Recurrent Neural Networks



Overview

- 1. Modeling sequences
- 2. Recurrent neural networks: An abstraction
- 3. Usage patterns for RNNs
- 4. BiDirectional RNNs
- 5. A concrete example: The Elman RNN
- 6. The vanishing gradient problem
- 7. Long short-term memory units

Overview

- 1. Modeling sequences
- 2. Recurrent neural networks: An abstraction
- 3. Usage patterns for RNNs
- 4. <u>BiDirectional RNNs</u>
- 5. A concrete example: The Elman RNN
- 6. The vanishing gradient problem
- 7. Long short-term memory units

Why left to right?

Everything we saw so far models sequences (e.g. words) from left to right

Implicit assumption: If we want to represent a word in a sentence, the words before are useful

Is this right?

Why left to right?

Everything we saw so far models sequences (e.g. words) from left to right

Implicit assumption: If we want to represent a word in a sentence, the words before are useful

Is this right? Not really

For example: For a sequence labeling task, the words after a target word may also be useful in deciding its label

How do we address this?

Bidirectional RNNs

[Schuster and Paliwal 1997]

One answer: Maintain two separate RNNs – one forward and one reverse

Forward

John ate cake



First, the forward case. We have seen this before.

Forward

John ate cake



First, the forward case. We have seen this before.

The forward RNN

Forward

cake



John ate

First, the forward case. We have seen this before.

BiRNN: A simple example Forward



BiRNN: A simple example Forward

John ate cake











Reverse

John ate cake





Reverse

John ate cake



Reverse

John ate cake







BiRNN: Putting both parts together

John ate cake



Another way of seeing this

Concatenate to get the representation for the word **John** that accounts for both left and right contexts



Another way of seeing this

Concatenate to get the representation for the word *ate* that accounts for both left and right contexts



Another way of seeing this

Concatenate to get the representation for the word *cake* that accounts for both left and right contexts



A Bidirectional RNN

- Two RNNs
 - Forward, defined by functions $R^{f}(\mathbf{s}_{t-1}^{f}, \mathbf{x}_{t})$ and $O^{f}(\mathbf{s}_{t})$
 - Backward, defined by functions $R^b(\mathbf{s}_{t+1}^b, \mathbf{x}_t)$ and $O^b(\mathbf{s}_t)$

A Bidirectional RNN

- Two RNNs
 - Forward, defined by functions $R^f(\mathbf{s}_{t-1}^f, \mathbf{x}_t)$ and $O^f(\mathbf{s}_t)$
 - Backward, defined by functions $R^b(\mathbf{s}_{t+1}^b, \mathbf{x}_t)$ and $O^b(\mathbf{s}_t)$
- The i^{th} output is defined by

 $\mathbf{y}_i = [O^f(\mathbf{s}_t^f), O^b(\mathbf{s}_t^b)]$

A Bidirectional RNN

- Two RNNs
 - Forward, defined by functions $R^f(\mathbf{s}_{t-1}^f, \mathbf{x}_t)$ and $O^f(\mathbf{s}_t)$
 - Backward, defined by functions $R^b(\mathbf{s}_{t+1}^b, \mathbf{x}_t)$ and $O^b(\mathbf{s}_t)$
- The *ith* output is defined by

 $\mathbf{y}_i = [O^f(\mathbf{s}_t^f), O^b(\mathbf{s}_t^b)]$

• Another way to write this $biRNN(\mathbf{x}_{1:n}, t) = [RNN^{f}(\mathbf{x}_{1:t}), RNN^{b}(\mathbf{x}_{n:t})]$

BiRNNs: Summary

- Allows capturing both left and right contexts
- Commonly used if RNNs are used as a base encoding layer for text
 Often stacked
- Specific versions of RNNs give us different BiRNNs
 - BiLSTMs or BiGRUs typically used