# Recurrent Neural Networks (RNNs)

# Recap

- MP neuron
- Perceptron
- MLP
- CNNs
- In other words, we have seen feedforward neural nets
    - No loops in the computational graphs

# Sequential data

- Many real-world problems have to process data with sequential nature

# Sequential data

- Many real-world problems have to process data with sequential nature

  - Sentiment analysis
  - Action recognition
  - DNA sequence classification

Sequence classification

# Sequential data

- Many real-world problems have to process data with sequential nature

- Sentiment analysis
- Action recognition
- DNA sequence classification

- Text synthesis
- Music synthesis
- Motion synthesis

Sequence classification

Sequence Synthesis

# Sequential data

- Many real-world problems have to process data with sequential nature

- Sentiment analysis
- Action recognition
- DNA sequence classification

Sequence classification

- Text synthesis
- Music synthesis
- Motion synthesis

Sequence Synthesis

- Machine translation
- PoS tagging

Sequence-to-sequence translation

# Formally

Given a set $\mathcal{X}$, and if $S(\mathcal{X})$ is the set of sequences of elements from $\mathcal{X}$

$$S(\mathcal{X}) = \bigcup_{t=1}^{\infty} \mathcal{X}^t$$

# Formally

Given a set $\mathcal{X}$, and if $S(\mathcal{X})$ is the set of sequences of elements from $\mathcal{X}$

$$S(\mathcal{X}) = \bigcup_{t=1}^{\infty} \mathcal{X}^t$$

$$f : S(\mathcal{X}) \rightarrow \{1, \ldots, C\}$$

Sequence classification

$$f : \mathcal{R}^D \rightarrow S(\mathcal{X})$$

Sequence Synthesis

$$f : S(\mathcal{X}) \rightarrow S(\mathcal{Y})$$

Sequence-to-sequence translation

# Temporal Convolution

# Temporal Convolutional Networks

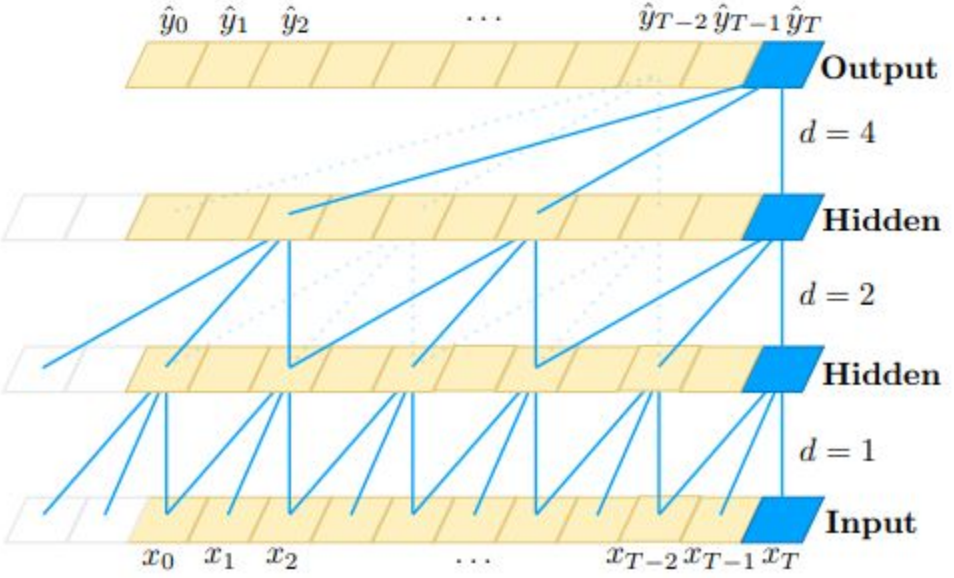



Figure credits: Raushan Roy

# RNNs and backprop through time

# Key is the recurrent state

- Maintains a recurrent state updated at each time step

# Key is the recurrent state

- Maintains a recurrent state updated at each time step

$$\text{With } \mathcal{X} = \mathcal{R}^D, \text{and}$$

$$\text{given}, \phi(\cdot; w) : \mathcal{R}^D \times \mathcal{R}^Q \to \mathcal{R}^Q,$$

# Key is the recurrent state

- Maintains a recurrent state updated at each time step

$$
\begin{aligned}
\text{With } \mathcal{X} = \mathcal{R}^D, \text{and} \\
\text{given, } \phi(\cdot; w) : \mathcal{R}^D \times \mathcal{R}^Q \to \mathcal{R}^Q, \\
\text{an input sequence } x \in \mathcal{S}(\mathcal{R}^D), \\
\text{an initial recurrent state } h_0 \in \mathcal{R}^Q,
\end{aligned}
$$

# Key is the recurrent state

- Maintains a recurrent state updated at each time step

$$\text{With } \mathcal{X} = \mathcal{R}^D, \text{and}$$

$$\text{given}, \phi(\cdot; w) : \mathcal{R}^D \times \mathcal{R}^Q \to \mathcal{R}^Q,$$

$$\text{an input sequence } x \in \mathcal{S}(\mathcal{R}^D),$$

$$\text{an initial recurrent state } h_0 \in \mathcal{R}^Q,$$

$$\text{model computes sequence of recurrent states iteratively}$$

$$\forall t = 1, \ldots, T(x), h_t = \phi(x_t, h_{t-1}; w)$$

# State computes the output

- Prediction can be computed at any time step using the recurrent state

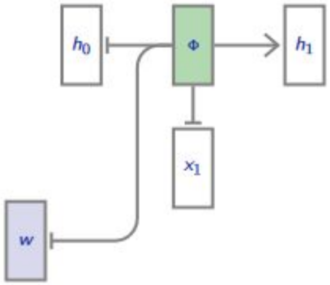
# State computes the output

- Prediction can be computed at any time step using the recurrent state

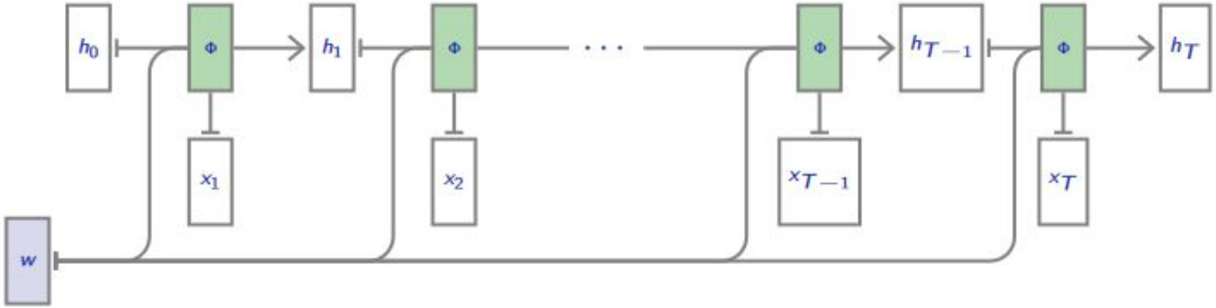
$$y_t = \psi(h_t; w)$$

$$\psi(\cdot; w) : \mathcal{R}^Q \to \mathcal{R}^C$$

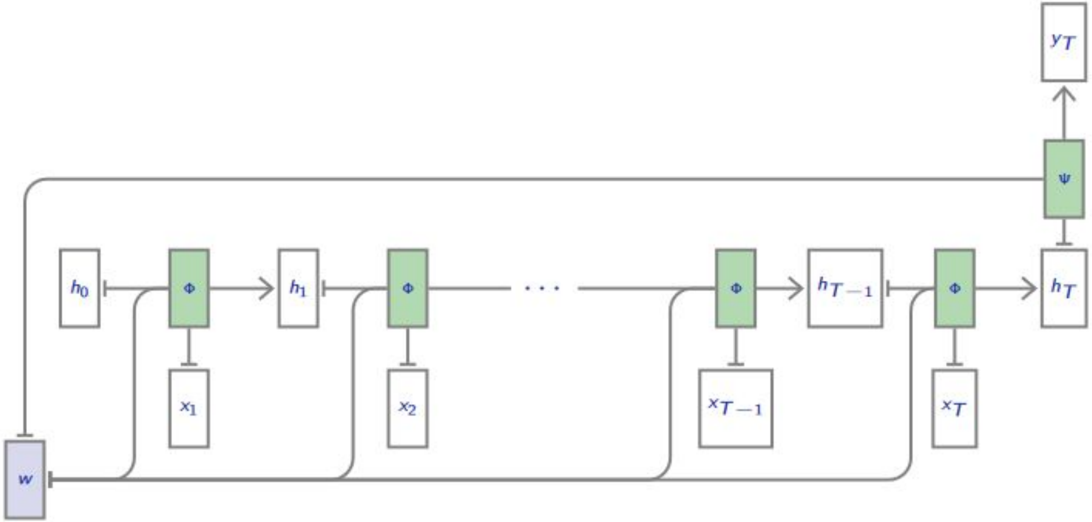
# Recurrence in a graph



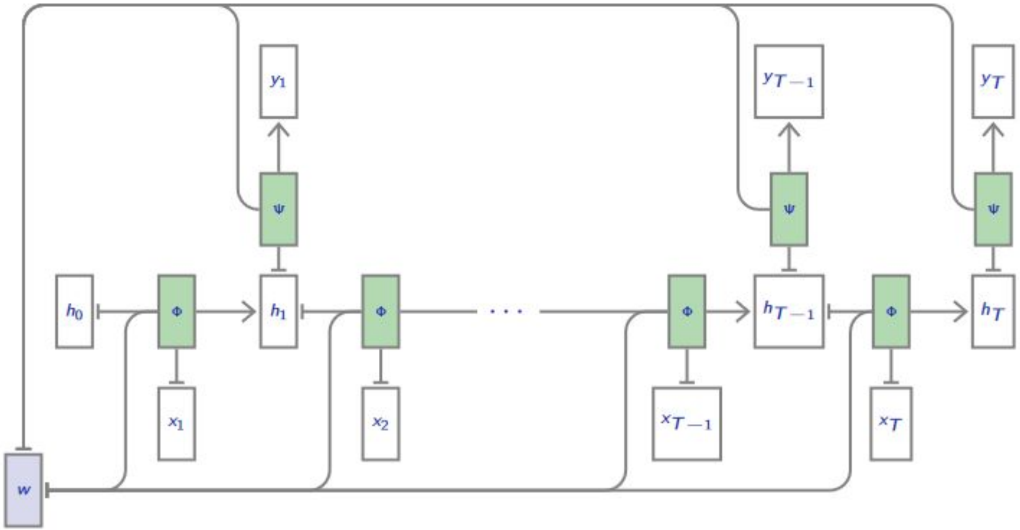
# Recurrence in a graph



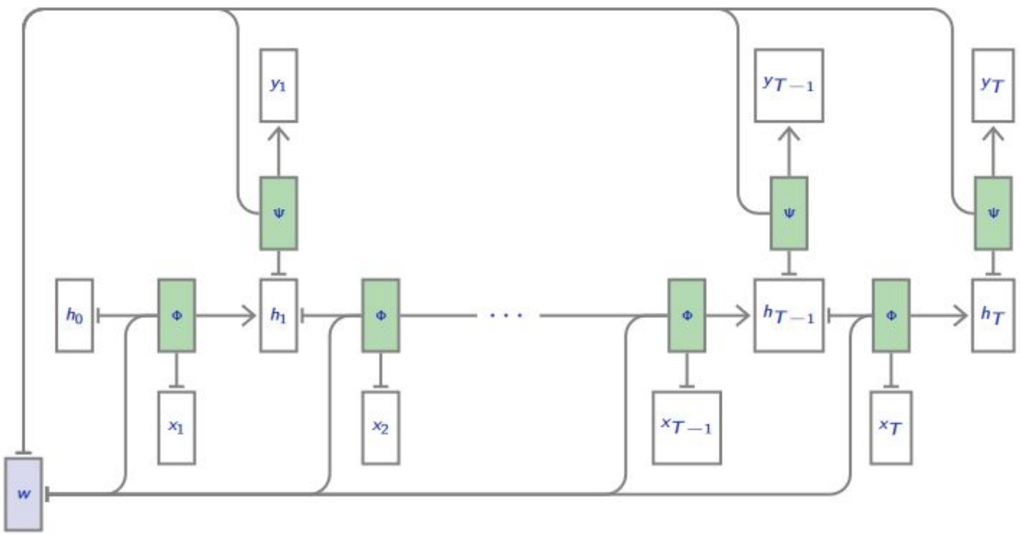
# Recurrence in a graph



# Recurrence in a graph



# Backprop in time




Number of steps is equal to the length of sequence T. The rest is similar to the DAGs we know, and autograd can handle.

# Sample problem

# Elman Network (Elman, 1990)

$$
\begin{aligned}
h_0 &= 0 \\
h_t &= \mathrm{ReLU}\left(W_{xh} x_t + W_{hh} h_{t-1} + b_h\right) \\
y_t &= W_{hy} h_t + b_y
\end{aligned}
$$

# Sequence classification

Class 1 : sequence is concatenation of two identical halves

Class 0: otherwise

# Sequence classification

Class 1 : sequence is concatenation of two identical halves

Class 0: otherwise

$$
\begin{aligned}
x &\rightarrow y \\
(1,2,3,4,5,6) &\rightarrow 0 \\
(3,9,9,3) &\rightarrow 0 \\
(7,4,4,7,5,4) &\rightarrow 0 \\
(7,7) &\rightarrow 1 \\
(1,2,3,1,2,3) &\rightarrow 1 \\
(5,1,1,2,5,1,1,2) &\rightarrow 1
\end{aligned}
$$

# RNN hands-on

# While unfolding in time

- What is the depth of the model?

# While unfolding in time

- What is the depth of the model?
    - Length of the input

# While unfolding in time

- What is the depth of the model?
  - Length of the input
- → vanishing gradient issue

$$
\begin{aligned}
h_0 &= 0 \\
h_t &= \mathrm{ReLU}\ (W_{xh} x_t + W_{hh} h_{t-1} + b_h)
\end{aligned}
$$

# While unfolding in time

- What is the depth of the model?
    - Length of the input
- → vanishing gradient issue
- Introduce a ‘pass-through’
    - recurrent state does not go repeatedly through a squashing nonlinearity

# Pass-through

- Recurrent state update can be weighted avg. of previous value and current full update

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \bar{h}_t$$

$$\text{where, } \bar{h}_t = \phi(x_t, h_{t-1}) \text{ and}$$

$$\text{weight } z_t = f(x_t, h_{t-1})$$

# Pass-through

- Recurrent state update can be weighted avg. of previous value and current full update

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \bar{h}_t$$

where, $\bar{h}_t = \phi(x_t, h_{t-1})$ and
weight $z_t = f(x_t, h_{t-1})$

Acts as a 'forget' gate

# Gating

- Update equations will now become

$$
\begin{aligned}
h_0 =& 0 \\
\bar{h}_t =& \text{ ReLU } (W_{xh}x_t + W_{hh}h_{t-1} + b_h) \text{ (full update)} \\
z_t =& sigm(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \text{ (forget gate)} \\
h_t =& z_t \odot h_{t-1} + (1 - z_t) \odot \bar{h}_t \text{ (recurrent state )} \\
y_t =& W_{hy}h_t + b_y \text{ (output)}
\end{aligned}
$$

# LSTM

# Assignment

- Improve the sample problem with the updated model

# Long-Short Term Memory unit

- Hochreiter and Schmidhuber (1997)
- Later improved by a forget gate (Gers, et al 2000)

# Long-Short Term Memory unit

- Hochreiter and Schmidhuber (1997)
- Later improved by a forget gate (Gers, et al 2000)

It uses the structure founded on the short-term processes to create a long-term memory

# Long-Short Term Memory unit

- Recurrent state consists of a cell state ($c_t$) and an output state ($h_t$)
- Gate $f_t$ modulates if the cell state should be forgotten, $i_t$ if the new update should be taken into account
- $o_f$ if the output state should be reset

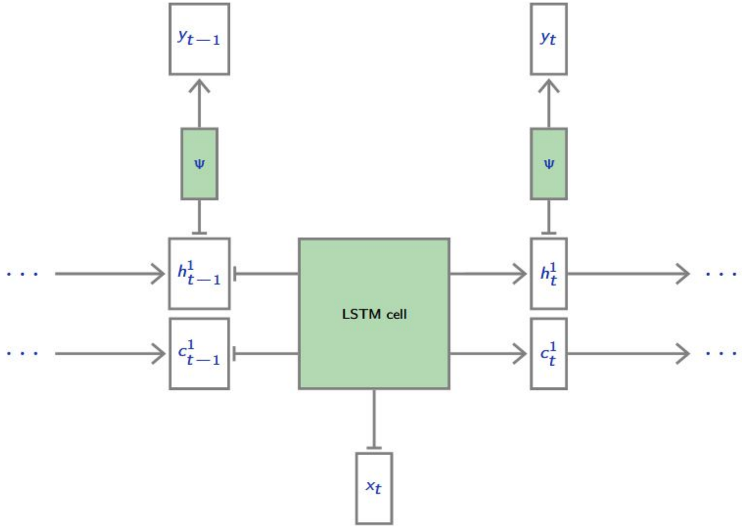
# Long-Short Term Memory unit

- Recurrent state consists of a cell state ($c_t$) and an output state ($h_t$)
- Gate $f_t$ modules if the cell state should be forgotten, $i_t$ if the new update should be taken into account
- $o_t$ if the output state should be reset

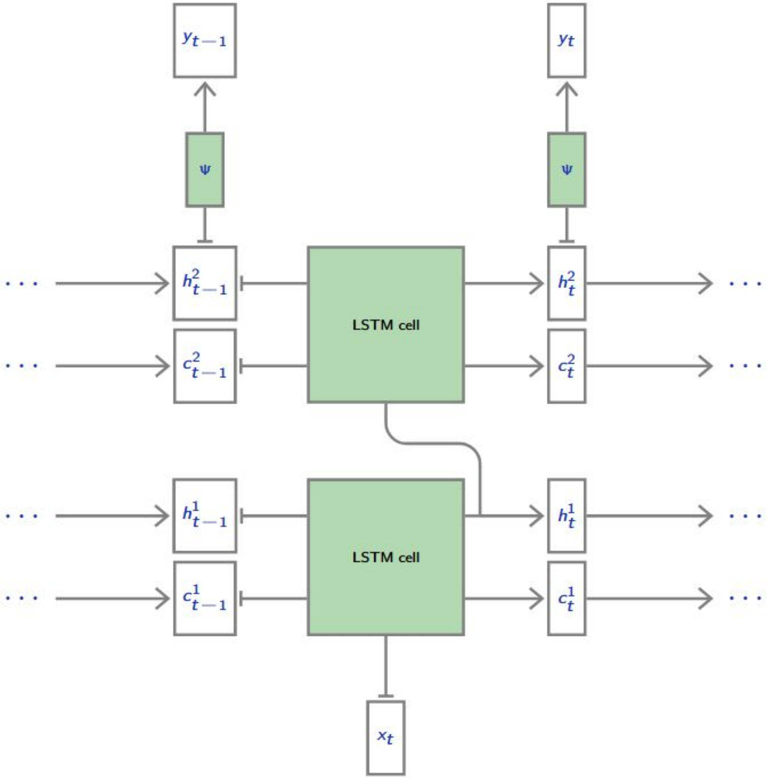
$$f_t = sigm(W_{xf}x_t + W_{hf}h_{t-1} + b_f)$$
$$i_t = sigm(W_{xi}x_t + W_{hi}h_{t-1} + b_i)$$
$$o_t = sigm(W_{xo}x_t + W_{ho}h_{t-1} + b_o)$$

$$g_t = tanh(W_{xc}X_t + W_{hc}h_{t-1} + b_c)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g_t$$
$$h_t = o_t \odot tanh(c_t)$$

# LSTM unit



# LSTM layers



$y_{t-1}$
$y_t$
$\psi$
$\psi$
. . .
$h^2_{t-1}$
LSTM cell
$h^2_t$
. . .
. . .
$c^2_{t-1}$
$c^2_t$
. . .
. . .
$h^1_{t-1}$
LSTM cell
$h^1_t$
. . .
. . .
$c^1_{t-1}$
$c^1_t$
. . .
$x_t$

# torch.nn.LSTM

- Layers D
- Processes sequence of length T and outputs
- Outputs for all the layers at the last time step T: $h_T^1$, $h_T^2$, .... $h_T^D$
- Outputs for the last layer at all the time steps: $h_1^D$, $h_2^D$, .... $h_T^D$

# Try LSTM on the toy task

```
class LSTMNet(nn.Module):
  def __init__(self, dim_input, dim_recurrent, num_layers, dim_output):
     super().__init__()
     self.lstm = nn.LSTM(input_size = dim_input,hidden_size = dim_recurrent,num_layers =
num_layers)
     self.fc_o2y = nn.Linear(dim_recurrent, dim_output)
  def forward(self, input):
     # Get the last layer's last time step activation
     output, _ = self.lstm(input.permute(1, 0, 2))
     output = output[-1]
     return self.fc_o2y(F.relu(output))
```

# Gated Recurrent Unit (GRU)

- LSTM was simplified by Cho et al. (2014)
- Has a gating for recurrent state
- Also has a reset gate

# Gated Recurrent Unit (GRU)

$$r_t = sigm(W_{xr}x_t + W_{hr}h_{t-1} + b_r) \quad \text{(reset gate)}$$

$$z_t = sigm(W_{xz}x_t + W_{hz}h_{t-1} + b_z) \quad \text{(forget gate)}$$

$$\bar{h}_t = tanh(W_{xh}x_t + W_{hh}(r_t \odot h_{t-1}) + b_h) \quad \text{(full update)}$$

$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \bar{h}_t \quad \text{(hidden update)}$$

# Different sequence tasks

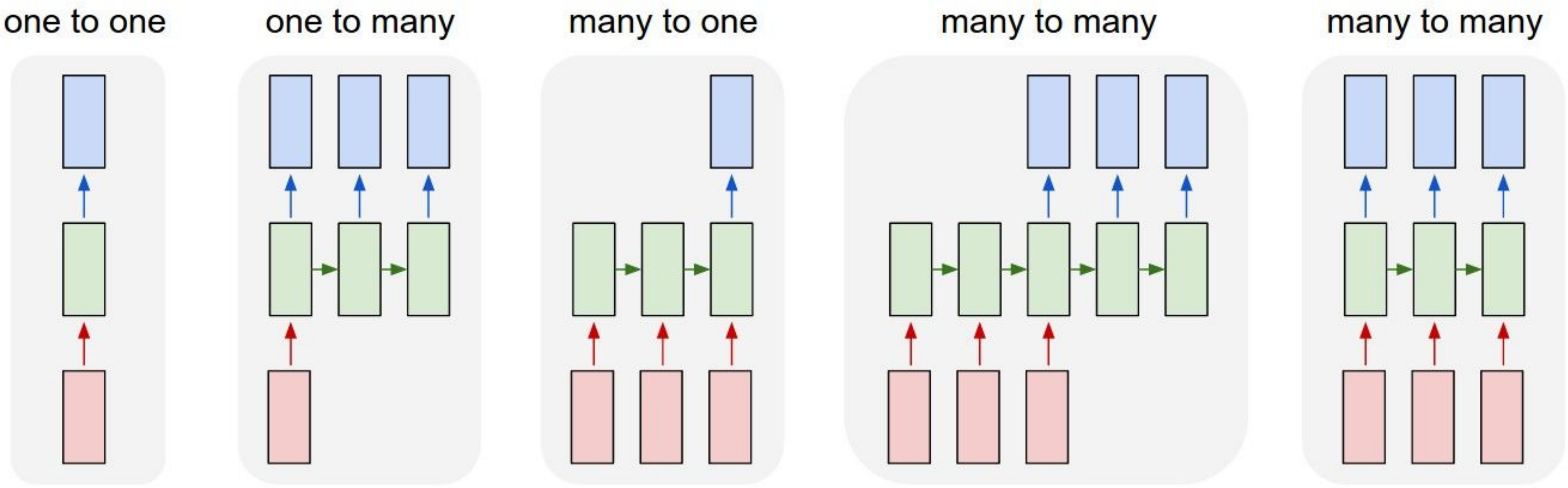
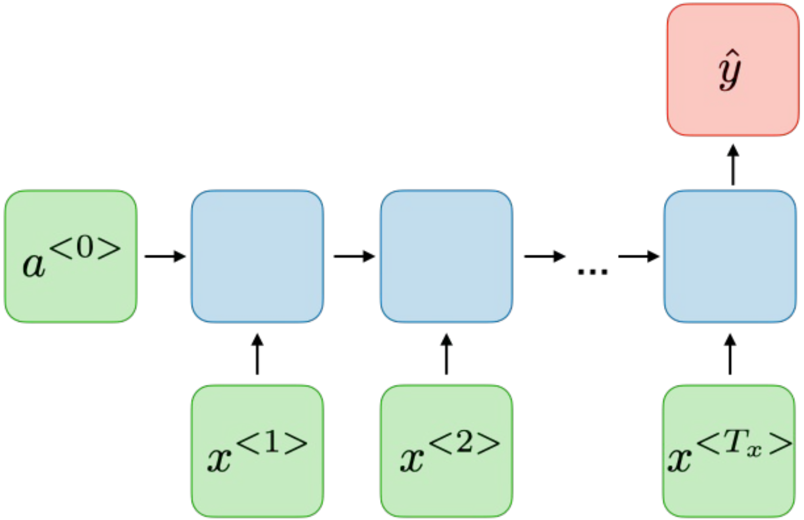



Figure Credit [Andrej Karpathy]

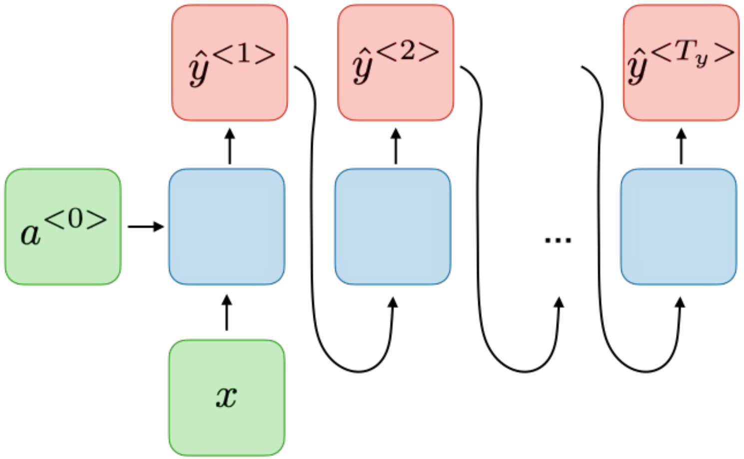
# Many-to-One




Sentiment classification, etc.

Figure Credit CS321N, Stanford

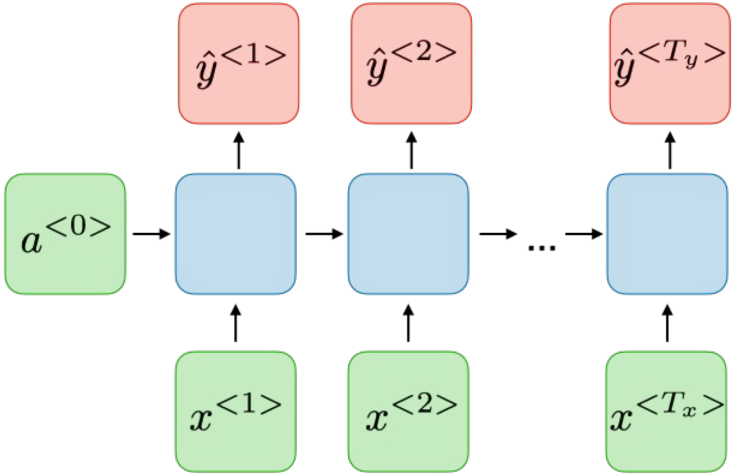
# One-to-Many




Music generation, image captioning, etc.

Figure Credit CS321N, Stanford

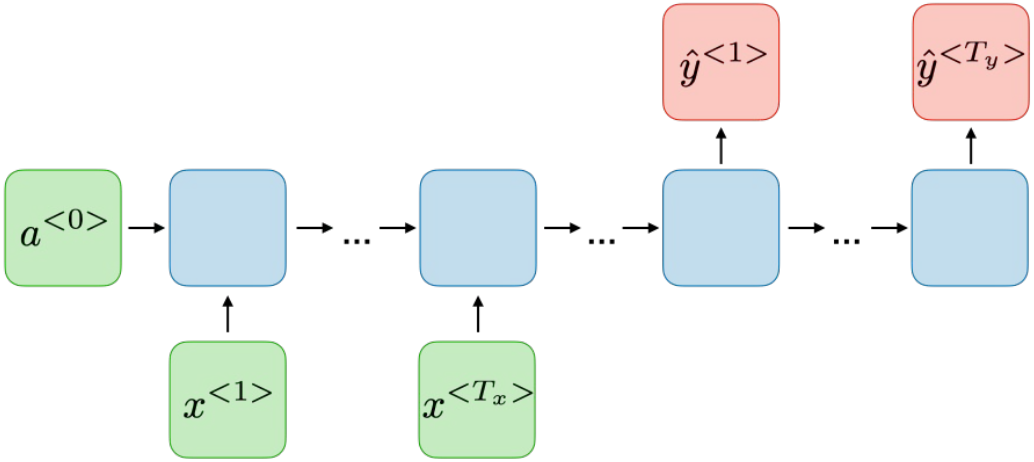
# Many-to-Many




PoS tagging, etc.

Figure Credit CS321N, Stanford

# Many-to-Many




Machine Translation, etc.

Figure Credit CS321N, Stanford

# Course Project presentations

- Wednesday(17 Nov)
  - 11-12 PM
  - 4 teams ($T_1$, $T_2$, $T_4$, $T_{16}$)
- Saturday (20 Nov)
  - 10AM - 12PM and 2-3 PM
  - 12 teams (rest 12)

# Course Project presentations

- ~10 minutes per team
- Slides on
    - Problem detailing
    - Proposed solution/Analysis performed
    - Code walkthrough

Thank You