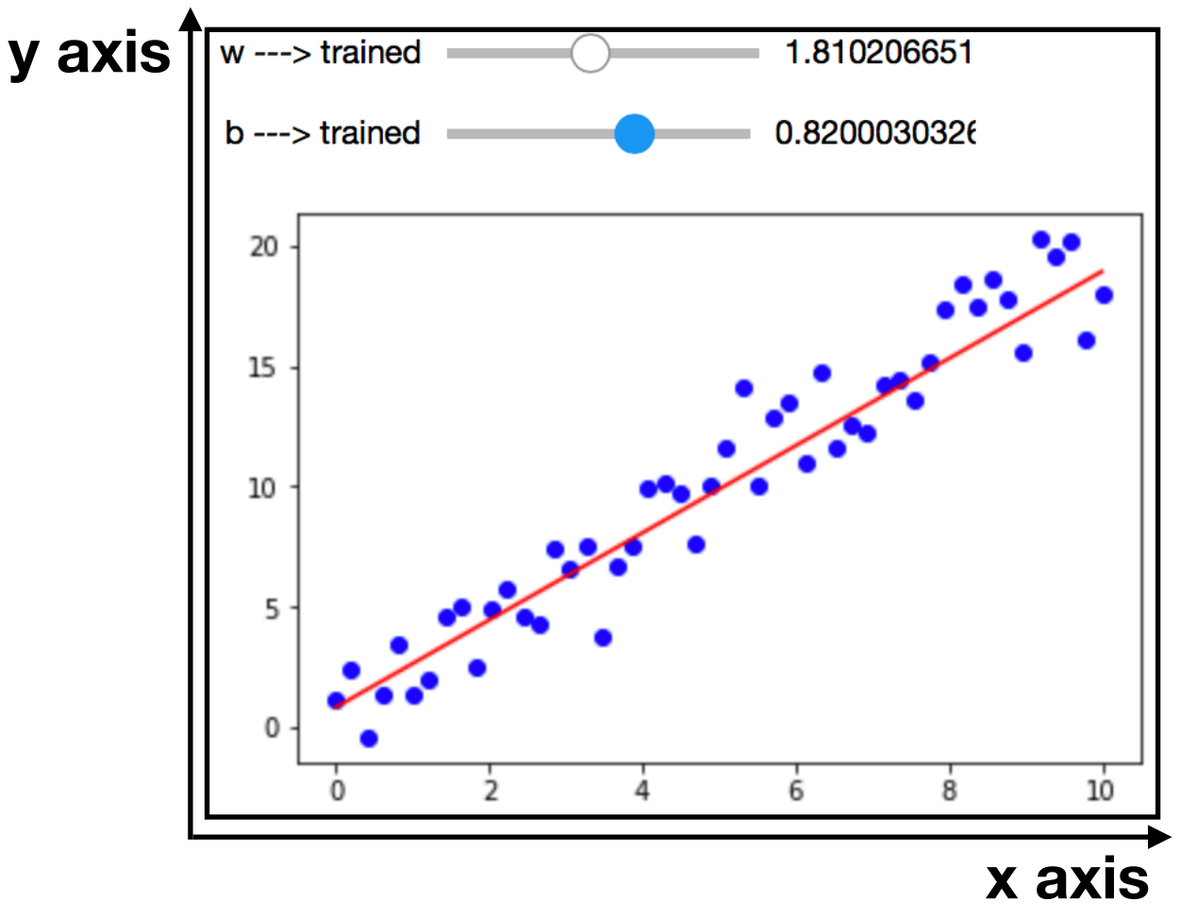
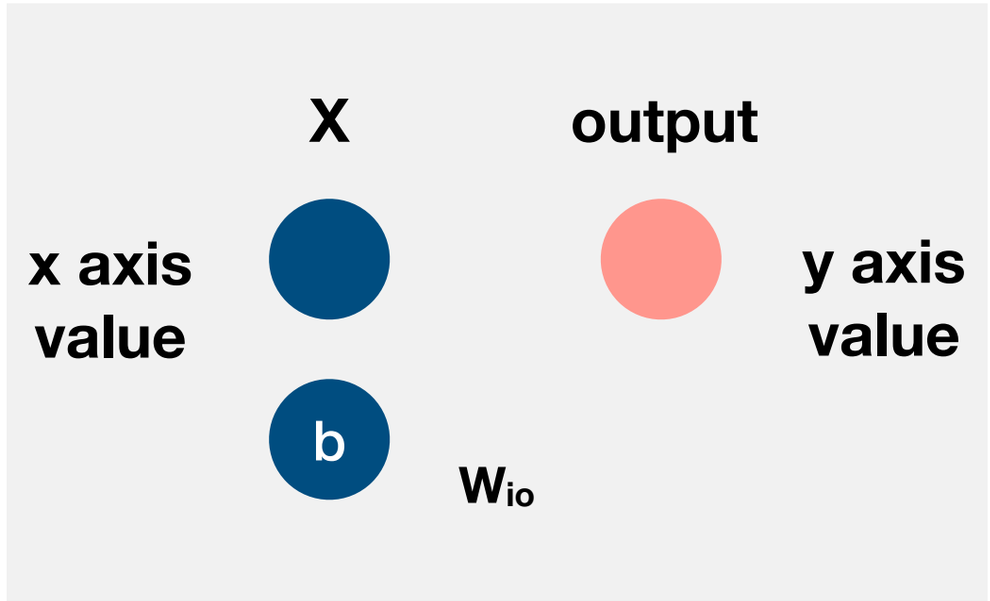
Neural Net basics

Least Square Regression

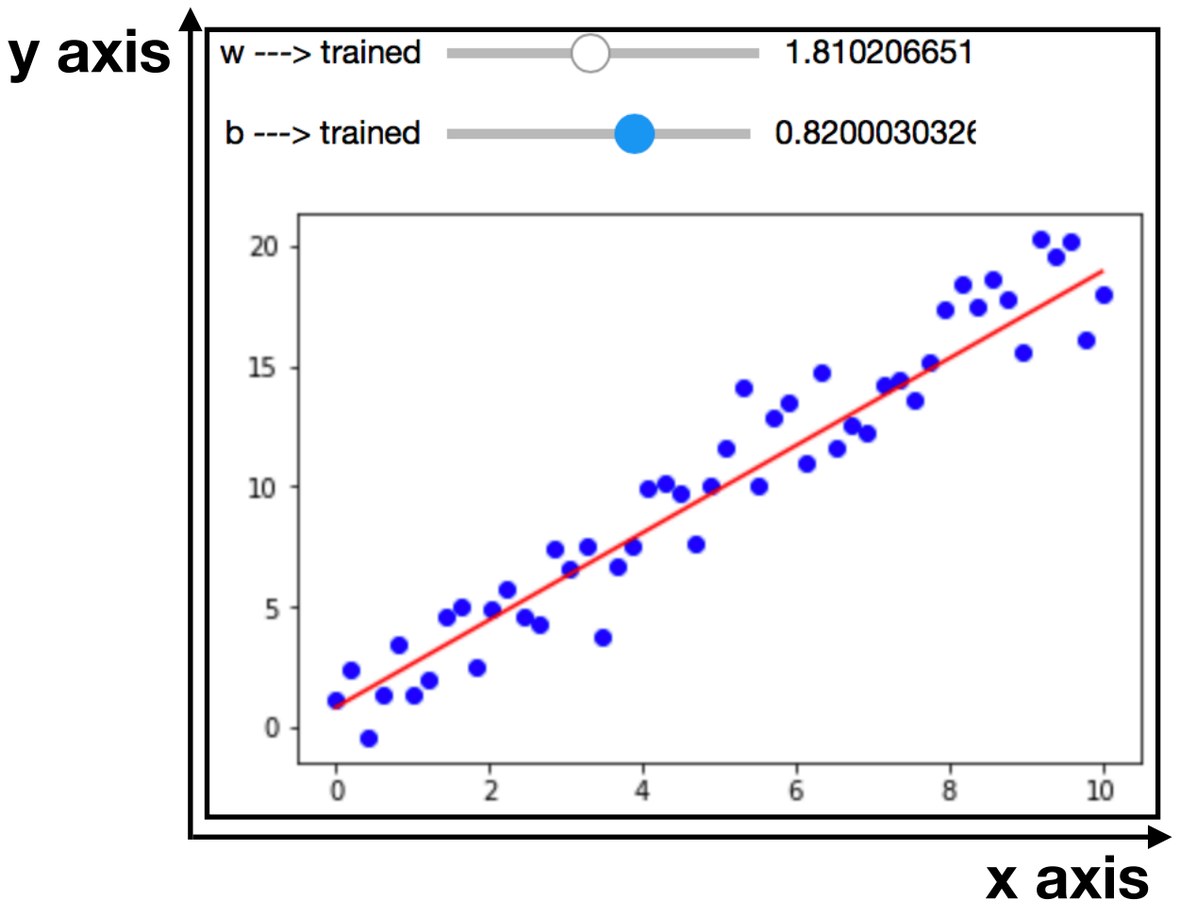
Least Square Regression

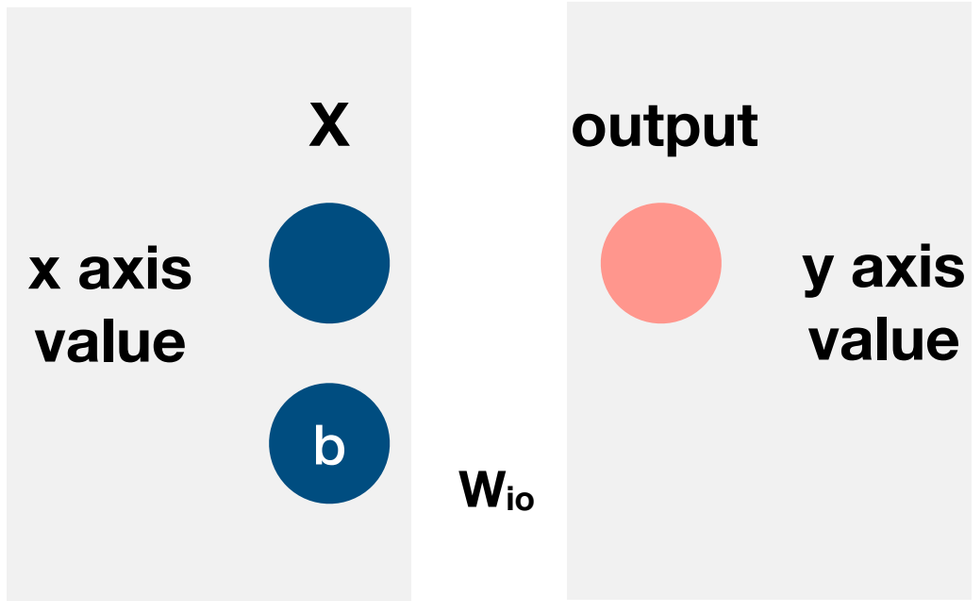




perceptrons를 이용한 least square regression graphical model

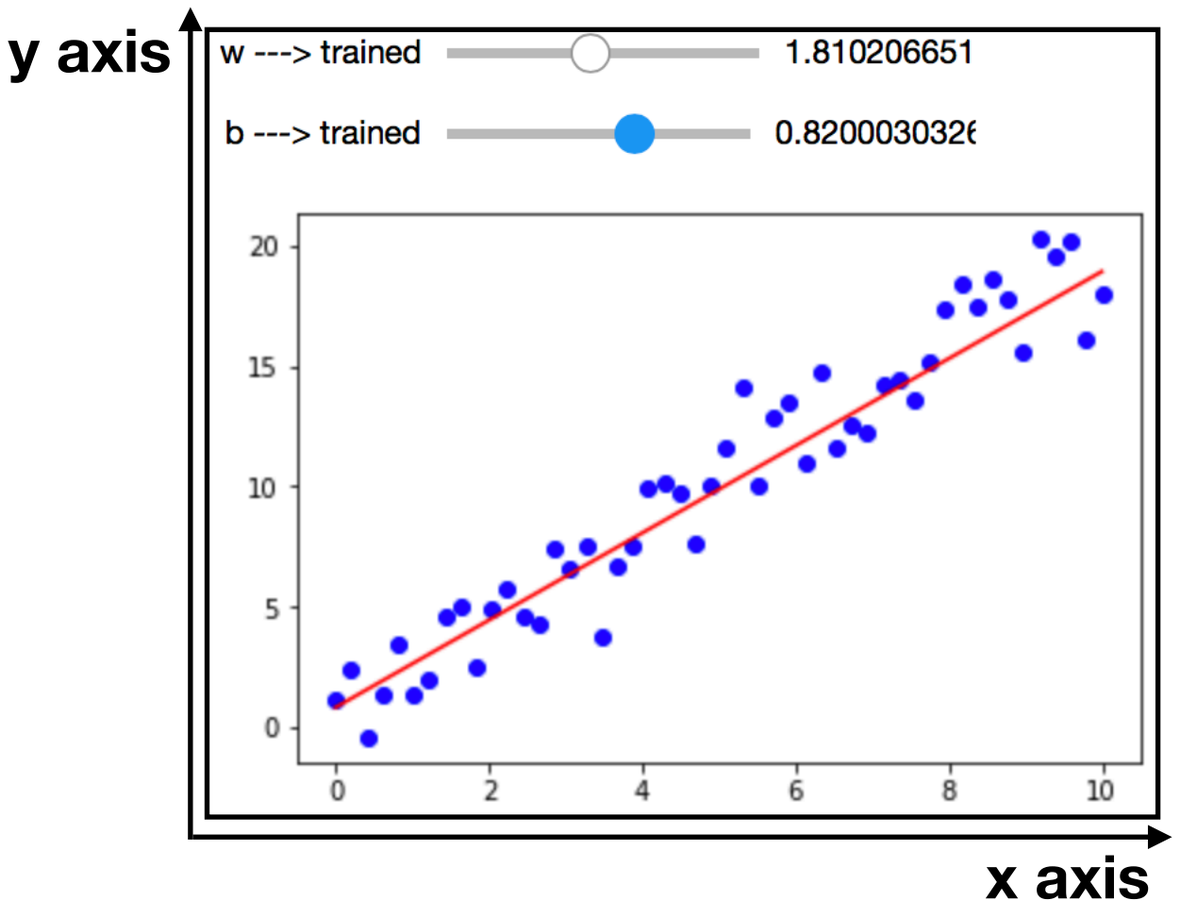
Least Square Regression

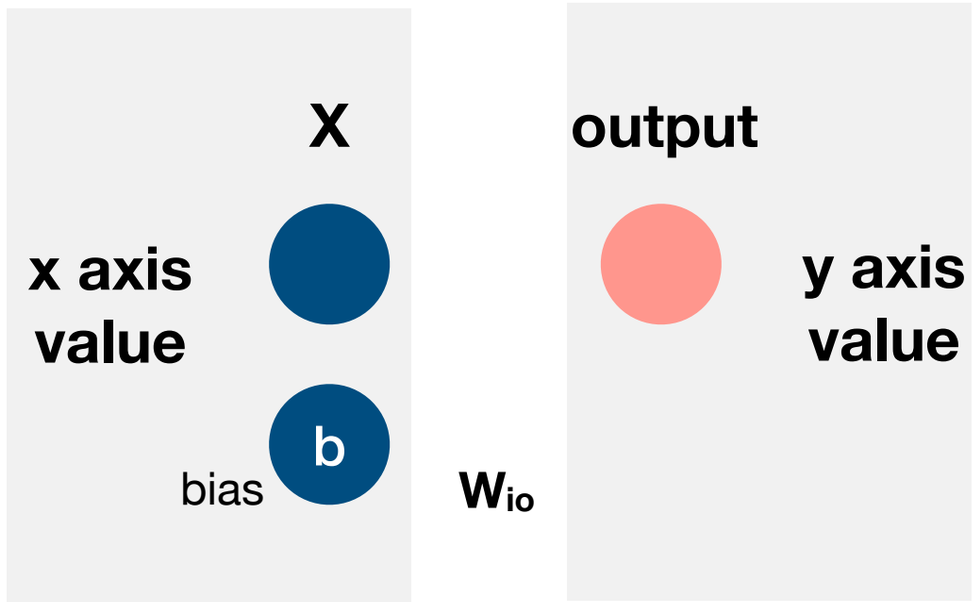




least square regression의 예시
input: 파란 데이터 포인트의 x axis value
target: 파란 데이터 포인트의 y axis value
output: 빨간 선형 모델 상의 y axis value
목적: 파란 데이터를 가장 잘 나타내는 빨간 선형 모델을 그리는 것

Least Square Regression

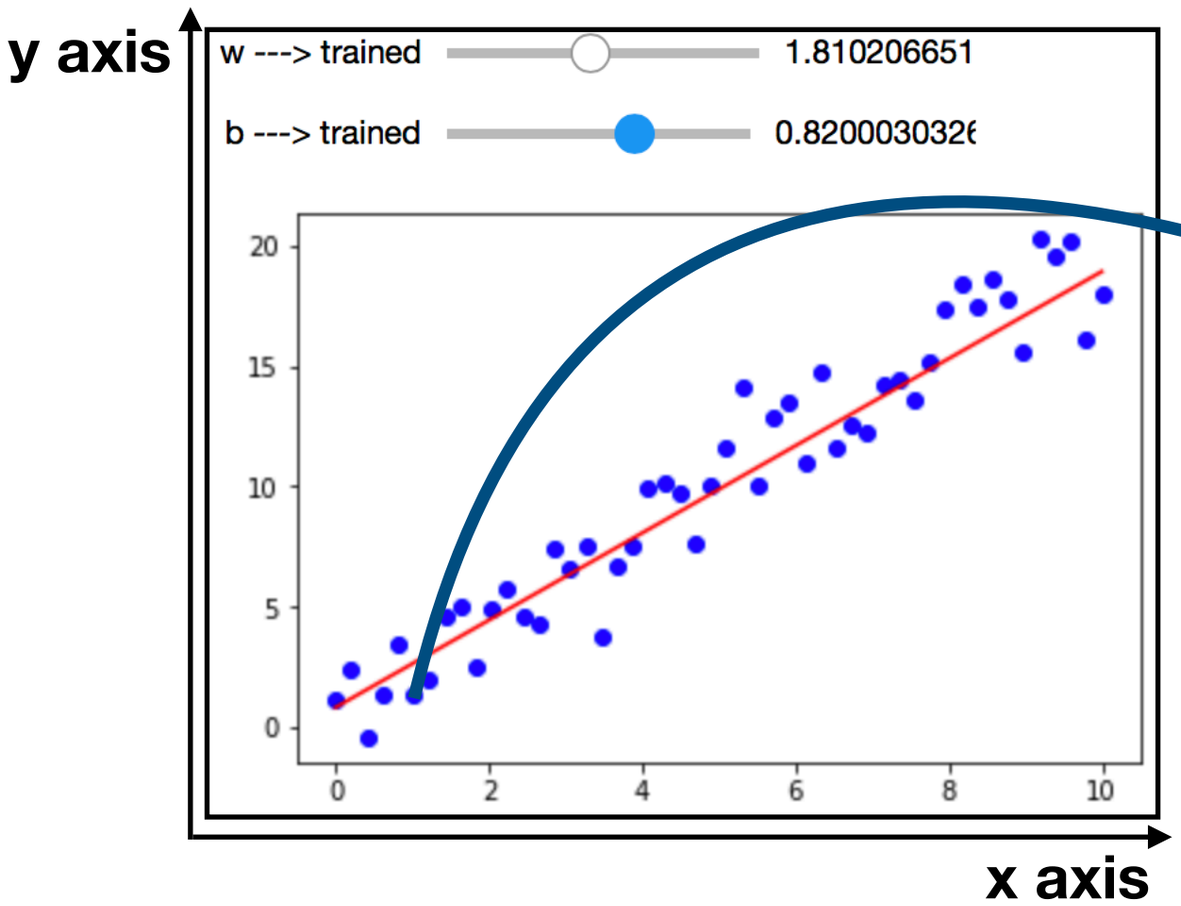


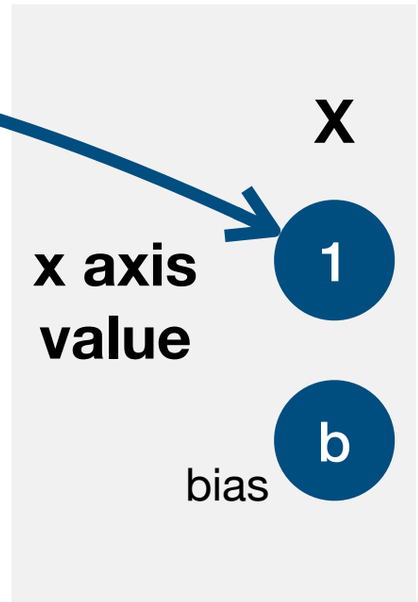


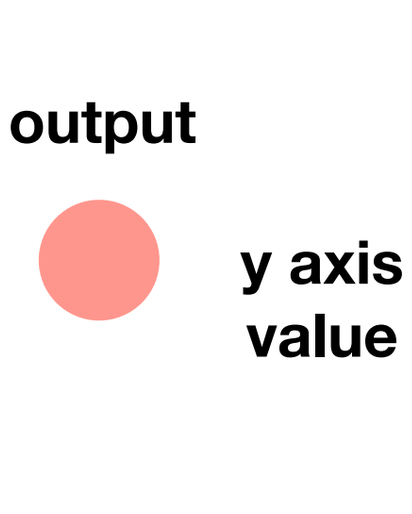
모델구조:

input layer (1 node),
output layer (1 node)
노드 숫자를 셀 때 bias node는 제외

Least Square Regression

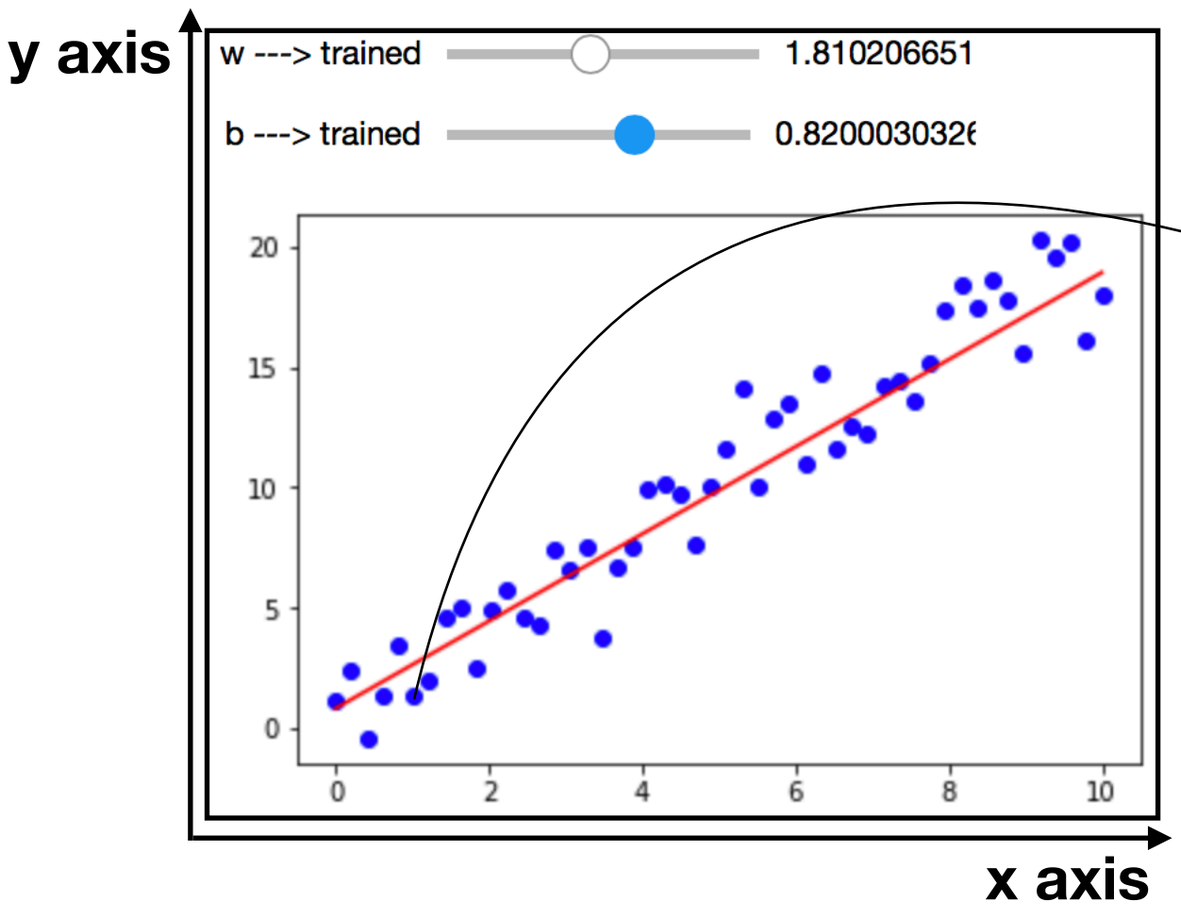


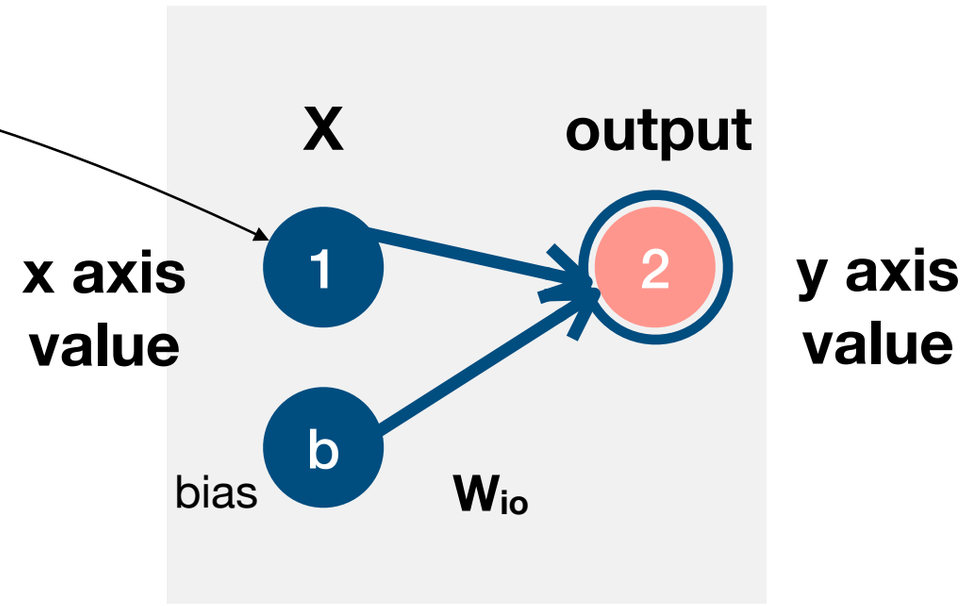




훈련:
파란 데이터 포인트의 x axis value를 input layer의 node에 넣어줍니다.

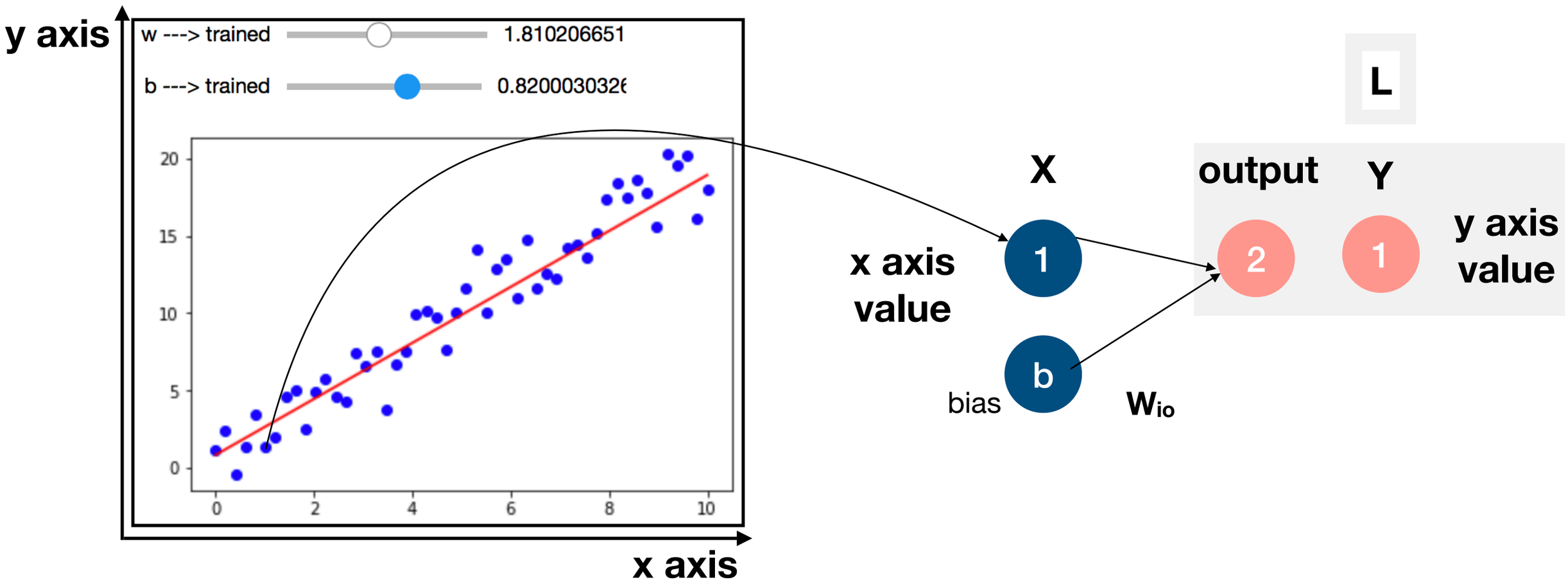
Least Square Regression





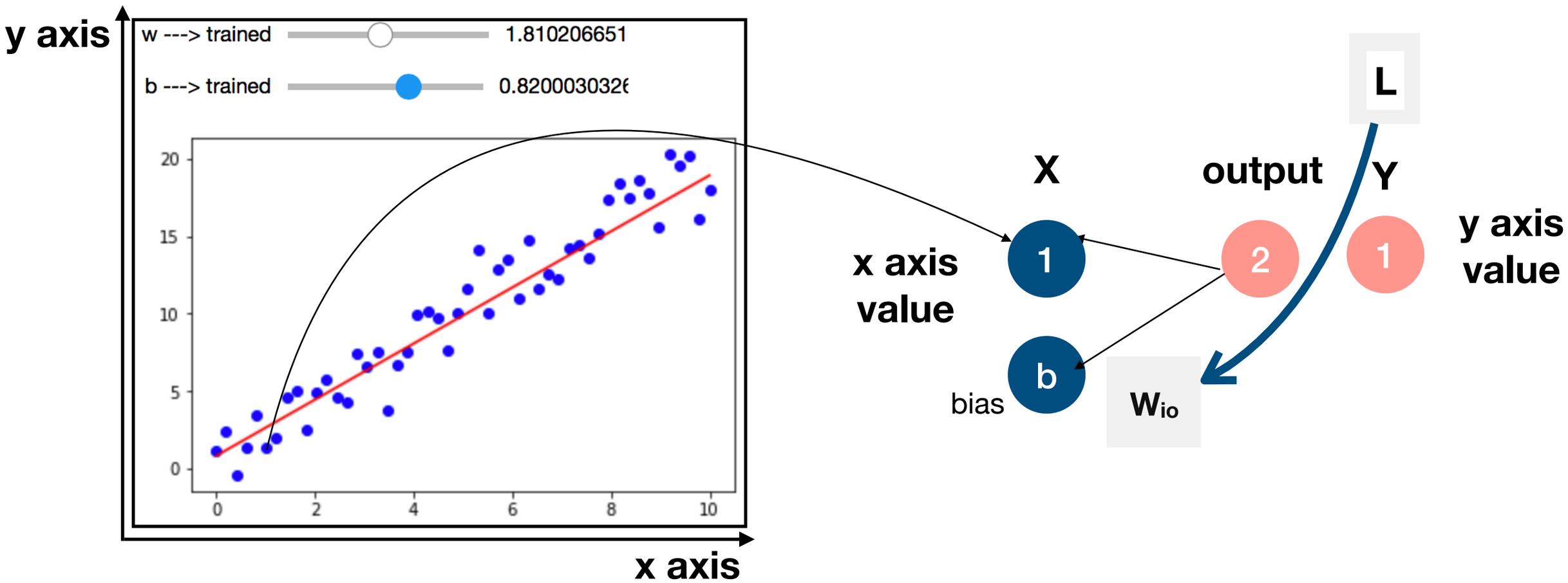
각 input layer의 node 값에 weight (진한 화살표)을 곱하고,
곱한 값을 모두 더해 output layer node에 넣어줍니다.

Least Square Regression



그렇게 구한 output과 정답 target (Y)을 비교하여 loss를 구합니다.

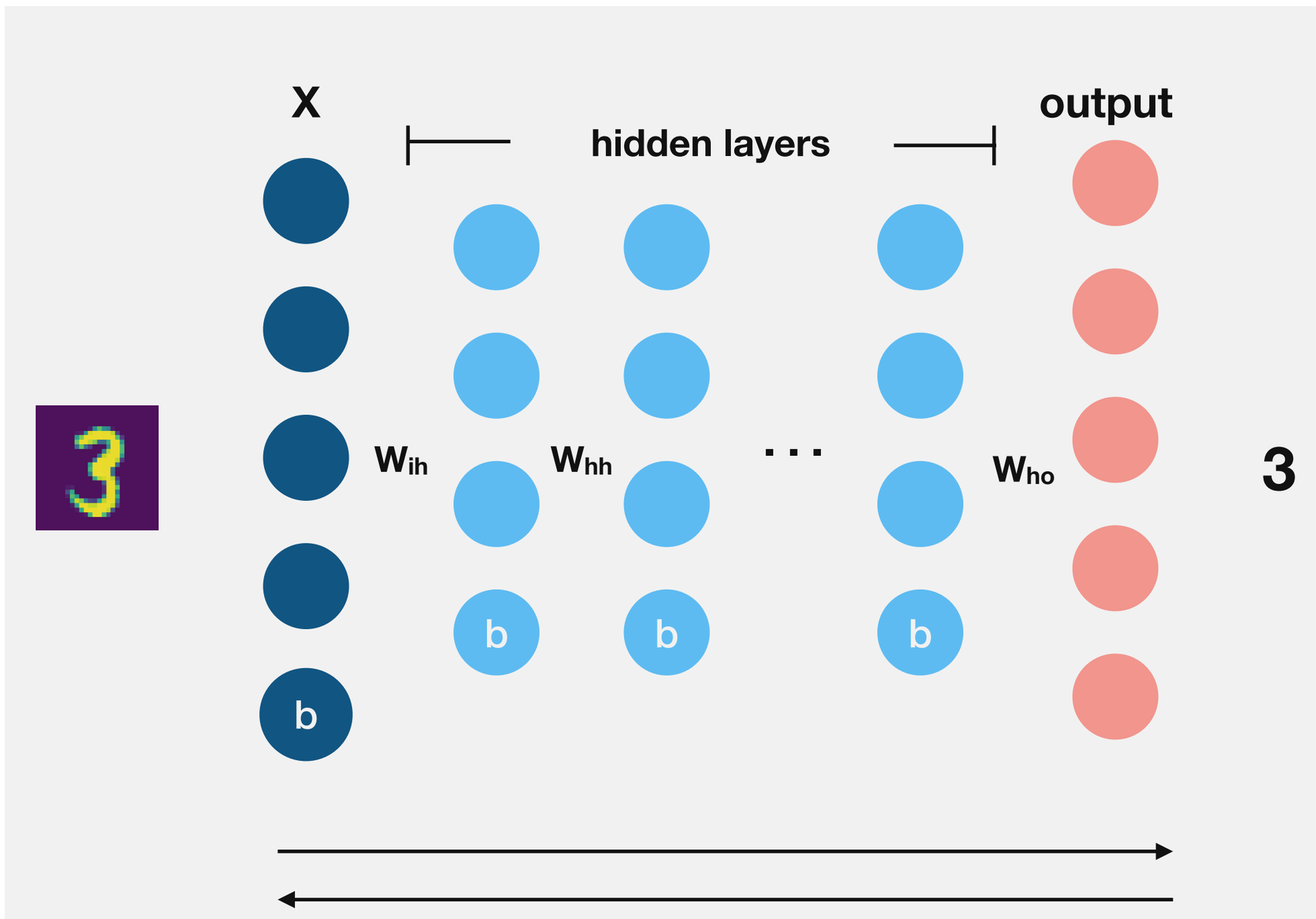
Least Square Regression



loss를 최소화하는 방향으로, weight을 update 합니다.

ANN / DNN

ANN DNN



perceptrons를 이용한 ANN/DNN classifier graphical model

ANN DNN

5

5

x

b

input nodes
= 25

hidden_1

b

hidden nodes
= 3

W_{ih}

hidden_2

b

hidden nodes
= 3

W_{hh}

W_{ho}

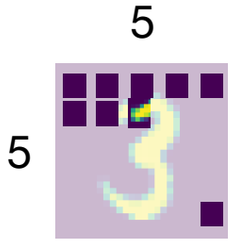
output

3

output nodes
= 10

ANN/DNN classifier의 예시
input: 5 by 5의 이미지(X)
target: 0에서 9까지의 라벨(Y)
목적: input이 0~9 중 어떤 숫자인지 분류

ANN DNN



5

5

x

0.1

0.3

0.8

⋮

0.2

bias b

input nodes
= 25

hidden_1

hidden_2

b bias

b bias

hidden nodes
= 3

hidden nodes
= 3

W_{ih} W_{hh} W_{ho}

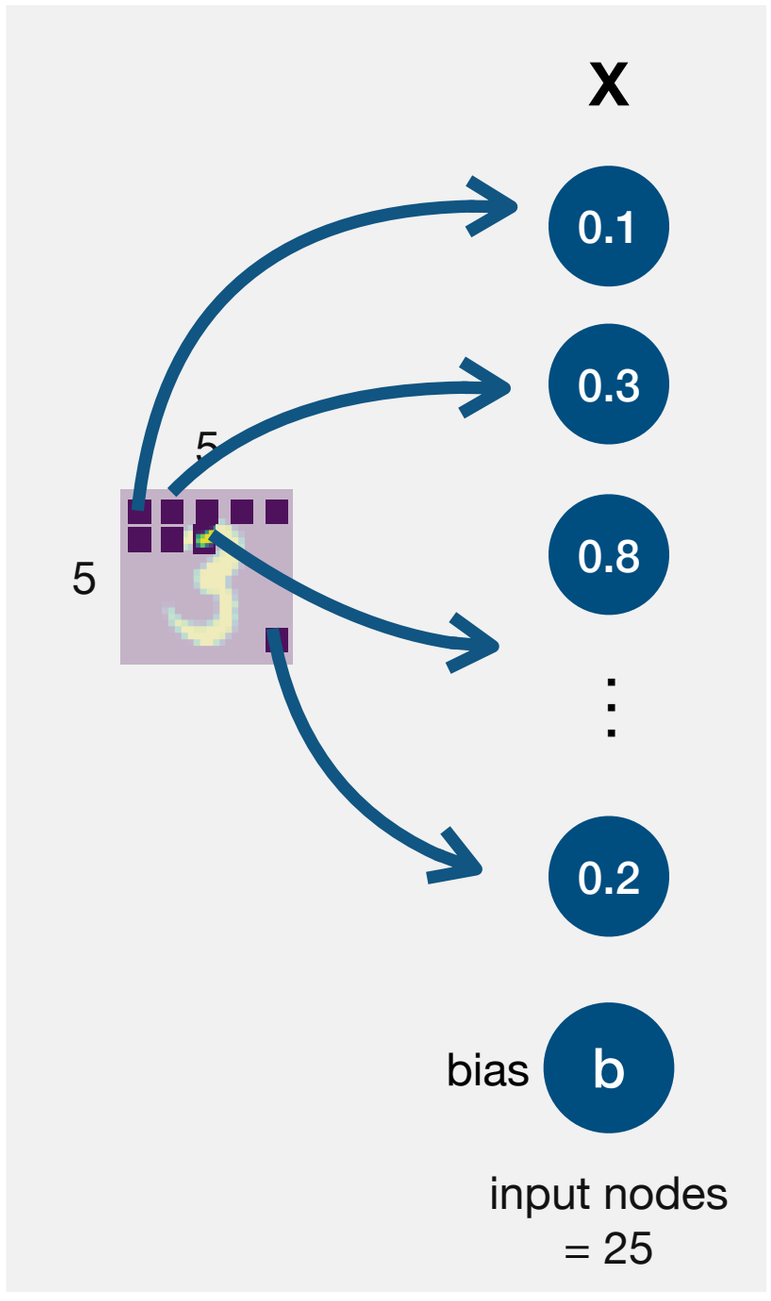
output

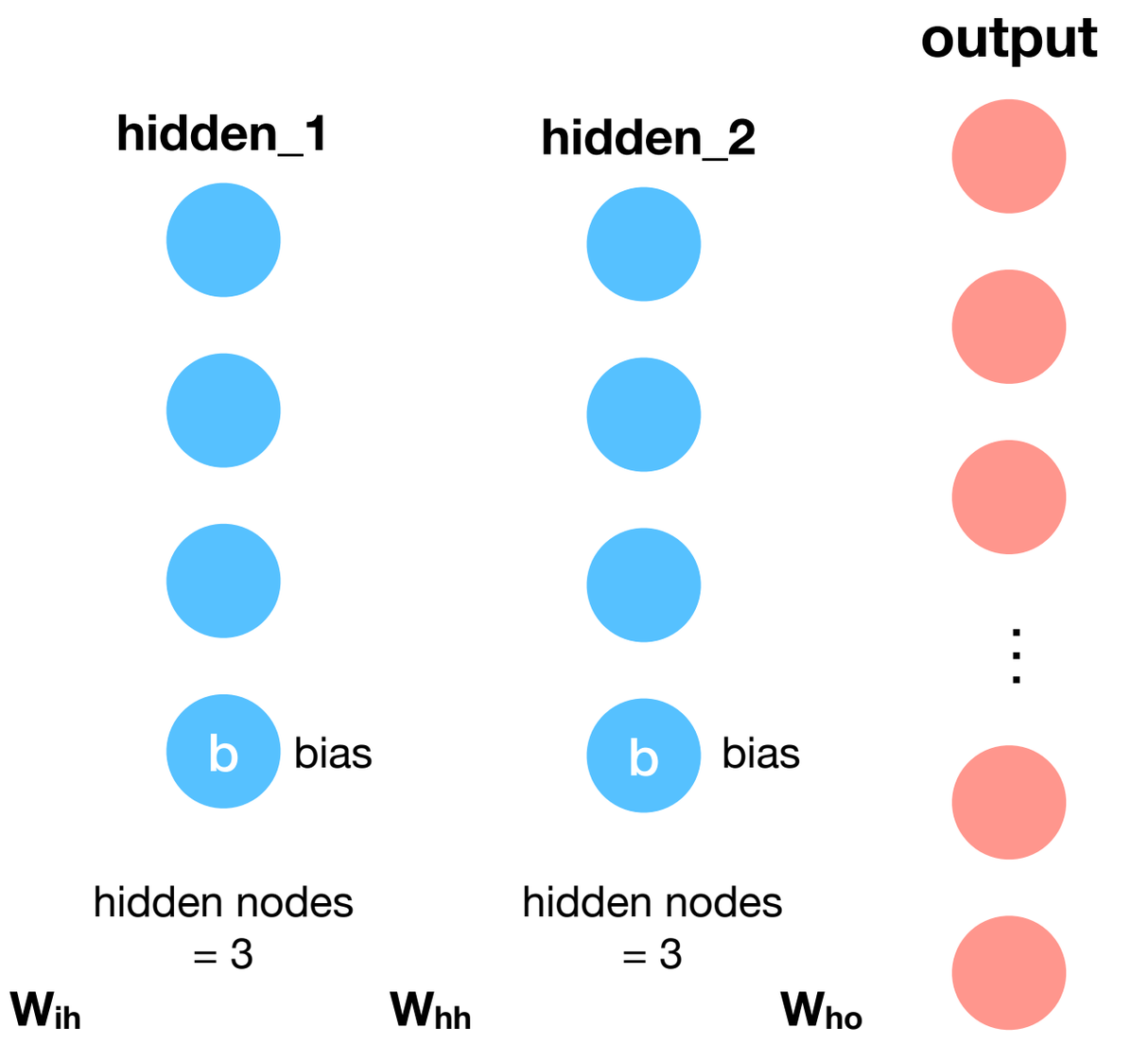
⋮

output nodes
= 10

모델구조:
input layer (25 nodes),
2 hidden layers (3 nodes each),
output layer (10 nodes)
노드 숫자를 셀 때 bias node는 제외

ANN DNN

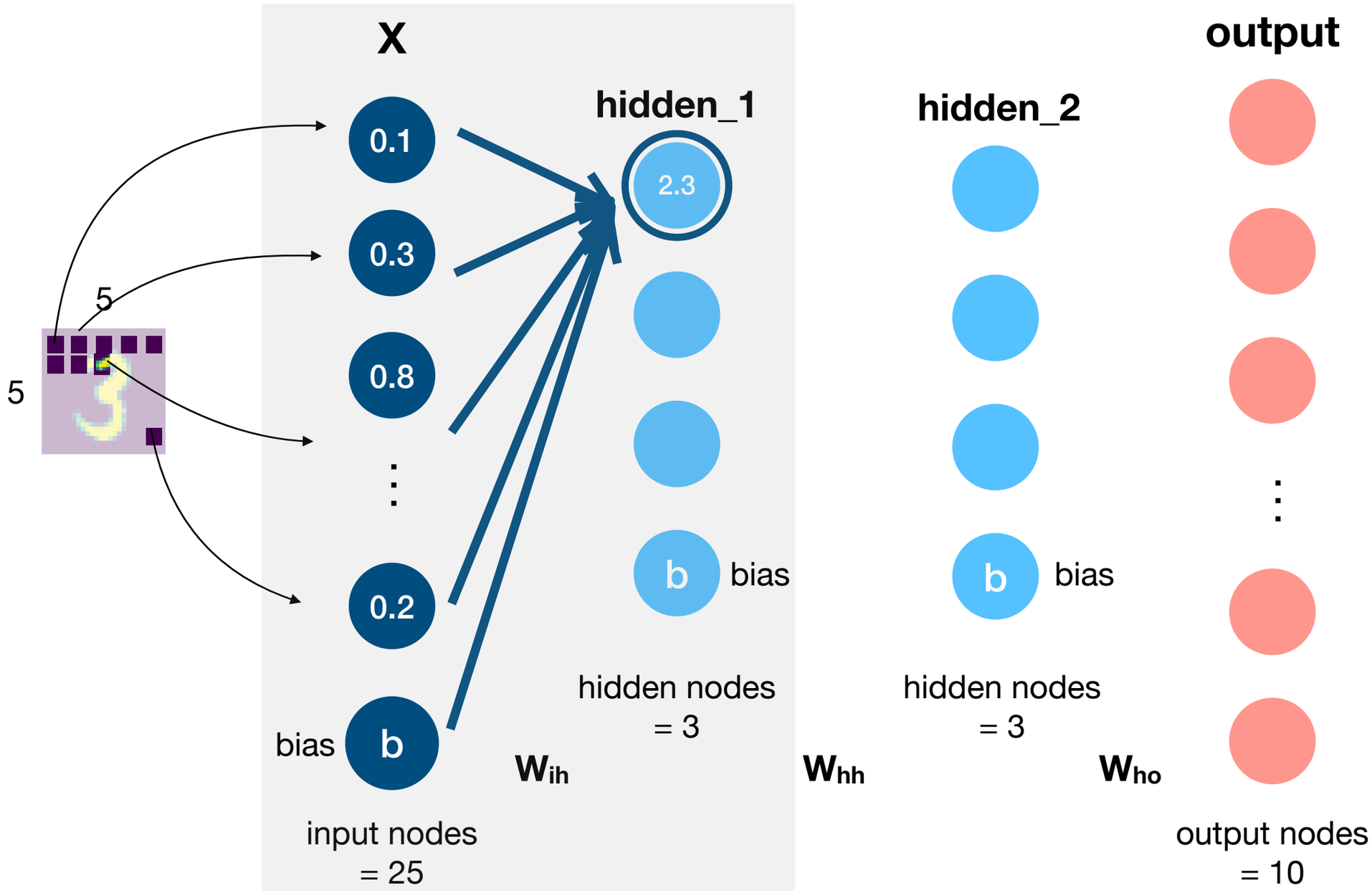




3

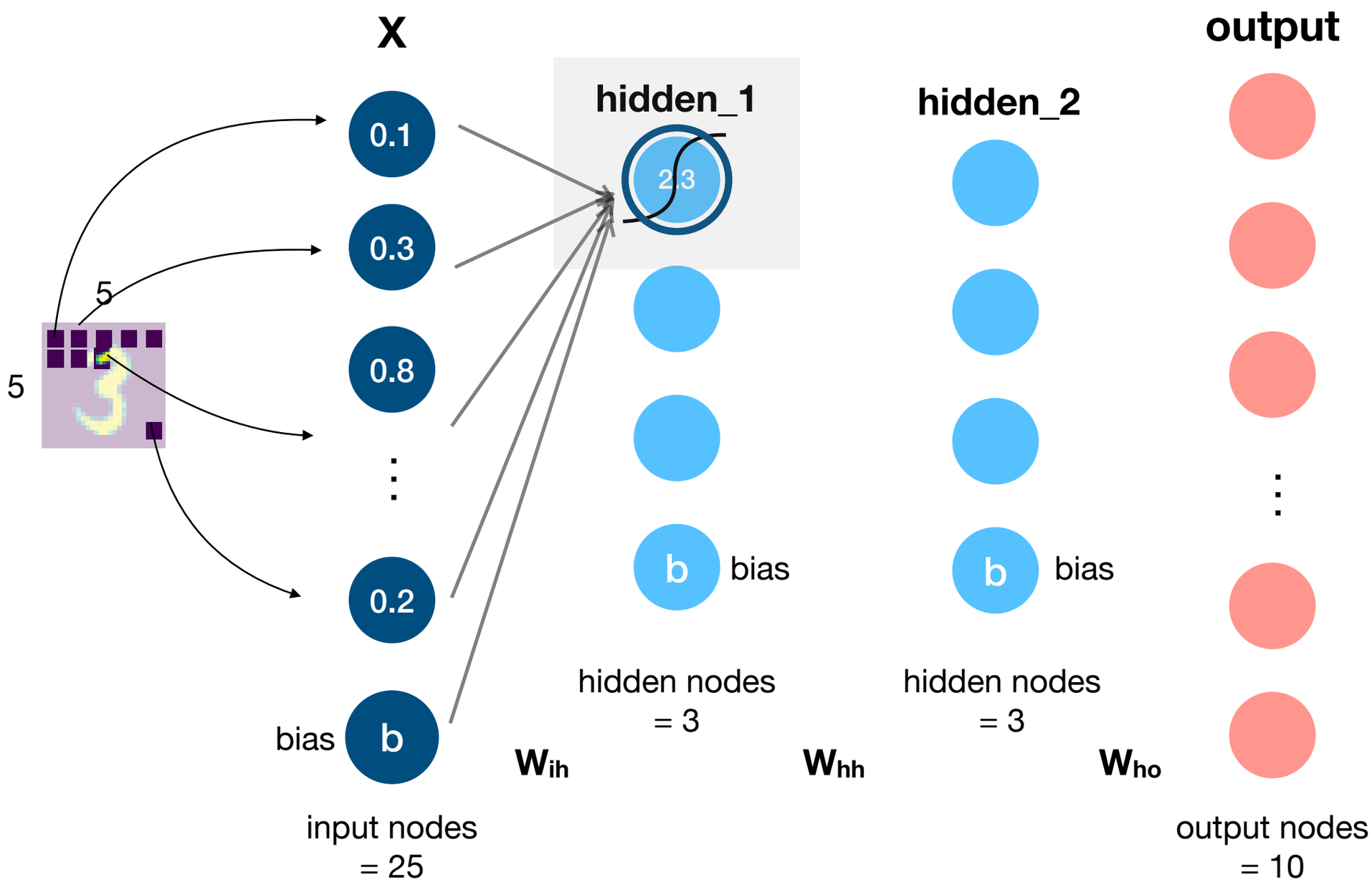
훈련:
이미지를 pixel 단위로 쪼개서
그 값을 각각 input layer의 nodes에 넣어줍니다.

ANN DNN



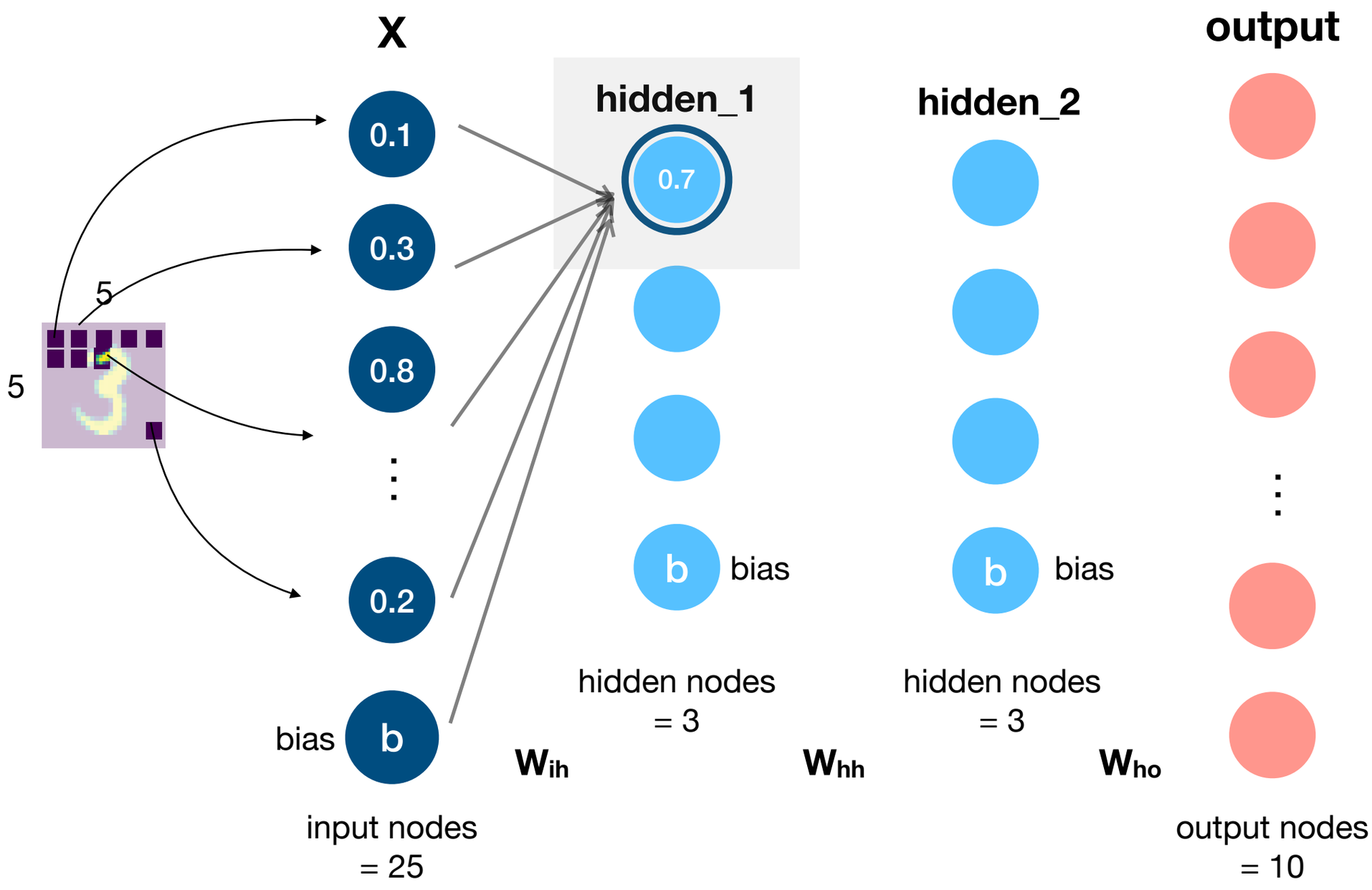
각 input layer의 node 값에 weight (진한 화살표)을 곱하고,
곱한 값을 모두 더해 첫 번째 hidden layer node에 넣어줍니다.

ANN DNN



activation function을 통해서 node 값을
0과 1 사이의 값(sigmoid function)으로 바꿔줍니다.

ANN DNN



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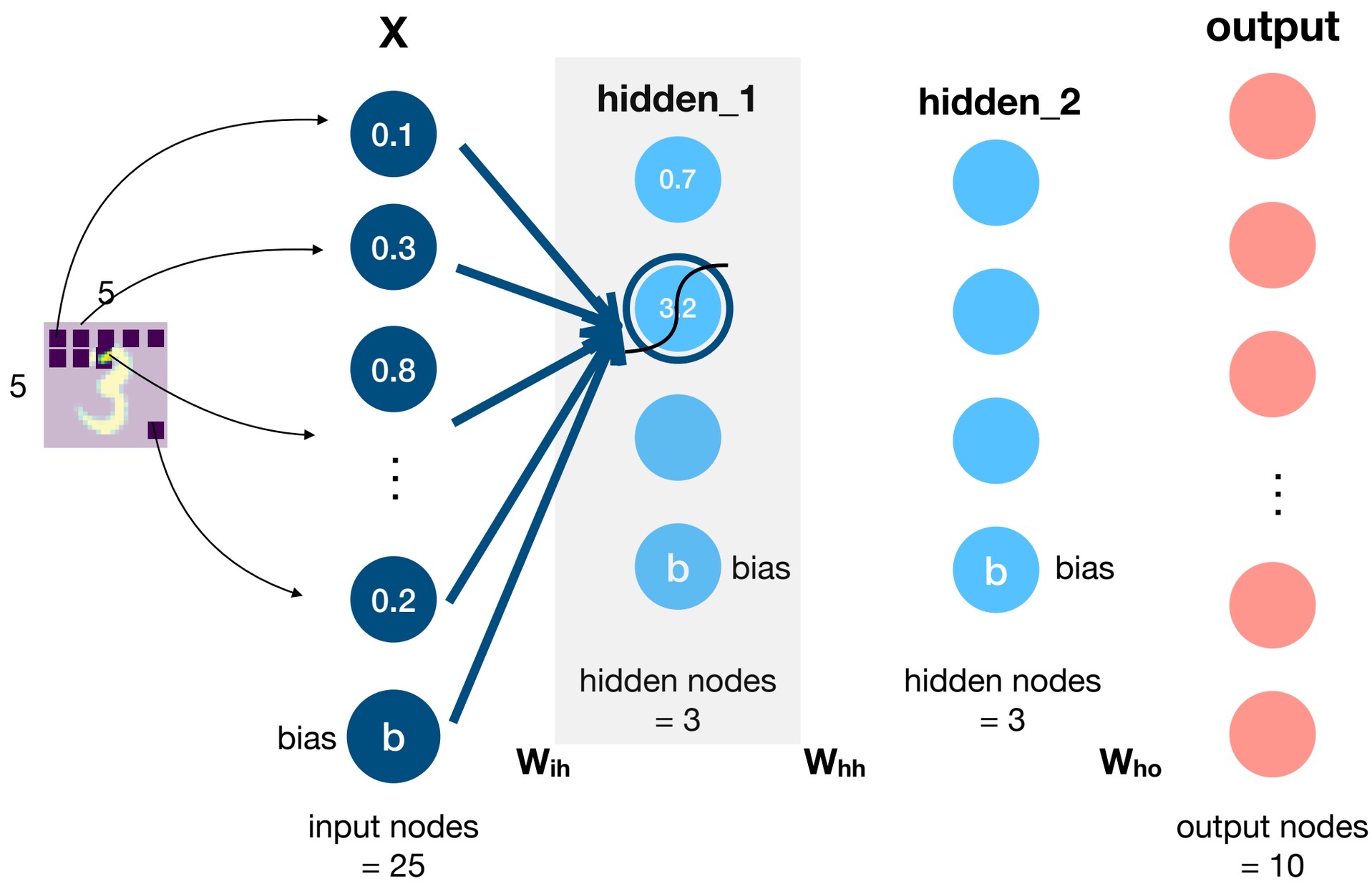
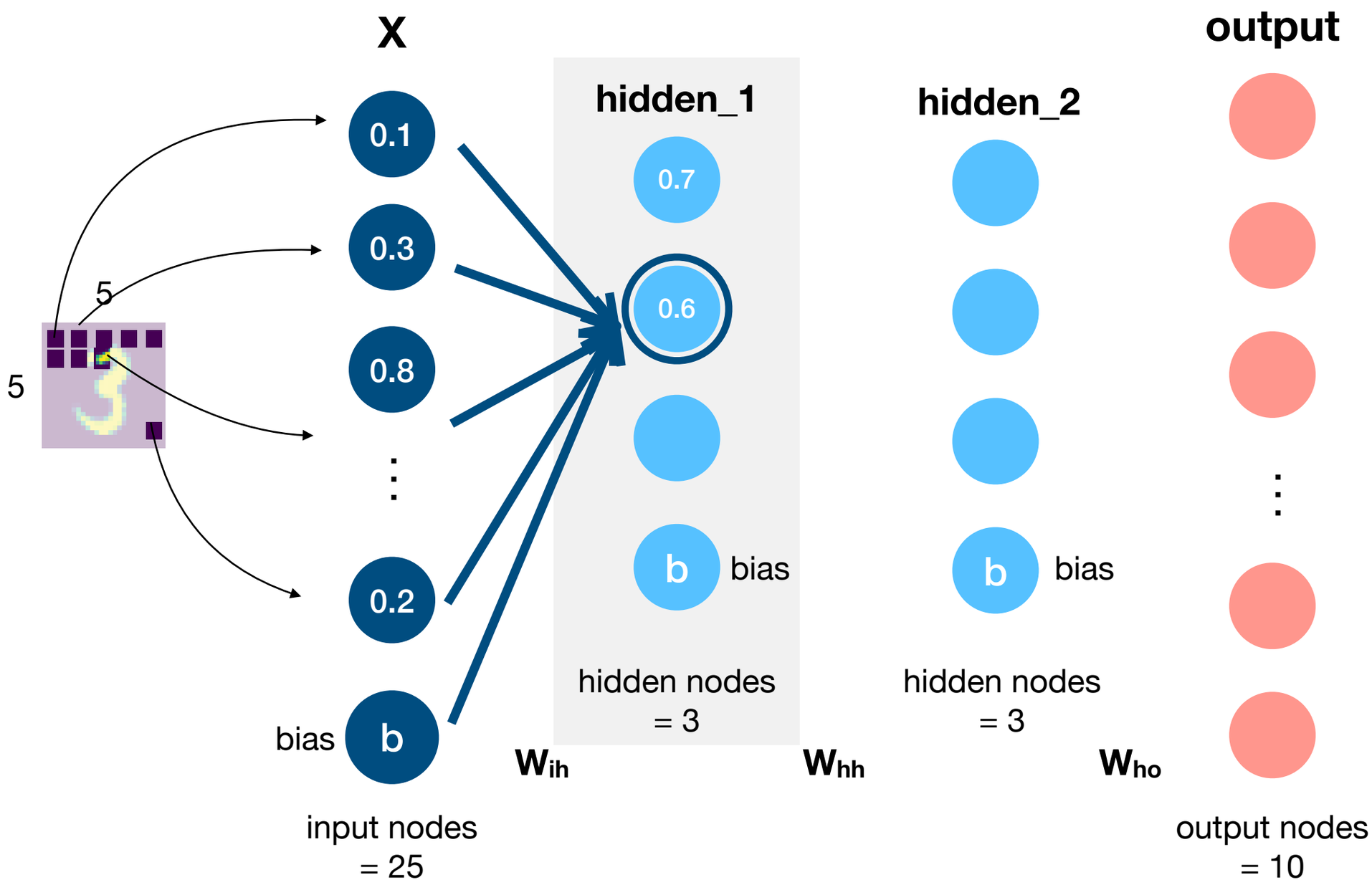
ANN DNN



모든 hidden layer 1의 nodes에 대해 반복합니다.

ANN DNN



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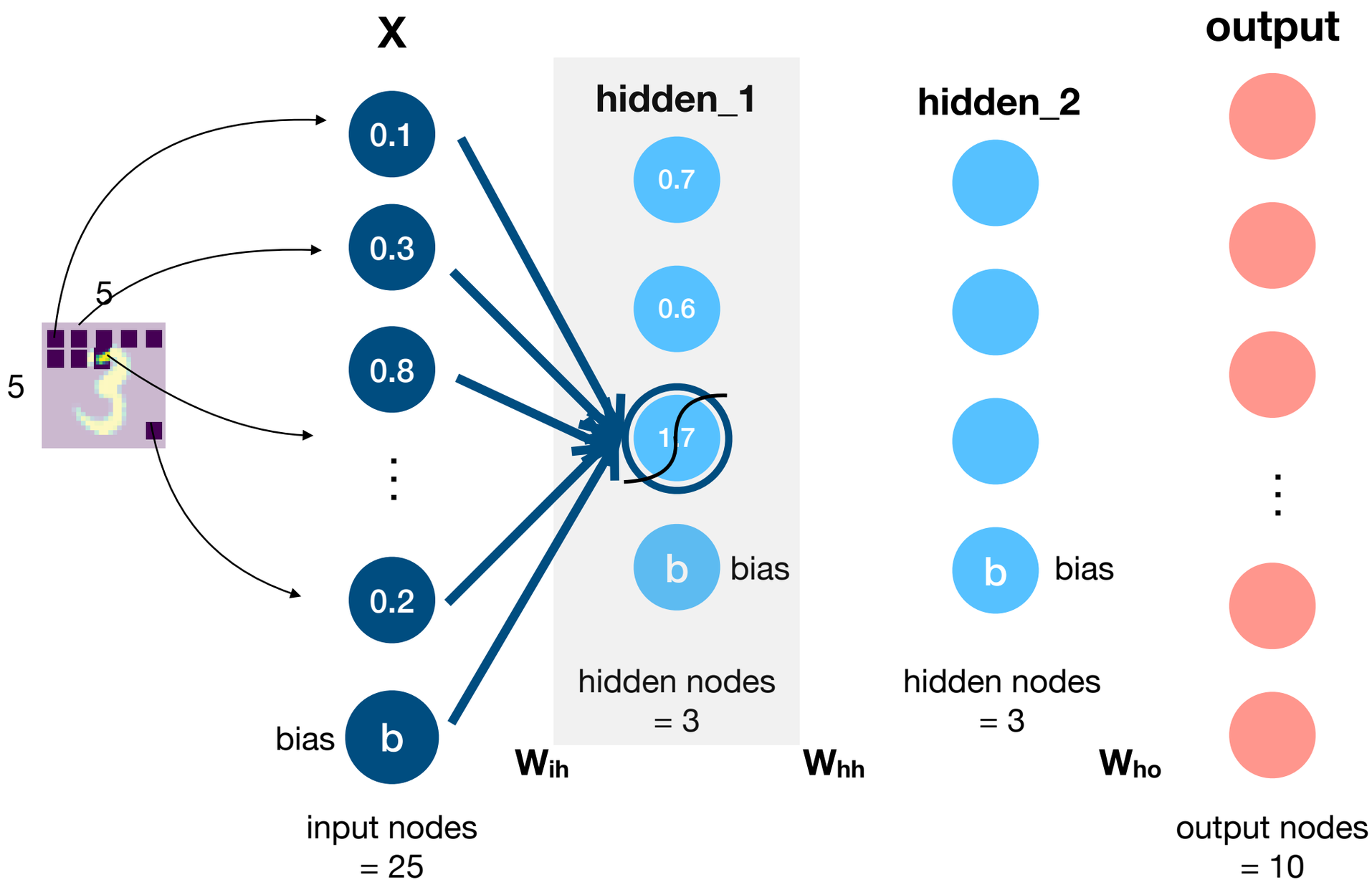
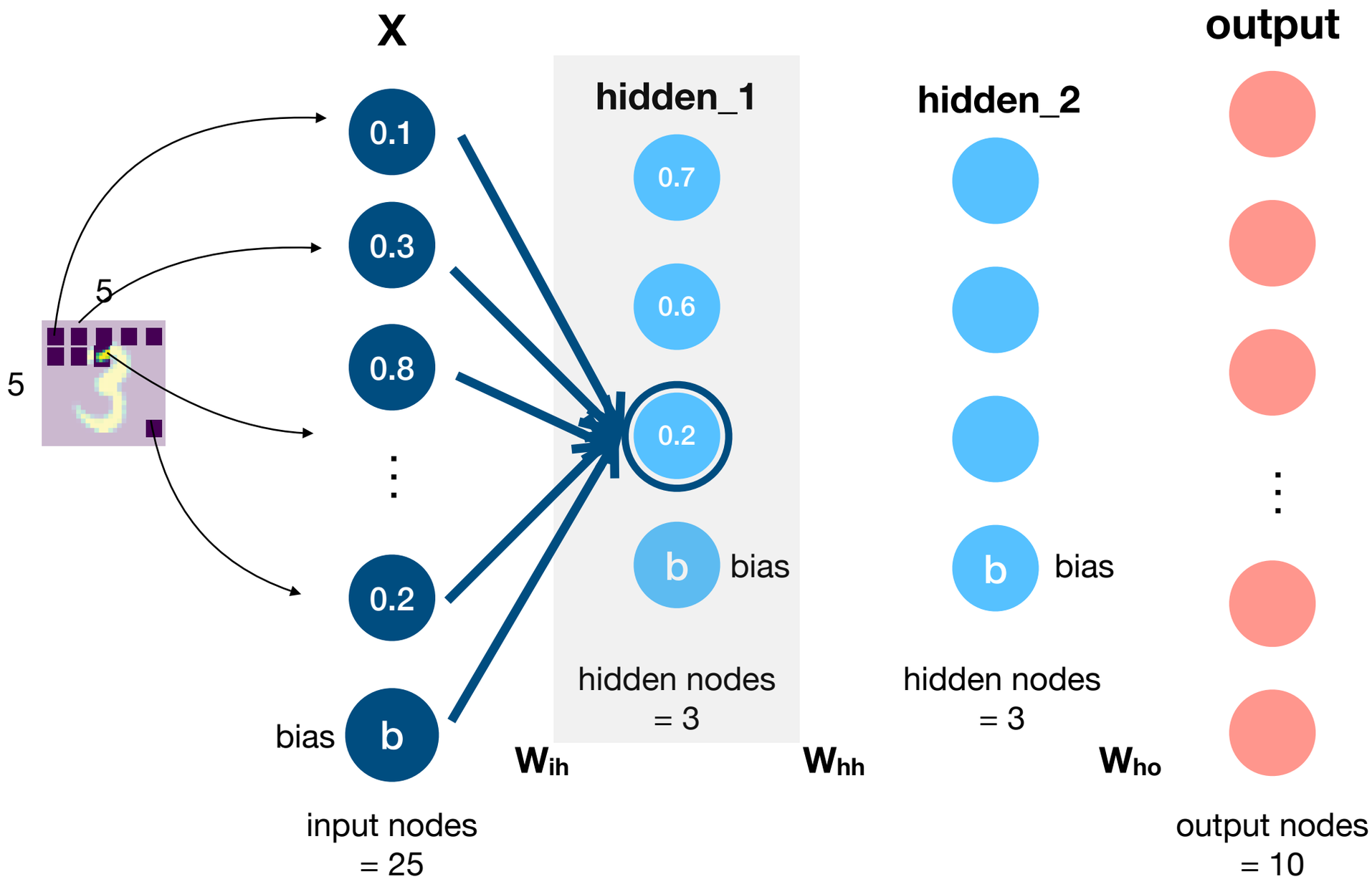
ANN DNN



모든 hidden layer 1의 nodes에 대해 반복합니다.

ANN DNN



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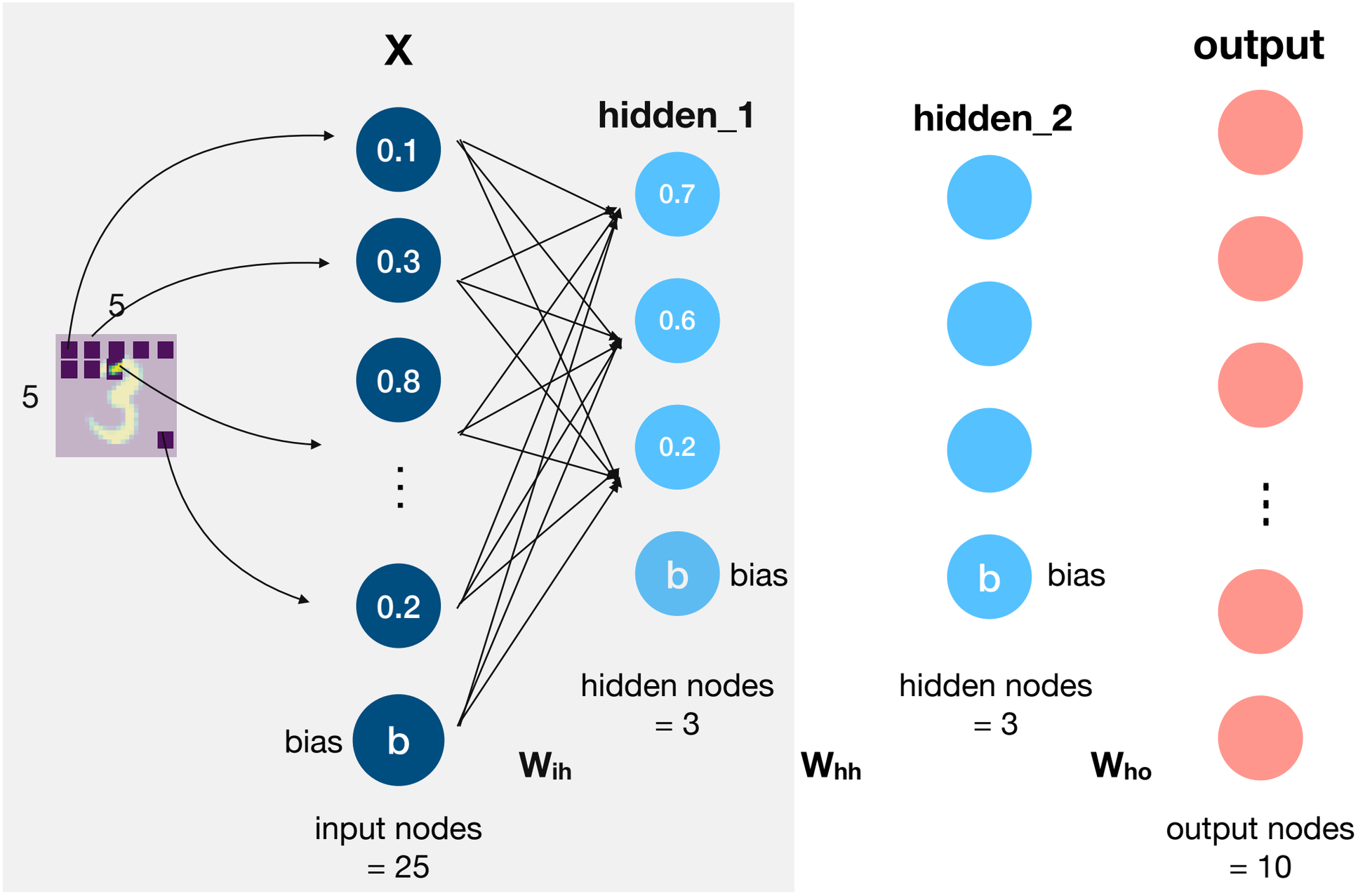
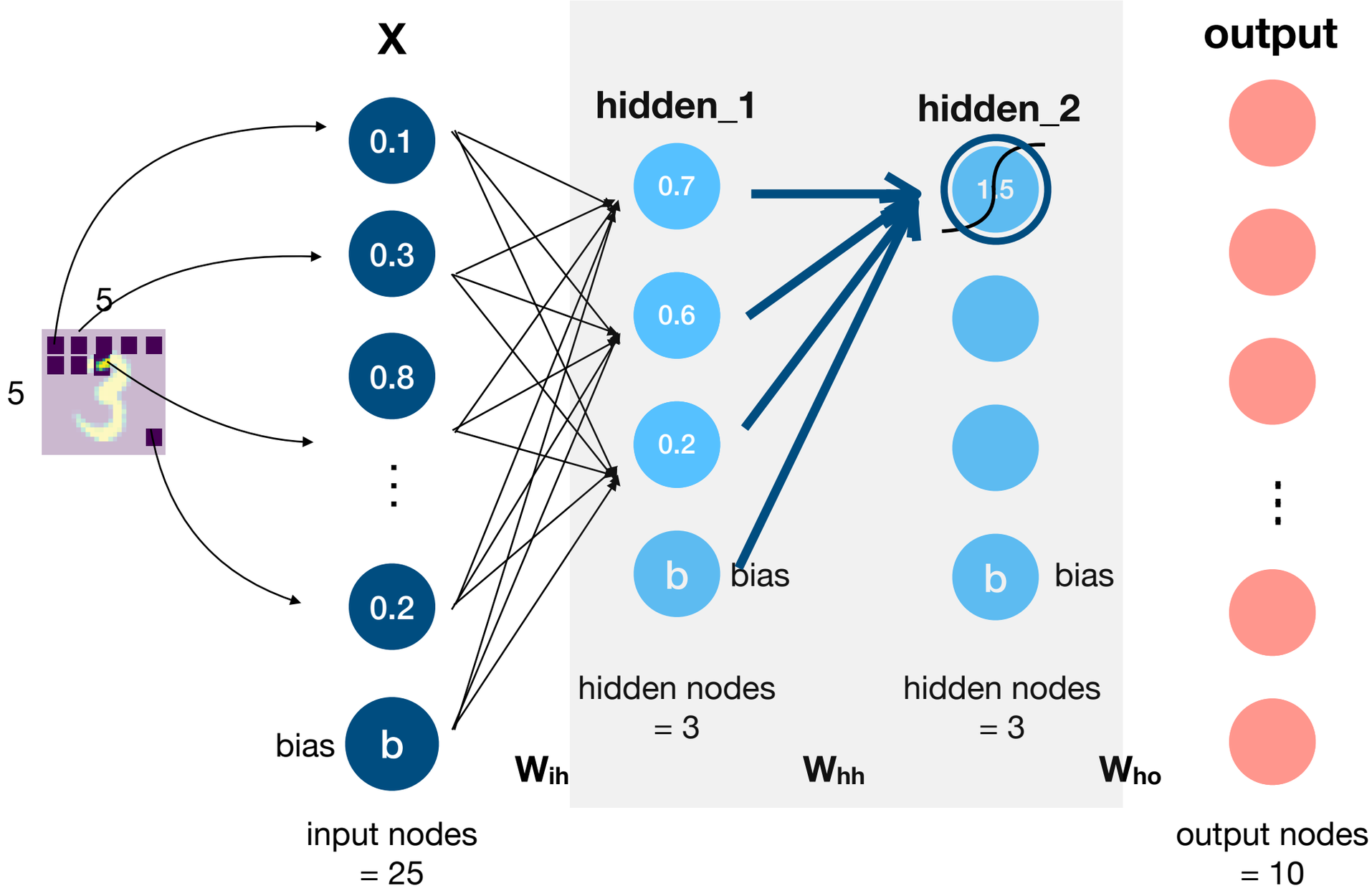
ANN DNN



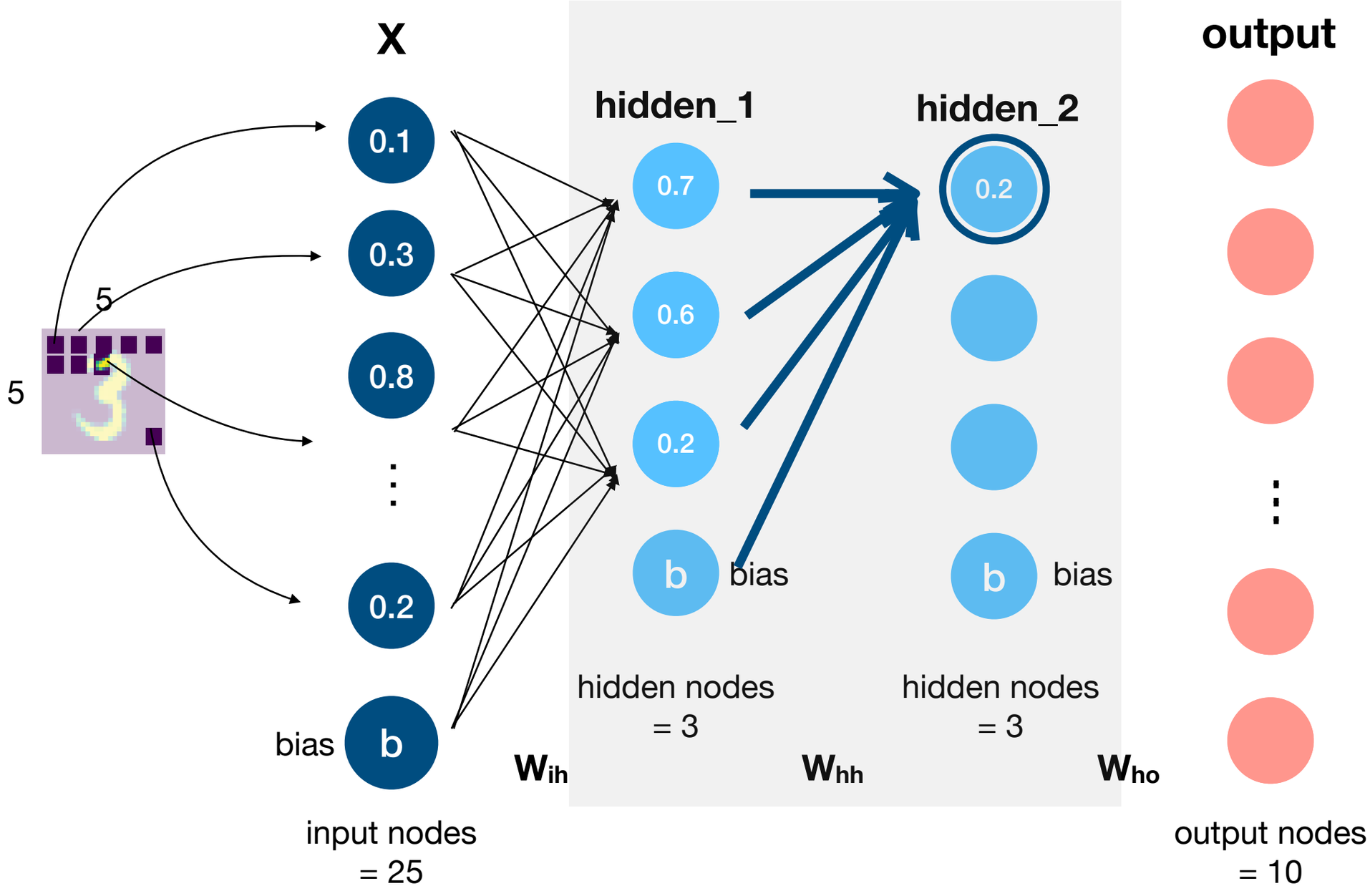
hidden layer 1까지의 nodes가 모두 계산되었습니다.
이제 hidden layer 2로 넘어갈 차례입니다.

ANN DNN



전과 같이, 각 hidden layer 1의 node 값에 weight (진한 화살표)을 곱하고 모두 더해 activation function을 건 후 hidden layer 2의 첫 번째 node에 넣어줍니다.

ANN DNN



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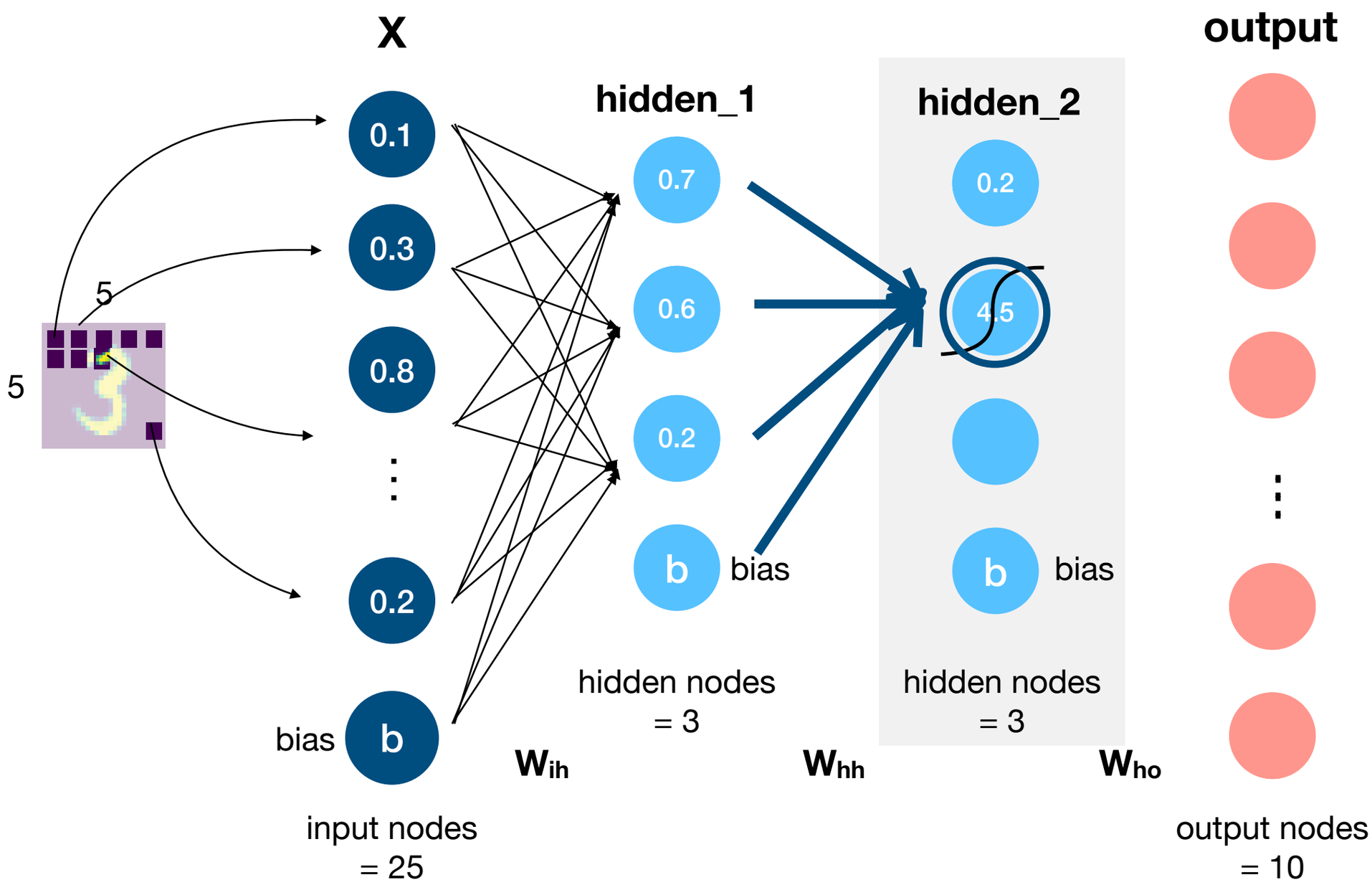
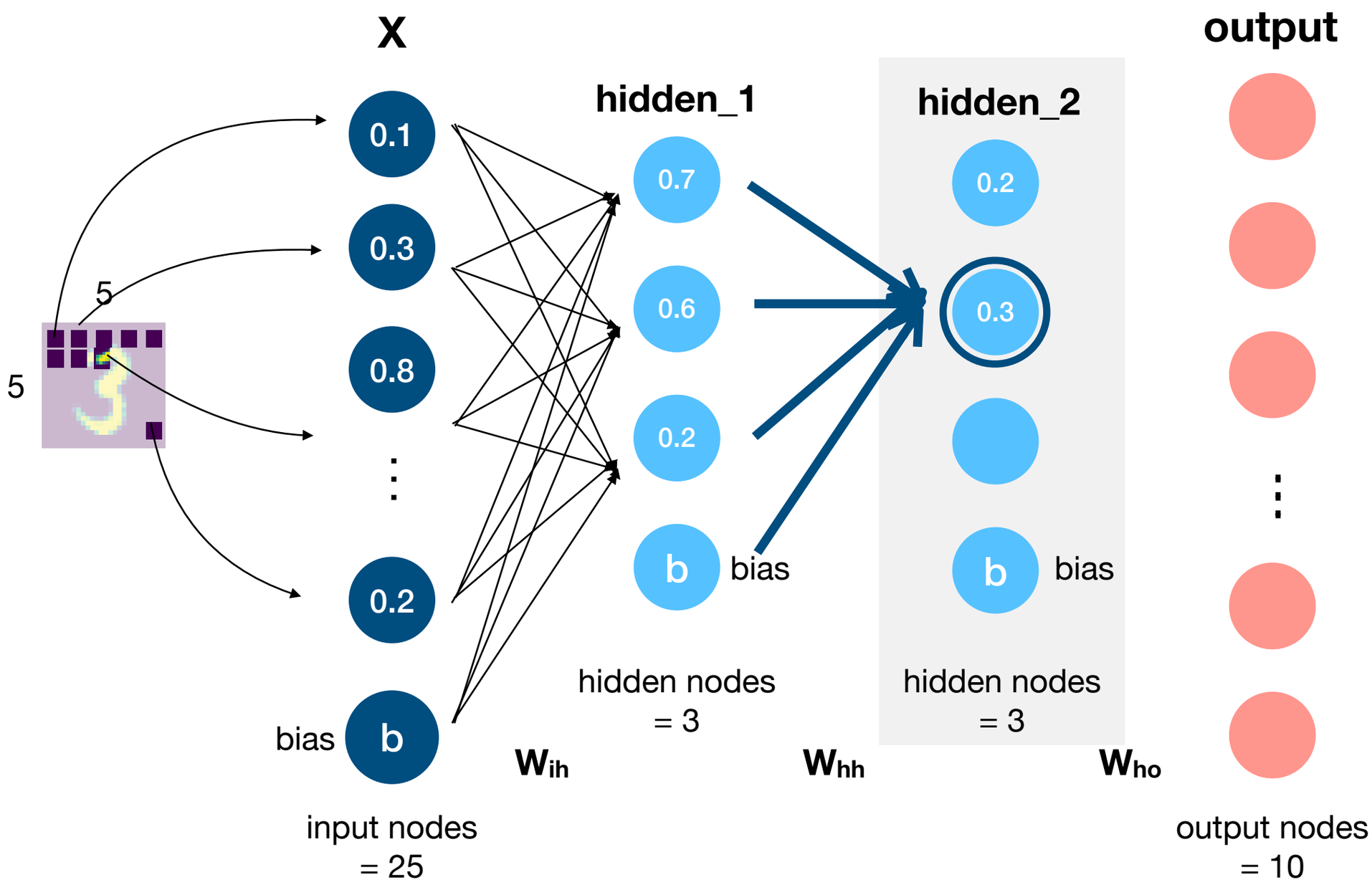
ANN DNN



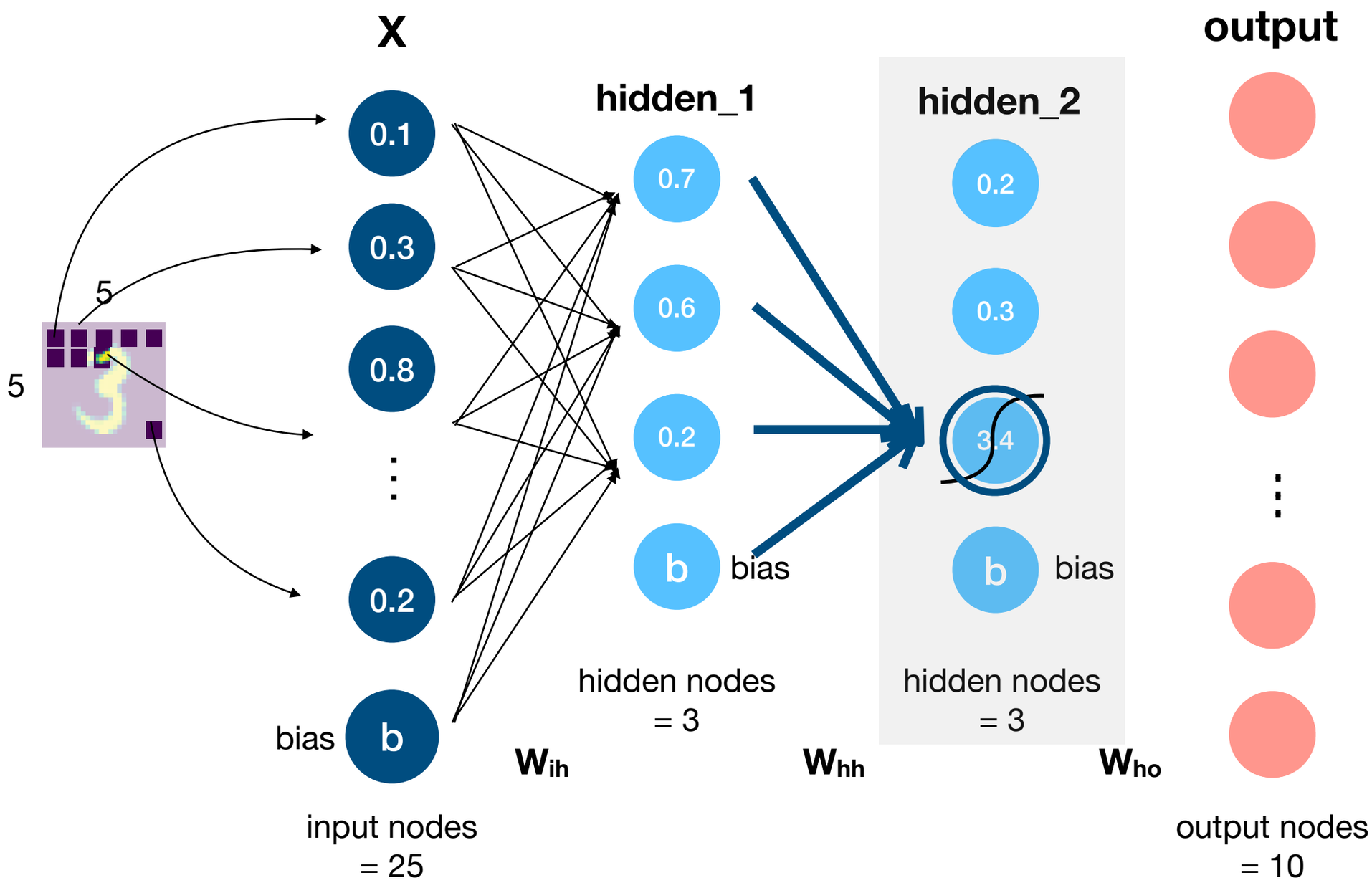
모든 hidden layer 2의 nodes에 대해 반복합니다.

ANN DNN



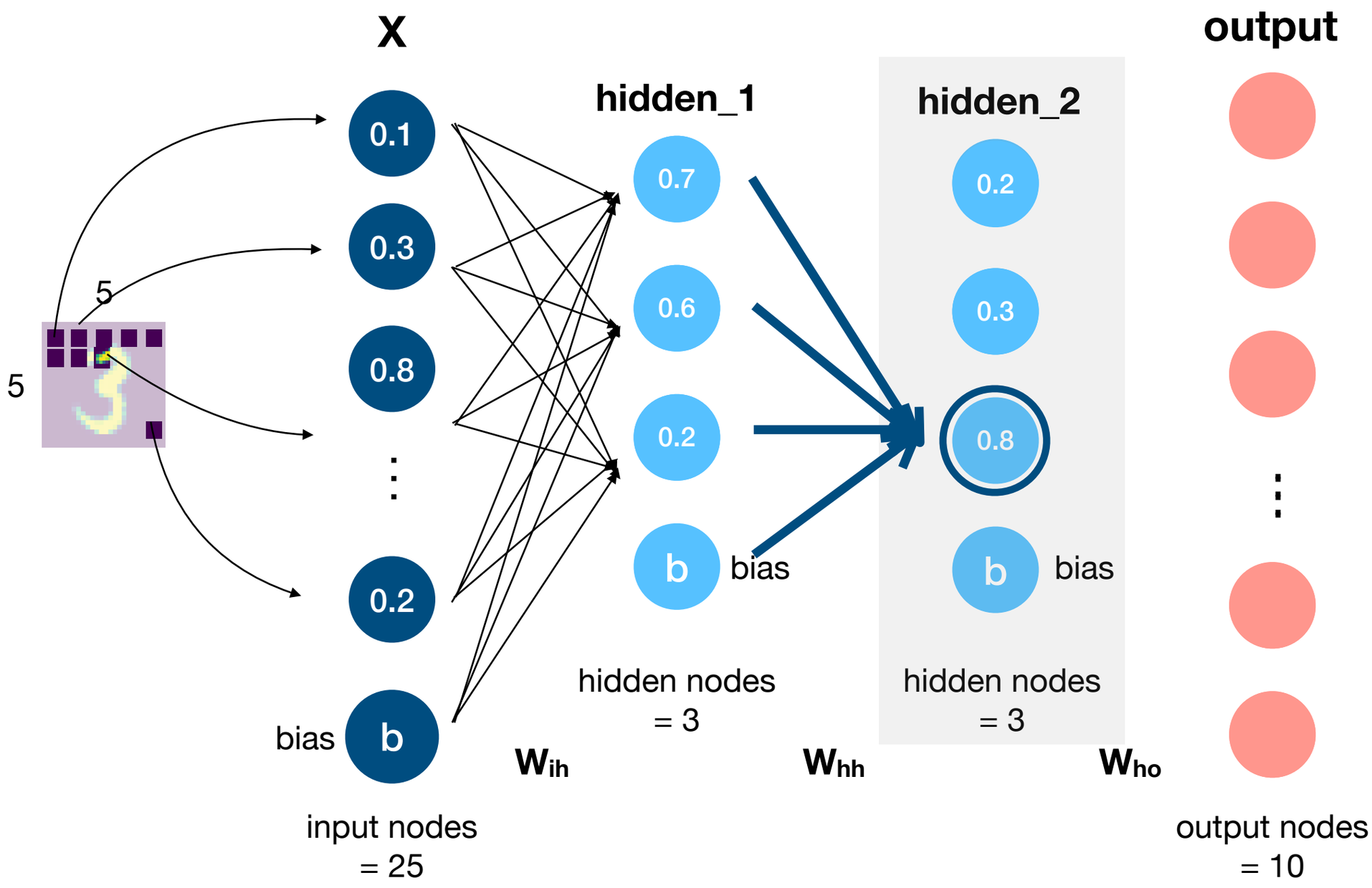
모든 hidden layer 2의 nodes에 대해 반복합니다.

ANN DNN



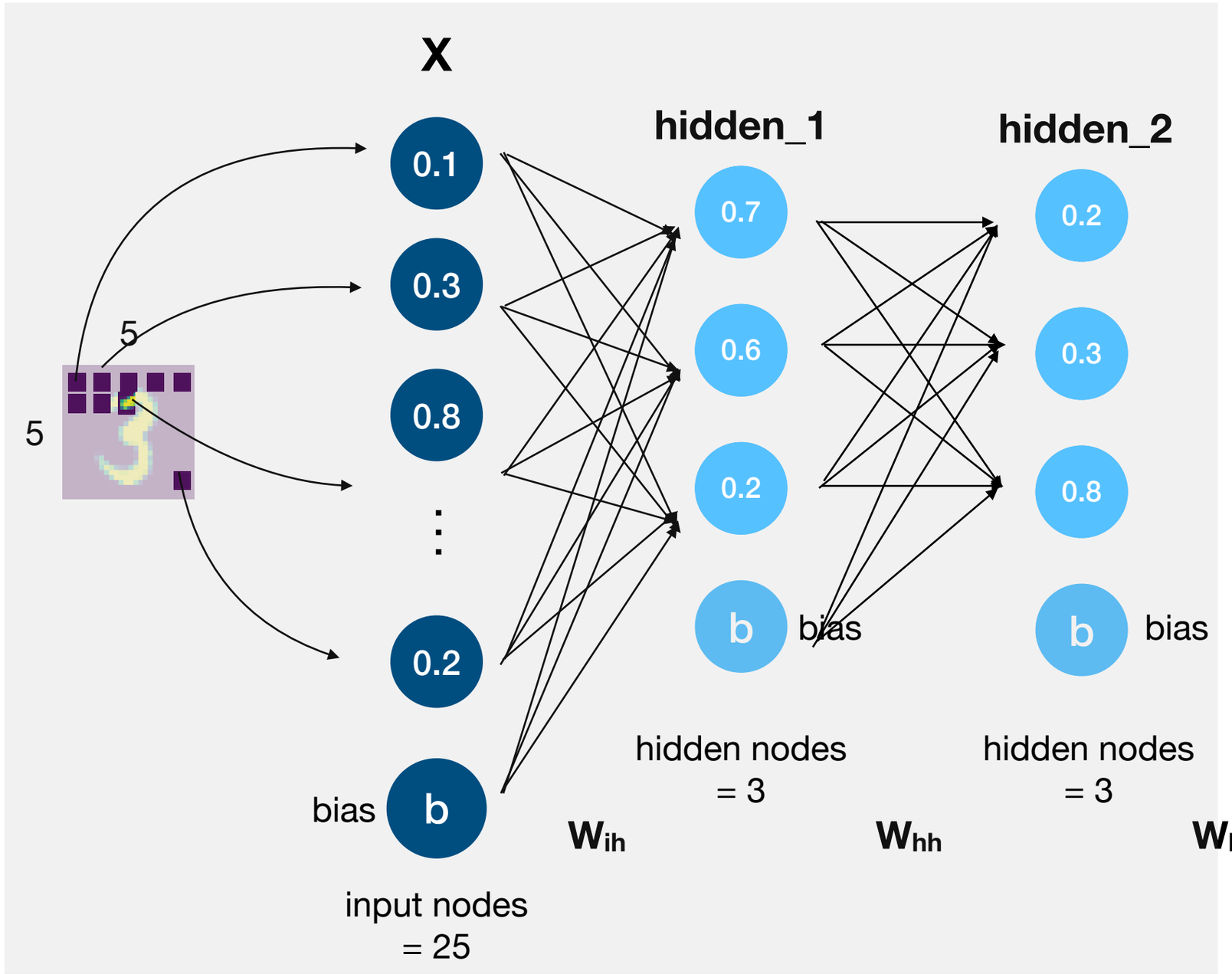
모든 hidden layer 2의 nodes에 대해 반복합니다.

ANN DNN



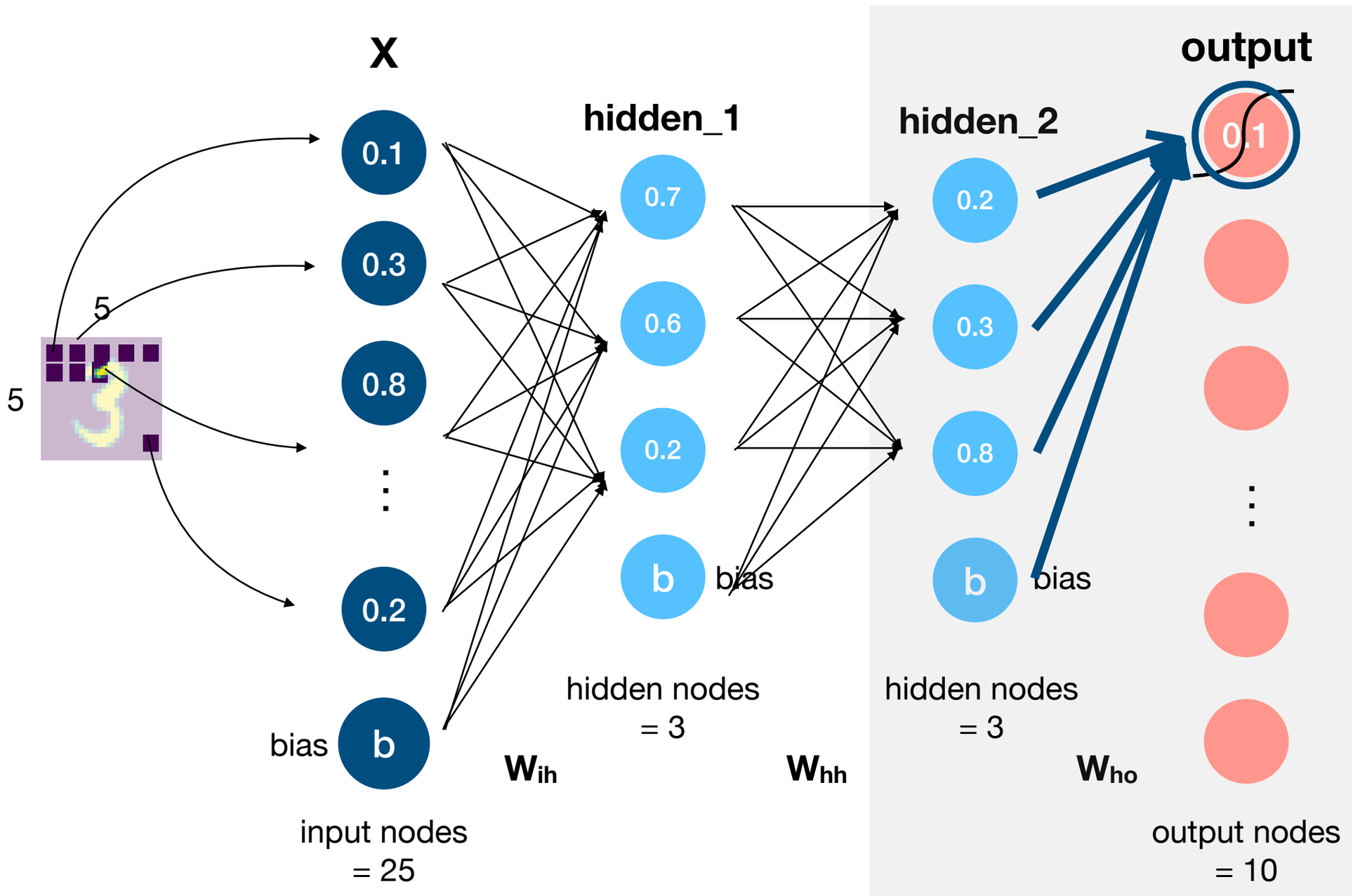
모든 hidden layer 2의 nodes에 대해 반복합니다.

ANN DNN



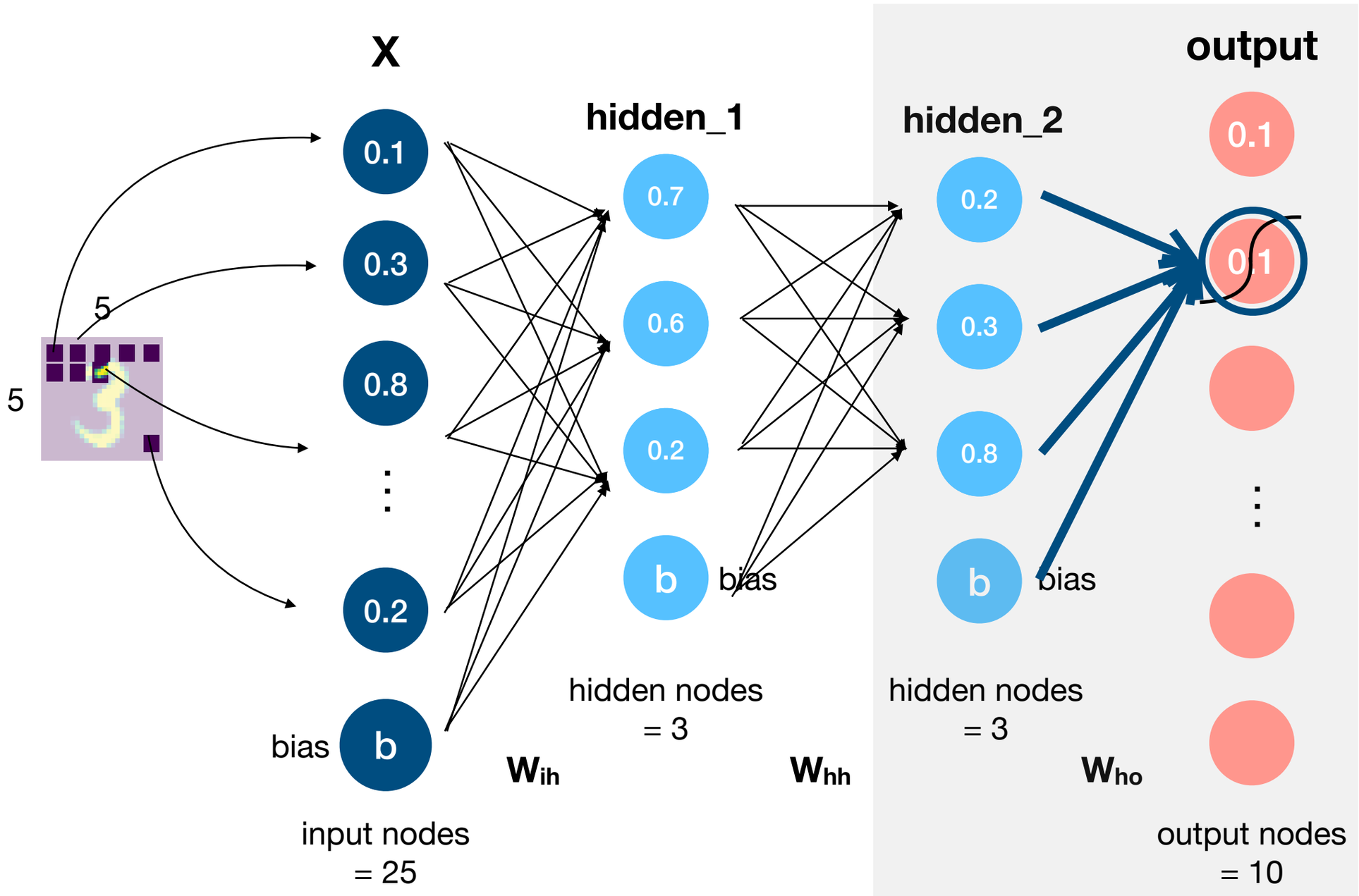
hidden layer 2까지의 nodes가 모두 계산되었습니다.
이제 output layer로 넘어갈 차례입니다.

ANN DNN



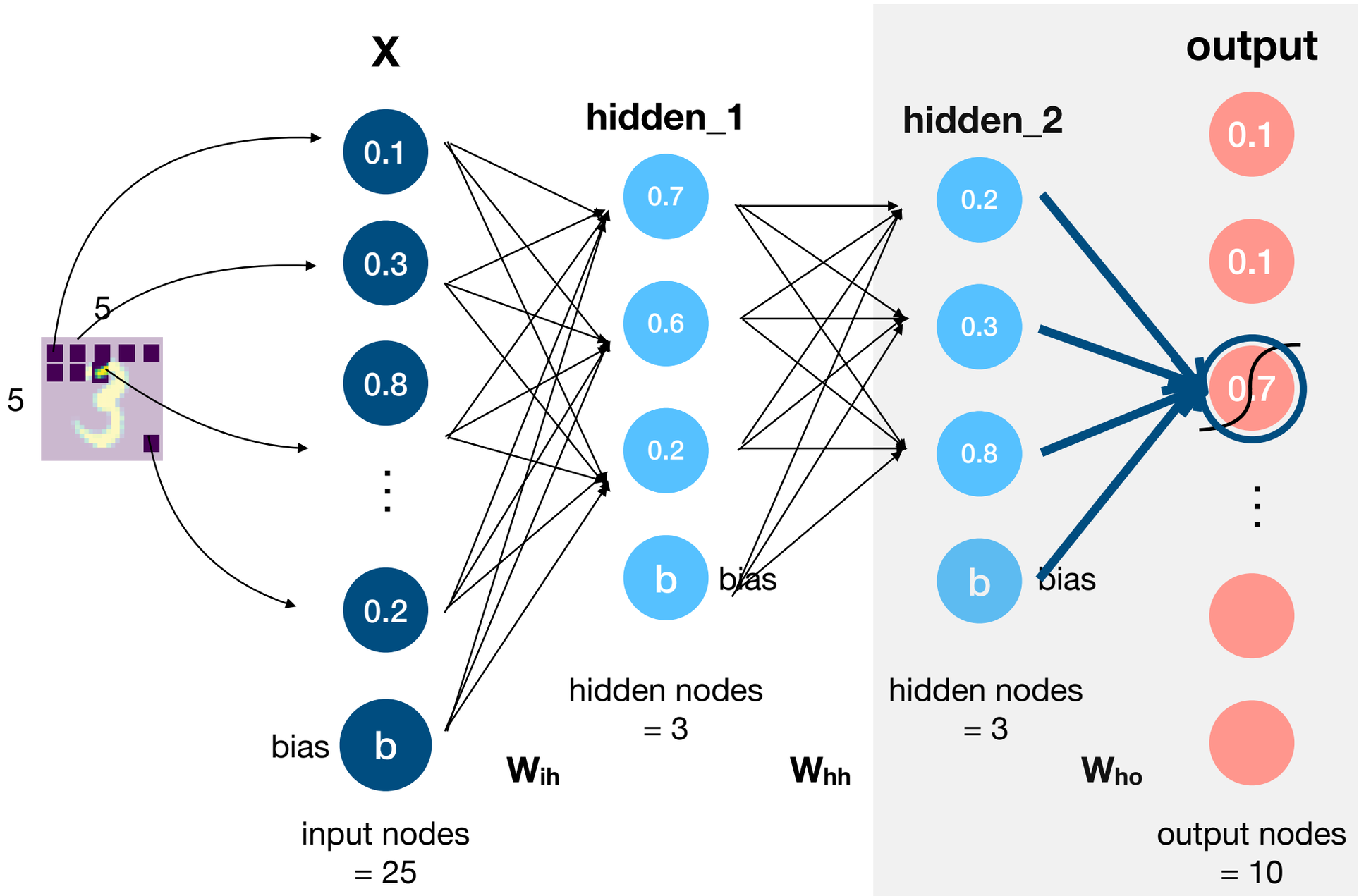
전과 같이, 각 hidden layer 2의 node 값에 weight (진한 화살표)을 곱하고 모두 더해 activation function을 건 후 output layer의 첫 번째 node에 넣어줍니다.

ANN DNN



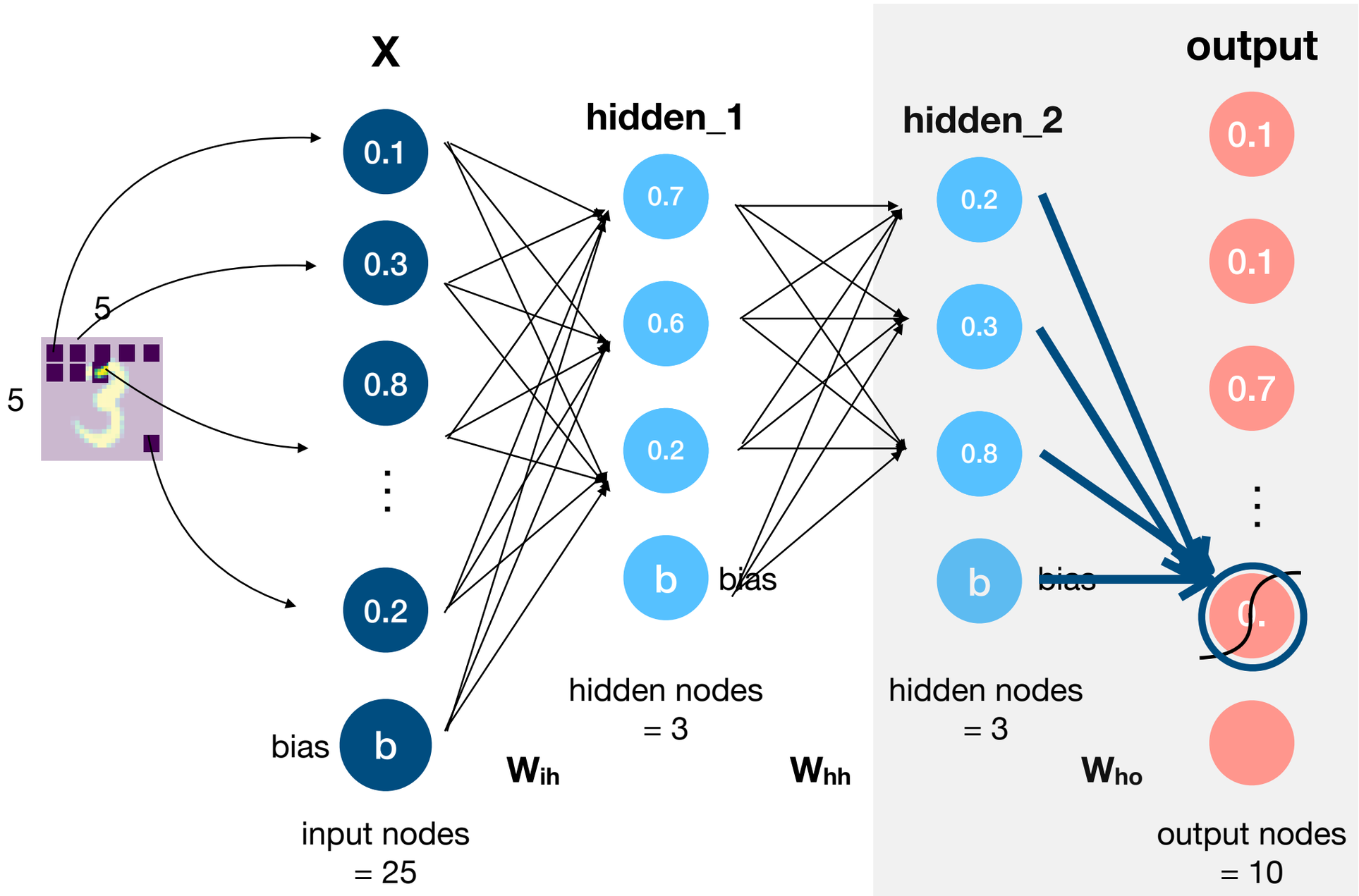
마찬가지 방식으로 반복합니다.

ANN DNN



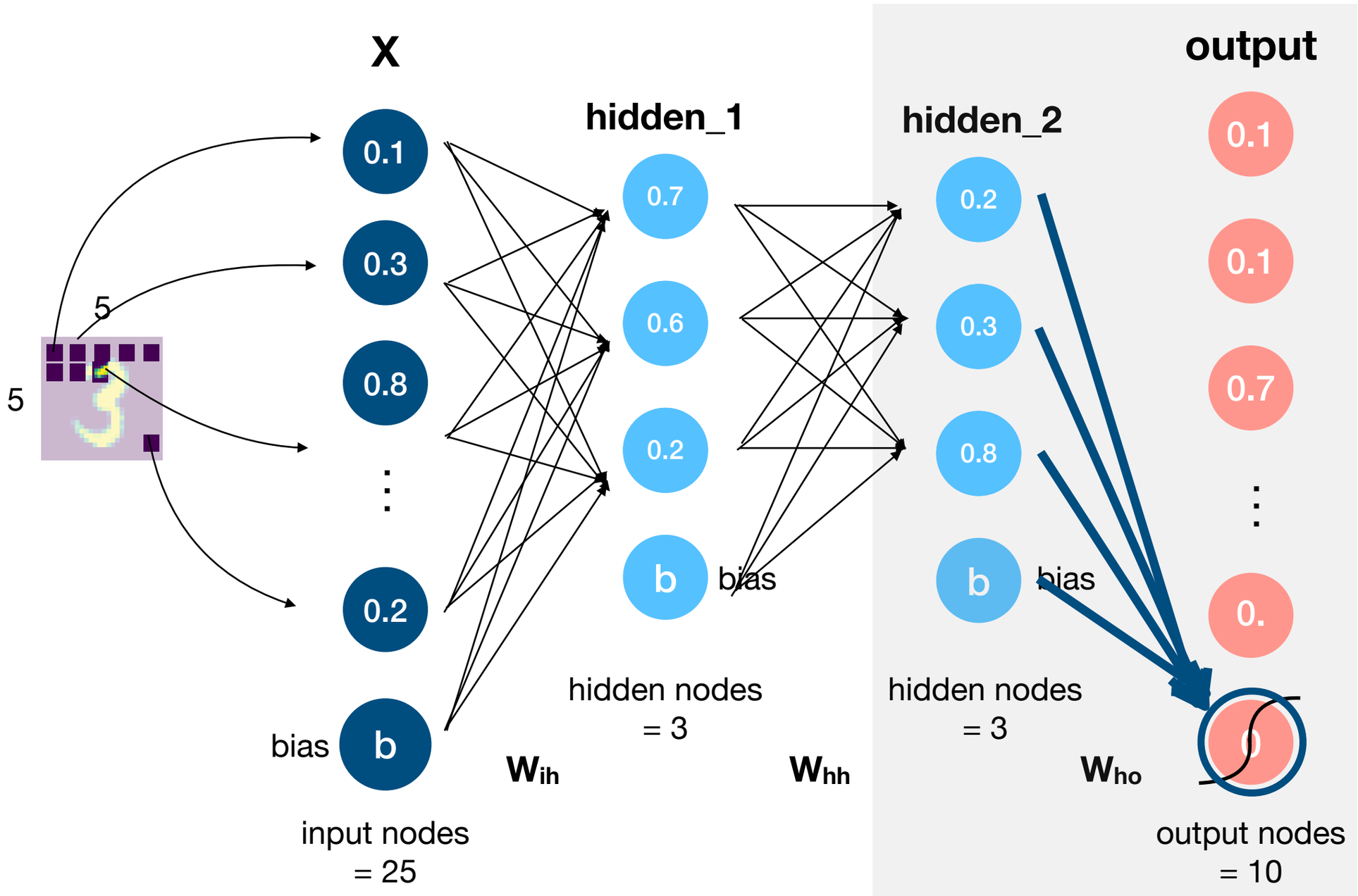
마찬가지 방식으로 반복합니다.

ANN DNN



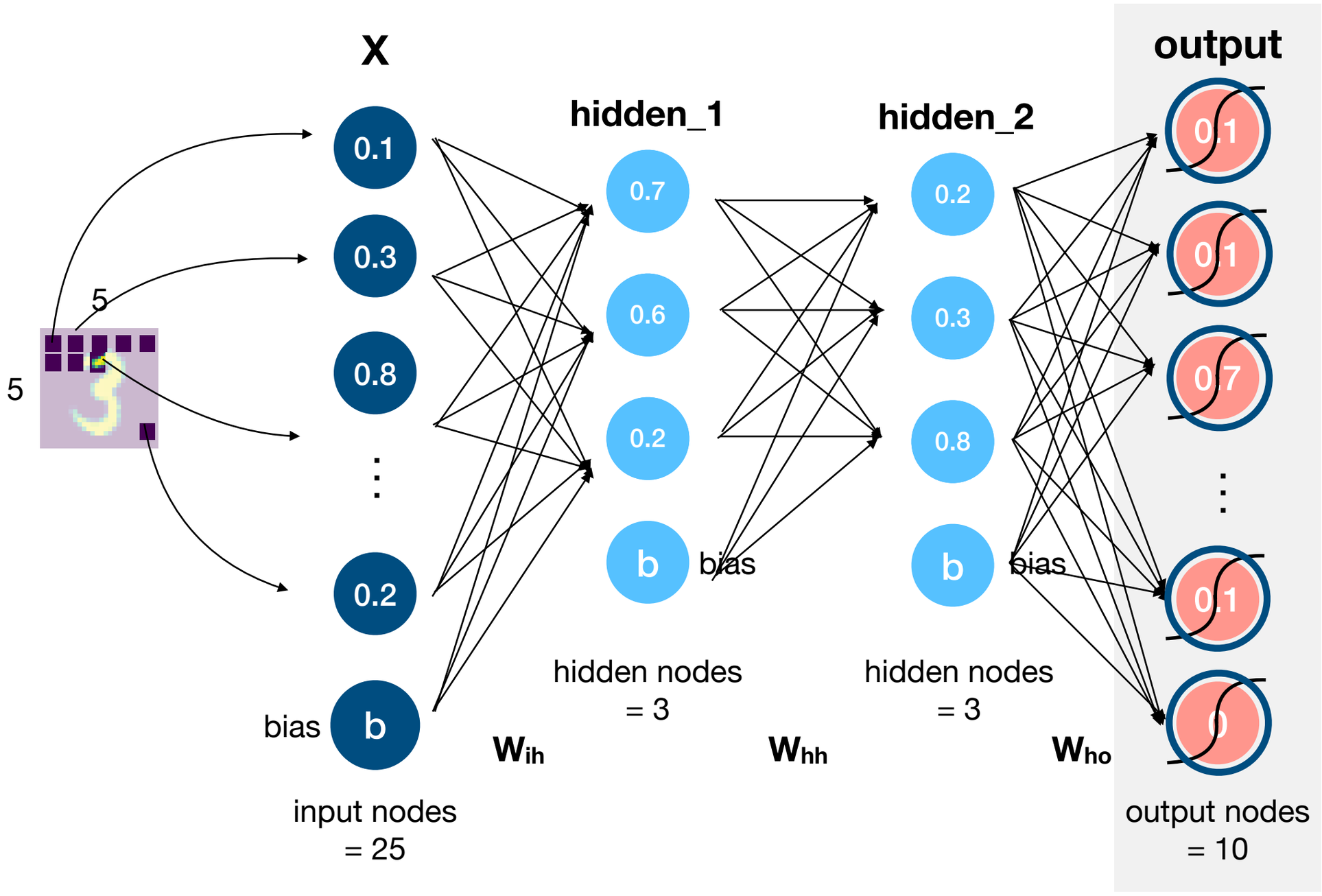
마찬가지 방식으로 반복합니다.

ANN DNN



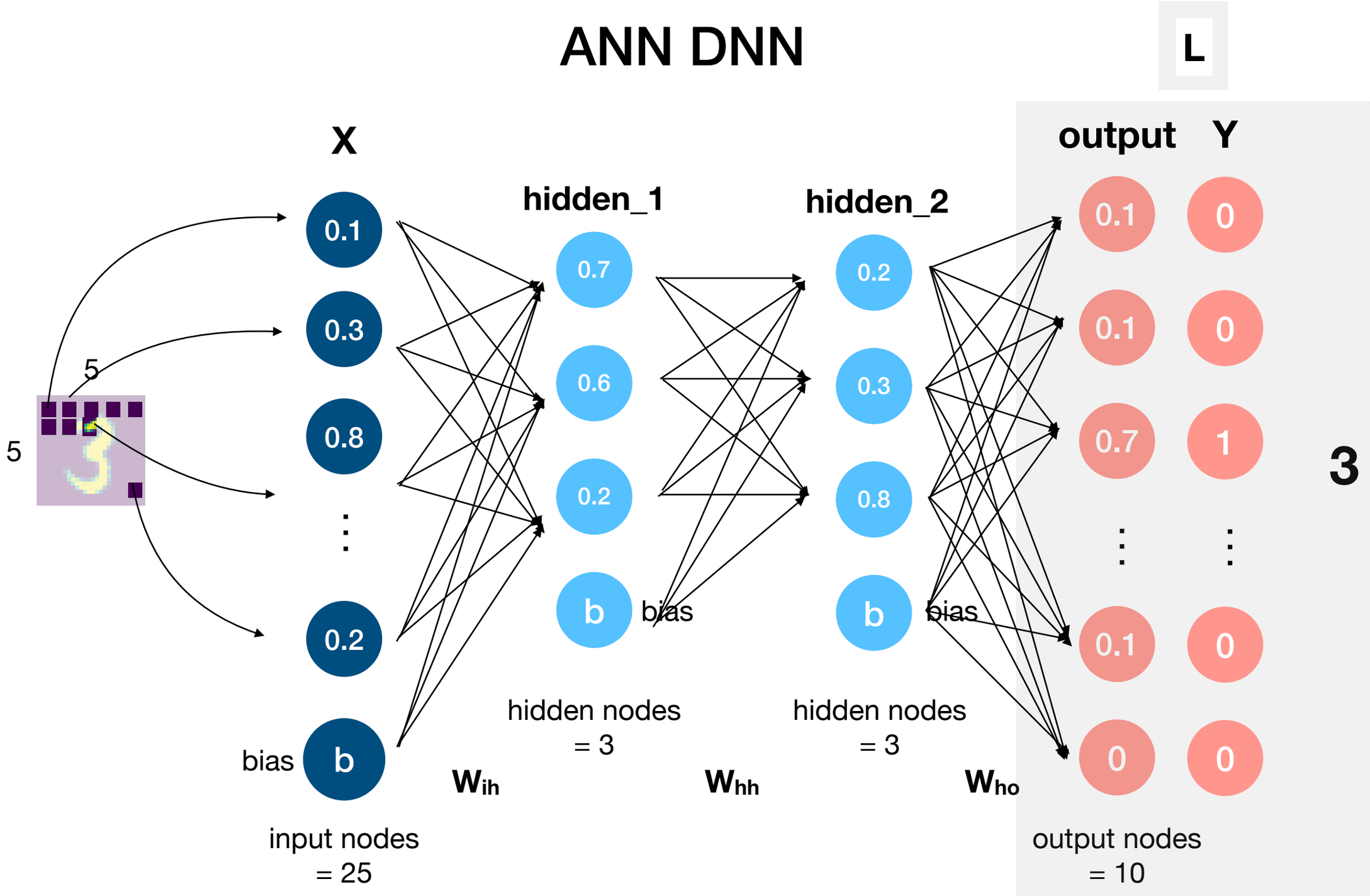
마찬가지 방식으로 반복합니다.

ANN DNN



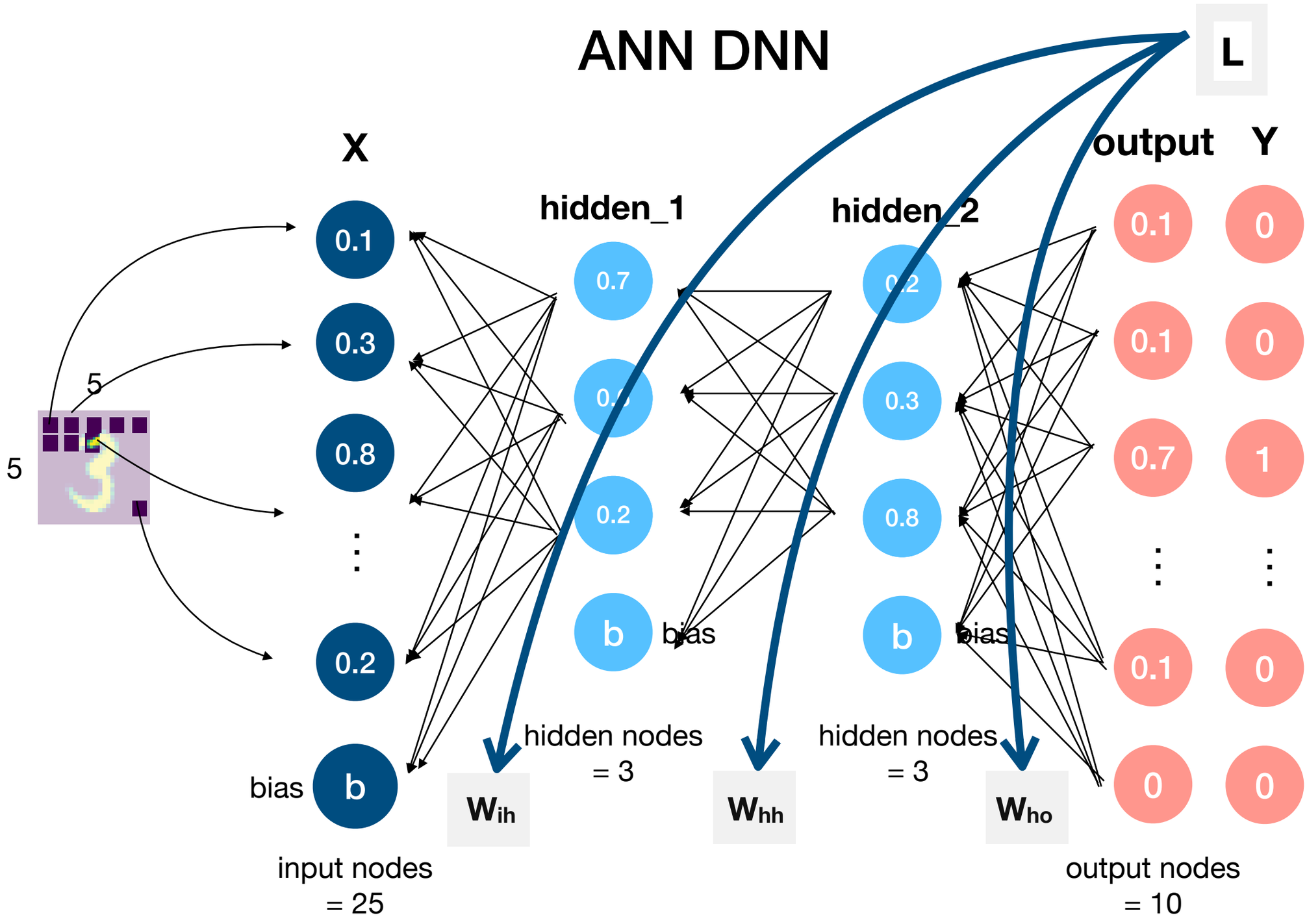
hidden layers의 activation function과는 다르게
output layer에서는 activation function으로
softmax function을 사용하며 이는 input이 각 숫자일 확률을 계산해 줍니다.

ANN DNN



그렇게 구한 output probability와 정답 target (Y)을 비교하여 loss를 구합니다.

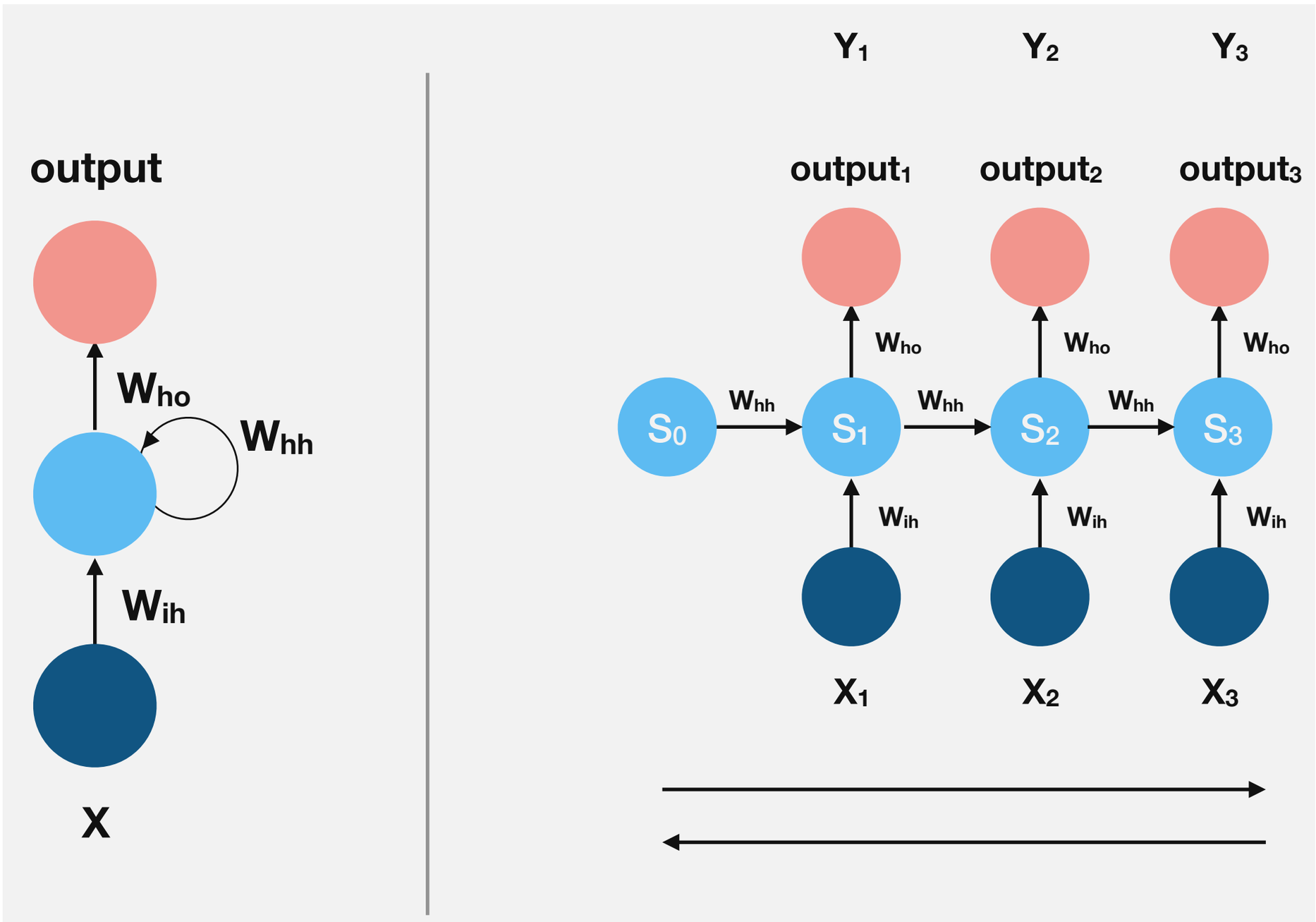
이 때, target은 0~9 중에 정답인 3에 해당하는
세번째 칸만 1, 나머지는 0인 one-hot vector



loss를 최소화하는 방향으로, weight을 update 합니다.

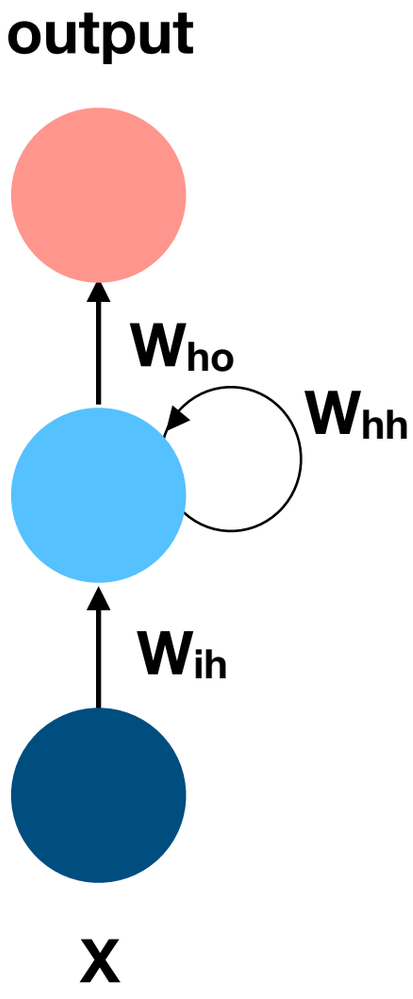
RNN

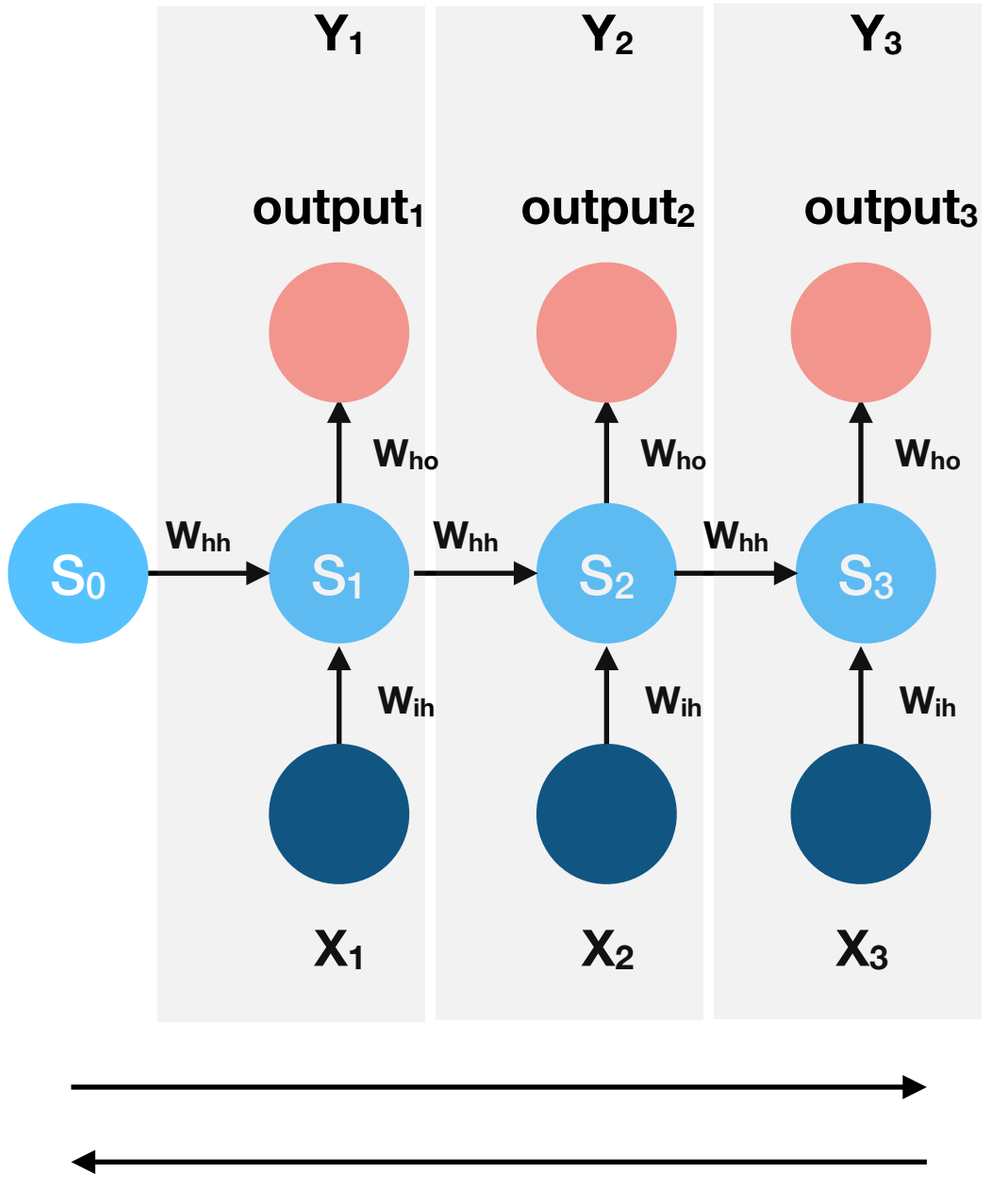
RNN



'나는 오늘 집에 간다'라는 문장을 단어 단위로 훈련해봅시다.

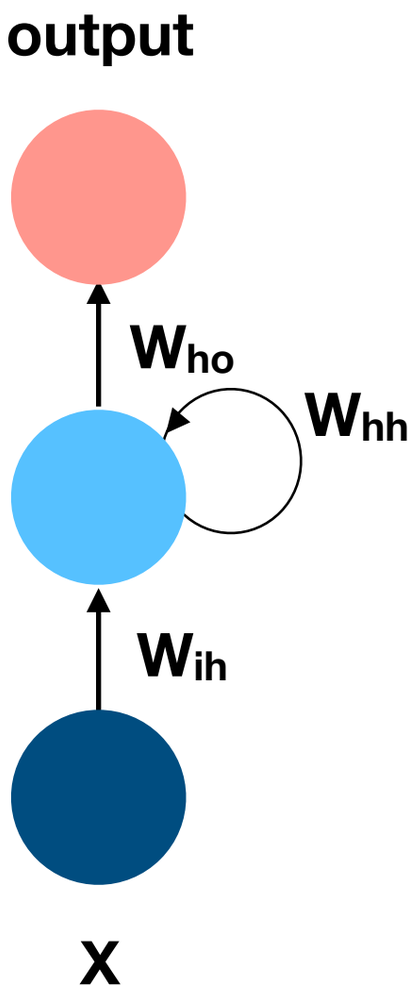
RNN

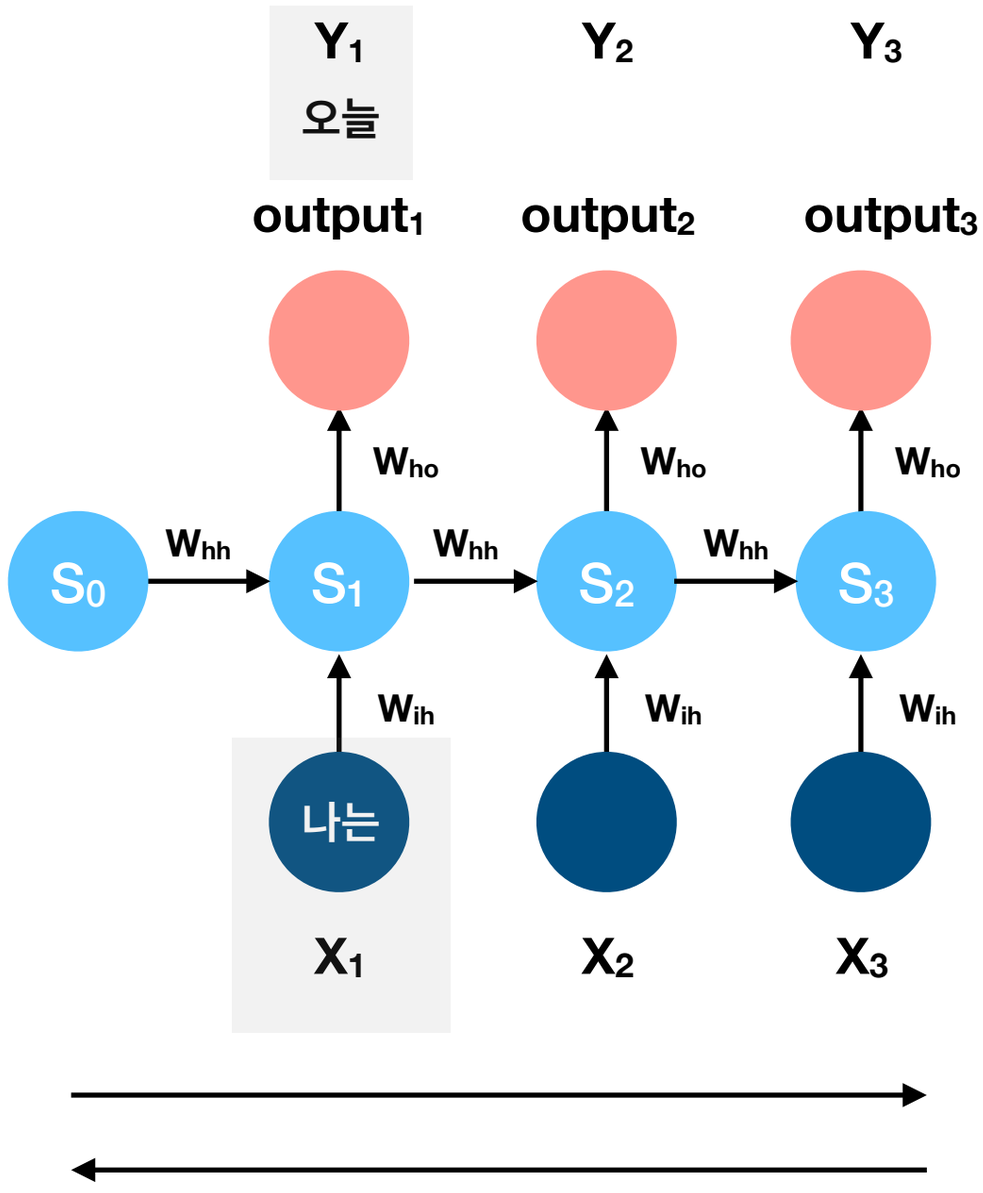




이 예시에서는 총 3개의 time step을 가지는 RNN을 훈련할 것입니다.

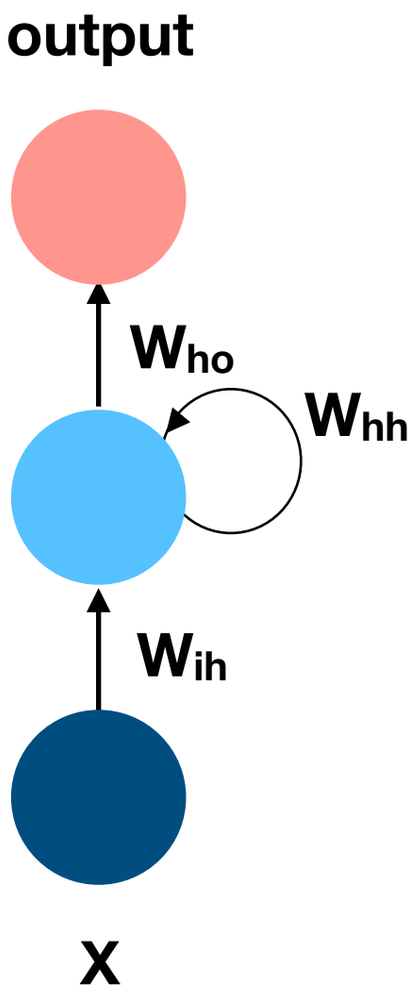
RNN

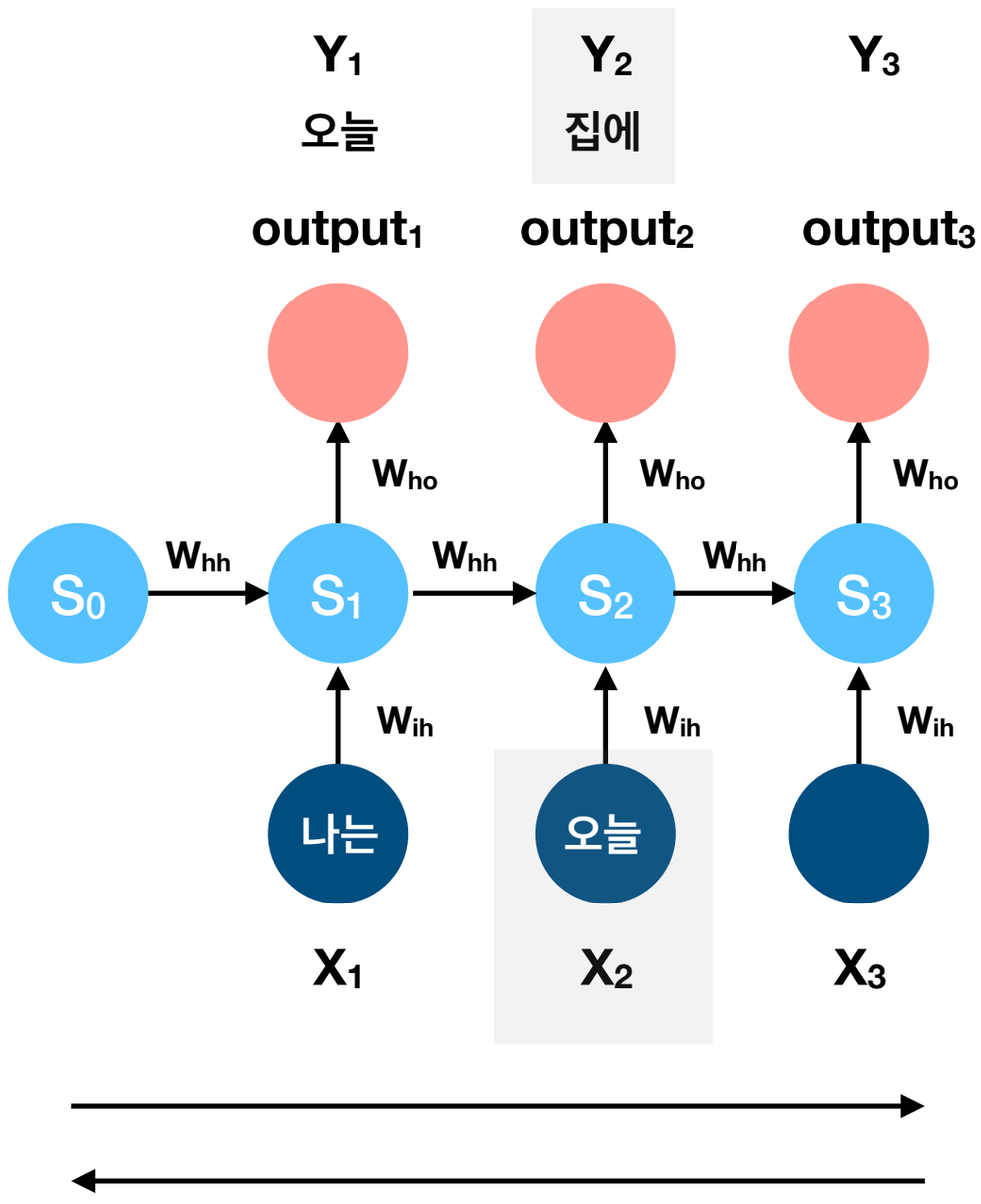




한 단어가 오면 그 다음 단어를 예측하도록 input과 target을 설정해줍니다.
첫 time step에서는 '나는'이 input일 때 '오늘'이 target이 되도록

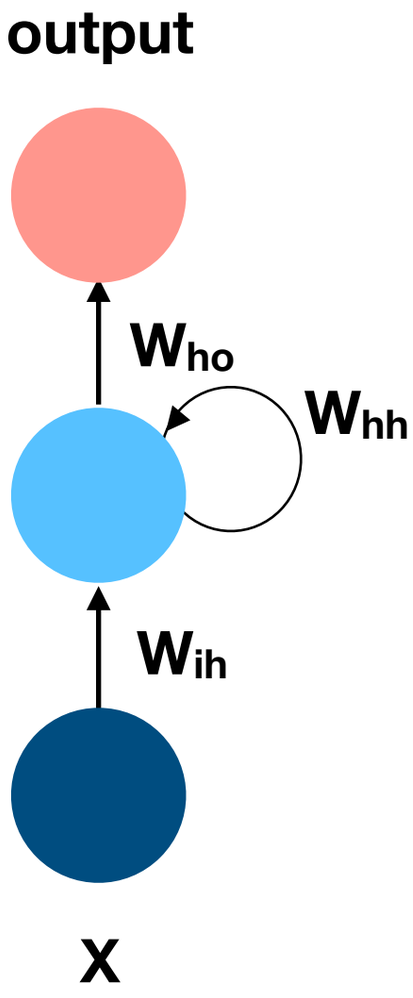
RNN

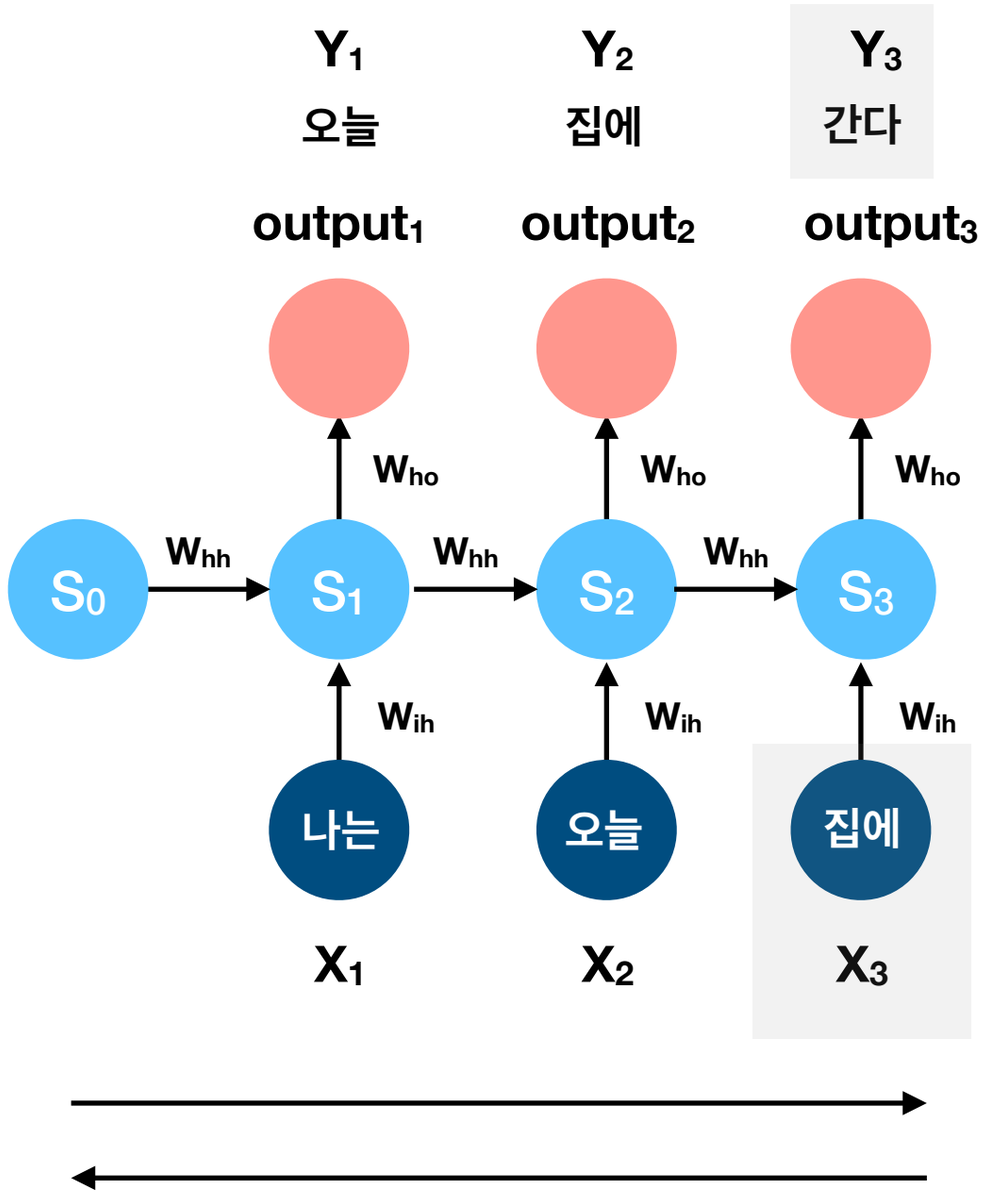




두 번째 time step에서는 '오늘'이 input일 때 '집에'가 target이 되도록

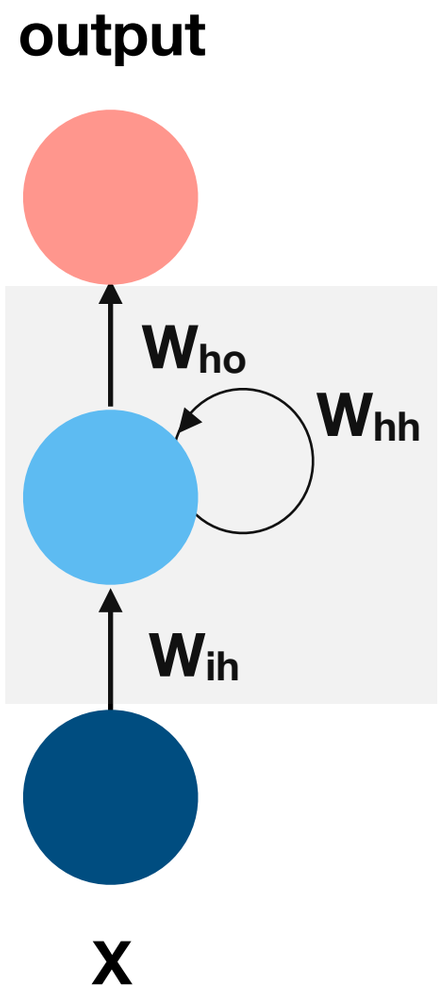
RNN

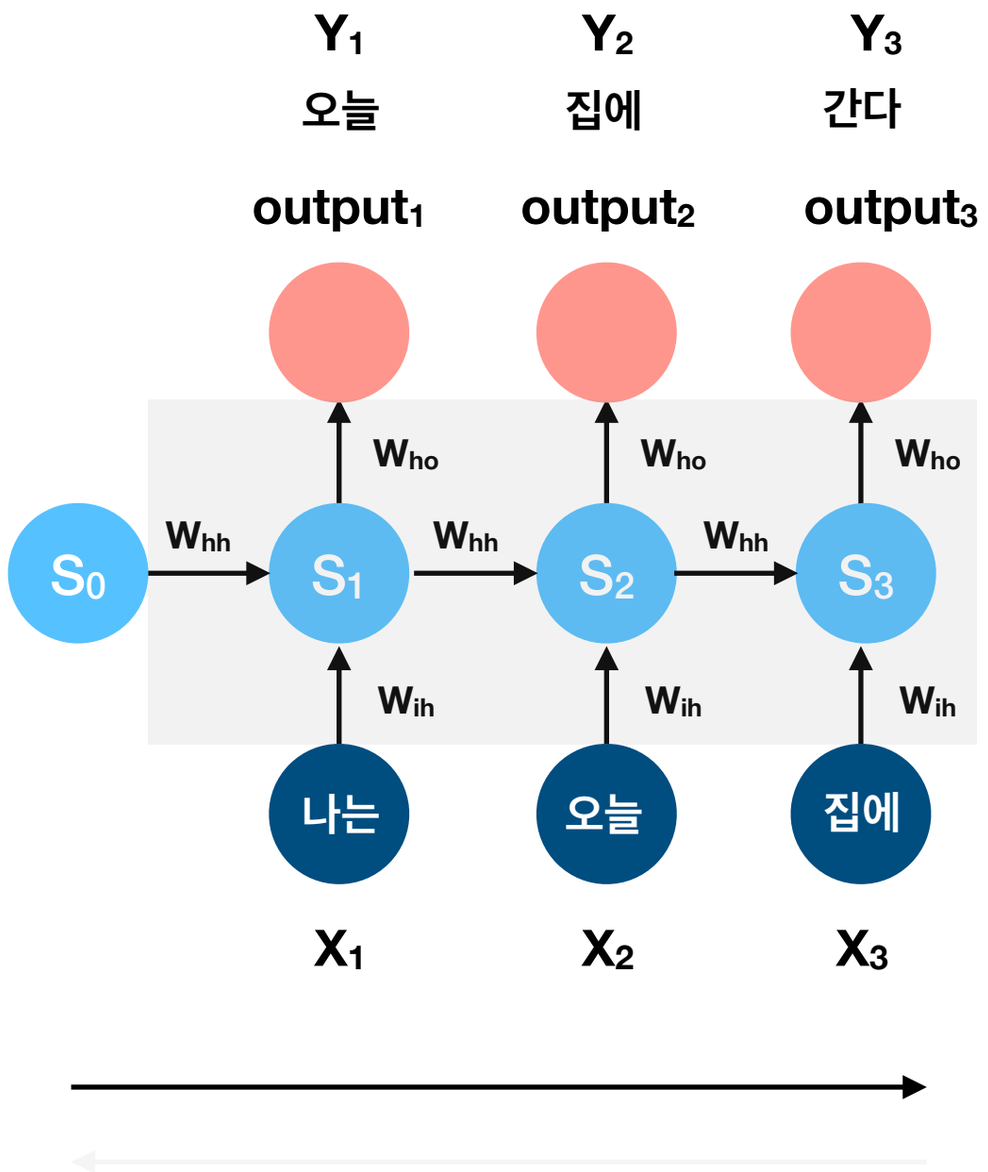




세 번째 time step에서는 '집에'가 input일 때 '간다'가 target이 되도록 RNN을 훈련해봅시다.

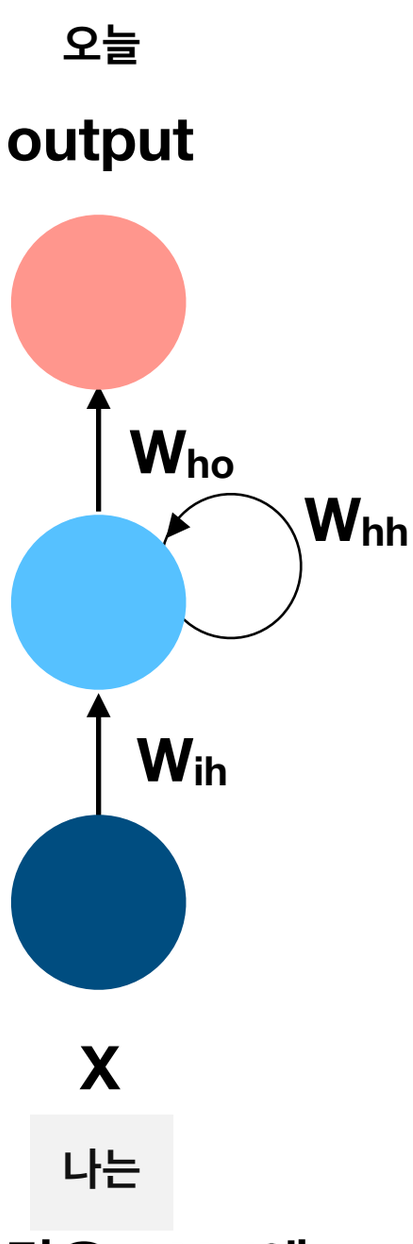
RNN

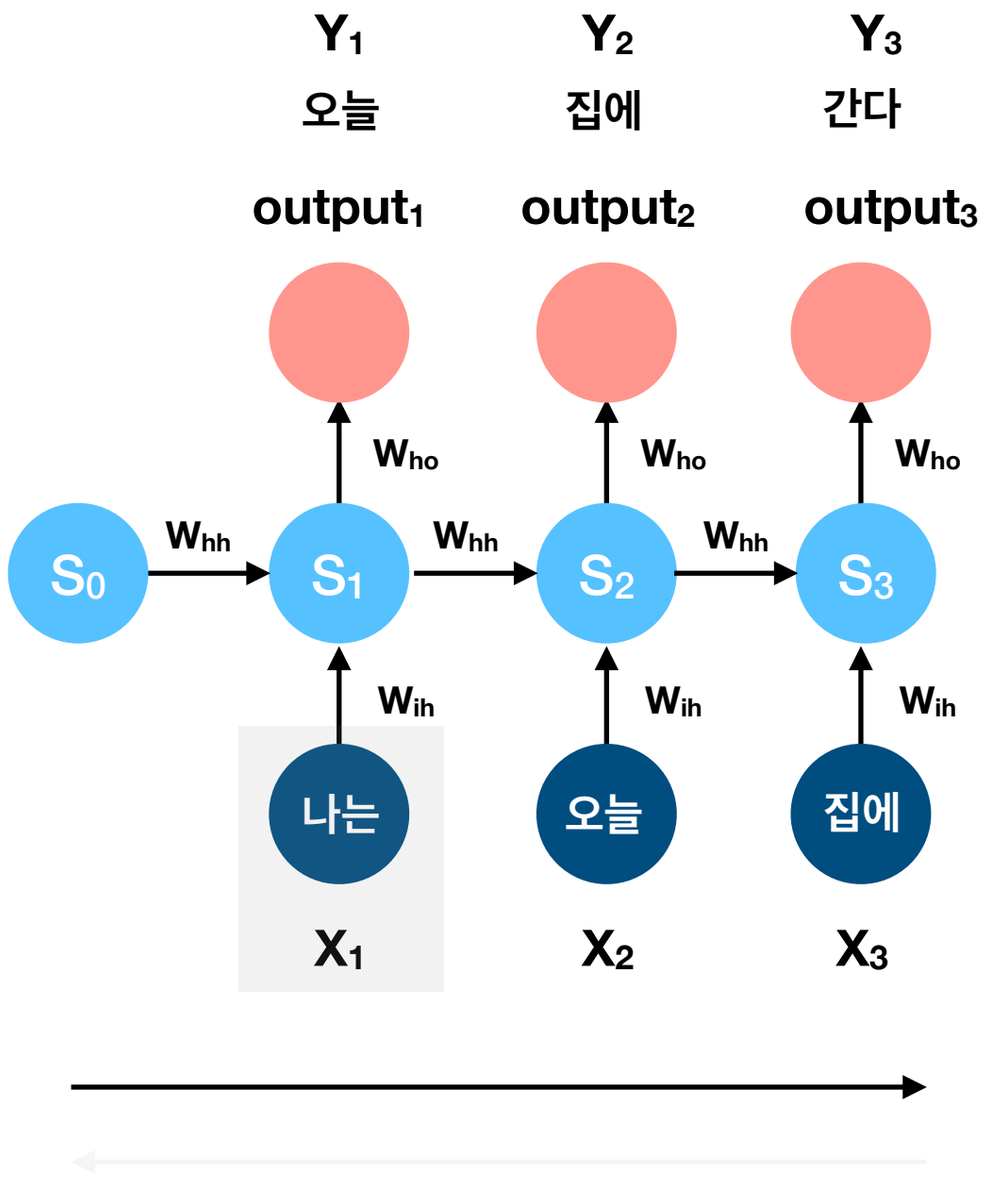




각 time step에서의 W_{ih}, W_{hh}, W_{ho}는 각각 동일한 weight입니다.

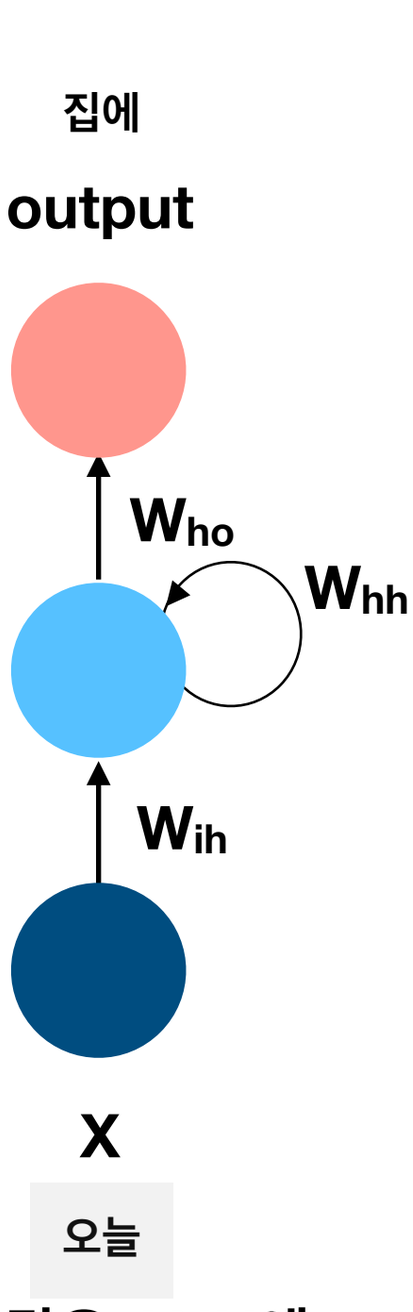
RNN

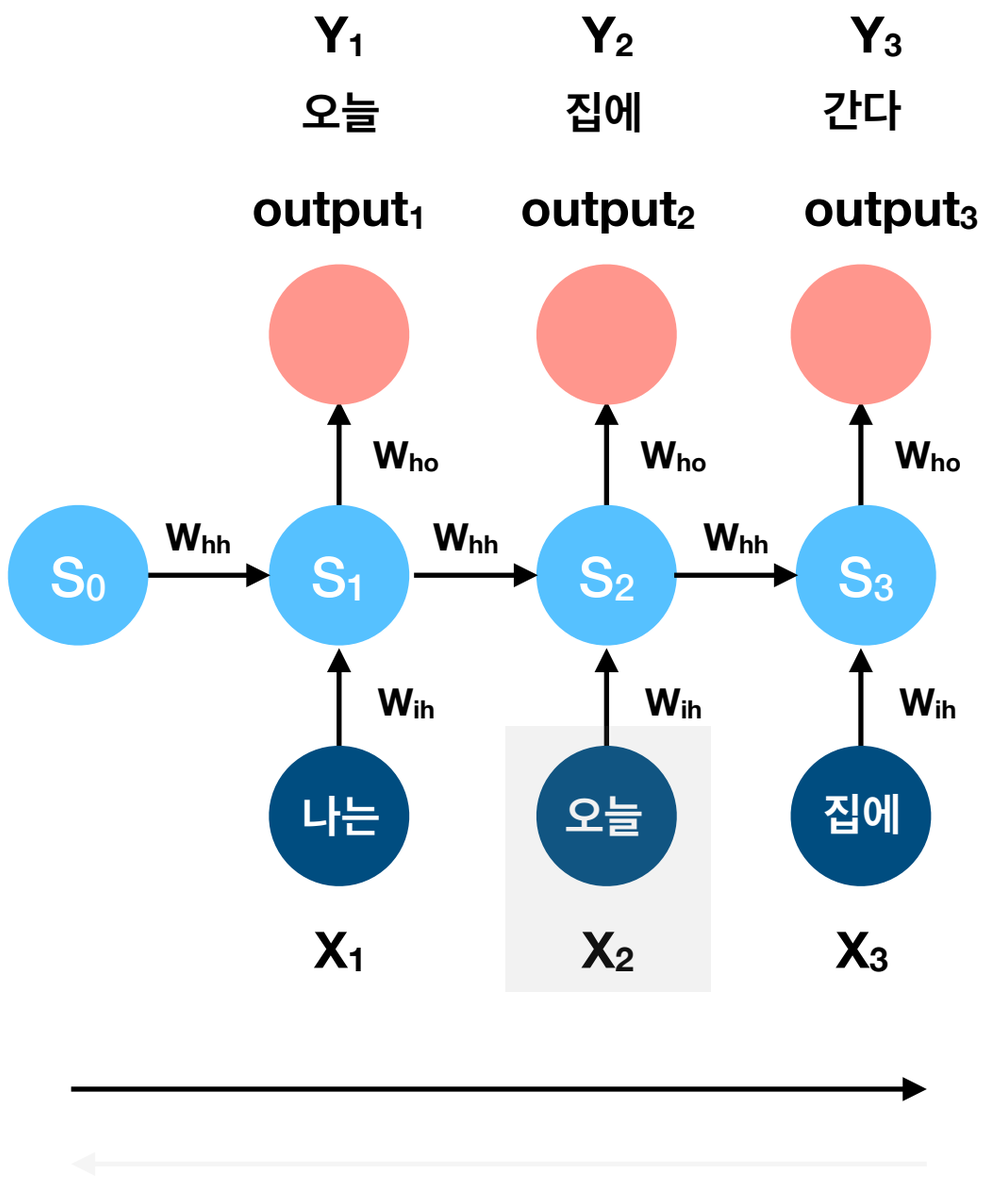




왼쪽 그림과 같은 ANN에 input X_1, X_2, X_3가 순서대로 들어간다고 생각하면 됩니다.

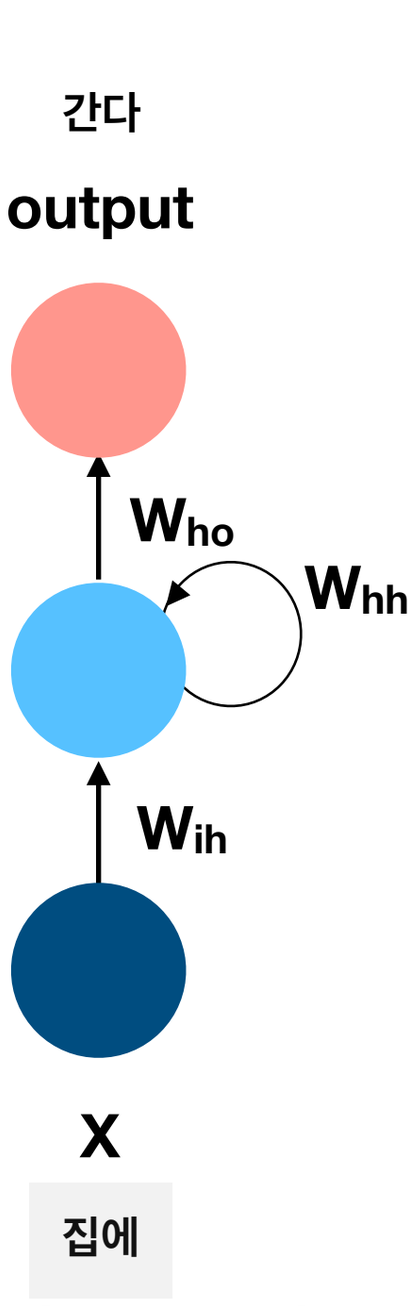
RNN

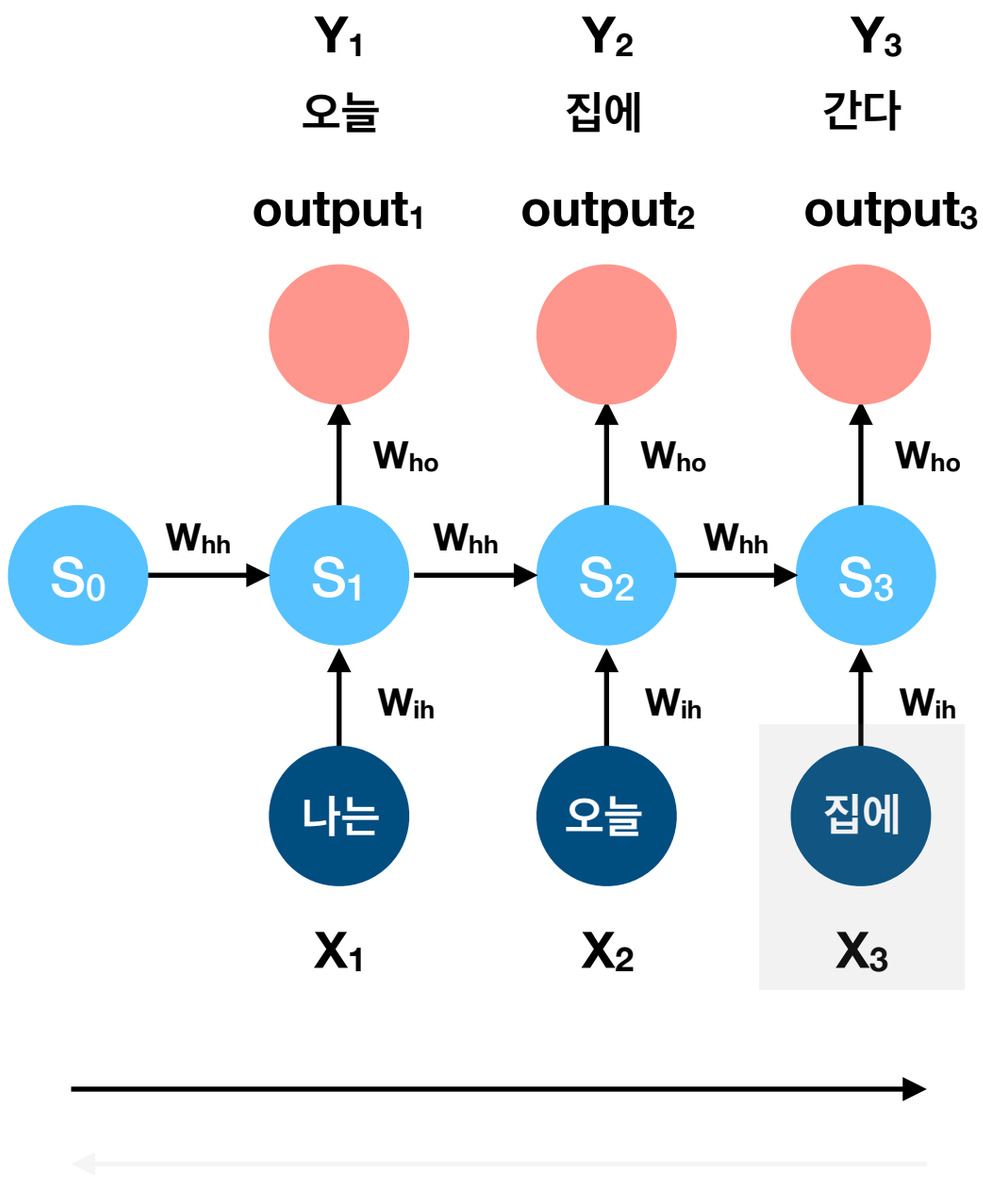




왼쪽 그림과 같은 ANN에 input X_1, X_2, X_3가 순서대로 들어간다고 생각하면 됩니다.

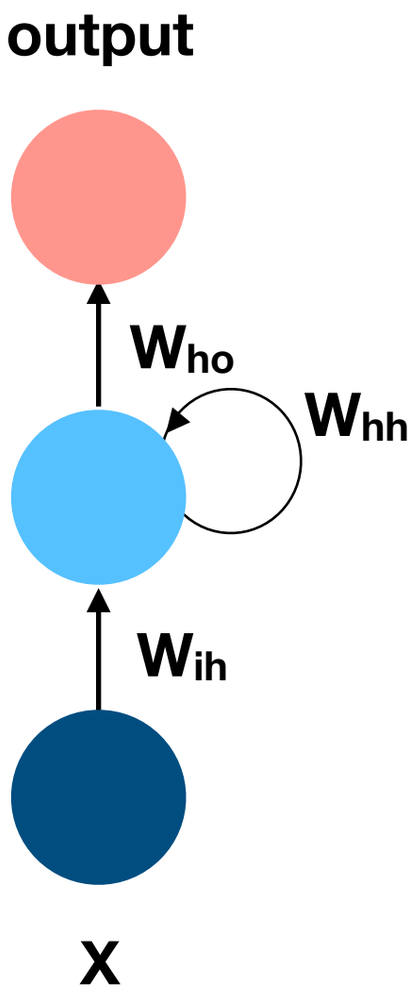
RNN

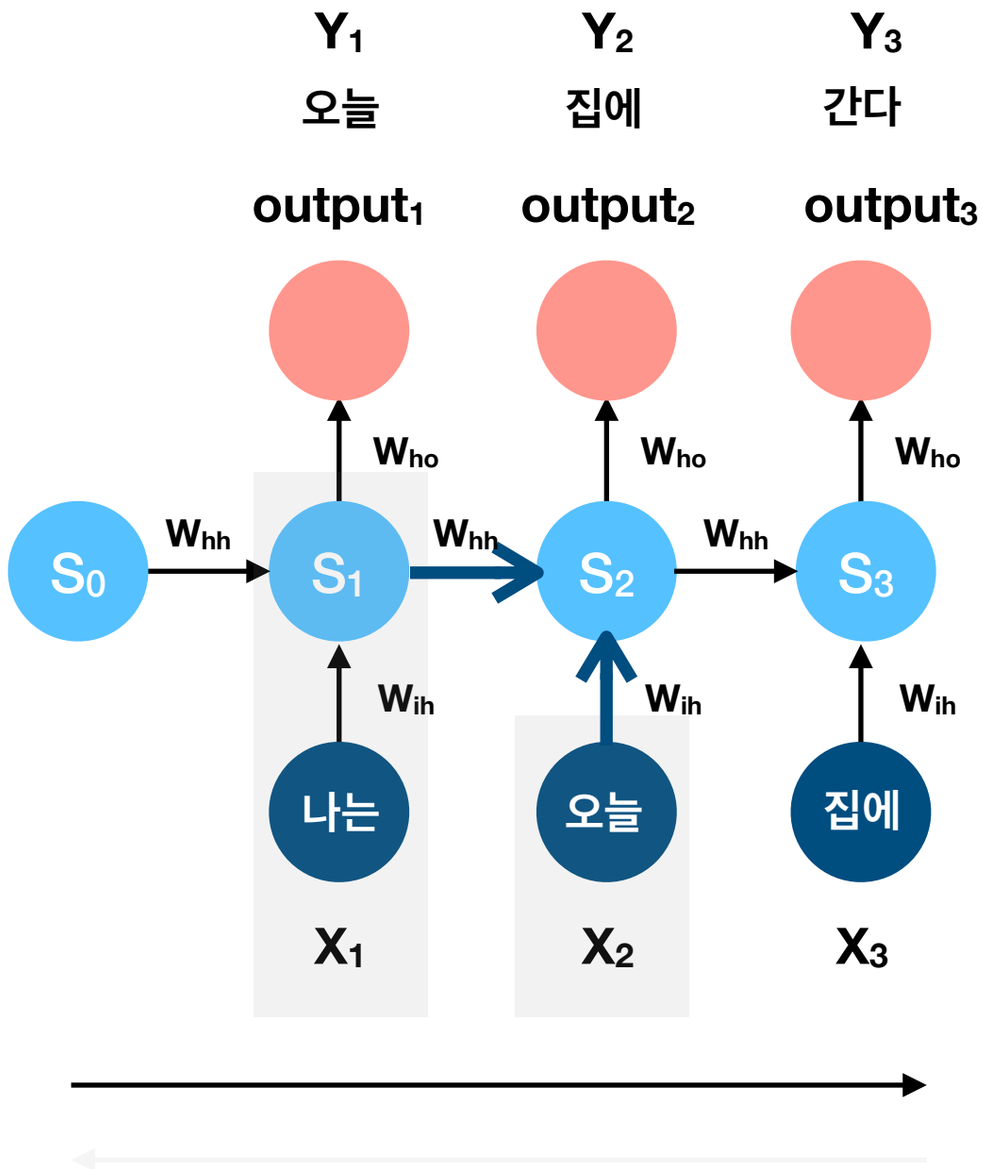




왼쪽 그림과 같은 ANN에 input X_1, X_2, X_3가 순서대로 들어간다고 생각하면 됩니다.

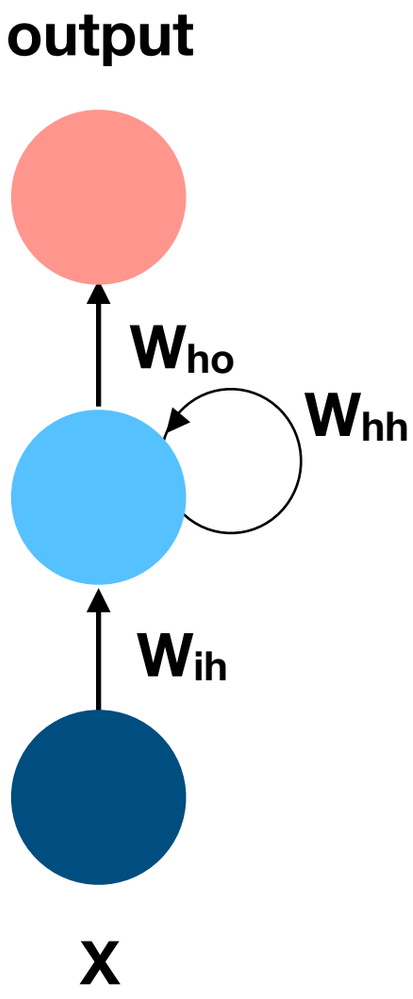
RNN

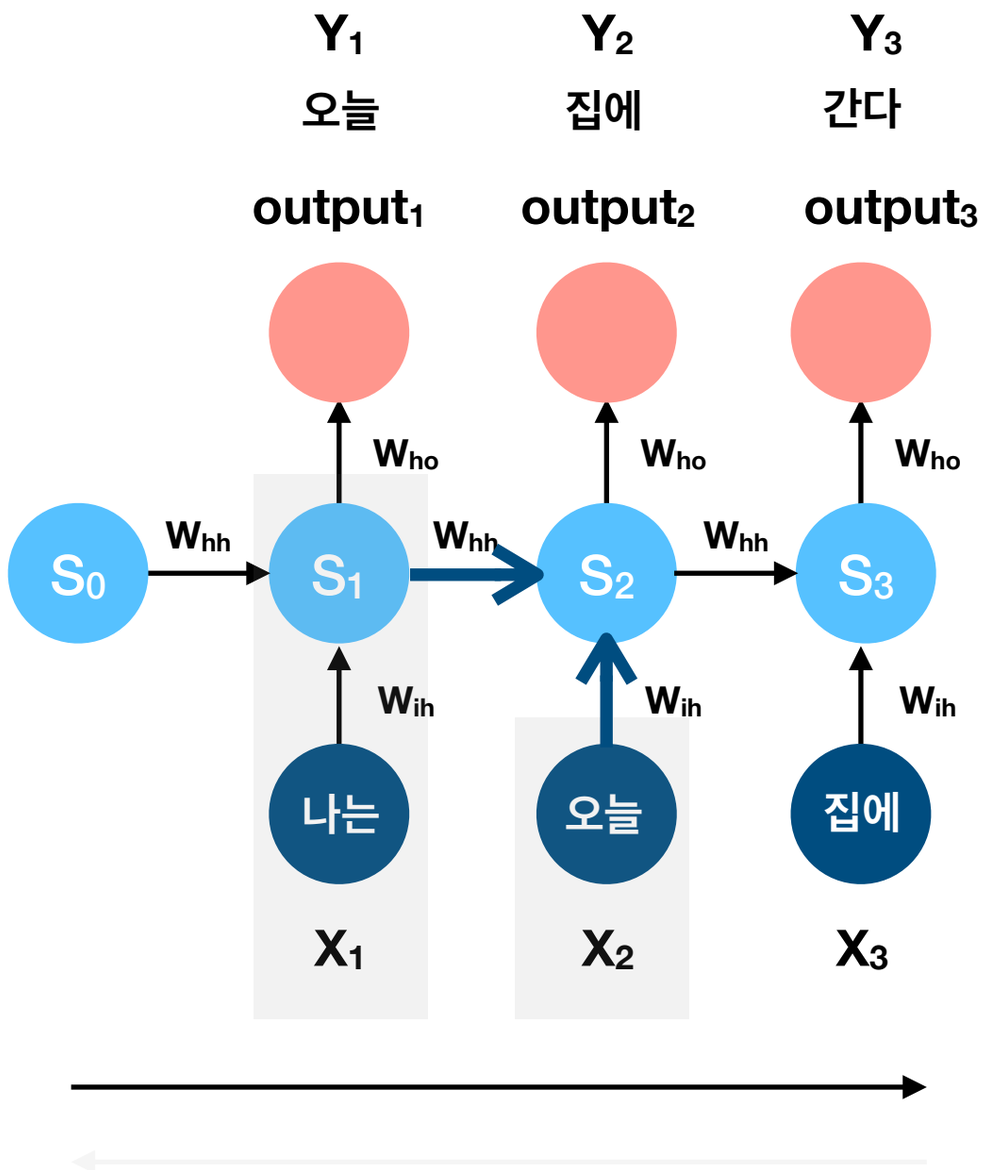




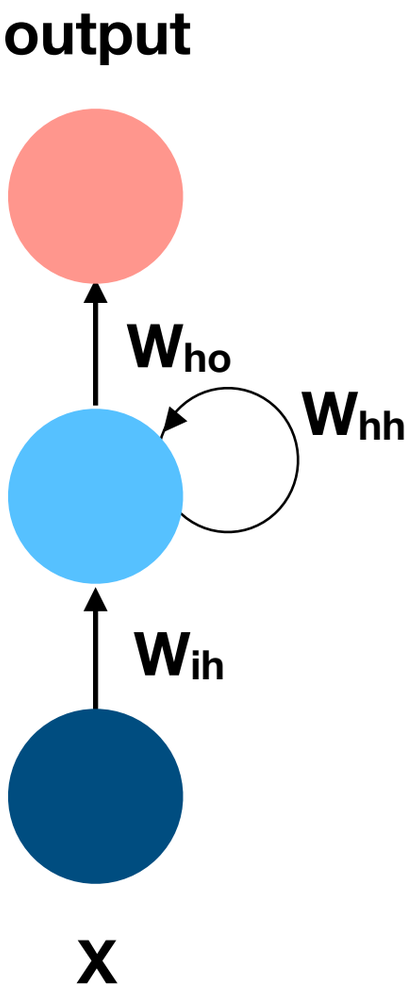
하지만 ANN과는 다르게 hidden layer는 현재 time step의 input 뿐만 아니라
이전 time step의 hidden layer의 영향도 받습니다. ($S(t) = S(t-1) * W_{hh} + X(t) * W_{ih}$)

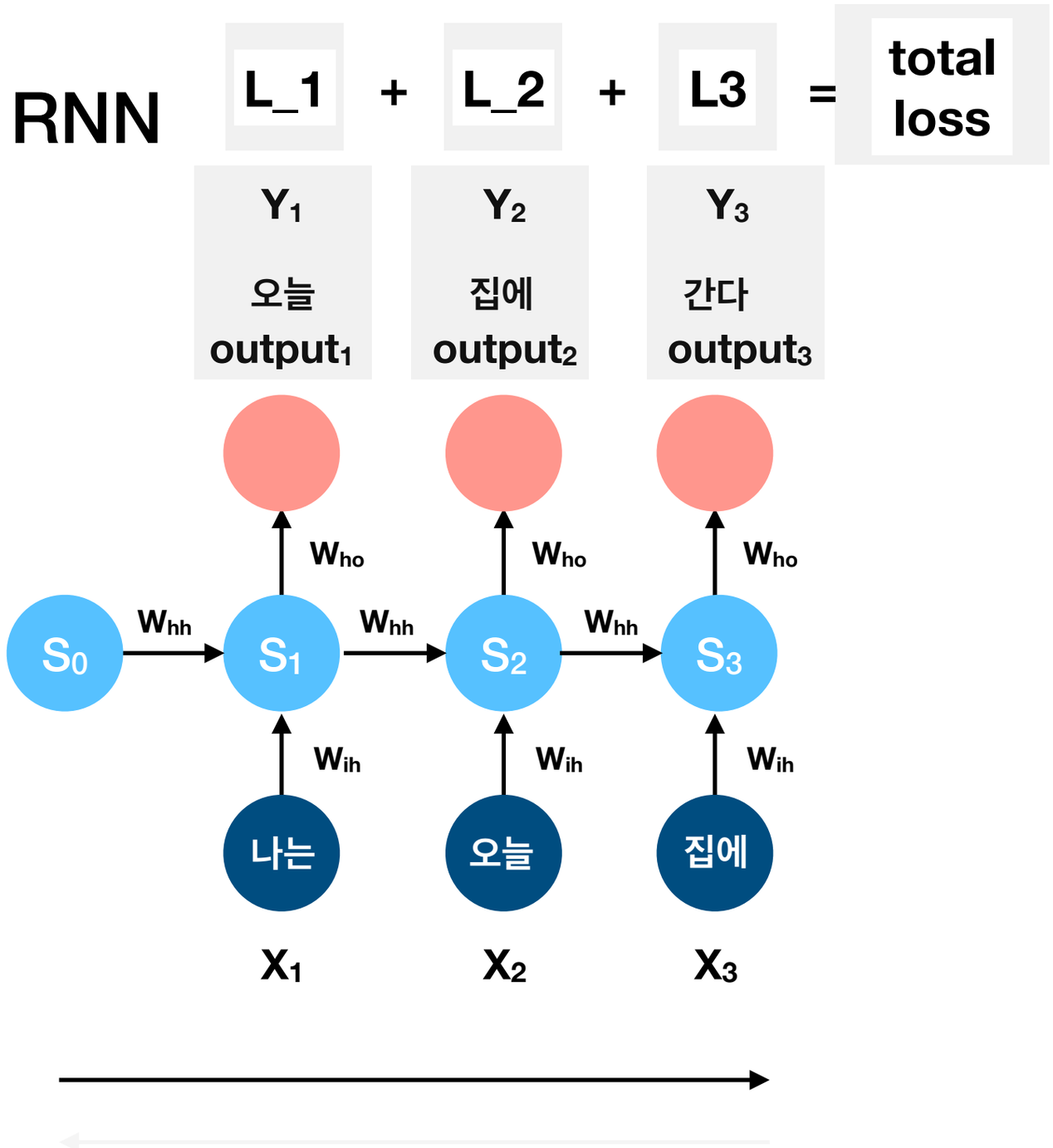
RNN



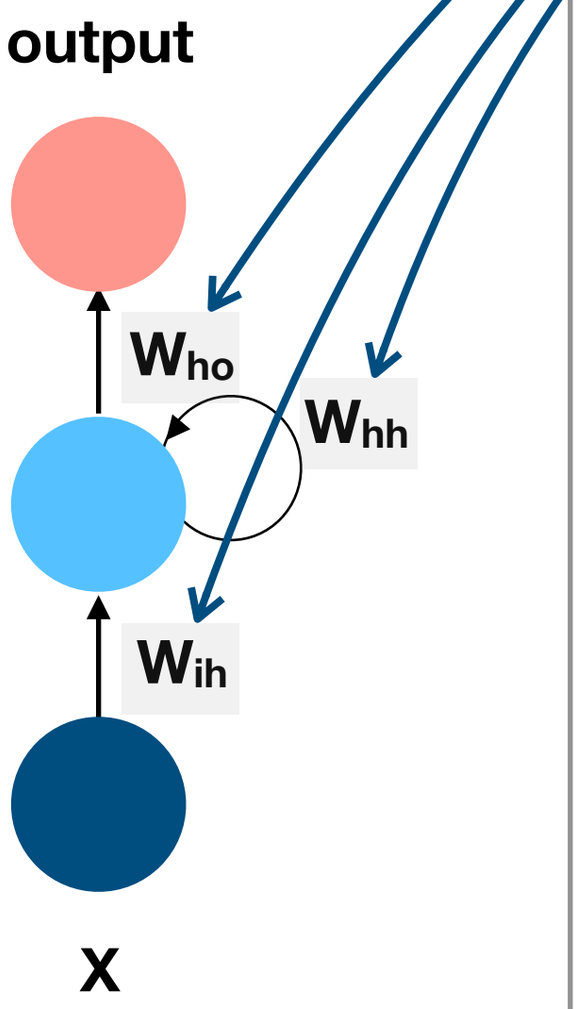


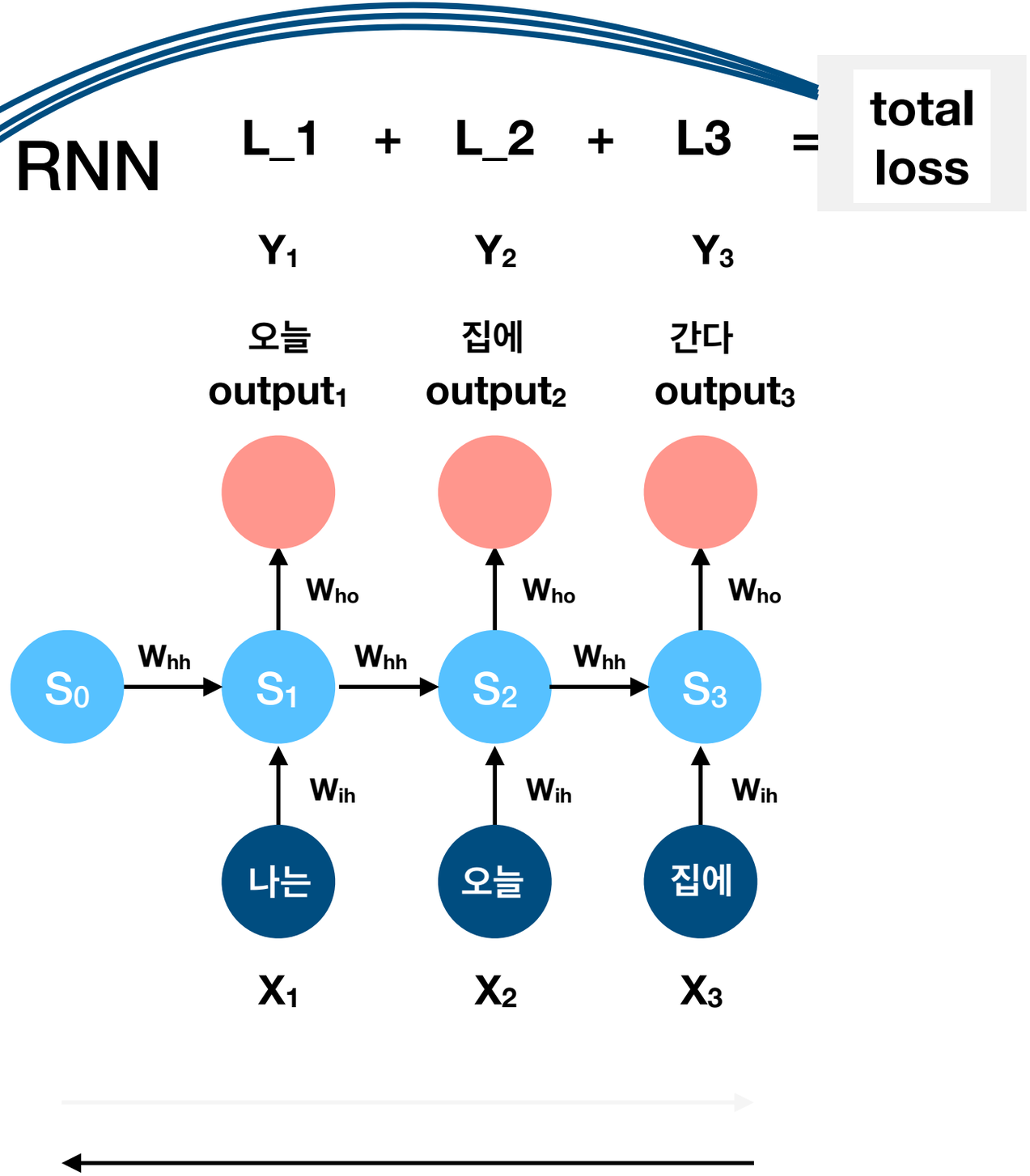
즉 '오늘'이란 단어가 두 번째 input (X_2)으로 들어갔을 때 이전 input (X_1)인 '나는'이 영향을 줍니다.





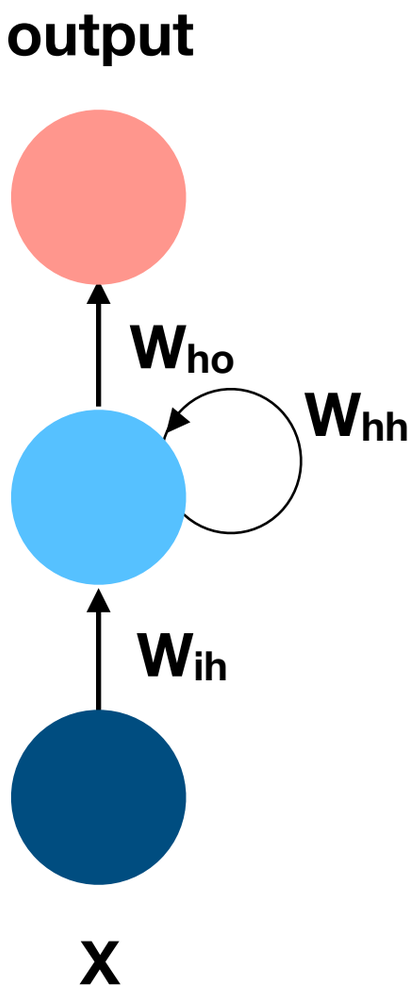
output과 정답 target (Y)을 비교하여 loss를 구합니다.
그러면 각각의 time step에서 loss가 나오게 될 것이고 이를 모두 더하여 전체 loss라고 정의합니다.

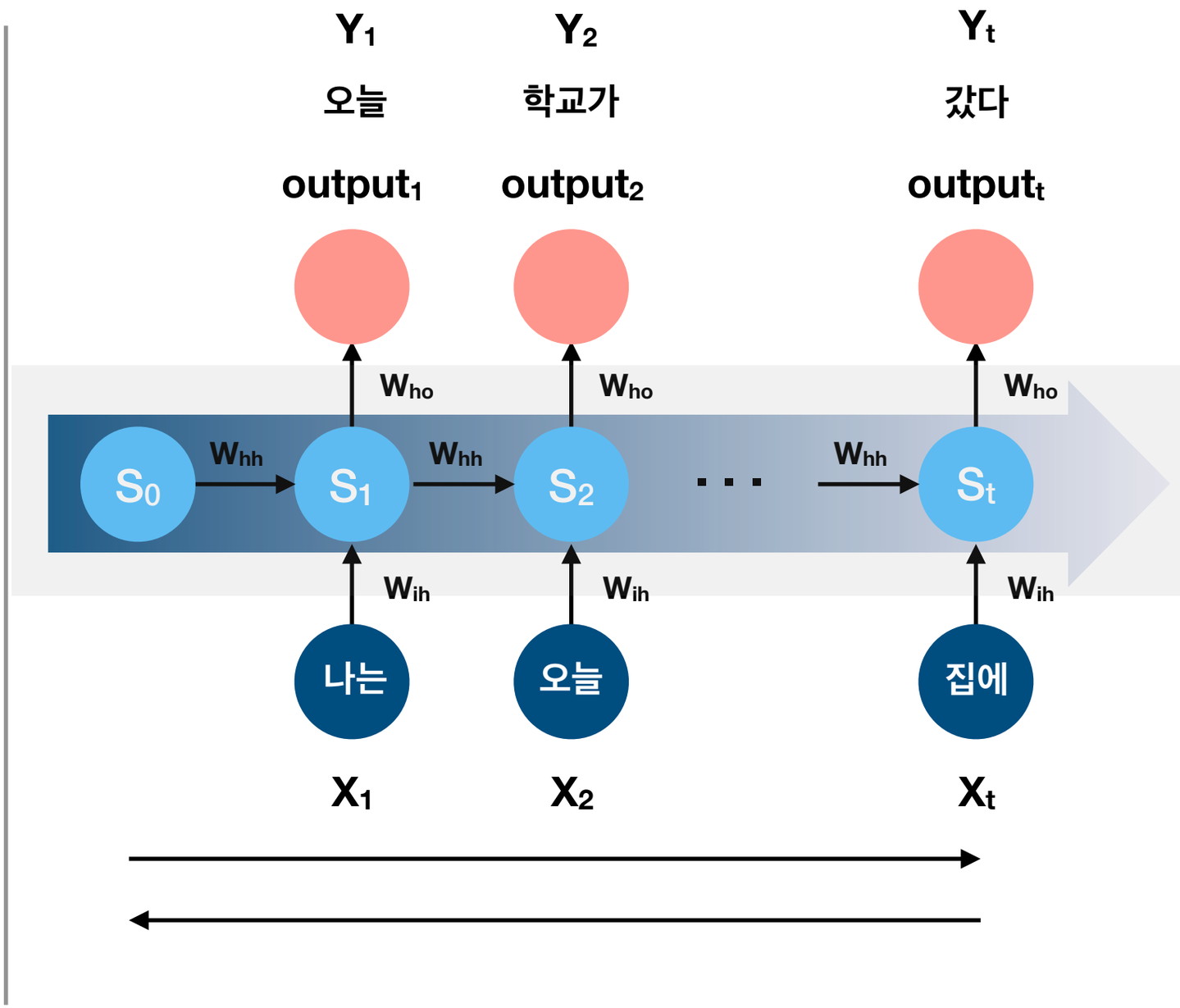




이 전체 loss를 최소화하는 방향으로, weight을 update 합니다.

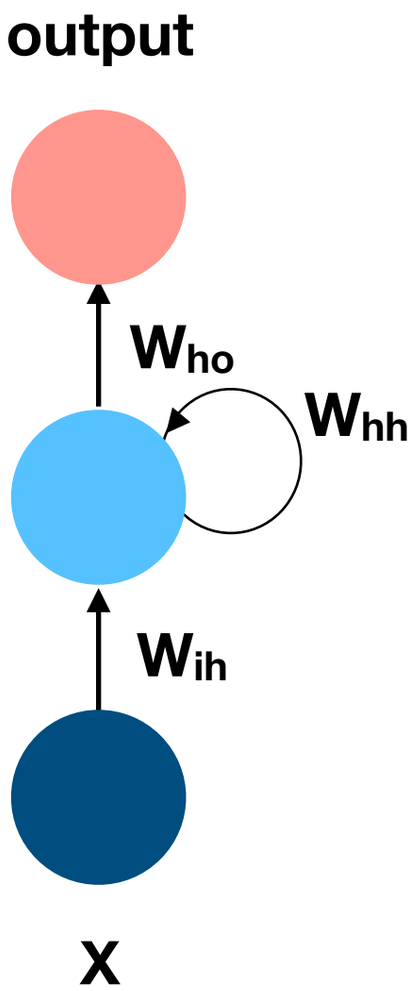
RNN

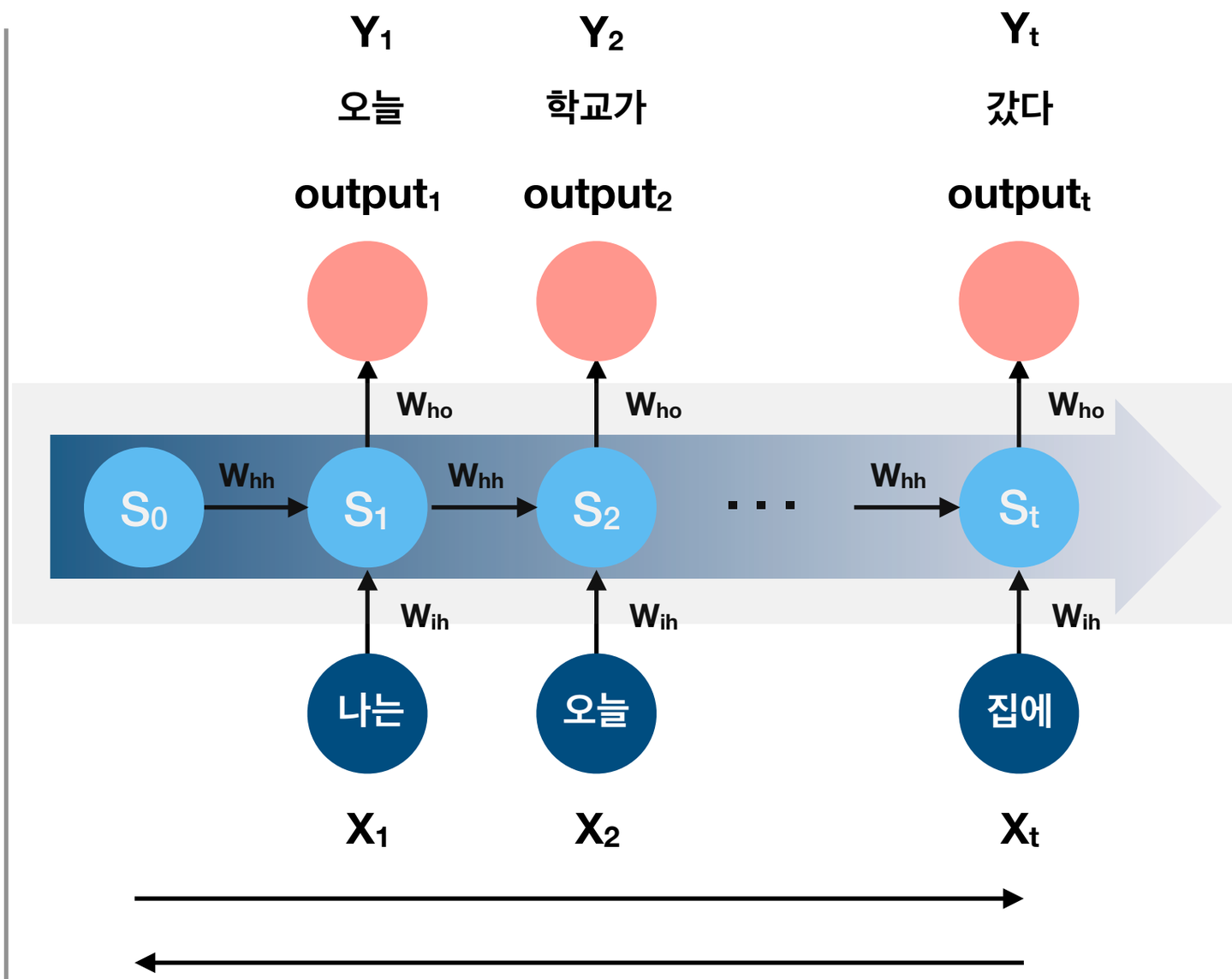




가장 기본적인 RNN은 훈련할 time step의 수가 많아졌을 때,
뒤쪽의 time step이 앞쪽 time step의 정보를 제대로 반영하지 못하는 한계가 있습니다.

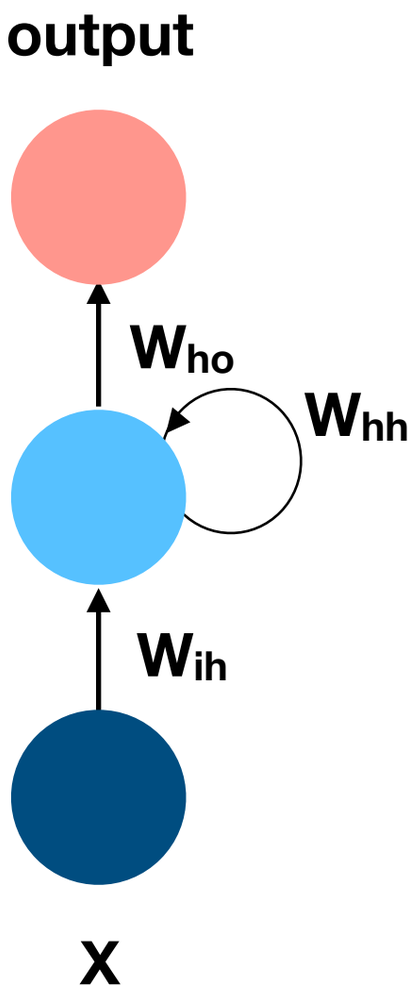
RNN

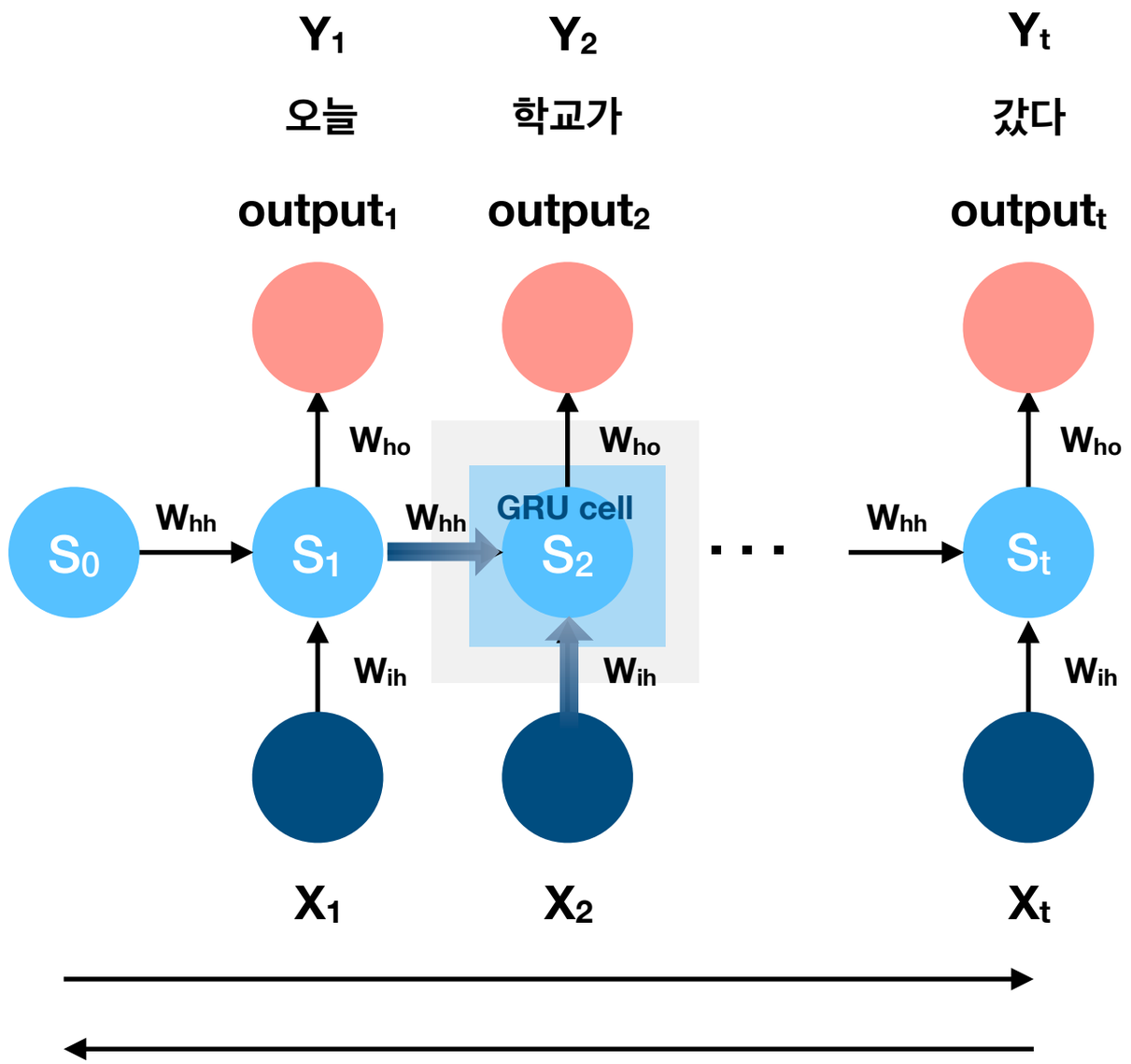




예를 들어, '나는 오늘 학교가 끝나고 서점에 들러 책을 산 후 집에 갔다'라는
11개의 time step으로 이루어진 문장을 훈련할 때
마지막 11번째 time step의 hidden node S_{11}은
첫 번째 time step의 input인 '나는'에 대한 정보를 거의 갖고 있지 않습니다.

RNN

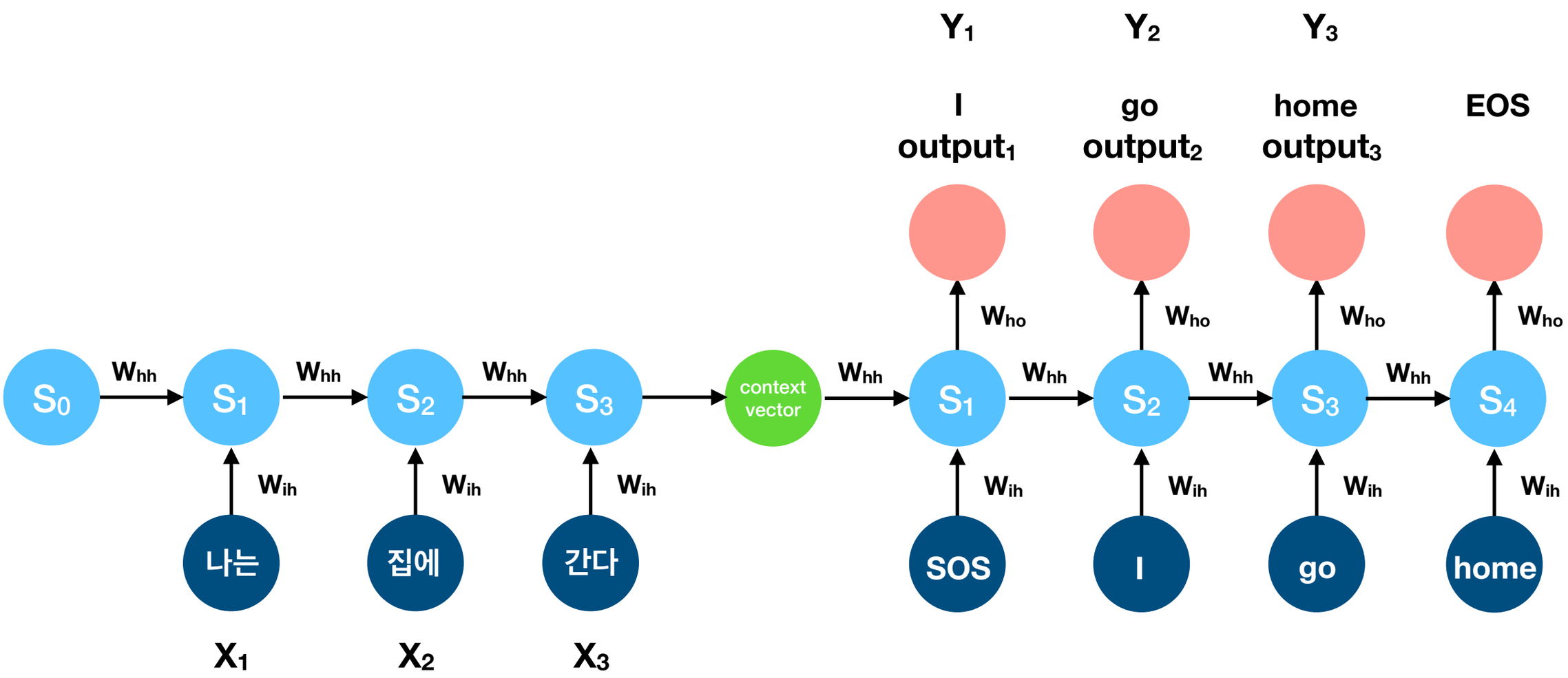




따라서 hidden layer가 이전 time step의 정보를 보다 효율적으로
기억할 수 있도록 하는 방법이 고안되었습니다.

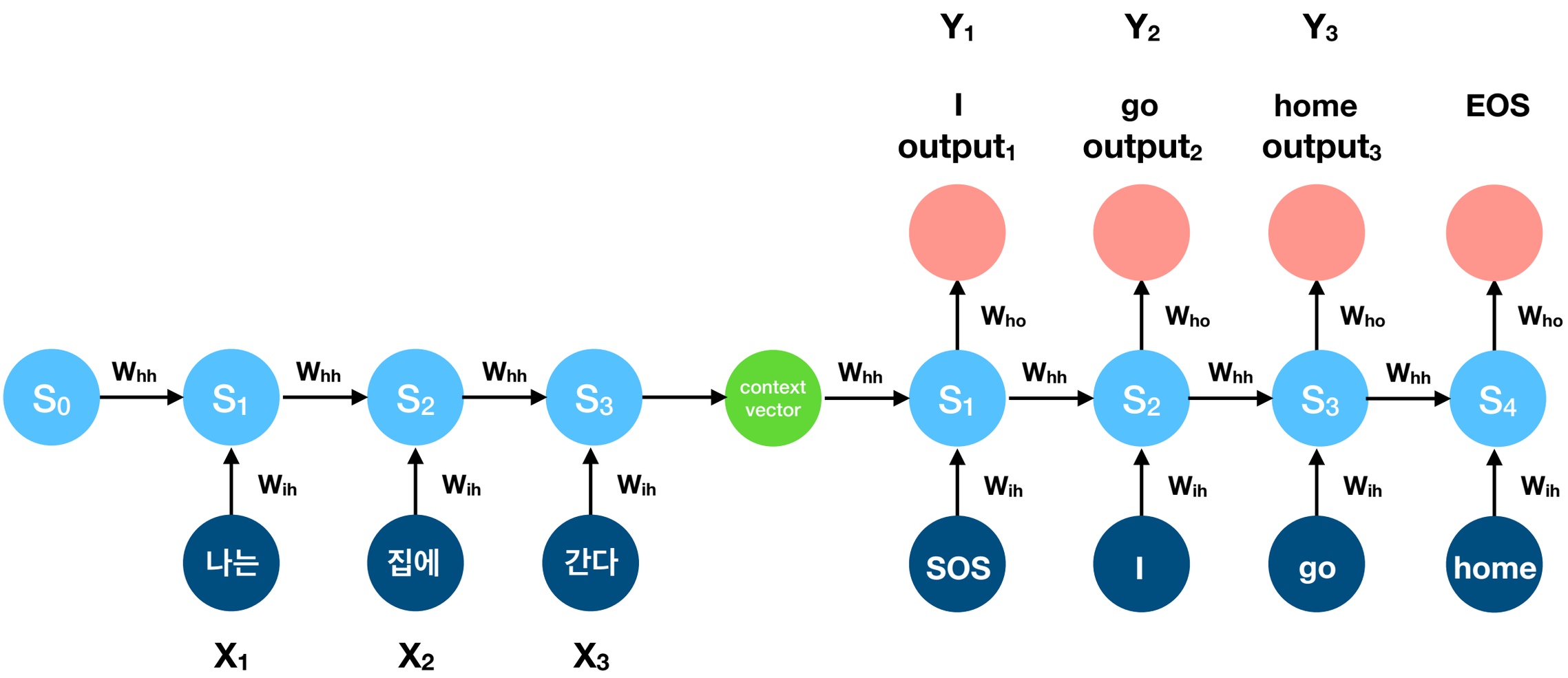
SEQ2SEQ

SEQ2SEQ

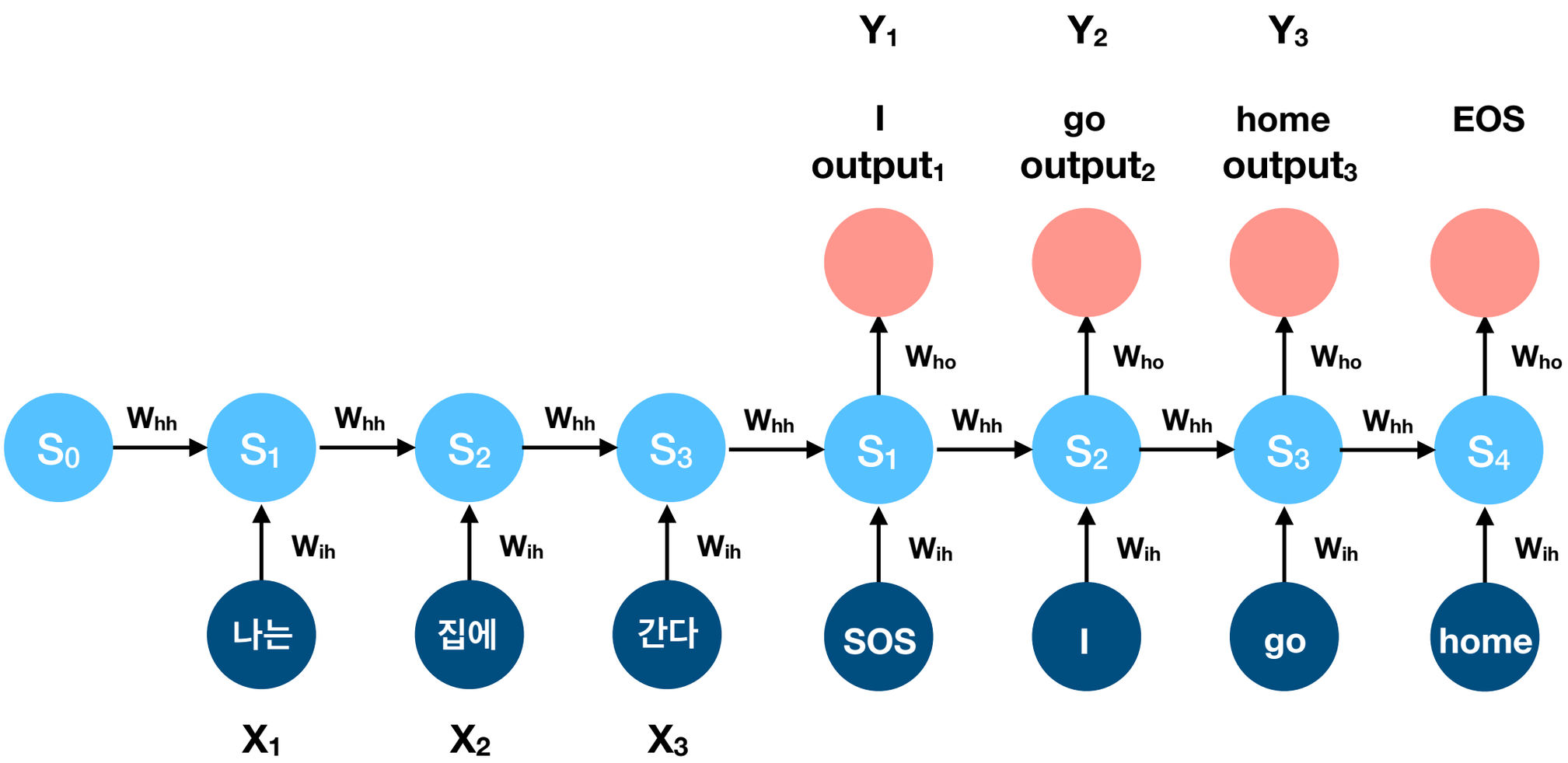

Y1
Y2
Y3
I
go
home
EOS
output1
output2
output3
Who
Who
Who
Who
S0
Whh
S1
Whh
S2
Whh
S3
context vector
Whh
S1
Whh
S2
Whh
S3
Whh
S4
Wih
Wih
Wih
Wih
Wih
Wih
나는
집에
간다
SOS
I
go
home
X1
X2
X3

Transformer

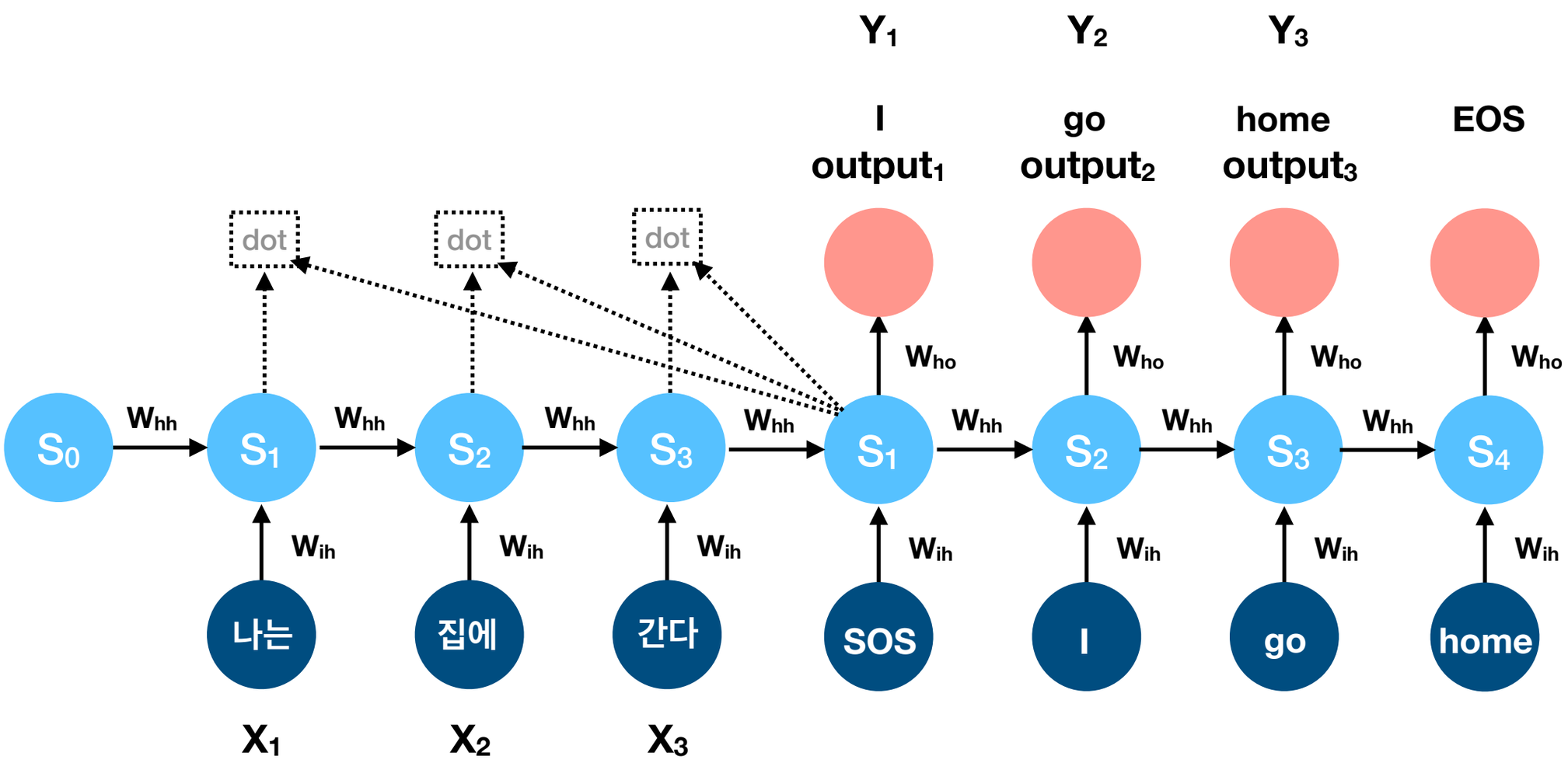
SEQ2SEQ


Y1
Y2
Y3
I
go
home
EOS
output1
output2
output3
Who
Who
Who
Who
S0
Whh
S1
Whh
S2
Whh
S3
context vector
Whh
S1
Whh
S2
Whh
S3
Whh
S4
Wih
Wih
Wih
Wih
Wih
Wih
나는
집에
간다
SOS
I
go
home
X1
X2
X3

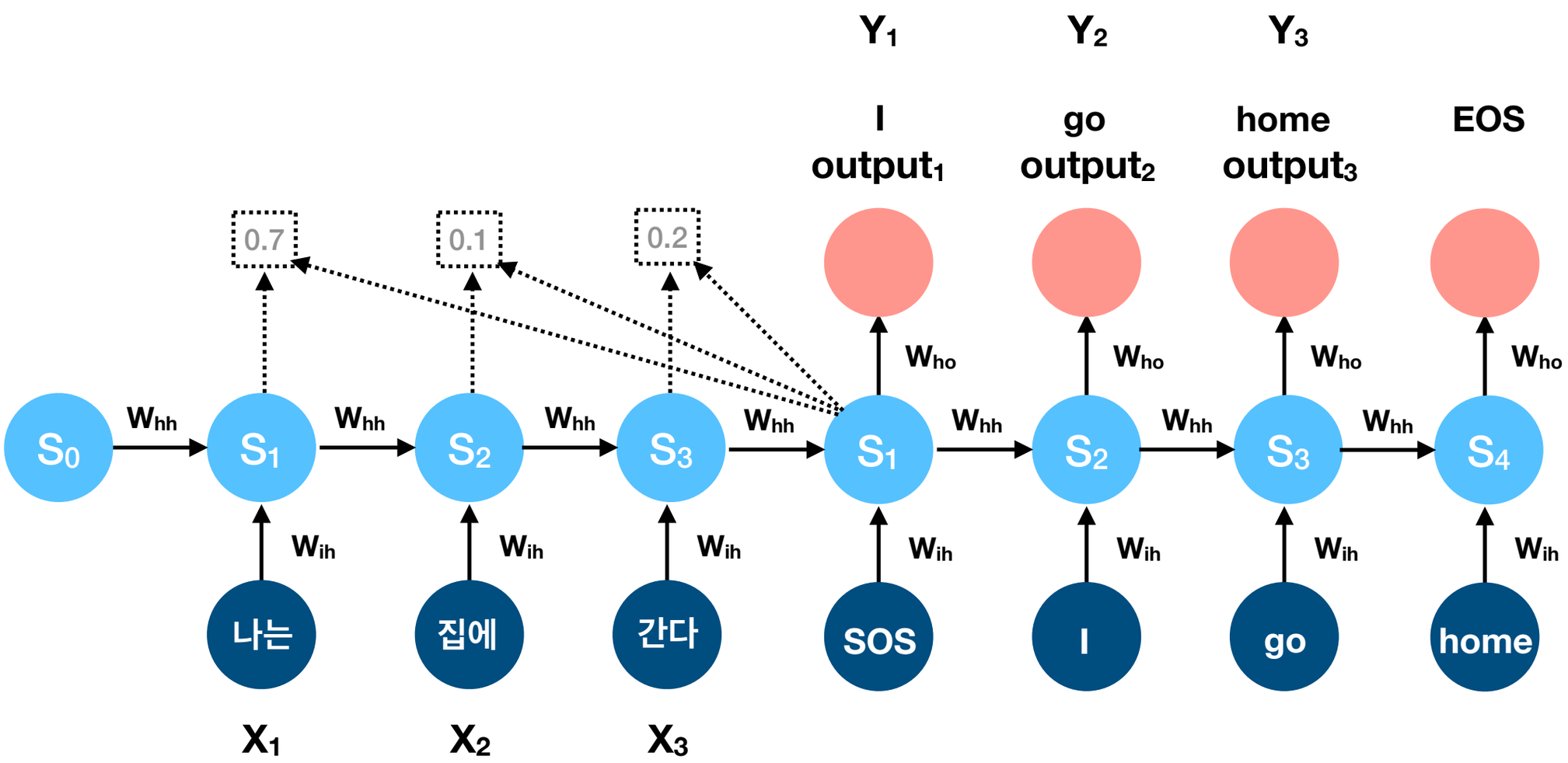
Transformer



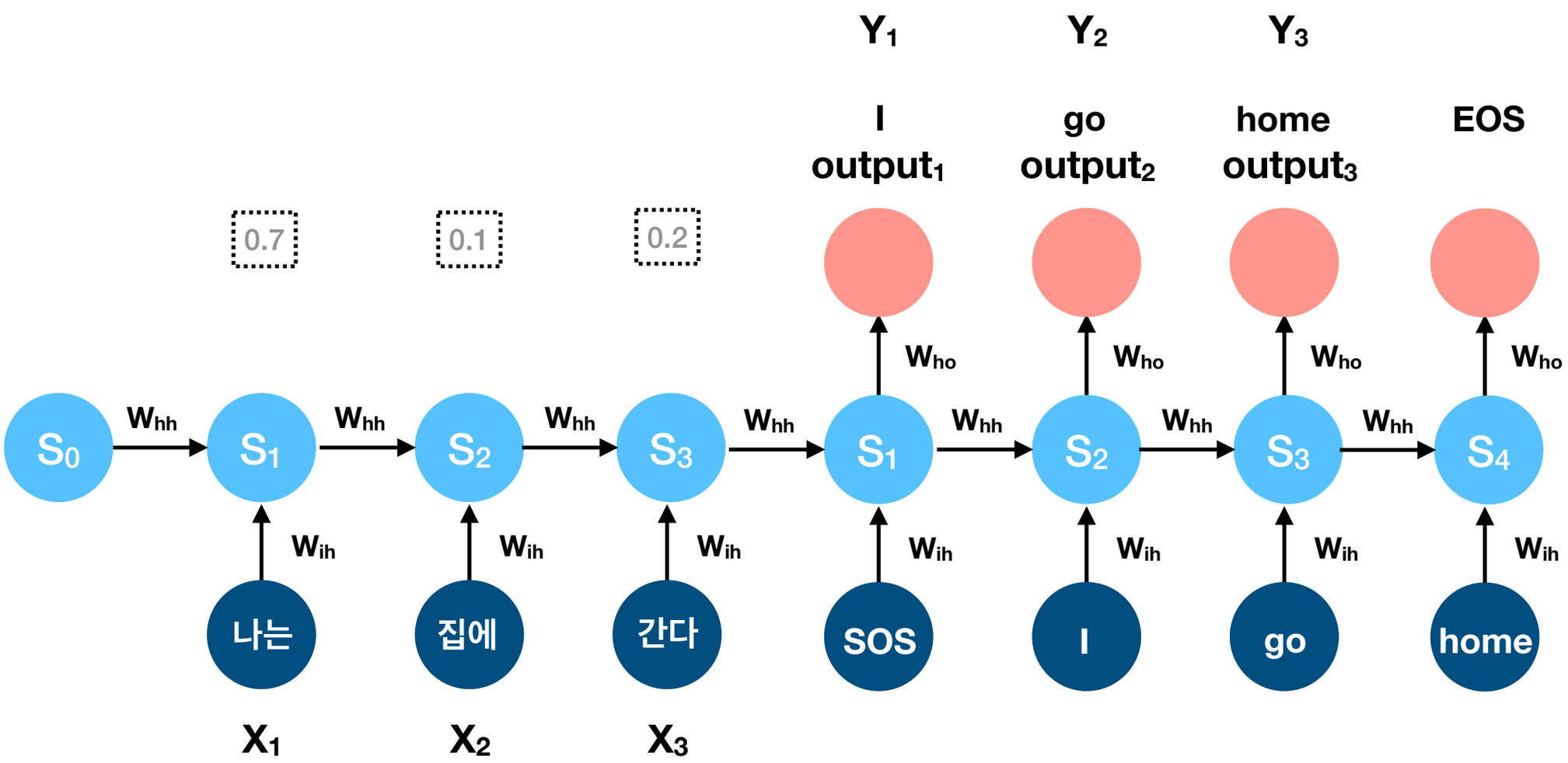
Transformer



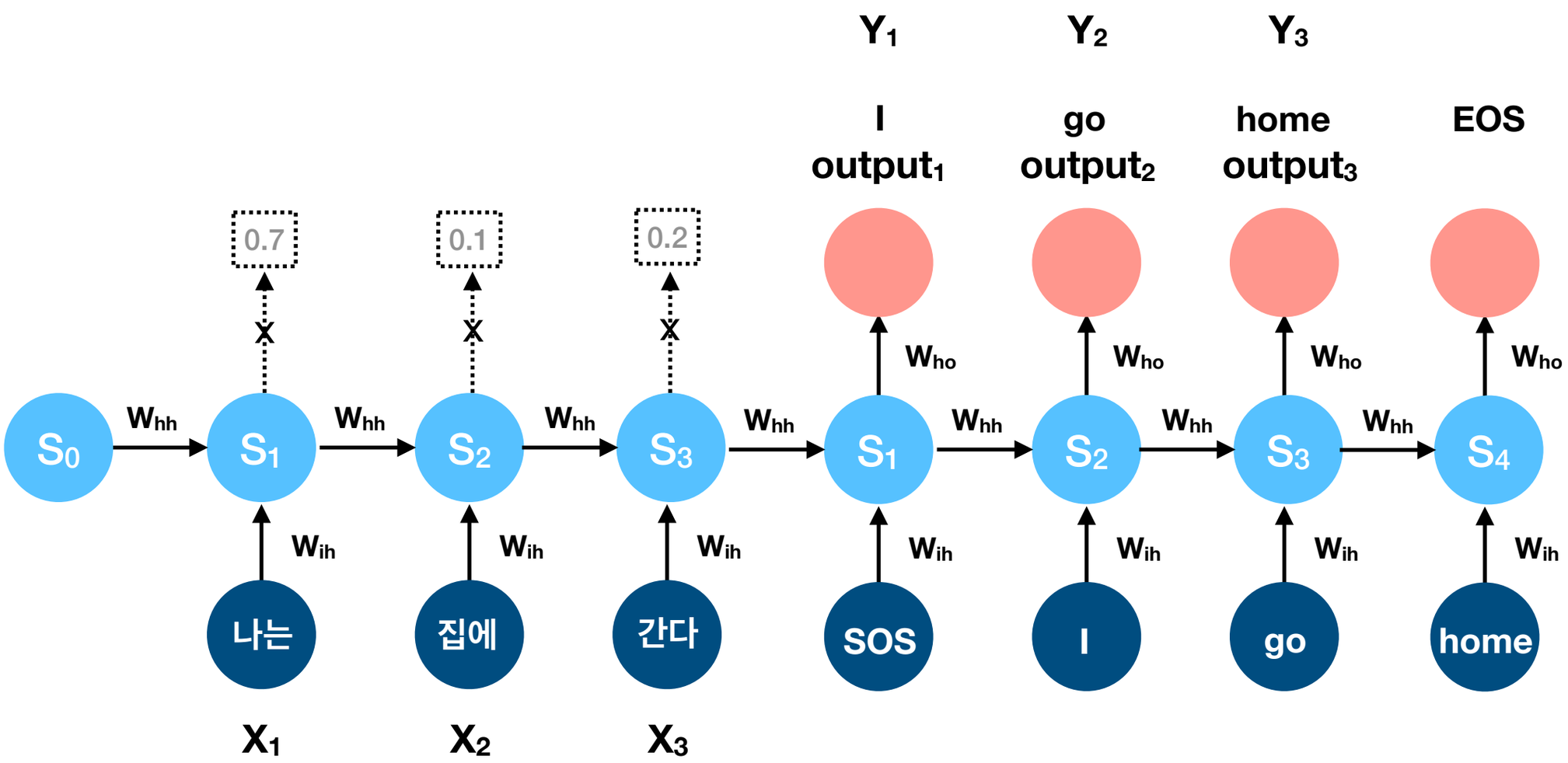
Transformer



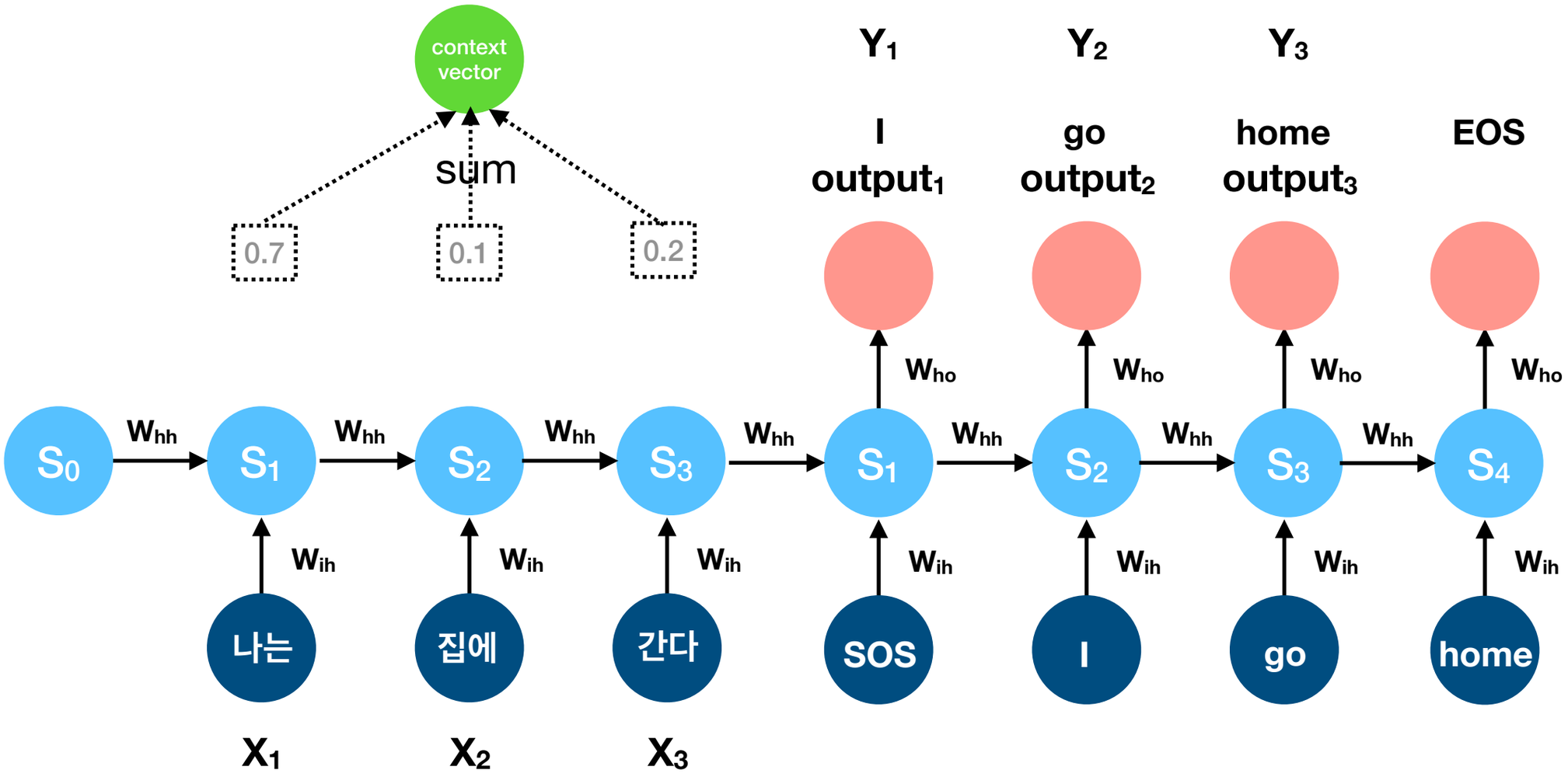
Transformer



Transformer



Transformer



Transformer