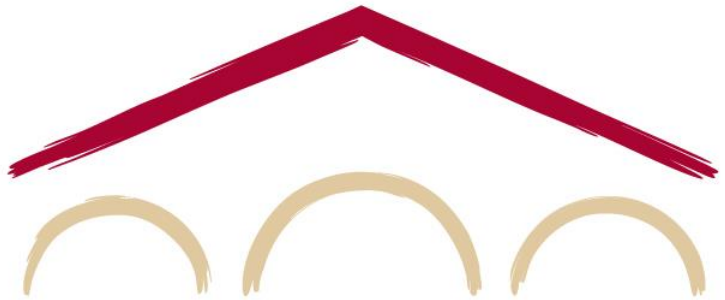
Language models
and
Seq2Seq Architecture



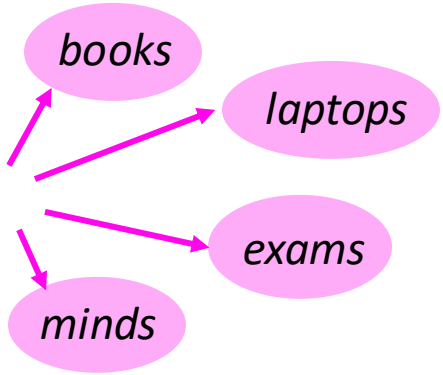
Tatsunori Hashimoto

Presented by Arash Rasouli

1. Language Modeling

- **Language Modeling** is the task of predicting what word comes next

the students opened their _____



- More formally: given a sequence of words $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \ldots, \boldsymbol{x}^{(t)}$, compute the probability distribution of the next word $\boldsymbol{x}^{(t+1)}$:

$$P(\boldsymbol{x}^{(t+1)} | \ \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})$$

where $\boldsymbol{x}^{(t+1)}$ can be any word in the vocabulary $V = \{\boldsymbol{w}_1, \ldots, \boldsymbol{w}_{|V|}\}$

- A system that does this is called a **Language Model**

Language Modeling

- You can also think of a Language Model as a system that assigns a probability to a piece of text

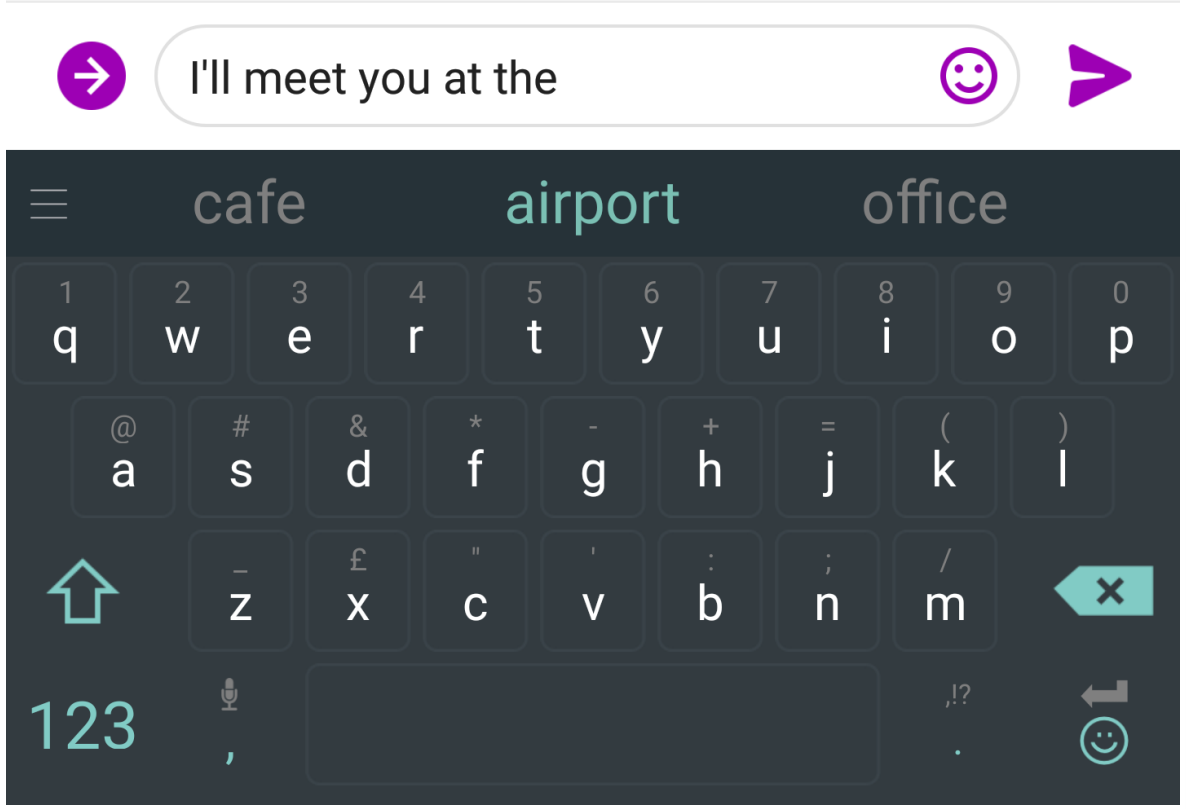
- For example, if we have some text $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}$, then the probability of this text (according to the Language Model) is:

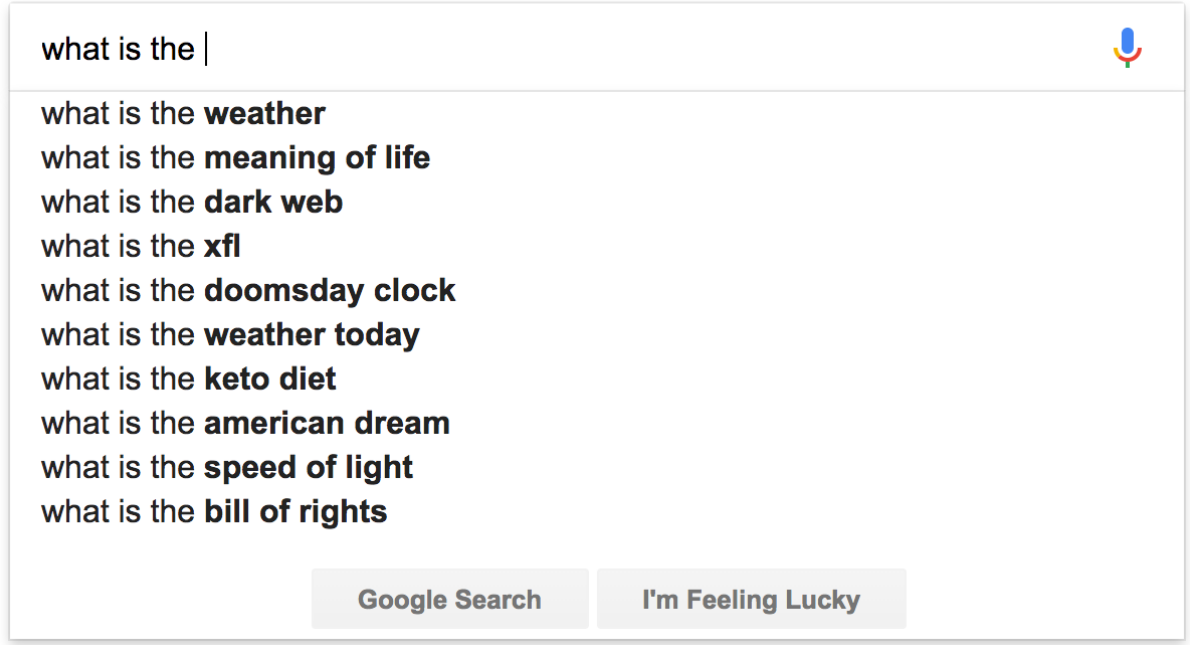
$$P(\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}) = P(\boldsymbol{x}^{(1)}) \times P(\boldsymbol{x}^{(2)} | \boldsymbol{x}^{(1)}) \times \cdots \times P(\boldsymbol{x}^{(T)} | \boldsymbol{x}^{(T-1)}, \ldots, \boldsymbol{x}^{(1)})$$

$$= \prod_{t=1}^{T} P(\boldsymbol{x}^{(t)} | \boldsymbol{x}^{(t-1)}, \ldots, \boldsymbol{x}^{(1)})$$

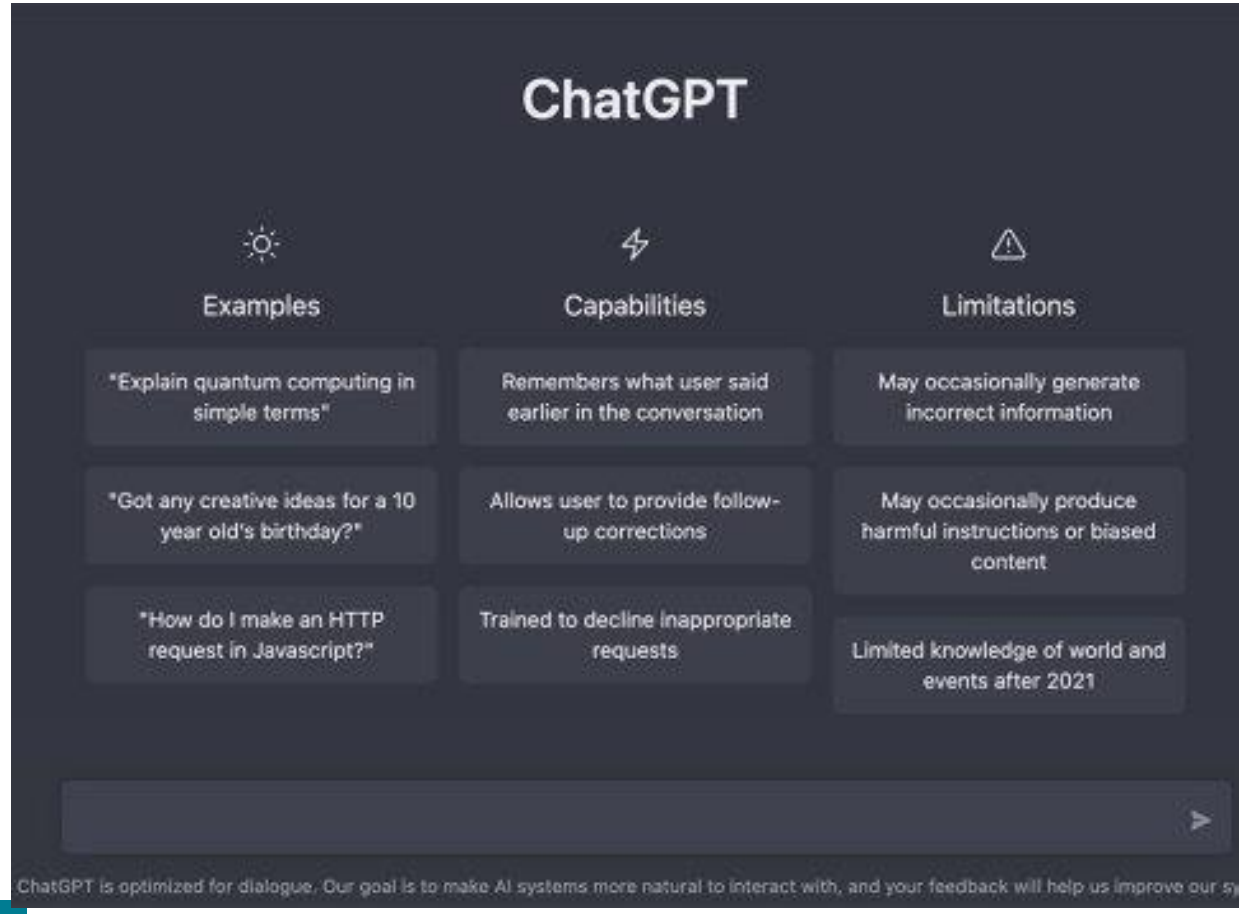
This is what our LM provides

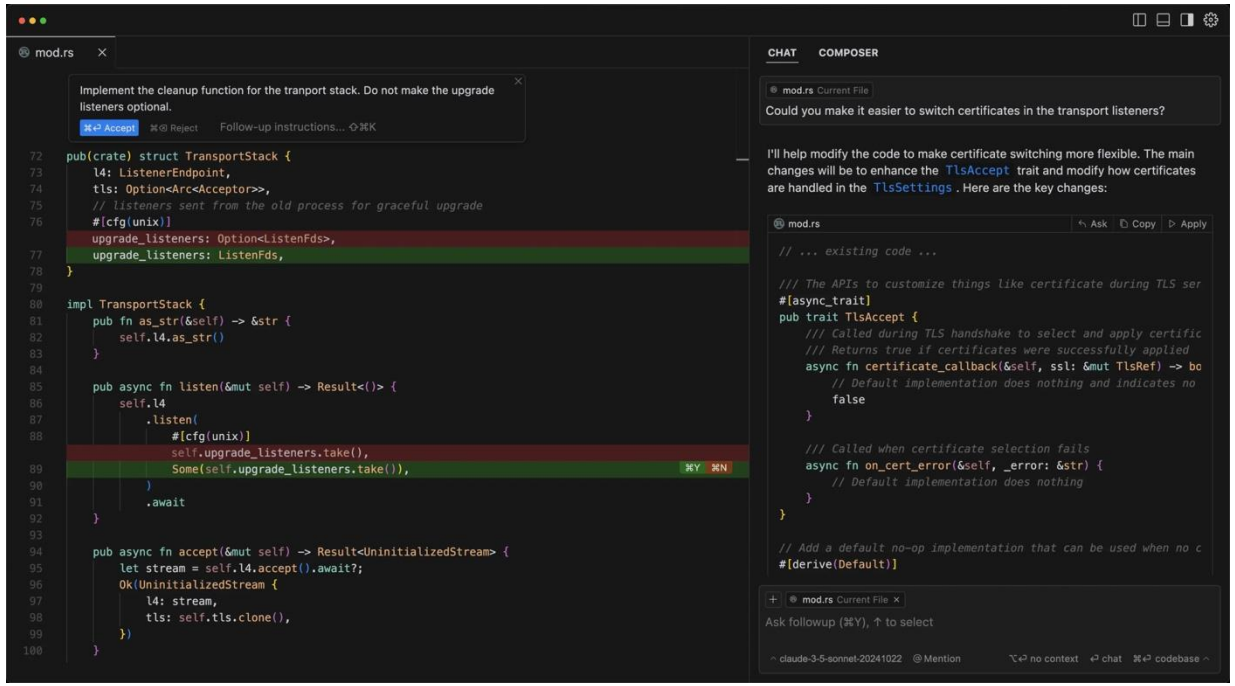
You use Language Models every day!





You use Language Models every day!





Why should we care about Language Modeling?

- Language Modeling is a benchmark task that helps us measure our progress on predicting language use
- Language Modeling is a subcomponent of many NLP tasks, especially those involving generating text or estimating the probability of text:
    - Predictive typing
    - Speech recognition
    - Handwriting recognition
    - Spelling/grammar correction
    - Authorship identification
    - Machine translation
    - Summarization
    - Dialogue
    - etc.
- Everything else in NLP has been rebuilt upon Language Modeling: ChatGPT is an LM!

What can you do with next-word prediction?

- A sufficiently strong (!) language model can do many, many things

Stanford University is located in _____, California. [Trivia]

I put ___ fork down on the table. [syntax]

The woman walked across the street, checking for traffic over ___ shoulder. [coreference]

I went to the ocean to see the fish, turtles, seals, and _____. [lexical semantics/topic]

Overall, the value I got from the two hours watching it was the sum total of the popcorn and the drink. The movie was ___. [sentiment]

Iroh went into the kitchen to make some tea. Standing next to Iroh, Zuko pondered his destiny. Zuko left the _____. [some reasoning – this is harder]

I was thinking about the sequence that goes 1, 1, 2, 3, 5, 8, 13, 21, ____ [some basic arithmetic]

Next word prediction (2019 – GPT2)

- Fixing /.ssh/ Permissions in Cygwin

- In Cygwin on Windows I found that I could not set the permissions of my /.ssh/ folder to be 0600, as is required for ssh to allow you to use keys. The symptom I had was that I no matter what I did, it always modfied the owner and the group

, making these files read-only. I tried just starting ssh and using a program like passwd which modifies the owner/group to 0644 permissions, but it didn't work. It was annoying but not nearly as bad as it could be, just annoying to have to fiddle with permissions. So I decided to do this as the reverse: For each .ssh folder in your Cygwin directory, set the permission of each file and directory to 2644. Then start ssh with: ssh-add /.ssh/ The first time you connect, your permissions of the /.ssh folder that you just had in Cygwin will be set to 0600. Then every time you connect again, your permissions will change to 0644.

Stylistically correct, content wise, questionable

Next word prediction (2020 – GPT3)

Context →	Title: The_Blitz Background: From the German point of view, March 1941 saw an improvement. The Luftwaffe flew 4,000 sorties that month, including 12 major and three heavy attacks. The electronic war intensified but the Luftwaffe flew major inland missions only on moonlit nights. Ports were easier to find and made better targets. To confuse the British, radio silence was observed until the bombs fell. X- and Y-Gerät beams were placed over false targets and switched only at the last minute. Rapid frequency changes were introduced for X-Gerät, whose wider band of frequencies and greater tactical flexibility ensured it remained effective at a time when British selective jamming was degrading the effectiveness of Y-Gerät. Q: How many sorties were flown in March 1941? A: 4,000 Q: When did the Luftwaffe fly inland missions? A:
Target Completion →	only on moonlit nights

The model can perform tasks when given a few examples (‘in-context learning’)

n-gram Language Models

the students opened their _____

- **Question**: How to learn a Language Model?
- **Answer** (pre- Deep Learning): learn an *n*-gram Language Model!

- **Definition:** An *n*-gram is a chunk of *n* consecutive words.
  - unigrams: “the”, “students”, “opened”, ”their”
  - bigrams: “the students”, “students opened”, “opened their”
  - trigrams: “the students opened”, “students opened their”
  - four-grams: “the students opened their”

- **Idea:** Collect statistics about how frequent different n-grams are and use these to predict next word.

n-gram Language Models

- First we make a Markov assumption: $x^{(t+1)}$ depends only on the preceding *n*-1 words

n-1 words

$$P(\boldsymbol{x}^{(t+1)}|\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(1)}) = P(\boldsymbol{x}^{(t+1)}|\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)})$$

(assumption)

prob of a n-gram

prob of a (n-1)-gram

$$= \frac{P(\boldsymbol{x}^{(t+1)},\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)})}{P(\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)})}$$

(definition of conditional prob)

- **Question:** How do we get these *n*-gram and (*n*-1)-gram probabilities?
- **Answer:** By counting them in some large corpus of text!

$$\approx \frac{\text{count}(\boldsymbol{x}^{(t+1)},\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)})}{\text{count}(\boldsymbol{x}^{(t)},\ldots,\boldsymbol{x}^{(t-n+2)})}$$

(statistical approximation)

n-gram Language Models: Example

Suppose we are learning a 4-gram Language Model.

~~*as the proctor started the clock, the*~~ *students opened their* _____

~~as the proctor started the clock, the~~ — discard

students opened their — condition on this

$$P(\boldsymbol{w}|\text{students opened their}) = \frac{\text{count}(\text{students opened their } \boldsymbol{w})}{\text{count}(\text{students opened their})}$$

For example, suppose that in the corpus:

- "students opened their" occurred 1000 times
- "students opened their books" occurred 400 times
  - → P(books | students opened their) = 0.4
- "students opened their exams" occurred 100 times
  - → P(exams | students opened their) = 0.1

Should we have discarded the "proctor" context?

Sparsity Problems with n-gram Language Models

Sparsity Problem 1

Problem: What if *"students opened their w"* never occurred in data? Then *w* has probability 0!

(Partial) Solution: Add small δ to the count for every $w \in V$. This is called *smoothing*.

$$P(\boldsymbol{w}|\text{students opened their}) = \frac{\text{count}(\text{students opened their } \boldsymbol{w})}{\text{count}(\text{students opened their})}$$

Sparsity Problem 2

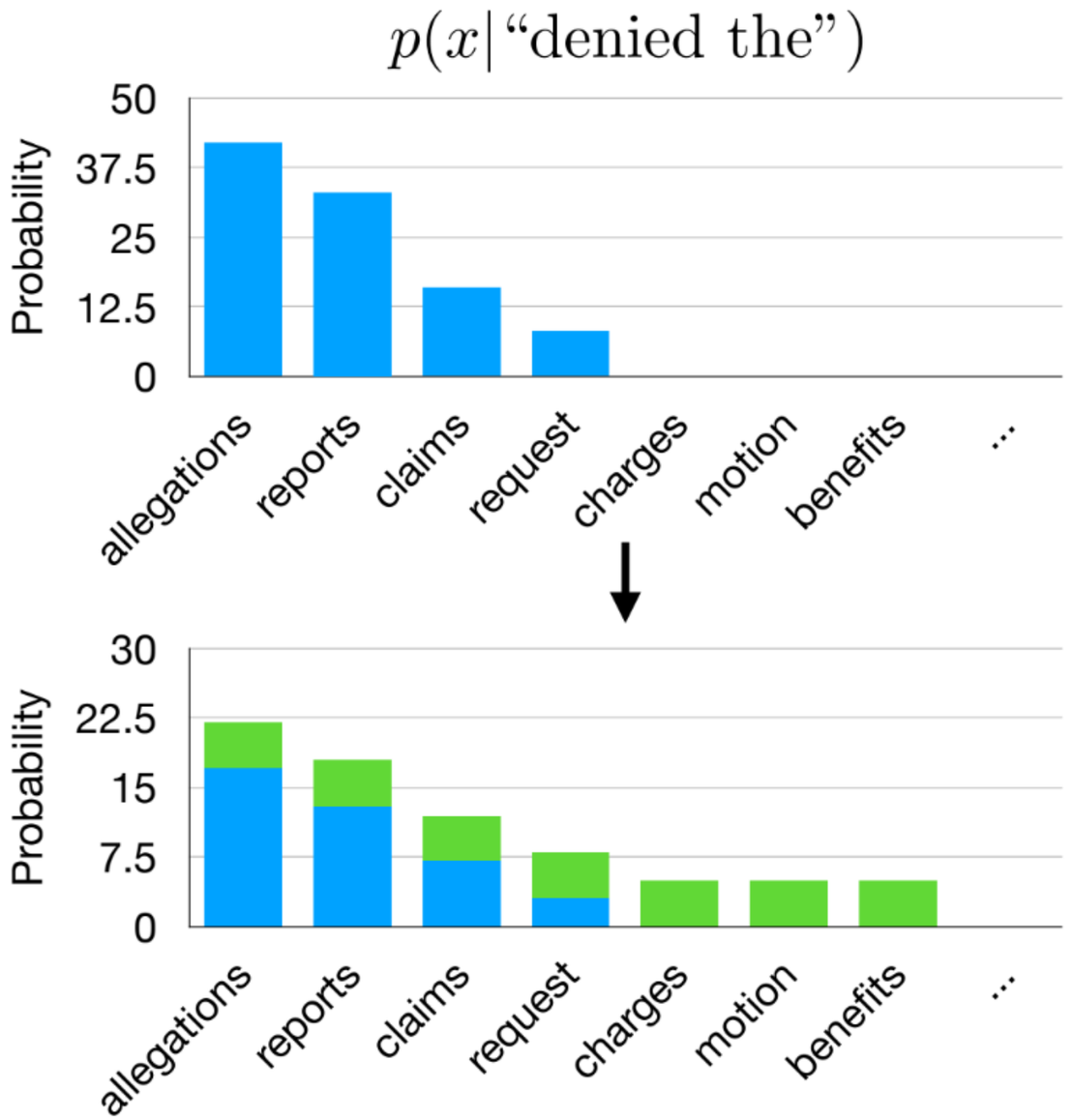
Problem: What if *"students opened their"* never occurred in data? Then we can't calculate probability for *any w*!

(Partial) Solution: Just condition on *"opened their"* instead. This is called *backoff*.

Note: Increasing *n* makes sparsity problems *worse.* Typically, we can't have *n* bigger than 5.

Smoothing (regularization)

- Often want to make estimates from sparse statistics
- Smoothing flattens spiky distributions so they generalize better
- Regularization is very important in NLP (and ML generally), but easy to do badly!
- Question: *what are potential ways to do it?*



Add-one estimation

- Also called *Laplace smoothing*
- Pretend that we saw each word one more time than we did
- Just add one to all the counts!

$$\hat{q}_{\text{MLE}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1}) = \frac{\text{count}_{\mathcal{D}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1})}{\sum_{x_i \in \mathcal{V}'} \text{count}_{\mathcal{D}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1})}$$

$$\hat{q}_{\text{ADD-1}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1}) = \frac{\text{count}_{\mathcal{D}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1}) + 1}{\left[\sum_{x_i \in \mathcal{V}'} \text{count}_{\mathcal{D}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1})\right] + |\mathcal{V}'|}$$

Add-k

- In general, can add do add-k (for $k > 0, k \in \mathbb{R}$)
- Pretend that we saw each word k more times than we did

$$\hat{q}_{\text{ADD-k}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1}) = \frac{\text{count}_{\mathcal{D}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1}) + k}{\left[\sum_{x_i \in \mathcal{V}'} \text{count}_{\mathcal{D}}(x_i \mid x_{i-(N-1)}, \ldots, x_{i-1})\right] + k|\mathcal{V}'|}$$

Storage Problems with n-gram Language Models

Storage: Need to store count for all *n*-grams you saw in the corpus.

$$P(\boldsymbol{w}|\text{students opened their}) = \frac{\text{count}(\text{students opened their } \boldsymbol{w})}{\text{count}(\text{students opened their})}$$

Increasing *n* or increasing corpus increases model size!

n-gram Language Models in practice

- You can build a simple trigram Language Model over a 1.7 million word corpus (Reuters) in a few seconds on your laptop*

Business and financial news

today the _____

get probability distribution

company	0.153
bank	0.153
price	0.077
italian	0.039
emirate	0.039
…	

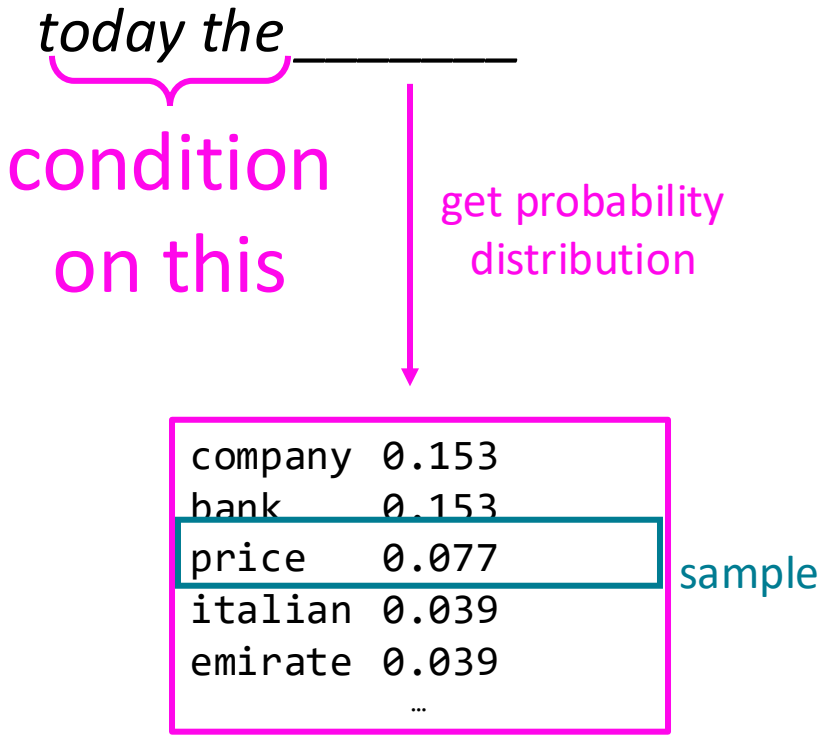
Sparsity problem: not much granularity in the probability distribution

Otherwise, seems reasonable!

*** Try for yourself:** https://nlpforhackers.io/language-models/

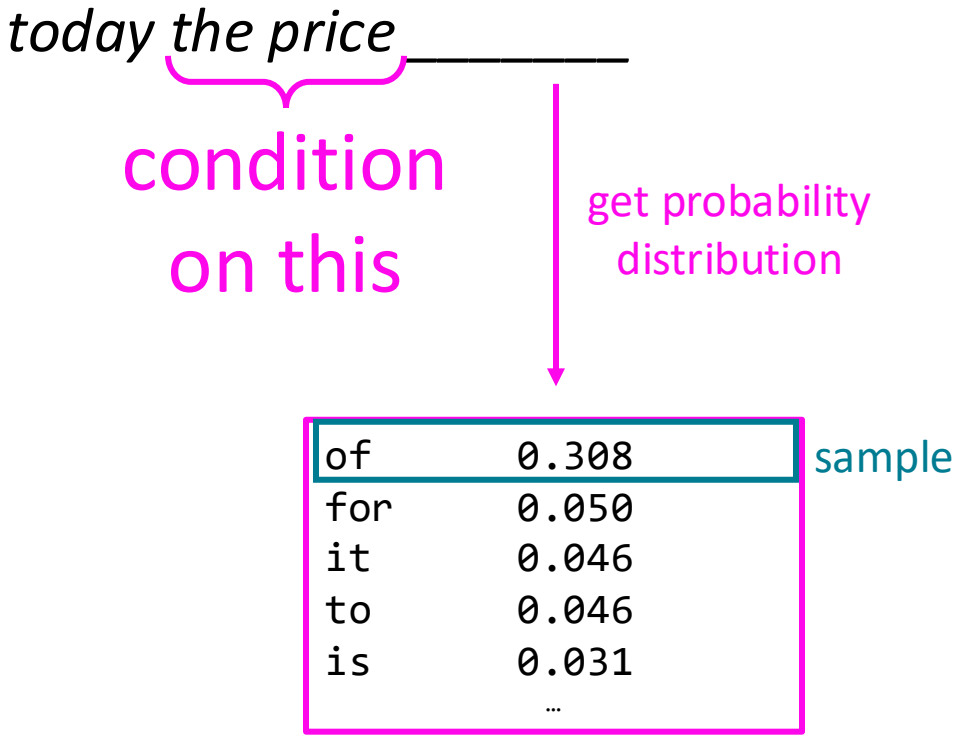
Generating text with a n-gram Language Model

You can also use a Language Model to generate text



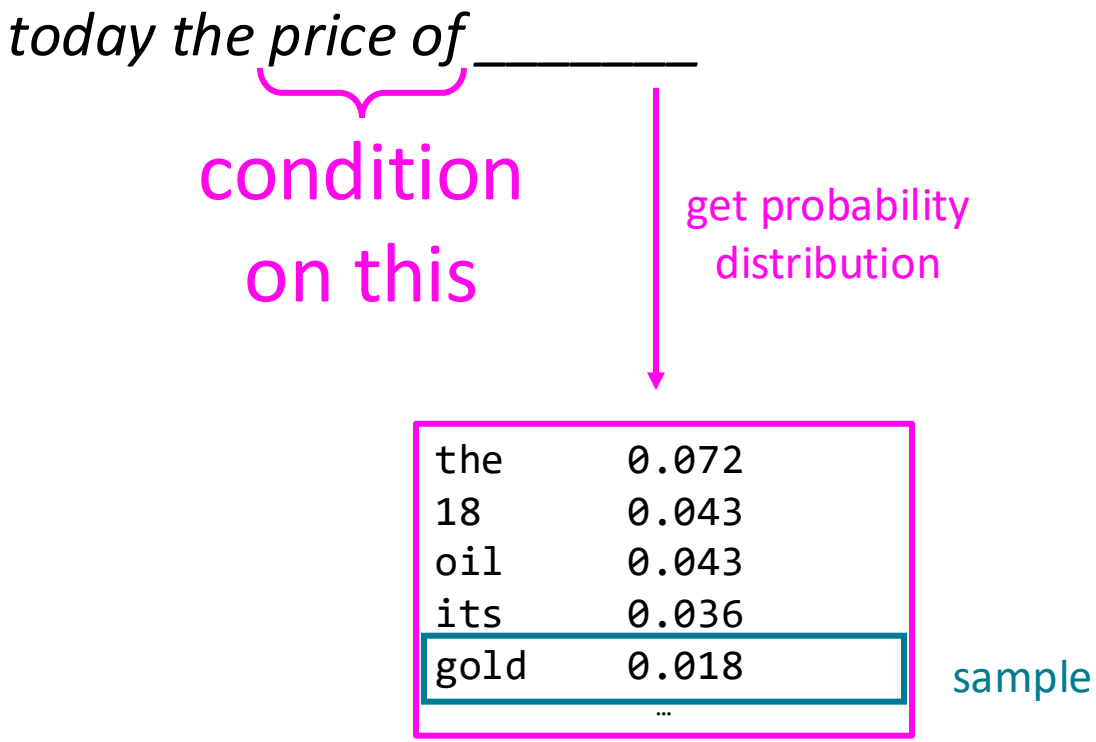
Generating text with a n-gram Language Model

You can also use a Language Model to generate text



Generating text with a n-gram Language Model

You can also use a Language Model to generate text



Generating text with a n-gram Language Model

You can also use a Language Model to generate text

today the price of gold per ton , while production of shoe lasts and shoe industry , the bank intervened just after it considered and rejected an imf demand to rebuild depleted european stocks , sept 30 end primary 76 cts a share .

Surprisingly grammatical!

…but **incoherent.** We need to consider more than three words at a time if we want to model language well.

But increasing *n* worsens sparsity problem, and increases model size…

Evaluating Language Models

- The standard evaluation metric for Language Models is perplexity.

$$\text{perplexity} = \prod_{t=1}^{T} \left(\frac{1}{P_{\text{LM}}(\boldsymbol{x}^{(t+1)} | \ \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})} \right)^{1/T}$$

Normalized by number of words

Inverse probability of corpus, according to Language Model

- This is equal to the exponential of the cross-entropy loss $J(\theta)$:

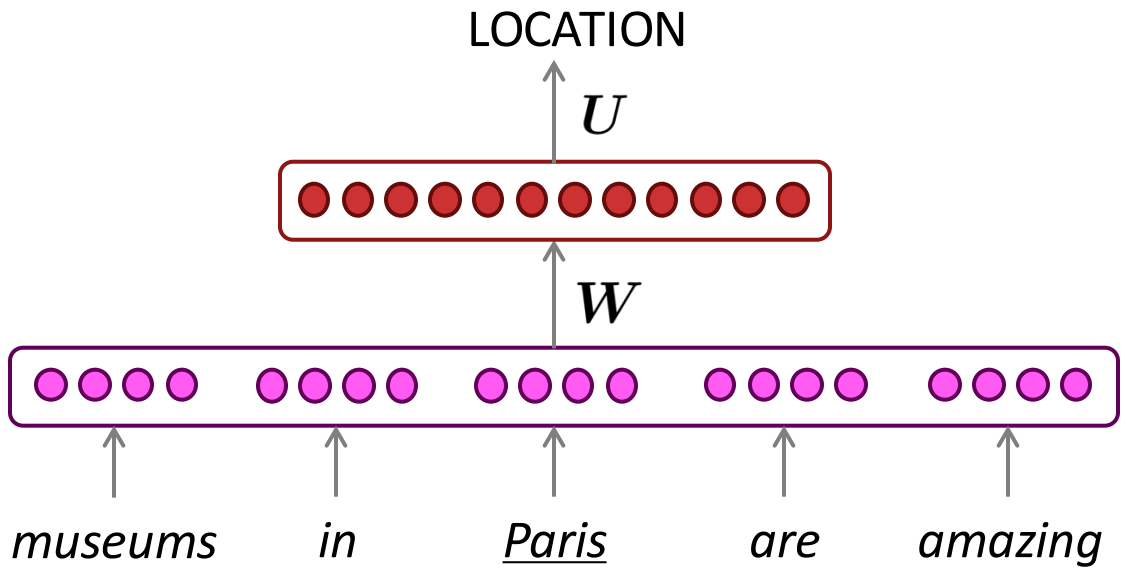
$$= \prod_{t=1}^{T} \left(\frac{1}{\hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}}} \right)^{1/T} = \exp\left(\frac{1}{T} \sum_{t=1}^{T} -\log \hat{\boldsymbol{y}}^{(t)}_{\boldsymbol{x}_{t+1}} \right) = \exp(J(\theta))$$

Lower perplexity is better!

How to build a *neural* language model?

- Recall the Language Modeling task:
  - Input: sequence of words $\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \ldots, \boldsymbol{x}^{(t)}$
  - Output: prob. dist. of the next word $P(\boldsymbol{x}^{(t+1)} | \boldsymbol{x}^{(t)}, \ldots, \boldsymbol{x}^{(1)})$

- How about a window-based neural model?



A fixed-window neural Language Model

~~as the proctor started the clock~~ the students opened their _____

discard

fixed window

A fixed-window neural Language Model

output distribution

$$\hat{\boldsymbol{y}} = \text{softmax}(\boldsymbol{U}\boldsymbol{h} + \boldsymbol{b}_2) \in \mathbb{R}^{|V|}$$

hidden layer

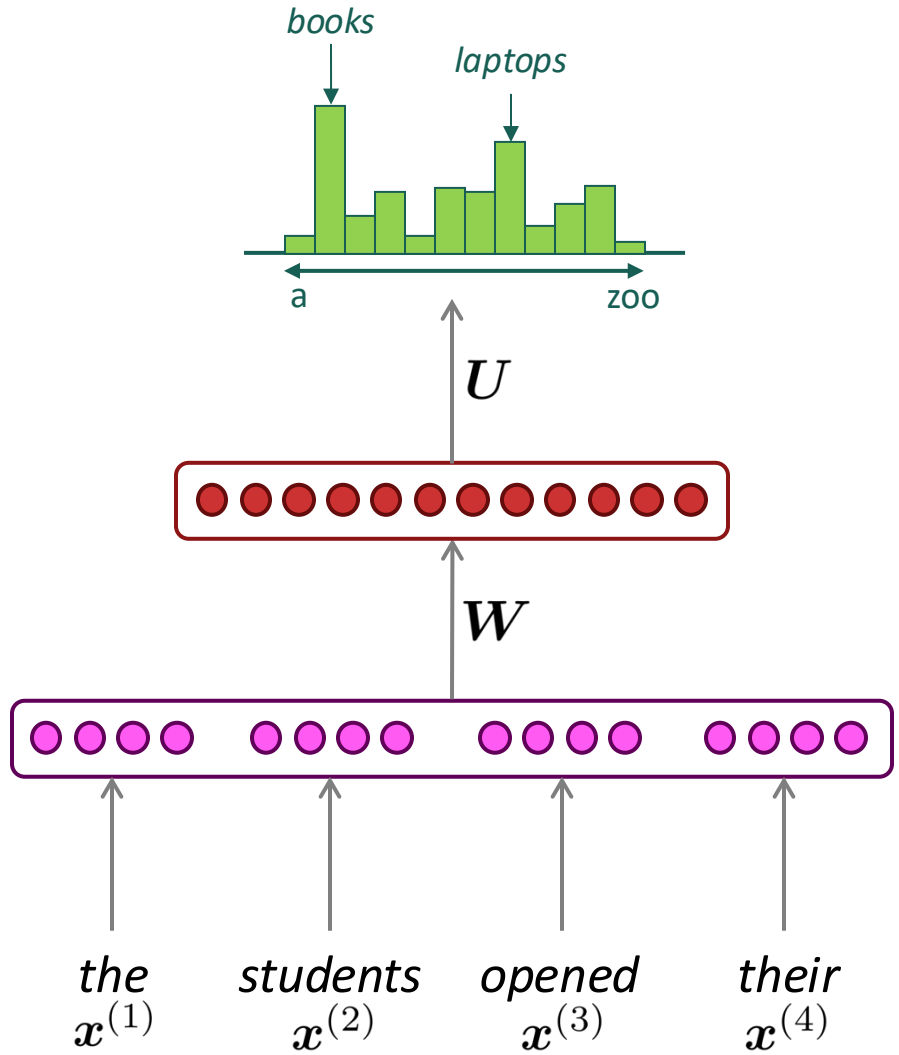
$$\boldsymbol{h} = f(\boldsymbol{W}\boldsymbol{e} + \boldsymbol{b}_1)$$

concatenated word embeddings

$$\boldsymbol{e} = [\boldsymbol{e}^{(1)}; \boldsymbol{e}^{(2)}; \boldsymbol{e}^{(3)}; \boldsymbol{e}^{(4)}]$$

words / one-hot vectors

$$\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \boldsymbol{x}^{(3)}, \boldsymbol{x}^{(4)}$$



A fixed-window neural Language Model

Approximately: Y. Bengio, et al. (2000/2003): A Neural Probabilistic Language Model

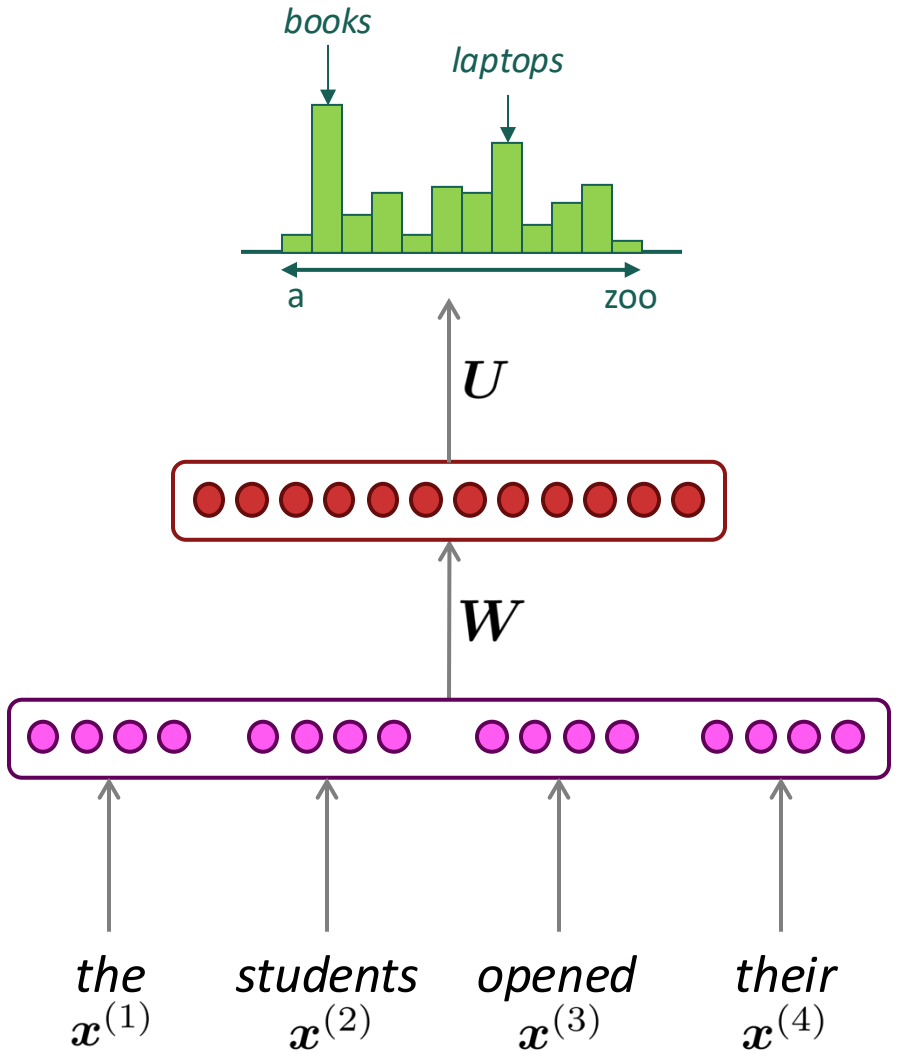
Improvements over *n*-gram LM:

- No sparsity problem
- Don't need to store all observed *n*-grams

Remaining **problems**:

- Fixed window is too small
- Enlarging window enlarges W
- Window can never be large enough!
- $x^{(1)}$ and $x^{(2)}$ are multiplied by completely different weights in W. No symmetry in how the inputs are processed.

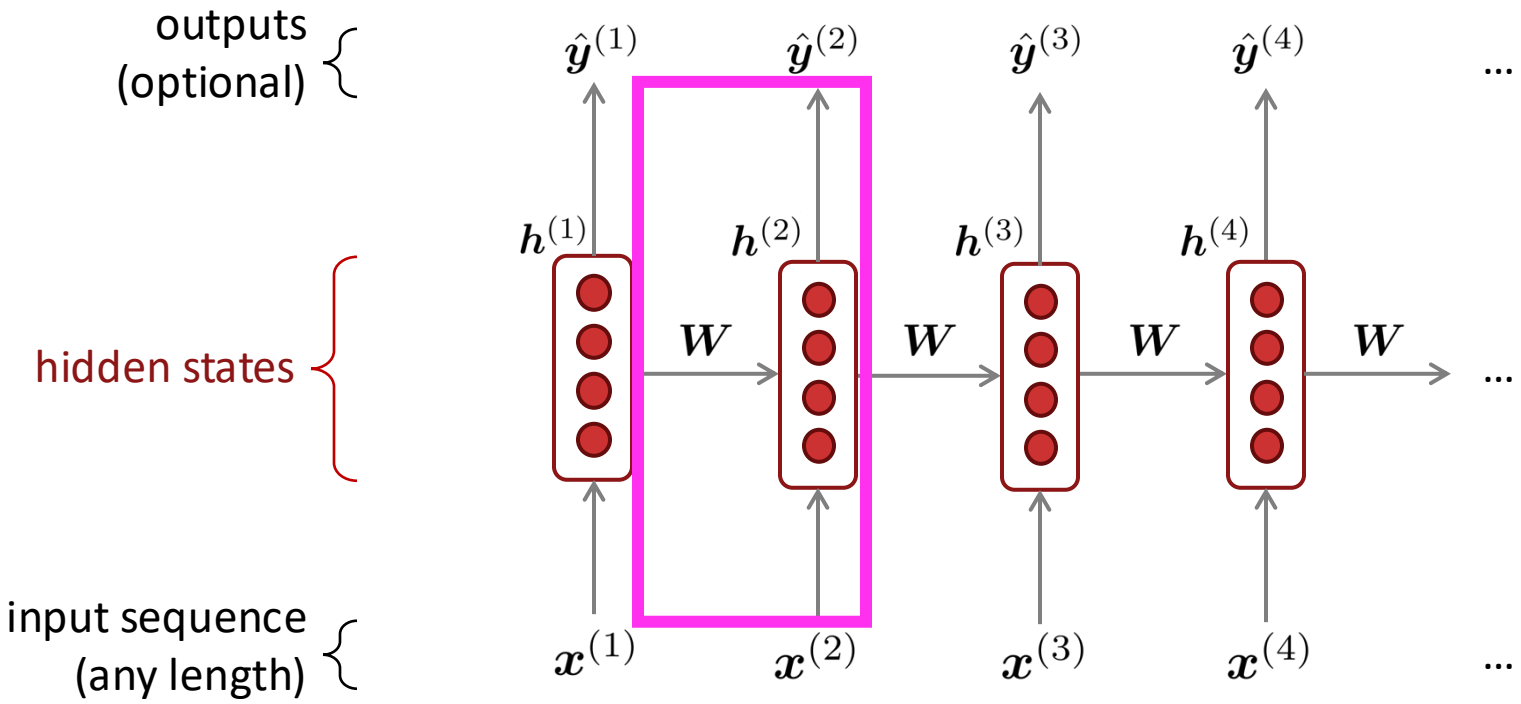
We need a neural architecture that can process *any length input*



2. Recurrent Neural Networks (RNN)

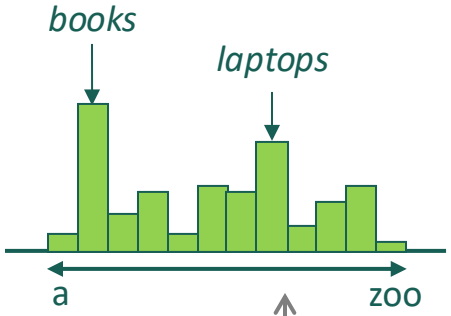
A family of neural architectures

Core idea: Apply the same weights *W repeatedly*



A Simple RNN Language Model

$\hat{\boldsymbol{y}}^{(4)} = P(\boldsymbol{x}^{(5)}|\text{the students opened their})$



output distribution

$$\hat{\boldsymbol{y}}^{(t)} = \text{softmax}\left(\boldsymbol{U}\boldsymbol{h}^{(t)} + \boldsymbol{b}_2\right) \in \mathbb{R}^{|V|}$$

hidden states

$$\boldsymbol{h}^{(t)} = \sigma\left(\boldsymbol{W}_h\boldsymbol{h}^{(t-1)} + \boldsymbol{W}_e\boldsymbol{e}^{(t)} + \boldsymbol{b}_1\right)$$

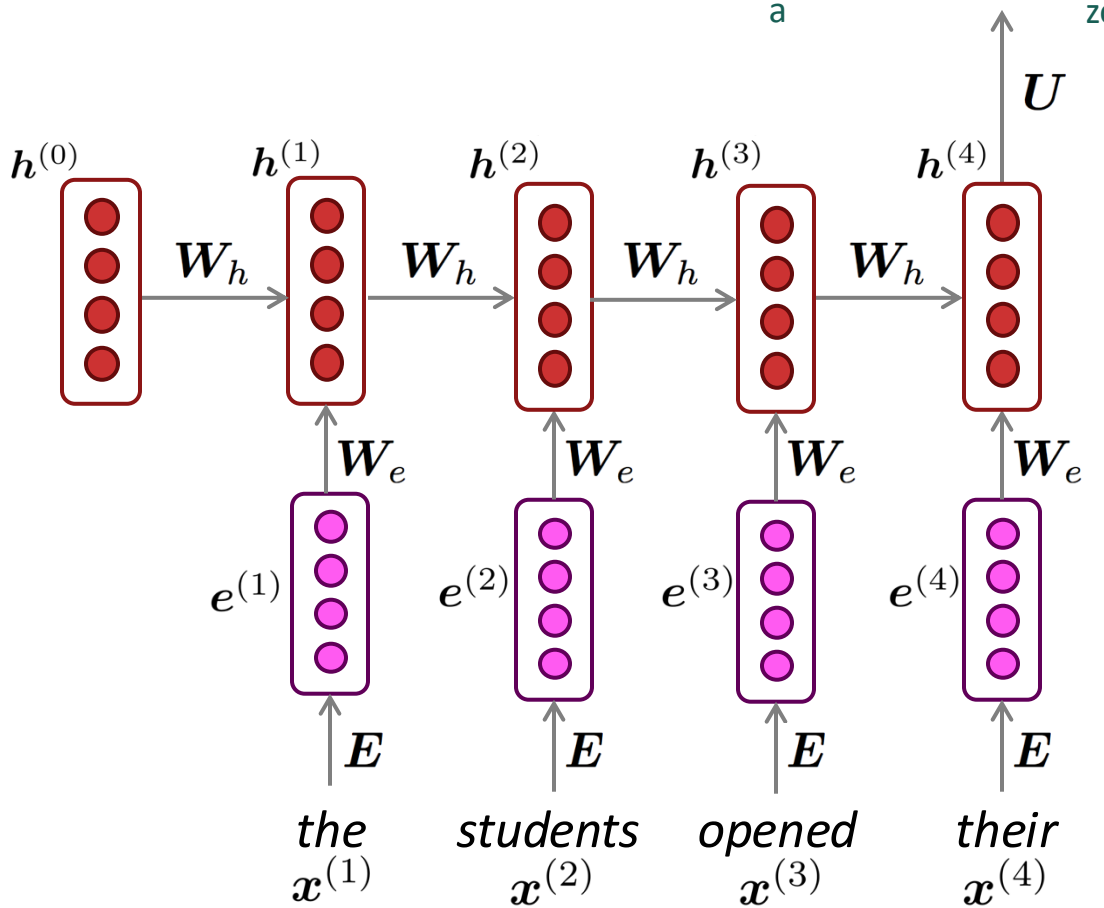
$\boldsymbol{h}^{(0)}$ is the initial hidden state

word embeddings

$$\boldsymbol{e}^{(t)} = \boldsymbol{E}\boldsymbol{x}^{(t)}$$

words / one-hot vectors

$$\boldsymbol{x}^{(t)} \in \mathbb{R}^{|V|}$$



***Note**: this input sequence could be much longer now!*

RNN Language Models

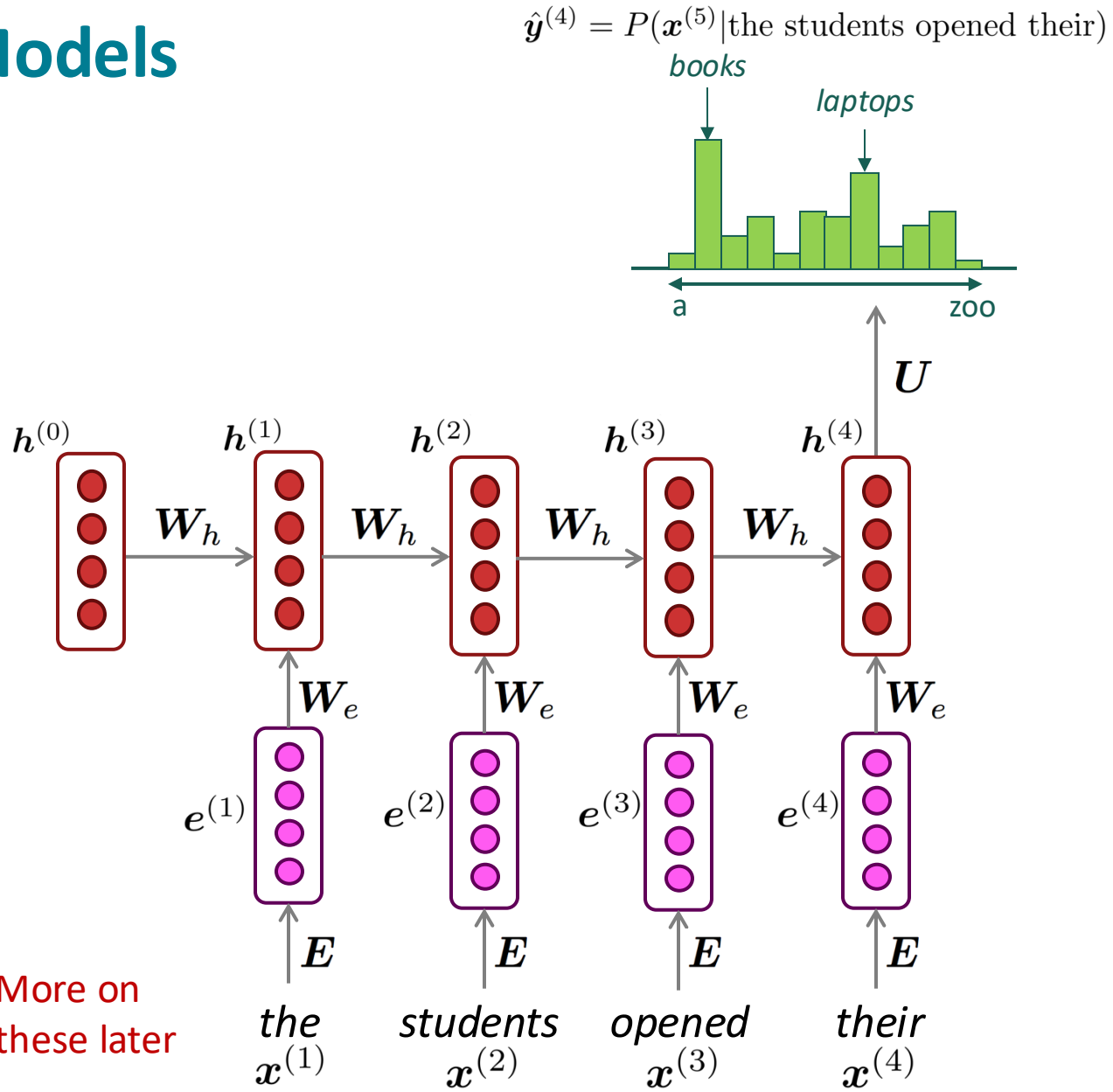
RNN **Advantages**:

- Can process any length input
- Computation for step *t* can (in theory) use information from many steps back
- Model size doesn't increase for longer input context
- Same weights applied on every timestep, so there is symmetry in how inputs are processed.

RNN **Disadvantages**:

- Recurrent computation is slow
- In practice, difficult to access information from many steps back

More on these later



Training an RNN Language Model

- Get a big corpus of text which is a sequence of words $x^{(1)}, \ldots, x^{(T)}$
- Feed into RNN-LM; compute output distribution $\hat{\boldsymbol{y}}^{(t)}$ for *every step t*.
  - i.e., predict probability dist of *every word*, given words so far

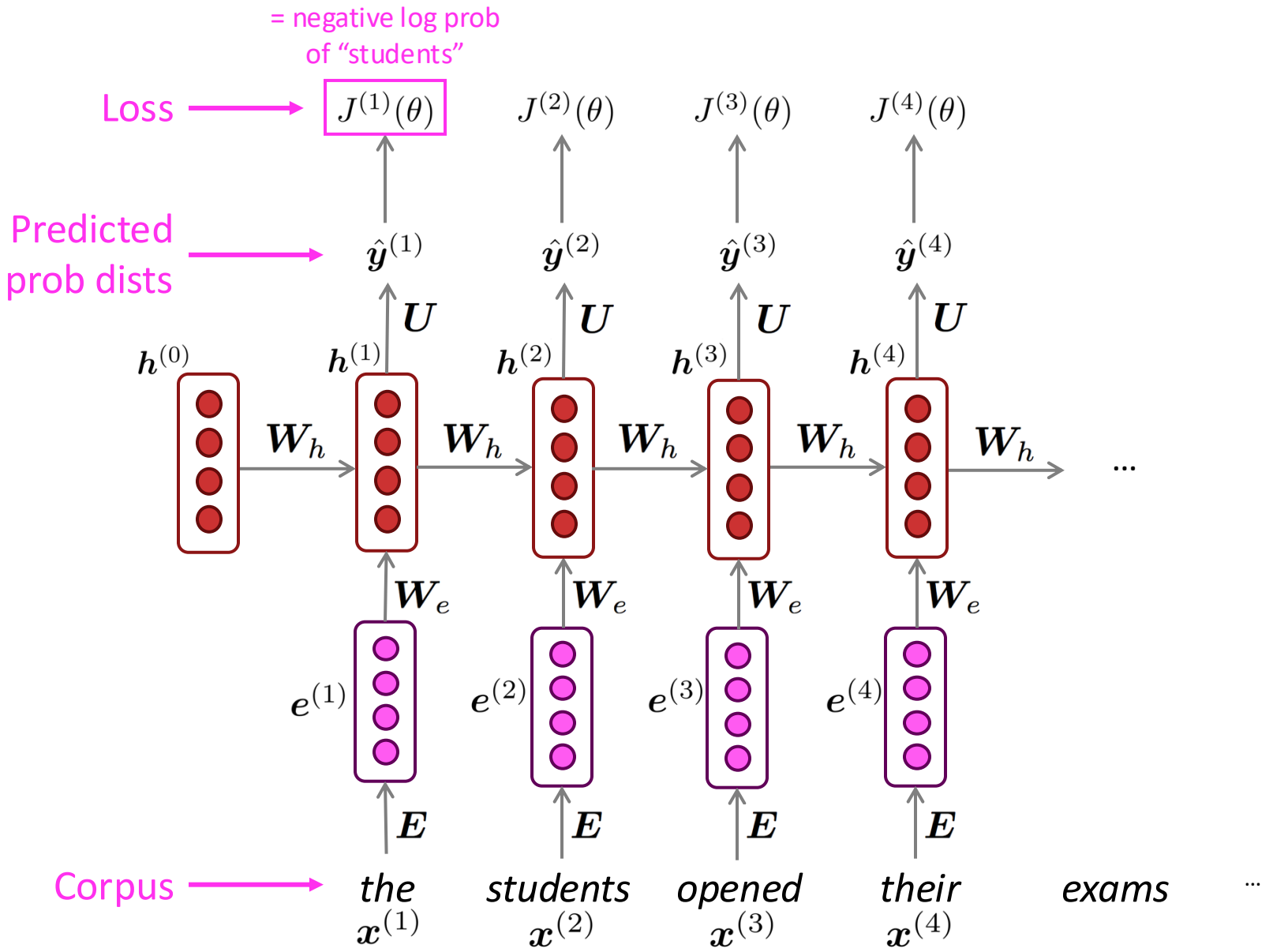
- Loss function on step *t* is cross-entropy between predicted probability distribution $\hat{\boldsymbol{y}}^{(t)}$, and the true next word $\boldsymbol{y}^{(t)}$ (one-hot for $\boldsymbol{x}^{(t+1)}$):

$$J^{(t)}(\theta) = CE(\boldsymbol{y}^{(t)}, \hat{\boldsymbol{y}}^{(t)}) = -\sum_{w \in V} \boldsymbol{y}_w^{(t)} \log \hat{\boldsymbol{y}}_w^{(t)} = -\log \hat{\boldsymbol{y}}_{\boldsymbol{x}_{t+1}}^{(t)}$$

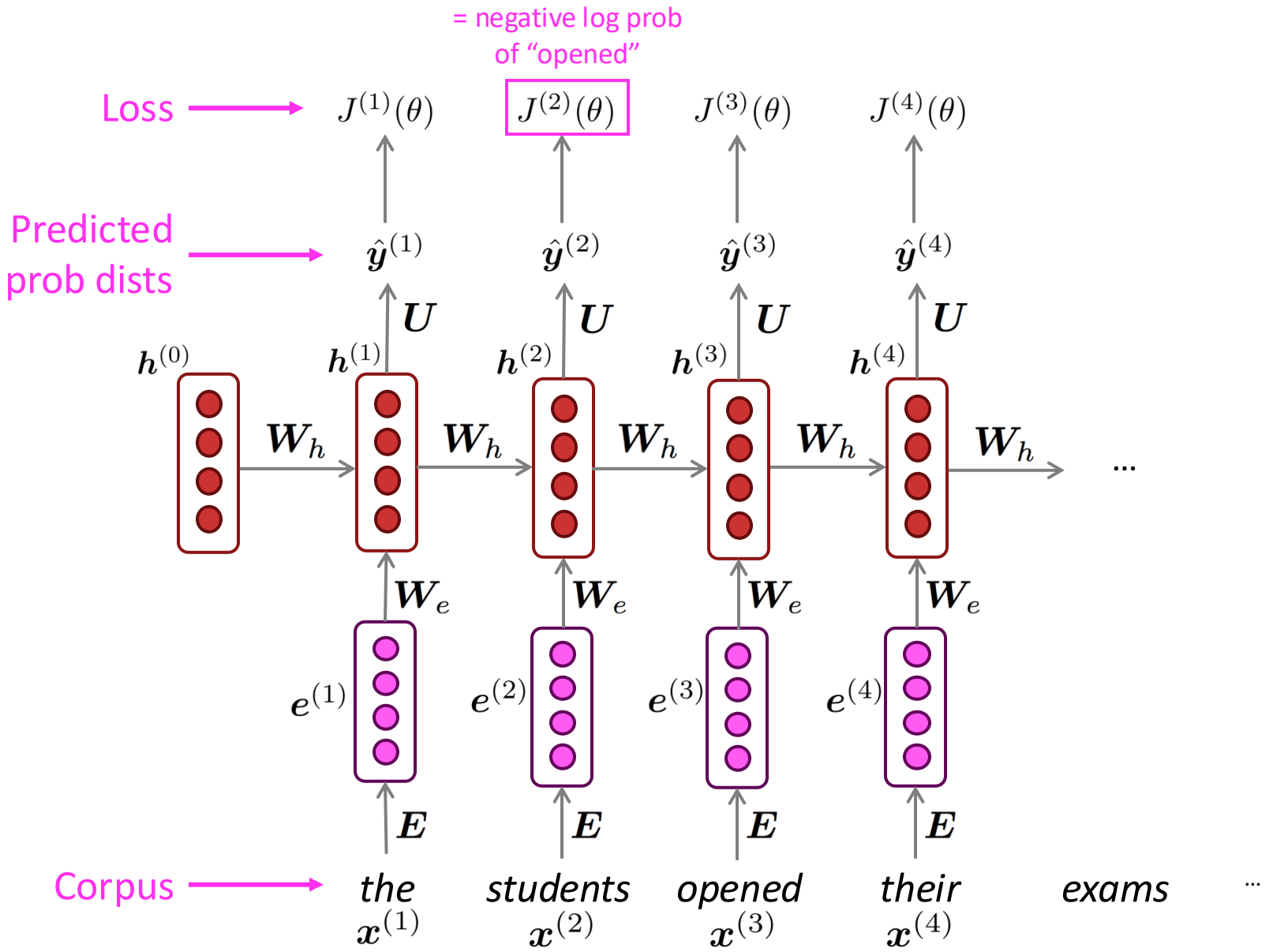
- Average this to get overall loss for entire training set:

$$J(\theta) = \frac{1}{T} \sum_{t=1}^{T} J^{(t)}(\theta) = \frac{1}{T} \sum_{t=1}^{T} -\log \hat{\boldsymbol{y}}_{\boldsymbol{x}_{t+1}}^{(t)}$$

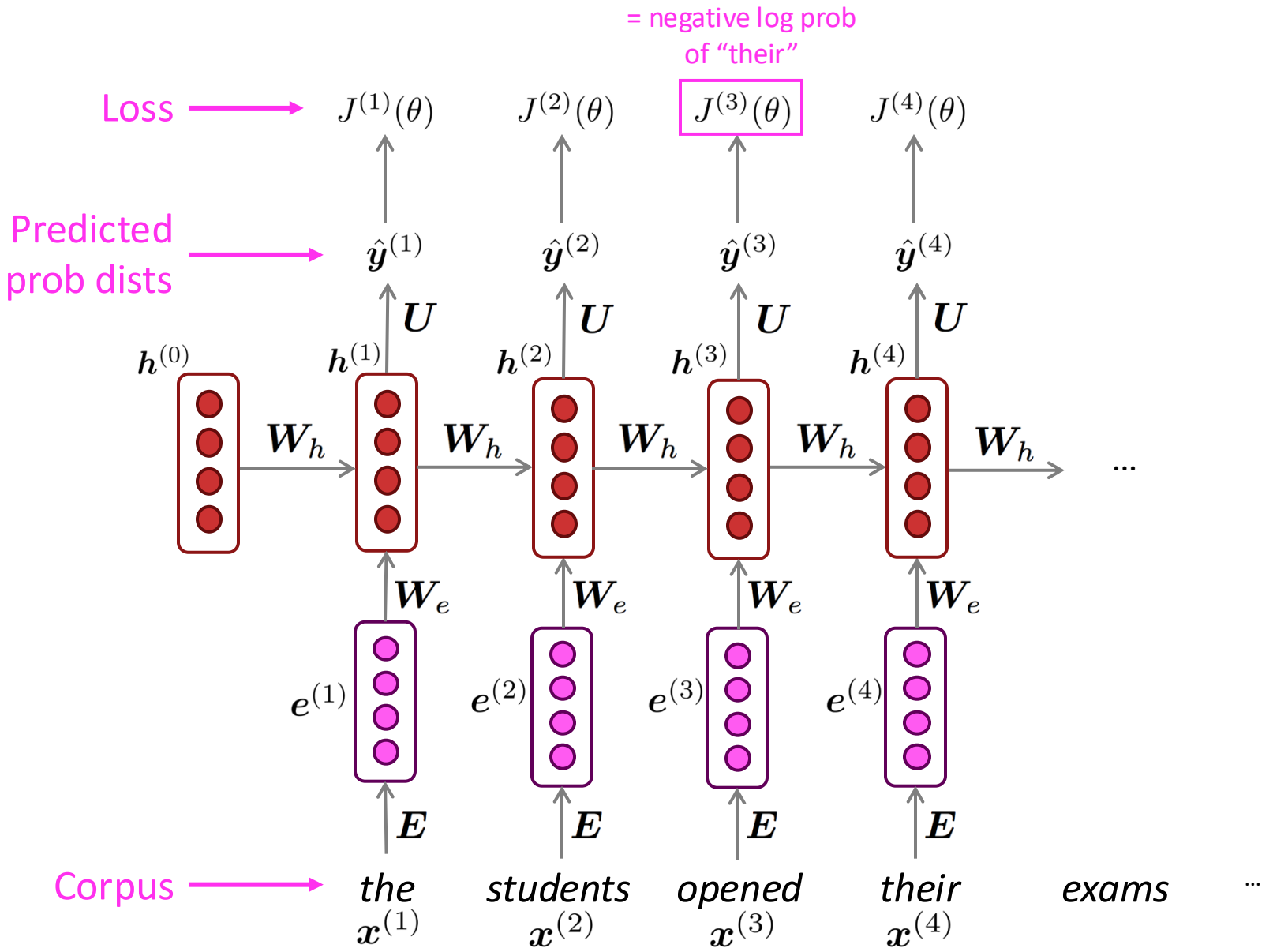
Training an RNN Language Model



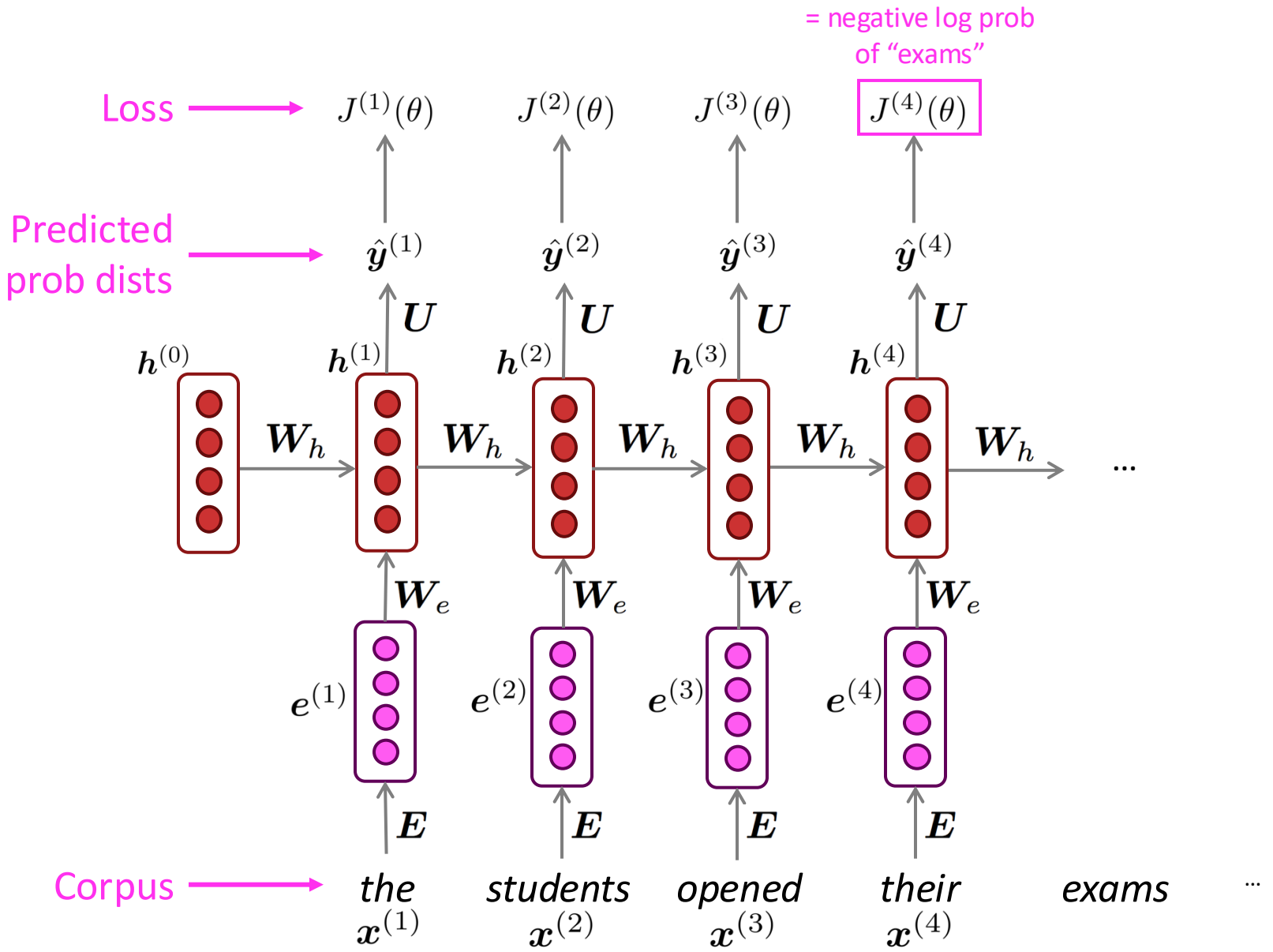
Training an RNN Language Model



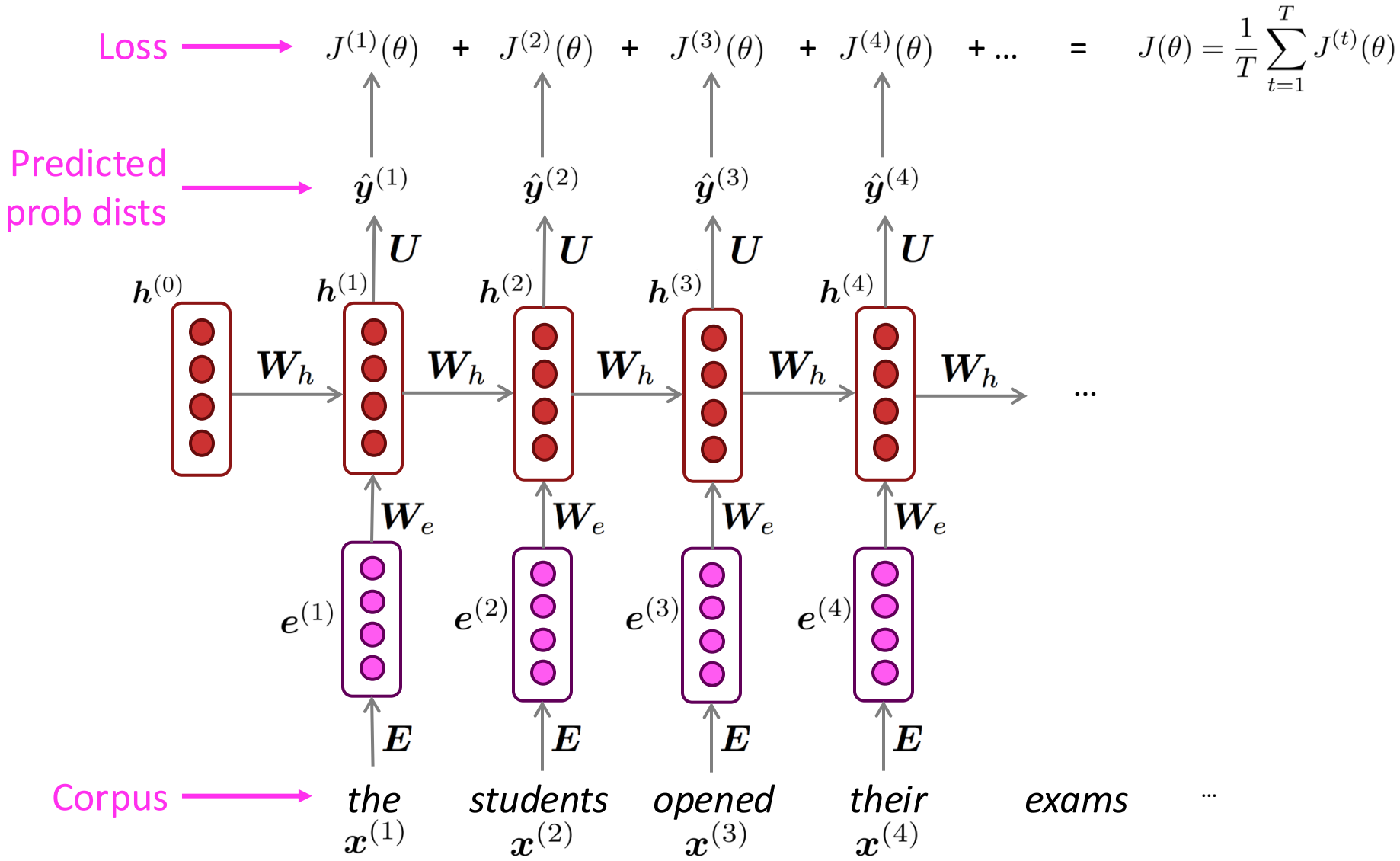
Training an RNN Language Model



Training an RNN Language Model



Training an RNN Language Model



Training a RNN Language Model

- However: Computing loss and gradients across entire corpus $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}$ at once is too expensive (memory-wise)!

$$J(\theta) = \frac{1}{T} \sum_{t=1}^{T} J^{(t)}(\theta)$$

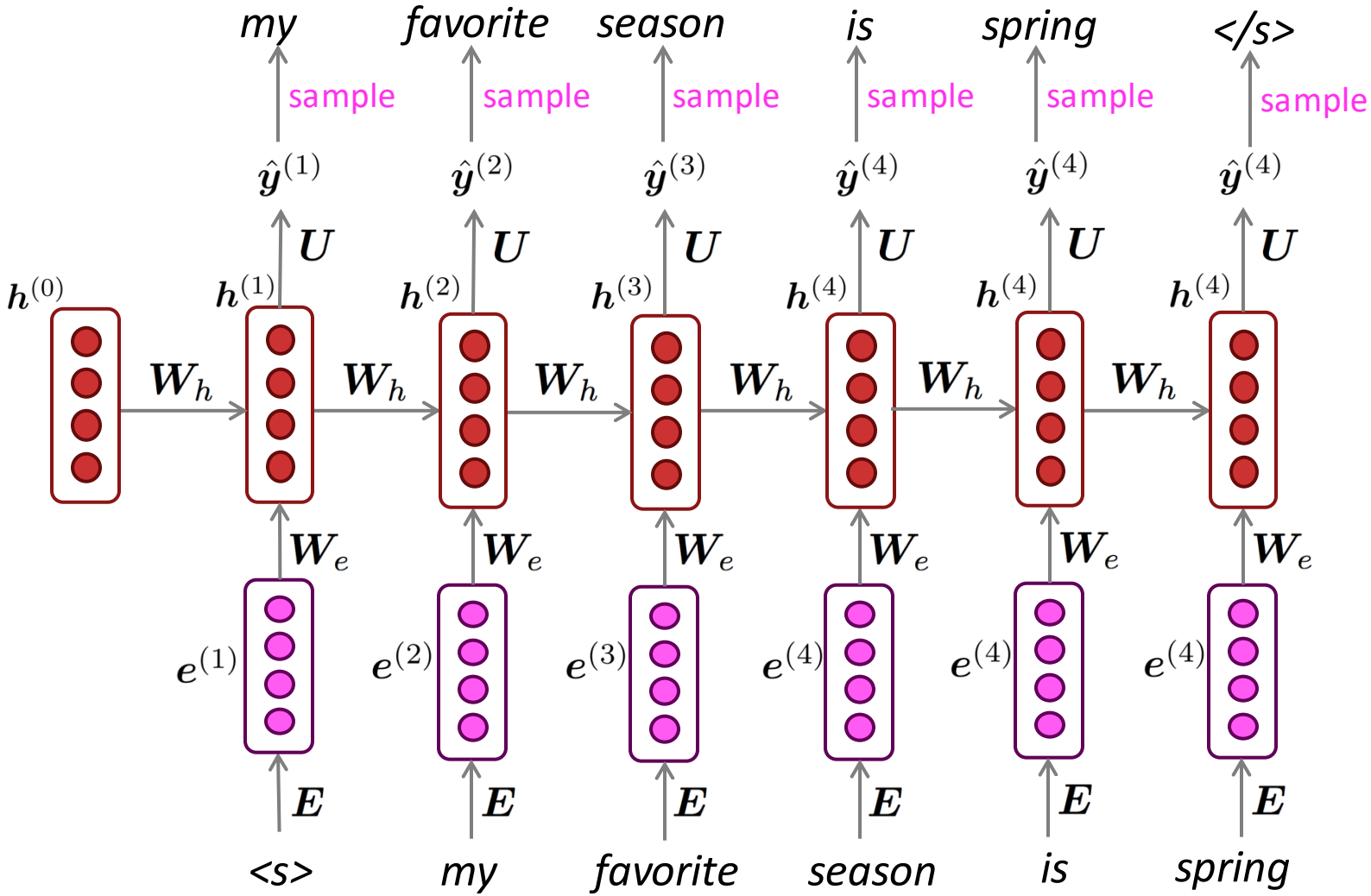
- In practice, consider $\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(T)}$ as a sentence (or a document)

- Recall: Stochastic Gradient Descent allows us to compute loss and gradients for small chunk of data, and update.

- Compute loss $J(\theta)$ for a sentence (actually, a batch of sentences), compute gradients and update weights. Repeat on a new batch of sentences.

Generating with an RNN Language Model ("Generating roll outs")

Just like an n-gram Language Model, you can use a RNN Language Model to generate text by repeated sampling. Sampled output becomes next step's input.

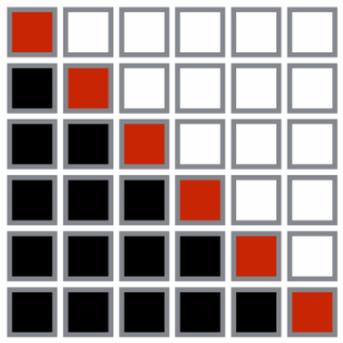


Types of Unconditioned Prediction

Left-to-right Autoregressive Prediction

$$P(X) = \prod_{i=1}^{|X|} P(x_i | x_1, \ldots, x_{i-1})$$

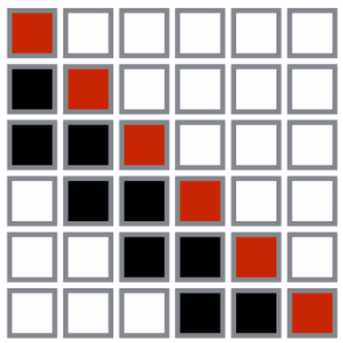
(e.g. RNN or Transformer LM)



Left-to-right Markov Chain (order n-1*)*

$$P(X) = \prod_{i=1}^{|X|} P(x_i | x_{i-n+1}, \ldots, x_{i-1})$$

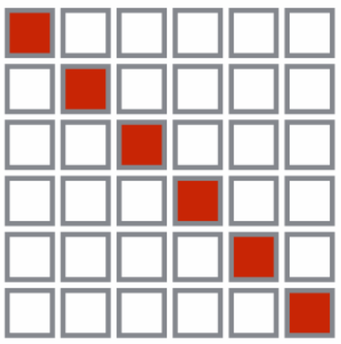
(e.g. n-gram LM, feed-forward LM)



Independent Prediction

$$P(X) = \prod_{i=1}^{|X|} P(x_i)$$

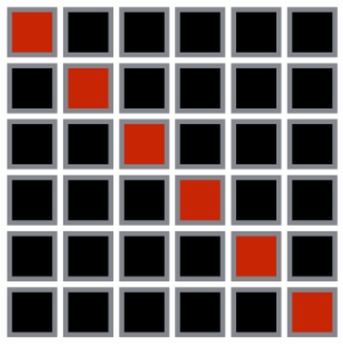
(e.g. unigram model)



Bidirectional Prediction

$$P(X) \neq \prod_{i=1}^{|X|} P(x_i | x_{\neq i})$$

(e.g. masked language model)



Generating text with an RNN Language Model

Let's have some fun!

- You can train an RNN-LM on any kind of text, then generate text in that style.
- RNN-LM trained on *Harry Potter*:

"Sorry," Harry shouted, panicking—"I'll leave those brooms in London, are they?"

"No idea," said Nearly Headless Nick, casting low close by Cedric, carrying the last bit of treacle Charms, from Harry's shoulder, and to answer him the common room perched upon it, four arms held a shining knob from when the spider hadn't felt it seemed. He reached the teams too.

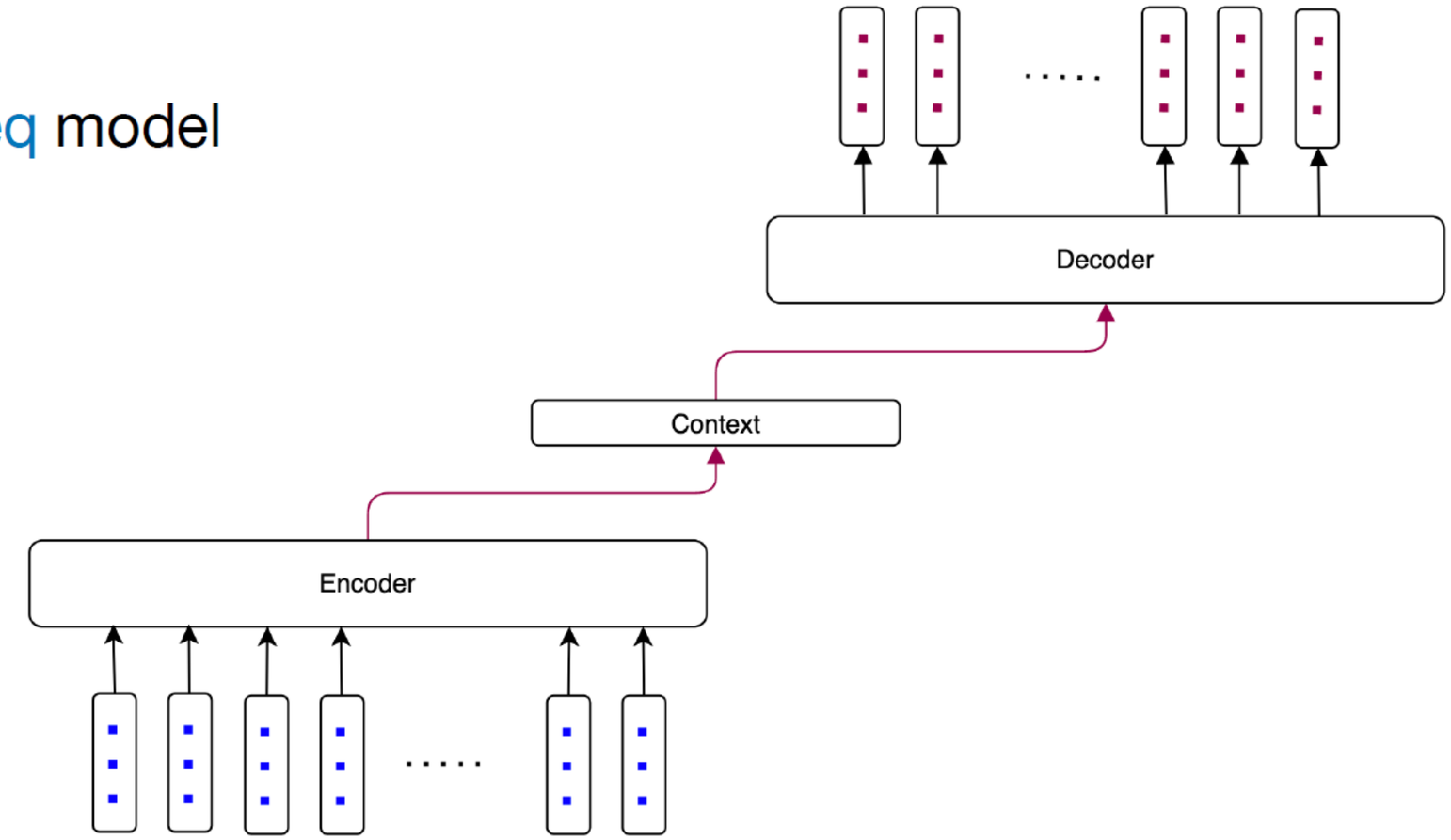
Source: https://medium.com/deep-writing/harry-potter-written-by-artificial-intelligence-8a9431803da6

4. Recap

- **Language Model**: A system that predicts the next word
- **Recurrent Neural Network**: A family of neural networks that:
  - Take sequential input of any length
  - Apply the same weights on each step
  - Can optionally produce output on each step
- Recurrent Neural Network ≠ Language Model
- We've shown that RNNs are a great way to build a LM (despite some problems)
- RNNs – still relevant today with the rise of *state space models*

Basic Idea of encoder–decoder

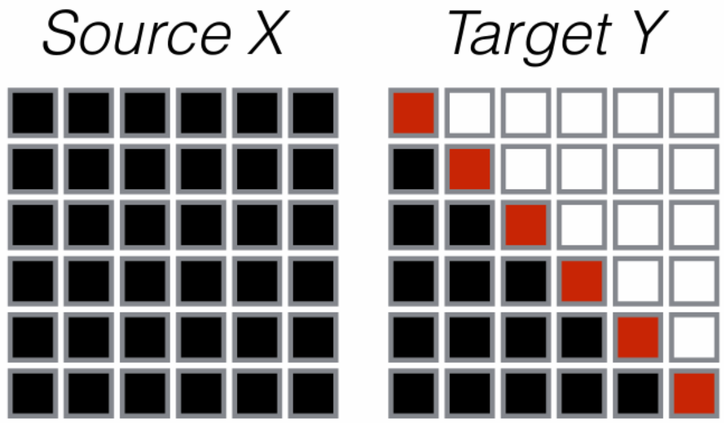
- The encoder encodes the input into a context vector
- The decoder produces task-specific output given the context
  - Output: contextually relevant, variable-length
- Also known as seq-to-seq model



Types of Conditioned Prediction

Autoregressive Conditioned Prediction

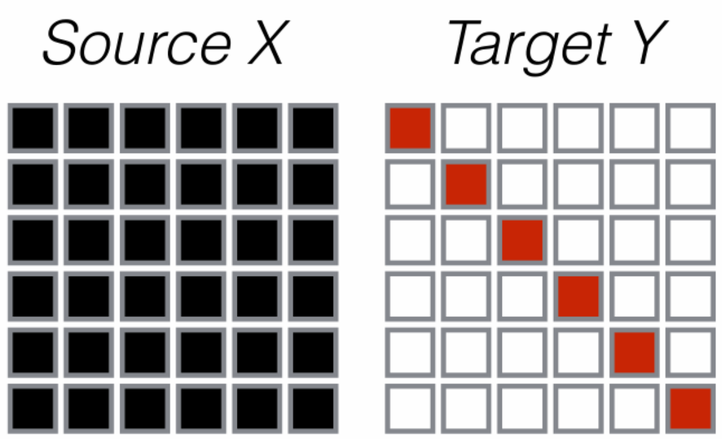
$$P(Y|X) = \prod_{i=1}^{|Y|} P(y_i|X, y_1, \ldots, y_{i-1})$$



(e.g. seq2seq model)

Non-autoregressive Conditioned Prediction

$$P(Y|X) = \prod_{i=1}^{|Y|} P(y_i|X)$$

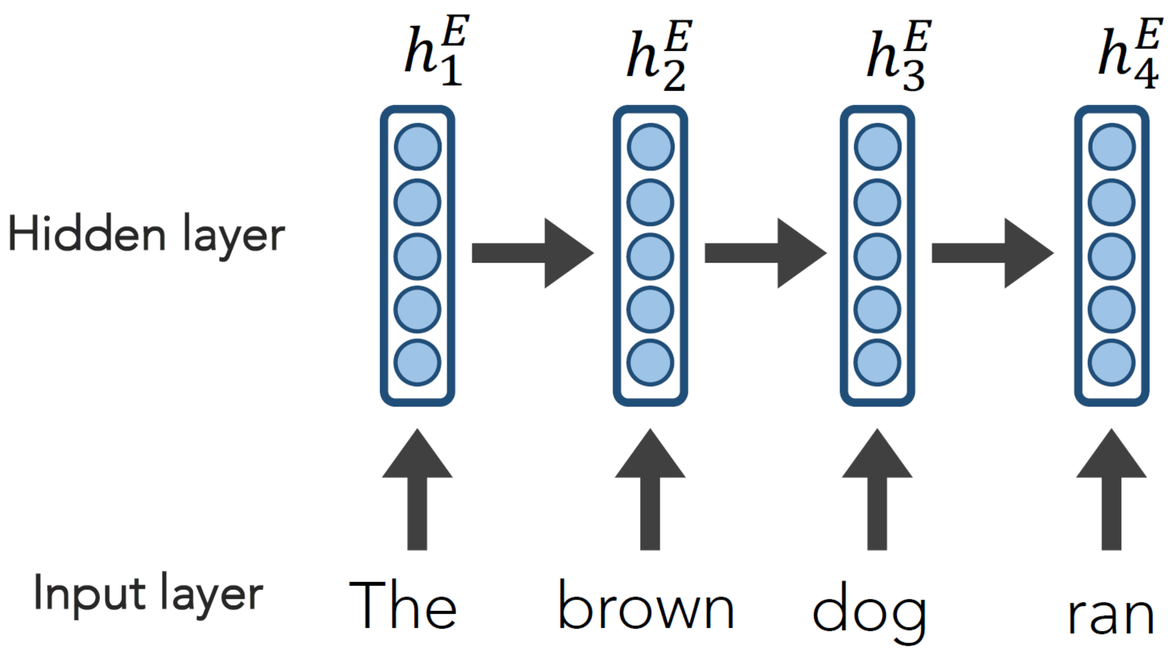


(e.g. sequence labeling, non-autoregressive MT)

Sequence-to-Sequence (seq2seq)

- If our input is a sentence in Language A, and we wish to translate it to Language B, it is clearly sub-optimal to translate word by word (like our current models are suited to do).
- Instead, let a ***sequence*** of tokens be the unit that we ultimately wish to work with (a sequence of length **N** may emit a sequences of length **M**)
- seq2seq models are comprised of **2 RNNs**: 1 encoder, 1 decoder

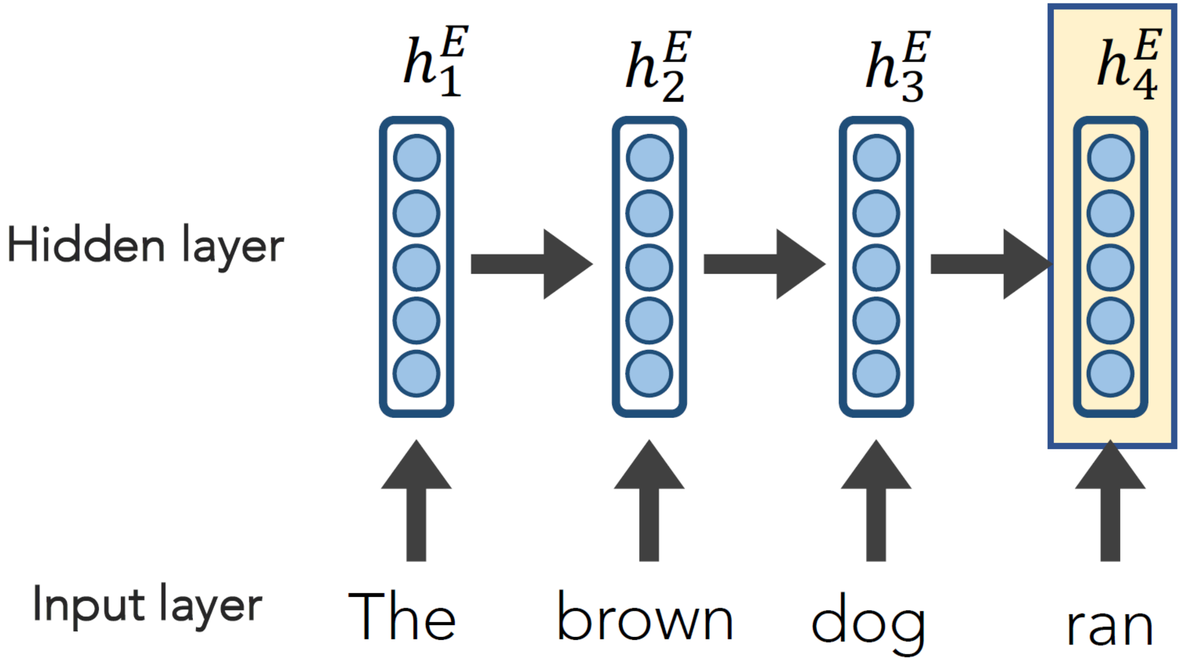
Sequence-to-Sequence (seq2seq)



ENCODER RNN

Sequence-to-Sequence (seq2seq)

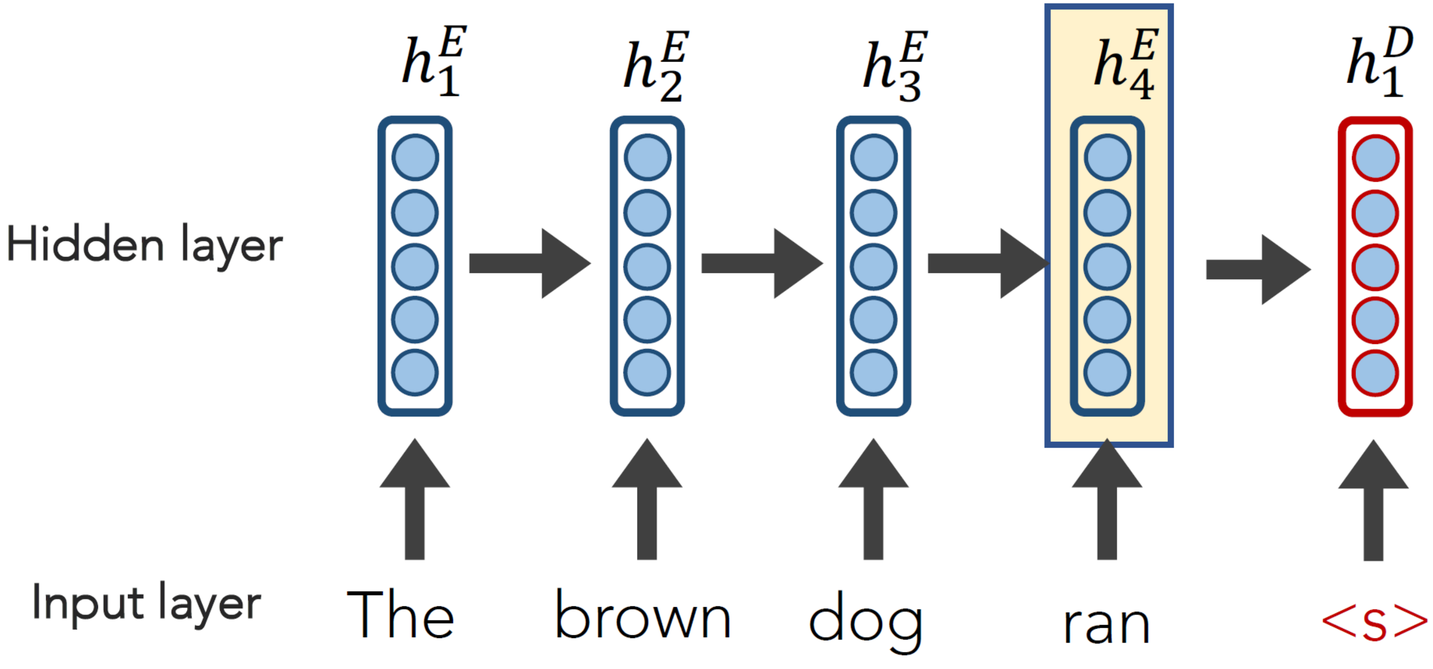
The final hidden state of the encoder RNN
is the initial state of the decoder RNN



ENCODER RNN

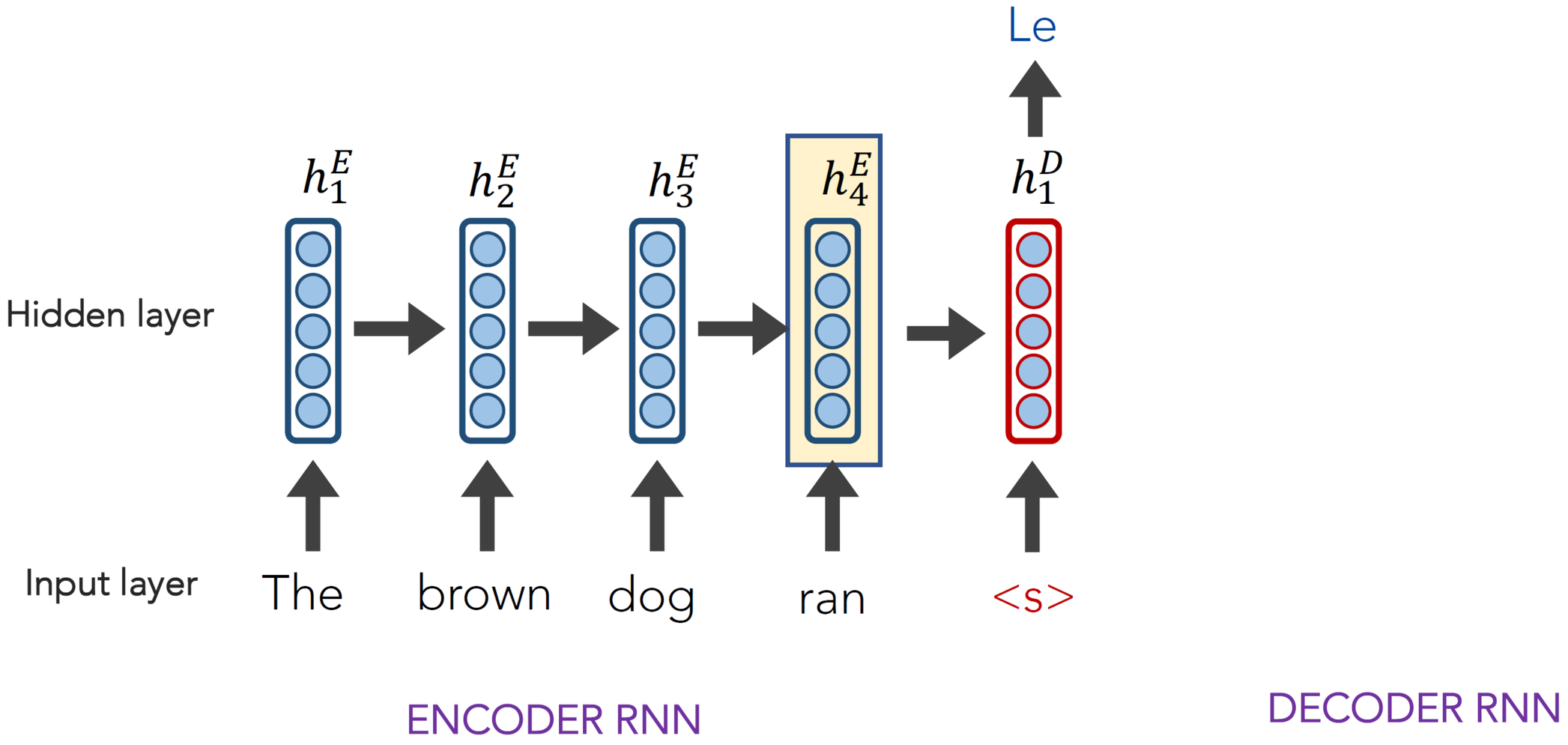
Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN



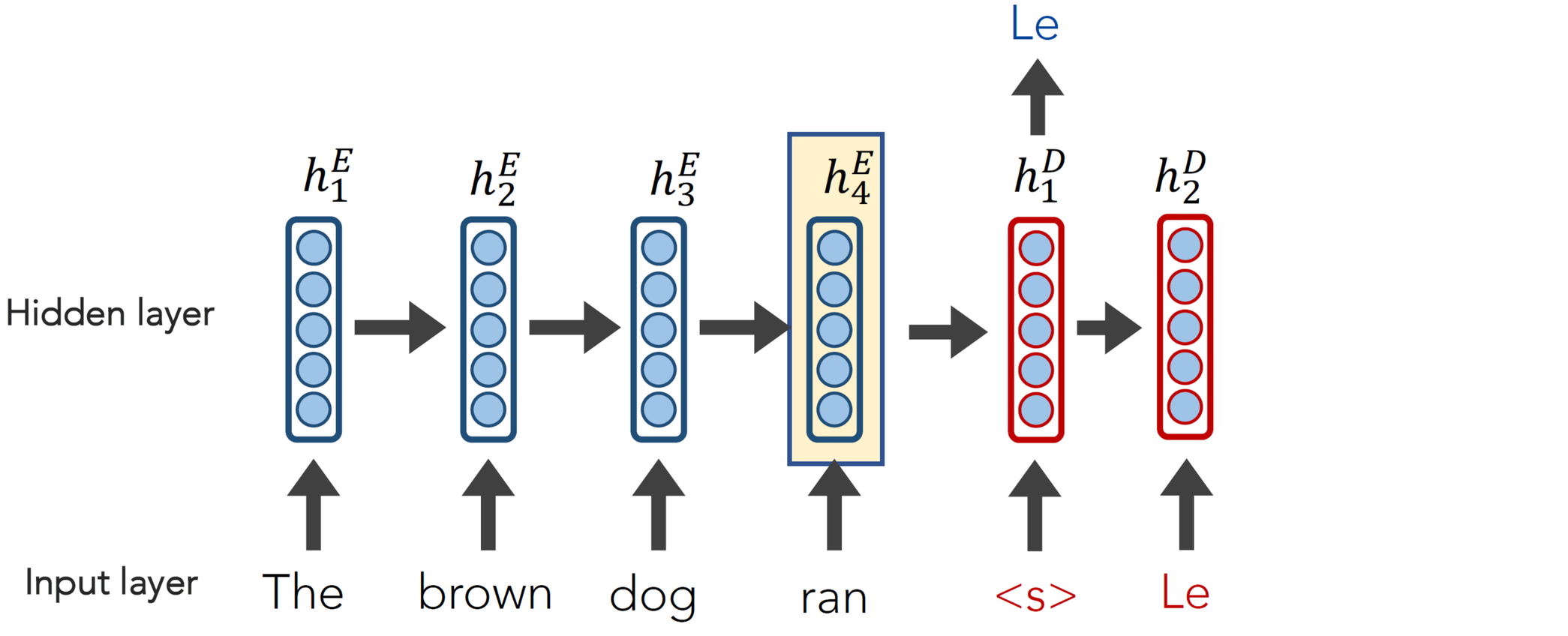
Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN



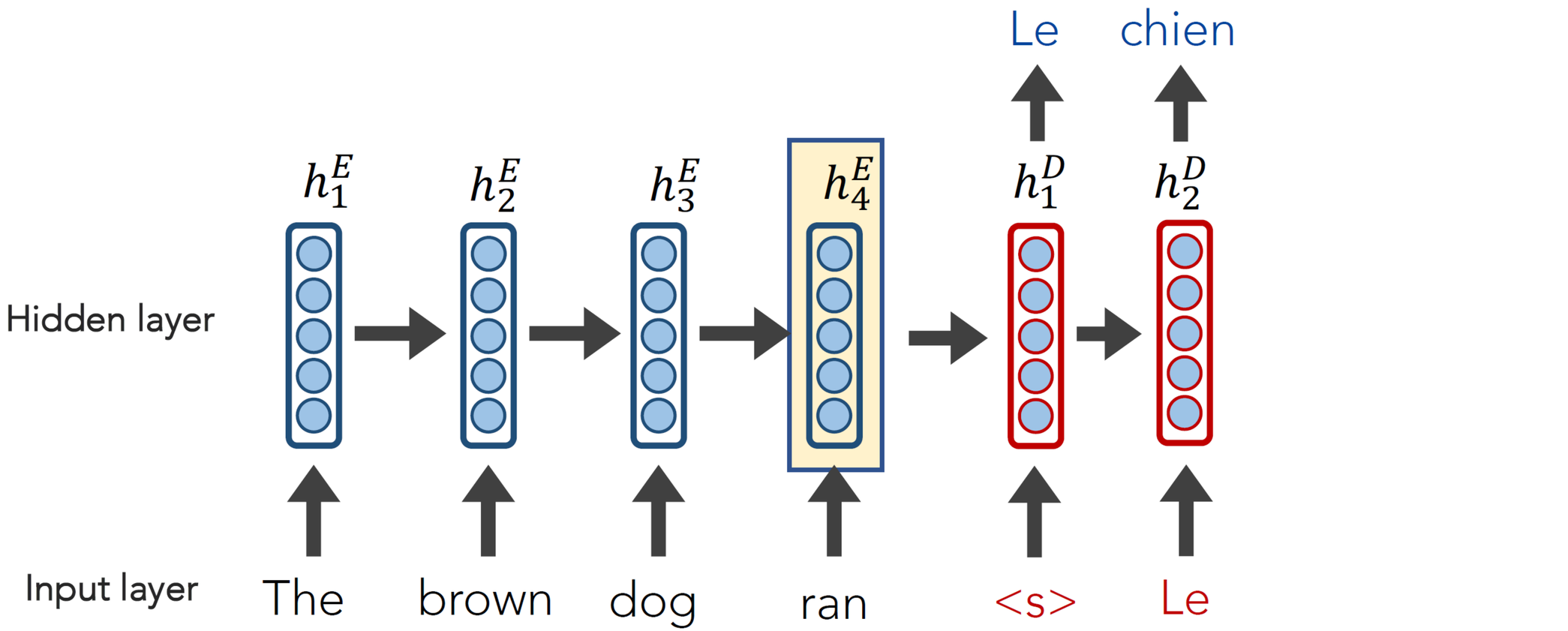
Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN



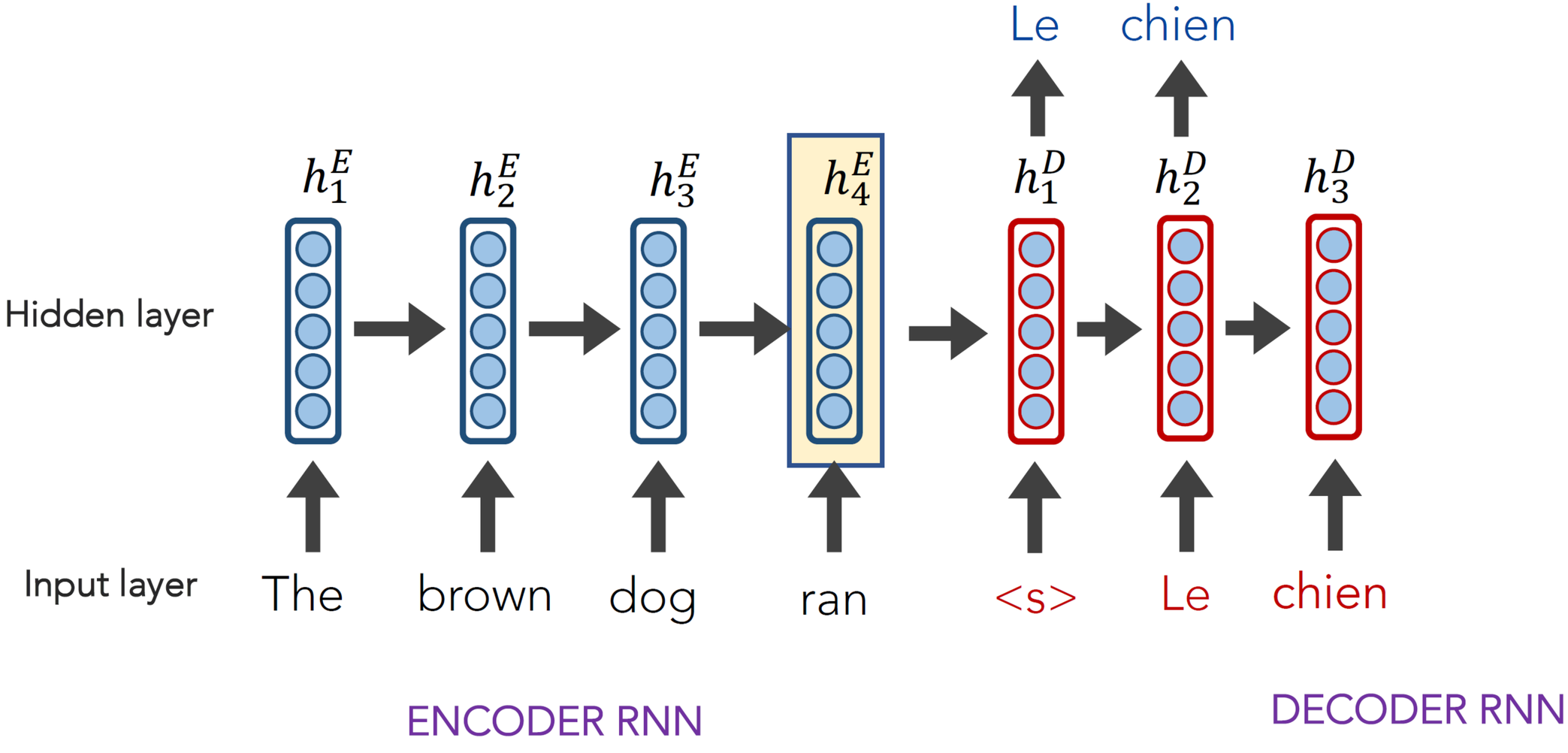
Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN

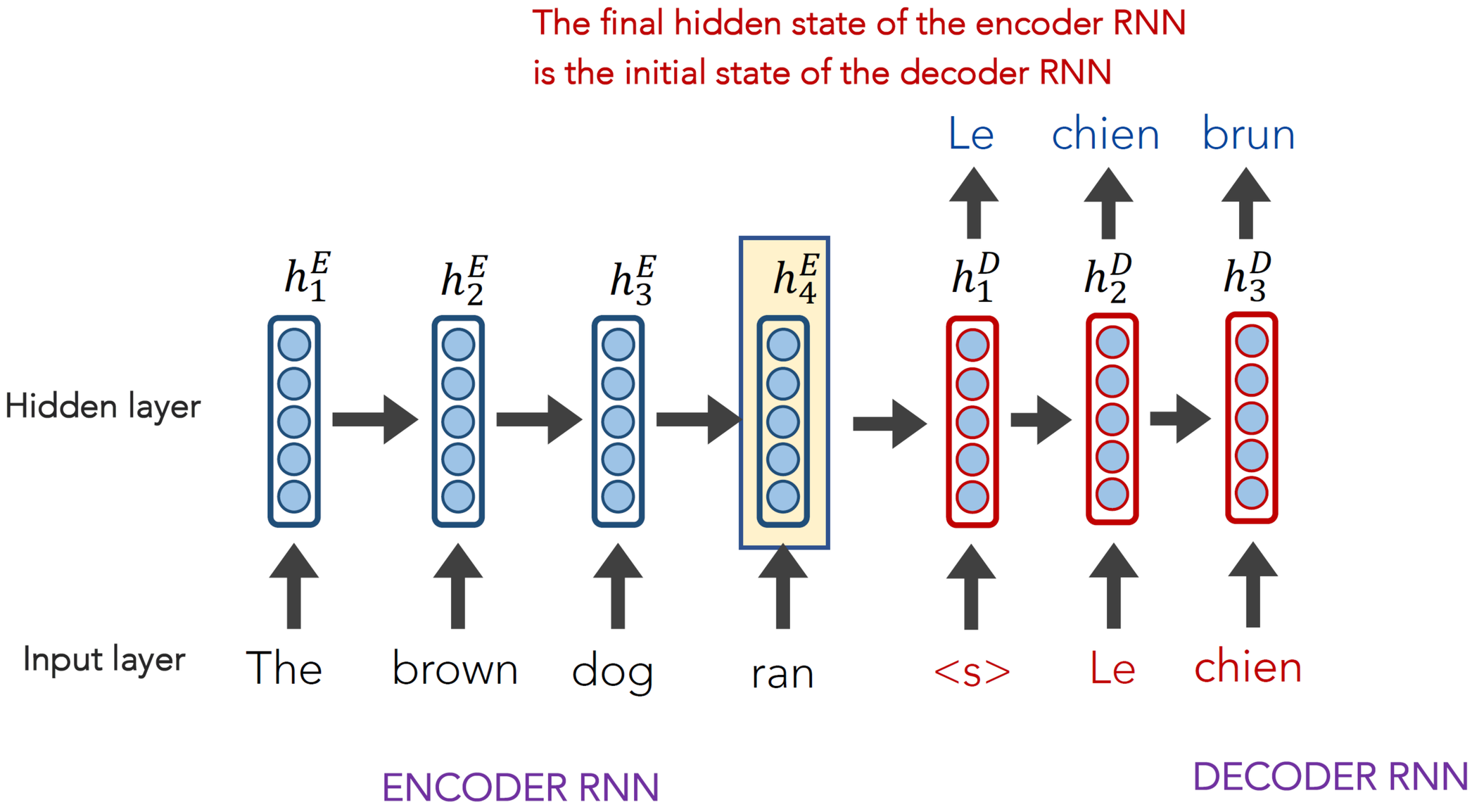


Sequence-to-Sequence (seq2seq)

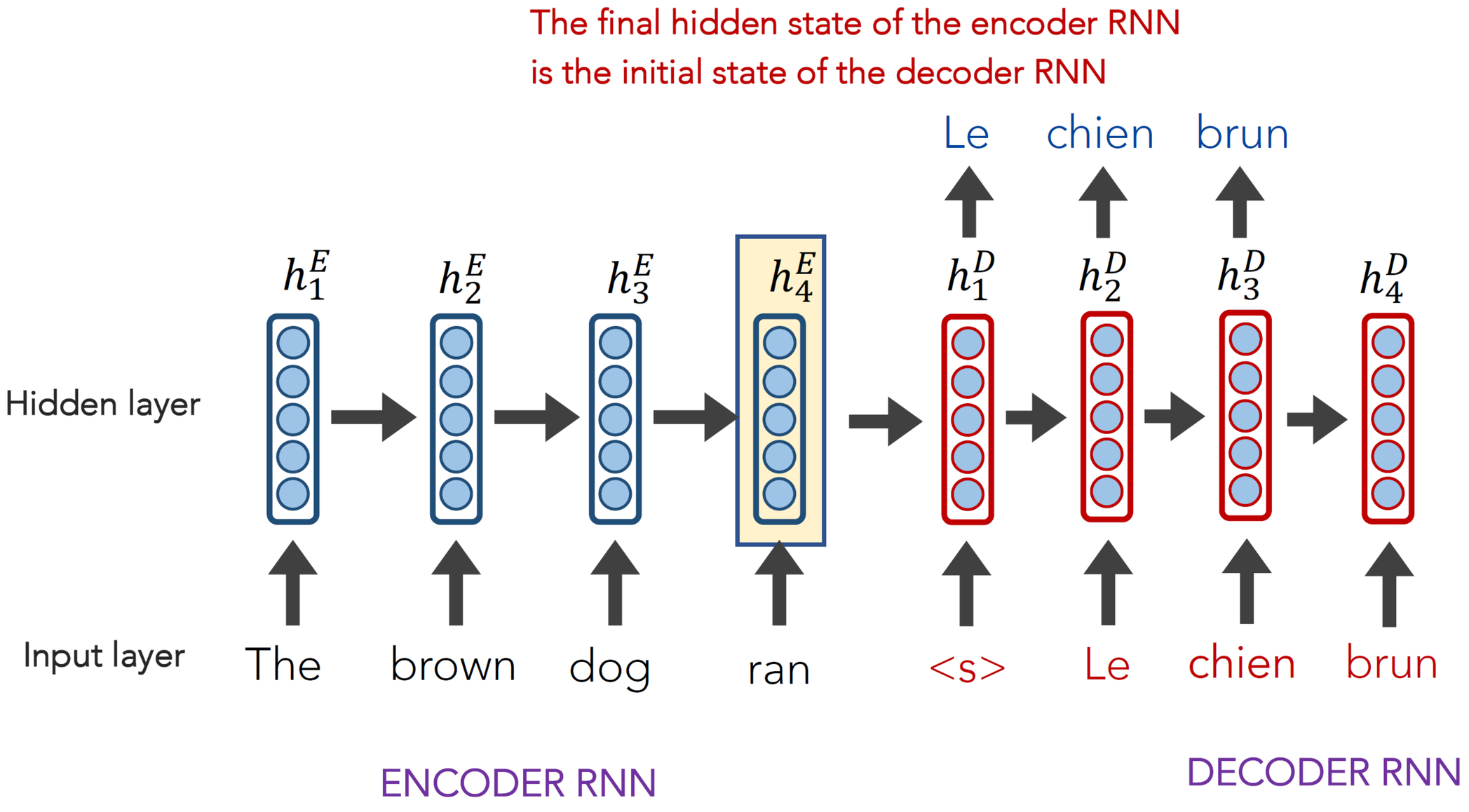
The final hidden state of the encoder RNN
is the initial state of the decoder RNN



Sequence-to-Sequence (seq2seq)

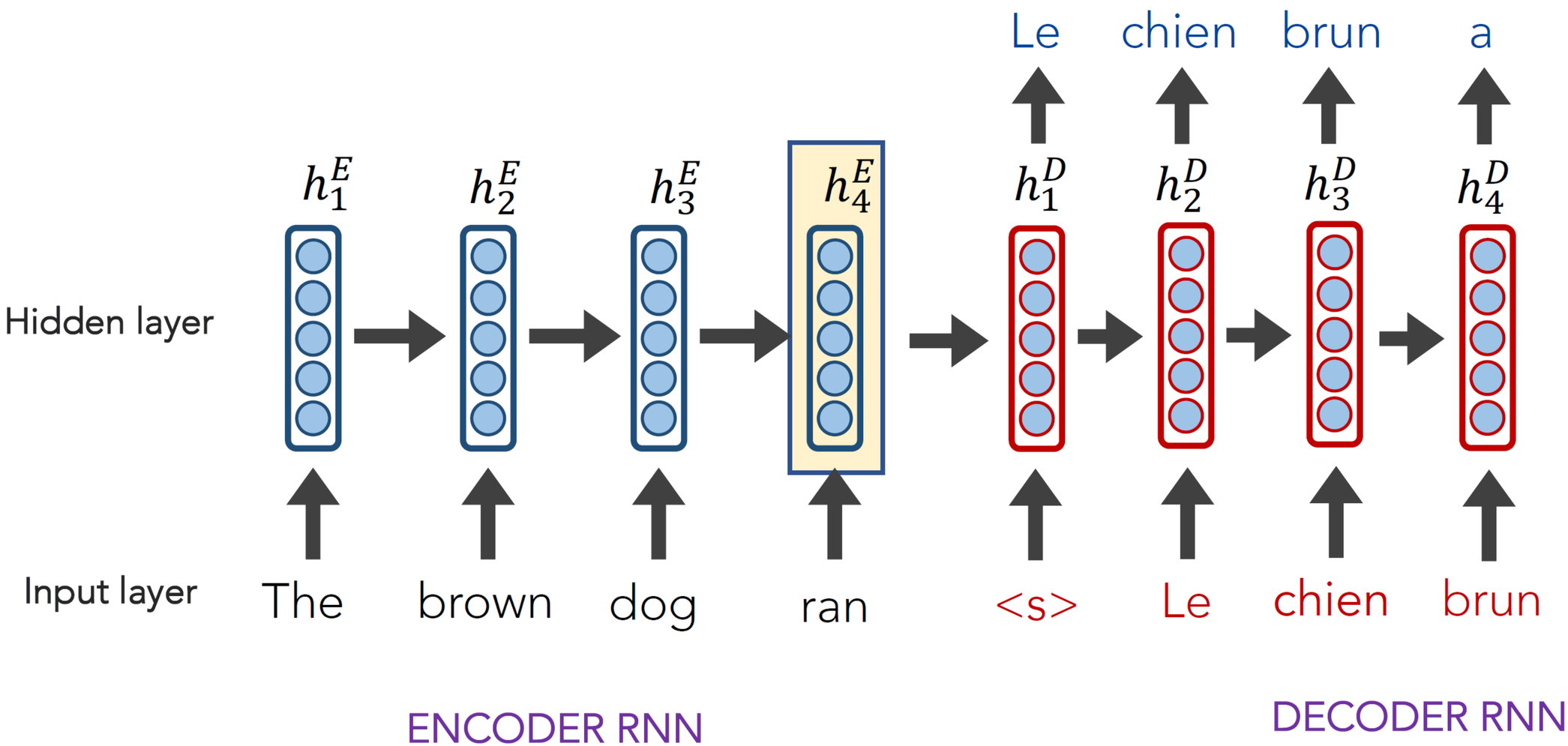


Sequence-to-Sequence (seq2seq)



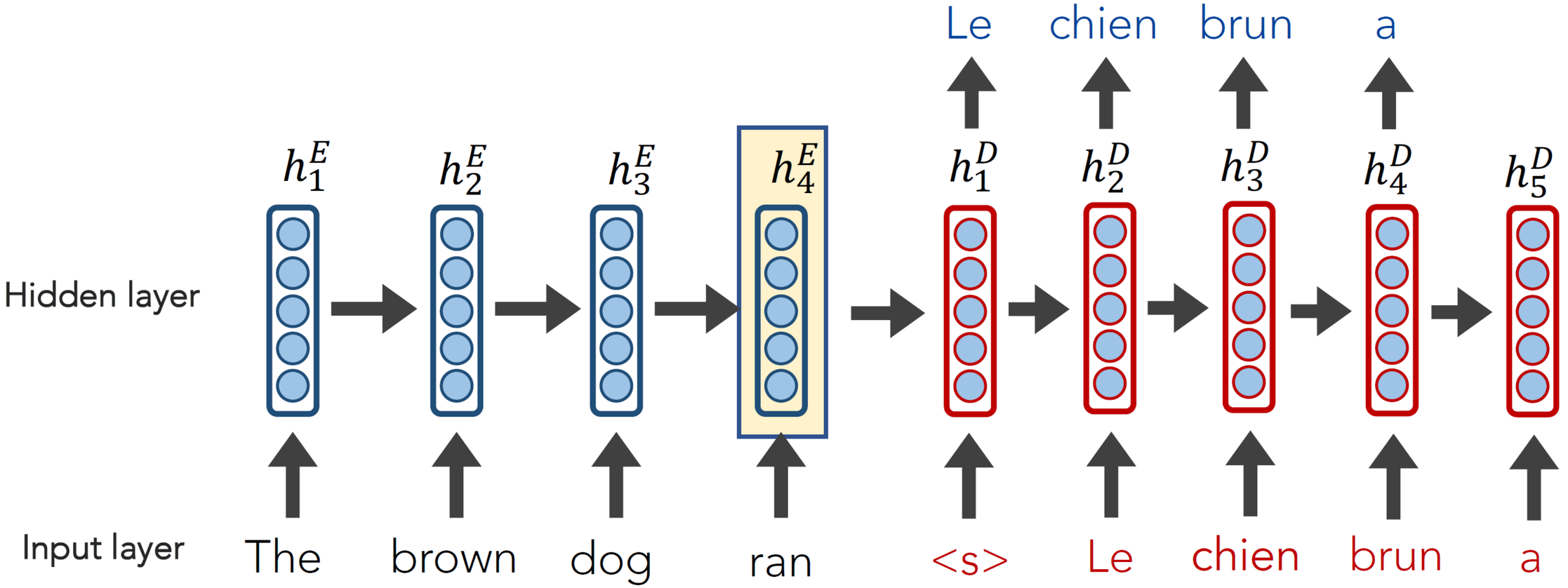
Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN

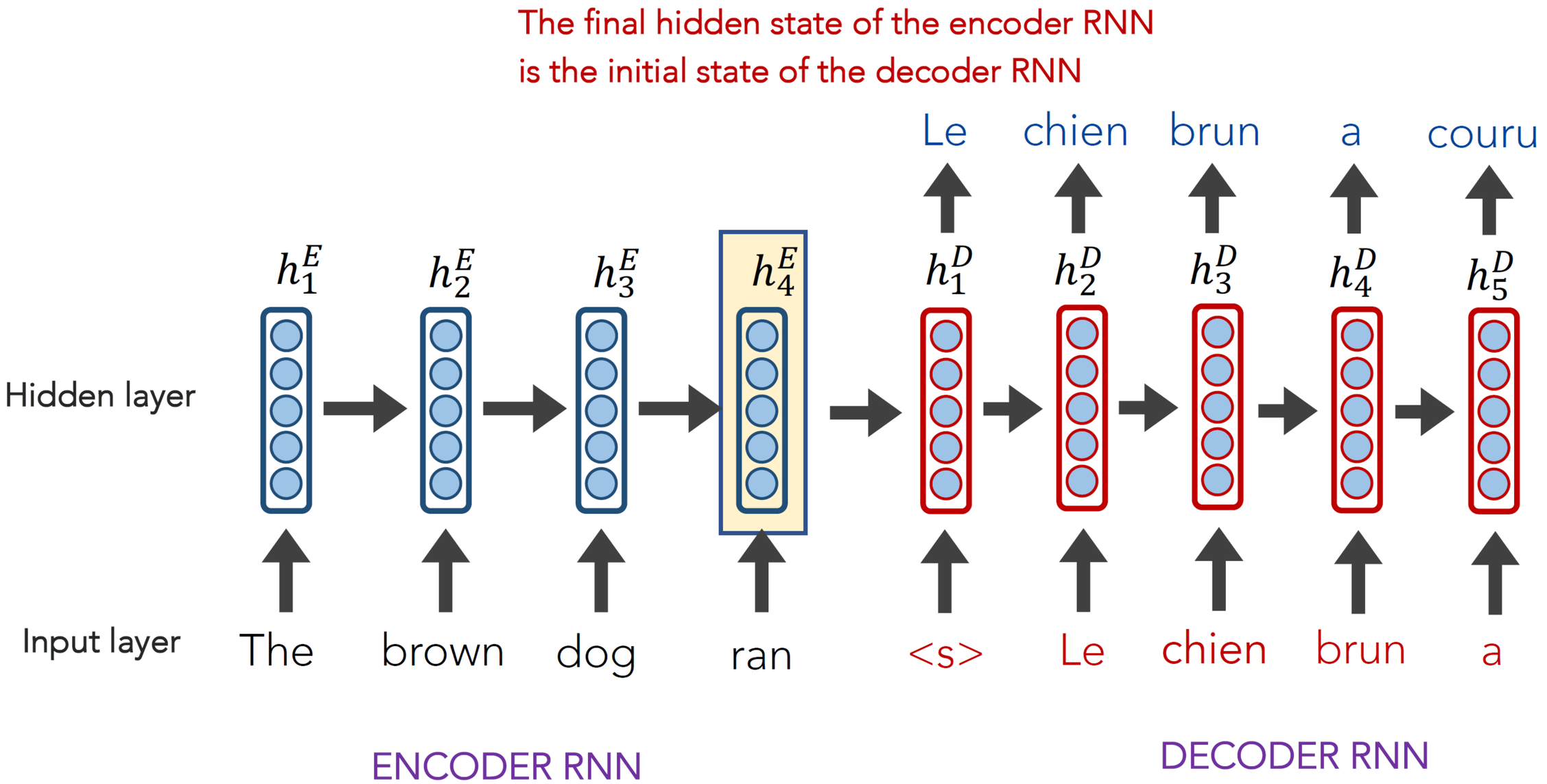


Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN

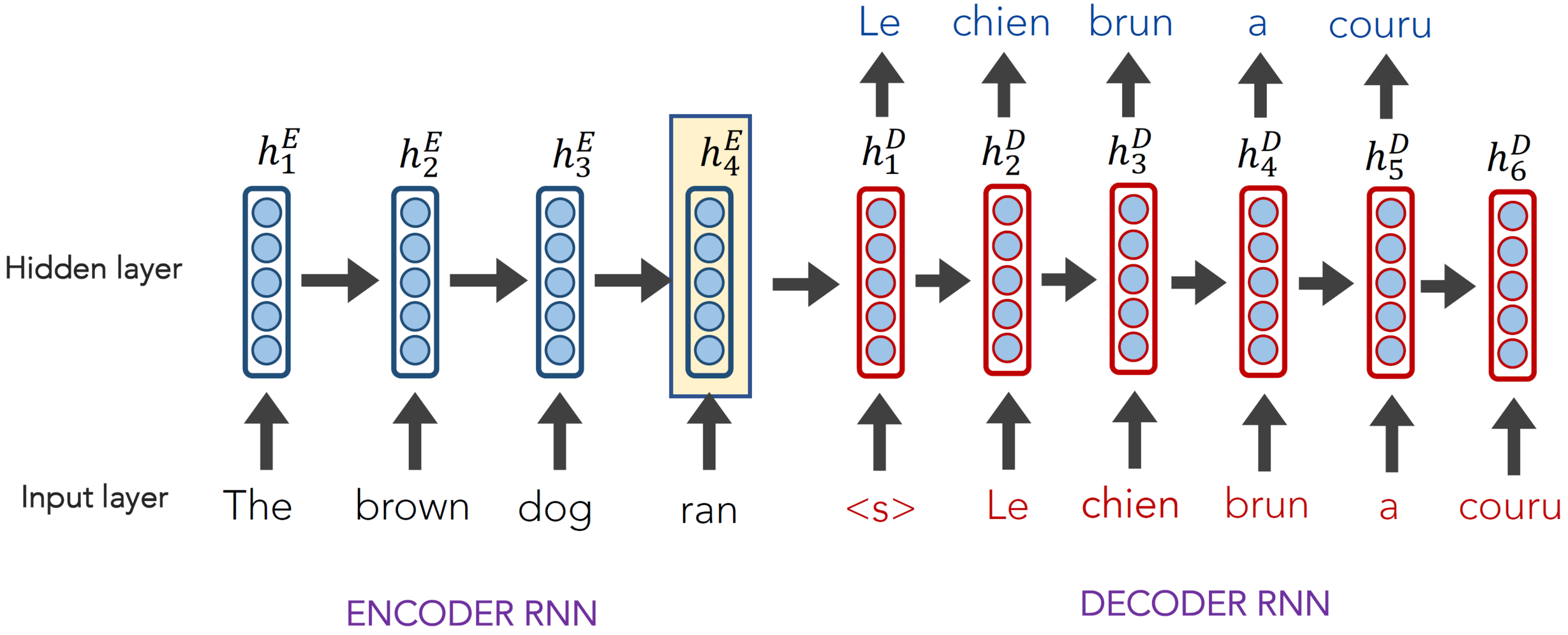


Sequence-to-Sequence (seq2seq)



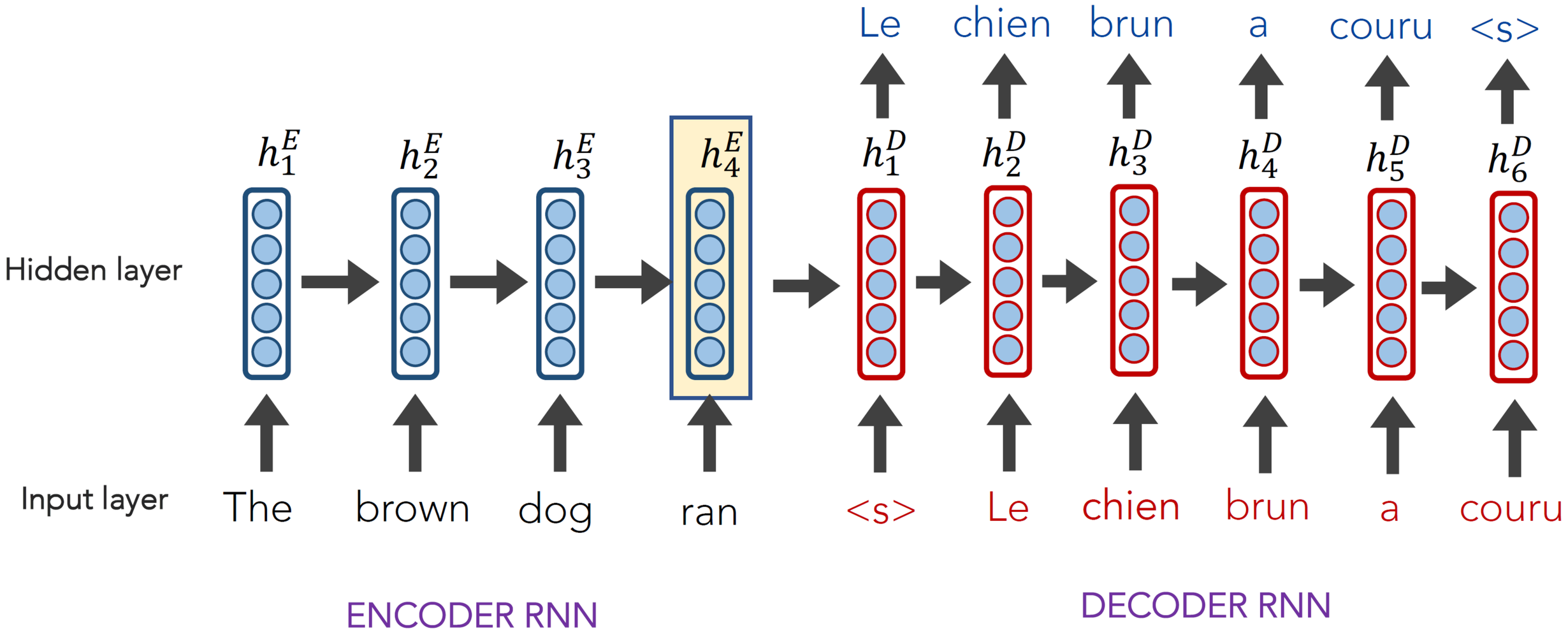
Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN



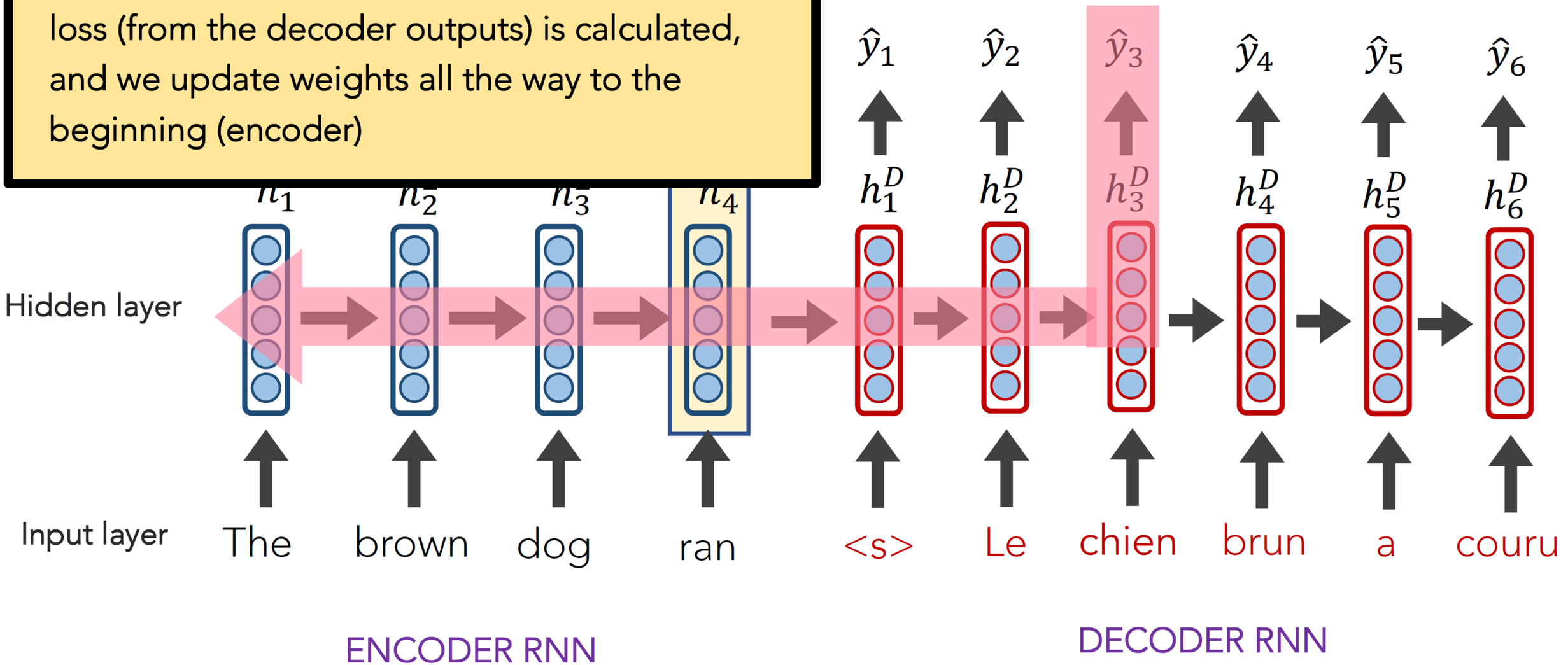
Sequence-to-Sequence (seq2seq)

The final hidden state of the encoder RNN
is the initial state of the decoder RNN

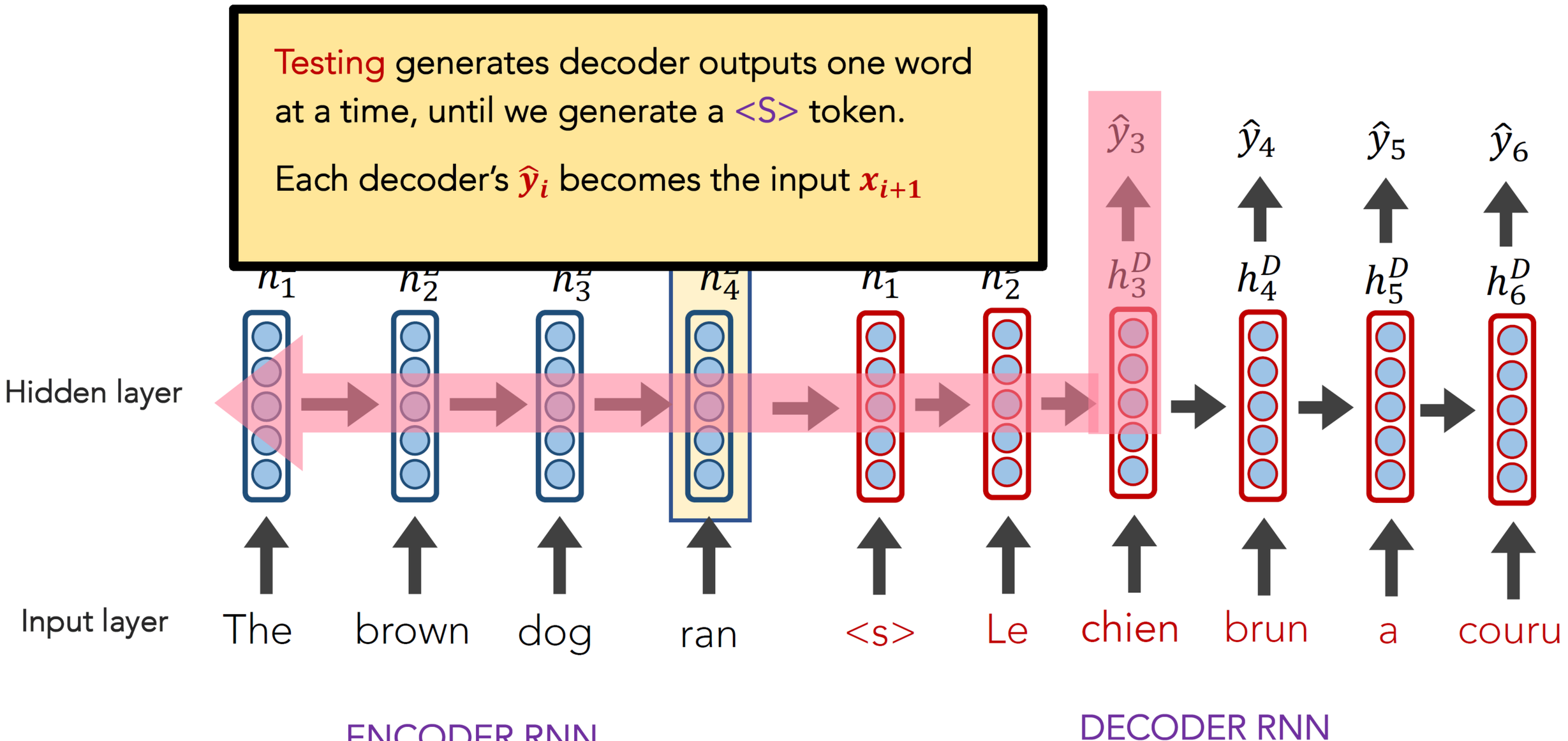


Sequence-to-Sequence (seq2seq)

Training occurs like RNNs typically do; the loss (from the decoder outputs) is calculated, and we update weights all the way to the beginning (encoder)



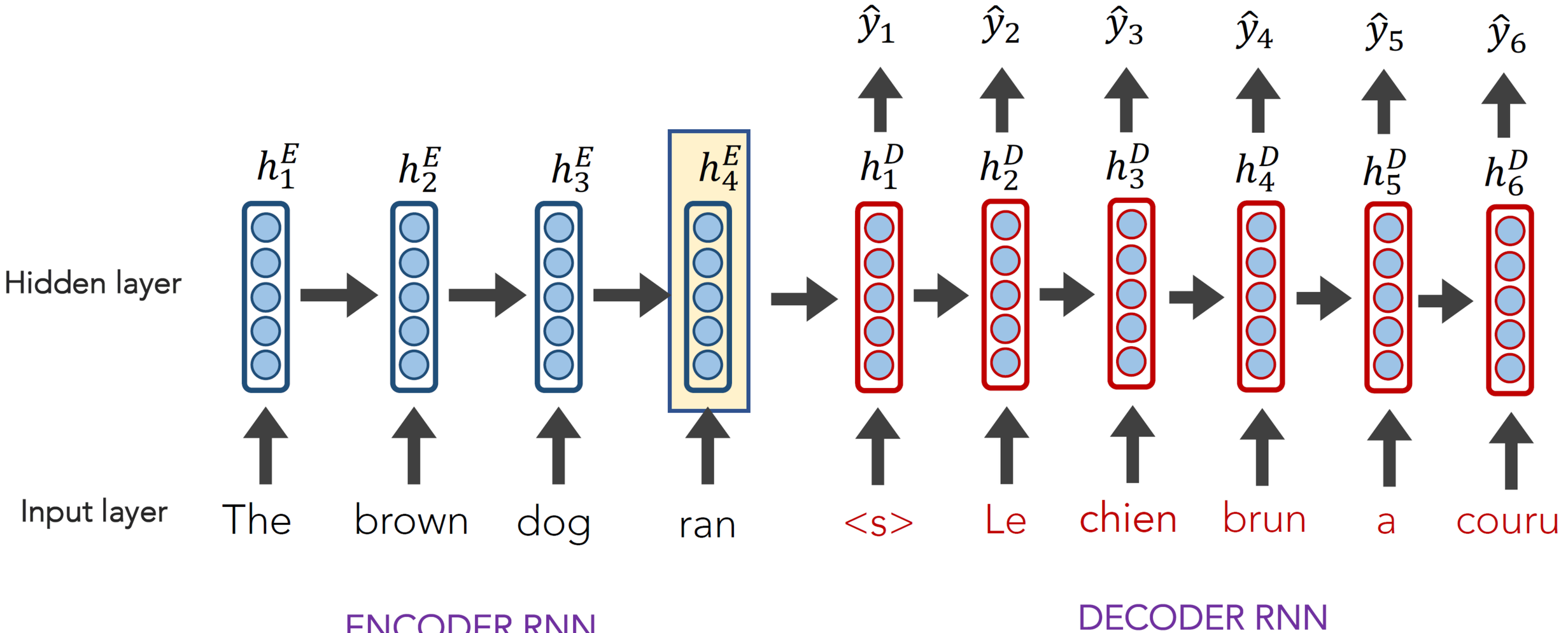
Sequence-to-Sequence (seq2seq)



Sequence-to-Sequence (seq2seq)

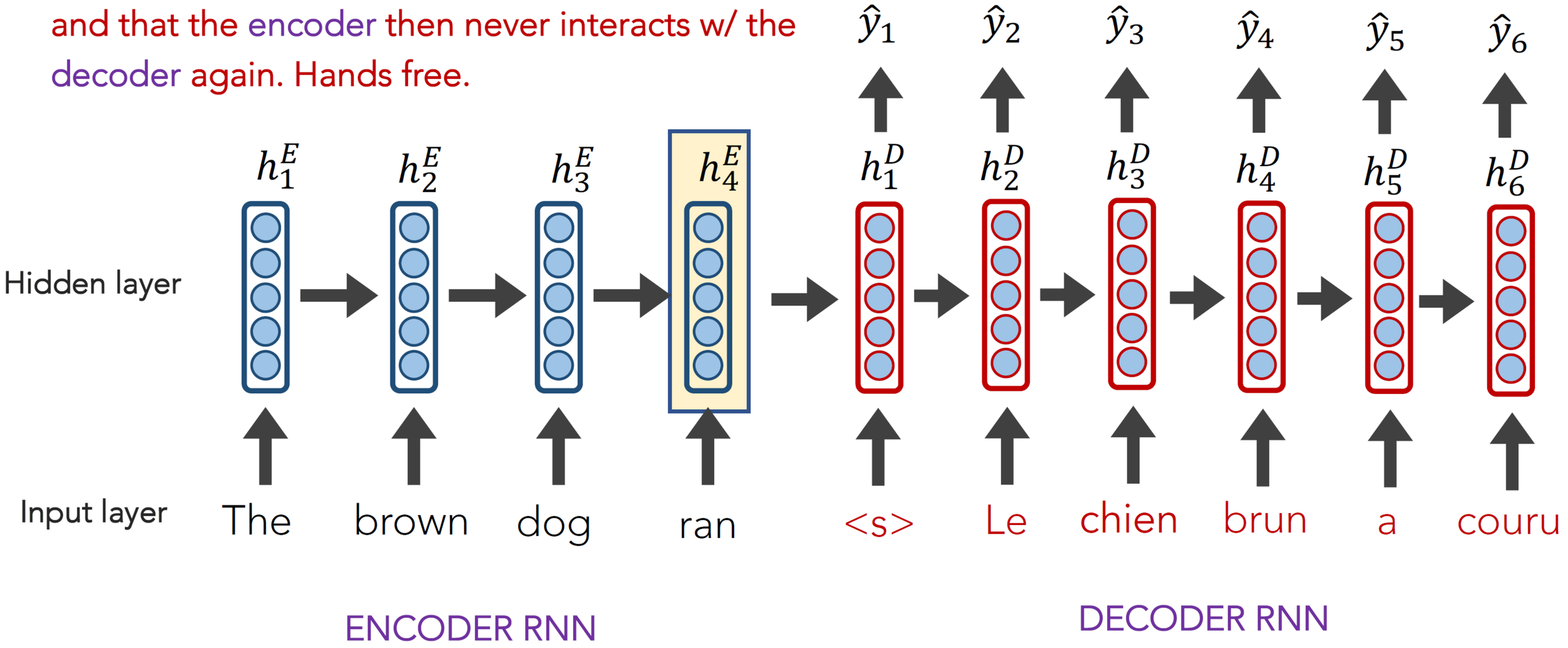
See any issues with this traditional **seq2seq** paradigm?

Sequence-to-Sequence (seq2seq)



Sequence-to-Sequence (seq2seq)

It's crazy that the entire "meaning" of the 1st sequence is expected to be packed into this one embedding, and that the encoder then never interacts w/ the decoder again. Hands free.



Sequence-to-Sequence (seq2seq)

Instead, what if the decoder, at each step, pays attention to a *distribution* of all of the encoder's hidden states?

Sequence-to-Sequence (seq2seq)

Instead, what if the decoder, at each step, pays attention to a *distribution* of all of the encoder's hidden states?

Intuition: when we (humans) translate a sentence, we don't just consume the original sentence, reflect on the meaning of the last word, then regurgitate in a new language; we continuously think back at the original sentence while focusing on different parts.

Attention

The concept of attention within cognitive neuroscience and psychology dates back to the 1800s. [William James, 1890].

Nadaray-Watson kernel regression proposed in 1964. It *locally weighted* its predictions.