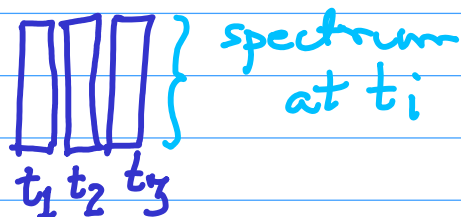


RNN: RECURRENT NEURAL NETWORK

RNN: modelling sequence data

— One snapshot of a ball cannot help us predict where it will go next, but a sequence of images will help us make a better prediction

— Audio: raw waveform or spectrogram



— Text: sequence of words/characters

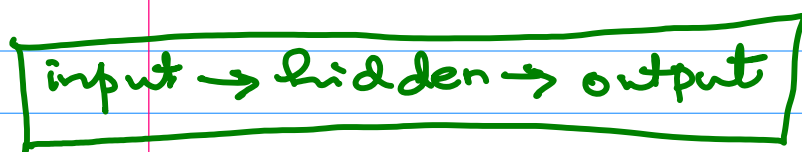
We often learn sequences e.g. alphabet

A B C D ... Z. Other way round? tough!

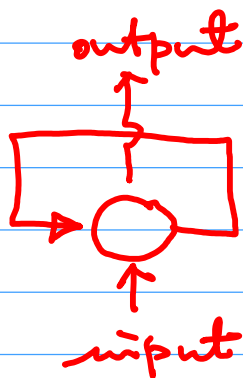
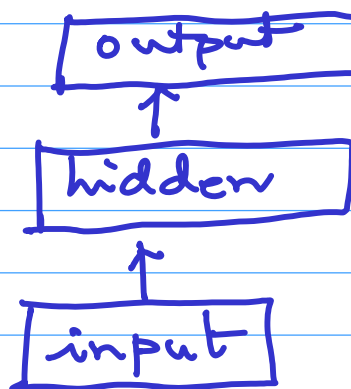
Break it up into smaller parts e.g. start at F:

after a few tries, we can get it right.

Model (in terms of the familiar feedforward neural network)

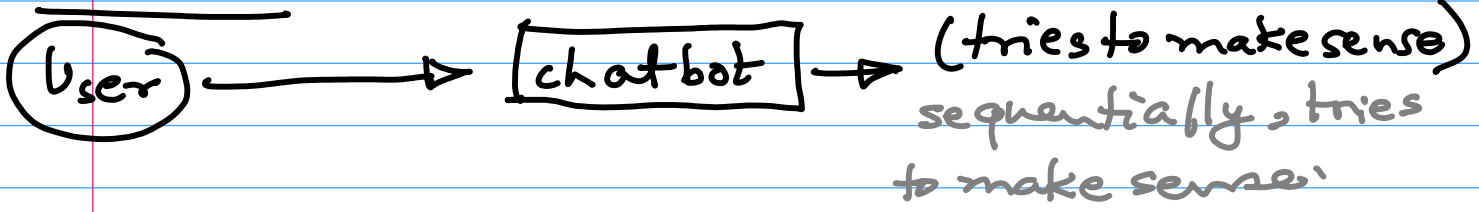


write this: top to bottom



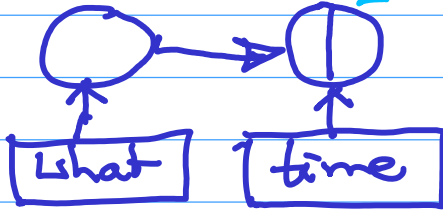
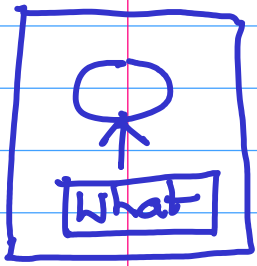
Add a loop in the feedforward neural network to make it use previous information

Chatbot:

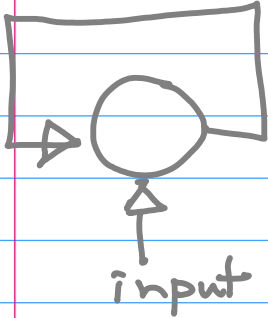


What time is it?

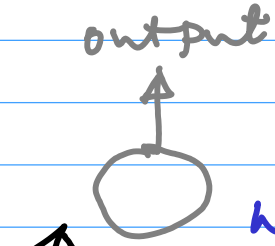
sequence of words



get the new
input &
the previous
state

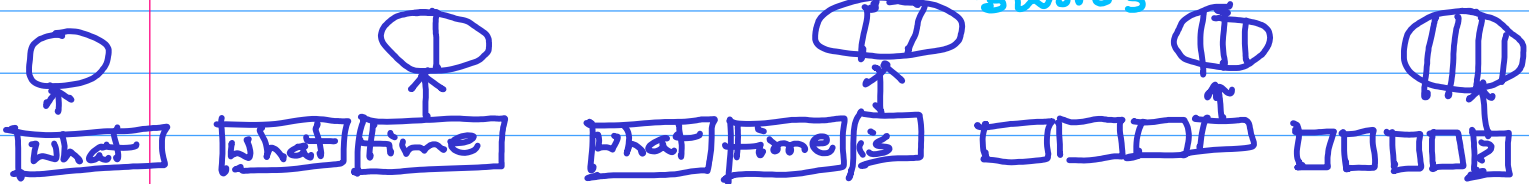


As the input comes in, feed the input and the previous hidden state \rightarrow once there is no more input



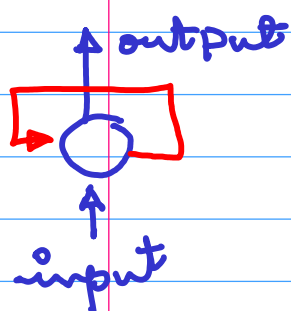
we feed this
to the output
of the ordinary
feed forward
network

* representational illustration of the short-term memory problem in RNNs:—

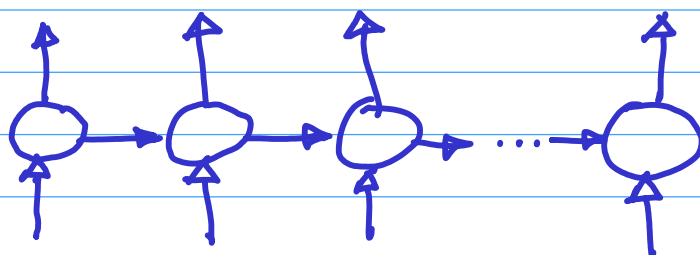


important words

RNN (contd.)



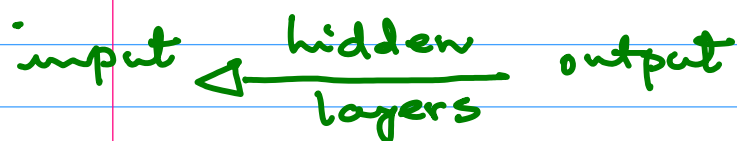
unroll



unrolled RNN

The effect: As the RNN processes more input, it has trouble retaining information from previous steps. Information from the word "what" is almost non-existent at the final step.

Cause: the infamous vanishing gradient problem



The gradient vanishes as we go from the output to the input side.

In the propagation of the error from the output side towards the input, the gradient gets so small that the weights in the layers towards the input side (via the chain rule) do not change at all.

Interpretation for an RNN:

Think of each time step as a layer of a feedforward neural network. "Backpropagation through time"

'SHORT-TERM MEMORY' →

causes early layers not to learn. In this example: there is a possibility that the words "what" and "time" are not considered at all, when trying to predict the user's intuition. The network makes the best guess with "is it?"

Andrey Karpathy's notes:

* What does training with characters (for example) mean in the input and output?

e.g., training with 4 characters h, e, l, o

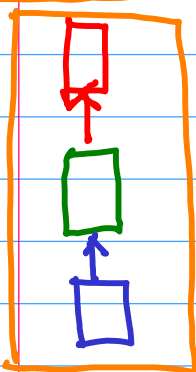
→ "1-hot encoding" or "1-of-k-encoding"

$$h: \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad e: \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \quad l: \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \quad o: \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

→ If the output is also expected to be a character, we will try to get similar values (approximate) from the outputs of a suitable neural network.

RNN uses: even if the data is not in the form of sequences, one can still formulate and train RNNs which process data sequentially.

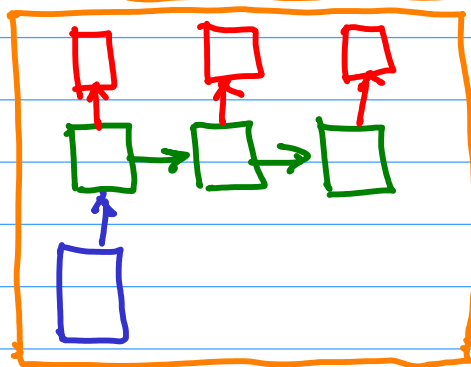
one-to-one



Without RNN:

fixed sized input
to a fixed-size
output e.g., image classification

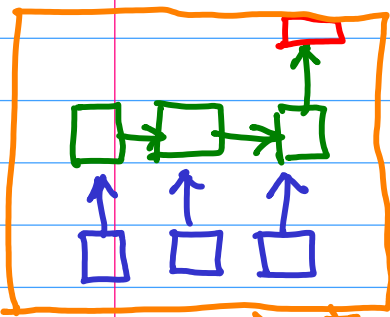
one-to-many



Sequence output

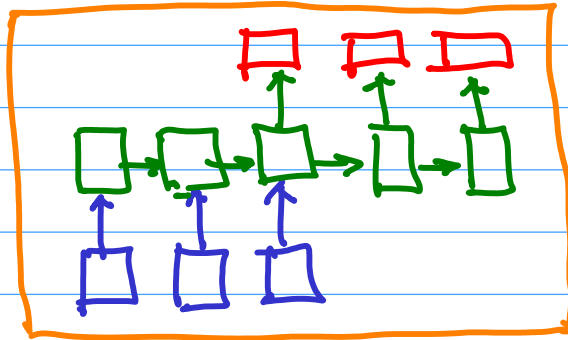
e.g., image captioning
takes an image as input
and gives as output: a
sentence of words.

many-to-one



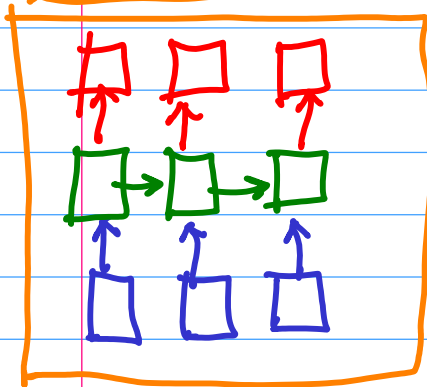
sequence input
e.g., sentiment
analysis: given a
sentence, it is
classified as
expressing positive
or negative sentiment

many-to-many



sequence i/p & sequence o/p
e.g., machine translation
from English to French.

many-to-many



Synchronised sequence
input and output

e.g., video classification:
to label each video frame.

Basic Structure:

There are no pre-specified
constraints on the lengths of
the sequences because the
recurrent transformation
(hidden) is fixed, and can be
applied as many times
as we like.