Temporal Pattern Classification using Spiking Neural Networks

Master's thesis Artificial Intelligence,

Olaf Booij

Begeleider: Hieu Tat Nguyen

Afstudeer-docent: Marcel Worring

olaf.booij@xs4all.nl

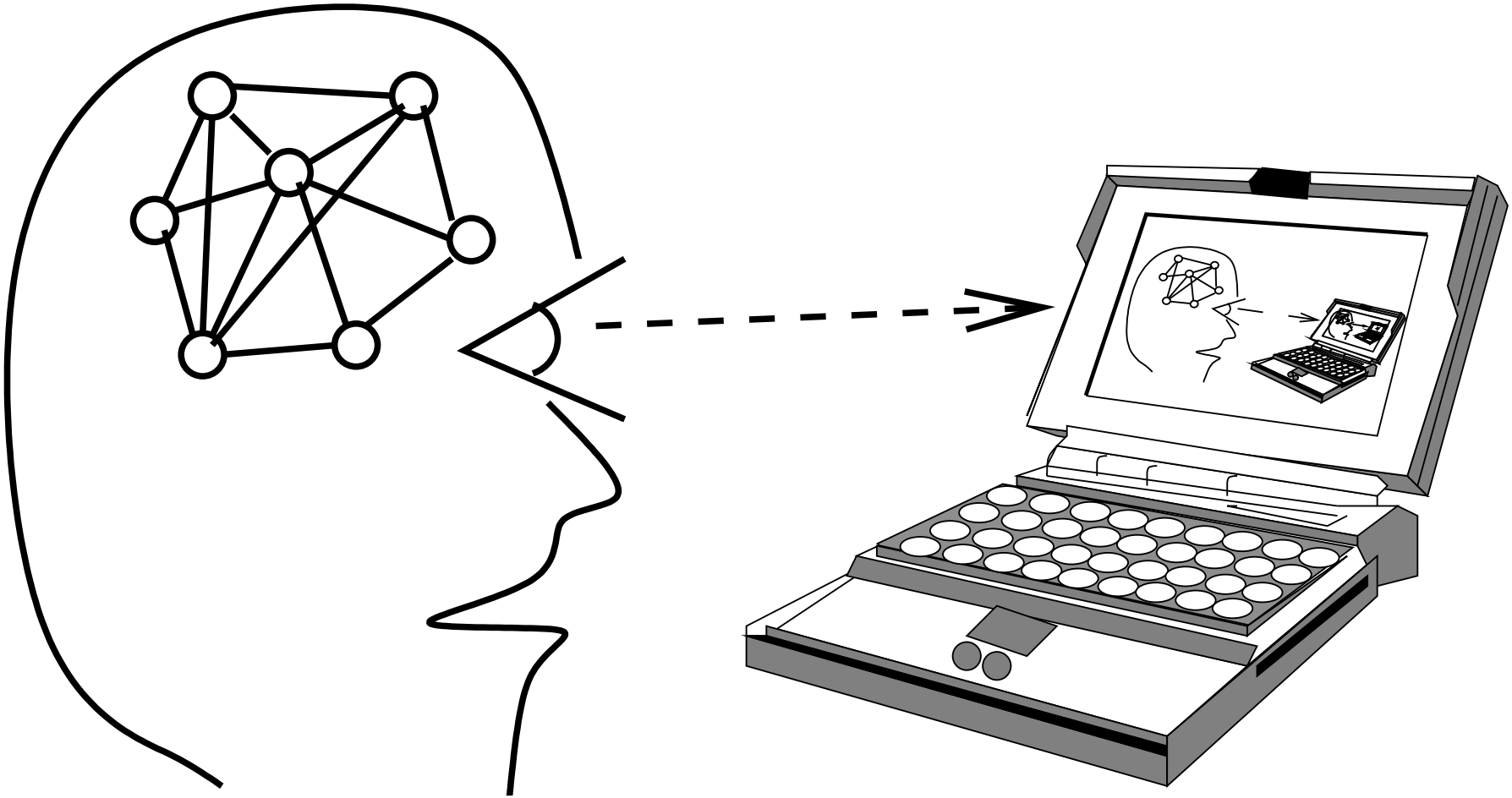
Overview

- Temporal Patterns
- Spiking Neurons
- Learning-rule
- Experiments
- Conclusion & Discussion

Temporal Pattern

- Audio recognition
- Video recognition
- Robot-control
- Weather-prediction

Spiking Neurons



Spiking Neurons

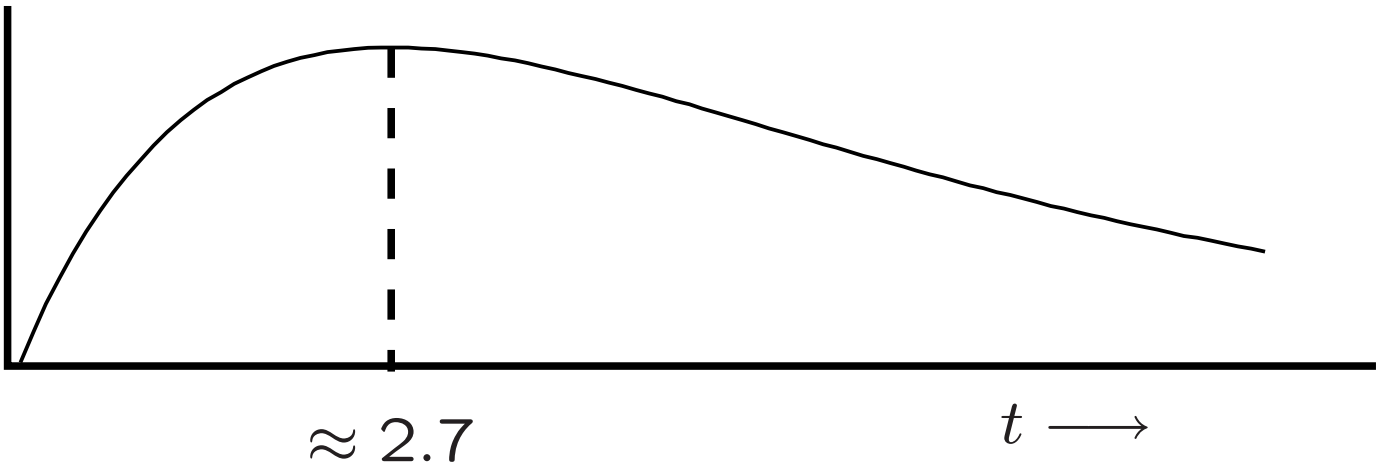
$$u_j(t) = \sum_{t_j^f \in \mathcal{F}_j} \eta(t - t_j^f) + \sum_{i \in \Gamma_j} \sum_{t_i^g \in \mathcal{F}_i} w_{ji} \varepsilon(t - t_i^g - d_{ji})$$

$$\mathcal{F}_j = \{t_j^f; 1 \leq f \leq n\} = \{t | u_j(t) = \vartheta\}$$

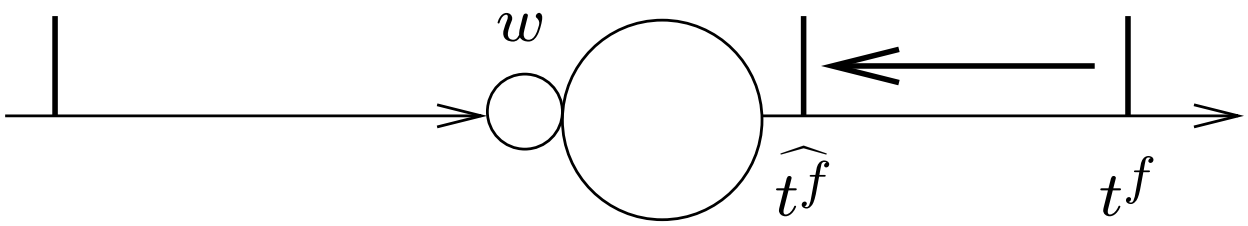
$$\varepsilon(s) = \left[\exp\left(-\frac{s}{\tau_m}\right) - \exp\left(-\frac{s}{\tau_s}\right)\right] \mathcal{H}(s)$$

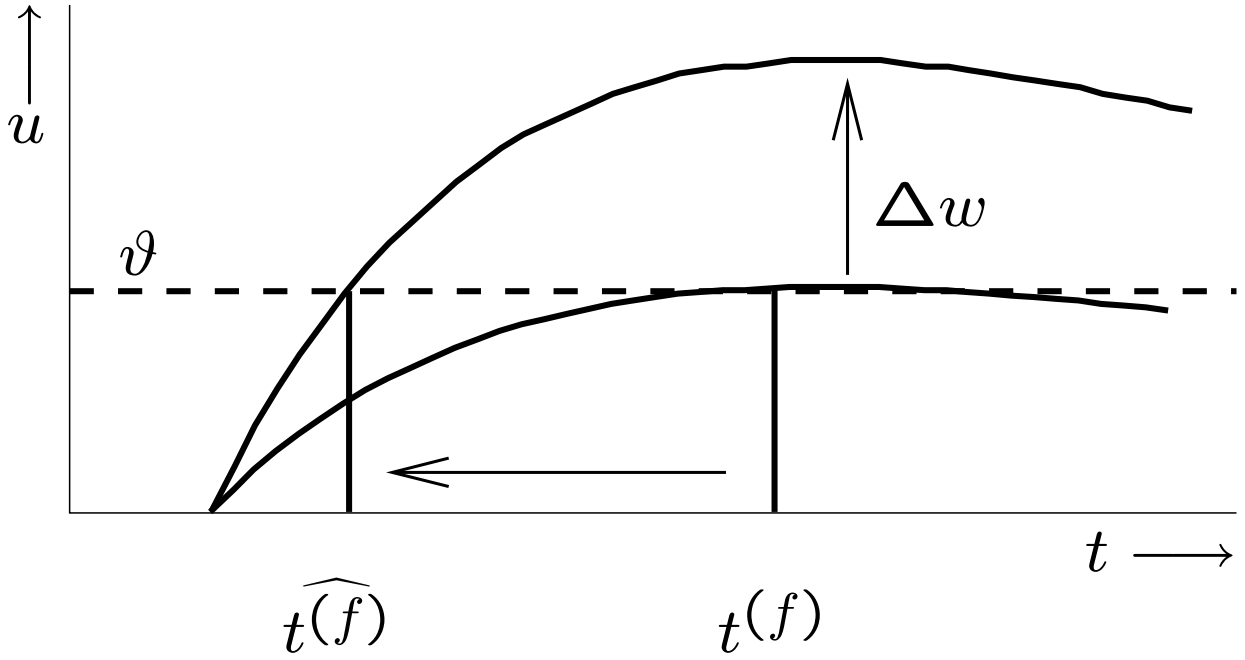
$$\eta(s) = -\vartheta \exp\left(-\frac{s}{\tau_r}\right) \mathcal{H}(s)$$

Spiking Neurons

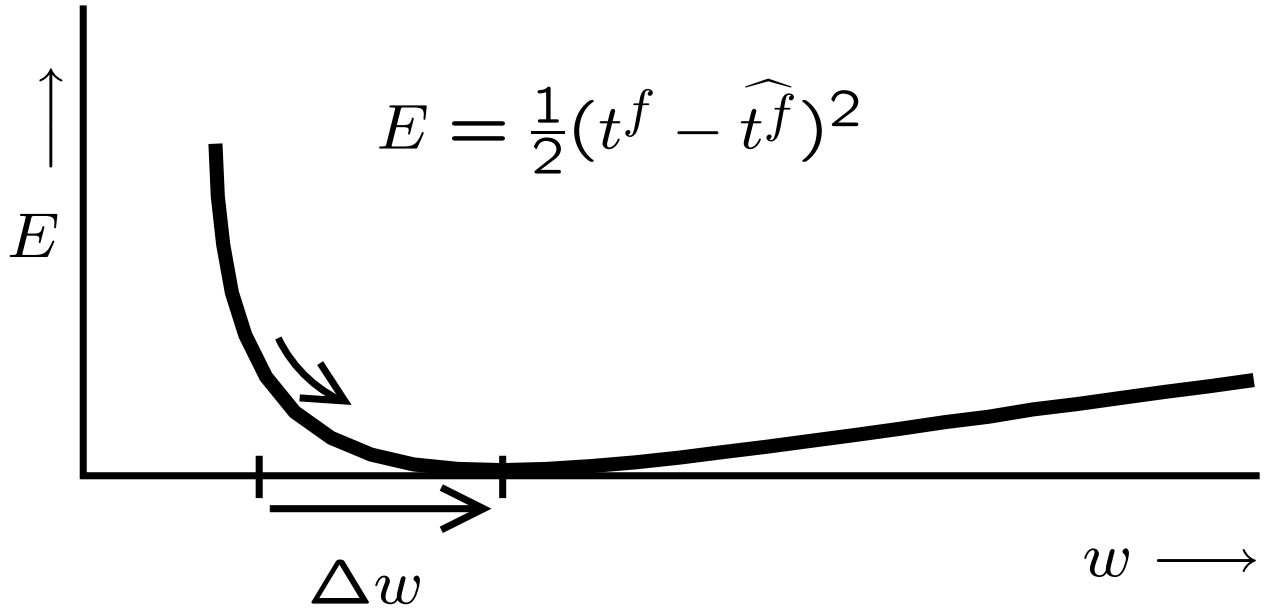


Learning-rule



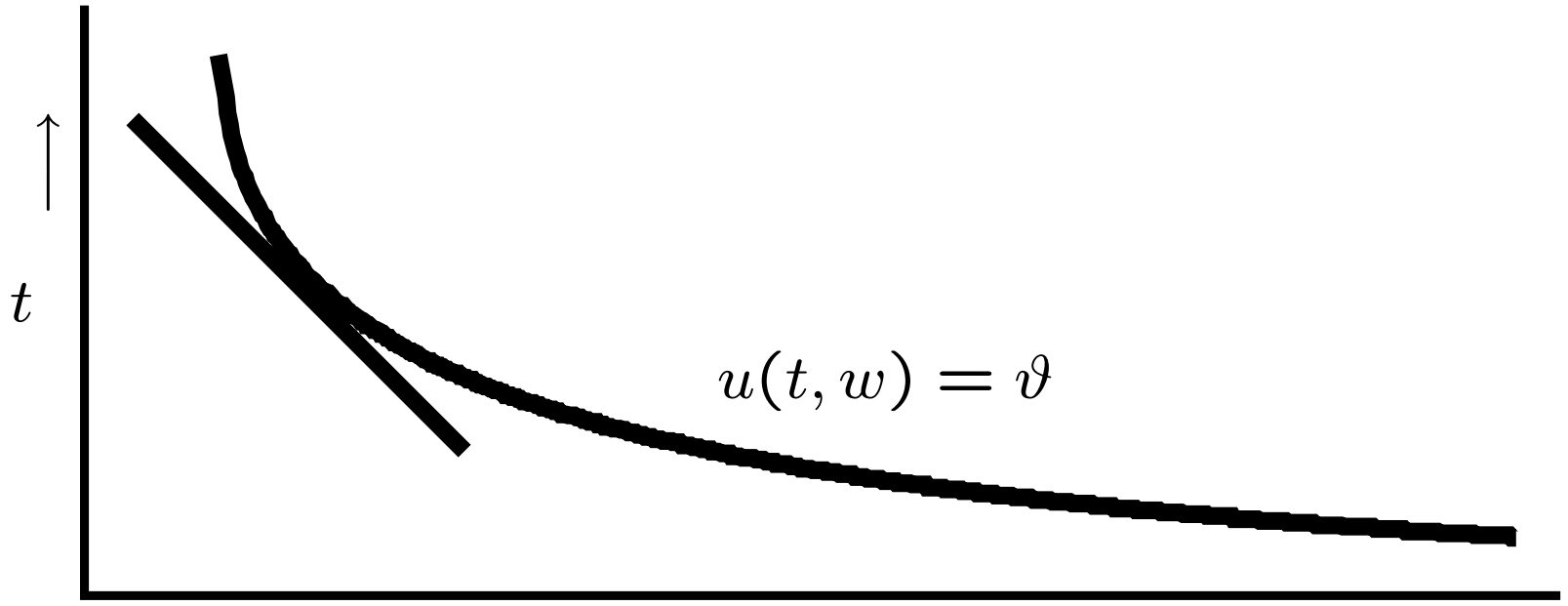


Learning-rule



$$\Delta w = -\eta \frac{\partial E}{\partial w} = -\eta \frac{\partial E}{\partial t^f} \frac{\partial t^f}{\partial w}$$

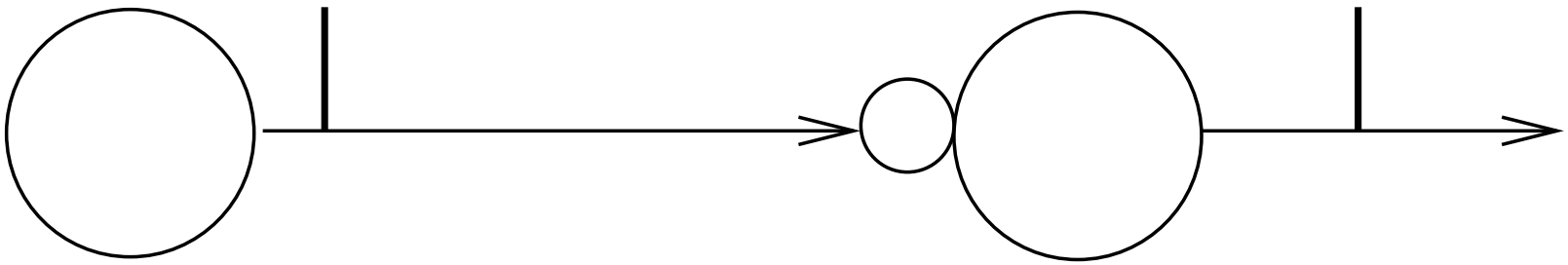
Learning-rule



$$du(t^f(w), w) = 0$$

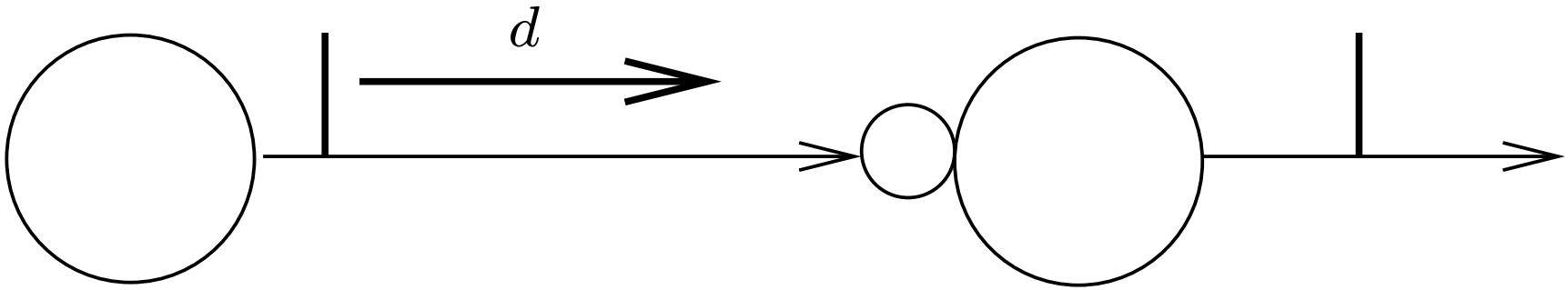
$$\frac{\partial u(t^f(w), w)}{\partial t^f(w)} \underbrace{\frac{\partial t^f(w)}{\partial w}}_{!} dw + \frac{\partial u(t^f(w), w)}{\partial w} dw = 0$$

Learning-rule



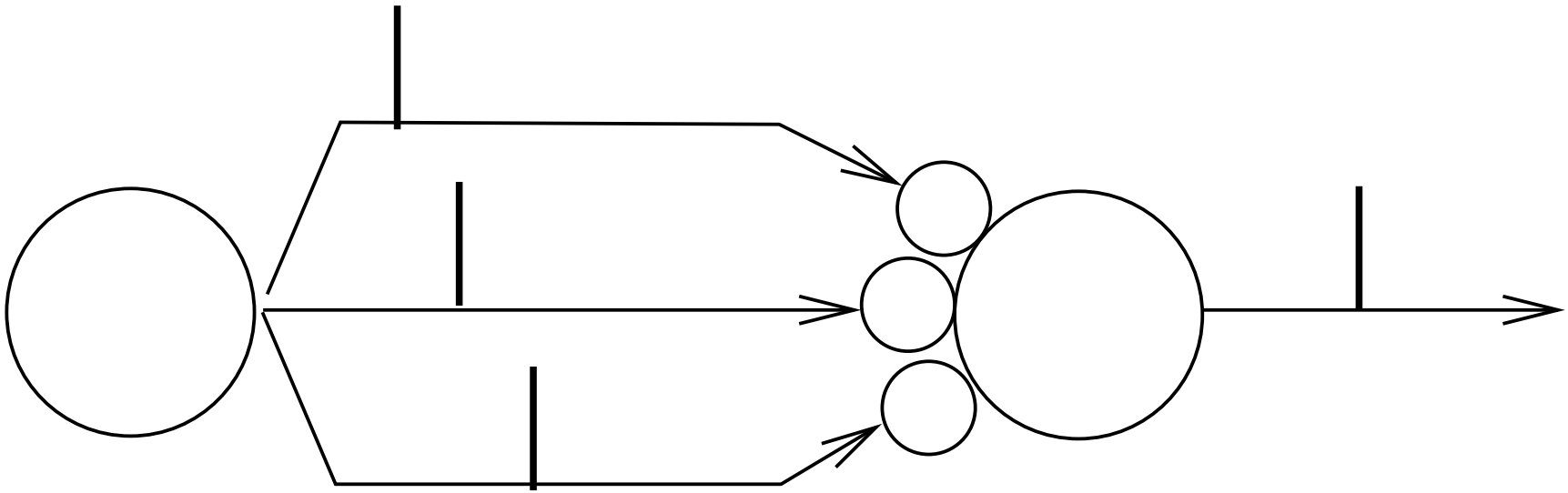
$$\frac{\partial t^f(w)}{\partial w} = \frac{-\varepsilon(t^f)}{w\varepsilon'(t^f)}$$

Learning-rule



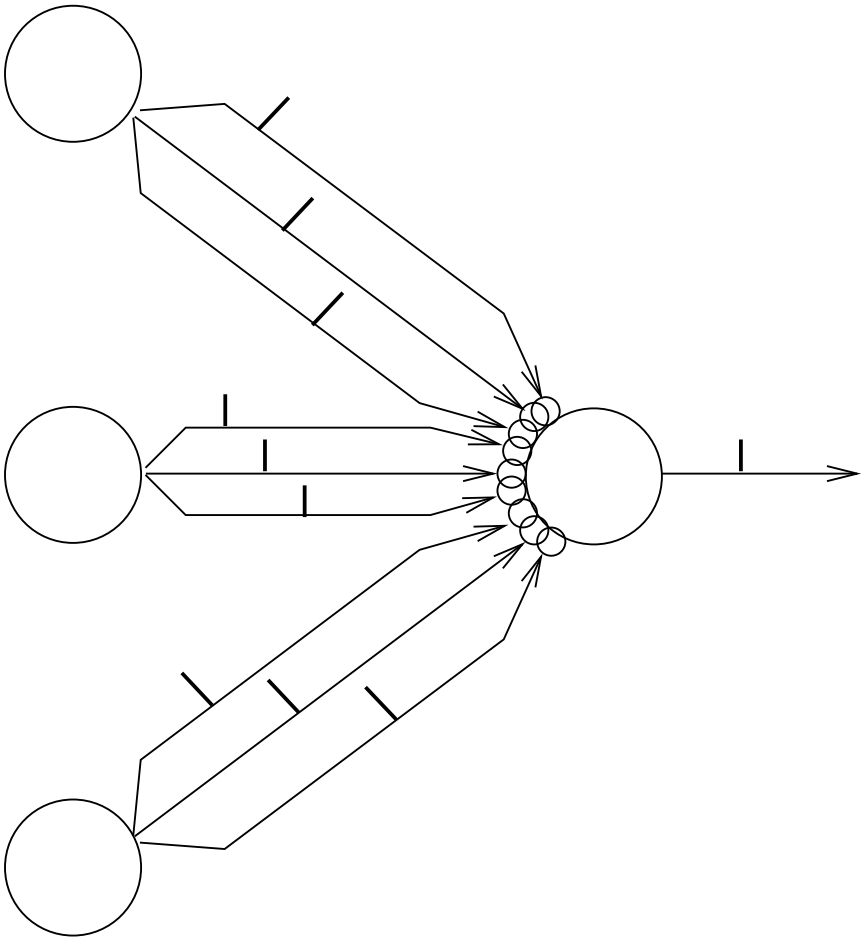
$$\frac{\partial t^f}{\partial w_i} = \frac{-\varepsilon(t^f - t_i^g - d)}{w_i \varepsilon'(t^f - t_i^g - d)}$$

Learning-rule



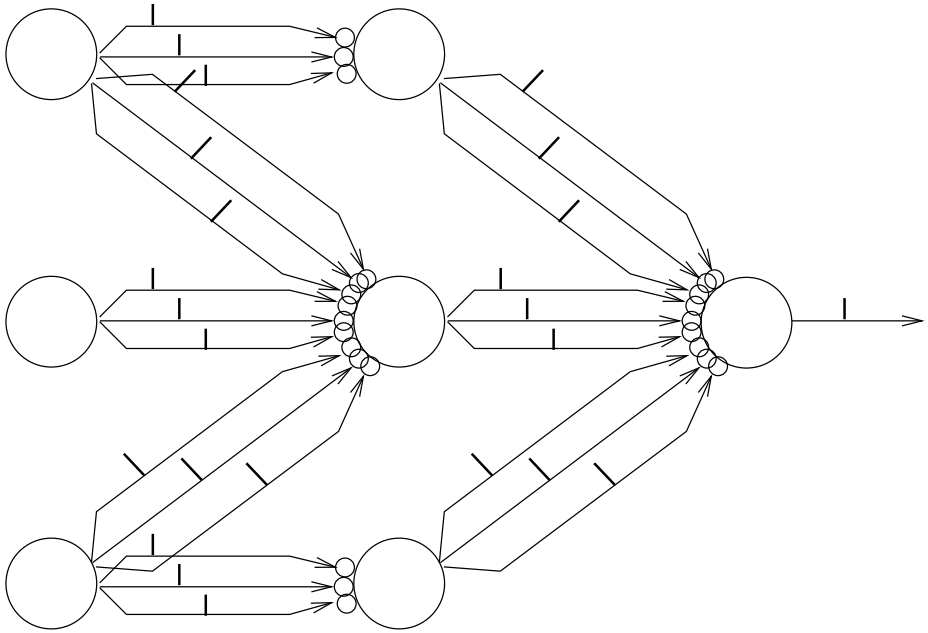
$$\frac{\partial t^f}{\partial w_i^k} = \frac{-\varepsilon(t^f - t_i^g - d^k)}{\sum_k w_i^k \varepsilon'(t^f - t_i^g - d^k)}$$

Learning-rule



$$\frac{\partial t^f}{\partial w_i^k} = \frac{-\varepsilon(t^f - t_i^g - d^k)}{\Sigma_{i \in \Gamma_j} \Sigma_k \, w_i^k \varepsilon'(t^f - t_i^g - d^k)}$$

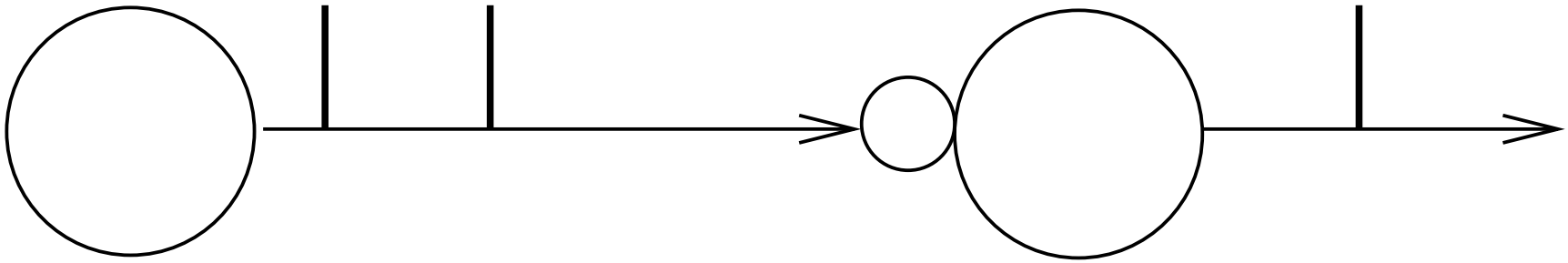
Learning-rule



$$\frac{\partial t_j^f}{\partial w_{ji}^k} = \frac{-\varepsilon(t_j^f - t_i^g - d^k)}{\sum_{i,k} w_{ij}^k \varepsilon'(t_j^f - t_i^g - d^k)}$$

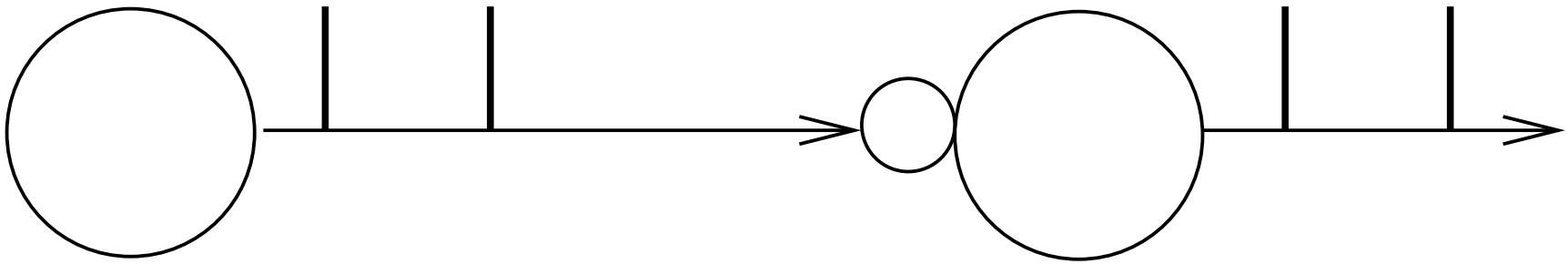
$$\frac{\partial t_j^f}{\partial t_i^g} = \frac{\sum_k w_{ji}^k \varepsilon'(t_j^f - t_i^g - d^k)}{\sum_{i,k} w_{ji}^k \varepsilon'(t_j^f - t_i^g - d^k)}$$

Learning-rule



$$\frac{\partial t^f}{\partial w_i} = \frac{-\sum_{t_i^g \in \mathcal{F}_i} \varepsilon(t^f - t_i^g - d)}{\sum_{t_i^g \in \mathcal{F}_i} w_i \varepsilon'(t^f - t_i^g - d)}$$

Learning-rule



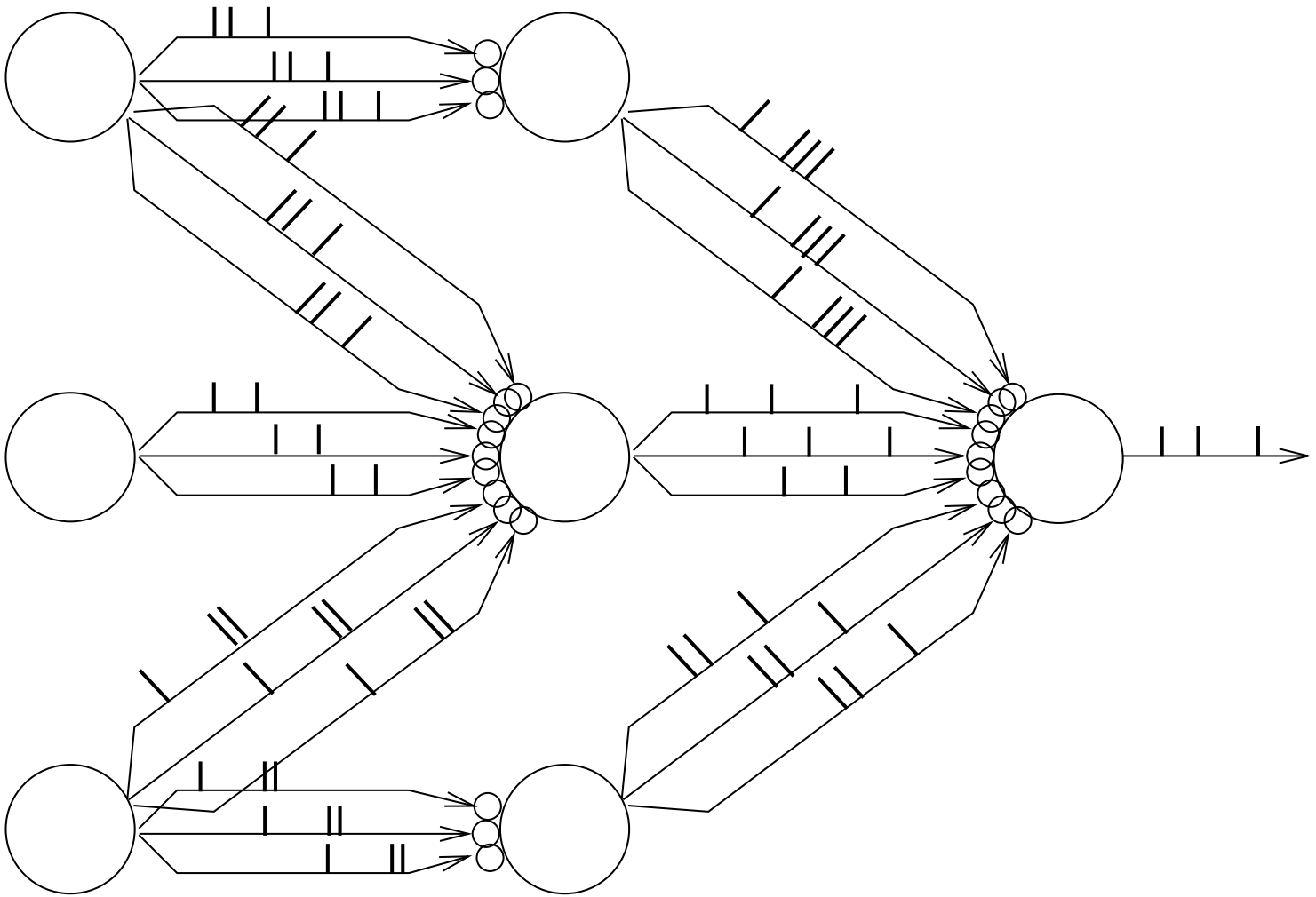
Learning-rule

$$du(w, t^f(w), \sum_{g<f} t^g(w)) = 0$$

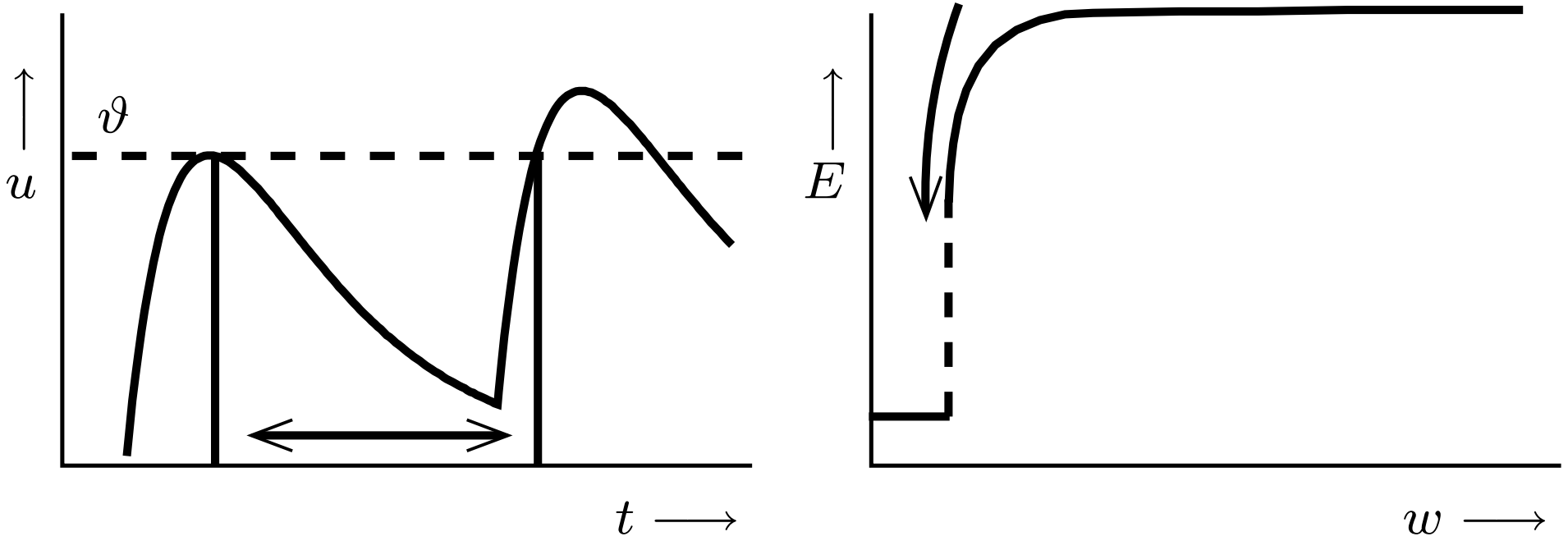
$$\frac{\partial u}{\partial w} + \frac{\partial u}{\partial t^f}\frac{\partial t^f}{\partial w} + \sum_{g<f} \frac{\partial u}{\partial t^g}\underbrace{\frac{\partial t^g}{\partial w}}_{!} = 0$$

$$\frac{\partial t^f}{\partial w} = \frac{-\sum_{t_i^g \in \mathcal{F}_i} \varepsilon(t^f - t_i^g - d) + \sum_{t_j^g \in \mathcal{F}_j} \eta'(t_j^f - t_i^g)\frac{dt_j^g}{dw_{ji}^k}}{\sum_{t_i^g \in \mathcal{F}_i} w_i \varepsilon'(t^f - t_i^g - d) + \sum_{t_j^g \in \mathcal{F}_j} \eta'(t_j^f - t_i^g)}$$

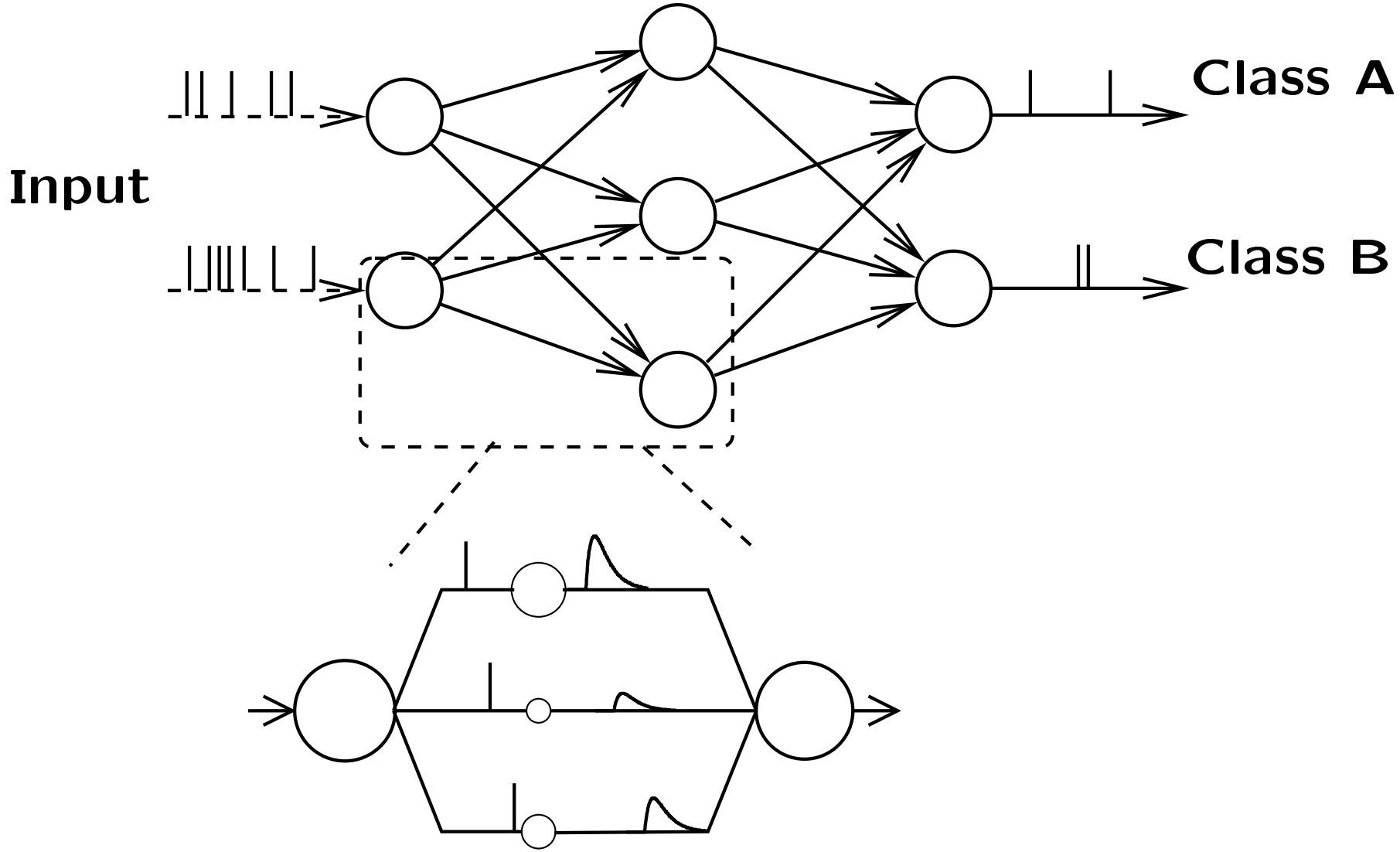
Learning-rule



Learning-rule

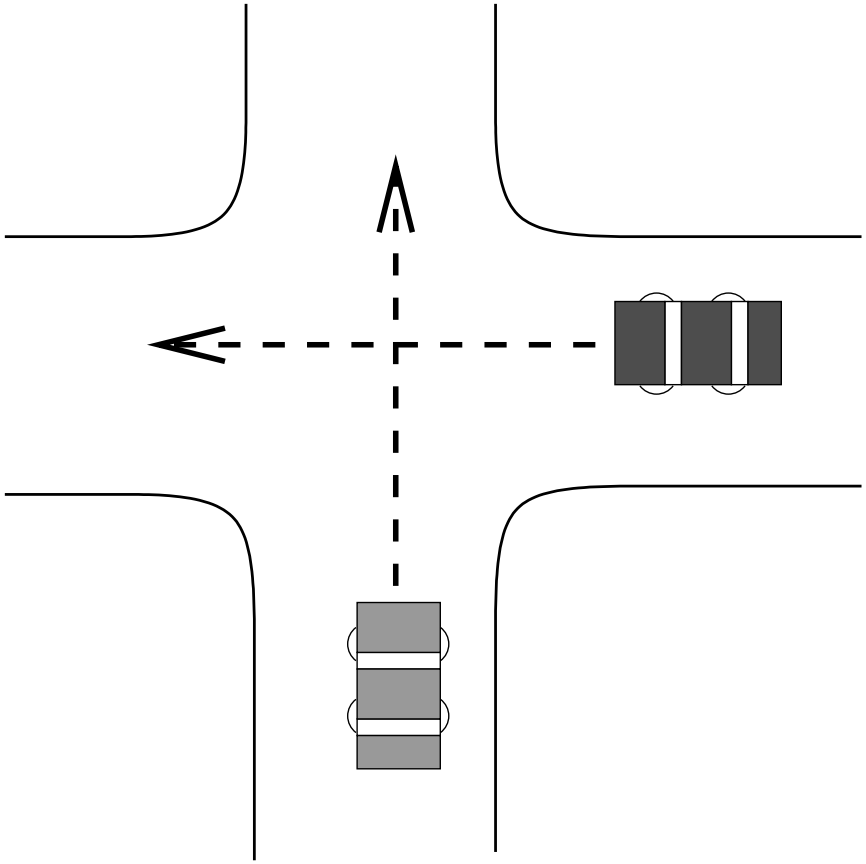


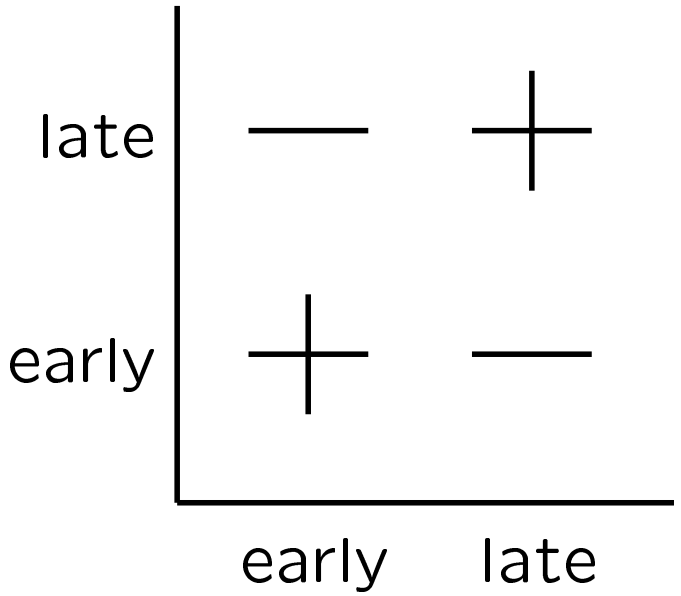
Experiments



Experiments

Exclusive-OR





Experiments

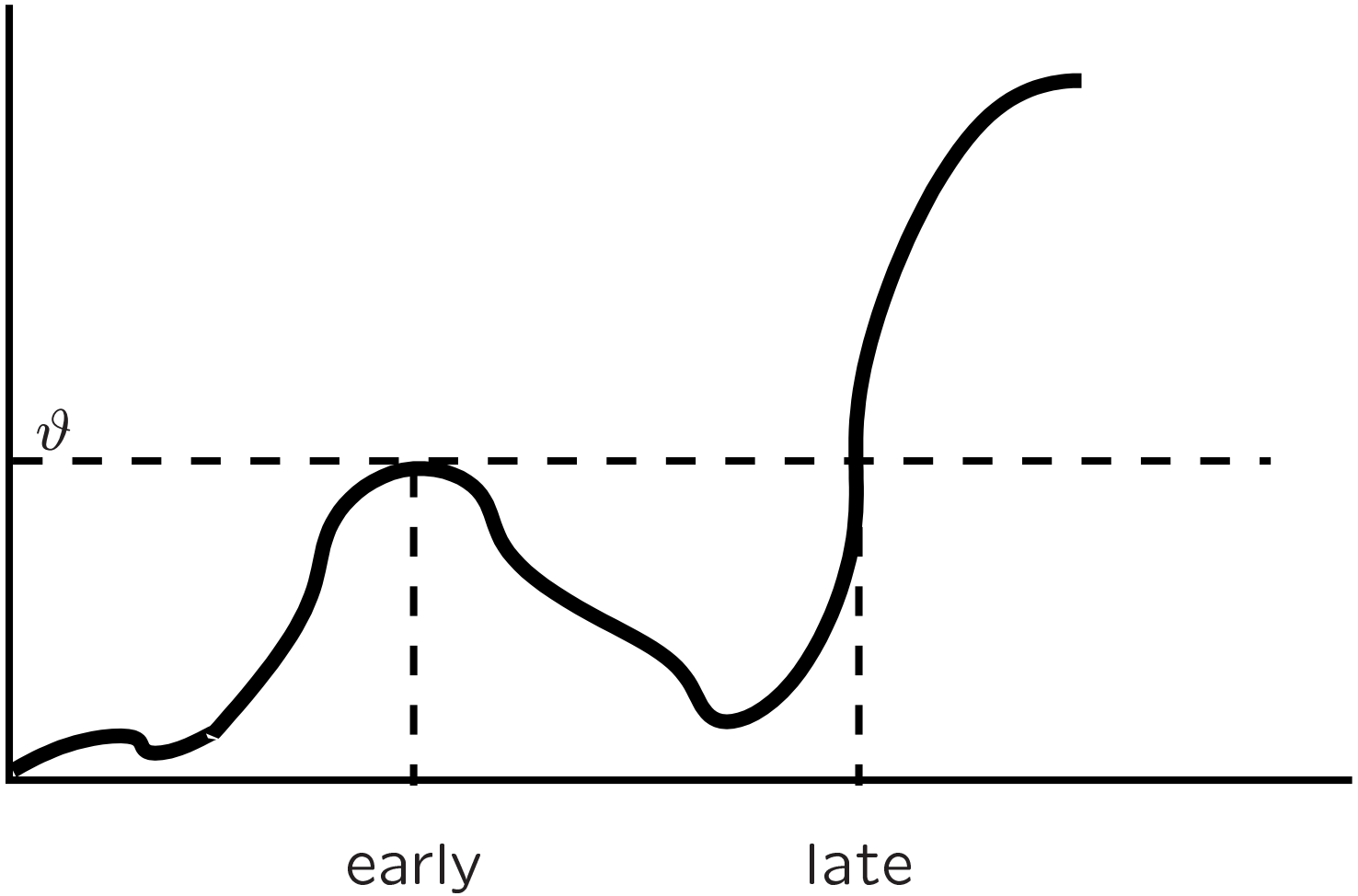
Exclusive-OR

Input 1	Input 2	Bias		Output
0	0	0	→	16
0	6	0	→	10
6	0	0	→	10
6	6	0	→	16

Input		Output
0 5 10	→	20
0 5	→	15
0 10	→	15
0	→	20

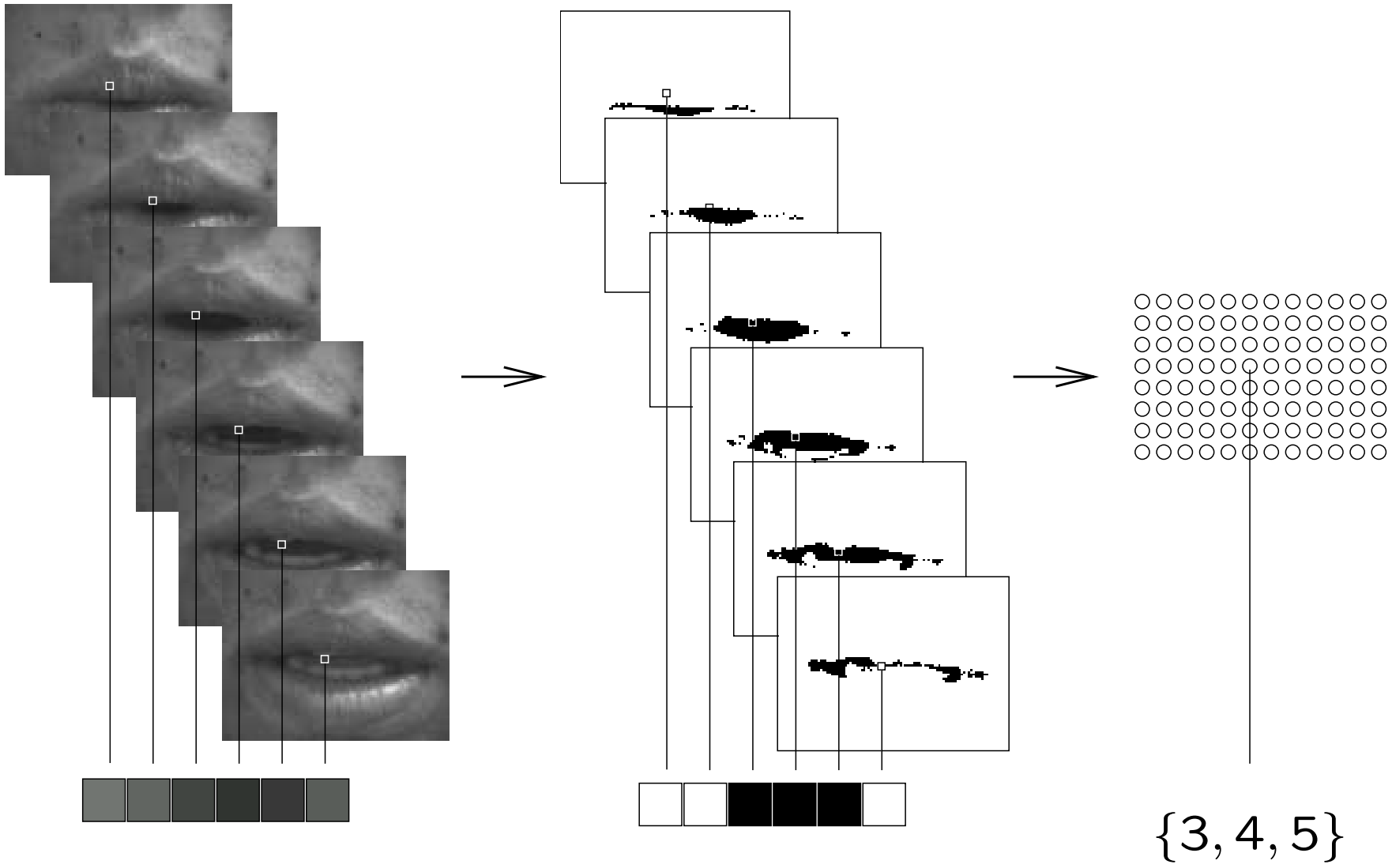
Experiments

Exclusive-OR



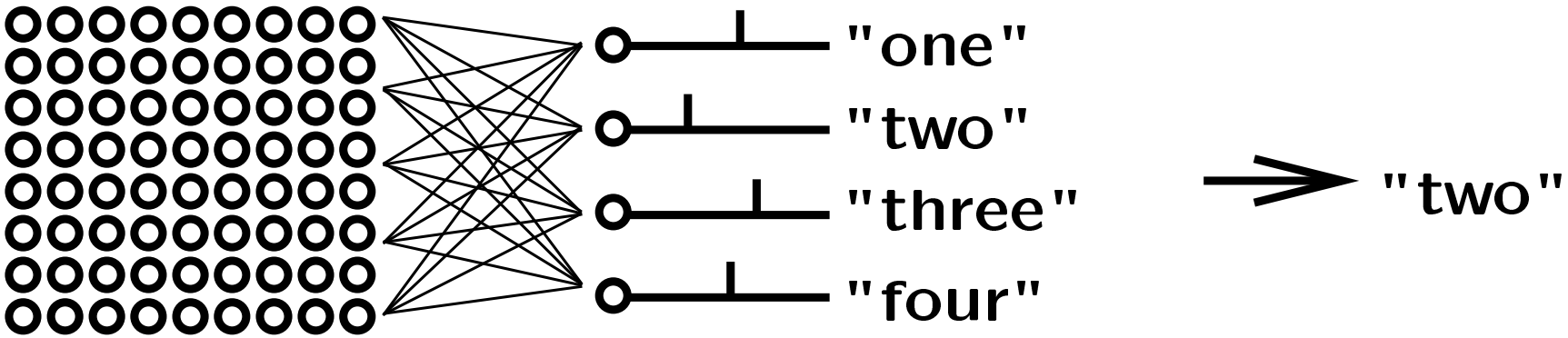
Experiments

Lipreading



Experiments

Lipreading



Method	Accuracy
SNN	57%
HMM	65-90%

Conclusion

- Spiking Neural Networks can learn temporal patterns
- Spiking neurons are more powerful then conventional neurons

Future Work

- Learn transmission-delays besides weights
- Apply on audio, trackdata, etc.

Discussion

- Error-measure for multiple spikes
- How to avoid no spikes
- Multiple precise spike coding biological plausible?