Deep Learning

16 Transformer Applications

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Transformer Layer - Powerful Building Block

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2. E.g., Large Language Models (LLMs)

Transformer Applications - NLP

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భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

1. Three broad configurations - based on the form of i/p and o/p

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1. A single vector as input and a sequence as output (Transformer acts as a ‘Decoder’)

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   - E.g., Caption generation from an image

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1. Sequence-to-Sequence processing tasks

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4. $p(x_n/x_1, x_2, \ldots, x_{n-1})$

Decoder Transformers - GPT

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3. o/p - $\tilde{x}_1, \tilde{x}_2, \ldots, \tilde{x}_N$
4. Each o/p token needs to represent a probability distribution over the dictionary (say, K words)

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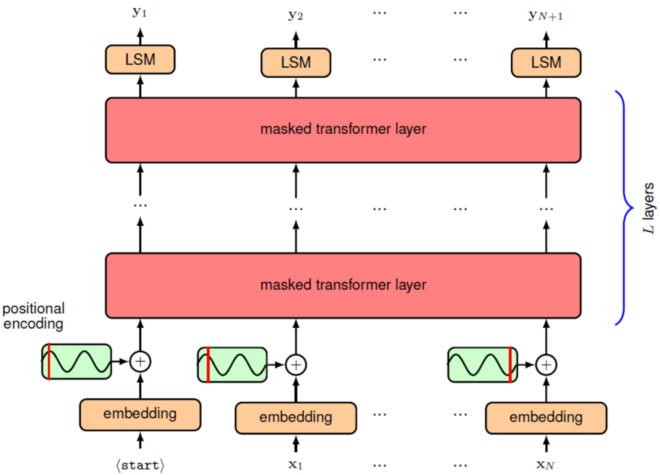
2. $\mathbf{Y} = \text{Softmax}(\tilde{\mathbf{X}}\mathbf{W^{(p)}})$

Decoder Transformers



Bishop's Book

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2. Self-supervised approach
3. Predicting x_{n+1} from an input of $x_1, x_2, \ldots, x_{n-1}$

Decoder Transformers

1. Employs 'Masked' or 'Causal' attention

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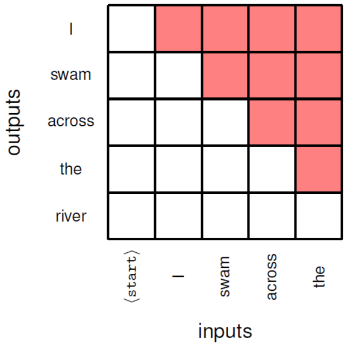
2. Sets the attention weights of all the 'later' tokens



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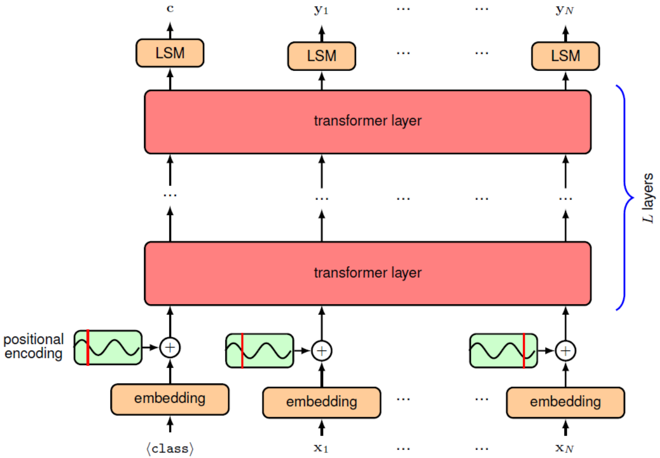
3. Goal is to pre-train a language model using a large corpus of text
   - Then, to fine-tune it for a broad range of downstream tasks

Encoder Transformers



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3. Pre-training goal is to predict the missing tokens

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3. Model should predict is and floor at 3 and 7 nodes respectively

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2. Only a fraction of tokens act as labels
3. Doesn't generate sequences

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3. A new layer (LSM in the figure) predicts the probability distribution over the dictionary

Sequnce-to-Sequence Transformers

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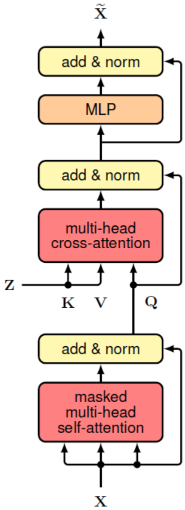
4. Conditioned on the entire input sequence corresponding to the English sentence $\rightarrow$ 'cross attention'

Sequnce-to-Sequence Transformers



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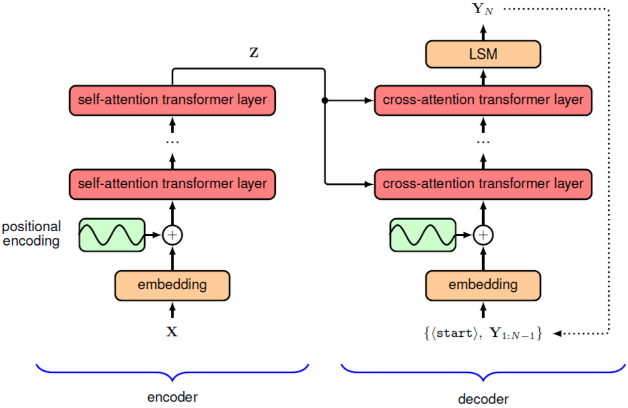

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LLM - Large Language Models

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1. Recent development in ML and NLP

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4. Unlike earlier language models, these are self-supervised first on large corpuses then finetuned with (small) labeled data

LLM

1. 'Foundation Model' $\leftarrow$ A model with broad capabilities that can be subsequently fine-tuned for specific tasks

LLM- Finetuning

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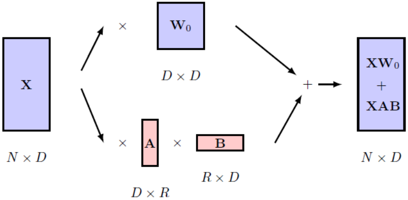
2. A trained overparameterized model has a low intrinsic dimensionality with respect to fine-tuning



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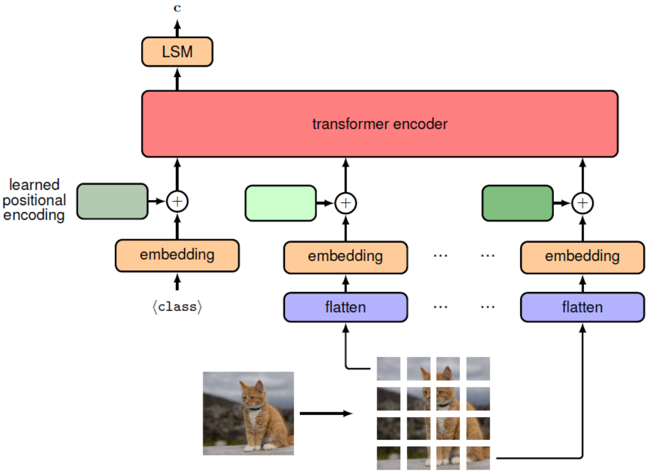
2. Generative language models are now able to solve a broad range of tasks through text-based interaction (prompt)
3. Fine-tuning large language models through human evaluation of generated output (e.g., reinforcement learning through human feedback or RLHF)

Transformers - Computer Vision



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