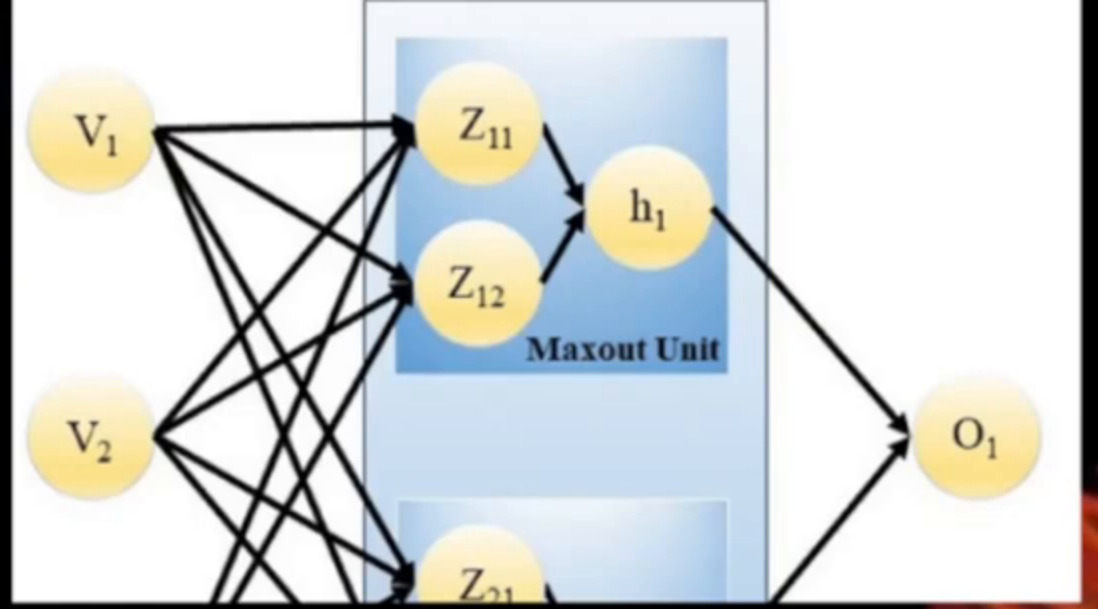
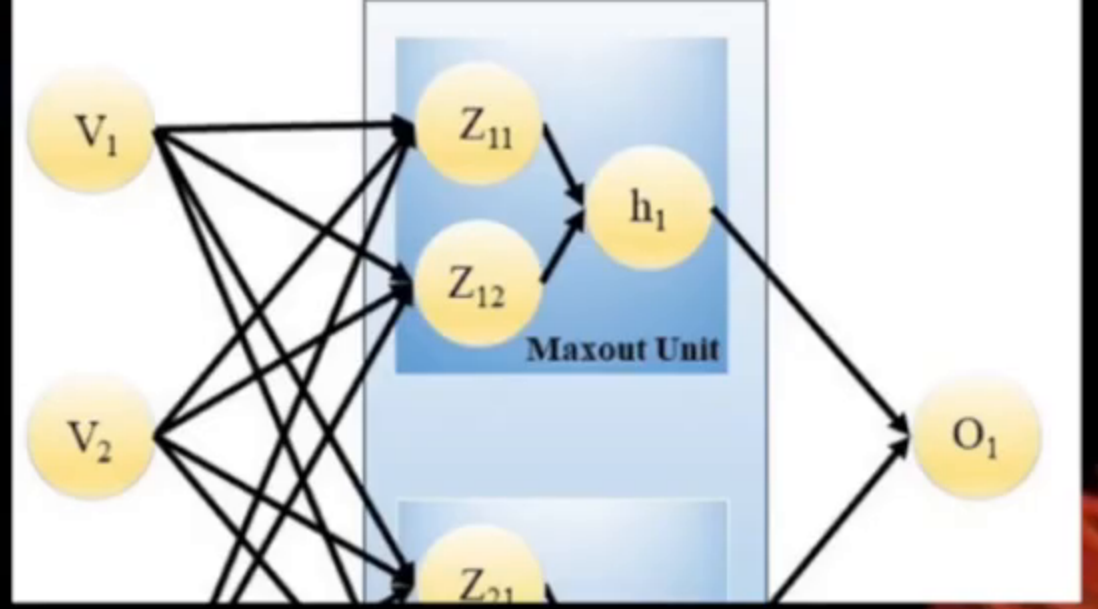
ACTIVATION FUNCTIONS



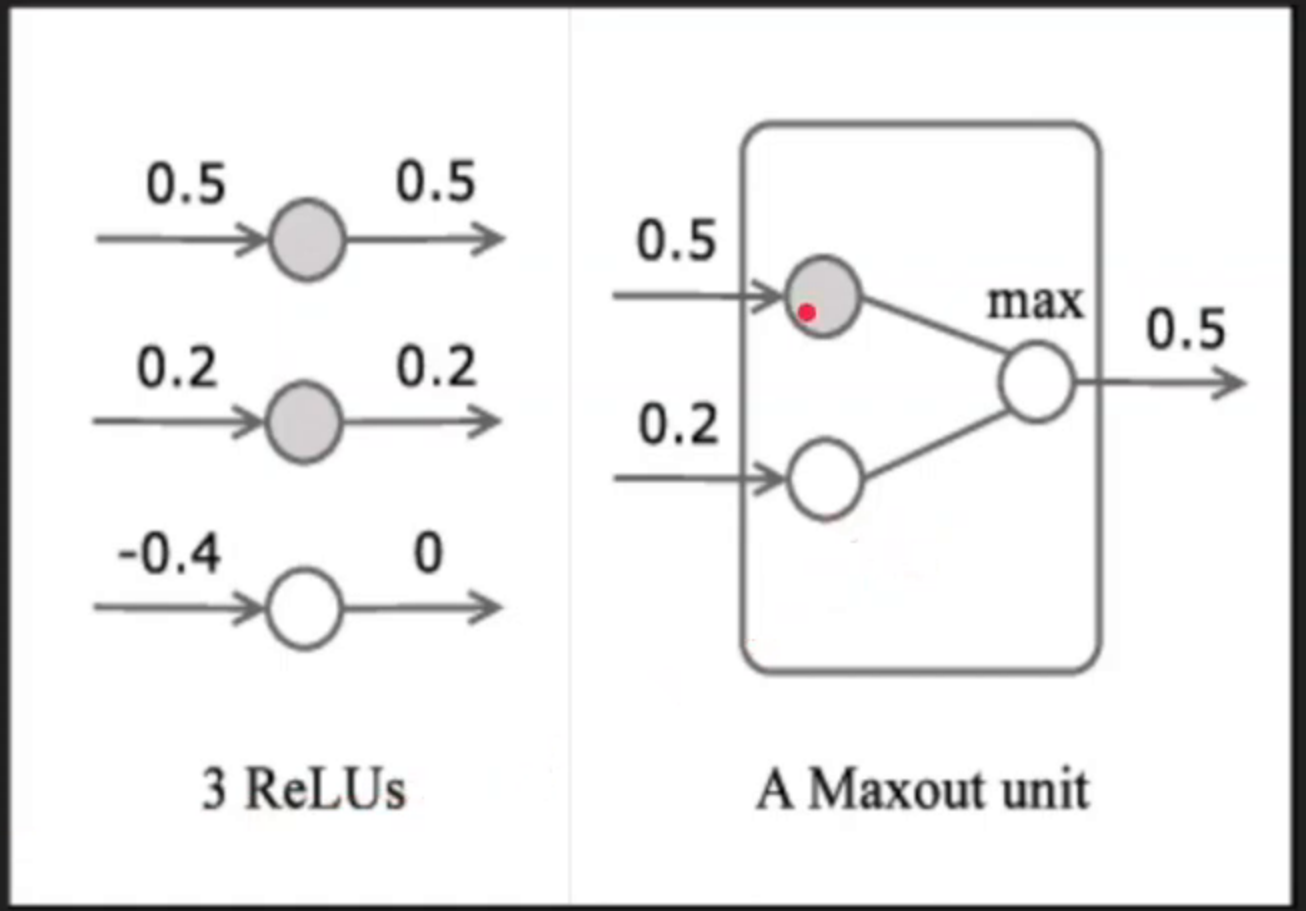
MAXOUT ACTIVATION

ACTIVATION FUNCTIONS



MAXOUT ACTIVATION

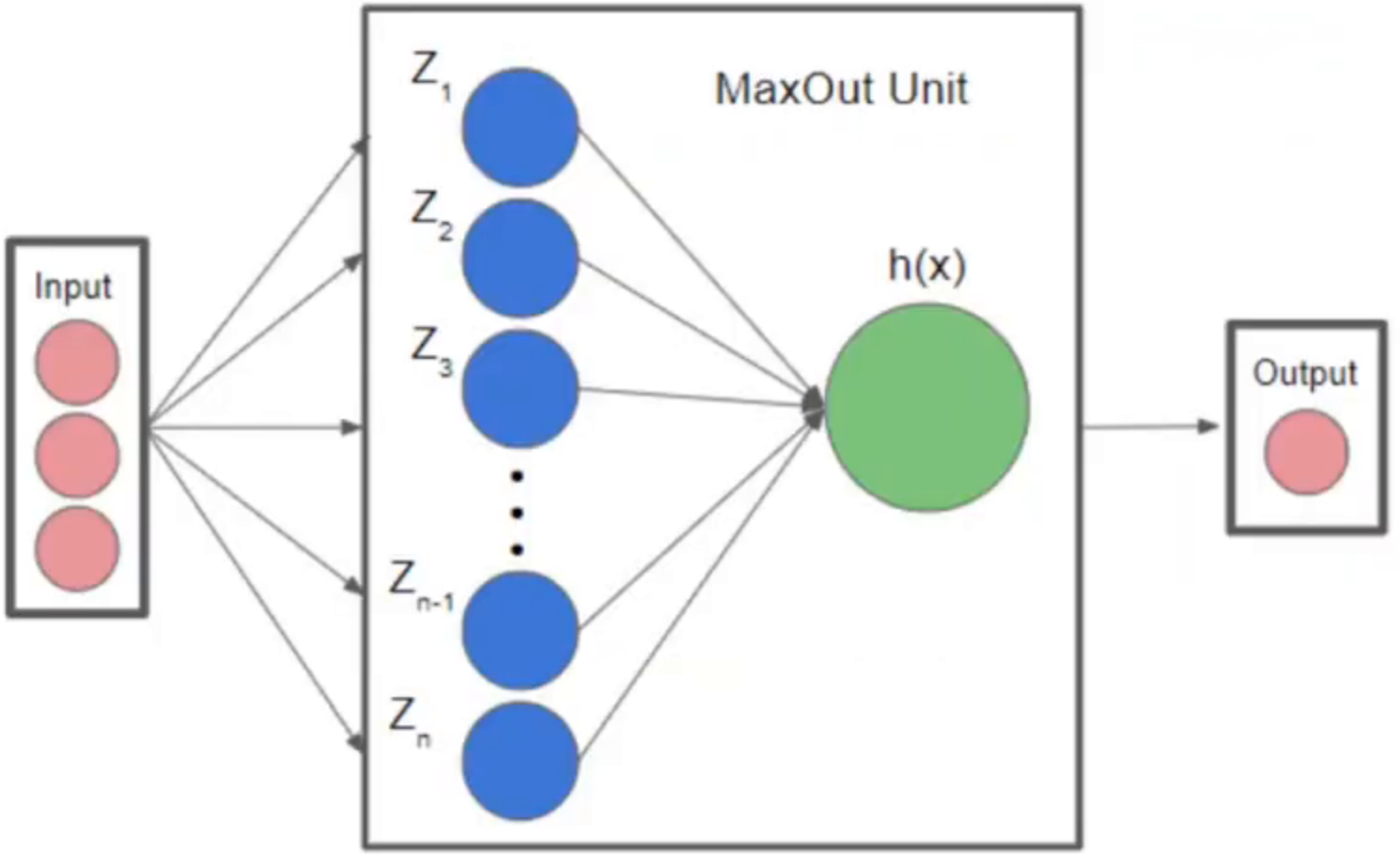
Illustration



Maxout

$$h(x) = \max\left(Z_1, Z_2, \ldots, Zn\right)$$

$$h(x) = \max\left(W_1 \cdot x + b_1, W_2 \cdot x + b_2, \ldots, Wn \cdot x + bn\right)$$



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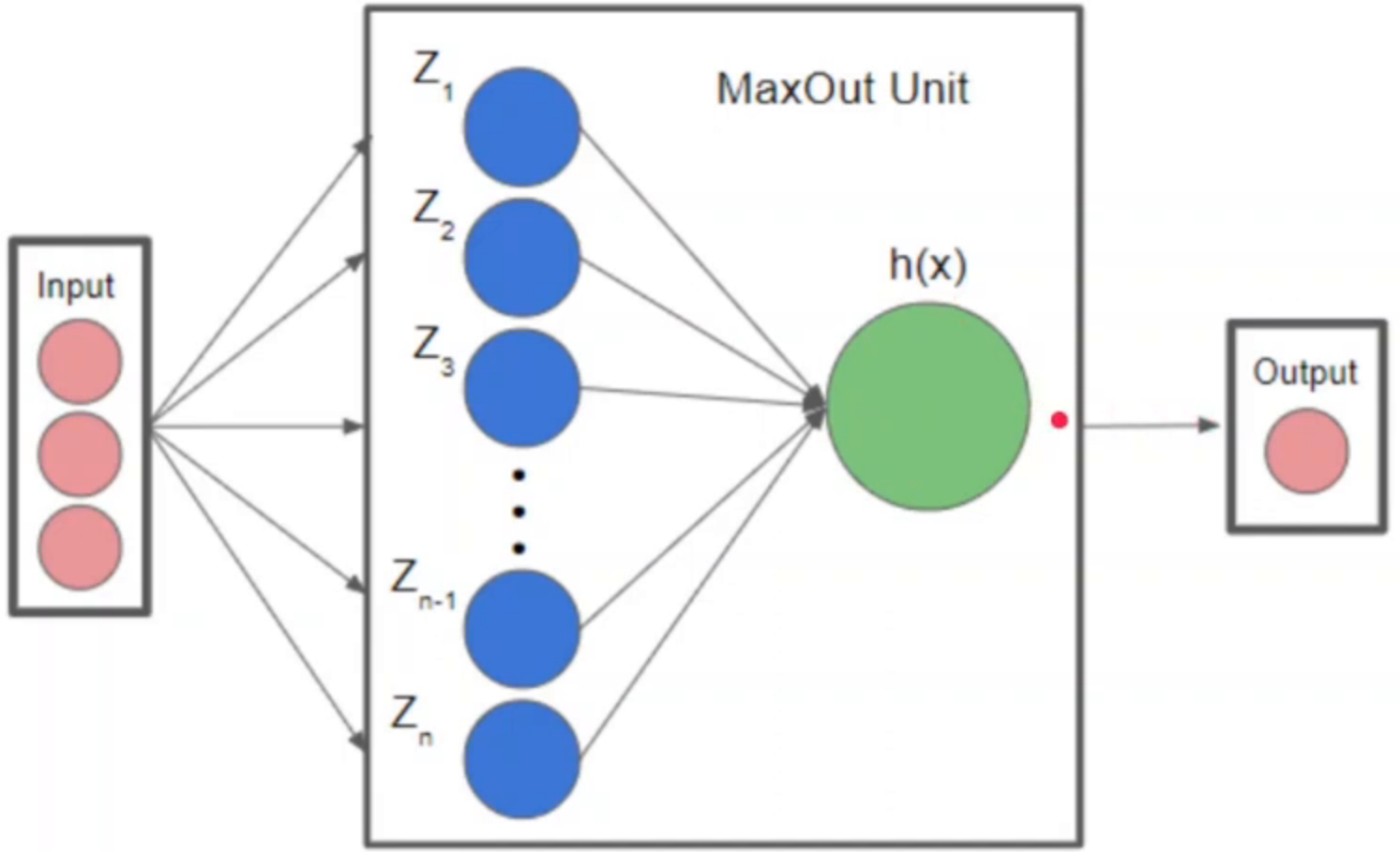

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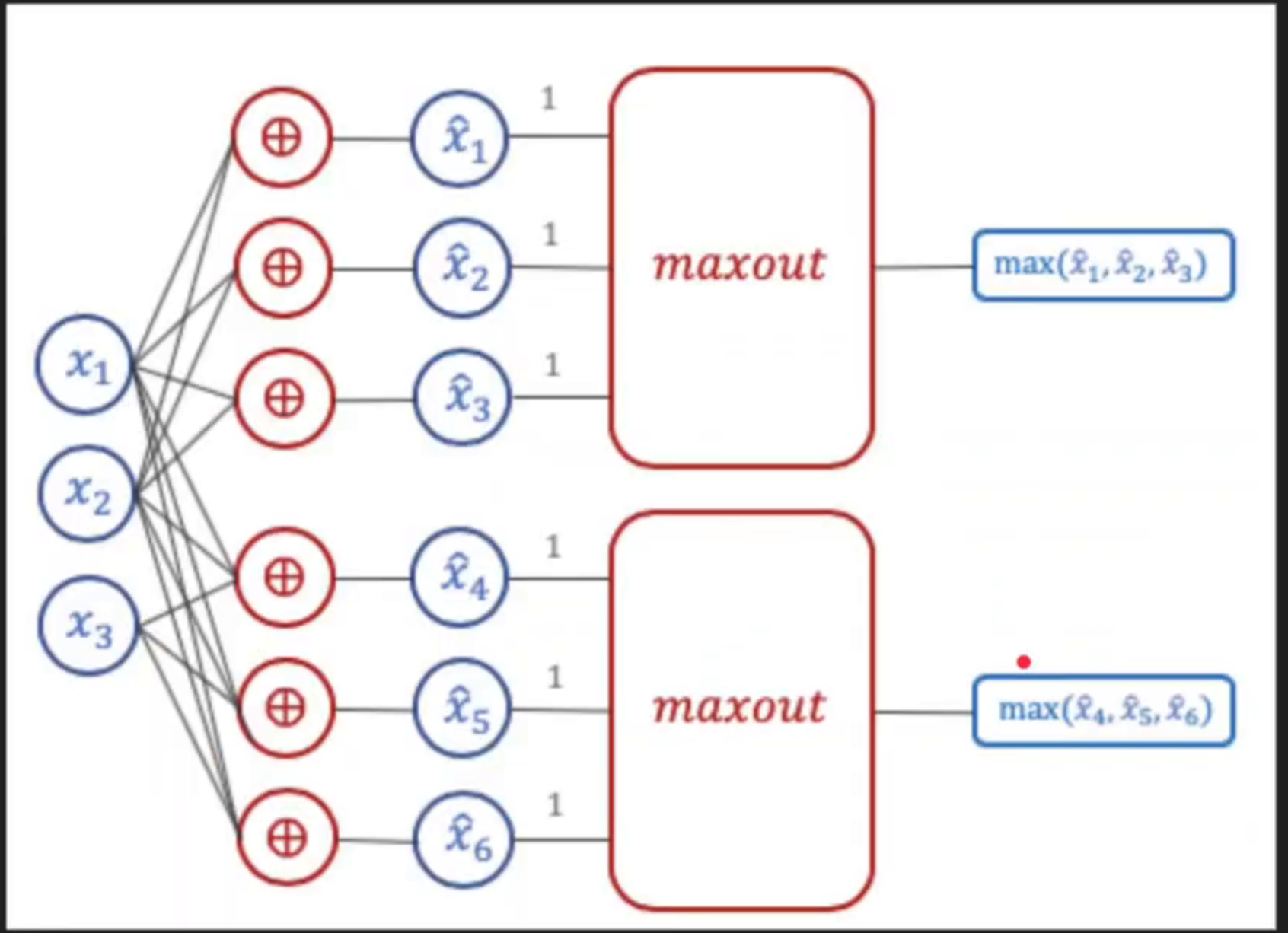

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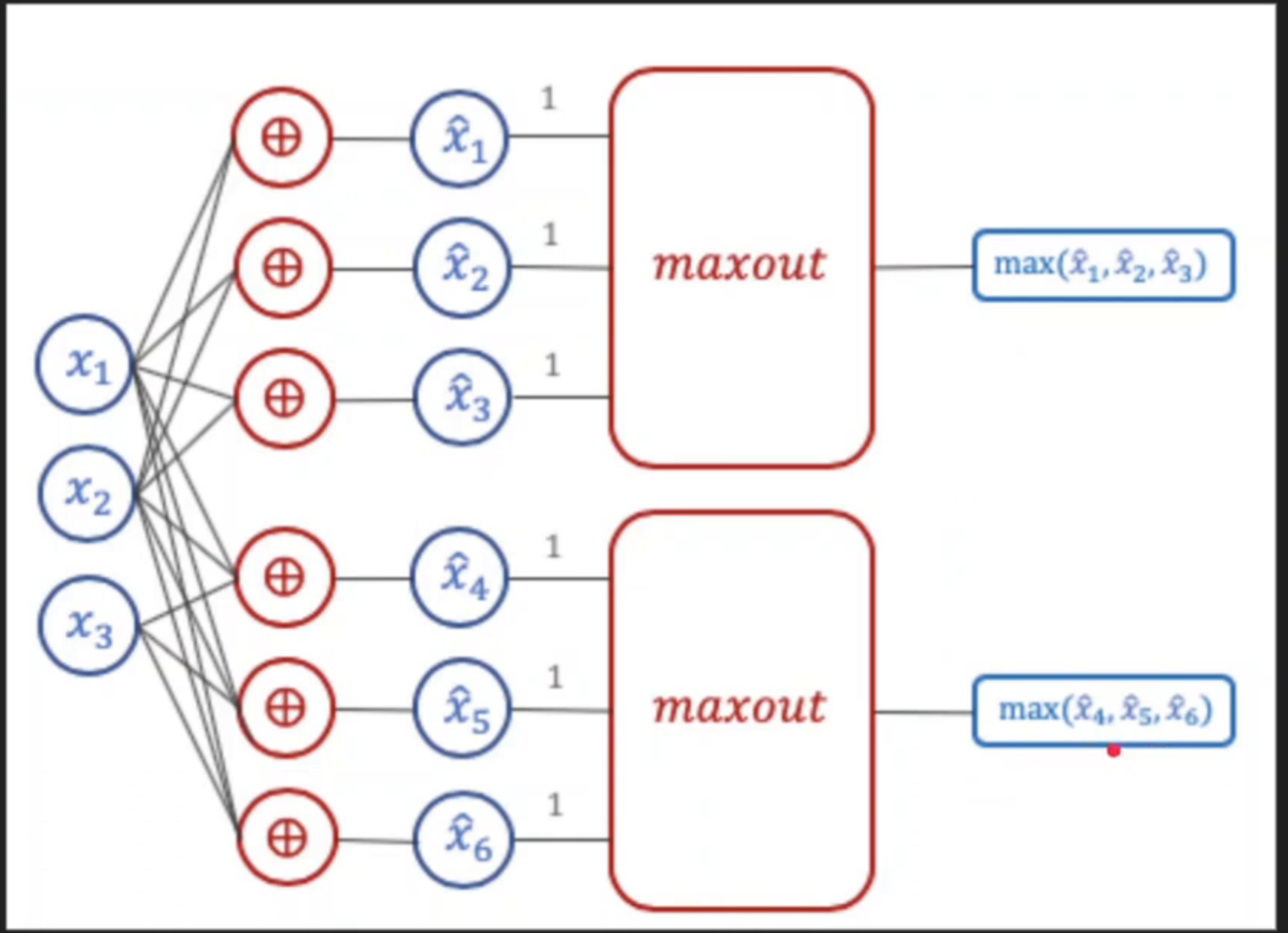

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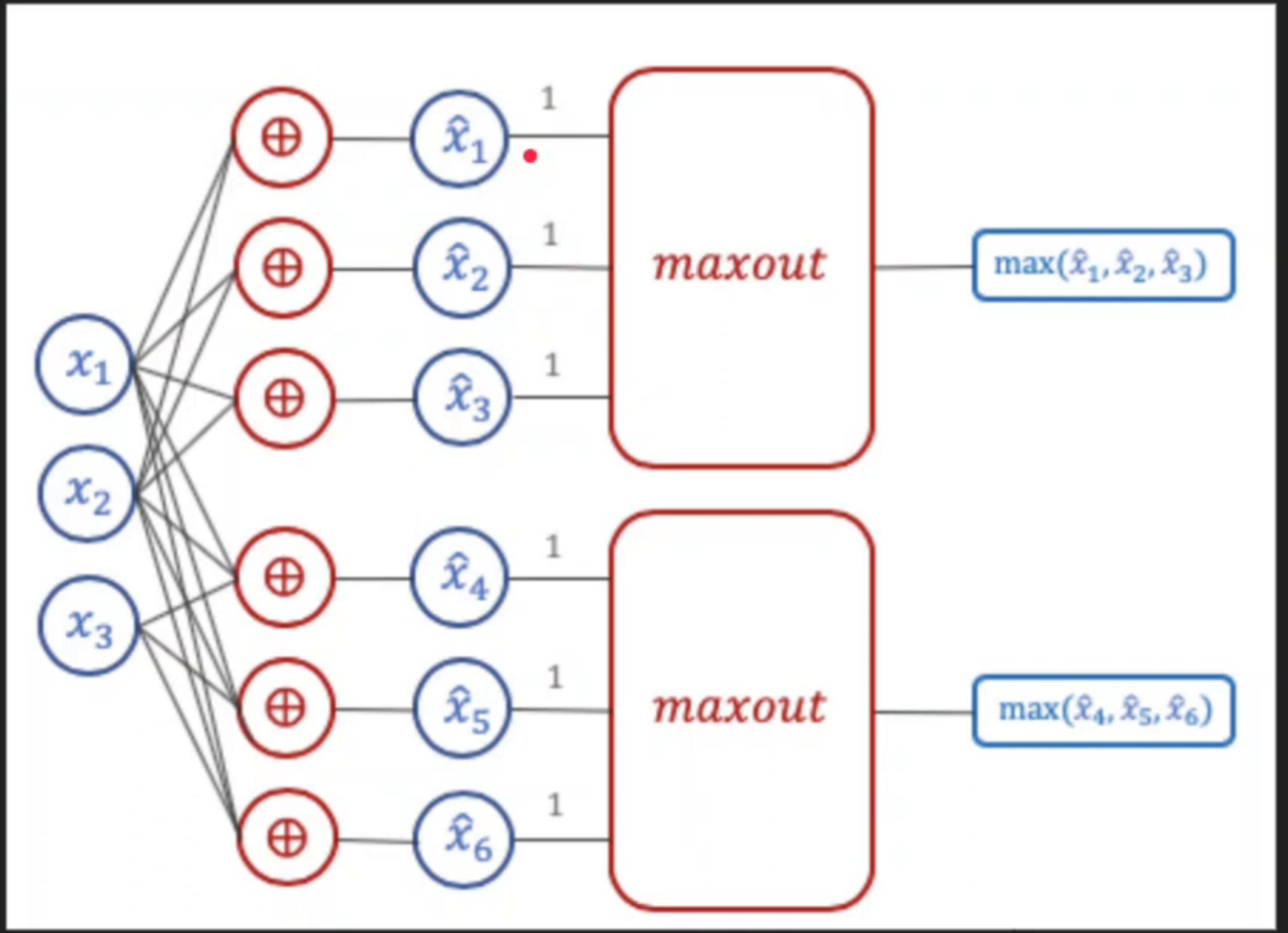
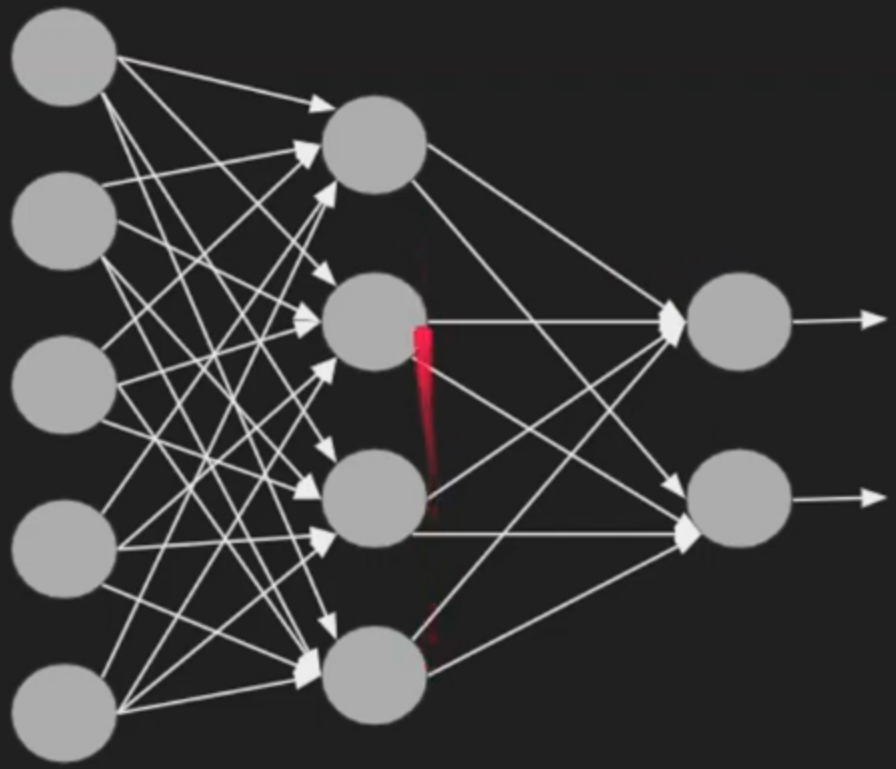


Network - (5,4,2)

Input Hidden Output



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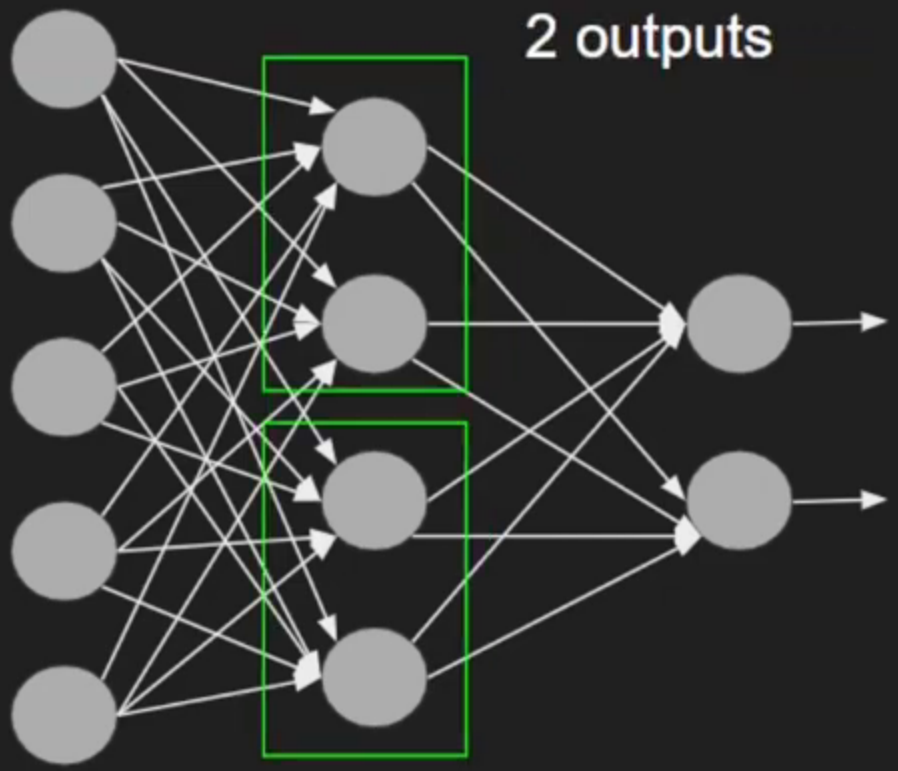

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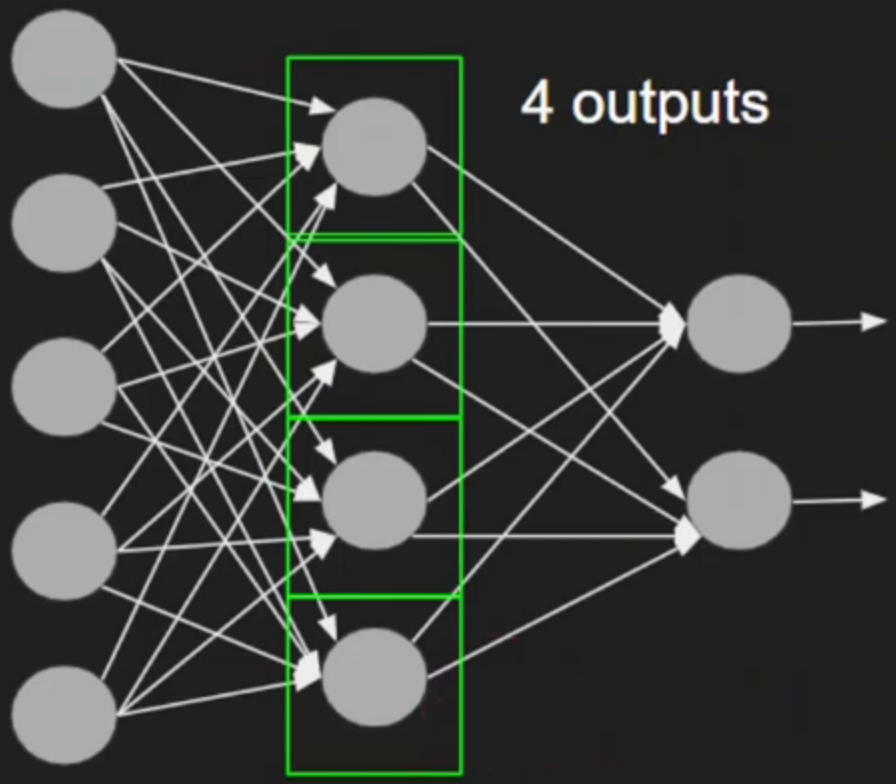

Number of outputs = Number of Groups

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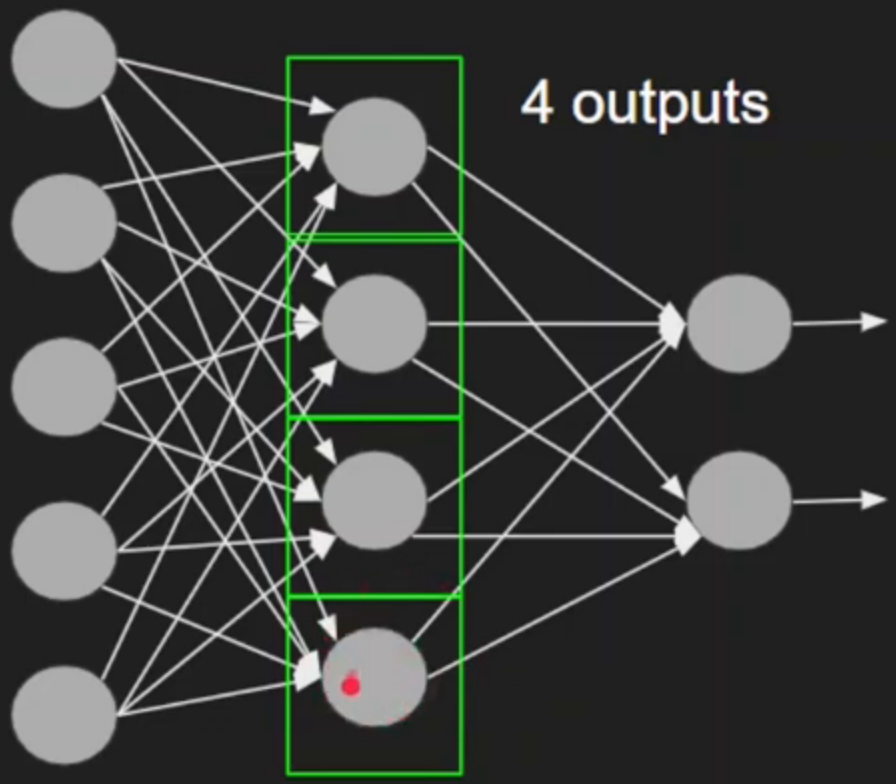

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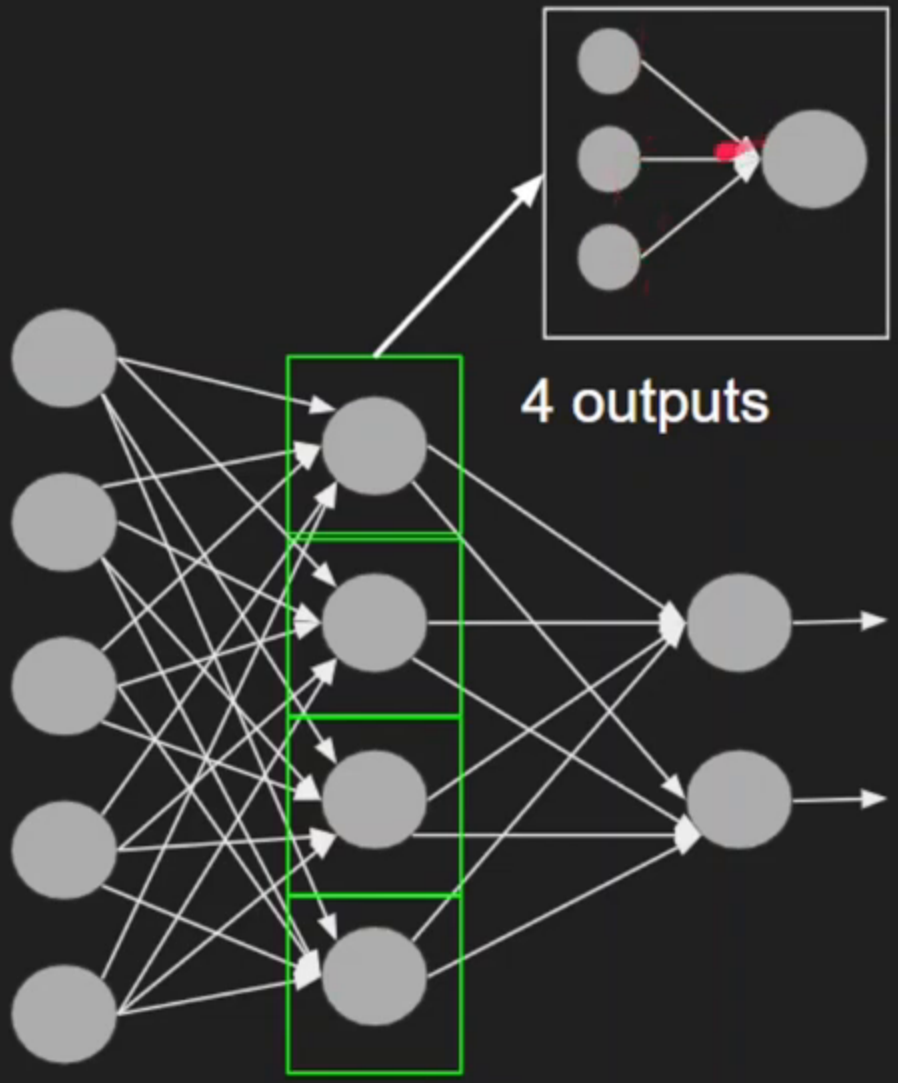

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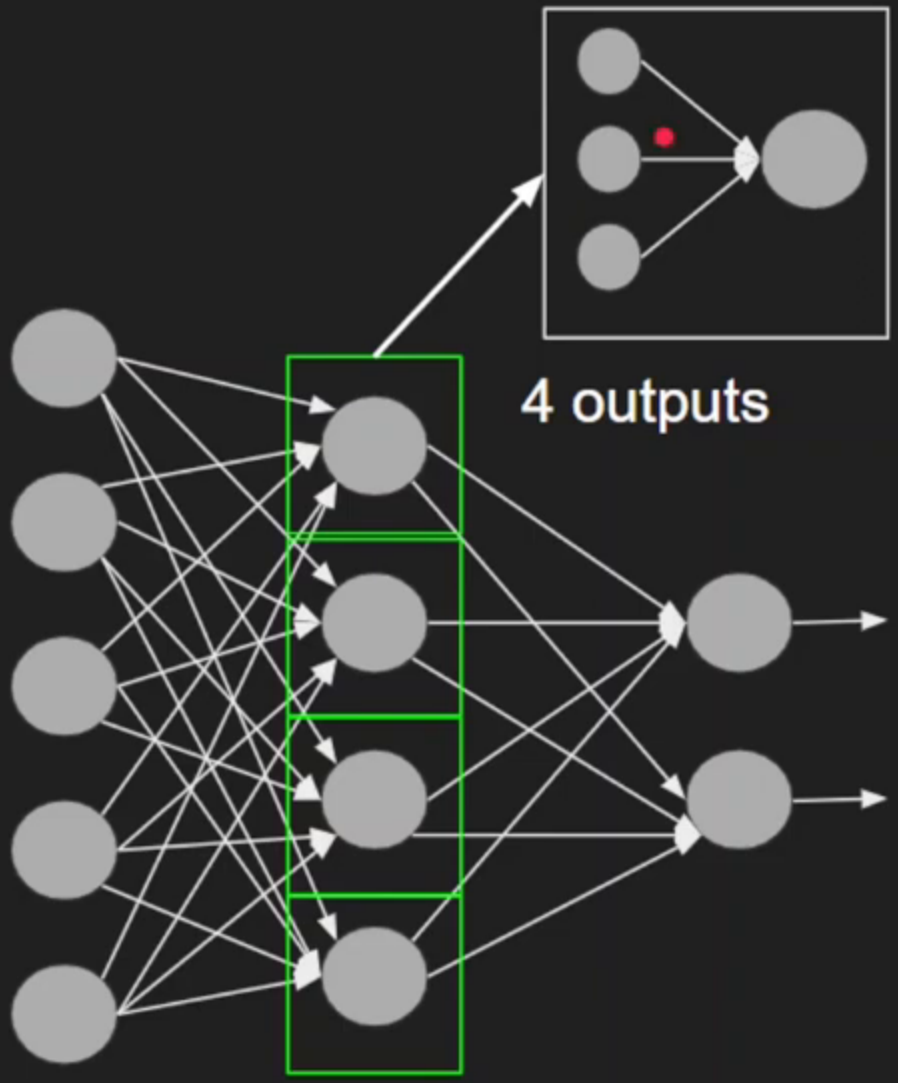

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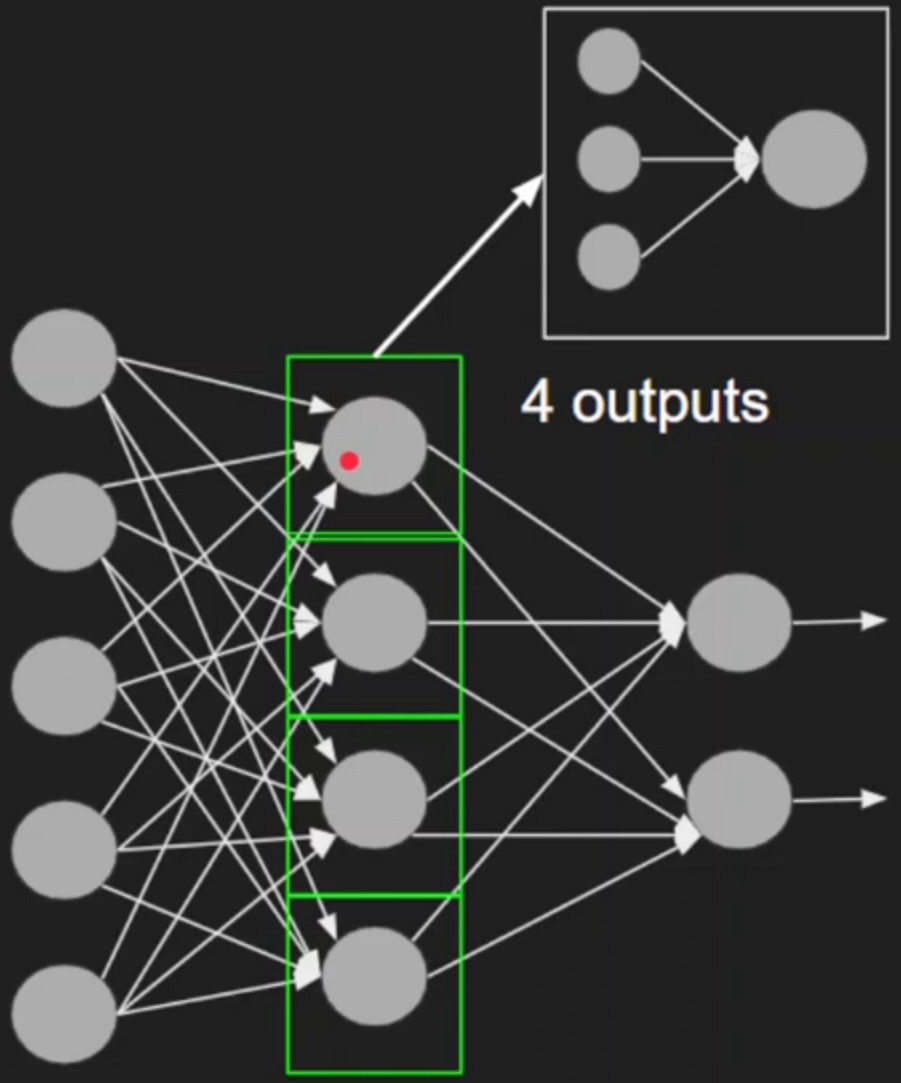

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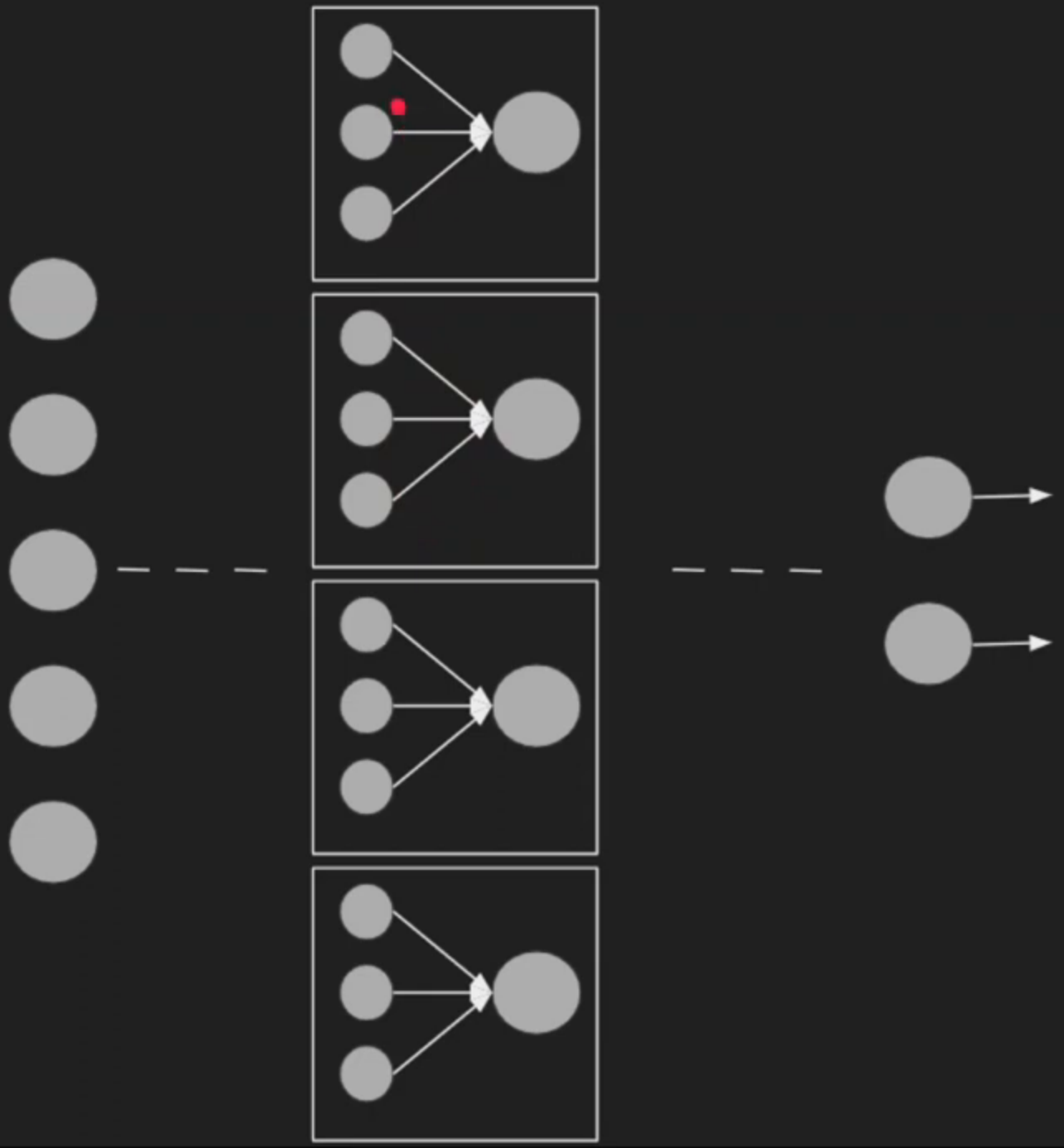

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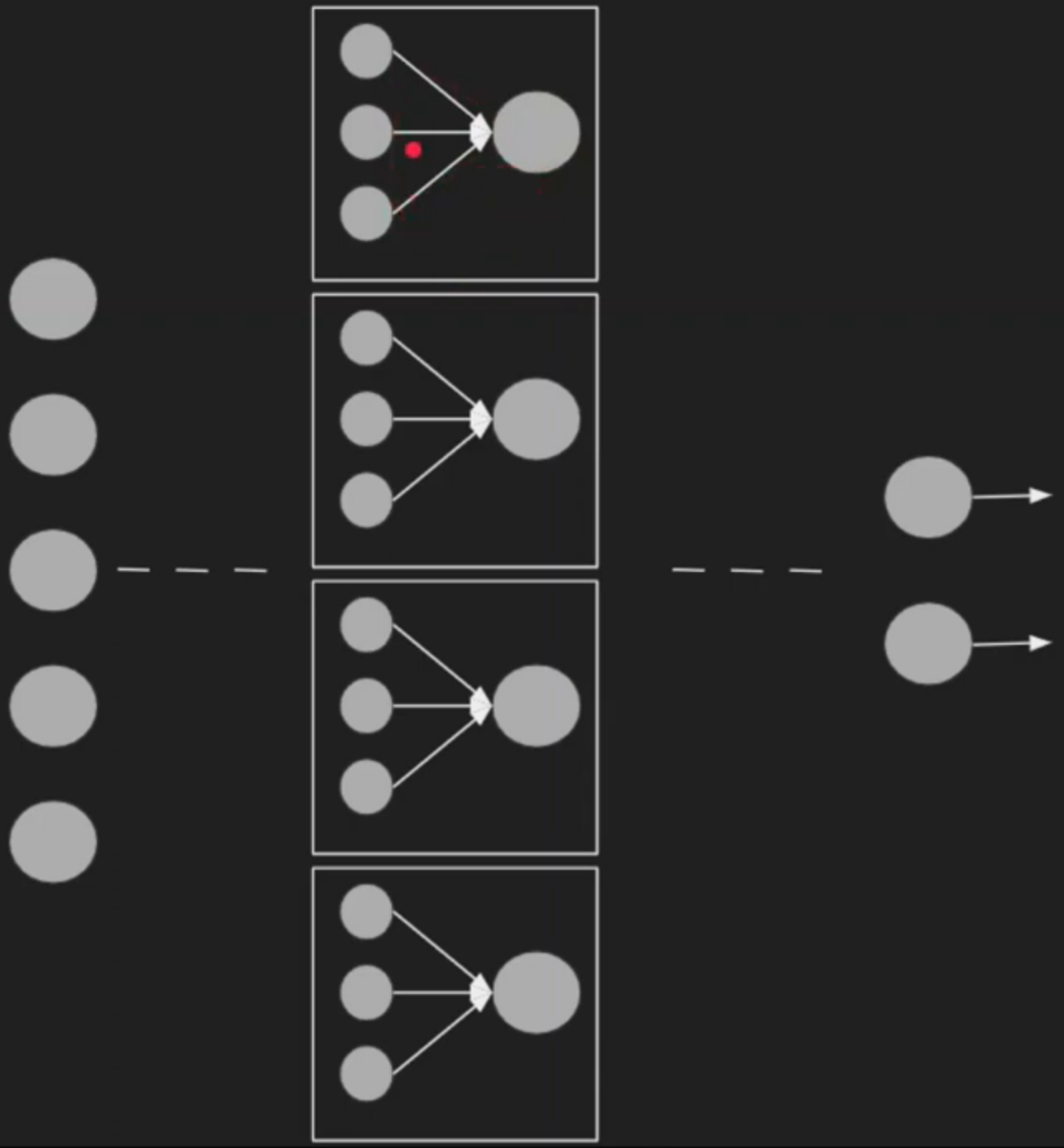

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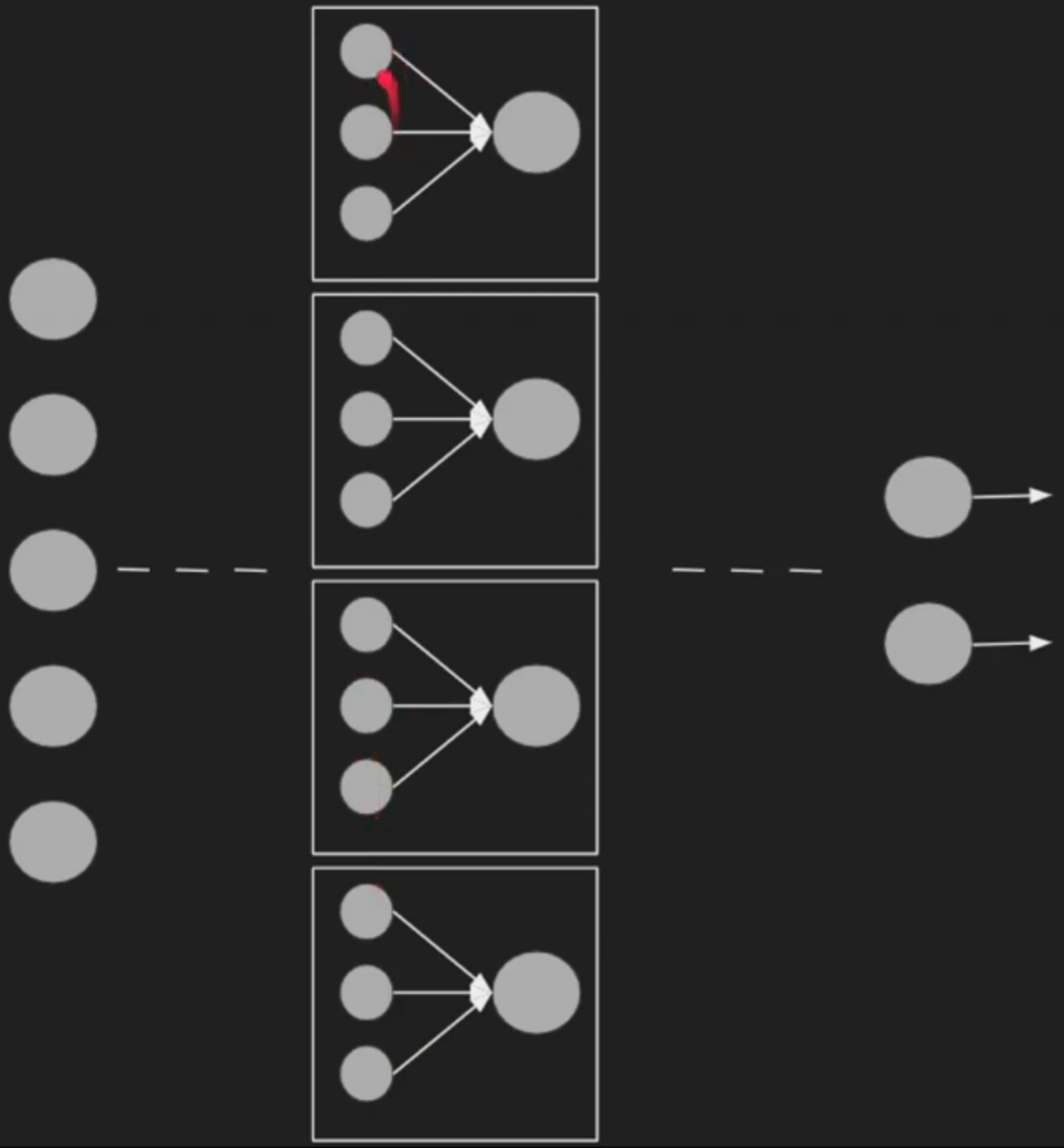

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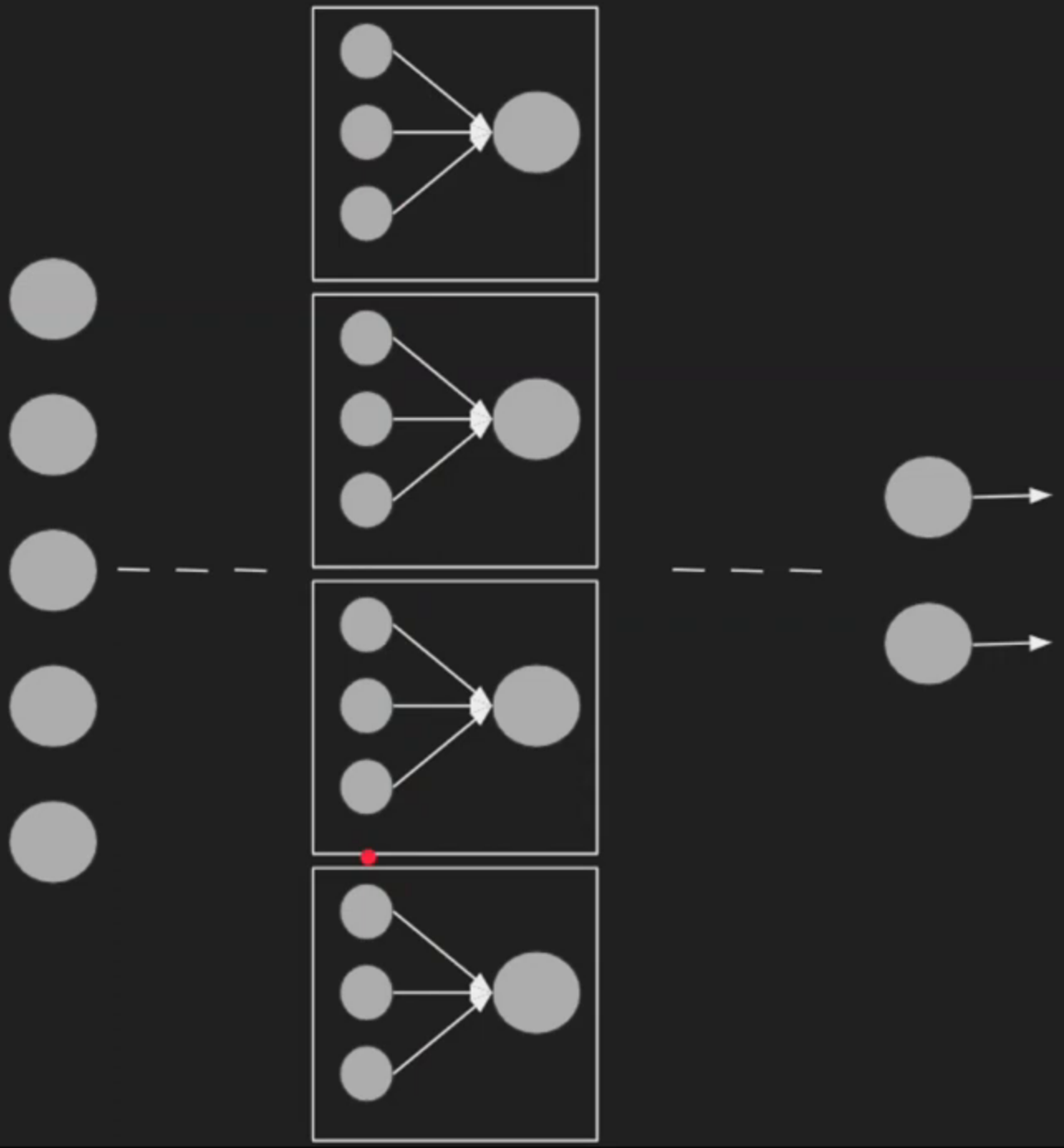

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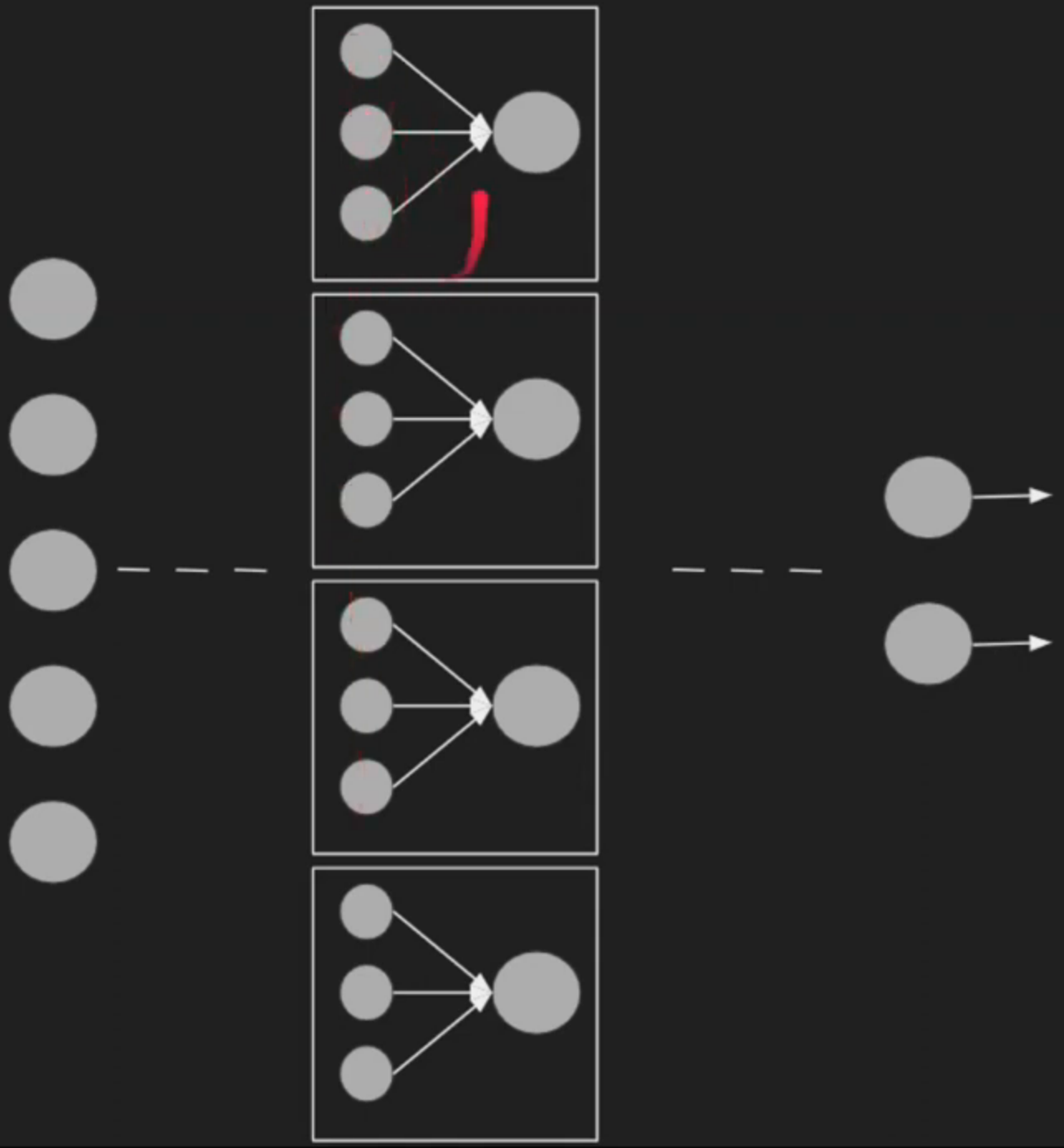

Notation

$$z_{ij} = x^T W_{...ij} + b_{ij}$$

$$h_i(x) = \max_{j \in [1,k]} z_{ij}$$

i - Index for outputs/groups
j - Index for neurons in a group
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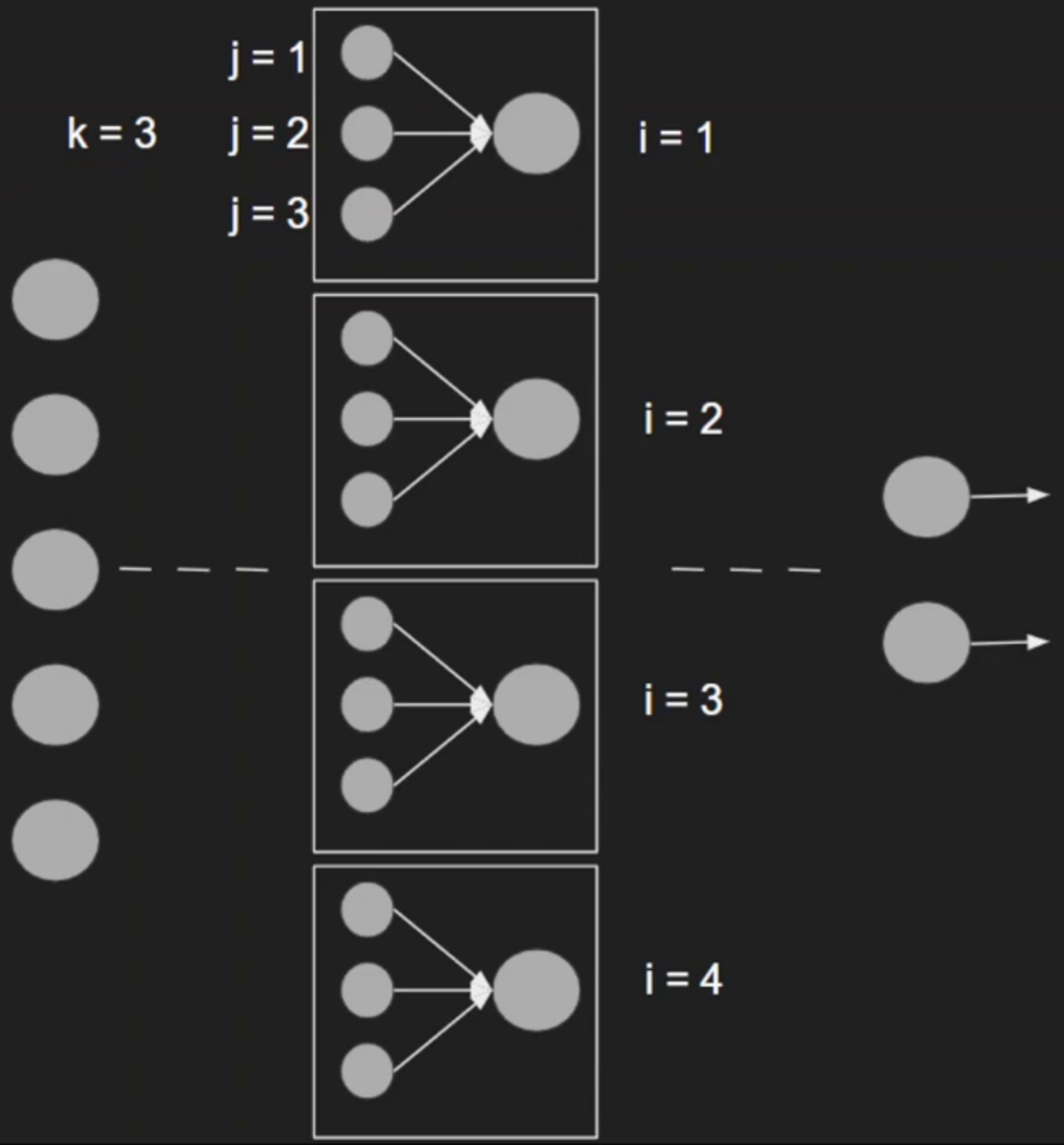

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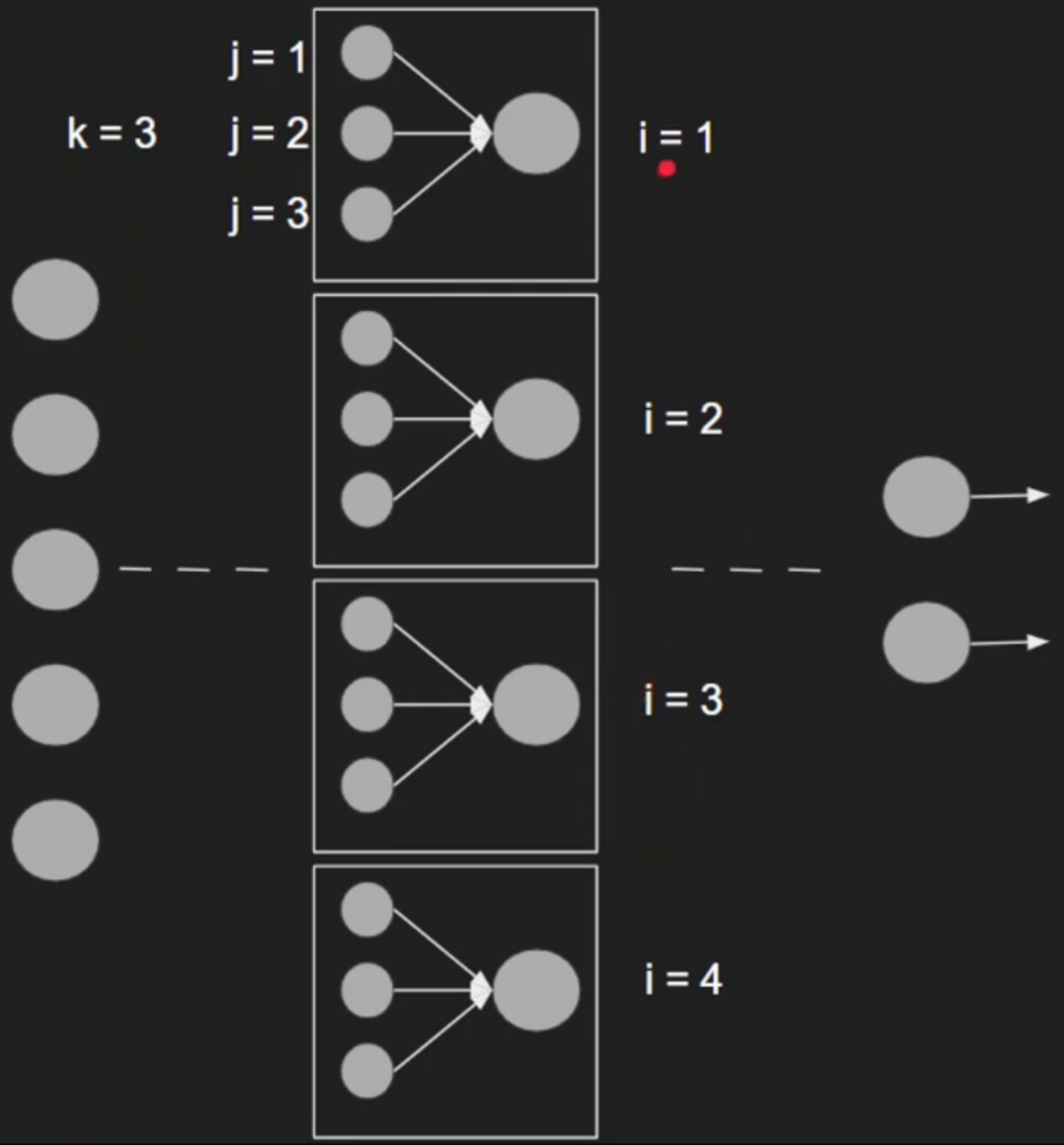

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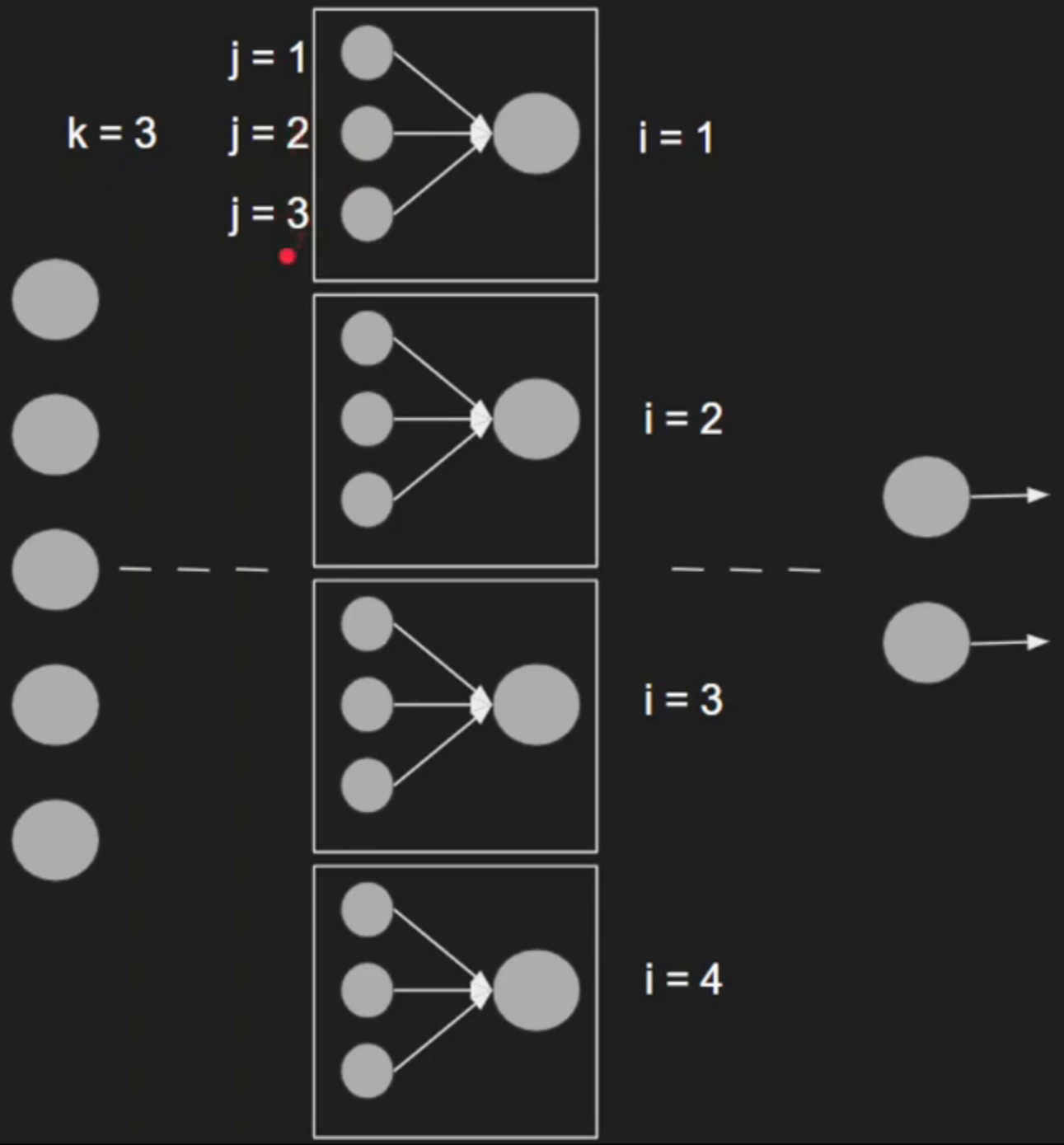

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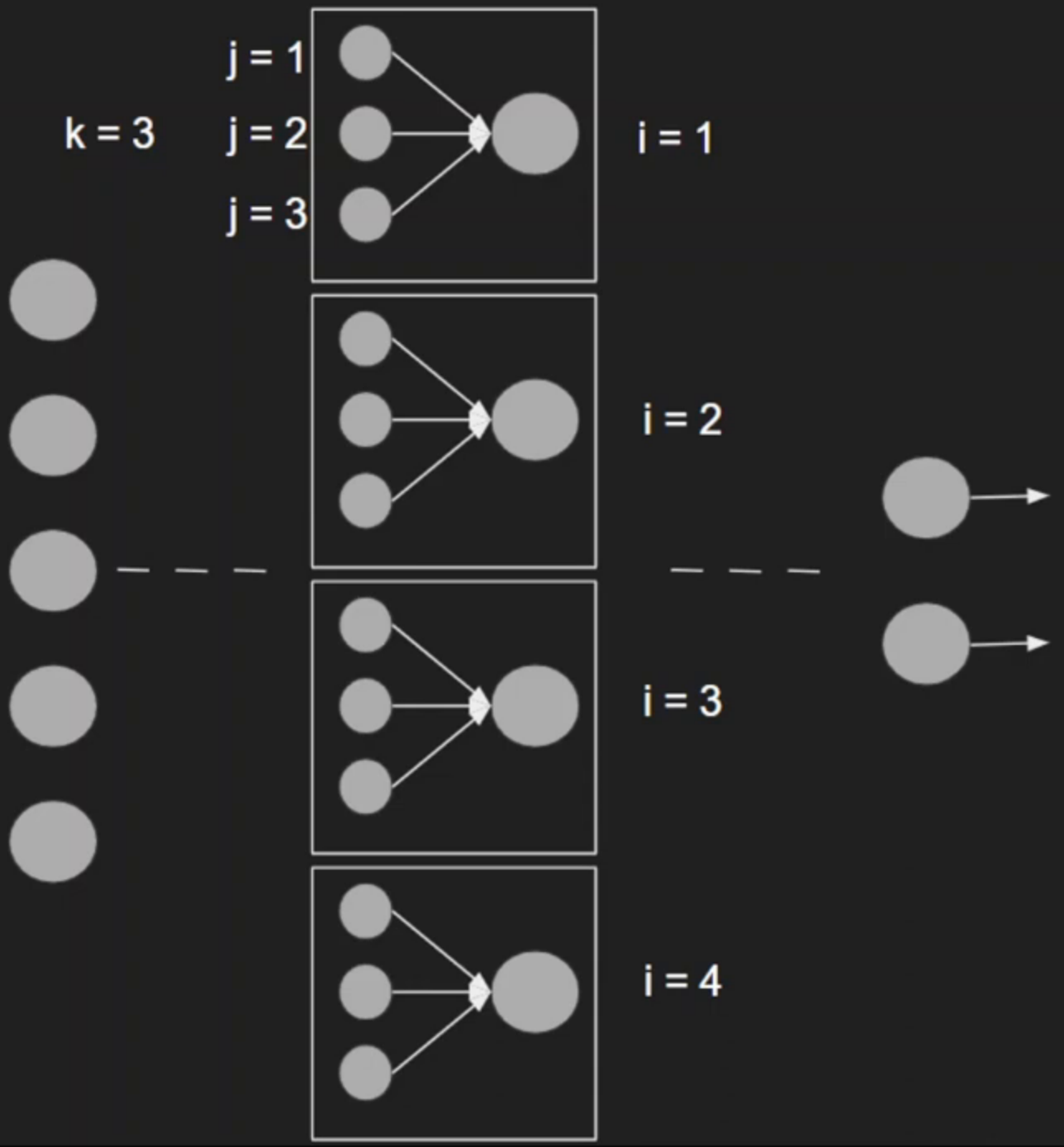

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Example

If k=5

$$z1 = x^T W_1 + b_1$$

$$z2 = x^T W_2 + b_2$$

$$z3 = x^T W_3 + b_3$$

$$z4 = x^T W_4 + b_4$$

$$z5 = x^T W_5 + b_5$$

$$z = max(z1, z2, z3, z4, z5)$$

→ 1 Maxout unit

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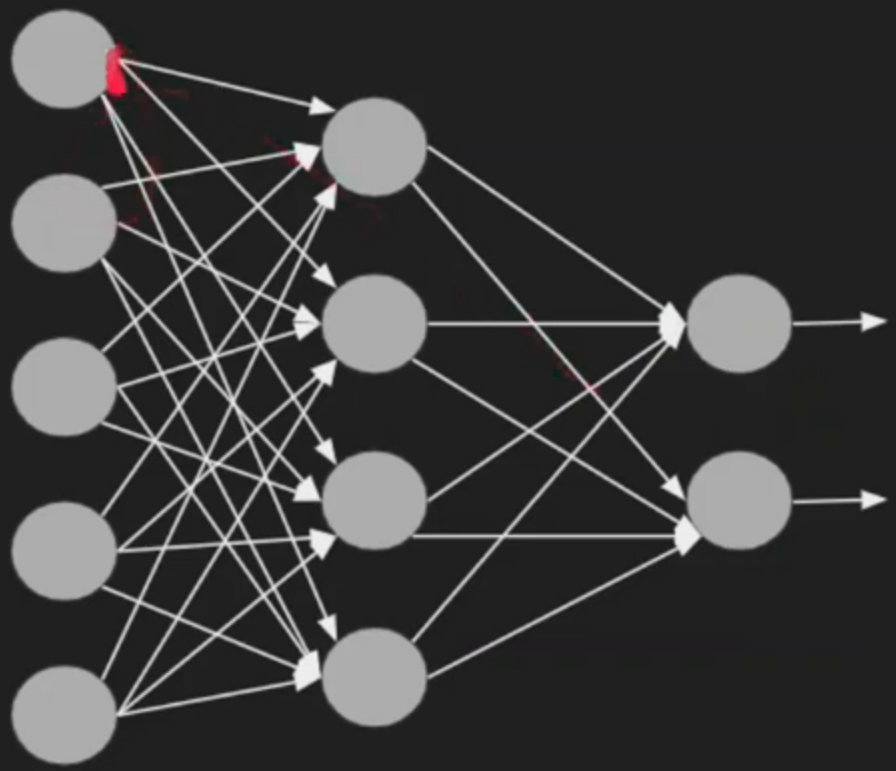
Example - ReLU

Input - [2,5]
Weights - [4,5]
Biases - [4]

Batch size = 2
Input features = 5
Hidden neurons = 4



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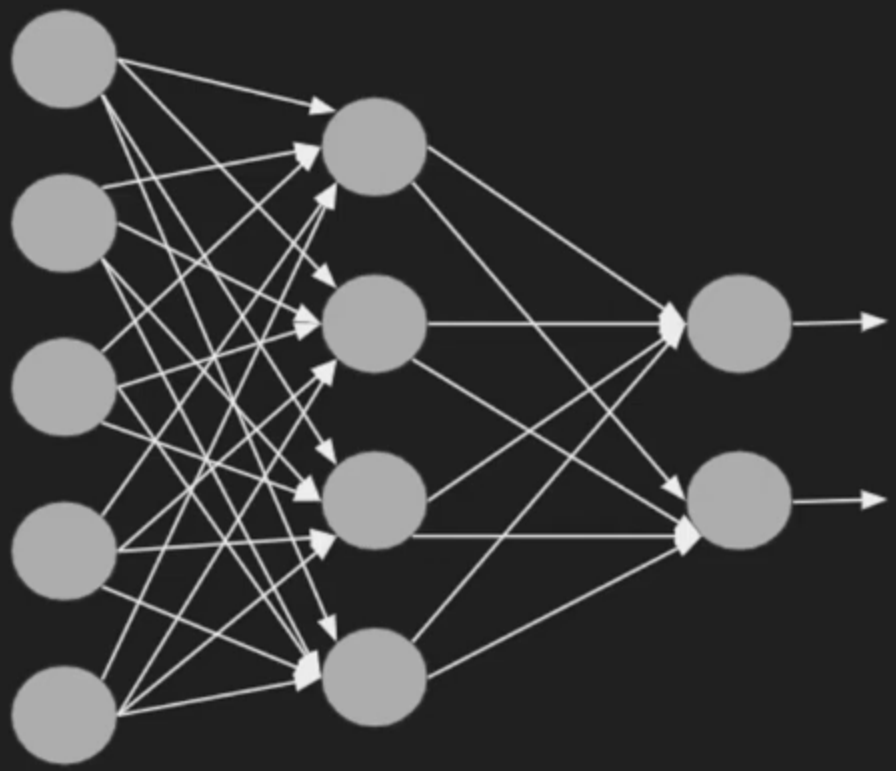

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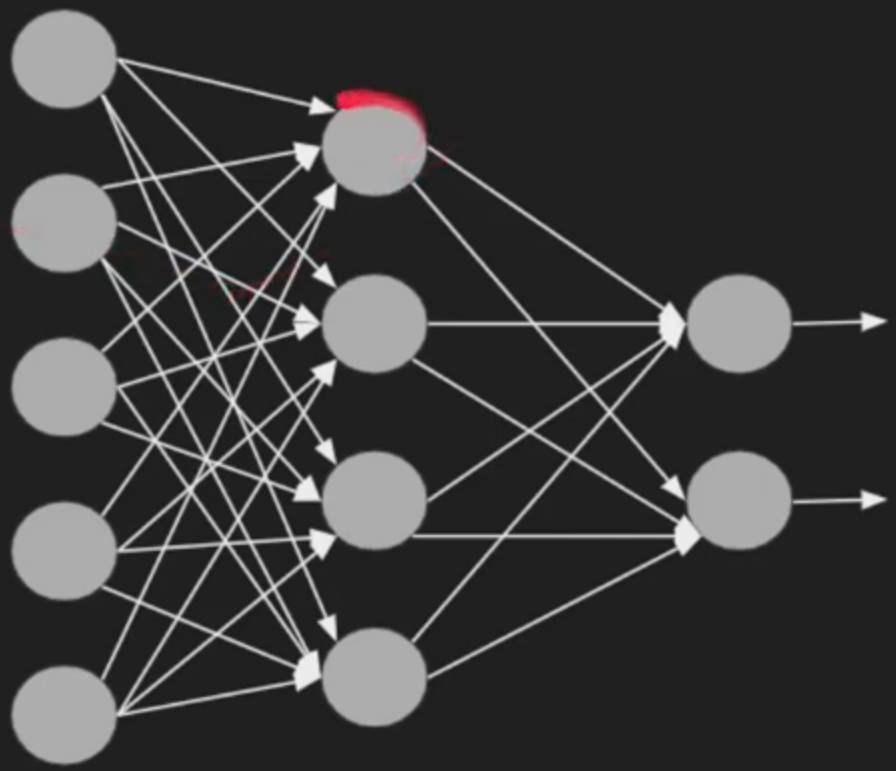
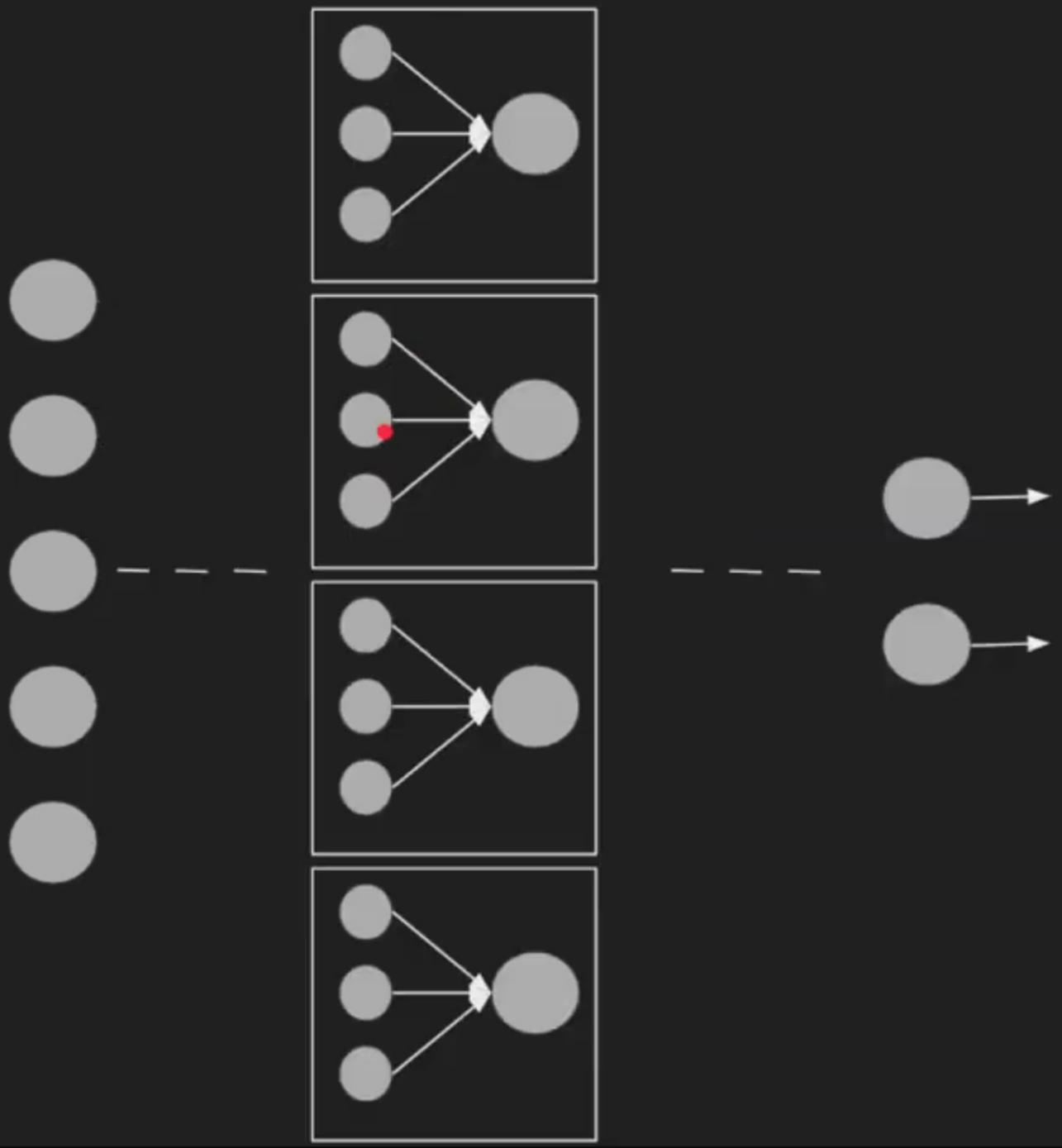


Example - Maxout

Input - [2,5]
Weights - [12,5]
Biases - [12]



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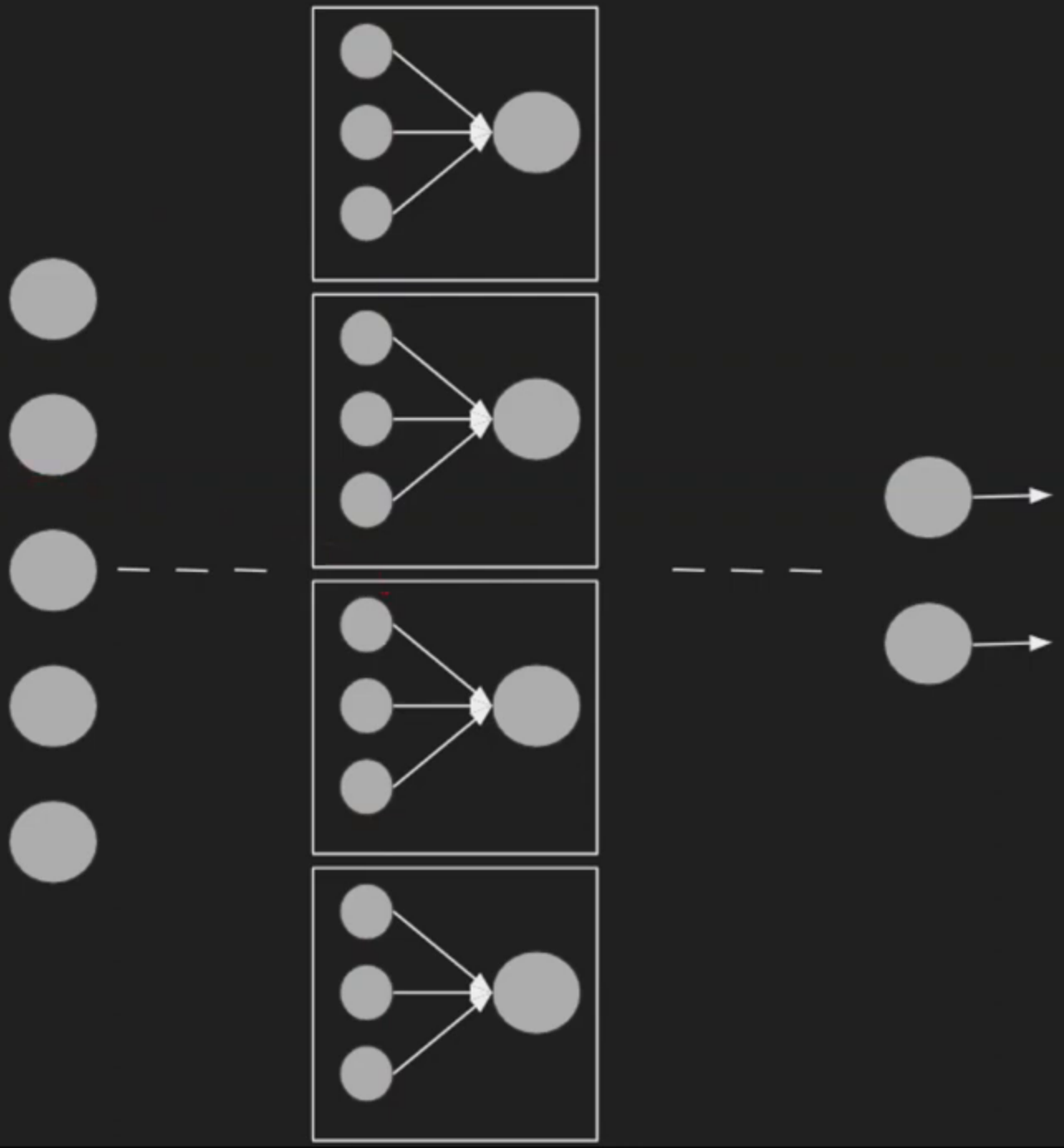

Example - Maxout

Input - [2,5]
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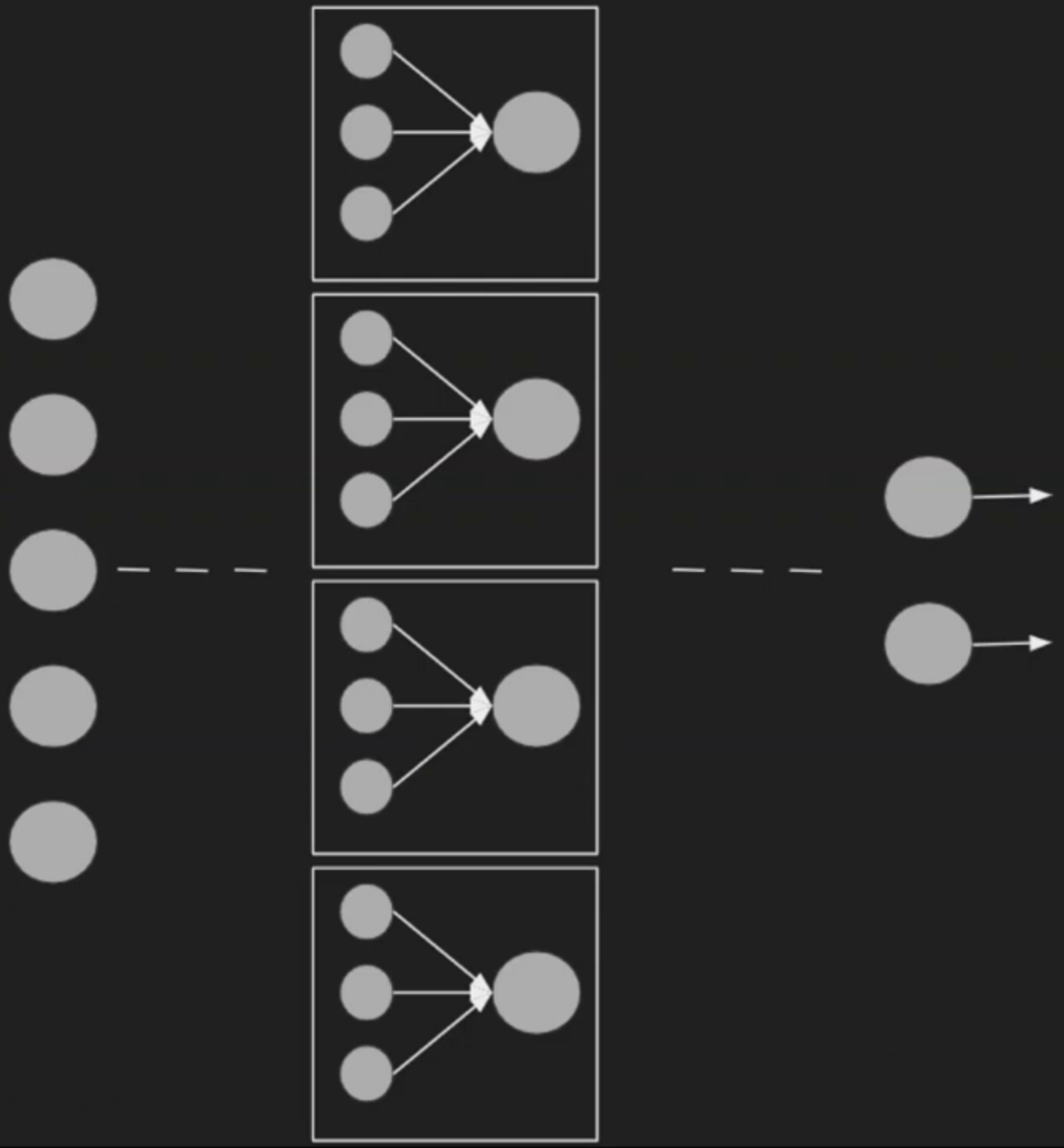
Z - [2,12] - [2,4,3]
O = max(Z, axis=2) - [2,4]



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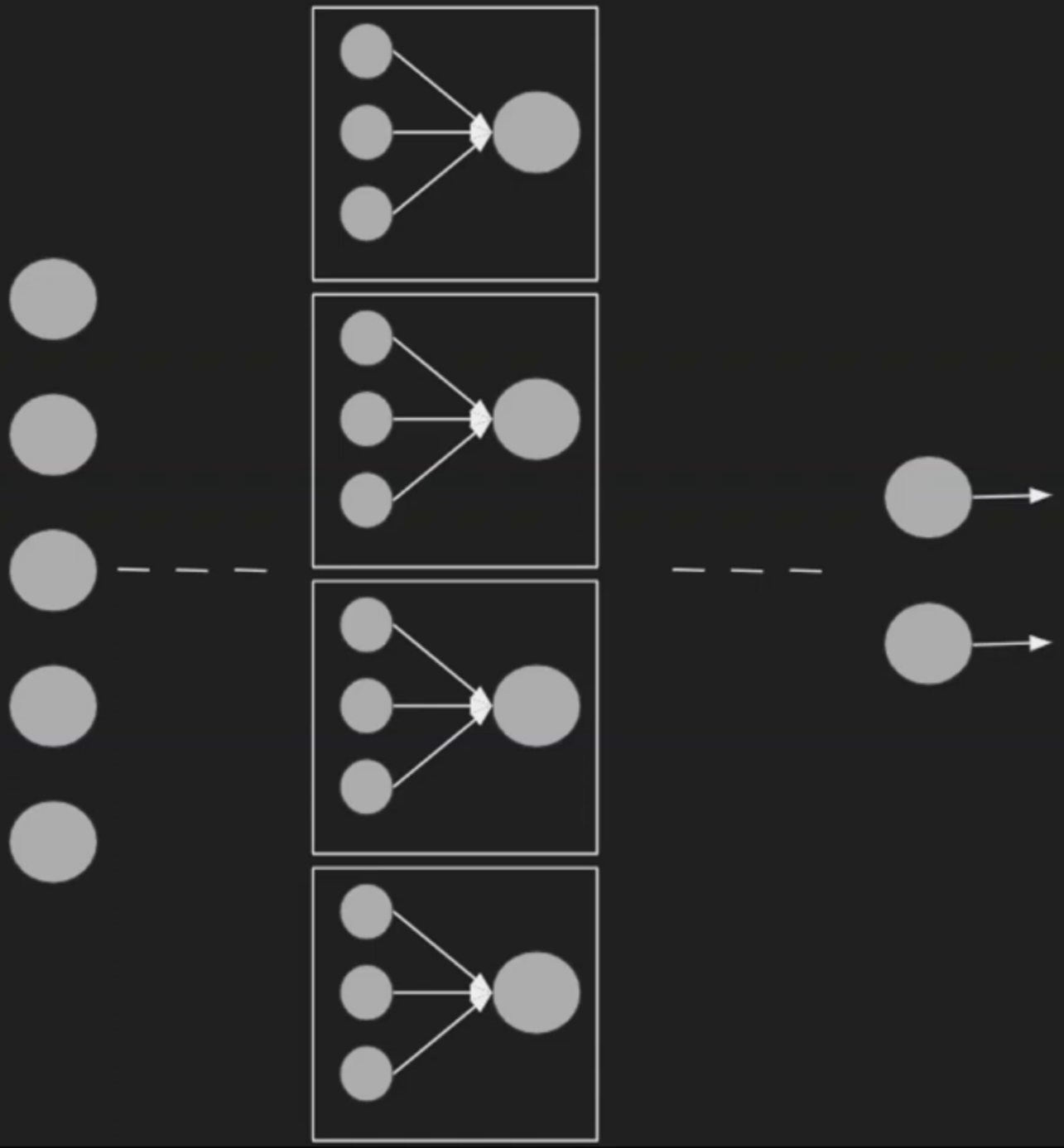

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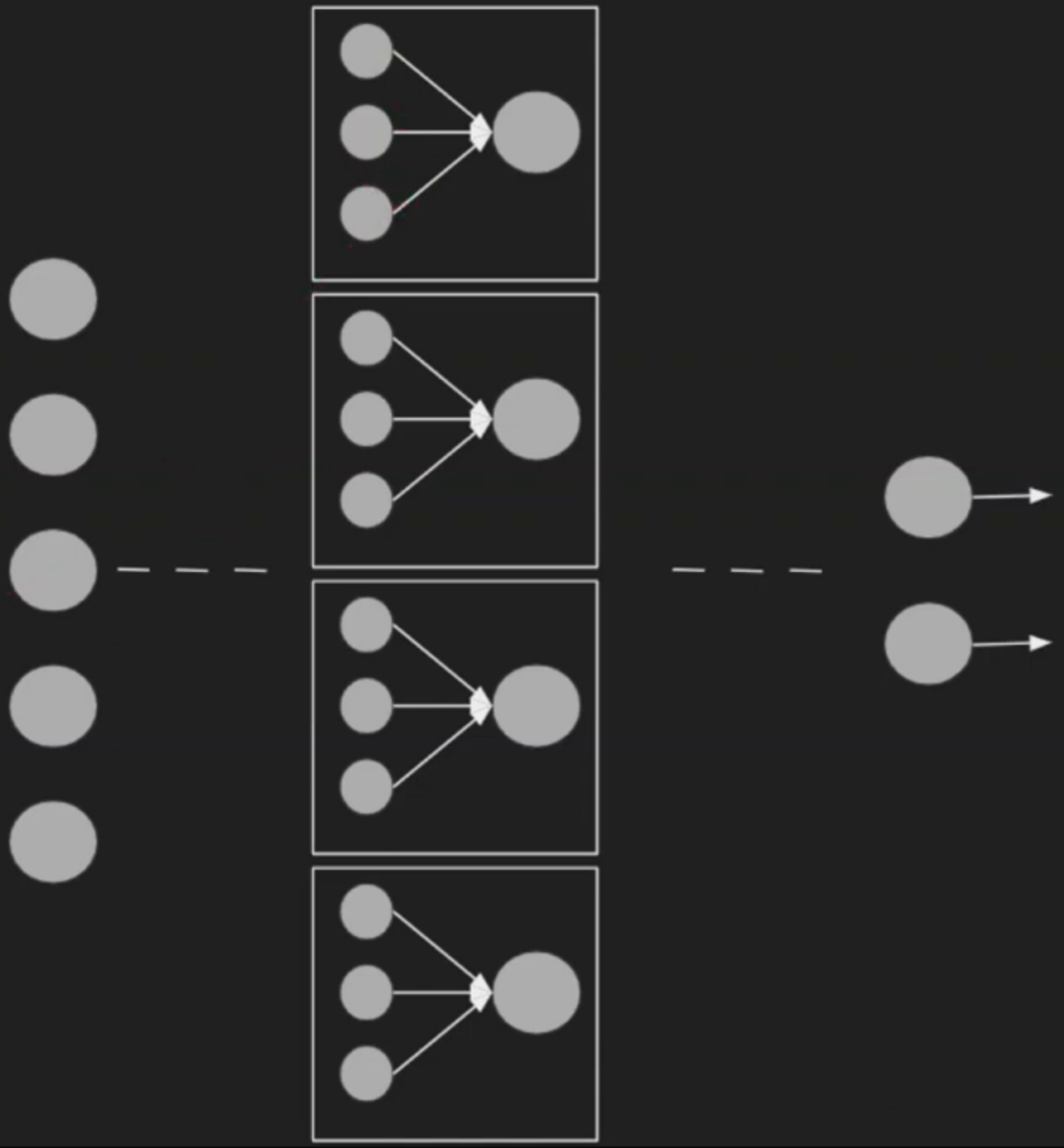

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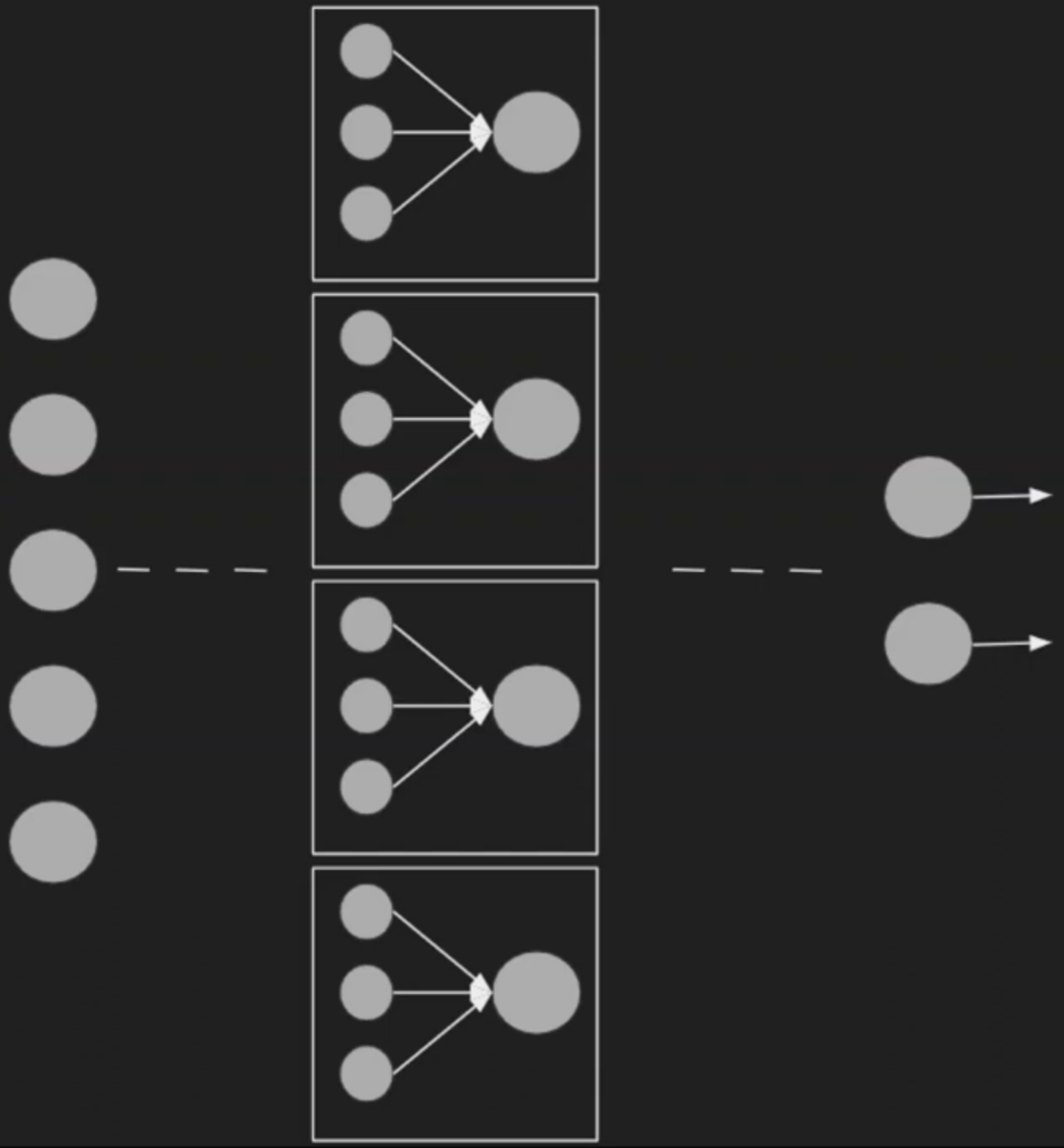

Implementation

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import numpy as np

x = np.random.random((2,5))
print(x.shape)

# 12 hidden neurons
W = np.random.random((12,5))
b = np.random.random((12))
print(W.shape,b.shape)
z = np.dot(x, W.T) + b
print(z.shape)
z_ = z.reshape((2,4,3))
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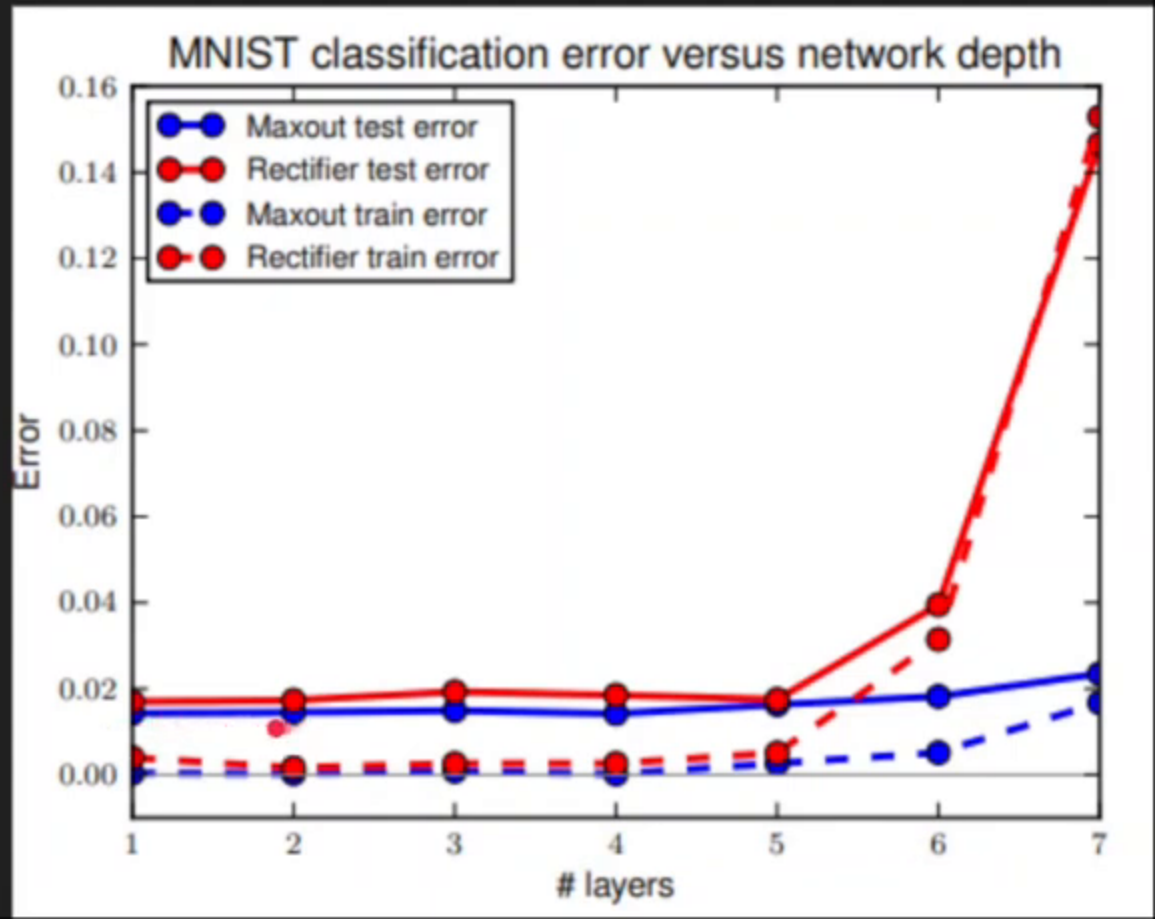

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- Used along with dropout regularization
- Doubles the number of parameters compared to other activations

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