A Comprehensive Overview of Large Language Models

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A Comprehensive Overview of Large Language Models

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***Abstract*—**
Large Language Models (LLMs) have recently demonstrated remarkable capabilities in natural language processing tasks and beyond. This success of LLMs has led to a large influx of research contributions in this direction. These works encompass diverse topics such as architectural innovations of the underlying neural networks, context length improvements, model alignment, training datasets, benchmarking, efficiency and more. With the rapid development of techniques and regular breakthroughs in LLM research, it has become considerably challenging to perceive the bigger picture of the advances in this direction. Considering the rapidly emerging plethora of literature on LLMs, it is imperative that the research community is able to benefit from a concise yet comprehensive overview of the recent developments in this field. This article provides that overview to the research community. It not only focuses on a systematic treatment of the existing literature on a broad range of LLM related concept, but also pays special attention to providing comprehensive summaries with extensive details about the individual existing models, datasets and major insights. We also pay heed to aligning our overview with the emerging outlook of this research direction by accounting for the other recently materializing reviews of the broader research direction of LLMs. Our self-contained comprehensive overview of LLMs discusses relevant background concepts along with covering the advanced topics at the frontier of this research direction. This review article is intended to not only provide a systematic survey, but also a quick comprehensive reference for the researchers and practitioners to draw insights from extensive informative summaries of the existing works to advance the LLM research direction.

***Index Terms*—**
Large Language Models, LLMs, chatGPT, LLM training, LLM Benchmarking

I. Introduction

Language plays a fundamental role in facilitating communication and self-expression for humans, and likewise, communication holds paramount importance for machines in their interactions with humans and other systems. Large Language Models (LLMs) have emerged as cutting-edge artificial intelligence systems designed to process and generate text, aiming to communicate coherently [1]. The need for LLMs stems from the growing demand for machines to handle complex language tasks, including translation, summarization, information retrieval, and conversational interactions. Recently, significant breakthroughs have been witnessed in language models, primarily attributed to deep learning techniques, advancements in neural architectures like transformers, increased computational capabilities, and the accessibility of training data extracted from the internet [2]. These developments have brought about a revolutionary transformation by enabling the creation of Large Language Models (LLMs) that can approximate human-level performance on certain evaluation benchmarks [3], [4].

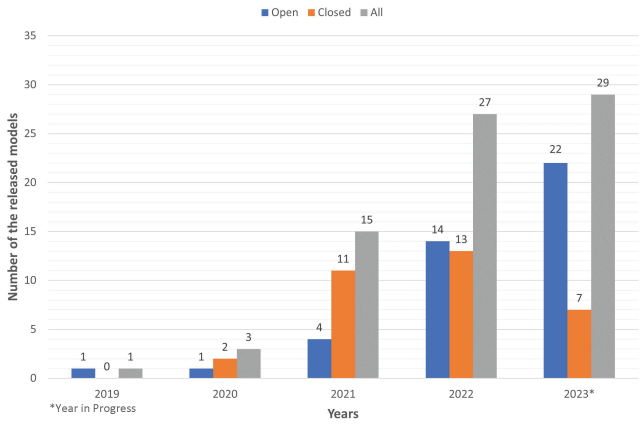

Fig. 1: The trends in the number of LLM models introduced over the years.

LLMs, particularly pre-trained language models (PLM), have shown tremendous generalization abilities for text understanding and generation tasks while trained in a self-supervised setting on a large corpus of text [5], [6], [7]. The performance of pre-trained language models (PLMs) improves significantly when fine-tuned for downstream tasks, surpassing the performance of models trained from scratch. These characteristics of language models motivated researchers to train larger PLMs on even bigger datasets and found that scaling model and dataset size further improve the generalization abilities.

Now modern LLMs are capable of performing various tasks like code generation, text generation, tool manipulation, reasoning, and understanding in zero-shot and few-shot settings in diverse domains, even without requiring any fine-tuning on downstream tasks [8], [9], [10]. Such generalization was previously unattainable with smaller models, marking a significant advancement in language modeling. This development has sparked enthusiasm and excitement within the research community for the enhancement of LLM architectures and training strategies, leading to the development of numerous LLMs [11], [12], [13], [8], [9], [10], [14].

The graph presented in Fig 1 depicts an increasing trend

Version: 01 (update on July 10, 2023).
GitHub link: https://github.com/humza909/LLM_Survey.git
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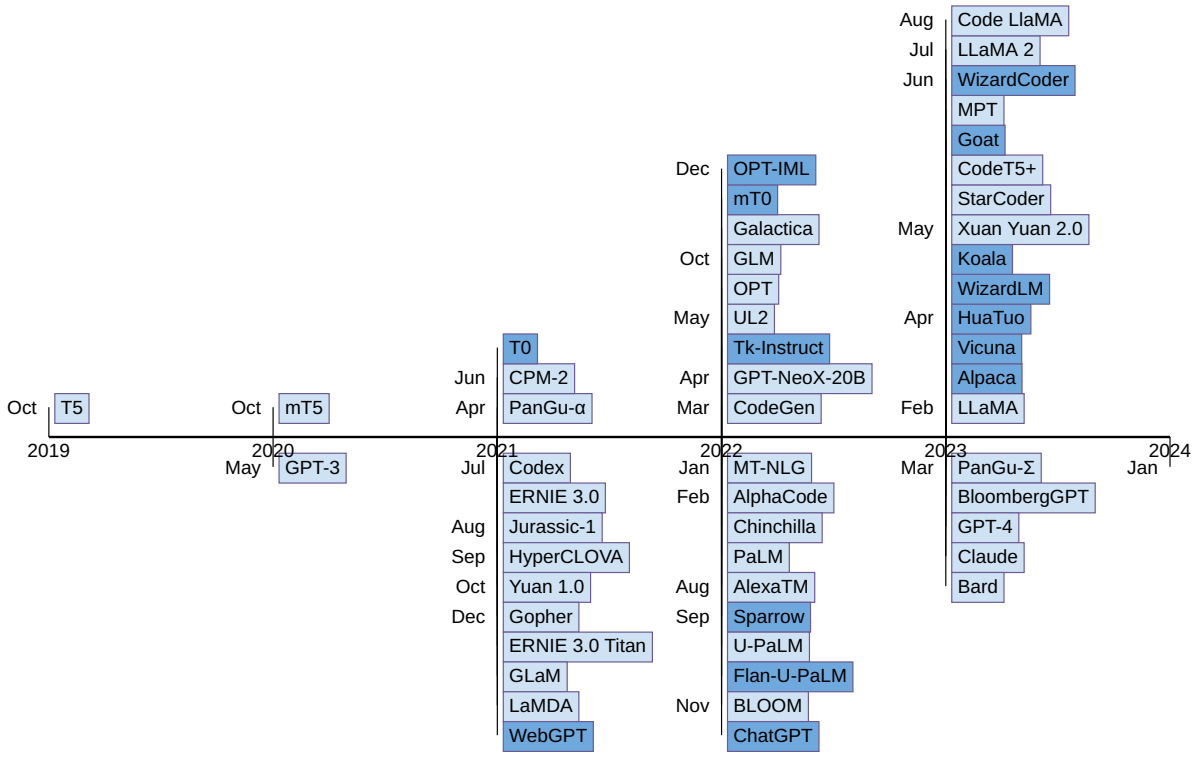

Fig. 2: Chronological display of LLM releases: light blue rectangles represent 'pre-trained' models, while dark rectangles correspond to 'instruction-tuned' models. Models on the upper half signify open-source availability, whereas those on the bottom half are closed-source. The chart illustrates the increasing trend towards instruction-tuned models and open-source models, highlighting the evolving landscape and trends in natural language processing research.

in the number of released LLMs, including open-source and closed-source models, over the years. Furthermore, Fig 2 highlights the names of significant releases of various LLMs and Fig 3 provides a broader overview of LLMs.

During the early days of Large Language Models (LLMs), many research efforts focused on developing models for transfer learning to downstream tasks [11], [12], [15] until the emergence of models like GPT-3 [8], which demonstrated impressive performance even without fine-tuning. Due to the closed-source nature of GPT-3, there was a demand for open-source alternatives, leading to the development of various models [9], [10] operating at the scale of GPT-3 and trained on extensive web-based datasets [16], [17], [18], [19]. Subsequently, researchers proposed several architectural designs and training strategies that showed superior performance compared to GPT-3 across various tasks [15], [14], [20], [21].

The performance of LLMs improves further with instruction fine-tuning, outperforming pre-trained LLMs on various benchmarks [22], [23]. Instruction fine-tuning of LLMs refers to a specific training approach by incorporating additional prompts or instructions during the fine-tuning phase to guide the output and thus enable the users to have more fine-grained control over the outputs of LLMs. These prompts can be natural language instructions or example demonstrations based on the task's requirement. In the literature, different datasets have been curated for instruction fine-tuning. These datasets include more instances and tasks that further improve the performance over baselines [24], [23], [25], [26]. When performing instruction fine-tuning, all the model parameters need to be updated. However, parameter-efficient fine-tuning takes a different approach by updating only a small number of parameters while still maintaining good performance. This method keeps the original model frozen and adds a few extra parameters at different locations within the model [27], [28], [29], [30], [31]. This approach helps achieve efficient fine-tuning while minimizing the impact on the model's overall performance.

Due to the success of LLMs on a wide variety of tasks, the research literature has recently experienced a large influx of LLM related contributions. Naturally, the research community has started the effort of organizing this literature as survey articles. For instance, Zhou et al. [32] presented an overview of the foundation models. An impressive effort is recently made by Zhou et al. [33] in their survey that also discusses aspects related to model architectures, fine-tuning, emergent abilities, and more. Another recent survey on augmented language models provides a historical account of the foundation models [34]. In contrast to these surveys, our contribution focuses on providing a comprehensive yet concise overview of the general direction of LLM research. On one hand, this

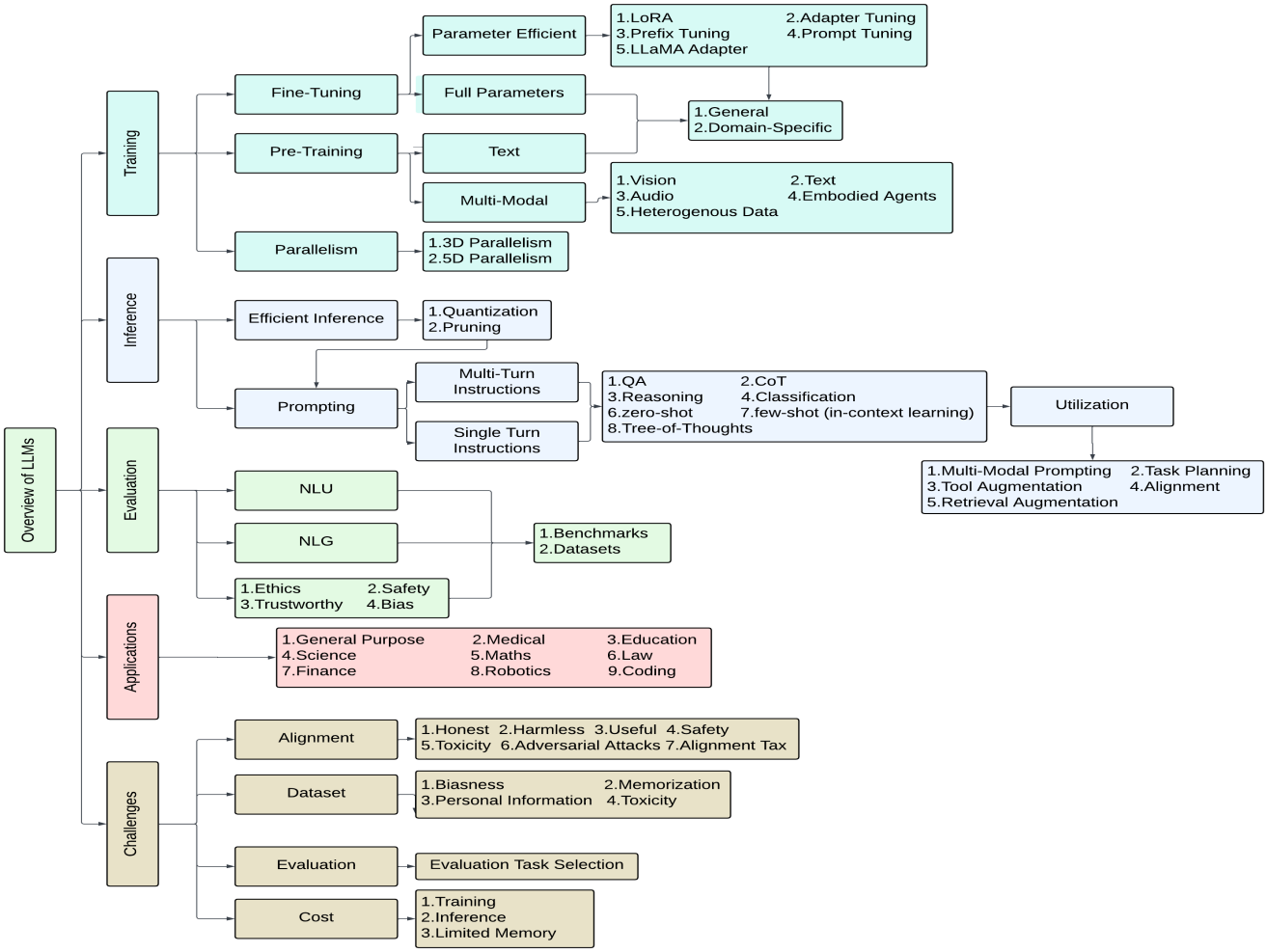

Fig. 3: A broader overview of LLMs, dividing LLMs into five branches: 1. Training 2. Inference 3. Evaluation 4. Applications 5. Challenges

article summarizes more details of the individual models as compared to the existing efforts. On the other, it also covers more models in providing their summaries. It also delves into the details of model development, architectures, training datasets, and other related concepts to provide a self-contained comprehensive overview of this direction. Hence, this article addresses an important gap of providing a concise yet comprehensive overview of the rapidly developing general direction of LLM research. Our key contributions are summarized as follows.

- We present the first survey on the developments in LLM research with the specific aim of providing concise yet comprehensive overview of the direction. We present extensive summaries that include fine-grained details of the reviewed contributions.
- In this self-contained article, we cover a range of concepts to comprehend the general direction of LLMs, including background concepts, popular models, crucial discoveries, related datasets and evaluation details etc.
- Besides paying special attention to the chronological order of LLMs throughout the article, we also summarize major findings of the popular contributions, and provide detailed discussion on the key design and deployment aspects of LLMs to help practitioners to effectively leverage this technology.

It is noteworthy that although this article is the first contribution in its own right in terms of providing a concise yet comprehensive overview of LLMs, our work complements the recent (and emerging) surveys of this direction, e.g., [33], [32]. Infrequently, we also loosely follow the existing terminologies to ensure providing a more standardized outlook of this research direction. For instance, following [33], our survey considers a language model to be *large* if it has 10B parameters or more. Hence, we discuss such models in detail in this survey. We refer the readers interested in smaller models to [35], [36], [32].

The organization of this paper is as follows. Section II discusses the background of LLMs. Section III focuses on LLMs overview, architectures, and training pipelines and strategies. Section IV presents the key findings derived from each LLM. Section V highlights the configuration and parameters that play a crucial role in the functioning of these models. The LLM training and evaluation benchmarks are discussed in section VI, followed by concluding remarks and future direction

in the conclusion section.

II. Background

We provide the relevant background to understand the key concepts related to LLM in this section. Aligned with our objective of providing a comprehensive overview of this direction, this section offers a comprehensive yet concise outline of the fundamental concepts. In natural language processing literature, these concepts are of standard nature. Hence, we focus more on the intuitive aspects and refer the readers interested in details to the original works we cite in our discussion.

A. Tokenization

LLMs are trained on text to predict text, and similar to other natural language processing systems, they use tokenization [37] as the essential preprocessing step. It aims to parse the text into non-decomposing units called tokens. Tokens can be characters, subwords [38], symbols [39], or words, depending on the size and type of the model. Some of the commonly used tokenization schemes in LLMs are briefed here. Readers are encouraged to refer to [40] for a detailed survey.

1. WordPiece [41]: It was introduced in [41] as a novel text segmentation technique for Japanese and Korean languages to improve the language model for voice search systems. WordPiece selects tokens that increase the likelihood of an n-gram-based language model trained on the vocabulary composed of tokens.

2. BPE [39]: Byte Pair Encoding (BPE) has its origin in compression algorithms. It is an iterative process of generating tokens where pairs of adjacent *symbols* are replaced by a new symbol, and the occurrences of the most occurring symbols in the input text are merged together.

3. UnigramLM [38]: In this tokenization, a simple unigram language model (LM) is trained using an initial vocabulary of *subword* units. The vocabulary is pruned iteratively by removing the lowest-probability items from the list, which are the worst performing on the unigram LM.

B. Attention

Attention, particularly *selective attention*, has been widely studied under perception, psychophysics and psychology. Selective attention can be conceived as "the programming by the O of which stimuli will be processed or encoded and in what order this will occur" [42]. While this definition has its roots in visual perception, it has uncanny similarities with the recently formulated *attention* [43], [44] (which stimuli will be processed) and *positional encoding* (in what order this will occur) [44] in LLMs. We discuss both in sections II-C and II-D, respectively.

C. Attention in LLMs

The attention mechanism computes a representation of the input sequences by relating different positions (*tokens*) of these sequences. There are various approaches to calculating and implementing attention, out of which some famous types are given below.

1. Self-Attention [44]: The self-attention is also known as intra-attention since all the queries, keys and values come from the same block (encoder or decoder). The self-attention layer connects all the sequence positions to each other with $O(1)$ space complexity which is highly desirable for learning long-range dependencies in the input.

2. Cross Attention: In encoder-decoder architectures, the outputs of the encoder blocks act as the queries to the intermediate representation of the decoder, which provides the keys and values to calculate a representation of the decoder conditioned on the encoder. This attention is called cross-attention.

3. Full Attention: The naive implementation of calculating self-attention is known as full attention.

4. Sparse Attention [45]: The self-attention has a time complexity of $O(n^2)$, which becomes prohibitive when scaling the LLMs to large context windows. An approximation to the self-attention was proposed in [45], which greatly enhanced the capacity of GPT series LLMs to process a greater number of input tokens in a reasonable time.

5. Flash Attention [46]: The bottleneck for calculating the attention using GPUs lies in the memory access rather than the computational speed. Flash Attention uses the classical input tiling approach in order to process the blocks of the input in GPU on-chip SRAM rather than doing IO for every token from the High Bandwith Memory (HBM). An extension of this approach to sparse attention follows the speed gains of the full attention implementation. This trick allows even greater context-length windows in the LLMs as compared to those LLMs with sparse attention.

D. Encoding Positions

The *attention* modules do not consider the order of processing by design. Transformer [44] introduced "positional encodings" to feed information about the position of the tokens in input sequences. Several variants of positional encoding have been proposed [47], [48]. Interestingly, a recent study [49] suggests that adding this information may not matter for the state-of-the-art decoder-only Transformers.

1. Absolute: This is the most straightforward approach to adding the sequence order information by assigning a unique identifier to each position of the sequence before passing it to the attention module.

2. Relative: In order to pass the information of the relative dependencies of different tokens appearing at different locations in the sequence, a relative positional encoding is calculated by some kind of learning. Two famous types of relative encodings are:

***Alibi** [47]* In this approach, a scalar bias is subtracted from the attention score calculated using two tokens which increases with the distance between the positions of the tokens. This learned approach effectively favors using recent tokens for attention.

RoPE Keys, queries and values are all vectors in the LLMs. RoPE [48] involves the rotation of the query and key representations at an angle proportional to their absolute positions of the tokens in the input sequence. This step results in a relative

positional encoding scheme which decays with the distance between the tokens.

E. Activation Functions

The activation functions serve a crucial role in the curve-fitting abilities of the neural networks, as proved in [50]. The modern activation functions used in LLMs are different from the earlier squashing functions but are critical to the success of LLMs. We discuss these activation functions in this section.

1. ReLU [51]: Rectified linear unit (ReLU) is defined as

$$ReLU(x) = max(0, x) \tag{1}$$

2. GeLU [52]: Gaussian Error Linear Unit (GeLU) is the combination of ReLU, dropout [53] and zoneout [54]. It is the most widely used activation function in contemporary LLM literature.

3. GLU variants [55]: Gated Linear Unit [56] is a neural network layer that is an element-wise product ($\otimes$) of a linear transformation and a sigmoid transformed (σ) linear projection of the input given as

$$GLU(x, W, V, b, c) = (xW + b) \otimes \sigma(xV + c), \tag{2}$$

where X is the input of layer and l, W, b, V and c are learned parameters.

GLU was modified in [55] to evaluate the effect of different variations in the training and testing of transformers, resulting in better empirical results. Here are the different GLU variations introduced in [55] and used in LLMs.

$$\begin{aligned} ReGLU(x, W, V, b, c) &= max(0, xW + b) \otimes, \\ GEGLU(x, W, V, b, c) &= GELU(xW + b) \otimes (xV + c), \\ SwiGLU(x, W, V, b, c, \beta) &= Swish\beta(xW + b) \otimes (xV + c). \end{aligned}$$

F. Layer Normalization

Layer normalization leads to faster convergence and is a widely used component in transformers. In this section, we provide different normalization techniques widely used in LLM literature.

1. LayerNorm: Layer norm computes statistics over all the hidden units in a layer (l) as follows:

$$u^l = \frac{1}{n}\sum_i^n a_i^l \qquad \sigma^l = \sqrt{\frac{1}{n}\sum_i^n (a_i^l - u^l)^2}, \tag{3}$$

where n is the number of neurons in the layer l and a_i^l is the summed input of the i neuron in layer l. LayerNorm provides invariance to rescaling of the weights and re-centering of the distribution.

2. RMSNorm: [57] proposed that the invariance properties of LayerNorm are spurious, and we can achieve the same performance benefits as we get from LayerNorm by using a computationally efficient normalization technique that trades off re-centering invariance with speed. LayerNorm gives the normalized summed input to layer l as follows

$$\overline{a_i^l} = \frac{a_i^l - u^l}{\sigma} g_i^l \tag{4}$$

where g_i^l is the gain parameter. RMSNorm [57] modifies $\overline{a_i^l}$ as

$$\overline{a_i^l} = \frac{a_i^l}{\text{RMS}(\mathbf{a}^l)} g_i^l, \text{ where RMS}(\mathbf{a}^l) = \sqrt{\frac{1}{n}\sum_i^n (a_i^l)^2}. \tag{5}$$

3. Pre-Norm and Post-Norm: LLMs use transformer [44] architecture with some variations. The original implementation [44] used layer normalization after the residual connection, commonly called post-LN, concerning the order of *Multihead attention – Residual – LN*. There is another order of the normalization, referred to as pre-LN [58] due to the position of the normalization step before the self-attention layer as in *LN – Multihead attention – Residual*. Pre-LN is known to provide more stability in the training [59].

4. DeepNorm: While pre-LN has certain benefits over post-LN training, pre-LN training has an unwanted effect on the gradients [59]. The earlier layers have larger gradients than those at the bottom. DeepNorm [60] mitigates these adverse effects on the gradients. It is given as

$$\mathbf{x}^{l_f} = LN(\alpha \mathbf{x}^{l_p} + G^{l_p}(\mathbf{x}^{l_p}, \theta^{l_p}), \tag{6}$$

where α is a constant and θ^{l_p} represents the parameters of layer l_p. These parameters are scaled by another constant β. Both of these constants depend only on the architecture.

G. Distributed LLM Training

This section describes distributed LLM training approaches briefly. More details are available in [9], [61], [62], [63].

1. Data Parallelism: Data parallelism replicates the model on multiple devices where data in a batch gets divided across devices. At the end of each training iteration weights are synchronized across all devices.

2. Tensor Parallelism: Tensor parallelism shards a tensor computation across devices. It is also known as horizontal parallelism or intra-layer model parallelism.

3. Pipeline Parallelism: Pipeline parallelism shards model layers across different devices. This is also known as vertical parallelism.

4. Model Parallelism: A combination of tensor and pipeline parallelism is known as model parallelism.

5. 3D Parallelism: A combination of data, tensor, and model parallelism is known as 3D parallelism.

6. Optimizer Parallelism: Optimizer parallelism also known as zero redundancy optimizer [61] implements optimizer state partitioning, gradient partitioning, and parameter partitioning across devices to reduce memory consumption while keeping the communication costs as low as possible.

H. Libraries

Some commonly used libraries for LLM training are: 1) Transformer [64], 2) DeepSpeed [65], 3) Megatraon-LM [62], 4) JAX [66], 5) Colossal-AI [67], 6) BMTrain [63], 7) FastMoE [68], and frameworks are 1) MindSpore [69], 2) PyTorch [70], 3) Tensorflow [71], 4) MXNet [72].

I. Data PreProcessing

This section briefly summarizes data preprocessing techniques used in LLMs training.

1. Quality Filtering: For better results, training data quality is essential. Some approaches to filtering data are: 1) classifier-based and 2) heuristics-based. Classifier-based approaches train a classifier on high-quality data and predict the quality of text for filtering, whereas heuristics-based employ some rules for filtering like language, metrics, statistics, and keywords.

2. Data Deduplication: Duplicated data can affect model performance and increase data memorization; therefore, to train LLMs, data deduplication is one of the preprocessing steps. This can be performed at multiple levels, like sentences, documents, and datasets.

3. Privacy Reduction: Most of the training data for LLMs is collected through web sources. This data contains private information; therefore, many LLMs employ heuristics-based methods to filter information such as names, addresses, and phone numbers to avoid learning personal information.

J. Architectures

Here we discuss the variants of the transformer architectures at a higher level which arise due to the difference in the application of the attention and the connection of transformer blocks. An illustration of attention patterns of these architectures is shown in Figure 4.

1. Encoder Decoder: Transformers were originally designed as sequence transduction models and followed other prevalent model architectures for machine translation systems. They selected encoder-decoder architecture to train human language translation tasks. This architecture is adopted by [11], [15]. In this architectural scheme, an encoder encodes the input sequences to variable length context vectors, which are then passed to the decoder to maximize a joint objective of minimizing the gap between predicted token labels and the actual target token labels.

2. Causal Decoder: The underlying objective of an LLM is to predict the next token based on the input sequence. While additional information from the encoder binds the prediction strongly to the context, it is found in practice that the LLMs can perform well in the absence of encoder [73], relying only on the decoder. Similar to the original encoder-decoder architecture's decoder block, this decoder restricts the flow of information backward, i.e., the predicted token t_k only depends on the tokens preceded by and up to t_{k-1}. This is the most widely used variant in the state-of-the-art LLMs.

3. Prefix Decoder: The causal masked attention is reasonable in the encoder-decoder architectures where the encoder can attend to all the tokens in the sentence from every position using self-attention. This means that the encoder can also attend to tokens t_{k+1} to t_n in addition to the tokens from t_1 to t_{k-1} while calculating the representation for t_k. But when we drop the encoder and only keep the decoder, we also lose this flexibility in attention. A variation in the decoder-only architectures is by changing the mask from strictly causal to fully visible on a portion of the input sequence, as shown in Figure 4. The Prefix decoder is also known as non-causal decoder architecture.

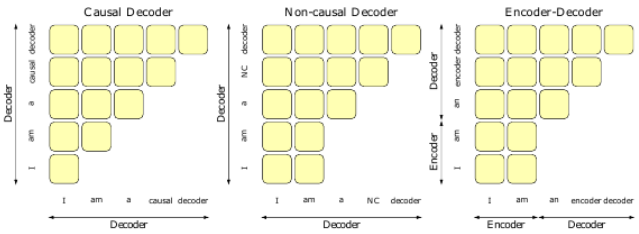

Fig. 4: An example of attention patterns in language models, image is taken from [74].

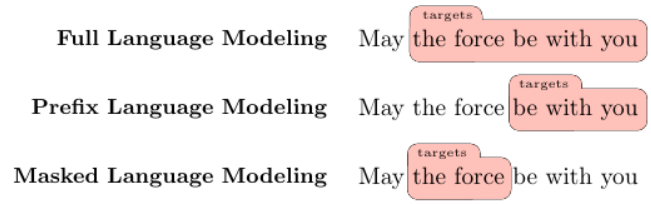

Fig. 5: An example of language model training objectives, image from [74].

K. Pre-Training Objectives

This section describes LLMs pre-training objectives. For more details see the paper [74].

1. Full Language Modeling: An autoregressive language modeling objective where the model is asked to predict future tokens given the previous tokens, an example is shown in Figure 5.

2. Prefix Language Modeling: A non-causal training objective, where a prefix is chosen randomly and only remaining target tokens are used to calculate the loss. An example is shown in Figure 5.

3. Masked Language Modeling: In this training objective, tokens or spans (a sequence of tokens) are masked randomly and the model is asked to predict masked tokens given the past and future context. An example is shown in Figure 5.

4. Unified Language Modeling: Unified language modeling [75] is a combination of causal, non-causal, and masked language training objectives. Here in masked language modeling, the attention is not bidirectional but unidirectional, attending either left-to-right or right-to-left context.

L. Model Adaptation

This section discusses various model adaptation techniques, where a model is pre-trained on large data and then adapted for downstream tasks. An example of different training stages and inference in LLMs is shown in Figure 6.

1. Transfer Learning: Fine-tuning a pre-trained model with data for the downstream task is known as transfer learning. In this type of model adaptation, the model is initialized with pre-trained weights and updated according to the new data. Some of the LLMs employing this technique are [11], [12], [15], [20].

2. Parameter Efficient Learning: The parameter efficient learning fine-tunes a few parameters either by adding new parameters to the model or the existing ones.

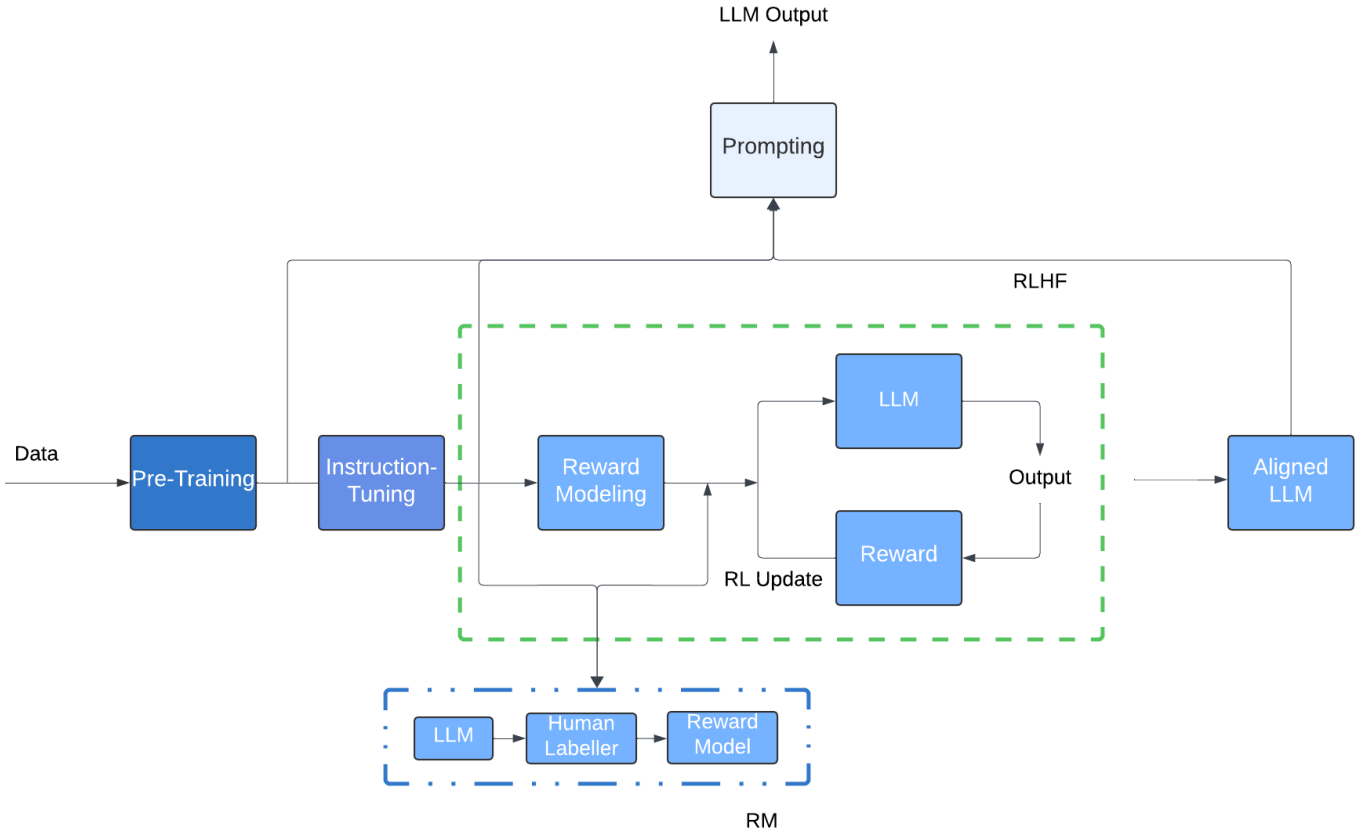

Fig. 6: A basic flow diagram depicting various stages of LLMs from pre-training to prompting/utilization. Prompting LLMs to generate responses is possible at different training stages like pre-training, instruction-tuning, or alignment tuning.

Prompt Tuning: [30], [76] adds trainable prompt token embeddings as prefixes or free-style to the input token embeddings. During fine-tuning only these embeddings parameters are trained for the downstream task while keeping the rest of the weights frozen.

Prefix Tuning: [31] adds task-specific trainable prefix vectors to the transformer layers, where only prefix parameters are fine-tuned, and the rest of the model stays frozen. The input sequence tokens can attend prefixes acting as virtual tokens.

Adapter Tuning: module is an encoder-decoder architecture that is placed either sequential or parallel to the attention and feed-forward layers in the transformer block [77], [28], [29]. Only these layers are fine-tuned, and the rest of the model is kept frozen.

3. Instruction Finetuning: Instruction tuning is an approach to fine-tuning pre-trained models on instruction formatted data. Instructions generally comprise multiple tasks in plain natural language, guiding the model to respond according to the prompt and the input. The training data consists of an instruction and an input-output pair. More details on formatting instruction data and its various styles are available in [33].

4. Alignment Tuning: Alignment techniques play a crucial role in ensuring large language models (LLMs) operate according to human intentions and values. These models can generate text and make decisions, making it vital to control their behavior and outputs to avoid undesirable outcomes. Alignment techniques aim to bridge the gap between what humans expect from LLMs and their actual behavior. A model is defined to be an "aligned" model if the model fulfills three criteria of helpful, honest, and harmless or "HHH" [78].
To align a model with human values, researchers widely employ reinforcement learning with human feedback (RLHF) [79]. In RLHF, a fine-tuned model on demonstrations is further trained with reward modeling (RM) and reinforcement learning (RL), shown in Figure 6. Below we briefly discuss RM and RL pipelines in RLHF.

4.1 Reward modeling: Reward modeling trains a model to rank generated responses according to human preferences using a classification objective. To train the classifier humans annotate the responses based on HHH criteria.

4.2 Reinforcement Learning: In this stage, the reward model trained previously ranks LLM-generated responses into preferred vs. dispreferred. The output of the reward model is used to train the model with proximal policy optimization (PPO). This process repeats iteratively until convergence.

5. Prompting/Utilization: Prompting is a method to query trained LLMs for generating responses, as illustrated in Figure 6. LLMs can be prompted in various prompt setups, where they can be adapted to the instructions without fine-

tuning and in other cases with fine-tuning on data containing different prompt styles [25], [80], [81]. A good guide on prompt engineering is available at [82]. Below, we will discuss various widely used prompt setups.

In-context Learning: Multiple input-output demonstration pairs are shown to the model to generate the desired response. This adaptation style is also called few-shot learning. A discussion on formatting in-context learning (ICL) templates is available in [83], [33], [26], [25].

Chain-of-Thought: Chain-of-thought prompting (CoT) is a special case of prompting where demonstrations contain reasoning information aggregated with inputs and outputs so that the model generates outcomes with reasonings. Some examples in literature train LLMs with CoT reasoning, whereas other utilizes LLMs' CoT abilities without fine-tuning. More details on CoT prompts are available in [84], [85], [80].

Self-Consistency: Improves CoT reasoning performance by generating multiple responses and selecting the most frequent answer [86].

Tree-of-Thought: Explores multiple reasoning paths with possibilities to look ahead and backtrack for problem-solving [87].

III. Large Language Models

This section reviews LLMs, briefly describing their architectures, training objectives, pipelines, datasets, and fine-tuning details.

A. Pre-Trained LLMs

Here, we provide summaries of various well-known pre-trained LLMs with significant discoveries, changing the course of research and development in NLP. These LLMs have considerably improved the performance in NLU and NLG domains, and are widely fine-tuned for downstream tasks.

1. General Purpose:

1.1 T5 [11]: An encoder-decoder model employing a unified text-to-text training for all NLP problems, shown in Figure 7. T5 places layer normalization outside the residual path in a conventional transformer model [44]. It uses masked language modeling as a pre-training objective where spans (consecutive tokens) are replaced with a single mask instead of separate masks for each token. This type of masking speeds up the training as it produces shorter sequences. After pre-training, the model is fine-tuned using adapter layers [77] for downstream tasks.

1.2 GPT-3 [8]: The GPT-3 architecture is same as the GPT-2 [88] but with dense and sparse attention in transformer layers similar to the Sparse Transformer [45]. It shows that large models can train on larger batch sizes with a lower learning rate; in order to decide the batch size during training, GPT-3 uses the gradient noise scale as in [89]. Overall, GPT-3 increases model parameters to 175B showing that the performance of large language models improves with the scale and is competitive with the fine-tuned models.

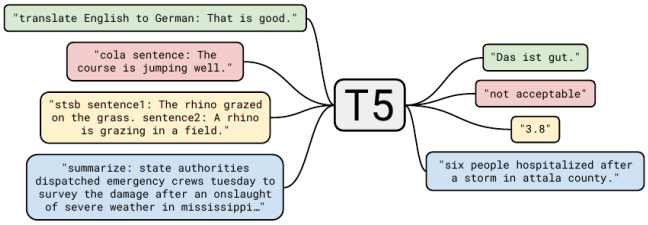

Fig. 7: Unified text-to-text training example, source image from [11].

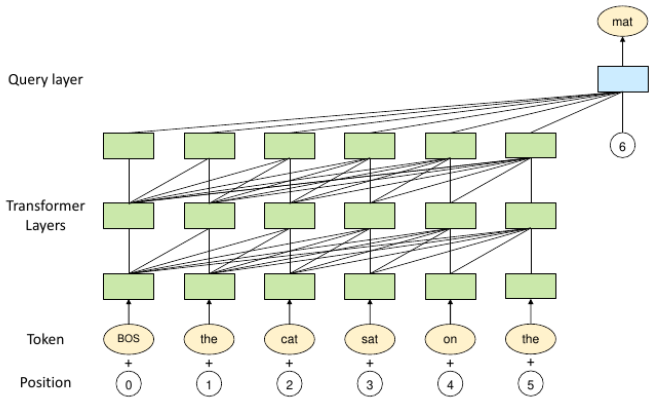

Fig. 8: The image is the article of [90], showing an example of PanGu-α architecture.

1.3 mT5 [12]: A multilingual T5 model [11] trained on the mC4 dataset with 101 languages. The dataset is extracted from the public common crawl scrape. The model uses a larger vocab size of 250,000 to cover multiple languages. To avoid over-fitting or under-fitting for a language, mT5 employs a data sampling procedure to select samples from all languages. The paper suggests using a small amount of pre-training datasets, including all languages when fine-tuning for a task using English language data. This allows the model to generate correct non-English outputs.

1.4 PanGu-α [90]: An autoregressive model that has a query layer at the end of standard transformer layers, example shown in Figure 8, with aim to predict next token. Its structure is similar to the transformer layer but with an additional embedding for the next position in the attention mechanism, given in Eq. 7.

$$a = p_n W_h^q W_h^k T H_L^T \tag{7}$$

1.5 CPM-2 [13]: Cost-efficient Pre-trained language Models (CPM-2) pre-trains bilingual (English and Chinese) 11B and 198B mixture-of-experts (MoE) models on the Wu-DaoCorpus [91] dataset. The tokenization process removes "_" white space tokens in the sentencepiece tokenizer. The models are trained with knowledge inheritance, starting with only the Chinese language in the first stage and then adding English and Chinese data. This trained model gets duplicated multiple times to initialize the 198B MoE model. Moreover, to use the model for downstream tasks, CPM-2 experimented with both complete fine-tuning and prompt fine-tuning as in [27] where only prompt-related parameters are updated by inserting

prompts at various positions, front, middle, and back. CPM-2 also proposes INFMOE, a memory-efficient framework with a strategy to dynamically offload parameters to the CPU for inference at a 100B scale. It overlaps data movement with inference computation for lower inference time.

1.6 ERNIE 3.0 [92]: ERNIE 3.0 takes inspiration from multi-task learning to build a modular architecture using Transformer-XL [93] as the backbone. The universal representation module is shared by all the tasks, which serve as the basic block for task-specific representation modules, which are all trained jointly for natural language understanding, natural language generation, and knowledge extraction. This LLM is primarily focused on the Chinese language, claims to train on the largest Chinese text corpora for LLM training, and achieved state-of-the-art in 54 Chinese NLP tasks.

1.7 Jurassic-1 [94]: A pair of auto-regressive language models, including a 7B-parameter J1-Large model and a 178B-parameter J1-Jumbo model. The training vocabulary of Jurassic-1 comprise word pieces, complete words, and multi-word expressions without any word boundaries, where possible out-of-vocabulary instances are interpreted as Unicode bytes. Compared to the GPT-3 counterparts, the Jurassic-1 models apply a more balanced depth-to-width self-attention architecture [95] and an improved tokenizer for a faster prediction based on broader resources, achieving a comparable performance in zero-shot learning tasks and a superior performance in few-shot learning tasks given the ability to feed more examples as a prompt.

1.8 HyperCLOVA [96]: A Korean language model with GPT-3 architecture.

1.9 Yuan 1.0 [97]: Trained on a Chinese corpus with 5TB of high-quality text collected from the Internet. A Massive Data Filtering System (MDFS) built on Spark is developed to process the raw data via coarse and fine filtering techniques. To speed up the training of Yuan 1.0 with the aim of saving energy expenses and carbon emissions, various factors that improve the performance of distributed training are incorporated in architecture and training like increasing the number of hidden size improves pipeline and tensor parallelism performance, larger micro batches improve pipeline parallelism performance, and higher global batch size improve data parallelism performance. In practice, the Yuan 1.0 model performs well on text classification, Winograd Schema, natural language inference, and reading comprehension tasks.

1.10 Gopher [98]: The Gopher family of models ranges from 44M to 280B parameters in size to study the effect of *scale* on the LLMs performance. The 280B model beats GPT-3 [8], Jurrasic-1 [94], MT-NLG [21], and others on 81% of the evaluated tasks.

1.11 ERNIE 3.0 TITAN [99]: ERNIE 3.0 Titan extends ERNIE 3.0 by training a larger model with 26x the number of parameters of the latter. This bigger model outperformed other state-of-the-art models in 68 NLP tasks. LLMs produce text with incorrect facts. In order to have control of the generated text with factual consistency, ERNIE 3.0 Titan adds another task, *Credible and Controllable Generations*, to its multi-task learning setup. It introduces additional self-supervised adversarial and controllable language modeling losses to the pre-training step, which enables ERNIE 3.0 Titan to beat other LLMs in their manually selected Factual QA task set evaluations.

1.12 GPT-NeoX-20B [100]: An auto-regressive model that largely follows GPT-3 with a few deviations in architecture design, trained on the Pile dataset without any data deduplication. GPT-NeoX has parallel attention and feed-forward layers in a transformer block, given in Eq. 8, that increases throughput by 15%. It uses rotary positional embedding [48], applying it to only 25% of embedding vector dimension as in [101]. This reduces the computation without performance degradation. Opposite to GPT-3, which uses dense and sparse layers, GPT-NeoX-20B uses only dense layers. The hyperparameter tuning at this scale is difficult; therefore, the model chooses hyperparameters from the method [8] and interpolates values between 13B and 175B models for the 20B model. The model training is distributed among GPUs using both tensor and pipeline parallelism.

$$x + Attn(LN_1(x)) + FF(LN_2(x)) \tag{8}$$

1.13 OPT [10]: It is a clone of GPT-3, developed with the intention to open-source a model that replicates GPT-3 performance. Training of OPT employs dynamic loss scaling [102] and restarts from an earlier checkpoint with a lower learning rate whenever loss divergence is observed. Overall, the performance of OPT-175B models is comparable to the GPT3-175B model.

1.14 BLOOM [9]: A causal decoder model trained on ROOTS corpus with the aim of open-sourcing an LLM. The architecture of BLOOM is shown in Figure 9, with differences like ALiBi positional embedding, an additional normalization layer after the embedding layer as suggested by the bitsandbytes[1] library. These changes stabilize training with improved downstream performance.

1.15 GLaM [103]: Generalist Language Model (GLaM) represents a family of language models using a sparsely activated decoder-only mixture-of-experts (MoE) structure [104], [105]. To gain more model capacity while reducing computation, the experts are sparsely activated where only the best two experts are used to process each input token. The largest GLaM model, GLaM (64B/64E), is about 7$\times$ larger than GPT-3 [8], while only a part of the parameters is activated per input token. The largest GLaM (64B/64E) model achieves better overall results as compared to GPT-3 while consuming only one-third of GPT-3's training energy.

1.16 MT-NLG [21]: A 530B causal decoder based on GPT-2 architecture that is roughly 3$\times$ GPT-3 model parameters. MT-NLG is trained on filtered high-quality data collected from various public datasets and blends various types of datasets in a single batch, which beats GPT-3 on a number of evaluations.

1.17 Chinchilla [106]: A causal decoder trained on the same dataset as the Gopher [98] but with a little different data sampling distribution (sampled from MassiveText). The model architecture is similar to the one used for Gopher, with the exception of AdamW optimizer instead of Adam.

[1] https://github.com/TimDettmers/bitsandbytes

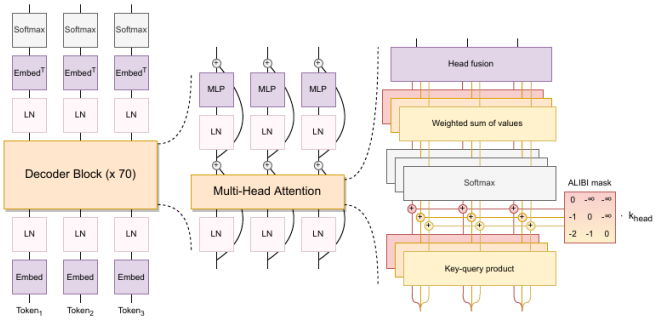

Fig. 9: The BLOOM architecture example sourced from [9].

Chinchilla identifies the relationship that model size should be doubled for every doubling of training tokens. Over 400 language models ranging from 70 million to over 16 billion parameters on 5 to 500 billion tokens are trained to get the estimates for compute-optimal training under a given budget. The authors train a 70B model with the same compute budget as Gopher (280B) but with 4 times more data. It outperforms Gopher [98], GPT-3 [8], and others on various downstream tasks, after fine-tuning.

1.18 AlexaTM [107]: An encoder-decoder model, where encoder weights and decoder embeddings are initialized with a pre-trained encoder to speedup training. The encoder stays frozen for initial 100k steps and later unfreezed for end-to-end training. The model is trained on a combination of denoising and causal language modeling (CLM) objectives, concatenating $[CLM]$ token at the beginning for mode switiching. During training, the CLM task is applied for 20% of the time, which improves the in-context learning performance.

1.19 PaLM [14]: A causal decoder with parallel attention and feed-forward layers similar to Eq. 8, speeding up training 15 times faster. Additional changes to the conventional transformer model include SwiGLU activation, RoPE embeddings, multi-query attention that saves computation cost during decoding, and shared input-output embeddings. During training, loss spiking was observed, and to fix it, model training was restarted from a 100 steps earlier checkpoint by skipping 200-500 batches around the spike. Moreover, the model was found to memorize around 2.4% of the training data at the 540B model scale, whereas this number was lower for smaller models.

PaLM-2 *[108]:* A smaller multi-lingual variant of PaLM, trained for larger iterations on a better quality dataset. The PaLM-2 shows significant improvements over PaLM, while reducing training and inference costs due to its smaller size. To lessen toxicity and memorization, it appends special tokens with a fraction of pre-training data, which shows reduction in generating harmful responses.

1.20 U-PaLM [20]: This method trains PaLM for 0.1% additional compute with UL2 (also named as UL2Restore) objective [15] using the same dataset and outperforms baseline significantly on various NLP tasks, including zero-shot, few-shot, commonsense reasoning, CoT, etc. Training with UL2R involves converting a causal decoder PaLM to a non-causal decoder PaLM and employing 50% sequential denoising, 25% regular denoising, and 25% extreme denoising loss functions.

1.21 UL2 [15]: An encoder-decoder architecture trained using a mixture of denoisers (MoD) objectives. Denoisers include 1) R-Denoiser: a regular span masking, 2) S-Denoiser: which corrupts consecutive tokens of a large sequence and 3) X-Denoiser: which corrupts a large number of tokens randomly. During pre-training, UL2 includes a denoiser token from R, S, X to represent a denoising setup. It helps improve fine-tuning performance for downstream tasks that bind the task to one of the upstream training modes. This MoD style of training outperforms the T5 model on many benchmarks.

1.22 GLM-130B [109]: GLM-130B is a bilingual (English and Chinese) model trained using an auto-regressive mask infilling pre-training objective similar to the GLM [110]. This training style makes the model bidirectional as compared to GPT-3, which is unidirectional. Opposite to the GLM, the training of GLM-130B includes a small amount of multi-task instruction pre-training data (5% of the total data) along with the self-supervised mask infilling. To stabilize the training, it applies embedding layer gradient shrink.

1.23 LLaMA [111], [112]: A set of decoder-only language models varying from 7B to 70B parameters. LLaMA models series is the most famous among the community for parameter-efficient and instruction tuning.

LLaMA-1 *[111]:* Implements efficient causal attention [113] by not storing and computing masked attention weights and key/query scores. Another optimization is reducing number of activations recomputed in backward pass, as in [114].

LLaMA-2 *[112]:* This work is more focused towards fine-tuning a safer and better LLaMA-2-Chat model for dialogue generation. The pre-trained model has 40% more training data with a larger context length and grouped-query attention.

1.24 PanGu-Σ [115]: An autoregressive model with parameters copied from PanGu-α and extended to a trillion scale with Random Routed Experts (RRE), the architectural diagram is shown in Figure 10. RRE is similar to the MoE architecture, with distinctions at the second level, where tokens are randomly routed to experts in a domain instead of using a learnable gating method. The model has bottom layers densely activated and shared across all domains, whereas top layers are sparsely activated according to the domain. This training style allows extracting task-specific models and reduces catastrophic forgetting effects in case of continual learning.

2. Coding:

2.1 CodeGen [116]: CodeGen has similar architecture to the PaLM [14], i.e., parallel attention, MLP layers, and RoPE embeddings. The model is trained on both natural language and programming language data sequentially (trained on the first dataset, then the second and so on) on the following datasets 1) PILE, 2) BIGQUERY and 3) BIGPYTHON. CodeGen proposed a multi-step approach to synthesizing code. The purpose is to simplify the generation of long sequences where the previous prompt and generated code are given as input with the next prompt to generate the next code sequence. CodeGen opensource a Multi-Turn Programming Benchmark (MTPB) to evaluate multi-step program synthesis.

2.2 Codex [117]: This LLM is trained on a subset of public Python Github repositories to generate code from

docstrings. Computer programming is an iterative process where the programs are often debugged and updated before fulfilling the requirements. Similarly to this, Codex generates 100 versions of a program by repetitive sampling for a given description, which produces a working solution for 77.5% of the problems passing unit tests. Its powerful version powers Github Copilot[2].

2.3 AlphaCode [118]: A set of large language models, ranging from 300M to 41B parameters, designed for competition-level code generation tasks. It uses the multi-query attention [119] to reduce memory and cache costs. Since competitive programming problems highly require deep reasoning and an understanding of complex natural language algorithms, the AlphaCode models are pre-trained on filtered GitHub code in popular languages and then fine-tuned on a new competitive programming dataset named CodeContests. The CodeContests dataset mainly contains problems, solutions, and test cases collected from the Codeforces platform[3]. The pre-training employs standard language modeling objectives, while GOLD [120] with tempering [121] serves as the training objective for the fine-tuning on CodeContests data. To evaluate the performance of AlphaCode, simulated programming competitions are hosted on the Codeforces platform: overall, AlphaCode ranks at the top 54.3% among over 5000 competitors, where its Codeforces rating is within the top 28% of recently participated users.

2.4 CodeT5+ [122]: CodeT5+ is based on CodeT5 [123], with shallow encoder and deep decoder, trained in multiple stages initially unimodal data (code) and later bimodal data (text-code pairs). Each training stage has different training objectives and activates different model blocks encoder, decoder, or both according to the task. The unimodal pre-training includes span denoising and CLM objectives, whereas bimodal pre-training objectives contain contrastive learning, matching, and CLM for text-code pairs. CodeT5+ adds special tokens with the text to enable task modes, for example, $[CLS]$ for contrastive loss, $[Match]$ for text-code matching, etc.

2.5 StarCoder [124]: A decoder-only model with SantaCoder architecture, employing Flash attention to scale up the context length to 8k. The StarCoder trains an encoder to filter names, emails, and other personal data from the training data. Its fine-tuned variant outperforms PaLM, LLaMA, and LAMDA on HumanEval and MBPP benchmarks.

3. Scientific Knowledge:

3.1 Galactica [125]: A large curated corpus of human scientific knowledge with 48 million papers, textbooks, lecture notes, millions of compounds and proteins, scientific websites, encyclopedias, and more are trained using metaseq library3, which is built on PyTorch and fairscale [126]. The model wraps reasoning datasets with $< work >$ token to provide step-by-step reasoning context to the model, which has been shown to improve the performance on reasoning tasks.

4. Dialog:

[2]https://github.com/features/copilot
[3]https://codeforces.com/

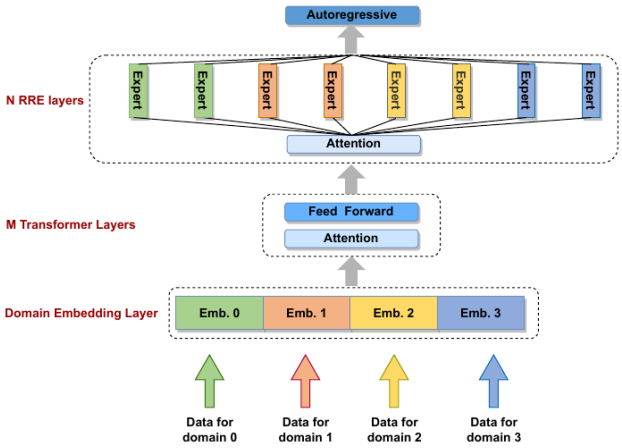

Fig. 10: This example illustrates the PanGu-$\sum$ architecture, as depicted in the image sourced from [115].

4.1 LaMDA [127]: A decoder-only model pre-trained on public dialog data, public dialog utterances, and public web documents, where more than 90% of the pre-training data is in English. LaMDA is trained with the objective of producing responses that exhibit high levels of quality, safety, and groundedness. To achieve this, discriminative and generative fine-tuning techniques are incorporated to enhance the model's safety and quality aspects. As a result, the LaMDA models can be utilized as a general language model performing various tasks.

5. Finance:

5.1 BloombergGPT [128]: A non-causal decoder model trained using both financial ("FINPILE" from the Bloomberg archive) and general-purpose datasets. The model's architecture is similar to the BLOOM [9] and OPT [10]. It allocates 50B parameters to different blocks of the model using the approach [129]. For effective training, BloombergGPT packs documents together with $< |endoftext| >$ to use maximum sequence length, use warmup batch size starting from 1024 to 2048, and manually reduces the learning rate multiple times during the training.

5.2 Xuan Yuan 2.0 [130]: A Chinese financial chat model with BLOOM's [9] architecture trained on a combination of general purpose, financial, general purpose instructions, and financial institutions datasets. Xuan Yuan 2.0 combined the pre-training and fine-tuning stages to avoid catastrophic forgetting.

B. Fine-Tuned LLMs

Pre-trained LLMs have excellent generalization abilities to unseen tasks. However, because they are generally trained with the objective of next token prediction, LLMs have limited capacity to follow user intent and are prone to generate unethical, toxic or inaccurate responses [137]. For their effective utilization, LLMs are fine-tuned to follow instructions [25], [22], [24] and generate safe responses [137], which also results in increasing zero-shot, few-shot, and cross-task generalization [24], [25], [26], with minimal compute increment, e.g., 0.2% of the total pre-training for PaLM 540B [25].

TABLE I: Noteworthy findings and insights from *pre-trained* Large Language Model.

Models	Findings & Insights
T5	• Encoder and decoder with shared parameters perform equivalently when parameters are not shared • Fine-tuning model layers (adapter layers) work better than the conventional way of training on only classification layers
GPT-3	• Few-shot performance of LLMs is better than the zero-shot, suggesting that LLMs are meta-learners
mT5	• Large multi-lingual models perform equivalently to single language models on downstream tasks. However, smaller multi-lingual models perform worse
PanGu-α	• LLMs are good at a few shot capabilities
CPM-2	• Prompt fine-tuning requires updating very few parameters while achieving performance comparable to full model fine-tuning • Prompt fine-tuning takes more time to converge as compared to full model fine-tuning • Inserting prompt tokens in-between sentences can allow the model to understand relations between sentences and long sequences • In an analysis, CPM-2 finds that prompts work as a provider (additional context) and aggregator (aggregate information with the input text) for the model
Codex	• This LLM focuses on code evaluations and introduces a novel way of selecting the best code samples. • The results indicate it is possible to accurately select code samples using heuristic ranking in lieu of a detailed evaluation of each sample, which may not be feasible or feasible in some situations.
ERNIE 3.0	• ERNIE 3.0 shows that a modular LLM architecture with a universal representation module and task-specific representation module helps in finetuning phase. • Optimizing the parameters of a task-specific representation network during the fine-tuning phase is an efficient way to take advantage of the powerful pretrained model.
Jurassic-1	• The performance of an LLM is highly related to the network size. • To improve runtime performance, more operations can be performed in parallel (width) rather than sequentially (depth). • To efficiently represent and fit more text in the same context length, the model uses a larger vocabulary to train a SentencePiece tokenizer without restricting it to word boundaries. This tokenizer improvement can further benefit few-shot learning tasks.
HyperCLOVA	• By employing prompt-based tuning, the performances of models can be improved, often surpassing those of state-of-the-art models when the backward gradients of inputs are accessible.
Yuan 1.0	• The model architecture that excels in pre-training and fine-tuning cases may exhibit contrasting behavior in zero-shot and few-shot learning.
Gopher	• Relative encodings enable models to be evaluated for longer sequences than those on which it was trained.
ERNIE 3.0 Titan	• This LLM builds on top of ERNIE 3.0 and add a self-supervised adversarial loss to distinguish whether a text is generated or the original one. • This distinction ability between real and generate text improves the LLM's performance as compared to ERNIE 3.0.
GPT-NeoX-20B	• Parallel attention + FF layers speed-up training 15% with the same performance as with cascaded layers • Initializing feed-forward output layers before residuals with scheme in [131] avoids activations from growing with increasing depth and width • Training on Pile outperforms GPT-3 on five-shot
OPT	• Restart training from an earlier checkpoint with a lower learning rate if loss diverges • Model is prone to generate repetitive text and stuck in a loop
BLOOM	• None
Galactica	• Galactica's performance has continued to improve across validation set, in-domain, and out-of-domain benchmarks, even with multiple repetitions of the corpus, which is superior to existing research on LLMs. • A working memory token approach can achieve strong performance over existing methods on mathematical MMLU and MATH benchmarks. It sets a new state-of-the-art on several downstream tasks such as PubMedQA (77.6%) and MedMCQA dev (52.9%).
GLaM	• The feed-forward component of each Transformer layer can be replaced with a mixture-of-experts (MoE) module consisting of a set of independent feed-forward networks (*i.e.*, the 'experts'). By sparsely activating these experts, the model capacity can be maintained while much computation is saved. • By leveraging sparsity, we can make significant strides toward developing high-quality NLP models while simultaneously reducing energy consumption. Consequently, MoE emerges as a robust candidate for future scaling endeavors. • The model trained on filtered data shows consistently better performances on both NLG and NLU tasks, where the effect of filtering is more significant on the former tasks. • Filtered pretraining corpora plays a crucial role in the generation capability of LLMs, especially for the downstream tasks. • The scaling of GLaM MoE models can be achieved by increasing the size or number of experts in the MoE layer. Given a fixed budget of computation, more experts contribute to better predictions.
LaMDA	• The model can be fine-tuned to learn to call different external information resources and tools.
MT-NLG	• None.
AlphaCode	• For higher effectiveness and efficiency, a transformer model can be asymmetrically constructed with a shallower encoder and a deeper decoder. • To achieve better performances, it is necessary to employ strategies such as massively scaling up sampling, followed by the filtering and clustering of samples into a compact set. • The utilization of novel sampling-efficient transformer architectures designed to facilitate large-scale sampling is crucial. • Simplifying problem descriptions can effectively improve the model's performance.

Table Continued on Next Page

Models	Findings & Insights
Chinchilla	• The experiments that culminated in the development of Chinchilla determined that for optimal computation during training, the model size and the number of training tokens should be scaled proportionately: for each doubling of the model size, the number of training tokens should be doubled as well.
PaLM	• English-centric models produce better translations when translating to English as compared to non-English • Generalized models can have equivalent performance for language translation to specialized small models • Larger models have a higher percentage of training data memorization • Performance has not yet saturated even at 540B scale, which means larger models are likely to perform better
AlexaTM	• Compared to commonly used Decoder-only Transformer models, seq2seq architecture is more suitable for training generative LLMs given stronger bidirectional attention to the context. • An extra Causal Language Modeling (CLM) task can be added to benefit the model with a more efficient in-context learning, especially for few-shot learning tasks. • The key to training powerful seq2seq-based LLMs lies in mixed pre-training, rather than additional multitask training. • Placing layernorms at the beginning of each transformer layer can improve the training stability of large models.
U-PaLM	• Training with a mixture of denoisers outperforms PaLM when trained further for a few more FLOPs • Training with a mixture of denoisers improves the infilling ability and open-ended text generation diversity
UL2	• Mode switching training enables better performance on downstream tasks • CoT prompting outperforms standard prompting for UL2
GLM-130B	• Pre-training data with a small proportion of multi-task instruction data improves the overall model performance
CodeGen	• Multi-step prompting for code synthesis leads to a better user intent understanding and code generation
LLaMA	• LLaMA is open-source and can be fine-tuned or continually pre-trained to develop new models or instruction-based tools. • A few optimizations are proposed to improve the training efficiency of LLaMA, such as efficient implementation of multi-head self-attention and a reduced amount of activations during back-propagation. • Training exclusively on public data can also achieve state-of-the-art performance. • A constant performance improvement is gained when scaling the model. • Smaller models can also realize good performances using more training data and time.
PanGu-Σ	• Sparse models provide the benefits of large models at a lower computation cost • Randomly Routed Experts reduces catastrophic forgetting effects which in turn is essential for continual learning • Randomly Routed Experts allow extracting a domain-specific sub-model in deployment which is cost-efficient while maintaining a performance similar to the original
BloombergGPT	• Pre-training with general-purpose and task-specific data improves task performance without hurting other model capabilities
XuanYuan 2.0	• Combining pre-training and fine-tuning stages in single training avoids catastrophic forgetting
CodeT5+	• Causal LM is crucial for a model's generation capability in encoder-decoder architectures • Multiple training objectives like span corruption, Causal LM, matching, etc complement each other for better performance
StarCoder	• HHH prompt by Anthropic allows the model to follow instructions without fine-tuning
LLaMA-2	• Model trained on unfiltered data is more toxic but may perform better on downstream tasks after fine-tuning • Model trained on unfiltered data requires fewer samples for safety alignment
PaLM-2	• Data quality is important to train better models • Model and data size should be scaled with 1:1 proportions • Smaller models trained for larger iterations outperform larger models

We review various fine-tuned LLMs and strategies for effective fine-tuning in this section.

1. Instruction-Tuning with Manually Created Datasets: Numerous hand-crafted instruction-tuning datasets with different design choices are proposed in the literature to instruction-tune LLMs. The performance of fine-tuned LLMs depends on multiple factors, such as dataset, instruction diversity, prompting templates, model size, and training objectives. Keeping this in view, diverse fine-tuned models have emerged in the literature using manually created datasets. The models T0 [22] and mT0 (multi-lingual) [134] employ templates to convert existing datasets into prompt datasets. They have shown improvements in generalization to zero-shot and held-out tasks. Tk-Instruct [26] fine-tuned the T5 model with in-context instructions to study generalization on unseen tasks when given in-context instructions during test time. The model outperformed Instruct-GPT, despite being smaller in size, i.e., 11B parameters as compared to 175B of GPT-3.

Increasing Tasks and Prompt Setups: Zero-shot and few-shot performance improves significantly by expanding task collection and prompt styles. OPT-IML [24] and Flan [25] curated larger 2k and 1.8k task datasets, respectively. While increasing task size alone is not enough, OPT-IML and Flan add more prompting setups in their datasets, zero-shot, few-shot, and CoT. In continuation, CoT Collection [80] fine-tunes Flan-T5 further on 1.88M CoT samples. Another method [81] uses symbolic tasks with tasks in T0, Flan, etc.

2. Instruction-Tuning with LLMs Generated Datasets: Generating an instruction-tuning dataset requires carefully writing instructions and input-output pairs, which are often written by humans, smaller in size, and less diverse. To overcome this, self-instruct [138] proposed an approach to prompt available LLMs to generate instruction-tuning datasets. Self-instruct outperformed models trained on manually created dataset SUPER-NATURALINSTRUCTIONS (a dataset with 1600+ tasks) [26] by 33%. It starts with a seed of 175 tasks, 1 instruction, and 1 sample per task and iteratively generates

TABLE II: Key insights and findings from the study of *instruction-tuned* Large Language Models.

Models	Findings & Insights
T0	• Multi-task prompting enables zero-shot generalization and outperforms baselines • Even a single prompt per dataset task is enough to improve performance
WebGPT	• The answer quality of LLMs can be further improved with human feedback. • To aid the model in effectively filtering and utilizing relevant information, human labelers play a crucial role in answering questions regarding the usefulness of the retrieved documents. • Interacting a fine-tuned language model with a text-based web-browsing environment can improve end-to-end retrieval and synthesis via imitation learning and reinforcement learning. • Generating answers with references can make labelers easily judge the factual accuracy of answers.
Tk-INSTRUCT	• Instruction tuning leads to a stronger generalization of unseen tasks • More tasks improve generalization whereas only increasing task instances does not help • Supervised trained models are better than generalized models • Models pre-trained with instructions and examples perform well for different types of inputs
mT0 and BLOOMZ	• Instruction tuning enables zero-shot generalization to the tasks never seen before • Multi-lingual training leads to even better zero-shot generalization for both English and non-English • Training on machine-translated prompts improves performance for held-out tasks with non-English prompts • English only fine-tuning on multilingual pre-trained language model is enough to generalize to other pre-trained language tasks
OPT-IML	• Task size sampling to create a batch with most of the task examples is important for better performance • Only example proportional sampling is not enough, training datasets/benchmarks should also be proportional for better generalization/performance • Fully held-out and partially supervised tasks performance improves by scaling tasks or categories whereas fully supervised tasks have no effect • Including small amounts i.e. 5% of pretraining data during fine-tuning is effective • Only 1% reasoning data improves the performance, adding more deteriorates performance • Adding dialogue data makes the performance worse
Flan	• Finetuning with CoT improves performance on held-out tasks • Fine-tuning along with CoT data improves reasoning abilities • CoT tuning improves zero-shot reasoning • Performance improves with more tasks • Instruction fine-tuning improves usability which otherwise is challenging for pre-trained models • Improving the model's performance with instruction tuning is compute-efficient • Multitask prompting enables zero-shot generalization abilities in LLM
Sparrow	• The judgments of labelers and the alignments with defined rules can help the model generate better responses. • Good dialogue goals can be broken down into detailed natural language rules for the agent and the raters. • The combination of reinforcement learning (RL) with reranking yields optimal performance in terms of preference win rates and resilience against adversarial probing.
WizardCoder	• Fine-tuning with re-written instruction-tuning data into a complex set improves the performance significantly
LLaMA-2-Chat	• Model learns to write safe responses with fine-tuning on safe demonstrations, while additional RLHF step further improves model safety and make it less prone to jailbreak attacks

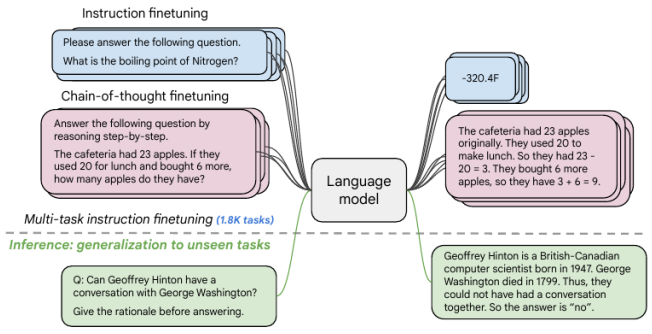

Fig. 11: An example image shows an instance of the Flan training paradigm, taken from [25].

new instructions (52k) and instances (82k input-output pairs) using GPT-3 [8]. Contrary to this, Dynosaur [139] uses the meta-data of datasets on Huggingface to prompt LLMs to generate multiple task instruction-tuning datasets.

LLaMA Tuned Various models in literature instruction-tune LLaMA [140] with GPT-3 [8] or GPT-4 [141] generated datasets. Among these, Alpaca, Vicuna, and LLaMA-GPT-4 are a few general-purpose fine-tuned models, where Alpaca is trained on 52k samples from text-davinci-003, Vicuna on 70k samples from ShareGPT.com, and LLaMA-GPT-4 by re-creating Alpaca instructions from GPT-4. Goat [142] fine-tunes LLaMA for arithmetic tasks (1 million samples) by generating data from ChatGPT and outperforms GPT-4, PaLM, BLOOM, OPT, etc, attributing its success to the LLaMA's consistent tokenization of numbers. HuaTuo [143] is a medical knowledge model, fine-tuned with a generated QA dataset of 8k instructions.

Complex Instructions Evol-Instruct [144], [136] prompts LLMs to convert given instructions into a more complex set. The instructions are iteratively evolved with re-writing instructions in complex wording and creating new instructions. With this style of automated instruction generation, WizardLM [144] (fine-tuned LLaMA on 250k instructions), outperforms Vicuna and Alpaca, and WizardCoder [136] (fine-tuned StarCoder) beats Claude-Plus,

TABLE III: Summary of pre-trained LLMs. Only the LLMs discussed individually in the previous sections are summarized. "Data/Tokens" is the model's pre-training data which is either the number of tokens or data size. "Data Cleaning" indicates whether the data cleaning is performed or not. This includes heuristics (Heur), deduplication (Dedup), quality filtering (QF), and privacy filtering (PF), "Cost" is the calculated training cost obtained by multiplying the GPUs/TPUs hourly rate with the number of GPUs and the training time. The actual cost may vary due to many reasons such as using in-house GPUs or getting a discounted rate, re-training, number of employees working on the problem, etc. "Training Parallelism" indicates distributed training using data parallelism (D), tensor parallelism (T), pipeline parallelism (P), model parallelism (M), optimizer parallelism (OP), and rematerialization (R), where for "Library" column, "DS" is a short form for Deep Speed. In column "Commercial Use", we assumed a model is for non-commercial purposes if its license is not available.

Models	Publication Venue	License Type	Model Creators	Purpose	No. of Params	Commercial Use	Steps Trained	Data/ Tokens	Data Cleaning	No. of Processing Units	Processing Unit Type	Training Time	Calculated Train. Cost	Training Parallelism	Library
T5 [11]	JMLR'20	Apache-2.0	Google	General	11B	✓	1M	1T	Heur+Dedup	1024	TPU v3	-	-	D+M	Mesh TensorFlow
GPT-3 [8]	NeurIPS'20	-	OpenAI	General	175B	×	-	300B	Dedup+QF	-	V100	-	-	M	-
mT5 [12]	NAACL'21	Apache-2.0	Google	General	13B	✓	1M	1T	-	-	-	-	-	-	-
PanGu-α [90]	arXiv'21	Apache-2.0	Huawei	General	200B	✓	260k	1.1TB	Heur+Dedup	2048	Ascend 910	-	-	D+OP+P+O+R	MindSpore
CPM-2 [13]	AI Open'21	MIT	Tsinghua	General	198B	✓	1M	2.6TB	Dedup	-	-	-	-	D+M	JAXFormer
Codex [117]	arXiv'21	-	OpenAI	Coding	12B	×	-	100B	Heur	-	-	-	-	-	-
ERNIE 3.0 [92]	arXiv'21	-	Baidu	General	10B	×	120k*	375B	Heur+Dedup	384	V100	-	-	M*	PaddlePaddle
Jurassic-1 [94]	White-Paper'21	Apache-2.0	AI21	General	178B	✓	-	300B	-	800	GPU	-	-	D+M+P	Megatron+DS
HyperCLOVA [96]	EMNLP'21	-	Naver	General	82B	×	-	300B	Clf+Dedup+PF	1024	A100	321h	1.32 Mil	M	Megatron
Yuan 1.0 [97]	arXiv'21	Apache-2.0	-	General	245B	✓	26k*	180B	Heur+Clf+Dedup	2128	GPU	-	-	D+T+P	-
Gopher [98]	arXiv'21	-	Google	General	280B	×	-	300B	QF+Dedup	4096	TPU v3	920h	13.19 Mil	D+M	JAX+Haiku
ERNIE 3.0 Titan [99]	arXiv'21	-	Baidu	General	260B	×	-	300B	Heur+Dedup	-	Ascend 910	-	-	D+M+P+D*	PaddlePaddle
GPT-NeoX-20B [132]	BigScience'22	Apache-2.0	EleutherAI	General	20B	✓	150k	825GB	None	96	40G A100	-	-	M	Megatron+DS+PyTorch
OPT [10]	arXiv'22	MIT	Meta	General	175B	✓	150k	180B	Dedup	992	80G A100	-	-	D+T	Megatron
BLOOM [9]	arXiv'22	RAIL-1.0	BigScience	General	176B	✓	-	366B	Dedup+PR	384	80G A100	2520h	3.87 Mil	D+T+P	Megatron+DS
Galactica [125]	arXiv'22	Apache-2.0	Meta	Science	120B	×	225k	106B	Dedup	128	80GB A100	-	-	-	Metaseq
GLaM [103]	ICML'22	-	Google	General	1.2T	×	600k*	600B	Clf	1024	TPU v4	-	-	M	GSPMD
LaMDA [127]	arXiv'22	-	Google	Dialog	137B	×	3M	2.81T	Filtered	1024	TPU v3	1384h	4.96 Mil	D+M	Lingvo
MT-NLG [21]	arXiv'22	Apache-v2.0	MS.+Nvidia	General	530B	×	-	270B	-	4480	80G A100	-	-	D+T+P	Megatron+DS
AlphaCode [118]	Science'22	Apache-v2.0	Google	Coding	41B	✓	205k	967B	Heur+Dedup	-	TPU v4	-	-	M	JAX+Haiku
Chinchilla [106]	arXiv'22	-	Google	General	70B	×	-	1.4T	QF+Dedup	-	TPUv4	-	-	-	JAX+Haiku
PaLM [14]	arXiv'22	-	Google	General	540B	×	255k	780B	Heur	6144	TPU v4	-	-	D+M	JAX+T5X
AlexaTM [107]	arXiv'22	Apache v2.0	Amazon	General	20B	×	500k	1.1T	Filtered	128	A100	2880h	1.47 Mil	M	DS
U-PaLM [20]	arXiv'22	-	Google	General	540B	×	20k	-	-	512	TPU v4	120h	0.25 Mil	-	-
UL2 [15]	ICLR'23	Apache-2.0	Google	General	20B	✓	2M	1T	-	512	TPU v4	-	-	M	JAX+T5X
GLM [109]	ICLR'23	Apache-2.0	Multiple	General	130B	×	-	400B	-	768	40G A100	1440h	3.37 Mil	M	-
CodeGen [116]	ICLR'23	Apache-2.0	Salesforce	Coding	16B	✓	650k	577B	Heur+Dedup	-	TPU v4	-	-	D+M	JAXFormer
LLaMA [111]	arXiv'23	-	Meta	General	65B	×	350k	1.4T	Clf+Heur+Dedup	2048	80G A100	504h	4.12 Mil	D+M	xFormers
PanGuΣ [115]	arXiv'23	-	Huawei	General	1.085T	×	-	329B	-	512	Ascend 910	2400h	-	D+OP+P+O+R	MindSpore
BloombergGPT [128]	arXiv23	-	Bloomberg	Finance	50B	×	139k	569B	Dedup	512	40G A100	1272h	1.97 Mil	M	PyTorch
Xuan Yuan 2.0 [130]	arXiv23	RAIL-1.0	Du Xiaoman	Finance	176B	✓	-	366B	Filtered	80GB	A100	-	-	P	DS
CodeT5+ [122]	arXiv'23	BSD-3	Salesforce	Coding	16B	✓	110k	51.5B	Dedup	16	40G A100	-	-	-	DS
StarCoder [124]	arXiv'23	OpenRAIL-M	BigCode	Coding	15.5B	✓	250k	1T	Dedup+QF+PF	512	80G A100	624h	1.28 Mil	D+T+P	Megatron-LM
LLaMA-2 [112]	arXiv'23	LLaMA-2.0	Meta	General	70B	✓	500k	2T	Minimal Filtering	-	80G A100	1.7Mh	-	-	-
PaLM-2 [108]	arXiv'23	-	Google	General	-	×	-	-	Ddedup+PF+QF	-	-	-	-	-	-

TABLE IV: Summary of instruction tuned LLMs. All abbreviations are the same as Table III. Entries in "Data/Tokens" starting with "S-" represents the number of training samples.

Models	Publication Venue	License Type	Model Creators	Purpose	No. of Params	Commercial Use	Pre-trained Models	Steps Trained	Data/ Tokens	No. of Processing Units	Processing Unit Type	Train. Time	Calculated Train. Cost	Train. Parallelism	Library
WebGPT [133]	arXiv'21	-	OpenAI	General	175B	×	GPT-3	-	-	-	-	-	-	-	-
T0 [22]	ICLR'22	Apache-2.0	BigScience	General	11B	✓	T5	-	250B	512	TPU v3	270h	0.48 Mil	-	-
Tk-Instruct [26]	EMNLP'22	MIT	AI2+	General	11B	✓	T5	1000	-	256	TPU v3	4h	0.0036 Mil	-	Google T5
OPT-IML [24]	arXiv'22	-	Meta	General	175B	×	OPT	8k	2B	128	40G A100	-	-	D+T	Megatron
Flan-U-PaLM [25]	ICLR'22	Apache-2.0	Google	General	540B	✓	U-PaLM	30k	-	512	TPU v4	-	-	-	JAX+T5X
mT0 [134]	ACL'23	Apache-2.0	HuggingFace+	General	13B	✓	mT5	-	-	-	-	-	-	-	-
Sparrow [135]	arXiv'22	-	Google	Dialog	70B	×	Chinchilla	-	-	64	TPU v3	-	-	M	-
WizardCoder [136]	arXiv'23	Apache-2.0	HK Bapt.	Coding	15B	×	StarCoder	200	S-78k	-	-	-	-	-	-

Bard, and others.

3. Aligning with Human Preferences: Incorporating human preferences into LLMs presents a significant advantage in mitigating undesirable behaviors and ensuring accurate outputs. The initial work on alignment, such as InstructGPT [137] aligns GPT-3 using a 3-step approach, instruction-tuning, reward modeling, and fine-tuning with reinforcement learning (RL). The supervised fine-tuned GPT-3 on demonstrations is queried to generate responses, which human labelers rank according to human values, and a reward model is trained on the ranked data. Lastly, the GPT-3 is trained with proximal policy optimization (PPO) using rewards on the generated data from the reward model. LLaMA 2-Chat [112] improves alignment by dividing reward modeling into helpfulness and safety rewards and using rejection sampling in addition to PPO. The initial four versions of LLaMA 2-Chat are fine-tuned with rejection sampling and then with PPO on top of rejection sampling.

Aligning with Supported Evidence: This style of alignment allows the model to generate responses with proofs and facts, reduces hallucination, and assists humans more effectively, which increases trust in the model's output. Similar to the RLHF training style, a reward model is trained to rank generated responses containing web citations in answers to questions, which is later used to train the model, as in GopherCite [145], WebGPT [133], and Sparrow [135]. The ranking model in Sparrow [135] is divided into two branches, preference reward and rule reward, where human annotators adversarial probe the model to break a rule. These two rewards together rank a response to train with RL.

Aligning Directly with SFT: The PPO in the RLHF pipeline is complex, memory-intensive, and unstable, requiring multiple models, reward, value, policy, and reference models. Avoiding this sophisticated alignment pipeline is possible by incorporating minimal changes in supervised fine-tuning (SFT) pipeline as in [146], [147], [148], with better or comparable performance to PPO. Direct preference optimization (DPO) [146] trains a model directly on the human-preferred responses to maximize the likelihood of preferred against unpreferred responses, with per-sample importance weight. Reward ranked fine-tuning RAFT [147] fine-tunes the model on ranked responses by the reward model. Preference ranking optimization (PRO) [149] and RRHF [148] penalize the model to rank responses with human preferences and supervised loss. On the other hand, chain-of-hindsight (CoH) [150] provides feedback to the model in language rather than reward, to learn good versus bad responses.

Aligning with Synthetic Feedback: Aligning LLMs with human feedback is slow and costly. The literature suggests a semi-automated process to align LLMs by prompting LLMs to generate helpful, honest, and ethical responses to the queries, and fine-tuning using the newly created dataset. Constitutional AI [151] replaces human feedback in RLHF with AI, calling it RL from AI feedback (RLAIF). AlpacaFarm [152] designs prompts to imitate human feedback using LLMs APIs. Opposite to constitutional AI, AlpacaFarm injects noise in feedback to replicate human mistakes. Self-Align [153] prompts the LLM with ICL examples, instructing the LLM about what the response should contain to be considered useful and ethical. The same LLM is later fine-tuned with the new dataset.

Aligning with Prompts: LLMs can be steered with prompts to generate desirable responses without training [154], [155]. The self-correction prompting in [155] concatenates instructions and CoT with questions, guiding the model to answer its instruction following strategy to ensure moral safety before the actual answer. This strategy is shown to reduce the harm in generated responses significantly.

Red-Teaming/Jailbreaking/Adversarial Attacks: LLMs exhibit harmful behaviors, hallucinations, leaking personal information, and other shortcomings through adversarial probing. The models are susceptible to generating harmful responses even though they are aligned for safety [156], [157]. Red-teaming is a common approach to address illicit outputs, where the LLMs are prompted to generate harmful outputs [157], [158]. The dataset collected through red-teaming is used to fine-tune models for safety. While red-teaming largely relies on human annotators, another work [159] red-team LLMs to find prompts that lead to harmful outputs of other LLMs.

4. Continue Pre-Training: Although fine-tuning boosts a model's performance, it leads to catastrophic forgetting of previously learned information. Concatenating fine-tuning data with a few randomly selected pre-training samples in every iteration avoids network forgetting [160], [130]. This is also effective in adapting LLMs for cases where fine-tuning data is small and the original capacity is to be maintained. Prompt-based continued pre-training (PCP) [161] trains model with text and instructions related to tasks and then finally instruction-tunes the model for downstream tasks.

5. Sample Efficiency: While fine-tuning data is generally many-fold smaller than the pre-training data, it still has to be large enough for acceptable performance [25], [24], [26] and requires proportional computing resources. To study the effects on performance with less data, existing literature [162], [163] finds that the models trained on lesser data can outperform models trained with more data. In [162], 25% of the total downstream data is found enough for state-of-the-art performance. Selecting coreset-based 0.5% of the total instruction-tuning data improves the model performance by 2% in [163], as compared to the complete data tuning. Less is more for alignment (LIMA) [164] uses only 1000 carefully created demonstrations to fine-tune the model and has achieved comparable performance to GPT-4.

C. Robotics

LLMs have been rapidly adopted across various domains in the scientific community due to their multipurpose capabilities [33]. In robotics research, the LLMs have very promising applications as well, such as enhancing human-robot interaction [165], [166], [167], [168], task planning [169], [170], [171], navigation [172], [173], and learning [174], [175]. They can enable robots to understand and generate natural language, aiding in instruction following, data annotation, and collaborative problem-solving. They can facilitate continuous learning by allowing robots to access and integrate information from a wide range of sources. This can help robots acquire new skills, adapt to changes, and refine their performance based on real-time data.

LLMs have also started assisting in simulating environments for testing and offer potential for innovative research in robotics, despite challenges like bias mitigation and integration complexity. The work in [176] focuses on personalizing robot household cleanup tasks. By combining language-based planning and perception with LLMs, such that having users provide object placement examples, which the LLM summarizes to generate generalized preferences, they show that robots can generalize user preferences from a few examples. An embodied LLM is introduced in [177], which employs a Transformer-based language model where sensor inputs are embedded alongside language tokens, enabling joint processing to enhance decision-making in real-world scenarios. The model is trained end-to-end for various embodied tasks, achieving positive transfer from diverse training across language and vision domains. LLMs have also been explored as zero-shot human models for enhancing human-robot interaction.

The study in [165] demonstrates that LLMs, trained on vast text data, can serve as effective human models for certain HRI tasks, achieving predictive performance comparable to specialized machine-learning models. However, limitations were identified, such as sensitivity to prompts and difficulties with spatial/numerical reasoning. In another study [178], the authors enable LLMs to reason over sources of natural language feedback, forming an "inner monologue" that enhances

their ability to process and plan actions in robotic control scenarios. They combine LLMs with various forms of textual feedback, allowing the LLMs to incorporate conclusions into their decision-making process for improving the execution of user instructions in different domains, including simulated and real-world robotic tasks involving tabletop rearrangement and mobile manipulation. All of these studies employ LLMs as the core mechanism for assimilating everyday intuitive knowledge into the functionality of robotic systems.

D. Multimodal LLMs

Inspired by the success of LLMs in natural language processing applications, an increasing number of research works are now facilitating LLMs to perceive different modalities of information like image [179], [180], [181], video [182], [183], [184], audio [185], [184], [186], *etc.* Multimodal LLMs (MLLMs) present substantial benefits compared to standard LLMs that process only text. By incorporating information from various modalities, MLLMs can achieve a deeper understanding of context, leading to more intelligent responses infused with a variety of expressions. Importantly, MLLMs align closely with human perceptual experiences, leveraging the synergistic nature of our multisensory inputs to form a comprehensive understanding of the world [186], [177]. Coupled with a user-friendly interface, MLLMs can offer intuitive, flexible, and adaptable interactions, allowing users to engage with intelligent assistants through a spectrum of input methods. According to the ways of constructing models, current MLLMs can be generally divided into three streams: pre-training, fine-tuning, and prompting. In this section, we will discuss more details of these main streams, as well as the important application of MLLMs in visual reasoning.

Pre-training This stream of MLLMs intends to support different modalities using unified end-to-end models. For instance, Flamingo [179] applies gated cross-attention to fuse vision and language modalities, which are collected from pre-trained and frozen visual encoder and LLM, respectively. Moreover, BLIP-2 [180] proposes a two-stage strategy to pre-train a Querying Transformer (Q-Former) for the alignment between vision and language modalities: in the first stage, vision-language representation learning is bootstrapped from a frozen visual encoder; and in the second stage, a frozen LLM bootstraps vision-to-language generative learning for zero-shot image-to-text generation. Similarly, MiniGPT-4 [187] also deploys pre-trained and frozen ViT [188], Q-Former and Vicuna LLM [189], while only a linear projection layer needs to be trained for vision and language modalities alignment.

Fine-tuning Derived from instruction tuning [25] for NLP tasks [137], [25], [24], researchers are now fine-tuning pre-trained LLMs using multimodal instructions. Following this method, LLMs can be easily and effectively extended as multimodal chatbots [187], [181], [190] and multimodal task solvers [191], [192], [193]. The key issue of this stream of MLLMs is to collect multimodal instruction-following data for fine-tuning [194]. To address this issue, the solutions of benchmark adaptation [191], [195], [196], self-instruction [138], [197], [198], and hybrid composition [199], [193] are employed, respectively. To mitigate the gap between the original language modality and additional modalities, the learnable interface is introduced to connect different modalities from frozen pre-trained models. Particularly, the learnable interface is expected to work in a parameter-efficient tuning manner: *e.g.*, LLaMA-Adapter [200] applies an efficient transformer-based adapter module for training, and LaVIN [199] dynamically learns the multimodal feature weights using a mixture-of-modality adapter. Different from the learnable interface, the expert models can directly convert multimodalities into language: *e.g.*, VideoChat-Text [182] incorporates Whisper [201], a speech recognition expert model, to generate the captions of given videos for the understanding of following LLMs.

Prompting Different from the fine-tuning technique that directly updates the model parameters given task-specific datasets, the prompting technique provides certain context, examples, or instructions to the model, fulfilling specialized tasks without changing the model parameters. Since prompting can significantly reduce the needs of large-scale multimodal data, this technique is widely used to construct MLLMs. Particularly, to solve multimodal Chain of Thought (CoT) problems [85], LLMs are prompted to generate both the reasoning process and the answer given multimodal inputs [202]. On this front, different learning paradigms are exploited in practice: for example, Multimodal-CoT [202] involves two stages of rationale generation and answer inference, where the input of the second stage is a combination of the original input and the output of the first stage; and CoT-PT [203] applies both prompt tuning and specific visual bias to generate a chain of reasoning implicitly. In addition to CoT problems, LLMs can also be prompted with multimodal descriptions and tools, effectively dividing complex tasks into sub-tasks [204], [205].

Visual Reasoning Application Recent visual reasoning systems [206], [207], [208], [209] tend to apply LLMs for better visual information analysis and visual-language integration. Different from previous works [210], [211] that rely on limited VQA datasets and small-scale neural networks, current LLM-aided methods offer benefits of stronger generalization ability, emergent ability, and interactivity [194]. To realize visual reasoning with the help of LLMs, the prompting and the fine-tuning techniques can also be utilized: for example, PointClip V2 [207] applies LLMs to generate 3D-specific prompts, which are encoded as textual features and then combined with visual features for 3D recognition; and GPT4Tools [197] employs LoRA [212] to fine-tune LLMs following tool-related instructions. Serving as a controller [209], decision maker [213], or semantics refiner [206], [214], LLMs significantly facilitates the progress of visual reasoning research.

IV. Findings & Insights

Training a billion-scale model is difficult as compared to a smaller model. LLMs are prone to various instabilities during training, such as hardware failure and instability. Other than this, LLMs exhibit different behaviors such as emergent abilities, improved zero-shot, few-shot, and reasoning abilities. Researchers report these essential details in their papers for results reproduction and field progress. We identify critical information in Table I and II such as architecture, training

strategies, and pipelines that improve LLMs' performance or other abilities acquired because of changes mentioned in section III.

V. Model Configurations

We provide different statistics of pre-trained and instruction-tuned models in this section. This includes information such as publication venue, license type, model creators, steps trained, parallelism, etc in Table III and Table IV. Architecture details of pre-trained LLMs are available in Table V. Providing these details for instruction-tuned models is unnecessary because it fine-tunes pre-trained models for instruction datasets. Hence, architectural details are the same as the baselines. Moreover, optimization settings for various LLMs are available in Table VI and Table VII. We do not include details on precision, warmup, and weight decay in Table VII. Neither of these details are important as others to mention for instruction-tuned models nor provided by the papers.

VI. Datasets and Evaluation

LLMs are known to require a huge amount of data for training. Hence, datasets for training and benchmarking these models are currently a topic of key importance. In Fig. 12, we show the distribution of datasets currently available for benchmarking language models for a variety of natural language processing tasks. It is noteworthy that this distribution is restricted to only the tasks for which at least 20 datasets have already been proposed in the literature. LLMs can directly benefit from these dataset for training and evaluation. In general, the performance of LLMs greatly depends on the training dataset. A model trained on a good-quality data is likely to perform better on evaluation benchmarks. Specific training and evaluation datasets used by LLMs are summarized in Table IX and X.

A. Evaluation Tasks

The evaluation of LLMs is a critical step in gauging their proficiency and identifying their limitations. This process provides a measure of the model's ability to comprehend, generate, and interact with human language across a spectrum of tasks. For Natural Language Understanding (NLU), these tasks encompass sentiment analysis, natural language inference, semantic understanding, closed book question answering, and reading comprehension, among others. While Natural Language Generation (NLG) is commonly associated with tasks like text summarization and translation, it is also intrinsically involved in other functionalities like responding to queries and generating contextually appropriate dialogue. Both NLU and NLG tasks form part of established benchmarks that facilitate the comparison of different models. For a detailed performance comparison of the LLMs on these tasks, please refer to Table VIII.

B. Evaluation Datasets

The role of specific datasets, particularly those commonly used, is fundamental in the evaluation of Large Language Models. These datasets, each with its unique design and set of challenges, serve as the basis for assessing the capabilities of LLMs. They offer a comprehensive measure of performance across a variety of tasks, providing insights into the models' proficiency. In the following discussion, we provide a concise overview of a selection of these key datasets. While the Tables IX and X include a larger set of datasets, we focus on the most commonly used ones in the evaluation of LLMs. Each dataset description encapsulates the core aspects it evaluates in an LLM, offering a snapshot of the model's potential strengths and limitations.

1. HellaSwag [215]: A dataset that challenges models to pick the best ending to a context uses Adversarial Filtering to create a 'Goldilocks' zone of complexity, where generated text is absurd to humans but often misclassified by models.

2. PIQA [216]: A dataset that probes the physical knowledge of models, aiming to understand how well they are learning about the real world.

3. TriviaQA [217]: A dataset that tests models on reading comprehension and open domain question answering (QA) tasks, with a focus on Information Retrieval (IR)-style QA.

4. LAMBADA [218]: This dataset evaluates contextual text understanding through a word prediction task. Models must predict the last word of a passage, which is easy for humans when given the whole passage, but not when given only the last sentence.

5. WinoGrande [219]: A large-scale dataset inspired by the original Winograd [220] Schema Challenge tests models on their ability to resolve pronoun ambiguity and encourages the development of models that understand the broad context in natural language text.

6. MMLU [221]: A benchmark that measures the knowledge acquired by models during pretraining and evaluates models in zero-shot and few-shot settings across 57 subjects, testing both world knowledge and problem-solving ability.

7. SuperGLUE [3]: A more challenging and diverse successor to the GLUE [222] benchmark, SuperGLUE includes a variety of language understanding tasks, such as question answering, natural language inference, and coreference resolution. It is designed to provide a rigorous test of language understanding and requires significant progress in areas like sample-efficient, transfer, multitasking, and unsupervised or self-supervised learning.

8. StoryCloze [223]: It introduces a new "StoryCloze Test", a commonsense reasoning framework for evaluating story understanding, generation, and script learning. It considers a model's ability to understand and generate coherent and sensible stories.

9. BoolQ [224]: A dataset derived from Google search queries, BoolQ challenges models to answer binary (yes/no) questions. The questions are naturally occurring and are paired with a paragraph from a Wikipedia article containing the answer. It's a test of reading comprehension and reasoning.

TABLE V: Architecture details of LLMs. Here, "PE" is the positional embedding, "nL" is the number of layers, "nH" is the number of attention heads, "HS" is the size of hidden states.

Models	Type	Training Objective	Attention	Vocab	Tokenizer	Norm	PE	Activation	Bias	nL	nH	HS
T5 (11B)	Enc-Dec	Span Corruption	Standard	32k	SentencePiece	Pre-RMS	Relative	ReLU	×	24	128	1024
GPT3 (175B)	Causal-Dec	Next Token	Dense+Sparse	-	-	Layer	Learned	GeLU	✓	96	96	12288
mT5 (13B)	Enc-Dec	Span Corruption	Standard	250k	SentencePiece	Pre-RMS	Relative	ReLU	-	-	-	-
PanGu-α (200B)	Causal-Dec	Next Token	Standard	40k	BPE	Layer	-	-	-	64	128	16384
CPM-2 (198B)	Enc-Dec	Span Corruption	Standard	250k	SentencePiece	Pre-RMS	Relative	ReLU	-	24	64	-
Codex (12B)	Causal-Dec	Next Token	Standard	-	BPE+	Pre-Layer	Learned	GeLU	-	96	96	12288
ERNIE 3.0 (10B)	Causal-Dec	Next Token	Standard	-	WordPiece	Post-Layer	Relative	GeLU	-	48	64	4096
Jurassic-1 (178B)	Causal-Dec	Next Token	Standard	256k	SentencePiece*	Pre-Layer	Learned	GeLU	✓	76	96	13824
HyperCLOVA (82B)	Causal-Dec	Next Token	Dense+Sparse	-	BPE*	Pre-Layer	Learned	GeLU	-	64	80	10240
Yuan 1.0 (245B)	Causal-Dec	Next Token	Standard	-	-	-	-	-	-	76	-	16384
Gopher (280B)	Causal-Dec	Next Token	Standard	32k	SentencePiece	Pre-RMS	Relative	GeLU	✓	80	128	16384
ERNIE 3.0 Titan (260B)	Causal-Dec	Next Token	Standard	-	WordPiece	Post-Layer	Relative	GeLU	-	48	192	12288
GPT-NeoX-20B	Causal-Dec	Next Token	Parallel	50k	BPE	Layer	Rotary	GeLU	✓	44	64	-
OPT (175B)	Causal-Dec	Next Token	Standard	-	BPE	-	-	ReLU	✓	96	96	-
BLOOM (176B)	Causal-Dec	Next Token	Standard	250k	BPE	Layer	ALiBi	GeLU	✓	70	112	14336
Galactica (120B)	Causal-Dec	Next Token	Standard	50k	BPE+custom	Layer	Learned	GeLU	×	96	80	10240
GLaM (1.2T)	MoE-Dec	Next Token	Standard	256k	SentencePiece	Layer	Relative	GeLU	✓	64	128	32768
LaMDA (137B)	Causal-Dec	Next Token	Standard	32k	BPE	Layer	Relative	GeGLU	-	64	128	8192
MT-NLG (530B)	Causal-Dec	Next Token	Standard	50k	BPE	Pre-Layer	Learned	GeLU	✓	105	128	20480
AlphaCode (41B)	Enc-Dec	Next Token	Multi-query	8k	SentencePiece	-	-	-	-	64	128	6144
Chinchilla (70B)	Causal-Dec	Next Token	Standard	32k	SentencePiece-NFKC	Pre-RMS	Relative	GeLU	✓	80	64	8192
PaLM (540B)	Causal-Dec	Next Token	Parallel+Multi-query	256k	SentencePiece	Layer	RoPE	SwiGLU	×	118	48	18432
AlexaTM (20B)	Enc-Dec	Denoising	Standard	150k	SentencePiece	Pre-Layer	Learned	GeLU	✓	78	32	4096
Sparrow (70B)	Causal-Dec	Pref.&Rule RM	-	32k	SentencePiece-NFKC	Pre-RMS	Relative	GeLU	✓	16*	64	8192
U-PaLM (540B)	Non-Causal-Dec	MoD	Parallel+Multi-query	256k	SentencePiece	Layer	RoPE	SwiGLU	×	118	48	18432
UL2 (20B)	Enc-Dec	MoD	Standard	32k	SentencePiece	-	-	-	-	64	16	4096
GLM (130B)	Non-Causal-Dec	AR Blank Infilling	Standard	130k	SentencePiece	Deep	RoPE	GeGLU	✓	70	96	12288
CodeGen (16B)	Causal-Dec	Next Token	Parallel	-	BPE	Layer	RoPE	-	-	34	24	-
LLaMA (65B)	Causal-Dec	Next Token	Standard	32k	BPE	Pre-RMS	RoPE	SwiGLU	-	80	64	8192
PanGu-Σ (1085B)	Causal-Dec	Next Token	Standard	-	BPE	Fused Layer	-	FastGeLU	-	40	40	5120
BloombergGPT (50B)	Causal-Dec	Next Token	Standard	131k	Unigram	Layer	ALiBi	GeLU	✓	70	40	7680
Xuan Yuan 2.0 (176B)	Causal-Dec	Next Token	Self	250k	BPE	Layer	ALiBi	GeLU	✓	70	112	14336
CodeT5+ (16B)	Enc-Dec	SC+NT+Cont.+Match	Standard	-	Code-Specific	-	-	-	-	-	-	-
StarCoder (15.5B)	Causal-Dec	FIM	Multi-query	49k	BPE	-	Learned	-	-	40	48	6144
LLaMA (70B)	Causal-Dec	Next Token	Grouped-query	32k	BPE	Pre-RMS	RoPE	SwiGLUE	-	-	-	-
PaLM-2	-	MoD	Parallel	-	-	-	-	-	-	-	-	-

TABLE VI: Summary of optimization settings used for pre-trained LLMs. The values for weight decay, gradient clipping, and dropout are 0.1, 1.0, and 0.1, respectively, for most of the LLMs.

Models	Batch Size	Sequence Length	LR	Warmup	LR Decay	Optimizers			Precision			Weight Decay	Grad Clip	Dropout
						AdaFactor	Adam	AdamW	FP16	BF16	Mixed			
T5 (11B)	2^{11}	512	0.01	×	inverse square root	✓					-	-	-	✓
GPT3 (175B)	32K	-	6e-5	✓	cosine		✓		✓			✓	✓	-
mT5 (13B)	1024	1024	0.01	-	inverse square root	✓					-	-	-	✓
PanGu-α (200B)	-	1024	2e-5	-	-	-	-			✓	-	-		
CPM-2 (198B)	1024	1024	0.001	-	-	✓					-	-	-	✓
Codex (12B)	-	-	6e-5	✓	cosine		✓		✓			✓	-	-
ERNIE 3.0 (12B)	6144	512	1e-4	✓	linear		✓				-	✓	-	-
Jurassic-1 (178B)	3.2M	2048	6e-5	✓	cosine		✓		✓			✓	✓	-
HyperCLOVA (82B)	1024	-	6e-5	-	cosine			✓			-	✓	-	-
Yuan 1.0 (245B)	<10M	2048	1.6e-4	✓	cosine decay to 10%		✓				-	✓	-	-
Gopher (280B)	3M	2048	4e-5	✓	cosine decay to 10%		✓			✓		-	✓	-
ERNIE 3.0 Titan (260B)	-	512	1e-4	✓	linear		✓		✓			✓	✓	-
GPT-NeoX-20B	1538	2048	0.97e-5	✓	cosine			✓	✓			✓	✓	×
OPT (175B)	2M	2048	1.2e-4	-	linear			✓	✓			✓	✓	✓
BLOOM (176B)	2048	2048	6e-5	✓	cosine		✓			✓		✓	✓	×
Galactica (120B)	2M	2048	7e-6	✓	linear decay to 10%			✓			-	✓	✓	✓
GLaM (1.2T)	1M	1024	0.01	-	inverse square root	✓				FP32 + ✓		-	✓	×
LaMDA (137B)	256K	-	-	-	-	-	-	-	-	-	-	-	-	-
MT-NLG (530B)	1920	2048	5e-5	✓	cosine decay to 10%		✓			✓		✓	✓	-
AlphaCode (41B)	2048	1536+768	1e-4	✓	cosine decay to 10%			✓		✓		✓	✓	-
Chinchilla (70B)	1.5M	2048	1e-4	✓	cosine decay to 10%			✓		✓		-	-	-
PaLM (540B)	2048	2048	0.01	-	inverse square root	✓					-	✓	✓	×
AlexaTM (20B)	2M	1024	1e-4	-	linear decay to 5%		✓			✓		✓	-	✓
Sparrow (70B)	RM: 8+16, RL:16	-	2e-6	✓	cosine decay to 10%	✓	✓			✓		-	✓	×
U-PaLM (540B)	32	2048	1e-4	-	cosine	✓					-	-	-	-
UL2 (20B)	1024	1024	-	-	inverse square root	-	-	-	-	-	-	×		
GLM (130B)	4224	2048	8e-5	✓	cosine			✓	✓			✓	✓	✓
CodeGen (16B)	2M	2048	5e-5	✓	cosine		✓				-	✓	✓	-
LLaMA (65B)	4M Tokens	2048	1.5e-4	✓	cosine decay to 10%			✓			-	✓	✓	-
PanGu-Σ (1.085T)	512	1024	2e-5	✓	-		✓				✓	-	-	-
BloombergGPT (50B)	2048	2048	6e-5	✓	cosine			✓			✓	✓	✓	×
Xuan Yuan 2.0 (176B)	2048	2048	6e-5	✓	cosine		✓		✓			✓	✓	-
CodeT5+ (16B)	2048	1024	2e-4	-	linear			✓			✓	✓	-	-
StarCoder (15.5B)	512	8k	3e-4	✓	cosine		✓			✓		✓	-	-
LLaMA-2 (70B)	4M Tokens	4k	1.5e-4	✓	cosine			✓		✓		✓	✓	-

TABLE VII: Summary of optimization settings used for instruction-tuned LLMs. Values for gradient clipping and dropout are the same as the pre-trained models, while no model is using weight decay for instruction tuning.

Models	Batch Size	Sequence Length	LR	Warmup	LR_Decay	Optimizer		Grad Clip	Dropout
						AdaFactor	Adam		
WebGPT (175B)	BC:512, RM:32	-	6e-5	-	-		✓	-	-
T0 (11B)	1024	1280	1e-3	-	-	✓		-	✓
Tk-Instruct (11B)	1024	-	1e-5	-	constant	-	-	-	-
OPT-IML (175B)	128	2048	5e-5	×	linear		✓	✓	✓
Flan-U-PaLM (540B)	32	-	1e-3	-	constant	✓		-	✓
WizardCoder (15B)	512	2048	2e-5	✓	cosine	-	-	-	-

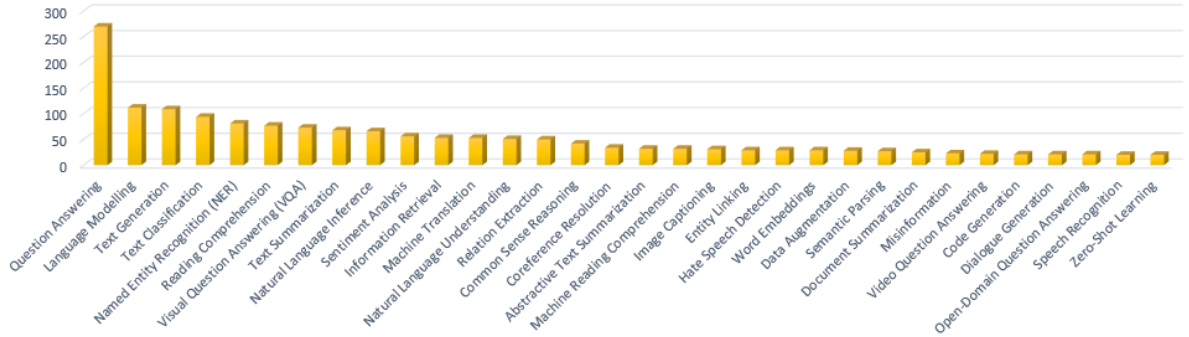

Fig. 12: Distribution of benchmark datasets available for different natural language processing tasks. We include only the tasks for which at least 20 datasets have already been proposed.

TABLE VIII: Performance comparison of top performing LLMs across various NLU and NLG tasks. Here, 'N-Shots' indicate the number of example prompts provided to the model during the evaluation, representing its capability in few-shot or zero-shot learning settings, and 'B' represents the benchmark.

Task	Dataset/Benchmark	Model	Model Size	N-Shots	Score
Multi-Task	BIG-bench (B)	Chinchilla	70B	5-shot	65.1
		Gopher	280B	5-shot	53.97
		PaLM	540B	5-shot	53.7
	MMLU (B)	PaLM	540B	5-shot	69.3
		Chinchilla	70B	5-shot	67.6
		LLaMA	65B	5-shot	63.4
Language Understanding	SuperGLUE (B)	ERNIE 3.0	12B	-	90.6
		T5	11B	-	88.9
		GPT3	175B	32-shot	71.8
Story Comprehension and Generation	HellaSwag	LLaMa	65B	zero shot	84.2
		PaLM	540B	zero shot	83.6
		Chinchilla	70B	zero shot	80.8
	StoryCloze	GPT3	175B	few shot	87.7
		OPT	175B	-	79.82
Physical Knowledge and World Understanding	PIQA	Chinchilla	70B	zero shot	85.0
		LLaMa	65B	zero shot	82.8
		MT-NLG	530B	zero shot	81.8
	TriviaQA	PaLM	540B	one shot	81.4
		GlaM	62B	one shot	75.8
		LLaMa	65B	64-shot	73.0
	OpenBookQA	AlexaTM	20B	-	94.4
		OPT	175B	few shot	65.4
		GPTNeoX-20B	20B	one shot	44.2
Contextual Language Understanding	LAMBADA	PaLM	540B	few shot	89.7
		GPT3	175B	few shot	86.4
		GLM	130B	-	80.2
Commonsense Reasoning	WinoGrande	PaLM	540B	zero shot	81.1
		LLaMa	65B	zero shot	77.0
		Chinchilla	70B	zero shot	74.9
	SIQA	LLaMA	65B	zero shot	52.3
		Chinchilla	70B	zero shot	51.3
		Gopher	280B	zero shot	50.6
Reading Comprehension	BoolQ	LLaMA	65B	zero shot	85.3
		Chinchilla	70B	zero shot	83.7
Truthfulness	Truthful-QA	LLaMA	65B	-	57

10. RACE-High [225]: A subset of the RACE [225] dataset, RACE-High consists of high school-level English exam questions. It is designed to evaluate the comprehension ability of models in a more academic and challenging context.

11. RACE-Middle [225]: Another subset of the RACE [225] dataset, RACE-Middle, contains middle school-level English exam questions. It offers a slightly less challenging but academically oriented evaluation of a model's comprehension skills.

12. Truthful-QA [226]: A unique benchmark that measures a language model's truthfulness when generating answers. The dataset includes questions across various categories like health, law, and politics, some of which are designed to test the model against common human misconceptions.

13. ANLI [227]: A large-scale dataset designed to test the robustness of machine learning models in Natural Language Inference (NLI) is created through an iterative, adversarial process where humans try to generate examples that models cannot correctly classify.

14. ARC-Challenge [228]: A rigorous question-answering dataset, ARC-Challenge includes complex, grade-school level questions that demand reasoning beyond simple retrieval, testing the true comprehension capabilities of models.

15. XNLI [229]: A cross-lingual benchmark, XNLI extends the MultiNLI [230] corpus to 15 languages, including low-resource ones like Urdu. It tests models on cross-lingual sentence understanding, with 112,500 annotated pairs across three categories: entailment, contradiction, and neutral.

16. PAWS-X [231]: PAWS-X, or Cross-lingual Paraphrase Adversaries from Word Scrambling, is a multilingual version of the PAWS [232] dataset for paraphrase identification. It includes examples in seven languages and is designed to evaluate the performance of cross-lingual paraphrase identification models.

17. ARC [228]: A larger version of the ARC-Challenge, this dataset contains both easy and challenging grade-school level, multiple-choice science questions. It's a comprehensive test of a model's ability to understand and answer complex questions.

18. ARC-Easy [228]: A subset of the ARC dataset, ARC-Easy, contains questions that are answered correctly by either a retrieval-based algorithm or a word co-occurrence algorithm. It's a great starting point for models beginning to explore advanced question-answering.

19. CoQA [233]: A conversational question-answering dataset, CoQA challenges models with questions that rely on conversation history and require free-form text answers. Its diverse content from seven domains makes it a rigorous test for models' ability to handle a wide range of topics and conversational contexts.

20. DROP [234]: DROP, or Discrete Reasoning Over the content of Paragraphs, is designed to test a model's ability to understand a wide variety of reading phenomena. It encourages comprehensive and reliable evaluation of reading comprehension capabilities.

21. RTE [235]: The Recognizing Textual Entailment (RTE) datasets come from a series of annual competitions on textual entailment, predicting whether a given sentence logically follows from another and evaluating a model's understanding of logical relationships in a text.

22. BIG-bench [236]: The BIG-bench (Behavior of Intelligent Generative Models Benchmark) is a large-scale benchmark designed to test the abilities of LLMs across a wide range of tasks, including reasoning, creativity, ethics, and understanding of specific domains.

23. SQUADv2 [237]: The Stanford Question Answering Dataset (SQuAD) [238] is a collection of questions posed by crowdworkers on a set of Wikipedia articles, where the answer to every question is a segment of text from the corresponding reading passage. SQuADv2 combines the original SQuAD1.1 dataset with over 50,000 unanswerable questions. The aim is to evaluate a model's ability to understand and answer questions based on a given context and to determine when a question is unanswerable.

24. GSM8K [239]: A dataset of diverse grade school math word problems, testing a model's ability to perform multi-step mathematical reasoning.

25. WiC [240]: This dataset assesses a model's ability to discern word meanings based on context, aiding in tasks related to Word Sense Disambiguation.

26. Math23k [241]: This one challenges a model's ability to understand and solve mathematical word problems. It contains 23,000 Chinese arithmetic word problems that require models to perform reasoning and computation based on the problem description.

27. LCQMC [242]: The Large-scale Chinese Question Matching Corpus (LCQMC) is a dataset for evaluating the performance of models in semantic matching tasks. It contains pairs of questions in Chinese and their matching status, making it a valuable resource for research in Chinese language understanding.

28. MATH [243]: This dataset is a platform for evaluating the mathematical problem-solving abilities of AI models. It contains a diverse set of math problems, ranging from arithmetic to calculus, and is designed to test the model's ability to understand and solve complex mathematical problems.

29. ETHOS [244]: ETHOS is a hate speech detection dataset built from YouTube and Reddit comments. It's a tool in the fight against online hate speech, offering binary and multi-label variants for robust content moderation.

30. StereoSet [245]: StereoSet is a comprehensive dataset designed to measure and evaluate the presence of stereotypical biases in language models. It focuses on four key domains: gender, profession, race, and religion. By contrasting stereotypical bias against language modeling ability, it provides a valuable tool for understanding and mitigating biases in large language models.

31. HumanEval [246]: A dataset for the problem-solving ability of AI models, which includes a diverse set of tasks that require various cognitive abilities, makes it a comprehensive tool for assessing general intelligence in AI.

32. WebQA [247]: A dataset for open-domain question answering, WebQA offers a large collection of web-based question-answer pairs. It is designed to assess the ability of

AI models to understand and answer questions based on web content.

33. CMRC2018 [248]: This dataset is a test of Chinese language models' ability to reason comprehensively and is designed with a challenging span-extraction format that pushes the boundaries of machine performance.

34. Wikitext103 [249]: With over 100 million tokens from Wikipedia's top articles, this dataset is a rich resource for tasks that require understanding long-term dependencies, such as language modeling and translation.

35. PG19 [250]: This is a digital library of diverse books from Project Gutenberg. It's specifically designed to facilitate research in unsupervised learning and language modeling, with a special focus on long-form content.

36. C4 [11]: A clean, multilingual dataset, C4 offers billions of tokens from web-crawled data. It's a comprehensive resource for training advanced Transformer models on various languages.

37. QuAC [251]: This dataset simulates an information-seeking dialog between students and teachers using hidden Wikipedia text. It introduces unique challenges not found in machine comprehension datasets, making it a valuable resource for advancing dialog systems.

38. COPA [252]: This dataset evaluates a model's progress in open-domain commonsense causal reasoning. Each question comprises a premise and two alternatives, and the model must select the more plausible alternative, testing a model's ability to understand and reason about cause and effect.

39. WSC [220]: The Winograd Schema Challenge (WSC) is a reading comprehension task in which a system must resolve references in a text, often requiring world knowledge and reasoning about the text.

40. RACE [225]: The RACE is a reading comprehension dataset collected from English examinations in China, which benchmarks AI models for understanding and answering questions on long and complex passages, simulating the challenge of a real-world examination.

41. StrategyQA [253]: A question-answering dataset that requires reasoning over multiple pieces of evidence to evaluate the strategic reasoning ability of AI models, pushing the boundaries of what machines can understand and answer.

42. CSQA [254]: The CommonsenseQA is a question-answering dataset that requires commonsense knowledge to answer the ability of AI models to understand and answer questions that require commonsense reasoning.

43. GLUE [222]: The General Language Understanding Evaluation (GLUE) benchmark is a collection of resources for training, evaluating, and analyzing natural language understanding systems. It includes a variety of tasks that test a wide range of linguistic phenomena, making it a comprehensive tool for evaluating language understanding in AI.

VII. Summary and Discussion

A. Architecture

Due to the gigantic scale of LLMs, minor changes in architecture and training strategies have a big impact on performance and stability. Here, we summarize key architectural modules used in various LLMs, leading to better performance, reduced training time and memory, and better training stability.

Layer Normalization is found to have a significant effect on the performance and training stability of LLMs. Pre-norm, that is normalizing inputs rather than outputs, is more common among LLMs stabilizing the training [8], [111], [90]. BLOOM [9] and AlexaTM [107] utilize an additional layer normalization before embedding layer to stabilize the training of large-scale models, while the model's zero-shot generalization ability can be negatively impacted [9]. However, another study [109] finds that pre-norm degrades fine-tuned model performance as compared to post-norm, and there are no stability benefits of pre-norm beyond the 100B scale. Therefore, GLM-130B [109] used deep-norm which is a variant of post-norm for better downstream task performance after fine-tuning.

Positional Encoding effect performance and training stability of LLMs like other building blocks of a model. BLOOM [9] finds ALiBi outperforming learned and rotary positional encodings. Contrary to this, GLM-130B [109] identifies rotary positional encoding better than ALiBi. So, there is no conclusion in literature about the positional encodings yet.

Parallel Attention where attention and feed-forward layers are parallel to each other rather than sequential in transformer block has shown to reduce training time by 15%. There is no evidence of performance drop due to this change in literature and used by the models PaLM [14], GPT-NeoX [100], and CodeGen [116].

Multi-Query Attention has shared key and value attention heads in a transformer block while query attention heads are projected as usual. This reduces memory usage and speeds up sampling in autoregressive decoding. No performance degradation has been observed with this change and makes the training efficient allowing larger batch sizes. Multi-query attention is used in [14], [118].

Mixture of Experts allows easily scaling model to trillion of parameters [115], [103]. Only a few experts are activated during the computation making them compute-efficient. The performance of MoE models is better than the dense models for the same amount of data and requires less computation during fine-tuning to achieve performance similar to the dense models as discussed in [103]. MoE architectures are less prone to catastrophic forgetting, therefore are more suited for continual learning [115]. Extracting smaller sub-models for downstream tasks is possible without losing any performance, making MoE architecture hardware-friendly [115].

Sparse vs Dense Activated GPT-3 [8] uses sparse transformers [45] whereas GLaM [103] and PanGu-$\sum$ [115] use MoE [104] architecture to lower computational costs and increase the model size and capacity. According to the literature, sparse modules do not degrade the model's performance [45]. However, more experiments are required to verify this statement.

TABLE IX: Training and evaluation dataset for pre-trained LLMs. Here,"D" denotes Dialogue, "QA" denotes question answering, "CR" is for commonsense reasoning, "CoT" is for chain-of-thought, "RC" for reading comprehension, "LU" for language understanding, "IRC" for in-context reading comprehension, "NLI" for natural language inference, "WT" for winograd-style tasks, "SC" for sentence completion, "WSD" for word sense disambiguation, "CorefR" for coreference resolution.

Models	Training Dataset	Evaluation Dataset
T5	C4 [11]	GLUE [222], CNNDM, SQuAD [238], SuperGLUE [3], EnDe, ENFr, EnRo, QQP [255], MNLI-m [256], MNLI-mm [256], QNLI [238], WNLI [220], CB [257], WiC [240], WMT [258], CNN/DM
GPT-3	Common Crawl, WebText, Books Corpora, Wikipedia	QA: NaturalQS, WebQS, TriviaQA, ARC, CoQA, DROP SuperGLUE, WMT, LAMBADA, StoryCloze, HellaSwag
mT5	mC4 [12]	SP: XNLI [229], PAWS-X [231] S: WikiAnn NER [259] QA: MLQA [260], TyDiQA-GoldP [261]
PanGu-α	1.1TB Chinese Text Corpus	-
CPM-2	WuDaoCorpus [91]	CCPM [262], C^3 [263], Sogou-Log, WMT20 [264], Math23k [241], LCSTS [265], LCQMC [242], AdGen [266], CUGE [267]
Codex	54 million public software repositories hosted on GitHub containing python files under 1MB	HumanEval [246], 64 original programming problems with unit test
ERNIE3.0	Chinese text corpora, Baidu Search, Web text, QA-long, QA-short, Poetry & Couplet Domain-specific data from medical, law and financial area Baidu knowledge graph with more than 50 million facts	NLU: NLPCC2014-SC, SE-ABSA16_PHNS, SE-ABSA16_CAME, BDCI2019, COTE-BD [268], COTE-DP [268], COTE-MFW [268], XNLI [229], OCNLI [269], CMNLI [269], CLUEWSC2020 [269], FinRE [270], SanWen [271], CCKS2020, AFQMC [269], LCQMC [242], CSL [269], PAWS-X [231], BQ Corpus [272], TNEWS, IFLYTEK [273], THUCNEWS, CNSE [274], CNSS [274], NLPCC-DBQA, CHIP2019, cMedQA [275], cMedQA2 [276], CKBQA 13 [277], WebQA [247], CLUENER [269], Weibo [278], OntoNotes [279], CCKS2019, CMRC 2018 [248], CMRC2019 [280], DRCD [281], DuReader [282], $\text{Dureader}_{\text{robust}}$ [283], $\text{Dureader}_{\text{checklist}}$, $\text{Dureader}_{\text{yesno}}$, C^3 [263], CHID [284], CAIL2018-Task1 & Task2 [285], DogWhistle Insider & Outsider [286], Sogou-log [287]; NLG: LCSTS [265], KBQG, DuReader-QG [282], $\text{Dureader}_{\text{robust}}$-QG [283], MATINF-QA [288], Math23KMath23k [241], AdGen [266], WMT20-enzh [264], KdConv [289]
Jurassic-1	Wikipedia, OWT, Books, C4 [11], PileCC [290], arXiv, GitHub	ARC-Challenge [228], ARC-Easy [228], BoolQ [224], HellaSwag [215], PIQA [216], RACE-high [225], RACE-middle [225], RTE [235], StoryCloze [223], WinoGrande [219]
HyperCLOVA	Korean blogs, Community sites, News, KiN Korean Wikipedia, Wikipedia (English and Japanese); Modu-Corpus: Messenger, News, Spoken and written language corpus, Web corpus	NSMC: a movie review dataset from NAVER movies; KorQuAD 1.0 [291], Korean ML dataset AI Hub Korean-English, YNAT [292], KLUE-TC [292], KLUE-STS [292]
Yuan 1.0	Common Crawl, SogouT, Sogou News, Baidu Baike, Wikipedia, Books	FewCLUE [293], ZeroCLUE [269], CMRC2018 [248], WebQA [247]
Gopher	subsets of MassiveWeb [98] Books, C4 [11], News, GitHub and Wikipedia samples from MassiveText [98]	LM: Pile [290], LAMBADA [218], Wikitext103 [249], PG-19 [250], C4 [11]; LU: MMLU [221], BIG-bench [236]; RC: RACE-middle [225], RACE-high [225] QA: TriviaQA [217], TruthfulQA [226], Natural Questions [294]; Fact Checking on Fever [295], MultiFC [296]; HellaSwag [215], PIQA [216], WinoGrande [219], SIQA [297]; RealToxicityPrompts [298], Twitter Dataset [299], CivilComments toxicity classification [300]
ERNIE3.0 TITAN	Chinese text corpora, Baidu Search, Web text, QA-long, QA-short, Poetry & Couplet Domain-specific data from medical, law and financial area Baidu knowledge graph with more than 50 million facts ERNIE 3.0 adversarial dataset, ERNIE 3.0 controllable dataset	NLU: NLPCC2014-SC, SE-ABSA16_PHNS, SE-ABSA16_CAME, BDCI2019, EPRSTMT [293], COTE-BD [268], COTE-MFW [268], OCNLI [269], CMNLI [269], OCNLI-FC [293], CLUEWSC [269] CLUEWSC-FC [293], FinRE [270], SanWen [271], AFQMC [269], LCQMC [242], PAWS-X [231], BQ Corpus [272], CSL [269] CSL-FC [293], BUSTM, TNEWS, TNEWS-FC [293], IFLYTEK [273], IFLYTEK-FC THUCNEWS, CNSE [274], CNSS [274], CSLDCP NLPCC-DBQA, CHIP2019, cMedQA [275], cMedQA2 [276], CKBQA 13 [277], WebQA [247], PD&CFT, CMRC2017 [301], CMRC2019 [280] CHID [284], CHID-FC [293], WPLC, DRCD [281], DuReader [282], $\text{Dureader}_{\text{robust}}$ [283], $\text{Dureader}_{\text{checklist}}$, $\text{Dureader}_{\text{yesno}}$, C^3 [263], CMRC 2018 [248], CAIL2018-Task1 & Task2 [285] DogWhistle Insider & Outsider [286]
GPT-NeoX-20B	Pile [290]	ANLI [227], ARC [228], HeadQA [302], HellaSwag [215], LAMBADA [218], LogiQA [303], OpenBookQA [304], PIQA [216], PROST [305], QA4MRE [306], SciQ [307], TriviaQA [217], WinoGrande [219], SuperGLUE [3], MATH [243], Advanced Knowledge-Based Tasks
OPT	RoBERTa [308], Pile [290], PushShift.io Reddit [309]	HellaSwag [215], StoryCloze [223], PIQA [216], ARC-Easy [228], ARC-Challenge [228], OpenBookQA [304], WinoGrad [220], WinoGrande [219], SuperGLUE [3], Wizard of Wikipedia [310], Empathetic Dialogues [311], ConvAI2 [312], Blended Skill Talk [313], Wizard of Internet [314] ETHOS [244], CrowS-Pairs [315], StereoSet [245], RealToxicPrompts [298], Dialogue Responsible AI evaluations

Table Continued on Next Page

Models	Training Dataset	Evaluation Dataset
BLOOM	ROOTS [316]	-
Galactica	arXiv, PMC, Semantic Scholar Wikipedia, StackExchange, LibreText, Open Textbooks RefSeq Genome, OEIS, LIPID MAPS, NASAExoplanet Common Crawl, ScientificCC, AcademicCC GitHub repositories Khan Problems [317], GSM8K [239], OneSmallStep	Knowledge probes, Latex equations, AminoProbe [125], BioLAMA [125], Chemical Reactions [125], Galaxy Clusters [125], Mineral Groups [125]
GLaM	Filtered Webpages, Social media conversations Wikipedia, Forums, Books, News	NLG: TriviaQA [217], NQS, WebQS, SQuADv2 [237], LAMBADA [218], DROP [234], QuAC [251], CoQA [233]; NLU: HellaSwag [215], StoryCloze [223], WinoGrad [220], WinoGrande [219], RACE-middle [225], RACE-high [225], PIQA [216], ARC-Challenge [228], ARC-Easy [228], OpenbookQA [304], BoolQ [224], COPA [318], RTE [235], WiC [240], MultiRC [319], WSC [220], ReCoRD [320], CB [257], ANLI R1 [227], ANLI R2 [227], ANLI R3 [227]
LaMDA	Infiniset [127]: Public documents, Dialogs, Utterances	Mini-Turing Benchmark (MTB) [4]; Self-collected dialogs with turns by asking crowdworkers to interact with LaMDA; Wizard of Wikipedia [310]
MT-NLG	Twosnapshots of Common Crawl and Books3, OpenWebText2, Stack Exchange, PubMed Abstracts, Wikipedia, PG-19 [250], BookCorpus2, NIH ExPorter, PileCC [290], CC-Stories [321], RealNews [322]	Completionprediction: LAMBADA [218] RC: RACE [225], BoolQ [224] CR:PiQA [216] NaturalLanguage Interface: ANLI [227], HANS [323]
AlphaCode	Selected GitHub repositories CodeContests [118]: Codeforces [324], Description2Code [325], CodeNet [326]	Codeforces competitions, CodeContests [118], APPS [243]
Chinchilla	MassiveWeb [98], MassiveText [98] Books, C4 [11], News, GitHub, Wikipedia	LM: Pile [290], LAMBADA [218], Wikitext103 [249], PG-19 [250], C4 [11]; LU: 57 MMLU [221] tasks, 62 BIG-bench [236] tasks; QA: TriviaQA [217], Natural Questions [294]; RC: RACE-middle [225], RACE-high [225]; HellaSwag [215], PIQA [216], WinoGrande [219], SIQA [297], BoolQ [224], TruthfulQA [226]
PaLM	webpages, books, wikipedia, news, articles, source code, social media conversations	QA: TriviaQA [217], Natural Questions [294], Web Questions [327], TyDiQA-GoldP [261]; CR: PIQA [216], ARC [228], OpenBookQA [304]; IRC: DROP [234], CoQA [233], QuAC [251], SQuADv2 [237], RACE [225]; NLI: ANLI [227]; WT: WinoGrad [220], WinoGrande [219]; CoT: GSM8K [239], StrategyQA [253], CSQA [254], SVAMP [328], MAWPS [329], AQuA [330]; LU: MMLU [221] SuperGLUE [3], LAMBADA [218], HellaSwag [215], StoryCloze [223], BIG-bench [236], WMT language pairs
AlexaTM	Wikipedia, mC4 [12]	NLG: MLSum [331], XSum [332], E2E [333], WebNLG [334]; Machine Translation: Flores-101 [335], English-German WMT'16, English-French WMT'14, German-French WMT'19 [336]; NLP: XNLI [229], XCOPA [252], PAWS-X [231], XWinograd [337], SuperGLUE [3], SQUADv2 [237], MultiArith [338]
Sparrow	Human data for rule violations and per-turn response preferences, Self-play data accumulated through training, GopherCite FilteredELI5	Per-turn response preference and adversarial probing, Multi-turn dialogues, Information-seeking dialogues, Chinchilla-generated [106] conversational questions, GopherCite human evaluation interface, FilteredELI5 "Free" dialogues, DPC-generated [106] dialogues WinoGender [339], Winobias [340], BBQ [341], Natural Questions [294], Quiz Bowl [342], TriviaQA [217]
U-PaLM	Same as PaLM	MMLU [221], QA: TriviaQA [217], Natural Questions [294], TydiQA [261]; RC: LAMBADA [218]; CR: BoolQ [224], PIQA [216], HellaSwag [215], WinoGrande [219]; CoT: GSM8K [239], BBH [236], StrategyQA [253], CSQA [254]; LU: MMLU [221] SuperGLUE [3], MGSM [343]
UL2	-	SuperGLUE [3], GSM8K [239], SVAMP [328], ASDiv [344], MAWPS [329], AQuA [330]
GLM-130B	-	LAMBADA [218], Pile [290], MMLU [221], CLUE [269], CrowS-Pairs [315], StereoSet [245], ETHOS [244], RealToxicPrompts [298]
CodeGen	Pile [290], BigQuery, BigPython [116]	Mostly Basic Python Problems
LLaMA	CommonCrawl, C4 [11], Github, Wikipedia, Books, arXiv, StackExchange	CR: BoolQ [224], PIQA [216], SIQA [297], HellaSwag [215], WinoGrande [219], ARC-Challenge [228], OpenBookQA [304]; QA: TriviaQA [217], Natural Questions [294]; RC: RACE-middle [225], RACE-high [225]; Mathematical Reasoning: MATH [243], GSM8K [239]; Code Generation: HumanEval [246], MBPP [345]; MMLU [221], RealToxicityPrompts [298], CrowS-Pairs [315], WinoGender [339], TruthfulQA [226]
PanGUΣ	WuDaoCorpora [91], CLUE [269], Pile [290], C4 [11], and Python code	-
BloombergGPT	FinPile [128], The Pile [290], C4 [11], Wikipedia [17]	Financial Data, BIG-bench [236], MMLU [221], ARC, PiQA [216], CommonsenseQA [254], BoolQ [224], OpenBookQA [304], RACE [225], MultiRC [319], ReCoRD [320], ANLI [227], RTE [235], COPA [252], WIC [240], WinoGrad [220], WinoGrande [219], HellaSWAG [215], StoryCloze [223]
XuanYuan 2.0	Internet	-
CodeT5+	CodeSearchNet [346], Github Code	HumanEval [246], MathQA [347], GSM8K [239]
StarCoder	The Stack v1.2 [348]	HumanEval [246], MBPP [345], DS-1000 [349], HELM [350], Multi-Language Evaluation, GSM8K [239], MMLU [221], CoQA [233]
LLAMA-2	-	CR: PIQA [216], SIQA [297], HellaSwag [215], WinoGrande [219], ARC-Easy [228], ARC-Challenge [228], OpenBookQA [304], CSQA [254]; QA: TriviaQA [217], Natural Questions [294]; RC: BoolQ [224], QuAC [251], SQuADv2 [237] Mathematical Reasoning: MATH [243], GSM8K [239]; Code Generation: HumanEval [246], MBPP [345]; MMLU [221], Big Bench Hard [236], AGI Eval
PaLM-2	Web documents, Code, Books, Maths, Conversation	QA: TriviaQA [217], Natural Questions [294], WebQuestions Cloze: StoryCloze [223], HellaSwag [215], BIG-Bench [236], SuperGLUE [3] WT: Winograd [220], WinoGrande [219], RC: SQuAD v2 [237], RACE [225] CR: PIQA [216], ARC [228], OpenBookQA [304], NLI: ANLI [227]

TABLE X: Training and evaluation datasets for instruction-tuned LLMs. All the abbreviations are the same as Table IX

Models	Training Datasets	Evaluation Datasets
T0	-	NLI: ANLI [227], CB [257], RTE [235]; SC: COPA [318], HellaSwag [215] StoryCloze [223]; WSD: WiC [240]; CorefR: WSC [220], Wino (XL) [219]
WebGPT	ELI5 [351], ELI5 fact-check [133], TriviaQA [217], ARC-Challenge [228], ARC-Easy [228], Hand-written data, Demonstrations of humans, Comparisons between model-generated answers	ELI5 [351], TruthfulQA [226], TriviaQA [217]
Tk-INSTRUCT	SUP-NATINST [26]	SUP-NATINST [26]
mT0	xP3 [134]	-
OPT-IML	PromptSource [22], FLAN [25], Super-NaturalInstructions [352], UnifiedSKG [353], CrossFit [354], ExMix [355], T5 [11], Reasoning	PromptSource [22], FLAN [25], Super-NaturalInstructions [352], UnifiedSKG [353], CrossFit [354], ExMix [355], T5 [11], Reasoning, MMLU [221], BBH [236], RAFT [356]
Flan	Muffin, T0-SF, NIv2, CoT	MMLU [221], BBH [236], TyDiQA [261], MGSM [343]
WizardCoder	Code Alpaca	HumanEval [246], MBPP [345], DS-1000 [349]

B. Training Strategies

Training models at a huge scale require some tricks to reduce training costs, avoid loss divergence and achieve better performance. We summarize and discuss some of these key tricks used in different LLMs.

Mixed Precision is a famous method for LLMs to reduce memory usage and improve training efficiency. In mixed precision, forward and backward passes are performed in FP16 format whereas optimizer states and master weights are kept in FP32 format [357]. A drawback associated with this format change is training instability due to a smaller value range resulting in loss spikes [109]. An alternative to FP16 is BF16 which has a comparatively larger range and performs some precision-sensitive operations like gradient accumulation and softmax in FP32 [9]. BF16 has better performance and training stability but uses more memory and is supported on specific hardware, for example, A100 GPUs. Therefore, its adoption in LLMs is limited.

Training Instability is a common issue in LLMs where loss divergence or spiking is observed multiple times during training. This happens in the presence of gradient clipping [14]. To mitigate this problem, many approaches suggest restarting training from an earlier checkpoint [14], [109], [103], skipping 200-500 earlier data batches at the point of divergence in [14] and re-shuffling batches in [103]. The embedding layer gradient shrink proves to further stabilize the training as its gradient norm is significantly larger than the other layers [109]. Another suggestion to improve training stability for larger models is not to use **biases** in dense and norm layers as in [14].

Weight Initialization plays a significant role in model convergence and training stability. GPT-NeoX [100] initializes feed-forward layers before residuals with $\frac{2}{L\sqrt{d}}$ as in [131] and other layers with small initialization scheme [358]. This avoids activations growing exponentially with the increasing depth. MT-NLG [21] found higher variance for weight initialization leads to unstable training, hence validating small initialization scheme [358]. Various models perform random weight initialization which can cause bad initialization, Galactica [125] suggests a longer warmup to negate the effect.

Learning Rate is important for stable training. It is suggested to use a lower value [9], [14], [20] with warmup and decay (cosine or linear). Usually, the learning rate is within the range $1e^{-4}$ to $8e^{-4}$. Moreover, MT-NLG (530B) [21] and GPT-NeoX (20B) [100] suggest interpolating learning rates based on the model size using the GPT-3 [8] models ranging between 13B and 175B. This avoids tuning the learning rate hyperparameter.

Training Parallelism 3D parallelism, a combination of data, pipeline and tensor parallelism, is the most utilized training parallelism approach in LLMs [109], [14], [10], [9], [21], [97], [94]. In addition to the 3D parallelism, BLOOM [9] uses zero optimizer [61] to shard optimizer states. PanGu-α [90] and PanGu-Σ [115] go beyond the 3D parallelism and apply 5D parallelism which additionally contains optimizer parallelism and rematerialization.

Mode Switching adds task-related tokens at the beginning of the text during training. These tokens refer to the natural language understanding and natural language generation tasks which are shown to improve the downstream task performance in [15], [20], [107]. During fine-tuning and inference, tokens are appended based on the downstream tasks.

Controllable Text Generation Generating credible and controlled text from a pre-trained model is challenging. GPT-3 [8] and other LLMs use in-context learning to control generated text. While in-context learning helps in controlling the generated text, ERNIE 3.0 Titan [99] suggests using adversarial loss to rank its generated text for credibility and soft prompts such as genre, topic, keywords, sentiment, and length for better control on generated text.

C. Pre-Training vs Instruction Tuning

While pre-training is important for the generalization of LLMs, instruction-tuning improves the performance of LLMs further and makes them useable. Therefore, it is suggested to perform instruction fine-tuning of pre-trained LLMs to use them effectively [25], [26], [137], [24], [133].

D. Supervised Models vs Generalized Models

Although generalized models are capable of performing diverse tasks with good performance they have not yet outperformed models trained in supervised settings. The supervised trained models are still state-of-the-art in various NLP tasks by a large margin as shown in [8], [14], [26].

E. Zero-Shot vs Few-Shot

LLMs perform well in zero-shot and few-shot settings. But the performance difference between zero-shot and few-shot is large for pre-trained models [8], [14], naming LLMs as meta-learners [8]. LLMs zero-shot evaluations underperform unsupervised methods in neural machine translation [8]. The literature shows pre-training is not enough for good zero-shot performance [14], [25]. To improve the zero-shot performance the literature suggests using instruction fine-tuning that improves the zero-shot performance significantly and outperforms baselines. Instruction fine-tuning has also been shown to improve zero-shot generalization to unseen tasks. Another model Flan-PaLM [25] unlocks zero-shot reasoning with CoT training.

F. Encoder vs Decoder vs Encoder-Decoder

Traditionally, these architectures perform well for different tasks, for example, encoder-only for NLU tasks, decoder-only for NLG, and encoder-decoder for sequence2sequence modeling. Encoder-only models are famous for smaller models such as Bert [5], RoBERTa [359], etc, whereas LLMs are either decoder-only [8], [100], [9] or encoder-decoder [11], [12], [107]. While decoder-only models are good at NLG tasks, various LLMs, PaLM [14], OPT [10], GPT-3 [8], BLOOM [9], LLaMA [140], are decoder-only models with significant performance gains on both NLU and NLG tasks. In contradiction to this, T5 [11] and UL2 [15] identify encoder-decoder models out-performing decoder-only models. In another study, PaLM [14] finds increasing the size of decoder-only models can reduce the performance gap between decoder-only and encoder-decoder architectures.

Although decoder-only architectures have become a trend for LLMs, many recently proposed approaches [15], [107] use mode-switching tokens in text with encoder-decoder architectures to enable task-specific modes. Similarly, CodeT5+ [122] uses an encoder-decoder architecture with multiple training objectives for different tasks, activating the encoder, decoder, or both according to the tasks. These variations in architecture and training objectives allow a model to perform well in different settings. Because of this dynamic configuration, the future of LLMs can be attributed to encoder-decoder architectures.

VIII. Conclusion

This paper has reviewed various LLMs, discussing the pros and cons of multiple models. Our review concluded significant findings and provided a detailed analysis of the design aspects of each LLM, including architecture, datasets, and training pipelines. We have identified crucial architectural components and training strategies employed by different LLMs and presented a summary and discussion. Moreover, we have compared the performance of LLMs in zero-shot and few-shot settings, explored the impact of fine-tuning, and compared supervised vs generalized models, and encoder vs decoder vs encoder-decoder architectures. This paper will serve as a valuable resource for researchers, offering insights into the recent advancements in LLMs and providing fundamental concepts and details to develop improved LLMs.

IX. Versioning

We keep track of the versions of this paper we release as the content updates.

Version 1.0: We covered 30 pre-trained models and 6 instruction-tuned models, including their overview, findings, training, and evaluation datasets, and discussed important architectural and training tricks by various LLMs.

Version 1.1: Further pre-trained LLMs added along with discussion on on self-instruct LLMs. Categorized LLMs according to the application, provided descriptions of widely used evaluation datasets, added a section on robotics, and extended discussion in section VII. Tables have been updated.

Version 1.2: Added sections on Alignment tuning and multimodal LLMs. A performance comparison table on various benchmarks and datasets. Added LLaMA-2 and PaLM-2.

Note: If you find any mistakes, or have issues and conflicts with the writing in this paper, please email us. We welcome suggestions to improve this paper.

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