Deep Learning (CS324)

6. Recurrent Neural Networks*
(Continued)

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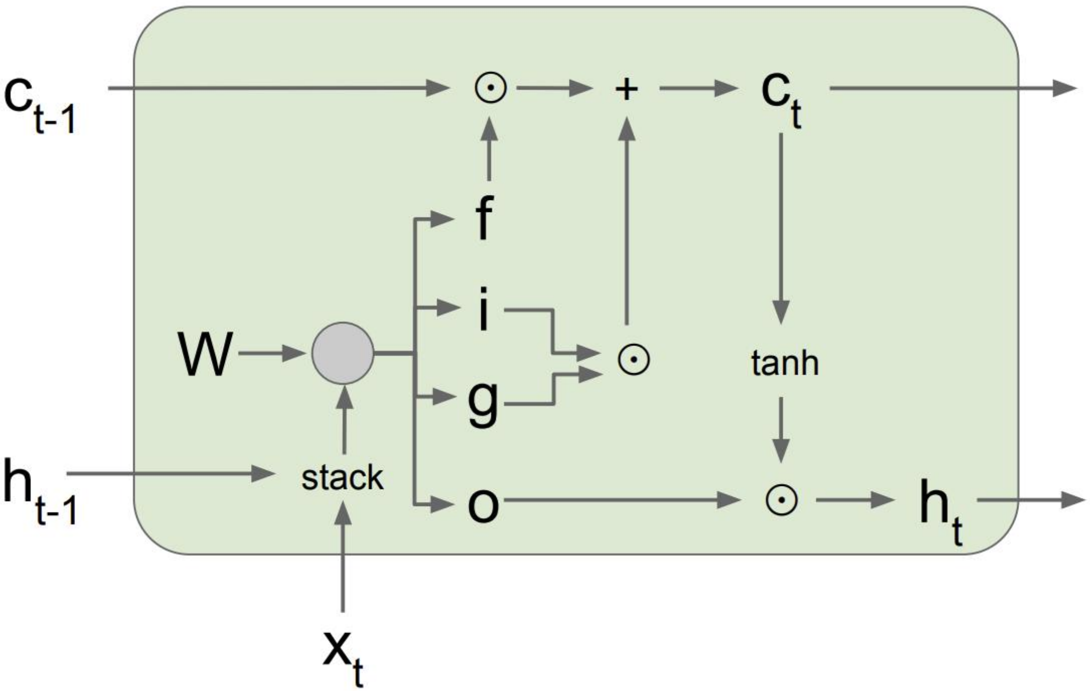
*Based on http://www.deeplearningbook.org chapter 10 + sources mentioned in slides

RNN

- Gated Recurrent Neural Network
- Different architectures of RNN.

LSTM Forward Pass Summary



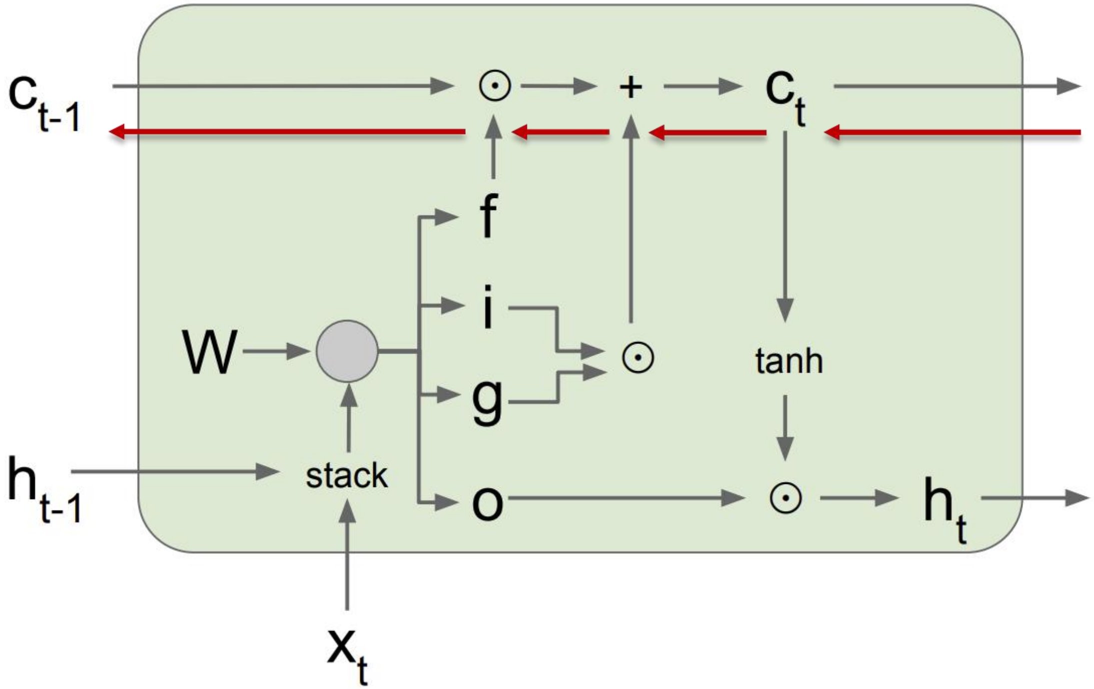
$$\begin{pmatrix} g_t \\ i_t \\ f_t \\ o_t \end{pmatrix} = \begin{pmatrix} \tanh \\ \sigma \\ \sigma \\ \sigma \end{pmatrix} \begin{pmatrix} W_g \\ W_i \\ W_f \\ W_o \end{pmatrix} \begin{pmatrix} x_t \\ \mathrm{h}_{t-1} \end{pmatrix}$$

$$c_t = f_t \odot c_{t-1} + i_t \odot g_t$$

$$\mathrm{h}_t = o_t \odot \tanh c_t$$

Figure source

LSTM Backward Pass

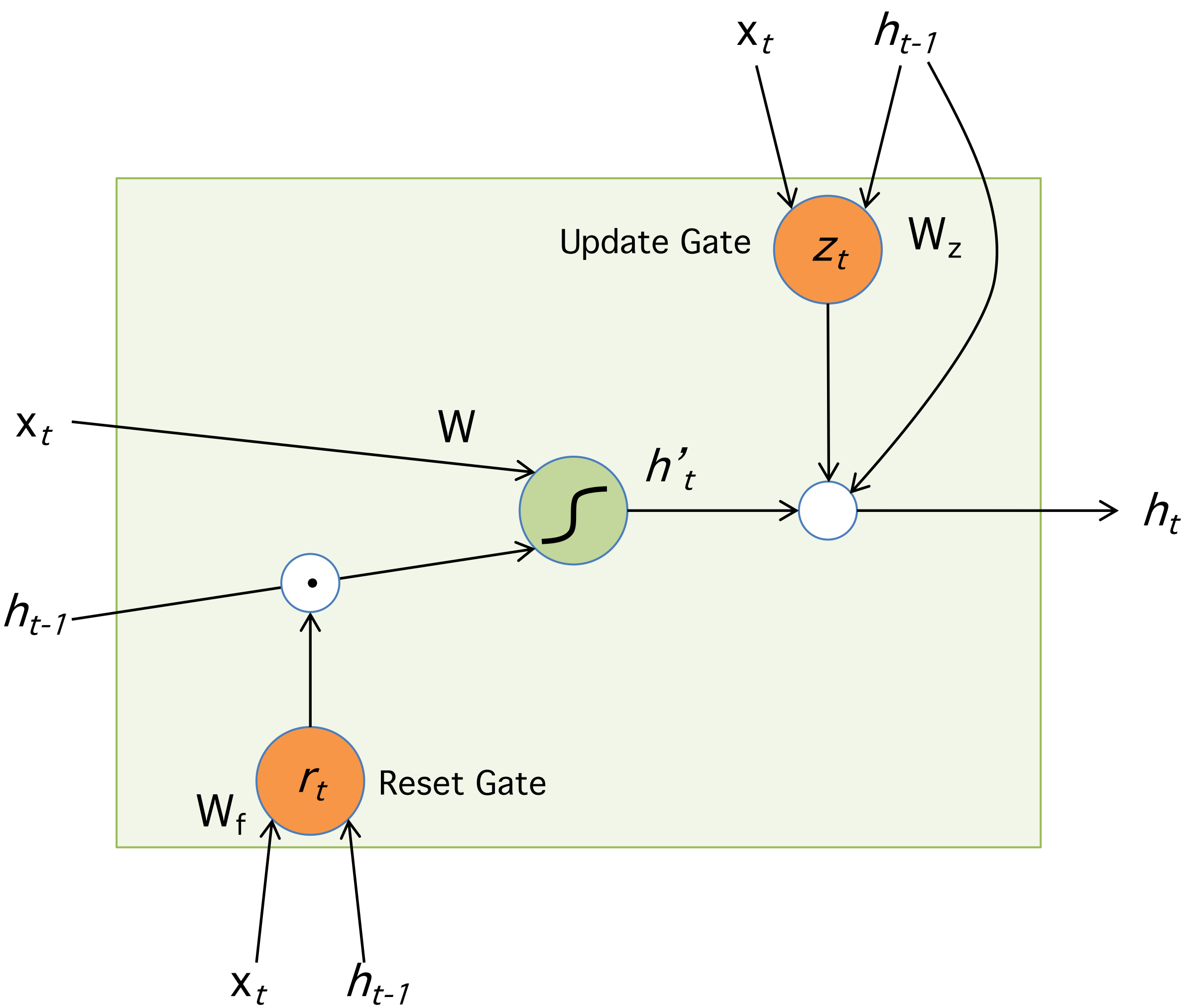


Gradient flow from c_t to c_{t-1} only involves back-propagating through addition and elementwise multiplication, not matrix multiplication or tanh

For complete details: [Illustrated LSTM Forward and Backward Pass]

Figure source

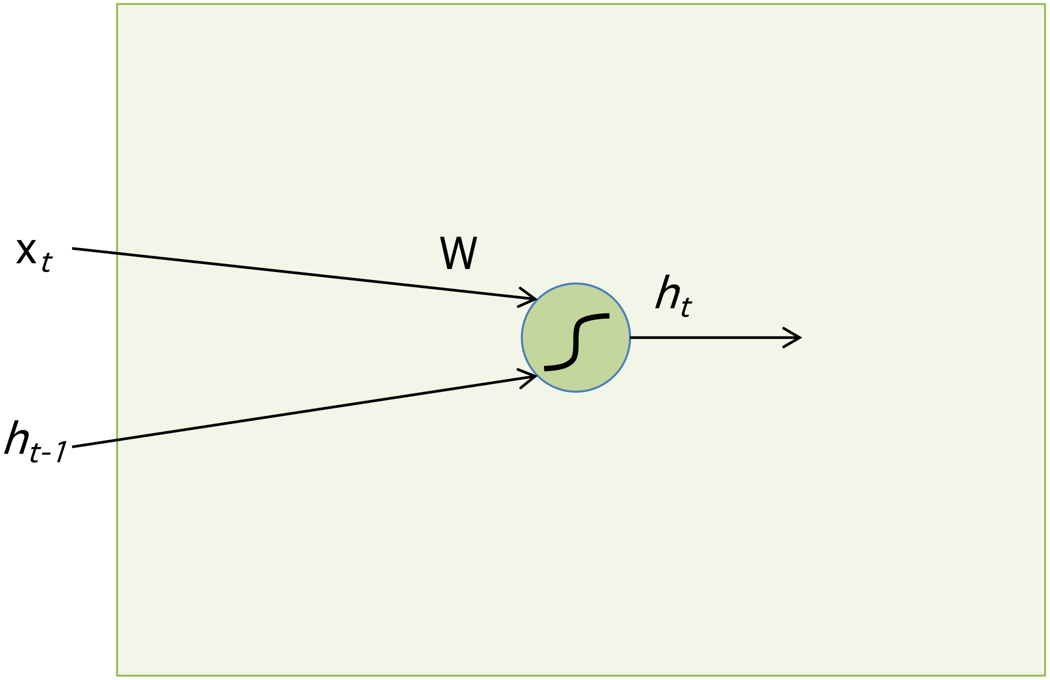
Gated Recurrent Unit (GRU)



- Get rid of separate cell state
- Merge "forget" and "output" gates into "update" gate

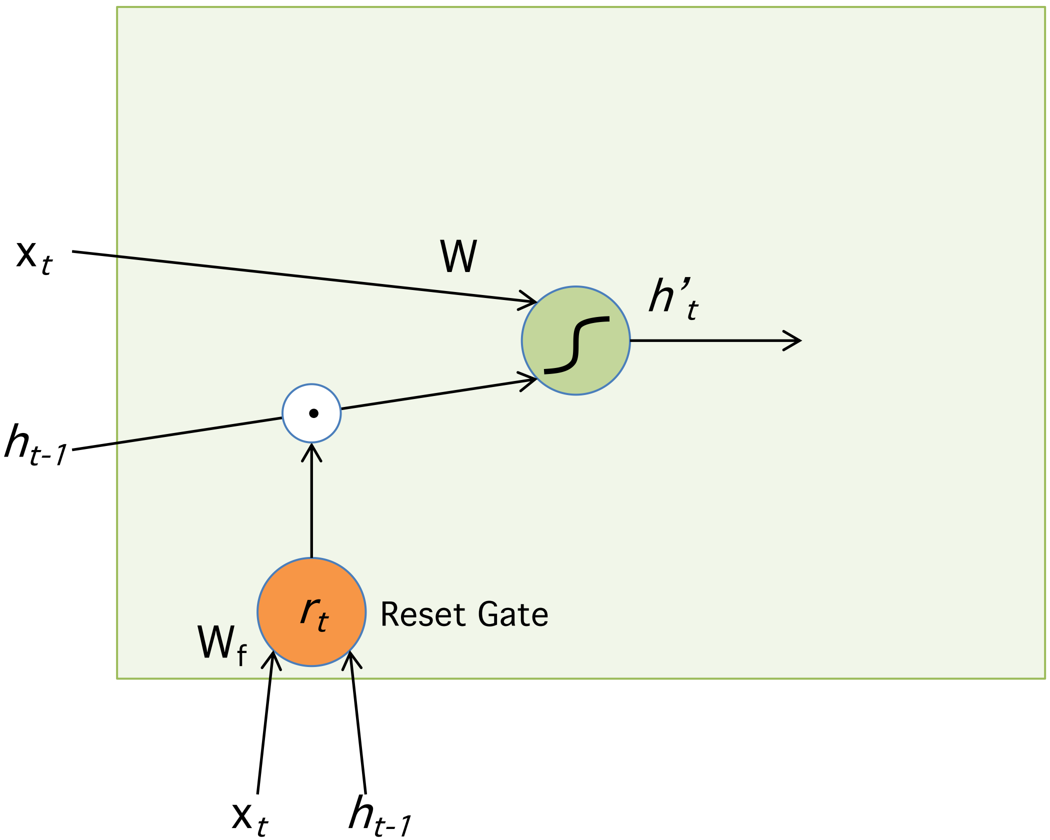
K. Cho, B. Van Merrienboer, C. Gulcehre, D. Bahdanau, F. Bougares, H. Schwenk, and Y. Bengio, [Learning phrase representations using RNN encoder-decoder for statistical machine

Gated Recurrent Unit (GRU)



$$h_t = \tanh W \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix}$$

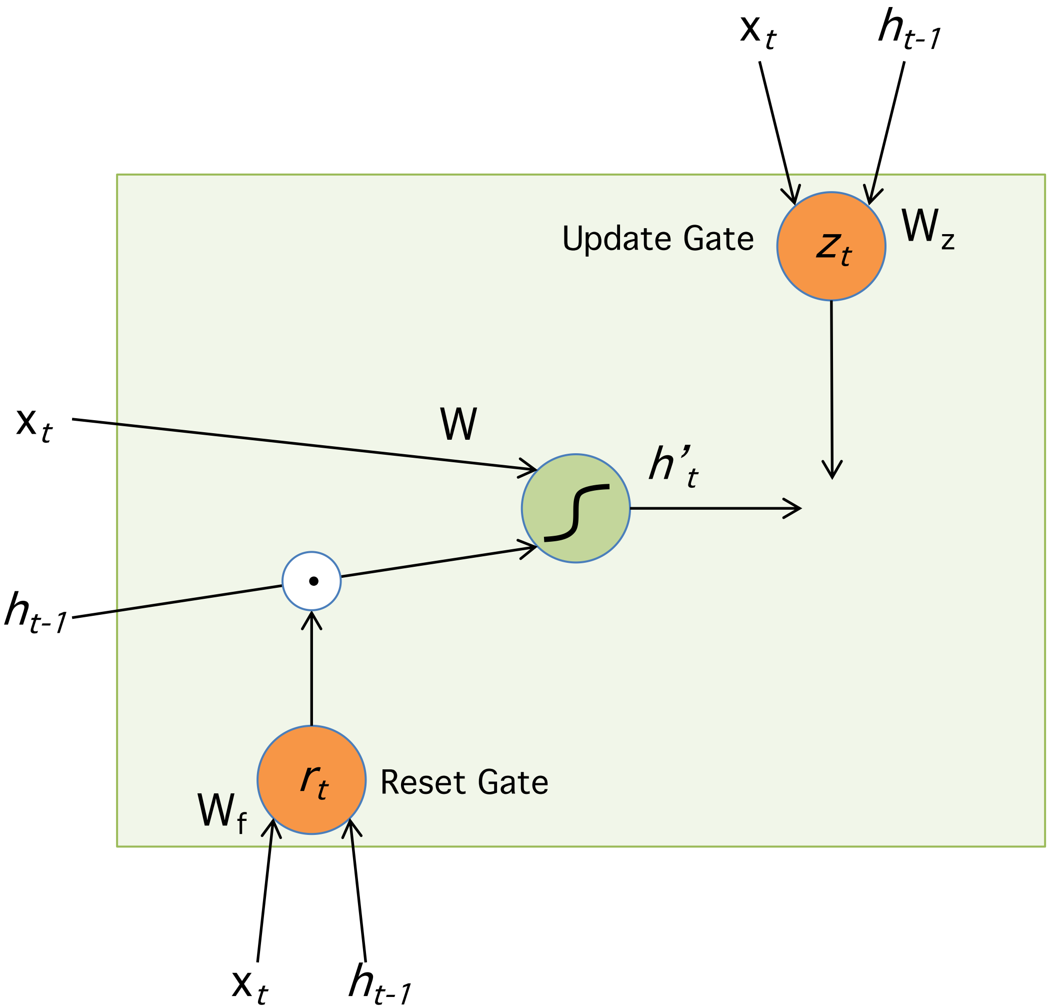
Gated Recurrent Unit (GRU)



$$r_t = \sigma\left(W_r \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix} + b_t\right)$$

$$h'_t = \tanh W \begin{pmatrix} x_t \\ r_t \odot h_{t-1} \end{pmatrix}$$

Gated Recurrent Unit (GRU)

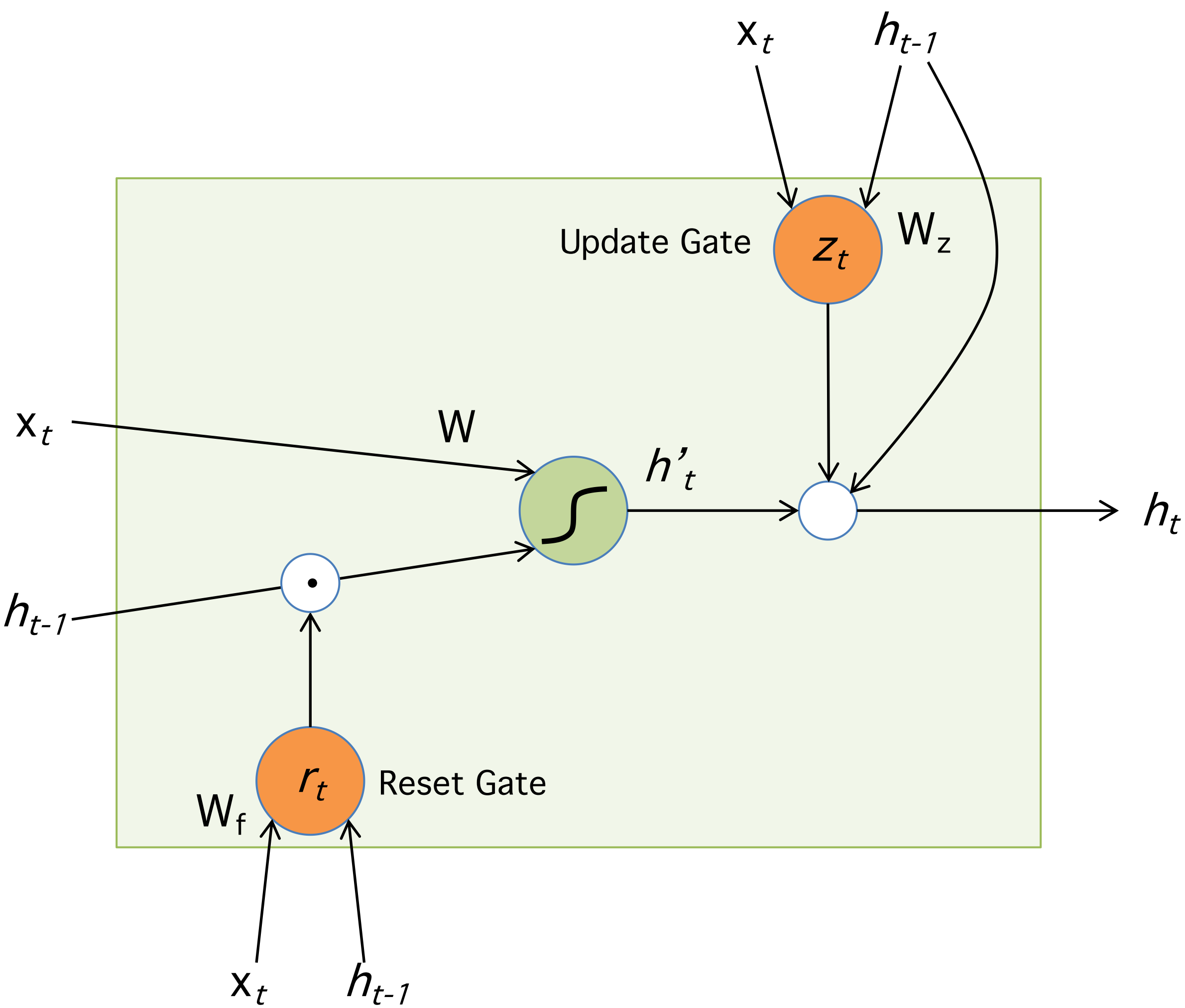


$$r_t = \sigma\left(W_r \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix} + b_t\right)$$

$$h'_t = \tanh W \begin{pmatrix} x_t \\ r_t \odot h_{t-1} \end{pmatrix}$$

$$z_t = \sigma\left(W_z \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix} + b_z\right)$$

Gated Recurrent Unit (GRU)



$$r_t = \sigma\left(W_r \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix} + b_t\right)$$

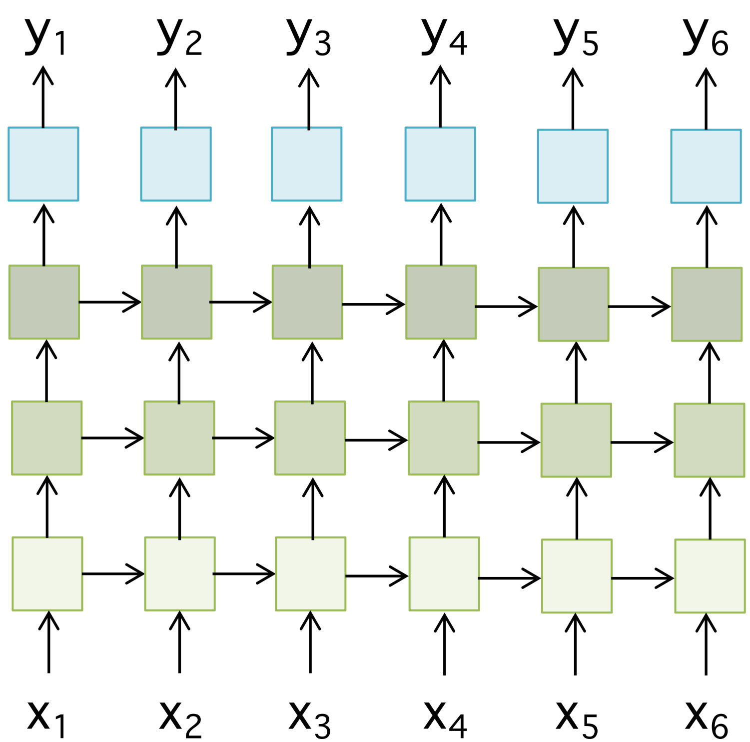
$$h'_t = \tanh W \begin{pmatrix} x_t \\ r_t \odot h_{t-1} \end{pmatrix}$$

$$z_t = \sigma\left(W_z \begin{pmatrix} x_t \\ h_{t-1} \end{pmatrix} + b_z\right)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot h'_t$$

Multi-layer RNNs

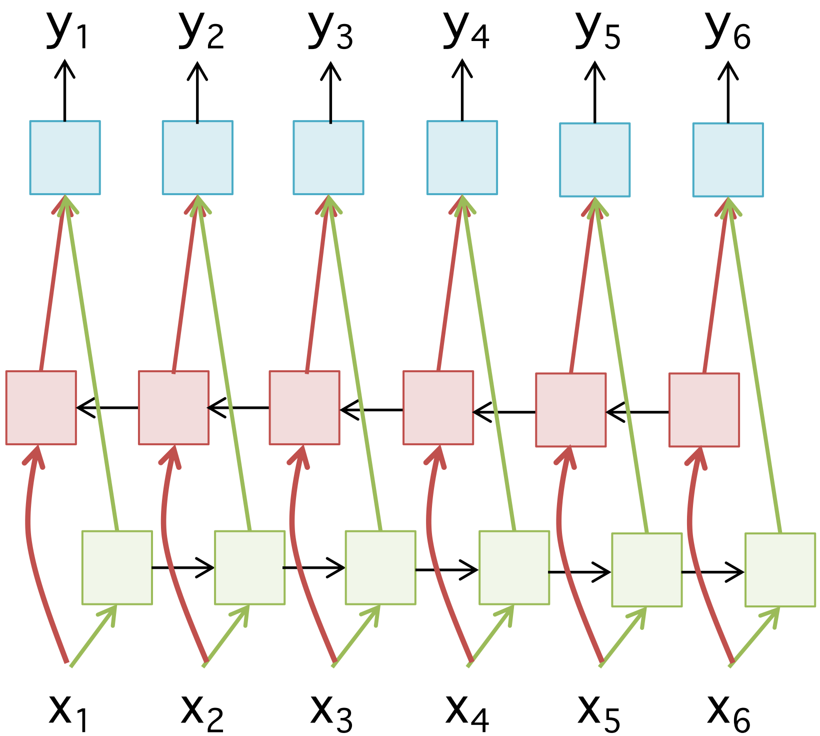
- We can of course design RNNs with multiple hidden layers



- Anything goes: skip connections across layers, across time, …

Bi-directional RNNs

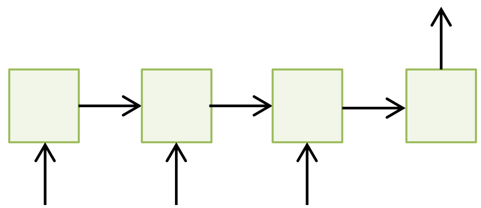
- RNNs can process the input sequence in forward and in the reverse direction



- Popular in speech recognition

Use Cases

Multiple input – Single output



Sequence Classification

Single - Multiple

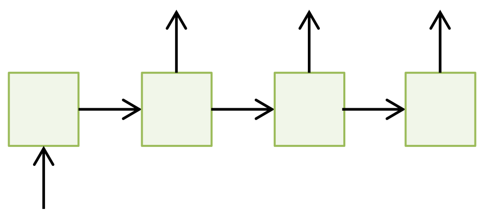


Image Captioning

Multiple - Multiple

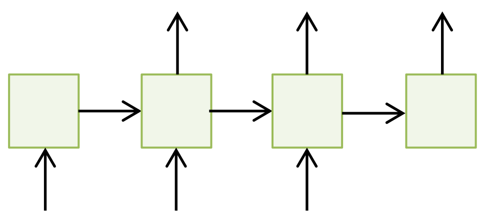
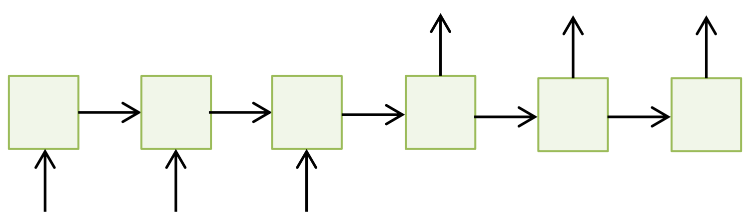


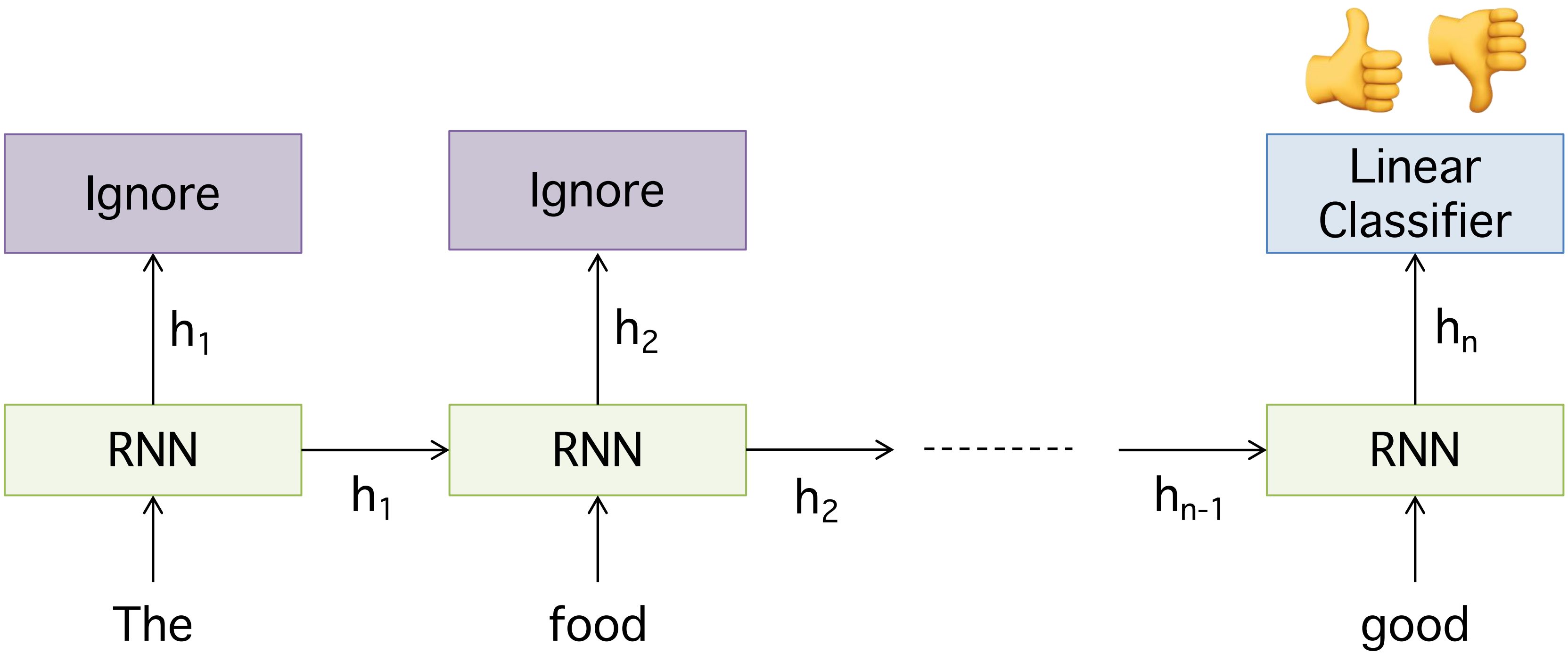
Image Captioning

Multiple - Multiple

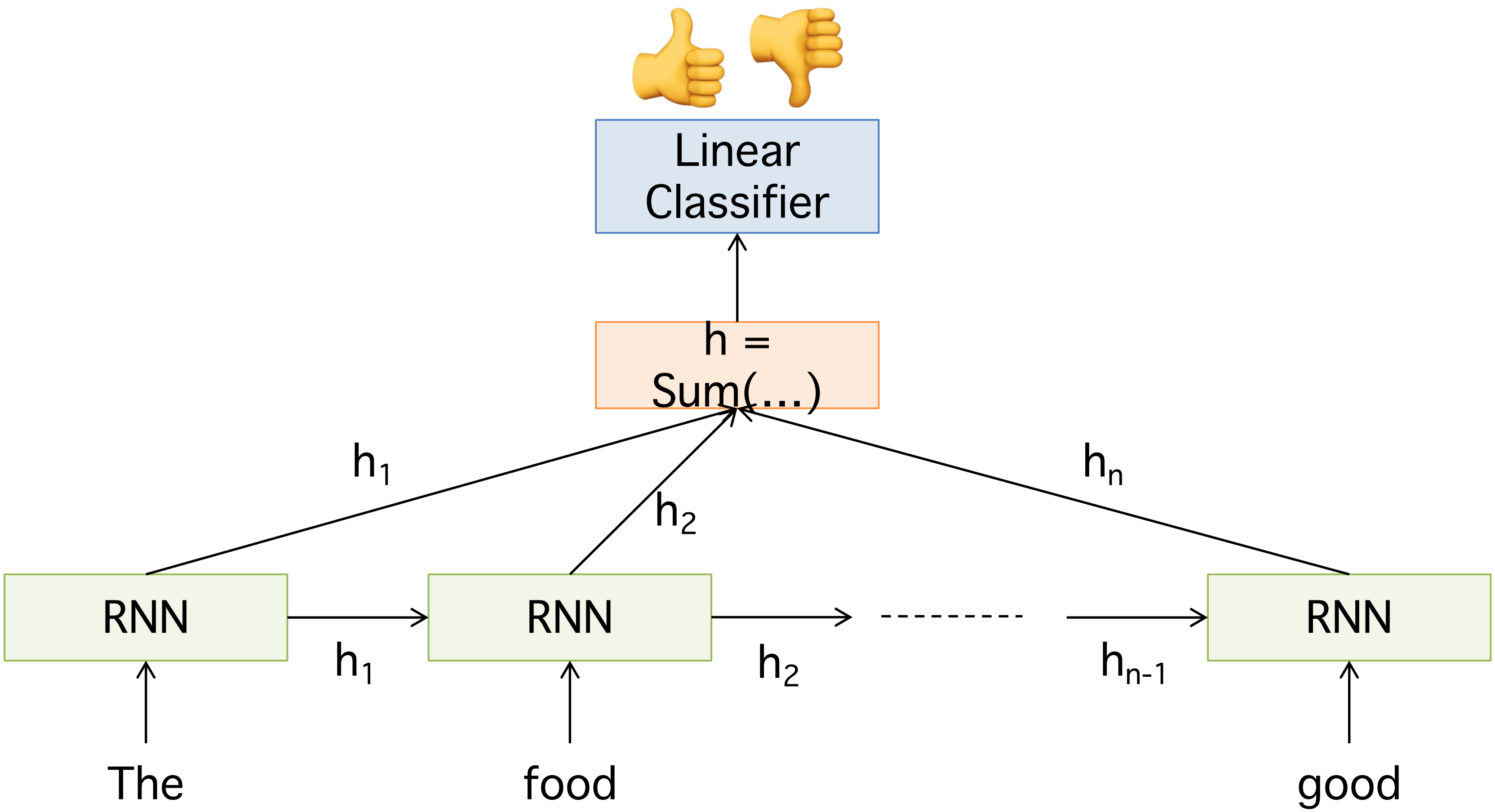


Translation

Sequence Classification



Sequence Classification



http://deeplearning.net/tutorial/lstm.html

Sequence Classification

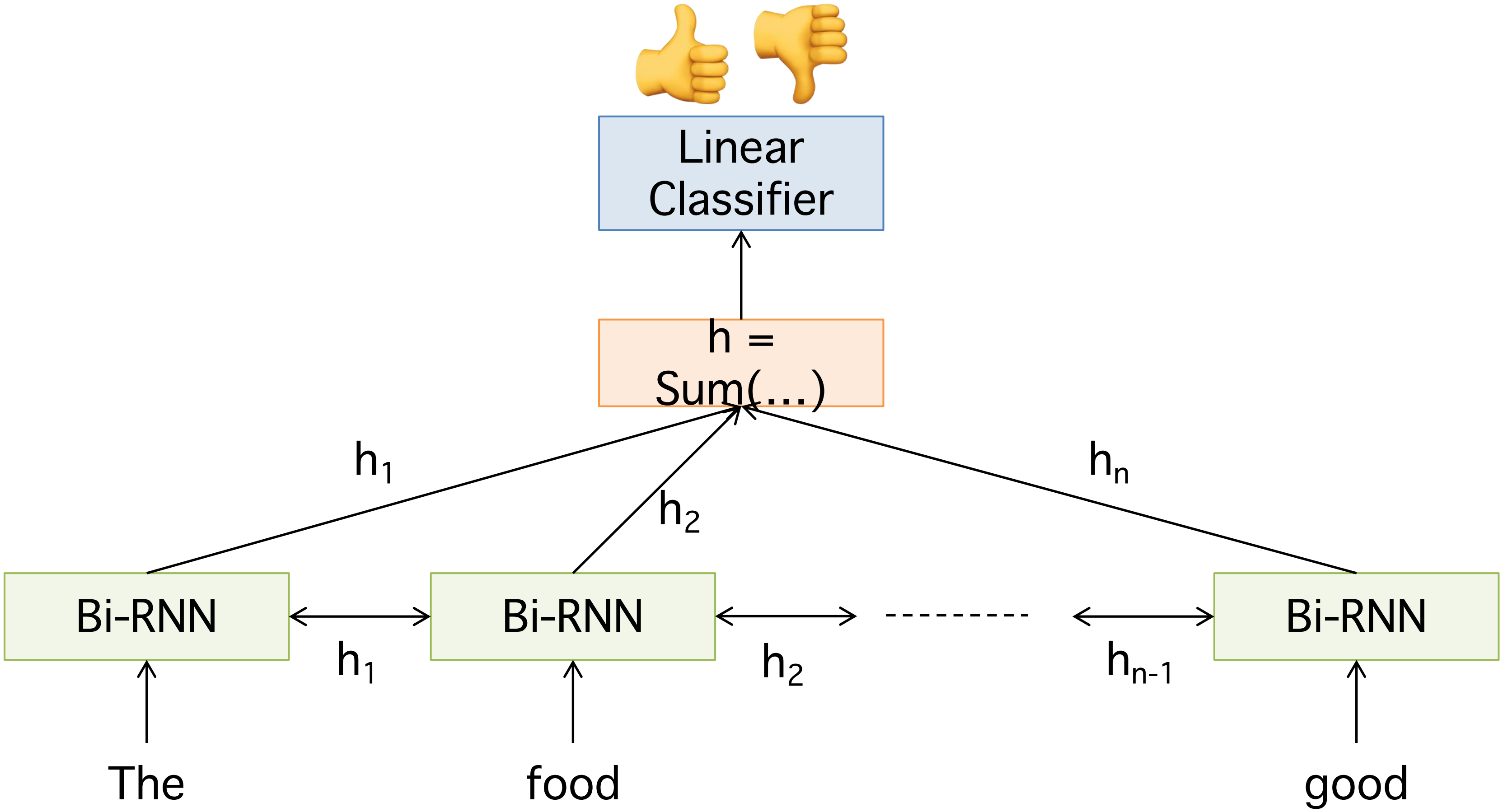
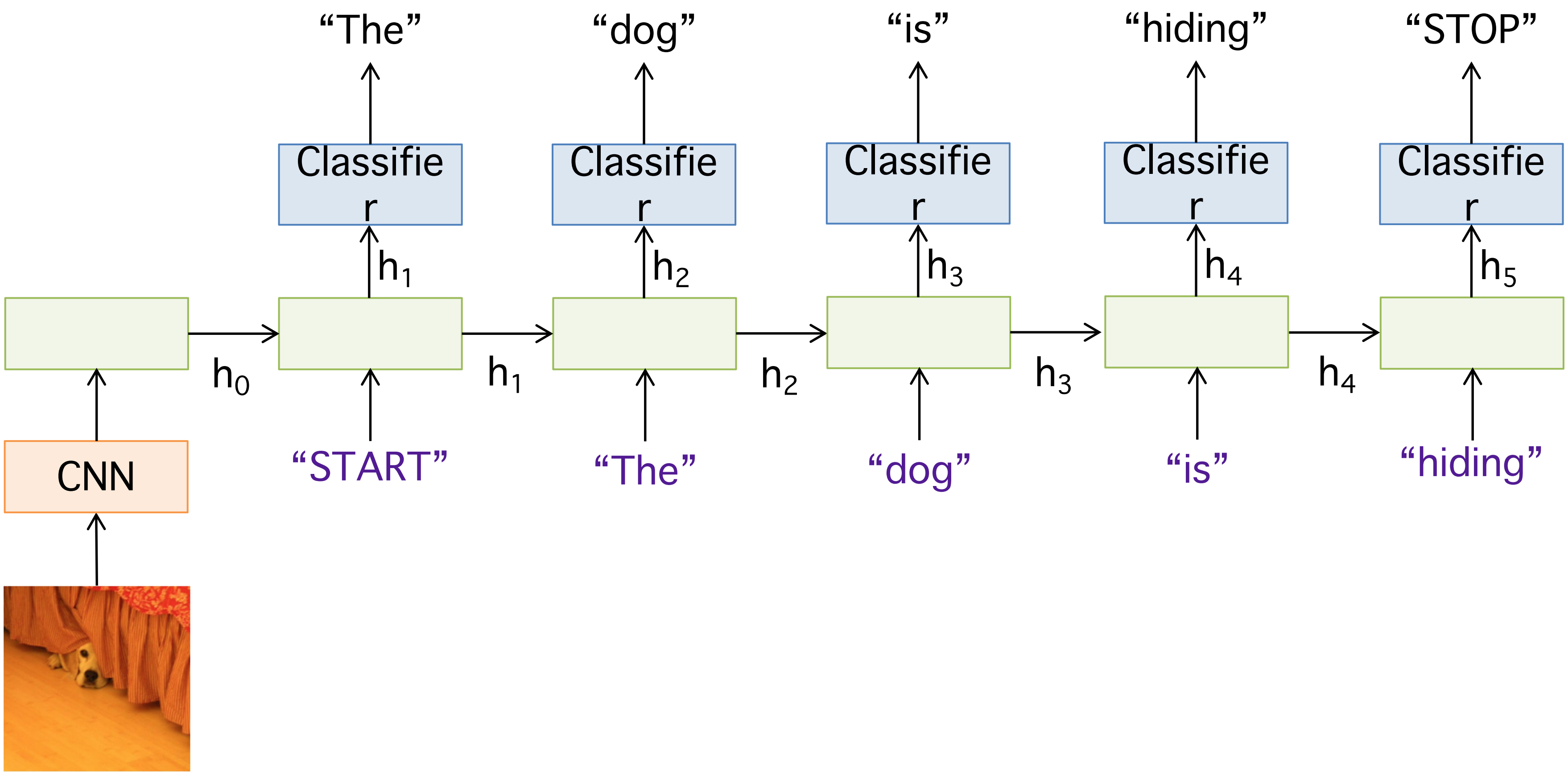


Image Caption Generation



It’s raining LSTMs

- There exist countless variations of LSTMs, with different researchers proposing different arrangements of the LSTM units
- So, which one is better?
- None: https://arxiv.org/pdf/1503.04069.pdf
- Also, RNNs can outperform both LSTMs and GRUs: http://proceedings.mlr.press/v37/jozefowicz15.pdf

A Zoo of RNNs

- If you are interested in the details for the following topics:
  - Bidirectional RNNs (Sec. 10.3 book)
  - Teacher forcing (Fig. 10.6 book)
  - Image captioning RNNs (Fig. 10.9 book)
  - Encoder-decoder architectures (Sec. 10.4 book)
  - …

Online resources

- Music composition: http://www.hexahedria.com/2015/08/03/composing-music-with-recurrent-neural-networks/
- Characters prediction: https://cs.stanford.edu/people/karpathy/recurrentjs/
- Transformer networks: https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html
- RNN-Ts on your phone: https://ai.googleblog.com/2019/03/an-all-neural-on-device-speech.html

Summary

- Sequential data and temporal dependances
- Recurrent Neural Network and BPTT
- Long Short-Term Memory
- Gated Recurrent Unit
- Different application cases of RNN