Recurrent Neural Networks

Remembering Past Data

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Diplomado Ciencia de Datos con Python

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- **Successive data are dependent on past data**. Therefore, it is helpful to receive a particular input x_t only after the earlier inputs have already been received and converted into a hidden state.
- The traditional type of feed-forward network in which all inputs feed into the first layer does not achieve this goal.

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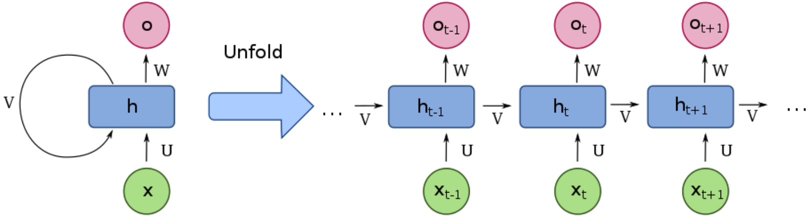
  - In the text-setting, we are predicting the next word.
  - In some applications, we do not output y_t at each time stamp, but only at the end of the sequence (sentiment analysis).

General Architecture of a RNN



Examples of RNN

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- Gated recurrent units (GRUs)

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- In some cases, the gradient will be very small, preventing the weight from changing its value.
- For example, the hyperbolic tangent function have gradients in the range $(0, 1]$, therefore, the gradient decreases exponentially with the number of layers.
- With activation functions whose derivatives can take on larger values, one risks encountering the related opposite exploding gradient problem.

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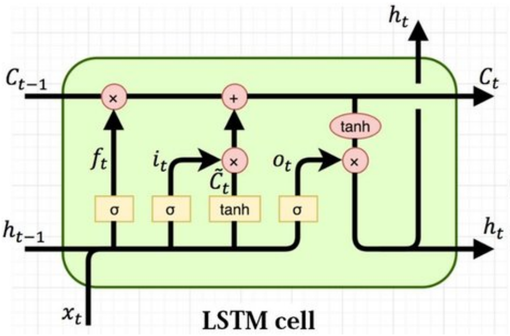
LSTM



$$i_t = \sigma\left(x_t U^i + h_{t-1} W^i\right)$$
$$f_t = \sigma\left(x_t U^f + h_{t-1} W^f\right)$$
$$o_t = \sigma\left(x_t U^o + h_{t-1} W^o\right)$$
$$\tilde{C}_t = \tanh\left(x_t U^g + h_{t-1} W^g\right)$$
$$C_t = \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}_t\right)$$
$$h_t = \tanh(C_t) * o_t$$

$\mathbf{c_t}$: Cell state, *memoría de la célula*

$\mathbf{f_t}$: Forget gate, *¿qué tanto olvidamos de* c_t

$\mathbf{o_t}$: Output gate

$\mathbf{i_t}$: Input gate

$\mathbf{i_t} * \mathbf{\tilde{C}_t}$: *La contribución de esta entrada a la memoria*

$\mathbf{h_t}$: Hidden-state vector, output

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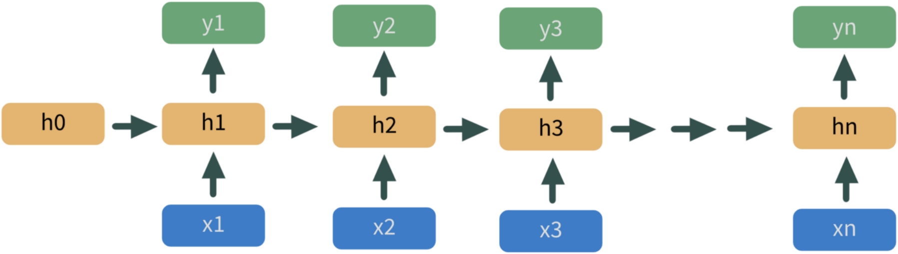
- LSTM networks are well-suited to classifying, and making predictions based on time series data.
- **LSTMs were developed to deal with the vanishing gradient problem** that can be encountered when training traditional RNNs.

LSTM: Unfolded



Input shape

The input to every LSTM layer must be three-dimensional.
The three dimensions of this input are:

- Samples. One sequence is one sample. A batch is comprised of one or more samples.
- Time Steps. One time step is one point of observation in the sample.
- Features. One feature is one observation at a time step.

https://machinelearningmastery.com/reshape-input-data-long-short-term-memory-networks-keras/
https://stackoverflow.com/questions/60571934/which-axis-does-keras-simplernn-lstm-use-as-the-temporal-axis-by-default