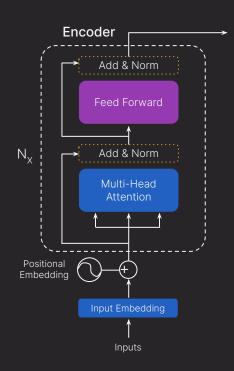


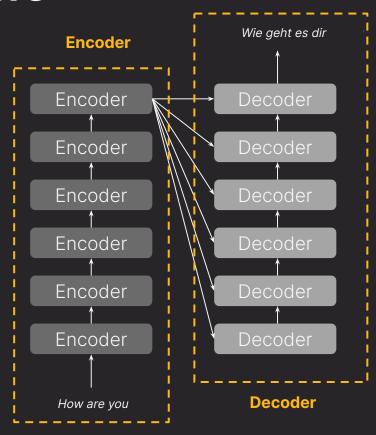
Recap



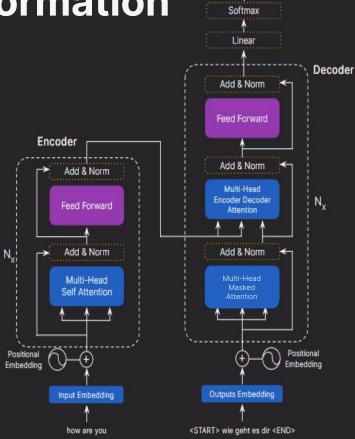




Transformers

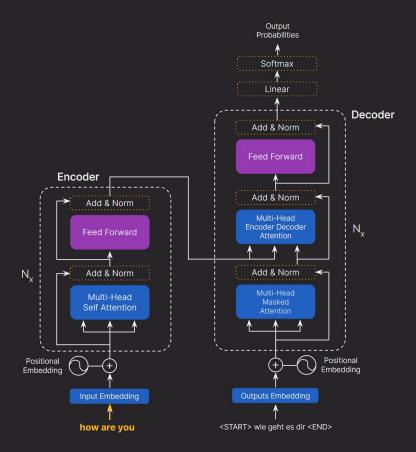






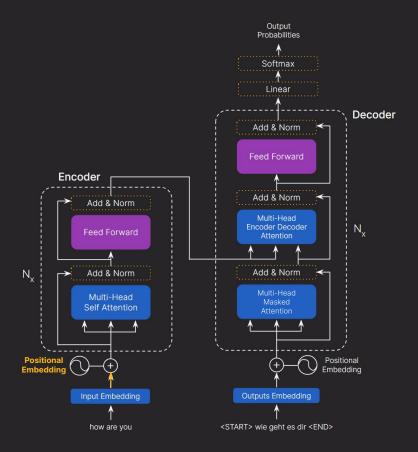
Output Probabilities





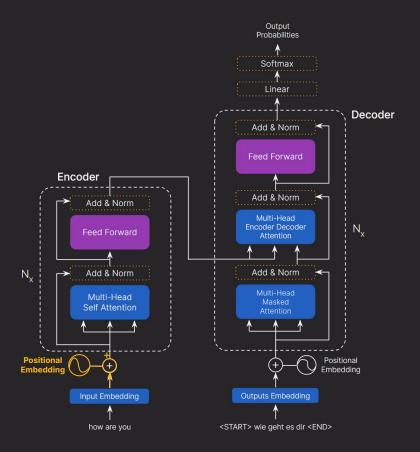
 Word embeddings of tokens goes as input in encoder.





 The transformers use positional embedding to capture sequential information of the tokens.

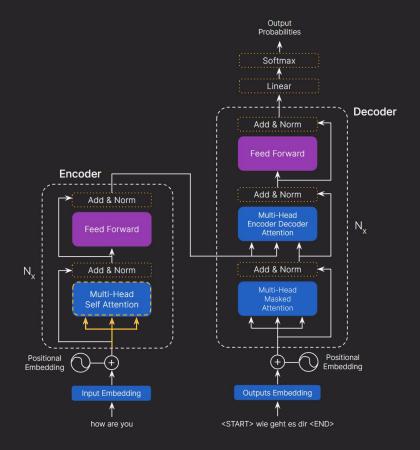




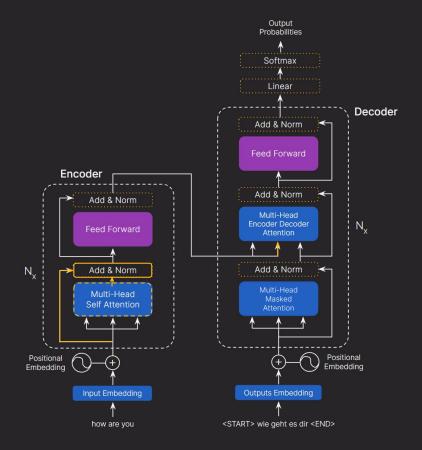
 The model uses positional encoding with word embeddings to generate a unique vector for each token.

P = Positional Embedding + Word embedding

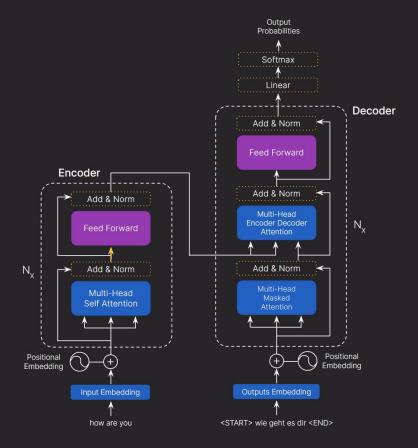




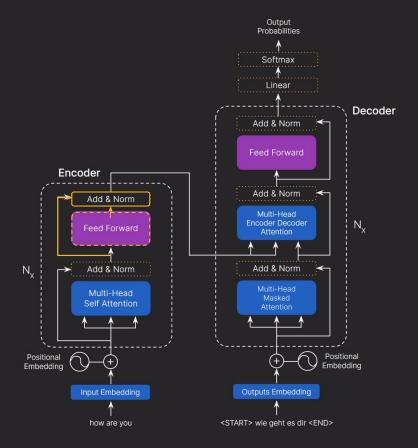












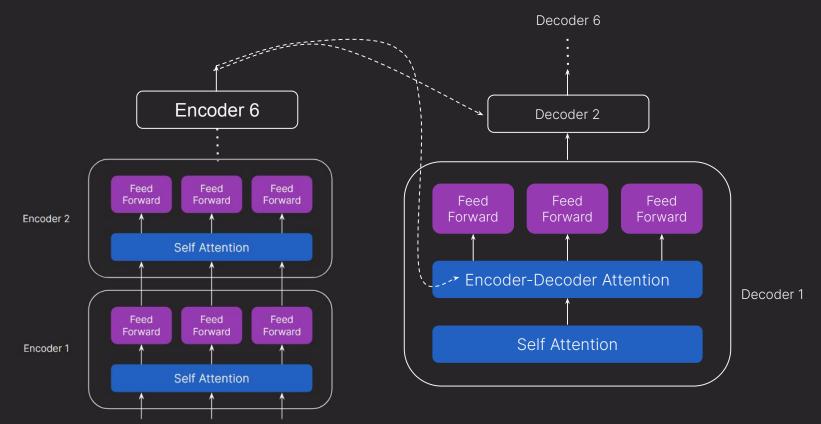


Multi-Head Self Attention

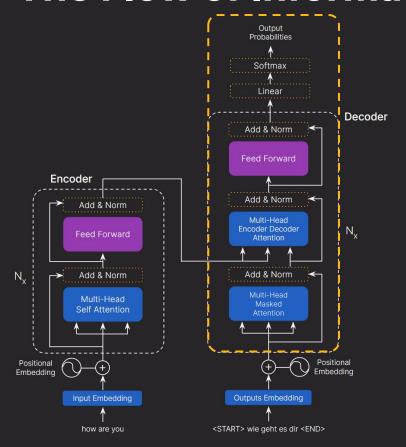
How

are

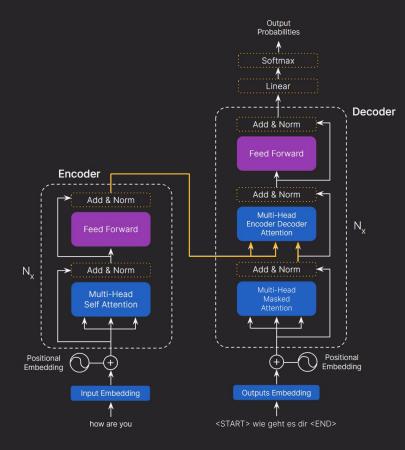
you







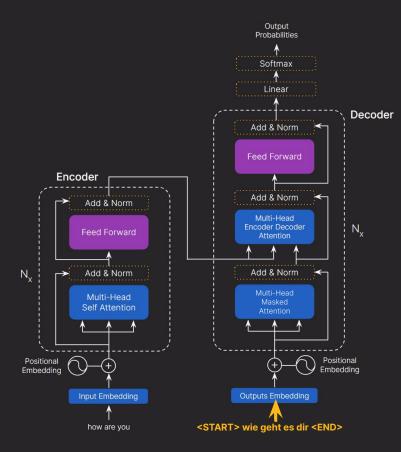




There are **2 inputs** to the decoder from the encoder:

 First input: Output matrix serves as the query and key matrix

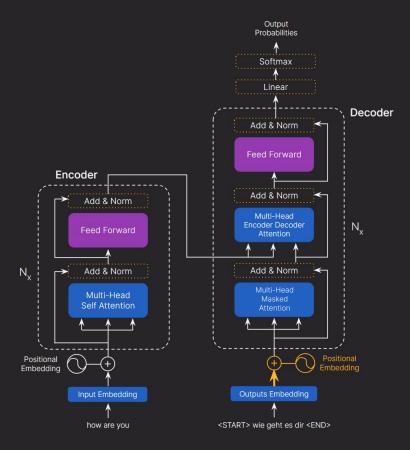




There are **2 inputs** to the decoder from the encoder:

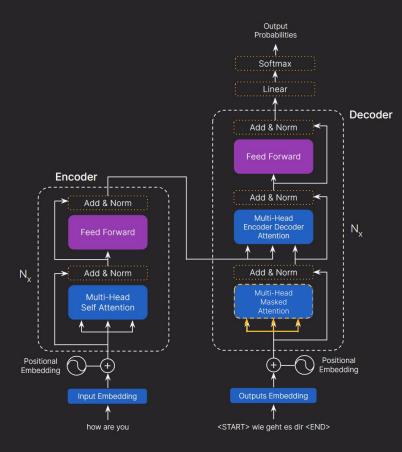
- First input: Output matrix "R" which serves as the query and key matrix
- **Second input:** Predicted text





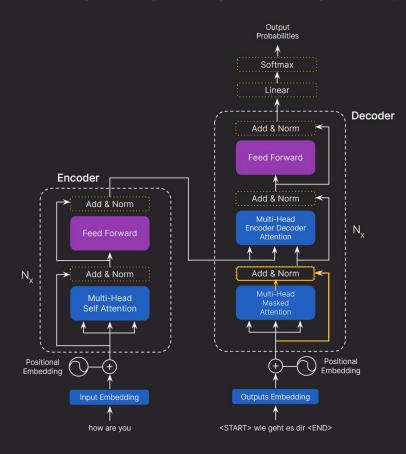
Inputs are embedded just like the encoder part.





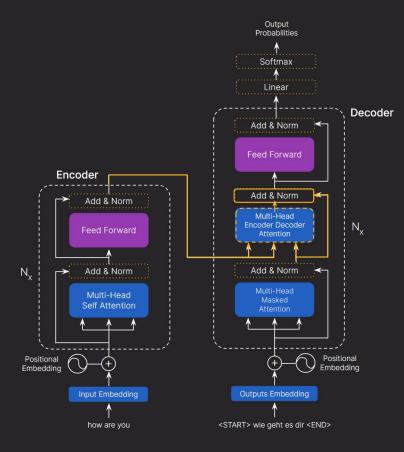
- Masked multi-headed attention is performed.
- This method focuses on relevant sentence parts without previewing future words.





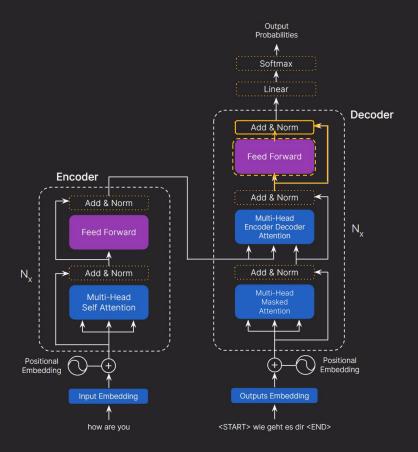
 The resultant matrix is added to the original matrix of the decoder part and then normalized.





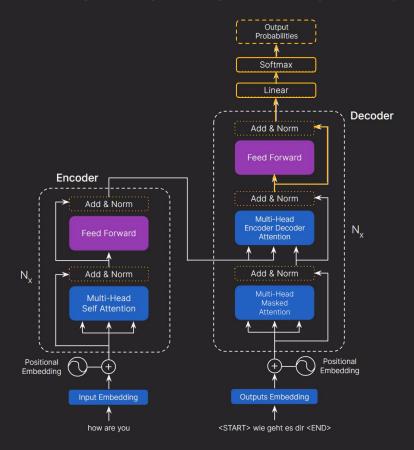
- 3 inputs to the multi-head encoder decoder attention:
 - Value vector from the encoder
 - Key vector from the encoder
 - Query vector after the first add and normalize step





- The output matrix is passed through a feed forward network
- It is added to the resultant matrix from earlier add and norm step to get the decoder stack output.





 Output of the decoder is passed through a linear layer followed by a softmax layer to get the prediction.



Up Next: Implementation of Transformers in Jupyter



IN AIR



