MCEVAL: MASSIVELY MULTILINGUAL CODE EVALUATION

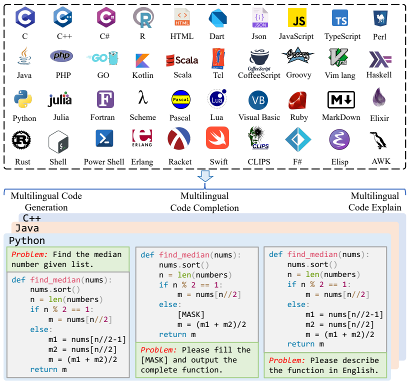
Linzheng Chai[1 *], **Shukai Liu**[1 *], **Jian Yang**[1 *†], **Yuwei Yin**[2], **Ke Jin**[1], **Jiaheng Liu**[1], **Tao Sun**[1], **Ge Zhang**[3], **Changyu Ren**[1], **Hongcheng Guo**[1], **Zekun Wang**[1], **Boyang Wang**[1], **Xianjie Wu**[1], **Bing Wang**[1], **Tongliang Li**[4], **Liqun Yang**[1], **Sufeng Duan**[5], **Zhoujun Li**[1]
[1]CCSE, Beihang University, [2]University of British Columbia, [3]University of Waterloo
[4]Beijing Information Science and Technology University, [5]Shanghai Jiao Tong University

ABSTRACT

Code large language models (LLMs) have shown remarkable advances in code understanding, completion, and generation tasks. Programming benchmarks, comprised of a selection of code challenges and corresponding test cases, serve as a standard to evaluate the capability of different LLMs in such tasks. However, most existing benchmarks primarily focus on Python and are still restricted to a limited number of languages, where other languages are translated from the Python samples degrading the data diversity. To further facilitate the research of code LLMs, we propose a massively multilingual code benchmark covering 40 programming languages (MCEVAL) with 16K test samples, which substantially pushes the limits of code LLMs in multilingual scenarios. The benchmark contains challenging code completion, understanding, and generation evaluation tasks with finely curated massively multilingual instruction corpora MCEVAL-INSTRUCT. In addition, we introduce an effective multilingual coder MCODER trained on MCEVAL-INSTRUCT to support multilingual programming language generation. Extensive experimental results on MCEVAL show that there is still a difficult journey between open-source models and closed-source LLMs in numerous languages. The instruction corpora and evaluation benchmark are available at `https://github.com/MCEVAL/McEval`.

1 INTRODUCTION

Large language models (LLMs) designed for code, such as Codex (Chen et al., 2021), CodeGen (Nijkamp et al., 2023), Code Llama (Rozière et al., 2023), DeepSeek-Coder (Guo et al., 2024), and CodeQwen (Hui et al., 2024) excel at code understanding, completion, and generation tasks.



```
Problem: Find the median
number given list.

def find_median(nums):
    nums.sort()
    n = len(numbers)
    if n % 2 == 1:
        m = nums[n//2]
    else:
        m1 = nums[n//2-1]
        m2 = nums[n//2]
        m = (m1 + m2)/2
    return m
```

```
def find_median(nums):
    nums.sort()
    n = len(numbers)
    if n % 2 == 1:
        m = nums[n//2]
    else:
        [MASK]
        m = (m1 + m2)/2
    return m

Problem: Please fill the
[MASK] and output the
complete function.
```

```
def find_median(nums):
    nums.sort()
    n = len(numbers)
    if n % 2 == 1:
        m = nums[n//2]
    else:
        m1 = nums[n//2-1]
        m2 = nums[n//2]
        m = (m1 + m2)/2
    return m

Problem: Please describe
the function in English.
```

Figure 1: MCEVAL comprised three tasks: code generation, code completion, and code explanation.

Code LLMs with a large number of parameters (e.g. 7B, 13B, or larger) are pre-trained on large-scale code databases with self-supervised autoregressive objectives, followed by instruction tuning (Ouyang et al., 2022) for aligning to human preferences and downstream code-related tasks. Most code benchmarks (Chen et al., 2021; Austin et al., 2021; Athiwaratkun et al., 2023) are introduced to evaluate the performance of code LLMs by assessing their ability to generate executable code based on the problem descriptions. The assessments aim to gauge the capacity of the models to understand and generate code effectively, thereby contributing to facilitating and streamlining the programming process for developers. The execution-based method executes generated code against test cases to measure the

[*] Equal contribution.
[†] Corresponding Author.

success rate. Due to the difficulty of creating the problem and its corresponding solution (requiring specialized programming staff), the development of evaluation benchmarks is limited within Python, with a few other languages being translated from Python. *Therefore, the community desperately needs a massively multilingual programming benchmark (not from HumanEval or MBPP) comprised of instruction corpora and evaluation set to comprehensively facilitate and evaluate the generation, completion, and understanding capability of LLMs.*

To facilitate the development of code LLMs, we introduce a complete framework that includes the multilingual code instruction corpora, multilingual coder (mCoder), and multilingual code evaluation benchmark. First, we propose McEval, the first massively multilingual code evaluation benchmark (from human handwriting) covering 40 languages (16K samples in total), encompassing multilingual code generation, multilingual code explanation, and multilingual code completion tasks. Then, we create a massively multilingual instruction corpora McEval-Instruct of 40 languages. We initially select and refine high-quality code snippets from various programming languages (PLs) using an LLM. The LLM then generates clear and self-contained instructional content, including problem descriptions and corresponding solutions, based on the refined snippets. To ensure consistency and enhance learning across languages, we introduce cross-lingual code transfer, adapting instructional content to different PLs while increasing sample complexity. Based on open-source models and McEval-Instruct, mCoder is used as a strong baseline to explore the transferability of LLMs among different PLs.

The contributions are summarized as follows: (1) We propose McEval with enough test samples (16K), a true massively multilingual multitask code evaluation benchmark (not from HumanEval or MBPP) covering 40 languages, encompassing multilingual code generation, multilingual code explanation, and multilingual code completion tasks. (2) We introduce McEval-Instruct, the massively multilingual code instruction corpora covering from the multilingual code snippet from 40 languages. Based on McEval-Instruct, an effective multilingual coder mCoder is used as a strong baseline for McEval. (3) We systematically evaluate the understanding and generation capabilities of 20+ models on our created McEval and create a leaderboard to evaluate them on 40 programming languages dynamically. Notably, extensive experiments suggest that comprehensive multilingual multitask evaluation can realistically measure the gap between open-source (e.g. DeepSeekCoder and CodeQwen1.5) and closed-source models (e.g. GPT-3.5 and GPT-4).

2 Multilingual Code Evaluation: McEval

2.1 Dataset Statistics

The created McEval is comprised of three key code-related tasks covering 40 programming languages, including multilingual code generation, multilingual code explanation, and multilingual code completion tasks. The multilingual code generation and explanation tasks separately contain 2K samples, where each language has nearly 50 samples. The code completion task can be decomposed into*multi-line completion* (3K samples), *single-line completion* (3K samples), *span completion* (4K samples), and *span completion (light)* (2K samples) (Bavarian et al., 2022).

Table 1: McEval dataset statistics.

Statistics	**Value**
Questions	
Code Generation	2,007
Code Explanation	2,007
Code Completion	12,017
- *Single-Line*	2,998
- *Multi-Line*	2,998
- *Span*	4,014
- *Span(light)*	2,007
Total Test Cases	10,086
Difficulty Level	
- Easy	1,221
- Medium	401
- Hard	385
Length	
Prompt	
- *maximum length*	793 tokens
- *minimum length*	16 tokens
- *avg length*	173.8 tokens
Solution(Output)	
- *maximum length*	666 tokens
- *minimum length*	4 tokens
- *avg length*	120.9 tokens

In Table 1, we display the number of questions, test cases, and difficulty levels corresponding to the three tasks in McEval and the number of questions in the four sub-tasks of the completion task. Moreover, we counted the token length of the prompt and solutions. (The tokens are calculated based on the Llama-3 tokenizer.) Among these tasks, the *span completion (light)* task is similar in form to the *span completion* task. However, in the *span completion (light)* task, each problem is paired with all the corresponding code, making it a balanced version of the *span completion* task (fewer samples for fast inference and the same test size of

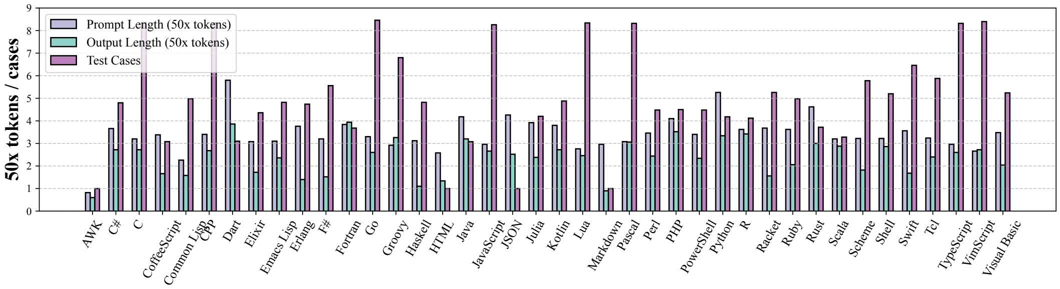


Figure 2: Data statistics of the MCEVAL benchmark involving 40 programming languages.

each programming language). The results of *span completion (light)* can better reflect the differences in model performance across different languages.

Figure 2 plots the length of the prompt, solution(output), and the number of test cases of each programming language. In Table 2, We compared MCEVAL with other multilingual benchmarks. It is noteworthy that our benchmark provides a significant supplement to current benchmarks in terms of both the variety of programming languages and the number of questions.

Table 2: Comparison between MCEVAL and other multilingual code benchmarks. $^{\diamondsuit}$The number of each of the three tasks (Generation, Explanation, and Completion).

Benchmark	Multi-Task	#Languages	Data source	#Questions
MuliPL-E (Cassano et al., 2023)	✗	18	Translate	~3,000
MBXP Athiwaratkun et al. (2023)	✓	10	Translate	12,425
HumanEval-X Zheng et al. (2023b)	✓	5	Hand-Written	820
HumanEval-XL Peng et al. (2024)	✗	12	Hand-Written	22,080
MCEVAL	✓	40	Hand-Written	16,031 (2007/2007/12017)$^{\diamondsuit}$

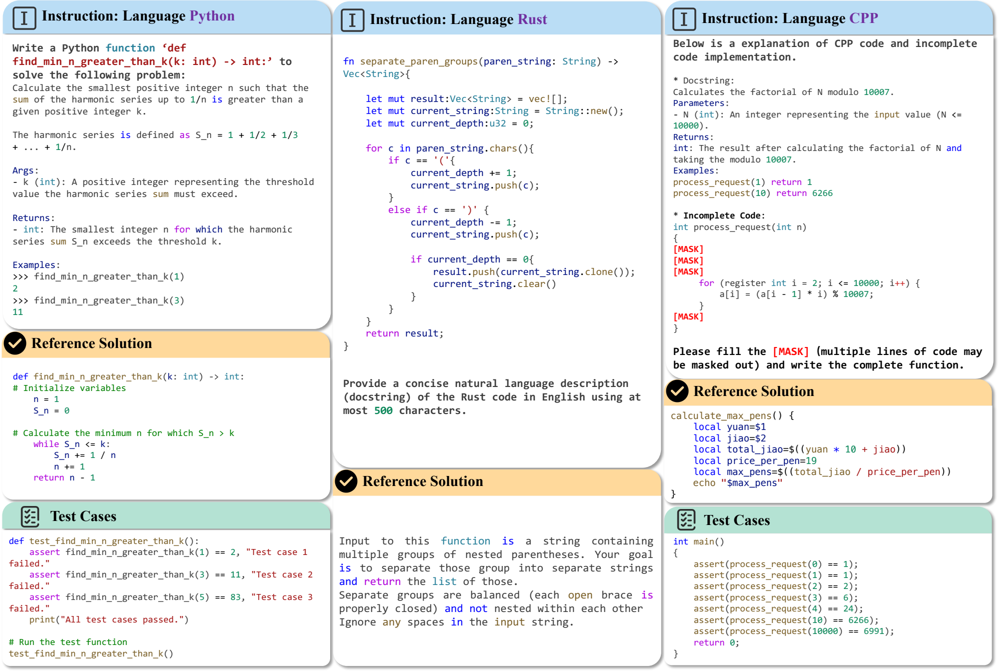
2.2 HUMAN ANNOTATION & QUALITY CONTROL

To create the massively multilingual code evaluation benchmark MCEVAL, the annotation of multilingual code samples is conducted utilizing a comprehensive and systematic human annotation procedure, underpinned by rigorously defined guidelines to ensure accuracy and consistency. Initially, 10 software developers in computer science are recruited as multilingual programming annotators with proven proficiency in the respective programming languages. Following a detailed training session on the annotation protocol, which emphasizes the importance of context, syntactical correctness, and semantic fidelity across languages, annotators are tasked with creating problem definitions and the corresponding solution. The annotators should follow: (1) Provide a clear and self-contained problem definition, answer the question with any tools, and design the test cases to evaluate the correctness of the code. (2) Classify them into multiple difficulties (Easy/Middle/Hard), based on algorithmic complexity and functionality. Each sample is independently annotated by at least two annotators to minimize subjective bias and errors. Discrepancies between annotators are resolved through consensus or adjudication by a senior annotator. Finally, three volunteers are employed to evaluate the correctness of the benchmark (> 90% accuracy) and correct the errors. (See Appendix A.2 for more details).

2.3 EVALUATION TASKS

Multilingual Code Generation. Given the k-th programming language $L_k \in \{L_i\}_{i=1}^{K}$, where $K = 40$ is the number of programming languages, we provide the problem description q^{L_k} and examples test cases e^{L_k} as the input for code LLMs $\mathcal{M}$ to generate the corresponding code a^{L_k}. We obtain the sampled code result from the code generation distribution $P(a^{L_k}|q^{L_k}, e^{L_k}; \mathcal{M})$ from code LLM $\mathcal{M}$, and then feed the test cases into the generated code, where the generated outputs by code should equal the expected outputs. The process can be described as:

$$r^{L_k} = \mathbb{I}(P(a^{L_k}|q^{L_k}, e^{L_k}; \mathcal{M}); u^{L_k}) \tag{1}$$



Instruction: Language Python

```
Write a Python function ‘def
find_min_n_greater_than_k(k: int) -> int:’ to
solve the following problem:
Calculate the smallest positive integer n such that the
sum of the harmonic series up to 1/n is greater than a
given positive integer k.

The harmonic series is defined as S_n = 1 + 1/2 + 1/3
+ ... + 1/n.

Args:
- k (int): A positive integer representing the threshold
value the harmonic series sum must exceed.

Returns:
- int: The smallest integer n for which the harmonic
series sum S_n exceeds the threshold k.

Examples:
>>> find_min_n_greater_than_k(1)
2
>>> find_min_n_greater_than_k(3)
11
```

Reference Solution

```python
def find_min_n_greater_than_k(k: int) -> int:
# Initialize variables
    n = 1
    S_n = 0

# Calculate the minimum n for which S_n > k
    while S_n <= k:
        S_n += 1 / n
        n += 1
    return n - 1
```

Test Cases

```python
def test_find_min_n_greater_than_k():
    assert find_min_n_greater_than_k(1) == 2, "Test case 1
failed."
    assert find_min_n_greater_than_k(3) == 11, "Test case 2
failed."
    assert find_min_n_greater_than_k(5) == 83, "Test case 3
failed."
    print("All test cases passed.")

# Run the test function
test_find_min_n_greater_than_k()
```

(1) Code Generation

Instruction: Language Rust

```rust
fn separate_paren_groups(paren_string: String) ->
Vec<String>{

    let mut result:Vec<String> = vec![];
    let mut current_string:String = String::new();
    let mut current_depth:u32 = 0;

    for c in paren_string.chars(){
        if c == '('{
            current_depth += 1;
            current_string.push(c);
        }
        else if c == ')' {
            current_depth -= 1;
            current_string.push(c);

            if current_depth == 0{
                result.push(current_string.clone());
                current_string.clear()
            }
        }
    }
    return result;
}
```

```
Provide a concise natural language description
(docstring) of the Rust code in English using at
most 500 characters.
```

Reference Solution

```
Input to this function is a string containing
multiple groups of nested parentheses. Your goal
is to separate those group into separate strings
and return the list of those.
Separate groups are balanced (each open brace is
properly closed) and not nested within each other
Ignore any spaces in the input string.
```

(2) Code Explain

Instruction: Language CPP

```cpp
Below is a explanation of CPP code and incomplete
code implementation.

* Docstring:
Calculates the factorial of N modulo 10007.
Parameters:
- N (int): An integer representing the input value (N <=
10000).
Returns:
int: The result after calculating the factorial of N and
taking the modulo 10007.
Examples:
process_request(1) return 1
process_request(10) return 6266

* Incomplete Code:
int process_request(int n)
{
[MASK]
[MASK]
[MASK]
     for (register int i = 2; i <= 10000; i++) {
         a[i] = (a[i - 1] * i) % 10007;
     }
[MASK]
}

Please fill the [MASK] (multiple lines of code may
be masked out) and write the complete function.
```

Reference Solution

```
calculate_max_pens() {
    local yuan=$1
    local jiao=$2
    local total_jiao=$((yuan * 10 + jiao))
    local price_per_pen=19
    local max_pens=$((total_jiao / price_per_pen))
    echo "$max_pens"
}
```

Test Cases

```cpp
int main()
{
    assert(process_request(0) == 1);
    assert(process_request(1) == 1);
    assert(process_request(2) == 2);
    assert(process_request(3) == 6);
    assert(process_request(4) == 24);
    assert(process_request(10) == 6266);
    assert(process_request(10000) == 6991);
    return 0;
}
```

(3) Code Completion

Figure 3: Examples of multilingual code generation, explanation, and completion.

where $\mathbb{I}(\cdot)$ is the indicator function by executing the generated code with the given test cases u^{L_k}. when the generated code a^{L_k} passes all test cases, the evaluation result $r = 1$, else $r = 0$.

Multilingual Code Explanation. To evaluate the understanding capability of code LLMs, we adopt two-pass generation (Code-to-Natural-Language and Natural-Language-to-Code), since the text-similar metrics (e.g. BLEU (Papineni et al., 2002)) are hindered by the n-gram text matching and can not produce an accurate score. We first prompt the code LLMs to generate the natural language description t^{L_k} based on the code a^{L_k} and then we force the model to restore the original code based on t^{L_k}. The sampled code from $P(a^{L_k}|t^{L_k};\mathcal{M})$ is used to evaluate the understanding capability as:

$$r = \mathbb{I}(P(t^{L_k}|a^{L_k};\mathcal{M})P(a^{L_k}|t^{L_k};\mathcal{M});u^{L_k}) \tag{2}$$

where $\mathbb{I}(\cdot)$ is used to check the correctness of the generated code by running the code with test cases.

Multilingual Code Completion. Another important scenario is code completion, where the code LLM produces the middle code $a_m^{L_k}$ based on the prefix code $a_p^{L_k}$ and suffix code snippet $a_s^{L_k}$. Hence, we concatenate $a_p^{L_k}$, $a_m^{L_k}$, and $a_s^{L_k}$ as the complete code for evaluation as:

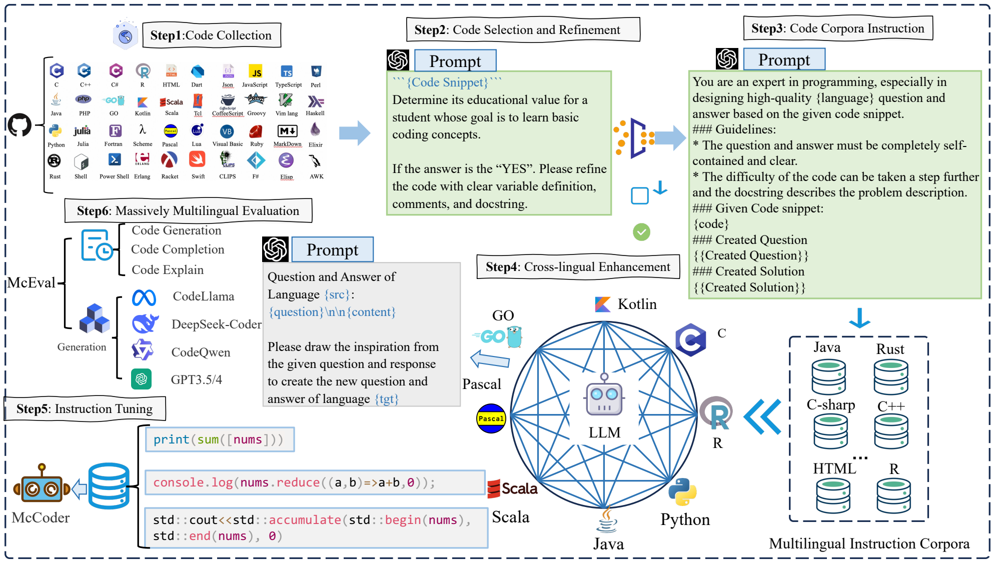
$$r = \mathbb{I}(P(a_m^{L_k}|a_p^{L_k}, a_s^{L_k};\mathcal{M});u^{L_k}) \tag{3}$$

where $a_p^{L_k}$, $a_q^{L_k}$, and $a_m^{L_k}$ are concatenated as the complete code to be executed with test cases u^{L_k}.

3 MCODER

3.1 MCEVAL-INSTRUCT

Collection from Code Snippet. For a programming language L_k ($L_k \in \{L_i\}_{i=1}^{K}$) and K is the number of programming languages), consider an existing code snippet $c \in D_c^{L_k}$, we prompt the LLM to select the high-quality code and refine the code to a self-contained code snippet by using the prompt “{Code Snippet}\nDetermine its educational value for a student whose goal is to learn basic coding concepts.\n\nIf the answer is ‘YES’. Please refine the code with clear variable definitions, comments, and docstring.”. Then, we can obtain the multilingual refined code snippets. (More details can be found in Appendix A.3)



```{Code Snippet}```
Determine its educational value for a student whose goal is to learn basic coding concepts.

If the answer is the "YES". Please refine the code with clear variable definition, comments, and docstring.

You are an expert in programming, especially in designing high-quality {language} question and answer based on the given code snippet.
### Guidelines:
* The question and answer must be completely self-contained and clear.
* The difficulty of the code can be taken a step further and the docstring describes the problem description.
### Given Code snippet:
{code}
### Created Question
{{Created Question}}
### Created Solution
{{Created Solution}}

Question and Answer of Language {src}: {question}\n\n{content}

Please draw the inspiration from the given question and response to create the new question and answer of language {tgt}

```
print(sum([nums]))
```

```
console.log(nums.reduce((a,b)=>a+b,0));
```

```
std::cout<<std::accumulate(std::begin(nums),
std::end(nums), 0)
```

Figure 4: The framework of MCODER. We first create MCEVAL-INSTRUCT covering 40 languages from code snippets to fine-tune MCODER. 20+ existing LLMs and MCODER are then evaluated on MCEVAL comprised of multilingual code generation, explanation, and completion.

Instruction Corpora Generation. To construct a comprehensive massively multilingual code instruction corpora $\{D^{L_i}\}_{i=1}^{K}$, we prompt the LLMs (`gpt-4-1106-preview`) to create a problem description q^{L_k} and the corresponding solution a^{L_k} by drawing inspiration from the refined code snippet c^{L_k}. We use LLM to generate instruction dataset by using the prompt "You are an expert in programming, especially in designing high-quality language question and answer based on the given code snippet.\n\n ### Guidelines: * The question and answer must be completely self-contained and clear.*\n The difficulty of the code can be taken a step further and the docstring describes the problem description.\n ### Given Code snippet: code\n ### Created Question Created Question\n ### Created Solution\n Created Solution" in Figure 4.

Cross-lingual Code Transfer. Since the created instruction samples of different programming languages focus on different aspects of coding, we adopt the cross-lingual code transfer to minimize the gap among multiple languages. Given the instruction dataset D^{L_i} of language L_i, we randomly sample a pair (q^{L_i}, a^{L_i}) and force the LLM to modify them to another language L_j with a more complex sample $(q^{L_i \to L_j}, a^{L_i \to L_j})$. In this way, we can get the derived instruction corpora $\{D^{L_i \to L_j}\}(i \neq j \wedge 1 \leq i, j \leq K)$. Finally, we combine $\{D^{L_k}\}_{k=1}^{K}$ and $\{D^{L_i \to L_j}\}(i \neq j \wedge 1 \leq i, j \leq K)$ as the multilingual instruction corpora MCEVAL-INSTRUCT $\{D_{mc}^{L_k}\}_{k=1}^{K}$ covering 40 programming languages.

3.2 MULTILINGUAL CODE INSTRUCTION TUNING

The training objective $\mathcal{L}_{all}$ of the multilingual instruction fine-tuning can be described as:

$$\mathcal{L}_{all} = -\sum_{k=1}^{K} \mathbb{E}_{q^{L_k}, a^{L_k} \sim \{D^{L_k}\}_{k=1}^{K}} \left[\log P(a^{L_k} | q^{L_k}; \mathcal{M}) \right] \tag{4}$$

where q^{L_k} and a^{L_k} are the code-related question and answer from the dataset D^{L_k} of language L_k, respectively. K is the number of programming languages.

4 EXPERIMENTS

4.1 EXPERIMENT SETUP

Code LLMs. We evaluate 30 + models with sizes ranging from 7B to 236B parameters, including general/code LLMs, open/closed-source models, and base/instruction models. For general models, we evaluate GPT series (Brown et al., 2020; OpenAI, 2023), Qwen1.5 (Bai et al., 2023), Llama3 (AI,

Table 3: Pass@1 (%) scores of different code LLMs for multilingual code generation tasks on MCEVAL. “Avg$_{all}$” represents the average scores of all code languages.

Method	Size	AWK	C	C++	C#	Clisp	Coffee	Dart	Elisp	Elixir	Erlang	Fortran	F#	Go	Groovy	Haskell	Html	Java	JS	Json	Julia
GPT-4o (240513)	🔒	54.0	**60.0**	58.0	72.0	60.0	82.0	**54.9**	**64.0**	**66.0**	44.0	66.0	**78.0**	**62.0**	80.0	**90.0**	32.0	81.1	62.0	74.0	**72.0**
GPT-4 Turbo (231106)	🔒	**70.0**	**60.0**	64.0	**80.0**	64.0	72.0	45.1	62.0	56.0	38.0	54.0	74.0	56.0	82.0	78.0	30.0	**83.0**	60.0	72.0	70.0
GPT-3.5 Turbo (240125)	🔒	14.0	54.0	58.0	68.0	54.0	76.0	41.2	26.0	30.0	46.0	40.0	68.0	54.0	**86.0**	50.0	18.0	71.7	60.0	76.0	54.0
Yi-Large-Turbo	🔒	52.0	44.0	50.0	54.0	54.0	52.0	31.4	30.0	46.0	30.0	58.0	52.0	46.0	80.0	58.0	22.0	41.5	52.0	**78.0**	56.0
DeepSeekCoder-V2-Instruct	236B	62.0	**60.0**	**66.0**	72.0	**74.0**	80.0	43.1	52.0	62.0	32.0	**80.0**	76.0	56.0	84.0	72.0	30.0	77.4	**64.0**	74.0	70.0
Qwen1.5-Chat	72B	50.0	48.0	46.0	56.0	46.0	44.0	19.6	14.0	18.0	24.0	34.0	32.0	50.0	42.0	32.0	22.0	39.6	46.0	74.0	32.0
CodeLlama-Instruct	34B	38.0	32.0	32.0	40.0	42.0	34.0	7.8	16.0	28.0	32.0	24.0	18.0	34.0	20.0	32.0	14.0	26.4	42.0	68.0	28.0
WizardCoder-Python	34B	36.0	42.0	46.0	52.0	42.0	46.0	13.7	14.0	38.0	38.0	26.0	26.0	50.0	54.0	40.0	26.0	43.4	52.0	70.0	52.0
DeepSeekCoder-Instruct	33B	50.0	58.0	66.0	70.0	60.0	**86.0**	25.5	40.0	50.0	40.0	**66.0**	48.0	54.0	78.0	56.0	30.0	73.6	62.0	42.0	56.0
Codestral-v0.1	22B	54.0	48.0	56.0	66.0	60.0	62.0	43.1	28.0	34.0	24.0	56.0	58.0	58.0	76.0	52.0	**34.0**	73.6	58.0	72.0	52.0
DeepSeekCoder-V2-Lite-Instruct	16B	58.0	58.0	64.0	74.0	56.0	76.0	35.3	30.0	40.0	26.0	68.0	56.0	56.0	66.0	60.0	26.0	66.0	64.0	68.0	60.0
OCTOCODER	16B	28.0	28.0	28.0	38.0	40.0	18.0	5.9	14.0	28.0	16.0	22.0	4.0	34.0	30.0	20.0	8.0	34.0	30.0	58.0	20.0
WizardCoder-V1.0	15B	18.0	38.0	28.0	36.0	36.0	50.0	17.6	0.0	24.0	24.0	28.0	30.0	38.0	62.0	40.0	6.0	30.2	52.0	14.0	38.0
Granite-34B-code-instruct-8K	34B	48.0	38.0	54.0	50.0	60.0	64.0	19.6	16.0	36.0	36.0	50.0	40.0	52.0	64.0	44.0	28.0	37.7	54.0	66.0	48.0
Granite-20B-code-instruct-8K	20B	38.0	42.0	40.0	56.0	40.0	56.0	23.5	18.0	40.0	16.0	32.0	42.0	46.0	48.0	40.0	20.0	35.8	50.0	74.0	48.0
Granite-8B-code-instruct-4K	8B	36.0	28.0	44.0	48.0	50.0	56.0	11.8	20.0	36.0	22.0	32.0	38.0	46.0	48.0	40.0	26.0	35.8	48.0	64.0	48.0
Granite-3B-code-instruct-128K	3B	16.0	14.0	42.0	38.0	40.0	30.0	9.8	12.0	36.0	16.0	26.0	26.0	30.0	32.0	34.0	22.0	26.4	50.0	62.0	28.0
Phi-3-medium-4k-instruct	14B	52.0	46.0	40.0	52.0	34.0	42.0	13.7	14.0	16.0	8.0	30.0	32.0	42.0	42.0	42.0	20.0	39.6	52.0	68.0	48.0
CodeLlama-Instruct	13B	36.0	38.0	38.0	40.0	46.0	30.0	7.8	16.0	32.0	32.0	16.0	26.0	34.0	22.0	38.0	18.0	22.6	34.0	56.0	32.0
Llama-3-Instruct	8B	32.0	46.0	50.0	54.0	38.0	48.0	15.7	14.0	32.0	30.0	12.0	26.0	48.0	52.0	38.0	16.0	45.3	54.0	70.0	40.0
CodeQwen-2.5-Chat	7B	58.0	58.0	58.0	74.0	56.0	**86.0**	37.3	54.0	56.0	38.0	56.0	62.0	58.0	84.0	66.0	34.0	69.8	60.0	76.0	64.0
Codegemma-it	7B	26.0	40.0	42.0	48.0	20.0	18.0	23.5	10.0	4.0	4.0	8.0	22.0	46.0	58.0	32.0	24.0	56.6	48.0	70.0	38.0
CodeLlama-Instruct	7B	32.0	34.0	26.0	40.0	42.0	32.0	5.9	14.0	22.0	20.0	20.0	14.0	32.0	22.0	32.0	14.0	18.9	28.0	64.0	24.0
Codeshell-chat	7B	24.0	30.0	36.0	26.0	20.0	38.0	5.9	4.0	14.0	6.0	8.0	8.0	28.0	30.0	22.0	24.0	22.6	42.0	66.0	24.0
DeepSeekCoder-1.5-Instruct	7B	40.0	54.0	56.0	60.0	56.0	80.0	23.5	24.0	40.0	40.0	40.0	46.0	52.0	80.0	26.0	24.0	60.4	56.0	66.0	42.0
Magicoder-S-DS	7B	44.0	50.0	50.0	60.0	58.0	72.0	19.6	32.0	34.0	**62.0**	62.0	54.0	50.0	80.0	54.0	16.0	66.0	60.0	56.0	40.0
Nxcode-CQ-orpo	7B	38.0	52.0	58.0	50.0	46.0	62.0	23.5	22.0	38.0	36.0	52.0	46.0	52.0	72.0	46.0	28.0	56.6	50.0	64.0	62.0
OpenCodeInterpreter-DS	7B	38.0	54.0	52.0	68.0	44.0	78.0	17.6	30.0	42.0	48.0	52.0	54.0	48.0	72.0	40.0	28.0	66.0	46.0	72.0	34.0
CodeQwen-1.5-Chat	7B	40.0	52.0	56.0	62.0	48.0	62.0	29.4	22.0	38.0	38.0	50.0	44.0	50.0	70.0	44.0	30.0	58.5	54.0	64.0	62.0
MCODER (Our Method)	7B	40.0	44.0	52.0	62.0	46.0	66.0	21.6	30.0	44.0	52.0	56.0	44.0	48.0	70.0	32.0	34.0	54.7	54.0	66.0	56.0

Method	Kotlin	Lua	MD	Pascal	Perl	PHP	Power	Python	R	Racket	Ruby	Rust	Scala	Scheme	Shell	Swift	Tcl	TS	VB	VimL	**Avg**$_{all}$
GPT-4o (240513)	**84.0**	**60.0**	32.0	52.0	**64.0**	64.0	72.0	76.0	**66.0**	**66.0**	64.0	83.0	32.0	**76.0**	**76.0**	**84.0**	**68.0**	56.0	**78.0**	**40.0**	**65.2**
GPT-4 Turbo (231106)	80.0	56.0	**38.0**	46.0	**64.0**	**68.0**	76.0	**78.0**	58.0	62.0	**66.0**	71.7	66.0	58.0	72.0	82.0	56.0	**60.0**	68.0	38.0	63.4
GPT-3.5 Turbo (240125)	62.0	58.0	24.0	40.0	56.0	58.0	68.0	60.0	56.0	40.0	56.0	52.8	68.0	46.0	60.0	58.0	44.0	54.0	74.0	24.0	52.6
Yi-Large-Turbo	36.0	48.0	24.0	46.0	44.0	46.0	64.0	44.0	50.0	34.0	64.0	0.0	48.0	50.0	48.0	64.0	52.0	50.0	40.0	30.0	46.6
DeepSeekCoder-V2-Instruct	80.0	58.0	36.0	**54.0**	54.0	**68.0**	**78.0**	64.0	64.0	**66.0**	64.0	**84.9**	**76.0**	74.0	70.0	74.0	**68.0**	50.0	72.0	**40.0**	64.6
Qwen1.5-Chat	20.0	50.0	22.0	36.0	40.0	36.0	40.0	32.0	22.0	26.0	44.0	34.0	30.0	30.0	34.0	40.0	26.0	44.0	30.0	28.0	35.8
CodeLlama-Instruct	24.0	30.0	10.0	28.0	40.0	24.0	38.0	32.0	18.0	26.0	30.0	26.4	28.0	20.0	20.0	42.0	24.0	38.0	36.0	22.0	29.1
WizardCoder-Python	36.0	46.0	12.0	36.0	36.0	38.0	44.0	40.0	20.0	22.0	46.0	35.8	48.0	22.0	2.0	48.0	30.0	28.0	40.0	24.0	36.5
DeepSeekCoder-Instruct	66.0	58.0	32.0	**54.0**	32.0	48.0	60.0	56.0	48.0	46.0	**66.0**	66.0	62.0	60.0	58.0	60.0	58.0	56.0	44.0	30.0	54.3
Codestral-v0.1	64.0	56.0	16.0	6.0	54.0	56.0	64.0	56.0	48.0	36.0	40.0	71.7	48.0	32.0	48.0	72.0	44.0	52.0	62.0	28.0	50.5
DeepSeekCoder-V2-Lite-Instruct	64.0	56.0	28.0	48.0	56.0	44.0	68.0	64.0	50.0	52.0	56.0	71.7	60.0	54.0	52.0	76.0	38.0	60.0	58.0	24.0	54.7
OCTOCODER	14.0	32.0	10.0	6.0	26.0	24.0	38.0	30.0	6.0	24.0	0.0	32.1	4.0	22.0	26.0	30.0	24.0	38.0	28.0	14.0	23.3
WizardCoder-V1.0	26.0	40.0	0.0	12.0	32.0	32.0	48.0	30.0	20.0	10.0	40.0	24.5	40.0	10.0	0.0	30.0	20.0	42.0	36.0	18.0	28.0
Granite-34B-code-instruct-8K	44.0	50.0	22.0	40.0	34.0	40.0	56.0	44.0	32.0	36.0	38.0	45.3	34.0	36.0	36.0	52.0	32.0	50.0	44.0	16.0	42.2
Granite-20B-code-instruct-8K	38.0	48.0	22.0	32.0	34.0	40.0	48.0	44.0	28.0	32.0	40.0	39.6	36.0	40.0	30.0	46.0	28.0	46.0	38.0	16.0	38.3
Granite-8B-code-instruct-4K	32.0	38.0	20.0	34.0	38.0	34.0	42.0	36.0	22.0	34.0	36.0	43.4	40.0	30.0	20.0	50.0	30.0	48.0	42.0	12.0	36.5
Granite-3B-code-instruct-128K	20.0	32.0	8.0	32.0	24.0	28.0	38.0	34.0	12.0	24.0	42.0	24.5	30.0	22.0	16.0	36.0	14.0	42.0	34.0	16.0	28.0
Phi-3-medium-4k-instruct	30.0	48.0	18.0	28.0	36.0	42.0	50.0	48.0	38.0	30.0	26.0	26.4	18.0	30.0	26.0	50.0	22.0	52.0	44.0	12.0	35.2
CodeLlama-Instruct	20.0	30.0	10.0	8.0	28.0	32.0	34.0	30.0	12.0	20.0	28.0	24.5	24.0	26.0	20.0	40.0	18.0	40.0	38.0	10.0	27.7
Llama-3-Instruct	34.0	40.0	14.0	32.0	36.0	38.0	40.0	42.0	30.0	22.0	34.0	41.5	38.0	32.0	26.0	48.0	24.0	50.0	42.0	16.0	36.0
CodeQwen-2.5-Chat	72.0	58.0	32.0	50.0	56.0	64.0	72.0	62.0	**66.0**	58.0	60.0	69.8	60.0	64.0	66.0	82.0	50.0	56.0	68.0	**40.0**	60.3
Codegemma-it	36.0	48.0	8.0	14.0	40.0	36.0	42.0	24.0	16.0	18.0	40.0	39.6	40.0	20.0	12.0	54.0	10.0	38.0	38.0	16.0	30.7
CodeLlama-Instruct	16.0	30.0	14.0	6.0	28.0	12.0	34.0	32.0	14.0	24.0	28.0	17.0	26.0	20.0	16.0	32.0	22.0	28.0	34.0	14.0	24.6
Codeshell-chat	28.0	34.0	14.0	10.0	22.0	28.0	32.0	30.0	16.0	14.0	34.0	30.2	18.0	8.0	12.0	18.0	12.0	42.0	26.0	12.0	23.0
DeepSeekCoder-1.5-Instruct	38.0	48.0	30.0	38.0	42.0	54.0	64.0	44.0	32.0	44.0	54.0	45.3	50.0	40.0	42.0	42.0	40.0	50.0	58.0	20.0	46.0
Magicoder-S-DS	42.0	48.0	24.0	48.0	50.0	44.0	56.0	48.0	44.0	42.0	54.0	45.3	54.0	44.0	54.0	56.0	46.0	50.0	68.0	16.0	48.8
Nxcode-CQ-orpo	42.0	46.0	18.0	42.0	38.0	40.0	44.0	44.0	36.0	42.0	46.0	47.2	44.0	40.0	42.0	66.0	30.0	48.0	60.0	18.0	44.7
OpenCodeInterpreter-DS	48.0	50.0	26.0	46.0	50.0	30.0	54.0	56.0	42.0	34.0	40.0	50.9	38.0	44.0	36.0	46.0	36.0	50.0	60.0	18.0	46.0
CodeQwen-1.5-Chat	44.0	48.0	18.0	46.0	38.0	44.0	42.0	44.0	38.0	40.0	46.0	45.3	48.0	38.0	42.0	66.0	30.0	54.0	56.0	18.0	45.5
MCODER (Our Method)	48.0	52.0	30.0	42.0	36.0	32.0	54.0	44.0	40.0	36.0	48.0	52.8	58.0	44.0	46.0	64.0	38.0	52.0	58.0	20.0	46.7

2024), Phi-3 (Abdin et al., 2024), and Yi (Young et al., 2024). For code models, we test CodeQwen (Hui et al., 2024), DeepSeekCoder (Guo et al., 2024), CodeLlama (Rozière et al., 2023), OCTOCODER (Muennighoff et al., 2023), CodeShell (Xie et al., 2024), MagiCoder (Wei et al., 2023), WizardCoder (Luo et al., 2023), Codegemma (Gemma Team, 2024) and Granite (Mishra et al., 2024). Furthermore, we further fine-tune MCODER based on CodeQwen1.5 and DeepSeekCoder to explore the language transfer capabilities of code LLMs.

Evaluation Metrics. We assess the models by executing the code and evaluating it using the Pass@1 metric. Pass@1 is a widely recognized measure in machine learning, particularly for code generation, as it gauges the model's accuracy in producing correct solutions on the first attempt.

Instruction Corpora. The resulting dataset, MCEVAL-INSTRUCT (110K samples), is comprised of created question-answer pairs and open-source collection (Wei et al., 2023). We apply data decontamination before training our MCODER. Following Li et al. (2023); Wei et al. (2023), we adopt the N-gram exact match decontamination method with MCEVAL, HumanEval(Chen et al., 2021), MultiPL-E(Cassano et al., 2023), MBPP(Austin et al., 2021). For supervised fine-tuning (SFT), we utilize CodeQwen-1.5 as the foundational code LLMs. Specifically, we select all Python data from MCEVAL-INSTRUCT, comprising 50K training samples, for MCODER-Python training.

Optimization & Evaluation. Our MCODER based on CodeQwen1.5 are trained for 2 epochs with a cosine scheduler, starting at a learning rate of 2e-5 (3% warmup steps). We use AdamW (Loshchilov & Hutter, 2017) as the optimizer and a batch size of 512 (max length 4096). We adopt the greedy Pass@1 (%) metric (Kulal et al., 2019; Chen et al., 2021) for evaluations. For closed-source LLMs, the answers are generated by the official API. For code explanation, we prompt the LLM to describe the code and then restore the descriptions to the original code. (Details can be found in Appendix A.6).

4.2 MAIN RESULTS

Multilingual Code Generation. Table 3 shows the Pass@1 results of various models on MCEVAL for multilingual code generation task. The results reveal a significant disparity between closed-source

Table 4: Pass@1 (%) scores of different models for multilingual code completion tasks on MCEVAL. "Avg$_{all}$" represents the average scores of all code languages.

Single-line Completion

Method	Size	AWK	C	C++	C#	Clisp	Coffee	Dart	Elisp	Elixir	Erlang	Fortran	F#	Go	Groovy	Haskell	Html	Java	JS	Json	Julia
GPT-4 Turbo (231106)	🔒	**92.9**	**74.4**	75.6	89.3	**91.1**	**97.5**	76.5	**84.2**	**82.4**	54.2	79.6	69.6	81.7	92.6	**76.2**	**57.1**	93.9	80.0	**93.1**	93.3
GPT-3.5 Turbo (240125)	🔒	14.3	32.9	20.7	41.7	53.6	68.8	28.6	44.7	19.1	6.3	14.3	37.5	67.1	76.6	11.9	21.4	40.8	35.0	4.2	76.7
DeepSeekCoder-Instruct	33B	50.0	61.0	72.0	79.8	62.5	78.8	70.4	63.2	66.2	45.8	68.4	60.7	67.1	83.0	38.1	52.4	82.7	65.0	77.8	83.3
OCTOCODER	16B	42.9	47.6	52.4	82.1	35.7	56.3	60.2	34.2	8.8	0.0	0.0	48.2	58.5	73.4	0.0	2.4	81.6	56.3	6.9	0.0
StarCoder2-instruct-V0.1	15B	28.6	**74.4**	**81.7**	86.9	71.4	7.5	**82.7**	68.4	75.0	62.5	76.5	64.3	**82.9**	88.3	47.6	0.0	91.8	**83.8**	16.7	83.3
WizardCoder-V1.0	15B	21.4	37.8	36.6	38.1	3.6	18.8	28.6	0.0	38.2	14.6	9.2	10.7	59.8	66.0	14.3	16.7	38.8	41.3	0.0	53.3
Qwen1.5-Chat	14B	35.7	50.0	54.9	61.9	19.6	51.3	37.8	6.6	27.9	16.7	30.6	30.4	46.3	51.1	28.6	28.6	59.2	50.0	54.2	53.3
CodeLlama-Instruct	13B	78.6	57.3	75.6	79.8	48.2	56.3	48.0	52.6	54.4	41.7	43.9	46.4	68.3	68.1	26.2	21.4	52.0	61.3	48.6	66.7
Yi-1.5-Chat	9B	35.7	63.4	65.9	84.5	39.3	61.3	66.3	38.2	48.5	27.1	68.4	35.7	59.8	85.1	38.1	21.4	77.6	58.8	69.4	75.6
CodeLlama-Instruct	7B	78.6	62.2	73.2	54.8	30.4	66.3	48.0	31.6	47.1	35.4	52.0	42.9	61.0	61.7	33.3	26.2	22.4	18.8	61.1	67.8
CodeQwen1.5-Chat	7B	35.7	68.3	63.4	76.2	67.9	47.5	78.6	35.5	72.1	45.8	57.1	60.7	73.2	69.1	31.0	42.9	90.8	68.8	69.4	88.9
Magicoder-S-DS	7B	71.4	67.1	72.0	84.5	71.4	77.5	80.6	69.7	79.4	62.5	**85.7**	**85.7**	75.6	**96.8**	52.4	40.5	94.9	72.5	73.6	74.4
MCODER	7B	85.7	74.4	82.9	**90.5**	69.6	91.3	78.6	69.7	77.9	**70.8**	67.3	75.0	80.5	83.0	45.2	28.6	**95.9**	81.3	54.2	**94.4**

Method	Kotlin	Lua	MD	Pascal	Perl	PHP	Power	Python	R	Racket	Ruby	Rust	Scala	Scheme	Shell	Swift	Tcl	TS	VB	VimL	**Avg$_{all}$**
GPT-4 Turbo (231106)	83.3	**80.0**	**28.6**	70.7	91.4	86.2	**92.2**	86.7	87.0	**88.7**	**89.5**	81.5	87.8	**85.3**	87.8	**86.1**	**85.9**	77.5	**76.9**	63.2	**82.7**
GPT-3.5 Turbo (240125)	64.3	58.8	21.4	20.7	52.9	20.2	65.6	84.4	23.9	41.9	47.4	27.2	50.0	39.7	54.9	63.9	57.7	46.3	28.2	80.3	43.6
DeepSeekCoder-Instruct	73.8	71.3	14.3	68.3	65.7	81.9	86.7	83.3	79.3	59.7	86.8	75.0	84.1	72.1	80.5	79.2	83.3	57.5	70.5	67.1	72.4
OCTOCODER	70.2	50.0	3.6	15.9	32.9	0.0	28.9	78.9	2.2	38.7	15.8	0.0	56.1	41.2	48.8	27.8	37.2	67.5	59.0	**69.7**	39.2
StarCoder2-instruct-V0.1	**85.7**	61.3	0.0	75.6	80.0	**93.6**	**87.8**	87.8	**88.0**	66.1	73.7	**89.1**	39.0	75.0	78.0	54.2	62.8	**82.5**	64.1	72.4	71.4
WizardCoder-V1.0	40.5	35.0	0.0	28.0	28.6	29.8	40.0	52.2	48.9	1.6	28.9	18.5	28.0	0.0	17.1	33.3	37.2	35.0	51.3	65.8	31.6
Qwen1.5-Chat	51.2	51.3	7.1	36.6	51.4	62.8	56.7	63.3	63.0	29.0	52.6	50.0	17.1	26.5	50.0	63.9	43.6	46.3	43.6	36.8	44.7
CodeLlama-Instruct	58.3	66.3	0.0	41.5	55.7	54.3	76.7	77.8	69.6	51.6	60.5	58.7	64.6	47.1	67.1	63.9	62.8	62.5	66.7	68.4	59.3
Yi-1.5-Chat	75.0	66.3	17.9	53.7	64.3	83.0	76.7	78.9	76.1	38.7	67.1	65.2	45.1	42.6	65.9	75.0	62.8	57.5	60.3	53.9	62.2
CodeLlama-Instruct	61.9	41.3	0.0	19.5	57.1	22.3	42.2	73.3	62.0	35.5	67.1	46.7	72.0	33.8	73.2	33.3	61.5	43.8	61.5	63.2	49.9
CodeQwen1.5-Chat	78.6	57.5	0.0	70.7	80.0	83.0	82.2	84.4	68.5	66.1	75.0	80.4	67.1	50.0	89.0	77.8	80.8	63.8	48.7	65.8	68.6
Magicoder-S-DS	82.1	77.5	7.1	75.6	91.4	90.4	90.0	**87.8**	84.8	66.1	85.5	78.3	**89.0**	79.4	**91.5**	**86.1**	83.3	70.0	**76.9**	39.5	78.4
MCODER	82.1	**80.0**	0.0	**79.3**	**97.1**	86.2	88.9	82.2	**88.0**	77.4	77.6	82.6	80.5	72.1	**91.5**	80.6	84.6	**82.5**	73.1	67.1	78.9

Multi-line Completion

Method	Size	AWK	C	C++	C#	Clisp	Coffee	Dart	Elisp	Elixir	Erlang	Fortran	F#	Go	Groovy	Haskell	Html	Java	JS	Json	Julia
GPT-4 Turbo (231106)	🔒	**78.6**	**69.5**	**69.5**	**83.3**	**71.4**	**96.3**	**68.4**	**77.6**	**75.0**	**54.2**	67.3	**64.3**	**64.6**	**92.6**	64.3	33.3	**84.7**	71.3	**90.3**	**83.3**
GPT-3.5 Turbo (240125)	🔒	42.9	58.5	54.9	70.2	28.6	65.0	53.1	39.5	22.1	4.2	20.4	35.7	62.2	**92.6**	26.2	31.0	75.5	58.8	43.1	60.0
DeepSeekCoder-Instruct	33B	71.4	61.0	62.2	75.0	37.5	51.3	50.0	42.1	50.0	27.1	**69.4**	42.9	47.6	87.2	26.2	31.0	80.6	70.0	83.3	65.6
OCTOCODER	16B	35.7	35.4	45.1	61.9	23.2	30.0	30.6	7.9	5.9	0.0	0.0	25.0	37.8	60.6	0.0	0.0	71.4	47.5	6.9	1.1
StarCoder2-instruct-V0.1	15B	7.1	59.8	67.1	78.6	53.6	3.8	58.2	52.6	57.4	39.6	62.2	39.3	56.1	89.4	28.6	0.0	81.6	71.3	9.7	65.6
WizardCoder-V1.0	15B	42.9	28.0	31.7	34.5	3.6	13.8	21.4	0.0	20.6	10.4	11.2	10.7	39.0	61.7	9.5	14.3	24.5	20.0	1.4	28.9
Qwen1.5-Chat	14B	7.1	40.2	41.5	42.9	7.1	26.3	27.6	5.3	14.7	4.2	23.5	12.5	36.6	47.9	11.9	14.3	49.0	42.5	41.7	45.6
CodeLlama-Instruct	13B	50.0	39.0	50.0	63.1	25.0	40.0	31.6	13.2	22.1	18.8	16.3	23.2	35.4	50.0	19.0	7.1	41.8	45.0	54.2	45.6
Yi-1.5-Chat	9B	35.7	47.6	48.8	64.3	14.3	52.5	42.9	18.4	20.6	16.7	51.0	25.0	39.0	73.4	23.8	16.7	61.2	55.0	75.0	60.0
CodeLlama-Instruct	7B	28.6	36.6	45.1	42.9	17.9	46.3	16.3	17.1	22.1	25.0	22.4	28.6	37.8	43.6	23.8	31.0	24.5	12.5	73.6	34.4
CodeQwen1.5-Chat	7B	0.0	52.4	53.7	73.8	30.4	25.0	58.2	34.2	42.6	43.8	51.0	42.9	58.5	67.0	31.0	**35.7**	78.6	71.3	72.2	68.9
Magicoder-S-DS	7B	21.4	64.6	64.6	81.0	51.8	55.0	59.2	52.6	60.3	45.8	**69.4**	**66.1**	62.2	91.5	35.7	16.7	78.6	65.0	69.4	62.2
MCODER	7B	21.4	57.3	53.7	78.6	42.9	71.3	56.1	50.0	57.4	47.9	45.9	51.8	56.1	80.9	23.8	23.8	80.6	**75.0**	62.5	72.2

Method	Kotlin	Lua	MD	Pascal	Perl	PHP	Power	Python	R	Racket	Ruby	Rust	Scala	Scheme	Shell	Swift	Tcl	TS	VB	VimL	**Avg$_{all}$**
GPT-4 Turbo (231106)	**84.5**	**66.3**	**32.1**	**67.1**	**84.3**	**85.1**	**94.4**	83.3	**80.4**	**64.5**	**78.9**	**81.5**	**84.1**	**86.8**	**90.2**	**81.9**	**78.2**	**75.0**	**75.6**	52.6	**76.6**
GPT-3.5 Turbo (240125)	70.2	63.8	17.9	51.2	67.1	11.7	63.3	**88.9**	32.6	30.6	42.1	34.8	37.8	44.1	69.5	72.2	65.4	56.3	55.1	**53.9**	51.6
DeepSeekCoder-Instruct	69.0	58.8	21.4	50.0	60.0	73.4	82.2	72.2	65.2	40.3	64.5	58.7	74.4	47.1	81.7	68.1	66.7	57.5	66.7	34.2	61.8
OCTOCODER	53.6	30.0	3.6	3.7	35.7	0.0	26.7	52.2	4.3	27.4	2.6	0.0	34.1	23.5	32.9	33.3	25.6	45.0	33.3	35.5	27.1
StarCoder2-instruct-V0.1	76.2	48.8	0.0	64.6	64.3	80.9	76.7	75.6	77.2	48.4	51.3	64.1	50.0	61.8	68.3	47.2	50.0	65.0	60.3	47.4	58.3
WizardCoder-V1.0	46.4	15.0	0.0	7.3	30.0	31.9	22.2	38.9	33.7	0.0	23.7	16.3	14.6	0.0	15.9	19.4	23.1	23.8	37.2	14.5	22.8
Qwen1.5-Chat	36.9	30.0	3.6	19.5	24.3	48.9	34.4	42.2	39.1	8.1	31.6	29.3	12.2	10.3	32.9	47.2	21.8	38.8	24.4	19.7	29.9
CodeLlama-Instruct	47.6	37.5	0.0	28.0	31.4	43.6	60.0	46.7	42.4	22.6	39.5	41.3	35.4	19.1	40.2	48.6	41.0	42.5	47.4	34.2	39.0
Yi-1.5-Chat	52.4	50.0	3.6	37.8	52.9	67.0	60.0	63.3	53.3	29.0	42.1	39.1	39.0	17.6	57.3	69.4	38.5	56.3	50.0	26.3	46.6
CodeLlama-Instruct	44.0	20.0	0.0	14.6	30.0	8.5	38.9	45.6	27.2	22.6	31.6	27.2	40.2	14.7	46.3	38.9	41.0	27.5	44.9	28.9	31.4
CodeQwen1.5-Chat	69.0	51.3	3.6	47.6	61.4	70.2	76.7	57.8	62.0	46.8	44.7	67.4	69.5	38.2	76.8	70.8	60.3	56.3	46.2	40.8	56.3
Magicoder-S-DS	77.4	57.5	10.7	64.6	68.6	72.3	84.4	76.7	70.7	51.6	64.5	64.1	82.9	58.8	75.6	73.6	66.7	62.5	64.1	23.7	65.4
MCODER	66.7	56.3	0.0	58.5	57.1	71.3	80.0	66.7	64.1	50.0	57.9	71.7	63.4	54.4	80.5	63.9	57.7	60.0	66.7	32.9	60.7

Span Completion

Method	Size	AWK	C	C++	C#	Clisp	Coffee	Dart	Elisp	Elixir	Erlang	Fortran	F#	Go	Groovy	Haskell	Html	Java	JS	Json	Julia
GPT-4 Turbo (231106)	🔒	**80.0**	**65.0**	**67.0**	**84.0**	**74.0**	**88.0**	**63.7**	**71.0**	**74.0**	68.0	69.0	78.0	**67.0**	**94.0**	**80.0**	**49.0**	**91.5**	**65.0**	**83.0**	**87.0**
GPT-3.5 Turbo (240125)	🔒	39.0	41.0	51.0	70.0	55.0	67.0	58.8	43.0	31.0	9.0	27.0	55.0	57.0	85.0	14.0	30.0	58.5	47.0	30.0	48.0
DeepSeekCoder-Instruct	33B	52.0	55.0	59.0	70.0	58.0	57.0	48.0	45.0	57.0	58.0	65.0	61.0	48.0	86.0	53.0	42.0	70.8	54.0	61.0	68.0
OCTOCODER	16B	29.0	41.0	46.0	51.0	41.0	29.0	31.4	19.0	9.0	0.0	0.0	44.0	40.0	52.0	0.0	4.0	57.5	39.0	12.0	1.0
StarCoder2-instruct-V0.1	15B	34.0	63.0	**67.0**	75.0	62.0	2.0	49.0	48.0	56.0	58.0	62.0	59.0	59.0	80.0	59.0	0.0	82.1	59.0	10.0	76.0
WizardCoder-V1.0	15B	19.0	24.0	40.0	35.0	6.0	11.0	6.9	3.0	6.0	11.0	4.0	7.0	44.0	57.0	26.0	9.0	16.0	13.0	0.0	14.0
Qwen1.5-Chat	14B	27.0	43.0	47.0	43.0	21.0	10.0	26.5	12.0	25.0	31.0	22.0	25.0	37.0	38.0	39.0	17.0	26.4	43.0	23.0	43.0
CodeLlama-Instruct	13B	47.0	36.0	51.0	56.0	40.0	29.0	25.5	22.0	36.0	45.0	35.0	40.0	39.0	46.0	36.0	28.0	39.6	44.0	43.0	44.0
Yi-1.5-Chat	9B	37.0	56.0	60.0	66.0	27.0	47.0	51.0	23.0	33.0	40.0	48.0	30.0	43.0	72.0	51.0	23.0	70.8	49.0	57.0	61.0
CodeLlama-Instruct	7B	25.0	43.0	51.0	53.0	41.0	39.0	27.5	20.0	38.0	41.0	35.0	41.0	43.0	50.0	43.0	25.0	26.4	29.0	58.0	43.0
CodeQwen1.5-Chat	7B	41.0	57.0	59.0	65.0	54.0	22.0	46.1	34.0	54.0	56.0	58.0	62.0	57.0	74.0	52.0	39.0	79.2	55.0	55.0	76.0
Magicoder-S-DS	7B	48.0	59.0	**67.0**	74.0	63.0	63.0	57.8	50.0	64.0	**72.0**	**79.0**	**79.0**	57.0	**94.0**	60.0	40.0	81.1	59.0	55.0	64.0
MCODER	7B	43.0	64.0	66.0	77.0	62.0	76.0	52.9	44.0	61.0	71.0	70.0	69.0	55.0	84.0	65.0	25.0	83.0	59.0	54.0	83.0

Method	Kotlin	Lua	MD	Pascal	Perl	PHP	Power	Python	R	Racket	Ruby	Rust	Scala	Scheme	Shell	Swift	Tcl	TS	VB	VimL	**Avg$_{all}$**
GPT-4 Turbo (231106)	**90.0**	**66.0**	**34.0**	**59.0**	**92.0**	**80.0**	**87.0**	**87.0**	**80.0**	**79.0**	**80.0**	**81.1**	**82.0**	**76.0**	**82.0**	**86.0**	**71.0**	**67.0**	**73.0**	49.0	**75.0**
GPT-3.5 Turbo (240125)	68.0	61.0	25.0	45.0	68.0	8.0	62.0	80.0	13.0	56.0	24.0	26.4	39.0	47.0	72.0	70.0	57.0	60.0	68.0	58.0	48.1
DeepSeekCoder-Instruct	69.0	58.0	16.0	50.0	54.0	65.0	72.0	66.0	61.0	58.0	63.0	56.6	73.0	53.0	64.0	68.0	59.0	60.0	72.0	43.0	59.5
OCTOCODER	47.0	47.0	3.0	10.0	24.0	0.0	31.0	51.0	0.0	37.0	2.0	0.0	37.0	25.0	22.0	38.0	26.0	44.0	42.0	30.0	26.6
StarCoder2-instruct-V0.1	68.0	41.0	0.0	58.0	74.0	69.0	67.0	71.0	67.0	67.0	58.0	68.9	43.0	60.0	60.0	56.0	51.0	63.0	59.0	**51.0**	55.4
WizardCoder-V1.0	25.0	11.0	0.0	10.0	38.0	12.0	19.0	26.0	27.0	1.0	8.0	10.4	12.0	0.0	7.0	6.0	20.0	15.0	47.0	22.0	17.0
Qwen1.5-Chat	33.0	47.0	8.0	30.0	37.0	44.0	38.0	45.0	46.0	25.0	41.0	32.1	15.0	22.0	35.0	48.0	28.0	46.0	38.0	23.0	32.0
CodeLlama-Instruct	45.0	44.0	0.0	27.0	51.0	38.0	49.0	47.0	44.0	38.0	48.0	29.2	47.0	33.0	33.0	55.0	37.0	45.0	49.0	44.0	40.5
Yi-1.5-Chat	56.0	52.0	12.0	49.0	57.0	61.0	63.0	64.0	56.0	33.0	57.0	37.7	28.0	30.0	43.0	66.0	38.0	53.0	53.0	37.0	47.3
CodeLlama-Instruct	39.0	30.0	1.0	24.0	41.0	15.0	41.0	46.0	40.0	38.0	41.0	28.3	48.0	22.0	40.0	53.0	39.0	37.0	53.0	35.0	37.5
CodeQwen1.5-Chat	70.0	52.0	15.0	49.0	76.0	62.0	59.0	66.0	62.0	58.0	64.0	70.8	57.0	48.0	70.0	72.0	59.0	58.0	44.0	45.0	56.4
Magicoder-S-DS	75.0	59.0	16.0	53.0	80.0	67.0	72.0	69.0	69.0	64.0	72.0	58.5	78.0	59.0	77.0	78.0	69.0	61.0	70.0	30.0	64.8
MCODER	67.0	63.0	0.0	58.0	73.0	65.0	69.0	67.0	64.0	63.0	68.0	72.6	56.0	61.0	71.0	79.0	63.0	64.0	70.0	43.0	62.6

Span Completion Light

Method	Size	AWK	C	C++	C#	Clisp	Coffee	Dart	Elisp	Elixir	Erlang	Fortran	F#	Go	Groovy	Haskell	Html	Java	JS	Json	Julia
GPT-4 Turbo (231106)	🔒	**76.0**	**66.0**	**70.0**	**84.0**	**80.0**	**94.0**	**66.7**	**74.0**	**76.0**	60.0	**72.0**	72.0	**66.0**	90.0	**86.0**	**46.0**	**88.7**	62.0	**88.0**	**86.0**
GPT-3.5 Turbo (240125)	🔒	40.0	52.0	46.0	60.0	62.0	68.0	49.0	40.0	34.0	20.0	38.0	62.0	58.0	92.0	28.0	44.0	52.8	60.0	28.0	32.0
DeepSeekCoder-Instruct	33B	60.0	54.0	60.0	76.0	50.0	56.0	35.3	44.0	54.0	60.0	58.0	66.0	60.0	88.0	44.0	38.0	73.6	64.0	66.0	64.0
OCTOCODER	16B	22.0	40.0	40.0	58.0	42.0	22.0	27.5	20.0	8.0	0.0	0.0	40.0	36.0	52.0	0.0	2.0	54.7	40.0	12.0	0.0
StarCoder2-instruct-V0.1	15B	34.0	48.0	60.0	74.0	62.0	4.0	47.1	44.0	64.0	56.0	58.0	68.0	56.0	82.0	60.0	0.0	73.6	66.0	6.0	66.0
WizardCoder-V1.0	15B	24.0	20.0	30.0	36.0	10.0	14.0	9.8	2.0	4.0	10.0	6.0	2.0	44.0	48.0	24.0	8.0	28.3	14.0	0.0	22.0
Qwen1.5-Chat	14B	40.0	38.0	44.0	52.0	16.0	20.0	21.6	14.0	28.0	24.0	18.0	24.0	36.0	38.0	38.0	14.0	37.7	44.0	34.0	50.0
CodeLlama-Instruct	13B	48.0	46.0	42.0	58.0	34.0	20.0	23.5	30.0	36.0	40.0	30.0	38.0	42.0	36.0	36.0	26.0	49.1	42.0	44.0	36.0
Yi-1.5-Chat	9B	36.0	52.0	58.0	68.0	38.0	54.0	39.2	24.0	26.0	34.0	52.0	24.0	50.0	70.0	46.0	34.0	71.7	52.0	58.0	56.0
CodeLlama-Instruct	7B	30.0	38.0	46.0	44.0	40.0	32.0	19.6	28.0	34.0	38.0	32.0	42.0	50.0	34.0	36.0	20.0	32.1	38.0	50.0	38.0
CodeQwen1.5-Chat	7B	48.0	52.0	60.0	78.0	60.0	22.0	47.1	32.0	54.0	52.0	48.0	30.0	48.0	76.0	52.0	44.0	**88.7**	68.0	48.0	68.0
Magicoder-S-DS	7B	54.0	54.0	66.0	80.0	60.0	60.0	56.9	52.0	66.0	70.0	**72.0**	**78.0**	**66.0**	**94.0**	60.0	30.0	83.0	58.0	56.0	62.0
MCODER	7B	58.0	56.0	68.0	82.0	64.0	76.0	58.8	40.0	62.0	**76.0**	62.0	74.0	56.0	88.0	64.0	18.0	**88.7**	**70.0**	56.0	72.0

Method	Kotlin	Lua	MD	Pascal	Perl	PHP	Power	Python	R	Racket	Ruby	Rust	Scala	Scheme	Shell	Swift	Tcl	TS	VB	VimL	**Avg$_{all}$**
GPT-4 Turbo (231106)	**84.0**	**74.0**	**44.0**	**70.0**	**90.0**	74.0	**88.0**	**90.0**	**86.0**	**82.0**	**88.0**	**81.1**	**80.0**	**76.0**	**80.0**	**86.0**	**82.0**	**64.0**	**80.0**	**58.0**	**76.5**
GPT-3.5 Turbo (240125)	60.0	56.0	24.0	52.0	70.0	24.0	56.0	82.0	36.0	60.0	36.0	43.4	48.0	46.0	70.0	62.0	58.0	50.0	64.0	52.0	50.4
DeepSeekCoder-Instruct	58.0	60.0	32.0	52.0	68.0	60.0	80.0	66.0	72.0	56.0	66.0	54.7	76.0	54.0	66.0	70.0	68.0	56.0	68.0	46.0	60.9
OCTOCODER	42.0	46.0	2.0	8.0	40.0	0.0	32.0	52.0	2.0	32.0	4.0	0.0	34.0	34.0	28.0	38.0	28.0	50.0	54.0	36.0	27.0
StarCoder2-instruct-V0.1	70.0	54.0	0.0	60.0	76.0	**78.0**	78.0	80.0	70.0	58.0	50.0	71.7	36.0	54.0	52.0	60.0	54.0	66.0	62.0	**58.0**	55.5
WizardCoder-V1.0	38.0	8.0	0.0	8.0	42.0	14.0	20.0	26.0	28.0	2.0	6.0	3.8	18.0	0.0	6.0	12.0	10.0	24.0	46.0	24.0	17.6
Qwen1.5-Chat	26.0	46.0	6.0	26.0	32.0	46.0	40.0	44.0	44.0	32.0	46.0	32.1	16.0	16.0	34.0	50.0	20.0	40.0	44.0	24.0	32.4
CodeLlama-Instruct	44.0	52.0	0.0	26.0	44.0	38.0	58.0	48.0	34.0	38.0	46.0	37.7	40.0	38.0	36.0	58.0	40.0	38.0	58.0	42.0	39.9
Yi-1.5-Chat	52.0	56.0	8.0	50.0	56.0	70.0	62.0	62.0	62.0	40.0	58.0	50.9	32.0	26.0	56.0	60.0	38.0	56.0	68.0	36.0	48.6
CodeLlama-Instruct	34.0	36.0	2.0	22.0	44.0	12.0	42.0	48.0	28.0	38.0	40.0	34.0	44.0	32.0	42.0	44.0	36.0	40.0	58.0	36.0	36.3
CodeQwen1.5-Chat	70.0	60.0	22.0	54.0	76.0	68.0	72.0	66.0	64.0	64.0	60.0	66.0	62.0	46.0	76.0	72.0	56.0	22.0	40.0	34.0	55.7
Magicoder-S-DS	74.0	66.0	18.0	66.0	84.0	72.0	78.0	76.0	72.0	58.0	64.0	58.5	78.0	66.0	74.0	78.0	72.0	56.0	68.0	34.0	65.4
MCODER	62.0	68.0	4.0	62.0	72.0	74.0	70.0	62.0	66.0	66.0	70.0	66.0	68.0	48.0	74.0	74.0	56.0	62.0	70.0	40.0	63.1

state-of-the-art models and open-source models across nearly all programming languages. Notably, GPT-4o and GPT-4 Turbo lead the benchmark with substantial performance margins over other models. The MCEVAL apart from previous benchmarks (such as HumanEval), where various open models have achieved comparable or superior performance. The results indicate that MCODER

Table 5: Pass@1 (%) scores of different models for multilingual code explanation tasks on MCEVAL. "Avg$_{all}$" represents the average scores of all code languages.

Method	Size	AWK	C	C++	C#	Clisp	Coffee	Dart	Elisp	Elixir	Erlang	Fortran	F#	Go	Groovy	Haskell	Html	Java	JS	Json	Julia
GPT-4o (240513)	🔒	74.0	68.0	**72.0**	72.0	**78.0**	**76.0**	**54.9**	**60.0**	**66.0**	38.0	**62.0**	**78.0**	**74.0**	**88.0**	**86.0**	**16.0**	79.2	68.0	24.0	**76.0**
GPT-4 Turbo (231106)	🔒	**84.0**	**70.0**	**72.0**	52.0	60.0	**76.0**	**54.9**	50.0	64.0	42.0	50.0	**78.0**	68.0	**88.0**	76.0	10.0	81.1	**74.0**	18.0	70.0
GPT-3.5 Turbo (240125)	🔒	8.0	68.0	64.0	62.0	56.0	66.0	29.4	26.0	42.0	34.0	28.0	56.0	54.0	84.0	54.0	6.0	73.6	58.0	6.0	62.0
Yi-Large-Turbo	🔒	76.0	52.0	48.0	50.0	60.0	60.0	25.5	44.0	42.0	44.0	42.0	60.0	54.0	74.0	68.0	14.0	47.2	48.0	26.0	60.0
DeepSeekCoder-Instruct	33B	70.0	62.0	66.0	**78.0**	56.0	68.0	45.1	44.0	58.0	40.0	44.0	64.0	56.0	**88.0**	52.0	8.0	67.9	52.0	**32.0**	70.0
OCTOCODER	16B	32.0	32.0	32.0	26.0	48.0	4.0	5.9	22.0	32.0	34.0	22.0	16.0	52.0	42.0	34.0	2.0	37.7	36.0	8.0	28.0
Qwen1.5-Chat	14B	50.0	52.0	30.0	42.0	36.0	26.0	23.5	28.0	24.0	12.0	14.0	34.0	44.0	28.0	46.0	8.0	35.8	44.0	14.0	42.0
CodeLlama-Instruct	13B	32.0	42.0	34.0	44.0	44.0	0.0	7.8	16.0	30.0	38.0	16.0	30.0	32.0	32.0	40.0	10.0	28.3	36.0	10.0	24.0
Yi-1.5-Chat	9B	38.0	62.0	60.0	58.0	38.0	38.0	29.4	14.0	50.0	26.0	36.0	20.0	52.0	68.0	44.0	10.0	67.9	46.0	22.0	66.0
CodeLlama-Instruct	7B	34.0	34.0	32.0	42.0	34.0	8.0	11.8	22.0	28.0	24.0	14.0	26.0	40.0	22.0	36.0	0.0	34.0	22.0	8.0	14.0
CodeQwen1.5-Chat	7B	58.0	62.0	58.0	50.0	54.0	56.0	17.6	26.0	50.0	52.0	34.0	50.0	48.0	76.0	46.0	2.0	67.9	58.0	18.0	56.0
Magicoder-S-DS	7B	58.0	62.0	56.0	70.0	58.0	4.0	37.3	28.0	50.0	**58.0**	54.0	66.0	58.0	86.0	60.0	4.0	**84.9**	60.0	2.0	54.0
MCODER (Our Method)	7B	52.0	62.0	56.0	68.0	70.0	48.0	33.3	44.0	64.0	40.0	40.0	56.0	70.0	66.0	58.0	6.0	71.7	60.0	28.0	60.0

Method	Kotlin	Lua	MD	Pascal	Perl	PHP	Power	Python	R	Racket	Ruby	Rust	Scala	Scheme	Shell	Swift	Tcl	TS	VB	VimL	**Avg$_{all}$**
GPT-4o (240513)	**70.0**	**74.0**	**12.0**	**56.0**	**78.0**	64.0	84.0	62.0	**60.0**	**70.0**	**78.0**	**84.9**	70.0	**72.0**	52.0	**84.0**	**62.0**	70.0	**76.0**	42.0	**65.8**
GPT-4 Turbo (231106)	68.0	64.0	8.0	**56.0**	68.0	**68.0**	82.0	66.0	**60.0**	62.0	70.0	66.0	70.0	58.0	**68.0**	**90.0**	50.0	**72.0**	68.0	**50.0**	62.6
GPT-3.5 Turbo (240125)	62.0	54.0	4.0	46.0	40.0	40.0	**56.0**	54.0	44.0	50.0	62.0	47.2	**72.0**	48.0	38.0	62.0	40.0	62.0	62.0	36.0	47.9
Yi-Large-Turbo	48.0	56.0	6.0	48.0	58.0	48.0	66.0	50.0	42.0	54.0	72.0	52.8	54.0	56.0	42.0	66.0	50.0	60.0	56.0	44.0	50.6
DeepSeekCoder-Instruct	56.0	64.0	6.0	42.0	52.0	52.0	68.0	58.0	52.0	50.0	70.0	49.1	64.0	54.0	34.0	68.0	56.0	62.0	66.0	40.0	55.8
OCTOCODER	24.0	36.0	0.0	24.0	14.0	32.0	44.0	62.0	26.0	34.0	10.0	26.4	30.0	34.0	40.0	30.0	24.0	34.0	38.0	8.0	29.4
Qwen1.5-Chat	30.0	36.0	6.0	22.0	38.0	34.0	34.0	32.0	24.0	48.0	66.0	22.6	18.0	24.0	16.0	60.0	20.0	58.0	44.0	30.0	32.4
CodeLlama-Instruct	26.0	36.0	0.0	4.0	28.0	30.0	36.0	26.0	20.0	32.0	28.0	20.8	32.0	26.0	26.0	38.0	32.0	42.0	50.0	24.0	29.3
Yi-1.5-Chat	50.0	56.0	4.0	30.0	42.0	52.0	62.0	**70.0**	52.0	34.0	74.0	30.2	50.0	42.0	24.0	52.0	30.0	68.0	36.0	28.0	43.3
CodeLlama-Instruct	24.0	30.0	0.0	4.0	32.0	2.0	30.0	22.0	14.0	28.0	28.0	17.0	32.0	24.0	20.0	42.0	28.0	30.0	40.0	12.0	23.8
CodeQwen1.5-Chat	48.0	46.0	4.0	50.0	44.0	40.0	44.0	50.0	38.0	40.0	58.0	47.2	52.0	44.0	40.0	70.0	46.0	62.0	64.0	28.0	46.4
Magicoder-S-DS	64.0	50.0	2.0	52.0	50.0	46.0	58.0	54.0	48.0	46.0	62.0	47.2	64.0	62.0	48.0	60.0	42.0	56.0	62.0	24.0	51.4
MCODER (Our Method)	62.0	52.0	0.0	48.0	46.0	44.0	62.0	58.0	38.0	50.0	74.0	67.9	32.0	46.0	44.0	60.0	50.0	58.0	58.0	**50.0**	51.4

exhibits clear improvement over the base model in nearly all the studied programming languages. It is noteworthy that MCODER, despite being trained with very limited multilingual data, still outperforms other large language models (LLMs) of similar or even larger sizes.

Multilingual Code Explanation. Table 5 displays the Pass@1 results for multilingual code explanation tasks. The results show that GPT models still significantly outperform open-source models in the code explanation task. For markup languages (Json and Markdown), the complexity of the code structure makes it difficult to describe accurately in natural language, resulting in generally poorer performance. Code LLMs need instruction-following capabilities for such complex structures.

Multilingual Code Completion. The completion tasks consist of *single-line completion*, *multi-line completion*, *span completion*, and *span completion (light)*. As shown in Table 4, the Pass@1 results for multilingual code completion tasks indicate that GPT-4 Turbo still achieves the best performance. Additionally, since this task is relatively easier compared to code generation, some open-source models perform comparably to GPT-4 Turbo in certain programming languages.

5 FURTHER ANALYSIS

Programming Classification. In Figure 5, we categorize the programming languages of MCEVAL into 5 programming paradigms and 11 application scenarios and summarize the performance of code LLMs on the code generation task in Figure 6. It can be observed that code LLMs generally perform better in object-oriented and multi-paradigm programming languages (high-resource languages), while perform worse in functional and procedural programming languages (low-resource Languages). In areas like web development and scientific computing, the gap between open-source and closed-source models is narrowing. However, for application scenarios, there is still a substantial gap between open-source models and the closed-source GPT-4 series in low-resource languages related to scripting, mobile development, and educational research. MCODER performs superior over multiple same-size models and even some larger open-source models.

Unbalance on Different Languages. We compare the results of several open-source models on the MultiPL-E multilingual benchmark with corresponding languages on MCEVAL. We obtained scores for 11 programming languages (including Python, Java, JavaScript, C++, PHP, Rust, Swift, R, Lua, Racket, Julia) from the BigCode leaderboard.[1] As shown in Figure 7(1), due to the simplicity of Python language tasks in this dataset, many models exhibit significant score discrepancies between the two benchmarks. Figure 7(2) highlights a majority of models within the blue circle, indicating that the current state-of-the-art performance of most models primarily lies in high-resource languages like Python, while their proficiency in low-resource languages awaits further exploration and enhancement. By examining Figure 7(2) and (3), it becomes evident that all LLMs demonstrate consistent multilingual capabilities between MultiPL-E and MCEVAL.

[1] `https://huggingface.co/spaces/bigcode/bigcode-models-leaderboard`

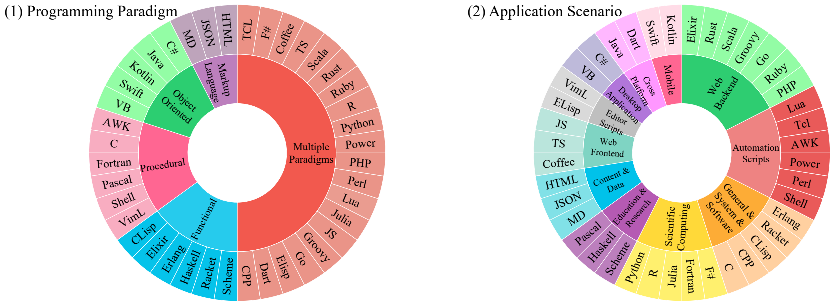
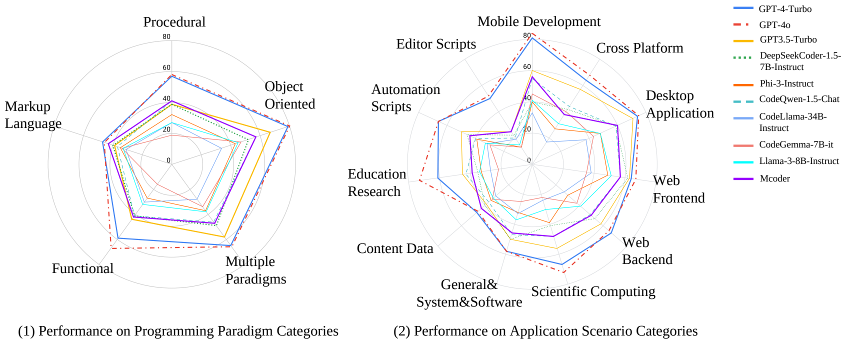


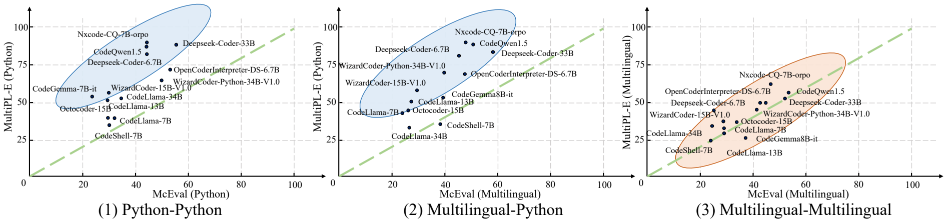
Figure 5: Classification of McEval. The programming languages in McEval can be categorized into 5 programming paradigms and 11 application scenarios.



(1) Performance on Programming Paradigm Categories

(2) Performance on Application Scenario Categories

Figure 6: The performance of models in code completion tasks under different categories.



(1) Python-Python

(2) Multilingual-Python

(3) Multilingual-Multilingual

Figure 7: Unbalanced performance on different languages across MultiPL-E and our McEval.

Cross-lingual Transfer. We fine-tune the CodeQwen-1.5 model using Python-only data in McEval-Instruct and compare it with mCoder. In Figure 8, CodeQwen-1.5 performs well in most high-resource languages, but CodeQwen without alignment exhibits unsatisfactory results in some low-resource languages due to the inability to follow instructions. As such, with fine-tuning using only Python data, CodeQwen-1.5-Python improves significantly across most languages. It shows that the CodeQwen foundation model already possesses strong coding capabilities but lacks adequate instruction-following skills. Therefore, fine-tuning with Python-only data can still effectively transfer instruction-following abilities to other languages, resulting in superior multilingual performance.

Difficulty of McEval. Based on algorithmic complexity, we classify McEval into three levels (Easy/Medium/Hard). In Figure 9, we conduct a statistical analysis of CodeQwen-1.5-Chat's performance on code generation tasks across various languages. For most languages, the code LLM can answer the majority of easy questions but struggles with medium and hard ones.

6 Related Work

For the field of soft engineering, code LLMs (Feng et al., 2020; Chen et al., 2021; Scao et al., 2022; Li et al., 2022; Allal et al., 2023; Fried et al., 2022; Wang et al., 2021; Zheng et al., 2024; Guo et al., 2024) pre-trained on billions of code snippets, such as StarCoder (Li et al., 2023; Lozhkov et al.,

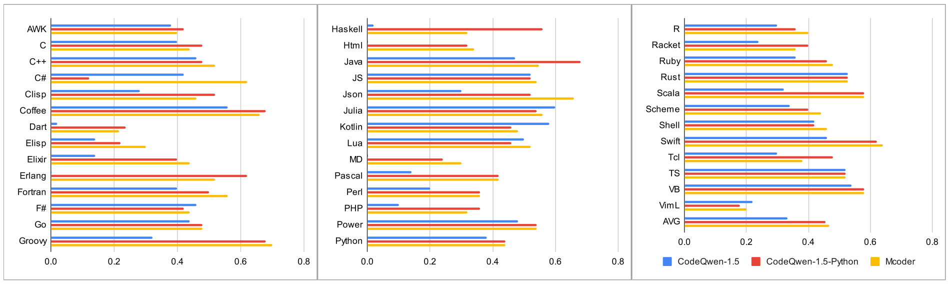


Figure 8: Cross-lingual transferability of LLMs among different languages. We fine-tune CodeQwen-1.5 using Python data in MCEVAL-INSTRUCT and OSS-Instruct to create CodeQwen-1.5-Python.

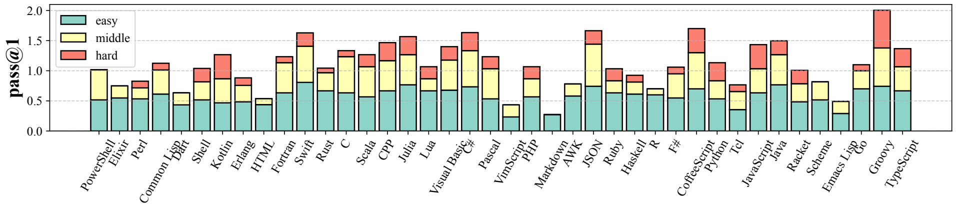


Figure 9: CodeQwen-1.5-Chat performance on MCEVAL for problems of different difficulty levels.

2024), CodeLlama (Rozière et al., 2023), DeepSeekCoder (Guo et al., 2024), and Code-Qwen (Hui et al., 2024). The development and refinement of code LLMs have been pivotal in automating software development tasks, and supporting code generation/translation/summarization.

Many benchmarks (Yu et al., 2024; Yin et al., 2023; Khan et al., 2023; Orlanski et al., 2023; Jain et al., 2024) have been woven to accurately assess code quality, functionality, and efficiency, such as HumanEval (Chen et al., 2021), MBPP (Austin et al., 2021), their upgraded version EvalPlus (Liu et al., 2023b). Studies have explored a variety of approaches, ranging from static evaluation using text matching to dynamic methods that involve code execution under a controlled environment. The current benchmarks support code LLMs to evaluate a series of different types of tasks, such as code understanding, function calling Zhuo et al. (2024), code repair (Lin et al., 2017; Tian et al., 2024; Jimenez et al., 2023; Zhang et al., 2023; Prenner & Robbes, 2023; He et al., 2022), code translation (Yan et al., 2023). Some works focus on the multilingual scenarios (Wang et al., 2023; Athiwaratkun et al., 2023; Peng et al., 2024; Zheng et al., 2023b) by extending the Python-only HumanEval/MBPP benchmark (e.g. MultiPL-E (Cassano et al., 2023)), which is challenged by the number of the languages.

7 CONCLUSION

In this work, we push a significant advancement in the assessment of code LLMs by proposing the first massively multilingual code evaluation benchmark (MCEVAL) by involving an annotation and verification process conducted by professional developers, which spans 40 programming languages and helps comprehensively tackle various tasks, including code generation, explanation, and completion. The multilingual SFT on created instruction corpora MCEVAL-INSTRUCT further emphasizes the proficiency of LLMs in multiple coding languages. Systematic evaluations of existing code LLMs on MCEVAL illuminate the performance disparities among open-source and closed-source models. Extensive multilingual multitask assessment on MCEVAL provides a realistic and comprehensive measurement of code LLMs, marking a leap forward for developers utilizing AI techniques to understand and generate code effectively across a wide spectrum of programming languages.

ACKNOWLEDGMENTS

This work was supported in part by the National Natural Science Foundation of China (Grant Nos. 62276017, 62406033, U1636211, 61672081), and the State Key Laboratory of Complex & Critical Software Environment (Grant No. SKLCCSE-2024ZX-18).

References

Marah Abdin, Sam Ade Jacobs, Ammar Ahmad Awan, Jyoti Aneja, Ahmed Awadallah, Hany Awadalla, Nguyen Bach, Amit Bahree, Arash Bakhtiari, Harkirat Behl, et al. Phi-3 technical report: A highly capable language model locally on your phone. *arXiv preprint arXiv:2404.14219*, 2024. URL https://arxiv.org/abs/2404.14219.

Meta AI. Introducing meta llama 3: The most capable openly available llm to date. https://ai.meta.com/blog/meta-llama-3/, apr 2024.

Loubna Ben Allal, Raymond Li, Denis Kocetkov, Chenghao Mou, Christopher Akiki, Carlos Munoz Ferrandis, Niklas Muennighoff, Mayank Mishra, Alex Gu, Manan Dey, et al. SantaCoder: Don't reach for the stars! *arXiv preprint arXiv:2301.03988*, 2023. URL https://arxiv.org/abs/2301.03988.

Ben Athiwaratkun, Sanjay Krishna Gouda, Zijian Wang, Xiaopeng Li, Yuchen Tian, Ming Tan, Wasi Uddin Ahmad, Shiqi Wang, Qing Sun, Mingyue Shang, Sujan Kumar Gonugondla, Hantian Ding, Varun Kumar, Nathan Fulton, Arash Farahani, Siddhartha Jain, Robert Giaquinto, Haifeng Qian, Murali Krishna Ramanathan, and Ramesh Nallapati. Multi-lingual evaluation of code generation models. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/forum?id=Bo7eeXm6An8.

Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*, 2021. URL https://arxiv.org/abs/2108.07732.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, Binyuan Hui, Luo Ji, Mei Li, Junyang Lin, Runji Lin, Dayiheng Liu, Gao Liu, Chengqiang Lu, Keming Lu, Jianxin Ma, Rui Men, Xingzhang Ren, Xuancheng Ren, Chuanqi Tan, Sinan Tan, Jianhong Tu, Peng Wang, Shijie Wang, Wei Wang, Shengguang Wu, Benfeng Xu, Jin Xu, An Yang, Hao Yang, Jian Yang, Shusheng Yang, Yang Yao, Bowen Yu, Hongyi Yuan, Zheng Yuan, Jianwei Zhang, Xingxuan Zhang, Yichang Zhang, Zhenru Zhang, Chang Zhou, Jingren Zhou, Xiaohuan Zhou, and Tianhang Zhu. Qwen technical report. *arXiv preprint arXiv:2309.16609*, abs/2309.16609, 2023. URL https://arxiv.org/abs/2309.16609.

Mohammad Bavarian, Heewoo Jun, Nikolas Tezak, John Schulman, Christine McLeavey, Jerry Tworek, and Mark Chen. Efficient training of language models to fill in the middle. *arXiv preprint arXiv:2207.14255*, 2022. URL https://arxiv.org/abs/2207.14255.

Luca Beurer-Kellner, Marc Fischer, and Martin T. Vechev. Prompting is programming: A query language for large language models. *Proc. ACM Program. Lang.*, 7(PLDI):1946–1969, 2023. doi: 10.1145/3591300. URL https://doi.org/10.1145/3591300.

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33: 1877–1901, 2020. URL https://proceedings.neurips.cc/paper/2020/hash/1457c0d6bfcb4967418bfb8ac142f64a-Abstract.html.

Federico Cassano, John Gouwar, Daniel Nguyen, Sydney Nguyen, Luna Phipps-Costin, Donald Pinckney, Ming-Ho Yee, Yangtian Zi, Carolyn Jane Anderson, Molly Q Feldman, et al. Multipl-e: A scalable and polyglot approach to benchmarking neural code generation. *IEEE Transactions on Software Engineering*, 2023. URL https://ieeexplore.ieee.org/abstract/document/10103177.

Bei Chen, Fengji Zhang, Anh Nguyen, Daoguang Zan, Zeqi Lin, Jian-Guang Lou, and Weizhu Chen. Codet: Code generation with generated tests. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/pdf?id=ktrw68Cmu9c.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Pondé de Oliveira Pinto, Jared Kaplan, Harrison Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Joshua Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, abs/2107.03374, 2021. URL https://arxiv.org/abs/2107.03374.

Wenhu Chen, Xueguang Ma, Xinyi Wang, and William W. Cohen. Program of thoughts prompting: Disentangling computation from reasoning for numerical reasoning tasks. *arXiv preprint arXiv:2211.12588*, abs/2211.12588, 2022. doi: 10.48550/ARXIV.2211.12588. URL https://doi.org/10.48550/arXiv.2211.12588.

Chris Cummins, Volker Seeker, Dejan Grubisic, Mostafa Elhoushi, Youwei Liang, Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Kim M. Hazelwood, Gabriel Synnaeve, and Hugh Leather. Large language models for compiler optimization. *arXiv preprint arXiv:2309.07062*, abs/2309.07062, 2023. doi: 10.48550/ARXIV.2309.07062. URL https://doi.org/10.48550/arXiv.2309.07062.

Gautier Dagan, Frank Keller, and Alex Lascarides. Dynamic planning with a LLM. *arXiv preprint arXiv:2308.06391*, abs/2308.06391, 2023. doi: 10.48550/ARXIV.2308.06391. URL https://doi.org/10.48550/arXiv.2308.06391.

Peng Di, Jianguo Li, Hang Yu, Wei Jiang, Wenting Cai, Yang Cao, Chaoyu Chen, Dajun Chen, Hongwei Chen, Liang Chen, Gang Fan, Jie Gong, Zi Gong, Wen Hu, Tingting Guo, Zhichao Lei, Ting Li, Zheng Li, Ming Liang, Cong Liao, Bingchang Liu, Jiachen Liu, Zhiwei Liu, Shaojun Lu, Min Shen, Guangpei Wang, Huan Wang, Zhi Wang, Zhaogui Xu, Jiawei Yang, Qing Ye, Gehao Zhang, Yu Zhang, Zelin Zhao, Xunjin Zheng, Hailian Zhou, Lifu Zhu, and Xianying Zhu. Codefuse-13b: A pretrained multi-lingual code large language model. *arXiv preprint arXiv:2310.06266*, abs/2310.06266, 2023. doi: 10.48550/ARXIV.2310.06266. URL https://doi.org/10.48550/arXiv.2310.06266.

Yihong Dong, Xue Jiang, Zhi Jin, and Ge Li. Self-collaboration code generation via chatgpt. *arXiv preprint arXiv:2304.07590*, abs/2304.07590, 2023.

Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, and Ming Zhou. Codebert: A pre-trained model for programming and natural languages. In Trevor Cohn, Yulan He, and Yang Liu (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2020*, pp. 1536–1547, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.findings-emnlp.139. URL https://aclanthology.org/2020.findings-emnlp.139.

Daniel Fried, Armen Aghajanyan, Jessy Lin, Sida I. Wang, Eric Wallace, Freda Shi, Ruiqi Zhong, Wen tau Yih, Luke Zettlemoyer, and Mike Lewis. Incoder: A generative model for code infilling and synthesis. *arXiv preprint arXiv:2204.05999*, abs/2204.05999, 2022. URL https://arxiv.org/abs/2204.05999.

Google Gemma Team. Gemma: Open models based on gemini research and technology. *arXiv preprint arXiv:2403.08295*, 2024. URL https://arxiv.org/abs/2403.08295.

Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Y Wu, YK Li, et al. Deepseek-coder: When the large language model meets programming – the rise of code intelligence. *arXiv preprint arXiv:2401.14196*, 2024. URL https://arxiv.org/abs/2401.14196.

Jingxuan He, Luca Beurer-Kellner, and Martin Vechev. On distribution shift in learning-based bug detectors. In Kamalika Chaudhuri, Stefanie Jegelka, Le Song, Csaba Szepesvari, Gang Niu, and

Sivan Sabato (eds.), *Proceedings of the 39th International Conference on Machine Learning*, volume 162 of *Proceedings of Machine Learning Research*, pp. 8559–8580. PMLR, 17–23 Jul 2022. URL `https://proceedings.mlr.press/v162/he22a.html`.

Binyuan Hui, Jian Yang, Zeyu Cui, Jiaxi Yang, Dayiheng Liu, Lei Zhang, Tianyu Liu, Jiajun Zhang, Bowen Yu, Kai Dang, et al. Qwen2. 5-coder technical report. *arXiv preprint arXiv:2409.12186*, 2024.

Naman Jain, King Han, Alex Gu, Wen-Ding Li, Fanjia Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica. Livecodebench: Holistic and contamination free evaluation of large language models for code. *arXiv preprint arXiv:2403.07974*, 2024. URL `https://arxiv.org/abs/2403.07974`.

Carlos E Jimenez, John Yang, Alexander Wettig, Shunyu Yao, Kexin Pei, Ofir Press, and Karthik Narasimhan. Swe-bench: Can language models resolve real-world github issues? *arXiv preprint arXiv:2310.06770*, 2023. URL `https://arxiv.org/abs/2310.06770`.

Mohammad Abdullah Matin Khan, M Saiful Bari, Xuan Long Do, Weishi Wang, Md Rizwan Parvez, and Shafiq Joty. xcodeeval: A large scale multilingual multitask benchmark for code understanding, generation, translation and retrieval. *arXiv preprint arXiv:2303.03004*, 2023. URL `https://arxiv.org/abs/2303.03004`.

Sumith Kulal, Panupong Pasupat, Kartik Chandra, Mina Lee, Oded Padon, Alex Aiken, and Percy S Liang. Spoc: Search-based pseudocode to code. *Advances in Neural Information Processing Systems*, 32, 2019. URL `https://proceedings.neurips.cc/paper/2019/hash/7298332f04ac004a0ca44cc69ecf6f6b-Abstract.html`.

Woosuk Kwon, Zhuohan Li, Siyuan Zhuang, Ying Sheng, Lianmin Zheng, Cody Hao Yu, Joseph E. Gonzalez, Hao Zhang, and Ion Stoica. Efficient memory management for large language model serving with pagedattention. In *Proceedings of the ACM SIGOPS 29th Symposium on Operating Systems Principles*, 2023. URL `https://dl.acm.org/doi/abs/10.1145/3600006.3613165`.

Raymond Li, Loubna Ben Allal, Yangtian Zi, Niklas Muennighoff, Denis Kocetkov, Chenghao Mou, Marc Marone, Christopher Akiki, Jia Li, Jenny Chim, Qian Liu, Evgenii Zheltonozhskii, Terry Yue Zhuo, Thomas Wang, Olivier Dehaene, Mishig Davaadorj, Joel Lamy-Poirier, João Monteiro, Oleh Shliazhko, Nicolas Gontier, Nicholas Meade, Armel Zebaze, Ming-Ho Yee, Logesh Kumar Umapathi, Jian Zhu, Benjamin Lipkin, Muhtasham Oblokulov, Zhiruo Wang, Rudra Murthy V, Jason Stillerman, Siva Sankalp Patel, Dmitry Abulkhanov, Marco Zocca, Manan Dey, Zhihan Zhang, Nour Moustafa-Fahmy, Urvashi Bhattacharyya, Wenhao Yu, Swayam Singh, Sasha Luccioni, Paulo Villegas, Maxim Kunakov, Fedor Zhdanov, Manuel Romero, Tony Lee, Nadav Timor, Jennifer Ding, Claire Schlesinger, Hailey Schoelkopf, Jan Ebert, Tri Dao, Mayank Mishra, Alex Gu, Jennifer Robinson, Carolyn Jane Anderson, Brendan Dolan-Gavitt, Danish Contractor, Siva Reddy, Daniel Fried, Dzmitry Bahdanau, Yacine Jernite, Carlos Muñoz Ferrandis, Sean Hughes, Thomas Wolf, Arjun Guha, Leandro von Werra, and Harm de Vries. Starcoder: may the source be with you! *arXiv preprint arXiv:2305.06161*, abs/2305.06161, 2023. doi: 10.48550/arXiv.2305.06161. URL `https://arxiv.org/abs/2305.06161`.

Yujia Li, David H. Choi, Junyoung Chung, Nate Kushman, Julian Schrittwieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, Thomas Hubert, Peter Choy, Cyprien de Masson d'Autume, Igor Babuschkin, Xinyun Chen, Po-Sen Huang, Johannes Welbl, Sven Gowal, Alexey Cherepanov, James Molloy, Daniel J. Mankowitz, Esme Sutherland Robson, Pushmeet Kohli, Nando de Freitas, Koray Kavukcuoglu, and Oriol Vinyals. Competition-level code generation with alphacode. *arXiv preprint arXiv:2203.07814*, abs/2203.07814, 2022. URL `https://arxiv.org/abs/2203.07814`.

Derrick Lin, James Koppel, Angela Chen, and Armando Solar-Lezama. Quixbugs: a multi-lingual program repair benchmark set based on the quixey challenge. In *Proceedings Companion of the 2017 ACM SIGPLAN international conference on systems, programming, languages, and applications: software for humanity*, pp. 55–56, 2017. URL `https://dl.acm.org/doi/abs/10.1145/3135932.3135941`.

Chao Liu, Xuanlin Bao, Hongyu Zhang, Neng Zhang, Haibo Hu, Xiaohong Zhang, and Meng Yan. Improving chatgpt prompt for code generation. *arXiv preprint arXiv:2305.08360*, abs/2305.08360, 2023a. URL https://arxiv.org/abs/2305.08360.

Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and Lingming Zhang. Is your code generated by chatgpt really correct? rigorous evaluation of large language models for code generation. *arXiv preprint arXiv:2305.01210*, abs/2305.01210, 2023b. URL https://arxiv.org/abs/2305.01210.

Ilya Loshchilov and Frank Hutter. Decoupled weight decay regularization. *arXiv preprint arXiv:1711.05101*, 2017. URL https://arxiv.org/abs/1711.05101.

Anton Lozhkov, Raymond Li, Loubna Ben Allal, Federico Cassano, Joel Lamy-Poirier, Nouamane Tazi, Ao Tang, Dmytro Pykhtar, Jiawei Liu, Yuxiang Wei, et al. Starcoder 2 and the stack v2: The next generation. *arXiv preprint arXiv:2402.19173*, 2024. URL https://arxiv.org/abs/2402.19173.

Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. WizardCoder: Empowering code large language models with evol-instruct. *arXiv preprint arXiv:2306.08568*, 2023. URL https://arxiv.org/abs/2306.08568.

Mayank Mishra, Matt Stallone, Gaoyuan Zhang, Yikang Shen, Aditya Prasad, Adriana Meza Soria, Michele Merler, Parameswaran Selvam, Saptha Surendran, Shivdeep Singh, et al. Granite code models: A family of open foundation models for code intelligence. *arXiv preprint arXiv:2405.04324*, 2024.

Niklas Muennighoff, Qian Liu, Armel Zebaze, Qinkai Zheng, Binyuan Hui, Terry Yue Zhuo, Swayam Singh, Xiangru Tang, Leandro von Werra, and Shayne Longpre. OctoPack: Instruction tuning code large language models. *arXiv preprint arXiv:2308.07124*, abs/2308.07124, 2023. URL https://arxiv.org/abs/2308.07124.

Fionn Murtagh and Pedro Contreras. Algorithms for hierarchical clustering: an overview. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 2(1):86–97, 2012. doi: 10.1002/WIDM.53. URL https://doi.org/10.1002/widm.53.

Erik Nijkamp, Bo Pang, Hiroaki Hayashi, Lifu Tu, Huan Wang, Yingbo Zhou, Silvio Savarese, and Caiming Xiong. CodeGen: An open large language model for code with multi-turn program synthesis. In *The Eleventh International Conference on Learning Representations, ICLR 2023, Kigali, Rwanda, May 1-5, 2023*. OpenReview.net, 2023. URL https://openreview.net/forum?id=iaYcJKpY2B_.

OpenAI. Gpt-4 technical report. *arXiv preprint arXiv:2303.08774*, 2023. URL https://arxiv.org/abs/2303.08774.

Gabriel Orlanski, Kefan Xiao, Xavier Garcia, Jeffrey Hui, Joshua Howland, Jonathan Malmaud, Jacob Austin, Rishabh Singh, and Michele Catasta. Measuring the impact of programming language distribution. In Andreas Krause, Emma Brunskill, Kyunghyun Cho, Barbara Engelhardt, Sivan Sabato, and Jonathan Scarlett (eds.), *Proceedings of the 40th International Conference on Machine Learning*, volume 202 of *Proceedings of Machine Learning Research*, pp. 26619–26645. PMLR, 23–29 Jul 2023. URL https://proceedings.mlr.press/v202/orlanski23a.html.

Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul F Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback. In S. Koyejo, S. Mohamed, A. Agarwal, D. Belgrave, K. Cho, and A. Oh (eds.), *Advances in Neural Information Processing Systems*, volume 35, pp. 27730–27744. Curran Associates, Inc., 2022. URL https://proceedings.neurips.cc/paper_files/paper/2022/hash/b1efde53be364a73914f58805a001731-Abstract-Conference.html.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, July 6-12, 2002, Philadelphia, PA, USA*, pp. 311–318. ACL, 2002. doi: 10.3115/1073083.1073135. URL https://aclanthology.org/P02-1040/.

Qiwei Peng, Yekun Chai, and Xuhong Li. Humaneval-xl: A multilingual code generation benchmark for cross-lingual natural language generalization. *arXiv preprint arXiv:2402.16694*, 2024. URL https://arxiv.org/abs/2402.16694.

Julian Aron Prenner and Romain Robbes. Runbugrun – an executable dataset for automated program repair. *arXiv preprint arXiv:2304.01102*, 2023. URL https://arxiv.org/abs/2304.01102.

Laria Reynolds and Kyle McDonell. Prompt programming for large language models: Beyond the few-shot paradigm. In *CHI '21: CHI Conference on Human Factors in Computing Systems, Virtual Event / Yokohama Japan, May 8-13, 2021, Extended Abstracts*, pp. 314:1–314:7. ACM, 2021. doi: 10.1145/3411763.3451760. URL https://doi.org/10.1145/3411763.3451760.

Baptiste Rozière, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, et al. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950*, 2023. URL https://arxiv.org/abs/2308.12950.

Teven Le Scao, Angela Fan, Christopher Akiki, Ellie Pavlick, Suzana Ilić, Daniel Hesslow, Roman Castagné, Alexandra Sasha Luccioni, François Yvon, Matthias Gallé, et al. Bloom: A 176b-parameter open-access multilingual language model. *arXiv preprint arXiv:2211.05100*, 2022. URL https://arxiv.org/abs/2211.05100.

Runchu Tian, Yining Ye, Yujia Qin, Xin Cong, Yankai Lin, Zhiyuan Liu, and Maosong Sun. Debugbench: Evaluating debugging capability of large language models. *arXiv preprint arXiv:2401.04621*, 2024. URL https://arxiv.org/abs/2401.04621.

Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of Machine Learning Research*, 9(11), 2008. URL https://www.jmlr.org/papers/volume9/vandermaaten08a/vandermaaten08a.pdf.

Yue Wang, Weishi Wang, Shafiq Joty, and Steven CH Hoi. Codet5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation. *arXiv preprint arXiv:2109.00859*, 2021. URL https://arxiv.org/abs/2109.00859.

Zhiruo Wang, Shuyan Zhou, Daniel Fried, and Graham Neubig. Execution-based evaluation for open-domain code generation. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 1271–1290, 2023. URL https://arxiv.org/abs/2212.10481.

Yuxiang Wei, Zhe Wang, Jiawei Liu, Yifeng Ding, and Lingming Zhang. Magicoder: Source code is all you need. *arXiv preprint arXiv:2312.02120*, abs/2312.02120, 2023. doi: 10.48550/ARXIV.2312.02120. URL https://arxiv.org/abs/2312.02120.

Rui Xie, Zhengran Zeng, Zhuohao Yu, Chang Gao, Shikun Zhang, and Wei Ye. Codeshell technical report. *arXiv preprint arXiv:2403.15747*, 2024. URL https://arxiv.org/abs/2403.15747.

Weixiang Yan, Yuchen Tian, Yunzhe Li, Qian Chen, and Wen Wang. CodeTransOcean: A comprehensive multilingual benchmark for code translation. In Houda Bouamor, Juan Pino, and Kalika Bali (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2023*, pp. 5067–5089, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.337. URL https://aclanthology.org/2023.findings-emnlp.337.

Pengcheng Yin, Wen-Ding Li, Kefan Xiao, Abhishek Rao, Yeming Wen, Kensen Shi, Joshua Howland, Paige Bailey, Michele Catasta, Henryk Michalewski, Oleksandr Polozov, and Charles Sutton. Natural language to code generation in interactive data science notebooks. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 126–173, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.9. URL https://aclanthology.org/2023.acl-long.9.

Alex Young, Bei Chen, Chao Li, Chengen Huang, Ge Zhang, Guanwei Zhang, Heng Li, Jiangcheng Zhu, Jianqun Chen, Jing Chang, et al. Yi: Open foundation models by 01.ai. *arXiv preprint arXiv:2403.04652*, 2024. URL https://arxiv.org/abs/2403.04652.

Hao Yu, Bo Shen, Dezhi Ran, Jiaxin Zhang, Qi Zhang, Yuchi Ma, Guangtai Liang, Ying Li, Qianxiang Wang, and Tao Xie. Codereval: A benchmark of pragmatic code generation with generative pre-trained models. In *Proceedings of the 46th IEEE/ACM International Conference on Software Engineering*, pp. 1–12, 2024. URL https://dl.acm.org/doi/abs/10.1145/3597503.3623316.

Daoguang Zan, Ailun Yu, Bo Shen, Jiaxin Zhang, Taihong Chen, Bing Geng, Bei Chen, Jichuan Ji, Yafen Yao, Yongji Wang, and Qianxiang Wang. Can programming languages boost each other via instruction tuning? *arXiv preprint arXiv:2308.16824*, abs/2308.16824, 2023. URL https://arxiv.org/abs/2308.16824.

Quanjun Zhang, Tongke Zhang, Juan Zhai, Chunrong Fang, Bowen Yu, Weisong Sun, and Zhenyu Chen. A critical review of large language model on software engineering: An example from chatgpt and automated program repair. *arXiv preprint arXiv:2310.08879*, 2023. URL https://arxiv.org/abs/2310.08879.

Qinkai Zheng, Xiao Xia, Xu Zou, Yuxiao Dong, Shan Wang, Yufei Xue, Zihan Wang, Lei Shen, Andi Wang, Yang Li, Teng Su, Zhilin Yang, and Jie Tang. Codegeex: A pre-trained model for code generation with multilingual evaluations on humaneval-x. *arXiv preprint arXiv:2303.17568*, abs/2303.17568, 2023a. doi: 10.48550/ARXIV.2303.17568. URL https://doi.org/10.48550/arXiv.2303.17568.

Qinkai Zheng, Xiao Xia, Xu Zou, Yuxiao Dong, Shan Wang, Yufei Xue, Zihan Wang, Lei Shen, Andi Wang, Yang Li, et al. Codegeex: A pre-trained model for code generation with multilingual evaluations on humaneval-x. *arXiv preprint arXiv:2303.17568*, 2023b. URL https://arxiv.org/abs/2303.17568.

Tianyu Zheng, Ge Zhang, Tianhao Shen, Xueling Liu, Bill Yuchen Lin, Jie Fu, Wenhu Chen, and Xiang Yue. Opencodeinterpreter: Integrating code generation with execution and refinement. *arXiv preprint arXiv:2402.14658*, 2024. URL https://arxiv.org/abs/2402.14658.

Terry Yue Zhuo, Minh Chien Vu, Jenny Chim, Han Hu, Wenhao Yu, Ratnadira Widyasari, Imam Nur Bani Yusuf, Haolan Zhan, Junda He, Indraneil Paul, et al. Bigcodebench: Benchmarking code generation with diverse function calls and complex instructions. *arXiv preprint arXiv:2406.15877*, 2024.

A Appendix

A.1 Limitations

Cover more languages and tasks Our work focuses on evaluating models on multilingual programming tasks, currently supporting assessments in 40 programming languages. Many models claim to support over 80 programming languages, so our work can continue to expand the range of programming languages, the number of test cases, and types of tasks to provide a more comprehensive evaluation of the models.

Research on cross-lingual transfer We do not delve deeply into the cross-lingual transfer capabilities of models, leaving room for exploring a wider variety of models and models of different sizes. In the future, we will explore the programming language transferability scaling law of the code LLMs with different sizes.

A.2 Data Annotation

A.2.1 Human Annotation

To create the massively multilingual code evaluation benchmark McEval, the annotation of multilingual code samples is conducted utilizing a comprehensive and systematic human annotation procedure, underpinned by rigorously defined guidelines to ensure accuracy and consistency.

We recruited annotators with backgrounds in computer software development from universities. During recruitment, we evaluated their programming and system operation skills to ensure they could handle tasks like question writing, code static analysis, and unit testing. Each annotator was assigned tasks based on their proficiency in specific programming languages.

Initially, 10 software developers in computer science are recruited as multilingual programming annotators with proven proficiency in the respective programming languages.

Following a detailed training session on the annotation protocol, annotators are tasked with creating problem definitions and the corresponding solution.

The guidelines for our annotation training session primarily cover the following aspects:

- **Standardized Format:** We provide an annotation example for 40 programming languages. Annotators are required to adhere to this standardized format when annotating data.
- **Accessibility:** The reference data for our annotations is sourced from materials available under permissive licenses, allowing unrestricted use and redistribution for research purposes.
- **Difficulty Level:** We provide annotators with detailed guidelines on the difficulty classification for each language. Annotators must strictly follow these guidelines to label problems according to their respective difficulty levels based on algorithmic complexity and functionality.
- **Self-Contained:** Annotators are required to thoroughly review their annotated problems to ensure that the problem descriptions include all necessary information for solving them without ambiguity. The provided example inputs and outputs must be correct, the reference answers must execute correctly, and the test cases written should comprehensively evaluate the accuracy of the functions.

A.2.2 Reference Data

We use reference data (The annotators only draw the inspiration from the reference website, and create the question manually.) to draft questions and solutions with the help of GPT-4-Turbo. The draft questions initially may contain numerous issues, such as self-contained errors, inconsistent difficulty levels, overly simple unit tests, and incorrect unit tests. To address these issues, annotators revised and tested the draft questions to ensure that all questions and code were accurate and that the unit tests would pass. These reference data came from the following websites: For the algorithmic types of questions, we refer to the following websites:

- https://www.dotcpp.com/
- https://www.luogu.com.cn
- https://www.codecademy.com/
- https://www.codewars.com/

For markup language and design-type questions, we refer to the following websites:

- https://www.runoob.com/
- https://www.w3schools.com/

A.2.3 QUALITY CONTROL

We adopt a dual-pass system to ensure the quality of our benchmark MCEVAL. First, one annotator labels the code snippets and their corresponding unit tests. Then, another annotator independently reviews these annotations, verifying their correctness, code accuracy, and unit test integrity. Following this, three senior annotators evaluate the overall unit test pass rate of the annotated dataset. If the pass rate exceeds 90%, the senior annotators proceed to perform additional reviews and corrections. Otherwise, the data is returned to the annotators for refinement. Finally, the canonical solution (labeled by the annotator) passes all corresponding test cases to ensure the correctness of each created problem (100% pass rate). This rigorous process ensures the creation of a high-quality, multilingual programming benchmark that supports in-depth analysis and understanding of code examples across diverse programming languages.

A.2.4 ANNOTATION COSTS

We paid all the annotators the equivalent of $6 per question and provided them with a comfortable working environment, free meals, and souvenirs. We also provided the computer equipment and GPT-4 interface required for labeling. We labeled about 2,000 questions in total and employed them to check the quality of the questions/answers, and the total cost was about $12,000 in US dollars. The annotators checked the derived tasks, including multilingual code explanation and code completion.

A.3 DETAILED ABOUT MCEVAL-INSTRUCT

Here we describe in detail the specific methods and processes of code sampling and quality control in the process of constructing MCEVAL-INSTRUCT.

Code Sampling

- (1) We crawled a large amount of code data from GitHub and preprocessed the data according to the StarCoder processing flow. Then, we can get a high-quality code dataset.
- (2) For each programming language, we randomly sampled the data to build an original dataset containing 40 languages, where the instances of each language are sampled to the same number of samples.
- (3) In addition, in the refined stage, we further used GPT-4 to refine the code snippets to the clearer and more standardized code (the code with docstring, code comments, and clear variables) and verified the refined code snippet through static code analysis and unit testing methods to ensure the correctness and quality of the code.

Quality Control To check the correctness of the generated code from the GPT-4, we use static analysis and unit testing to ensure the accuracy of generated data as much as possible:

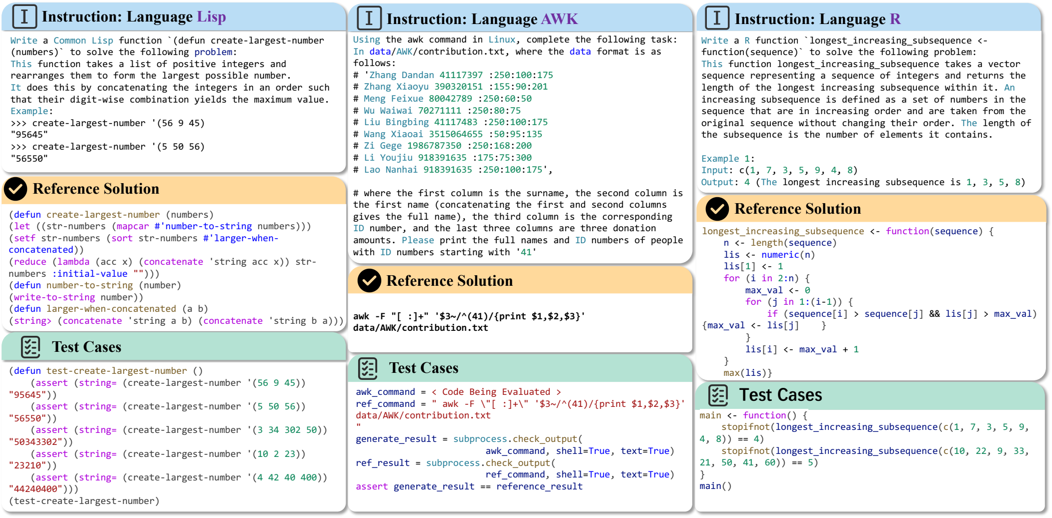
- Code Correctness: We use static code analysis tools and Abstract Syntax Tree (AST) parsing to ensure the correctness of the code.
- Automated Testing: We leverage an LLM to automatically generate unit tests, filtering out code that fails to pass these tests.
- Harmful Content Filtering: We filter out code snippets containing harmful information using keyword-based filters.

A.4 EXAMPLES IN MCEVAL

Figure 10 display three examples of multilingual generation.

In Figure 11, we show three examples of multilingual explanation.

In Figure 12, we display three examples of multilingual explanation. The three examples from left to right correspond to the span completion task, the single-line completion task, and the multi-line completion task.



Instruction: Language Lisp

```
Write a Common Lisp function `(defun create-largest-number
(numbers)` to solve the following problem:
This function takes a list of positive integers and
rearranges them to form the largest possible number.
It does this by concatenating the integers in an order such
that their digit-wise combination yields the maximum value.
Example:
>>> create-largest-number '(56 9 45)
"95645"
>>> create-largest-number '(5 50 56)
"56550"
```

Reference Solution

```
(defun create-largest-number (numbers)
(let ((str-numbers (mapcar #'number-to-string numbers)))
(setf str-numbers (sort str-numbers #'larger-when-
concatenated))
(reduce (lambda (acc x) (concatenate 'string acc x)) str-
numbers :initial-value "")))
(defun number-to-string (number)
(write-to-string number))
(defun larger-when-concatenated (a b)
(string> (concatenate 'string a b) (concatenate 'string b a)))
```

Test Cases

```
(defun test-create-largest-number ()
    (assert (string= (create-largest-number '(56 9 45))
"95645"))
    (assert (string= (create-largest-number '(5 50 56))
"56550"))
    (assert (string= (create-largest-number '(3 34 302 50))
"50343302"))
    (assert (string= (create-largest-number '(10 2 23))
"23210"))
    (assert (string= (create-largest-number '(4 42 40 400))
"44240400")))
(test-create-largest-number)
```

Instruction: Language AWK

```
Using the awk command in Linux, complete the following task:
In data/AWK/contribution.txt, where the data format is as
follows:
# 'Zhang Dandan 41117397 :250:100:175
# Zhang Xiaoyu 390320151 :155:90:201
# Meng Feixue 80042789 :250:60:50
# Wu Waiwai 70271111 :250:80:75
# Liu Bingbing 41117483 :250:100:175
# Wang Xiaoai 3515064655 :50:95:135
# Zi Gege 1986787350 :250:168:200
# Li Youjiu 918391635 :175:75:300
# Lao Nanhai 918391635 :250:100:175',

# where the first column is the surname, the second column is
the first name (concatenating the first and second columns
gives the full name), the third column is the corresponding
ID number, and the last three columns are three donation
amounts. Please print the full names and ID numbers of people
with ID numbers starting with '41'
```

Reference Solution

```
awk -F "[ :]+" '$3~/^(41)/{print $1,$2,$3}'
data/AWK/contribution.txt
```

Test Cases

```
awk_command = < Code Being Evaluated >
ref_command = " awk -F \"[ :]+\" '$3~/^(41)/{print $1,$2,$3}'
data/AWK/contribution.txt
"
generate_result = subprocess.check_output(
                        awk_command, shell=True, text=True)
ref_result = subprocess.check_output(
                        ref_command, shell=True, text=True)
assert generate_result == reference_result
```

Instruction: Language R

```
Write a R function `longest_increasing_subsequence <-
function(sequence)` to solve the following problem:
This function longest_increasing_subsequence takes a vector
sequence representing a sequence of integers and returns the
length of the longest increasing subsequence within it. An
increasing subsequence is defined as a set of numbers in the
sequence that are in increasing order and are taken from the
original sequence without changing their order. The length of
the subsequence is the number of elements it contains.

Example 1:
Input: c(1, 7, 3, 5, 9, 4, 8)
Output: 4 (The longest increasing subsequence is 1, 3, 5, 8)
```

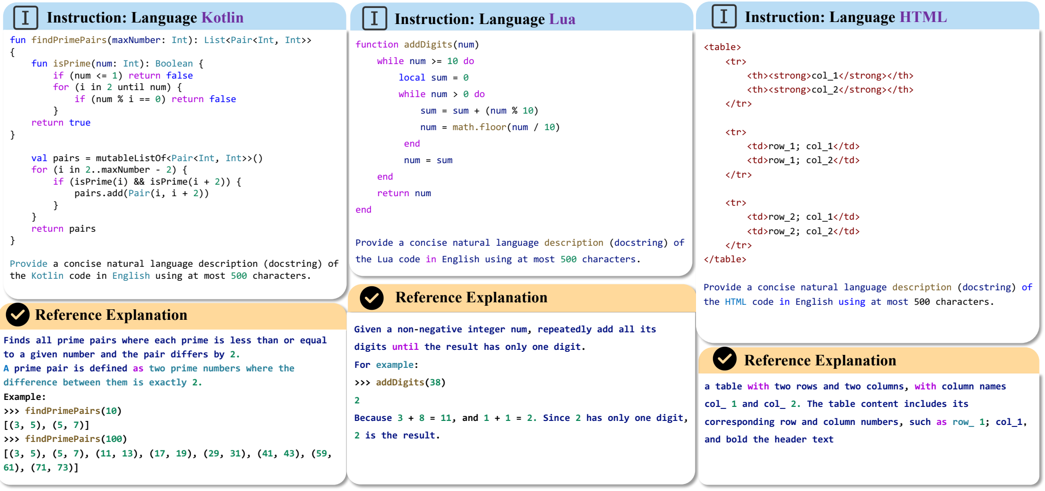
Reference Solution

```
longest_increasing_subsequence <- function(sequence) {
    n <- length(sequence)
    lis <- numeric(n)
    lis[1] <- 1
    for (i in 2:n) {
        max_val <- 0
        for (j in 1:(i-1)) {
            if (sequence[i] > sequence[j] && lis[j] > max_val)
{max_val <- lis[j]    }
        }
        lis[i] <- max_val + 1
    }
    max(lis)}
```

Test Cases

```
main <- function() {
    stopifnot(longest_increasing_subsequence(c(1, 7, 3, 5, 9,
4, 8)) == 4)
    stopifnot(longest_increasing_subsequence(c(10, 22, 9, 33,
21, 50, 41, 60)) == 5)
}
main()
```

Figure 10: Examples of multilingual generation. The data mainly consists of an instruction part (including function name, function description, and function call cases), a reference solution, and a test cases part. **Left.** Shows an example of the Lisp language. **Middle.** Shows a file processing programming task in AWK language. During the evaluation, the corresponding file processing result by the generated code will be compared with the reference answer. **Right.** Shows an example of the R language.



Instruction: Language Kotlin

```
fun findPrimePairs(maxNumber: Int): List<Pair<Int, Int>>
{
    fun isPrime(num: Int): Boolean {
        if (num <= 1) return false
        for (i in 2 until num) {
            if (num % i == 0) return false
        }
    return true
}

    val pairs = mutableListOf<Pair<Int, Int>>()
    for (i in 2..maxNumber - 2) {
        if (isPrime(i) && isPrime(i + 2)) {
            pairs.add(Pair(i, i + 2))
        }
    }
    return pairs
}

Provide a concise natural language description (docstring) of
the Kotlin code in English using at most 500 characters.
```

Reference Explanation

```
Finds all prime pairs where each prime is less than or equal
to a given number and the pair differs by 2.
A prime pair is defined as two prime numbers where the
difference between them is exactly 2.
Example:
>>> findPrimePairs(10)
[(3, 5), (5, 7)]
>>> findPrimePairs(100)
[(3, 5), (5, 7), (11, 13), (17, 19), (29, 31), (41, 43), (59,
61), (71, 73)]
```

Instruction: Language Lua

```
function addDigits(num)
    while num >= 10 do
        local sum = 0
        while num > 0 do
            sum = sum + (num % 10)
            num = math.floor(num / 10)
         end
         num = sum
    end
    return num
end

Provide a concise natural language description (docstring) of
the Lua code in English using at most 500 characters.
```

Reference Explanation

```
Given a non-negative integer num, repeatedly add all its
digits until the result has only one digit.
For example:
>>> addDigits(38)
2
Because 3 + 8 = 11, and 1 + 1 = 2. Since 2 has only one digit,
2 is the result.
```

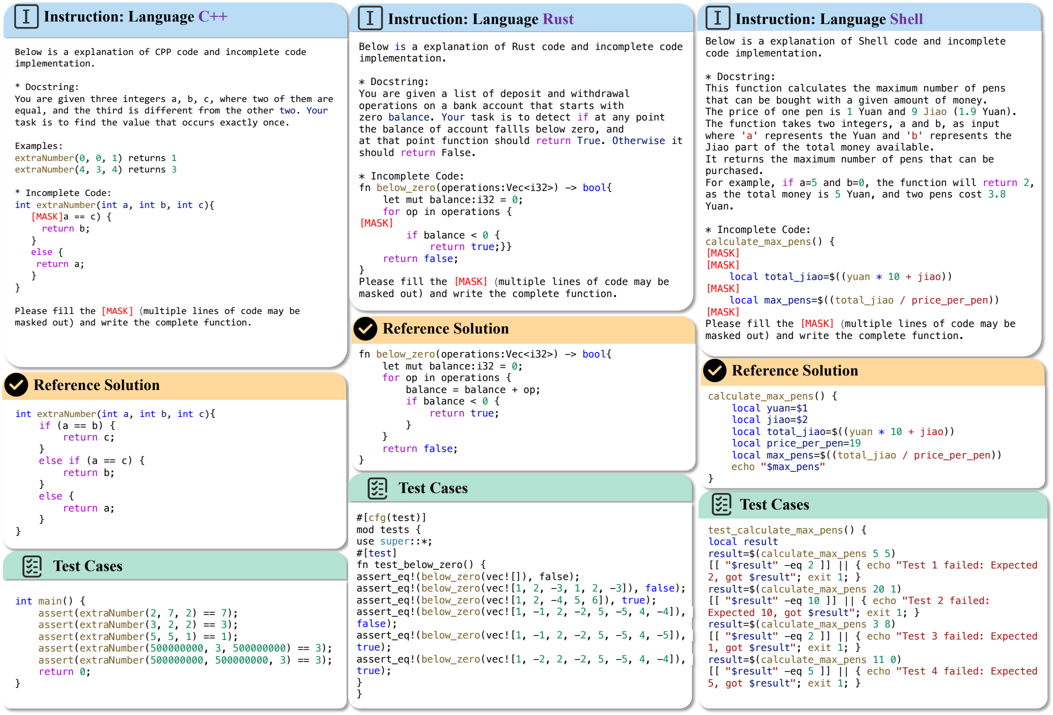
Instruction: Language HTML

```
<table>
    <tr>
        <th><strong>col_1</strong></th>
        <th><strong>col_2</strong></th>
    </tr>

    <tr>
        <td>row_1; col_1</td>
        <td>row_1; col_2</td>
    </tr>

    <tr>
        <td>row_2; col_1</td>
        <td>row_2; col_2</td>
    </tr>
</table>

Provide a concise natural language description (docstring) of
the HTML code in English using at most 500 characters.
```

Reference Explanation

```
a table with two rows and two columns, with column names
col_ 1 and col_ 2. The table content includes its
corresponding row and column numbers, such as row_ 1; col_1,
and bold the header text
```

Figure 11: Examples of multilingual explanation. The data mainly consists of an instruction part (including a complete function), a reference Explanation. **Left.** Shows an example of the Kotlin language. **Middle.** Shows an example of the Lua language. **Right.** Shows an example of the HTML language.



Instruction: Language C++

```
Below is a explanation of CPP code and incomplete code
implementation.

* Docstring:
You are given three integers a, b, c, where two of them are
equal, and the third is different from the other two. Your
task is to find the value that occurs exactly once.

Examples:
extraNumber(0, 0, 1) returns 1
extraNumber(4, 3, 4) returns 3

* Incomplete Code:
int extraNumber(int a, int b, int c){
   [MASK]a == c) {
     return b;
   }
   else {
    return a;
   }
}

Please fill the [MASK] (multiple lines of code may be
masked out) and write the complete function.
```

Reference Solution

```
int extraNumber(int a, int b, int c){
    if (a == b) {
        return c;
    }
    else if (a == c) {
        return b;
    }
    else {
        return a;
    }
}
```

Test Cases

```
int main() {
    assert(extraNumber(2, 7, 2) == 7);
    assert(extraNumber(3, 2, 2) == 3);
    assert(extraNumber(5, 5, 1) == 1);
    assert(extraNumber(500000000, 3, 500000000) == 3);
    assert(extraNumber(500000000, 500000000, 3) == 3);
    return 0;
}
```

Instruction: Language Rust

```
Below is a explanation of Rust code and incomplete code
implementation.

* Docstring:
You are given a list of deposit and withdrawal
operations on a bank account that starts with
zero balance. Your task is to detect if at any point
the balance of account fallls below zero, and
at that point function should return True. Otherwise it
should return False.

* Incomplete Code:
fn below_zero(operations:Vec<i32>) -> bool{
    let mut balance:i32 = 0;
    for op in operations {
[MASK]
        if balance < 0 {
            return true;}}
    return false;
}
Please fill the [MASK] (multiple lines of code may be
masked out) and write the complete function.
```

Reference Solution

```
fn below_zero(operations:Vec<i32>) -> bool{
    let mut balance:i32 = 0;
    for op in operations {
        balance = balance + op;
        if balance < 0 {
            return true;
        }
    }
    return false;
}
```

Test Cases

```
#[cfg(test)]
mod tests {
use super::*;
#[test]
fn test_below_zero() {
assert_eq!(below_zero(vec![]), false);
assert_eq!(below_zero(vec![1, 2, -3, 1, 2, -3]), false);
assert_eq!(below_zero(vec![1, 2, -4, 5, 6]), true);
assert_eq!(below_zero(vec![1, -1, 2, -2, 5, -5, 4, -4]),
false);
assert_eq!(below_zero(vec![1, -1, 2, -2, 5, -5, 4, -5]),
true);
assert_eq!(below_zero(vec![1, -2, 2, -2, 5, -5, 4, -4]),
true);
}
}
```

Instruction: Language Shell

```
Below is a explanation of Shell code and incomplete
code implementation.

* Docstring:
This function calculates the maximum number of pens
that can be bought with a given amount of money.
The price of one pen is 1 Yuan and 9 Jiao (1.9 Yuan).
The function takes two integers, a and b, as input
where 'a' represents the Yuan and 'b' represents the
Jiao part of the total money available.
It returns the maximum number of pens that can be
purchased.
For example, if a=5 and b=0, the function will return 2,
as the total money is 5 Yuan, and two pens cost 3.8
Yuan.

* Incomplete Code:
calculate_max_pens() {
[MASK]
[MASK]
    local total_jiao=$((yuan * 10 + jiao))
[MASK]
    local max_pens=$((total_jiao / price_per_pen))
[MASK]
Please fill the [MASK] (multiple lines of code may be
masked out) and write the complete function.
```

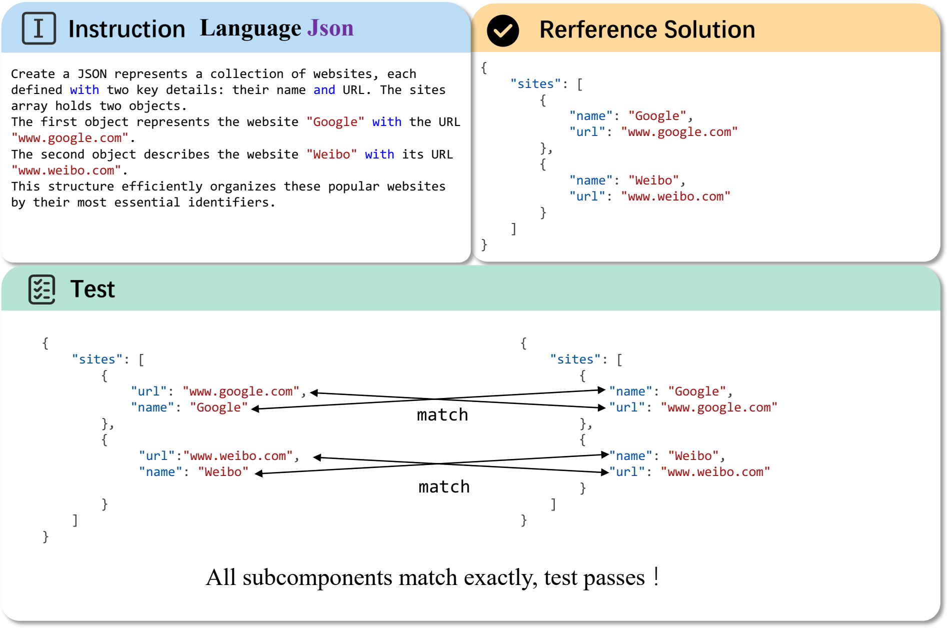
Reference Solution

```
calculate_max_pens() {
    local yuan=$1
    local jiao=$2
    local total_jiao=$((yuan * 10 + jiao))
    local price_per_pen=19
    local max_pens=$((total_jiao / price_per_pen))
    echo "$max_pens"
}
```

Test Cases

```
test_calculate_max_pens() {
local result
result=$(calculate_max_pens 5 5)
[[ "$result" -eq 2 ]] || { echo "Test 1 failed: Expected
2, got $result"; exit 1; }
result=$(calculate_max_pens 20 1)
[[ "$result" -eq 10 ]] || { echo "Test 2 failed:
Expected 10, got $result"; exit 1; }
result=$(calculate_max_pens 3 8)
[[ "$result" -eq 2 ]] || { echo "Test 3 failed: Expected
1, got $result"; exit 1; }
result=$(calculate_max_pens 11 0)
[[ "$result" -eq 5 ]] || { echo "Test 4 failed: Expected
5, got $result"; exit 1; }
```

Figure 12: Examples of multilingual completion. The data mainly consists of an instruction part (including a incomplete function), a reference complete code solution and test cases. **Left.** Shows an span completion example of the C++ language. **Middle.** Shows an single line completion example of the Rust language. **Right.** Shows an multiple line completion example of the Shell language.



Instruction Language Json

```
Create a JSON represents a collection of websites, each
defined with two key details: their name and URL. The sites
array holds two objects.
The first object represents the website "Google" with the URL
"www.google.com".
The second object describes the website "Weibo" with its URL
"www.weibo.com".
This structure efficiently organizes these popular websites
by their most essential identifiers.
```

Rerference Solution

```
{
    "sites": [
        {
            "name": "Google",
            "url": "www.google.com"
        },
        {
            "name": "Weibo",
            "url": "www.weibo.com"
        }
    ]
}
```

Test

```
{
    "sites": [
        {
            "url": "www.google.com",
            "name": "Google"
        },
        {
             "url":"www.weibo.com",
             "name": "Weibo"
        }
    ]
}
```

```
{
    "sites": [
        {
            "name": "Google",
            "url": "www.google.com"
        },
        {
            "name": "Weibo",
            "url": "www.weibo.com"
        }
    ]
}
```

All subcomponents match exactly, test passes !

Figure 13: Examples of Markup language (Json) generation task evaluation.

A.5 Evaluation

For programming languages other than markup languages, we use an execution-based correctness metric by running the code with the provided test cases. For markup languages, we use the Exact

Table 6: Runtime environments for different programming languages.

Language	Runtime Environments
AWK	GNU bash, version 4.4.20(1)-release (x86_64-pc-linux-gnu)
C	gcc (Ubuntu 7.5.0-3ubuntu11̃8.04) 7.5.0
C#	dotnet 8.0.100
CPP	g++ (Ubuntu 7.5.0-3ubuntu11̃8.04) 7.5.0
CoffeeScript	CoffeeScript version 1.12.7
Common Lisp	SBCL 1.4.5.debian
Dart	Dart SDK version: 3.3.1 (stable)
Elixir	elixir 1.3.3
Emacs Lisp	GNU Emacs 25.2.2
Erlang	Erlang/OTP 20 [erts-9.2]
F#	dotnet 8.0.100
Fortran	GNU Fortran (Ubuntu 7.5.0-3ubuntu11̃8.04) 7.5.0
Go	go version go1.18.4 linux/amd64
Groovy	Groovy Version: 4.0.16 JVM: 17.0.9 Vendor: Oracle Corporation OS: Linux
HTML	-
Haskell	The Glorious Glasgow Haskell Compilation System, version 9.4.7
Json	-
Java	javac 11.0.19
JavaScript	Node.js v16.14.0
Julia	julia v1.9.4
Kotlin	kotlinc-jvm 1.9.21 (JRE 17.0.9+11-LTS-201)
Lua	Lua 5.4.6 Copyright (C) 1994-2023 Lua.org, PUC-Rio
Markdown	-
PHP	PHP 7.2.24-0ubuntu0.18.04.17 (cli) (built: Feb 23 2023 13:29:25) (NTS)
Pascal	Free Pascal Compiler version 3.2.2 [2021/05/16] for x86_64
Perl	perl 5, version 26, subversion 1 (v5.26.1) built for x86_64-linux-gnu-thread-multi
PowerShell	PowerShell 7.4.0
Python	Python 3.8.12
R	R version 3.4.4
Racket	Racket v6.11
Ruby	ruby 2.5.1p57 (2018-03-29 revision 63029) [x86_64-linux-gnu]
Rust	rustc 1.74.0 (79e9716c9 2023-11-13)
Scala	Scala code runner version 3.3.1 – Copyright 2002-2023, LAMP/EPFL
Scheme	Racket v6.11
Shell	GNU bash, version 4.4.20(1)-release (x86_64-pc-linux-gnu)
Swift	Swift version 5.9.2 (swift-5.9.2-RELEASE)
Tcl	tclsh 8.6.11
TypeScript	tsc Version 5.3.3
VimScript	VIM - Vi IMproved 9.0 (2022 Jun 28, compiled Dec 20 2023 18:57:50)
Visual Basic	dotnet 8.0.100

Match metric for evaluation. Taking Json as an example, we parse all subcomponents in Json. If the model result is exactly the same as the subcomponent of the reference solution, the model generation result is considered correct. An example of Markup language (Json) is shown in Figure 13.

We adopt the greedy Pass@1 (%) metric (Kulal et al., 2019; Chen et al., 2021) for our evaluations. For closed-source models, we generate answers through the official API service. For open-source models, we prioritize using vLLM (Kwon et al., 2023) for faster inference if the model is supported by vLLM. Otherwise, we perform inference with the Distributed Data Parallel (DDP) module from PyTorch. For the code generation and code completion tasks, we extract the functional part of the code from the model outputs and combine it with corresponding test cases to form compilable and executable code. For the code explanation task, we adopt a two-pass generation approach (Code-to-Natural-Language and Natural-Language-to-Code). The extraction and execution process for this task is consistent with the previous two tasks. We conduct all evaluations in a Docker environment. Detailed information on the code compilation and execution environment are displayed in Table 6. We have uploaded the Docker image to docker hub to facilitate the reproduction of results and the evaluation of new models.

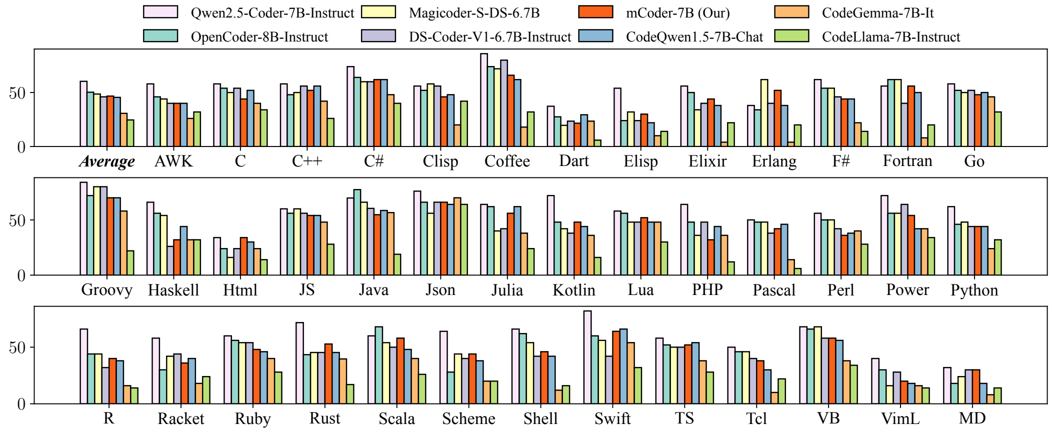


Figure 14: Pass@1 (%) scores of different code LLMs (<10B) for multilingual code generation tasks on MCEVAL. “AVG” represents the average scores of all code languages.

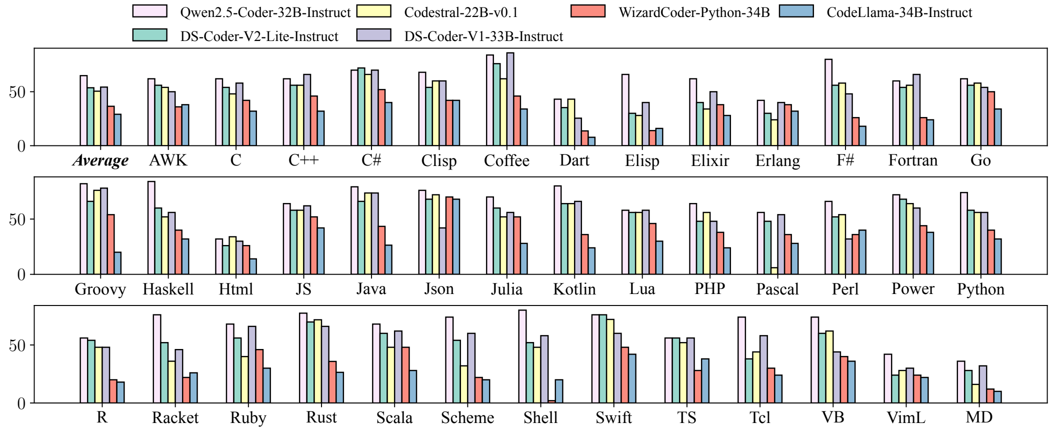


Figure 15: Pass@1 (%) scores of different code LLMs (10B to 40B) for multilingual code generation tasks on MCEVAL. “AVG” represents the average scores of all code languages.

A.6 OPTIMIZATION DETAILS

All MCODER models are fine-tuned using 8 NVIDIA A800-80GB GPUs. The models are trained for 2 epochs with a cosine scheduler, starting at a learning rate of 2e-5 and incorporating a 3% warmup phase. Training a model takes about 5 hours. We used AdamW (Loshchilov & Hutter, 2017) as the optimizer and a batch size of 512 with a sequence truncation length of 4096. We use PyTorch’s Fully Sharded Data Parallel (FSDP) to perform distributed training of the model, and use gradient checkpointing technology and gradient accumulation to save memory and achieve training with a larger batch size.

A.7 EXTRA RESULTS

A.8 PROGRAMMING CLASSIFICATION

As shown in Table 7 and Table 8, we comprehensively display the code generation performance of the models we tested across various programming paradigms and application scenarios.

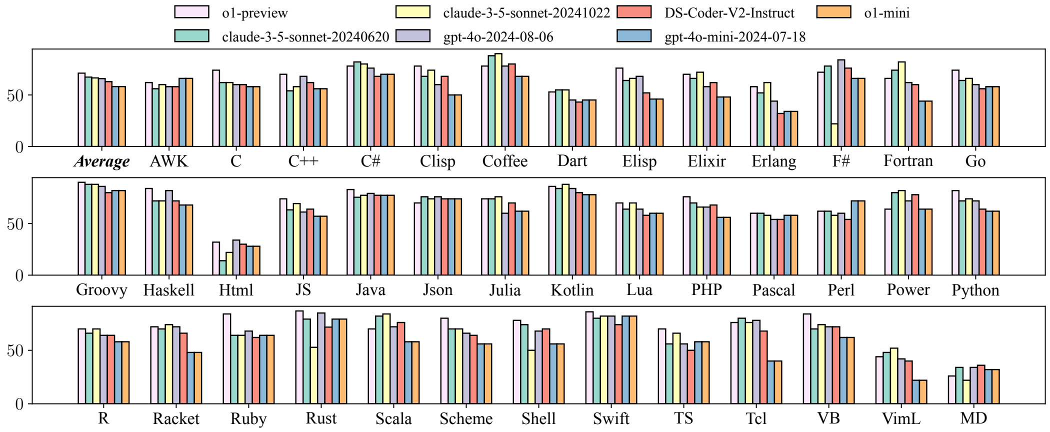


Figure 16: Pass@1 (%) scores of different code LLMs (Closed Source & 200B+) for multilingual code generation tasks on MCEVAL. "AVG" represents the average scores of all code languages.

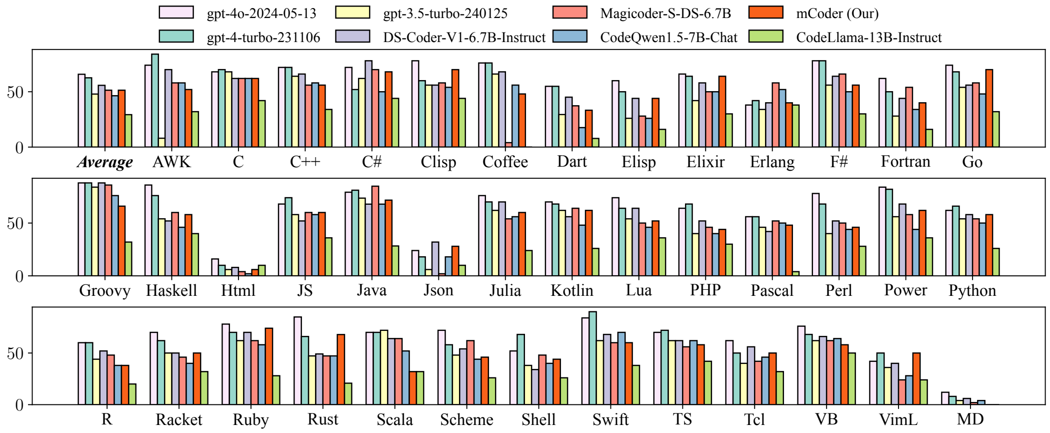


Figure 17: Pass@1 (%) scores of different code LLMs for multilingual code explain tasks on MCEVAL. "AVG" represents the average scores of all code languages.

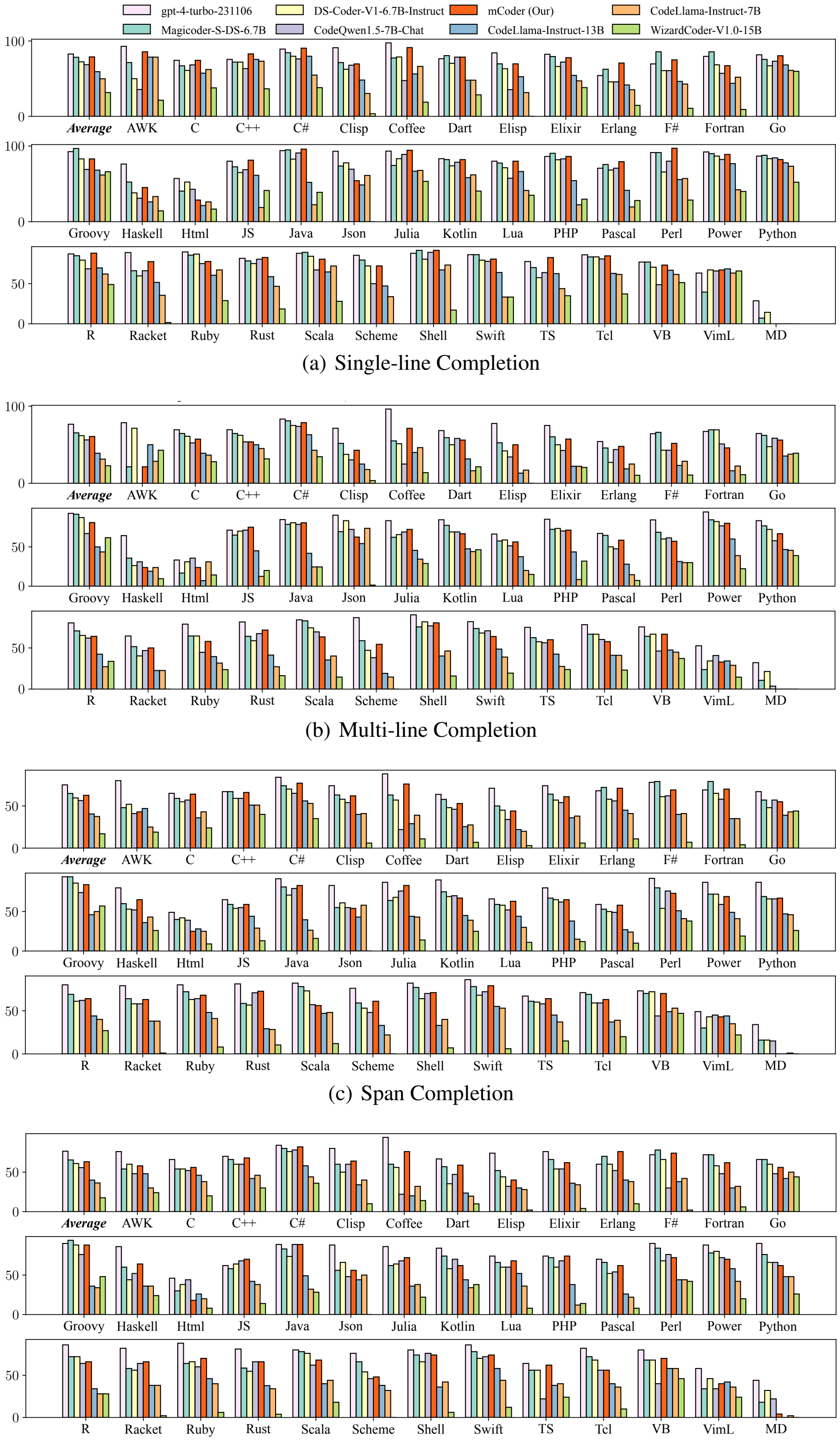
A.9 MCODER RESULT

In Table 9, we show some extra MCODER Pass@1 (%) results on multilingual code generation tasks. We evaluate the base models CodeQwen-1.5 and DeepsSeek-Coder-1.5 respectively. In addition to CodeQwen-1.5, we also selected DeepSeek-Coder-1.5-base as the base model for fine-tuning.

A.10 PARALLEL QUESTIONS ACROSS LANGUAGES & PROGRAMMING GRAMMAR

Due to the large number of languages, it is difficult to ensure parallel problem annotation. For most language annotations, we follow the characteristics of the language and perform independent annotations. For example, structured languages such as Markdown and HTML need independent annotations. For some similar languages, such as Typescript and Javascript, we use parallel annotation on some data.

As shown in Figure 19, we analyzed the programming languages in the MCEVAL from the representation perspective. We used CodeBERT (Feng et al., 2020) to extract code representations from code snippets in MCEVAL. These representations were visualized using t-SNE (Van der Maaten & Hinton, 2008) and hierarchical clustering (Murtagh & Contreras, 2012) methods. The figure clearly shows that languages with similar syntax have closely related representations. For example, other functional programming languages similar to Common Lisp, as well as C, C++, Java, and scripting languages, exhibit high grammar similarity.



(a) Single-line Completion

(b) Multi-line Completion

(c) Span Completion

(d) Span Completion Light

Figure 18: Pass@1 (%) scores of different models for multilingual code completion tasks on MCEVAL. “Avg” represents the average scores of all code languages.

Table 7: Pass@1(%) results of code generation performance of across various programming paradigms

Method	Procedural	Object Oriented	Multiple Paradigms	Functional	Markup Language
GPT-4o (240517)	**58.0**	**79.8**	**65.9**	**67.0**	46.0
GPT-4 Turbo (231106)	56.7	78.7	65.2	59.3	**46.7**
GPT-3.5-Turbo (240125)	38.7	66.8	57.6	44.3	39.3
Codegemma-7b-it	19.3	46.6	34.0	16.3	34.0
CodeLlama-13b-Instruct	21.3	32.0	27.0	32.3	28.0
CodeLlama-34b-Instruct	27.3	33.6	28.0	30.0	30.7
CodeLlama-7b	20.3	28.1	23.4	26.7	30.7
CodeQwen-1.5-7b-Chat	41.3	57.3	46.3	41.0	37.3
Codeshell-7b-chat	16.0	24.1	25.7	14.0	34.7
Codestral-22B-v0.1	40.0	67.6	54.1	39.7	40.7
DeepSeekCoder-33b-instruct	52.7	62.8	56.3	52.0	34.7
DeepSeekCoder-1.5-7b-instruct	39.0	51.8	48.8	41.0	40.0
Magicoder-S-DS-6.7B	45.7	58.5	49.4	49.0	32.0
Llama-3-8B-Instruct	27.3	44.7	38.0	32.0	33.3
Nxcode-CQ-7B-orpo	40.7	54.9	45.5	41.3	36.7
OCTOCODER	20.7	28.9	21.9	25.0	25.3
OpenCodeInterpreter-DS-6.7B	40.7	57.7	46.4	42.0	42.0
Phi-3-medium-4k-instruct	32.3	43.1	36.6	26.7	35.3
Qwen1.5-72B-Chat	38.3	37.2	36.2	29.3	39.3
WizardCoder-15B-V1.0	19.0	31.6	34.2	24.0	6.7
WizardCoder-Python-34B	27.7	43.9	38.2	33.7	36.0
MCODER	41.3	57.3	47.4	42.3	43.3

Table 8: Pass@1(%) results of code generation performance of across various application scenarios

Method	Mobile	Cross	Desktop	Frontend	Backend	Scientific	General	Content	Education	Scripts	Editor
GPT-4o (230517)	**84.0**	**68.3**	**75.0**	**66.7**	64.6	**71.6**	**57.6**	46.0	**72.7**	**65.7**	**52.0**
GPT-4 Turbo (231106)	81.0	64.4	74.0	64.0	**66.6**	66.8	**57.6**	**46.7**	60.7	**65.7**	50.0
GPT-3.5 (240125)	60.0	56.7	71.0	63.3	57.5	55.6	50.4	39.3	45.3	50.0	25.0
Codegemma-7b-it	45.0	40.4	43.0	34.7	37.7	21.6	24.8	34.0	22.0	29.7	13.0
code-Llama-13b	30.0	15.4	39.0	34.7	28.0	23.2	34.8	28.0	24.0	27.7	13.0
CodeLlama-34b-Instruct	33.0	17.3	38.0	38.0	27.2	24.0	32.8	30.7	26.7	31.7	19.0
Code-Llama-7b-Instruct	24.0	12.5	37.0	29.3	22.7	20.8	29.2	30.7	19.3	27.0	14.0
CodeQwen-1.5-7b	55.0	44.2	59.0	56.7	48.7	47.6	46.8	37.3	42.7	40.0	20.0
Codeshell-7b-chat	23.0	14.4	26.0	40.7	26.1	17.2	21.2	34.7	13.3	22.7	8.0
Codestral-22B-v0.1	68.0	58.7	64.0	57.3	55.0	54.0	44.8	40.7	30.0	53.3	28.0
DeepSeekCoder-33b-instruct	63.0	50.0	57.0	68.0	60.6	54.8	54.0	34.7	56.7	52.7	35.0
DeepSeekCoder-1.5-7b-instruct	40.0	42.3	59.0	62.0	52.7	40.8	50.0	40.0	34.7	46.0	22.0
Magicoder-S-DS-6.7B	49.0	43.3	64.0	60.7	50.4	49.6	52.4	32.0	48.7	49.7	24.0
Llama-3-8B-Instruct	41.0	30.8	48.0	50.7	40.5	30.0	37.2	33.3	34.0	33.0	15.0
Nxcode-CQ-7B-orpo	54.0	40.4	55.0	53.3	48.4	48.0	46.8	36.7	42.7	39.7	20.0
OCTOCODER	22.0	20.2	33.0	28.7	21.8	16.4	27.2	25.3	16.0	29.0	14.0
OpenCodeInterpreter-DS-6.7B	47.0	42.3	64.0	58.0	45.9	47.6	46.4	42.0	43.3	44.0	24.0
Phi-3-medium-4k-instruct	40.0	26.9	48.0	48.7	30.3	39.2	31.6	35.3	33.3	39.0	13.0
Qwen1.5-72B-Chat	30.0	29.8	43.0	44.7	36.3	30.4	38.0	39.3	32.7	40.0	21.0
WizardCoder-15B-V1.0	28.0	24.0	36.0	48.0	37.1	29.2	27.2	6.7	20.7	26.3	9.0
WizardCoder-Python-34B	42.0	28.8	46.0	42.0	44.2	32.8	38.0	36.0	32.7	32.3	19.0
MCODER	56.0	38.5	60.0	57.3	50.4	48.0	46.0	43.3	39.3	44.3	25.0

We selected training data from several languages in MCEVAL-INSTRUCT, which exhibit significant grammatical differences (approximately 10K samples of Python and 1K samples for other languages) and fine-tuned the model. The results are as shown in Table 10.

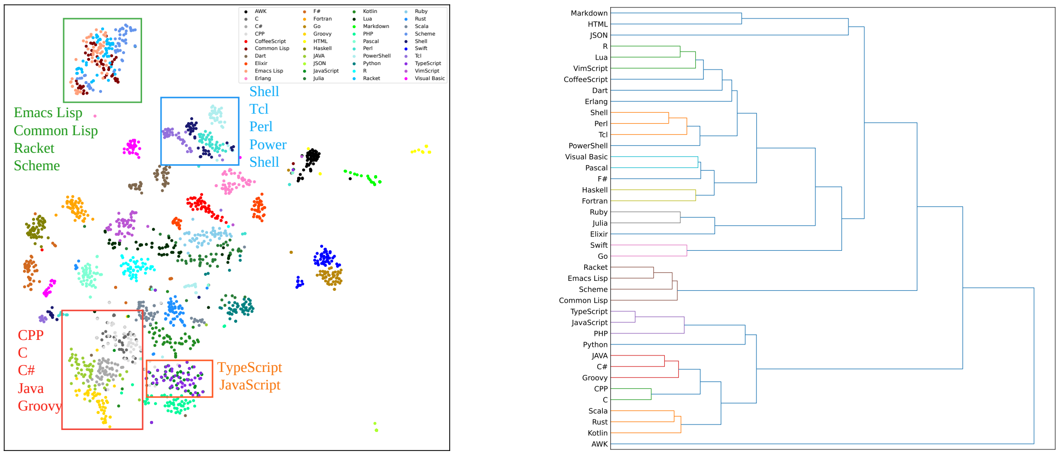
When trained using **only Python data**, the performance on Python and AWK improved. However, this led to the scores for TypeScript and JavaScript dropping to 0. Upon inspection, we found that the generated code for these two languages contained syntax errors (Less data may lead to instability in model training).

When training on **a mixture of several languages**, Python performance decreased slightly compared to using only Python data, while Scheme performance improved significantly. Furthermore, the syntax generation for TypeScript and JavaScript returned to normal (even without adding JavaScript data, as TypeScript and JavaScript share similar syntax). However, there was no significant improvement compared to the base model.

Thus, fine-tuning multilingual code models presents significant challenges. Similar languages can provide mutual benefits, while languages with greater differences may negatively impact performance.

Table 9: Additional MCODER Pass@1 (%) results on multilingual code generation tasks. "Avg$_{all}$" represents the average Pass@1 scores across all programming languages in the MCEVAL. Here, MCODER-DS indicates that the fine-tuned base model is DeepSeekCoder-1.5-7b-base.

Method	Size	AWK	C	C++	C#	Clisp	Coffee	Dart	Elisp	Elixir	Erlang	Fortran	F#	Go	Groovy	Haskell	Html	Java	JS	Json	Julia
DeepSeekCoder-1.5-base	7B	30.0	36.0	38.0	40.0	40.0	58.0	0.0	18.0	2.0	14.0	50.0	44.0	48.0	26.0	2.0	4.0	49.1	32.0	16.0	34.0
CodeQwen-1.5	7B	38.0	40.0	46.0	42.0	28.0	56.0	2.0	14.0	14.0	0.0	40.0	46.0	44.0	32.0	2.0	0.0	47.2	52.0	30.0	60.0
CodeQwen-1.5-Python	7B	42.0	48.0	48.0	12.0	52.0	68.0	23.5	22.0	40.0	62.0	50.0	42.0	48.0	68.0	56.0	32.0	67.9	52.0	52.0	54.0
MCODER-DS	7B	34.0	46.0	50.0	26.0	30.0	72.0	19.6	6.0	26.0	24.0	58.0	30.0	48.0	12.0	26.0	28.0	67.9	48.0	62.0	48.0
MCODER	7B	40.0	44.0	52.0	62.0	46.0	66.0	21.6	30.0	44.0	52.0	56.0	44.0	48.0	70.0	32.0	34.0	54.7	54.0	66.0	56.0
Method	Kotlin	Lua	MD	Pascal	Perl	PHP	Power	Python	R	Racket	Ruby	Rust	Scala	Scheme	Shell	Swift	Tcl	TS	VB	VimL	**Avg$_{all}$**
DeepSeekCoder-1.5-7B-base	42.0	20.0	0.0	24.0	24.0	36.0	42.0	54.0	24.0	20.0	38.0	39.6	44.0	20.0	18.0	32.0	10.0	44.0	22.0	22.0	28.9
CodeQwen-1.5	58.0	50.0	0.0	14.0	20.0	10.0	48.0	38.0	30.0	24.0	36.0	52.8	32.0	34.0	42.0	46.0	30.0	52.0	54.0	22.0	33.2
CodeQwen-1.5-Python	46.0	46.0	24.0	42.0	36.0	36.0	54.0	44.0	36.0	40.0	46.0	52.8	58.0	40.0	42.0	62.0	48.0	52.0	58.0	18.0	45.5
MCODER-DS	36.0	42.0	22.0	34.0	8.0	34.0	46.0	42.0	22.0	40.0	56.0	45.3	48.0	30.0	38.0	48.0	34.0	46.0	50.0	28.0	37.8
MCODER	48.0	52.0	30.0	42.0	36.0	32.0	54.0	44.0	40.0	36.0	48.0	52.8	58.0	44.0	46.0	64.0	38.0	52.0	58.0	20.0	46.7



(1) Representation visualization based on t-SNE

(2) Representation visualization based on Hierarchical Cluster

Figure 19: Analysis from the representation perspective on MCEVAL. Languages with similar syntax have closely related representations

Table 10: Preliminary explorations on the impact of finetuning across different languages on model performance.

Setting	Python	Scheme	TypeScript	JavaScript	AWK
CodeQwen1.5-base	38.0	34.0	**52.0**	**52.0**	38.0
+ Python	**48.0**	12.0	0.0	0.0	**40.0**
+ Python&Scheme&TypeScript&AWK	44.0	**38.0**	50.0	48.0	**42.0**

A.11 DETAILED RELATED WORK

Code Large Language Model. In recent years, numerous large language models (LLMs) have been developed specifically for code-related tasks. For the field of soft engineering, code LLMs (Feng et al., 2020; Chen et al., 2021; Scao et al., 2022; Li et al., 2022; Allal et al., 2023; Fried et al., 2022; Wang et al., 2021; Zheng et al., 2024; Guo et al., 2024) pre-trained on billions of code snippets, such as StarCoder (Li et al., 2023; Lozhkov et al., 2024), CodeLlama (Rozière et al., 2023), DeepSeekCoder (Guo et al., 2024), and Code-Qwen (Bai et al., 2023). The development and refinement of code LLMs have been pivotal in automating software development tasks, providing code suggestions, and supporting code generation/translation.

To improve the performance of code generation, researchers used optimized prompts (Liu et al., 2023a; Reynolds & McDonell, 2021; Zan et al., 2023; Beurer-Kellner et al., 2023), bring test cases (Chen et al., 2023) and collaborative roles (Dong et al., 2023). There are also some related studies on using large language models for other code tasks, such as dynamic programming (Dagan et al., 2023), compiler optimization (Cummins et al., 2023), multi-lingual prompts (Di et al., 2023), and Program of Thoughts (Chen et al., 2022).

Code Evaluation. In the domain of code evaluation, a rich tapestry of benchmarks (Zheng et al., 2023b; Yu et al., 2024; Yin et al., 2023; Peng et al., 2024; Khan et al., 2023; Orlanski et al., 2023) has been woven to address the challenges of accurately assessing code quality, functionality, and efficiency, such as HumanEval (Chen et al., 2021), MBPP (Austin et al., 2021), their upgraded version EvalPlus (Liu et al., 2023b). Studies have explored a variety of approaches, ranging from static analysis techniques (e.g. exact match (EM) and edit similarity (ES)), which examine code without executing it, to dynamic methods that involve code execution in controlled environments (e.g. Pass@k). The current benchmarks support code models to evaluate a series of different types of tasks, such as code understanding, function calling (Zhuo et al., 2024), code repair (Lin et al., 2017; Tian et al., 2024; Jimenez et al., 2023; Zhang et al., 2023; Prenner & Robbes, 2023; He et al., 2022), code translation (Yan et al., 2023). Recently, many works Wei et al. (2023); Zhuo et al. (2024) have leveraged LLMs to construct large-scale evaluation datasets and instruction-tuning corpora, further enhancing the evaluation and performance of code models. In our work, we used a similar approach to construct an instruction dataset and proposed the Cross-lingual Code Transfer method to expand the number of languages to 40. Some recent works pay attention to the multilingual scenarios (Cassano et al., 2023; Wang et al., 2023; Athiwaratkun et al., 2023; Zheng et al., 2023a; Peng et al., 2024; Zheng et al., 2023b) by extending the existing python-only HumanEval or MBPP benchmark, such as MultiPL-E (Cassano et al., 2023) and MBXP (Athiwaratkun et al., 2023), which is challenged by the number of the covering languages and data leaking problem (Li et al., 2023; Jain et al., 2024).