

Plastic Bistable Recurrent Cells

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Abstract

This is the abstract.

Introduction

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Background

Recurrent Neural Networks

A recurrent neural network (RNN) is a type of neural network that excels at temporal prediction tasks. Inputs are fed into the network one at a time, and the model maintains a memory in the form of a hidden state vector \mathbf{h}_t that is updated at each timestep. The model can then make predictions based on the contents of the input as well as the memory. At each timestep, the model updates the hidden state using the rule

$$\mathbf{h}_t = \sigma(W_h \mathbf{h}_{t-1} + W_x \mathbf{x}_t + b_h)$$

The output of the model can then be computed as

$$\mathbf{y}_t = \sigma(W_y \mathbf{h}_t + b_y)$$

where σ is a nonlinear activation function, W_h , W_x and W_y are weight matrices learned by the model, b_h and b_y are learned bias vectors and \mathbf{x}_t is the input at time t . These weight matrices and bias vectors are typically learned using gradient descent.

While RNNs have proven effective for many tasks, in this standard form their ability to capture long-term dependencies is limited. This is because of the so-called vanishing/exploding gradient problem, which is a result of the repeated application of the weight matrix W_h at each timestep. Various approaches have been proposed to address this problem. One approach is to use a modified

update rule that avoids changing the hidden state unless necessary. This is the approach used by the Gated Recurrent Unit.

Gated Recurrent Units

Gated Recurrent Units (GRUs) [1] are a type of RNN that preserves the gradient using a modified update rule. At each timestep the model calculates

$$\begin{aligned}\mathbf{z}_t &= \sigma(W_{zh}\mathbf{h}_{t-1} + W_{zx}\mathbf{x}_t + b_z) \\ \mathbf{r}_t &= \sigma(W_{rh}\mathbf{h}_{t-1} + W_{rx}\mathbf{x}_t + b_r)\end{aligned}$$

known as the update and reset gate, respectively. These are then used to calculate

$$\begin{aligned}\tilde{\mathbf{h}}_t &= \tanh(\mathbf{r}_t \odot W_{hh}\mathbf{h}_{t-1} + W_{hx}\mathbf{x}_t + b_h) \\ \mathbf{h}_t &= \mathbf{z}_t \odot \tilde{\mathbf{h}}_t + (1 - \mathbf{z}_t)\mathbf{h}_{t-1}\end{aligned}$$

Bistable Recurrent Cells

Plastic Recurrent Cells

Method

Plastic Bistable Recurrent Cells

Results

These are the results.

Conclusion

This is the conclusion.

References

- [1] Kyunghyun Cho, Bart Van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using rnn encoder-decoder for statistical machine translation. *arXiv preprint arXiv:1406.1078*, 2014.