# Neural Machine Translation

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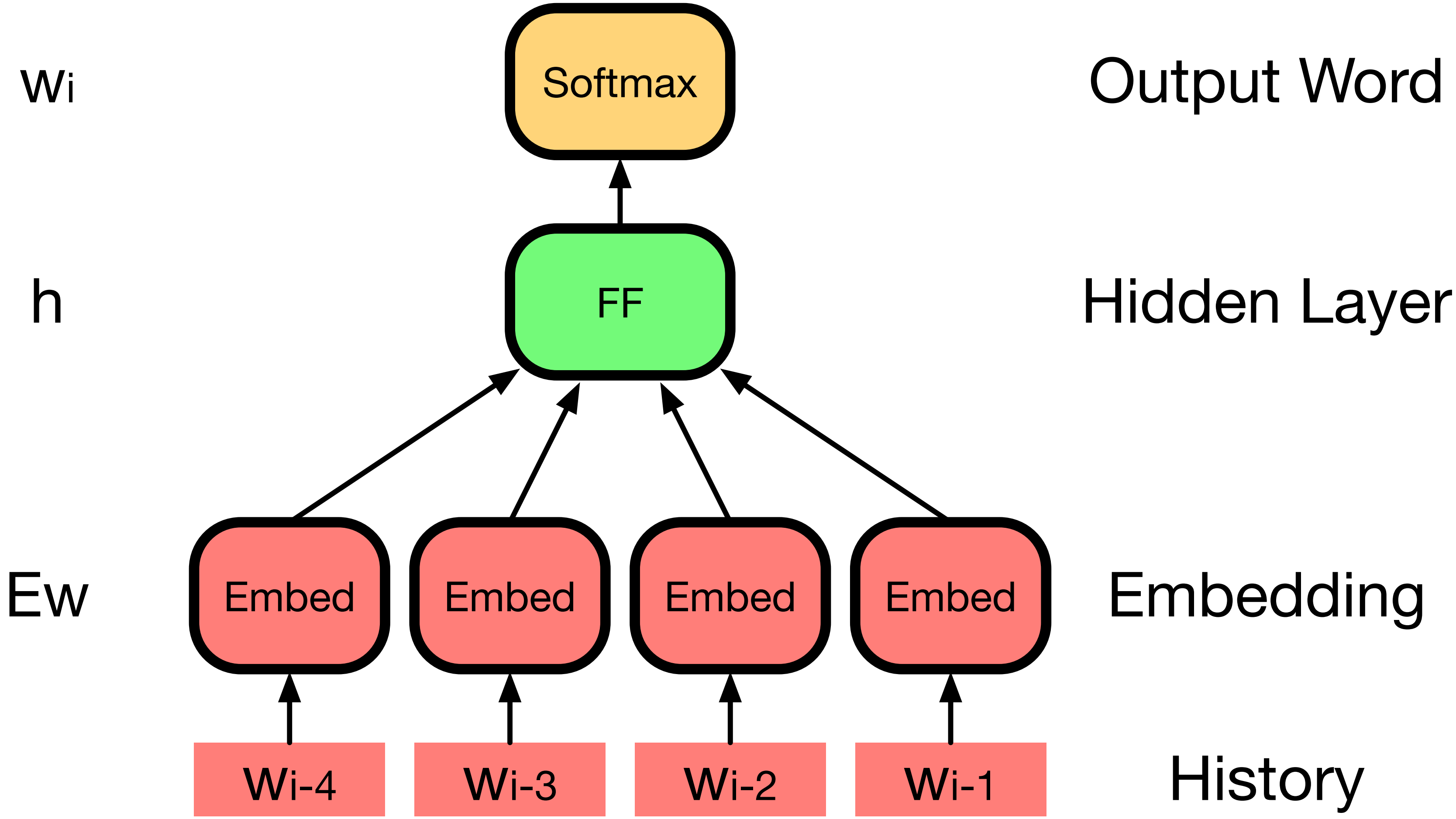
# Language Models



- Modeling variants
  - feed-forward neural network
  - recurrent neural network
  - long short term memory neural network
- May include input context

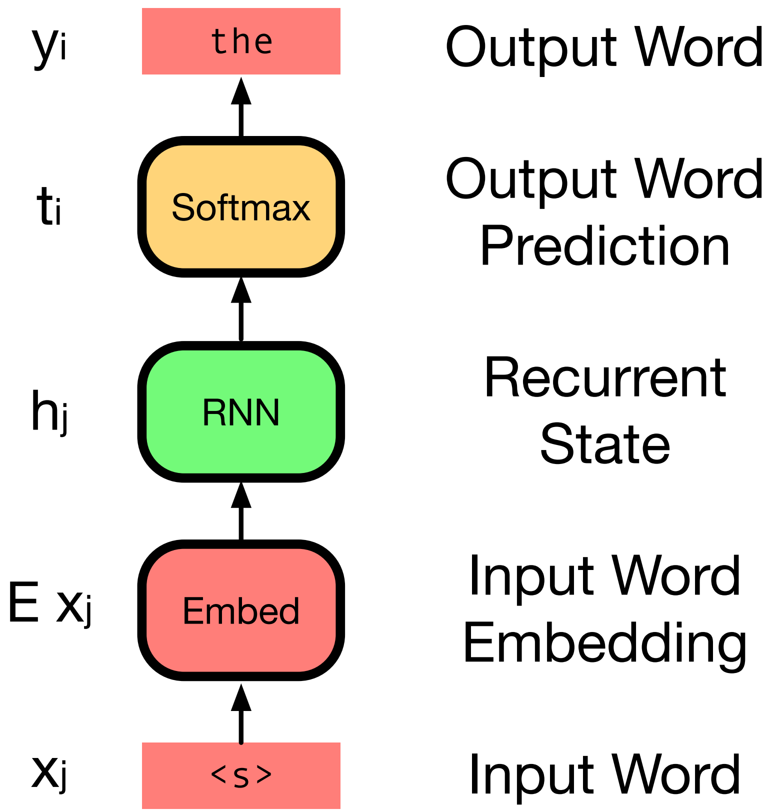
# Feed Forward Neural Language Model





# Recurrent Neural Language Model

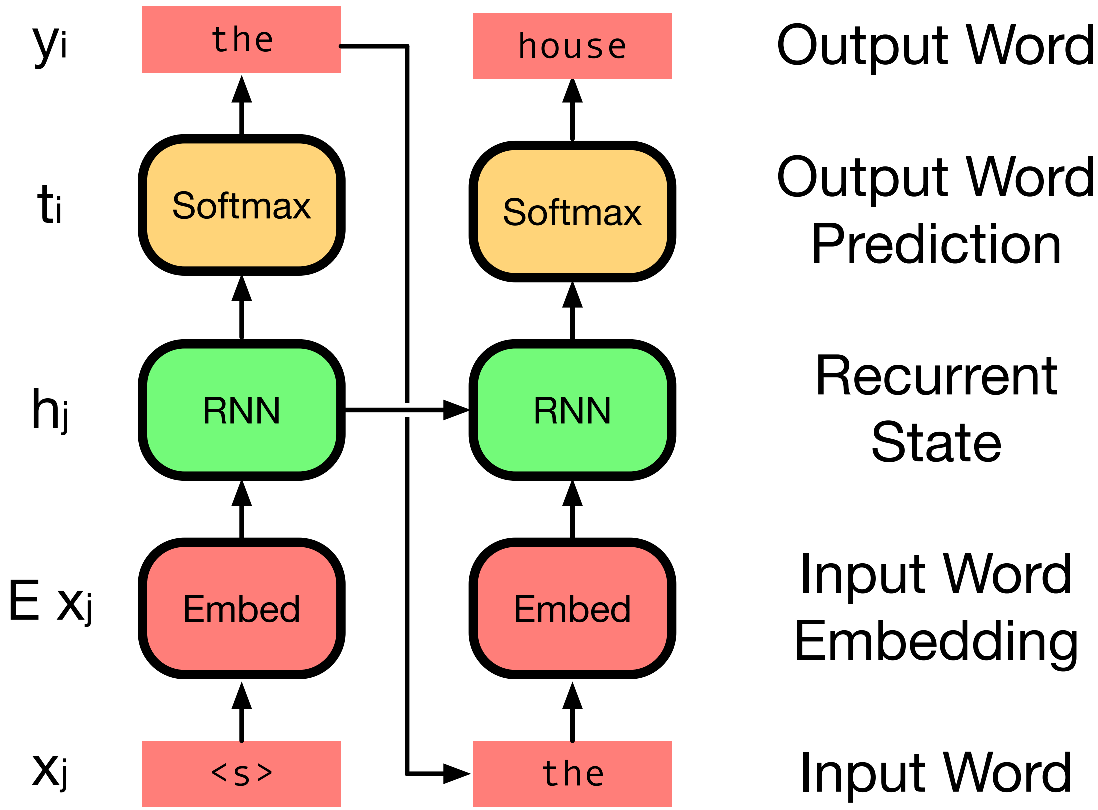





Predict the first word of a sentence

# Recurrent Neural Language Model

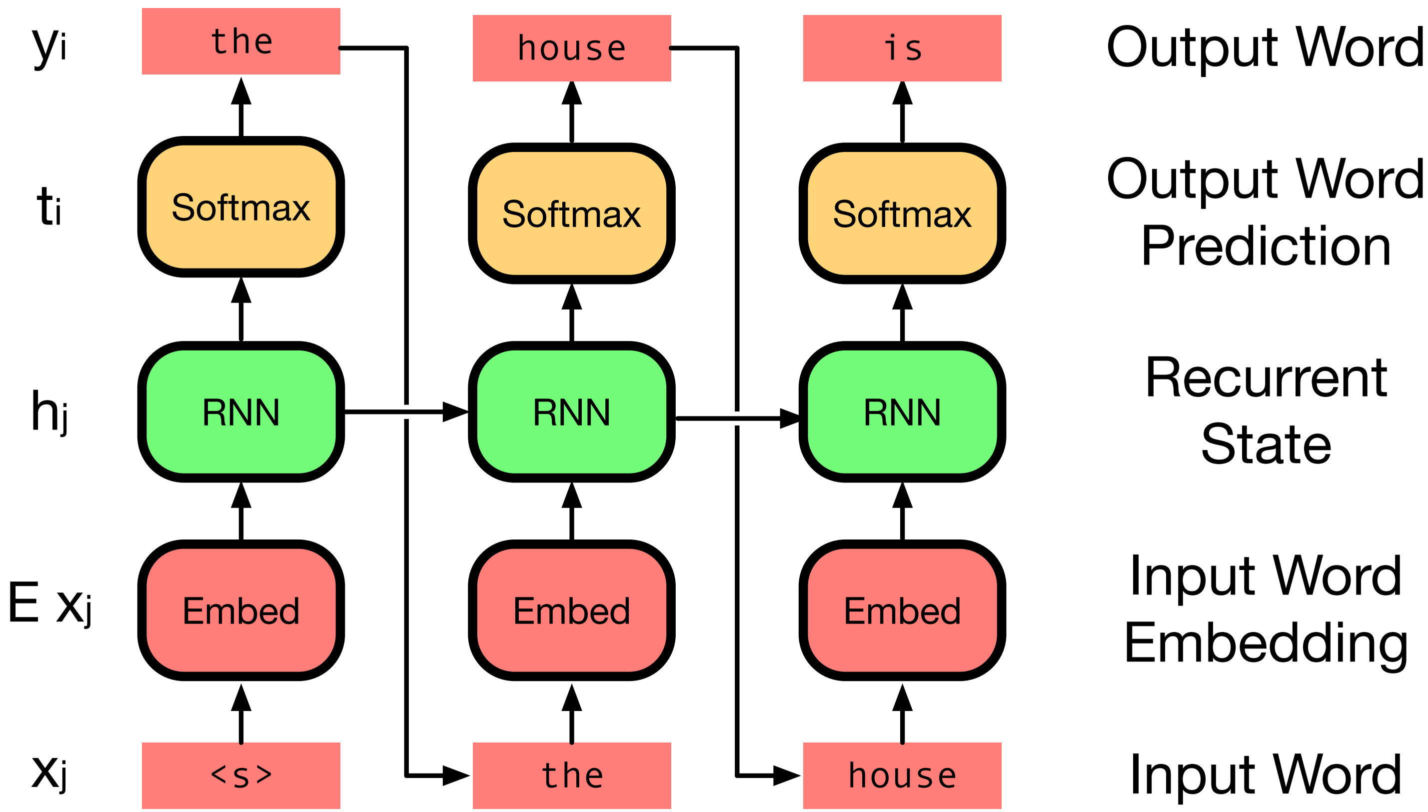





Predict the second word of a sentence

Re-use hidden state from first word prediction

# Recurrent Neural Language Model

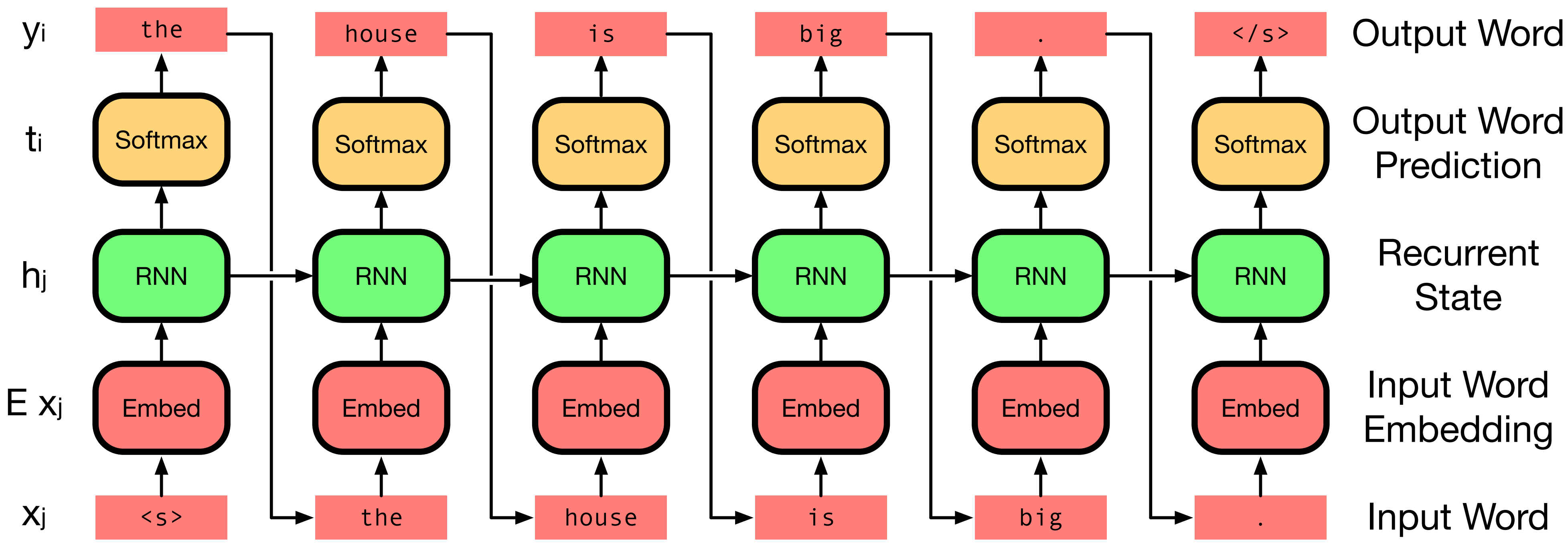



Predict the third word of a sentence

... and so on

# Recurrent Neural Language Model





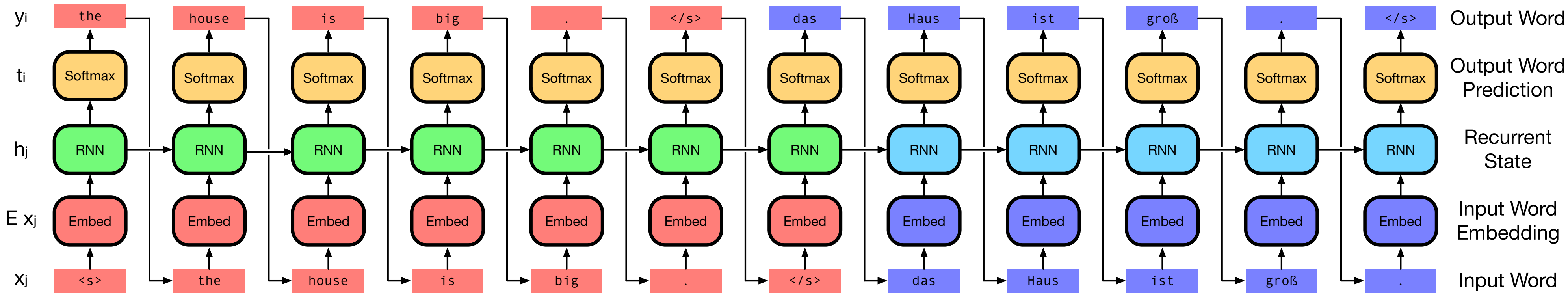
# Recurrent Neural Translation Model



- We predicted the words of a sentence

- Why not also predict their translations?

# Encoder-Decoder Model




- Obviously madness
- Proposed by Google (Sutskever et al. 2014)

# What is Missing?

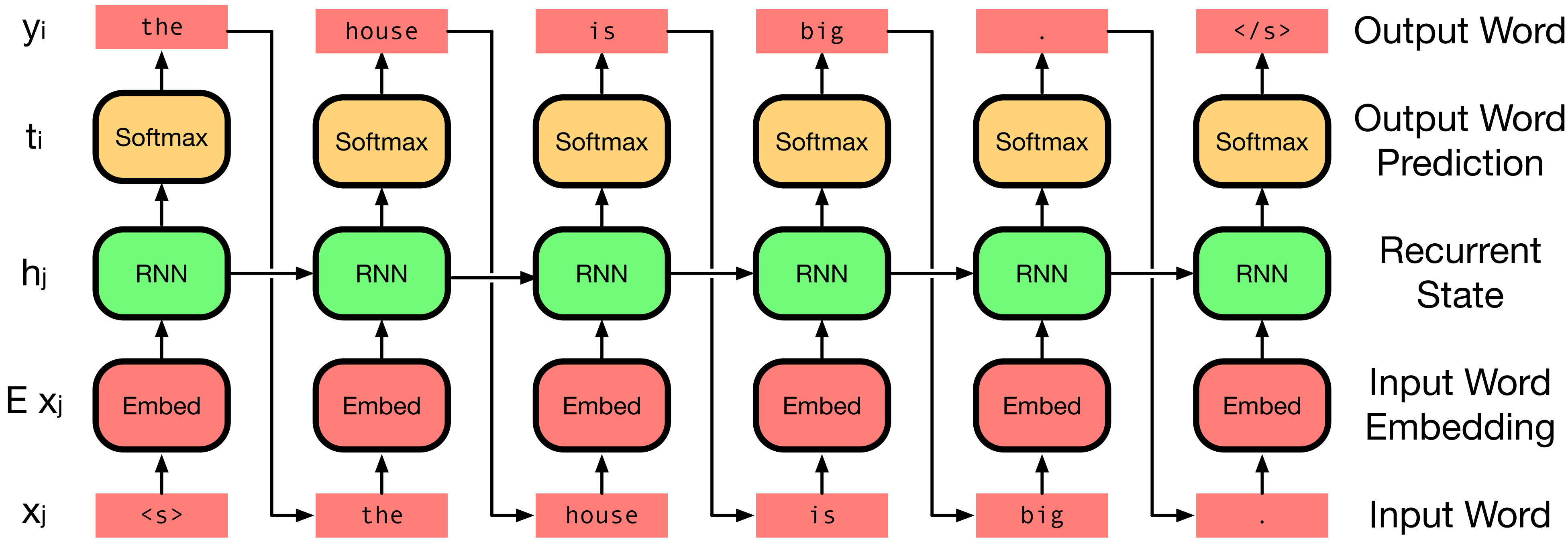


- Alignment of input words to output words

⇒ Solution: attention mechanism

# neural translation model with attention

# Input Encoding

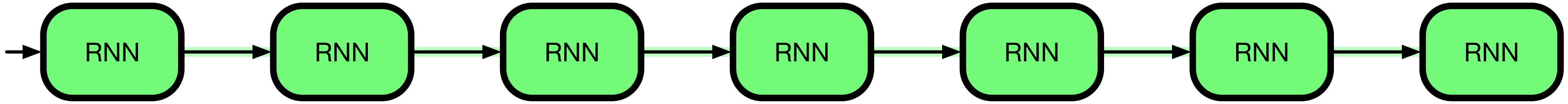



- Inspiration: recurrent neural network language model on the input side

# Hidden Language Model States

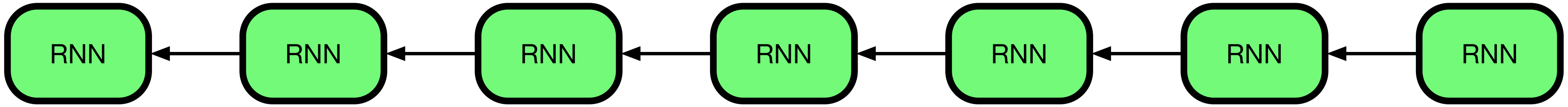


- This gives us the hidden states

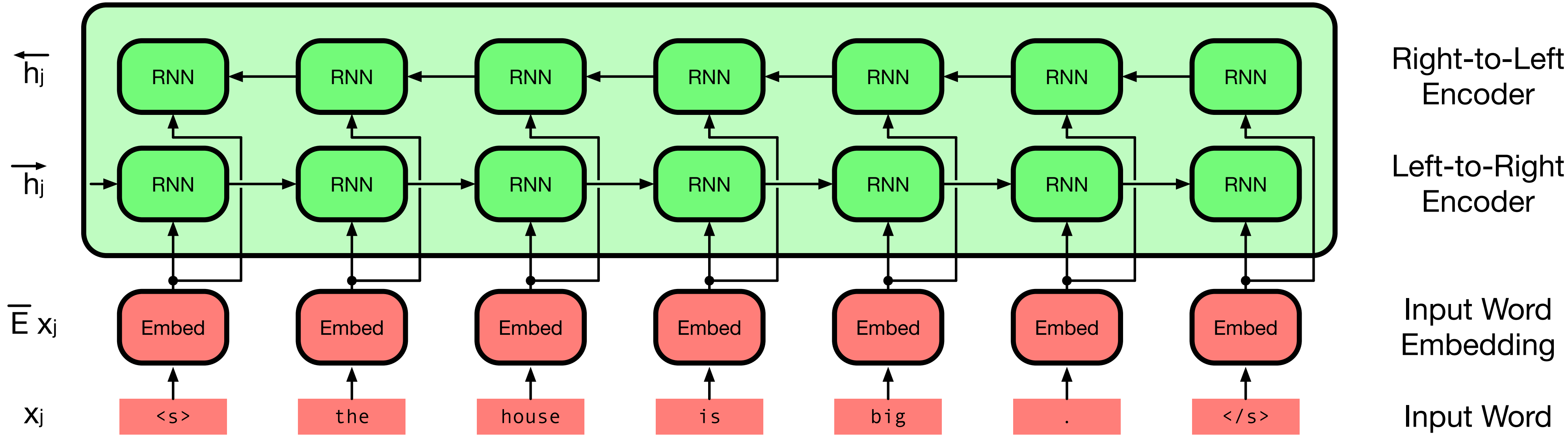



- These encode left context for each word

- Same process in reverse: right context for each word



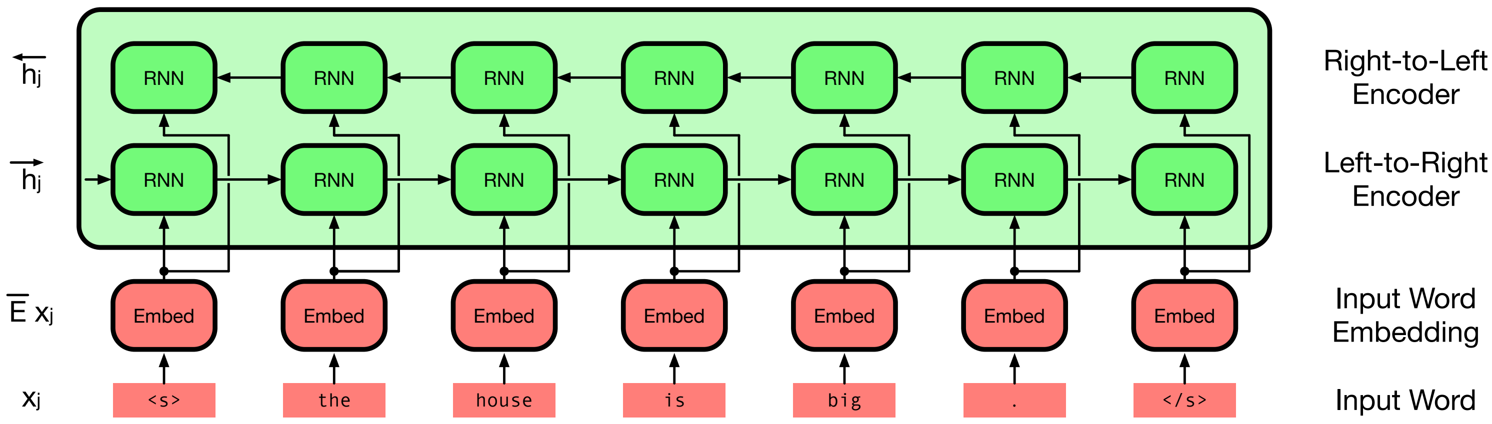
# Input Encoder




- Input encoder: concatenate bidrectional RNN states
- Each word representation includes full left and right sentence context

# Encoder: Math






- Input is sequence of words $x_j$, mapped into embedding space $\bar{E}\ x_j$

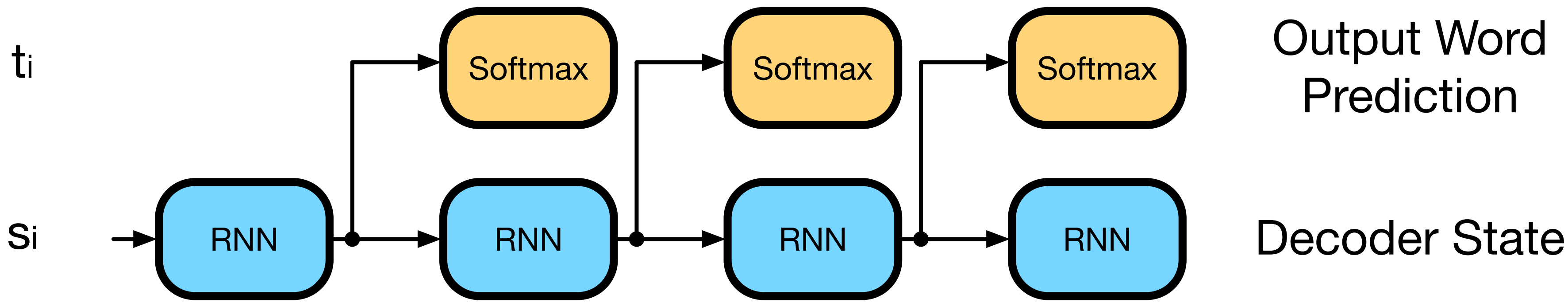
- Bidirectional recurrent neural networks

$$\overleftarrow{h_j} = f(\overleftarrow{h_{j+1}}, \bar{E}\ x_j)$$
$$\overrightarrow{h_j} = f(\overrightarrow{h_{j-1}}, \bar{E}\ x_j)$$

- Various choices for the function $f()$: feed-forward layer, GRU, LSTM, ...

# Decoder

- We want to have a recurrent neural network predicting output words



# Decoder

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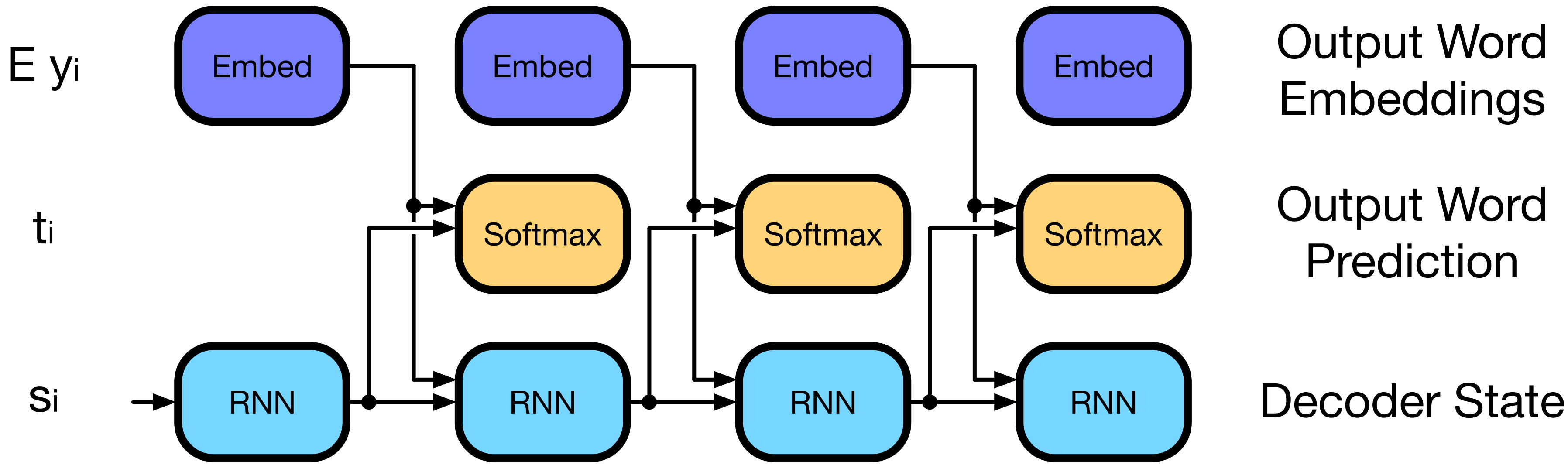
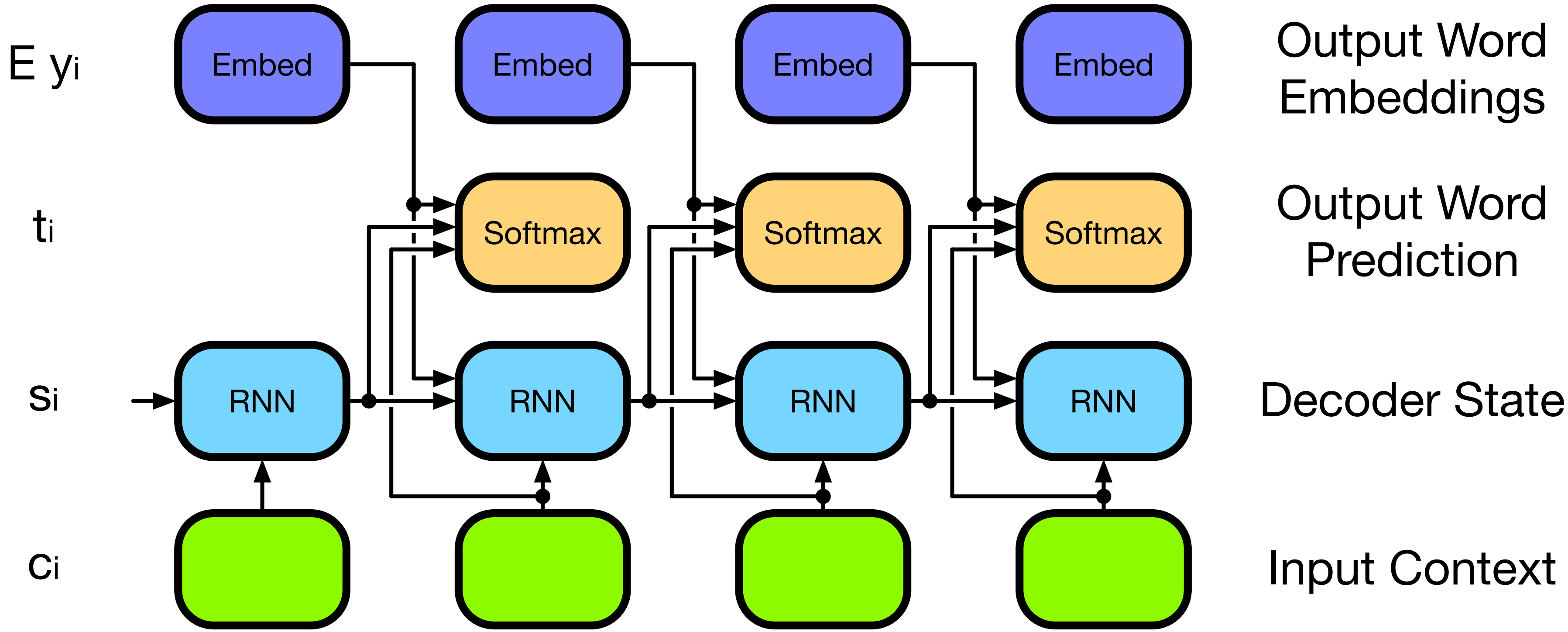



- We feed decisions on output words back into the decoder state

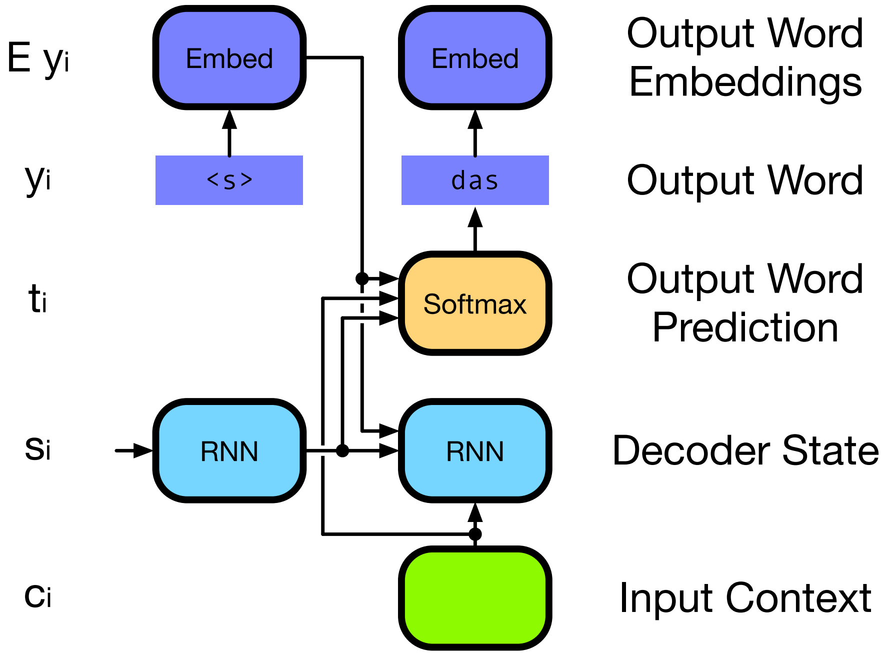
# Decoder

- We want to have a recurrent neural network predicting output words




- We feed decisions on output words back into the decoder state
- Decoder state is also informed by the input context

# More Detail




- Decoder is also recurrent neural network over sequence of hidden states $s_i$

$$s_i = f(s_{i-1},\ Ey_{-1}, c_i)$$

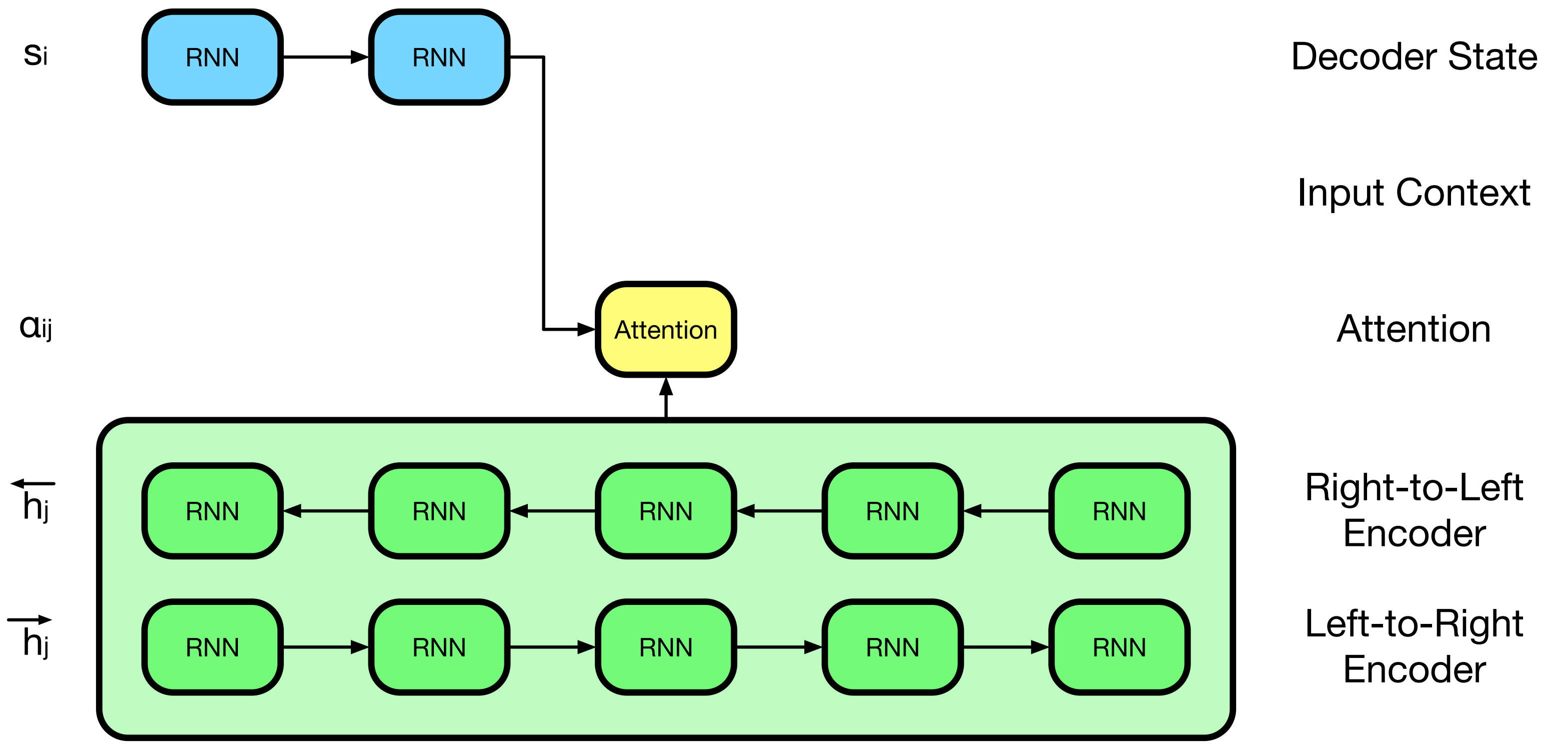
- Again, various choices for the function $f()$: feed-forward layer, GRU, LSTM, ...
- Output word $y_i$ is selected by computing a vector $t_i$ (same size as vocabulary)

$$t_i = W(Us_{i-1} + VEy_{i-1} + Cc_i)$$

then finding the highest value in vector $t_i$

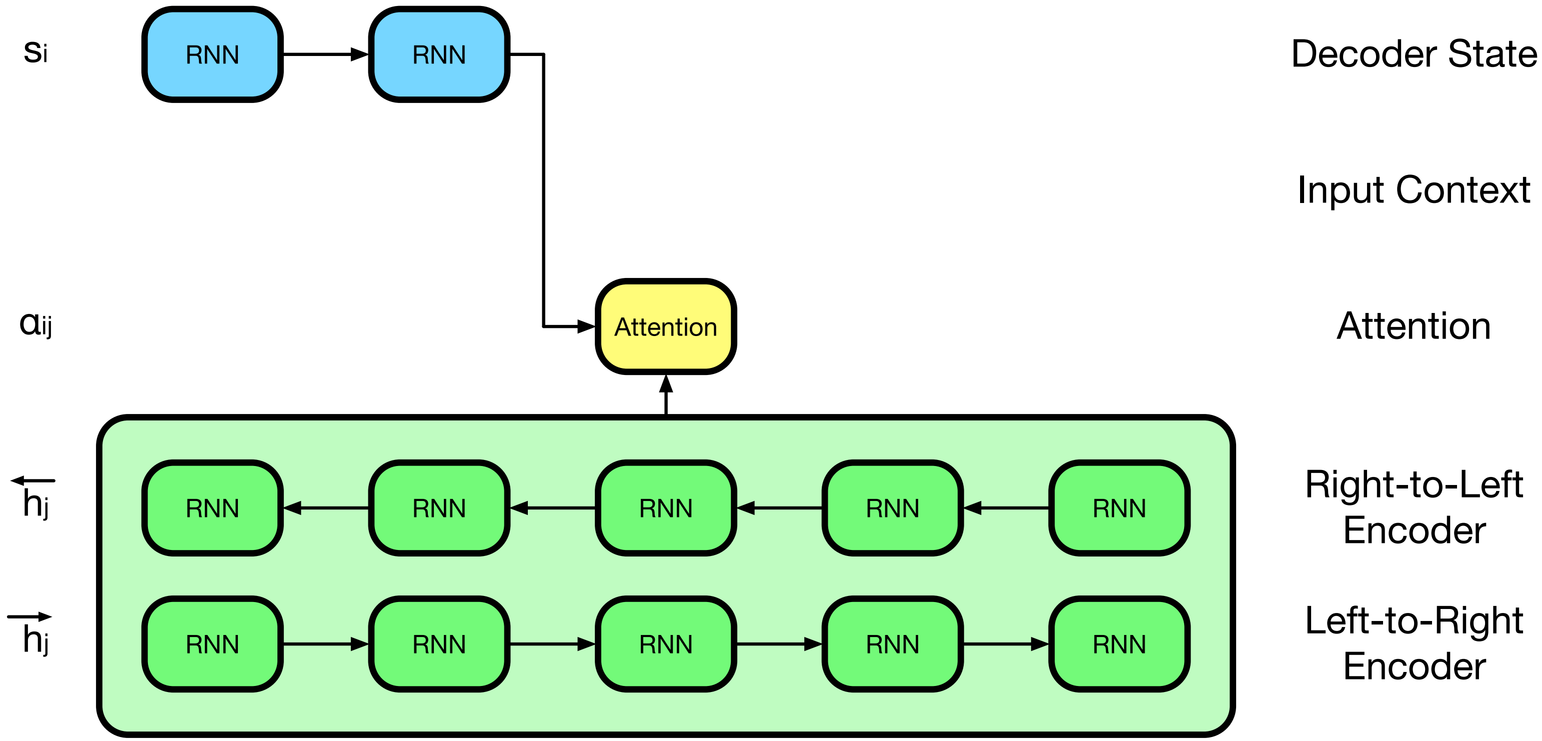
- If we normalize $t_i$, we can view it as a probability distribution over words
- $Ey_i$ is the embedding of the output word $y_i$

# Attention



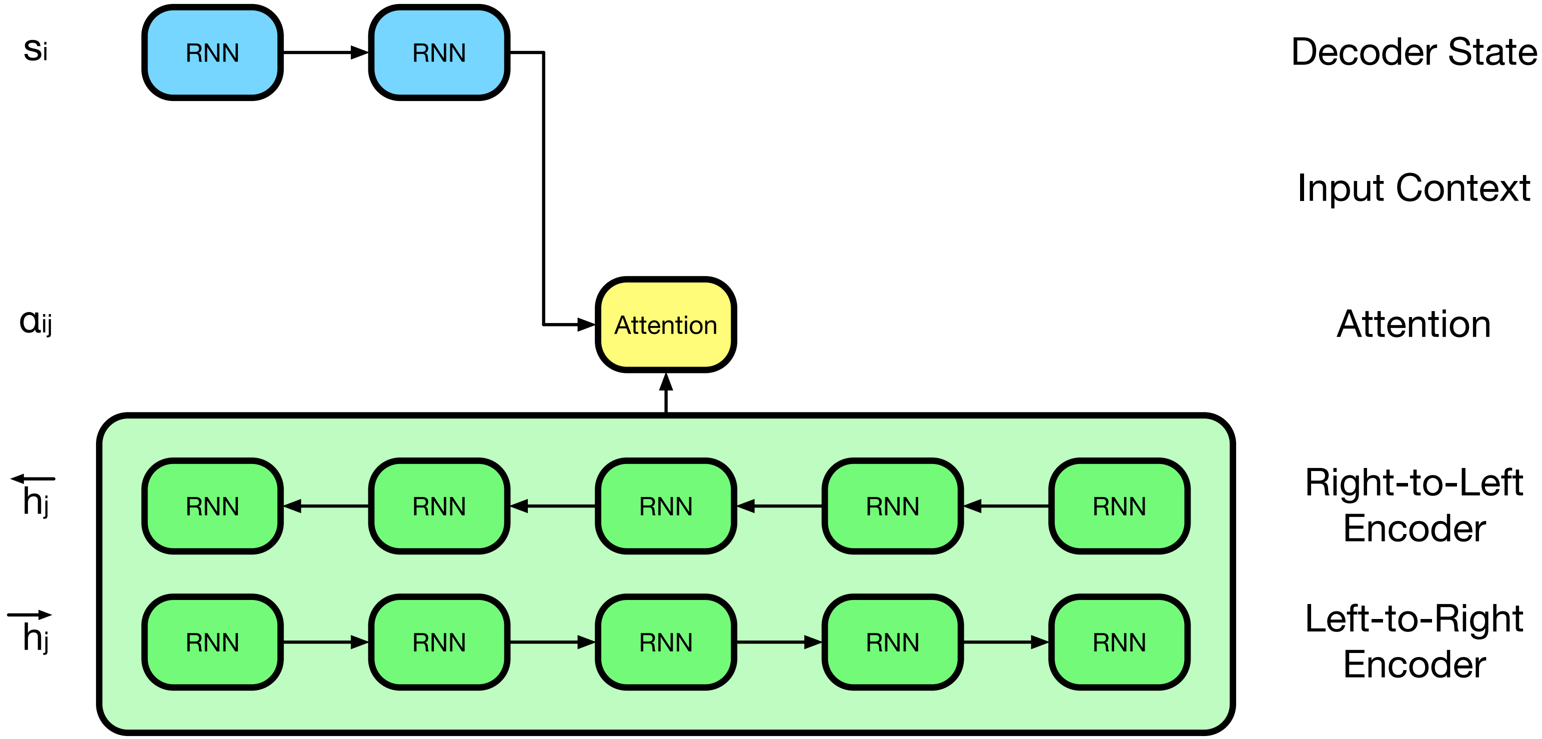

- Given what we have generated so far (decoder hidden state)
- ... which words in the input should we pay attention to (encoder states)?

# Attention




- Given: – the previous hidden state of the decoder $s_{i-1}$
  – the representation of input words $h_j = (\overleftarrow{h_j}, \overrightarrow{h_j})$
- Predict an alignment probability $a(s_{i-1}, h_j)$ to each input word $j$ (modeled with with a feed-forward neural network layer)

# Attention

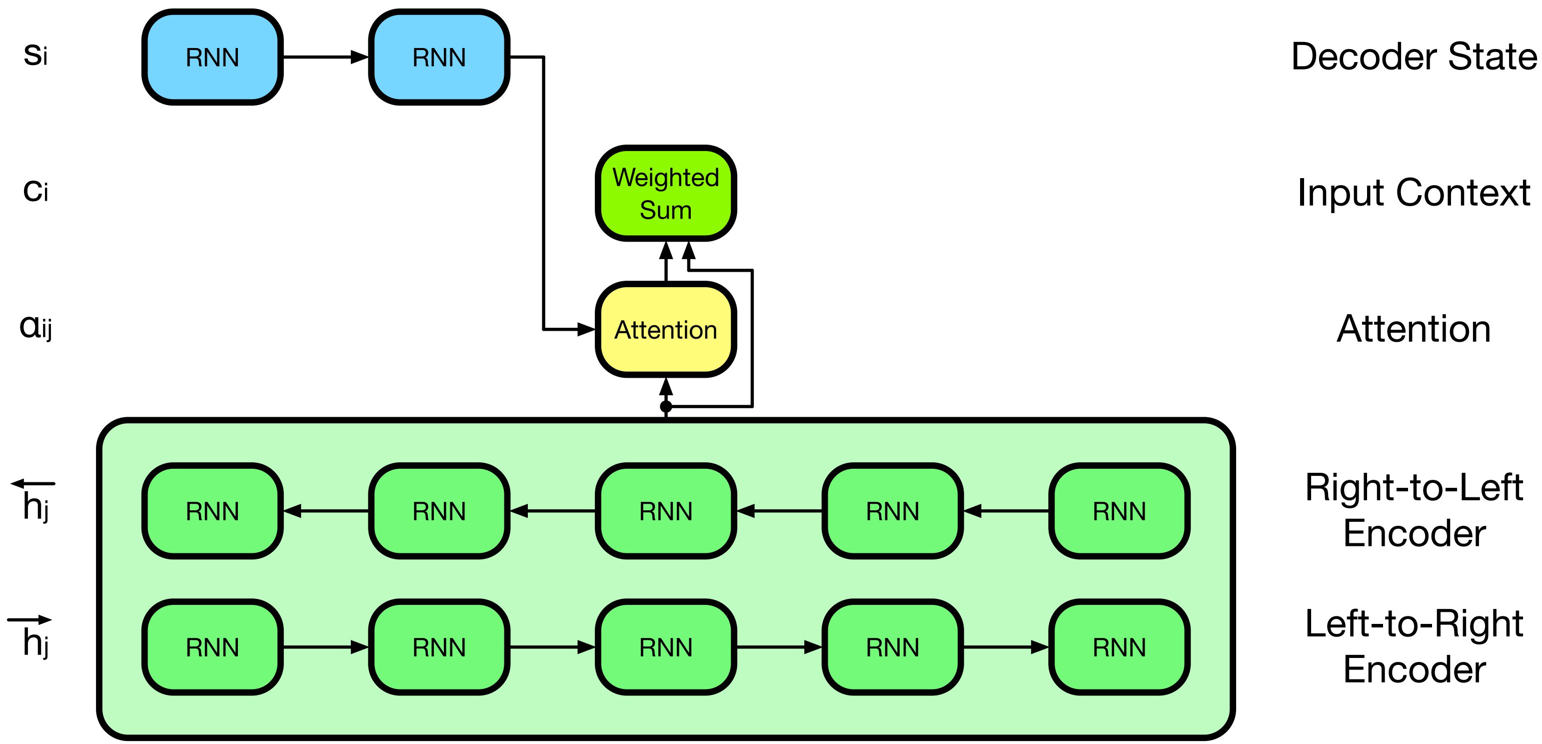



- Normalize attention (softmax)

$$\alpha_{ij} = \frac{\exp(a(s_{i-1}, h_j))}{\sum_k \exp(a(s_{i-1}, h_k))}$$

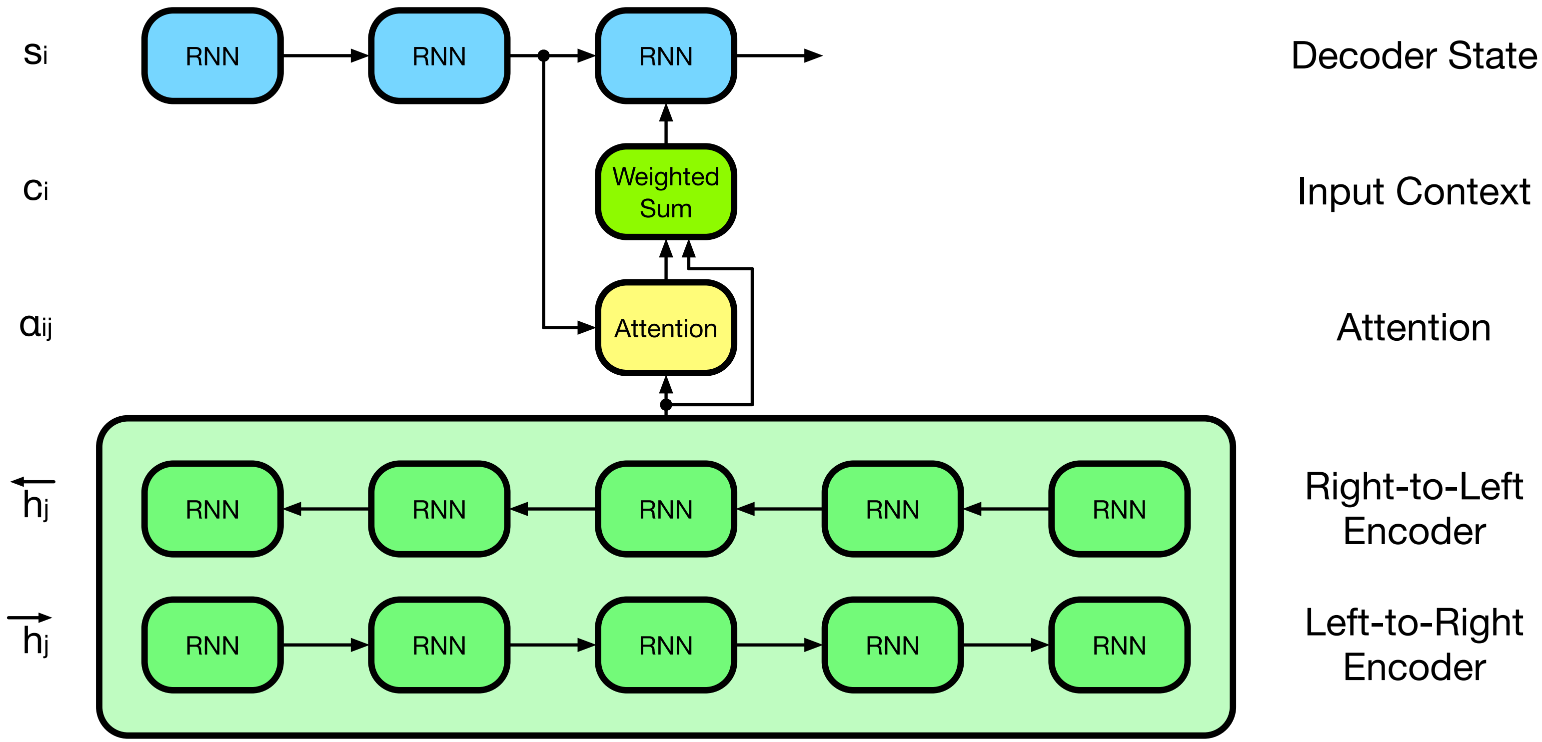
# Attention






- Relevant input context: weigh input words according to attention: $c_i = \sum_j \alpha_{ij} h_j$

# Attention

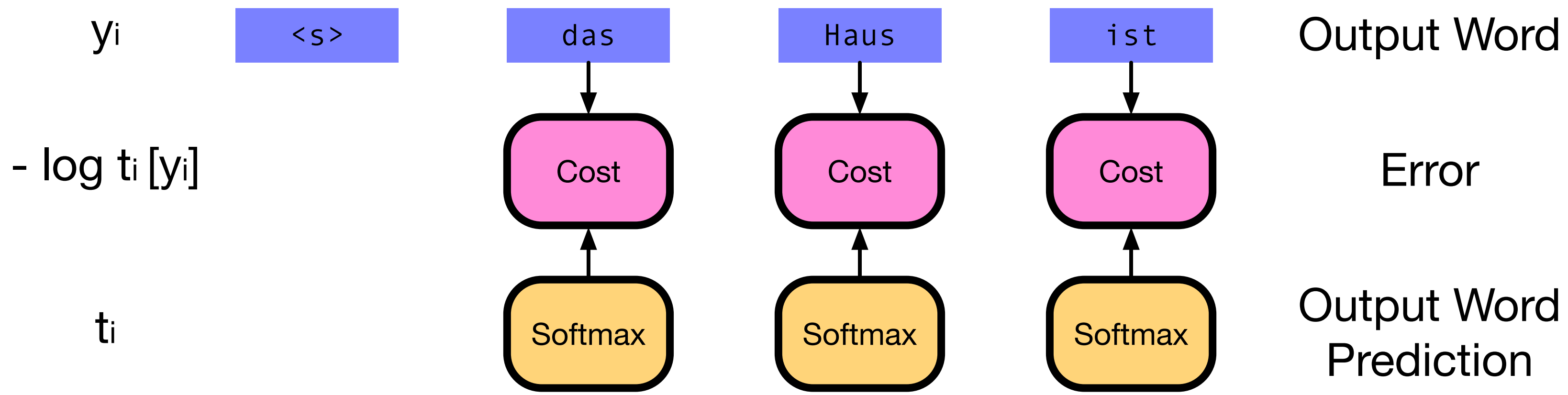



- Use context to predict next hidden state and output word

# training

# Comparing Prediction to Correct Word

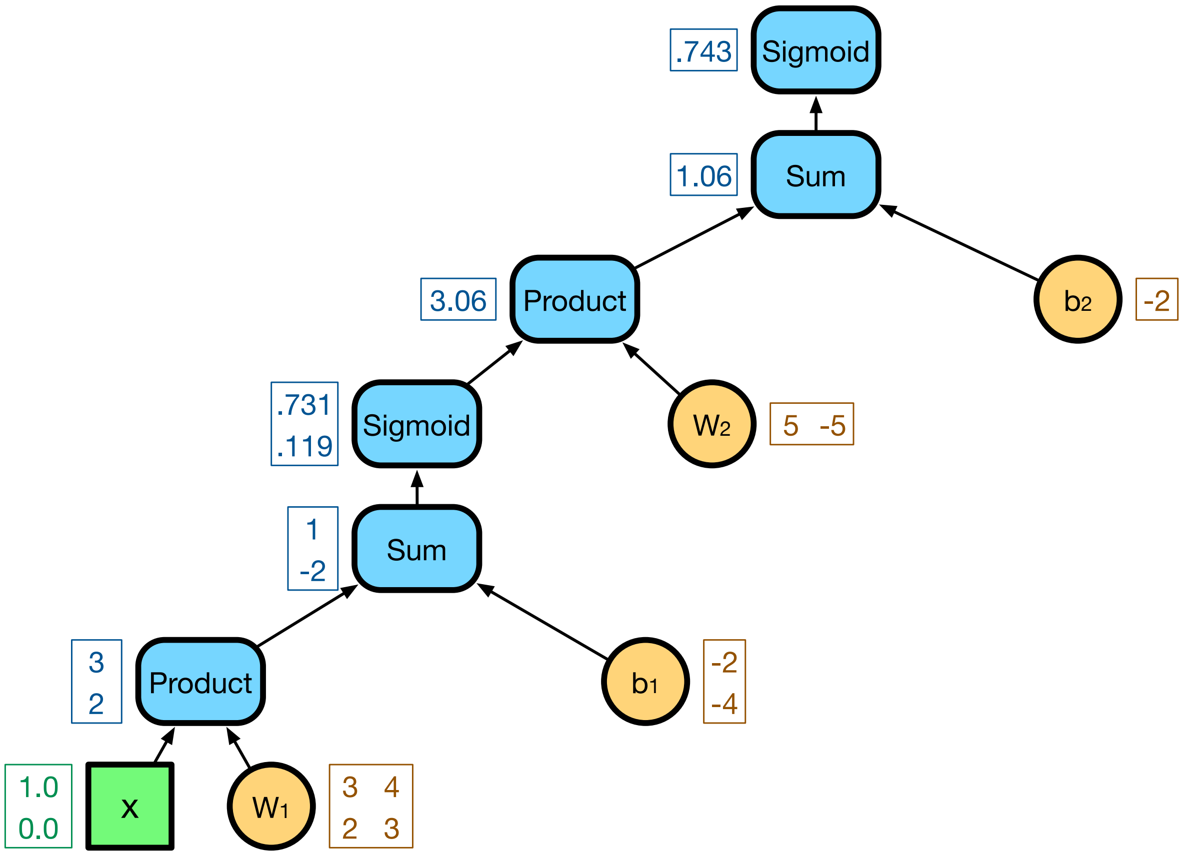




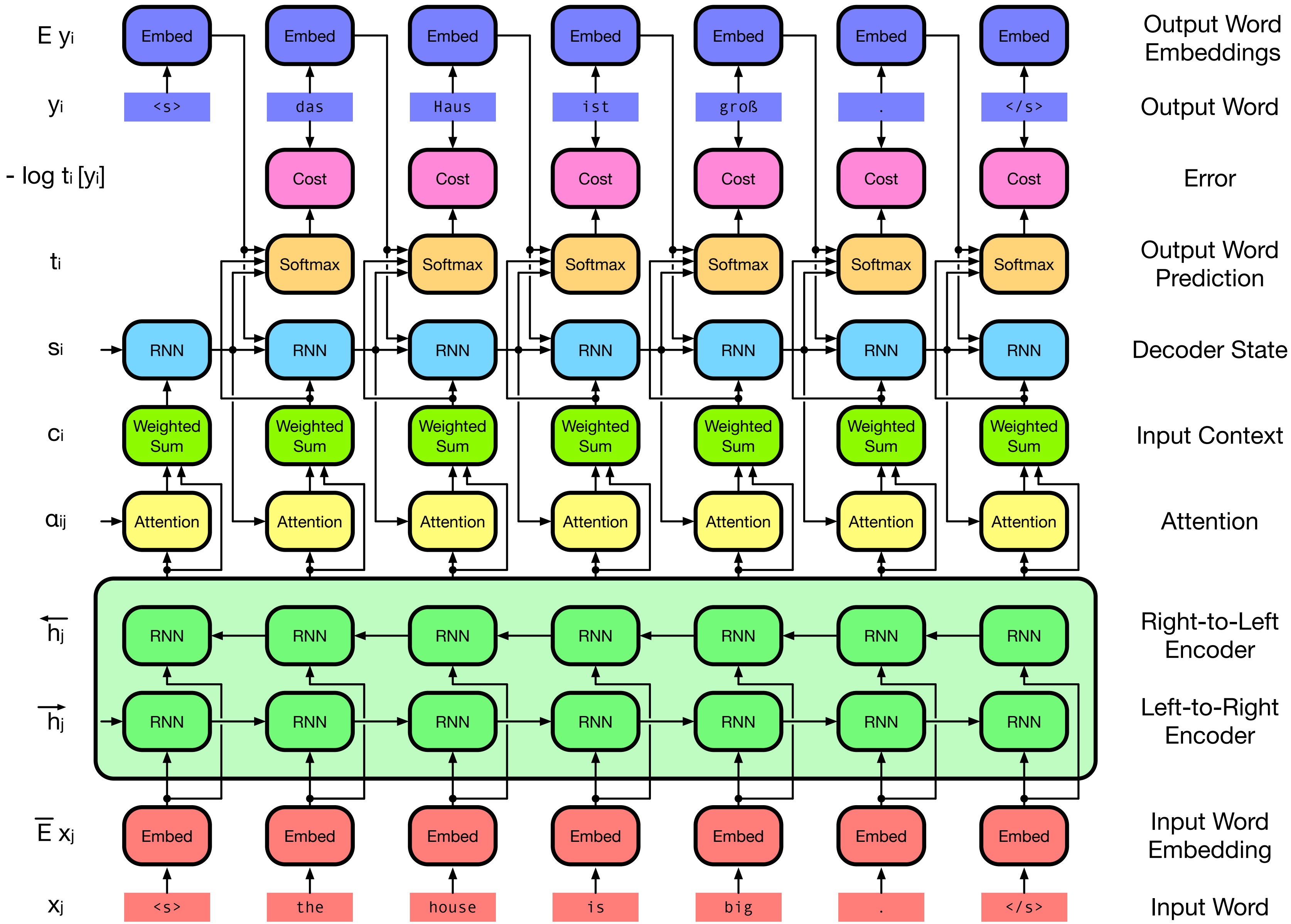

- Current model gives some probability $t_i[y_i]$ to correct word $y_i$
- We turn this into an error by computing cross-entropy: $-\log t_i[y_i]$

# Computation Graph

- Math behind neural machine translation defines a computation graph
- Forward and backward computation to compute gradients for model training



# Unrolled Computation Graph



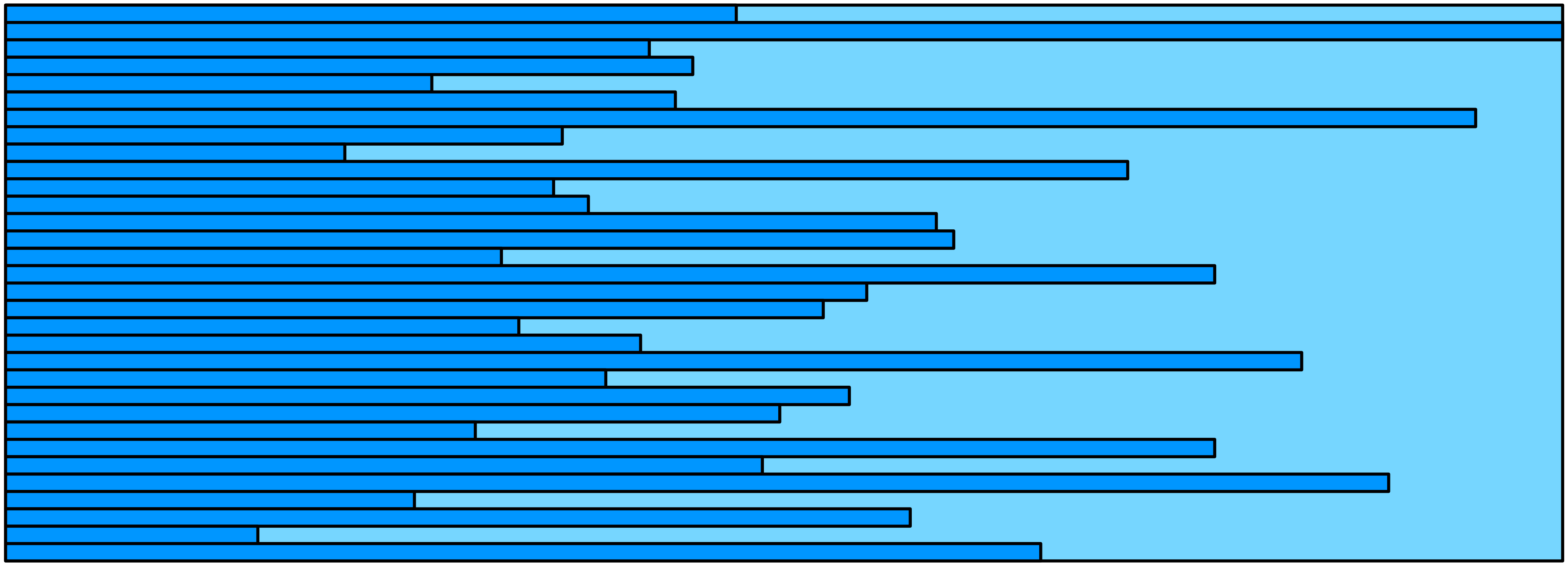
# Batching

- Already large degree of parallelism
  - most computations on vectors, matrices
  - efficient implementations for CPU and GPU
- Further parallelism by batching
  - processing several sentence pairs at once
  - scalar operation $\rightarrow$ vector operation
  - vector operation $\rightarrow$ matrix operation
  - matrix operation $\rightarrow$ 3d tensor operation
- Typical batch sizes 50–100 sentence pairs

# Batches



- Sentences have different length
- When batching, fill up unneeded cells in tensors

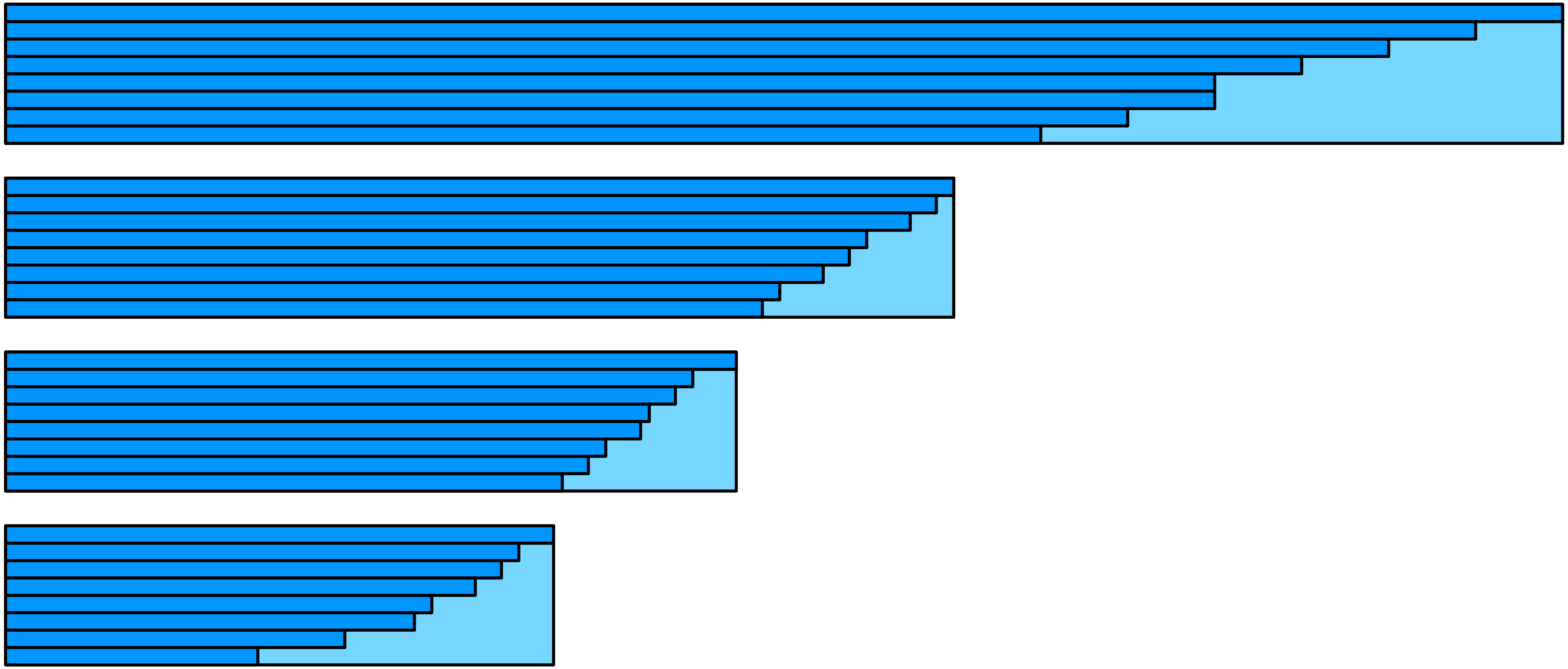


⇒ A lot of wasted computations

# Mini-Batches



- Sort sentences by length, break up into mini-batches



- Example: Maxi-batch 1600 sentence pairs, mini-batch 80 sentence pairs

# Overall Organization of Training

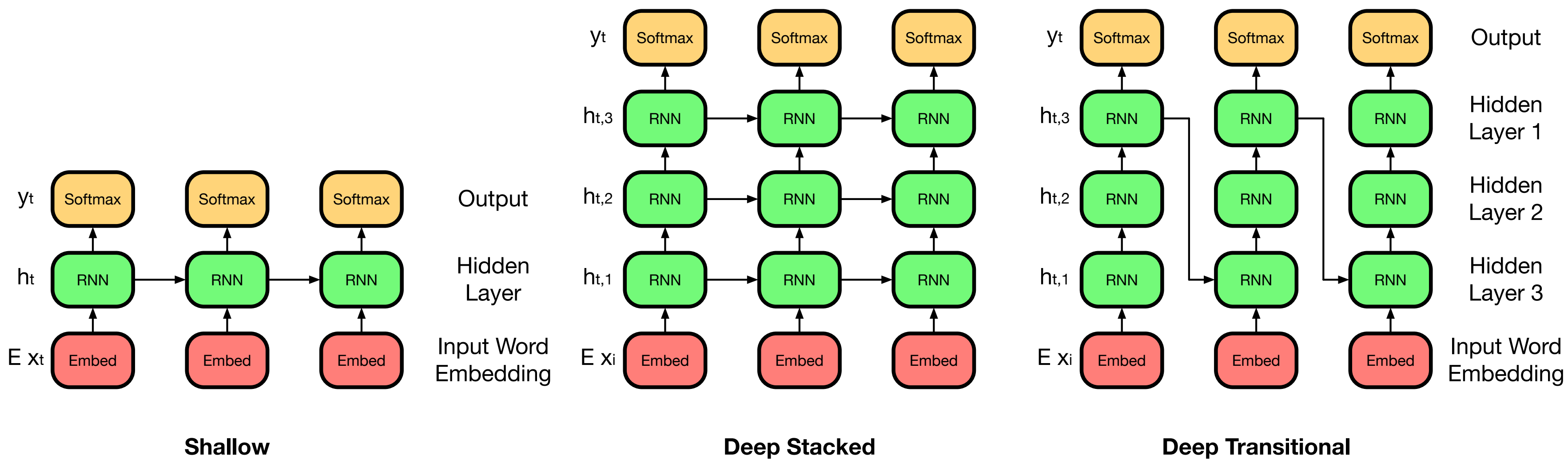


- Shuffle corpus
- Break into maxi-batches
- Break up each maxi-batch into mini-batches
- Process mini-batch, update parameters
- Once done, repeat
- Typically 5-15 epochs needed (passes through entire training corpus)

# deeper models

# Deeper Models

- Encoder and decoder are recurrent neural networks
- We can add additional layers for each step
- Recall shallow and deep language models

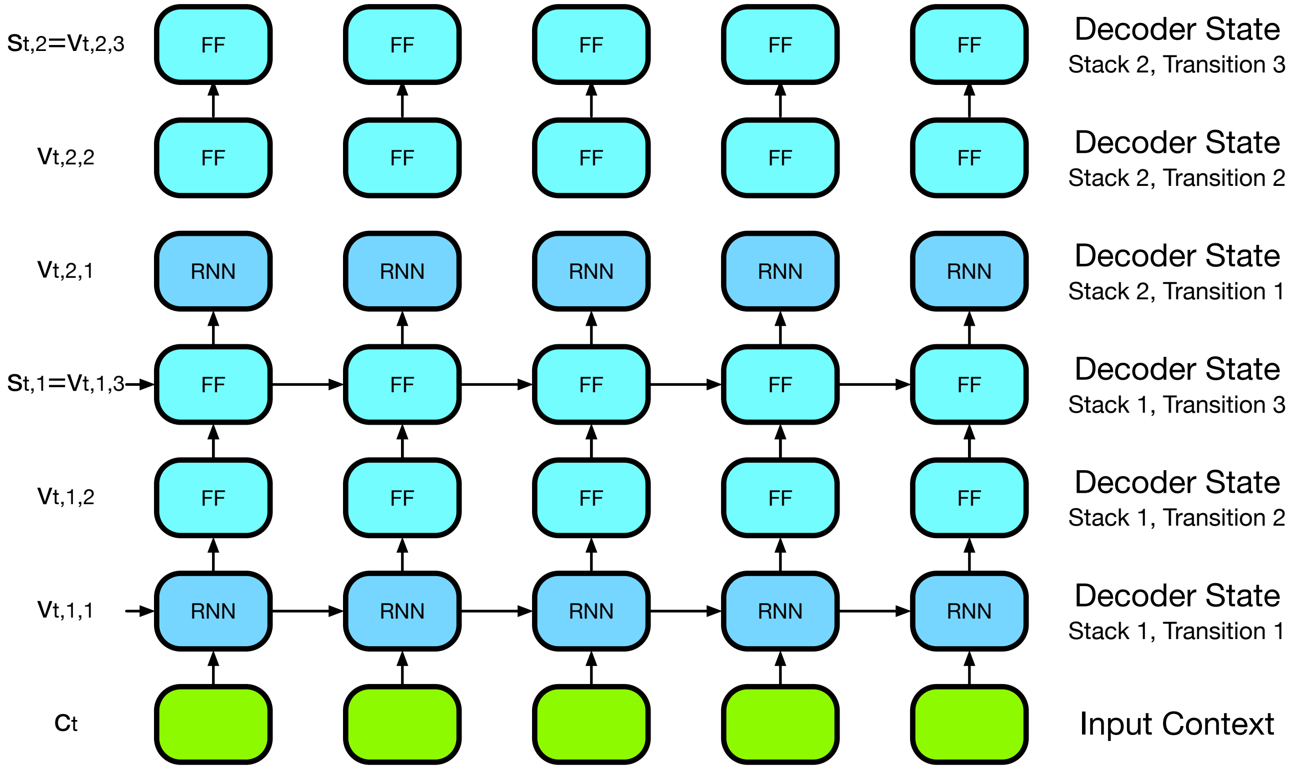



- Adding residual connections (short-cuts through deep layers) help

# Deep Decoder

- Two ways of adding layers
  - deep transitions: several layers on path to output
  - deeply stacking recurrent neural networks

- Why not both?



# Deep Encoder

- Previously proposed encoder already has 2 layers
  - left-to-right recurrent network, to encode left context
  - right-to-left recurrent network, to encode right context

⇒ Third way of adding layers