

For C/C++ tasks in CodeNet, Codex, Code Llama, SantaCoder, and CodeGen are likely the top performers, with GPT-4 also being highly competitive in complex coding tasks. However, exact performance metrics for each task in CodeNet might vary based on the specific problem type (e.g., code completion vs. complex algorithm generation).

A Survey on Large Language Models for Code Generation

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Large Language Models (LLMs) have garnered remarkable advancements across diverse code-related tasks, known as Code LLMs, particularly in code generation that generates source code with LLM from natural language descriptions. This burgeoning field has captured significant interest from both academic researchers and industry professionals due to its practical significance in software development, e.g., *GitHub Copilot*. Despite the active exploration of LLMs for a variety of code tasks, either from the perspective of natural language processing (NLP) or software engineering (SE) or both, there is a noticeable absence of a comprehensive and up-to-date literature [review dedicated to LLM for code generation](#). In this survey, we aim to bridge this gap by providing a systematic literature review that serves as a valuable reference for researchers investigating the cutting-edge progress in LLMs for code generation. We introduce a taxonomy to categorize and discuss the recent developments in LLMs for code generation, covering aspects such as data curation, latest advances, performance evaluation, and real-world applications. In addition, we present a historical overview of the evolution of LLMs for code generation and offer an empirical comparison using the widely recognized HumanEval and MBPP benchmarks to highlight the progressive enhancements in LLM capabilities for code generation. We identify critical challenges and promising opportunities regarding the gap between academia and practical development. Furthermore, we have established a dedicated resource website (<https://codellm.github.io>) to continuously document and disseminate the most recent advances in the field.

CCS Concepts: • **General and reference** → **Surveys and overviews**; • **Software and its engineering** → **Software development techniques**; • **Computing methodologies** → **Artificial intelligence**.

Additional Key Words and Phrases: Large Language Models, Code Large Language Models, Code Generation

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1 INTRODUCTION

The advent of Large Language Models (LLMs) such as ChatGPT¹ [171] has profoundly transformed the landscape of automated code-related tasks [45], including code completion [78, 152, 233, 244], code translation [48, 121, 211], and code repair [109, 170, 176]. A particularly intriguing application of LLMs is code generation, a task that involves producing source code from natural language descriptions. Despite varying definitions across studies [47, 191, 204, 232], for the purposes of this survey, we adopt a consistent definition of code generation as the natural-language-to-code (NL2Code) task [15, 16, 264]. This area has garnered substantial interest from both academia and industry, as evidenced by the development of tools like GitHub Copilot² [45], CodeGeeX³ [275], and Amazon CodeWhisperer⁴, which leverage groundbreaking code LLMs to facilitate software development.

Initial investigations into code generation primarily utilized heuristic rules or expert systems, such as probabilistic grammar-based frameworks [9, 57, 113] and specialized language models [59, 74, 106]. These early techniques were typically rigid and difficult to scale. However, the introduction of Transformer-based LLMs has shifted the paradigm, establishing them as the preferred method due to their superior proficiency and versatility. One remarkable aspect of LLMs is their capability to follow instructions [51, 164, 173, 238, 250], enabling even novice programmers to write code by simply articulating their requirements. This emergent ability has democratized coding, making it accessible to a broader audience [264]. The performance of LLMs on code generation tasks has seen remarkable improvements, as illustrated by the HumanEval leaderboard⁵, which showcases the evolution from PaLM 8B [49] of 3.6% to LDB [279] of 95.1% on Pass@1 metrics. As can be seen, the HumanEval benchmark [45] has been established as a de facto standard for evaluating the coding proficiency of LLMs [45].

To offer a comprehensive chronological evolution, we present an overview of the development of LLMs for code generation, as illustrated in Figure 1. The landscape of LLMs for code generation is characterized by a spectrum of models, with certain models like ChatGPT [173], GPT4 [5], LLaMA [217, 218], and Claude 3 [13] serving general-purpose applications, while others such as StarCoder [132, 151], Code LLaMA [196], DeepSeek-Coder [79], and Code Gemma [54] are tailored specifically for code-centric tasks. The convergence of code generation with the latest LLM advancements is pivotal, especially when programming languages can be considered as distinct dialects of multilingual natural language [15, 275]. These models are not only tested against software engineering (SE) requirements but also propel the advancement of LLMs into practical production [271].

While recent surveys have shed light on code LLMs from the lenses of Natural Language Processing (NLP), Software Engineering (SE), or a combination of both disciplines [91, 264, 271, 278], they have often encompassed a broad range of code-related tasks. There remains a dearth of literature specifically reviewing advanced topics in code generation, such as meticulous data curation, instruction tuning, alignment with feedback, prompting techniques, the development of autonomous coding agents, retrieval augmented code generation, LLM-as-a-Judge for code generation, among others. A notably pertinent study [15, 264] also concentrates on LLMs for text-to-code generation (NL2Code), yet it primarily examines models released from 2020 to 2022. Consequently, this noticeable temporal gap has resulted in an absence of up-to-date literature reviews that contemplate the

¹<https://chat.openai.com>

²<https://github.com/features/copilot>

³<https://codegeex.cn/en-US>

⁴<https://aws.amazon.com/codewhisperer>

⁵<https://paperswithcode.com/sota/code-generation-on-humaneval>

latest advancements, including models like CodeQwen [215], WizardCoder [154], and PPOCoder [204], as well as the comprehensive exploration of the advanced topics previously mentioned.

Recognizing the need for a dedicated and up-to-date literature review, this survey endeavors to fill that void. We provide a systematic review that will serve as a foundational reference for researchers quickly exploring the latest progress in LLMs for code generation. A taxonomy is introduced to categorize and examine recent advancements, encompassing data curation [154, 231, 240], advanced topics [42, 47, 94, 125, 146, 152, 164, 166, 177, 205, 266], evaluation methods [45, 85, 111, 284], and practical applications [45, 275]. This category aligns with the comprehensive lifecycle of an LLM for code generation. Furthermore, we pinpoint critical challenges and identify promising opportunities to bridge the research-practicality divide. Therefore, this survey allows NLP and SE researchers to seamlessly equip with a thorough understanding of LLM for code generation, highlighting cutting-edge directions and current hurdles and prospects.

The remainder of the survey is organized following the structure outlined in our taxonomy in Figure 3. In Section 2, we introduce the preliminaries of LLM with Transformer architecture and formulate the task of LLM for code generation. Then, in Section 3, we propose a taxonomy, categorizing the complete process of LLMs in code generation. Section 4 delves into the specifics of LLMs for code generation within this taxonomy framework. In Section 5, we underscore the critical challenges and promising opportunities for bridging the research-practicality gap and conclude this work in Section 6.

2 BACKGROUND

2.1 Large Language Models

The effectiveness of large language models (LLMs) is fundamentally attributed to their substantial quantity of model parameters, large-scale and diversified datasets, and the immense computational power utilized during training [87, 114]. Generally, scaling up language models consistently results in enhanced performance and sample efficiency across a broad array of downstream tasks [238, 273]. However, with the expansion of the model size to a certain extent (e.g., GPT-3 [31] with 175B-parameters and PaLM [49] with 540B), LLMs have exhibited an unpredictable phenomenon known as emergent abilities⁶, including instruction following [173], in-context learning [65], and step-by-step reasoning [95, 239], which are absent in smaller models but apparent in larger ones [238].

Adhering to the same architectures of the Transformer [222] in LLMs, code LLMs are specifically pre-trained on large-scale unlabeled code corpora, whereas general-purpose LLMs (e.g., ChatGPT [171]) are pre-trained on a blend of code and text data. Analogous to LLMs, Code LLMs can also be classified into three architectural categories: encoder-only models, decoder-only models, and encoder-decoder models. For encoder-only models, such as CodeBERT [68], they are typically suitable for code comprehension tasks including type prediction, code retrieval, and clone detection. For decoder-only models, such as StarCoder [31], they predominantly excel in generation tasks, such as code generation, code translation, and code summarization. Encoder-decoder models, such as CodeT5 [234], can accommodate both code understanding and generation tasks but do not necessarily outperform encoder-only or decoder-only models. The overall architectures of the different Code LLMs for code generation are depicted in Figure 2.

In the following subsection, we will delineate the key modules of the Transformer layers in Code LLMs.

2.1.1 Multi-Head Self-Attention Modules. Each Transformer layer incorporates a multi-head self-attention (MHSA) mechanism to discern the inherent semantic relationships within a sequence

⁶It should be noted that an LLM is not necessarily superior to a smaller language model, and emergent abilities may not manifest in all LLMs [273].

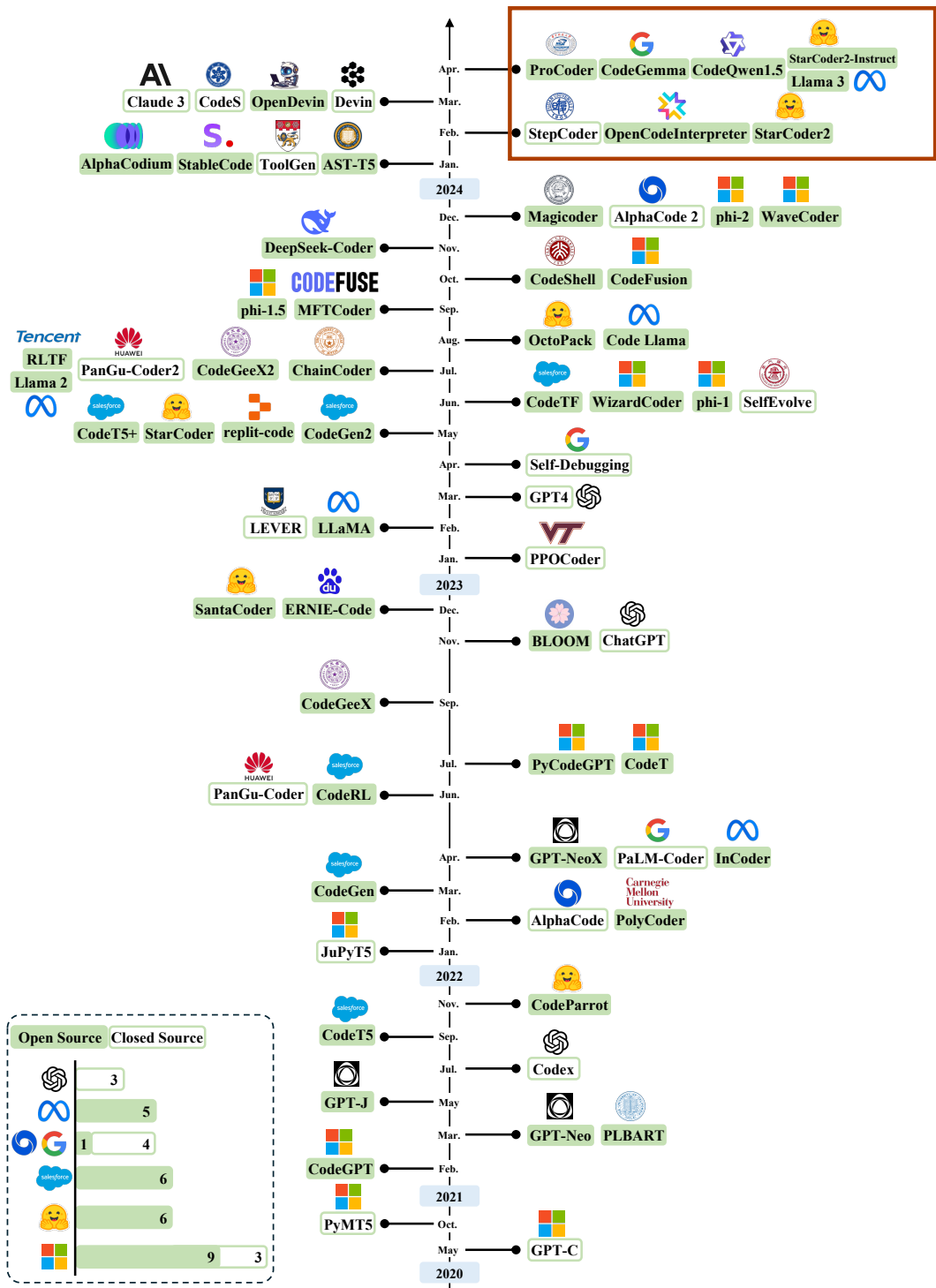


Fig. 1. A chronological overview of large language models (LLMs) for code generation in recent years. The timeline was established mainly according to the release date. The models with publicly available model checkpoints are highlighted in green color.

of tokens across h distinct latent representation spaces. Formally, the MHSA employed by the Transformer can be formulated as follows:

$$\mathbf{h}^{(l)} = \text{MultiHeadSelfAttn}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{Concat} \{ \text{Head}_i \}_{i=1}^h \mathbf{W}^O, \quad (1)$$

$$\text{Head}_i = \text{Attention}(\underbrace{\mathbf{H}^{(l-1)} \mathbf{W}_i^Q}_Q, \underbrace{\mathbf{H}^{(l-1)} \mathbf{W}_i^K}_K, \underbrace{\mathbf{H}^{(l-1)} \mathbf{W}_i^V}_V), \quad (2)$$

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax} \left(\frac{\mathbf{QK}^T}{\sqrt{d_{\text{model}}/h}} \right) \mathbf{V}, \quad (3)$$

where $\mathbf{H}^{(l-1)} \in \mathbb{R}^{n \times d_{\text{model}}}$ denotes the input to the l -th Transformer layer, while $\mathbf{h}^{(l)} \in \mathbb{R}^{n \times d_{\text{model}}}$ represents the output of MHSA sub-layer. The quantity of distinct attention heads is represented by h , and d_{model} refers to the model dimension. The set of projections $\{\mathbf{W}_i^Q, \mathbf{W}_i^K, \mathbf{W}_i^V, \mathbf{W}_i^O\} \in \mathbb{R}^{d_{\text{model}} \times d_{\text{model}}/h}$ encompasses the affine transformation parameters for each attention head Head_i , transforming the Query \mathbf{Q} , Key \mathbf{K} , Value \mathbf{V} , and the output of the attention sub-layer. The softmax function is applied in a row-wise manner. The dot-products of queries and keys are divided by a scaling factor $\sqrt{d_{\text{model}}/h}$ to counteract the potential risk of excessive large inner products and correspondingly diminished gradients in the softmax function, thus encouraging a more balanced attention landscape.

In addition to multi-head self-attention, there are two other types of attention based on the source of queries and key-value pairs:

- **Masked Multi-Head Self-Attention.** Within the decoder layers of the Transformer, the self-attention mechanism is constrained by introducing an attention mask, ensuring that queries at each position can only attend to all key-value pairs up to and inclusive of that position. To facilitate parallel training, this is typically executed by assigning a value of 0 to the lower triangular part and setting the remaining elements to $-\infty$. Consequently, each item attends only to its predecessors and itself. Formally, this modification in Equation 3 can be depicted as follows:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax} \left(\frac{\mathbf{QK}^T}{\sqrt{d_{\text{model}}/h}} + \mathbf{M}_{\text{mask}} \right) \mathbf{V}, \quad (4)$$

$$\mathbf{M}_{\text{mask}} = (m_{ij})_{n \times n} = (\mathbb{I}(i \geq j))_{n \times n} = \begin{cases} 0 & \text{for } i \geq j \\ -\infty & \text{otherwise} \end{cases}, \quad (5)$$

This form of self-attention is commonly denoted as autoregressive or causal attention [141].

- **Cross-Layer Multi-Head Self-Attention.** The queries are derived from the outputs of the preceding (decoder) layer, while the keys and values are projected from the outputs of the encoder.

2.1.2 Position-wise Feed-Forward Networks. Within each Transformer layer, a Position-wise Feed-Forward Network (PFFN) is leveraged following the MHSA sub-layer to refine the sequence embeddings at each position i in a separate and identical manner, thereby encoding more intricate feature representations. The PFFN is composed of a pair of linear transformations, interspersed with a ReLU activation function. Formally,

$$\text{PFFN}(\mathbf{h}^{(l)}) = \left(\text{Concat} \left\{ \text{FFN}(\mathbf{h}_i^{(l)})^T \right\}_{i=1}^n \right)^T, \quad (6)$$

$$\text{FFN}(\mathbf{h}_i^{(l)}) = \text{ReLU}(\mathbf{h}_i^{(l)} \mathbf{W}^{(1)} + \mathbf{b}^{(1)}) \mathbf{W}^{(2)} + \mathbf{b}^{(2)}, \quad (7)$$

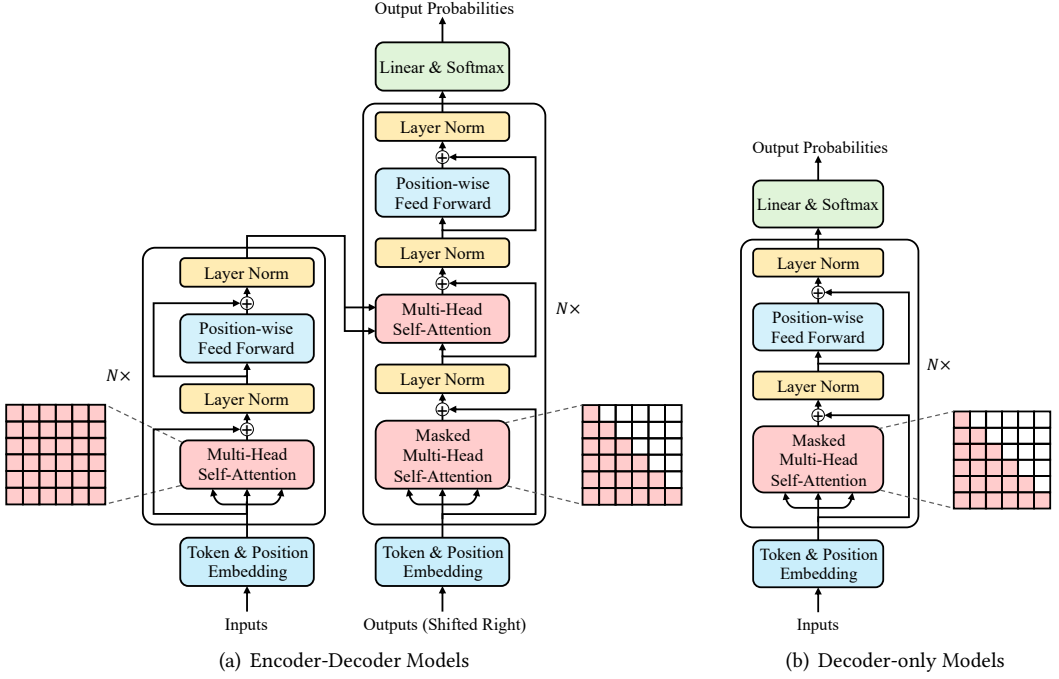


Fig. 2. The overview of large language models (LLMs) with encoder-decoder and decoder-only Transformer architecture for code generation, adapted from [222].

where $h^{(l)} \in \mathbb{R}^{n \times d_{model}}$ is the outputs of MHSA sub-layer in l -th Transformer layer, and $h_i^{(l)} \in \mathbb{R}^{d_{model}}$ denotes the latent representation at each sequence position. The projection matrices $\{\mathbf{W}^{(1)}, (\mathbf{W}^{(2)})^T\} \in \mathbb{R}^{d_{model} \times 4d_{model}}$ and bias vectors $\{\mathbf{b}^{(1)}, \mathbf{b}^{(2)}\} \in \mathbb{R}^{d_{model}}$ are parameters learned during training. These parameters remain consistent across all positions while are individually initialized from layer to layer. In this context, T represents the transpose operation on a matrix.

2.1.3 Residual Connection and Normalization. To alleviate the issue of vanishing or exploding gradients resulting from network deepening, the Transformer model incorporates a residual connection [84] around each of the aforementioned modules, followed by Layer Normalization [17]. For the placement of Layer Normalization operation, there are two widely used approaches: 1) **Post-Norm**: Layer normalization is implemented subsequent to the element-wise residual addition, in accordance with the vanilla Transformer [222]. 2) **Pre-Norm**: Layer normalization is applied to the input of each sub-layer, as seen in models like GPT-2 [186]. Formally, it can be formulated as:

$$\begin{aligned} \text{Post-Norm : } \mathbf{H}^{(l)} &= \text{LayerNorm}(\text{PFFN}(\mathbf{h}^{(l)}) + \mathbf{h}^{(l)}), \\ \mathbf{h}^{(l)} &= \text{LayerNorm}(\text{MHSA}(\mathbf{H}^{(l-1)}) + \mathbf{H}^{(l-1)}) \end{aligned} \quad (8)$$

$$\begin{aligned} \text{Pre-Norm : } \mathbf{H}^{(l)} &= \text{PFFN}(\text{LayerNorm}(\mathbf{h}^{(l)})) + \mathbf{h}^{(l)}, \\ \mathbf{h}^{(l)} &= \text{MHSA}(\text{LayerNorm}(\mathbf{H}^{(l-1)})) + \mathbf{H}^{(l-1)} \end{aligned} \quad (9)$$

2.1.4 Positional Encoding. Given that self-attention alone cannot discern the positional information of each input token, the vanilla Transformer introduces an absolute positional encoding method to

supplement this positional information, known as sinusoidal position embeddings [222]. Specifically, for a token at position pos , the position embedding is defined as:

$$p_{pos,2i} = \sin\left(\frac{pos}{10000^{2i/d_{model}}}\right), \quad (10)$$

$$p_{pos,2i+1} = \cos\left(\frac{pos}{10000^{2i/d_{model}}}\right), \quad (11)$$

where $2i, 2i+1$ represent the dimensions of the position embedding, while d_{model} denotes the model dimension. Subsequently, each position embedding is added to the corresponding token embedding, and the sum is fed into the Transformer. Since the inception of this method, a variety of innovative positional encoding approaches have emerged, such as learnable embeddings [61], relative position embeddings [199], RoPE [209], and ALiBi [183]. For more detailed descriptions of each method, please consult [141, 272].

2.2 Code Generation

Large language models (LLMs) for code generation refer to the use of LLM to generate source code from natural language descriptions, a process also known as a **natural-language-to-code task**. Typically, these natural language descriptions encompass programming problem statements (or docstrings) and may optionally include some programming context (e.g., function signatures, assertions, etc.). Formally, these natural language (NL) descriptions can be represented as \mathbf{x} . Given \mathbf{x} , the use of an LLM with model parameters θ to generate a code solution \mathbf{y} can be denoted as $P_\theta(\mathbf{y} \mid \mathbf{x})$. To verify the functionality correctness of the code solution, \mathbf{y} is subsequently executed via a compiler or interpreter, represented as $\text{Exe}(\cdot)$, on a suit of unit tests. The feedback from this execution can be denoted as $\text{Feedback}(\text{Exe}(\mathbf{y}))$.

The advent of in-context learning abilities in LLM [238] has led to the appending of exemplars to the natural language description \mathbf{x} as demonstrations to enhance code generation performance or constrain the generation format [131, 178]. A fixed set of M exemplars is denoted as $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^M$. Consequently, following [166], a more general formulation of LLMs for code generation with few-shot (or zero-shot) exemplars can be revised as:

$$P_\theta(\mathbf{y} \mid \mathbf{x}) = P_\theta(\mathbf{y} \mid \text{prompt}(\mathbf{x}, \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^k)), k = \{0, 1, \dots, M\} \quad (12)$$

where $\text{prompt}(\mathbf{x}, \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^k)$ is a string representation of the overall input, and $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^k$ denotes a set of k exemplars randomly selected from $\{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^M$. In particular, when $k = 0$, this denotes zero-shot code generation, equivalent to vanilla ones without in-context learning. Subsequently, a variety of decoding strategies can be performed for code generation, including deterministic-based strategies (e.g., greedy search and beam search) and sampling-based strategies (e.g., temperature sampling, top-k sampling, and top-p (nucleus) sampling). For more detailed descriptions of each decoding strategy, please consult [89].

$$\textbf{Greedy Search} : \mathbf{y}^* = \underset{\mathbf{y}}{\operatorname{argmax}} P_\theta(\mathbf{y} \mid \text{prompt}(\mathbf{x}, \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^k)), k = \{0, 1, \dots, M\} \quad (13)$$

$$\textbf{Sampling} : \mathbf{y} \sim P_\theta(\mathbf{y} \mid \text{prompt}(\mathbf{x}, \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^k)), k = \{0, 1, \dots, M\} \quad (14)$$

3 TAXONOMY

The recent surge in the development of Large Language Models (LLMs) has led to a significant number of these models being repurposed for code generation task through continued pre-training or fine-tuning. This trend is particularly observable in the realm of open-source models. For instance, **Meta AI initially made the LLaMA [217] model publicly available, which was followed by the release of Code LLaMA [196], designed specifically for code generation. Similarly, DeepSeek LLM [25]**

developed and released by DeepSeeker has been extended to create DeepSeek Coder [79], a variant tailored for code generation. The Qwen team has developed and released Code Qwen [215], building on their original Qwen [19] model. Microsoft, on the other hand, has unveiled WizardLM [250] and is exploring its coding-oriented counterpart, WizardCoder [154]. Google has joined the fray by releasing Gemma [214], subsequently followed by Code Gemma [54]. Beyond simply adapting general-purpose LLMs for code-related tasks, there has been a proliferation of models specifically engineered for code generation. Notable examples include StarCoder [132], OctoCoder [164], and CodeGen [169]. These models underscore the trend of LLMs being developed with a focus on code generation.

Recognizing the importance of these developments, we propose a taxonomy that categorizes and evaluates the latest advances in LLMs for code generation. This taxonomy, depicted in Figure 3, serves as a comprehensive reference for researchers seeking to quickly familiarize themselves with the state-of-the-art in this dynamic field.

In the subsequent sections, we will provide an in-depth analysis of each category related to code generation. This will encompass a definition of the problem, the challenges to be addressed, and a comparison of the most prominent models and their performance evaluation.

4 LARGE LANGUAGE MODELS FOR CODE GENERATION

Large language models (LLMs) with Transformer architecture have revolutionized a multitude of fields, and their application in code generation has been particularly impactful. These models follow a comprehensive process that starts with the curation and synthesis of code data, followed by a structured training approach that includes pre-training and fine-tuning, and the use of sophisticated prompt engineering techniques. Recent advancements have seen the integration of repository-level and retrieval-augmented code generation, as well as the development of autonomous coding agents. Furthermore, the evaluation of coding abilities of LLMs has become a critical component of this research area.

In the forthcoming sections, we will explore these dimensions of LLMs in the context of code generation in detail. Section 4.1 will address the data curation and processing strategies employed throughout the various stages of LLM development. Section 4.2 will discuss data synthesis methods designed to mitigate the scarcity of high-quality data. Section 4.3 will outline the prevalent model architectures used in LLMs for code generation. Moving to Section 4.4, we will examine the techniques for full parameter fine-tuning and parameter-efficient fine-tuning, which are essential for tailoring LLMs to code generation task. Section 4.5 will shed light on enhancing code quality through reinforcement learning, utilizing the power of feedback. Section 4.6 will delve into the strategic use of prompts to maximize the coding capabilities of LLMs. The innovative approaches of repository-level and retrieval-augmented code generation will be elaborated in Sections 4.7 and 4.8, respectively. Additionally, Section 4.9 will discuss the exciting field of autonomous coding agents. Lastly, Section 4.11 will provide insights into some of the practical applications that leverage LLMs for code generation, demonstrating the real-world impact of these sophisticated models. Through this comprehensive exploration, we aim to highlight the significance and potential of LLMs within the domain of automated code generation.

4.1 Data Curation & Processing

The exceptional performance of Large Language Models (LLMs) can be attributed to their training on large-scale and diverse datasets [264]. Meanwhile, the extensive parameters of these models necessitate substantial data to unlock their full potential, in alignment with established scaling law [87, 114]. For a general-purpose LLM, amassing a large-scale corpus of natural language from a variety of sources is imperative. Such sources include webpages, conversation data, books and

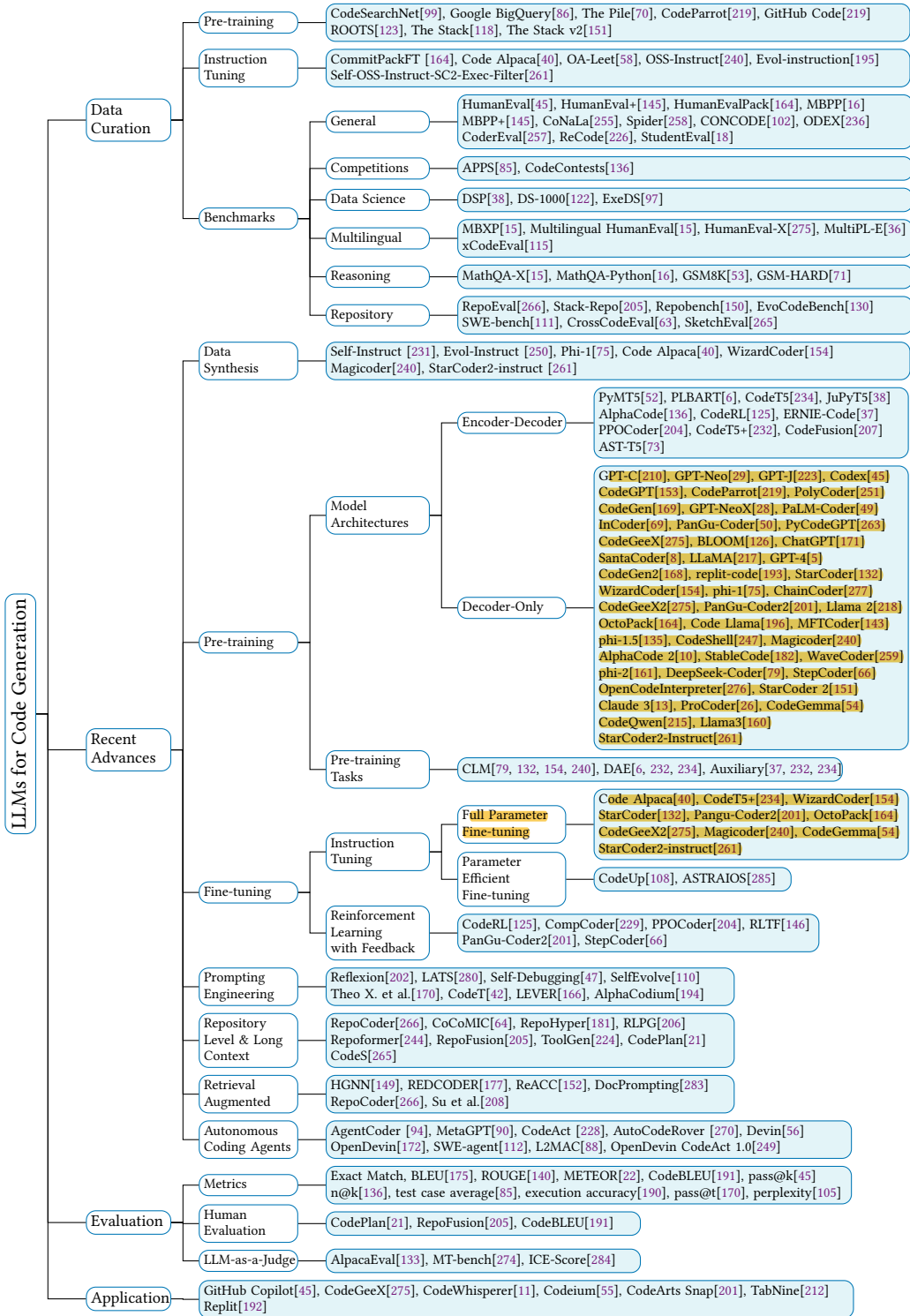


Fig. 3. Taxonomy of large language models (LLMs) for code generation.

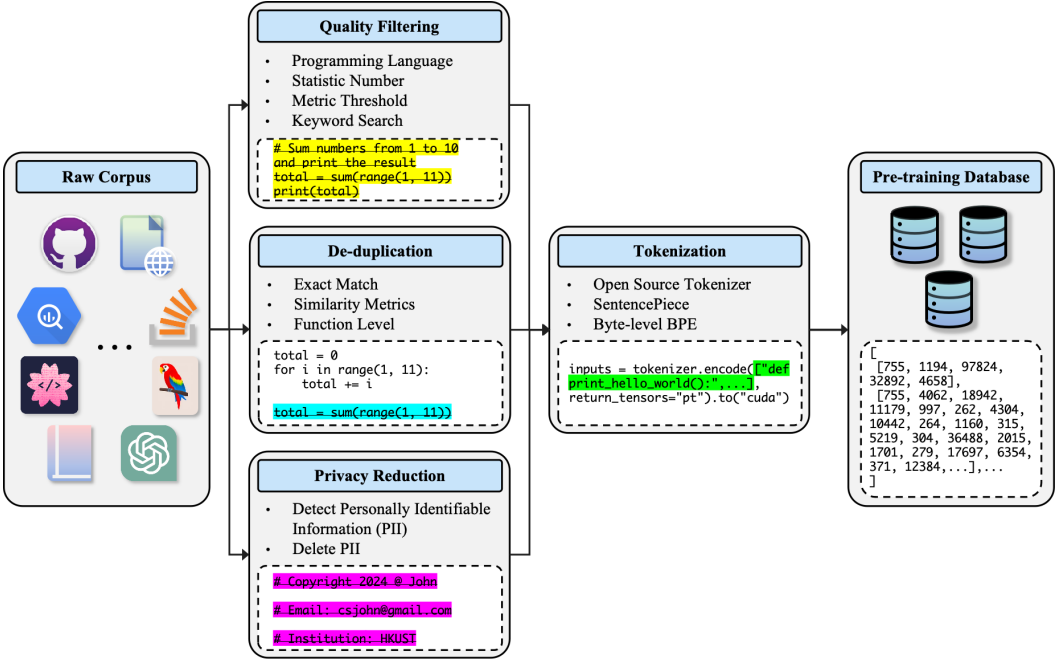


Fig. 4. A diagram depicting the standard data preprocessing workflow utilized in the pre-training phase of large language models (LLMs) for code generation.

news, scientific data, and code [19, 31, 49, 217, 218, 256], while these data are often crawled from the web and must undergo meticulous and aggressive pre-processing [189, 271]. Fortunately, multiple platforms and websites offer large-scale, open-source, and permissively licensed code corpora, such as GitHub⁷ and Stack Overflow⁸. Notably, the number of stars or forks of GitHub repositories has emerged as a valuable metric for filtering high-quality code datasets. In a similar vein, the quantity of votes on Stack Overflow can serve to discern the most relevant and superior answers.

Nonetheless, raw datasets are frequently laden with redundant, noisy data and personal information, eliciting concerns regarding privacy leakage, which may include the names and email addresses of repository contributors [7, 34, 123]. Consequently, it is essential to undertake rigorous data-cleaning procedures. Typically, this process encompasses exact match deduplication, code data filtering based on average line length and a defined threshold for the fraction of alphanumeric characters, the removal of auto-generated files through keyword searches, and the expunction of personal user data [118, 219]. Specifically, the standard data preprocessing workflow is depicted in Figure 4.

The development of a proficient LLM for code generation necessitates the utilization of various types of code data at different developmental stages. Therefore, we categorize code data into three distinct classes: pre-training datasets, instruction-tuning datasets, and benchmarks for performance evaluation. The subsequent subsections will provide a detailed illustration of code data within each classification.

⁷<https://github.com>

⁸<https://stackoverflow.com>

4.1.1 Pre-training. The remarkable success of bidirectional pre-trained language models (PLMs) such as BERT [61] and unidirectional PLMs like GPT [185] has firmly established the practice of pre-training on large-scale unlabeled datasets to endow models with a broad spectrum of general knowledge. Extending this principle to the realm of code generation enables Large Language Models (LLMs) to assimilate fundamental coding principles, including the understanding of code structure dependencies, the semantics of code identifiers, and the intrinsic logic of code sequences [45, 76, 232, 234]. In light of this advancement, there has been a proliferation of large-scale unlabeled code datasets proposed to serve as the foundational training ground for LLMs to develop coding proficiency. A brief introduction of these datasets is as follows, with the statistics available in Table 1.

- **CodeSearchNet [99]:** CodeSearchNet corpus is a comprehensive dataset, consisting of 2 million (comment, code) pairs from open-source repositories on GitHub. It includes code and documentation in several programming languages including Go, Java, PHP, Python, JavaScript, and Ruby. The dataset was primarily compiled to promote research into the problem of code retrieval using natural language.
- **Google BigQuery [86]:** the Google BigQuery Public Datasets program offers a full snapshot of the content of more than 2.8 million open source GitHub repositories in BigQuery.
- **The Pile [70]:** the Pile is an 825 GiB diverse and open source language modeling dataset aggregating 22 smaller, high-quality datasets including GitHub, Books3, and Wikipedia (en). It aims to encompass text from as many modalities as possible, thereby facilitating the development of models with broader generalization capabilities. For code generation, the GitHub composite is specifically utilized.
- **CodeParrot [219]:** the CodeParrot dataset contains Python files used to train the code generation model in Chapter 10: Training Transformers from Scratch in the “NLP with Transformers book” [219]. Created with the GitHub dataset available via Google’s BigQuery, the CodeParrot dataset includes approximately 22 million Python files and is 180 GB (50 GB compressed) big.
- **GitHub Code [219]:** the GitHub Code dataset comprises 115M code files derived from GitHub, spanning 32 programming languages and 60 extensions totaling 1TB of data. The dataset was created from the public GitHub dataset on Google BigQuery.
- **ROOTS [123]:** the BigScience ROOTS Corpus is a 1.6TB dataset spanning 59 languages that was used to train the 176B BigScience Large Open-science Open-access Multilingual (BLOOM) language model. For the code generation task, the code subset of the ROOTS Corpus will be specifically utilized.
- **The Stack [118]:** the Stack contains over 6TB of permissively licensed source code files that cover 358 programming languages. The dataset was compiled as part of the BigCode Project, an open scientific collaboration working on the responsible development of Large Language Models for Code (Code LLMs).
- **The Stack v2 [151]:** The Stack v2, a dataset created as part of the BigCode Project, contains over 3B files across more than 600 programming and markup languages. The dataset is derived from the Software Heritage archive⁹, the largest public archive of software source code and accompanying development history.

4.1.2 Instruction Tuning. Instruction tuning refers to the process of fine-tuning large language models (LLMs) using a collection of datasets that are structured as instructions. This method has demonstrated a considerable improvement in model performance and an enhanced ability to generalize to unseen tasks that the model has not previously encountered, as evidenced by

⁹<https://archive.softwareheritage.org>

Table 1. The statistics of some commonly-used pre-training datasets for large language models (LLMs) aimed at code generation. The column labeled ‘#PL’ indicates the number of programming languages included in each dataset. It should be noted that in the CodeSearchNet [99] dataset, each file represents a function, and for the Pile [70] and ROOTS [123] datasets, only the code components are considered.

Dataset	Size (GB)	Files (M)	#PL	Date	Link
CodeSearchNet [99]	20	6.5	6	2022-01	https://huggingface.co/datasets/code_search_net
Google BigQuery[86]	-	-	-	2016-06	github-on-bigquery-analyze-all-the-open-source-code
The Pile [70]	95	19	-	2022-01	https://huggingface.co/datasets/EleutherAI/pile
CodeParrot [219]	180	22	1	2021-08	https://huggingface.co/datasets/transformersbook/codeparrot
GitHub Code[219]	1,024	115	32	2022-02	https://huggingface.co/datasets/codeparrot/github-code
ROOTS [123]	163	15	13	2023-03	https://huggingface.co/bigscience-data
The Stack [118]	3,136	317	30	2022-10	https://huggingface.co/datasets/bigcode/the-stack
The Stack v2 [151]	32K	3K	619	2024-04	https://huggingface.co/datasets/bigcode/the-stack-v2

Table 2. The statistics of several representative datasets used in instruction-tuning large language models (LLMs) for code generation. The column labeled ‘#PL’ indicates the number of programming languages encompassed by each dataset.

Dataset	Size	#PL	Date	Link
CodeAlpaca-20K [40]	20k	-	2023-03	https://huggingface.co/datasets/sahil2801/CodeAlpaca-20k
CommitPackFT [164]	2GB	277	2023-08	https://huggingface.co/datasets/bigcode/commitpackft
Evol-Instruct-Code-80k [195]	80k	-	2023-07	https://huggingface.co/datasets/nickrosh/Evol-Instruct-Code-80k-v1
Magocoder-OSS-Instruct-75k [240]	75k	Python, Shell, TypeScript, C++, Rust, PHP, Java, Swift, C#	2023-12	https://huggingface.co/datasets/ise-uiuc/Magocoder-OSS-Instruct-75K
Self-OSS-Instruct-SC2-Exec-Filter-50k [261]	50k	Python	2024-04	https://huggingface.co/datasets/bigcode/self-oss-instruct-sc2-exec-filter-50k

recent studies [51, 173]. Leveraging the benefits of instruction tuning, instruction tuning has been expanded into coding domains, especially for code generation, which involves the automatic generation of the intended code from a natural language description. The promise of instruction tuning in this area has led numerous researchers to develop large-scale instruction-tuning datasets tailored for code generation. Below, we provide an overview of several notable datasets tailored for instruction tuning, with their respective statistics detailed in Table 2.

- **CodeAlpaca-20k [40]:** CodeAlpaca-20k is a collection of 20K instruction-following data generated using the data synthesis techniques termed Self-Instruct outlined in [231], with modifications for code generation, editing, and optimization tasks instead of general tasks.
- **CommitPackFT [164]:** CommitPackFT is a 2GB refined version of CommitPack. It is filtered to only include high-quality commit messages that resemble natural language instructions.
- **Evol-Instruct-Code-80k [195]:** Evol-Instruct-Code-80k is an open-source implementation of Evol-Instruct-Code described in the WizardCoder paper [154], which enhances the fine-tuning effect of pre-trained code large models by adding complex code instructions.
- **Magocoder-OSS-Instruct-75k [240]:** is a 75k synthetic data generated through OSS-Instruct with gpt-3.5-turbo-1106 and used to train both Magocoder and Magocoder-S series models.
- **Self-OSS-Instruct-SC2-Exec-Filter-50k [261]:** Self-OSS-Instruct-SC2-Exec-Filter-50k is generated by StarCoder2-15B using the OSS-Instruct [240] data synthesis approach. It was subsequently used to fine-tune StarCoder-15B without any human annotations or distilled data from huge and proprietary LLMs.

4.1.3 Benchmarks. To rigorously assess the efficacy of Large Language Models (LLMs) for code generation, the research community has introduced a variety of high-quality benchmarks in recent years. Building on the foundational work by [45], numerous variations of the HumanEval

dataset and additional benchmarks have emerged, aiming to evaluate a broader spectrum of code generation capabilities in LLMs. We roughly divide these benchmarks into six distinct categories based on their application contexts, including general-purpose, competitive programming, data science, multilingual, logical reasoning, and repository-level. The statistics for these benchmarks are presented in Table 3.

General

- HumanEval [45]: HumanEval comprises 164 manually scripted Python programming problems, each featuring a function signature, docstring, body, and multiple unit tests.
- HumanEval+ [145]: HumanEval+ extends the original HumanEval [45] benchmark by increasing the scale of the test cases by 80 times. As the test cases increase, HumanEval+ can catch significant amounts of previously undetected incorrect code synthesized by LLMs.
- HumanEvalPack [164]: expands HumanEval [45] by extending it to encompass three coding tasks across six programming languages, namely code synthesis, code repair, and code explanation.
- MBPP [16]: MBPP is a collection of approximately 974 Python programming problems, crowd-sourced and designed for entry-level programmers. Each problem comes with an English task description, a code solution, and three automated test cases.
- MBPP+ [145]: MBPP+ enhances MBPP [16] by eliminating ill-formed problems and rectifying problems with incorrect implementations. The test scale of MBPP+ is also expanded by 35 times for test augmentation.
- CoNaLa [255]: CoNaLa contains almost 597K data samples for evaluating Python code generation. The curated part of CoNaLa is crawled from Stack Overflow, automatically filtered, and then curated by annotators. The mined part of CoNaLa is automatically mined, with almost 600k examples.
- Spider [258]: Spider is large-scale complex text-to-SQL dataset covering 138 different domains. It has over 10K questions and 5.6K complex SQL queries on 200 databases. This dataset aims to test a model's ability to generalize to SQL queries, database schemas, and new domains.
- CONCODE [102]: CONCODE is a dataset with over 100K samples consisting of Java classes from public GitHub repositories. It provides near zero-shot conditions that can test the model's ability to generalize to unseen natural language tokens with unseen environments.
- ODEX [236]: ODEX is an open-domain dataset focused on the execution-based generation of Python code from natural language. It features 945 pairs of natural language queries and their corresponding Python code, all extracted from StackOverflow forums.
- CoderEval [257]: CoderEval is a pragmatic code generation benchmark that includes 230 Python and 230 Java code generation problems. It can be used to evaluate the model performance in generating pragmatic code beyond just generating standalone functions.
- ReCode [226]: ReCode serves as a comprehensive robustness evaluation benchmark. ReCode applies perturbations to docstrings, function and variable names, code syntax, and code format, thereby providing multifaceted assessments of a model's robustness performance.
- StudentEval [18]: StudentEval is a dataset of 1,749 prompts for 48 problems, authored by 80 students who have only completed a one-semester Python programming class. Unlike many other benchmarks, it has multiple prompts per problem and multiple attempts by the same participant, each problem is also accompanied by a set of instructor-written test cases.

Competitions

- APPS [85]: The APPS benchmark is composed of 10K Python problems, spanning three levels of difficulty: introductory, interview, and competition. Each entry in the dataset includes a

programming problem described in English, corresponding ground truth Python solutions, test cases defined by their inputs and outputs or function names if provided.

- CodeContests [136]: is a competitive programming dataset consisting of samples from various sources including Aizu, AtCoder, CodeChef, Codeforces, and HackerEarth. The dataset encompasses programming problems accompanied by test cases in the form of paired inputs and outputs, along with both correct and incorrect human solutions in multiple programming languages.

Data Science

- DSP [38]: DSP allows for model evaluation based on real data science pedagogical notebooks. It includes well-structured problems, along with unit tests to verify the correctness of solutions and a Docker environment for reproducible execution.
- DS-1000 [122]: DS-1000 has 1K science questions from seven Python libraries, namely NumPy, Pandas, TensorFlow, PyTorch, SciPy, Scikit-learn, and Matplotlib. The DS-1000 benchmark features: (1) realistic problems with diverse contexts (2) implementation of multi-criteria evaluation metrics, and (3) defense against memorization.
- ExeDS [97]: ExeDS is a data science code generation dataset specifically designed for execution evaluation. It contains 534 problems with execution outputs from Jupyter Notebooks, as well as 123K examples for training and validation.

Multilingual

- MBXP [15]: MBXP is a multilingual adaptation of the original MBPP [16] dataset. It is created using a framework that translates prompts and test cases from the original Python datasets into the corresponding data in the targeted programming language.
- Multilingual HumanEval [15]: Multilingual HumanEval is a dataset derived from HumanEval [45]. It is designed to assess the performance of models in a multilingual context. It helps uncover the generalization ability of the given model on languages that are out-of-domain.
- HumanEval-X [275]: HumanEval-X is developed for evaluating the multilingual ability of code generation models with 820 hand-writing data samples in C++, Java, JavaScript, and Go.
- MultiPL-E [36]: MultiPL-E is a dataset for evaluating LLMs for code generation across 18 programming languages. It adopts the HumanEval [45] and the MBPP [16] Python benchmarks and uses little compilers to translate them to other languages.
- xCodeEval [115]: xCodeEval is an executable multilingual multitask benchmark consisting of 25M examples covering 17 programming languages. Its tasks include code understanding, generation, translation, and retrieval.

Reasoning

- MathQA-X [15] MathQA-X is the multilingual version of MathQA [12]. It is generated by utilizing a conversion framework that converts samples from Python datasets into the target language.
- MathQA-Python [16] MathQA-Python is a Python version of the MathQA benchmark [12]. The benchmark, containing more than 23K problems, is designed to assess the capability of models to synthesize code from complex textual descriptions.
- GSM8K [53]: GSM8K is a dataset of 8.5K linguistically diverse grade school math problems. The dataset is crafted to facilitate the task of question answering on basic mathematical problems that requires multi-step reasoning.
- GSM-HARD [71]: GSM-HARD is a more challenging version of the GSM8K [53] dataset. It replaces the numbers in the GSM8K questions with larger, less common numbers, thereby increasing the complexity and difficulty level of the problems.

Table 3. The detailed statistics of commonly-used benchmarks used in evaluating large language models (LLMs) for code generation. The column labeled ‘#PL’ indicates the number of programming languages included in each dataset. For the sake of brevity, we list the programming languages (PLs) for benchmarks that support fewer than or include five PLs. For benchmarks with six or more PLs, we provide only a numerical count of the PLs supported.

Scenario	Benchmark	Size	#PL	Date	Link
General	HumanEval [45]	164	Python	2021-07	https://huggingface.co/datasets/openai_humaneval
	HumanEval+ [145]	164	Python	2023-05	https://huggingface.co/datasets/evalplus/humanevalplus
	HumanEvalPack [164]	164	6	2023-08	https://huggingface.co/datasets/bigcode/humanevalpack
	MBPP [16]	974	Python	2021-08	https://huggingface.co/datasets/mbpp
	MBPP+ [145]	378	Python	2023-05	https://huggingface.co/datasets/evalplus/mbppplus
	CoNaLa [255]	596.88K	Python	2018-05	https://huggingface.co/datasets/neulab/conala
	Spider [258]	8,034	SQL	2018-09	https://huggingface.co/datasets/xlangai/spider
	CONCODE [102]	104K	Java	2018-08	https://huggingface.co/datasets/AhmedSoliman/CONCOD
	ODEX [236]	945	Python	2022-12	https://huggingface.co/datasets/neulab/odex
	CoderEval [257]	460	Python, Java	2023-02	https://github.com/CoderEval/CoderEval
Competitions	ReCode [226]	1,138	Python	2022-12	https://github.com/amazon-science/recode
	StudentEval [18]	1,749	Python	2023-06	https://huggingface.co/datasets/wellesley-easel/StudentEval
Competitions	APPS [85]	10,000	Python	2021-05	https://huggingface.co/datasets/codeparrot/apps
	CodeContests [136]	13,610	C++, Python, Java	2022-02	https://huggingface.co/datasets/deepmind/code_contests
Data Science	DSP [38]	1,119	Python	2022-01	https://github.com/microsoft/DataScienceProblems
	DS-1000 [122]	1,000	Python	2022-11	https://huggingface.co/datasets/xlangai/DS-1000
	ExeDS [97]	534	Python	2022-11	https://github.com/Jun-jie-Huang/ExeDS
Multilingual	MBXP [15]	12.4K	13	2022-10	https://huggingface.co/datasets/mxeval/mbxp
	Multilingual HumanEval [15]	1.9K	12	2022-10	https://huggingface.co/datasets/mxeval/multi-humaneval
	HumanEval-X [275]	820	Python, C++, Java, JavaScript, Go	2023-03	https://huggingface.co/datasets/THUDM/humaneval-x
	MultiPL-E [36]	161	18	2022-08	https://huggingface.co/datasets/nuprl/MultiPL-E
	xCodeEval [115]	5.5M	11	2023-03	https://github.com/ntunlp/xCodeEval
Reasoning	MathQA-X [15]	5.6K	Python, Java, JavaScript	2022-10	https://huggingface.co/datasets/mxeval/mathqa-x
	MathQA-Python [16]	23,914	Python	2021-08	https://github.com/google-research/google-research
	GSM8K [53]	8.5K	Python	2021-10	https://huggingface.co/datasets/gsm8k
	GSM-HARD [71]	1.32K	Python	2022-11	https://huggingface.co/datasets/reasoning-machines/gsm-hard
Repository	RepoEval [266]	3,573	Python, Java	2023-03	https://paperswithcode.com/dataset/repoeval
	Stack-Repo [205]	200	Java	2023-06	https://huggingface.co/datasets/RepoFusion/Stack-Repo
	Repobench [150]	27k	Python, Java	2023-01	https://github.com/Leoty/repobench
	EvoCodeBench [130]	275	Python	2024-03	https://huggingface.co/datasets/LJ0815/EvoCodeBench
	SWE-bench [111]	2,294	Python	2023-10	https://huggingface.co/datasets/princeton-nlp/SWE-bench
	CrossCodeEval [63]	10K	Python, Java, TypeScript, C#	2023-10	https://github.com/amazon-science/cceval
	SketchEval [265]	20,355	Python	2024-03	https://github.com/nl2code/codes

Repository

- RepoEval [266]: RepoEval enables the evaluation of repository-level code completion. It can offer different levels of granularity and improved evaluation accuracy through the use of unit tests.
- Stack-Repo [205]: Stack-Repo is a dataset of 200 Java repositories from GitHub with near-duplicated files. These files are augmented with three types of repository contexts: prompt proposal contexts, BM25 Contexts (based on BM25 similarity scores), and RandomNN Contexts (obtained using the nearest neighbors in the representation space of an embedding model).
- Repobench [150]: Repobench is a benchmark specifically used for evaluating repository-level code auto-completion systems. Supporting both Python and Java, it consists of three interconnected evaluation tasks: RepoBench-R (Retrieval), RepoBench-C (Code Completion), and RepoBench-P (Pipeline).

- EvoCodeBench [130]: EvoCodeBench is an evolutionary code generation benchmark, constructed through a rigorous pipeline and aligned with real-world repositories. This benchmark also provides comprehensive annotations and robust evaluation metrics.
- SWE-bench [111]: SWE-bench is a dataset that tests a model's ability to automatically solve GitHub issues. The dataset has 2,294 Issue-Pull Request pairs from 12 popular Python repositories.
- CrossCodeEval [63]: CrossCodeEval is a diverse and multilingual scope completion dataset covering four languages: Python, Java, TypeScript, and C#. This benchmark tests the model's ability to understand in-depth cross-file information and accurately complete the code.
- SketchEval [265]: SketchEval is a repository-oriented benchmark that encompasses data from 19 repositories, each varying in complexity. In addition to the dataset, SketchEval introduces a metric, known as SketchBLEU, to measure the similarity between two repositories based on their structures and semantics.

4.2 Data Synthesis

Numerous studies have demonstrated that high-quality datasets are integral to enhancing the performance of large language models (LLMs) in various downstream tasks [31, 119, 159, 242, 248, 281]. For instance, the LIMA model, a 65B parameter LLaMa language model fine-tuned with a standard supervised loss on a mere 1,000 meticulously curated prompts and responses, achieved performance on par with, or even superior to, GPT-4 in 43% of evaluated cases. This figure rose to 58% when compared to Bard and 65% against DaVinci003, all without the use of reinforcement learning or human preference modeling [281]. The QuRating initiative strategically selects pre-training data embodying four key textual qualities — writing style, facts & trivia, required expertise, and educational value — that resonate with human intuition. Training a 1.3B parameter model on such data resulted in reduced perplexity and stronger in-context learning compared to baseline models [242].

Despite these advancements, acquiring quality data remains a significant challenge due to issues such as data scarcity, privacy concerns, and prohibitive costs [148, 231]. Human-generated data is often labor-intensive and expensive to produce, and it may lack the necessary scope and detail to navigate complex, rare, or ambiguous scenarios. As a resolution to these challenges, synthetic data has emerged as a viable alternative. By generating artificial datasets that replicate the intricacies of real-world information, models such as GPT-3.5-turbo [171] and GPT-4 [5] have enabled the creation of rich datasets without the need for human annotation [82, 124, 148, 231]. This approach is particularly beneficial in enhancing the instruction-following capabilities of LLMs, with a focus on generating synthetic instruction-based data.

A notable example of this approach is the Self-Instruct [231] framework, which employs an off-the-shelf language model to generate a suite of instructions, inputs, and outputs. This data is then refined by removing invalid or redundant entries before being used to fine-tune the model. The empirical evidence supports the efficacy of this synthetic data generation methodology. Building upon this concept, the Alpaca [213] model, fine-tuned on 52k pieces of instruction-following data from a 7B parameter LLaMa [217] model, exhibits performance comparable to the text-davinci-003 model. WizardLM [250] introduced the Evol-Instruct technique, which incrementally transforms simple instructions into more complex variants. The fine-tuned LLaMa model using this technique has shown promising results in comparison to established proprietary LLMs such as ChatGPT [171] and GPT-4 [5], to some extent. Moreover, Microsoft has contributed to this field with their Phi series of models, predominantly trained on synthetic high-quality data, which includes Phi-1 (1.3B) [75] for Python coding, Phi-1.5 (1.3B) [135] for common sense reasoning and language understanding, Phi-2 (2.7B) [161] for advanced reasoning and language understanding, and Phi-3 (3.8B) [4] for

general purposes. These models have consistently outperformed larger counterparts across various benchmarks, demonstrating the efficacy of synthetic data in model training.

Drawing on the successes of data synthesis for general-purpose Large Language Models (LLMs), researchers have expanded the application of synthetic data to the realm of code generation. The Code Alpaca model, as described in [40], has been fine-tuned on a 7B and 13B LLaMA model using a dataset of 20k instruction-following examples for code generation. This dataset was created by text-davinci-003¹⁰ and employed the Self-Instruct technique [231]. Building on this, the WizardCoder 15B [154] utilizes the Evol-Instruct technique to create an enhanced dataset of 78k evolved code instruction examples. This dataset originates from the initial 20k instruction-following dataset used by Code Alpaca [40], which was also generated by text-davinci-003. The WizardCoder model, fine-tuned on the StarCoder [132] base model, achieved a 57.3% pass@1 on the HumanEval benchmarks. This performance not only surpasses all other open-source Code LLMs by a significant margin but also outperforms leading closed LLMs such as Anthropic’s Claude and Google’s Bard. In a similar vein, Magicoder [240] introduces a novel data synthesis approach termed OSS-INSTRUCT which enlightens LLMs with open-source code snippets to generate high-quality instruction data for coding tasks. It aims to address the inherent biases often present in synthetic data produced by LLMs. Building upon CodeLlama [196], the MagicoderS-CL-7B model — fine-tuned with 75k synthetic instruction data using the OSS-INSTRUCT technique and with gpt-3.5-turbo-1106 as the data generator — has outperformed the prominent ChatGPT on the HumanEval Plus benchmark, achieving pass@1 of 66.5% versus 65.9%. In a noteworthy development, Microsoft has introduced the phi-1 model [75], a more compact LLM of only 1.3B parameters. Despite its smaller size, phi-1 has been trained on high-quality textbook data sourced from the web (comprising 6 billion tokens) and supplemented with synthetic textbooks and exercises generated with GPT-3.5 (1 billion tokens). It has achieved pass@1 of 50.6% on HumanEval and 55.5% on MBPP, setting a new state-of-the-art for Python coding performance among existing small language models (SLMs). The latest contribution to this field is from the BigCode team, which has presented StarCoder2-15B-instruct [261], the first entirely self-aligned code LLM trained with a transparent and permissive pipeline. This model aligns closely with the OSS-INSTRUCT principles established by Magicoder, generating instructions based on seed functions filtered from the Stack v1 dataset [118] and producing responses through self-validation. Unlike Magicoder, StarCoder2-15B-instruct employs its base model, StarCoder2-15B, as the data generator, thus avoiding reliance on large and proprietary LLMs like GPT-3.5-turbo [171].

While synthetic data has demonstrated its potential across both small- and large-scale LMs for a variety of general and specialized tasks, including code generation, it also poses several challenges that must be addressed. These challenges include a lack of data diversity [242], the need to ensure the factuality and fidelity of the information [221, 243], and the potential to amplify existing biases or introduce new ones [23, 80].

4.3 Pre-Training

4.3.1 Model Architectures. Since the inception of the Transformer architecture for machine translation [222], it has become the de facto backbone for a multitude of large language models (LLMs) that address a wide range of downstream tasks. The Transformer and its derivatives owe their prominence to their exceptional ability to parallelize computation and their powerful representational capacities [256, 273]. Through innovative scaling techniques, such as Mixture-of-Experts (MoE) [33, 200] and Depth-Up-Scaling (DUS) [117], the capacity of Transformer-based LLMs has expanded to encompass hundreds of billions or even trillions of parameters. These scaled-up models

¹⁰<https://platform.openai.com>

Table 4. The overview of large language models (LLMs) with encoder-decoder architectures for code generation.

Architecture	Model	Institution	Size	Vocabulary	Context Window	Date	Open Source
Encoder-Decoder	PyMT5[52]	Microsoft	374M	50K	1024+1024	2020-10	
	PLBART[6]	UCLA	140M	50K	1024+1024	2021-03	✓
	CodeT5 [234]	Salesforce	60M, 220M, 770M	32K	512+256	2021-09	✓
	JuPyT5[38]	Microsoft	350M	50K	1024+1024	2022-01	
	AlphaCode[136]	DeepMind	284M, 1.1B, 2.8B, 8.7B, 41.1B	8K	1536+768	2022-02	
	CodeRL[125]	Salesforce	770M	32K	512+256	2022-06	✓
	ERNIE-Code[37]	Baidu	560M	250K	1024+1024	2022-12	✓
	PPOCoder[204]	Virginia Tech	770M	32K	512+256	2023-01	
	CodeT5+ [232]	Salesforce	220M, 770M, 2B, 6B, 16B	50K	2048+2048	2023-05	✓
	CodeFusion[207]	Microsoft	75M	32k	128+128	2023-10	✓
	AST-T5[73]	UC Berkeley	226M	32k	512+200/300	2024-01	✓

have exhibited a range of emergent abilities [87, 114, 238], such as instruction following [173], in-context learning [65], and step-by-step reasoning [95, 239] that were previously unforeseen.

In the domain of code generation using LLMs, the architecture of contemporary models generally falls into one of two categories: encoder-decoder models, such as CodeT5 [234], CodeT5+ [232], and CodeRL [125]; or decoder-only models, such as Codex [45], StarCoder [132], Code Llama [196], and CodeGemma [54]. These architectures are depicted in Figure 2(b) and (c), respectively. For a comprehensive overview, Table 4 details the encoder-decoder architectures, while Table 5 focuses on the decoder-only models utilized in code generation.

4.3.2 Pre-training Tasks. In the initial phase, language models for code generation are typically trained from scratch using datasets consisting of manually annotated pairs of natural language descriptions and corresponding code snippets, within a supervised learning framework. However, manual annotation is not only laborious and time-consuming, but the efficacy of the resulting models is also constrained by both the volume and the quality of the available annotated data. This limitation is especially pronounced in the context of low-resource programming languages, such as Swahili and Yoruba, where annotated examples are scarce [35, 43]. In light of these challenges, there has been a shift towards an alternative training strategy that involves pre-training models on extensive and unlabelled code corpora. This method is aimed at imbuing the models with a broad understanding of programming knowledge, encompassing elements like identifiers, code structure, and underlying semantics [45]. In this regard, two pre-training tasks have gained prominence for their effectiveness, namely Causal Language Modeling (CLM), also known as unidirectional language modeling or next-token prediction, and Denoising Autoencoding (DAE). The CLM task can be applied to both decoder-only and encoder-decoder model architectures, while DAE tasks are specifically designed for encoder-decoder frameworks. It should also be noted that there is a variety of additional auxiliary pre-training tasks that can further enhance model performance. These include Masked Identifier Prediction, Identifier Tagging, Bimodal Dual Generation [234], Text-Code Matching, and Text-Code Contrastive Learning [232]. These tasks contribute to a more nuanced and comprehensive pre-training process, equipping the models with the capabilities necessary to handle a wide range of code generation scenarios.

Causal Language Modeling. In decoder-only LLMs, given a sequence of tokens $\mathbf{x} = \{x_1, \dots, x_n\}$, the CLM task refers to autoregressively predict the target tokens x_i based on the preceding tokens $x_{<i}$ in a sequence. The causal language modeling objective for training decoder LLMs is to minimize

Table 5. The overview of large language models (LLMs) with decoder-only architectures for code generation.

Architecture	Model	Institution	Size	Vocabulary	Context Window	Date	Open Source
Decoder-Only	GPT-C [210]	Microsoft	366M	60K	1024	2020-05	
	CodeGPT [153]	Microsoft	124M	50K	1024	2021-02	✓
	GPT-Neo[29]	EleutherAI	125M, 1.3B, 2.7B	50k	2048	2021-03	✓
	GPT-J [223]	EleutherAI	6B	50k	2048	2021-05	✓
	Codex [45]	OpenAI	12M, 25M, 42M, 85M, 300M, 679M, 2.5B, 12B	-	4096	2021-07	
	CodeParrot [219]	Hugging Face	110M, 1.5B	33k	1024	2021-11	✓
	PolyCoder [251]	CMU	160M, 400M, 2.7B	50k	2048	2022-02	✓
	CodeGen [169]	Salesforce	350M, 2.7B, 6.1B, 16.1B	51k	2048	2022-03	✓
	GPT-NeoX [28]	EleutherAI	20B	50k	2048	2022-04	✓
	PaLM-Coder [49]	Google	8B, 62B, 540B	256k	2048	2022-04	
	InCoder [69]	Meta	1.3B, 6.7B	50k	2049	2022-04	✓
	PanGu-Coder [50]	Huawei	317M, 2.6B	42k	1024	2022-07	
	PyCodeGPT [263]	Microsoft	110M	32k	1024	2022-06	✓
	CodeGeeX [275]	Tsinghua	13B	52k	2048	2022-09	✓
	BLOOM [126]	BigScience	176B	251k	-	2022-11	✓
	ChatGPT [171]	OpenAI	-	-	16k	2022-11	✓
	SantaCoder [8]	Hugging Face	1.1B	49k	2048	2022-12	✓
	LLaMA [217]	Meta	6.7B, 13.0B, 32.5B, 65.2B	32K	2048	2023-02	✓
	GPT-4 [5]	OpenAI	-	-	32K	2023-03	
	CodeGen2 [168]	Salesforce	1B, 3.7B, 7B, 16B	51k	2048	2023-05	✓
	replit-code [193]	replit	3B	33k	2048	2023-05	✓
	StarCoder [132]	Hugging Face	15.5B	49k	8192	2023-05	✓
	WizardCoder [154]	Microsoft	15B, 34B	49k	8192	2023-06	✓
	phi-1 [75]	Microsoft	1.3B	51k	2048	2023-06	✓
	CodeGeeX2 [275]	Tsinghua	6B	65k	8192	2023-07	✓
	PanGu-Coder2 [201]	Huawei	15B	42k	1024	2023-07	
	Llama 2 [218]	Meta	7B, 13B, 70B	32K	4096	2023-07	✓
	OctoCoder [164]	Hugging Face	15.5B	49k	8192	2023-08	✓
	Code Llama [196]	Meta	7B, 13B, 34B	32k	16384	2023-08	✓
	CodeFuse [143]	Ant Group	350M, 13B, 34B	101k	4096	2023-09	✓
	phi-1.5 [135]	Microsoft	1.3B	51k	2048	2023-09	✓
	CodeShell [247]	Peking University	7B	70k	8192	2023-10	✓
	Magicoder [240]	UIUC	7B	32k	16384	2023-12	✓
	AlphaCode 2 [10]	Google DeepMind	-	-	-	2023-12	
	StableCode [182]	StabilityAI	3B	50k	16384	2024-01	✓
	WaveCoder [259]	Microsoft	6.7B	32k	16384	2023-12	✓
	phi-2 [161]	Microsoft	2.7B	51k	2048	2023-12	✓
	DeepSeek-Coder [79]	DeepSeek	1.3B, 6.7B, 33B	32k	16384	2023-11	✓
	StarCoder 2 [151]	Hugging Face	15B	49k	16384	2024-02	✓
	Claude 3 [13]	Anthropic	-	-	200K	2024-03	
	CodeGemma [54]	Google	2B, 7B	25.6k	8192	2024-04	✓
	Code-Qwen [215]	Qwen Group	7B	92K	65536	2024-04	✓
	Llama3 [160]	Meta	8B, 70B	128K	8192	2024-04	✓
	StarCoder2-Instruct [261]	Hugging Face	15.5B	49K	16384	2024-04	✓

the following likelihood:

$$\mathcal{L}_{CLM}^{Decoder-only}(\mathbf{x}) = -\log\left(\prod_{i=1}^n P_{\theta}(x_i | \mathbf{x}_{<i})\right) = \sum_{i=1}^n -\log P_{\theta}(x_i | \mathbf{x}_{<i}) \quad (15)$$

where $\mathbf{x}_{<i}$ represents the sequence of preceding tokens $\{x_1, \dots, x_{i-1}\}$ before x_i in the input, θ denotes the model parameters. The conditional probability $P_{\theta}(x_i|\mathbf{x}_{<i})$ is modeled by adding a

causal attention mask to the multi-head self-attention matrix of each Transformer block. To be specific, causal attention masking is implemented by setting the lower triangular part of the matrix to 0 and the remaining elements to $-\infty$, ensuring that each token x_i attends only to its predecessors and itself. On the contrary, in encoder-decoder LLMs, a pivot token x_k is randomly selected in a sequence of tokens and then regarding the context before it as the source sequence $\mathbf{x}_{in} = \{x_1, \dots, x_k\}$ of the encoder and the sequence after it as the target output $\mathbf{x}_{out} = \{x_{k+1}, \dots, x_n\}$ of decoder. Formally, the causal language modeling objective for training encoder-decoder LLMs is to minimize loss function as follows:

$$\mathcal{L}_{CLM}^{Encoder-Decoder}(\mathbf{x}) = -\log\left(\prod_{i=k+1}^n P_{\theta}(x_i \mid \mathbf{x}_{\leq k}, \mathbf{x}_{< i})\right) = \sum_{i=k+1}^n -\log P_{\theta}(x_i \mid \mathbf{x}_{\leq k}, \mathbf{x}_{< i}) \quad (16)$$

where $\mathbf{x}_{\leq k}$ is the source sequence input and $\mathbf{x}_{< i}$ denotes the target sequence autoregressively generated so far. During the inference phase, pre-trained LLMs that have been trained on large-scale code corpus can generate code in a zero-shot manner without the need for fine-tuning. This is achieved through the technique of prompt engineering, which guides the model to produce the desired output¹¹ [31, 186]. Additionally, recent studies have explored the use of few-shot learning, also referred to as in-context learning, to enhance model performance further [131, 178].

Denoising Autoencoding. In addition to causal language modeling (CLM), the denoising autoencoding (DAE) task has been extensively applied in pre-training encoder-decoder architectures for code generation, such as PLBART [6], CodeT5 [234], and its enhanced successor, CodeT5+ [232]. Following T5 [189] and CodeT5 [234], the DAE refers to initially perturbing the source sequence by introducing randomly masked spans of varying lengths. This corrupted sequence serves as the input for the encoder. Subsequently, the decoder employs an autoregressive strategy to reconstruct the masked spans, integrating sentinel tokens to facilitate the generation process. This method has proven effective in improving the model's ability to generate semantically and syntactically accurate code by learning robust contextual representations [232, 234]. Formally, the denoising autoencoding objective for training encoder-decoder LLMs is to minimize the following likelihood:

$$\mathcal{L}_{DAE}^{Encoder-Decoder}(\mathbf{x}) = \sum_{i=1}^k -\log P_{\theta}(\mathbf{x}_i^{masked_spans} \mid \mathbf{x}^{\setminus masked_spans}, \mathbf{x}_{< i}^{masked_spans}) \quad (17)$$

where θ denotes the model parameters, $\mathbf{x}^{\setminus masked_spans}$ is the noisy input with masked spans, $\mathbf{x}^{masked_spans}$ is the masked spans to predict from the decoder with k denoting the number of tokens in $\mathbf{x}^{masked_spans}$, and $\mathbf{x}_{< i}^{masked_spans}$ is the span sequence autoregressively generated so far. Compared with CLM, the DAE task presents a more challenging scenario, as it necessitates a deeper understanding and capture of the intrinsic semantic relationships among token sequences by LLMs [189].

4.4 Instruction Tuning

After pre-training Large Language Models (LLM) on large-scale datasets, the next phase typically involves augmenting the model's ability to process and follow instructions, known as instruction tuning. Instruction tuning generally refers to the supervised fine-tuning of pre-trained LLMs using datasets comprised of structured examples framed as natural language instructions [103, 173, 237, 268]. Two exemplars of instruction data sampled from Code Alpaca [40] are demonstrated in Figure 5. It capitalizes on the heterogeneity of instruction types, positioning instruction tuning as a form of multi-task prompted training that significantly enhances the model's generalization to unseen tasks [51, 173, 197, 237].

¹¹For more information on prompt engineering, visit <https://www.promptingguide.ai>

<p>Instruction:</p> <p>Write code to create a list of all prime numbers between 2 and 100.</p> <p>Input:</p> <p>N/A</p> <p>Output:</p> <pre>def find_primes(n): prime_list = [2] for number in range(2, n + 1): is_prime = True for k in range(2, number): if number % k == 0: is_prime = False if is_prime: prime_list.append(number) return prime_list</pre>	<p>Instruction:</p> <p>Generate a snippet of code to extract all the URLs from the given string.</p> <p>Input:</p> <p>This string contains some urls such as https://www.google.com and https://www.facebook.com.</p> <p>Output:</p> <pre>import re string = "This string contains some urls such as https://www.google.com and https://www.facebook.com." urls = re.findall('http[s]?://(?:[a-zA-Z] [0-9] [\$-_@.&+] [*\\(\\)]) (?:%[0-9a-fA-F][0-9a-fA-F])+', string) print(urls)</pre>
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Fig. 5. Two exemplars of instruction data sampled from Code Alpaca [40] used to instruction-tune pre-trained code LLM to enhance their alignment with natural language instructions. The instruction corpus encompasses a variety of tasks, each accompanied by distinct instructions, such as prime numbers generation and URLs extraction.

In the realm of code generation, natural language descriptions serve as the instructions guiding the model to generate corresponding code snippets. Consequently, a line of research on instruction tuning LLMs for code generation has garnered substantial interest across academia and industry. To perform instruction tuning, instruction data are typically compiled from source code with permissive licenses [99, 118, 151] (refer to Section 4.1.2) or are constructed from synthetic code data [154, 240, 261] (refer to Section 4.2). These datasets are then utilized to fine-tune LLMs through a supervised learning paradigm. However, the substantial computational resources required for full parameter fine-tuning (FFT) LLM pose a notable challenge, particularly in scenarios with constrained resources [62, 138]. To mitigate this issue, parameter-efficient fine-tuning (PEFT) has emerged as a compelling alternative strategy, gaining increasing attention for its potential to reduce resource consumption [62]. In the following subsection, we categorize existing works based on their instruction-tuning strategies to provide a comprehensive and systematic review.

4.4.1 Full Parameter Fine-tuning. Full parameter fine-tuning (FFT) involves updating all parameters within a pre-trained model, as shown in Figure 6(a). This approach is often preferred when ample computational resources and substantial training data are available, as it typically leads to better performance. [234] introduces an encoder-decoder pre-trained language model for code generation, named CodeT5+. They instruction-tune this model on a dataset comprising 20k instruction samples from Code Alpaca [40], resulting in an instruction-following model called InstructCodeT5+, which exhibited improved capabilities in code generation. [154] leverages the Evol-Instruct data synthesis technique from WizardLM [250] to evolve 20K code Alpaca [40] instruction samples into a 78K code instruction dataset. This enriched dataset is then used to fine-tune the StarCoder base model,

resulting in WizardCoder, which showcases notable advancements in code generation. In a similar vein, inspired by the successes of WizardCoder [154] and RRHF [260], Pangu-Coder 2 [201] applies the Evol-Instruct method to generate 68k high-quality instruction samples from the initial 20k Code Alpaca [40] instruction samples. Additionally, they introduce a novel reinforcement learning via Rank Responses to align Test & Teacher Feedback (RRTF), which further enhances the performance of Pangu-Coder 2 in code generation. Diverging from synthetic instruction data generation methods, OctoPack [164] utilizes real-world data by curating CommitPack from the natural structure of Git commits, which inherently pair code changes with human-written instructions. This dataset, consisting of 4 terabytes of Git commits across 350 programming languages, is employed to fine-tune StarCoder [132] and CodeGeeX2 [275], leading to the instruction-following code models of OctoCoder and OctoGeeX for code generation, respectively. The most recent innovation comes from Magicoder [240], who proposes OSS-INSTRUCT, a novel data synthesis method that leverages open-source code snippets to generate high-quality instruction data for code generation. This approach seeks to reduce the bias often present in synthetic data generated by LLM. In line with OSS-INSTRUCT, the BigCode team introduces StarCoder2-15B-instruct [261], which they claim to be the first entirely self-aligned Large Language Model (LLM) for code generation, trained with a fully permissive and transparent pipeline. Moreover, [54] harnesses open-source mathematics datasets, such as MATH [85] and GSM8k [53], along with synthetically generated code following the OSS-INSTRUCT [240] paradigm, to instruction-tune CodeGemma 7B, yielding exceptional results in mathematical reasoning and code generation tasks.

4.4.2 Parameter-Efficient Fine-tuning. To mitigate the extensive computational and resource demands inherent in fine-tuning large language models (LLMs), the concept of parameter-efficient fine-tuning (PEFT) has emerged to focus on updating a minimal subset of parameters, which may either be a selection of the model's parameters or an array of additional parameters specifically introduced for the tuning process [62, 138]. The categorization of these methods is depicted in Figure 6(b), (c), and (d). A plethora of innovative PEFT approaches have been developed, among which BitFit [262], Adapter [92], Prompt tuning [128], Prefix-tuning [134], LoRA [93], IA³ [144], QLoRA [60], and AdaLoRA [267] are particularly noteworthy. A seminal study in this field, LoRA [93], proposes a parameter update mechanism for a pre-trained weight matrix — such as those found in the key or value projection matrices of a Transformer block's multi-head self-attention layer — by factorizing the update into two low-rank matrices. Crucially, all original model parameters remain frozen, with only the pair of low-rank matrices being trainable. After fine-tuning, the product of these low-rank matrices can be seamlessly incorporated into the existing weight matrix through an element-wise addition. This process can be formally described as:

$$(\mathbf{W}_0 + \Delta\mathbf{W})x = \mathbf{W}_0x + \Delta\mathbf{W}x = \mathbf{W}_0^{\text{frozen}}x + \underbrace{\frac{\alpha}{r}\mathbf{B}_{\text{up}}^{\text{trainable}}\mathbf{A}_{\text{down}}^{\text{trainable}}}_{\Delta\mathbf{W}}x \quad (18)$$

where $\mathbf{W}_0 \in \mathbb{R}^{d \times k}$ denotes a pre-trained weight matrix, $\mathbf{B}_{\text{up}}^{\text{trainable}} \in \mathbb{R}^{d \times r}$ and $\mathbf{A}_{\text{down}}^{\text{trainable}} \in \mathbb{R}^{r \times k}$ are two trainable low-rank matrixes and initialized by a zero matrix and a random Gaussian distribution $\mathcal{N}(0, \sigma^2)$ respectively, to ensure $\Delta\mathbf{W} = 0$ at the beginning of training. The rank $r \ll \min(d, k)$, the $\frac{\alpha}{r}$ is a scaling coefficient to balance the importance of the LoRA module, like a learning rate.

Despite the advancements in PEFT methods, their application in code generation remains limited. For instance, [108] pioneered the use of parameter-efficient instruction-tuning on a Llama 2 [218] model with a single RTX 3090 GPU, leading to the development of a multilingual code generation model called CodeUp. More recently, ASTRAIOS [285] conducted a thorough empirical examination of parameter-efficient instruction tuning for code comprehension and generation tasks. This study

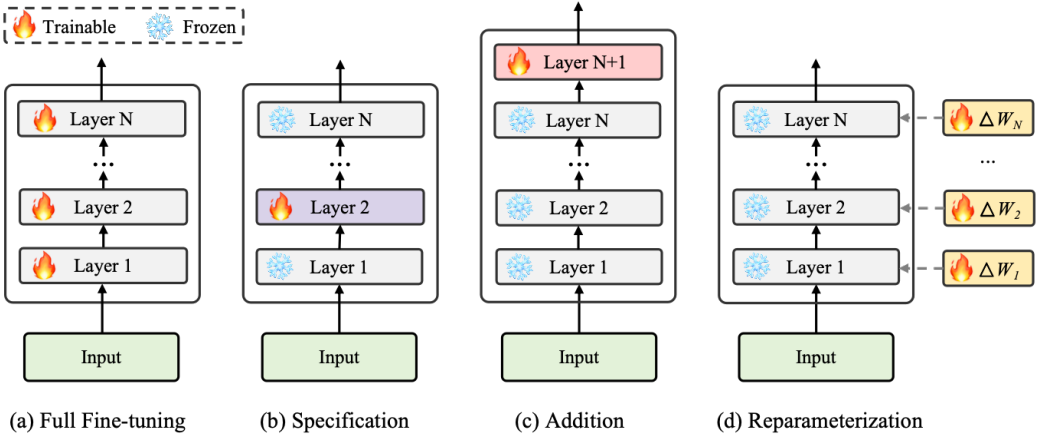


Fig. 6. An illustration of full parameter fine-tuning (FFT) and parameter-efficient fine-tuning (PEFT) methods. (a) refers to the Full Fine-tuning method, which updates all parameters of the base model during fine-tuning. (b) stands for the Specification-based PEFT method that conditionally fine-tunes a small subset of the model parameters while freezing the rest of the model, e.g., BitFit [262]. (c) represents the Addition-based PEFT method that fine-tunes the incremental parameters introduced into the base model or input, e.g., Adapter [92], Prefix-tuning [134], and Prompt-tuning [128]. (d) symbolizes the Reparameterization-based method which reparameterizes existing model parameters by low-rank transformation, e.g., LoRA [93], QLoRA [60], and AdaLoRA [267].

yielded several perceptive observations and conclusions, contributing valuable insights to the domain.

4.5 Reinforcement Learning with Feedback

Large language models (LLMs) have exhibited remarkable instruction-following capabilities through instruction tuning. However, they often produce outputs that are unexpected, toxic, biased, or hallucinated outputs that do not align with users' intentions or preferences [107, 173, 235]. Consequently, aligning LLMs with human preference has emerged as a pivotal area of research. A notable work is InstructGPT [173], which further fine-tunes an instruction-tuned model utilizing reinforcement learning with human feedback (RLHF) on a dataset where labelers have ranked model outputs in order of quality, from best to worst. This method has been instrumental in the development of advanced conversational language models, such as ChatGPT [171] and Bard [157]. Despite its success, acquiring high-quality human preference ranking data is a resource-intensive process [127]. To address this, Reinforcement Learning from AI Feedback (RLAIF) [20, 127] has been proposed to leverage powerful off-the-shelf LLMs (e.g., ChatGPT [171] and GPT-4 [5]) to simulate human annotators by generating preference data.

Building on RLHF's success, researchers have explored reinforcement learning with feedback to enhance code generation in LLMs. Unlike RLHF, which relies on human feedback, this approach employs compilers or interpreters to automatically provide feedback on code samples through code execution on unit test cases, catalyzing the advancement of this research domain. CodeRL [125] introduced an actor-critic reinforcement learning framework for code generation. In this setup, the language model serves as the actor-network, while a token-level functional correctness reward predictor acts as the critic. Generated code is assessed through unit test signals from a compiler, which can indicate compiler errors, runtime errors, unit test failures, or passes. CompCoder [229]

enhances code compilability by employing compiler feedback, including language model fine-tuning, compilability reinforcement, and compilability discrimination strategies. Subsequently, PPOCoder [204] integrates pre-trained code model CodeT5 [234] with Proximal Policy Optimization (PPO) [198]. This integration not only utilizes execution (*i.e.*, compilers or interpreters) feedback to assess syntactic and functional correctness but also incorporates a reward function that evaluates the syntactic and semantic congruence between abstract syntax tree (AST) sub-trees and data flow graph (DFG) edges in the generated code against the ground truth. Additionally, the framework applies a KL-divergence penalty to maintain fidelity between the actively learned policy and the referenced pre-trained model, enhancing the optimization process. More recently, RLTF [146] has proposed an online reinforcement learning framework that provides fine-grained feedback based on compiler error information and location, along with adaptive feedback that considers the ratio of passed test cases.

Despite these successes, reinforcement learning algorithms face inherent limitations such as inefficiency, instability, extensive resource requirements, and complex hyperparameter tuning, which can impede the performance and scalability of LLMs. To overcome these challenges, recent studies have introduced various variants of RL methods that do not rely on PPO, including DPO [188], RRHF [260], and sDPO [116]. In essence, these methods aim to maximize the likelihood between the logarithm of conditional probabilities of preferred and rejected responses, which may be produced by LLMs with varying capabilities. Inspired by RRHF [260], PanGu-Coder 2 [201] leverages a novel framework, Reinforcement Learning via Rank Responses to align Test & Teacher Feedback (RRTF), significantly enhancing code generation capabilities, as evidenced by pass@1 of 62.20% on the HumanEval benchmark.

Taking a step forward, the integration of more non-differentiable code features, such as coding style [41, 158] and readability [32], into the reinforcement learning feedback for LLM-based code generation, presents an exciting avenue for future research.

4.6 Prompting Engineering

Large-scale language models (LLMs) such as GPT-3 and its successors have been trained on large-scale data corpora, endowing them with substantial world knowledge [31, 173, 237]. Despite this, crafting an effective prompt to harness the full potential of LLMs remains a long-standing challenge [147]. Recent advancements in prompting engineering have expanded the capabilities of LLMs, enabling more sophisticated task completion and enhancing both reliability and performance. Notable techniques include Chain-of-Thought (CoT) [239], Self-Consistency [230], Tree-of-Thought (ToT) [253], Reasoning via Planning (RAP) [83], ReAct [254], Self-Refine [156], Reflexion [202], and LATs [280].

Prompting engineering is particularly advantageous as it bypasses the need for additional training and can significantly elevate performance. Consequently, numerous studies have leveraged this technique for iterative and self-improving (refining) code generation within proprietary LLMs such as ChatGPT and GPT-4. Figure 7 illustrates the general pipeline for self-improving code generation with LLMs. For instance, Self-Debugging [47] involves prompting an LLM to iteratively refine a predicted program by utilizing feedback composed of code explanations combined with execution results, which assists in identifying and rectifying errors. When unit tests are unavailable, this feedback can rely solely on code explanations. In parallel, SelfEvolve [110] employs a two-stage process where LLMs first generate domain-specific knowledge for a problem, followed by a trial code. This code is then iteratively refined through interactive prompting and execution feedback. An empirical investigation by [170] provides a comprehensive analysis of the self-repairing capabilities for code generation in models like Code Llama, GPT-3.5, and GPT-4, using problem sets from HumanEval and APPS. This study yields a series of insightful observations and findings, shedding

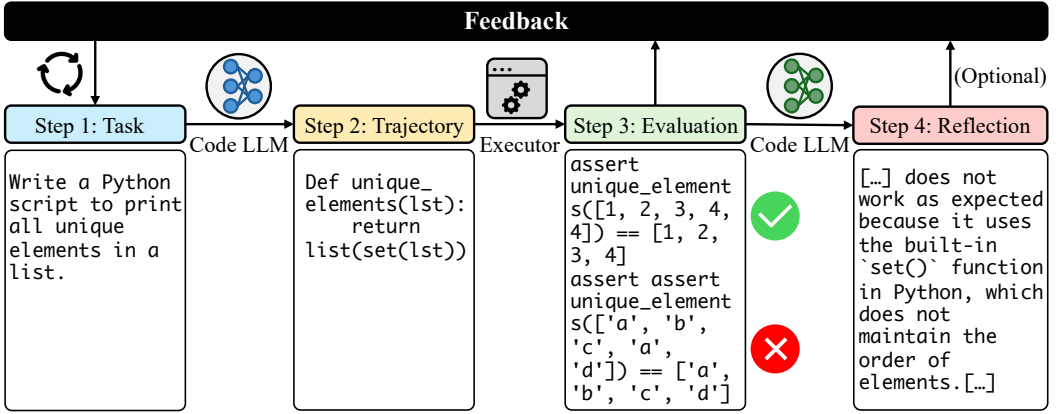


Fig. 7. An illustration of the self-improving code generation pipeline using prompts for large language models (LLMs). This process incorporates iterative self-refinement by integrating execution outcomes and includes an optional self-reflection mechanism to enhance generation quality.

light on the self-refinement effectiveness of these LLMs. Moreover, Reflexion [202] introduces a general approach for code generation wherein LLM-powered agents engage in verbal self-reflection on task feedback signals, storing these reflections in an episodic memory buffer to inform and improve decision-making in subsequent interactions. LATS [280] adopts a novel strategy, utilizing LLMs as agents, value functions, and optimizers. It enhances decision-making by meticulously constructing trajectories through Monte Carlo Tree Search (MCTS) algorithms, integrating external feedback, and learning from experience. This approach has demonstrated remarkable results in code generation, achieving a pass@1 of 94.4% on the HumanEval benchmark with GPT-4.

Distinct from the aforementioned methods, CodeT [42] and LEVER [166] prompt LLMs to generate numerous code samples, which are then re-ranked based on execution outcomes to select the optimal solution. Notably, these approaches do not incorporate a self-refinement step to further improve code generation.

4.7 Repository Level & Long Context

In contemporary software engineering practices, modifications to a code repository are widespread and encompass a range of activities, including package migration, temporary code edits, and the resolution of GitHub issues. While large language models (LLMs) showcase impressive prowess in function-level code generation, they often falter when grappling with the broader context inherent to a repository, such as import dependencies, parent classes, and files bearing similar names. These deficiencies result in suboptimal performance in repository-level code generation, as identified in recent studies [205, 206]. The challenges faced by LLMs in this domain are primarily due to the following factors:

- Code repositories typically contain intricate interdependencies scattered across various files, including shared utilities, configurations, and cross-API invocations, which arise from modular design principles [21, 266].
- Repositories are characterized by their unique structures, naming conventions, and coding styles, which are essential for maintaining clarity and facilitating ongoing maintenance [41].
- The vast context of an entire repository often exceeds the context length limitations of LLMs, thus hindering their ability to integrate comprehensive contextual information [21].

- LLMs may not have been adequately trained on extensive sets of repository data, such as proprietary software or projects that are still in development [205].

Given that the scope of a typical software repository encompasses hundreds of thousands of tokens, it is imperative to enhance the capacity of LLMs to handle extensive contexts when they are employed for repository-level code generation. Fortunately, recent advancements in positional encoding techniques, such as ALiBi [183] and RoPE [209], have shown promise in improving the Transformer’s ability to generalize from shorter training sequences to longer inference sequences [272]. This progress addresses the third challenge mentioned above to a certain degree, thereby enabling better contextualization of coding activities within full repositories.

To further refine LLMs for repository-level code completion, several innovative approaches have been introduced. RepoCoder [266] leverages a similarity-based retrieval system within an iterative retrieval-generation paradigm to enrich the context and enhance code completion quality. In a similar vein, CoCoMIC [64] employs a cross-file context finder named CCFINDER to pinpoint and retrieve the most relevant cross-file contexts within a repository. RepoHyper [181] introduces a semantic graph structure, termed RSG, to encapsulate the expansive context of code repositories and uses an “Expand and Refine” retrieval method to obtain relevant code snippets. Moreover, a framework known as RLPG [206] has been proposed to generate repository-level prompts that integrate the repository’s structure with the relevant context across all files. However, the constant reliance on retrieval mechanisms has raised concerns regarding efficiency and robustness, as some retrieved contexts may prove unhelpful or harmful. In response, Repoformer [244] introduces a selective Retrieval-Augmented Generation (RAG) framework that judiciously bypasses retrieval when it is deemed redundant. This approach incorporates a self-supervised learning strategy that equips a code LLM with the ability to perform a self-assessment on the utility of retrieval for enhancing the quality of its output, thereby effectively utilizing potentially noisy retrieved contexts.

Additionally, RepoFusion [205] has been developed to train models to combine multiple relevant contexts from a repository, aiming to produce more precise and context-aware code completions. In a novel approach, Microsoft’s CodePlan [21] frames repository-level coding tasks as a planning problem, generating a multi-step chain of edits (plan) where each step involves invoking an LLM on a specific code location, considering context from the entire repository, preceding code modifications, and task-specific instructions.

Advancing the state-of-the-art, [265] tackles the formidable challenge of NL2Repo, an endeavor that seeks to create a complete code repository from natural language requirements. To address this complex task, they introduce the CodeS framework, which strategically breaks down NL2Repo into a series of manageable sub-tasks using a multi-layer sketch approach. The CodeS framework comprises three distinct modules: 1) RepoSketcher, for creating a directory structure of the repository based on given requirements; 2) FileSketcher, for sketching out each file within that structure; and 3) SketchFiller, for fleshing out the specifics of each function within the file sketches [265].

Accordingly, a surge of benchmarks tailored for repository-level code generation has emerged, such as RepoEval [266], Stack-Repo [205], Repobench [150], EvoCodeBench [130], SWE-bench [111], CrossCodeEval [63], and SketchEval [265]. The detailed statistics and comparisons of these benchmarks are presented in Table 3.

Despite the progress made by these methods in repository-level code generation, significant challenges remain to be addressed. Programming developers are often required to invest considerable time in editing and debugging [24, 27, 163, 205, 220]. However, the advent of LLM-powered coding agents, such as AutoCodeRover [270], SWE-Agent [112], and OpenDevin [172], has demonstrated their potential to tackle complex problems, paving the way for future exploration in this field (for more details, see Section 4.9).

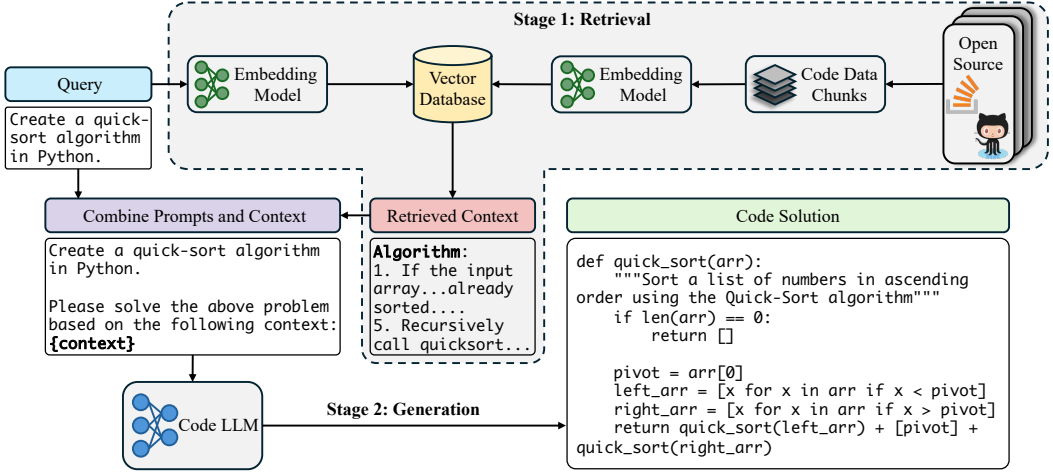


Fig. 8. A workflow illustration of the Retrieval-Augmented Code Generation (RACG). Upon receiving a query (instruction), the retriever selects the relevant contexts from a large-scale vector database. Subsequently, the retrieved contexts are merged with the query, and this combined input is fed into the generator (LLM) to produce the target code solution.

4.8 Retrieval Augmented

Large Language Models (LLMs) have exhibited impressive capabilities but are hindered by several critical issues such as hallucination [139, 269], obsolescence of knowledge [104], and non-transparent [30], untraceable reasoning processes [72, 96, 239, 282]. While techniques like instruction-tuning (see Section 4.4) and reinforcement learning with feedback (see Section 4.5) mitigate these issues, they also introduce new challenges, such as catastrophic forgetting and the requirement for substantial computational resources during training [81, 174].

Recently, Retrieval-Augmented Generation (RAG) has emerged as an innovative approach to overcoming these limitations by integrating knowledge from external databases. Formally defined, RAG denotes a model that, in response to queries, initially sources relevant information from an extensive corpus of documents, and then leverages this retrieved information in conjunction with the original query to enhance the response's quality and accuracy, especially for knowledge-intensive tasks. The RAG framework typically consists of a vector database, a retriever, a re-ranker, and a generator. It is commonly implemented using tools such as LangChain¹² and LlamaIndex¹³. By performing continuous knowledge updates of the database and the incorporation of domain-specific data, RAG circumvents the need for re-training LLMs from scratch [72]. Consequently, RAG has substantially advanced LLM performance across a variety of tasks [44, 129].

Due to the nature of code, code LLMs are also susceptible to the aforementioned issues that affect general-purpose LLMs. For instance, they may exhibit a hallucination phenomenon when instructions fall outside the scope of their training data or necessitate the latest programming packages. Given the dynamic nature of publicly available source-code libraries like PyTorch, which undergo frequent expansion and updates, deprecated calling methods can become a significant challenge. If Code LLMs are not updated in tandem with the latest functions and APIs, this can introduce potential errors and safety risks. Retrieval-Augmented Code Generation (RACG) stands

¹²LangChain facilitates the development of LLM-powered applications. <https://www.langchain.com>

¹³LlamaIndex is a leading data framework for building LLM applications. <https://www.llamaindex.ai>

as a promising solution to these concerns. A workflow illustration of the RACG is depicted in Figure 8.

Despite its potential, the adoption of RAG for code generation remains limited. Drawing inspiration from the common practice among programmers of referencing related code snippets, [149] introduced a novel retrieval-augmented mechanism with graph neural networks (GNNs), termed HGNN, which unites the advantages of similar examples retrieval with the generalization capabilities of generative models for code summarization, which is the reverse process of code generation. [177] pioneered a retrieval augmented framework named REDCODER for code generation by retrieving and integrating relevant code snippets from a source-code database, thereby providing supplementary context for the generation process. Subsequently, a retrieval-augmented code completion framework termed ReACC [152] is proposed to leverage both lexical copying and semantic referencing of related code, achieving state-of-the-art performance on the CodeXGLUE benchmark [153]. In the spirit of how programmers often consult textual resources such as code manuals and documentation to comprehend functionalities, DocPrompting [283] explicitly utilizes code documentation by retrieving the relevant documentation pieces based on a natural language query and then generating the target code by blending the query with the retrieved information.

More recently, RepoCoder [266], an iterative retrieval-generation framework, is proposed for enhancing repository-level code completion by effectively utilizing code analogies across different files within a repository to inform and improve code suggestions. Furthermore, breaking away from reliance on a singular source of retrieval, [208] developed a multi-faceted “knowledge soup” that integrates web searches, documentation, execution feedback, and evolved code snippets. Then, it incorporates an active retrieval strategy that iteratively refines the query and enriches the knowledge soup, expanding the scope of information available for code generation.

Despite these advancements, several limitations in retrieval-augmented code generation warrant further exploration: 1) the quality of the retrieved information significantly impacts overall performance; 2) the effective integration of retrieved code information with the query needs optimization; 3) an over-reliance on retrieved information may lead to inadequate responses that fail to address the query’s intent; 4) additional retrieved information necessitates larger context windows for the LLM, resulting in increased computational demands.

4.9 Autonomous Coding Agents

The advent of large language models (LLMs) has marked the beginning of a new era of potential pathways toward artificial general intelligence (AGI), capturing significant attention in both academia and industry [98, 225, 241, 246]. A rapidly expanding array of applications for LLM-based autonomous agents, including AutoGPT [2], AgentGPT [1], BabyAGI [3], and AutoGen [245], underlines the promise of this technology.

LLM-powered autonomous agents are systems endowed with sophisticated reasoning abilities, leveraging an LLM as a central computational engine or controller. This allows them to formulate and execute problem-solving plans through a series of tool-enabled functions or API calls. Moreover, these agents are designed to function within a shared environment where they can communicate and engage in cooperative, competitive, or negotiating interactions [94, 225, 245]. The typical architecture of such an agent encompasses an LLM-based Agent, a memory module, a planning component, and a tool utilization module, as depicted in Figure 9.

In the realm of automated code generation, LLM-powered autonomous agents have demonstrated remarkable proficiency. For instance, AgentCoder [94] achieved a groundbreaking pass@1 of 96.3% on the HumanEval benchmark, forwarding a step closer to the future of automated software development [100]. The innovative meta-programming framework termed MetaGPT [90] integrates human workflow efficiencies into LLM-based multi-agent collaboration. Furthermore,

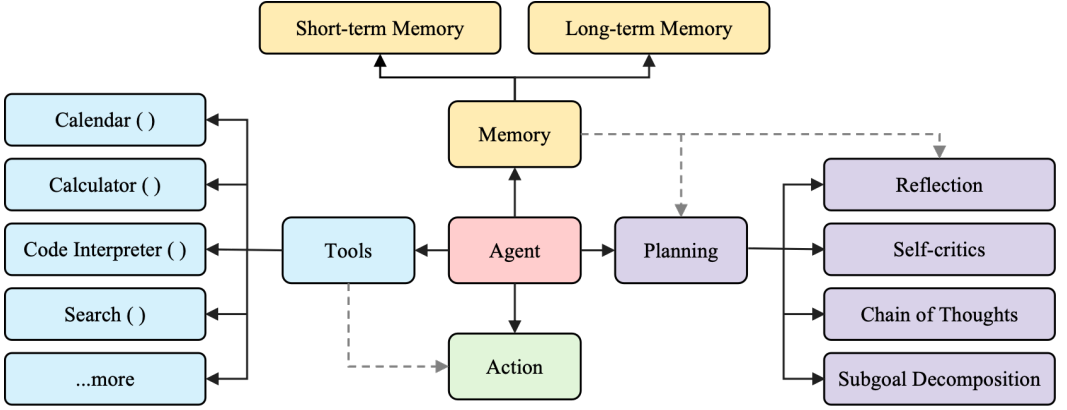


Fig. 9. The general architecture of an LLM-powered autonomous agent system, adapted from [241]. **Planning:** The agent decomposes large tasks into smaller, manageable sub-goals or engages in self-criticism and self-reflection on past actions to learn from mistakes and improve future performance. **Memory:** This component enables the agent to store and retrieve past information. **Tools:** The agent is trained to invoke external functions or APIs. **Action:** The agent executes actions, with or without the use of tools, to interact with the environment. The gray dashed lines represent the data flow within the system.

[94] introduces AgentCoder, a multi-agent framework composed of three specialized agents, each with distinct roles and capabilities. These roles include a programmer agent responsible for code generation, a test designer agent tasked with generating unit test cases, and a test executor agent that executes the code and provides feedback. This division of labor within AgentCoder promotes more efficient and effective code generation. CodeAct [228] distinguishes itself by utilizing executable Python code to consolidate LLM agent actions within a unified action space, in contrast to the generation of JSON or textual formats. Additionally, AutoCodeRover [270] is proposed to autonomously resolve GitHub issues for program enhancement.

To address the complexity of tasks within software engineering, two innovative autonomous AI software engineers Devin¹⁴[56] and OpenDevin¹⁵[172], have been released and rapidly garnered considerable interest within the software engineering (SE) and artificial general intelligence (AGI) community. Subsequently, an autonomous system, SWE-agent [112], leverages a language model to interact with a computer to address software engineering tasks, successfully resolving 12.5% of issues on the SWE-bench benchmark [111]. L2MAC [88] has been introduced as the first practical, LLM-based, multi-agent, general-purpose stored-program automatic computer that utilizes a von Neumann architecture, designed specifically for the generation of long and consistent outputs. At the time of writing this survey, OpenDevin has enhanced CodeAct with bash command-based tools, leading to the release of OpenDevin CodeAct 1.0 [249], which sets a new state-of-the-art performance on the SWE-Bench Lite benchmark [111].

Despite these remarkable advancements, the journey toward fully realized AI software engineers employing LLM-powered autonomous agents is far from complete [225, 246]. Critical aspects such as prompt design, context length, agent count, and toolsets call for further refinement and optimization, especially as problem complexities escalate [100].

4.10 Evaluation

¹⁴<https://www.cognition.ai/introducing-devin>

¹⁵<https://github.com/OpenDevin/OpenDevin>

Despite the impressive capabilities of large language models (LLMs), they exhibit a range of behaviors that are both beneficial and potentially risky. These behaviors can enhance performance across various downstream tasks but may also introduce reliability and trustworthiness concerns in LLM deployment [39, 45, 251]. Consequently, it is imperative to develop precise evaluation approaches to discern the qualitative and quantitative differences between models, thereby encouraging further advancements in LLM capabilities.

Evaluation strategies for LLMs in code generation mirror those for general-purpose LLMs and can be divided into three principal categories: metrics-based, human-centered, and LLM-based approaches. Detailed benchmarks for these evaluation strategies are presented in Section 4.1.3 and summarized in Table 3. Subsequent subsections will provide a thorough analysis of each approach.

4.10.1 Metrics. The pursuit of effective and reliable automatic evaluation metrics for generated content is a long-standing challenge within the field of natural language processing (NLP) [46, 140, 175]. At the early stage, most works directly leverage token-matching-based metrics, such as Exact Match, BLEU [175], ROUGE [140], and METEOR [22], which are prevalent in text generation of NLP, to assess the quality of code generation.

While these metrics offer a rapid and cost-effective approach for assessing the quality of generated code, they often fall short of capturing the syntactical and functional correctness, as well as the semantic features of the code. To eliminate this limitation, CodeBLEU [191] was introduced, enhancing the traditional BLEU metric [175] by incorporating syntactic information through abstract syntax trees (AST) and semantic understanding via data-flow graph (DFG). Despite these improvements, the metric does not fully resolve issues pertaining to execution errors or discrepancies in the execution results of the generated code. In light of these challenges, execution-based metrics have

Table 6. The performance comparison of LLMs for code generation on the **HumanEval** [45] benchmark, measured by Pass@{1, 10, 100}. For models with various sizes, we report only the largest size version of each model.

Model	Size	pass@k		
		k = 1	k = 10	k = 100
GPT-4 [5]	-	84.1	-	-
GPT-3.5-Turbo [171]	-	76.2	-	-
Claude-3-Opus [13]	-	82.9	-	-
Claude-3-Haiku [13]	-	76.8	-	-
Claude-3-Sonnet [13]	-	70.7	-	-
StarCoder2-Instruct [261]	15.5B	72.6	-	-
Llama3 [160]	70B	81.7	-	-
CodeGemma [54]	7B	44.5	-	-
StarCoder 2 [151]	15B	46.3	-	-
phi-2 [161]	2.7B	49.4	-	-
WaveCoder [259]	6.7B	75	-	-
StableCode [182]	3B	29.3	-	-
CodeShell [247]	7B	34.32	-	-
CodeQwen [215]	14B	45.1	-	-
DeepSeek-Coder [79]	33B	56.1	-	-
replit-code [193]	3B	20.12	-	-
Phi-1.5 [135]	1.3B	41.4	-	-
PanGu-Coder2 [201]	15B	61.64	79.55	91.75
WizardCoder [154]	15B	57.3	73.2	90.46
CodeFuse [143]	34B	74.4	-	-
Phi-1 [75]	1.3B	50.6	-	-
Code Llama [196]	34B	48.8	76.8	93.0
OctoCoder [164]	15.5B	46.2	-	-
PaLM-Coder [49]	540B	36	-	88.4
CodeGeeX2 [275]	6B	35.9	62.6	88.3
InstructCodeT5+ [232]	16B	35.0	54.5	77.9
CodeGen-NL [169]	16.1B	14.24	23.46	38.33
CodeGen-Multi [169]	16.1B	18.32	32.07	50.8
CodeGen-Mono [169]	16.1B	29.28	49.86	75
StarCoder [132]	15B	33.60	45.78	79.82
CodeT5+ [234]	16B	30.9	51.6	76.7
LLaMA2 [218]	70B	30.5	59.4	87.0
Codex [45]	12B	28.81	46.81	72.31
PaLM [49]	540B	26.2	-	76.2
PanGu-Coder [50]	2.6B	23.78	35.36	51.24
LLaMA [217]	65B	23.7	-	79.3
CodeGeeX [275]	13B	22.89	39.57	60.92
Replit [192]	3B	21.9	-	-
CodeGen2 [168]	16B	20.46	36.5	56.71
SantaCoder [8]	1.1B	18	29	49
AlphaCode [136]	1.1B	17.1	28.2	45.3
BLOOM [126]	176B	15.52	32.20	55.45
GPT-NeoX [28]	20B	15.4	25.6	41.2
InCoder [69]	6.7B	15.2	27.8	47.0
GPT-J [223]	6B	11.62	15.74	27.74
PyCodeGPT [263]	110M	8.33	13.36	19.13
GPT-Neo [29]	2.7B	6.41	11.27	21.37
PolyCoder [251]	2.7B	5.59	9.84	17.68
JuPyT5 [38]	300M	5.4	15.46	25.60
CodeParrot [219]	1.5B	3.99	8.69	17.88

gained prominence for evaluating code generation, including pass@k [45], n@k [136], test case average [85], execution accuracy [190], and pass@t [170]. In particular, the pass@k, serving as a principal evaluation metric, assesses the probability that at least one out of k code samples generated by a model will pass all unit tests. An unbiased estimator for pass@k introduced by [45] is defined as:

$$\text{pass@k} := \mathbb{E}_{\text{task}} \left[1 - \frac{\binom{n-c}{k}}{\binom{n}{k}} \right] \quad (19)$$

where n is the total number of sampled candidate code solutions, k is the number of randomly selected code solutions from these candidates for each programming problem, with $n \geq k$, and c is the count of correct samples within the k selected. Tables 6 and 7 illustrate the performance of contemporary large language models (LLMs) for code generation, measured by the pass@k metric across different values of $k \in \{1, 10, 100\}$ on the HumanEval and MBPP benchmarks, respectively.

Nevertheless, these execution-based methods are heavily dependent on the quality of unit tests and are limited to evaluating executable code [264]. Consequently, when unit tests are unavailable, token-matching-based metrics are often employed as an alternative for evaluation. Furthermore, in scenarios lacking a ground truth label, unsupervised metrics such as perplexity (PPL) [105] can serve as evaluative tools. Perplexity quantifies an LLM's uncertainty in predicting new content, thus providing an indirect measure of the model's generalization capabilities and the quality of the generated code.

Taken together, while the aforementioned methods primarily focus on the functional correctness of code, they do not provide a holistic evaluation that encompasses other critical dimensions such as code vulnerability [165], maintainability [14], readability [32], complexity and efficiency [180], stylistic consistency [158], and execution stability [187]. A comprehensive evaluation framework that integrates these aspects remains an open area for future research and development in the field of code generation assessment.

4.10.2 Human Evaluation. Given the intrinsic characteristics of code, the aforementioned automatic evaluation metrics are inherently limited in their capacity to fully assess code quality. For instance, metrics specifically designed to measure code style consistency are challenging to develop and often fail to capture this aspect adequately [41]. When it comes to repository-level code generation, the evaluation of overall code quality is substantially complicated due to the larger scale of the task, which involves cross-file designs and intricate internal as well as external dependencies, as discussed by [21, 205].

To overcome these challenges, conducting human evaluations becomes necessary, as it yields relatively robust and reliable results. Human assessments also offer greater adaptability across various tasks, enabling the simplification of complex and multi-step evaluations. Moreover, human evaluations are essential for demonstrating the effectiveness of certain token-matching-based metrics, such as CodeBLEU [191]. These studies typically conduct experiments to evaluate the correlation coefficient between proposed metrics and quality scores assigned by actual users, demonstrating their superiority over existing metrics.

Moreover, in an effort to better align large language models (LLMs) with human preferences and intentions, InstructGPT [173] employs human-written prompts and demonstrations, and model output ranking in the fine-tuning of LLMs using reinforcement learning from human feedback (RLHF). Although similar alignment learning techniques have been applied to code generation, the feedback in this domain typically comes from a compiler or interpreter, which offers execution feedback, rather than from human evaluators. Notable examples include CodeRL [125], PPOCoder

[204], RLTF [146], and PanGu-Coder2 [201]. Further information on this topic is available in Section 4.5.

Nonetheless, human evaluations are not without drawbacks, as they can be prone to certain issues that may compromise their accuracy and consistency. For instance, 1) personalized tastes and varying levels of expertise among human evaluators can introduce biases and inconsistencies into the evaluation process; 2) conducting comprehensive and reliable human evaluations often necessitates a substantial number of evaluators, leading to significant expenses and time-consuming; 3) the reproducibility of human evaluations is often limited, which presents challenges in extending previous evaluation outcomes or monitoring the progress of LLMs, as highlighted by [273].

4.10.3 LLM-as-a-Judge. The powerful instruction-following capabilities of large language models (LLMs) have stimulated researchers to innovatively investigate the potential of LLM-based evaluations. The LLM-as-a-Judge [274] refers to the application of advanced proprietary LLMs (e.g., GPT4, Gemini, and Claude 3) as proxies for human evaluators. This involves designing prompts with specific requirements to guide LLMs in conducting evaluations, as demonstrated by AlpacaEval [133] and MT-bench [274]. This method reduces reliance on human participation, thereby facilitating more efficient and scalable evaluations. Moreover, LLMs can offer insightful explanations for the assigned rating scores, thereby augmenting the interpretability of evaluations [273].

Nevertheless, the use of LLM-based evaluation for code generation remains relatively underexplored compared with general-purpose LLM. A recent work [284] introduces the ICE-Score evaluation metric, which instructs LLM for code assessments. This approach attains superior correlations with functional correctness and human preferences, thereby eliminating the requirement for test oracles or references. As the capabilities of LLM continue to improve, we anticipate seeing more research in this direction.

Despite their scalability and explainability, the effectiveness of LLM-based evaluation is constrained by the inherent limitations of the chosen LLM. Several studies have shown that most LLMs, including GPT-4, suffer from several issues, including position, verbosity, and self-enhancement biases, as well as restricted reasoning ability [274]. Specifically, position bias refers to the tendency

Table 7. The performance comparison of LLMs for code generation on the MBPP [16] benchmark, measured by Pass@{1, 10, 100}. For models with various sizes, we report only the largest size version of each model.

Model	Size	pass@k		
		k = 1	k = 10	k = 100
GPT-3.5-Turbo [171]	-	52.2	-	-
Claude-3-Opus [13]	-	89.4	-	-
Claude-3-Haiku [13]	-	80.2	-	-
Claude-3-Sonnet [13]	-	83.6	-	-
StarCoder2-Instruct [261]	15.5B	78	-	-
CodeGemma [54]	7B	65.1	-	-
StarCoder 2 [151]	15B	50.6	-	-
phi-2 [161]	2.7B	64	-	-
WaveCoder [259]	6.7B	74.9	-	-
CodeFuse [143]	34B	61.0	-	-
CodeQwen [215]	14B	51.4	-	-
DeepSeek Coder [79]	33B	66.0	-	-
Phi-1.5 [135]	1.3B	43.5	-	-
WizardCoder [154]	16B	51.8	-	-
StarCoder [132]	5.5B	52.7	-	-
SantaCoder [8]	1.1B	3.65	21.33	41.92
PyCodeGPT [263]	110M	9.39	28.37	48.71
PolyCoder [251]	2.7B	4.39	17.99	38.17
phi-1 [75]	1.3B	55.5	-	-
PaLM-Coder [49]	540B	47	-	-
PaLM [49]	540B	36.8	-	-
LLaMA [217]	65B	37.7	-	-
LLaMA 2 [218]	70B	45.4	66.2	83.1
CodeT5+ [234]	16B	56.6	-	-
InCoder [69]	6.7B	21.3	46.5	66.2
GPT-Neo [29]	2.7B	5.89	23.09	44.26
GPT-J [223]	6B	11.30	35.62	53.63
CodeT5 [234]	770M	15.78	38.63	50.35
CodeParrot [219]	1.5B	1.29	8.66	27.17
Code Llama [196]	34B	55	76.2	86.6
CodeGen-NL [169]	16.1B	10.92	38.43	62.76
CodeGen-Multi [169]	16.1B	20.94	51.61	70.02
CodeGen-Mono [169]	16.1B	35.28	67.32	80.09
CodeGeeX [275]	13B	24.4	48	-
BLOOM [126]	1.7B	3.16	14.23	31.38
PanGu-Coder [50]	2.6B	23.0	43.60	59.64
CodeGeeX2 [275]	6B	24.37	47.95	-

of large language models (LLMs) to disproportionately favor responses that are presented in certain positions, which can skew the perceived quality of answers based on their order of presentation. Meanwhile, verbosity bias describes the inclination of LLMs to prefer lengthier responses, even when these are not necessarily of higher quality compared to more concise ones. Self-enhancement bias, on the other hand, is observed when LLMs consistently overvalue the quality of the text they generate [273, 274]. Moreover, due to their inherent limitations in tackling complex reasoning challenges, LLMs may not be entirely reliable as evaluators for tasks that require intensive reasoning, such as those involving mathematical problem-solving. However, these shortcomings can be partially addressed through the application of deliberate prompt engineering and fine-tuning techniques, as suggested by [274].

4.11 Applications

Code LLMs have been integrated with development tools and platforms, such as integrated development environments (IDEs) and version control systems, improving programming efficiency substantially. In this section, we will briefly introduce several widely used applications as coding assistants. The statistics of these applications are provided in Table 8.

GitHub Copilot. GitHub Copilot, powered by OpenAI's Codex, is an AI pair programmer that helps you write better code faster. Copilot suggests whole lines or blocks of code as you type, based on the context provided by your existing code and comments. It's trained on a dataset that includes a significant portion of the public code available on GitHub, which enables it to understand a wide range of programming languages and coding styles. Copilot not only improves productivity but also serves as a learning tool by providing programmers with examples of how certain functions can be implemented or how specific problems can be solved.

CodeGeeX. CodeGeeX stands out as a multifaceted programming assistant, proficient in code completion, comment generation, code translation, and developer interactions. Its underlying code generation LLM has been refined with extensive training on vast amounts of code data, exhibiting superior performance on benchmarks like HumanEval, HumanEval-X, and DS1000. Renowned for supporting multilingual code generation, CodeGeeX plays a pivotal role in enhancing the efficiency of code development.

CodeWhisperer. Amazon's CodeWhisperer is a versatile, machine learning-driven code generator that offers on-the-fly code recommendations. Tailored to your coding patterns and comments, CodeWhisperer provides personalized suggestions that range from succinct comments to complex functions, all aimed at streamlining your coding workflow.

Codeium. Codeium is an AI-accelerated coding toolkit that offers a suite of functions, including code completion, explanation, translation, search, and user chatting. Compatible with over 70 programming languages, Codeium delivers fast and cutting-edge solutions to coding challenges, simplifying the development process for its users.

CodeArts Snap. Huawei's CodeArts Snap is capable of generating comprehensive function-level code from both Chinese and English descriptions. This tool not only reduces the monotony of manual coding but also efficiently generates test code, in addition to providing automatic code analysis and repair services.

Tabnine. Tabnine is an AI coding assistant that empowers development teams to leverage AI for streamlining the software development lifecycle while maintaining strict standards for privacy, security, and compliance. With a focus on enhancing coding efficiency, code quality, and developer satisfaction, Tabnine offers AI-driven automation that is tailored to the needs of your team. Supporting over one million developers worldwide, Tabnine is applicable across various industries.

Table 8. The overview of code assistant applications powered by large language models (LLMs). The column labeled ‘PLs’ and ‘IDEs’ indicate programming languages and integrated development environments, respectively [264].

Institution	Products	Model	Supported Features	Supported PLs	Supported IDEs
GitHub & OpenAI	GitHub Copilot [45]	CodeX	Code Completions, Code Generation, Coding Questions Answering, Code Refactoring, Code Issues Fix, Unit Test Cases Generation, Code Documentation Generation	Java, Python, JavaScript, TypeScript, Perl, R, PowerShell, Rust, SQL, CSS, Ruby, Julia, C#, PHP, Swift, C++, Go, HTML, JSON, SCSS, .NET, Less, T-SQL, Markdown	Visual Studio, VS Code, Neovim, JetBrains IDE
Zhipu AI	CodeGeex [275]	CodeGeex	Code Generation, Code Translation, Code Completion, Code Interpretation, Code Bugs Fix, Comment Generation, AI Chatbot	PHP, Go, C, C#, C++, Rust, Perl, CSS, Java, Python, JavaScript, TypeScript, Objective C++, Objective C, Pascal, HTML, SQL, Kotlin, R, Shell, Cuda, Fortran, Tex, Lean, Scala	Clion, RubyMine, AppCode, Aqua, IntelliJ IDEA, VS Code, PyCharm, Android Studio, WebStorm, Rider, Goland, DataGrip, DataSpell
Amazon	CodeWhisperer [11]	–	Code Completion, Code Explanation, Code Translation, Code Security Identification, Code Suggestion	Java, Python, TypeScript, JavaScript, C#	JetBrains IDE, VS Code, AWS Cloud9, AWS Lambda
Codeium	Codeium [55]	–	Code Completion, Bug Detection, Code Suggestions, AI Chatbot, Test Type Generation, Test Plan Creation, Codebase Search	More than 70 languages in total, including but not limited to: C, C#, C++, Dart, CSS, Go, Elixir, HTML, Haskell, Julia, Java, JavaScript, Lisp, Kotlin, Lua, Objective-C, Perl, Pascal, PHP, Protobuf, R, Python, Ruby, Scala, Rust, Swift, SQL, TS, Vue	JetBrains, VSCode, Visual Studio, Colab, Jupyter, Deepnote, Notebooks, Databricks, Chrome, Vim, Neovim, Eclipse, Emacs, VSCode Web IDEs, Sublime Text
Huawei	CodeArts Snap [201]	PanGu-Coder	Code Generation, Code Explanation Research and Development Knowledge Question and Answer Code Comment, Code Debug Unit Test Case Generation	Java, Python	PyCharm, VS Code, IntelliJ
Tabnine	TabNine [212]	–	Code Generation, Code Completion, Code Explanation, Bug Fix, Code Recommendation, Code Refactoring, Code Test Generation, Docstring Generation	Python, JavaScript, Java, TypeScript, HTML, Haskell, Matlab, Kotlin, Sass, Go, PHP, Ruby, C, C#, C++, Swift, Rust, CSS, Perl, Angular, Dart, React, Objective C, NodeJS, Scala,	Sublime, PyCharm, Neovim, Rider, VS Code, IntelliJ IDE, Visual Studio, PupsStorm, Vim, RubyMine, DataGrip, Android Studio, WebStorm, Emacs, Clion, Jupyter Notebook, JupyterLab, Eclipse, Goland, AppCode
Replit	Replit [92]	replit-code	Code Completion, Code Editing, Code Generation, Code Explanation, Code Suggestion, Code Test Generation	C#, Bash, C, CSS, C++, Java, Go, HTML, JavaScript, Perl, PHP, Ruby, Python, R, SQL, Rust	–

Replit. Replit is a multifunctional platform that caters to a diverse array of software development needs. As a complimentary online IDE, it facilitates code collaboration, and cloud services, and fosters a thriving developer community. Replit also enables users to compile and execute code in more than 50 programming languages directly within a web browser, eliminating the need for local software installations.

5 CHALLENGES & OPPORTUNITIES

According to our investigations, the LLMs have revolutionized the paradigm of code generation and achieved remarkable performance. Despite this promising progress, there are still numerous challenges that need to be addressed. These challenges are mainly caused by the gap between academia and practical development. For example, in academia, the HumanEval benchmark has been established as a de facto standard for evaluating the coding proficiency of LLMs. However, many works have illustrated the evaluation of HumanEval can't reflect the scenario of practical development [63, 67, 111, 145]. In contrast, these serious challenges offer substantial opportunities for further research and applications. In this section, we pinpoint critical challenges and identify promising opportunities, aiming to bridge the research-practicality divide.

Enhancing complex code generation at repository and software scale. In practical development scenarios, it often involves a large number of complex programming problems of varying difficulty levels. While LLMs have shown proficiency in generating function-level code snippets, these models often struggle with more complex, unseen programming problems, repository- and software-level problems that are commonplace in real-world software development. To this end, it requires strong problem-solving skills in LLM beyond simply functional-level code generation. For example, AlphaCode [136] achieved an average ranking in the top 54.3% in programming competitions where an understanding of algorithms and complex natural language is required to solve competitive programming problems. [111] argues that existing LLMs can't resolve real-world GitHub issues well since the best-performing model, Claude 2, is able to solve a mere 1.96% of the issues. The reason for poor performance is mainly attributed to the weak reasoning capabilities [95], complex internal- and external- dependencies [21], and context length limitation of LLMs [21]. Therefore, the pursuit of models that can handle more complex, repository- and software-level code generation opens up new avenues for automation in software development and makes programming more productive and accessible.

Innovating model architectures tuned to code structures. Due to their scalability and effectiveness, Transformer-based LLM architectures have become dominant in solving code generation task. Nevertheless, they might not be optimally designed to capture the inherent structure and syntax of programming languages (PLs) [76, 77, 120, 155]. Code has a highly structured nature, with a syntax that is more rigid than natural language. This presents a unique challenge for LLMs, which are often derived from models that were originally designed for natural language processing (NLP). The development of novel model architectures that inherently understand and integrate the structural properties of code represents a significant opportunity to improve code generation and comprehension. Innovations such as tree-based neural networks [162], which mirror the abstract syntax tree (AST) representation of code, can offer a more natural way for models to learn and generate programming languages. Additionally, leveraging techniques from the compiler theory, such as intermediate representations (IR) [137], could enable models to operate on a more abstract and generalizable level, making them effective across multiple programming languages [179]. By exploring architectures beyond the traditional sequential models, researchers can unlock new potentials in code generation.

Curating high-quality code data for pre-training and fine-tuning of LLMs. The efficacy of LLMs largely depends on the quality and diversity of code datasets used during pre-training and

fine-tuning phases [119, 242, 281]. Currently, there is a scarcity of large, high-quality datasets that encompass a wide range of programming tasks, styles, and languages. This limitation constrains the ability of LLMs to generalize across unseen programming tasks, different coding environments, and real-world software development scenarios. The development of more sophisticated data acquisition techniques, such as automated code repositories mining [142], advanced filtering algorithms, and code data synthesis [148] (see Section 4.2), can lead to the creation of richer datasets. Collaborations with industry partners (e.g., GitHub) could also facilitate access to proprietary codebases, thereby enhancing the practical relevance of the training material. Furthermore, the adoption of open-source models for dataset sharing can accelerate the collective effort to improve the breadth and depth of code data available for LLM research.

Developing comprehensive benchmarks and metrics for coding proficiency evaluation in LLMs. Current benchmarks like HumanEval may not capture the full spectrum of coding skills required for practical software development [167]. Additionally, metrics often focus on syntactic correctness or functional accuracy, neglecting aspects such as code efficiency [180], style [41], readability [32], or maintainability [14]. The design of comprehensive benchmarks that simulate real-world software development challenges could provide a more accurate assessment of LLMs' coding capabilities. These benchmarks should include diverse programming tasks of varying difficulty levels, such as debugging [279], refactoring [203], and optimization [101], and should be complemented by metrics that evaluate qualitative aspects of code. The establishment of community-driven benchmarking platforms could facilitate continuous evaluation and comparison of LLMs for code generation across the industry and academia.

Support for low-resource, low-level, and domain-specific programming languages. LLMs are predominantly trained in popular high-level programming languages, leaving low-resource, low-level, and domain-specific languages underrepresented. This lack of focus restricts the applicability of LLMs in certain specialized fields and systems programming [216]. Intensifying research on transfer learning and meta-learning approaches may enable LLMs to leverage knowledge from high-resource languages to enhance their performance on less common ones [35, 43]. Additionally, partnerships with domain experts can guide the creation of targeted datasets and fine-tuning strategies to better serve niche markets. The development of LLMs with a capacity for multilingual code generation also presents a significant opportunity for broadening the scope of applications.

Continuous learning for LLMs to keep pace with evolving coding knowledge. The software development landscape is continuously evolving, with new languages, frameworks, and best practices emerging regularly. LLMs risk becoming outdated if they cannot adapt to these changes and incorporate the latest programming knowledge [104, 227]. While retrieval augmented code generation mitigates these issues, the performance is limited by the quality of the retrieval context. While retrieval-augmented code generation offers a partial solution to these issues, its effectiveness is inherently constrained by the quality of retrieved context. [152, 266, 283]. Therefore, establishing mechanisms for continuous learning and updating of LLMs can help maintain their relevance over time. This could involve real-time monitoring of code repositories to identify trends and innovations, as well as the creation of incremental learning systems that can assimilate new information without forgetting previously acquired knowledge. Engaging the LLMs in active learning scenarios where they interact with human developers may also foster ongoing knowledge acquisition.

Ensuring code safety and aligning LLM outputs with human coding preferences. Ensuring the safety and security of code generated by LLMs is a paramount concern, as is their ability to align with human preferences and ethical standards. Current models may inadvertently introduce vulnerabilities or generate code that does not adhere to desired norms [45, 252]. Research into the integration of formal verification tools within the LLM pipeline can enhance the safety of the

produced code. Additionally, developing frameworks for alignment learning that capture and reflect human ethical preferences can ensure that the code generation process aligns with societal values [173, 184]. Transparent and explainable AI methodologies can also contribute to building trust in the LLM-generated code by making the decision-making process more accessible to developers.

6 CONCLUSION

In this survey, we provide a systematic literature review, serving as a valuable reference for researchers investigating the cutting-edge progress in LLMs for code generation. A thorough introduction and analysis for data curation, the latest advances, performance evaluation, and real-world applications are illustrated. In addition, we present a historical overview of the evolution of LLMs for code generation in recent years and offer an empirical comparison using the widely recognized HumanEval and MBPP benchmarks to highlight the progressive enhancements in LLM capabilities for code generation. Critical challenges and promising opportunities regarding the gap between academia and practical development are also identified for future investigation. Furthermore, we have established a dedicated resource website to continuously document and disseminate the most recent advances in the field. We hope this survey can contribute to a comprehensive and systematic overview of LLM for code generation and promote its thriving evolution. We optimistically believe that LLM will ultimately change all aspects of coding and automatically write safe, helpful, accurate, trustworthy, and controllable code, like professional programmers, and even solve coding problems that currently cannot be solved by humans.

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