Recurrent Neural Networks II

CS 4391 Introduction Computer Vision

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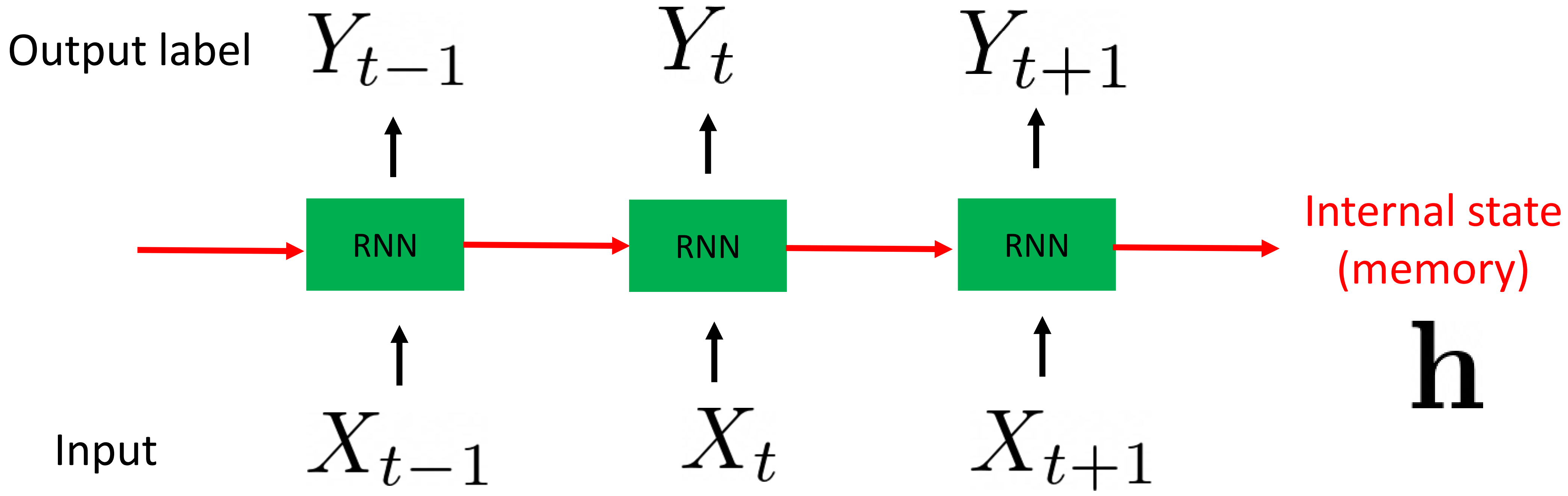
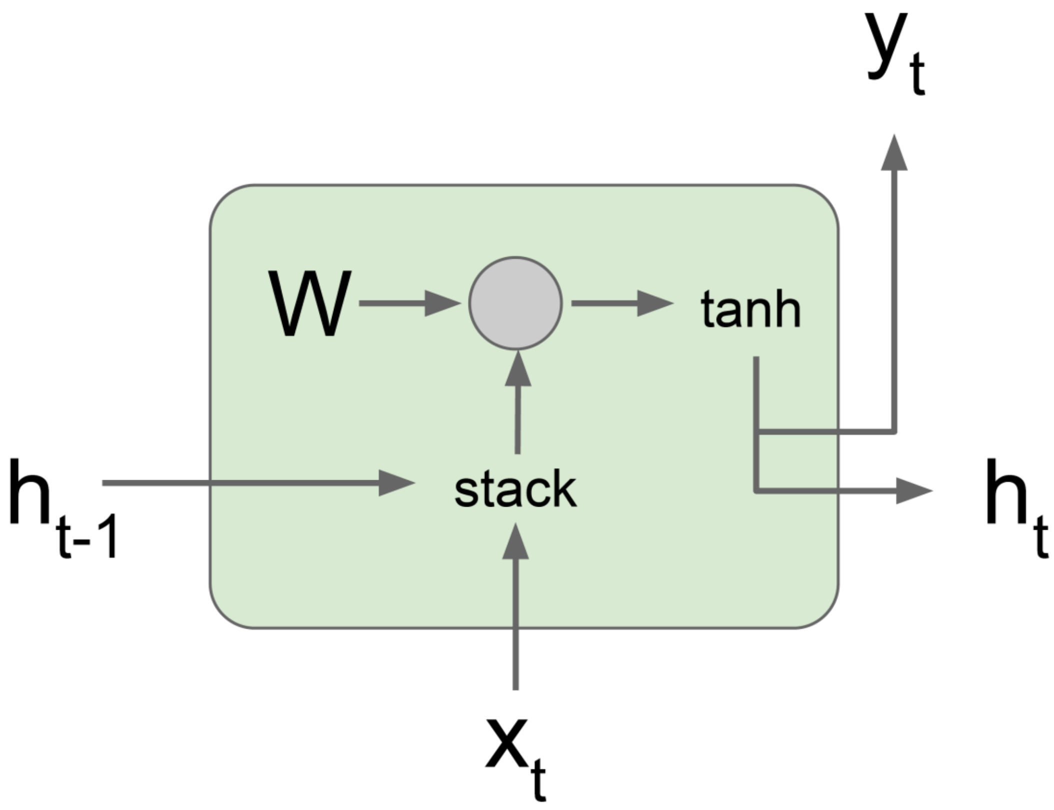
Some slides of this lecture are courtesy Stanford CS231n

Recurrent Neural Networks



Vanilla RNN



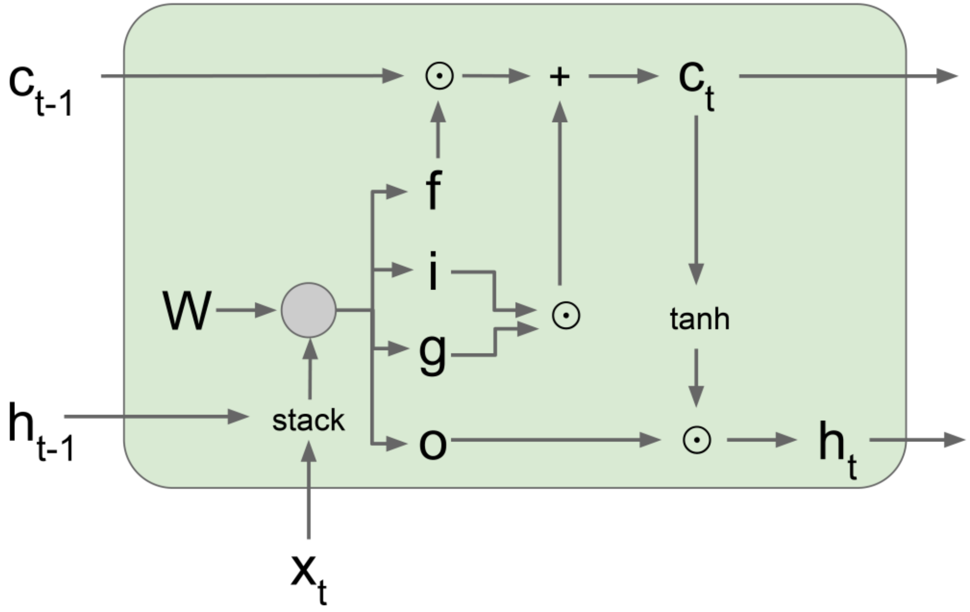
$$\mathbf{h}_t = \tanh(W_{hh}\mathbf{h}_{t-1} + W_{xh}\mathbf{x}_t)$$

$$= \tanh\left(\begin{pmatrix} W_{hh} & W_{hx} \end{pmatrix} \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

$$= \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

$$\mathbf{y}_t = W_{hy}\mathbf{h}_t$$

Long Short Term Memory (LSTM)



LSTM

$$\begin{array}{l} \text{Input gate} \\ \text{forget gate} \\ \text{output gate} \\ \text{gate gate} \end{array} \quad \begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

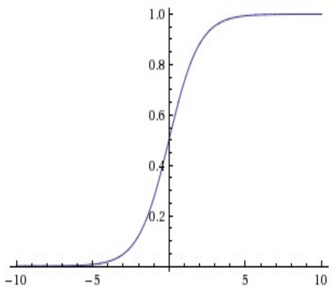
Cell $c_t = f \odot c_{t-1} + i \odot g$

Hidden state $h_t = o \odot \tanh(c_t)$

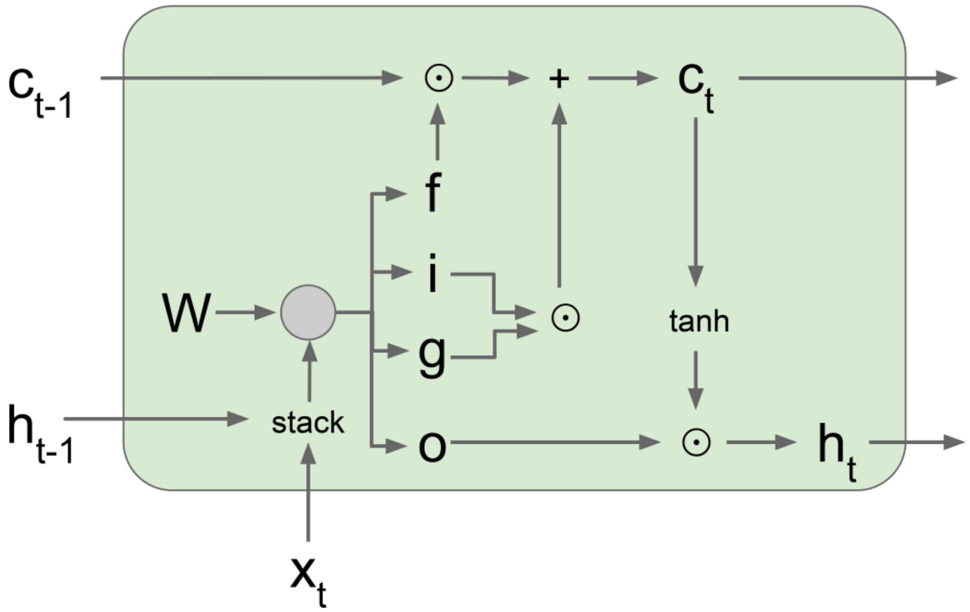
Store Cell and hidden states

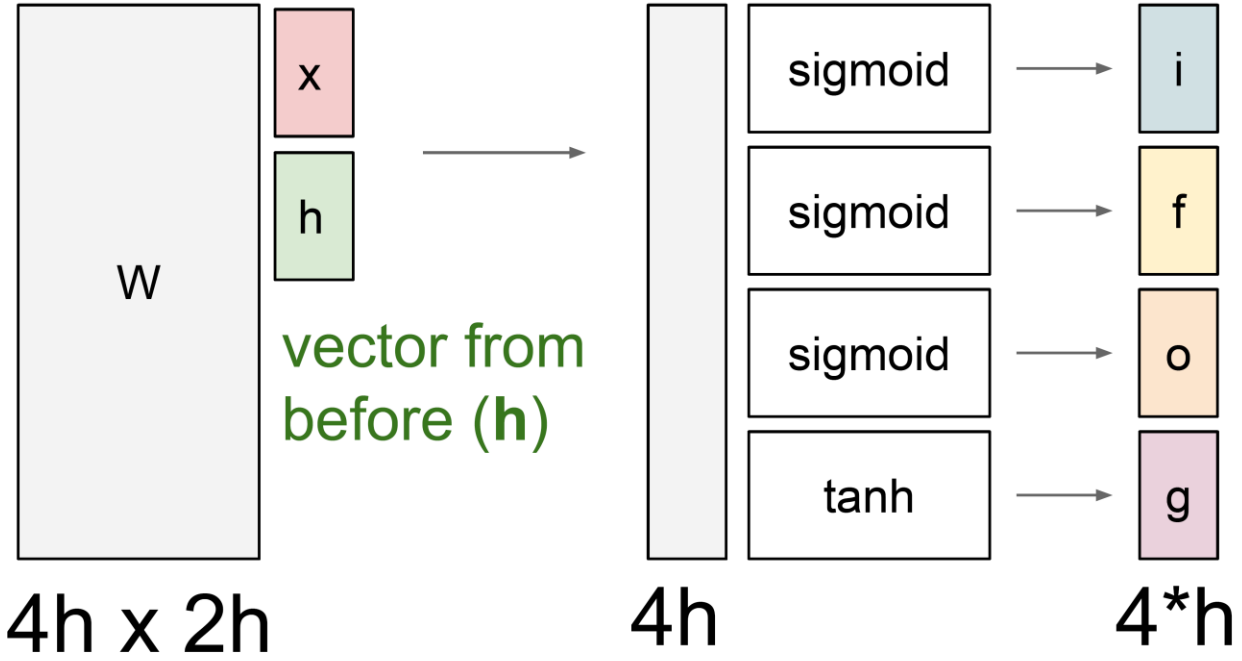
Sigmoid

$$\sigma(x) = 1/(1 + e^{-x})$$



Long Short Term Memory (LSTM)





$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

- **g**: Gate gate, how much to write to cell
- **i**: Input gate, whether to write to cell
- **f**: Forget gate, whether to erase cell
- **o**: Output gate, how much to reveal cell

Long Short Term Memory (LSTM)

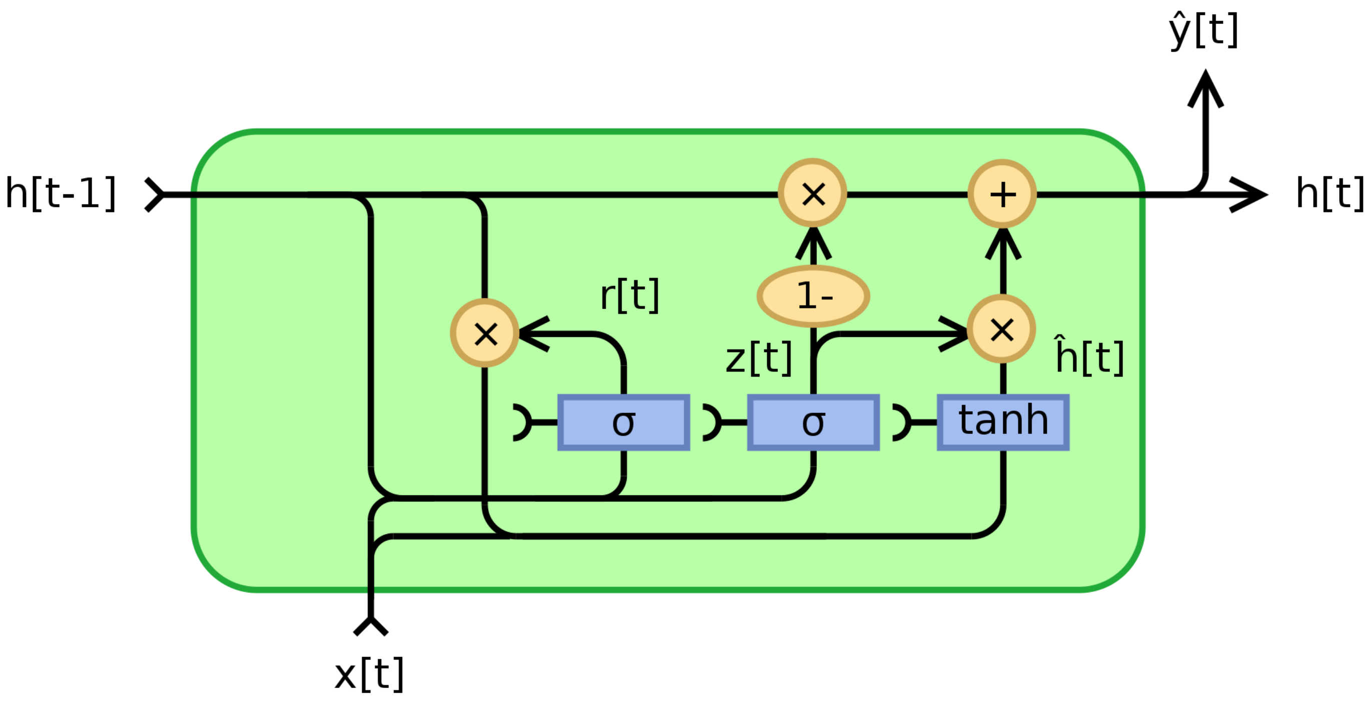
- Make the RNN easier to preserve information over many steps
  - E.g., f = 1 and i = 0
  - This is difficult for vanilla RNN
- LSTM does not guarantee that there is no vanishing or exploding gradient
- It provides an easier way to learn long-distance dependencies

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

$$h_t = o \odot \tanh(c_t)$$

Gated Recurrent Unit (GRU)



https://en.wikipedia.org/wiki/Gated_recurrent_unit

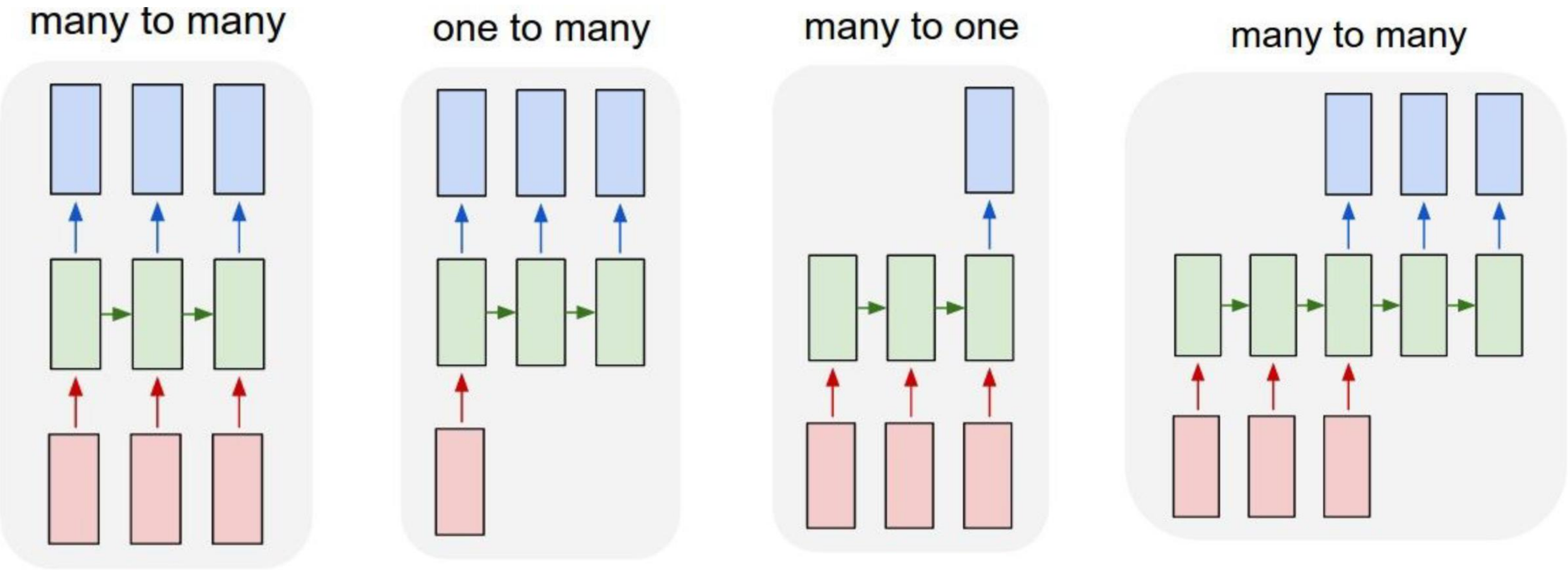
$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z)$$
$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r)$$
$$\hat{h}_t = \phi_h(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$$
$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \hat{h}_t$$

- x_t: input vector
- h_t: output vector
- $\hat{h}_t$: candidate activation vector
- z_t: update gate vector
- r_t: reset gate vector
- W, U and b: parameter matrices and vector

GRUs vs. LSTMs

- Both have a forget gate
- GRU has fewer parameters, no output gate
- GRUs have similar performance compared to LSTMs, have shown better performance on certain datasets

Recurrent Neural Networks



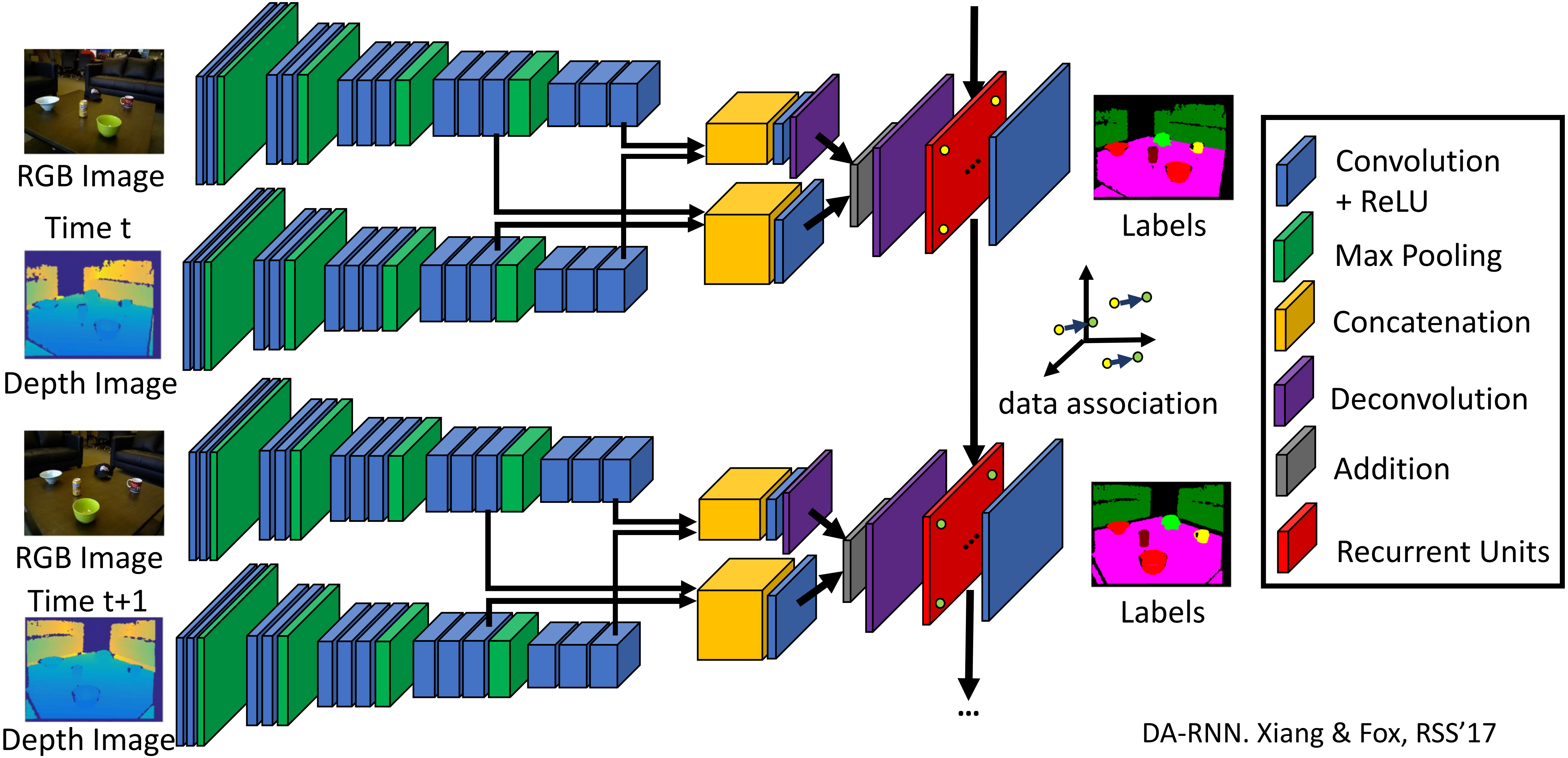
E.g., action recognition on video frames

E.g., image captioning, image -> sequences of words

E.g., action prediction, sequences of frames -> action class

E.g., Video Captioning Sequence of video frames -> caption

Recurrent Units on CNN Features



DA-RNN. Xiang & Fox, RSS'17

Machine Translation

- Translate a phrase from one language to anther
  - E.g., English phrase to French phrase

Google Translation

13 words

15 words

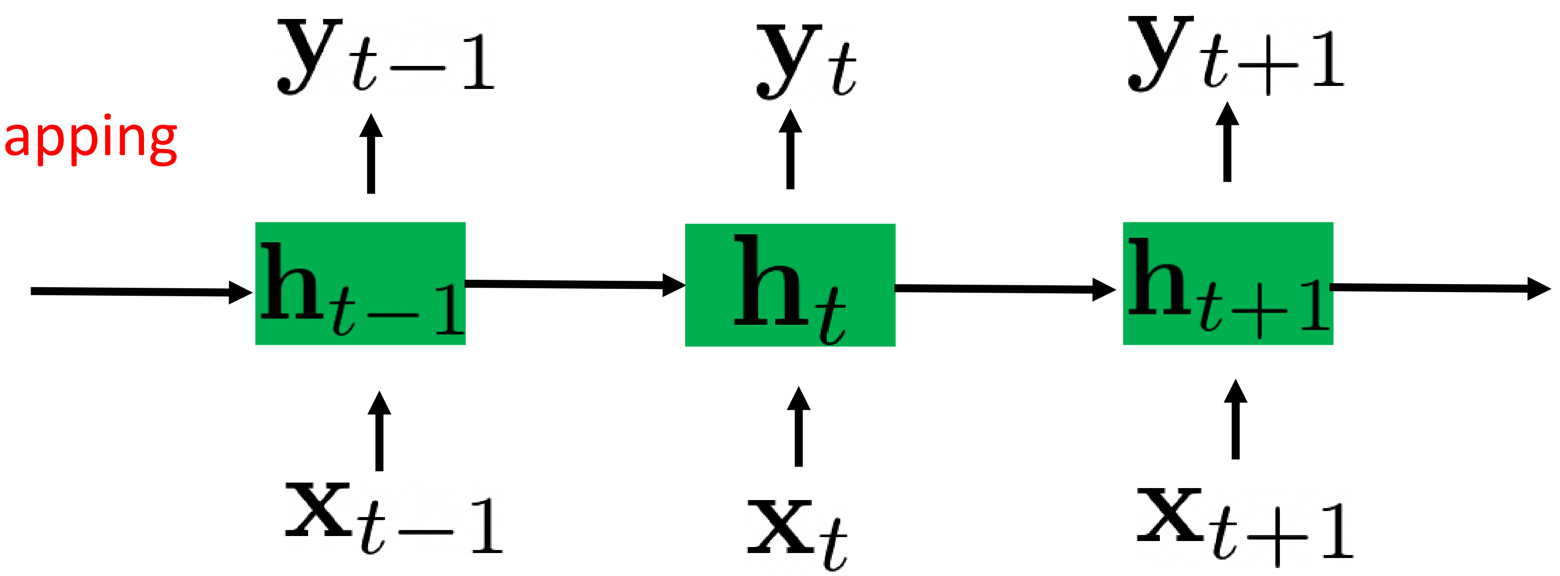
Machine Translation

- Input $\mathbf{x} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_T)$
- Output $\mathbf{y} = (\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_{T'})$

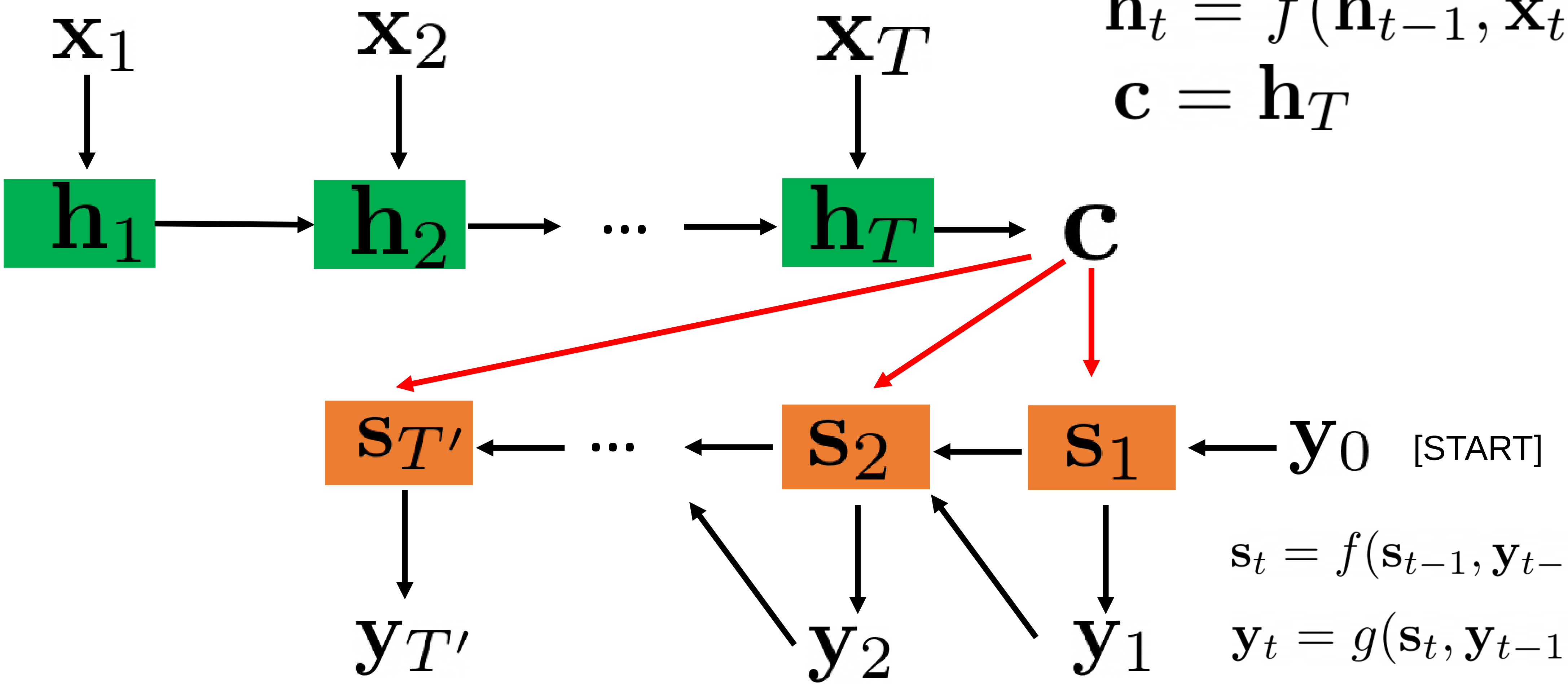
$$T \neq T'$$

Not one to one mapping

RNN



RNN Encoder-Decoder



$$\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t)$$

$$\mathbf{c} = \mathbf{h}_T$$

$$\mathbf{s}_t = f(\mathbf{s}_{t-1}, \mathbf{y}_{t-1}, \mathbf{c})$$

$$\mathbf{y}_t = g(\mathbf{s}_t, \mathbf{y}_{t-1}, \mathbf{c})$$

Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation. Cho et al., EMNLP’14

RNN Encoder-Decoder

- Encoder $\mathbf{h}_t = f(\mathbf{h}_{t-1}, \mathbf{x}_t) \quad \mathbf{c} = \mathbf{h}_T$
- Decoder $\mathbf{s}_t = f(\mathbf{s}_{t-1}, \mathbf{y}_{t-1}, \mathbf{c}) \quad \mathbf{y}_t = g(\mathbf{s}_t, \mathbf{y}_{t-1}, \mathbf{c})$

- Pros
  - Can deal with different input size and output size

- Cons
  - The fixed length embedding $\mathbf{c}$ cannot handle long sentence well (long-distance dependencies)

Limitations of RNNs

- The sequential computation of hidden states precludes parallelization within training examples

$$\longrightarrow \mathbf{h}_{t-1} \longrightarrow \mathbf{h}_t \longrightarrow \mathbf{h}_{t+1} \longrightarrow$$

- Cannot handle long sequences well
  - Truncated back-propagation due to memory limits
  - Difficult to capture dependencies in long distances

Summary

- RNNs can be used for sequential data to capture dependencies in time
- LSTMs and GRUs are better then vanilla RNNs
- It is difficult to capture long-term dependencies in RNNs
- Use transformers (in future lectures)

Further Reading

- Stanford CS231n, lecture 10, Recurrent Neural Networks http://cs231n.stanford.edu/
- Long Short Term Memory https://www.researchgate.net/publication/13853244_Long_Short-term_Memory
- Gated Recurrent Units https://arxiv.org/pdf/1412.3555.pdf