Brains, Dynamics & Computation

A workshop on network neuroscience

Does excitation/inhibition ratio have an effect in one-to-one learning of neural networks using Hebb's Rule?

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Organized by:
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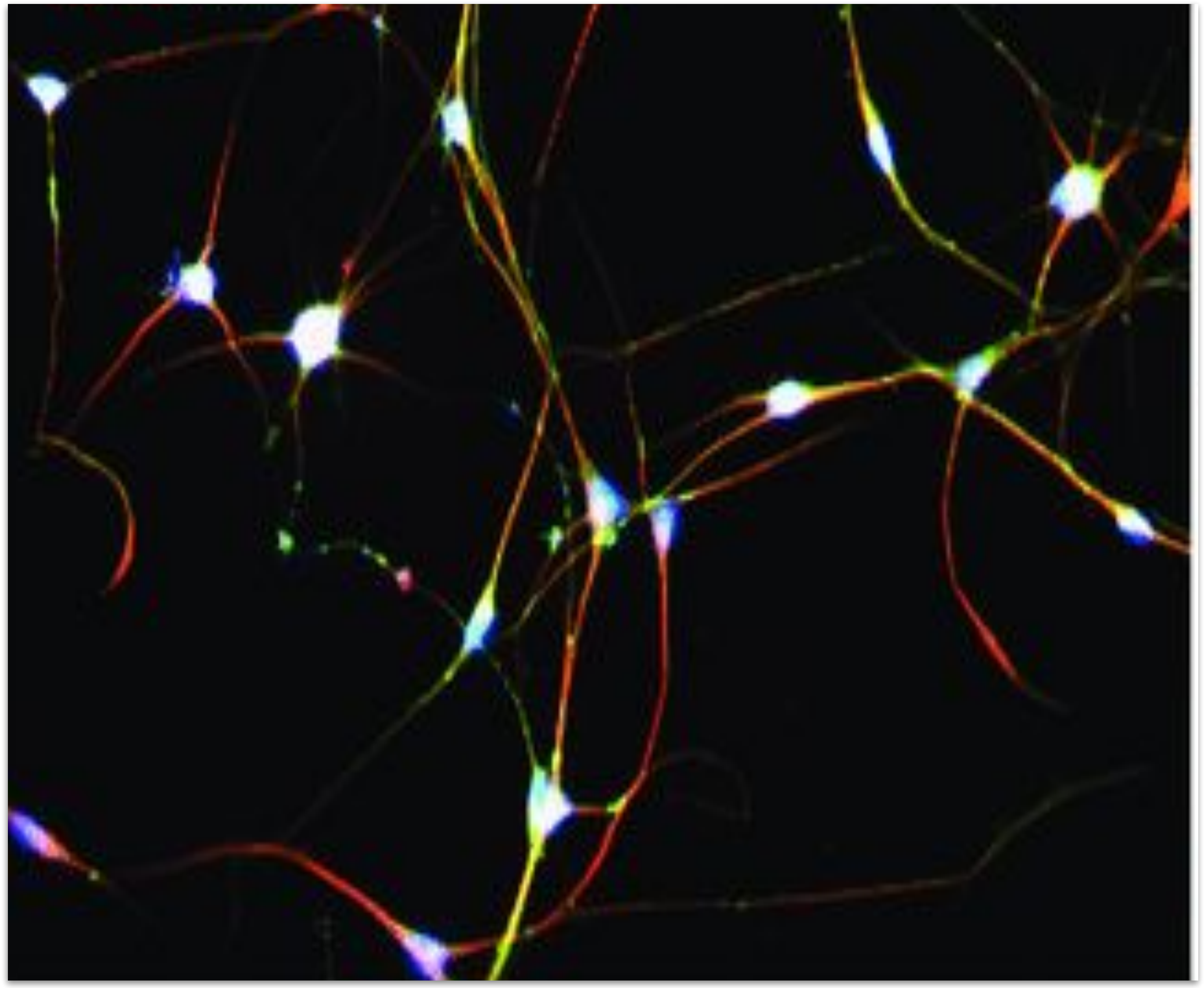
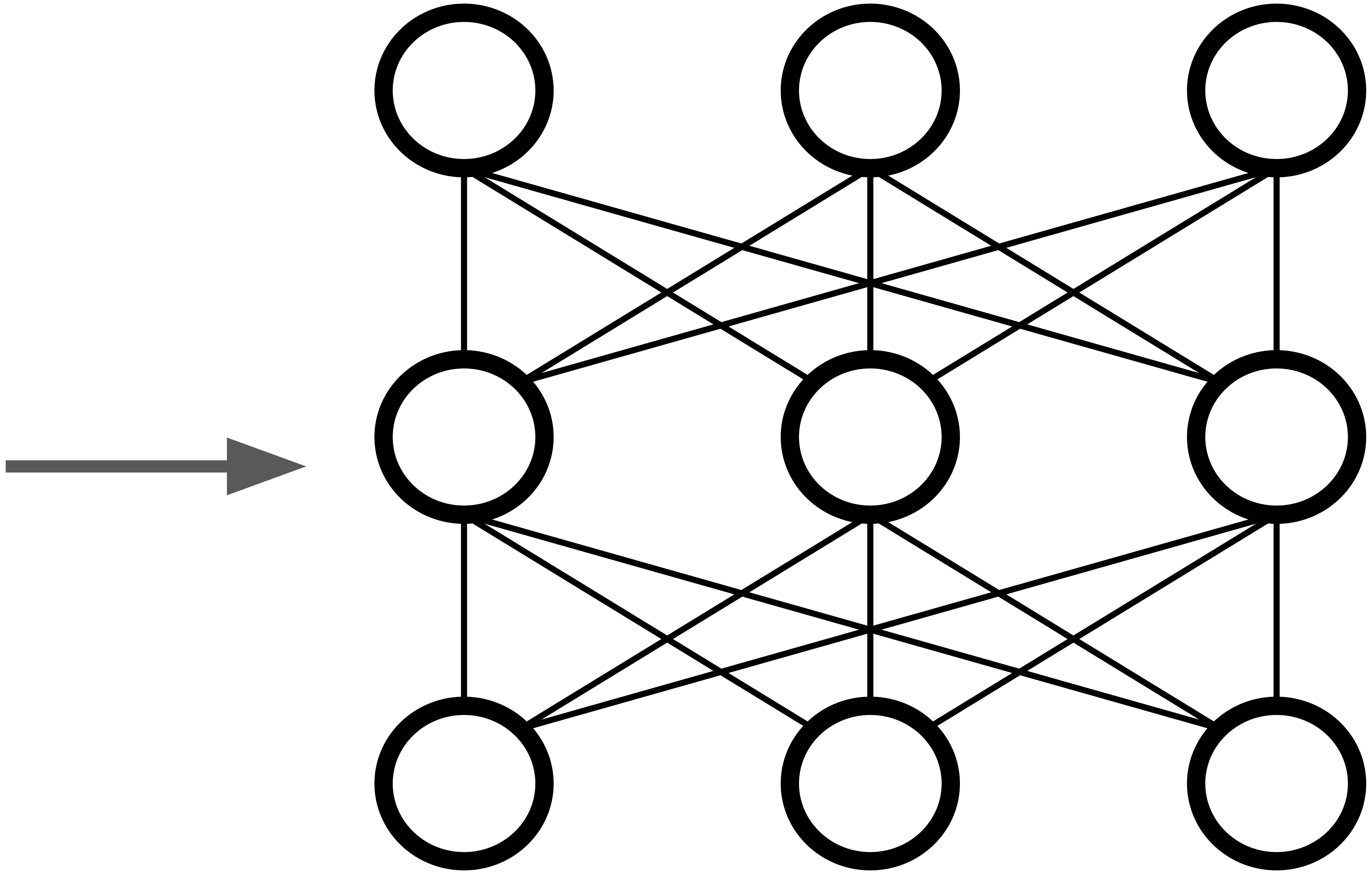
Introduction



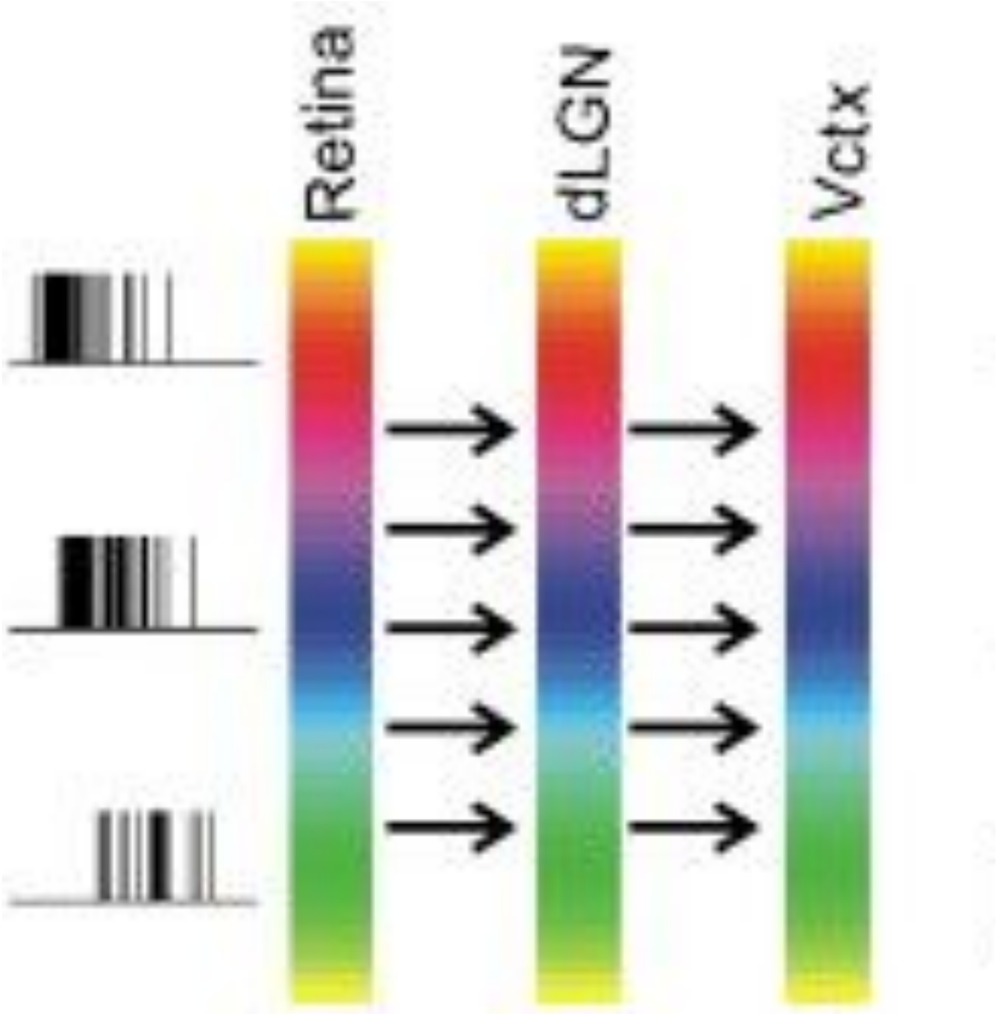
Alexanian AR, Fehlings MG, Zhang Z, Maiman DJ. Transplanted Neurally Modified Bone Marrow–Derived Mesenchymal Stem Cells Promote Tissue Protection and Locomotor Recovery in Spinal Cord Injured Rats. *Neurorehabilitation and Neural Repair*. 2011;25(9):873-880. doi:10.1177/1545968311416823



Modelling a feed-forward neural network and exploring its dynamic behavior, focussing on its ability to adapt to one-to-one mapping, can offer insights into information processing and circuit organisation in the brain.

One-to-one mapping and its importance in biological systems

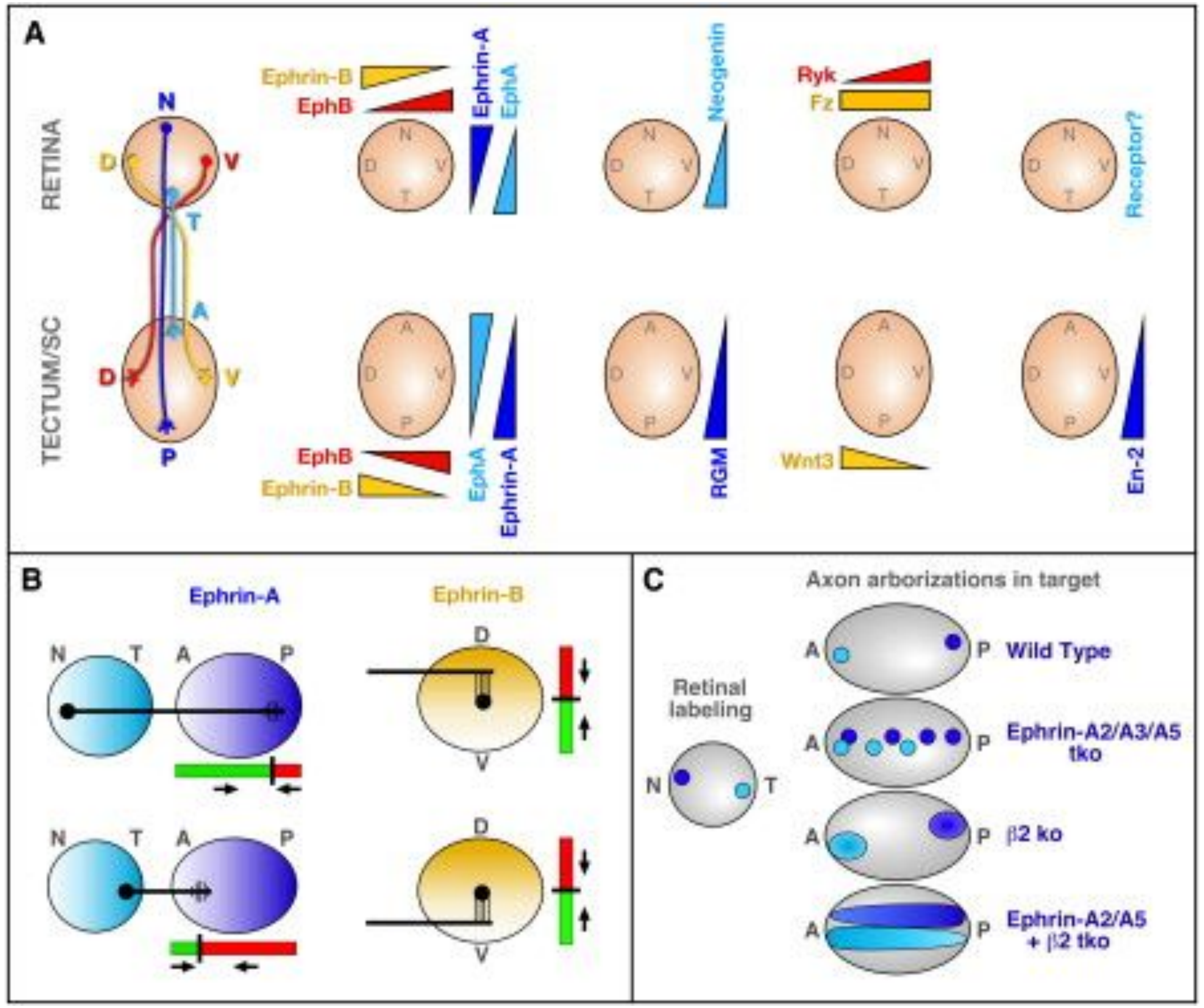
One-to-one mapping in the human brain is crucial for maintaining the fidelity of information transfer between regions, enabling accurate perception and response.



Retinotopic system: Each point on the retina maps to a corresponding point in the visual cortex, preserving spatial structure for precise visual processing.

Somatosensory cortex: Each body part has a dedicated region, allowing fine-grained tactile discrimination.

Image source: [Development of Precise Maps in Visual Cortex Requires Patterned Spontaneous Activity in the Retina: Neuron]



Cell PRESS
Neuron
Review

Development of Continuous and Discrete Neural Maps

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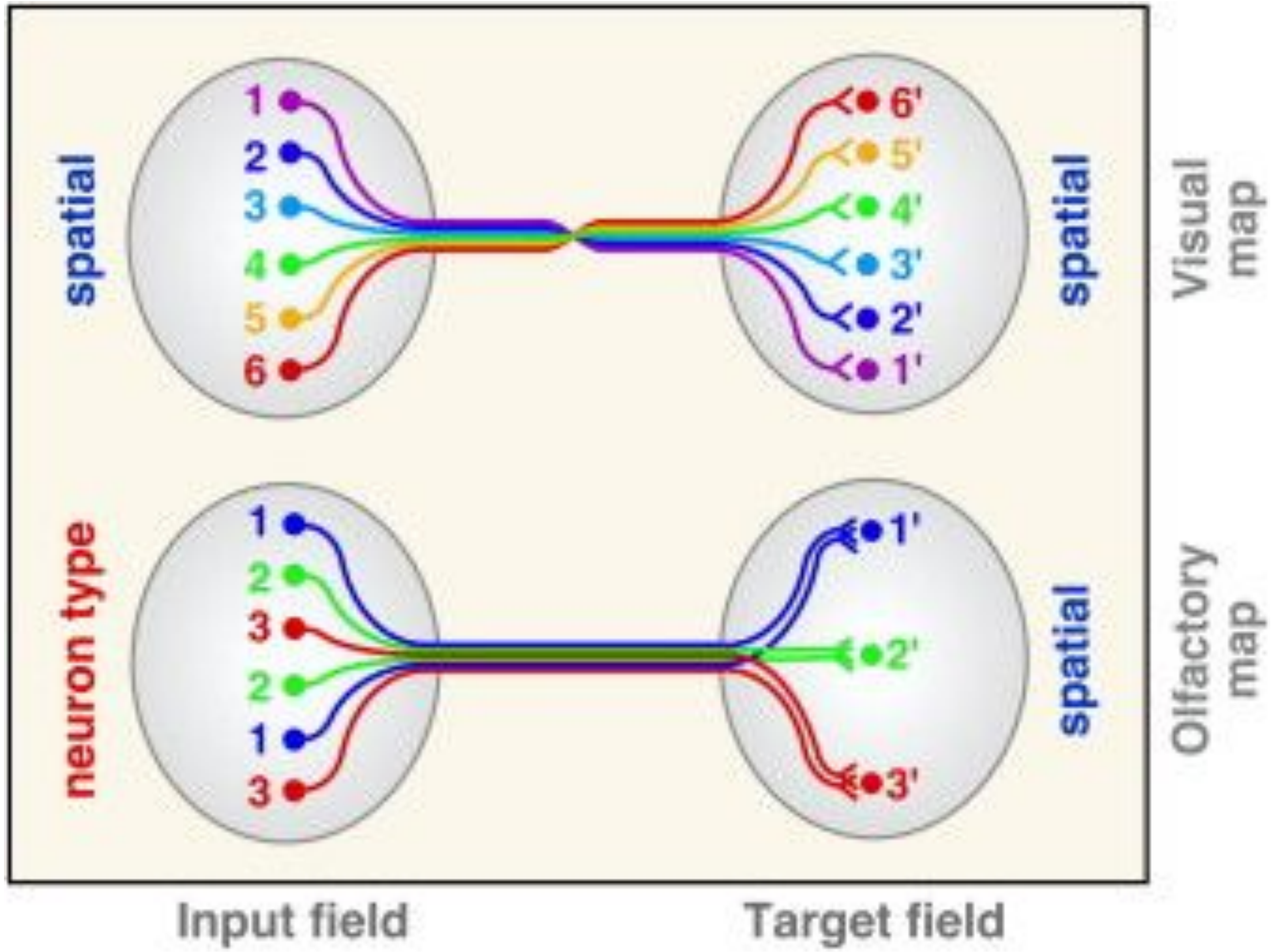
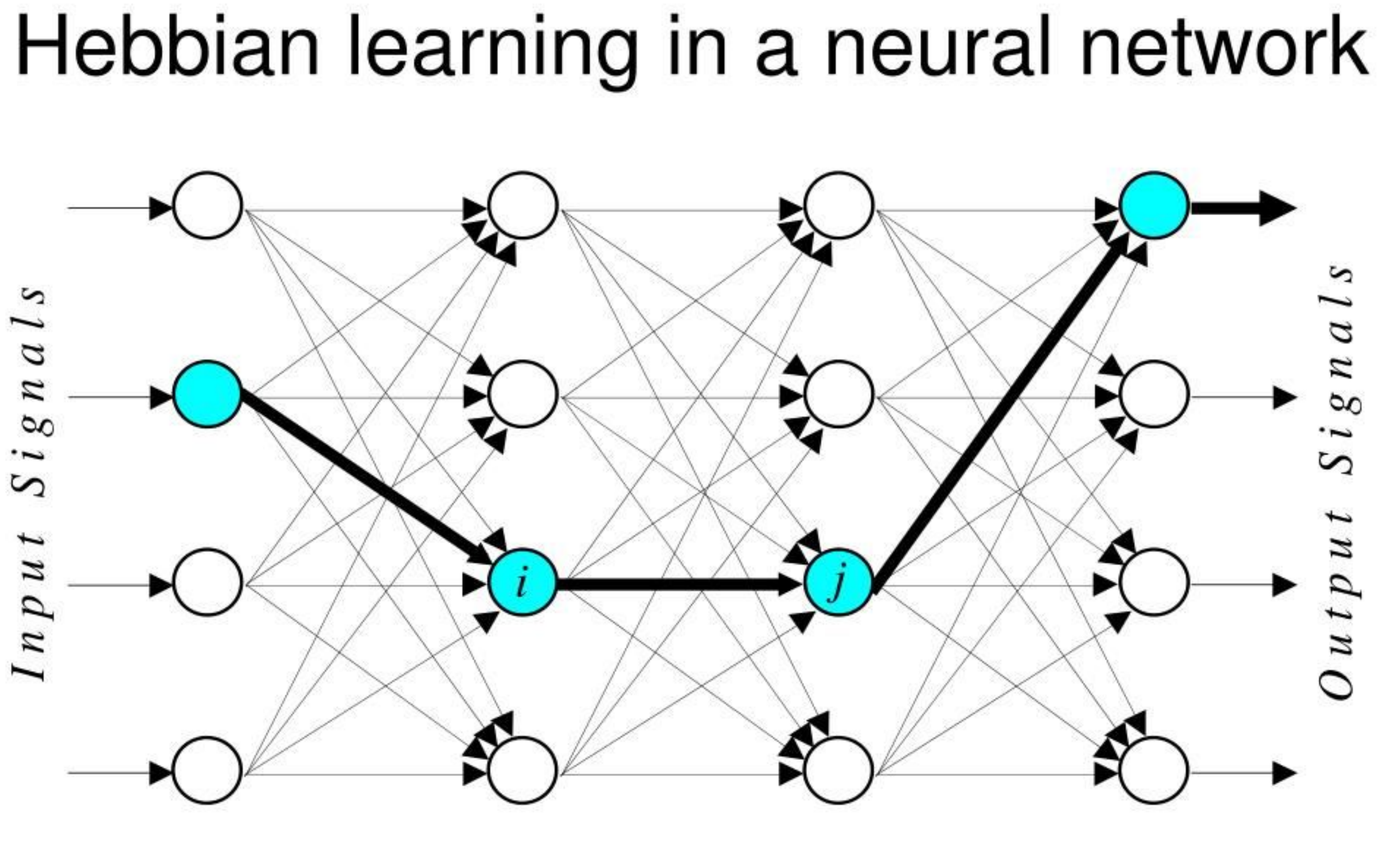


The chemoaffinity theory proposes that growing neurons use specific chemical cues to identify and connect with their correct targets. These unique molecular "labels" guide the formation of precise and organized neural circuits during development.

Self-organising maps, and Hebbian learning

- Neural networks self-organize by adapting their connections according to patterns of neural activity.
- Hebbian learning strengthens synapses between neurons that fire together, reinforcing these connections.
- Together, these processes enable the network to autonomously develop precise one-to-one mappings during development.



$$\Delta w_{ij}(p) = \alpha \; y_j(p) \; x_i(p)$$

E/I Ratio – Importance in topology of such maps

When the excitation/inhibition (E/I) balance is disrupted, one-to-one mapping in neural circuits becomes less precise.

Excess excitation - neurons are overly active, leading to noisy, overlapping connections.

Excessive inhibition - suppress neural activity too much, preventing proper synaptic strengthening.

Imbalance in E/I ratio can cause several neurological and psychiatric disorders.

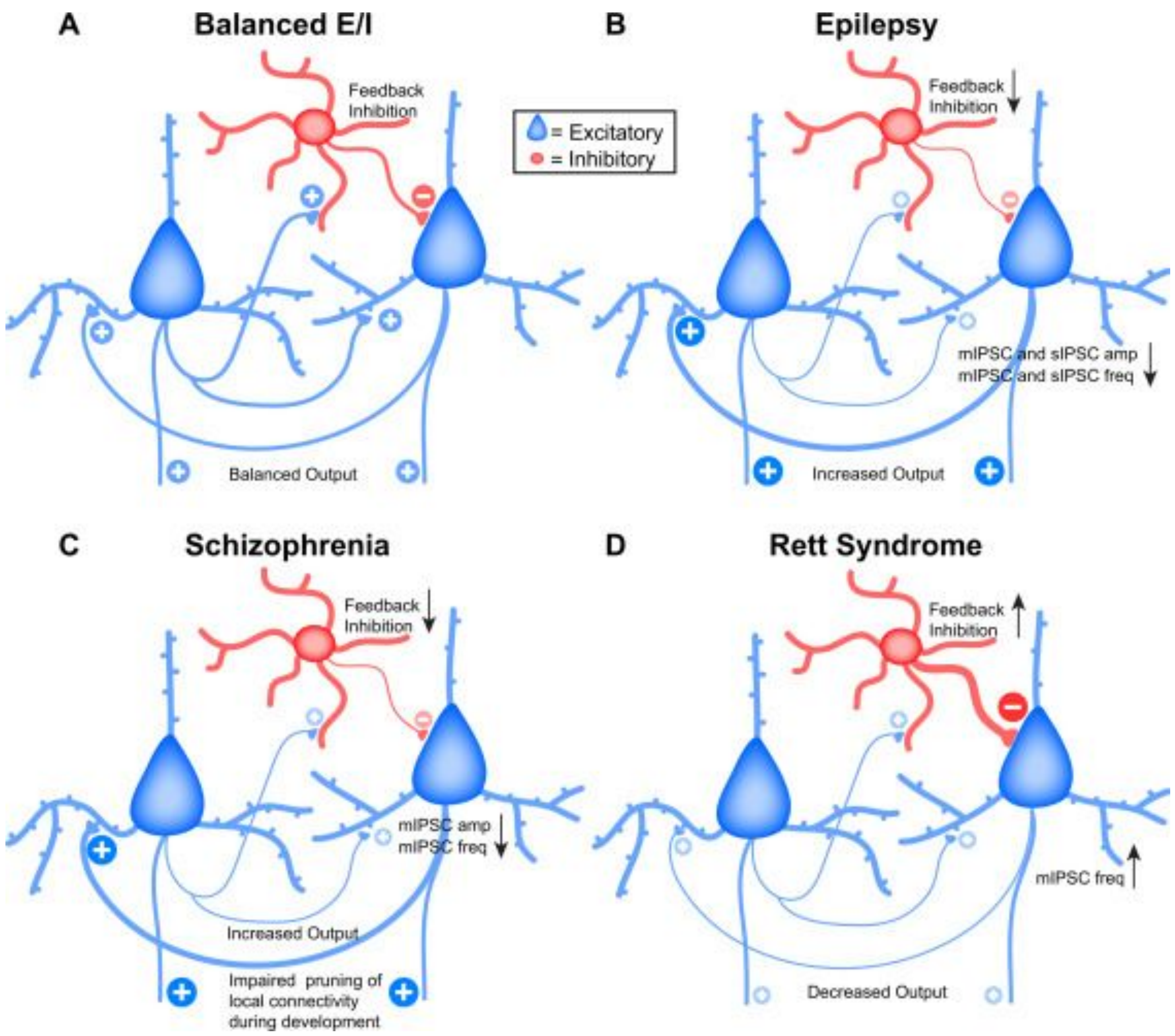


Image source: [Neurophysiology and Regulation of the Balance Between Excitation and Inhibition in Neocortical Circuits - Biological Psychiatry]

Excitatory/inhibitory (E/I) imbalance is a shared feature of both epilepsy and neurodevelopmental disorders, such as autism.

Rubenstein and Merzenich (2003) proposed a model of autism suggesting that an increased ratio of excitation to inhibition (E/I) in key neural systems—particularly in the cerebral cortex—leads to the core symptoms of autism.

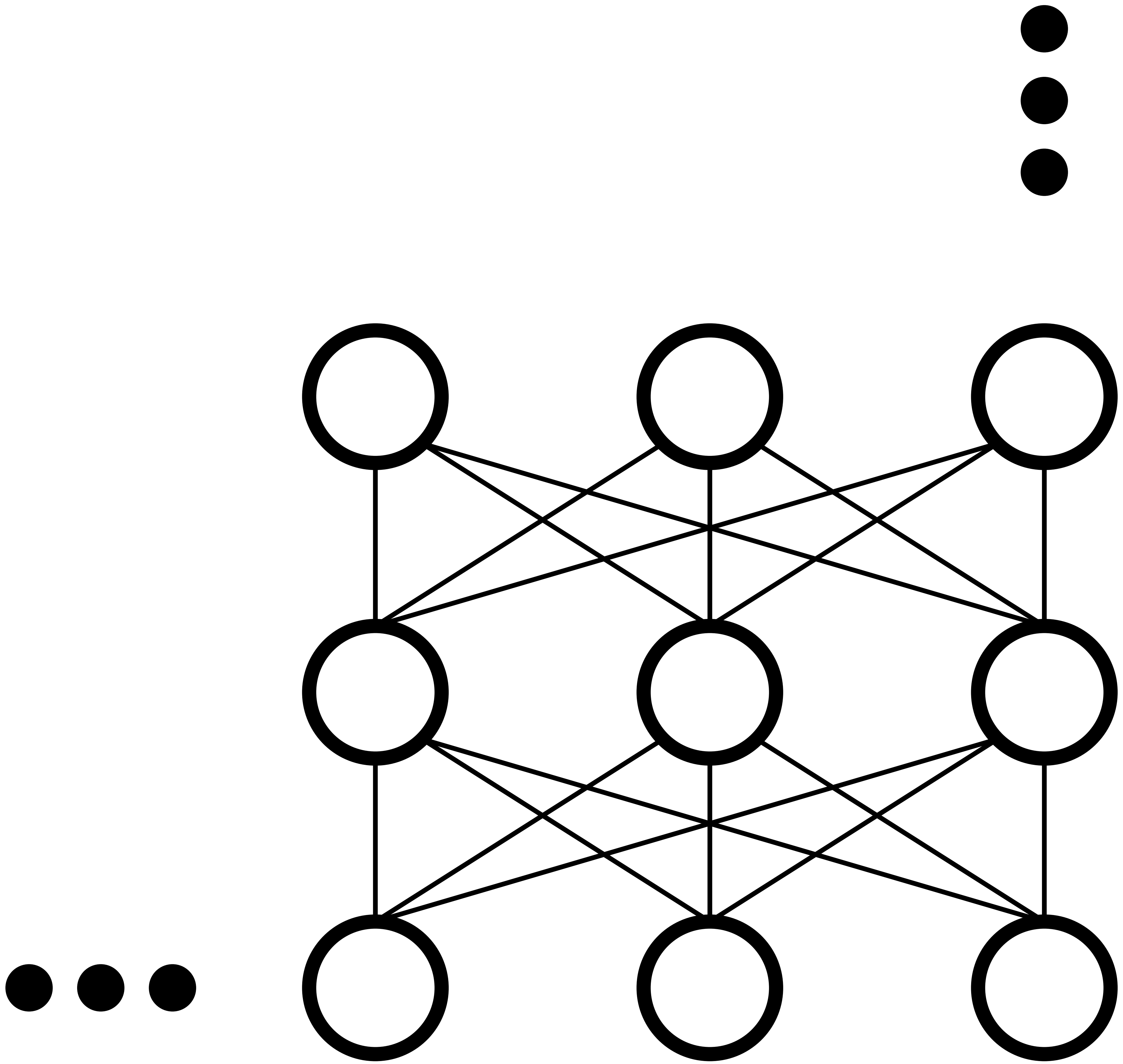
Disruption in E/I balance, particularly in cortical circuits, is linked to cognitive deficits and psychotic symptoms of schizophrenia.

Aim

- To build a neural network that learns one-to-one mapping using Hebbian rule and how this learning process is affected by varying the excitatory/inhibitory ratio.
- Can the network learn the fixed one-to-one mapping through Hebbian rule ?
- Investigating the weight dynamics
- Is there any E/I ratio such that the network learns the one-to-one association faster ?

Our model

- Input layer, hidden layer, output layer.
- No connections within layers.
- All nodes in one layer are connected to all the nodes in the immediately succeeding layer.



In 1949, Donald Hebb proposed in his book *The Organization of Behavior* about how long-lasting cellular changes are induced in the nervous system:

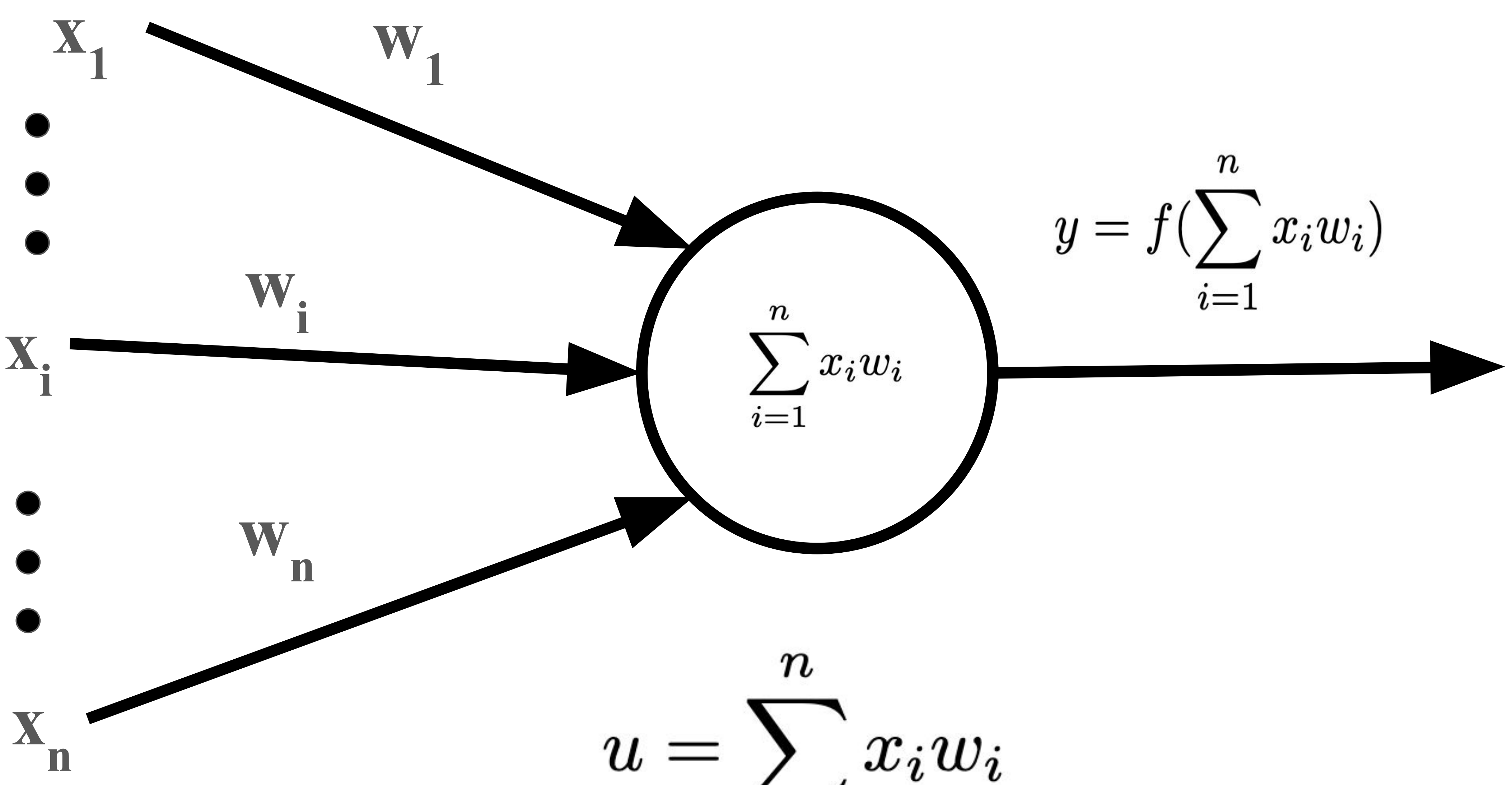
> When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased.

which is often simplified to:

> Neurons wire together if they fire together.

Source: https://www.sciencedirect.com/topics/neuroscience/hebbian-theory

McCulloch-Pitts (MCP) neuron model



$$y = \begin{cases} 1 & \text{if } u \geq 0 \\ 0 & \text{if } u < 0 \end{cases}$$

$$u = \sum_{i=1}^{n} x_i w_i$$

$$x_i \in \{1, 0\}$$

Implementation of Hebbian learning

$$W_{ij}(t+1) = W_{ij}(t) + \epsilon S_i S_j - \epsilon W_{ij}(t)$$

S_j \ S_i	1	0
1	$W_{ij}(t+1) = W_{ij}(t) + \epsilon - \epsilon W_{ij}(t)$	$W_{ij}(t+1) = W_{ij}(t) - \epsilon W_{ij}(t)$
0	$W_{ij}(t+1) = W_{ij}(t) - \epsilon W_{ij}(t)$	$W_{ij}(t+1) = W_{ij}(t) - \epsilon W_{ij}(t)$

$W_{ij}(t+1)$ = new weight between presynaptic and postsynaptic neurons.

$W_{ij}(t)$ = previous weight between presynaptic and postsynaptic neurons.

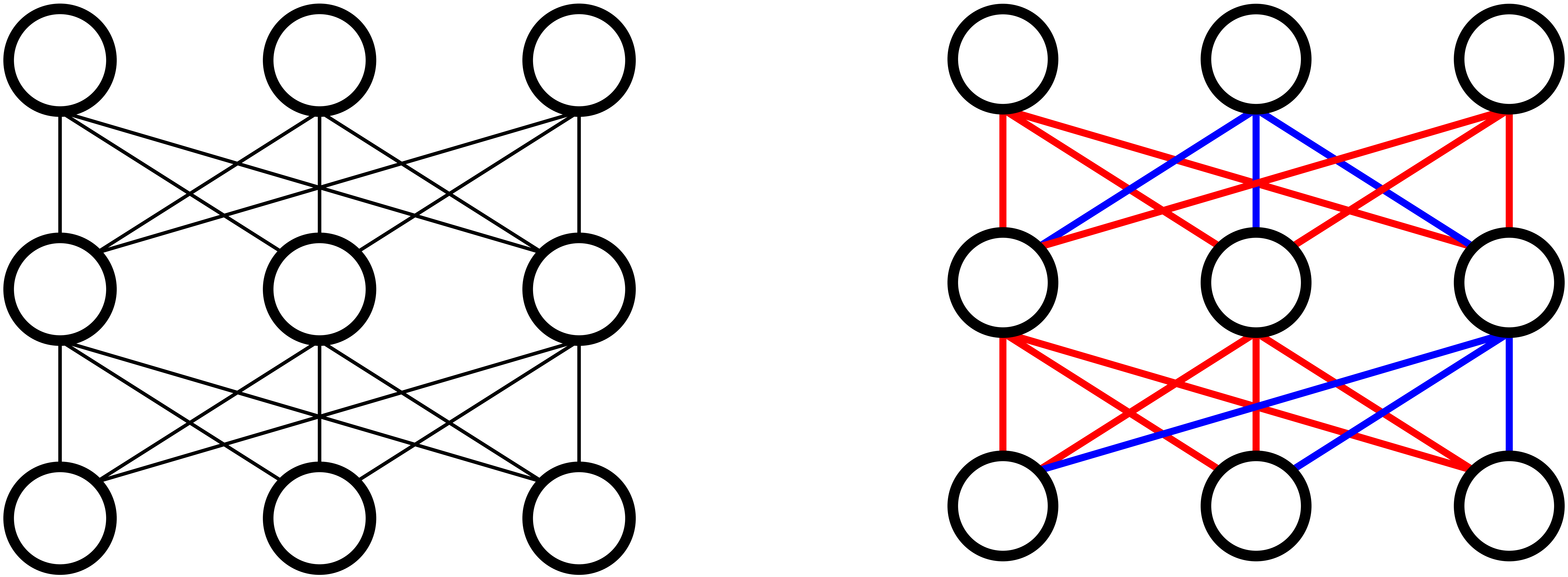
S_i, S_j = activity of presynaptic (i) and postsynaptic (j) neurons.

$S \in \{1, 0\}$

ϵ = learning rate

Excitatory neuron: $W_{ij} \in (0, 1]$

Inhibitory neuron: $W_{ij} \in [-1, 0)$



The mechanism of clamping: what, how, and why

What?

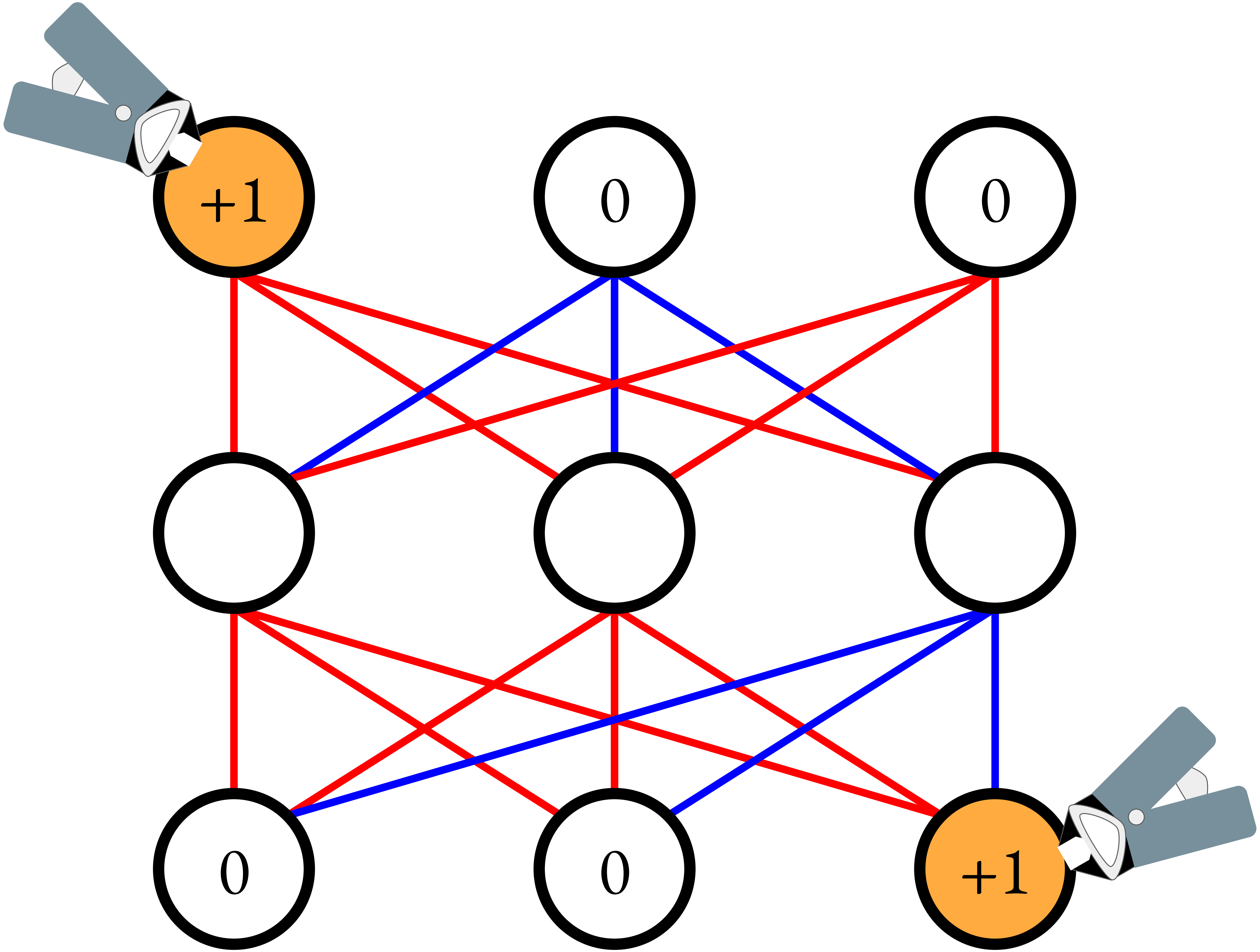
Activation of only a specific pair of neurons in the input and output layers.

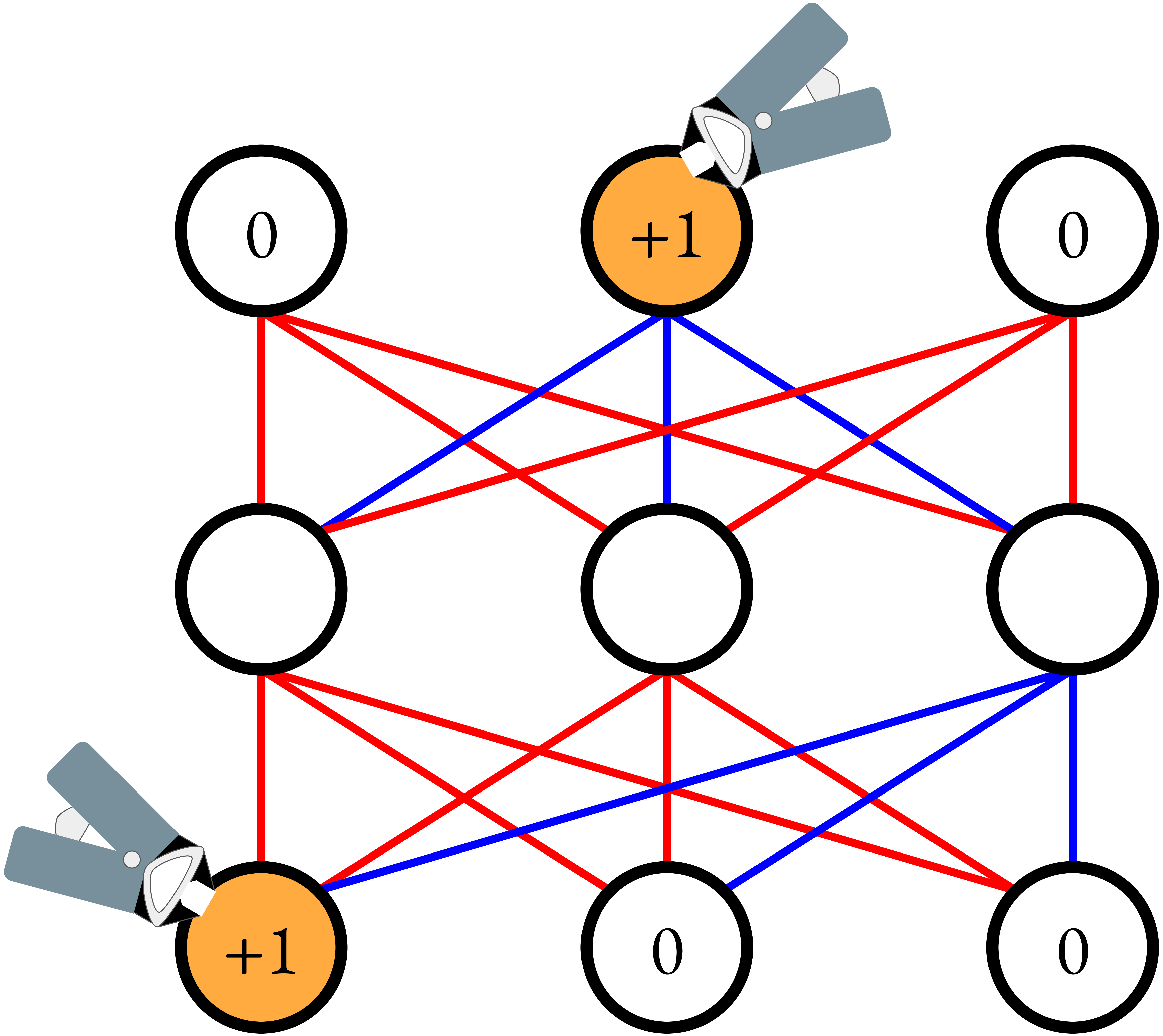
How?

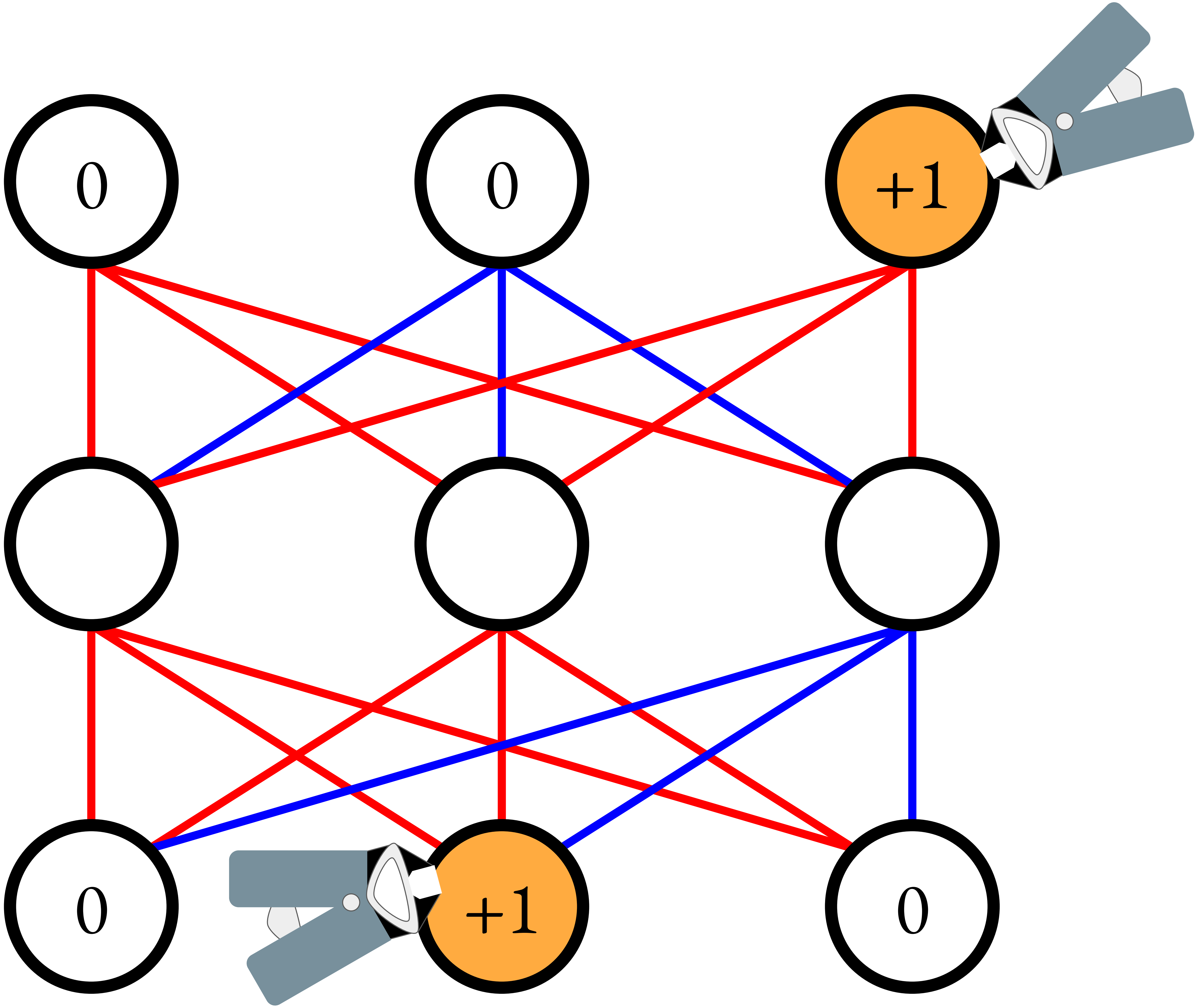
We try to enforce the learning of one-to-one mapping through binary sequence for input and output layers [1,0,0] to [0,0,1] etc.

Why?

One-to-one maps play an important role in signalling of neurons.


+1
0
0
0
0
+1


0
+1
0
+1
0
0

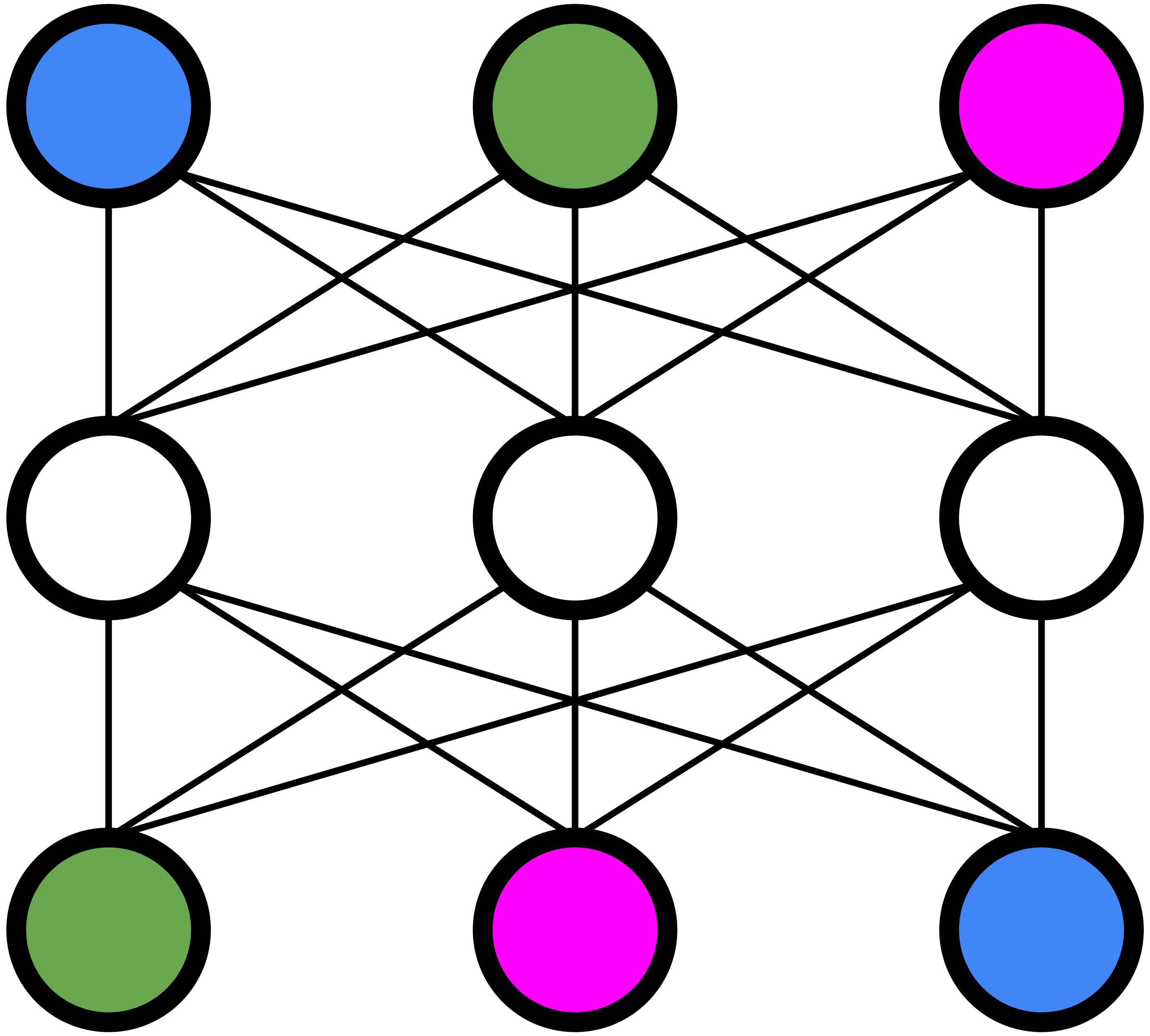

0
0
+1
0
+1
0

Convergence

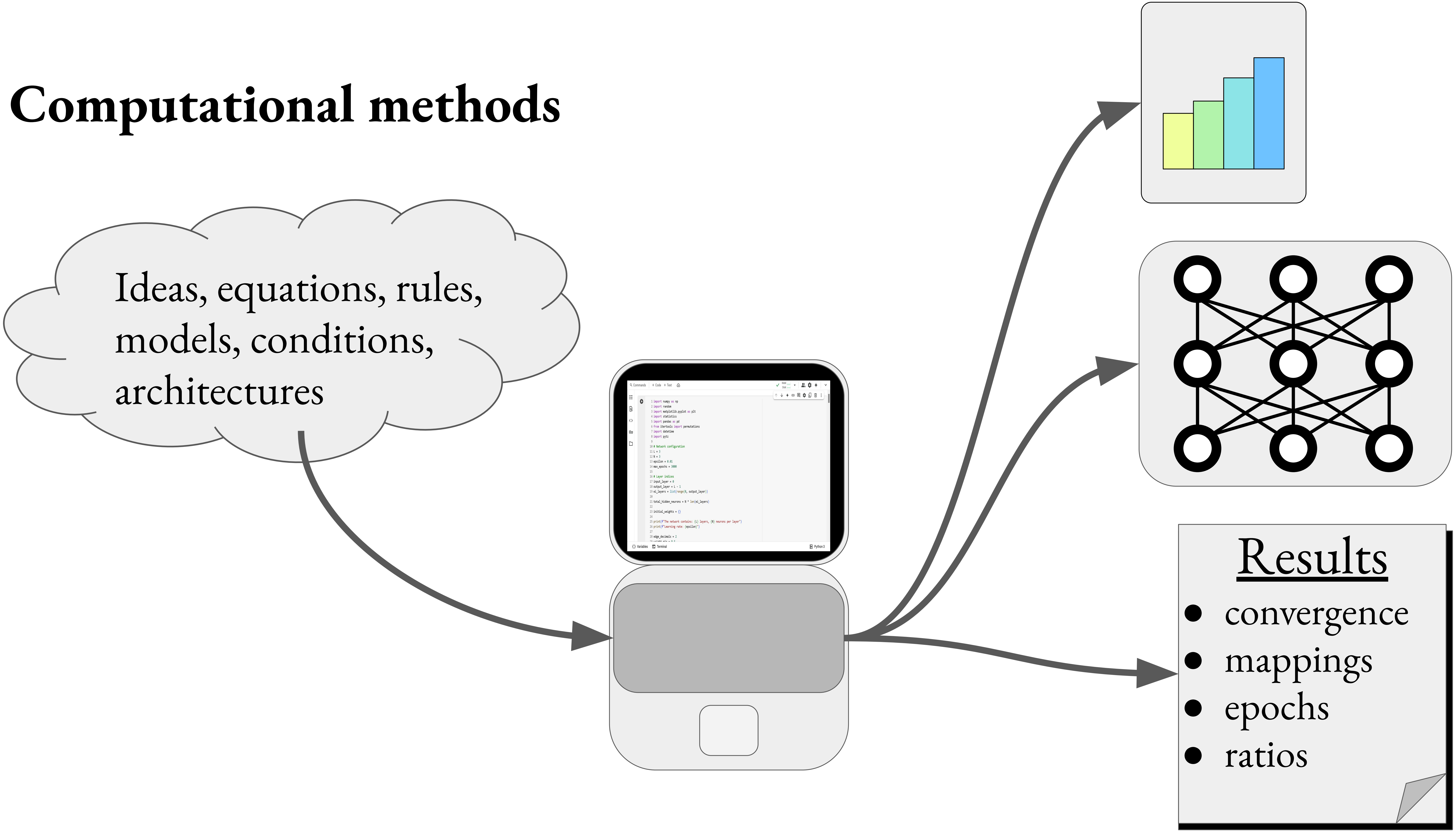
When the network is organised in such a way that it has 'learnt' all the one-to-one pairs of input and output that were clamped, the state of the network will no longer need to be updated, and this state is called convergence.

Means of measuring:

- Weights no longer update.
- Activation of input leads to desired output.
- Total no. of epochs taken.



Computational methods



Translating the ideas into code

```python

# Network configuration
L = 3
N = 3
epsilon = 0.01
max_epochs = 3000

```

```python

def generate_ei_ratios():
    # Generate achievable E/I ratios based on actual neuron counts
    ei_ratios = []
    ratios_checked = set()

    # For total_hidden_neurons, generate all possible integer combinations
    for excitatory_count in range(1, total_hidden_neurons):
        inhibitory_count = total_hidden_neurons - excitatory_count

        actual_excitatory_ratio = excitatory_count / total_hidden_neurons
        actual_inhibitory_ratio = inhibitory_count / total_hidden_neurons

        # to avoid potential duplicate ratios up to 3 decimals
        rounded_e_value = round(actual_excitatory_ratio, 3)
        rounded_i_value = round(actual_inhibitory_ratio, 3)

        ratio = (rounded_e_value, rounded_i_value)
        if ratio not in ratios_checked:
            ratios_checked.add(ratio)
            ei_ratios.append((actual_excitatory_ratio, actual_inhibitory_ratio, excitatory_count, inhibitory_count))

    return ei_ratios

```

```
def run_experiment()

def generate_ei_ratios()

def initialize_weights()

def clamp_neurons()

def forward_pass()

def activation_function()

def update_weights_using_hebbian()

def check_convergence()
```

https://github.com/aviswaroop/network_neuroscience

Modelling decisions

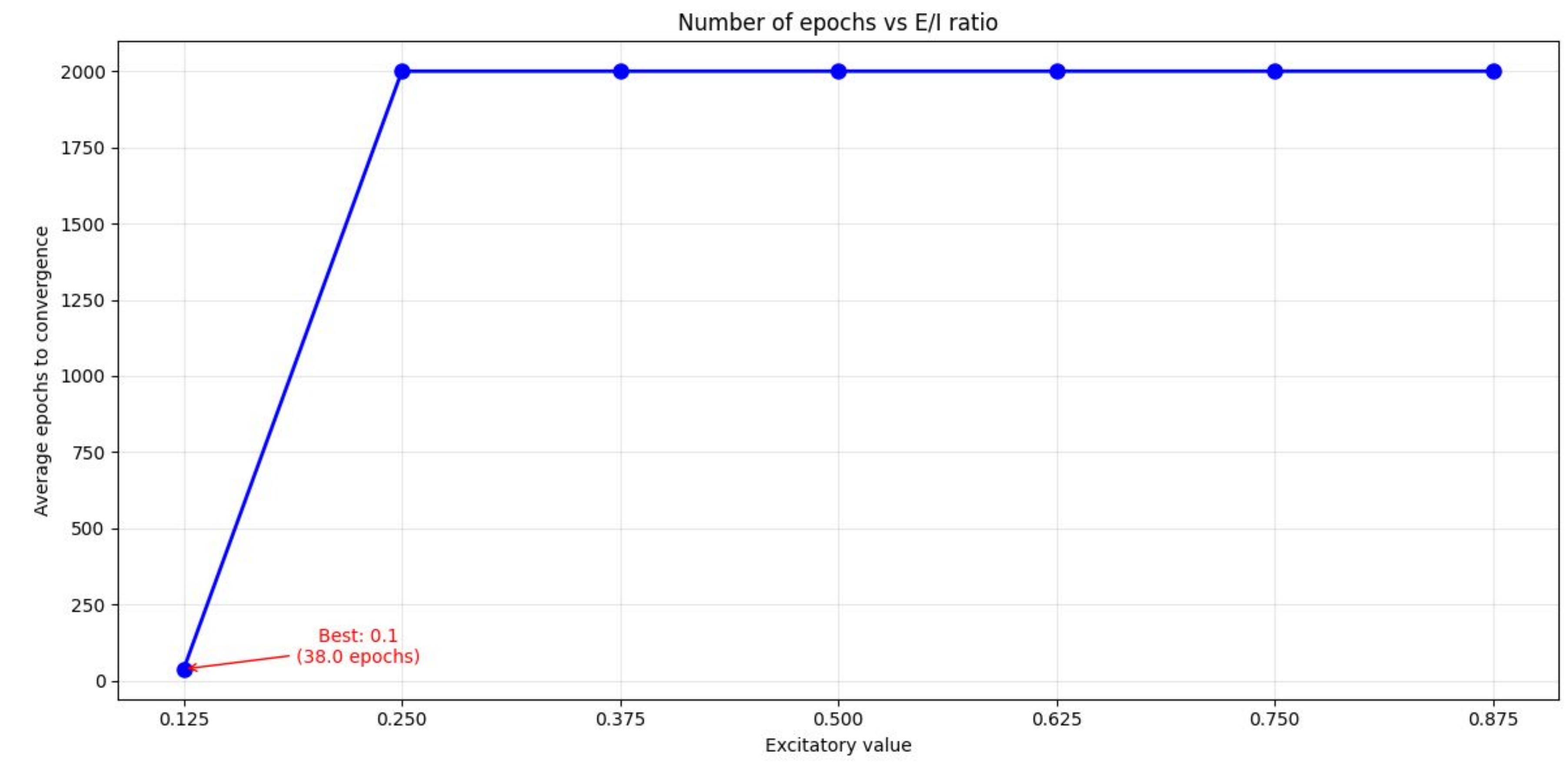
```python

edge_decimals = 2
weight_min = 0.01
weight_max = 0.1

```

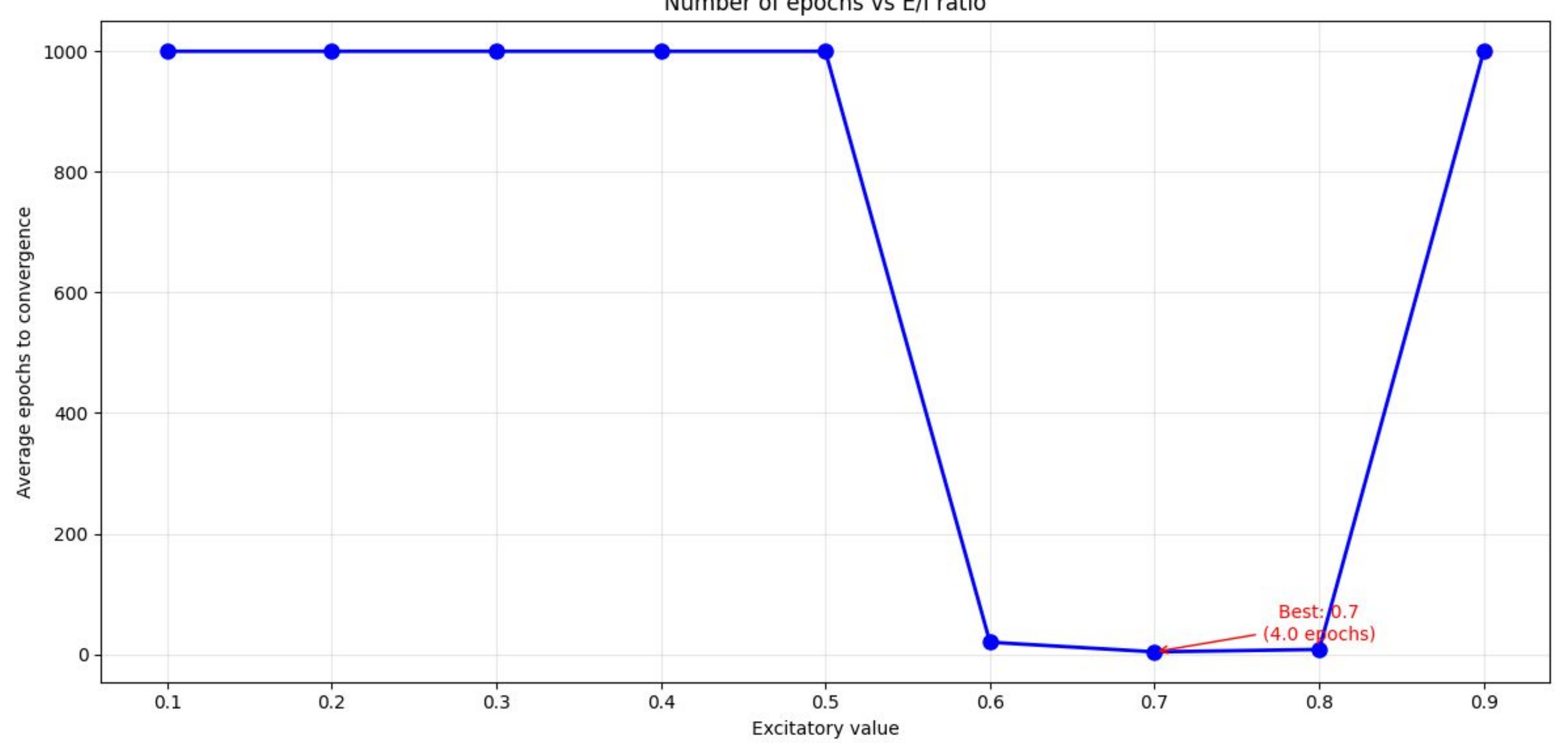
```python

            for j in range(N):
                if neuron_type == 1:
                    weight_matrix[i, j] = round(random.uniform(weight_min, weight_max), edge_decimals)
                else:
                    weight_matrix[i, j] = round(random.uniform(-weight_max, -weight_min), edge_decimals)

```

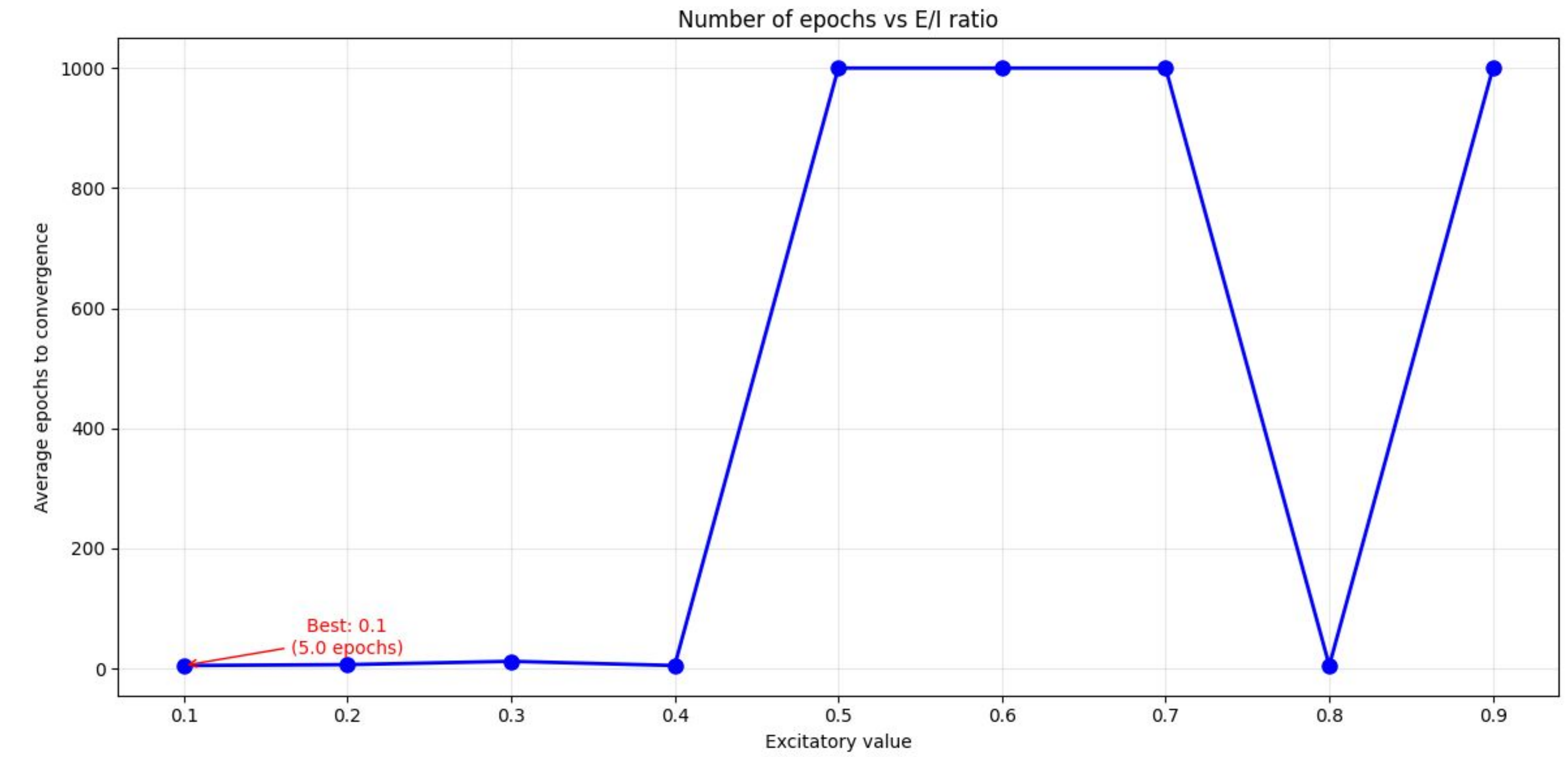
```python

def activation_function(x):
    return np.where(x >= 0, 1.0, -1.0)

```

```python
def clamp_neurons(neuron_states, input_idx, output_idx):
    # Clamp specific input and output neurons to +1, others to 0
    neuron_states.fill(0)
    neuron_states[input_layer, input_idx] = 1
    neuron_states[output_layer, output_idx] = 1

```

```python

                # Hebbian update rule
                current_weight = weight_matrix[i, j]
                weight_change = epsilon * pre_activity * post_activity * neuron_type
                new_weight = (1 - epsilon) * current_weight + weight_change

```







	A	B	C	D	E	F
1	excitatory_value	inhibitory_value	target_mapping	epochs_to_convergence	converged	converged_weights
16	0.125	0.875	[2, 1, 0, 3]	2000	FALSE	
17	0.125	0.875	[2, 1, 3, 0]	2000	FALSE	
18	0.125	0.875	[2, 3, 0, 1]	2000	FALSE	
19	0.125	0.875	[2, 3, 1, 0]	2000	FALSE	
20	0.125	0.875	[3, 0, 1, 2]	2000	FALSE	
21	0.125	0.875	[3, 0, 2, 1]	38	TRUE	{(0, 1): array([[-0.00604529, -0.00521571, 0.00432965, -0.00521571],
22	0.125	0.875	[3, 1, 0, 2]	2000	FALSE	
23	0.125	0.875	[3, 1, 2, 0]	2000	FALSE	
24	0.125	0.875	[3, 2, 0, 1]	2000	FALSE	
25	0.125	0.875	[3, 2, 1, 0]	2000	FALSE	
26	0.25	0.75	[0, 1, 2, 3]	2000	FALSE	
27	0.25	0.75	[0, 1, 3, 2]	2000	FALSE	
28	0.25	0.75	[0, 2, 1, 3]	2000	FALSE	
29	0.25	0.75	[0, 2, 3, 1]	2000	FALSE	
30	0.25	0.75	[0, 3, 1, 2]	2000	FALSE	
31	0.25	0.75	[0, 3, 2, 1]	2000	FALSE	
32	0.25	0.75	[1, 0, 2, 3]	2000	FALSE	
33	0.25	0.75	[1, 0, 3, 2]	2000	FALSE	
34	0.25	0.75	[1, 2, 0, 3]	2000	FALSE	
35	0.25	0.75	[1, 2, 3, 0]	2000	FALSE	
36	0.25	0.75	[1, 3, 0, 2]	2000	FALSE	

```
The network contains: 3 layers, 3 neurons per layer
Learning rate: 0.01
Edge weight assignment with 2 decimal places
Excitatory neuron's edge weight range from 0.5 to 0.5
Inhibitory neuron's edge weight range from -0.5 to -0.5
```

```
Starting experiment...
Testing 6 mappings for each of 5 E/I ratios
Available E/I configurations:
  0.167/0.833 (1E/5I)
  0.333/0.667 (2E/4I)
  0.500/0.500 (3E/3I)
```

```
Testing E/I ratio: 0.667/0.333
  Converged: 0/6 mappings

Testing E/I ratio: 0.833/0.167
  Converged: 0/6 mappings
```

What’s the answer?

Does excitation/inhibition ratio have an effect in one-to-one learning of neural networks using Hebb’s Rule ?

What's the answer?

Does excitation/inhibition ratio have an effect in one-to-one learning of neural networks using Hebb's Rule ?

- Lateral inhibition?
- Multiple edges between two nodes?
- Checking for uniqueness?
- Back-and-forth updates?
- Removing constraint of direction?
- Partial convergence?

Implications of the results obtained

- For a particular E/I ratio, there are many ways in which the E/I allotment can be done.
- For a given number of nodes in a layer, there can be n! different sets of one-to-one mapping possible.
- Hebbian rule may not be enough for the network to converge by learning all the one-to-one mapping

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References

- Rubenstein, J.L.R. and Merzenich, M.M. (2003), Model of autism: increased ratio of excitation/inhibition in key neural systems. Genes, Brain and Behavior, 2: 255-267. https://doi.org/10.1034/j.1601-183X.2003.00037.x
- van van Hugte EJH, Schubert D, Nadif Kasri N. Excitatory/inhibitory balance in epilepsies and neurodevelopmental disorders: Depolarizing γ-aminobutyric acid as a common mechanism. Epilepsia. 2023 Aug;64(8):1975-1990. doi: 10.1111/epi.17651. Epub 2023 Jun 4. PMID: 37195166.
- Daniela L. Uliana, Joao Roberto F. Lisboa, Felipe V. Gomes, Anthony A. Grace,
- The excitatory-inhibitory balance as a target for the development of novel drugs to treat schizophrenia, Biochemical Pharmacology, Volume 228, 2024, 116298,ISSN 0006-2952,https://doi.org/10.1016/j.bcp.2024.116298.
- Development of Continuous and Discrete Neural Maps, Luo, Liqun et al. , Neuron, Volume 56, Issue 2, 284 - 300
- Development of Precise Maps in Visual Cortex Requires Patterned Spontaneous Activity in the Retina, Cang, Jianhua et al. ,Neuron, Volume 48, Issue 5, 797 - 809
- Geoffrey J. Goodhill, Contributions of Theoretical Modeling to the Understanding of Neural Map Development, Neuron,Volume 56, Issue 2,2007