

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

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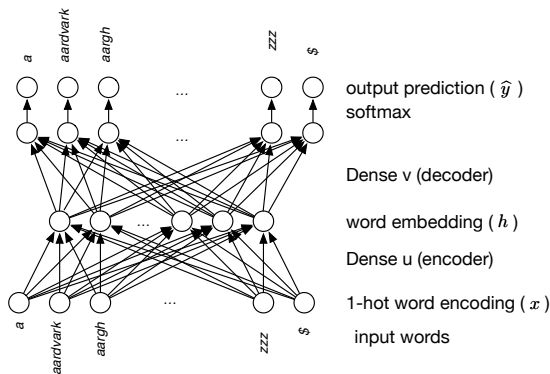
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- In a character-level model, the vocabulary could be the set of Unicode characters that appear in the corpus.

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 $[u[i, 0], u[i, 1], u[i, 2], \dots]$, 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

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 $j \in \{-k, \dots, -1, 1, \dots, k\}$, 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 .

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

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- Some other relationships found:

$$\textit{scientist} - \textit{Einstein} + \textit{Messi} \approx \textit{midfielder}$$

$$\textit{scientist} - \textit{Einstein} + \textit{Mozart} \approx \textit{violinist}$$

$$\textit{scientist} - \textit{Einstein} + \textit{Picasso} \approx \textit{painter}$$

$$\textit{sushi} - \textit{Japan} + \textit{Germany} \approx \textit{bratwurst}$$

$$\textit{sushi} - \textit{Japan} + \textit{USA} \approx \textit{pizza}$$

$$\textit{sushi} - \textit{Japan} + \textit{France} \approx \textit{tapas}.$$

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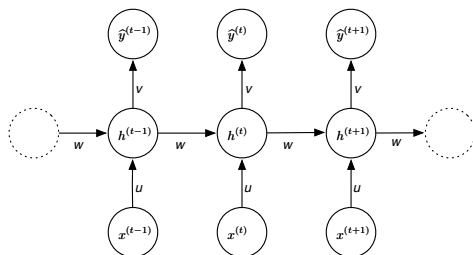
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- There was about 60% accuracy picking the mode compared to what the authors considered to be the correct answer.

Matched Recurrent Neural Network

A recurrent neural network with matched input–output:



- takes sequence $x^{(0)}, x^{(1)}, x^{(2)} \dots$ and outputs $y^{(0)}, y^{(1)}, y^{(2)} \dots$, 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 i th 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 .

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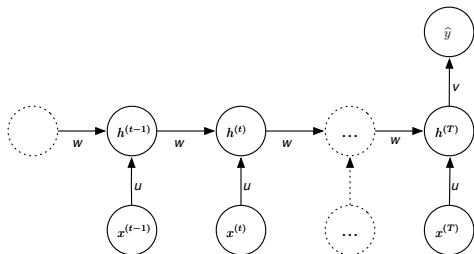
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- **command function:** $h^{(t)} \rightarrow \hat{y}^{(t)}$.
If the m th component of $\hat{y}^{(t)}$ is Boolean:

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

Single output recurrent neural network

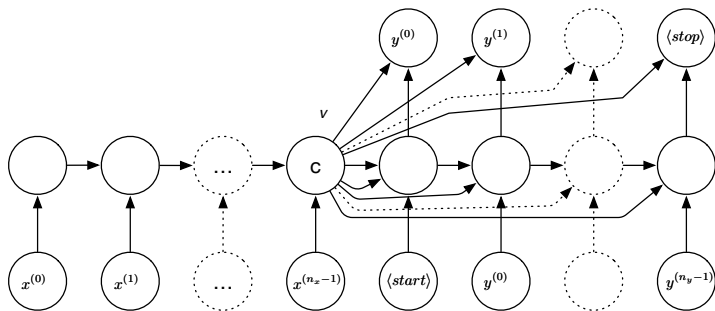
A recurrent neural network with single output after time T :



- takes sequence $x^{(0)}, x^{(1)}, x^{(2)} \dots$ and outputs \hat{y} .
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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.