womentech GLOBAL CONFERENCE

7-10 June 2022

Attention? Attention!

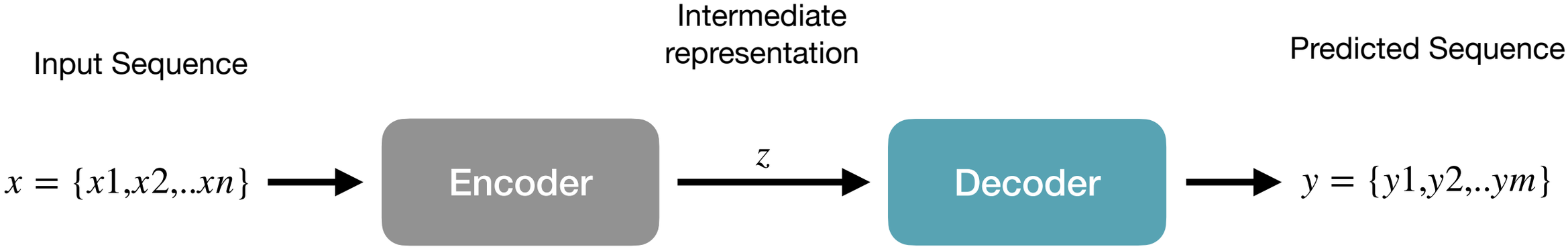
- Attention Mechanism in Deep Learning

Nicole Königstein

Outline

- Background
- Types of attention
- Soft and multi-head attention
- Practical examples

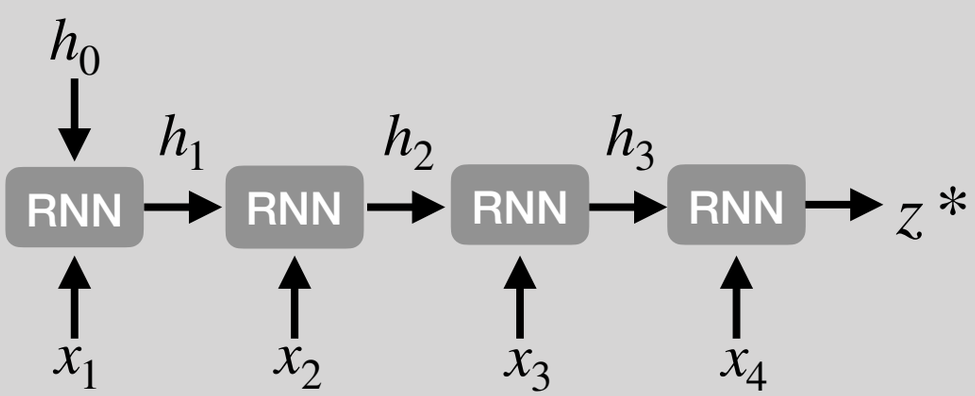
Sequence to Sequence Learning



High-level view of encoder and decoder

Encoder

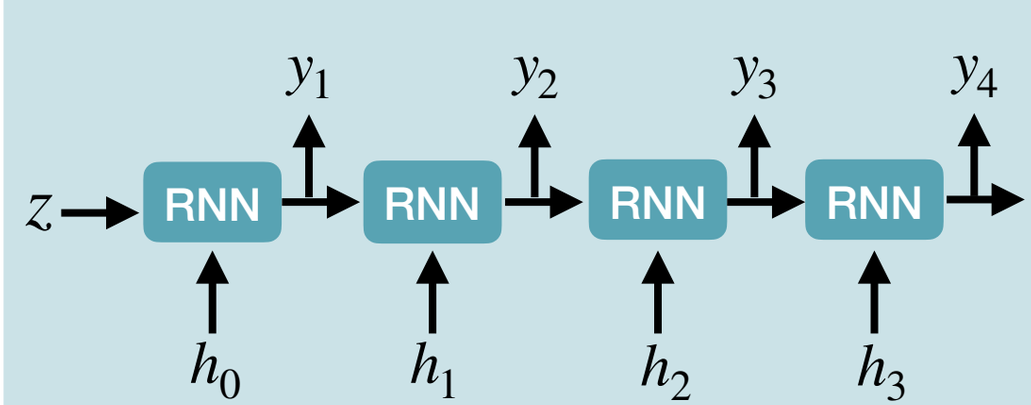
Sequential Data Processing



Note: each RNN block **requires** the output of the **previous**

Decoder

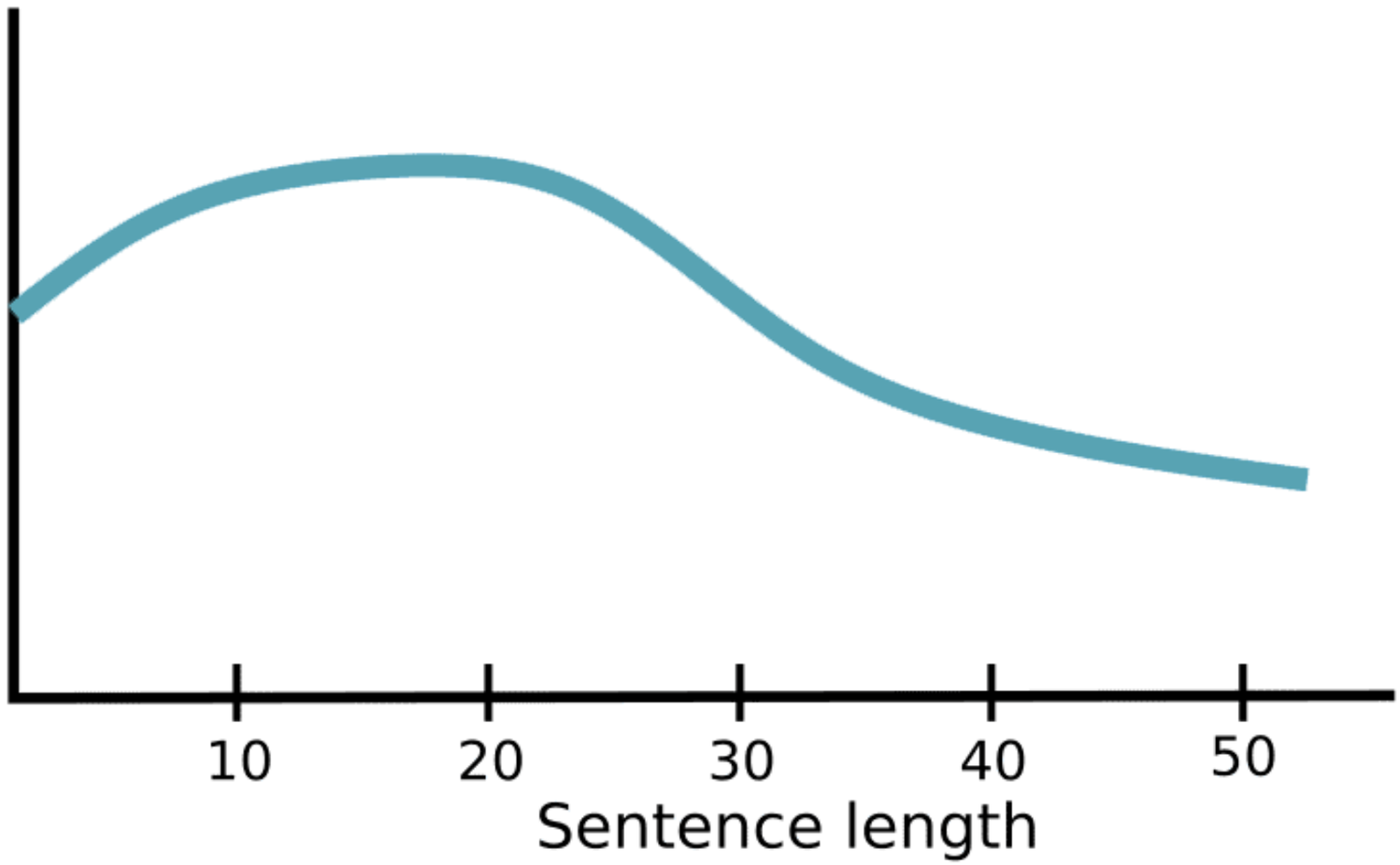
Output Tokens



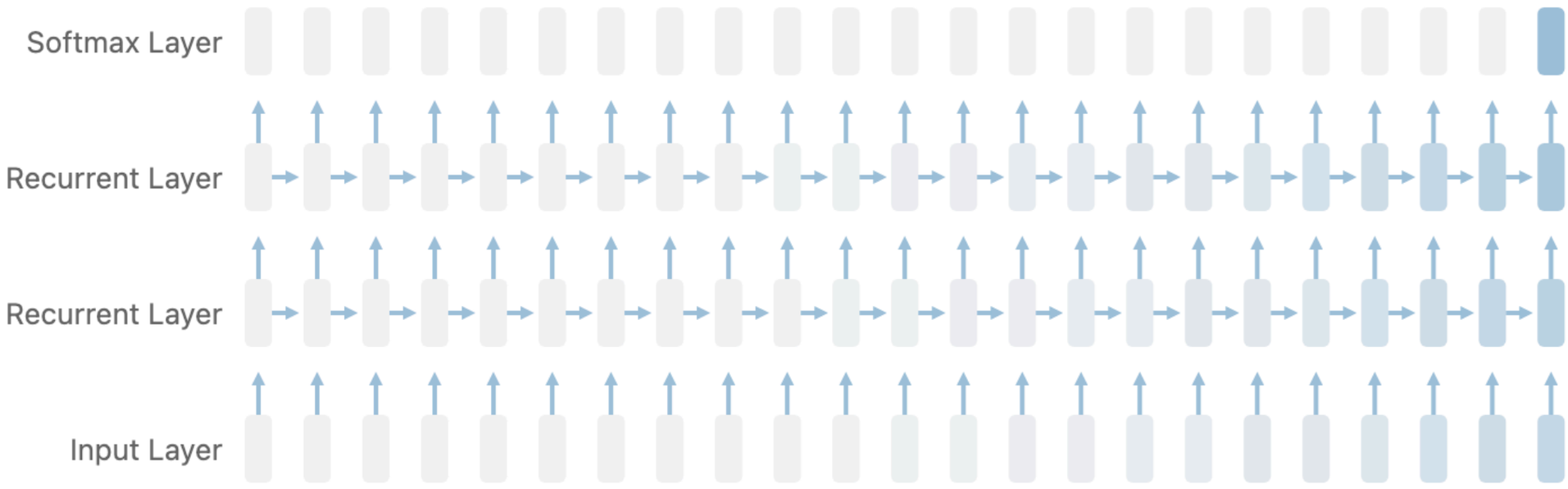
Note: predictions **MUST** be performed **sequentially**

* Encoded sequence representation

Memorization in RNNs



Visualizing memorization in RNNs



Vanishing Gradient: where the contribution from the earlier steps becomes insignificant in the gradient for the RNN.

Image source: https://distill.pub/2019/memorization-in-rnns/

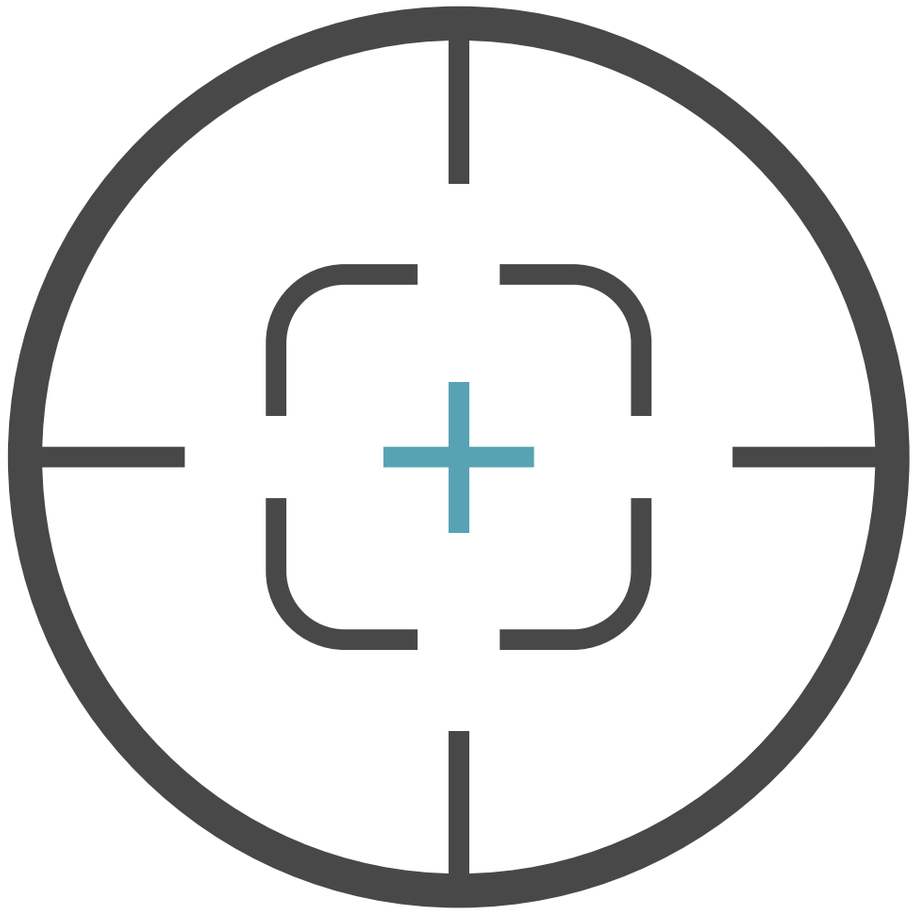
Memory is attention through time.

~ Alex Graves 2020*

*Alex Graves is a research scientist at DeepMind.

Human attention

“Humans seldom utilize all available inputs to complete a task.”



Attention Types

- Soft attention
- Hard attention
- Global attention
- Local attention
- Self-attention

Attention Types - Soft vs. Hard Attention

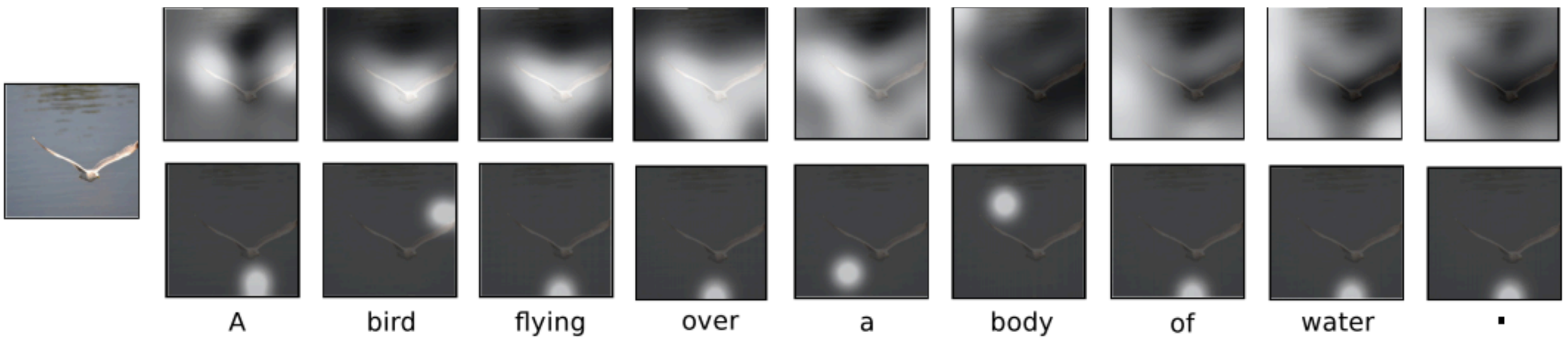
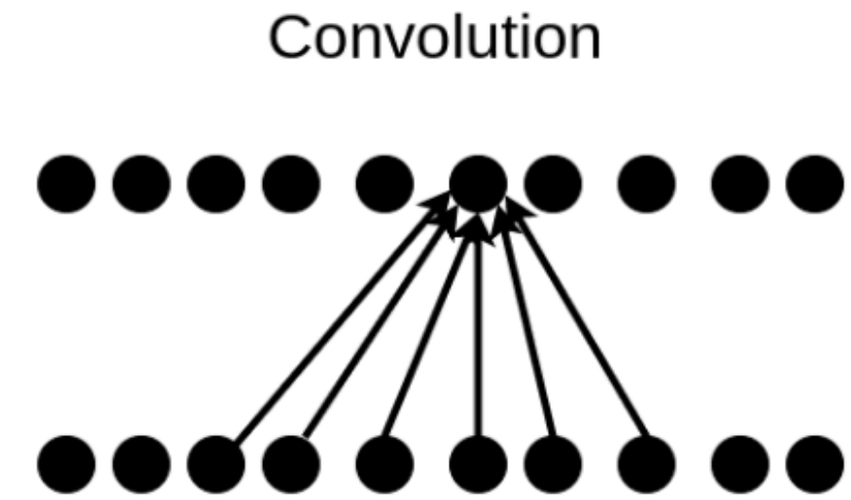
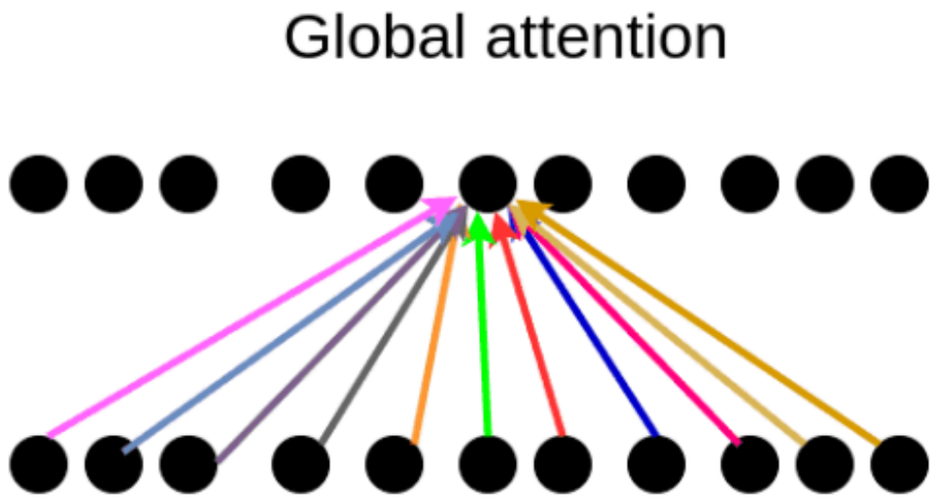
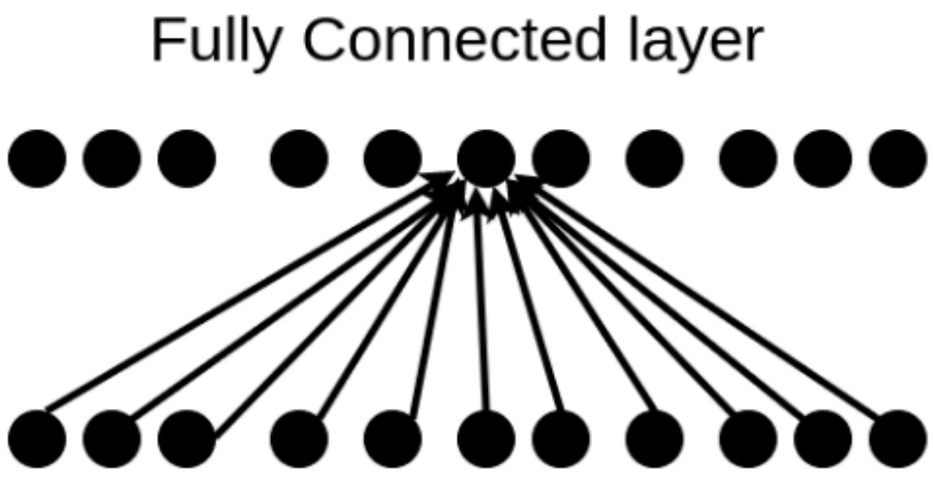


Image source: Fig. 6(b) in Xu et al. 2015

Attention Types - Global vs. Local Attention







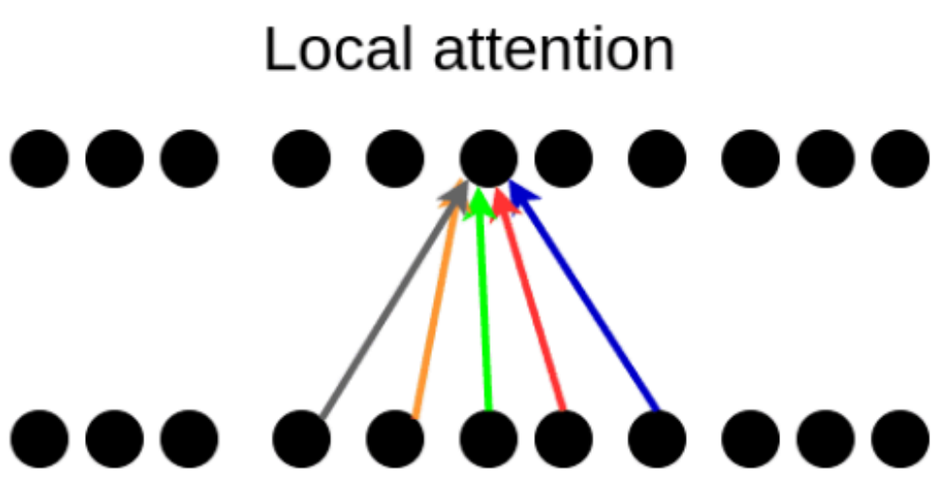


Image source: https://theaisummer.com/attention/

Self-Attention

Self-Attention

Probability Score Matrix

	This	movie	was	not	bad
This	0.65	0.1	0.05	0.05	0.15
movie	0.1	0.5	0.1	0.05	0.25
was	0.05	0.2	0.45	0.1	0.2
not	0.2	0.1	0.05	0.05	0.6
bad	0.05	0.1	0.05	0.2	0.6

Softmax (Attention) equation

Self-Attention Basics

- Input: sequence of tensors $x_1, x_2, \ldots x_t$
- Output: sequence of tensors, each one a weighted sum of the input sequence $y_1, y_2, \ldots y_t$, $\mathbf{y}_i = \sum_j w_{ij} \mathbf{x}_j$

x_i and $x_j \longrightarrow w'_{ij} = x_i^\top x_j$

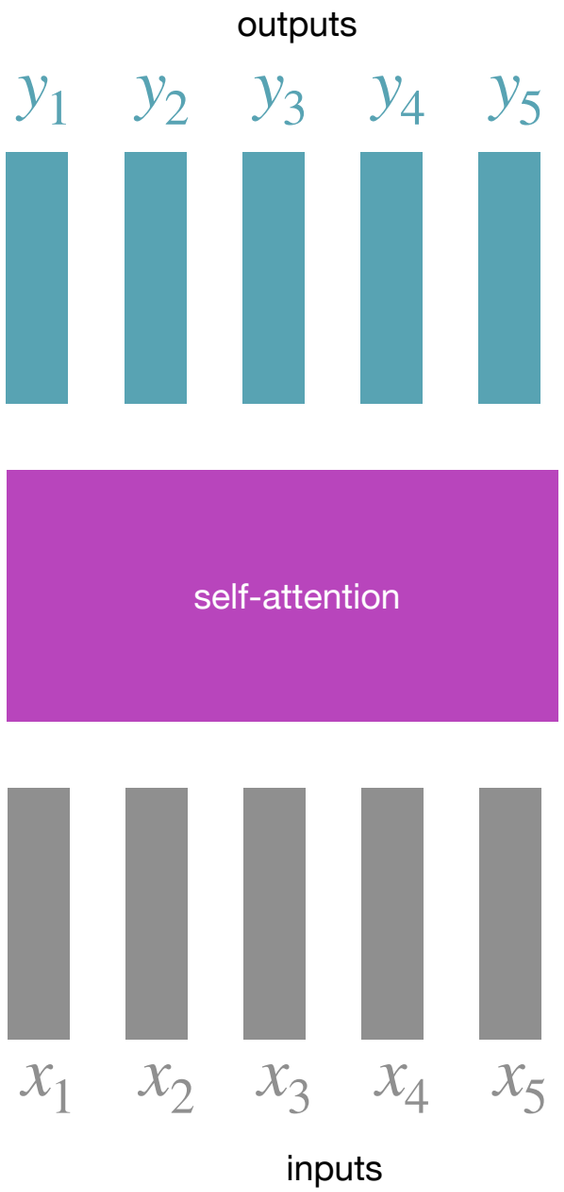
dot product

weighted average

$$w_{ij} = \frac{\exp w'_{ij}}{\sum_j \exp w'_{ij}}$$

http://peterbloem.nl/blog/transformers

Self-Attention Basics



$$y_i = \sum_j w_{ij} x_j$$

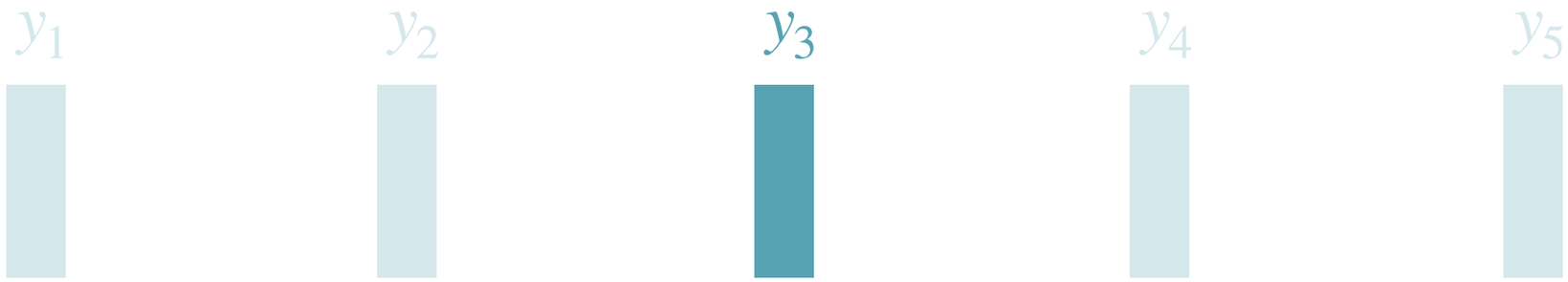
Self-Attention Basics

$$y_i = \sum_j w_{ij} x_j$$

$$w'_{ij} = \mathbf{x}_i^\top \mathbf{x}_j$$

$$w_{ij} = \frac{\exp w'_{ij}}{\sum_j \exp w'_{ij}}$$

Self-Attention Basics



Self-Attention Basics

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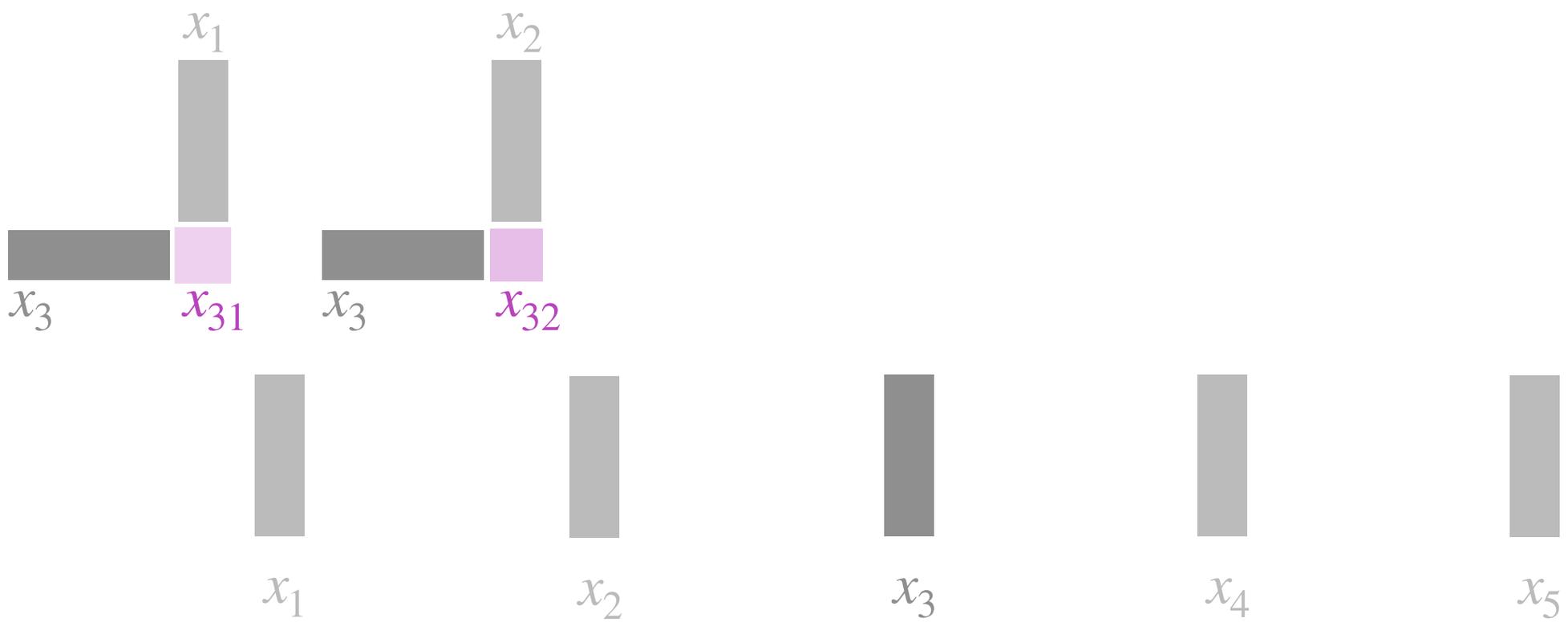

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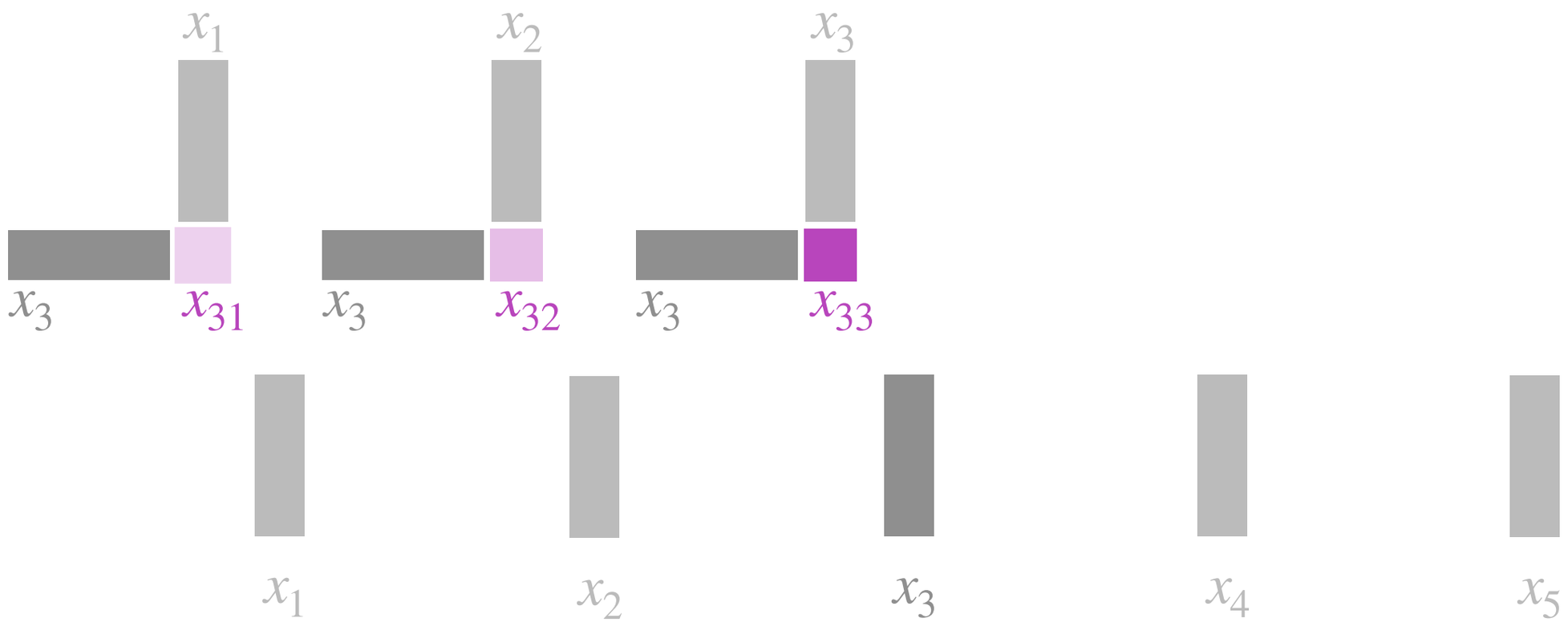

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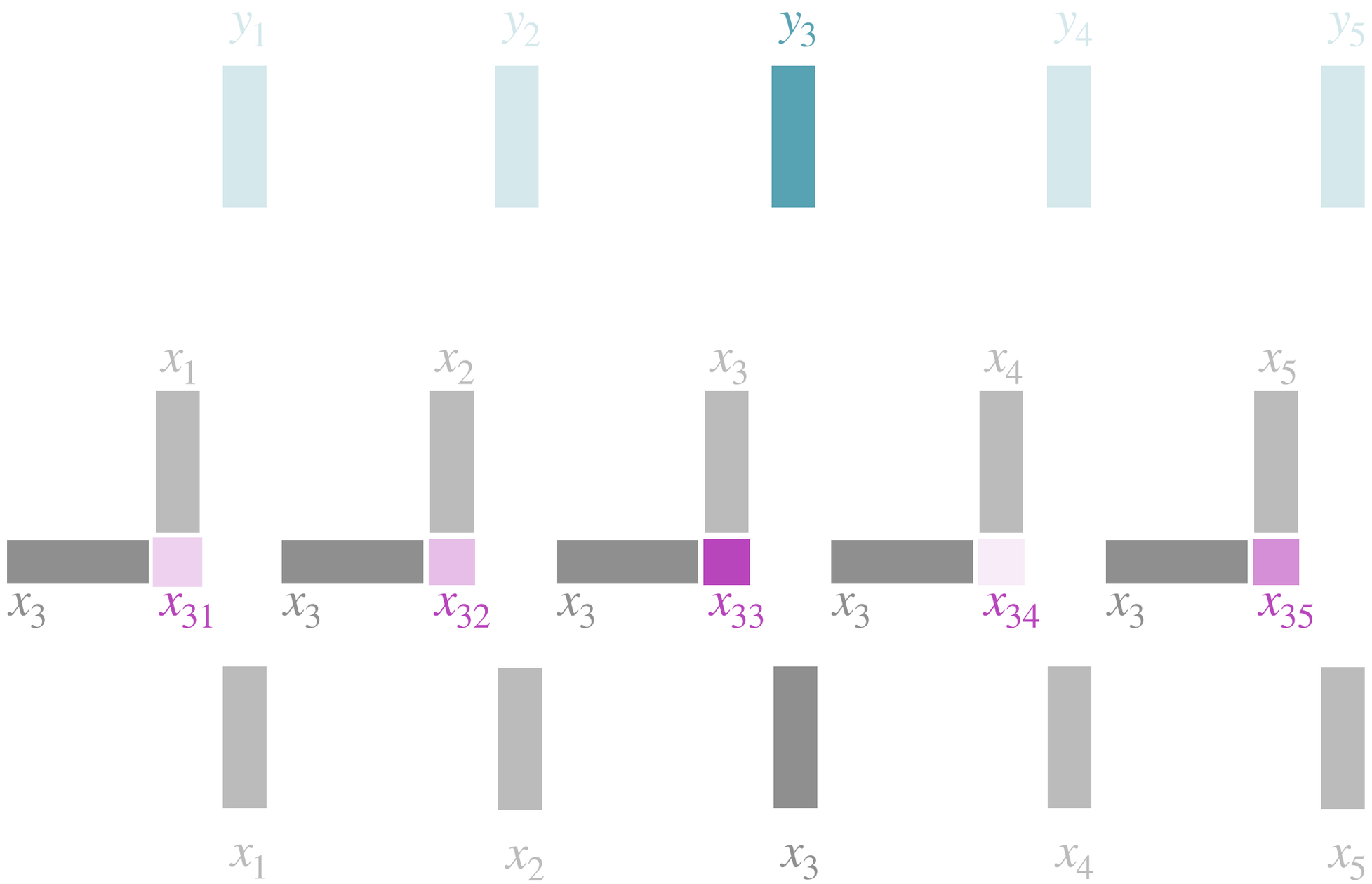

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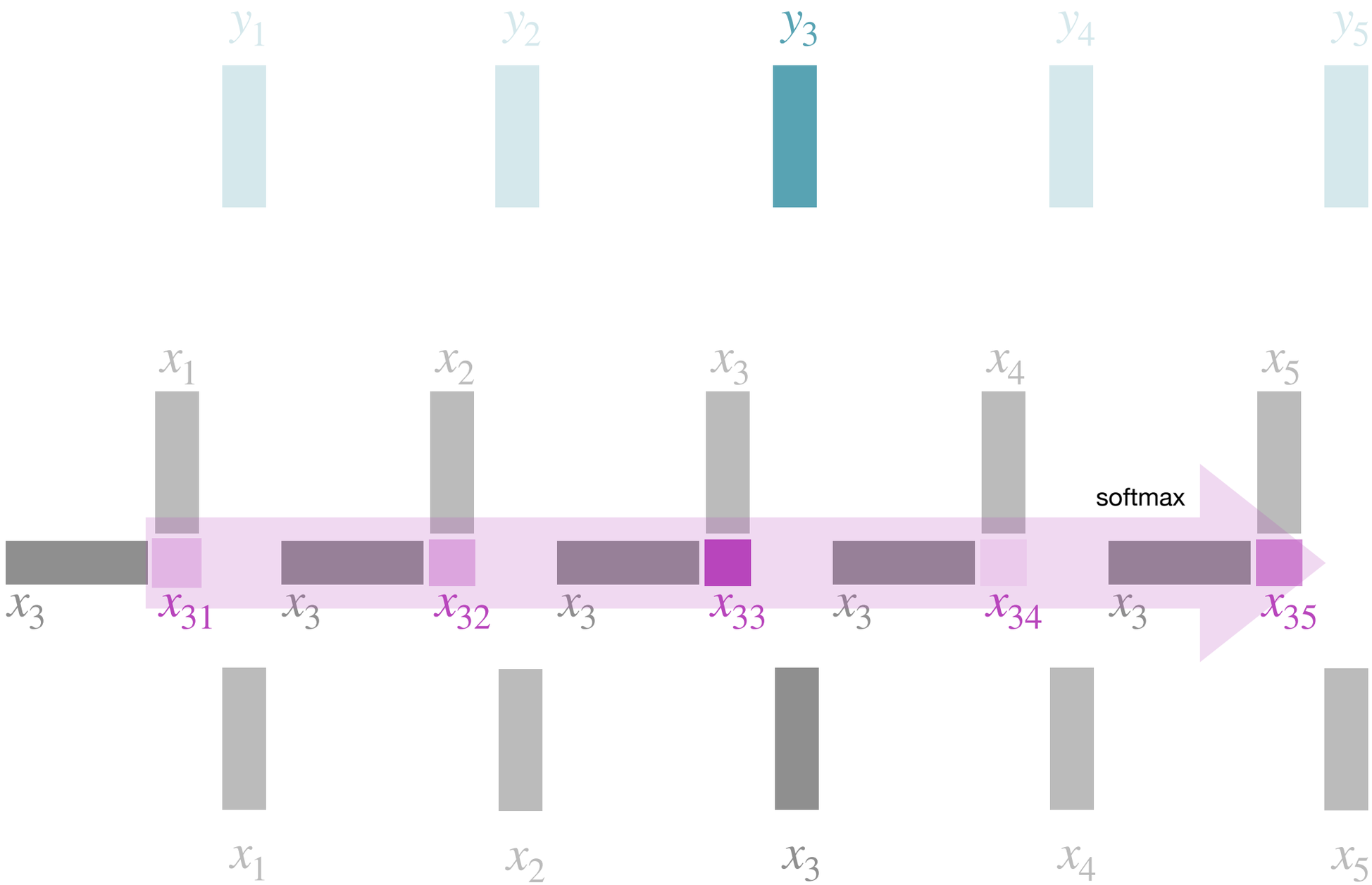

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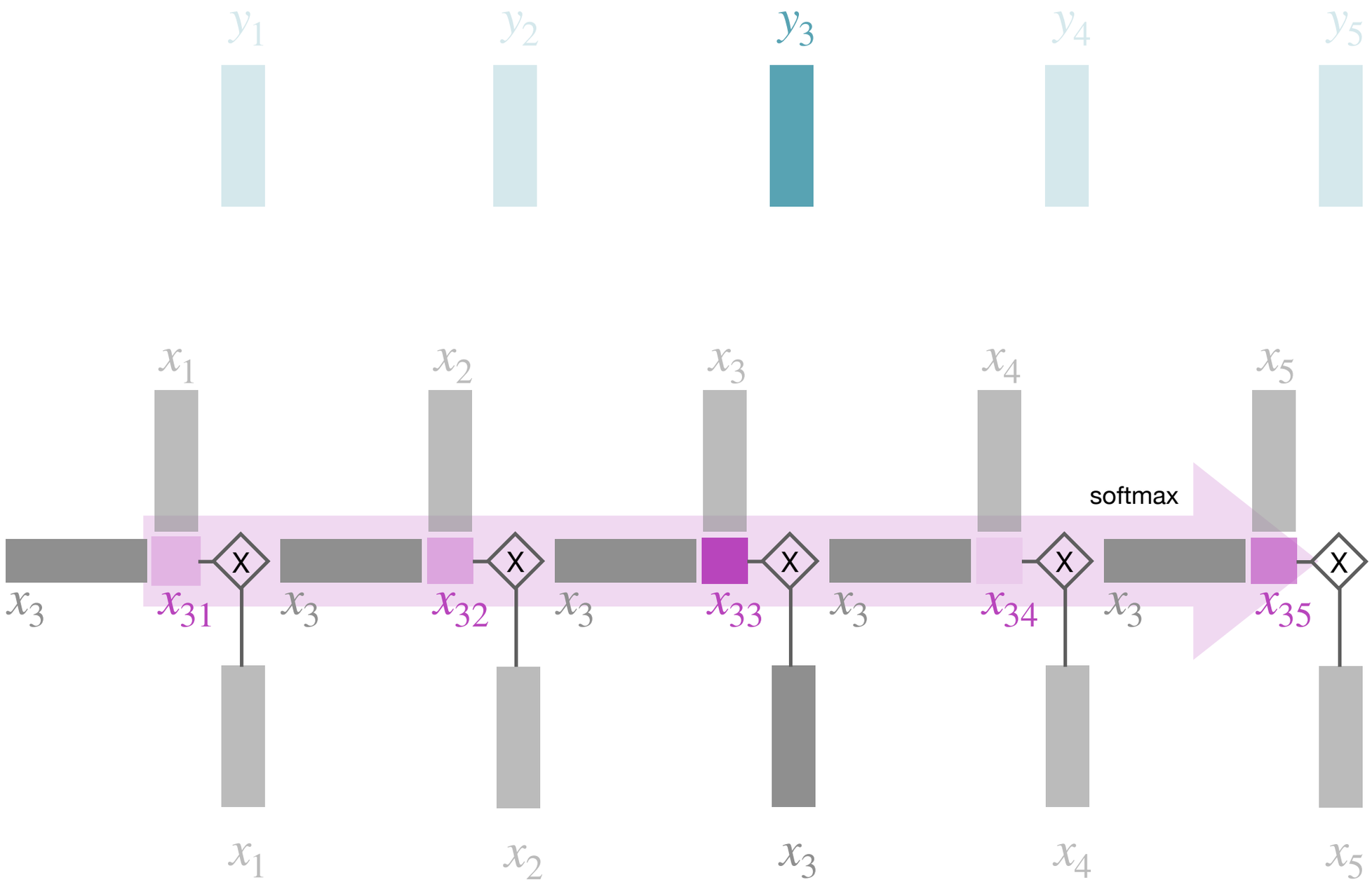

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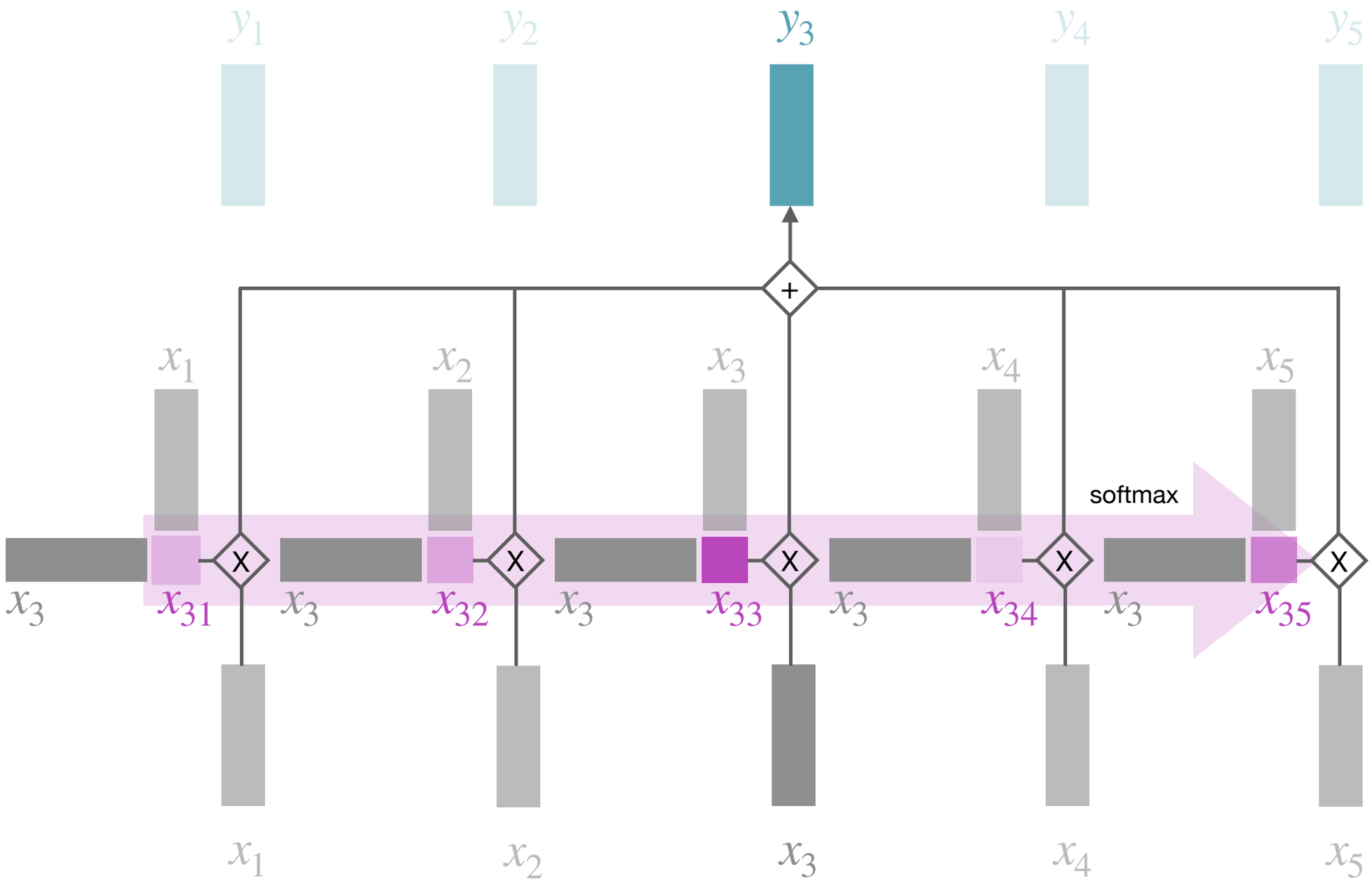
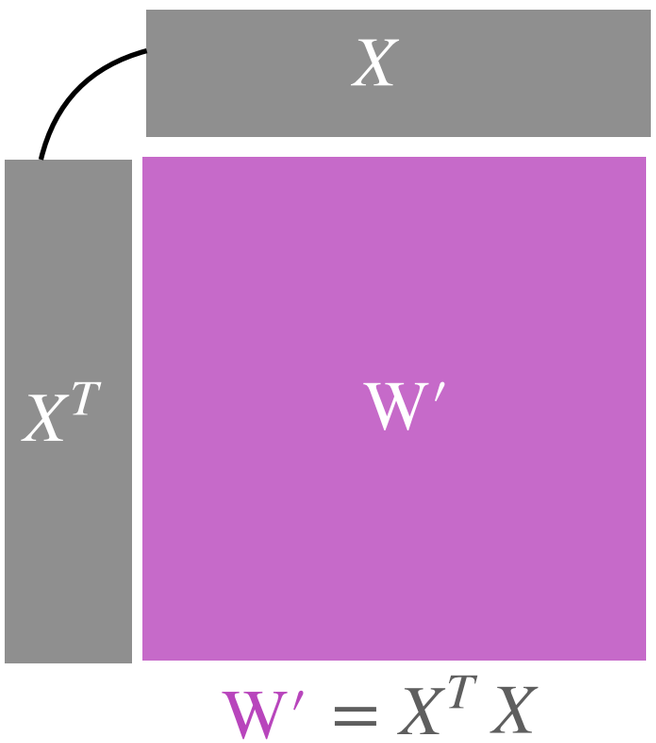
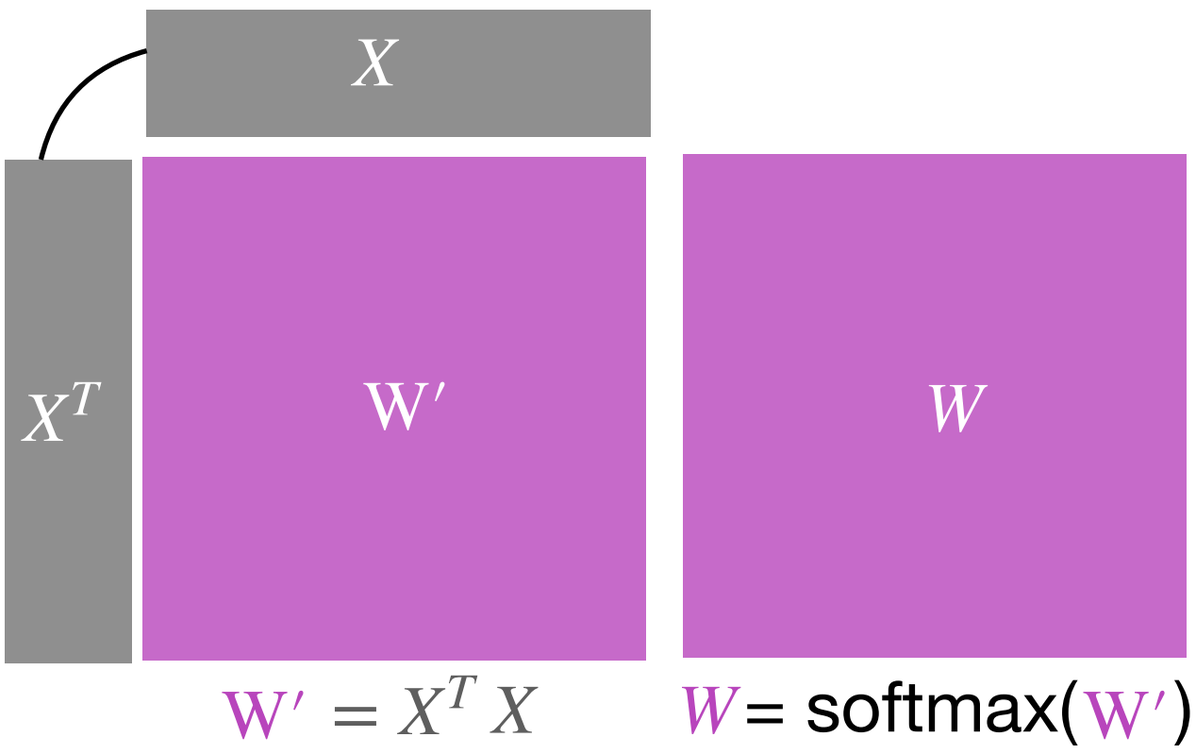


Self-Attention Basics



Vectorized version

Self-Attention Basics



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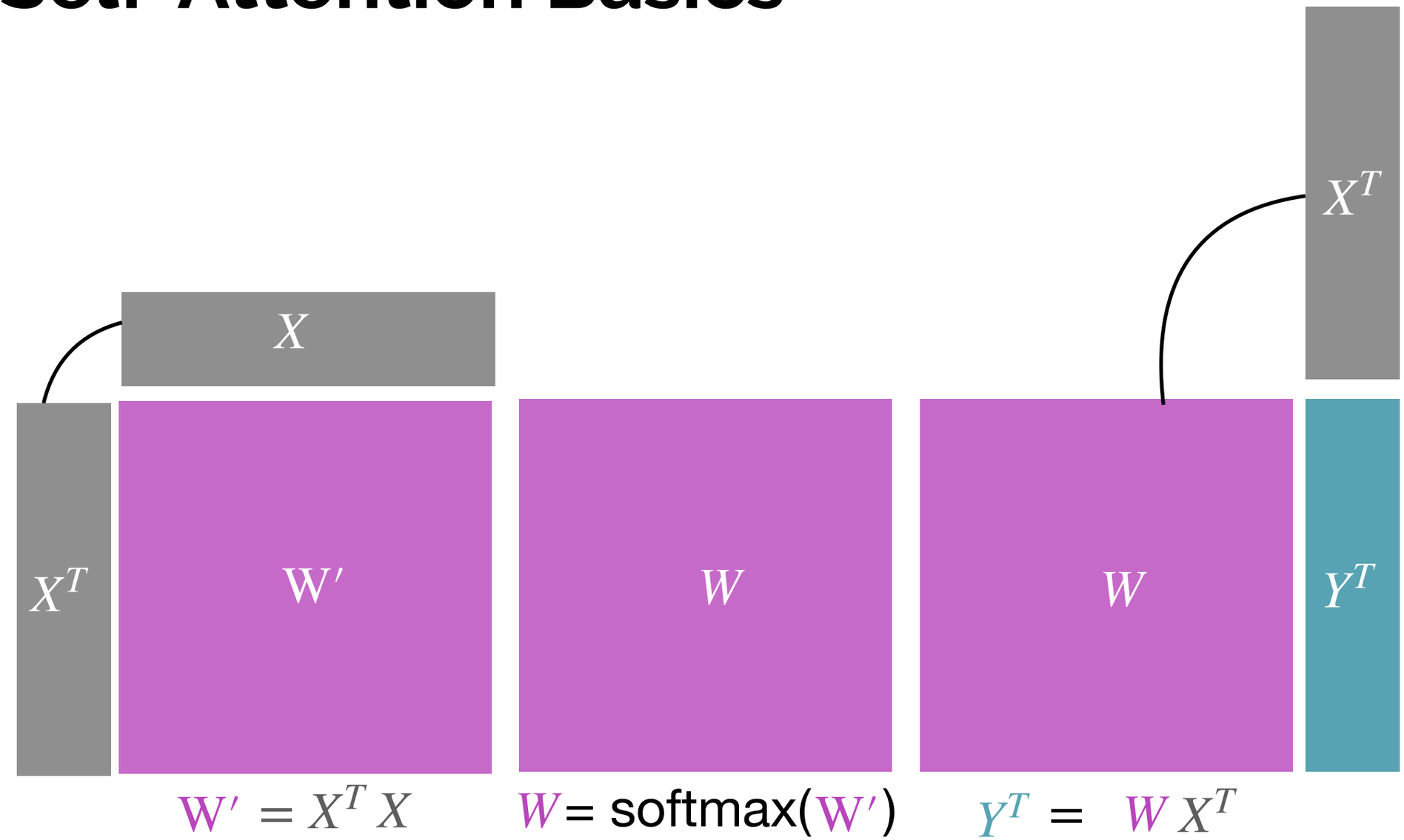
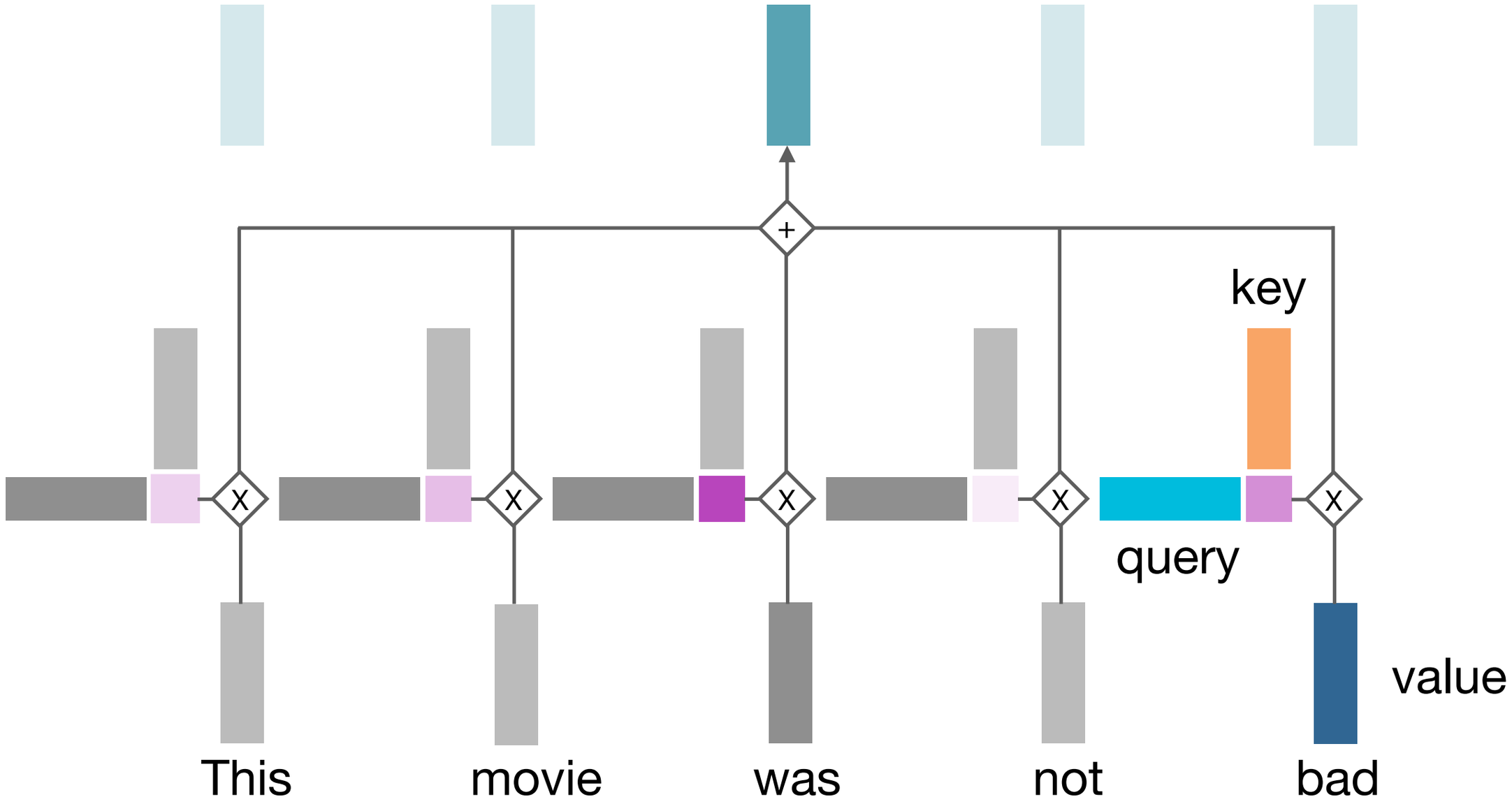


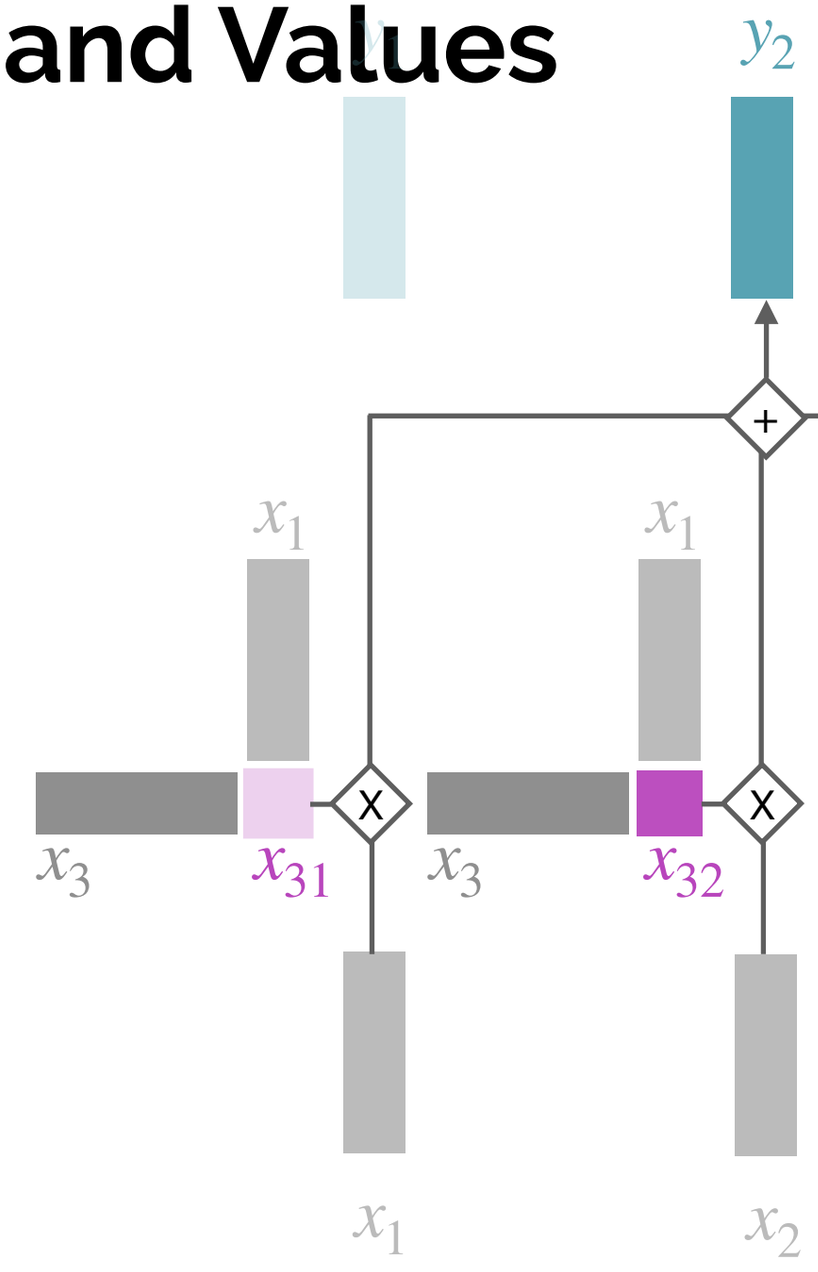
Vectorized version

Self-Attention: Keys, Queries and Values



Self-Attention: Keys, Queries and Values

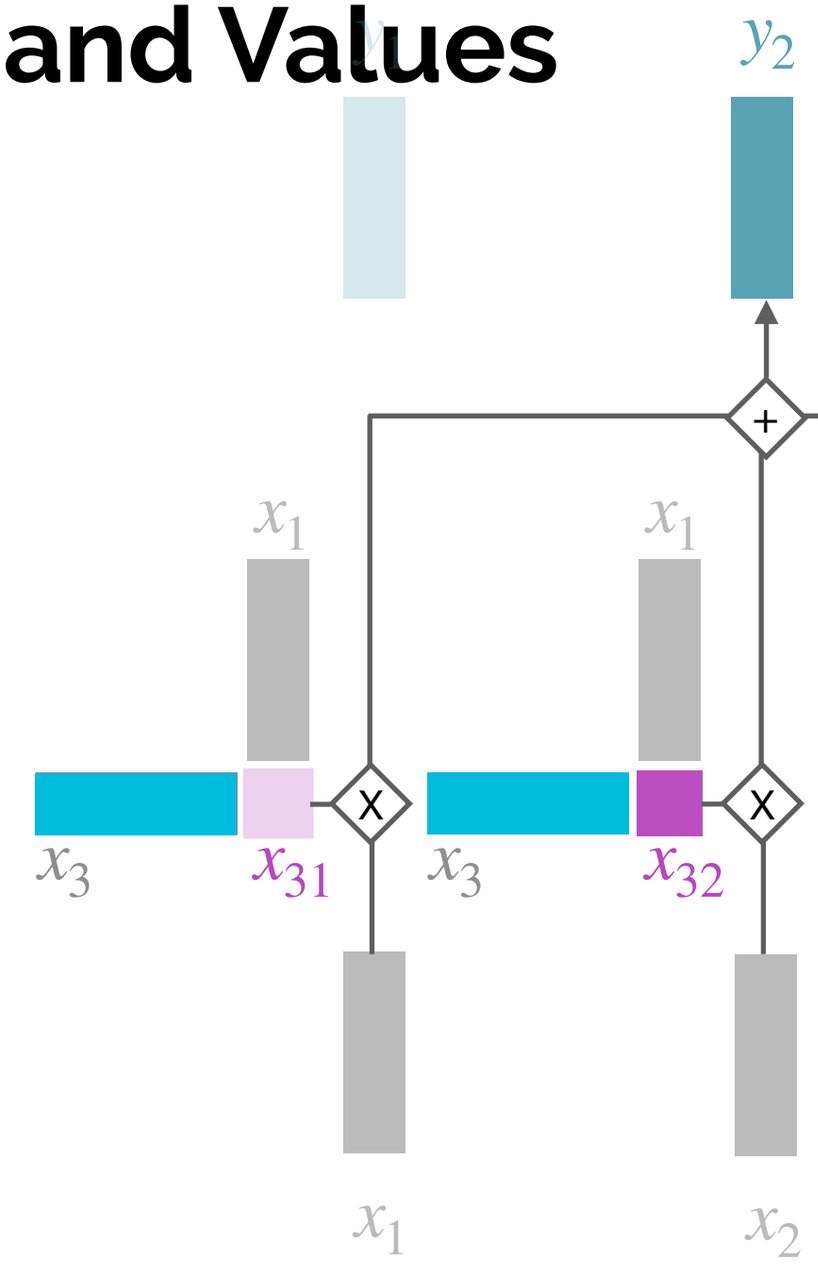
Every input vector x_i is used in 3 ways:



Self-Attention: Keys, Queries and Values

Every input vector x_i is used in 3 ways:

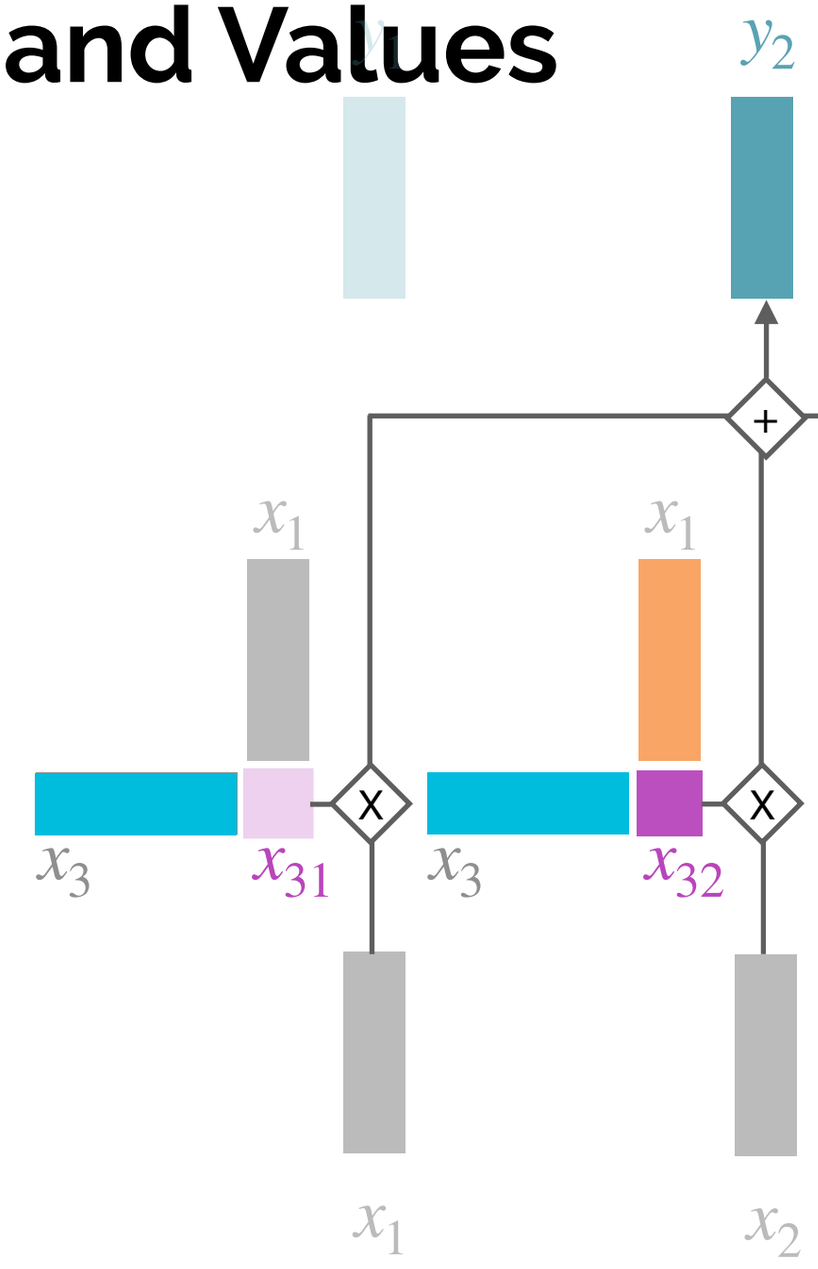
- Compared to every other vector to compute attention weights for its own output y_i (query)



Self-Attention: Keys, Queries and Values

Every input vector x_i is used in 3 ways:

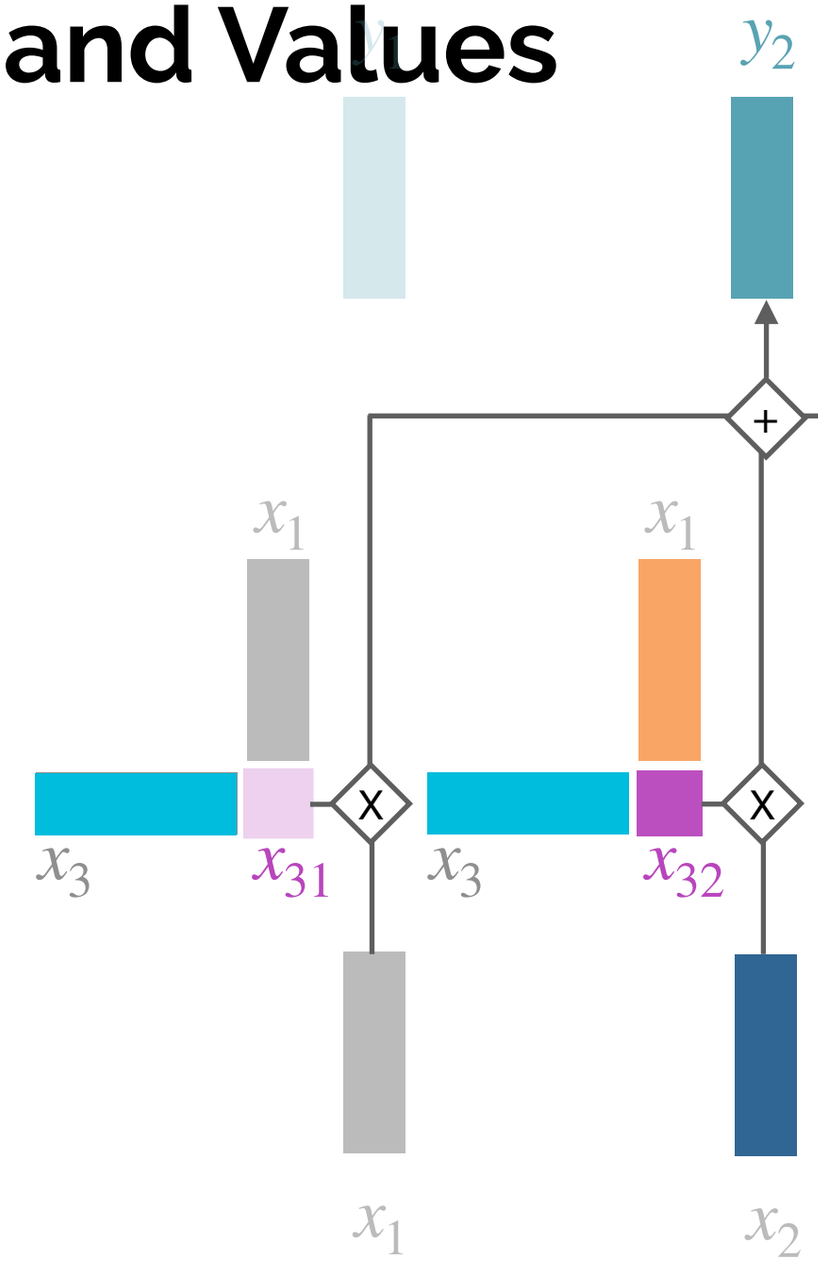
- Compared to every other vector to compute attention weights for its own output y_i (query)
- Compared to every other vector to compute attention weight w_{ij} for output y_j (key)



Self-Attention: Keys, Queries and Values

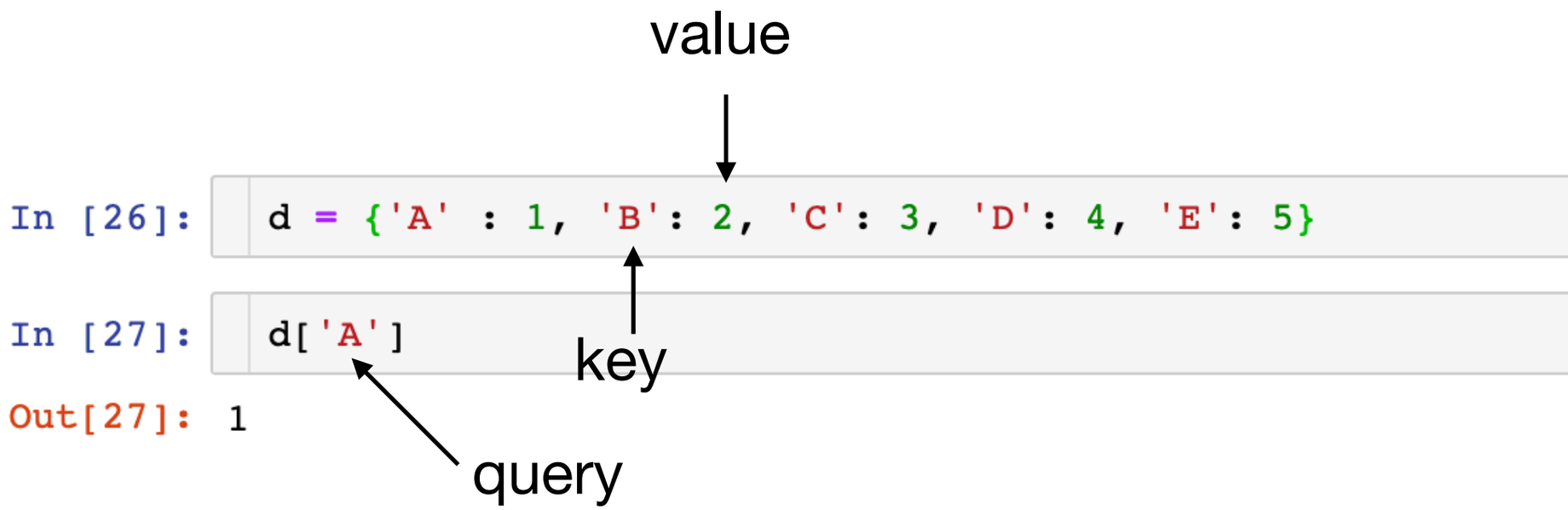
Every input vector x_i is used in 3 ways:

- Compared to every other vector to compute attention weights for its own output y_i (query)
- Compared to every other vector to compute attention weight w_{ij} for output y_j (key)
- Summed with other vectors to form the result of the attention weighted sum (value)



Self-Attention: Keys, Queries and Values

Intuition:

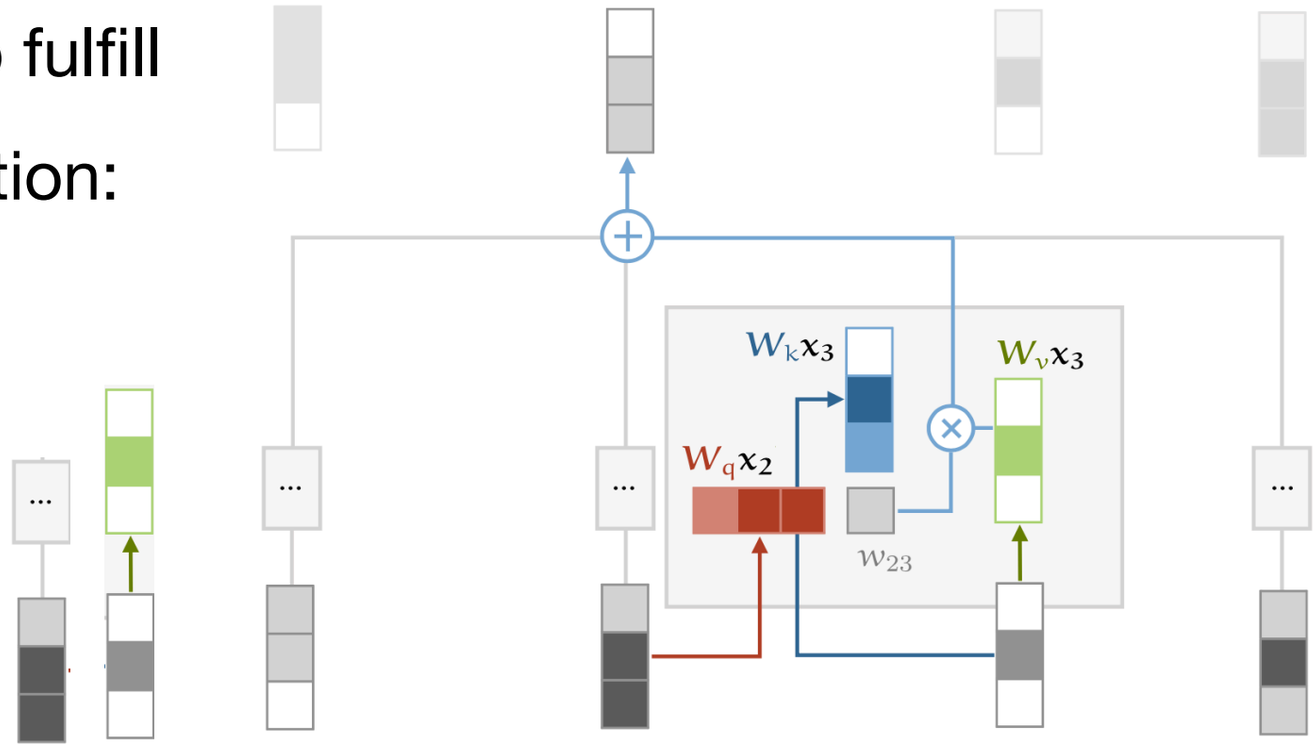


Self-Attention: Keys, Queries and Values

We can process each input vector to fulfill the three roles with matrix multiplication:

$$\mathbf{q}_i = \mathbf{W}_\mathrm{q} \boldsymbol{x}_i \qquad \mathbf{k}_i = \mathbf{W}_\mathrm{k} \boldsymbol{x}_i \qquad \mathbf{v}_i = \mathbf{W}_\mathrm{v} \boldsymbol{x}_i$$

Learning the matrices → learning attention



$$w'_{ij} = \mathbf{q}_i^\top k_j$$

$$w_{ij} = \mathrm{softmax}\left(w'_{ij}\right)$$

$$\mathbf{y}_i = \sum_j w_{ij} v_j$$

Self-Attention: Scaled Dot-Product

$$w'_{ij} = \frac{\mathbf{x}_i^\top \mathbf{x}_j}{\sqrt{d}}$$

Input dimension

Self- and Multi-Head-Attention

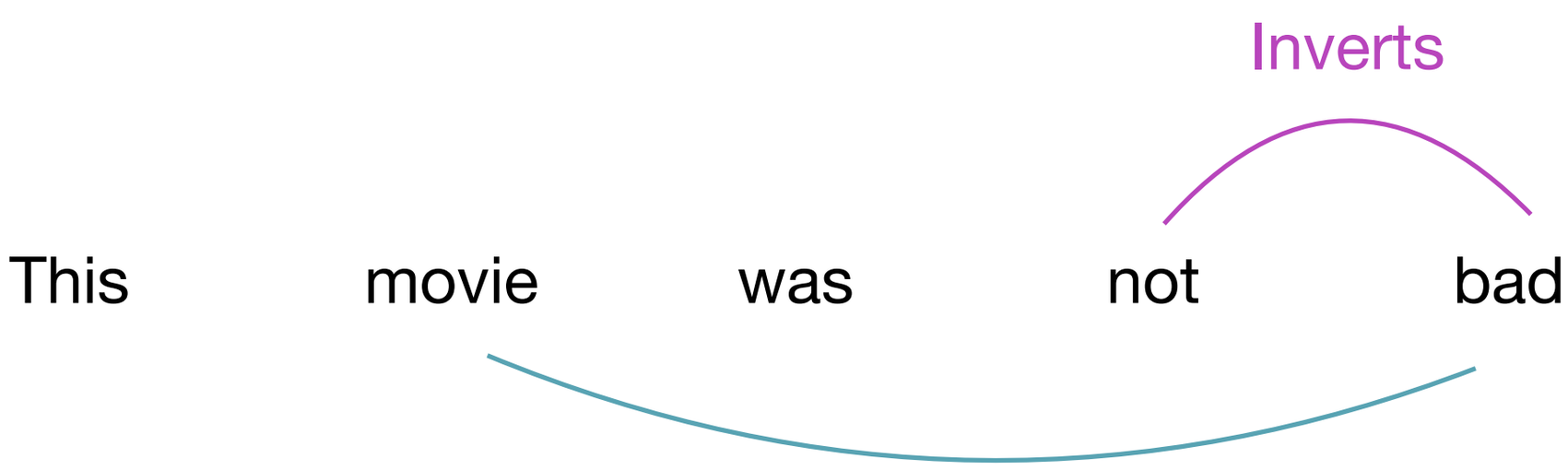
$$\text{MultiHead}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat}\left(\text{ head }_1, \ldots, \text{head h}\right)\mathbf{W}^O$$

$$\text{where head i} = \text{ Attention}\left(\mathbf{Q}\mathbf{W}_i^Q, \mathbf{K}\mathbf{W}_i^K, \mathbf{V}\mathbf{W}_i^V\right)$$

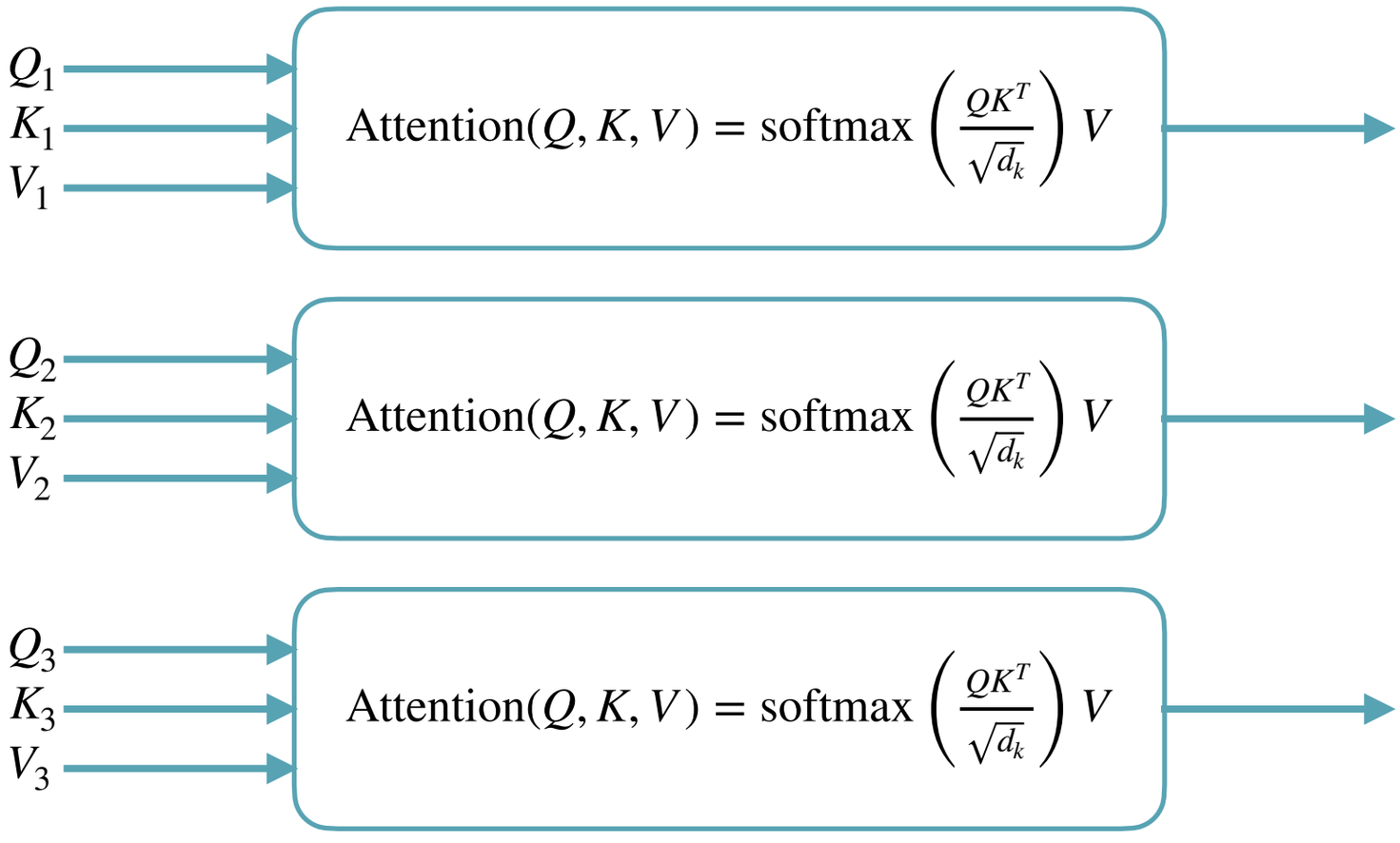
which results in:

$$\mathbf{W}_i^Q, \mathbf{w}_i^K, \mathbf{w}_i^V \in R^{d_{\text{model}} \times dk}$$

Self- and Multi-Head-Attention

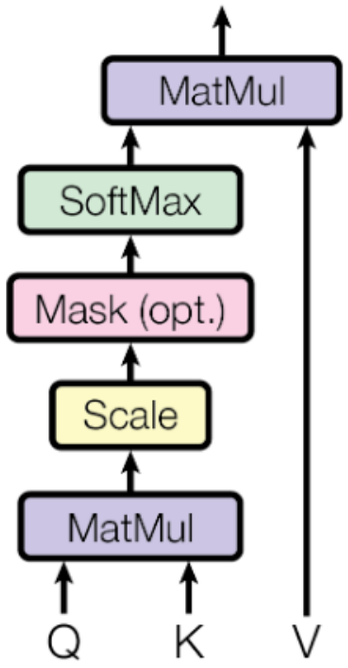


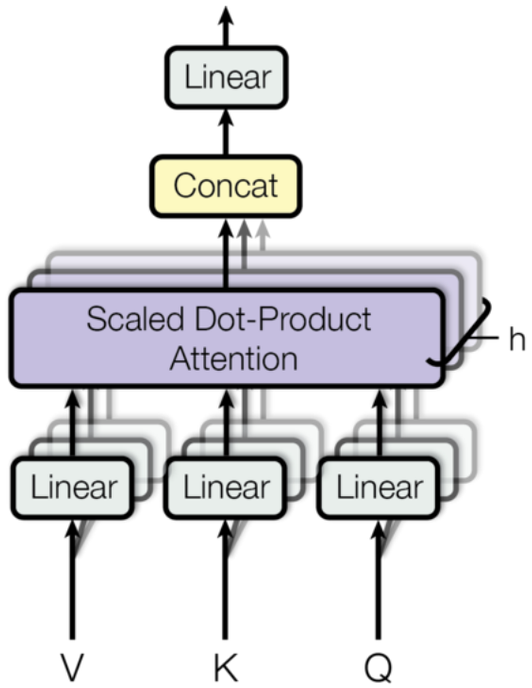
Self- and Multi-Head-Attention

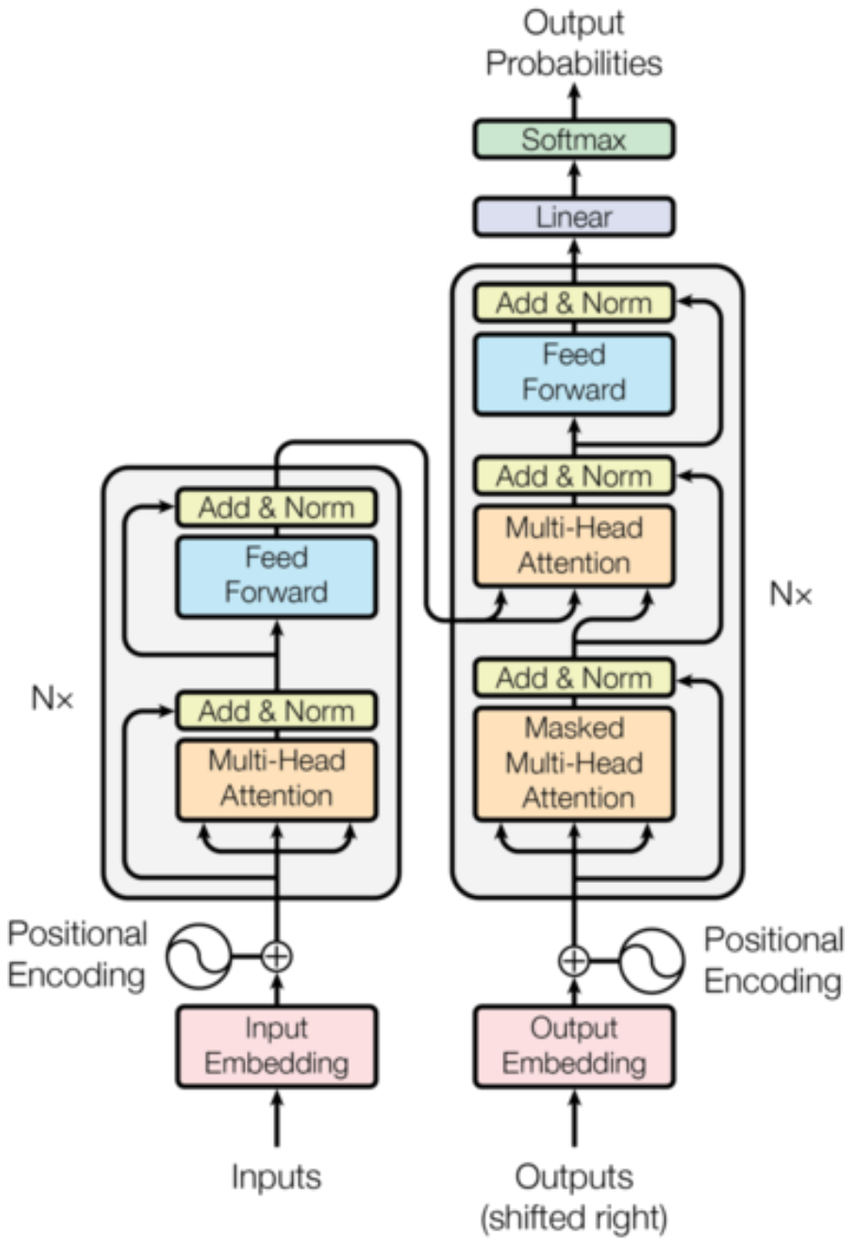


Use Cases

Machine Translation







Vision Transformer (ViT)

Vision Transformer (ViT)

- An image is worth 16X16 words

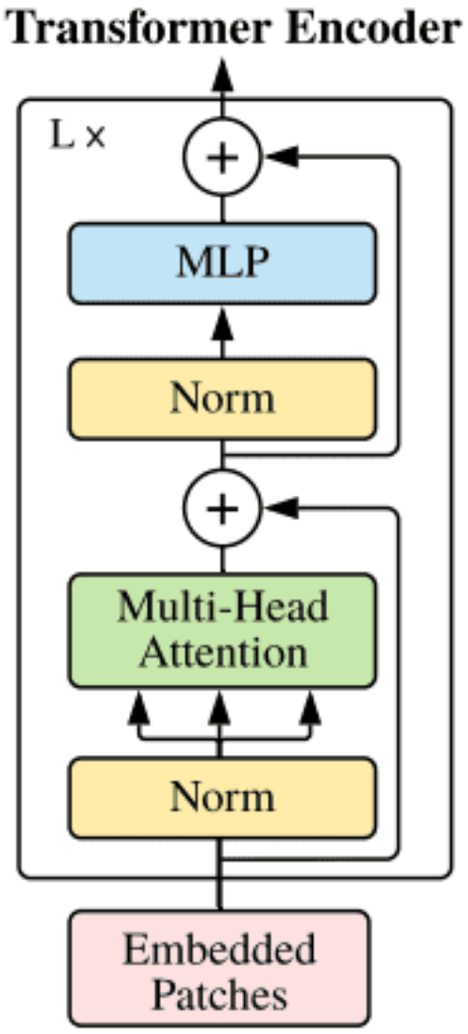
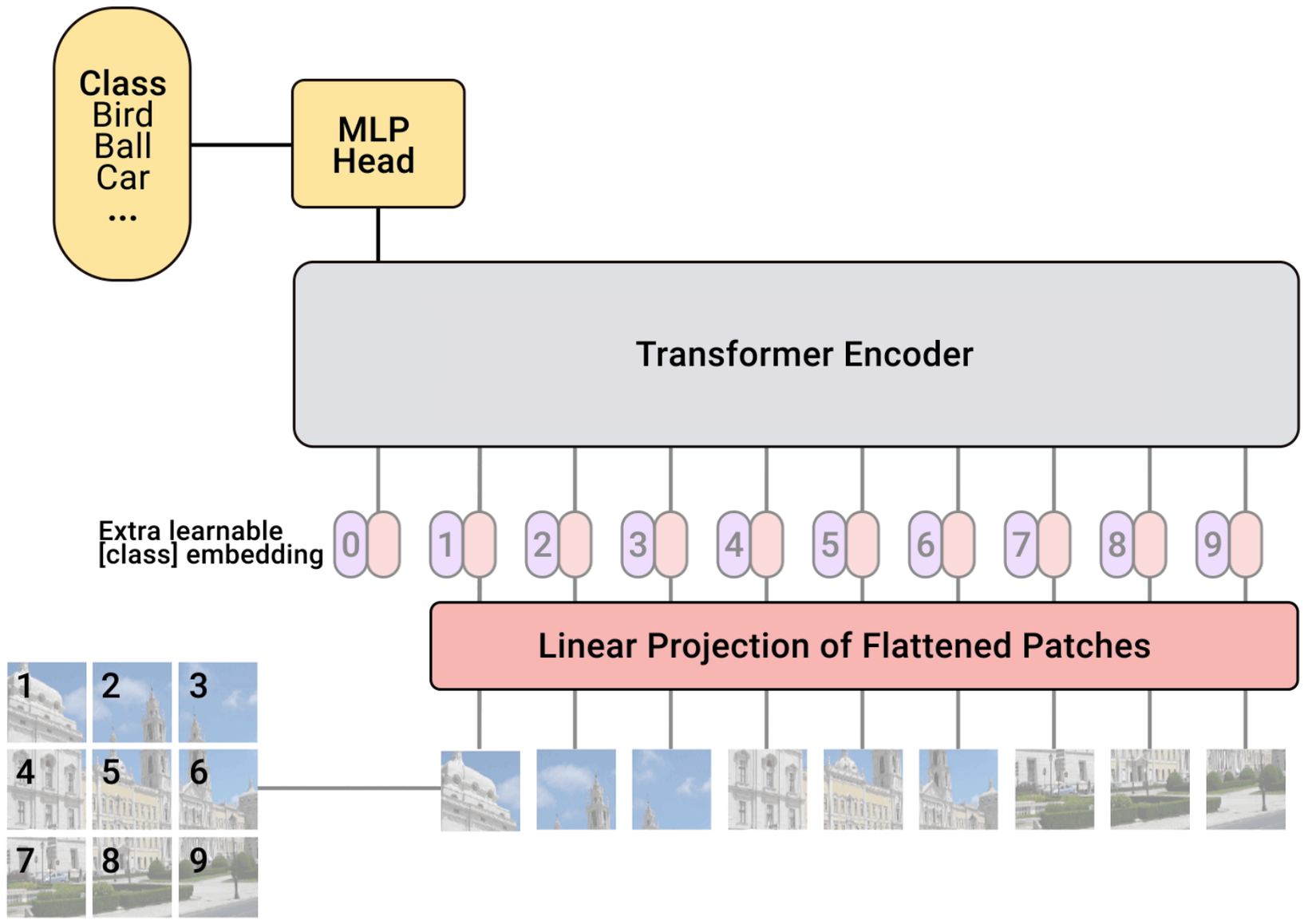


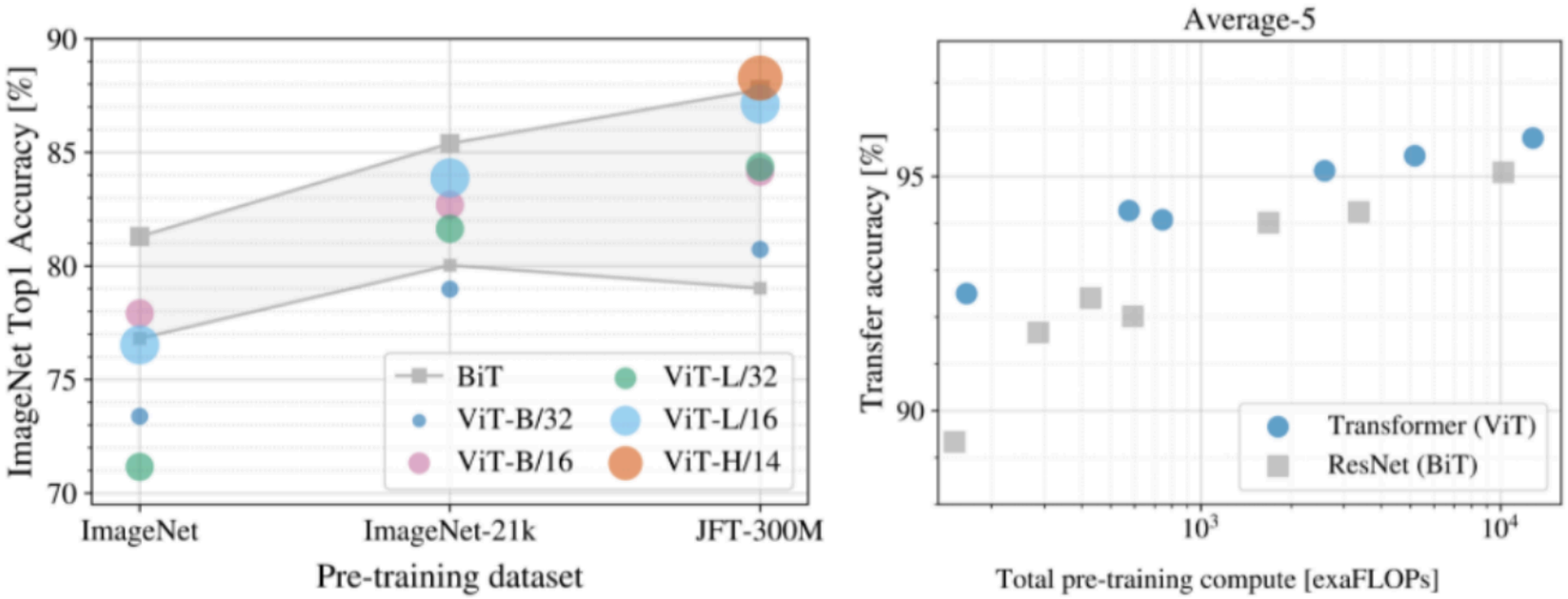
Image by Alexey Dosovitskiy et al 2020. Source: An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale

Vision Transformer (ViT)



Source: Google AI Blog

Vision Transformer (ViT)



Source: Google AI Blog

Time Series Anomalie Detection

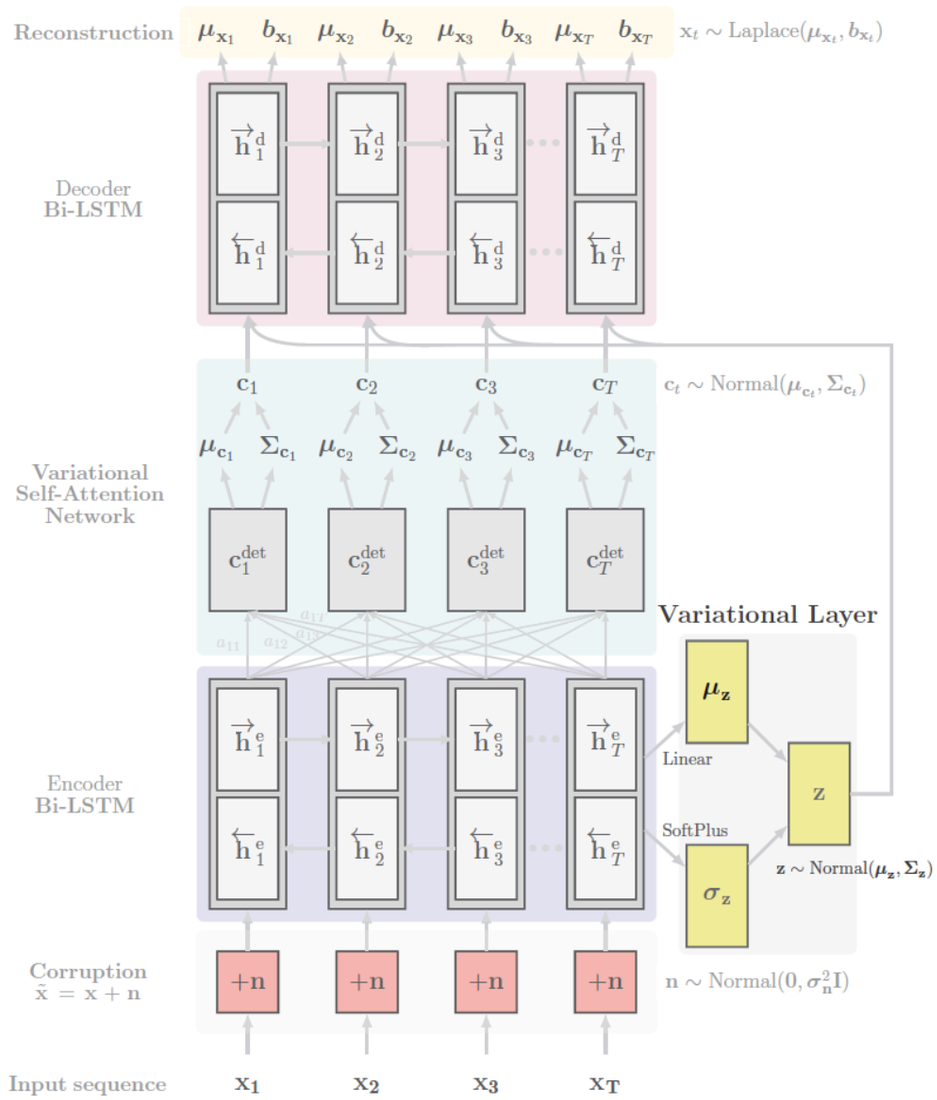
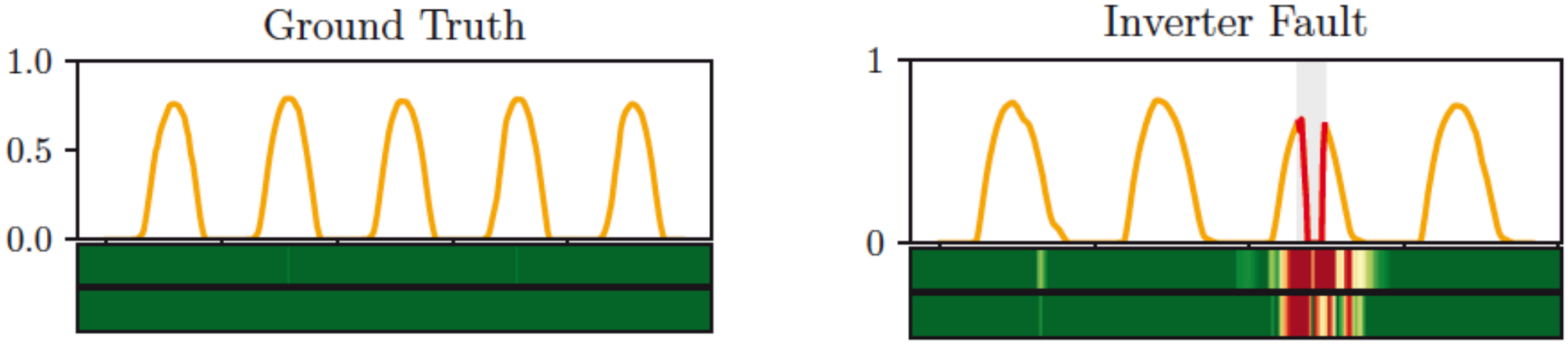


Image source: Unsupervised Anomaly Detection in Energy Time Series Data using Variational Recurrent Autoencoders with Attention

Time Series Anomalie Detection



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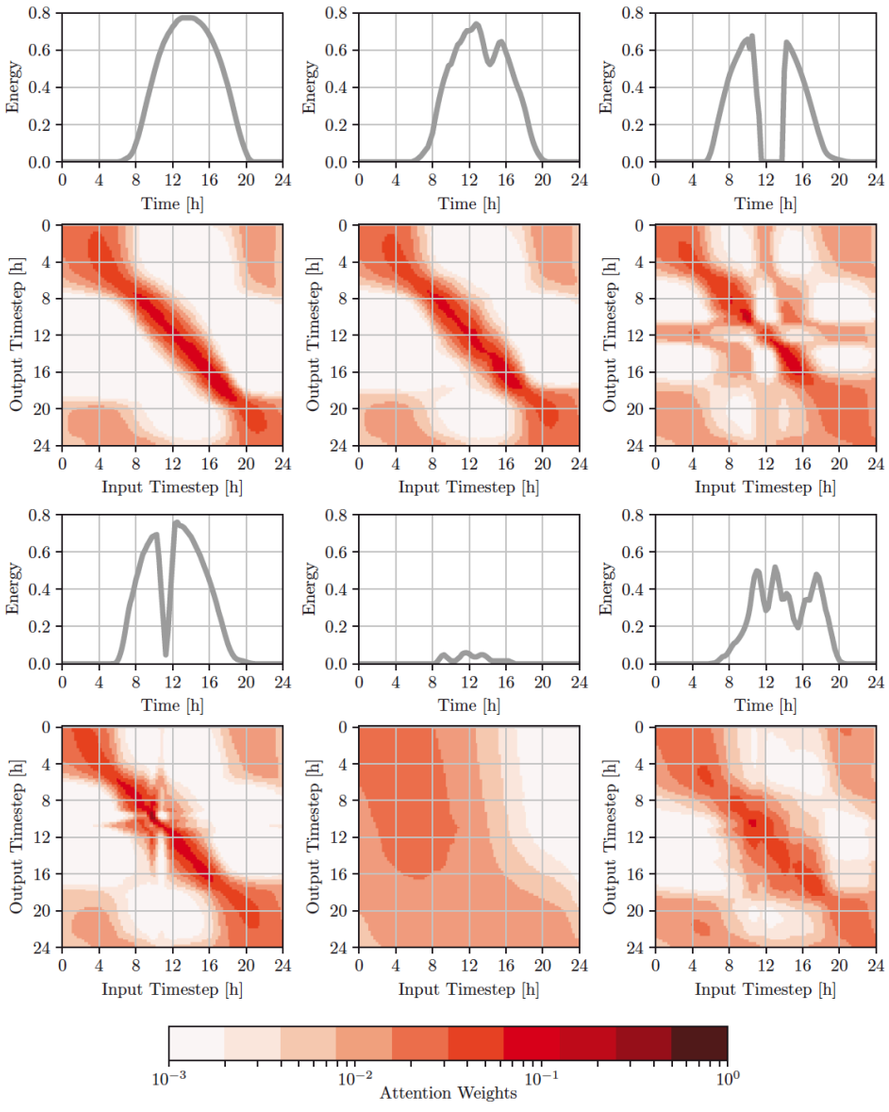

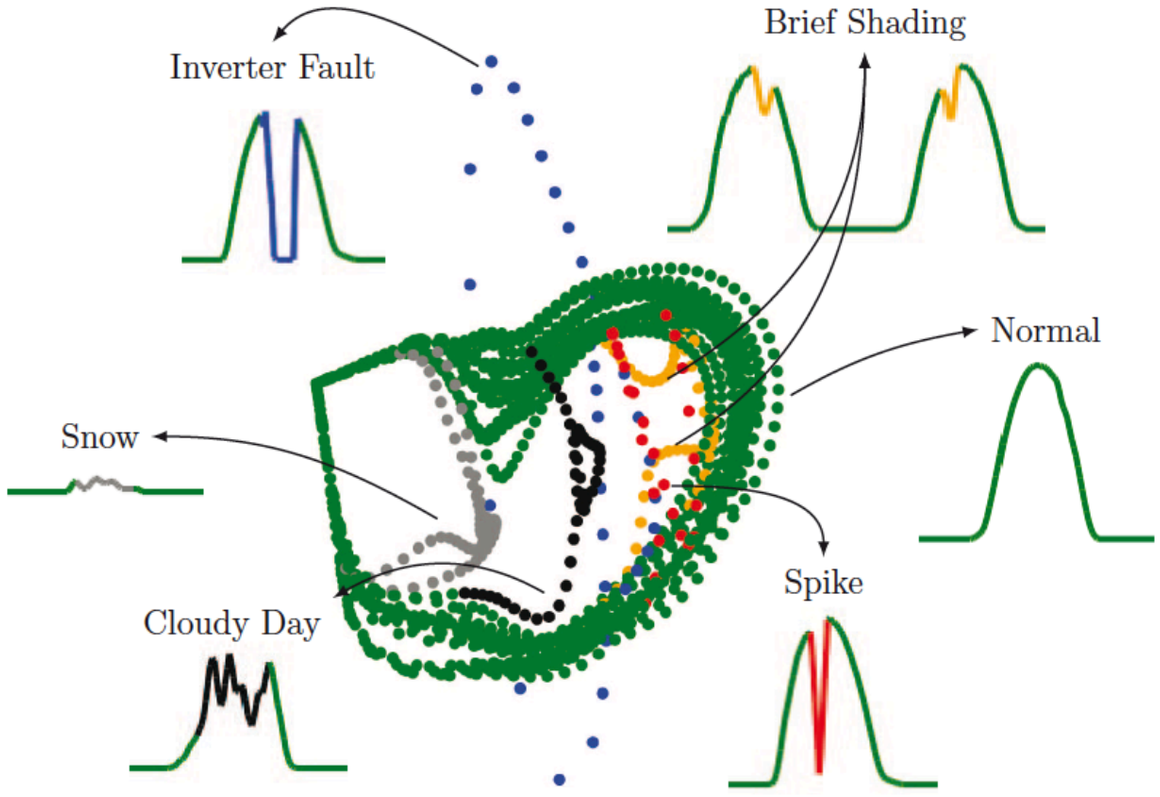

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Stock Price Prediction

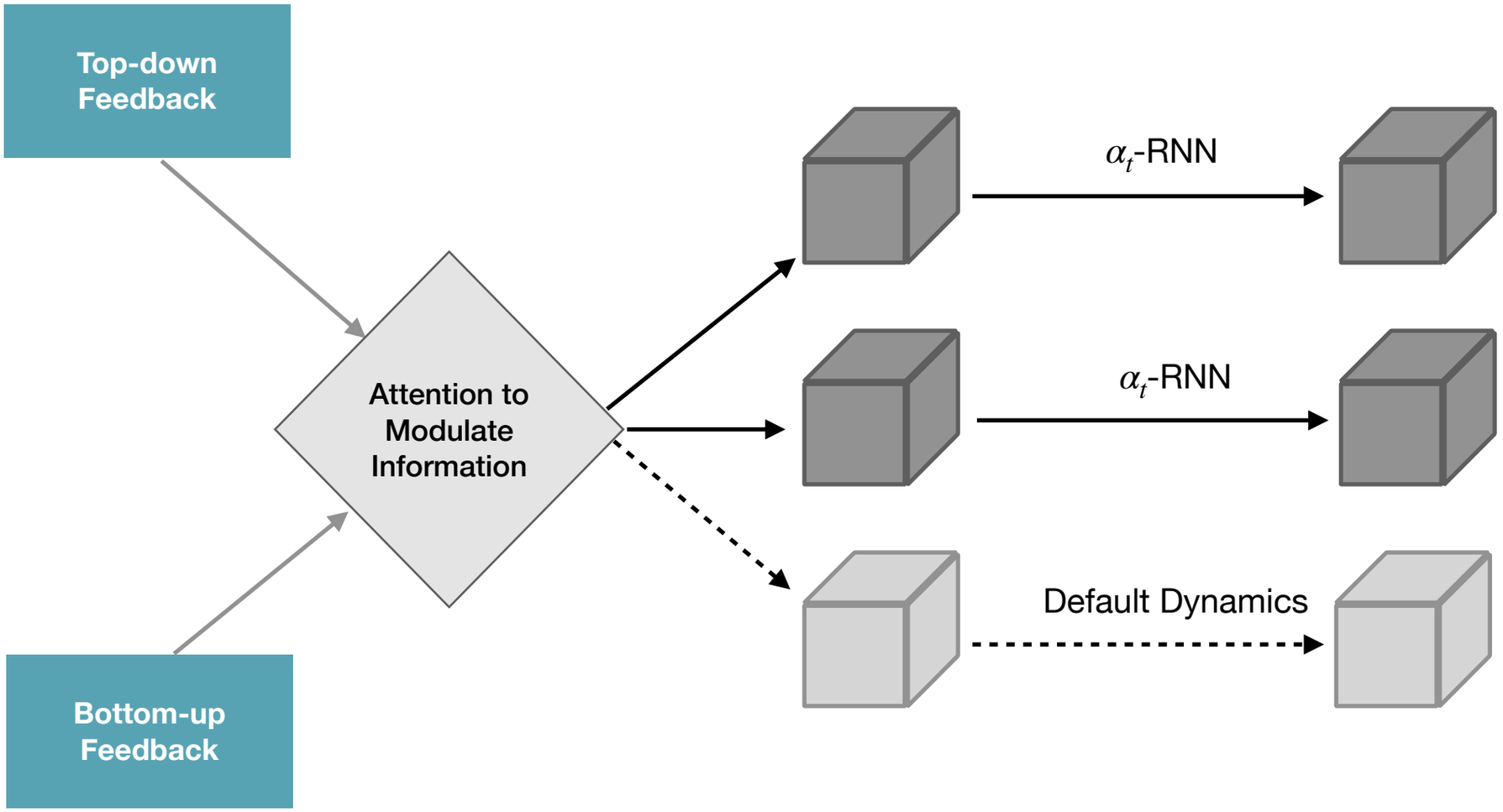
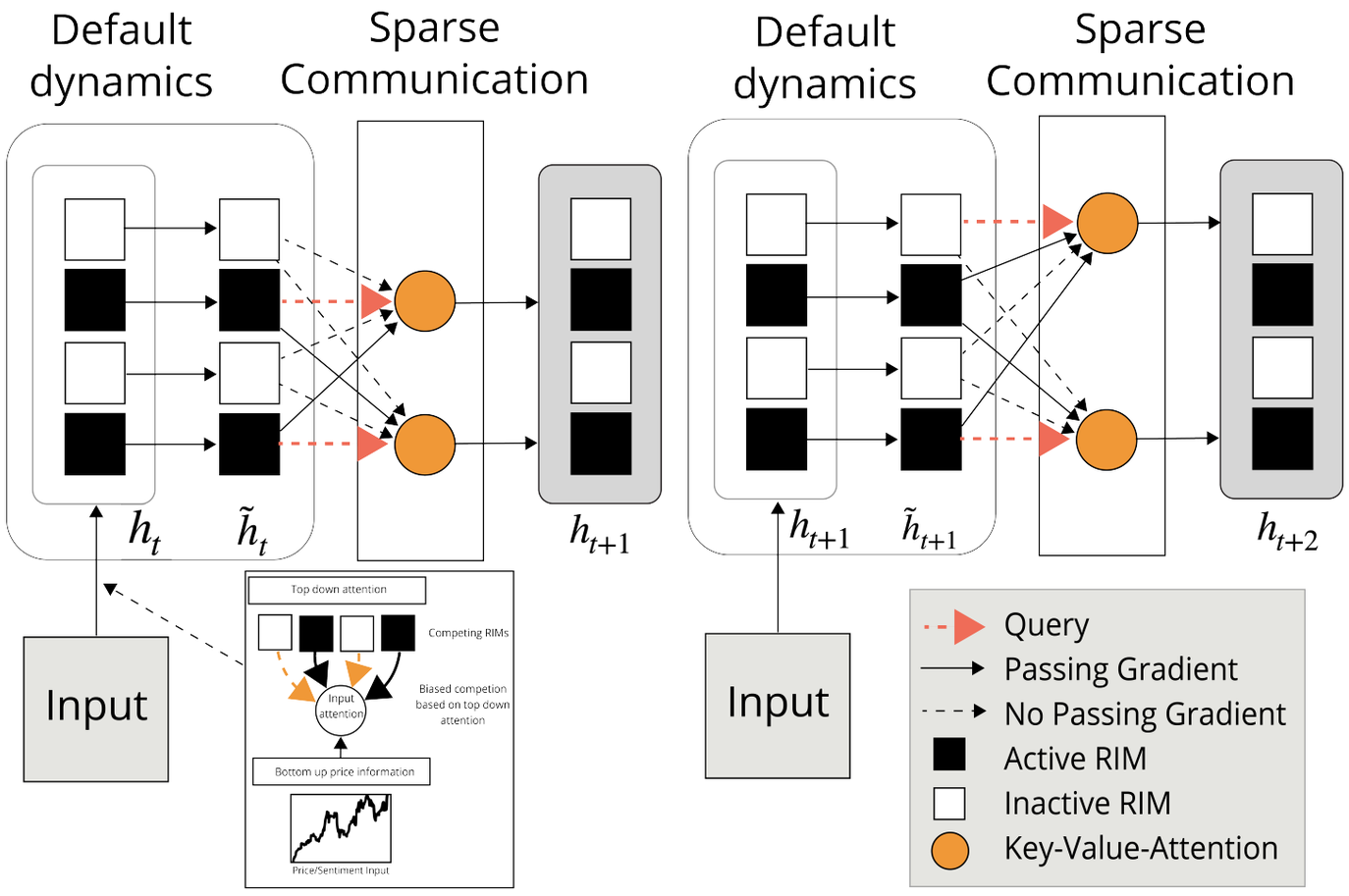


Image by the author, link to the paper: https://arxiv.org/abs/2205.01639

Stock Price Prediction



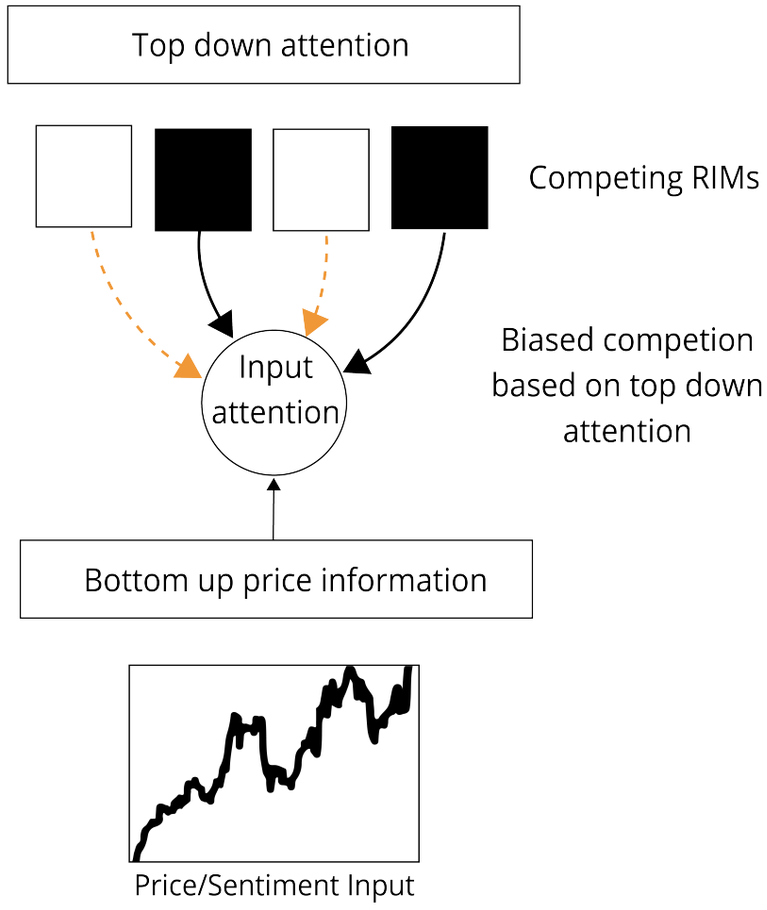


Image by the author, link to the paper: https://arxiv.org/abs/2205.01639

Stock Price Prediction

Thermo Fischer - ten lags input, five steps ahead prediction

Closing price

	RNN	LSTM	α_t -RIM
Lag	MAPE*	MAPE	MAPE
1	4.9015	11.0398	2.7522
2	3.4432	12.4441	2.9103
3	5.2922	10.1909	**2.4824**
4	3.5335	10.8379	2.5419
5	4.2818	8.9843	2.5887

Closing price and Sentiment

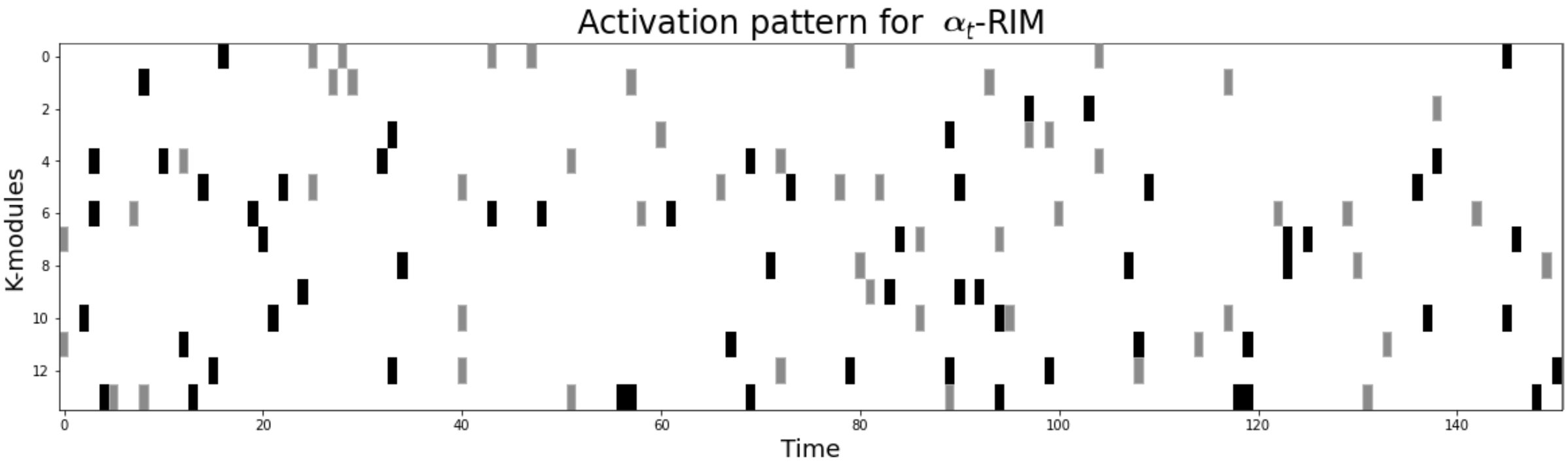
	RNN	LSTM	α_t -RIM
Lag	MAPE	MAPE	MAPE
1	17.8271	18.6483	**1.7189**
2	13.5076	19.7892	1.9708
3	18.0445	20.2516	2.2388
4	11.2579	18.7996	2.4439
5	15.5029	17.4120	2.7314

* MAPE: Mean absolute percentage error

Image by the author

Stock Price Prediction

Attention can be used to enhance the explainability



Activation pattern of the α_t-RIM, for the Brown Forman stock,
with only the closing price (black) and closing price and sentiment score (grey).

Image by the author

Sources Use Cases

- Attention Is All You Need
  https://arxiv.org/abs/1706.03762
- An Image is Worth 16x16 Words:
  Transformers for Image Recognition at Scale
  https://arxiv.org/abs/2010.11929
- Unsupervised Anomaly Detection in Energy Time Series Data using Variational Recurrent Autoencoders with Attention
  https://ieeexplore.ieee.org/document/8614232
- Dynamic and Context-Dependent Stock Price Prediction Using Attention Modules and News Sentiment
  https://arxiv.org/abs/2205.01639

Sources

https://github.com/Nicolepcx/women_in_tech_2022

https://www.linkedin.com/in/nicole-koenigstein/