Neural Models for Sequences

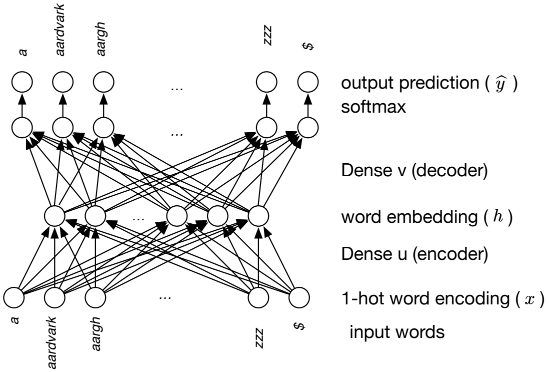
- Fully-connected networks, perhaps including convolutional layers, can handle fixed-size images and sequences.
- What about variable-length sequences?
- Sequences arise in natural language processing, biology, and any domain involving time.

Neural Language Models

- A corpus is the text used for training. The corpus could be, for example, a novel, a set of news articles, all of Wikipedia, or a subset of the text on the web.
- A token is a sequence of characters that are grouped together, such as the characters between blanks or punctuation. The process of splitting a corpus into tokens is called tokenization.
- The vocabulary, the set of words that will be considered, typically including names, common phrases, slang, punctuation, and markers for the beginning and end: $\langle start \rangle$ and $\langle stop \rangle$.
- Sometimes there is processing to group words into tokens, or to split words into tokens (such as the word "eating" becoming the tokens "eat" and "ing").
- In a character-level model, the vocabulary could be the set of Unicode characters that appear in the corpus.

Word Embeddings

Consider a model takes a single word and makes a prediction about what word appears near (e.g., following) it:



The vector of values in the hidden layer for the input word i, namely $[u[i,0], u[i,1], u[i,2], \ldots]$, is its word embedding.

Simple Word Embedding Example

The text "The history of AI is a history of fantasies, possibilities, demonstrations, and promise..." (ignore punctuation, with $\langle start \rangle$ as the start of a sentence) becomes the training data:

Input	Target
$\langle start \rangle$	the
the	history
history	of
of	ai
ai	is
is	a
a	history
history	of
of	fantasies

Word2vec

It usually works better to make predictions based on multiple surrounding words, rather than just one. The following methods use the k words before and after as a context:

- In the continuous bag of words (CBOW) model, each word in the context contributes $n/(2 * k)$ in the one-hot encoding, where n is the number of times the word appears in the context.
- In the Skip-gram model, the neural network model is used for each (w_{i+j}, w_i), for $j \in \{-k, \ldots, -1, 1, \ldots, k\}$, and the prediction of w_i is proportional to the product of each of the predictions. Thus, this assumes that each context word gives an independent prediction of word w_i.

Word2vec

- The embeddings resulting from these models can be added or subtracted point-wise, for example

$$Paris - France + Japan \approx Tokyo$$

where value after "$\approx$" is the mode of the prediction.

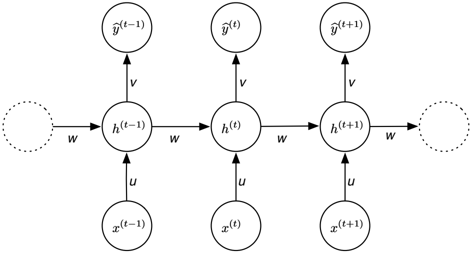
- Mikolov et al [2013] trained them on a corpus of 1.6 billion words, with up to 600 hidden units.
- Some other relationships found:

$$\begin{aligned}
&scientist - Einstein + Messi \approx midfielder\\
&scientist - Einstein + Mozart \approx violinist\\
&scientist - Einstein + Picasso \approx painter\\
&sushi - Japan + Germany \approx bratwurst\\
&sushi - Japan + USA \approx pizza\\
&sushi - Japan + France \approx tapas.
\end{aligned}$$

- There was about 60% accuracy picking the mode compared to what the authors considered to be the correct answer.

Matched Recurrent Neural Network

A recurrent neural network with matched input–output:



- takes sequence $x^{(0)}, x^{(1)}, x^{(2)} \ldots$ and outputs $y^{(0)}, y^{(1)}, y^{(2)} \ldots$, where $y^{(i)}$ only depends on $x^{(j)}$ for $j \leq i$.
- $h^{(t)}$ represents a memory or belief state: the information remembered from the previous times.
- A recurrent neural network represents
  - belief state transition function: $x^{(t)}, h^{(t-1)} \rightarrow h^{(t)}$
  - command function: $h^{(t)} \rightarrow \hat{y}^{(t)}$

Basic Matched Recurrent Neural Network

- belief state transition function: $x^{(t)}, h^{(t-1)} \rightarrow h^{(t)}$.
  The ith component of vector $h^{(t)}$ is

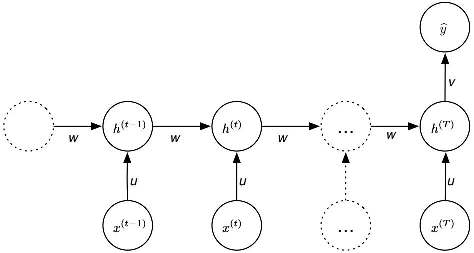
$$h^{(t)}[i] = \phi\left(b[i] + \sum_j w[i,j] * h^{(t-1)}[j] + \sum_k u[i,k] * x^{(t)}[k]\right)$$

  for nonlinear activation function ϕ, bias weight vector b, weight matrices w and u.
  Weight vector and matrices do not depend on time, t.
- command function: $h^{(t)} \rightarrow \hat{y}^{(t)}$.
  If the mth component of $\widehat{y}^{(t)}$ is Boolean:

$$\widehat{y}^{(t)}[m] = sigmoid(b'[m] + \sum_i v[m,i] * h^{(t)}[i])$$

Single output recurrent neural network

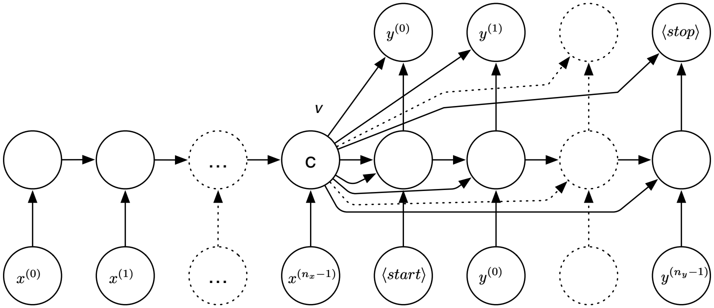
A recurrent neural network with single output after time T:



- takes sequence $x^{(0)}, x^{(1)}, x^{(2)} \dots$ and outputs $\hat{y}$.
- A recurrent neural network represents
  - belief state transition function: $x^{(t)}, h^{(t-1)} \rightarrow h^{(t)}$
  - command function: $h^{(T)} \rightarrow \hat{y}$

Encoder–decoder recurrent neural network

An encoder–decoder recurrent neural network does sequence-to-sequence mapping:



- c is a vector representing the context for the decoder.
- The decoder is a generative language model that takes the context and emits an output sequence.
- The decoder is like the matched RNN, but with c as an input for each hidden value and each output value.

Long short-term memory (LSTM)

- In a basic RNN, the gradients either exponentially vanish and explode.
- A long short-term memory (LSTM) network is a special kind of recurrent neural network designed so that the memory is maintained unless replaced by new information.
- Instead of learning a function from $h^{(t-1)}$ to $h^{(t)}$, it learns the change in h, written $\Delta h^{(t)}$, so that $h^{(t)} = h^{(t-1)} + \Delta h^{(t)}$.
- The value of $h^{(t)}$ is $h^{(0)} + \sum_{i \leq t} \Delta h^{(i)}$.
- The error in $h^{(t)}$ is passed to all predecessors, and is not vanishing exponentially as it does in a traditional RNN.