Applied Text Analytics & Natural Language Processing

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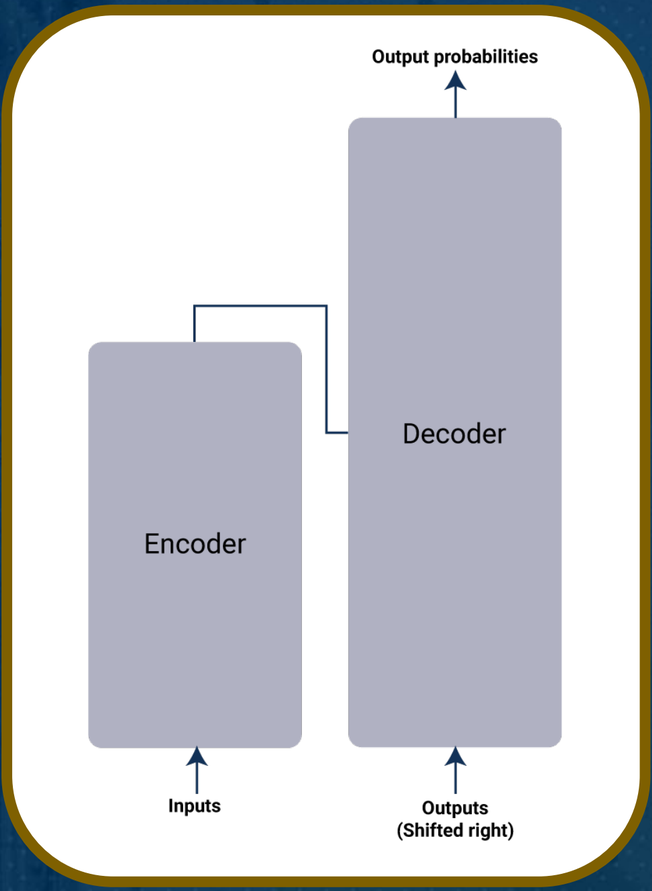
Transformers
Introduction – Part 2

Structure of the Transformer Model

This is the overall structure of the Transformer model.

- **Encoder**: gets the input and creates a representation of it.
- **Decoder**: gets the input representation along with the target output and generates the new output (outputs are generated one word at a time and is fed back to the decoder)

Representation: a set of vectors produced by the encoder that can be read by the decoder to acquire information about the input. Embeddings of similar words are similar to each other.



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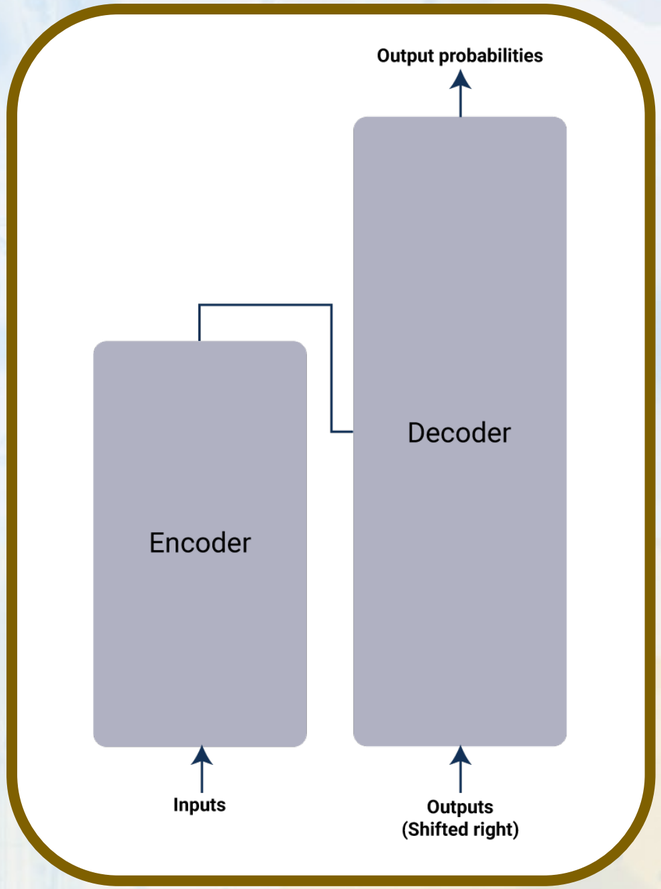
Encoder and Decoder Can Be Used Separately in Structures:

Encoder-only models: for tasks that require understanding the input. *E.g., what is the meaning of this sentence?, Fill in the blank with the right word.*

- Good in the understanding of input, extracting meaningful information, sequence classification, masked language modeling, and natural language understanding (NLU)
- BERT, RoBERTa, ALBERT
- Bi-directional



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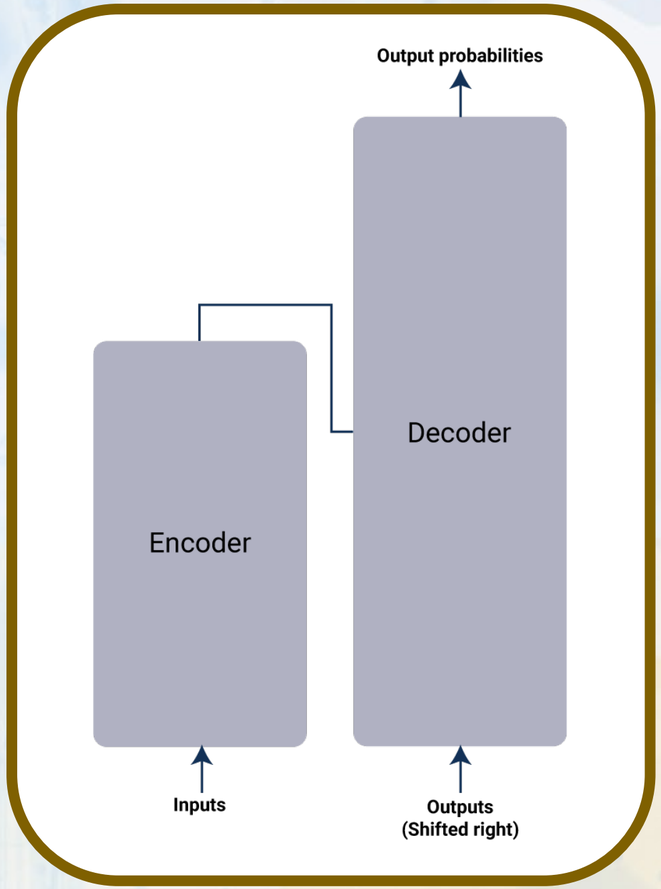
BERT Neural Network - EXPLAINED! (https://www.youtube.com/watch?v=xI0HHN5XKDo)

Encoder and Decoder Can Be Used Separately in Structures:

Decoder-only models: for generative tasks. *E.g., Guessing the next word in a sentence.*

- Good in generating sequences, natural language generation (NLG)
- GPT, GPT-2, GPT-3
- Uni-directional



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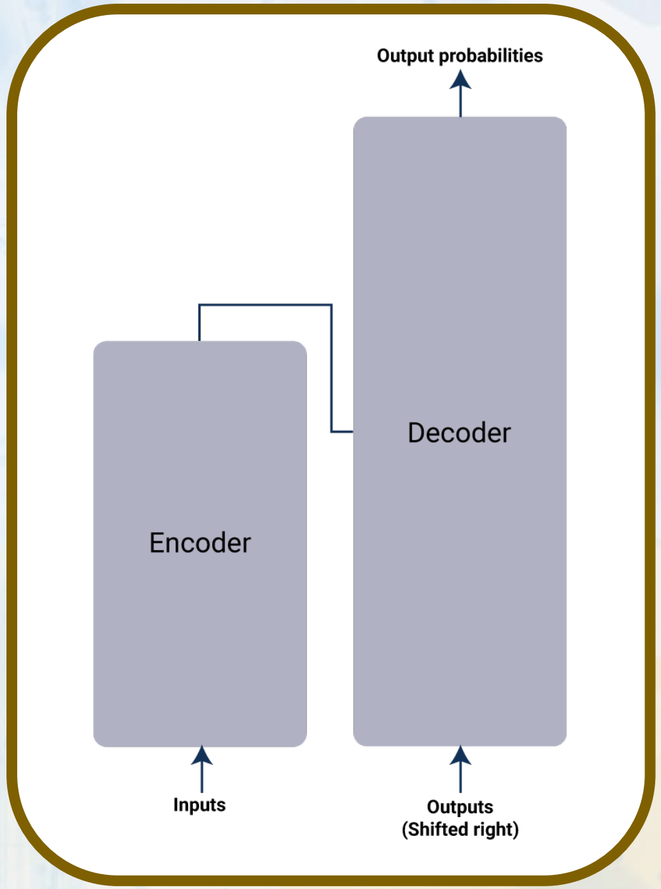
Encoder and Decoder Models (Sequence-To-Sequence)

Encoder-decoder models: for generative tasks that require input. They are good for seq2seq tasks. *E.g., Translation, text summarization*

- BART and T5 use this structure



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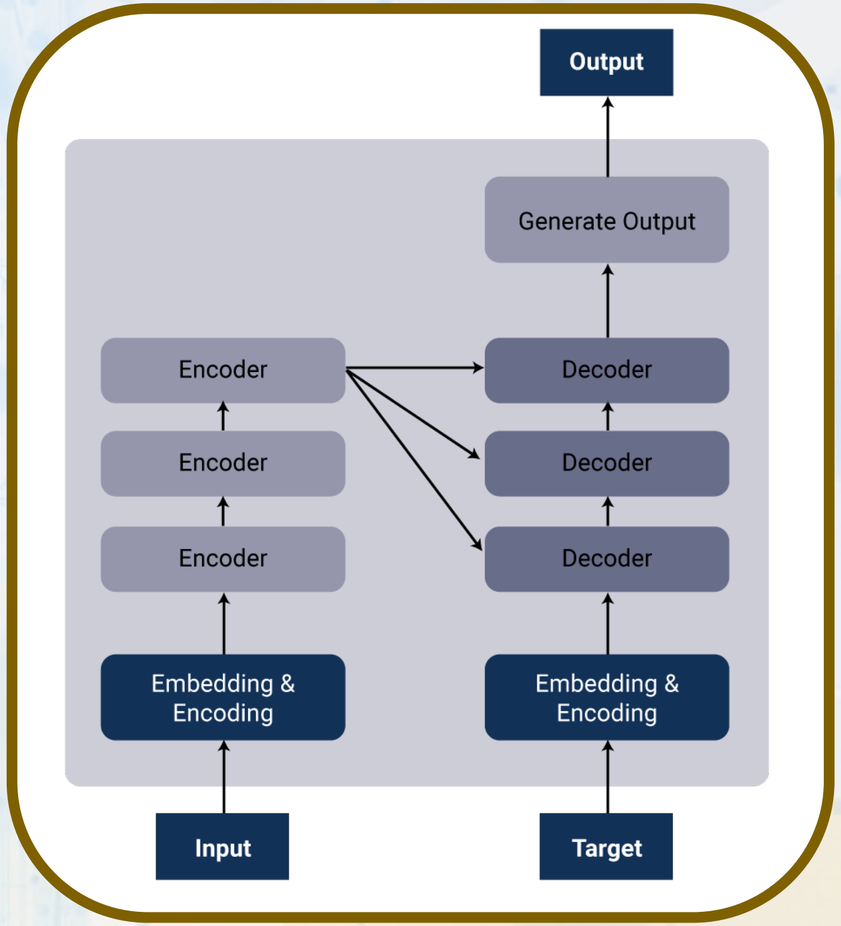
Transformer Architecture Encoder Stack

- It contains encoder blocks (usually 6, here 3)
- Receives its input from Embedding and Position Encoding
- Encoder duty: mapping its input to a fixed-length vector, called a context vector
  - It contains a crucial component = Self-Attention
  - The context vector is fed to the decoder.

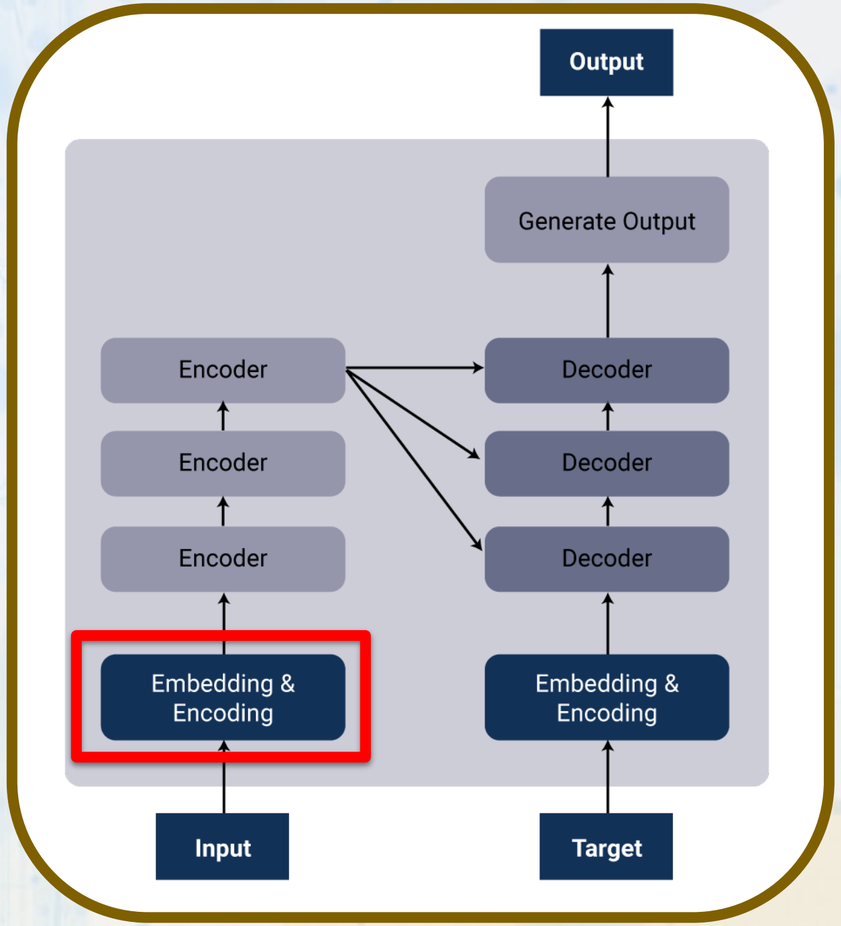


Embedding + Positional Encoding

- Embeddings come from pre-trained models
  - Pre-trained models such as Word2Vec (Google), GloVe (Stanford), …
- Ordering words is important to grasp the meaning of a sentence
- Encoding (Positional Encoding) encodes the position of each word. This information is added to the embedding result and is fed to the encoder

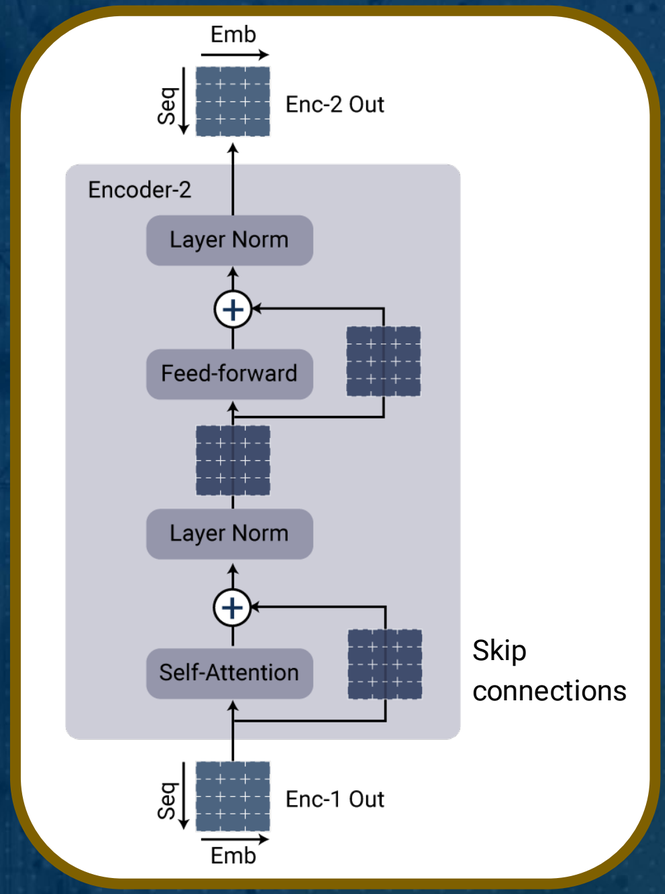
PE: positional Encoding
Pos: position of the word
d: length of encoding vector (i.e. word2vec)

$$PE_{(pos,2i)} = \sin(pos/10000^{2i/d_{model}})$$
$$PE_{(pos,2i+1)} = \cos(pos/10000^{2i/d_{model}})$$



Encoder Block

- **Self-attention layer**
  - Computes the relationship between words in the input sequence
- **Skip connections**
  - Helps with exploding/vanishing gradient problems
- **Normalization layers**
  - Provides smoother gradients, faster training, and better generalization accuracy by normalizing the distribution of intermediate layers
- **Feed-forward (linear) layer**
  - Consists of two linear layers with ReLU activation between them. Its main purpose is to transform the attention vectors into a form that is acceptable by the next encoder or decoder layer
  - Each feed-forward layer has its own parameters:
    - $FFN(x) = ReLu(x\theta_1 + b_1) * \theta_2 + b_2$



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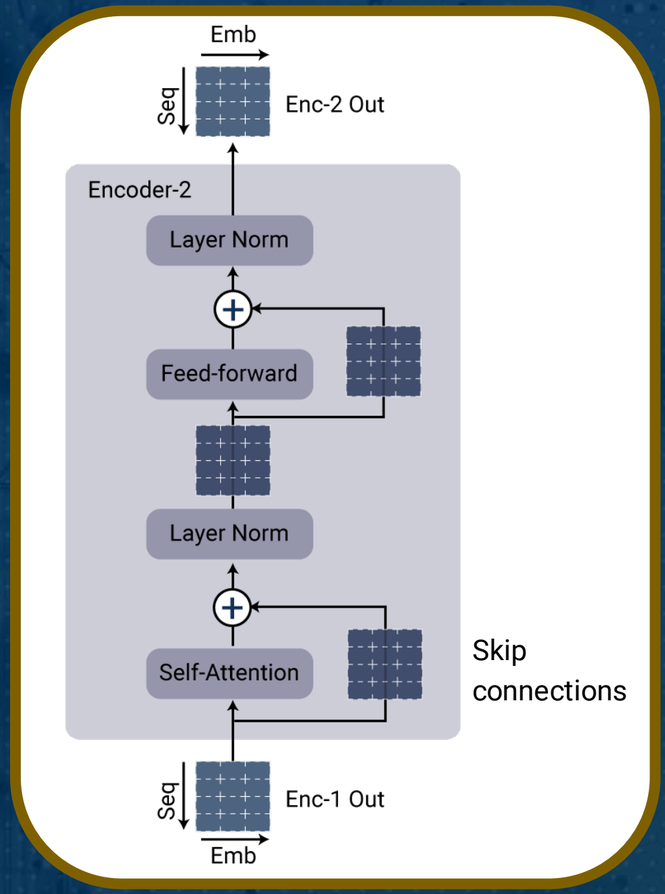

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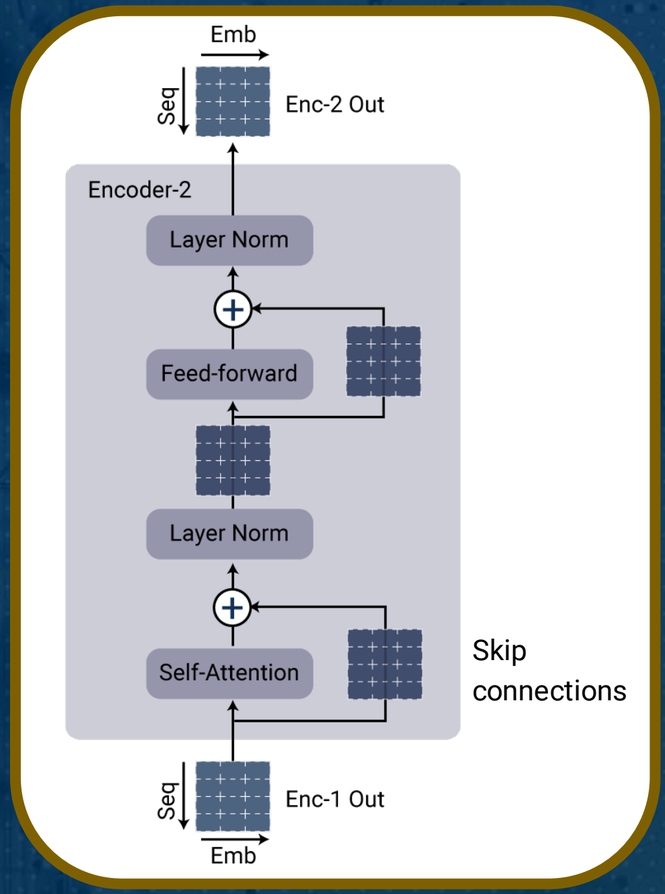

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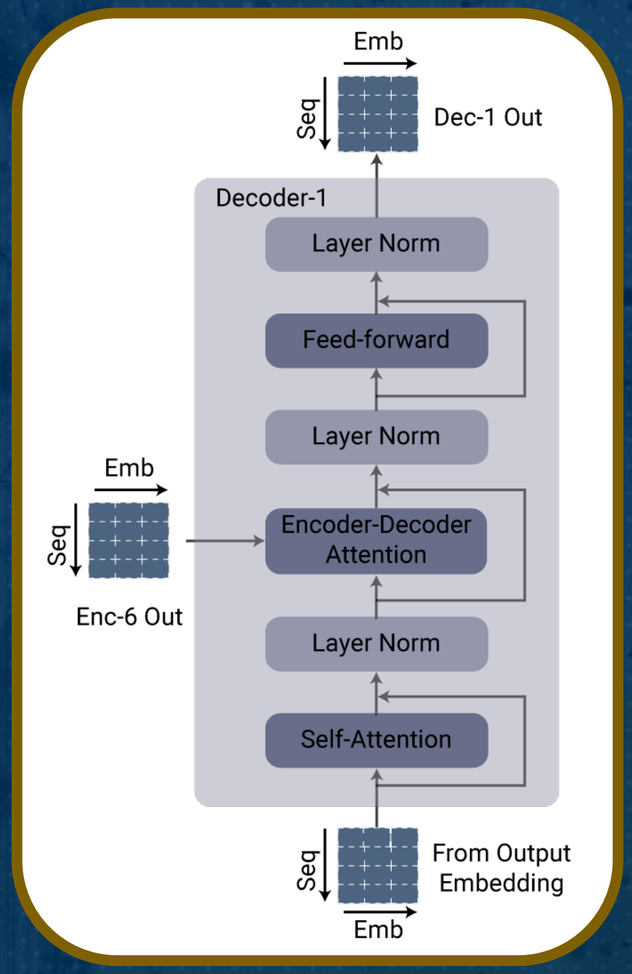
Decoder Block

- **Self-attention layer**
  - Computes the relationship between words in the target sequence
- **Encoder-decoder attention layer**
- **Normalization layer**
- **Feed-forward (linear) layer**



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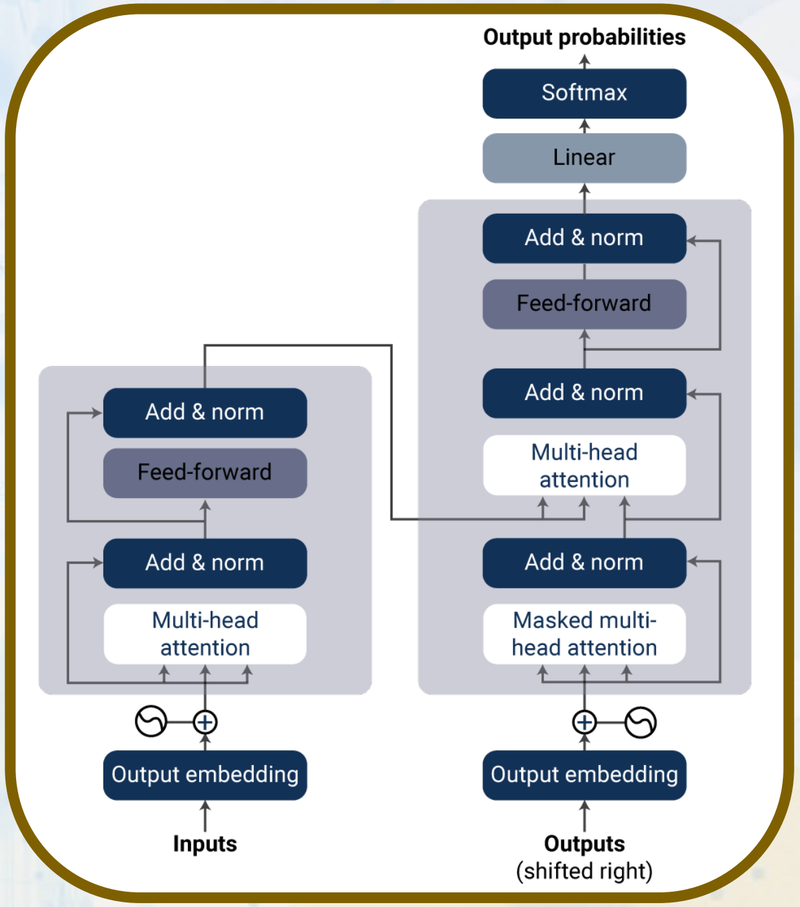
Original Transformer Architecture

- The attention layer in the encoder has access to the whole input sequence since it needs to pay attention to other words (before and after) when creating a representation for a specific word
- The bottom attention layer in the decoder is a self-attention unit and has access to only the words translated so far. The top attention layer is a regular attention unit and uses the output of the encoder to produce the most accurate output
- The Transformer model is "auto-regressive"; it receives the recently generated output as the new input for prediction



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Vaswani, Ashish, et al. "Attention is all you need." *Advances in neural information processing systems* 30 (2017).