CMPT 733

Further Topics in Deep Learning

Sequence learning, Sentiment analysis, Word2Vec, DL-Vis

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Overview

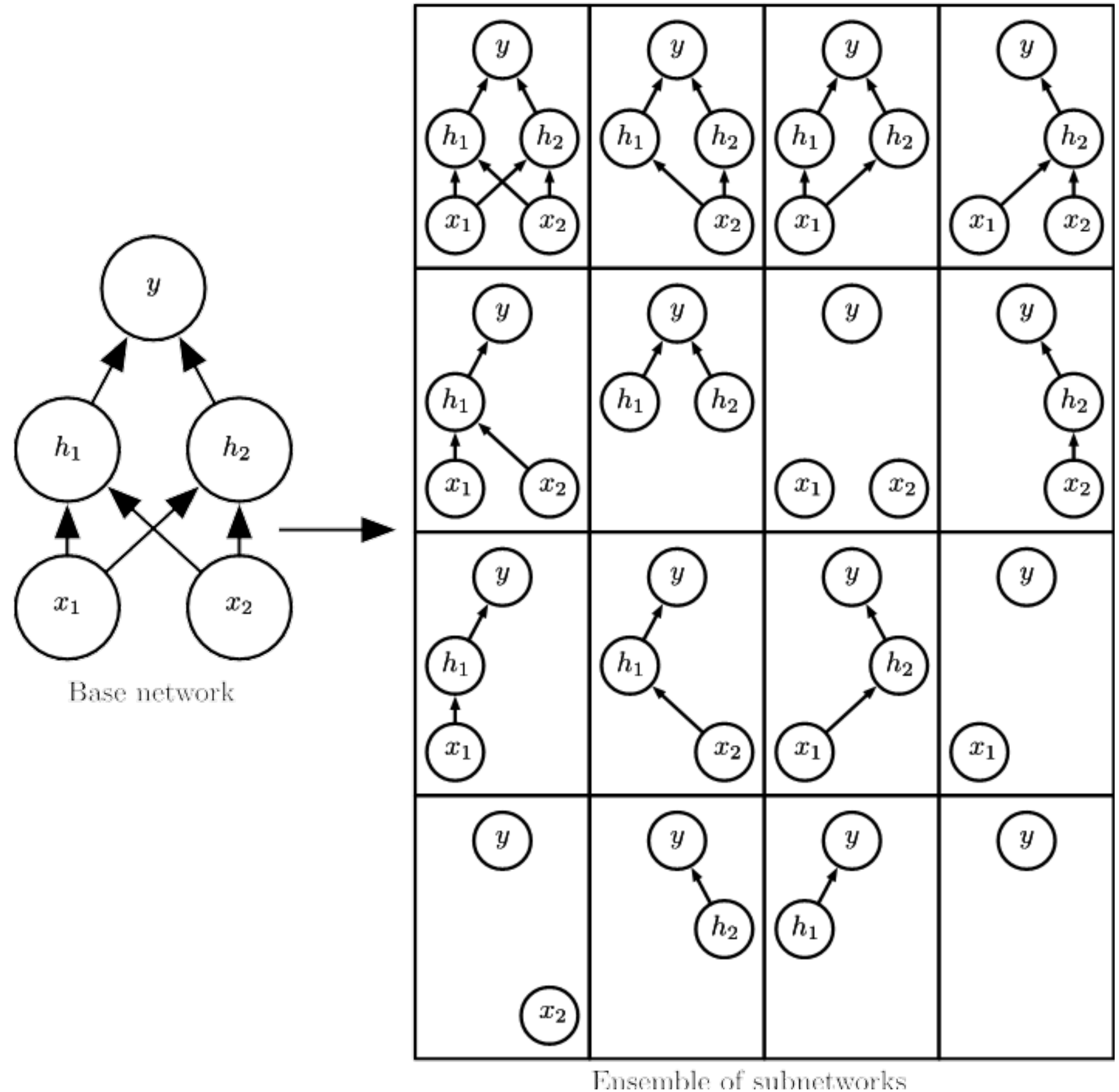
- Recap: Overfitting remedies
- Deep learning for sequences
- Natural language processing, e.g.
  - Sentiment analysis
  - Word embeddings
- Visualization for Deep Learning

Strategies against Overfitting (continued)

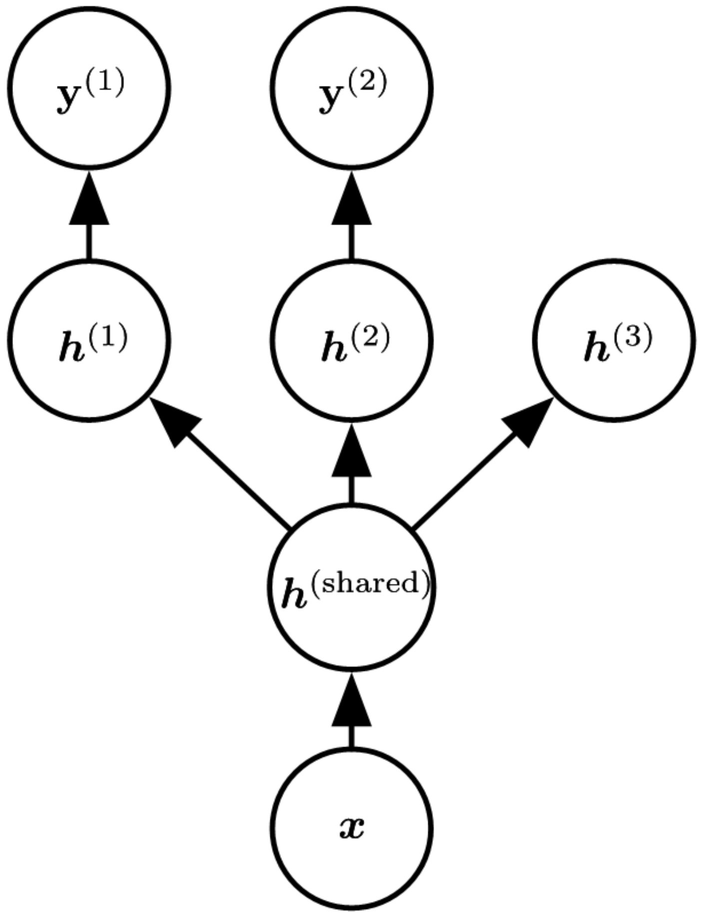
Lower generalization error
without impacting training error

Dropout

- Random sample of connection weights is set to zero
- Train different network model each time
- Learn more robust, generalizable features



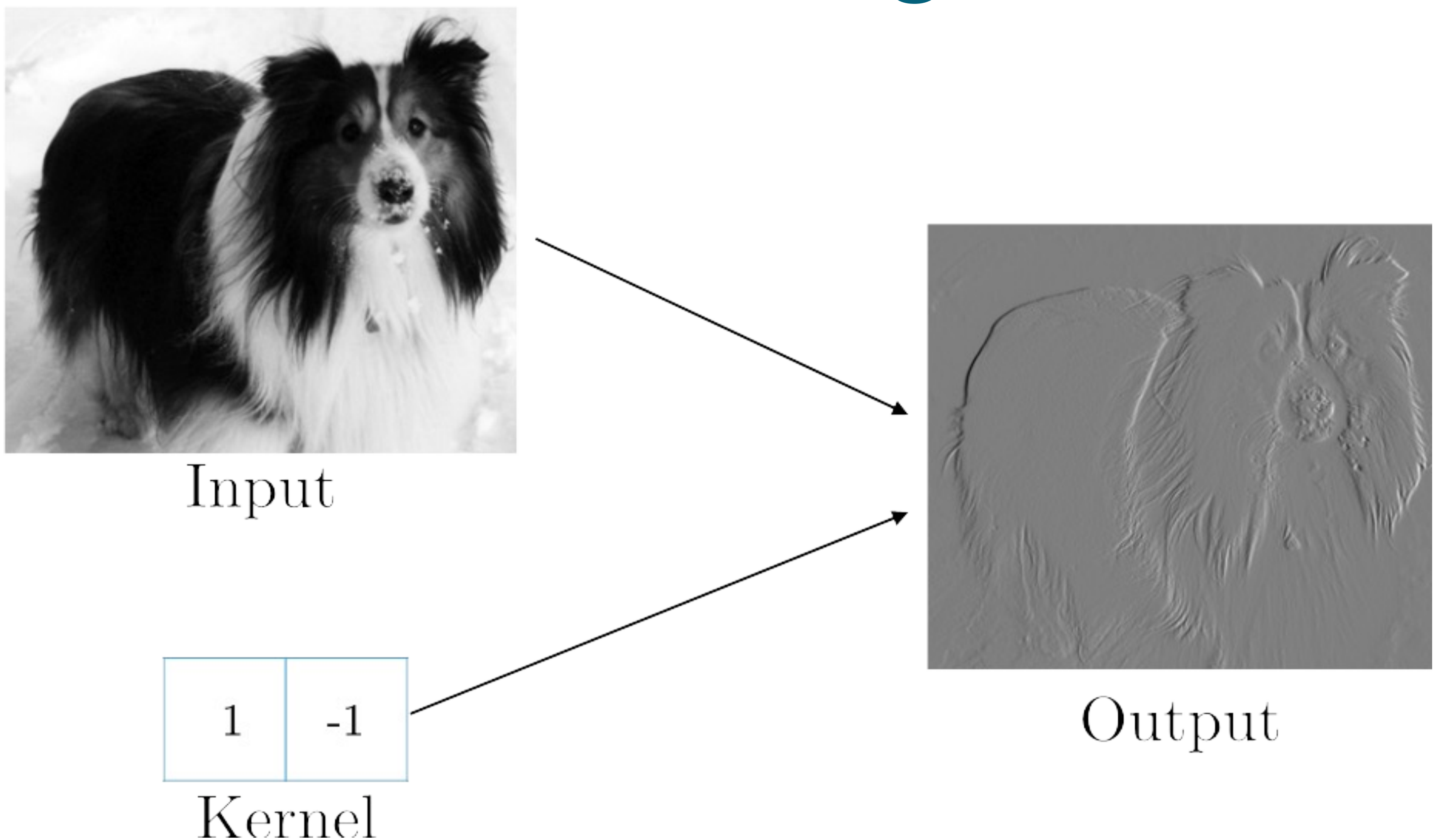
Multitask learning



- Shared parameters are trained with more data
- Improved generalization error due to increased statistical strength
- Missing components of y are masked from the loss function

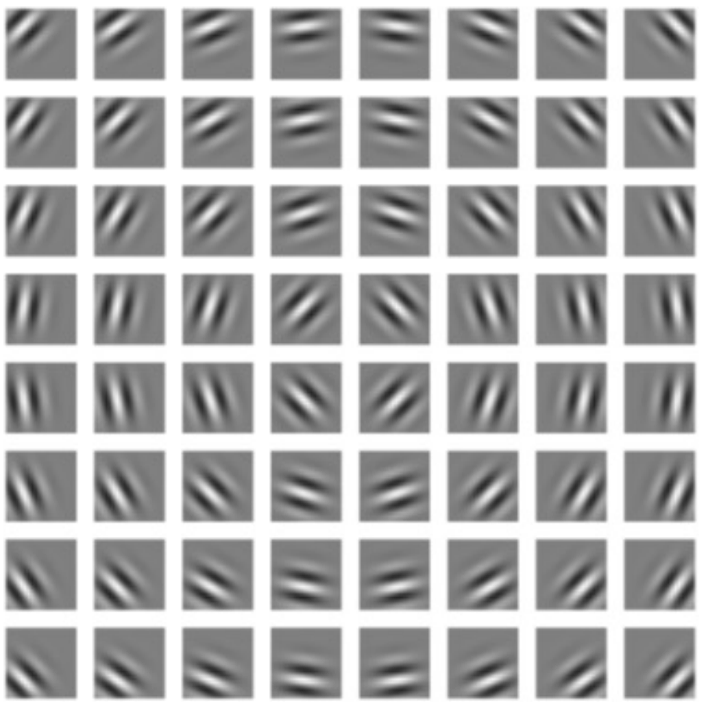
Components of popular architectures

Convolution as edge detector

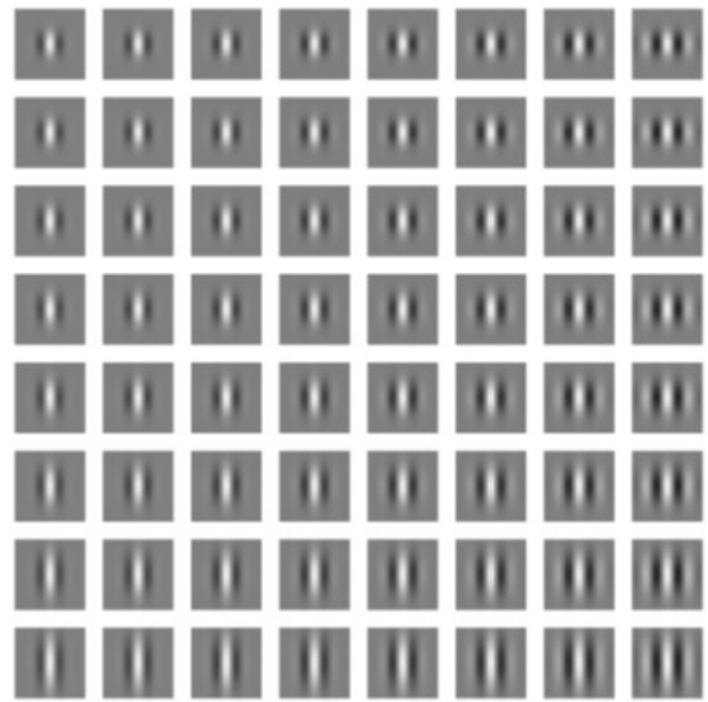


[Goodfellow, Bengio, Courville 2016]

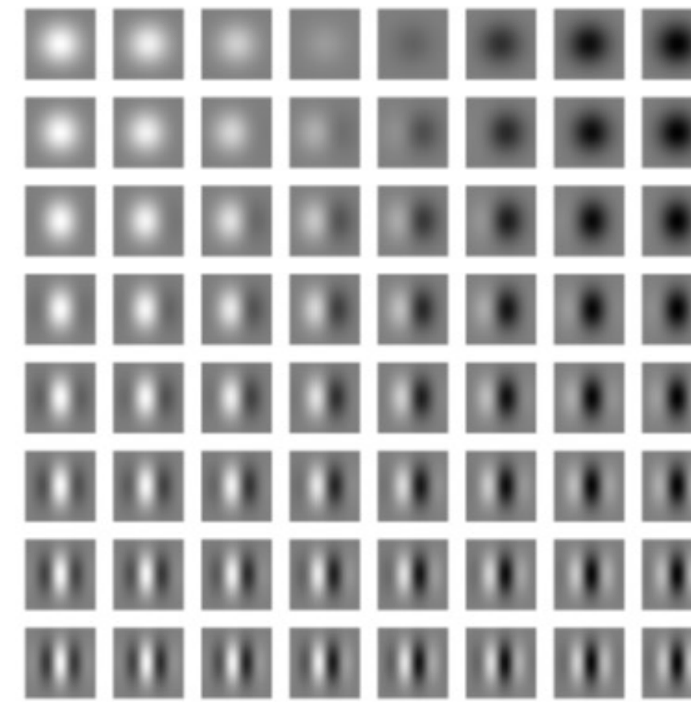
Gabor wavelets (kernels)



Directional second derivative



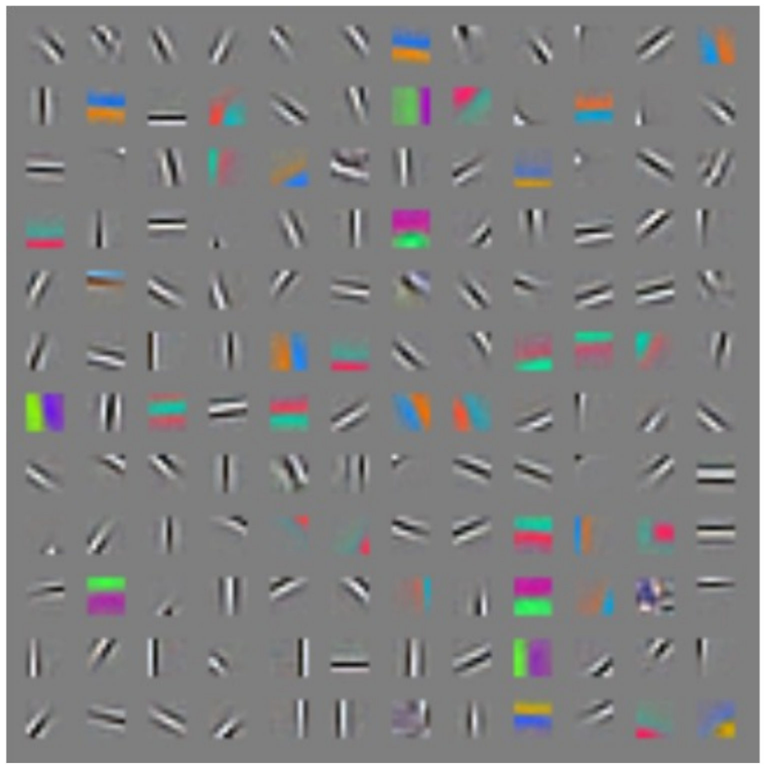
Second derivative (curvature)

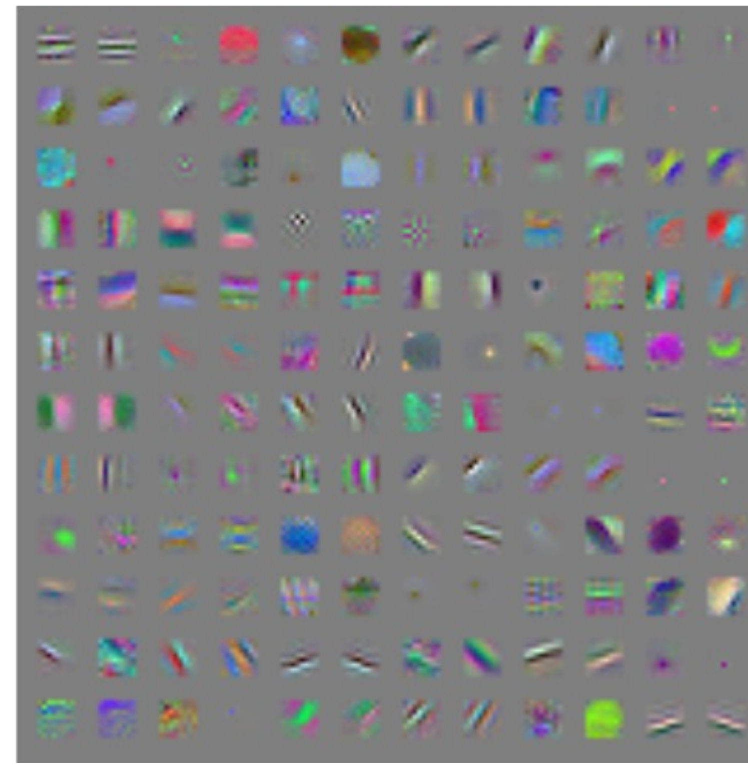


Local average, first derivative

[Goodfellow, Bengio, Courville 2016]

Gabor-like learned kernels

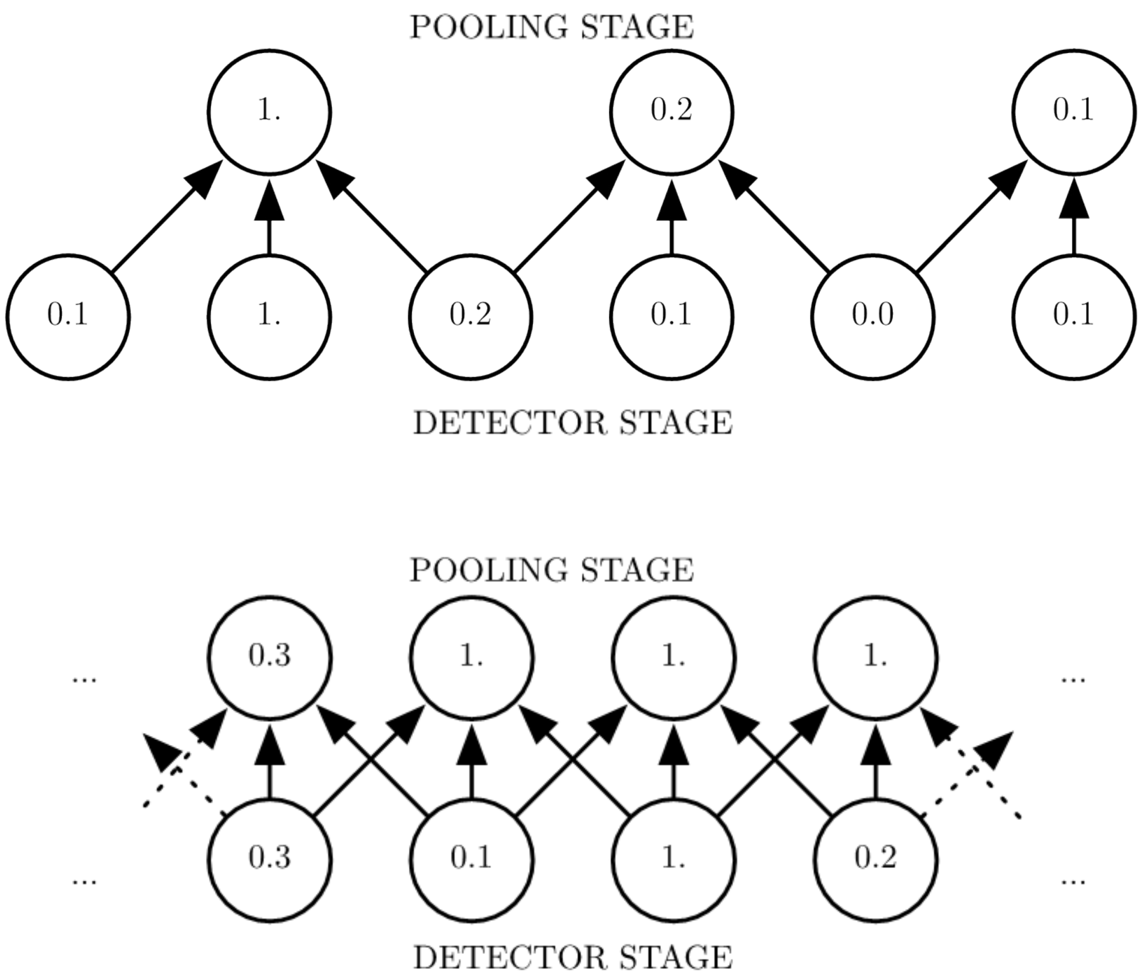




- Features extractors provided by pretrained networks

[Goodfellow, Bengio, Courville 2016]

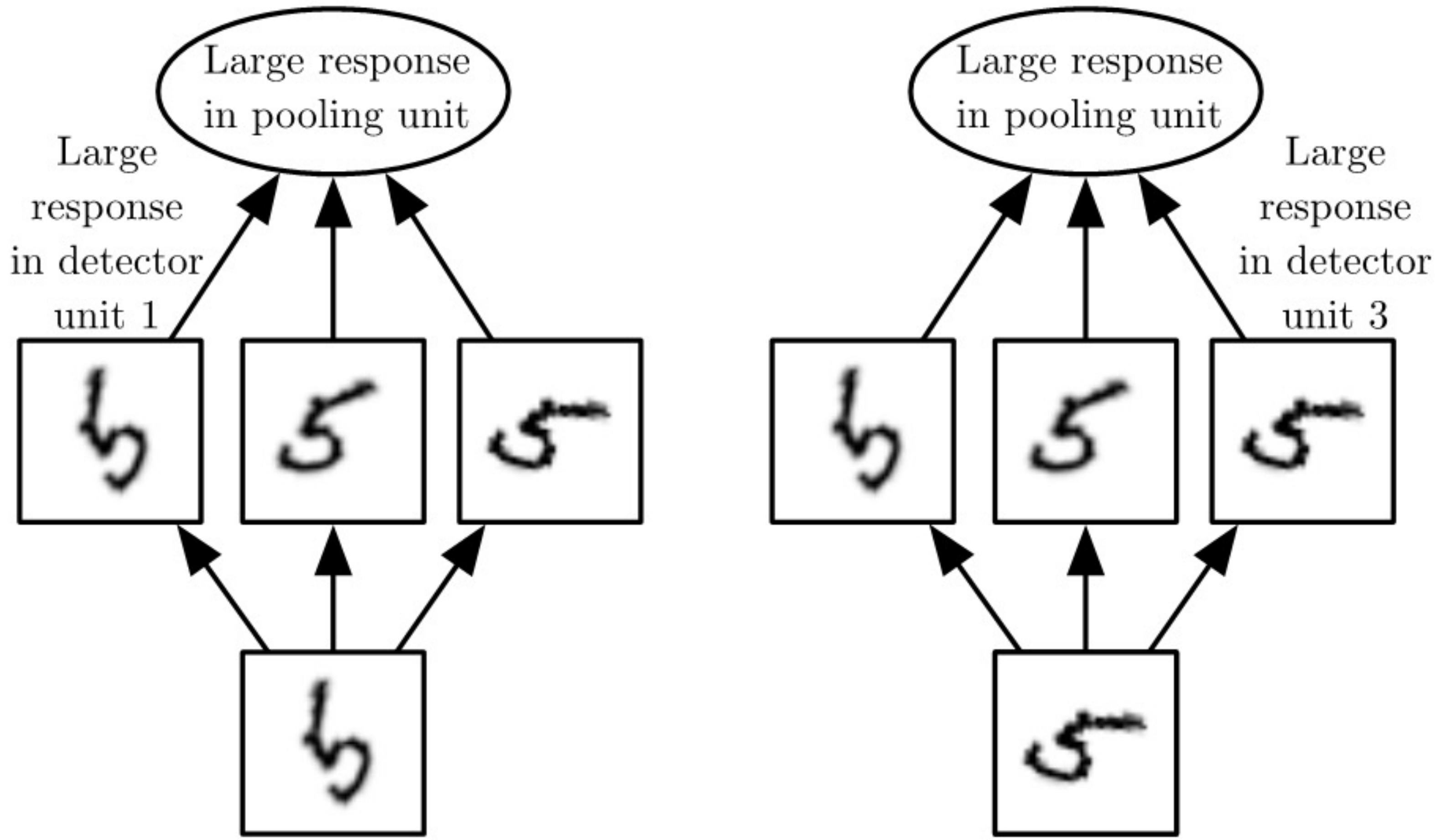
Max pooling translation invariance



- Take max of certain neighbourhood
- Often combined, followed by downsampling

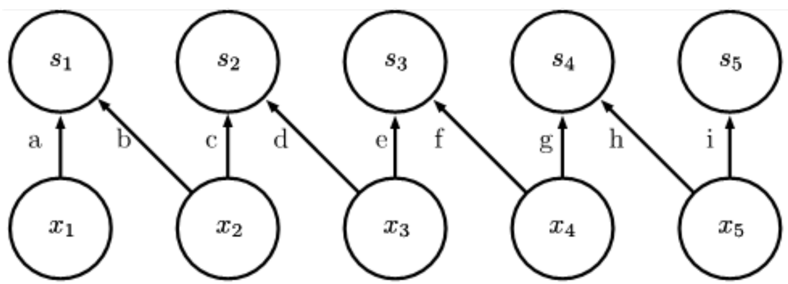
[Goodfellow, Bengio, Courville 2016]

Max pooling transform invariance



[Goodfellow, Bengio, Courville 2016]

Types of connectivity



Local connection:
like convolution,
but no sharing

$$\begin{bmatrix} a & b & & & \\ & & c & d & \\ & & & & e & f \\ & & & & & & \ddots \end{bmatrix}$$

$$\begin{bmatrix} a & b & & \\ & a & b & \\ & & a & b \\ & & & & \ddots \end{bmatrix}$$

$$\begin{bmatrix} a & b & c & d & \cdots \\ h & i & j & k & \cdots \\ o & p & q & r & \cdots \\ & & & & \ddots \end{bmatrix}$$

Convolution calculation illustrated

$$[1\ 1\ 2\ 4\ 5\ 5\ 5\ 3\ 0\ 0]$$

$$*\ [-1\ 1]$$

Choosing architecture family

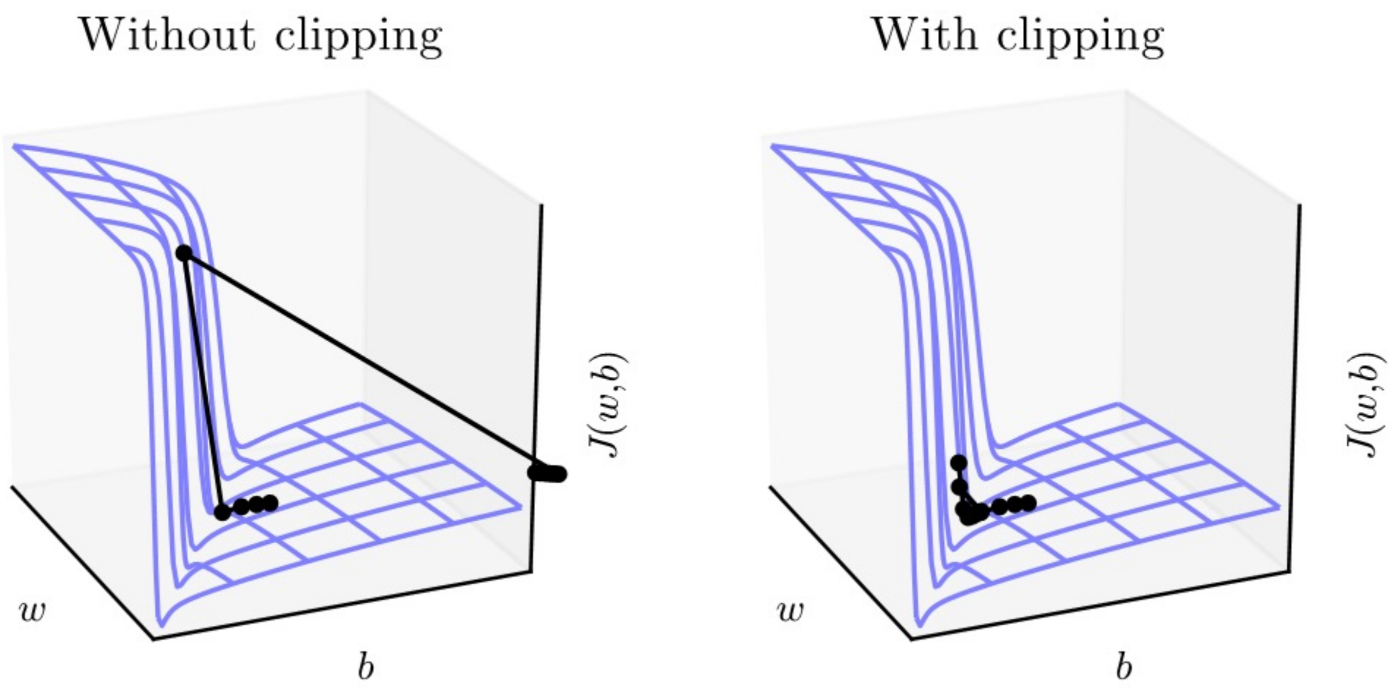
- No structure → fully connected
- Spatial structure → convolutional
- Sequential structure → recurrent

Optimization Algorithm

- Lots of variants address choice of learning rate
- See Visualization of Algorithms
- AdaDelta and RMSprop often work well

Gradient Clipping

- Add learning rate time gradient to update parameters
- Believe direction of gradient, but not its magnitude



[Goodfellow, Bengio, Courville 2016]

Development strategy

- Identify needs: High accuracy or low accuracy?
- Choose metric
  - Accuracy (% of examples correct), Coverage (% examples processed)
  - Precision TP/(TP+FP), Recall TP/(TP+FN)
  - Amount of error in case of regression
- Build end-to-end system
  - Start from baseline, e.g. initialize with pre-trained network
- Refine driven by data

Software for Deep Learning

Current Frameworks

- Tensorflow / Keras
- PyTorch
- DL4J
- Caffe (superseded by Caffe2, which is merged into PyTorch)
- And many more
- Most have CPU-only mode but much faster on NVIDIA GPU

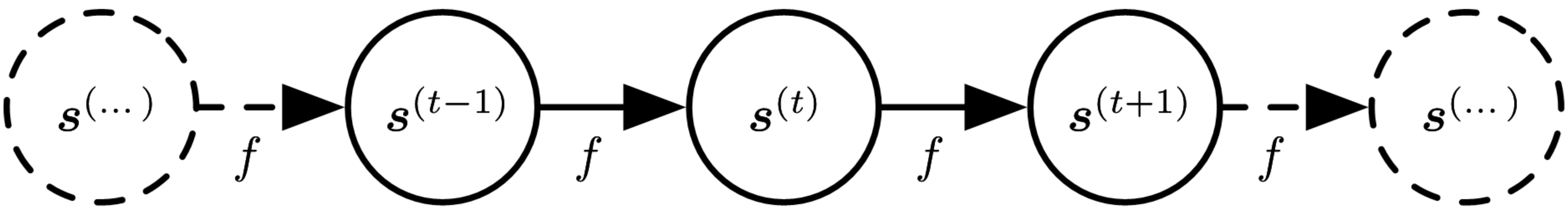
Recap: Choosing architecture family

- No structure → fully connected
- Spatial structure → convolutional
  - Adjacency or order of inputs has meaning
- Sequential structure → recurrent

Sequence Modeling with Recurrent Nets

Classical Dynamical Systems

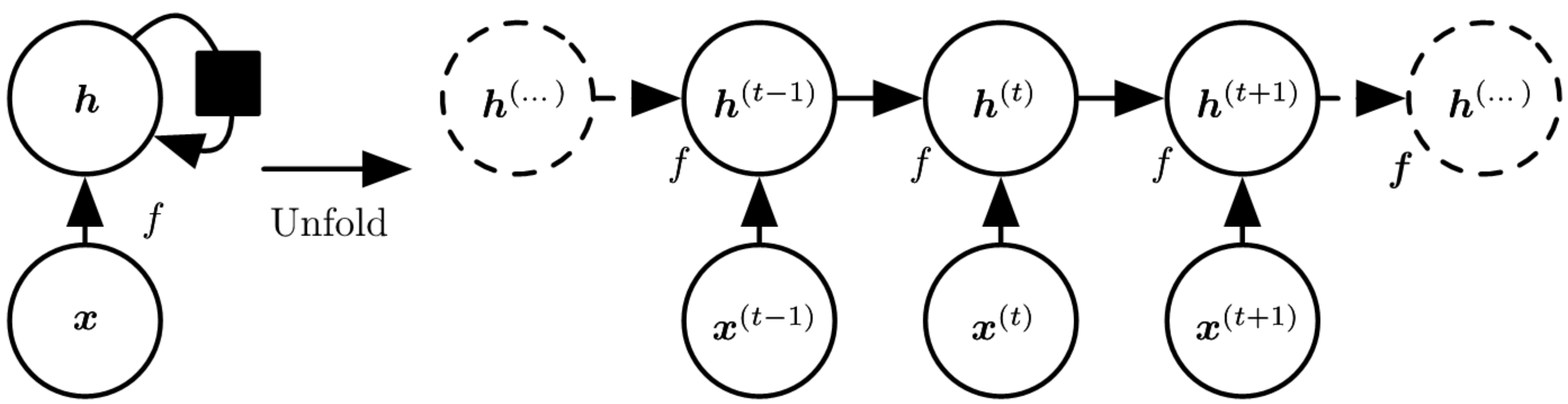
- Recurrent network models a dynamical system that is updated in discrete steps over time
- Function *f* takes input from time *t* to output at time *t+1*
- Rules persist across time



[Goodfellow, Bengio, Courville 2016]

Unfolding Computation Graphs

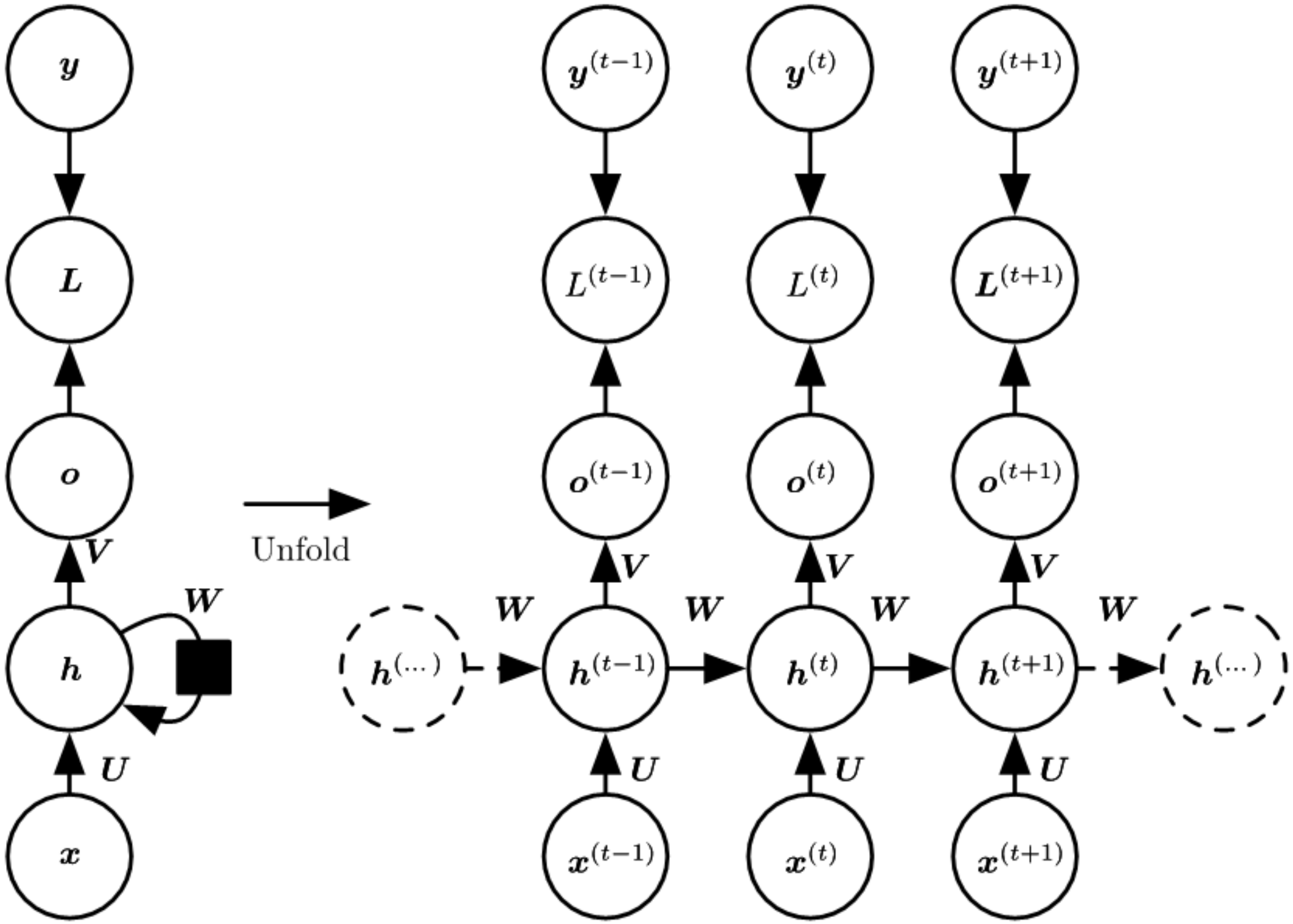
- Recurrent graph can be unfolded, where hidden state h is influencing itself
- Backprop through time is just backprop on unfolded graph



[Goodfellow, Bengio, Courville 2016]

Recurrent Hidden Units

- Can have more than one layer

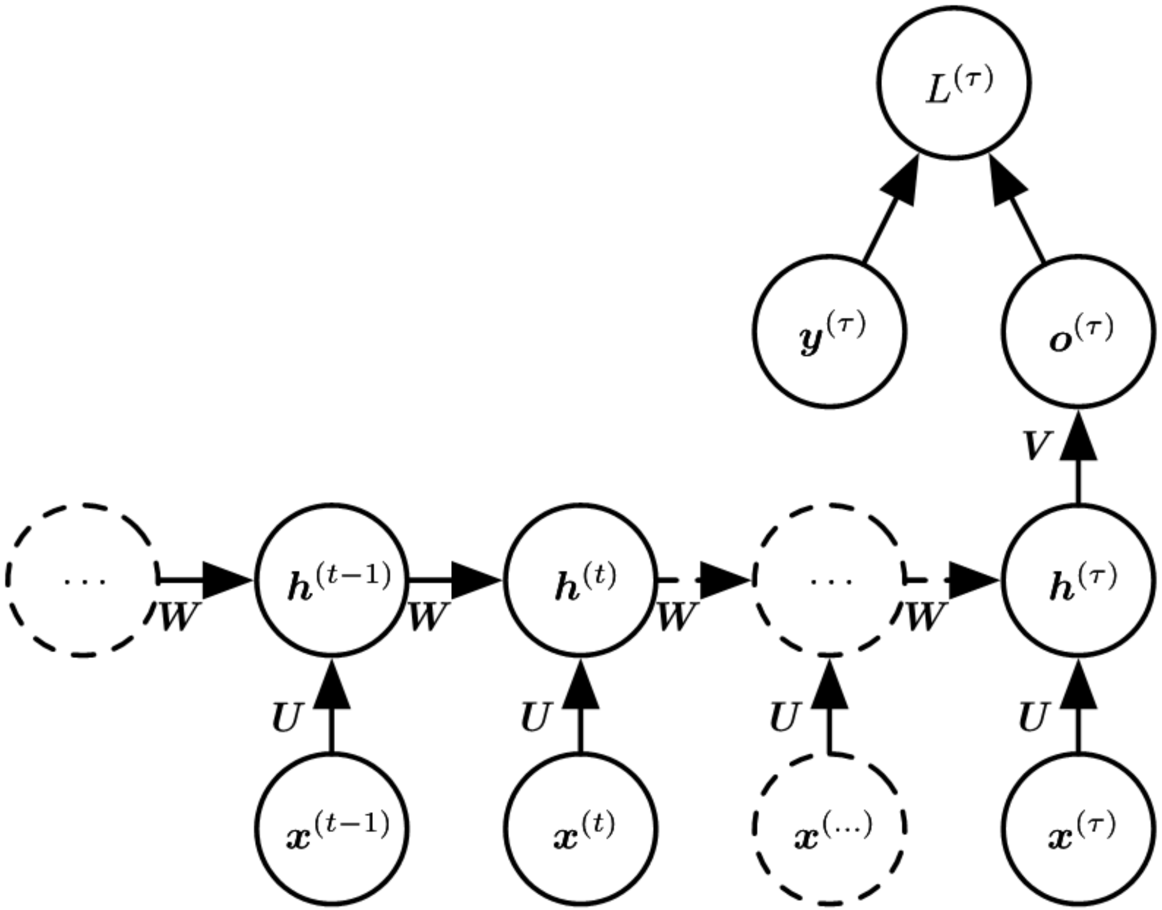


[Goodfellow, Bengio, Courville 2016]

Sequence Input, Single Output

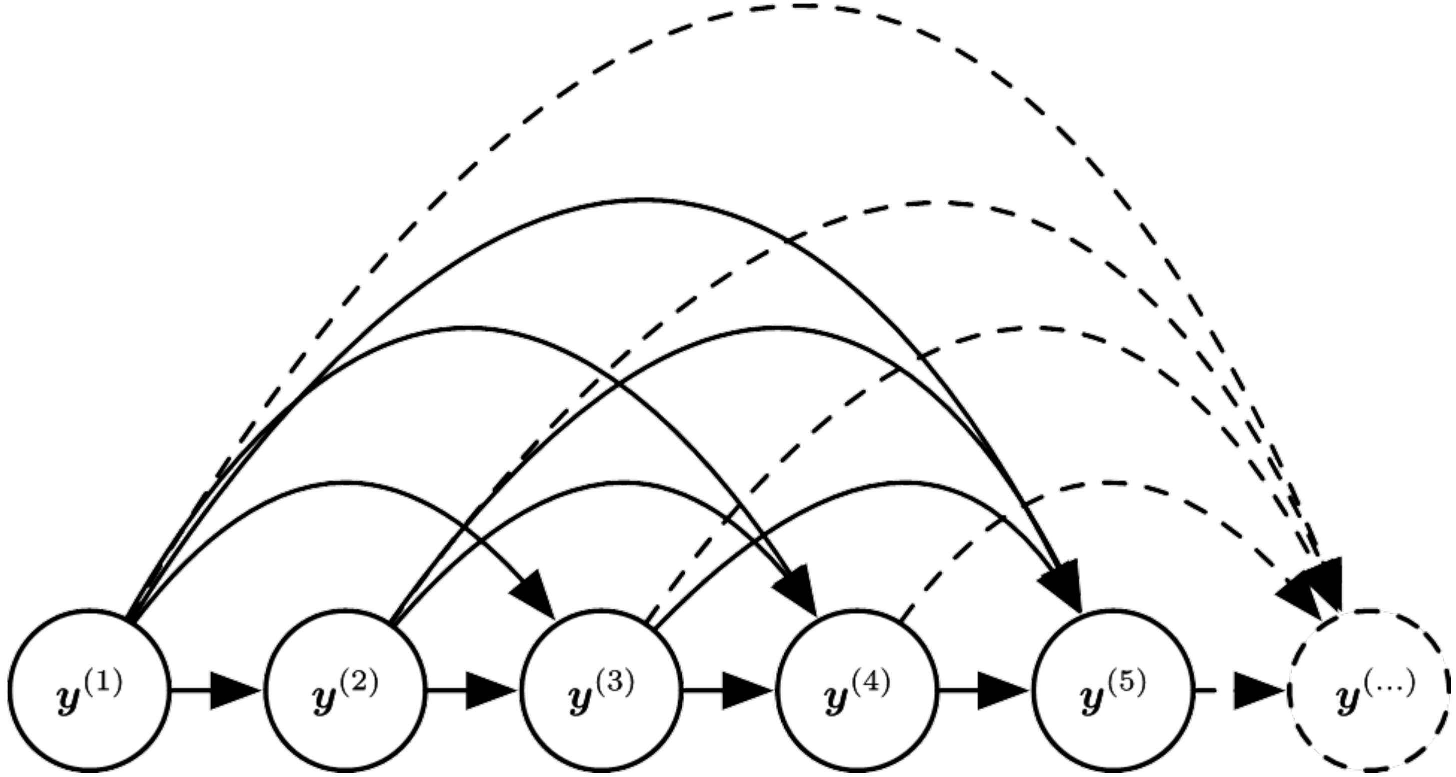
Example

Sentiment analysis of text



Fully Connected Graphical Model

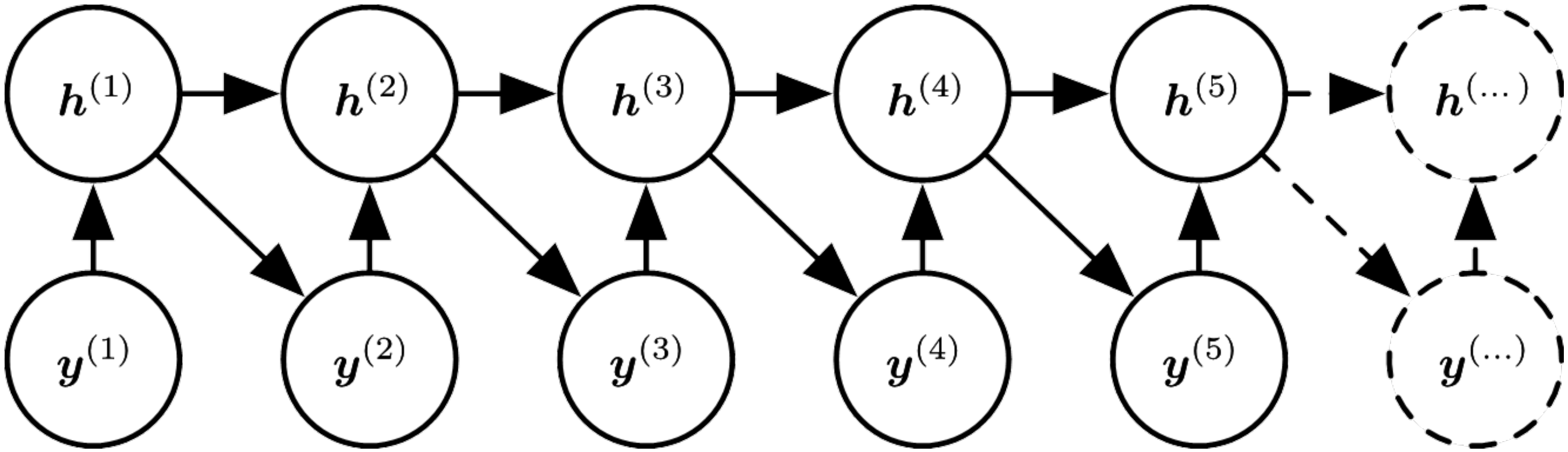
- Too many dependencies among variables, if each has its own set of parameters



[Goodfellow, Bengio, Courville 2016]

RNN Graphical Model

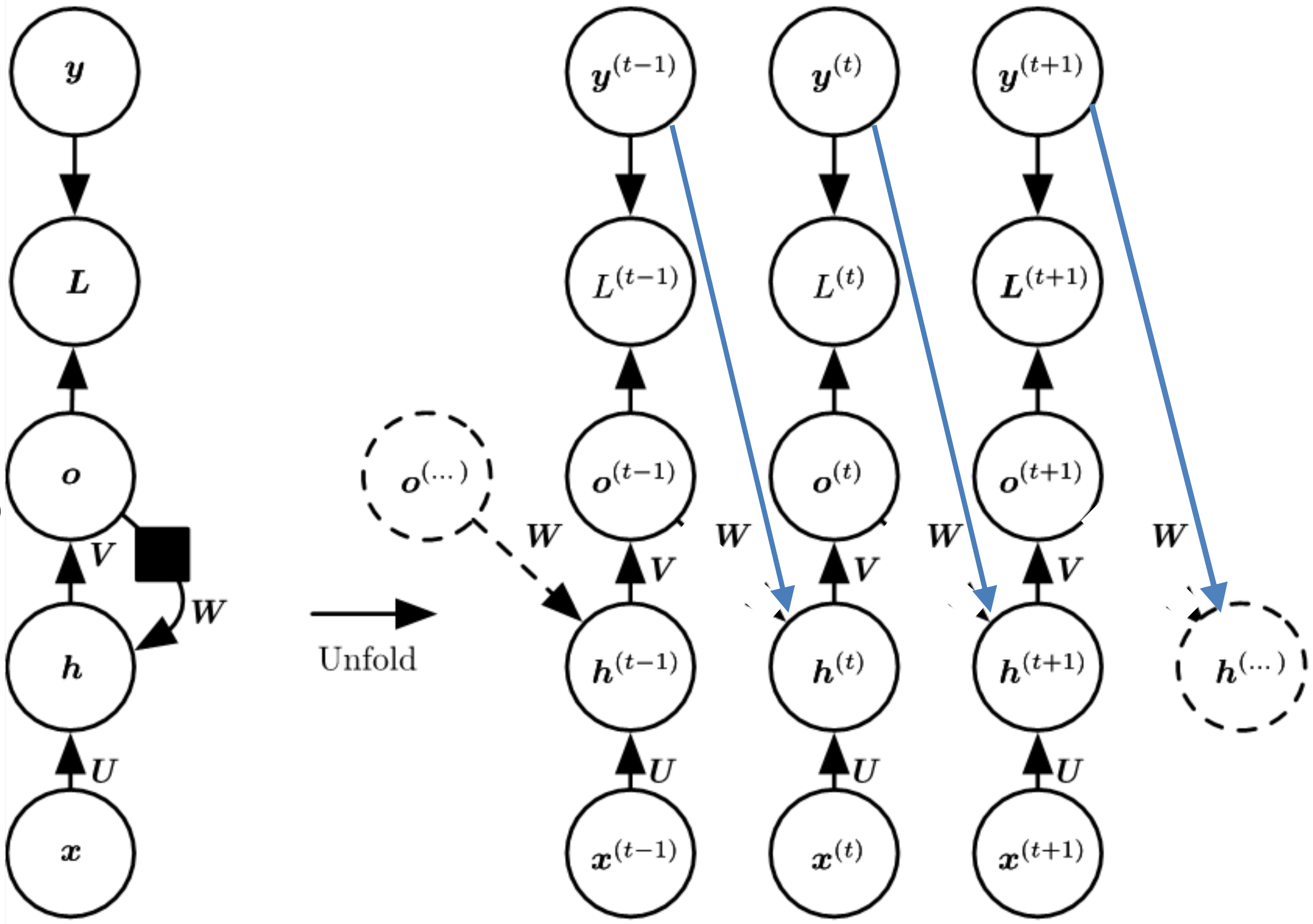
- Organize variables according to time with single update rule
- Finite set of relationships may extend to infinite sequences
- *h* acts as "memory state" summarizing relevant history



[Goodfellow, Bengio, Courville 2016]

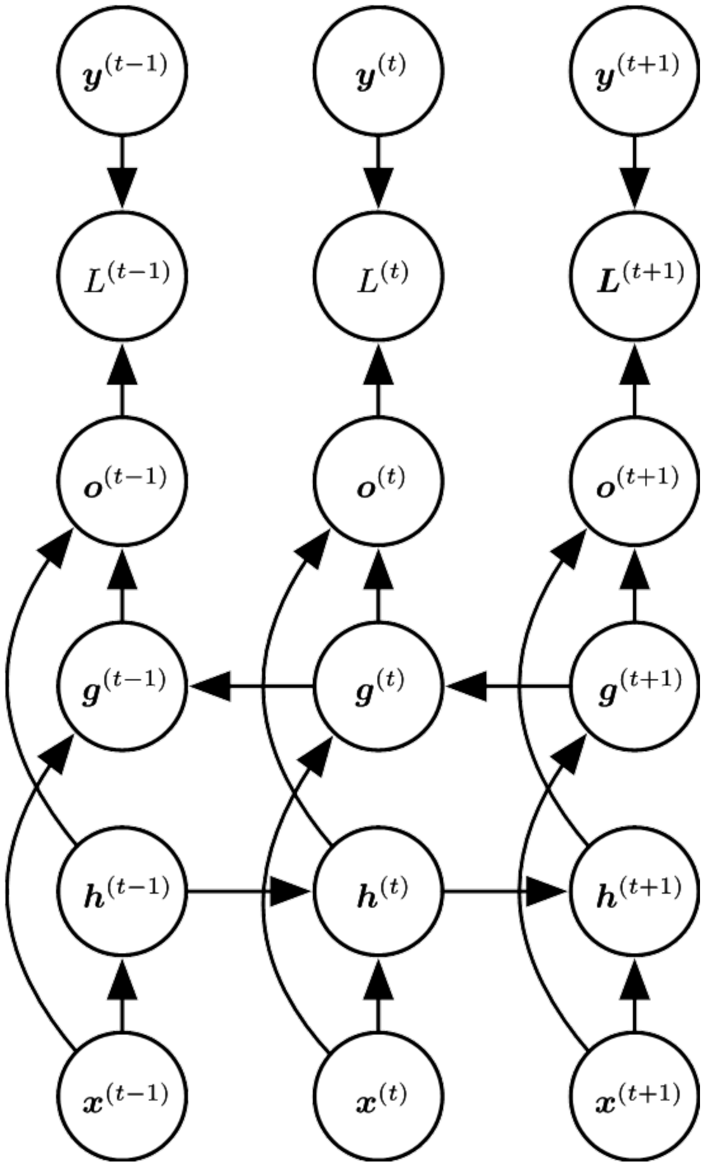
Recurrence only through output

- Avoid backprop through time
- Mitigation: Teacher forcing
  - Use actual or expected output from the training dataset at current time y(t) as input o(t) to the next time step, rather than generated output
  - Backprop stops when it reaches y(t-1) via o(t-1)



Bidirectional RNN

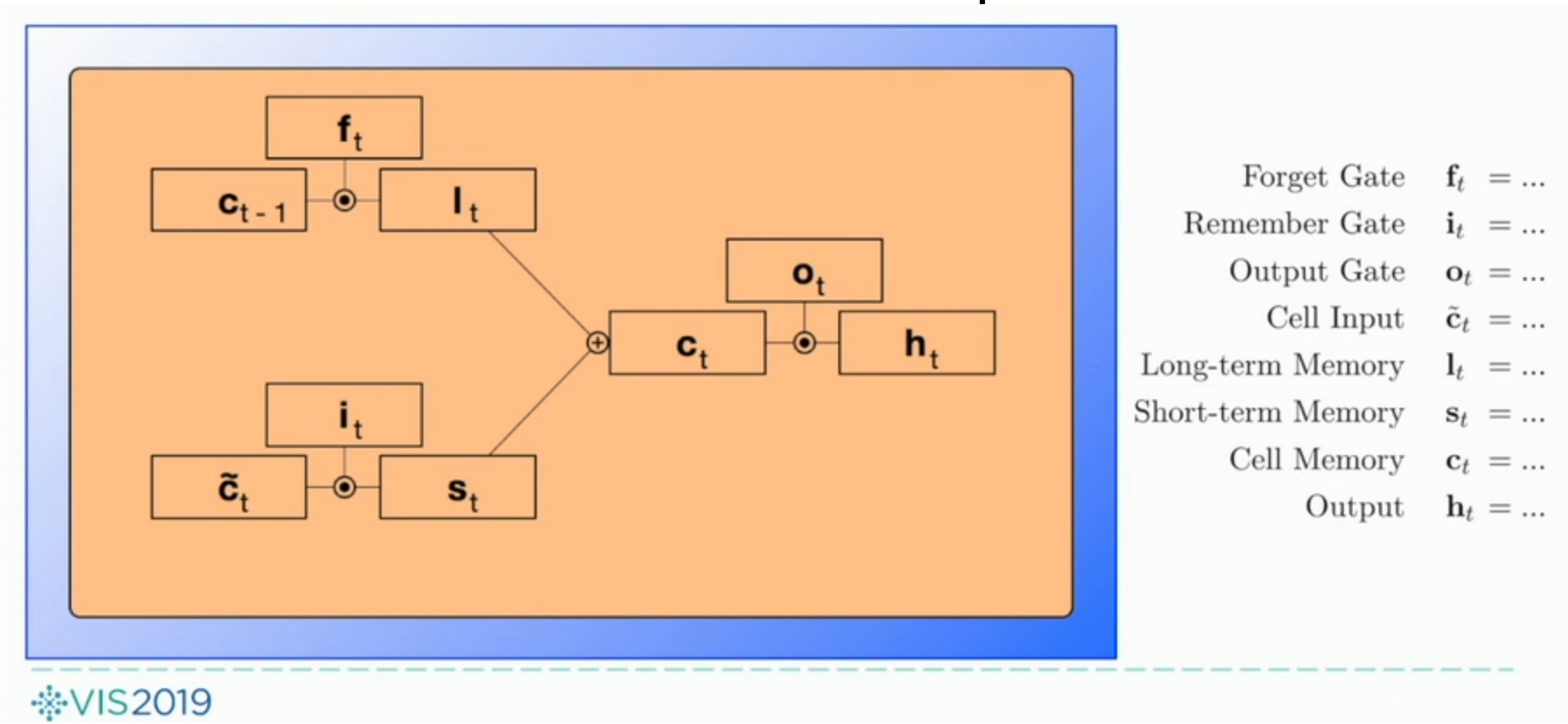
- Later information may be used to reassess previous observations



[Goodfellow, Bengio, Courville 2016]

LSTMs

- Use addition over time instead of multiplication



Further Architectures

- [Transformers]
- [Deep Reinforcement Learning]

Visualization for DL

- **Tensorboard: Visualizing Learning**
- How to use t-SNE efficiently

Model visualization

- **LSTM-Vis**: http://lstm.seas.harvard.edu/client/index.html
- Building blocks of interpretability

Sources

- I. Goodfellow, Y. Bengio, A. Courville "Deep Learning" MIT Press 2016 [link]
- Zhang et al. "Dive into Deep Learning" [link]