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# CodeScope: An Execution-based Multilingual Multitask Multidimensional Benchmark for Evaluating LLMs on Code Understanding and Generation

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# Motivations

Existing benchmarks for evaluating the code understanding and generation capacities of LLMs suffer from severe limitations:

01

### Limited Language and Task Scope

Most benchmarks are insufficient as they focus on a narrow range of programming languages and specific tasks.

02

### Neglecting Executability and Consistency

Most benchmarks fail to consider the actual executability and the consistency of execution results of the generated code.

# Related Work

| Benchmark | Execution-Based | Multilingual | Multitask | Multidimensional |
|---|---|---|---|---|
| HumanEval | ✓ | ✗ | ✗ | ✗ |
| MBPP | ✓ | ✗ | ✗ | ✗ |
| CodeXGlue | ✗ | ✓(9) | ✓(10) | ✗ |
| XLCoST | ✗ | ✓(7) | ✓(5) | ✗ |
| MathQA | ✓ | ✗ | ✗ | ✗ |
| MBXP | ✓ | ✓(13) | ✗ | ✗ |
| ClassEval | ✓ | ✗ | ✗ | ✗ |
| MultiPL-E | ✓ | ✓(18) | ✗ | ✗ |
| AiXBench | ✓ | ✗ | ✗ | ✗ |
| DS-1000 | ✓ | ✗ | ✗ | ✗ |
| APPS | ✓ | ✗ | ✗ | ✗ |
| HumanEval-X | ✓ | ✓(5) | ✓(2) | ✗ |
| XCodeEval | ✓ | ✓(11) | ✓(5) | ✗ |
| **CodeScope** | ✓ | ✓(43) | ✓(8) | ✓ |

**Comparisons between our CodeScope and existing code evaluation benchmarks.**

# Introduction

**CodeScope**, a benchmark that evaluates the coding proficiency of LLMs using **execution-based** metrics in a **multilingual** and **multitask** setting. CodeScope consists of **eight tasks** for code understanding and generation, covering **43 programming languages**. We develop a multilingual code execution engine, **MultiCodeEngine**, which supports the compilation and execution of **14 programming languages**.

| Category | Dimension | Task | #Lang. | #Samples | Length |
|---|---|---|---|---|---|
| Understanding | Length | Code Summarization | 43 | 4,838 | 385 |
| | | Code Smell | 2 | 200 | 650 |
| | | Code Review | 9 | 900 | 857 |
| | | Automated Testing | 4 | 400 | 251 |
| Generation | Difficulty | Program Synthesis | 14 | 803 | 538 |
| | | Code Translation | 14 | 5,382 | 513 |
| | | Code Repair | 14 | 746 | 446 |
| | Efficiency | Code Optimization | 4 | 121 | 444 |

**Summary of our CodeScope.**

# Contributions

01 **CodeScope benchmark**: We built the first-ever comprehensive benchmark for evaluating LLMs on code understanding and generation tasks.

02 **Multidimensional fine-grained evaluation**: We comprehensively evaluate the performance of LLMs on eight tasks from three dimensions (length, difficulty, efficiency).

03 **Comprehensive evaluations and in-depth analyses**: We evaluate the coding capabilities of eight mainstream LLMs and conduct comprehensive validations and analyses of the utility of the CodeScope benchmark.

# Multidimensional Evaluation

| Code Summarization | | | | | |
|---|---|---|---|---|---|
| Model | Short | Medium | Long | Avg. | SD |
| GPT-4 | 33.78 | 33.27 | 33.88 | **33.66** | 0.33 |
| GPT-3.5 | 33.21 | 32.87 | 33.51 | 33.14 | **0.32** |
| Vicuna | 32.12 | 32.21 | 31.62 | 32.06 | **0.32** |
| WizardCoder | 32.85 | 32.05 | 29.01 | 31.99 | 2.03 |
| Code LLaMA | 32.39 | 31.36 | 28.59 | 31.52 | 1.97 |
| LLaMA 2 | 32.03 | 31.25 | 29.34 | 31.40 | 1.38 |
| StarCoder | 31.63 | 30.69 | 30.08 | 31.18 | 0.78 |
| PaLM 2 | 31.83 | 29.95 | 24.20 | 30.27 | 3.98 |

| Code Smell | | | | | |
|---|---|---|---|---|---|
| Model | Short | Medium | Long | Avg. | SD |
| WizardCoder | 45.09 | 48.29 | 53.03 | **48.80** | **3.99** |
| LLaMA 2 | 41.13 | 31.77 | 49.28 | 40.73 | 8.76 |
| Vicuna | 38.94 | 30.66 | 39.54 | 36.38 | 4.96 |
| GPT-4 | 30.44 | 40.02 | 37.60 | 36.02 | 4.98 |
| PaLM 2 | 28.48 | 41.61 | 36.14 | 35.41 | 6.60 |
| GPT-3.5 | 29.12 | 38.13 | 37.55 | 34.93 | 5.04 |
| Code LLaMA | 34.78 | 40.79 | 24.10 | 33.22 | 8.45 |
| StarCoder | 28.75 | 19.79 | 14.13 | 20.89 | 7.37 |

| Code Review | | | | | |
|---|---|---|---|---|---|
| Model | Short | Medium | Long | Avg. | SD |
| Code LLaMA | 39.34 | 44.70 | 43.66 | **42.57** | 2.84 |
| GPT-4 | 44.08 | 39.93 | 41.69 | 41.90 | 2.08 |
| LLaMA 2 | 45.74 | 40.05 | 39.14 | 41.64 | 3.58 |
| PaLM 2 | 41.56 | 42.13 | 39.79 | 41.16 | **1.22** |
| Vicuna | 43.92 | 38.70 | 40.43 | 41.02 | 2.66 |
| GPT-3.5 | 45.75 | 37.88 | 34.56 | 39.40 | 5.75 |
| WizardCoder | 32.68 | 41.05 | 43.36 | 39.03 | 5.62 |
| StarCoder | 45.34 | 39.02 | 32.20 | 38.85 | 6.57 |

| Automated Testing | | | | | |
|---|---|---|---|---|---|
| Model | Short | Medium | Long | Avg. | SD |
| GPT-3.5 | 87.49 | 86.37 | 80.91 | **84.92** | 3.52 |
| PaLM 2 | 84.52 | 81.97 | 80.38 | 82.29 | 2.09 |
| LLaMA 2 | 83.46 | 80.48 | 80.27 | 81.40 | 1.78 |
| Code LLaMA | 82.65 | 79.34 | 80.27 | 80.75 | **1.71** |
| WizardCoder | 82.25 | 82.13 | 77.87 | 80.75 | 2.49 |
| StarCoder | 78.70 | 80.77 | 72.96 | 77.48 | 4.05 |
| GPT-4 | 80.80 | 75.03 | 75.33 | 77.05 | 3.25 |
| Vicuna | 75.19 | 74.85 | 79.15 | 76.40 | 2.39 |

| Length | | |
|---|---|---|
| Model | Overall | Avg.(SD) |
| WizardCoder | 50.14 | 3.53 |
| LLaMA 2 | 48.79 | 3.88 |
| GPT-3.5 | 48.10 | 3.66 |
| PaLM 2 | 47.28 | 3.47 |
| GPT-4 | 47.16 | 2.66 |
| Code LLaMA | 47.02 | 3.74 |
| Vicuna | 46.47 | 2.68 |
| StarCoder | 42.10 | 4.69 |

**Length-dimension**

**(Short, Medium, Long)**

# Multidimensional Evaluation

## Difficulty-dimension

## (Easy & Hard)

| Program Synthesis | | | | Code Translation | | | | Code Repair | | | | Difficulty | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Model** | **Easy** | **Hard** | **Avg.** | **Model** | **Easy** | **Hard** | **Avg.** | **Model** | **Easy** | **Hard** | **Avg.** | **Model** | **Overall** |
| GPT-4 | 58.57 | 12.01 | **36.36** | GPT-4 | 40.26 | 22.06 | **31.29** | GPT-4 | 43.56 | 14.04 | **30.03** | GPT-4 | **32.56** |
| GPT-3.5 | 39.29 | 4.96 | 22.91 | GPT-3.5 | 28.50 | 14.03 | 21.37 | GPT-3.5 | 18.56 | 7.60 | 13.54 | GPT-3.5 | 19.27 |
| Code LLaMA | 7.14 | 0.26 | 3.86 | WizardCoder | 8.83 | 3.24 | 6.07 | PaLM 2 | 7.43 | 7.02 | 7.24 | WizardCoder | 4.85 |
| WizardCoder | 5.95 | 0.26 | 3.24 | StarCoder | 5.75 | 1.89 | 3.85 | Wizardcoder | 4.95 | 5.56 | 5.23 | PaLM 2 | 4.25 |
| PaLM 2 | 3.81 | 0.78 | 1.99 | PaLM 2 | 5.27 | 1.70 | 3.51 | Code LLaMA | 4.21 | 3.51 | 3.89 | Code LLaMA | 3.68 |
| LLaMA 2 | 1.43 | 0.00 | 0.75 | Code LLaMA | 4.91 | 1.66 | 3.31 | Vicuna | 3.47 | 2.34 | 2.95 | StarCoder | 2.39 |
| StarCoder | 0.95 | 0.00 | 0.50 | LLaMA 2 | 1.10 | 0.26 | 0.69 | Starcoder | 2.23 | 3.51 | 2.82 | Vicuna | 1.24 |
| Vicuna | 0.71 | 0.00 | 0.37 | Vicuna | 0.62 | 0.19 | 0.41 | LLaMA 2 | 1.49 | 1.46 | 1.47 | LLaMA 2 | 0.97 |

# Multidimensional Evaluation

| Model | Python | | C | | C++ | | C# | | Overall |
|---|---|---|---|---|---|---|---|---|---|
| | Memory | Time | Memory | Time | Memory | Time | Memory | Time | |
| GPT-4 | 46.67 | 36.67 | 43.33 | 6.67 | 29.04 | 3.23 | 36.67 | 23.33 | **28.20** |
| GPT-3.5 | 40.00 | 20.00 | 76.67 | 6.67 | 29.03 | 19.35 | 0.00 | 20.00 | 26.46 |
| WizardCoder | 50.00 | 16.67 | 50.00 | 0.00 | 38.71 | 12.90 | 10.00 | 16.67 | 24.37 |
| Code LLaMA | 43.33 | 13.33 | 40.00 | 0.00 | 35.48 | 3.22 | 10.00 | 23.33 | 21.09 |
| PaLM 2 | 20.00 | 13.33 | 20.00 | 0.00 | 6.45 | 6.45 | 0.00 | 6.67 | 9.11 |
| StarCoder | 20.00 | 6.67 | 13.33 | 0.00 | 16.13 | 0.00 | 3.33 | 6.67 | 8.27 |
| LLaMA 2 | 16.67 | 3.33 | 16.67 | 6.67 | 6.45 | 0.00 | 6.67 | 0.00 | 7.06 |
| Vicuna | 20.00 | 6.67 | 13.33 | 0.00 | 6.45 | 0.00 | 0.00 | 6.67 | 6.64 |

**Efficiency-dimension**

**(Memory & Time)**

# Results Analysis & Comparison

| Ranking | CodeScope (Understanding) | CodeScope (Generation) | CodeScope (Overall) | HumanEval Pass@1 | MBPP Pass@1 |
|---|---|---|---|---|---|
| 1 | WizardCoder (50.14) | GPT-4 (31.47) | GPT-4 (39.31) | GPT-4 (67.0) | GPT-4 (61.8) |
| 2 | LLaMA 2 (48.79) | GPT-3.5 (21.07) | GPT-3.5 (34.58) | WizardCoder (57.3) | Code LLaMA (57.0) |
| 3 | GPT-3.5 (48.10) | WizardCoder (9.73) | WizardCoder (29.94) | GPT-3.5 (48.1) | GPT-3.5 (52.2) |
| 4 | PaLM 2 (47.28) | Code LLaMA (8.04) | Code LLaMA (27.53) | Code LLaMA (41.5) | WizardCoder (51.8) |
| 5 | GPT-4 (47.16) | PaLM 2 (5.46) | PaLM 2 (26.37) | PaLM 2 (37.6) | PaLM 2 (50.0) |
| 6 | Code LLaMA (47.02) | StarCoder (3.86) | LLaMA 2 (25.64) | StarCoder (33.6) | LLaMA 2 (45.4) |
| 7 | Vicuna (46.47) | Vicuna (2.59) | Vicuna (24.53) | LLaMA 2 (30.5) | StarCoder (43.6) |
| 8 | StarCoder (42.10) | LLaMA 2 (2.49) | StarCoder (22.98) | Vicuna (15.2) | Vicuna (22.4) |

**Comparison of results of eight baseline models on CodeScope, HumanEval and MBPP benchmarks.**

# Conclusion

**Multilingual**

**43 programming languages**

**Multitask**

**8 coding tasks**

**CodeScope**

**Multidimensional**

**3 evaluation dimensions**

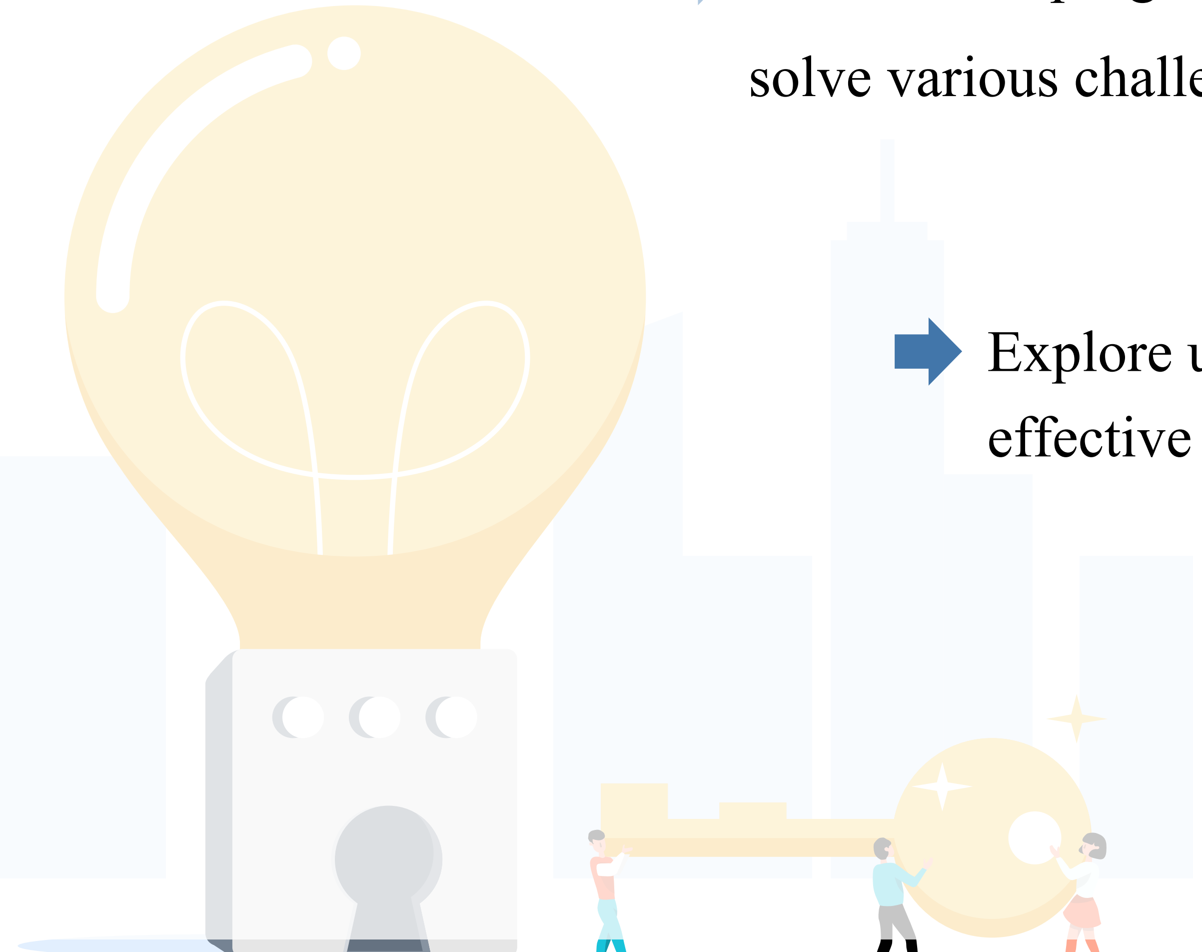
**Execution-based**

**MultiCodeEngine** (14 programming languages)

# Further Work

- Enhance the programming capabilities of **LLMs** to directly solve various challenging problems.

- Explore using autonomous **agents** to achieve a more effective collaborative division of labor



# Limitations

## DATA LEAKAGE

- Data memorization and recitation represent a unique form of knowledge capability.
- Constructing a fully zero-leakage evaluation dataset is technically unfeasible.
- The ability to generalize downstream tasks beyond data memorization.

# Thank you!

For more details, please see paper & Github.

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