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.

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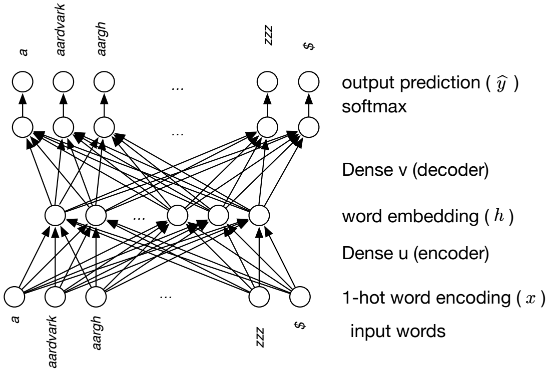
- In a character-level model, the vocabulary could be the set of Unicode characters that appear in the corpus.

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.

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- 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.

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- Some other relationships found:

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

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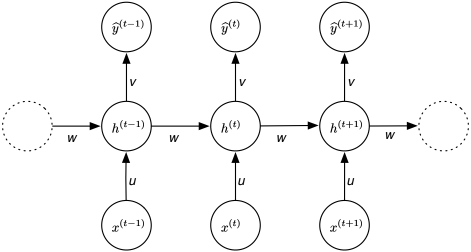
$$\begin{aligned}
&\mathit{scientist} - \mathit{Einstein} + \mathit{Messi} \approx \mathit{midfielder}\\
&\mathit{scientist} - \mathit{Einstein} + \mathit{Mozart} \approx \mathit{violinist}\\
&\mathit{scientist} - \mathit{Einstein} + \mathit{Picasso} \approx \mathit{painter}\\
&\mathit{sushi} - \mathit{Japan}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

- 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

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

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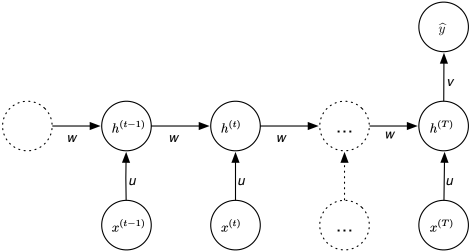
  Weight vector and matrices do not depend on time, t.
- command function: $h^{(t)} \rightarrow \hat{y}^{(t)}$.
  If the mth component of $\widehat{y}^{(t)}$ is Boolean:

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

Single output recurrent neural network

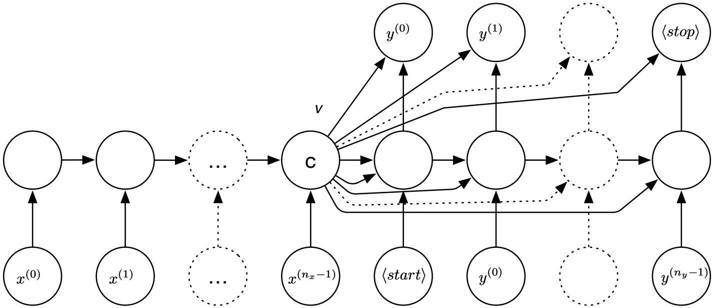
A recurrent neural network with single output after time T:



- takes sequence $x^{(0)}, x^{(1)}, x^{(2)} \ldots$ 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.

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- 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.