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Large Language Models: Key Concepts and Training

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Large Language Model

- A neural model designed to process and generate human-like text based on massive datasets.
- Large ~
 - The model's size (number of parameters) and
 - The scale of the training data size
- Train on <diverse> and <vast> amount of datasets
- Transformer architecture:
 - Handling sequential data and capturing long-range dependencies in text.
 - Self Attention and Positional Encoding

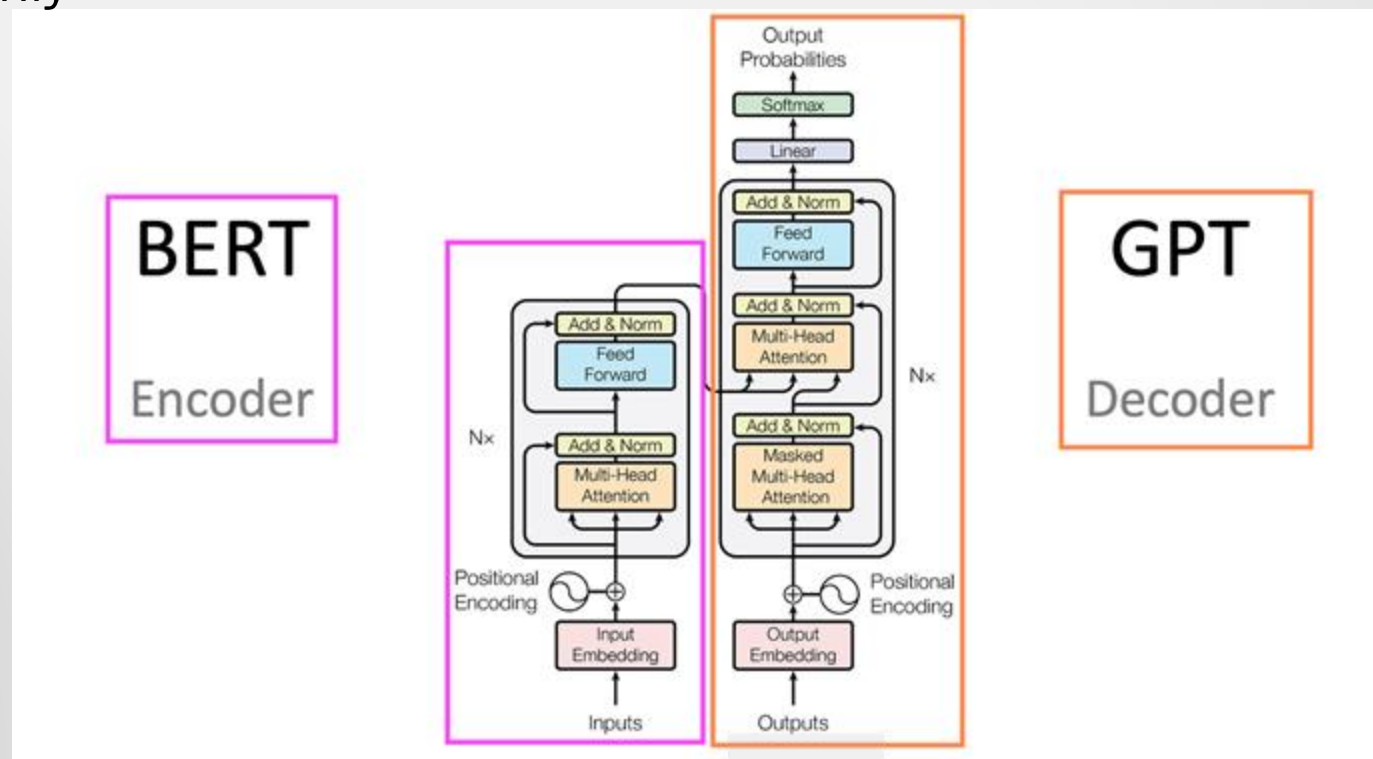
Large Language Model

- Perform both
 - "Understanding" ~ interpreting and analyzing text
 - "Generation" ~ producing new text

- Examples
 - GPT, ChatGPT (by OpenAI)
 - BERT, T5 (by Google)
 - Llama (Meta)
 - Mistral (Mistral AI)
 - Gemma (Google)

LLM Structures

- Encoder-Decoder
- Encoder-Only
- Decoder-Only



Encoder-Decoder LLMs

- Uses both an encoder and a decoder
 - The encoder processes the input sequence
 - The decoder generates an output sequence based on the encoded information.
- Encoder part: Trained bidirectionally
- Decoder part: Trained unidirectionally (auto-regressive way)
- Tasks where the model needs to transform one sequence into another.
 - Machine Translation
 - Summarization
- T5 (Text-To-Text Transfer Transformer)

Bidirectional or Unidirectional ?

➤ *Bidirectional*

- The model processes input data from both directions; from start to end and from end to start
- Helps the encoder better understand the relationships between words within the entire input sequence.

➤ *Unidirectional (Auto-regressive)*

- The model processes data in one direction only.
- During the training, the model only looks at the previous words, not the ones that come after to predict the next word.

Encoder-Only LLMs

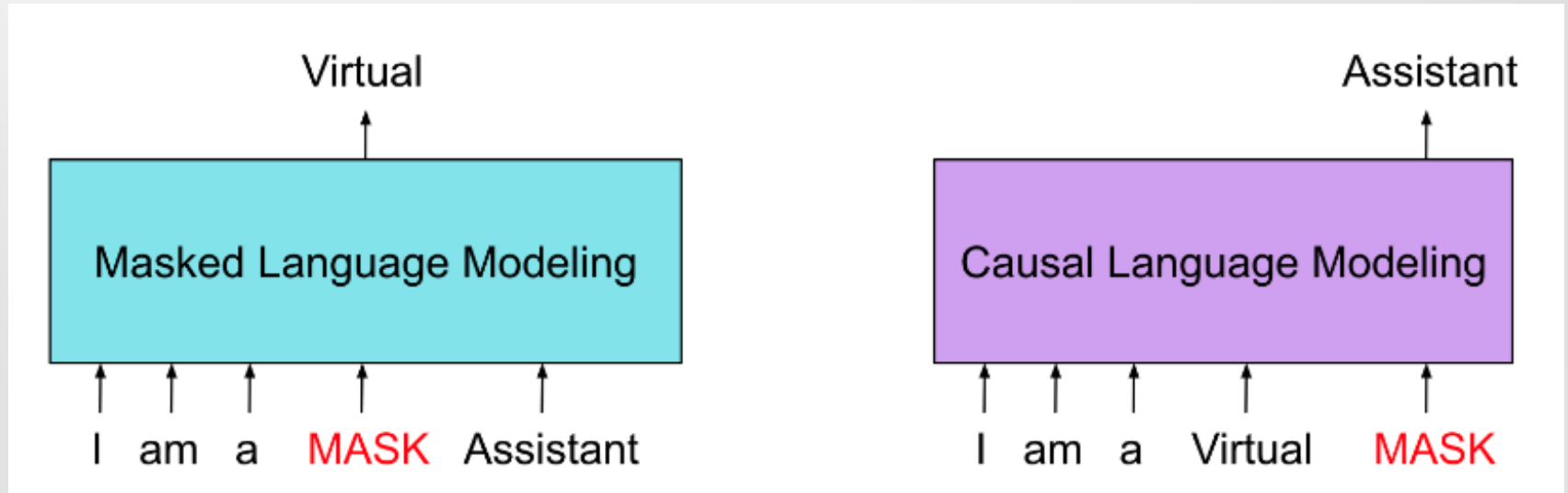
- Uses only the encoder component of the transformer
 - Processes the input text and,
 - Outputs a fixed-length vector representation (embedding) of the input sequence.
- Trained bidirectionally
- Tasks where require text understanding or classification without the need to generate new sequences.
 - Sentiment Analysis
 - Classification, tagging tasks
- BERT (Bidirectional Encoder Representations from Transformers),
RoBERTa (a robustly optimized BERT approach)

Decoder-Only LLMs

- Uses only the decoder component of the transformer.
- Decoder works in an auto-regressive manner:
 - Generates one token at a time by using each previous token in sequence generation.
- Generative tasks where the model generates new text based on a prompt.
- GPT (Generative Pretrained Transformer)
LLaMA
Mistral

Masked Language Modeling

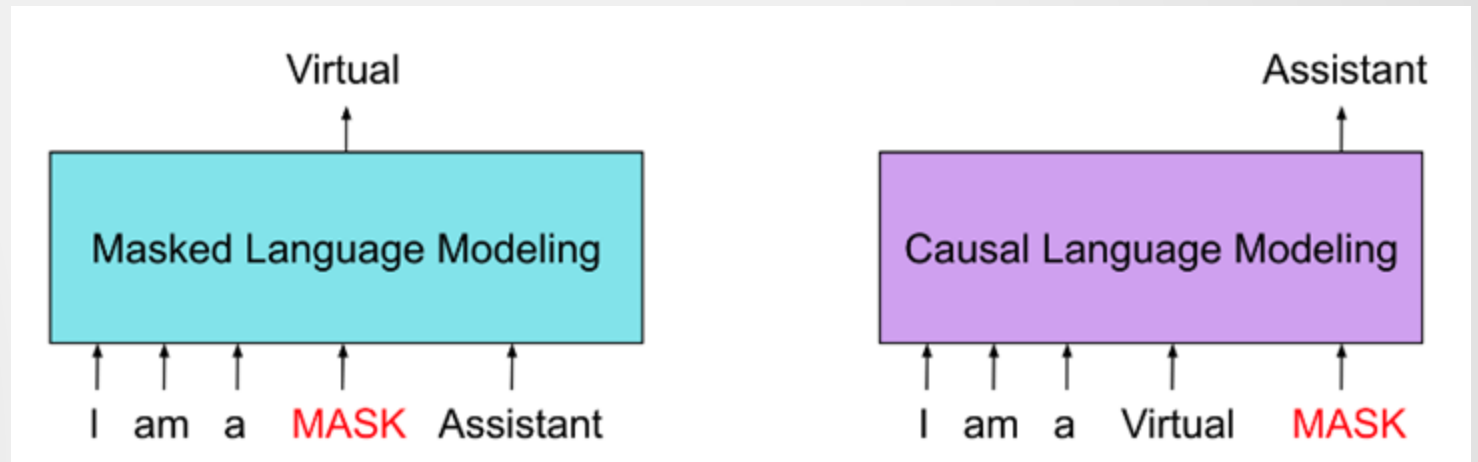
- Training:
A portion of the input tokens is randomly replaced with a special token, [MASK]
The model is tasked with predicting the [MASK] based on the surrounding context.
- Bidirectional context
 - Trained to understand context from both directions.
- BERT



Causal Language Modeling

- Autoregressive Generation:
The model is trained to predict the next token in a sequence given all previous tokens.
The model generates one token at a time, with each token prediction conditioned only on the previous tokens.
- Unidirectional context
 - Only consider the past context (tokens before the current token) when predicting the next token

- GPT



Pre-Training

- ◆ The initial phase where a model is trained on large, general-purpose datasets
- ◆ Unsupervised or Self-supervised
- ◆ Learns general language knowledge, but without focusing on any specific task.
- ◆ For example:
- ◆ in Masked Language Models (MLMs) like BERT,
 - Training objective: To predict the [MASK] tokens.
- ◆ in Causal Language Models (LMs) like GPT,
 - Training objective: To predict the next word in a sequence.

Fine-Tuning

- ◆ The pre-trained model is adapted to a specific task by training it further on a smaller, labeled dataset.
- ◆ Supervised
- ◆ Adjusts the parameters of the model to specialize it for a particular application
- ◆ Learns general language knowledge, but without focusing on any specific task.
- ◆ Allows the model to specialize in a specific task or domain, improving its performance for that task.
 - A pre-trained BERT model can be fine-tuned on a labeled dataset for a Sentiment Analysis
 - Input text (e.g., reviews) is classified into POS or NEG sentiment labels.

Continual Training

- ◆ Allows the model to dynamically update its knowledge without requiring retraining from scratch

>>> Efficiency

- ◆ Models can operate effectively in dynamic, real-world environments where data or tasks evolve over time. >>> Adaptability

- ◆ Key Challenge

!!! Avoiding Catastrophic Forgetting !!!

The tendency of neural networks to overwrite old knowledge when learning new tasks.

Instruction Tuning

- ◆ Fine-tuning pre-trained models to better understand and follow natural language instructions.
- ◆ Aligns models to better understand and follow human-like instructions.
- ◆ Boosts model performance in zero-shot and few-shot learning scenarios.
- ◆ Use instruction-labeled datasets to train the fine-tuned model.
 - ◆ Need to convert the current task into instruction-containing I/O for training.
- Example Models:
 - InstructGPT
 - FLAN (Fine-tuned LLaMA models)

Prompting

→ **Prompt**: The input text or query that is fed into the model to generate a response.

Ex. A question, an incomplete sentence, or a set of instructions.

→ Types of Prompting:

→ **Zero-Shot Prompting:**

- The model is provided with a task or question without any examples or extra context.
- The model performs the task based on its general knowledge.

→ **Few-Shot Prompting:**

- The model is given a few examples of the task before it attempts the task on its own.

Prompting

→ Chain-of-Thoughts Prompting:

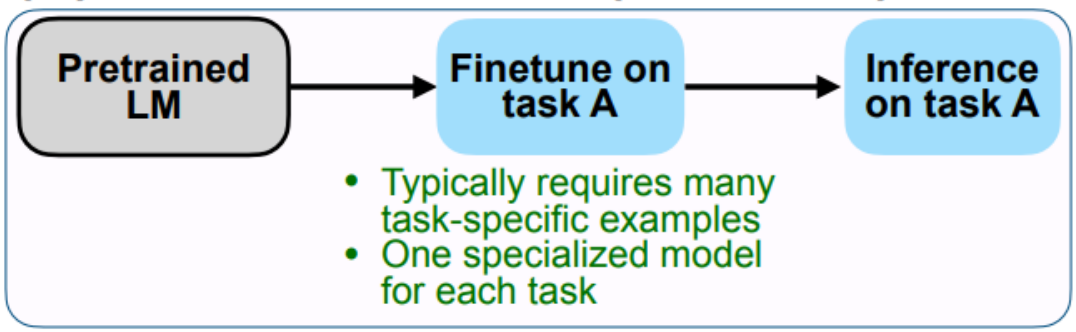
- The model is prompted to reason through a problem step-by-step.

| Standard Prompting | Chain-of-Thought Prompting |
|---|---|
| <p>Model Input</p> <p>Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?</p> <p>A: The answer is 11.</p> <p>Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?</p> | <p>Model Input</p> <p>Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?</p> <p>A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. $5 + 6 = 11$. The answer is 11.</p> <p>Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?</p> |
| <p>Model Output</p> <p>A: The answer is 27. ❌</p> | <p>Model Output</p> <p>A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had $23 - 20 = 3$. They bought 6 more apples, so they have $3 + 6 = 9$. The answer is 9. ✅</p> |

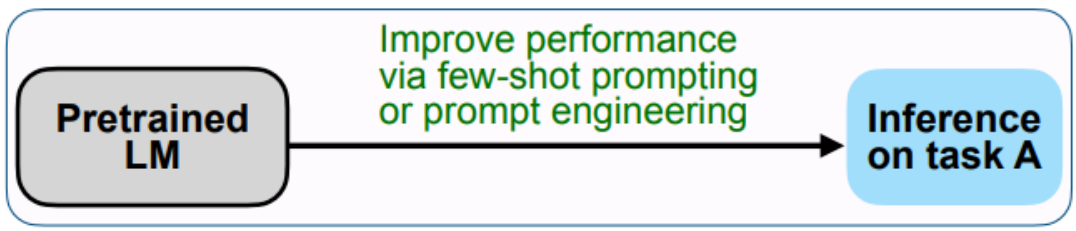


Fine-Tuning vs Instruction Tuning vs Prompting

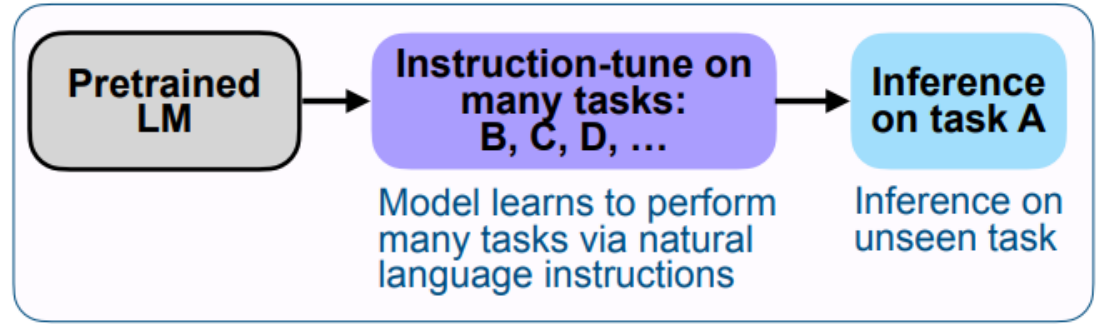
(A) Pretrain–finetune (BERT, T5)



(B) Prompting (GPT-3)



(C) Instruction tuning (FLAN)



Wei, J., Wang, X., Schuurmans, D., Bosma, M., Xia, F., Chi, E., ... & Zhou, D. (2022). Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35, 24824-24837.



How to Supervised Fine-Tune an LLM ?

- via SFTTrainer
 - designed for Supervised Fine-Tuning (SFT) tasks, particularly when working with instruction-following models.
 - It is tailored for fine-tuning large language models on datasets that consist primarily of text.
- SFTTrainer vs general Trainer
 - Trainer class requires you to manually handle tokenization.
 - SFTTrainer simplifies this by managing these processes automatically.
- Consider using SFTTrainer if:
 - You're working with instruction-following models or datasets that require specific handling of text input.
 - You are implementing PEFT (Parameter Efficient Fine-Tuning) methods like LoRA, which can be easily integrated into SFTTrainer for efficient tuning.