07 – TRANSFORMER ARCHITECTURE

MACHINE LEARNING FOR NATURAL LANGUAGE PROCESSING, AIMS 2024

Lecture 07
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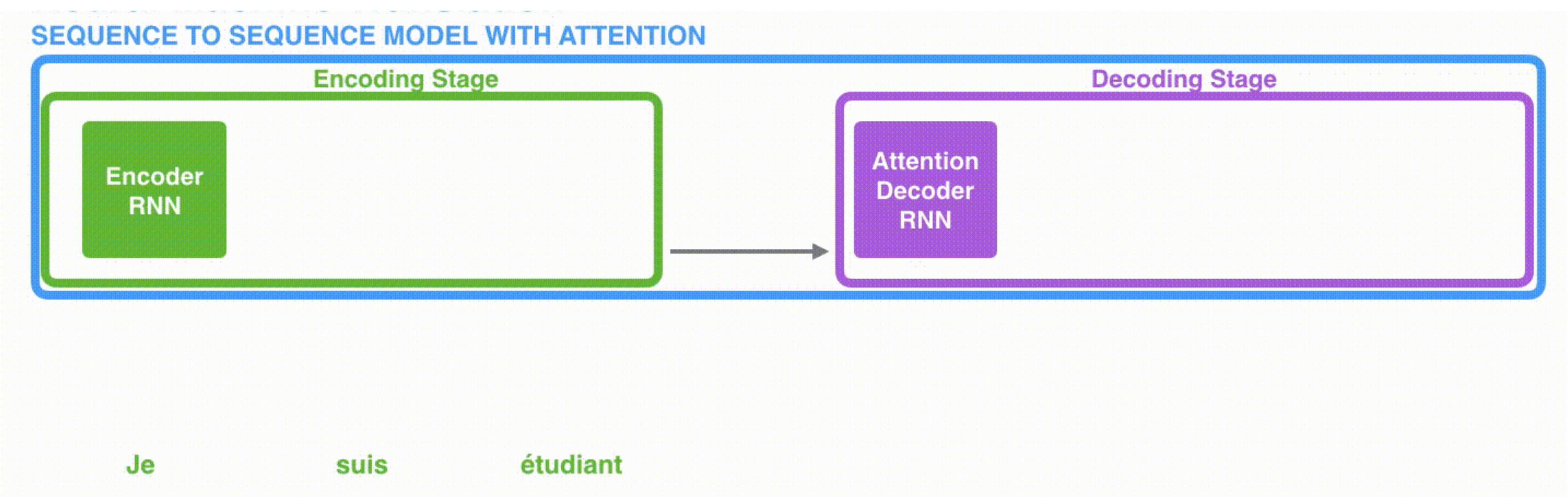
OVERVIEW

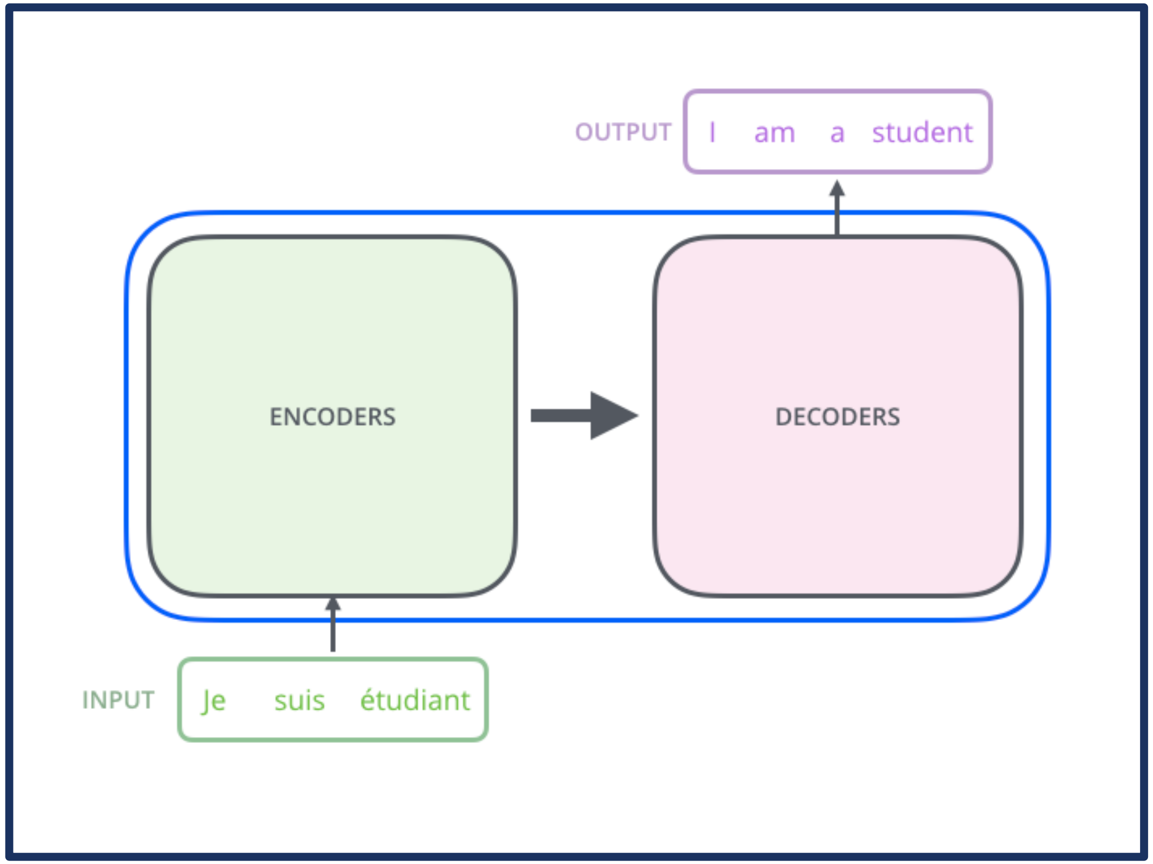
1. What is a Transformer
2. Transformer architecture
3. How transformers work
4. How to calculate self-attention
5. Multi-head attention
6. Transfer Learning

WHAT IS A TRANSFORMER



WHAT IS A TRANSFORMER

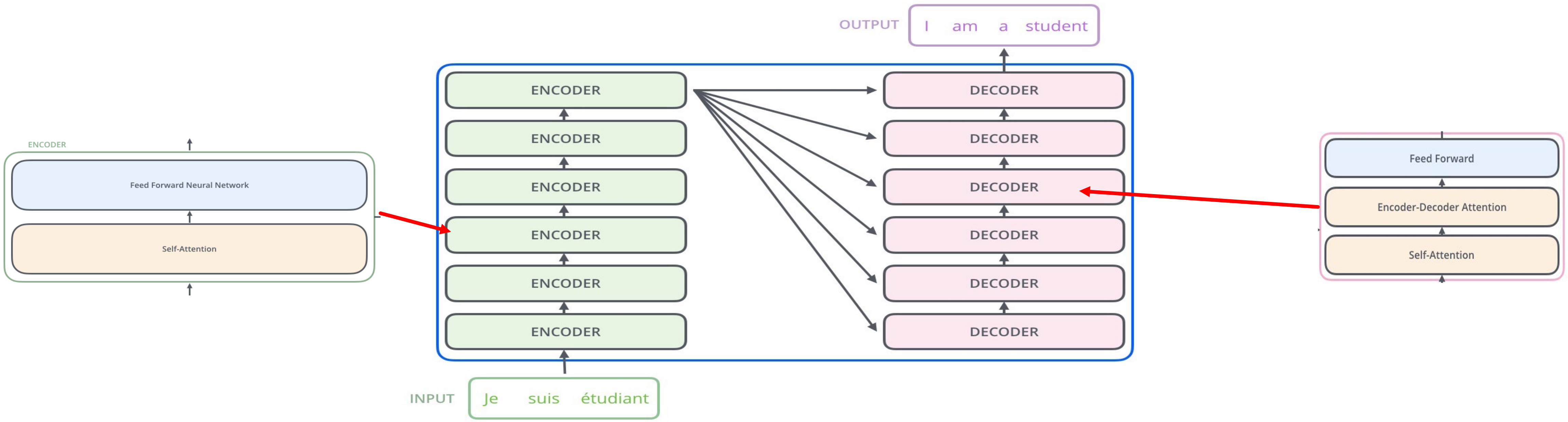
TRANSFORMERS



- **Transformer** – proposed by Vaswani A., 2017 (Attention is all you need)
  - uses attention to boost the speed with which these models can be trained.
  - The transformer is based on a feedforward neural network rather than RNN.
  - The biggest benefit of the Transformer is the speed of computation due to parallelization.
  - All input sequences are processed simultaneously.

TRANSFORMER – ARCHITECTURE

- Architecture: stacked encoder – decoder architecture
- Encoding component: stack of encoders (original paper had 6 encoders)
- encoders are all identical in structure
- Decoding component: stack of decoders (same number as the encoder)



TRANSFORMER – ARCHITECTURE

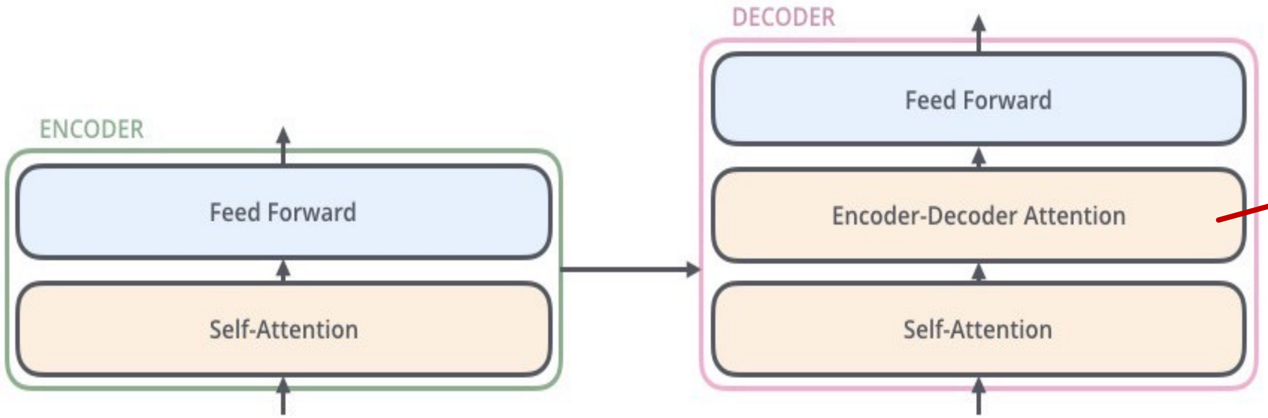
Encoder

Inputs first flow through a self-attention layer

Outputs of the self-attention layer are fed to a feed-forward neural network.

Decoder

Input from encoder flows through self-attention layer then Encoder-Decoder Attention layer and finally through Feedforward layer

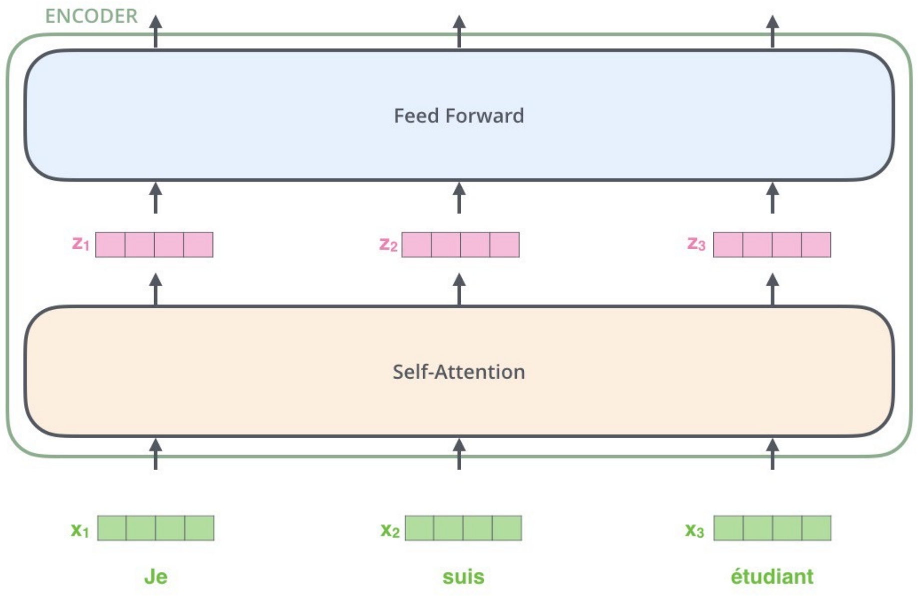


Attention layer:

- helps decoder focus on relevant parts of the input

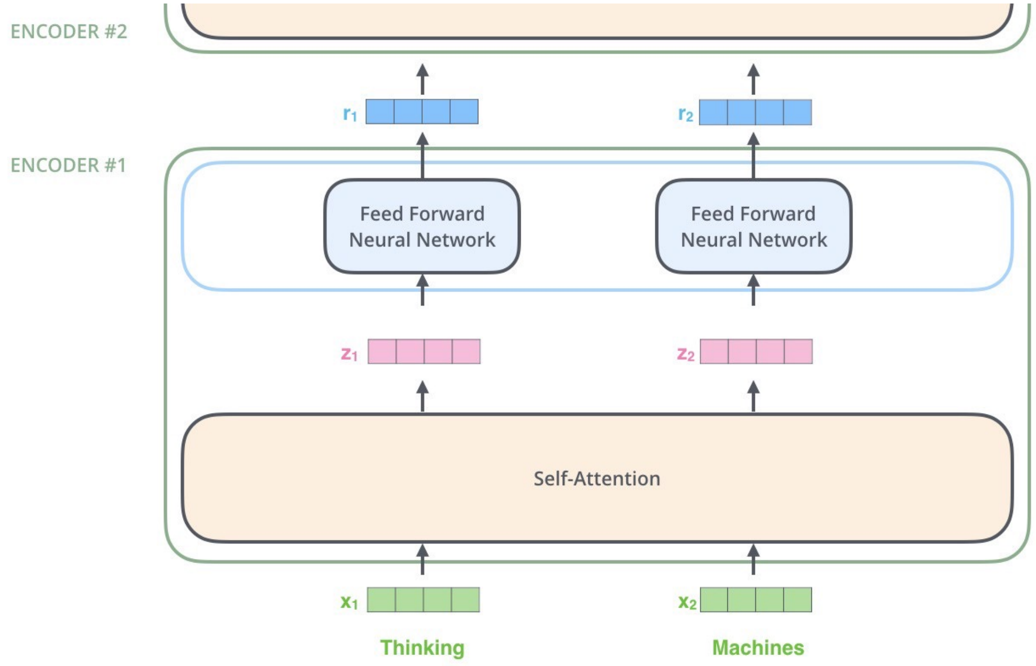
HOW THE TRANSFORMER WORKS

- Convert input word into a word embedding vectors
- Each word in the sentence flows through its own path in the encoder



HOW THE TRANSFORMER WORKS – ENCODING

- Encoder receive input words as vectors
- Self attention processes the input and sent to the feedforward network
- Feedforward sends output to next encoder layer.



TRANSFORMER – WHAT IS SELF ATTENTION?

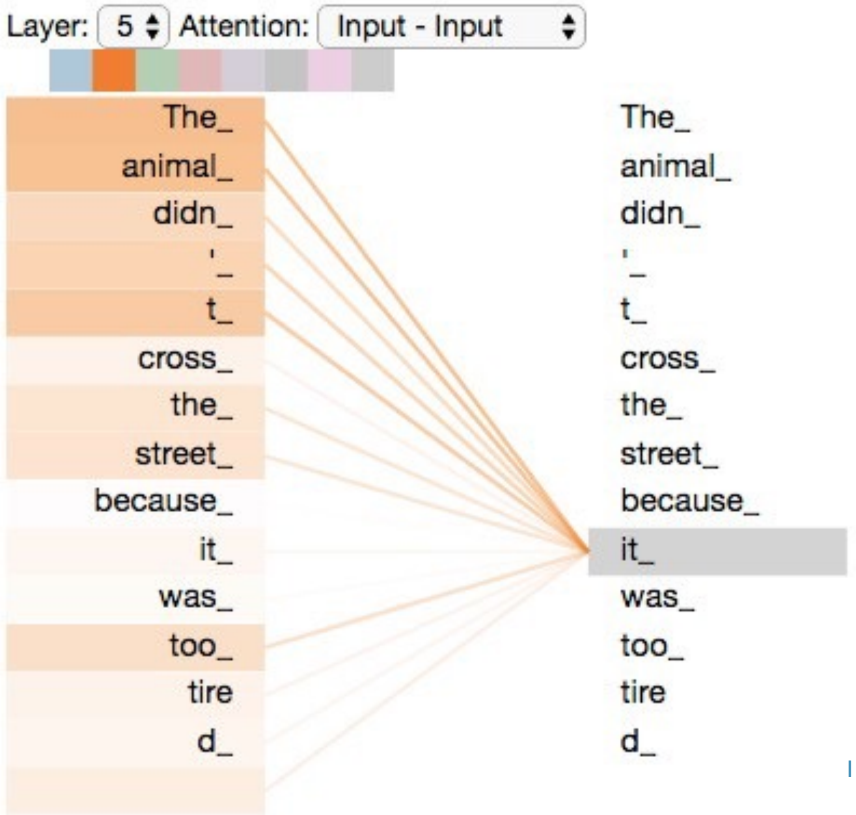
Example:

The animal didn't cross the street because it was too tired.

- What does *it* in this sentence refer to?
  - *the street*
  - *the animal*

- self-attention allows the transformer model to associate
  - *it* with *animal*

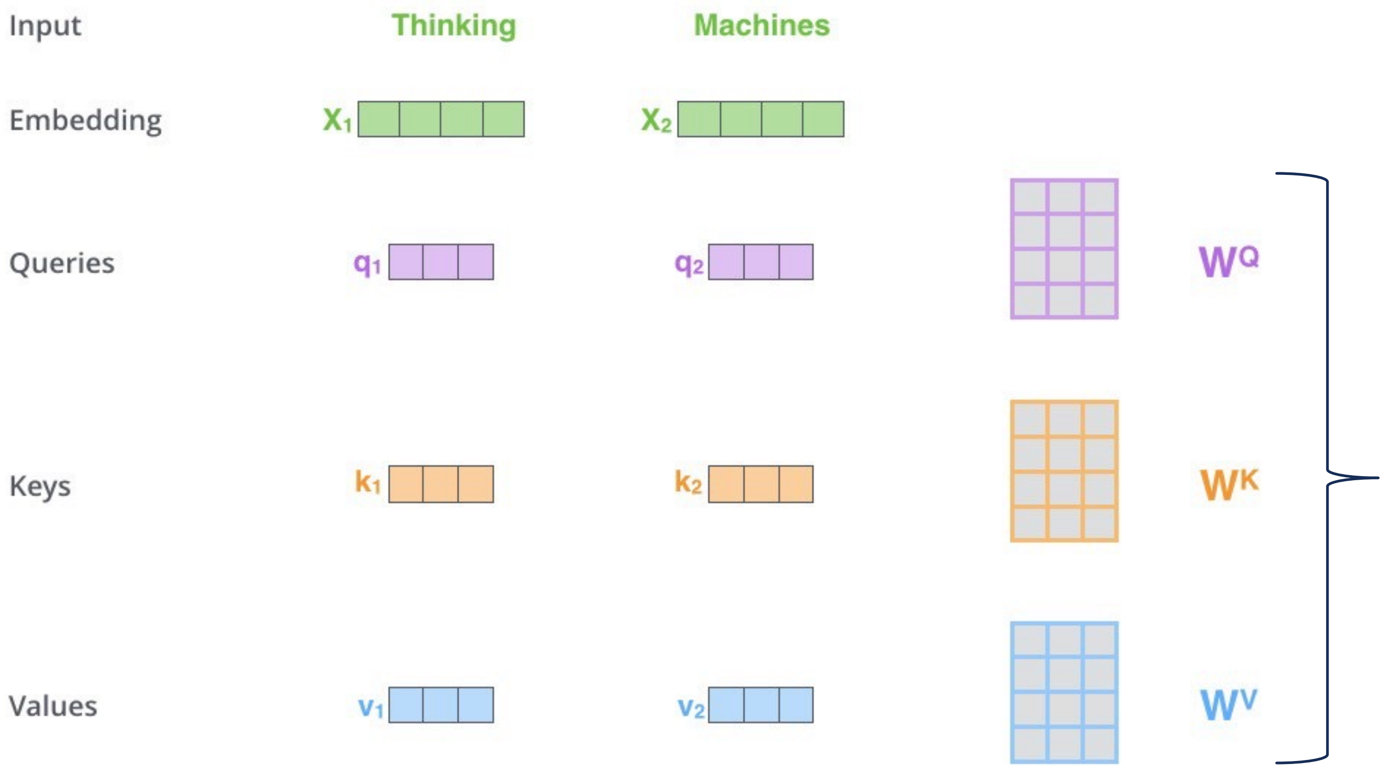
- self attention allows it to look at other positions for clues to help the model better encode the word *it*



https://colab.research.google.com/github/tensorflow/tensor2tensor/blob/master/tensor2tensor/notebooks/hello_t2t.ipynb

HOW TO CALCULATE SELF ATTENTION

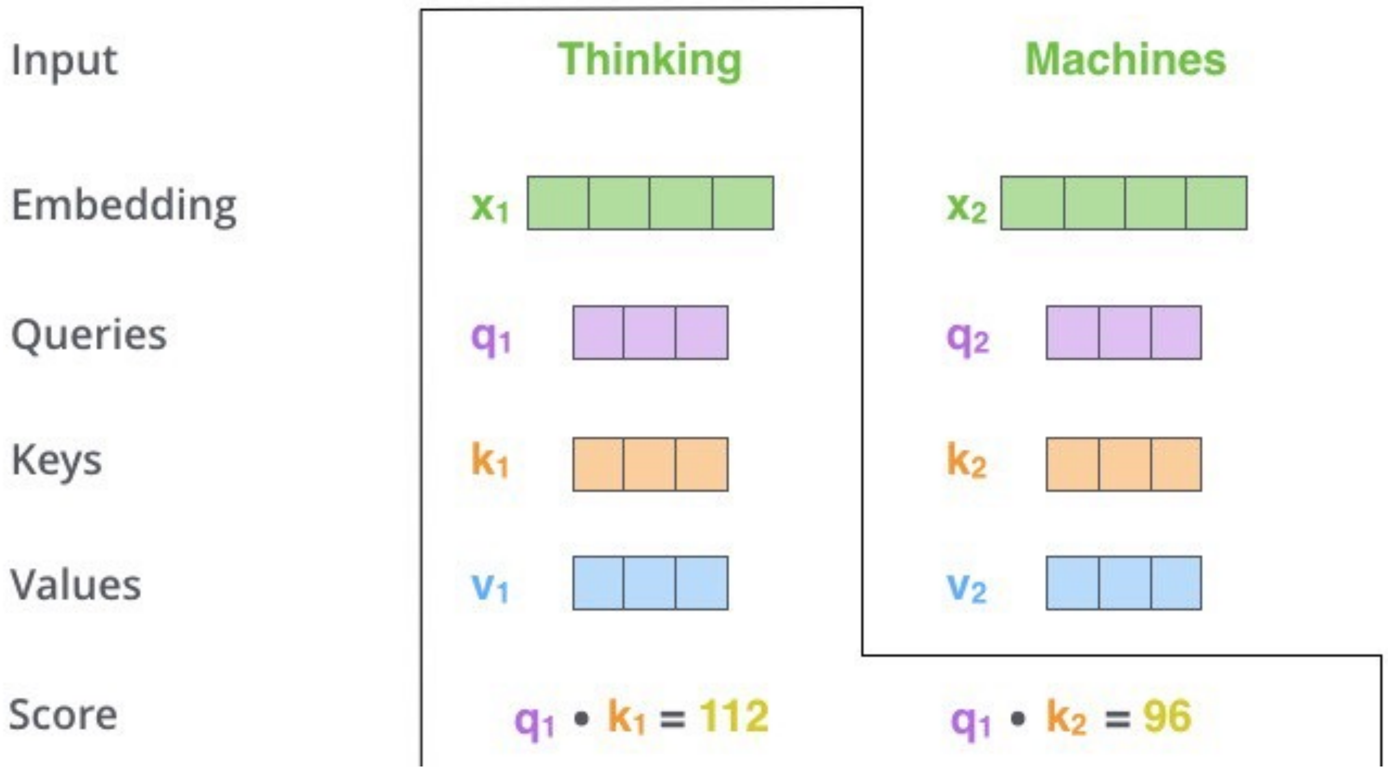
- Step 1: Create 3 vectors (***Q***uery, ***k***ey, ***V***alue – dimension 64) from each encoder's input vector



These matrices estimated during training.

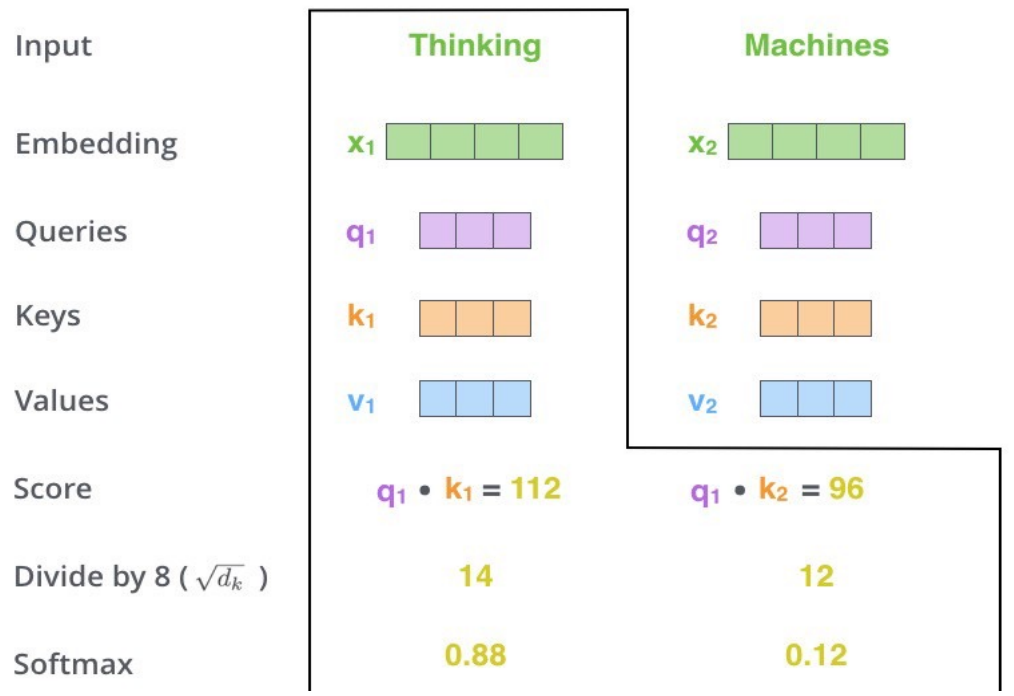
HOW TO CALCULATE SELF ATTENTION

- Step 2: calculate self-attention score



HOW TO CALCULATE SELF ATTENTION

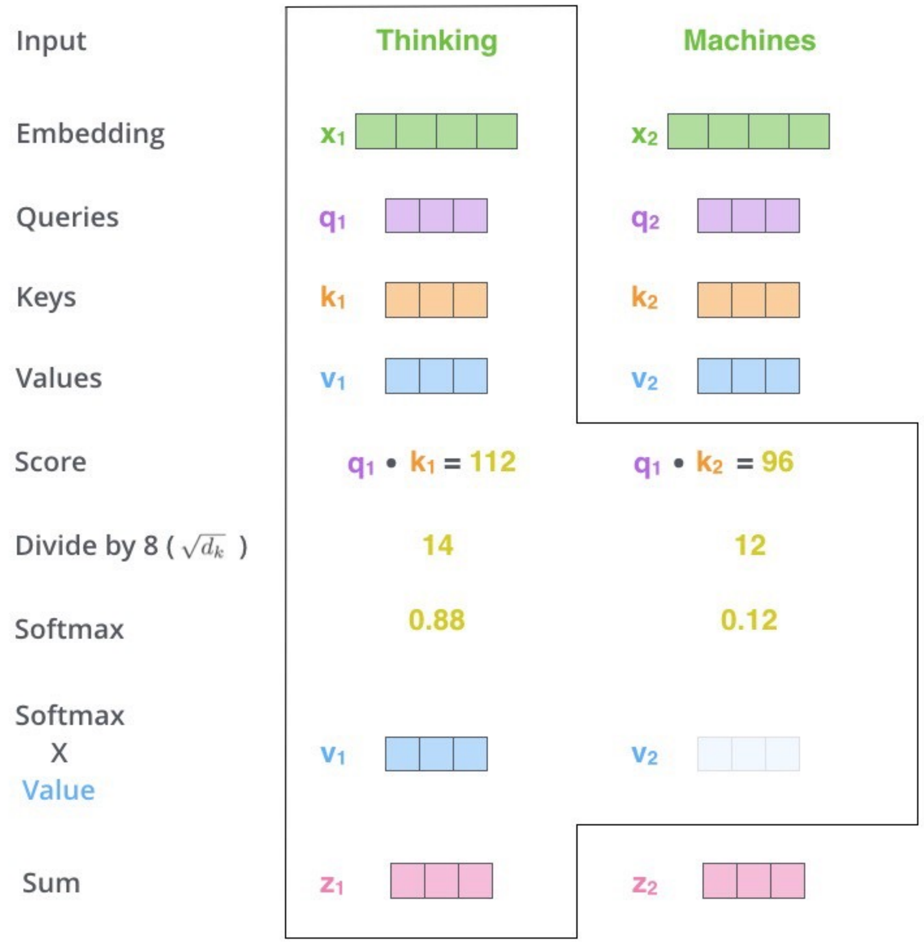
- Step 3:
  - Divide the core by 8
  - Take the square root of the dimension of the key vector
- Step 4:
  - Apply SoftMax to normalizes scores



HOW TO CALCULATE SELF ATTENTION

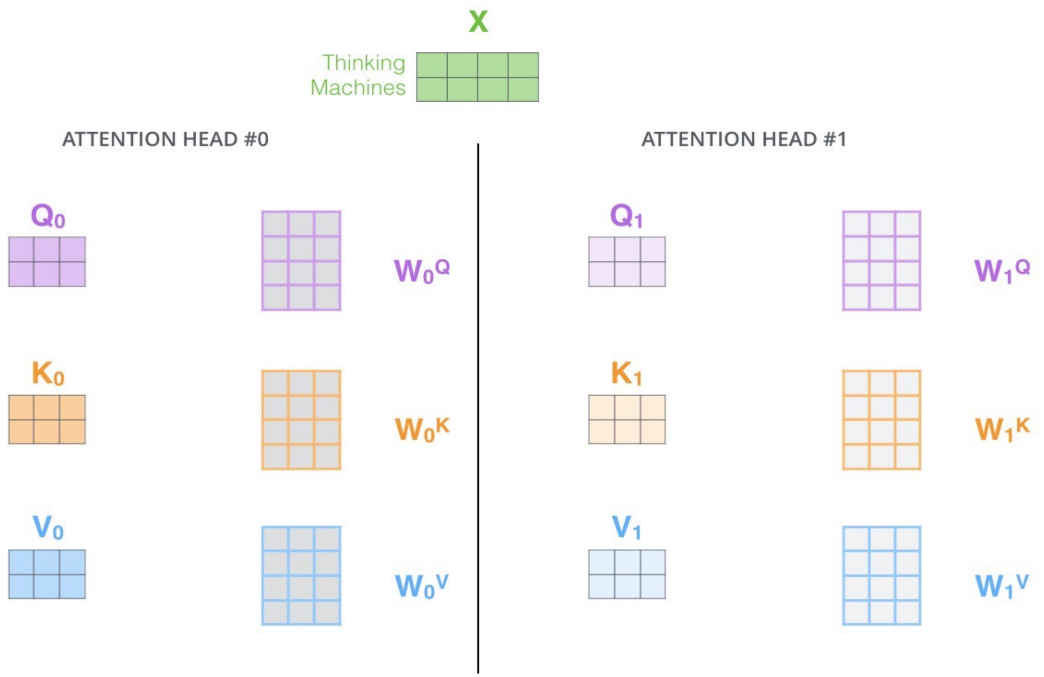
- Step 5:
  - multiply each value vector by the SoftMax score
  - **Intuition:** to amplify relevant words and down grade irrelevant words

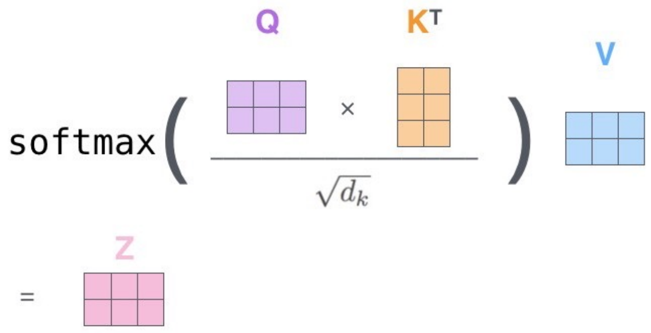
- Step 6:
  - sum up the weighted value vectors.
  - produces the output of the self- attention layer



MULTI-HEADED ATTENTION

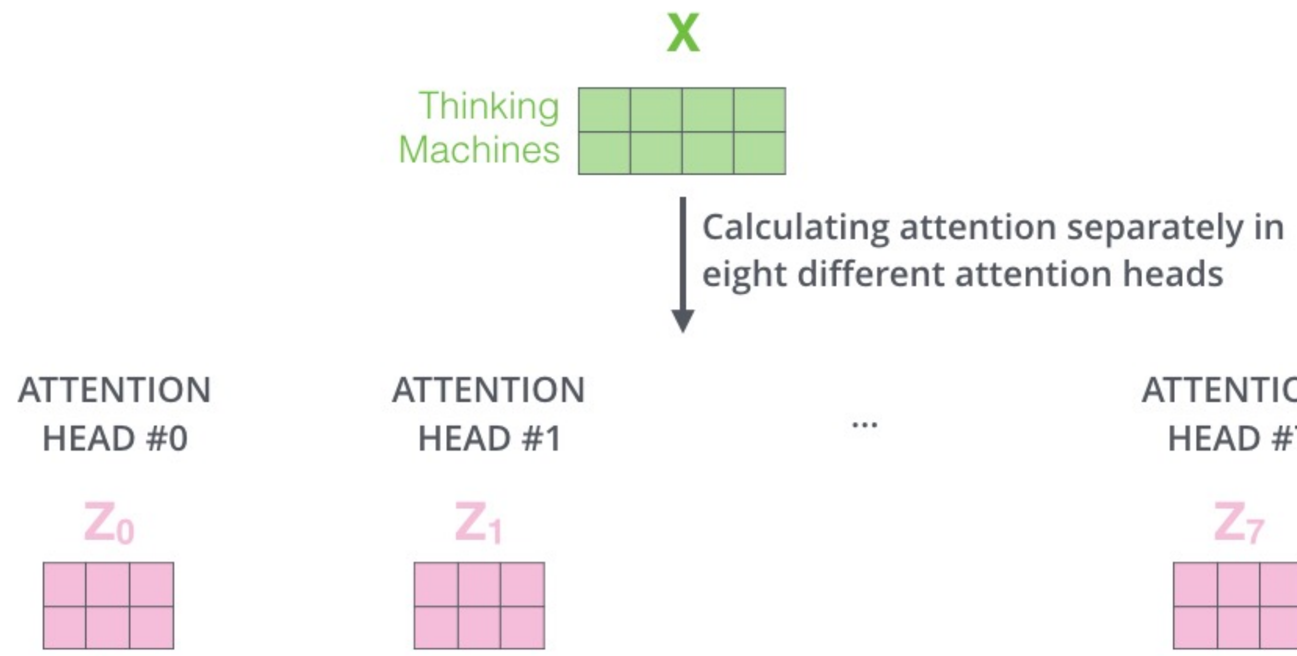
- Multi-headed attention improves the performance of the attention layer by allowing for:
  1. It expands the model's ability to focus on different positions.
  2. It gives the attention layer multiple "representation subspaces".





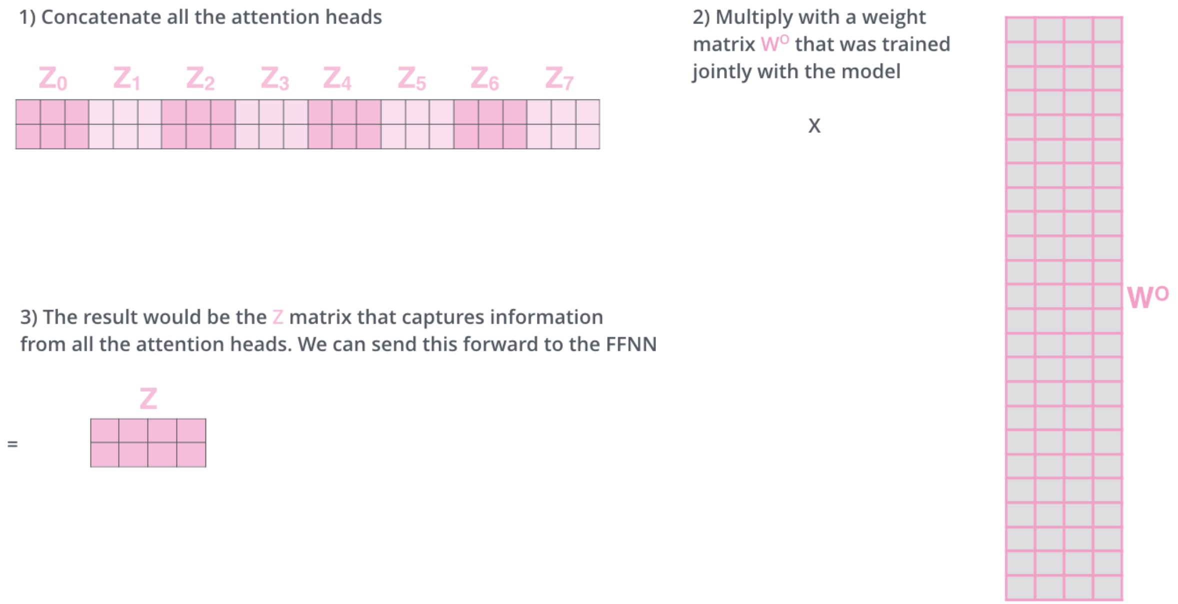
MULTI-HEADED ATTENTION

- Assume we have multi-headed attention with 8 self attention (eight *Z* matrices)



MULTI-HEADED ATTENTION

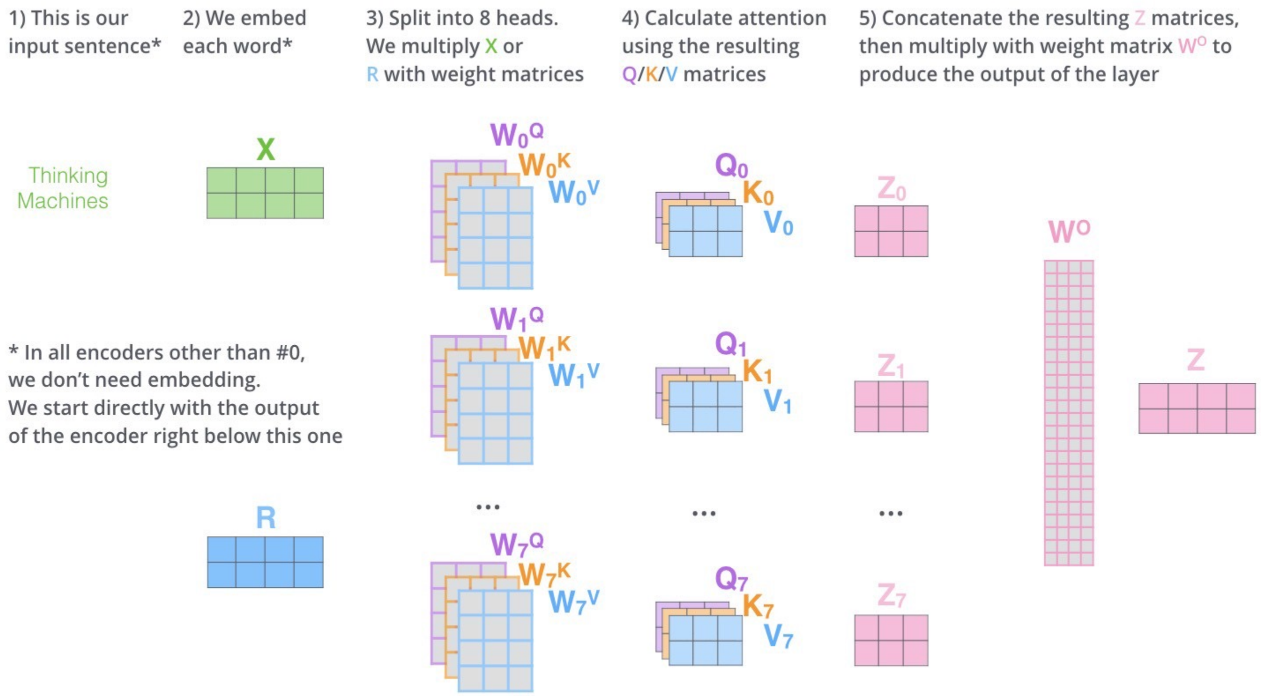
- Assume we have multi-headed attention with 8 self attention (eight ***Z*** matrices)
  - the feedforward layer expects a single matrix
  - We concatenate the matrices then multiply them by an additional weight matrix W^O



MULTI-HEADED ATTENTION

Assume we have multi-headed attention with 8 self attention (eight *Z* matrices)

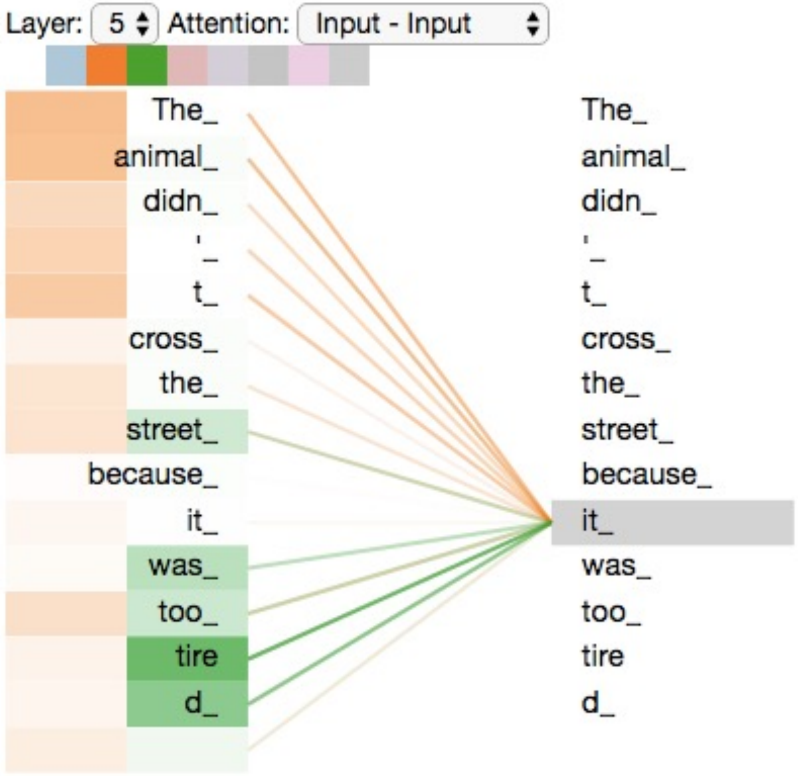
- Concatenate all 8 the feedforward layer expects a single matrix



MULTI-HEADED ATTENTION

Multi head attention *it*

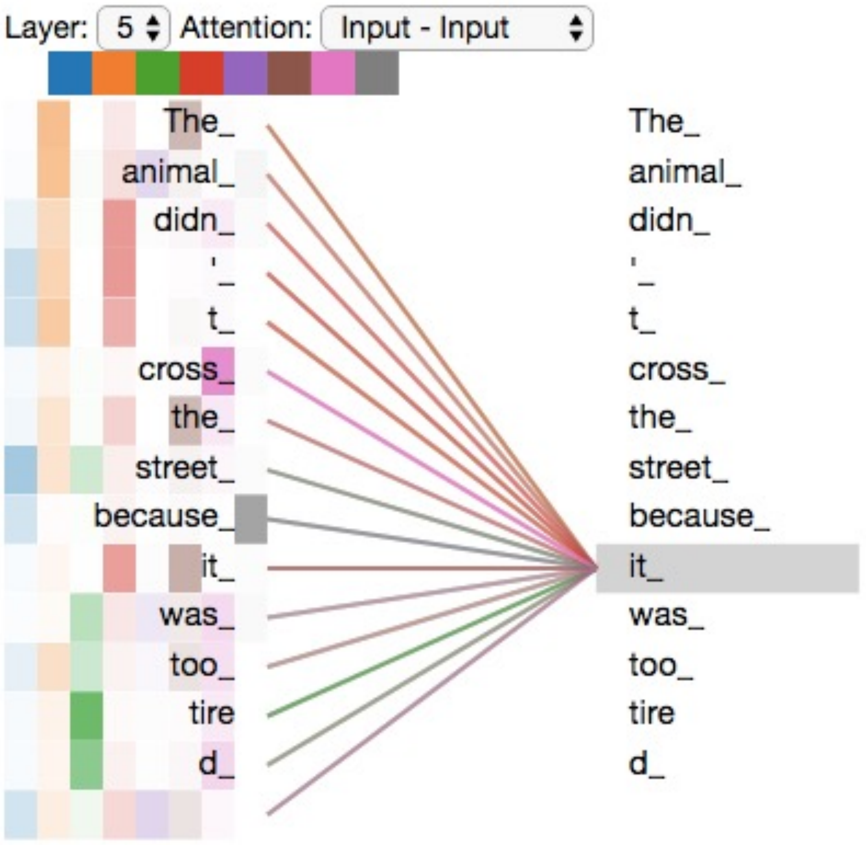
- one attention head is focusing on most on ***the animal***
- another is focusing on ***tired***



https://colab.research.google.com/github/tensorflow/tensor2tensor/blob/master/tensor2tensor/notebooks/hello_t2t.ipynb

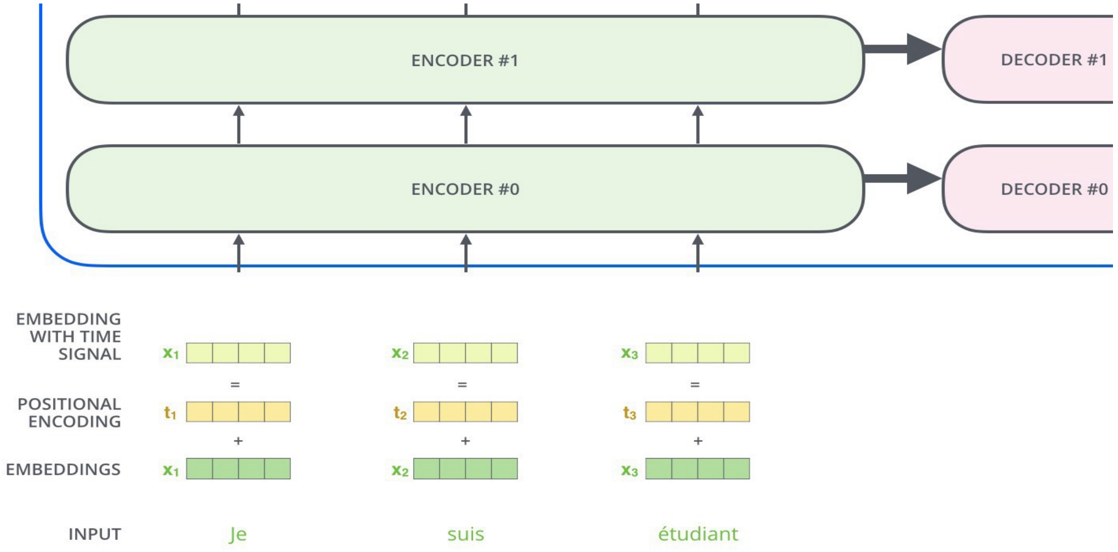
MULTI-HEADED ATTENTION

Visualizing all 8 attention heads



POSITIONAL ENCODING IN TRANSFORMERS

- Positional encoding describes the position of a token in a sequence.
- Each position is assigned a unique representation.
- Each position is mapped to a vector.
- The output of the positional encoding layer is a matrix, where each row of the matrix represents an encoded object of the sequence summed with its positional information.

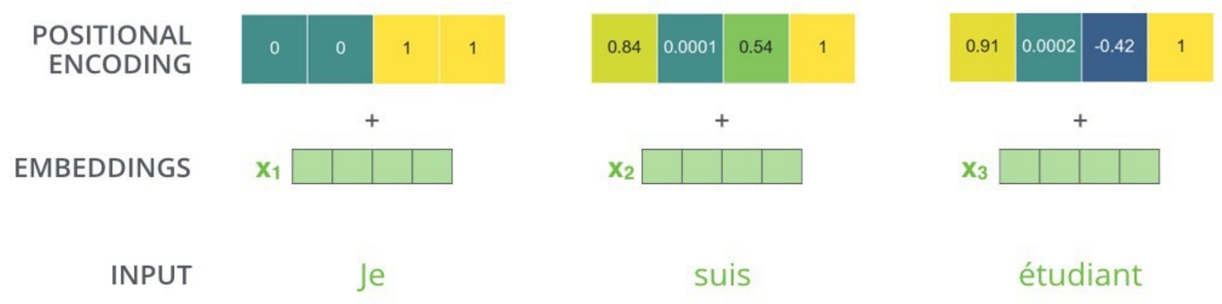


https://machinelearningmastery.com/a-gentle-introduction-to-positional-encoding-in-transformer-models-part-1/

POSITIONAL ENCODING IN TRANSFORMERS

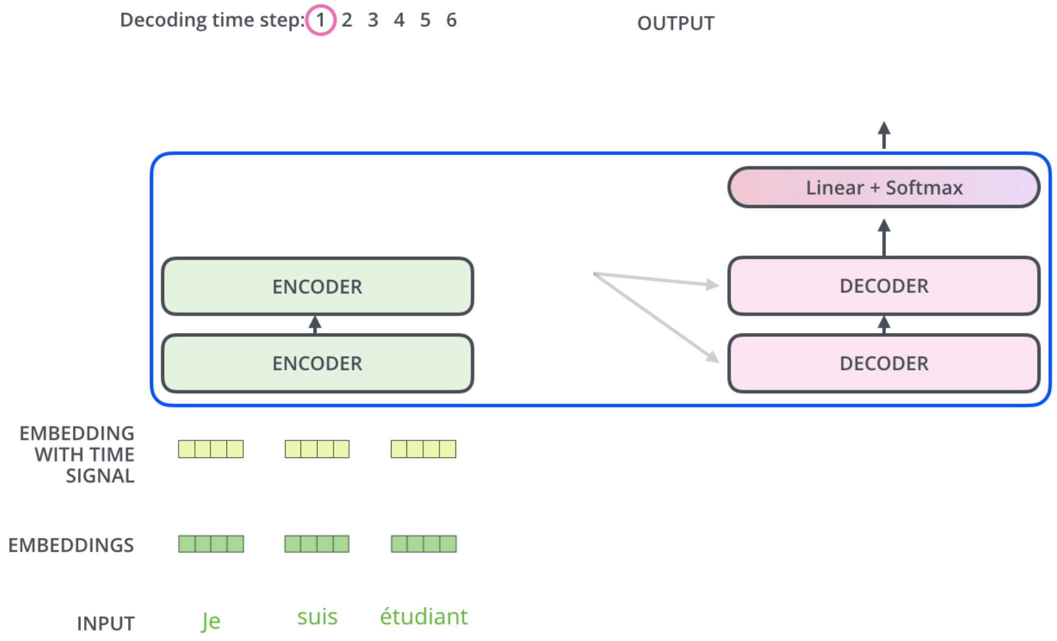
- **Intuition:**
  - Adding these values to the embeddings provides meaningful distances between the embedding vectors once they are projected into Q/K/V vectors and during dot-product attention.
  - These positional encoding are generated during training (detail in the paper)

- Assume encoding of dimension 4, the positioning will look like



THE DECODER SIDE

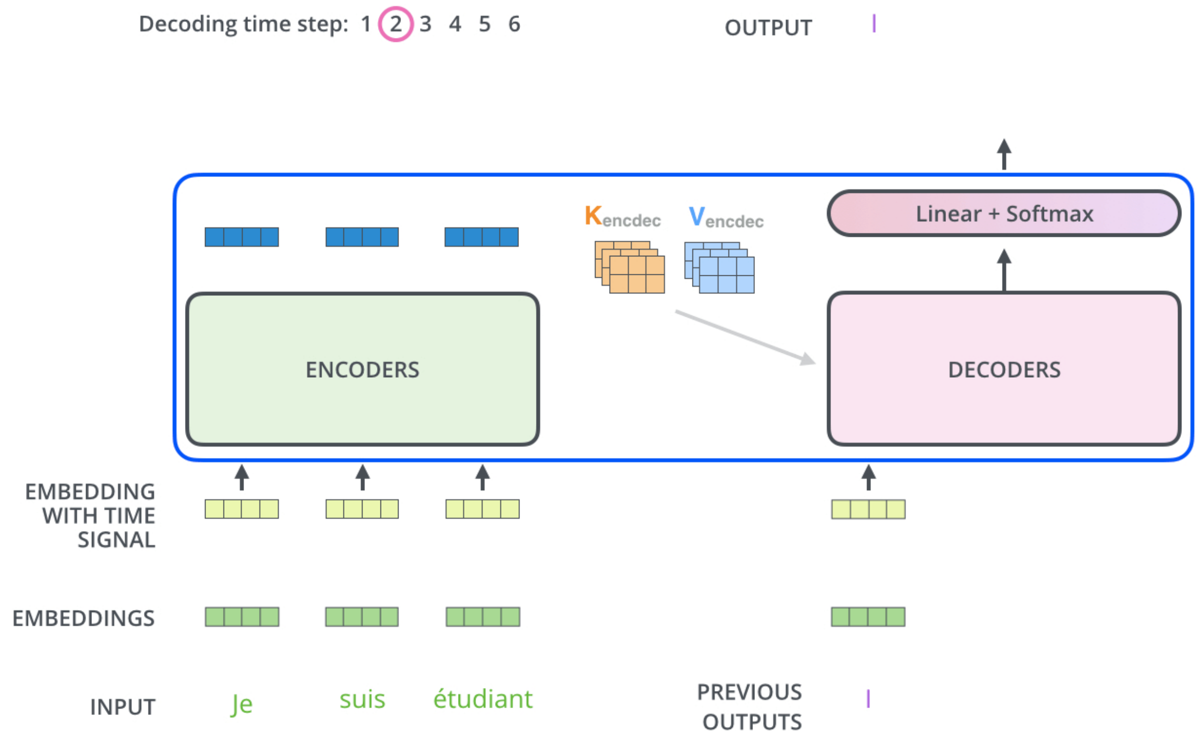
- The encoder process the input sentence
- Output of top encoder layer is converted to attention vectors K and V.
- K & V vectors are used by each decoder in its “encoder-decoder attention” layer
- K & V helps decoder focus on appropriate words.



https://jalammar.github.io/illustrated-transformer/

THE DECODER SIDE

The following steps repeat the process until a special symbol is reached indicating the transformer decoder has completed its output



https://jalammar.github.io/illustrated-transformer/

THE DECODER SIDE

The self attention layers is only allowed to focus on earlier positions in the output sequence.

This is done by masking future positions (setting them to -inf) before the SoftMax step in the self-attention calculation.

The "Encoder-Decoder Attention" layer is like multiheaded self-attention

except it creates its Queries matrix from the layer below it,

takes the Keys and Values matrix from the output of the encoder stack.

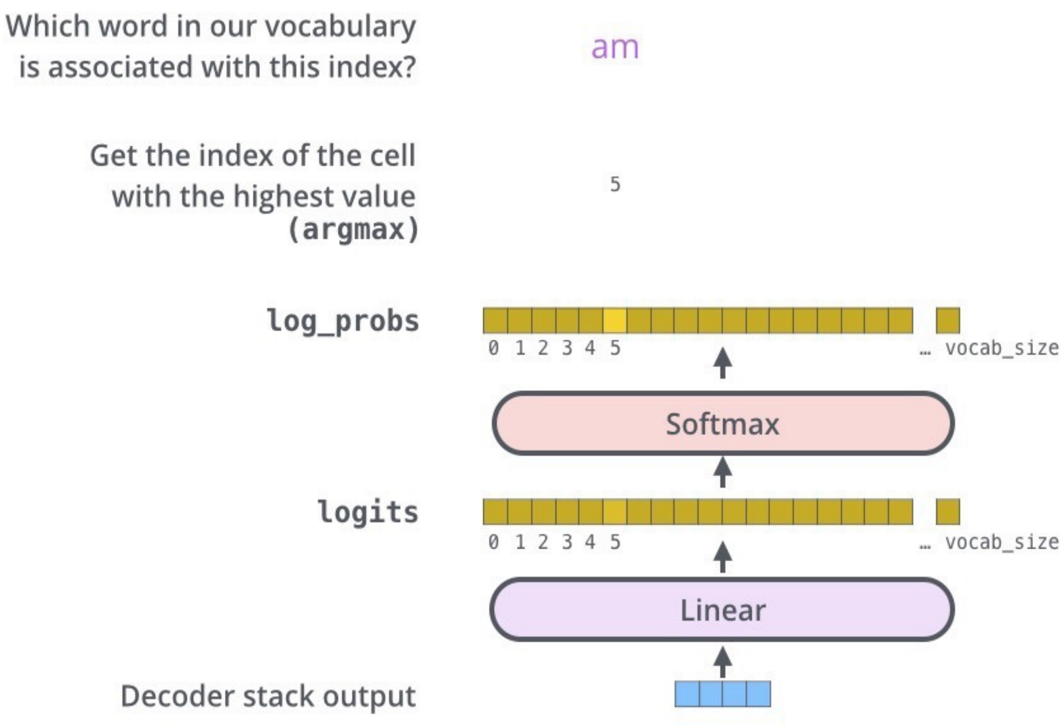
FINAL LINEAR AND SOFTMAX LAYER

Final Linear Layer:

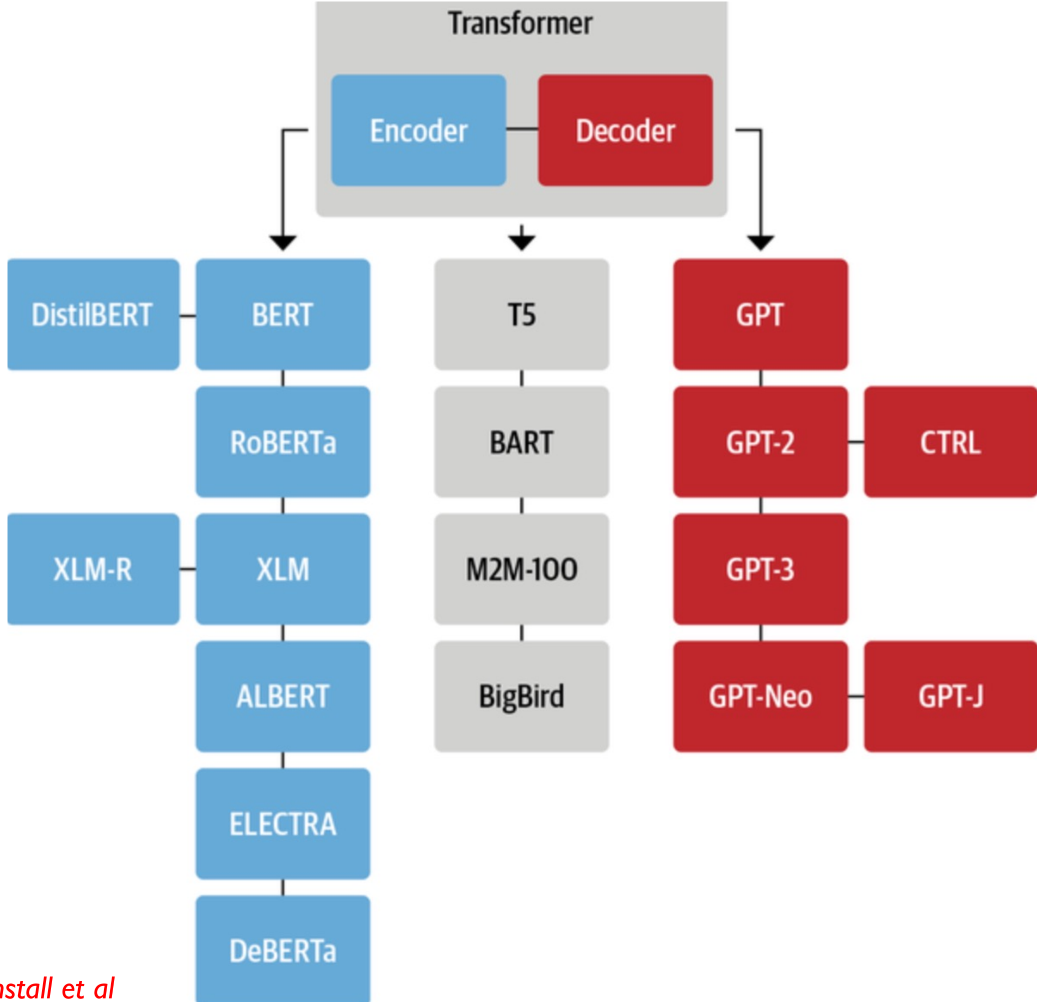
- fully connected connected neural network that projects the vector produced by the decoders into a logits vector.

Assume our model was trained on a 1000-word vocabulary

- Then logit vector has dimension 1000 cells
- Each cell the score of a unique word
- The SoftMax layers turns these scores into probabilities and the word with the highest probability is chosen.



OVERVIEW OF MOST PROMINENT TRANSFORMERS

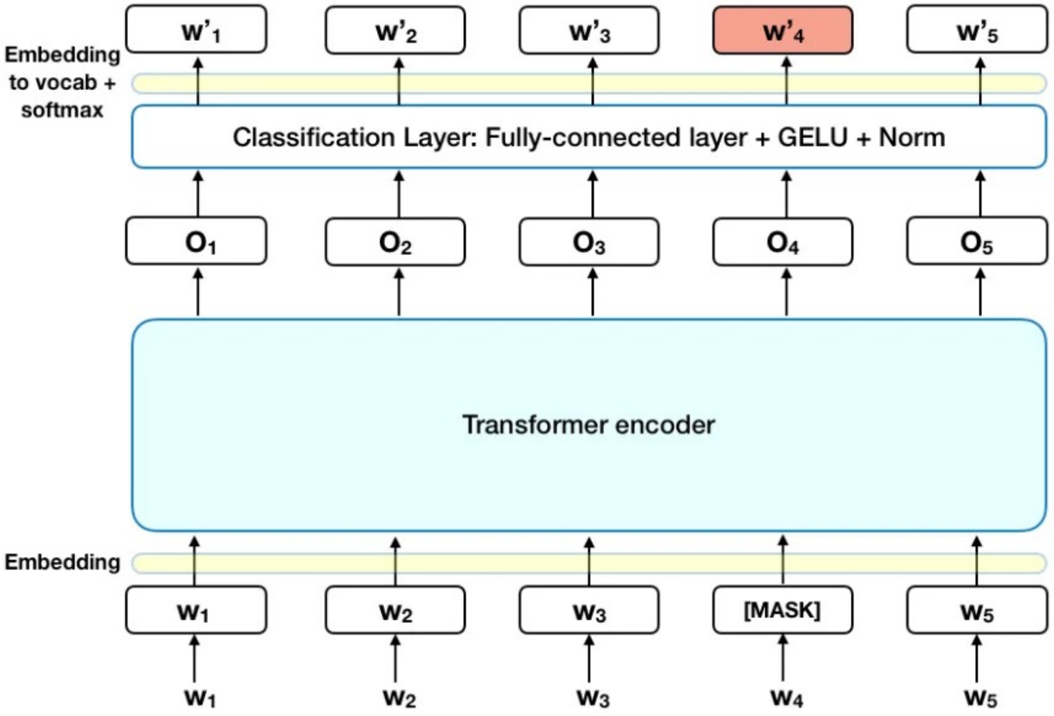


Natural language processing with transformers by Tunstall et al

OVERVIEW OF MOST PROMINENT TRANSFORMERS – BERT

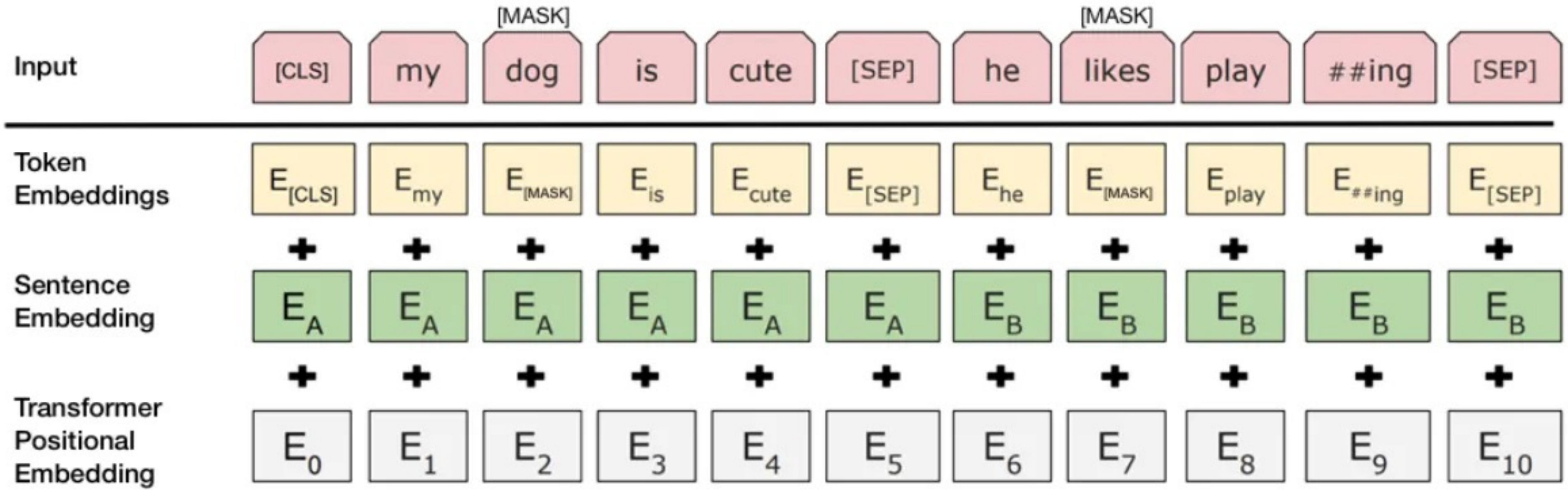
Dual training of Masked language model and next sentence prediction.

Masked language model



https://towardsdatascience.com/bert-explained-state-of-the-art-language-model-for-nlp-f8b21a9b6270

BERT – NEXT SENTENCE PREDICTION

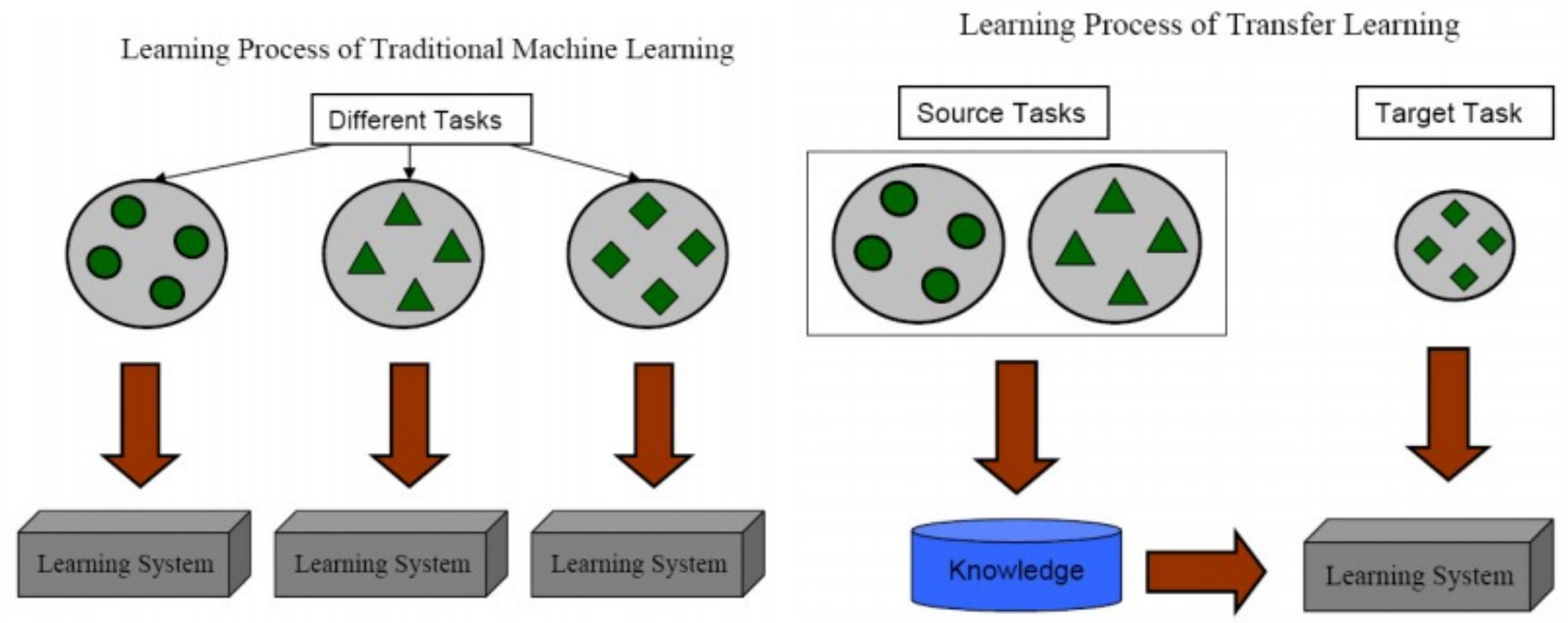


https://towardsdatascience.com/bert-explained-state-of-the-art-language-model-for-nlp-f8b21a9b6270

TRANSFER LEARNING

TRANSFER LEARNING

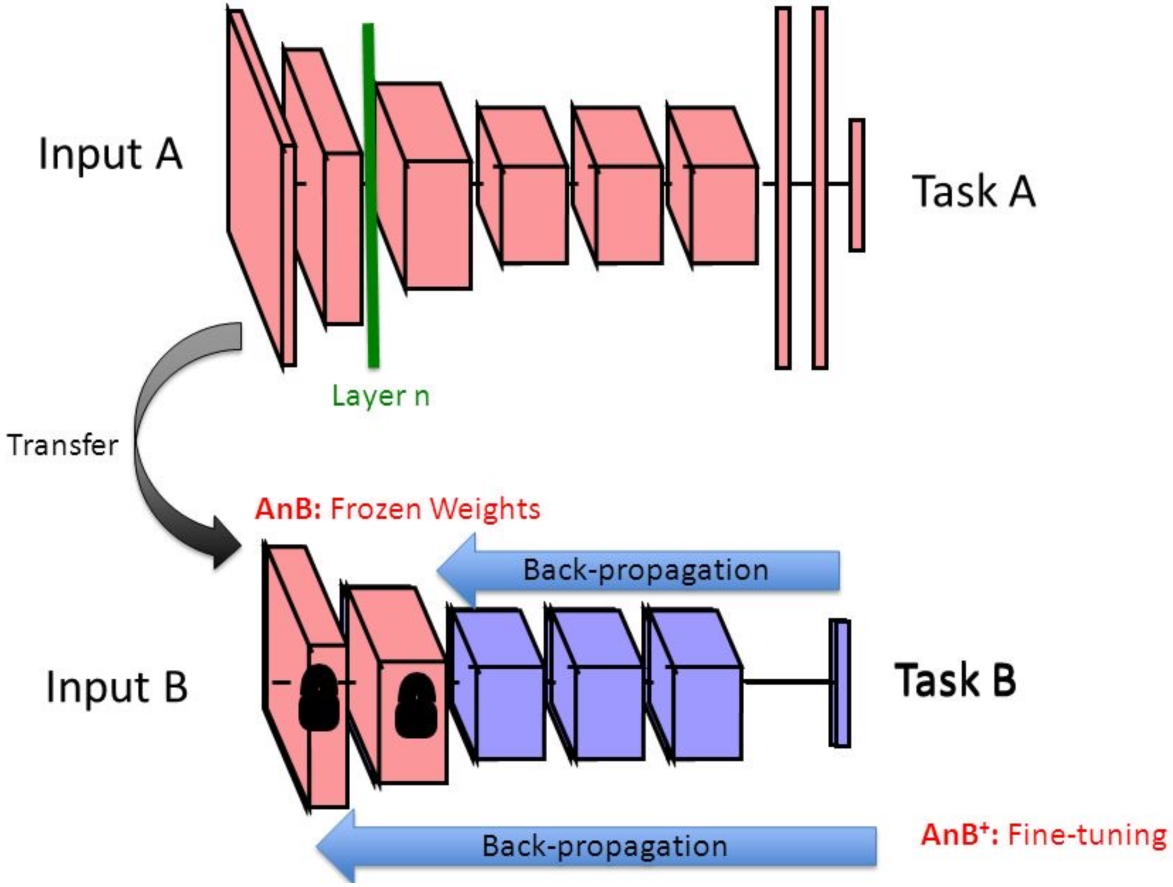
Transferring the knowledge of one model to perform a new task.



(a) Traditional Machine Learning (b) Transfer Learning

https://lisaong.github.io/mldds-courseware/03_TextImage/transfer-learning.slides.html

TRANSFER LEARNING



https://lisaong.github.io/mldds-courseware/03_TextImage/transfer-learning.slides.html

TRANSFER LEARNING

Diffferent types of transfer learning

Type	Description	Examples
Inductive	Adapt existing **supervised** training model on new **labeled** dataset	Classification, Regression
Transductive	Adapt existing **supervised** training model on new **unlabeled** dataset	Classification, Regression
Unsupervised	Adapt existing **unsupervised** training model on new **unlabeled** dataset	Clustering, Dimensionality Reduction

https://lisaong.github.io/mldds-courseware/03_TextImage/transfer-learning.slides.html

USEFUL LINKS

- Attention is all you need https://proceedings.neurips.cc/paper_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf
- BERT https://aclanthology.org/N19-1423.pdf
- Transfer learning https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.147.9185&rep=rep1&type=pdf
- Hugging face
  - https://huggingface.co/transformers/index.html
  - https://github.com/huggingface/transformers
  - https://huggingface.co/docs/transformers/training
  - https://neptune.ai/blog/hugging-face-pre-trained-models-find-the-best