

E9 205 Machine Learning for Signal Processing

Recurrent Networks

05-11-2018



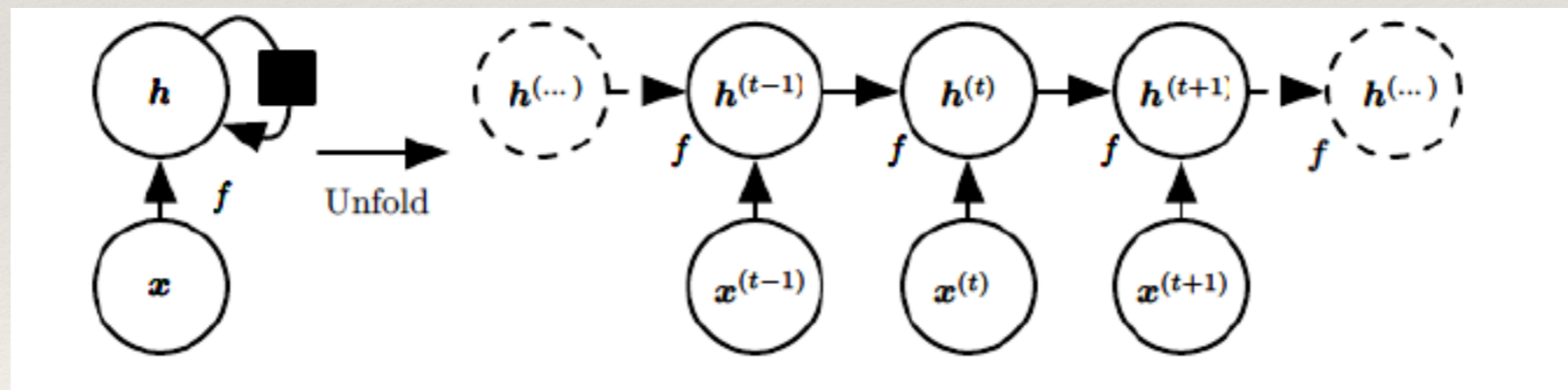
Recurrent Networks

$$\mathbf{s}^{(t)} = f(\mathbf{s}^{(t-1)}; \boldsymbol{\theta}),$$

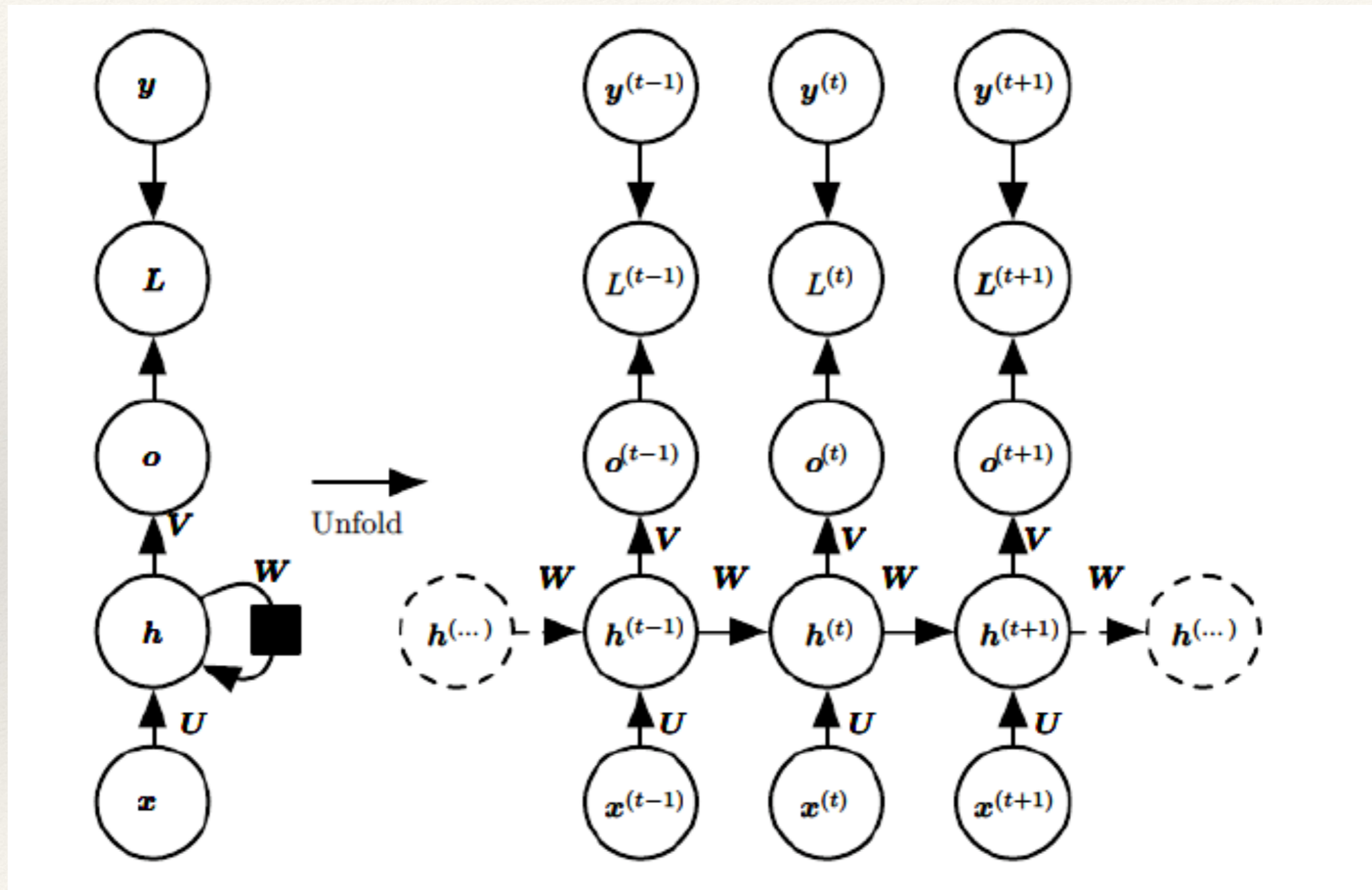
$$\begin{aligned} \mathbf{s}^{(3)} &= f(\mathbf{s}^{(2)}; \boldsymbol{\theta}) \\ &= f(f(\mathbf{s}^{(1)}; \boldsymbol{\theta}); \boldsymbol{\theta}) \end{aligned}$$

$$\mathbf{s}^{(t)} = f(\mathbf{s}^{(t-1)}, \mathbf{x}^{(t)}; \boldsymbol{\theta}),$$

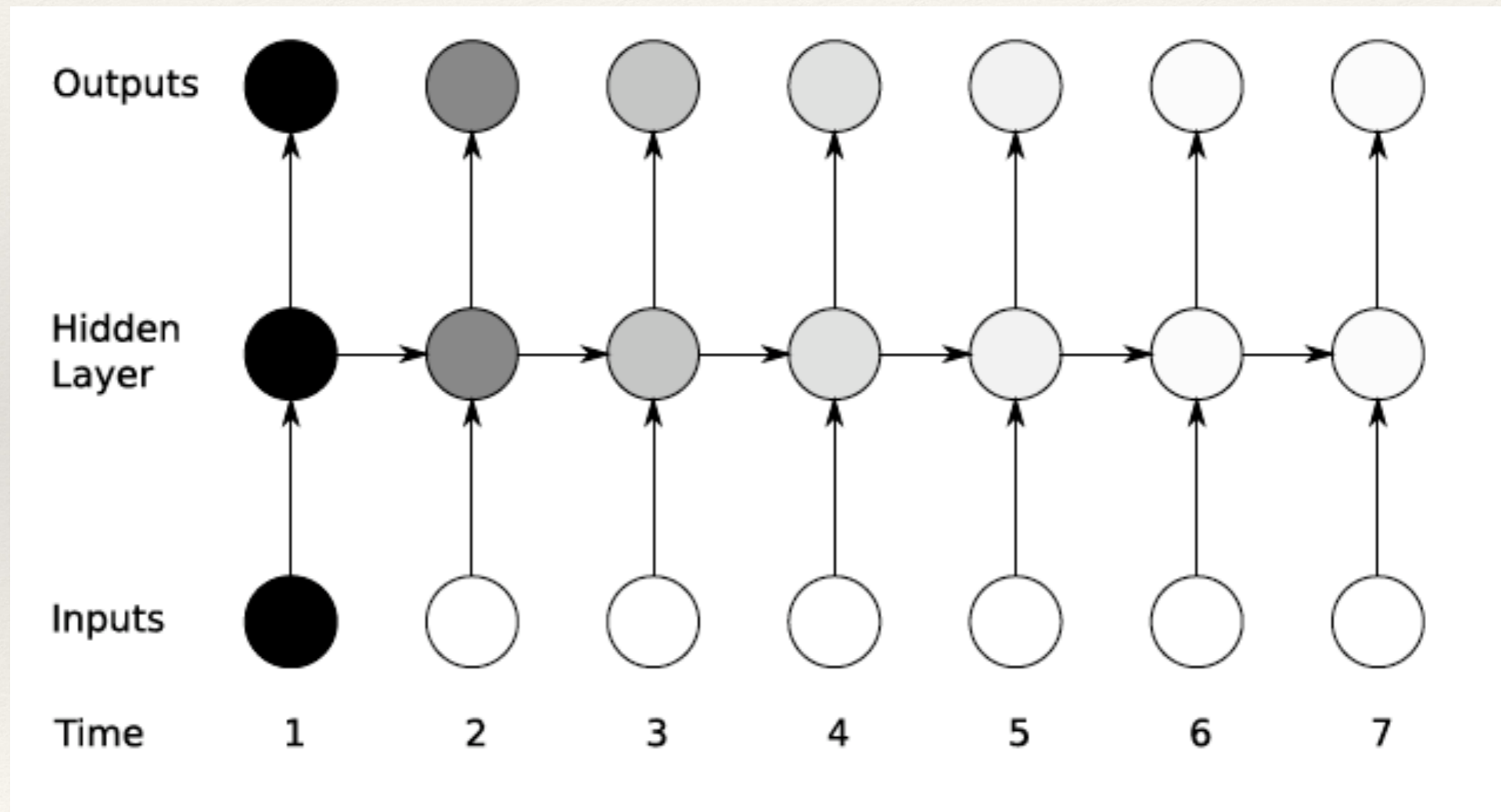
$$\mathbf{h}^{(t)} = f(\mathbf{h}^{(t-1)}, \mathbf{x}^{(t)}; \boldsymbol{\theta}),$$



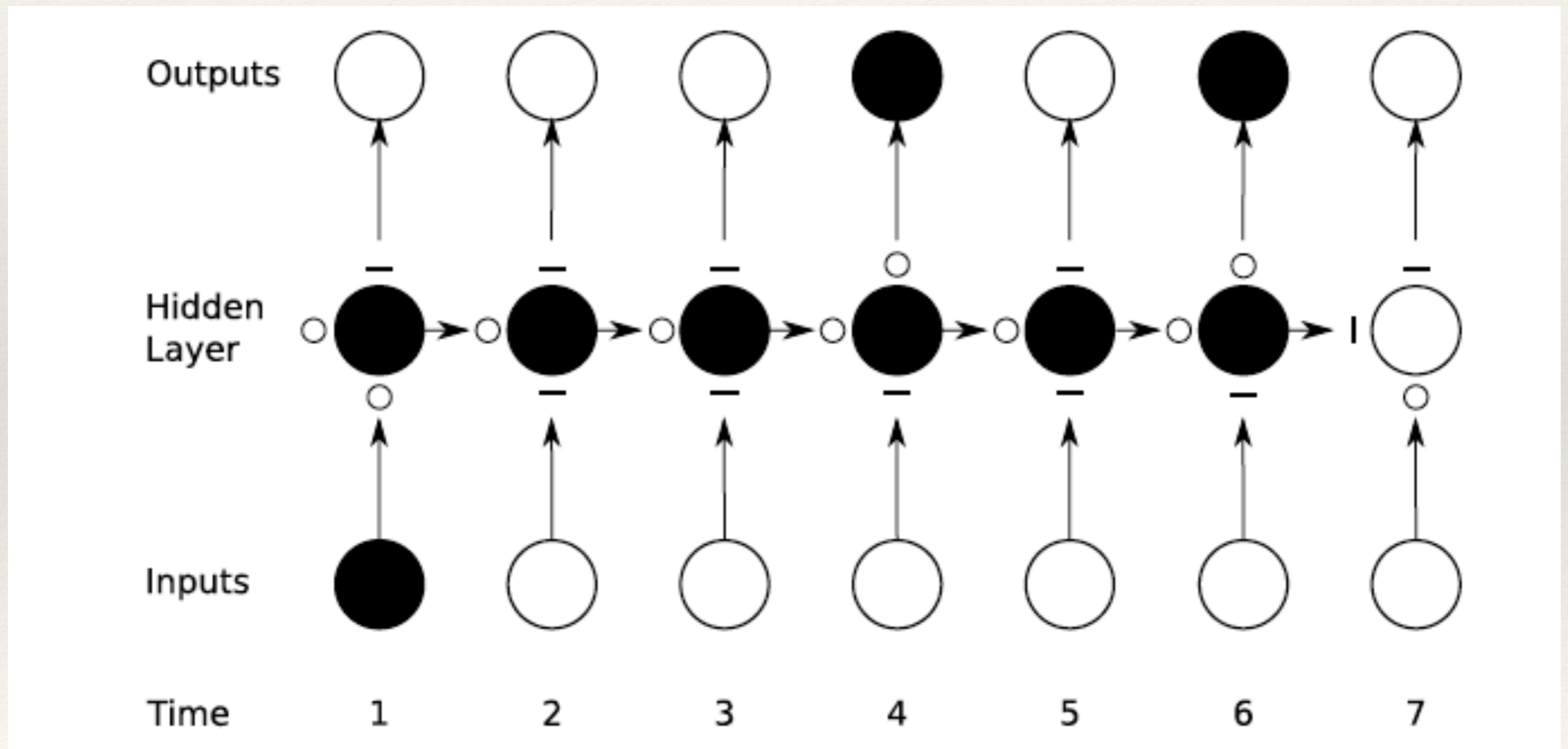
Recurrent Networks



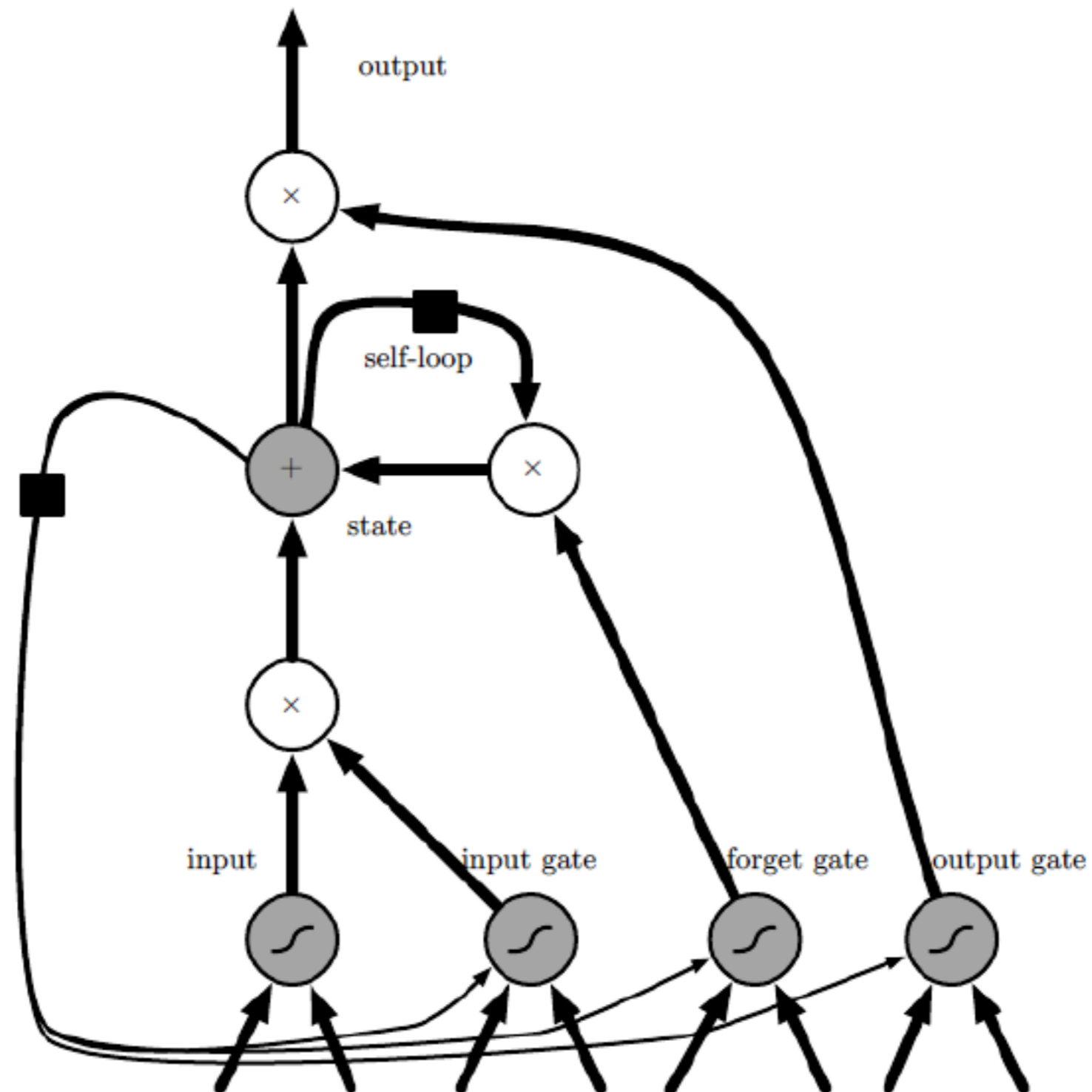
Long-term Dependency Issues



Long-Short Term Memory



Long Short Term Memory Networks



Long Short Term Memory Networks

$$f_i^{(t)} = \sigma \left(b_i^f + \sum_j U_{i,j}^f x_j^{(t)} + \sum_j W_{i,j}^f h_j^{(t-1)} \right)$$

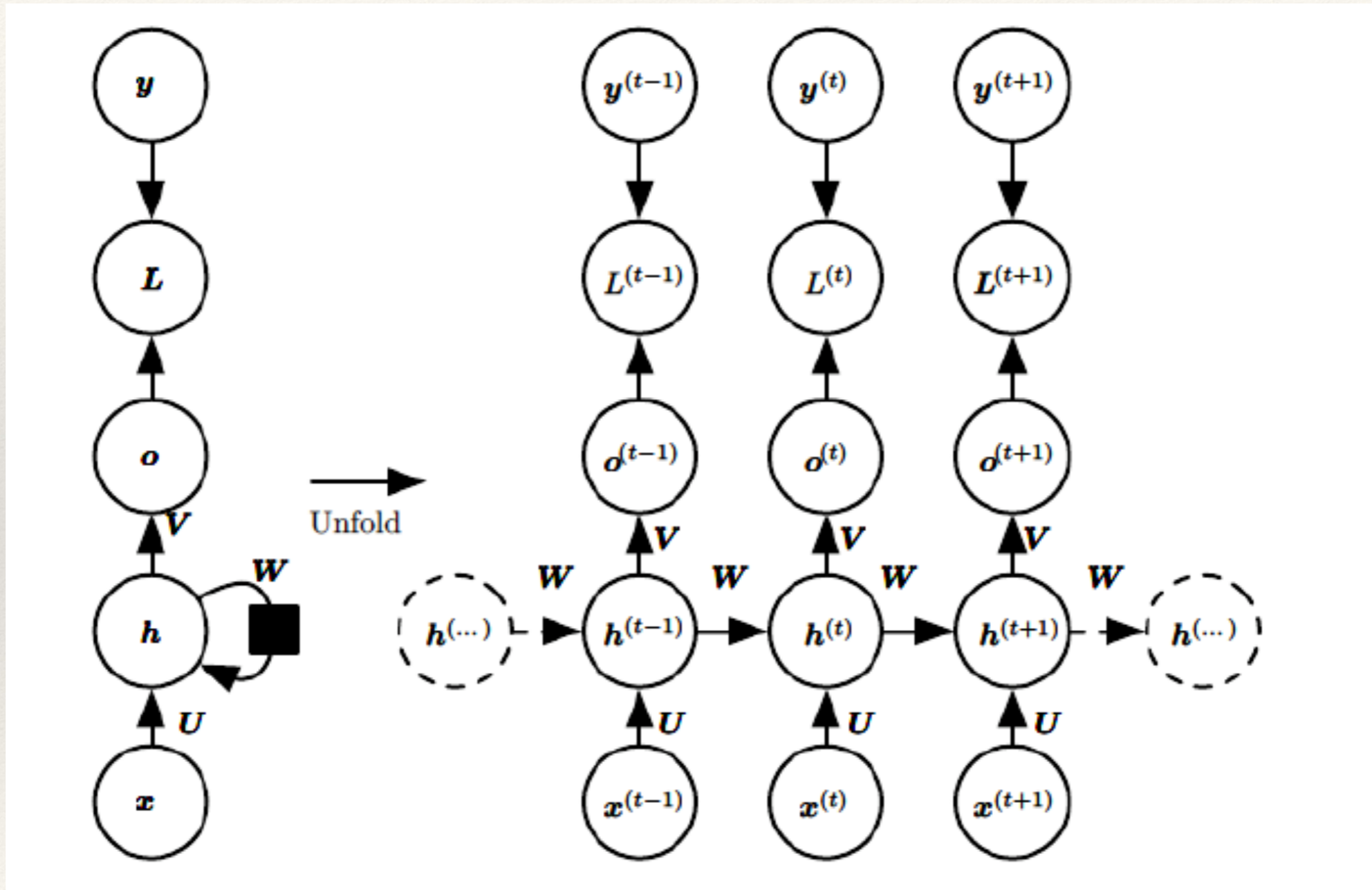
$$s_i^{(t)} = f_i^{(t)} s_i^{(t-1)} + g_i^{(t)} \sigma \left(b_i + \sum_j U_{i,j} x_j^{(t)} + \sum_j W_{i,j} h_j^{(t-1)} \right)$$

$$g_i^{(t)} = \sigma \left(b_i^g + \sum_j U_{i,j}^g x_j^{(t)} + \sum_j W_{i,j}^g h_j^{(t-1)} \right)$$

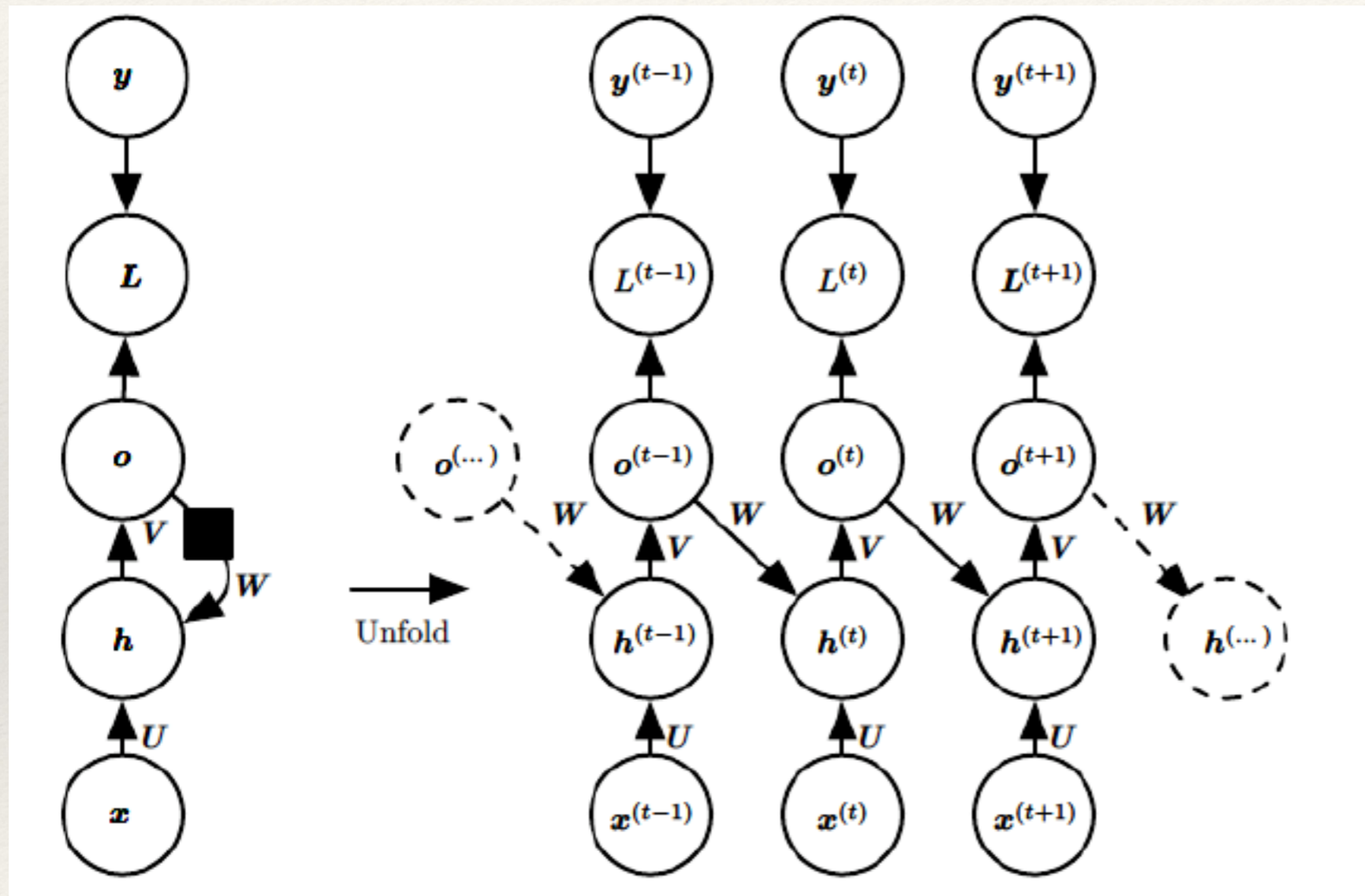
$$h_i^{(t)} = \tanh \left(s_i^{(t)} \right) q_i^{(t)}$$

$$q_i^{(t)} = \sigma \left(b_i^o + \sum_j U_{i,j}^o x_j^{(t)} + \sum_j W_{i,j}^o h_j^{(t-1)} \right)$$

Standard Recurrent Networks

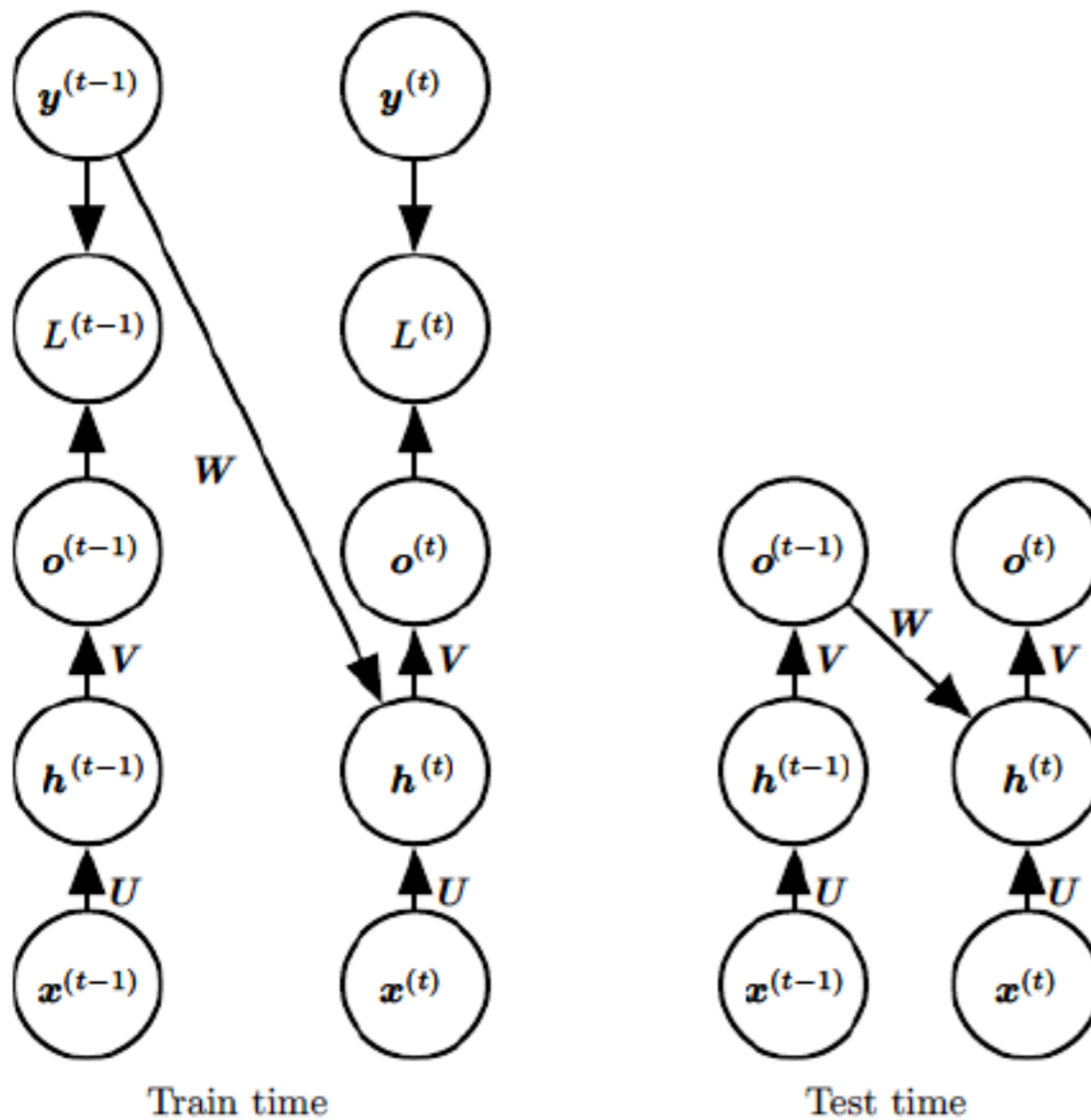


Other Recurrent Networks



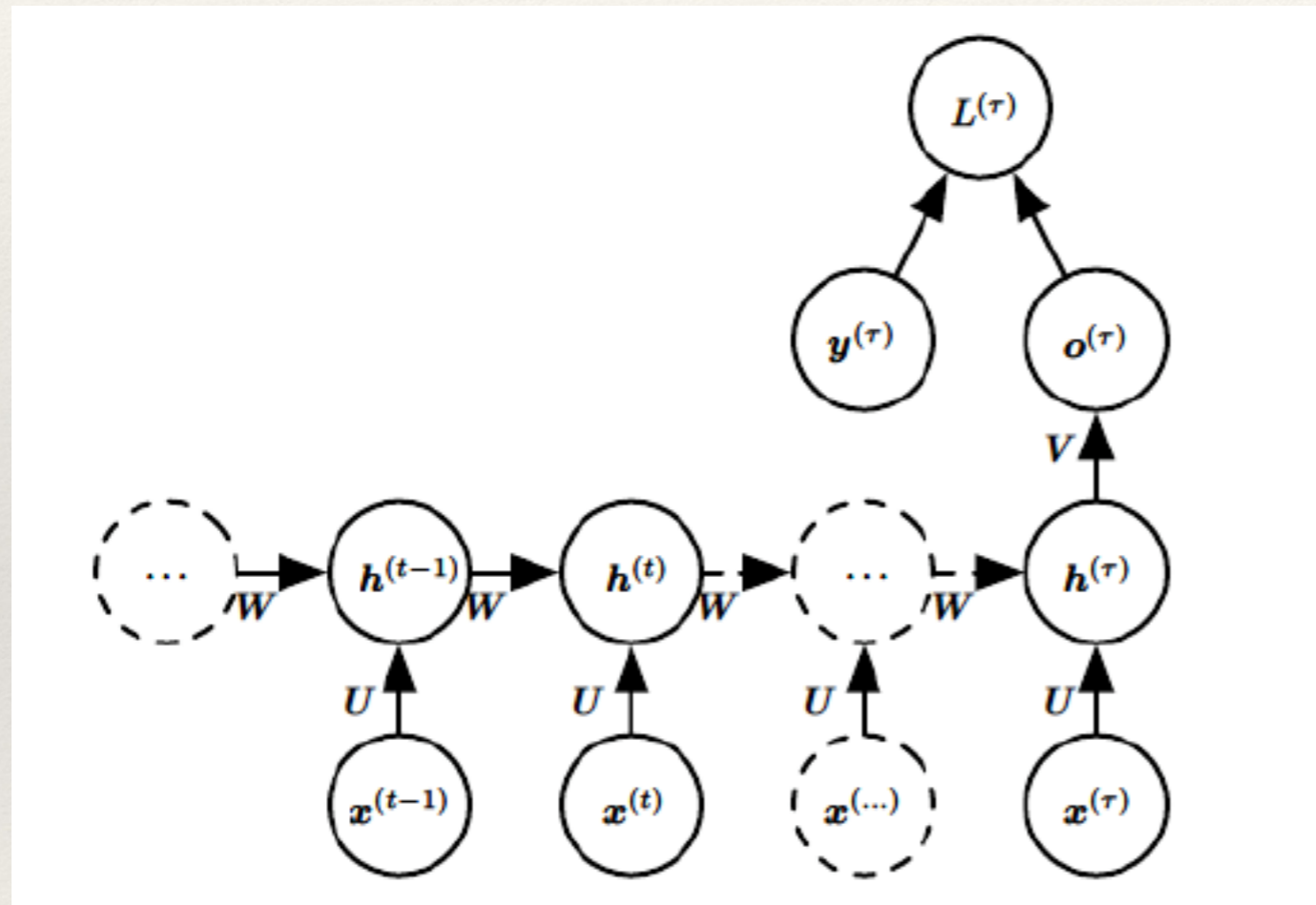
**Teacher
Forcing Networks**

Recurrent Networks



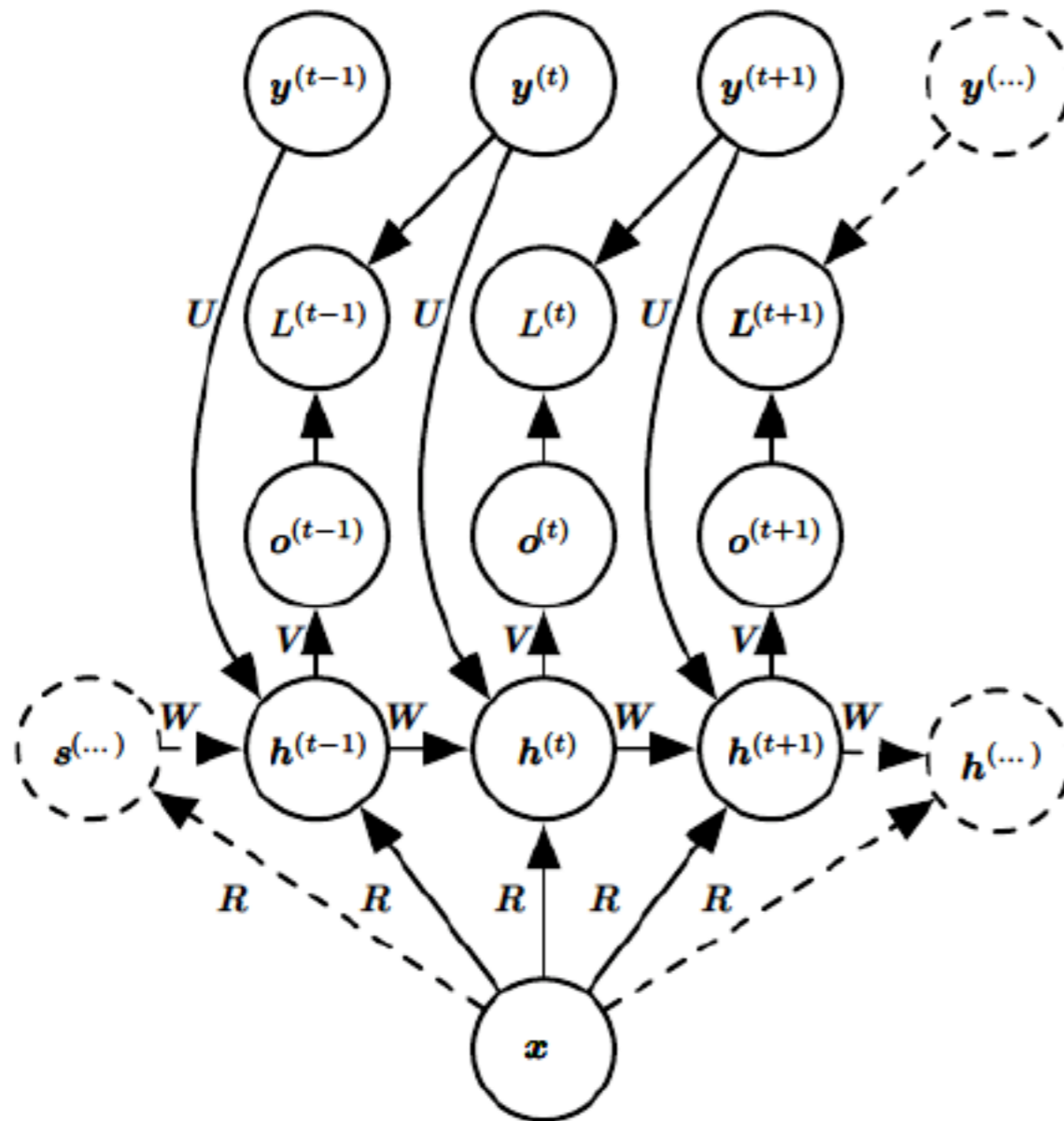
**Teacher
Forcing Networks**

Recurrent Networks



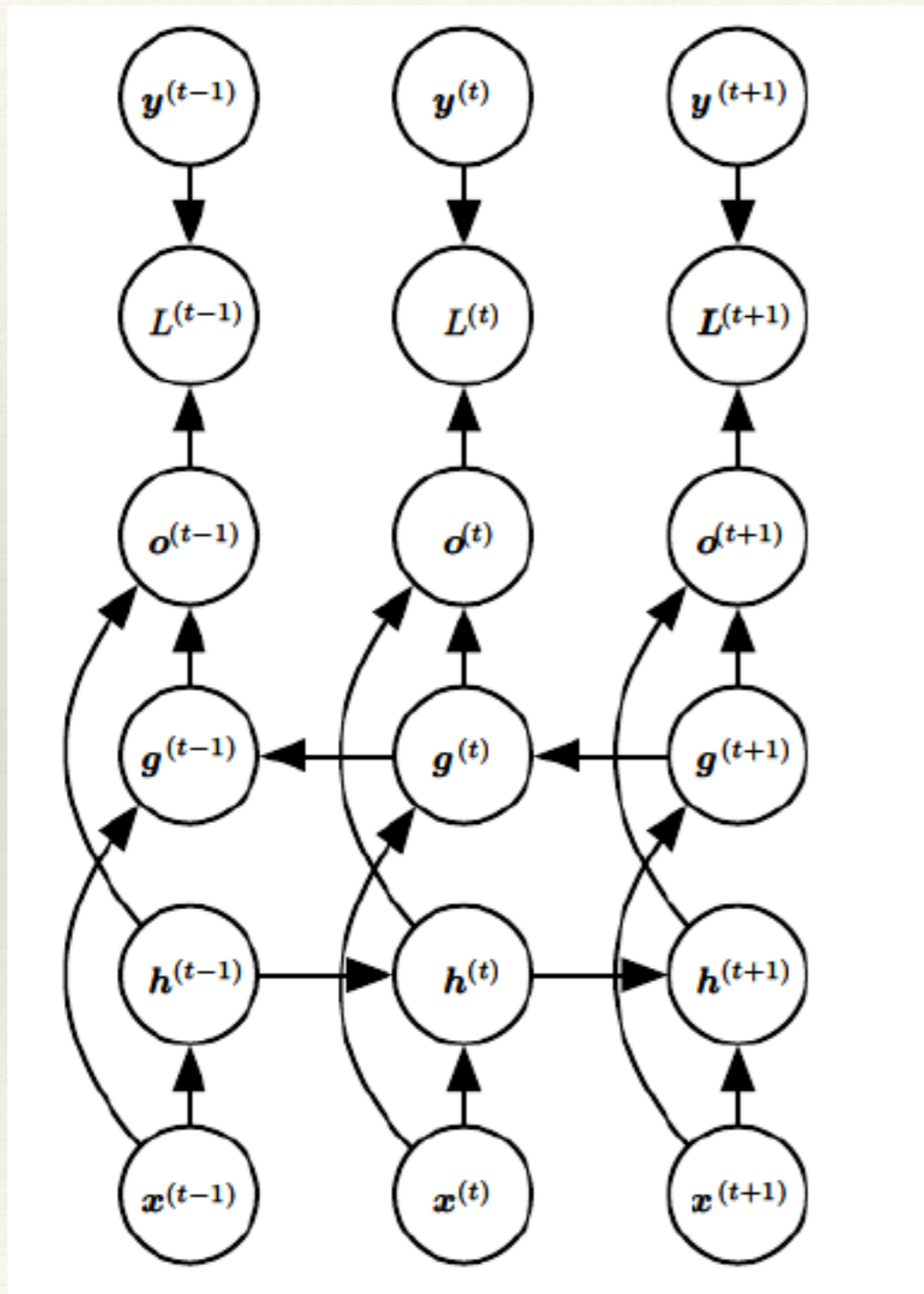
**Multiple Input
Single Output**

Recurrent Networks



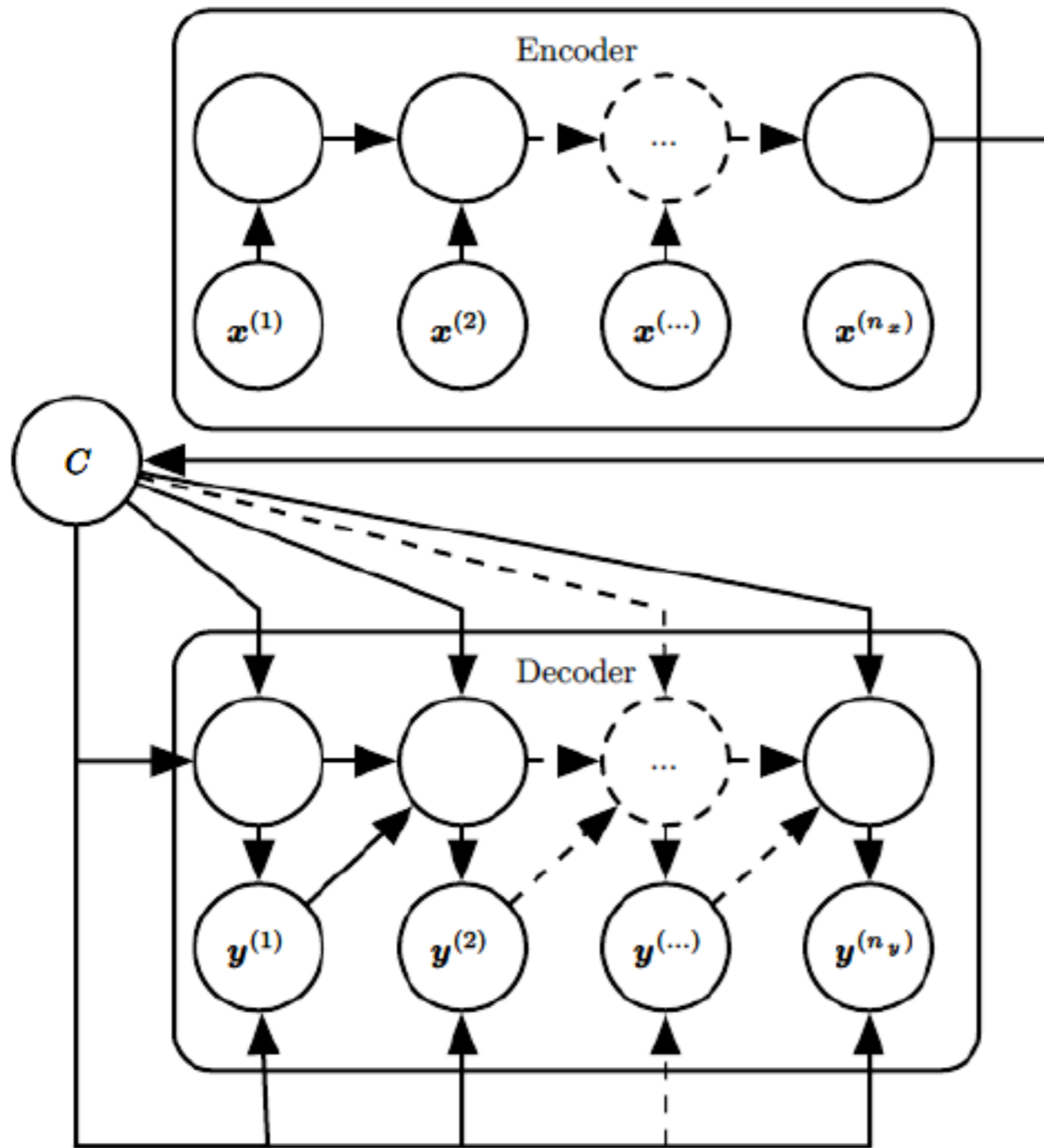
**Single Input
Multiple Output**

Recurrent Networks



**Bi-directional
Networks**

Recurrent Networks



**Sequence to
Sequence
Mapping Networks**