

E9 205 Machine Learning for Signal Processing

Convolutional and Recurrent Networks

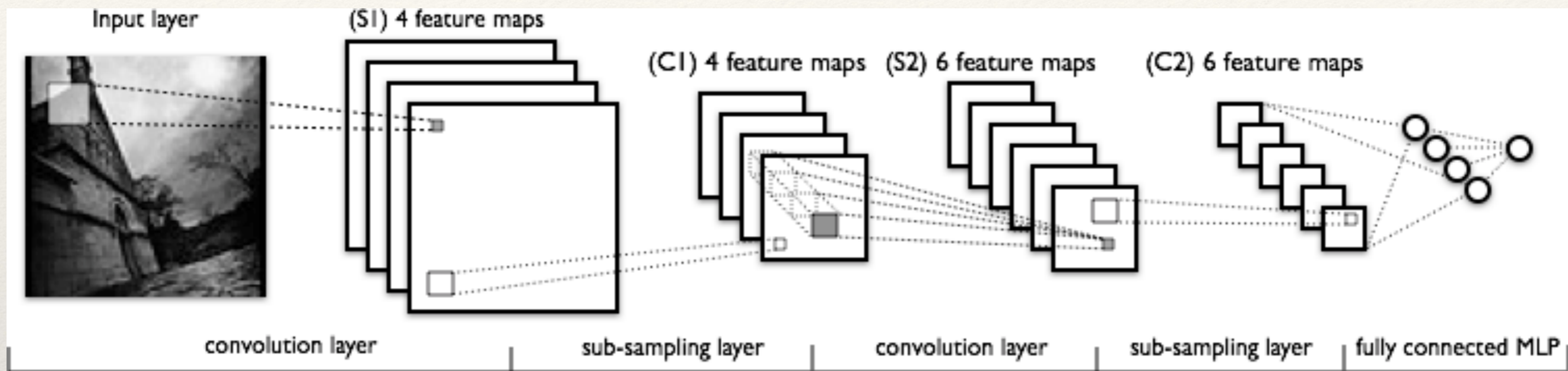
18-11-2017

Bias Variance Trade Off and Overfitting

$$(\text{bias})^2 = \frac{1}{2} \int \{\mathcal{E}_D[y(\mathbf{x})] - \langle t|\mathbf{x} \rangle\}^2 p(\mathbf{x}) d\mathbf{x}$$

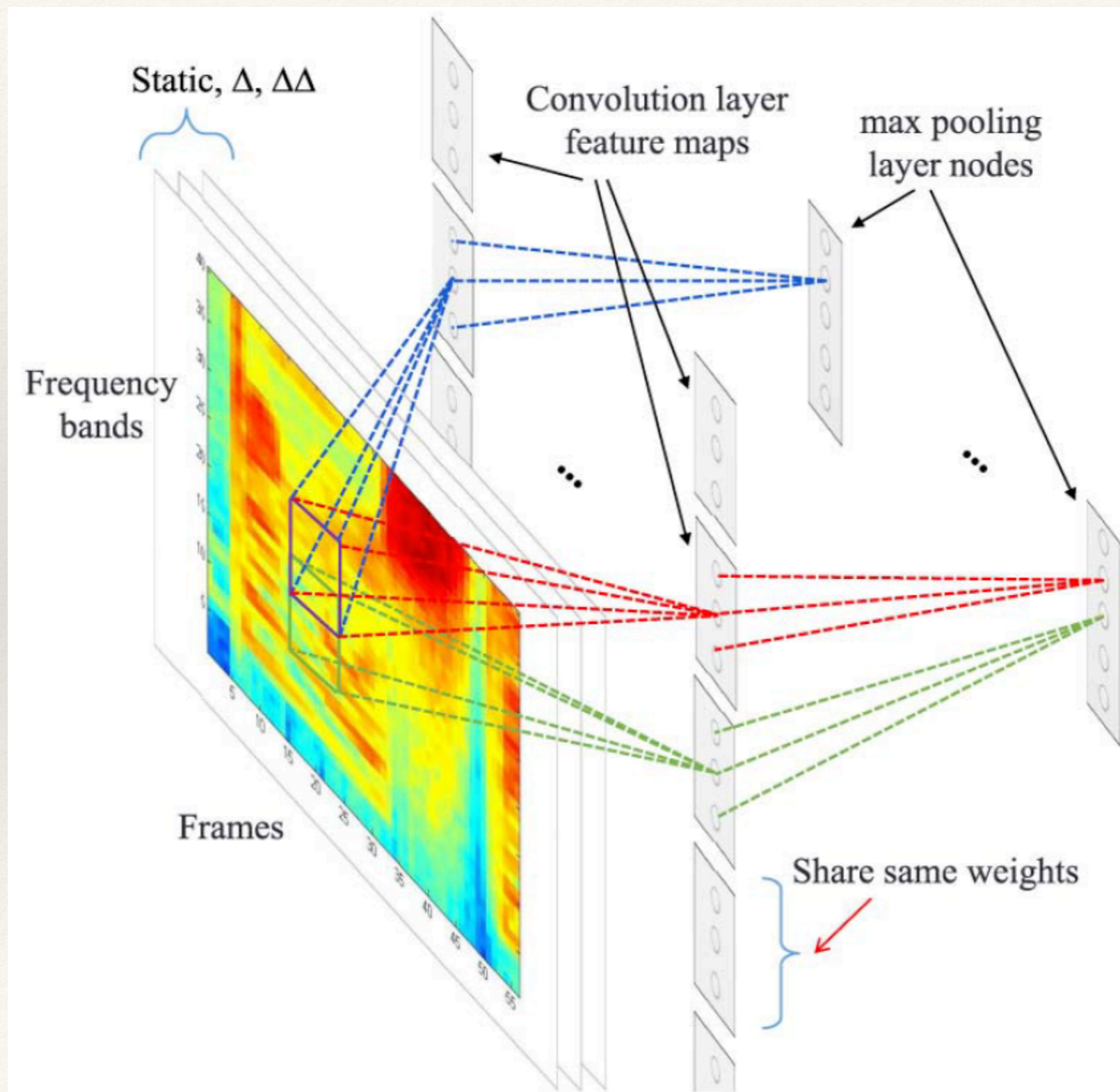
$$\text{variance} = \frac{1}{2} \int \mathcal{E}_D[\{y(\mathbf{x}) - \mathcal{E}_D[y(\mathbf{x})]\}^2] p(\mathbf{x}) d\mathbf{x}.$$

Convolutional Neural Networks



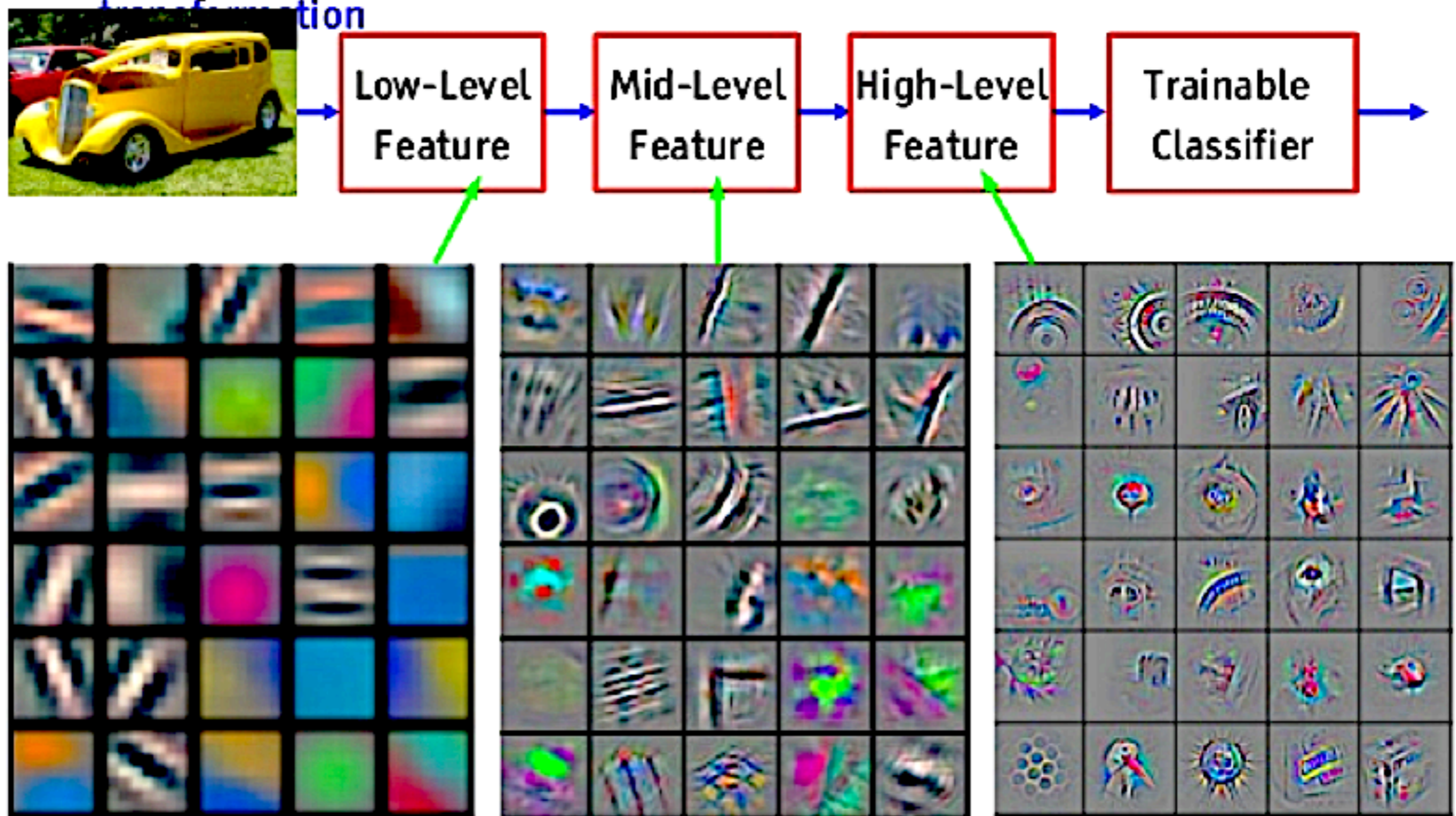
- Multiple levels of filtering and subsampling operations.
- Feature maps are generated at every layer.

CNNs for Speech and Audio



Representation Learning in CNNs

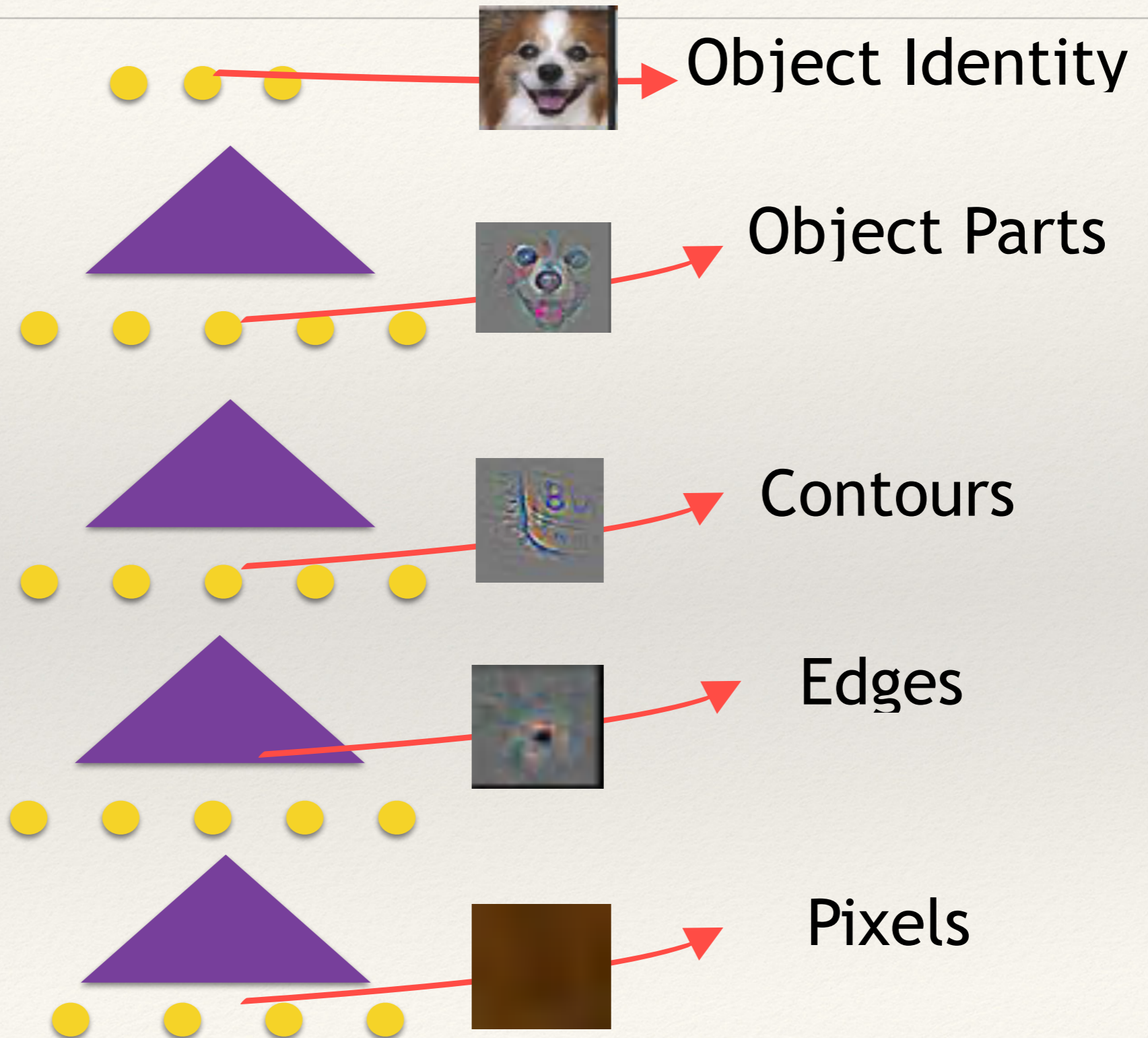
■ It's **deep** if it has **more than one stage** of non-linear feature transformation



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Representation Learning in CNNs

[Zeiler, 2014]



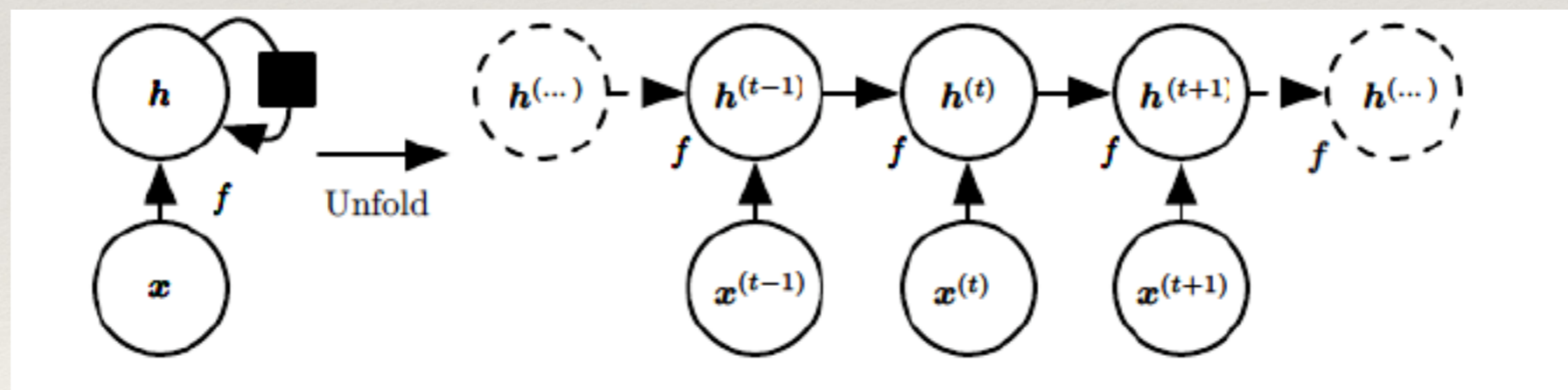
Recurrent Networks

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

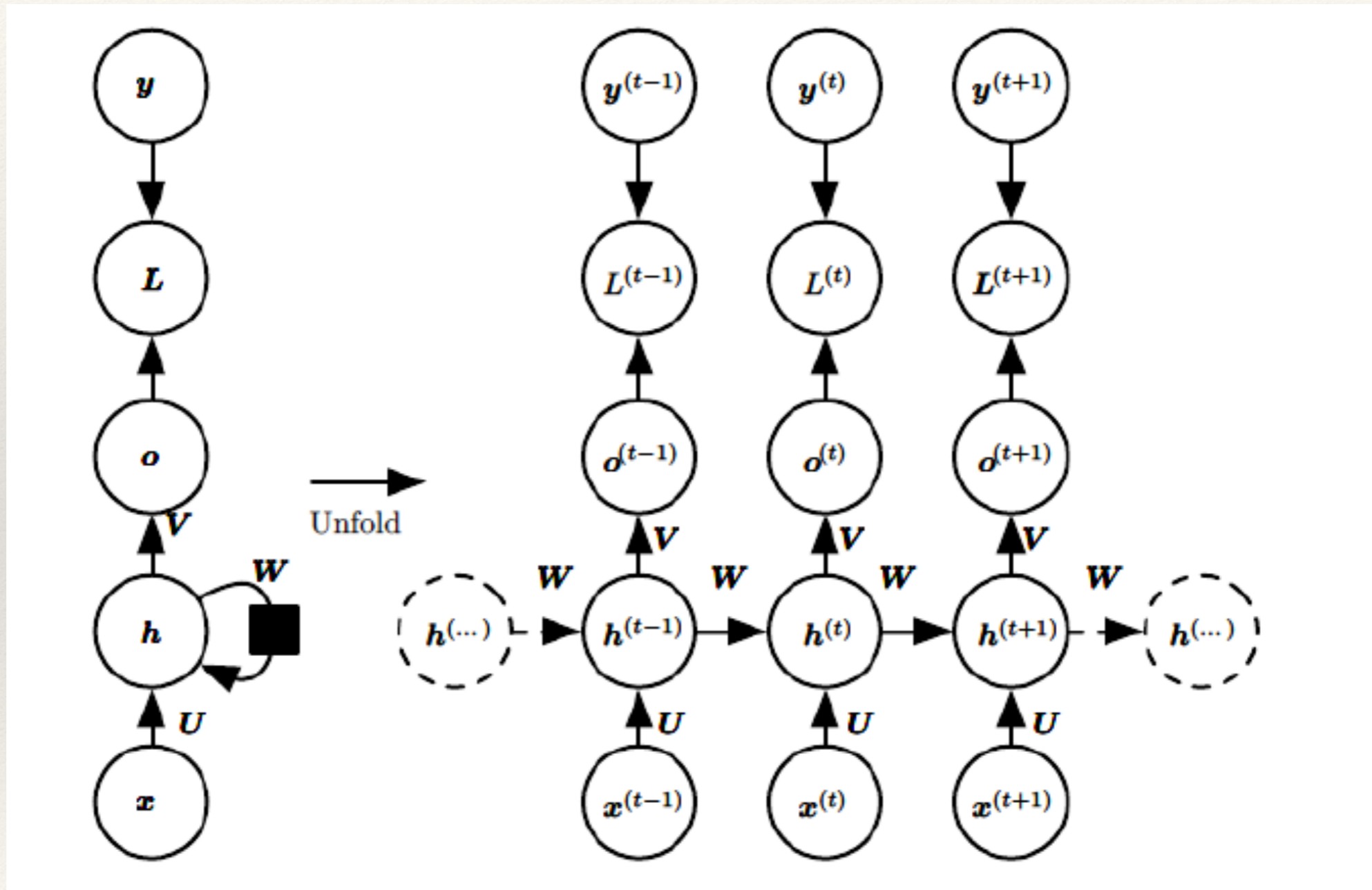
$$\begin{aligned}\mathbf{s}^{(3)} &= f(\mathbf{s}^{(2)}; \boldsymbol{\theta}) \\ &= f(f(\mathbf{s}^{(1)}; \boldsymbol{\theta}); \boldsymbol{\theta})\end{aligned}$$

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

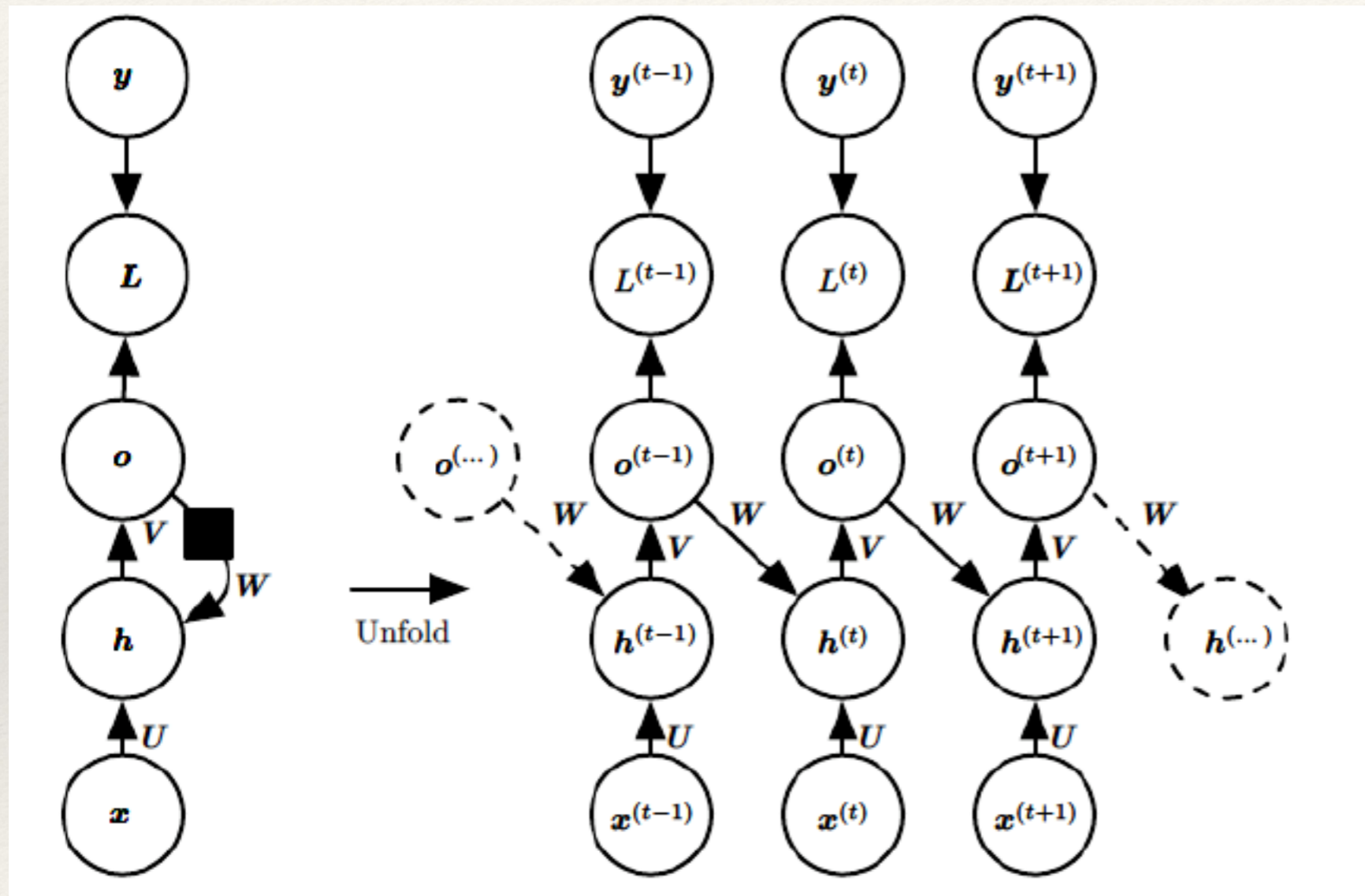
$$\mathbf{h}^{(t)} = f(\mathbf{h}^{(t-1)}, \mathbf{x}^{(t)}; \boldsymbol{\theta}),$$



Recurrent Networks

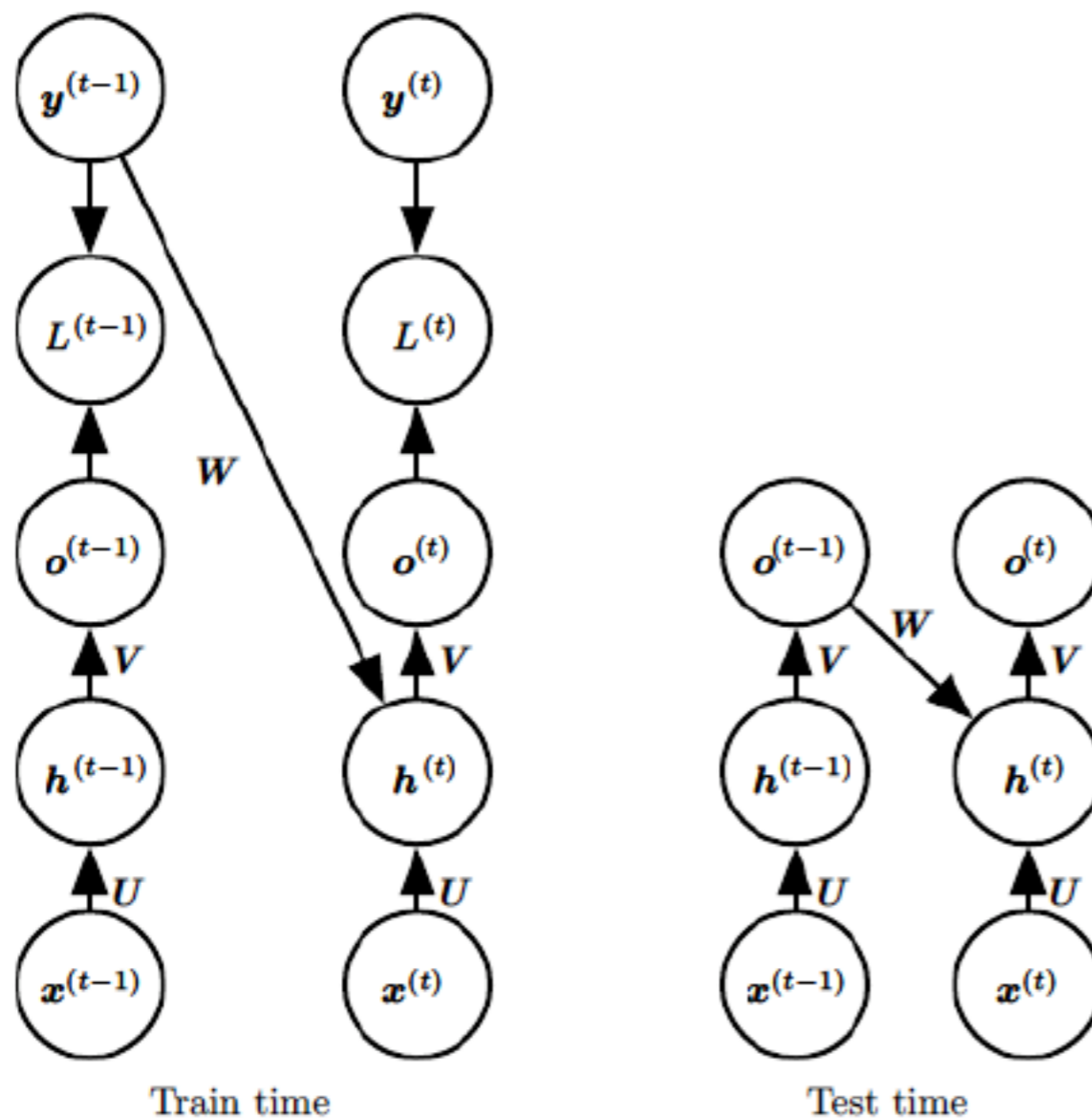


Recurrent Networks



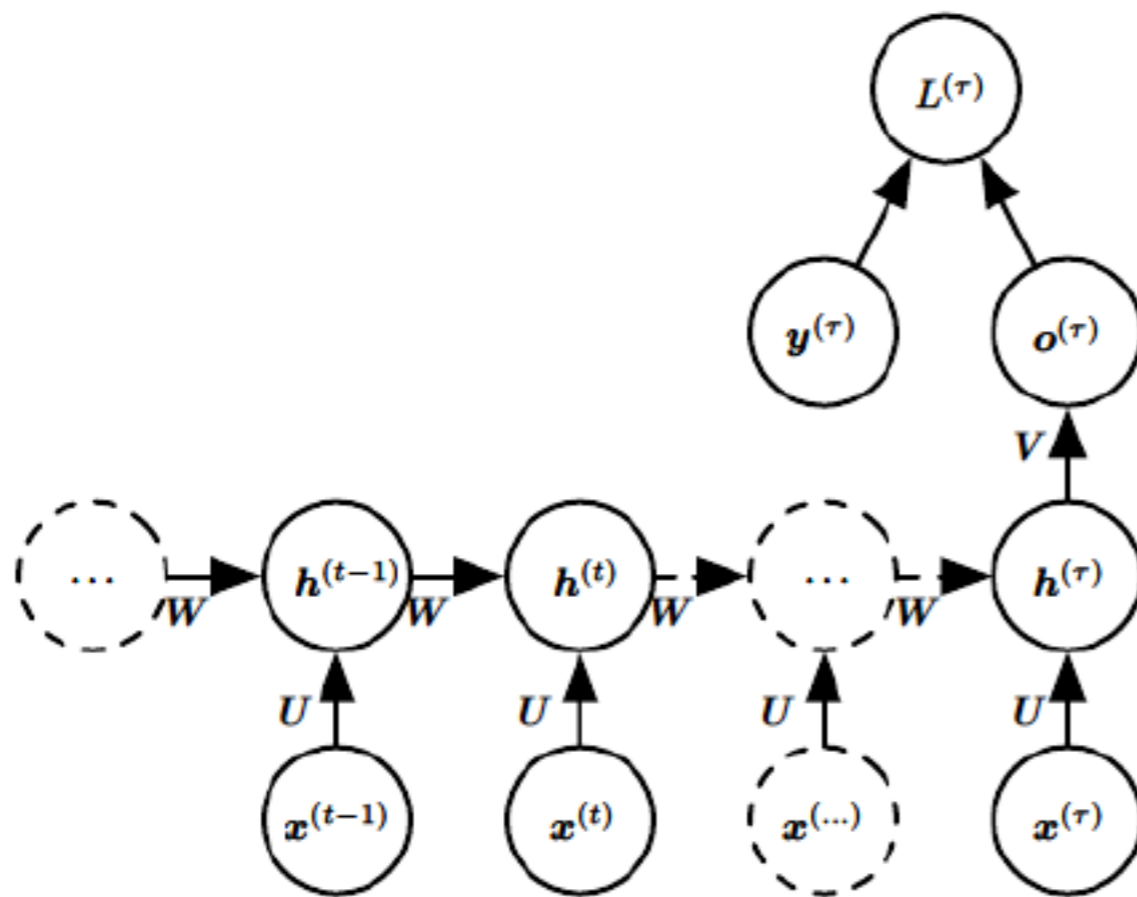
**Teacher
Forcing Networks**

Recurrent Networks



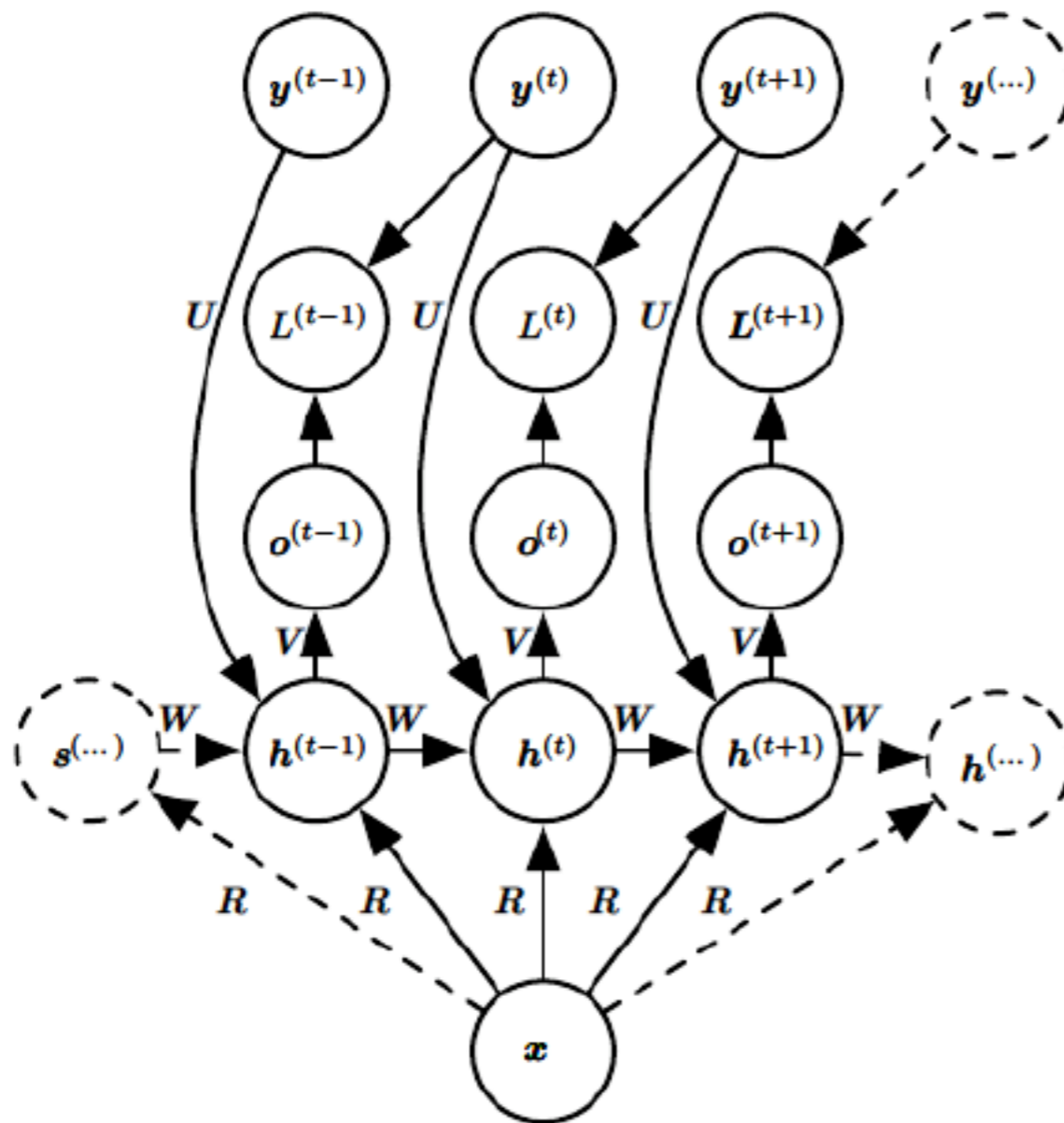
**Teacher
Forcing Networks**

Recurrent Networks



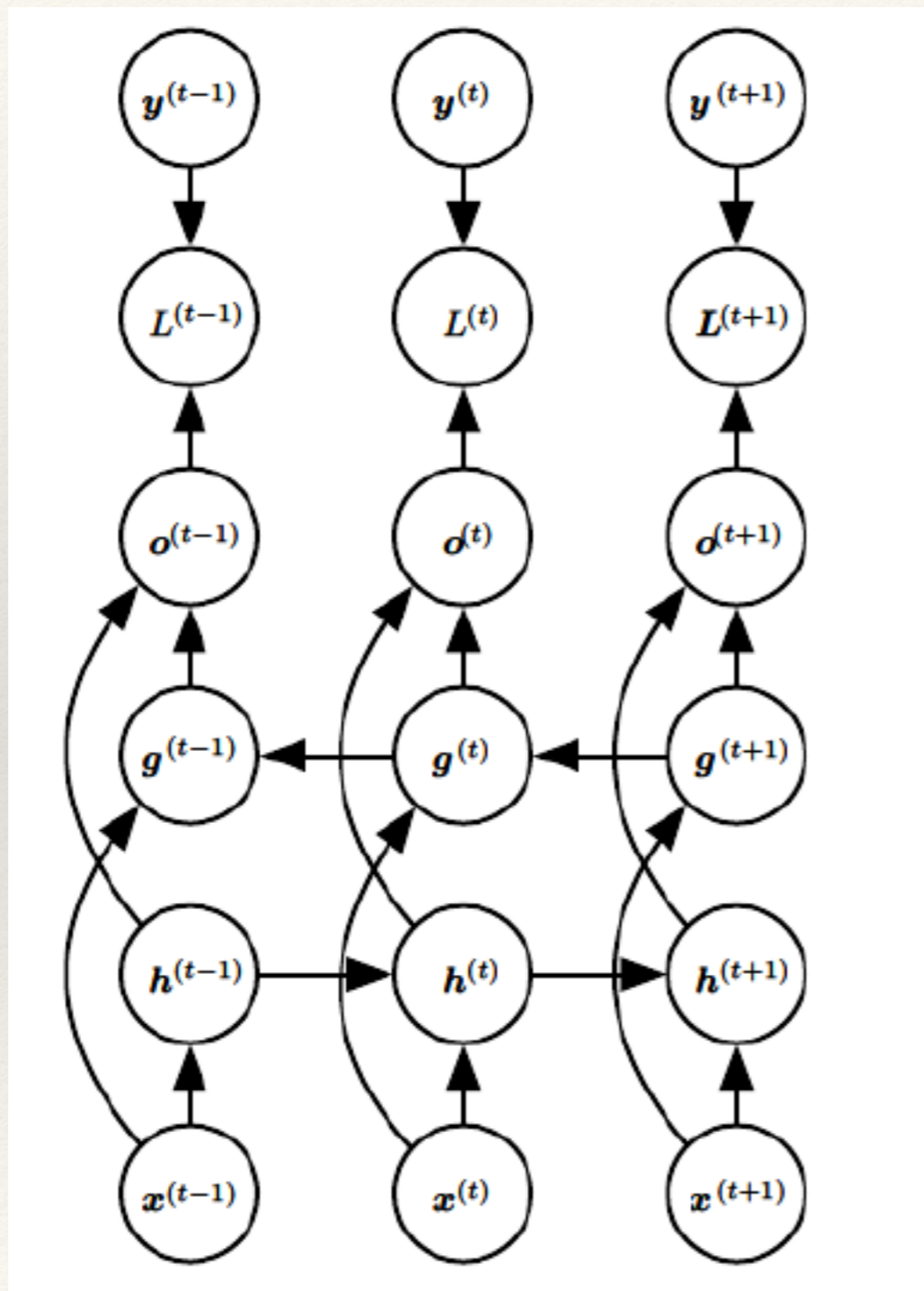
**Multiple Input
Single Output**

Recurrent Networks



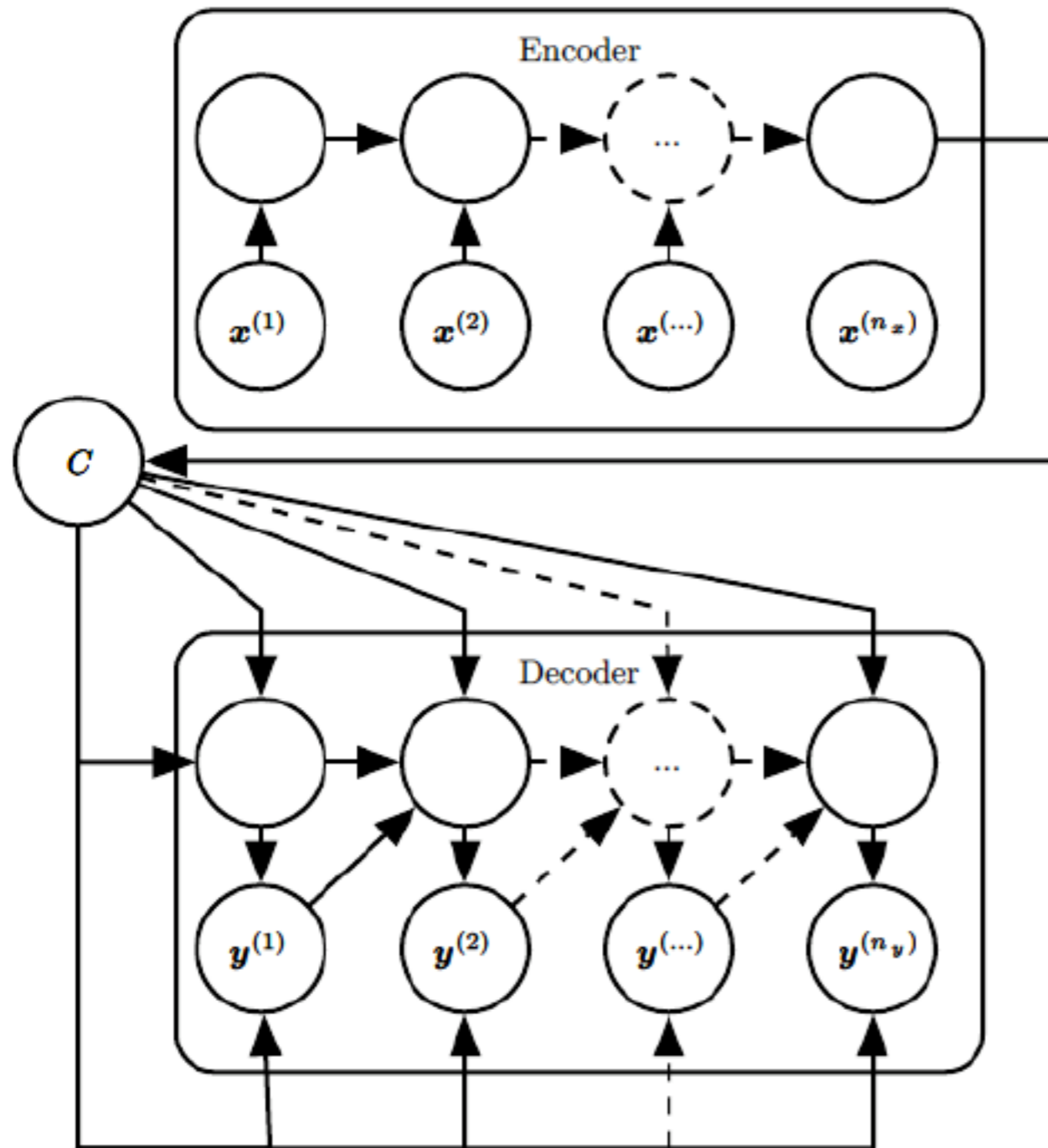
**Single Input
Multiple Output**

Recurrent Networks



**Bi-directional
Networks**

Recurrent Networks



**Sequence to
Sequence
Mapping Networks**