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Introduction

Recurrent neural networks (RNN) constitute a family of neural network architectures specialized to process sequential data. They do so by leveraging the simple idea of sharing parameters across the model[1]. They have been used in diverse domains for generating sequences such as music and text. They can be trained by processing real data sequences one step at a time and predicting what comes next. In practice, early RNNs designs are unable to store information about far past inputs. This fact diminishes their efficiency at modeling long structure. If the network's predictions are based only on the last few inputs, which are themselves predicted by the networks, then it has less chance to recover from past mistakes. The solution to this problem seems to be a better memory and especially a long-term memory for the network.

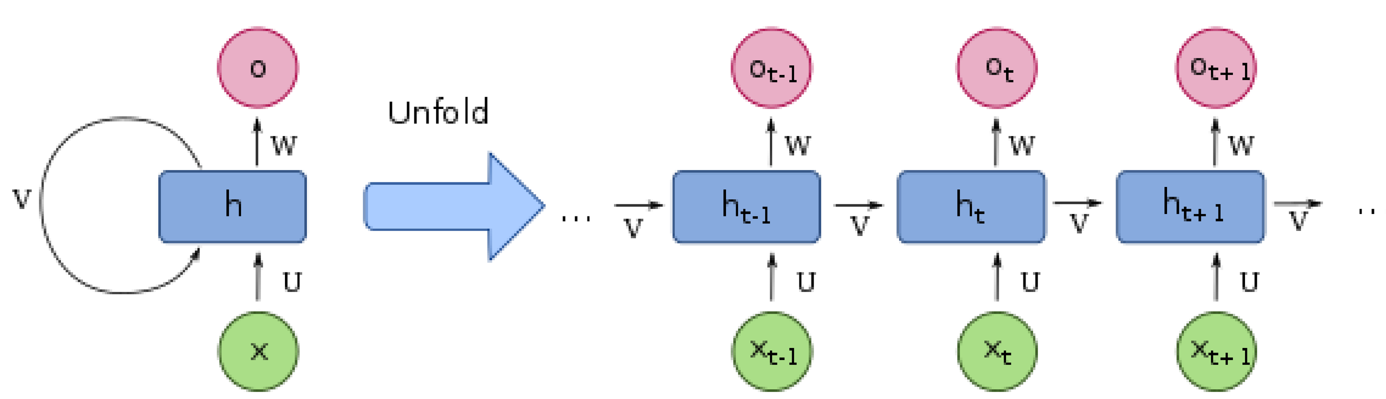
Long Short-Term Memory (LSTM) are RNN designed to solve this problem. They are better at storing informations than standard RNNs. It is important to note that LSTM gives state-of-the-art results in a variety of sequence processing tasks. This is the main reason why we decided to implement a LSTM for our text generation project. We worked on 4 differents dataset: Harry Potter's books, Lord of the ring's books, random quotes and a text from Shakespeare.

RNN structure

RNN comes from the following question: is there a neural network that depends on the full previous context that would model:

$$P(o_1, \ldots, o_T) = \prod_{t=1}^{T} P(o_t | o_1, \ldots o_{t-1})$$

They are feedforward neural networks with the addition of time dependency in the model by introducing edges that span the adjacent time steps in the network. At a given time, the nodes with recurrent edges receive input from the current data and from the output of the hidden layer in the previous state, see figure below. Thus, an input at time t can influence the output at time $t+\delta$.



RNN parameter udpates and vanishing-exploding gradient

$$h_t = \sigma(Ux_t + Vh_{(t-1)} + b_h),$$
$$o_t = \text{softmax}(Wh_t + b_o)$$

Here, U, V and W are weights matrix. The vectors b are bias parameters. Learning with RNN is challenging due to dependencies between long time steps. Consider the gradient with respect to h_t of $o_{t+\delta}$. How does it vary with δ? Following the graph above and applying the chain rule we can see that

$$\nabla_{h_t} o_{t+\delta} = \left(\prod_{k=t+1}^{t+\delta} V^T \text{diag}(1 - h_k^2) \right) \nabla_{h_{t+\delta}} o_{t+\delta}.$$

Thus, as δ grows, the gradient grows exponentially with V. If V is small or large than the gradient will either vanish or explode. This problem is well known. Solutions exist, which brings us to present the LSTM.

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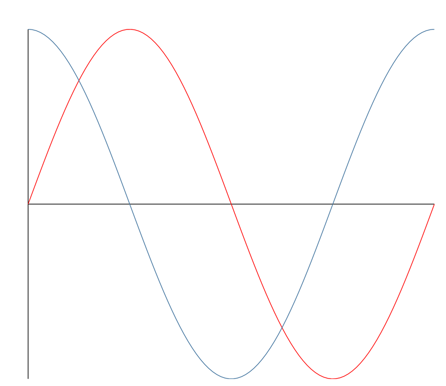

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Foo	13.37	384,394	α
Bar	2.17	1,392	β
Baz	3.14	83,742	δ
Qux	7.59	974	γ

Table: A table caption.

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References