# 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:

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

- (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 $w_{i-n} \dots w_{i-1}$

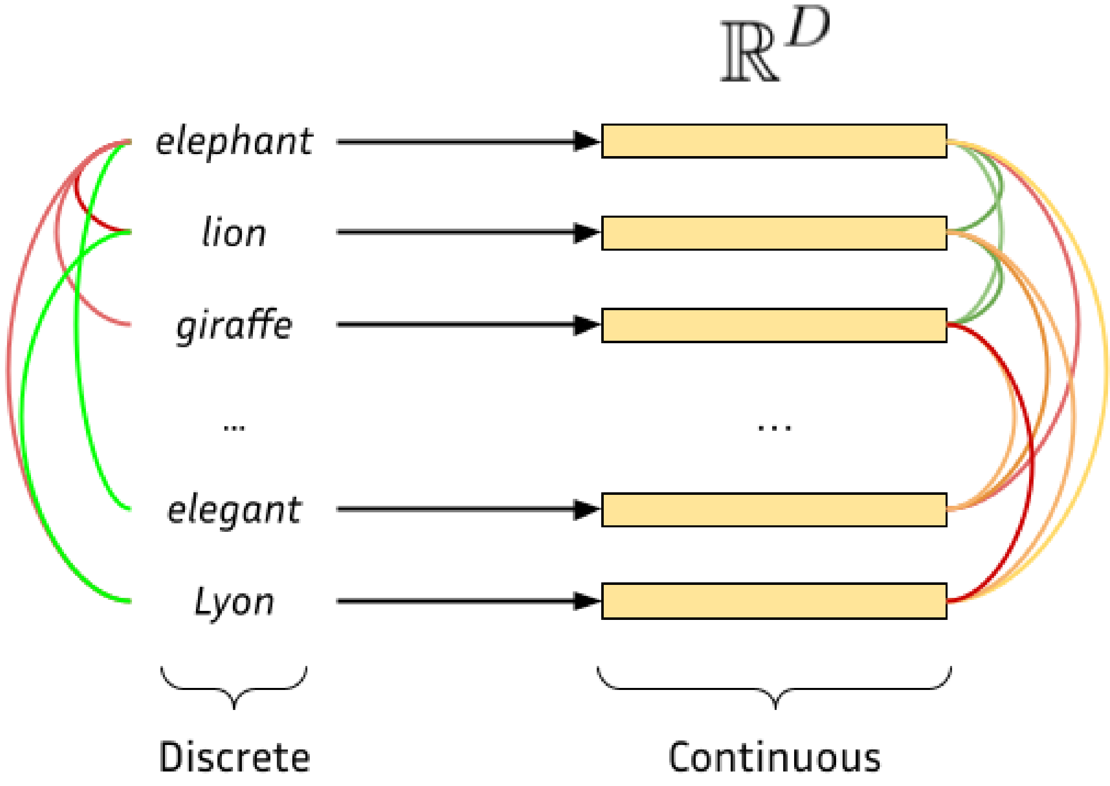
**Example (n=4)**

*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*

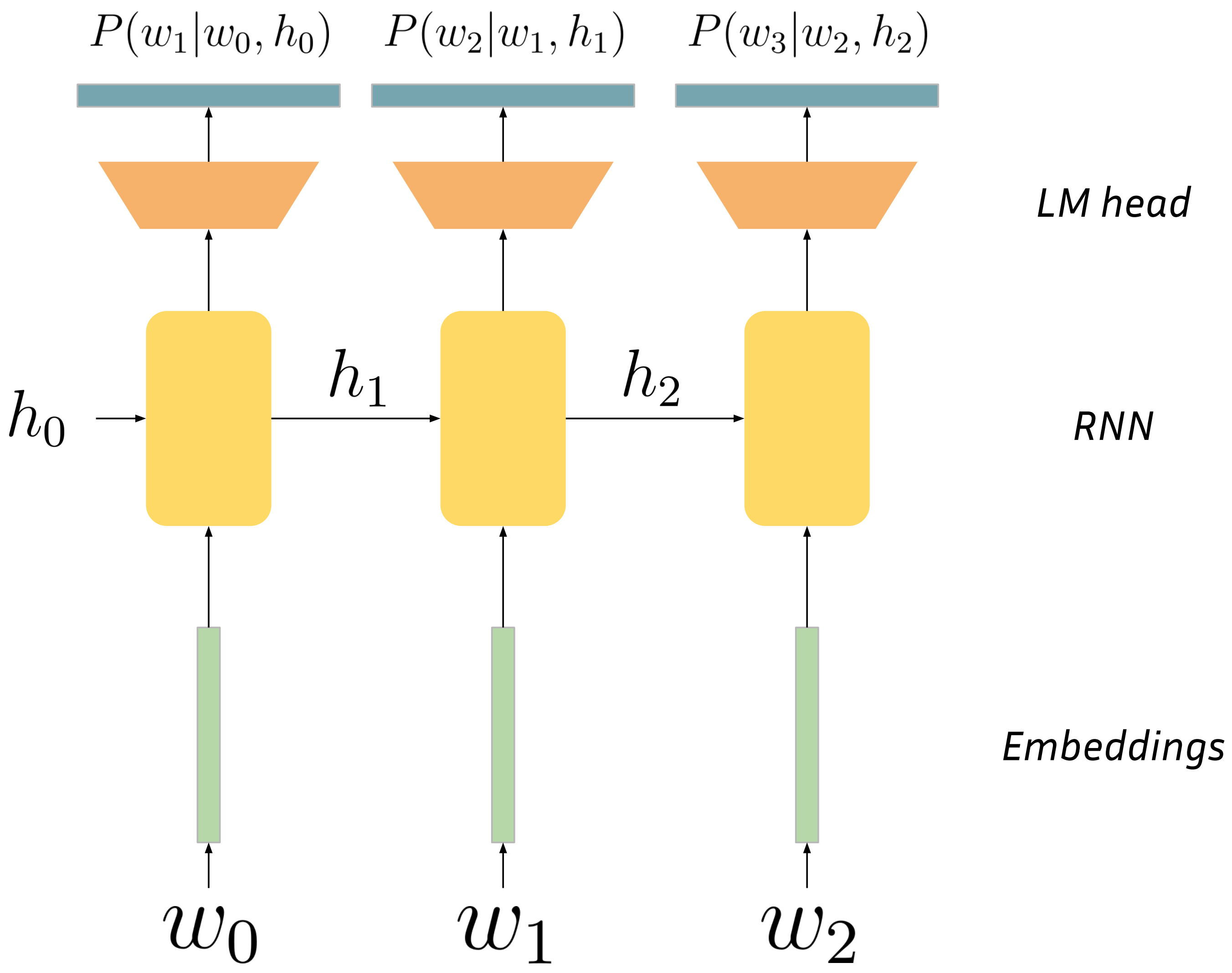
# Statistical n-grams: pro/cons

- 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
$w_0$
$w_1$
$w_2$

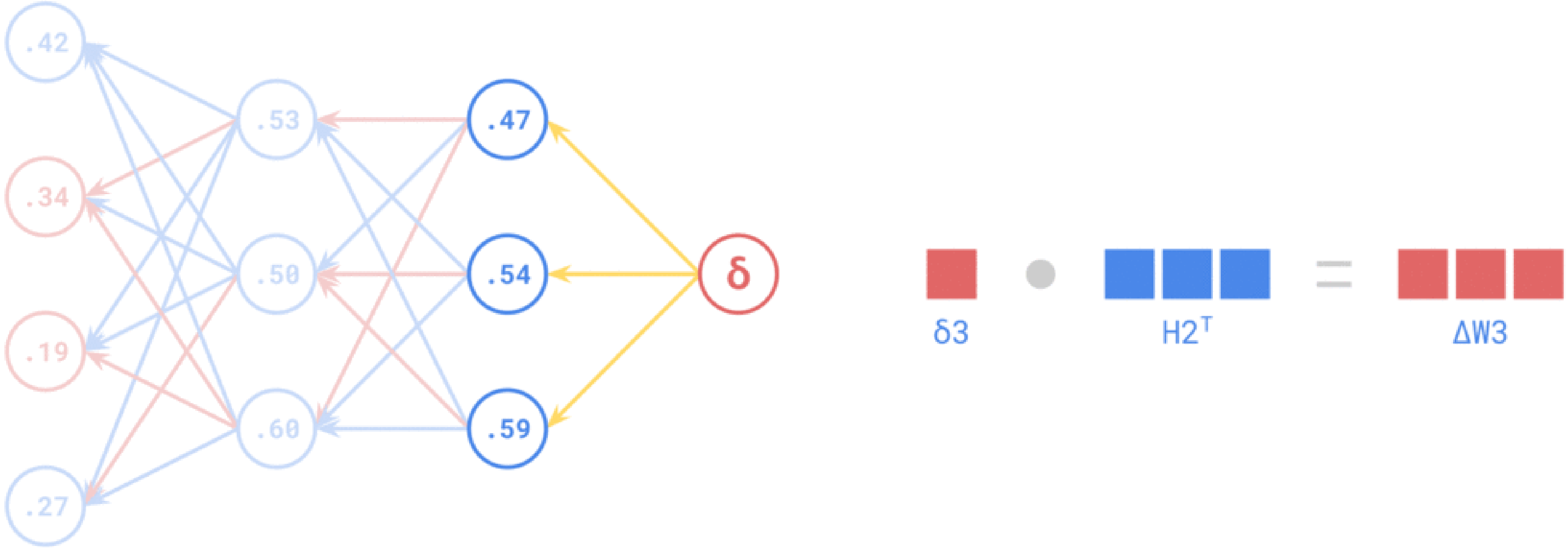
# LM with RNNs - Training

- $\theta$: 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

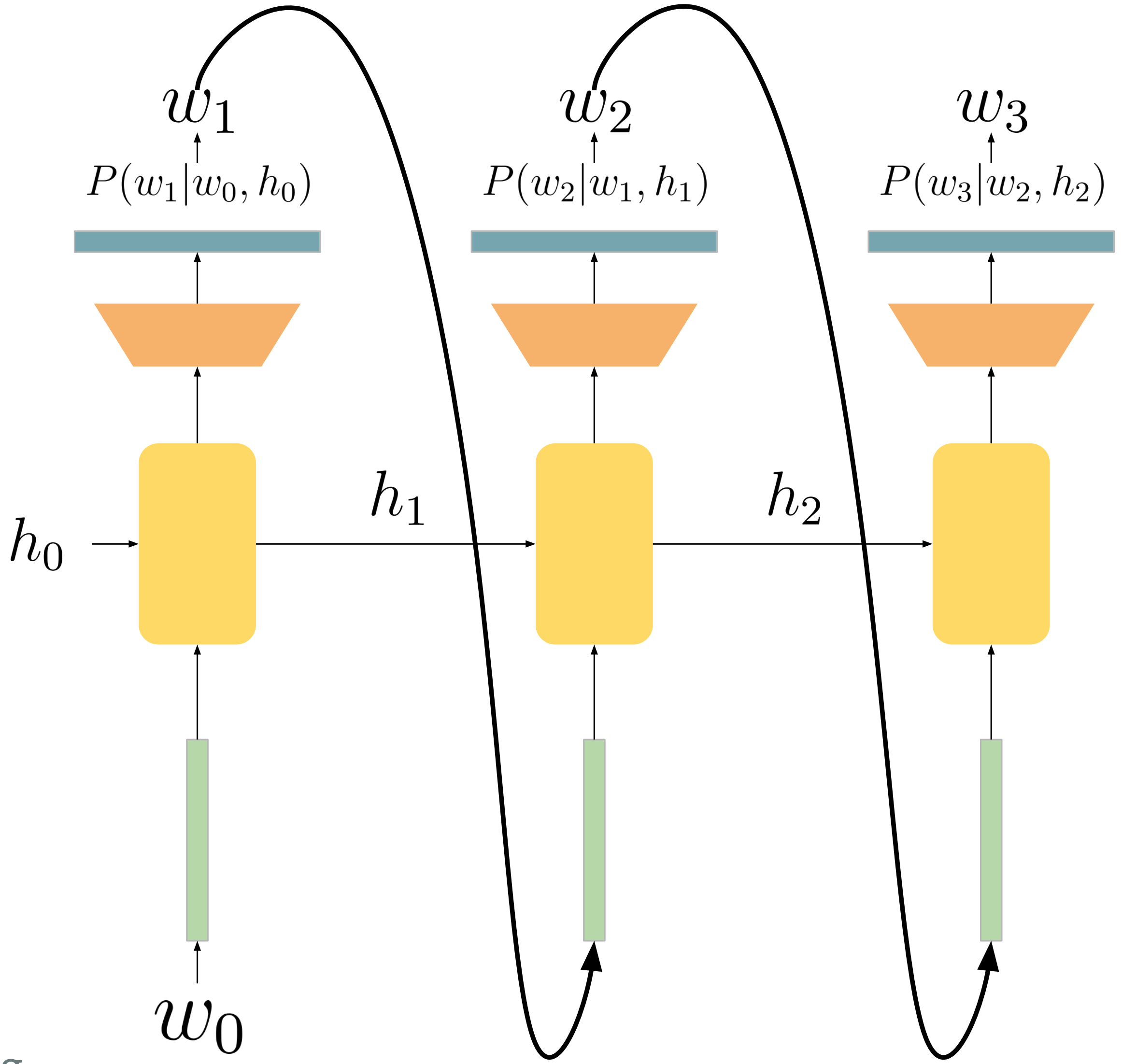
# Reminder - Back-propagation



# Reminder - Stochastic Gradient Descent

- **Goal** : Minimize a loss function $\mathcal{L}(X, \theta)$ for given data $X$ with respect to model parameters $\theta$
- **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

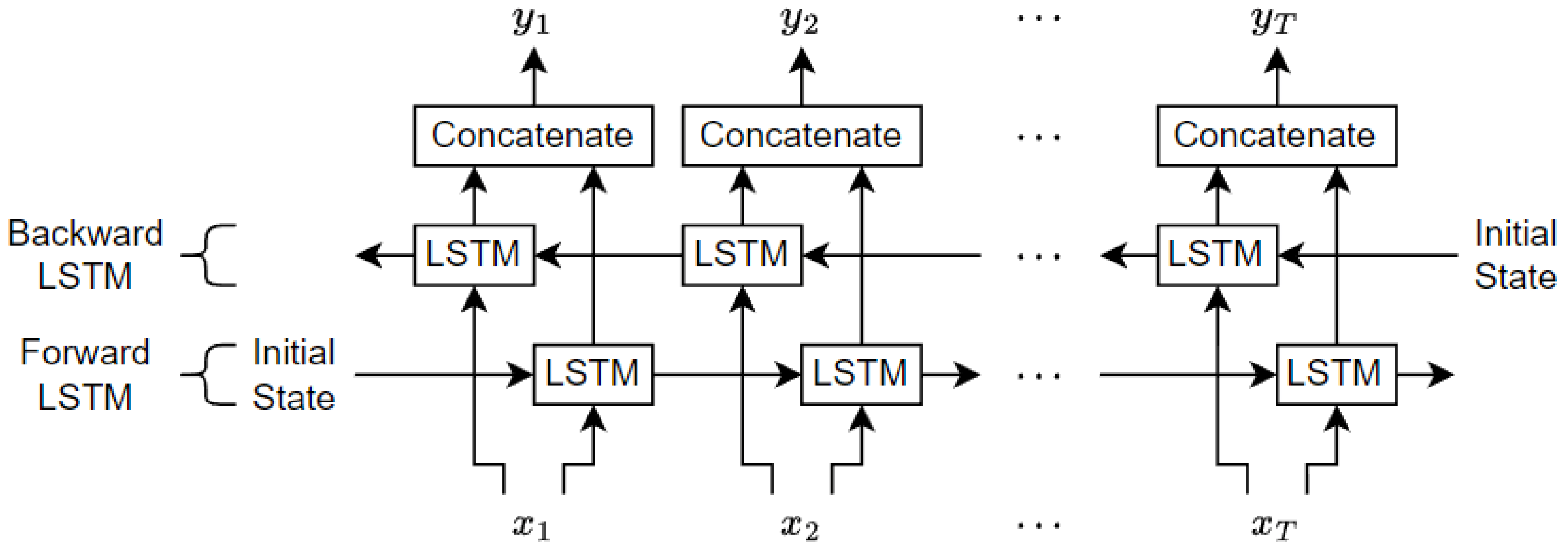


# RNNs: pro/cons

- 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

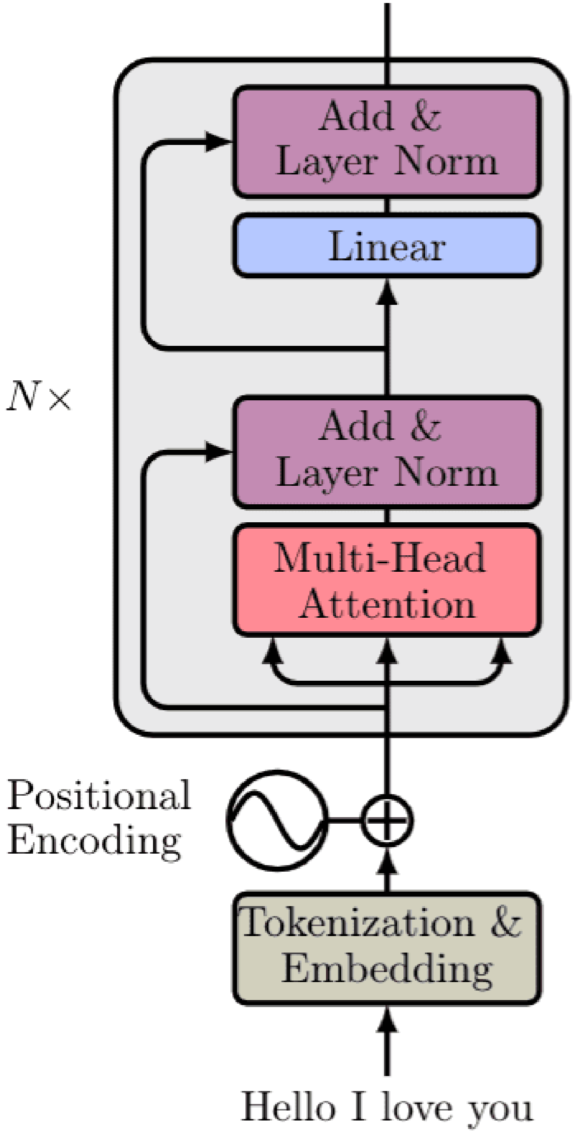
How many steps between source of info and current position?

- *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 $T_\theta$
- 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 whole input sequence $(e_1, \ldots, e_n)$

# Inside Transformers

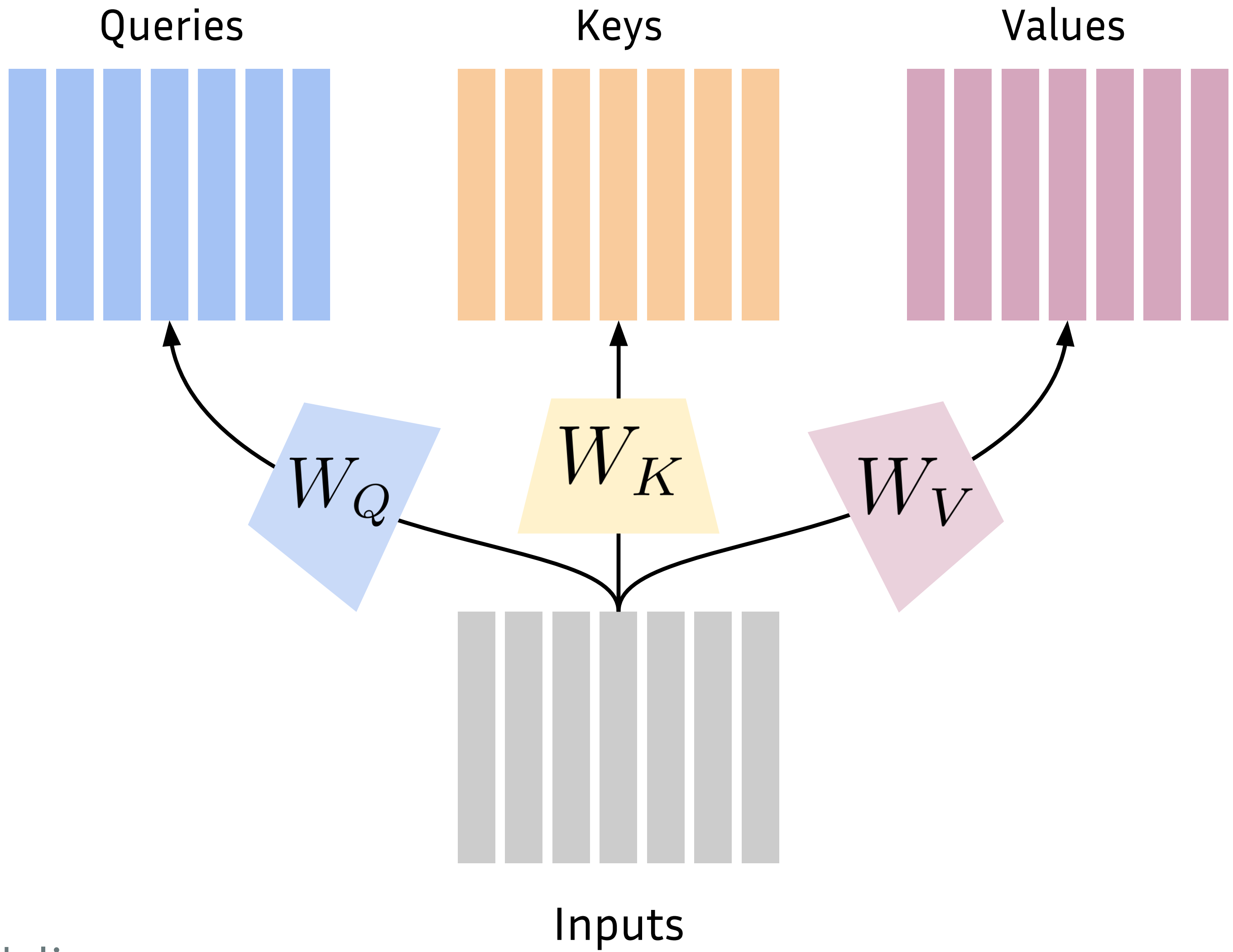


# Inside Transformers : Embeddings

Before going in the network:

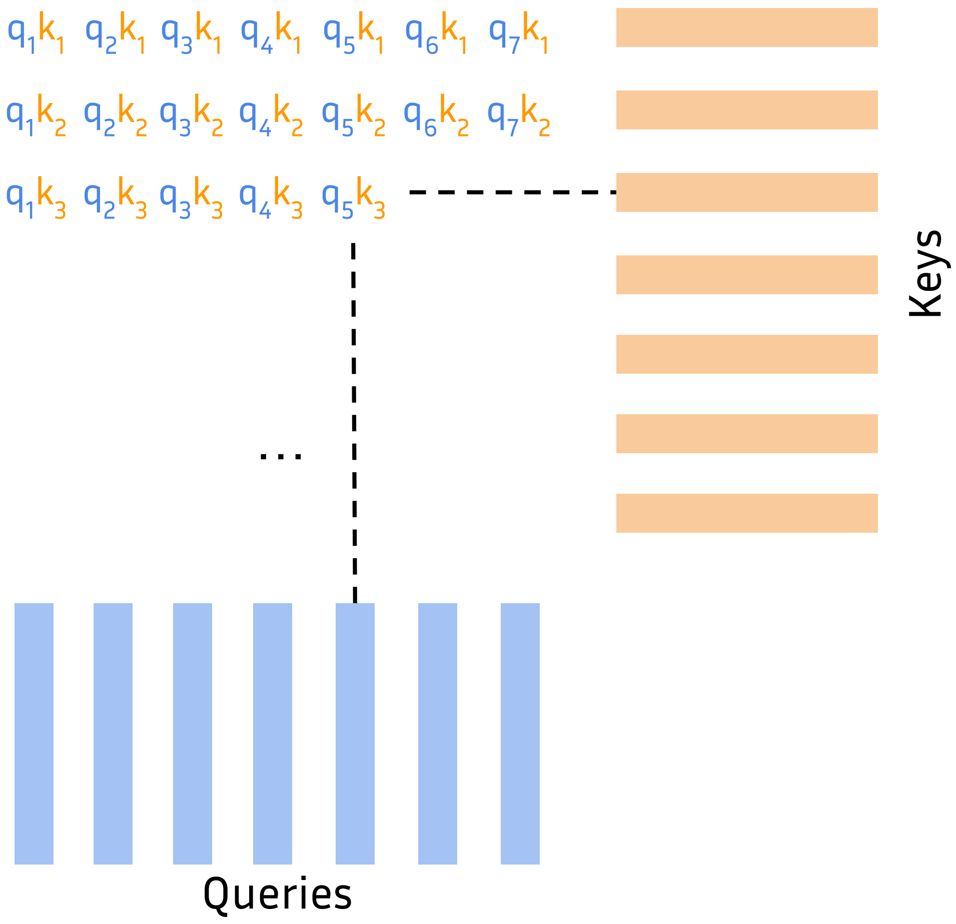
- Given an input token sequence $(w_1, \ldots, w_n)$
- We retrieve token embeddings $(e_w(w_1), \ldots, e_w(w_n)) \in \mathbb{R}^D$
- We retrieve position embeddings $(e_p(1), \ldots, e_p(n)) \in \mathbb{R}^D$
- We compute input embeddings: $e_i = e_w(w_i) + e_p(i)$

# Inside Transformers : Self-attention



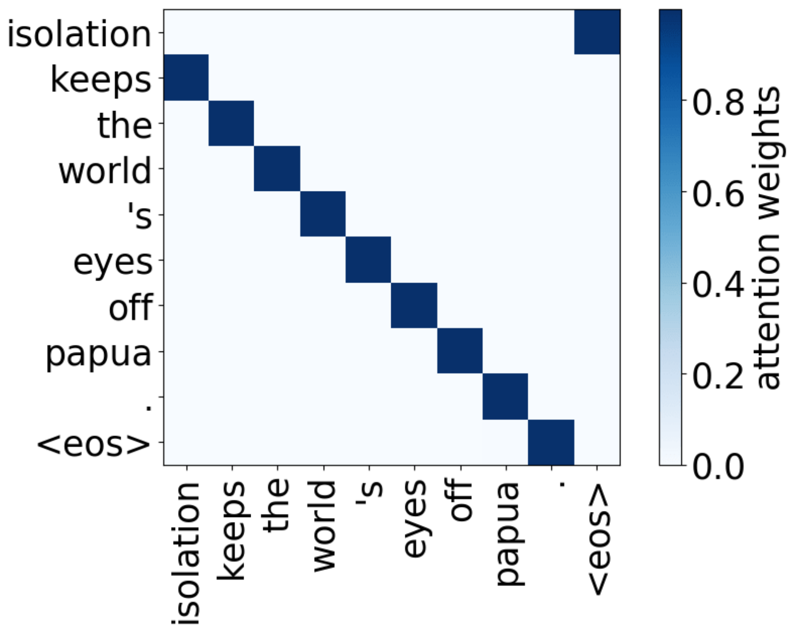
# Inside Transformers : Q and K

=> Model interactions between tokens:



# Inside Transformers : Q and K

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



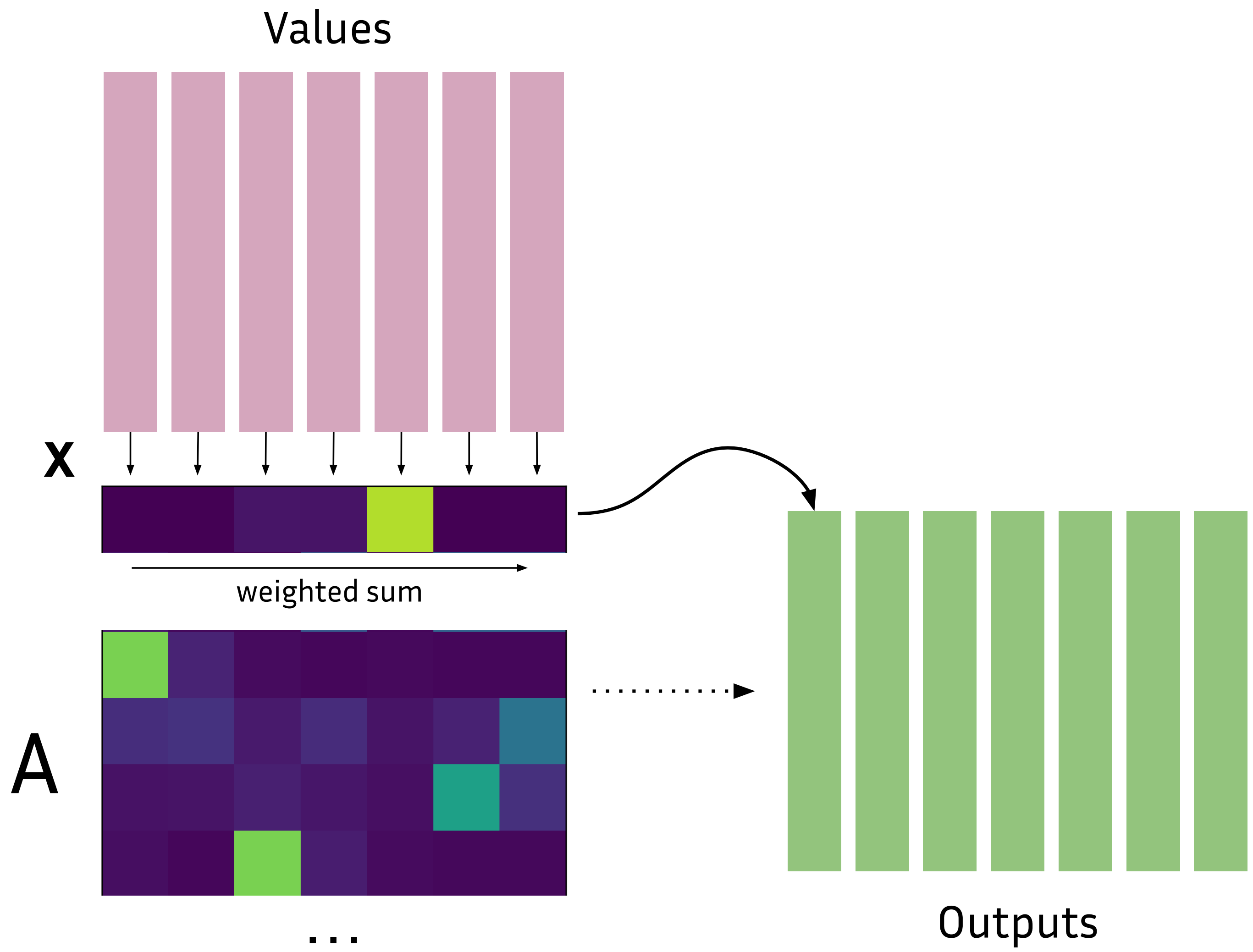
# Inside Transformers : Q and K

- Formally:

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

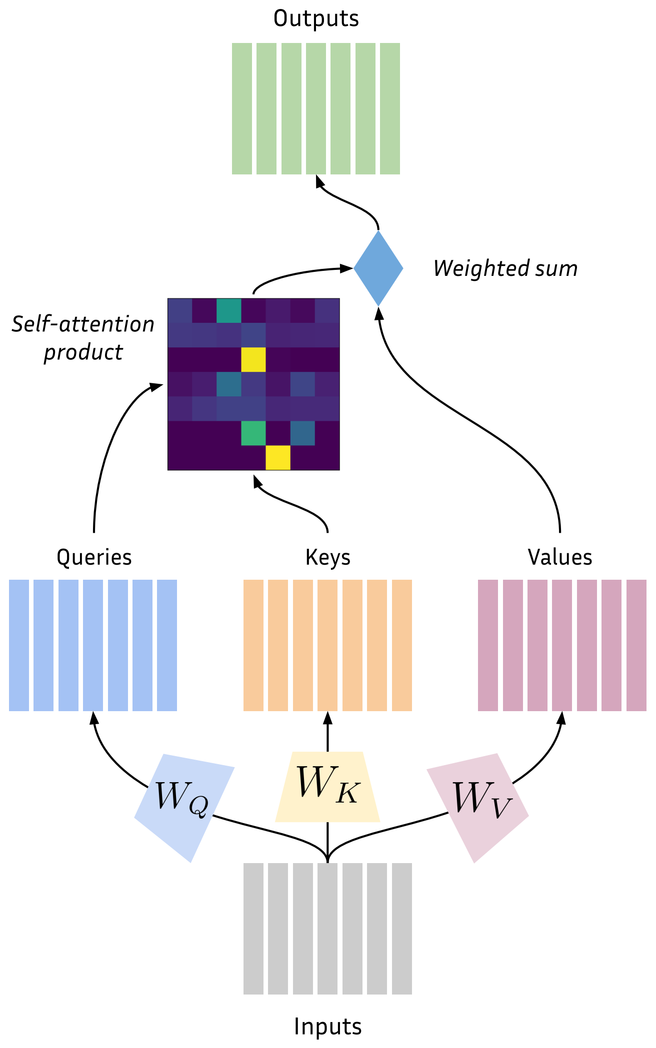
where $d_h$ is the hidden dimension of the model

# Inside Transformers : A and V

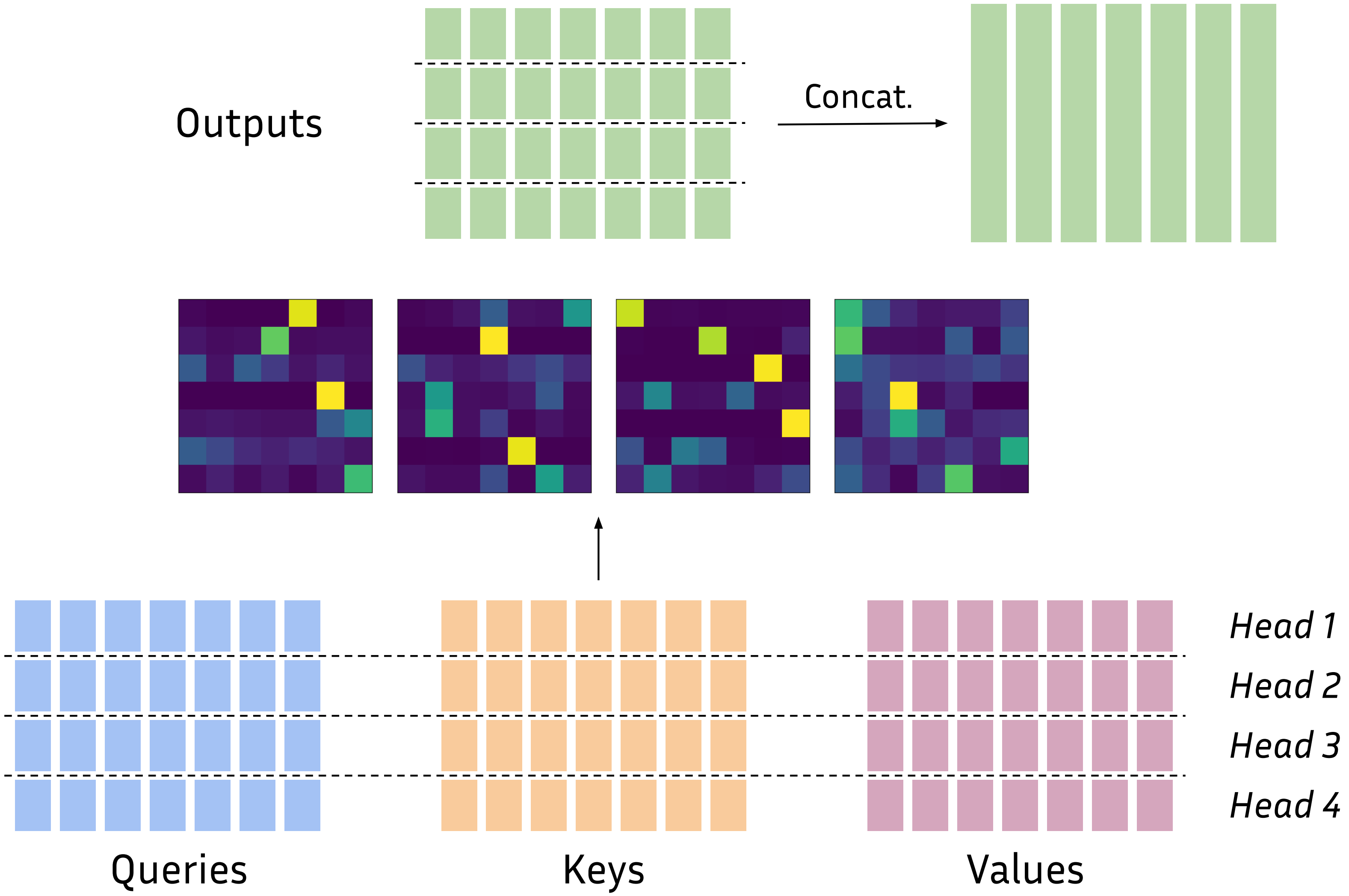


# Inside Transformers : Self-attention summary

- 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)**

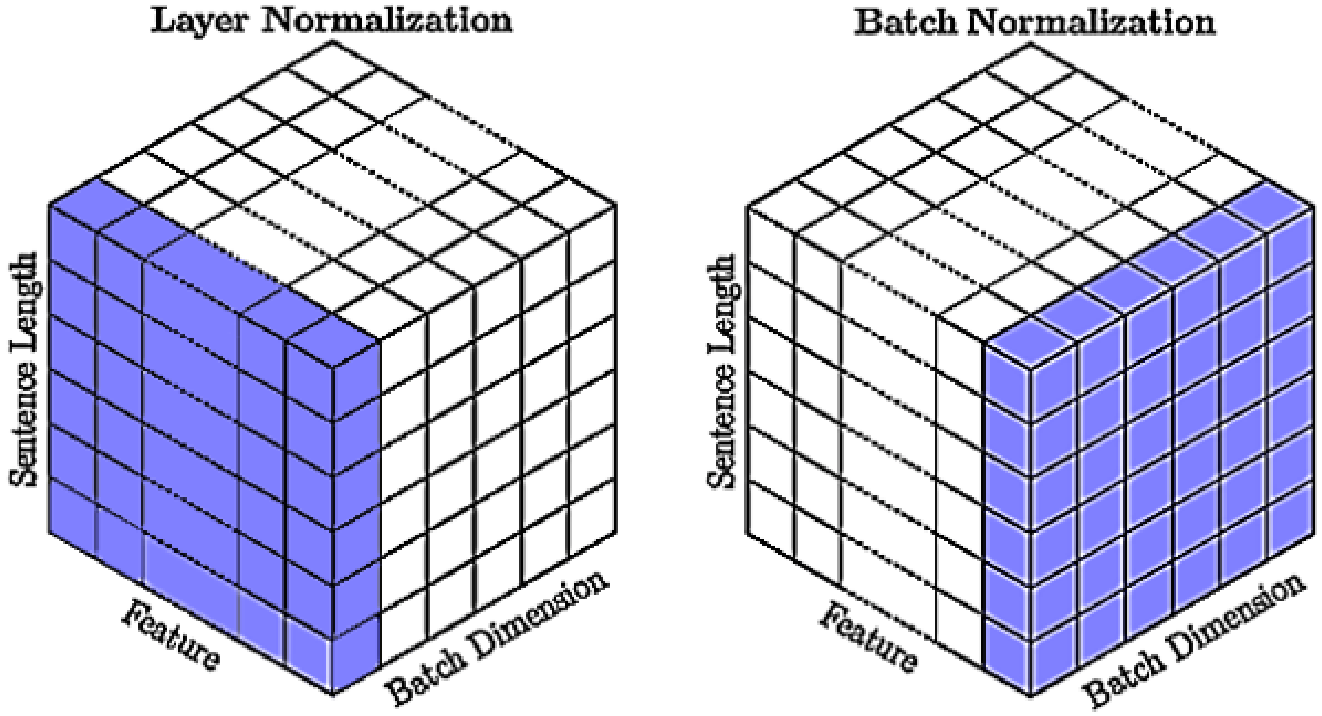


# Inside Transformers : Multi-head attention

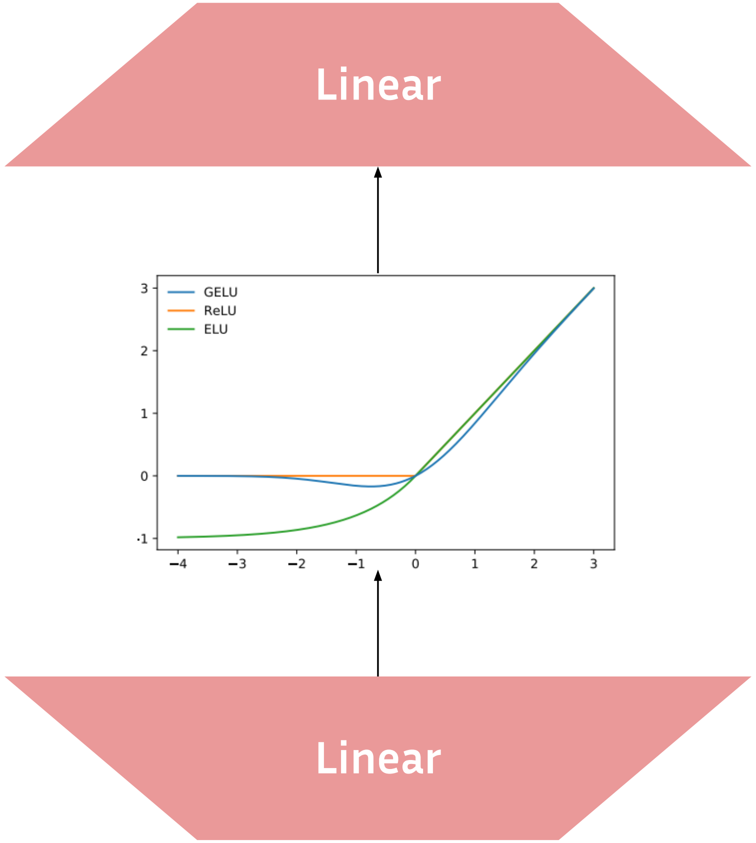


# Inside Transformers : LayerNorm

- Avoids gradient explosion

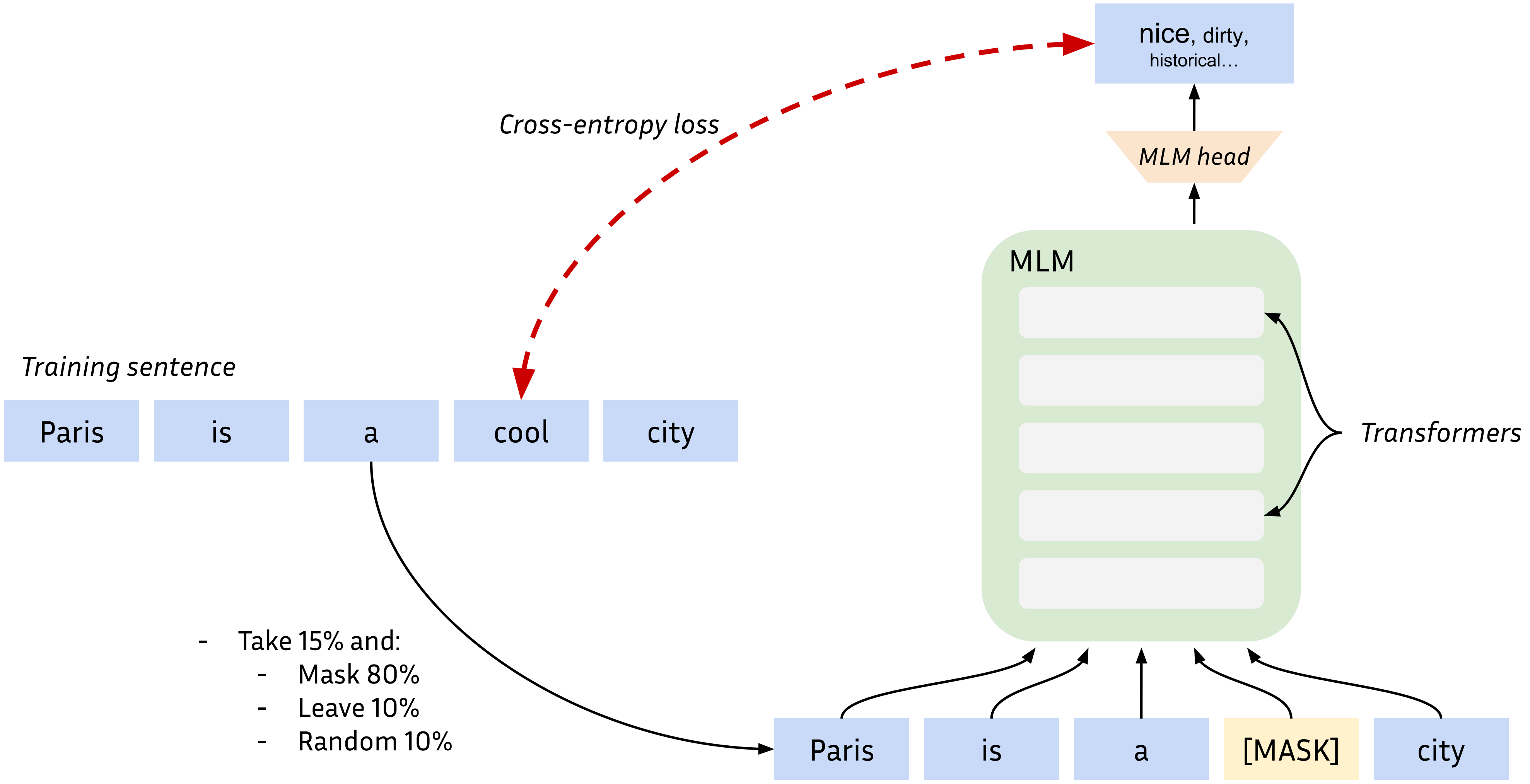


# Inside Transformers : Output layer



# Encoder Models

# Masked Language Models




- Take 15% and:
  - Mask 80%
  - Leave 10%
  - Random 10%

# BERT (Devlin et al., 2018)

- Pre-trained on 128B tokens from Wikipedia + BooksCorpus
- Additional Next Sentence Prediction (NSP) loss
- Two versions:
  - BERT-base (110M parameters)
  - BERT-large (350M parameters)
- **Cost**: ~1000 GPU hours

# RoBERTa (Liu et al., 2019)

- Pre-trained on ~~128B~~ **2T** tokens from web data (BERT x10)
- **No more** Next Sentence Prediction (NSP) loss
- Two versions:
  - RoBERTa-base (110M parameters)
  - RoBERTa-large (350M parameters)
- Better results in downstream tasks
- **Cost**: ~25000 GPU hours

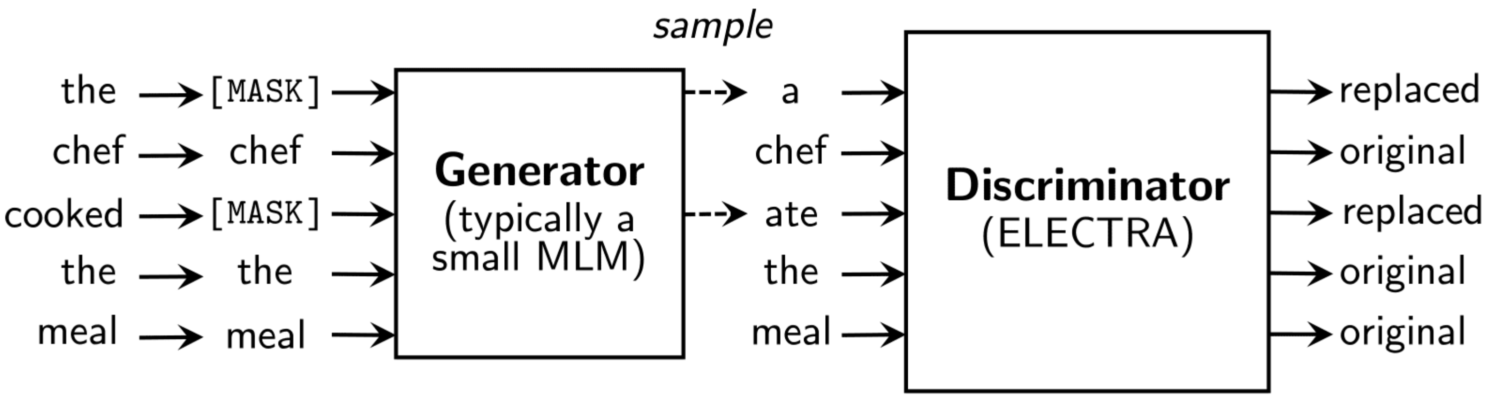
# Multilingual BERT (mBERT)

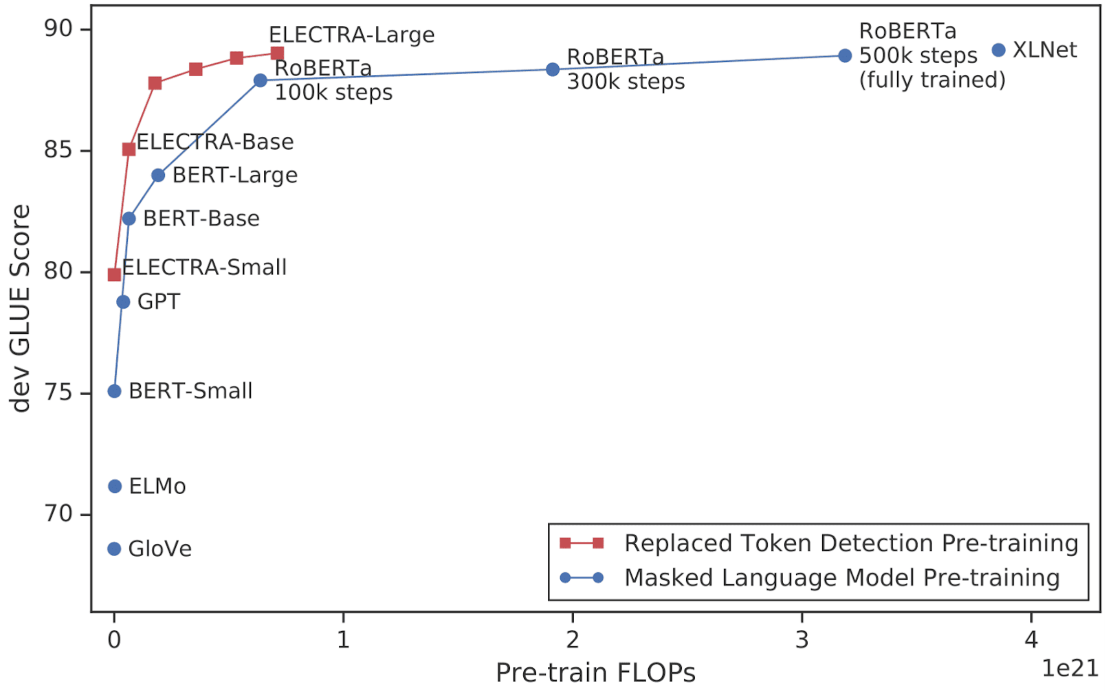
- Pre-trained on 128B tokens from multilingual Wikipedia
- 104 languages
- One version:
  - mBERT-base (179M parameters)
- **Cost**: *unknown*

# XLM-RoBERTa (Conneau et al., 2019)

- Pre-trained on **63T** tokens from CommonCrawl
- 100 languages
- Two versions:
  - XLM-RoBERTa-base (279M parameters)
  - XLM-RoBERTa-large (561M parameters)
- **Cost**: ~75000 GPU hours

# ELECTRA (Clark et al., 2020)

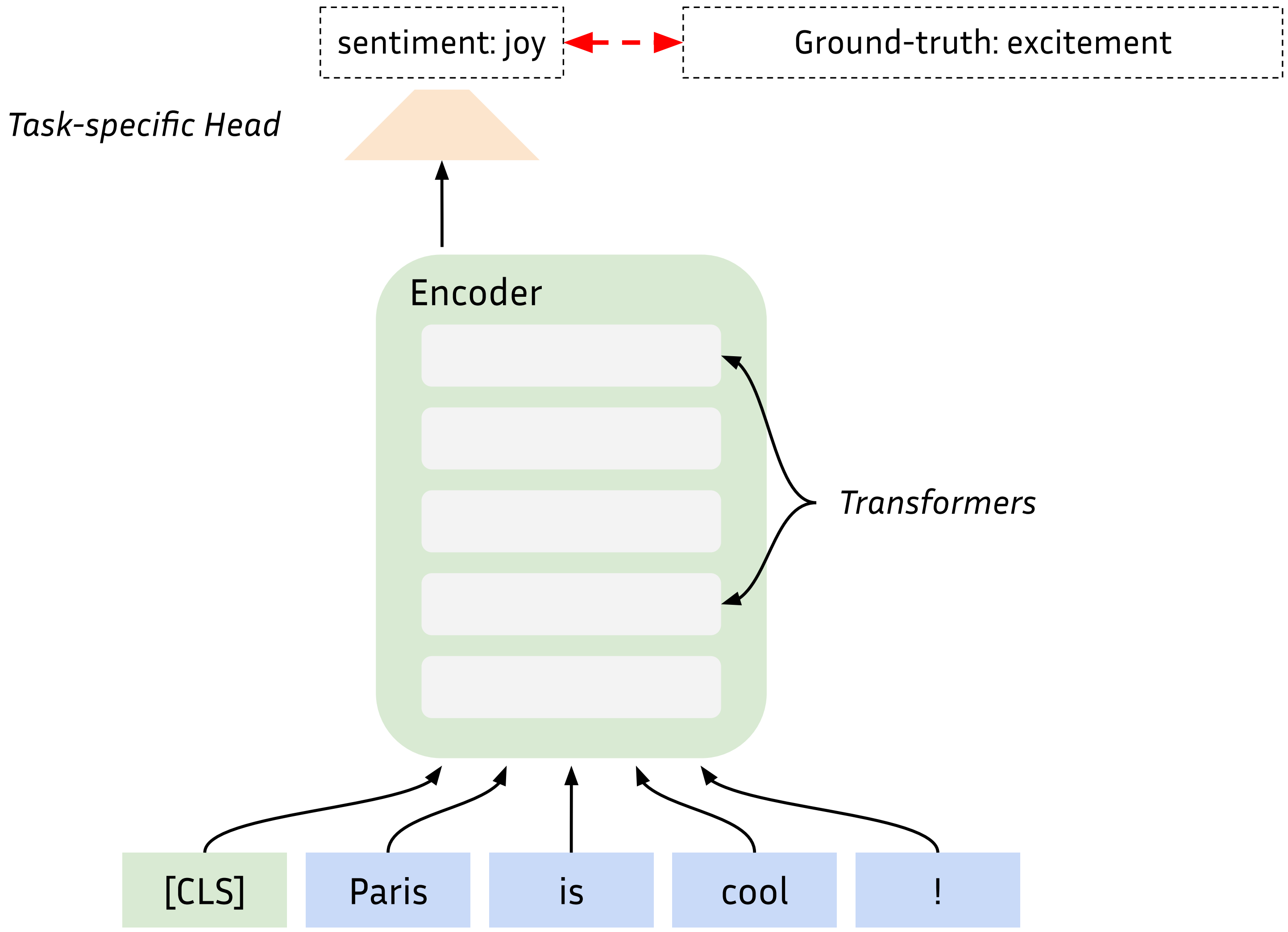


# ELECTRA (Clark et al., 2020)

- Pre-trained on **63T** tokens from CommonCrawl
- 100 languages
- Three versions:
  - ELECTRA-small (14M parameters)
  - ELECTRA-base (110M parameters)
  - ELECTRA-large (350M parameters)
- Really better than BERT/RoBERTa
- **Cost**: =BERT

# Encoders: Fine-tuning



# Encoders: Classical applications

- Natural Language Inference (NLI)
  - *I like cake! / Cake is bad* => ~~same~~|~~neutral~~|**opposite**
- Text classification (+ clustering)
  - *I'm so glad to be here!* => joy
- Named Entity Recognition (NER)
  - *I voted for Obama!* => (Obama, pos:3, class:PER)
- and many others...

# Decoders

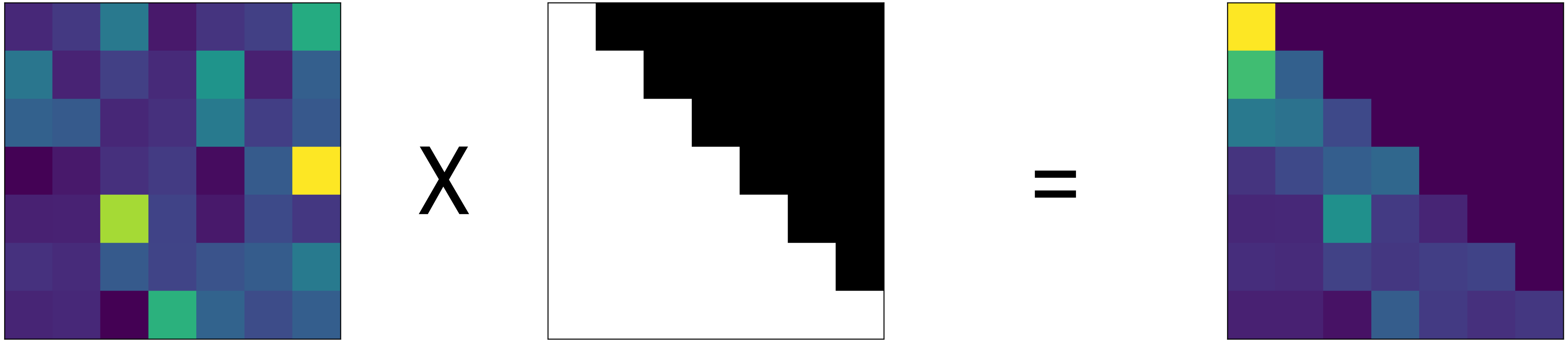
# Decoders - Motivation

- Models that are designed to **generate text**
- Next-word predictors:

$$P(w_i \,|(w_j)_{j\neq i}) = P_\theta(w_i|w_1 \ldots w_{i-1})$$

- **Problem**: How do we impede self-attention to consider future tokens?

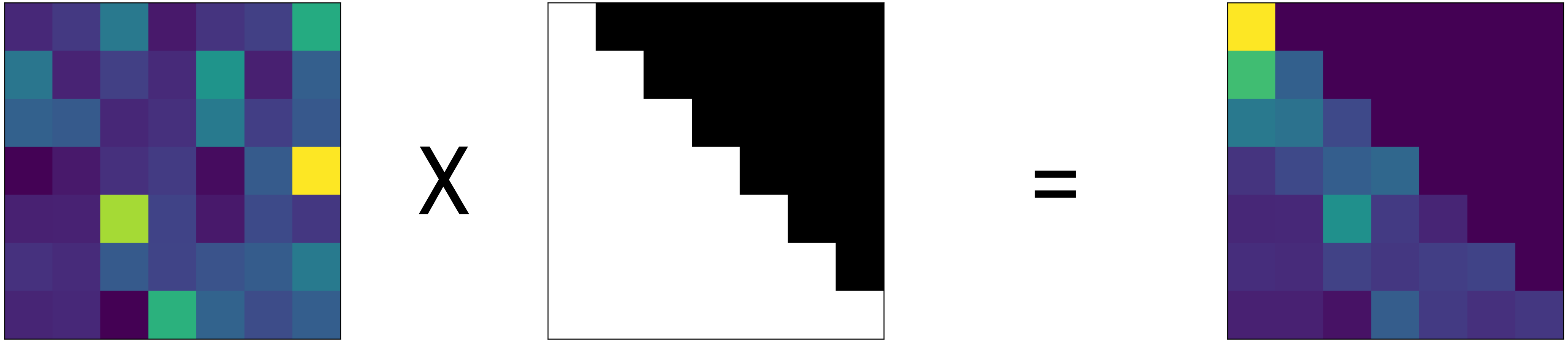
# Decoders - Attention mask




*Attention* *Attention mask* ***Causal** attention*

- Each attention input can only attend to previous positions

# Decoders - Attention mask




*Attention* *Attention mask* ***Causal** attention*

- Each attention input can only attend to previous positions