Course 3: Language Modeling

You

Explain how ChatGPT works as if I was a 5 years old child.

ChatGPT

Alright, imagine you have a really smart friend who knows a lot of things. That friend is like a big, magical library with lots and lots of books. Now, this friend is called ChatGPT. When you ask ChatGPT a question or tell it something, it looks into all those books in its library (which are actually a huge amount of information it learned) and tries to give you the best answer or response it can find.

So, you can think of ChatGPT as a helpful buddy who loves to chat and share what it knows with you!

How does it really work?

What is Language Modeling?

Definition

- A sequence of tokens $(w_1, w_2, \ldots, w_n)$
- For a position i, a language model (**LM**) predicts

$$P(w_i \mid (w_j)_{j \neq i}) \in \Delta^V$$

- In words: a LM predicts the probability of a token given its context

Example

I went to the ***???*** *yesterday*

P(*park* | *I went to the* ***???*** *yesterday*) = 0.1

P(*zoo* | *I went to the* ***???*** *yesterday*) = 0.07

…

P(*under* | *I went to the* ***???*** *yesterday*) = 0

Why is it hard?

- **Large vocabularies**: 170,000 English words
- **Lots of possible contexts**:
  - For V possible tokens, there are V^L contexts of size L (in theory)
- **Inherent uncertainty**: not obvious even for humans

Basic approach - Unigram

- Learn the *non-contextual* probability (=frequency) of each token:

$$P(w_i \,|(w_j)_{j\neq i}) = f$$

Example

chart against operations at influence the surface plays crown a inaro the three @ but the court lewis on hand american of seamen mu role due roger executives

Include context - Bigram

- Predict based on the last token only:

$$P(w_i \mid (w_j)_{j \neq i}) = P_\theta(w_i | w_{i-1})$$

- (MLE): Measure next token frequency

Example

the antiquamen lost to dios nominated former is carved stone oak were problematic, 1910. his willingness to receive this may have been seen anything

Include more context - n-gram

- Predict based on the n last tokens only:

$$P(w_i \,|(w_j)_{j\neq i}) = P_\theta(w_i|w_{i-n}\dots w_{i-1})$$

- (MLE): Measure occurences of tokens after $w_{i-n}\dots w_{i-1}$

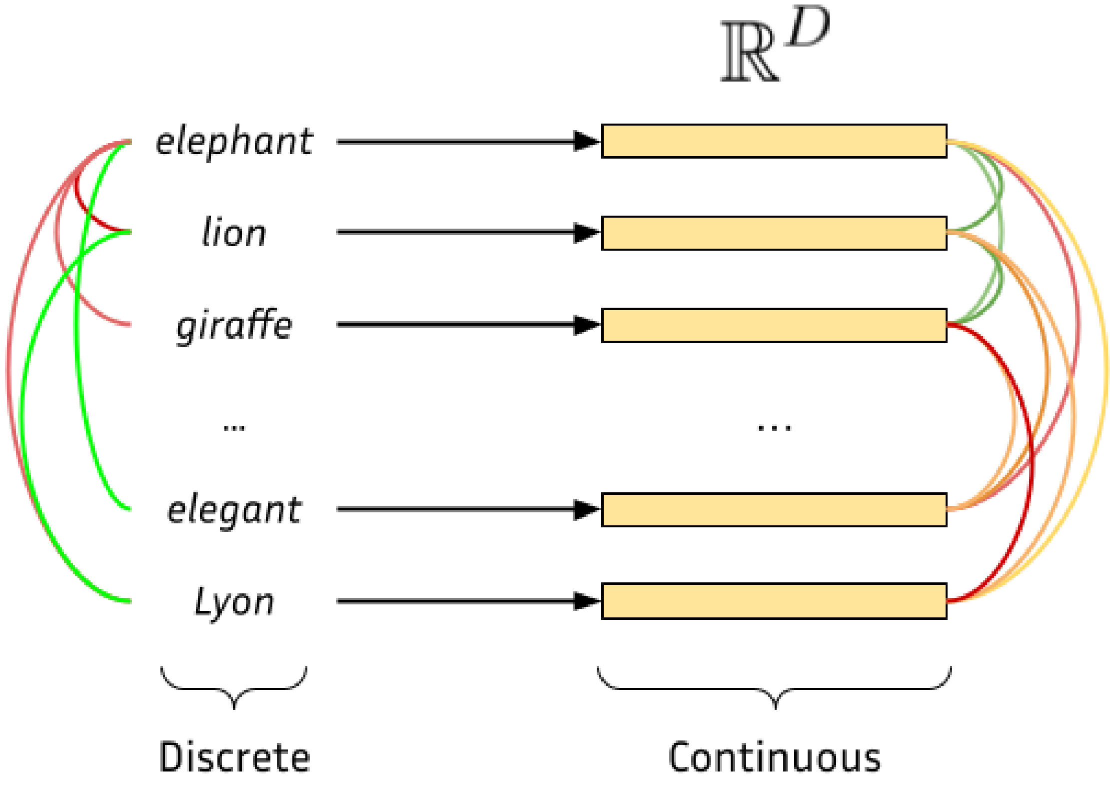
Example (n=4)

eva gauthier performed large amounts of contemporary french music across the united states marshals service traveled to frankfurt, germany and took custody of the matthews

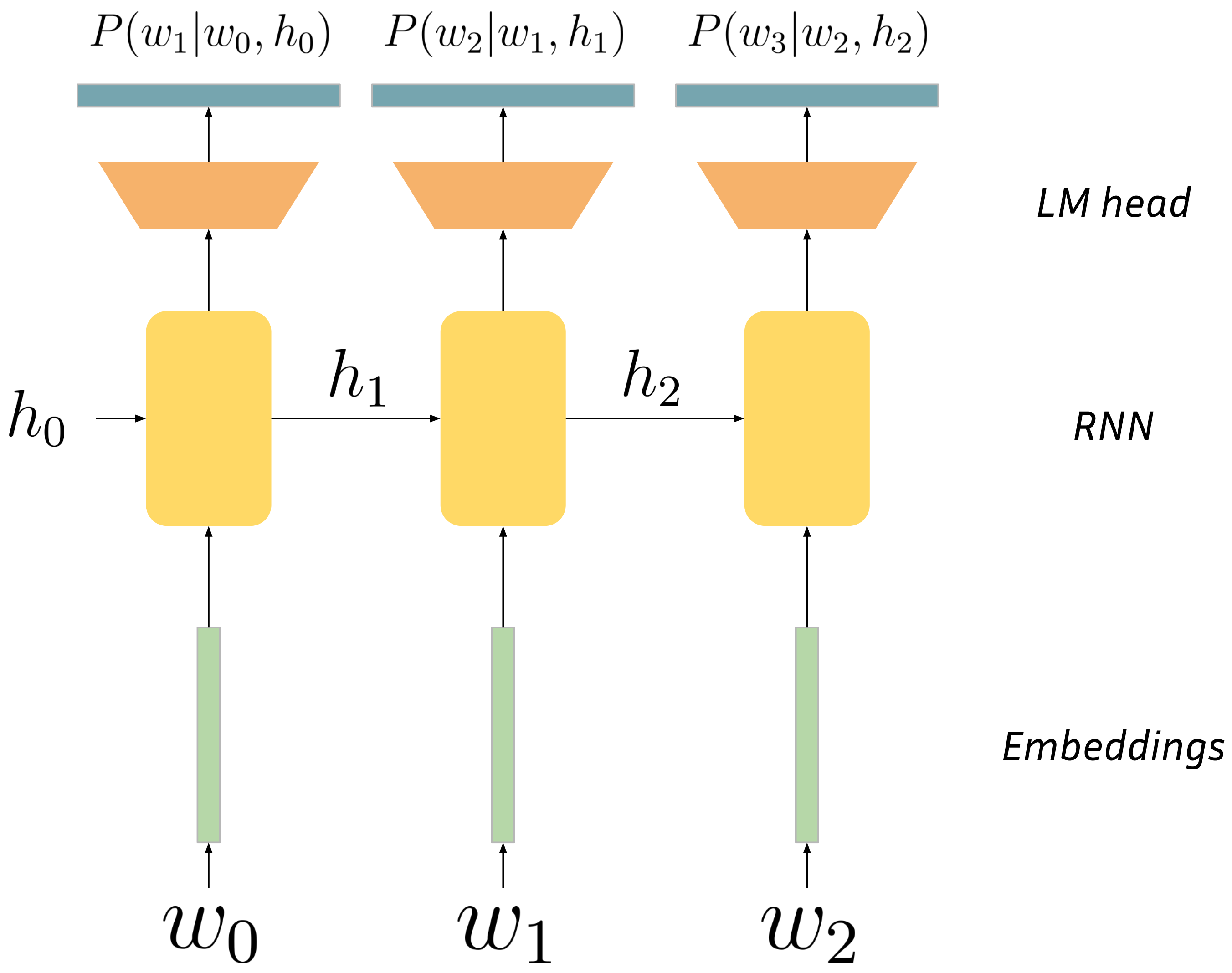
Statistical n-grams: pro/cons

- Strenghts:
  - Easy to train
  - Easy to interpret
  - Fast inference
- Limitations:
  - Very limited context
  - **Unable to extrapolate** : can only model what it has seen

The embedding paradigm



LM with RNNs



$P(w_1|w_0, h_0)$
$P(w_2|w_1, h_1)$
$P(w_3|w_2, h_2)$
LM head
h_0
h_1
h_2
RNN
Embeddings
w_0
w_1
w_2

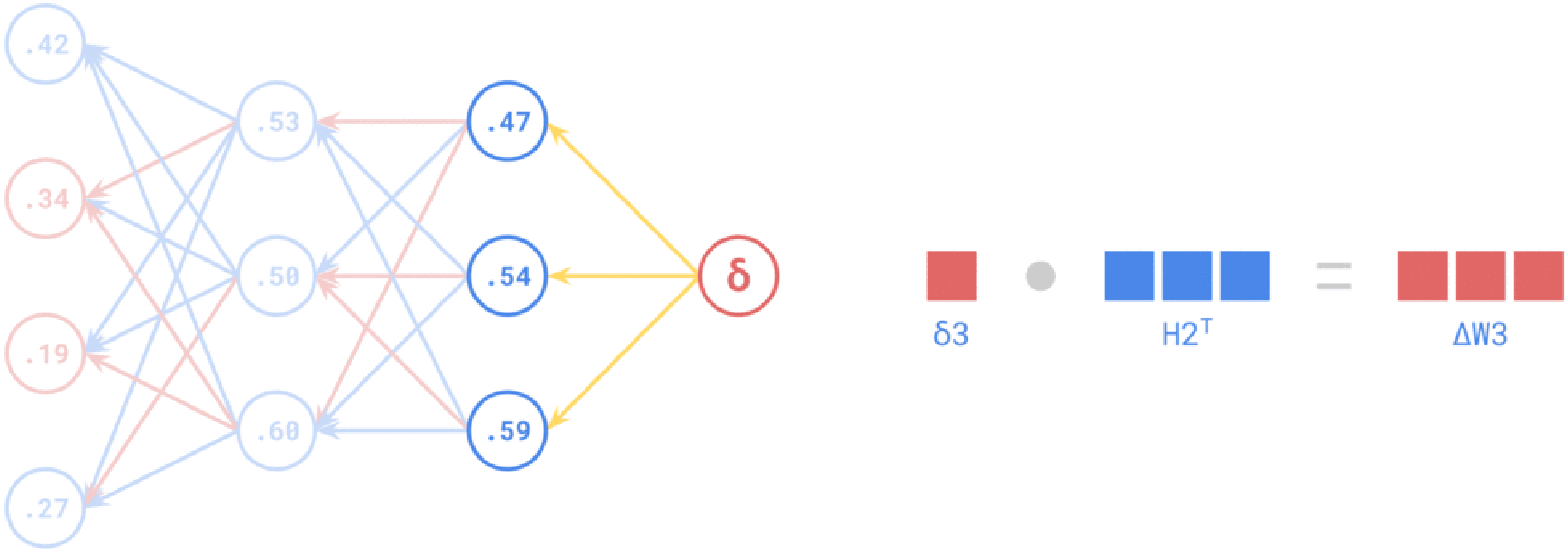
LM with RNNs - Training

- θ: parameters of the RNN
- $(w_1, \ldots, w_n)$: training sequence
- Cross-entropy loss $\mathcal{L}_{ce}$:

$$\mathcal{L}_{ce}(w, \theta) = -\sum_{i=2}^{n} 1_{w_i} \cdot \log P_\theta(w_i | w_{i-1}, h_{i-1})$$

- Train via back-propagation + SGD

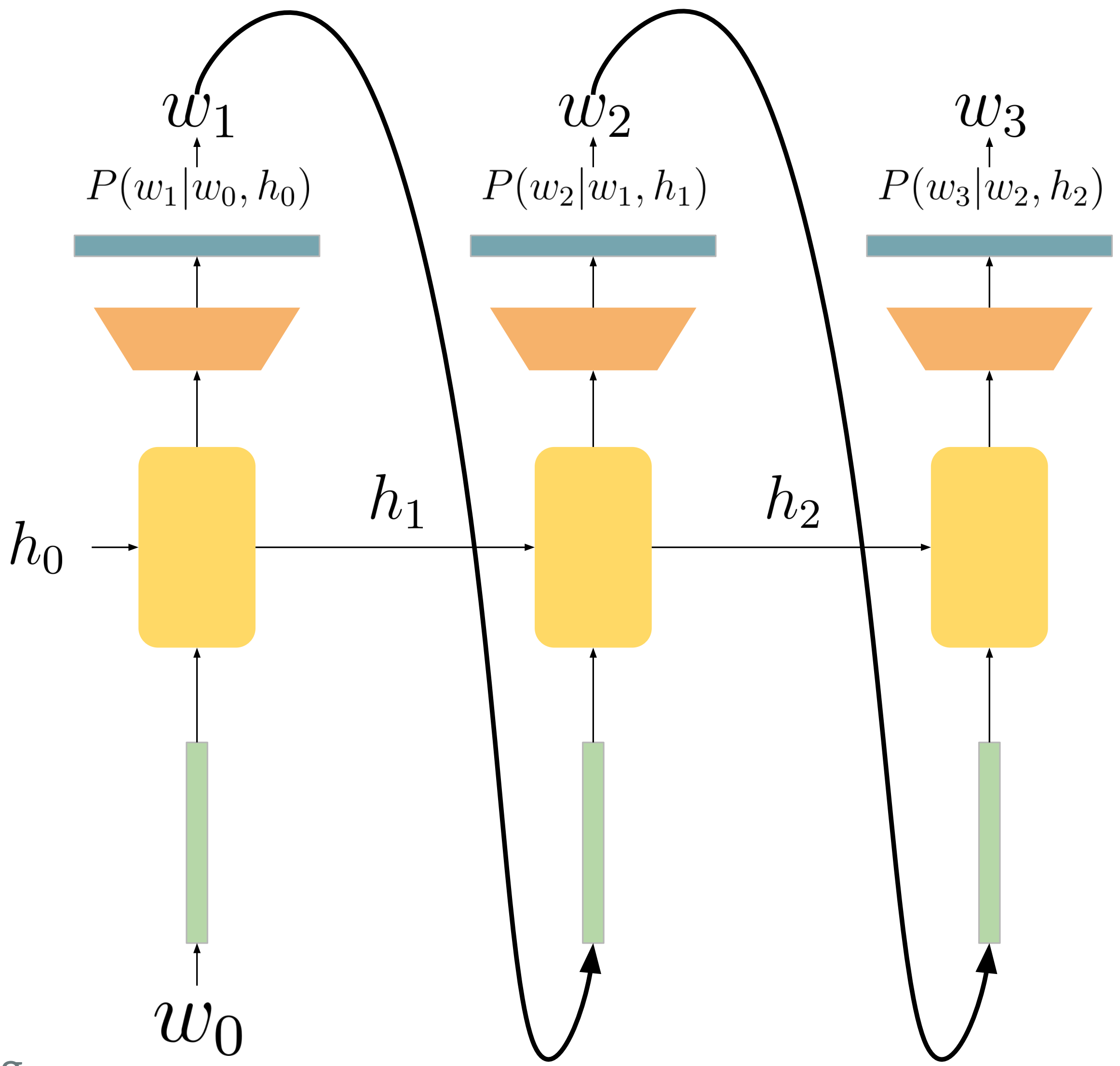
Reminder - Back-propagation



Reminder - Stochastic Gradient Descent

- **Goal** : Minimize a loss function $\mathcal{L}(X, \theta)$ for given data X with respect to model parameters θ
- **Method** :
  - Split X in smaller parts x^i (called mini-batches)
  - Compute $\mathcal{L}(x^i, \theta)$ (forward) and $\nabla_\theta \mathcal{L}(x^i, \theta)$ (back-prop)
  - Update: $\theta \leftarrow \theta - \eta \nabla_\theta \mathcal{L}(x^i, \theta) \qquad (\eta \ll 1$, learning rate)

LM with RNNs: Generation

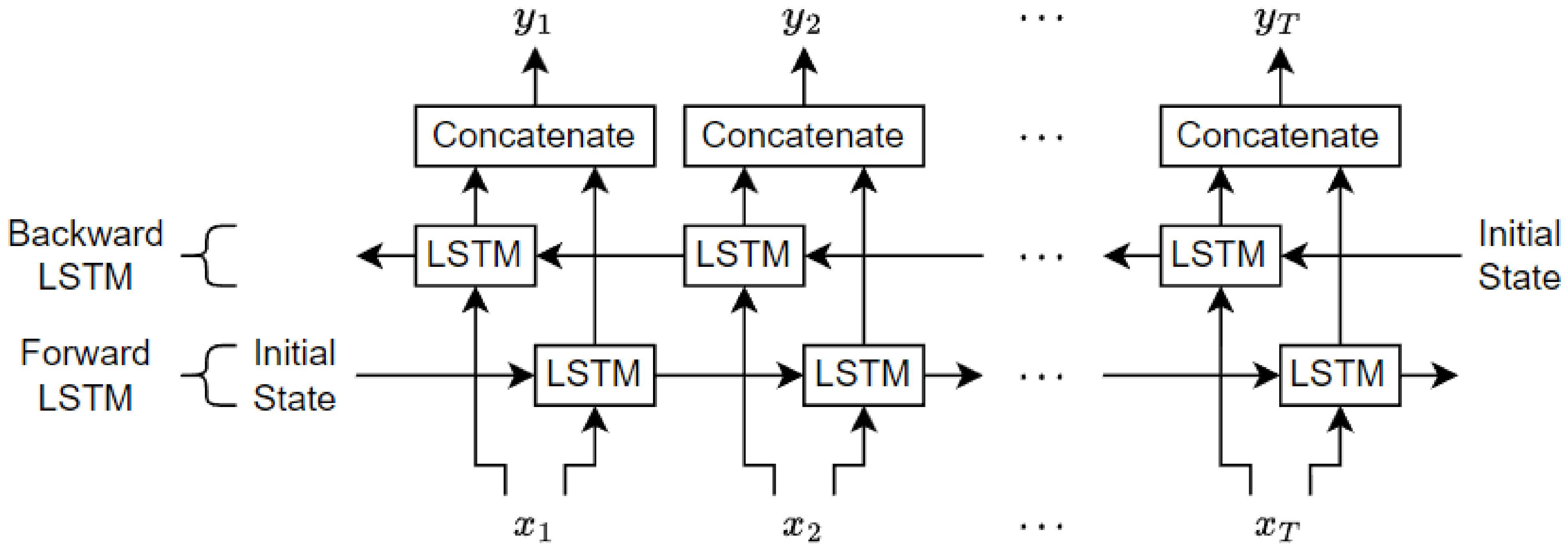


RNNs: pro/cons

- Strenghts
  - Still relatively fast to train
  - ... and for inference ($O(L)$)
  - **Can extrapolate** (works with continuous features)
- Limitations
  - **Context dilution** when information is far away

Extending RNNs: BiLSTMs

- LSTM: improves context capacity
- Read the sequence in both directions



Transformers

Information flow - RNN

How many steps between source of info and current position?

- *What is the previous word?* => $O(L)$
- *What is the subject of verb X?* => $O(L)$
- *What are the other occurences of current word?* => $O(L^2)$
- ...

Information flow - Transformers

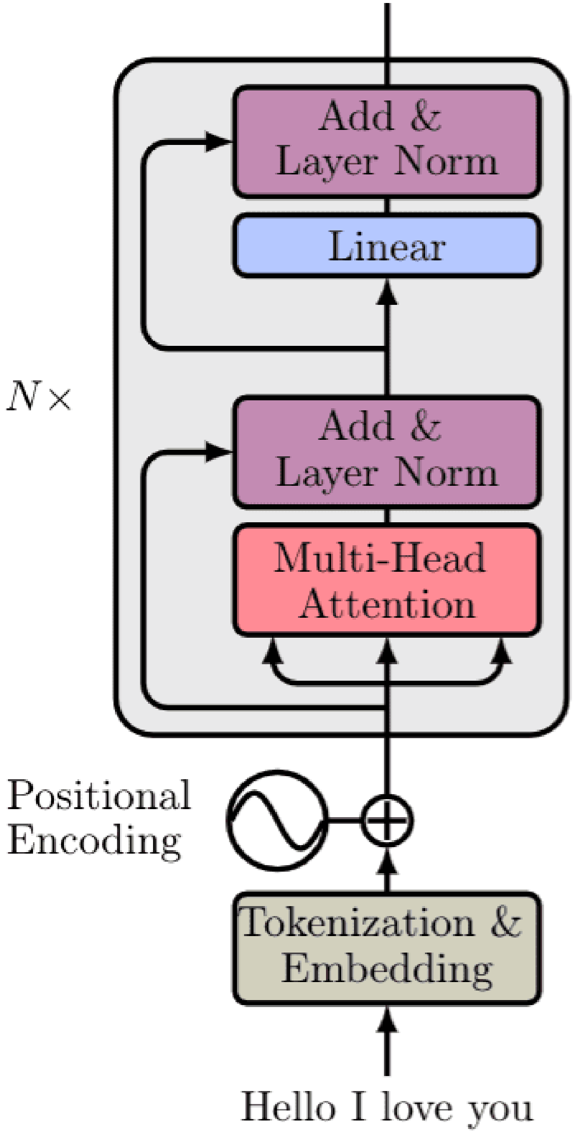
How many steps between source of info and current position?

- *What is the previous word?* => $O(1)$
- *What is the subject of verb X?* => $O(1)$
- *What are the other occurences of current word?* => $O(1)$
- ... => $O(1)$

Outside Transformers

- A Transformer network T_θ
- Input: Sequence of vectors $(e_1, \ldots, e_n) \in \mathbb{R}^D$
- Output: Sequence of vectors $(h_1, \ldots, h_n) \in \mathbb{R}^D$
- Each h_i may depend on the <u>whole</u> input sequence $(e_1, \ldots, e_n)$

Inside Transformers

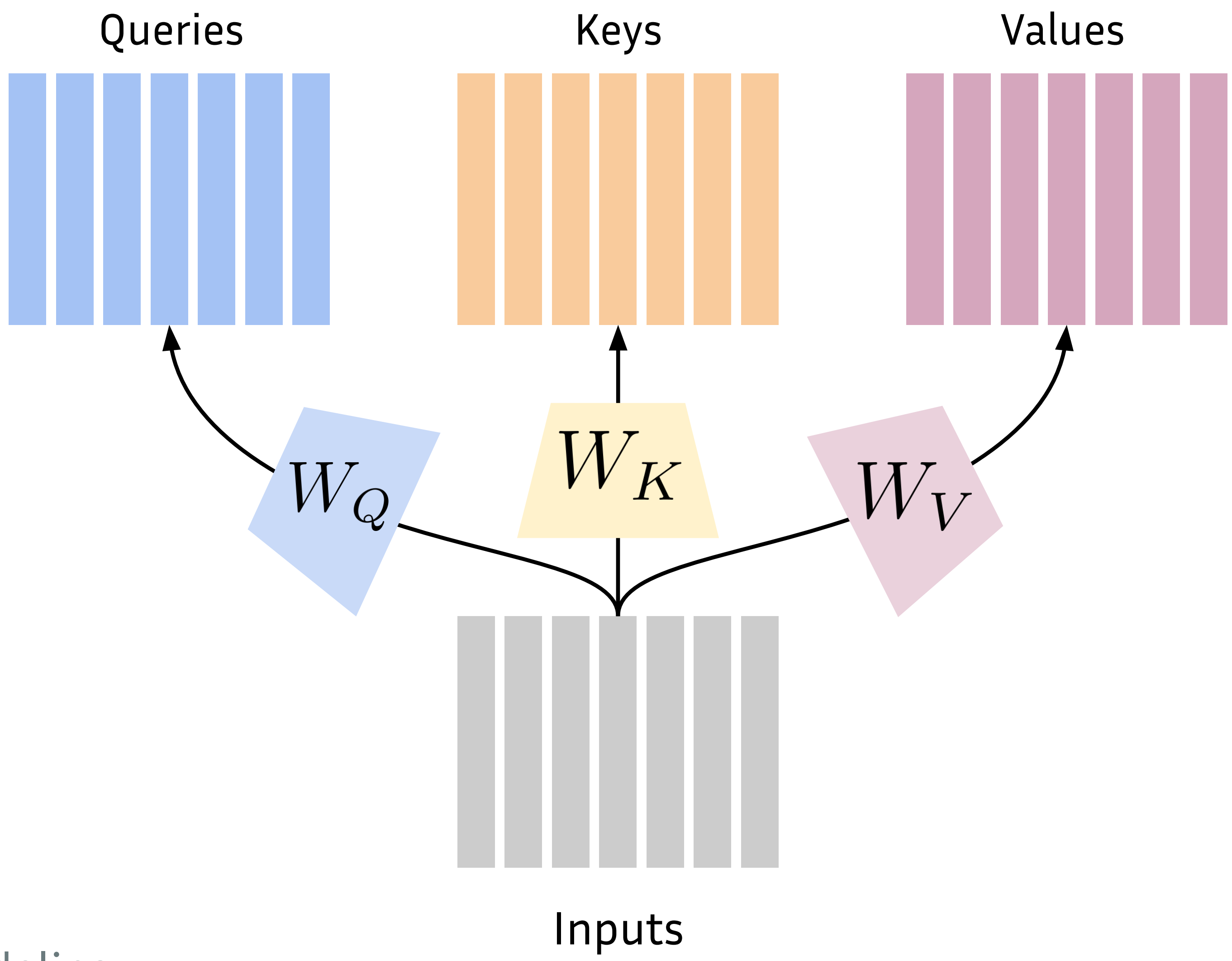


Inside Transformers : Embeddings

Before going in the network:

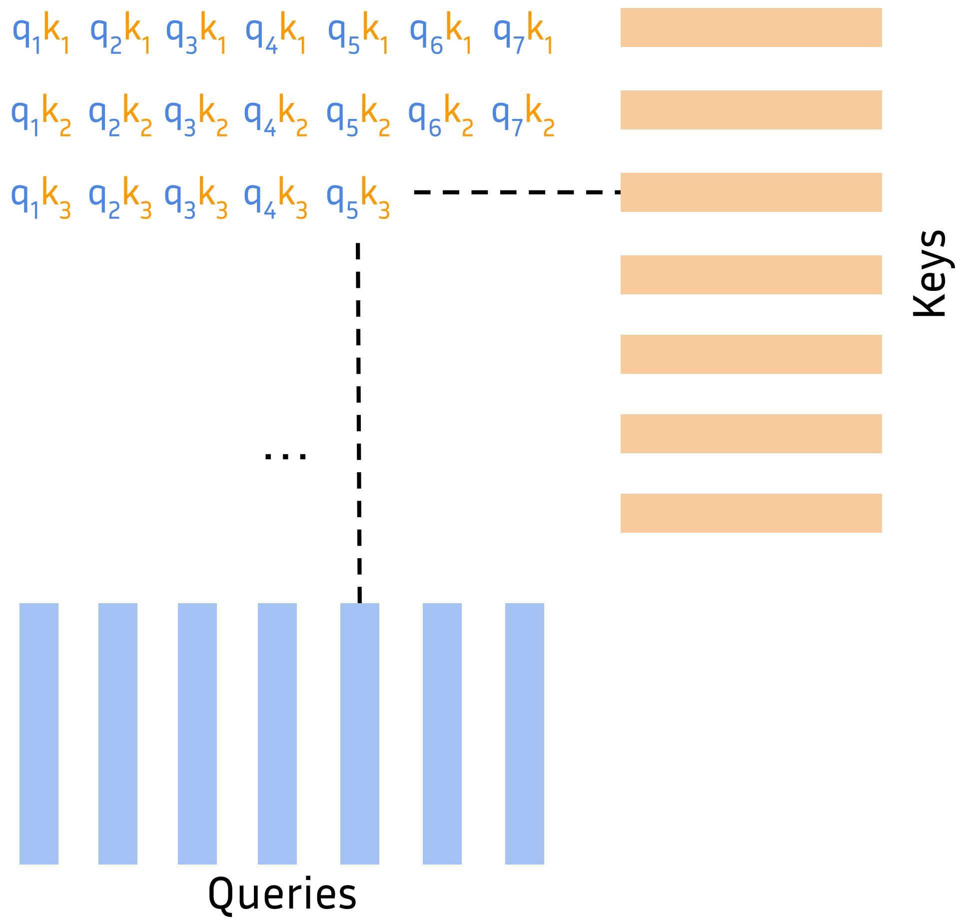
- Given an input token sequence $(w_1, \dots, w_n)$
- We retrieve token embeddings $(e_w(w_1), \dots, e_w(w_n)) \in \mathbb{R}^D$
- We retrieve position embeddings $(e_p(1), \dots, e_p(n)) \in \mathbb{R}^D$
- We compute input embeddings: $e_i = e_w(w_i) + e_p(i)$

Inside Transformers : Self-attention



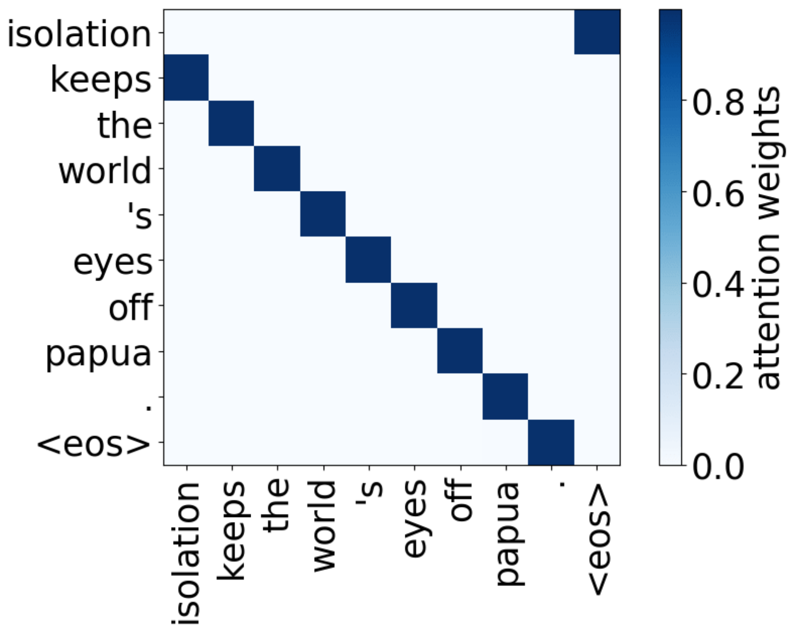
Inside Transformers : Q and K

=> Model interactions between tokens:



Inside Transformers : Q and K

- Each row of QK^T is then normalized using softmax
- Interpretable patterns:



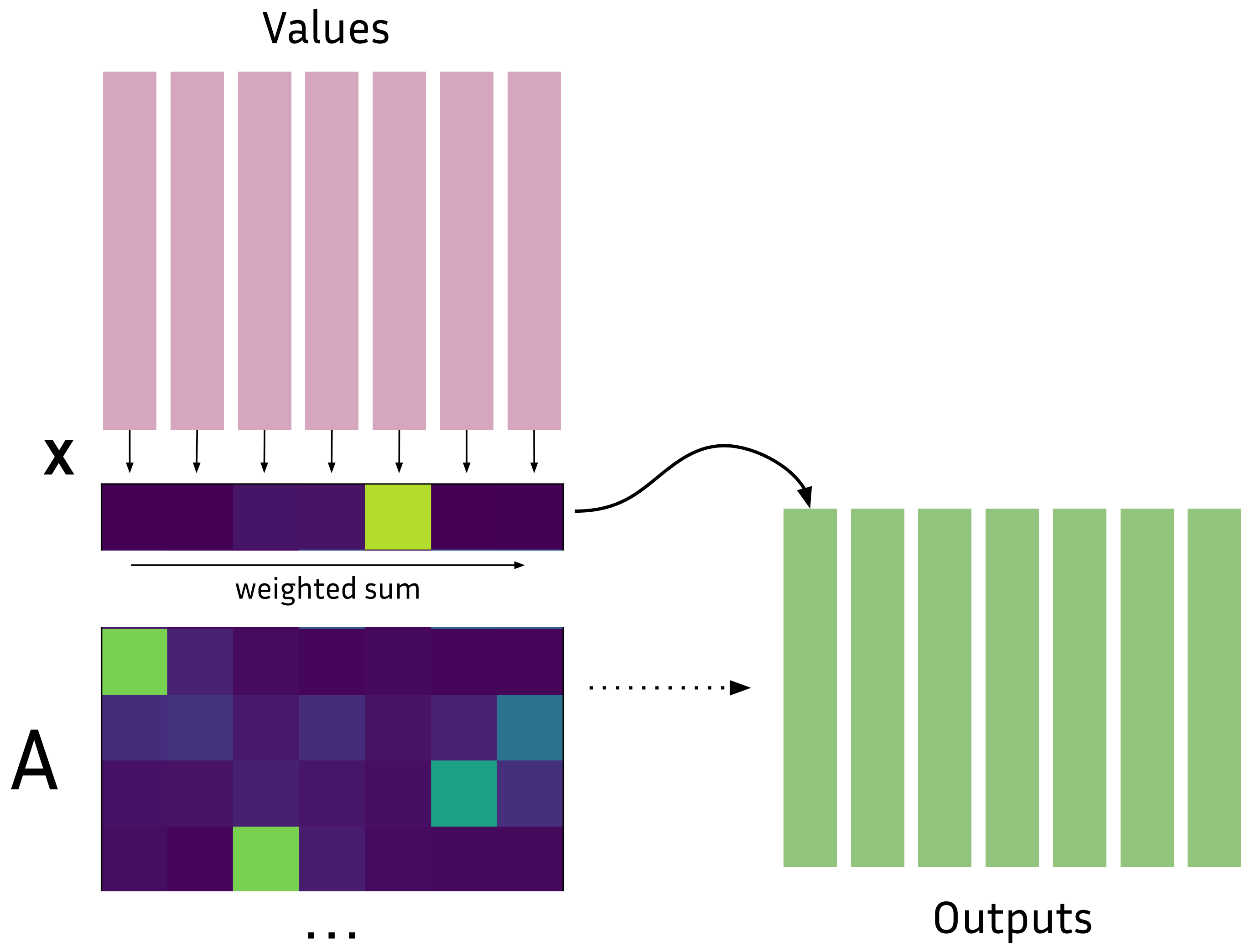
Inside Transformers : Q and K

- Formally:

$$A_{i,j} = \frac{1}{\sqrt{d_h}} \cdot \frac{e^{(QK^T)_{i,j}}}{\sum_k e^{(QK^T)_{i,k}}}$$

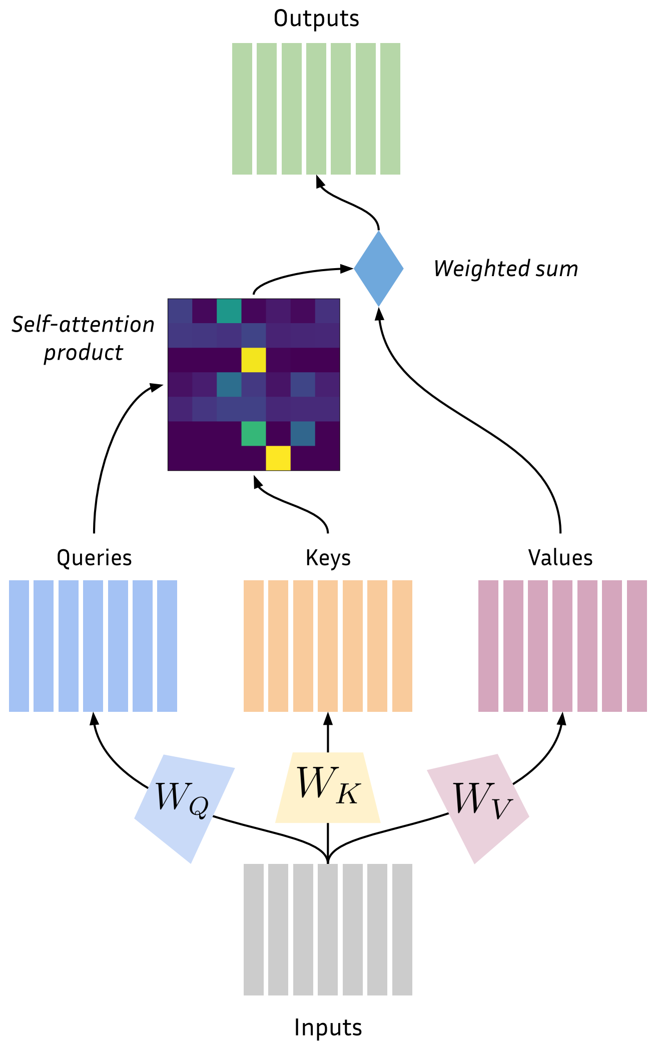
where d_h is the hidden dimension of the model

Inside Transformers : A and V

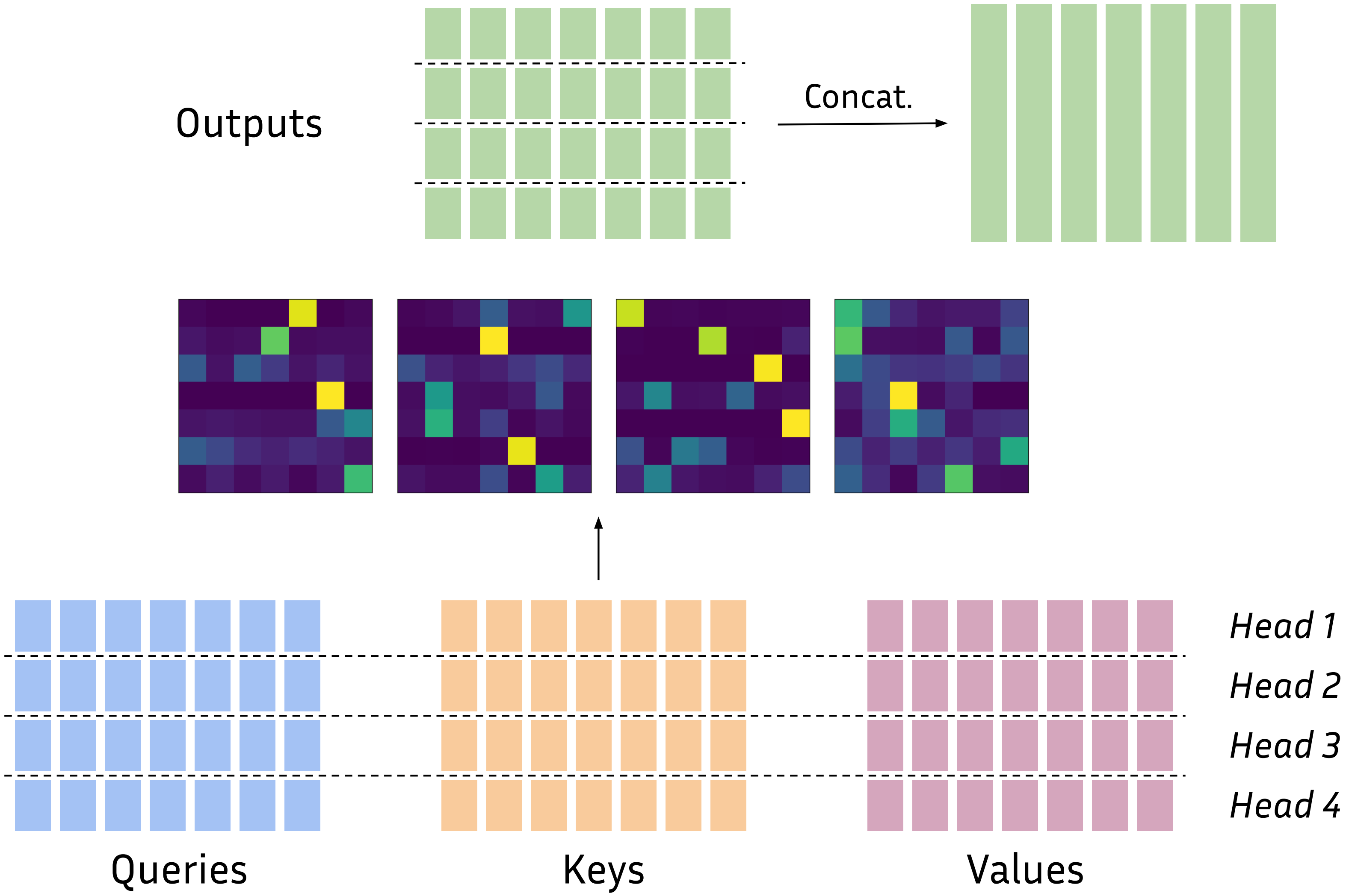


Inside Transformers : Self-attention summary

- Inputs are mapped to Queries, Keys and Values
- Queries and Keys are used to measure interaction (A)
- Interaction weights are used to "select" relevant Values combinations
- **Complexity: O(L^2)**

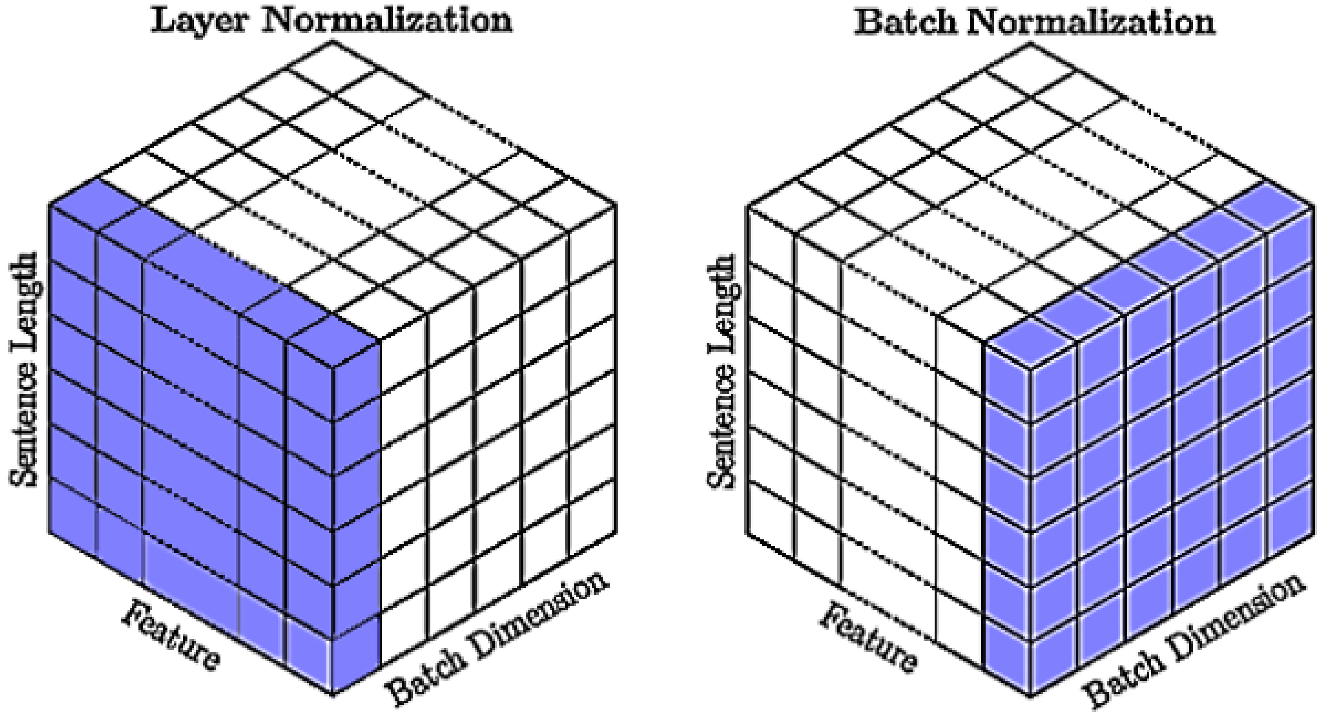


Inside Transformers : Multi-head attention



Inside Transformers : LayerNorm

- Avoids gradient explosion



Inside Transformers : Output layer

- Avoids gradient explosion