1 Attention

Motivation: One of the core mechanisms inside of current LLMs.

Warning: Convolution takes in a single node, while attention takes in all nodes.

1.1 Transformer

Notes:

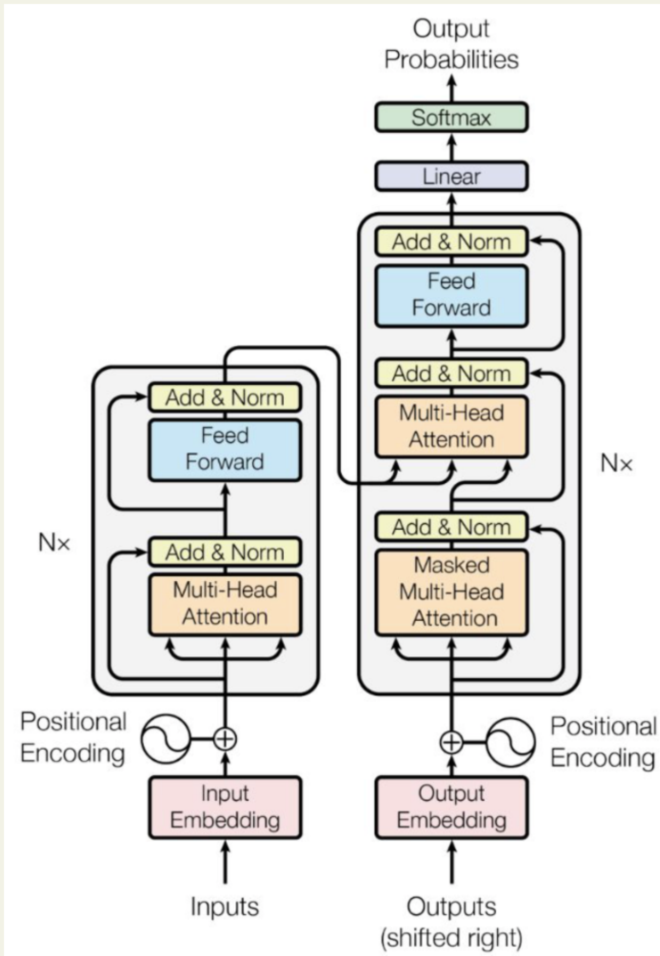

Figure 1

- **Transformer Layer:**
  - Attention mechanism (multi-headed)
  - Positional encodings
- With massive unsupervised datasets:
  - Masked self-supervised training
  - Contrastive training

1.1.1 Transformer Layer

Summary:

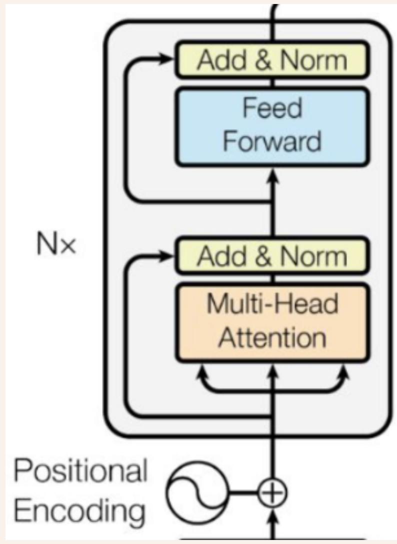

Figure 2

Component	Description
Positional encoding	Learn to map integer positions into a vectorized representation. $$\mathrm{PE}_{(\mathrm{pos},i)} = \begin{cases} \sin\left(\frac{\mathrm{pos}}{10000^{\frac{i}{d_{model}}}}\right) & \text{if } i \text{ is even} \\ \cos\left(\frac{\mathrm{pos}}{10000^{\frac{i-1}{d_{model}}}}\right) & \text{if } i \text{ is odd} \end{cases}$$
Multi-Head Attention	Computes attention scores for each token in the sequence.
LayerNorm	Stabilizes activations and accelerates training.
Residual Connection	Preserve information and enable deeper networks.
FFN/MLP	Increases the expressive power of the learned representation, often using GELU activations.

1.2 Attention Mechanism

Process:

1. **Inputs:** Tokens tensor, Mask
   - **Tokens:** Inputs for Transformer/Attention Layers, which is a numerical representation of pieces of data.
   - **Mask:** A binary matrix that indicates which tokens to give attention to.
2. **Preprocessing:** Linear maps Tokens into Queries, Keys, and Values.
   - $Q = \text{Tokens} \cdot W_Q$: Represents the current token's context.
   - $K = \text{Tokens} \cdot W_K$: Represents the context of all tokens.
   - $V = \text{Tokens} \cdot W_V$: Represents the information to be passed on.
3. **Attention scores:** $\text{Scores} = \frac{QK^T}{\sqrt{d_k}} \cdot \text{Mask}$
   - $\text{score}_{ij} = \frac{(q_i \cdot k_j)m_{ij}}{\sqrt{d_k}}$
4. **Attention Normalization:** Attention Weights = softmax(scores)
   - $\text{score}_{ij}^{\text{normalized}} = \frac{\exp(\text{score}_{ij})}{\sum_{k=1}^{n} \exp(\text{score}_{ik})}$
5. **Value update:** $\text{New Values} = \text{Attention Weights} \cdot V$
   - $v_i^{\text{new}} = \sum_{j=1}^{n} \text{score}_{ij}^{\text{normalized}} v_j$
6. **Post Processing:** Apply LayerNorm, Residual connections, and a FFN.
7. **Outputs:** Updated tokens tensor

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k} \cdot \text{Mask}}\right) V \tag{1}$$

1.2.1 Self-Attention vs. Cross-Attention

Notes:

1.2.2 Multi-Head Attention

Notes:

1.3 Transformers

Notes:

1.3.1 Transformer Block

Notes:

1.3.2 Transformers are GNNs

Summary: Transformers are a special case of GNN

1.4 Examples

1.4.1 Tokens

Example:

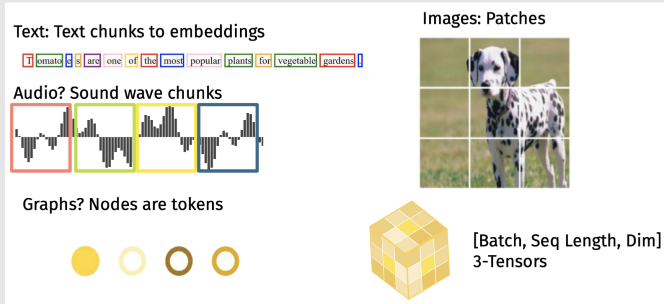

Figure 3

1.4.2 Positional Encoding

Example:

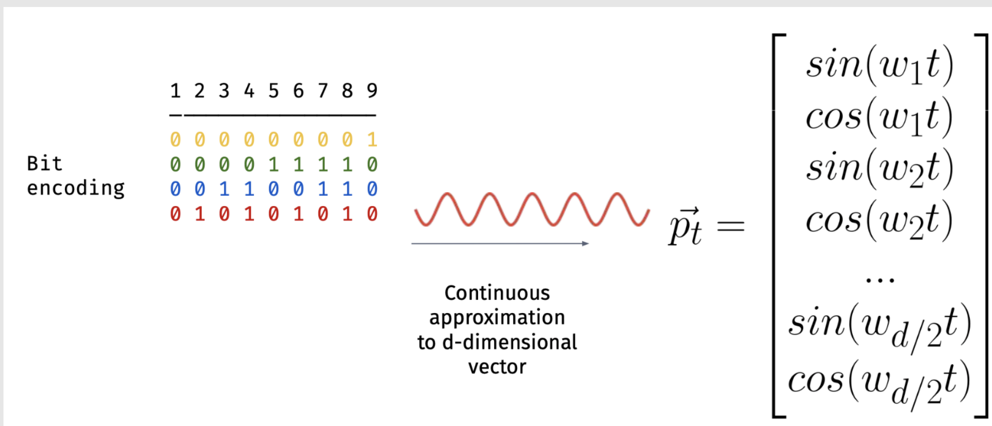

Figure 4

2 LLMs

Notes:
- Transformers on large text-like datasets.
- Transformers on "tokens" (discretized data)
- Foundational models

2.1 Transformers & LLMs

Summary:

2.1.1 Inputs: Tolenizing Text & Embedding Layers

2.1.2 Outputs: Auto-Regressive Decoding of Tokens

2.1.3 Sizes of Text Datasets for LLMs

2.1.4 Text to Text Tasks

2.1.5 Transformers and Masking: Encoders and Decoders

2.1.6 Masking Language Modelling (Self-Supervised)

2.2 Scaling LLMs

Motivation:

2.2.1 Techniques

Summary: Table format

2.2.2 High-Level Impacts

Summary:

3 Transformers