# **CodeApex: A Bilingual Programming Evaluation Benchmark** for Large Language Models

LINGYUE FU, HUACAN CHAI, KOUNIANHUA DU, WEIMING ZHANG, SHUANG LUO, JIANGHAO LIN, YUCHEN FANG, RENTING RUI, HAO GUAN, JIANXING LIU, SIYUAN QI, LONGTENG FAN, JIAYI LEI, YIFAN LIU, JINGKUAN WANG, KANGNING ZHANG, WEINAN ZHANG, and YONG YU\*, Apex Data & Knowledge Management Lab, Shanghai Jiao Tong University, China

https://apex.sjtu.edu.cn/codeapex/

With the emergence of Large Language Models (LLMs), there has been a significant improvement in the programming capabilities of models, attracting growing attention from researchers. Evaluating the programming capabilities of LLMs is crucial as it reflects the multifaceted abilities of LLMs, and it has numerous downstream applications. In this paper, we propose CodeApex, a bilingual benchmark dataset focusing on the programming comprehension, code generation, and code correction abilities of LLMs. Programming comprehension task tests LLMs on multiple-choice exam questions covering conceptual understanding, commonsense reasoning, and multi-hop reasoning. The code generation task evaluates LLMs through completing C++ functions based on provided descriptions and prototypes. The code correction task asks LLMs to fix real-world erroneous code segments with different error messages. We evaluate 12 widely used LLMs, including both general-purpose and specialized models. GPT-4 exhibits the best programming capabilities, achieving approximate accuracy of 69%, 54%, and 66% on the three tasks, respectively. Compared to human performance, there is still significant room for improvement in LLM programming. We hope that CodeApex can serve as a reference for evaluating the coding capabilities of LLMs, further promoting their development and growth.

CCS Concepts: • Computing methodologies → Natural language processing.

Additional Key Words and Phrases: Large Language Model, Benchmark

# **ACM Reference Format:**

# 1 INTRODUCTION

Due to the widespread adaption of the Transformer [51] architecture and advancements in computational power, Large Language Models (LLMs) have been widely employed in various tasks,

\*The leading author is Lingyue Fu <fulingyue@sjtu.edu.cn>. Shuang Luo has graduated from SJTU and is now at KTH. Correspondence to Weinan Zhang <wnzhang@sjtu.edu.cn> and Yong Yu <yyu@sjtu.edu.cn>.

Authors' address: Lingyue Fu; Huacan Chai; Kounianhua Du; Weiming Zhang; Shuang Luo; Jianghao Lin; Yuchen Fang; Renting Rui; Hao Guan; Jianxing Liu; Siyuan Qi; Longteng Fan; Jiayi Lei; Yifan Liu; Jingkuan Wang; Kangning Zhang; Weinan Zhang; Yong Yu, Apex Data & Knowledge Management Lab, Shanghai Jiao Tong University, Shanghai, China https://apex.sjtu.edu.cn/codeapex/.

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Table 1. Comparison between commonly used programming benchmarks in the era of LLMs and CodeApex. P.C. stands for programming comprehension. C.G. stands for code generation. C.C. stands for code correction. The number of plus symbols (i.e., +) in the *Data Scale* column represents the order of magnitude of the test samples.

Benchmark	Programming Task			Fine-grained	Data Scale	Bilingual	Human Expert
Deficilitate	P.C.	C.G.	C.C.	Categorization	Data Scarc	Diniguai	Truman Expert
MBPP [4]	X	<b>√</b>	X	X	+++	X	X
CoderEval [59]	X	✓	X	×	++	X	×
HumanEval [9]	X	✓	X	×	+	X	×
HumanEval-X [65]	X	✓	X	×	++	X	×
DebugBench [50]	X	X	✓	✓	+++	×	✓
CodeApex (Ours)	<b>✓</b>	<b>√</b>	<b>√</b>	<b>√</b>	+++	<b>√</b>	<b>✓</b>

including recommender systems [36, 37], dialogue systems [1, 63], summarization [39, 62], sentiment analysis [6, 21], etc. This trend highlights the need for robust evaluation frameworks to measure the effectiveness of LLMs in these diverse applications such as education [10, 17, 23], social science [18, 20] and medical [22, 31]. Establishing these benchmarks can provide quantitatively thorough assessments for the capabilities of LLMs from various perspectives, thereby guiding model optimization, validating model performance, and analyzing model differences. Among these diverse benchmarks, we argue that the code and programming capability is one of the most crucial aspects for the evaluation of LLMs for the following two reasons.

Firstly, the performance of LLMs on code and programming tasks largely reflects their inherent capabilities of logical reasoning, instruction following, and structural data understanding. Code and programming serve as the bridge between humans and computers, and translate high-level human need into executable steps, logical consistency, featuring standard syntax, and functional modularity [57]. Various works [41, 43, 57] have identified the importance of code data for model tuning to help unlock the reasoning ability of LLMs and steer LLMs to produce structured and precise intermediate steps. As a result, various benchmarks and leaderboards [27] that focus on general reasoning ability evaluation of LLMs would include code-related tasks in addition to traditional tasks like arithmetic [3, 14] and symbolic reasoning [55], which draws a thorough assessment over the fundamental capabilities of large language models.

Secondly, apart from the potential relationship with basic reasoning abilities of LLMs, code-related tasks also play crucial roles in a wide range of downstream applications, such as education [16] and software engineering [7]. A variety of code foundation models [7, 35, 53, 65] have been proposed for different programming tasks. Copilot [7] achieves code auto-completion and auto-correction during the programming process, therefore greatly promoting the coding experience of human programmers. CodeGeeX [65], as an interactive programming assistant, can solve various programming problems, including code interpretation, code translation, code correction, document generation, etc. Google DeepMind team proposes AlphaCode [35], which aims to solve programming problems that require deep reasoning abilities to find novel solutions. CodeT5 [53] employs a unified framework to seamlessly support both code understanding and generation tasks, with the allowance of multi-task learning. Such a emergence of code foundation models with different programming goals (e.g., code completion, code debugging) draws demand on the corresponding evaluation to ensure their performance in real-world production scenarios.

These factors discussed above yield an urgent need for a comprehensive benchmark to thoroughly evaluate the code and programming capabilities of large language models. In Table 1, we illustrate the important properties of the commonly used programming evaluation benchmarks [4, 9, 50, 59, 65],

and discuss their potential limitations as follows: (1) Existing benchmarks only focus on a single programming task for LLMs within uni-lingual test cases (i.e., English), which makes the evaluation incomprehensive. (2) Existing benchmarks, excluding DebugBench [50], generally lack fine-grained categorization over the test data and human-expert evaluation, which are crucial to derive deeper insights and analysis for different aspects of programming, as well as the thorough comparison between LLMs and human-level abilities.

To this end, we propose the CodeApex benchmark, which gives a comprehensive code and programming evaluation of large language models. As shown in Table 1, CodeApex is a pioneering bilingual (English and Chinese) programming benchmark over three different code-related tasks (i.e., programming comprehension, code generation, and code correction) with fine-grained categorization, large test data scale, as well as human-expert evaluation. We have comprehensively evaluated 12 different LLMs using CodeApex, including both API-based and open-source models. Our work analyzes the overall code capabilities of LLMs by comparing their performance across different tasks. Fine-grained categorization experiments provide an analysis of LLMs across different strategies and data types. Experimental results demonstrate the varying performance of different models in code-related tasks, with GPT models showcasing exceptional competitiveness and distinct advantages. Additionally, the experiment compares the performance of LLMs in bilingual and different prompt strategy scenarios. We also organize human testing on code comprehension and code generation tasks, comparing performance between humans and LLMs. Overall, within the leaderboard of the CodeApex, there remains significant room for improvement in LLM accuracy, indicating an untapped potential for LLMs in code-related tasks.

The rest of the paper is organized as follows. In Section 2, we review previous work on evaluating the code-related capabilities of LLMs. We present the evaluation protocol for three programming tasks in Section 3. We present and discuss the evaluation results across three tasks and multiple categorizations in Section 4. Finally, we conclude this paper and discuss future work in Section 5.

## 2 RELATED WORK

## 2.1 Code Foundation Models

The implementation of programming comprehension heavily relies on the alignment of code space and natural language space through encoding. Graph2Code [58] employs graph neural networks to convert source code into a graph structure, capturing structural information within the code and thereby enhancing the accuracy of programming comprehension. Code2Vec [2] represents the Abstract Syntax Tree (AST) as token sequences along paths, enabling code transformation into fixed-length vector representations and facilitating the learning of code semantics. The introduction of the Transformer architecture [52] has provided novel approaches for code comprehension tasks. One prominent model in this regard is CodeT5 [53], an extension of the Text-to-Text Transfer Transformer (T5) [45] specifically designed for natural language processing tasks on source code. CodeBERT [25] maps both natural language and code into a shared vector space and leverages attention mechanisms to capture semantic relationships between them. Furthermore, there are models [42, 56] that focus on specific programming tasks such as code comment generation and API documentation generation within the source code context.

The task of code generation has garnered significant attention after the emergence of LLMs. These language models are pre-trained on massive text datasets, enabling them to learn rich language representations. General-purpose LLMs, such as GPT and Llama [46], have a certain ability to generate code. Some LLMs are specifically designed training schemes for the programming tasks, aimed at improving their coding performance. One common approach to code generation is fine-tuning existing large-scale language models. In this method, a pre-trained language model

Lingyue Fu, Huacan Chai, Kounianhua Du, Weiming Zhang, Shuang Luo, Jianghao Lin, Yuchen Fang, Renting Rui, Hao Guan, Jianxing Liu, Siyuan Qi, Longteng Fan, Jiayi Lei, Yifan Liu, Jingkuan Wang, Kangning Zhang, Weinan Zhang, 111:4 and Yong Yu is used as the initial model and further trained on specific code generation datasets. Codex [9], PaLMCoder[11], CodeGeeX2[65] are further trained on GPT-3, PaLM[11], ChatGLM2[19, 61] with extensive public code datasets, demonstrating better comprehension and generation abilities on programming languages. With the development of instruction tuning techniques, a series of models, like WizardCoder[40], Code Llama-Instruct[47], PanguCoder[12] demonstrate powerful capabilities in multilingual code generation and debugging tasks. Another prevalent approach is prompt engineering, which involves designing suitable prompts or guiding statements to direct the model in completing specific code generation tasks. By providing insightful inputs, models can generate more accurate and expected code outputs. CodeGen [44] converts natural language questions into code generation tasks and improves generation effectiveness through appropriate prompt engineering techniques. DocPrompting [66] leverages keyword retrieval to integrate information from code repositories into prompt phrases, guiding the LLMs to enhance the performance of LLMs in code generation tasks.

# 2.2 Programming Evaluation

Evaluating large language models' (LLMs) capabilities can be effectively achieved through multichoice formats, where models are tasked with selecting the correct answer from given options. Multi-choice RACE transforms the original reading comprehension dataset RACE [32] into a set of questions with answer choices, facilitating the evaluation of the model's score. AI2 Reasoning Challenge (ARC) [13] serves as a benchmark to measure how well language models can reason and draw conclusions within the domain of science. C-Eval [27] provides multiple-choice questions from multiple subjects, enabling us to evaluate the competency of LLMs in different academic domains. CodeApex employs multiple choice question formats to evaluate LLM's programming comprehension ability.

Another crucial dimension in assessing LLMs' capabilities involves their performance on coderelated tasks. The development of specialized benchmark datasets offers nuanced insights into LLMs' programming comprehension and generation skills. In the earlier days, FlashFill++ [8] provides a benchmark dataset for inferring string transformation programs from input-output examples. CodeSearchNet [28] serves code search tasks by offering a vast collection of code snippets for code retrieval and documentation generation. With the development of deep learning, NLP tasks have become more diverse. Benchmark datasets have started combining code-related tasks with natural language. CodeXGLUE [26] is a benchmark that encompasses natural language understanding of code, covering various tasks such as code summarization, code translation, code completion, and more. APPS [24] is a benchmark designed to evaluate program synthesis systems, with a focus on probabilistic programs and their ability to generalize to new tasks. With the emergence of LLMs, [9] proposed the HumanEval benchmark, specifically designed to assess the quality of generated code. HumanEval-X[65] benchmark introduces support for multiple programming languages, including C++, Python, Go, and Java, aiming to facilitate research in cross-language code generation and understanding. CoderEval[60] benchmark specifically focuses on evaluating large language models' abilities to tackle complex, industrial-level coding challenges through a series of practical programming tasks. DebugBench [50] implants bugs into standard code by GPT4 and evaluates five LLMs in a zero-shot scenario. CodeApex focuses on evaluating the reasoning capabilities of LLMs by presenting them with algorithmic challenges and associated test cases.

# 3 EVALUATION PROTOCOL

In this section, we introduce the evaluation framework of CodeApex for three code tasks: (1) programming comprehension, (2) code generation, and (3) code correction. The overall experiment scenarios of CodeApex are listed in Figure 1.

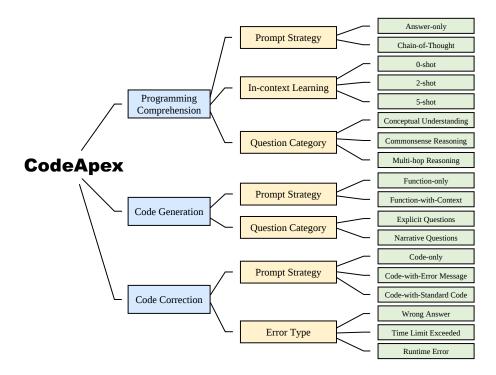


Fig. 1. Overview diagram of CodeApex benchmark.

- The first task is *programming comprehension*, whose test set includes 250 multiple-choice exam questions, which are categorized into conceptual understanding, commonsense reasoning, and multi-hop reasoning questions. The questions are selected from the final exams of different classes (Programming, Data Structure, Algorithm) at the university, which reduces the risk that the test data is already in the training corpus of LLMs. LLMs are asked to choose the correct option under the 0-shot, 2-shot, and 5-shot in-context learning scenarios. Due to the effective application of Chain-of-Thought (CoT), we also compare the performances of LLMs under the answer-only and CoT settings.
- The second task is *code generation*, whose test set includes 476 C++-based coding questions, covering explicit questions and narrative questions. The description of the question and the prototype of the function to implement the question are given, and LLMs are asked to complete the main part of the function. We also provide both the function-only and function-with-context scenarios, which indicate whether the calling code of the objective function is given in addition to the description of the objective function (i.e., the context information of the code).
- The third task is *code correction*, whose test set includes 1330 erroneous code segments with three types of error messages (Wrong Answer, Time Limit Exceeded, and Runtime Error).
   We introduce three types of prompts to simulate code-only, code-with-error message, and code-with-standard code scenarios.

For each task, we first provide an overview and then discuss about the data processing, prompting strategy, and evaluation metric. To facilitate a fine-grained comparison of the differences in the

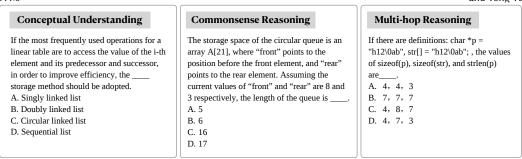


Fig. 2. Examples of the three categories of questions in the programming comprehension task.

abilities of LLMs across different natural languages, we provide *aligned Chinese and English versions* for all test data in the three tasks.

# 3.1 Programming Comprehension Task

- *3.1.1 Overview.* In the programming comprehension task, LLMs have to answer multiple-choice questions that are closely related to code & programming topics. This evaluates the basic capabilities of LLMs in understanding the code from various dimensions such as syntax, execution flow and code structure. The ability of programming comprehension lays the foundation for LLMs to accomplish other code-related tasks, and is therefore indispensable to thoroughly integrate LLMs into real-world code production scenarios.
- 3.1.2 Data Processing. We evaluate the programming comprehension capability of LLMs via multiple-choice questions, which generally cover the key knowledge points of programming, data structure and algorithms. The multiple-choice question data is obtained from the final exams of real-world college courses under strict confidentiality, greatly decreasing the possibility of the test data overlapping with the training data of LLMs crawled online (i.e., test data leakage). Questions with multiple correct answers are manually modified into single-choice questions to facilitate testing consistency. Similar to C-Eval [27], we format the options of the multiple-choice questions for alignment. The question prompts are provided in Markdown format, i.e., code blocks are marked using triple quotes. All questions are manually cross-validated to ensure the unambiguity of the question descriptions and the correctness of the answers.

In order to facilitate further exploration of the fine-grained abilities of LLMs, we manually classify the questions into three categories: (1) conceptual understanding, (2) commonsense reasoning, and (3) multi-hop reasoning. Example questions of three categories are demonstrated in Figure 2. Conceptual understanding questions assess LLMs' basic understanding of programming concepts, typically involving selecting the correct concept or natural language description without requiring specific code writing or comprehension. Commonsense Reasoning questions primarily evaluate LLMs' ability to read and understand code. These two types of questions focus on a single knowledge point, with relatively simple problem-solving steps that can be deduced through single-step reasoning. Multi-hop reasoning questions evaluate LLMs' ability to reason about code. These questions often involve chains of thought and require multiple steps of inference to get the correct answer. These three categories of questions correspond to LLMs' elementary grasp of programming concepts, basic understanding of code, and advanced comprehension of code, respectively. The categorized results could provide us with deeper insights into the fine-grained levels of programming comprehension capabilities of LLMs.

```
Answer-only Scenario (Chinese Version)
以下是一次编程考试的单项选择题,请选出其中的正确答案。
若森林F有15条边、25个结点,则F包含树的个数是_
A 8
B. 9
C. 10
D. 11
答案: C
...[x-shots]
若有定义: ```char str[] = {'h','1','2','0','a','b'};const char *p =
str;```下列语句正确的是: ____。
A. p[2] = 's'
B. strcpy(str,"123456")
C. strcpy(p,"abc")
D. strcpy(str,"abc")
答案:D
```

(a) Answer-only setting (Chinese).

```
Answer-only Scenario (English Version)
The following is a single choice question about a programming
exam, please select the correct answer among them, please output
only one answer.
If forest F has 15 edges and 25 nodes, the number of trees contained
A. 8
B. 9
C. 10
D. 11
Answer: C
...[x-shots]
If there is a definition: ```char str[] = \{'h', '1', '2', '0', 'a', 'b'\}; const
char *p = str; ```. Which of the following statements is correct:_
A. p[2] = 's'
B. strcpy(str,"123456")
C. strcpv(p,"abc")
D. strcpy(str,"abc")
Answer: D
```

(b) Answer-only setting (English).

Chain-of-Thought Scenario (English Version)
The following is a single choice question about a programming

If forest F has 15 edges and 25 nodes, the number of trees contained

exam, please select the correct answer among them.

in F is

A. p[2] = 's'
B. strcpy(str,"123456")

1, .....

2. . . . . . .

C. strcpy(p,"abc")

D. strcpy(str,"abc")

Answer: Let's think step by step.

Therefore, the correct answer to this question is D.

A. 8

```
Chain-of-Thought Scenario (Chinese Version)
以下是一次编程考试的单项选择题,请选出其中的正确答案。
若森林F有15条边、25个结点,则F包含树的个数是_
A. 8
B. 9
C. 10
D. 11
答案: 让我们一步一步思考。
1,15条边、25个结点,即有25个点构成15条边,且25个点只能
围成有限的森林
2, 因此求森林中树的个数等价于求这25个点可以组成多少个孤
立的组,即有多少颗独立的树。
3,森林中有m颗树,则结点数量为25-m,边数为15-m,从而可
得: 25-m=2×(15-m),即 m=10, 因此森林F包含10棵树, 答
案为C。
因此这道题的正确答案是C。
...[x-shots]
若有定义: ```char str[] = {'h','1','2','0','a','b'};const char *p =
str;```下列语句正确的是:___。
A. p[2] = 's'
B. strcpy(str,"123456")
C. strcpy(p,"abc")
D. strcpy(str,"abc")
答案:让我们一步一步思考。
1, ......
因此这道题正确答案是D。
```

 $(c) \ \ Chain-of-Thought \ setting \ (Chinese).$ 

```
B. 9
C. 10
D. 11
Answer: Let's think step by step.
1, 15 edges and 25 nodes, that is, 25 points form 15 edges and 25 points can only form a limited forest.
2, ...
3, ...[explanations to the example question]
Therefore, the correct answer to this question is C.
...[x-shots]
If there is a definition: ```char str[] = {'h', '1', '2', '0', 'a', 'b'}; const char *p = str; ```. Which of the following statements is correct:
```

(d) Chain-of-Thought setting (English).

- Fig. 3. Examples illustrating the programming comprehension task in answer-only and chain-of-thought scenarios, presented in both English and Chinese versions. The completed responses from LLMs are highlighted in red, while the input prompts are shown in black text.
- 3.1.3 Prompting Strategy. We evaluate the code comprehension abilities of LLMs under two different prompting strategies, i.e., answer-only and chain-of-thought. In the answer-only setting, LLMs are required to generate only a single option (i.e., the selected choice), and the correctness of the generated option contributes to the final accuracy score. In the chain-of-thought setting, LLMs

```
Problem: Given an integer array nums whose size is n and a target integer, write a code to determine if there exists a contiguous subarray in nums that sums up to the target. If such a subarray exists, return True; otherwise, return False. The first number of input is n, and then input n numbers consecutively to represent array[1] to array[n]. Here 1 \le n \le 1e7. Example input: ```3 1 2 3 5 ```
Example output: ``` True```
Testcase 1: 3 1 2 3 5 ...
Testcase 5: 1000 ... ...
Testcase 6: 10000 ... ...
Testcase 9: 10000000 ... ...
Testcase 10: 10000000 ... ...
```

Fig. 4. Illustration of testcases of different difficulty levels. If the complexity of the code is  $O(n^2)$ , it could pass at least the first six testcases. If the tester uses the prefix sum algorithms with O(n) complexity, he can pass all test points.

would first generate a piece of analytical text followed by a final answer, and the accuracy of the final answer serves as the measure of model performance. We illustrate the prompt examples under both settings in Figure 3.

3.1.4 Evaluation Metric. We adopt the accuracy (ACC) as the evaluation metric for the programming comprehension task. After LLMs provide a response under either answer-only or chain-of-thought settings, we extract the final choice using regular expressions. If the choice cannot be extracted via regular expressions, it is regarded as an incorrect answer. The final accuracy of the LLM is calculated as:

$$ACC = \frac{\text{#Correct Answers}}{\text{#Questions}}.$$

## 3.2 Code Generation Task

- *3.2.1 Overview.* In the code generation task, LLMs have to extract relevant algorithm requirements from natural language descriptions, and then, in conjunction with a given code function framework, generate executable and accurate codes to pass the test cases. Such a task demands that large language models possess the comprehension ability for both natural languages and code structures, as well as the capability to analyze, design, and ultimately generate functional code snippets.
- 3.2.2 Data Processing. The test data is sourced from basic exercises on an internal Online Judge platform, which provides question descriptions, sample inputs/outputs, code templates, and test cases of varying difficulty levels. The question descriptions are typically provided in natural language, some of which also contain scenario-based descriptions. The sample inputs/outputs illustrate the format of the test case inputs and outputs, represented in Markdown format. The code templates represent fully functional code that passes all the tests and is used to generate test examples for CodeApex. The difficulty levels of the test cases are illustrated in Figure 4. Taking binary search as an example, the first five test cases have small input sizes n and can be solved using a regular loop-based search. However, the last five test cases have larger input sizes, and if a regular loop-based search is used, it will exceed the time limit. The privacy of data sources and the diversity of question descriptions decrease the possibility of test data appearing in the training corpus of LLMs. This promotes the fairness of evaluation and contributes to rational cognition of the programming abilities of different LLMs.

```
Code Generation (Question-Description-Only)
Prompt: I will provide you with a specific question description. Your
task is to generate the code that accomplishes this target task. You
only need to provide the C++ code; please do not include additional
Problem: input integer a and b, output the value of a+b.
Time Limit: 1000 ms
Space Limit: 1 MB
GPT3.5-turbo:
#include <iostream>
int main() {
    int a, b;
    std::cout << "Enter the value of a: ";
     std::cin >> a;
     std::cout << "Enter the value of b: ";
     std::cin >> b;
    int sum = a + b:
    std::cout << "The sum of a and b is: " <<
sum << std::endl;
    return 0;
```

Fig. 5. Illustration of the Question-Description-Only mode, where only the code question description is fed into LLMs for generation. The generated code by GPT3.5-turbo is demonstrated below. The code contains additional boot outputs, causing this logically correct code to fail the testcases.

Most LLMs are unable to generate code that meets the given input-output conditions based solely on question descriptions. When we directly input the original question description into LLMs, it is highly likely that the generated code will contain additional prompt-related output. Although the logic of the code itself may be correct, these extra outputs are not included in the original test cases, causing the generated code to fail the tests. Figure 5 illustrates an example of this situation, which occurs during code generation with GPT-3.5-turbo. In such cases, in order to more accurately evaluate code generation capability of LLMs itself, we utilize GPT-4 to assist in generating functional form test examples. With an in-context learning approach, we guide the LLMs in rewritting the template code and dividing it into a main function and some auxiliary functions. The main function includes (i) library references, (ii) the main function itself (with input and output code), and (iii) calls to auxiliary functions. The auxiliary functions contain the main algorithmic logic with input parameters and return the output to the main function.

To further explore the different types of code generation abilities of LLMs, we divide the questions into two categories: explicit questions and narrative questions. Explicit questions directly specify the functionality that the program needs to implement, such as "Implement a quicksort" or "Calculate the number of characters in the input." Narrative questions consist of more complex natural language descriptions, with the code requirements hidden within a scenario. For example, given a class of students, you need to inquire about the grade of the k-th student. This question requires storing the grades of the students in an array, sorting them, and then outputting the k-th largest element. Previous benchmarks [9] focus on explicit questions, and do not pay attention to the importance of evaluating narrative questions.

3.2.3 Prompting Strategy. We describe our approach for generating target functions that adhere to function templates by designing prompts. These prompts consist of three components: question description, function description, and data range specification. In the 'function-only' scenario, no additional information is included in the prompts. In this case, LLMs are asked to generate a runnable function code that conforms to the function prototype and the question description. In the function-with-context scenario, we incorporate the context of the main function as an additional

## Function-only Scenario (Chinese)

我会给你一个需要用C++编程解决的问题和一个C++的函数声明,你的任务是按照这个函数声明生成对应的C++函数去解决这个问题,你只需要返回C++函数,不要返回额外的说明文字。问题:输入两个整数a,b,输出a+b的值。函数声明:int sum\_a\_b(int a, int b);

(a) Function-only scenario (Chinese).

#### Function-with-context Scenario (Chinese)

我会给你一个用于解决某个问题但缺少了函数定义的C++代 码,这个缺失函数定义的函数声明,这个C++代码解决的问题 及输入输出示例,你的任务是用这个函数声明生成函数定义去 填补所给的C++代码缺少的部分,并满足时间限制和空间限 制。你只需要返回C++代码的函数定义,不要返回额外的说明文 问题:输入两个整数a,b,输出a+b的值。 函数声明: int sum a b(int a, int b); 代码: #include <iostream> //function start //function end int main() { int a, b; std::cin >> a >> b; //calling start int sum = sum a b(int a, int b); //calling end std::cout << sum << std::endl; return 0; 输入输出示例: 输入: ```12```,输出: ```3``` 时间限制: 1000 ms 空间限制: 1 MB

(c) Function-with-Context scenario (Chinese).

## Function-only Scenario (English)

(b) Function-only scenario (English).

### Function-with-context Scenario (English)

I will give you a C++ code that solves a problem but is missing a function definition, a function declaration that is missing a function definition, a problem that the C++ code solves and an input/output example. Your task is to use this function declaration to generate a function definition that fills in the missing parts of the given C++ code and satisfies the time and space constraints. You only need to return the C++ function, without any additional explanatory text. Problem: input integers a and bm output the value of a+b. Function Declaration: int sum a b(int a, int b); Code: #include <iostream> //function start //function end int main() { int a, b; std::cin >> a >> b; //calling start int sum = sum\_a\_b(int a, int b); //calling end std::cout << sum << std::endl; return 0; Input-Output Examples: Input: ""1 2"", Output: ""3"" Time Limit: 1000 ms Space Limit: 1 MB

(d) Function-with-Context scenario (English).

Fig. 6. Examples of specific design of the prompts for code generation task. The model generates the text highlighted in yellow.

input to guide the LLM to generate the target function. The specific design of the prompts is illustrated in Figure 6.

3.2.4 Evaluation Metric. To evaluate the effectiveness of the code, we use the original question's test cases to measure its correctness. Each question provides 5-10 test cases that cover various possible input scenarios and edge conditions. CodeApex benchmark aligns with real-world scenarios of human programming by using the number of passed test cases as the model's score. All test case scores are equally weighted, regardless of their difficulty.

CodeApex introduces an evaluation metric called accept rate as the evaluation function for the generated code by the model. When the language model generates a response, we extract the runnable C++ code function from it and concatenate it into the main function in the dataset. The concatenated code remains executable, and the target input-output pairs are aligned with the test cases in the original dataset. By comparing the output of the test cases with the actual output, we

can get the number of the test cases the generated code passes, i.e., #passes(q). We calculate the AC@k, which represents the quality of the model-generated code

$$AC@k = \frac{1}{|Q|} \sum_{q \in O} \left[ \mathbb{I}(\# \operatorname{passes}(q) \ge k) \right],$$

where Q is the question set, and the indicator function  $\mathbb{I}$  presents

$$\mathbb{I}(condition) = \begin{cases} 1, & \text{if condition is true,} \\ 0, & \text{otherwise.} \end{cases}$$

When k is set to 1, the code can pass at least one test case. AC@1 reflects the functional correctness of the model-generated code. In this case, some test cases may not pass, which may result from inappropriate algorithm selection in the generation process or exceeding the time/space limits of the question itself. When k is set to all, AC@all represents the proportion of questions that have passed all test cases. This is a relatively strict metric for evaluating performance. In addition, we introduce the Accept Rate (AC Rate) metric to measure how well the generated code meets. The AC Rate is calculated as follows:

AC Rate = 
$$\frac{1}{|Q|} \sum_{q \in O} \left[ \frac{\text{\# passes}(q)}{\text{\# testcases}(q)} \right]$$
.

It reflects the overall performance of LLMs in the code generation task, including both algorithm selection and implementation.

## 3.3 Code Correction Task

- 3.3.1 Overview. In code correction task, LLMs need to revise the generated code with the question description, error message and standard code. Code correction is an essential stage in the programming procedure, the mastering of which could offer practical assistance in software engineering. In addition, utilizing the self-inspiration ability of LLMs to correct codes has emerged as a principle way for improving the accuracy of code generation [10]. Therefore, we include the evaluation for code correction, which is a fundamental ability of programming by LLMs.
- 3.3.2 Data Processing. The test data is originated from real students' submission of exercises on the internal Online Judge platform. Each submission contains the exercise ID, submission code, error type, and submission time. The types of error include: Wrong Answer (WA), Time Limit Exceeded (TLE), and Runtime Error (RE). If the submission answers all testcases correctly, then the error type is empty.

To ensure that erroneous code can be corrected within a certain number of steps rather than rewritten, we sample examples from submissions of the same users, where both the incorrect version and the correct version of the same problem exist. The incorrect version is then sampled to be the test sample, where we restrict the edit distance [33] between the incorrect version and the correct version to be less or equal to 50. From the generated code pairs, we select code pairs for each error type. Due to varying frequencies of difference error types, the resulting error codes primarily consist of WA error, along with a portion of other error types. We also ensure that the number of code pairs for each question is roughly equal.

3.3.3 Prompting Strategy. We design three types of prompts for simulating different code correction scenarios. The first type of prompt, Code-only, contains only the erroneous code and the question description without any additional information. This prompt is used to evaluate code correction capability of LLMs, simulating humans directly reading code and identifying errors. The second type of prompt, Code-with-Error Message, includes the erroneous code, task description, and the

# Code-only Scenario (Chinese)

```
下面给你一道题目描述以及学生的错误代码,请你将在
现有代码的基础上修正,使其可以通过原有题目的测试
题目描述:输入一个字符,判断该字符是大写或小写字
母。
错误代码为: ```
#include <bits/stdc++.h>
using namespace std;
int main() {
 char aa;
 if( ( aa>='a' && aa<='z' ) ||
( aa>='A' && aa<='Z' ) )
 cout<<"yes";
 else cout<<"no";
     return 0;
请仅仅输出修正之后的正确代码,不要输出多余信息。
```

(a) Code-only scenario (Chinese).

# Code-with-Error Message Scenario (Chinese)

下面给你一道题目描述以及学生的错误代码,请你将在 现有代码的基础上修正, 使其可以通过原有题目的测试 占。 题目描述:输入一个字符,判断该字符是大写或小写字 错误原因为: Partially Accepted 错误代码为: 请仅仅输出修正之后的正确代码,不要输出多余信息。

(c) Code-with-Standard Code scenario (Chinese).

## Code-only Scenario (English)

Below you are given a task description and the student's erroneous code, please correct the existing code so that it can pass the test cases of the task.

Task description: Enter a character, check if the character is an uppercase or lowercase letter.

```
Erroneous code is:
#include <bits/stdc++.h>
using namespace std;
int main() {
  char aa;
  if( ( aa>='a' && aa<='z' ) ||
( aa>='A' && aa<='Z' ) )
  cout<<"yes";
  else cout<<"no":
      return 0;
```

Please output only the correct code after the correction and do not output redundant information.

(b) Code-only scenario (English).

#### Code-with-Error Message Scenario (English)

Below you are given a task description and the student's erroneous code, please correct the existing code so that it can pass the test cases of the task.

Task description: Enter a character, check if the character is an uppercase or lowercase letter.

Error type is: Partially Accepted

Erroneous code is:

Please output only the correct code after the correction and do not output redundant information.

(d) Code-with-Error Message scenario (English).

```
Code-with-Standard Code Scenario (Chinese)
```

```
下面给你一道题目描述以及学生的错误代码,请你将在
现有代码的基础上修正, 使其可以通过原有题目的测试
题目描述:输入一个字符,判断该字符是大写或小写字
母。
错误原因为: Partially Accepted
错误代码为:
标准代码为: ```
#include <bits/stdc++.h>
using namespace std;
int main() {
 if( ( aa>='a' && aa<='z' ) ||
( aa>='A' && aa<='Z' ) )
 cout<<"yes";
 else cout<<"no";
```

请仅仅输出修正之后的正确代码,不要输出多余信息。

```
Code-with-Standard Code Scenario (English)
```

Below you are given a task description and the student's erroneous code, please correct the existing code so that it can pass the test cases of the task.

Task description: Enter a character, check if the character is an uppercase or lowercase letter.

Error type is: Partially Accepted

do not output redundant information.

Erroneous code is:

```
Standard code is:""
#include <bits/stdc++.h>
using namespace std;
int main() {
  char aa;
  if( ( aa>='a' && aa<='z' ) ||
( aa>='A' && aa<='Z' ) )
  cout<<"yes";
  else cout<<"no";
      return 0;
Please output only the correct code after the correction and
```

- (e) Code-with-Error Message scenario (Chinese). (f) Code-with-Standard Code scenario (English).

Fig. 7. Examples of specific design of the prompts for code correction task.

return 0;

type of error. This prompt simulates engineers debugging their code based on actual feedback from the compiler, aligning with real-world development scenarios. The third type of prompt is called Code-with-Standard Code. It builds upon the Code-with-Error Message prompt by adding standard code as additional input. In the development process, engineers can refer to existing code for correction. Evaluating code correction ability of LLMs in this scenario can assess its comprehensive programming capabilities, providing a guidance for LLM-assisted programming. The specific design of three types of prompts is demonstrated in Figure 7.

3.3.4 Evaluation Metric. Similar to code generation, we use the same test cases and same metrics (AC@1, AC@all, AC Rate) to measure the correctness of modified code. LLMs should realize code correction based on the input erroneous code. If the difference between the input and output code is too large (edit distance greater than 50), the output code is considered invalid. The score for invalid code is recorded as 0, regardless of whether it passes the test cases. In code-with-standard code scenario, in order to prevent the LLM from directly outputting standard code, we validate the generated code in the Code-with-Standard Code scenario. Any output code that is identical to the standard code is directly marked as an incorrect answer.

## 4 EVALUATION RESULTS

# 4.1 Experimental Setup

4.1.1 Dataset Statistics. In the programming comprehension task, CodeApex releases a total of 250 multiple-choice questions, which are divided into three categories: conceptual understanding (90 questions), commonsense reasoning (99 questions), and multi-hop reasoning (61 questions). In the code generation task, CodeApex releases 476 algorithm questions in total. These questions are divided into 258 functional questions and 218 descriptive questions. In the code correction task, CodeApex releases 1330 segments of erroneous code, corresponding to solving 116 questions in the code generation task. Each erroneous code has an error message, with a total of three types of error messages: Wrong Answer (1175 code segments), Time Limit Exceeded (69 code segments) and Runtime Error (86 code segments).

The test data is available on GitHub<sup>1</sup> for users to download and run. The standard answers are not publicly disclosed to ensure the appropriate usage of CodeApex, as its data might unintentionally include web-crawled content. Users are required to submit their model predictions to the provided webpage<sup>2</sup> to obtain an automated accuracy assessment, and a public leaderboard is maintained on the webpage. Users can choose whether to publish their models' scores on the leaderboard.

4.1.2 LLMs to Evaluate. CodeApex totally evaluates 12 LLMs, comprising a total of 41 variants. The tested LLMs and their variants are listed in Table 2. The variants of the models encompass the chatbot mode and the completion mode, as well as different parameter sizes and versions within the same base model. In the programming comprehension task, we conduct experiments on 10 LLMs, including both open-source models and API-based models. In the code generation task, we evaluate 11 accessible LLMs, including both general-purpose and code-specialized models. In the code correction task, due to the inability of some LLMs to output recognizable code, our experiments showcase the results of 7 models. The largest open-source models have 13 billion parameters, while the largest parameterized model based on API is GPT4.

*Parameter Settings.* When LLMs generate responses, we choose two distinct temperatures to cater to different application scenarios. For the programming comprehension task, we set temperature=0.01 to generate more conservative results, preventing the model from producing responses

<sup>&</sup>lt;sup>1</sup>https://github.com/APEXLAB/CodeApex.git

<sup>&</sup>lt;sup>2</sup>https://apex.sjtu.edu.cn/codeapex/

	and Y
Table 2. CodeApex evaluates 14 LLMs along with their variants.	

Model	Model Size	Form	Creator
ChatGLM[38]	6B	open, general-purpose	
ChatGLM2[38]	6B	open, general-purpose	Tsinghua & Zhipu
ChatGLM3[38]	6B	open, general-purpose	
MOSS[48]	16B	open, general-purpose	Fudan University
Chinese-Alpaca[15]	7B	open, general-purpose	Cui et al. [15]
BELLE[29, 30]	7B	open, general-purpose	Beike
BELLE-LLaMA[29, 30]	7B, 13B	open, general-purpose	Beike
InternLM-Chat[49]	7B	open, general-purpose	Shanghai AI Lab & Sense Time
Baichuan[5]	7B	open, general-purpose	Baichuan Inc.
EduChat-base[16]	7B, 13B	open, Edu-Use	East China Normal University
EduChat-sft[16]	7B	open, Edu-Use	East Clinia Normal University
CodeT5-plus[53]	6B, 16B	open, code-specialized	Salesforce AI
WizardCoder[40]	15B	open, code-specialized	Microsoft
StarCoder[34]	undisclosed	api, code-specialized	BigCode
Vicuna[64]	13B	open, general-purpose	LM-SYS
GPT-3.5-turbo[63]	undisclosed	api, general-purpose	OpenAI
GPT-4	undisclosed	api, general-purpose	ОренАі

that do not align with the desired answers. For the code generation and code correction task, we opted for a temperature of 0.7 and a top-p value of 0.8 to encourage the model to generate a broader range of possible codes, introducing more randomness in each code generation instance.

# 4.2 Programming Comprehension Results

The overall performance of the programming comprehension task in the answer-only and CoT scenarios are presented in Table 3 and Table 4. The tables display the best results achieved in the 0-shot, 2-shot, and 5-shot settings. Detailed results for the N-shot (N=0,2,5) settings are provided in the Appendix A. GPT4 obtains the highest average accuracy among all the models, followed by GPT3.5-turbo. The third best model in Answer-only scenario is InternLM-Chat-7B, which has an accuracy of 37%, which still have a huge gap between GPT. It is noteworthy that the accuracy of most LLMs is below 50%, highlighting that CodeApex Benchmark is challenging in the programming comprehension task.

Bilingual Accuracy Comparison. The Chinese version scored higher than the English version. There are two main reasons: (1) The source question descriptions are obtained from final exams in Chinese universities, and thus the exam questions are initially presented in Chinese. Even after translating them into English version, they still contain some language habits specific to Chinese speakers. As a result, when inputting these English questions with biases into the LLM, some noise might be introduced into the model's encoding results. (2) Most evaluated models are primarily trained on Chinese data, which leads to a poor understanding of English. In Table 3 and 4, LLM trained primarily on English corpus, such as codeT5 and GPT3.5-turbo, tend to have approximate performance on Chinese and English versions.

Accuracy Comparison on Different Question Categories. Among the three question categories, approximately half of the models perform best in conceptual comprehension, followed by commonsense reasoning, with the lowest accuracy on multi-hop reasoning. This result

Table 3. Accuracy results of Programming Comprehension Task in the answer-only setting. C.U., C.R., and M.H.R. indicate conceptual understanding, commonsense reasoning, and multi-hop reasoning questions, respectively. Each column displays the best accuracy among 5-shot, 2-shot, and 0-shot scenarios. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined. \* represents chat-bot mode of the LLM. ZH and EN represent the results of Chinese and English test versions.

				g Compre	hension (	Answer-o		
Model			Ή			E		
	C.U.	C.R.	M.H.R.	Total	C.U.	C.R.	M.H.R.	Total
ChatGLM-6B	0.3222	0.2626	0.3115	0.2960	0.3556	0.2424	0.3115	0.2960
ChatGLM-6B*	0.3333	0.2727	0.3115	0.2960	0.3926	0.2727	0.3770	0.3200
ChatGLM2-6B	0.3667	0.2727	0.3388	0.2987	0.4111	0.3165	0.2951	0.2987
ChatGLM2-6B*	0.3444	0.2626	0.3115	0.3040	0.3556	0.2828	0.3115	0.3040
ChatGLM3-6B	0.3770	0.2626	0.3770	0.3013	0.3667	0.3300	0.2951	0.3240
ChatGLM3-6B*	0.4593	0.2727	0.2789	0.3080	0.3407	0.2256	0.2951	0.2733
MOSS-16B*	0.3148	0.3401	0.3279	0.3120	0.2630	0.3468	0.3333	0.3120
Chinese-Alpaca-7B	0.3481	0.2929	0.2678	0.2880	0.3111	0.2727	0.3279	0.2947
Chinese-Alpaca-7B*	0.3000	0.2896	0.2787	0.2840	0.2926	0.2896	0.2350	0.2840
Chinese-Alpaca-plus-7B	0.2333	0.3367	0.2623	0.2653	0.3407	0.2963	0.3279	0.2987
Chinese-Alpaca-plus-7B*	0.3259	0.3030	0.2459	0.2853	0.2630	0.2929	0.2295	0.2573
Chinese-Alpaca-13B	0.2593	0.2929	0.2623	0.2733	0.3111	0.2323	0.2131	0.2733
Chinese-Alpaca-13B*	0.2741	0.2929	0.2077	0.2627	0.2778	0.2795	0.2514	0.2547
Chinese-Alpaca-plus-13B	0.2667	0.3401	0.2131	0.2827	0.2444	0.3569	0.3060	0.2827
Chinese-Alpaca-plus-13B*	0.2741	0.2997	0.1967	0.2573	0.2889	0.3569	0.2459	0.2973
BELLE-7B-1M	0.3333	0.3199	0.2787	0.2947	0.3333	0.3199	0.2787	0.3080
BELLE-7B-1M*	0.3481	0.3131	0.2459	0.3013	0.3889	0.3131	0.2404	0.3040
BELLE-7B-2M	0.2444	0.3367	0.2842	0.2760	0.2556	0.3165	0.2842	0.2613
BELLE-7B-2M*	0.2111	0.3165	0.2787	0.2413	0.2667	0.3165	0.2459	0.2400
BELLE-LLaMA-7B-0.6M	0.2926	0.3401	0.3169	0.3053	0.3222	0.3333	0.3279	0.2880
BELLE-LLaMA-7B-0.6M*	0.2778	0.3131	0.3115	0.3000	0.3444	0.2963	0.3115	0.3000
BELLE-LLaMA-7B-2M	0.2222	0.2963	0.1967	0.2387	0.3000	0.3333	0.2623	0.2680
BELLE-LLaMA-7B-2M*	0.2778	0.3064	0.2623	0.2840	0.2778	0.3232	0.2623	0.2840
BELLE-LLaMA-13B-2M	0.2889	0.3333	0.1967	0.2840	0.2222	0.3131	0.2131	0.2840
BELLE-LLaMA-13B-2M*	0.3444	0.2929	0.2186	0.2827	0.2667	0.2660	0.2186	0.2693
InternLM-Chat-7B	0.4556	0.3434	0.3443	0.3720	0.4444	0.3636	0.3443	0.3733
Baichuan-7B	0.3407	0.3367	0.2623	0.3147	0.2926	0.3064	0.2951	0.3147
EduChat-base-002-7B*	0.2259	0.3131	0.2295	0.2480	0.3296	0.3434	0.3279	0.3147
EduChat-base-002-13B*	0.2815	0.3535	0.2459	0.3013	0.3667	0.3636	0.2459	0.3267
EduChat-sft-002-7B*	0.2444	0.2424	0.2951	0.2560	0.2889	0.3434	0.2459	0.2920
CodeT5-plus-16B	0.2556	0.3030	0.3224	0.2640	0.2074	0.2997	0.3224	0.2640
CodeT5-plus-16B*	0.2815	0.3737	0.2732	0.3160	0.1963	0.3737	0.2787	0.2467
CodeT5-plus-6B	0.2333	0.3535	0.2404	0.2693	0.2778	0.3535	0.2896	0.3173
CodeT5-plus-6B*	0.2296	0.2828	0.2568	0.2573	0.2704	0.2828	0.2568	0.3040
GPT-3.5-turbo	0.6074	0.3300	0.6066	0.4893	0.5222	0.3468	0.6066	0.4893
GPT-3.5-turbo*	0.5963	0.3603	0.6393	0.5053	0.5333	0.3603	0.6066	0.4413
GPT4	0.6741	0.5455	0.8360	0.6600	0.6444	0.4848	0.8033	0.6160
GPT4*	0.7000	0.5455	0.8197	0.6680	0.6222	0.4848	0.8033	0.6120
Human (closed-book)	0.5818	0.6599	0.6683	0.6343	-	-	-	-
Human (open-book)	0.8596	0.6821	0.8878	0.7960	-	-	-	-

Lingyue Fu, Huacan Chai, Kounianhua Du, Weiming Zhang, Shuang Luo, Jianghao Lin, Yuchen Fang, Renting Rui, Hao Guan, Jianxing Liu, Siyuan Qi, Longteng Fan, Jiayi Lei, Yifan Liu, Jingkuan Wang, Kangning Zhang, Weinan Zhang, and Yong Yu Table 4. Accuracy results of Programming Comprehension Task in CoT setting. C.U., C.R., and M.H.R. indicate conceptual understanding, commonsense reasoning, and multi-hop reasoning questions, respectively. Each column displays the best accuracy among 5-shot, 2-shot, and 0-shot scenarios. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined. \* represents chat-bot mode of the LLM. ZH and EN represent the results of Chinese and English test versions. Since CodeT5 fails to generate a response with chain-of-thought, we exclude it in this setting.

		Progra	mming C	omprehe	nsion (Ch	ain-of-Th	ought)	
Model		Z	Ή				N	
	C.U.	C.R.	M.H.R.	Total	C.U.	C.R.	M.H.R.	Total
ChatGLM-6B	0.3111	0.2121	0.3770	0.2880	0.3444	0.1818	0.3115	0.2640
ChatGLM-6B*	0.3333	0.2222	0.2787	0.2480	0.2889	0.2525	0.3115	0.2760
ChatGLM2-6B	0.4778	0.2525	0.3115	0.3240	0.3667	0.2525	0.2951	0.2960
ChatGLM2-6B*	0.4111	0.2929	0.3770	0.3360	0.4000	0.2525	0.2787	0.2960
ChatGLM3-6B	0.3630	0.2626	0.2514	0.2827	0.3963	0.2963	0.2841	0.2867
ChatGLM3-6B*	0.3519	0.2256	0.3497	0.2733	0.3370	0.2054	0.2842	0.2693
MOSS-16B*	0.2667	0.1717	0.3279	0.2240	0.2667	0.2020	0.2787	0.2360
Chinese-Alpaca-7B	0.2889	0.3030	0.2131	0.2680	0.2556	0.3333	0.2131	0.2640
Chinese-Alpaca-7B*	0.2778	0.3232	0.2623	0.2640	0.2667	0.3232	0.2295	0.2800
Chinese-Alpaca-plus-7B	0.3667	0.3131	0.2787	0.3240	0.2778	0.3030	0.2951	0.2880
Chinese-Alpaca-plus-7B*	0.2667	0.2626	0.2295	0.2400	0.2778	0.2626	0.2623	0.2480
Chinese-Alpaca-13B	0.2889	0.2929	0.2459	0.2640	0.3111	0.2323	0.2295	0.2520
Chinese-Alpaca-13B*	0.3111	0.2727	0.2295	0.2640	0.2444	0.2121	0.2623	0.2160
Chinese-Alpaca-plus-13B	0.3111	0.2929	0.2131	0.2600	0.3111	0.2525	0.2951	0.2560
Chinese-Alpaca-plus-13B*	0.3556	0.2727	0.2295	0.2920	0.3000	0.2222	0.2951	0.2560
BELLE-7B-1M	0.3333	0.2929	0.2459	0.2720	0.2444	0.2222	0.2131	0.2120
BELLE-7B-1M*	0.3333	0.2525	0.2131	0.2600	0.2111	0.2020	0.1475	0.1840
BELLE-7B-2M	0.2889	0.2626	0.2295	0.2240	0.2556	0.2222	0.1311	0.2040
BELLE-7B-2M*	0.2667	0.2424	0.2131	0.2400	0.1889	0.2222	0.1311	0.1880
BELLE-LLaMA-7B-0.6M	0.2667	0.3030	0.2951	0.2760	0.2222	0.2323	0.2623	0.2320
BELLE-LLaMA-7B-0.6M*	0.3444	0.3636	0.3115	0.3200	0.3333	0.2424	0.2623	0.2600
BELLE-LLaMA-7B-2M	0.2444	0.3030	0.2295	0.2640	0.2222	0.2121	0.1311	0.1880
BELLE-LLaMA-7B-2M*	0.2778	0.3030	0.2459	0.2800	0.2111	0.2020	0.1967	0.1880
BELLE-LLaMA-13B-2M	0.2889	0.2727	0.1967	0.2560	0.2556	0.2222	0.1967	0.2120
BELLE-LLaMA-13B-2M*	0.2667	0.2828	0.2131	0.2600	0.2778	0.1717	0.1803	0.2120
InternLM-Chat-7B	0.3556	0.1818	0.3607	0.2880	0.4222	0.2525	0.2623	0.3160
Baichuan-7B	0.0667	0.1111	0.0656	0.0720	0.1222	0.1111	0.2960	0.1000
EduChat-base-002-7B*	0.2778	0.2323	0.2623	0.2480	0.2556	0.2424	0.2623	0.2360
EduChat-base-002-13B*	0.3000	0.2424	0.3279	0.2800	0.3111	0.2424	0.2787	0.2680
EduChat-sft-002-7B*	0.3111	0.2121	0.2623	0.2520	0.3111	0.2222	0.2623	0.2560
GPT-3.5-turbo	0.5944	0.4141	0.6803	0.5260	0.5278	0.3687	0.6393	0.4740
GPT-3.5-turbo*	0.5667	0.4242	0.6503	0.5187	0.5074	0.3737	0.6339	0.4853
GPT4	0.7111	0.5152	0.8361	0.6640	0.6444	0.5051	0.8689	0.6320
GPT4*	0.7222	0.5859	0.7869	0.6960	0.6556	0.5152	0.8361	0.6280
Human (closed-book)	0.5818	0.6599	0.6683	0.6343	-	-	-	-
Human (open-book)	0.8596	0.6821	0.8878	0.7960	-	-	-	-

indicates that LLMs are likely to incorporate knowledge of programming concepts during training. Most models scored higher in commonsense reasoning compared to multi-hop reasoning, suggesting that the capability of LLMs significantly decreases with an increase in the number of reasoning steps.

Effects of Chain-of-Thought Prompting. Most of the models achieve approximate or lower accuracy than the answer-only setting. The accuracy results of the CoT setting are depicted in Table 4. The reasons for this observation are two folds: (1) Models we evaluate do not reach model sizes that have the emergent ability of CoT. According to [54], the emergence of CoT requires LLM to have at least 60B parameters. When the parameter number is not enough, the CoT setting might introduce additional noise, and the generated response of LLM would be unstable. That's why GPT3.5-turbo, which has reached the emergence point, achieves higher accuracy in the CoT setting. (2) When answering conceptual understanding and commonsense reasoning questions, we do not require multi-step reasoning. Thus, the CoT ability of LLMs does not provide assistance for these categories of questions. However, for multi-hop reasoning questions, there is a noticeable improvement in accuracy in the CoT scenario for some models (such as ChatGLM2, educhat, and GPT3.5-turbo). Since CodeT5 fails to generate a response with chain-of-thought, we exclude it in the CoT setting.

Human Performance. Novice programmers perform similarly to GPT-4 in closed-book tests after learning, while human performance in open-book exams is significantly better than all LLMs. The performance of human testers is shown in Table 3. Note that programming comprehension tasks in CodeApex is considered a semi-open-book exam for LLMs, i.e., they have limited offline knowledge base.

# 4.3 Code Generation Results

Code generation task results of all the models are shown in Table 5 and Table 6. Two prompt strategies (function-only and function-with-context) are employed for each language version. The evaluation metrics include AC@1, AC@all, and AC Rate. GPT outperforms the other LLMs, with the best accepted rate over 66% (GPT4). WizardCoder and StarCoder ranked second and third, highlighting the significant improvement in code generation capability through code-based fine-tuning. There is no noticeable performance difference between the Chinese and English versions.

Effects of Contexts in Prompt. As shown in Table 5 and Table 6, providing the context of function calls for LLM can effectively enhance the accuracy of generating target function code. Meanwhile, Table 7 shows the proportion of compilable code in each scenario. The majority of models are capable of generating over 50% of compilable code, which demonstrates the ability of LLM to adhere to the function prototype. After concatenating the generated function and the main function, the code that could be compiled can be checked by testcases. Generally, providing contextual information about the function can assist LLMs in generating compilable code.

Question Category Comparison. Table 8 shows the performance on explicit and narrative questions. The data is selected from function-only and function-with-context scenarios, with the betterperforming data chosen. The table demonstrates that **LLMs perform better on explicit questions than narrative questions**. This is because explicit questions only require atomic code generation ability of LLMs, while narrative questions require LLM to first understand the question description, convert natural language into program logic, and finally generate code. It is indeed a significant challenge to extract program logic from natural language, requiring a deep understanding of language semantics and context. Meanwhile, three metrics of LLM on narrative questions are mostly consistent, indicating that the generated code is either entirely correct or entirely incorrect.

Lingyue Fu, Huacan Chai, Kounianhua Du, Weiming Zhang, Shuang Luo, Jianghao Lin, Yuchen Fang, Renting Rui, Hao Guan, Jianxing Liu, Siyuan Qi, Longteng Fan, Jiayi Lei, Yifan Liu, Jingkuan Wang, Kangning Zhang, Weinan Zhang, 111:18 and Yong Yu Table 5. Performance on AC@1, AC@all, and AC Rate metrics of code generation task in Chinese version. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined. General-purpose LLMs that are not able to generate code are removed from the table.

		Со	de Generat	ion (Chir	nese)	
Model	F	unction-or	nly	Funct	ion-with-0	Context
	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate
ChatGLM-6B	0.2143	0.0924	0.1371	0.1576	0.0693	0.1063
ChatGLM2-6B	0.2143	0.1197	0.1560	0.1996	0.0777	0.1274
ChatGLM3-6B	0.1387	0.1092	0.1330	0.0903	0.0651	0.0854
MOSS-16B*	0.2374	0.1492	0.1879	0.2458	0.1282	0.1770
Chinese-Alpaca-plus-13B	0.2773	0.1387	0.1867	0.2710	0.1366	0.1886
BELLE-7B-1M	0.1639	0.0588	0.0954	0.1513	0.0651	0.0941
BELLE-LLaMA-13B-2M	0.1912	0.0903	0.1283	0.1996	0.0840	0.1274
InternLM-Chat-7B	0.1450	0.0735	0.1039	0.1513	0.0924	0.1128
Baichuan-Chat-13B	0.3130	0.1786	0.2303	0.1723	0.0987	0.1263
WizardCoder-15B	0.4496	0.2773	0.3468	0.4328	0.2668	0.3329
StarCoder	0.2227	0.1366	0.1679	0.1870	0.0924	0.1340
Vicuna-13B	0.2689	0.1261	0.1790	0.3046	0.1492	0.2045
GPT3.5-turbo	0.6429	0.4265	0.5240	0.6660	0.4853	0.5644
GPT4	0.6216	0.4968	0.5411	0.7672	0.6336	0.6659
Human (one-submission)	-	-	-	0.7099	0.7099	0.7099
Human (three-submission)	-	-	-	0.9288	0.9288	0.9288
Human (five-submission)	-	-	-	0.9766	0.9766	0.9766

This may be due to the fact that narrative questions in the dataset are designed for real-world problem-solving, with relatively low requirements for code time and space complexity.

Human Performance. We extract real student learning records from online platforms to evaluate human performance in code generation tasks. We calculated the pass rates for human submissions in n times (n=1, 3, 5), and the average results are shown in the Table 5, Table 6 and Table 8. Experimental results suggest that human performance can outperform all LLMs, and they have a better performance on narrative questions. This is mainly due to the ease with which human programmers can translate between natural language and code languages.

# 4.4 Code Correction Results

The overall performance of LLMs in the code correction task is shown in Table 9 and 10. There is a significant difference in debugging ability among different models. GPT-4 performs the best among all LLMs with the best accuracy of 66%, followed by GPT3.5-turbo, StarCoder and WizardCoder. Baichuan and ChatGLM3 could correct over 25% erroneous code, which is equipped with code correction capability. Other models perform poorly in code correction tasks, with a success rate of less than 20%. The code correction capability of LLMs still has a lot of room for improvement.

Feedback Analysis. Providing error types does not significantly help LLMs in the code correction task. This may be because the online judge platform only provides three types of error without specific line numbers or other detailed error messages, which is not sufficient to assist LLMs in code correction. LLMs that are unable to complete code correction tasks can

Table 6. Performance on AC@1, AC@all, and AC Rate metrics of code generation task in English version. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined. General-purpose LLMs that are not able to generate code are removed from the table.

		Сс	de Genera	tion (Eng	lish)	
Model	F	unction-or	ıly	Funct	ion-with-C	Context
	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate
ChatGLM-6B	0.2080	0.0693	0.1203	0.1828	0.0672	0.1031
ChatGLM2-6B	0.1891	0.0819	0.1243	0.1029	0.0462	0.0668
ChatGLM3-6B	0.1450	0.1176	0.1363	0.1324	0.0987	0.1232
MOSS-16B*	0.2626	0.1513	0.2002	0.1534	0.0882	0.1178
Chinese-Alpaca-plus-13B	0.2878	0.1345	0.1963	0.2542	0.1092	0.1682
BELLE-7B-1M	0.2038	0.0651	0.1161	0.1618	0.0525	0.0863
BELLE-LLaMA-13B-2M	0.1870	0.0777	0.1197	0.2227	0.0861	0.1434
InternLM-Chat-7B	0.0945	0.0525	0.0707	0.3025	0.1597	0.2126
Baichuan-Chat-13B	0.3298	0.1618	0.2310	0.3319	0.1681	0.2273
WizardCoder-15B	0.4244	0.2500	0.3248	0.4391	0.2752	0.3444
StarCoder	0.3382	0.1891	0.2494	0.2794	0.1723	0.2116
Vicuna-13B	0.1870	0.0861	0.1236	0.2983	0.1218	0.1861
GPT3.5-turbo	0.6134	0.4286	<u>0.5105</u>	0.6597	0.4832	0.5606
GPT4	0.5839	0.4623	0.5176	0.7032	0.5705	0.5992
Human (one-submission)	-	-	-	0.7099	0.7099	0.7099
Human (three-submission)	-	-	-	0.9288	0.9288	0.9288
Human (five-submission)	-	-	-	0.9766	0.9766	0.9766

Table 7. Compilable code proportion on each scenario. All models except MOSS-16B\* use the completion pattern to generate code. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined.

		Compilable Co	Compilable Code Proportion							
Model		ZH	EN							
	Function-only	Function-with-Context	Function-only	Function-with-Context						
ChatGLM-6B	0.5693	0.5231	0.6429	0.5336						
ChatGLM2-6B	0.5105	0.5399	0.5399	0.4034						
ChatGLM3-6B	0.6828	0.4601	0.7353	0.6261						
MOSS-16B*	0.5231	0.5147	0.6092	0.3739						
Chinese-Alpaca-plus-13B	0.7164	0.6744	0.7017	0.6723						
BELLE-7B-1M	0.4244	0.4244	0.5273	0.4307						
BELLE-LLaMA-13B-2M	0.5105	0.4601	0.4580	0.5357						
InternLM-Chat-7B	0.3466	0.4265	0.2017	0.7626						
Baichuan-Chat-13B	0.6218	0.3908	0.7605	0.7437						
WizardCoder-15B	0.8529	0.8634	0.8361	0.7899						
StarCoder	0.4685	0.4853	0.6765	0.5945						
Vicuna-13B	0.7122	0.7983	0.4496	0.7815						
GPT3.5-turbo	0.9118	0.8950	0.8929	0.8929						
GPT4	0.7865	0.9159	0.7883	0.8674						

exhibit code correction capability after being provided with standard code. This is because

Table 8. Best performance comparison between explicit and narrative questions on AC@1, AC@all and AC Rate metric of code generation in English version. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined.

		Сс	de Genera	tion (Eng	lish)	
Model	Exp	olicit Ques	tions	Narı	rative Que	stions
	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate
ChatGLM-6B	0.2558	0.1008	0.1240	0.1560	0.1560	0.1560
ChatGLM2-6B	0.2326	0.1202	0.1153	0.1376	0.1376	0.1376
ChatGLM3-6B	0.1387	0.1092	0.1330	0.0903	0.0651	0.0854
MOSS-16B*	0.3488	0.2403	0.2562	0.1606	0.1606	0.1606
Chinese-Alpaca-plus-13B	0.3876	0.2054	0.2384	0.1835	0.1835	0.1835
BELLE-7B-1M	0.2674	0.0930	0.1335	0.1330	0.1330	0.1330
BELLE-LLaMA-13B-2M	0.2946	0.1395	0.1933	0.1422	0.1422	0.1422
InternLM-Chat-7B	0.3992	0.2287	0.2502	0.1927	0.1927	0.1927
Baichuan-Chat-13B	0.4147	0.2481	0.2680	0.2523	0.2523	0.2523
Wizard-Coder-15B	0.5388	0.3488	0.3943	0.3440	0.3440	0.3440
StarCoder	0.4264	0.2597	0.2744	0.2385	0.2385	0.2385
Vicuna-13B	0.3953	0.1822	0.2393	0.1881	0.1881	0.1881
GPT3.5-turbo	0.7054	0.5271	0.5770	0.6193	0.6193	0.6193
GPT4	0.7276	0.5837	0.6025	0.6743	0.5550	0.5959
Human (one-submission)	0.6970	0.6970	0.6970	0.7457	0.7457	0.7457
Human (three-submissions)	0.9169	0.9169	0.9169	0.9618	0.9618	0.9618
Human (five-submissions)	0.9731	0.9731	0.9731	0.9865	0.9865	0.9865

Table 9. Performance on AC@1, AC@all, and AC Rate metrics of code generation task in Chinese version. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined.

	Code Correction (Chinese)									
Model		Code-onl	y	Code-w	ith-Error	Message	Code-with-Standard Code			
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	
ChatGLM-6B	0.1323	0.0519	0.0899	0.1286	0.0511	0.0851	0.1699	0.1566	0.1086	
ChatGLM2-6B	0.2549	0.0902	0.1574	0.2316	0.0887	0.1402	0.2022	0.1654	0.1476	
ChatGLM3-6B	0.4293	0.2436	0.2944	0.4414	0.2376	0.2918	0.2917	0.2805	0.2220	
BELLE-7B-1M	0.0526	0.0226	0.0345	0.0256	0.0060	0.0156	0.0880	0.0496	0.0724	
BELLE-LLaMA-13B-2M	0.0647	0.0218	0.0386	0.0496	0.0165	0.0276	0.0429	0.0398	0.0241	
InternLM-Chat-7B	0.1150	0.0677	0.0785	0.1271	0.0662	0.0831	0.1474	0.1338	0.1334	
Baichuan-Chat-13B	0.3654	0.2534	0.2887	0.3782	0.2556	0.2762	0.2376	0.2083	0.1803	
WizardCoder-15B	0.5767	0.4331	0.4568	0.5556	0.4120	0.4490	0.2556	0.2429	0.1963	
StarCoder	0.6639	0.4090	0.4869	0.6421	0.3767	0.4638	0.4737	0.3030	0.3452	
GPT3.5-turbo	0.5699	0.5466	0.4909	0.5722	0.5481	0.5015	0.3436	0.3316	0.2908	
GPT4	0.6970	0.6594	0.6453	0.7143	0.6767	0.6677	0.6038	0.5940	0.5269	

the standard code serves as a reference point or template, guiding the model to make corrections based on the provided code structure and logic.

*Error Type Analysis.* We compare the performance on three types of error (WA, TLE, and RE) in Table 11 and Table 12. Results shows correcting these three types of errors has different emergence ability of LLMs. Correcting wrong answer codes is the hardest task for LLMs since errors might occur everywhere. TLE usually occurs in closed loops or too many loops, which is relatively easy

Table 10. Performance on AC@1, AC@all, and AC Rate metrics of code generation task in English version. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined.

	Code Correction (English)									
Model		Code-only			Code-with-Error Message			Code-with-Standard Code		
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	
ChatGLM-6B	0.1489	0.0579	0.0950	0.0128	0.0030	0.0088	0.1241	0.1113	0.1056	
ChatGLM2-6B	0.2323	0.0850	0.1284	0.1835	0.0797	0.1023	0.2504	0.2113	0.1943	
ChatGLM3-6B	0.3692	0.2248	0.2769	0.3022	0.1609	0.2163	0.2105	0.2075	0.1612	
BELLE-7B-1M	0.1609	0.0549	0.0959	0.0023	0.0008	0.0007	0.1158	0.1008	0.0914	
BELLE-LLaMA-13B-2M	0.1105	0.0571	0.0795	0.2150	0.0579	0.1307	0.1692	0.1466	0.1142	
InternLM-Chat-7B	0.1850	0.1113	0.1289	0.1150	0.0609	0.0757	0.2632	0.2436	0.1978	
Baichuan-Chat-13B	0.2414	0.1737	0.1963	0.0955	0.0549	0.0582	0.1842	0.1805	0.1398	
WizardCoder-15B	0.4504	0.3331	0.3347	0.2917	0.2316	0.2443	0.1571	0.1391	0.1052	
StarCoder	0.5992	0.3602	0.4326	0.5586	0.3113	0.4017	0.3602	0.2782	0.2694	
GPT3.5-turbo	0.5083	0.4925	0.4332	0.3632	0.3459	0.3161	0.2617	0.2594	0.2003	
GPT4	0.6436	0.6143	0.5775	0.6617	0.6323	0.6022	0.4812	0.4752	0.4032	

Table 11. Best performance comparison between correcting three types of code error (WA, TLE, RE) on AC@1, AC@all and AC Rate metric of code correction task in Chinese version. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined.

				Code C	orrection (	Chinese)				
Models		WA			TLE			RE		
	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate	
ChatGLM-6B	0.1736	0.1591	0.1148	0.2609	0.2609	0.1988	0.1512	0.1163	0.0941	
ChatGLM2-6B	0.2493	0.1711	0.1525	0.3623	0.1884	0.3854	0.2442	0.1744	0.1487	
ChatGLM3-6B	0.4468	0.2805	0.2826	0.4348	0.3768	0.5030	0.3837	0.3372	0.3383	
BELLE-7B-1M	0.0894	0.0519	0.0742	0.1159	0.0435	0.1055	0.0465	0.0348	0.0218	
BELLE-LLaMA-13B-2M	0.0655	0.0357	0.0379	0.0870	0.0580	0.1034	0.1279	0.1279	0.0750	
InternLM-Chat-7B	0.1498	0.1362	0.1371	0.1594	0.1594	0.1116	0.1046	0.0814	0.1214	
Baichuan-13B-Chat	0.3728	0.2477	0.2837	0.5362	0.4348	0.5639	0.3256	0.2674	0.2606	
WizardCoder-15B	0.5864	0.4264	0.4487	0.4493	0.4058	0.5497	0.5698	0.5465	0.5498	
StarCoder	0.6843	0.4162	0.4934	0.4783	0.2319	0.4361	0.5349	0.4535	0.4188	
GPT-3.5-turbo	0.5668	0.5405	0.4932	0.4493	0.4348	0.4077	0.7791	0.7791	0.7162	
GPT-4	0.6996	0.6612	0.6546	0.8261	0.7391	0.7667	0.8605	0.8488	0.8240	

to locate. RE is also easy to locate, usually because the divisor is 0, the subscript is out of bounds, and so on. Thus when parameter size is limited (StarCoder, GPT3.5), RE and TLE are easy to find, while the ability to find WA error emergents until the parameter size of GPT4.

# 5 CONCLUSION

We present CodeApex, a bilingual benchmark focusing on the programming capabilities of LLMs. First, we evaluate LLMs in the programming comprehension task by assessing their accuracy in three categories of multiple-choice questions. We design two types of prompts, answer-only and chain-of-thought, with three in-context learning scenarios, to compare LLMs' performance. Second, we evaluate LLMs' code generation capabilities by testing the acceptance rate of test cases. The test set includes 476 C++-based coding questions, categorized as either explicit questions or narrative questions. We also provide a comparison on function-only and function-with-context scenarios, in order to compare the impact of context information of the target code. Third, we introduce 1332 real-world erroneous code segments to evaluate LLMs' code correction capability. We compare

Table 12. Best performance comparison between correcting three types of code error (WA, TLE, RE) on AC@1, AC@all and AC Rate metric of code correction task in English version. The best performance of LLMs is in bold, the second-best performance is underlined, and the third-best performance is wave underlined.

				Code C	orrection	(English)			
Models		WA			TLE	(6)		RE	
	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate
ChatGLM-6B	0.1506	0.1038	0.1078	0.2319	0.2319	0.1379	0.1395	0.1163	0.0941
ChatGLM2-6B	0.2647	0.2213	0.2011	0.2609	0.1159	0.2840	0.2093	0.2093	0.1910
ChatGLM3-6B	0.3745	0.2187	0.2726	0.3188	0.2464	0.3773	0.3372	0.2907	0.2783
BELLE-7B-1M	0.1591	0.1089	0.0968	0.1739	0.0725	0.1318	0.1744	0.1512	0.1596
BELLE-LLaMA-13B-2M	0.2204	0.1404	0.1300	0.2754	0.2464	0.2738	0.1511	0.1511	0.1091
InternLM-Chat-7B	0.2570	0.2383	0.2010	0.3623	0.3623	0.1318	0.2674	0.2209	0.1924
Baichuan-13B-Chat	0.2289	0.1821	0.1844	0.3913	0.2754	0.4118	0.2907	0.2326	0.2374
WizardCoder	0.4553	0.3277	0.3241	0.3913	0.2754	0.4118	0.4302	0.4070	0.3861
StarCoder	0.6136	0.3617	0.4349	0.5217	0.2899	0.4178	0.5233	0.4535	0.4052
GPT-3.5-turbo	0.4945	0.4783	0.4171	0.4638	0.4348	0.4178	0.7326	0.7326	0.6958
GPT-4	0.6460	0.6170	0.5837	0.7391	0.6667	0.7079	0.8372	0.8372	0.8213

the performance in code-only, code-with-error message, and code-with-standard code scenarios, and analysis the result of different code error types. We organize experiments on 12 famous LLMs, including general-purpose LLMs and specialized models based on code fine-tuning. Currently, GPT achieves top-tier performance in programming abilities, but human tests indicate that there is still significant room for improvement. Furthermore, specialized LLMs demonstrate competitiveness and show their potential for further enhancement.

We also incorporate human performance into the leaderboard, comparing the coding abilities of the CodeApex with human-level performance. The experiments indicate that the programming capabilities of LLMs still have some distance from human performance. In the future, the test set within CodeApex will undergo continuous updates, encompassing an expanded range of question types and additional programming languages. We hope that CodeApex could provide a reference for later study on the programming capabilities of LLMs, fostering their development and prosperity together.

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# A BREAKDOWN PERFORMANCE IN PROGRAMMING COMPREHENSION

Table 1, Table 2, Table 3, and Table 4 present the breakdown of performance of LLMs in programming comprehension task in the 5-shot, 2-shot, and 0-shot scenarios.

Table 1. 5-shot, 2-shot, and 0-shot accuracy results of Chinese version Programming Comprehension Task in the answer-only setting. C.U., C.R, and M.H.R indicate conceptual understanding, commonsense reasoning, and multi-hop reasoning questions, respectively. \* represents chat-bot mode of the LLM. - indicates that the model does not have the ability to complete the test in that setting.

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Model	- 1 .	C.U.	0 1 1	- 1 ·	C.R.	0.1.	- 1 ·	M.H.R.	0.1.	F 1 .	Total	0 1 1
OL TOTAL CB	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot
ChatGLM-6B	0.32	0.30	0.32	0.16	0.12	0.26	0.30	0.26	0.31	0.25	0.22	0.30
ChatGLM-6B*	0.31	0.33	0.31	0.27	0.25	0.16	0.25	0.31	0.23	0.28	0.30	0.23
ChatGLM2-6B	0.32	0.33	0.37	0.25	0.27	0.21	0.30	0.28	0.34	0.29	0.30	0.30
ChatGLM2-6B*	0.34	0.31	0.32	0.26	0.26	0.19	0.31	0.31	0.23	0.30	0.29	0.25
ChatGLM3-6B	0.29	0.30	0.34	0.24	0.26	0.24	0.38	0.34	0.34	0.29	0.30	0.30
ChatGLM3-6B*	0.23	0.35	0.46	0.21	0.27	0.19	0.25	0.17	0.28	0.23	0.28	0.31
MOSS-16B*	0.31	0.30	0.28	0.24	0.28	0.34	0.33	0.25	0.32	0.29	0.28	0.31
Chinese-Alpaca-7B	0.21	0.26	0.35	0.27	0.29	0.25	0.18	0.27	0.26	0.23	0.27	0.29
Chinese-Alpaca-7B*	0.24	0.24	0.30	0.29	0.29	0.27	0.21	0.15	0.28	0.25	0.24	0.28
Chinese-Alpaca-plus-7B	0.21	0.19	0.23	0.30	0.34	0.30	0.14	0.16	0.26	0.23	0.24	0.27
Chinese-Alpaca-plus-7B*	0.33	0.20	0.28	0.29	0.30	0.16	0.21	0.25	0.25	0.29	0.25	0.22
Chinese-Alpaca-13B	0.24	0.21	0.26	0.23	0.20	0.29	0.15	0.20	0.26	0.22	0.20	0.27
Chinese-Alpaca-13B*	0.23	0.27	0.27	0.23	0.29	0.24	0.21	0.20	0.18	0.23	0.26	0.24
Chinese-Alpaca-plus-13B	0.27	0.24	0.24	0.34	0.28	0.20	0.21	0.20	0.19	0.28	0.25	0.21
Chinese-Alpaca-plus-13B*	0.27	0.23	0.27	0.27	0.30	0.28	0.13	0.20	0.20	0.23	0.25	0.26
BELLE-7B-1M	0.27	0.26	0.33	0.32	0.25	0.28	0.28	0.25	0.26	0.29	0.25	0.29
BELLE-7B-1M*	0.35	0.31	0.26	0.31	0.29	0.26	0.21	0.21	0.25	0.30	0.28	0.26
BELLE-7B-2M	0.20	0.22	0.24	0.32	0.34	0.26	0.28	0.26	0.19	0.27	0.28	0.24
BELLE-7B-2M*	0.20	0.21	0.20	0.32	0.30	0.25	0.18	0.15	0.28	0.24	0.23	0.24
BELLE-LLaMA-7B-0.6M	0.29	0.24	0.14	0.33	0.34	0.27	0.28	0.32	0.21	0.31	0.30	0.21
BELLE-LLaMA-7B-0.6M*	0.28	0.28	0.28	0.30	0.31	0.31	0.30	0.31	0.28	0.29	0.30	0.29
BELLE-LLaMA-7B-2M	0.17	0.22	0.20	0.30	0.29	0.28	0.16	0.17	0.20	0.22	0.24	0.23
BELLE-LLaMA-7B-2M*	0.19	0.28	0.23	0.21	0.30	0.31	0.09	0.26	0.20	0.17	0.28	0.25
BELLE-LLaMA-13B-2M	0.19	0.21	0.29	0.31	0.31	0.33	0.18	0.19	0.20	0.24	0.25	0.28
BELLE-LLaMA-13B-2M*	0.34	0.24	0.19	0.27	0.29	0.27	0.22	0.21	0.21	0.28	0.25	0.23
InternLM-Chat-7B	0.46	0.42	0.44	0.22	0.27	0.34	0.34	0.33	0.31	0.34	0.34	0.37
Baichuan-7B	0.34	0.24	0.34	0.26	0.24	0.34	0.26	0.25	0.24	0.29	0.25	0.31
EduChat-base-002-7B*	0.19	0.23	0.18	0.31	0.22	0.14	0.23	0.20	0.16	0.25	0.22	0.16
EduChat-base-002-13B*	0.28	0.25	0.17	0.35	0.34	0.03	0.25	0.22	0.13	0.30	0.28	0.10
EduChat-sft-002-7B*	0.22	0.24	0.17	0.19	0.24	0.15	0.25	0.30	0.27	0.21	0.26	0.19
CodeT5-plus-16B	0.16	0.17	0.26	0.28	0.29	0.30	0.32	0.26	0.21	0.25	0.24	0.26
CodeT5-plus-16B*	0.28	0.18	-	0.37	0.26	-	0.27	0.23	-	0.32	0.22	-
CodeT5-plus-6B	0.20	0.19	0.23	0.35	0.35	0.19	0.24	0.23	0.18	0.32	0.26	0.20
CodeT5-plus-6B*	0.23	0.17	-	0.28	0.23	-	0.24	0.18	-	0.26	0.21	-
GPT-3.5-turbo	0.58	0.56	0.61	0.30	0.23	0.33	0.61	0.59	0.57	0.47	0.47	0.49
GPT-3.5-turbo*	0.60	0.57	0.57	0.36	0.35	0.33	0.61	0.64	0.54	0.47	0.50	0.44
GPT-4	0.67	0.57	0.63	0.55	0.54	0.49	0.84	0.82	0.34	0.51	0.64	0.44
GPT-4*	0.07	0.67	0.66	0.55	0.34	0.49	0.84	0.82	0.30	0.67	0.63	0.64
Gr 1-4	0.70	0.07	0.00	0.55	0.46	0.55	0.62	0.62	0.77	0.07	0.03	0.04

# **B** BREAKDOWN PERFORMANCE IN CODE GENERATION

Table 5 and Table 6 present the breakdown of performance of LLMs in code generation task in the code-only and code-with-context scenarios. The breakdown performance of explicit questions and narrative questions is also shown in the table.

Table 2. 5-shot, 2-shot, and 0-shot accuracy results of Chinese version Programming Comprehension Task in CoT setting. C.U., C.R, and M.H.R indicate conceptual understanding, commonsense reasoning, and multi-hop reasoning questions, respectively. \* represents chat-bot mode of the LLM. - indicates that the model does not have the ability to complete the test in that setting.

			F	rogramn	ning Con	prehens	ion (Cha	in-of-The	ought)-Zl	H		
Model		C.U.		8	C.R.	- F		M.H.R.			Total	
	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot
ChatGLM-6B	0.31	0.27	0.22	0.21	0.16	0.18	0.38	0.26	0.23	0.29	0.22	0.21
ChatGLM-6B*	0.33	0.26	0.27	0.20	0.22	0.17	0.18	0.28	0.28	0.24	0.25	0.23
ChatGLM2-6B	0.48	0.36	0.30	0.23	0.25	0.20	0.25	0.31	0.28	0.32	0.30	0.26
ChatGLM2-6B*	0.41	0.32	0.30	0.24	0.29	0.26	0.38	0.23	0.21	0.34	0.29	0.26
ChatGLM3-6B	0.33	0.34	0.36	0.26	0.34	0.24	0.25	0.24	0.22	0.28	0.28	0.28
ChatGLM3-6B*	0.34	0.26	0.35	0.22	0.26	0.23	0.27	0.35	0.22	0.27	0.25	0.27
MOSS-16B*	0.09	0.27	0.27	0.09	0.12	0.17	0.23	0.33	0.20	0.12	0.22	0.21
Chinese-Alpaca-7B	0.28	0.29	0.21	0.25	0.30	0.10	0.20	0.18	0.21	0.25	0.27	0.17
Chinese-Alpaca-7B*	0.28	0.24	0.27	0.24	0.32	0.12	0.16	0.20	0.26	0.24	0.26	0.21
Chinese-Alpaca-plus-7B	0.20	0.37	0.23	0.27	0.31	0.20	0.18	0.28	0.18	0.22	0.32	0.21
Chinese-Alpaca-plus-7B*	0.27	0.27	0.22	0.26	0.24	0.24	0.15	0.20	0.23	0.24	0.24	0.23
Chinese-Alpaca-13B	0.29	0.23	0.27	0.29	0.20	0.20	0.18	0.23	0.25	0.26	0.22	0.24
Chinese-Alpaca-13B*	0.28	0.27	0.31	0.27	0.23	0.17	0.23	0.16	0.13	0.26	0.23	0.21
Chinese-Alpaca-plus-13B	0.24	0.26	0.31	0.25	0.29	0.18	0.13	0.21	0.18	0.22	0.26	0.23
Chinese-Alpaca-plus-13B*	0.29	0.24	0.36	0.25	0.24	0.27	0.15	0.23	0.23	0.24	0.24	0.29
BELLE-7B-1M	0.33	0.30	0.26	0.23	0.29	0.19	0.25	0.20	0.18	0.27	0.27	0.21
BELLE-7B-1M*	0.33	0.28	0.18	0.22	0.25	0.10	0.21	0.16	0.15	0.26	0.24	0.14
BELLE-7B-2M	0.20	0.20	0.29	0.24	0.26	0.18	0.23	0.18	0.11	0.22	0.22	0.20
BELLE-7B-2M*	0.26	0.20	0.27	0.23	0.24	0.23	0.15	0.21	0.21	0.22	0.22	0.24
BELLE-LLaMA-7B-0.6M	0.27	0.23	0.23	0.21	0.30	0.28	0.16	0.30	0.18	0.22	0.28	0.24
BELLE-LLaMA-7B-0.6M*	0.28	0.28	0.34	0.20	0.36	0.28	0.21	0.31	0.20	0.23	0.32	0.28
BELLE-LLaMA-7B-2M	0.24	0.19	0.12	0.30	0.19	0.14	0.23	0.21	0.15	0.26	0.20	0.14
BELLE-LLaMA-7B-2M*	0.28	0.28	0.17	0.26	0.30	0.12	0.25	0.25	0.13	0.26	0.28	0.14
BELLE-LLaMA-13B-2M	0.22	0.29	0.20	0.19	0.27	0.19	0.20	0.18	0.16	0.20	0.26	0.19
BELLE-LLaMA-13B-2M*	0.21	0.27	0.17	0.22	0.28	0.15	0.18	0.21	0.11	0.21	0.26	0.15
InternLM-Chat-7B	0.36	0.32	0.34	0.18	0.18	0.14	0.36	0.20	0.23	0.29	0.24	0.24
Baichuan-7B	0.04	0.06	0.07	0.11	0.02	0.04	0.05	0.02	0.07	0.07	0.03	0.06
EduChat-base-002-7B*	0.28	0.27	0.11	0.23	0.22	0.21	0.18	0.26	0.15	0.24	0.25	0.16
EduChat-base-002-13B*	0.30	0.29	0.18	0.23	0.24	0.18	0.18	0.33	0.16	0.24	0.28	0.18
EduChat-sft-002-7B*	0.31	0.24	0.27	0.20	0.21	0.19	0.25	0.23	0.26	0.25	0.23	0.24
CodeT5-plus-16B	-	-	-	-	-	-	_	-	-	-	-	-
CodeT5-plus-16B*	-	-	-	-	-	-	-	-	-	-	-	-
CodeT5-plus-6B	_	-	-	-	-	-	_	-	-	-	-	-
CodeT5-plus-6B*	-	-	-	-	-	-	-	-	-	-	-	-
GPT-3.5-turbo	0.59	0.55	0.50	0.37	0.41	0.35	0.68	0.63	0.52	0.53	0.52	0.45
GPT-3.5-turbo*	0.57	0.56	0.54	0.39	0.42	0.33	0.65	0.57	0.56	0.52	0.51	0.46
GPT-4	0.71	0.71	0.63	0.52	0.52	0.51				0.66	0.66	0.62
GPT-4*	0.72	0.68	0.57	0.59	0.52	0.45	0.84	0.85	0.79	0.70	0.66	0.58

# C BREAKDOWN PERFORMANCE IN CODE CORRECTION

Table 7, 9, 11, 8, 10, and 12 present the breakdown of performance of LLMs in code correction task with wrong answer error, time limited error and runtime error. The breakdown performance of code-only, code-with-error message and code-with-standard code scenarios are also shown in the table.

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Lingyue Fu, Huacan Chai, Kounianhua Du, Weiming Zhang, Shuang Luo, Jianghao Lin, Yuchen Fang, Renting Rui, Hao Guan, Jianxing Liu, Siyuan Qi, Longteng Fan, Jiayi Lei, Yifan Liu, Jingkuan Wang, Kangning Zhang, Weinan Zhang, 111:28 and Yong Yu Table 3. 5-shot, 2-shot, and 0-shot accuracy results of English version Programming Comprehension Task in the answer-only setting. C.U., C.R, and M.H.R indicate conceptual understanding, commonsense reasoning, and multi-hop reasoning questions, respectively. \* represents chat-bot mode of the LLM. - indicates that the model does not have the ability to complete the test in that setting.

				Program	nming C	omprehe	nsion (A		nly)-EN			
Model		C.U.			C.R.			M.H.R.			Total	
	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot
ChatGLM-6B	0.32	0.34	0.36	0.16	0.21	0.24	0.30	0.31	0.30	0.29	0.28	0.30
ChatGLM-6B*	0.32	0.25	0.39	0.27	0.24	0.23	0.25	0.38	0.30	0.32	0.28	0.23
ChatGLM2-6B	0.34	0.33	0.41	0.25	0.26	0.32	0.30	0.30	0.23	0.29	0.30	0.30
ChatGLM2-6B*	0.36	0.32	0.28	0.26	0.28	0.23	0.31	0.28	0.21	0.30	0.30	0.25
ChatGLM3-6B	0.31	0.31	0.37	0.33	0.32	0.30	0.28	0.30	0.30	0.31	0.31	0.32
ChatGLM3-6B*	0.24	0.30	0.34	0.23	0.17	0.20	0.23	0.19	0.30	0.23	0.22	0.27
MOSS-16B*	0.26	0.25	0.26	0.24	0.27	0.35	0.33	0.33	0.15	0.28	0.28	0.31
Chinese-Alpaca-7B	0.31	0.30	0.28	0.27	0.26	0.25	0.18	0.21	0.33	0.29	0.26	0.29
Chinese-Alpaca-7B*	0.17	0.26	0.29	0.29	0.29	0.19	0.21	0.16	0.23	0.17	0.25	0.28
Chinese-Alpaca-plus-7B	0.34	0.24	0.28	0.30	0.29	0.28	0.14	0.22	0.33	0.30	0.26	0.27
Chinese-Alpaca-plus-7B*	0.24	0.26	0.21	0.29	0.21	0.20	0.21	0.20	0.23	0.26	0.23	0.22
Chinese-Alpaca-13B	0.26	0.20	0.31	0.23	0.21	0.23	0.15	0.16	0.21	0.23	0.20	0.27
Chinese-Alpaca-13B*	0.10	0.23	0.28	0.23	0.28	0.21	0.21	0.25	0.16	0.10	0.25	0.24
Chinese-Alpaca-plus-13B	0.24	0.21	0.24	0.34	0.36	0.27	0.21	0.26	0.31	0.28	0.28	0.21
Chinese-Alpaca-plus-13B*	0.21	0.27	0.29	0.27	0.36	0.19	0.13	0.25	0.22	0.26	0.30	0.26
BELLE-7B-1M	0.33	0.32	0.33	0.32	0.31	0.26	0.28	0.28	0.23	0.31	0.31	0.29
BELLE-7B-1M*	0.39	0.36	0.33	0.31	0.27	0.28	0.21	0.23	0.24	0.30	0.29	0.26
BELLE-7B-2M	0.26	0.24	0.24	0.32	0.26	0.30	0.28	0.20	0.26	0.26	0.24	0.24
BELLE-7B-2M*	0.23	0.21	0.27	0.32	0.23	0.19	0.18	0.20	0.25	0.23	0.22	0.24
BELLE-LLaMA-7B-0.6M	0.24	0.32	0.29	0.33	0.23	0.27	0.28	0.33	0.20	0.26	0.29	0.21
BELLE-LLaMA-7B-0.6M*	0.27	0.31	0.34	0.30	0.28	0.27	0.30	0.31	0.25	0.29	0.30	0.29
BELLE-LLaMA-7B-2M	0.30	0.28	0.21	0.30	0.27	0.33	0.16	0.14	0.26	0.27	0.24	0.23
BELLE-LLaMA-7B-2M*	0.28	0.26	0.27	0.21	0.32	0.29	0.09	0.26	0.25	0.26	0.28	0.25
BELLE-LLaMA-13B-2M	0.18	0.20	0.22	0.31	0.22	0.25	0.18	0.18	0.21	0.24	0.20	0.28
BELLE-LLaMA-13B-2M*	0.24	0.27	0.26	0.27	0.27	0.23	0.22	0.20	0.15	0.27	0.25	0.23
InternLM-Chat-7B	0.43	0.41	0.44	0.22	0.33	0.36	0.34	0.26	0.31	0.37	0.34	0.37
Baichuan-7B	0.26	0.29	0.27	0.26	0.27	0.31	0.26	0.27	0.30	0.22	0.28	0.31
EduChat-base-002-7B*	0.33	0.24	0.26	0.31	0.34	0.25	0.23	0.31	0.33	0.31	0.30	0.16
EduChat-base-002-13B*	0.37	0.30	0.21	0.35	0.36	0.12	0.25	0.25	0.18	0.33	0.31	0.10
EduChat-sft-002-7B*	0.29	0.26	0.23	0.19	0.34	0.25	0.25	0.25	0.15	0.29	0.29	0.19
CodeT5-plus-16B	0.19	0.20	0.21	0.28	0.30	0.29	0.32	0.24	0.22	0.25	0.25	0.26
CodeT5-plus-16B*	0.20	0.20	-	0.37	0.27	-	0.27	0.28	-	0.24	0.25	-
CodeT5-plus-6B	0.28	0.27	0.24	0.35	0.29	0.19	0.24	0.29	0.16	0.32	0.28	0.20
CodeT5-plus-6B*	0.26	0.27	-	0.28	0.28	-	0.26	0.25	-	0.30	0.27	-
GPT3.5-turbo	0.51	0.51	0.52	0.30	0.30	0.35	0.61	0.55	0.51	0.42	0.44	0.49
GPT3.5-turbo*	0.53	0.52	0.53	0.36	0.32	0.25	0.61	0.50	0.55	0.44	0.44	0.44
GPT-4	0.62	0.64	0.63	0.48	0.44	0.48	0.75	0.75	0.80	0.60	0.59	0.62
GPT-4*	0.61	0.62	0.62	0.48	0.42	0.48	0.82	0.77	0.80	0.61	0.58	0.61

Table 4. 5-shot, 2-shot, and 0-shot accuracy results of English version Programming Comprehension Task in CoT setting. C.U., C.R, and M.H.R indicate conceptual understanding, commonsense reasoning, and multi-hop reasoning questions, respectively. \* represents chat-bot mode of the LLM. - indicates that the model does not have the ability to complete the test in that setting.

			]	Programn	ning Cor	nprehens	ion(Chai	n-of-Tho	ught)-EN	J		
Model		C.U.			C.R.	•		M.H.R.			Total	
	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot	5-shot	2-shot	0-shot
ChatGLM-6B	0.31	0.34	0.23	0.16	0.16	0.18	0.25	0.31	0.26	0.24	0.26	0.22
ChatGLM-6B*	0.28	0.29	0.20	0.25	0.17	0.25	0.31	0.28	0.28	0.28	0.24	0.24
ChatGLM2-6B	0.37	0.36	0.33	0.25	0.24	0.15	0.23	0.30	0.21	0.29	0.30	0.23
ChatGLM2-6B*	0.30	0.29	0.40	0.25	0.23	0.25	0.23	0.28	0.21	0.26	0.26	0.30
ChatGLM3-6B	0.35	0.33	0.40	0.20	0.30	0.17	0.28	0.21	0.27	0.27	0.29	0.27
ChatGLM3-6B*	0.34	0.28	0.31	0.21	0.21	0.20	0.27	0.19	0.28	0.27	0.23	0.26
MOSS-16B*	0.13	0.27	0.26	0.10	0.19	0.20	0.28	0.26	0.18	0.16	0.24	0.22
Chinese-Alpaca-7B	0.23	0.26	0.23	0.33	0.30	0.14	0.13	0.21	0.13	0.25	0.26	0.17
Chinese-Alpaca-7B*	0.23	0.27	0.22	0.30	0.32	0.14	0.11	0.23	0.10	0.23	0.28	0.16
Chinese-Alpaca-plus-7B	0.20	0.27	0.28	0.23	0.30	0.09	0.28	0.30	0.13	0.23	0.29	0.17
Chinese-Alpaca-plus-7B*	0.22	0.26	0.28	0.26	0.18	0.20	0.26	0.21	0.16	0.25	0.22	0.22
Chinese-Alpaca-13B	0.31	0.26	0.26	0.23	0.21	0.14	0.20	0.23	0.20	0.25	0.23	0.20
Chinese-Alpaca-13B*	0.20	0.24	0.22	0.21	0.16	0.19	0.18	0.26	0.21	0.20	0.22	0.21
Chinese-Alpaca-plus-13B	0.24	0.31	0.24	0.22	0.19	0.25	0.30	0.28	0.10	0.25	0.26	0.21
Chinese-Alpaca-plus-13B*	0.30	0.30	0.21	0.22	0.15	0.20	0.25	0.30	0.18	0.26	0.24	0.20
BELLE-7B-1M	0.23	0.17	0.24	0.22	0.16	0.18	0.16	0.08	0.21	0.21	0.14	0.21
BELLE-7B-1M*	0.21	0.19	0.12	0.19	0.20	0.11	0.11	0.15	0.07	0.18	0.18	0.10
BELLE-7B-2M	0.13	0.14	0.26	0.22	0.19	0.20	0.11	0.13	0.13	0.16	0.16	0.20
BELLE-7B-2M*	0.19	0.19	0.14	0.22	0.22	0.08	0.13	0.07	0.07	0.19	0.17	0.10
BELLE-LLaMA-7B-0.6M	0.22	0.20	0.08	0.22	0.23	0.13	0.26	0.18	0.03	0.23	0.21	0.09
BELLE-LLaMA-7B-0.6M*	0.33	0.22	0.20	0.19	0.21	0.24	0.26	0.21	0.25	0.26	0.22	0.23
BELLE-LLaMA-7B-2M	0.22	0.07	0.09	0.21	0.08	0.10	0.10	0.05	0.13	0.19	0.07	0.10
BELLE-LLaMA-7B-2M*	0.21	0.11	0.21	0.20	0.11	0.15	0.13	0.03	0.20	0.19	0.09	0.18
BELLE-LLaMA-13B-2M	0.26	0.21	0.11	0.21	0.22	0.13	0.15	0.13	0.20	0.21	0.20	0.14
BELLE-LLaMA-13B-2M*	0.28	0.21	0.16	0.17	0.10	0.09	0.18	0.11	0.10	0.21	0.14	0.12
InternLM-Chat-7B	0.42	0.32	0.37	0.25	0.20	0.21	0.26	0.25	0.25	0.32	0.26	0.28
Baichuan-7B	0.12	0.10	0.08	0.09	0.11	0.02	0.08	0.02	0.30	0.10	0.08	0.04
EduChat-base-002-7B*	0.24	0.26	0.13	0.19	0.24	0.12	0.26	0.20	0.15	0.23	0.24	0.13
EduChat-base-002-13B*	0.31	0.24	0.12	0.24	0.22	0.12	0.25	0.28	0.13	0.27	0.24	0.12
EduChat-sft-002-7B*	0.29	0.31	0.24	0.22	0.20	0.17	0.26	0.25	0.15	0.26	0.25	0.19
CodeT5-plus-16B	-	-	-	-	-	-	-	-	-	-	-	-
CodeT5-plus-16B*	-	-	-	-	-	-	-	-	-	-	-	-
CodeT5-plus-6B	-	-	-	-	-	-	-	-	-	-	-	-
CodeT5-plus-6B*	-	-	-	-	-	-	-	-	-	-	-	-
GPT3.5-turbo	0.44	0.49	0.53	0.34	0.35	0.37	0.64	0.61	0.57	0.45	0.46	0.47
GPT3.5-turbo*	0.51	0.50	0.47	0.37	0.34	0.33	0.63	0.61	0.50	0.49	0.47	0.42
GPT-4	0.60	0.64	0.62	0.51	0.51	0.51	0.87	0.82	0.75	0.63	0.63	0.61
GPT-4*	0.61	0.63	0.66	0.52	0.52	0.49	0.84	0.79	0.75	0.63	0.62	0.62

Table 5. Best performance comparison between explicit questions and narrative questions on AC@1, AC@all and AC Rate metric of code generation in Chinese version.

						Code Gene	eration-Z	Н				
			Code	-only					Code-wit	h-Contex	t	
Model	Exp	plicit Ques	tions	Nar	rative Que	stions	Ex	plicit Ques	tions	Nar	rative Que	stions
	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate
baichuan	0.42	0.26	0.29	0.18	0.18	0.18	0.24	0.16	0.16	0.09	0.09	0.09
BELLE	0.27	0.15	0.16	0.10	0.10	0.10	0.27	0.14	0.15	0.12	0.12	0.12
BELLE-7B-1M	0.20	0.09	0.10	0.12	0.12	0.12	0.19	0.10	0.11	0.10	0.10	0.10
chatglm	0.27	0.14	0.17	0.15	0.15	0.15	0.21	0.11	0.12	0.10	0.10	0.10
chatglm2	0.29	0.17	0.20	0.12	0.12	0.12	0.27	0.12	0.20	0.12	0.12	0.12
cn-alpaca-plus-13B	0.36	0.20	0.22	0.19	0.19	0.19	0.37	0.21	0.24	0.16	0.16	0.16
gpt3.5-turbo	0.70	0.48	0.57	0.58	0.58	0.58	0.72	0.52	0.60	0.61	0.61	0.61
gpt-4	0.66	0.53	0.57	0.57	0.46	0.51	0.77	0.64	0.67	0.77	0.62	0.66
intern	0.19	0.11	0.11	0.09	0.09	0.09	0.21	0.14	0.13	0.08	0.08	0.08
moss	0.34	0.22	0.23	0.11	0.11	0.11	0.34	0.20	0.24	0.14	0.14	0.14
starcoder	0.28	0.18	0.21	0.16	0.16	0.16	0.23	0.12	0.15	0.15	0.15	0.15
vicuna	0.35	0.18	0.23	0.17	0.17	0.17	0.37	0.21	0.26	0.23	0.23	0.23
wizard	0.54	0.35	0.37	0.34	0.34	0.34	0.53	0.36	0.39	0.32	0.32	0.32

Table 6. Best performance comparison between explicit questions and narrative questions on AC@1, AC@all and AC Rate metric of code generation in English version.

						Code Gene	eration-E	N				
			Code	-only					Code-wit	h-Contex	t	
Model	Exp	olicit Ques	tions	Nar	rative Que	stions	Exp	plicit Ques	tions	Nar	rative Que	stions
	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate	AC@1	AC@all	AC Rate
baichuan	0.41	0.23	0.27	0.24	0.24	0.24	0.40	0.25	0.25	0.25	0.25	0.25
BELLE	0.28	0.13	0.16	0.08	0.08	0.08	0.29	0.14	0.19	0.14	0.14	0.14
BELLE-7B-1M	0.27	0.09	0.13	0.13	0.13	0.13	0.19	0.08	0.10	0.12	0.12	0.12
chatglm	0.26	0.10	0.12	0.16	0.16	0.16	0.22	0.09	0.11	0.14	0.14	0.14
chatglm2	0.23	0.12	0.12	0.14	0.14	0.14	0.14	0.07	0.07	0.06	0.06	0.06
cn-alpaca-plus-13B	0.39	0.21	0.24	0.17	0.17	0.17	0.32	0.17	0.20	0.18	0.18	0.18
gpt3.5-turbo	0.69	0.50	0.56	0.53	0.53	0.53	0.71	0.53	0.58	0.62	0.62	0.62
gpt-4	0.60	0.47	0.52	0.56	0.45	0.51	0.73	0.58	0.60	0.67	0.56	0.60
intern	0.14	0.09	0.08	0.04	0.04	0.04	0.40	0.23	0.25	0.19	0.19	0.19
moss	0.35	0.24	0.26	0.16	0.16	0.16	0.22	0.13	0.15	0.08	0.08	0.08
starcoder	0.43	0.26	0.27	0.24	0.24	0.24	0.35	0.23	0.24	0.19	0.19	0.19
vicuna	0.25	0.12	0.14	0.11	0.11	0.11	0.40	0.18	0.24	0.19	0.19	0.19
wizard	0.54	0.34	0.39	0.29	0.29	0.29	0.52	0.35	0.39	0.34	0.34	0.34

Table 7. Performance on AC@1, AC@all, and AC Rate metrics of code correction task (Wrong Answer Error) in Chinese version.

			Coc	le Correct	ion (Wror	ng Answer)	-ZH		
Model		Code-onl	y	Code-w	ith-Error	Message	Code-wit	h-Standar	d Code
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate
ChatGLM-6B	0.1362	0.0511	0.0906	0.1243	0.0468	0.0814	0.1736	0.1591	0.1148
ChatGLM2-6B	0.2493	0.0791	0.1482	0.2315	0.0851	0.1361	0.2119	0.1711	0.1525
ChatGLM3-6B	0.4323	0.2298	0.2826	0.4468	0.2230	0.2798	0.2917	0.2805	0.2220
BELLE-7B-1M	0.0553	0.0221	0.0346	0.0272	0.0051	0.0155	0.0894	0.0519	0.0742
BELLE-LLaMA-13B-2M	0.0655	0.0196	0.0379	0.0494	0.0136	0.0253	0.0391	0.0357	0.0219
InternLM-Chat-7B	0.1234	0.0706	0.0832	0.1362	0.0681	0.0859	0.1498	0.1362	0.1371
Baichuan-Chat-13B	0.3643	0.2477	0.2837	0.3728	0.2443	0.2649	0.2400	0.2102	0.1890
WizardCoder-15B	0.5864	0.4264	0.4487	0.5626	0.4034	0.4387	0.2511	0.2383	0.2000
StarCoder	0.6843	0.4162	0.4934	0.6621	0.3821	0.4691	0.4757	0.3047	0.3447
GPT3.5-turbo	0.5643	0.5396	0.4818	0.5668	0.5405	0.4932	0.3404	0.3268	0.2916
GPT4	0.6774	0.6417	0.6287	0.6996	0.6612	0.6546	0.5838	0.5728	0.5152

Table 8. Performance on AC@1, AC@all, and AC Rate metrics of code correction task (Wrong Answer Error) in English version.

			Coc	le Correct	ion (Wro	ng Answer)	-EN		
Model		Code-onl	y	Code-w	ith-Error	Message	Code-wit	h-Standar	d Code
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate
ChatGLM-6B	0.1506	0.0562	0.0950	0.0136	0.0034	0.0093	0.1174	0.1038	0.1078
ChatGLM2-6B	0.2332	0.0791	0.1196	0.1872	0.0765	0.1018	0.2647	0.2213	0.2011
ChatGLM3-6B	0.3745	0.2187	0.2726	0.3123	0.1583	0.2161	0.2145	0.2111	0.1622
BELLE-7B-1M	0.1591	0.0468	0.0903	0.0026	0.0009	0.0008	0.1260	0.1089	0.0968
BELLE-LLaMA-13B-2M	0.1123	0.0553	0.0785	0.2204	0.0553	0.1300	0.1660	0.1404	0.1161
InternLM-Chat-7B	0.1864	0.1038	0.1269	0.1209	0.0604	0.0768	0.2570	0.2383	0.2010
Baichuan-Chat-13B	0.2289	0.1634	0.1844	0.0970	0.0553	0.0587	0.1864	0.1821	0.1451
WizardCoder-15B	0.4553	0.3277	0.3241	0.3081	0.2417	0.2535	0.1498	0.1311	0.1018
StarCoder	0.6136	0.3617	0.4349	0.5770	0.3183	0.4079	0.3566	0.2774	0.2660
GPT3.5-turbo	0.4945	0.4783	0.4171	0.3609	0.3430	0.3144	0.2536	0.2511	0.2020
GPT4	0.6247	0.5957	0.5581	0.6460	0.6170	0.5837	0.4664	0.4596	0.3949

Table 9. Performance on AC@1, AC@all, and AC Rate metrics of code correction task (Time Limit Exceeded Error) in Chinese version.

			Co	de Correc	tion (CPU	Timeout)-	·ZH		
Model		Code-onl	y	Code-w	ith-Error	Message	Code-wit	h-Standar	d Code
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate
ChatGLM-6B	0.1159	0.0870	0.1359	0.1739	0.1304	0.1988	0.2609	0.2609	0.0913
ChatGLM2-6B	0.3623	0.1884	0.3854	0.3043	0.1449	0.2941	0.0580	0.0580	0.0487
ChatGLM3-6B	0.4348	0.3623	0.5030	0.4203	0.3623	0.5010	0.3768	0.3768	0.1136
BELLE-7B-1M	0.0580	0.0435	0.0730	0.0145	0.0145	0.0203	0.1159	0.0290	0.1055
BELLE-LLaMA-13B-2M	0.0870	0.0580	0.0913	0.0870	0.0580	0.1034	0.0000	0.00000	0.0000
InternLM-Chat-7B	0.0725	0.0580	0.0345	0.1014	0.0870	0.1116	0.1594	0.1594	0.0649
Baichuan-Chat-13B	0.4783	0.3768	0.4665	0.5362	0.4348	0.5639	0.3188	0.2899	0.1075
WizardCoder-15B	0.4203	0.4058	0.5071	0.4493	0.4058	0.5497	0.3188	0.3043	0.0933
StarCoder	0.4783	0.2319	0.4361	0.4638	0.2173	0.4260	0.4783	0.1739	0.3327
GPT3.5-turbo	0.4058	0.3768	0.3692	0.4493	0.4348	0.4077	0.3913	0.3913	0.2252
GPT4	0.8261	0.7246	0.7667	0.8116	0.7391	0.7565	0.7391	0.7391	0.5761

Table 10. Performance on AC@1, AC@all, and AC Rate metrics of code correction task (Time Limit Exceeded Error) in English version.

			Cc	de Correc	tion(CPI)	Timeout)-	FN		
Model		Code-onl			ith-Error			h-Standar	d Code
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate
ChatGLM-6B	0.1304	0.0870	0.1379	0.0000	0.0000	0.0000	0.2319	0.2319	0.0730
ChatGLM2-6B	0.2609	0.1159	0.2840	0.0870	0.0290	0.0446	0.0580	0.0435	0.0406
ChatGLM3-6B	0.3188	0.2464	0.3773	0.2319	0.1884	0.2515	0.1304	0.1304	0.0933
BELLE-7B-1M	0.1739	0.0725	0.1318	0.0000	0.0000	0.0000	0.0290	0.0290	0.0406
BELLE-LLaMA-13B-2M	0.1449	0.1014	0.1643	0.2754	0.1159	0.2738	0.2464	0.2464	0.0771
InternLM-Chat-7B	0.1304	0.1159	0.1318	0.0435	0.0290	0.0730	0.3623	0.3623	0.1318
Baichuan-Chat-13B	0.3913	0.2754	0.4118	0.1159	0.0870	0.0994	0.1884	0.1884	0.0325
WizardCoder-15B	0.3913	0.3333	0.5051	0.1304	0.1304	0.1846	0.2319	0.2319	0.0913
StarCoder	0.4493	0.2174	0.4178	0.4058	0.1304	0.3448	0.5217	0.2899	0.3124
GPT3.5-turbo	0.4638	0.4348	0.4178	0.4058	0.3768	0.2860	0.3623	0.3623	0.0933
GPT4	0.7391	0.6667	0.6815	0.7101	0.6377	0.7079	0.5072	0.5072	0.3144

Table 11. Performance on AC@1, AC@all, and AC Rate metrics of code correction task (Runtime Error) in Chinese version.

			Co	de Correc	tion(Runt	ime Error)-	-ZH		
Model		Code-onl			ith-Error			h-Standar	d Code
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate
ChatGLM-6B	0.0930	0.0347	0.0477	0.1512	0.0465	0.0682	0.1279	0.1163	0.0941
ChatGLM2-6B	0.2442	0.1628	0.1487	0.1744	0.0930	0.1010	0.1860	0.1744	0.1378
ChatGLM3-6B	0.3837	0.3372	0.3383	0.3837	0.3372	0.3383	0.2907	0.2791	0.2278
BELLE-7B-1M	0.0116	0.0116	0.0068	0.0116	0.0116	0.0136	0.0465	0.0348	0.0218
BELLE-LLaMA-13B-2M	0.0349	0.0233	0.0150	0.0233	0.0233	0.0136	0.1279	0.1279	0.0750
InternLM-Chat-7B	0.0349	0.0349	0.0341	0.0233	0.0233	0.0205	0.1046	0.0814	0.1214
Baichuan-Chat-13B	0.2907	0.2326	0.2483	0.3256	0.2674	0.2606	0.1395	0.1163	0.0928
WizardCoder-15B	0.5698	0.5465	0.5498	0.5465	0.5349	0.5416	0.2674	0.2558	0.2087
StarCoder	0.5349	0.4535	0.4188	0.5116	0.4302	0.4052	0.4419	0.3837	0.3615
GPT3.5-turbo	0.7791	0.7791	0.7162	0.7442	0.7442	0.6958	0.3488	0.3488	0.3220
GPT4	0.8605	0.8488	0.8240	0.8372	0.8372	0.8131	0.7674	0.7674	0.6767

Table 12. Performance on AC@1, AC@all, and AC Rate metrics of code correction task (Runtime Error) in English version.

	Code Correction(Runtime Error)-EN								
Model	Code-only			Code-with-Error Message			Code-with-Standard Code		
	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate	AC@1	AC@n	AC Rate
ChatGLM-6B	0.1395	0.0581	0.0655	0.0116	0.0000	0.0068	0.1279	0.1163	0.0941
ChatGLM2-6B	0.1977	0.1395	0.1610	0.2093	0.1628	0.1487	0.2093	0.2093	0.1910
ChatGLM3-6B	0.3372	0.2907	0.2783	0.2209	0.1744	0.1951	0.2209	0.2209	0.1910
BELLE-7B-1M	0.1744	0.1512	0.1596	0.0000	0.0000	0.0000	0.0465	0.0465	0.0409
BELLE-LLaMA-13B-2M	0.0581	0.0465	0.0382	0.0930	0.0465	0.0450	0.1511	0.1511	0.1091
InternLM-Chat-7B	0.2093	0.2093	0.1569	0.0930	0.0930	0.0614	0.2674	0.2209	0.1924
Baichuan-Chat-13B	0.2907	0.2326	0.2374	0.0581	0.0233	0.0231	0.1512	0.1512	0.1296
WizardCoder-15B	0.4302	0.4070	0.3861	0.1977	0.1744	0.1405	0.1977	0.1744	0.1692
StarCoder	0.5233	0.4535	0.4052	0.4302	0.3605	0.3424	0.2791	0.2791	0.2933
GPT3.5-turbo	0.7326	0.7326	0.6958	0.3605	0.3605	0.3629	0.2907	0.2906	0.2469
GPT4	0.8256	0.8256	0.8117	0.8372	0.8372	0.8213	0.6628	0.6628	0.5935