Recurrent Neural Networks

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Goodfellow, Bengio, and Courville: Deep Learning textbook
Ch. 10

Sequential Data with Neural Networks

- Sequential input / output
  - Many inputs, many outputs $x_{1:T} \rightarrow y_{1:S}$
    - c.f. object tracking, speech recognition with HMMs; on-line/batch processing
  - One input, many outputs $x \rightarrow y_{1:S}$
    - e.g. image captioning
  - Many inputs, one output $x_{1:T} \rightarrow y$
    - e.g. video classification

Outline

Recurrent Neural Networks

Long Short-Term Memory

Temporal Convolutional Networks

Examples

Hidden State

- Basic idea: maintain a state $\boldsymbol{h}_t$
- State at time t depends on input $\boldsymbol{x}_t$ and previous state $\boldsymbol{h}_{t-1}$
- It's a neural network, so relation is non-linear function of these inputs and some parameters $\boldsymbol{W}$:

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

- Parameters $\boldsymbol{W}$ and function $f(\cdot)$ reused at all time steps

Outputs

- Output y_t also depends on the hidden state:

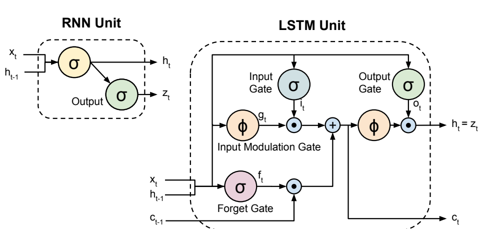
$$y_t = f(\boldsymbol{h}_t; \boldsymbol{W}_y)$$

- Again, parameters/function reused across time

Gradients

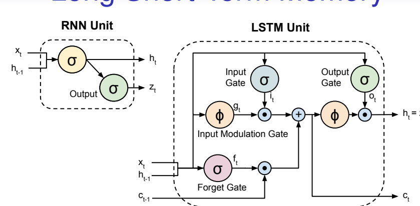
- Basic RNN not very effective
- Need many time steps / complex model for challenging tasks
- Gradients in learning are a problem
  - Too large: can be handled with gradient clipping (truncate gradient magnitude)
  - Too small: can be handled with network structures / gating functions (LSTM, GRU)

Long Short-Term Memory



- Hochreiter and Schmidhuber, Neural Computation 1997
  - (Figure from Donohue et al. CVPR 2015)
- Gating functions $g(\cdot), f(\cdot), o(\cdot)$, reduce vanishing gradients

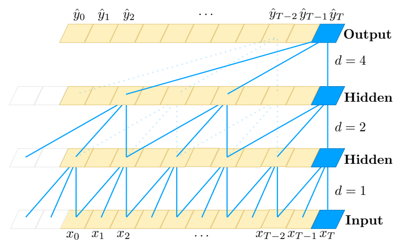
Long Short-Term Memory



$$i_t = \sigma(W_{xi}x_t + W_{hi}h_{t-1} + b_i) \tag{1}$$
$$f_t = \sigma(W_{xf}x_t + W_{hf}h_{t-1} + b_f) \tag{2}$$
$$o_t = \sigma(W_{xo}x_t + W_{ho}h_{t-1} + b_o) \tag{3}$$
$$g_t = tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c) \tag{4}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot g_t \tag{5}$$
$$h_t = o_t \odot tanh(c_t) \tag{6}$$

see Graves, Liwicki, Fernandez, Bertolami, Bunke, and Schmidhuber, TPAMI 2009

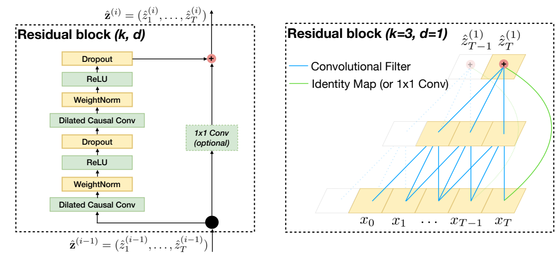
Convolutions to Aggregate over Time



(a)

- Control history by d (dilation, holes in the filter) and k (width of the filter)
- Causal convolution, only use elements from the past
- Bai, Kolter, Koltun arXiv 2018

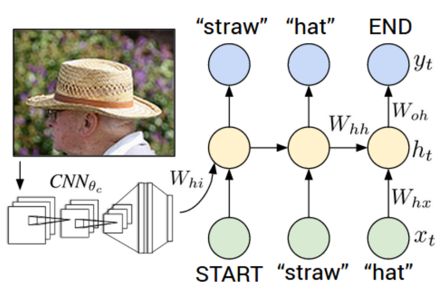
Residual (skip) Connections



(b) (c)

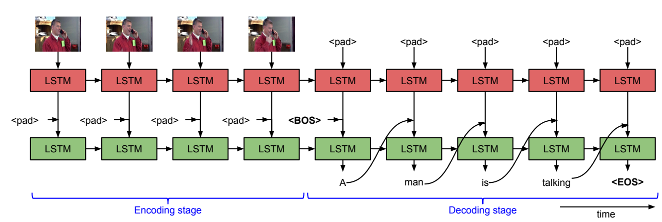
- Include residual connections to allow long-range modeling and gradient flow

Example: Image Captioning



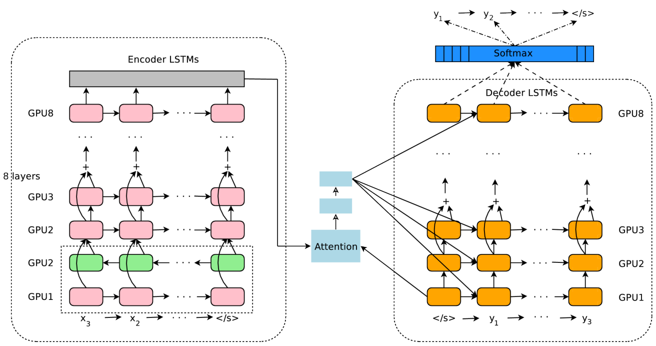
- Karpathy and Fei-Fei, CVPR 2015

Example: Video Description



- S. Venugopalan, M. Rohrbach, J. Donahue, R. Mooney, T. Darrell, K. Saenko, ICCV 2015

Example: Machine Translation



- Wu et al., *Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation*, arXiv 2016

Conclusion

- Readings: `http://www.deeplearningbook.org/contents/rnn.html`
- Recurrent neural networks, can model sequential inputs/outputs
  - Input includes state (output) from previous time
  - Different structures:
    - RNN with multiple inputs/outputs
    - Gated recurrent unit (GRU)
    - Long short-term memory (LSTM)
  - Error gradients back-propagated across entire sequence