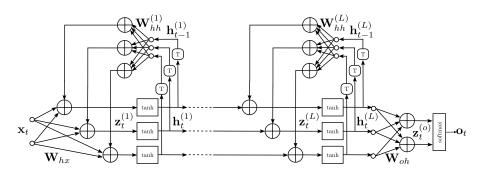
5. Sequence modeling with recurrent neural networks
5.3. Deep Recurrent Neural Networks and Bidirectional Neural
Networks

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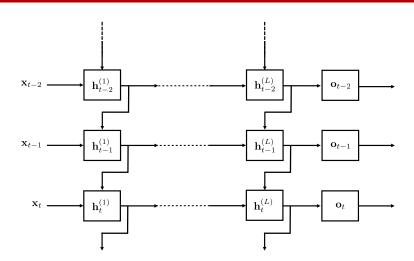
Deep Recurrent Neural Networks

Structure



• The deep RNN follows the same idea as the one in the MLP or CNN: construct a sequence of hidden states $\mathbf{h}^{(l)}$, $1 \le l \le L$

Deep Recurrent Neural Networks Unrolled GRNN



• The GRNN can be represented in a compact, unrolled way.

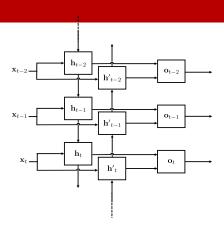
Deep Recurrent Neural Networks

Backpropagation

- The DRNN has a training that is similar to the one of the standard RNN.
- The generalization of the training can be found by computing the gradient with respect to each hidden state $\mathbf{h}_t^{(l)}$ and then the expression of the backpropagated error.
- Each weight matrix $\mathbf{W}_{hh}^{(l)}$ is trained with the product of the backpropagation error and its input $\mathbf{h}_t^{(l-1)}$.
- The derivation is left as an exercise for the student.

Bidirectional Recurrent Neural Networks

Structure



- Bidirectional RNNs make sense when the prediction tasks can extract information of input patterns in both time directions.
- A common example is the task of part of speech detection.

Bidirectional Recurrent Neural Networks

State equations

• The BRNN has forward and backward state equations.

$$\mathbf{h}_{t} = \tanh\left(\mathbf{W}_{hx}^{\top}\mathbf{x}_{t} + \mathbf{W}_{hh}^{\top}\mathbf{h}_{t-1} + \mathbf{b}_{h}\right)$$

$$\mathbf{h}'_{t} = \tanh\left(\mathbf{W}_{h'x}^{\top}\mathbf{x}_{t} + \mathbf{W}_{h'h'}^{\top}\mathbf{h}'_{t+1} + \mathbf{b}_{h'}\right)$$
(1)

• And the output is computed as

$$\mathbf{o}_t = \operatorname{softmax} \left(\mathbf{W}_{oh}^{\top} \mathbf{h}_t + \mathbf{W}_{oh'}^{\top} \mathbf{h}_t' + \mathbf{b}_o \right)$$
 (2)

• The BRNN has also a training that is similar to the one of the standard RNN, so the derivation is left as an exercise for the student.