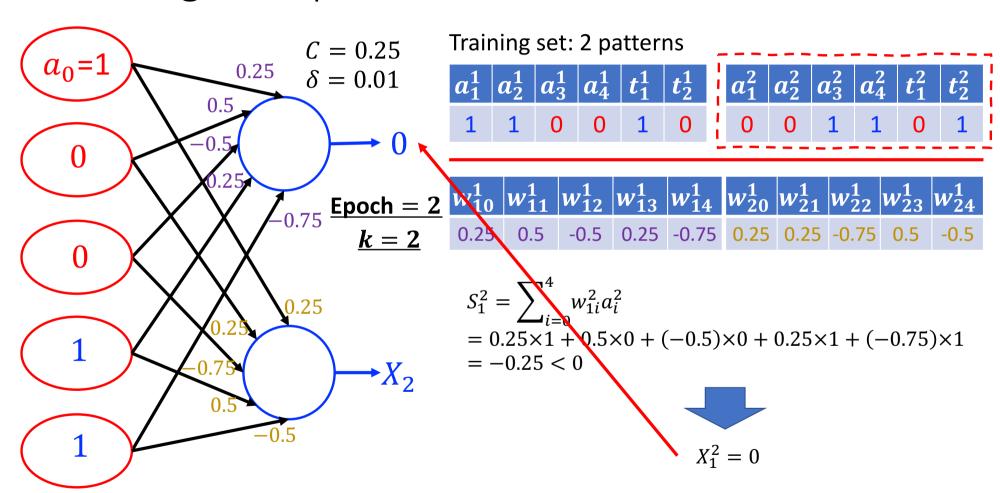


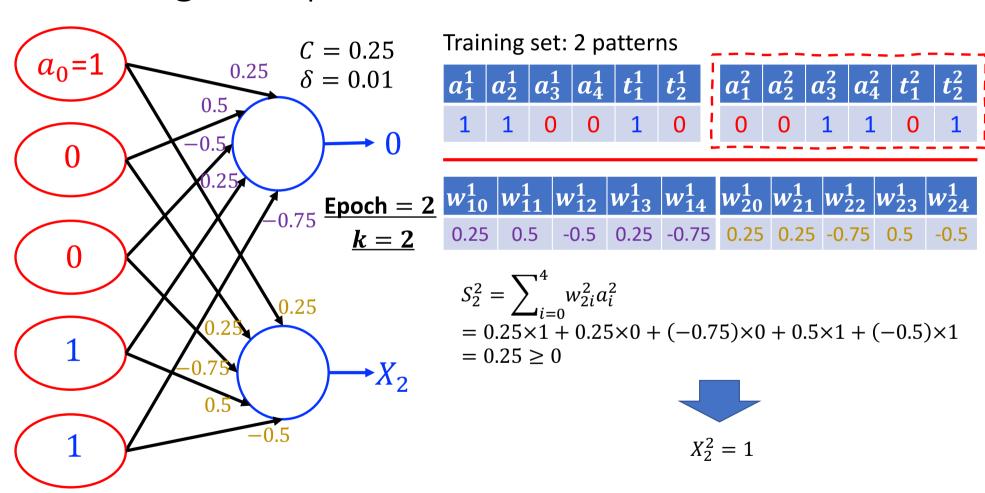


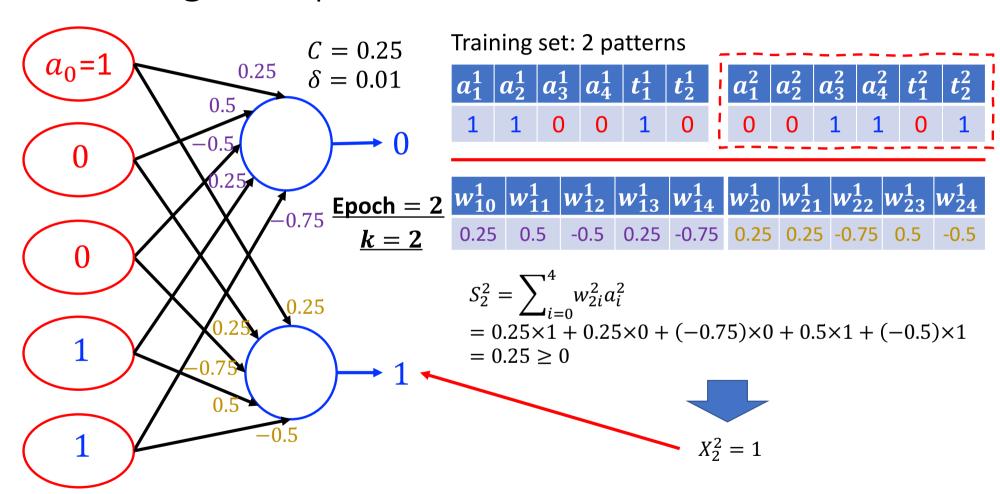


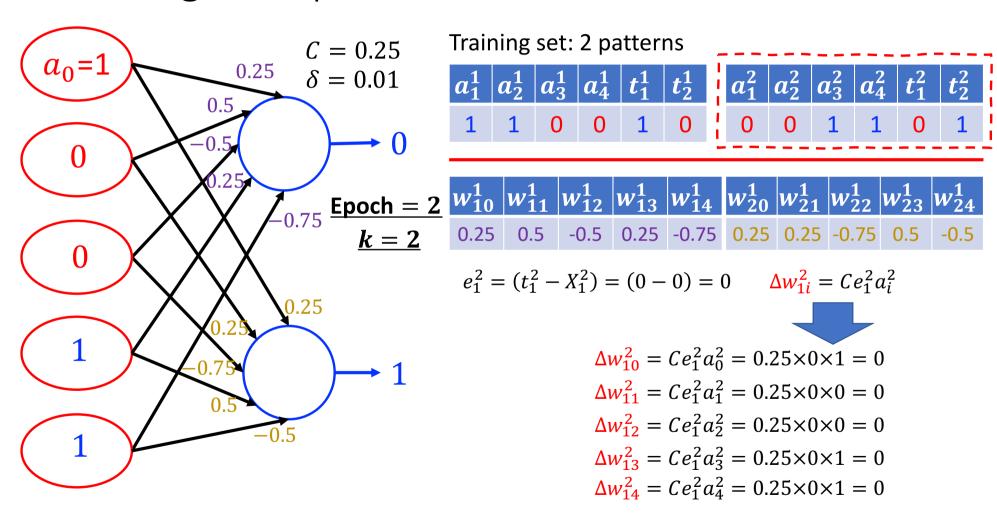


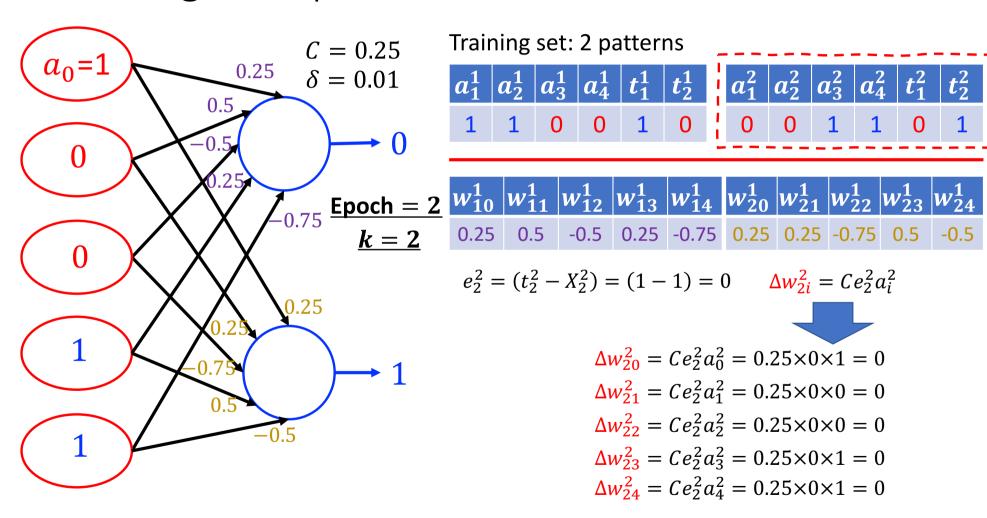


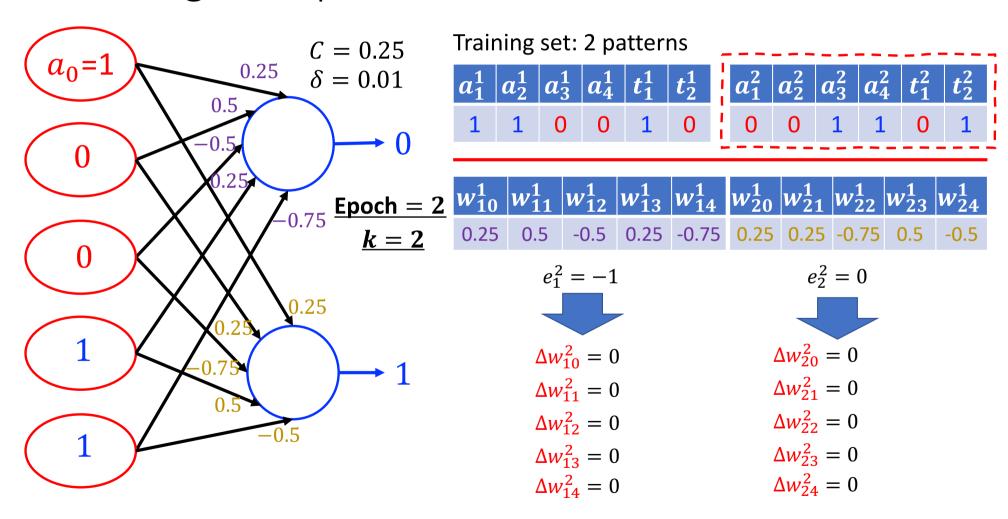


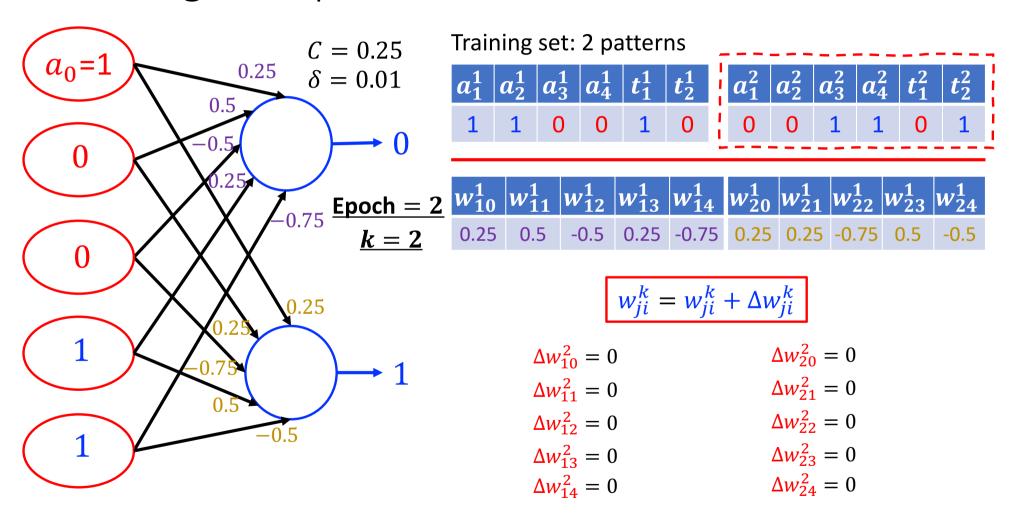


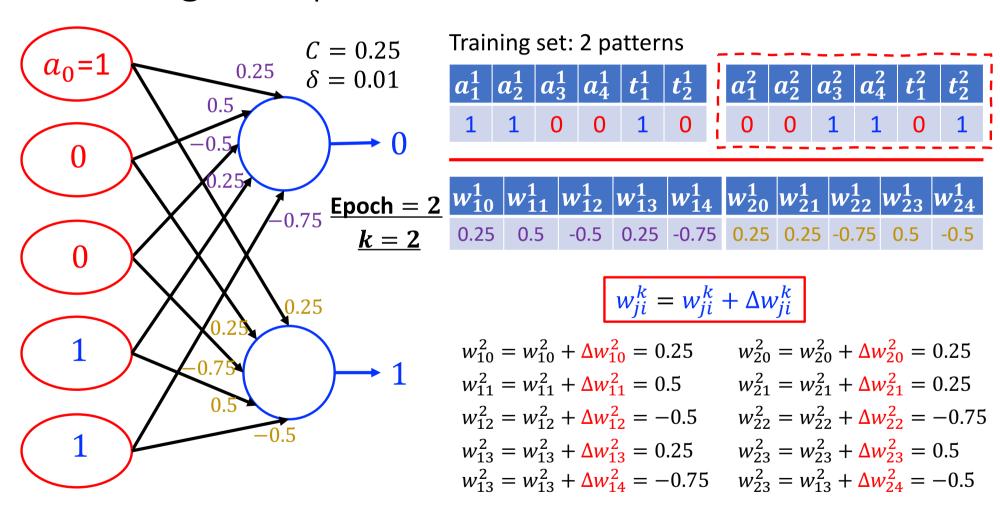


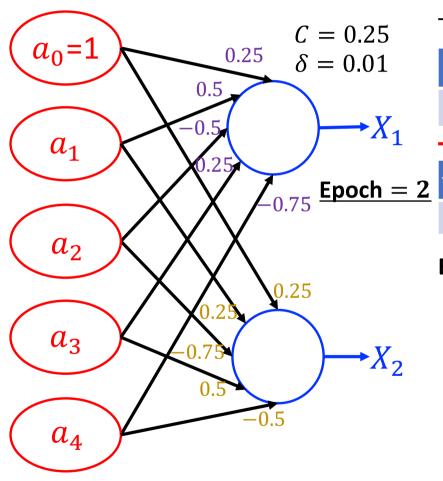












Training set: 2 patterns

$\overline{a_1^1}$	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

a_1^2	a_2^2	a_3^2	a_4^2	t_1^2	t_2^2
0	0	1	1	0	1

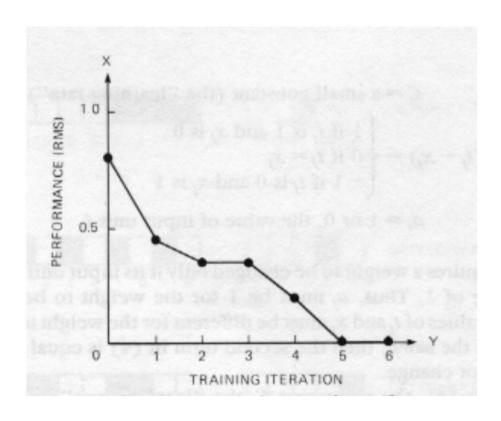
w_{10}^{2}	w_{11}^{2}	w_{12}^{2}	w_{13}^{2}	w_{14}^{2}	w_{20}^{2}	w_{21}^{2}	w_{22}^{2}	w_{23}^{2}	w_{24}^{2}
0.25	0.5	-0.5	0.25	-0.75	0.25	0.25	-0.75	0.5	-0.5

Epoch 2 finishes. Evaluate performance.

RMS =
$$\sqrt{\frac{\sum_{k=1}^{r} \sum_{j=1}^{m} (e_j^k)^2}{rm}} = \sqrt{\frac{\sum_{k=1}^{2} \sum_{j=1}^{2} (e_j^k)^2}{2 \times 2}}$$
$$= \sqrt{\frac{(e_1^1)^2 + (e_2^1)^2 + (e_1^2)^2 + (e_2^2)^2}{2 \times 2}} = 0 < \delta = 0.01$$

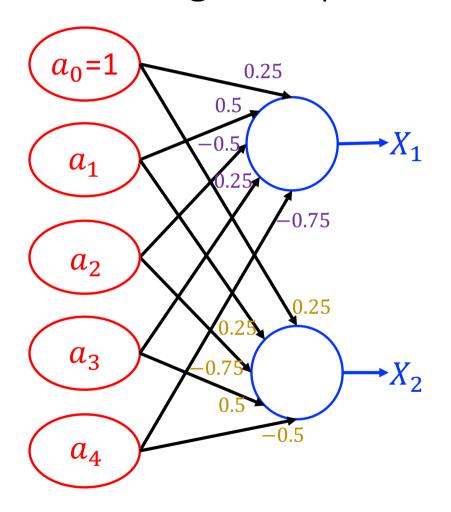
Great! Stop.

Network Performance



Learning curve: dependency of the RMS error on the number of iterations.

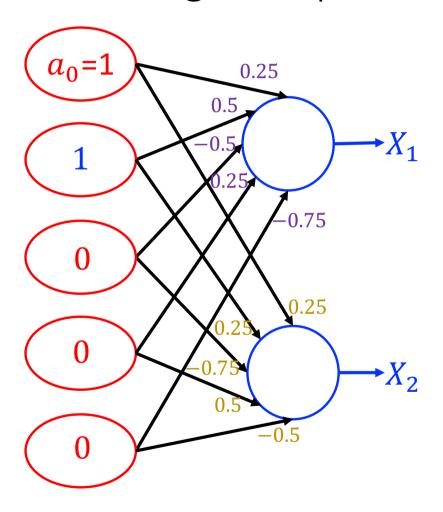
- Initially, the adaptable weights are all set to small random values, and the network does not perform very well;
- Performance improves during training;
- Finally, the error gets close to zero, training stops. We say the network has converged.



Training set: 2 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

a_1^2	a_2^2	a_3^2	a_4^2	t_1^2	t_2^2
0	0	1	1	0	1



Training set: 2 patterns

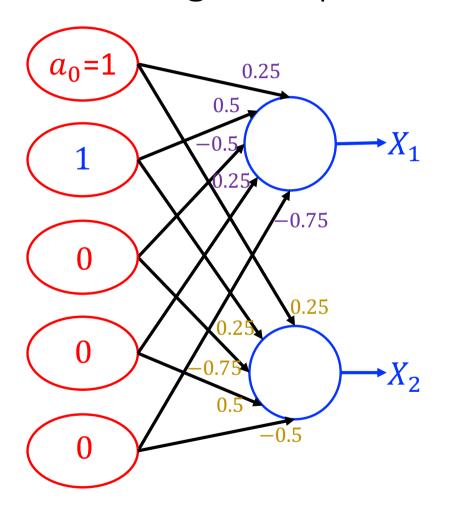
a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

a_1^2	a_2^2	a_3^2	a_4^2	t_1^2	t_2^2
0	0	1	1	0	1

Test set: 1 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	0	0	0	1	0

TEST



Training set: 2 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

a_1^2	a_2^2	a_3^2	a_4^2	t_{1}^{2}	t_2^2
0	0	1	1	0	1

Test set: 1 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	0	0	0	1	0

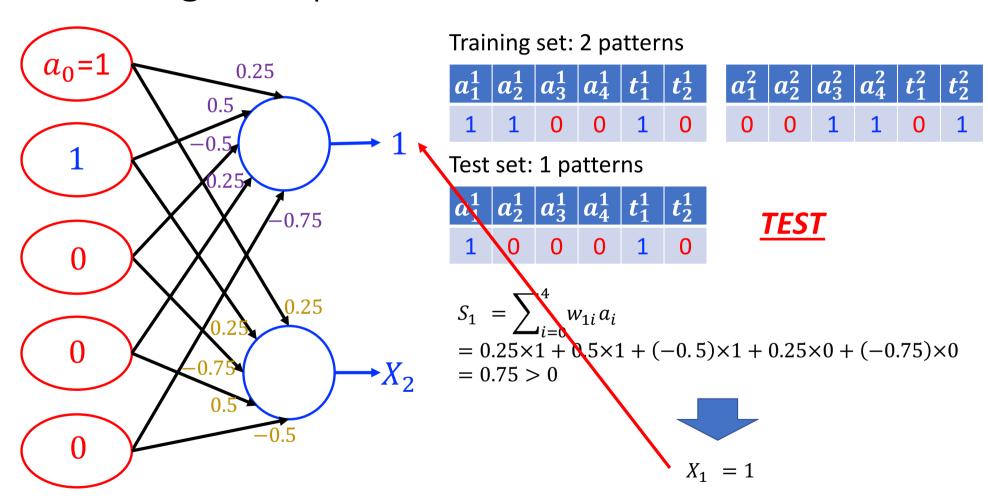
TEST

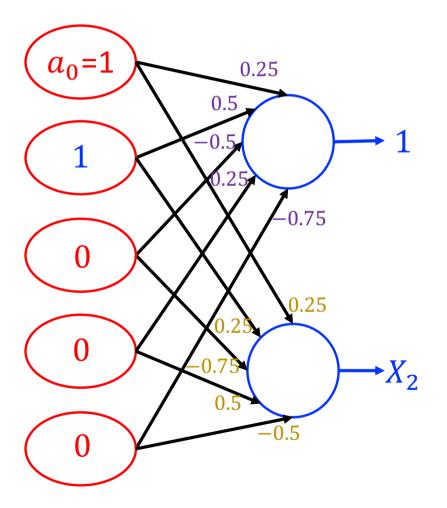
$$S_1 = \sum_{i=0}^{4} w_{1i} a_i$$

= 0.25×1 + 0.5×1 + (-0.5)×1 + 0.25×0 + (-0.75)×0
= 0.75 > 0



$$X_1 = 1$$





Training set: 2 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

a_1^2	a_2^2	a_3^2	a_4^2	t_1^2	t_2^2
0	0	1	1	0	1

Test set: 1 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	0	0	0	1	0

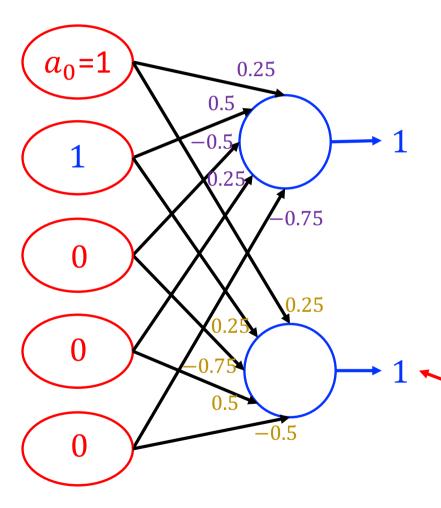
TEST

$$S_2 = \sum_{i=0}^4 w_{2i} a_i$$

= 0.25×1 + 0.25×1 + (-0.75)×0 + 0.5×0 + (-0.5)×0
= 0.5 > 0



$$X_2 = 1$$



Training set: 2 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	1	0	0	1	0

a_1^2	a_2^2	a_3^2	a_4^2	t_1^2	t_2^2
0	0	1	1	0	1

Test set: 1 patterns

a_1^1	a_2^1	a_3^1	a_4^1	t_1^1	t_2^1
1	0	0	0	1	0

$$S_2 = \sum_{i=0}^4 w_{2i} a_i$$
 does not necessarily we well on a test set.
= $0.25 \times 1 + 0.25 \times 1 + (-0.75) \times 0 + 0.5 \times 0 + (-0.5) \times 0$

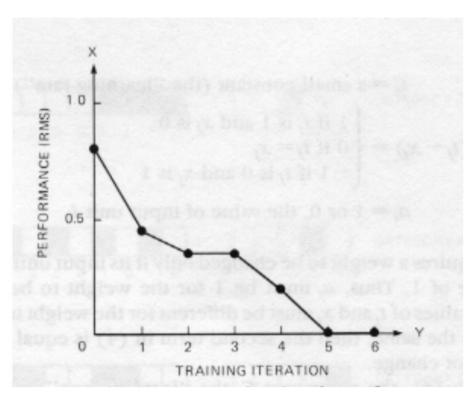
= 0.5 > 0

TEST

The network after training does not necessarily work well on a test set.



Network Performance



Q: Does the learning algorithm always converge?

Learning curve: dependency of the RMS error on the number of iterations.

- Initially, the adaptable weights are all set to small random values, and the network does not perform very well;
- Performance improves during training;
- Finally, the error gets close to zero, training stops. We say the network has converged.