

Process Sequences

Recurrent Neural Networks

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A lot of the ideas in this lecture come from Andrej Karpathy's blog post on the Unreasonable Effectiveness of RNNs (<http://karpathy.github.io/2015/05/21/rnn-effectiveness/>). Many of the images and animations were made by Adam Prügel-Bennett.

Recurrent Neural Networks - Motivation

x: Jon and Ethan gave deep learning lectures

y: 1 0 1 0 0 0 0

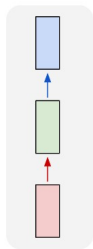
Recurrent Neural Networks - Motivation

x :	$x^{(1)}$...	$x^{(t)}$...	$x^{(T_x)}$
x :	Jon	...	Ethan	...	lectures
y :	$y^{(1)}$...	$y^{(t)}$...	$y^{(T_y)}$
y :	1	...	1	...	0

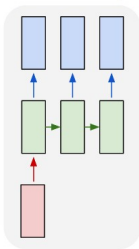
In this example, $T_x = T_y = 7$ but T_x and T_y can be different.

Recurrent Neural Networks

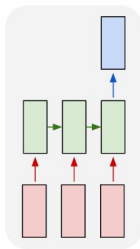
one to one



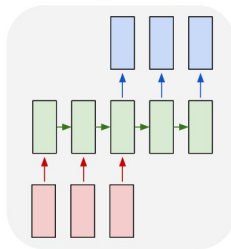
one to many



many to one



many to many



many to many

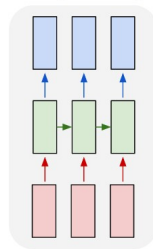


Image from <http://karpathy.github.io/2015/05/21/rnn-effectiveness/>

Aside: One Hot Encoding

How can we represent individual words (or other discrete tokens)?

"a"	"abbreviations"		"zoology"	"zoom"
1	0		0	0
0	1		0	1
0	0		0	0
.
.	.		.	.
.	.		.	.
0	0		0	0
0	0		1	0
0	0		0	1

Image from <https://ayearofai.com>

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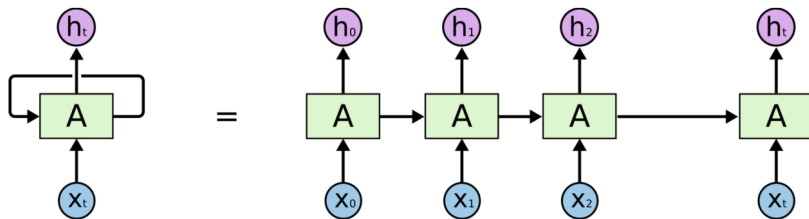
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- To facilitate this we would like to add a feedback loop delayed in time

Recurrent Neural Networks

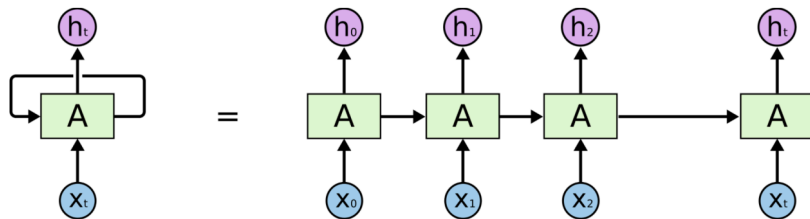


1

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¹Image taken from <https://towardsdatascience.com>

Recurrent Neural Networks



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- RNNs are a family of ANNs for processing sequential data
- RNNs have directed cycles in their computational graphs

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Recurrent Neural Networks

RNNs combine two properties which make them very powerful.

- 1 Distributed hidden state that allows them to store a lot of information about the past efficiently. This is because several different units can be active at once, allowing them to remember several things at once.
- 2 Non-linear dynamics that allows them to update their hidden state in complicated ways².

²Often said to be difficult to train, but this is not necessarily true - dropout can help with overfitting for example

Recurrent Neural Networks

RNNs are Turing complete in the sense they can simulate arbitrary programs³.

³Don't read too much into this - like universal approximation theory, just because they can doesn't mean its necessarily learnable!

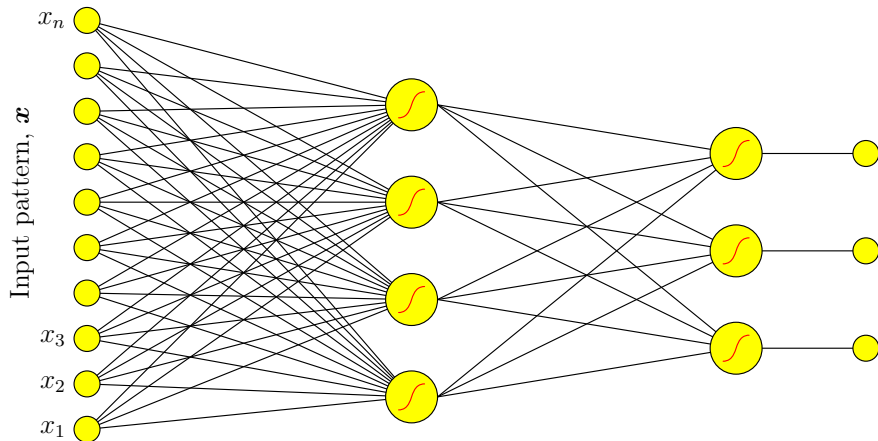
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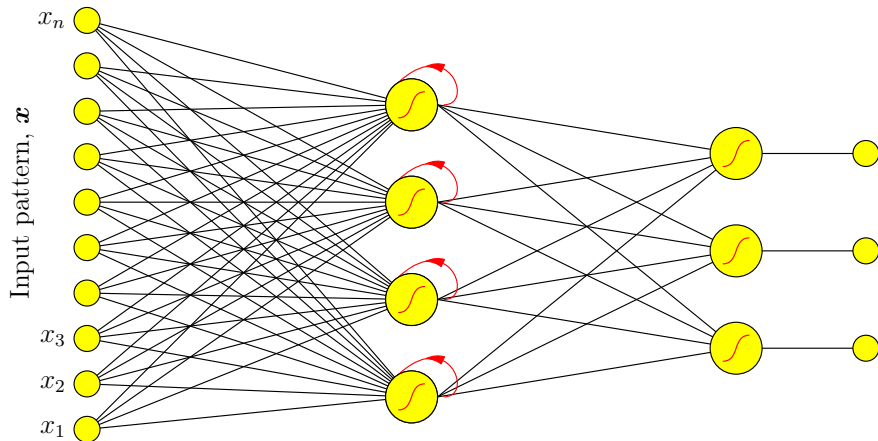
If training vanilla neural nets is optimisation over functions, training recurrent nets is optimisation over programs.

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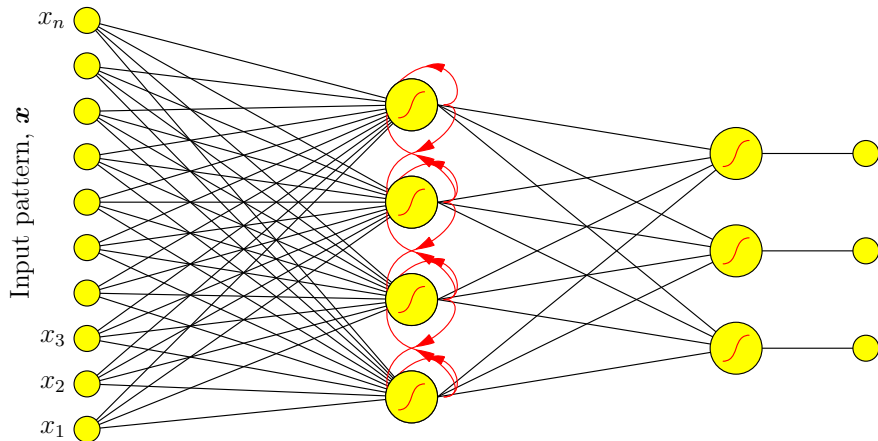
Recurrent Network



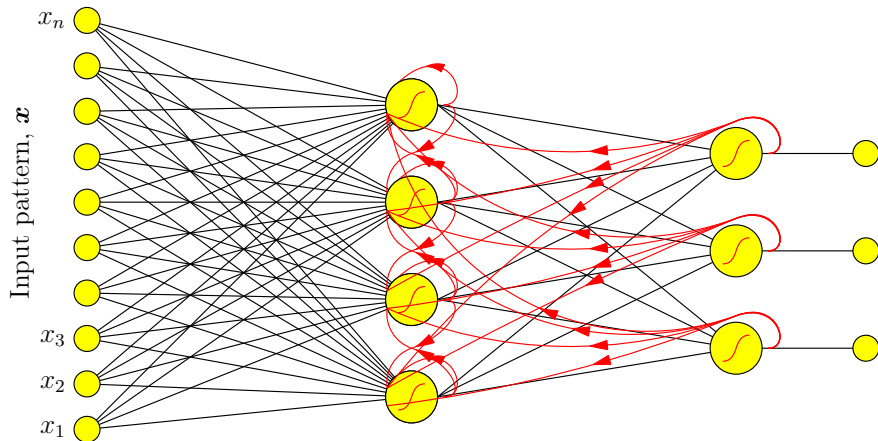
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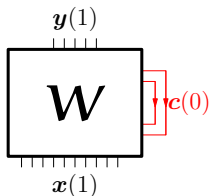


Training Recurrent Networks

- Given a set of inputs $\mathcal{D} = ((\mathbf{x}(t), \mathbf{y}(t)) | t = 1, 2, \dots, T)$

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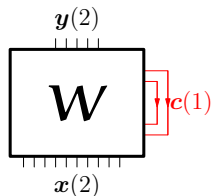


- Minimise an error (here MSE, but your choice):

$$E(\mathbf{W}) = \sum_{t=1}^T \|\mathbf{y}(t) - \mathbf{f}(\mathbf{x}(t), \mathbf{c}(t-1) | \mathbf{W})\|^2$$

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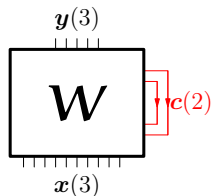


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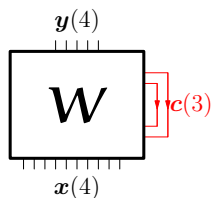


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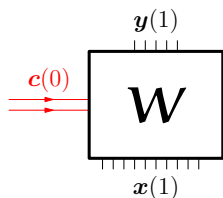


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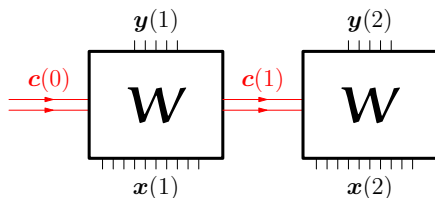


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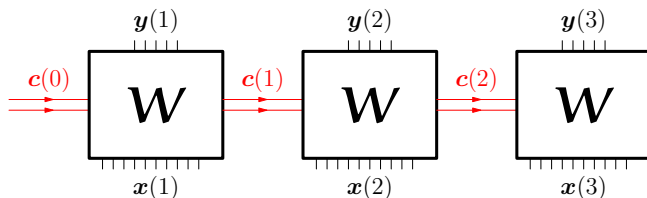


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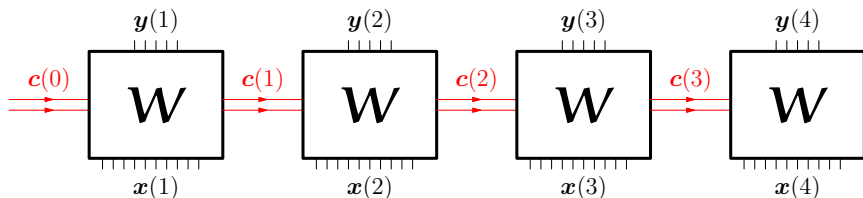


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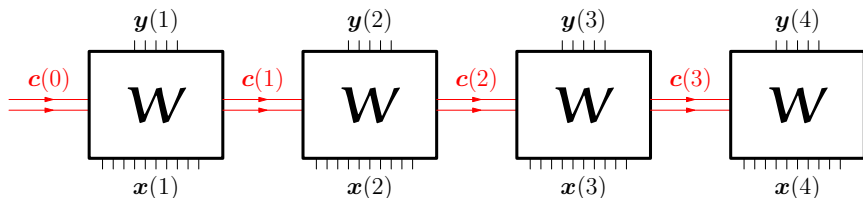


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- This is known as *back-propagation through time*

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- it should be clear that the gradients of this with respect to the weights can be found with the chain rule

What is the state update $g()$?

- It depends on the variant of the RNN!
 - Elman
 - Jordan
 - LSTM
 - GRU

Elman Networks (“Vanilla RNNs”)

$$\begin{aligned}\mathbf{h}_t &= \sigma_h(\mathbf{W}_{ih}\mathbf{x}_t + \mathbf{b}_{ih} + \mathbf{W}_{hh}\mathbf{h}_{t-1} + \mathbf{b}_{hh}) \\ \mathbf{y}_t &= \sigma_y(\mathbf{W}_y\mathbf{h}_t + \mathbf{b}_y)\end{aligned}$$

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- σ_h is usually tanh
- σ_y is usually identity (linear) – the y ’s could be regressed values or logits
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- the hidden state at time t is a summation of a projection of the input and a projection of the previous hidden state

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- Also note: RNNs are most often not used in isolation - it's quite common to process the inputs and outputs with MLPs (or even convolutions)

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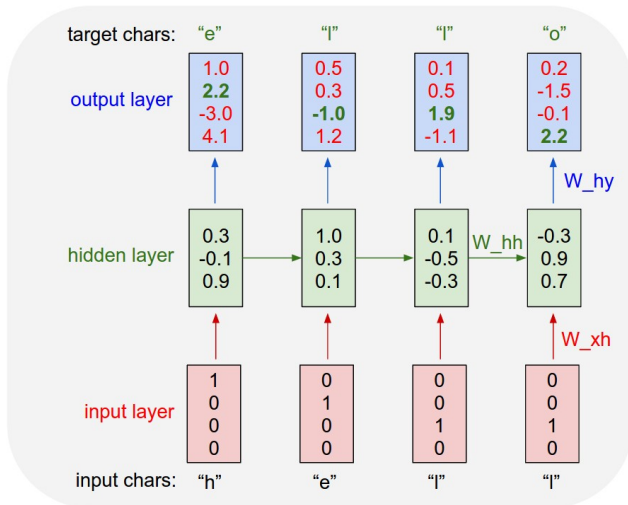


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Training a Char-RNN

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 - Overfitting could be a problem: dropout is very useful here

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 - you could pick the most likely (maximum-likelihood solution), but this might lead to generated text with very low variance (it might be boring and repetitive)
 - you could treat the softmax probabilities defined by the logits as a categorical distribution and sample from them
 - you might increase the 'temperature', T , of the softmax to make the distribution more diverse (less 'peaky'): $q_i = \frac{\exp(z_i/T)}{\sum_j \exp(z_j/T)}$

A lot of the ideas in this lecture on the input $c(t-1)$, $g(x(t-2), g(t-1) - W)$

Integrated into the Mnt Net) the
pl

On a feed forward prediction couponet on the
logits its outputs used as input to the
next layer. The next layer is a
vocabulary layer

- Sampled from a single layer RNN⁴.

⁴LSTM, 128 dim hidden size, with linear input projection to 8-dimensions and output to the number of characters (84). Trained on the text of these slides for 50 epochs.