Recurrent neural networks
Modelling sequential data

Recurrent Neural Networks 1: Modelling sequential data

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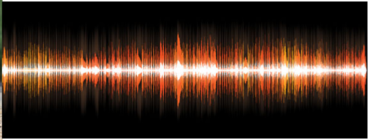
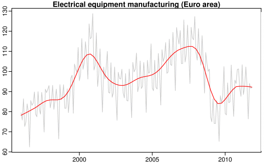
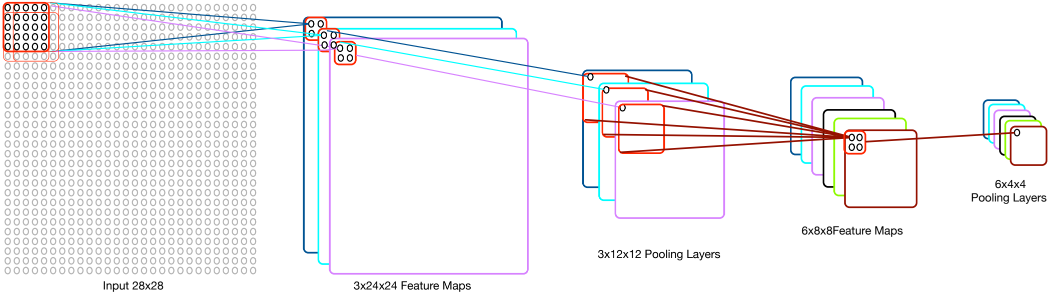
Machine Learning Practical — MLP Lecture 9
15 November 2017 / 20 November 2017

Sequential Data



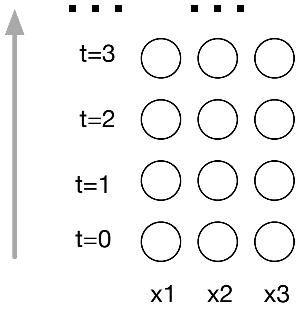


- We often wish to model data that is a sequence or trajectory through time, for instance audio signals, text (sequences of characters/words), currency exchange rates, motion of animal
- Modelling sequential data
  - Invariances across time
  - The current state depends on the past
  - Need to share data across time
- Convolutional networks model invariances across space – can we do something similar across time?
  - Yes - time-delay neural networks
- Can we use units to act as memories?
  - Yes - recurrent networks



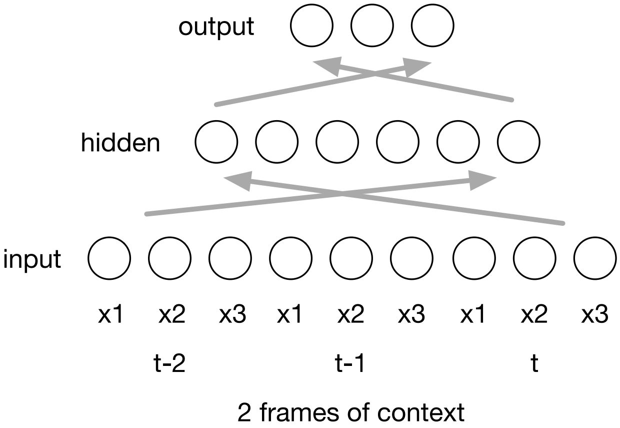
- Local connectivity
- Weight sharing

Modelling sequences

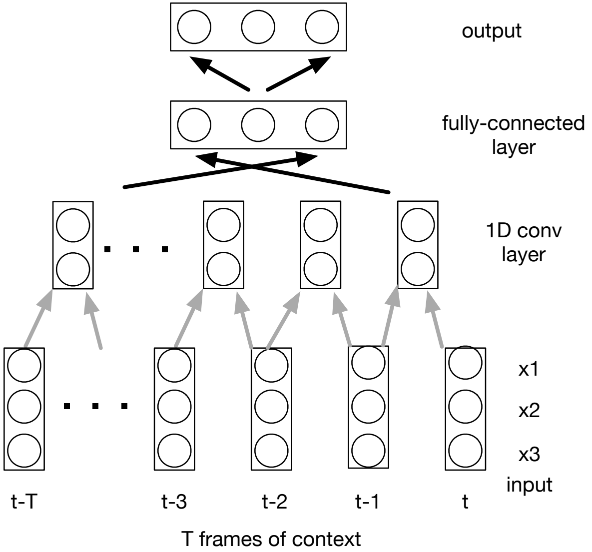


- Imagine modelling a time sequence of 3D vectors

Modelling sequences

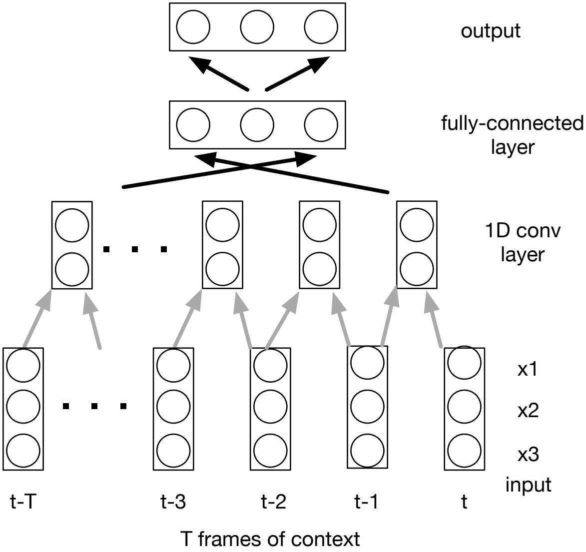


- Imagine modelling a time sequence of 3D vectors
- Can model fixed context with a feed-forward network with previous time input vectors added to the network input



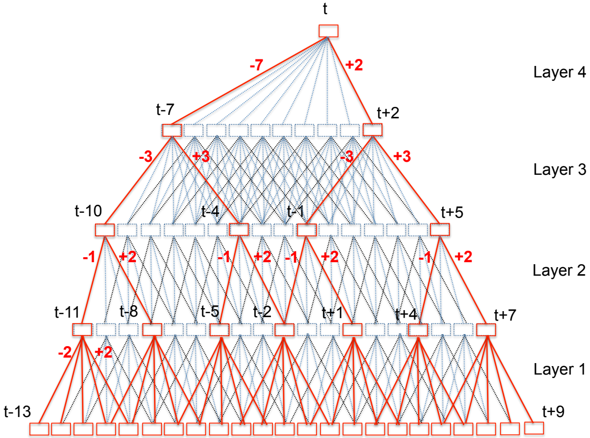
- Imagine modelling a time sequence of 3D vectors
- Can model fixed context with a feed-forward network with previous time input vectors added to the network input
- Model using 1-dimension convolutions in time - **time-delay neural network** (TDNN)

Modelling sequences



- Imagine modelling a time sequence of 3D vectors
- Can model fixed context with a feed-forward network with previous time input vectors added to the network input
- Model using 1-dimension convolutions in time - **time-delay neural network** (TDNN)
- Network takes into account a *finite context*

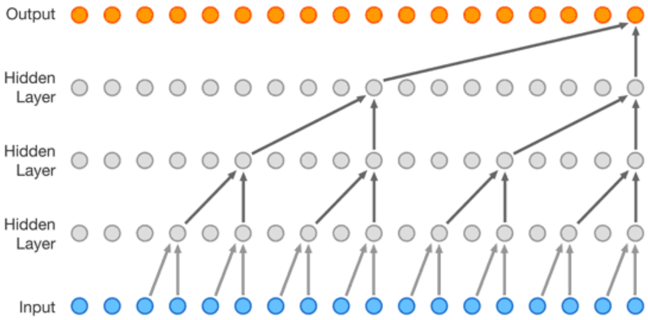
TDNNs in action



- TDNN operating on 23 frames of context
- Without sub-sampling (blue+red)
- With sub-sampling (red)

Peddinti et al, " Reverberation robust acoustic modeling using i-vectors with time delay neural networks", Interspeech-2015, http://www.danielpovey.com/files/2015_interspeech_aspire.pdf

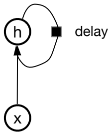
Wavenet



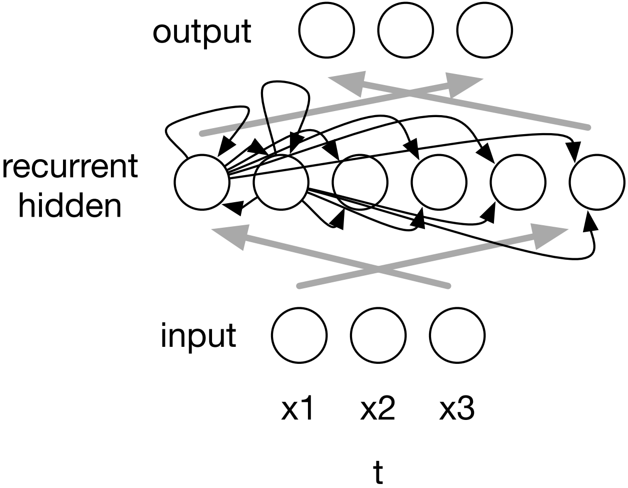
van den Oord et al (2016), "WaveNet: A Generative Model for Raw Audio",
https://arxiv.org/abs/1609.03499

Networks with state

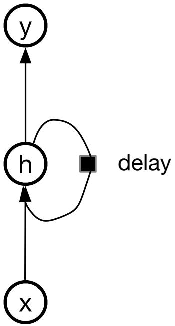
- Feed-forward = finite context: feed-forward networks (even fancy ones like Wavenet) compute the output based on a finite input history. Sometimes the required context is known, but often it is not
- State units: we would like a network with *state* across time – if an event happens, we can potentially know about that event many time steps in the future
  - State units as memory – remember things for (potentially) an infinite time
  - State units as information compression – compress a sequence into a state representation
- Recurrent networks with state units



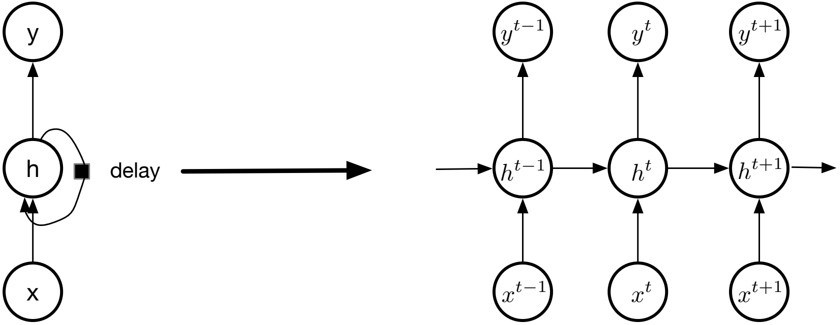
Recurrent networks



Graphical model of a recurrent network



Graphical model of a recurrent network

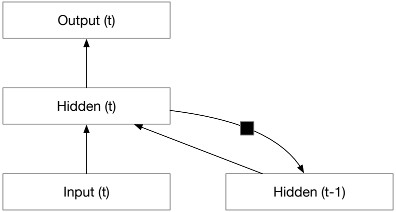


Unfold a recurrent network in time

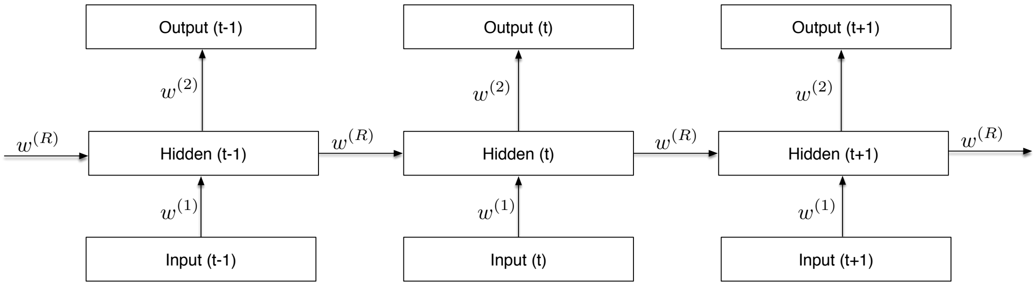
Simple recurrent network

$$y_k(t) = \text{softmax}\left(\sum_{r=0}^{H} w_{kr}^{(2)} h_r(t) + b_k\right)$$

$$h_j(t) = \text{sigmoid}\left(\sum_{s=0}^{d} w_{js}^{(1)} x_s(t) + \underbrace{\sum_{r=0}^{H} w_{jr}^{(R)} h_r(t-1)}_{\text{Recurrent part}} + b_j\right)$$

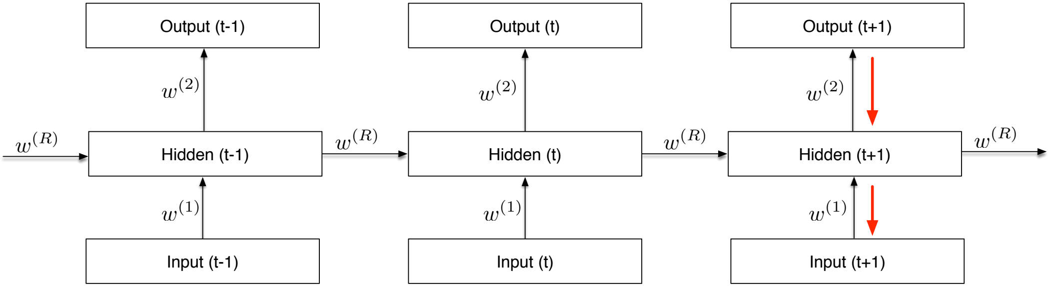


Recurrent network unfolded in time



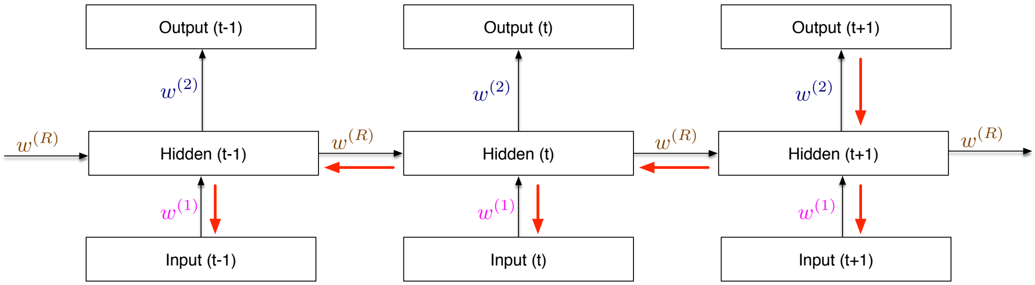
- View an RNN for a sequence of T inputs as a T-layer network with shared weights

Recurrent network unfolded in time



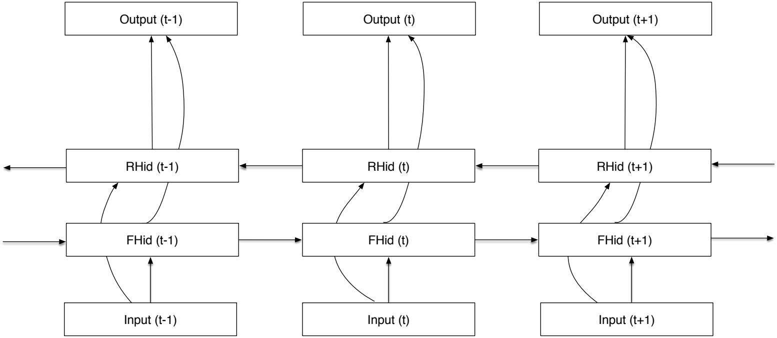
- View an RNN for a sequence of T inputs as a T-layer network with shared weights

Recurrent network unfolded in time



- View an RNN for a sequence of T inputs as a T-layer network with shared weights
- Train an RNN by doing backprop through this unfolded network
- Weight sharing
  - if two weights are constrained to be equal ($w_1 = w_2$) then they will stay equal if the weight changes are equal ($\partial E/\partial w_1 = \partial E/\partial w_2$)
  - achieve this by updating with ($\partial E/\partial w_1 + \partial E/\partial w_2$) (cf Conv Nets)

Bidirectional RNN

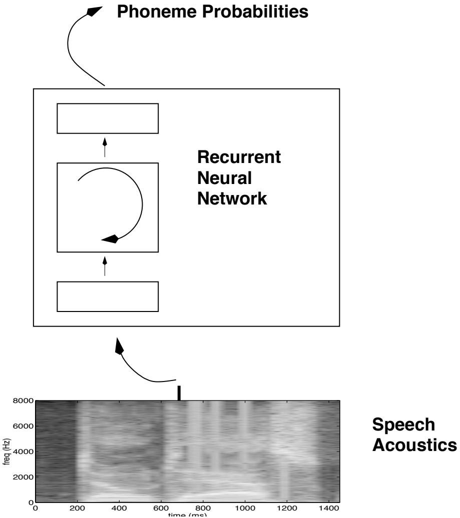


- Output a prediction that depends on the whole input sequence
- Bidirectional RNN – combine an RNN moving forward in time, with one moving backwards in time
- State units provide a combined representation that depends on both the past and the future

Back-propagation through time (BPTT)

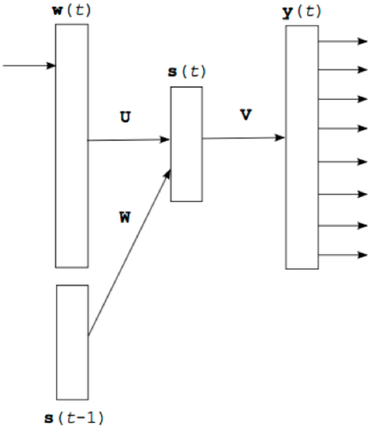
- We can train a network by unfolding and *back-propagating through time*, summing the derivatives for each weight as we go through the sequence
- More efficiently, run as a recurrent network
  - cache the unit outputs at each timestep
  - cache the output errors at each timestep
  - then backprop from the final timestep to zero, computing the derivatives at each step
  - compute the weight updates by summing the derivatives across time
- Expensive – backprop for a 1,000 item sequence equivalent to a 1,000-layer feed-forward network
- Truncated BPTT – backprop through just a few time steps (e.g. 20)

Example 1: speech recognition with recurrent networks



T Robinson et al (1996).
"The use of recurrent networks in continuous speech recognition",
in *Automatic Speech and Speaker Recognition Advanced Topics*
(Lee et al (eds)), Kluwer, 233–258.
http://www.cstr.ed.ac.uk/downloads/publications/1996/rnn4csr96.pdf

Example 2: recurrent network language models



T Mikolov et al (2010).
"Recurrent Neural Network Based Language Model",
Interspeech
http://www.fit.vutbr.cz/research/groups/speech/publi/2010/mikolov_interspeech2010_IS100722.pdf

Summary

- Model sequences using finite context using feed-forward networks with convolutions in time (TDNNs, Wavenet)
- Model sequences using infinite context using recurrent neural networks (RNNs)
- Unfolding an RNN gives a deep feed-forward network with shared weights
- Train using back-propagation through time
- Back-propagation through time
- (Historical) examples on speech recognition and language modelling
- Reading: Goodfellow et al, chapter 10 (sections 10.1, 10.2, 10.3) `http://www.deeplearningbook.org/contents/rnn.html`
- Next lecture: LSTM, sequence-sequence models