



neural networks

Inteligencia artificial y control

Gerardo Marx Chávez-Campos

Part 2

Recurrent Neural Networks

Recurrent Neural Networks (RNN)

Supervised

Artificial Neural Networks

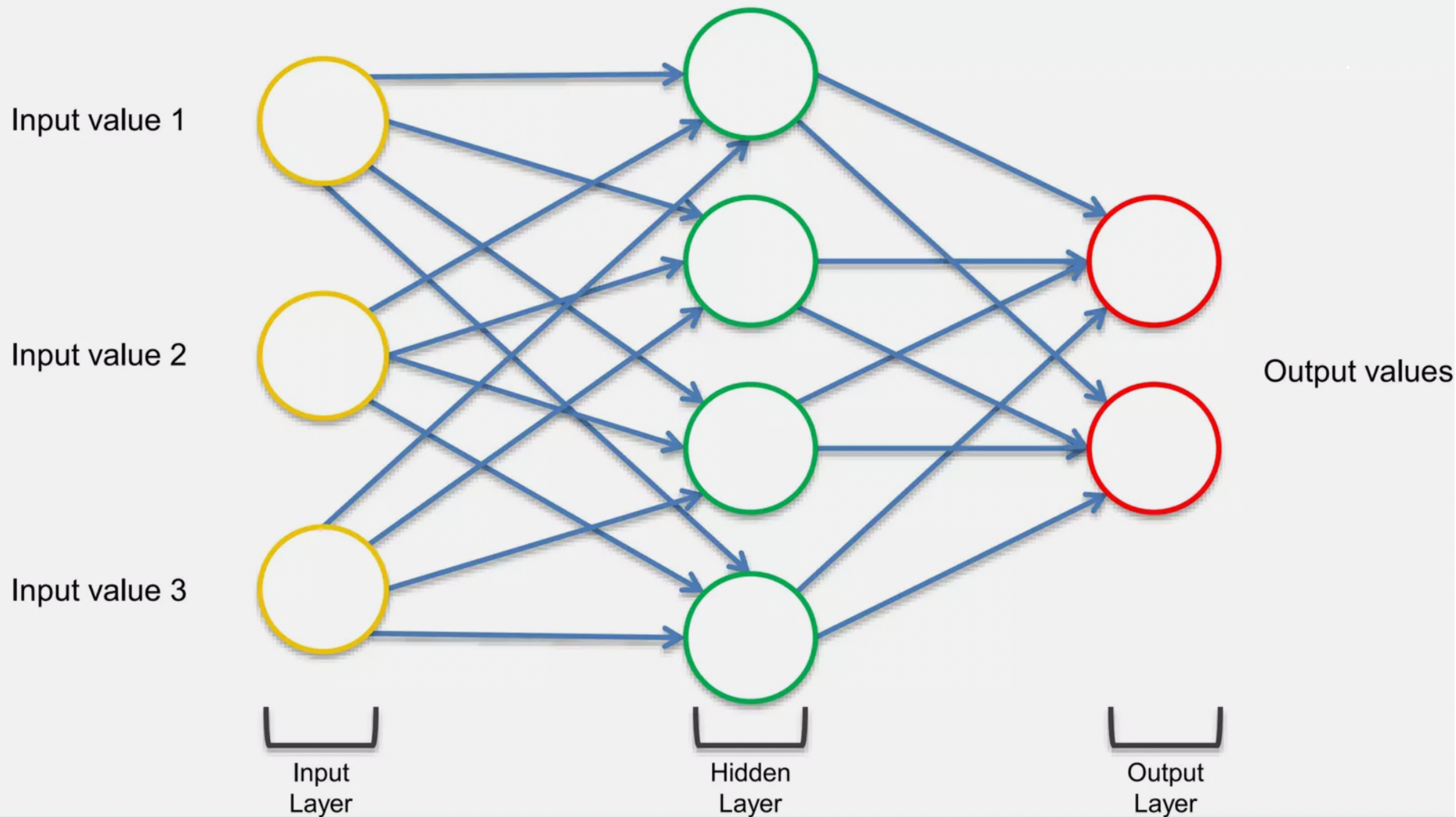
Regression and classification

Convolutional Neural
Networks

Computer Vision

Recurrent Neural Networks

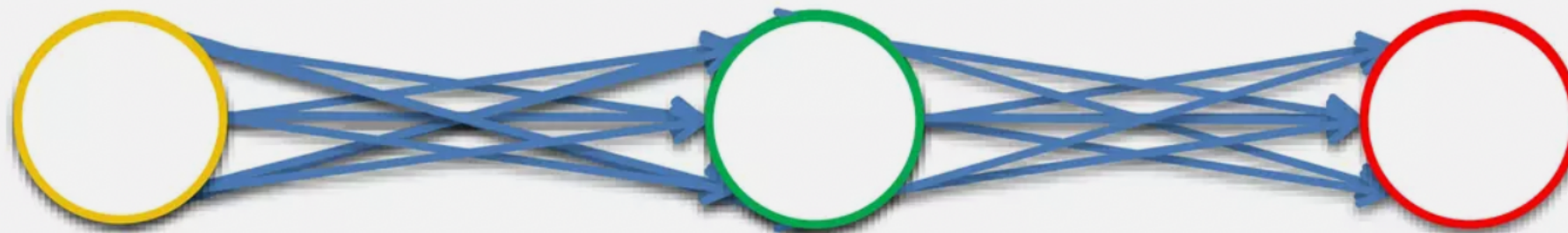
Time Series Analysis



Input value 1

Input value 2

Input value 3



Output values



Input
Layer

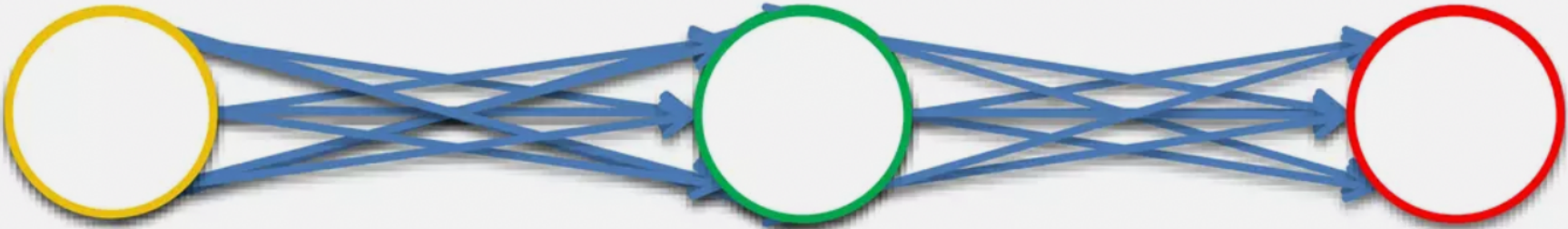


Hidden
Layer



Output
Layer

Input Vector



Output Vector



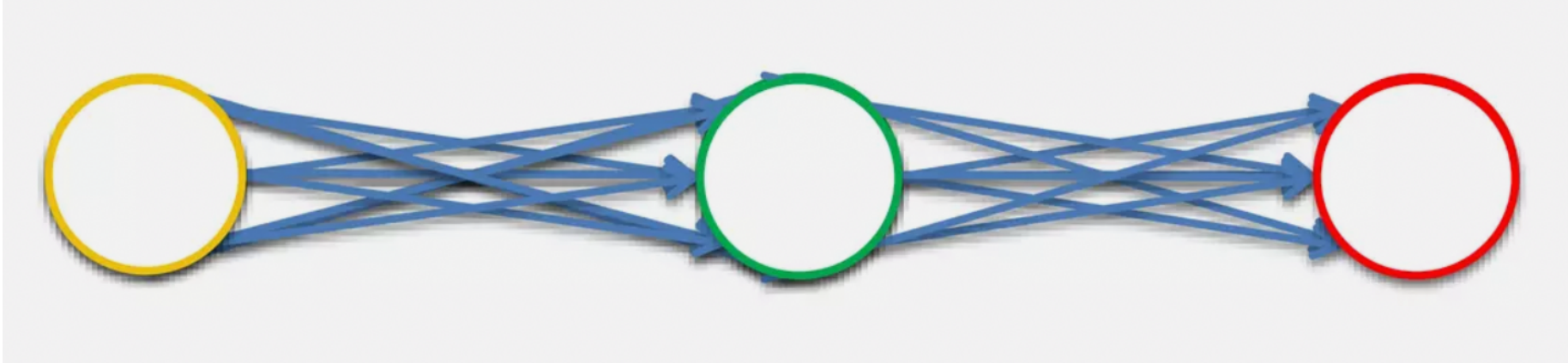
Input
Layer

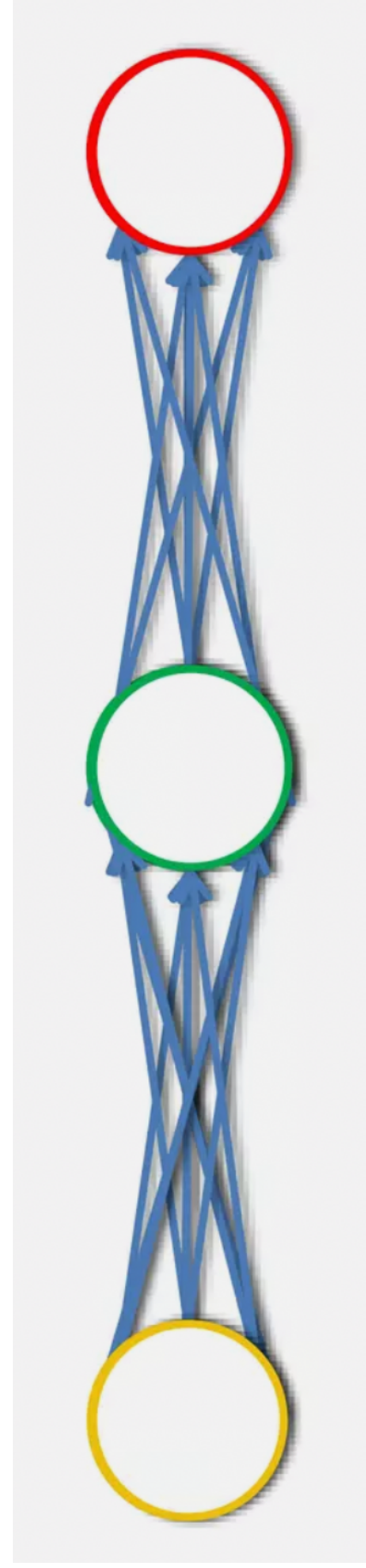


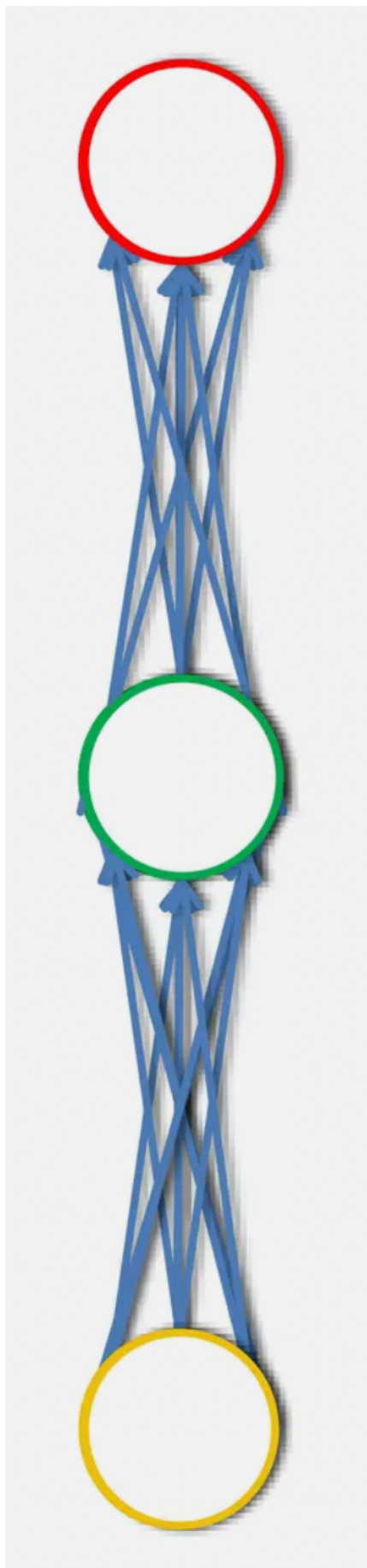
Hidden
Layer

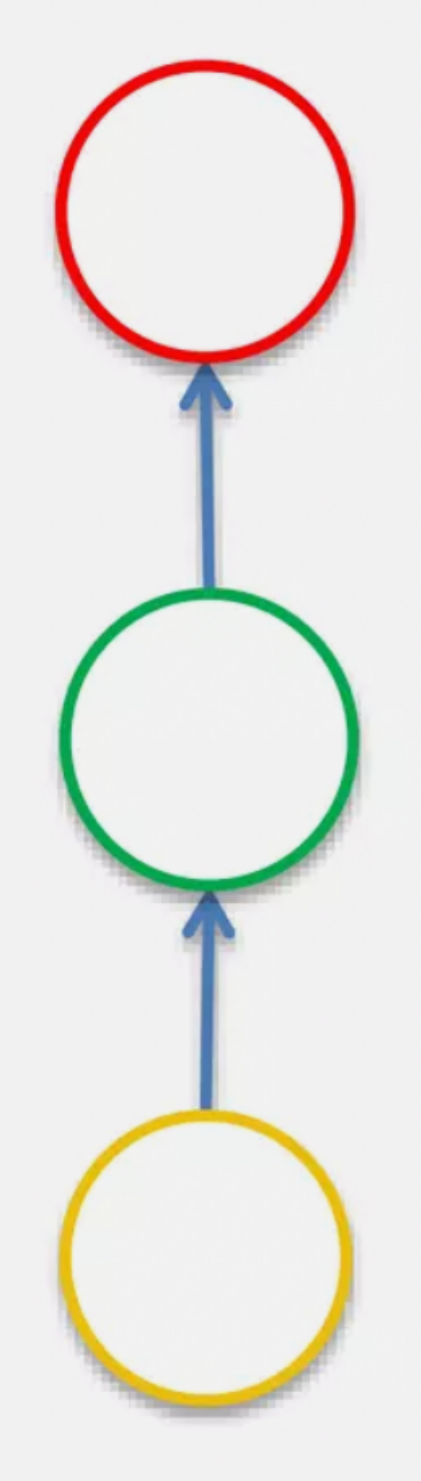


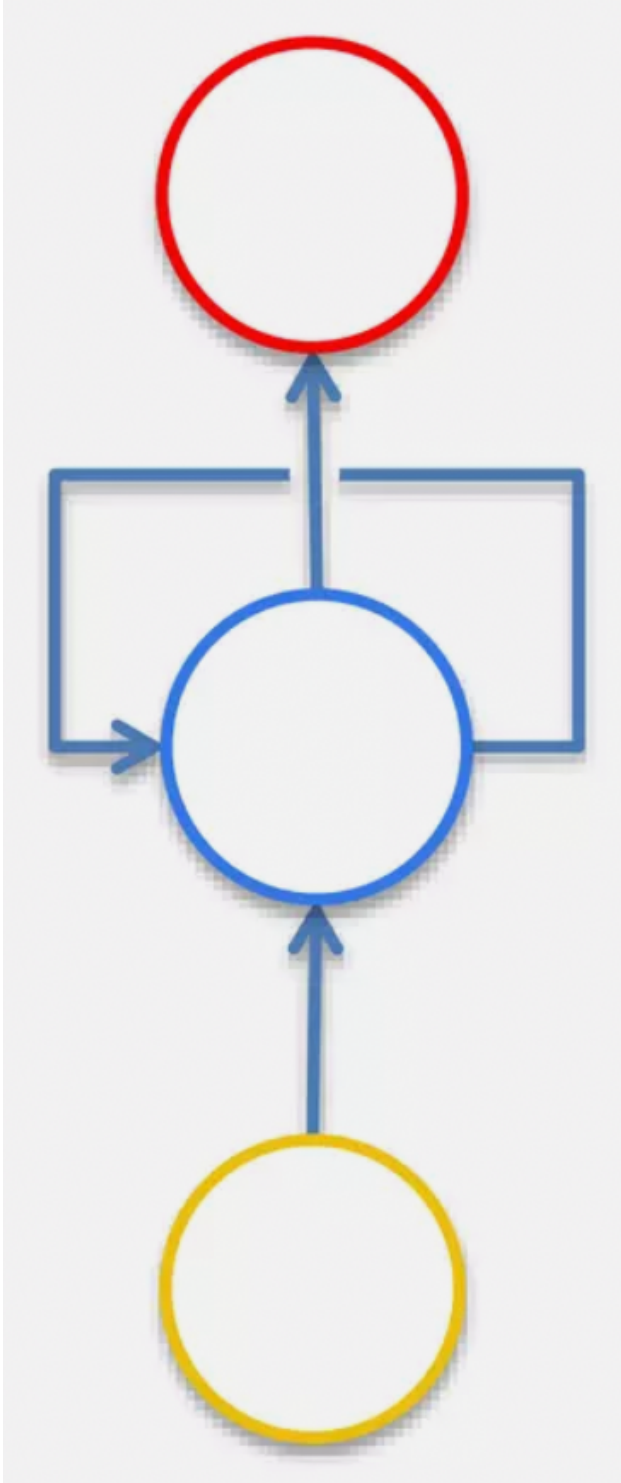
Output
Layer

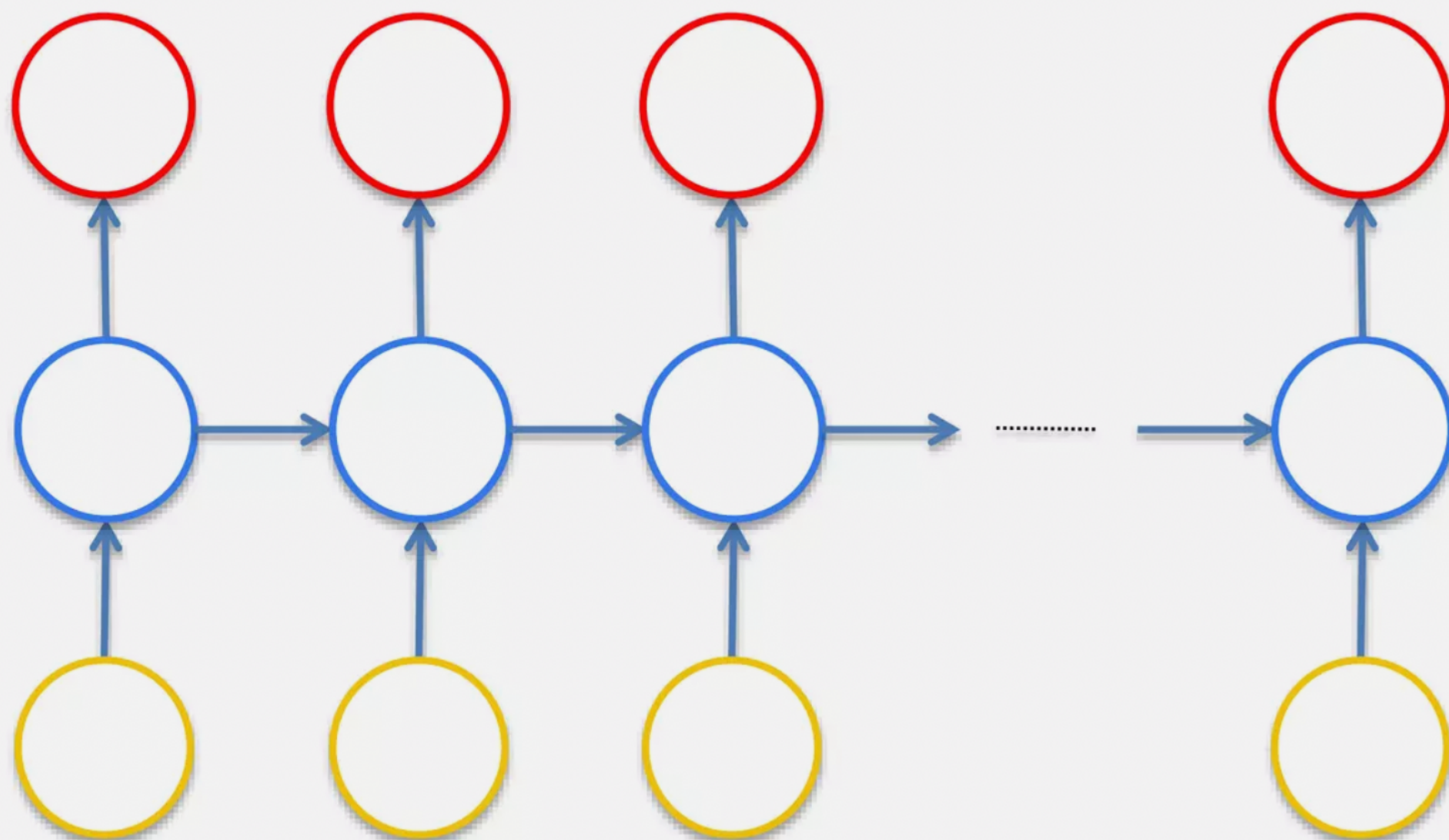




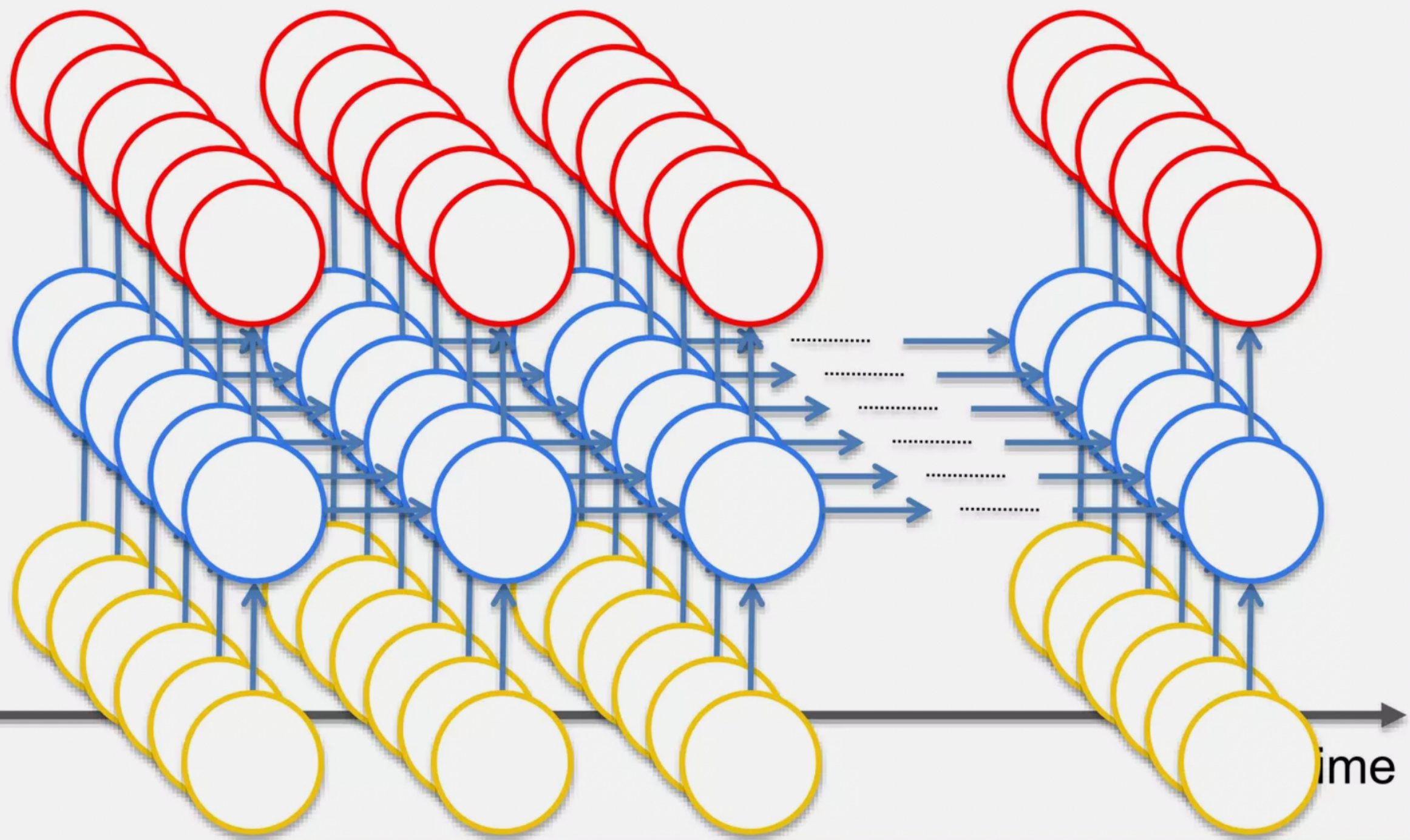


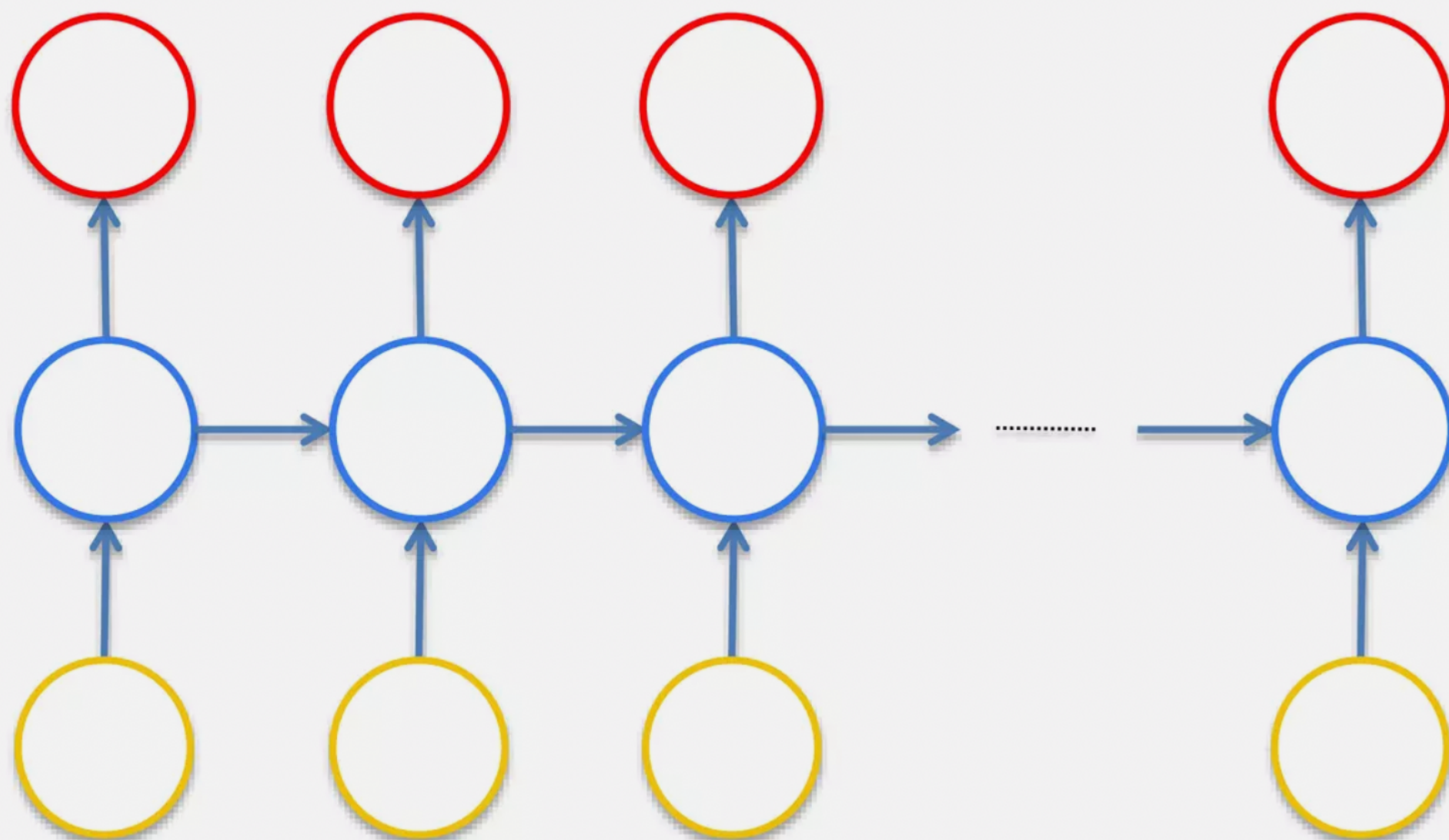






Time





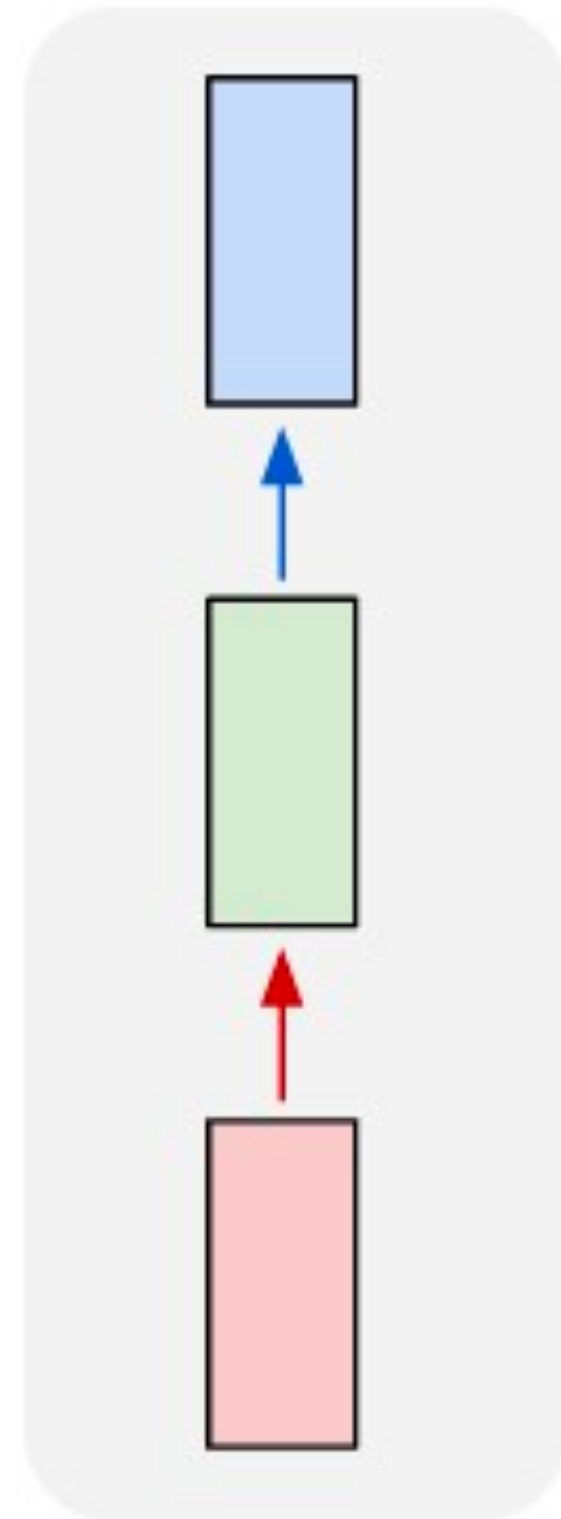
Time

RRN's Applications

One to one

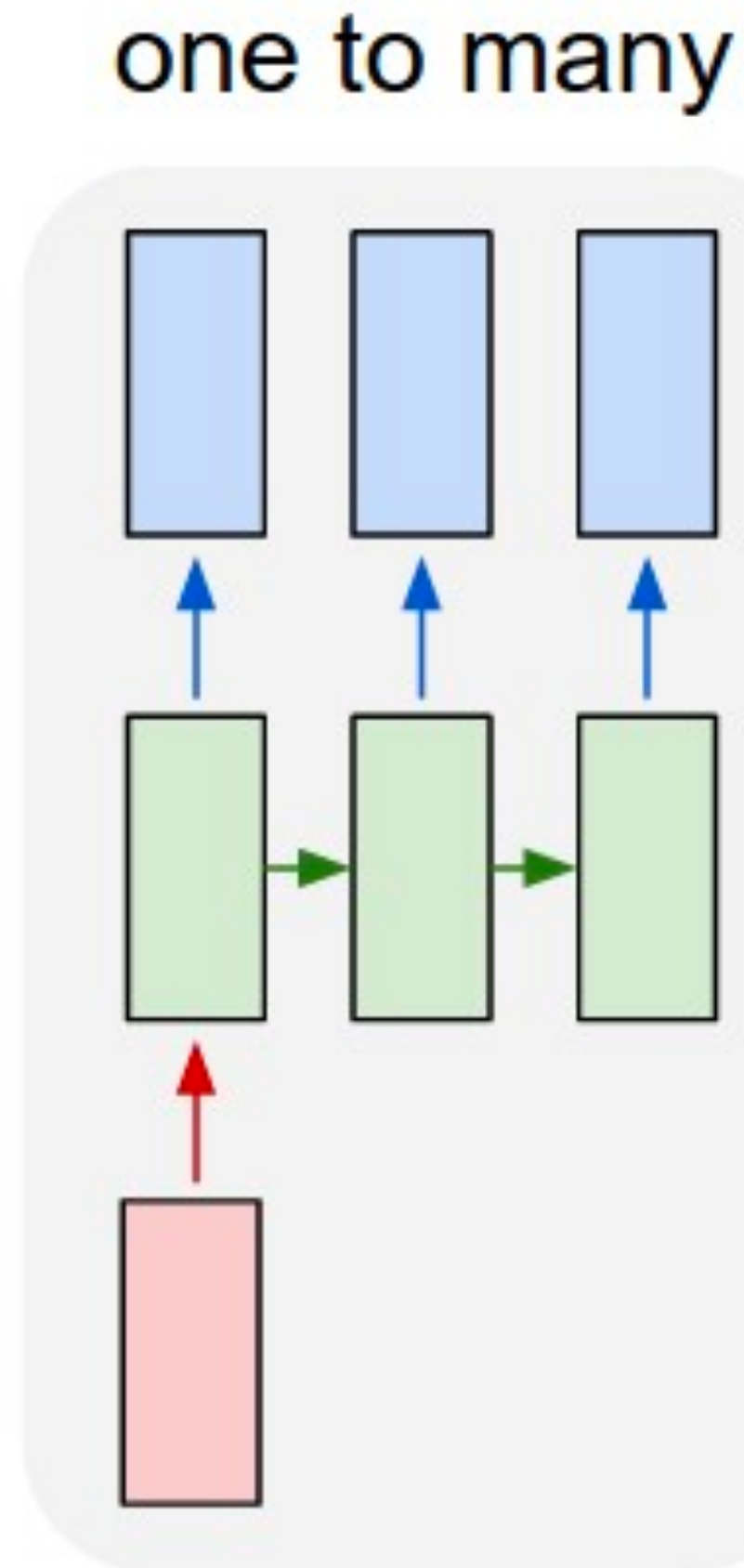
- Vanilla type without RNN
- fixed-sized input
- fixed-sized output
- Image classification

one to one



One to many

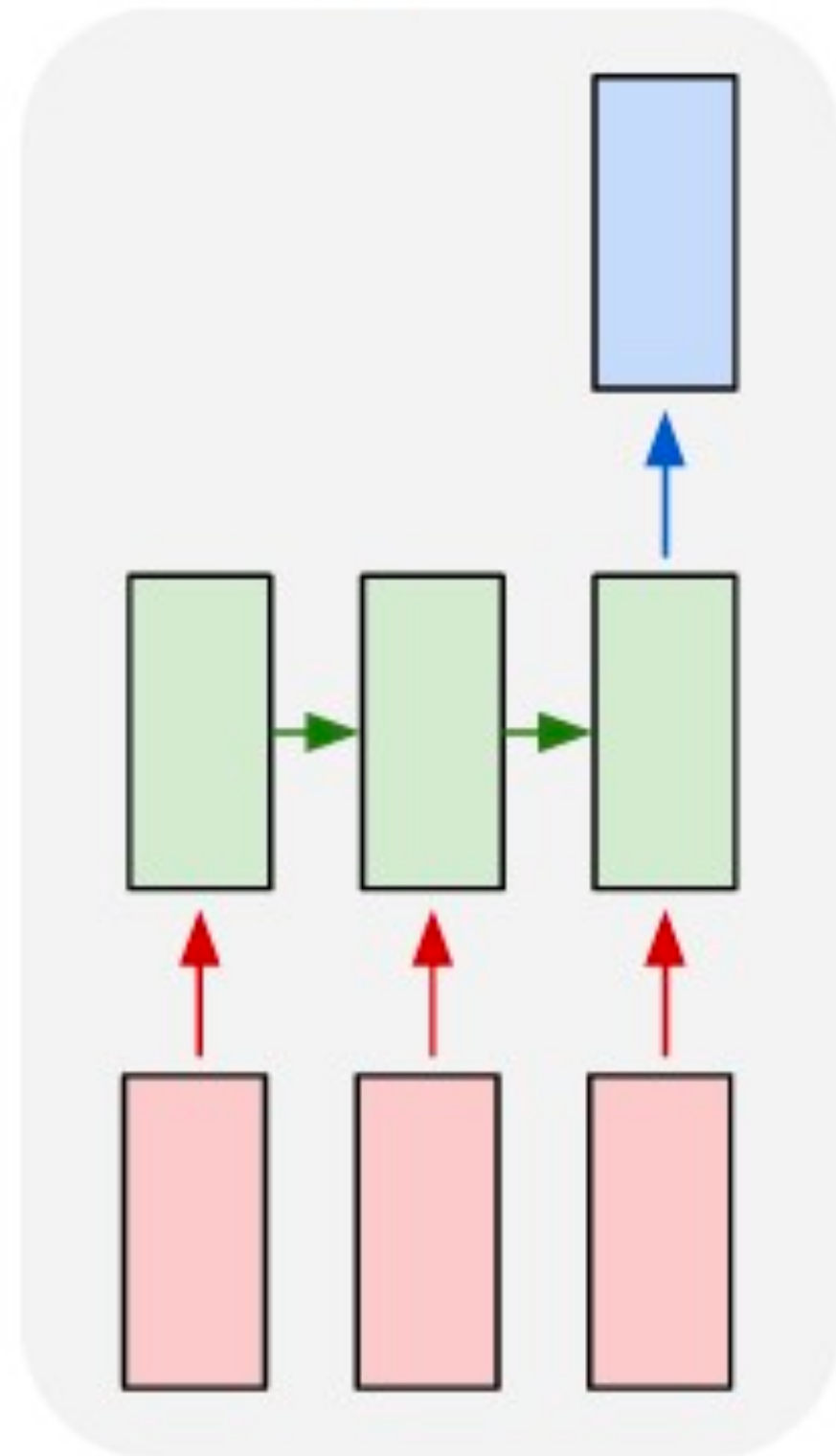
- Sequence output
- image captioning takes an image and outputs a sentence of words
- OCR (Optical Character Recognition)



Many to one

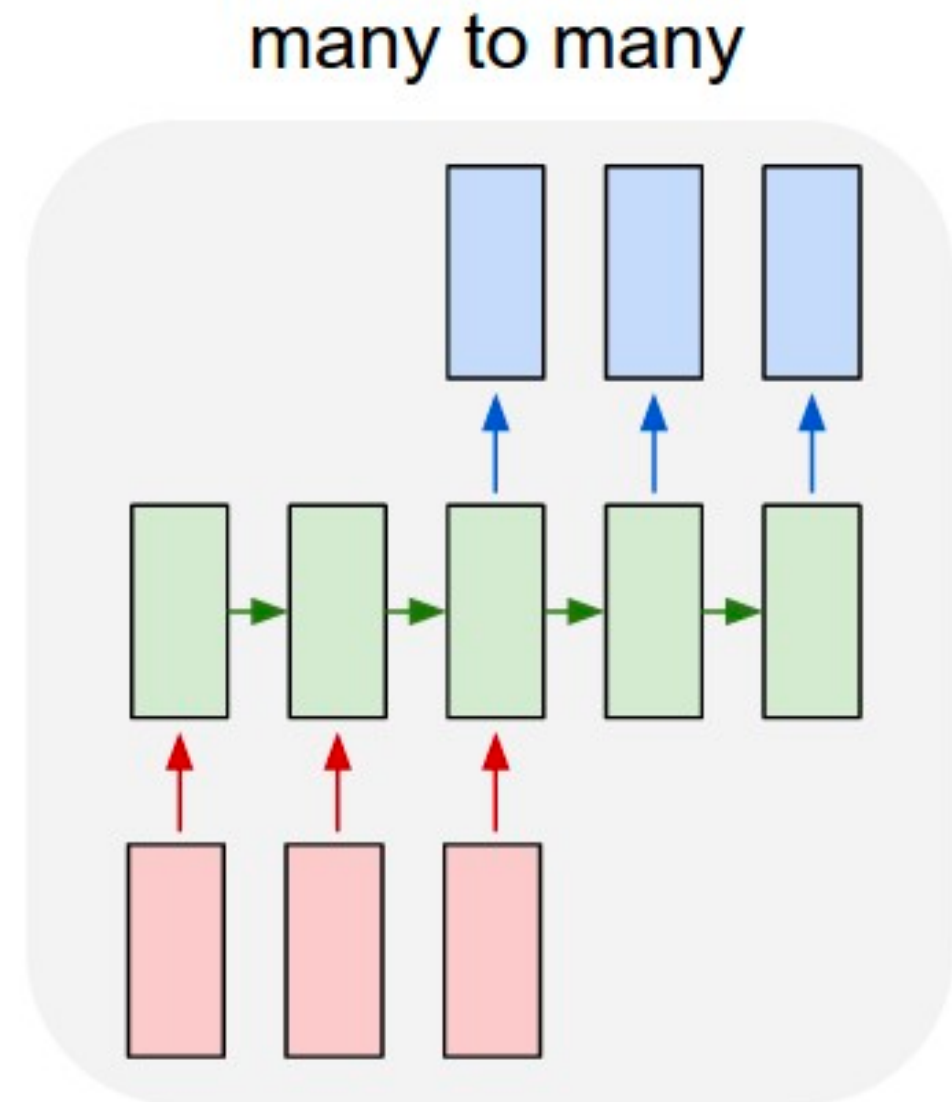
- Sequence input
- sentiment analysis where a given sentence is classified as expressing positive or negative sentiment
- Grammarly intent checker

many to one



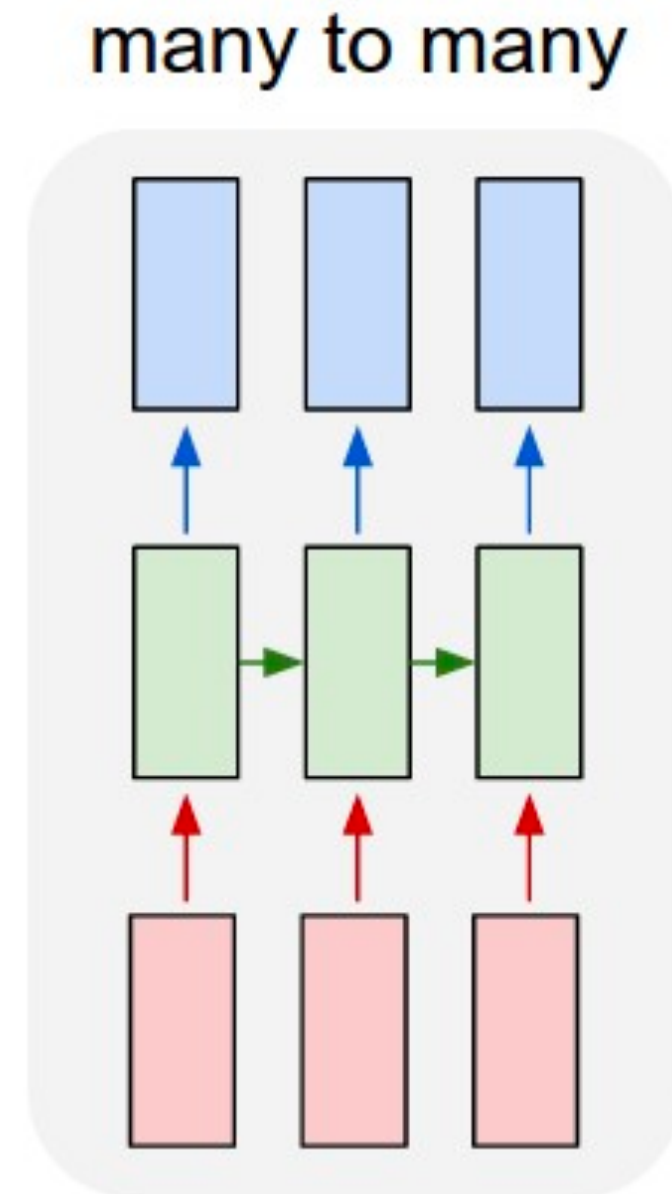
Many to many

- Sequence input and sequence output
- Machine Translation: an RNN reads a sentence in English and then outputs a sentence in French
- Grammarly spelling checker

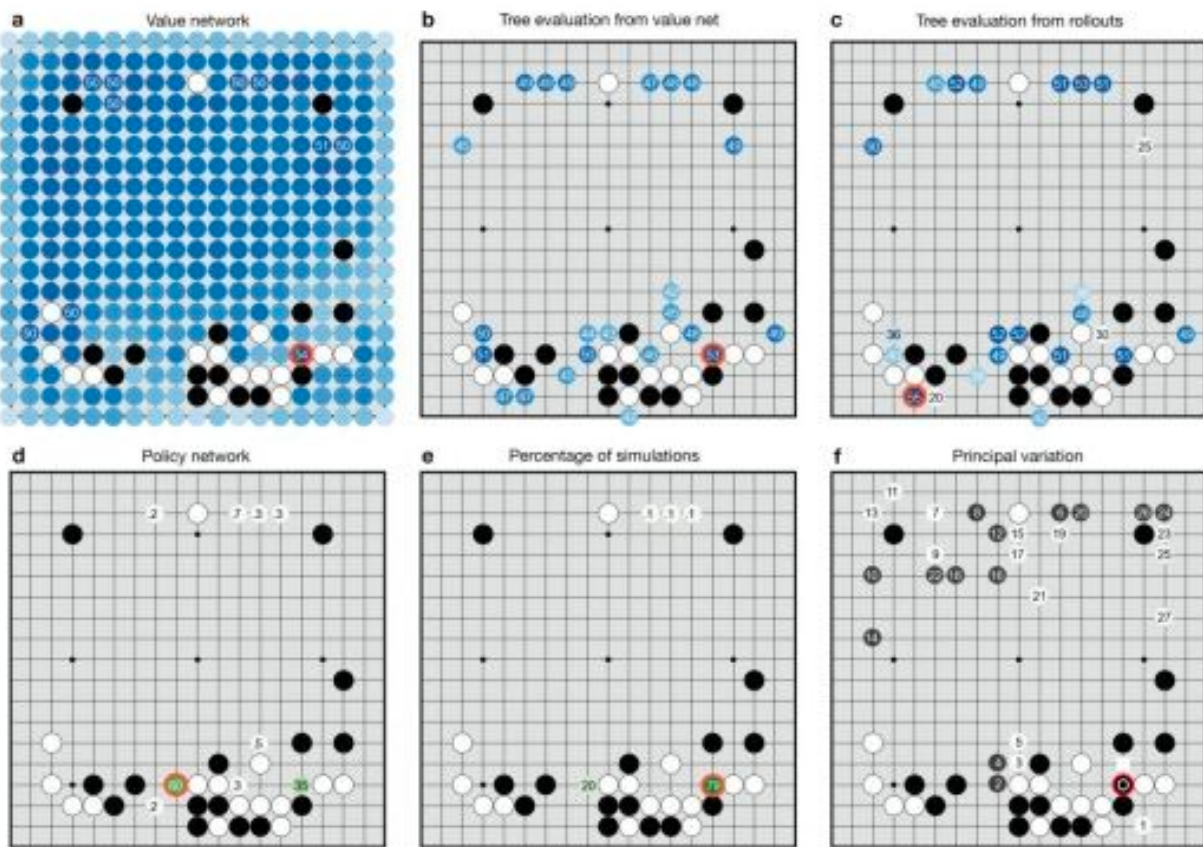


Many to many

- Synced sequence input and output
- video classification where we wish to label each frame of the video



Vanishing Gradient

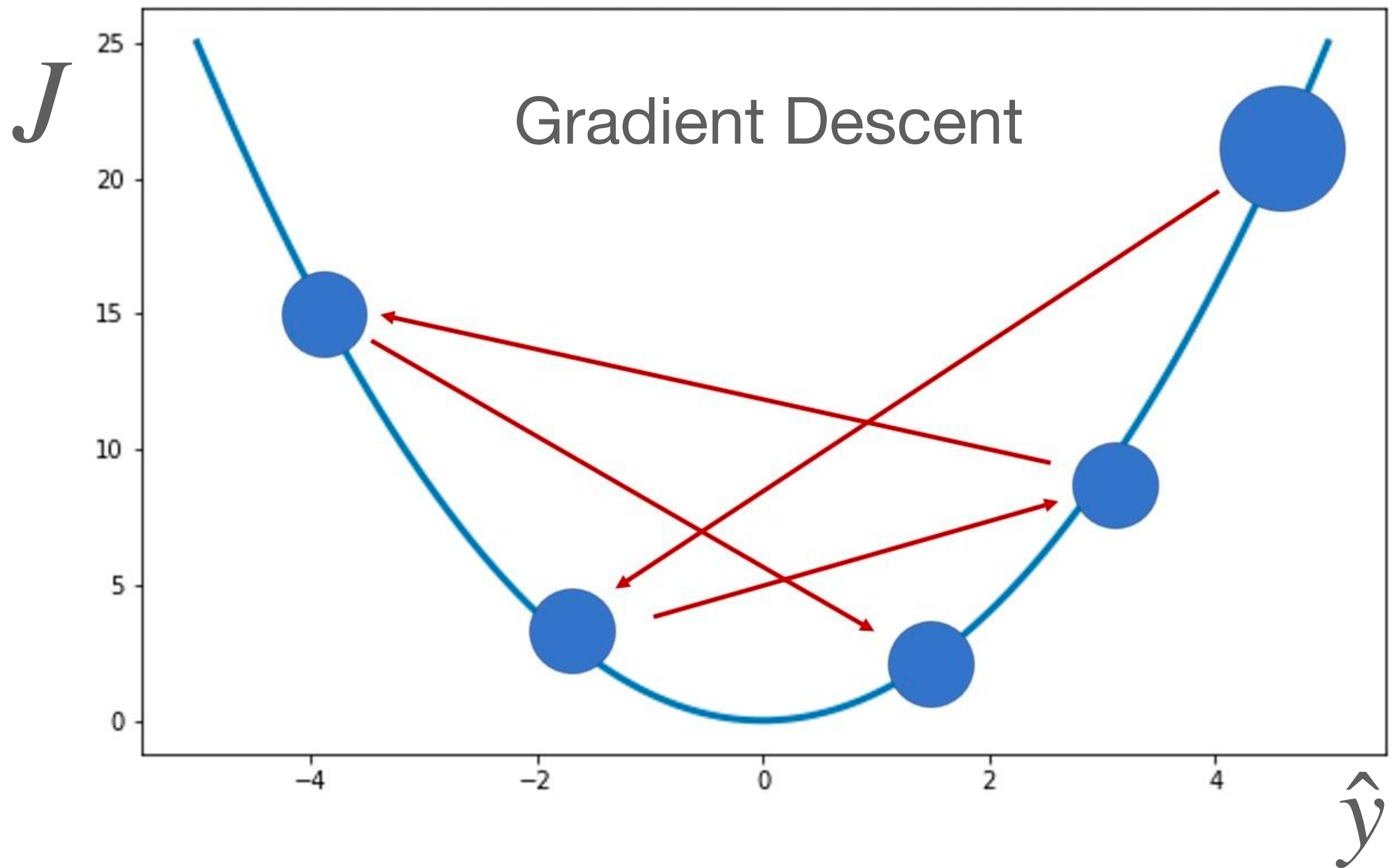


IARI



Sepp Hochreiter

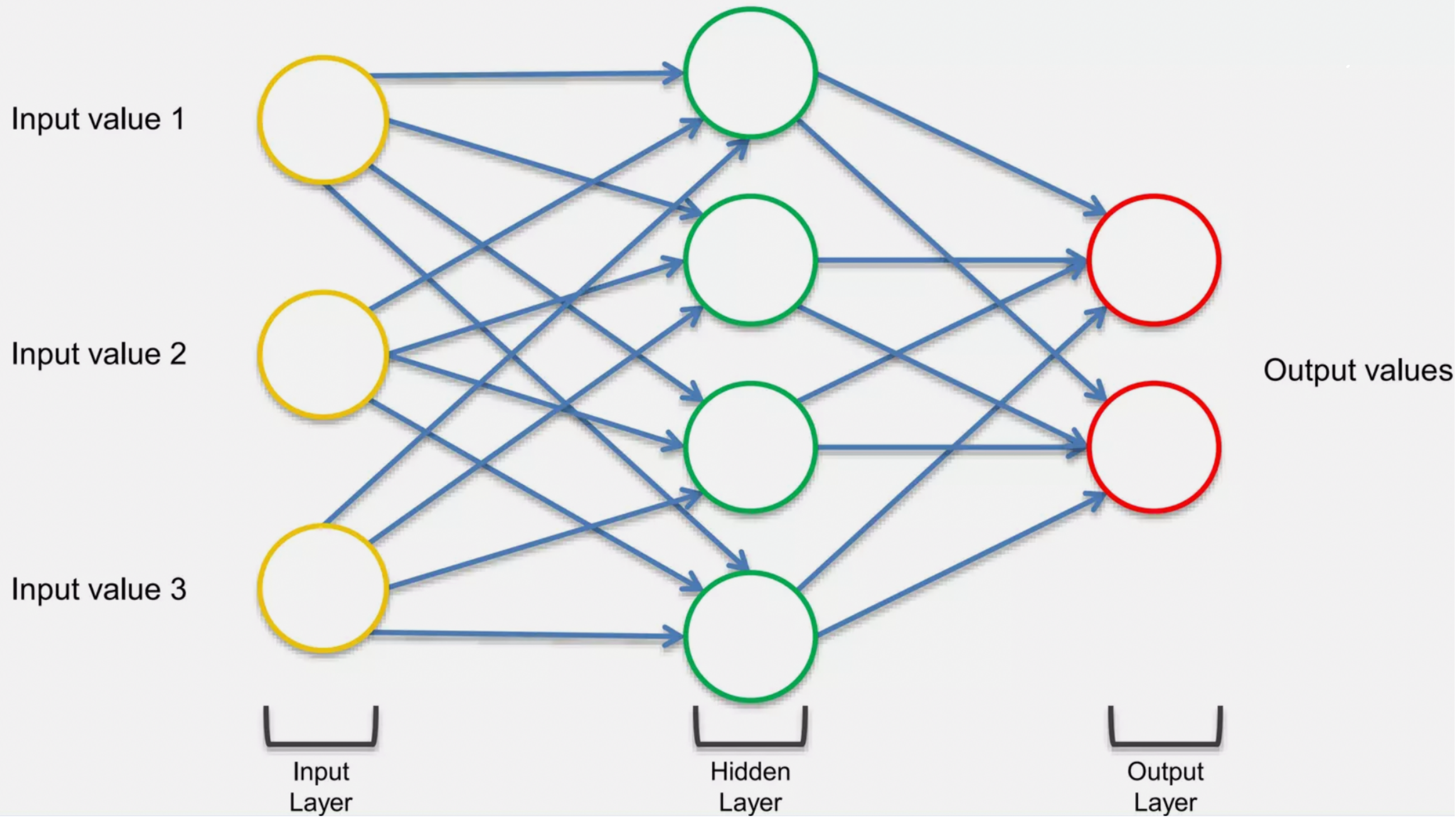
institute of advanced
research in artificial
intelligence



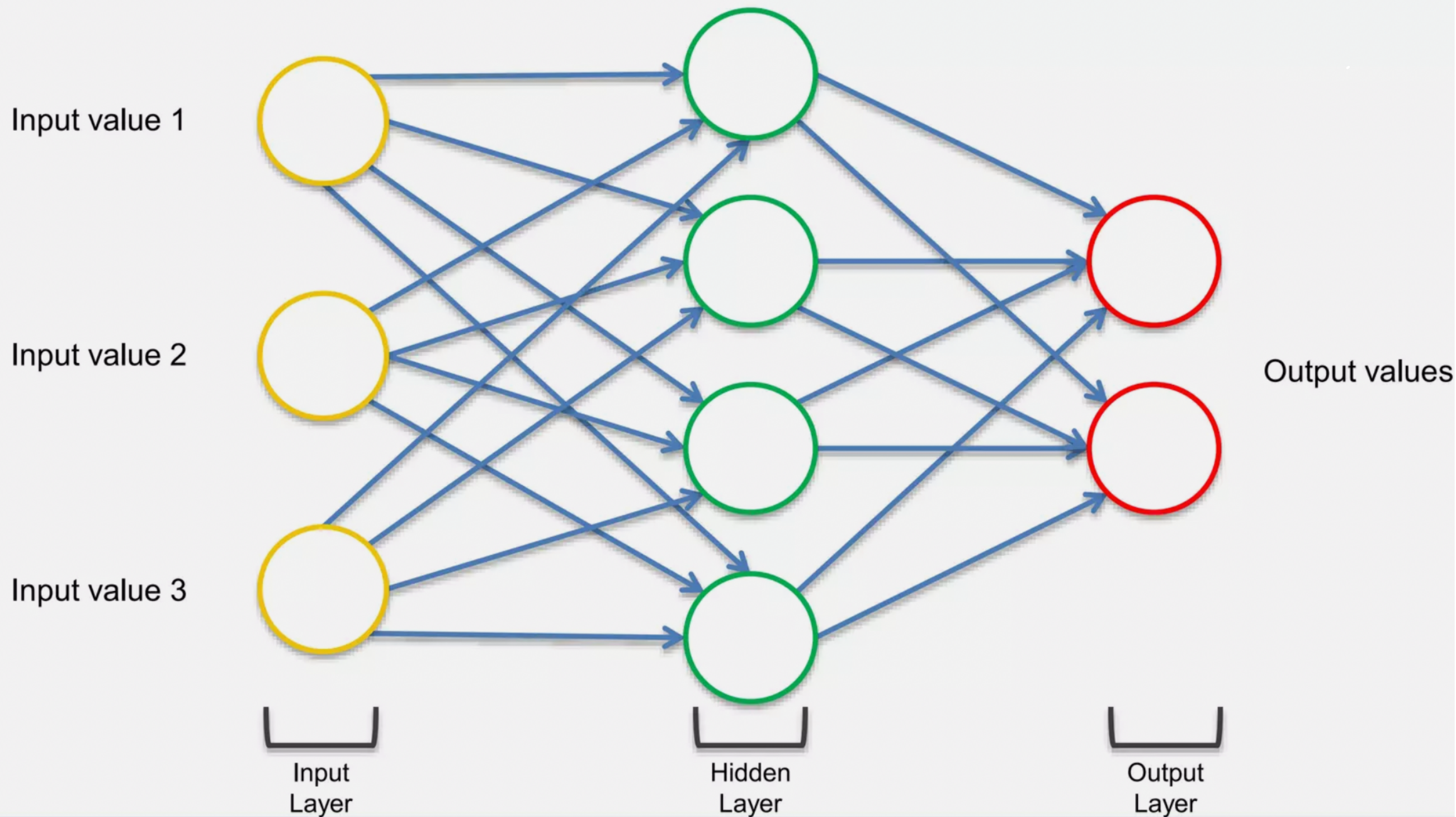
$$J = \frac{1}{2m} \sum_{i=1}^m (\hat{y} - y)^2$$

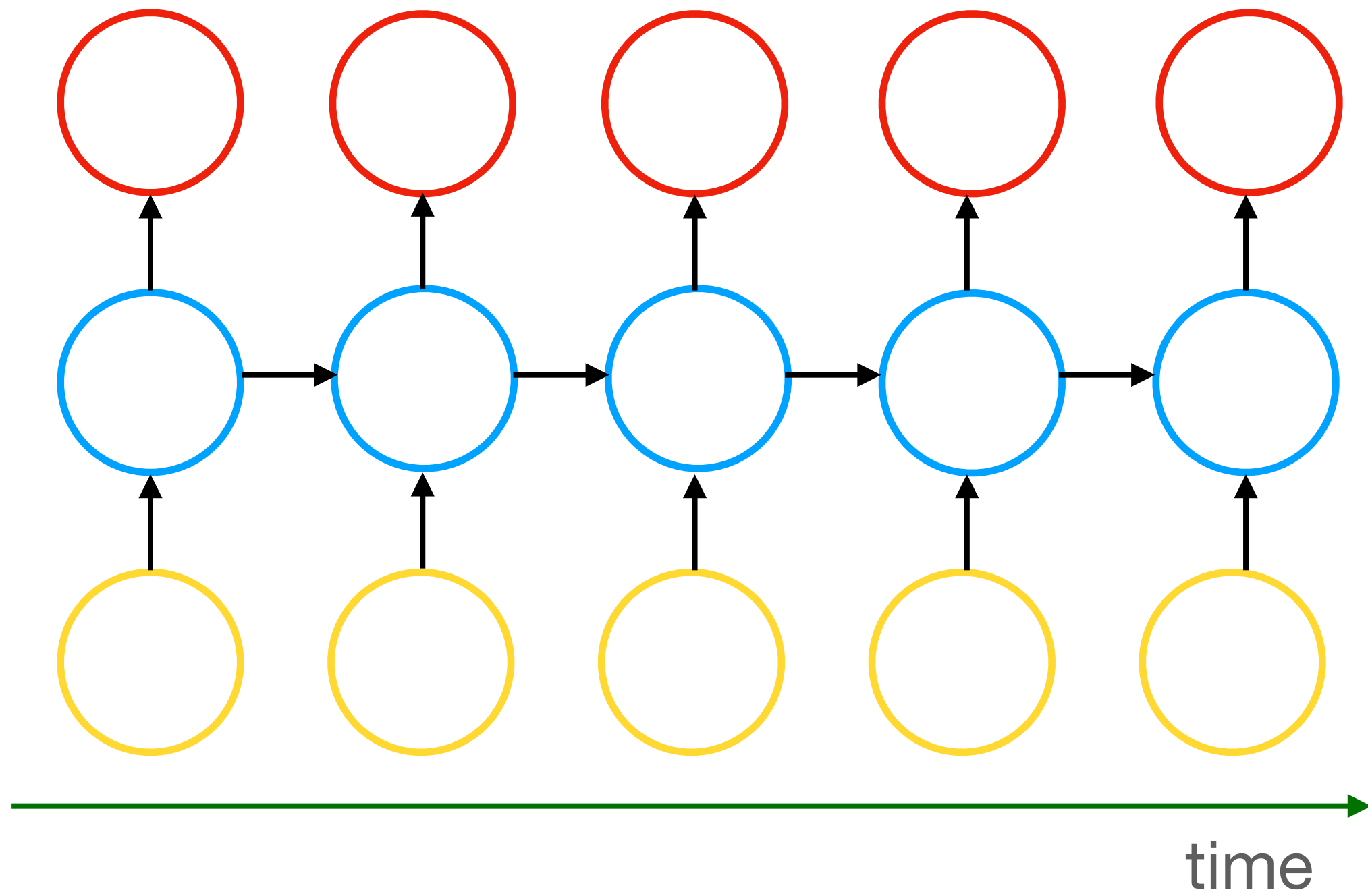
$$J = \frac{1}{2m} \sum_{i=1}^m (h_{\theta}(X) - y)^2$$

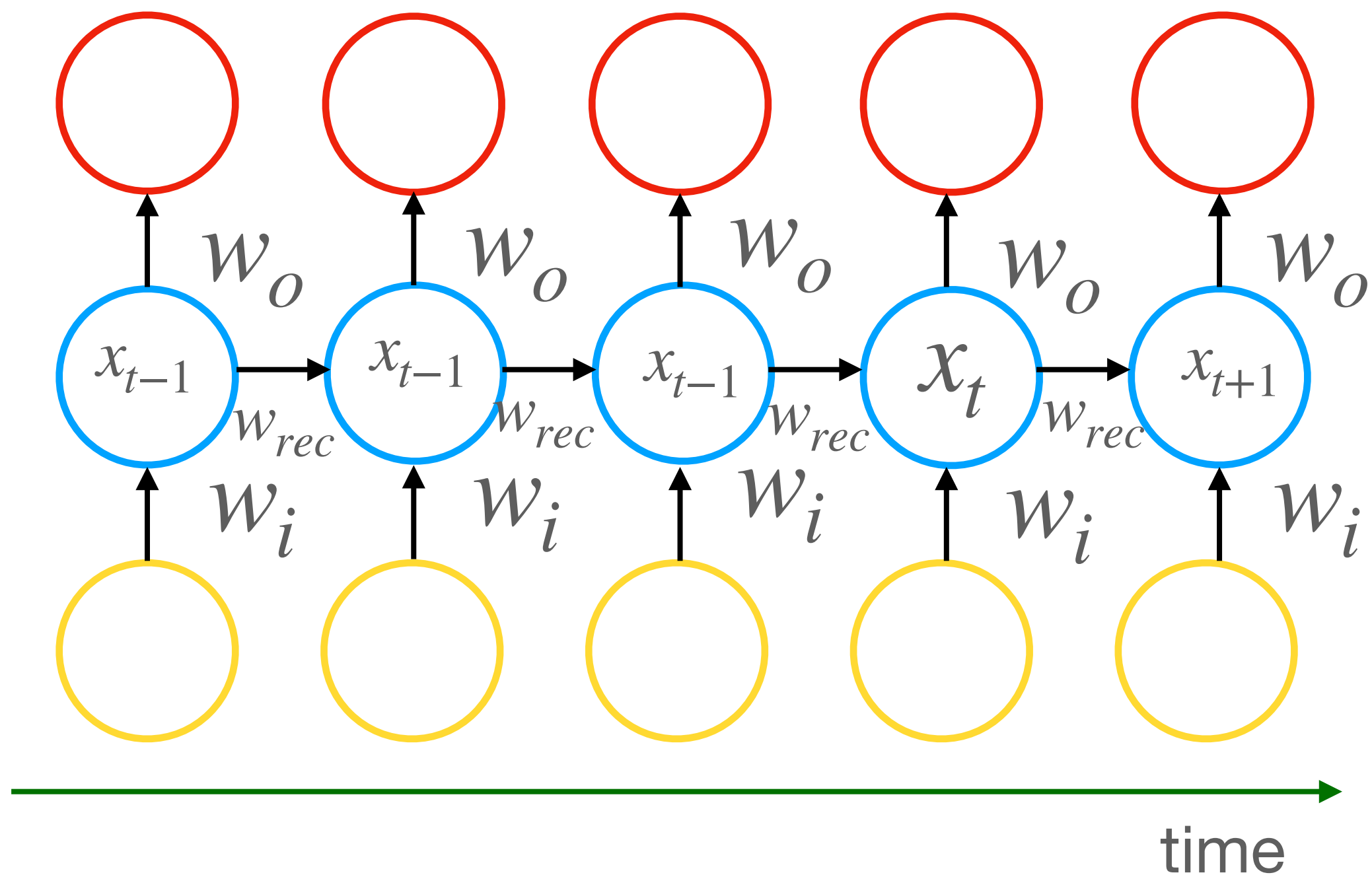
Feedforward

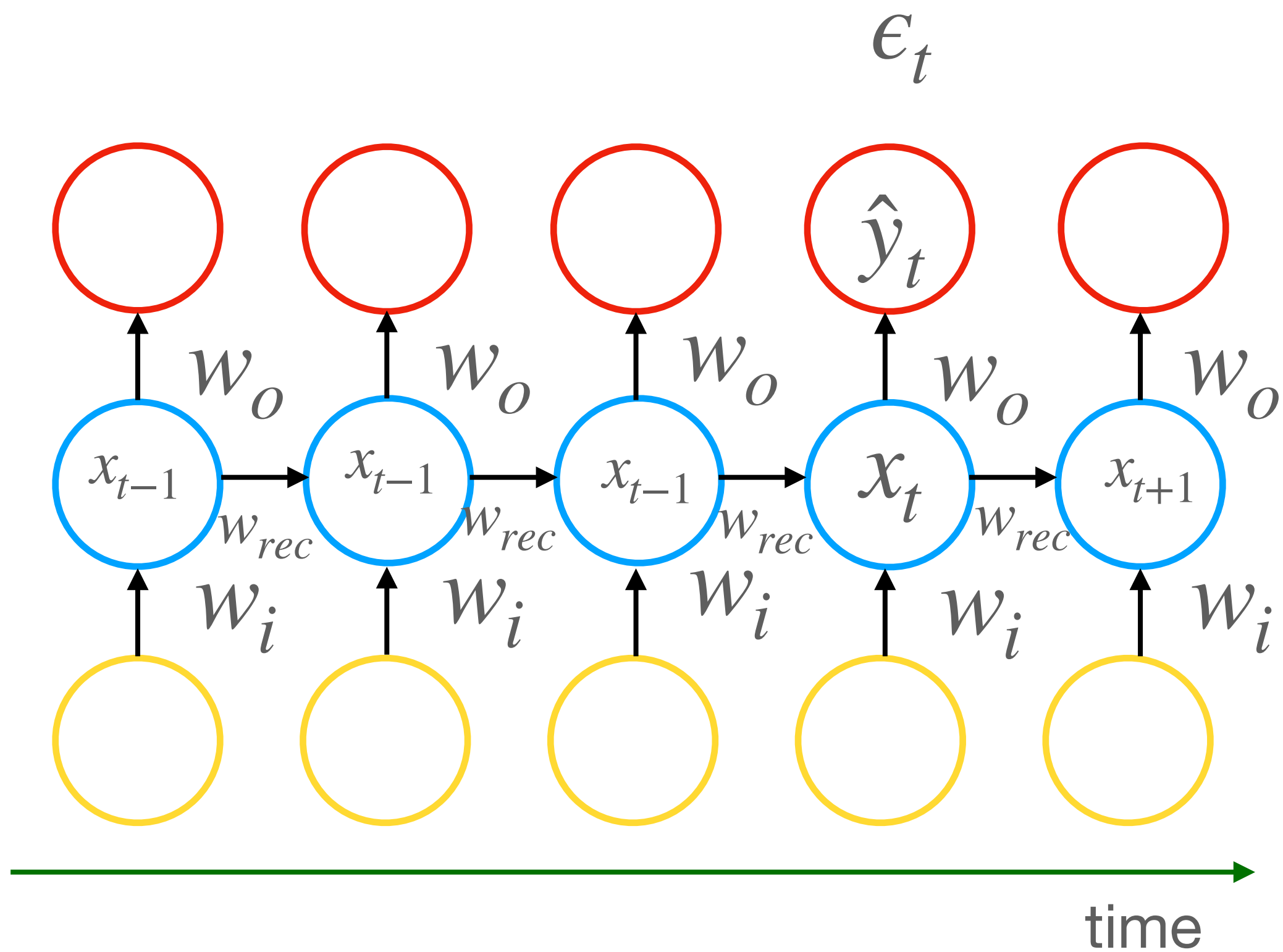


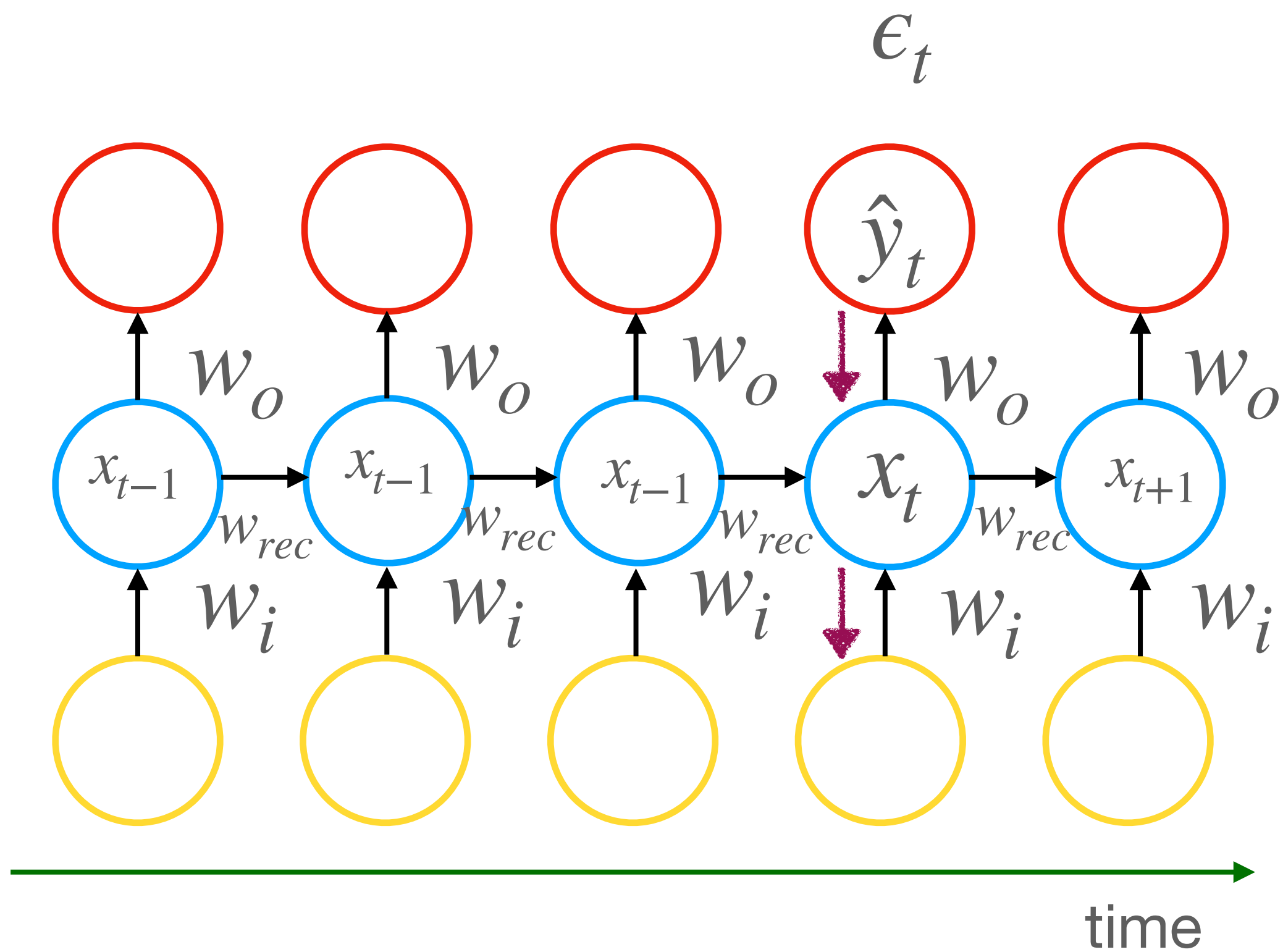
Backpropagation

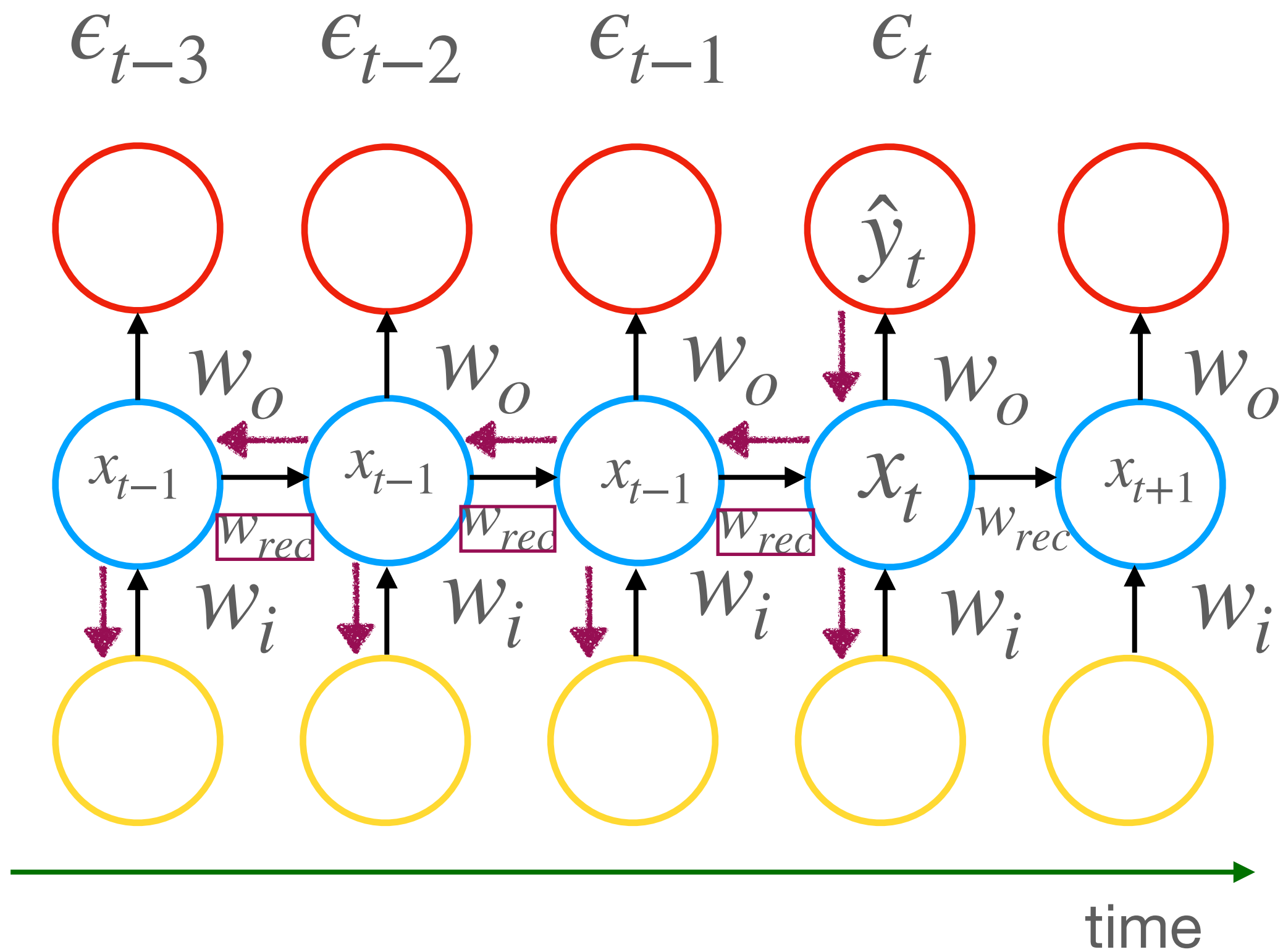


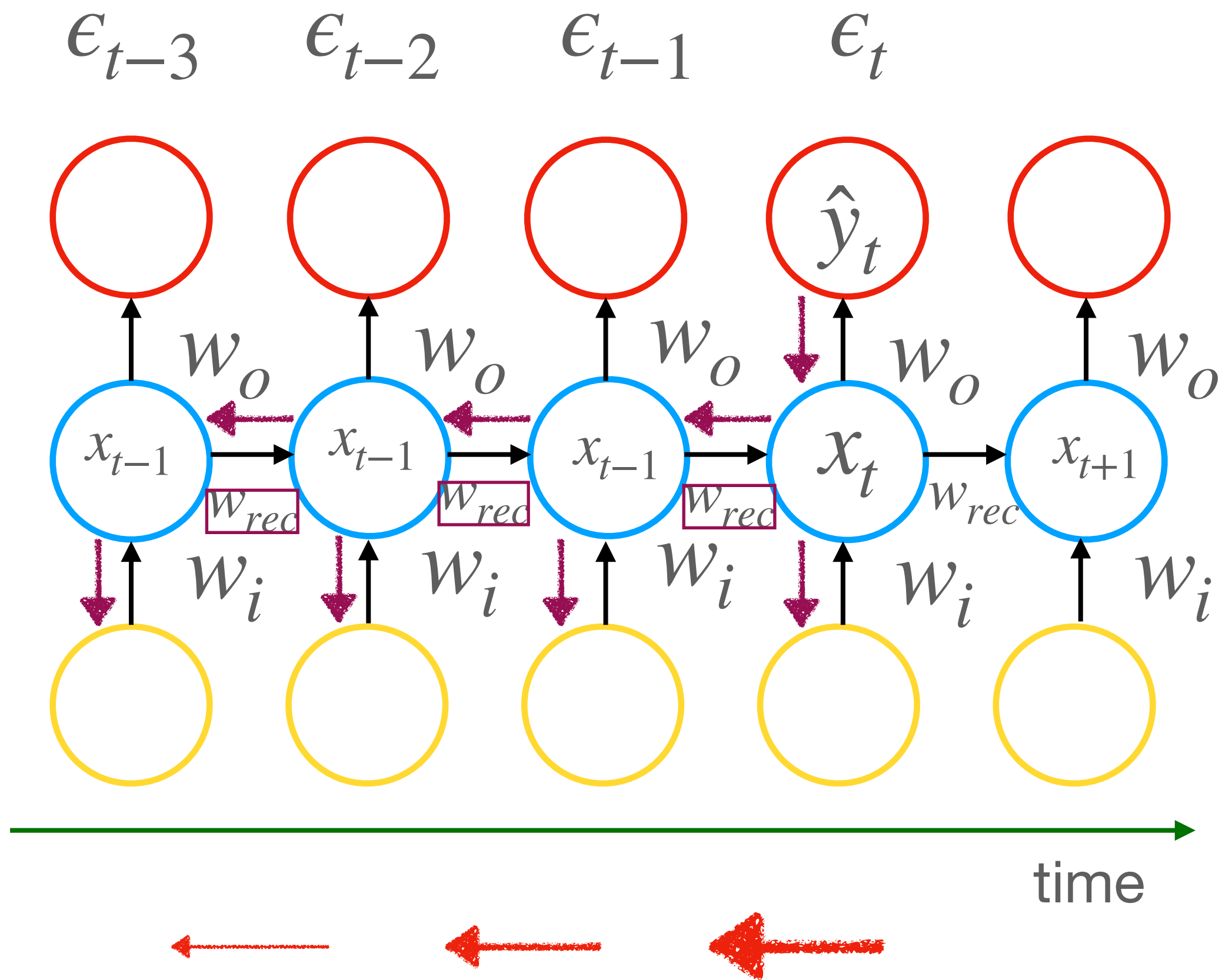












$$\frac{\partial \epsilon}{\partial \theta} = \sum_{1 \leq t \leq T} \frac{\partial \epsilon_t}{\partial \theta}$$

$$\frac{\partial \epsilon_t}{\partial \theta} = \sum_{1 \leq t \leq T} \left(\frac{\partial \epsilon_t}{\partial X_t} \frac{\partial X_t}{\partial X_k} \frac{\partial X_k}{\partial \theta} \right)$$

$$\frac{\partial X_t}{\partial X_k} = \prod_{1 \leq i \leq k} \frac{\partial X_i}{\partial X_{i-1}} = \prod_{1 \leq i \leq k} W_{rec}^T \text{diag}(\sigma'(x_{i-1}))$$

$$\frac{\partial X_t}{\partial X_k} = \prod_{1 \leq i \leq k} \frac{\partial X_i}{\partial X_{i-1}} = \prod_{1 \leq i \leq k} W_{rec}^T \text{diag}(\sigma'(x_{i-1}))$$

$$W_{rec}$$

$$W_{rec}$$

The vanishing gradient problem

Solutions

- Exploding Gradient
 - Truncated Backpropagation
 - Penalties
 - Gradient clipping
- Vanishing Gradient
 - Weight initialization
 - Echo state networks
 - Long Short-Term Memory Networks