IN5550: Neural Methods in Natural Language Processing
Sub-lecture 5.4
Gated RNNs: LSTM and GRU

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RNNs In a Nutshell



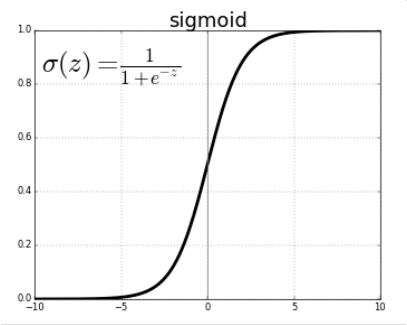
- State vectors $\boldsymbol{s_i}$ reflect the complete history up to time point i;
- RNNs are sensitive to basic natural language structures: sequences;
- applicable to arbitrary length inputs (in principle);
- few parameters: matrices $\boldsymbol{W^s}$ and $\boldsymbol{W^x}$ shared across all time points;
- analogous to (potentially) deep nesting: repeated multiplications;
- near-crippling practical limitation: 'exploding' or 'vanishing' gradients;
- Solution [$\rightarrow$] gated RNNs:
  - LSTM [Hochreiter and Schmidhuber, 1997]
  - GRU [Cho et al., 2014]

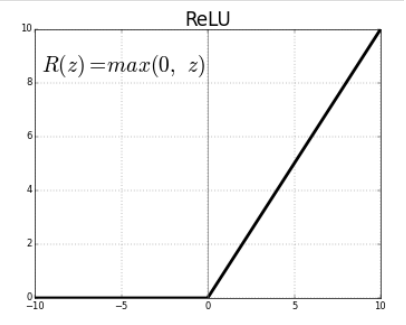
Contents



1 Gated architectures

Vanishing (or Exploding) Gradients



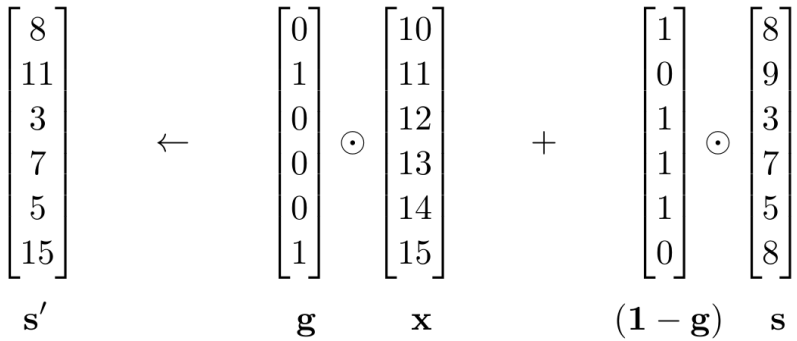


- Shared RNN parameter values can decrease (or grow) monotonically
- gradients for parameters 'deep' down diminish (or get out of hand, 'explode')

→ ineffective back-propagation of error signals through the network

→ can make it difficult for the RNN to learn long-range dependencies

Gatekeeping



- Let's filter and control memory access
- Hadamard product ($\odot$) simply performs element-wise multiplication
- vector $\boldsymbol{g}$ acts as a gate: masks out parts of the memory and input
- gating should depend on memory state and input; learn its behavior
- differentiable gates: assume $\boldsymbol{g} \in \mathbb{R}^n$ but squash into $(0, 1)$ with σ

Long Short-Term Memory RNNs (LSTMs)

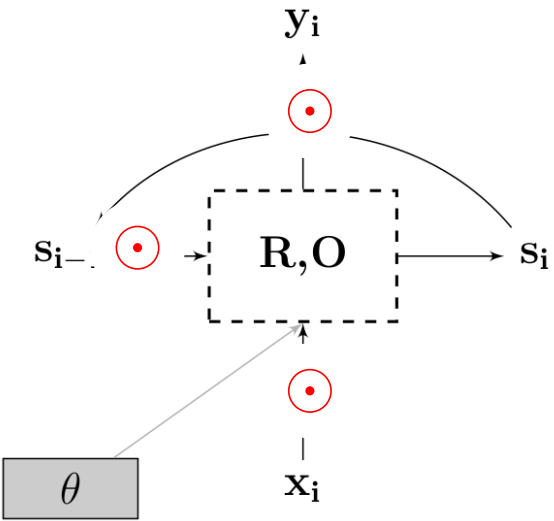


- LSTM: state vectors $\boldsymbol{s_i}$ partitioned into context memory and hidden state [Hochreiter and Schmidhuber, 1997];
- forget gate $\boldsymbol{f}$: how much of the previous memory to keep;
- input gate $\boldsymbol{i}$: how much of the proposed update to apply;
- output gate $\boldsymbol{o}$: what parts of the updated memory to output.

$$
\begin{aligned}
\boldsymbol{s_i} &= \mathrm{R}(\boldsymbol{x_i}, \boldsymbol{s_{i-1}}) = [\boldsymbol{c_i}; \boldsymbol{h_i}] \\
\boldsymbol{f_i} &= \sigma(\boldsymbol{x_i}\boldsymbol{W^{xf}} + \boldsymbol{h_{i-1}}\boldsymbol{W^{hf}} + \boldsymbol{b_f}) \\
\boldsymbol{i_i} &= \sigma(\boldsymbol{x_i}\boldsymbol{W^{xi}} + \boldsymbol{h_{i-1}}\boldsymbol{W^{hi}} + \boldsymbol{b_i}) \\
\boldsymbol{o_i} &= \sigma(\boldsymbol{x_i}\boldsymbol{W^{xo}} + \boldsymbol{h_{i-1}}\boldsymbol{W^{ho}} + \boldsymbol{b_o}) \\
\boldsymbol{c_i} &= \boldsymbol{f_i} \odot \boldsymbol{c_{i-1}} + \boldsymbol{i_i} \odot \tanh(\boldsymbol{x_i}\boldsymbol{W^{x}} + \boldsymbol{h_{i-1}}\boldsymbol{W^{h}} + \boldsymbol{b}) \\
\boldsymbol{h_i} &= \boldsymbol{o_i} \odot \tanh(\boldsymbol{c_i}) \\
\boldsymbol{y_i} &= O(\boldsymbol{s_i}) = \boldsymbol{h_i}
\end{aligned}
$$

- More parameters: separate $\boldsymbol{W^{x\cdot}}$ and $\boldsymbol{W^{h\cdot}}$ matrices for each gate.

Learning to Forget: Schematically



Gated Recurrent Units (GRUs)

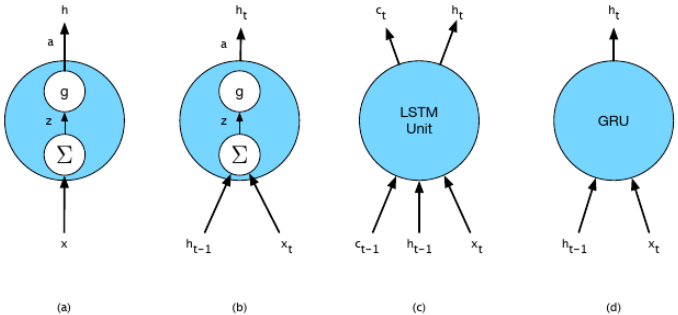
GRUs simplify the idea

- No separate context memory
- Less gates

$$
\begin{aligned}
\boldsymbol{s_j} &= \mathrm{R}_{\mathrm{GRU}}(\boldsymbol{s_{j-1}}, \boldsymbol{x_j}) = (1 - \boldsymbol{z}) \odot \boldsymbol{s_{j-1}} + \boldsymbol{z} \odot \tilde{\boldsymbol{s}}_{\boldsymbol{j}} \\
\boldsymbol{z} &= \sigma(\boldsymbol{x_j}\boldsymbol{W^{xz}} + \boldsymbol{s_{j-1}}\boldsymbol{W^{sz}}) \\
\boldsymbol{r} &= \sigma(\boldsymbol{x_j}\boldsymbol{W^{xr}} + \boldsymbol{s_{j-1}}\boldsymbol{W^{sr}}) \\
\tilde{\boldsymbol{s}}_{\boldsymbol{j}} &= \tanh(\boldsymbol{x_j}\boldsymbol{W^{xs}} + (\boldsymbol{r} \odot \boldsymbol{s_{j-1}})\boldsymbol{W^{sg}}) \\
\boldsymbol{y_j} &= O_{GRU}(\boldsymbol{s_j}) = \boldsymbol{s_j}
\end{aligned}
\tag{1}
$$

[Cho et al., 2014]

Basic neural units



- a) feed-forward unit
- b) simple recurrent unit (Elman, etc)
- c) LSTM unit
- d) GRU unit

[Jurafsky and Martin, 2023]

Streams of Fashion in NLP



'To a first approximation, the de facto consensus in NLP in 2017 is that, no matter what the task, you throw a BiLSTM at it [...]'

Christopher Manning, March 2017

(`https://simons.berkeley.edu/talks/christopher-manning-2017-3-27`)

'RNNs, particularly ones with gated architectures such as the LSTM and the GRU, [...] are arguably the strongest contribution of deep learning to the statistical natural language processing tool set.'

[Goldberg, 2017]

But wait for Transformers and the 'Attention is all you need' motto of the recent years!
(next week)

References I

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