Seq2seq model (Encoder-Decoder model)

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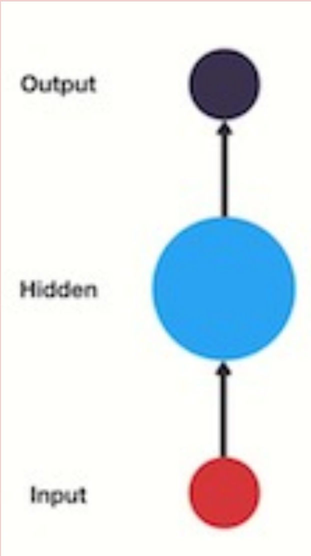
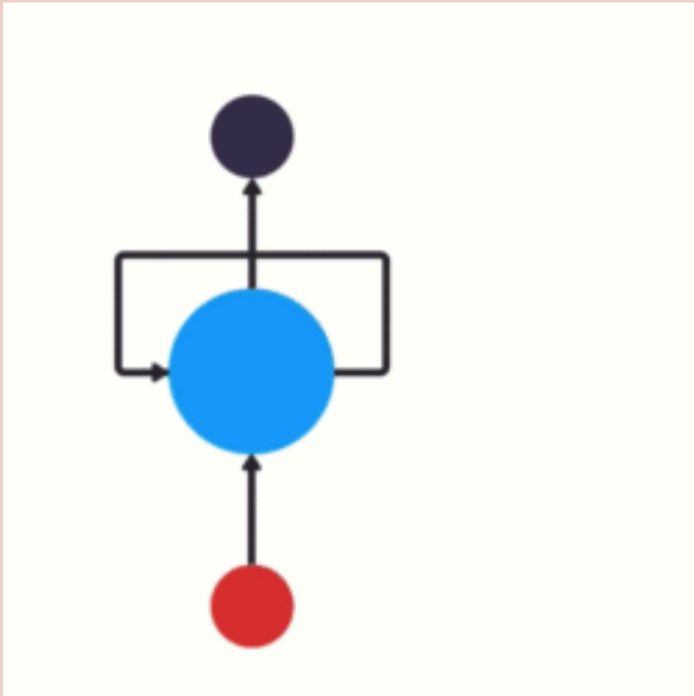
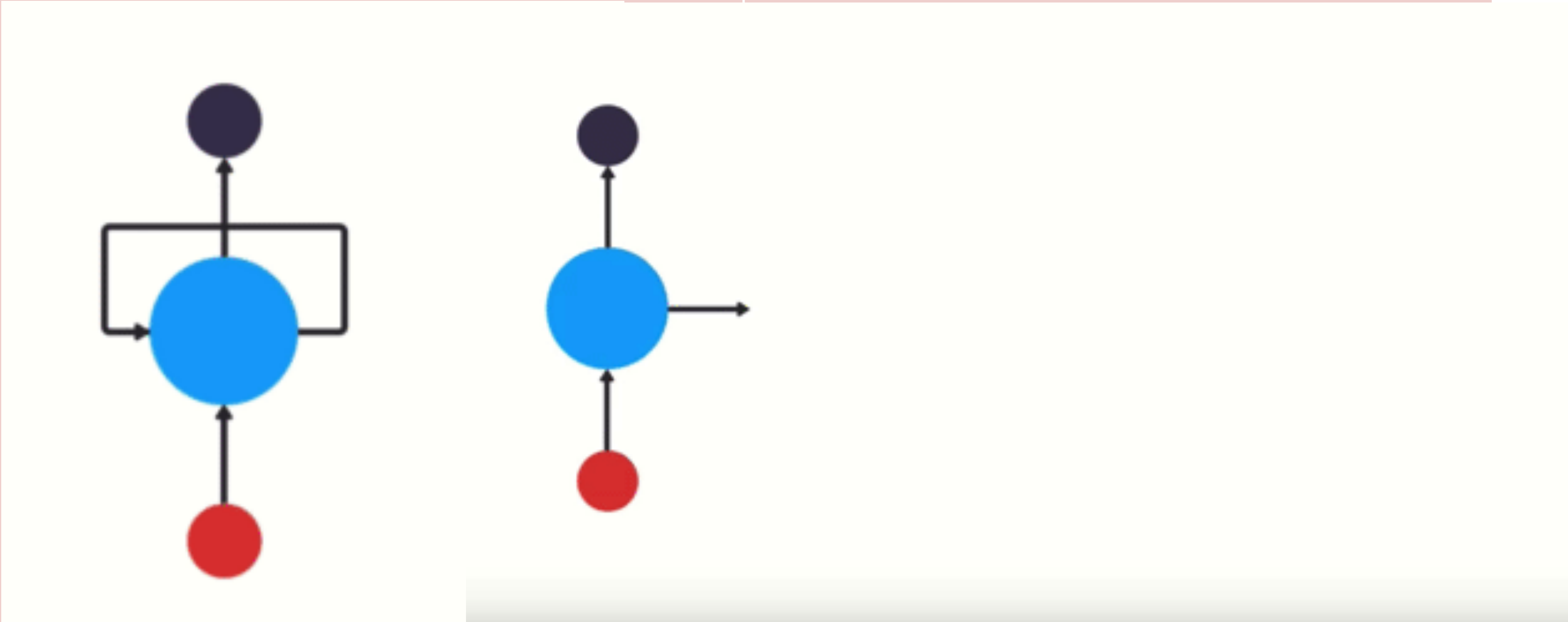
Remember

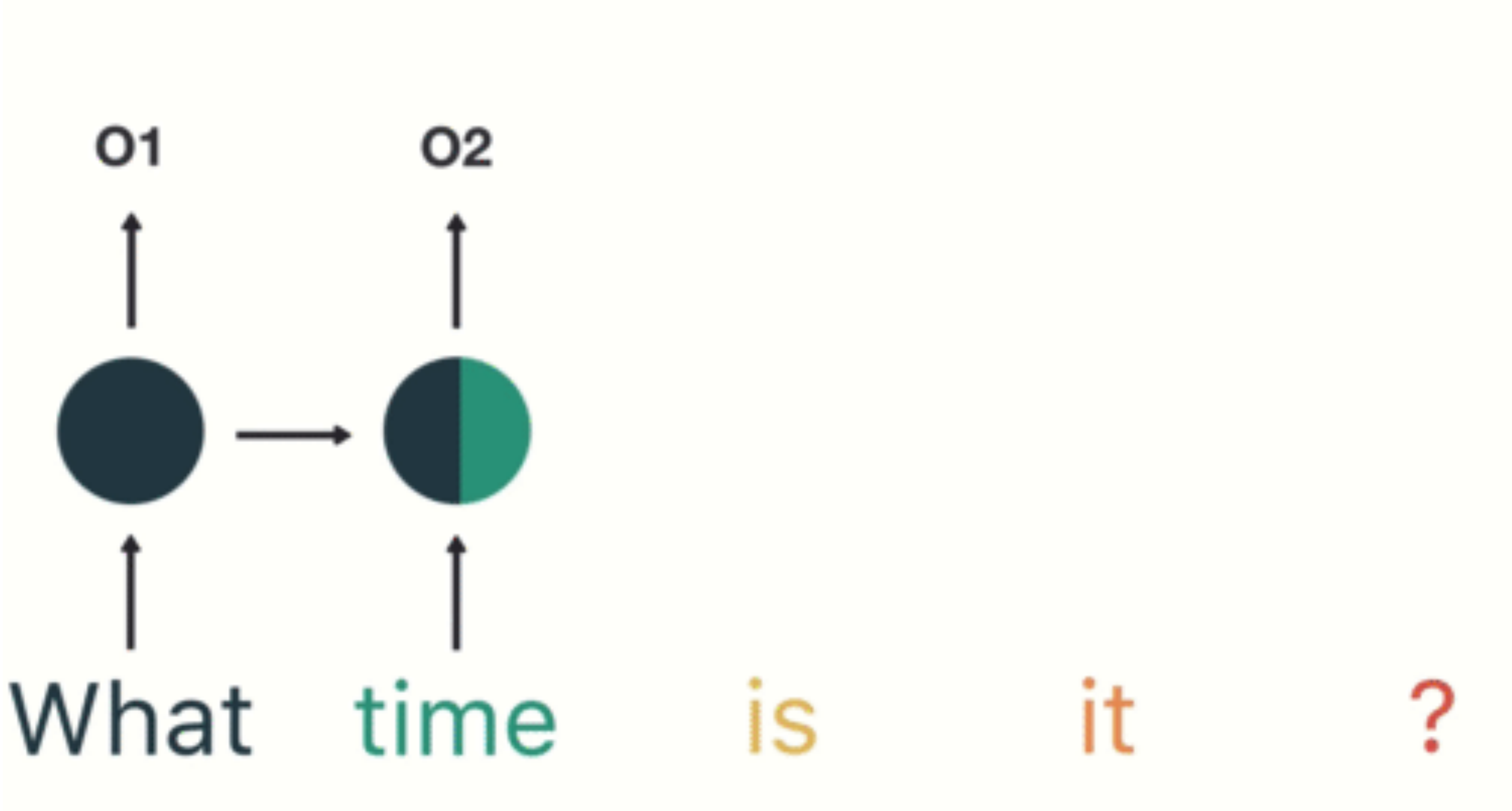
From	To
	

Remember

From	To

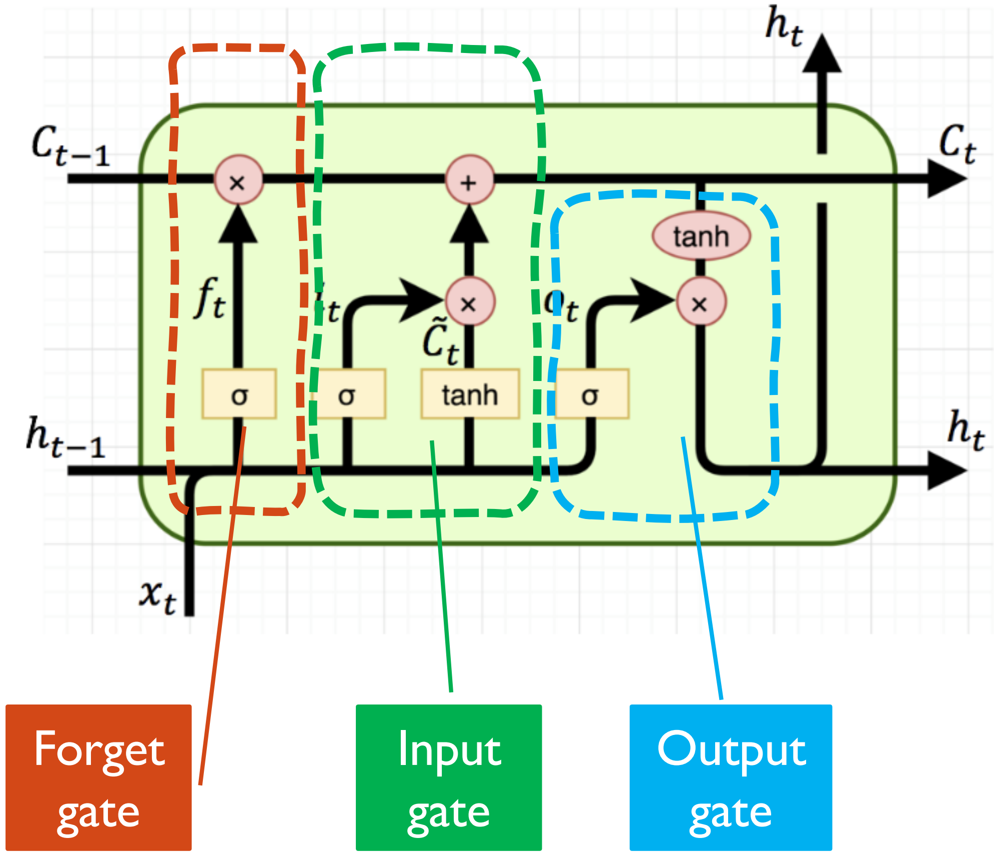


RNN in action



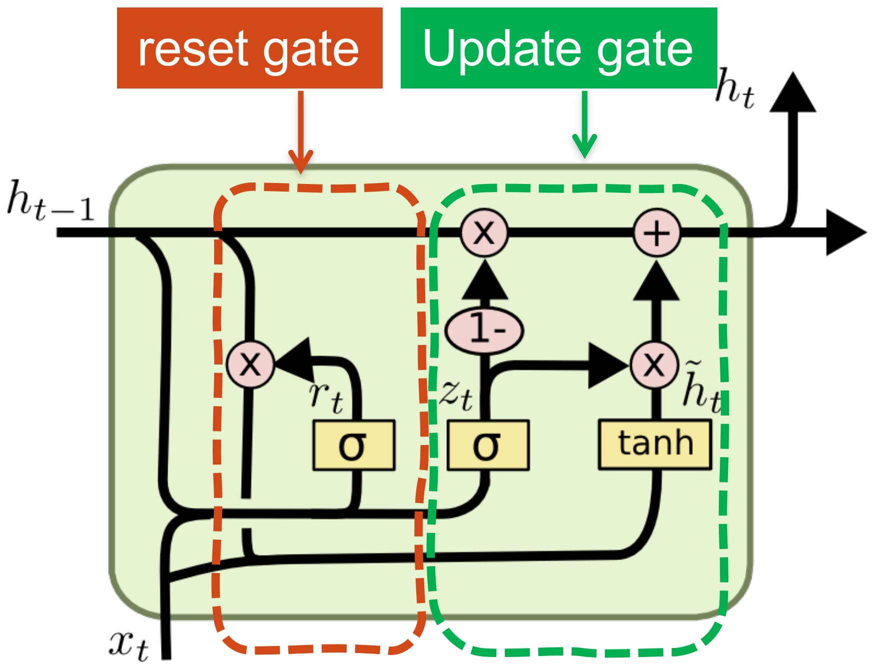
LSTM cell

- Cell made up of three "gates": these are calculation zones which regulate the flow of information (by carrying out specific actions).
  - Forget gate (porte d'oubli)
  - Input gate (porte d'entrée)
  - Output gate (porte de sorti
- Cell state (état de la cellu
  - Like residual
- Hidden state (état caché)



GRU – gated recurrent unit

- GRU = a light LSTM Cell



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

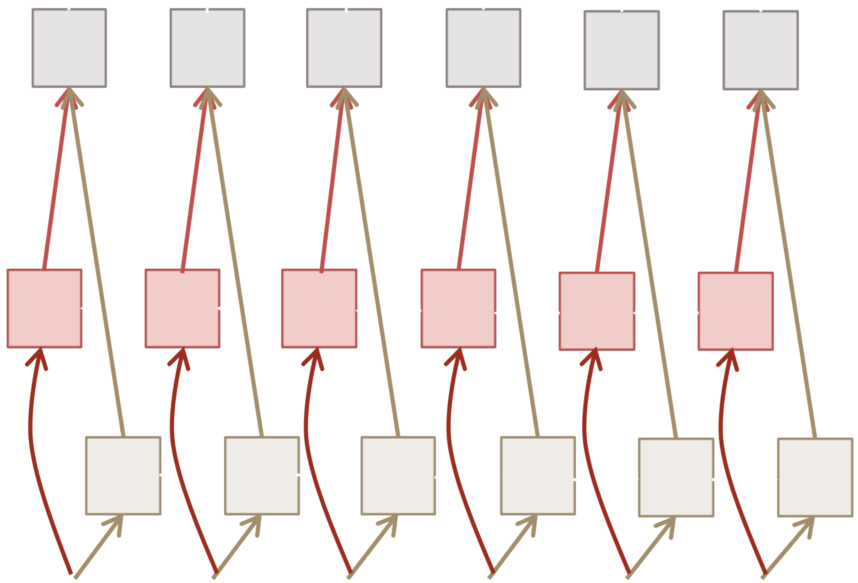
$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

- It combines the forget and input into a single update gate.
- It also merges the cell state and hidden state.

→ This is simpler than LSTM.

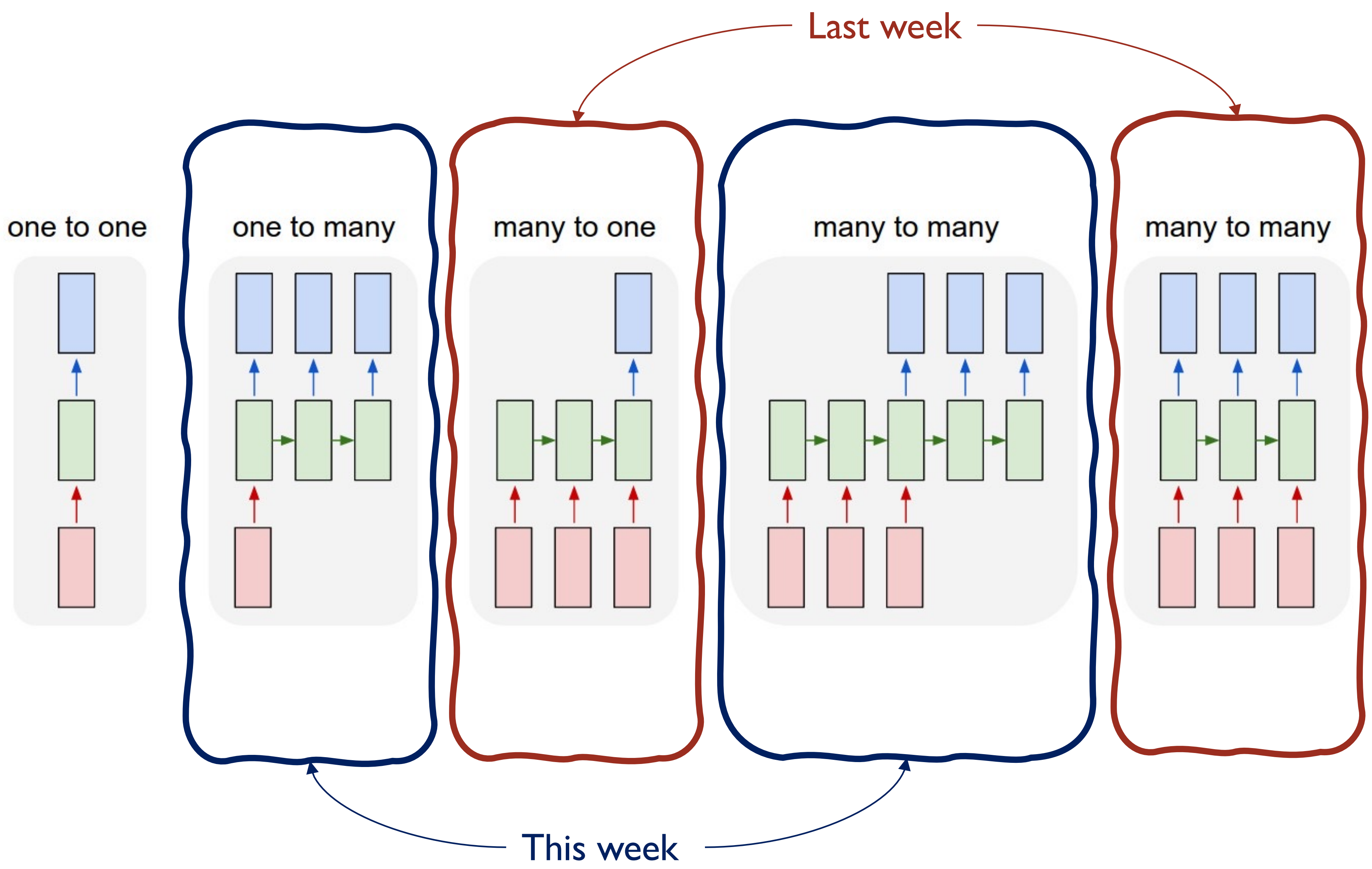
Bi-directional RNNs

- RNNs can process the input sequence in forward and in the reverse direction



Popular in speech recognition used also with text

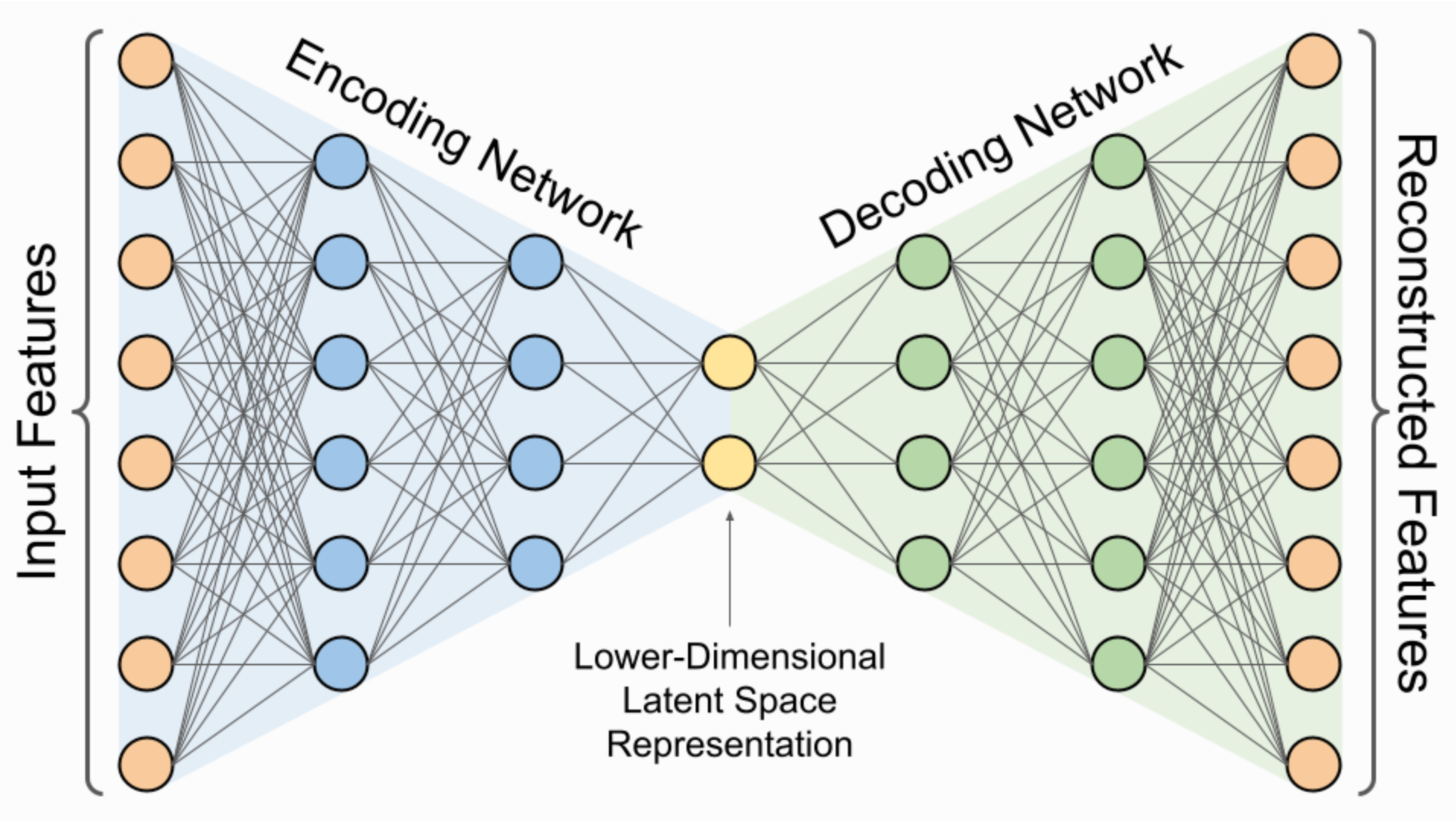
Different RNN architecture



Seq2seq model (Encoder-Decoder model)

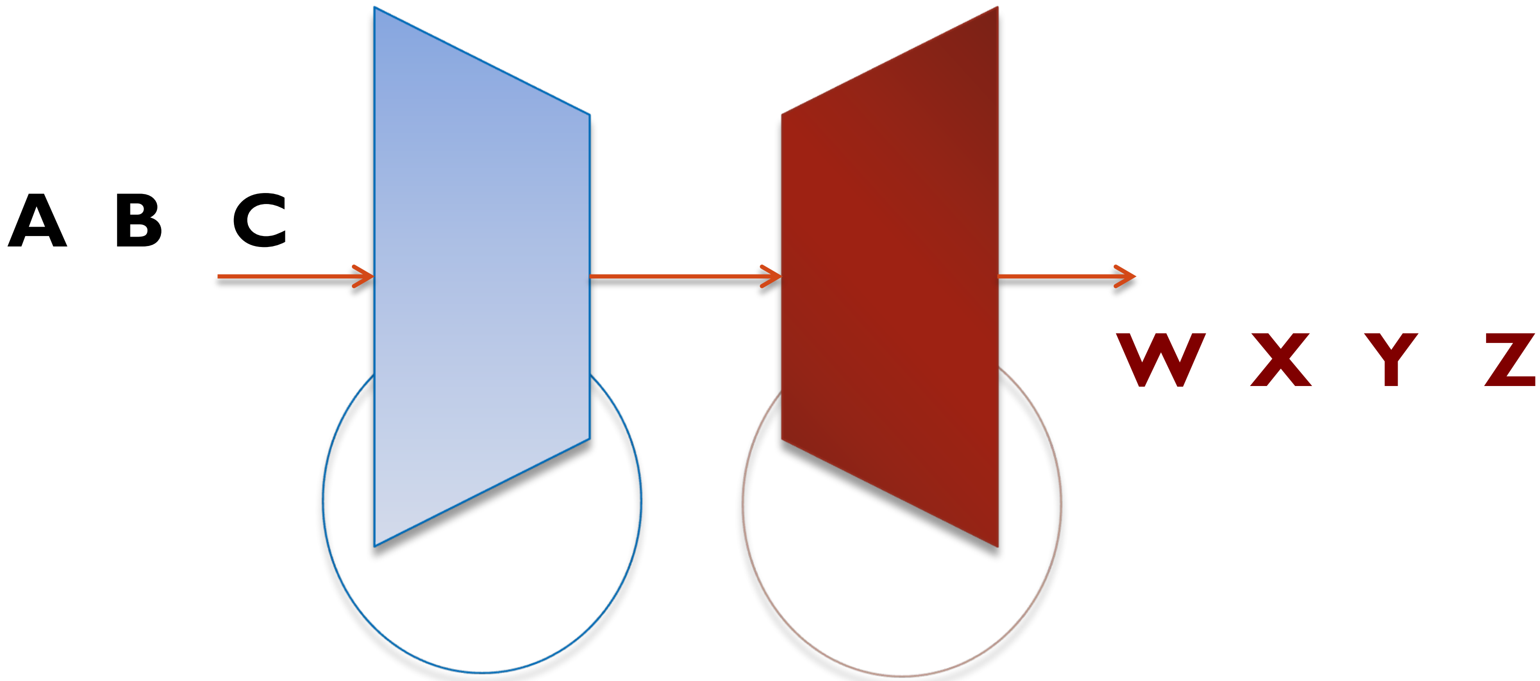
len(input) != len(output)
And generally, the two lengths are unknow

Auto-encoder architure



Seq2seq – original approach

- Extend encoder-decoder architecture
  - to a sequence data
  - in order to develop an architecture capable of generating contextually appropriate, arbitrary length, output sequences



Seq2Seq model

- Applications with text
  - Machine translation
  - Text summarization
  - Question answering
  - Dialogue modeling
- But also
  - Forecasting
  - Image captioning

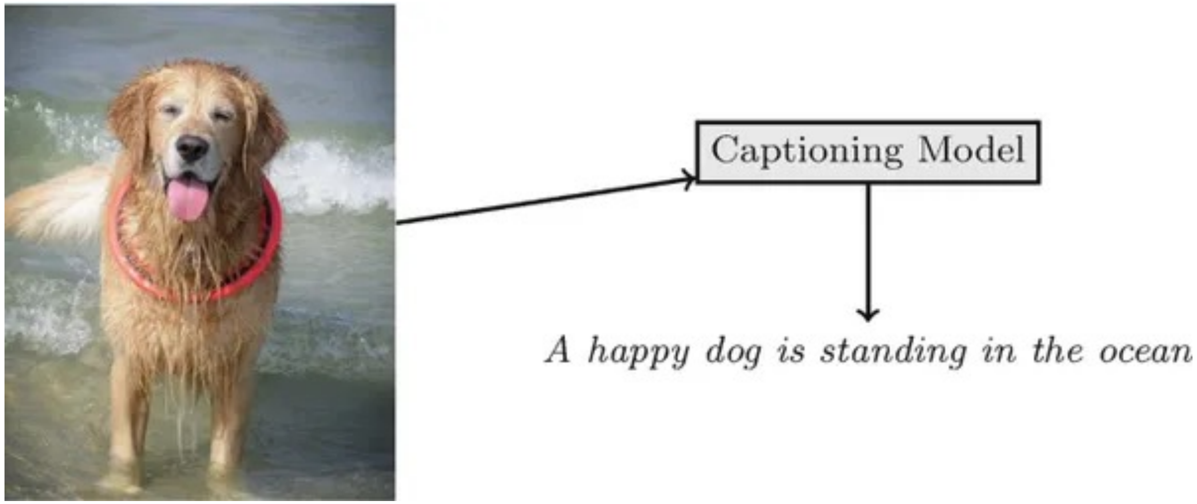
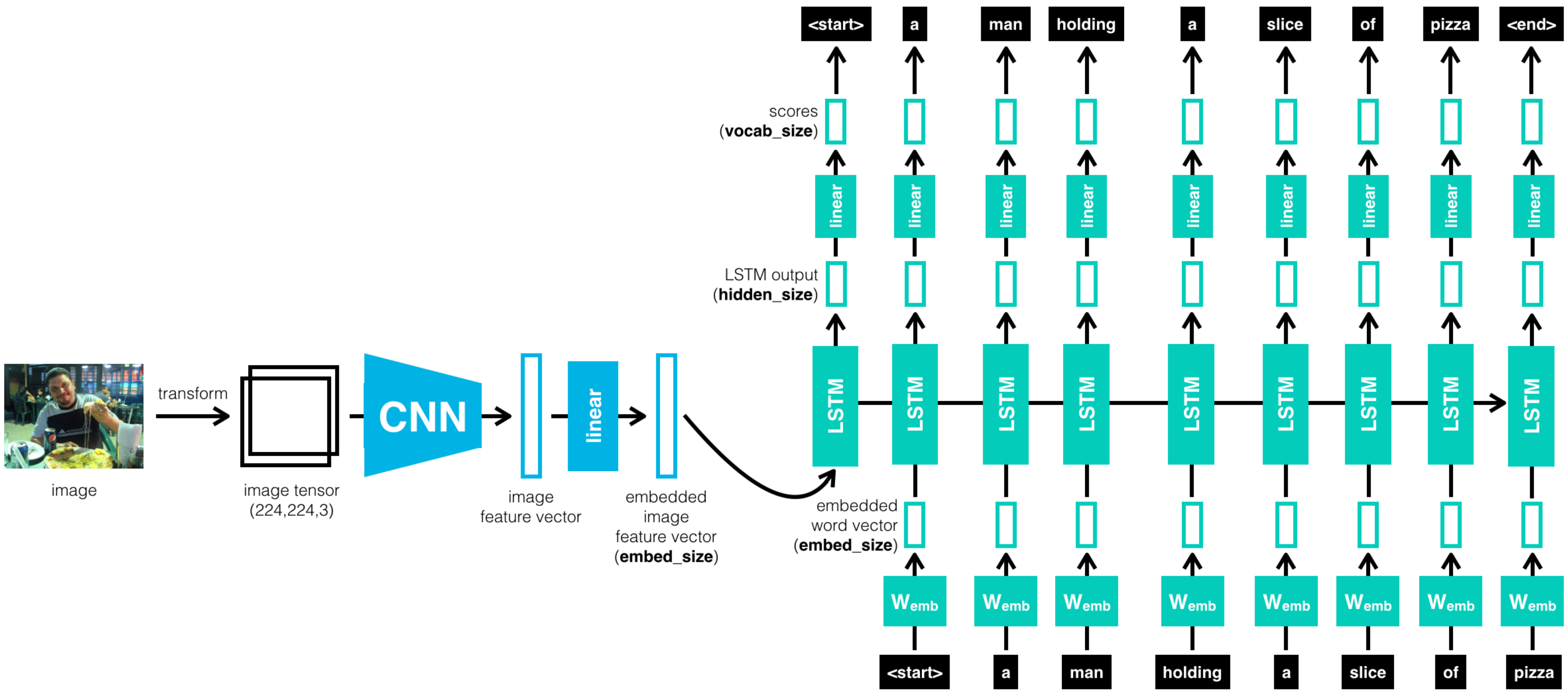
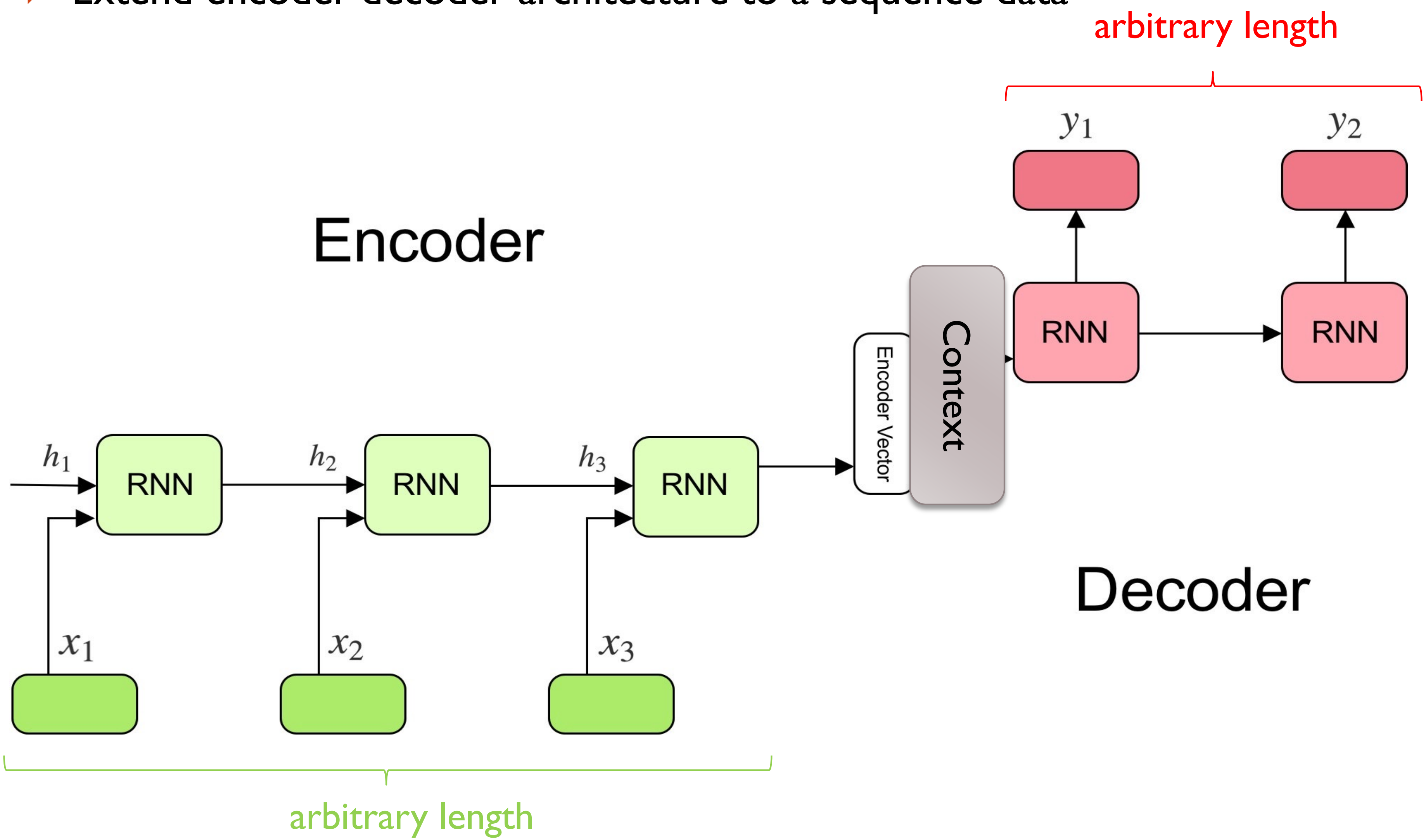


Image captioning model



Seq2seq – original approach

- Extend encoder-decoder architecture to a sequence data



Sequence-to Sequence Architectures

- Three main part:
  - Encoder: processes the input sequence (ordinary sequence-to-vector RNN)

  - Context: output of the encoder
    - is usually a simple function of its final hidden state (h + c)
    - aims to encapsulate the information for all input elements in order to help the decoder make accurate predictions

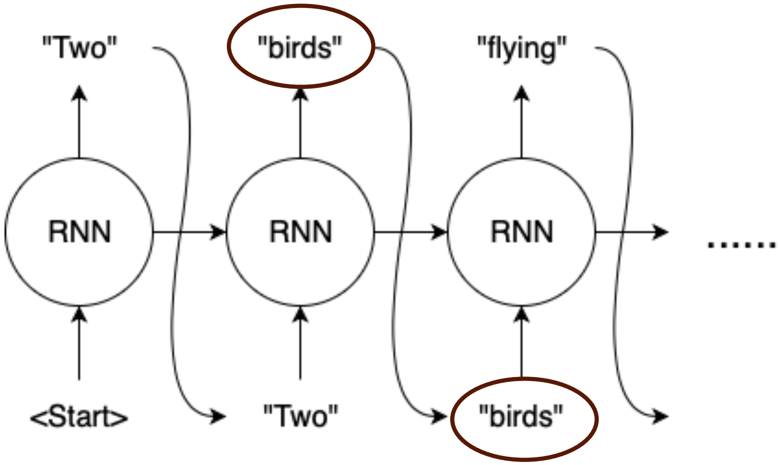
  - Decoder: is conditioned on the context to generate the output sequence
    - the context acts as the initial hidden state of the decoder part of the model
    - produces output at each step

How to train seq2seq architecture

Without teacher forcing

model.fit(input_sent, output_sent)

Decoder part

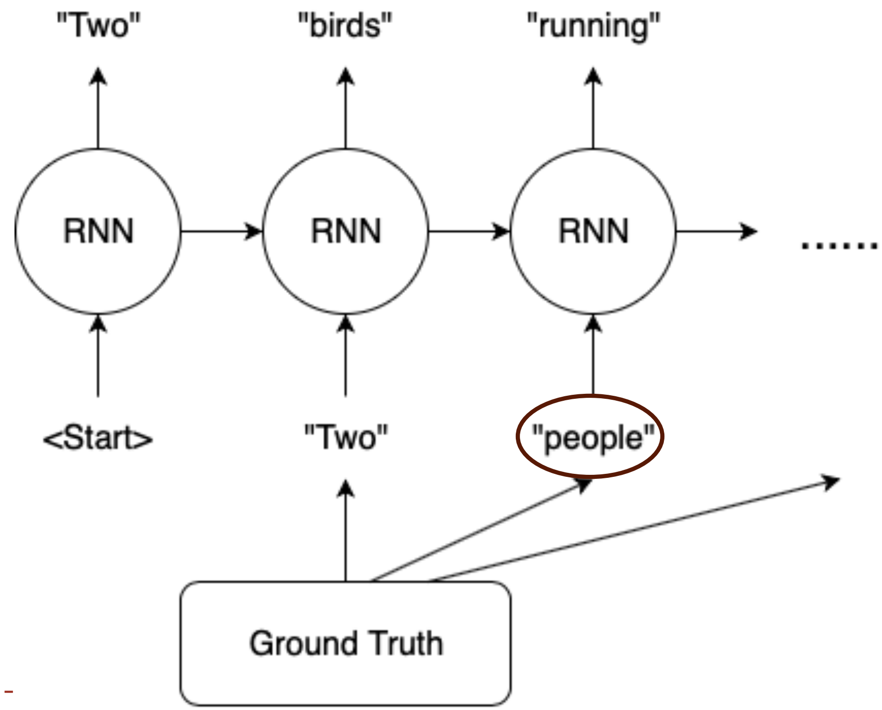


An error is propagated during the training phase → penalizes it

With teacher forcing

model.fit([input_sent, teacher_sent], output_sent)

Decoder part



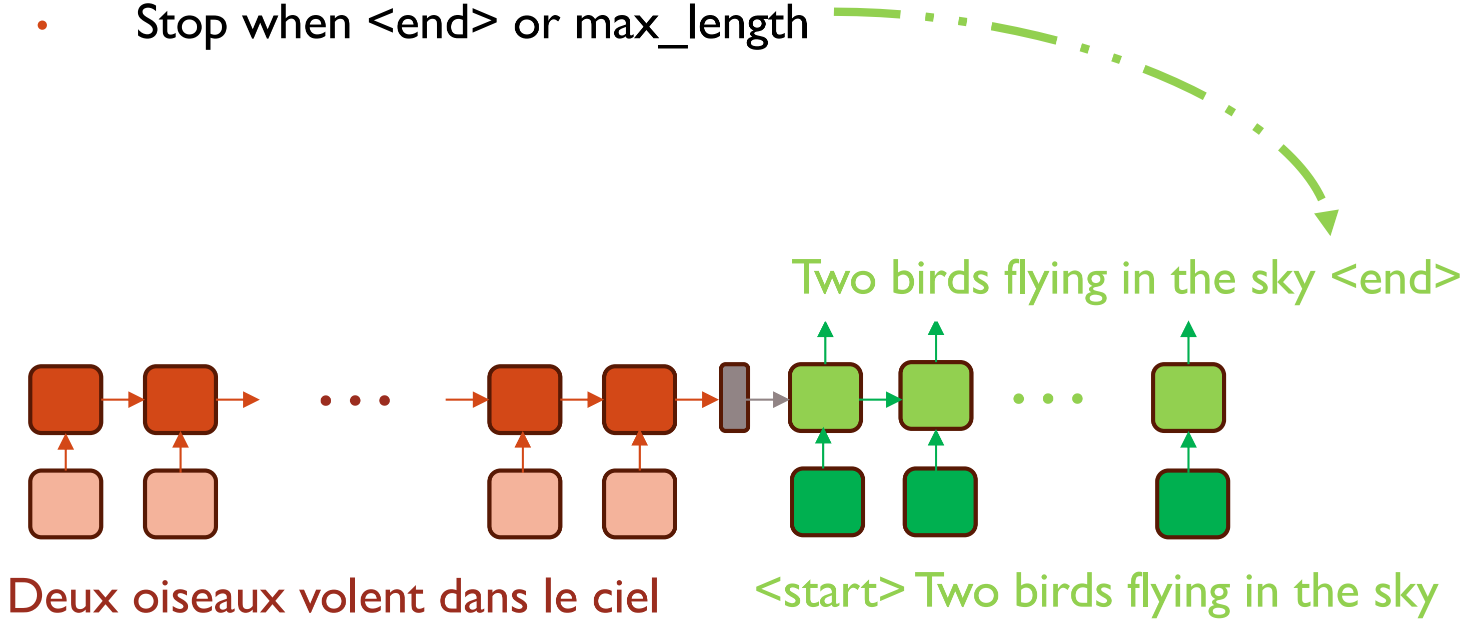
The teacher containt the ground truth

How to infer with seq2seq architecture

- Without/ With teacher forcing → no access to a ground Truth
- Greedy approach

1. Encode the sentence
2. iterate to successively decode each time step, reusing the time steps already decoded
   - Then reuse step by step the prediction

- Stop when <end> or max_length



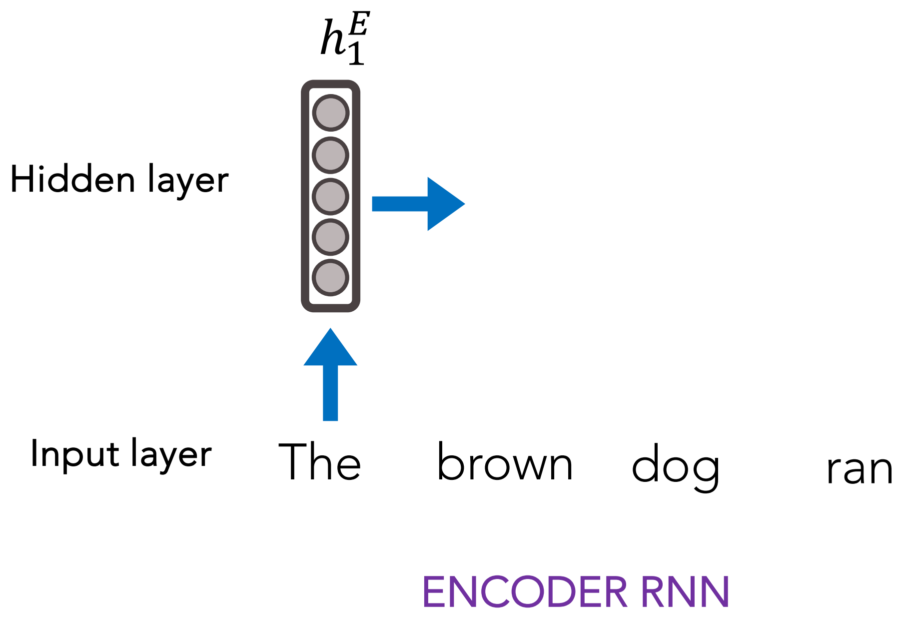
Pros and Cons of Teacher Forcing

- Pros:
  - If we do not use Teacher Forcing
    - the hidden states of the model will be updated by a sequence of wrong predictions
    - **errors will accumulate**
    - and it is difficult for the model to learn from that.
  - **Training with Teacher Forcing converges faster**.

- Cons:
  - **Unfortunately, during inference, there is no ground truth available**
    - the RNN model will have to re-inject its own prediction for the next prediction.
  - There is a difference between
    - learning (no propagation of error)
    - inference (propagation of error),

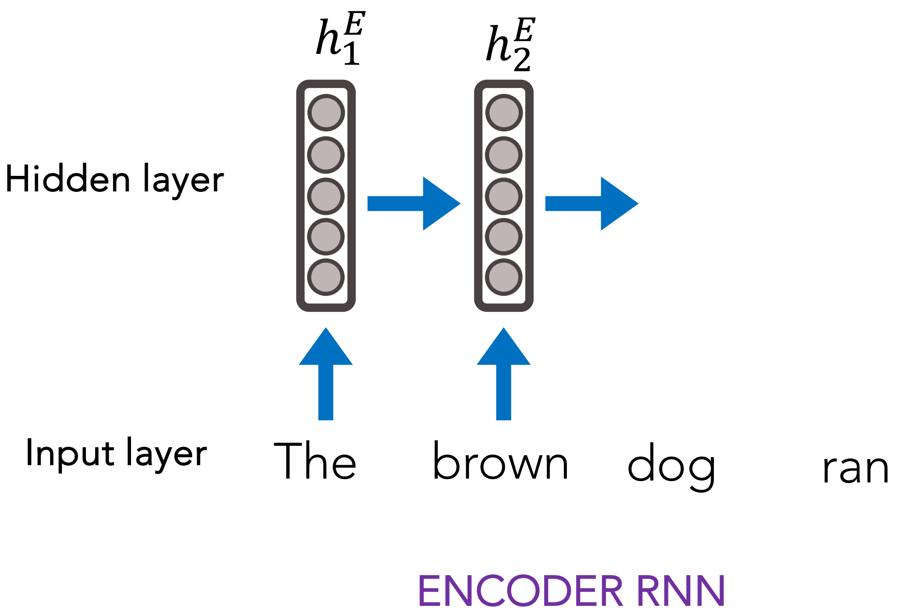
    which leads to poor performance and model instability.
  - This phenomenon is known as **exposure bias** in the litterature.

Train seq2seq model
Step 1 : encode input sentence



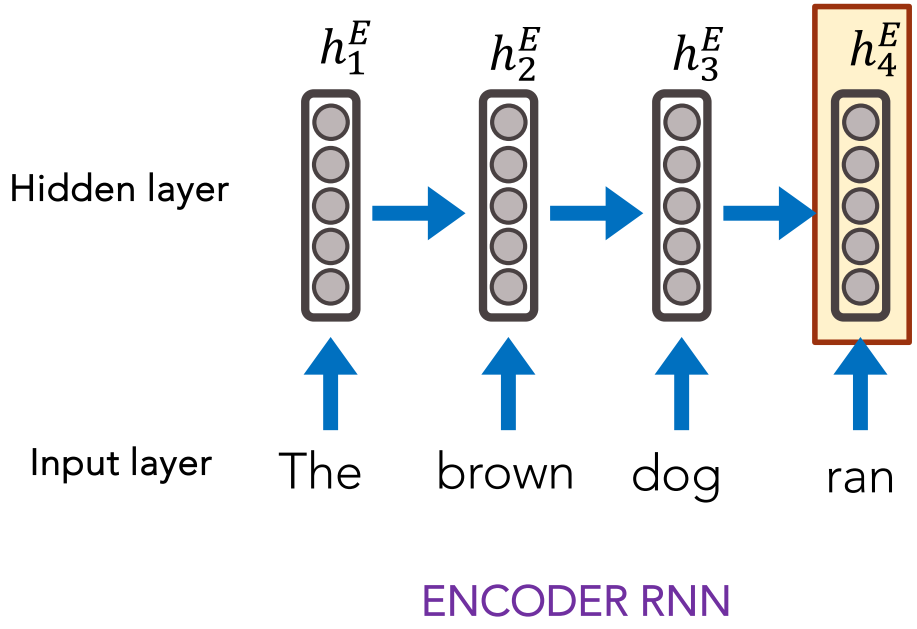
Train seq2seq model
Step 1 : encode input sentence

Remember: it's an iterative process until the end of the input sentence



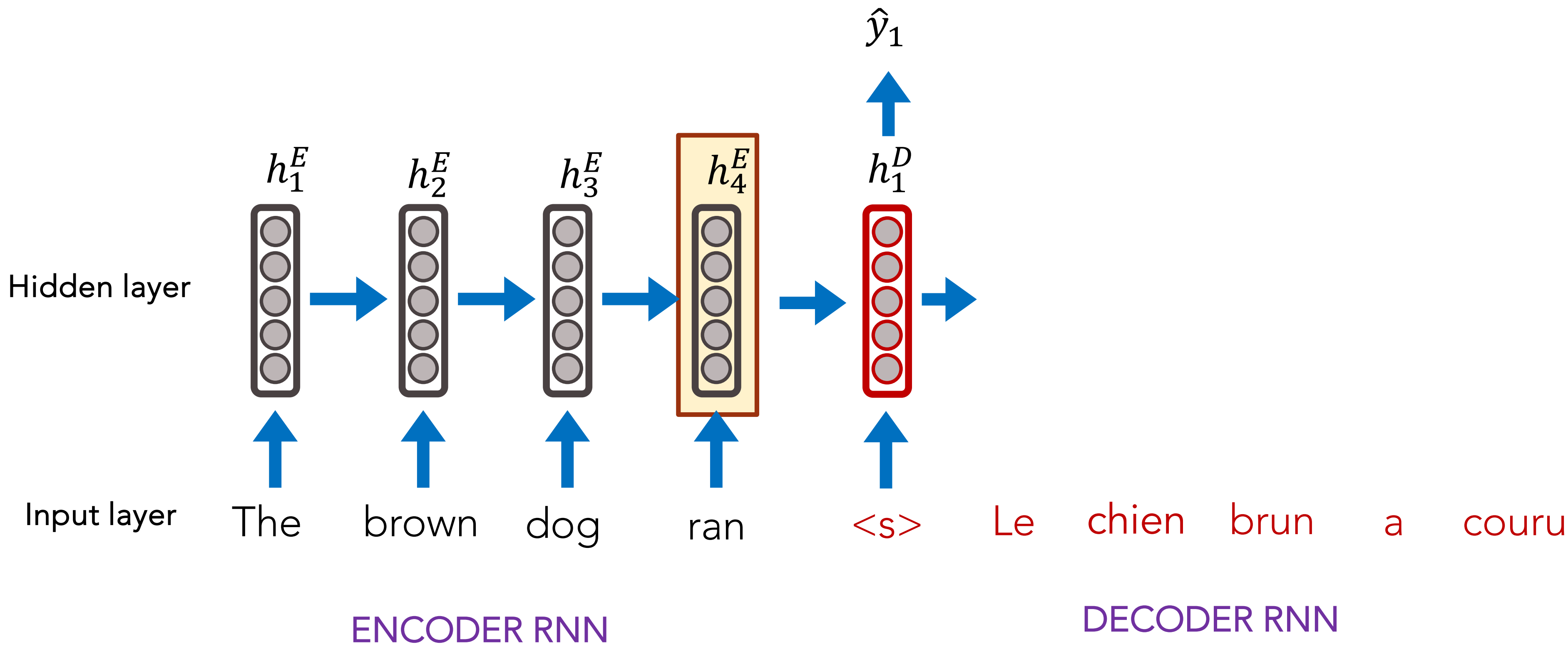
Train seq2seq model
Step 1 : encode input sentence

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



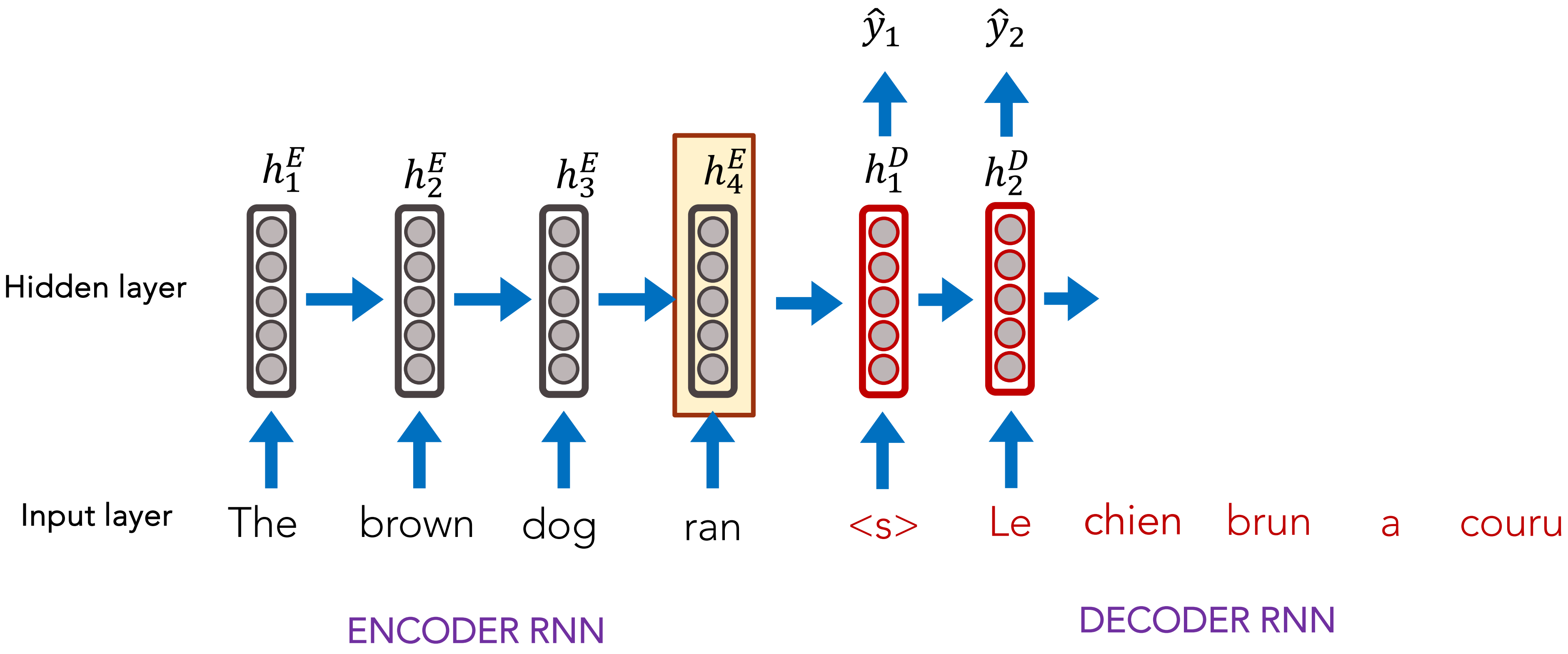
Train seq2seq model
Step 2 : decode the sentence

Remember: teacher, help in this task

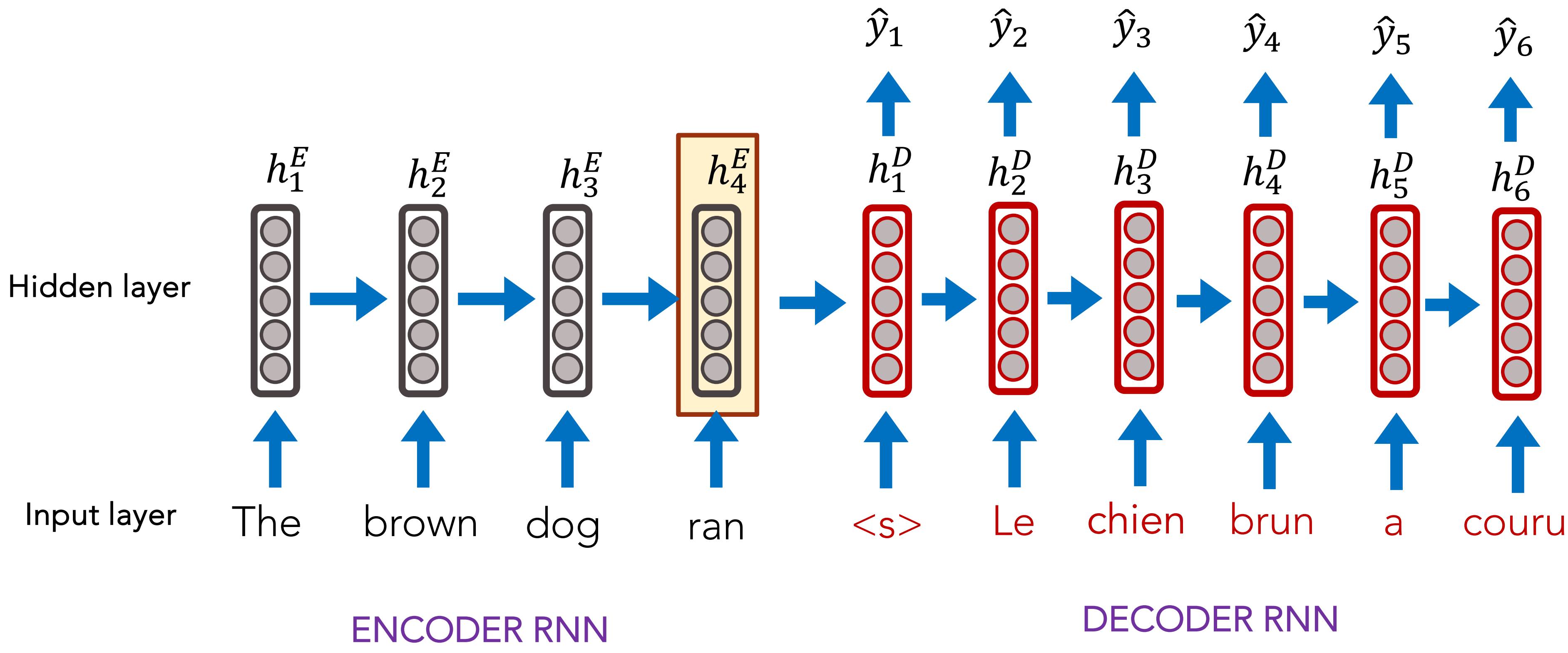


Train seq2seq model
Step 2 : decode the sentence

Remember: it's also an iterative process
until the end of the teacher sentence



Train seq2seq model
Step 2 : decode the sentence



How to build Teacher Seq2Seq model

- For example
  - Translation from Spanish to English

- Input sequence = Spanish = (None, None, in_features)
  - in_features: spanish_vocab_size=521
  - Use spanish_vectorizer

- Output sequence = English = (None, None, out_features)
  - out_features: english_vocab_size = 262
  - Use english_vectorizer

- Embedding dim → as usual (**50**, 100, 150, 300)
- Latent dim
  - Represent the size of the latent space (**64**, 128, 256 or more)
  - Latent space = 2*latent_dim for LSTM / latent_dim for GRU

https://blog.keras.io/a-ten-minute-introduction-to-sequence-to-sequence-learning-in-keras.html

How to build Teacher Seq2Seq model

```
# Define encoder
    enc_inputs = Input(shape=(None,), name="spanish_input")
    # Why input_shape=(None, None) ?
    enc = Embedding(sp_vocab_size, emb_dim, name="sp_embedding")(enc_inputs)
    _, enc_state_h, enc_state_c = LSTM(latent_dim, return_sequences=False,
                                       return_state=True)(enc)


# Define context
    context = [enc_state_h, enc_state_c]
```

How to build Teacher Seq2Seq model

\# Define decoder layers

layer_embedding = **Embedding**(en_vocab_size, emb_dim, name="en_embedding")

layer_lstm = **LSTM**(latent_dim, **return_sequences=True**, return_state=True)

 # We use return states in inference.

layer_dense = **Dense**(en_vocab_size, activation='softmax')

\# Define decoder

dec_inputs = **Input** (shape=(None,))

 # Why input_shape=(None, None) ?

dec **= layer_embedding** (dec_inputs)

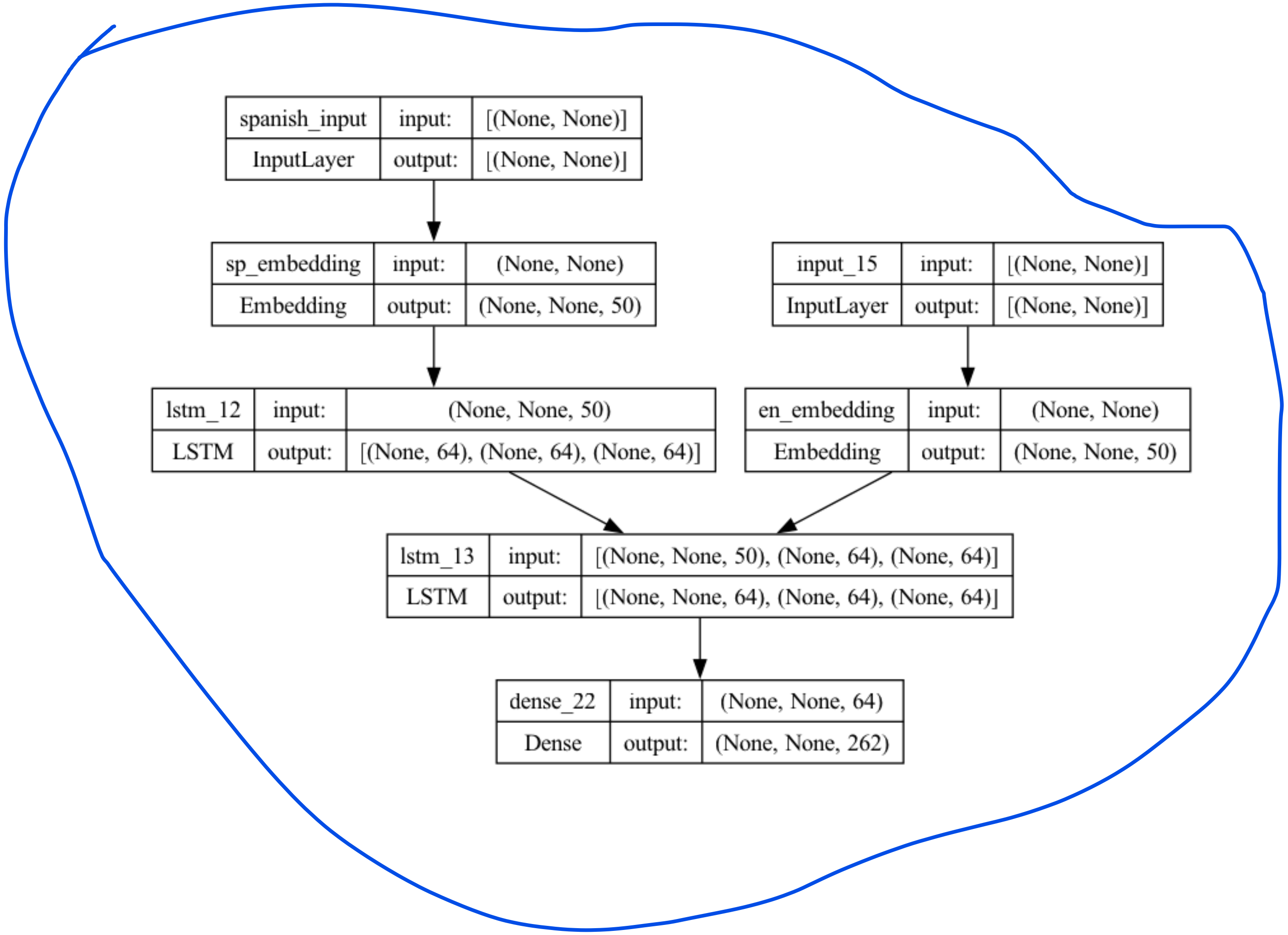
dec, _, _ = layer_lstm(dec, initial_state=**context**)

dec_outputs = layer_dense(dec)

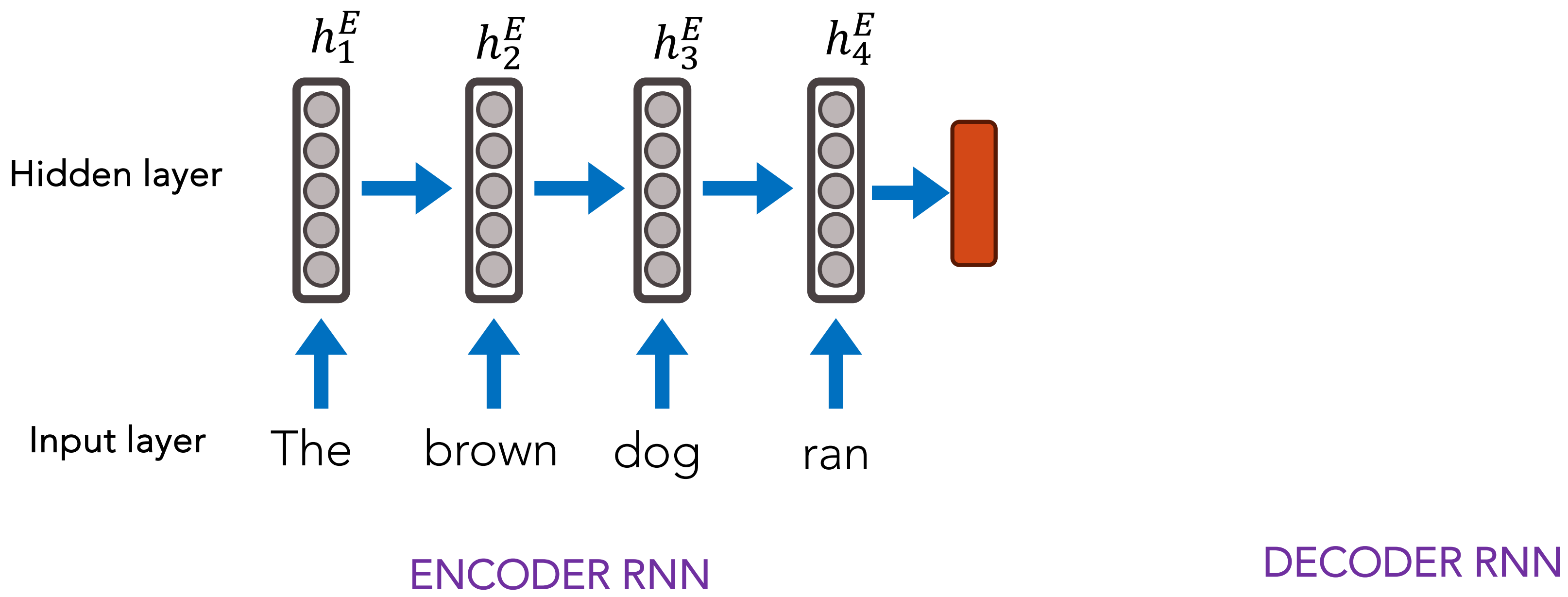
\# Define the Encoder_Decoder model

model = Model ([enc_inputs, dec_inputs], dec_outputs)

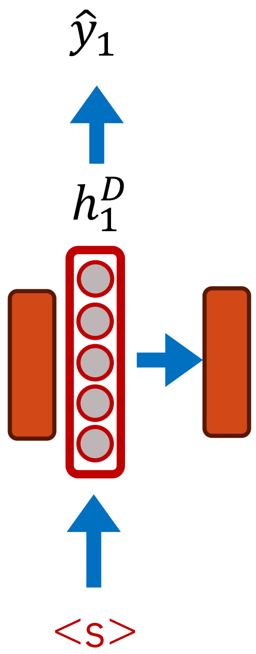
Seq2Seq model with teacher



Predict with seq2seq model
Step 1 : Use encode to define context



Predict with seq2seq model
Step 2 : decode the first output



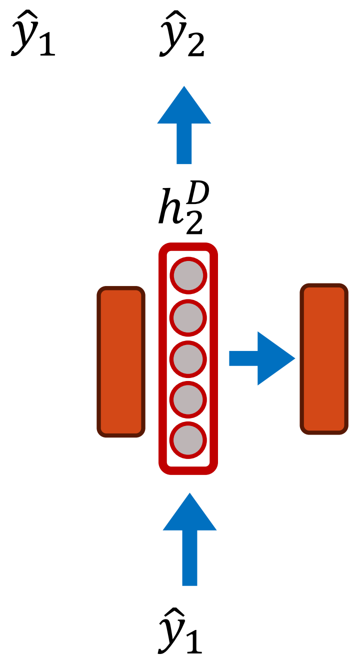
ENCODER RNN

DECODER RNN

Predict with seq2seq model
Step 2 : step by step… decode sentence

Decode step by step

Reuse at each step, the previous output



ENCODER RNN

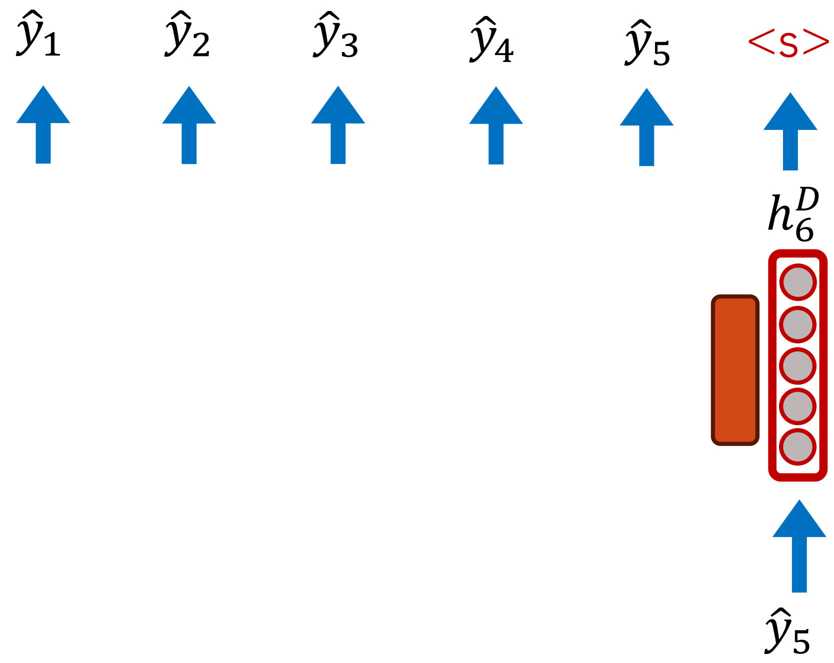
DECODER RNN

Predict with seq2seq model
Step 2 : step by step… decode sentence

Decode step by step

Reuse at each step, the previous output

Stop, when generate "stop" label



ENCODER RNN

DECODER RNN

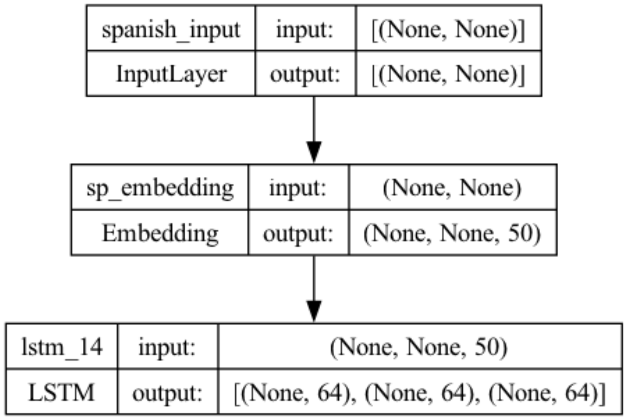
How to predict ?

\# Build encoder and decoder model

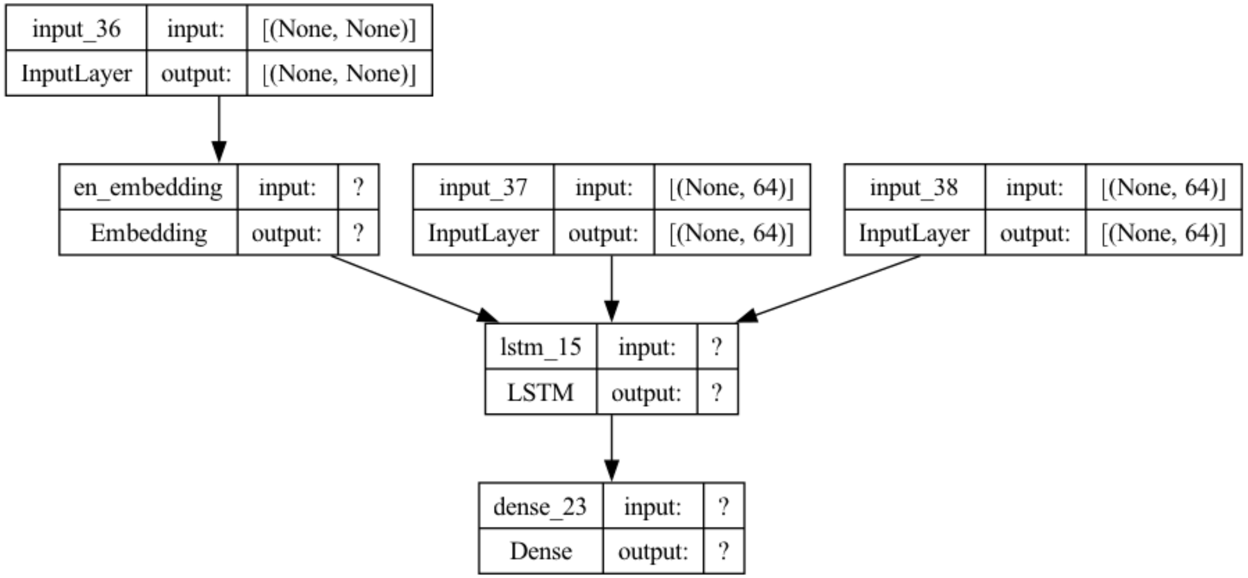
```
encoder_model = Model(enc_inputs, context)

dec_inputs = Input(shape=(None,)
dec_input_h = Input(shape=(latent_dim,))
dec_input_c = Input(shape=(latent_dim,))

dec = layer_embedding(dec_inputs)                    # Same cell as previously
dec, dec_h, dec_c = layer_lstm(dec_inputs,                    # Same cell as
previously
            initial_state=[dec_input_h, dec_input_c])
decoder_outputs = layer_dense(dec)                   # Same cell as previously

decoder_model = Model( [dec_inputs, dec_input_h, dec_input_c],
                       [decoder_outputs, dec_h, dec_c])
```

https://blog.keras.io/a-ten-minute-introduction-to-sequence-to-sequence-learning-in-keras.html

Encoder model



Decoder model



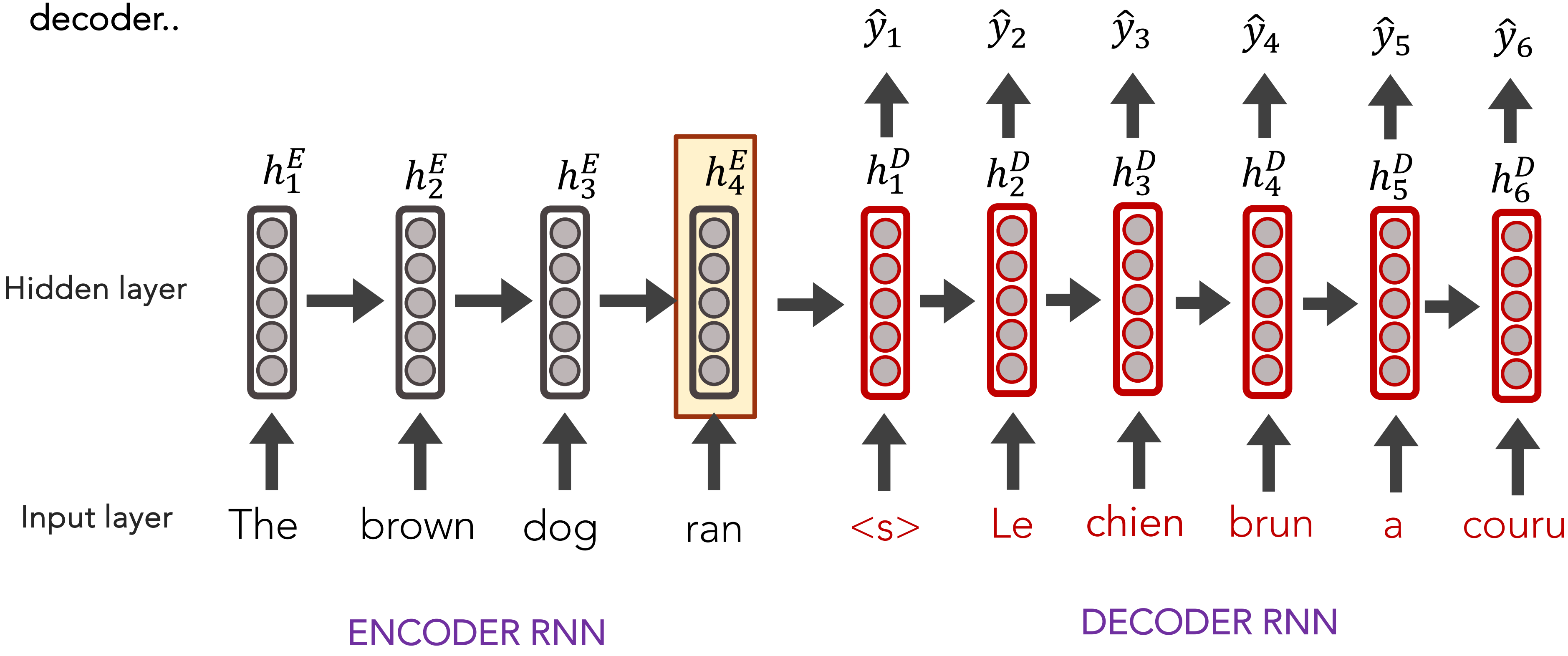
How to predict ?

```
def decode_sequence(input_seq):
    # Encode the input as state vectors.
    states_value = encoder_model.predict(input_seq)

    # Iterate over decoded sentence.Target_seq is the input of the decoder
    target_seq = np.zeros((len(input_seq), 1))
    target_seq[:, 0] = « initialize the first input »

    output_sequence = []  # Output_sequence is the output of the decoder
    For _ in range(max_output_length):
        output_value, h, c = decoder_model.predict( [target_seq] + states_value)
        # Update the target sequence (of length 1) and state
        target_seq[:, 0] = decode(output_value)
        states_value = [h, c]
        # extend output sequence
        output_sequence += [target_seq]

    return output_sequence # eventually format it
```

Must necessarily be adapted, as must the architecture of the network according to the problem :
- presence or absence of the embedding layer
- binary classification, categorical classification or mono or multi regression

Sequence-to-Sequence (seq2seq)

With a Seq2Seq model, we assume that the entire input sequence can be represented by a vector that is the only interaction between the encoder and the decoder..



Lab – Build a Deep Learning Translator

- Must necessarily be **finished before next week** as we will continue adding attentions to this model

- **Dataset:** download your own pair of language and prepare the dataset (code next slide)
  - https://www.manythings.org/anki/
  - For good performance, it is necessary to have a large dataset
  - But unfortunately, training a recurrent network is time consuming
  - We will therefore work with a reduced number of sentences
- Build a seq2seq neural network
  - 2 possibilities
    - At character level
    - At word level (preferable)
  - Over-fit your network (very low error rate) with a teacher
    - We use only a training set (we predict on test)
    - A very small validation split in order to visualize the overfitting
    - No EarlyStopping
- Build model for inference and predict

Data preparation

```
def step1(sent): # sent = on sentence in a language
    def unicode_to_ascii(s): # In order to reduce the possibility
        return ''.join(c for c in unicodedata.normalize('NFD', s) if
unicodedata.category(c) != 'Mn')
    sent = unicode_to_ascii(sent.lower().strip()) # Only lower charater

    # replacing everything with space except (a-z, A-Z, ".", "?", "!", ",",
"¿")
    sent = re.sub(r"[^a-zA-Z?.!,¿]+", " ", sent)    # To be adapted
according to the languages chosen

    # creating a space between a word and the punctuation following it.
E.g. "he is a boy." => "he is a boy ."
    # Reference:- https://stackoverflow.com/questions/3645931/python-
padding-punctuation-with-white-spaces-keeping-punctuation
    sent = re.sub(r"([?.!,¿])", r" \1 ", sent)              # To be adapted
according to the languages chosen

    return '<start> ' + sent.strip() + ' <end>'     # Suppress extra space
```

Data preparation

```
# Loading data
def read_data(path, num_examples):
    # path : path to spa-eng.txt file
    # num_examples : Limit the total number of training example for faster training
    lines = io.open(path, encoding='UTF-8').read().strip().split('\n')
    print(lines[0])
    sentences1, sentences2= zip(*[[step1(sent) for sent in l.split('\t')[:2]] for l in lines[:num_examples]])

    return np.array(sentences1), np.array(sentences2)
```

Data preparation

```
# Search vocabulary and max_length for each language
def voc(lang):
    # a list of sentences in the same language
    lengths = [len(txt.split()) for txt in lang]
    vocab = set([w for txt in lang for w in txt.split()])

    return max(lengths), list(vocab), len(vocab)+2 # for padding and OOV

max_length1, vocab1, vocab_size1 = voc(sentences1)

# Build vectorizer layer
vectorizer1 = layers.TextVectorization(standardize=None,
                                       output_mode='int',
                                       vocabulary=vocab1,
                                       name= "language1")

# Do the same for language 2
```