MACHINE LEARNING FOR SIGNAL PROCESSING

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STORY SO FAR

EM algorithm

Classification Problem

Decision Theory

Generative Modeling

Gaussian Modeling

Gaussian Mixture Modeling

Function Modeling

Linear Models for Regression and Classification

Kernel Machines & Max-margin classifiers

Support Vector Machines

Data Representations PCA, LDA

Discriminative Modeling

Gradient Descent

Neural Networks

Learning Rules & Normalization

Deep neural architectures

STORY SO FAR

Feed-forward Models

Learning with Regularization

Ensembling

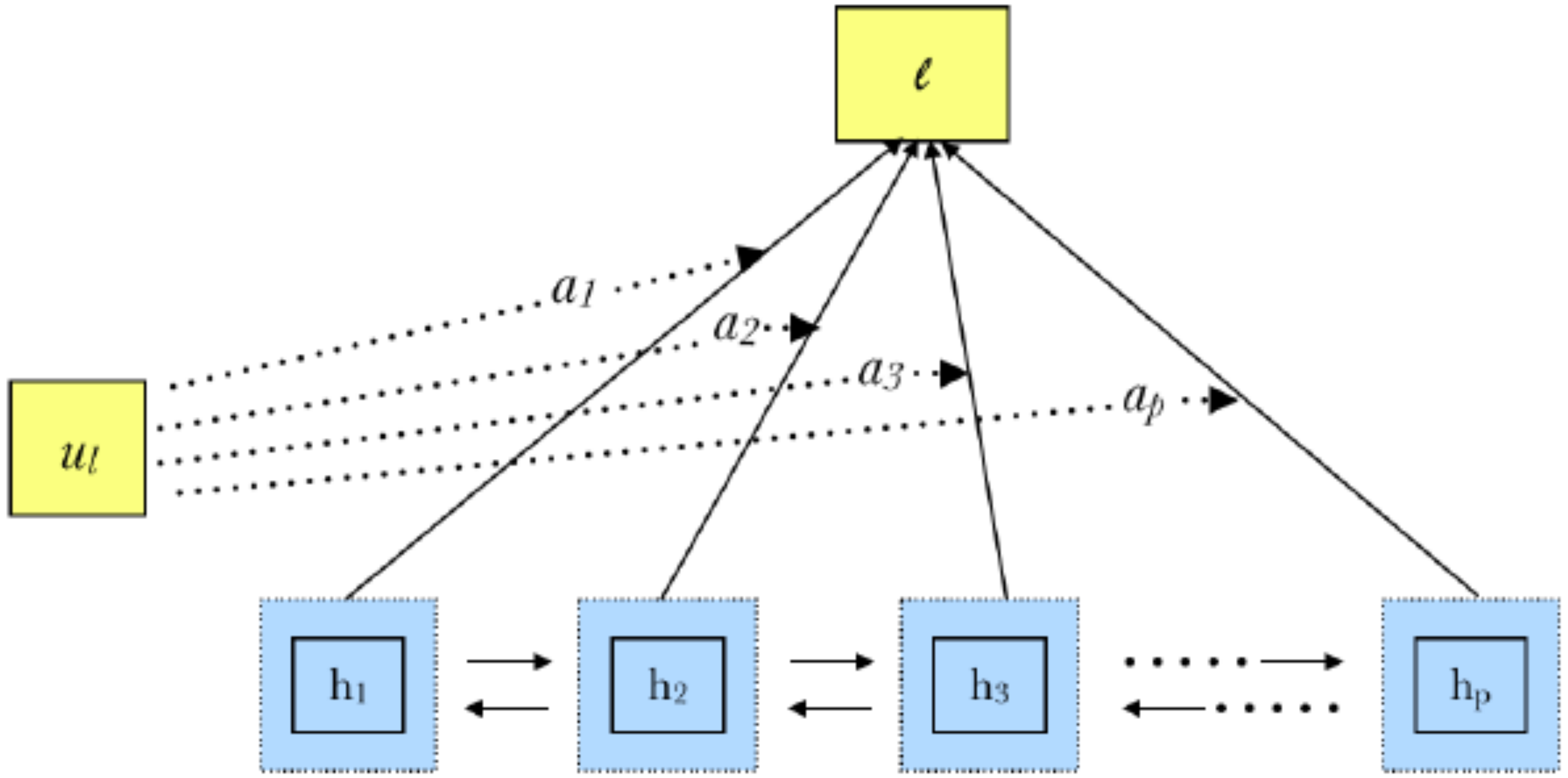
Deep neural architectures

Convolutional Neural N/w

Recurrent Neural N/w

Attention & Transformers

Attention in LSTM Networks



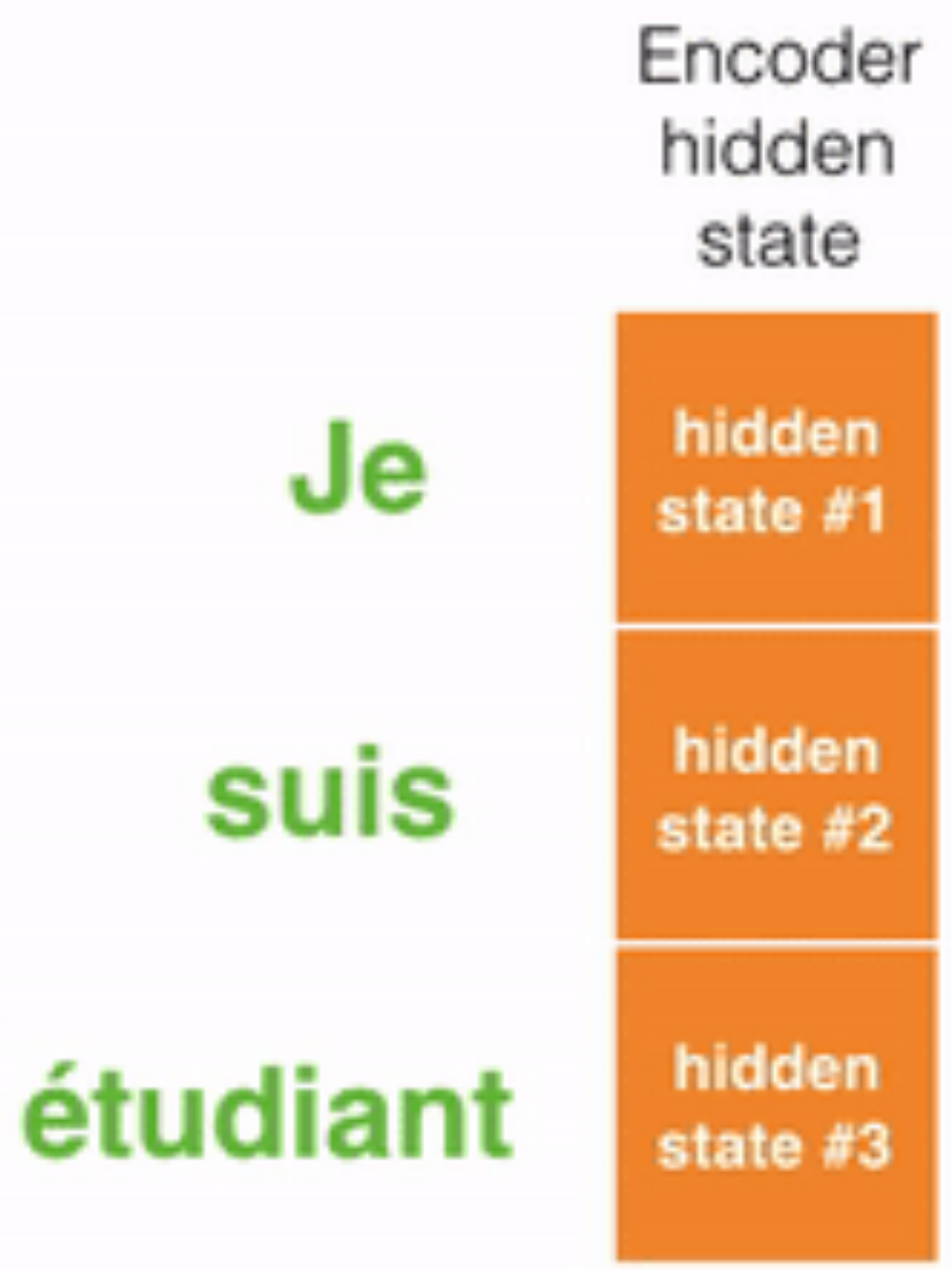
$$\mathbf{u}_t = tanh(\mathbf{W}_l \mathbf{h}_t + \mathbf{b}_l)$$

$$a_t = \frac{exp(\mathbf{u}_t^T \mathbf{u}_l)}{\sum_t exp(\mathbf{u}_t^T \mathbf{u}_l)}$$

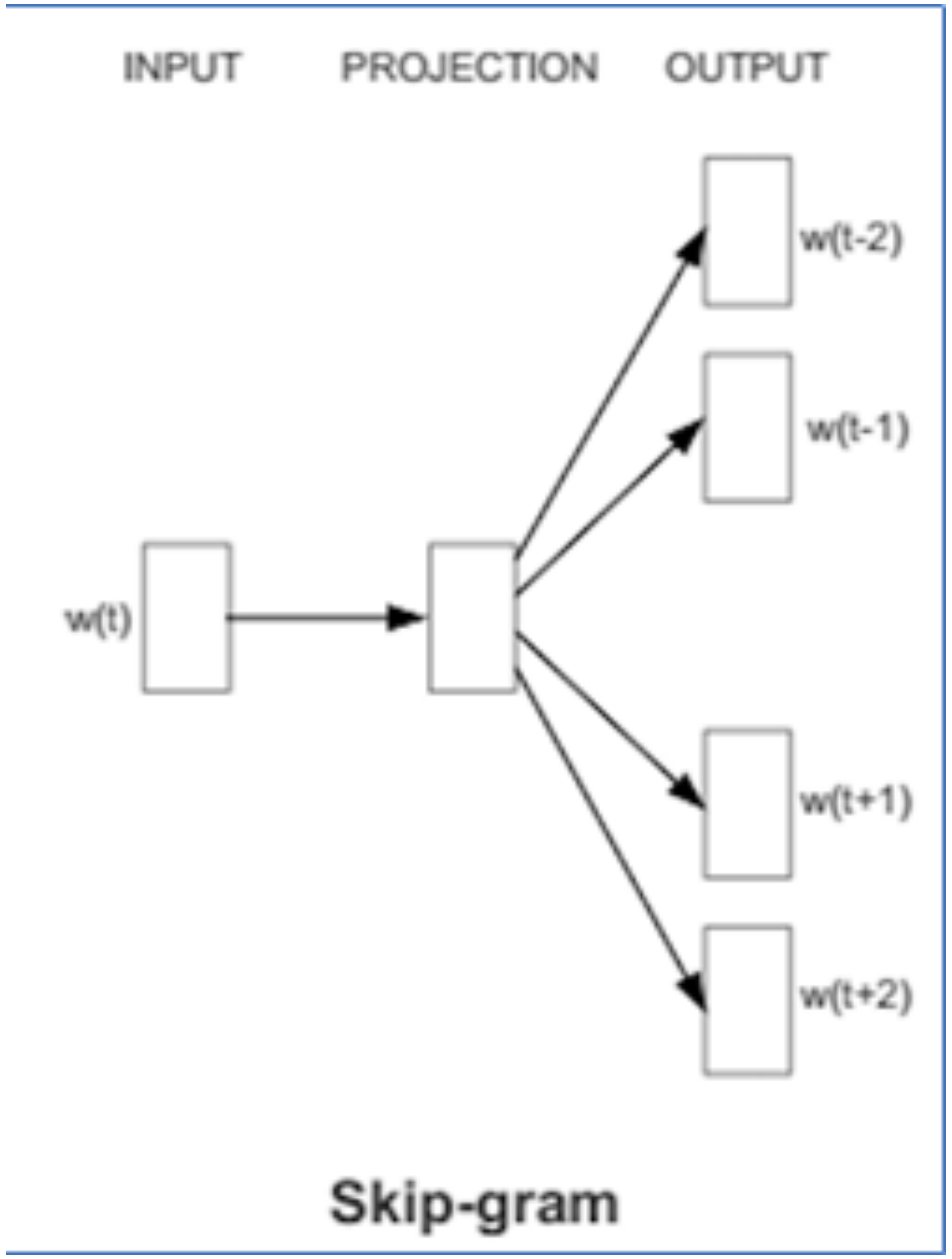
$$\boldsymbol{l} = \sum_t a_t \mathbf{h}_t$$

- Attentions allows a mechanism to add relevance
  - Certain regions of the audio have more importance than the rest for the task at hand.

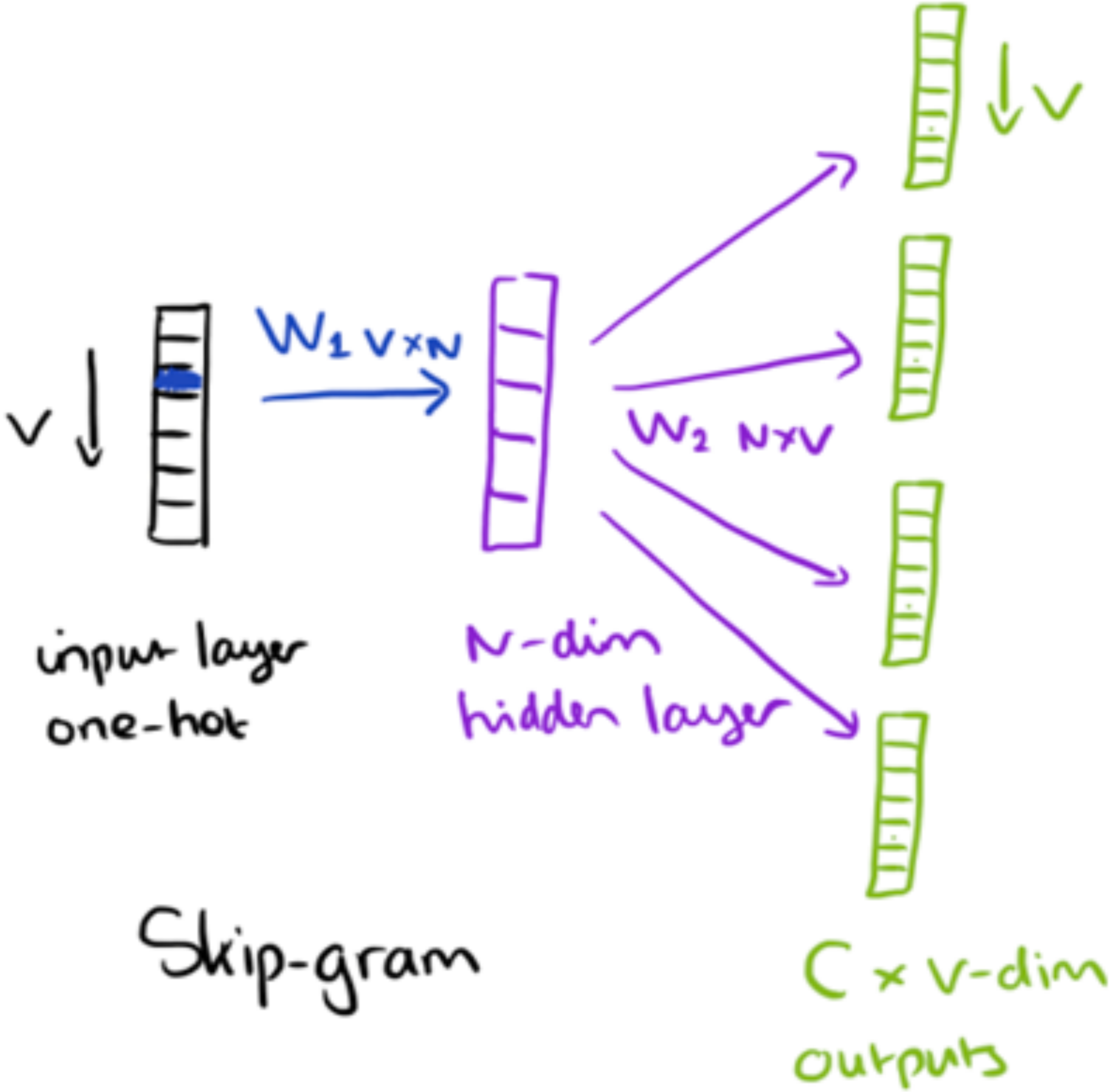
Encoder-Decoder Attention



word2vec models as text representations



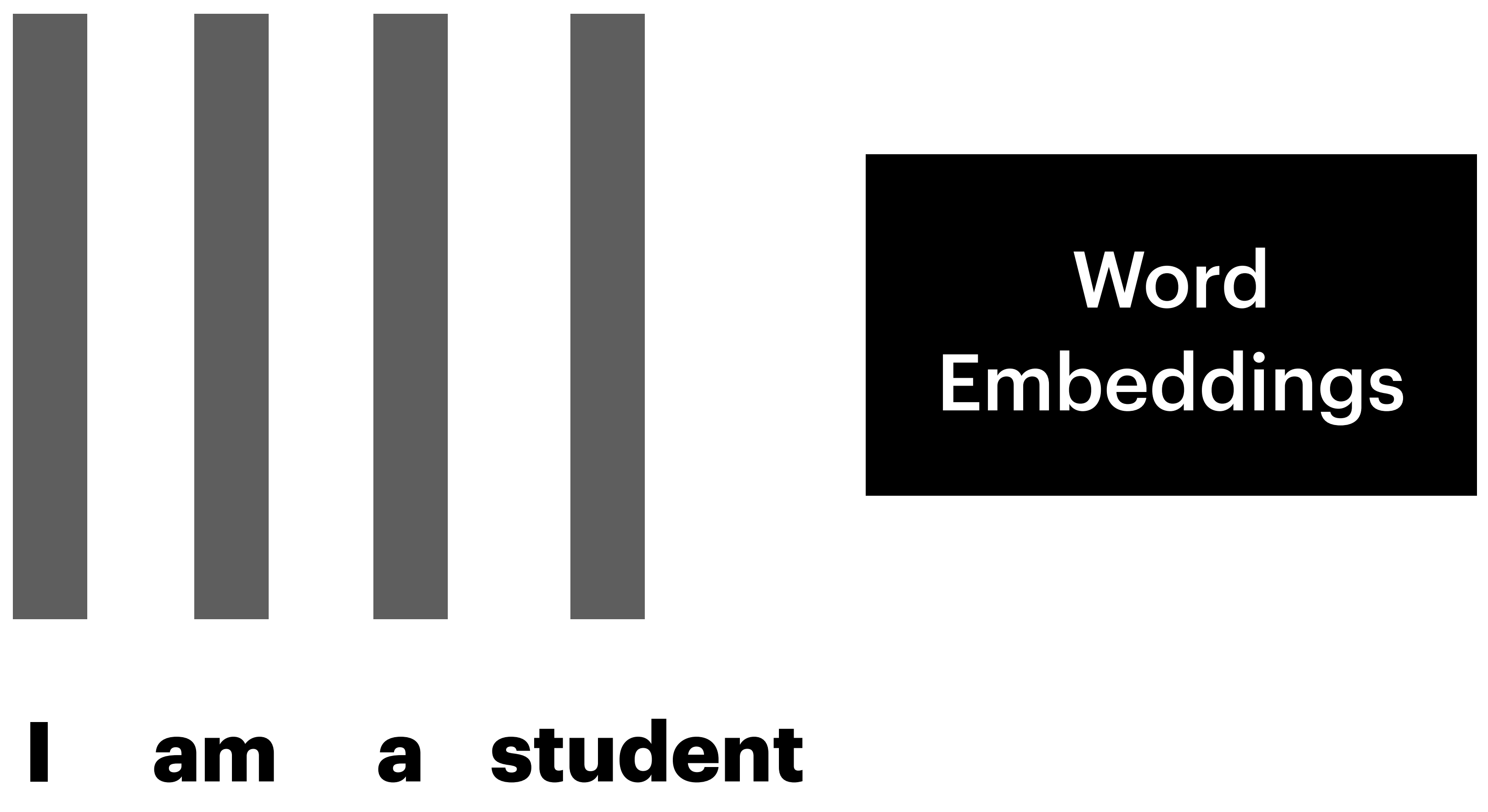
word2vec representations



$$\begin{array}{cccc} \text{input} & W_1 & & \text{hidden} \\ 1\times V & V\times N & & 1\times N \\ \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} & \begin{bmatrix} a & b & c & d \\ e & f & g & h \\ i & j & k & l \end{bmatrix} & = & \begin{bmatrix} e & f & g & h \end{bmatrix} \\ & W_1 & & \end{array}$$

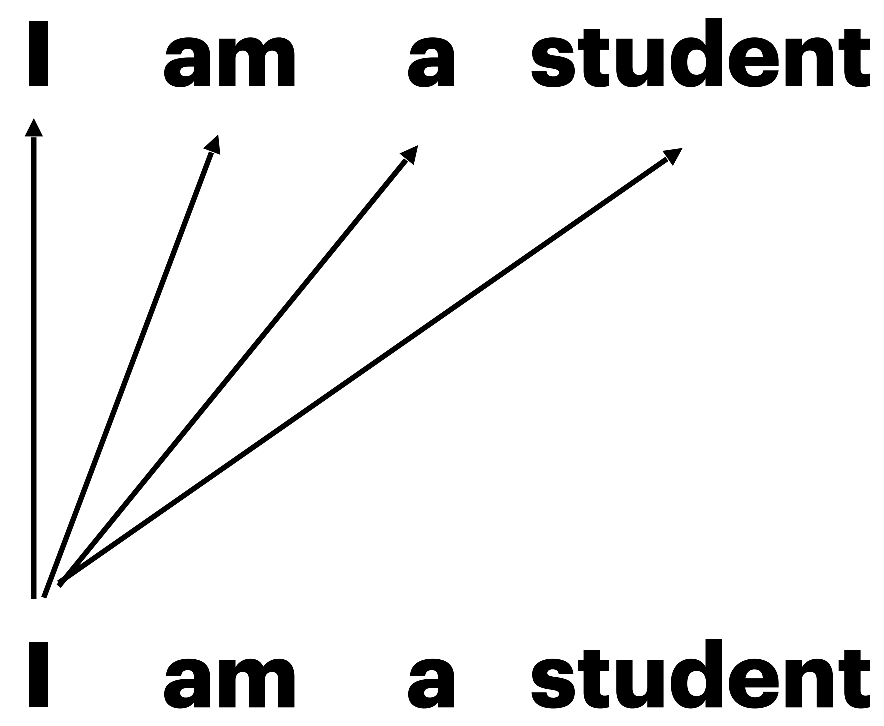
Transformers

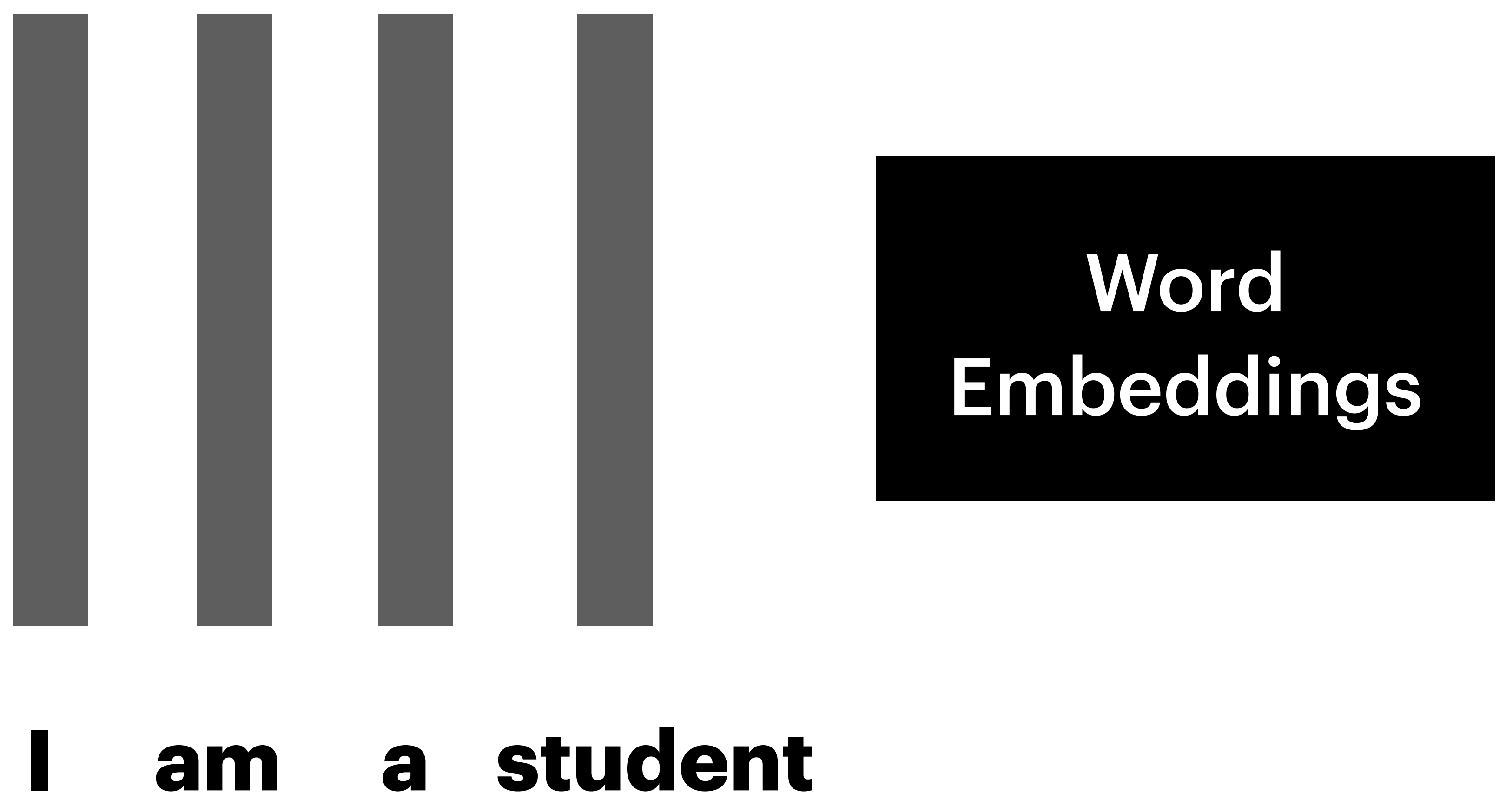
- Embedding context in sequence inputs



Transformers - self-attention

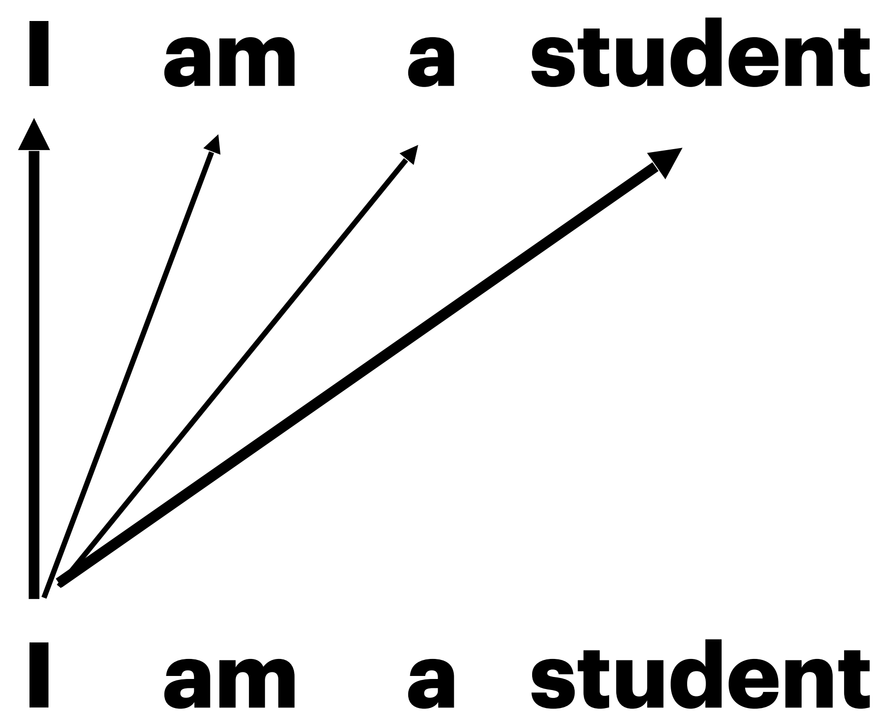
- Embedding context in sequence inputs
  - ✳ Let us take an example

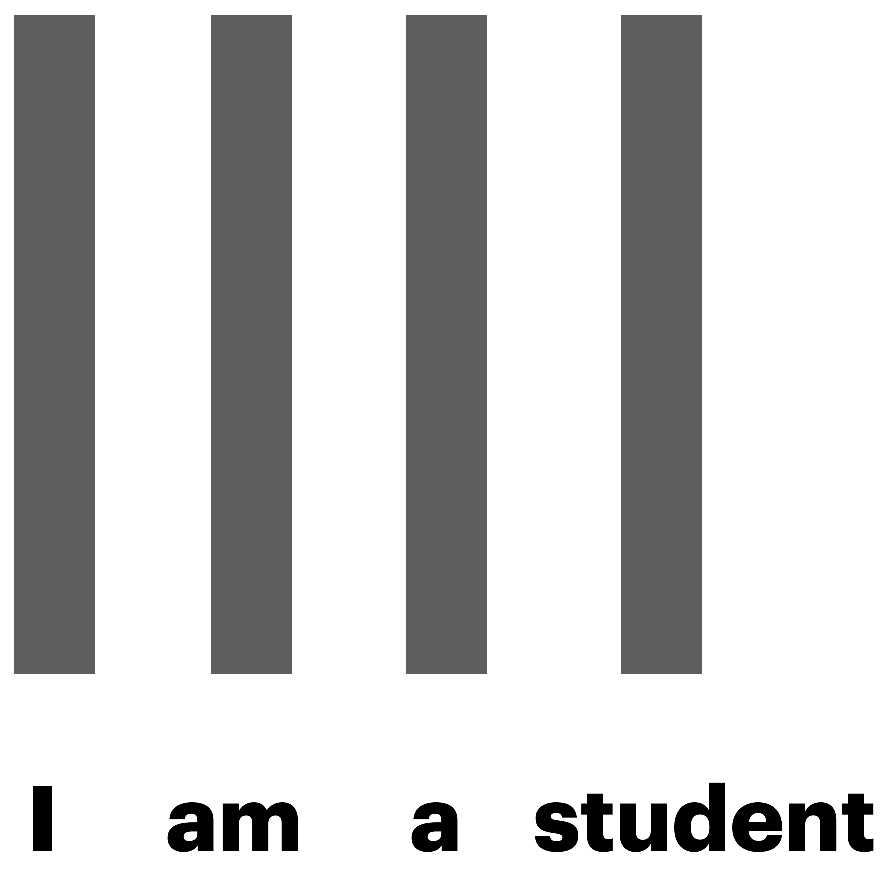




Transformers - self-attention

- Embedding context in sequence inputs
  - ✳ Let us take an example
  - ✳ Using word embeddings as the input representation





$$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots \mathbf{x}_T\}; \mathbf{x}_t \in \mathscr{R}^D$$

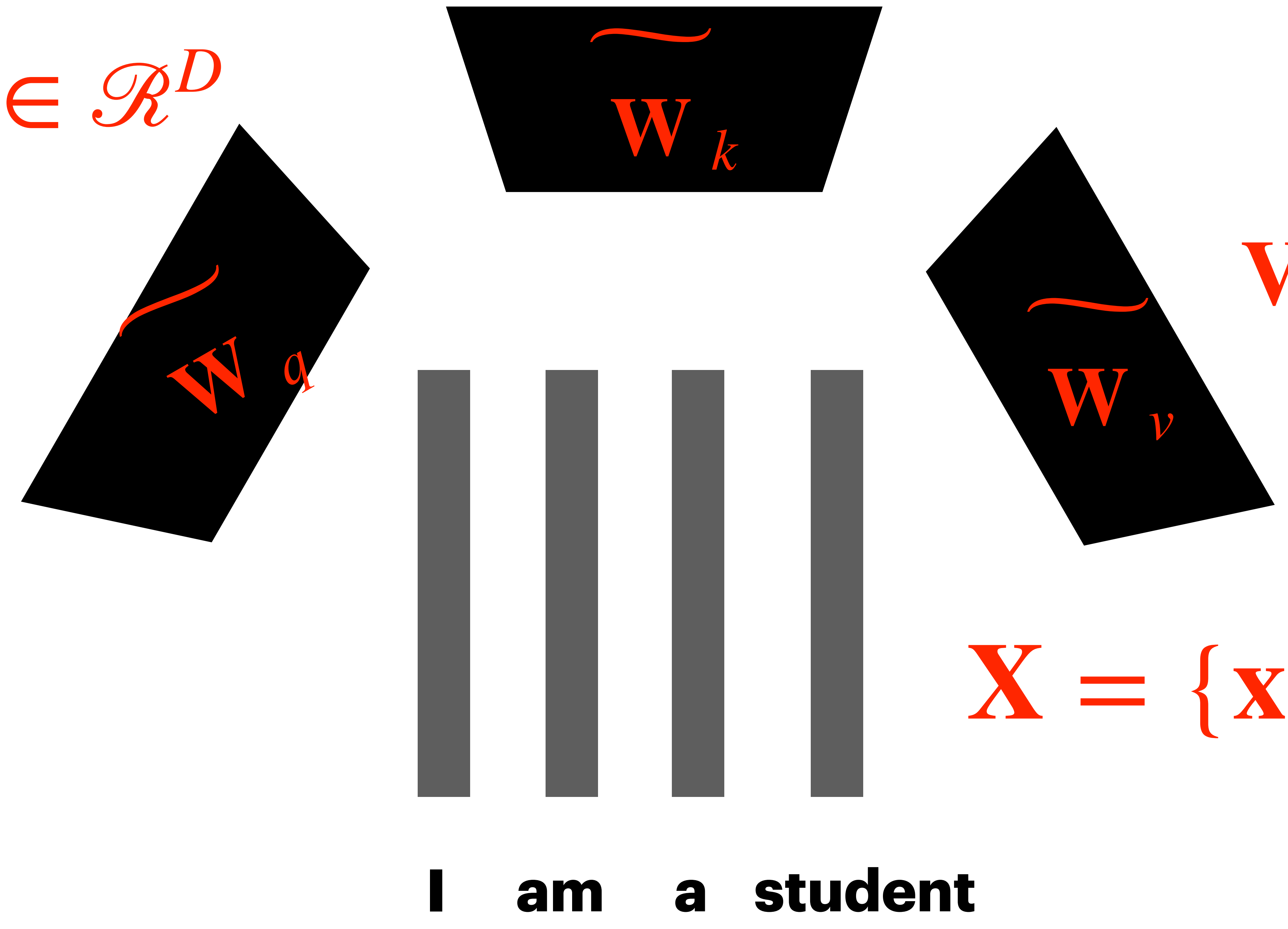
Word Embeddings

Transformers - self-attention

$$\mathbf{K} = \{\mathbf{k}_1, \mathbf{k}_2, \ldots \mathbf{k}_T\}; \mathbf{k}_t \in \mathcal{R}^D$$

$$\mathbf{Q} = \{\mathbf{q}_1, \mathbf{q}_2, \ldots \mathbf{q}_T\}; \mathbf{q}_t \in \mathcal{R}^D$$

$$\mathbf{V} = \{\mathbf{v}_1, \mathbf{v}_2, \ldots \mathbf{v}_T\}; \mathbf{v}_t \in \mathcal{R}^D$$



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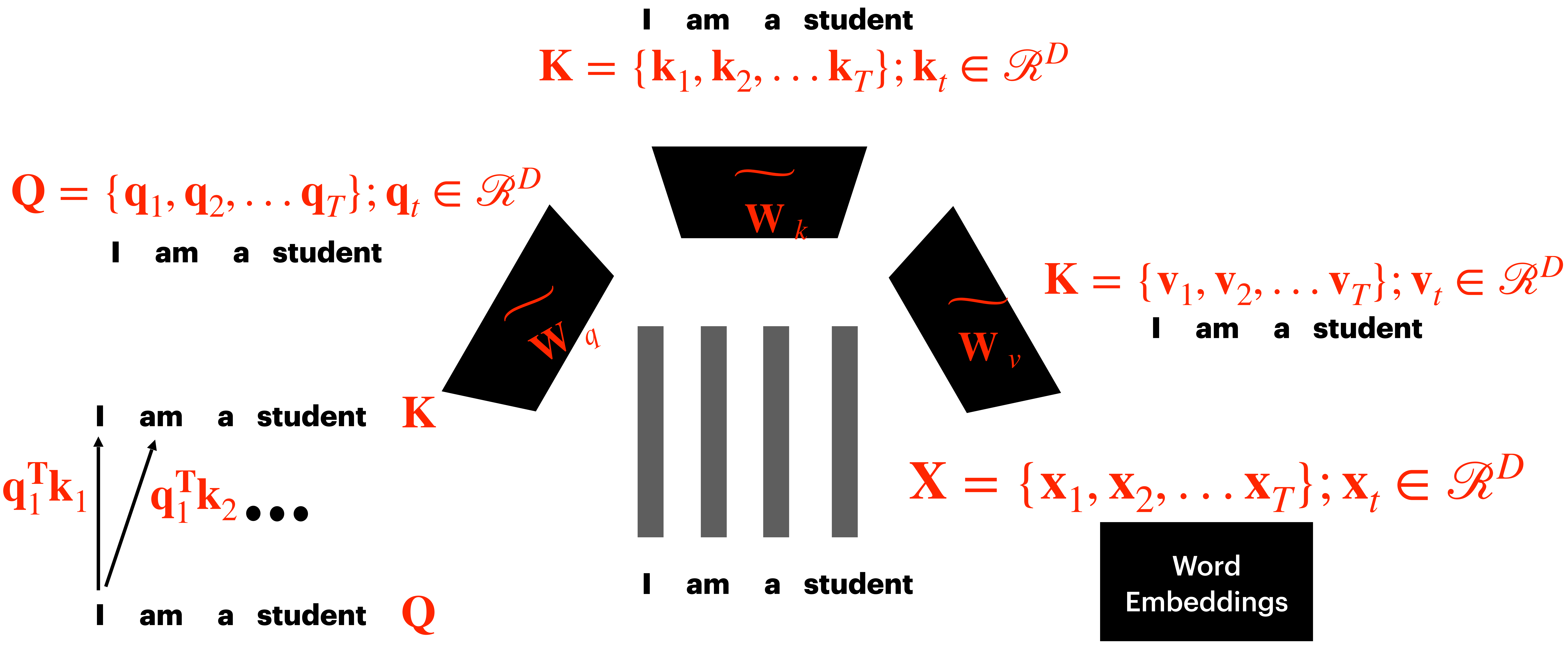
Word Embeddings

Transformers - self-attention



Transformers - self-attention

I am a student

$$\mathbf{K} = \{\mathbf{k}_1, \mathbf{k}_2, \ldots \mathbf{k}_T\}; \mathbf{k}_t \in \mathscr{R}^D$$

I am a student

$$\mathbf{Q} = \{\mathbf{q}_1, \mathbf{q}_2, \ldots \mathbf{q}_T\}; \mathbf{q}_t \in \mathscr{R}^D$$

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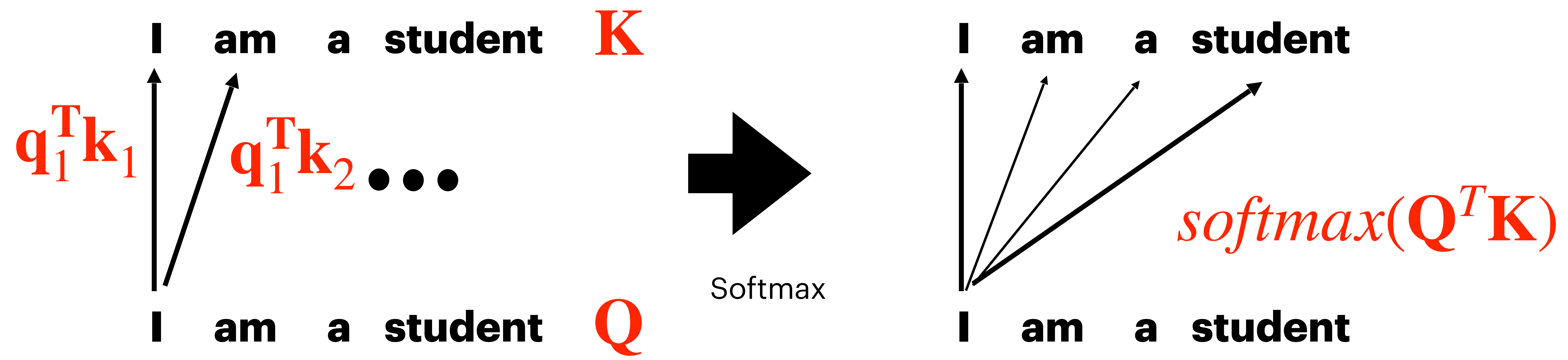

Pics taken from : https://jalammar.github.io/illustrated-transformer/

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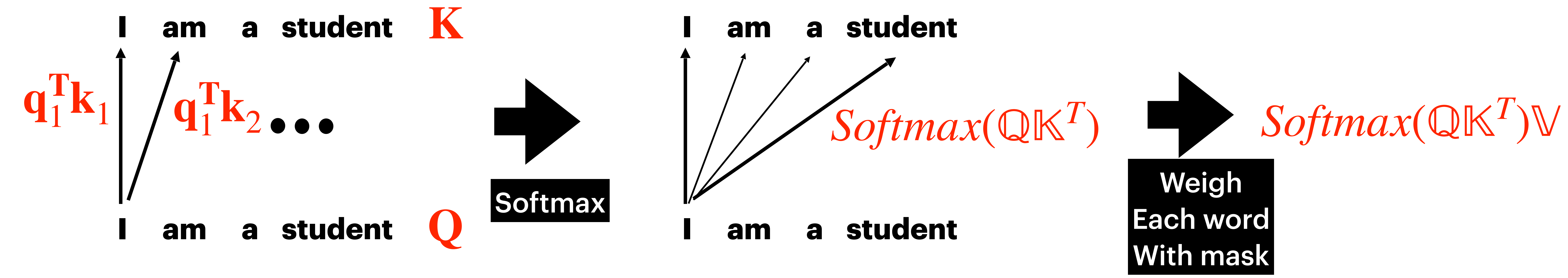

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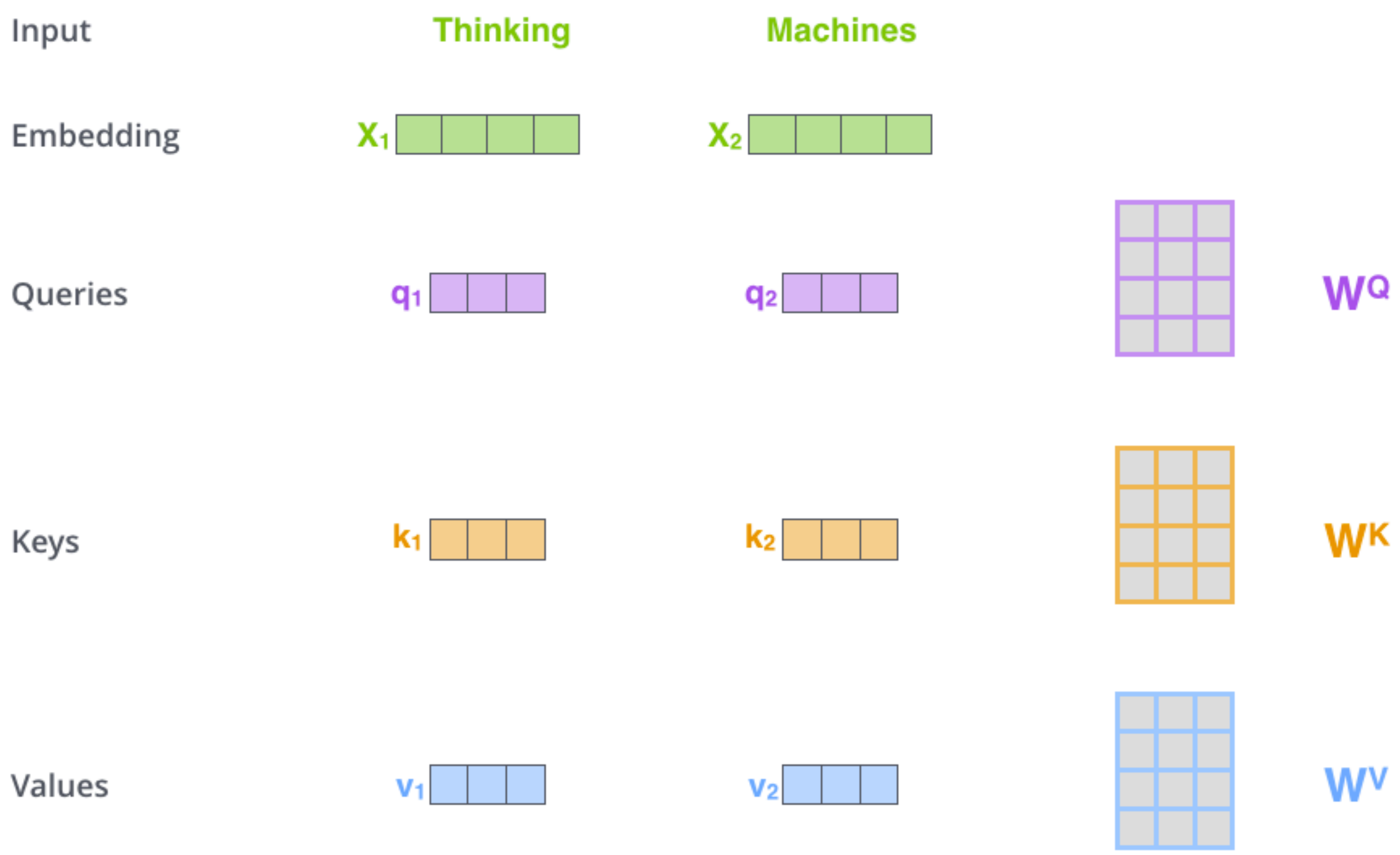
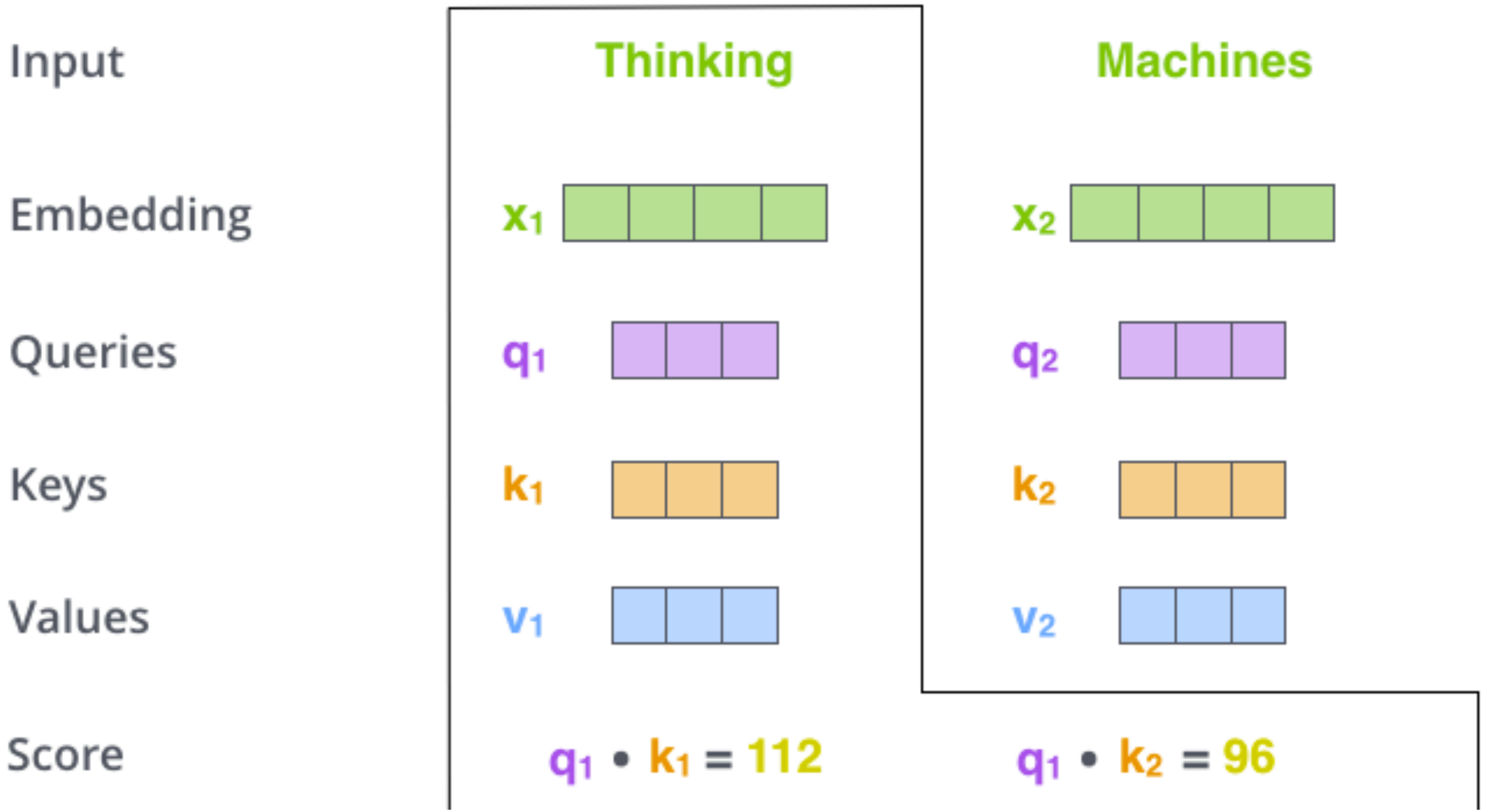
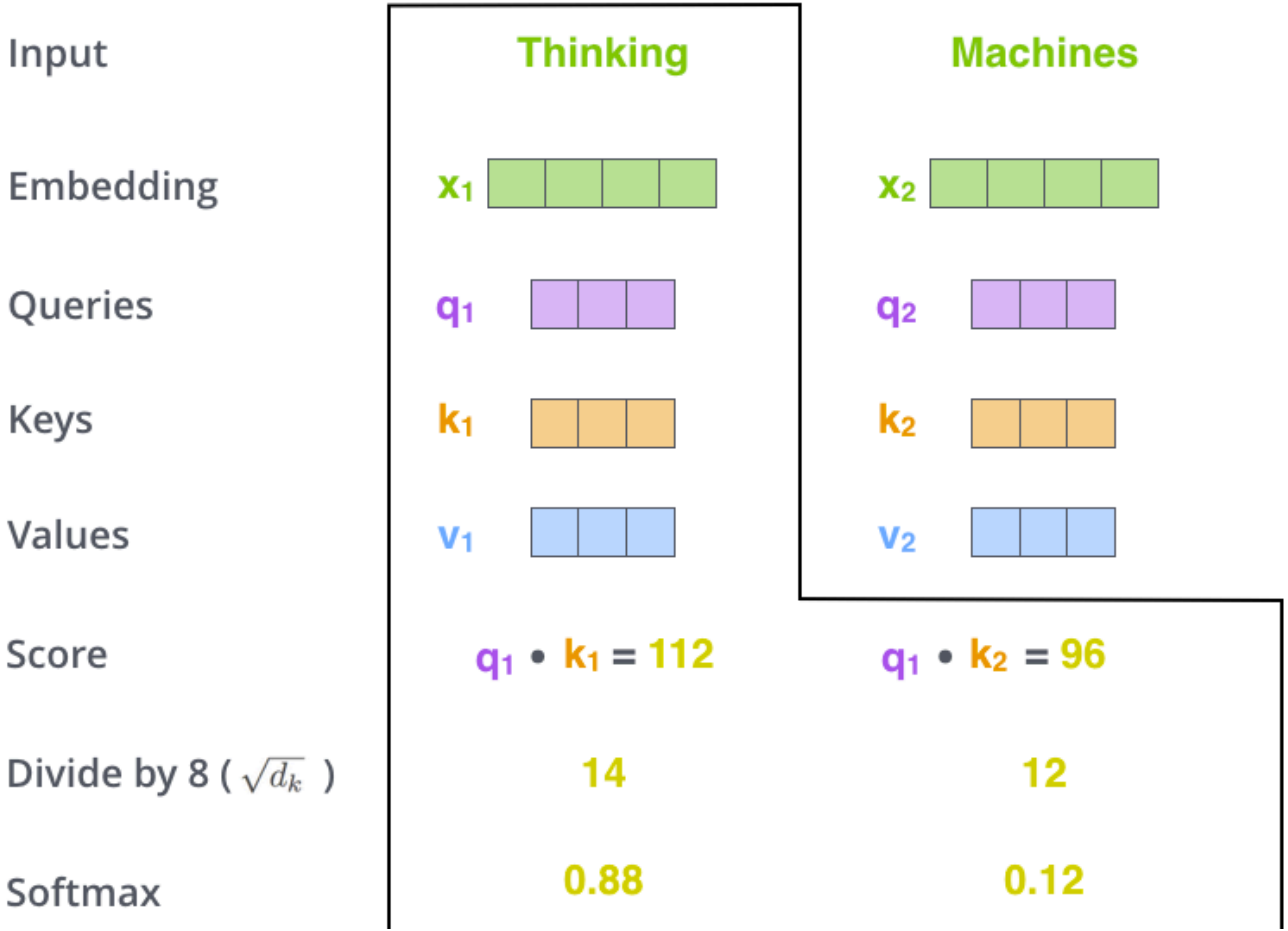
Transformers - self-attention



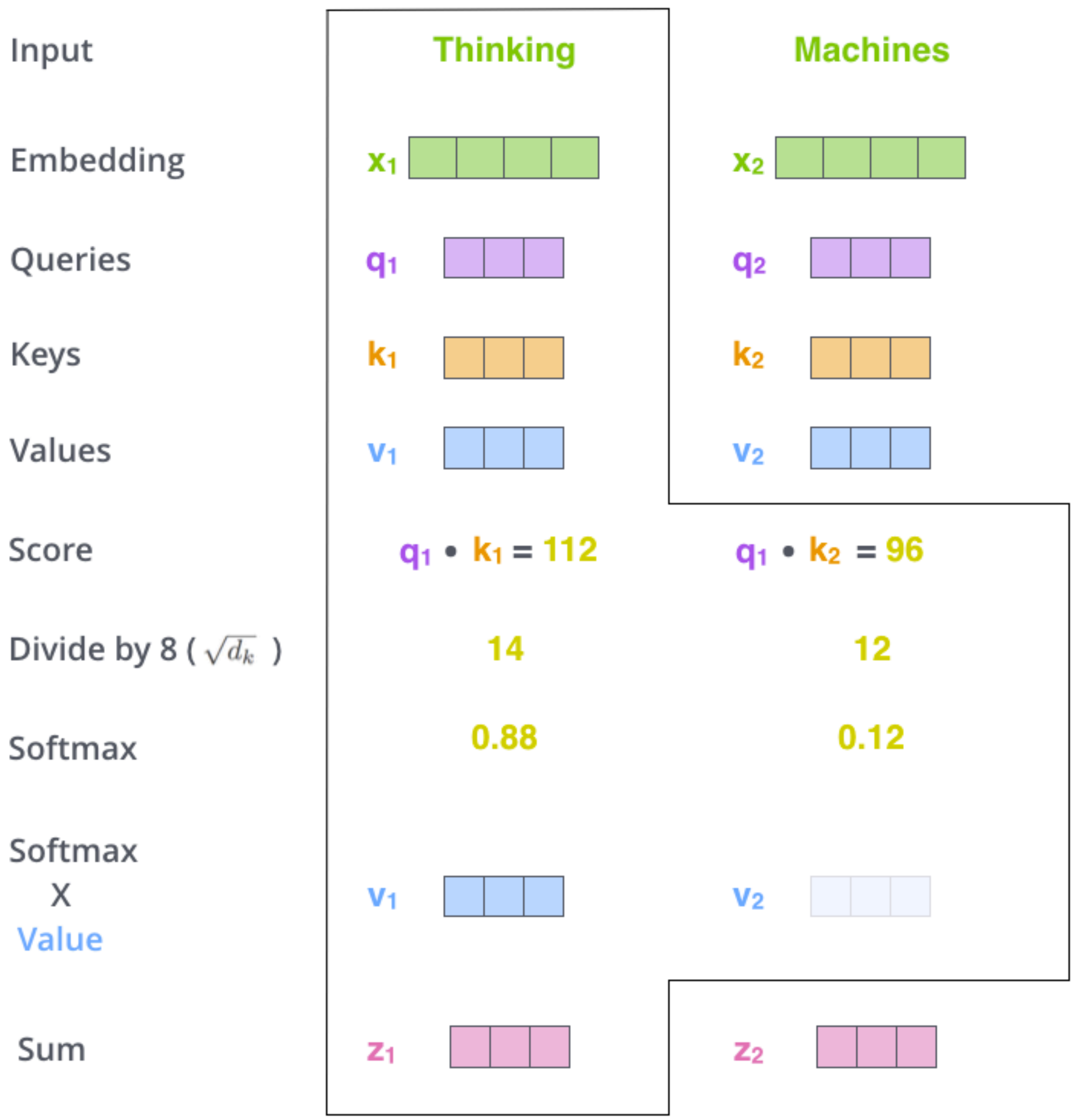
Transformers - self-attention



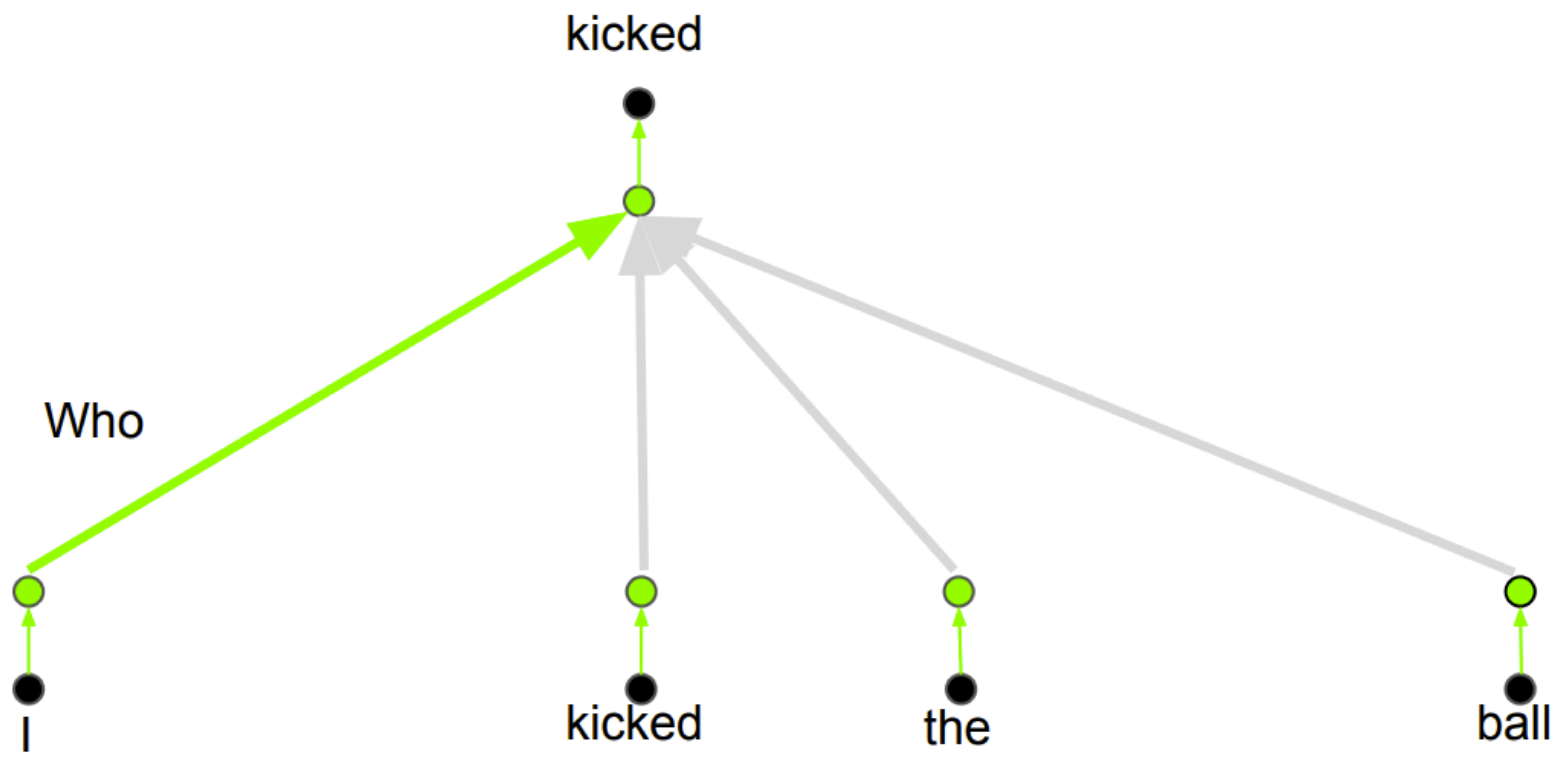
Transformers - self-attention



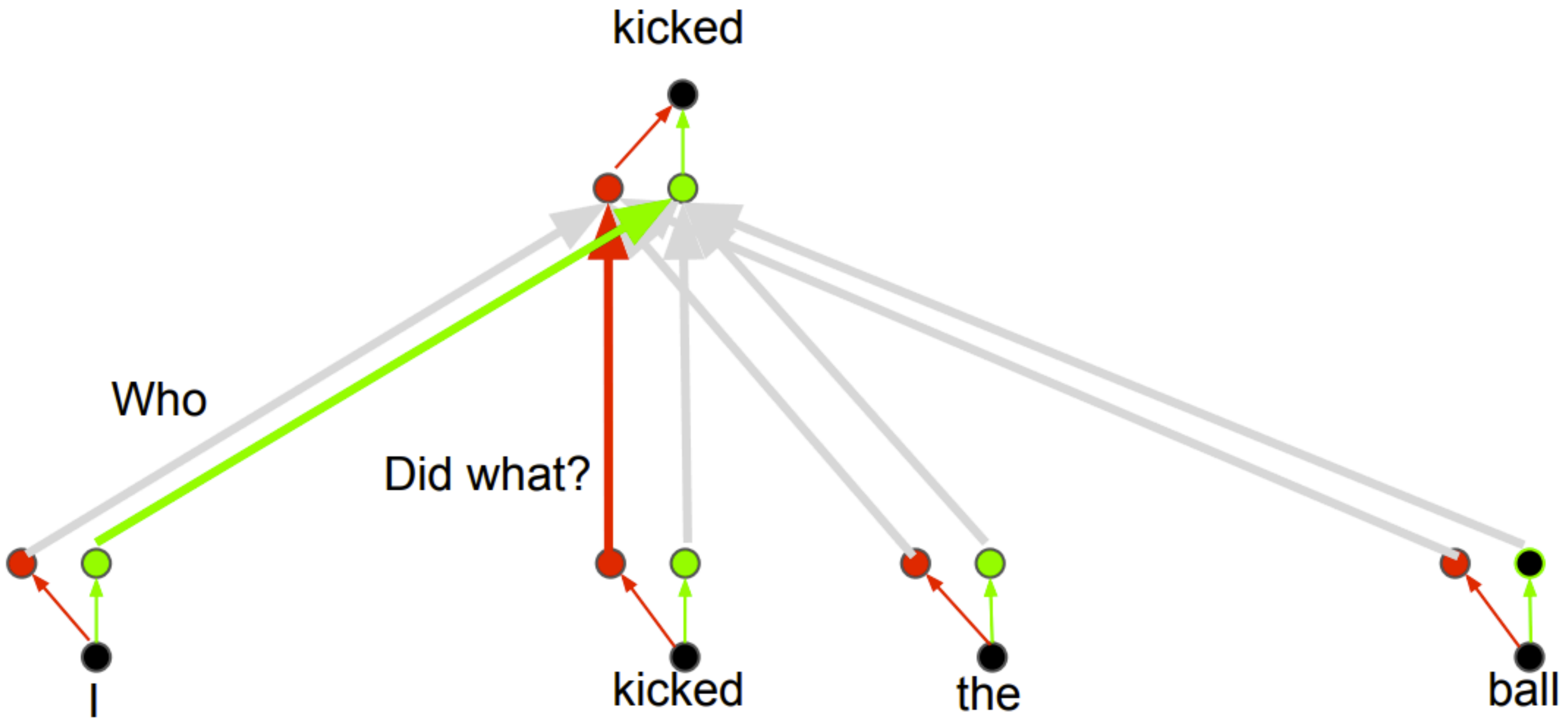
Transformers - self-attention



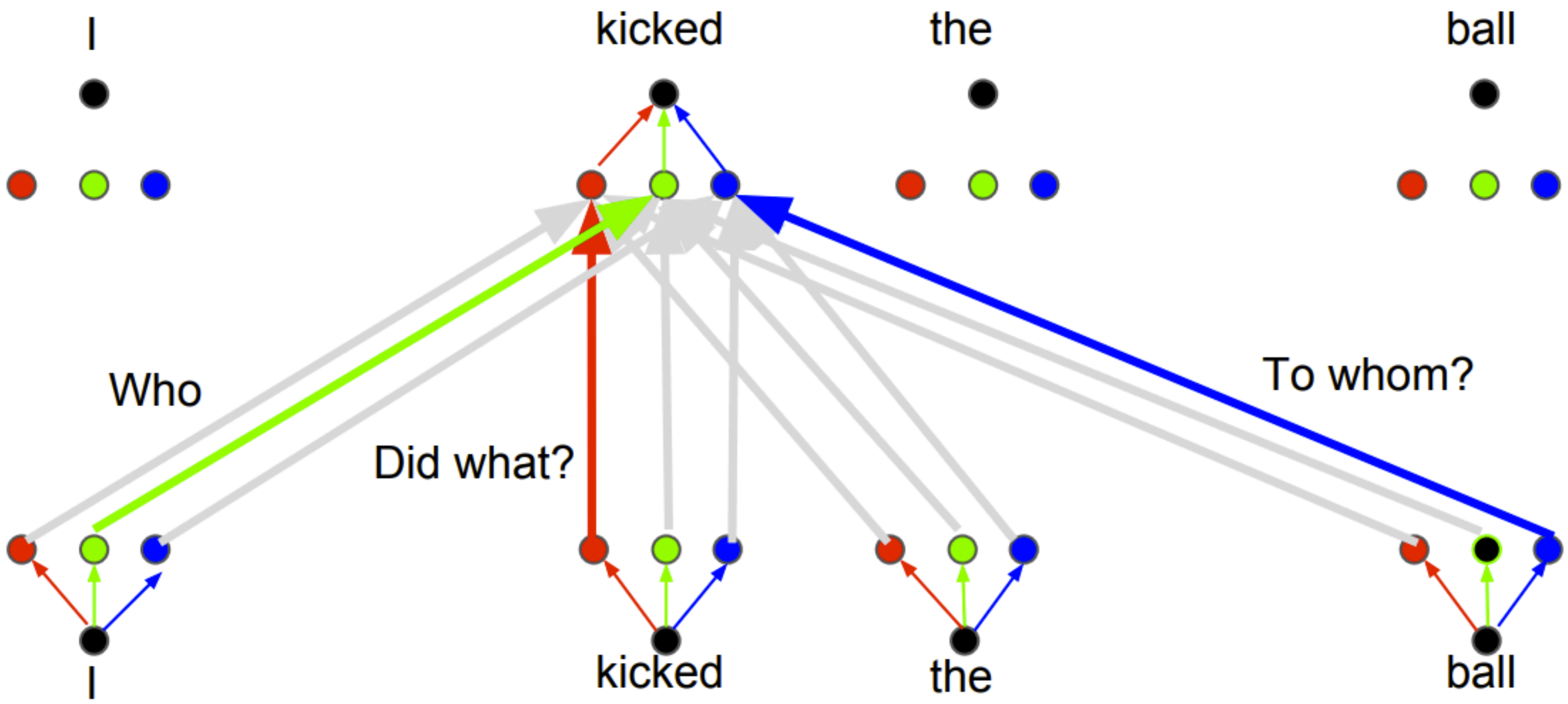
Multi-head



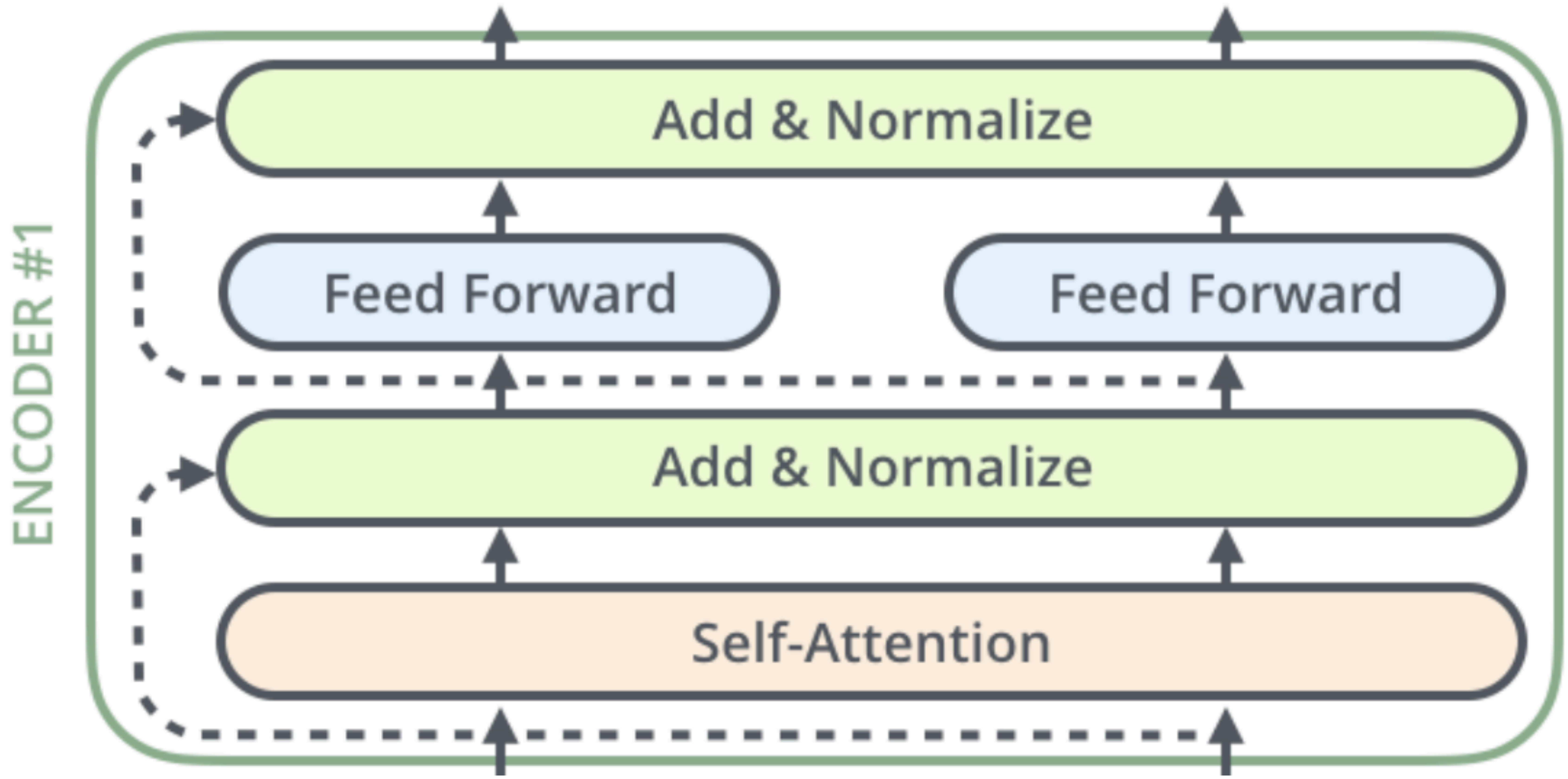
Multi-head



Multi-head

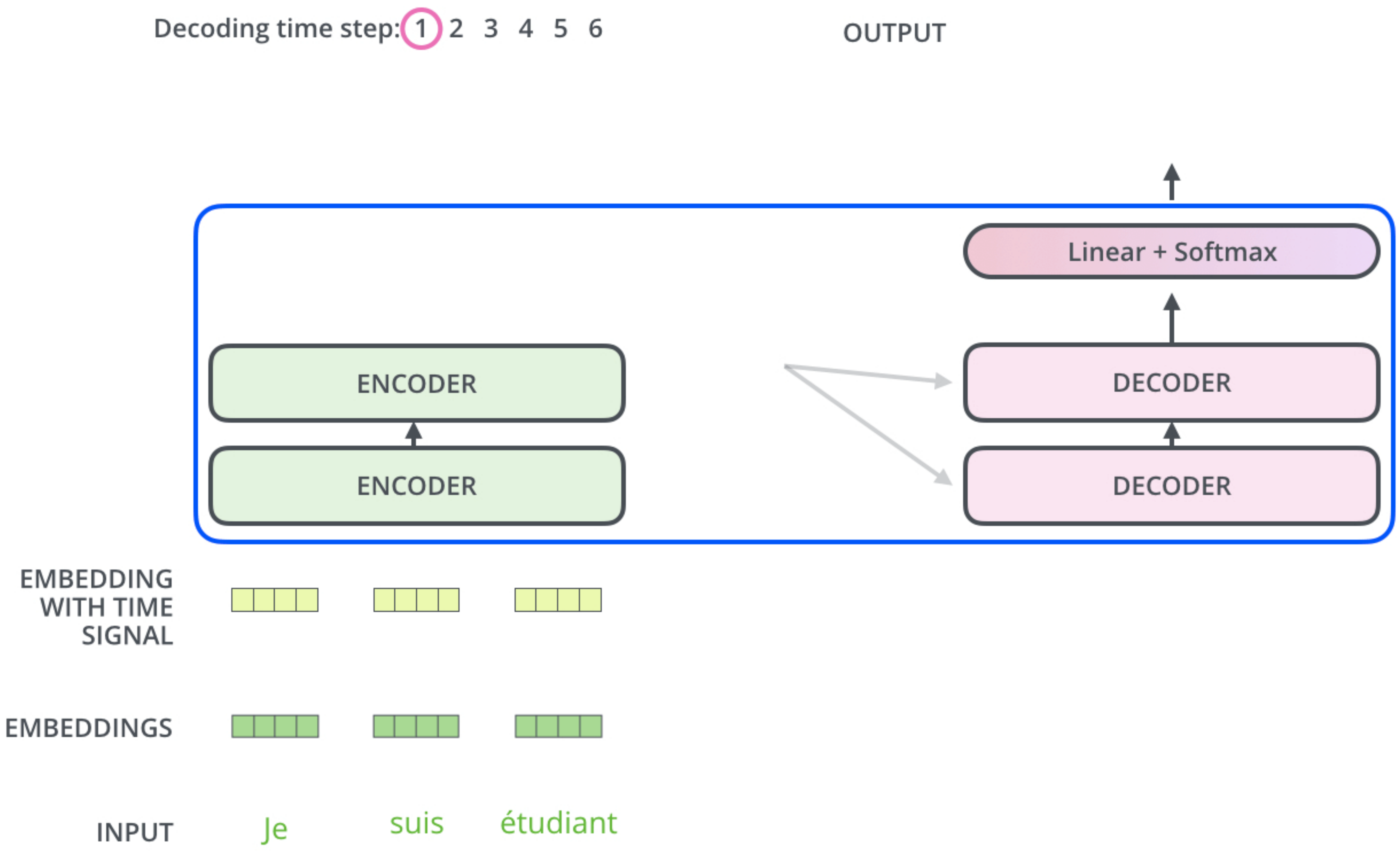


Transformer encoder



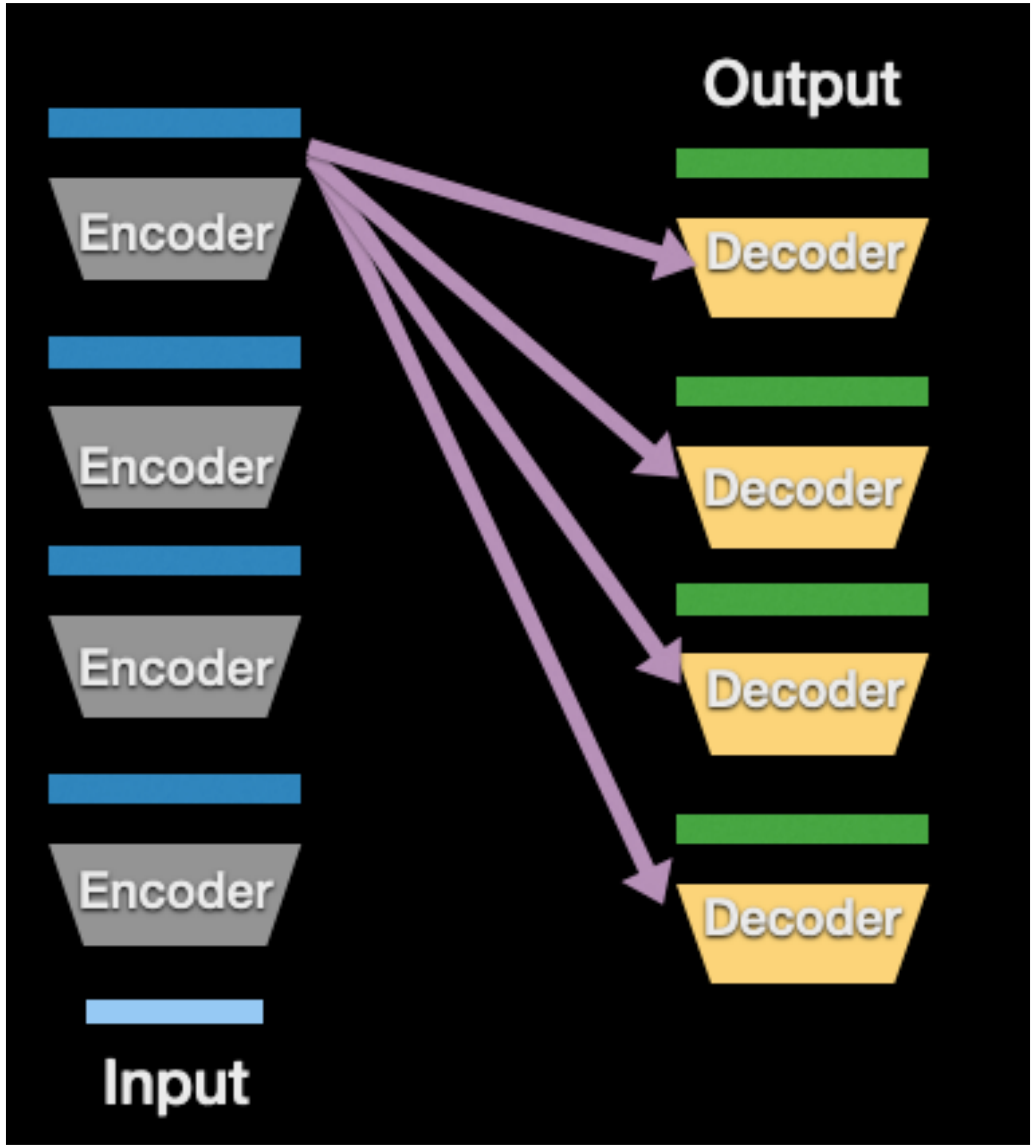
Pics taken from : https://jalammar.github.io/illustrated-transformer/

Transformer

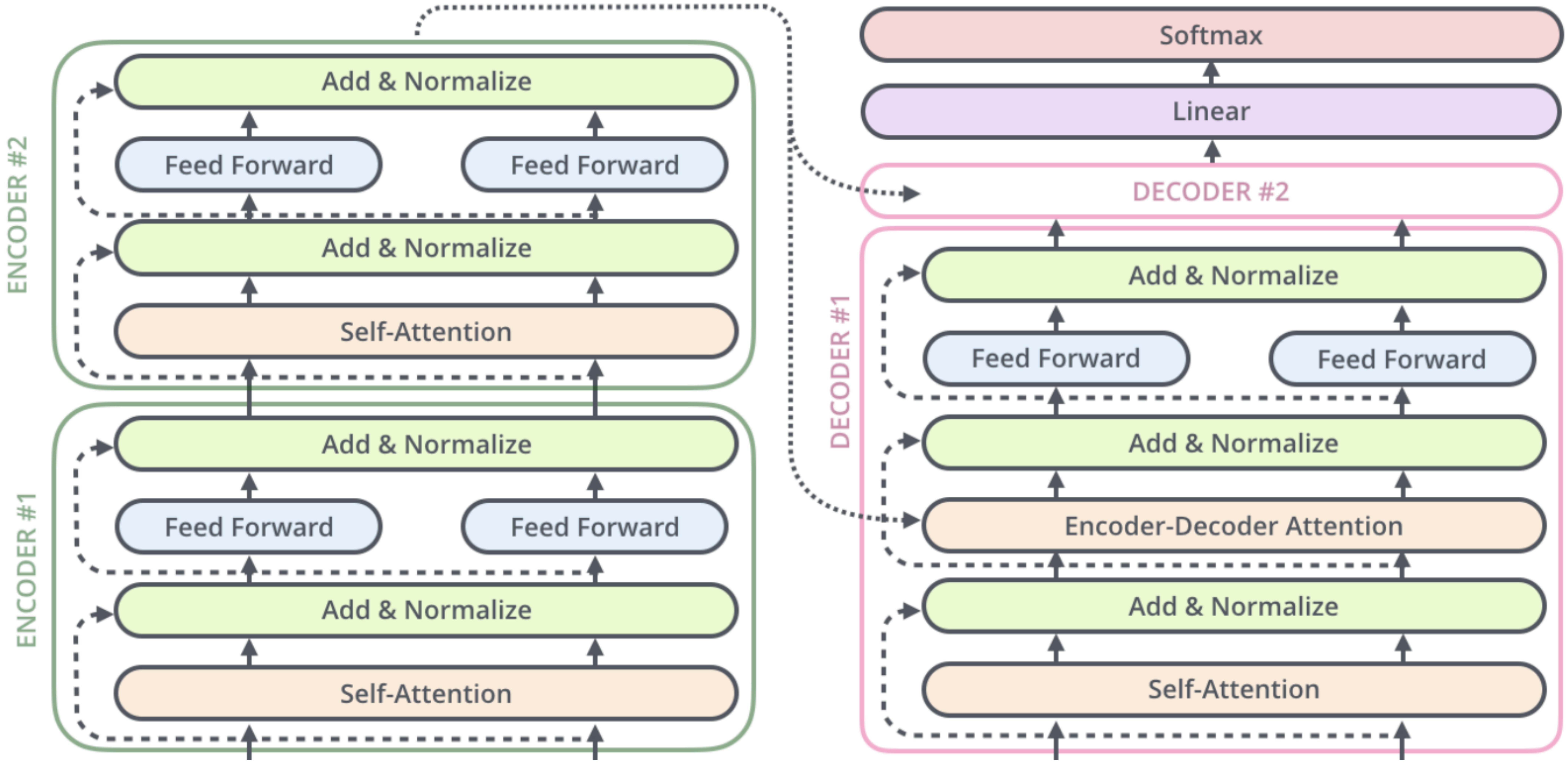


Pics taken from : https://jalammar.github.io/illustrated-transformer/

Encoder- Decoder Attention



Transformer decoder



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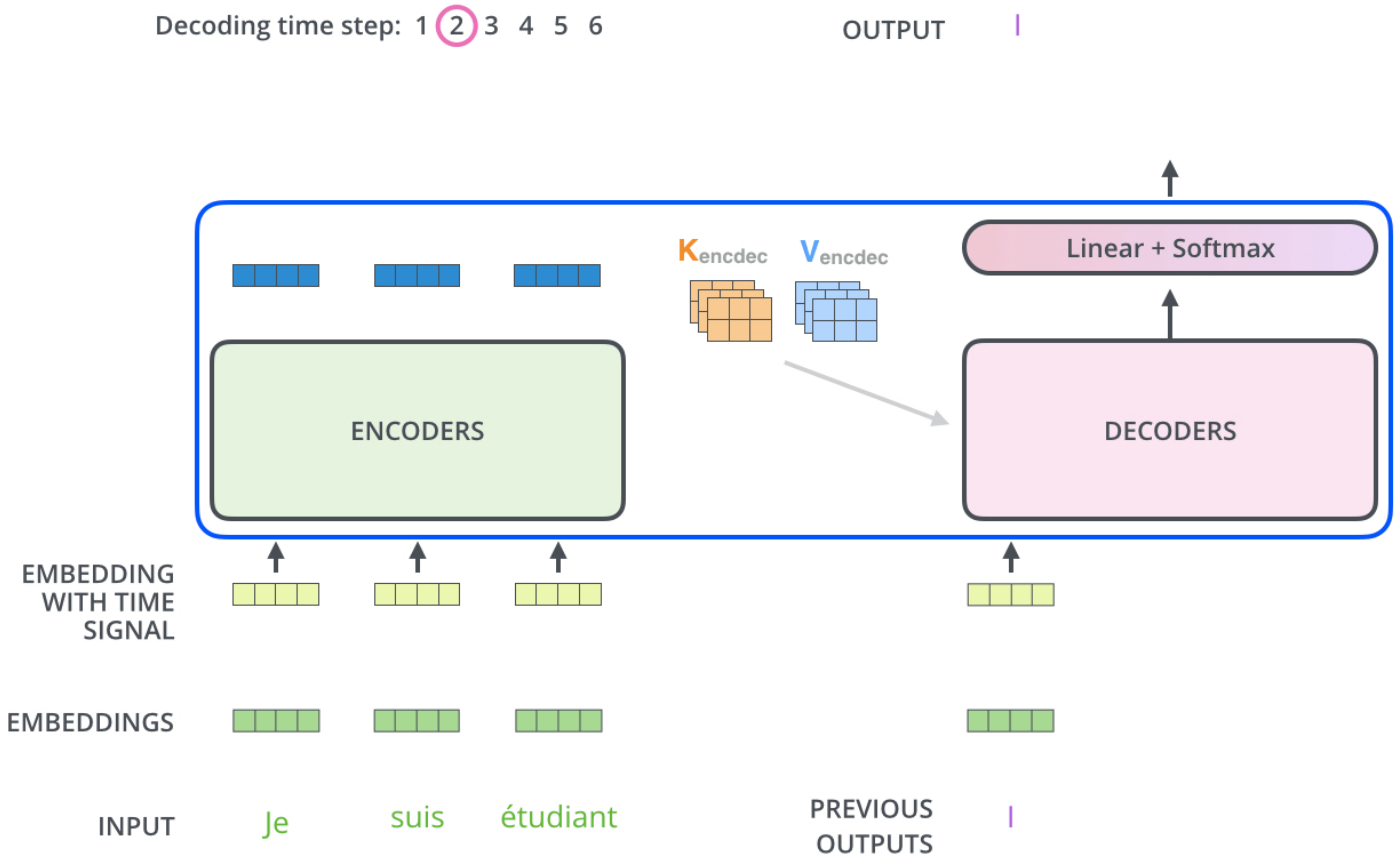
Transformer Example



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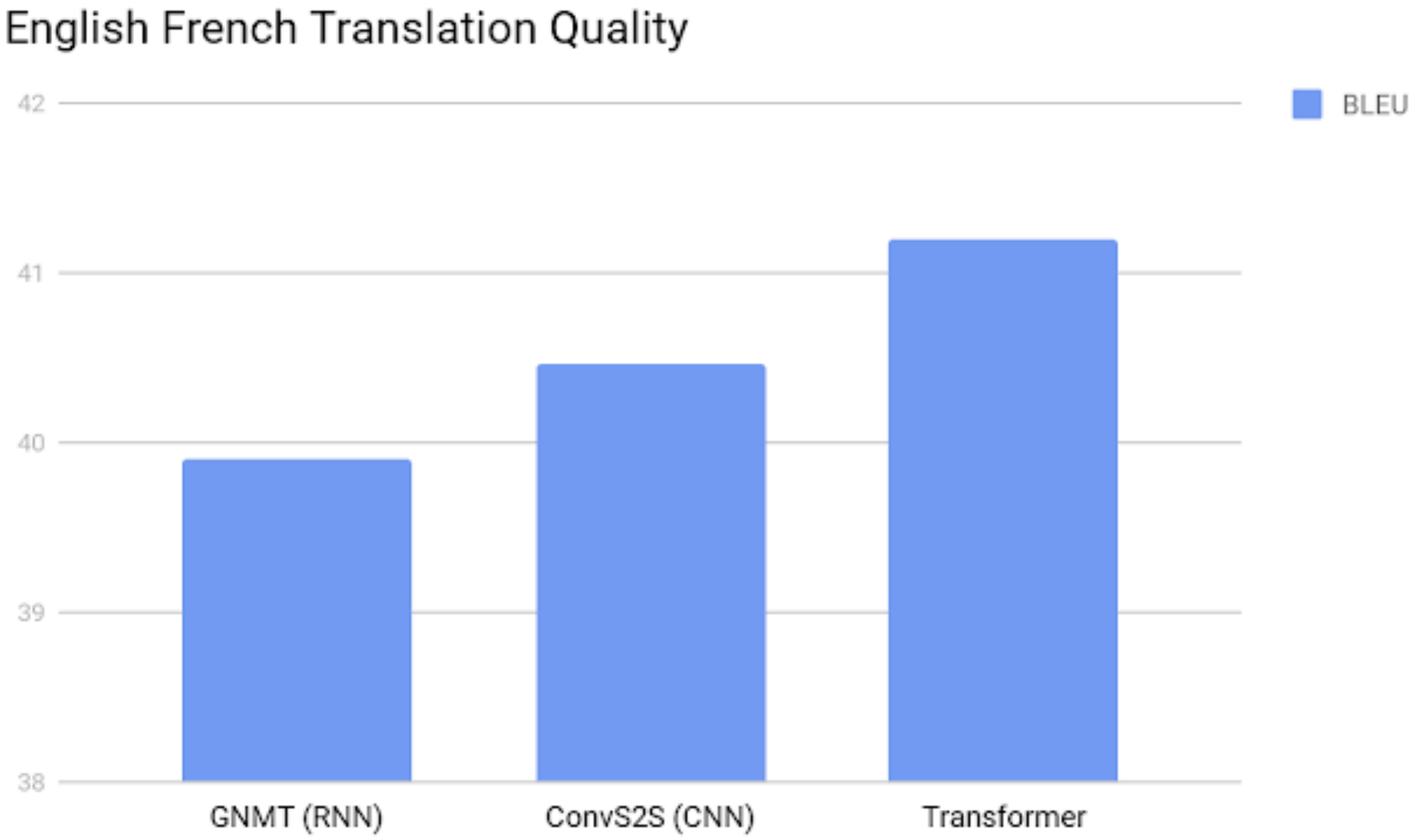
Neural Machine Translation Example

https://ai.googleblog.com/2017/08/transformer-novel-neural-network.html

Neural Machine Translation Example

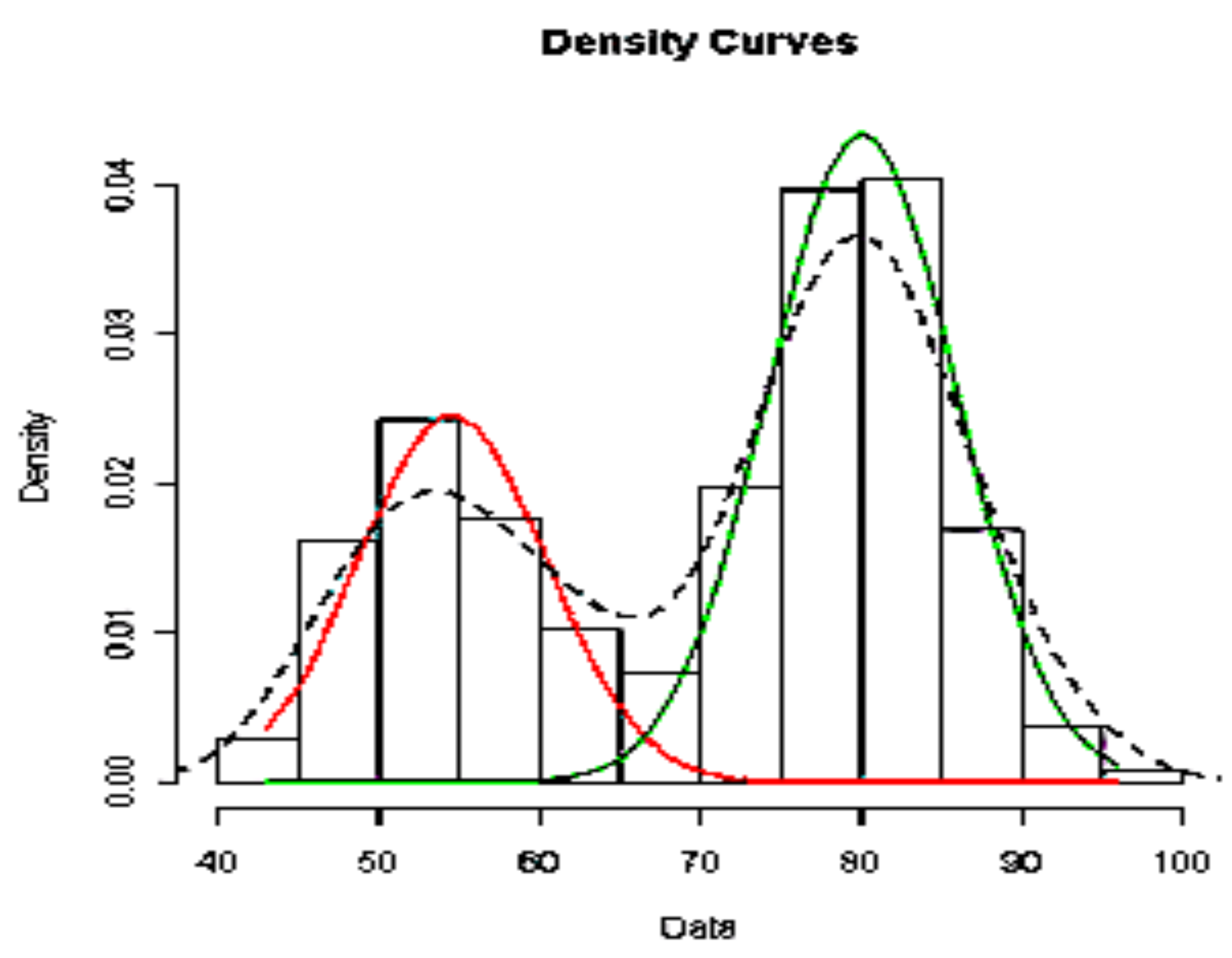


Unsupervised Learning

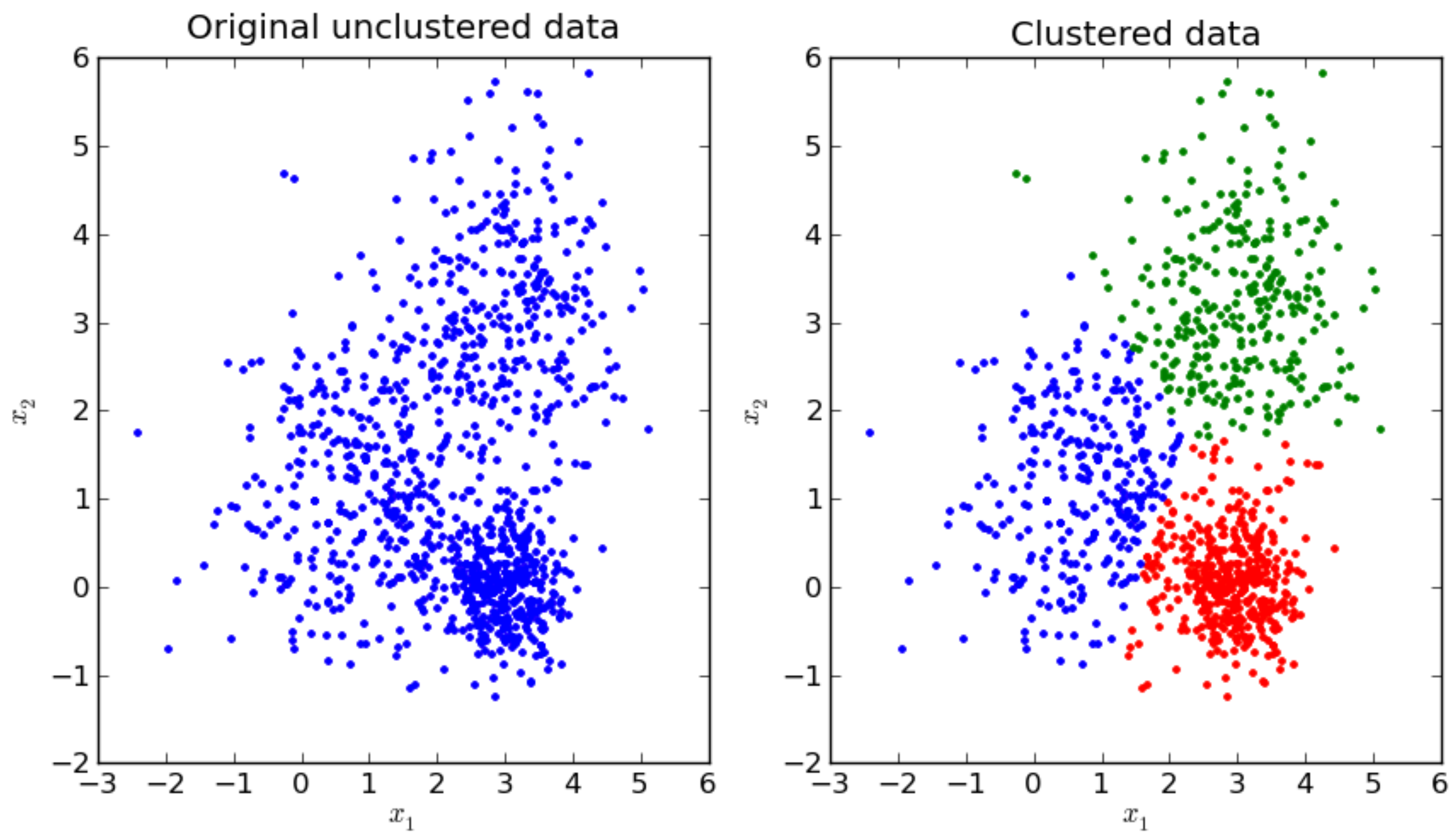
Unsupervised Learning

- Developing models that do not need labels
  - May model the generation of data.
  - May allow generation of new data samples
- Broad strategies for unsupervised learning

Learning the distribution of the data

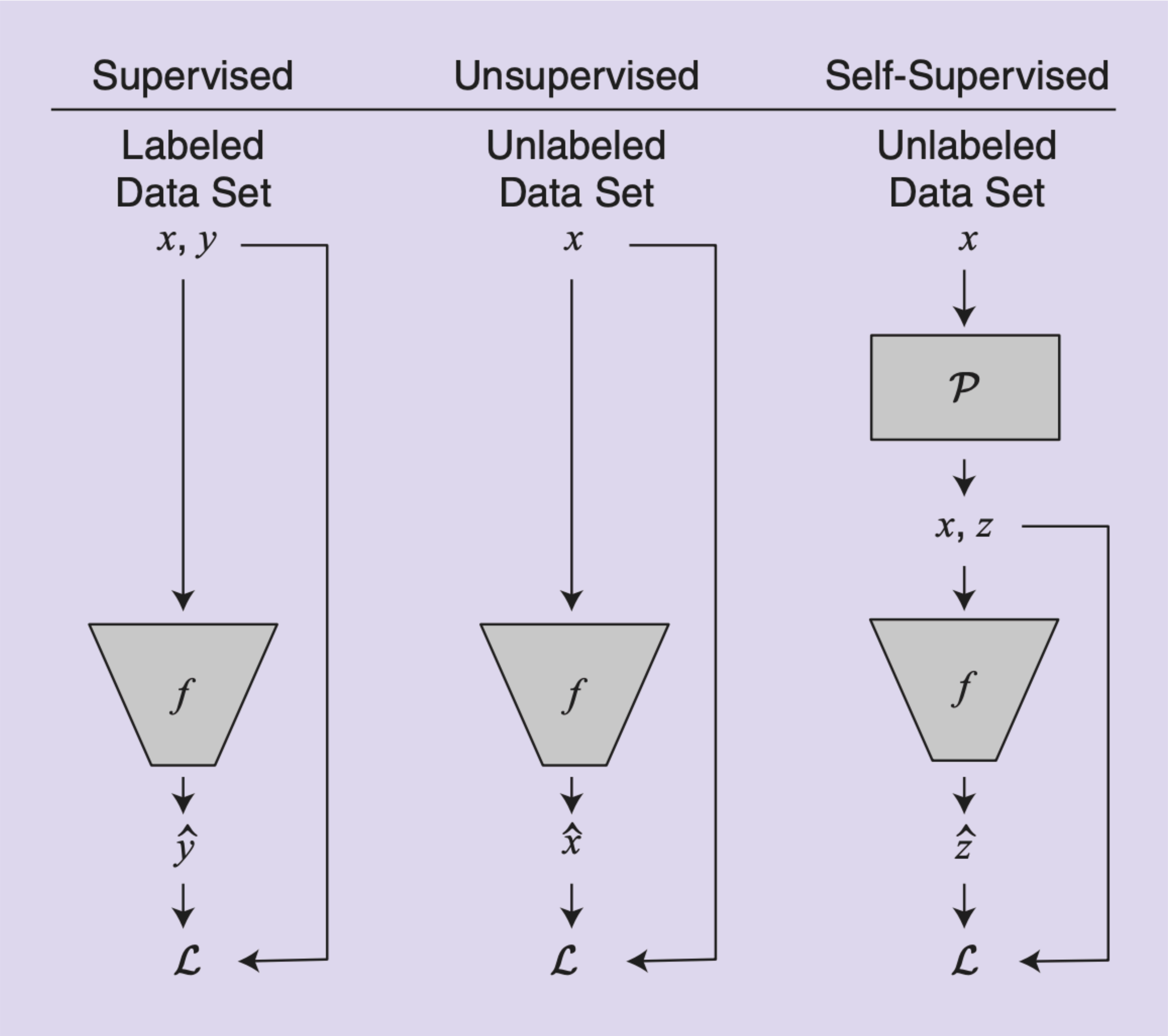


Detecting clusters in the data



Self supervision

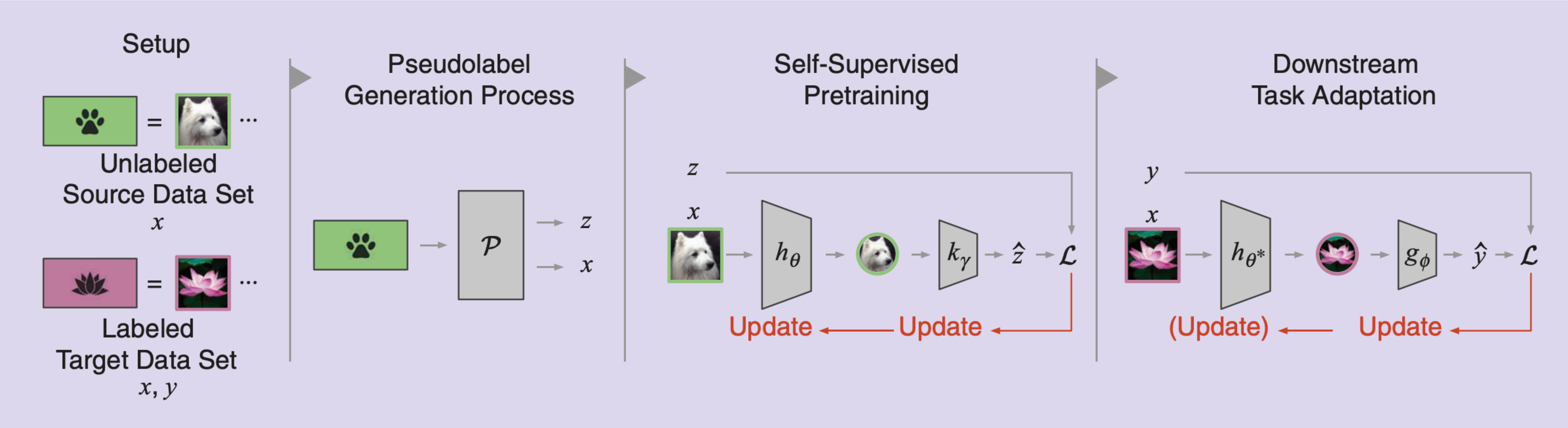
- ✦ Different from supervised and unsupervised learning
  - ✳ Does not perform distribution learning or reconstruction
  - ✳ Uses a pretext task
  - ✳ Performing contrastive or predictive learning
- ✦ Using large volumes of unsupervised data



Ericsson, Linus, et al. "Self-supervised representation learning: Introduction, advances, and challenges." *IEEE Signal Processing Magazine* 39.3 (2022): 42-62.

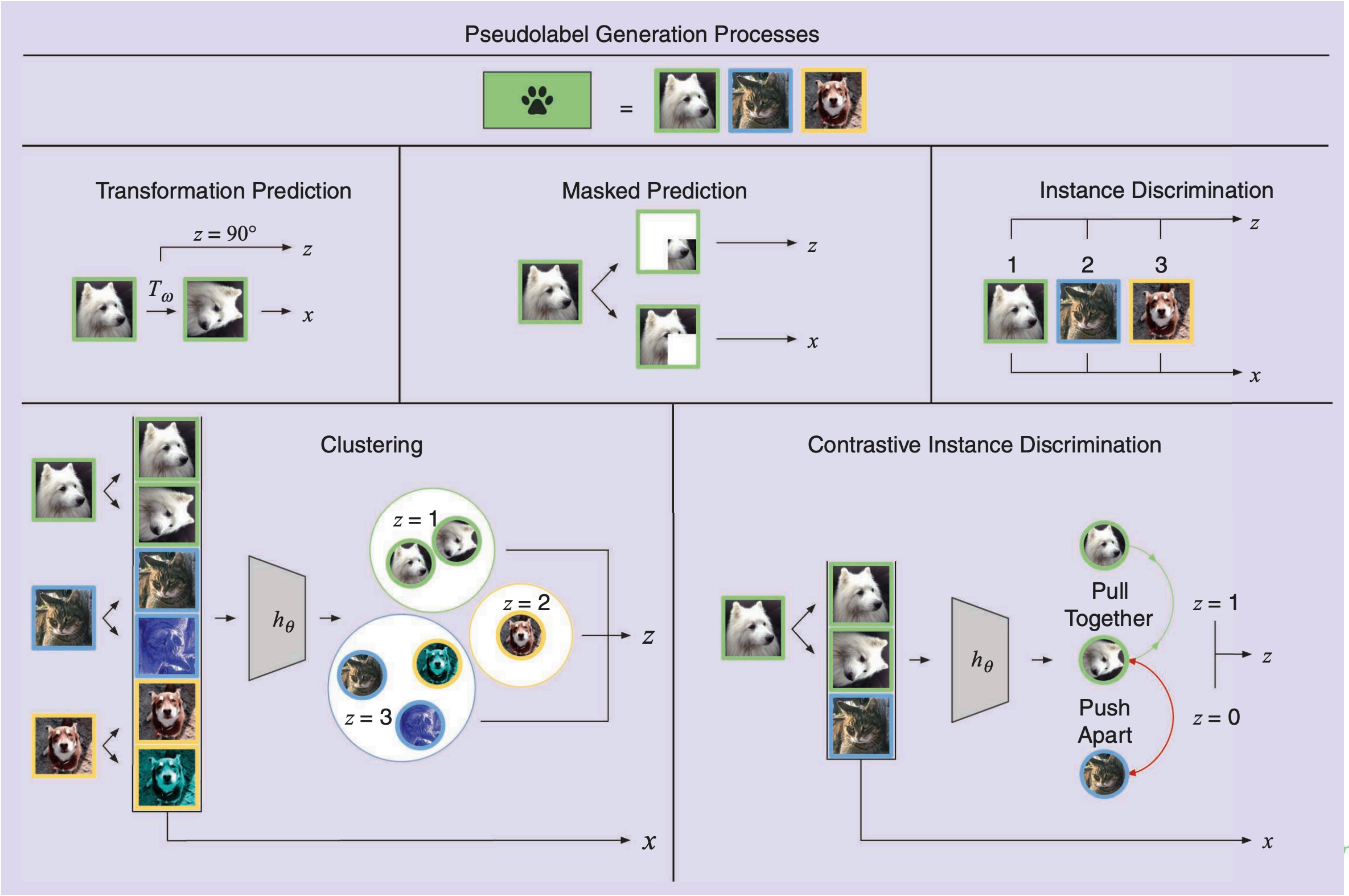
Self supervision - principle

- ✦ Two levels of modeling with unsupervised data
  - ❖ Generating a pseudo-label
  - ❖ Learning the upstream model
- ✦ Downstream task performs fine-tuning of the SSL model.



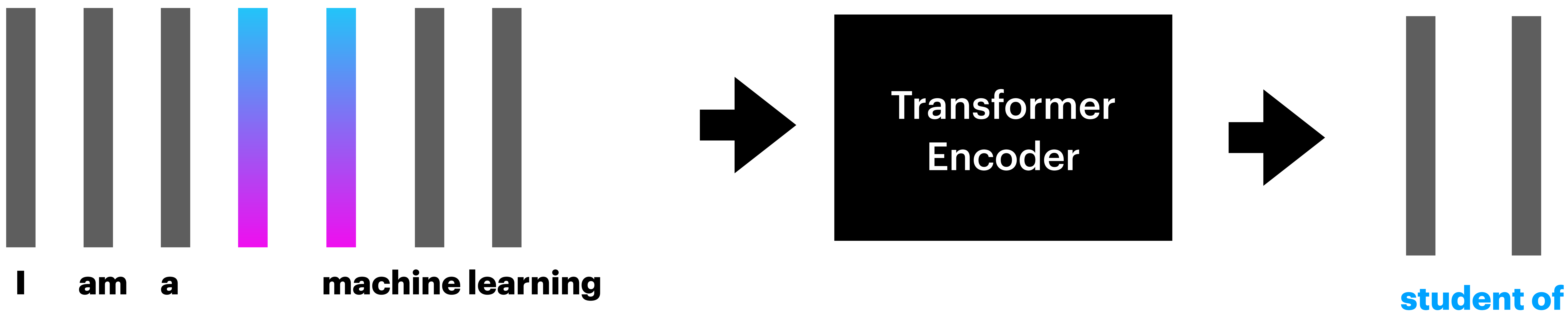
Ericsson, Linus, et al. "Self-supervised representation learning: Introduction, advances, and challenges." *IEEE Signal Processing Magazine* 39.3 (2022): 42-62.

Self supervision - pre-text task



Self-supervision as a task

- Masking out portions of the input data
  - ✳ Pass the rest of the embeddings (with zeros or random entries at the masked locations) to the transformer encoder
  - ✳ Have the model predict the word tokens in the masked portions - Masked Language Modelling (MLM)



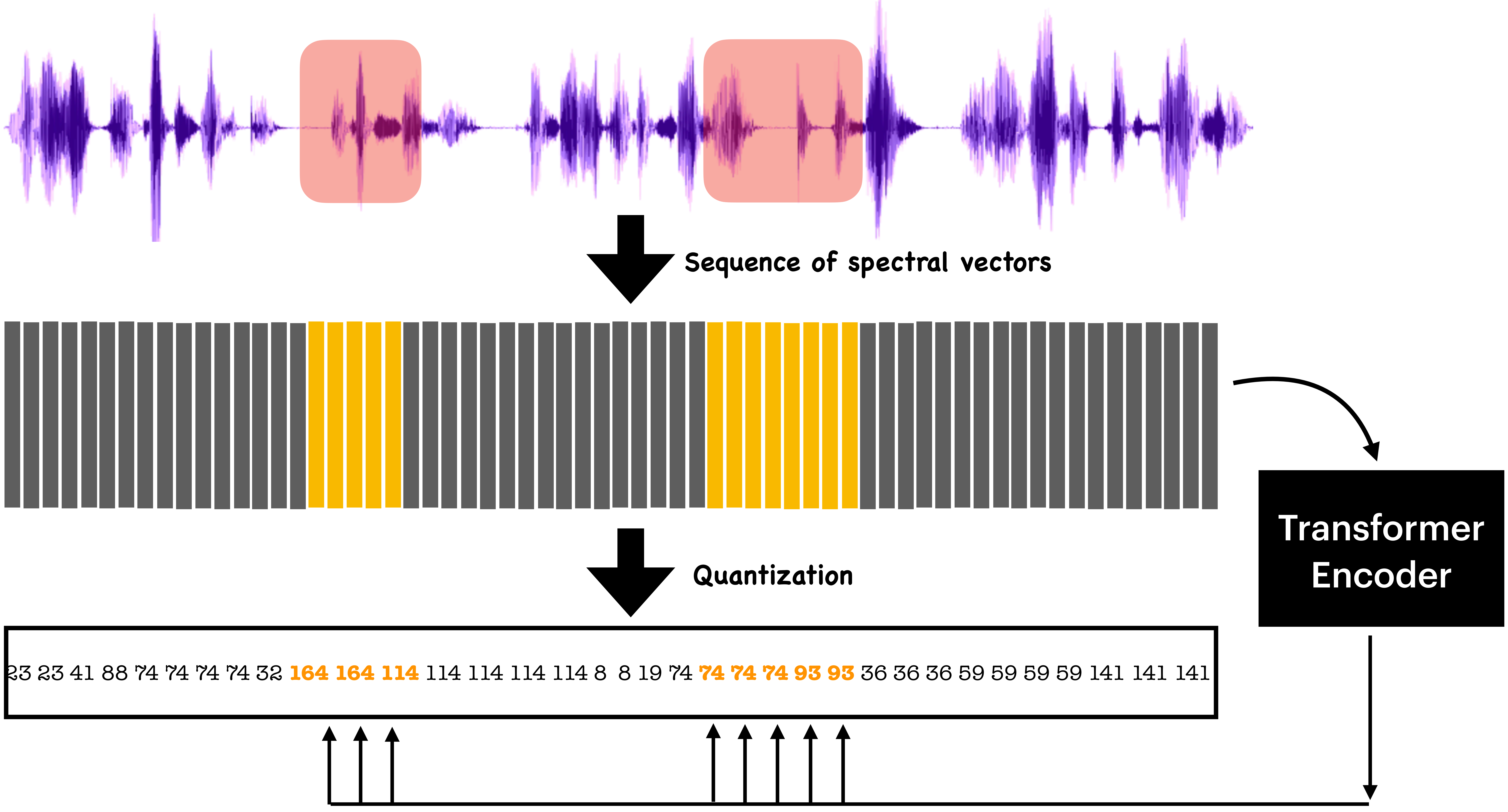
Large language models (LLMs)

- Extending the task of self-supervision
- Mine lots of text data
  - ✳ Crawled from the web, as well as, from other resources.
- Design the model with large capacity (Millions —> Billions of parameters)
- Pre-train the model
  - ✳ With MLM and similar style of losses
  - ✳ High resource of computations.
- Final trained model can be fine-tuned for supervised tasks
  - ✳ Load the parameters as initialization and perform supervised learning.

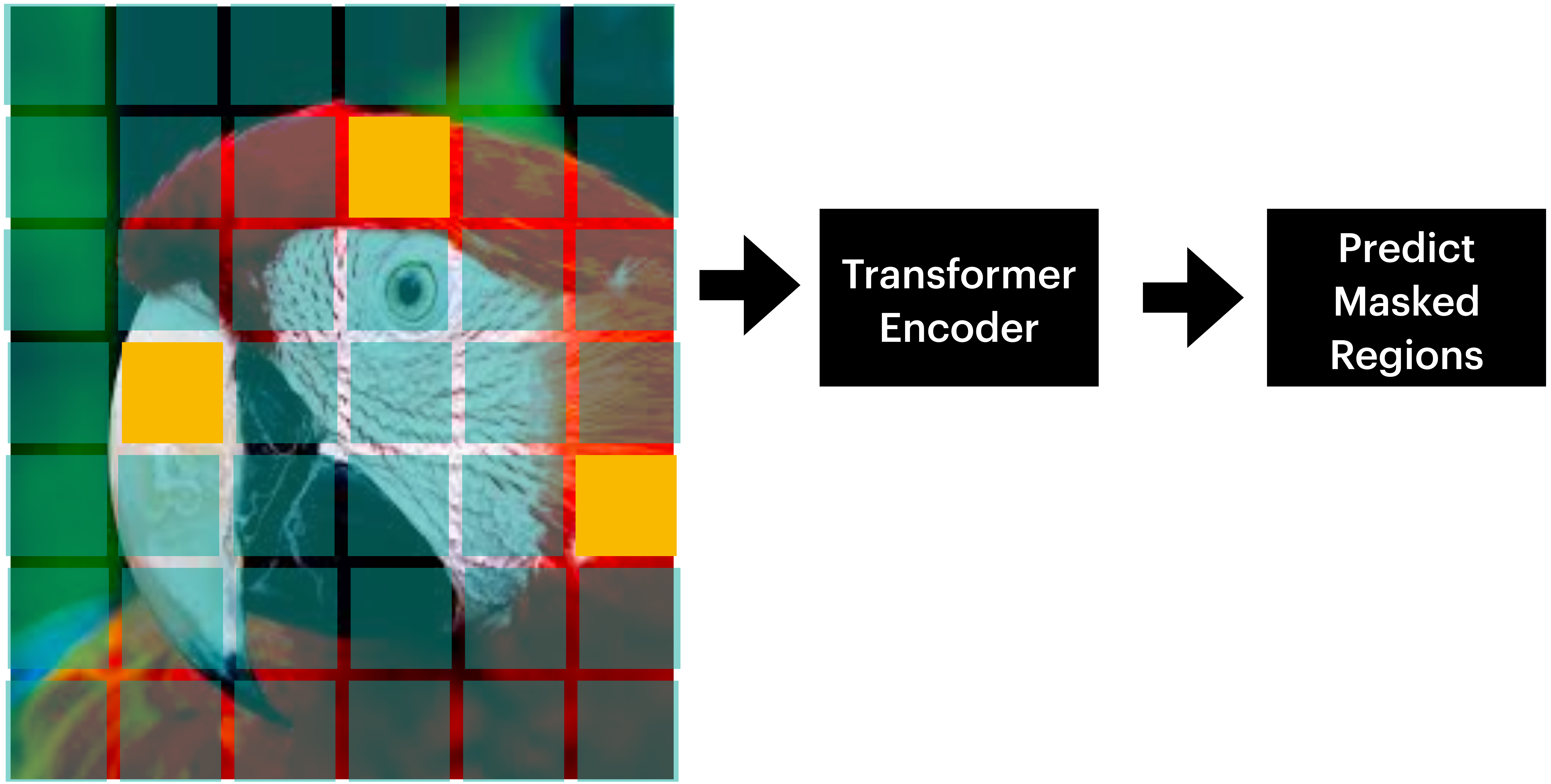
Large language models (LLMs)

- Self-supervised learning
  - ✳ Has shown emergent abilities to generalise to wide variety of downstream tasks.
    - ✓ Tasks that the model was not trained on
    - ✓ Not seen in smaller models
  - ✳ Enables to build reasoning capabilities in the model.
  - ✳ Applicable for several domains - text, speech and images.

Self-supervision in audio - wav2vec



Self-supervision in images - Vision Transformer



LLM - Examples

- Generative Pre-trained Transformers (GPT) series

	Architecture	Data Used	Model Size
GPT-1	Transformer (12 layer, decoder only model)	Book Corpus (4.5GB)	117M
GPT-2	GPT-1 with additional normalisation layers	Web Text (40GB)	1.5B
GPT-3/3.5	GPT-2 with more layers Adding Fine-tuning tasks and human feedback	Large Web Crawl (570B)	175B
GPT-4/4o	Details Undisclosed [Trained with Text + Images]	—	—

Future works (some already underway)

- Multi-modal
  - ✳ Incorporating learning across modalities
    - ✓ Create a domain specific encoder/decoder and learning the joint language model.
- Combining some labeled data with the self-supervised data to further improve the models.
  - ✓ Current models like GPT use human feedback.
- Understanding the risks and vulnerabilities of these models.

THANK YOU

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