

TRANSFORMERS

Embeddings

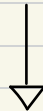
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|------------------------|--|
| 1. Tokenization | Vocabulary - No of Tokens - 50257 |
| 2. Token Embedding | $50,257 \times 768 = 39$ Million Parameters |
| 3. Positional Encoding | 768 - Usually same as Token Vector Dim |
| 4. Final Embedding | $\text{Emb Vec} + \text{Enc Vec} = \text{Final Vec}$
(Element wise Vector Addition) |



Transformers Block

Multi-Head Self Attention

Multi-Layer Perception (MLP)



Output Probabilities

Final Linear Layer. This layer projects the models final representation into a 50,257 dimensional space.

LOGITS \rightarrow SOFTMAX \rightarrow PROBABILITIES

Temperature

Top-K

Top-P

To Fine - Tune the models output to be more deterministic or more diverse.

Embedding

Step 1: Tokenization

Breaking down words into unique tokens from a set of 50,257 unique tokens with distinct ID's. All done with the models fixed vocabulary.

Step 2: Token Embedding

Each token is represented as a 768-dimensional vector. These vectors are stored in lookup matrix of shape (50,257 x 768). Which makes up 39 million parameters, helps in capturing the semantic meaning.

Step 3: Positional Encoding

Adds info about the position of each token in sequence. Each position gets a unique 768-dimensional vector (Emb V / Enc V / No of hidden layer are in same count to maintain consistency).
Sequential relationship and Context.

Step 4: Final Embedding

Embedding Vector + Encoding Vector = Final Embedding

Both vectors are added element-wise.

Final vector contains both Meaning and Position of each token.

Transformer Block

Transformers contain 2 main components:

1. Multiple-Head Self-Attention. → Multiple Perspectives.

2. Multi-Layer Perception (MLP)

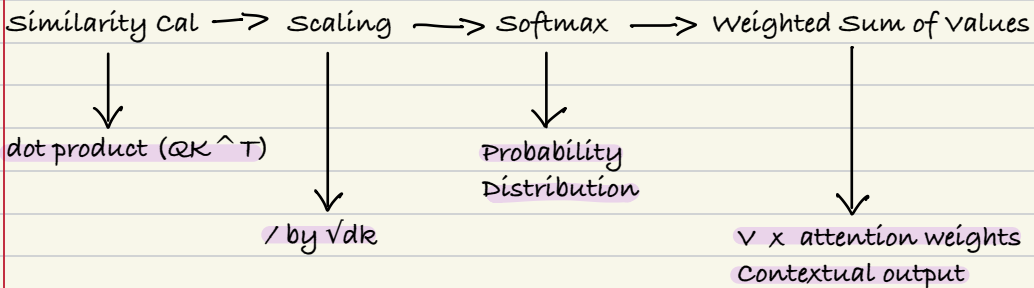
These blocks are stacked sequentially to allow the model build more complex representations of input over time.

What is Attention: At high level attention is way to look at other tokens in same sequence & decide how much focus it should give to each one.

Analogy: GROUP CHAT

Based on what I'm saying (Query) & what others are offering (Key).

Once I decide who matters, I read their message (values) & build a response based on that.



Multi-Head Self Attention:

Query, Key and Value Matrices (Q, K, V)

Multi-Head Splitting

Masked Self-Attention

Output and Concatenation

Multiple heads focus on different aspects (syntax, semantics, position) and then they are concatenated and linearly transformed before going deeper into model.

Transformer Block

Multi - Layer Perception (MLP): Token vec \rightarrow MLP \rightarrow Refined Token Vec

Analogy:

So each token first says \rightarrow "Let me see what others are saying (Attention)"

Then \rightarrow "Let me process what I just learned (MLP)"

Working:

- Applies linear transformation
- Passes it through a non-linear function (GELU or ReLU)
- Applies another linear transformation (To bring it back to original size)

Importance:

- Add non-linearity (So model can learn complex patterns).
- Refine token meaning based on the context already gathered.
- Boost model capacity - this is where a lot of "learning power" is.

Output Probabilities

Final Linear Layer, Vector of Logits.

Logits \rightarrow Softmax \rightarrow Probabilities \rightarrow Sampling \rightarrow Next Token

Logits : Raw scores

Not yet probabilities

Positive or negative

Softmax : Converts Logits to

Probabilities between

0 and 1

Temperature: Scaling factor applied
to Logits before softmax

= 1 : No change

< 1 : More confident

> 1 : More random & creative

Advance Sampling Strategies:

Top - k

Limits the choice of TOP-K
tokens with highest probabilities.

Helps focus on likely options.

Top - P

Chooses the smallest group of
tokens whose combined
probabilities exceed threshold p

Allows diversity without unlikely
outliers