CIS 6930 Topics in Computing for Data Science
Week 6a: Recurrent Neural Networks (2)
Encoder-Decoder Models

9/30/2021 & 10/5/2021

Yoshihiko (Yoshi) Suhara

2pm-3:20pm

This Week & Next Week

- Thu 10/7 Midterm exam (written exam **on campus**)
  - Time: 2pm-3:20pm
  - Location: LBR 252

- Fall Break

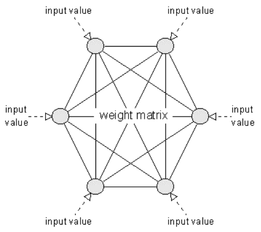
Week 6!

- ~~Week 1: Deep Learning Basics (Thu 9/9)~~
- ~~Week 2: AutoEncoder (Tue 9/14)~~
- ~~Week 3: Convolutional Neural Networks (Thu 9/16)~~
- ~~Week 4: GAN (Tue 9/21)~~
- ~~Week 5: Word embeddings: Word2vec, GloVe (Thu 9/23)~~
- **Week 6: Recurrent Neural Networks (Tue 9/28, Thu 9/30)**
- Week 7: Review/Project pitch & Mid-term (Tue 10/5, Thu 10/7)
- Fall Break
- ...

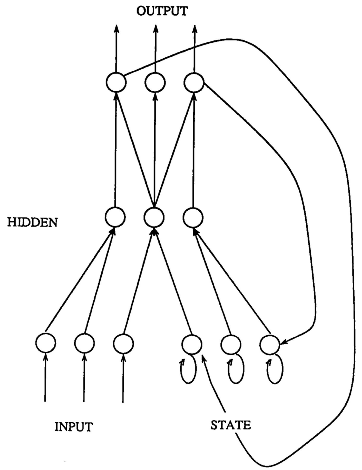
Recap: Recurrent Neural Networks (1)

Recurrent Neural Networks for Sequential Input

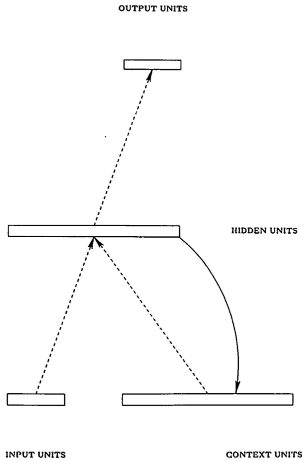
- Inspired by Hopfield Network (1982)
- "Simple" Recurrent Neural Networks
  - Jordan Net (1986)
  - **Elman Net (1990)**



Hopfield Network

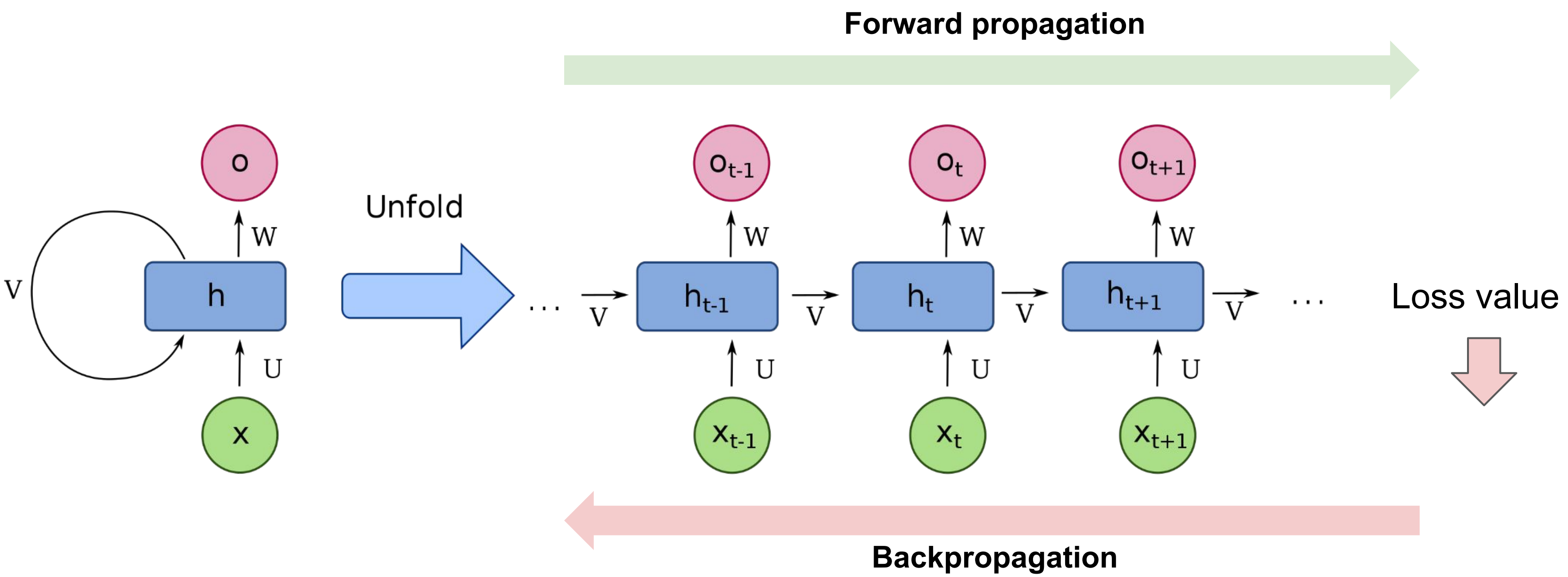


Jordan Net



Elman Net

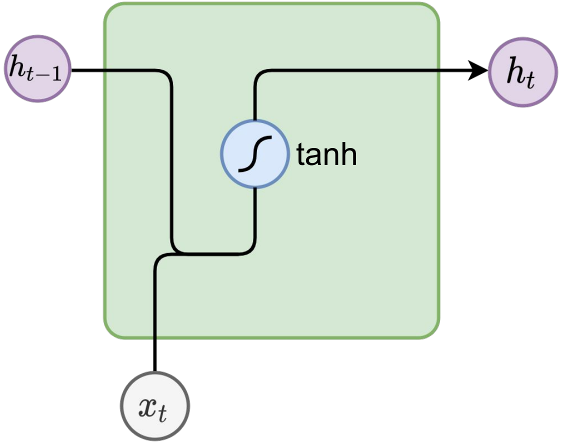
Unfolding RNN
Backpropagation Through Time (BPTT)



RNN Cell for Sequential Data

RNN = Elman Net

- Input value + previous hidden state → Next hidden state



$$h_t = \tanh(\underline{W_{ih}} x_t + b_{ih} + \underline{W_{hh}} h_{(t-1)} + b_{hh})$$

$$W_h\left[x_t ; h_{(t-1)}\right] + b_h$$

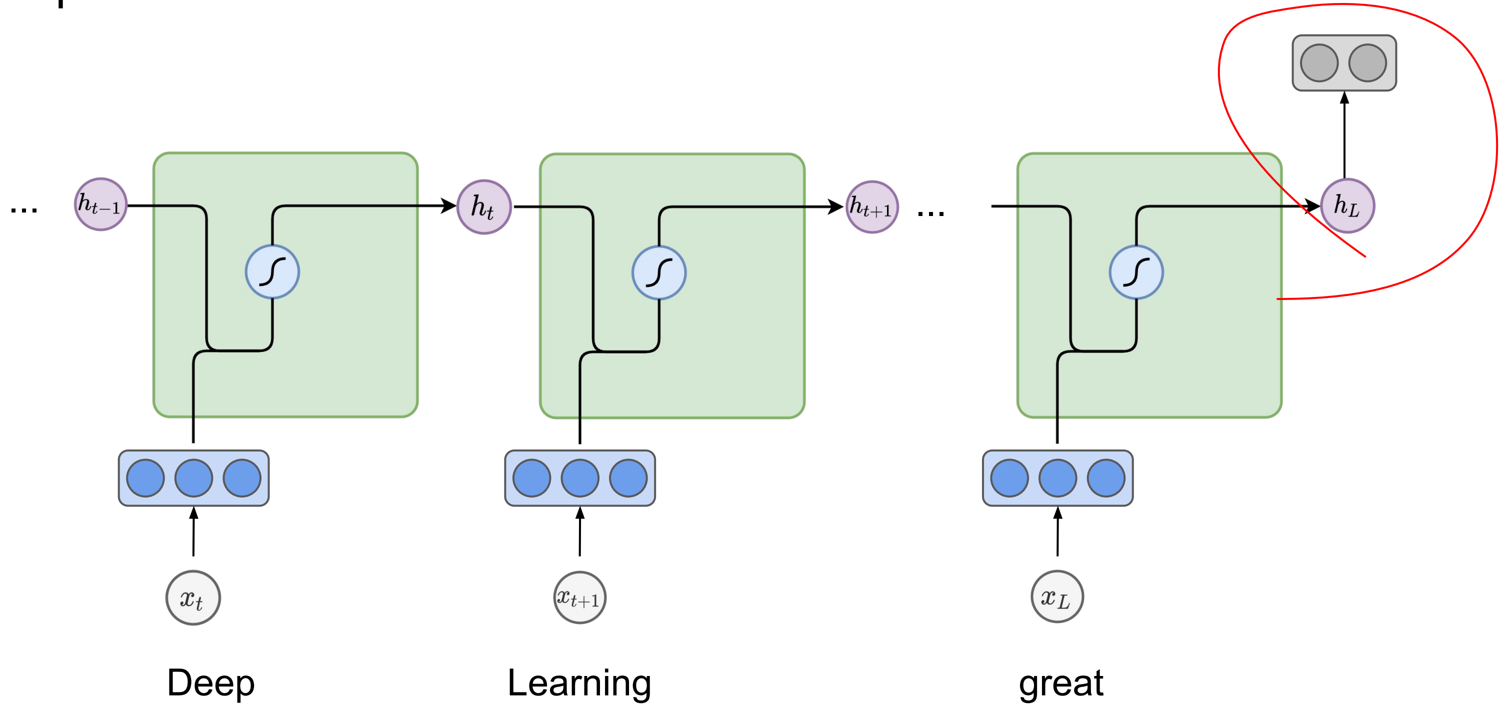
Another notation

The figures are based on the following blog article (highly recommended!)
[Illustrated Guide to LSTM's and GRU's: A step by step explanation]

Text Classification Example

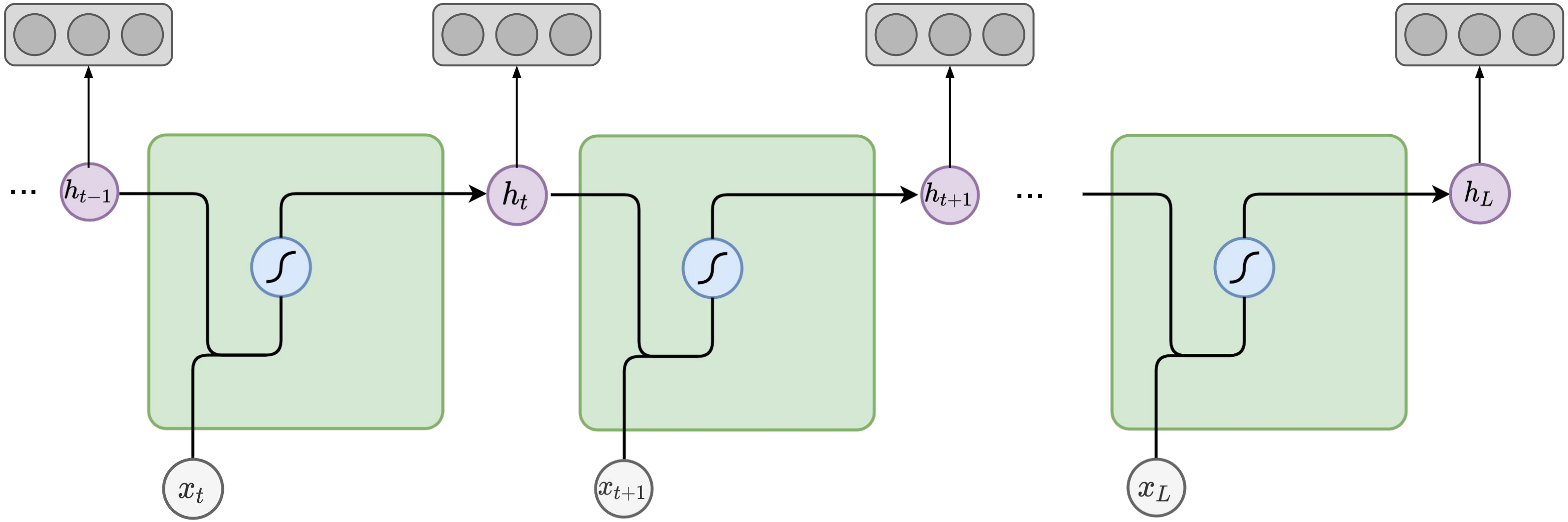
- Input: “Deep Learning is great”
- Label: positive

Any other options?



Where to Attach Output Layer?

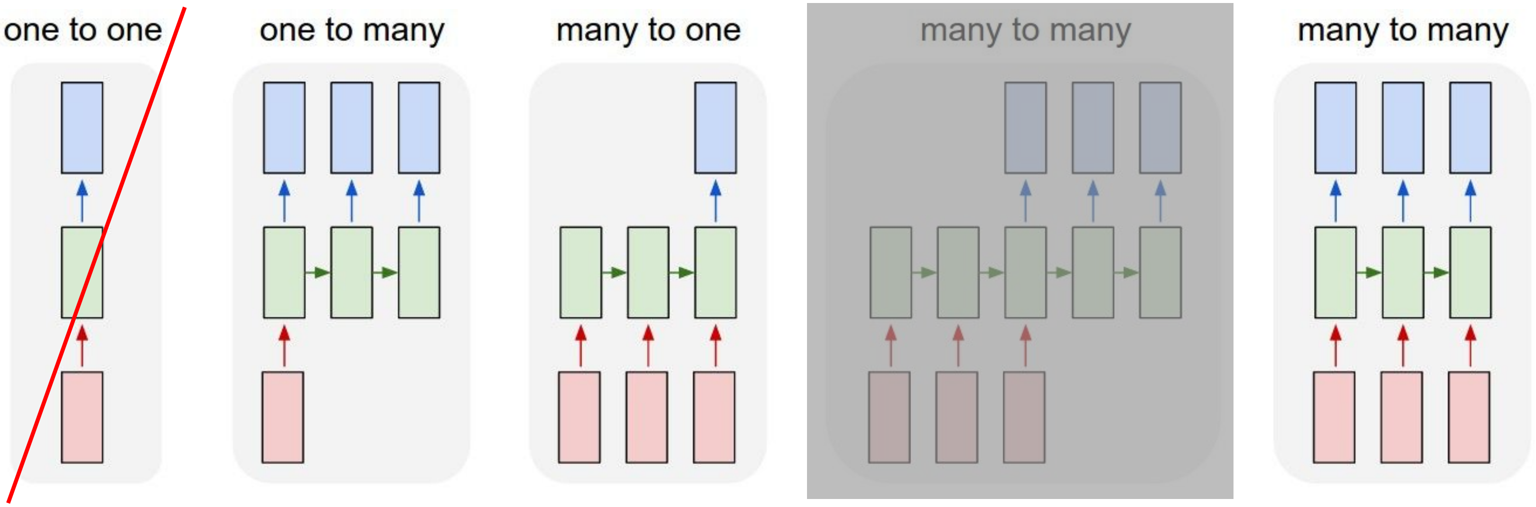
- Where?



Any other options?

→ RNN for **sequential tagging**

RNN Application Patterns



Single-input Generation?

Classification

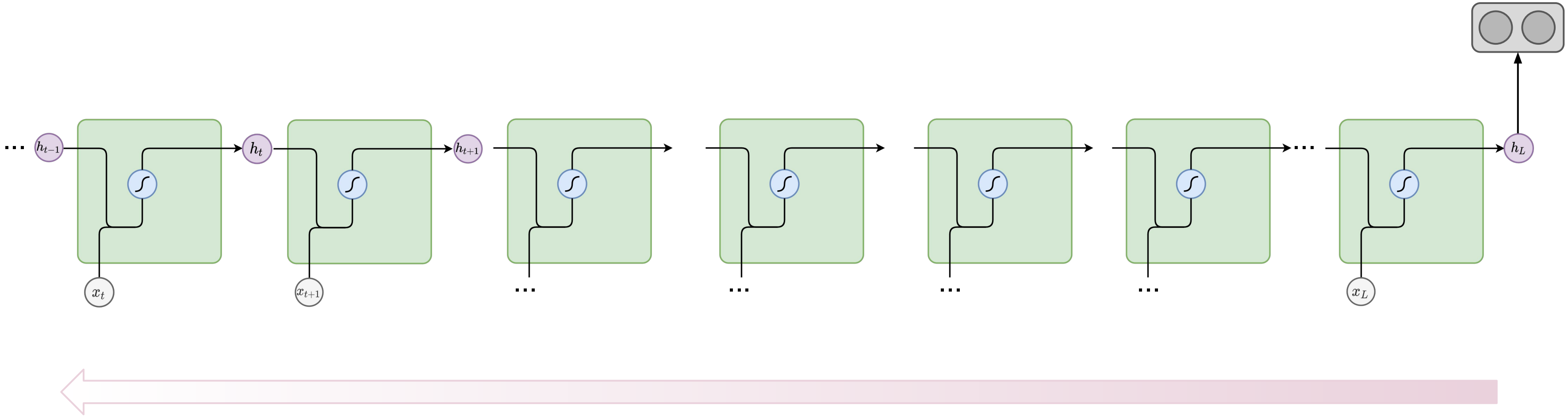
Encoder-decoder model
(aka seq2seq)

Sequential tagging

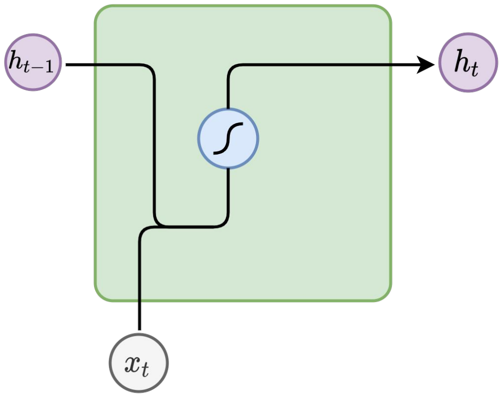
http://karpathy.github.io/2015/05/21/rnn-effectiveness/

What’s the issue with RNNs?

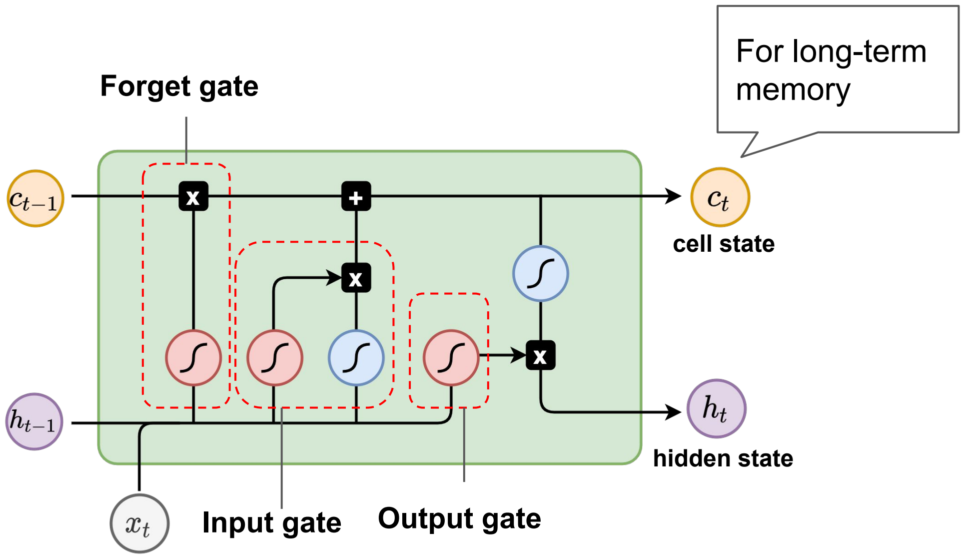
- Not a very good design for **a long sequence**
  - **Later input values** have higher impact on the last hidden state
  - Gradient vanishing problem



LSTM: Cell State + Gating Mechanism



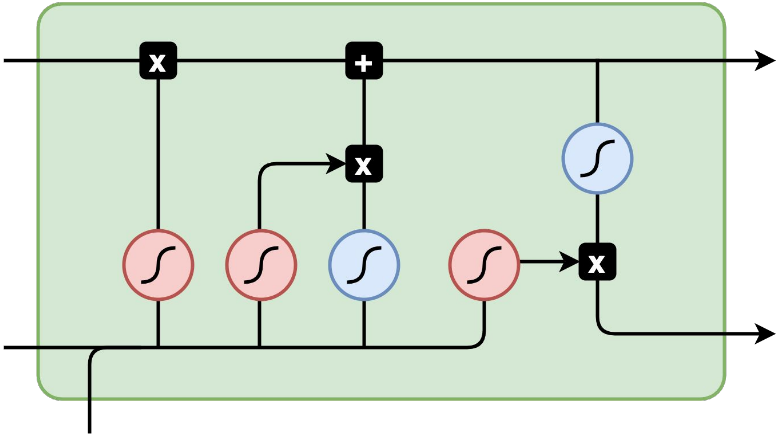
RNN Cell



LSTM Cell

Recap

Long-short Term Memory (LSTM) Cell
[Hochreiter and Schmidhuber 1997]



$$
\begin{aligned}
i_t &= \sigma(W_{ii}x_t + b_{ii} + W_{hi}h_{t-1} + b_{hi}) \\
f_t &= \sigma(W_{if}x_t + b_{if} + W_{hf}h_{t-1} + b_{hf}) \\
g_t &= \tanh(W_{ig}x_t + b_{ig} + W_{hg}h_{t-1} + b_{hg}) \\
o_t &= \sigma(W_{io}x_t + b_{io} + W_{ho}h_{t-1} + b_{ho}) \\
c_t &= f_t \odot c_{t-1} + i_t \odot g_t \\
h_t &= o_t \odot \tanh(c_t)
\end{aligned}
$$

Agenda (1st Half)

- Advanced topics (contd.)
  - GRU
  - Stacked GRU/LSTM
  - Bidirectional GRU/LSTM
- Hands-on Session
- Assignment 3

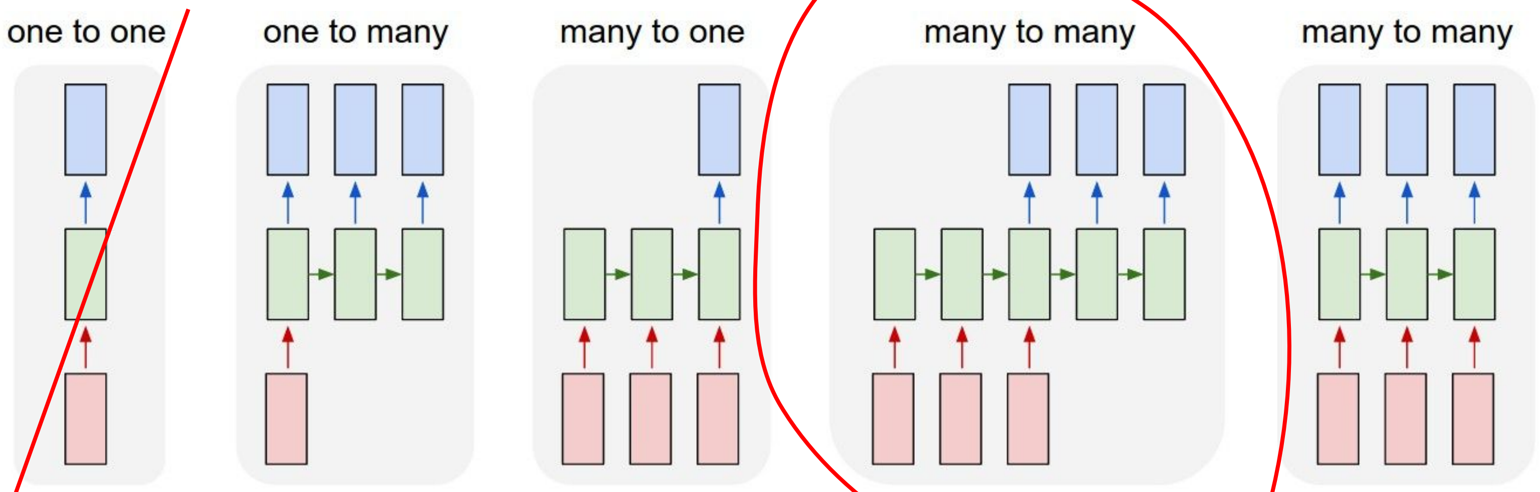
Link to the previous slide deck

- https://github.com/suhara/cis6930-fall2021/blob/main/slides/cis6930-week6a-recurrent-neural-networks-1.pdf

Agenda (2nd Half)

- Encoder-Decoder Models (aka seq2seq Models)
- Decoding Algorithms
- Attention mechanism

RNN Application Patterns



Single-input Generation?

Classification

Encoder-decoder model (aka seq2seq)

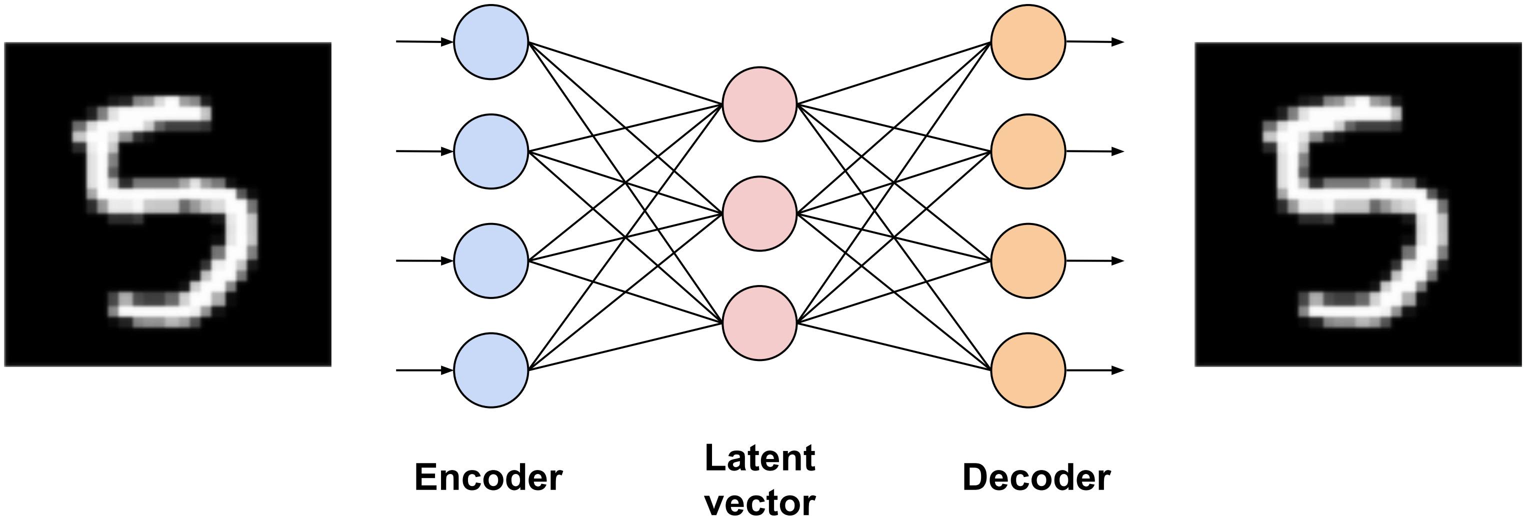
Sequential tagging

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Autoencoders

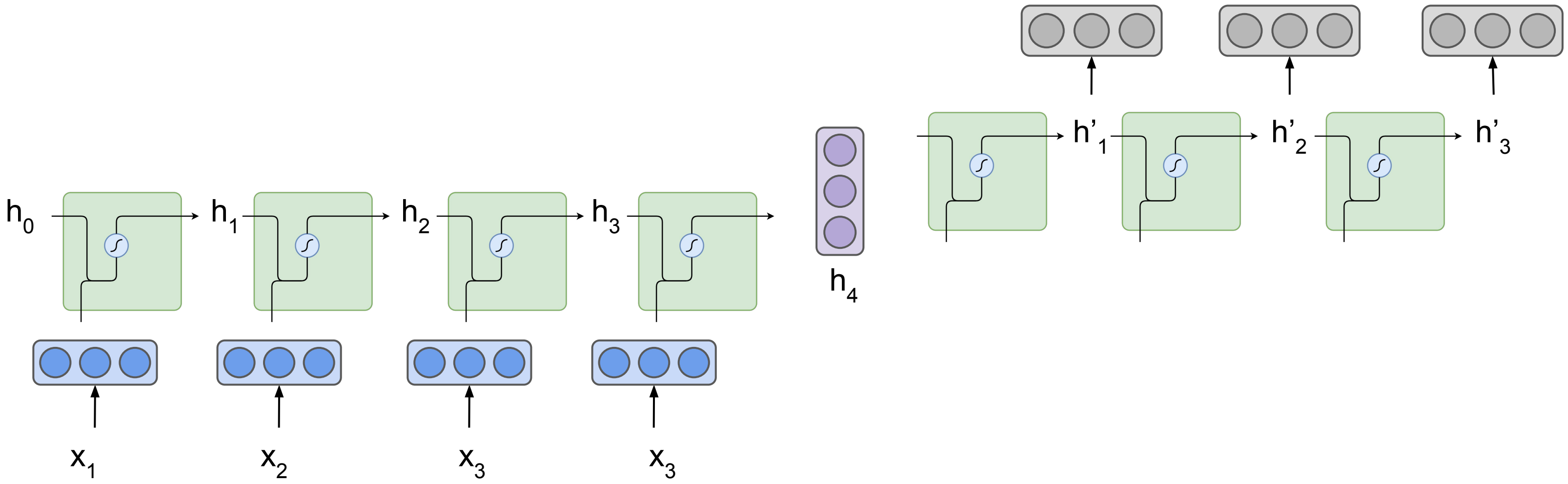
Recap

- **Encoder-decoder models** that **learn to reconstruct the original data**



Encoder-Decoder Model
aka Sequence-to-sequence (seq2seq) Model

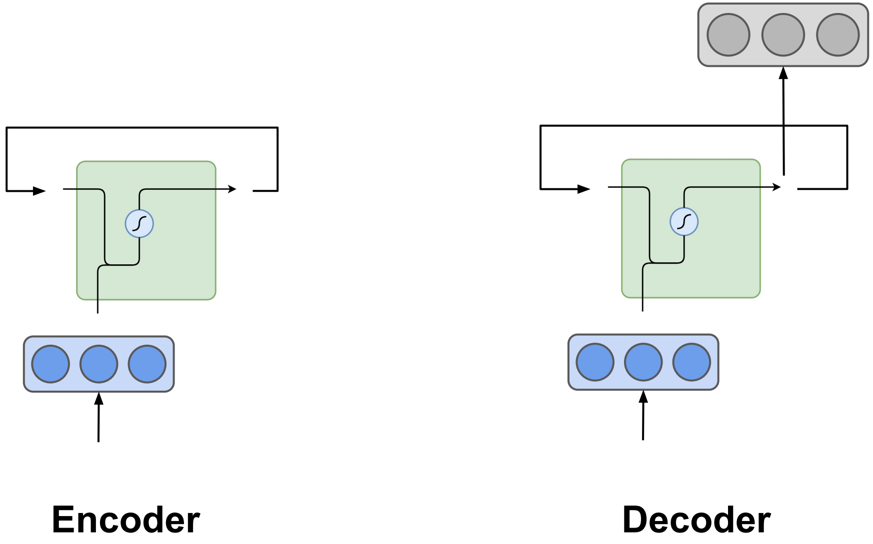
- Input: Variable length sequence
- Output: Variable length sequence



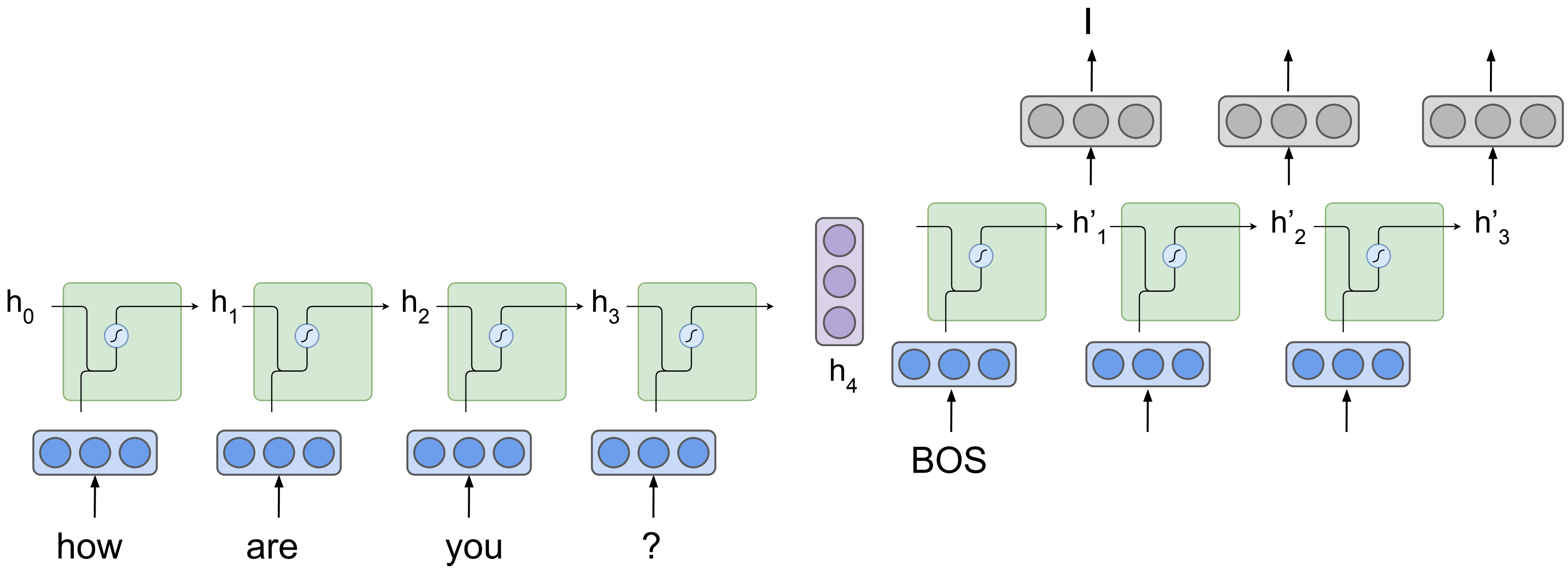
(* RNN Cell can be LSTM/GRU Cell)

Encoder Model + Decoder Model

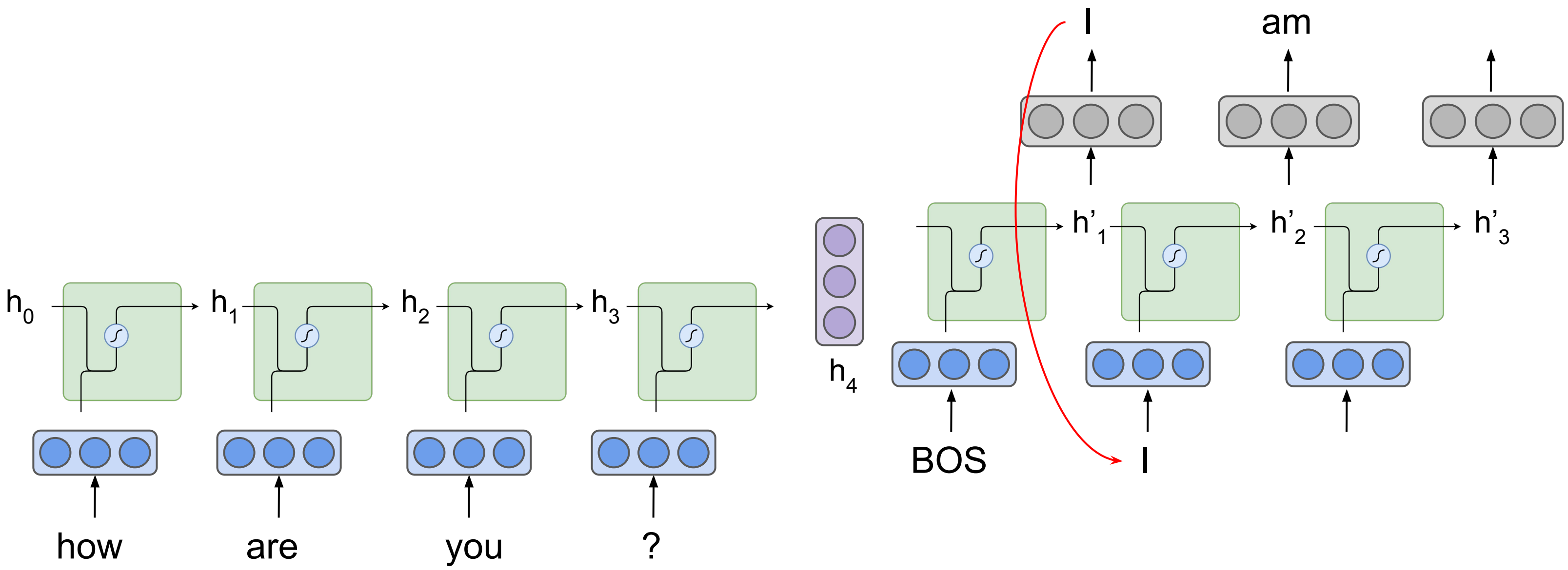
- Two different RNN models



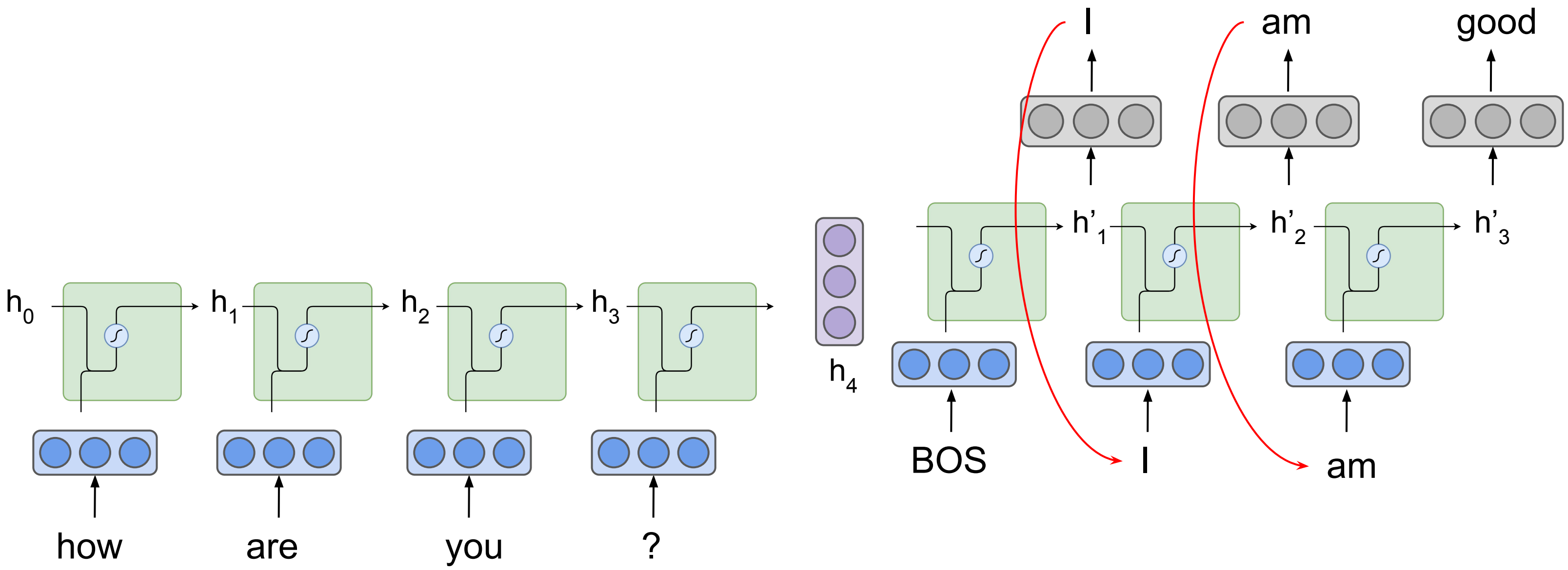
Example 1: Response Generation



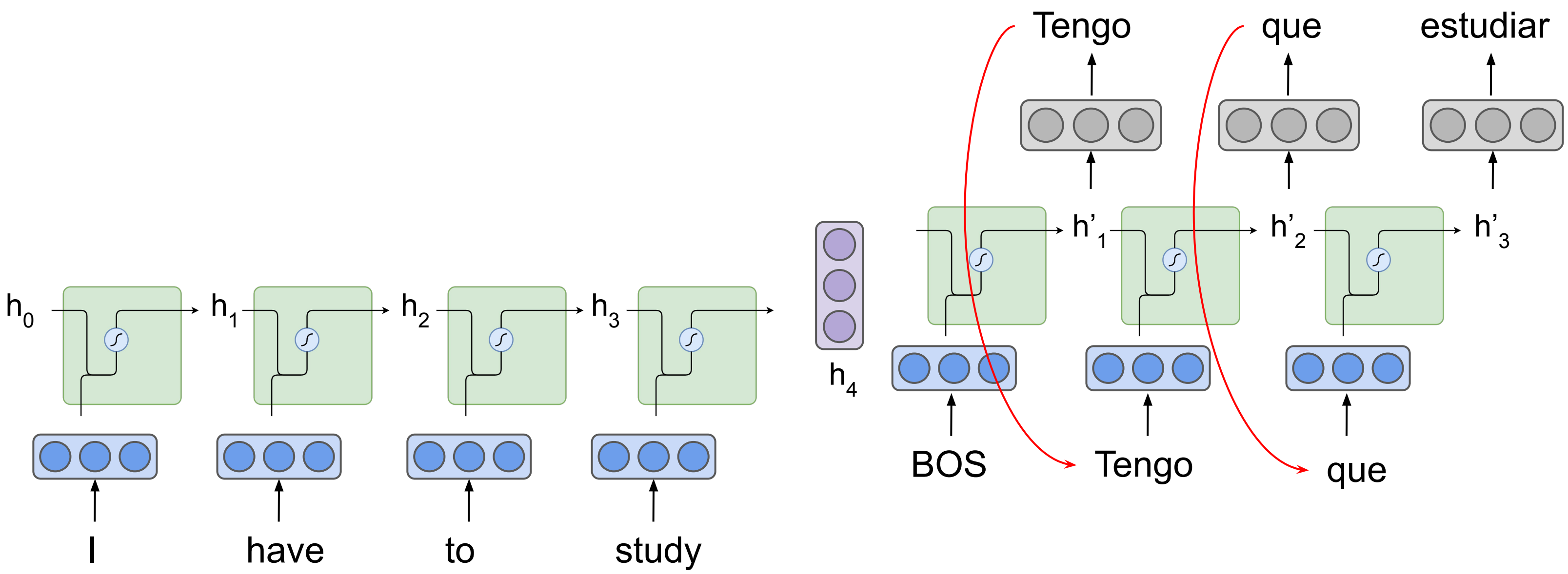
Example 1: Response Generation



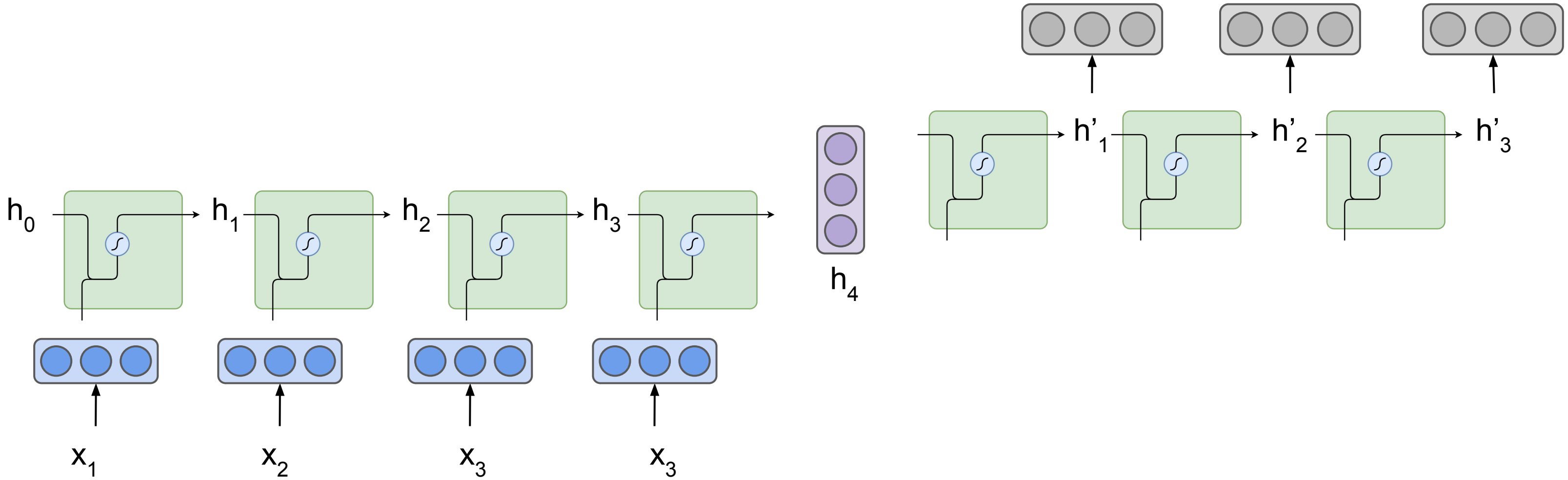
Example 1: Response Generation

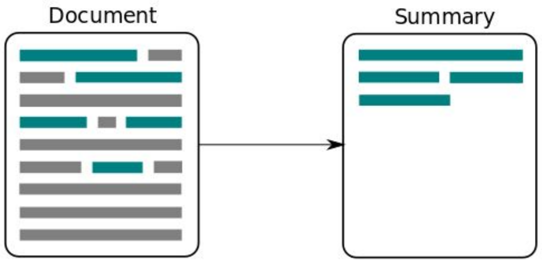


Example 2: Machine Translation



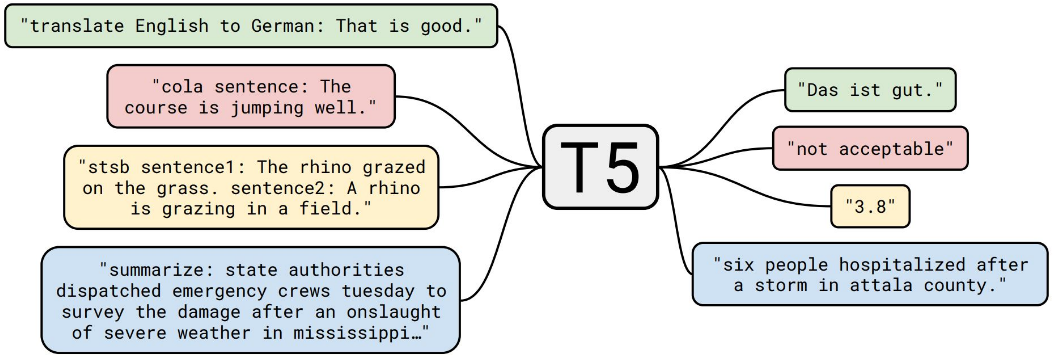
Example 3: Text Summarization





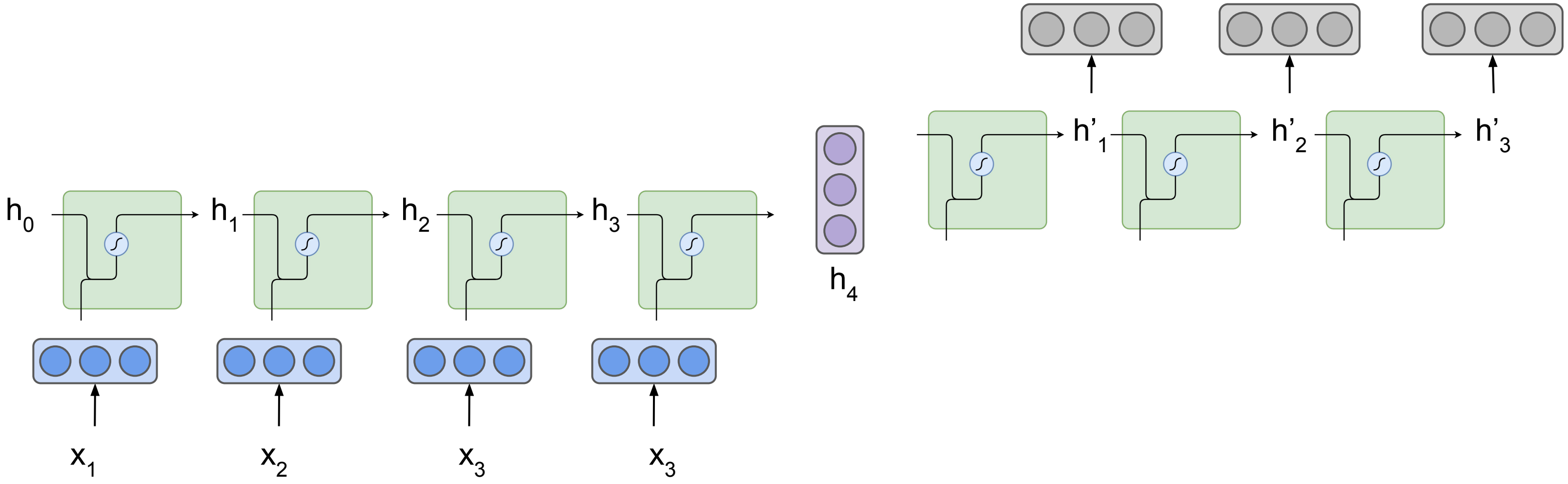
What Can We Do with Encoder-Decoder Models?

- Almost anything! (even classification!)
- …. as long as you have a sufficient amount of **parallel data** (**input-output pairs**)



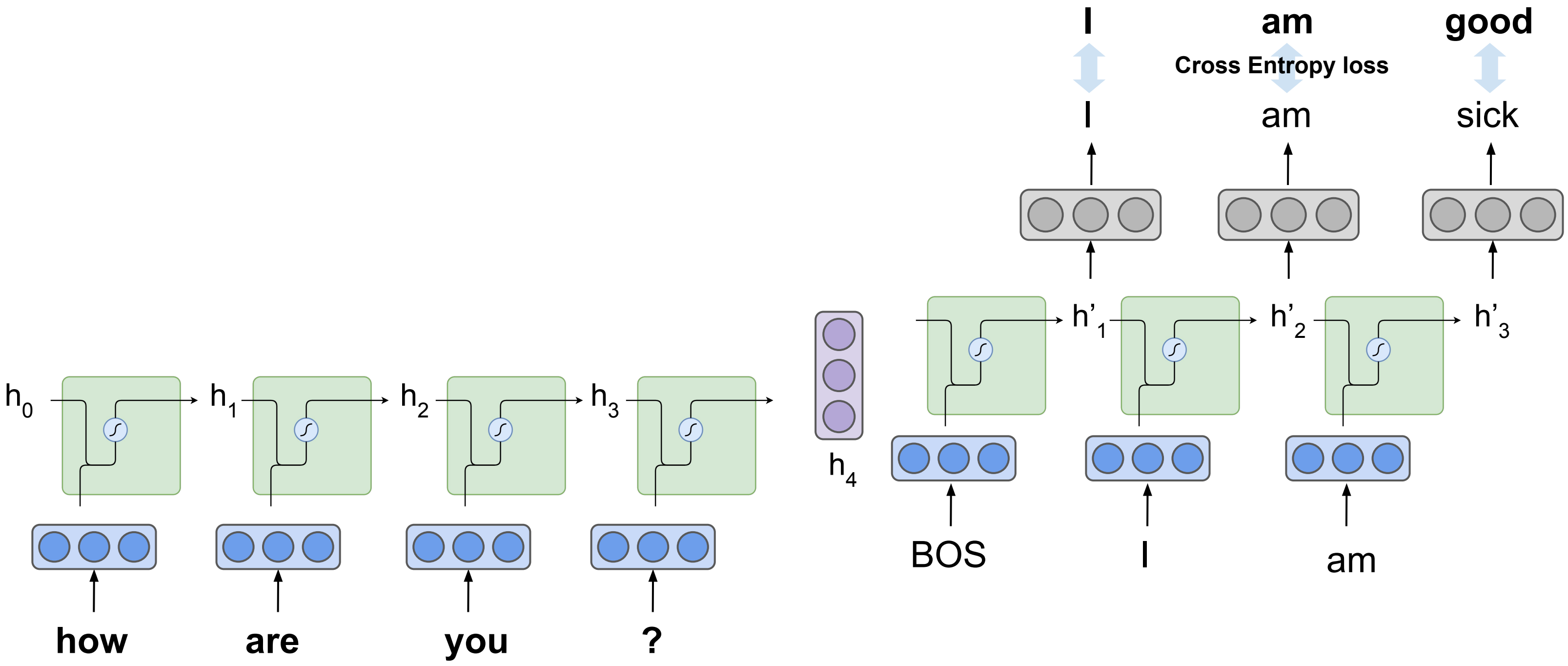
Check: Input & Output

- **Token ID** → One-hot vector → Dense vector → **RNN**
- **RNN** → Output layer + softmax → **Token ID**



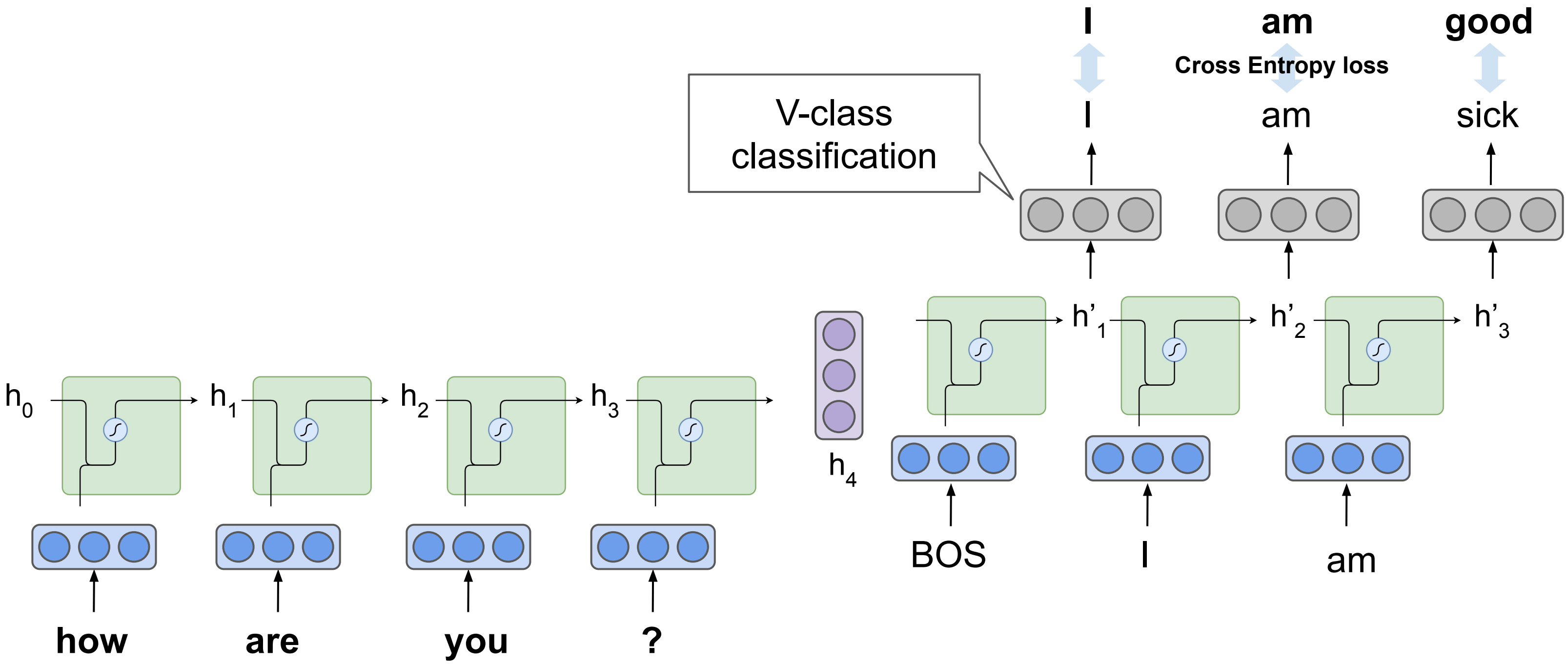
Training Encoder-Decoder Models: Training Data

- Training data: **Pairs of text sequences** (called a **parallel corpus)**
  - e.g., ("How are you?", "I am good")



Training Encoder-Decoder Models: “Teacher Forcing”

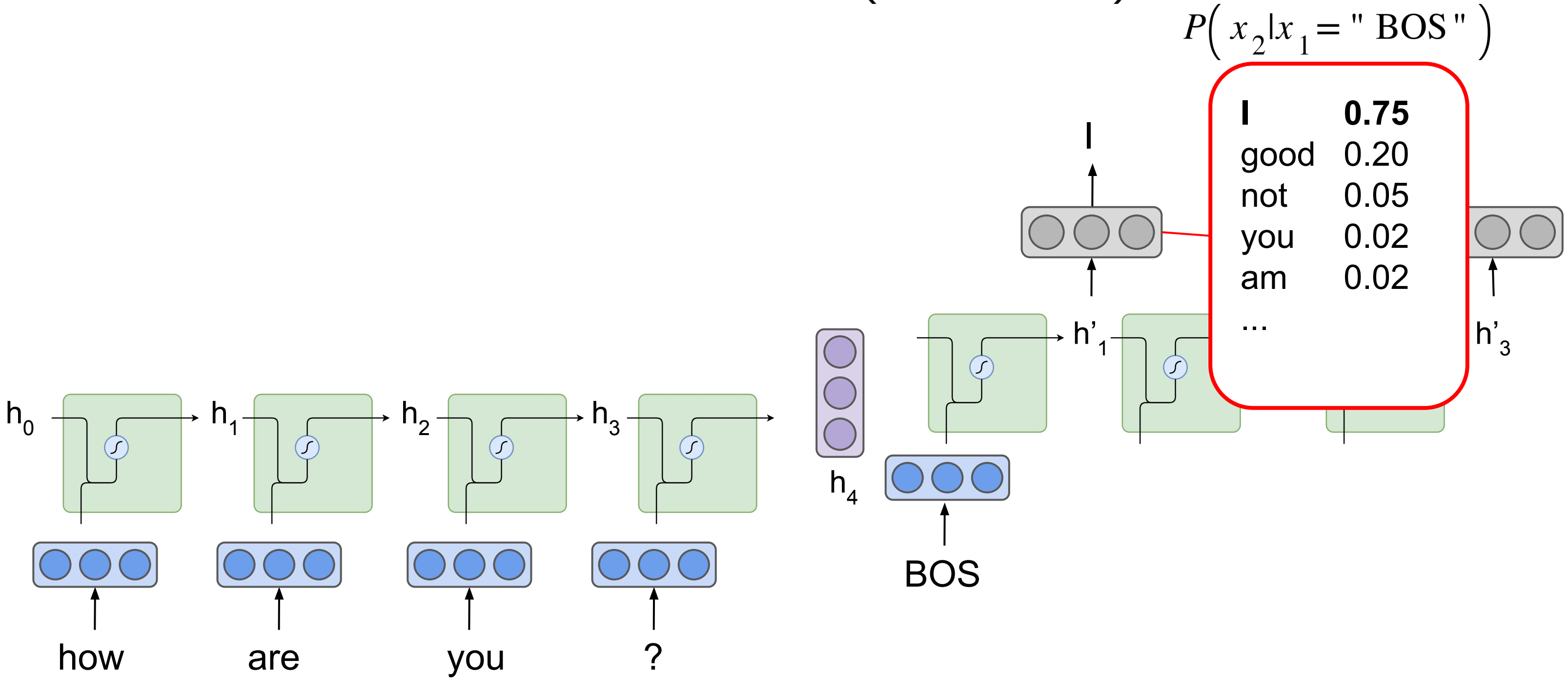
- Train the model to output **ground-truth outputs**



Decoding Algorithms

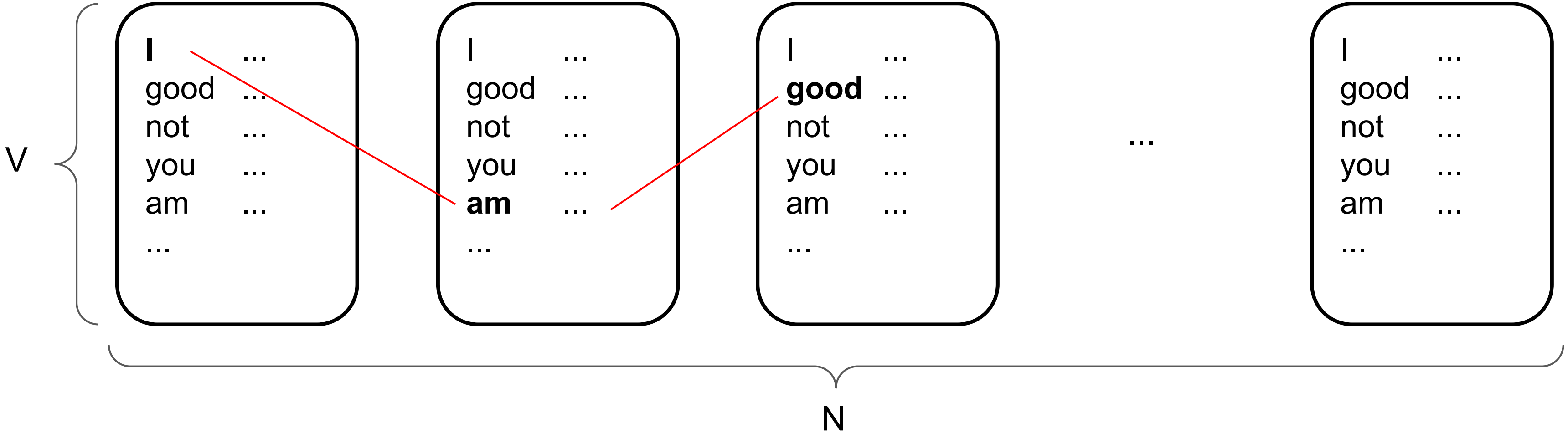
What does the output layer do at each step?

- **Token probability** given the context $P\left(x_t | x_{1:t-1}\right)$



Exhaustive Search is Intractable!

- We want to find the best sequence $\underset{X}{\operatorname{argmax}}\, P(X) = \underset{X}{\operatorname{argmax}} \prod_{t=1}^{N} P\left(x_t | x_{1:t-1}\right)$
- Number of candidates: V^N
  - for a sequence length of N and a vocabulary size of V

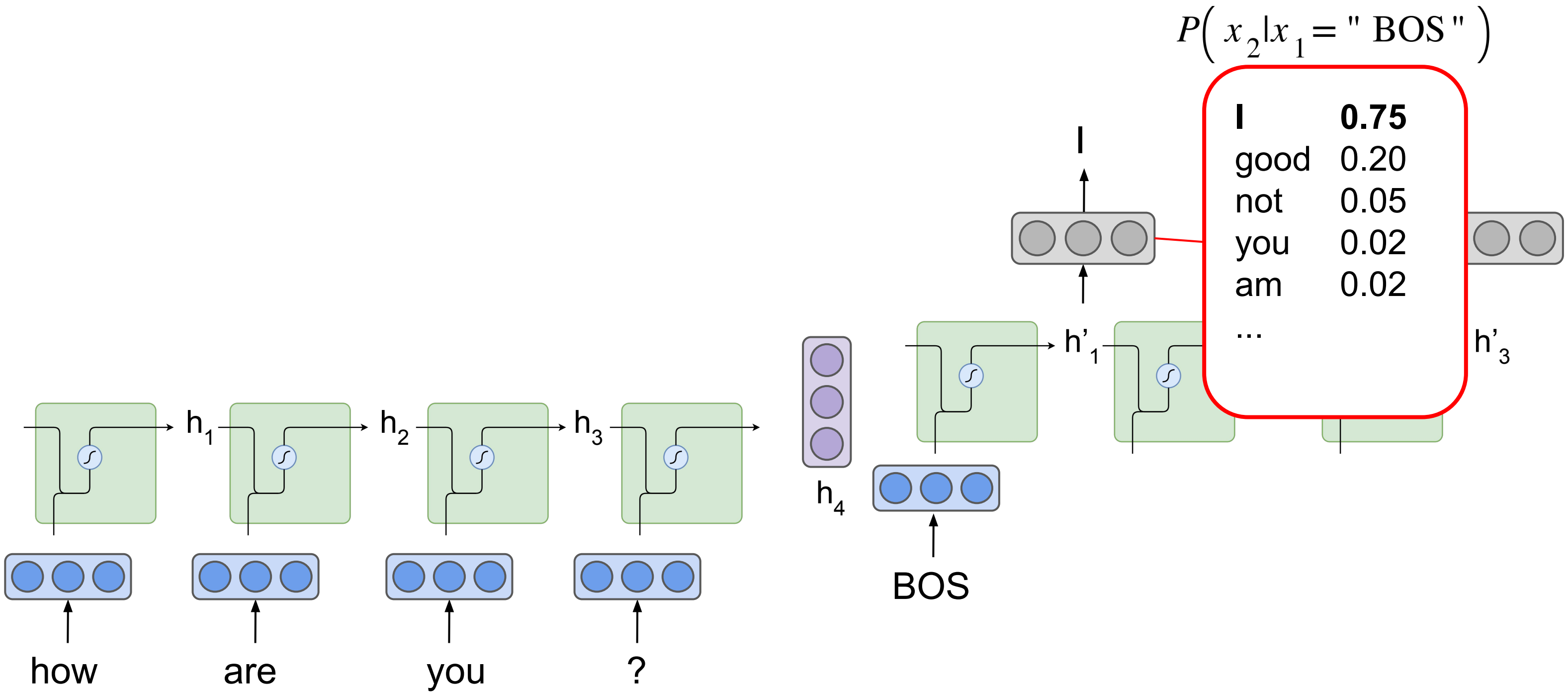


Decoding Algorithm (i.e., Approximate Search)

- Greedy Search
- Beam Search
- Top-k Sampling (covered in Week 8-9)
- Nucleus Sampling (covered in Week 8-9)

Greedy Search

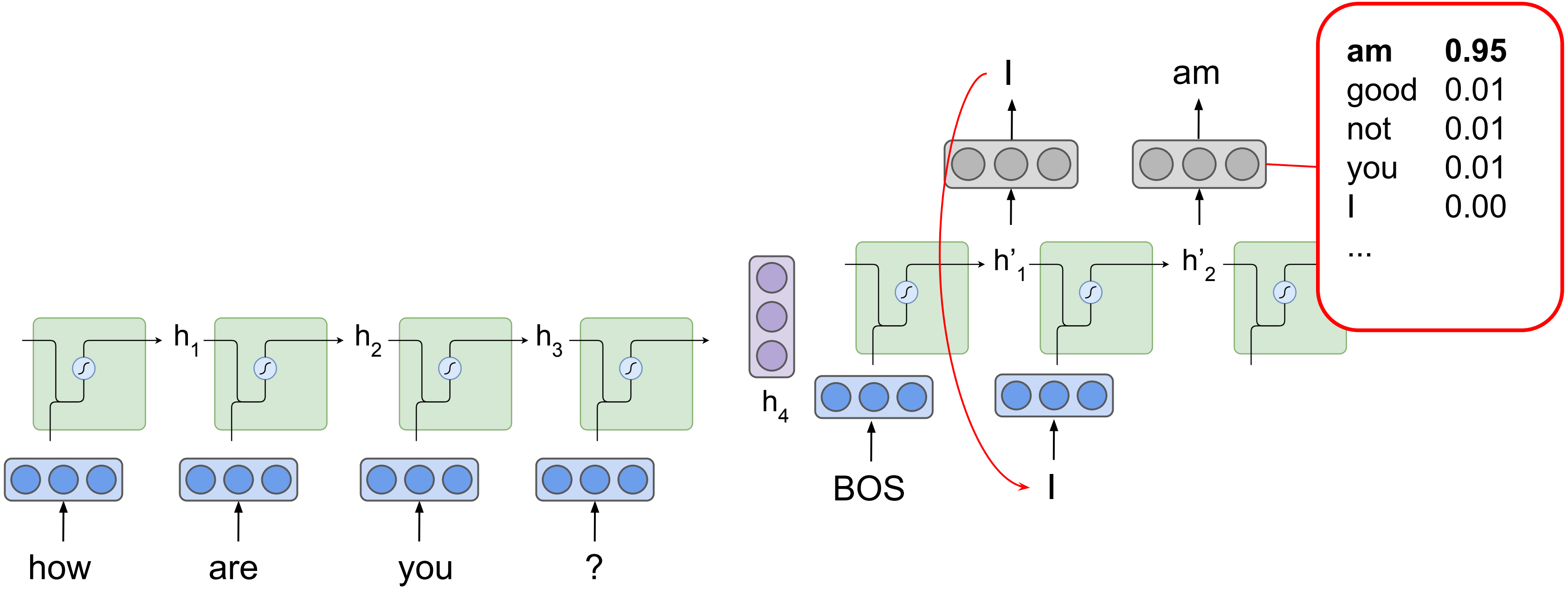
- Always choose the token with the highest probability



Greedy Search

- Always choose the token with the highest probability

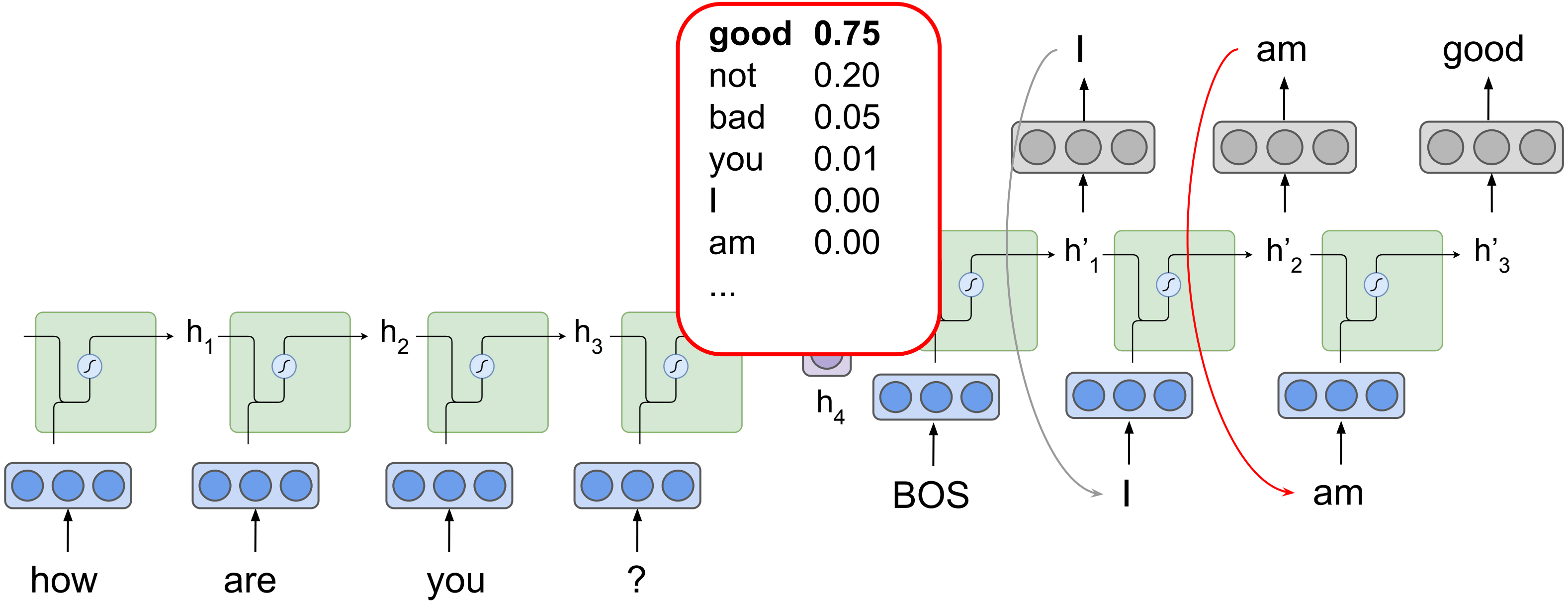
$$P\left(x_3 | x_{1:2} = (\text{"BOS"}, \text{"I"})\right)$$



Greedy Search

- Always choose the token with the highest probability

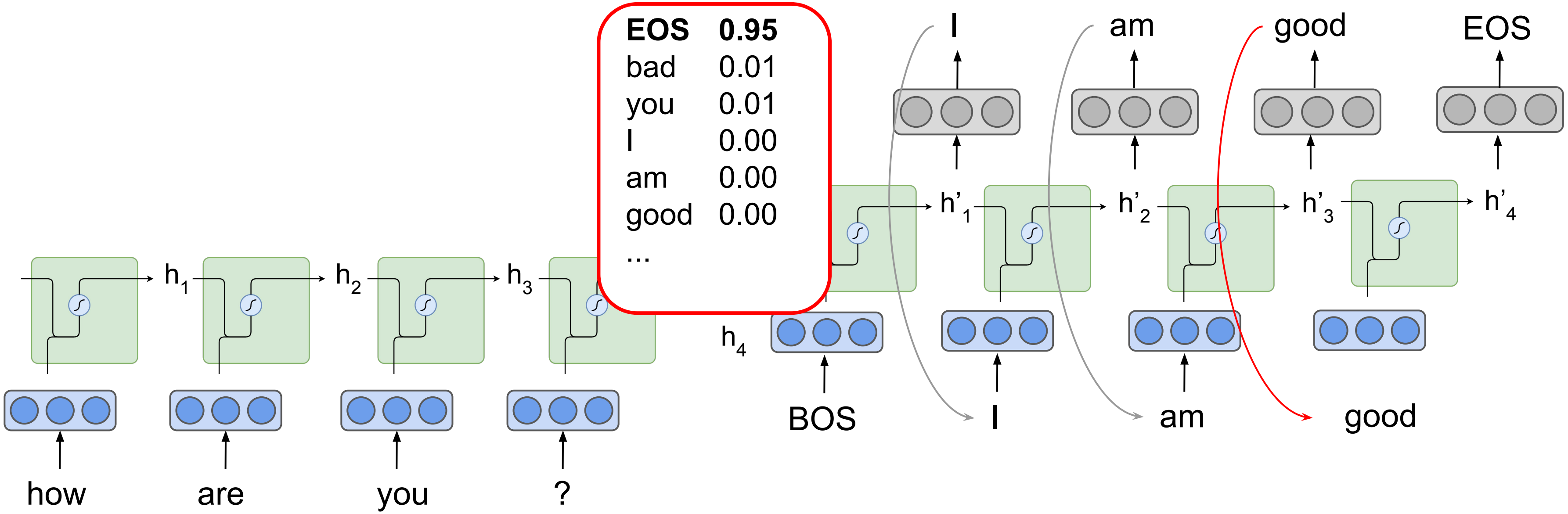
$$P\left(x_4 | x_{1:3} = (\text{"BOS"}, \text{"I"}, \text{"am"})\right)$$



When Does the Decoder Stop?

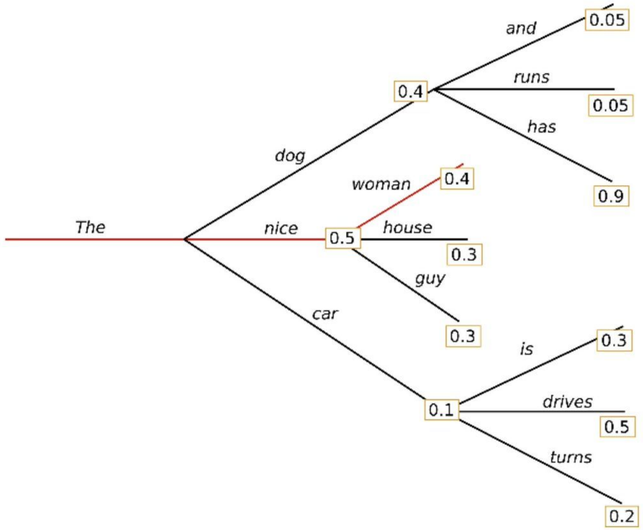
- When it selects the dummy symbol for the end of sequence (e.g., EOS)

$$P\left(x_5 | x_{1:4} = (\text{" BOS "}, \text{" I "}, \text{" am "}, \text{" good "})\right)$$



Beam Search

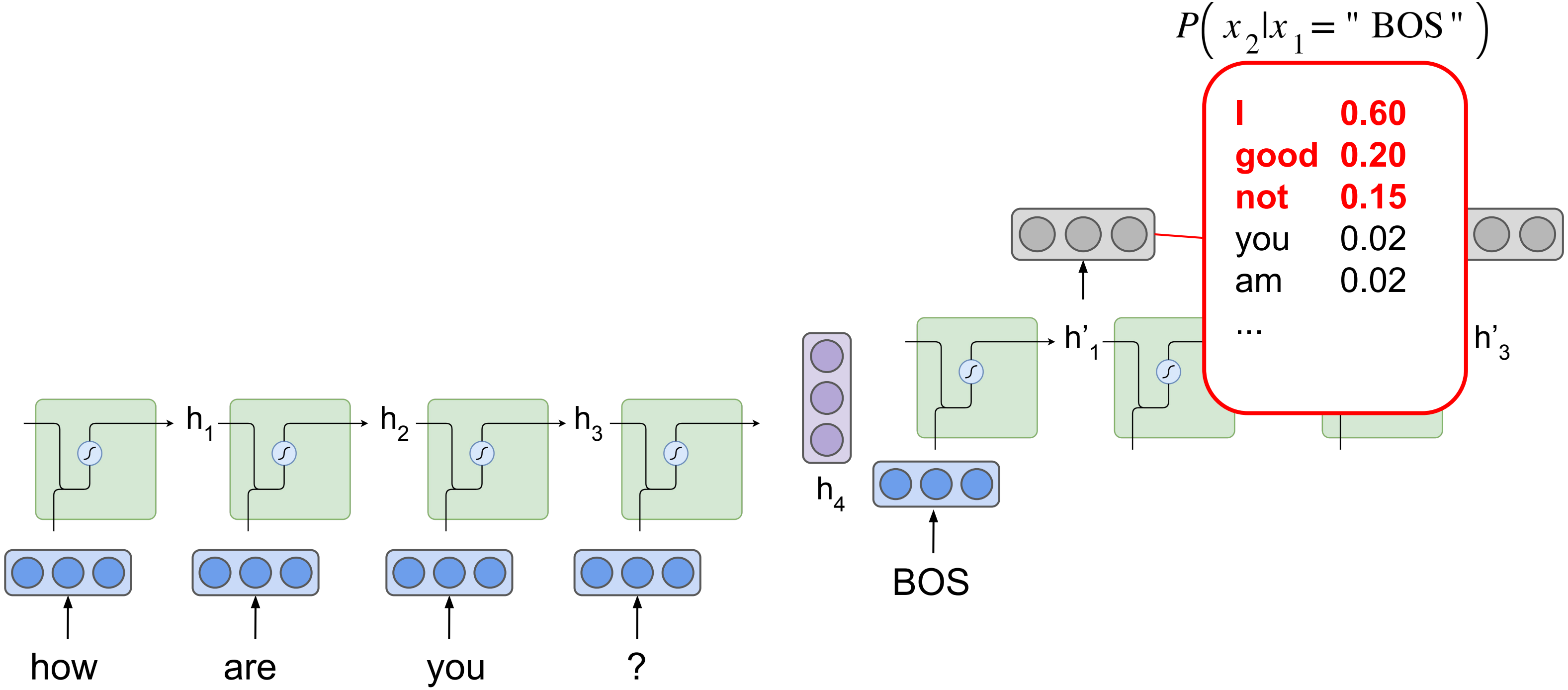
- Select top-k candidates at each step and grow the search tree



Beam Search (k = 3)

k is often called “beam width”

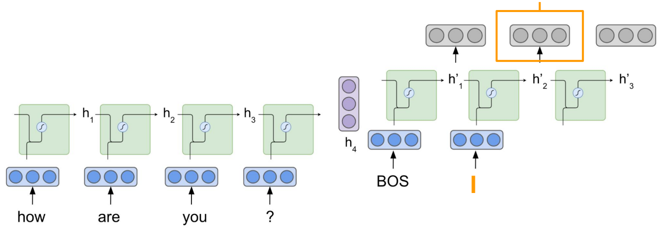
- Choose top-k tokens



Step 2: Calculate Next Token Probability

am	0.80
good	0.05
not	0.01
...	

I	0.40
good	0.20
not	0.19
you	0.02
am	0.02
...	



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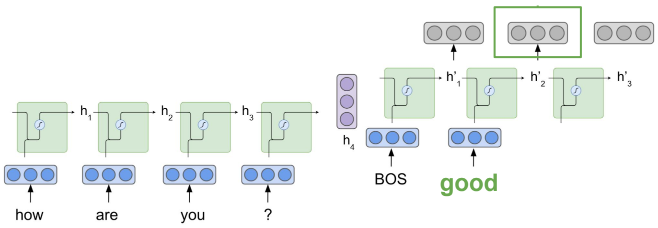
good	0.02
not	0.01
...	



Step 2: Calculate Next Token Probability

I	0.40
good	0.20
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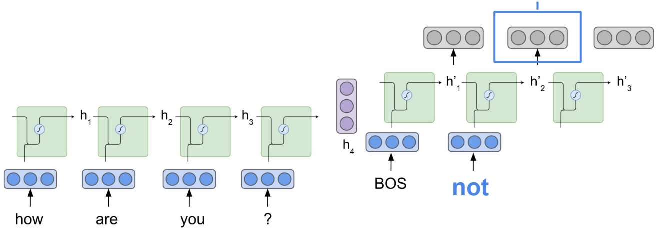
am	0.02
...	

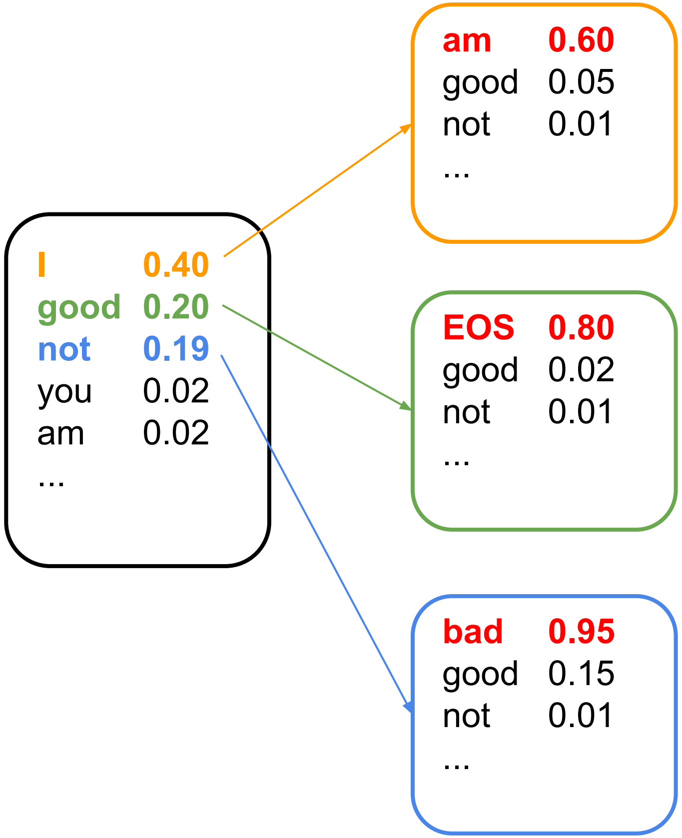
am	0.80
good	0.05
not	0.01
...	

EOS	0.80
good	0.02
not	0.01
...	

bad	0.95
good	0.15
not	0.01
...	



Step 3: Choose Top-3 Candidates



0.40 * 0.60 = 0.24
0.40 * 0.05 = 0.02
0.40 * 0.01 = 0.004

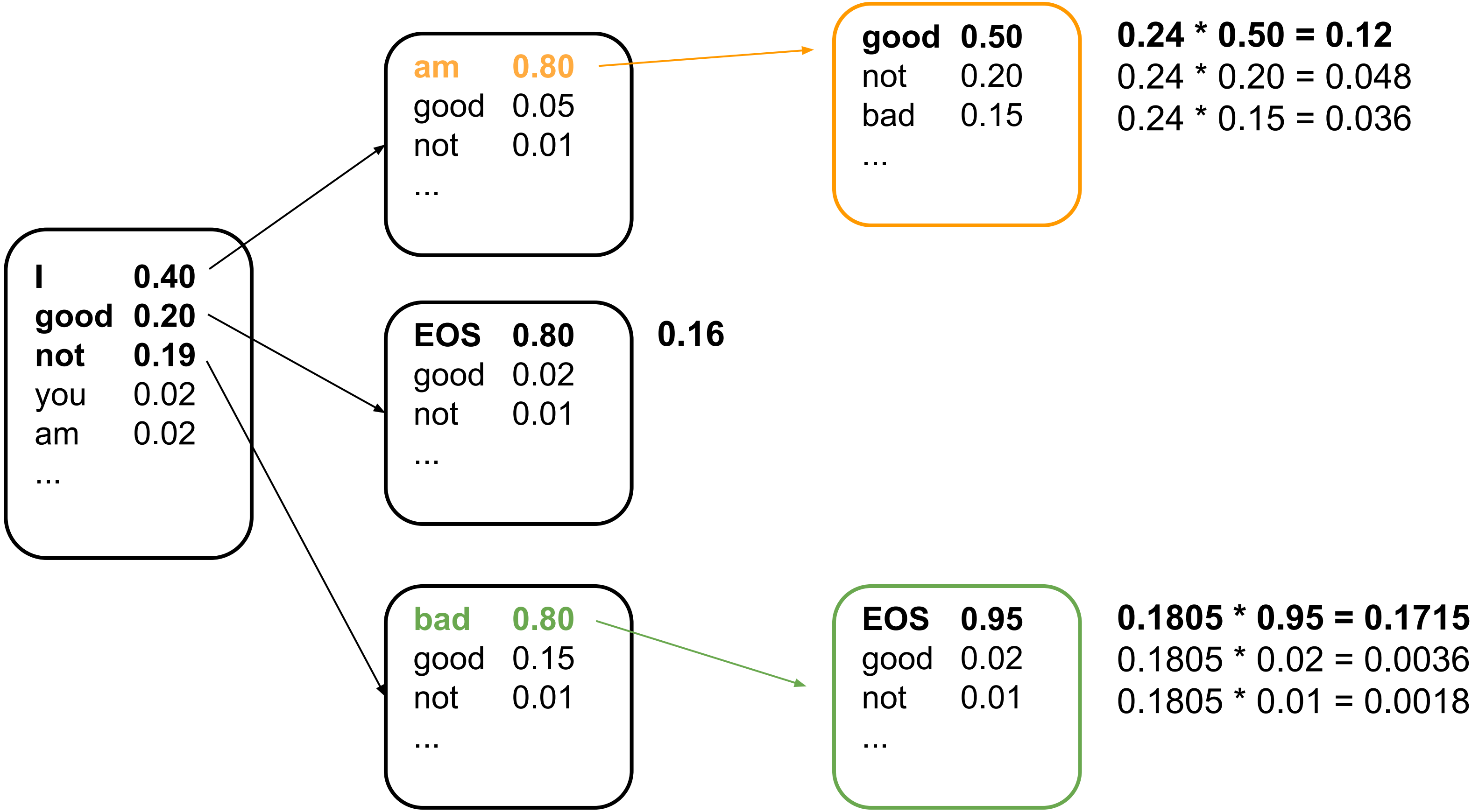
0.20 * 0.80 = 0.16
0.20 * 0.02 = 0.004
0.20 * 0.01 = 0.002

0.19 * 0.95 = 0.1805
0.19 * 0.15 = 0.0285
0.19 * 0.01 = 0.0019

Candidate ranking

1: “I am ...”	0.24
2: “not bad ...”	0.1805
3: “good”	0.16

Repeat the Steps



Update the Candidate List

I	**0.40**
good	**0.20**
not	**0.19**
you	0.02
am	0.02
...	

am	0.80
good	0.05
not	0.01
...	

EOS	**0.80**
good	0.02
not	0.01
...	

0.16

bad	**0.80**
good	0.15
not	0.01
...	

good	**0.50**
not	0.20
bad	0.15
...	

0.24 * 0.50 = 0.12
0.24 * 0.20 = 0.048
0.24 * 0.15 = 0.036

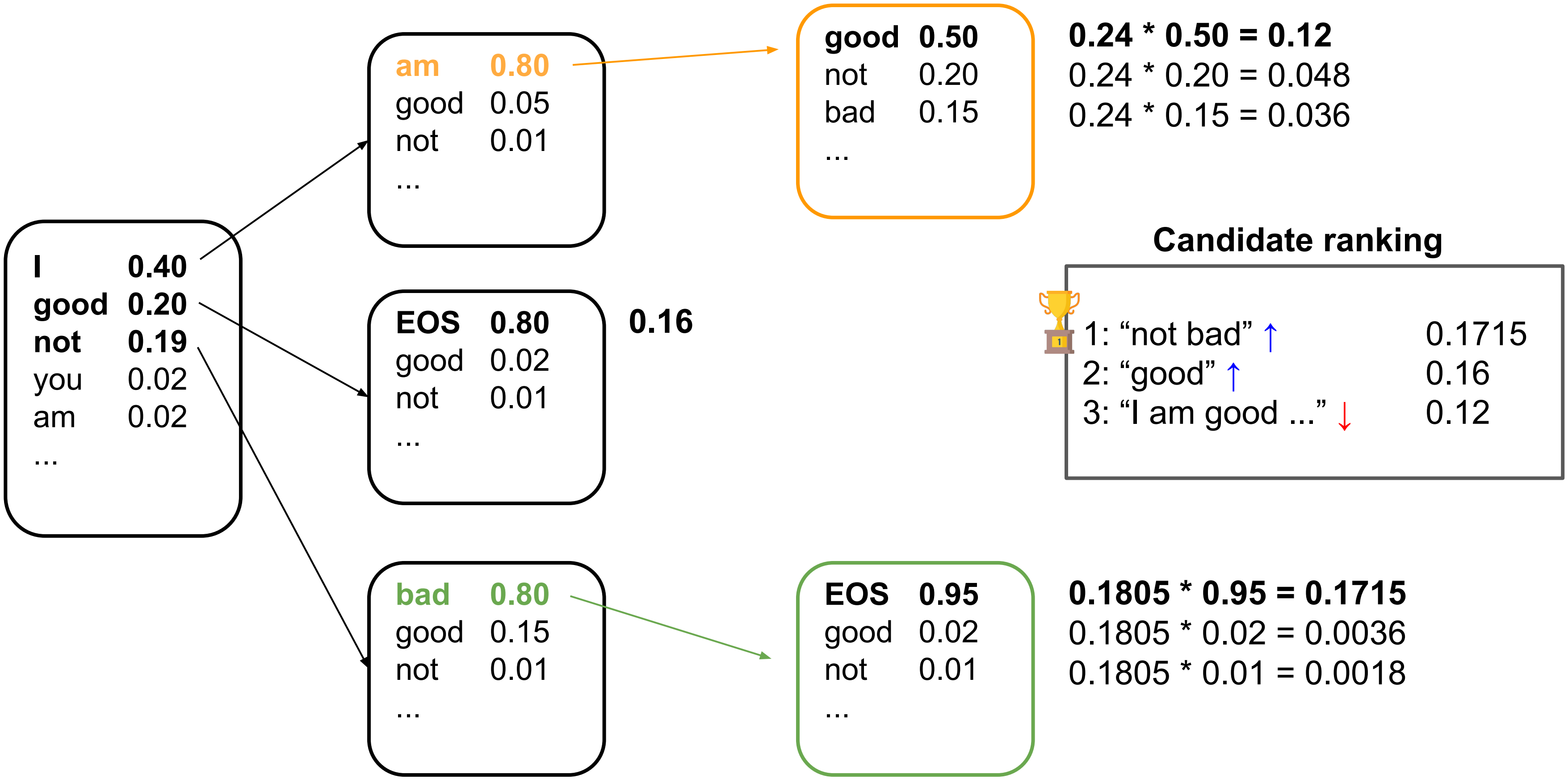
EOS	**0.95**
good	0.02
not	0.01
...	

0.1805 * 0.95 = 0.1715
0.1805 * 0.02 = 0.0036
0.1805 * 0.01 = 0.0018

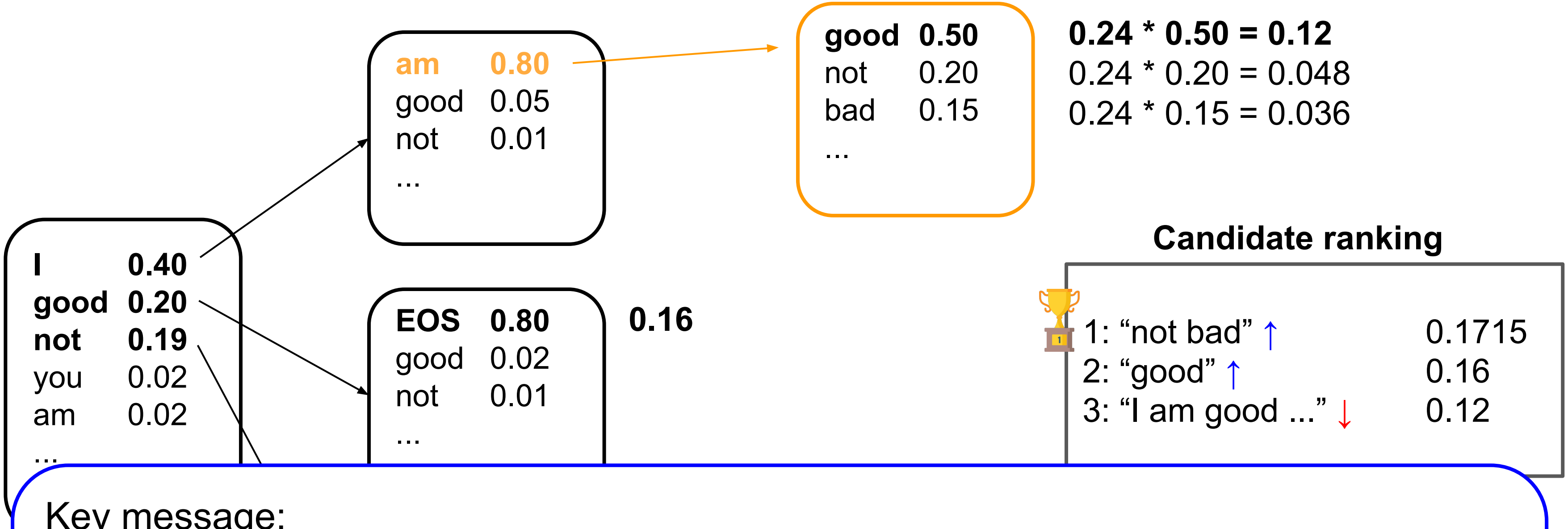
Candidate ranking

1: “not bad” ↑	0.1715
2: “good” ↑	0.16
3: “I am good ...” ↓	0.12

Update the Candidate List



Update the Candidate List



Key message:
The **same model** can return **a different sequence** with a different decoding algorithm

Greedy: “I am good”
Beam Search (k=2): “good”
Beam Search (k=3): “not bad”

Summary: Decoding Algorithm

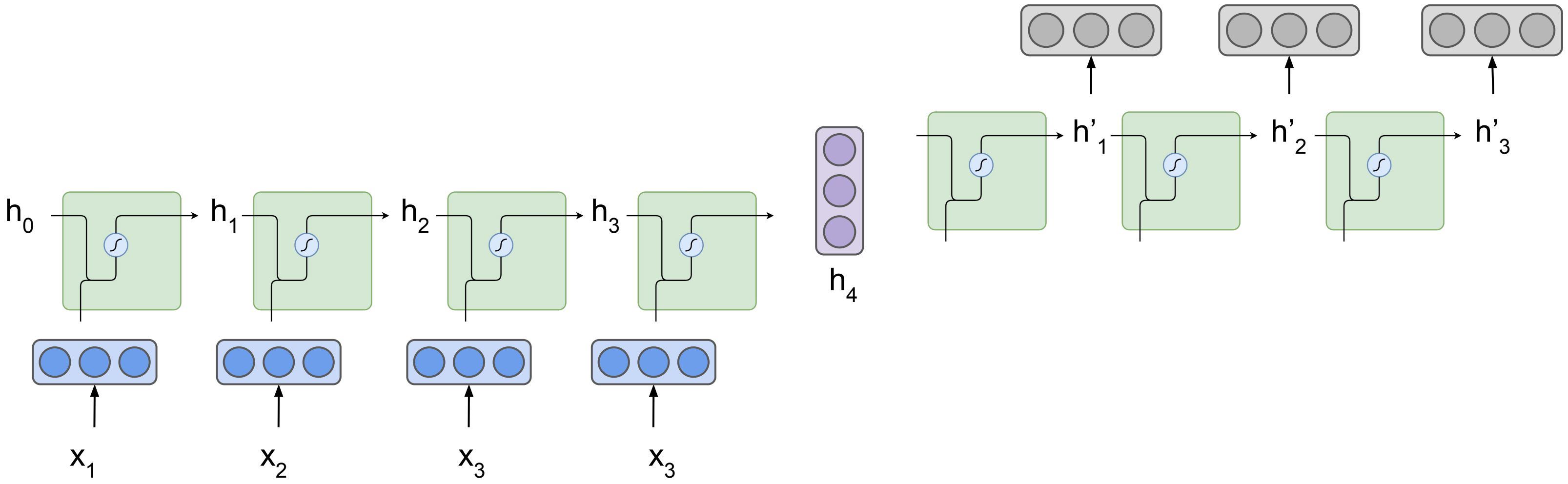
- Greedy Search
  - Time complexity: O(N)
- Beam Search
  - Time complexity: O(k N)
  - Common choice: Beam width = 5 ~ 10

Key Concept

- Encoder-Decoder Model

  = Encoder + Decoder + Decoding algorithm

  Model **Not model**

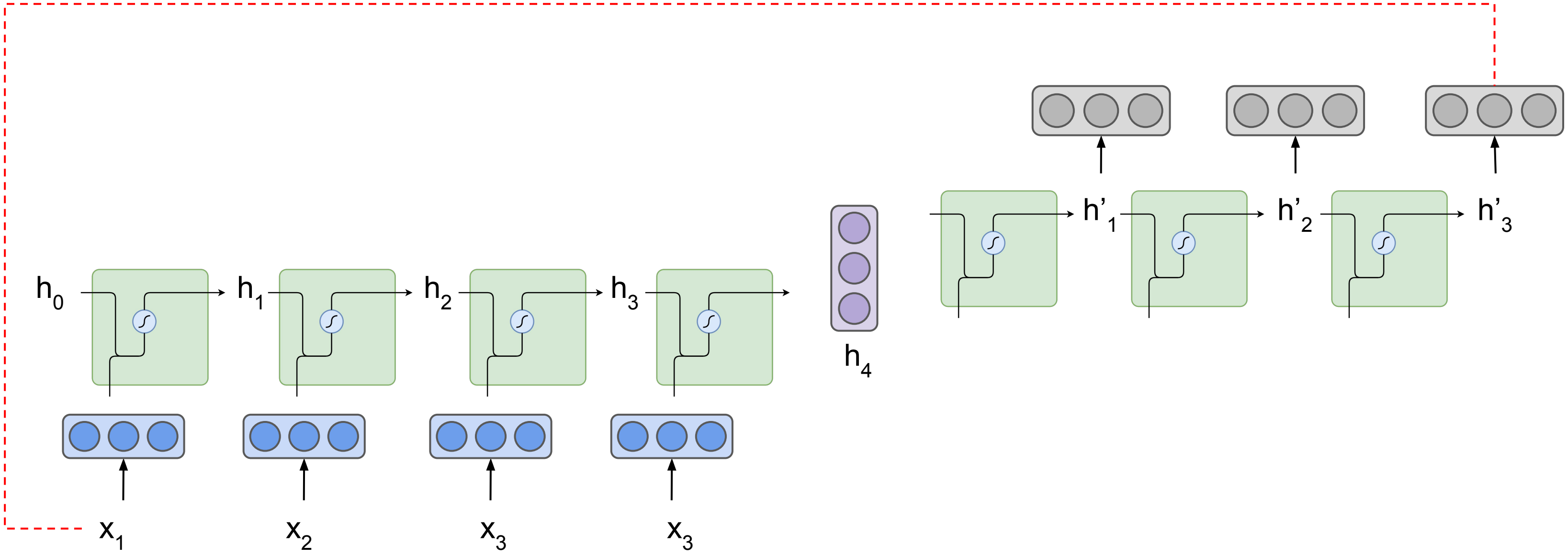


Questions?

Attention Mechanism

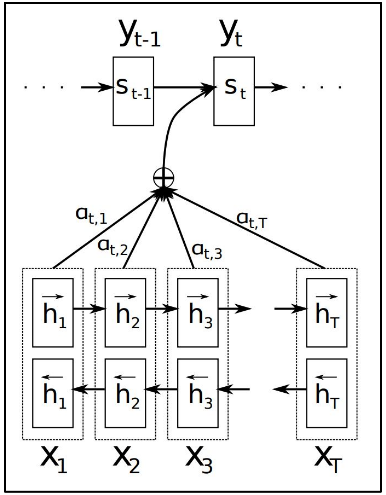
What's the issue with Encoder-Decoder Models?

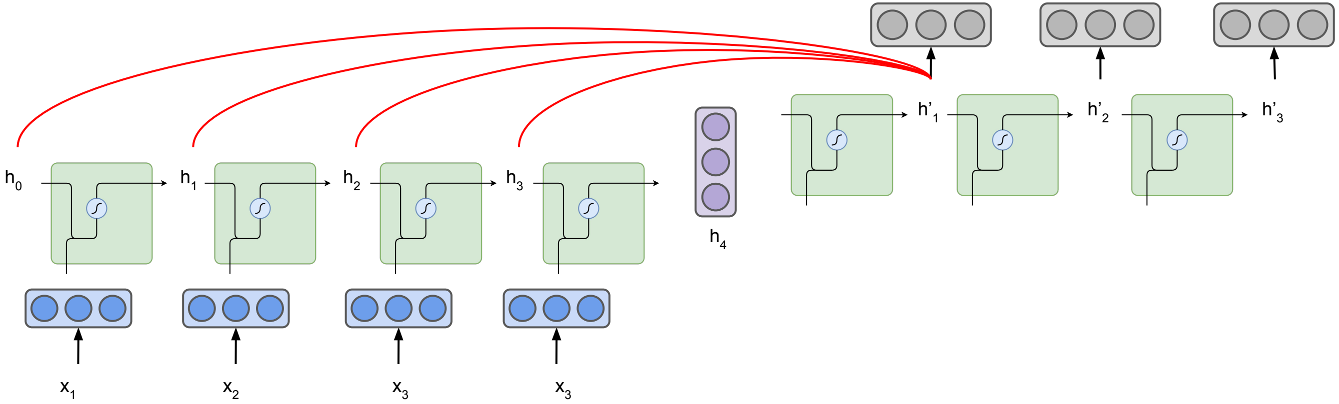
- Not a very good design for **long input/output sequence** even with LSTM/GRU
  - e.g., dependency b/w the beginning of input & the end of output



Attention Mechanism [Bahdanau, Cho, and Bengio ICLR 2016]

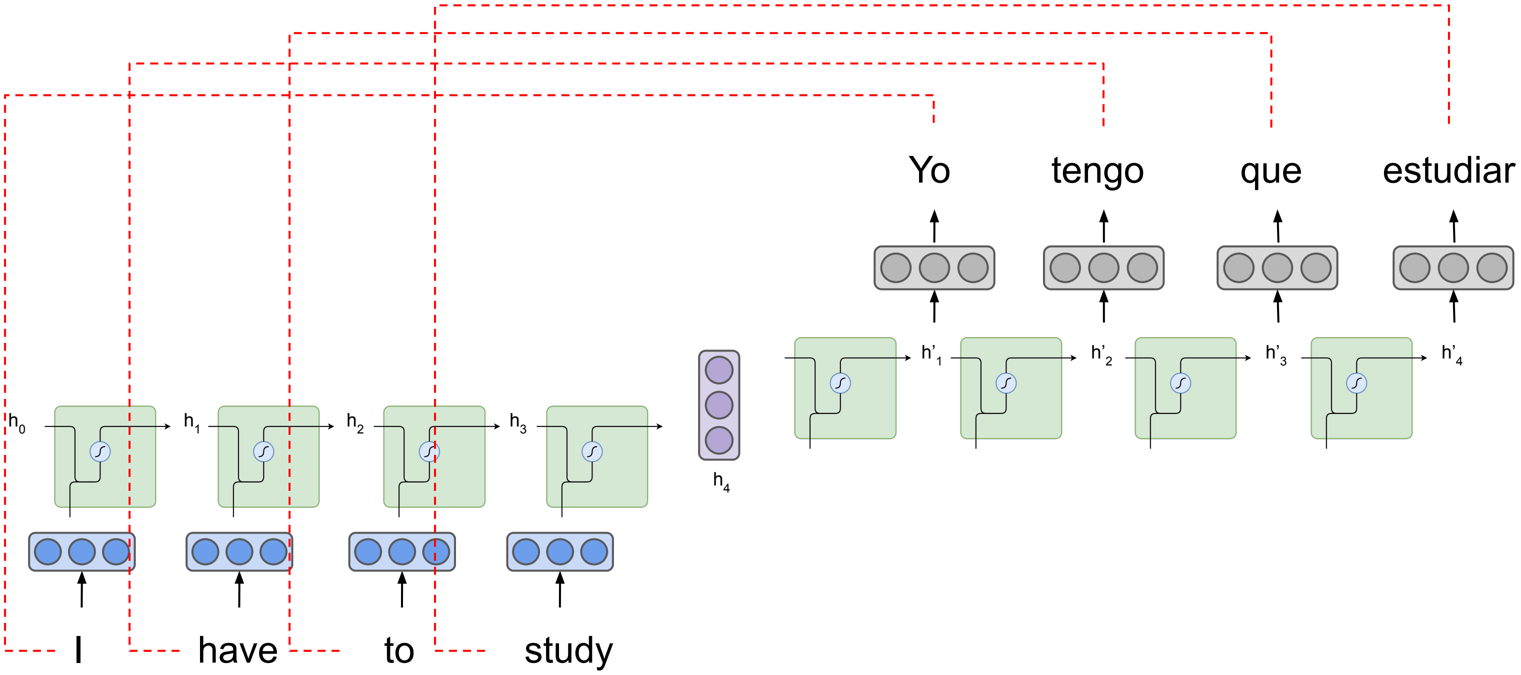
- Additional input to the decoder based on **the alignments b/w encoder and decoder steps**



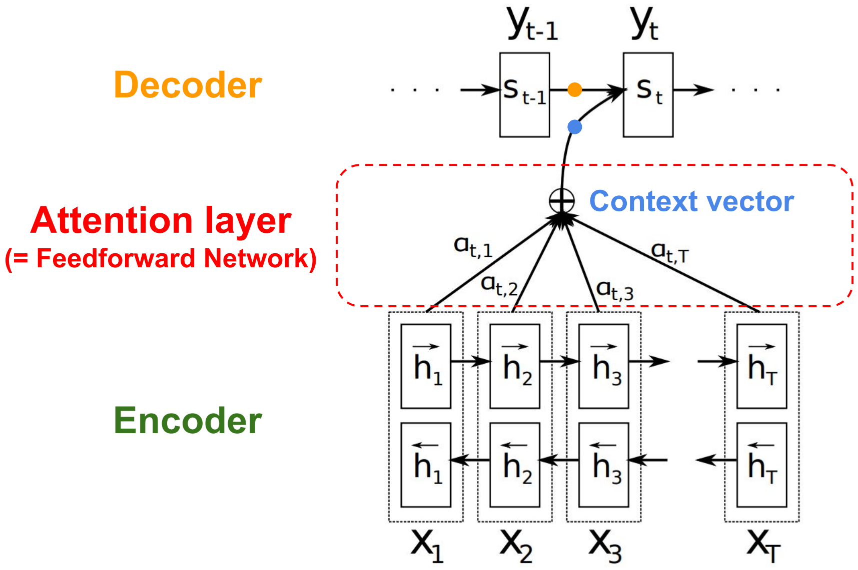


Attention Mechanism: Intuition

- "Direct" connections between any steps in the encoder/decoder model



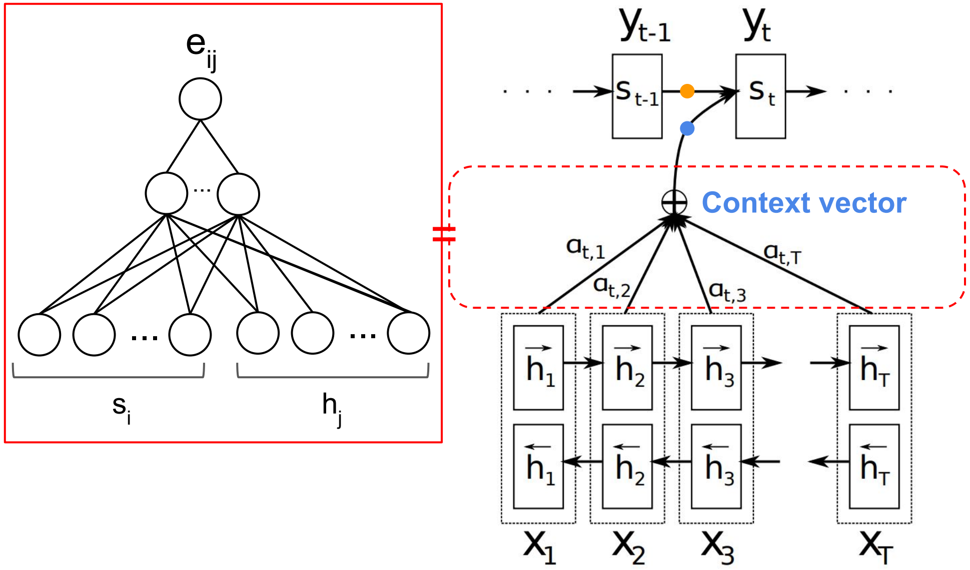
Attention Mechanism: Attention Layer



Previous hidden state
+ context vector

$$\underline{c_i} = \sum_{j=1}^{T_x} \underbrace{\alpha_{ij}}_{\text{alignment score}} \underline{h_j}$$

Attention Layer in Depth



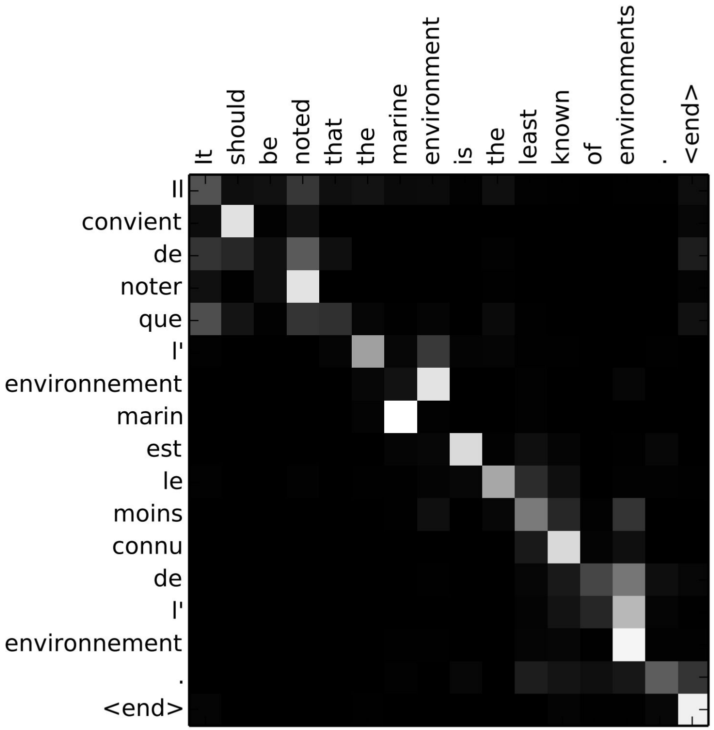
$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

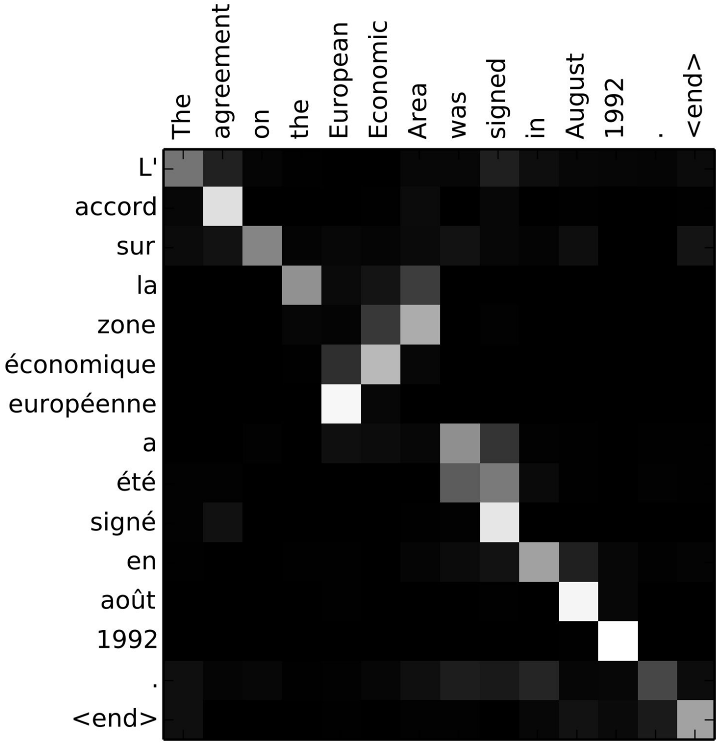
$$\alpha_{ij} = \frac{\exp\left(e_{ij}\right)}{\sum_{k=1}^{T_x} \exp\left(e_{ik}\right)}$$

$$e_{ij} = \text{score}\left(s_i, h_j\right)$$

$$\boxed{\text{score}\left(s_i, h_j\right) = \mathbf{v}_\mathbf{a}^\mathbf{T} \tanh\left(\mathbf{W}_a [s_i; h_j]\right)}$$

Attention Weight Analysis

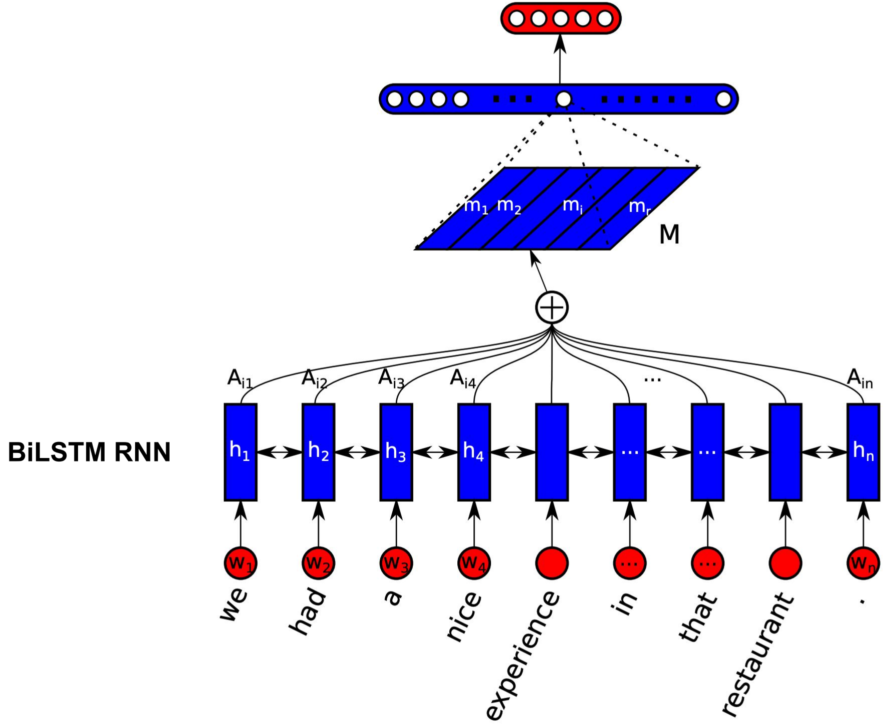




Alignment Score Options

	Name	Alignment score function	Citation
	Content-base attention	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \text{cosine}[\boldsymbol{s}_t, \boldsymbol{h}_i]$	Graves2014
Original →	Additive(*)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \mathbf{v}_a^\top \tanh(\mathbf{W}_a[\boldsymbol{s}_t; \boldsymbol{h}_i])$	Bahdanau2015
	Location-Base	$\alpha_{t,i} = \text{softmax}(\mathbf{W}_a \boldsymbol{s}_t)$ Note: This simplifies the softmax alignment to only depend on the target position.	Luong2015
	General	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \mathbf{W}_a \boldsymbol{h}_i$ where $\mathbf{W}_a$ is a trainable weight matrix in the attention layer.	Luong2015
	Dot-Product	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \boldsymbol{s}_t^\top \boldsymbol{h}_i$	Luong2015
Transformer →	Scaled Dot-Product(^)	$\text{score}(\boldsymbol{s}_t, \boldsymbol{h}_i) = \frac{\boldsymbol{s}_t^\top \boldsymbol{h}_i}{\sqrt{n}}$ Note: very similar to the dot-product attention except for a scaling factor; where n is the dimension of the source hidden state.	Vaswani2017

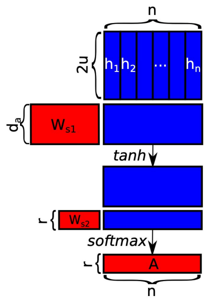
Self-Attention Mechanism for Text Classification



$$M = AH$$

$$A = softmax\left(W_{s2} tanh\left(W_{s1} H^T\right)\right)$$

$$H = (\mathbf{h_1}, \mathbf{h_2}, \cdots \mathbf{h_n})$$



Zhouhan Lin, Minwei Feng, Cicero Nogueira dos Santos, Mo Yu, Bing Xiang, Bowen Zhou, Yoshua Bengio, A Structured Self-attentive Sentence Embedding, ICLR 2017.

Takeaway

- Encoder-Decoder Models (aka seq2seq Models)
  - Many applications: Response Generation, Machine Translation, Text Summarization, etc.
- Decoding Algorithms
  - Greedy Search
  - Beam Search
- Attention mechanism
  - Alignment scores
  - Self-attention mechanism

Next Week

- Tue 10/5 Review session & initial discussion about term projects
  - Quick survey: Do you have any ideas in your mind? (Text? Image? or else?)
- Thu 10/7 Midterm exam (written exam on campus)
  - Time: 2pm-3:20pm
  - Location: TBA
- Fall Break!