Imperial College
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Machine Learning in Finance

Lecture 8

RNN Applications and Attention Mechanisms

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Outline:

- The Sentiment Analysis Pipeline
- The Various Applications of RNNs
- The Sequence to Sequence Framework
- Introducing the Attention Mechanism
- Attention is all you need

Part 1 : The Sentiment Analysis Pipeline

The Embedding Layer

- The **Embedding Layer** takes as input the sequences of integers. But all the sequences should be of the same length T, so that we can pack them into the same tensor :
  - Sequences that are shorter than T are padded with zeros.
  - Sequences that are longer that T are truncated.

Row Data

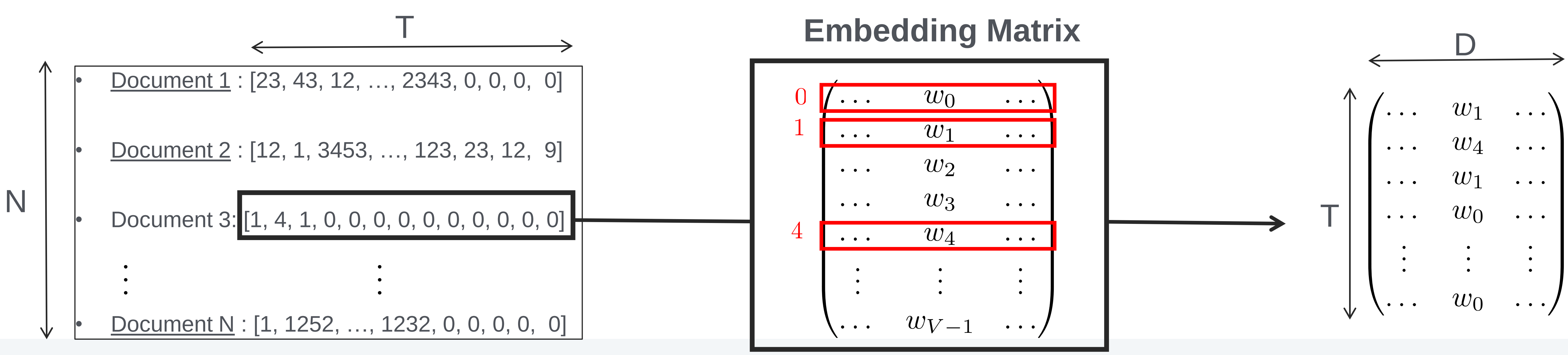
- Document 1 : « There were no wolves in the movie. »
- Document 2 : « This movie has one star and that star is Ryan Gosling. Great flick, highly recommend it. »
- ⋮
- Document N : « How many times must Willy be freed before he’s freed?. »

Preprocessed Data

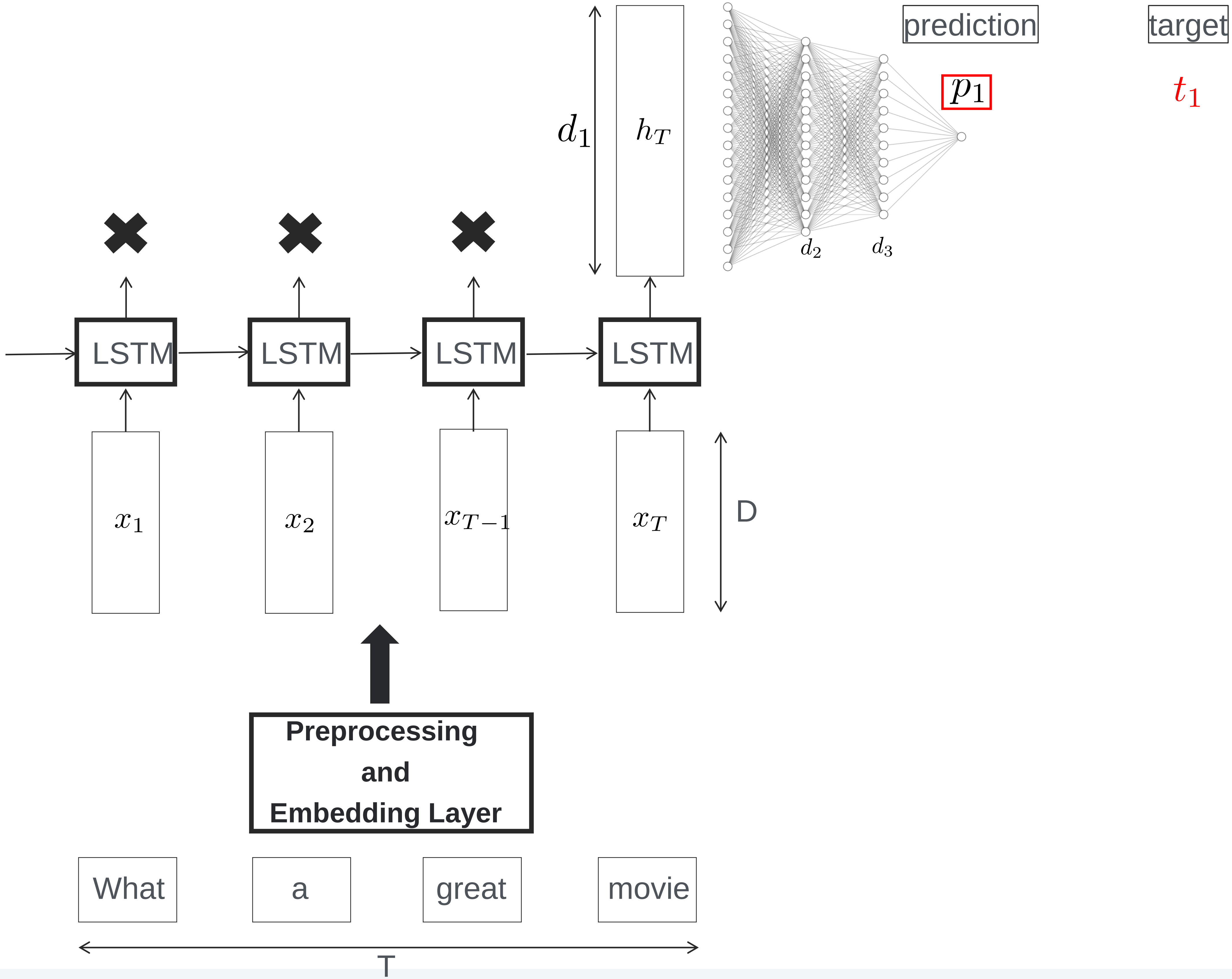
- Document 1 : [23, 43, 12, …, 2343, 0, 0, 0, 0]
- Document 2 : [12, 1, 3453, …, 123, 23, 12, 9]
- ⋮
- Document N : [1, 1252, …, 1232, 0, 0, 0, 0, 0]

2D tensor of integers, of shape (N, T)

- The Embedding Layer transforms the 2-dim input tensor of shape (N, T) into a tensor of shape (N, T, D).



The Sentiment Analysis Pipeline – Part 1 –



The Sentiment Analysis Pipeline – Part 2 –

- Let’s keep track of the evolution of the tensor shape after each layer transformation:

$$\overbrace{\text{Input Data}}^{\text{Sequences of Integers}} \hspace{40em} \text{Predictions}$$

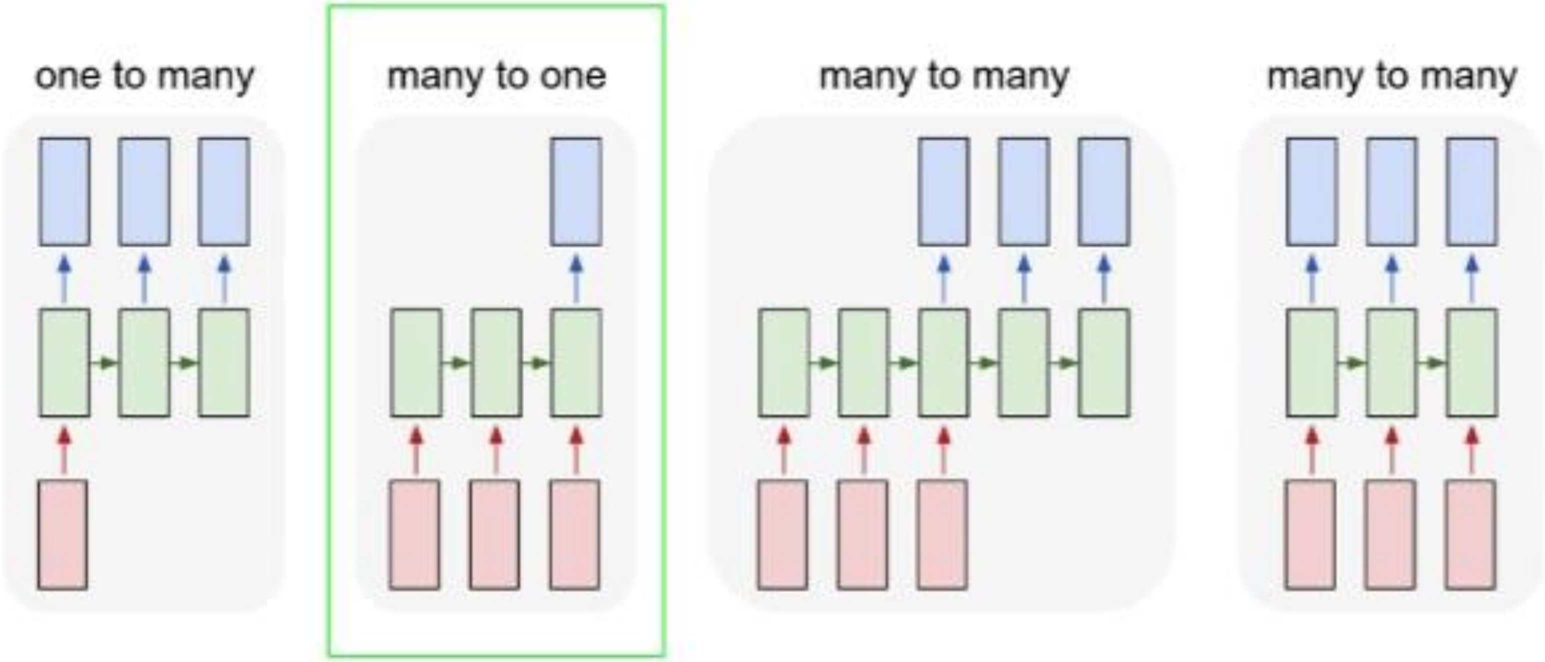
$$(N,T) \xrightarrow[\textbf{Embedding layer}]{} (N,T,D) \xrightarrow[\textbf{LSTM layer}]{} (N,d_1) \xrightarrow[\textbf{Dense layer}]{} (N,d_2) \xrightarrow[\textbf{Dense layer}]{} (N,d_3) \xrightarrow[\textbf{Dense layer}]{} (N,)$$

$$\xrightarrow[\textbf{The Forward Propagation}]{\hspace{30em}}$$

Part 2 : The Various Applications of RNNs

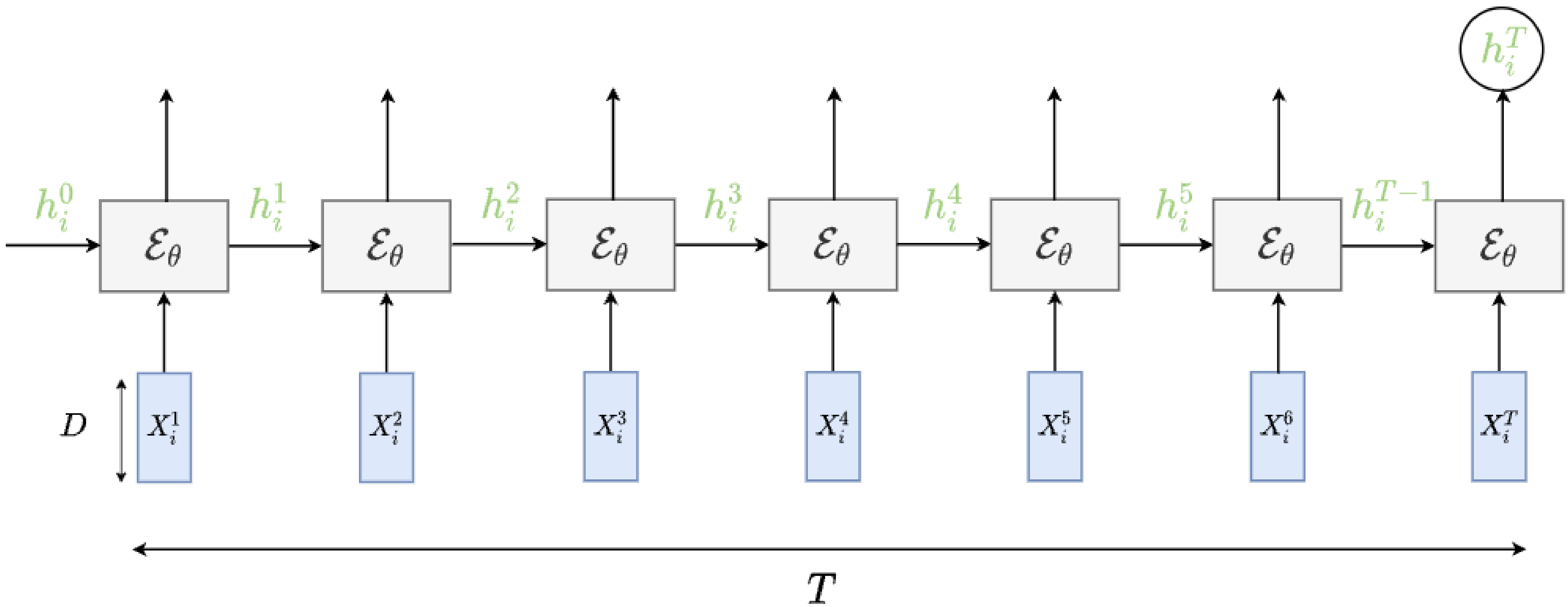
The Various Applications of RNNs

- There are principally 4 types of applications to Recurrent Neural Networks.
  - **One to Many:** Mapping a vector to a sequence of vectors.
  - **Many to One:** Mapping a sequence of vectors to one vector.
  - **Many to Many:**
    - Aligned case: Mapping a sequence to another sequence of the same length T
    - Unaligned case: Mapping a sequence of length T_x into another sequence of length T_y $(\text{with } T_x \neq T_y)$



The Many to One problem – The architecture –

- In the Many to One framework, the objective is to map a sequence $(X_i^1, \ldots, X_i^T) \in \mathbb{R}^{T \times D}$ into a vector $h_i^T \in \mathbb{R}^d$ using the LSTM layer $\mathcal{E}_\theta$ parameterized by θ



- So far, we have only discussed models that are part of the Many to One framework.
  - Sentiment Analysis (Lecture 6).
  - News Classification (programming session 7).

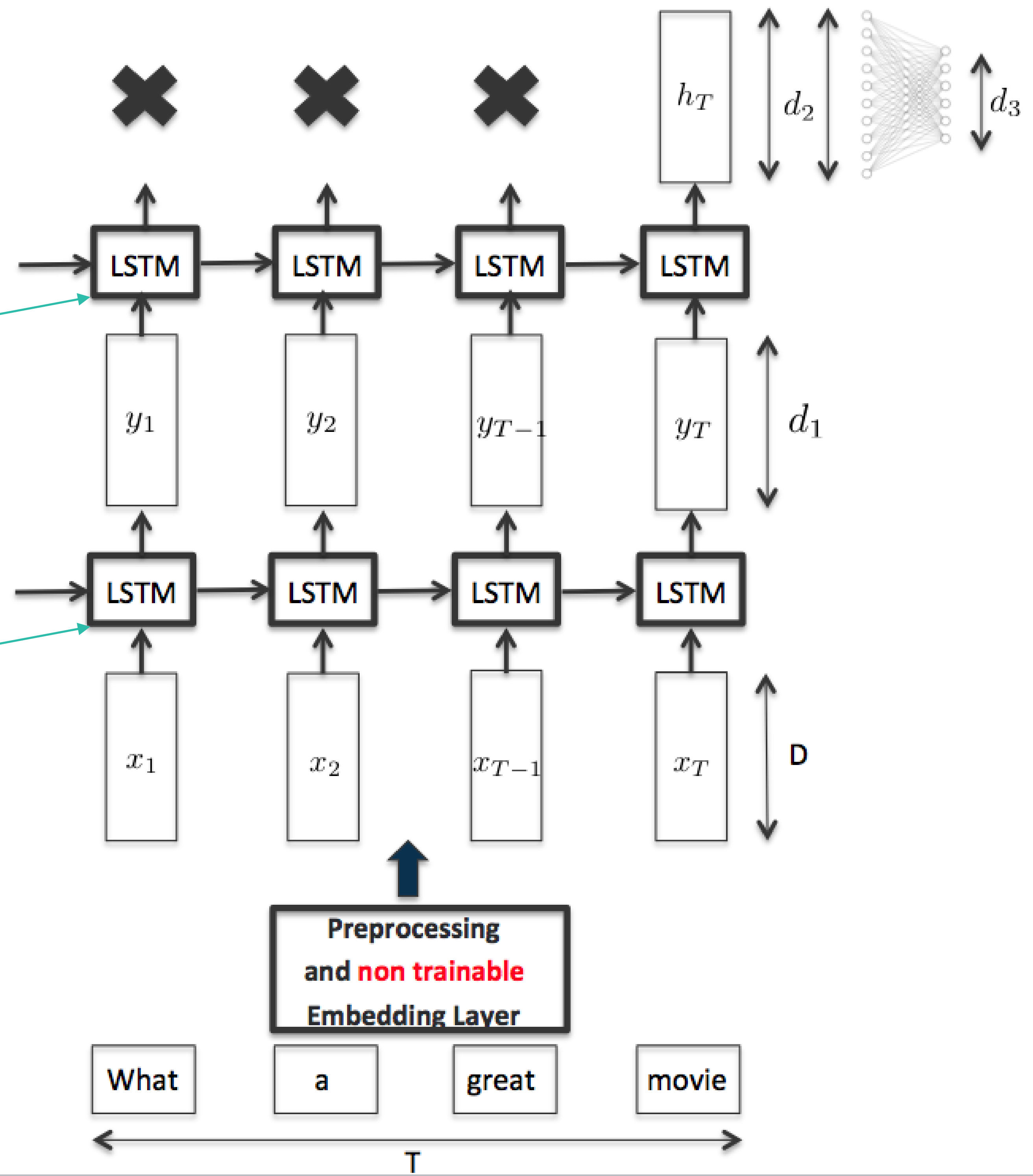
- Let us consider some examples in the next slides.

Stacking LSTM layers for a Multiclass classification Problem

```
from tensorflow.keras.layers import LSTM
```

```
lstm_2 = LSTM(d_2, return_sequences = False)
```

```
lstm_1 = LSTM(d_1, return_sequences = True)
```



Stacking LSTM layers for a Multiclass classification Problem

- Let’s keep track of the evolution of the tensor shape after each layer transformation:

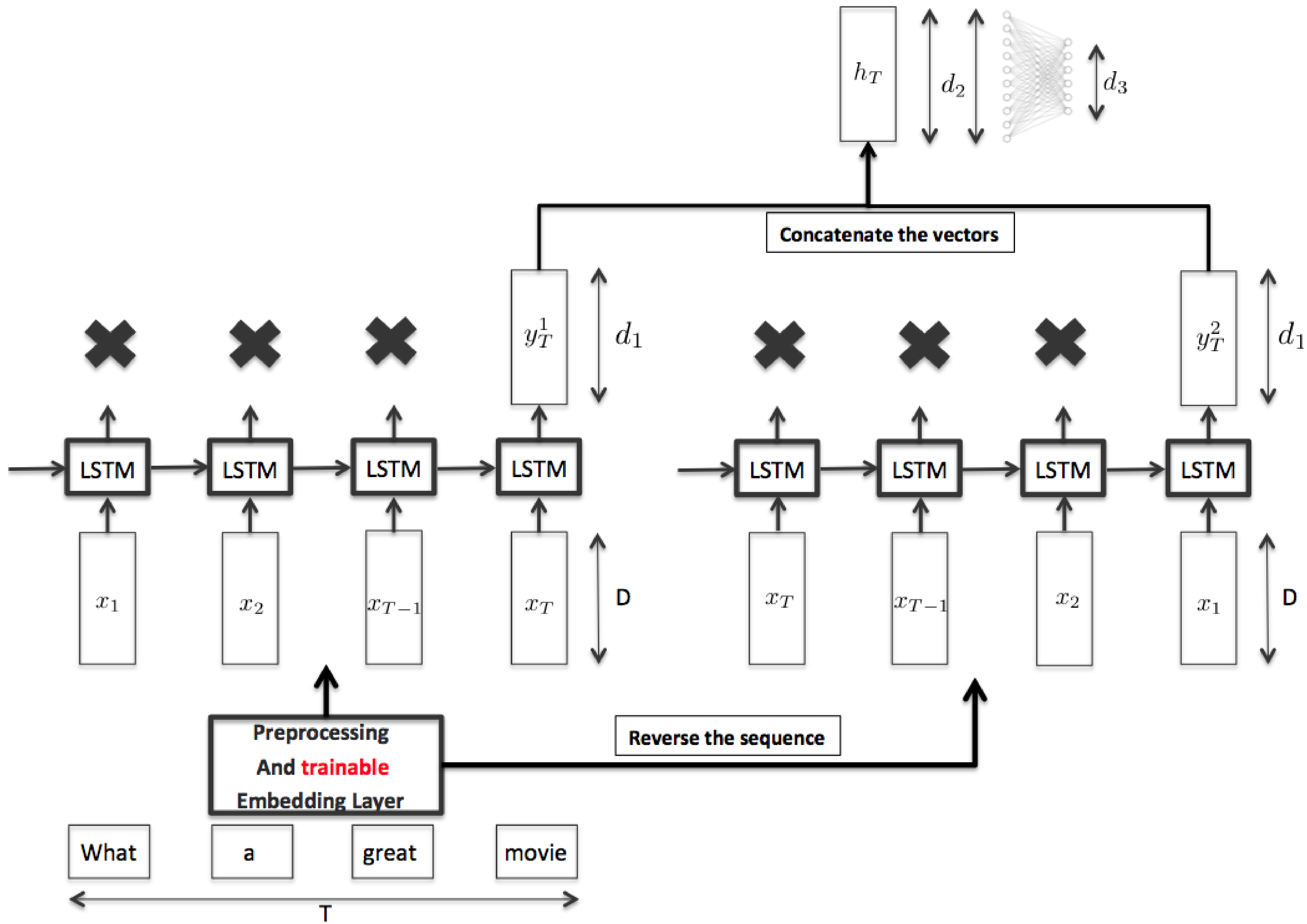
Sequences of Integers

Input Data | Predictions

$$\underset{\text{Input Data}}{(N,T)} \xrightarrow[\text{layer}]{\text{Embedding}} (N,T,D) \xrightarrow[\text{LSTM layer}]{\text{First}} (N,T,d_1) \xrightarrow[\text{LSTM layer}]{\text{Second}} (N,d_2) \xrightarrow[\text{layer}]{\text{Dense}} \underset{\text{Predictions}}{(N,d_3)}$$

The Forward Propagation

Bidirectional LSTM for a Multiclass classification Problem



Bidirectional LSTM for a Multiclass classification Problem

- Let’s keep track of the evolution of the tensor shape after each layer transformation:

$$\overbrace{\boxed{\text{Input Data}}}^{\boxed{\text{Sequences of Integers}}} \qquad\qquad\qquad\qquad \boxed{\text{Predictions}}$$

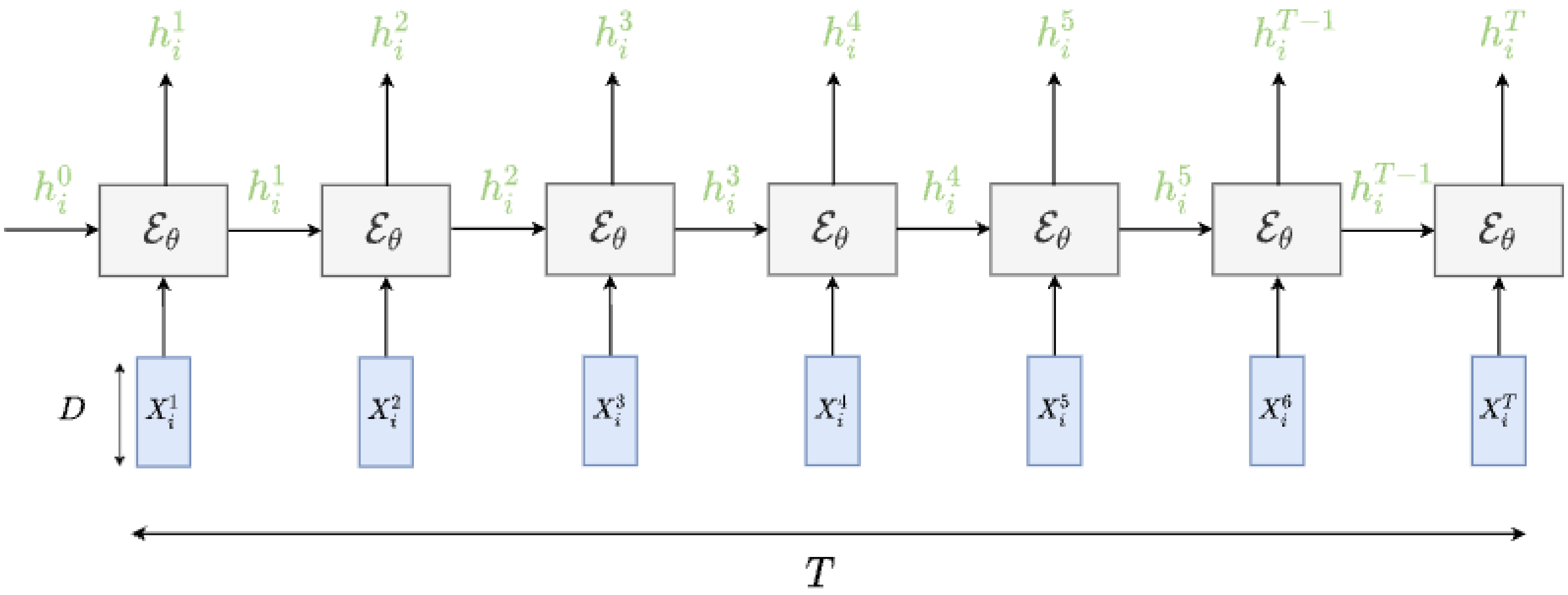
$$(N,T) \xrightarrow[\text{Embedding layer}]{} (N,T,D) \xrightarrow[\text{Bidirectional LSTM layer}]{} (N, 2\times d_1) \xrightarrow[\text{Dense layer}]{} (N, d_3)$$

$$\xrightarrow[\text{The Forward Propagation}]{\qquad\qquad\qquad\qquad\qquad\qquad}$$

The Many to Many Problem (Aligned case) – The Architecture –

- In the Many to Many framework, the objective is to map a sequence $(X_i^1, \ldots, X_i^T) \in \mathbb{R}^{T \times D}$ into a sequence $(h_i^1, \ldots, h_i^T) \in \mathbb{R}^{T \times d}$ using the LSTM layer $\mathcal{E}_\theta$ parameterized by θ

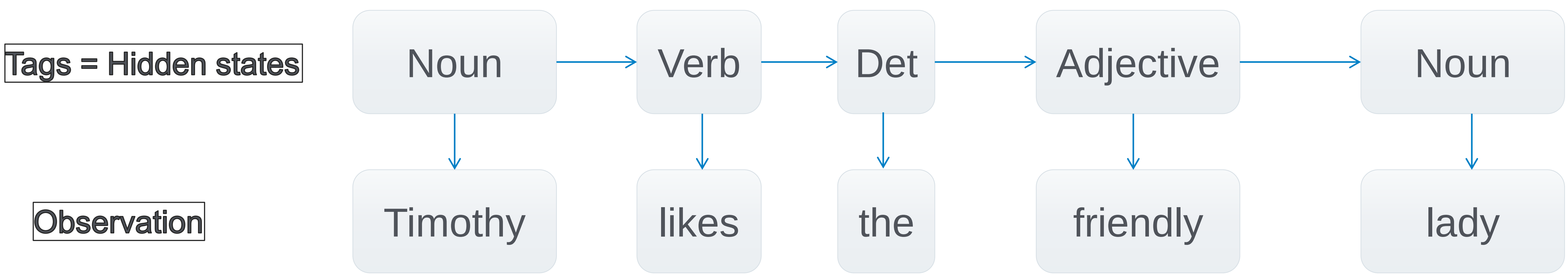
- We are considering the **aligned case** where the input and the output sequences are of the same length T



The Many to Many Problem (Aligned case) – an Example –

- POS (Part Of Speech) Tagging is a typical example, where the objective is to tag each word of a sentence with its "Part-of-Speech" tag.

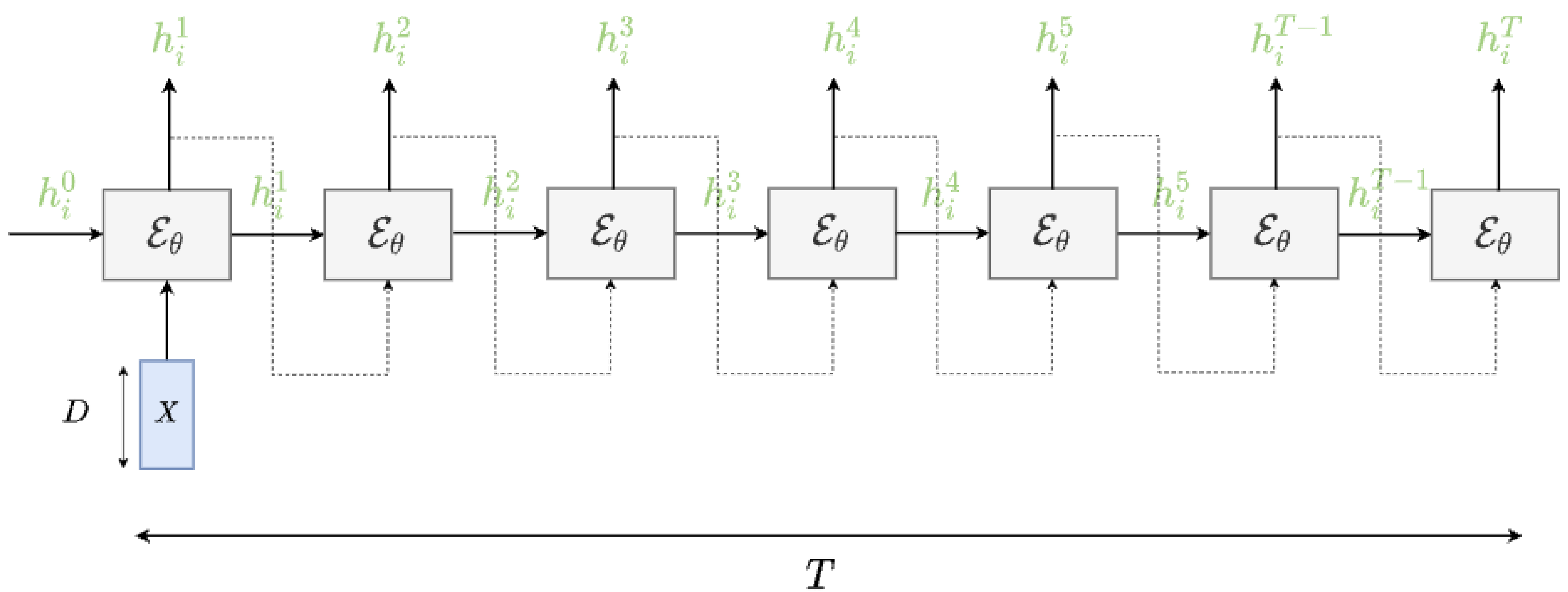
- Another popular model can be used for POS tagging: The Hidden Markov Model (HMM).



(See the Optional Reading) for more details about the HMM

The One to Many Problem – The Architecture –

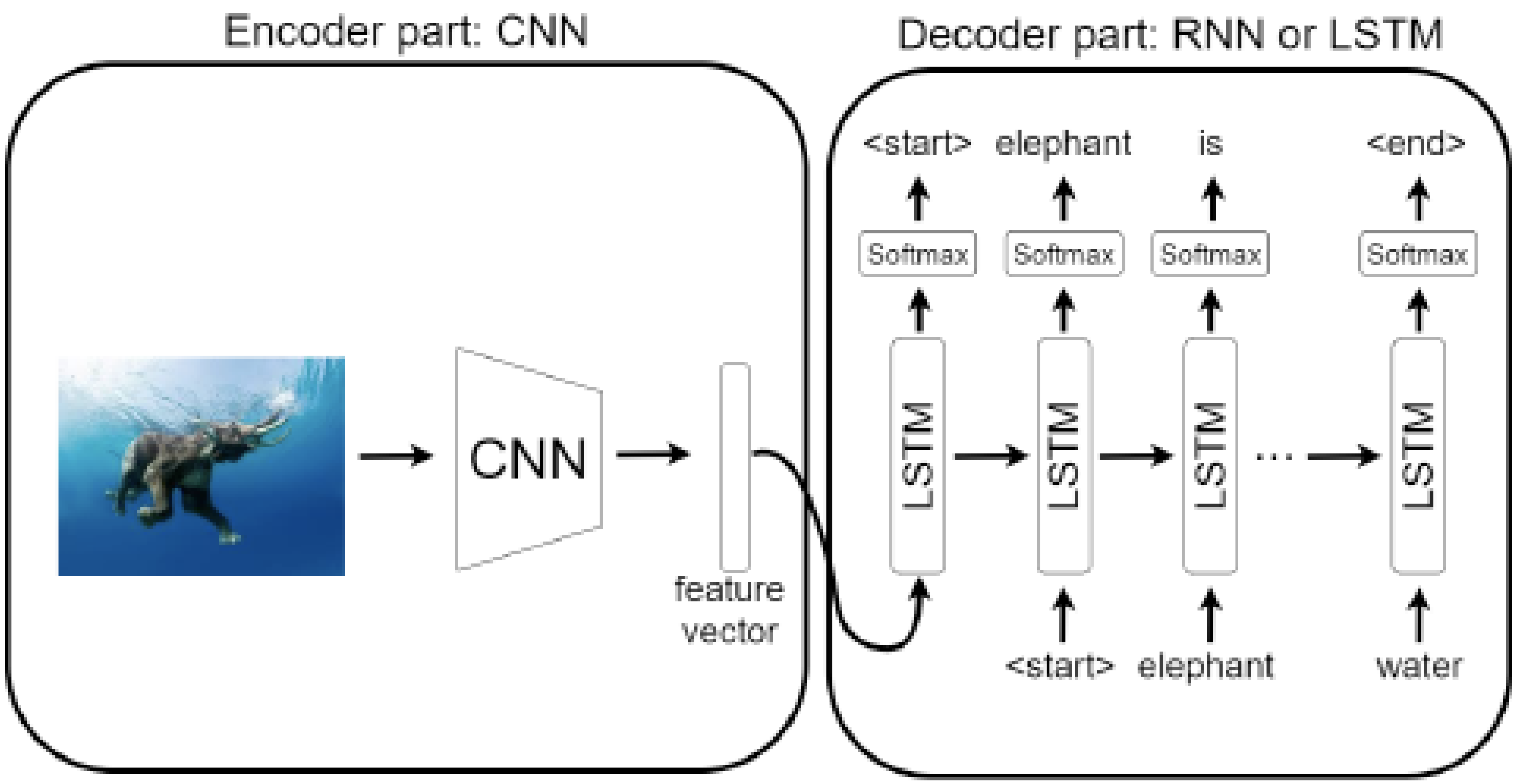
- In the One to Many framework, the objective is to map a vector $X \in \mathbb{R}^D$ into a sequence $(h_i^1, \ldots, h_i^T) \in \mathbb{R}^{T \times d}$ using the LSTM layer $\mathcal{E}_\theta$ parameterized by θ
- The vector $X \in \mathbb{R}^D$ is typically the output of an encoder layer processing an image or another sequence for instance.
- At each step of the generation process, the output h_i^t is fed back into the model to get the new hidden state h_i^{t+1}



The One to Many Problem – an Example –

- **Image captioning** is a typical example, where the description of an image is generated.

- An image is mapped into a **feature vector**, which in turn becomes the input for an LSTM architecture.



Interactive Session

Part 3 : The Sequence to Sequence Framework

The Sequence to Sequence Framework –The architecture –

- For Many to Many applications, the LSTM models can only be applied in the aligned case (i.e, if the input and the output sequences are of the same length).

- However, if we want to learn a mapping from a sequence of input vectors of length T_x into a sequence of output vectors of length T_y (where $T_x \neq T_y$), we need to introduce a new framework, composed of two steps.

  - An encoder $\mathcal{E}_{\theta_e}$ maps the input sequence $(X_i^1, \dots, X_i^{T_x}) \in \mathbb{R}^{T_x \times D_x}$ into the final hidden state $h_i^{T_x}$

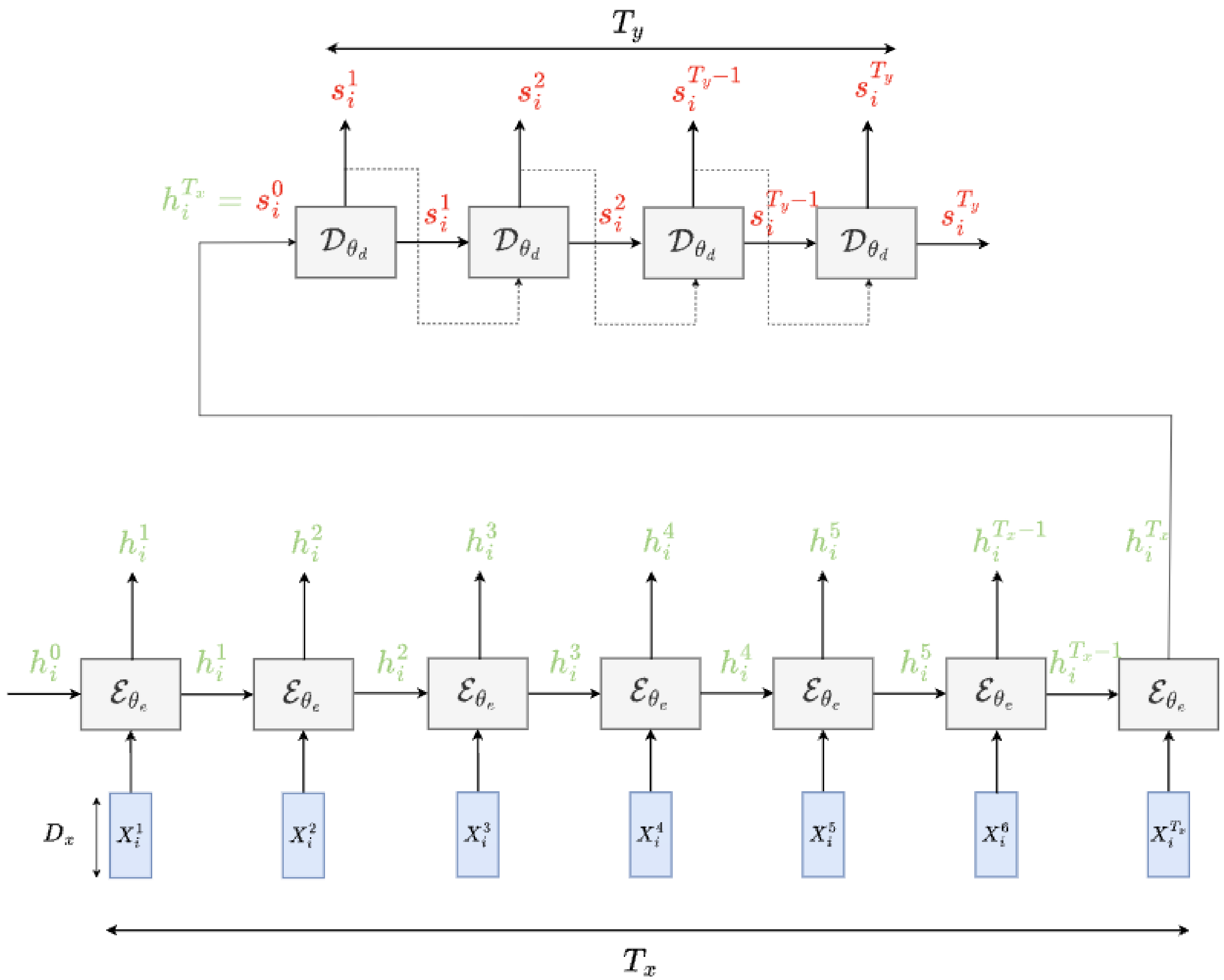
  - A decoder $\mathcal{D}_{\theta_d}$ is initialized with the final encoder hidden state:

$$h_i^{T_x} = s_i^0$$

.

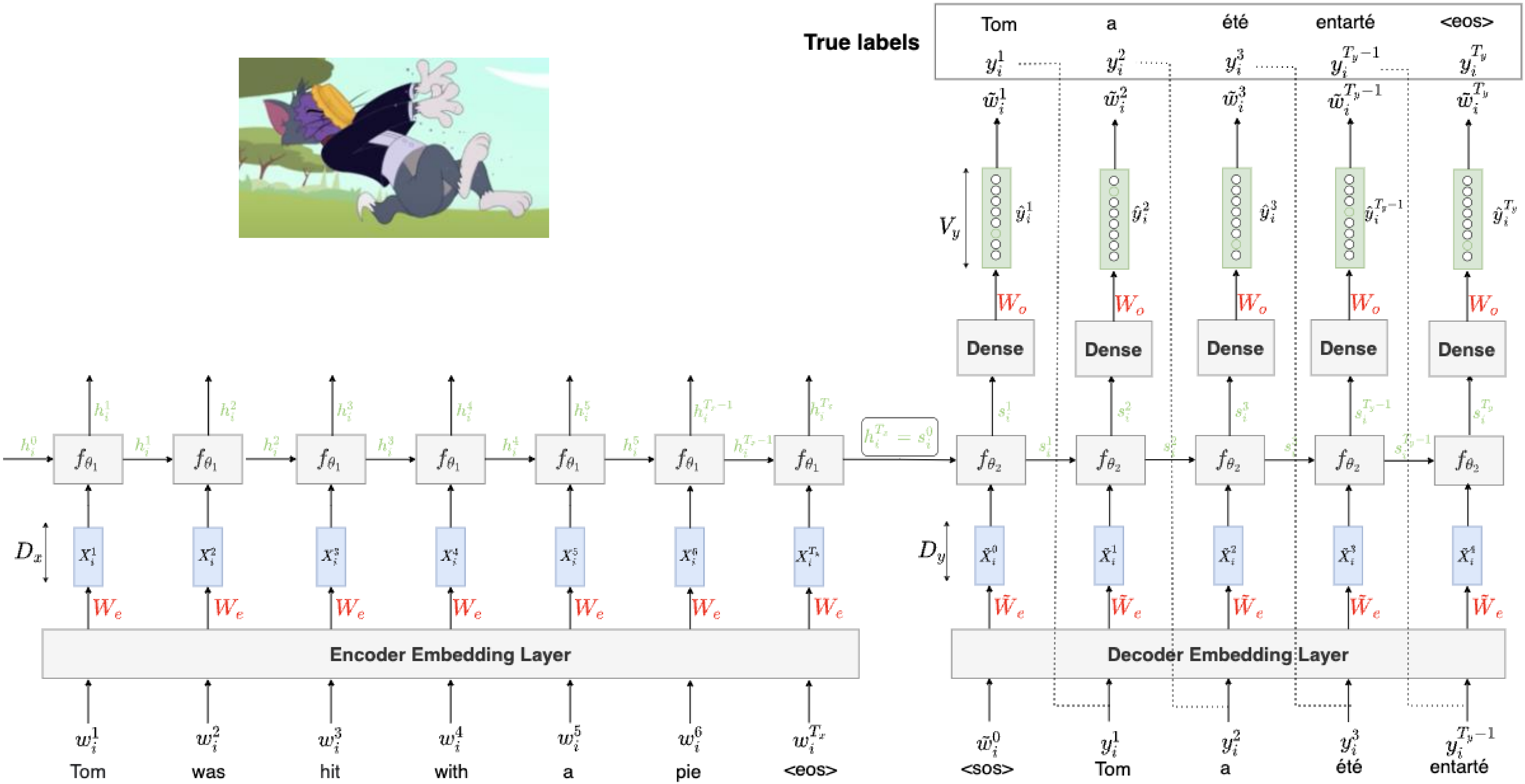
- We can then generate the sequence of hidden states associated with the decoder

$$(s_i^1, \dots, s_i^{T_y})$$



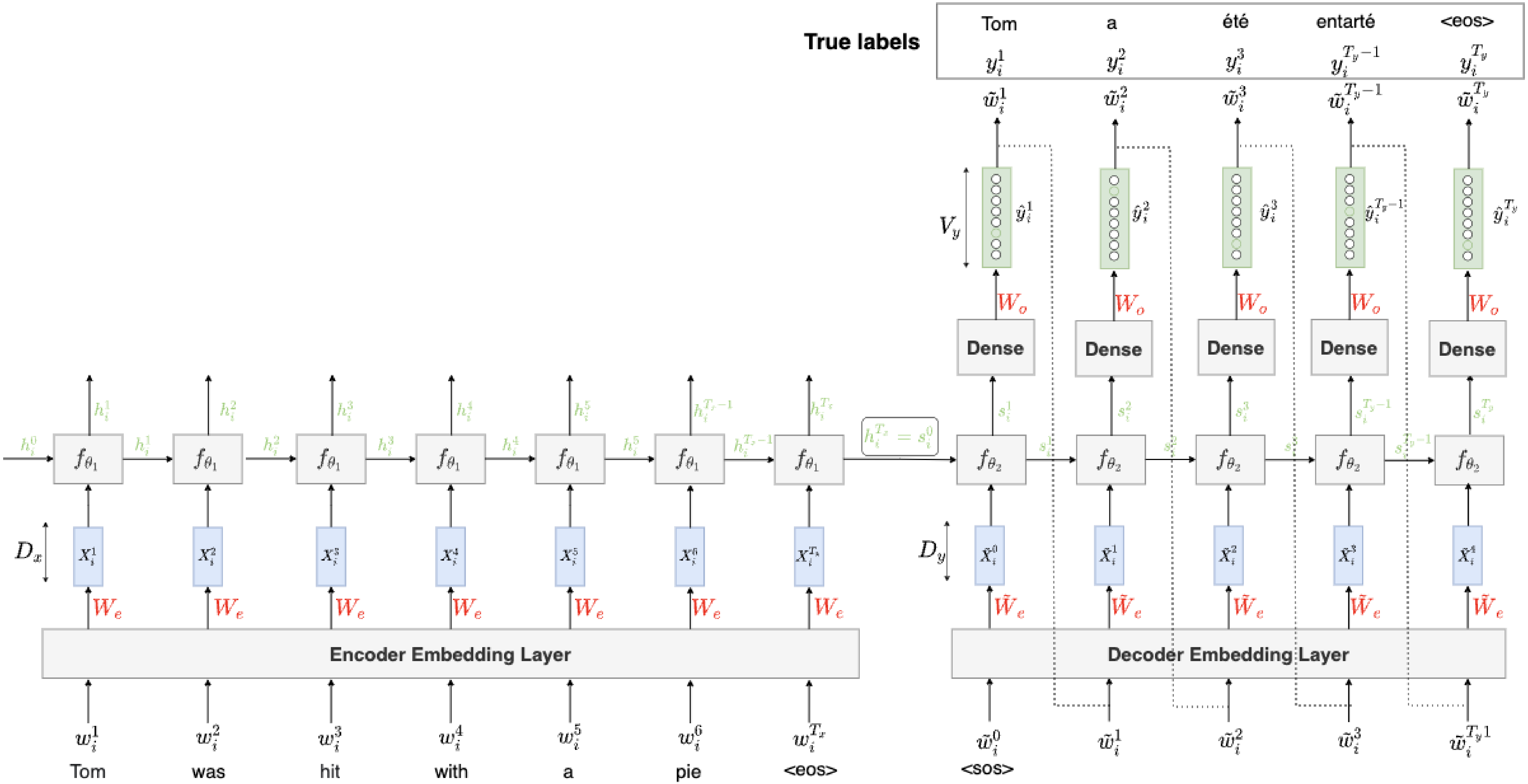
The Sequence to Sequence Framework – an Example –

- A Typical example for the Sequence to Sequence Framework is Neural Machine Translation (NMT).
- We usually use **Teacher Forcing** during the training process.



The Sequence to Sequence Framework – an Example –

- During the prediction phase, at each iteration, the decoder output is fed back into the model.

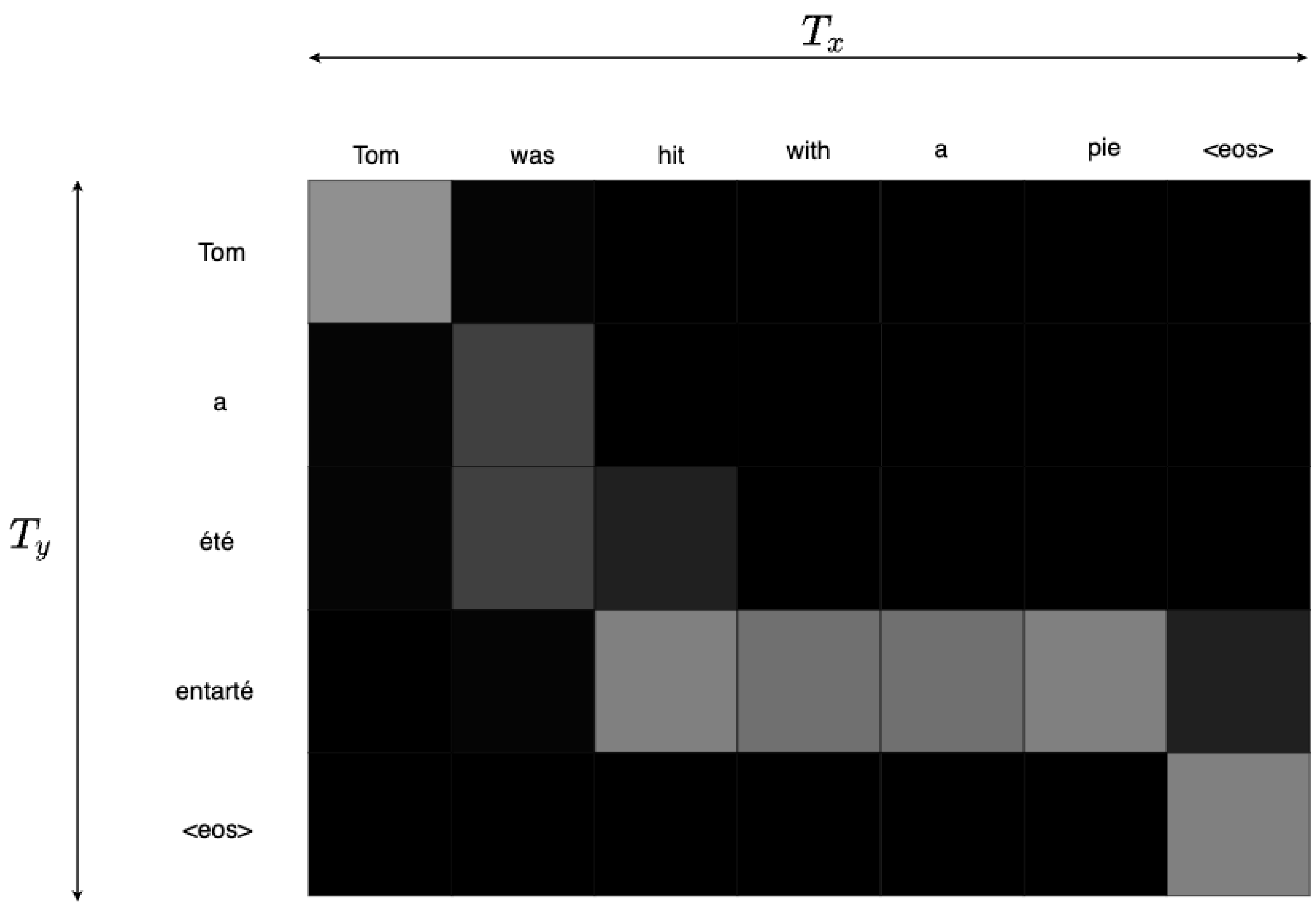


Limitations of the Sequence to Sequence Framework

- There are two main challenges with the sequence to sequence framework using RNNs:

  - First, by feeding a single fixed length vector to the decoder, the encoder has to compress all the input information in few dimensions, which leads to a loss of information.
  - This architecture doesn't allow model alignment between the input and the output sequences.

- We would like each output sequence to selectively focus on relevant parts of the input sequence.



Part 4 : Introducing the Attention Mechanism

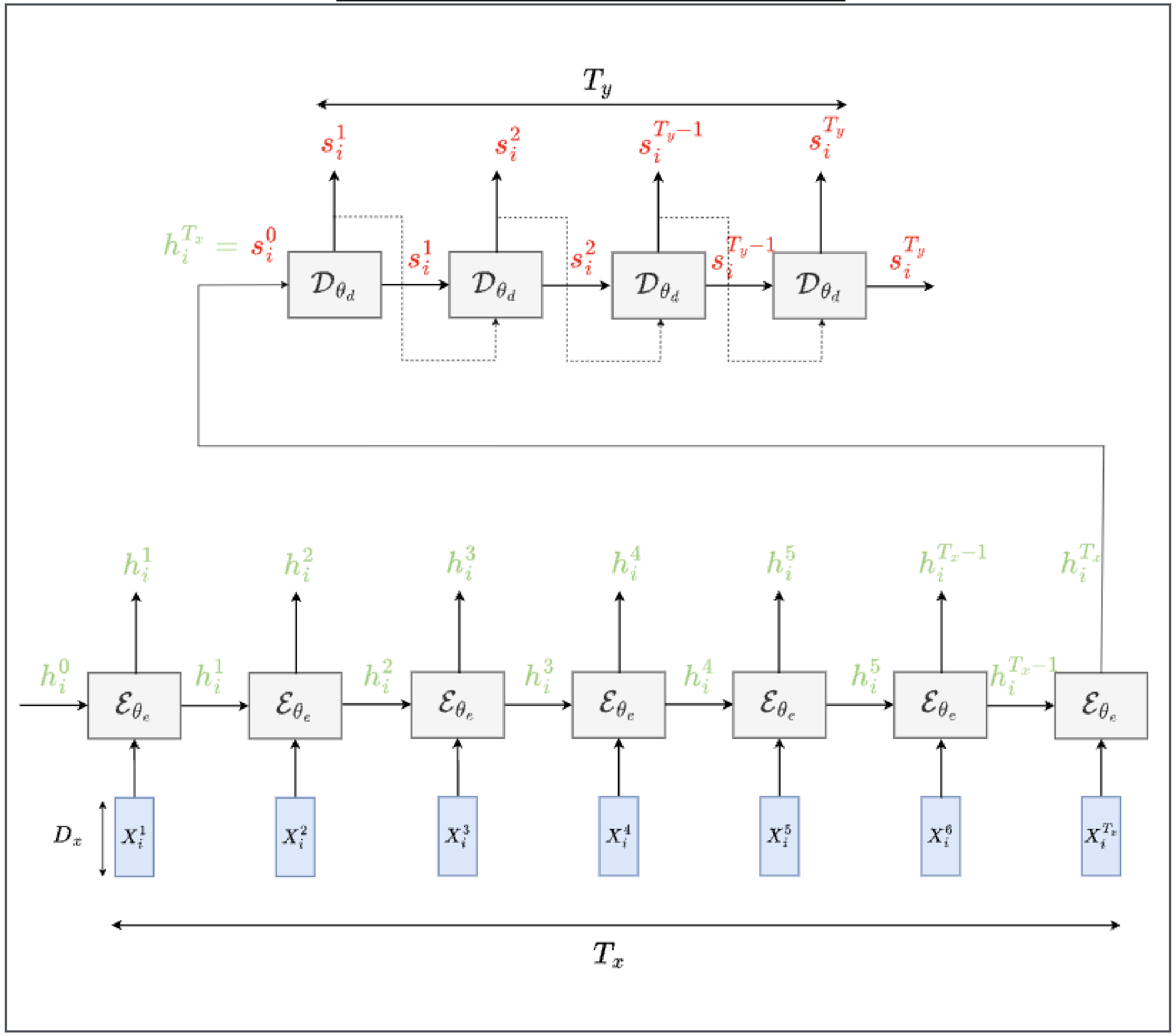
Sequence to Sequence with Attention Mechanisms

- The vanilla Sequence to Sequence model has to boil the entire input sequence into a single vector.
- At each decoder time step $t_y \in \{1, \ldots, T_y\}$, we would like the input vector to be: $c_i^{t_y} = \sum_{t_x=1}^{T_x} \boxed{\alpha_i^{<t_y,t_x>}} h_i^{t_x}$

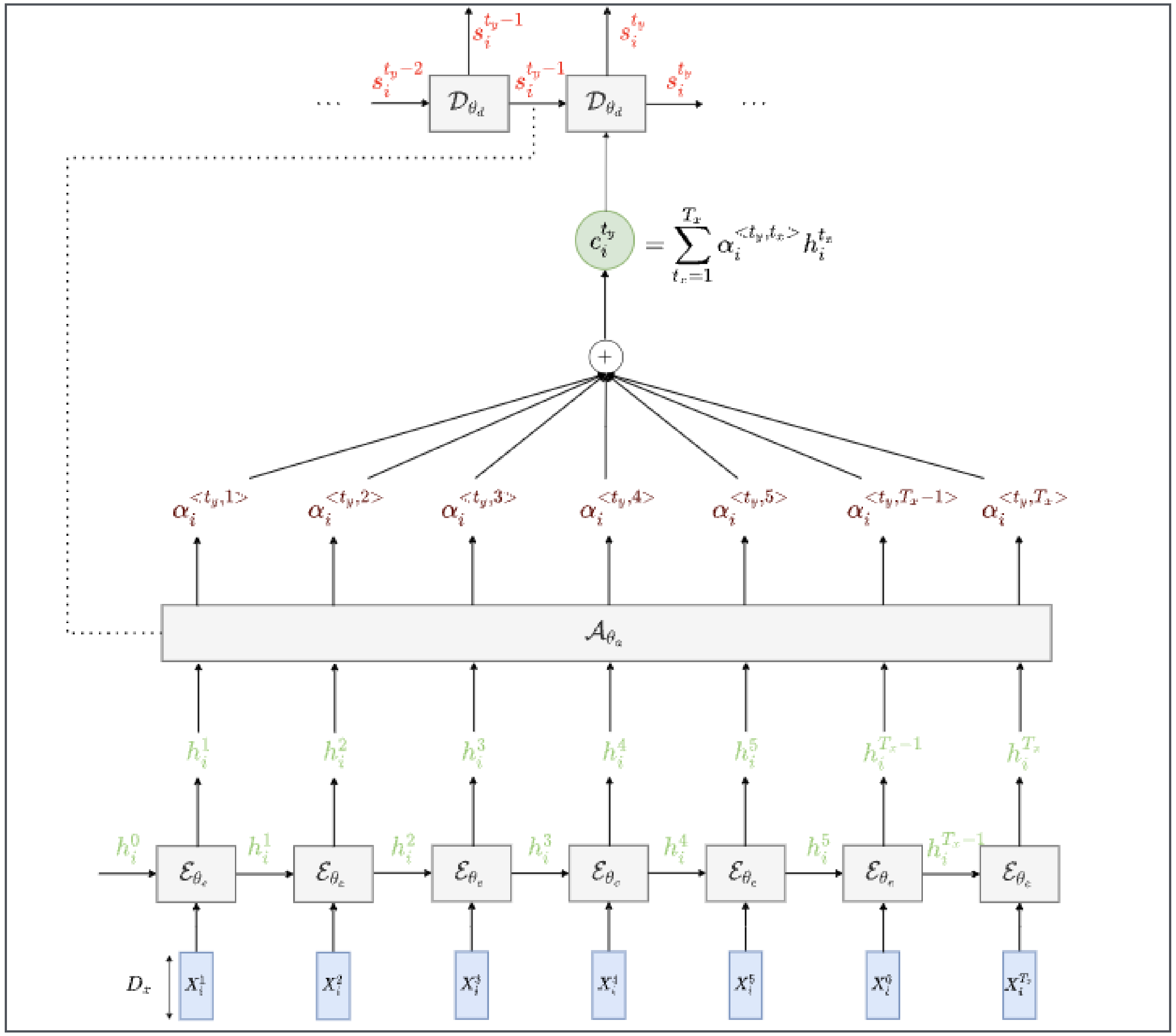
attention weights

such that: $\forall t_x \in \{1, \ldots, T_x\} \quad \alpha_i^{<t_y,t_x>} \geq 0 \quad \text{and} \quad \sum_{t_x=1}^{T_x} \alpha_i^{<t_y,t_x>} = 1$

Vanilla Sequence to Sequence



Sequence to Sequence with Attention

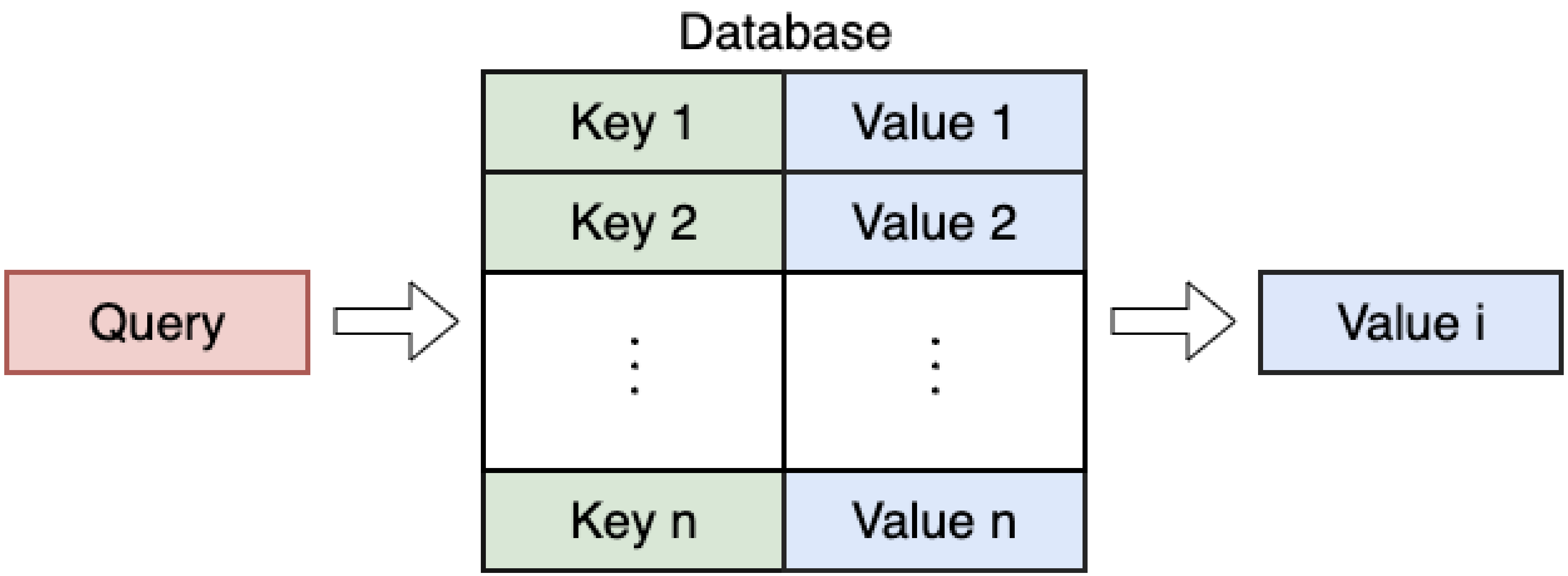


Interactive Session

Query-Retrieval Modeling

- Attention mechanisms intuition originates from database Query-Retrieval Problems.

- In the following database, the query retrieval problem consists in searching a query through the keys in order to retrieve a value.



Query Retrieval Modeling – an Example –

query

Attention mechanism

Database (key/value)

key

Yoshua Bengio: Attention and Consciousness (NeurIPS 2019)

value

key

Lecture 10: Neural Machine Translation and Models with Attention

value

key

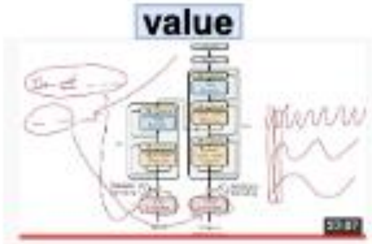
C5W3L07 Attention Model Intuition

value

key

Attention Is All You Need

value



key

CS480/680 Lecture 19: Attention and Transformer Networks

value

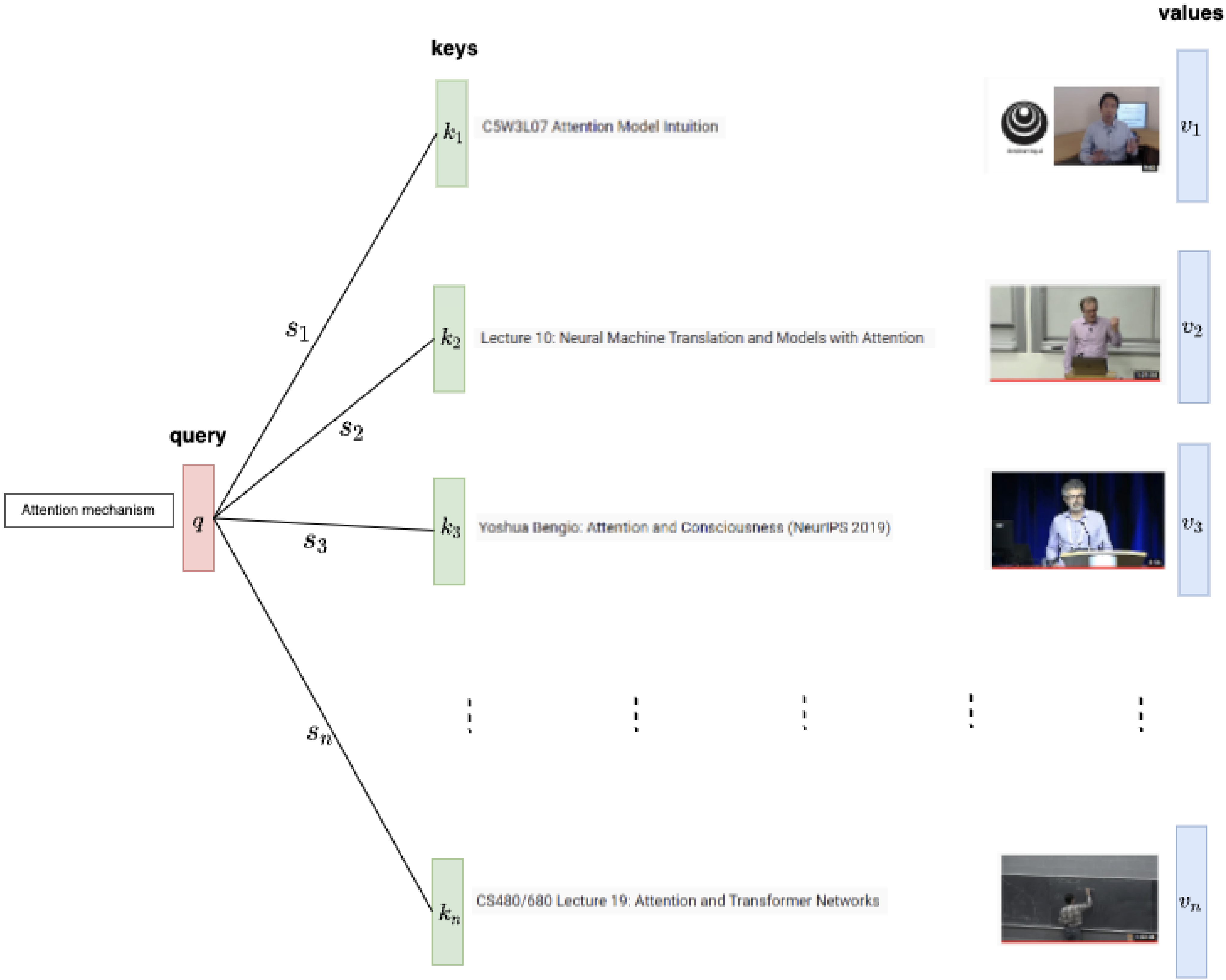
⋮ ⋮ ⋮

key

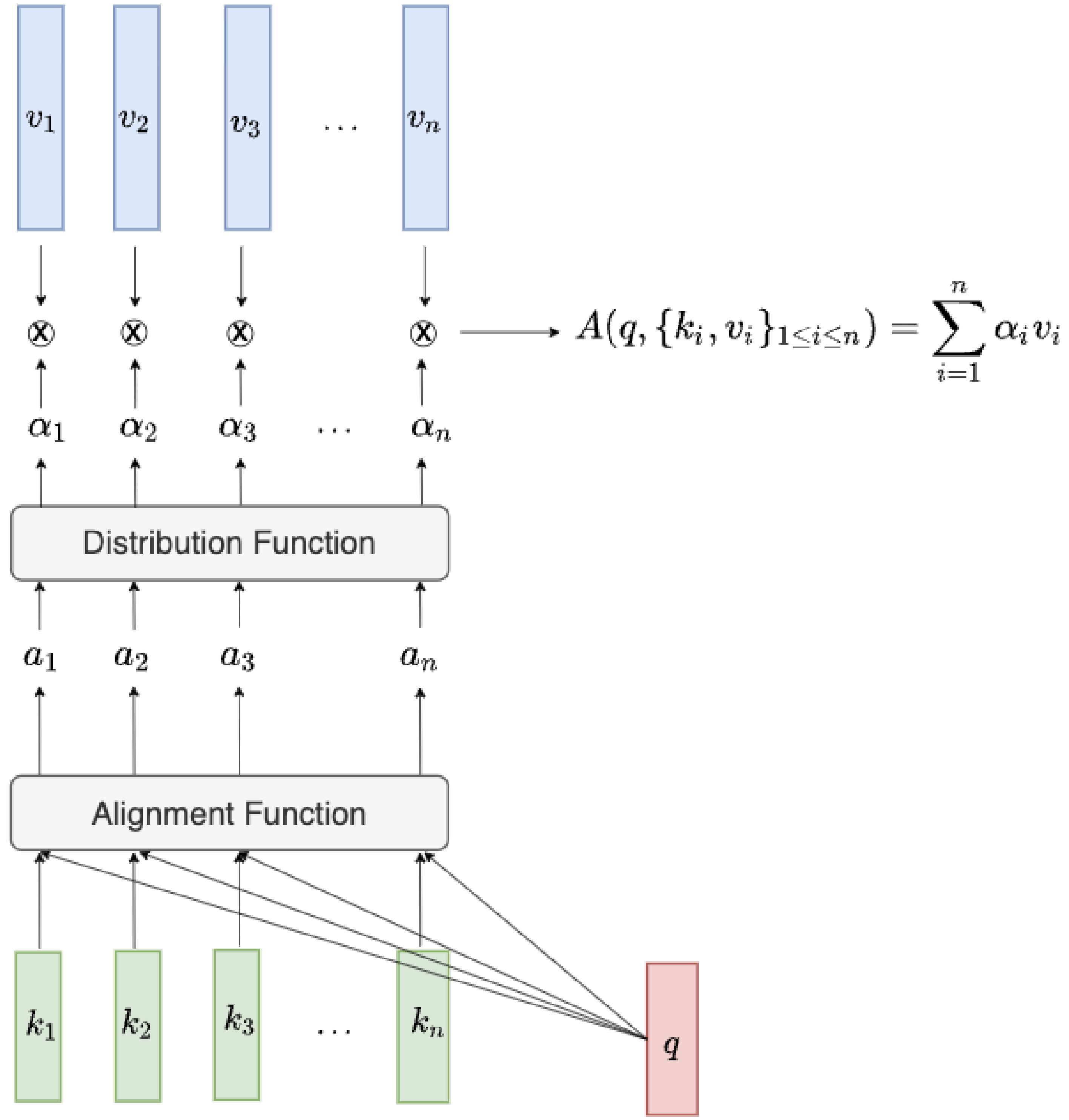
Deep Learning 7. Attention and Memory in Deep Learning

value

Query Retrieval Modeling – an Example –



Attention Mechanism as a Soft Query-Retrieval Problem

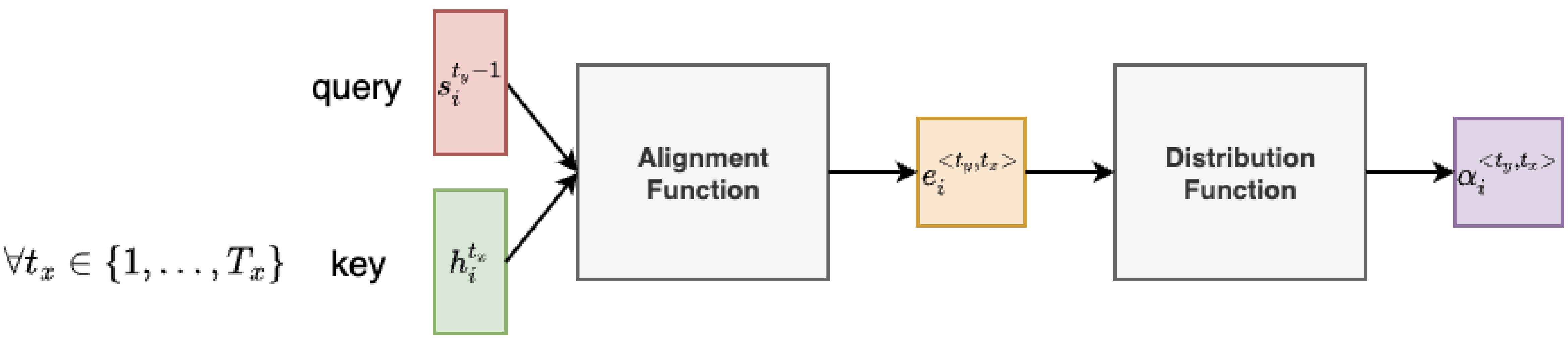


Function	Equation
Dot Product	$a(q, k_i) = q^T k_i$
Scaled Dot Product	$a(q, k_i) = \frac{q^T k_i}{\sqrt{d_k}}$
Luong's Multiplicative alignment	$a(q, k_i) = q^T W k_i$
Bahdanau's Additive alignment	$a(q, k_i) = v_a^T \tanh(W_1 q + W_2 k_i)$
Feature-based	$a(q, k_i) = W_{imp}^T \mathrm{act}(W_1 \phi_1(k_i) + W_2 \phi_2(q) + b)$
Kernel Method	$a(q, k_i) = \phi(q)^T \phi(k_i)$

Interactive Session

The Attention Weights

- The **Attention weights**:



- The decoder input at time $t_y \in \{1,\dots,T_y\}$, also called the **context vector** is:

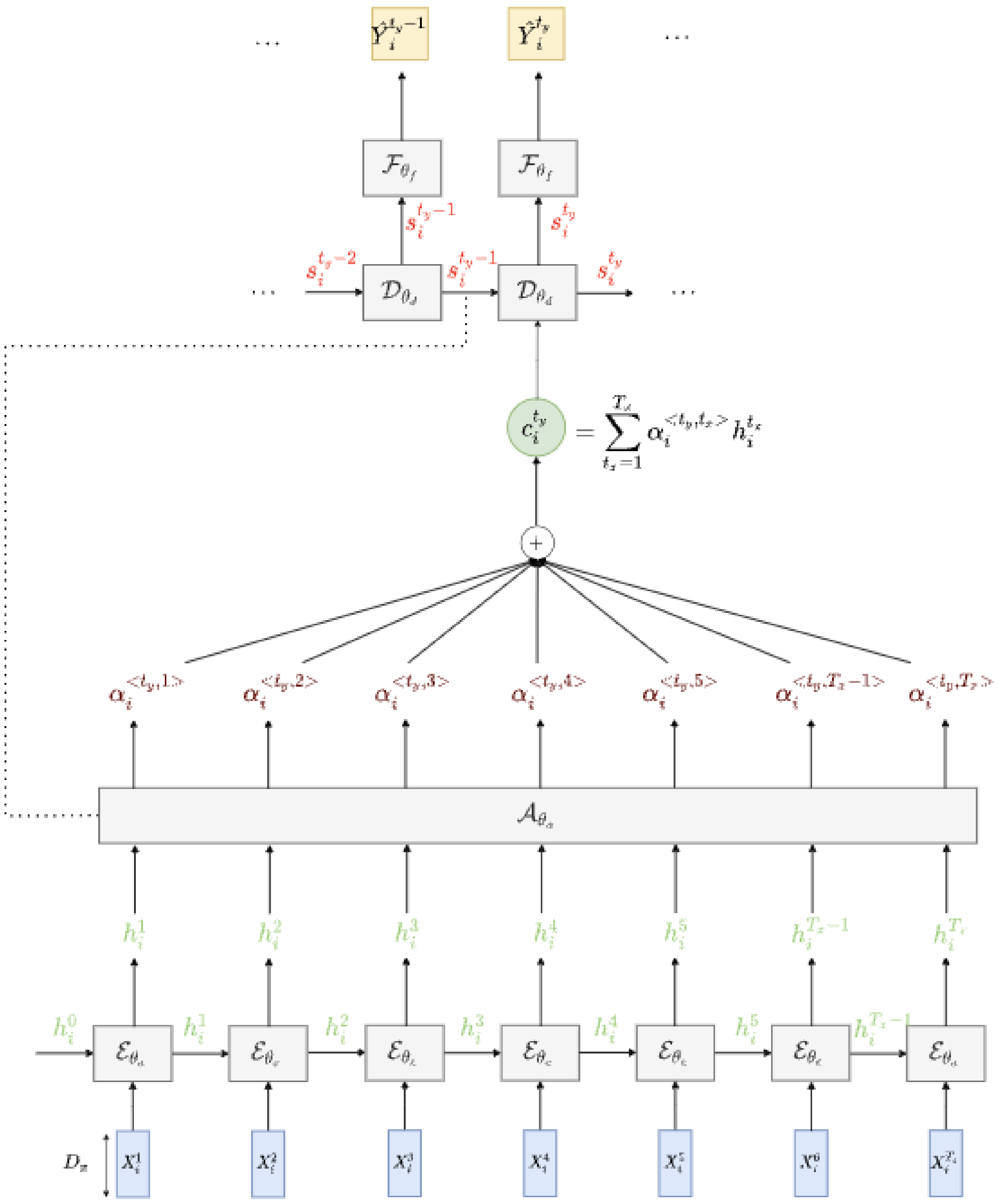
$$\boxed{c_i^{t_y} = \sum_{t_x=1}^{T_x} \alpha_i^{<t_y,t_x>} h_i^{t_x}}$$

values

Wrap-up: The Sequence to Sequence model with Attention

Generating $(\hat{Y}_i^1, \ldots, \hat{Y}_i^{T_y})$ using the final model:

- An Encoder $\mathcal{E}_{\theta_e}$ parameterized by θ_e maps the input embeddings $(X_i^1, \ldots, X_i^{T_x})$ to the decoder hidden states $(h_i^1, \ldots, h_i^{T_x})$
- An Attention Layer $\mathcal{A}_{\theta_a}$ parameterized by θ_a is used to compute the attention weights $\alpha_i^{<t_y,t_x>}$ in order to get the context vector $c_i^{t_y}$, which be fed into the decoder at time $t_y \in \{1, \ldots, T_y\}$
- A Decoder Layer $\mathcal{D}_{\theta_d}$ parameterized by θ_d which generates the decoder hidden states $(s_i^1, \ldots, s_i^{T_y})$
- A final Dense Layer $\mathcal{F}_{\theta_f}$ parameterized by θ_f can be used to map each decoder hidden state $s_i^{t_y}$ into the prediction $\hat{Y}_i^{t_y}$



Part 5 : Attention is all you need

Addressing The polysemy Problem: Building Contextual Embeddings

- Let us consider the sentence: “Tom a été entarté cet été” (which meansTom was hit with a pie this summer).

- Although the token “été” has two different meanings in the sentence, the Word2vec/GloVe approach will assign the same embedding vector to the token “été”.

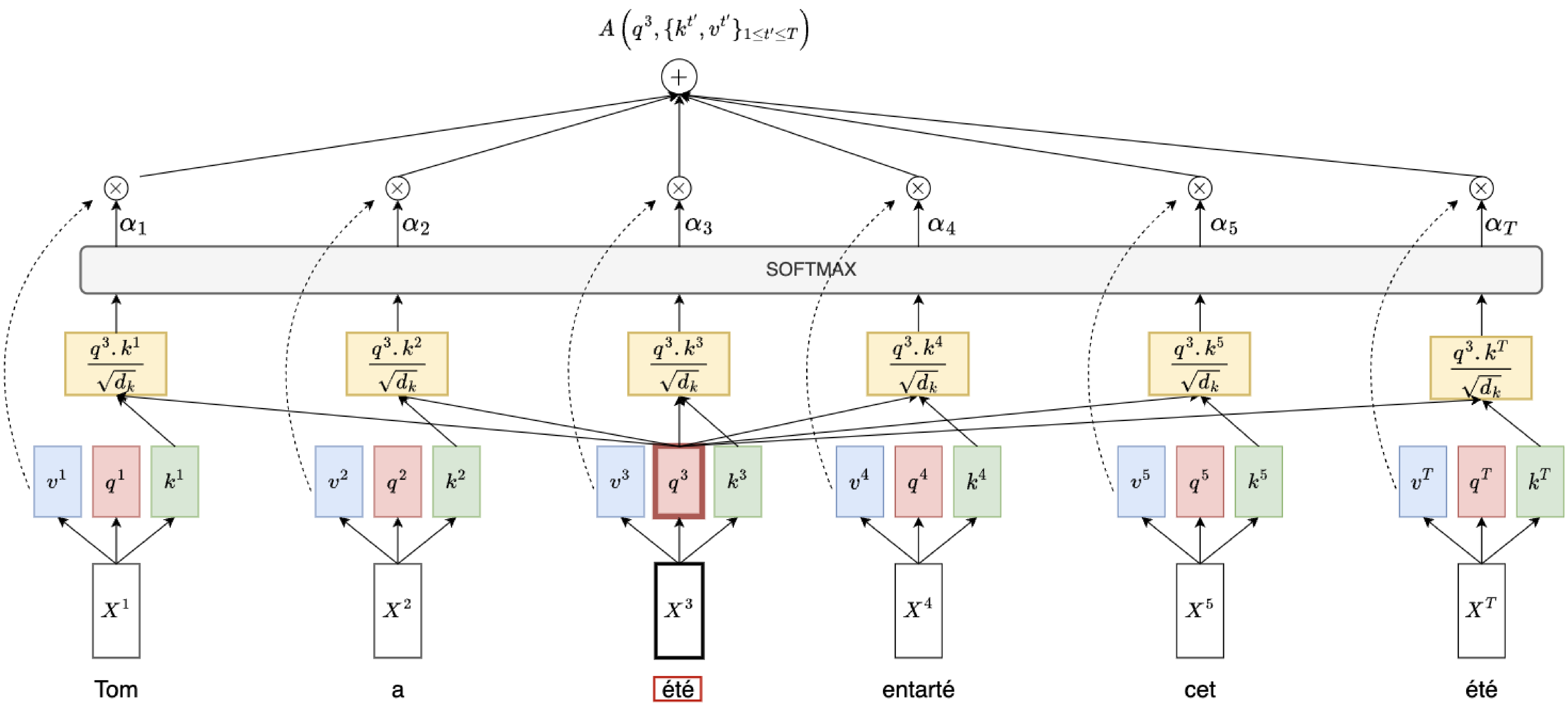
- To overcome the polysemy problem, we need to introduce **Contextual Embedding Vectors.**

- Contextual embeddings assign each word a representation based on its context, thereby capturing uses of words across varied contexts.

Interactive Session

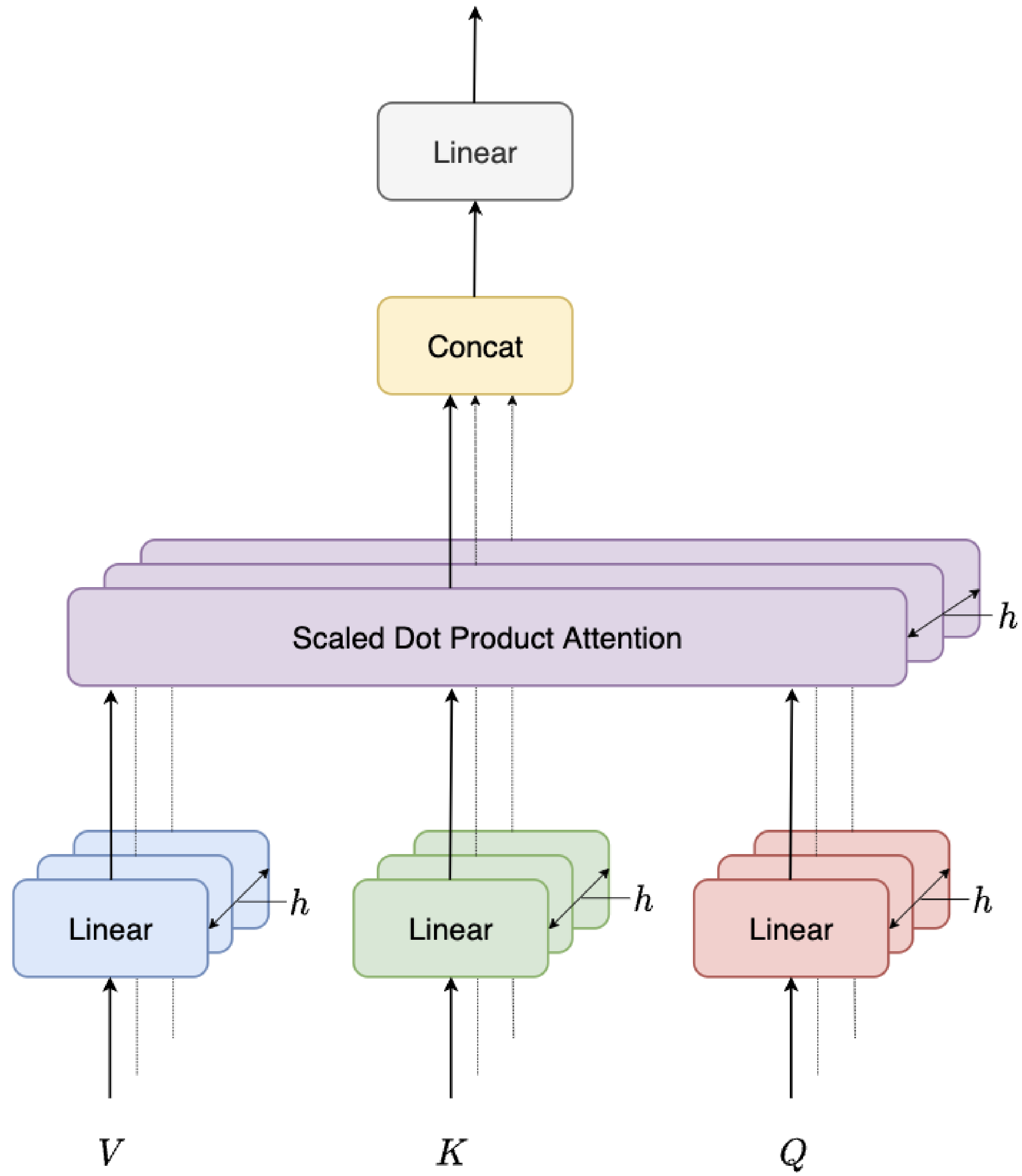
The Self Attention Layer

- Calculating the contextual embedding of the word “été”.



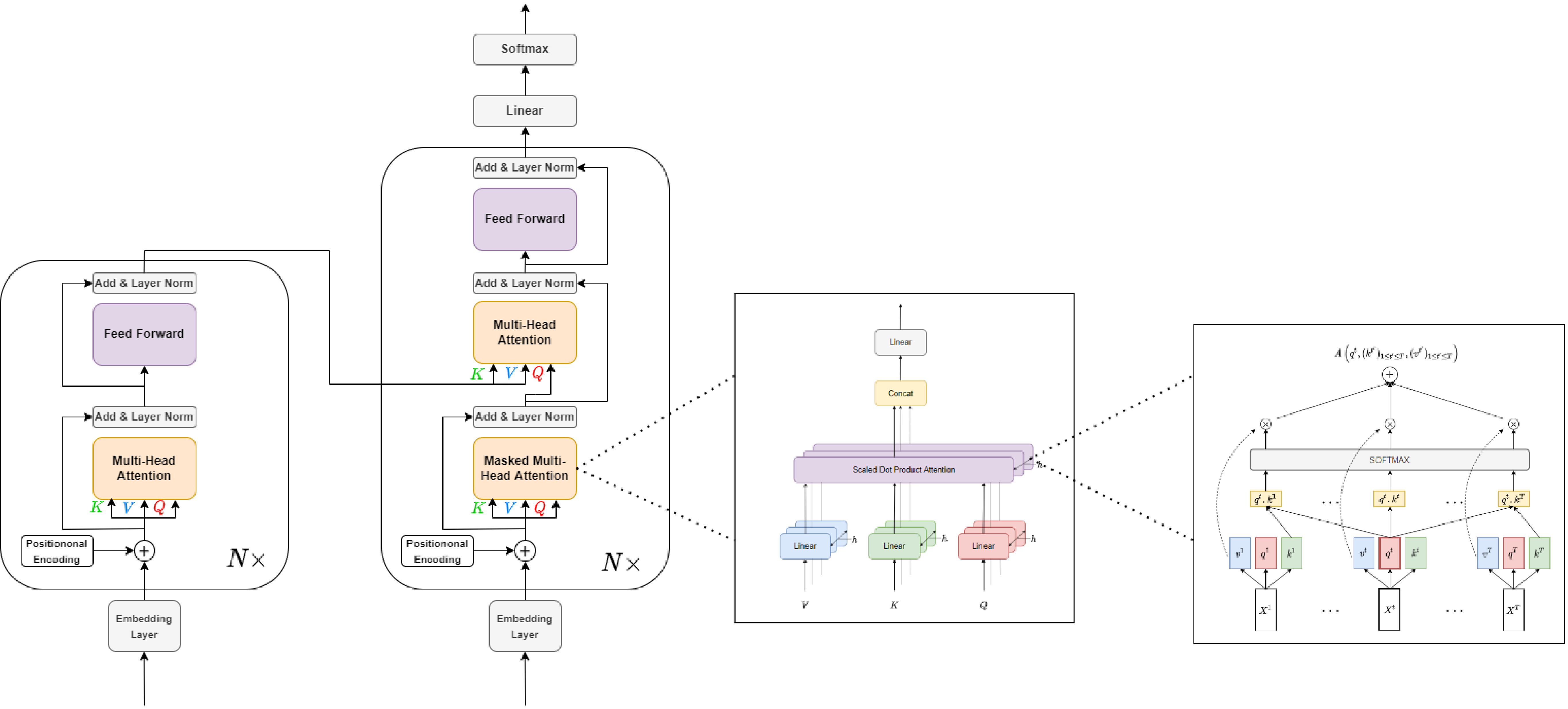
The Multi-Head Attention Layer

- The Multi-Head Attention module consists in applying the self attention mechanism defined previously h times in order to capture different notions of similarity.



The Transformer Architecture

- “Attention is all you need” (Vaswani, et al., 2017) stands out among the most important and interesting papers of the recent years.



Self Attention Applications:

- Language Processing:

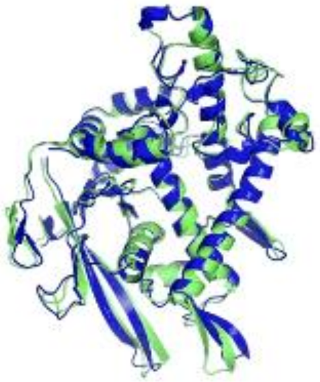
- Bert: Pre-training of Deep Bidirectional Transformer for Language Understanding[Devlin et al., NAACL 2019]
- Language Models are Few-Shot Learners [Brown et al., NeurIPS 2020]

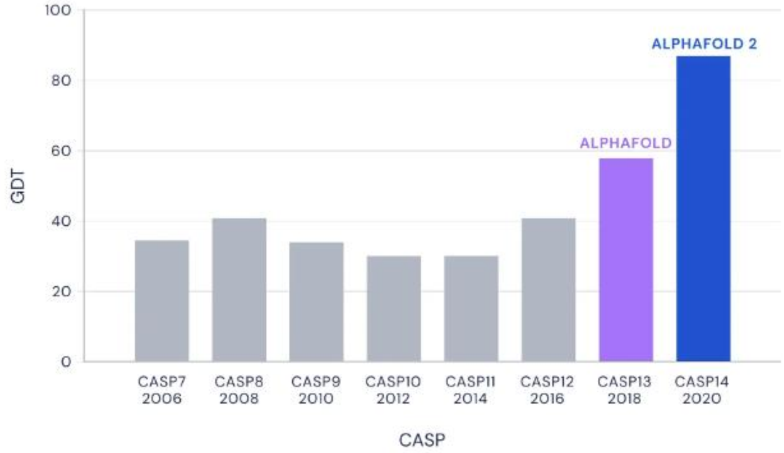
- Vision:

A woman is throwing a frisbee in a park.

- Show, Attend and Tell: Neural Image Caption Generation with visual Attention [Xu et. Al, 2015]
- Transformers for Image Recignition at Scale [Dosovitskiy et al., 2020]

- Biology:





- AlphaFold2 [Jumper et al., Nature 2021]

Programming Session

https://mlfbg.github.io/MachineLearningInFinance/