

Deep learning for sequence processing: Section 9.2, Speech and Language Processing, 3rd edition draft, Jurafsky & Martin (2021).

# 8.2 Recurrent Neural Networks

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# Sequence Processing with Feedforward Networks

- A sentence can have the same meaning if it comes at the start, middle or end of a document
- But, in a feedforward network...
  - Different weights are applied to each input position, so "good day to you" is processed differently to "a good day to you".
  - All data must be passed in at once, even if it is a document with thousand of words.
  - This makes learning harder and scalability trickier.

# Sequence Labelling and Text Classification

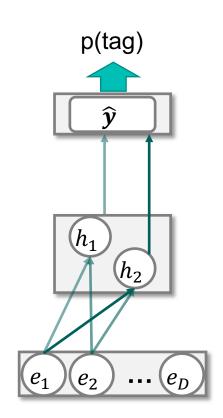
- Sequence labelling:
  - HMMs use information from the previous and next tokens in a sequence.
  - Viterbi algorithm passes messages forward and then backward.
  - Strong assumption that the current tag depends only on the previous tag.
  - How can we perform sequence labelling with a neural network?
- Text classification:
  - We want to process the tokens sequentially, then predict the class label for the whole document.
- Solution: recurrent neural networks (RNNs).

#### **RNN: Recurrent Connections**

Task: sequence labelling.

Input to the recurrent layer includes both the current input and the activation of the recurrent layer at the previous time-step.

Recurrent layer



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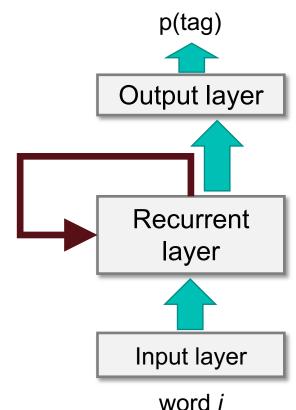
p(tag) Recurrent layer

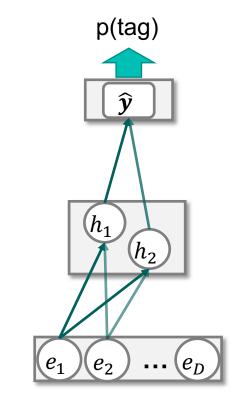
## **RNN: Recurrent Connections**

Task: sequence labelling.

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Simplified view:

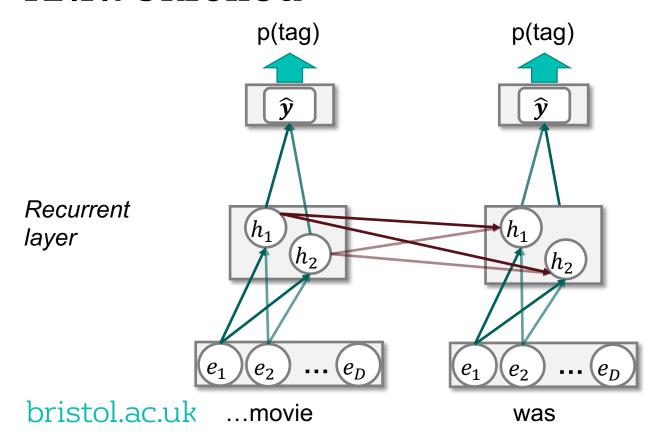


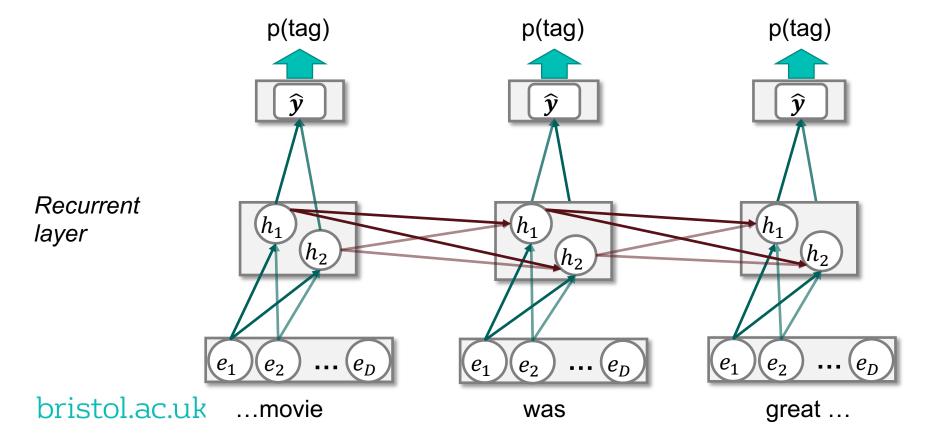


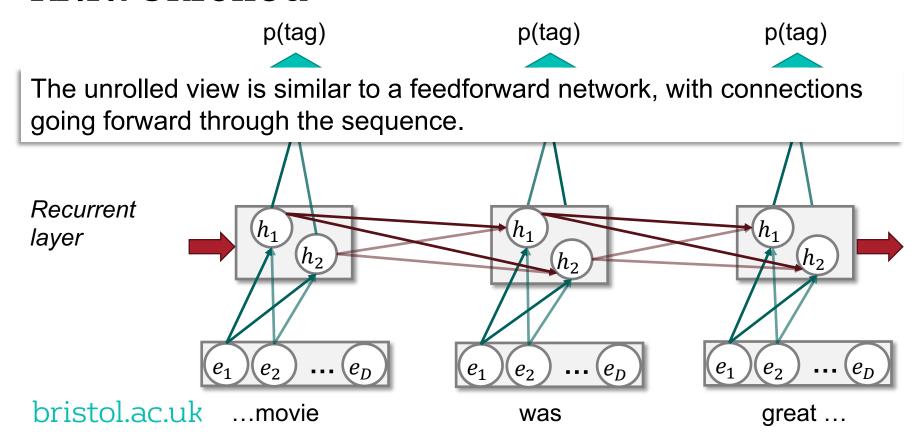
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Recurrent

layer







# RNN Equations

#### Feedfoward Neural Network:

1. 
$$h = g(W^{(1)}x)$$

- -g is the activation function, e.g., ReLU, sigmoid.
- $-W^{(1)}$  is the weight matrix of the first hidden layer

2. 
$$\hat{y} = softmax(\mathbf{W}^{(2)}\mathbf{h})$$

 $-\hat{y}$  is the output probability vector.

#### RNN:

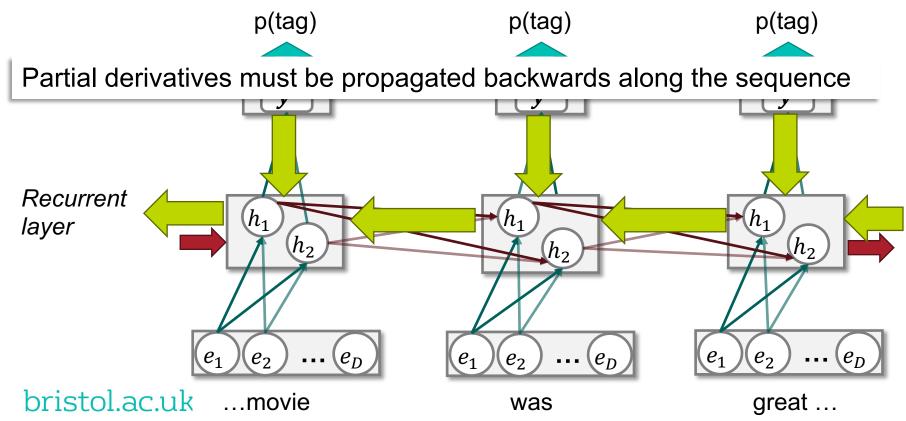
1. 
$$h_t = g(W^{(1)}x_t + Uh_{t-1})$$

- − *U* is weight matrix for the recurrent connection.
- $-\mathbf{h}_t$  is the activation for token t, called the **hidden state**.

2. 
$$\widehat{\mathbf{y}_t} = softmax(\mathbf{W}^{(2)}\mathbf{h}_t)$$

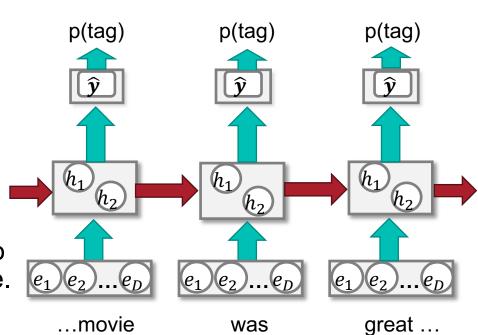
 Predicts the sequence label for time-step t.

# Training: Backpropagation Through Time



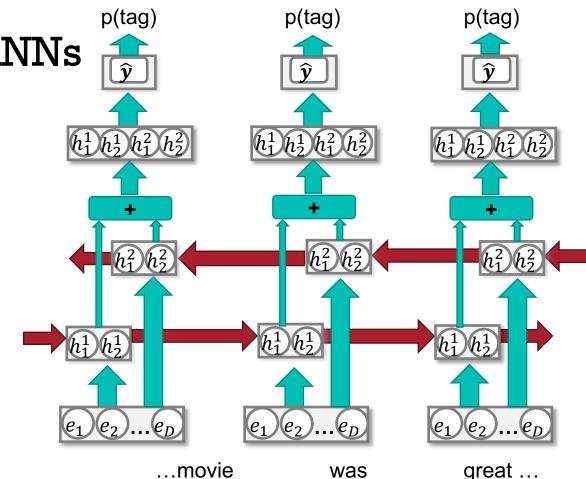
## Inference: Uni-directional RNNs

- Forward inference passes information from left to right.
- The tag at time-step i depends only on previous tokens.
- But seeing later later tokens can help to choose the label for earlier ones.
- Viterbi algorithm for HMM also passed information backwards to select most likely label sequence.



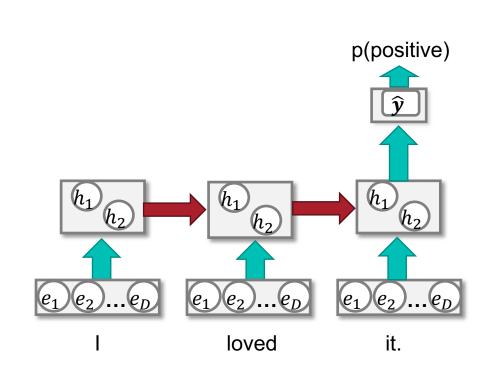
# **Bi-Directional RNNs**

- Introduce a second RNN layer, which runs from right to left.
- Concatenate the hidden states from both layers as input to the next layer.
- Training: backprop for the backward layer passes derivatives from left to right.



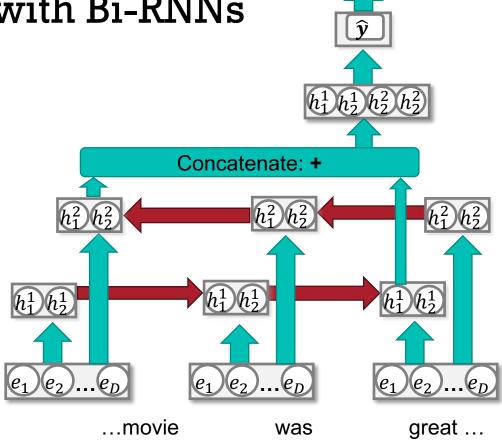
#### Text Classification with RNNs

- How can we use an RNN to classify an entire document or sentence?
- The last hidden state is taken as a representation of the whole sequence.
- Only the final hidden state is passed to the output layer.



# Text Classification with Bi-RNNs

- How can we use an RNN to classify an entire document or sentence?
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p(positive)

# Summary

- Sequential processing must rely on syntactic structure rather than the position of features within a document.
- Recurrent neural networks (RNNs) have an additional input connection, which is the activation of the previous time-step.
- This allows them to pass information in one direction during inference.
- Bi-directional RNNs concatenate the hidden states (RNN activations) of two RNNs running in opposite directions.
- The final hidden states can represent the whole sequence.