



[Evolution of Foundation LLM models]

- Closed to open source, their size, their performance, scale, interesting characteristics, pros and cons
- From specialist models to general purpose assistants
- [ChatGPT benchmarking paper](#)
- [Llama2 LLM](#)

[Understanding Finetuning, RLHF and In-context Learning]

- Different types of finetuning mechanisms and their examples in LLMs
- [What In-Context Learning "Learns" In-Context: Disentangling Task Recognition and Task Learning](#)

- ICL reference
- [In-context Learning and Induction Heads](#)
- [Finetuning with human preference](#)
- RLHF (paper-pdf, InstructGPT), RLHF - base paper
- Prompt functions, Program aided LLMs
- Some more papers:
- [Paper 1, Integrating human feedback in RL](#)

[Walkthrough Prompting Techniques]

What is it? What are the different ways? Is there any best/general way that is better than others? Cover the most important ones in the permitted time.

- **Prompting**
- [RAG, other paper](#)
- **CoT** - Chain-of-Thought Prompting Elicits Reasoning in Large Language Models
 - [CoT collection paper](#)
- **Tree of Thoughts**: Deliberate Problem Solving with Large Language Models
- Multimodal CoT
- Self consistency
- Auto - prompting
- **Zero-shot** prompting
- ReACT
- **Active Prompting** with Chain-of-Thought for Large Language Models
- **GraphPrompt**: Unifying Pre-Training and Downstream Tasks for Graph Neural Networks

[Alignment, Interpretability and Robustness in LLMs]

- Alignment problem in LLMs
- Ethics, toxicity in LLMs and role of prompting / finetuning
- [Automated interpretability](#)
- [Attention visualization](#): using dimensionality reduction to visualize the joint embedding space of key-query pairs
- Robustness & **adversarial** prompting
- [Zero-Resource Hallucination Prevention for Large Language Models](#)
- [Certifying LLM Safety against Adversarial Prompting](#)
- [Improving Code Generation by Dynamic Temperature Sampling](#)
- [Limitations and challenges - blog](#)
- Some more papers:
- [Paper 1 on reasoning hallucinations.](#)

[Self-attention and improvements in terms of speed]

- Multi-head self-attention: from self attention to its hardware level improvements:
- [Flash attention](#), [paged attention](#): based on reducing the IO in GPU's HBM and on-chip SRAM. Also improves the approximate block-sparse attention.

[Distributed large scale training of LLMs and associated challenges]

- Discrimination between models based on how they were trained: can take up models which differ in their training strategy and may discuss the differences. [Related Survey](#)
- Training spikes and divergences: [use this as the starting point of your exploration of how large scale training converges](#)
- [ZeRO-fashion data parallel \(distributed optimizer\)](#), Model parallel

[Concept of vector database and LLM application dev. tools like Langchain]

- Can discuss about performance, scalability, and flexibility in vector database
- Focus on pinecone
- Other database:, Chroma, Weaviate, Milvus, etc.
- [Term vector database paper](#) to get some idea on early vector databases
- Application development using LLMs:
- [Langchain](#): framework for developing applications powered by LLMs. Agents ←use Tools. Memory ← to integrate and remember contexts.
- Other frameworks: [FlowiseAI](#), [AutoGPT](#), [AgentGPT](#), [BabyAGI](#), [Langdock](#), [GradientJ](#), [Llamaindex](#), [MetaGPT](#)

[Parameter efficient finetuning and its application to LLMs]

- [Adapters - Parameter efficient fine tuning](#)
- [Prefix tuning](#)
- [Low Rank Adaptation of LLMs \(LoRA\)](#)
- How does it compare with Prompting / In context learning? Is there any study or observation from literature?