Recurrent neural networks and attention mechanisms

Gustave Cortal

Introduction

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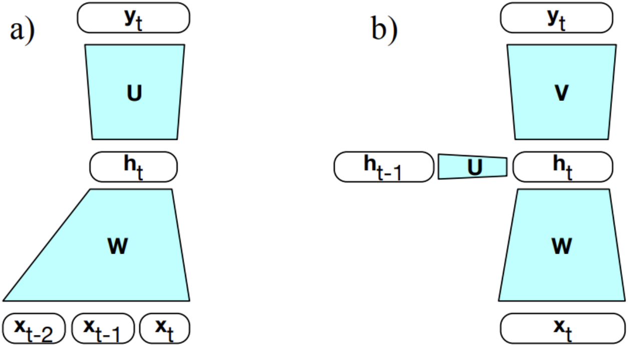
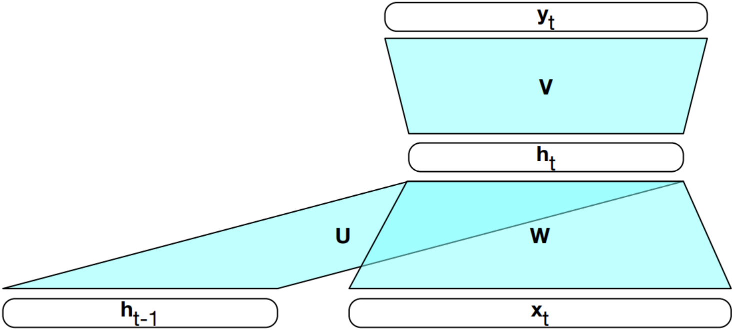
Recurrent neural networks handle the temporal nature of language without using arbitrary fixed-sized windows: the hidden layer from the previous step provides a **memory** that encodes earlier processing and informs the decisions to be made at later steps

Feedforward vs recurrent neural networks

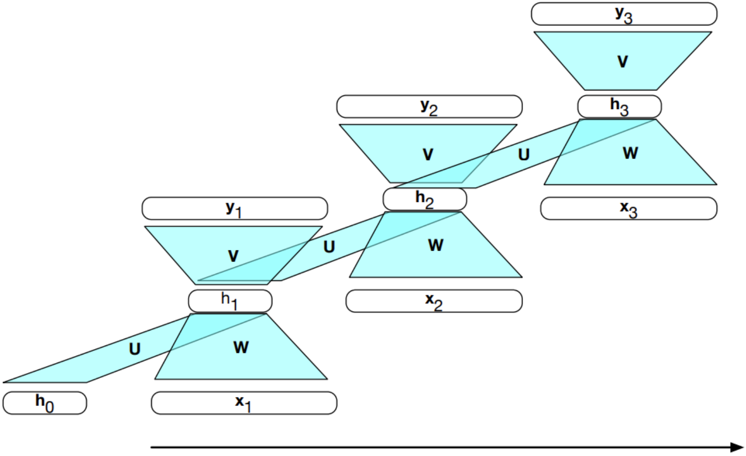


Recurrent neural networks

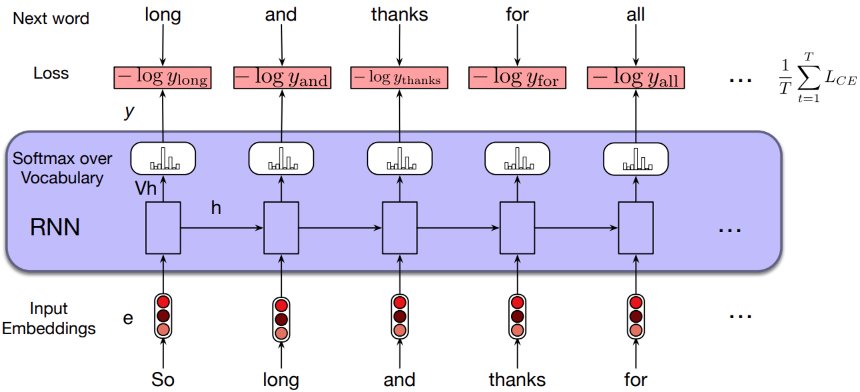


$$h_t = g(Uh_{t-1} + Wx_t)$$
$$y_t = softmax(Vh_t)$$

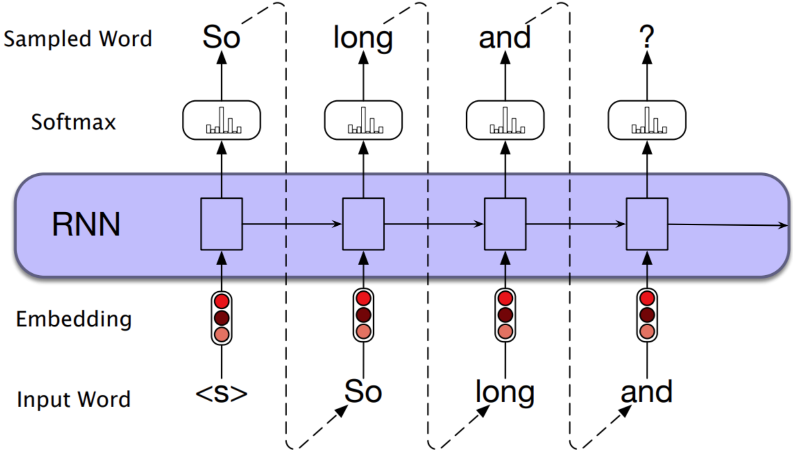
Recurrent neural networks



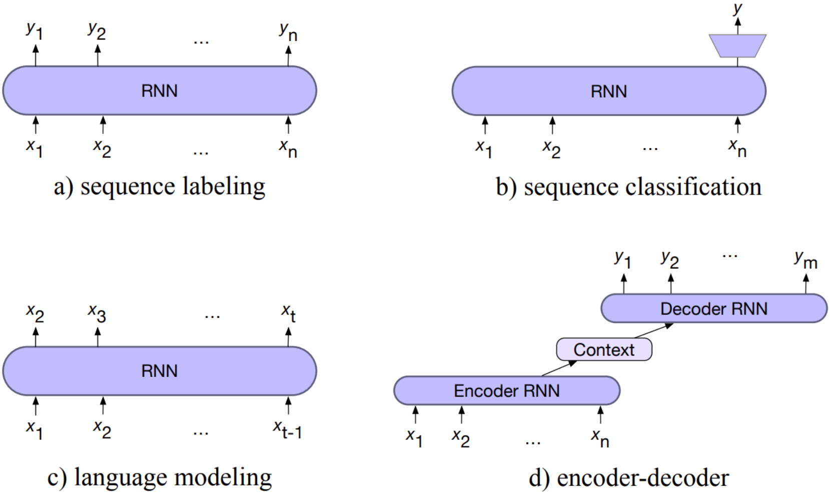
RNNs for language modeling



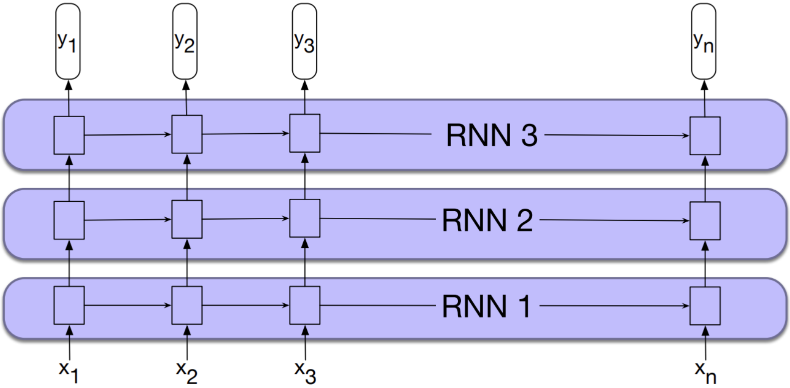
Sampling


Sampled Word
So
long
and
?
Softmax
RNN
Embedding
Input Word
<s>
So
long
and

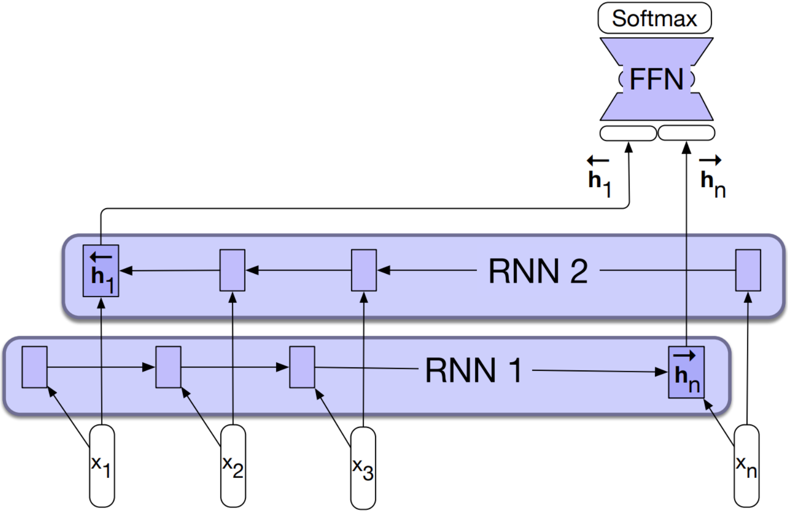
RNNs for other tasks



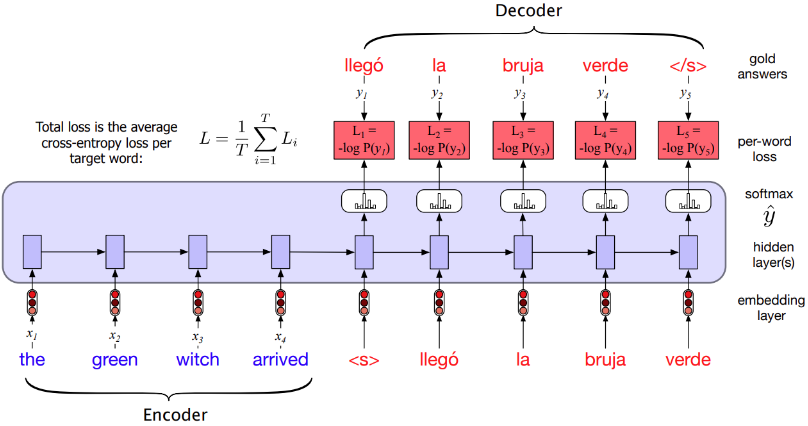
Stacked RNNs



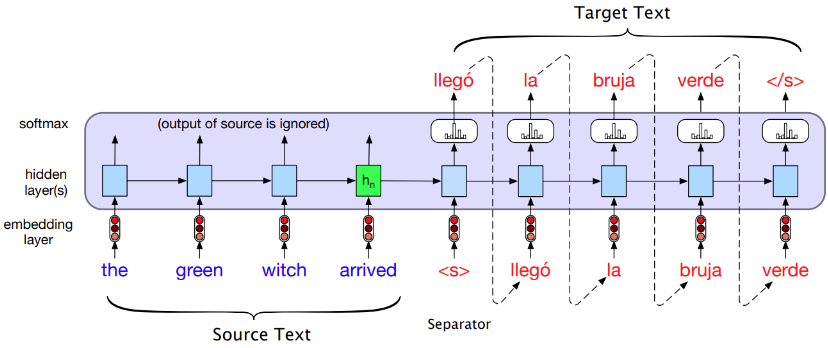
Bidirectional RNNs



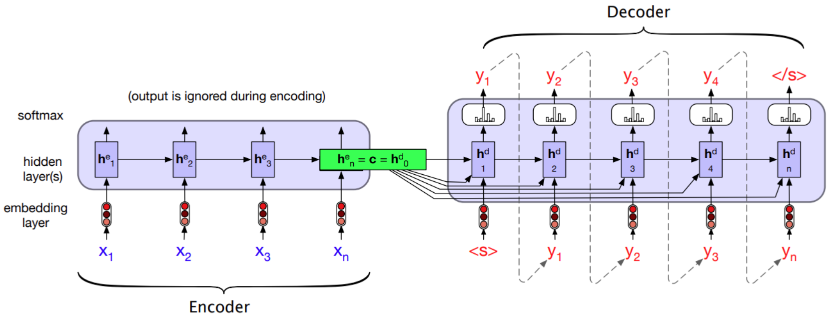
Training with encoder-decoder networks



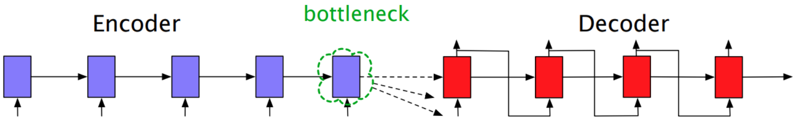
Inference with encoder-decoder networks



Final hidden state as a fixed context vector for the decoder



The final hidden state acts as a bottleneck



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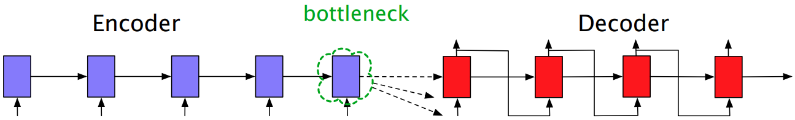

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However, information at the beginning of the sentence may not be equally well represented in the context vector

Attention mechanisms: introduction

The attention mechanism is a **solution to the bottleneck problem**: it allows the decoder to get information from all the hidden states of the encoder

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The idea of attention is to create the single fixed-length vector c by taking **a weighted sum of all the encoder hidden states**. The weights focus on a particular part of the source text that is relevant to the token the decoder is currently producing

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Attention thus replaces the static context vector with one that is **dynamically** derived from the encoder hidden states, **different** for each token in

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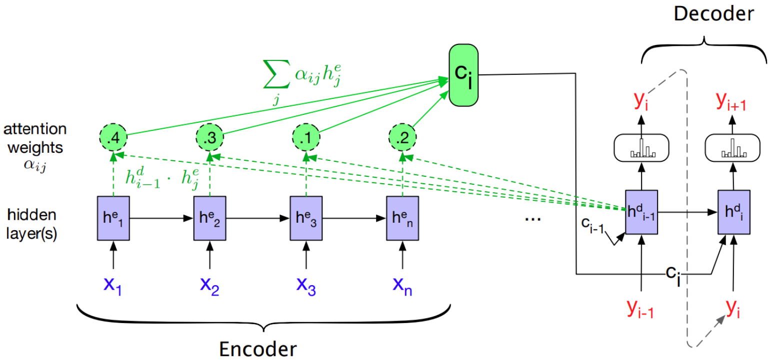
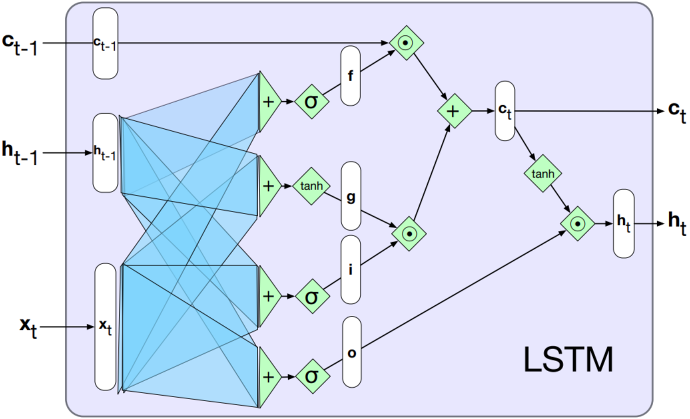
Finally, compute a fixed-length context vector for the current decoder state by taking a weighted average over all the encoder hidden states:

$$c_i = \sum_j \alpha_{ij} h^e_j$$

Encoder-decoder networks with dot-product attention



Long Short Term Memory network



FNN vs RNN vs LSTM units