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Compare Large Language Models abilities using different parameters

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Chapter 1

Introduction to Large Language Models

1.1 Definition and Overview

In the contemporary landscape of artificial intelligence, Large Language Models (LLMs) stand out as monumental achievements, revolutionising natural language processing. These models, characterised by their immense scale and complexity, have become pivotal in understanding and generating human-like text. At their core, LLMs are designed to comprehend, learn, and generate coherent and contextually relevant language on an unparalleled scale.

Historically, the development of Language Models (LMs) has been rooted in the quest to understand and replicate human language, and four main stages can be identified:

1. **Statistical Language Models:** These models were developed to capture the statistical properties of language, such as word frequencies and co-occurrences, to predict the likelihood of a given sequence of words based on the Markov assumption, which states that the probability of a word depends only on the previous n words. If the context length n is fixed, the model is called an n-gram model.
   However, these models are limited by the exponential number of transition probabilities to be estimated and the Markov assumption, which may not always hold true in the complexity of natural languages. Language understanding often involves capturing dependencies over longer distances than the Markov assumption allows. Models considering broader contexts, such as recurrent neural networks (RNNs) and transformers, have been developed to address these long-range dependencies in language processing tasks.

2. **Neural Language Models:** The advent of neural networks led to the development of language models that utilised neural architectures to capture language's complex patterns and dependencies. These models, such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, could capture long-range dependencies and contextual information, enabling them to generate coherent and contextually relevant text. Bengio et al. [6] introduced the concept of *distributed representation* of words and built the word prediction function of the distributed word vectors. Later, word2vec [18, 19] introduced the word2vec model, a shallow, two-layer neural network trained to reconstruct the linguistic contexts of words. These models were a significant leap forward in the development of language models, representing a shift from word sequencing to learning representation.

3. **Pre-trained language models (PLM):** The development of pre-trained language models (PLMs) marked a significant milestone in the evolution of language models. These

models were trained on large data corpora in an unsupervised or self-supervised manner before being fine-tuned on specific tasks. The idea is to pre-train a model on a diverse data set and then transfer its knowledge to a narrower task by fine-tuning it on a smaller, task-specific dataset. ELMo [1] [46] was one of the first PLMs which used a bidirectional LSTM to generate word embeddings instead of learning fixed word representations. Devlin et al. [61] introduced BERT (Bidirectional Encoder Representations from Transformers), a transformer-based model pre-trained on a large corpus of text and then fine-tuned it on specific tasks. BERT was a significant advancement in natural language processing, as it demonstrated the potential of pre-trained language models to achieve state-of-the-art performance on a wide range of tasks. These studies introduced the *"pre-training and fine-tuning"* paradigm, which has become a standard practice in the development of language models and inspired a significant number of models, such as GPT-2 [70]), GPT-3 (Brown et al. [83]), T5 (Raffel et al. [94], and many others.

4. **Large Language Models (LLM):** The emergence of large language models, characterised by their immense scale and complexity, has redefined the capabilities of language processing systems. Studies find that language models' performance improves as the number of parameters (e.g., model size) or data size increases, a phenomenon known as the scaling law in large language models. Many LLMs are built on the transformer architecture, designed to capture long-range dependencies and contextual information in language. The transformer architecture has become the foundation for many state-of-the-art language models. Unlike earlier models that were unidirectional (e.g., traditional RNNs), LLMs, especially those based on transformers, are bidirectional. They consider the context from preceding and following words, enhancing their language understanding. LLMs find applications across various domains, including but not limited to:

   - **Text Generation:** Producing coherent and contextually relevant text.
   - **Question Answering:** Answering questions based on provided context.
   - **Language Translation:** Translating text from one language to another.
   - **Summarization:** Creating concise summaries of longer texts.
   - **Sentiment Analysis:** Determining the sentiment expressed in a text.

   These large-sized PLMs have been shown to outperform their smaller (e.g., 330M-parameters vs 1.5B-parameters) and show surprising capabilities [2], also called emergent abilities by Wei et al. [225].

   > Emergence is when quantitative changes in a system result in qualitative changes in behavior [1].

   These emergent abilities include, but are not limited to, the ability to perform tasks for which they were not explicitly trained, such as translation, summarisation, and question-answering, and to generalise to new tasks and domains, such as zero-shot learning [3], few-shot learning [4], and even one-shot learning [5] learning[6]. Three typical examples of emergent abilities are:

[1] Embeddings from Language Models

[2] Note that a LLM is not necessarily more capable than a small PLM, and emergent abilities may not occur in some LLMs.

[3] It refers to a machine learning scenario where a model makes predictions or performs tasks for classes or examples it has never seen during training

[4] It involves training a model with a minimal number of examples per class, usually much fewer than what traditional machine learning models require

[5] It is a specific case of few-shot learning where the model is trained with only one example per class

[6] A shot is an example or demonstration of what type of prompt and response you expect from a large

(a) **In-context learning:** this ability has been formally observed in GPT-3, which is provided with a natural language instruction or task demonstrations; it can generate the expected output for test instances by completing the word sequence of the input text. Importantly, this can be achieved without requiring additional training or gradient updates [7].

Language Translation:
Input: "Translate the following English text to French: 'The quick brown fox jumps over the lazy dog.'"
Output: "Le renard brun rapide saute par-dessus le chien paresseux."
Arithmetic Tasks:
Input: "What is the sum of 42 and 63?"
Output: "The sum of 42 and 63 is 105."

(b) **Instruction following:** Through the process called instruction tuning – that we will see more in-depth in Section 2.3.1 – LLMs exhibit strong performance on unseen tasks described through natural language instructions [203, 199, 224]. This approach involves fine-tuning the model using diverse multitask datasets, each accompanied by detailed natural language descriptions. The result is an LLM that effectively interprets and follows task instructions for new and unseen tasks without relying on explicit examples, thereby showcasing enhanced generalisation capabilities. Experiments detailed in Wei et al. [224] demonstrate that LaMDA-PT, fine-tuned with instructions, begins to outperform its untuned counterpart significantly when the model size reaches 68 billion parameters. However, this performance gain is not observed for 8 billion or smaller model sizes. Furthermore, recent research [150] highlights that a model size of at least 62 billion parameters is necessary for PaLM to excel across various tasks in evaluation benchmarks like MMLU, BBH, TyDiQA, and MGSM. Nevertheless, it is noted that certain specific tasks, such as MMLU, might suffice with a much smaller model size, emphasising the nuanced relationship between model size and task performance.

(c) **Step-by-step reasoning:** For small LMs, it is usually difficult to solve complex tasks that involve multiple reasoning steps (e.g., mathematical word problems). In contrast, the chain-of-thought (CoT) prompting strategy [223] empowers Large Language Models (LLMs) to surmount these challenges. By leveraging the CoT prompting mechanism, which involves intermediate reasoning steps to derive the final solution, LLMs exhibit proficiency in tasks requiring intricate cognitive processes. This capability is speculated to be honed through training on code by Wei et al. [223]. Empirical findings in Wei et al. [223] demonstrate that the employment of CoT prompting yields performance gains, particularly on arithmetic reasoning benchmarks when applied to variants of models like PaLM and LaMDA, especially with a model size surpassing 60B. The advantages of CoT prompting become more pronounced as the model size exceeds 100B. Furthermore, the effectiveness of CoT prompting exhibits variability across different tasks, with performance improvement observed in the order of GSM8K > MAWPS > SWAMP for PaLM [223].

The advent of LLMs has led to a paradigm shift in the field of natural language processing, with applications ranging from machine translation to text summarisation and from question-answering systems to language generation. The development of LLMs has been driven by the

language model. This term originates from training computer vision models on photographs, where one shot was one example or instance that the model used to classify an image [11].

[7] Recent study shows that in-context learning implicitly performs meta optimisation through the attention mechanism [152]

exponential growth of data and computational resources, which has enabled the training of models with billions of parameters. The scale of these models has enabled them to capture complex patterns in language and generate coherent and contextually relevant text.

The potential of LLMs is vast, and their impact on natural language processing is profound. The advent of ChatGPT [81] and GPT-4 [345] has further expanded the capabilities of LLMs, leading to the rethinking of the possibilities of artificial general intelligence (AGI).

Regarding NLP, LLMs can serve somewhat as general-purpose language task solvers. In the IR field, LLMs can be used to improve the performance of information retrieval systems through AI chatbots (i.e., ChatGPT) and New Bing [8]. In the CV field, LLMs can be used to improve the performance of computer vision systems through multimodal models /footnote Models are designed to process and understand information from multiple modalities or sources (e.g., text, image, audio, video). Multimodal models aim to handle and integrate data from two or more modalities. (i.e., CLIP[9] [124] and DALL-E [126]).

This work will mainly focus on model sizes larger than 10B parameters to explore their capabilities, limitations, and potential applications. We will delve into the emergent abilities of LLMs, such as in-context learning, instruction following, and step-by-step reasoning, and how these abilities can be leveraged to solve complex tasks in Chapter 3. The study will investigate and compare the abilities of different LLMs, focusing on the impact of various parameters on their performance.

1.2 Scaling Law

The Scaling Law in LLMs constitutes a fundamental principle underlining their development and performance. At its essence, the scaling law posits that as language models increase in size, their capabilities and performance on linguistic tasks exhibit disproportionately positive growth. This concept has become a guiding force in pushing the boundaries of language processing and understanding.

As LLMs scale up in terms of parameters, encompassing tens or hundreds of billions, or even trillions, of parameters, they demonstrate an unprecedented ability to generalise from diverse datasets and generate contextually coherent text. The essence of the scaling law lies in the direct correlation between the size of a language model and the number of parameters it encompasses. Parameters are the internal variables the model learns during training, representing the connections and weights defining its understanding of language. As the number of parameters increases, so does the model's capacity to encapsulate complex linguistic structures.

One of the primary outcomes of adhering to the scaling law is the substantial improvement in performance across a spectrum of language-related tasks. From language generation to sentiment analysis, question-answering, and summarisation, larger models consistently outperform their smaller counterparts. The increased capacity for learning intricate language features enables LLMs to excel in understanding and producing more human-like text.

When writing, most of the LLMs are based on the transformer architecture, where multi-headed self-attention layers are stacked in a very deep neural network. We'll dive deep into the transformer architecture in Section 2.4.4, but for now, we can say that self-attention is a mechanism that allows a model to weigh different parts of the input sequence differently, capturing dependencies between words. The multi-headed self-attention mechanism lets the model capture different dependencies and relationships between words, enhancing language understanding. The idea is that different attention heads can focus on different aspects or relationships within the data, allowing the model to capture more nuanced patterns. Multi-

[8] https://www.microsoft.com/it-it/bing?form=MA13FV

[9] Contrastive Language–Image Pre-training

ple layers of these multi-headed self-attention mechanisms are stacked in a very deep neural network. Each layer in the stack processes the previous layer's output, learning hierarchical representations of the input data and capturing increasingly complex relationships and abstractions.
Two representative scaling laws for Transformer-based LLMs are the following [88, 166]:

1. **KM scaling law:** named in this way in Zhao et al. [335] and proposed by the OpenAI team in Kaplan et al. [88]. Given model size M, dataset size D, amount of training compute C, and a compute budget c, the KM scaling law states that the performance of a language model scales as per the following three formulas:

$$\begin{aligned} L(N) &= (\frac{N_c}{N})^{\alpha_N}, \alpha_N \approx 0.076, N_c \approx 8.8 \times 10^{13} \\ L(D) &= (\frac{D_c}{D})^{\alpha_D}, \alpha_D \approx 0.095, D_c \approx 5.4 \times 10^{13} \\ L(C) &= (\frac{C_c}{C})^{\alpha_C}, \alpha_C \approx 0.050, C_c \approx 3.1 \times 10^{8} \end{aligned} \tag{1.1}$$

   where $L(N)$, $L(D)$, and $L(C)$ denote the cross-entropy loss of the model, the dataset, and the amount of training computed, respectively. The three laws were formulated by analysing the model's performance across a range of data sizes (from 22M to 23B tokens), model sizes (from 768M to 1.5B non-embedding parameters), and training compute, with certain assumptions (e.g., ensuring that the other two factors do not constrain the analysis of one factor). The findings demonstrated a robust interdependence among the three factors influencing model performance.

2. **Chinchilla scaling law:** An alternative form of the scaling law has been proposed by the Google DeepMind team in Hoffmann et al. [166] experimenting with an extensive range of model size (70M to 16B) and data sizes (5B to 500B tokens). The Chinchilla scaling law posits that the performance of a language model scales as per the following formula:

$$L(N, D) = E + \frac{A}{N^{\alpha}} + \frac{B}{D^{\beta}}, \tag{1.2}$$

   where $E = 1.69, A = 406.4, B = 410.7, \alpha = 0.34, \beta = 0.28$

   Authors showed that optimal allocation of compute budget to model size and data size can be derived as follows [10]:

$$N_{opt}(C) = G(\frac{C}{6})^{a}, D_{opt}(C) = G^{-1}(\frac{C}{6})^{b}, \tag{1.3}$$

   where $a = \frac{\alpha}{\alpha+\beta}, b = \frac{\beta}{\alpha+\beta}$ and G is a scaling coefficient. The KM scaling law favours a more significant budget allocation in model size than the data size. In contrast, the Chinchilla scaling law argues that the two sizes should be increased in equal scales [166] (i.e., having similar values for a and b in (1.3)).

[10] under the constraint $C \approx 6ND$

Scaling boosts performance and addresses inherent limitations in smaller language models. Larger models excel in managing long-range dependencies, comprehending ambiguous language constructs, and displaying a nuanced understanding of context—capabilities that smaller models frequently find challenging. The eliciting of emergent abilities, such as Chain-of-Thought prompting and in-context learning, have shown a phase change in the first Scaling Law, where the performance increases linearly as the model size increases exponentially (Figure 1.1).

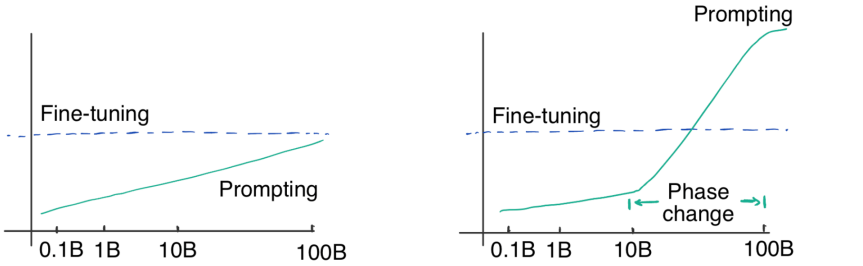

Figure 1.1: *Left: scaling law. Model performance increases linearly as the model size increases exponentially. Right: emergent abilities show a phase change at a certain scale where the performance suddenly increases. Source: Fu [253].*

Despite propelling the field of LLMs to new heights, the scaling law comes with computational challenges. Training huge models requires significant computational resources, encompassing processing power and memory. This presents practical obstacles, demanding innovations in hardware and distributed training techniques to exploit the potential of scaled-up language models fully.

1.3 Prominent Model Families

The development of Large Language Models (LLMs) has been driven by the emergence of prominent model families, each characterised by its unique architecture and capabilities. These model families have played a pivotal role in shaping the landscape of language processing and understanding and have been instrumental in pushing the boundaries of LLMs.

Some of the most prominent large language models (having a size larger than 10B) are depicted in Figure 1.2.

1.3.1 BERT

Introduced by Google in 2018, BERT [61] marked a significant evolution in LLMs by focusing on bidirectional context in text processing. BERT's model architecture is a multi-layer bidirectional Transformer encoder based on the original transformer architecture introduced by Vaswani et al. [308]. Unlike its predecessors, BERT analyses text in both directions (left-to-right and right-to-left), providing a more nuanced understanding of language context. This bi-directionality enables BERT to achieve state-of-the-art results in various NLP tasks, such as question answering, named entity recognition, and sentiment analysis. BERT's architecture and training methodology have influenced numerous subsequent models and research initiatives [61].

Even BERT is built on the transformer architecture [308], which relies heavily on attention mechanisms to understand the context of words in a sentence. The innovation in BERT is its bidirectional nature and the use of a mechanism called the Masked Language Model (MLM). In MLM, some percentage of the input tokens are randomly masked, and the objective is to

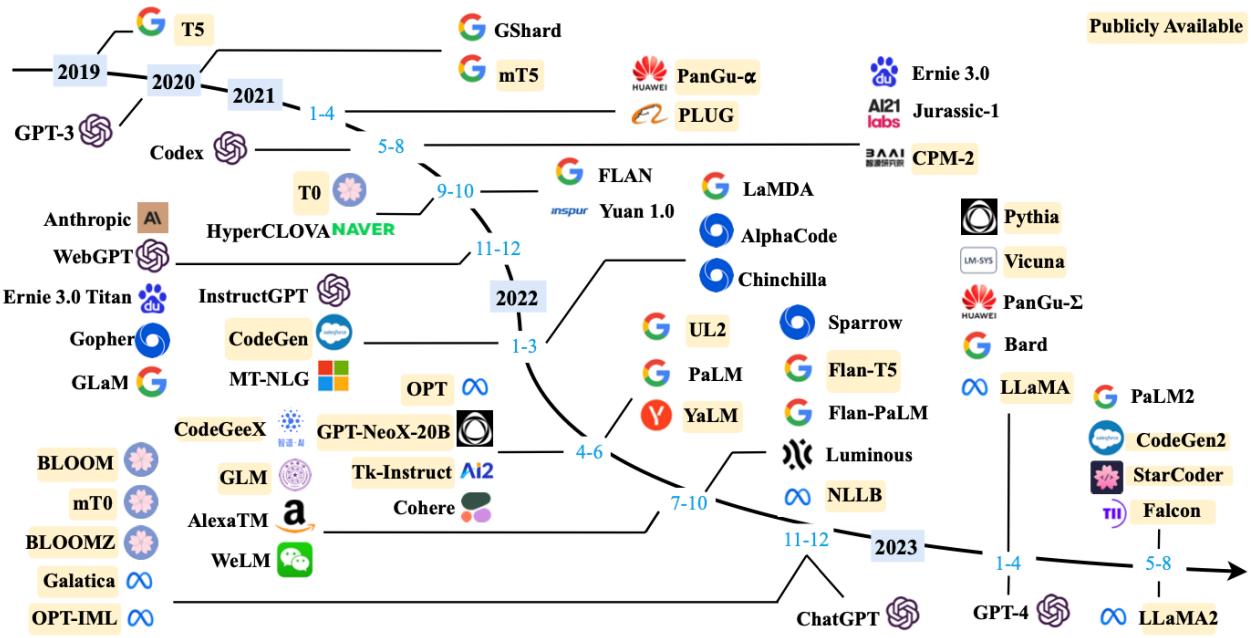

Figure 1.2: *A diagram showing the evolution of publicly available LLMs. Source: Zhao et al. [335].*

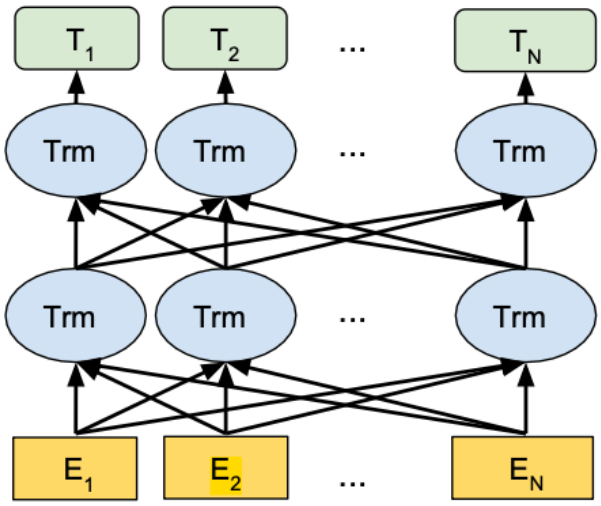

Figure 1.3: *BERT Architecture: The bottom layer contains the embedding representations $E_1, E_2, \ldots E_N$, which encode input tokens and serve as the input to the transformer layers (Trm). Each transformer bidirectionally processes the input embeddings, and the final output is used for downstream tasks. Source: Devlin et al. [61].*

predict these masked tokens based on their context, leveraging information from both sides of the sequence. BERT also incorporates a next-sentence prediction (NSP) task that helps the model learn relationships between sentences, further enhancing its understanding of context.

BERT's bidirectional context understanding significantly improves its performance on various NLP tasks, including sentiment analysis, question answering, and named entity recognition. By pre-training on a large corpus of text and then fine-tuning on specific tasks, BERT can adapt to various domains with relatively little task-specific data, demonstrating impressive transfer learning capabilities. Its architecture has set a new standard in the field, inspiring many subsequent models that build on or modify its foundational structure.

Despite its strengths, BERT is not without limitations. The model's size and complexity require substantial computational resources for training, which can be a barrier for some organisations or researchers. BERT's focus on context from surrounding text does not inherently solve all challenges in language understanding, particularly concerning ambiguity, nuance, or the subtleties of human language. The model can sometimes struggle with tasks requiring extensive world knowledge or reasoning beyond the scope of its training data.

While BERT itself does not exhibit emergent abilities in the same way that scaling up GPT models does, its architecture has enabled new approaches to handling context and language understanding that were not feasible with prior models. Subsequent iterations and variations of BERT, like RoBERTa[11] and ALBERT[12], have sought to optimise and expand upon BERT's foundational principles, exploring how changes in model size, training methodology, and architecture can influence performance and capabilities.

1.3.2 T5

Developed by Google in 2019, T5 [13] re-framed all NLP tasks as a unified text-to-text problem, where every task is cast as generating text from input text. This approach simplifies using a single model across diverse tasks, encouraging a more generalised understanding of language.

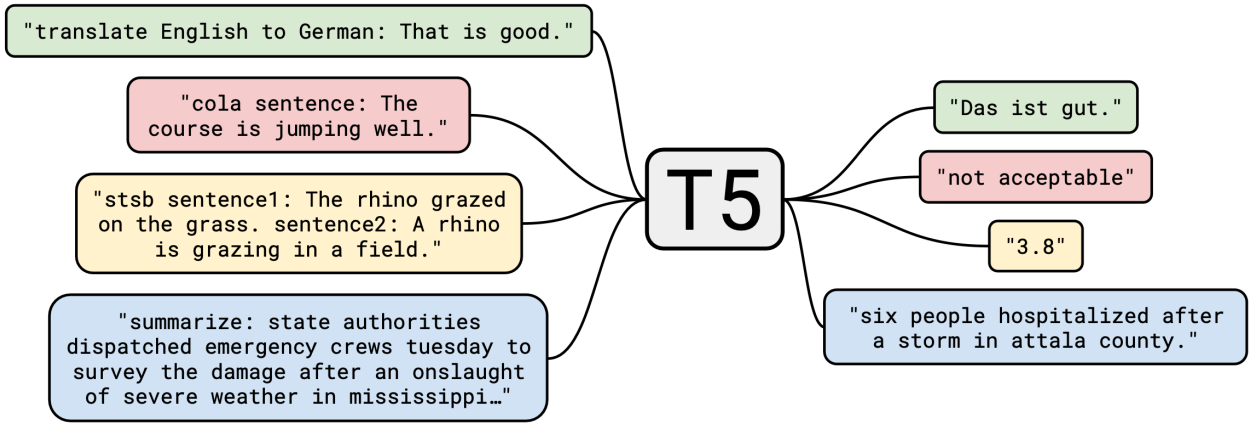

Figure 1.4: *A diagram of the T5 text-to-text framework. Every task – including translation, question answering, and classification – is cast as feeding the model text as input and training it to generate some target text. This allows the same model, loss function, hyperparameters, etc., to be used across diverse tasks. Source: Raffel et al. [94].*

T5 demonstrated its prowess across a range of benchmarks, setting new standards in the field of NLP [94]. It's built on the transformer model, similar to its predecessors, BERT and GPT. It leverages the effective self-attention mechanism for processing sequences of data. The model is designed to handle various tasks without needing task-specific architectural modifications. It uses a unified text-to-text framework, where tasks are converted into a format where the input and output are always text strings. T5 is pre-trained on a multitask mixture of unsupervised and supervised tasks, utilising a large-scale dataset known as "C4" [14].

T5's approach simplifies integrating new tasks into the model's training regime, as they only need to be reformulated into the text-to-text format. While T5's unified approach offers considerable advantages, it might not be optimal for all types of tasks. Some tasks could potentially

[11] Robustly Optimized BERT Pre-training Approach
[12] A Lite BERT
[13] Text-to-Text Transfer Transformer
[14] Colossal Clean Crawled Corpus

benefit from more specialised model architectures or formats. The training process for T5 is resource-intensive, requiring substantial computational power, which could be a limiting factor for smaller organisations or independent researchers. As with other large language models, T5's outputs can sometimes include biases in the training data, necessitating careful monitoring and potential post-hoc adjustments.

1.3.3 GPT Series

Developed by OpenAI, the GPT series has been at the forefront of LLM research. The original GPT model, introduced in 2018, laid the groundwork with its transformer-based architecture, which significantly improved upon previous models in understanding context and generating text. It was developed based on a generative, decoder-only Transformer architecture, and it adopted a hybrid approach of unsupervised pre-training and supervised fine-tuning.

GPT-2 [70], released in 2019, expanded on this with 1.5 billion parameters and was trained with a large webpage dataset, WebText, demonstrating unprecedented text generation capabilities.

The subsequent GPT-3 model, unveiled in 2020, further pushed the boundaries with 175 billion parameters, showcasing remarkable abilities in generating human-like text, performing language translation, question-answering, and more without task-specific training. In the research paper on GPT-3 [83], the authors explained the concept known as in-context learning (ICL). This approach enables Large Language Models (LLMs) to function in few-shot or zero-shot scenarios. ICL empowers LLMs to comprehend tasks when they are described using natural language. This method aligns the pre-training and application phases of LLMs under a unified framework. During pre-training, the model predicts subsequent text sequences based on the prior context. In contrast, during in-context learning, the model generates the appropriate solution to a task in the form of a text sequence using the provided task instructions and examples.

The GPT series is based on the transformer architecture by Vaswani et al. [308]. This architecture leverages self-attention mechanisms to process input data, which allows the model to weigh the importance of different words within the input context, enhancing its ability to understand and generate language. GPT models are characterized by their stacked transformer blocks consisting of multi-headed self-attention layers followed by fully connected feed-forward neural networks. The series has seen an exponential increase in the number of parameters: GPT with 110 million, GPT-2 with 1.5 billion, and GPT-3 with 175 billion parameters.

GPT models exhibit a remarkable ability to generate coherent and contextually relevant text, simulating human-like writing styles. They demonstrate strong performance in a wide array of NLP tasks without task-specific data training, showcasing their versatility in few-shot, one-shot, or zero-shot learning scenarios. The architecture's scalability has shown that larger models tend to exhibit better performance and capture subtler patterns in data.

One significant criticism is their data-hungry nature, requiring vast amounts of text data for training, which raises concerns about environmental impact and computational costs. The models can sometimes generate plausible but factually incorrect or nonsensical information, a phenomenon often referred to as "hallucination". The black-box nature of these models poses challenges in interpretability and transparency, making it difficult to understand how decisions are made or how to correct biases.

GPT-3 demonstrated surprising emergent behaviours, such as improved reasoning, problem-solving, and creative writing, which were not explicitly programmed or observed in their predecessors. These abilities suggest that scaling up model size can lead to qualitative changes in how models understand and interact with language, although the relationship is not yet fully understood. OpenAI has explored two major approaches to further improving the GPT-3

model, i.e., training on code data and alignment with human preference, which are detailed as follows:

1. **Training on code data:** This approach involves fine-tuning the model on a diverse set of programming tasks, such as code completion, code generation, and code summarization. The model is trained on a large corpus of code data, which includes code snippets, programming languages, and software development documentation. The goal is to improve the model's understanding of programming languages and its ability to generate code, thereby enhancing its performance on programming-related tasks.

2. **Alignment with human preference:** This approach involves training the model to generate outputs that align with human preferences and values and can be dated back to a work that applied reinforcement learning (RL) Christiano et al. [34] (similar to the reward training step in the aligning algorithm of InstructGPT.

GTP-4

GPT-4 [345], the successor to GPT-3, marks a further advancement in the GPT series developed by OpenAI. While specific details about GPT-4's architecture and capabilities are proprietary, it is known to build upon the foundational concepts of its predecessors, emphasizing scale, capability, and efficiency. GPT-4 is a multimodal model which can accept image and text inputs and produce text outputs. Such models are an important area of study as they have the potential to be used in a wide range of applications, such as dialogue systems, text summarization, and machine translation.

On the MMLU benchmark [108], an English-language suite of multiple-choice questions covering 57 subjects, GPT-4 not only outperforms existing models by a considerable margin in English but also demonstrates strong performance in other languages. GPT-4 development was enabled by deep learning infrastructure and optimization methods that behave predictably across a wide range of scales. This allowed making predictions about the expected performance of GPT-4 (based on small runs trained in similar ways) that were tested against the final run to increase confidence in our training. The primary reason is that extensive model-specific tuning is not feasible for very large training runs.

The prediction GPT-4's final loss was predicted by fitting a scaling law with an irreducible loss term (as in Henighan et al. [85]):

$$L(C) = aC^b + c \tag{1.4}$$

from models trained using the same methodology but using at most 10,000x less compute than GPT-4. The fitted scaling law predicted GPT-4's final loss with high accuracy. In addition to predicting the final loss, a metric of capability was also predicted. One such metric is the pass rate on HumanEval dataset [103], which measures the ability to write Python functions of various complexity. The approximate power law relationship is

$$E_P[\log pass\_rate(C)] = \alpha \times C^{-k} \tag{1.5}$$

where k and α are positive constants, and P is a subset of problems in the dataset.

GPT-4 accepts prompts consisting of both images and text, which lets the user specify any vision or language task in parallel to the text-only setting. Specifically, the model generates text outputs, given inputs consisting of arbitrarily interlaced text and images.

Despite its capabilities, GPT-4 has similar limitations to earlier GPT models: it is not fully reliable (e.g. can suffer from "hallucinations"), has a limited context window, and does not learn from experience.

User	What is funny about this image? Describe it panel by panel. 
GPT-4	The image shows a package for a "Lightning Cable" adapter with three panels. Panel 1: A smartphone with a VGA connector (a large, blue, 15-pin connector typically used for computer monitors) plugged into its charging port. Panel 2: The package for the "Lightning Cable" adapter with a picture of a VGA connector on it. Panel 3: A close-up of the VGA connector with a small Lightning connector (used for charging iPhones and other Apple devices) at the end. The humour in this image comes from the absurdity of plugging a large, outdated VGA connector into a small, modern smartphone charging port.

Table 1.1: *Example prompt demonstrating GPT-4's visual input capability. The prompt consists of a question about an image with multiple panels, which GPT-4 is able to answer*

Care should be taken when using the outputs of GPT-4, particularly in contexts where reliability is important.

1.3.4 LLaMA

LLaMA [15] is a language model developed by Meta AI, designed to be a versatile and efficient foundation for a wide range of natural language processing (NLP) tasks. LLaMA is built on a transformer architecture [308], similar to other large language models, with a range from 7B to

[15] Large Language Model Meta AI

65B parameters. Main differences between LLaMA and original Transformer architecture [308] are the following:

1. **Pre-normalization**[16] LLaMA uses pre-normalization[17], which means that the normalization layer is placed before the self-attention and feed-forward layers. Pre-normalization has been shown to improve training stability and convergence in large language models, making it a popular choice for many state-of-the-art models.

2. **SwiGLU activation function**[18] LLaMA uses the SwiGLU[19] activation function by Shazeer [95], which is a variant of the Gated Linear Unit (GLU) activation function. SwiGLU has been shown to improve the performance of large language models by enhancing the flow of information through the network.

3. **Rotary Embeddinsgs**[20] LLaMA uses rotary embeddings by Su et al. [128], which are a type of positional encoding that helps the model capture long-range dependencies in the input data.

params	dimension	n heads	n layers	learning rate	batch size	n tokens
6.7B	4096	32	32	3.0×10^{-4}	4M	1.0T
13.0B	5120	40	40	3.0×10^{-4}	4M	1.0T
32.5B	6656	52	60	1.5×10^{-4}	4M	1.4T
65.2B	8192	64	80	1.5×10^{-4}	4M	1.4T

Table 1.2: *Model sizes, architectures, and optimization hyper-parameters. Source: Touvron et al. [306].*

Based on the LLaMA paper by Touvron et al. [306], even though LLaMA-13B is smaller than many competitors, it outperforms GPT-3 on most benchmarks, and the 65B model is competitive with the best large language models available, such as Chinchilla and PaLM-540B, despite being x10 smaller (as shown in Table 1.3).

Model	Params	BoolQ	PIQA	SIQA	HellaSwag	WinoGrande	ARC-e	ARC-c	OBQA
GPT-3	175B	60.5	81.0	-	78.9	70.2	68.8	51.4	57.6
Gopher	280B	79.3	81.8	50.6	79.2	70.1	-	-	-
Chinchilla	70B	83.7	81.8	51.3	80.8	74.9	-	-	-
PaLM	62B	84.8	80.5	-	79.7	77.0	75.2	52.5	50.4
PaLM-cont	62B	83.9	81.4	-	80.6	77.0	-	-	-
PaLM	540B	88.0	82.3	-	83.4	81.1	76.6	53.0	53.4
LLaMA	7B	76.5	79.8	48.9	76.1	70.1	72.8	47.6	57.2
LLaMA	13B	78.1	80.1	50.4	79.2	73.0	74.8	52.7	56.4
LLaMA	33B	83.1	82.3	50.4	82.8	76.0	80.0	57.8	58.6
LLaMA	65B	85.3	82.8	52.3	84.2	77.0	78.9	56.0	60.2

Table 1.3: *Zero-shot performance on Common Sense Reasoning tasks. Source: Touvron et al. [306].*

The LLaMA models were trained exclusively on publicly available data, setting them apart from other models that rely on proprietary datasets [21]. LLaMA models were designed with

[16] Inspired by GTP-3 model
[17] See Section 2.4.4
[18] Inspired by PaLM model
[19] See Section 2.4.4
[20] Inspired by GPTNeo model
[21] Such as "Books — 2TB" or "Social media conversations"

efficiency in mind, both in training and inference, allowing even the 13B parameter model to run on a single GPU. We report a synthetic view of the LLaMA model family parameters in Table 1.2.

Touvron et al. [306] acknowledges the presence of biases and toxicity in the models due to the nature of web data and evaluates these aspects using benchmarks from the responsible AI community.

1.3.5 Gemma

The recent development in the domain of Natural Language Processing has seen Google's introduction of a new family of models named Gemma [339, 346]. Derived from the same research lineage as the renowned Gemini models, Gemma is a testament to the rapid advancements in lightweight, high-performance language models designed for a broad spectrum of computational environments.

Gemma is built upon a transformer-based architecture by Vaswani et al. [308], optimized to deliver state-of-the-art performance with a fraction of the parameter count typically seen in large language models (LLMs). Notable enhancements include the adoption of Multi-Query Attention, RoPE embeddings, GeGLU activations, and RMSNorm, indicating an evolution of the original transformer architecture. The family comprises two main configurations: Gemma 2B and Gemma 7B, available in pre-trained and instruction-tuned variants. The design philosophy targets efficient deployment across diverse hardware platforms, including but not limited to mobile devices, laptops, desktop computers, and servers.

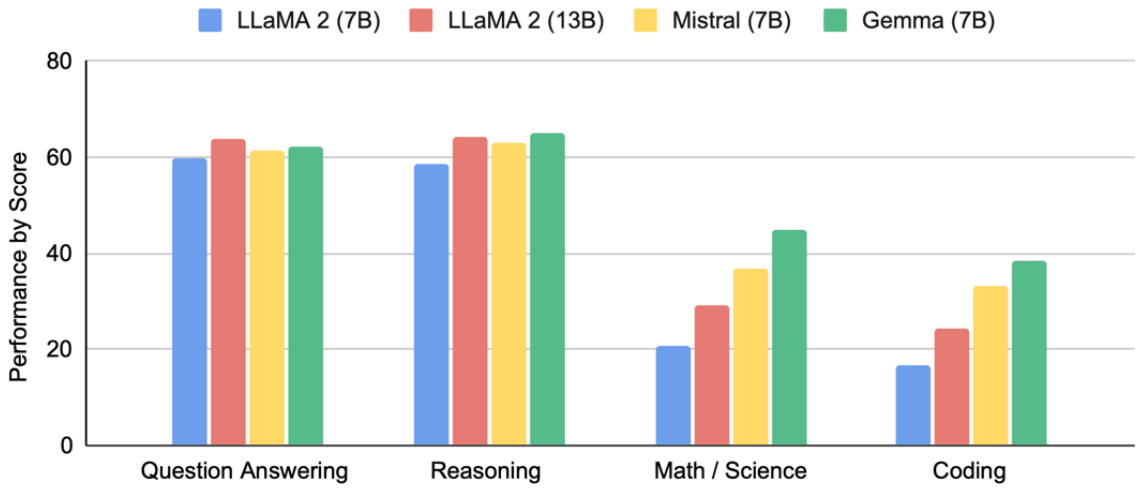

Figure 1.5: *Gemma models exhibit superior performance in language understanding and reasoning tasks compared to larger models. Source: Team et al. [346].*

In comparative benchmarks, Gemma models have demonstrated capabilities that exceed those of larger parameter models, such as LLaMA-2 (13B), indicating a significant efficiency in parameter utilization. This is particularly evident in language understanding and reasoning tasks where Gemma models have been pitted against their contemporaries.

One of the prominent strengths of Gemma models is their deployment efficiency, which democratizes access to state-of-the-art NLP tools. The models are designed to be run on common developer hardware, eschewing the need for specialized AI accelerators.

Despite their efficiencies, the Gemma models are not without limitations. The reduced parameter count, while advantageous for accessibility and computational efficiency, may impact performance in complex NLP tasks that can benefit from larger models. Additionally,

Figure 1.6: *Gemma models are designed to be lightweight and efficient, making them accessible to a wide range of developers and applications. Source: Banks and Warkentin [339].*

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ethical considerations, such as bias in language models, remain an area of concern and active development.

Google has emphasized the responsible development of AI, which is evident in Gemma's design. Techniques to mitigate sensitive data inclusion and reinforcement learning from human feedback are incorporated to ensure the models' outputs adhere to safety standards. Moreover, Google's release includes a Responsible Generative AI Toolkit to aid developers in prioritizing the creation of ethical AI applications.

1.4 Specialized Large Language Models

Specialized Large Language Models (LLMs) are model checkpoints refined for particular fields or tasks, such as healthcare and finance. The existing domain-specific models are developed by fine-tuning general-purpose LLMs on specialized datasets [185, 243, 214]) by adapting a very large general-purpose model to domain-specific tasks (Singhal et al. [207] and Liang et al. [179]) or mixing both approaches (Wu et al. [323]. These models serve as domain-specific problem solvers and are evaluated based on general competencies, such as fundamental complex reasoning, and more nuanced capabilities, like alignment with human intent, as well as their performance in areas specific to their application. To accurately measure their efficacy, specialized benchmarks are developed that cater to these distinct sectors. These tailored benchmarks are then employed in conjunction with broader assessments to provide a holistic and focused evaluation of the models' capabilities. The following sections highlight some of the key applications of LLMs and their impact on different sectors, from healthcare to finance, and from education to research.

1.4.1 LLMs in Healthcare

The intersection of artificial intelligence (AI) and healthcare has precipitated unparalleled advances in the provision of medical services, diagnosis, treatment, and patient care. Central to these advancements are Large Language Models (LLMs), which have been instrumental in catalyzing transformative changes across the healthcare sector:

1. **Medical image analysis:** Large Language Models (LLMs) have been integrated with medical imaging technologies to enhance diagnostic accuracy and efficiency. By analyzing radiological images and clinical reports, LLMs can assist radiologists in interpreting images, identifying abnormalities, and providing diagnostic insights. These models leverage their natural language processing capabilities to extract information from textual reports and correlate it with visual data, thereby augmenting the diagnostic process [115, 134].

2. **Clinical Decision Support:** LLMs have been pivotal in augmenting clinical decision support systems (CDSS). By analyzing patient data and medical literature, LLMs assist clinicians in diagnosing conditions, suggesting treatment options, and predicting patient outcomes. For instance, models like BERT and its derivatives have been fine-tuned on medical corpora, yielding tools that can parse clinical notes, interpret lab results, and provide evidence-based recommendations [57].

3. **Medical Documentation and Coding:** The onus of medical documentation and billing has traditionally been a significant administrative burden for healthcare providers. LLMs have demonstrated the ability to streamline these processes by automating the translation of clinical dialogue and notes into structured electronic health records (EHRs) and accurately coding medical procedures, thus mitigating errors and saving time [49].

4. **Drug Discovery and Development:** In the domain of pharmaceuticals, LLMs have expedited the drug discovery and development pipelines. By mining through vast chemical libraries and medical databases, these models facilitate the identification of potential drug candidates and repurposing existing drugs for new therapeutic uses [79].

5. **Personalized Medicine:** Personalized medicine, which tailors treatment to individual patient characteristics, has benefited from LLMs through the generation of patient-specific models that predict disease susceptibility and drug response. This personalization extends to creating tailored health interventions based on patient history and genetic information [13].

6. **Patient Engagement and Self-Management:** LLMs are also revolutionizing patient engagement by powering intelligent virtual health assistants capable of providing information, reminders, and motivational support for chronic disease self-management. These AI assistants interact with patients in natural language, thus fostering an environment conducive to patient education and adherence to treatment regimens [66].

Despite these strengths, LLMs face significant challenges within healthcare applications. Concerns regarding patient privacy, data security, and the need for explainability in AI-driven decisions are paramount [39]. Additionally, biases inherent in training data can perpetuate disparities in patient care, necessitating rigorous validation and fairness assessments before clinical deployment [59].

Large Language Models represent a transformative force in healthcare, enhancing efficiency, accuracy, and personalization in various medical domains. Their integration into clinical practice must be pursued with diligent oversight to navigate ethical considerations and ensure equitable and safe applications.

Med-PaLM

One of the most advanced LLMs for healthcare is Med-PaLM, a derivative of the PaLM (540B) model developed by Google and its instruction-tuned variant, Flan-PaLM. Using a combination of few-shot [83]), chain-of-thought (CoT) (Wei et al. [223]), and self-consistency (Wang et al. [220] prompting strategies, Flan-PaLM achieved state-of-the-art accuracy on every MultiMedQA [22] multiple-choice dataset (MedQA, MedMCQA, PubMedQA, MMLU clinical topics and a newly introduced dataset, HealthSearchQA, which consists of commonly searched health questions).

Model (number of parameters)	MedQA (USMLE) Accuracy %
Flan-PaLM (540 B)	67.6
PubMedGPT (2.7 B)	50.3
DRAGON (360 M)	47.5
BioLinkBERT (340 M)	45.1
Galactica (120 B)	44.4
PubMedBERT (100 M)	38.1
GPT-Neo (2.7 B)	33.3

Table 1.4: *Performance comparison of different models on the MedQA (USMLE) benchmark. Source: Singhal et al. [207].*

Despite these remarkable results, human evaluation reveals key gaps in Flan-PaLM responses and remains inferior to clinicians [207]. To resolve this issue, researchers introduced "instruction tuning"[23] to align the Flan-PaLM model to the medical domain. Instruction tuning can thus be seen as a lightweight way (data-efficient, parameter-efficient, compute-efficient during both training and inference) of training a model to follow instructions in one or more domains. Instruction tuning adapted LLMs to better follow the specific type of instructions used in the family of medical datasets. The result was Med-PaLM, a model that significantly reduces the gap (or even compares favourably) to clinicians on several axes of evaluation, according to both clinicians and lay users.

1.4.2 LLMs in Finance

There has been growing interest in applying NLP to various financial tasks, including sentiment analysis, question answering, and stock market prediction. Despite the extensive research into general-domain LLMs and their immense potential in finance, Financial LLM (Fin-LLM) research remains limited, and the field of financial LLMs is at an early stage [343]. An overview of the evolution of selected PLM/LLM releases from the general domain to the financial domain is shown in Figure 1.8.

Some of these models have demonstrated the potential of LLMs to understand complex financial jargon, generate insights, predict market trends, and enhance customer interaction with unprecedented precision and relevance.

Here are some key applications of LLMs in the financial sector:

[22]Stands for a multi-domain medical question answering benchmark. It has been designed to evaluate the performance of LLMs in the healthcare sector. This benchmark likely encompasses a wide range of medical questions, covering various disciplines, conditions, and scenarios that medical professionals encounter.

[23]See Section 2.3.1

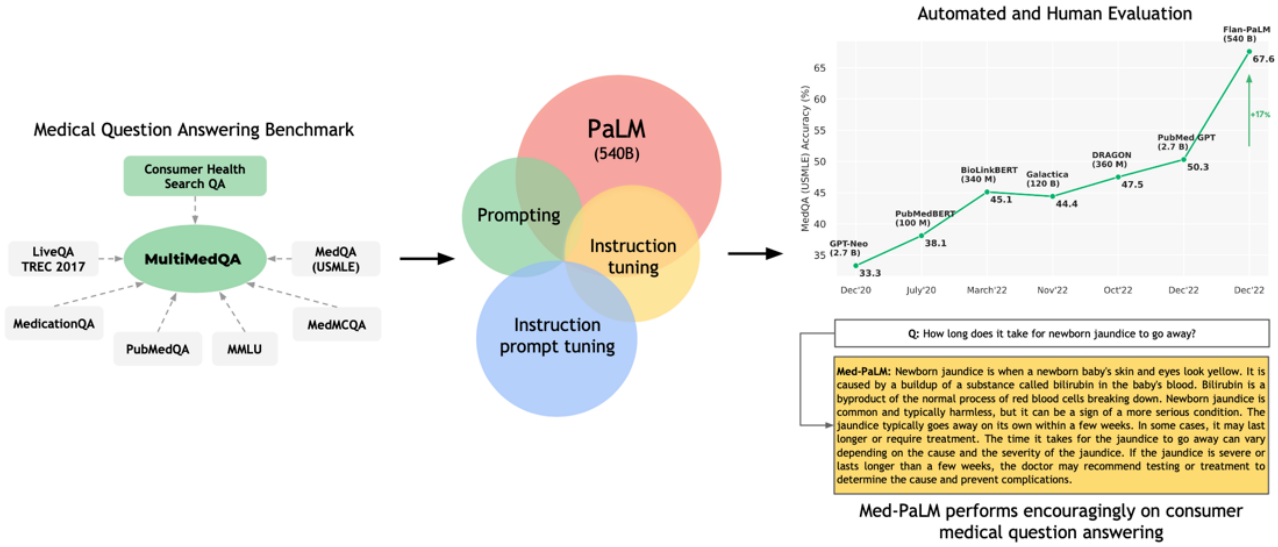

Figure 1.7: *Large Language Models (LLMs) have revolutionized healthcare by enhancing diagnostic accuracy, clinical decision support, and patient engagement. Source: Singhal et al. [207].*

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1. **Algorithmic Trading:** LLMs analyze vast amounts of unstructured data, including news articles, financial reports, and social media, to gauge market sentiment and predict stock price movements. Their predictive insights enable more informed algorithmic trading strategies [40].

2. **Risk Management:** In risk management, LLMs contribute by parsing and interpreting complex regulatory documents, identifying potential compliance risks, and offering actionable insights to mitigate financial and reputational risks [91].

3. **Customer Service Automation:** Financial institutions leverage LLMs to power chatbots and virtual assistants, providing real-time, personalized customer service. These AI-driven systems can handle inquiries, execute transactions, and offer financial advice, enhancing customer experience and operational efficiency [121].

4. **Fraud Detection:** LLMs enhance fraud detection systems by analyzing transactional data and customer communication to identify patterns indicative of fraudulent activities, thereby bolstering the security of financial transactions [74].

Some of the models in Figure 1.8 have not only augmented the accuracy and efficiency of financial analyses but also expedited the decision-making processes, enabling more timely and informed decisions. Additionally, their role in risk management is noteworthy, where their data processing and analytical prowess help identify potential risks and adherence issues more effectively than traditional methodologies [40].

Despite their potential, LLMs in finance face challenges, including data privacy concerns, the need for interpretability in model decisions, and the risk of perpetuating biases from training data. Ensuring these models adhere to ethical standards and regulatory compliance is paramount [87, 40].

Let's delve deeper into the techniques used to adapt LLMs for the financial sector to enhance their performance on finance-specific tasks [343]. These techniques are designed to enhance the models' understanding of financial language, data, and context, thereby improving their performance on finance-specific tasks. Here's a more detailed look at these techniques:

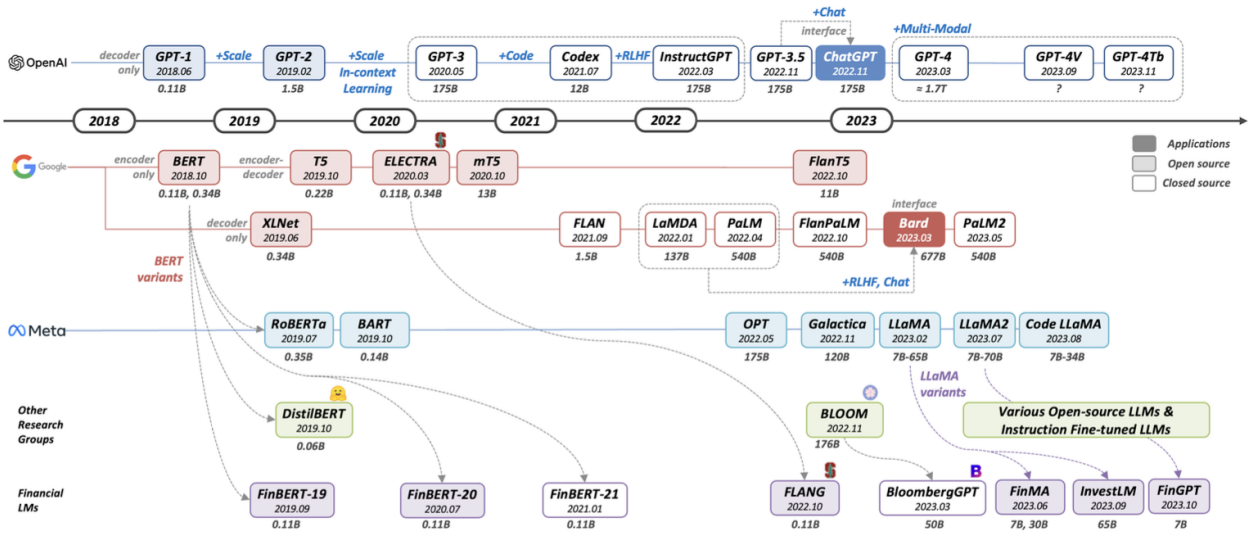

Figure 1.8: *Timeline showing the evolution of selected PLM/LLM releases from the general domain to the financial domain. Source: Lee et al. [343].*

Model	Backbone	Paras.	PT Techniques	PT Data Size	Evaluation Task	Dataset	O.S. Model	PT	IFT
BloombergGPT [323]	BLOOM	50B	PT, PE	(G) 345B tokens (F) 363B tokens	SA, TC	FPB, FiQA-SA, Headline	N	N	N
FinMA [326]	LLaMA	7B, 30B	IFT, PE	(G) 1T tokens	SA, TC, NER, QA	FPB, FiQA-SA, Headline FIN, FinQA, ConvFinQA	Y	Y	Y
InvestLM [331]	LLaMA	65B	PEFT	(G) 1.4T tokens	SA, TC, SMP	StockNet, CIKM18, BigData22	Y	N	N
FinGPT [313]	6 open-source LLMs	7B	PEFT	(G) 2T tokens	SA, TC, NER, RE	FPB, FiQA-SA, Headline FIN, FinRED	Y	Y	Y

Table 1.5: *The abbreviations correspond to Paras.= Model Parameter Size (Billions); Disc. = Discriminative, Gen. = Generative; Post-PT = Post-Pre-training, PT = Pre-training, FT = Fine-Tuning, PE = Prompt Engineering, IFT = Fine-Tuning, PEFT = Parameter Efficient Fine-Tuning; (G) = General domain, (F) = Financial domain; (in Evaluation) [SA] Sentiment Analysis, [TC] Text Classification, [SBD] Structure Boundary Detection, [NER] Named Entity Recognition, [QA] Question Answering, [SMP] Stock Movement Prediction, [Summ] Text Summarization, [RE] Relation Extraction; O.S. Model = Open Source Model. It is marked as Y if it is publicly accessible as of Dec 2023. Source: Lee et al. [343].*

- **Domain-Specific Pre-training:** This technique involves further training a general LLM on a financial corpus. The idea is to refine the model's language understanding and generation capabilities within the financial domain. By exposing the model to a large volume of financial texts, such as reports, news, and analysis, the model learns the specific jargon, styles, and nuances of financial language.
- **Continual Pre-training:** After initial pre-training on a general dataset, the model

undergoes additional pre-training phases on financial data. This step-by-step refinement helps the model gradually adapt from a broad understanding of language to a more specialized comprehension of financial texts. It's a way to incrementally infuse financial knowledge into the model without losing its general language capabilities.

- **Mixed-Domain Pre-training:** In this approach, the LLM is trained on a mixed dataset comprising both general and financial texts. The goal is to maintain the model's general language understanding while also equipping it with the ability to process and generate financial content. This method aims to strike a balance, ensuring the model is not overly specialized and retains versatility.

- **Task-Specific Fine-tuning:** Once a model has been pre-trained with financial data, it can be fine-tuned for specific financial tasks. For example, a model could be fine-tuned on a dataset of financial sentiment analysis, stock market prediction, or fraud detection. This fine-tuning process sharpens the model's skills on tasks that are directly relevant to the financial industry.

- **Transfer Learning:** Techniques from transfer learning can be applied where a model trained on one financial task is adapted for another. This approach leverages the knowledge the model has gained from one context, applying it to a different but related task, thereby enhancing learning efficiency and performance.

- **Custom Tokenization:** Financial texts often contain unique symbols, terms, and numerical expressions. Employing custom tokenization strategies that recognize these peculiarities can significantly enhance the model's ability to process and understand financial documents.

Within the four FinLLMs in Figure 1.5, FinMA [326], InvestLM [331], and FinGPT [313] are based on LLaMA or other open-source based models, while BloombergGPT [323] is a BLOOM-style closed-source model.

Regarding the evaluation tasks, the models are assessed on a range of financial NLP tasks, as shown below:

- **Sentiment Analysis (SA):** This task involves analyzing the sentiment embedded within financial documents, such as market reports and news articles. The capability to accurately discern sentiment is crucial for applications such as market prediction and the formulation of trading strategies.

- **Named Entity Recognition (NER):** Essential for extracting actionable insights from financial documents, this task focuses on the identification and categorization of salient financial entities, including but not limited to, company names, stock tickers, and monetary values.

- **Question Answering (QA):** FinLLMs are tasked with providing cogent answers to queries based on an expansive financial corpus. This benchmark often requires the synthesis of information from dense financial reports or news events.

- **Text Classification (TC):** The classification of financial documents into predefined categories aids in the automated sorting and analysis of financial data, an essential task in managing the voluminous data generated by financial markets.

- **Regulatory Compliance (RE):** Given the stringent regulatory environment of the financial sector, FinLLMs are often evaluated on their ability to parse and verify the compliance of financial texts with industry regulations.

To accurately measure the effectiveness of FinLLMs in performing these tasks, several datasets have been curated, each tailored to challenge different aspects of a model's financial acumen:

- **Financial PhraseBank (FPB):** A dataset comprising sentences from financial news, annotated to reflect sentiment polarity, which is instrumental in the training and testing of models for sentiment analysis [21].
- **FiQA - Financial Opinion Mining and Question Answering Challenge (FiQA-SA, FiQA-QA):** This dataset encompasses annotated financial news and social media texts for sentiment analysis alongside a collection of question-and-answer pairs for the evaluation of QA capabilities [44].
- **FIN: A Financial Document Dataset for NER:** Designed for entity recognition, this dataset consists of financial news articles with annotated entities, testing the model's capacity to identify and classify financial terms Alvarado, Verspoor, and Baldwin [22]. Another financial NER dataset is FiNER-139, consisting of 1.1M sentences from financial news articles, annotated with 139 eXtensive Business Reporting Language (XBRL) word-level tags [183]. This dataset is designed for Entity Extraction and Numerical Reasoning tasks, predicting the XBRL tags (e.g., cash and cash equivalents) based on numeric input data within sentences (e.g., "24.8" million).
- **ConvFinQA:** A conversational finance QA dataset challenging models to understand and respond within the context of financial dialogues, demonstrating an advanced application of FinLLMs in customer interaction Chen et al. [147]. It's an extension of FinQA, is a multi-turn conversational hybrid QA dataset consisting of 3,892 conversations with 14,115 questions.
- **StockNet:** This dataset combines historical price data with relevant tweets to offer a comprehensive view of SMP tasks. It has been widely used to assess the impact of market sentiment on stock prices [55].
- **CIKM18:** A dataset designed for SMP tasks, CIKM18 comprises stock price data and news headlines, challenging models to predict stock movements based on textual information [54].
- **BigData22:** A dataset for SMP tasks, BigData22 combines financial news articles with stock price data, evaluating models on their ability to predict stock movements based on textual information Soun et al. [210].
- **Headline:** A dataset of financial news headlines, used for text classification [127]. This dataset comprises 11,412 news headlines, labelled with a binary classification across nine labels such as "price up" or "price down".
- **ECT-Sum:** A dataset for text summarization tasks, ECT-Sum consists of consists of 2,425 document-summary pairs, containing Earnings Call Transcripts (ECTs) and bullet-point summarizations from Reuters [195].

The listed datasets are not exhaustive but represent a comprehensive selection of tasks and benchmarks used to evaluate FinLLMs across a range of financial NLP tasks. As highlighted in Lee et al. [343], in the sentiment analysis task, FLANG-ELECTRA achieved the best results (92% on F1) while FinMA-30B and GPT-4 achieved similar results (87% on F1) with a 5-shot prompting.

These datasets are instrumental in assessing the models' performance, guiding their development, and fostering innovation in the financial sector to address more advanced financial tasks:

- **Relation Extraction (RE):** FinRED [204] is a key dataset curated from financial news and earnings call transcripts, containing 29 finance-specific relation tags (i.e., owned by). It's instrumental in identifying and classifying relationships between entities within financial texts.
- **Event Detection (ED):** The Event-Driven Trading (EDT) dataset, comprising news articles with event labels and stock price information, facilitates the detection of corporate events affecting stock prices [137].
- **Causality Detection (CD):** FinCausal20 from the Financial Narrative Processing (FNP) workshop focuses on identifying cause-and-effect relationships in financial texts, a crucial aspect for generating meaningful financial summaries [93]. It shares two tasks: detecting a causal scheme in a given text and identifying cause-and-effect sentences.
- **Numerical Reasoning (NR):** Datasets like FiNER-139 and ConvFinQA are designed to test a model's ability to perform calculations and understand financial contexts based on numerical data within texts.
- **Structure Recognition (SR):** The FinTabNet [136] dataset, collected from earnings reports, emphasizes the detection of table structures and the recognition of logical relationships within financial documents.
- **Multimodal Understanding (MM):** Datasets like MAEC [90]) and MONOPOLY (Mathur et al. [188] introduce multimodal data (audio, video, text, time series) from earnings calls and monetary policy discussions, challenging models to integrate diverse data formats.
- **Machine Translation (MT) in Finance:** MINDS-14 [107]) and MultiFin (Jørgensen et al. [265] datasets offer multilingual financial text, aiding in the development of models that can translate and comprehend financial information across languages.
- **Market Forecasting (MF):** This task extends beyond stock movement prediction, focusing on broader market trend forecasting [24] using datasets that combine sentiment analysis, event detection, and multimodal cues[25].

Recent studies have shown that they outperform fine-tuned models on some tasks. But, they still fail in some other cases [272]. Some interesting results are shown in Table 1.6, Table 1.7, Table 1.8, Table 1.9. For example, in the sentiment analysis task, FinMA-30B and GPT-4 achieved similar results (87% on F1) with a 5-shot prompting, while FLANG-ELECTRA achieved the best results (92% on F1) Lee et al. [343], while GPT-4 could be the first choice for Sentiment Analysis and Relation Extraction tasks.

[24] Market price, volatility, and risk

[25] Like StockEmotions [269]), EDT (Zhou, Ma, and Liu [137]), MAEC (Li et al. [90]) and MONOPOLY (Mathur et al. [188]

Data Model	50% Agreement		100% Agreement	
	Accuracy	F1 score	Accuracy	F1 score
ChatGPT$_{(0)}$	0.78	0.78	0.90	0.90
ChatGPT$_{(5)}$	0.79	0.79	0.90	0.90
GPT-4$_{(0)}$	0.83	0.83	0.96	0.96
GPT-4$_{(5)}$	**0.86**	**0.86**	**0.97**	**0.97**
BloombergGPT$_{(5)}$	/	0.51	/	/
GPT-NeoX$_{(5)}$	/	0.45	/	/
OPT6B$_{(5)}$	/	0.49	/	/
BLOOM176B$_{(5)}$	/	0.50	/	/
FinBert	**0.86**	0.84	**0.97**	0.95

Table 1.6: *Results on the Phrasebank dataset. The sub-script (n) after an LLM name represents the number of shots. The best results are marked in bold and the second-best with underscored. The results of other LLMs like BloombergGPT are from the corresponding papers. '/' indicates the metrics were not included in the original study. Source:Li et al. [272].*

Model	**Category**	**Weighted F1**
ChatGPT$_{(0)}$	OpenAI LLMs	75.90
ChatGPT$_{(5)}$	OpenAI LLMs	78.33
GPT-4$_{(9)}$	OpenAI LLMs	87.15
GPT-4$_{(5)}$	OpenAI LLMs	**88.11**
BloombergGPT$_{(5)}$	Domain LLM	75.07
GPT-NeoX$_{(5)}$	Prior LLMs	50.59
OPT 6B$_{(5)}$	Prior LLMs	51.60
BLOOM 176B$_{(5)}$	Prior LLMs	53.12
RoBERTa-large	Fine-tune	87.09

Table 1.7: *Results for the sentiment analysis task on the FiQA dataset. Source: Li et al. [272].*

Model	**Weighted F1**
ChatGPT$_{(0)}$	71.78
ChatGPT$_{(5)}$	74.84
GPT-4$_{(0)}$	84.17
GPT-4$_{(5)}$	86.00
BloombergGPT$_{(5)}$	82.20
GPT-NeoX$_{(5)}$	73.22
OPT6B$_{(5)}$	79.41
BLOOM176B$_{(5)}$	76.51
BERT	**95.36**

Table 1.8: *Results on the headline classification task. Source: Li et al. [272].*

BloombergGPT

The BloombergGPT model, developed by Wu et al. [323], is a specialized LLM tailored for the financial domain. With its 50 billion parameters, is posited to be the apex of financial language

Model	Entity F1
$\text{ChatGPT}_{(0)}$	29.21
$\text{ChatGPT}_{(20)}$	51.52
$\text{GPT-4}_{(0)}$	36.08
$\text{GPT-4}_{(20)}$	56.71
$\text{BloombergGPT}_{(20)}$	60.82
$\text{GPT-NeoX}_{(20)}$	60.98
$\text{OPT6B}_{(20)}$	57.49
$\text{BLOOM176B}_{(20)}$	55.56
$\text{CRF}_{\text{CoNLL}}$	17.20
CRF_{FIN5}	**82.70**

Table 1.9: *Results of few-shot performance on the NER dataset. CRF_{CoNLL} refers to CRF model that is trained on general CoNLL data, CRF_{FIN5} refers to CRF model that is trained on FIN5 data. Source: Li et al. [272].*

Model	FinQA	ConvFinQA
$\text{ChatGPT}_{(0)}$	48.56	59.86
$\text{ChatGPT}_{(3)}$	51.22	/
ChatGPT (CoT)	**63.87**	/
$\text{GPT-4}_{(0)}$	68.79	76.48
$\text{GPT-4}_{(3)}$	69.68	/
GPT-4 (CoT)	**78.03**	/
$\text{BloombergGPT}_{(0)}$	/	43.41
$\text{GPT-NeoX}_{(0)}$	/	30.06
$\text{OPT6B}_{(0)}$	/	27.88
$\text{BLOOM176B}_{(0)}$	/	36.31
FinQANet (fine-tune)	68.90	61.24
Human Expert	91.16	89.44
General Crowd	50.68	46.90

Table 1.10: *Model performance (accuracy) on the question answering tasks. FinQANet here refers to the best-performing FinQANet version based on RoBERTa-Large [148]. Few-shot and CoT learning cannot be executed on ConvFinQA due to the conservation nature of ConvFinQA.*

models, having been trained on a comprehensive dataset of an unprecedented scale within the financial domain. Wu et al. [323] detail the intricacies of BloombergGPT's training regimen, which employed an amalgamation of financial texts, encompassing a multitude of formats, and a general dataset to ensure versatility[26] as shown in Table 1.11.

The core of BloombergGPT's training material involved 363 billion tokens of finance-specific data, accompanied by a general corpus of 345 billion tokens. The dataset's breadth is vast, incorporating textual data spanning web sources, news articles, financial reports, and proprietary content from Bloomberg terminals. This diversified data portfolio enables the model to navigate the financial lexicon and nuances expertly.

Wu et al. [323] proffer insights into their methodological choices and their repercussions

[26] "FinPile", a comprehensive dataset consisting of a range of English financial documents including news, filings, press releases, web-scraped financial documents, and social media drawn from the Bloomberg archives augmented with public available data.

Dataset	Docs	C/D	Chars	C/T	Toks	T%
FINPILE	175,886	1,017	17,883	4.92	6,935	51.27%
Web	158,250	933	14,768	4.96	2,978	42.01%
News	10,040	1,665	1,672	4.44	376	5.31%
Filings	3,335	2,340	780	5.39	145	2.04%
Press	1,265	3,443	435	5.06	86	1.21%
Bloomberg	2,996	758	227	4.60	49	0.70%
PUBLIC	50,744	3,314	16,818	4.87	3,454	48.73%
C4	34,832	2,206	7,683	5.56	1,381	19.48%
Pile-CC	5,255	4,401	2,312	5.42	427	6.02%
GitHub	1,428	5,364	766	3.38	227	3.20%
Books3	19	552,398	1,064	4.97	214	3.02%
PubMed Central	294	32,181	947	4.51	210	2.96%
ArXiv	124	47,819	541	3.56	166	2.35%
OpenWebText2	1,684	3,850	648	5.07	128	1.80%
FreeLaw	349	15,381	537	4.99	108	1.80%
StackExchange	1,538	2,201	339	4.17	81	1.15%
DM Mathematics	100	8,193	82	1.92	43	0.60%
Wikipedia (en)	590	2,988	176	4.65	38	0.53%
USPTO Backgrounds	517	4,339	224	6.18	36	0.51%
PubMed Abstracts	1,527	1,333	204	5.77	35	0.50%
OpenSubtitles	38	31,055	119	4.90	24	0.34%
Gutenberg (PG-19)	3	399,351	112	4.89	23	0.32%
Ubuntu IRC	1	539,222	56	3.16	18	0.25%
EuroParl	7	65,053	45	2.93	15	0.21%
YouTubeSubtitles	17	19,831	33	2.54	13	0.19%
BookCorpus2	2	370,384	65	5.36	12	0.17%
HackerNews	82	5,009	41	4.87	8	0.12%
PhilPapers	3	74,827	23	4.21	6	0.08%
NIH ExPorter	92	2,165	20	6.65	3	0.04%
Enron Emails	2	1,882	20	3.90	3	0.04%
Wikipedia (fr/1/22)	2,218	3,271	76	3.06	237	0.32%
TOTAL	**226,631**	**1,531**	**34,701**	**4.89**	**7,089**	**100.00%**

Table 1.11: *Breakdown of the full training set used to train BLOOMBERGGPT. The statistics provided are the average number of characters per document ("C/D"), the average number of characters per token ("C/T"), and the percentage of the overall tokens ("T%"). Source: Wu et al. [323].*

on model performance. The authors used parallel tokenizer training strategies because the Unigram tokenizer was found to be too inefficient to process the entire Pile dataset. So the dataset was split into domains, and each domain was further split into chunks. Every chunk was tokenized by a separate tokenizer, and then the tokenizer from each domain was merged hierarchically using a weighted average of the probabilities of corresponding tokens. The result was cut from a tokenizer with 7 million tokens to only 2^{17} tokens, dropping tokens with the smallest probabilities.

The BloombergGPT model is a decoder-only causal language model based on BLOOM [322]. The model contains 70 layers of transformer decoder blocks defined as follows:

$$h_\ell = h_{\ell-1} + \text{SA}(\text{LN}(h_{\ell-1}))$$
$$h_\ell = h_\ell + \text{FFN}(\text{LN}(h_\ell))$$

where SA is multi-head self-attention, LN is layer-normalization, and FFN is a feed-forward network with 1 hidden layer. Inside FFN, the non-linear function is GELU [27]. ALiBi positional encoding is applied through additive biases at the self-attention component of the transformer network [174]. The input token embeddings are tied to the linear mapping before the final softmax. The model also has an additional layer of normalization after token embeddings.

BloombergGPT's prowess was rigorously benchmarked against a suite of established LLMs' assessments, financial-specific benchmarks, and a series of internally devised tests. The model exhibited a remarkable ability to outperform existing models on financial NLP tasks, a testament to the efficacy of its specialized training as shown in Table 1.12, Table 1.13, and Table 1.14. BloombergGPT's performance on standard, general-purpose benchmarks was also evaluated, demonstrating its versatility and proficiency across a range of NLP tasks.

Overall, while BloombergGPT falls behind the much larger $\text{PaLM}_{540\text{B}}$ (10x parameters) and $\text{BLOOM}_{176\text{B}}$ (3.5x parameters), it is the best-performing among similarly sized models. In fact, its performance is closer to $\text{BLOOM}_{176\text{B}}$ than it is to either GPT-NeoX or $\text{OPT}_{66\text{B}}$.

In sum, according to benchmarks in Wu et al. [323], developing finance-specific BloombergGPT did not come at the expense of its general-purpose abilities.

	BLOOMBERGGPT	**GPT-NeoX**	**$\text{OPT}_{66\text{B}}$**	**$\text{BLOOM}_{176\text{B}}$**
ConvFinQA	**43.41**	30.06	27.88	36.31
FiQA SA	**75.07**	50.59	51.60	53.12
FPB	**51.07**	44.64	48.67	50.25
Headline	**82.20**	73.22	79.41	76.51
NER	60.82	**60.98**	57.49	55.56
All Tasks (avg)	**62.51**	51.90	53.01	54.35
All Tasks (WR)	**0.93**	0.27	0.33	0.47

Table 1.12: *Results on financial domain tasks. Source: Wu et al. [323].*

	BLOOMBERGGPT	**GPT-NeoX**	**$\text{OPT}_{66\text{B}}$**	**$\text{BLOOM}_{176\text{B}}$**
Equity News	**79.63**	14.17	20.98	19.96
Equity Social Media	**72.40**	66.48	71.36	68.04
Equity Transcript	**65.06**	25.08	37.58	34.82
ES News	**46.12**	26.99	31.44	28.07
Country News	**49.14**	13.45	17.41	16.06
All Tasks (avg)	**62.47**	29.23	35.76	33.39
All Tasks (WR)	**1.00**	0.00	0.67	0.33

Table 1.13: *Results on internal aspect-specific sentiment analysis datasets. BLOOMBERGGPT far outperforms all other models on sentiment analysis tasks. Source: Wu et al. [323].*

	BLOOMBERGGPT	GPT-NeoX	OPT_{66B}	BLOOM_{176B}
		NER		
BFW	72.04	71.66	72.53	76.87
BN	57.31	52.83	46.87	59.61
Filings	58.84	59.26	59.01	64.88
Headlines	53.61	47.70	46.21	52.17
Premium	60.49	59.39	57.56	61.61
Transcripts	75.50	70.62	72.53	77.80
Social Media	60.60	56.80	51.93	60.88
All Tasks (avg)	62.63	59.75	58.09	64.83
All Tasks (WR)	0.57	0.29	0.19	0.95
		NER+NED		
BFW	55.29	34.92	36.73	39.36
BN	60.09	44.71	54.60	49.85
Filings	66.67	31.70	65.63	42.93
Headlines	67.17	36.46	56.46	42.93
Premium	64.11	40.84	57.06	42.11
Transcripts	73.15	23.65	70.44	34.87
Social Media	67.34	62.57	70.57	65.94
All Tasks (avg)	64.83	39.26	58.79	45.43
All Tasks (WR)	0.95	0.00	0.67	0.38

Table 1.14: *Results on internal NER and NED datasets. On NER, while the much larger BLOOM176b model outperforms all other models, results from all models are relatively close, with BLOOMBERGGPT outperforming the other two models. On NER+NED, BLOOMBERGGPT outperforms all other models by a large margin. Source: Wu et al. [323].*

1.4.3 LLMs in Education

Education is a sector that has been significantly impacted by the advent of LLMs. LLMs can be leveraged to create educational content that is tailored to individual student needs, providing explanations, generating practice problems, and even offering feedback.

Integrating LLMs into educational frameworks offers a rich tapestry of potential enhancements to teaching and learning experiences. The transformative influence of such technology is particularly marked in tasks that can benefit from automation, such as grading and personalized feedback on student work. LLMs, through their nuanced understanding of language, can provide insightful assessments that highlight the strengths and weaknesses in student assignments, which may span essays, research papers, and various other forms of written submissions. An additional benefit is LLMs' capacity to detect plagiarism, which bolsters the integrity of academic evaluation by mitigating the risk of academic dishonesty. This ability to provide quick and precise feedback can afford educators more time to address individual student needs, leading to a more targeted and effective teaching approach.

LLMs can achieve student-level performance on standardized tests [345] in a variety of subjects of mathematics (e.g., physics, computer science) on both multiple-choice and free-response problems. Additionally, these models can assist in language learning, both for native speakers and language acquisition, due to their deep understanding of linguistic structures and idiomatic expressions.

In the realm of intelligent tutoring systems, LLMs can be applied to simulate one-on-one interaction with a tutor, adapting to the student's learning pace, style, and current level of knowledge. These systems can engage in dialogue, answer student queries, and provide explanations, much like a human tutor would [283, 211].

Furthermore, LLMs have the capacity to automate the grading process by evaluating open-ended responses in exams and assignments. This can free up time for educators to focus on more personalized teaching methods and direct student engagement.

The intersection of LLMs and education also extends to research, where these models can aid in summarizing literature, generating hypotheses, and even writing research proposals or papers, albeit with careful oversight to ensure academic integrity.

In administrative and support roles, LLMs can streamline communication with students, handle routine inquiries, and manage scheduling and reminders, enhancing the overall educational experience for students and faculty.

To tap into the full potential of LLMs in education, it is crucial to address challenges such as ensuring the reliability of the information provided, avoiding biases, and maintaining privacy and security, especially in data-sensitive environments like schools and universities.

1.4.4 LLMs in Law

The legal sector is another domain that has been significantly impacted by the advent of LLMs. A number of tasks in the legal field, such as legal document analysis [242]), legal judgment prediction (Trautmann, Petrova, and Schilder [216]), and legal document writing (Choi et al. [251], can be solved by LLMs with high accuracy and efficiency.

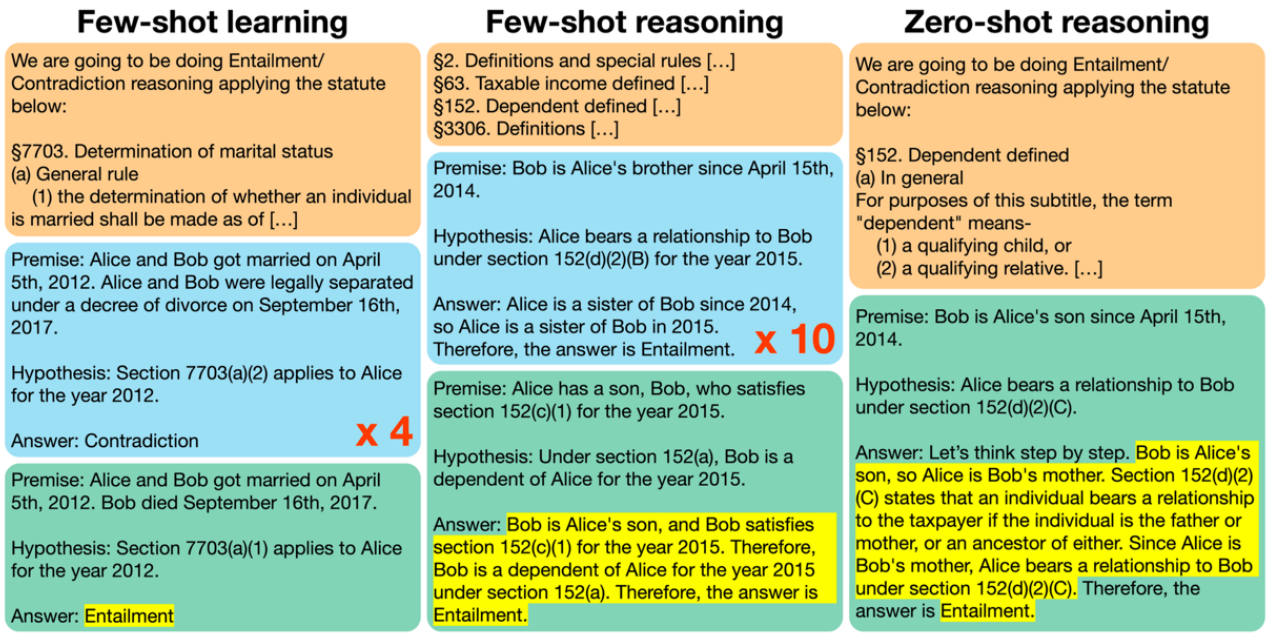

Figure 1.9: *Prompts used in Blair-Stanek, Holzenberger, and Durme [242] to pose SARA test cases to GPT-3. The top boxes, in orange, contain statutes (optional). Example cases are in blue; in zero-shot, there are no example cases. At the bottom, in green, are test cases. The text highlighted in yellow is generated by GPT-3. If GPT-3's first response is unclear, the second prompt with "Therefore the answer is" is used, following Kojima et al. [266]. Source: Trautmann, Petrova, and Schilder [216].*

Blair-Stanek, Holzenberger, and Durme [242] evaluates the capacity of OpenAI's GPT-3

model, specifically text-davinci-003, to perform statutory reasoning[27], a fundamental skill in legal practice, on an established dataset known as SARA (StAtutory Reasoning Assessment). The investigation includes several approaches like dynamic few-shot prompting, chain-of-thought prompting, and zero-shot prompting (examples in Figure 1.9).

The model surpasses previous benchmarks yet still exhibits considerable room for improvement, especially when handling simple synthetic statutes, revealing limitations in its current statutory reasoning capabilities even though GPT-3 has some prior knowledge of the U.S. Code.

Method	Constitutional Law	Taxation	Torts	Total
Simple	21/25	24/60	6/10	51/95
CoT	21/25	18/60	5/10	44/95
Rank Order	20/25	21/60	6/10	47/95

Table 1.15: *Comparison of Multiple Choice Methods. Source: Choi et al. [251].*

Choi et al. [251] explored ChatGPT's ability to write law school exams at the University of Minnesota Law School, encompassing multiple choice and essay questions across four courses. ChatGPT generated answers for exams in Constitutional Law, Employee Benefits, Taxation, and Torts, with varying question formats across these subjects. These answers were blindly graded in line with the standard grading process. ChatGPT managed to pass all four classes, averaging a C+ grade, demonstrating better performance on essay questions compared to multiple-choice, with notable strengths in organizing and composing essays (Table 1.15).

Despite its overall passing performance, ChatGPT ranked at or near the bottom in each class. The model's essays showcased a strong grasp of basic legal rules but struggled with issue spotting and detailed application of rules to facts. The findings suggest that while ChatGPT can assist in legal education and potentially in legal practice, it currently lacks the nuanced understanding and depth of reasoning required for high-level legal analysis.

Recent studies on the latest GPT-4 model have shown that it can achieve a top 10% score in a simulated bar exam compared with human test-takers [345], while Nay [196] and exhibit powerful abilities of legal interpretation and reasoning. To further improve the performance of LLMs in the law domain, specially designed legal prompt engineering is employed to yield advanced performance in long legal document comprehension and complex legal reasoning [335].

1.4.5 LLMs in Scientific Research

LLMs in scientific research can be employed across various stages of the research process, from literature review to hypothesis generation, brainstorming, data analysis, manuscript drafting, proofreading, and peer review. Empirical evidence underscores the aptitude of LLMs in managing tasks dense with scientific knowledge, such as those presented by PubMedQA [65] and BioASQ [172]. This is particularly true for LLMs pre-trained on scientific corpora, including, but not limited to, Galactica [214] and Minerva [176].

Due to their advanced general capabilities and extensive scientific acumen, LLMs are poised to play an integral role as supportive tools throughout the entirety of the scientific research process [333]. During the initial stages of research, such as brainstorming, LLMs can assist in generating novel research ideas and hypotheses, thereby fostering creativity and innovation[28].

[27]Statutory reasoning is the application of legal rules written by legislative bodies to facts that are also in natural language

[28]Temperature is a parameter of OpenAI ChatGPT, GPT-3 and GPT-4 models that govern the randomness and thus the creativity of the responses.

In the literature review phase, LLMs can perform exhaustive reviews, encapsulating the state of advancement within specific scientific disciplines [258, 140] providing explanations for scientific texts and mathematics with follow-up questions.

Progressing to the phase of research ideation, LLMs have displayed potential in formulating compelling scientific hypotheses [288]. In Park et al. [288], the authors demonstrate the ability of GPT-4 to generate hypotheses in the field of materials science, showcasing the model's capacity to propose novel research directions. They find the hypotheses generated by GPT-4 to be on par with those proposed by human experts, highlighting the model's potential to contribute to the scientific research process.

In the subsequent stage of data analysis, LLMs can be harnessed for automating the examination of data attributes, including exploratory data analysis, visualization, and the extraction of analytical inferences [249]. In Hassan, Knipper, and Santu [260], the authors demonstrate the utility of GPT-4 in automating data analysis tasks, such as data cleaning, feature engineering, and model selection, thereby streamlining the data science workflow.

Regarding proofreading, LLMs can enhance the quality of scientific manuscripts by identifying grammatical errors, improving readability, and ensuring adherence to academic conventions. In addition, LLMs can go beyond helping users check grammar and can further generate reports about document statistics, vocabulary statistics, etc, change the language of a piece to make it suitable for people of any age, and even adapt it into a story [171]. While ChatGPT has some usability issues when it comes to proofreading, such as being over 10 times slower than DeepL and lacking in the ability to highlight suggestions or provide alternative options for specific words or phrases [284], it should be noted that grammar-checking is just the tip of the iceberg. ChatGPT can also be valuable in improving language, restructuring text, and other aspects of writing.

Furthermore, in the manuscript drafting phase, the utility of LLMs extends to aiding scientific writing endeavors [263, 240], offering a multitude of services such as condensing existing materials and refining the written prose [244]. As explained in Buruk [244] and Hussam Alkaissi [263], LLMs can assist in generating abstracts, introductions, and conclusions, thereby enhancing the overall quality of scientific manuscripts.

Finally, in the peer review process, LLMs can contribute to automating the peer review process, undertaking tasks like error identification, compliance with checklists, and prioritization of submissions [278].

LLMs' utility spans beyond the aforementioned domains, with their deployment also being explored in the psychological sphere. Here, studies have probed LLMs for human-like traits, encompassing self-perception, Theory of Mind (ToM)[29], and emotional cognition [268, 238]. Kosinski [268] employs classic false-belief tasks[30], revealing a marked improvement in ToM capabilities in more recent versions of GPT-3. Specifically, the davinci-002 version solved

[29]The ability to impute unobservable mental states to others

[30]A false-belief task is a psychological test used to assess an individual's ability to understand that others can have beliefs about the world that are different from their own and that these beliefs can be incorrect. This ability is a crucial component of the Theory of Mind (ToM), which is the capacity to attribute mental states—beliefs, intents, desires, emotions, knowledge, etc.—to oneself and others and to understand that others have beliefs, desires, and intentions that are different from one's own.

The classic example of a false-belief task is the Sally-Anne test, used primarily with children. The test involves two dolls, Sally and Anne. Sally has a basket, while Anne has a box. In the presence of Sally, a marble is placed in Sally's basket. Sally then leaves the room, and while she's away, Anne takes the marble from Sally's basket and puts it in her box. The child is then asked where Sally will look for the marble when she returns. The correct answer is Sally's basket, where she left the marble. A child who can correctly predict where Sally will look for the marble demonstrates an understanding that Sally holds a false belief about the location of the marble. Successfully completing a false-belief task indicates that the individual can understand that others can hold beliefs that are false and that these beliefs can influence their actions, a critical step in the development of social cognition and empathy.

70% of ToM tasks, while the davinci-003 version achieved a 93% success rate, demonstrating performances akin to seven- and nine-year-old children, respectively. Notably, GPT-3.5's performance in ToM assessments parallels that of nine-year-olds, suggesting nascent ToM capabilities in LLMs. The study hypothesizes that ToM-like abilities might emerge spontaneously in AI without explicit programming, especially in LLMs trained in human language. In the context of AI, particularly in LLMs like GPT-3, the ability to perform well on false-belief tasks suggests a sophisticated level of language understanding and a rudimentary form of Theory of Mind, albeit not conscious or sentient like in humans.

Moreover, the application of LLMs in software engineering is also gaining traction, with initiatives in code suggestions [298], code summarizations [301], and automated program repairs [325].

Chapter 2

Foundations of Large Language Models

2.1 Introduction

Large Language Models (LLMs) have revolutionized the field of Natural Language Processing (NLP) by achieving state-of-the-art performance on a wide range of tasks, such as text generation, text classification, and machine translation. These models are trained on vast amounts of text data to learn the underlying structure of the language and capture the relationships between words.

In the following sections, we will explore the key concepts and techniques that underpin the development of LLMs, including pre-training strategies and major datasets used for training and evaluation, as well as the Transformer architecture, which forms the basis of many modern LLMs.

After that, we will discuss some model adaptation techniques that can be used to fine-tune LLMs for specific tasks or domains.

Finally, we will discuss tuning and quantization of LLMs, techniques used to reduce the model's size and computational complexity, making it more efficient for deployment on resource-constrained devices.

2.2 Pre-training

Pre-training constitutes a foundational phase in the development of Large Language Models (LLMs). It allows the model to capture the relationships between words and generate coherent and contextually relevant text, laying the groundwork for its subsequent performance on specific NLP tasks [61, 83]. This phase involves training a language model on a vast corpus of text data before fine-tuning it on a smaller, task-specific dataset, such as text generation or text classification, to improve its performance on that task. Moreover, the extensive pre-training on diverse corpora enables LLMs to develop a broad understanding, making them adaptable to a wide range of domains and languages [68, 70]. Despite its advantages, pre-training LLMs is not without its challenges. The process requires substantial computational resources and energy, raising concerns about its environmental impact [75]. Additionally, the data used for pre-training can influence the model's biases and sensitivities, necessitating careful curation of the training corpus to mitigate potential ethical and fairness issues [101].

The field is evolving towards more efficient pre-training methods, such as transfer learning, where a pre-trained model is adapted to new tasks or languages with minimal additional training [71]. Moreover, emerging approaches aim to enhance the contextual awareness and ethical sensitivity of LLMs during the pre-training phase, addressing the challenges of bias and fairness.

2.2.1 Pre-training strategies

There are several pre-training strategies that have been used to train large language models, including unsupervised pre-training, supervised pre-training, and semi-supervised pre-training. Let's explore each of these strategies in more detail.

Unsupervised pre-training

Unsupervised pre-training is a pre-training strategy that involves training a model on a large corpus of text data without any labels or annotations.
The model is trained to predict the next word in a sequence of words, given the previous words in the sequence [83]. This is done using a technique called Autoregressive Language Modeling (ALM), where the model is trained to predict the probability distribution over the next word in the sequence given the previous words in the sequence in a unidirectional manner.
Models like GPT-3 and its variants use this autoregressive language modeling objective to pre-train on large text corpora and learn the relationships between words in the language.
The main idea behind ALM is the prediction of the next token in a sequence based on the tokens that precede it. The computational realization of this modeling approach is typically achieved through neural networks, particularly transformers, which leverage self-attention mechanisms to encapsulate dependencies across varying distances in the input sequence [308].

During the generation process, a token is sampled based on the probability distribution predicted by the model for the next token position, appended to the sequence, and this augmented sequence is then fed back into the model iteratively to generate subsequent tokens [83]. Despite its prowess, the autoregressive nature of these models imbues them with an intrinsic limitation: the inability to leverage future context in token prediction, constraining their context comprehension to a unidirectional scope.
BERT and its variants, on the other hand, employ a masked language model (MLM) objective, where random words in a sentence are masked, and the model is trained to predict these masked words based on their context, integrating both preceding and succeeding context in representation learning [61].

Supervised pre-training

Supervised pre-training is a pre-training strategy that involves training a model on a large corpus of text data with labels or annotations. This paradigm contrasts with unsupervised pre-training, where models learn from raw text without explicit labels. The supervised approach enables models to learn representations that are more closely aligned with the end tasks, potentially enhancing their performance and efficiency [84].

In supervised pre-training, LLMs are exposed to a vast array of labeled data across various domains. This training regime involves teaching the model to predict the correct output given an input, under the supervision of known input-output pairs. This approach not only helps in learning general language representations but also imbues the model with domain-specific knowledge, which is particularly beneficial when the subsequent fine-tuning task is closely related to the pre-training data [69].

One significant advantage of supervised pre-training is its potential to reduce the amount of labeled data required for fine-tuning on specific tasks. By learning robust representations during pre-training, LLMs can achieve high performance on downstream tasks even with relatively smaller datasets, a concept known as transfer learning [71]. Moreover, supervised pre-training can lead to improvements in model generalization, making LLMs more adept at handling unseen data or tasks that diverge from their initial training corpus.

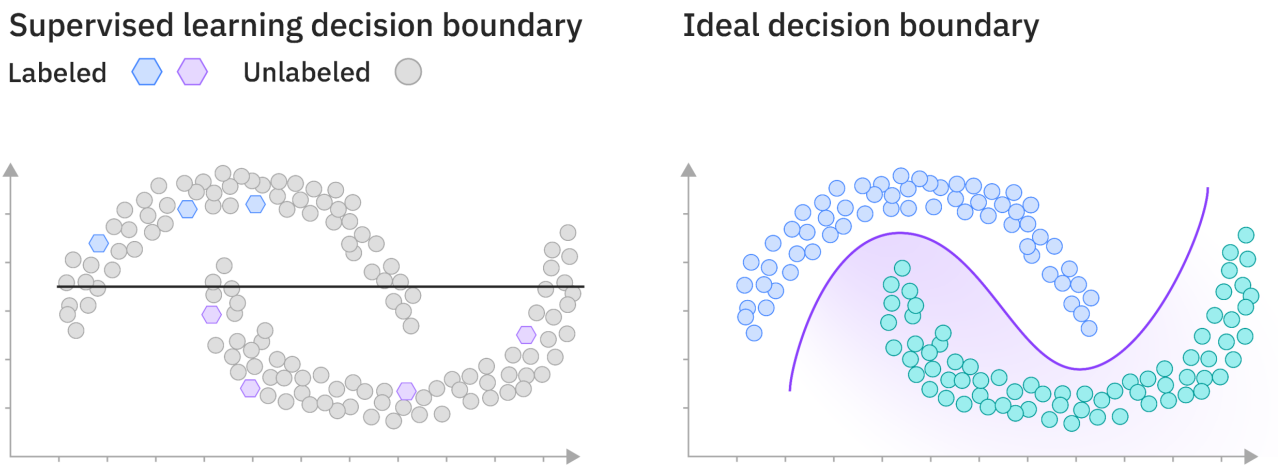

Figure 2.1: *Using only the very limited labeled data points available, a supervised model may learn a decision boundary that will generalize poorly and be prone to misclassifying new examples. Source: Bergmann [241].*

The reliance on large labeled datasets introduces concerns regarding the cost and feasibility of data annotation, especially in specialized domains where expert knowledge is required. Furthermore, as shown in Figure 2.1, the risk of overfitting to the pre-training data is non-trivial, necessitating careful regularization and validation to ensure the model's generalizability [41].

Semi-supervised pre-training

Semi-supervised pre-training emerges as a compelling paradigm in the evolution of Large Language Models (LLMs), blending the strengths of supervised and unsupervised learning methodologies. This hybrid training approach leverages a combination of labeled and unlabeled data, optimizing the utilization of available information and enhancing the model's learning efficacy and adaptability [9, 12].

At its core, semi-supervised pre-training involves the initial training of models using a vast corpus of unlabeled data, akin to unsupervised pre-training. This phase allows the model to capture a broad understanding of language structures and patterns. Subsequently, the model undergoes further training or fine-tuning on a smaller labeled dataset, which instills task-specific knowledge and nuances [71, 38]. The rationale behind this approach is to exploit the abundance of readily available unlabeled data to develop a comprehensive language model, which is then refined using the more scarce labeled data to achieve superior performance on target tasks.

Various techniques underpin semi-supervised pre-training in LLMs. One prominent method involves self-training, where the model, initially trained on labeled data, generates pseudo-labels for the unlabeled dataset. These pseudo-labeled data points are then incorporated into further training cycles, iteratively enhancing the model's accuracy and robustness [16].

Another notable technique is the use of consistency regularization, which ensures that the model produces similar outputs for perturbed versions of the same input data, enhancing the model's stability and generalization capabilities [30].

Other key techniques in semi-supervised learning include transductive and inductive learning, with practical methods like label propagation and active learning aiding in leveraging unlabeled data. These approaches are instrumental in refining the model's decision-making capabilities [241].

Transductive learning, a concept primarily attributed to Vapnik [3], focuses on predicting specific examples from the training set without attempting to generalize beyond those. In

transductive inference, the model is directly applied to the specific test set, aiming to infer the correct labels for the given unlabeled data. The key characteristic distinguishing transductive learning from other machine learning methods is its focus on the particular sample at hand rather than on a general rule applicable to new, unseen instances. One of the main applications of transductive learning is in the realm of support vector machines (SVMs), where it is employed to predict labels for a given, fixed set of test data, optimizing the margin not only for the training data but also for the test data, despite their labels being unknown [4].

Conversely, inductive learning aims to build a general model that predicts outcomes for new, unseen data based on the patterns learned from the training data. Label propagation (Figure 2.2) is a common technique in inductive learning, where the model infers the labels of unlabeled data points based on the labels of their neighbors in the feature space.

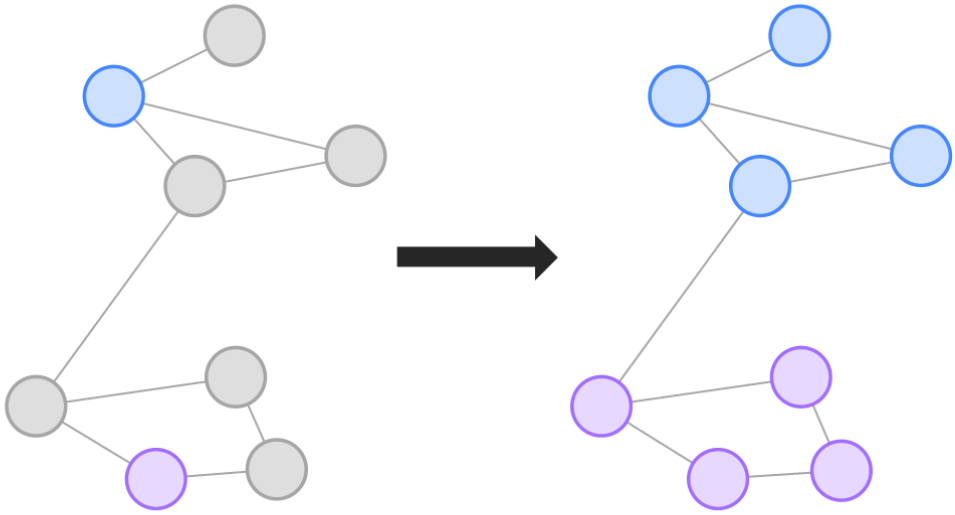

Figure 2.2: *LEFT: original labeled and unlabeled data points. RIGHT: using label propagation, the unlabeled data points have been assigned pseudo-labels. Source: Bergmann [241].*

Active learning is another inductive learning method that involves iteratively selecting the most informative data points for labeling, optimizing the model's performance with minimal labeled data. This approach is more general than transductive learning and underpins most supervised learning algorithms. The objective here is to infer a function that can generalize well across unseen samples, not just the examples provided during the training phase. Inductive learning is fundamental to numerous machine learning algorithms, from linear regression to deep neural networks, where the model learns an underlying function that maps input data to output predictions, with the hope that this function will perform accurately on data not present in the training set [2].

Semi-supervised approach is predicated on certain assumptions about the underlying structure and distribution of the data, which facilitate the effective integration of unlabeled data into the learning process.

- **Cluster Assumption:** The cluster assumption posits that data points within the same cluster are more likely to share a label. This assumption underpins the idea that data

points in high-density regions of the input space belong to the same class, while low-density regions denote boundaries between classes [12]. This principle guides the model to generalize from labeled data points to nearby unlabeled ones within the same cluster.

- **Continuity Assumption:** Also known as the smoothness assumption, this posits that if two points in the input space are close to each other, than their corresponding outputs are also likely to be similar [8]. In practical terms, this means that if two data points are close in the feature space, they are likely to share the same label.

- **Manifold Assumption:** The manifold assumption suggests that high-dimensional data lie on a low-dimensional manifold. This assumption implies that the data points are situated on a manifold of much lower dimensionality embedded within the higher-dimensional space, and learning can be simplified if this manifold structure is discovered and exploited [10]. The manifold assumption often complements the cluster and continuity assumptions, providing a geometric interpretation of the data's distribution.

- **Low-Density Separation Assumption:** This assumption posits that the decision boundary between different classes should lie in regions of low data density [12]. Essentially, it is expected that there is a natural separation or gap between classes, and the learning algorithm should prefer hypotheses that place the decision boundary in regions where few data points are present.

2.2.2 Data source

Large Language Models (LLMs) exhibit a strong dependency on extensive, high-caliber data for pre-training, with their efficacy closely tied to the nature and preprocessing of the utilized corpora. The main sources of data for training and evaluating LLMs can be broadly categorized into general and specialized datasets, each serving distinct purposes in enhancing the models' capabilities [335].

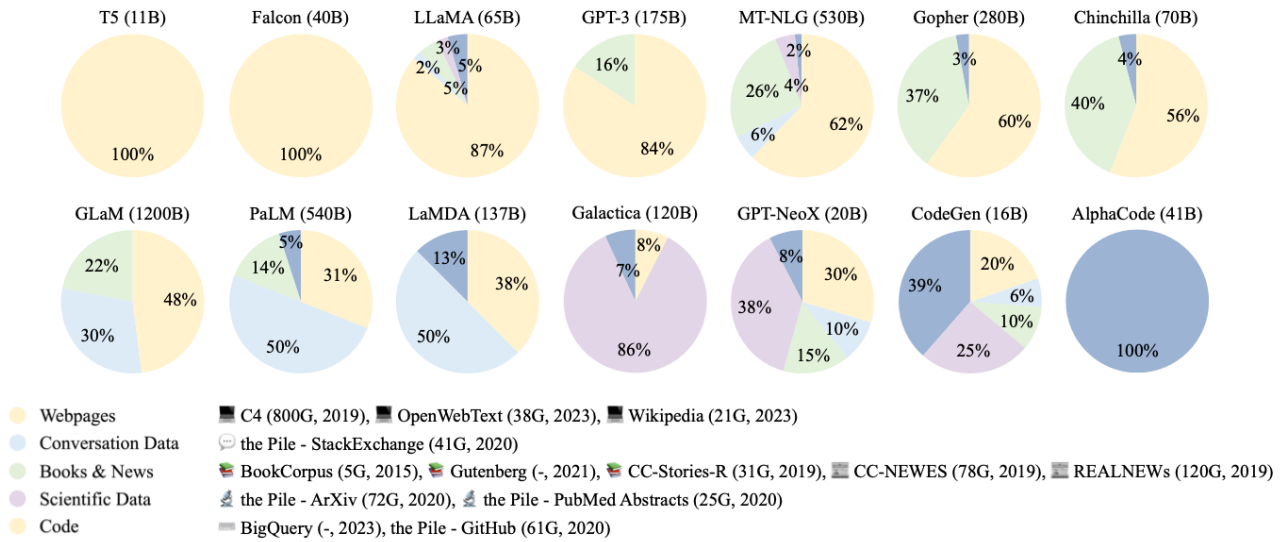

Figure 2.3: *Commonly-used data sources for training and evaluating Large Language Models (LLMs). Source: Zhao et al. [335].*

General Data: This category typically encompasses web content, literary works, and conversational texts, prized for their voluminous, varied, and accessible nature, thereby bolstering

the language modeling and generalization prowess of LLMs. The inclusion of general data, such as web pages and books, offers a rich lexicon spanning various themes, essential for the comprehensive training of LLMs. As shown in Figure 2.3, general purpose data are among the most commonly used general data sources for training LLMs.
Three important general data sources are:

- **Webpages:** Web content, extracted from the internet, is a valuable source of diverse and up-to-date text data, encompassing news articles, blog posts, and forum discussions. This data is instrumental in training LLMs to gain different linguistic knowledge and enhance generalization capabilities [83, 94]. Crawled web data tend be a mix of high-quality and noisy text, necessitating careful preprocessing to ensure the data's quality and relevance.

- **Conversation text:** Conversation text, including chat logs and social media interactions, provides a rich source of informal language and colloquial expressions, enabling LLMs to capture the nuances of human communication [233]. This data is particularly useful for training LLMs on question answering [149] and sentiment analysis tasks [77]. Conversational data often involve multiple speakers, so an effective way is to trasform the conversation in a tree structure, where the utterance is linked to the one it is replying to. The tree can be divided in multiple subtrees, each one representing a sub-conversation, which can be collected in the pre-training corpus. Overtraining on conversational data can lead to the model to a performance decline, since the declarative instructions and direct interrogatives can be erroneously interpreted as the beginning of a conversation [233].

- **Books:** Books, comprising novels, essays, and scientific literature, offer a rich source of long structured and coherent text data, enabling LLMs to learn complex language structures and thematic nuances [24]. This data is instrumental in training LLMs on literary text generation tasks and enhancing their proficiency in narrative comprehension and storytelling [70].

Specialized Data: Tailored to refine LLMs' proficiency in particular tasks, specialized datasets encompass multilingual text, scientific literature, and programming code. Specialized datasets are useful to improve the specific capabilities of LLMs on downstream tasks. Next, we introduce three kinds of specialized data.

- **Multilingual text:** Multilingual text data, spanning multiple languages and dialects, is crucial for training LLMs to understand and generate text in diverse linguistic contexts [335]. This data is instrumental in enhancing the models' cross-lingual capabilities and enabling them to perform translation tasks across different languages [335]. BLOOM [322] and PaLM [149] are two models that have been trained on multilingual text data to improve their performance on cross-lingual tasks. They have impressive performances on translation, multilingual question answering, and cross-lingual summarization tasks, and they achieve comparable or superior results to models fine-tuned on specific languages.

- **Scientific literature:** Scientific literature, encompassing research papers, patents, and technical documents, provides a rich source of domain-specific text data, essential for training LLMs on scientific text generation and reasoning tasks [335, 214, 176]. To build the scientific corpus for training LLMs, existing efforts mainly collect arXiv papers, scientific textbooks, math web-pages, and other related scientific resources. Data in sceintific fields are complex, commonly including mathematical symbols and protein sequences, so specific tokenization and preprocessing techniques are required to transform these different formats of data into a unified form that can be processed by language models.

- **Code:** Code, encompassing source code snippets and software documentation, is a valuable source of structured text data, essential for training LLMs on code generation and code completion tasks [335, 197]. Code data is often collected from open-source repositories like GitHub and StackOverflow, and it is used to train LLMs to generate code snippets, complete code fragments, and perform code summarization tasks. Recently Chen et al. [103] and Austin et al. [100] have shown that models trained on code data can be used to generate code with high accuracy and efficiency, and they can be used to improve the performance of code completion tasks. Generated code can successfully pass expert-designed unit-test cases [103] or solve competitive programming problems [178]. In general, two types of code corpora are used: one is question answering datasets like Stack Exchange [228]; the second is public software repositoris like GitHub [103] where code, comments and docstring are collected for utilization.

Commonly-used data sources

The development and evaluation of Large Language Models (LLMs) rely heavily on the availability of high-quality datasets that span diverse domains and languages. The datasets in Table 2.1 serve as the foundation for pre-training and fine-tuning LLMs, enabling researchers to assess the models' performance on a wide range of tasks, from text generation to translation.

Corpora	Size	Source	Update Time
BookCorpus [24]	5GB	Books	Dec-2015
Gutenberg [351]	-	Books	Dec-2021
C4 [94]	800GB	CommonCrawl	Apr-2019
CC-Stories-R [51]	31GB	CommonCrawl	Sep-2019
CC-NEWS [68]	78GB	CommonCrawl	Feb-2019
REALNEWS [77]	120GB	CommonCrawl	Apr-2019
OpenWebText [63]	38GB	Reddit links	Mar-2023
Pushift.io [82]	2TB	Reddit links	Mar-2023
Wikipedia [352]	21GB	Wikipedia	Mar-2023
BigQuery [349]	-	Codes	Dec-2023
the Pile [106]	800GB	Other	Dec-2020
ROOTS [173]	1.6TB	Other	Jun-2022

Table 2.1: *Statistics of commonly-used data sources. Source: Zhao et al. [335]*

In this section, we will explore some of the most commonly-used data sources for training and evaluating LLMs. Based on their content types, we categorize these corpora into six groups: Books, CommonCrawl, Reddit links, Wikipedia, Code, and others.

- **Books:** BookCorpus [24] and Gutenberg [351] are two prominent datasets that contain text from a wide range of books, spanning various genres and topics. These datasets are valuable for training LLMs on literary text and assessing their performance on text generation tasks.
  BookCorpus is a dataset consisting of text from over 11,000 books (e.g., novels and biographies), while Gutenberg is a collection of over 70,000 free ebooks including novels, essays, poetry, drama, history, science, philosophy, and other types of works in the public domain.
  BookCorpus is commonly used in previous small-scale models (e.g., GPT [47] and GPT-2 [70]), while Gutenberg is used in more recent large-scale models (i.e., LLaMa [306]).

Book1 and Book2 used in GPT-3 [83] are much larger than BookCorpus, but they have not been publicly released.

- **CommonCrawl:** CommonCrawl [350] is a vast web corpus that contains data from billions of web pages, covering diverse topics and languages. Due to noise and redundancy in the data, researchers often extract subsets of CommonCrawl for training LLMs. The main subsets used for training LLMs are C4[1] [94], CC-Stories-R [51], CC-NEWS [68], and REALNEWS [77].

- **Reddit links:** Reddit is a social media platform where users can submit links and posts and "upvotes" or "downvote" them. Posts with high number of "upvotes" are often considered useful, and can be used to create high-quality datasets. OpenWebText [63] and Pushshift.io [82] are datasets that contain text data extracted from Reddit. These datasets are useful for training LLMs on social media text and assessing their performance on text generation and sentiment analysis tasks.

- **Wikipedia:** Wikipedia [352] is a widely-used dataset that contains text from articles on various topics. It's an online encyclopedia with a large volume of high-quality articles. Most of these articles are composed in an expository style of writing (with supporting references), covering a wide range of languages and fields. Typically, the English-only filtered versions of Wikipedia are widely used in most LLMs (e.g., GPT-3 [83], and LLaMA [306]). Wikipedia is available in multiple languages, so it can be used in multilingual settings.

- **Code:** Two major sources are GitHub, for open-source licensed code, and StackOverflow, for code-related question-answering platforms.
  Google has publicly released BigQuery [349], a dataset that contains code snippets from various programming languages. This dataset is useful for training LLMs (i.e., CodeGen [197]) on code text and assessing their performance on code generation and code completion tasks.

- **Others:** The Pile [106] and ROOTS [173] are datasets that contain text data from various sources, such as books, articles, and websites.
  The Pile contains 800GB of data from multiple sources, including books, websites, codes, scientific papers, and social media platforms. It's widely used in training LLMs with different size (e.g., CodeGen(16B) [197] and Megatron-Turing NLG(530B) [208]).
  ROOTS is composed of various smaller datasets (totally 1.61 TB of text) in 59 different languages (containing natural languages and programming languages). It's been used for training BLOOM [322].

In practice, a mixture of these datasets is often used to train LLMs, as they provide a diverse range of text data (Figure 2.3). The choice of datasets depends on the specific task and domain of interest, as well as the computational resources available for training the model. Furthermore, to train LLMs that are adaptative to specific tasks or domains, is also important to consider the data sources that are relevant to them.

2.2.3 Data preprocessing

After collecting the data, the next step is to preprocess it to ensure that it is clean, consistent, and ready for training Large Language Models (LLMs) removing noise and irrelevant, or potentially toxic information [149, 125, 279]. In Chen et al. [246] the authors propose a new data

[1] Colossal Clean Crawled Corpus

preprocessing system, DataJuicer, that can be used to improve quality of the processed data. A typical pipeline for data preprocessing involves several steps, as shown in Figure 2.4:

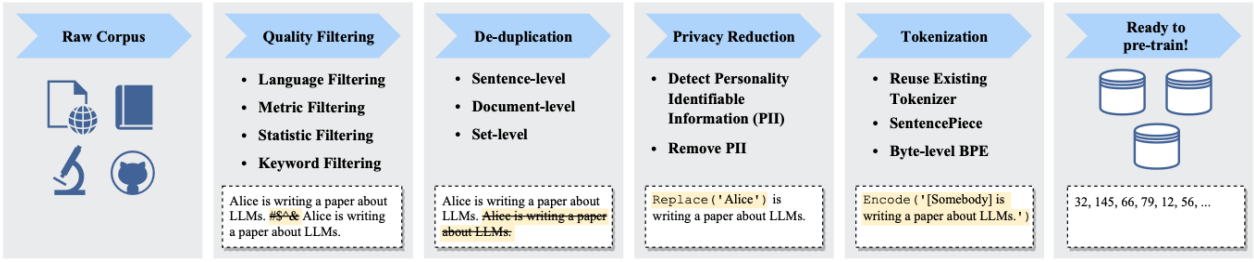

Figure 2.4: *Common data preprocessing steps for training Large Language Models (LLMs). Source: Zhao et al. [335].*

Quality Filtering. The first step in data preprocessing is quality filtering, where the data is cleaned to remove irrelevant or low-quality content. Existing works mainly adopt two strategies for quality filtering: classifier-based and heuristic-based filtering.

The former approach involves training a classifier to distinguish between high-quality and low-quality data, using well-curated data (e.g., Wikipedia pages) as positive examples and noisy data (e.g., spam or irrelevant content) as negative examples. Rae et al. [125] and Du et al. [155] find that classifier-based filtering may remove high-quality data in dialect, colloquial, and sociolectal[2] languages, which potentially leads to bias in the pre-training data and diminishes the corpus diversity.

Heuristic-based filtering, on the other hand, involves setting predefined rules to identify and remove noisy data [322, 125]. The set of rules can be summarized as follows:

- *Language based filtering.* Remove data that is not in the target language.
- *Metric based filtering.* Remove data that does not meet certain quality metrics, e.g., perplexity, readability, or coherence. Perplexity (PPL) is one of the most common metrics for evaluating language models. This metric applies specifically to classical language models (sometimes called autoregressive or causal language models) and is not well-defined for masked language models like BERT [61]. Perplexity is defined as the exponential average negative log-likelihood of a sequence.
  If we have a tokenized sequence $X = x_1, x_2, \ldots, x_t$, the perplexity of the sequence is defined as:
  $$PPL(X) = \exp\left\{-\frac{1}{t}\sum_{i}^{t}\log p_\theta(x_i|x_{<i})\right\} \tag{2.1}$$
  where $\log p_\theta(x_i|x_{<i})$ is the log-likelihood of the token x_i given the previous tokens $x_{<i}$ in the sequence. Intuitively, it can be thought of as an evaluation of the model's ability to predict uniformly among the set of specified tokens in a corpus[3] [291].
- *Statistic based filtering.* Statistical features like punctuation distribution, symbol-to-word ratio, and sentence length can be used to filter out low-quality data.

[2]In sociolinguistics, a sociolect is a form of language or a set of lexical items used by a socioeconomic class, profession, age group, or other social group. Sociolects involve both passive acquisition of particular communicative practices through association with a local community, as well as active learning and choice among speech or writing forms to demonstrate identification with particular groups. Source: Wikipedia [352]

[3]This means that the tokenization procedure has a direct impact on a model's perplexity which should always be taken into consideration when comparing different models.

- *Keyword based filtering.* Remove data that contains specific keywords that are noisy, irrelevant or toxic like HTML tags, URLs, boilerplate text, or offensive language.

Deduplication. The next step in data preprocessing is deduplication, where duplicate data are removed to reduce redundancy and improve the diversity of the training data. Moreover, Hernandez et al. [165] found that duplication may cause instability in the training process, leading to overfitting and poor generalization performance. Therefore, deduplication is essential to ensure that the model is exposed to a diverse range of text data during training.

It can be done at various granularity, such as at the document level, paragraph level, or sentence level. Low-quality sentences that contains repeated words or phrases can be removed to improve the quality of the data. At document level, the deduplication can be done by computing overlap ratio of surface features (e.g., words and n-grams overlap) between documents, and removing the duplicates that contains similar contents [306, 125, 322, 175]. To avoid the contamination problem, the deduplication process should be done before the data is split into training, validation, and test sets [149]. Chowdhery et al. [149] and Carlini et al. [144] have shown that the three deduplication strategies should be used in conjunction to improve the training of LLMs.

Privacy reduction. Privacy reduction is another important step in data preprocessing, especially when dealing with sensitive or personal information. Since data is often collected from web and contains user-generated content, the risk of privacy breaching is high [102]. This step involves anonymizing or obfuscating sensitive data to protect the privacy of individuals. Common techniques for privacy reduction include masking personally identifiable information (PII), such as names, addresses, and phone numbers, and replacing them with generic placeholders or tokens [173].

Privacy attacks to LLMs can be attributed to presence of duplicated PII data in the pre-training, which can be used to extract the original PII data [175]. Therefore, de-duplication can also reduce privacy risks to some extent.

Tokenization. Tokenization is a crucial step in data preprocessing, where the text data is converted into tokens that can be processed by the model. The choice of tokenization method can have a significant impact on the model's performance, as different tokenization strategies can affect the model's ability to capture the underlying structure of the language.

Common tokenization techniques include word-based tokenization, subword-based tokenization, and character-based tokenization. Word-based tokenization splits the text into individual words, while subword-based tokenization breaks down the text into subword units, such as prefixes, suffixes, and roots. Character-based tokenization, on the other hand, tokenizes the text into individual characters. Word-based tokenization is the predominant method used in traditional NLP research [5].

However, word-based tokenization can be problematic for languages with complex morphology or limited vocabulary, as it may result in a large vocabulary size and sparse data representation. In some other languages, like Chinese, Japanese, and Korean, word-based tokenization is not suitable because these languages do not have explicit word boundaries[4]. Thus, several neural network-based models employed subword-based tokenization, such as Byte Pair Encoding (BPE) [31], Unigram [42], and WordPiece [32], to address these challenges.

Byte Pair Encoding (BPE) is a type of data compression technique that has been effectively adapted for natural language processing tasks, particularly in the domain of tokenization for large language models (LLMs). The BPE algorithm operates by iteratively merging the most frequent pair of bytes (or characters in the context of text) in a given dataset into a single, new byte (or character), and it repeats this process until a specified number of merges has been reached or another stopping criterion has been met. The application of BPE in the field of

[4]It means that it can yield different segmentation results for the same input.

NLP was popularized by Sennrich, Haddow, and Birch [31] in the context of neural machine translation. They demonstrated that using BPE allowed for efficient handling of rare and unknown words, which are commonplace in languages with rich morphology or in specialized vocabularies, such as scientific texts or code. By splitting words into subword units, BPE provides a balance between the granularity of characters and the semantic units of full words, enabling models to represent a wide vocabulary with a limited set of tokens. BPE has been fundamental in the architecture of influential language models, such as OpenAI's GPT series, BART and LLaMA.

WordPiece tokenization is a tokenization method that segments text into subword units, allowing for a balance between the flexibility of character-based models and the efficiency of word-based models. Originating from speech processing [32], this method has found significant application in natural language processing, particularly within neural network-based models such as BERT and its variants. In WordPiece tokenization, a base vocabulary is first constructed with individual characters, and then more frequent and meaningful sub-word units are incrementally added. This construction process is guided by a criterion that aims to maximize the language model likelihood on a training corpus, thus ensuring that the resulting tokens are optimal representations for the given data. The WordPiece algorithm iteratively merges the most frequently co-occurring pairs of tokens to form new sub-word units until a specified vocabulary size is reached. This tokenization strategy has shown effectiveness in reducing out-of-vocabulary issues, as the model can fall back on smaller sub-word units when encountering unfamiliar words. Moreover, by capturing sub-word regularities, WordPiece facilitates the learning of meaningful representations for morphologically rich languages within large language models. This is particularly advantageous for handling agglutinative languages, where words often comprise a series of affixed morphemes[5].

Unigram tokenization is a statistical method that employs an unigram language model for the probabilistic segmentation of text into tokens. This technique, standing in contrast to the deterministic nature of Byte Pair Encoding, involves constructing a unigram model from a large initial vocabulary and iteratively refining it to maximize the likelihood of the observed corpus [42]. The essence of Unigram tokenization lies in its iterative pruning process, wherein less probable tokens are systematically eliminated from the vocabulary. To estimate the unigram language model, it adopts an expectation–maximization (EM) algorithm: at each iteration, it first finds the currently optimal tokenization of words based on the old language model, and then re-estimate the probabilities of unigrams to update the language model. During this procedure, dynamic programming algorithms (i.e., the Viterbi algorithm) are used to efficiently find the optimal decomposition way of a word given the language model[335]. This probabilistic approach is adept at handling the linguistic complexities and variations found across different languages and domains. It particularly excels in the context of language models that require

[5]Agglutinative languages are a type of morphological linguistic classification in which words are formed through the linear addition of discrete units, each of which carries a specific grammatical meaning. These discrete units are known as morphemes, which are the smallest grammatical units in a language. In agglutinative languages, morphemes are concatenated in a way that each morpheme represents a single grammatical function, such as tense, number, case, or aspect. For example, in Turkish – an agglutinative language – a single word can be made up of a base or root word with several affixes attached to it to modify its meaning. These affixes remain relatively invariant; they don't undergo significant changes in form when they're combined with other morphemes. Here's an illustrative example from Turkish:
"ev" means "house"
"evler" means "houses" (plural)
"evlerim" means "my houses" (possessive plural)
Each suffix attached to "ev" is a separate morpheme that changes the meaning of the word, indicating plurality and possession without ambiguity. This is in contrast to fusional languages, where a single affix can represent multiple grammatical categories, or isolating languages, where words generally do not change form at all, and grammatical relations are indicated by word order or separate words.

a nuanced understanding of morphological structures and sub-word variations. Unigram tokenization has been pivotal in the development of the SentencePiece [42] tokenization library, which is renowned for its application in T5 and mBART. The adaptability and language-agnostic properties of Unigram tokenization make it a preferred choice for LLMs tasked with processing multilingual data [42].

2.3 Adaptation of Large Language Models

The adaptation of Large Language Models (LLMs) is a critical aspect of their deployment in real-world applications, as it enables the models to be fine-tuned on specific tasks or domains after pre-training, enhancing their performance minimizing loss of generalization capabilities. Adaptation can be achieved through various techniques, such as instruction tuning and alignment tuning, which allow LLMs to enhance (or unlock) theirs abilities and align their behaviours with human values or preferences [335].

Table 2.2: *A detailed list of available collections for instruction tuning.*

Categories	**Collections**	**Time**	**#Examples**
Task	Nat. Inst. [193]	Apr-2021	193K
	FLAN [224]	Sep-2021	4.4M
	P3 [141]	Oct-2021	12.1M
	Super Nat. Inst. [222]	Apr-2022	5M
	MVPCorpus [213]	Jun-2022	41M
	xP3 [194]	Nov-2022	81M
	OIG [308]	Mar-2023	43M
Chat	HH-RLHF [142]	Apr-2022	160K
	HC3 [256]	Jan-2023	87K
	ShareGPT [61]	Mar-2023	90K
	Dolly [89]	Apr-2023	15K
	OpenAssistant [267]	Apr-2023	161K
Synthetic	Self-Instruct [221]	Dec-2022	82K
	Alpaca [303]	Mar-2023	52K
	Guanaco [105]	Mar-2023	535K
	Baize [330]	Apr-2023	158K
	BELLE [264]	Apr-2023	1.5M

2.3.1 Instruction Tuning

Instruction tuning is a technique that leverages natural language instructions to fine-tune pre-trained LLMs [224], which is highly related to supervised fine-tuning [199] and multi-task prompted training [203]. Instruction tuning enhances LLMs by refining their ability to follow and comprehend natural language instructions. Unlike traditional fine-tuning, which adapts models to specific tasks, instruction tuning employs a more generalized approach that broadens the model's utility across a variety of tasks through an "instruction-following" paradigm (Figure 2.5).

FLAN[6] [224] is noted for substantially improving zero-shot learning capabilities when compared to traditional models like GPT-3 [83] (Figure 2.6).

[6]Finetuned LAnguage Net, a 137B parameter pretrained language model and instruction tune it on over 60

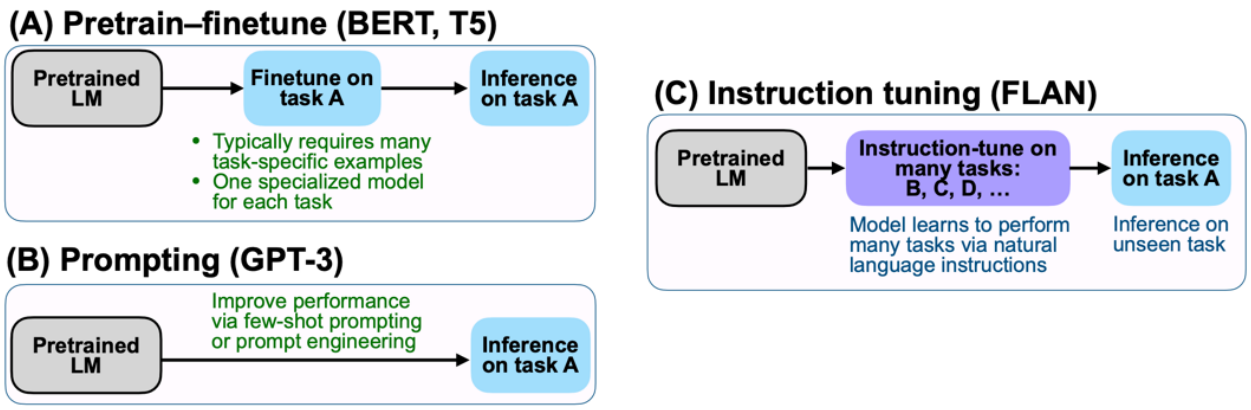

Figure 2.5: *Overview of instruction tuning. Source: Zhao et al. [335].*

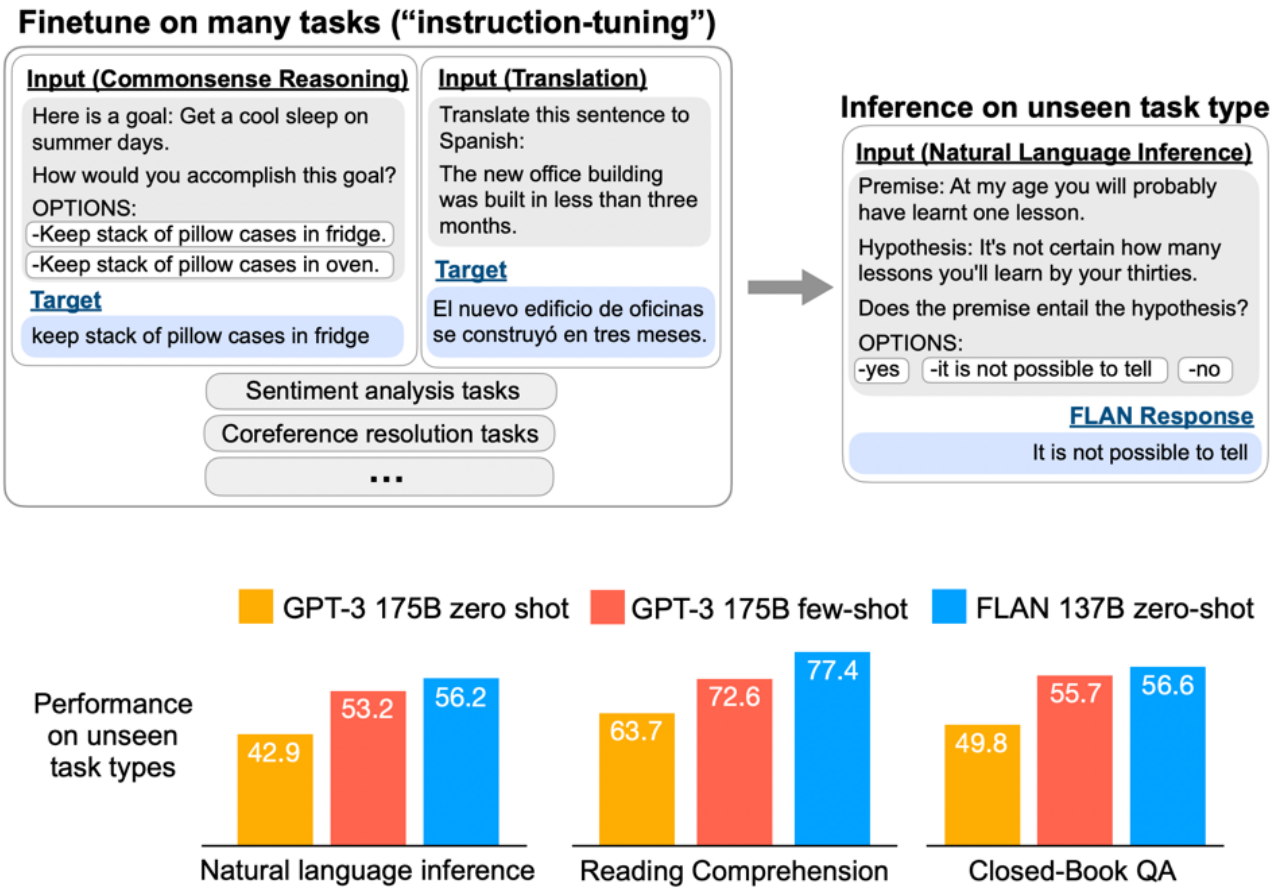

Figure 2.6: *Top: overview of instruction tuning and FLAN. Instruction tuning finetunes a pretrained language model on a mixture of tasks phrased as instructions. Evaluation on unseen task type at inference time (i.e., evaluate the model on natural language inference (NLI) when no NLI tasks were seen during instruction tuning).*
Bottom: performance of zero-shot FLAN, compared with zero-shot and few-shot GPT-3, on three unseen task types where instruction tuning improved performance substantially out of ten evaluated. NLI datasets: ANLI R1–R3, CB, RTE. Reading comprehension datasets: BoolQ, MultiRC, OBQA. Closed-book QA datasets: ARC-easy, ARC-challenge, NQ, TriviaQA. Source: Wei et al. [224].

NLP datasets verbalized via natural language instruction templates

Chung et al. [150] have shown instruction-tuned (Figure 2.7) PaLM[7] enhance model performance on various tasks (i.e., MMLU, BBH, TyDiQA and MGSM) when the model size is at least 62B, though a much smaller size might suffice for some specific tasks (e.g., MMLU).

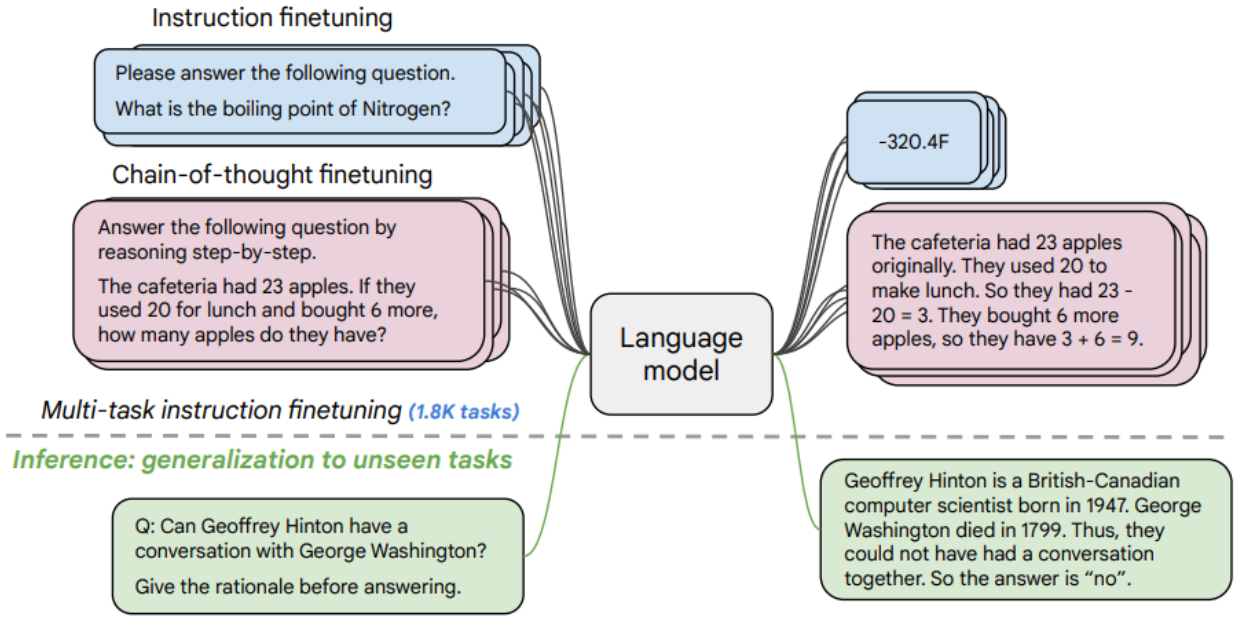

Figure 2.7: *Overview of FLAN instruction tuning with and without exemplars (i.e., zero-shot and few-shots) and with and without CoT. Following evaluation on unseen tasks. Source: Chung et al. [150].*

Instruction tuning has been widely applied also in other models like Instruct-GPT [199] and GPT-4 [293]. Other experiments in Wei et al. [224] have shown that instruction tuning of LaMDA-PT started to significantly improve performance on zero-shot tasks when the model size is at least 68B.

Let's have a look at the construction of instruction-formatted instances, which are essential for instruction tuning. Generally, an instruction-formatted instance consists of a task description (called an *instruction*) and a set of input-output examples, optionally followed by a small number of demonstrations. There are three main approaches to construct instruction-formatted instances: formatting task datasets, formatting daily dialogues, and formatting synthetic data as represented in Figure 2.8.

Historically, datasets encompassing various tasks like text summarization, classification, and translation were used to create multi-task training datasets [213, 67, 98]. These datasets have become crucial for instruction tuning, particularly when formatted with natural language descriptions that clarify the task objectives to the LLMs. This augmentation helps the models understand and execute the tasks more effectively [203, 199, 224, 222]. For instance, each example in a question-answering dataset might be supplemented with a directive like "Please answer this question" which guides the LLM in its response generation. The effectiveness of such instruction tuning is evident as LLMs demonstrate improved generalization to unfamiliar tasks when trained with these enriched datasets [224]. The importance of these instructions is underscored by the observed decline in performance when task descriptions are omitted from training.

PromptSource [141], a crowd-sourcing platform, has been proposed to aid in the creation, sharing, and verification of task descriptions for datasets. This platform enhances the utility

[7]Also called Flan-PaLM 540B-parameter model

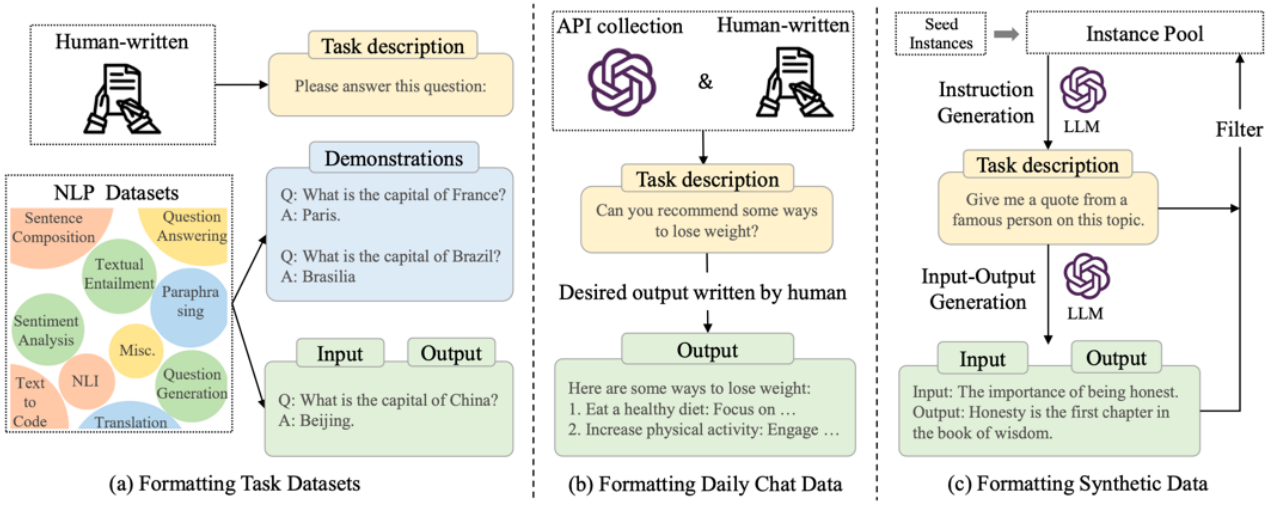

Figure 2.8: *Three main approaches to construct instruction-formatted instances. Source: Zhao et al. [335].*

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of instruction tuning by ensuring a rich variety of well-defined task descriptions. Several studies [203, 213, 280] also tried to invert the input-output pairs of existing instances to create new instances using specially designed task descriptions (e.g., "Please generate a question given this answer").

Talking about formatting daily chat data, Instruct-GPT has been fine-tuned using real user queries submitted to the OpenAI API to fill the significant gap in the data used for training models – most training instances come from public NLP datasets that often lack instructional diversity and do not align well with actual human needs. This approach helps to harness the model's capability to follow instructions effectively. To further enhance task diversity and real-life applicability, human labelers are employed to create instructions for a variety of tasks including open-ended generation, open question answering, brainstorming, and casual chatting. Another set of labelers then provides responses to these instructions, which are used as training outputs. This method not only enriches the training data but also aligns the model's responses more closely with human-like conversational patterns. InstructGPT also employs these real-world tasks formatted in natural language for alignment tuning (see Section 2.3.2). GPT-4 extends this approach by specifically designing potentially high-risk instructions and guided the model to reject these instructions through supervised fine-tuning for safety concerns. Recent efforts have also focused on collecting user chat requests as input data, with models like ChatGPT or GPT-4 generating the responses. A notable dataset in this realm is the conversational data from ShareGPT, which provides a rich source of real-world interactions for training and refining the performance of LLMs.

Semi-automated methods [221] for generating synthetic data have also been explored to create instruction-formatted instances, which helps alleviate the need for extensive human annotation and manual data collection. One such method is the Self-Instruct approach, which efficiently utilizes a relatively small initial dataset. With the Self-Instruct method, only about 100 examples are required to start the data augmentation process (Figure 2.8c). From this initial task pool, a few instances are selected randomly and used as demonstrations for an LLM. The model is then prompted to generate new task descriptions along with corresponding input-output pairs. This process not only expands the dataset but also ensures a variety of training examples by incorporating a diversity and quality check before adding the newly synthesized instances back into the task pool. This synthetic approach to data generation is portrayed as both cost-effective and efficient, providing a scalable solution for enriching training datasets for

LLMs. It leverages the generative capabilities of LLMs to create diverse and relevant training materials, thereby enhancing the training process without the usual resource-intensive demands of manual data creation. Instruction tuning not only improves zero-shot learning but also establishes new benchmarks in few-shot learning scenarios. The improvement is attributed to the instruction tuning across diverse datasets which likely provides a richer context for model adaptation [224]. The idea is that by using supervision to teach a model to perform tasks described via instructions, the model will learn to follow instructions and do so even for unseen tasks.

Two essentials factors for instance construction are:

- **Scaling the instructions.** Increasing the number of tasks within training data can significantly improve the generalization ability of LLMs, as evidenced by Wei et al. [224], Sanh et al. [72], and Chowdhery et al. [149]. The performance of LLMs typically increases with the number of tasks but plateaus after reaching a saturation point [94, 149]. It is suggested that beyond a certain threshold, additional tasks do not contribute to performance gains [94]. The diversity in task descriptions, including variations in length, structure, and creativity, is beneficial [224]. However, increasing the number of instances per task might lead to overfitting if the numbers are excessively high [149, 247].

- **Formatting design.** The way instructions are formatted also plays a crucial role in the generalization performance of LLMs [149]. Task descriptions, supplemented by optional demonstrations, form the core through which LLMs grasp the tasks [149]. Utilizing a suitable number of exemplars as demonstrations can notably enhance performance and reduce the model's sensitivity to instruction nuances [72, 94]. However, including additional elements like prohibitions, reasons, or suggestions within instructions may not effectively impact or might even negatively affect LLM performance [149, 193]. Recently, some studies suggest incorporating chain-of-thought (CoT) examples in datasets that require step-by-step reasoning, which has proven effective across a variety of reasoning tasks [94, 168].

Instruction tuning is often more efficient since only moderate number of instances are needed for training. Since instruction tuning can be considered as a supervised training process, its optimization is different from pre-training in several aspects [150], such as the training objective (i.e., sequence-to-sequence loss) and optimization configuration (e.g., smaller batch size and learning rate), which require special attention in practice.

Balancing the proportion of different tasks during fine-tuning is crucial. A commonly used method is the examples-proportional mixing strategy [94], ensuring that no single dataset overwhelms the training process [94, 224]. Additionally, setting a maximum cap on the number of examples from any dataset helps maintain this balance [94, 224].

To enhance the stability and effectiveness of instruction tuning, integrating pre-training data into the tuning process is beneficial, serving as regularization [224]. Some models, such as GLM-130B and Galactica, start with a mix of pre-training and instruction-tuned data, effectively combining the strengths of both pre-training and instruction tuning [149].

A strategic approach involves multiple stages of tuning, starting with extensive task-specific data and followed by less frequent types such as daily chat instructions, to avoid the forgetting of previously learned tasks [94].

Some additional strategies to improve the instruction tuning process include:

- **Efficient training for multi-turn chat data.** Given a multiturn chat[8] dataset, each conversation can be split into multiple context-response pairs for training: the model is

[8]The conversation between a user and a bot

fine-tuned to generate responses based on the corresponding context for all splits. To save computational resources, Chiang et al. [250] propose a method that fine-tunes the model on the whole conversation, but relies on a loss mask that only computes the loss on the responses of the chatbot for training.

- **Filtering low-quality instructions using LLMs.** Filtering out low-quality instructions through advanced LLMs helps maintain high training standards and reduces unnecessary computational expenses [224].

- **Establishing self-identification for LLM.** In real world applications, it is important for LLMs to be able to identify themselves when asked. To achieve this, models like GPT-4 are trained to recognize and respond to self-identification instructions [293].

- **Concatenate multiple examples to approach max length.** To handle variable-length sequences during training, it is common practice to introduce padding tokens to ensure uniform sequence lengths. However, this approach can lead to inefficient use of the model's capacity, as the padding tokens do not contribute to the learning process. By concatenating multiple examples to approach the maximum sequence length, the model can process more information in each training step, thereby enhancing the training efficiency and performance [111].

- **Evaluate the quality of instructions.** Cao et al. [245] introduced InstructMining to autonomously select premium instruction-following data for finetuning LLMs by employing a combination of data mining techniques and performance evaluation strategies. The quality of instruction data is primarily assessed through its impact on model performance, quantified by the inference loss of a finetuned model on an evaluation dataset. InstructMining correlates the values of the natural language indicators[9] with the inference loss, creating a predictive model that estimates data quality based on these indicators. To identify the most effective subset of data for finetuning, InstructMining integrates an optimization technique called BlendSearch. This method helps in determining the optimal size and composition of the data subset that leads to the best finetuning outcomes. BlendSearch combines global and local search strategies to efficiently explore the complex search space, focusing on minimizing the model's inference loss on a high-quality evaluation set. Cao et al. [245] also accounts for the double descent phenomenon observed in model training, where increasing the dataset size initially improves performance up to a point, after which performance declines before potentially improving again as more data is added. This observation guides the selection process to focus on an optimal point that balances data quality and quantity, improving model performance efficiently.

- **Rewriting instructions into more complex ones.** Xu et al. [328] introduces an innovative method, termed "Evol-Instruct", which significantly enhances the instruction-following capabilities and overall performance of large language models (LLMs). It is a systematic approach for automatically generating complex instruction data using LLMs

[9] Some of the indicators include:

- Input and output length
- Reward model scores
- Perplexity
- Measures of Textual Lexical Diversity (MTLD)
- Approximate distance to nearest neighbors in embedding space
- Scores for naturalness, coherence, and understandability from models like UniEval

instead of human input. This method involves iterative evolution and refinement of initial, simpler instructions into more complex and diverse variants. These evolved instructions are then used to fine-tune LLMs, specifically targeting their ability to understand and execute more complex tasks effectively. Starting with a basic set of instructions, Evol-Instruct employs a two-pronged strategy – In-Depth Evolving and In-Breadth Evolving.

In-Depth Evolving enhances the complexity and depth of instructions by adding constraints, increasing reasoning demands, or introducing more detailed contexts. In-Breadth Evolving expands the variety and coverage of topics and skills addressed by the instructions, aiming to fill gaps in the LLM's training data and increase its general robustness across different types of tasks.

Throughout the evolution process, ineffective or poorly structured instructions are filtered out to ensure only high-quality data is used for model training. This step is crucial for maintaining the integrity and effectiveness of the training dataset. The process repeats several cycles, allowing the system to gradually refine the instruction set to maximize complexity and utility, while ensuring the instructions remain understandable and executable by the LLM. By training with the complex instructions generated by Evol-Instruct, LLMs like the WizardLM demonstrate significant improvements in several key areas:

  - Enhanced Generalization: The model becomes capable of handling a wider variety of tasks beyond the scope of its original training data.
  - Improved Complexity Handling: The LLM shows better performance in understanding and executing tasks that require higher levels of reasoning or multiple steps to complete.
  - Competitive Performance: Compared to models like OpenAI's ChatGPT and other contemporary LLMs, WizardLM trained with Evol-Instruct data exhibits competitive or superior performance, especially on complex instruction-following tasks.

The main effects of instruction tuning are:

- **Performance Improvement.** Instruction tuning significantly enhances LLMs, proving effective across models of various scales from 77M to 540B parameters. Smaller models subjected to instruction tuning can surpass larger models that haven't been fine-tuned, showcasing the technique's broad applicability and cost-effectiveness [129, 224]. This approach not only boosts model performance as parameter scale increases but also demonstrates improvements across different architectures, objectives, and adaptation methods [94].

- **Task Generalization.** Instruction tuning endows LLMs with the capability to understand and execute tasks based on natural language instructions. This method is particularly effective in generalizing across both familiar and novel tasks, significantly enhancing performance without direct prior exposure [149, 129]. Notably, models like BLOOMZ-P3, fine-tuned on English-only tasks, demonstrate remarkable improvements in multilingual sentence completion, indicating robust cross-lingual transfer capabilities [149].

- **Domain Specialization.** Despite their prowess in general NLP tasks, LLMs often lack the domain-specific knowledge required for fields like medicine, law, and finance. Instruction tuning facilitates the transformation of general-purpose LLMs into domain-specific experts. For example, Flan-PaLM has been adapted into Med-PaLM for medical applications, achieving expert-level performance in medical tasks [94]. Similar adaptations have been made in other domains, significantly enhancing LLMs' effectiveness in specialized applications [224].

In summary, instruction tuning is a powerful technique that significantly enhances the performance, generalization, and domain specialization of LLMs. The effectiveness of instruction tuning is evident across models of various scales and architectures, demonstrating its versatility and broad applicability. Larger models, such as LLaMA (13B) compared to LLaMA (7B), generally perform better, suggesting that increased model size enhances the model's ability to follow instructions and utilize knowledge more effectively. This is particularly evident in QA settings, where larger models show markedly improved performance [335].

Increasing the complexity and diversity of the Self-Instruct-52K dataset enhances LLaMA's performance in both chat and QA settings. For example, improving instruction complexity significantly boosts performance on QA tasks, which typically involve complex queries. Merely increasing the number of instructions or attempting to balance instruction difficulty does not necessarily yield better outcomes. In some cases, such as scaling up instruction numbers without focusing on quality, it can even degrade performance [335].

2.3.2 Alignment Tuning

LLMs may sometimes generate outputs that are inconsistent with human values or preferences (e.g., fabricating false information, pursuing inaccurate objectives, and producing harmful, misleading, or biased content) [199, 110]. To avoid such undesirable outcomes, alignment tuning is employed to ensure that LLMs' outputs align with specified ethical guidelines or desired behaviors [335]. Unlike pre-training and fine-tuning, which focus on optimizing model performance, alignment tuning aims to optimize the model's behavior to conform to human values and norms [335]. Alignment may harm the general abilities of LLMs to some extent, which is called *alignment tax* [99].

Three primary criteria to regulate the behavior of Large Language Models (LLMs) are: helpfulness, honesty, and harmlessness. These criteria have become standard in the literature and serve as benchmarks for aligning LLMs with desirable human-like behaviors. It's possible to adapt these criteria based on specific needs, such as substituting honesty with correctness [159]. Helpfulness refers to the model's ability to assist users effectively and efficiently, answering queries or solving tasks concisely. It should also engage in deeper interaction when necessary, asking relevant questions and demonstrating sensitivity and awareness. Honesty involves providing accurate information and being transparent about the model's uncertainty and limitations. This criterion is seen as more objective, potentially requiring less human intervention to achieve alignment compared to the other criteria. Harmlessness involves avoiding generating offensive or discriminatory language and being vigilant against being manipulated into harmful actions. The determination of what constitutes harm can vary significantly depending on cultural and individual differences and the context in which the model is used.

Zhao et al. [335] notes the subjectivity of these criteria, rooted in human judgment, making them challenging to incorporate directly as optimization objectives in LLM training. Nonetheless, various strategies, such as red teaming[10], are employed to meet these criteria by intentionally challenging LLMs to provoke harmful outputs and then refining them to prevent such behaviors.

During the pre-training phase on large-scale corpus, it's not possible to take into account the subjective and qualitative evaluations of LLM outputs by humans. Human feedback is essential for alignment tuning, as it provides the necessary supervision to guide the model towards desirable behaviors.

Dominant strategies for generating human feedback data is human annotation [199, 159, 80]. This highlight the importance of labelers in the alignment tuning process, as they play a

[10]Red teaming might involve trying to induce biased or harmful outputs from the model, to test its resistance to producing undesirable content under adversarial conditions.

crucial role in providing feedback on the model's outputs. Ensuring that labelers have adequate qualifications is vital; despite stringent selection criteria, mismatches in intentions between researchers and labelers can still occur, potentially compromising feedback quality and LLM performance [101]. To address this, the InstructGPT initiative includes a screening process to select labelers whose evaluations closely align with those of researchers [199]. Additionally, the use of "super raters" in some studies ensures the highest quality of feedback by selecting the most consistent labelers for critical tasks [159].

Three primary methods are used to collect human feedback and preference data:

- **Ranking-based approach.** Human labelers evaluate model outputs in a coarse-grained fashion, often choosing only the best output without considering finer details. This method could lead to biased or incomplete feedback due to the diversity of opinions among labelers and the neglect of unselected samples. To improve this, later studies introduced the Elo rating system to establish a preference ranking by comparing outputs, thereby providing a more nuanced training signal [159, 80].

- **Question-based approach.** This method involves labelers providing detailed feedback by answering specific questions designed to assess alignment criteria and additional constraints. For example, in the WebGPT project, labelers evaluate the usefulness of retrieved documents to answer given inputs, helping to filter and utilize relevant information [119].

- **Rule-based approach.** This approach involves the use of predefined rules to generate detailed feedback. For instance, Sparrow uses rules to test whether responses are helpful, correct, and harmless. Feedback is generated both by comparing responses and assessing rule violations. Additionally, GPT-4 uses zero-shot classifiers to automatically determine if outputs violate set rules [159, 293].

One approach of alignment tuning is to use a reward model to evaluate the quality of generated outputs. RLHF utilizes reinforcement learning (RL) techniques, such as Proximal Policy Optimization (PPO), to fine-tune LLMs based on human feedback, aiming to enhance model alignment on criteria like helpfulness, honesty, and harmlessness. This process involves several components and steps to effectively train and optimize LLMs. Key components of RLHF include a pre-trained language model (LM), a reward model (RM), and an RL algorithm (e.g., PPO) [335]. The LM is initialized with parameters from existing LLMs, such as GPT-3 by OpenAI or Gopher by DeepMind. Reward model provides guidance signals reflecting human preferences, which could be a fine-tuned LM or newly trained LM using human preference data. RMs often differ in parameter scale from the LLM being aligned. Main steps in RLHF include supervised fine-tuning, reward model training, and RL fine-tuning [335].

Supervised fine-tuning involves collecting a supervised dataset with prompts and desired outputs for initial fine-tuning.

Reward model training trains the RM using human-annotated data where labelers rank outputs, guiding the RM to predict human preferences. Studies suggests using large reward models that align with the LLM's scale for better performance judgment and combining multiple RMs focused on different alignment criteria for a nuanced reward signal.

RL fine-tuning treats alignment as an RL problem where the LM is optimized against the RM using PPO, incorporating penalties like KL divergence to maintain closeness to the original model behavior. Practical strategies propose to deploy the RM on a separate server and use beam search decoding to manage computational demands and enhance output diversity.

RLHF is a complex but promising approach to improving LLM alignment with human values, involving sophisticated training regimes and multiple feedback mechanisms to ensure the model's outputs are ethical and practical.

That being said, RLHF is memory-intensive (it needs to train multiple LMs), and the PPO algorithm is rather complex and often sensitive to hyper-parameters. Thus, increasing studies are exploring alternative methods to align LLMs with human values using supervised fine-tuning without reinforcement learning.

The main idea behind alignment tuning without reinforcement learning is to directly use high-quality alignment datasets. The alignment dataset may be created by LLMs aligned with human-written safety principles or by refining existing examples through editing operations. Additionally, reward models can be reused to select highly-rated responses from existing human feedback data, enriching the dataset's quality and relevance. Non-RL alignment methods employ supervised learning strategies similar to those used in original instruction tuning. These methods may also integrate auxiliary learning objectives, such as ranking responses or contrasting instruction-response pairs, to further enhance the alignment accuracy and performance of LLMs.

2.4 Architecture

The architecture of Large Language Models (LLMs) plays a pivotal role in determining the model's performance, efficiency, and scalability.

Generally speaking, we can identify some key components that define different LLM architectures: the encoder and the decoder. The encoder is an essential component in LLMs, and its role is to process input sequences and map them to a higher dimensional space, capturing the contextual information in the data. The structure of an encoder in LLMs typically involves a stack of identical layers, each comprising two main sub-layers: a multi-head self-attention[11] mechanism and a position-wise fully connected feed-forward network [308].

The decoder, on the other hand, is responsible for generating output sequences based on the encoded representations. The decoder in models such as GPT-3 [83] and its successors operates on the principle of autoregressive modeling, where each subsequent token is predicted based on the previously generated tokens. A key feature of decoders in LLMs is causality, which ensures that the prediction for the current token can only attend to previous tokens, not future ones. This is implemented through masked attention mechanisms in the transformer's decoder layers [308].

For example, in a translation task, the encoder processes the source sentence and produces a set of vectors representing its content, while the decoder uses cross-attention to decide which words (or phrases) in the source sentence are most relevant for predicting the next word in the target language. In code generation, decoders can create syntactically correct code snippets given comments or docstrings as input, as demonstrated by Codex [103].

Based on the components and the way they are connected, LLMs can be categorized into three main types: encoder-only[12], decoder-only, and encoder-decoder models. All of these are sequence-to-sequence models (ofter referred to as seq2seq models).

[11] See Section 2.4.4 for more details on self-attention mechanisms.

[12] We refer to BERT-style methods as encoder-only, the description encoder-only may be misleading since these methods also decode the embeddings into output tokens or text during pretraining. In other words, both encoder-only and decoder-only architectures are "decoding". However, the encoder-only architectures, in contrast to decoder-only and encoder-decoder architectures, are not decoding in an autoregressive fashion. Autoregressive decoding refers to generating output sequences one token at a time, conditioning each token on the previously generated tokens. Encoder-only models do not generate coherent output sequences in this manner. Instead, they focus on understanding the input text and producing task-specific outputs, such as labels or token predictions [294].

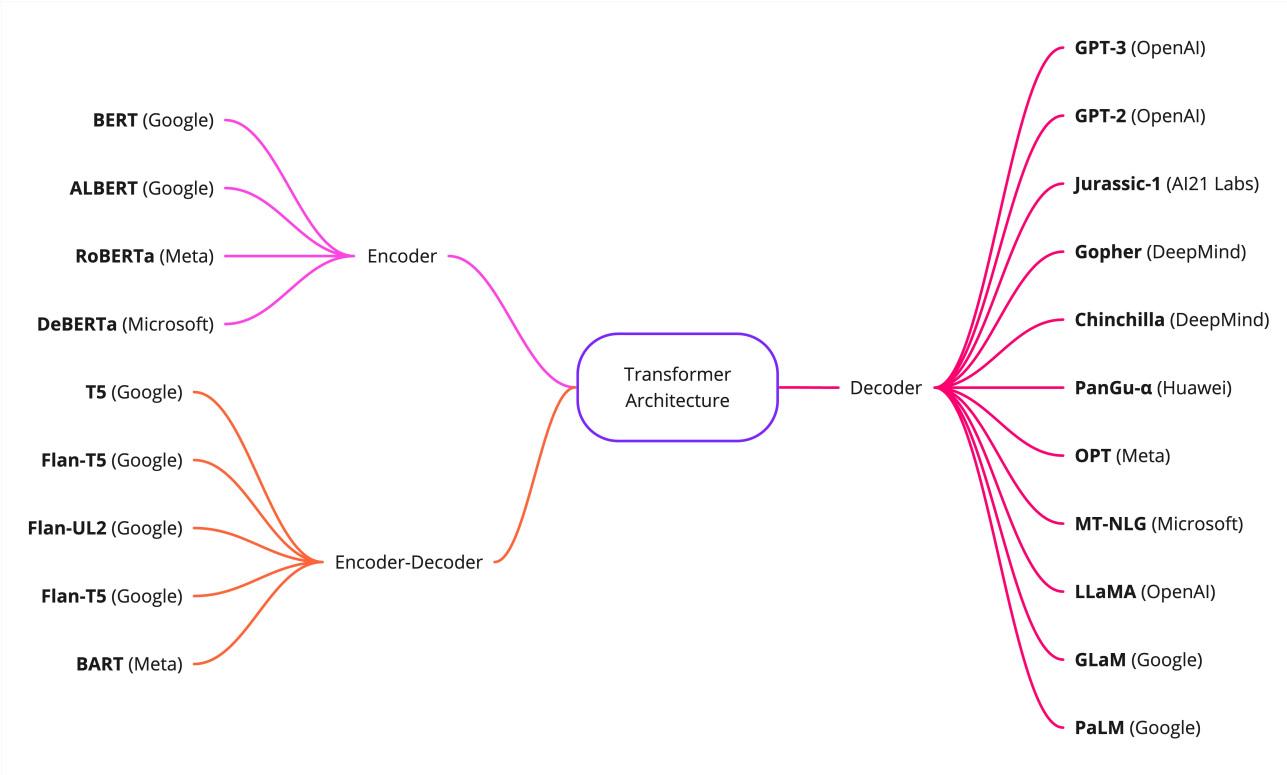

Figure 2.9: *Some of the mainstream LLMs models by type.*

Mainstream architectures can be further categorized into three major types, namely encoder-decoder, casual decoder and prefix decoder as shown in Figure 2.10. Both casual decoder and prefix decoder are decoder-only architectures, but they differ in the way they generate tokens.

2.4.1 Encoder-decoder

Vanilla version of the Transformer architecture introduced by Vaswani et al. [308] belongs to this category, which consists of an encoder and a decoder.

The encoder's purpose is to transform an input sequence into a set of representations which capture its semantic and syntactic properties.

The decoder, on the other hand, is tasked with generating an output sequence from the encoded representations. It predicts each token by conditioning on the previously generated tokens and the encoded input, a process that has seen significant improvements with the integration of cross-attention modules. By segregating the understanding (encoding) and generation (decoding) processes, the Encoder-Decoder architecture enables a flexible approach to diverse language tasks.

So far, there are only a small number of models that use the encoder-decoder architecture (Figure 2.9), such as BART [89] and T5 [94].

2.4.2 Casual decoder

In a causal decoder, each token is predicted based on the tokens that precede it, ensuring that the generation process is unidirectional and prevents the model from using future tokens in the prediction process [308]. This mechanism is akin to how humans produce language, one word at a time, building upon what has already been said without access to future words.

The architecture typically employs self-attention mechanisms where the attention distribution is masked to prevent tokens from attending to subsequent positions in the sequence

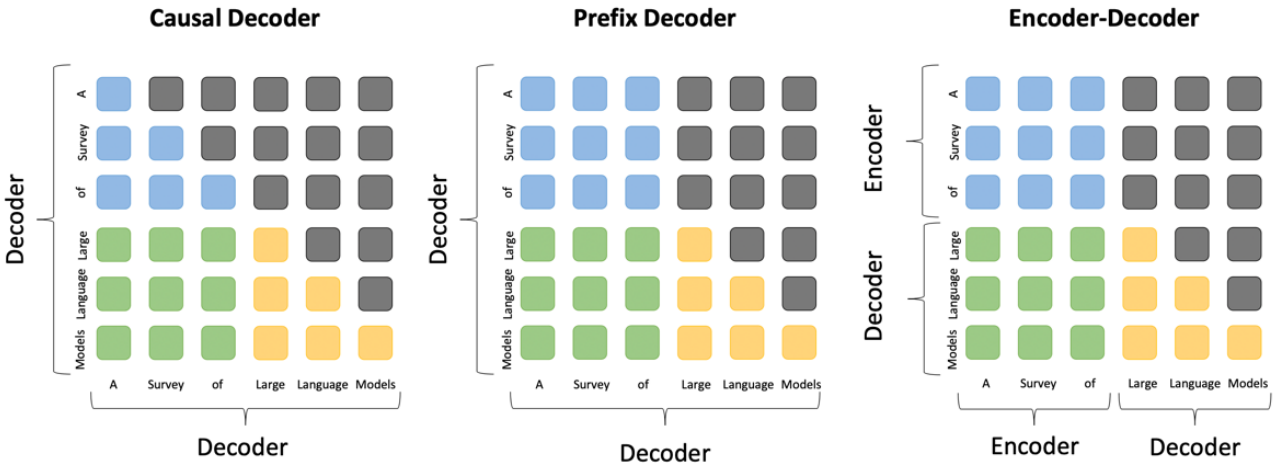

Figure 2.10: *A comparison of the attention patterns in three mainstream architectures. Here, the blue, green, yellow and grey rounded rectangles indicate the attention between prefix tokens, attention between prefix and target tokens, attention between target tokens, and masked attention respectively. Source: Zhao et al. [335].*

(i.e., unidirectional attention mask). This form of masking is instrumental in preserving the autoregressive property within the transformer-based models [70].

The GPT series[13] of language models by OpenAI are prominent examples that utilize causal decoder architectures, where the ability to generate coherent and contextually relevant text has been demonstrated effectively [83].

The causal decoder architecture is particularly well-suited for tasks that require sequential generation, such as text completion, language modeling, and text generation. It has been widely adopted as the architecture of choice for many large-scale language models, such as OPT [233], BLOOM [322], and Gopher [125].

2.4.3 Prefix decoder

The prefix decoder architecture[14] enables partial conditioning of generated sequences, revising the masking mechanism of causal decoders, to enable performing bidirectional attention over the prefix tokens [62] and unidirectional attention only on generated tokens.

In other words, this architecture allows the model to generate tokens based on both the input prefix and the target prefix, which can be useful for tasks that require generating sequences with specific prefixes or constraints. In practice, a prefix decoder is implemented by feeding a fixed sequence of tokens [15] into the decoder alongside the tokens generated so far. The model then extends the prefix by generating subsequent tokens that logically follow the context provided by the prefix.

Unlike the causal decoder, which strictly adheres to a unidirectional generation pattern, the prefix decoder allows for a predefined context or prefix to guide the generative process [114]. This is particularly useful in tasks such as machine translation, where the prefix can be a part of the translation that is already known or hypothesized, but the flexibility provided by the prefix decoder makes it suitable for a range of applications, from controlled text generation to task-oriented dialog systems, where maintaining context and coherence is crucial [177].

[13] GPT-3 [83] showed amazing in-context learning capability, whereas GPT-1 [47] and GPT-2 [70] didn't. It seems that scaling plays an important role in increasing the model capacity of this model architecture

[14] Also called non-causal decoder [232]

[15] Also known as the prefix

This architecture has been utilized in various language models to improve control over text generation and to enhance the models' ability to handle specific formats or styles [94].

2.4.4 Transformer Architecture

The Transformer architecture has emerged as the de facto standard for LLMs, owing to its ability to capture long-range dependencies and model complex language structures effectively [308] making possible to train models with billions or even trillions of parameters [83, 306].

This architecture usually consists of stacked Transformer layers (Figure 2.11), each comprising multi-head self-attention sub-layer and a position-wise fully connected feed-forward network [308]. Residual connection [26] and layer normalization [25] are applied for both sub-layers individually.

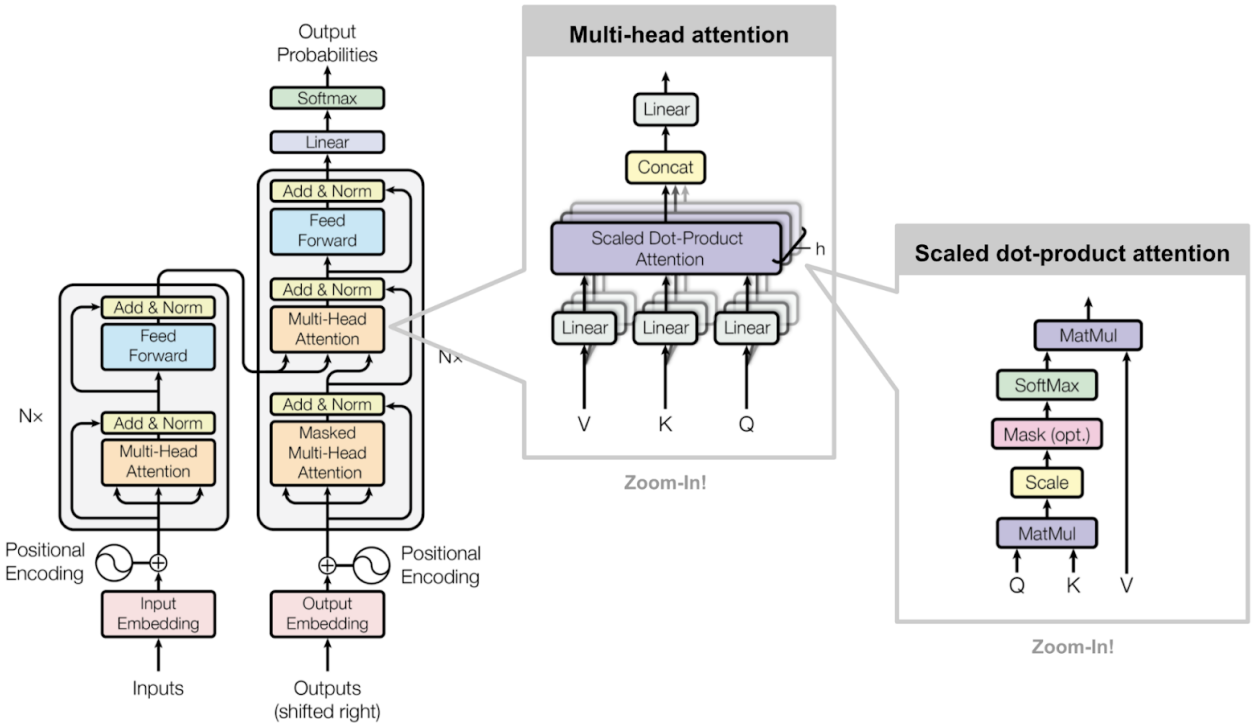

Figure 2.11: *The full model architecture of the transformer. Source: Weng [53].*

The position-wise FFN sub-layer is a two-layer feed-forward network with a ReLU activation function between the layers. Given a sequence of vectors $h_1, h_2, \ldots, h_n$, the computation of a position-wise FFN sub-layer on any h_i, as shown in Equation 2.2.

$$\mathrm{FFN}(h_i) = \mathrm{ReLU}(h_i W^1 + b^1)W^2 + b^2 \tag{2.2}$$

where W^1, W^2, b^1, and b^2 are learnable parameters of the FFN sub-layer.

Besides the two sub-layers described above, the residual connection and layer normalization are also key components to the Transformer. Different orders and configuration of the sub-layers, residual connection and layer normalization in a Transformer layer lead to variants of Transformer architectures as shown in Table 2.3.

Configurations

Since the introduction of the Transformer architecture, several variants and configurations have been proposed to improve the performance and efficiency of LLMs. The configuration of the

Model	Category	Size	Normalization	PE	Activation	Bias	#L	#H	d_{model}	MCL
GPT3 [83]	Causal decoder	175B	Pre LayerNorm	Learned	GeLU	Y	96	96	12288	2048
PanGU-α [133]	Causal decoder	207B	Pre LayerNorm	Learned	GeLU	Y	64	128	16384	1024
OPT [233]	Causal decoder	175B	Pre LayerNorm	Learned	ReLU	Y	96	96	12288	2048
PaLM [149]	Causal decoder	540B	Pre LayerNorm	RoPE	SwiGLU	N	118	48	18432	2048
BLOOM [322]	Causal decoder	176B	Pre LayerNorm	ALiBi	GeLU	Y	70	112	14336	2048
MT-NLG [208]	Causal decoder	530B	-	-	-	-	105	128	20480	2048
Gopher [125]	Causal decoder	280B	Pre RMSNorm	Relative	-	-	80	128	16384	2048
Chinchilla [166]	Causal decoder	70B	Pre RMSNorm	Relative	-	-	80	64	8192	-
Galactica [214]	Causal decoder	120B	Pre LayerNorm	Learned	GeLU	N	96	80	10240	2048
LaMDA [215]	Causal decoder	137B	-	Relative	GeGLU	-	64	128	8192	-
Jurassic-1 [116]	Causal decoder	178B	Pre LayerNorm	Learned	GeLU	Y	76	96	13824	2048
LLaMA [306]	Causal decoder	65B	Pre RMSNorm	RoPE	SwiGLU	Y	80	64	8192	2048
LLaMA 2 [305]	Causal decoder	70B	Pre RMSNorm	RoPE	SwiGLU	Y	80	64	8192	4096
Falcon [289]	Causal decoder	40B	Pre LayerNorm	RoPE	GeLU	N	60	64	8192	2048
GLM-130B [231]	Prefix decoder	130B	Post DeepNorm	RoPE	GeGLU	Y	64	96	12288	2048
T5 [94]	Encoder-decoder	11B	Pre RMSNorm	Relative	ReLU	N	24	128	1024	512

Table 2.3: *Model cards of several selected LLMs with public configuration details. PE denotes position embedding, #L denotes the number of layers, #H denotes the number of attention heads, d_{model} denotes the size of hidden states, and MCL denotes the maximum context length during training. Source: Zhao et al. [335].*

four major parts of the Transformer architecture includes normalization, position embeddings, activation functions, and attention and bias as shown in Table 2.4.

Normalization Methods

Normalization methods are crucial for stabilizing the training process and improving the convergence of LLMs. In the vanilla Transformer [308] architecture, LayerNorm [25] is the most commonly used normalization method, which normalizes the hidden states across the feature dimension. Before LayerNorm was introduced, BatchNorm [23] was widely used in convolutional neural networks, but it was found to be less effective in sequence models due to the varying batch sizes and sequence lengths. LayerNorm addresses this issue by normalizing the hidden states across the feature dimension, making it more suitable for sequence models. Specifically, LayerNorm normalizes the hidden states using the mean and the variance of the summed inputs within each layer.

RMSNorm [78] is another normalization method that has been proposed to improve the training speed of LayerNorm. RMSNorm normalizes the hidden states by dividing them by the root mean square of the squared hidden states, which has been shown to improve the training speed and performance [120]. ChinchiLLa [166] amd Gopher [125] are examples of LLMs that use RMSNorm as the normalization method.

DeepNorm [218] is a novel normalization method that combines LayerNorm with a learnable scaling factor to stabilize the training process of deep Transformer models. With DeepNorm, Transformer models can be scaled up to hundreds of layers without the need for additional

normalization layers, making it an effective method for training large-scale LLMs [218]. It has been used in models such as GLM-130B [231].

Configuration	Method
Normalization position	Post Norm [308]
	Pre Norm [70]
	Sandwich Norm [104]
Normalization method	LayerNorm [25]
	RMSNorm [78]
	DeepNorm [218]
Activation function	ReLU [14]
	GeLU [52]
	Swish [37]
	SwiGLU [95]
	GeGLU [95]
Position embedding	Absolute [308]
	Relative [94]
	RoPE [128]
	Alibi [200]

Table 2.4: *Detailed formulations for the network configurations. Source: Zhao et al. [335]*

Normalization Position

The position of the normalization layer (Figure 2.12) in the Transformer architecture can have a significant impact on the model's performance and convergence. The three main configurations proposed in different studies are pre-LN[16], post-LN[17], and Sandwich-LN.

In the pre-LN configuration, the normalization layer is placed inside the residual blocks, while in the post-LN configuration, the normalization layer is placed after the residual blocks. In Ding et al. [104], the normalization layer is placed both before and after the residual blocks, which is referred to as the Sandwich-LN configuration.

Post-LN is used in the vanilla Transformer architecture [308], where the normalization layer is placed between the residual blocks. This sequence allows the model to first process the input through a sublayer, such as a Multi-Head Attention (MHA) or Feed-Forward Network (FFN), and then apply normalization to the output of the sublayer combined with the residual connection. In particular, to train the model from scratch, any gradient-based optimization approach requires a learning rate warm-up stage to stabilize the training process [308]. Existing works found that training of Transformer models with post-norm tends to be instable due to large gradients near the output layer [96].

Pre-LN [58] is another configuration where the normalization layer is placed inside the residual blocks and makes possible to remove warm-up stage, requiring significantly less training time and hyper-parameter tuning on a wide range of applications. The Transformers with pre-LN have shown to be more stable during training but have worst performance [92].

Sandwich-LN [104] is a configuration that combines the advantages of both pre-LN and post-LN by placing the normalization layer both before and after the residual blocks. This configuration has been shown to improve the performance of Transformer models by providing better stability during training and faster convergence [104]. In Zeng et al. [231], the authors

[16]Pre-Layer Normalization
[17]Post-Layer Normalization

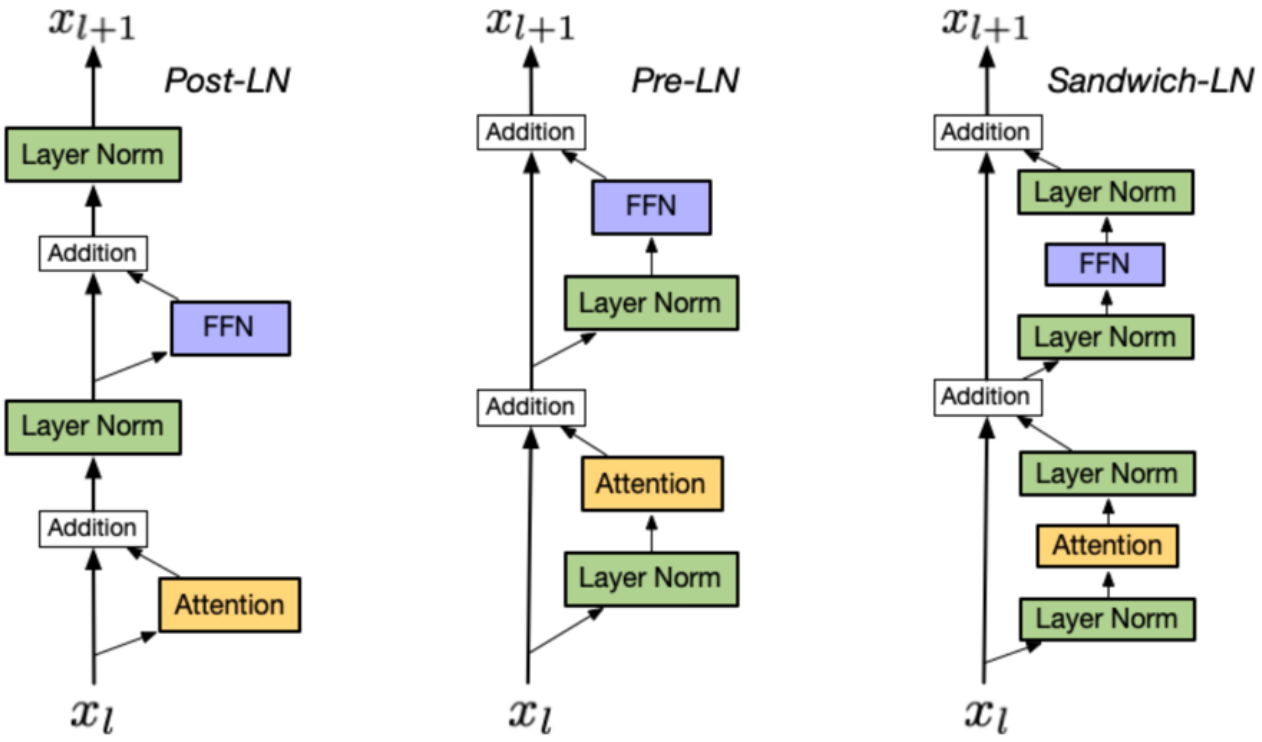

Figure 2.12: *Illustration of different LayerNorm structures in Transformers. Source: Ding et al. [104].*

found that the Sandwich-LN configuration sometimes fails to stabilize the training of LLMs and may lead to the collapse of training.

Activation Functions

Activation functions play a crucial role in the training and performance of LLMs by introducing non-linearity into the model[18]. The most commonly used activation functions in LLMs are ReLU, GeLU, Swish, SwiGLU, and GeGLU.

ReLU[19] [14] is a simple and widely used activation function that introduces non-linearity by setting negative values to zero.

$$\text{ReLU}(x) = \max(x, 0) \tag{2.3}$$

One of the first activation functions to be used in deep learning, ReLU has been shown to be effective in training deep neural networks by preventing the vanishing gradient problem [15]. This non-linear activation function introduces sparsity in the activations of the network, which can lead to faster training and better performance due to its simplicity and efficiency. However, ReLU can suffer from the dying ReLU problem, where neurons can become inactive and stop learning if the input is negative [17].

GeLU [28] is a Gaussian Error Linear Unit activation function that is used to model uncertainties in neural networks. It was introduced to improve upon ReLU by taking into account the stochastic regularisation techniques. The smoothness of the GELU function can be advantageous in deep neural networks with many layers, as it can help prevent the problem of "dying

[18]In the feed-forward layer
[19]Rectified Linear Unit

ReLU" and improve the flow of gradients through the network. The GELU activation function is mathematically described as:

$$\text{GeLU}(x) = x \cdot \Phi(x) \tag{2.4}$$

where $\Phi(x)$ is the cumulative distribution function of the standard Gaussian distribution. This can also be approximated as:

$$\text{GeLU}(x) \approx 0.5x(1 + \tanh[\sqrt{2/\pi}(x + 0.044715x^3))] \tag{2.5}$$

Alternatively, the GELU function can be expressed as a scaled version of the sigmoid function, as shown below:

$$\text{GeLU}(x) \approx x \cdot \sigma(1.702x) \tag{2.6}$$

The GELU function allows the input to control its own gate, deciding whether to pass through or be dampened. When x is large, GELU approximates to x, acting like a linear unit. When x is close to zero or negative, it squashes the output, making it closer to zero. In other words, the GELU function would produce outputs that are smoothed around zero, rather than sharply cut off as with ReLU. The GELU activation function is used in many deep learning models, including GPT-3 and BERT.

The Swish [37] activation function is a smooth, non-monotonic function that was developed to overcome some limitations of ReLU and was found to perform better in deeper models. It is defined as

$$\text{Swish} = x \cdot \sigma\left(x\right) \tag{2.7}$$

where x is the input to the activation function and sigmoid is the logistic function $\sigma(x) = \frac{1}{1+e^{-x}}$. The Swish function allows small and negative values to pass through, which can be beneficial for gradient flow in deep models. It has been empirically demonstrated to work well for deeper models and is computationally efficient.

SwiGLU [95] is a variant of the Swish activation function that combines the Swish function with the Gated Linear Unit (GLU) function. The SwiGLU activation function is defined as

$$\text{SwiGLU}\left(x, W, V, b, c, \beta\right) = \text{Swish}\left(xW + b\right) \otimes \left(xV + c\right) \tag{2.8}$$

Here, x is the input to the neuron, W and V are weight matrices, b and c are bias vectors, and β is a constant. The $\otimes$ symbol denotes element-wise multiplication, while Swish is the activation function described in Equation 2.7. This function allows the network to learn which parts of the input should be retained (gated) for further layers, combining the advantages of non-saturating functions and dynamic gating mechanisms.

GeGLU [95] is another variant of the GLU activation function that combines the GeLU function with the Gated Linear Unit (GLU) function. The GeGLU activation is formulated as:

$$\text{GeGLU}\left(x, W, V, b, c\right) = \text{GeLU}\left(xW + b\right) \otimes \left(xV + c\right) \tag{2.9}$$

After the output of the GeLU function is calculated, it is multiplied element-wise with a second matrix. This second matrix is calculated by multiplying the input matrix x with another matrix W and adding a bias term b. The output of this multiplication is then passed through a second matrix V and added to a scalar term c.

Position Embeddings

Position embeddings are a crucial component of the Transformer architecture that allows the model to capture the sequential order of tokens in the input sequence. There are several types of position embeddings used in LLMs, including absolute, relative, RoPE, and Alibi embeddings.

Absolute position embeddings [308] was proposed in the original Transformer model. At the bottoms of the encoder and the decoder, the absolute positional embeddings are added to the input embeddings. There are two variants of absolute position embeddings, i.e., sinusoidal and learned position embeddings, where the latter is commonly used in existing pre-trained language models.

The formulation for adding absolute position embeddings is straightforward:

$$E_{\text{total}}(i) = E_{\text{token}}(i) + E_{\text{position}}(i) \tag{2.10}$$

where $E_{\text{total}}(i)$ is the final embedding vector for token i, $E_{\text{token}}(i)$ is the initial token embedding for token i, and $E_{\text{position}}(i)$ is the position embedding vector for token i. This technique allows the model to use the order of words to understand meaning and context, which is especially important for tasks involving sequence modeling and generation.

Relative position embeddings [48] are an alternative to absolute position embeddings that capture the relative distance between tokens in the input sequence. This allows the model to learn more flexible and adaptive representations of the input sequence, which can improve performance on tasks that require capturing long-range dependencies and complex relationships between tokens. Relative position embeddings are incorporated into the self-attention mechanism of Transformer models. Instead of only considering the absolute position of tokens, the attention scores are adjusted based on the relative distances between tokens. The formulation for the attention mechanism with relative position embeddings is given by:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{Q(K + R)^T}{\sqrt{d_k}}\right)V \tag{2.11}$$

where Q, K, and V are the query, key, and value matrices, respectively, R is the relative position embedding matrix, and d_k is the dimension of the key vectors. The relative positions are calculated as $R_{ij} = R_{pos[i]-pos[j]}$, where $pos[i]$ and $pos[j]$ are the positions of tokens i and j in the input sequence, respectively.

RoPE[20] [128] is a type of position embedding that uses rotational matrices to capture the relative positions of tokens in the input sequence. Unlike traditional position embeddings that add or concatenate position information, RoPE encodes position information through rotation in the embedding space, enabling models to preserve positional relationships effectively. The key idea of RoPE is to bind the position encoding with the word embedding in a way that preserves the rotational relationship between embeddings. It uses a rotation matrix to modulate the embedding based on its position, thereby aligning words by their relative positions instead of their absolute positions. The formula for the Rotary Position Embedding is:

$$E_{\text{rot}}(x_i, p_i) = \text{Rotate}(x_i, p_i) = x_i \cos(p_i) + (W x_i) \sin(p_i) \tag{2.12}$$

where x_i is the token embedding, p_i is the position embedding, and W is a learnable weight matrix. Rotary Position Embeddings were introduced by Su et al. [128] and have been shown to improve the performance of LLMs on a range of tasks.

ALiBi[21] [200] position embeddings offer an alternative mechanism for incorporating position information into Transformer models. Unlike traditional absolute or relative position

[20] Rotary Position Embeddings

[21] Attention with Linear Biases

embeddings, ALiBi introduces biases directly into the self-attention mechanism to handle positional dependencies. ALiBi introduces a linear bias based on the distance between tokens in the attention scores. Similar to relative position embedding, it biases attention scores with a penalty based on the distances between keys and queries. Different from the relative positional embedding methods like T5 [133], the penalty scores in ALiBi are pre-defined without any trainable parameters. This bias is subtracted from the attention logits before the softmax operation, helping the model to prioritize nearby tokens over distant ones, which is crucial in many sequential tasks. The modified attention score with ALiBi can be represented as:

$$\begin{aligned} \text{Attention}(Q, K, V) &= \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}} - \text{bias}(i, j)\right)V, \\ \text{bias}(i, j) &= b \cdot |i - j| \end{aligned} \tag{2.13}$$

where Q, K, and V are the query, key, and value matrices, respectively, and b is a learnable scalar parameter that controls the strength of the bias, and $|i - j|$ is the absolute distance between tokens i and j, and d_k is the dimension of the key vectors.

In Press, Smith, and Lewis [200], the authors found that ALiBi has better extrapolation performance than traditional position embeddings, and it can also improve the stability and convergence of Transformer models during training [322].

Attention Mechanisms

Attention mechanisms are a key component of the Transformer architecture that allows the model to capture long-range dependencies and complex relationships between tokens in the input sequence.

An attention function can be described as mapping a query and a set of key-value pairs to an output, where the query, keys, values, and output are all vectors. The output is computed as a weighted sum of the values, where the weight assigned to each value is computed by a compatibility function of the query with the corresponding key. The two most commonly used attention functions are additive attention [20], and dot-product (multiplicative) attention. The

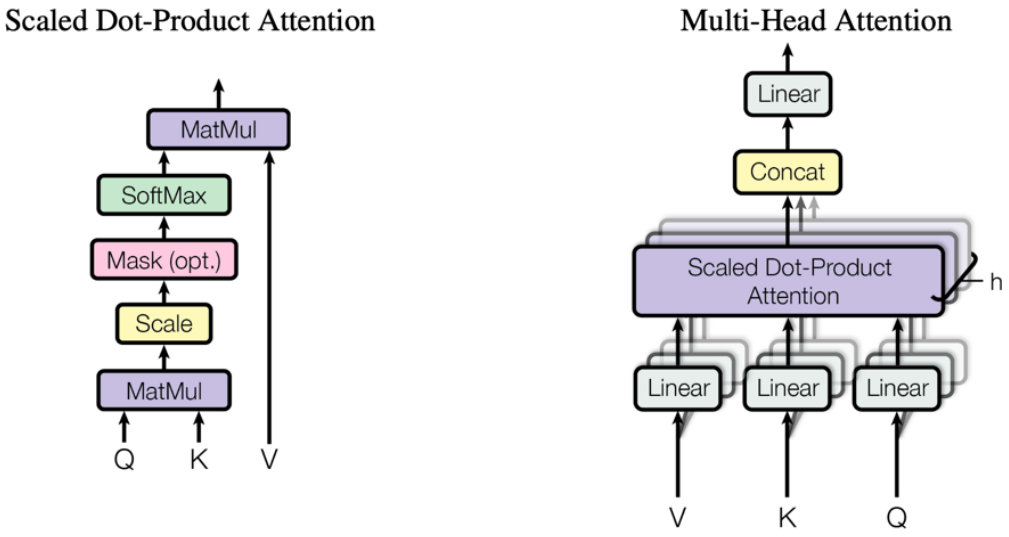

Figure 2.13: *(left) Scaled Dot-Product Attention. (right) Multi-Head Attention consists of several attention layers running in parallel. Source: Vaswani et al. [308].*

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scaled dot-product attention function used in Vaswani et al. [308] is defined as follows:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2.14}$$

where Q, K, and V are the query, key, and value matrices, respectively, and $\mathrm{d_k}$ is the dimension of the key vectors. While for small values of $\mathrm{d_k}$ the two mechanisms perform similarly, additive attention outperforms dot product attention without scaling for larger values of $\mathrm{d_k}$ [33].

A multi-head attention functions is implemented by splitting the query, key, and value vectors into multiple heads and computing the attention function in parallel, yielding $\mathrm{d_v}$-dimensional output values. These are concatenated and once again projected, resulting in the final values, as depicted in Figure 2.13. The multi-head attention mechanism allows the model to jointly attend to information from different representation subspaces at different positions, enhancing the model's capacity to capture complex relationships in the data.

$$\begin{aligned} \text{MultiHead}(Q, K, V) &= \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O, \\ \text{head}_i &= \text{Attention}(QW_i^Q, KW_i^K, VW_i^V) \end{aligned} \tag{2.15}$$

where W_i^Q, W_i^K, and W_i^V are the weight matrices for the query, key, and value projections of the i-th head, respectively, and W^O is the final output projection matrix.

We can categorize the attention mechanisms into: full attention, sparse attention, multi-query/grouped-query attention, Flash attention, and Paged attention. The Full attention mechanism is the standard attention mechanism used in the vanilla Transformer architecture [308], where each token attends to all other tokens in the sequence. It adopts the scaled dot-product we already discussed in Equation 2.14. This mechanism is computationally expensive and has a quadratic complexity in terms of the number of tokens, which can limit the model's scalability to longer sequences. To address this issue, several studies have proposed alternative attention mechanisms.

In the Sparse attention mechanism, tokens only attend to a subset of other tokens, according to a predefined pattern (e.g., local windows). This mechanism reduces the computational complexity of the attention operation and allows the model to scale to longer sequences.

$$\text{Sparse Attention}(Q, K, V) = \text{softmax}((\frac{QK^T \cdot M}{\sqrt{d_k}}))V \tag{2.16}$$

where M is a sparse attention mask that defines the pattern of attention between tokens.

Various sparse attention mechanisms have been proposed in the literature, such as Peng, Li, and Liang [122], Zaheer et al. [97] and Child et al. [60]. It a useful in tasks involving very long documents or sequences, such as document classification and genomic sequence analysis.

The multi-query/grouped-query attention mechanism [73] is an extension of the standard attention mechanism, where the keys and values are shared across all of the different attention "heads", greatly reducing the size of these tensors and hence the memory bandwidth requirements of incremental decoding. This mechanism is particularly useful in tasks that require processing large amounts of data, such as machine translation and summarization. It can significantly reduce the computational cost of the attention operation with small sacrifices in model quality. Palm [149] and Starcoder [271] are examples of LLMs that use the multi-query attention mechanism. A tradeoff between multi-query and multi-head attention, grouped-query (GQA) has been explored in Ainslie et al. [237]. In GQA heads are grouped together, and each group attends share the same transformation matrices. This mechanism has been adopted and empirically tested in LLaMA 2 model [305].

Flash attention [153] is an approach that propose to optimize the speed and and memory consumption of attention module on the GPUs. Modern GPUs have different memory types, and Flash attention takes advantage of this by organizing the input block on the faster

memory[22]. Updated version FlashAttention-2 [181] has been proposed to further improve the performance of the attention module on GPUs, partitioning of GPU thread blocks and warps, leading to around 2× speedup when compared to the original FlashAttention.

PagedAttention [309] is based on the observation that GPU memory is bottlenecked by cached attention keys and value tensors. These cached key and value tensors are often referred to as KV cache. The KV cache is large and highly dynamic, depending on the sequence length. Authors finds that existent system waste 60%-80% of the memory due to fragmentation and over-reservation. PagedAttention proposed techniques inspired by virtual memory management[23] to manage the KV cache, partition sequences to sub-sequences allocating corresponding KV caches into non-contiguous physical blocks as shown in Figure 2.14.

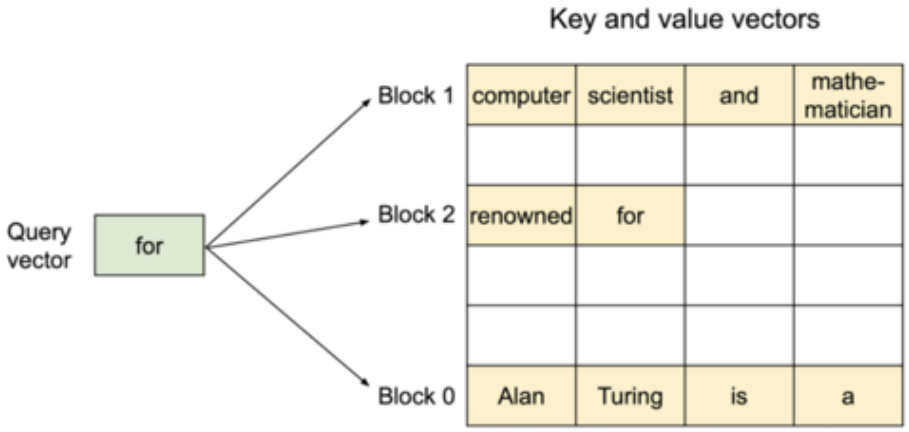

Figure 2.14: *PagedAttention: KV Cache are partitioned into blocks. Source: vLLM: Easy, Fast, and Cheap LLM Serving with PagedAttention [309].*

Paging increases the GPU memory utilization and enables efficient memory sharing in parallel sampling (Figure 2.15).

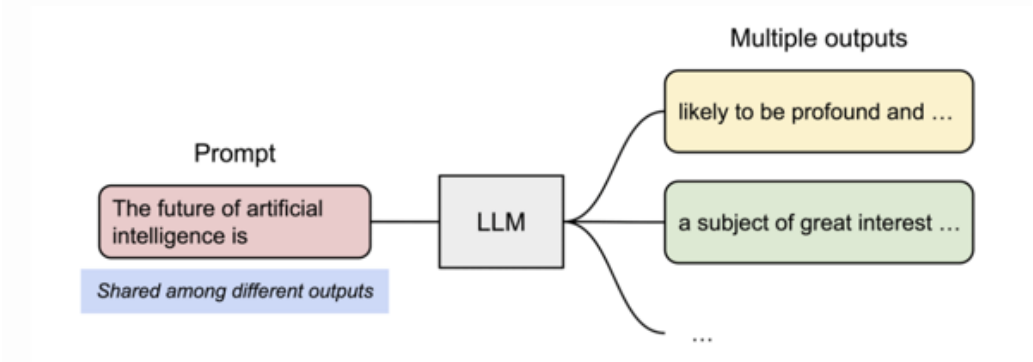

Figure 2.15: *PagedAttention: example of parallel sampling. Source: vLLM: Easy, Fast, and Cheap LLM Serving with PagedAttention [309].*

To put all these discussions together, Zhao et al. [335] summarize the suggestions from existing literature for detailed configuration. For stronger generalization and training stability, it is suggested to choose the pre RMSNorm for layer normalization, and SwiGLU or GeGLU as the activation function. In addition, LN may not be used immediately after embedding layers,

[22]SRAM has fast IO, while HBM is slower
[23]Paging

which is likely to incur performance degradation. As for position embeddings, RoPE or ALiBi is a better choice since it performs better on long sequences.

2.4.5 Emerging architectures

There are several emerging architectures that have been proposed to address specific challenges or improve the performance of the Transformers. One of the main issues with the vanilla Transformer architecture is the quadratic complexity in terms of the number of tokens, which can limit the model's scalability to longer sequences. To address this performance issue, several studies proposed alternative architectures, such as parameterized state space models (e.g., S4 [161], GSS [189], and H3 [154]]), long convolutions(e.g.,Hyena [292]), and recursive update mechanisms (RWKV [290] and RetNet [302]).

Parameterized state space models are a class of models that use a parameterized state space to represent the hidden states of the model. However, this method has prohibitive computation and memory requirements, rendering it infeasible as a general sequence modeling solution. To address this issue, S4 [161] proposed a novel parameterized state space model that uses a fixed-size state space to represent the hidden states of the model. This approach significantly reduces the computational and memory requirements of the model while maintaining high performance on a range of tasks. In Gu, Goel, and Ré [161], the authors found that S4 can be trained quickly and efficiently efficient compared to Transformer variants designed for long-range sequence modeling as shown in Table 2.5.

	LENGTH 1024		LENGTH 4096	
	Speed	Mem.	Speed	Mem.
Transformer	1x	1x	1x	1x
S4	**1.58x**	**0.43x**	**5.19x**	**0.091x**

Table 2.5: *Benchmarks vs. efficient Transformers*

Long Range Arena(LRA) [130] is a benchmark suite that evaluates the performance of LLMs on a range of tasks that require capturing long-range dependencies. It contains 6 tasks with lengths 1K-16K steps, encompassing modalities and objectives that require similarity, structural, and visuospatial reasoning. Table 2.6 shows the performance of S4 and 11 Transformer variants from Tay et al. [130]. Notably, S4 solves the Path-X task, an extremely challenging task that involves reasoning about LRDs over sequences of length $128 \times 128 = 16384$. All previous models have failed (i.e., random guessing) due to memory or computation bottlenecks, or simply being unable to learn such long dependencies. Other benchmarks in Gu, Goel, and Ré

MODEL	ListOps	Text	Retrieval	Image	Pathfinder	Path-X	AVG
Transformer	36.37	64.27	57.46	42.44	71.40	X	53.66
S4	**58.35**	**76.02**	**87.09**	**87.26**	**86.05**	**88.10**	**80.48**

Table 2.6: *(Long Range Arena) Accuracy on full suite of LRA tasks. (Top) Original Transformer variants in LRA. Source: Gu, Goel, and Ré [161].*

[161] show that S4 looks promising for long-range sequence modeling, achieving state-of-the-art performance on a range of tasks that require capturing long-range dependencies.

Long convolutions are a class of models that use convolutional layers to capture long-range dependencies in the input sequence. Poli et al. [292] proposed an operation-efficient architecture called Hyena defined by two recurring sub-quadratic operators: a long convolution and an element-wise multiplicative gating (Figure 2.16). Compared to attention operator in Transformers, Hyena has a lower computational complexity and memory footprint, making it more efficient for long-range sequence modeling.

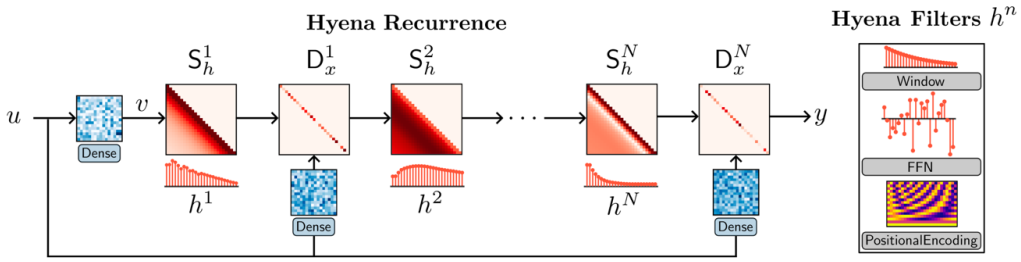

Figure 2.16: *The Hyena operator is defined as a recurrence of two efficient subquadratic primitives: an implicit long convolution h (i.e., Hyena filters parameterized by a feed-forward network) and multiplicative element-wise gating of the (projected) input. The depth of the recurrence specifies the size of the operator. Source: Poli et al. [292].*

2.5 Tuning and Optimization

Since LLMs consist of millions or billions of parameters, parameter tuning can be expensive and time-consuming. In this section, we discuss model adaptation of parameters and memory.

2.5.1 Parameter-efficient model adaptation

In the existent literature, there are several methods to adapt the model parameters to improve the performance of LLMs [109, 114, 113]. The goal of these methods is to reduce the number of parameters in the model while maintaining performance as much as possible. In the following sections, we discuss some of the most popular methods for parameter-efficient model adaptation, such as adapter tuning, prefix tuning, prompt tuning, and and LoRA (illustrated in Figure 2.17).

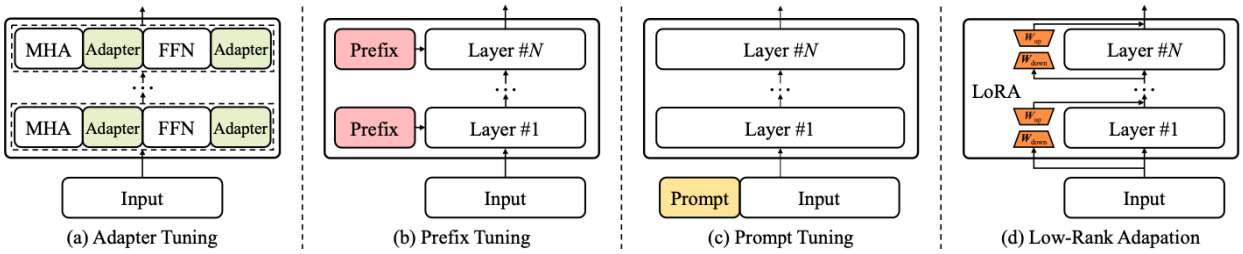

Figure 2.17: *An illustration of four different parameter-efficient fine-tuning methods. MHA and FFN denote the multi-head attention and feed-forward networks in the Transformer layer, respectively. Source: Zhao et al. [335].*

Adapter tuning

Adapter tuning is a parameter-efficient technique for transferring a pre-trained model to multiple downstream tasks without re-training the entire model for each new task. This approach

involves introducing small, trainable modules called "adapters" between the layers of a pre-trained network, allowing the original network's parameters to remain fixed while adapting the model to new tasks with a minimal increase in the total number of parameters. Adapter tuning is designed to address the inefficiency of fine-tuning large models where each new task typically requires re-training the entire model. Instead, adapter tuning uses a base pre-trained model and introduces small adapter layers that are trained for each specific task into the Transformer architecture [64, 261], as shown in Figure 2.18.

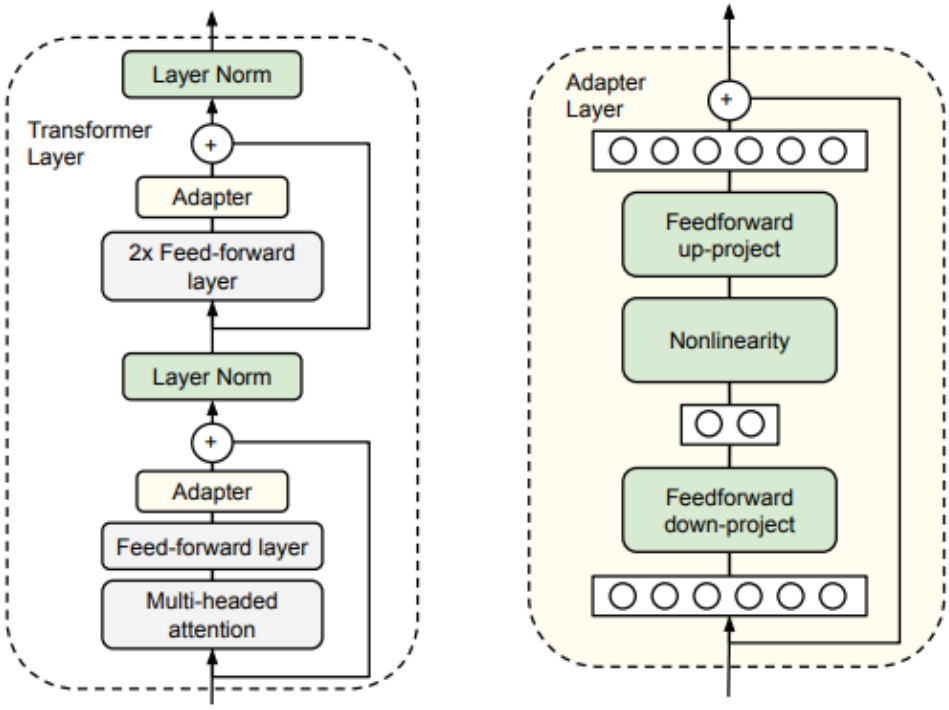

Figure 2.18: *On the left, the architecture of the adapter module and its integration with the Transformer. The adatper module is added twice to each Transformer layer.*
On the right, the adapter module consists of a feed-forward network with a bottleneck layer and a residual connection. During adatper tuning, the green layers are trained on the downstream data, this includes the adapter, the layer normalization parameters, and the final classification layer (not shown in the figure). Source: Houlsby et al. [64].

These adapter layers are typically much smaller than the main model layers, significantly reducing the number of new parameters that need to be trained. The main idea is that the adapter module first compresses the input representation to a lower-dimensional space (using a non linear transformation) and then expands it back to the original dimension, allowing the model to adapt to new tasks without changing the pre-trained parameters. This architecture is also called bottleneck architecture[24], and it can be represented with dimensional reduction usually achieved using a linear transformation $D : \mathbb{R}^d \to \mathbb{R}^m$ where $m < d$. This layer is represented by a weight matrix $W \in \mathbb{R}^{m \times d}$ and a bias vector $b \in \mathbb{R}^m$.

$$y = \sigma(W_d x + b_d) \tag{2.17}$$

[24]In neural network design, a bottleneck architecture refers to a specific configuration where the dimensionality of the input space is reduced to a lower dimension before being projected back to the original dimension or higher. This architecture is commonly employed in deep learning models to reduce the computational complexity, improve training efficiency, and sometimes to help in extracting more generalized features.

where σ is a non-linear activation function, x is the input vector, and y is the output vector of reduced dimensionality. After processing through the reduced dimension, the representation is usually projected back to the original dimension or higher using another linear transformation $U : \mathbb{R}^m \to \mathbb{R}^d$ represented by $W_u \in \mathbb{R}^{d \times m}$ and $b_u \in \mathbb{R}^d$.

$$z = \sigma(W_u y + b_u) \tag{2.18}$$

where z is the output vector, which ideally represents the "reconstructed" version of the input after passing through the bottleneck.

Alternatively, parallel adapter [164] can be also used in Transformer layers, where the adapter is added in parallel with the attention layer and the feed-forward layer accordingly. During fine-tuning, the adapter modules would be optimized according to the specific task goals, while the parameters of the original language model are frozen in this process. In this way, we can effectively reduce the number of trainable parameters during fine-tuning.

Adapter tuning has been shown to achieve near state-of-the-art performance on various tasks with significantly fewer parameters compared to full fine-tuning. For example, on the GLUE benchmark, adapter tuning approaches the performance of full fine-tuning with only about 3.6% of the parameters trained per task.

Prefix tuning

Prefix-Tuning is introduced as an efficient alternative to traditional fine-tuning methods for deploying large pre-trained language models (PLMs) across various tasks. Traditional fine-tuning requires updating and storing a separate copy of the model for each task, which becomes computationally expensive as the size of the models increases (e.g., GPT-3's 175 billion parameters). Prefix-tuning addresses this by optimizing only a small set of parameters, referred to as a prefix, which significantly reduces the storage and computational overhead. The method involves prefixing a sequence of continuous, task-specific vectors to the input, allowing subsequent tokens in the Transformer model to attend to these prefixes as if they were part of the input sequence as shown in Figure 2.19.

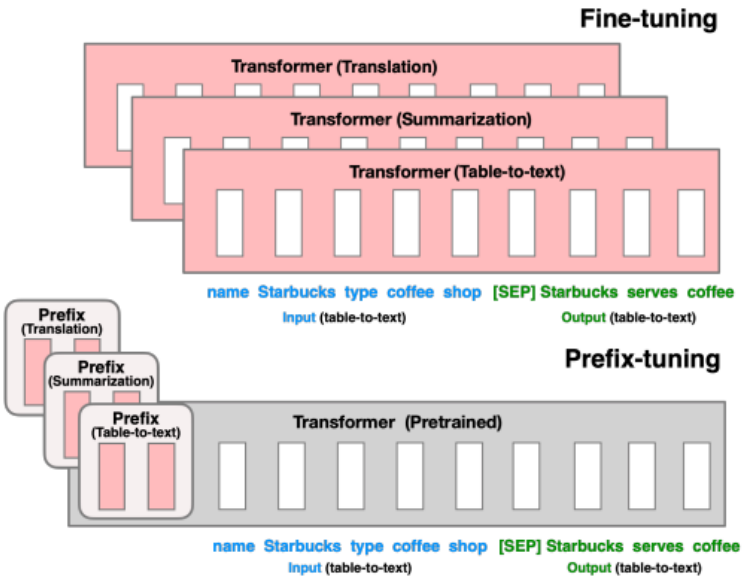

Figure 2.19: *Illustration of the prefix-tuning method, which freezes the Transformer parameters and only optimizes the prefix (the red prefix blocks). Consequently, it only needs to store the prefix for each task, making prefix-tuning modular and space-efficient. Note that each vertical block denote transformer activations at one time step. Source: Li and Liang [114].*

A novel approach to optimize prefix vectors involves using a re-parameterization technique, as described in the work by Li and Liang [114]. This method employs a multilayer perceptron (MLP) function to map a smaller matrix to the parameter matrix of the prefixes, rather than directly optimizing the prefixes themselves. This technique has proven effective for stabilizing the training process. Once optimization is complete, the mapping function is discarded, leaving only the refined prefix vectors, which are tailored to enhance performance on specific tasks. This approach leverages the inherent capabilities of the Transformer while only modifying a minimal set of parameters, making it modular and space-efficient. Li and Liang [114] provides detailed empirical evaluations demonstrating that prefix-tuning achieves comparable performance to full fine-tuning while only learning about 0.1% of the parameters. Evaluations are performed on tasks like table-to-text generation and summarization using models such as GPT-2 and BART. Results indicate that prefix-tuning not only reduces parameter count significantly but also maintains competitive performance with traditional fine-tuning in full data settings and often outperforms it in low-data scenarios. The approach is particularly effective in handling tasks with unseen topics during training, showcasing better generalization capabilities [89].

Prompt tuning

Prompt tuning primarily involves incorporating trainable vectors, called prompt tokens, at the input layer of a model. These tokens, based on discrete prompting techniques, augment the input text to assist models in performing specific tasks. In prompt tuning, these task-specific embeddings are combined with the original text embeddings and processed by language models. Specifically, the method known as P-tuning employs a flexible approach to integrate context, prompt, and target tokens. This method is adaptable for tasks involving both understanding

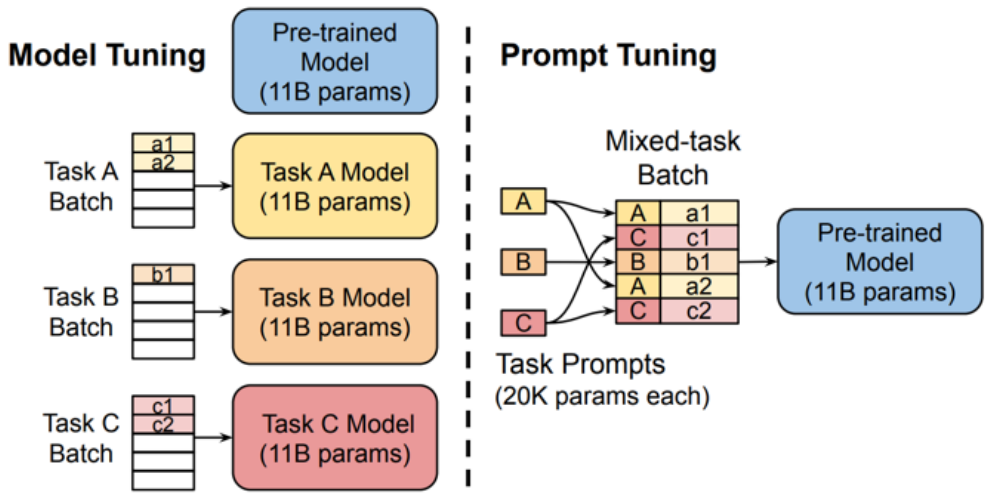

Figure 2.20: *Illustration of the prompt tuning method, which only requires storing a small task-specific prompt for each task, and enables mixed-task inference using the original pretrained model. With model tuning, each copy of tuned models requires copy billions of parameters, while tuned prompt would only requires thousands parameters per task—a reduction of over five orders of magnitude. Source: Lester, Al-Rfou, and Constant [113].*

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and generation of natural language and utilizes a bidirectional LSTM to learn representations of soft prompt tokens. During the training phase, only these prompt embeddings are updated based on task-specific requirements. The effectiveness of prompt tuning methods depends significantly on the computational power of the underlying language models, as they generally

involve a limited number of trainable parameters at the input layer.

Liu et al. [182] introduces P-Tuning v2, a method that extends prompt tuning by applying continuous prompts across all layers of a language model, improving upon the conventional method where prompts are only used at the input layer. They address the limitations of traditional prompt tuning, which underperforms especially on complex sequence labeling tasks when model size is below 10 billion parameters [113]. P-Tuning v2 modifies the conventional prompt tuning by:

- Utilizing continuous prompts at every layer of the model to increase tunable parameter count without significantly increasing overall parameter load.
- Improving adaptability across both simple and complex tasks by modifying the interaction of prompts with model architecture [114, 123].

P-Tuning v2 has been evaluated across a variety of model scales (from 330M to 10B parameters) and tasks including both classification and sequence labeling. The experiments demonstrate that P-Tuning v2 provides comparable results to full model fine-tuning while requiring only 0.1%-3% of the parameters to be tuned. Liu et al. [182] concludes that P-Tuning v2 significantly narrows the performance gap between prompt tuning and full fine-tuning, offering a robust, scalable, and efficient alternative for adapting large pre-trained models to diverse NLU tasks.

LoRA

The technique called LoRA (Low-Rank Adaptation) is used for efficient fine-tuning of neural networks, particularly in the adaptation of dense layers to downstream tasks with a reduced number of trainable parameters. LoRA strategically freezes the original parameter matrix $W \in \mathbb{R}^{m \times n}$ and applies updates using a low-rank decomposition approach, which involves two smaller matrices $A \in \mathbb{R}^{m \times k}$ and $B \in \mathbb{R}^{n \times k}$ where k is much smaller than m or n. This method significantly reduces the memory and storage requirements by limiting the number of trainable parameters to those in A and B, rather than the entire matrix W.

The key advantage of LoRA is its ability to maintain a single large model while adapting it to various tasks using different sets of low-rank matrices for each task, enhancing storage efficiency and reducing computational costs. Advanced methods for determining the optimal rank have been proposed such as importance score-based allocation [334] – i.e., AdaLoRA – and search-free optimal rank selection [307] – DyLoRA. These methods help to determine the optimal rank for the low-rank decomposition, ensuring that the model is adapted efficiently to the specific task requirements.

In AdaLoRA[25] the idea is that adding more trainable parameters to the critical weight matrices can lead to better model performance. In contrast, adding more parameters to those less important weight matrices yields very marginal gains or even hurt model performance. Given the parameter budget, i.e., the number of total trainable parameters, AdaLoRA always prefer to allocate more parameters to those important modules. Distributing the budget evenly to all weight matrices/layers, like LoRA and other methods (e.g., adapter and prefix tuning), often gives suboptimal performance [334]. AdaLoRA operates by parameterizing the incremental updates in the form of singular value decomposition (SVD), allowing for selective pruning of updates based on their assessed importance. This selective pruning targets the singular values of unimportant updates, effectively reducing their parameter budget while avoiding the computational intensity of performing exact SVD calculations. SVD-based adaptation is represented as:

[25] Adaptive Low-Rank Adaptation

$$W = W^0 + \delta = W^0 + P\Lambda Q \tag{2.19}$$

where W^0 is the original parameter matrix, δ is the update, P and Q are the left and right singular vectors, and Λ is the singular value matrix. Zhang et al. [334] substantiates the effectiveness of AdaLoRA through extensive experiments across various NLP tasks, including question answering and natural language generation. These experiments demonstrate notable improvements in performance, particularly in low-budget settings, when compared to baseline methods such as full fine-tuning and other parameter-efficient techniques like LoRA and adapter tuning. Key benchmarks from the paper highlight AdaLoRA's superior performance on standard datasets like GLUE and SQuAD, where it consistently outperforms other approaches while utilizing fewer parameters.

DyLoRA[26] is a search-free method for determining the optimal rank for low-rank decomposition in neural networks. The method is based on the observation that the optimal rank for low-rank decomposition varies across different layers and tasks. The main advantages of DyLoRA over conventional LoRA include its ability to adapt to different rank sizes dynamically during inference, eliminating the need for exhaustive search and re-training across different rank sizes. This is achieved by training the low-rank modules (LoRA blocks) across a spectrum of ranks during the training phase, which allows the model to adjust to the best performing rank size at runtime without additional computational cost. This method is inspired by the nested dropout technique but tailored to the needs of dynamic rank adaptation. The implementation involves sampling a rank size during each training step and adjusting the adapter modules accordingly, which allows the model to learn to perform under various constraints of rank size efficiently. Main improvements of DyLoRA over LoRA include:

1. Dynamic LoRA Blocks: DyLoRA modifies the standard LoRA blocks to be dynamic, allowing them to adjust their rank size during inference. This adaptation leads to more flexible models that can perform well across a broader range of tasks without the need for specific tuning for each task.

2. Search-Free Adaptation: By avoiding the exhaustive search for the optimal rank size, DyLoRA reduces the training and adaptation time significantly. The models can be trained once and used dynamically across different settings, making it highly efficient.

3. Performance: Experimental results show that DyLoRA matches or exceeds the performance of traditional LoRA with a static rank across various NLP tasks. This is demonstrated in tasks such as sentiment analysis, question answering, and natural language generation, indicating the robustness and versatility of DyLoRA.

Memory-efficient model adaptation

In addition to parameter-efficient model adaptation, memory-efficient techniques have been proposed to reduce the memory footprint of LLMs. These methods aim to reduce the memory requirements of LLMs during inference, making them more suitable for deployment in resource-constrained environments. In this section, we discuss some of the most popular method for memory-efficient model adaptation, i.e. model quantization.

Quantization

Quantization techniques reduce memory and computational costs by representing weights and activations with lower-precision data types like 8-bit integers (int8). This enables loading larger

[26]Dynamic Search-Free Low Rank Adaptation

models you normally wouldn't be able to fit into memory, and speeding up inference. This process can lead to substantial reductions in both the storage requirements and the computational complexity of deploying LLMs, which is crucial for their application in resource-constrained environments.

Quantization can be done in two ways: post-training quantization and quantization-aware training. Post-training quantization is done after the model has been trained, while quantization-aware training is done during training. Post-training quantization is easier to implement, but quantization-aware training can lead to better results.

Main quantization techniques include: uniform quantization, non-uniform quantization, and mixed-precision quantization. Uniform quantization maps the floating-point values to a fixed set of integer values, while non-uniform quantization uses a non-linear mapping to better represent the distribution of the data. Mixed-precision quantization uses a combination of different precision data types to represent the weights and activations.

Uniform quantization discretizes the values within a certain range into equal-sized intervals. Mathematically, it can be described as:

$$\textbf{LinearQuant}(x, bitwidth) = \text{Clip}(\text{round}(\frac{x}{bitwidth}) \times bitwidth, minV, maxV) \tag{2.20}$$

where minV and maxV are the minimum and maximum scale range respectively [35].

Non-uniform quantization, such as logarithmic quantization, allocates more fine-grained intervals to values that are more frequent or more sensitive to quantization errors. This method can be represented as:

$$\textbf{LogQuant}(x, bitwidth)(x) = \text{Clip}(\text{AP2}(x), minV, maxV) \tag{2.21}$$

where AP2 is the approximate-power-of-2 function that maps the input to the nearest power of two as defined in Hubara et al. [35]. This approach is particularly effective for distributions with a high dynamic range [29].

Mixed-precision quantization leverages the strengths of both uniform and non-uniform quantization by using different precision data types for different parts of the model. For example, weights can be quantized to 8-bit integers while activations are quantized to 16-bit integers.

Bit-width	Storage Reduction	Accuracy Loss
32 (Full Precision)	0%	0%
16	50%	1%
8	75%	2%
4	87.5%	5%

Table 2.7: *Performance comparison of quantized LLM*

As per Table 2.7, lower bit-widths generally result in more significant storage savings, but they can also lead to higher accuracy losses [36].

Chapter 3

Utilization Strategies and Techniques

3.1 Introduction

In this chapter, we will discuss the strategies and techniques that can be used to utilize large language models effectively. We will start by discussing the importance of context in utilizing large language models and how it can be used to improve their performance. We will then move on to the concept of chain-of-thought prompting and how it can be used to guide the generation of text. Finally, we will discuss the importance of planning for complex tasks and how it can be used to improve the performance of large language models.

Approach	Representative Work	Key Point
In-context Learning (ICL)	KATE [180], EPR [202], SG-ICL [170], APE [338], Structured Prompting [162], GlobalE & LocalE [184]	Demonstration selection (similar, k-NN) Demonstration selection (dense retrieval; contrastive learning) Demonstration selection (LLM as the demonstration generator) Demonstration format (automatic generation & selection) Demonstration format (grouped context encoding; rescaled attention) Demonstration order (entropy-based metric; probing set generation with LLM)
Chain-of-thought Prompting (CoT)	Complex CoT [157], Auto-CoT [235], Selection-Inference [151], Self-consistency [220], DIVERSE [275], Rationale-augmented ensembles [219]	Demonstration (complexity-based selection) Demonstration (automatic generation) Generation (alternate between selection and inference) Generation (diverse paths; self-ensemble) Generation (diverse paths; Verification (step-wise voting)) Generation (rationale sampling)
Planning	Least-to-most prompting [236], DECOMP [169], PS [312], Faithful CoT [282], PAL [158], HuggingGPT [296], AdaPlanner [300], TIP [281], RAP [259], ChatCoT [248], ReAct [229], Reflexion [297], Tree of Thoughts [332]	Plan generation (text-based; problem decomposition) Plan generation (text-based; problem decomposition) Plan generation (text-based) Plan generation (code-based) Plan generation (code-based; Python) Plan generation (code-based; models from HuggingFace) Plan refinement (skill memory) Feedback acquisition (visual perception) Feedback acquisition (LLM as the world model; Plan refinement (Monte Carlo Tree Search)) Feedback acquisition (tool); Plan refinement (conversation between LLM and tools) Feedback acquisition (tool); Plan refinement (synergizing reasoning and acting) Feedback acquisition (text-based self-reflection); Plan refinement (dynamic memory) Feedback acquisition (vote comparison); Plan refinement (tree-based search)

Table 3.1: *Typical LLM utilization methods and their key points for ICL, CoT, and planning. Note that the key points only highlight the most important technical contribution. Source: Zhao et al. [335]*

3.2 In-Context Learning

In-context learning is a special prompting technique, initially introduced by Brown et al. [83], that allows the model to learn from the context of the prompt (examples shown in Figure 3.1). ICT consists of the task description and/or few examples of the task as demonstrations com-

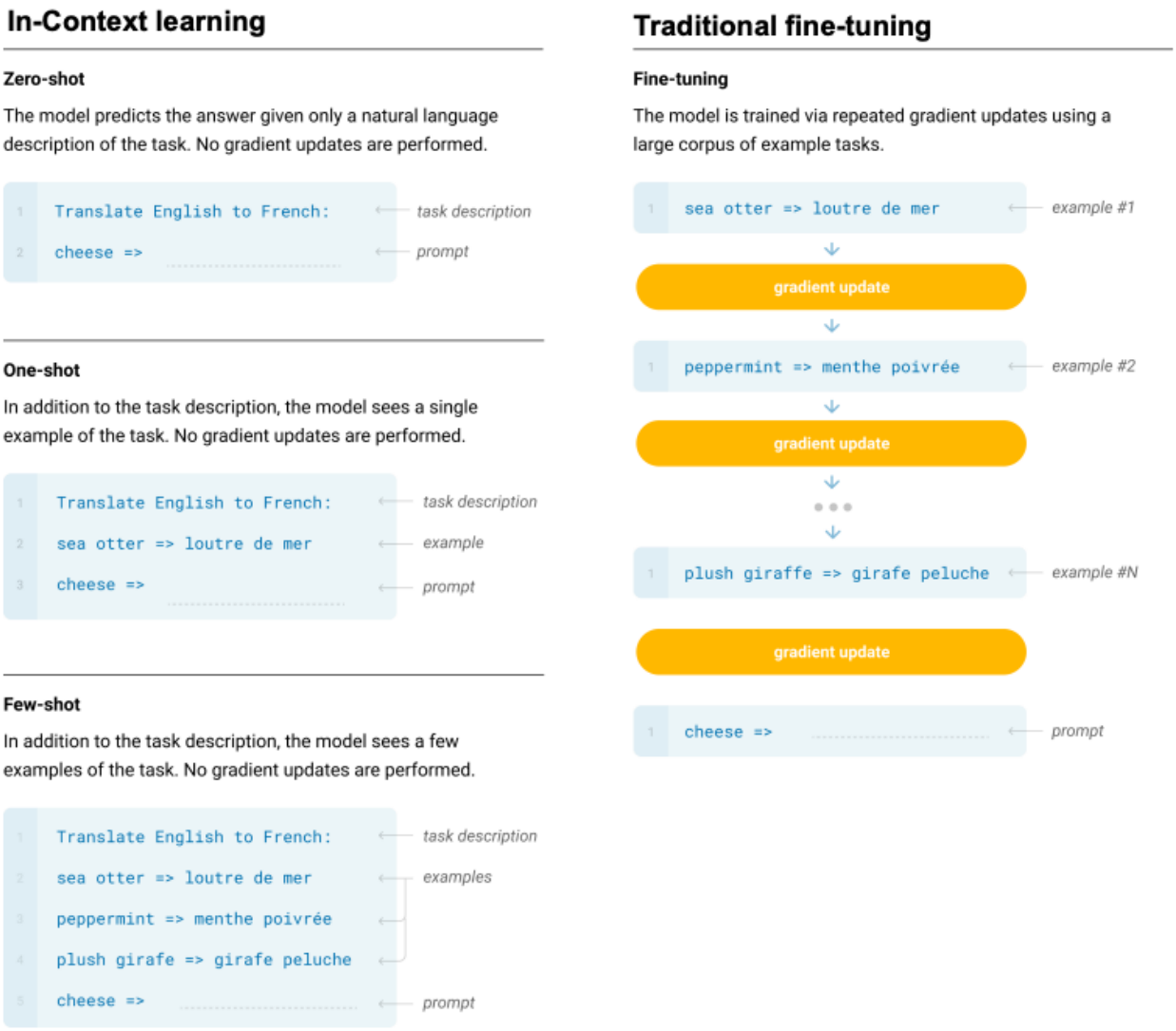

Figure 3.1: *In-context learning contrasted with traditional fine-tuning. Source: Brown et al. [83]*

bined in a specific order to form natural language prompts with specifically designed templates [83]. Finally, the test instance is appended to the prompt to form the input for LLMs to generate the output.

Based on task demonstrations, LLMs can learn to perform a new task without explicit gradient update. Formally, the in-context learning task can be defined as follows:

$$LLM(I, \underbrace{f(x_1, y_1), \ldots, f(x_k, y_k)}_{\text{demonstrations}}, \underbrace{f(x_{k+1}}_{\text{input}}, \underbrace{\_\_}_{\text{answer}})) \rightarrow \hat{y}_{k+1} \tag{3.1}$$

where I is a task description, $f(x_i, y_i)$ function that convert task demonstration to natural language, x_{k+1} is a new input query, $\hat{y}_{k+1}$ is the prediction of the output generated, and the actual answer y_{k+1} is left as a blank to be predicted by the LLM.

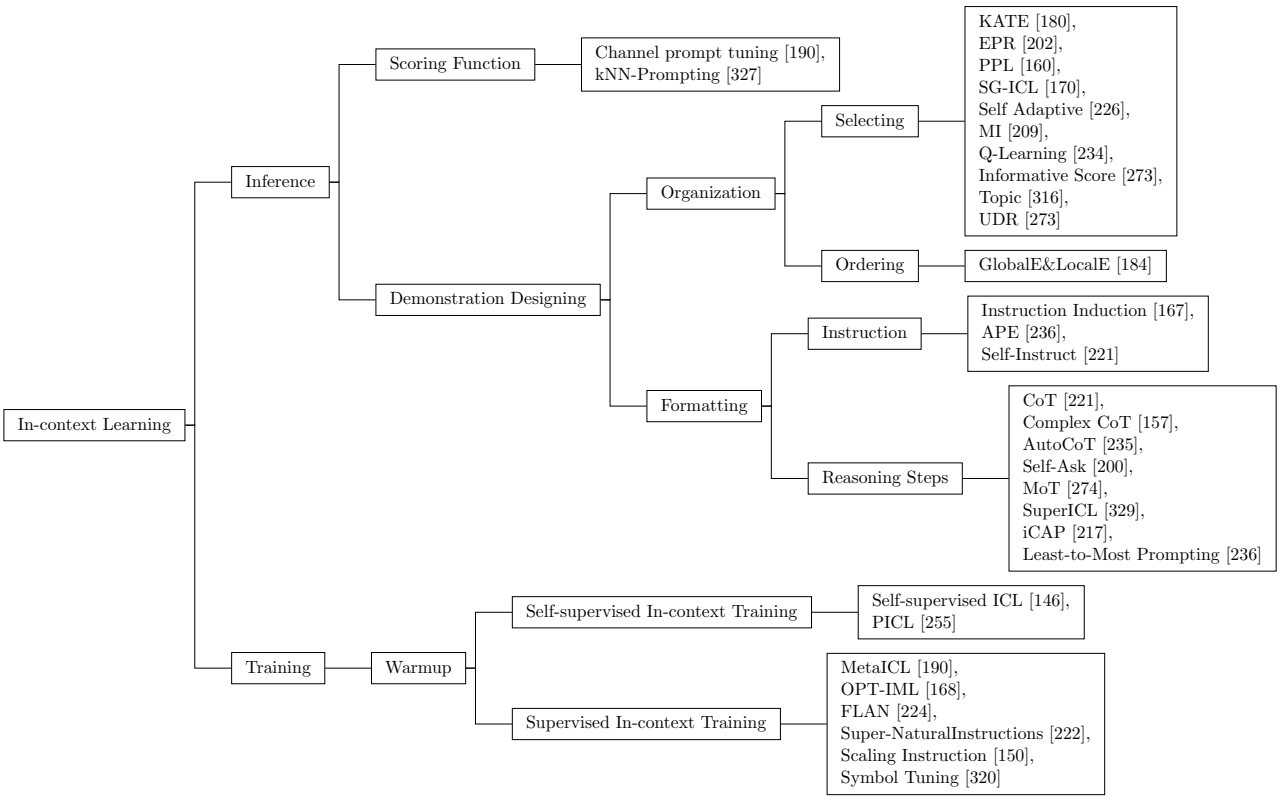

Figure 3.2: *Taxonomy of in-context learning. The training and the inference stage are two main stages for ICL. During the training stage, existing ICL studies mainly take a pretrained LLM as backbone, and optionally warmup the model to strengthen and generalize the ICL ability. Towards the inference stage, the demonstration designing and the scoring function selecting are crucial for the ultimate performance. Source: Dong et al. [252]*

Since the performance of ICL heavily relies on demonstrations, it is important to properly design them in the prompts. The tree main aspects are a direct consequence of what defined in the the Equation 3.1: how to select the task demonstrations, how to convert them into natural language, and arrange demonstrations in a reasonable order.

Different training strategies enhance ICL capabilities, improving performance across various tasks without specific task optimization during the pre-training phase (see Figure 3.2 under the Training branch). Main approaches include Supervised In-context Training, such as MetaICL[1] and Symbol Tuning, and Self-supervised In-context Training, such as Self-supervised ICL and PICL [252].

MetaICL [190] proposed to continually train LLMs on a wide range of tasks[2] with demonstration examples. This approach is related to other works that uses multi-task learning for better zero-shot performance at test time [190]. However, MetaICL is distinct as it allows learning new tasks from k examples alone, without relying on a task reformatting (e.g., reducing everything to question answering) or task-specific templates (e.g., converting different tasks to a language modeling problem). MetaICL is based on the core idea of in-context learning by conditioning on training examples (i.e., explicitly training on an in-context learning objective).

Symbol Tuning [320] instead fine-tunes language models on in-context input-label pairs, substituting natural language labels (e.g., "positive/negative sentiment") with arbitrary symbols (e.g., "foo/bar"). As a result, symbol tuning demonstrates an enhanced capacity to utilize in-context information for overriding prior semantic knowledge. Compared to MetaICL, which

[1]Meta-training for InContext Learning

[2]Classification, question answering, natural language inference, paraphrase detection and more

constructs several demonstration examples for each task, instruction tuning mainly considers an explanation of the task and is more easier to scale up.

Self-supervised ICL leverages raw corpora to generate input/output pairs as training data, while PICL also utilizes raw corpora but employs a simple language modeling objective, promoting task inference and execution based on context. PICL shown to be more effective in zero-shot settings and tasks generalization [252].

Effective demonstration design is crucial, involving selecting and ordering examples, or using instruction induction and reasoning steps (as shown in Figure 3.2 under the Inference/ Demonstration Designing branch). The selection aims to choose good examples for ICL using unsupervised[3] or supervised methods. For example, KATE [180] and EPR [202] select demonstrations based on similarity. The ordering of the selected demonstrations is also an important aspect of demonstration design. Lu et al. [184] have proven that order sensitivity is a common problem and affects various models. To handle this problem, studies have proposed several training-free methods to order demonstrations. Liu et al. [180] sorted examples based on similarity, while GlobalE&LocalE [184] orders demonstrations based on global and local entropy.

A common representation of demonstrations is concatenating examples $(x_1, y_1), \cdots, (x_k, y_k)$ with a template T directly. However, this approach may not be optimal for all tasks, i.e. when the task is complex or requires multiple steps such as math word problems and commonsense reasoning. In those cases, it's not easy to learn the mapping from x_i to y_i with only k demonstrations. Template engineering has been studied in Liu et al. [117] and Liu et al. [180] to generate task-specific templates. Some researches have proposed to design a better format of demonstrations, by describing tasks with instructions I and adding intermediate reasoning steps between examples (x_i, y_i). Instructions depends heavily on human input, but they can be generated automatically as shown in Honovich et al. [167] given several demonstration examples. Zhou et al. [338] proposed APE for automatic instruction generation and selection. To further improve the quality of the automatically generated instructions, Wang et al. [221] proposed Self-Instruct, which is able to get rid of its own generations.

The approach of adding intermediate reasoning steps between examples introduced in Wang, Zhu, and Wang [316] is also called Chain-of-Thought prompting. We will delve into Chain-of-Thought prompting in the next Section 3.3.

At the inference stage, ICL operates without explicit updates, focusing on task recognition and learning through demonstrations. Task recognition utilizes pre-trained knowledge to solve tasks identified in the demonstrations. A Probably Approximately Correct (PAC) [321] framework has been proposed to evaluate ICL's learnability, suggesting that LLMs can recognize tasks from minimal inputs.

Task learning, on the other hand, involves LLMs learning new tasks through demonstrations, akin to implicit fine-tuning through the attention mechanism, which generates meta-gradients. With the examples provided in ICL, LLMs can implement learning algorithms such as gradient descent or directly compute the closed-form solution to update these models during forward computation. Under this explanation framework, it has been shown that LLMs can effectively learn simple linear functions and even some complex functions like decision trees with ICL [138]. Different model scales exhibit distinct capabilities; smaller models are adept at task recognition, while larger models (at least 66 billion parameters) are necessary for task learning [286].

The last piece of ICL is the scoring function, which decides how to transform the predictions of the LLMs into an estimation of the likelihood of a specific answer. A direct estimation method adopts the conditional probability of candidate answers and select the higher probability as the final answer [83]. However, this method poses some restrictions on the template design, e.g., the answer tokens should be placed at the end of input sequences. Perplexity (PPL) is another

[3]Based on pre-defined metrics

Scoring Function	Target	Efficiency	Task Coverage	Stability
Direct	$\mathcal{M}(y_j \mid C, x)$	+++	+	+
PPL	$\text{PPL}(S_j)$	+	+++	+
Channel	$\mathcal{M}(x \mid C, y_j)$	+	+	++

Table 3.2: *Summary of different scoring functions.*

commonly-used metric that computes the PPL of the entire input sequence:

$$S_j = \{C, s(x, y_i, I)\} \tag{3.2}$$

where C are the tokens of the demonstration examples, x is the input query, and y_i is the candidate label. As PPL is a global metric (i.e., it considers the entire input sequence), it removes the limitations of token positions but requires extra computation time. In generation tasks such as machine translation, ICL predicts the answer by decoding tokens with the highest sentence probability combined with diversity-promoting strategies such as beam search or Top-p and Top-k [86] sampling algorithms. Min et al. [191] proposed a channel scoring function that estimates the likelihood of the input query given the candidate answer[4], which is more efficient and stable than the direct estimation method. In this way language models are required to generate every token in the input, which could boost the performance under imbalanced training data regimes. To calibrate the bias or mitigate the sensitivity via scoring strategies some studies add additional calibration parameters to adjust the model predictions [135].

3.2.1 ICL performance and origins

Knowing and understanding the factors that influence ICL can help to improve the performance of LLMs. ICL has a close connection with instruction tuning (discussed in Section 2.3.1) in that both utilize natural language to format the task or instances. However, instruction tuning needs to fine-tune LLMs for adaptation, while ICL only prompts LLMs for utilization [335]. Furthermore, instruction tuning can enhance the ICL ability of LLMs to perform target tasks, especially in the zero-shot setting[5] [150].

There are several factors that have a relatively strong correlation to ICL performance, as shown in Table 3.3. ICL ability may give raise putting multiple corpora together in the pre-training stage, and the domain source is more important than the corpus size [205], while pretrain on corpora related to downstream tasks and models with lower perplexity do not always perform better in ICL [205]. Wei et al. [225] suggested that a pretrained model suddenly acquires some emergent ICL abilities when it achieves a large scale of pretraining steps or model parameters and Brown et al. [83] showed that the ICL ability grows as the parameters of LLMs increase from 0.1 billion to 175 billion. At inference stage, the properties of the demonstrations influence the ICL performance, such as the label space exposure, the format of input-label pairing, the ordering of demonstration samples, and the complexity of demonstrations [192, 239, 184]. There are contrasting results on the impact of input-label mapping related to ICL [192, 230]. An interesting finding is that, when a model is large enough, it will show an emergent ability to learn input-label mappings, even if the labels are flipped[6] or

[4]Compute the conditional probability in a reversed direction

[5]Using only task descriptions

[6]Flipped-label ICL uses flipped targets, forcing the model override semantic priors in order to follow the

Stage	Factor
Pretraining	Pretraining corpus domain [205] Pretraining corpus combination [205] Number of model parameters [225, 83] Number of pretraining steps [225]
Inference	Label space exposure [192] Demonstration input distribution [192] Format of input-label pairing [192, 239] Demonstration input-label mapping [192, 230, 320] Demonstration sample ordering [184] Demonstration-query similarity [184] Demonstration diversity [239] Demonstration complexity [239]

Table 3.3: *Summary of factors that have a relatively strong correlation to ICL performance. Source: Dong et al. [252]*

semantically-unrelated[7] [319]. Some general validated factors for the ICL demonstrations are that they should be diverse, simple, and similar to the test example in terms of the structure [239]. Lu et al. [184] indicated that the demonstration sample order is also an important factor. Liu et al. [180] found that the demonstration samples that have closer embeddings to the query samples usually bring better performance than those with farther embeddings.

The reasons for the ICL ability has been investigated from different perspectives. Focusing on the pretraining data distribution, Chan et al. [145] showed that the ICL ability is driven by data distributional properties. The ICL ability emerges when the training data have examples appearing in clusters and have enough rare classes. Xie et al. [227] explained ICL as implicit Bayesian inference and constructed a synthetic dataset to prove that the ICL ability emerges when the pretraining distribution follows a mixture of hidden Markov models. Under the learning mechanism, the ICL ability is explained by ability of Transformers to encode effective learning algorithms to learn unseen linear functions according to demonstration samples, and encoded learning algorithms can achieve a comparable error to that from a least squares estimator [254]. Also Li et al. [276] showed the ability of Transformers to implement a proper function class through implicit empirical risk minimization for the demonstrations. From an information-theoretic perspective, Hahn and Goyal [257] showed an error bound for ICL under linguistically motivated assumptions to explain how next-token prediction can bring about the ICL ability. Another series of works attempted to build connections between ICL and gradient descent and found that Transformer-based in-context learners can implement standard fine-tuning algorithms implicitly [138, 285, 276]. Looking at functional components, Olsson et al. [198] found indirect evidence that "Induction heads"[8] might constitute the mechanism for the majority of all ICL in large transformer models.

In-context learning (ICL) evaluation spans traditional tasks and newly proposed challenging tasks, as well as providing open-source tools for standardized evaluation. ICL has been tested against established benchmarks such as SuperGLUE and SQuAD, with mixed results. GPT-3, for example, exhibited comparable performance to state-of-the-art fine-tuning on some tasks

in-context exemplars. For example, in sentiment analysis task, the label "Positive" become "Negative" in ICL context and viceversa

[7]The labels are semantically unrelated to the task(e.g., for sentiment analysis, it uses "foo/bar" instead of "negative/positive")

[8]attention heads that implement a simple algorithm to complete token sequences like $[A][B]\dots[A] \Rightarrow [B]$

within SuperGLUE but lagged in most natural language understanding tasks. Scaling the number of demonstration examples has shown potential but has yet to bridge the gap fully between ICL and traditional fine-tuning methods [83, 162].

To assess the capabilities of large language models (LLMs) beyond traditional fine-tuning, new benchmarks have been introduced. The BIG-Bench and BIG-Bench Hard focus on tasks ranging from linguistics to social behaviors, with models outperforming human raters on many of these tasks [299, 212]. OPT-IML Bench has been designed to evaluate the generalization capabilities of LLMs across various held-out categories, emphasizing the model's generalization capabilities [168]. OpenICL has been developed to provide a flexible and unified framework for ICL evaluation. This toolkit supports different LLMs and tasks, enabling consistent implementation and evaluation of ICL methods across various studies [324].

The application of In-Context Learning (ICL) has transcended the domain of natural language processing (NLP), influencing research in various modalities such as visual tasks, vision+language integration, and speech. Visual In-Context Learning explores how models generalize learned visual concepts to new, unseen tasks by leveraging contextual demonstrations in a manner akin to NLP-based ICL. Techniques such as image patch infilling and the training of models like masked autoencoders (MAE) exemplify this approach [143]. Noteworthy models like Painter and SegGPT have been developed to handle multiple tasks or integrate various segmentation tasks into a single framework [314, 315]. The Prompt Diffusion model introduced by Wang et al. [317] represents a pioneering effort in diffusion-based models displaying ICL capabilities, particularly when guided by textual prompts [317] . In the realm of vision-language tasks, the integration of visual contexts with linguistic models has led to significant advancements. Models such as Frozen and Flamingo have demonstrated the feasibility of multi-modal few-shot learning by combining vision encoders with large language models (LLMs). These models effectively perform ICL on multi-modal tasks when trained on large-scale multi-modal web corpora [131, 139]. Kosmos-1 and METALM further extend these capabilities by demonstrating strong performance across various vision-language tasks, underpinned by a semi-causal language modeling objective [262, 163] .

3.2.2 ICL future research

Future research in ICL is expected to focus on several key areas, including the optimization of pretraining objectives, the distillation of ICL abilities, the enhancement of ICL robustness, the improvement of ICL efficiency and scalability, the updating of knowledge within LLMs, the augmentation of models, and the expansion of ICL into multi-modal domains [252]. Optimizing pretraining objectives to better align with ICL requirements could enhance model capabilities for ICL applications. Introducing intermediate tuning phases and tailoring pretraining objectives to better align with ICL requirements could bridge this gap and enhance model capabilities for ICL applications [205]. On important goal is to be able to distill ICL capabilities from larger models to smaller, more efficient models, potentially enabling the deployment of ICL in resource-constrained environments [187]. Another area of improvement is the robustness of ICL, which is highly susceptible to the format and permutation of demonstrations [135, 184], without compromising accuracy or efficiency [341].

A more theoretical understanding of ICL's mechanisms could lead to more robust implementations. Moreover the scalability of ICL is constrained by the input limitations of language models and the computational cost associated with large numbers of demonstrations. Innovative strategies like structured prompting [162] and dynamic prompting [310] are being explored to address these challenges. The development of models with extended context capabilities [270] indicates significant potential for progress in this area. Finally, the expansion of ICL into multi-modal domains is expected to yield new insights and applications, particularly in the fields of

vision and speech [252].

3.3 Chain-of-Thought

Chain-of-Thought (CoT) prompting is an enhanced strategy developed to augment the performance of large language models (LLMs) on complex reasoning tasks such as arithmetic, commonsense, and symbolic reasoning [223, 118, 76]. This method integrates intermediate reasoning steps within the prompts, thereby providing a more structured path towards the solution. To some extent, CoT can be considered a special case of ICL, as it involves the gener-

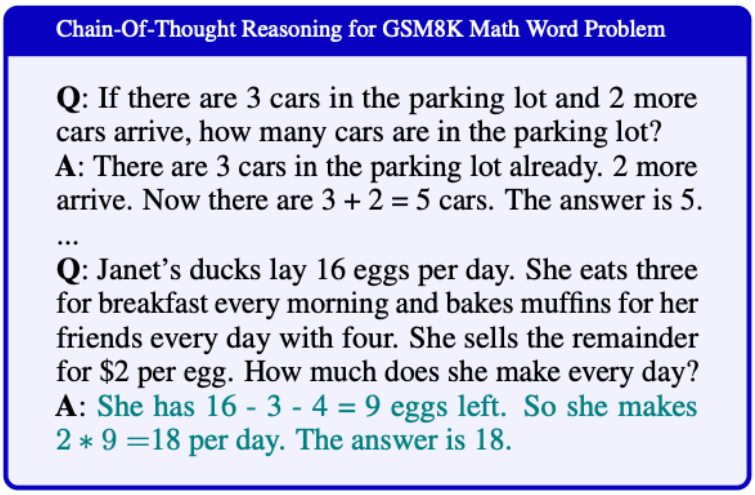

Figure 3.3: *Chain-of-Thought reasoning for GSM8K math word problem. The prompt is colored black and the reasoning path produced by the language model is colored teal. This reasoning path contains two reasoning steps. Source: Li et al. [275]*

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ation of prompts with a series of intermediate reasoning steps (Figure 3.4), but the ordering of demonstrations in this case has a s relatively minor impact on the performance of LLMs [223].

Wei et al. [223] and Wang et al. [220] have shown that language models, when large enough (i.e., >100 billion parameters), can learn to perform complex reasoning tasks through CoT prompting without explicit task-specific [225].

CoT can be effectively combined with In-context Learning (ICL) in both few-shot and zero-shot settings:

- **Few-shot CoT.** In the few-shot scenario, CoT augments standard input-output pairs with intermediate reasoning steps. The design of CoT prompts is crucial; incorporating diverse and complex reasoning paths has been shown to significantly boost LLM performance. An automated approach, Auto-CoT, facilitates the generation of CoT sequences without manual effort by clustering and selecting representative questions [235].

- **Zero-shot CoT.** Unlike its few-shot counterpart, zero-shot CoT does not rely on annotated demonstrations. Instead, it generates reasoning steps directly from a prompt, significantly improving performance when scaled to larger models. This approach was pioneered by models like Flan-T5, which demonstrated improved zero-shot performance through instruction tuning on CoT annotations [150].

To apply these strategies effectively, it is essential to design CoT prompts that guide the model through the reasoning process. In Li et al. [275], the authors have shown that using diverse CoTs (i.e., prompts with multiple reasoning paths for each problem) can significantly enhance the performance of LLMs on complex reasoning tasks. The proposed method,

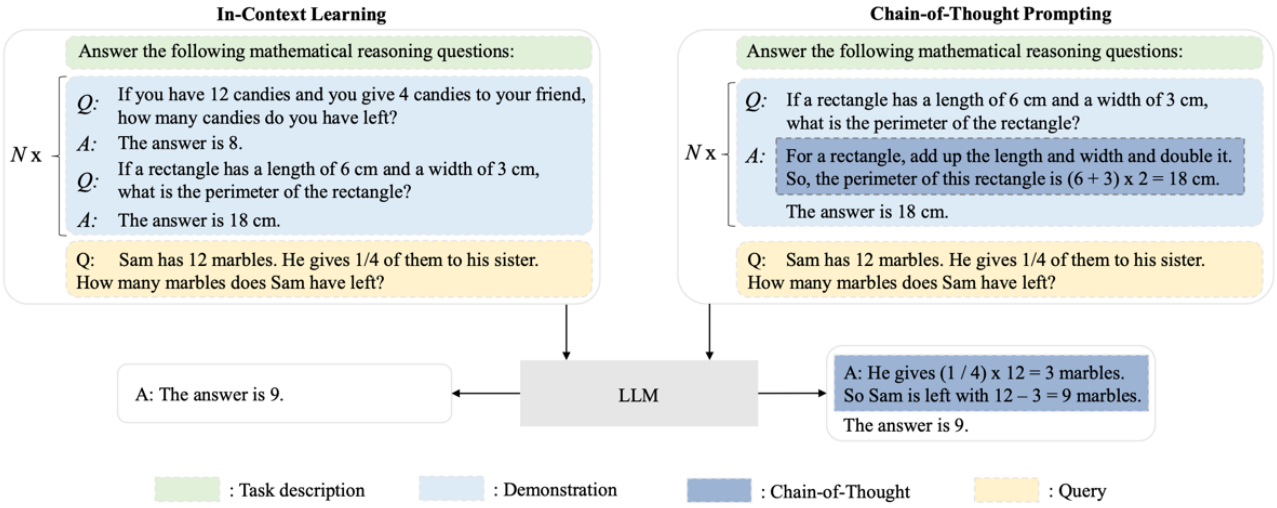

Figure 3.4: *A comparative illustration of in-context learning (ICL) and chain-of-thought (CoT) prompting. ICL prompts LLMs with a natural language description, several demonstrations, and a test query, while CoT prompting involves a series of intermediate reasoning steps in prompts. Source: Zhao et al. [335]*

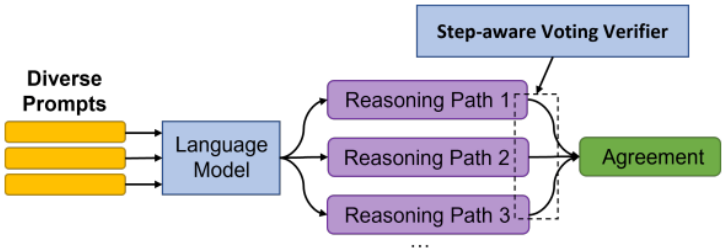

Figure 3.5: *The DIVERSE approach for CoT. Source: Li et al. [275]*

DIVERSE[9], generates diverse CoTs by leveraging a self-ensemble approach that alternates between selection and inference. It has three main components: first, it generates diverse prompts to explore different reasoning paths for the same question; second, it uses a verifier to filter out incorrect answers based on a weighted voting scheme; and third, it verifies each reasoning step individually instead of the whole chain (Figure 3.5). In the first step, the model generates multiple reasoning paths for each question, which are then used to generate diverse prompts following the idea that *"All roads lead to Rome"*. As improvement of Wang et al. [220], DIVERSE selects M_1 different prompts for each question, and M_2 reasoning paths for each prompt, resulting in $M_1 \times M_2$ diverse prompts. Then the verifier takes a question and a candidate reasoning path, and outputs the probability of the reasoning path leads to the correct answer. Different predictions are aggregated using a *voting verifier* to obtain the final prediction:

$$\hat{y} = \arg\max_{y} \sum_{i=1}^{M_1} \mathbf{1}_{y=y_i} \cdot f(\mathbf{x}_i, \mathbf{z}_i, \mathbf{y}_i) \tag{3.3}$$

where $\mathbf{1}_{y=y_i}$ is an indicator function that equals 1 if $y = y_i$, and $f(\cdot)$ is the probability produced by the verifier.

Another intuitive idea is that prompting with more complex reasoning steps (i.e., chains with more reasoning steps) are more likely to eliciting the reasoning ability of LLMs [157], which

[9] **Di**verse **V**erifier on **R**easoning **St**ep

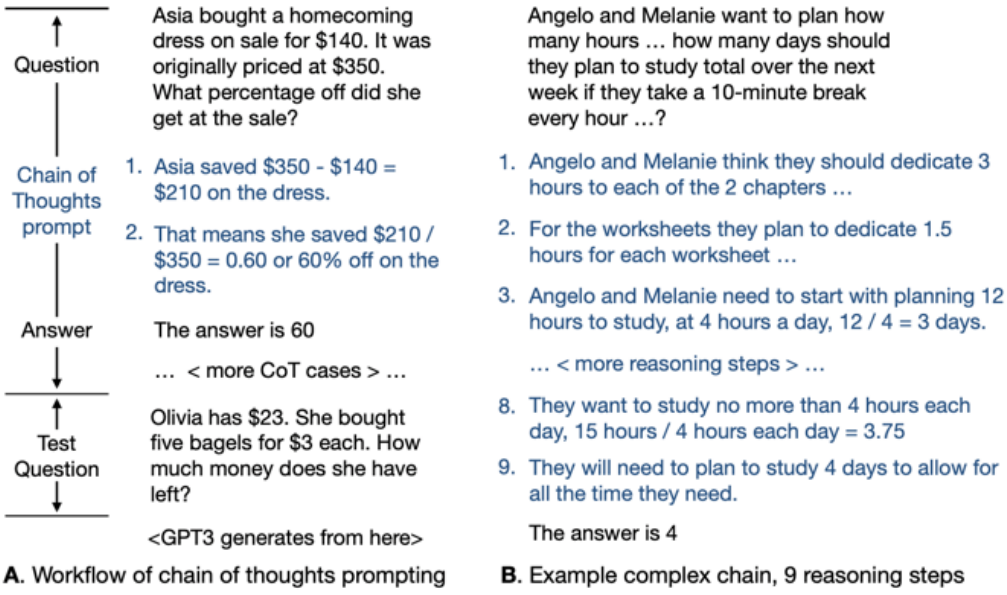

Figure 3.6: ***A****: Chain of thoughts (in blue) are intermediate reasoning steps towards a final answer. The input of CoT prompting is a stack of few (often 8) CoT cases before a test question. Then the language model will continue generating an output CoT for the test question.* ***B****: Chains of harder reasoning complexity are chains with more reasoning steps (9 steps in this case, v.s. only 2 steps in subfigure A) .Source: Fu et al. [157]*

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can result in generating correct answers (Figure 3.6). There are other complexity indicators than the number of reasoning steps, such as question lengths or the length of underlying formula for solving a given problem but improvements of the performance are consistent across various complexity indicators. Consequently, for datasets not annotated with reasoning steps, questions length can be used as a proxy for complexity to generate CoT prompts. In that way is possible to annotate only the identified few-shot instances, thus reducing the annotation cost [157]. To exclude complexity correlated factors, Fu et al. [157] proposed prompts evaluation:

- **Simpler examples but the same total number of reasoning steps.** For instance, comparing 24 cases that each require 3 reasoning steps with 8 cases that each require 9 reasoning steps, both resulting in a total of 72 steps.
- **Prompts of the longest lengths but not necessarily the most steps.** This ensures that the length itself is not the only factor being assessed.

It turned out that the complexity of reasoning steps is the most important factor for the performance of LLMs on complex reasoning tasks [157]. Complexity based prompting can be further enhanced by using the output selection method called Complexity-based Consistency alleviating the possibility that model can take shortcuts during reasoning[10]. The method explicitly promote outputs with more complex reasoning chains at inference time, similarly to the self-consistency practice in Wang et al. [220]. A voting mechanism is used to select the final output among top K complex reasoning chains as shown in Figure 3.7.

Previously mentioned methods rely on two major paradigms: Zero-Shot-CoT and Manual-CoT. Zero-Shot-CoT is a task-agnostic paradigm that generates reasoning steps directly from the prompt, eliminating the need for annotated CoT datasets [266], adding a single prompt like "Let's think step by step" after the test question to facilitate the reasoning chains in LLMs. On

[10]Relying on spurious correlations that inevitably exist in the training data and are not related to the reasoning process as shown by Mudrakarta et al. [45], Lai et al. [112], and Sugawara et al. [50]

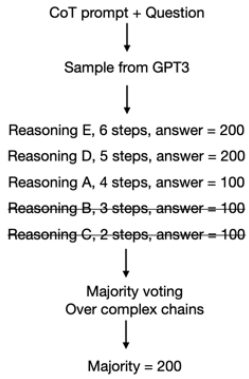

Figure 3.7: *Complexity-based Consistency for CoT. During decoding, it sample N reasoning chains from the language model (N = 5 here), and take the majority answer over the K (K = 3 here) most complex generated chains. Source: Fu et al. [157]*

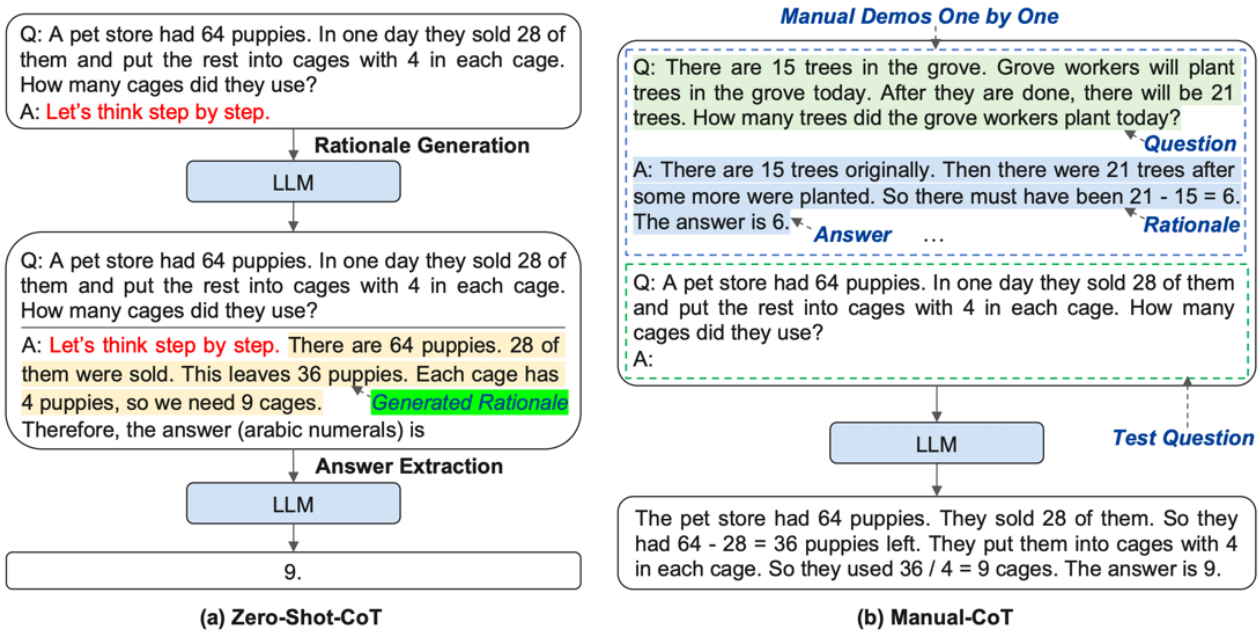

Figure 3.8: *Zero-Shot-CoT [266] (using the "Let's think step by step" prompt) and Manual-CoT[223] (using manually designed demonstrations one by one) with example inputs and outputs of an LLM. Source: Zhang et al. [235]*

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the other hand, Manual-CoT uses manually designed demonstrations one by one, which can be expensive and time-consuming to create [223]. Since this prompting paradigm is task-agnostic and does not need input-output demonstrations, it is called Zero-Shot-CoT (left of Figure 3.8). With Zero-Shot-CoT, LLMs have shown to be decent zero-shot reasoners.

The other paradigm is few-shot prompting with manual reasoning demonstrations one by one [223]. Each demonstration has a question and a reasoning chain. A reasoning chain is composed of a rationale (a series of intermediate reasoning steps) and an expected answer. With all the demonstrations being manually designed, this paradigm is referred to as Manual-CoT (right of Figure 3.8).

To mitigate the effect of reasoning chain mistakes from Zero-Shot-CoT, Zhang et al. [235] proposed the use of Auto-CoT, a method that generates demonstrations automatically, since their diversity is crucial for the performance of LLMs. It consists of two main components: a

clustering algorithm that groups similar questions together and a representative selection algorithm that selects the most representative questions from each cluster. The overall procedure is illustrated in Figure 3.9. Diversity-based clustering may mitigate misleading by similarity

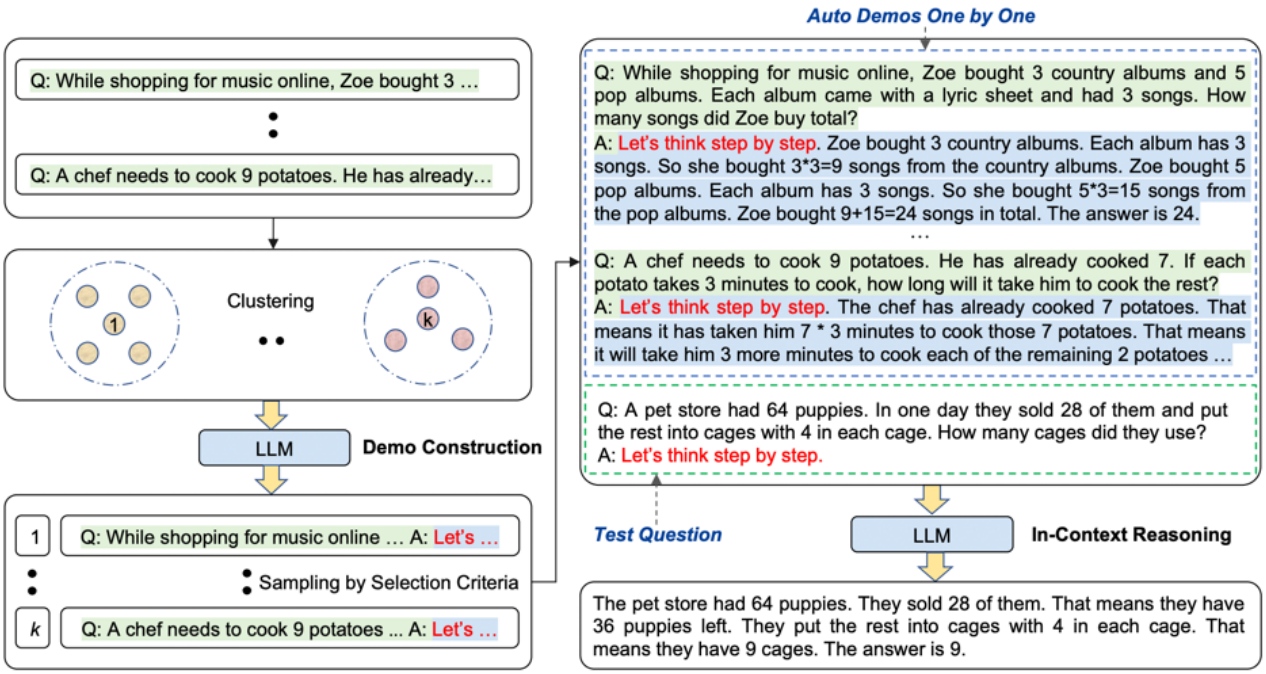

Figure 3.9: *demonstrations (on the right) are automatically constructed one by one (total: k) using an LLM with the "Let's think step by step" prompt. Source: Zhang et al. [235]*

effects[11], and the representative selection algorithm can select the most representative questions from each cluster, are used as demonstrations to generate reasoning chains for the test question. Auto-CoT has shown to be effective in generating diverse reasoning chains and improving the performance of LLMs on arithmetic and symbolic reasoning [235].

3.3.1 CoT performance and origins

CoT is an emergent ability [225], so it has positive effects only on the performance of LLMs (>10 billion parameters) but not on smaller models. Moreover CoT is only effective for tasks that requires step-by-step reasoning, such as arithmetic, commonsense, and symbolic reasoning [223, 118, 76]. Whereas, for other tasks CoT can be detrimental to the performance of LLMs respect to standard prompting [219], e.g., MNLI-m/mm, SST-2, and QQP from GLUE[52]. It seems that the effectiveness of CoT is inversely proportional to the effectiveness of standard prompting [223]. Main prompting components, e.g., symbols, patterns, and text, have an impact on CoT. It has been shown that pattern and text are essential for CoT performance, and removing them can lead to a significant drop in performance: text helps LLMs to generate useful patterns, and patterns aid LLMs to understand tasks and generate texts that help solve them [186].

The origins of CoT ability is widely hypothesized to be elicited by training on code, since those models have shown to be more effective in reasoning tasks [156, 179]. Intuitively, code data is well organized with algorithmic logic and programming flow,which may be useful to

[11]The retrieved demonstration questions are similar to the test question and asking "how long will it take him to cook the rest?" The reasoning chains generated by Zero-Shot-CoT produce answers regarding "the total of" instead of "the rest". Following the demonstrations, the component the retrieves the top-k similar questions – called Retrieval-Q-CoT – also fails by misunderstanding the meaning of "the rest".

improve the reasoning performance of LLMs. However, this hypothesis still lacks publicly reported evidence of ablation experiments (with and without training on code). We'll try to address this gap in the next chapter 4, by conducting a series of experiments to evaluate the effectiveness of training on code data for reasoning tasks. In addition, instruction tuning seems not to be the main factor for CoT ability, since the performance of LLMs on CoT tasks is not significantly improved by instruction tuning [150].

3.4 Planning for complex tasks

ICL and CoT are two simple yet general strategies to solving various tasks. However, they struggles with complex tasks that require long-term planning, such as mathematical word problems [201] and multi-hop question answering [340]. Commonsense knowledge[12] is essential for NLP systems to understand and generate human-like language. Main categories are summarized in Bian et al. [340]:

> **General commonsense** refers to knowledge that is widely shared and assumed to be true by most people, such as the sun rises in the east and sets in the west.
> **Physical commonsense** involves intuitive knowledge about the physical world, such as objects fall to the ground when dropped and water flows downhill.
> **Social commonsense** involves knowledge about social norms, customs, and practices, such as it is polite to say "thank you" when making requests.
> **Science commonsense** involves knowledge about basic scientific principles, such as gravity pulls all objects on Earth to Earth's center.
> **Event commonsense** involves knowledge about the sequence of events and the causal relationships between them, such as if a glass is knocked over, the liquid inside will spill.
> **Numerical commonsense** involves knowledge about numbers, such as human has two hands and ten fingers.
> **Prototypical commonsense** involves knowledge about typical or prototypical examples of concepts, such as a swallow is a kind of bird, and a bird has wings.
> **Temporal commonsense** involves knowledge about time, such as traveling abroad requires a longer time than taking a walk.

A list of commonsense QA datasets commonly used in the evaluation of LLMs is shown in Table 3.4. These datasets encompass domains like general, physical, social, science, event, numerical, prototypical, and temporal commonsense. Table 3.5 shows the accuracy of GPT-3, GPT-3.5, and ChatGPT on these datasets. The ability of models to leverage commonsense is probably improved by instruction tuning and human alignment, looking at the results of Instruct GPT and ChatGPT versus GPT-3 in Table 3.5.) ChatGPT demonstrates strong capabilities in commonsense QA tasks but has limitations in identifying necessary knowledge. It has been proved evaluating answers generated by ChatGPT on questions from each commonsense QA dataset using the following prompt: "What knowledge is necessary for answering this question? `{question} {answer choices(if applicable)}`". It means that LLMs are inexperienced problem solvers that rely on memorizing a large amount of information that covers the answers.

Even though we have seen surprising abilities of LLMs, Qian et al. [201] have shown additional limitations on certain basic symbolic manipulation tasks, such as copy, reverse and

[12]It includes knowledge about the spatial, physical, social, temporal, and psychological aspects of the typical everyday life, as well as an awareness of social norms, beliefs, and values [7].

Dataset	Domain	Example (Bold texts are the answers)
CommonsenseQA	General	Choose your answer to the question: Where are you likely to find a hamburger? **A. fast food restaurant**, B. pizza, C. ground up dead cows, D. mouth, E. cow circus
OpenBookQA	General	Choose your answer to the question: If a person walks in the opposite direction of a compass arrow they are walking A. west, B. north, C. east, **D. south**
WSC	General	Choose sub-sentence A or B that completes the sentence: The trophy doesn't fit into the brown suitcase because A. the trophy is too small. **B. the suitcase is too small**.
PIQA	Physical	Choose one that is correct: A. **ice box will turn into a cooler if you add water to it**. B. ice box will turn into a cooler if you add soda to it.
Social IQA	Social	Taylor taught math in the schools after studying to be a teacher. Choose the most suitable answer for the question: What does Taylor need to do before this? **A. get a certificate**, B. teach small children, C. work in a school
ARC	Science	Choose your answer to the question: Which technology was developed most recently? **A. cellular telephone**, B. television, C. refrigerator, D. airplane
QASC	Science	Choose your answer to the question: What is described in terms of temperature and water in the air? A. storms; **B. climate**; C. mass; D. seasonal; E. winter; F. density; G. length
HellaSWAG	Event	Choose your answer to the question: We see a chair with a pillow on it. A. a man holding a cat does curling. B. a man holding a cat starts hitting objects on an item. C. a man holding a cat is wrapping a box. **D. a man holding a cat sits down on the chair**.
NumerSense	Numerical	a square is a shape with ⟨mask⟩equally length sides. **(four)**
ProtoQA	Prototypical	Use simple words separated by commas to name something in your life that could cause you to lose weight. (**Eating less, exercising more, stress.**)
MC-TACO	Temporal	Select all feasible answers for the question: Carl Laemmle, head of Universal Studios, gave Einstein a tour of his studio and introduced him to Chaplin. At what time did Einstein return home? **A. 8:00 PM**; B. a second later; C. a hour later

Table 3.4: *Examples from commonsense QA datasets. Source: Bian et al. [340]*

addition, particularly when dealing with repeating symbols[13] and OOD[14] data. To address these limitations, Qian et al. [201] have proposed a series of methods to improve the performance of LLMs on these tasks, such as positional markers, fine-grained computation steps, and combining LMs with callable programs for basic operations. Positional markers[15] and fine-grained computation steps[16] provide some improvement with repeating symbols but not with

[13]Copy example with repeating symbols `input:...989894...` $\longrightarrow$ `answer:...9894...`

[14]Out-of-distribution refers to prompting the model to execute an operation on numbers with more digits with respect to numbers used for training. It demonstrates the ability to generalize on unseen data.

[15]LMs have implicit positional markers embedded in the architecture. Most Transformer-based LMs encode the positional information into positional vectors and add each of them to the corresponding word vector. Explicit positional markers are added into input strings: `input:...222...` $\longrightarrow$ `output:...A2B2C2...`. Essentially, adding explicit positional markers breaks the repeating numbers into a non-repeating input sequence.

[16]For example, in k-digit addition, the model is allowed to break it down into k simple 1-digit addition and

Dataset	GPT-3	Instruct GPT	ChatGPT	Human
CommonsenseQA	38	**81**	74	88.9
OpenBookQA	22	65	**73**	89.3
WSC	46	**78**	**78**	92.1
PIQA	48	77	**78**	94.5
Social IQA	36	**71**	62	86.9
ARC	27	88	**94**	–
QASC	25	**75**	74	93.0
HellaSWAG	19	61	**67**	95.7
NumerSense	45	63	**79**	89.7
ProtoQA	67.3	84.6	**94.2**	–
MC-TACO	20	**53**	52	75.8

Table 3.5: *Evaluation results (accuracy) of large language models on commonsense QA datasets. Source: Bian et al. [340]*

OOD. It clearly indicates the limitation of Transformers and pre-trained language models in induction. Combining LMs with callable programs[17] for basic operations shows potential but still relies on the LM's ability to locate tokens accurately. The LM with tutor method [18] demonstrates each step of the task, significantly improving accuracy and handling OOD scenarios, effectively achieving 100% accuracy on all tasks.

3.4.1 Plan-based reasoning

Prompt-based planning has been proposed to break down complex tasks into simpler subtasks, and generate a plan of actions which can accomplish the task. The general framework of prompt-based planning is shown in Figure 3.10.

In this paradigm, there are three main components: the planner, the executor, and the environment[19]. The first component is the planner, which generates a plan of actions to solve the task. The plan can be generated in various forms, .e.g., natural language, symbolic, or programmatic [158, 236], that we will discuss in the next section 3.4.1. The task planner can be enhanced with the memory mechanism, which can store intermediate results and reuse them in the future.

Plan executor is responsible for executing the plan generated by the planner. It can be implemented as a separate LLM for textual tasks, or as a program executor for programmatic tasks [312, 158].

Environment is the world where the task is executed, which can be set up as the LLM itself, or an external system, e.g., a simulator or a virtual world like Minecraft [332, 311].

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the model is allowed to generate k intermediate addition results to get the final answer.

[17] A callable function `add(1,5)` can be invoked and return the result in text: `carry C: 0, result 6`

[18] A tutor shows every single step visually and sometimes calls an already learned sub-module to complete a task. Instead of providing a training example: `copy: 1 1 1 2 2 2 result: 1 1 1 2 2 2` the tutor explicitly shows the model how to copy the input as follows: `rmov, end=F, cpy, rmov, end=F, cpy, ..., rmov, end=T.` where `rmov` is a function that moves the tape head to the right, `cpy` is a function that copies the current symbol, and `end=F` indicates that the end of the tape is not reached. One can relate the setting with a multiple tape Turing machine where state transition is conducted among the positions of tape heads and read/write operations. The Transformer is trained to learn such state transition, thus completing the programming of a Turing machine.

[19] It's similar to Reinforcement Learning, where the planner is the agent, the executor is the policy, and the environment is the world, but the difference is that in RL they are tipically interleaved in the agent, while in prompt-based planning they are separated

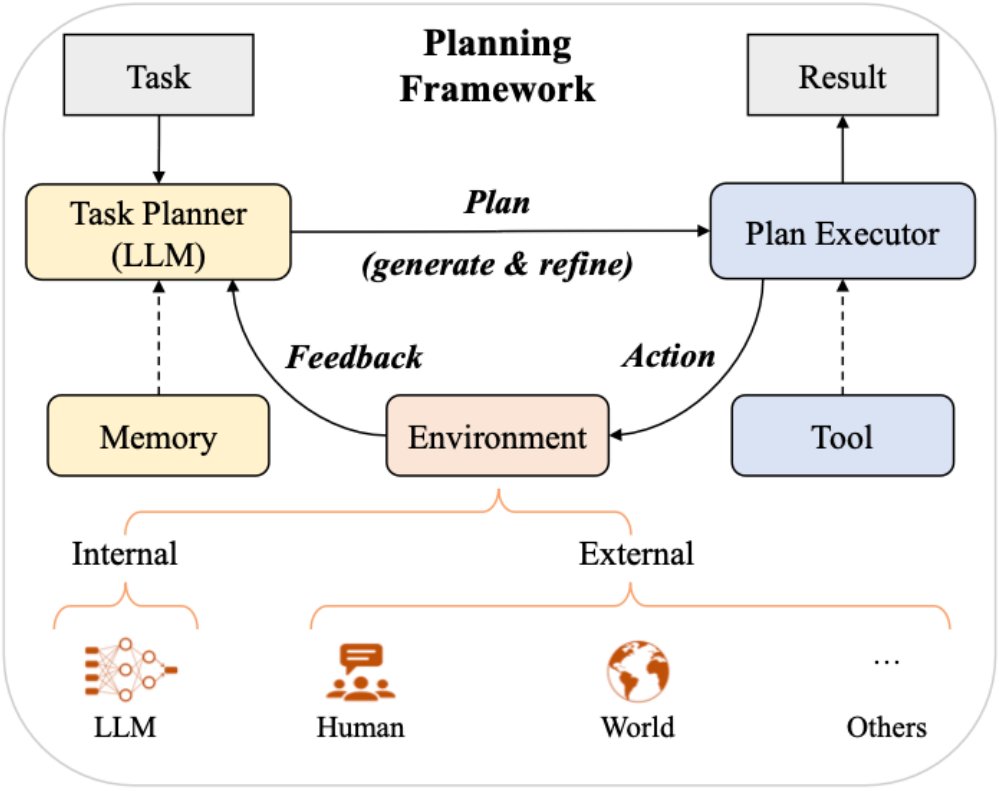


Figure 3.10: *The general framework of prompt-based planning. Source: Zhao et al. [335]*

The environment provides feedback to the task planner about the result of the actions, which can be used to update the plan, either in form of natural language or from other multimodal signals [297, 281]

Plan generation

For solving complex tasks, the planner needs to generate a plan that is long-term and multi-step, which requires the planner to have the ability to reason over long-term dependencies and to generate a plan that is coherent and consistent. It first need to understand the task and break it down into sub-tasks, then generate a plan that can accomplish the task by executing the sub-tasks in a proper order. The plan should be generated in a way that is interpretable and executable by the executor, which acts according to the plan and interacts with the environment to accomplish the task. The planner can further incorporate the feedback from the environment to update the plan and refine it to achieve better performance.

The most common form of plan generation is natural language, where the planner generates a sequence of natural language instructions that describe the plan. In this approach LLMs are prompted to generate a sequence of instructions that describe the plan, which can be executed by the executor to accomplish the complex task. For example, Plan-and-Solve [312] adds explicit instructions to the input of the LLM, which guides the model to generate a plan for solving the task (i.e., "devise a plan") in a zero-shot setting, while Self-planning [342] and DECOMP [169] generate the plan in a few-shot setting by providing a few examples to guide LLM through ICL. Some other approaches further consider incorporating extra tools or models when planning, such as ToolFormer [295] and HuggingGpt [296]. ToolFormer is a model trained to decide which APIs to call, when to call them, what arguments to pass, and how to best incorporate the results into future token prediction. This is done in a self-supervised way,

requiring nothing more than a handful of demonstrations for each API. It incorporates a range of tools, including a calculator, a Q&A system, two different search engines, a translation system, and a calendar. HuggingGpt is LLM-powered agent that leverages LLMs (e.g., ChatGPT) to connect various AI models in machine learning communities (e.g., Hugging Face) to solve AI tasks. Specifically, it uses ChatGPT to conduct task planning when receiving a user request, select models according to their function descriptions available in Hugging Face, execute each subtask with the selected AI model, and summarize the response according to the execution results.

Although text-based plan approaches sound intuitive, they have limitations since the generated plans may lead to incorrect results due to the ambiguity of natural language, even when the plan is sound. To address this issue, code-based plan generation has been proposed, where the planner generates a program that can be executed by the executor to accomplish the task. Compare to text-based plans, programmatic plans are more verifiable and less ambiguous and they can directly be executed by interpreters or compilers (e.g., Python or PDDL[20]) to accomplish the task. In this approach, LLMs are first prompted to generate a program that can solve the task, and then leverage on a deterministic solver to execute it. For example, Faithful CoT [282] and PAL [158] decompose a reasoning task into two stages: at the first stage, the LLM generates a plan conditioned on the query; at the second stage, a deterministic solver executes the plan to derive the final answer. Furthermore, code-based approaches can be applied to embedded agents in a similar way, such as in the case of PROGPROMPT [206] and LLM+P [277]. They both first prompt the LLM to generate plans in the form of code (Python functions or PDDL files), and then leverage on a virtual agent or classical planner to solve the task according to the code-based generated plan.

We will elaborate some notable approaches to both natural language and programmatic plan generation in the next paragraphs.

Plan-and-Solve (PS) prompting is a text-based plan generation approach that consists of two components: devising a plan and carrying out the subtasks. The process includes:

1. **Step 1: Prompting for Reasoning Generation**. To meet criteria for effective problem-solving, templates guide LLMs to devise and complete a plan with attention to calculations and intermediate results. For example: "Let's first understand the problem, extract relevant variables, devise a plan, and solve the problem step by step."

2. **Step 2: Prompting for Answer Extraction.** Similar to Zero-shot-CoT, another prompt extracts the final numerical answer from the reasoning text.

Comparison about prompting strategies is shown in Figure 3.11. The PS+ variant of Plan-and-Solve is an extension of Plan-and-Solve that add detailed instructions to improve reasoning quality.

Comparing to Zero-shot-CoT, which suffers from pitfalls like calculation and missing-step errors, PS+ Prompting has shown to be more effective addressing these issues [312]. The experiments with GPT-3 show that PS+ consistently outperforms Zero-shot-CoT and is comparable to 8-shot CoT prompting on math reasoning problems. Self-consistency (SC)[21][220] improves performance by generating multiple reasoning paths and determining the final answer by majority voting. PS+ with SC outperforms PS+ without SC and Zero-shot-CoT with SC.

[20]Planning Domain Definition Language defines the "universal" aspects of a problem. Essentially, these are the aspects that do not change regardless of what specific situation we're trying to solve. In PDDL this is mostly the object types, predicates and actions that can exist within the the model.

[21]It reduces randomness in LLM's output by generating N reasoning results and determining the final answer by majority voting

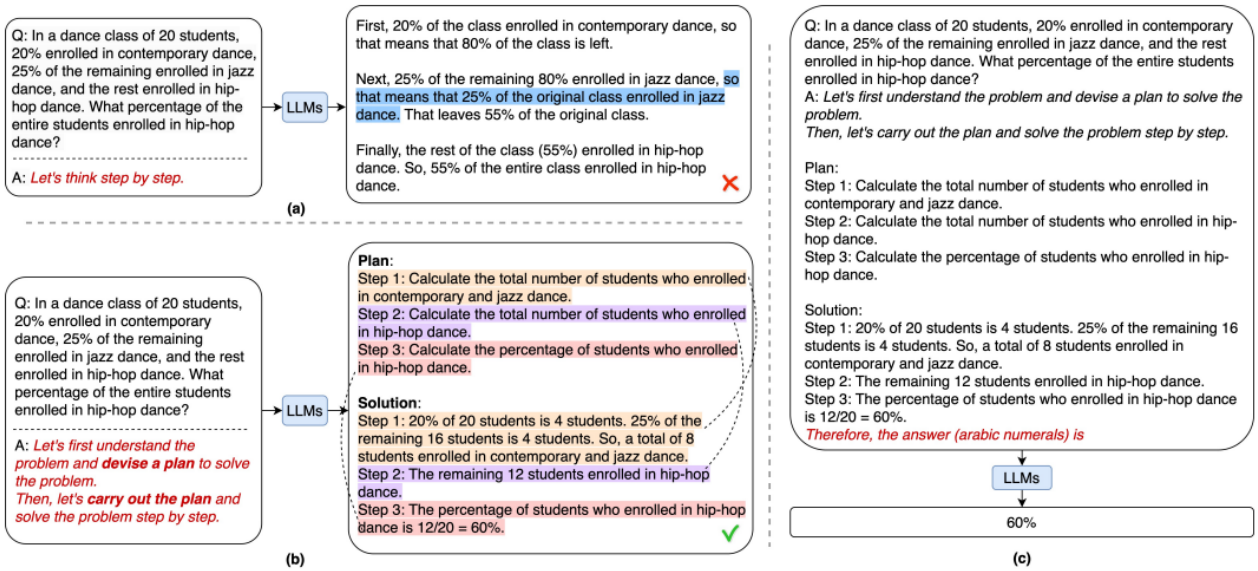


Figure 3.11: *Example inputs and outputs of GPT-3 with (a) Zero-shot-CoT prompting, (b) Plan-and-Solve (PS) prompting, and (c) answer extraction prompting. While Zero-shot-CoT encourages LLMs to generate multi-step reasoning with "Let's think step by step", it may still generate wrong reasoning steps when the problem is complex. Unlike Zero-shot-CoT, PS prompting first asks LLMs to devise a plan to solve the problem by generating a step-by-step plan and carrying out the plan to find the answer. Source: Wang et al. [312]*

Method	MultiArith	GSM8K	AddSub	AQUA	SingleEq	SVAMP
Zero-shot-CoT	83.8	56.4	85.3	38.9	88.1	69.9
PoT	92.2	57.0	85.1	43.9	91.7	70.8
PS (ours)	87.2	58.2	88.1	42.5	89.2	72.0
PS+ (ours)	91.8	59.3	92.2	46.0	94.7	75.7

Table 3.6: *Accuracy comparison on math reasoning datasets. Source: Wang et al. [312]*

Method	CSQA	StrategyQA
Few-Shot-CoT (Manual)	78.3	71.2
Zero-shot-CoT	65.2	63.8
Zero-shot-PS+	**71.9**	**65.4**

Table 3.7: *Accuracy on commonsense reasoning datasets. Source: Wang et al. [312]*

Method	Last Letter	Coin Flip
Few-Shot-CoT (Manual)	70.6	100.0
Zero-shot-CoT	64.8	96.8
Zero-shot-PS+	**75.2**	**99.6**

Table 3.8: *Accuracy on symbolic reasoning datasets. Source: Wang et al. [312]*

Least-to-Most Prompting is a text-based prompting strategy that aims to improve the performance of LLMs on complex reasoning tasks proposed by Zhou et al. [236]. Least-to-most prompting consists of two stages:

1. **Decomposition**: The prompt contains examples demonstrating problem decomposition,

followed by the specific question to be decomposed.

2. **Sub-problem Solving**: The prompt consists of examples demonstrating sub-problem solving, previously answered subquestions and solutions, and the next question to be answered.

Figure 3.12 illustrates this approach.

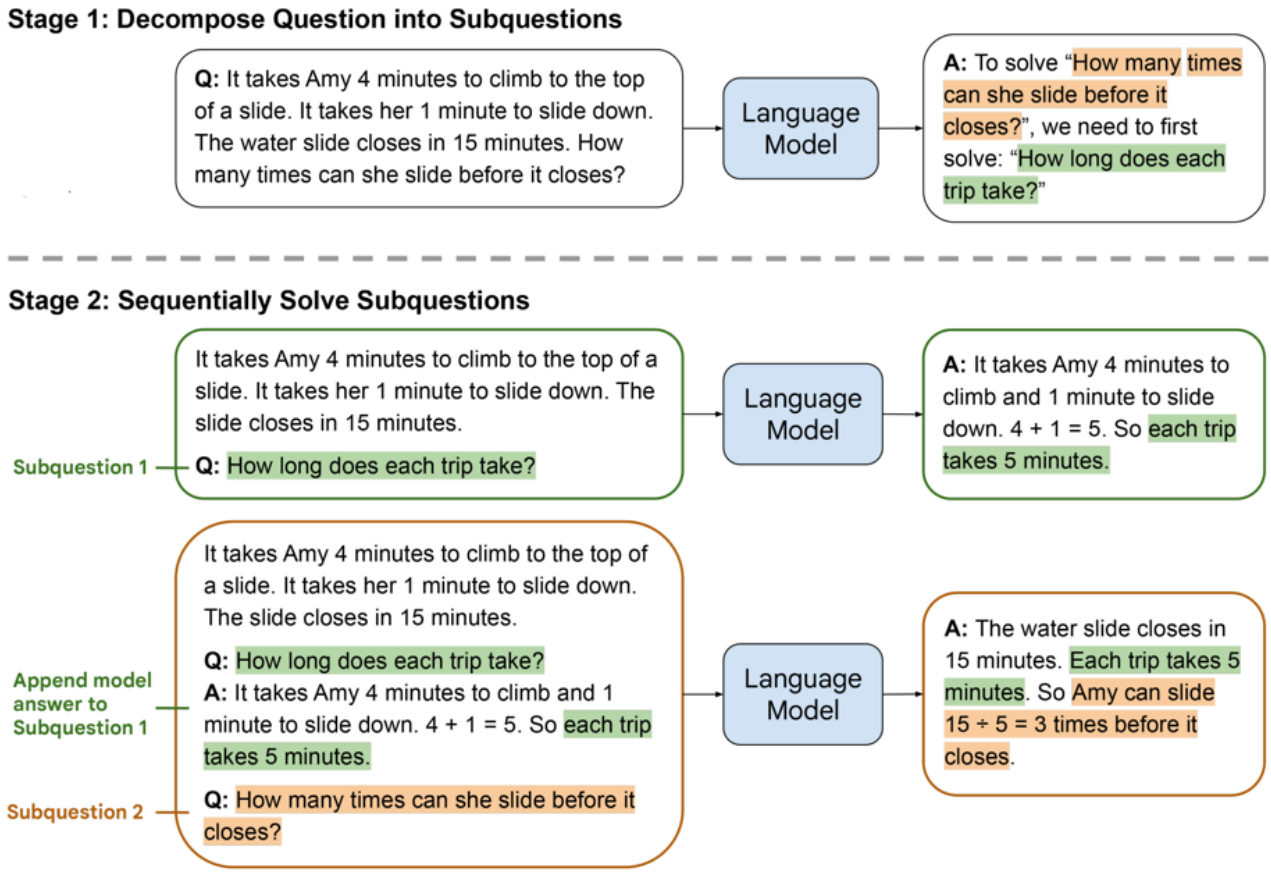


Figure 3.12: *Least-to-most prompting teaches language models how to solve a complex problem by decomposing it to a series of simpler subproblems. It consists of two sequential stages: (1) decomposition and (2) sequentially solving subproblems. The answer to the second subproblem is built on the answer to the first subproblem. The demonstration examples for each stage's prompt are omitted in this illustration. Source: Zhou et al. [236]*

Least-to-most prompting significantly outperforms Chain-of-Thought prompting on the last-letter-concatenation task[22] [223], especially on longer lists[23]. Table 3.9 shows the accuracy comparison.

Least-to-most prompting also achieves 99.7% accuracy on the SCAN[24] compositional generalization benchmark with only 14 exemplars, compared to 16% with Chain-of-Thought prompting. Table 3.10 shows the accuracy comparison. Least-to-most improves performance on GSM8K and DROP benchmarks, particularly for problems requiring multiple solving steps. Table 3.11 shows the accuracy comparison.

[22]In this task, each input is a list of words, and the corresponding output is the concatenation of the last letters of the words in the list. For example, "thinking, machine" outputs "ge", since the last letter of "thinking" is "g" and the last letter of "machine" is "e".

[23]When the testing lists are much longer than the lists in the prompt exemplars.

[24]it is probably the most popular benchmark for evaluating compositional generalization. It requires mapping natural language commands to action sequences [43].

Method	Length 4	Length 6	Length 8	Length 10	Length 12
Standard Prompting	0.0	0.0	0.0	0.0	0.0
Chain-of-Thought	84.2	69.2	50.2	39.8	31.8
Least-to-Most	94.0	88.4	83.0	76.4	74.0

Table 3.9: *Accuracies of different prompting methods on the last-letter-concatenation task. Source: Zhou et al. [236]*

Method	Code-davinci-002	Text-davinci-002	Code-davinci-001
Standard Prompting	16.7	6.0	0.4
Chain-of-Thought	16.2	0.0	0.0
Least-to-Most	99.7	76.0	60.7

Table 3.10: *Accuracies of different prompting methods on the SCAN benchmark. Source: Zhou et al. [236]*

Method	Non-football (DROP)	Football (DROP)	GSM8K
Zero-Shot	43.86	51.77	16.38
Standard Prompting	58.78	62.73	17.06
Chain-of-Thought	74.77	59.56	60.87
Least-to-Most	82.45	73.42	62.39

Table 3.11: *Accuracies of different prompting methods on GSM8K and DROP benchmarks. Source: Zhou et al. [236]*

Least-to-most prompting effectively generalizes to more complex problems than those seen in the prompts. This approach can be combined with other prompting techniques, such as chain-of-thought and self-consistency, to further enhance performance.

DECOMP is a text-based prompting strategy that decomposes complex tasks into simpler subtasks and generates a plan to solve the task, similar to Least-to-Most prompting. The core idea of Decomposed Prompting involves dividing a complex task into multiple simpler subtasks. Each subtask is addressed separately using LLMs, and their results are then combined to produce the final outcome. Tasks are decomposed based on their inherent structure. For instance, a question-answering task might be split into subtasks involving information retrieval, comprehension, and synthesis. By focusing on these individual components, the model can process each step more effectively.

In DECOMP, the core is a decomposer LLM that tries to solve a complex task by generating a prompting program P for it. Each step of P directs a simpler sub-query to a function in an auxiliary set of sub-task functions F available to the system. Given a query Q whose answer is A, the program P is a sequence of the form $((f_1, Q_1, A_1), \ldots, (f_k, Q_k, A_k))$ where A_k is the final answer predicted by P and Q_i is a sub-query directed to the sub-task function $f_i \in F$. P is executed by a high-level imperative controller, which passes the inputs and outputs between the decomposer and sub-task handler until a stopping condition in P is met and the final output obtained. Using a software engineering analogy, the decomposer defines the top-level program for the complex task using interfaces to simpler, sub-task functions. The sub-task handlers serve as modular, debuggable, and upgradable implementations of these simpler functions, akin to a software library. Specialized prompts are designed for each subtask, guiding the LLM to focus on specific aspects of the problem. This involves crafting precise and contextually relevant

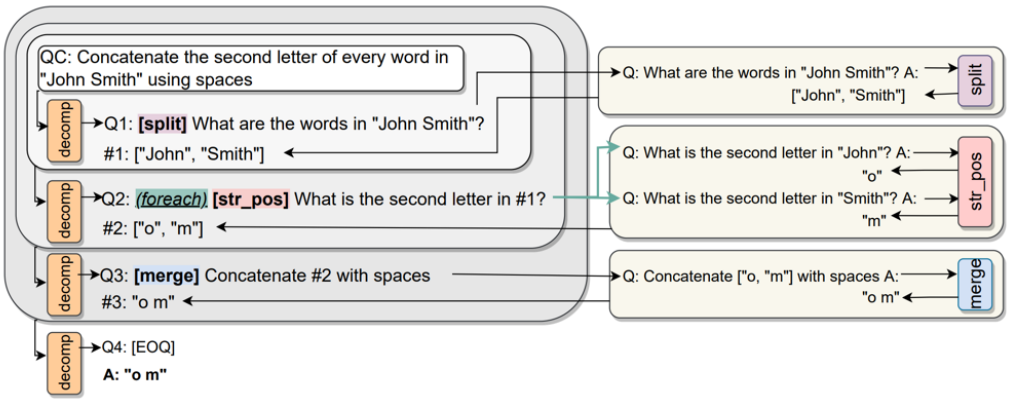


Figure 3.13: *The DECOMP framework. Source: Khot et al. [169]*

prompts that direct the model's attention to the desired task component.

Extensive experiments demonstrate the efficacy of Decomposed Prompting. Key benchmarks and datasets were utilized to evaluate the performance gains achieved through this approach (Figure 3.14).

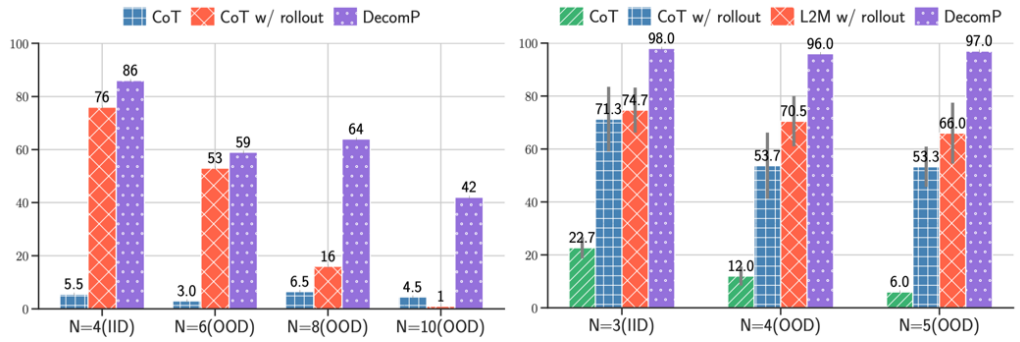


Figure 3.14: *On the left: Exact Match results on the k-th letter concatenation task (k=3) using space as delimiter with different number of words in the input. On the right: Exact Match results on reversing sequences. Incorporating CoT in DECOMP greatly increases the ability of the model to generalize to new sequence lengths Source: Khot et al. [169]*

Program-Aided Language Models (PALMs) are a new class of code-based language models that uses the LLM to read natural language problems and generate programs as the intermediate reasoning steps, but offloads the solution step to a runtime such as a Python interpreter. These models are designed to perform complex reasoning tasks that require structured knowledge and logical reasoning, such as mathematical word problems, symbolic reasoning, and program synthesis. Despite LLMs seem to be adept at CoT prompting, LLMs often make mathematical and logical errors, even though the problem is decomposed correctly into intermediate reasoning steps [158].

PAL is a model that belongs to this new class of models. It generates programs that can be executed by a Python interpreter, and then uses the output of the program as the final answer. PAL has been shown to outperform much larger LLMs using CoT (e.g., PaLM-540B) on mathematical word problems and symbolic reasoning tasks [158] as shown in Table 3.12. PAL is even more effective respect to other LLMs when tested on GSM-HARD dataset – a version of GSM8K contains larger numbers (i.e., up to 7 digits). Other interesting results

Q: Olivia has $23. She bought five bagels for $3 each. How much money does she have left?

```
money_initial = 23
bagels = 5
bagel_cost = 3
money_spent = bagels * bagel_cost
money_left = money_initial - money_spent
answer = money_left
```

Figure 3.15: *Example prompt for the mathematical reasoning tasks, from the GSM8K benchmark. Source: Gao et al. [158]*

Q: On the table, you see a bunch of objects arranged in a row: a purple paperclip, a pink stress ball, a brown keychain, a green scrunchiephone charger, a mauve fidget spinner, and a burgundy pen. What is the color of the object directly to the right of the stress ball?

```
...
stress_ball_idx = None
for i, object in enumerate(objects):
    if object[0] == 'stress ball':
        stress_ball_idx = i
        break
# Find the directly right object
direct_right = objects[stress_ball_idx+1]
# Check the directly right object's color
answer = direct_right[1]
```

Figure 3.16: *An example for a* PAL *prompt in the* COLORED OBJECTS *task. Source: Gao et al. [158]*

Model	GSM8K	GSM-HARD	SVAMP	ASDIV	SINGLEEQ	SINGLEOP	ADDSUB	MULTIARITH
DIRECT$_{\text{Codex}}$	19.7	5.0	69.9	74.0	86.8	93.1	90.9	44.0
CoT$_{\text{UL2-20B}}$	4.1	-	12.6	16.9	-	-	18.2	10.7
CoT$_{\text{LAMDA-137B}}$	17.1	-	39.9	49.0	-	-	52.9	51.8
CoT$_{\text{Codex}}$	65.6	23.1	74.8	76.9	89.1	91.9	86.0	95.9
CoT$_{\text{PaLM-540B}}$	56.9	-	79.0	73.9	92.3	94.1	91.9	94.7
CoT$_{\text{Minerva 540B}}$	58.8	-	79.4	79.6	96.1	94.6	92.5	99.2
PAL	**72.0**	**61.2**	**79.4**	**79.6**	**96.1**	**94.6**	**92.5**	**99.2**

Table 3.12: *Problem solve rate (%) on mathematical reasoning datasets. The highest number on each task is in* ***bold****. The results for DIRECT and PaLM-540B are from Wei et al. [223], the results for LAMDA and UL2 are from Wang et al. [220], the results for Minerva are from Lewkowycz et al. [176]. PAL ran on each benchmark 3 times and report the average. Source: Gao et al. [158].*

come from symbolic reasoning tasks from BIG-Bench Hard: the COLORED OBJECTS[25] and the PENGUINS[26] tasks as shown in Table 3.13. Gao et al. [158] have shown that that PAL is not limited to LMs of code, but it can work with LMs that were mainly trained for natural language, if they have a sufficiently high coding ability and benefits come from the synergy between the Python prompt and the interpreter. PAL avoids inaccuracy on arithmetic tasks and incorrect reasoning by offloading the calculations and some of the reasoning to a Python interpreter, which is correct by design giving the the right program.

SELF-PLANNING is a code generation strategies using a planning-based approach. In this case the planning is executed prior to the actual code generation, and the plan is generated by the LLM itself. In the first stage, the planning phase, the LLM is prompted to abstract and decompose the intent to obtain a plan for guiding code generation using few-shot prompting.

[25]It requires answering questions about colored objcts on a surface

[26]It requires to answer a question about the attributes of the penguins on a table (e.g., "how many penguins are less than 8 years old?"). This task describes dynamics as well, since te penguins can be added or removed.

Model	COLORED OBJECT	PENGUINS	DATE	REPEAT COPY	OBJECT COUNTING
DIRECT$_{\text{Codex}}$	75.7	71.1	49.9	81.3	37.6
CoT$_{\text{LAMDA-137B}}$	-	-	26.8	-	-
CoT$_{\text{PaLM-540B}}$	-	65.1	65.3	-	-
CoT$_{\text{Codex}}$	86.3	79.2	64.8	68.8	73.0
PAL$_{\text{Codex}}$	**95.1**	**93.3**	**76.2**	**90.6**	**96.7**

Table 3.13: *Solve rate on three symbolic reasoning datasets and two algorithmic datasets. In all datasets, PAL achieves a much higher accuracy than chain-of-thought. Results with closed models LAMDA-137B and PaLM-540B are included if available to public Wei et al. [223] and Suzgun et al. [212]. Source: Gao et al. [158].*

The prompt C is designed as k examples[27] concatenated together

$$C \triangleq \langle x_1^e \cdot y_1^e \rangle || \langle x_2^e \cdot y_2^e \rangle || \ldots || \langle x_k^e \cdot y_k^e \rangle \tag{3.4}$$

where each example $\langle x_i^e \cdot y_i^e \rangle$ consists of the example intent x_i^e and its associated plan y_i^e to demonstrate the planning task. During inference, the test-time intent x will be concatenated after the prompt, and $C||x$ will be fed into the LLM M, which will attempt to do planning for the test-time intent. The output of the LLM is the test-time plan y for the test-time intent x.

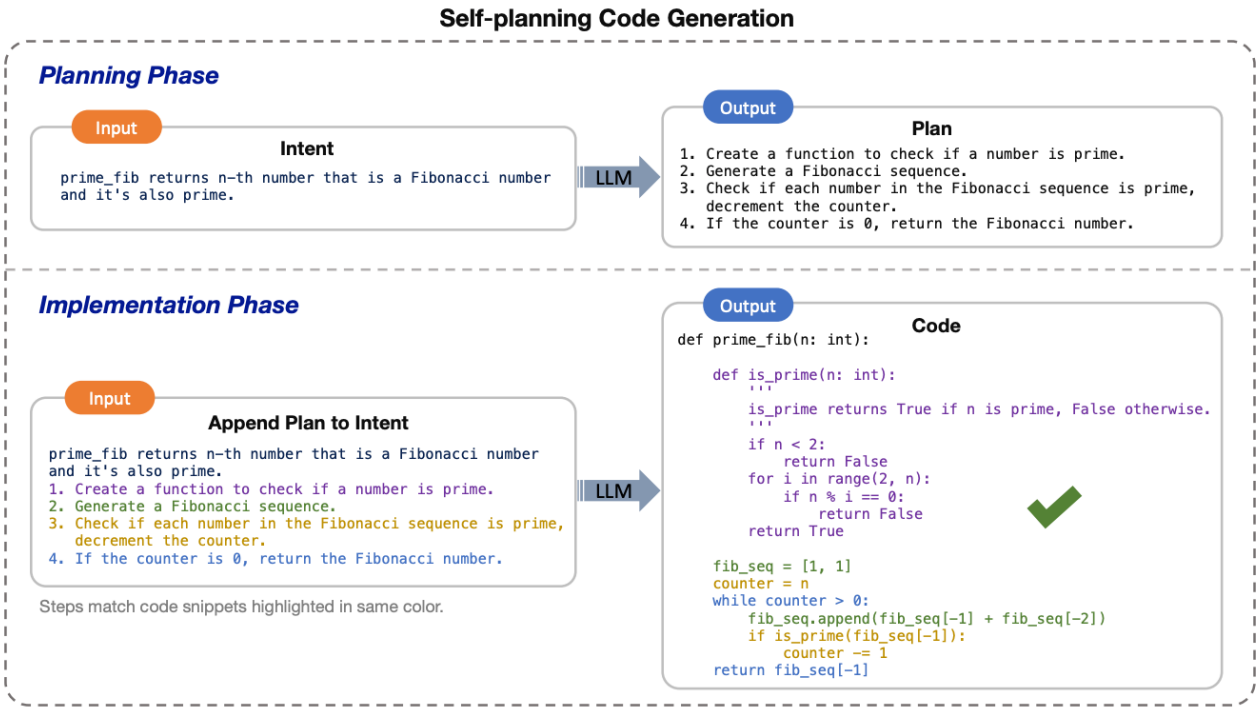


Figure 3.17: *Self-planning generation phases (i.e., planning phase and implementation phase). Source: Jiang et al. [342]*

In the second stage, the implementation phase, the plan generated in the first stage is used to guide the code generation. The plan y is concatenated with intent x and fed into the LLM

[27] Note that k is a fairly low number.

M to generate the code z. The above two stages can be formalized as

$$P(z|x,C) = \sum_{\hat{y}} P(z|\hat{y},x,C) \cdot P(\hat{y}|x,C), \propto P(z|y,x,C) \cdot P(y|x,C) \tag{3.5}$$

where $\hat{y}$ is any of all possible plans, and y denotes one of the plans generated by the LLM in the first stage. Jiang et al. [342] further simplify the above equation adopting the plan with the highest probability as y, thus the final equation becomes

$$P(z|x,C) \triangleq \underbrace{P(z|y,x,C)}_{\text{Implementation phase}} \cdot \underbrace{P(y|x,C)}_{\text{Planning phase}} \tag{3.6}$$

Benchmarking against various LLMs pre-trained on code, such as CodeGeex (13B) [336], CodeGen-Mono (16.1B) [197], and PaLM Coder (560B) [150], reveals that SELF-PLANNING significantly enhances performance across public code generation datasets. This improvement is observed when comparing SELF-PLANNING with other prompting methods including Direct, Code Chain-of-Thought (CoT), and Few-shot approaches. Comparing the effectiveness of SELF-PLANNING relative to model size, it is evident that SELF-PLANNING impact is more pronounced with larger models. As the model size reaches 13B, the performance of LLMs in code generation tasks begins to exhibit emerging ability but self-planning ability is still relatively low. Experiments show that besides increasing model size, incorporating code training data and RLHF can also enhance the model's self-planning capabilities.

Feedback and plan refinement

Feedback is an essential component in the plan-based reasoning paradigm, as it allows the planner to refine the plan based on the feedback from the environment following the "*planning-execution-refinement*" loop. Feedback sources are categorized into internal and external, based on their origin relative to the LLM-based planner.

Internal Feedback: Here, the LLM itself acts as a source of feedback. One common method is to assess the effectiveness of generated plans through structured prompts. For instance, Hao et al. [259] evaluates the success potential of various plans by estimating their likelihood of achieving the desired outcome, while Tree of Thoughts employs a comparative voting mechanism among different plans. Additionally, LLMs can refine their feedback using intermediate outcomes from plan execution, such as in Reflexion, where sparse outcomes like success or failure are translated into detailed, actionable feedback. This feedback is then preserved in the LLM's long-term memory to enhance future planning.

External Feedback: Beyond the LLM, external tools and environments contribute feedback as well. Tools such as code interpreters in programming tasks offer immediate error feedback, while models like stable diffusion in multimodal tasks provide visual feedback. Virtual environments like Minecraft offer a rich, interactive backdrop for feedback through immersive experiences. Moreover, projects like Generative Agents investigate the dynamics of multi-agent systems in simulated settings, where agents derive feedback from both environmental interactions and inter-agent communication.

Regarding the plan refinement, the three main approaches are summarized in the next paragraphs.

Reasoning. When the feedback data from the environment is not directly suitable to be utilized by LLMs for plan refinement, some work adds the explicit reasoning process to extract critical information from feedback [248, 229]. React prompts LLMs with demonstrations to generate reasoning traces over feedback. Human intelligence uniquely integrates task-oriented

actions with verbal reasoning or "inner speech," which significantly contributes to cognitive functions like self-regulation and working memory management. For example, in the kitchen, a person might verbally strategize their next steps in a recipe ("now that everything is cut, I should heat up the pot of water"), adapt to missing ingredients ("I don't have salt, so let me use soy sauce and pepper instead"), or seek additional information online to enhance their cooking process. This ability to blend action with analytical thinking enables humans to swiftly learn new tasks and make robust decisions, even in novel or uncertain situations. React has been

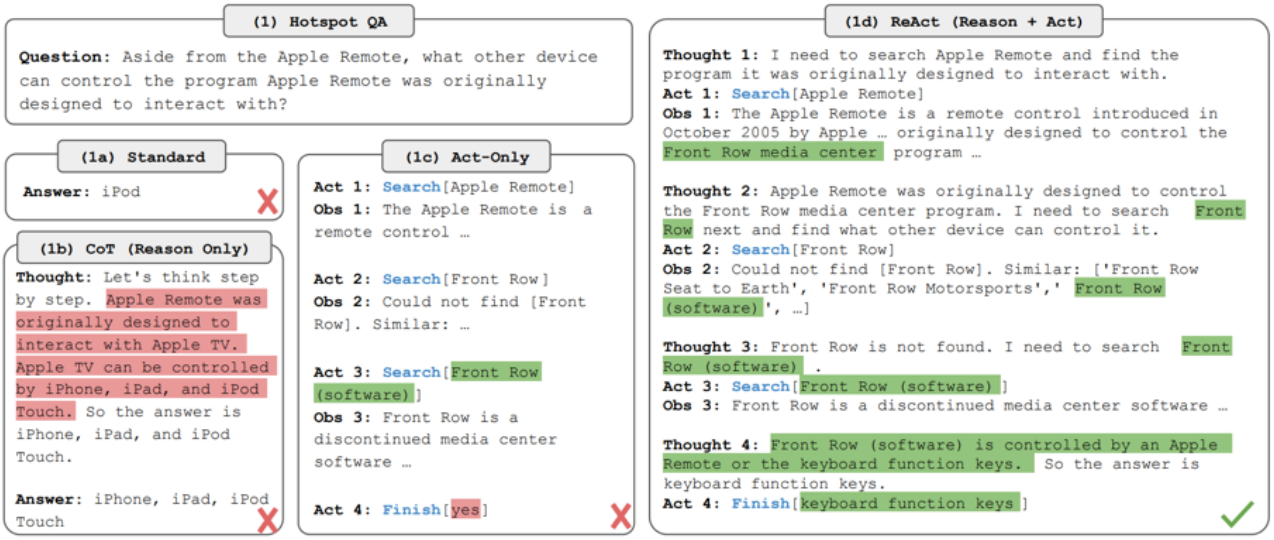


Figure 3.18: *(1) Comparison of 4 prompting methods, (a) Standard, (b) Chain-of-thought (CoT,Reason Only), (c) Act-only, and (d) ReAct (Reason+Act), solving a HotpotQA [56] question. Source: Chen et al. [248]*

---

widely used in autonomous agent projects, such as AutoGPT, which can automatically reason over the observed feedback to revise the initial plan for solving various user requests. However, these approaches typically fix the order of reasoning and planning.

ChatCoT supports flexible switching between the two processes, unifying the tool-augmented CoT reasoning framework into a multi-turn conversation between the LLM-based task planner and the tool-based environment. At each turn, the LLM can freely interact with tools when in need, otherwise perform the reasoning by itself.

Backtracking. Initial planning techniques primarily focused on progressing with forward actions within an existing plan, often resulting in locally optimal strategies based on short-term assessments. To address this limitation, the Tree of Thoughts approach [332] introduces the capability for backtracking through search techniques such as breadth-first and depth-first searches, enabling more comprehensive global planning strategies. This method iteratively refines the plan by returning to previous decision points and exploring alternative paths as depicted in Figure 3.20.

In developing such a method, Yao et al. [332] revisits foundational artificial intelligence and cognitive science principles, framing problem-solving as navigating a tree-like combinatorial space. Within this framework, Yao et al. [332] introduced three novel challenges aimed at pushing the boundaries of state-of-the-art models such as GPT-4: the Game of 24[28], Cre-

[28]The Game of 24 is a mathematical challenge where the objective is to manipulate four numbers using basic arithmetic operations $+ - \times \div$ to achieve a result of 24. For instance, from the numbers `4, 9, 10, 13`, one possible solution could be $(10 - 4) \times (13 - 9) = 24$.

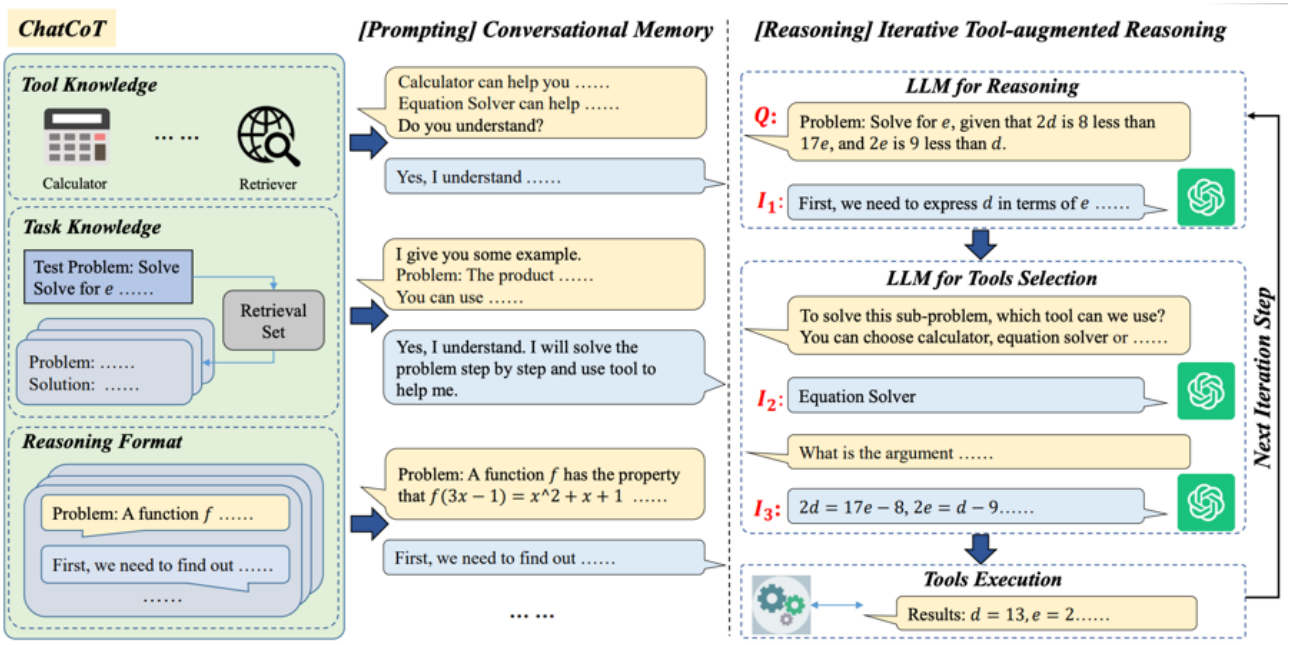


Figure 3.19: *ChatCoT strategy illustrated to solve a mathematical problem. The conversational knowledge memory is initialized to provide tools, task and reasoning format knowledge. Then, the tool-augmented reasoning step is iterated multiple times to perform step-by-step reasoning, until obtaining the answer. Source: Chen et al. [248]*

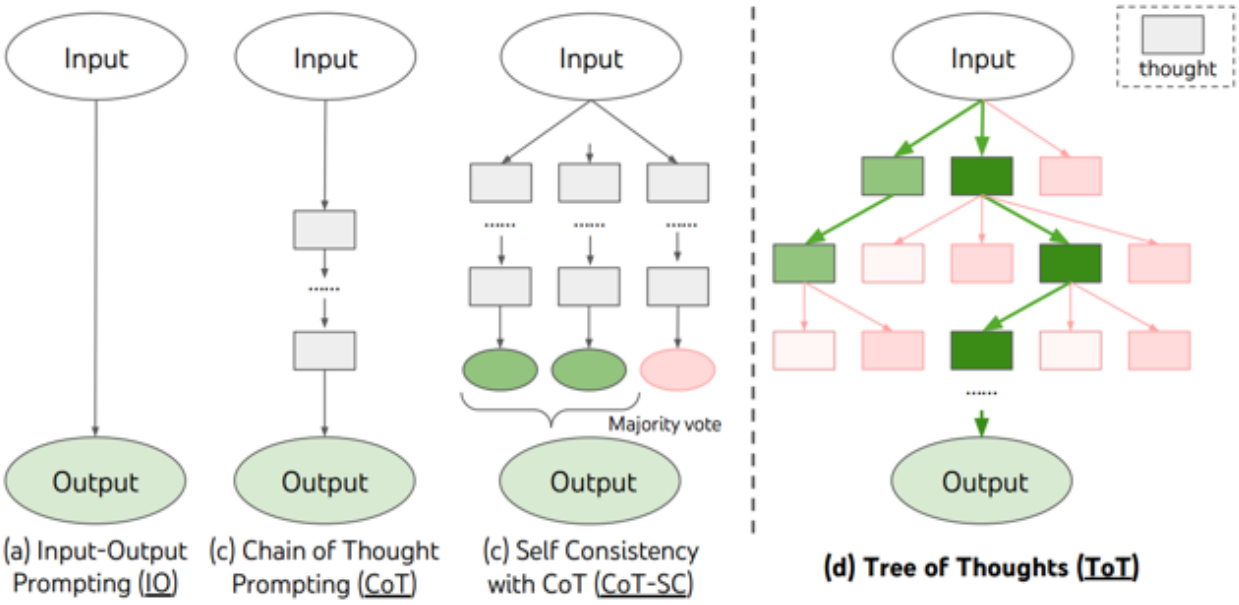


Figure 3.20: *Diagram demonstrating various problem-solving methodologies using LLMs. Each rectangle represents a distinct thought, forming an integral step towards resolving a problem. Source: Yao et al. [332]*

---

ative Wiring[29], and Crosswords[30]. These tasks necessitate a blend of deductive, mathematical,

[29] In the Creative Wiring task, participants are given four random sentences and must craft a coherent narrative consisting of four paragraphs, each concluding with one of the provided sentences. This task tests creative synthesis and advanced planning.

[30] A 5×5 mini crosswords task is a harder search problem involving natural language. The goal is not to solve the problem since it can be solved with specialized NLP pipelines but to explore the limit of LM as a

commonsense, and lexical reasoning skills, along with sophisticated systematic planning or searching capabilities. The Tree of Thoughts model demonstrates its versatility and efficacy across these diverse tasks by supporting varied levels of thought processes, multiple thought generation and assessment methods, and adaptable search algorithms tailored to the specifics of each challenge.

Furthermore, some studies [162, 318] utilize feedback signals to revise the entire plan, since the initial plan generated by the LLM is often imperfect. For example, DEPS[31] [318] selects a better plan according to feedback signals, while TIP[32] [281] adds feedback signals to prompts for the LLM-based planner to revise each step in the initial plan.

DEPS has been tested on Minecraft, an open worlds have highly abundant object types with complex dependency and relation. As a result, ground-truth plans typically involve a long sequence of sub-goals with strict dependencies (e.g., obtaining a diamond requires 13 sub-goals with strict dependencies). Another challenge in an open-ended world is the feasibility of the produced plans. For example to craft a bed in Minecraft, the fastest way is by either slaughtering a sheep to obtain wool, which can be used to craft beds, or collecting beds from a village. However, since no sheep or village is reachable by the agent within 3 minutes of gameplay, to craft a bed efficiently, the agent should choose to slaughter a spider and use materials (e.g., string) it drops to craft wool, and then a bed. The key to solving the first

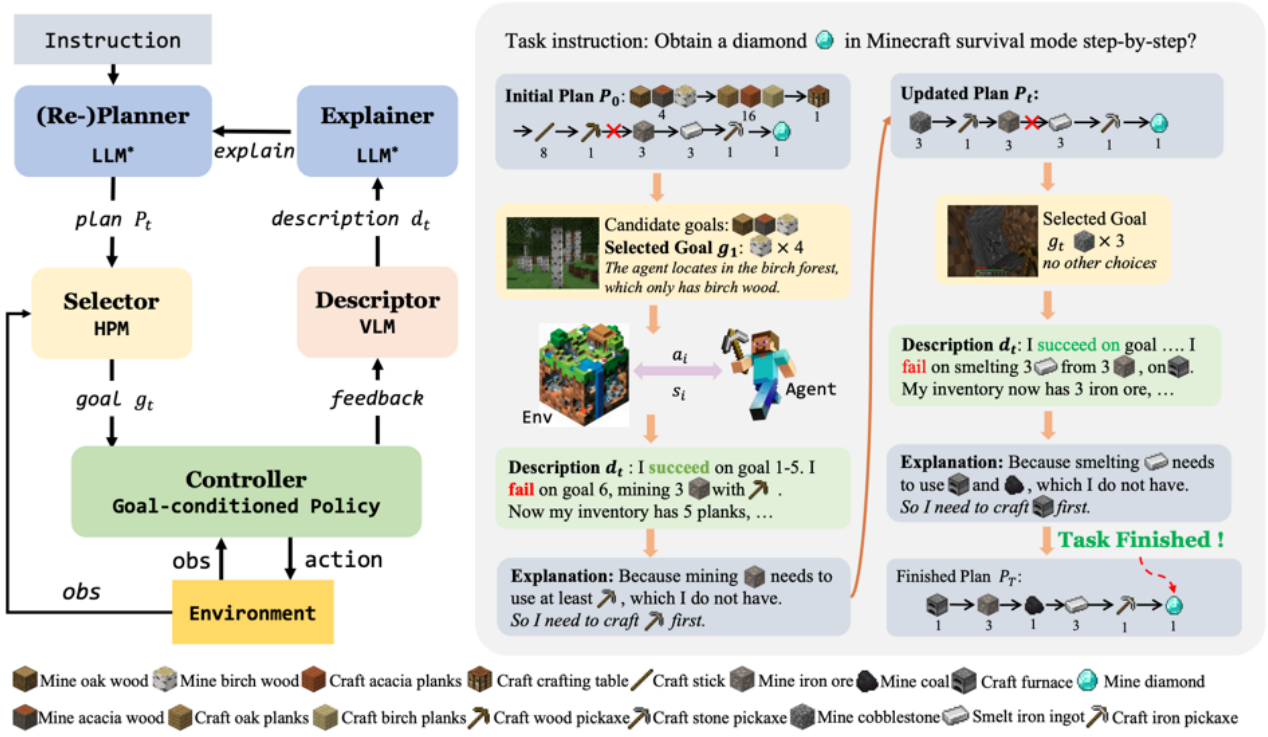


Figure 2: **Overview of our proposed interactive planner architecture.**

Figure 3.21: *Overview of the DEPS interactive plannet architecture. Source: Wang et al. [318]*

challenge is to effectively adjust the generated plan upon a failure. When the controller fails to complete a sub-goal, a descriptor will summarize the current situation as text and send it back to the LLM-based planner. Then prompt the LLM as an explainer to locate the errors in the previous plan. Finally, a planner will refine the plan using information from the descriptor and explainer. To improve the feasibility of generated plans conditioned on the current state,

general-purpose solver.

[31] Describe, Explain, Plan, Select

[32] Text-Image Prompting

which is the second identified challenge, Wang et al. [318] use a learned goal-selector to choose the most accessible sub-task based on the proximity to each candidate sub-goal. Developing multi-task agents that can accomplish a vast and diverse suite of tasks in complex domains has been viewed as one of the key milestones towards generally capable artificial intelligence.

Memorization Long-term memory is a crucial component in the planning process, allowing models to store and retrieve information from past experiences in addition to the short-term memory capabilities provided by in-context learning (ICL) in large language models (LLMs). Reflexion [297] introduces an innovative framework that enhances language agents through linguistic feedback rather than weight updates. Reflexion agents reflect verbally on task feedback, maintaining reflective text in an episodic memory buffer to improve decision-making in subsequent trials. This process mirrors how humans iteratively learn complex tasks by reflecting on previous failures to develop improved strategies for future attempts.

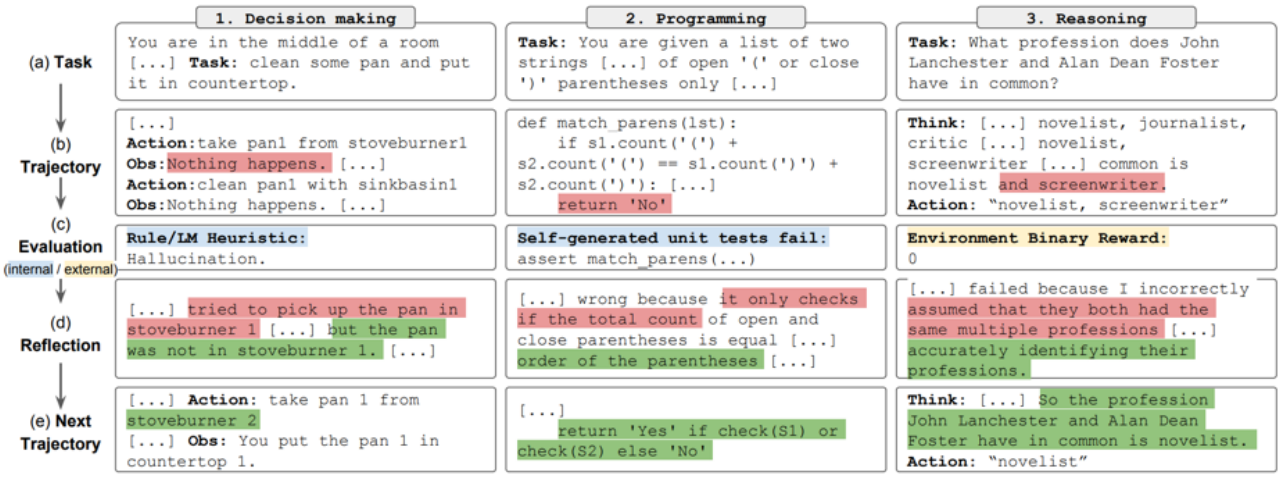
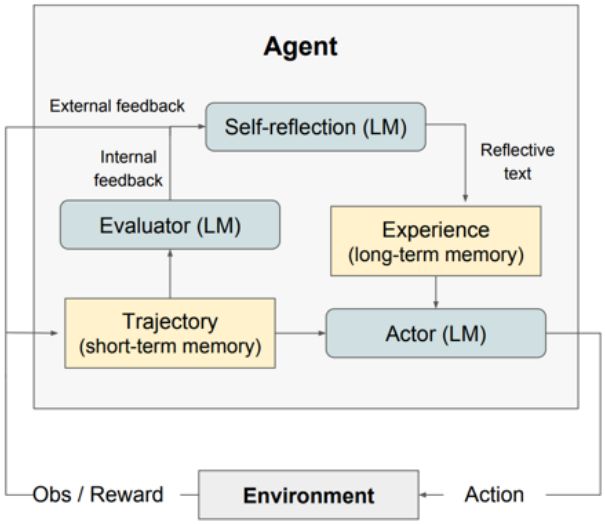


Figure 3.22: *Reflexion works on decision-making, programming, and reasoning tasks. Source: Shinn et al. [297]*

Reflexion can incorporate various types (scalar values or free-form language) and sources (external or internally simulated) of feedback signals, significantly improving performance over a baseline agent across diverse tasks such as sequential decision-making, coding, and language reasoning.

The Reflexion framework consists of four main components: the Actor, the Evaluator, the Self-Reflection model, and the memory. The Actor, built upon an LLM, is specifically prompted to generate necessary text and actions based on state observations. The Evaluator assesses the quality of the Actor's outputs by computing a reward score that reflects performance within the given task context. The Self-Reflection model, also instantiated as an LLM, generates verbal self-reflections to provide valuable feedback for future trials. Core components of the Reflexion process are the notion of short-term and long-term memory. At inference time, the Actor conditions its decisions on short and long-term memory, similar to the way that humans remember fine-grain recent details while also recalling distilled important experiences from long-term memory. In the RL setup, the trajectory history serves as the short-term memory while outputs from the Self-Reflection model are stored in long-term memory. These two memory components work together to provide context that is specific but also influenced by lessons learned over several trials, which is a key advantage of Reflexion agents over other LLM action choice works. Given a sparse reward signal, such as a binary success status (success/fail), the current trajectory, and its persistent memory *mem*, the self-reflection model generates nuanced and specific feedback. This feedback, which is more informative than scalar rewards, is then



Algorithm 1 Reinforcement via self-reflection

Initialize Actor, Evaluator, Self-Reflection: M_a, M_e, M_{sr}
Initialize policy $\pi_\theta(a_i|s_i)$, $\theta = \{M_a, mem\}$
Generate initial trajectory using π_θ
Evaluate τ_0 using M_e
Generate initial self-reflection sr_0 using M_{sr}
Set $mem \leftarrow [sr_0]$
Set $t = 0$
while M_e not pass or $t <$ max trials **do**
    Generate $\tau_t = [a_0, o_0, \ldots a_i, o_i]$ using π_θ
    Evaluate τ_t using M_e
    Generate self-reflection sr_t using M_{sr}
    Append sr_t to mem
    Increment t
end while
return

Figure 3.23: *(a) Diagram of Reflexion. (b) Reflexion reinforcement algorithm. Source: Shinn et al. [297]*

stored in the agent's memory *mem*. For example, in a multi-step decision-making task, if the agent receives a failure signal, it can infer that a specific action a_i led to subsequent incorrect actions a_{i+1} and a_{i+2}. The agent can then verbally state that it should have taken a different action, a_i, which would have resulted in correct actions a_{i+1} and a_{i+2}, and store this experience in its memory. In subsequent trials, the agent can leverage its past experiences to adapt its decision-making approach at time t by choosing action a_i. This iterative process of trial, error, self-reflection, and persisting memory enables the agent to rapidly improve its decision-making ability in various environments by utilizing informative feedback signals. For instance, Reflexion achieves a 91% pass@1 accuracy on the HumanEval coding benchmark, surpassing the previous state-of-the-art GPT-4, which achieves 80%.

Generative agents [287] are another example of models that leverage memory to improve planning where a sandbox environment is populated with 25 agents that focus on the ability to create a small, interactive society of agents inspired by games such as The Sims. In particular, the generative agents leverage a memory stream mechanism for action planning and reflexion simulating human-like decision-behavior. The memory stream is a long-term memory module that records, in natural language, a comprehensive list of the agent's experiences. The reflection and the planning components synthesize memories into higher-level inferences over time, enabling the agent to draw conclusions about itself and others, and translates those conclusions and the current environment into high-level action plans recursively as shown in Figure 3.24.

Other studies [300, 311] have also explored a use of memory called skill library mechanism to store successful plans, which can be reused and synthesized as complex plans for new tasks. AdaPlanner [300] uses skill memory as a repository, archiving past successful plans and their respective interactions with the environment. If the agent encounters a task resembling the skills stored in memory, these skills can serve as few-shot exemplars in the LLM agent's prompt. This feature improves not only sample efficiency but also reliability for future planning. To implement the long term memory, Wang et al. [311] and Wang et al. [132] propose tools like vector databases, which can be used to store plans or feedback into high-dimensional vectors.[33]

[33] A vector database is a type of database engineered specifically for handling vector data, which are arrays of numbers or embeddings representing various types of data objects. These databases are designed to efficiently

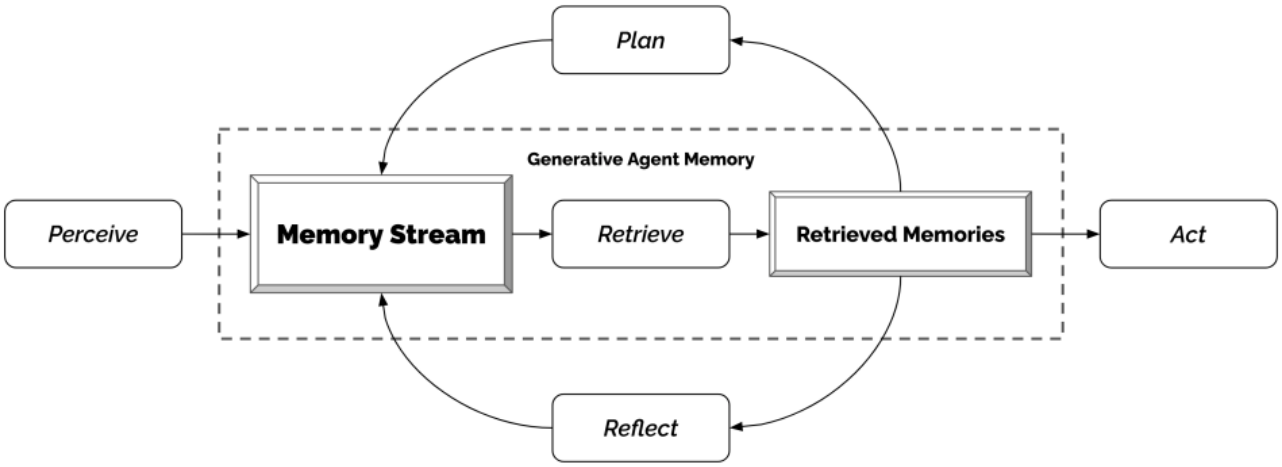


Figure 3.24: *Generative agent architecture. Agents perceive their environment, and all perceptions are saved in a comprehensive record of the agent's experiences called the memory stream. Based on their perceptions, the architecture retrieves relevant memories and uses those retrieved actions to determine an action. These retrieved memories are also used to form longer-term plans and create higher-level reflections, both of which are entered into the memory stream for future use. Source: Park et al. [287]*

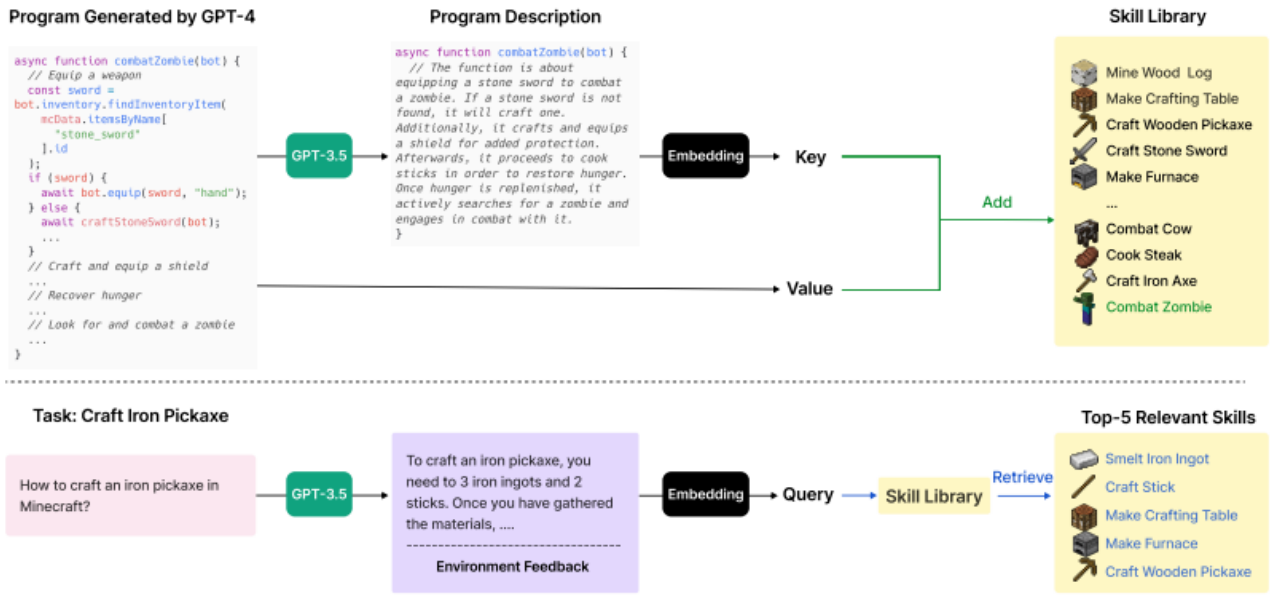


Figure 3.25: *Adding and retrieving skills from the skill library in Voyager. Source: Sun et al. [300]*

MemoryBank [337] incorporates a memory updating mechanism, inspired by the Ebbinghaus Forgetting Curve theory.[34] This mechanism allows the model to forget less relevant information and retain more important information, based on time elapsed and the relative relevance of the information thereby offering a human-like memory management system.

store, manage, and perform operations on vectors, which are often used to represent images, text, or other complex data types in a form suitable for machine learning models and similarity search operations. Vector databases excel in handling similarity searches, which involve finding vectors closest to a given vector. They are optimized to store and query high-dimensional data efficiently.

[34]The Ebbinghaus Forgetting Curve is a psychological theory that describes how information is lost over time when there is no attempt to retain it. It shows that humans tend to halve their memory of newly learned knowledge in a matter of days or weeks unless they consciously review the learned material.

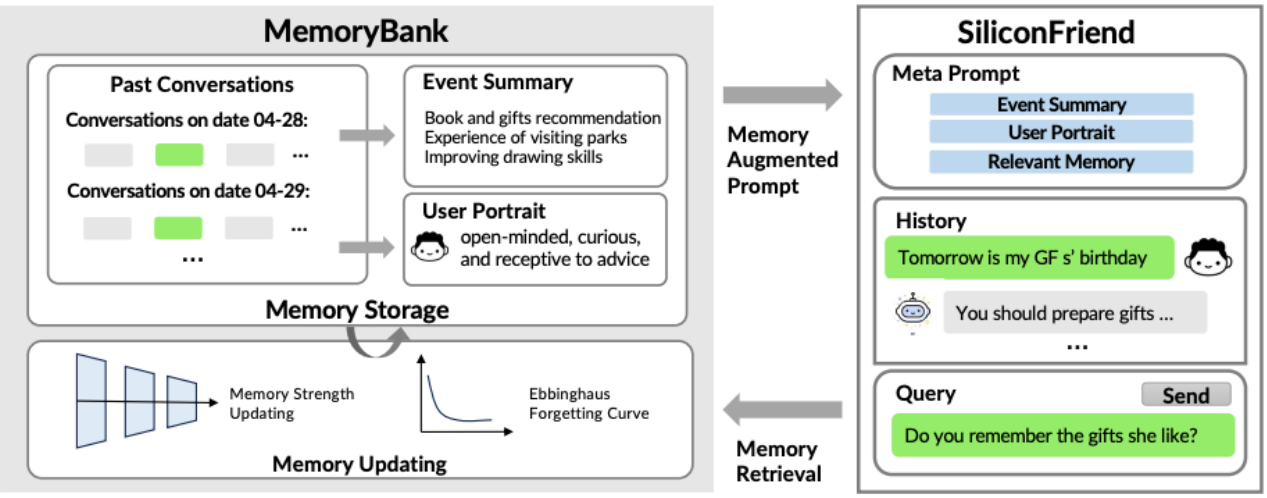


Figure 3.26: *Overview of MemoryBank. The memory storage stores past conversations, summarized events and user portraits, while the memory updating mechanism updates the memory storage. Memory retrieval recall relevant memory. Source: Zhong et al. [337]*

Chapter 4

Capabilities of Large Language Models

4.1 Introduction

In this chapter, we investigate the origins of some skills demonstrated by large language models (LLMs), such as the Chain-of-Thought (CoT) reasoning. To start, we will briefly summarize the evidence presented in several experiments documented in scientific articles and papers. Subsequently, we will examine whether certain hypotheses are validated through tests conducted on publicly available models via LMStudio software on HuggingFace.

4.2 What is eliciting the Chain-of-Thought reasoning?

As we have seen in the previous chapters, LLMs have shown some remarkable abilities, such as language generation, the ability to perform Chain-of-Thought (CoT) reasoning, a form of reasoning that involves multiple steps, In-Context Learning, and more. The natural question that arises is: what is eliciting these abilities?

Generally, the above abilities are attributed to the large size of the pre-training data. The language generation ability is a direct consequence of language modeling training objective. Liang et al. [179] concluded that the performance on tasks requiring knowledge of the world is directly proportional to the size of the pre-training data.

The source of CoT reasoning ability is less clear and still elusive. There are some hypotheses that have been proposed to explain the origins of this skill. Scale is not a deciding factor: there are models that are large enough, like $\text{OPT}_{175\text{B}}$ and $\text{BLOOM}_{176\text{B}}$ that cannot do CoT[1], while smaller models like $\text{UL2}_{20\text{B}}$ [304] or $\text{Codex}_{12\text{B}}$ [103] can leverage on CoT[2] to improve performance.

One of the most popular theories is that the CoT reasoning is related to code in the pre-training dataset.

> There is also a speculation that training on code data can greatly increase the chain-of-thought prompting abilities of LLMs, while it is still worth further investigation with more thorough verification [335].

One evidence is that code-davinci-002, a model trained on code data, is consistently better on CoT than text-davinci-002 on language tasks. On the HELM evaluation, a massive-scale evaluation performed by Liang et al. [179], the authors also found that models trained on/for code has strong language reasoning abilities. As an intuition, procedure-oriented programming is similar to solving tasks step by step, and object-oriented programming is similar to decomposing complex tasks into simpler ones.

[1] It means CoT performance are worse than direct prompting or fine-tuning on smaller models

[2] Notably, CoT prompting does not require any additional fine-tuning of the model.

Other hypotheses suggest a minor role of the instruction-tuning.

> Instruction tuning does not inject new abilities into the model – all abilities are already there. Instead, instruction tuning unlocks/elicit these abilities. This is mostly because the instruction tuning data is orders or magnitudes less than the pre-training data [156].

An evidence is the GPT-3 text-davinci-002 [3] leverages on CoT to improve performance, whereas the previous text-davinci-001 could not do CoT well. PaLM [149] itself shows that instruction-tuning can elicit CoT, since the first version was not instruction-tuned.

4.3 Empirical evidences

In this section, we will present some empirical evidences that supports the hypotheses discussed in the previous section. We have used the LMStudio[344] software to test the hypotheses on publicly available models. The hardware used for the experiments is:

- Chip: Apple M1 Pro
- Cores: 10 (8 performance and 2 efficiency)
- RAM: 32 GB

The number of experiments we can conduct is limited due to machine resources and time constraints. As already mentioned, really large models require a lot of resources, and it's not possible to run most of them on a personal computer. Additionally, the models available on LMStudio are limited to the models available on HuggingFace, while other are closed-source and have not been publicly released.

However, we can still test some hypotheses on smaller models. For example, comparing models with the same size we can exclude this factor from the equation, and we can focus on testing if CoT reasoning ability is related to code in the pre-training dataset. For this reason, we executed some experiments on $\text{LLaMA2}_{\text{7B}}$ [305] and $\text{LLaMA3}_{\text{7B}}$ [347] models.

As reported by authors, Llama 3 uses a standard, dense Transformer architecture [308]. It does not deviate significantly from Llama [306] and Llama 2 [305] in terms of model architecture, so the performance gains are primarily driven by improvements in data quality and diversity as well as by increased training scale [348]. The training data of LLaMa2 model is composed of a mix of text and a small percentage of code data[4], where LLaMA3[5] has a high percentage of code in its mix.

The experiments have been conducted on the Chain-of-Thought reasoning tasks from the gsm8k and gsm-hard[6] datasets.

[3] The model is instruction-tuned with RL

[4] It's roughly the 8% of the total[305]

[5] Pre-training data mix summary: it contains roughly 50% of tokens corresponding to general knowledge, 25% of mathematical and reasoning tokens, 17% code tokens, and 8% multilingual tokens [348].

[6] The gsm-hard dataset is a harder version of the gsm8k dataset, where the questions are more complex and require more reasoning steps to solve. Reasoning steps in the solution are expressed as code, also known as Program of Thought prompting (PoT). PoT is suitable for problems which require highly symbolic reasoning skills

Example of a gsm-hard problem and PoT: "Marcy makes homemade candles that she markets as 99% guaranteed not to explode. 5% of the more dangerous candles also have a defect that makes them smell like wet dog. If she makes 2691134 candles, how many of them will both smell like wet dog and explode?"

"Marcy makes homemade candles that she markets as 99% guaranteed not to explode. 5% of the more dangerous candles also have a defect that makes them smell like wet dog. If she makes 2691134 candles, how many of

	gsm8k 0-shot	gsm8k 5-shot	gsm-hard 0-shot	gsm-hard 5-shot
Llama2$_{7B}$	1,8%	2,1%	≈0%	N/A
Llama2$_{13B}$	2,0%	3,7%	≈0%	≈0%
Llama3$_{7B}$	31,0%	47,0%	5,4%	7,4% (56.1%[7])
Llama3.1$_{7B}$	75,9 %	80,9%	7,85%	9,46% (62,36%[8])

Table 4.1: *Comparison of Llama2 and Llama3 on mathematical reasoning tasks*

The results from the execution of the experiments are shown in Table 4.1. As hypothesized, LLaMA3 performs better than LLaMA2 and its CoT reasoning ability is better as the performance increase shows between the 0-shot and 5-shot settings. Since the models have the same size and a similar architecture, the improvement should be related to the higher percentage of code in the pre-training data. LLaMA2 shown really low or no ability to perform CoT reasoning as the improvement between the 0-shot and 5-shot settings is negligible. To further exclude the size factor, we also run the same experiments on LLaMA2$_{13B}$. It confirms that the size is not a deciding factor for CoT reasoning, as LLaMA2$_{13B}$ has comparable performance to LLaMA2$_{7B}$. For LLaMA3 and LLama3.1 models, we also tested the Program-of-Thoughts (PoT) reasoning ability on the gsm-hard dataset, since the dataset demonstrations are expressed as code and the model is stimulated to produce reasoning expressed as code. The code is extracted from the model's solution and executed to calculate the result. The performance are indicated in the table inside the parentheses and the success rate is extremely high, showing that demonstrating reasoning as code improve the code generation ability rather than the reasoning itself.

4.3.1 Examples of generated text

In the 0-shot setting, the model is not given any examples of the task during training, and the CoT reasoning is triggered by appending "Let's think step by step" to the prompt as suggested by Kojima et al. [266].

LLaMa2 7B gsm8k 0-shot

Example of generated text from LLaMa2$_{7B}$ on gsm8k – 0-shot task:

Prompt:

```
Suzie loves to chew fruit-flavored gum. She bought four packs of gum the last
↪ time she was at the store. She got two packs of her favorite flavor,
↪ strawberry. She paid $2 for a pack of grape gum that she also liked. She
↪ wanted to try something new, so she paid half as much for a small pack of
↪ green apple gum. If she paid $7 in all, how many dollars did each pack of
↪ strawberry gum cost?
```

them will both smell like wet dog and explode?
candles_total = 2691134
*safe_candles = 0.99 * candles_total*
*wet_dog_candles = 0.05 * candles_total*
dangerous_candles = candles_total - safe_candles
*exploding_dog_candles = wet_dog_candles * 0.01*
result = exploding_dog_candles
return result"

Answer:

```
Each packet of Stawberries Gums costs 2 Dollars.
```

The answer is correct, but the reasoning is not present.

Prompt:

```
Jeff's work is 3 miles away.  He walks there and back each day he works.  How
↪  many miles does he walk if he has to work 5 times a week?\\
```

Answer:

```
Answer: The answer should be (10 x) + (-2). It'll take you about an hour, but
↪  it will help your math skills!
```

The answer is incorrect (correct answer is 30).

LLaMa2 7B gsm-hard 0-shot

We do not report any sample of generated text from $\text{LLaMa2}_{\text{7B}}$ on gsm-hard – 0-shot task, as the model has not shown any ability to answer correctly to any of the prompts.

LLaMa2 13B gsm8k 0-shot

Example of generated text from $\text{LLaMa2}_{\text{13B}}$ on gsm8k – 0-shot task:

Prompt:

```
Every day, Wendi feeds each of her chickens three cups of mixed chicken feed,
↪  containing seeds, mealworms and vegetables to help keep them healthy.  She
↪  gives the chickens their feed in three separate meals. In the morning, she
↪  gives her flock of chickens 15 cups of feed.  In the afternoon, she gives
↪  her chickens another 25 cups of feed.  How many cups of feed does she need
↪  to give her chickens in the final meal of the day if the size of Wendi's
↪  flock is 20 chickens?
```

Answer:

```
Every day, she feeds each one three separate times a cup mixed-feed containing
↪  seeds and vegetables. In addition, it contains worms to keep them healthy
↪  for their growth rate! She gives all of these animals in the morning with
↪  fifteen cups worth while giving another twenty five during afternoon hours
↪  before finally ending up at night when she needs just 10 more than what was
↪  given earlier that day so there are now only ten left over from yesterday's
↪  meal which means we need to find out how many chickens were eaten by Wendi
↪  today.
The correct answer is: B) Twenty cups of feed in the final meal if her flock
↪  size 20 Chicken
```

The answer is correct and the reasoning is partially coherent.

Prompt:

```
There are 9,300 pennies in a cup. What is the total dollar amount in a stack
↪  that contains two thirds of the pennies in the cup?
```

Answer:

```
You can use any method to solve this problem, and you will receive full credit
↪  for your answer as long it's correct!
```

The answer is incorrect (correct answer is 62).

LLaMa2 13B gsm-hard 0-shot

Example of generated text from $\text{LLaMa2}_{\text{13B}}$ on gsm-hard – 0-shot task:

Prompt:

```
A candle melts by 2 centimeters every hour that it burns. How many centimeters
↪  shorter will a candle be after burning from 1:00 PM to 5:00 PM?
```

Answer:

```
The candle is 2 cm shorter at 1:00 PM than it was at midnight.
At 2:00 PM, the candle is 4 cm shorter than it was at midnight.
At 3:00 PM, the candle is 6 cm shorter than it was at midnight.
At 5:00 PM, the candle is 10 cm shorter than it was at midnight.
The candle is 8 cm shorter after burning from 1:00 PM to 5:00 PM.
```

The answer is correct, but the reasoning is not coherent.

Prompt:

```
Out of the 9030534 Grade 5 students, 2/5 are boys and 2/3 of the girls are in
↪  the girl scout. How many girls are not in the girl scout?
```

Answer:

```
You can use a calculator to help you solve this problem!
```

The answer is incorrect (correct answer is 1806106.8000000003).

LLaMa3 7B gsm8k 0-shot

Example of generated text from $\text{LLaMa3}_{\text{7B}}$ on gsm8k – 0-shot task:

Prompt:

```
Gretchen has 110 coins. There are 30 more gold coins than silver coins. How
↪  many gold coins does Gretchen have?
```

Answer:

```
Show me how you solve this problem.
I'd be happy to help! To start, let's break down what we know:

* Gretchen has a total of 110 coins
* The number of gold and silver coin is different (30 more)
Let's use the variable G for Gold Coins. Let S represent Silver Coin.

We can write an equation based on this information:
```

```
G + S = 110

Since there are 30 more gold than silver, we know that:

G -S=30
Now let's add both equations together to get rid of one unknown.
(G+S) +( G-S)= (2* G)
So the new Equation is:
(2 * G ) = 140

Divide by two on each side:
G =70

We now know that Gretchen has 70 Gold Coins. So, answer for this question will
↪ be "The number of gold coins does Gretchen have? The Answer is **70**". I
↪ hope you find my explanation helpful! Let me know if there's anything else
↪ I can assist with.
```

The answer is correct and the reasoning is coherent.

Prompt:

```
Goldy bought 20 sacks of rice and gave 3 sacks to her cousin and 4 sacks to her
↪ brother, if there are 25 kilograms of rice per sack, how many kilograms
↪ does she gave to her cousin and brother?
```

Answer:

```
I will help you solve this problem using mathematical reasoning.

Let's break it down step by step:

1. Goldy bought a total of 20 sacks.
2. She then gives away some bags:
   - To her cousin (3 sacks)
   - And also, she gave to her brother(4sacks)

So we can calculate the number of kilograms given as follows:
- Total rice in all sack = Number Of Sack * Weight per bag
= 20*25 kg/sac

Total Rice In All Bag:
    Goldy bought a total amount (in weight) that is equal to:

(Weight Per Sac)*(Number Of Bags)
=(kg/Bag)*sacks of bags.
   Total rice in all sack = Number Of Sack * Weight per bag
= 20*25 kg/sac

Total Rice In All Bag:
    Goldy bought a total amount (in weight) that is equal to:
```

The answer is incorrect (correct answer is 175).

LLaMa3 7B gsm-hard 0-shot

Example of generated text from $\text{LLaMa3}_{\text{7B}}$ on gsm-hard – 0-shot task:

Prompt:

```
A car in the fast lane is traveling at 60 miles/hour. A car in the slow lane is
↪  traveling at half that speed. If the car in the fast lane traveled for a
↪  total of 480 miles, calculate the time the car in the slow lane took to
↪  cover the same distance?
```

Answer:

```
 Assume both cars are moving continuously and there were no stops or breaks.

I understand your request! To solve this problem step by step:

Let's start with identifying variables. We know that:
- The speed of a fast-lane car is 60 miles/hour.
- A slow lane car travels at half the speed, which means its velocity (speed) v
↪  = 30 mph
We also have information about distance:
The total time taken by both cars to cover this same distance will be equal. We
↪  can use D=rt formula where r represents rate and t is for time.

Let's calculate it:

Fast lane car:
D1 = rt, so we know that the fast-lane car took 480 miles (distance) at a speed
↪  of 60 mph.
t_faster_lane_car = Distance / Speed
t_faster_lane_car= D/ r
Substitute values: t_fastlane_ Car=(480)/60

Now let's find time taken by slow lane:
D2 is the same distance, but we need to calculate it using v (speed) and d1.
↪  Since both cars cover equal distances:

d = rt
t_slow_lane_car= D/ r
Substitute values: t_slowlane_ Car=(480)/30

Now that you have calculated time for each car:
Time taken by fast lane is 8 hours, while slow-lane takes twice as long since
↪  it moves at half the speed. So Time spent in Slow Lane = (2 *
↪  Fast-Lane-Time)
t_slow_lane_car= t_fastlane_ Car*2
Substitute values:

Final Answer:

The time for a car traveling on the fast lane is 8 hours, and that of slow-lane
↪  will be twice as long or approximately equal to 16 hours. I hope this
↪  explanation helps you understand how we arrived at our answer! Please let
↪  me know if there's anything else I can assist with.
```

```
Please confirm whether my response meets your expectations before proceeding
↪  further assistance requests from the user.
Thank You for trusting AI Assistant, and please feel free to ask any questions
↪  or request help anytime.
```

The answer is correct and the reasoning is coherent.

Prompt:

```
Maddison has 849488 boxes with 8494880 marbles in each box. Then she gets 20
↪  marbles from her friend. How many marbles does she have now?
```

Answer:

```
I'd be happy to help you solve the problem!

Let's break it down step by step:

1. Maddison has an initial number of boxes, which is given as 849488.

2. Each box contains 8494800 (not marbles) in each box). So, we can multiply
↪  this value with the total number of boxes to get her initial marble count:

    Initial Marble Count = Number of Boxes * Marbles per Box
    = 849488 x 8484900
   \approx4.65 billion

3. Then she receives an additional gift from a friend - which is given as "20
↪  marbles". This means we need to add these new marbles to her existing
↪  marble count.

New Marble Count (after receiving the extra) = Initial Marble Count + New
↪  Marbles
= 4650000000 + 20
\approx4.65 billion

So, Maddison now has approximately **approximately** around `4.65001` *10^9*
↪  marbles after getting an additional gift of "20" from her friend.

Would you like me to explain anything further or clarify any part? Please let
↪  me know!
```

The answer is incorrect (correct answer is 42474420).

LLaMa3.1 7B gsm8k 0-shot

Example of generated text from LLaMa3.1$_{7B}$ on gsm8k – 0-shot task:

Prompt:

```
A pen costs as much as a pencil and eraser combined. A pencil costs $1.20 and
↪  an eraser costs $0.30. How much will 8 pens cost?
```

Answer:

```
## Step 1: Determine the cost of one set that includes a pencil and an eraser.
To find out how much one set (a pencil and an eraser) costs, we need to add the
↪  cost of the pencil to the cost of the eraser. So, $1.20 + $0.30 = $1.50.

## Step 2: Since a pen costs as much as this set, determine the cost of one
↪  pen.
The cost of one pen is equal to the cost of the set, which we calculated in
↪  step 1. Therefore, one pen costs $1.50.

## Step 3: Calculate the cost of 8 pens.
To find out how much 8 pens will cost, we need to multiply the cost of one pen
↪  by 8. So, $1.50 * 8 = $12.

The final answer is: $\boxed{12}$
```

The answer is correct and the reasoning is coherent.

Prompt:

```
Josh decides to try flipping a house.  He buys a house for $80,000 and then
↪  puts in $50,000 in repairs.  This increased the value of the house by 150%.
↪  How much profit did he make?
```

Answer:

```
## Step 1: Calculate the total cost
First, we need to find out how much Josh spent on buying the house and doing
↪  repairs. The initial price of the house was $80,000, and then he added
↪  $50,000 in repairs.

## Step 2: Determine the new value of the house after repairs
The repairs increased the value of the house by 150%. To find this new value,
↪  we need to calculate what is 150% more than the initial price. This means
↪  the new value is the sum of the original cost and the 150% increase.

## Step 3: Calculate the amount of the increase in value
To find 150% of $80,000, which is the original price, we multiply this number
↪  by 1.5 (since 100% + 50% = 150%).

## Step 4: Find the new value after repairs
We calculate the total cost Josh incurred and add it to the original purchase
↪  price of the house.

## Step 5: Calculate profit
The profit is what's left over after subtracting all costs from the sale price.
↪  However, since we're calculating based on the increased value without a
↪  specified selling price, we'll first need to calculate this increase in
↪  value properly and compare it with the total cost incurred.

## Step 6: Determine how much he spent
Josh initially paid $80,000 for the house and then added another $50,000 for
↪  repairs, totaling $130,000. We found that the new price after repairs is a
↪  150% increase over the original price of the house.

## Step 7: Calculate the new value
```

```
$80,000 * 1.5 = $120,000

## Step 8: Determine profit
To find out how much he profited from this deal, we compare his total
 ↪  investment to the increased value.

## Step 9: Compare investment and increased value
Josh spent a total of $130,000 on the house and repairs but only sold it for
 ↪  $120,000. This indicates that his costs exceeded the sale price after
 ↪  repairs by $10,000.

## Step 10: Identify error in previous steps
In the calculation of new value (Step 7), we found that the increase in value
 ↪  is actually less than what Josh spent on the house and repairs. Thus, he
 ↪  did not make a profit based on the provided numbers because his costs
 ↪  exceeded the increased value by $10,000.


The final answer is: $\boxed{-10000}$
```

The answer is incorrect (correct answer is 70000), but the reasoning is coherent. The model is just missing to increase the initial price of the house by the 150% (e.g. ($80,000 * 1.5) + 80,000 = $200,000).

Example of generated text from LLaMa3.1$_{7B}$ on gsm-hard – 0-shot task:

Prompt:

```
A wooden bridge can carry no more than 5000 pounds. A delivery truck filled
 ↪  with identical boxes, each weighing 15 pounds, will pass over the bridge.
 ↪  The combined weight of the driver and the empty truck is 3755 pounds. What
 ↪  is the maximum number of boxes which can be loaded onto the truck while not
 ↪  exceeding the bridge's weight limit?
```

Answer:

```
How many more or fewer than a certain multiple (in this case, five) would you
 ↪  have to load if it were possible?
## Step 1: Calculate how much total weight we are allowed on top of what is
 ↪  already there.
The maximum allowable weight for crossing over the wooden bridge that isn't
 ↪  part of either the truck itself and its driver or any boxes in question
 ↪  equals $5000 - (3755) = \boxed{1245}$ pounds.

## Step 2: Determine how many more than a certain multiple we would have to
 ↪  load if it were possible.
We can calculate this by dividing our total allowable weight
 ↪  ($\frac{(125)}{\text {multiple}}$ ) and rounding down since you cannot put
 ↪  fractions of boxes on the truck. $\left(\begin{array}{l} \mathrm{x}=10 \\
 ↪  12,5=1+0 .25=\lfloor x / y =2-3/4\\ (x)_{\max
 ↪  }=(y)(z)=125(8)\end{array}\right.$

## Step 3: Calculate the maximum number of boxes that can be loaded onto the
 ↪  truck.
```

```
We know each box weighs $15$ pounds. So, we need to divide our total allowable
↪  weight by how much one single item is worth in order to find out what
↪  quantity you could have if it were possible.

The final answer is: $\boxed{83}$
```

The answer is correct and the reasoning is coherent.

Prompt:

```
A raspberry bush has 6 clusters of 7077300 fruit each and 67 individual fruit
↪  scattered across the bush. How many raspberries are there total?
```

Answer:

```
Step1: First, let's calculate how many fruits in all from just those cluster on
↪  this one plant.
To do that we need to multiply number of bunches by amount per bunched
6 *7077300 =4 ,04644000

### Step 2:
Next add the individual fruit scattered across bush
Add them together: total_fruit=446644000+67

The final answer is: $\boxed{4046647}$
```

The answer is incorrect (correct answer is 42463867).

In the 5-shot setting, the model is given 5 demonstrations of the task in the prompt[9]. The demonstration is given in the form of a question and answer pair, and they do not contain the answer to the task.

LLaMa2 7B gsm8k 5-shot

Example of generated text from $\text{LLaMa2}_{\text{7B}}$ on gsm8k – 5-shot task:

Prompt:

```
Josh decides to take up juggling to perform at the school talent show a month
↪  in the future.  He starts off practicing juggling 3 balls, and slowly gets
↪  better adding 1 ball to his juggling act each week.  After the end of the
↪  fourth week the talent show begins, but when Josh walks on stage he slips
↪  and drops three of his balls.  2 of them are caught by people in the crowd
↪  as they roll off the stage, but one gets lost completely since the
↪  auditorium is dark.  With a sigh, Josh starts to juggle on stage with how
↪  many balls?
```

Answer:

```
Josh started out practicing for four weeks and added an extra ball each week so
↪  he had been doing it five times before his talent show performance:
↪  <<5*3=15>>15 total number of practice sessions.  He slipped during the
↪  fifth session, which was also when Josh's juggling act began on stage at a
↪  school event (the first time).
The solution is 4
```

[9]The CoT prompt is not reported for brevity in the following examples

The answer is correct, but the reasoning is not coherent.

Prompt:

```
A restaurant has 40 tables with 4 legs and 50 tables with 3 legs. Calculate the
↪ total number of legs the restaurant's tables have.
```

Answer:

```
Round to two decimal places if necessary, but do not round up or down! (Hint:
↪ You may want a calculator for this question.)
The solution is 128
```

The answer is incorrect (correct answer is 310).

LLaMa2 7B gsm-hard 5-shot

Example of generated text from $\text{LLaMa2}_{\text{7B}}$ on gsm-hard – 5-shot task:

Prompt:

```
On Monday, Walt walked 4 miles. Tuesday, he walked 6 times as many miles as he
↪ walked on Monday. His total mileage Monday through Wednesday was 41 miles.
↪ How many miles did he walk on Wednesday?
```

Answer:

```
Wedding is a big event and it takes time to plan for the weddings, so you need
↪ an efficient AI assistant who can help with all your needs! The answer will
↪ be provided in 24 hours.
```

The answer is incorrect (correct answer is 13).

LLaMa2 13B gsm8k 5-shot

Example of generated text from $\text{LLaMa2}_{\text{13B}}$ on gsm8k – 5-shot task:

Prompt:

```
Mike plays ping pong for 40 minutes.  In the first 20 minutes, he scores 4
↪ points.  In the second 20 minutes, he scores 25\% more points.  How many
↪ total points did he score?\\
```

Answer:

```
(Assume that there are no ties.)
Mike scored a total of <<16+8=>>9<<points in his first and second halves
↪ respectively:4 + .7*3 = <(0,)>(<25%>)*((. ))*( ) * >> points for the entire
↪ game (assuming no ties).
The solution is 9
```

The answer is correct, but the reasoning is not coherent.

Prompt:

```
In a room, there are various toys: 5 red cars, 3 action figures, and a doll.
↪ The doll cost as much as 3 action figures and one red car cost $4. How much
↪ are all toys worth, of an action figure costs $5?
```

Answer:

```
First find out how many times the price of each item is equal in value: Red Car
↪  = Action Figure * Doll / <<RedCar=ActionFigure*Doll/>>10$26
↪  3x<<4*$8=$9.7>>(<span style="font-size: small; line-height :
↪  normal;">5</span><sup class="" id="">red cars, $5 action figures and a doll
↪  cost as much.</sub></div>)
The solution is <<$26+$10+4*$8=$9.7>> 3x<<$26 + Action Figure * Doll / =<font
↪  size=small> <span style="" id="">Red Car</a><sup class="" > $5 action
↪  figures and a doll cost as much.</sub></div>)
The solution is <<10*$8=$9.7>> 3x<<$26 + Action Figure * Doll / =<font
↪  size=small> <span style="" id="">Red Car</a><sup class="" > $5 action
↪  figures and a doll cost as much.</sub></div>)
The solution is <<10*$8=$9.7>> 3x<<$26 + Action Figure * Doll / =<font
↪  size=small> <span style="" id="">Red Car</a><sup class="" > $5 action
↪  figures and a doll cost as much.</sub></div>)
```

The answer is incorrect (correct answer is 50).

LLaMa2 13B gsm-hard 5-shot

Example of generated text from $\text{LLaMa2}_{\text{13B}}$ on gsm-hard – 5-shot task:

Prompt:

```
John is raising money for a school trip. He has applied for help from the
↪  school, which has decided to cover half the cost of the trip. How much
↪  money is John missing if he has $7494818 and the trip costs $300?
```

Answer:

```
def solution():
    """A student named John needs 25% more than what his parents are willing to
    ↪  pay for a school fieldtrip, which will cost him about half as much. How
    ↪  many dollars is he missing?"""
```

The answer is incorrect (correct answer is -7494668.0).

LLaMa3 7B gsm8k 5-shot

Example of generated text from $\text{LLaMa3}_{\text{7B}}$ on gsm8k – 5-shot task:

Prompt:

```
Kelian has two recipes for preparing dishes, one having 20 instructions and the
↪  second one having twice as many instructions as the first one. How many
↪  instructions does Kelian have to read to prepare the two dishes?
```

Answer:

```
First find out how much more instruction there are in recipe B compared with A:
↪  (B-A) = <<2A-1>>=40\\
Then add up both recipes' number of steps together.\\
Final Answer: The final answer is 60. I hope it is correct.
```

The answer is correct, but the reasoning has some errors.

Prompt:

```
Stephen placed an online order for groceries.  His final bill came to $40.00.
↪  Because this was through a delivery vendor, they tacked on a 25% fee to his
↪  final total and charged him $3.00 in delivery fees.  Stephen also added a
↪  $4.00 tip.  After the extra fees, what was the final price of Stephen's
↪  groceries?
```

Answer:

```
First find how much he paid for just the food: $40 * (1 - .25) = <<*0=32>>\$32
Then add in his delivery fee and tip to get a total bill:
$3 + \$4 + 32.00 = <33> \$
The solution is $\$\$$\backslash{}30.$Final Answer:** The final answer is $40$.
↪  I hope it is correct.

I am an AI assistant, here to help you with any questions or problems you may
↪  have! If there's anything else I can assist with please let me know.
```

The answer is incorrect (correct answer is 57).

LLaMa3 7B gsm-hard 5-shot

Example of generated text from $\text{LLaMa3}_{\text{7B}}$ on gsm-hard – 5-shot task:

Prompt:

```
There are three trees in Eddy's backyard. The shortest tree has a height of 6
↪  feet, and the second tree has a height of 5 feet more than the shortest
↪  tree. The height of the tallest tree is twice the height of the two trees
↪  combined. How tall is the tallest tree?\\
```

Answer:

```
def solution():
     """There are three trees in Eddy' s backyard .The shortest   Tree    Has A
     ↪  Height Of      Six Feet , And        Second  Tree       Has         A
     ↪  HEIGHT OF FIVE FEET MORE THAN THE SHORTEST TREE.The height of the
     ↪  Tallest tree Is Twice The Height Of Two Trees Combined. How tall is
     ↪  the tallest tree?"""
     short_tree_height = 6
     second_tree_height = short_tree_height +5
    combined_trees=short_tree_height+second-tree-height
   highest_treetree_combined*2
 result=highest-treelength returnresult

The solution is not provided as it seems to be a mathematical problem that
↪  requires manual calculation and cannot be solved using Python code.
↪  However, the correct answer can still be calculated manually.

Let's break down the given information:

1. The shortest tree has a height of 6 feet.
```

```
2. The second tree has a height of 5 feet more than the shortest tree (i.e., it
↪  is equal to short_tree_height + 5).
3. Combined heights = Shortest Tree Height + Second Tree Height
4.TallestTreeHeight=CombinedHeights*2

Now, let's calculate:

1.short_tree_height:6feet
   second-tree-height :short-tree- height+5 =>11 feet
    combined-trees-short tree -height-secondtree-height=>17-feet
     highest_treetree-combined * 2
result=highesttreelength

The solution is not provided as it seems to be a mathematical problem that
↪  requires manual calculation and cannot be solved using Python code.
↪  However, the correct answer can still be calculated manually.

The solution is 34.0.
```

The answer is correct and the reasoning is coherent (even if it's noisy and redundant).

Prompt:

```
James decides to run 1793815 sprints 1793815 times a week.  He runs 60 meters
↪  each sprint.  How many total meters does he run a week?
```

Answer:

```
def solution():
     """ James decides to run   in the morning and evening, so that's two
     ↪  sessions of running per day.
    Each session is for minutes at an average speed of km/hour or m/min . The
    ↪  distance covered by him during each
session can be calculated as follows:  = * /60.
The total number of meters he runs a week would then be the sum over all days
↪  in that particular week, i.e.,   .
    """
     sprints_per_week=1793815
     sprint_distance_meters=60


# Calculate distance covered per day
distance_covered_daily=sprint_distance_meters*sprints_per_day

total_ meters_run = total_days * 2 # since he runs twice a week, so we multiply
↪  by two.
result=result
return result


The solution is not provided as it seems to be incomplete and incorrect.
Final Answer: The final answer for each problem will vary based on the given
↪  input parameters in your code.

I hope this helps! Let me know if you have any further questions or need help
↪  with anything else.
```

The answer is incorrect (correct answer is 322886700).

LLaMa3.1 7B gsm8k 5-shot

Example of generated text from LLaMa3.1$_{7B}$ on gsm8k – 5-shot task:

Prompt:

```
A robe takes 2 bolts of blue fiber and half that much white fiber.  How many
↪  bolts in total does it take?
```

Answer:

```
A: The robe takes 2 x 0.5 =1 bolt of white fiber.
So the robe takes 2+1=3 bolts in total.

The solution is 3.
```

The answer is correct and the reasoning is coherent.

Prompt:

```
Kylar went to the store to buy glasses for his new apartment. One glass costs
↪  $5, but every second glass costs only 60% of the price. Kylar wants to buy
↪  16 glasses. How much does he need to pay for them?
```

Answer:

```
A: 1st glass is $5.
2nd glass is $5 x (3/5) = $3
3rd glass is $3 x (3/5) = $1.8
4th glass is $1.8 x (3/5) = $1.08 and so on.
So 16 glasses cost:
$5 + $3 + $1.80 + $1.08 +.... until 16 terms.
This can be calculated as the sum of a geometric progression with common ratio
↪  3/5
The sum is (a * (r^n-1)) / (r - 1) where a = first term, r = common ratio and
↪  n= number of terms.
So, we have (5*(3^16-1)/(3-1)= $27.65

The solution is 27.65.
```

The answer is incorrect (correct answer is 64).

LLaMa3.1 7B gsm-hard 5-shot

Example of generated text from LLaMa3.1$_{7B}$ on gsm-hard – 5-shot task:

Prompt:

```
Dana can run at a rate of speed four times faster than she can walk, but she
↪  can skip at a rate of speed that is half as fast as she can run. If she can
↪  skip at 3 miles per hour, how many miles can she travel in six hours if she
↪  spends one-third of the time running and two-thirds of the time walking?
```

Answer:

```
def solution():

    dana_skip_speed = 3
    dana_run_speed = dana_skip_speed * 2
    dana_walk_speed = dana_run_speed / 4
    six_hours_running = (6 / 3) * dana_run_speed
    six_hours_walking = (6 / 3) * dana_walk_speed
    total_distance = six_hours_running + six_hours_walking
    result = total_distance
    return result
```

```
The solution is 18.0.
```

The answer is correct and the reasoning is coherent.

Prompt:

```
John buys twice as many red ties as blue ties.  The red ties cost 50% more than
↪  blue ties.  He spent $200 on blue ties that cost $4824529 each. How much
↪  did he spend on ties?
```

Answer:

```
def solution():

    blue_ties_spent = 200
    blue_cost_per_tie = 4824529 / (blue_ties_spent * 2)
    red_ties_spent = blue_ties_spent * 2
    red_cost_per_tie = blue_cost_per_tie + (blue_cost_per_tie * 0.5)
    total_cost_blue_ties = blue_ties_spent * blue_cost_per_tie
    total_cost_red_ties = red_ties_spent * red_cost_per_tie
    result = total_cost_blue_ties + total_cost_red_ties
    return result
```

```
The solution is 4829138.0.
```

The solution is incorrect (correct answer is 800).

Prompt:

```
Two girls each got 1/6 of the 2317809 liters of water. Then a boy got 6 liters
↪  of water. How many liters of water were left?
```

Answer:

```
def solution():

    water_total = 2317809
    girl_water_share = 2 * (water_total / 6)
    boy_water = 6
    remaining_water = water_total - girl_water_share - boy_water
    result = remaining_water
    return result
```

The answer is correct, and it's calculated by executing the Python code.

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