

Deep Learning Lab 13-1: Seq2Seq Learning & Neural Machine Translation

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Outline

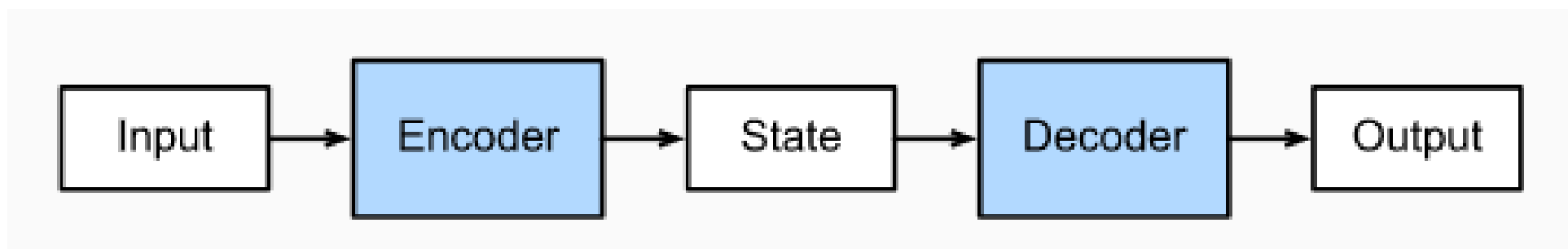
- Encoder-Decoder Model
- Sequence-to-Sequence (Seq2Seq)
- Attention Mechanism
- Teacher Forcing
- Assignment
- Extra Material: Transformer
- Reference

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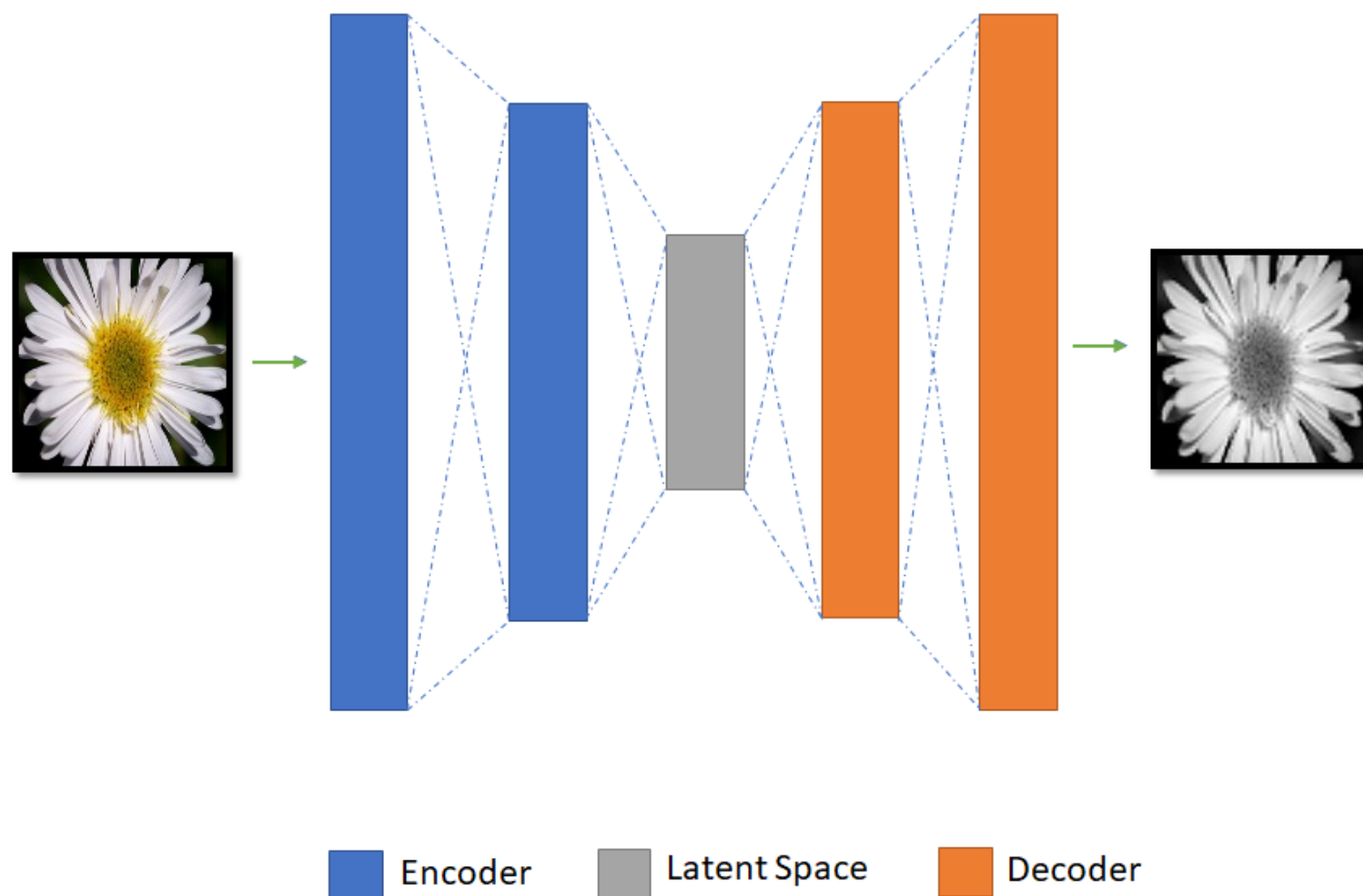
Encoder-Decoder Model

- As we have seen in lab12-2 (AdaIN),
 - Encoder: encode the inputs into **hidden state/context/code**
 - Decoder: the hidden state is passed into the decoder to generate the desired output



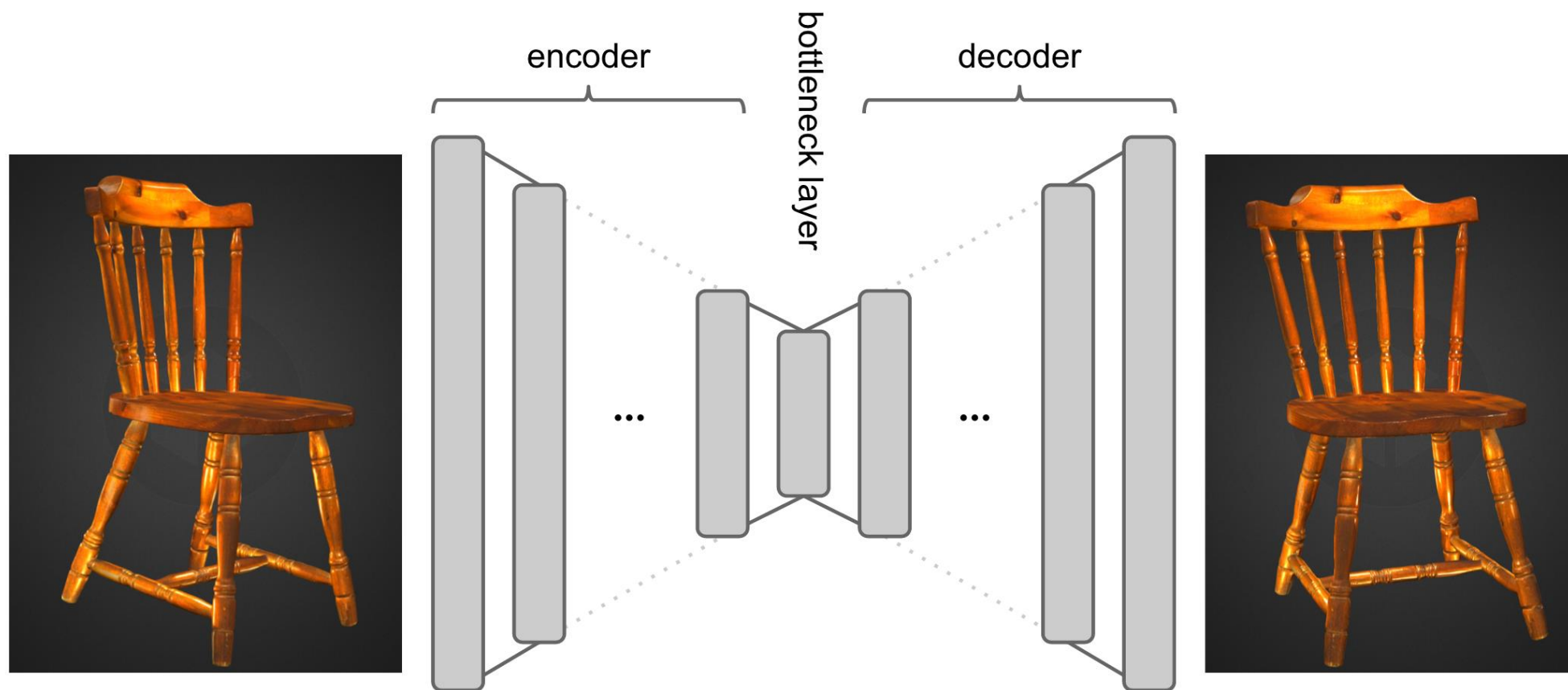
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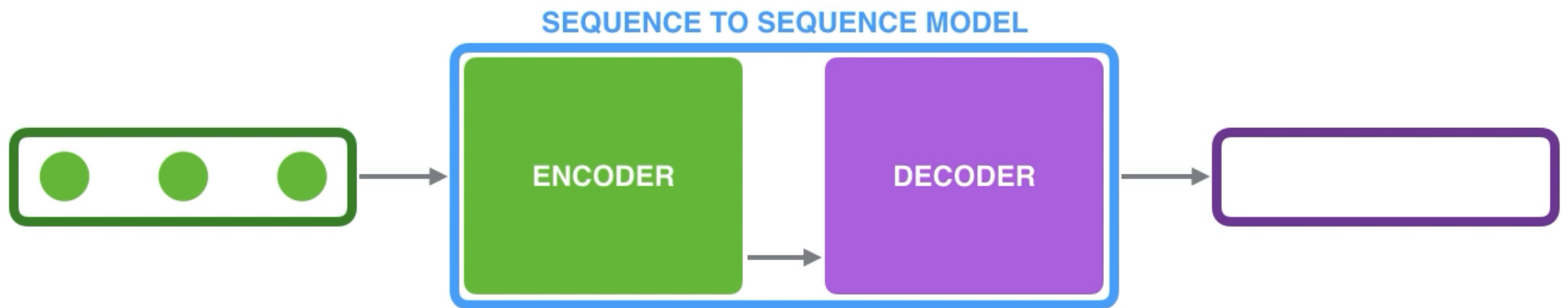
Sequence-to-Sequence (Seq2Seq)

- Sequence-to-Sequence (Seq2Seq) is an architecture based on the **encoder-decoder**, which transforms an input sequence to the target sequence
 - Both sequences can have arbitrary lengths
 - Have achieved a lot of success in tasks like machine translation, text summarization, and image captioning
 - Google Translate started using such a model in production in late 2016

The logo for Google Translate, featuring the word "Google" in its multi-colored font followed by the word "Translate" in a grey sans-serif font.

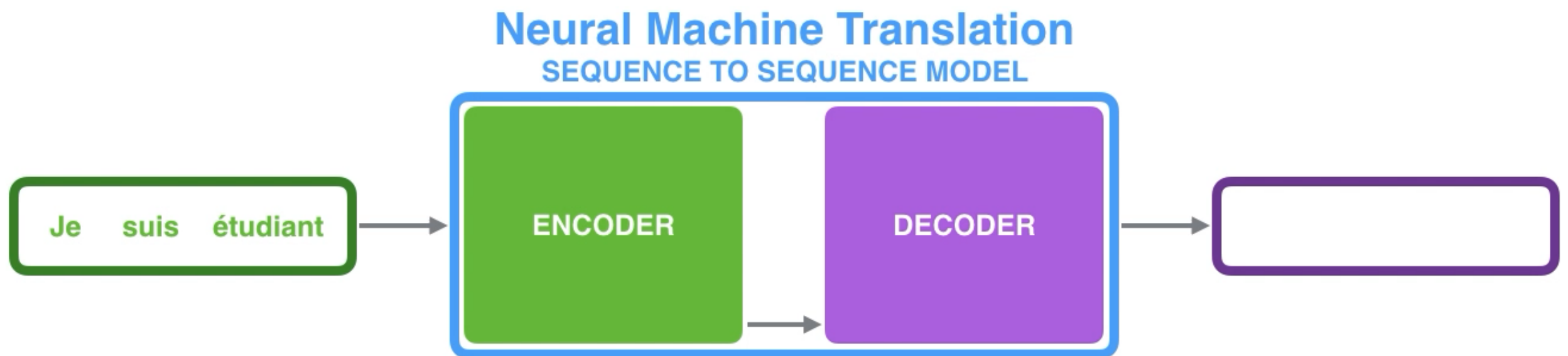
Seq2Seq

- Sequence-to-Sequence (Seq2Seq) is an architecture based on the **encoder-decoder**, which transforms an input sequence to the target sequence
- The **encoder** processes each item in the input sequence, it compiles the information it captures into a vector, called the **context**. After processing the entire input sequence, the **encoder** sends the **context** over to the **decoder**, which begins producing the output sequence item by item



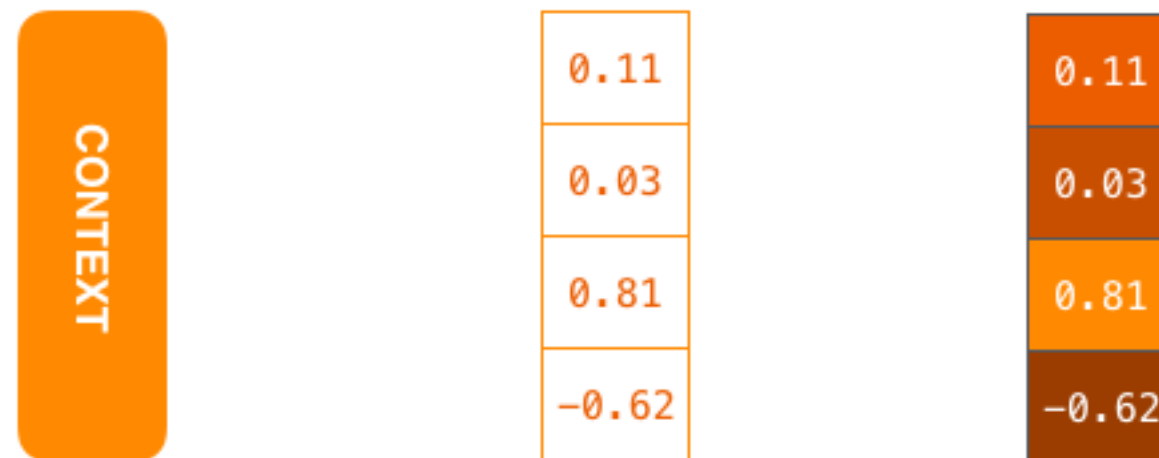
Seq2Seq

- In neural machine translation, a sequence is a series of words, processed one after another. The output is, likewise, a series of words:



Seq2Seq

- The **context** is a vector (an array of numbers, basically) in the case of machine translation. The **encoder** and **decoder** tend to both be recurrent neural networks (RNNs)
- You can set the size of the **context** vector when you set up your model. It is basically the number of hidden units in the **encoder** RNN



Seq2Seq

- By design, a RNN takes two inputs at each time step: **an input** (in the case of the encoder, one word from the input sentence), and a **hidden state**

Recurrent Neural Network

Time step #1:

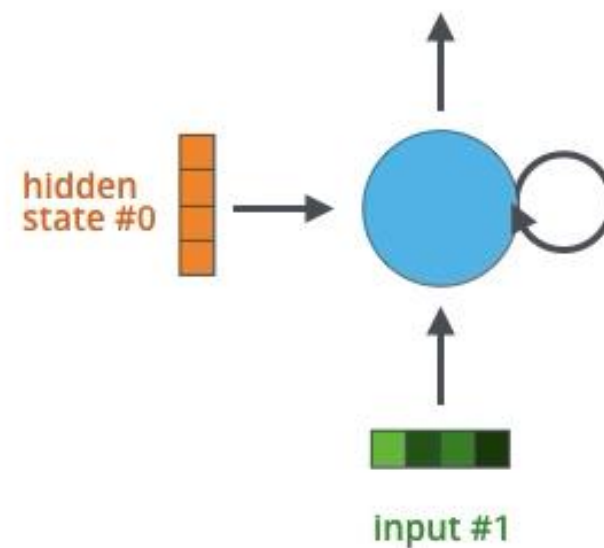
An RNN takes two input vectors:



hidden state #0



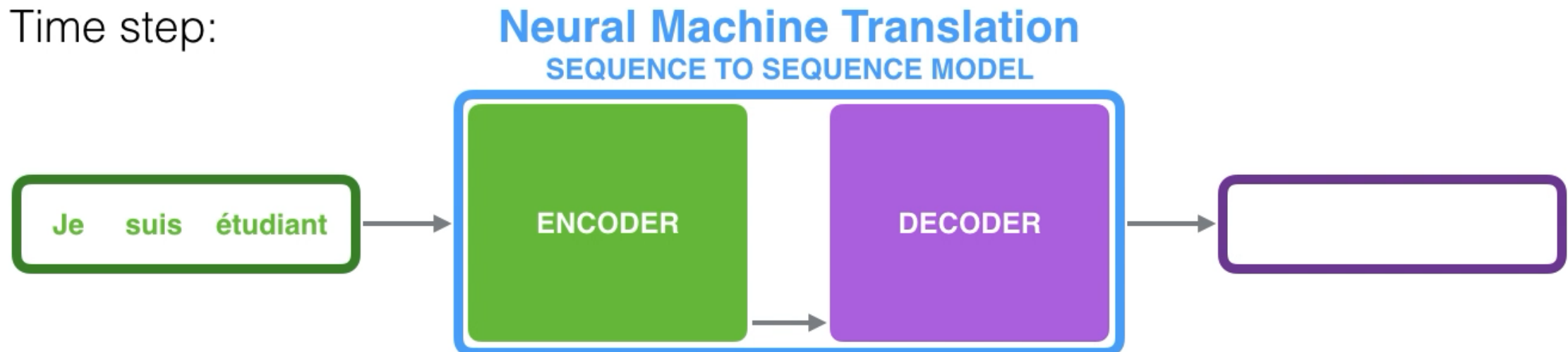
input vector #1



Seq2Seq

- Since the **encoder** and **decoder** are both RNNs, each time step one of the RNNs does some processing, it updates its **hidden state** based on its inputs and previous inputs it has seen
 - Notice the last **hidden state** is actually the **context** we pass along to the **decoder**

Time step:



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Why Attention?

- The **fixed-length context** vector turned out to be a bottleneck for these types of models. It made it challenging for the models to deal with long sentences
 - It is hard for the fixed-length context vector to store all information as the input sequence getting longer and longer
 - It has often forgotten the earlier part of input once it processed the whole input sequence

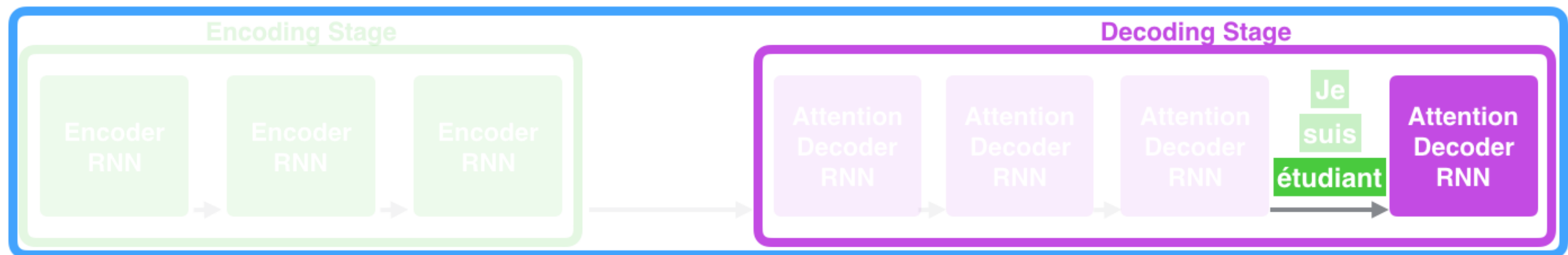
Attention Mechanism

- Attention allows the model to focus on the relevant parts of the input sequence as needed
 - The decoder can focus on different part of the input sequence at each time step, in order to make a better prediction

Time step: 7

Neural Machine Translation

SEQUENCE TO SEQUENCE MODEL WITH ATTENTION

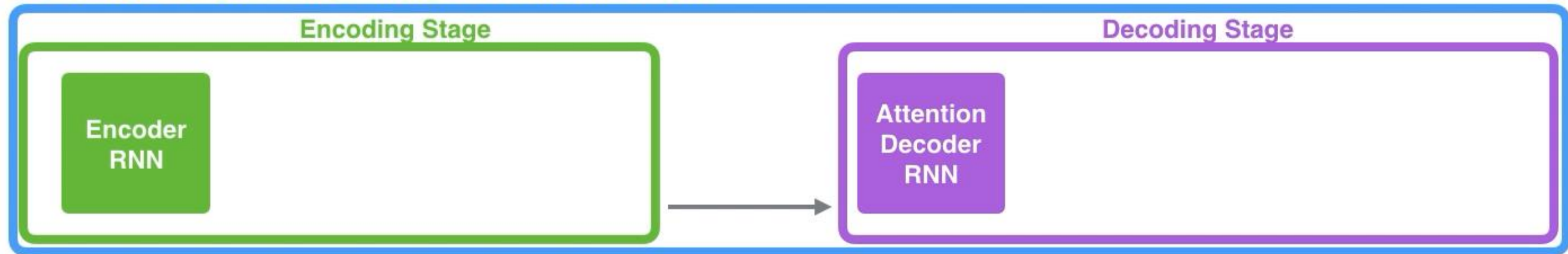


Attention Mechanism

1. First, the **encoder** passes a lot more data to the **decoder**. Instead of passing the last hidden state of the encoding stage, the **encoder** passes **all** the **hidden states** to the **decoder**:

Neural Machine Translation

SEQUENCE TO SEQUENCE MODEL WITH ATTENTION



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Attention Mechanism

2. Second, an attention **decoder** does an extra step before producing its output. In order to focus on the parts of the input that are relevant to this decoding time step, the **decoder** does the following:
 1. Look at the set of encoder **hidden states** it received – each **encoder hidden states** is most associated with a certain word in the input sentence
 2. Give each **hidden states** a score (let's ignore how the scoring is done for now)
 3. Multiply each **hidden states** by its softmax score, thus amplifying **hidden states** with high scores, and drowning out **hidden states** with low scores

Attention Mechanism

Attention at time step 4



Attention Mechanism

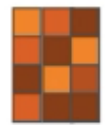
- Let us now bring the whole thing together in the following visualization and look at how the attention process works:
 1. The attention decoder RNN takes in the embedding of the **<END>** token, and an **initial decoder hidden state**
 2. The RNN processes its inputs, producing an output and a **new hidden state** vector (**h4**). The output is discarded
 3. Attention Step: We use the **encoder hidden states** and the **h4** vector to calculate a context vector (**C4**) for this time step
 4. We concatenate **h4** and **C4** into one vector
 5. We pass this vector through a **feedforward neural network** (one trained jointly with the model)
 6. The **output** of the feedforward neural networks indicates the output word of this time step
 7. Repeat for the next time steps

Attention Mechanism

Neural Machine Translation

SEQUENCE TO SEQUENCE MODEL WITH ATTENTION

Encoding Stage



$h_1 h_2 h_3$



Attention Decoding Stage

h_{init}



$\langle \text{END} \rangle$

4

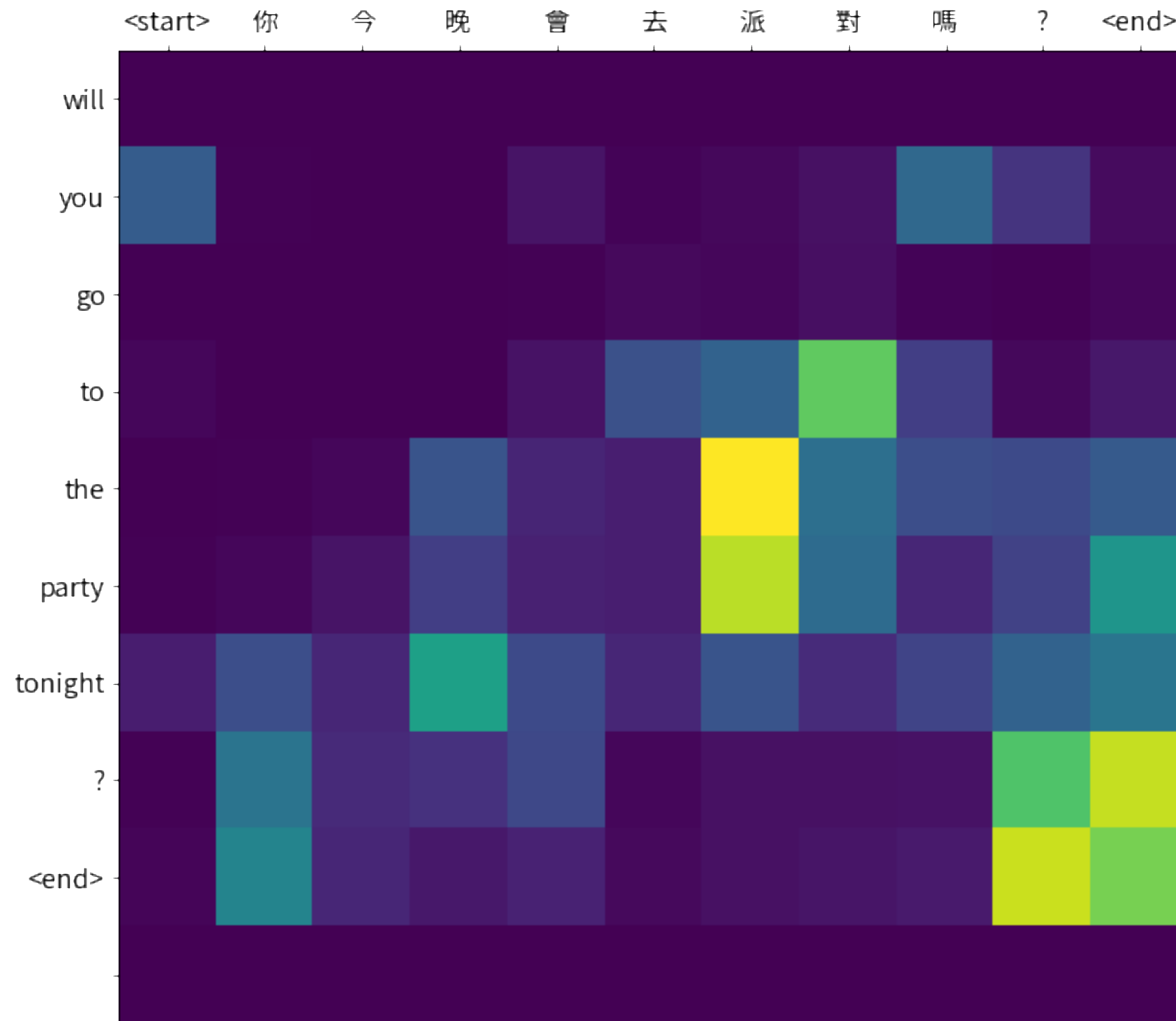
Attention Mechanism

- This is another way to look at which part of the input sentence we're paying attention to at each decoding step:



Attention Mechanism

- It actually learned from the training phase how to align words in that language pair



Attention Mechanism

- Let's dive into math!
 - Score: $e_{ij} = a(s_{i-1}, h_j)$
 - Score after softmax: $\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$
 - Context vector: $c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$

Attention Mechanism

- How to calculate the score $e_{ij} = a(s_{i-1}, h_j)$?
 - , where $a(\cdot)$ is the dot product in the following example

```
decoder_hidden = [10, 5, 10]
```

```
encoder_hidden  score
```

```
-----
```

[0, 1, 1]	15	(= 10×0 + 5×1 + 10×1, the dot product)
[5, 0, 1]	60	
[1, 1, 0]	15	
[0, 5, 1]	35	

Attention Mechanism

- Score after softmax $\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$ is straightforward

encoder_hidden	score	score^
[0, 1, 1]	15	0
[5, 0, 1]	60	1
[1, 1, 0]	15	0
[0, 5, 1]	35	0

Attention Mechanism

- Finally, we can multiply each hidden state of encoder by its score and sum up the alignment vectors to get the context

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

encoder	score	score^	alignment
[0, 1, 1]	15	0	[0, 0, 0]
[5, 0, 1]	60	1	[5, 0, 1]
[1, 1, 0]	15	0	[0, 0, 0]
[0, 5, 1]	35	0	[0, 0, 0]

context = [0+5+0+0, 0+0+0+0, 0+1+0+0] = [5, 0, 1]

Attention Mechanism

- There are many well-known score functions as follows
 - h represents hidden state of encoder
 - S represents decoder hidden states

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

Attention Mechanism

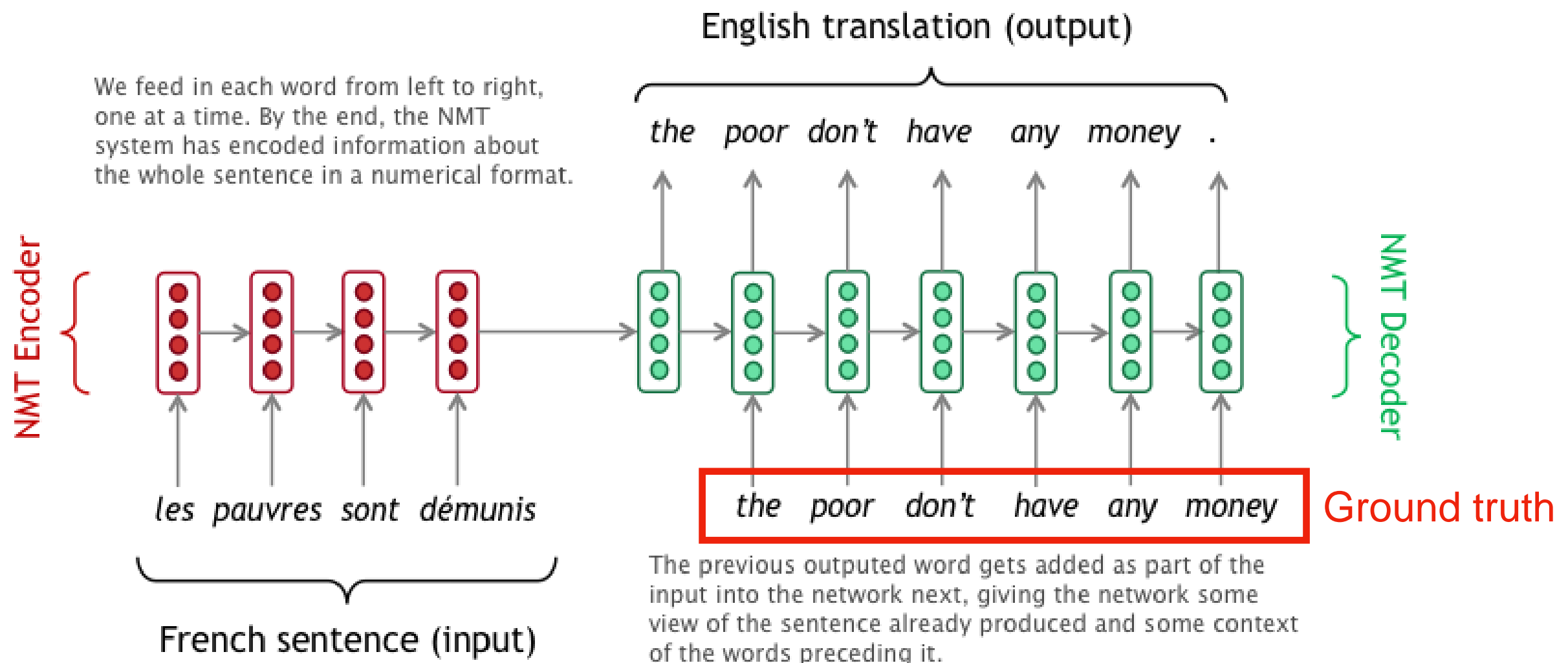
- Attention mechanism allows the decoder to focus on various part of input sequence, instead of forcing it to encode all information into one fixed-length vector
 - Pros: model interpretability, better performance
 - Cons: computationally expensive

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Teacher Forcing

- Teacher forcing is a method for quickly and efficiently training recurrent neural network models that use the ground truth from a prior time step as input
 - Accelerate the convergence speed
 - Stabilize the training process



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Assignment

- There are two parts in the notebook
 - Part I: neural machine translation
 - Part II: sentiment analysis (assignment)

Neural Machine Translation

- Overview

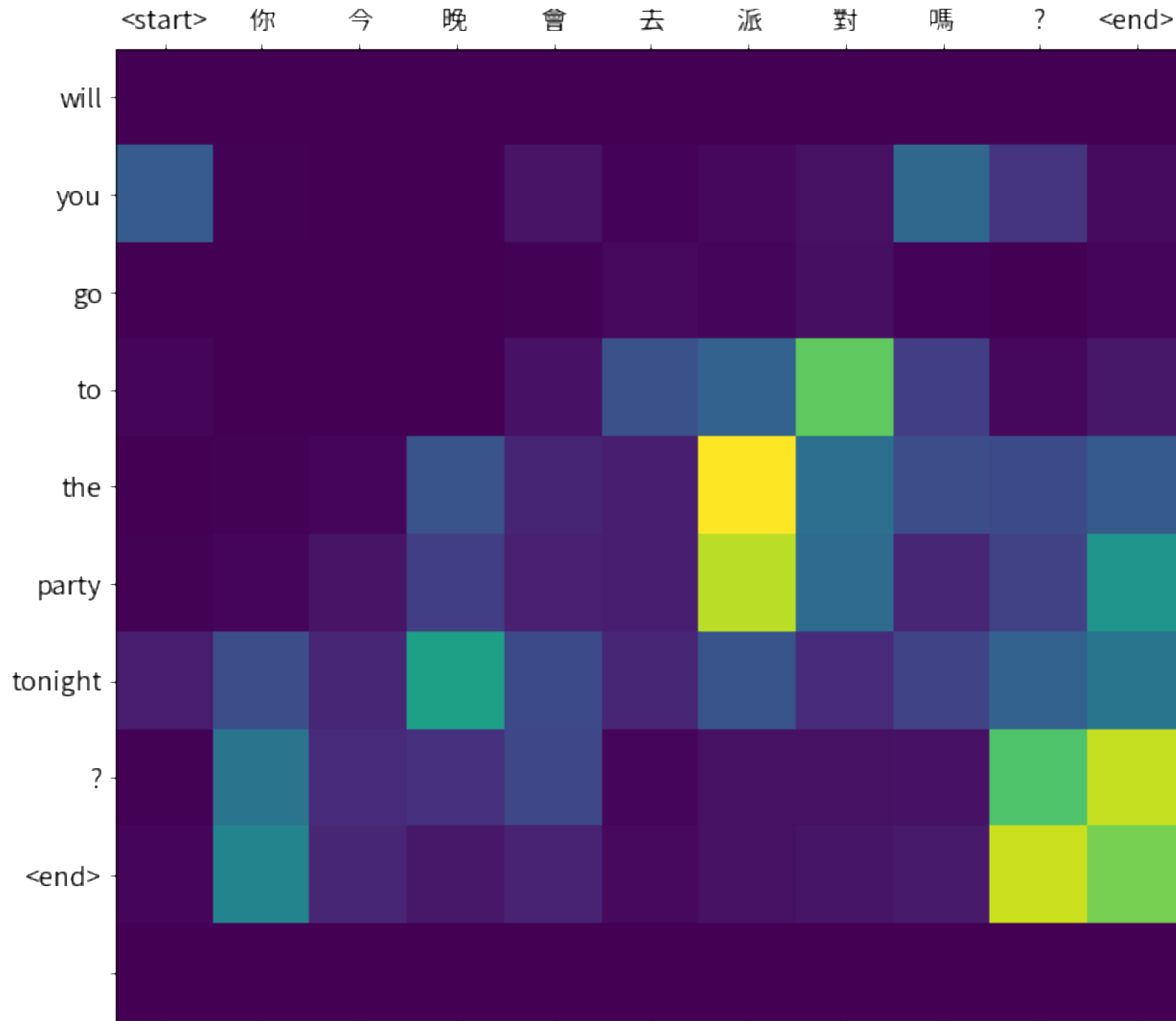
- Task: translate the sentence from Chinese to English
- Dataset size: 20289
- Encoder: RNN with GRU cell
- Decoder: RNN with GRU cell
- Attention mechanism: Bahdanau Attention

$$score(s_t, h_i) = v_a^T \tanh(W_a[s_t; h_i])$$

- It is worth noticing that in GRU, **the hidden state and the output are same**

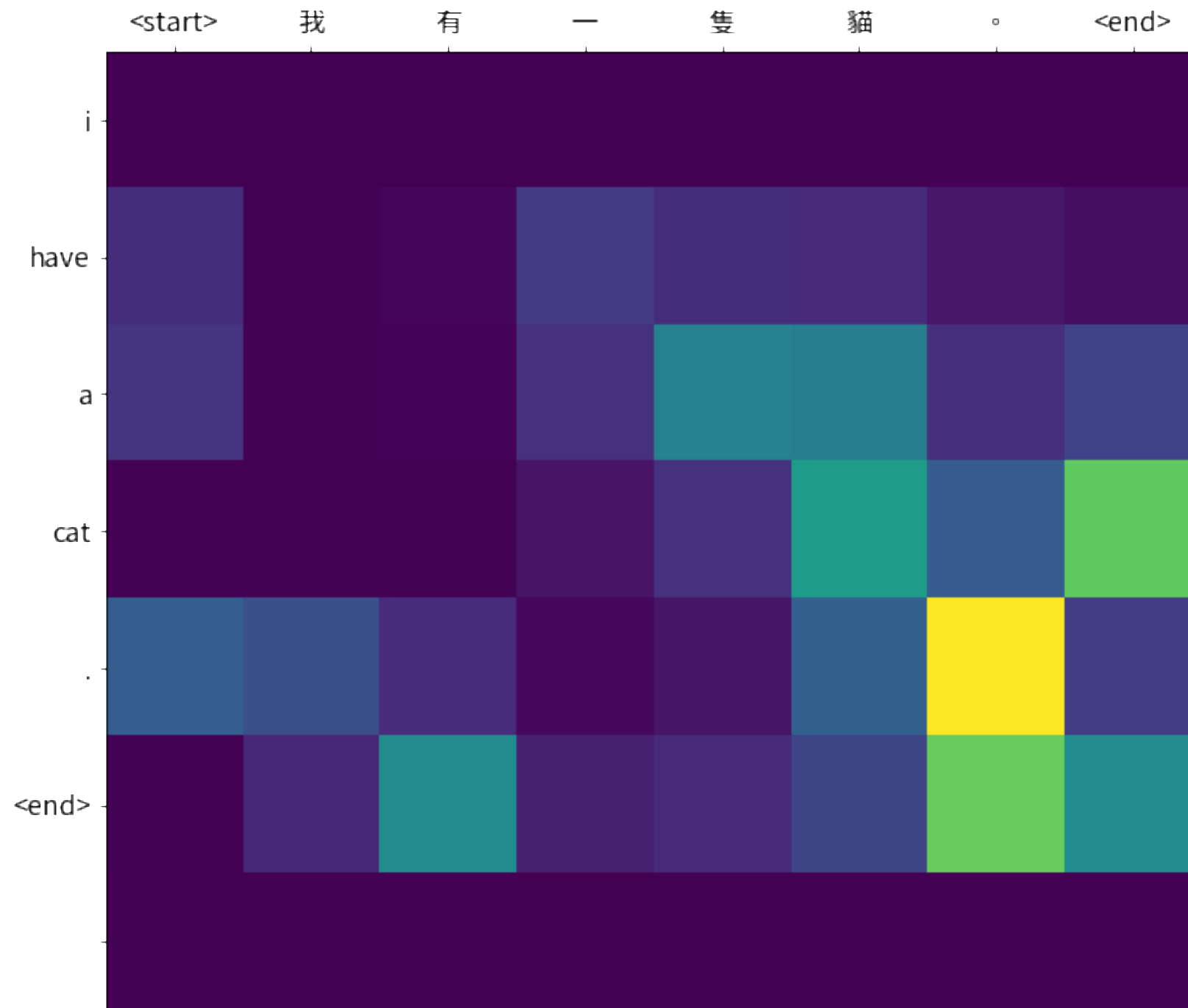
Neural Machine Translation

- It's a toy model with toy dataset. Here we focus on the main idea behind the model



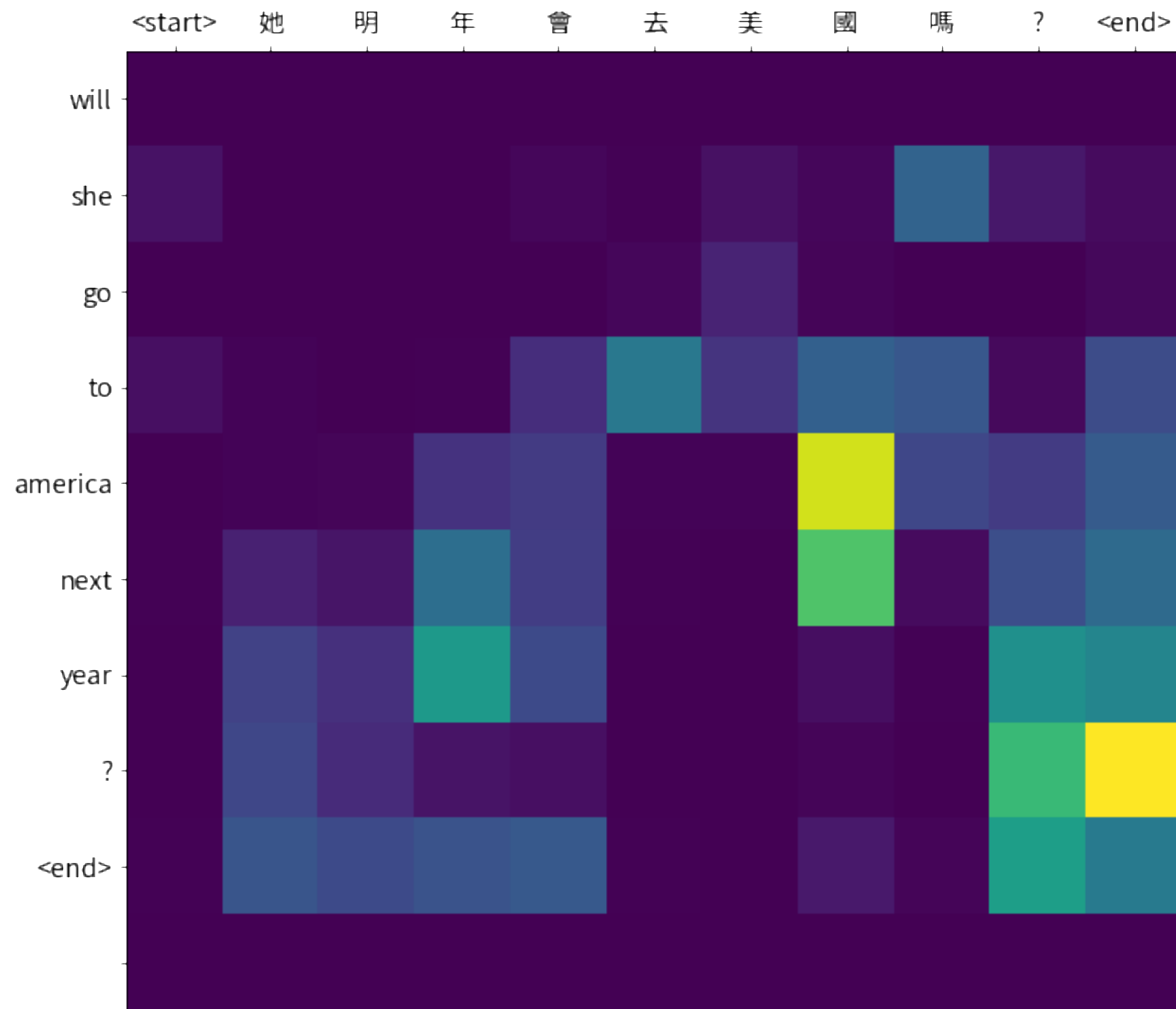
Neural Machine Translation

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Neural Machine Translation

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Neural Machine Translation

- In the plotting function, you need to change the path of the Chinese font. Otherwise, the Chinese character will not be displayed in the plot

```
def plot_attention(attention, sentence, predicted_sentence):  
    # you need to change the fname based on your system, and the Chinese can be displayed  
    in the plot  
    font = FontProperties(fname=r"./data/TaipeiSansTCBeta-Regular.ttf", size=14)
```

Sentiment Analysis

- Overview
 - Task: predict whether the comment is positive or negative
 - Dataset: IMDB
 - Dataset size: 50000
 - Encoder: RNN with GRU cell
 - Decoder: 4 fully-connected layers
 - Attention mechanism: Luong Attention

	review	sentiment
0	One of the other reviewers has mentioned that ...	positive
1	A wonderful little production. The...	positive
2	I thought this was a wonderful way to spend ti...	positive
3	Basically there's a family where a little boy ...	negative
4	Petter Mattei's "Love in the Time of Money" is...	positive

TODO

- Implement the **Luong Attention**, where the formula of the score function is:

$$score(s_t, h_i) = s_t^T W_a h_i$$

- h_i : hidden state of the encoder
- s_t : hidden state of the decoder
- W_a : the trainable weights

Demo

- This simple model achieves ~84.5% accuracy with only 10 epochs! Not bad at all!
- Besides the nice accuracy, let's try to do some more fascinating things. How about **visualize** our results?

Demo

Positive

y_true: 1

y_predict: 1

jane austen would definitely of this one paltrow does an **awesome** job capturing the attitude of emma she is funny without being silly yet elegant she puts on very convincing british accent not being british myself maybe i'm not the best judge but she fooled me she was also excellent in doors sometimes forget she american also brilliant are **jeremy northam and sophie thompson and** law emma **thompson sister** and mother as the bates women they nearly steal the show and ms law doesn't even have any lines highly **recommended**

Negative

y_true: 0

y_predict: 0

reaches the point where they become **obnoxious** and simply **frustrating** touch football puzzle family and talent shows are not how actual people behave it almost **sickening another big** flaw is the woman carell is **supposed** to be falling for her in her first scene with steve carell is like watching stroke victim trying to be what imagine is **supposed** to be unique and original in this woman comes off as mildly **retarded** it makes me think that this movie is taking place on another planet left the theater wondering what **just** saw after thinking **further** don't think it was much

Requirement

- The accuracy should be at least **0.80**
- Show the **10-most-focused words** in the sentence
- Only need to show the **first 10 results** in the test data
- Submit on eeclass your code file Lab13-1_{student id}.ipynb
- No need to submit the checkpoints file, but you should show the results in the notebook
- Deadline: **2021-11-25(Thur) 23:59**

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Attention Is All You Need

- The authors proposed the Transformer – a model that uses attention to **boost the performance** and **shorten the required training time**
- The Transformer is a **stand-alone attention-based model**, which entirely replace recurrence with self-attention

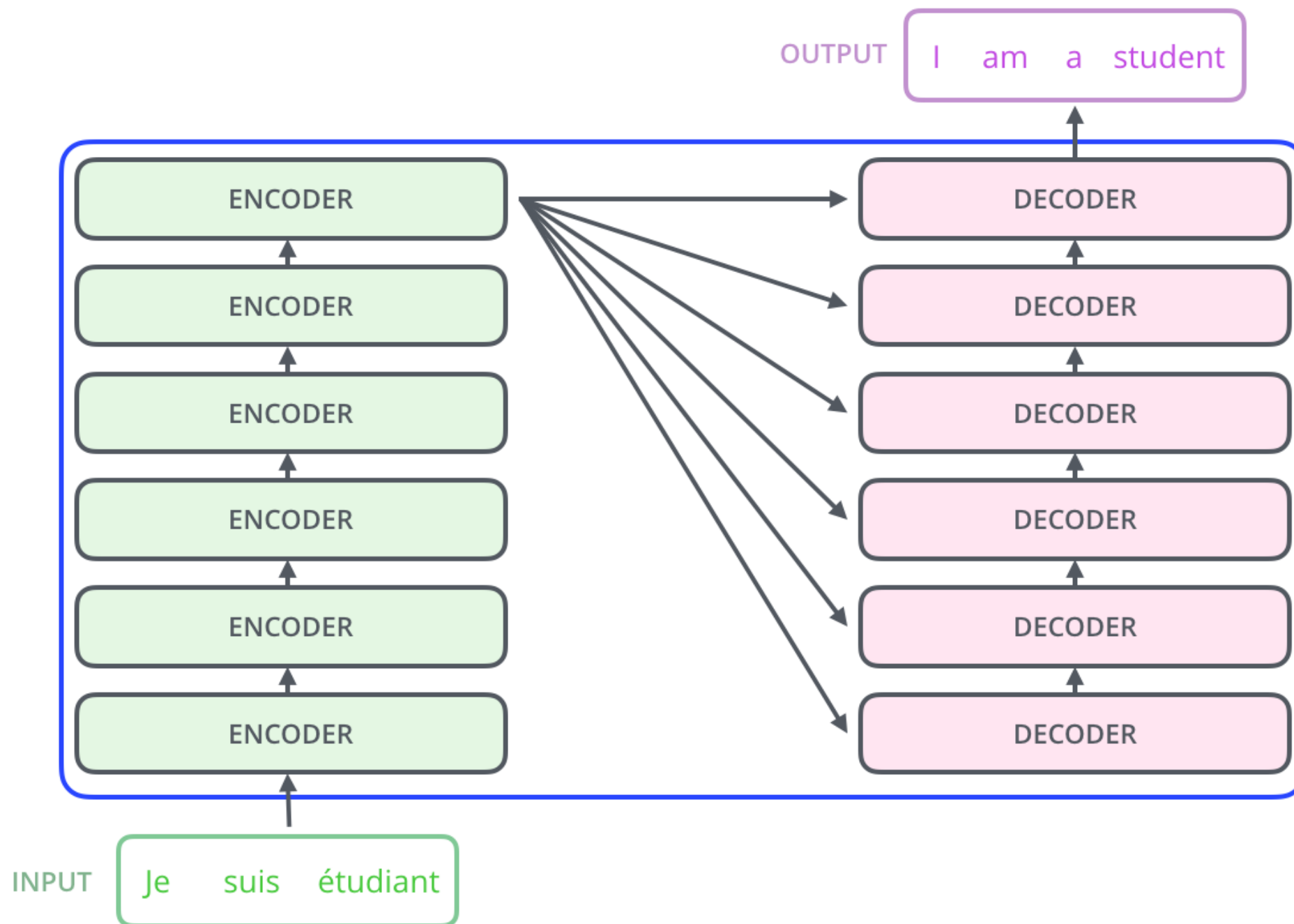
A High-Level Look

- Let's begin by looking at the model as a single black box. In a machine translation application, it would take a sentence in one language, and output its translation in another



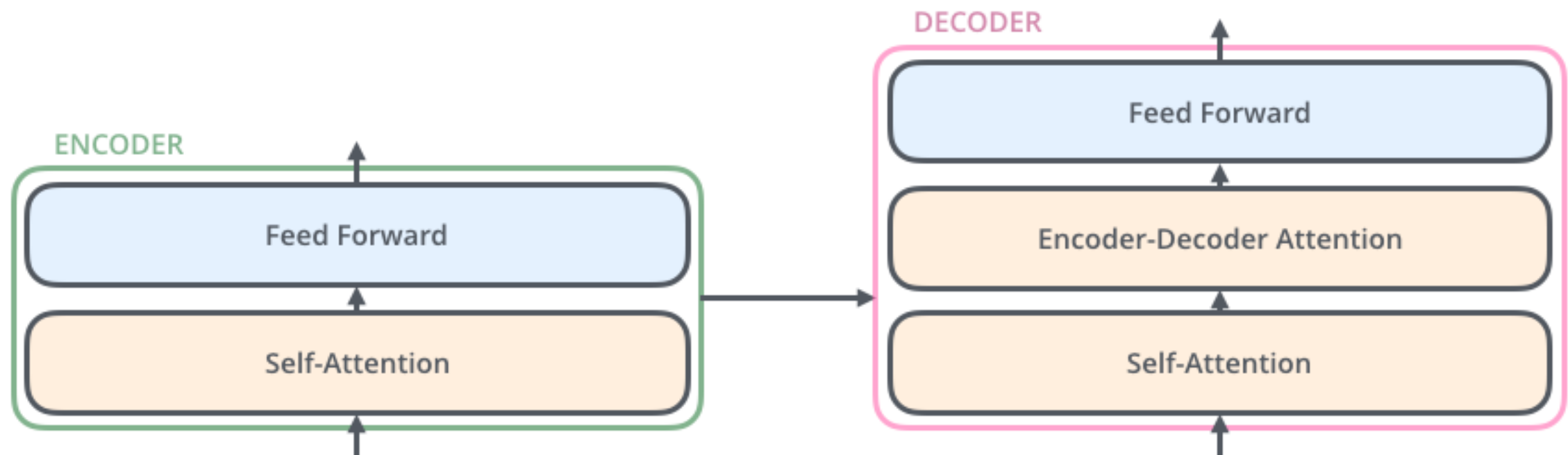
A High-Level Look

- The encoding component is a stack of encoders, while the decoding component is a stack of decoders of the same number



A High-Level Look

- The encoders are all identical in structure. Each one is broken down into two sub-layers, self-attention layer and feed-forward network



Self-Attention at a High Level

- A self-attention layer helps the encoder look at other words in the input sentence as it encodes a specific word, capturing long-distance interactions
- Different from traditional attention mechanism, self-attention is defined as attention applied to single context instead of across multiple contexts

Self-Attention at a High Level

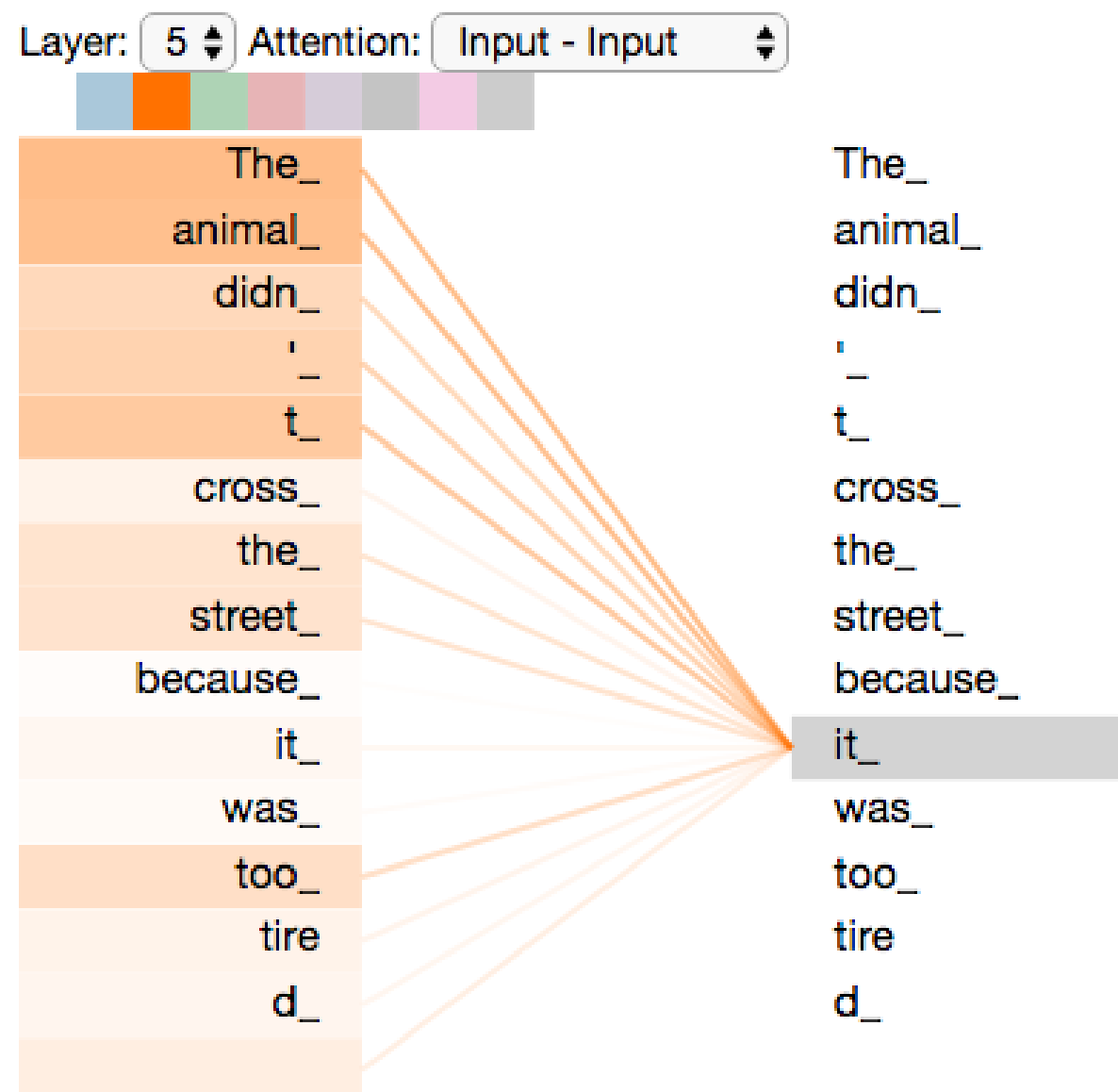
- For example, let's say the following sentence is an input sentence we want to translate:

**The animal didn't cross the street
because it was too tired.**

- What does “it” in this sentence refer to? Is it referring to the street or to the animal? It's a simple question to a human, but not as simple to an algorithm

Self-Attention at a High Level

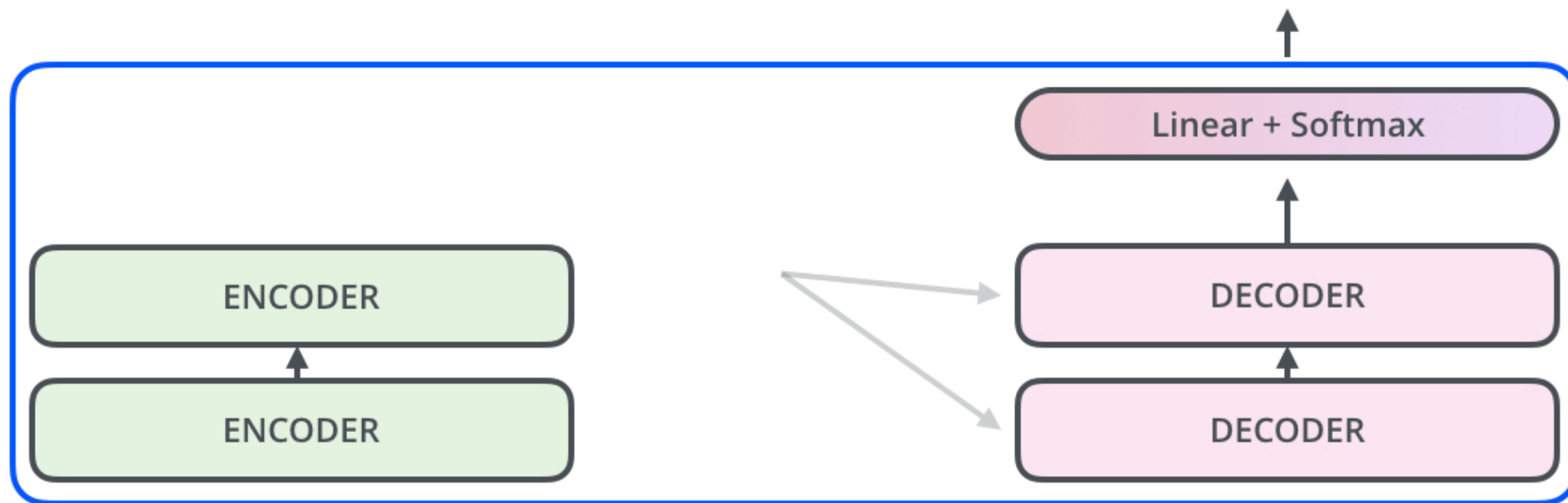
- As the model processes each word, self-attention allows it to look at other positions in the input sequence for clues that can help lead to a better encoding for this word



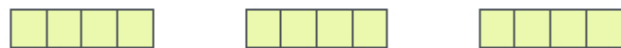
Self-Attention at a High Level

Decoding time step: 1 2 3 4 5 6

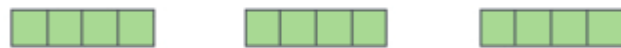
OUTPUT



EMBEDDING
WITH TIME
SIGNAL



EMBEDDINGS



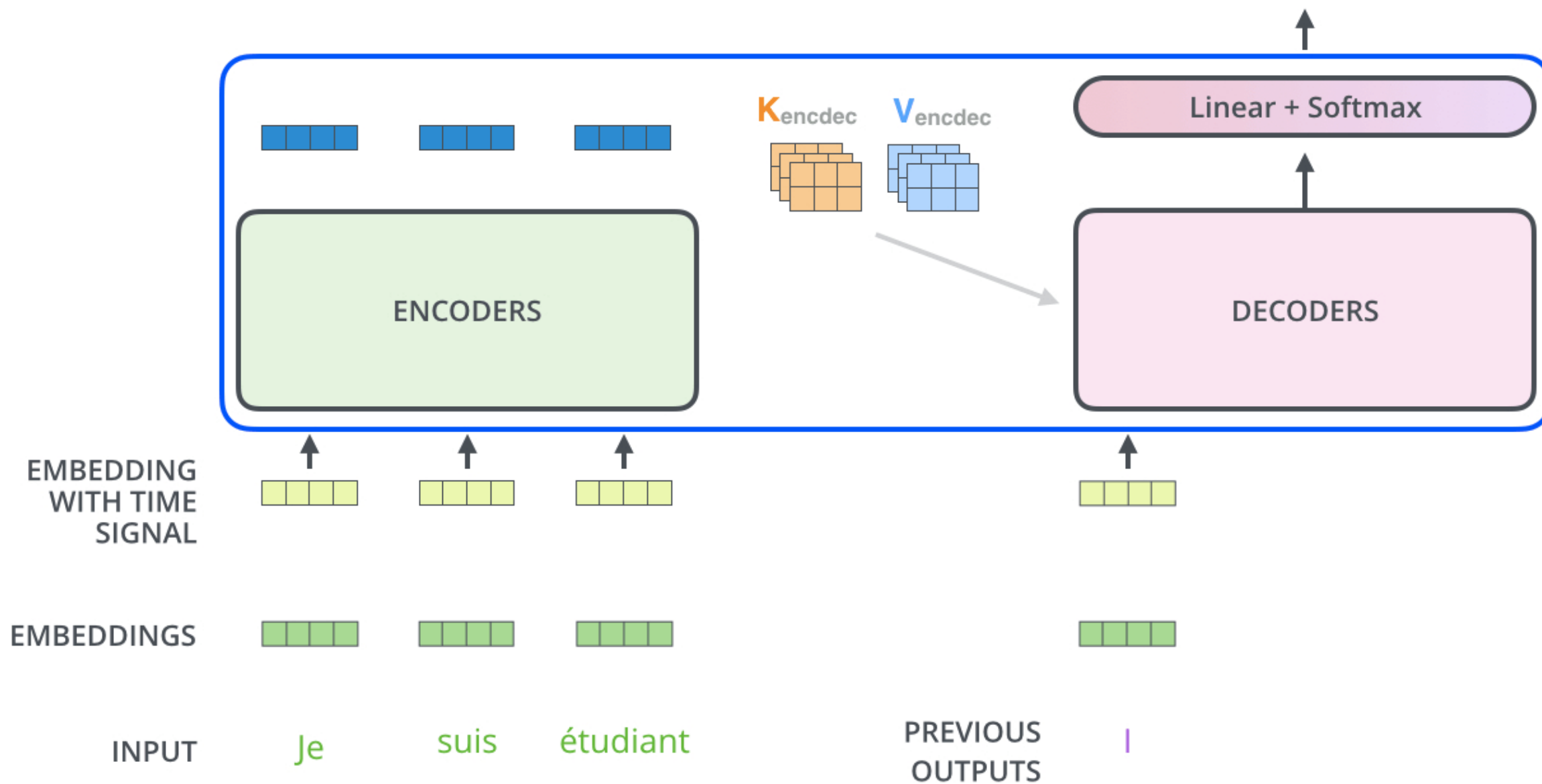
INPUT

Je suis étudiant

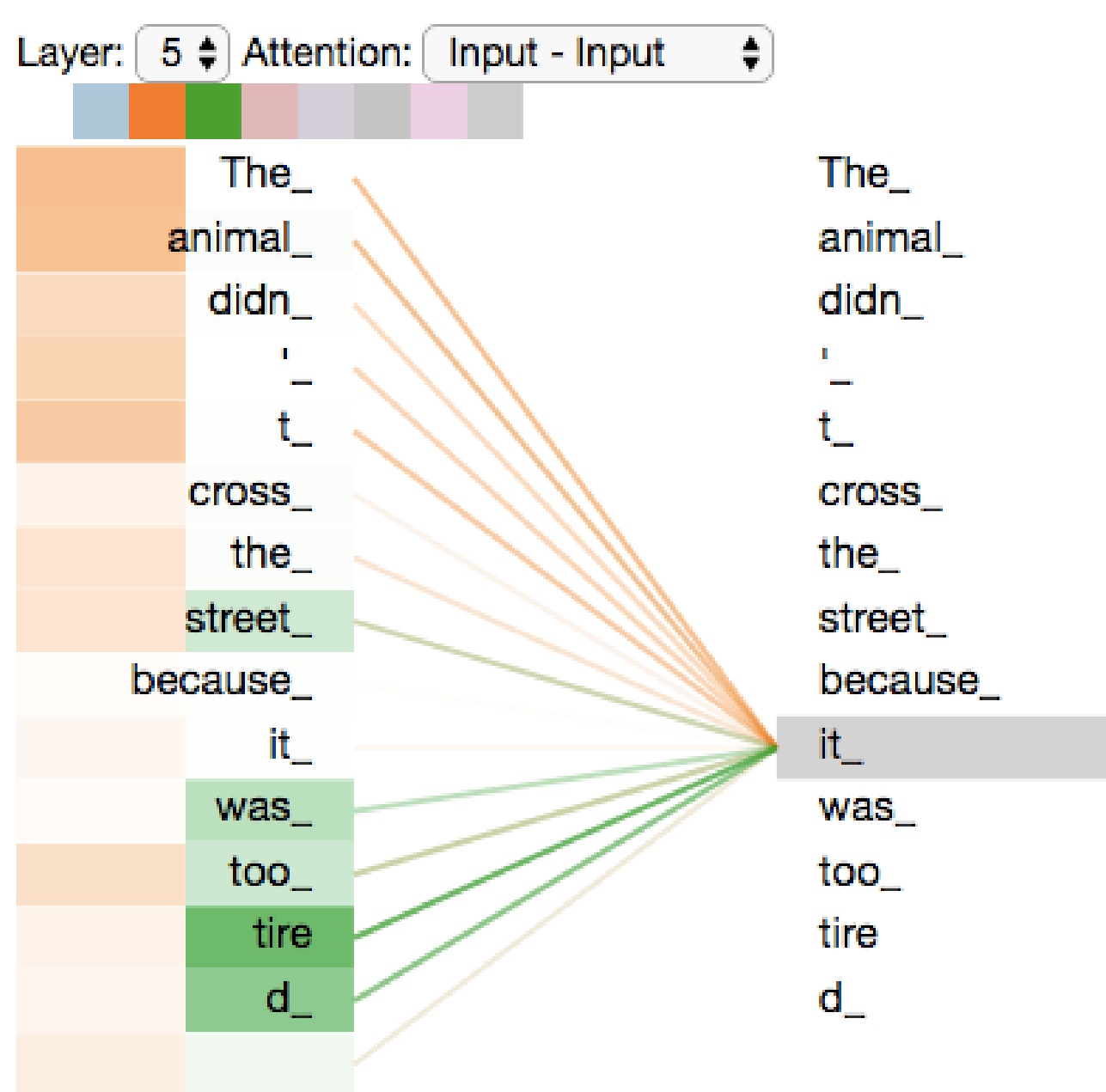
Self-Attention at a High Level

Decoding time step: 1 2 3 4 5 6

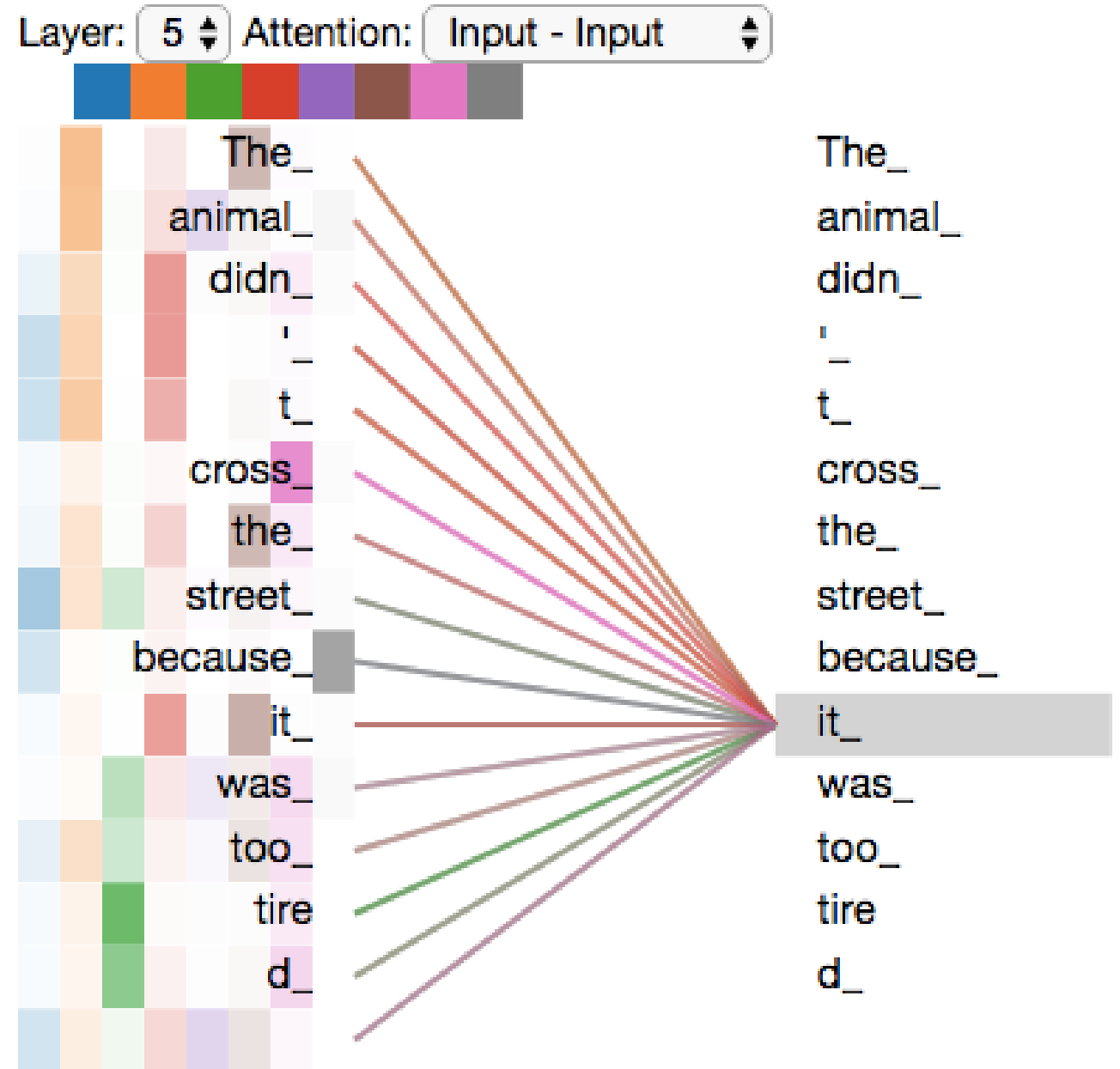
OUTPUT |



Multi-Head Self-Attention



One of the single head



All head

Transformer

- Self-attention is a powerful mechanism and has been already widely used in many applications including natural language processing (i.e. BERT, GPT-3, XLNet), signal processing
- For more details, please refer to the [main paper](#)

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- [Sequence to Sequence Learning with Neural Networks, I. Sutskever et al., NeurIPS'14](#)
- [Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation, K. Cho et al., EMNLP'14](#)
- [Neural Machine Translation by Jointly Learning to Align and Translate, D. Bahdanau et al., ICLR'15](#)
- [Effective Approaches to Attention-based Neural Machine Translation, M. T. Luong, EMNLP'15](#)
- [Attention Is All You Need, Google Brain, NeurIPS' 17](#)
- [Visualizing A Neural Machine Translation Model](#)
- [The Illustrated Transformer](#)