Lecture 24: Attention

NLP Lectures: Part 3 of 4

Harvard IACS

CS109B

Pavlos Protopapas, Mark Glickman, and Chris Tanner

Outline

- How to use embeddings
- seq2seq
- seq2seq + Attention
- Transformers (preview)

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- How to use embeddings
- seq2seq
- seq2seq + Attention
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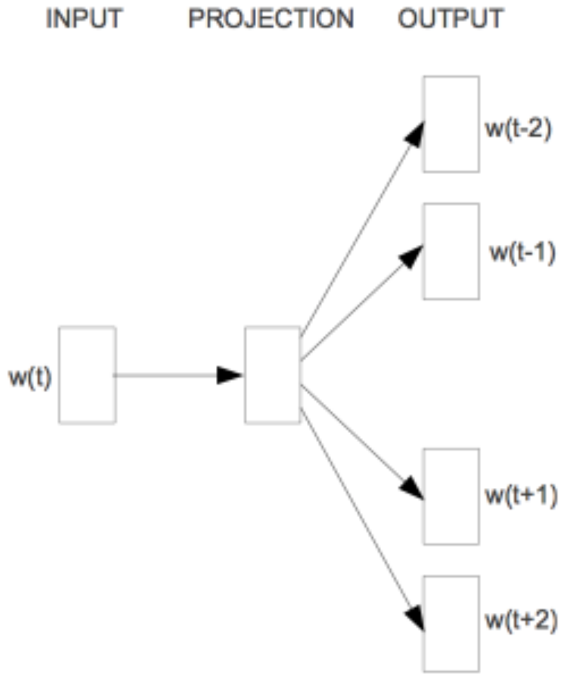
Previously, we learned about **word embeddings**

millions of books



word2vec

word embeddings (type-based)

approaches:

- count-based/DSMs (e.g., SVD, LSA)
- Predictive models (e.g., word2vec, GloVe)

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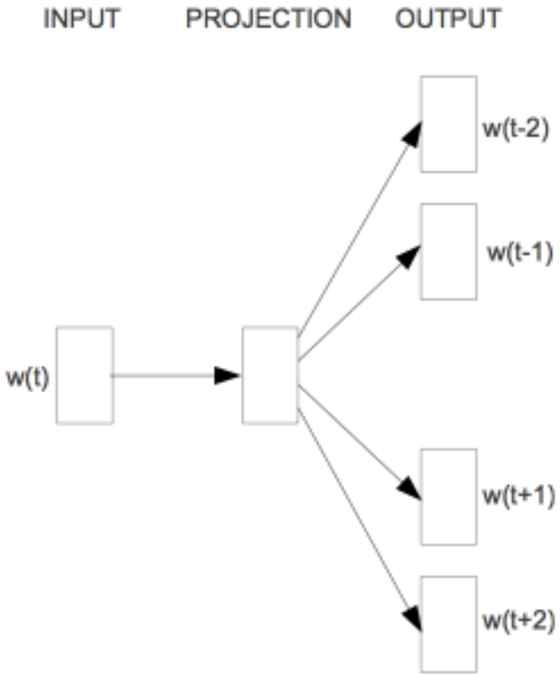

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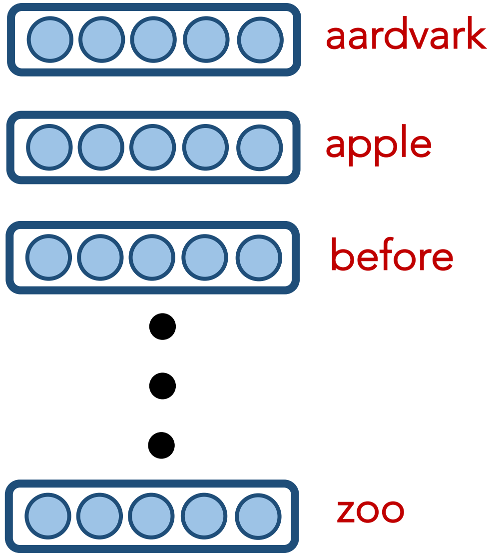

word embeddings

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"The food was delicious. Amazing!" → **4.8/5** yelp

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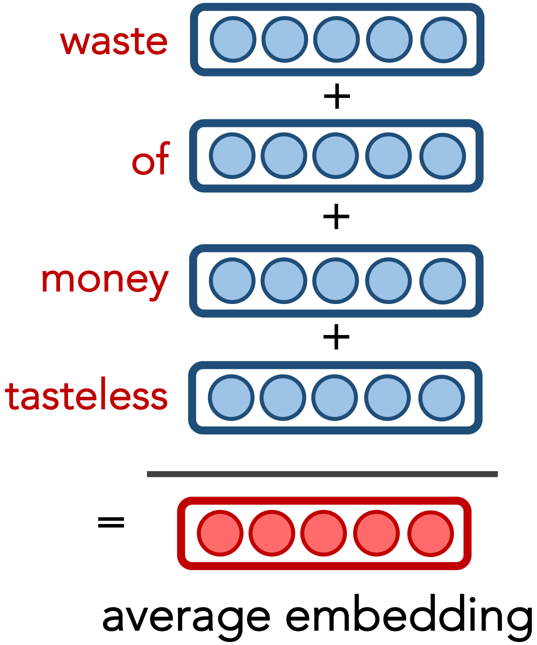
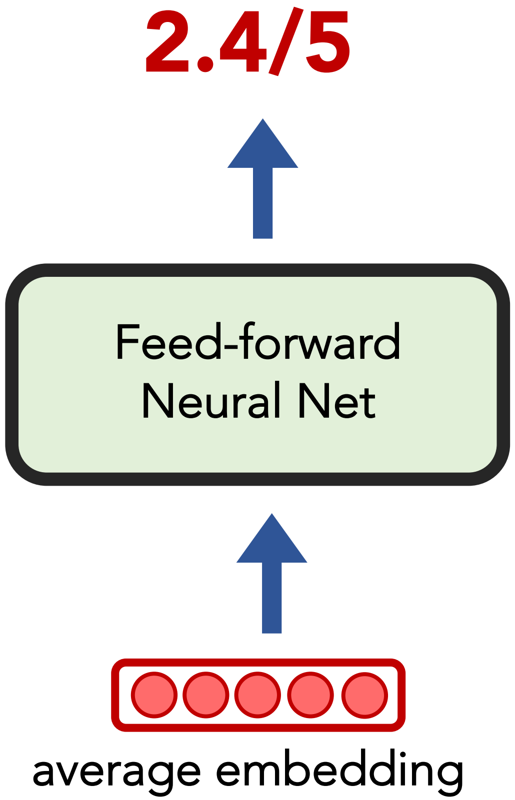
"*Waste of money. Tasteless!*" → **2.4/5** yelp





word embeddings (type-based)

approaches:

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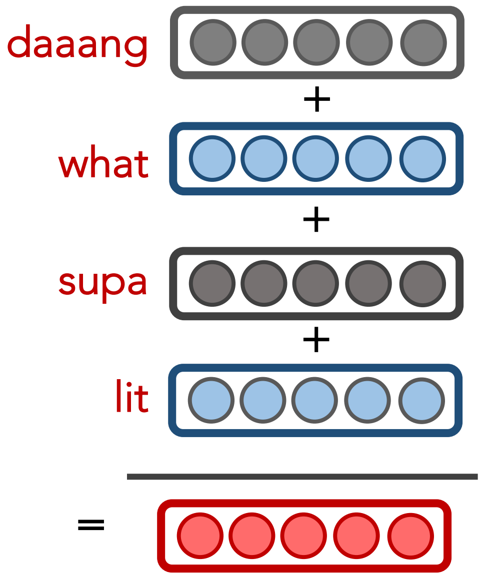
"Daaang. What?! Supa Lit" → **4.9/5** yelp



average embedding

Strengths and weaknesses of word embeddings (type-based)?

word embeddings (type-based)

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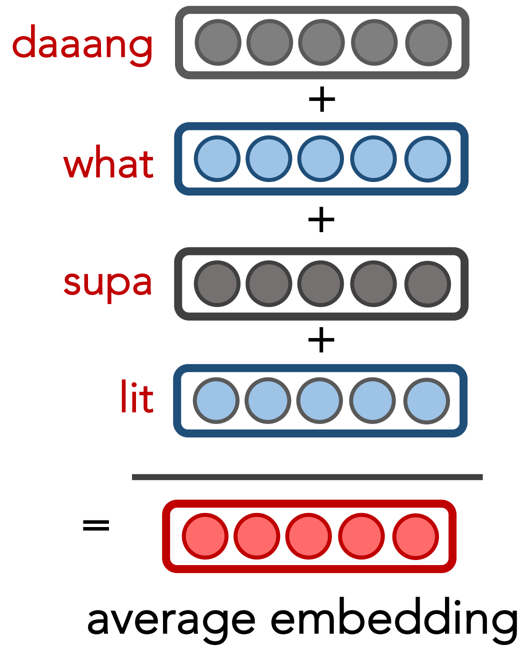

Strengths:

- Leverages tons of existing data
- Don’t need to depend on our data to create embeddings

word embeddings (type-based)

approaches:

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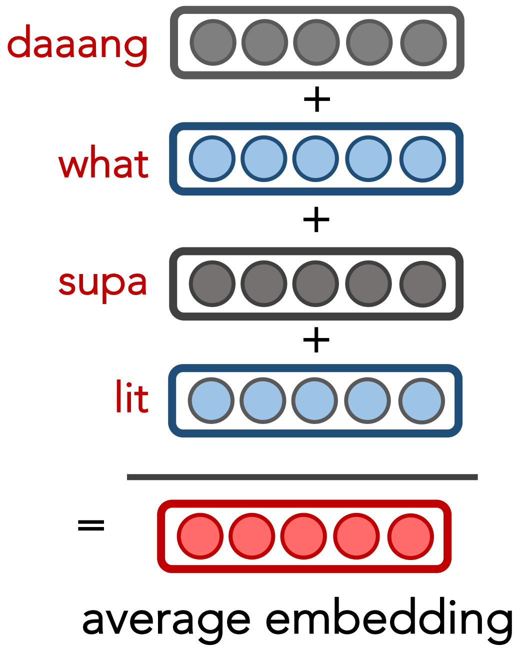

Issues:

- Out-of-vocabulary (OOV) words
- Not tailored to this dataset

word embeddings (type-based)

approaches:

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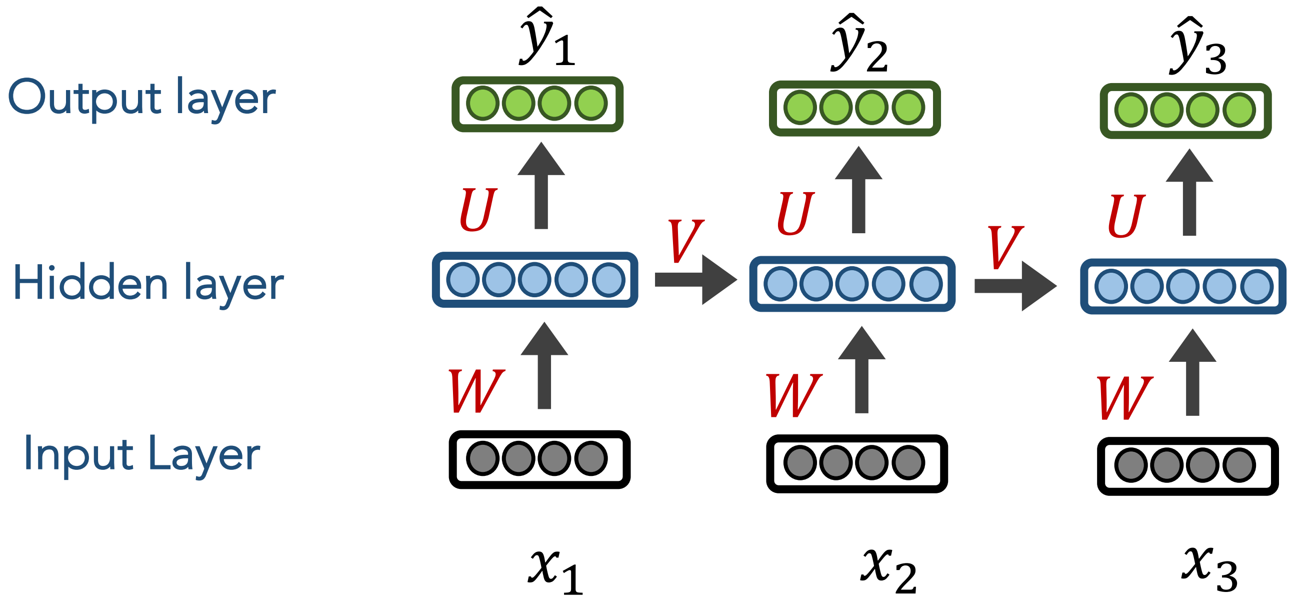
Previously, we learned about **word embeddings**

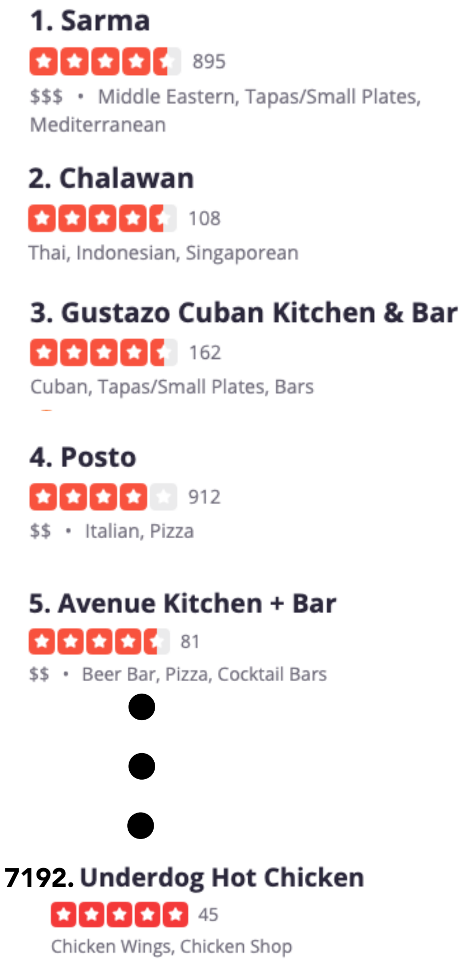


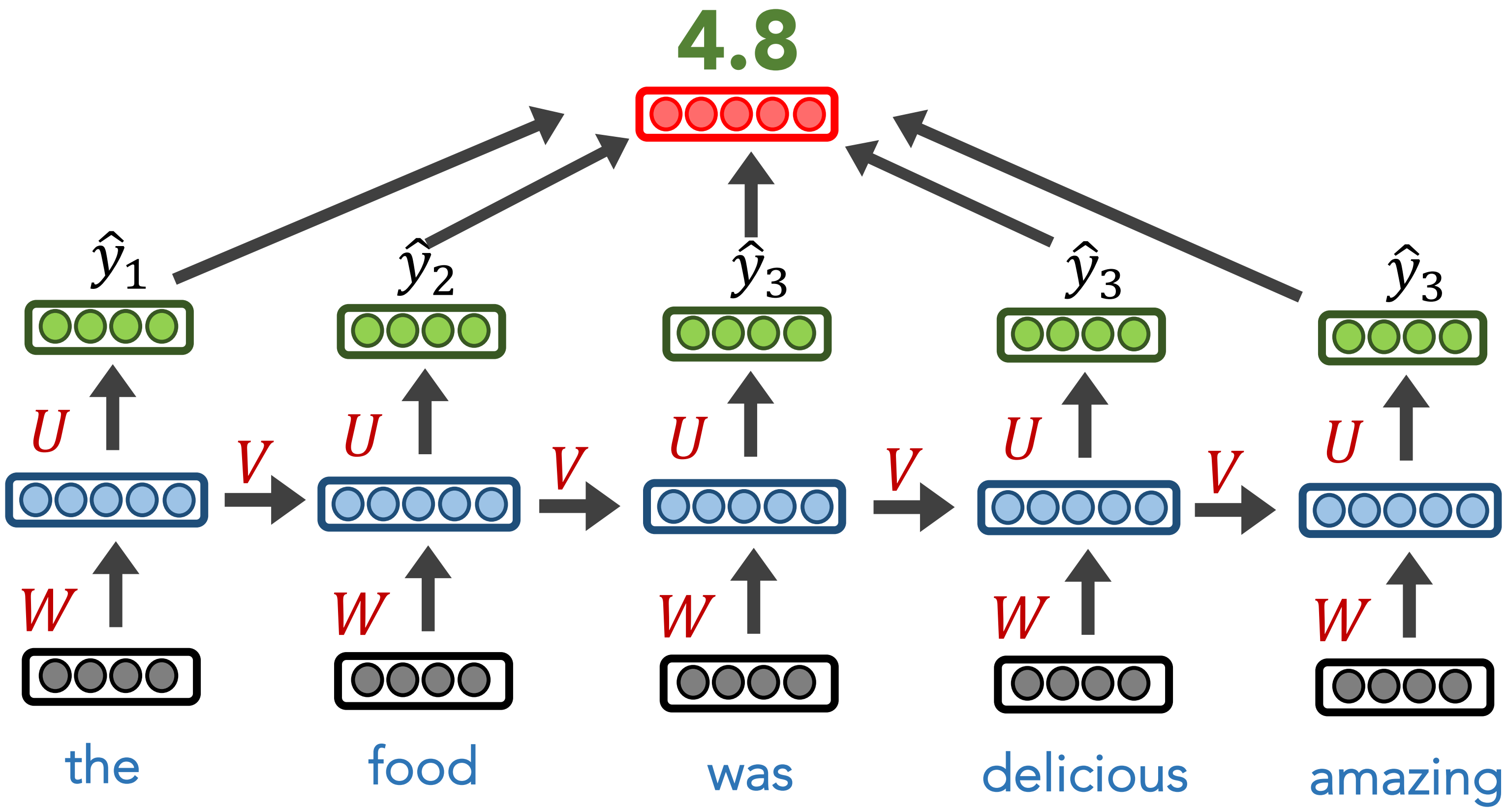
LSTM

contextualized embeddings (token-based)

approaches:

- Predictive models (e.g., BiLSTMs, GPT-2, BERT)



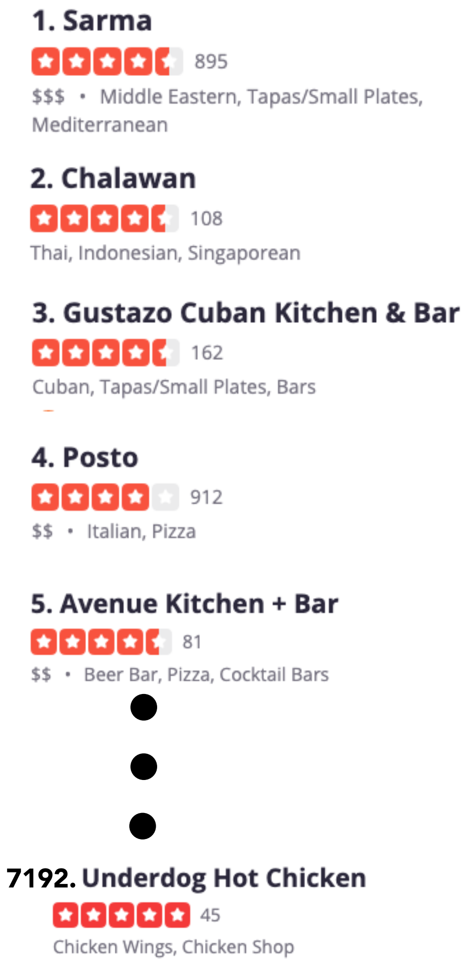


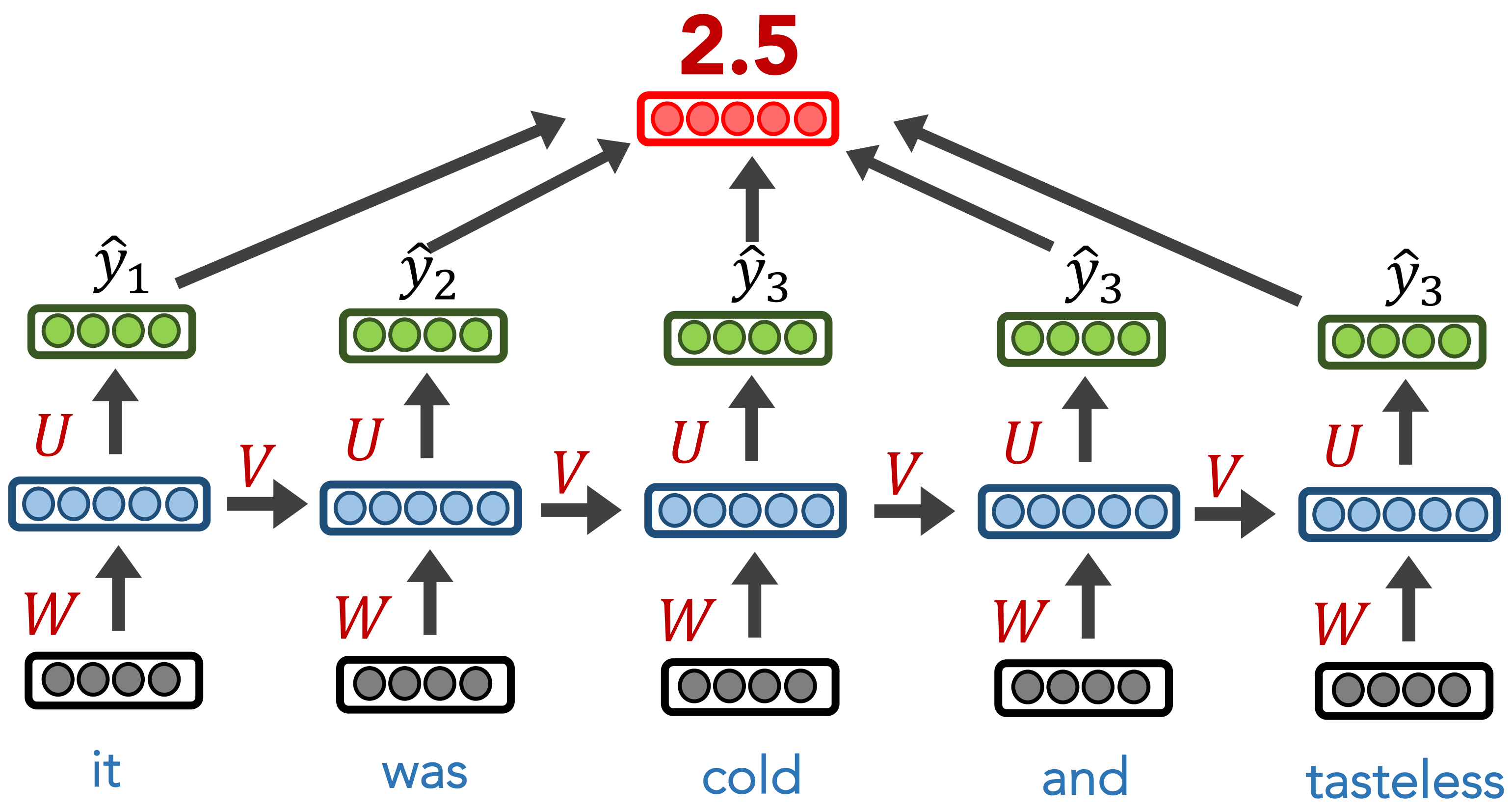
Review #1

contextualized embeddings (token-based)

approaches:

- Predictive models (e.g., BiLSTMs, GPT-2, BERT)





Review #2

contextualized embeddings (token-based)

approaches:

- Predictive models (e.g., BiLSTMs, GPT-2, BERT)

1. Sarma
895
$$$ • Middle Eastern, Tapas/Small Plates, Mediterranean

2. Chalawan
108
Thai, Indonesian, Singaporean

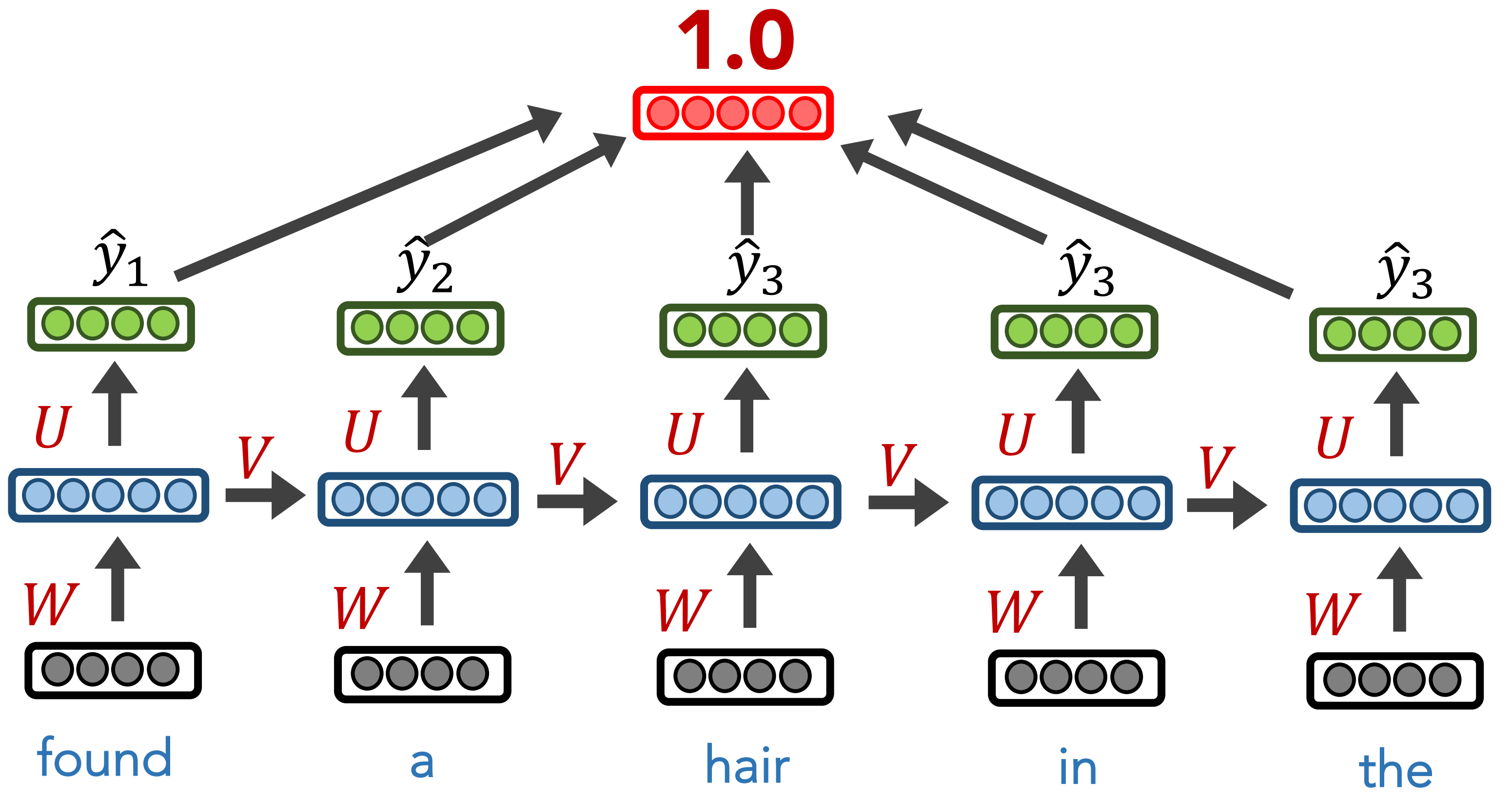
3. Gustazo Cuban Kitchen & Bar
162
Cuban, Tapas/Small Plates, Bars

4. Posto
912
$$ • Italian, Pizza

5. Avenue Kitchen + Bar
81
$$ • Beer Bar, Pizza, Cocktail Bars

•
•
•

7192. Underdog Hot Chicken
45
Chicken Wings, Chicken Shop



Review #53,781

contextualized embeddings (token-based)

approaches:

- Predictive models (e.g., BiLSTMs, GPT-2, BERT)

1. **Sarma**
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•
•
•

7192. **Underdog Hot Chicken**
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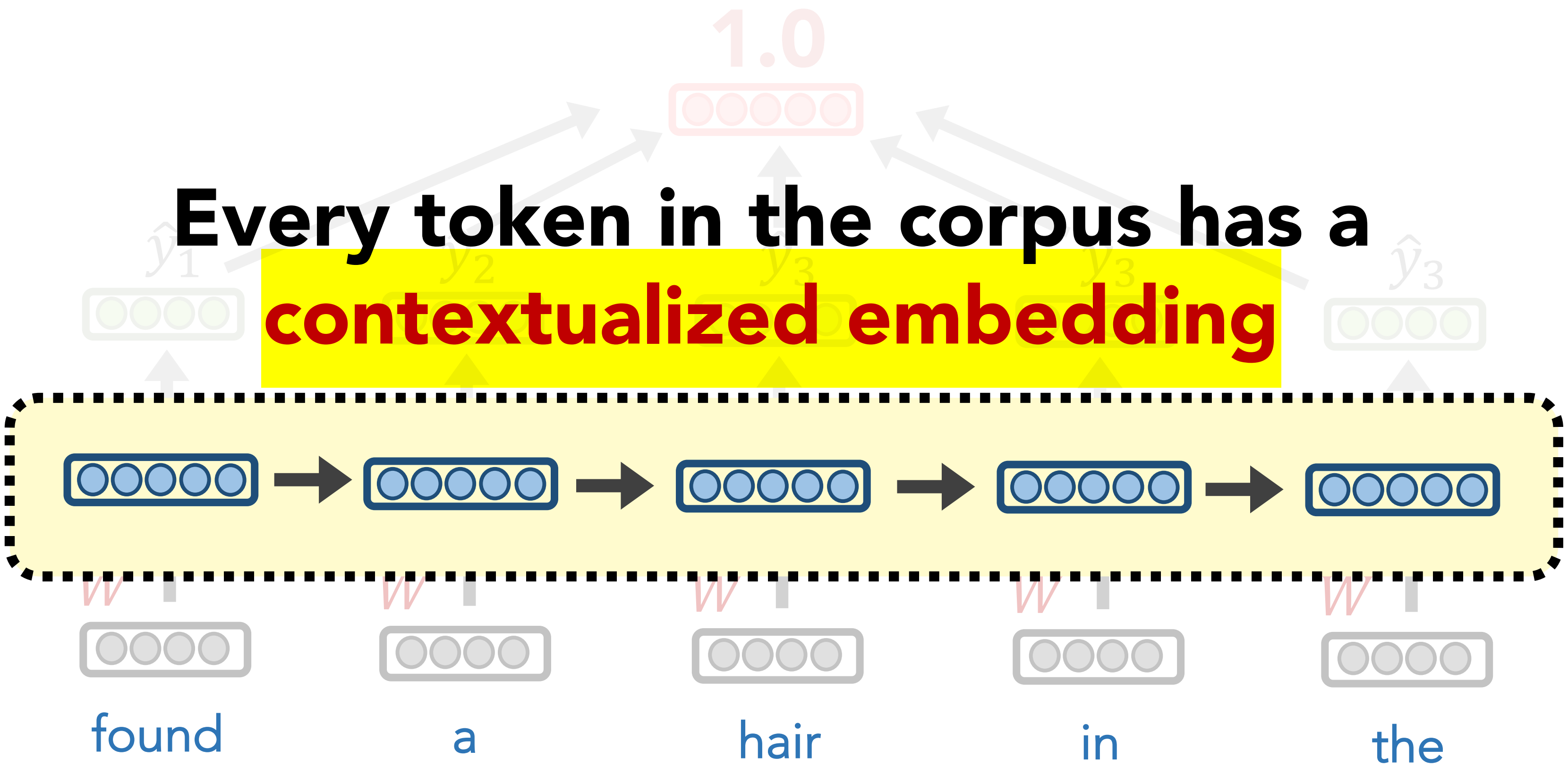
Every token in the corpus has a contextualized embedding



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contextualized embeddings (token-based)

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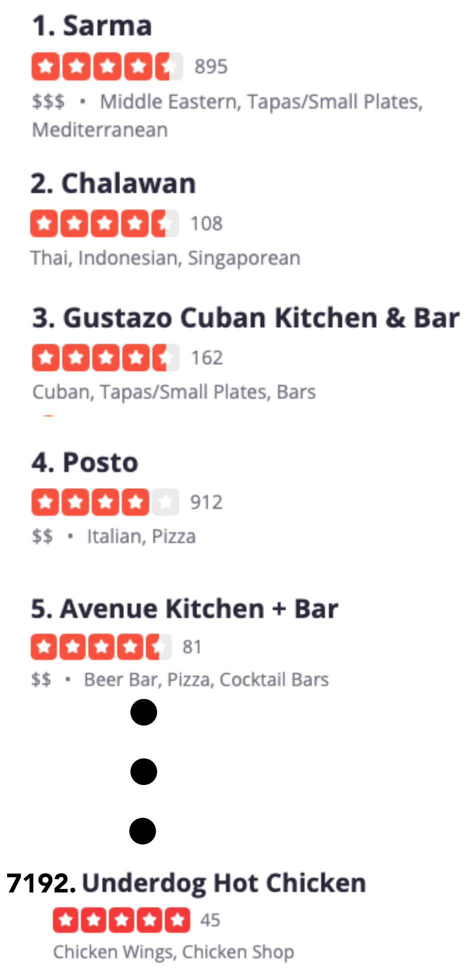
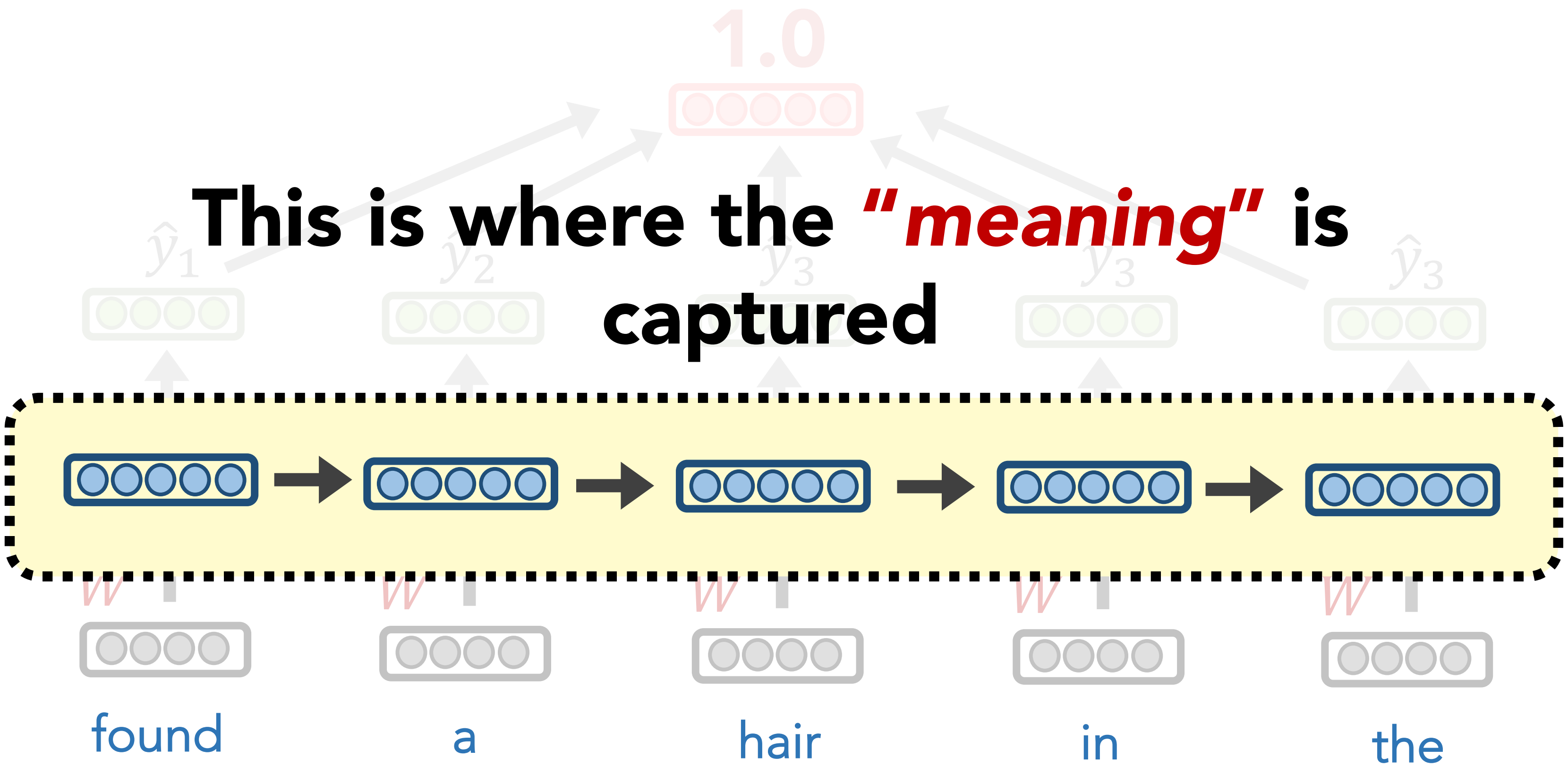


This is where the *"meaning"* is captured



Review #53,781

contextualized embeddings (token-based)

approaches:

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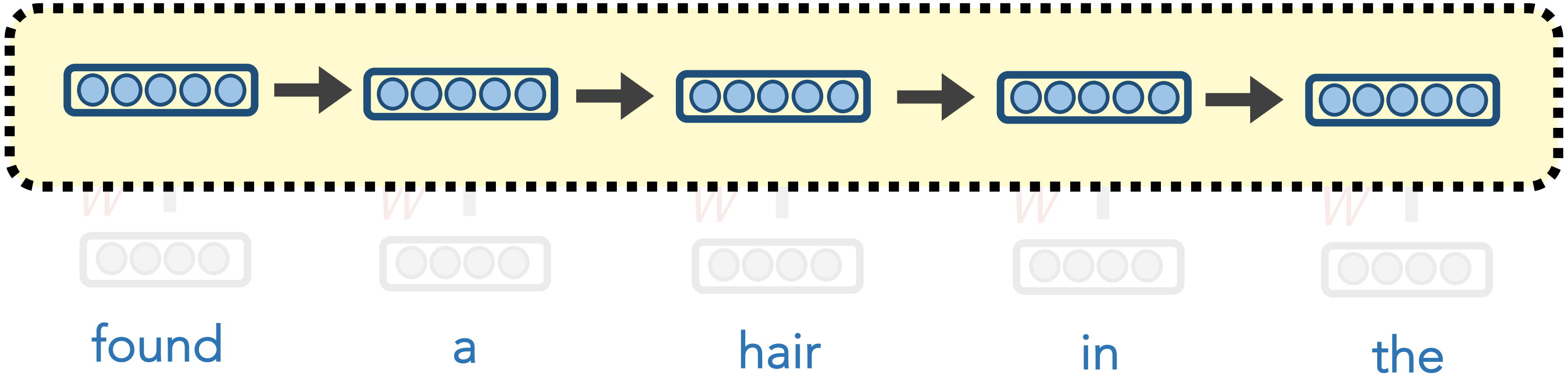
Strengths and weaknesses of contextualized embeddings (aka token-based)?



Review #53,781

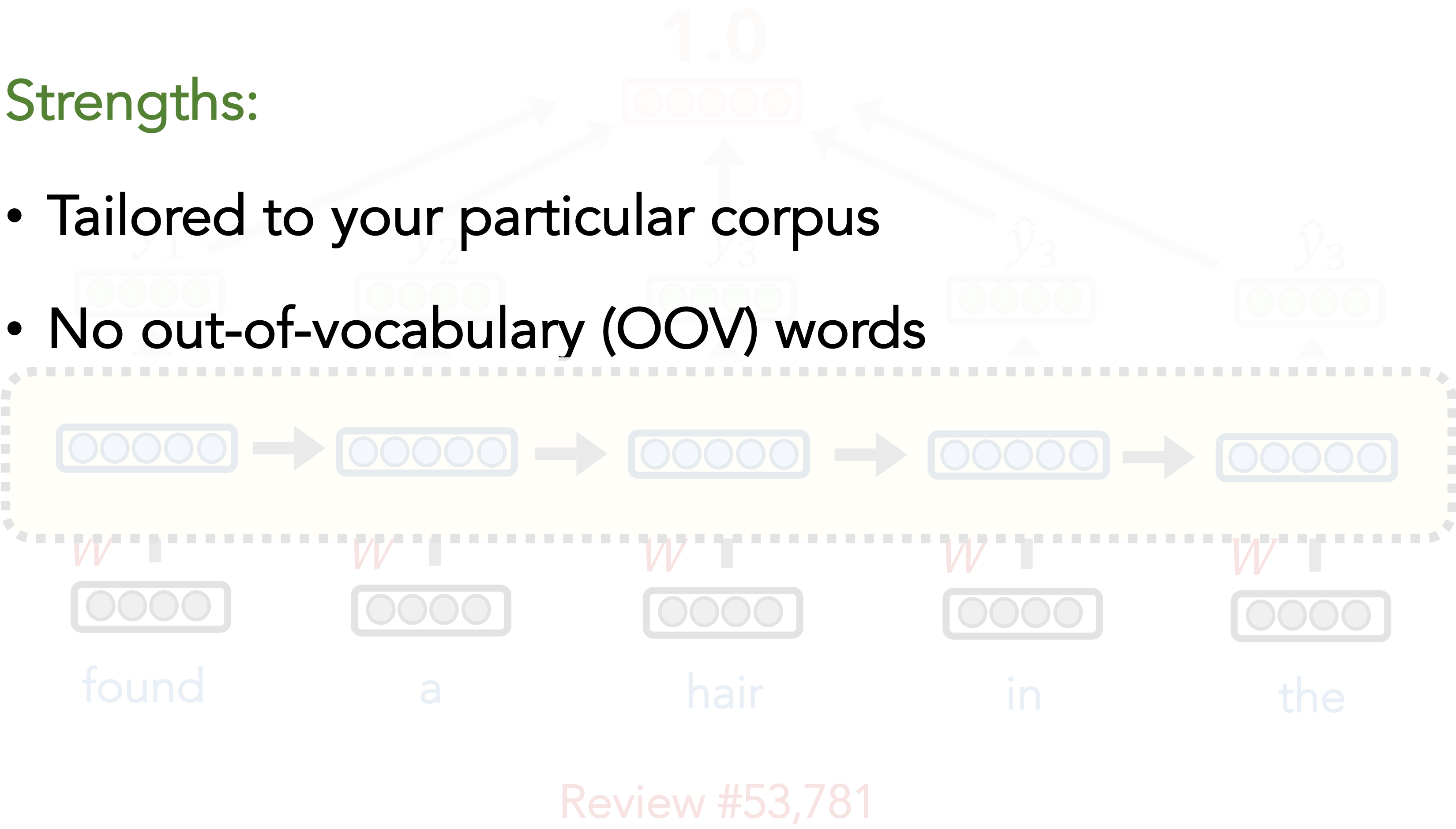
contextualized embeddings (token-based)

approaches:

- Predictive models (e.g., BiLSTMs, GPT-2, BERT)

Strengths:

- Tailored to your particular corpus
- No out-of-vocabulary (OOV) words



contextualized embeddings (token-based)

approaches:

- Predictive models (e.g., BiLSTMs, GPT-2, BERT)

Weaknesses:

- May not have enough data to produce good results
- Have to train new model for each use case
- Can't leverage a wealth of existed text data (millions of books)???

contextualized embeddings (token-based)

approaches:

- Predictive models (e.g., BiLSTMs, GPT-2, BERT)

Weaknesses:

- May not have enough data to produce good results
- Have to train new model for each use case
- ~~Can’t leverage a wealth of existed text data (millions of books)???~~

WRONG! We can leverage millions of books!

contextualized embeddings (token-based)

approaches:

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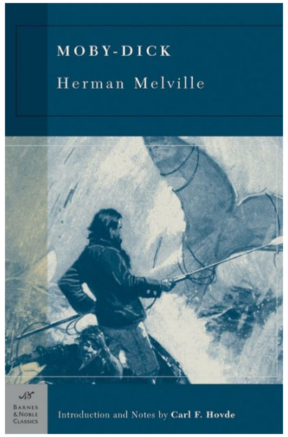
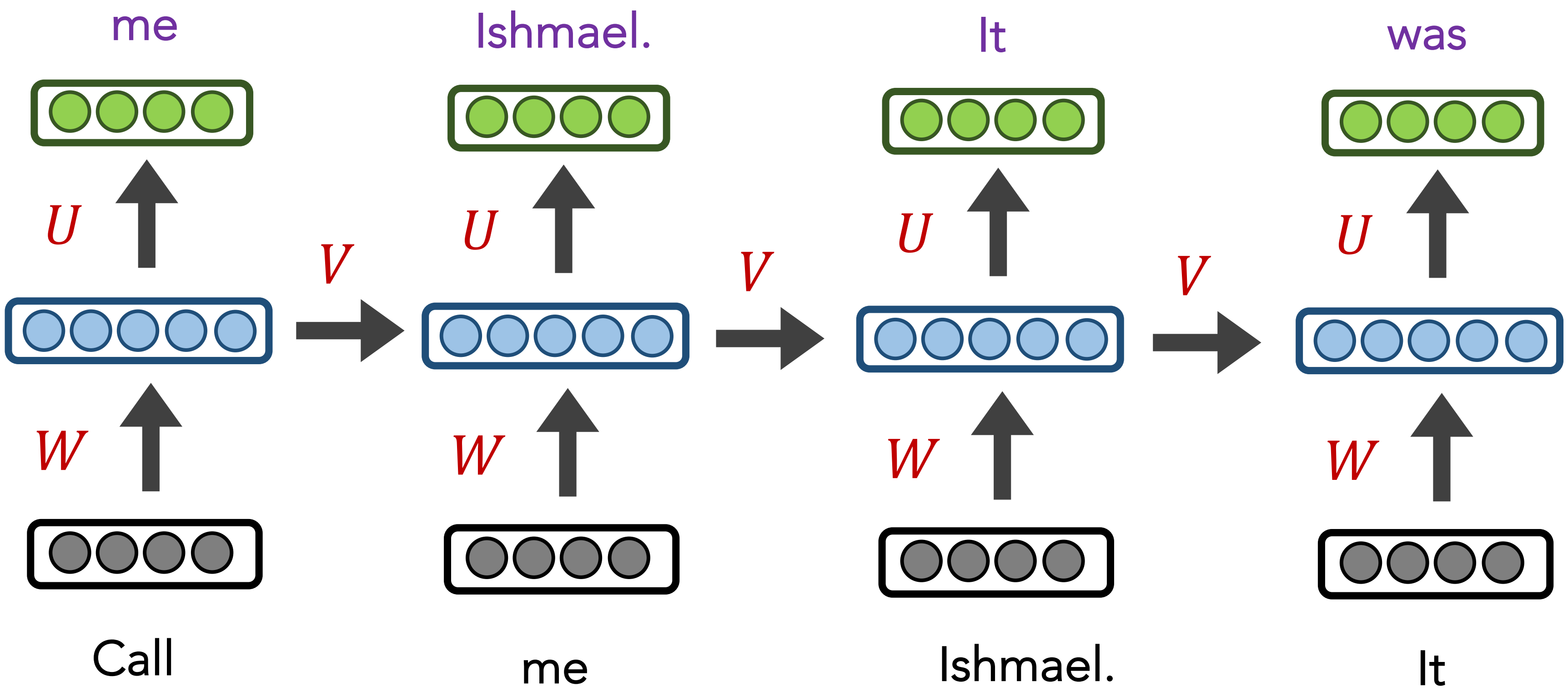


Language Modelling

(let's input 1 million documents)



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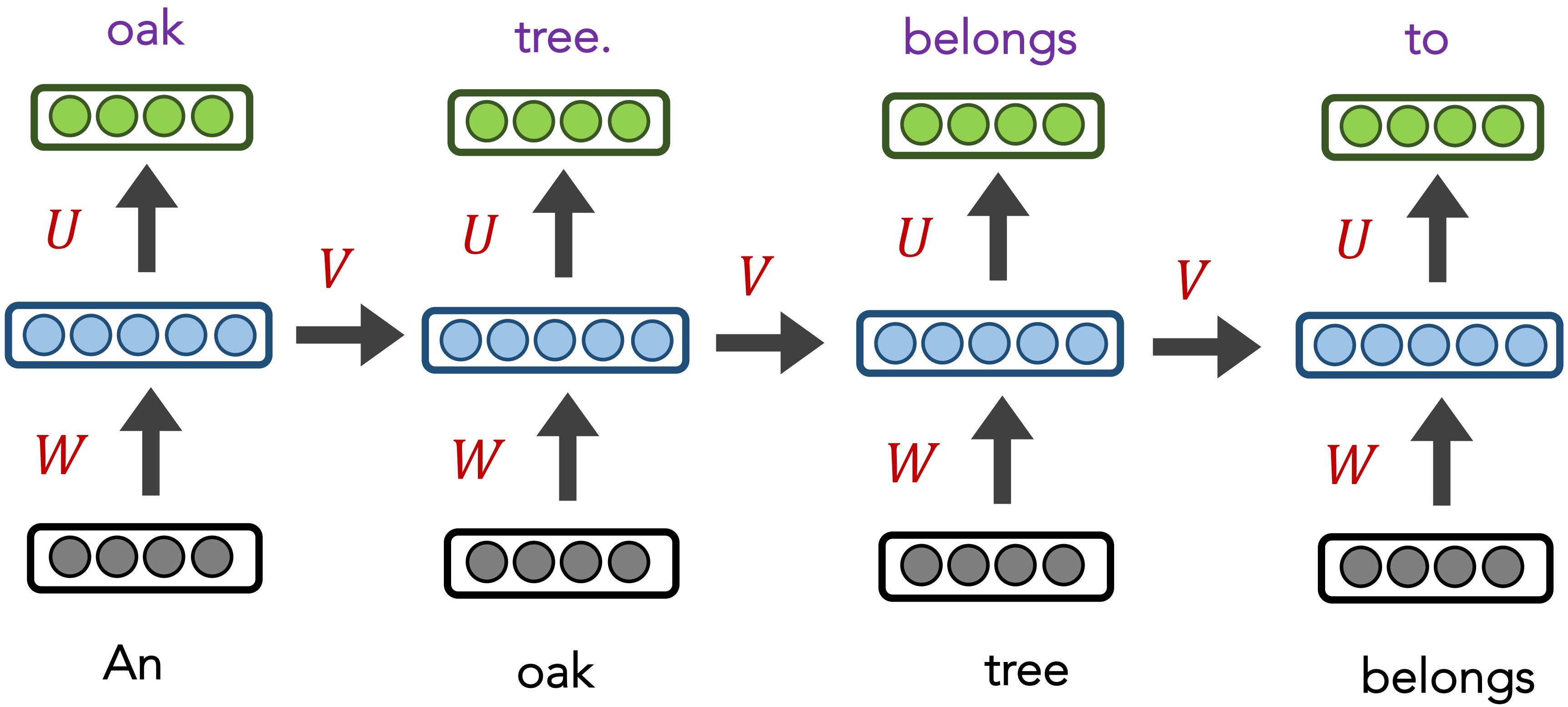
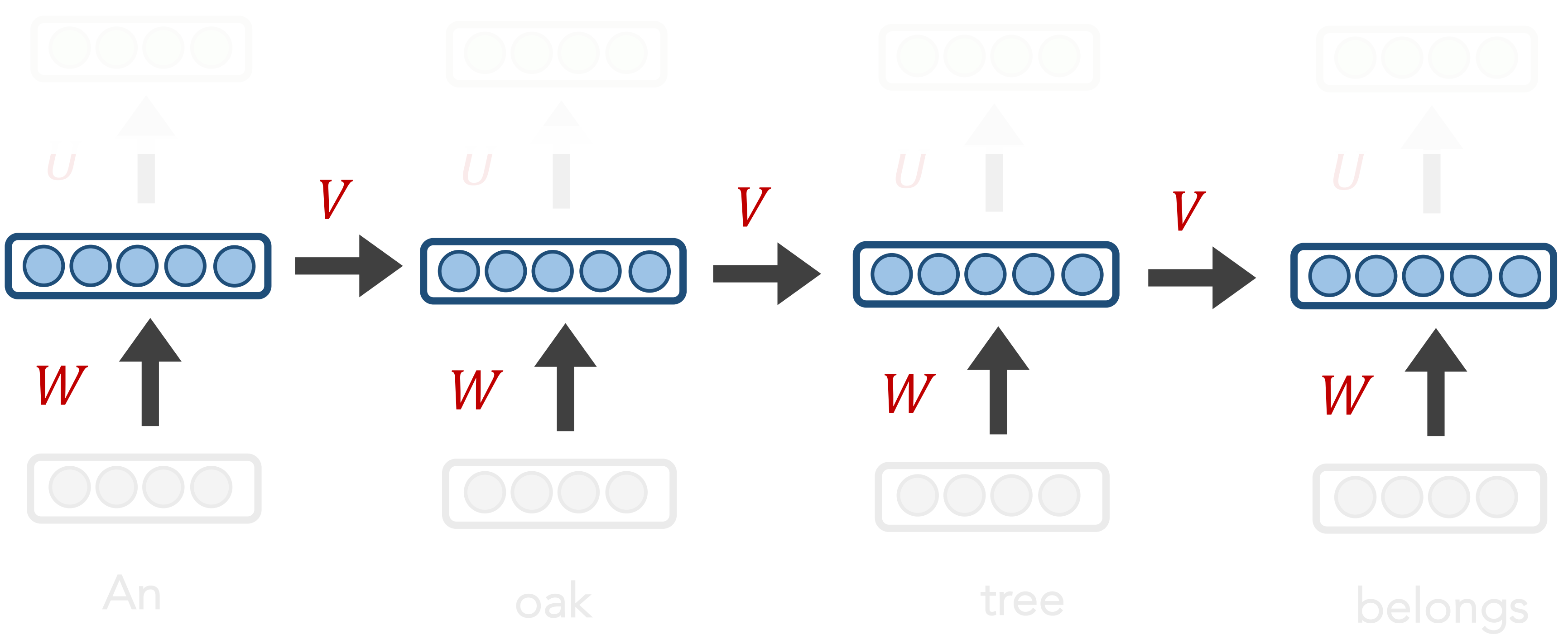
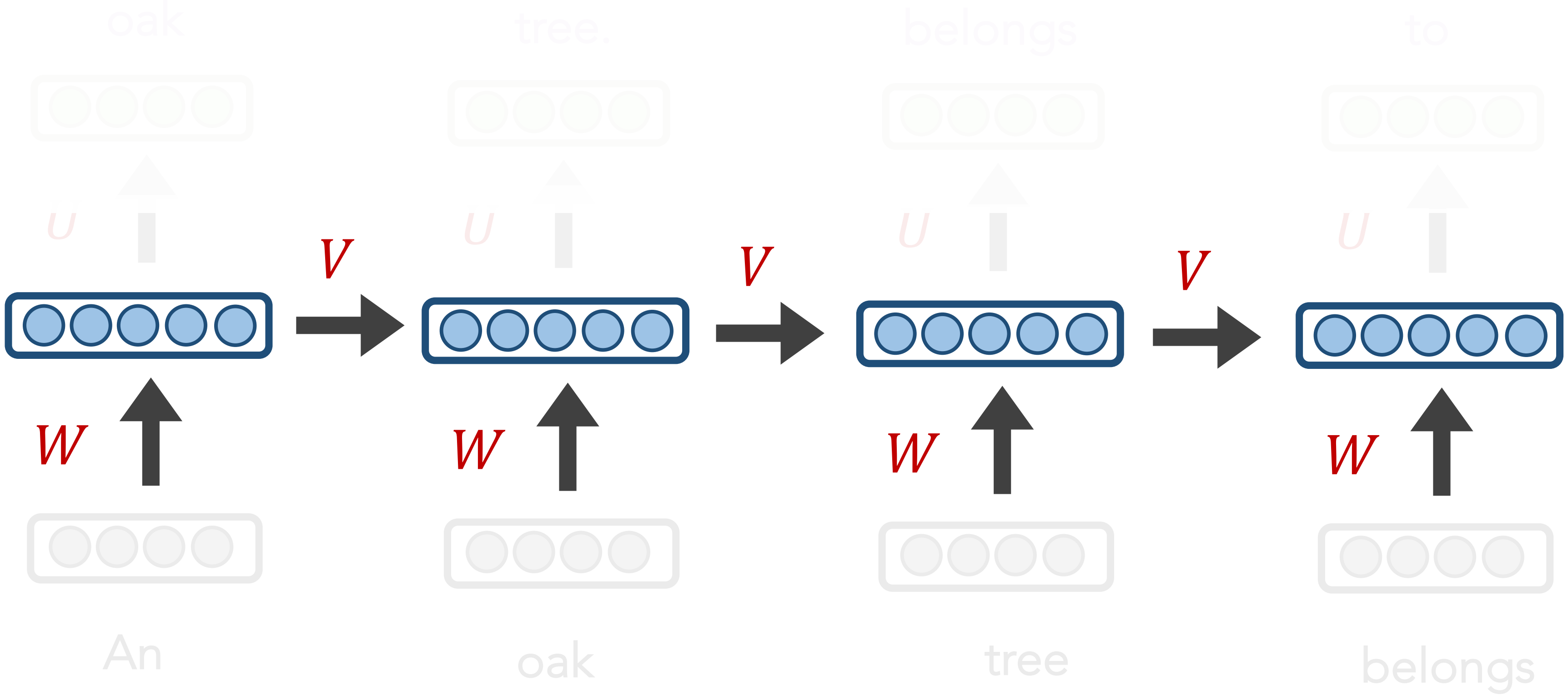


The contextualized embeddings for 1 million docs aren't useful to us for a new task (e.g., predicting Yelp reviews), but the learned weights could be!

Learn a rich, robust W and V



Using these "pre-trained" W and V, we can possibly increase our performance on other tasks (e.g., Yelp reviews), since they're very experienced with producing/capturing "meaning"



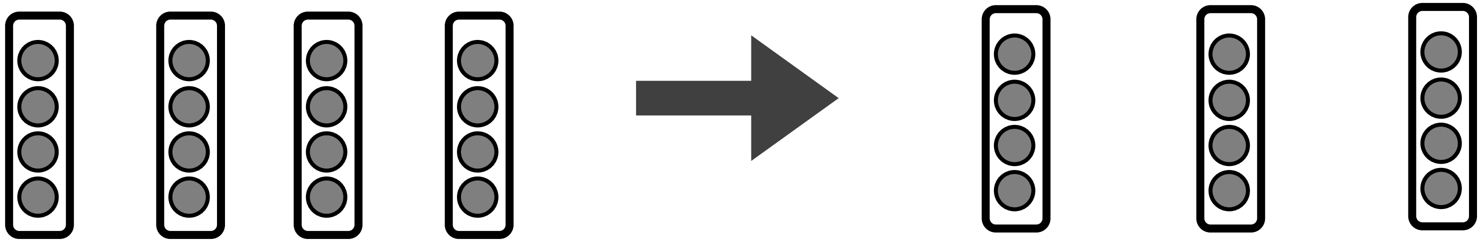
RECAP

- Language Modelling may help us for other tasks
- LSTMs do a great job of capturing "*meaning*", which can be used for almost every task
  - Given a sequence of N words, we can produce 1 output
  - Given a sequence of N words, we can produce N outputs

RECAP

- Language Modelling may help us for other tasks
- LSTMs do a great job of capturing "*meaning*", which can be used for almost every task
  - Given a sequence of N words, we can produce 1 output
  - Given a sequence of N words, we can produce N outputs
  - What if we wish to have M outputs?

We want to produce a **variable-length** output
(e.g., n → m predictions)



Thank you for visiting! Děkujeme za návštěvu!

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- seq2seq
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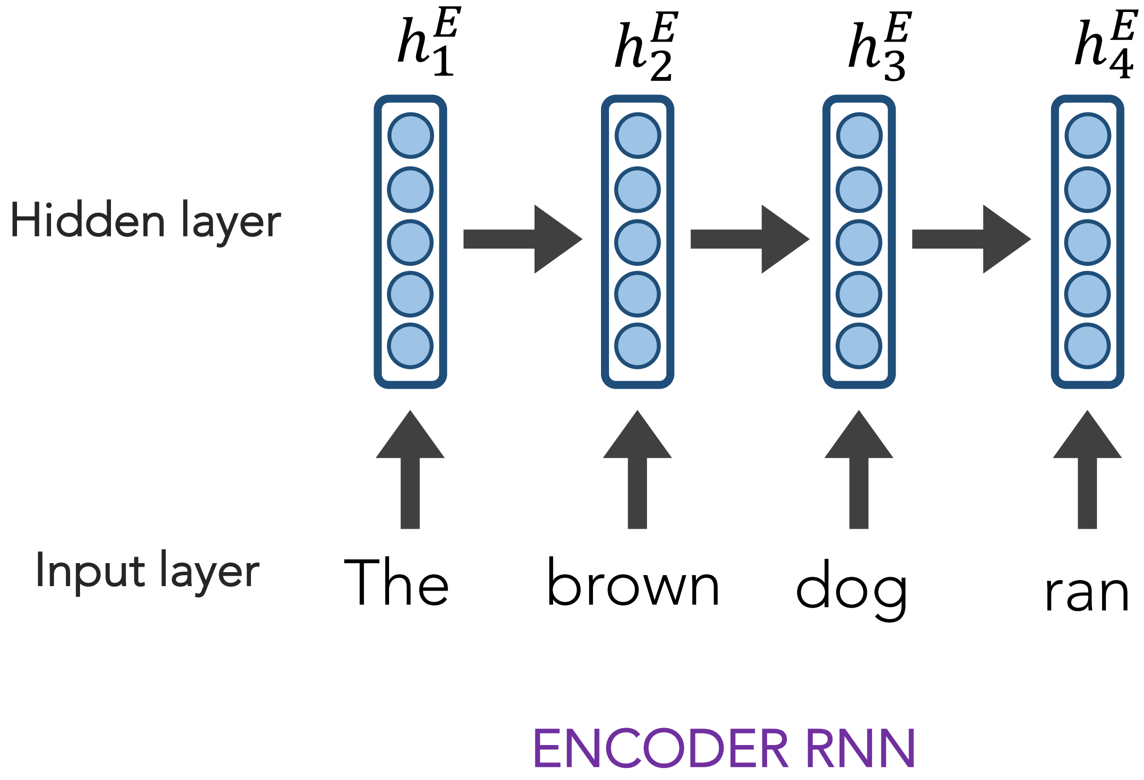
Sequence-to-Sequence (seq2seq)

- 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**)

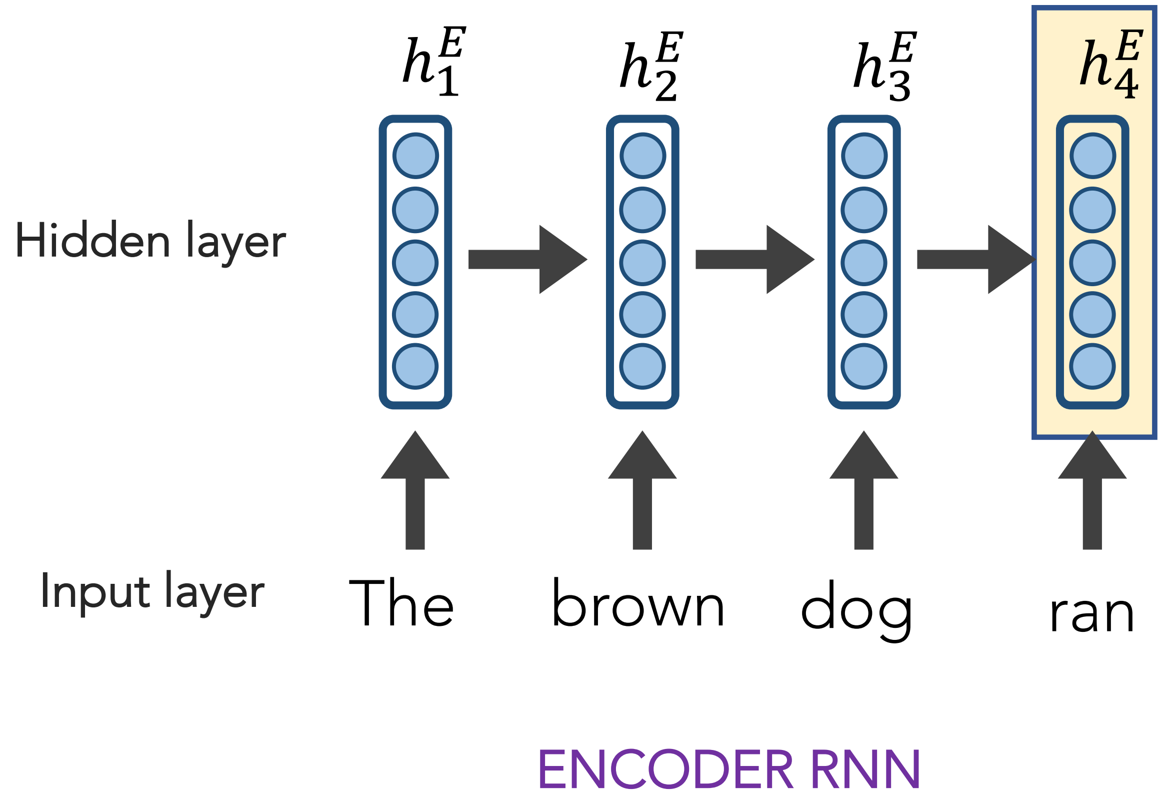
- Seq2seq models are comprised of **2 RNNs**: 1 encoder, 1 decoder

Sequence-to-Sequence (seq2seq)



Sequence-to-Sequence (seq2seq)

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



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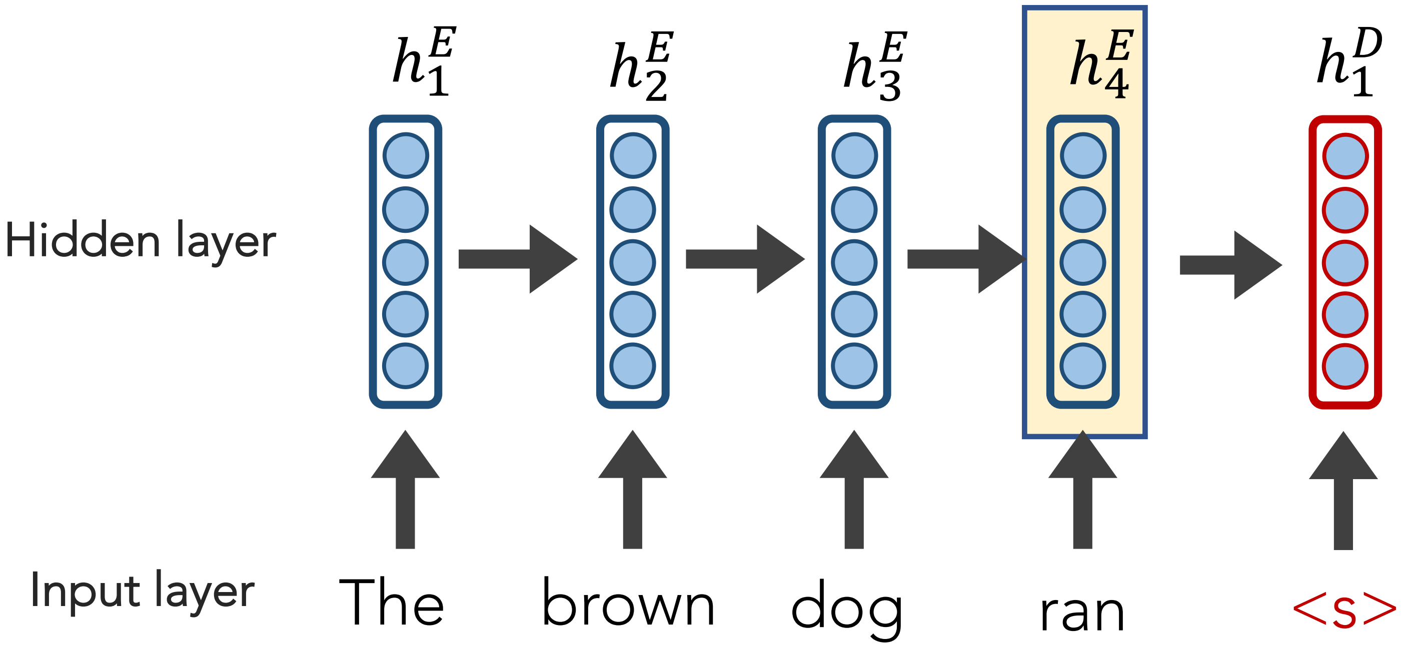

ENCODER RNN

DECODER RNN

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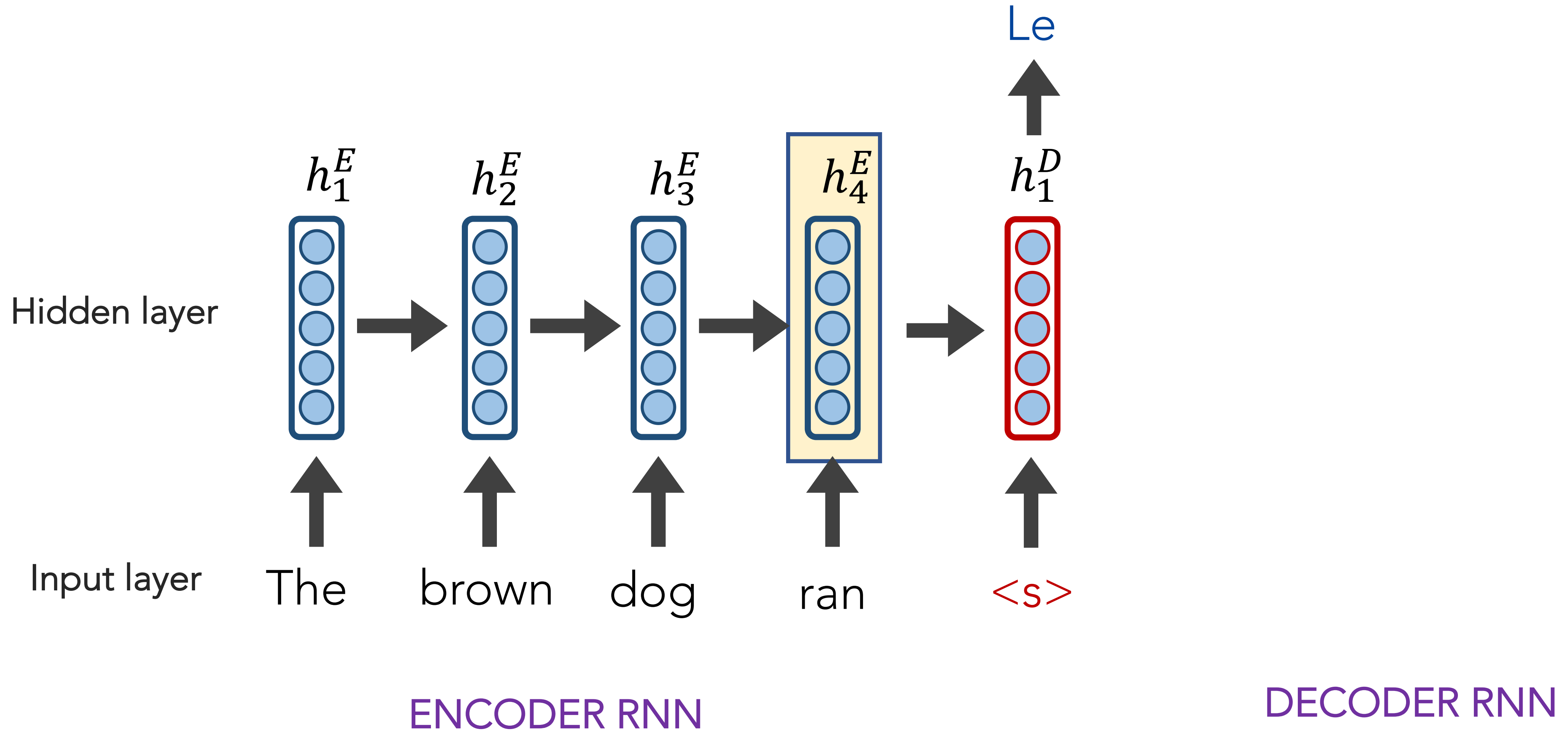

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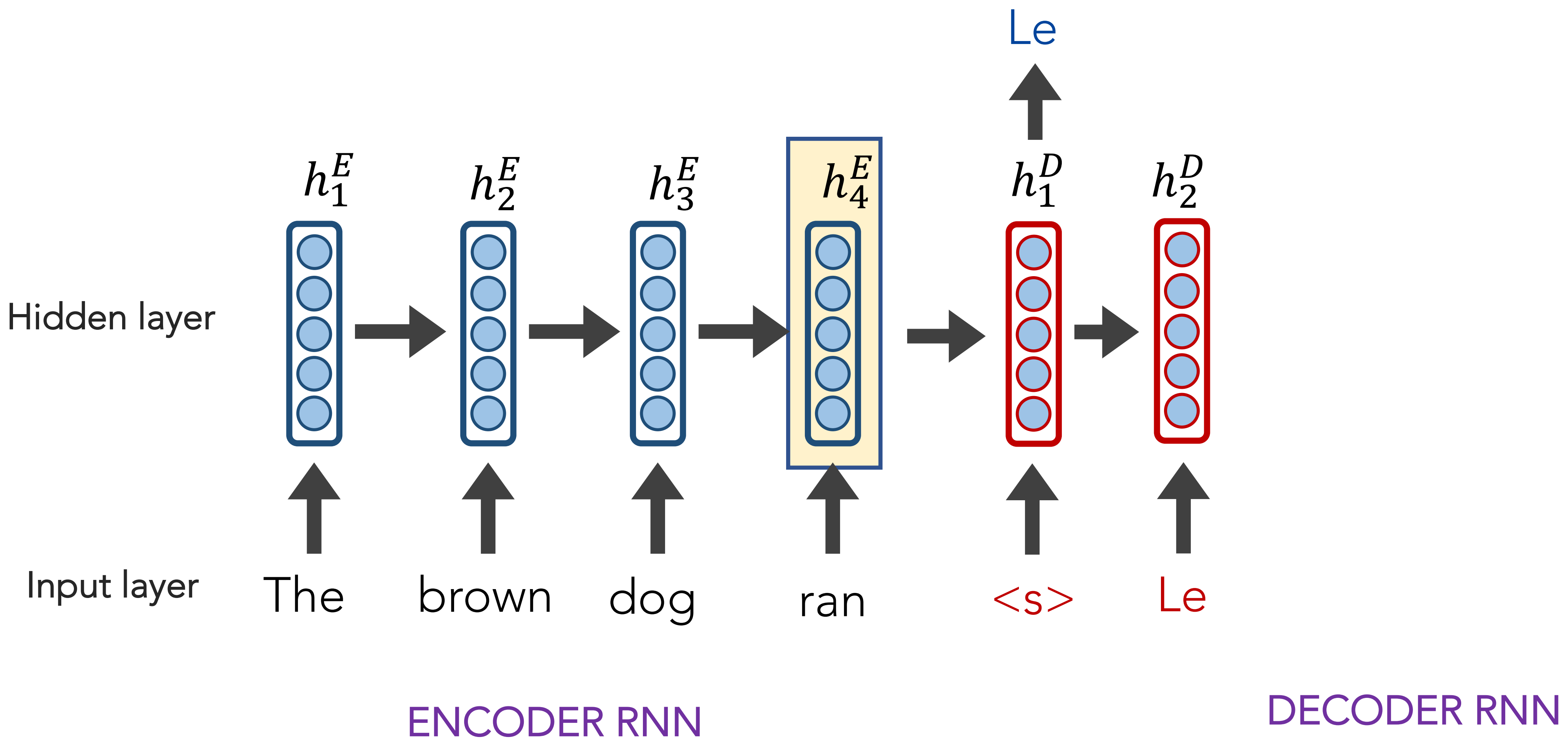

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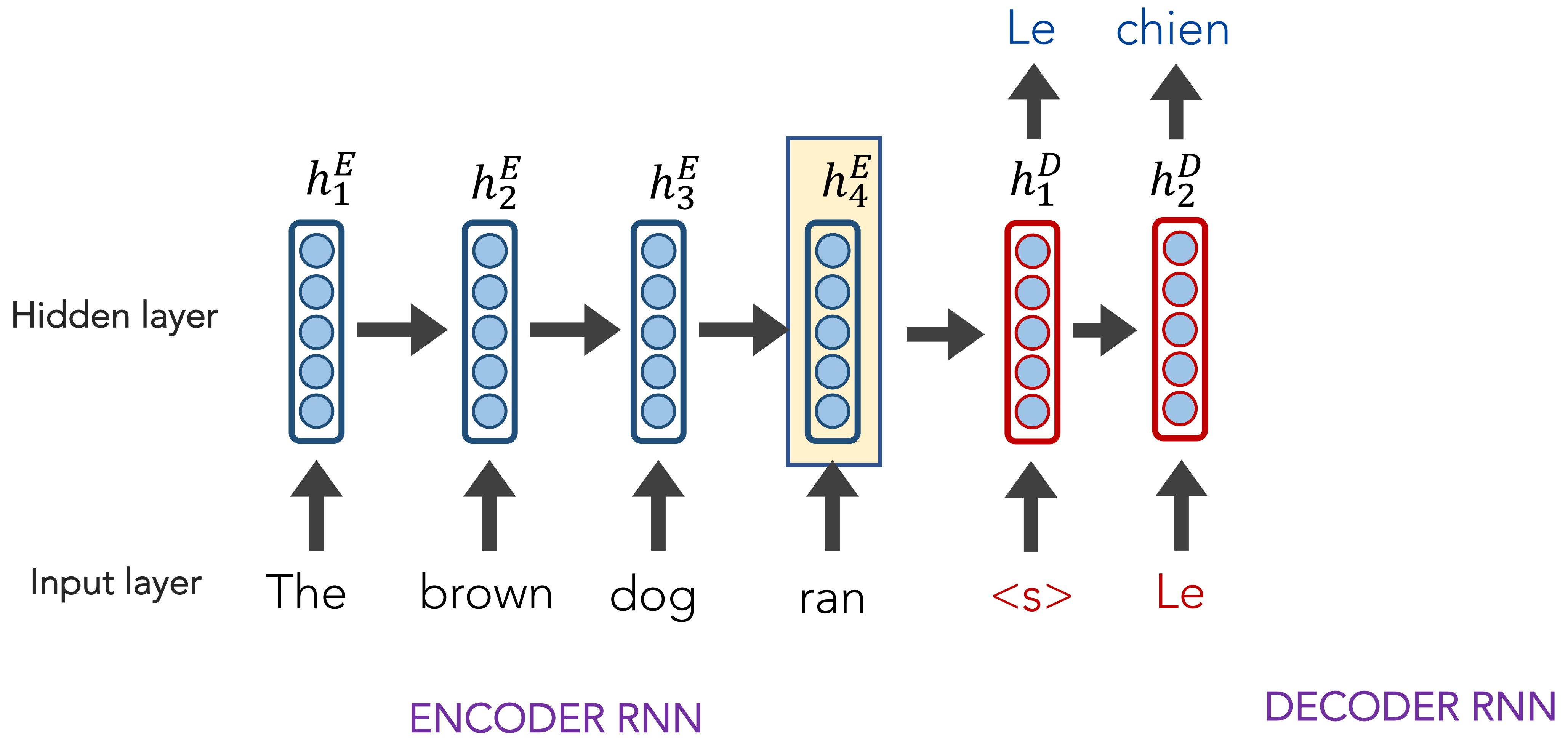

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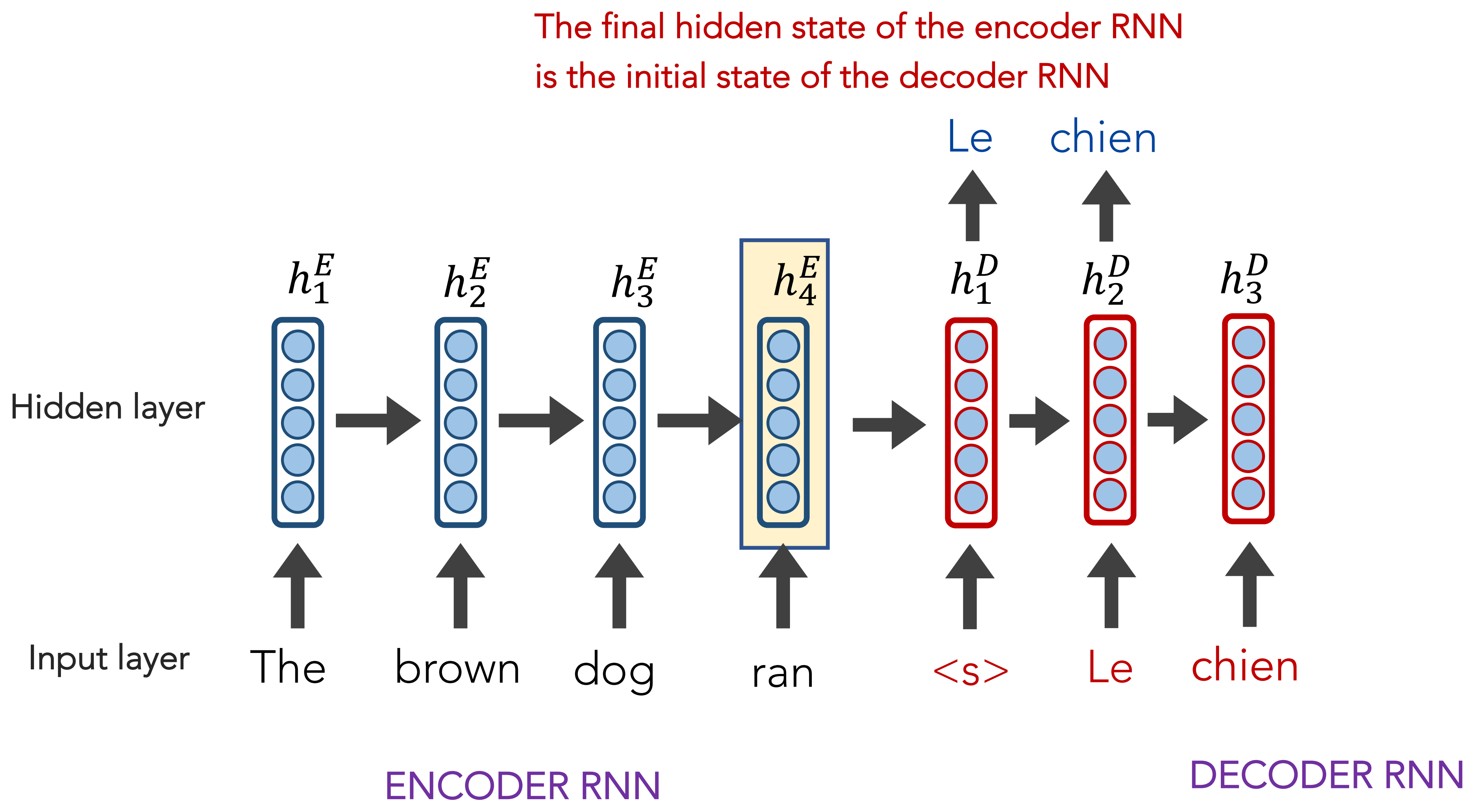

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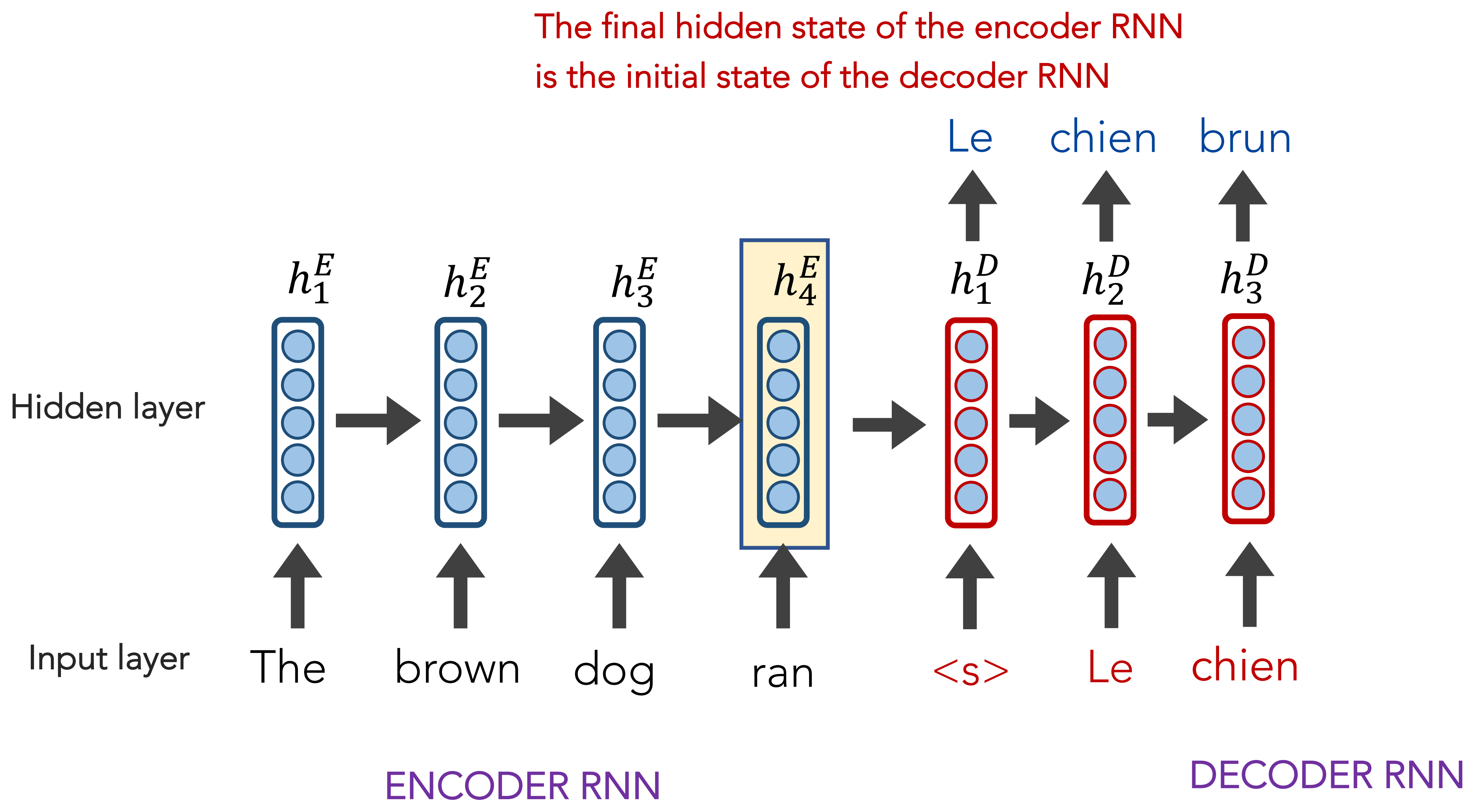

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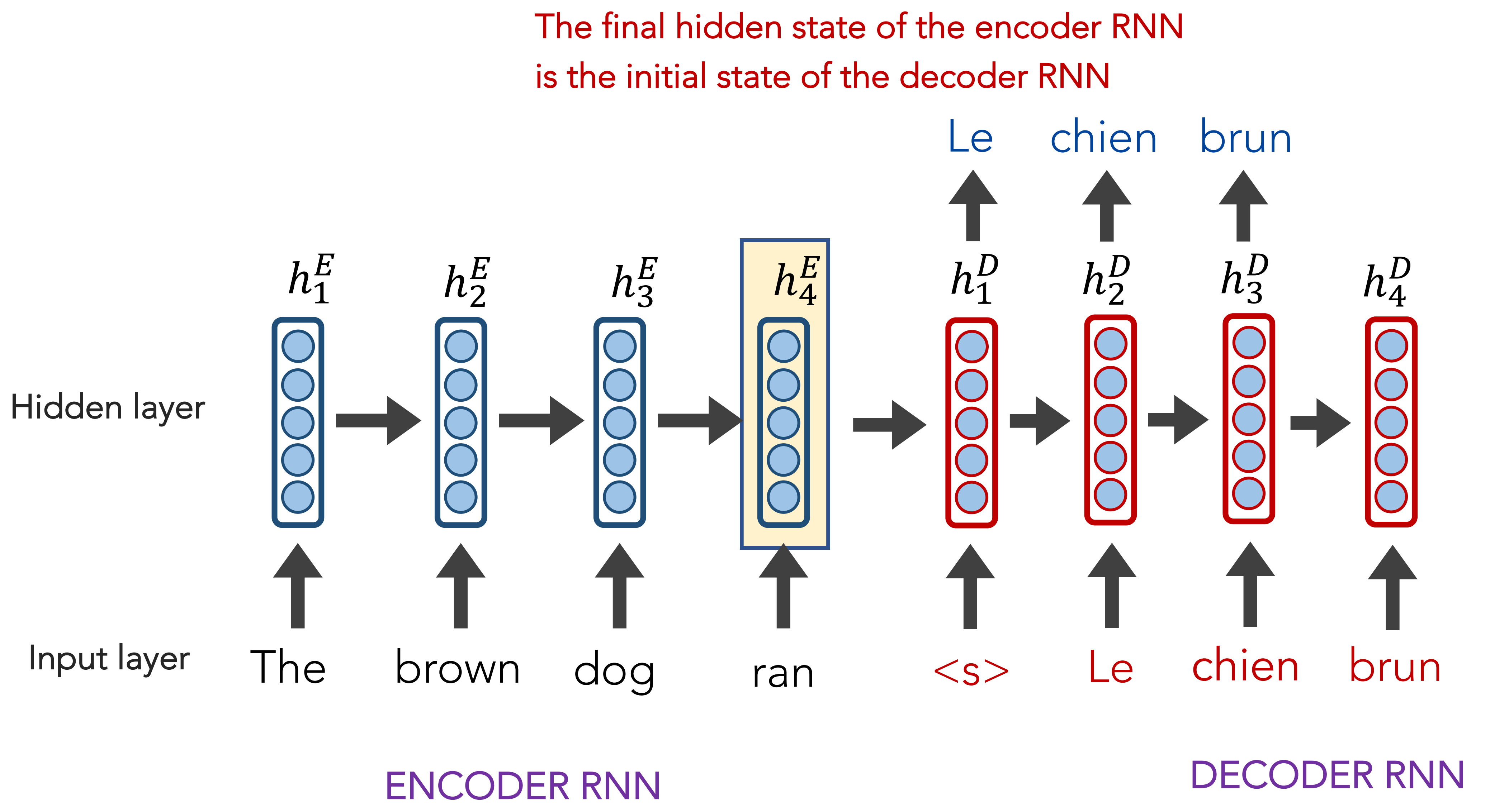

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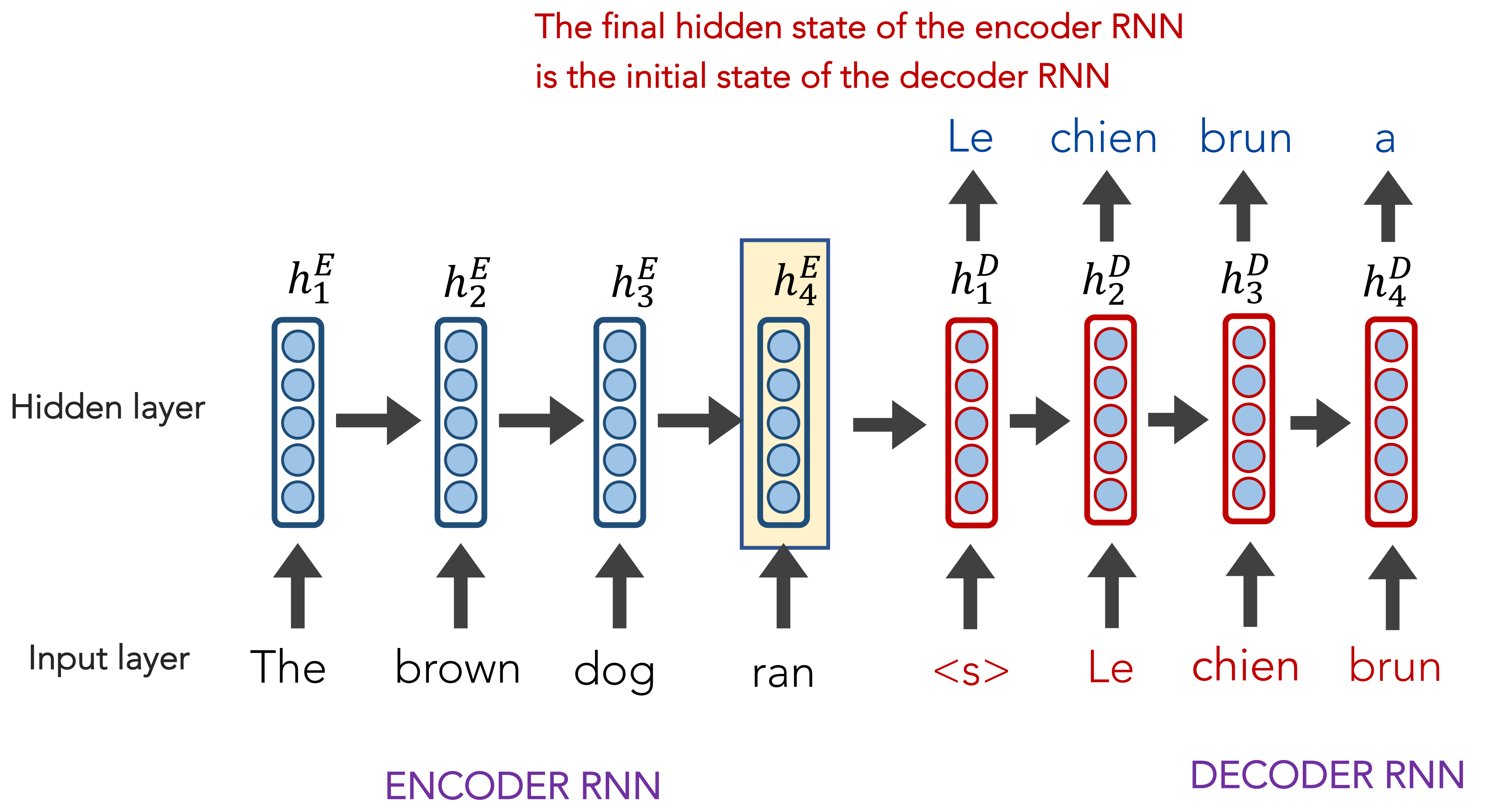

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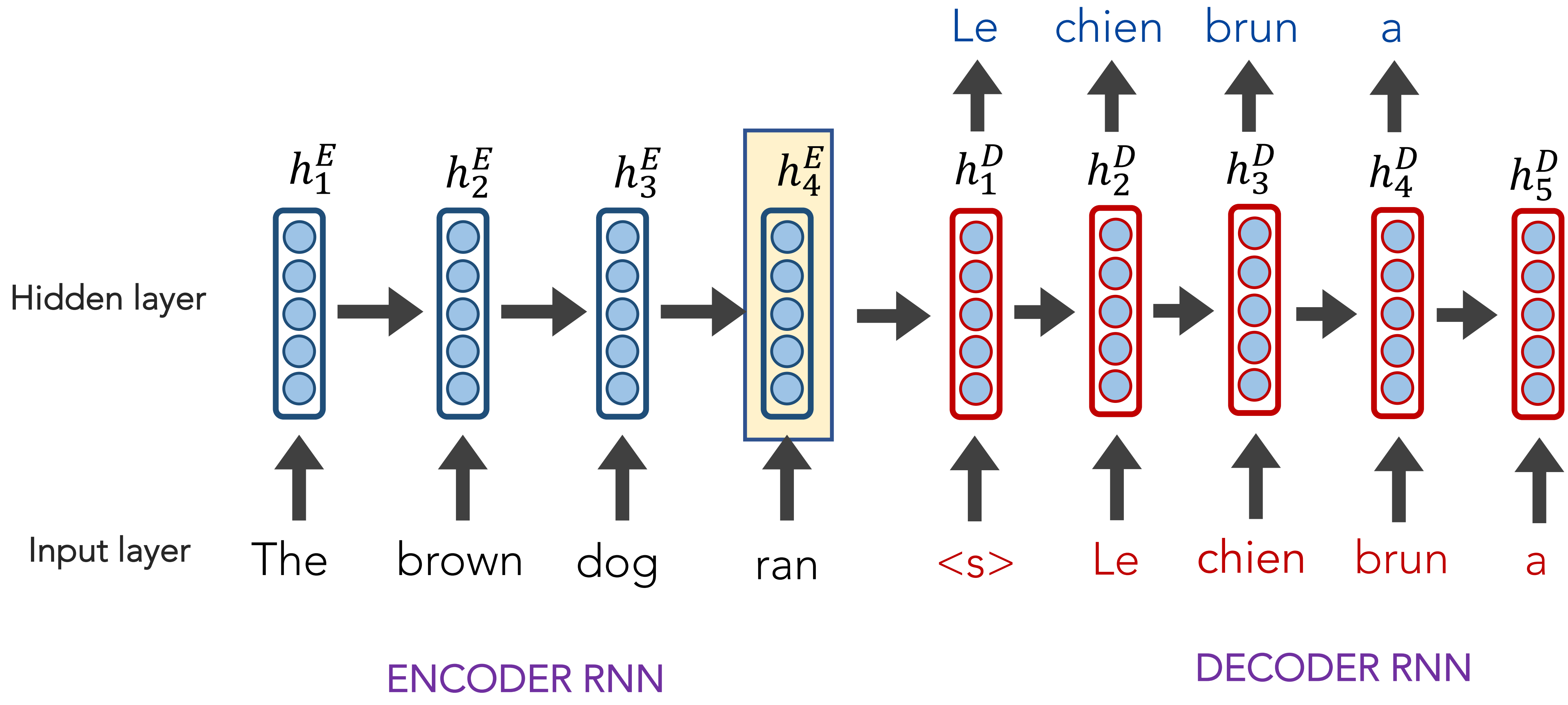

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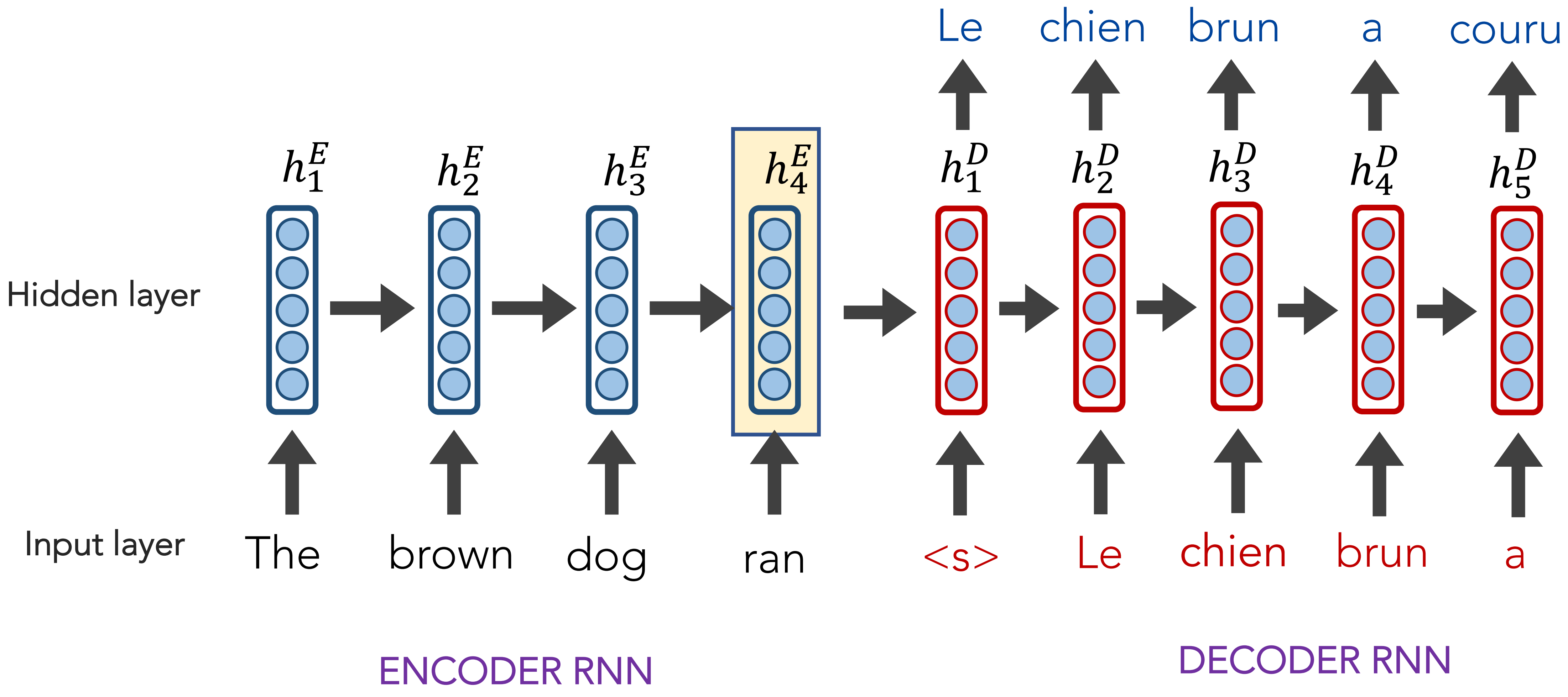

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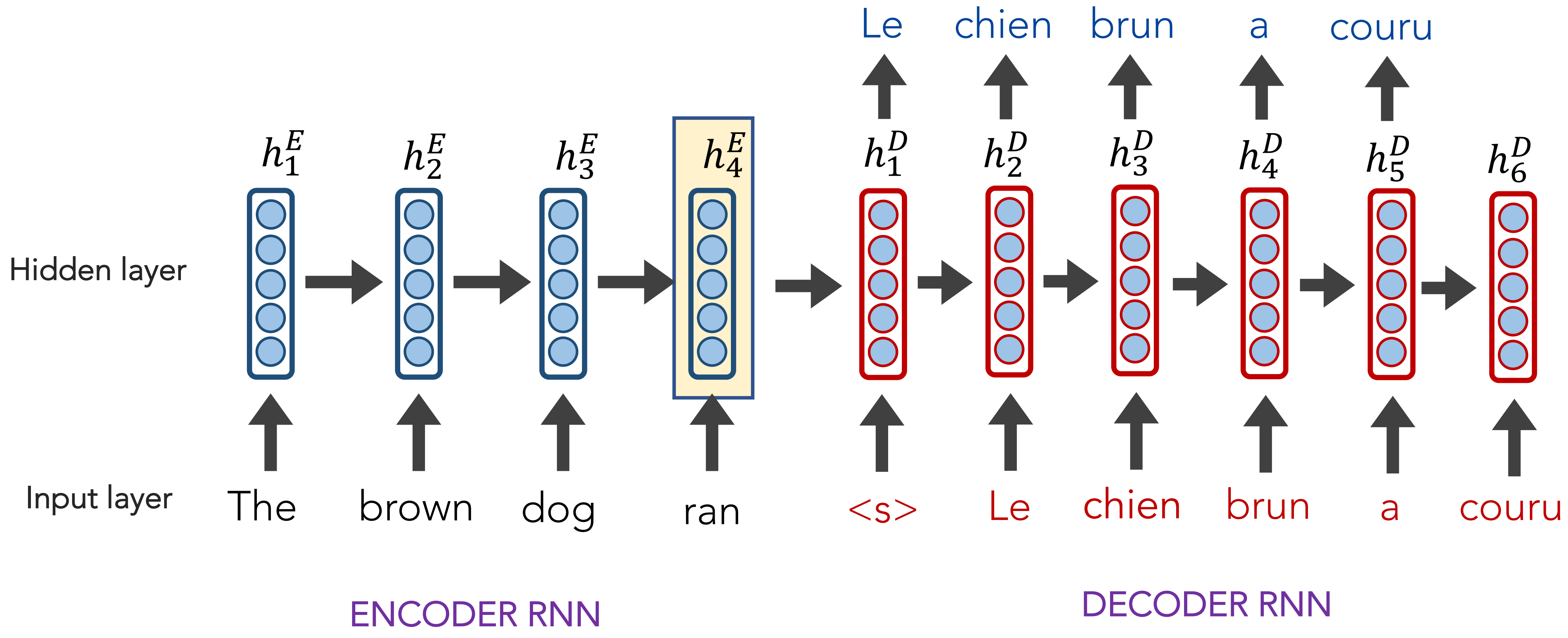

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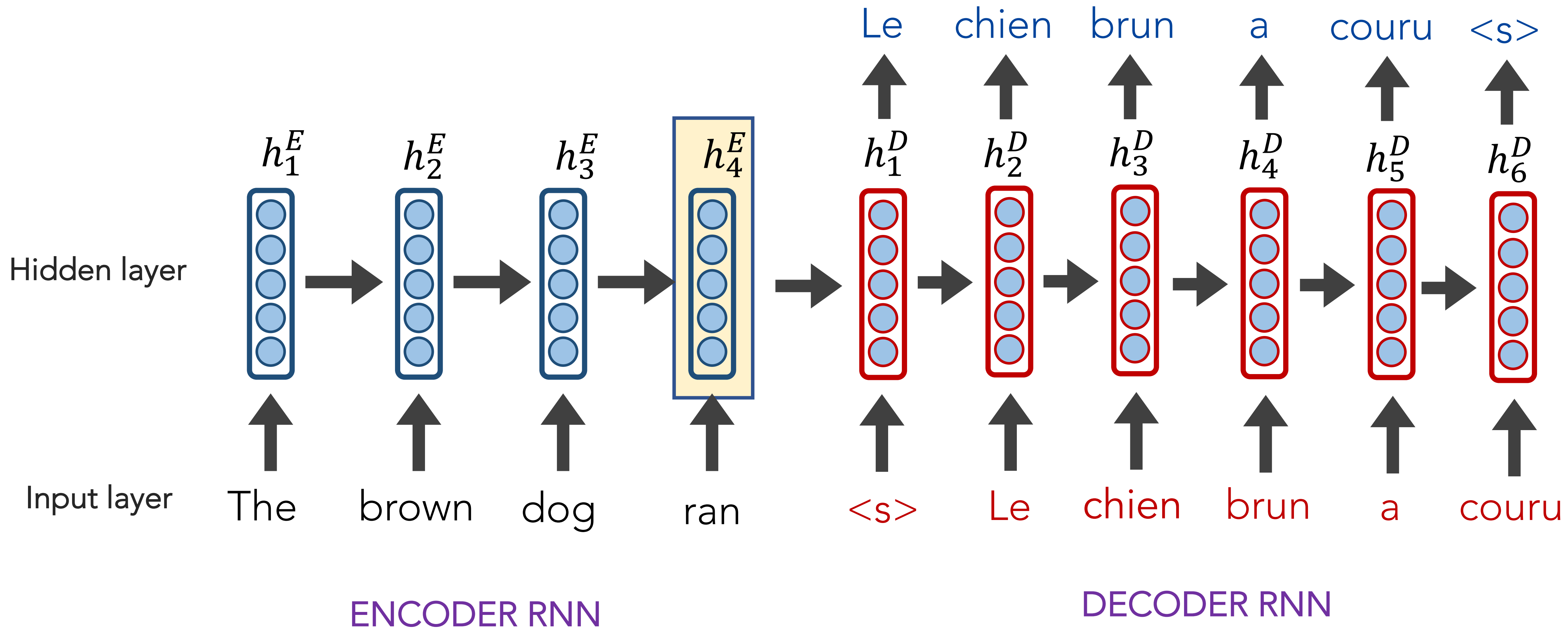

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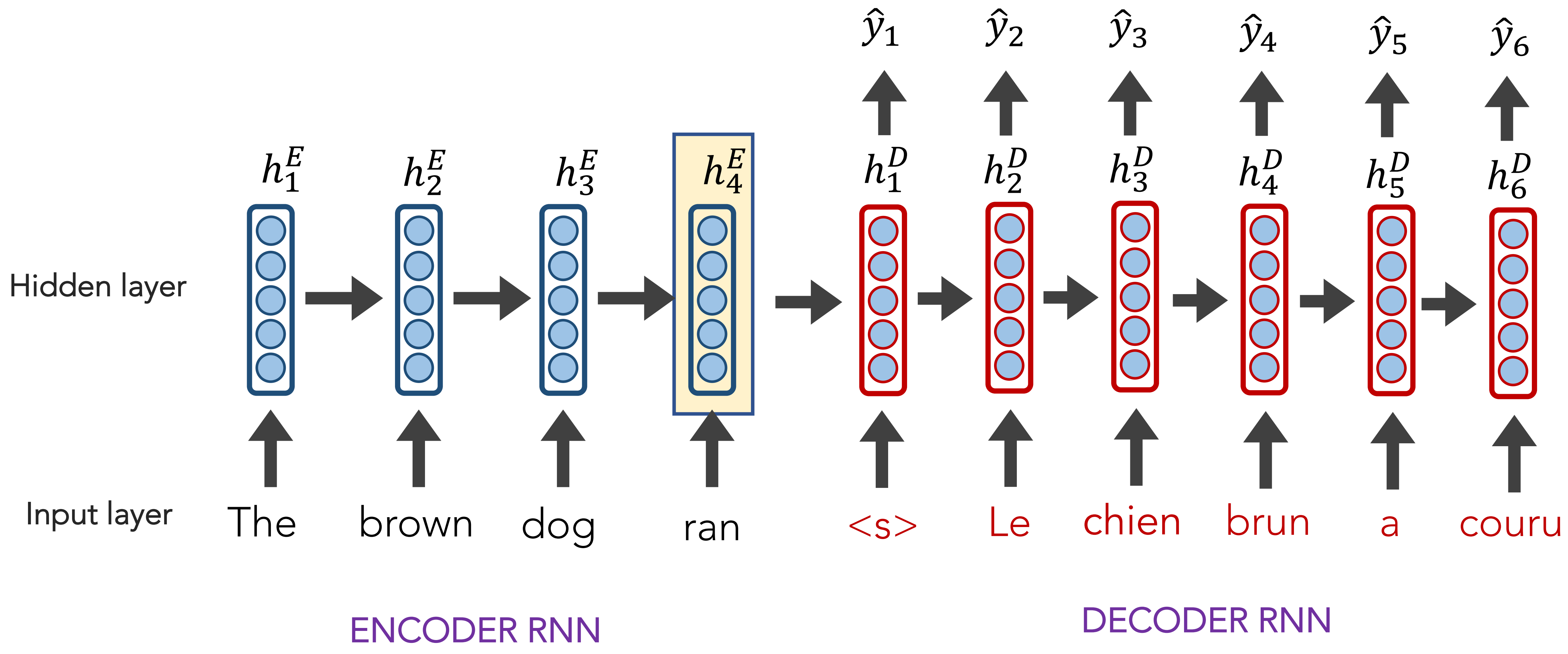
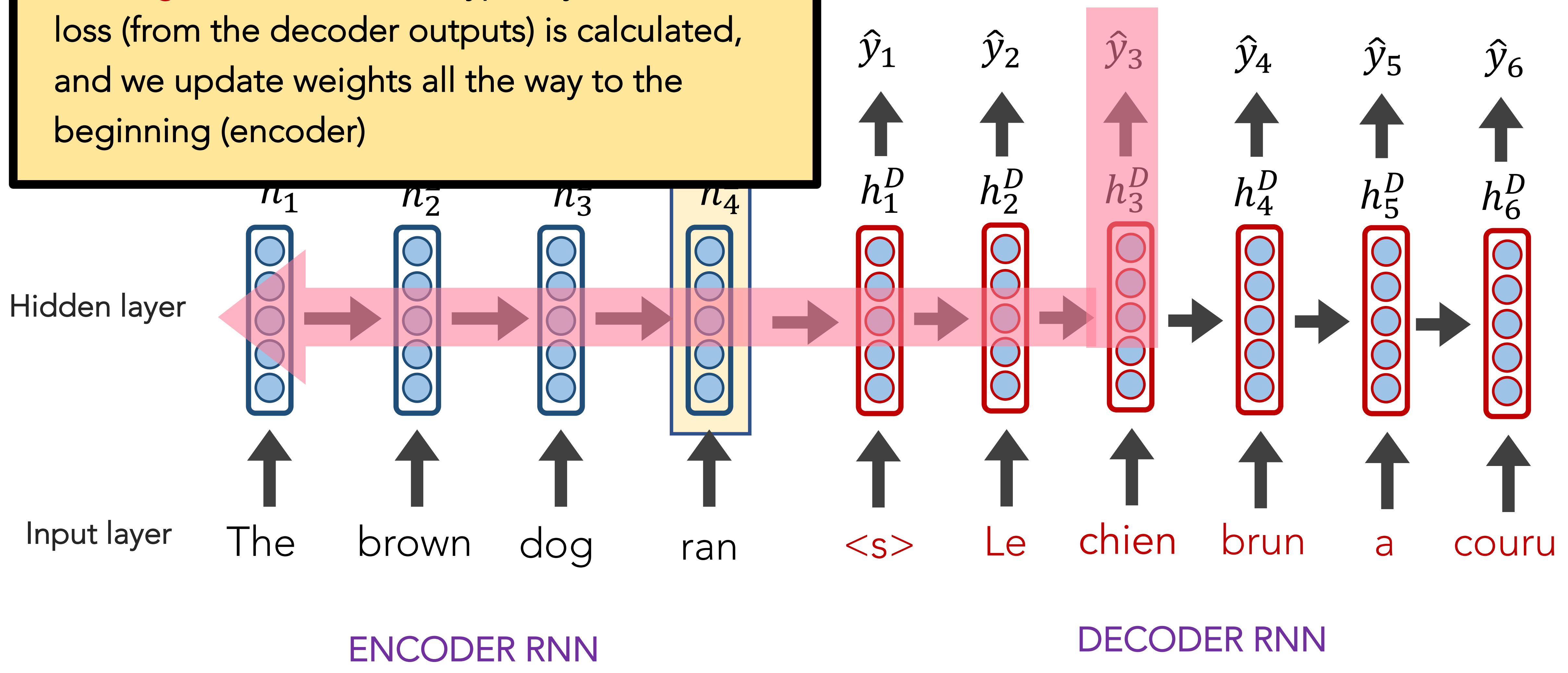


Sequence-to-Sequence (seq2seq)

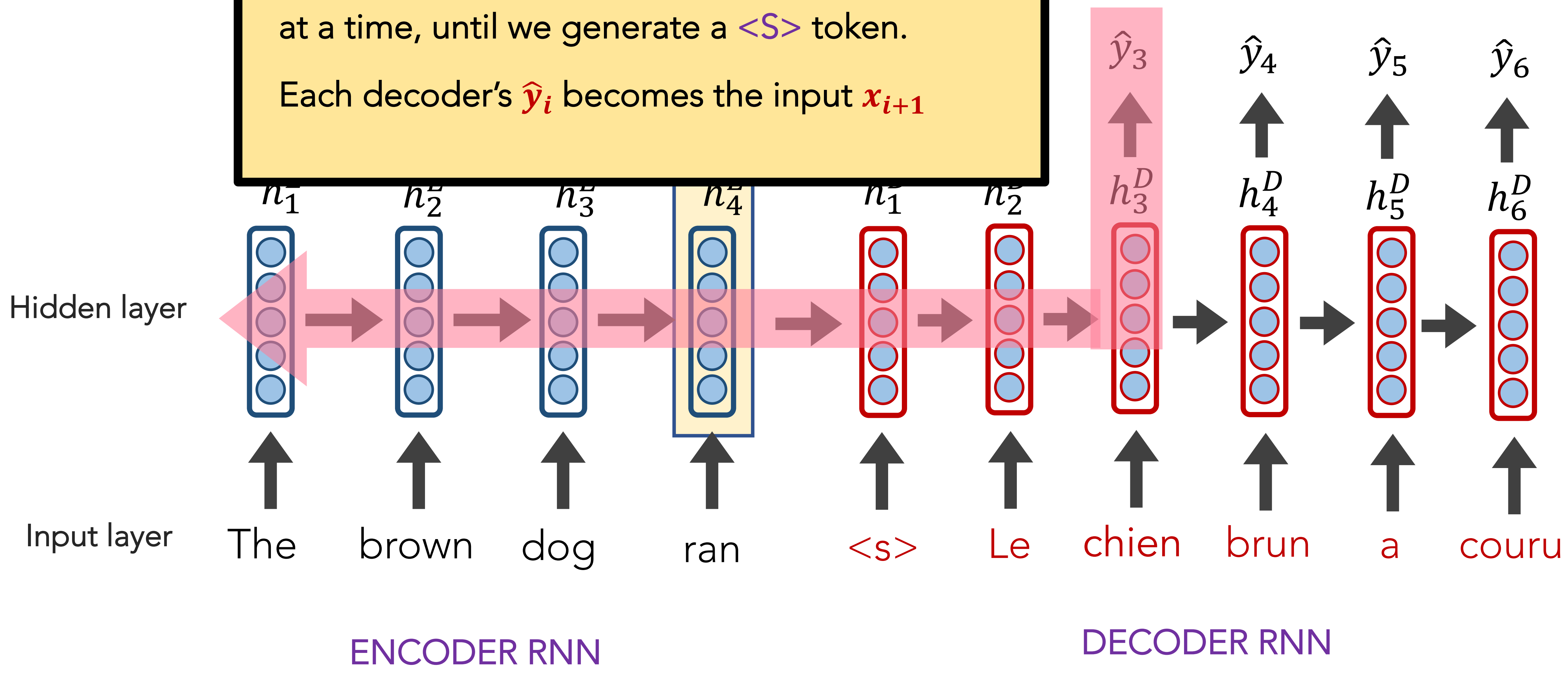
Training occurs like RNNs typically do; the loss (from the decoder outputs) is calculated, and we update weights all the way to the beginning (encoder)



Sequence-to-Sequence (seq2seq)

Testing generates decoder outputs one word at a time, until we generate a <S> token.

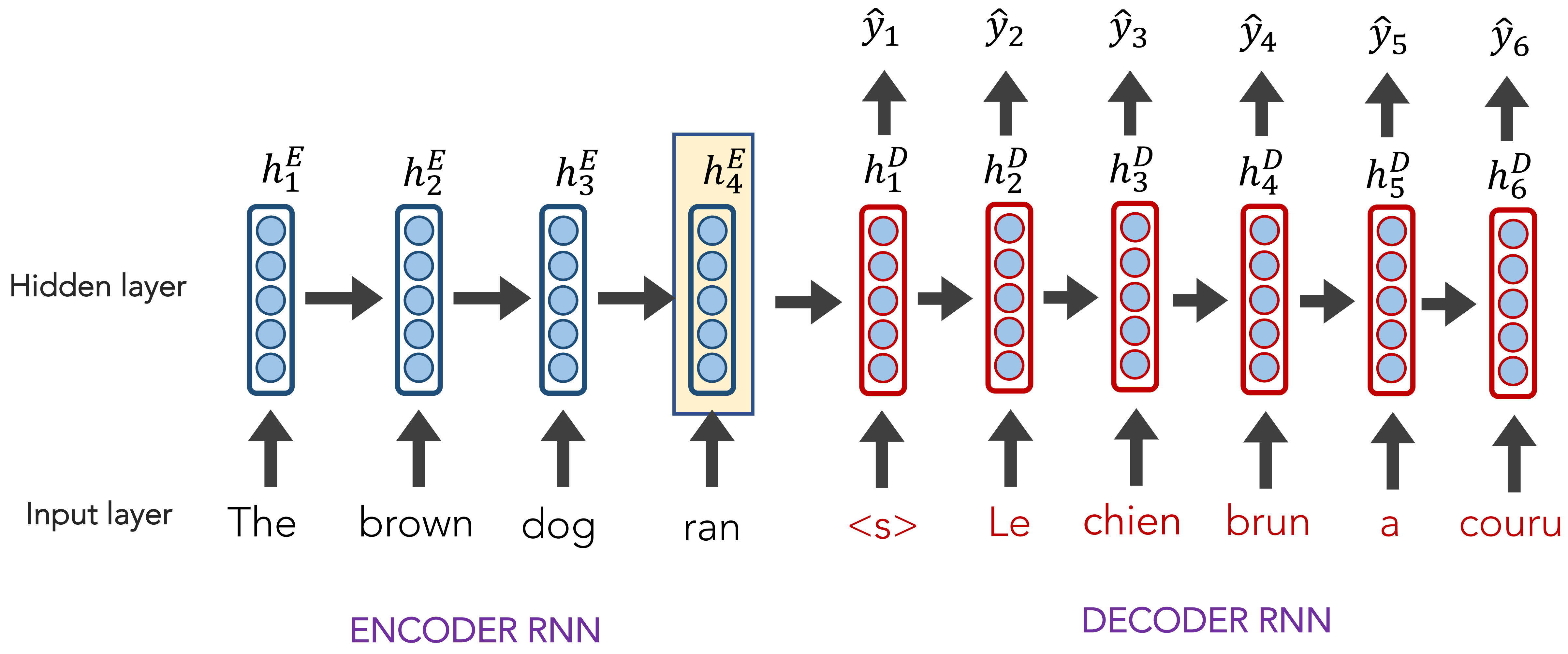
Each decoder's $\hat{\boldsymbol{y}}_i$ becomes the input $\boldsymbol{x}_{i+1}$



Sequence-to-Sequence (seq2seq)

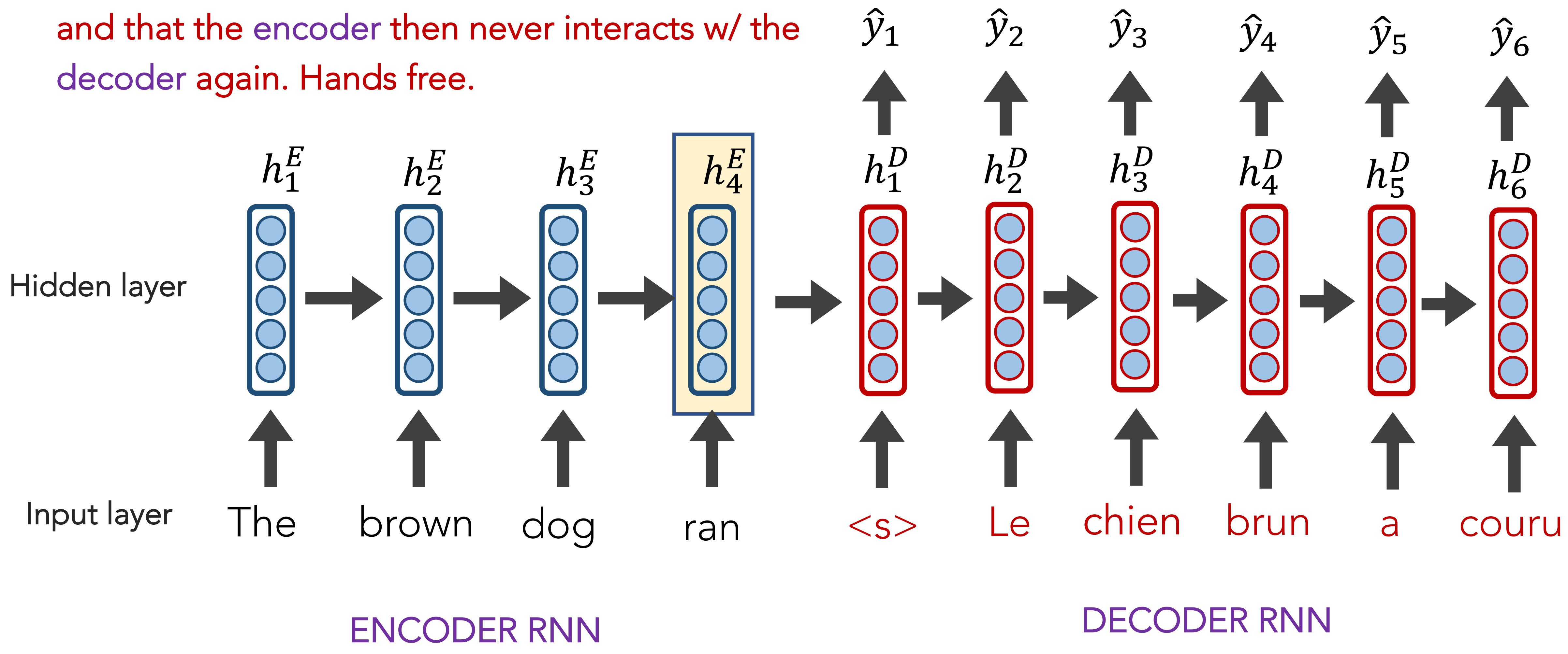
See any issues with this traditional **seq2seq** paradigm?

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 then regurgitate in a new language; we continuously look back at the original while focusing on different parts.

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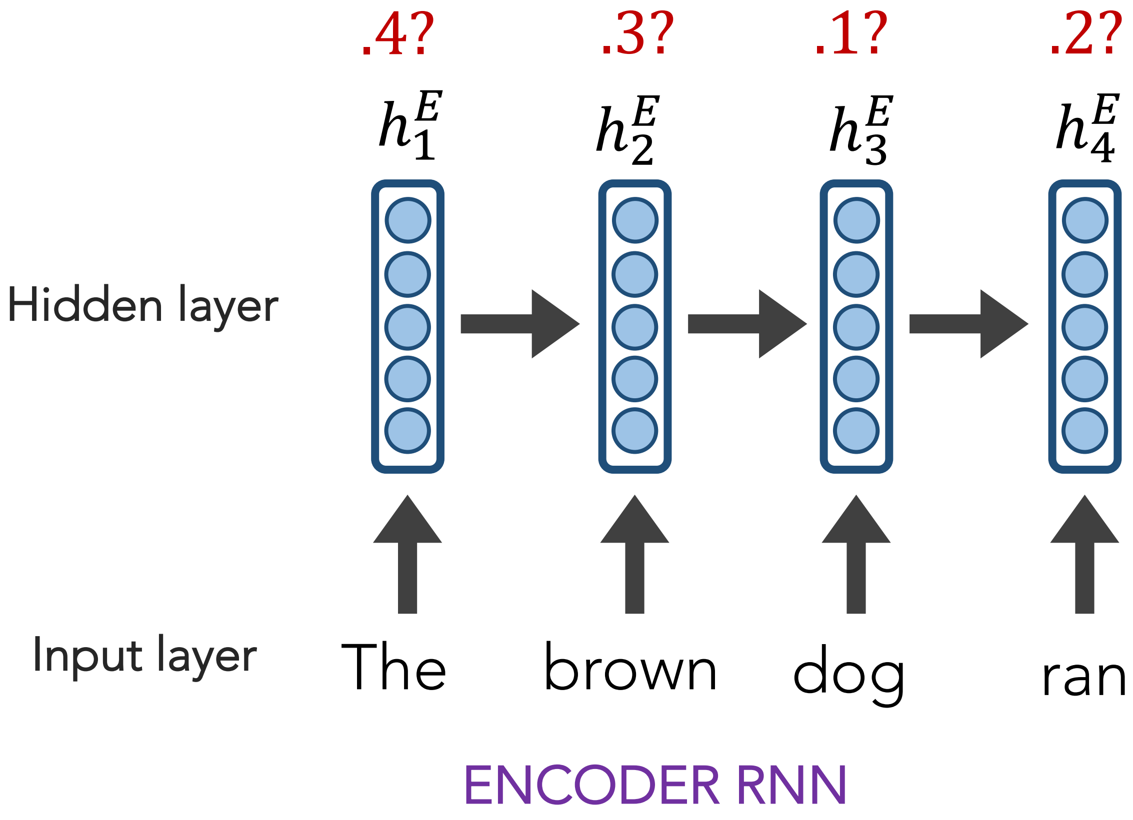
seq2seq + Attention

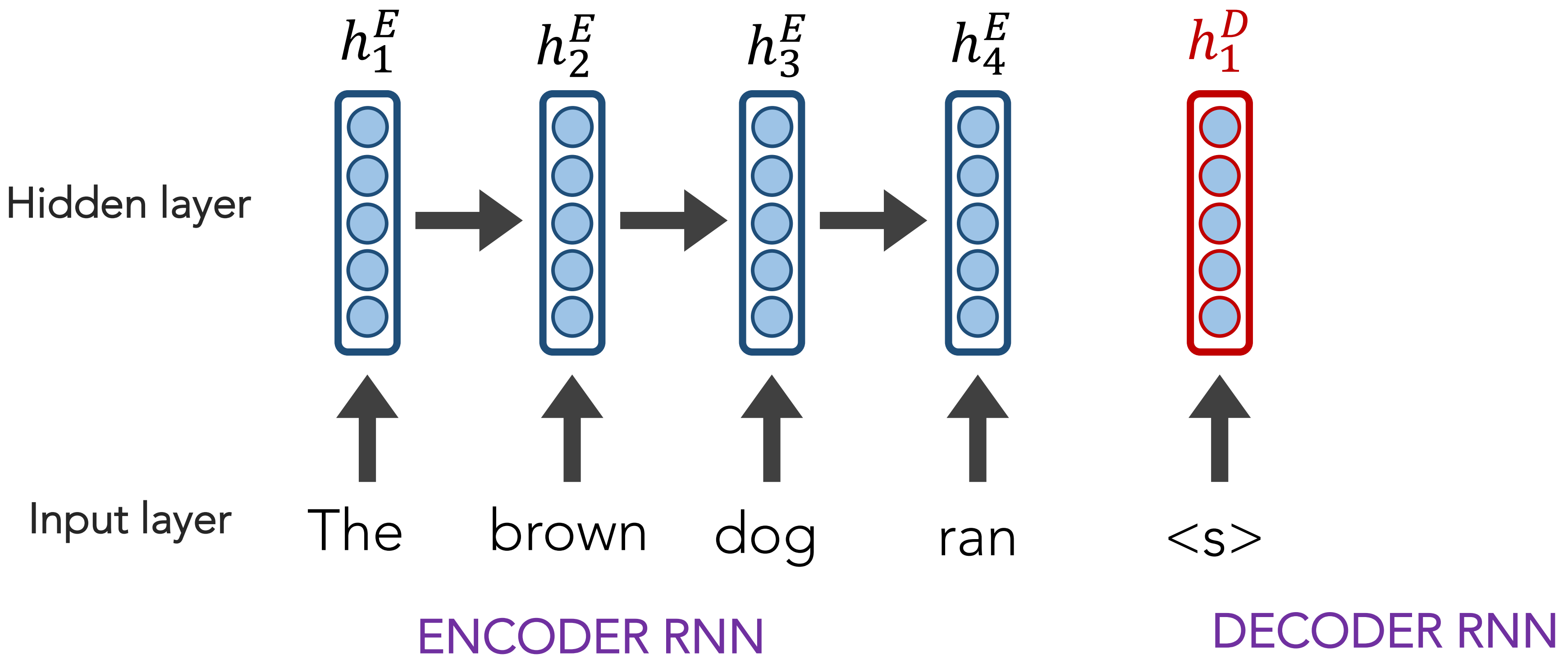
Q: How do we determine how much to pay attention to each of the encoder's hidden layers?



seq2seq + Attention

Q: How do we determine how much to pay attention to each of the encoder's hidden layers?

A: Let's base it on our decoder's current hidden state (our current representation of meaning) and all of the encoder's hidden layers!



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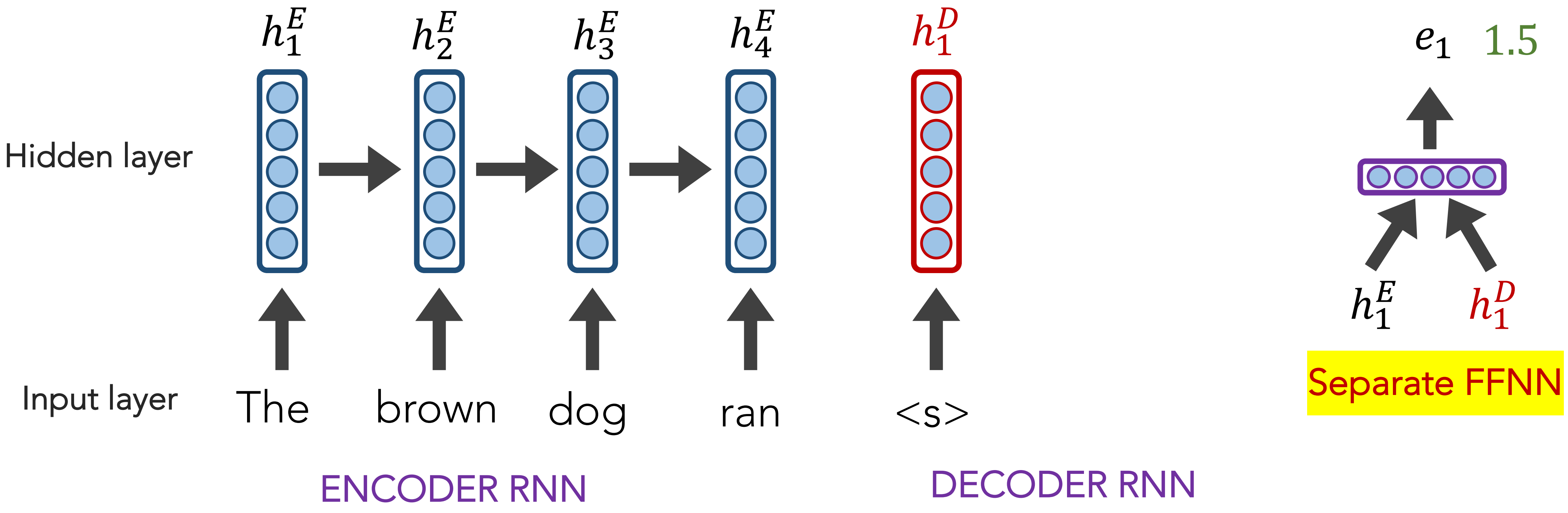

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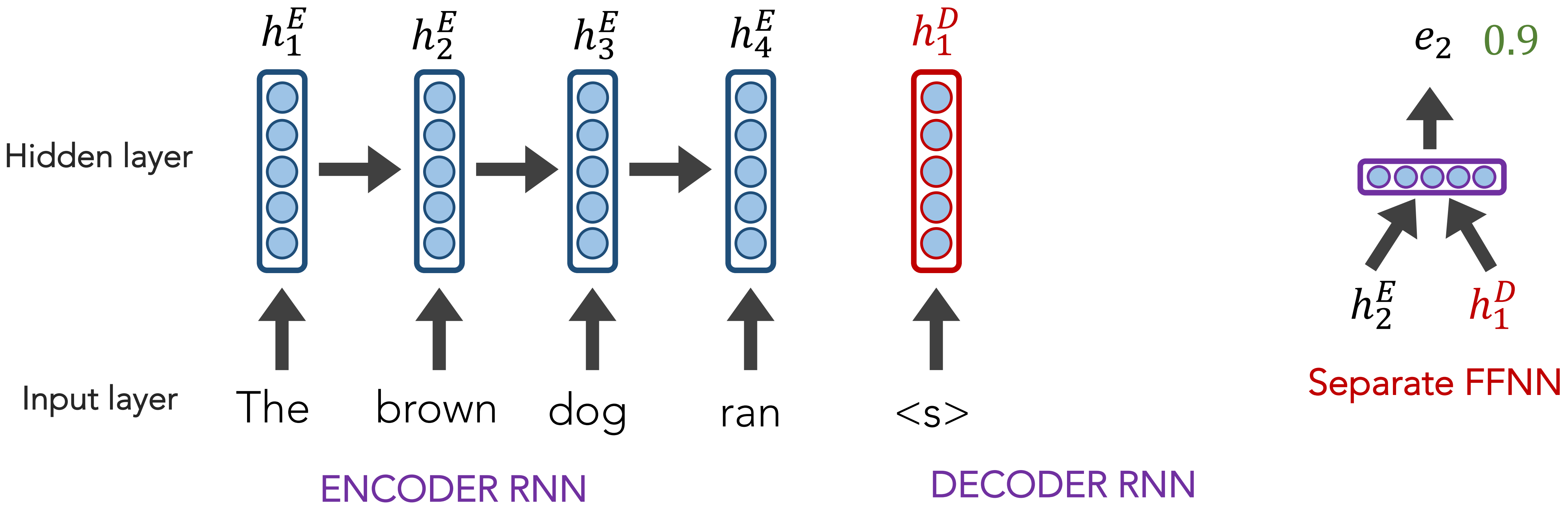

seq2seq + Attention

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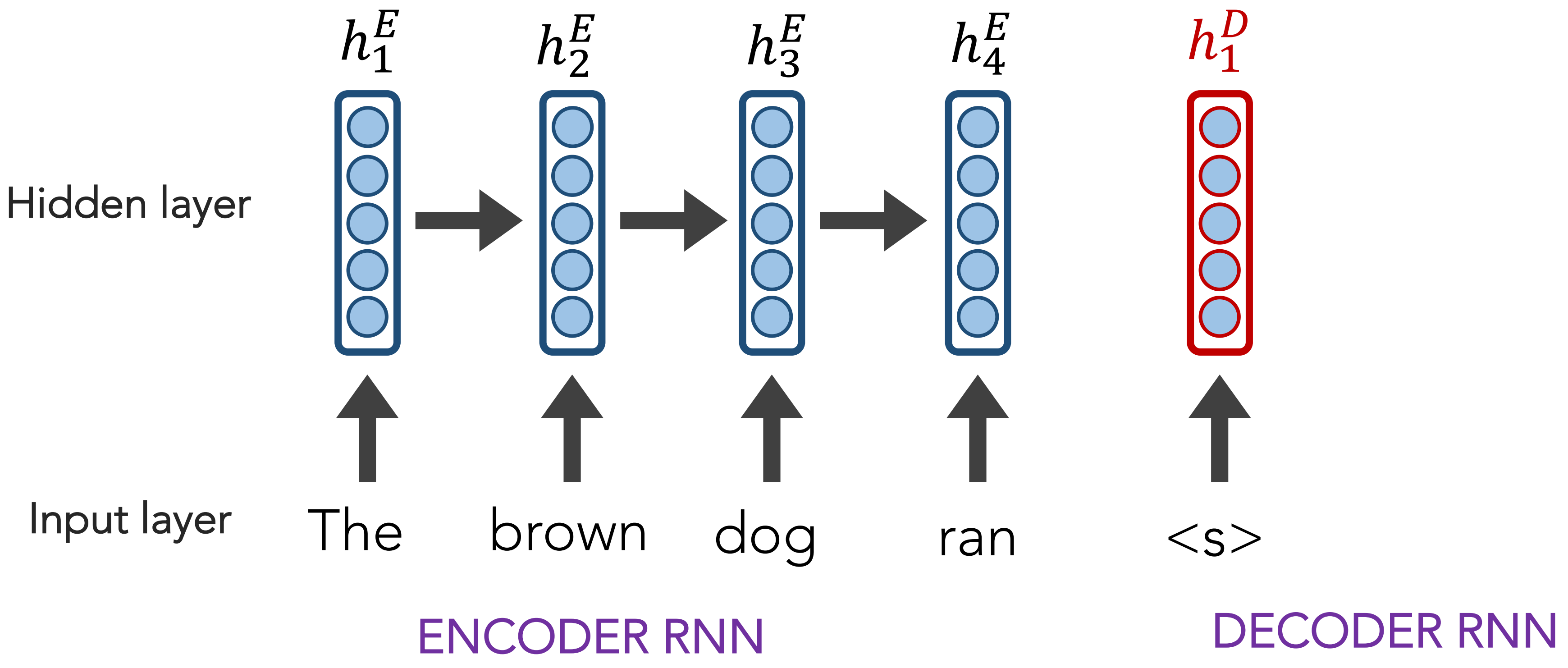

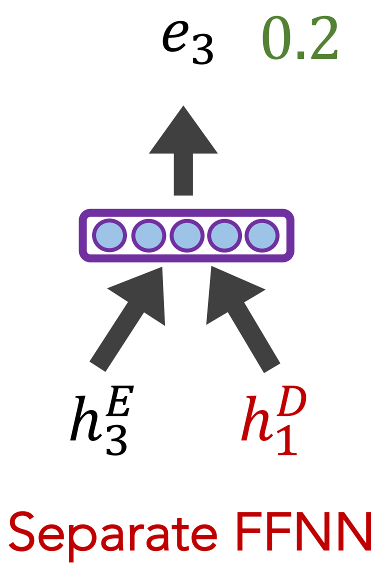

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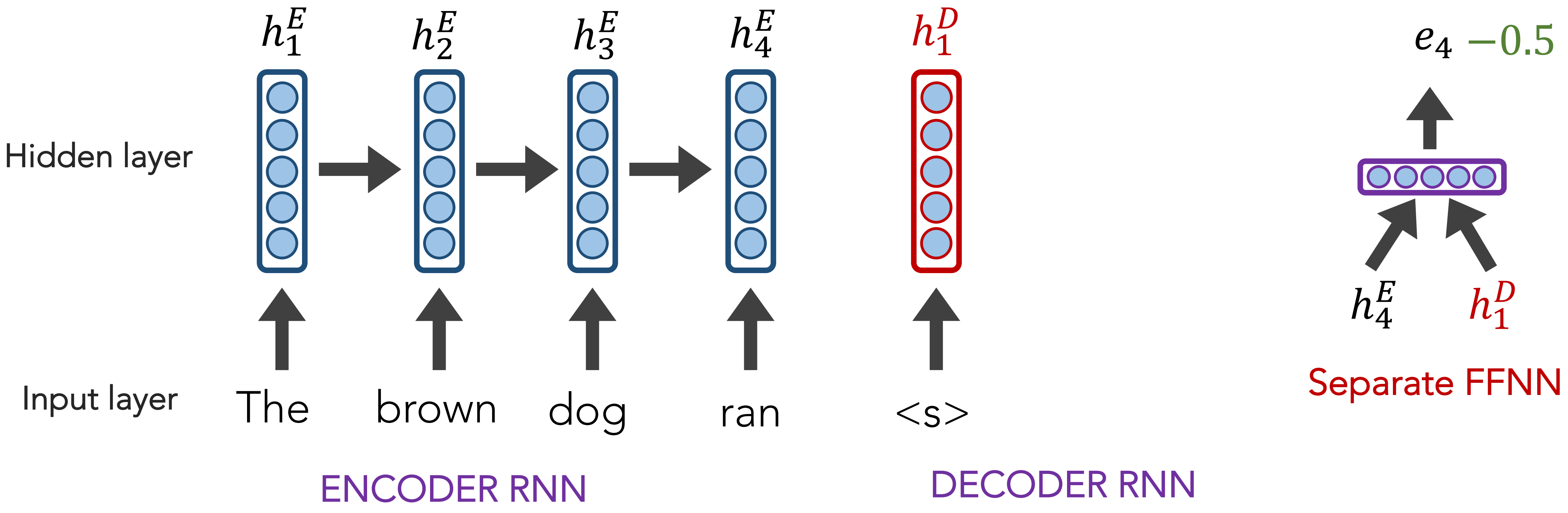

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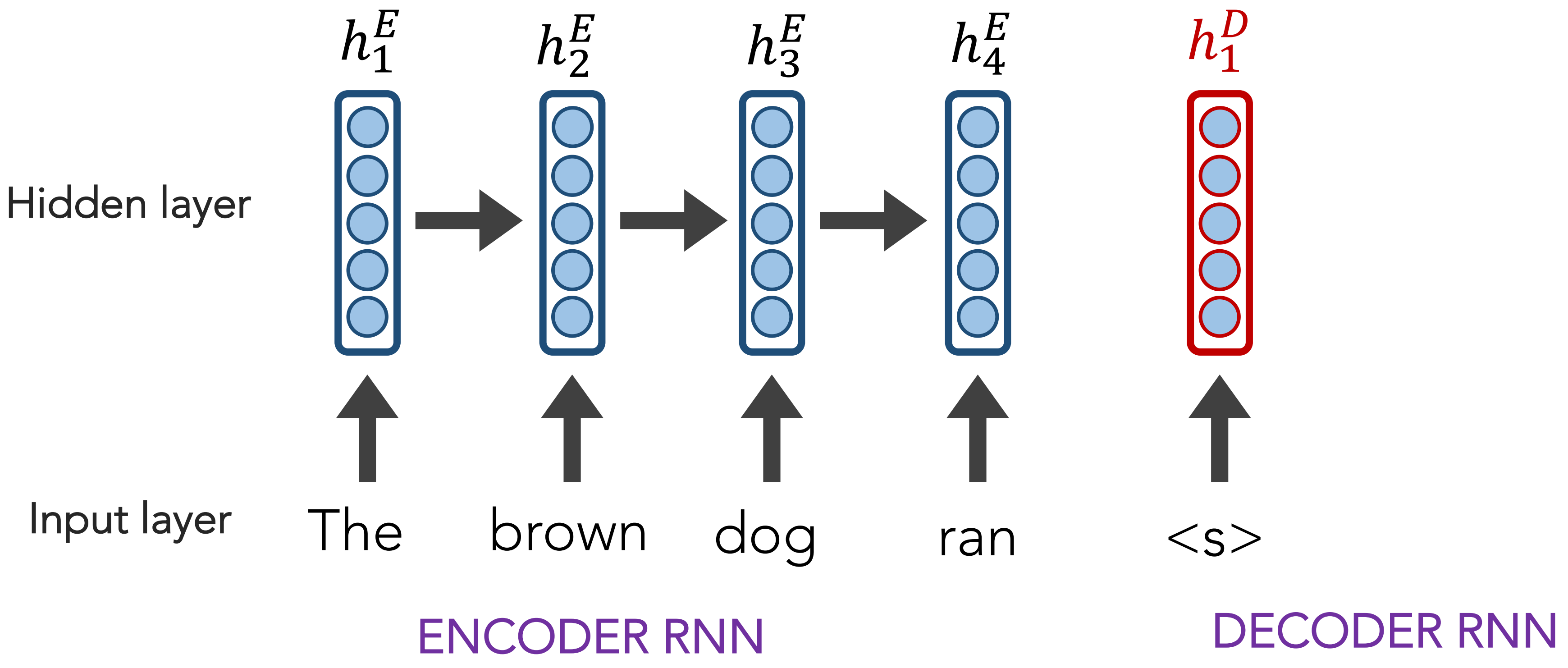

Attention (raw scores)

e_1 1.5

e_2 0.9

e_3 0.2

e_4 -0.5

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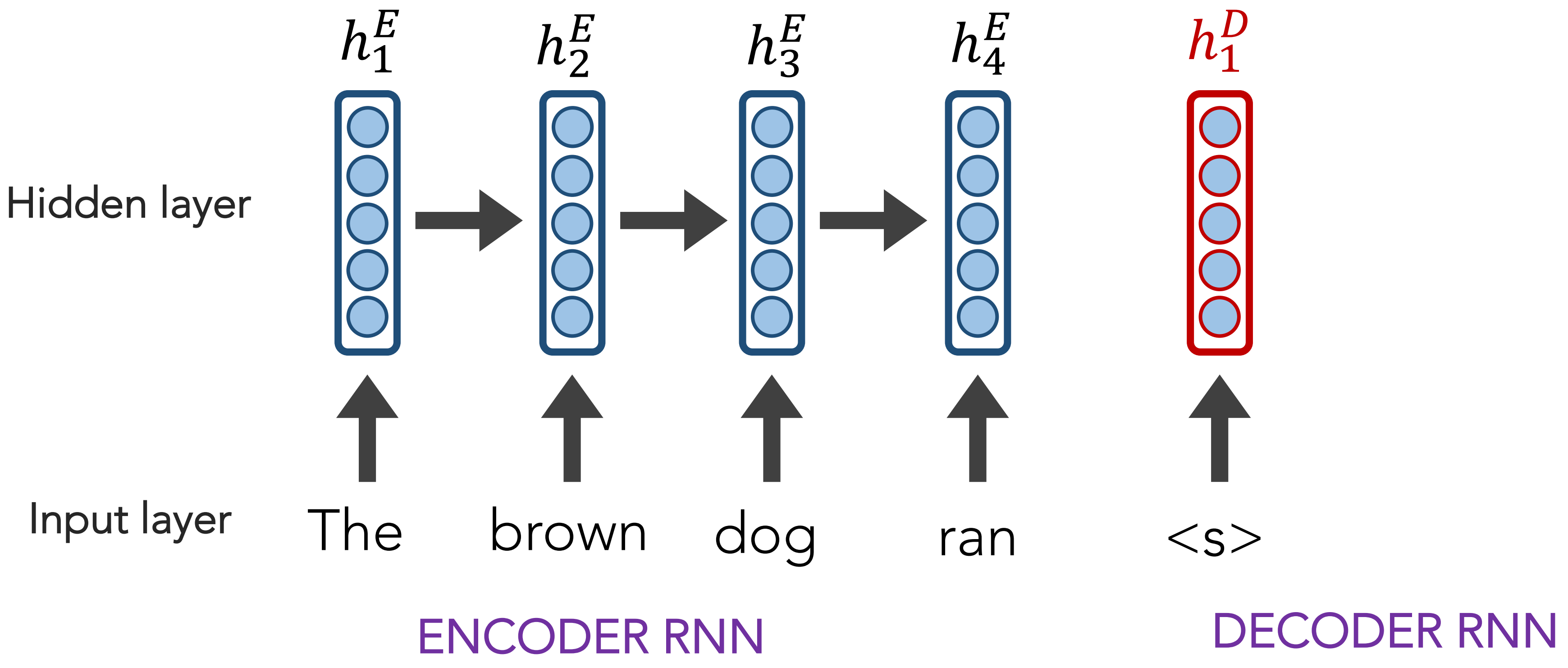

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Attention (softmax'd)

$$a_i^1 = \frac{\exp(e_i)}{\sum_i^N \exp(e_1)}$$

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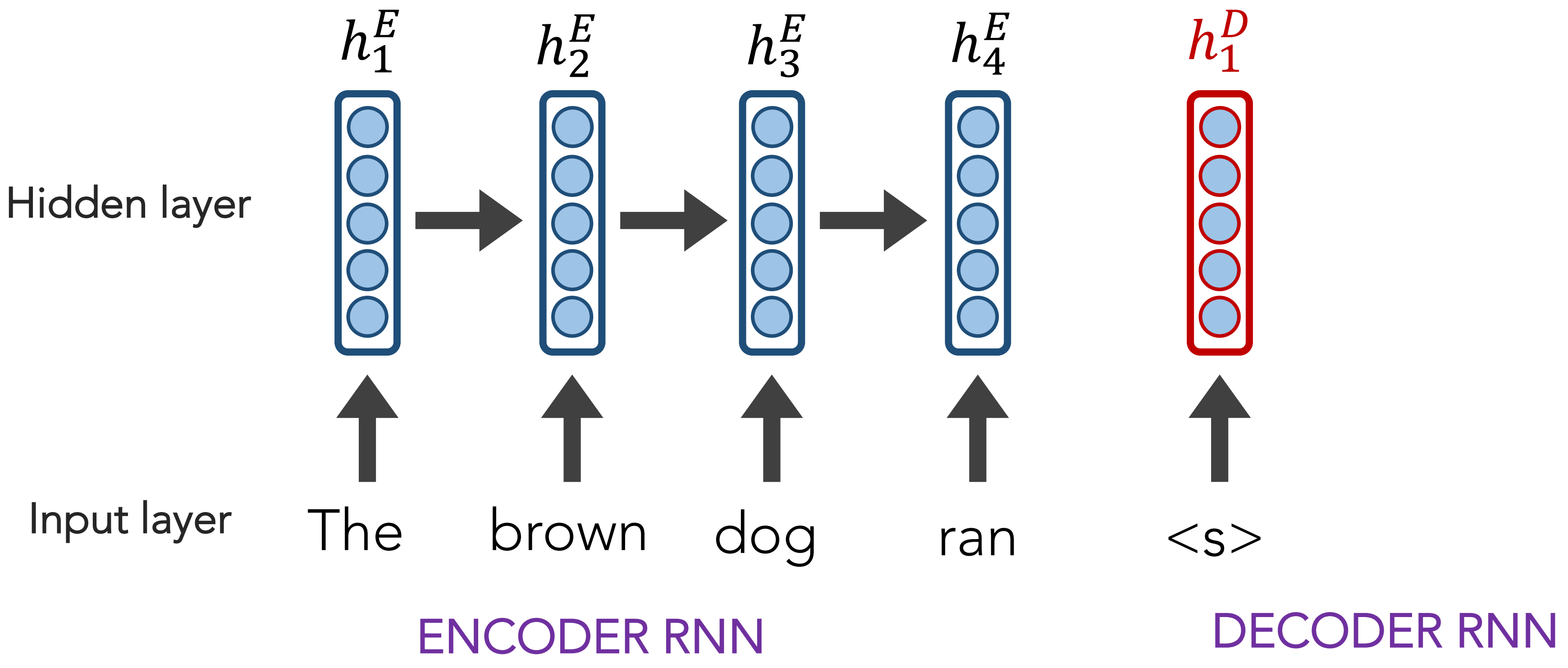

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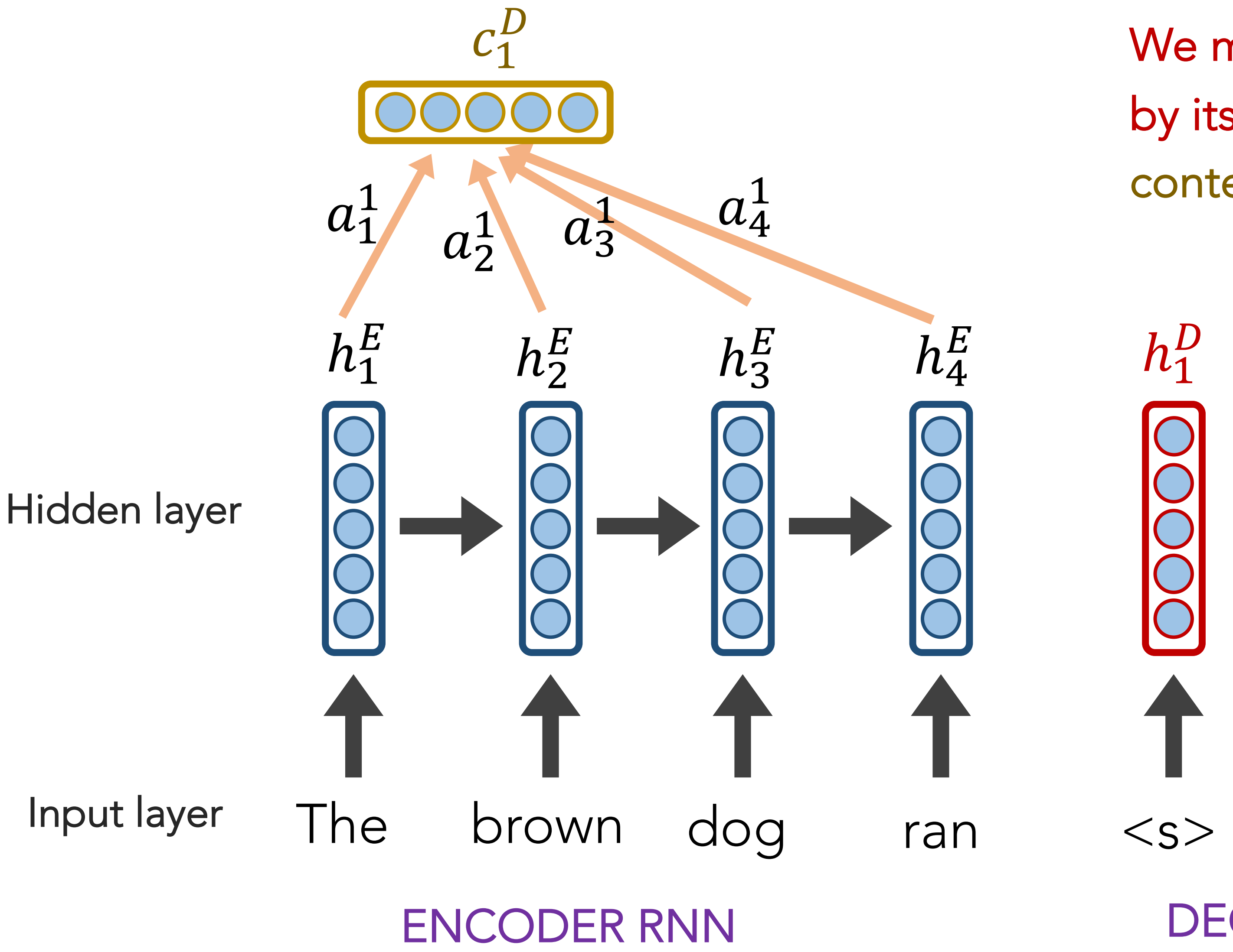
Attention (softmax'd)

$a_1^1 = 0.51$
$a_2^1 = 0.28$
$a_3^1 = 0.14$
$a_3^1 = 0.07$

seq2seq + Attention

We multiply each encoder's hidden layer by its a_i^1 attention weights to create a context vector c_1^D



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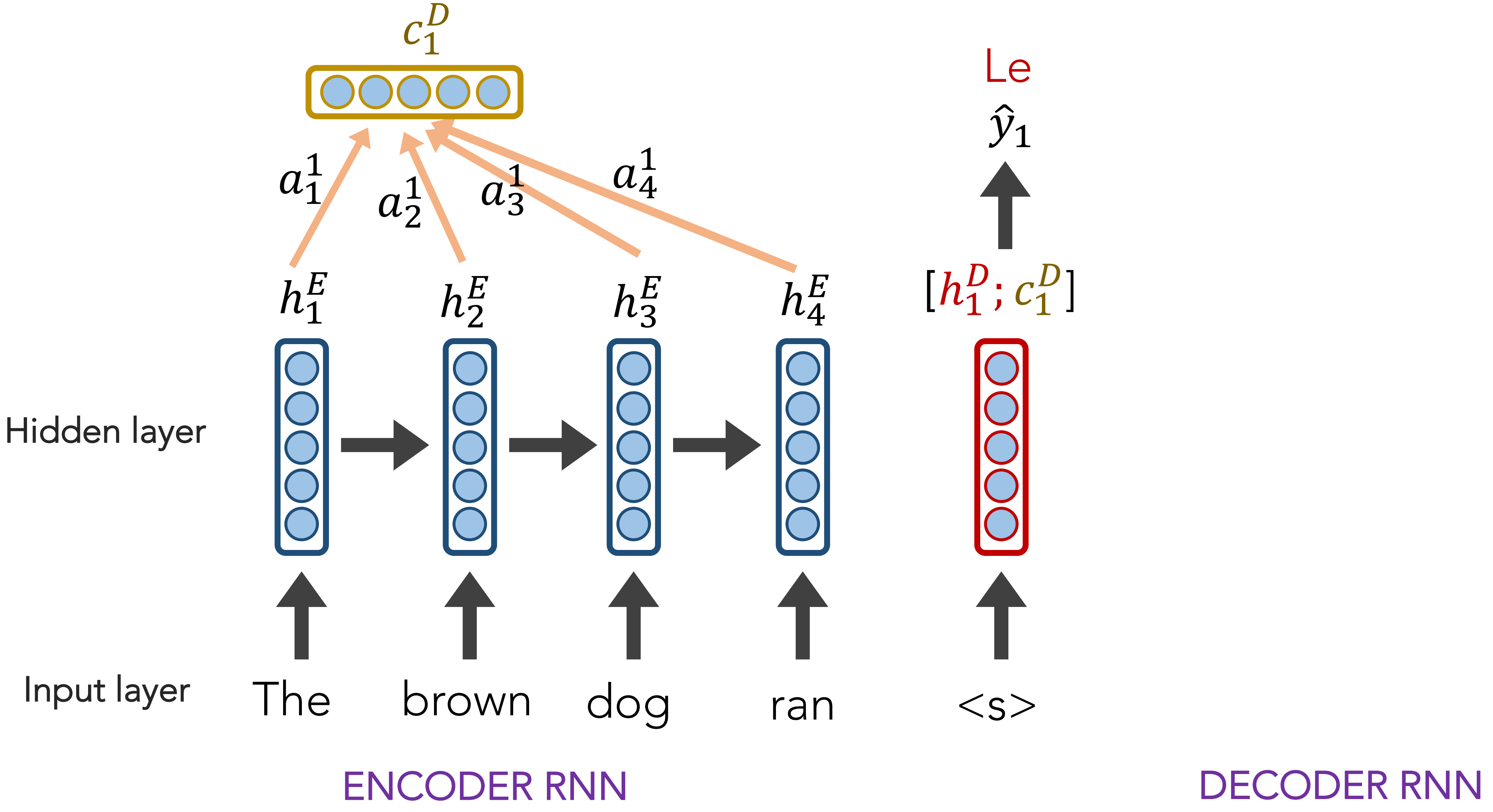
seq2seq + Attention

REMEMBER: each attention weight a_i^j is based on the decoder's current hidden state, too.



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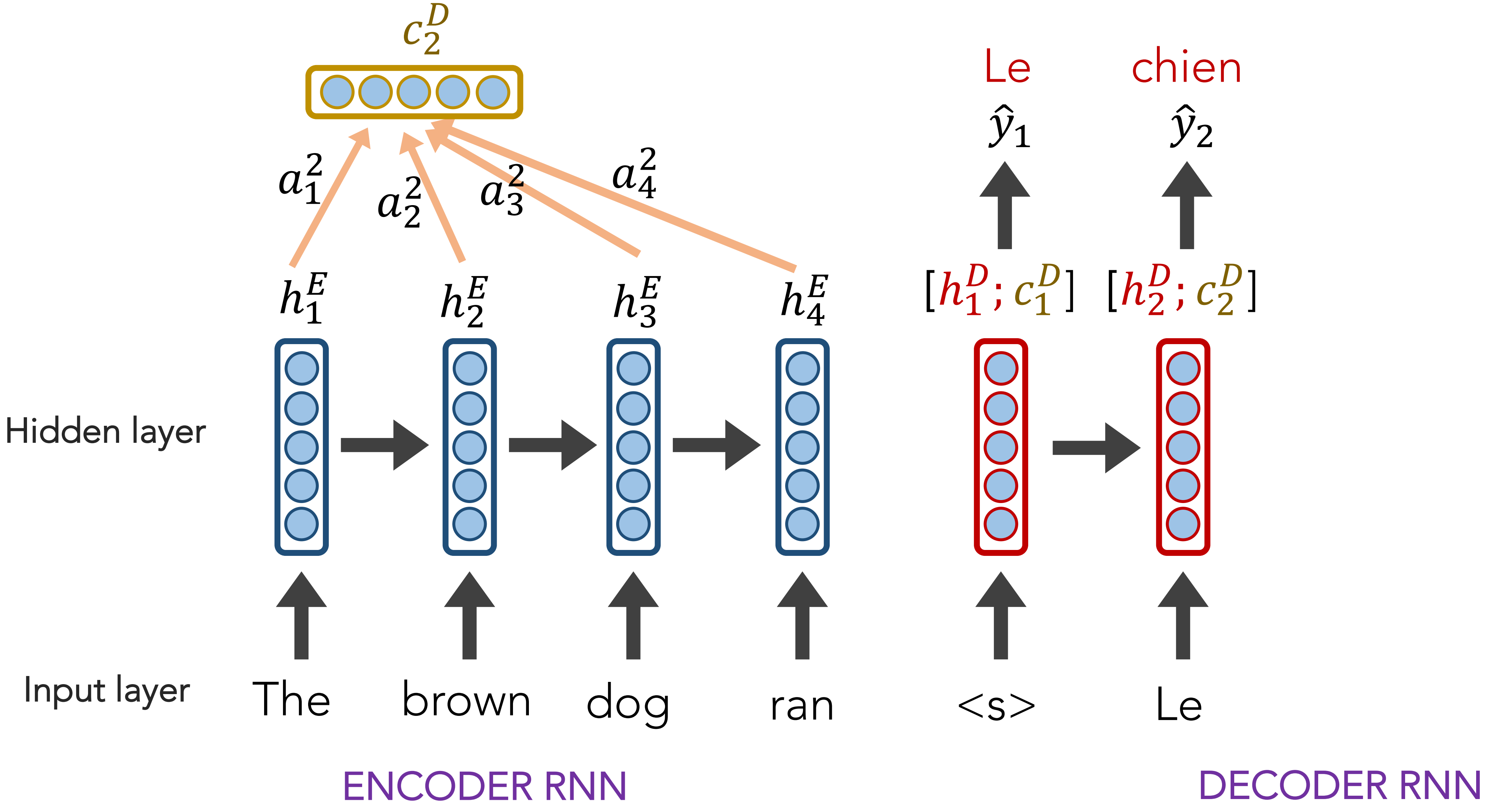

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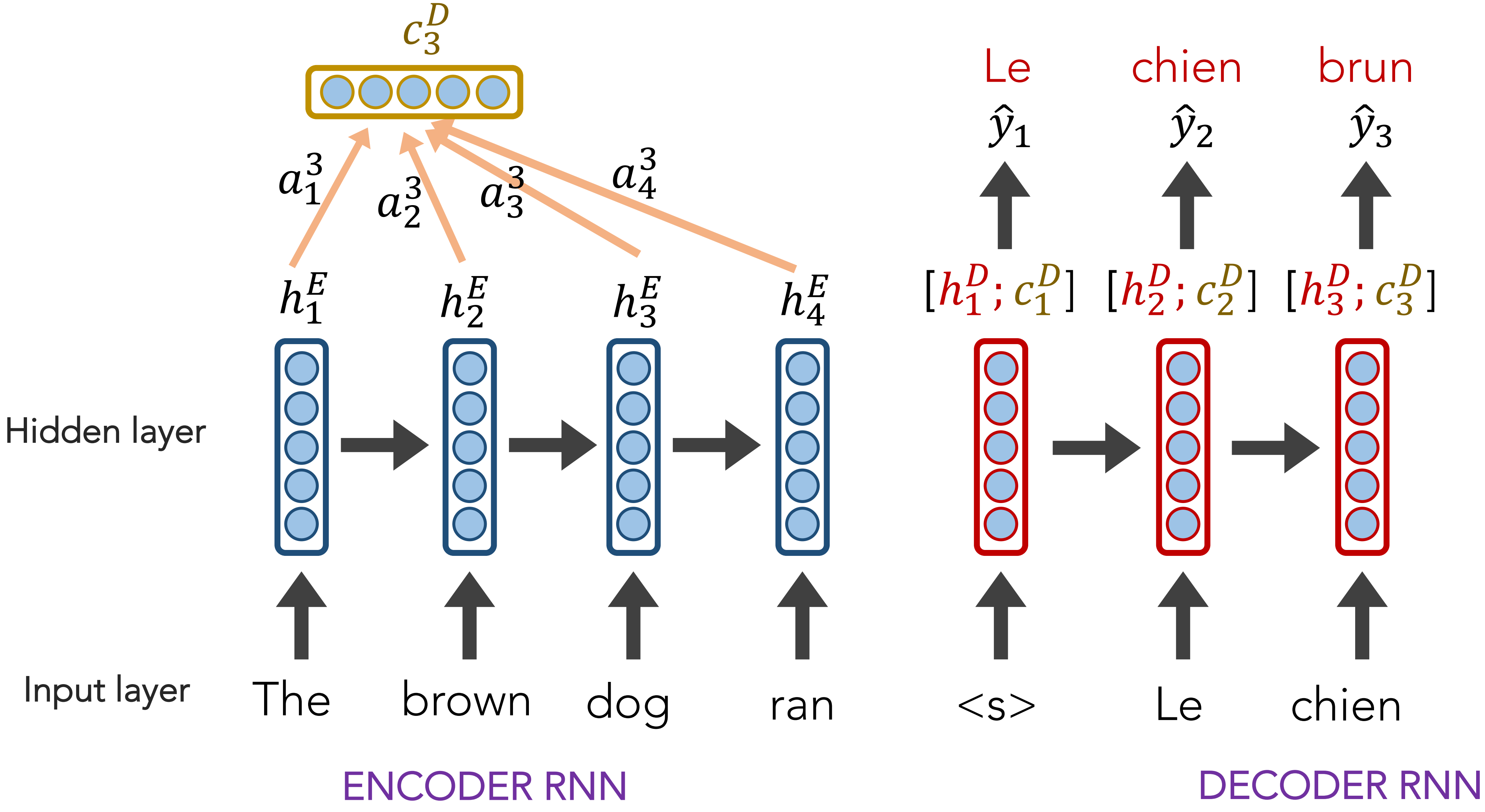

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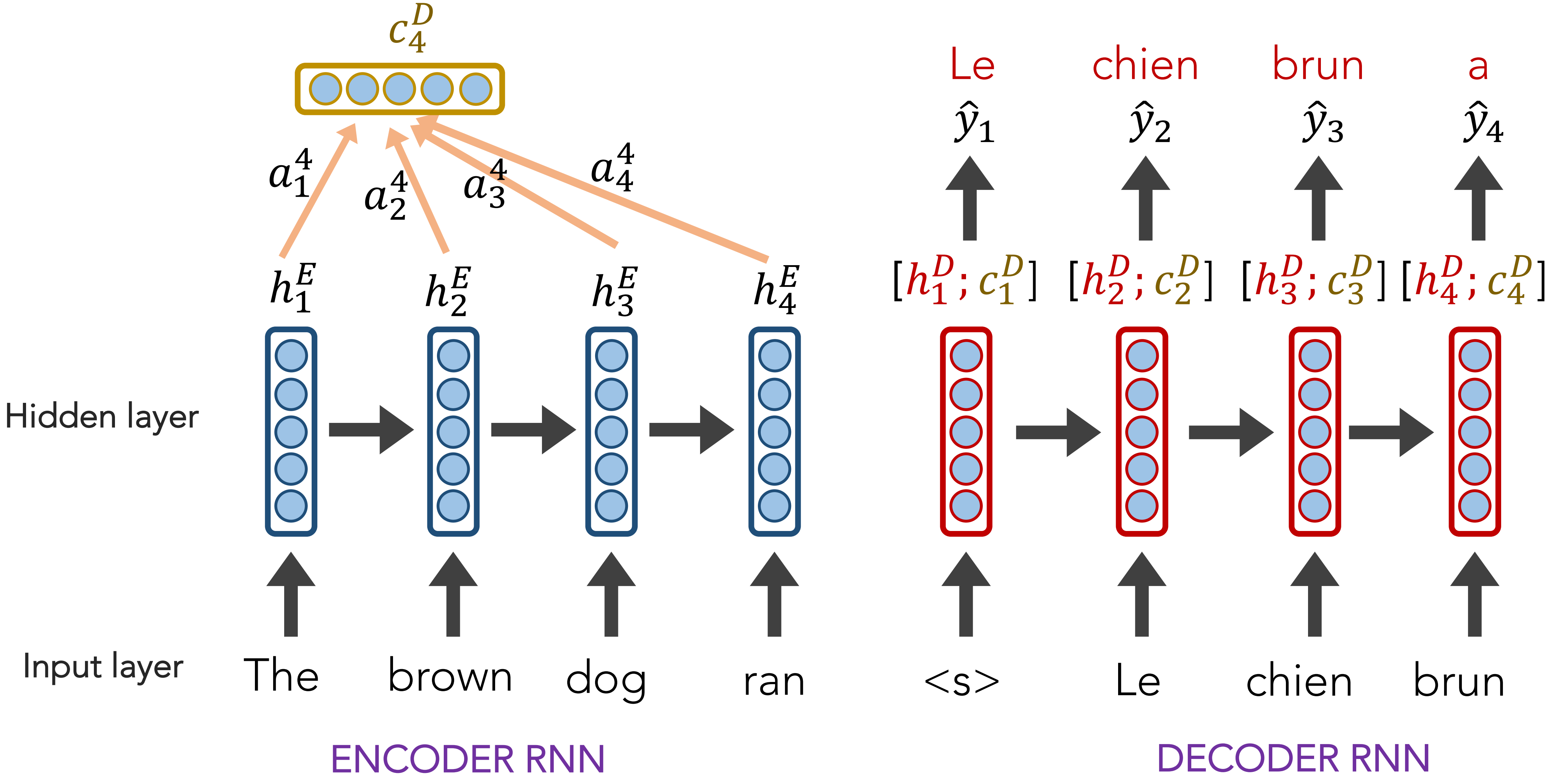

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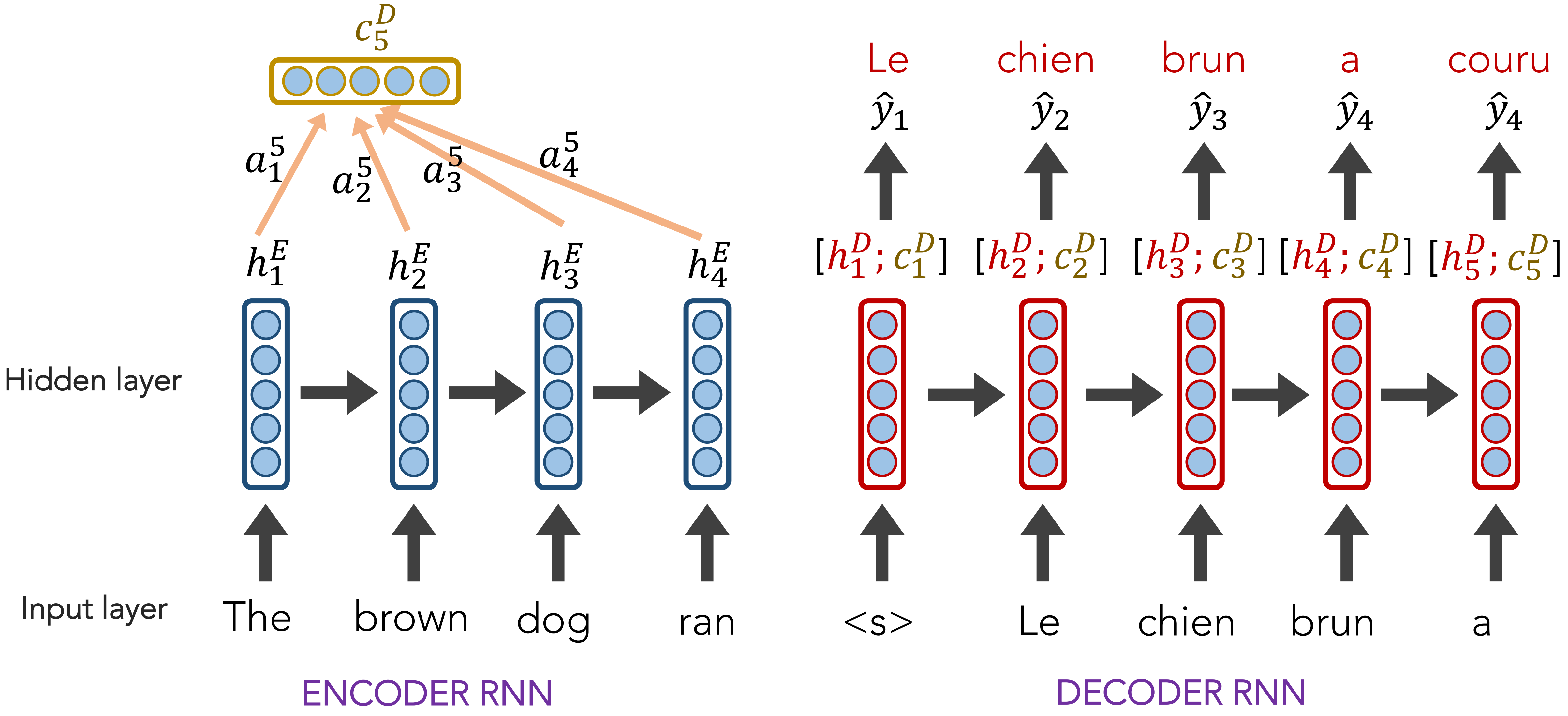


For convenience, here's the Attention calculation summarized on 1 slide

Attention output

$$c^{(t)} = a_1^{(t)} s_1 + a_2^{(t)} s_2 + \dots + a_m^{(t)} s_m = \sum_{k=1}^{m} a_k^{(t)} s_k$$

"source context for decoder step t"

↑ (weighted sum)

Attention weights

$$a_k^{(t)} = \frac{\exp(\text{score}(h_t, s_k))}{\sum_{i=1}^{m} \exp(\text{score}(h_t, s_i))}, \mathrm{k} = 1..\mathrm{m}$$

"attention weight for source token k at decoder step t"

↑ (softmax)

Attention scores

$$\text{score}(h_t, s_k), \mathrm{k} = 1..\mathrm{m}$$

"How relevant is source token k for target step t?"

↑

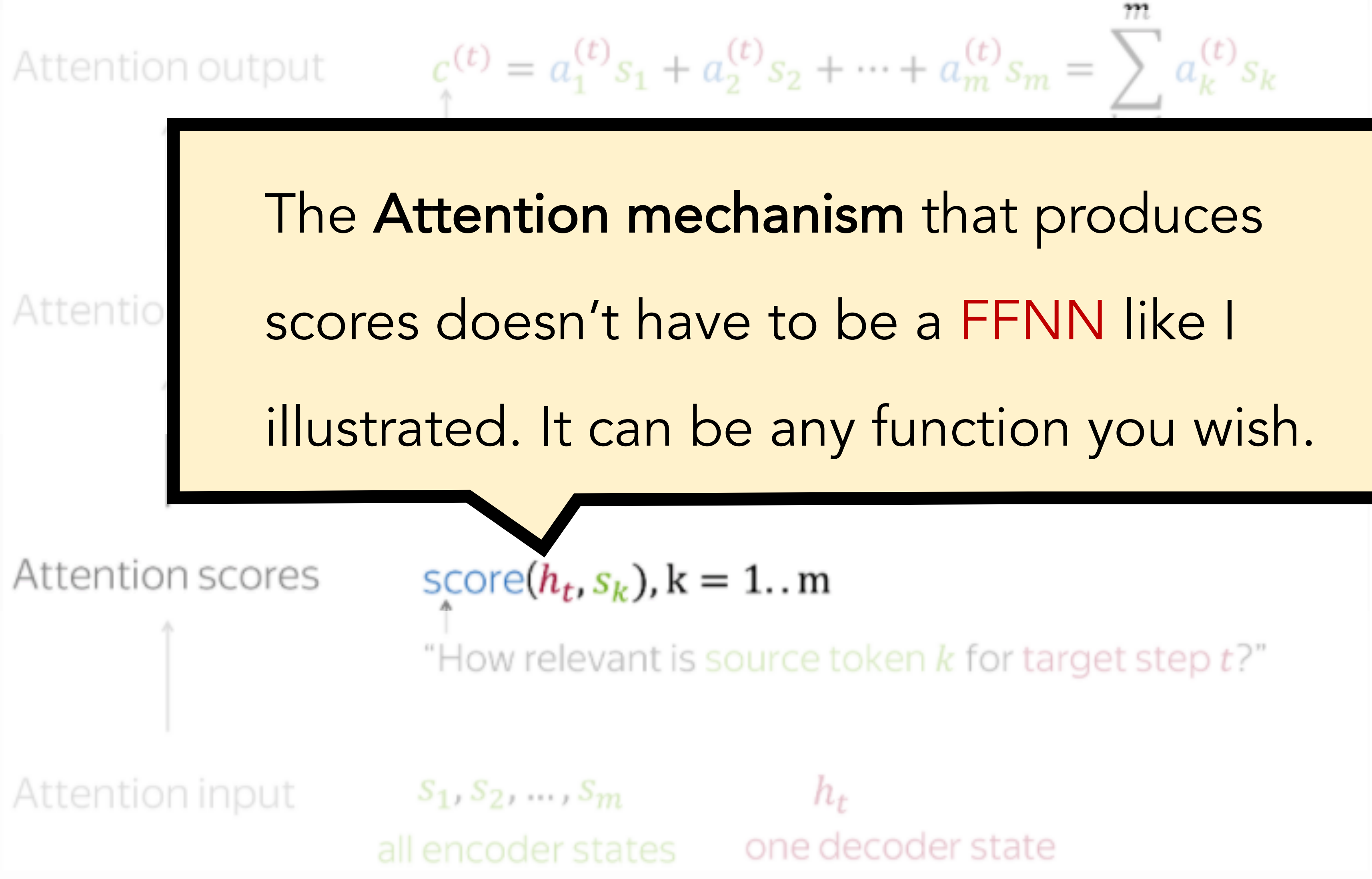
Attention input

$s_1, s_2, \dots, s_m$ — all encoder states

h_t — one decoder state

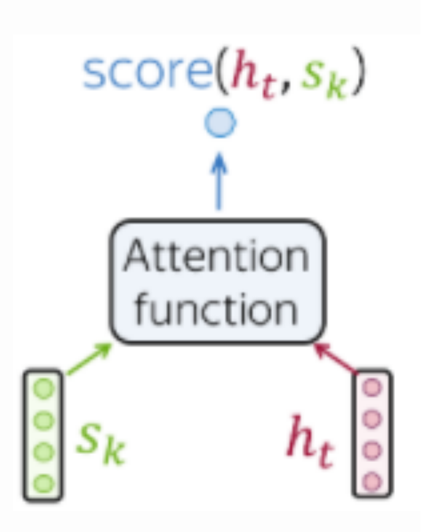
Photo credit: https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

For convenience, here's the Attention calculation summarized on 1 slide



The **Attention mechanism** that produces scores doesn't have to be a FFNN like I illustrated. It can be any function you wish.

Photo credit: https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html



Popular Attention Scoring functions:

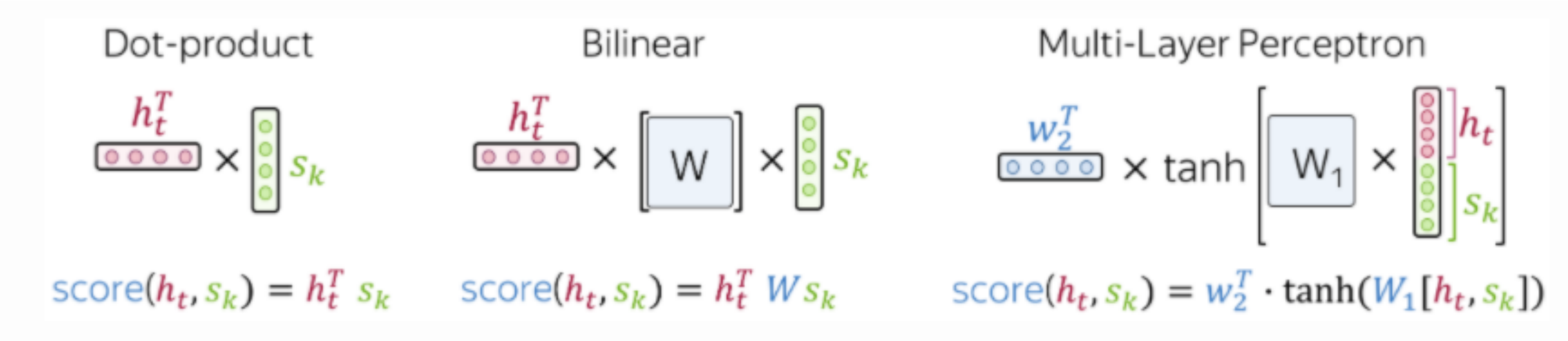


Photo credit: https://lena-voita.github.io/nlp_course/seq2seq_and_attention.html

seq2seq + Attention

Attention:

- greatly improves seq2seq results
- allows us to visualize the contribution each encoding word gave for each decoder's word

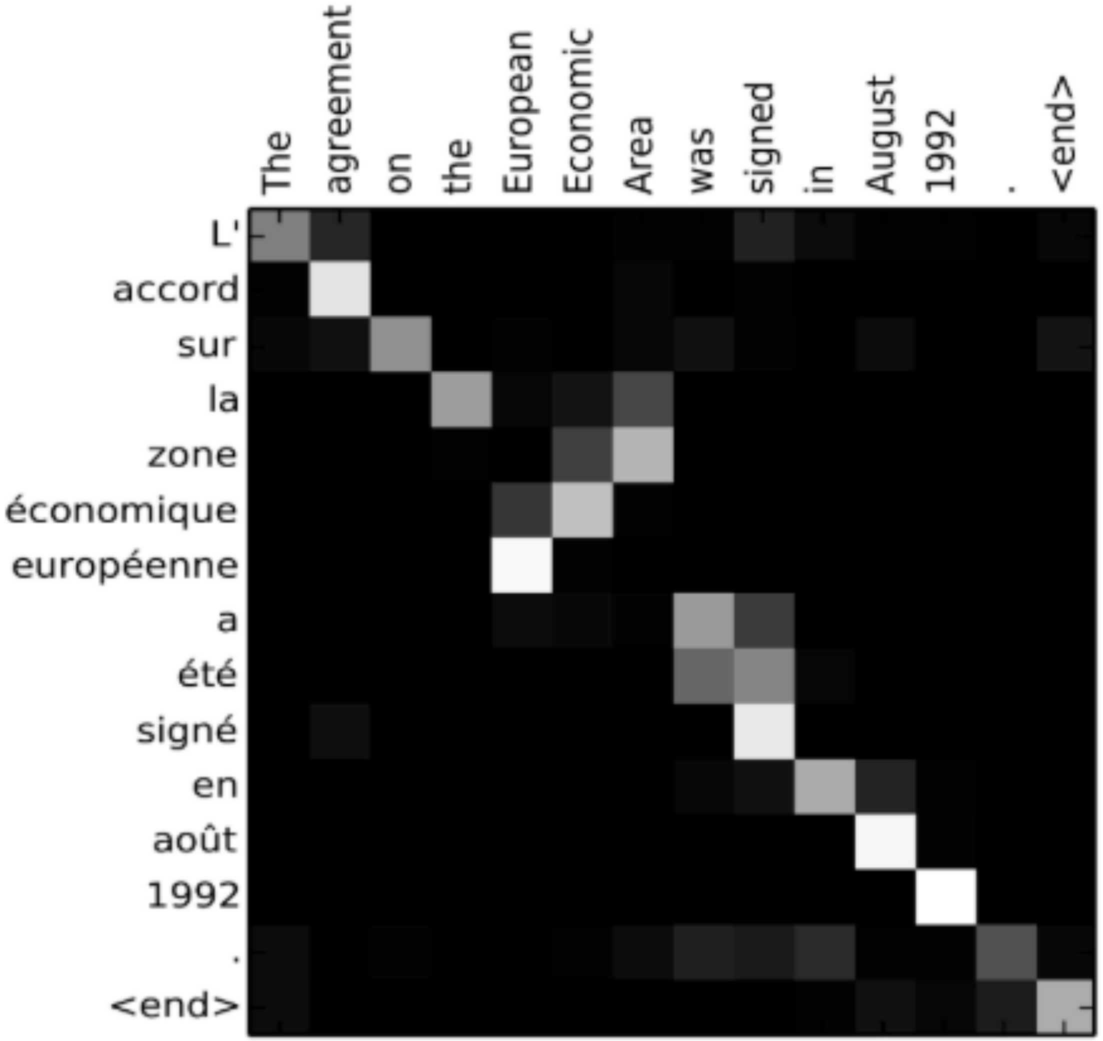


Image source: Fig 3 in [Bahdanau et al., 2015]

Takeaway:

Having a separate encoder and decoder allows for n → m length predictions.

Attention is powerful; allows us to conditionally weight our focus

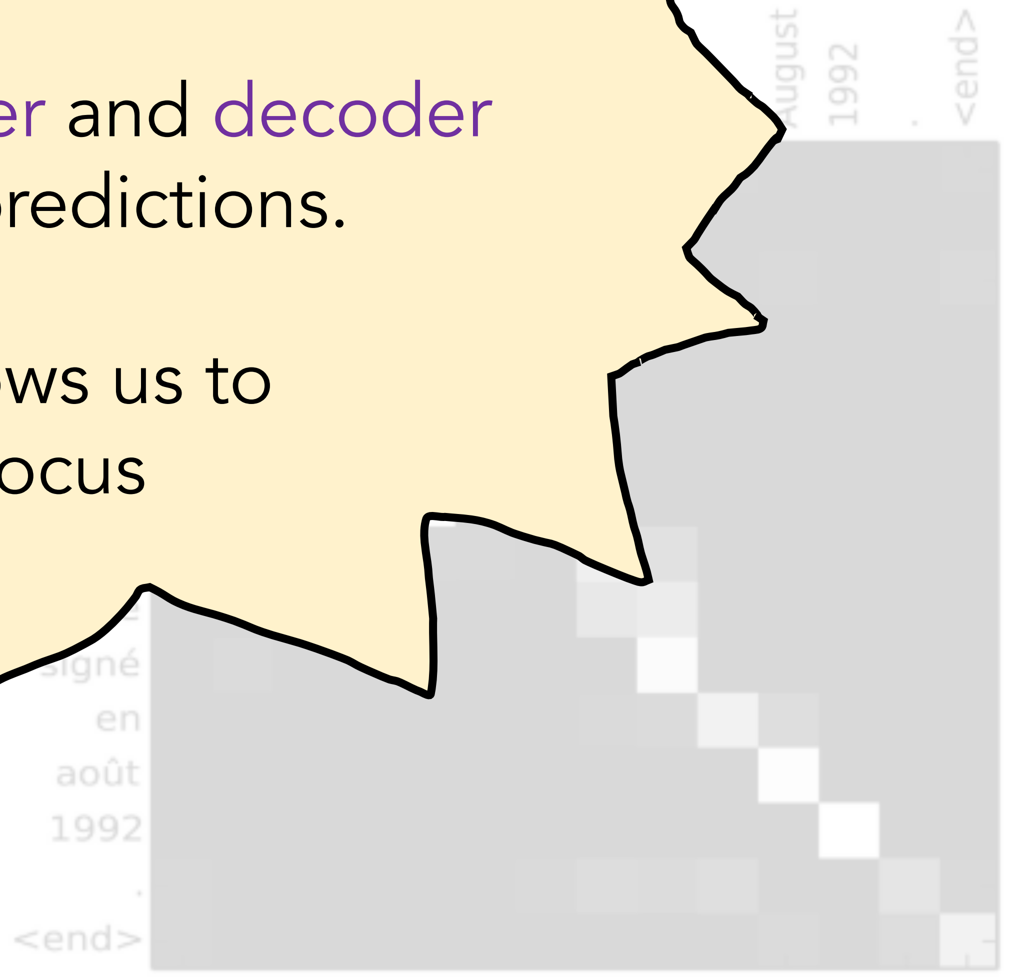


Image source: Fig 3 in Bahdanau et al., 2015

SUMMARY

- LSTMs yielded state-of-the-art results on most NLP tasks (2014-2018)
- seq2seq+Attention was an even more revolutionary idea (Google Translate used it)
- Attention allows us to place appropriate weight to the encoder's hidden states
- But, LSTMs require us to iteratively scan each word and wait until we're at the end before we can do anything

Outline

- How to use embeddings
- seq2seq
- seq2seq + Attention
- Transformers (preview)

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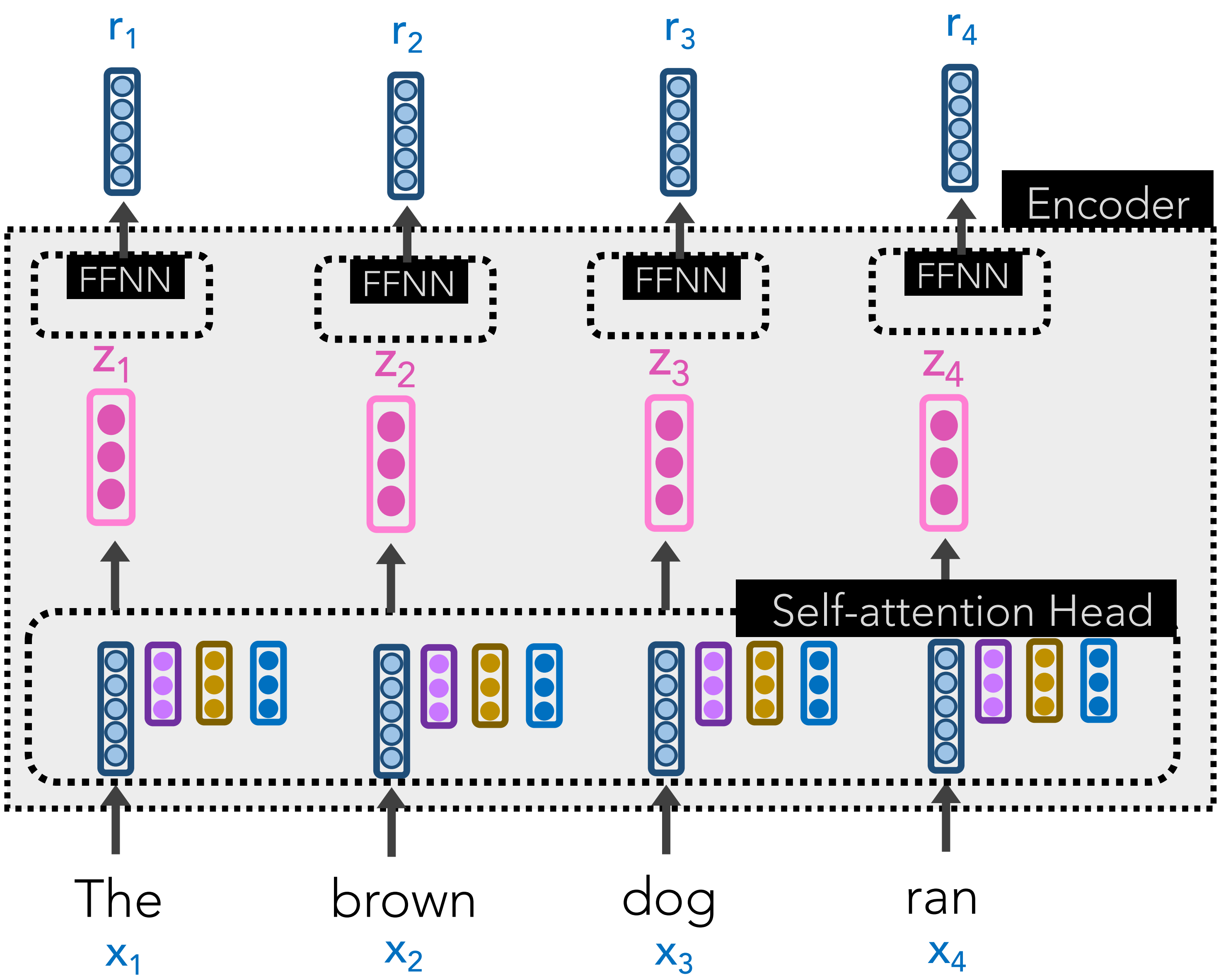
Transformer Encoder



Transformer Encoder uses attention on itself (self-attention) to create very rich embeddings which can be used for any task.

BERT is a *Bidirectional* **Transformer Encoder.** You can attach a final layer that performs whatever task you're interested in (e.g., Yelp reviews).

Its results are unbelievably good.

BERT (a Transformer variant)

BERT is trained on a lot of text data:

- BooksCorpus (800M words)
- English Wikipedia (2.5B words)

Yay, for transfer learning!

BERT-Base model has 12 transformer blocks, 12 attention heads,

110M parameters!

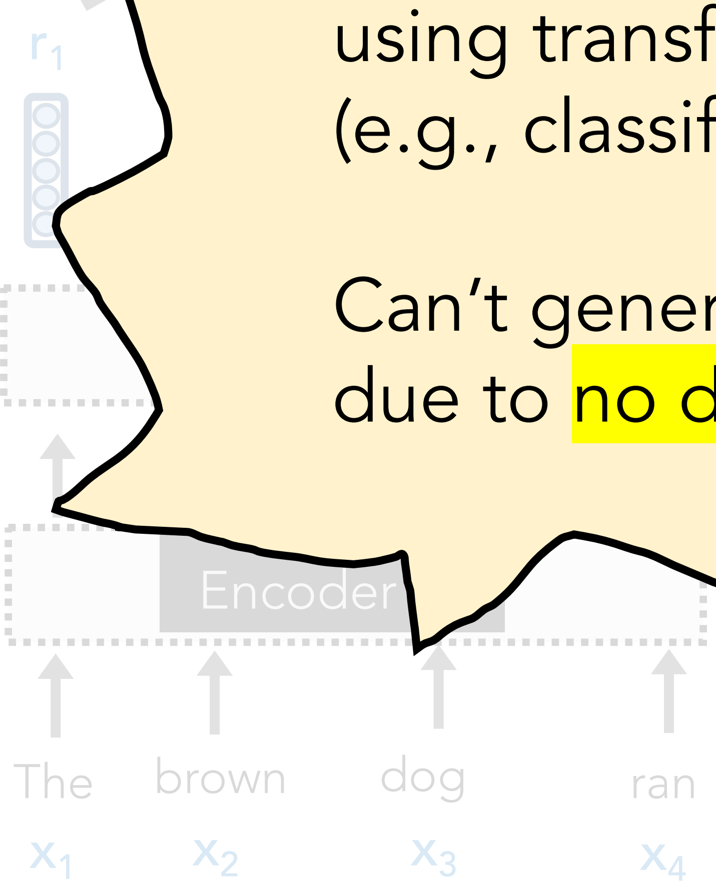
BERT-Large model has 24 transformer blocks, 16 attention heads,

340M parameters!

Takeaway:

BERT is incredible for learning **context-aware** representations of words and using transfer learning for other tasks (e.g., classification).

Can't generate new sentences though, due to no decoders.



Transformer

What if we want to generate a new output sequence?

GPT-2 model to the rescue!

Generative Pre-trained Transformer 2

GPT-2 (a Transformer variant)

- GPT-2 uses only Transformer Decoders (no Encoders) to generate new sequences
- As it processes each word/token, it cleverly masks the "future" words and conditions itself on the previous words
- Can generate text from scratch or from a starting sequence.
- Easy to fine-tune on your own dataset (language)

GPT-2

- GPT-2 u

new

- As it p

wor

- Can g
- Eas
- GPT-3 is an eve bigger version of GP but isn't open-source

Takeaway:
GPT-2 is astounding for generating realistic-looking new text

Can fine-tune toward other tasks, too.

GPT-2 (a Transformer variant)

GPT-2 is:

- trained on 40GB of text data (8M webpages)!
- 1.5B parameters

GPT-3 is an even bigger version (175B parameters) of GPT-2, but isn't open-source

Yay, for transfer learning!

QUESTIONS?