

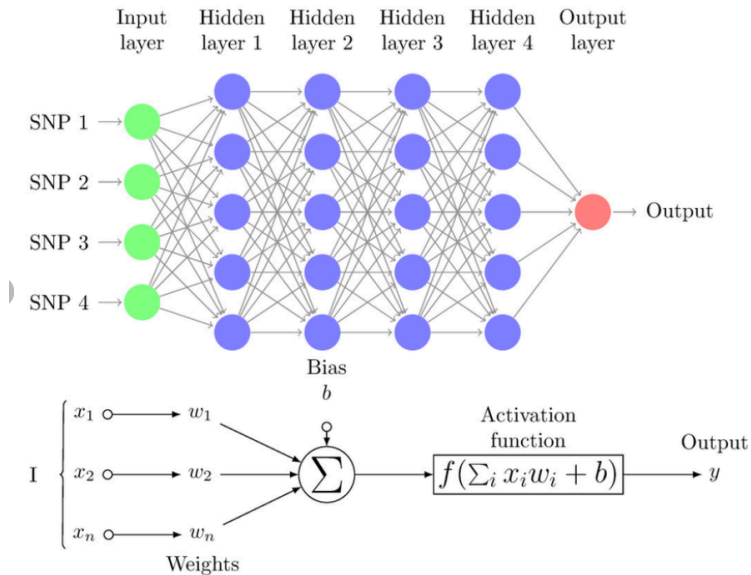
Computational analysis of efficient gated recurrent neural networks

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Multilayer perceptron



Recurrent neural network

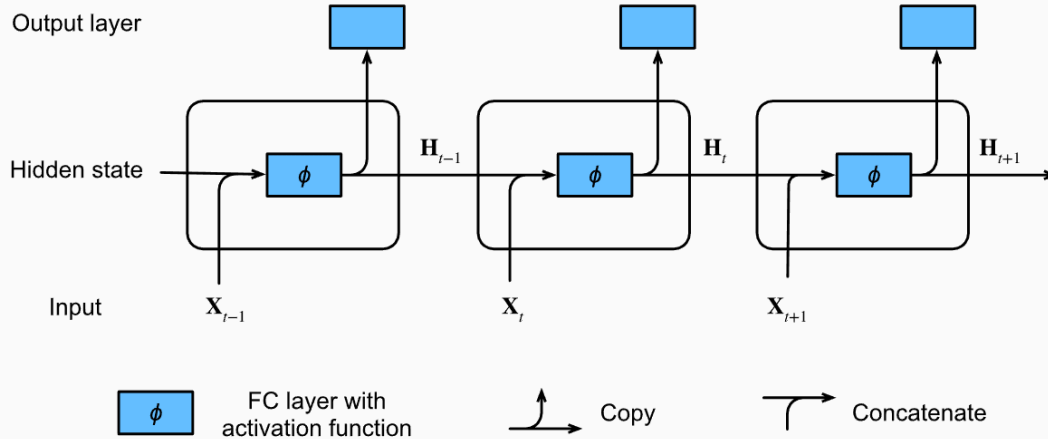
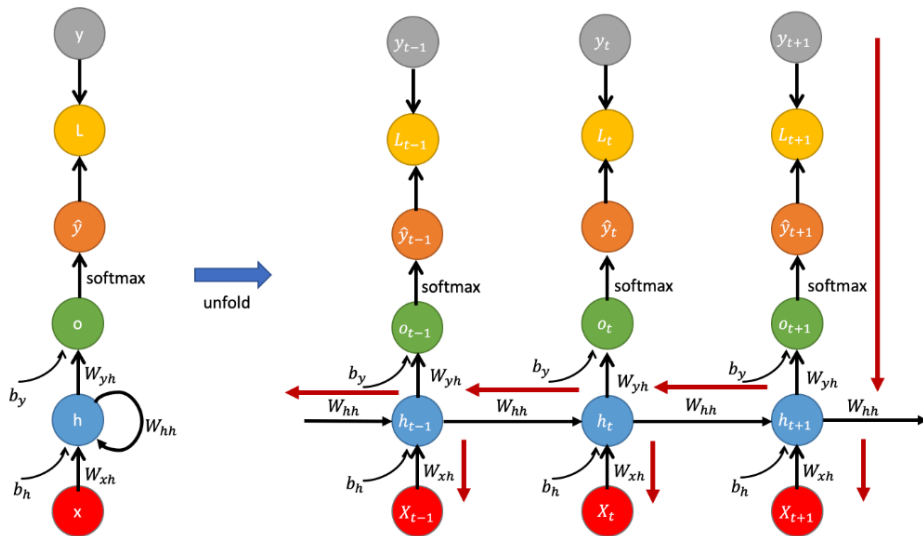


Fig. 9.4.1 An RNN with a hidden state.

Backpropagation through time

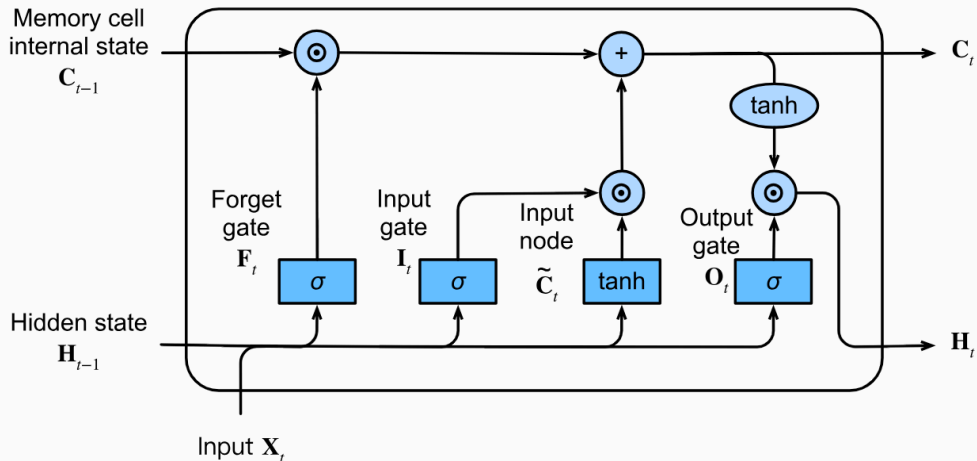


Problems with recurrent neural networks



1. Vanishing and exploding gradient
2. Parallel training

LSTM



FC layer with
activation function



Elementwise
operator



Copy



Concatenate

LSTM

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

$$\mathbf{o}_t = \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}]))$$

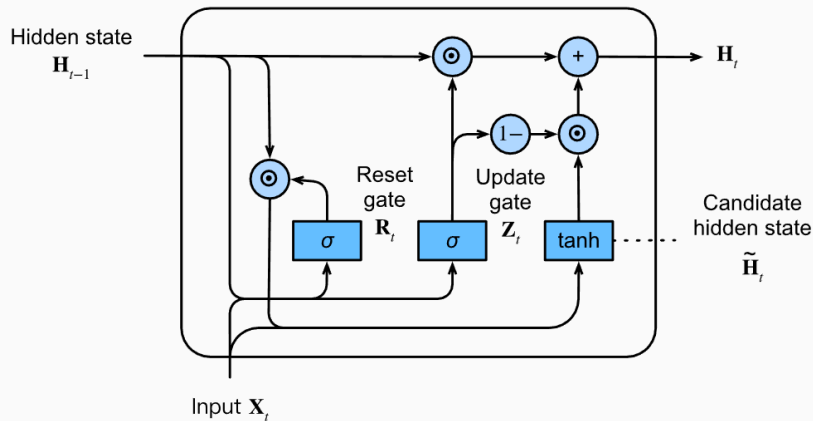
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t$$

$$\mathbf{f}_t = \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}]))$$

$$\mathbf{i}_t = \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}]))$$

$$\tilde{\mathbf{c}}_t = \tanh(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}]))$$

GRU



FC layer with
activation function



Elementwise
operator



Copy



Concatenate

GRU

$$\mathbf{h}_t = (\mathbf{1} - \mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t$$

$$\mathbf{z}_t = \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}]))$$

$$\mathbf{r}_t = \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}]))$$

$$\tilde{\mathbf{h}}_t = \tanh(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{r}_t \odot \mathbf{h}_{t-1}]))$$

GRU

$$\begin{aligned} \mathbf{h}_t &= (\mathbf{1} - \mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t \\ \mathbf{z}_t &= \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}])) \\ \mathbf{r}_t &= \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}])) \\ \tilde{\mathbf{h}}_t &= \tanh(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{r}_t \odot \mathbf{h}_{t-1}])) \end{aligned}$$

\Rightarrow

minGRU

$$\begin{aligned} \mathbf{h}_t &= (\mathbf{1} - \mathbf{z}_t) \odot \mathbf{h}_{t-1} + \mathbf{z}_t \odot \tilde{\mathbf{h}}_t \\ \mathbf{z}_t &= \sigma(\text{Linear}_{d_h}(\mathbf{x}_t)) \\ \tilde{\mathbf{h}}_t &= \text{Linear}_{d_h}(\mathbf{x}_t) \end{aligned}$$

LSTM

$$\begin{aligned}h_t &= \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \\ \mathbf{o}_t &= \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}])) \\ \mathbf{c}_t &= \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \\ \mathbf{f}_t &= \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}])) \\ \mathbf{i}_t &= \sigma(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}])) \\ \tilde{\mathbf{c}}_t &= \tanh(\text{Linear}_{d_h}([\mathbf{x}_t, \mathbf{h}_{t-1}]))\end{aligned}$$

\Rightarrow

minLSTM

$$\begin{aligned}h_t &= \mathbf{f}_t \odot \mathbf{h}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{h}}_t \\ \mathbf{f}_t &= \sigma(\text{Linear}_{d_h}(\mathbf{x}_t)) \\ \mathbf{i}_t &= \sigma(\text{Linear}_{d_h}(\mathbf{x}_t)) \\ \tilde{\mathbf{h}}_t &= \text{Linear}_{d_h}(\mathbf{x}_t)\end{aligned}$$

Thesis goals

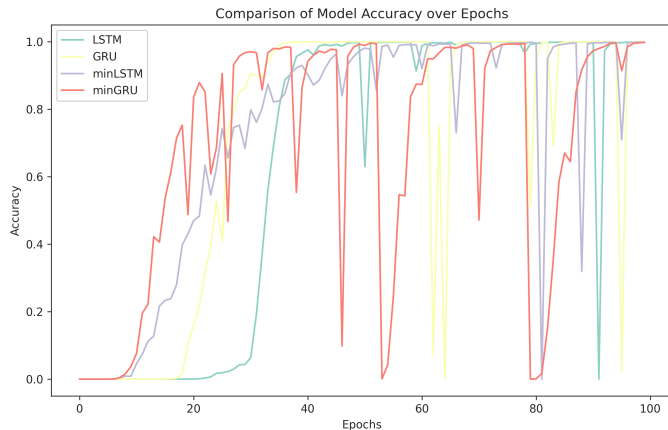


1. Implement newest models for example minLSTM, minGRU
2. Compare the models
3. Use methods Explainable AI

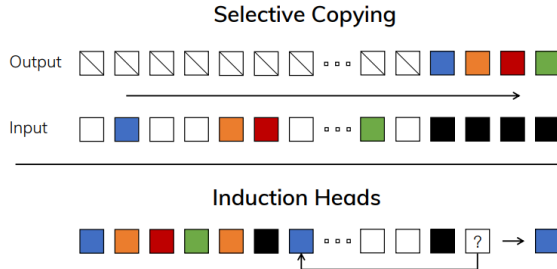
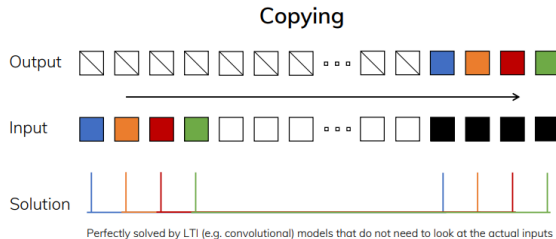
Work done on thesis



1. Script for generating Selective copying dataset
2. Basic comparisons of min models with originals



Selective copying



Planned work for now



1. Redo the comparisons multiple times to get more accurate readings
2. Implement scripts for better analyzing the neural networks

Zdroje



<https://arxiv.org/pdf/2410.01201>

<https://www.d2l.ai/index.html>

<https://mmuratarat.github.io/2019-02-07/bptt-of-rnn>

<https://arxiv.org/pdf/2312.00752>

https://www.researchgate.net/figure/Multi-Layer-Perceptron-MLP-diagram-with-four-hidden-layers-and-a-collection-of-single_fig1_334609713