

TaskEval: Assessing Difficulty of Code Generation Tasks for Large Language Models

FLORIAN TAMBON*, SnT, University of Luxembourg, Luxembourg

AMIN NIKANJAM*, Huawei Distributed Scheduling and Data Engine Lab, Canada

CYRINE ZID, Polytechnique Montreal, Canada

FOUTSE KHOMH, Polytechnique Montreal, Canada

GIULIANO ANTONIOL, Polytechnique Montreal, Canada

Large Language Models (LLMs) excel in code-related tasks like code generation, but benchmark evaluations often overlook task characteristics, such as difficulty. Moreover, benchmarks are usually built using tasks described with one single prompt, despite the formulation of prompts having a profound impact on the outcome. This paper introduces a generalist approach, TaskEval, a framework using diverse prompts and Item Response Theory (IRT) to efficiently assess LLMs' capabilities and benchmark task characteristics, improving the understanding of their performance.

Using two code generation benchmarks, *HumanEval+* and *ClassEval*, as well as 5 code generation LLMs, we show that *TaskEval* is capable of characterizing the properties of tasks. Using topic analysis, we identify and analyze the tasks of respectively 17 and 21 topics within the benchmarks. We also cross-analyze tasks' characteristics with programming constructs (e.g., variable assignment, conditions, etc.) used by LLMs, emphasizing some patterns with tasks' difficulty. Finally, we conduct a comparison between the difficulty assessment of tasks by human-annotators and LLMs. Orthogonal to current benchmarking evaluation efforts, *TaskEval* can assist researchers and practitioners in fostering better assessments of LLMs. The tasks' characteristics can be used to identify shortcomings within existing benchmarks. This could be used to generate additional related tasks for the evaluation or improvement of LLM.

CCS Concepts: • **Do Not Use This Code → Generate the Correct Terms for Your Paper;** *Generate the Correct Terms for Your Paper*; Generate the Correct Terms for Your Paper; Generate the Correct Terms for Your Paper.

Additional Key Words and Phrases: Do, Not, Us, This, Code, Put, the, Correct, Terms, for, Your, Paper

ACM Reference Format:

Florian Tambon, Amin Nikanjam, Cyrine Zid, Foutse Khomh, and Giuliano Antoniol. 2025. TaskEval: Assessing Difficulty of Code Generation Tasks for Large Language Models. *J. ACM* 37, 4, Article 111 (August 2025), 32 pages. <https://doi.org/XXXXXX.XXXXXXX>

*Work done while at Polytechnique Montreal.

Authors' Contact Information: [Florian Tambon](mailto:florian.tambon@uni.lu), florian.tambon@uni.lu, SnT, University of Luxembourg, Luxembourg, Luxembourg; Amin Nikanjam, amin.nikanjam@h-partners.com; amin.nikanjam@polymtl.ca, Huawei Distributed Scheduling and Data Engine Lab, Toronto, Ontario, Canada; Cyrine Zid, cyrine.zid@polymtl.ca, Polytechnique Montreal, Montreal, Quebec, Canada; Foutse Khomh, foutse.khomh@polymtl.ca, Polytechnique Montreal, Montreal, Quebec, Canada; Giuliano Antoniol, giuliano.antoniol@polymtl.ca, Polytechnique Montreal, Montreal, Quebec, Canada.

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from permissions@acm.org.

© 2025 Copyright held by the owner/author(s). Publication rights licensed to ACM.

Manuscript submitted to ACM

1 Introduction

Large Language Models (LLMs) have been widely used for various code-related tasks in Software Engineering (SE) [16, 40, 52, 54]. Although the performance of LLMs in generating code for different programming languages, such as Python, Java, and C [34, 45, 80] is promising, the LLM-generated code, like human-written code, is not flawless. Researchers have already acknowledged that LLM-generated code is prone to bugs [52, 65], and may suffer from vulnerability [36, 48, 67] and quality issues [79].

Generally, to assess LLMs on code generation tasks and compare them to each other, well-known benchmarks such as HumanEval [14, 45], MBPP [11], CoderEval [80], and ClassEval [20] are used. These benchmarks are obtained by handcrafting programming tasks or mining existing public repositories on GitHub and filtering them. In this way, the code generation capability of LLMs in programming tasks is assessed indirectly at the benchmark level based on general characteristics such as granularity level (e.g., function level being less difficult than class level) and through general metrics such as accuracy or Pass@k over the benchmark [14]. However, this limits the evaluation of the LLMs at the task level as the metric can only report aggregated results over a set of tasks. Moreover, most benchmarks only contain a single prompt for each task within the benchmark and recent studies [51, 71] showed that the way prompts are formulated has a high impact on the quality of LLM's output. As such, there is a need for a more fine-grained analysis of the evaluation of the capability of the LLMs at the *task-level*, that goes beyond general aggregation metrics. Better task-level analysis could also pave the way for more advanced and customized benchmarks, as traditional benchmarks have several limitations such as data contamination, adequate coverage of LLMs' ability, reliability, and robustness [32, 39, 50].

In the field of test theory, Item Response Theory (IRT) [12] was developed precisely to overcome the limitation of considering only an aggregation of the score rather than individual questions. To achieve this, an IRT model estimates a specific ability for each respondent (e.g., a student taking a test or an LLM being evaluated) based on their responses to a set of items (such as questions). These items have in turn some *characteristics*, for instance, a difficulty level, estimated by the respondents' answers as well. Contrary to using plain metrics such as Accuracy which do not account for the difference between items (i.e. all LLMs replying correctly on an item vs one LLM replying correctly to it is counted the same for the LLM being correct), IRT will consider each item independently and in conjunction allowing for a more fine-grained analysis. Moreover, by using IRT and the LLMs themselves, we can go beyond using human assessments as a proxy for concepts such as difficulty. Indeed, given that LLMs' perception of tasks might differ from humans [37, 55], LLMs' grasping of concepts is likely not to be aligned with humans. Recent studies [13, 68, 82] used IRT to assess the characteristics of the questions in a benchmark for an LLM. However, these studies present several limitations. First, they did not focus on code-based benchmarks, which have some differences compared to more classical Natural Language Processing (NLP) tasks. In addition, the assessment is generally conducted via a *single* prompt, which could affect the output of the LLM. Finally, the studies focused mainly on questions for which a single binary (true/false) answer is given. This limits the application of the methods when multiple code generations should be considered, as is the case when using non-deterministic temperature-based sampling for LLMs. Thus, current benchmarks' usage and assessment paint a general, yet incomplete picture, as they fail to provide a fine-grained analysis of individual tasks within a benchmark, accounting for variability in the prompt. To address this issue, we propose *TaskEval*, a framework for the evaluation, identification, and analysis of the difficulty of programming tasks for LLMs.

TaskEval is orthogonal to the usage of existing benchmarks and works on top of available benchmarks. *TaskEval* starts by generating a variety of prompts for each task on two well-known code generation benchmarks, HumanEval+

[14] and ClassEval [20], representing multiple possible formulations per task. For each programming task, we craft prompts with different levels of context information and distinctive phrasing to represent diverse possible wording of the task using GPT-4, resulting in 18 different prompts per task. The framework then queries an array of 5 LLMs, named CodeLLMs (i.e., CodeLLama 7B [59], MagiCoder 6.7B [77], DeepSeekCode 7B [28], CodeGemma 7B [66] and GPT-3.5 [1]) using the formulated prompts to obtain different outputs for every single task. Those outputs are then used to compute a task score per CodeLLM based on collected metrics from the obtained code snippets. The task scores are then processed using an IRT model to estimate the characteristics of each task (namely difficulty and discriminant) and the abilities of each model. From there, a more nuanced analysis can take place. We highlight the difference between the two benchmarks under study, showing that *ClassEval* tends to have more extreme tasks in terms of difficulty than *HumanEval+*. We further analyze the analysis by extracting from the available tasks, respectively 17 and 21 topics for both *HumanEval+* and *ClassEval*, highlighting some topics of interest (such as tasks dealing with sequences of numbers in *HumanEval+*) that tend to have a higher level of difficulty and be discriminant between CodeLLMs. We also analyze the prevalence of specific program constructs (e.g., variable assignments) by leveraging the Abstract Syntax Tree (AST) of the generated code, uncovering trends related to task characteristics. For example, we observe that the use of conditional statements increases with task difficulty, regardless of code length. Finally, we contrast the difficulty evaluated using *TaskEval* with human annotators and find a difference between both evaluations, emphasizing that the difficulty of the tasks for CodeLLMs should not be assessed by humans as is. To guide our study, we formulate the following Research Questions (RQs):

- RQ1** How do tasks' characteristics varies across benchmark?
- RQ2** Do tasks' topics affect their characteristics?
- RQ3** Do programming constructs affect tasks' characteristics?
- RQ4** Do human annotators and CodeLLMs rate tasks' difficulty similarly?

In summary, this paper makes the following contributions:

- We highlight the limitations of assessing difficulty using traditional evaluation with a single prompt.
- We present *TaskEval*, a framework for evaluating the characteristics of code generation tasks for LLMs,
- We perform a cross-analysis of task characteristics, examining their relation to task topics, program constructs (e.g., conditions, variable assignments) used in task codes, and comparisons with human annotators,
- We make the data and code used in our study publicly available for researchers to replicate our results [8].

The rest of this paper is organized as follows. In Section 3, we describe the methodology we followed to propose *TaskEval*. Our experimental setup for running *TaskEval* is detailed in Section 4. We report and then analyze the results obtained in Section 5. A discussion of our results and the insights for the community is presented in Section 6. We conclude the paper in Section 9 after discussing threats to the validity of our findings in Section 8.

2 Motivating examples

To motivate *TaskEval*, we will use two examples of tasks. In our study, we make the distinction between *task* and *prompt*: the *task* is the essence of the functionality to be implemented. For instance, “Quicksort” or “Fibonacci sequence” are examples of such tasks. A *prompt* is a way to formulate the task so it can be understood by and fed to an LLM. For instance, “Write a function to calculate the n-th element of the Fibonacci sequence.” or “Create a function to return the n-th element of the Fibonacci sequence. The Fibonacci sequence is defined as ...” are two instances of *prompts* for the *task* “Fibonacci sequence”. As such, each *task* can be expressed by many different (even infinite) *prompts*, including

different wordings, amount of contextual information about the task, like examples, etc. To compare the effect between *prompt* and *task*, we will thus calculate the difficulty using our proposed approach (Section 3) and a more traditional approach consisting of an ensemble method (i.e., how many CodeLLMs failed/managed the task). To emphasize the importance of using multiple prompts for estimating the task’s characteristics, our approach employs multiple prompts, in contrast to the traditional method, which relies solely on a single prompt (i.e., the original benchmark prompt). Moreover, to further contrast our results, we will compare with the difficulty as reported by human developers using a crowd-based approach (see Section 5.4).

```

1 def select_by_age_range(self, min_age, max_age):
2     """Generates a SQL statement to select records within a specified age range.
3     :param min_age: int. The minimum age.
4     :param max_age: int. The maximum age.
5     :return: str. The generated SQL statement.
6     >>> sql.select_by_age_range(20, 30)
7     'SELECT * FROM table1 WHERE age BETWEEN 20 AND 30;'
8     """
9
10 def select_by_age_range(self, min_age, max_age):
11     """ Generate a SQL statement to select records within a specified age range using
12     the "min_age" and "max_age" parameters. Return the generated SQL statement as a string.
13     :param min_age: int. The minimum age.
14     :param max_age: int. The maximum age.
15     :return: str. The generated SQL statement.
16     """

```

Listing 1. Example of discrepancy on a SQL task. (**Top**) Original Prompt, (**Bottom**) One of our generated prompt

In the first example (see Listing 1), which involves generating an SQL statement, all CodeLLMs manage to generate a correct code for this task using the original prompt. However, *TaskEval* returns a difficulty of 0.75 (out of 1) on this task, making it a quite complex task. As one can see from the example prompts, the main difference stems from the fact that our prompts will not contain the example included in the original prompt which basically gives what the SQL statement should be like. As such, without this help, the task becomes much harder for the CodeLLMs. And so, while the original prompt might be considered easy, the task itself is not easy, as many potentially generated prompts would not lead to a correct code. If we compare with human assessment, developers agreement settles on a difficulty of 3/6 (given the scale used in our experiment), meaning it is a task of relative medium difficulty. In the second example (see Listing 2), which involves checking if an array is correctly sorted in ascending order without more than one duplicate, all CodeLLMs failed to generate a correct code when using the single prompt. For all CodeLLMs, the main source of error is the handling of duplicates. We believe this issue arises because CodeLLMs struggle with cases involving “multiple duplicates”, and the provided examples are insufficient. However, by varying the prompts, the difficulty level computed by our approach is 0.17 – a relatively low value, among the lowest in this benchmark. Moreover, slight modifications to the prompt can lead to better-generated code compared to relying solely on the original prompt. For instance, the example we give in Listing 2 shows that by wording the condition with “appears more than twice”, the CodeLLMs manage to generate more correct codes. Note that, in that case, having an example did not appear to have helped the CodeLLMs generate a correct code, contrary to reformulating or adding information to the prompt. Through these examples, we see that traditional assessment may be limited in accurately evaluating the characteristics of tasks, which can, in turn, hinder benchmark analysis. If we compare with human assessment, developers agreement settles on a

difficulty of 4/6 (given the scale used in our experiment), meaning it is also a task of relative medium difficulty. All in all, we observe that difficulty can drastically change for LLMs based on the formulation of the prompts and that it also contrasts with human judgment of the tasks.

```

1 def is_sorted(lst):
2     """Given a list of numbers, return whether or not they are sorted in ascending order. If list has
3         more than 1 duplicate of the same number, return False. Assume no negative numbers and only
4         integers.
5
6     Examples
7     is_sorted([5]) -> True
8     ...
9     is_sorted([1, 2, 2, 2, 3, 4]) -> False
10    """
11
12    def is_sorted(lst):
13        """ Write a function named 'is_sorted' that checks if a given list of non-negative integers is
14            sorted in ascending order. Additionally, the function should return False if any integer appears
15            more than twice in the list.
16        """

```

Listing 2. Example of discrepancy on a Sorting Task. (**Top**) Original Prompt, (**Bottom**) One of our generated prompt

3 TaskEval

In this section, we discuss the methodology followed to propose *TaskEval*. After an overview of the framework, we describe how we generate different prompts for programming tasks. We then delve into the details of leveraging CodeLLMs to generate code for our prompts, fitting the IRT model and measuring the characteristics of tasks for CodeLLMs.

3.1 General Overview of *TaskEval*

TaskEval uses existing benchmarks to operate. Such benchmarks are generally composed of an ensemble of *tasks* which are represented by a single *prompt* per task. *TaskEval* aims to evaluate the characteristics of those *tasks*, and not of the prompts, for CodeLLMs to probe benchmarks and analyze their behavior regarding those tasks (too difficult? too easy? etc.)

A general overview of *TaskEval* is given in Figure 1. *TaskEval* is operated in four steps: ① First, transformations on the prompts are identified. Those transformations are any dimension that can lead to a variety of prompts for an LLM while keeping the essence of the task. In a way, such transformations can be seen as some metamorphic transformations [15] as they should not alter the semantics of the task. In our study, we focus on two transformations: *Rephrasing* and *Context Information*. Those transformations are then used in conjunction with each task to have a *Prompt LLM* generate prompts following the transformations' specifications. ② Secondly, the obtained prompts are fed into multiple CodeLLMs to generate code. The goal is to evaluate how each CodeLLM performs when confronted with different prompts. Using multiple CodeLLMs allows us to capture the diversity of architectures and training settings, which may respond differently to a given prompt. From the generated code, various metrics are extracted to assess performance for each task in the benchmark ③a. More precisely, task prompts will be processed using a topic modeling algorithm to cluster them into broader categories (e.g., sorting algorithms, SQL queries, etc.). The generated code will be parsed using

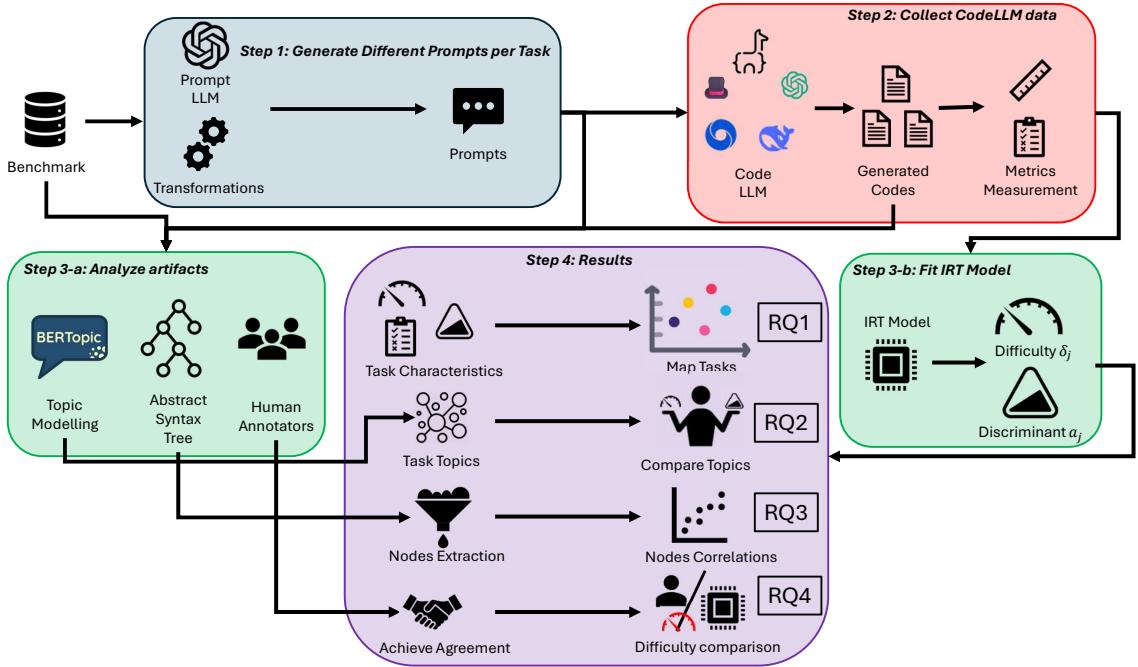


Fig. 1. Overview of *TaskEval* Framework.

its Abstract Syntax Tree (AST), and we have collected human annotators' difficulty assessments for comparison. More details can be found in Section 4.5. In parallel, various IRT models [12] are fitted on the data. These models estimate latent attributes of items and respondents based on observed responses. In our case, the tasks serve as items, while the CodeLLMs act as respondents (3b). Once we have collected both the parameters and artifacts of the tasks, we can perform various analyses. First, we examine the tasks in the *HumanEval+* and *ClassEval* benchmarks based on their characteristics. This enables us to compare them and establish a mapping between the two benchmarks. Then, we use our collected metrics (e.g., topics, AST structures, and human annotations) to further describe and contrast tasks both within and across benchmarks (4).

3.2 Generating Different Prompts based on Transformations

The first step involves choosing transformations to generate different prompts for the task. We want those transformations to introduce variabilities in our prompts to represent the many ways a CodeLLM could be prompted for the same task. However, those transformations should not introduce changes that alter the semantics of the tasks. In our case, we use two types of such transformations, but any number could be used and combined.

First, we use the *Context Information* transformation. Indeed, a straightforward way to act on the variability of a prompt is to simply disclose or withdraw certain information in the prompt, while not changing the task. EvoEval [78], for instance, proposes also to act on the difficulty. However, to modify the difficulty, they do so by adding/removing constraints in the prompt, thus modifying the semantics of the task, which is not desirable in our case. In our study, we instead propose to divide the information provided in the prompt into three levels. Those three levels of prompts are

generated incrementally using the previous level as the starting point. We assume that prompts with more information should be more likely to lead to correct code for CodeLLMs [19, 78]. The levels are defined such as:

- *First level*: contains a minimal amount of information that is the inputs/outputs of the task as well as a high-level description of what is intended. We could use the original prompt in benchmarks for each task as the first level, yet Siddiq et al. [64] showed that there can be inconsistencies across tasks' prompts in benchmarks. Thus, we prefer to generate a new prompt to have similar formatting across all tasks and levels to reduce biases. This level is the closest one to the original prompt in benchmarks and contains the same level of information regarding the tasks.
- *Second level*: further adds in the prompt a description of the targeted function in natural language using available oracle code. However, it does not include any direct reference to the function (variable names, helper functions used, ...) unless it was explicitly mentioned in the original prompt of the benchmark.
- *Third level*: complete the prompt with direct references to the function such as variable names, and helper functions used similarly to a pseudo-algorithm but in natural language.

We chose to devise these three levels based on our observations. They prove to generate a sufficient amount of fine-grainess and to discriminate between different levels of information. Trying to fit additional level (e.g, between level 1 and 2) did not lead to noticeable changes. We present an example of different prompt levels obtained for a task in Listing 3.

```

1 def unique(l: list):
2     Level1: """ Write a function named 'unique' that returns a sorted list of unique elements from a
3         given list. """
4     Level2: """ Write a function named 'unique' which takes a list as input and aims to return a
5         sorted list containing only the unique elements from the input list. The function should first
6         convert the list to a set to remove any duplicates and then convert it back to a list which
7         should be sorted before returning. """
8     Level3: """ Write a function named 'unique' which takes an input list 'l' and returns a list
9         containing only the unique elements from 'l', sorted in ascending order. The function should
10        first convert 'l' into a set, using 'set(l)', to remove any duplicates, then convert this set
11        back to a list, and finally return this list after sorting it in ascending order using 'sorted()
12        '.
13
14     return sorted(set(l))

```

Listing 3. Example of different prompt levels for the task *unique* from HumanEval+, with the oracle code at the bottom.

The second transformation used is *Rephrasing* which is paraphrasing a given prompt. Indeed, how the prompts or instructions are formulated has been shown to have an impact on LLM responses [51, 71, 75]. Thus, similarly to these studies, we try to see if different ways of rephrasing a given prompt for a CodeLLM can affect how the CodeLLM addresses the task. To rephrase our prompts, we will use a similar approach as done by Gonen et al. [25], that is prompting an LLM to rephrase a given text. Other techniques could be used to assist in rephrasing such as Chains-Of-Thoughts [76] but assessing the effectiveness of different rephrasing techniques is out-of-scope of this study.

Using those two transformations, we come up with general templates that can be used to generate prompts (see replication package [8]). Such general templates are then tailored for each task in the benchmark under consideration. Those templates are fed to a *Prompt LLM* (see Figure 1) to generate different prompts for a given task. The way prompts are generated is as follows: we start from the original docstring to have a common starting point for all prompts. Then, we apply the template to obtain different prompt levels with *Context Information* for a given task. Then, we apply the

obtained prompts to the *Rephrasing* template. In our case, we first remove the examples from the original prompt, if any, before using our templates with the *Prompt LLM*. While removing examples can decrease the performance of CodeLLMs [42], this allows for better control over the level of information we inject in our prompts. Indeed, examples can vary from simple basic examples to showcasing corner cases of the task. As such, this might artificially bias the output of CodeLLMs and the potential difficulty of the task because of the quality of the examples.

At each step of our generation, that is after using each template on the prompts, we do a sanity check by manually checking them. This is accomplished by the first author, and cross-checked by the second author independently. We make sure that the *Context Information* levels are respected and the *Rephrasing* does not alter the semantics of the tasks. This is done in order not to have tasks that are artificially considered hard further down the line because of misleading prompts for the CodeLLM and not because of the task itself.

3.3 Collecting metrics for code snippets

The second step is to gather metrics for a given task. To do so, we leverage several CodeLLMs that will serve as our evaluators for code generation. For each prompt per task, each CodeLLM is asked to generate code with varying seeds using the sampling mode of CodeLLMs. By seed, we mean a random number used in the sampling-based generation mode of CodeLLMs. The rationale is that most CodeLLMs, especially non-open-source ones, are used with this non-greedy approach in order to generate code. Moreover, using the sampling method for the generation allows us to have a wider variety of generated code in order to evaluate the difficulty of each task. Indeed, we assume an easier task should not be as impacted by the stochasticity of the generation compared to a harder task. The obtained code is then processed and executed. Sample codes were then executed against available test inputs in the benchmark.

Once we have obtained all code for all prompts of all tasks and executed them against tests, we collect different metrics. In our case, we are mainly interested in the *Functional* correctness of a code sample. *Functional* correctness quantifies if a given code sample is correct or not using available test cases. Formally, the *Functional* correctness $Func$ for a code sample s generated by CodeLLM LLM :

$$Func_{LLM}(s) = \begin{cases} 1 & \text{if } \forall (i, o) \in T, s(i) = o \\ 0 & \text{else} \end{cases} \quad (1)$$

where T is the set of test cases symbolized by an input i and an output o . That is, the code sample passes all test cases, i.e., gets a value of 1. Intuitively, we expect a harder task to lead to a lower number of prompts leading to correct codes across rephrasing and different levels of context information.

The previous score is obtained for a single code sample (i.e., using a single prompt and with a single seed). However, we want to obtain a score at the *task* level. Thus, we need to aggregate all scores for each prompt/seed of the same task. In the following, we note j for the task index, c_k for the k^{th} information context, r_l for the l^{th} rephrasing, and p for the seeded generation. As such, for example, $s_{1,c_1,r_1,1}$ is the code sample obtained for the first task, using the low-level information context with the first rephrasing with the first seed generated. As such, the aggregation over all variables for a task is as follows:

$$score_{LLM}(s_j) = \frac{1}{N_j} \sum_{c_k} \sum_{r_l} \sum_p Func_{LLM}(s_{j,c_k,r_l,p}) \quad (2)$$

where N_j is the total number of prompts for the task j . The final score $score_{LLM}(s_j)$ represents the score for the task j using a given LLM . We will use the scores for all CodeLLMs to determine the parameters of the task j .

3.4 Item Response Theory modelling

Since we have a metric measured across all tasks and multiple CodeLLMs, we can use these values as observed responses in an IRT model. IRT models, commonly used for analyzing and scoring psychological tests [81], have already been used in NLP settings [38, 57]. In the literature, several IRT models exist depending on the observed response distribution or the number of parameters of the model. A widely used model is the 2-Parameter (2PL) IRT model. Consider $j = 1, \dots, m$ items being assessed by $i = 1, \dots, n$ respondents, for example, students answering questions in an exam, leading to a true or false outcome $x_{ij} = 0, 1$, thus following a Bernoulli distribution of parameter p_{ij} . The 2PL IRT model in this case is defined as:

$$\mathbb{E}[p_{ij}|\theta_i, \delta_j, a_j] = \frac{1}{1 + e^{-a_j(\theta_i - \delta_j)}} \quad (3)$$

where θ_i is the ability of respondent i , δ_j is the difficulty, and a_j is discriminant of item j . The IRT model maps a respondent's ability to an expected response using the observed response through a logistic function with a difficulty parameter δ_j that indicates the "location" on the difficulty range, and a discriminant parameter a_j , discriminating items based on their difficulty and the ability of the respondents, reflected in the steepness of the slope of the item characteristic curves. Each parameter can be estimated using maximum likelihood. In our case, we do not have a binary response but a continuous one, as the aggregated score at the task level has a value in [0,1]. As such, we will rely on the β^3 -IRT model proposed by Chen et al. [17] which models the observed response as a continuous value in (0, 1) using a Beta distribution. The expected response for the model is defined as:

$$\mathbb{E}[p_{ij}|\theta_i, \delta_j, a_j] = \hat{p}_{ij} = \frac{1}{1 + \frac{\delta_j}{1-\delta_j} \times \frac{\theta_j}{1-\theta_j}^{-a_j}} \quad (4)$$

where p_{ij} is the response of respondent i for item j defined as $p_{ij} \sim B(\frac{\theta_i}{\delta_j}^{a_j}, \frac{1-\theta_i}{1-\delta_j}^{a_j})$, $\theta_i \sim Beta(1, 1)$, $\delta_j \sim Beta(1, 1)$ and $a_j \sim Normal(1, 1)$. In our approach, a respondent will be one of our CodeLLMs, an item one task from a benchmark, and p_{ij} is the score $score_{LLM}(s_j)$ on this task by the given CodeLLM as calculated in Equation 2. The parameters are estimated based on the observed response of the CodeLLM (i.e., the score) using Maximum Likelihood Estimation.

To illustrate the response obtainable given the different parameters, in Figure 2, we present a theoretical Item Characteristic Curve (ICC) mapping the ability of a CodeLLM with ability θ_i to the expected response $\mathbb{E}[p_{ij}|\theta_i, \delta_j, a_j]$ following the Equation 4 for four different tasks (in plain traits in Figure 2, each with its values of δ_j and a_j). It should be noted that since we are using functional correctness as our metric, the expected response translates to the likelihood of generating a correct code for a given task and CodeLLM, which is easily interpretable.

From the different curves of Figure 2, we can deduce the parameters of the different hypothetical tasks. Indeed, mathematically, the location parameter δ_j (the difficulty) corresponds to the ability value θ_i for which the expected response is 0.5 (black dashed line in Figure 2) while the discriminant a_j is such that the slope of the curve is $a_j/(4 \times \delta_j \times (1 - \delta_j))$ at that point (for example, the blue dashed line for the blue item). This explains why the blue task has a difficulty of 0.3 and a discriminant of 0.5.

For a task j , δ_j and a_j will ultimately affect how likely a given CodeLLM is to answer this task according to the IRT model: for instance, still for the blue task, a CodeLLM of ability 0.7 has an expected response of 0.7. For tasks that have the same a_j but different δ_j , the expected response is always higher for a CodeLLM with higher ability θ_i : for instance, the expected response on the green task is always higher compared to the black task no matter the CodeLLM ability, as the difficulty of the green task is lower. In that sense, the difficulty is enough to characterize a task. This is particularly

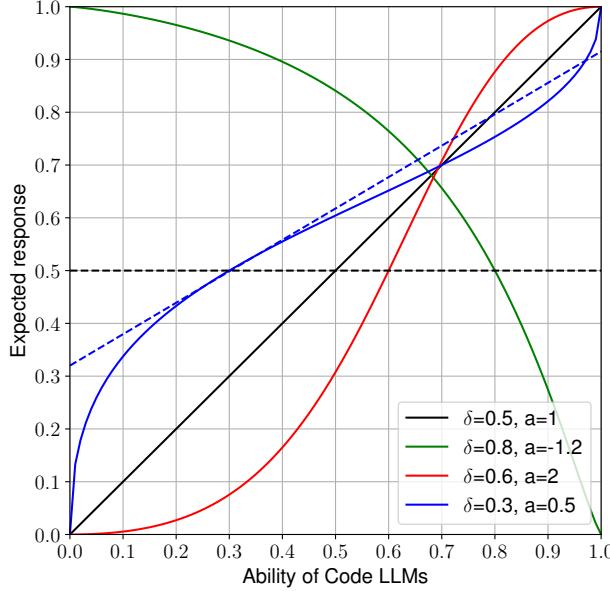


Fig. 2. ICC between ability θ_i of a CodeLLM and the expected response $\mathbb{E}[p_{ij}|\theta_i, \delta_j, a_j]$ for four tasks with different δ_j and a_j values.

used in the 1PL IRT model (i.e., Equation 4 with $\forall j, a_j = 1$). However, while it is easier to analyze, it is not necessarily the most realistic modelling. For instance, some tasks can have a disproportionate higher/lower expected response for different CodeLLMs of different capacities. This can arise, for instance, if these CodeLLMs were less trained on data similar to this particular task, and are more sensitive to how the task could be phrased. To account for this fact, the 2PL model offers a discriminant coefficient a_j for each task.

When the discriminant starts changing, a higher difficulty equaling a lower expected response no matter the CodeLLM is not always true: still in Figure 2, despite the black task being “easier” than the red one (difficulty of 0.5 compared to 0.6), CodeLLMs with an ability higher than 0.6 will have a higher expected response on the red task. Effectively, the red task is more discriminant than the blue task, as it better separates CodeLLMs according to their capacity. As $a_j \in \mathbb{R}$, it is even possible for $a_j < 0$ (green curve in Figure 2): in that case, a task can lead to a higher expected answer for a CodeLLM with a lower ability even with a higher difficulty. That last case can be indicative of potential noise [17], annotation errors [57] or could point towards actual tasks that less capable CodeLLMs have an easier time on for several possible reasons: more facilities with the given input prompts, non-determinism in the generation, example that was memorized or that is similar to what the model was trained on.

4 Experimental setup

4.1 Hyperparameters used

To have different prompts, we choose to generate 3 levels and 6 rephrasings per level. We chose those parameters as the trade-off between generating diverse enough prompts while limiting the amount to generate. For a benchmark of n tasks, this effectively means we have to generate $18 \times n$ prompts. We further ask each *CodeLLM* to generate 5 code samples per individual prompt resulting in $90 \times n$ code samples for each *CodeLLM* to generate. As an example, for a benchmark containing 200 tasks, this process yields **18,000** generated code for our evaluation *per CodeLLM*. We make available all the prompts and code generated in our replication package [8].

4.2 Benchmark used

In our experiment, we chose two benchmarks: HumanEval+ [45] and ClassEval [20]. Those benchmarks were chosen as they cover different types of tasks and dependency levels. HumanEval+ is widely used as a standard benchmark in code generation [3]. It is an extended variant of HumanEval [14], that contains more tests to assess the correctness of code samples. The benchmark consists of 164 handwritten Python programming problems with a function signature, docstring, body and several unit tests. HumanEval+ tasks are at the function level dependency as they do not require external libraries, besides Python standard library, or class/file contexts to be operated. For the original prompt, we use the docstring as given in HumanEval+.

ClassEval is a benchmark of 100 handcrafted classes coded in Python. Each class contains a description and on average 4 methods each with a docstring. We consider a task to be one of the 400 methods of ClassEval. Contrary to HumanEval+, ClassEval tasks are more similar to practical code used in projects and rely on a class context to operate. ClassEval proposes three prompting strategies: holistic, incremental and compositional. In our case, we use the compositional strategy, that is, providing the class context to the LLM and asking it to complete one method of the class, only modifying the docstring of the method to complete through our crafted prompts. We do not make use of the other generation approaches as it reduces the control we have over the prompts and could introduce biases: the holistic approach, as it implies asking the LLM to generate the whole class from scratch, can impact the performance artificially. Similarly, the incremental approach requires the reuse of codes generated by the LLM for other methods when generating new ones, which could also alter the difficulty. As we need to generate a high number of code samples and prompts, we reduce the number of tasks to evaluate by doing a stratified sampling at the 95% confidence interval. For 400 methods, this gives us 197 methods to sample which we round up to 200. Those 200 methods are sampled equally across classes resulting in 2 methods per class available. Methods chosen are available in our replication package [8].

4.3 Models used

In our experiments, we use GPT-4 [2] as both the *Prompt LLM* (to generate the different prompts) and the *Task LLM* (to generate new hard tasks). We do so as GPT-4 is the state-of-the-art LLM and so should provide answers with the best quality which would require a minimum human supervision. For the *CodeLLM*, we use 5 LLMs with different architecture: CodeLlama 7B [59], MagiCoder 6.7B [77], DeepSeekCode 7B [28], CodeGemma 7B [66] and GPT-3.5 [1]. We have not used GPT-4 as *CodeLLM* to avoid biases as it is used to generate the prompts fed to the *CodeLLM*. For all models, we used their instructions-tuned versions so that the models can handle the different prompts properly. This gives us a diverse array of architecture and training procedures. For all code generation in *TaskEval*, since we are using sampling generation, we set the temperature hyperparameter to 0.8 as it is one of the temperature settings commonly

used in other similar studies [14, 43, 45, 59]. In all cases except GPT models (for which we use OpenAI API), we use the HuggingFace [7] implementation of the models to allow for replication. Ranking of the LLMs’ performance follows the assessment obtained on the original benchmarks.

4.4 IRT model fit

For the IRT model, we use the library Birt-GD [22] which contains a gradient descent based Maximum Likelihood Estimation of the β^3 -IRT algorithm. We use the implementation exactly as is, except we modify the initial values of the parameters: δ_j and θ_i are initialized as the average of scores for each task/CodeLLMs while a_j is initialized as the Pearson correlation coefficient between the θ_i and the scores on each task of the i^{th} CodeLLM. This last initialization helps to solve the symmetry issue of the β^3 -IRT model [22]. The implementation details can be found in our replication package [8]. We use the scores collected as described in Section 2. Then, we will fit two IRT models, one for *HumanEval* and one for *ClassEval* data. The R^2 [22] after fitting the IRT models to our data are 0.928 and 0.927, respectively, showing an accurate fit.

4.5 Research Questions

In this part, we describe our RQs and how we plan to address them.

RQ1: How do tasks’ characteristics varies across benchmark? In our first RQ, we will analyze the tasks of both benchmarks through the prism of our IRT model. To do so, we will first compare the two benchmarks based on the expected probability of response of each CodeLLM, that is $E[p_{ij}|\theta_i, \delta_j, a_j]$, through their cumulative distributions across tasks. Besides observations of the cumulative distributions, we apply the Anderson-Darling (AD) [61] test, a statistical test to assess the difference between the two empirical distributions, between the distributions across benchmarks for the same CodeLLM. Then, using the obtained discriminant a_j and difficulty δ_j , as calculated by the IRT model, we will draw a portrait, task-wise, of both benchmarks. This will allow us to describe tasks present in the benchmark qualitatively.

RQ2: Do tasks’ topics affect their characteristics? In this RQ, we explore how tasks’ topics can affect how the difficulty/discriminant parameters are evaluated. We chose to explore at the topic level as it gives a good trade-off between a more nuanced analysis than the benchmark level while allowing us, compared to individual tasks analysis, to draw some conclusions over a group of tasks. To obtain meaningful topics, we will leverage the topic modeling approach with BERTopic [27], as was used in similar studies when dealing with natural language data [23, 29, 63]. For each benchmark, the topic modeling clusters all tasks using the prompts of Level 1 before rephrasing. We use this specific prompt type to have similar formatting across tasks while being as close as possible to the original prompt as mentioned in Section 3.2. We consider a topic to be valid only if it contains at least three tasks. This criterion ensures that in *ClassEval*, we avoid ending up with an excessive number of topics, each containing only two tasks for example, which could occur due to the sampling methodology used to select tasks from the benchmark. As the process will inherently label some tasks as “noise”, noisy tasks are not considered in the analysis. This results in 17 topics for *HumanEval+* and 21 topics for *ClassEval*. For the topics’ names, we use the names provided by BERTopic as a base before having the first two authors refine them by checking the tasks in the topic. Those topics constitute tasks that have a similar functionality/goal, for instance, tasks dealing with “sequence generation” or “SQL statements”. Then, for each topic, the mean accuracy of each CodeLLM as well as the difficulty and discriminant among all tasks in the topic is calculated and analyzed.

RQ3: Do programming constructs affect tasks' characteristics? In this RQ, we aim to explore the relationship between the difficulty or discriminative power of a task for a CodeLLM and the program constructs (e.g., *If* statements, *For-loops*, *Function Calls*) present in the generated code snippets used to solve the task. To achieve this, we will analyze the Abstract Syntax Tree (AST) of each code fragment generated for the task. By parsing these fragments, we will compute the average frequency of each program construct per task, enabling us to identify potential correlations between specific constructs and task complexity. To ensure that the selected tasks are not dominated by irrelevant or incorrect code fragments, we retain only those tasks for which, across all CodeLLMs, at least half of the generated samples are similar to the correct solution. This threshold of 50% similarity ensures that the majority of the code fragments are aligned with the intended task, even if they were generated from a single type of prompt. While we could have restricted our selection exclusively to code fragments that pass all tests (i.e., fully correct solutions), we opted to include similar-to-correct snippets to preserve a broader diversity of constructs. Indeed, code samples can be wrong to different degrees depending on the bugs affecting the code sample [65]. It could also bias the analysis towards code fragments obtained for higher-level prompts that are more likely to generate correct code. However, we also should not take *any* code fragments, as we may end up with generated code not even trying to solve the task if the CodeLLM misunderstood the prompt. To strike a balance, we will only consider code fragments that are similar enough to a correct one. We do so by using CodeBLEU [56] which measures the syntactical correctness of code samples. We thus measure the similarity between each code fragment and a correct code fragment that passed the tests. Note that, there is always one correct code fragment per task as a reference which is provided in the benchmark. We chose CodeBLEU as it is a widely used metric in code generation tasks [46, 47, 49, 74]. Regarding the decision threshold, in the original paper, CodeBLEU's authors found a correlation between human similarity assessment and CodeBLEU similarity on text-to-code generation, with a value of 0.3 for CodeBLEU representing an average subjective human assessment of 3 out of 5 [56]. In our case, we take 0.5 as a threshold to select/reject code fragments. This helps us preserve code snippets that are false but still address the task while discarding junk code fragments.

This leaves us with 81% of *HumanEval+* tasks and 86% of *ClassEval* tasks that are usable for the analysis. Though tasks cut out of the analysis are mostly in very high difficulty (> 0.9), we still have multiple tasks with a high difficulty > 0.5 for the analysis. Finally, we extract the AST nodes in each of the code fragments of the tasks considered using the *ast* package from the Python standard library. For each node extracted in that way, we register the node type as per the AST. Once the nodes are extracted, as the number of lines of code could bias the results (e.g., if harder tasks require more lines of code to be solved), we normalize by the number of lines of code of each fragment. Finally, we calculate the average number of each program construct across all code fragments within the same task. This gives us the number of each node type, across tasks and CodeLLMs, which will be compared with the difficulty/discriminant of each task using the Kendall- τ [35] to measure the correlation while handling ties. The node types with a positive significant correlation will signify an increasing trend with difficulty. Furthermore, we will also use the AD test to check whether the distributions of the top/bottom 50% difficult/discriminант tasks exhibit different behavior for each programming construct and each CodeLLMs.

RQ4: Do human annotators and CodeLLMs rate tasks' difficulty similarly? In our final RQ, we aim to compare task difficulty assessments made by human annotators with those generated by our approach. To achieve this, we collect human-labeled difficulty ratings for both *HumanEval+* and *ClassEval* by employing paid developers as crowd workers on the Prolific platform¹, which was used in previous studies [84]. To have the crowd-workers estimate the difficulty,

¹<https://www.prolific.com/>

the most straightforward approach would be to have them implement the selected tasks. However, a pilot study with 10 developers for 12 tasks we conducted revealed that several participants are inclined to use LLMs to code for themselves despite it being forbidden as advertised in the study. Given our limited control over how recruited participants might use LLMs, we adopted an alternative experimental setup that leverages effort estimation techniques, such as Planning Poker [26], which is familiar to developers. Since our study involves a crowd of workers, we followed the experimental design proposed by Alhamed et al. [9], which focuses on effort estimation when relying on a crowd of non-expert. Their approach simulates real-world effort estimation processes but eliminates the need for developers to resolve estimation conflicts. The method is structured into iterative rounds. In the initial round, individual participants are asked to estimate the difficulty of a task through a time-based scale (e.g., one hour or one day) using solely the information included in the task description. Participants are also required to provide comments justifying their estimates. Once a sufficient number of responses are collected, the level of agreement among participants is calculated. If the agreement exceeds a predefined threshold, the task's effort estimation is determined by taking the median of the responses. If the threshold is not met, a subsequent round is conducted with a new set of participants. These participants are provided with the task information, along with the comments and results from the previous round. This process repeats until either an agreement is reached or a maximum number of rounds is completed.

In this study, we implemented Alhamed et al.'s approach with 5 participants per task for a given round and a threshold of agreement level set to 0.6 (i.e., Substantial Agreement). Given that we have a limited budget (as crowd-workers are paid based on the time spent), we aimed for 50 developers in the first round. This results in 120 tasks (out of the 364 of both benchmarks) being considered, which were sampled at random. Tasks were then sorted into 10 questionnaires of 12 assessments (6 for *HumanEval+* and 6 for *ClassEval*). To balance the time required to complete the questionnaires, we categorized tasks into three groups based on the number of lines of code and the cyclomatic complexity of their oracles before sampling. All questionnaires can be found in our replication package [8]. Each assessment is decomposed into several parts: First, several prompts for the same tasks are provided to the participants, which have to summarize what the task is about. This allows us to check that the participant properly read the task. Then, the participant is invited to estimate the duration it would take them (from 1 minute to over 40 minutes) as well as the subjective difficulty of the task (using a Likert scale from "Very Easy" to "Very Difficult"). They then had to explain their choice, based on considerations such as the time it would take to look for a particular concept, and how to use a given library. At the beginning of the questionnaire, participants were given two examples to clarify expectations. Responses were collected until 5 participants provided acceptable answers. To ensure quality, we manually reviewed responses, verifying that participants provided meaningful explanations for at least two items (e.g., avoiding one-word answers for reasoning questions or random difficulty/time estimations). In particular, while we rely on the time estimation for our analysis but still ask for the subjective difficulty, we could analyze the trend between the two variables for each participant and potentially detect incoherence (e.g., Easy tasks with 40 minutes estimation and Hard tasks with 10 minutes) which could signal random filling of the questionnaire. We followed Alhamed et al. [9] procedure until all tasks have been assessed with a substantial agreement. We then analyzed the difference between human-assessed difficulty and the difficulty for CodeLLMs obtained using our IRT-based approach. Since human assessments are discrete, we discretized the difficulty scores obtained via IRT within the interval [0,1] for comparison.

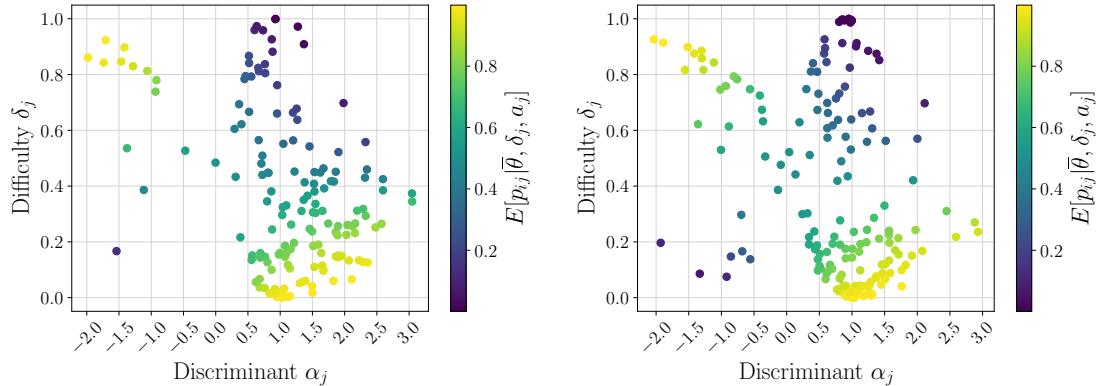


Fig. 3. Maps of the difficulty δ_j vs discriminant α_j of each task for a given benchmark. The color represents the expected probability obtained on a given task by a hypothetical CodeLLM whose capacity $\bar{\theta}$ is the average of the capacity of our CodeLLMs: **(Left)** HumanEval+ tasks, **(Right)** ClassEval tasks.

5 Results

5.1 RQ1: How do tasks' characteristics varies across benchmark?

We first calculated the cumulative distribution of the expected probability of having a correct answer, based on IRT modeling, for each task in each benchmark. The results are presented in Figure 4 and can be read as follows: for instance, for *HumanEval+*, 70% of the tasks for *Code Gemma* have an expected probability of a correct answer of 80% or less (and so 30% have 80% probability or more). These graphs allow us to compare how, globally, tasks are handled by CodeLLMs in both benchmarks. The first observation we can make is regarding the discrepancies between CodeLLMs inside the same benchmark. In the case of *HumanEval+*, there are wider variations between CodeLLMs compared to *ClassEval*. Notably, *Code Gemma* and *Code Llama* seem to struggle more on *HumanEval+* with less than 50% chance of generating a correct code on over 40% of the tasks compared to the other CodeLLMs which are around 25%. In a second time, we can observe the difference for the same CodeLLM across benchmarks. Doing so, we observe that *ClassEval* tends to have more extreme tasks compared to *HumanEval+*. Indeed, there are more very easy (90% or more probability of correct answer) and very hard tasks (10% or less probability of correct answer) for *ClassEval* compared to *HumanEval+* for most CodeLLMs. On the contrary, *HumanEval+* have more, on average, medium task (probability of correct answer between 40% and 60%). However, the difference is smaller for more capable models such as *GPT3.5* than for less capable models like *Code Llama*. Overall, for the same CodeLLM, there is a difference among benchmarks in terms of the expected probability of answer: computing the AD test returns a statistically significant difference ($p\text{-value} < 0.1$) in all cases.

We now present the mapping of difficulty and discriminant parameters for each task in both benchmarks, as computed by the IRT models, in Figure 3. For each task, we also report the expected probability $E[p_{ij}|\bar{\theta}, \delta_j, \alpha_j]$ as predicted by the model for a hypothetical CodeLLM with a capacity $\bar{\theta}$ as the average of all our CodeLLMs. For both benchmark, CodeLLMs obtained capacity θ_i follows the outcome we could expect: *GPT3.5* is the most capable CodeLLM, closely followed by *Deepseek* and *MagiCoder* that are tied together, then *Code Gemma* and finally *Code Llama*. From the mapping, we first observe a similar general shape on the positive discriminant side with some forms of tail on the negative discriminant side. Secondly, still on the positive discriminant side, we see that the difficulty correlates with the expected probability: intuitively, the higher the difficulty of the task, the smaller the probability of answer should be. We also observe some “peak” of high discriminability around tasks of difficulty between 0.2 and 0.4 for both benchmarks

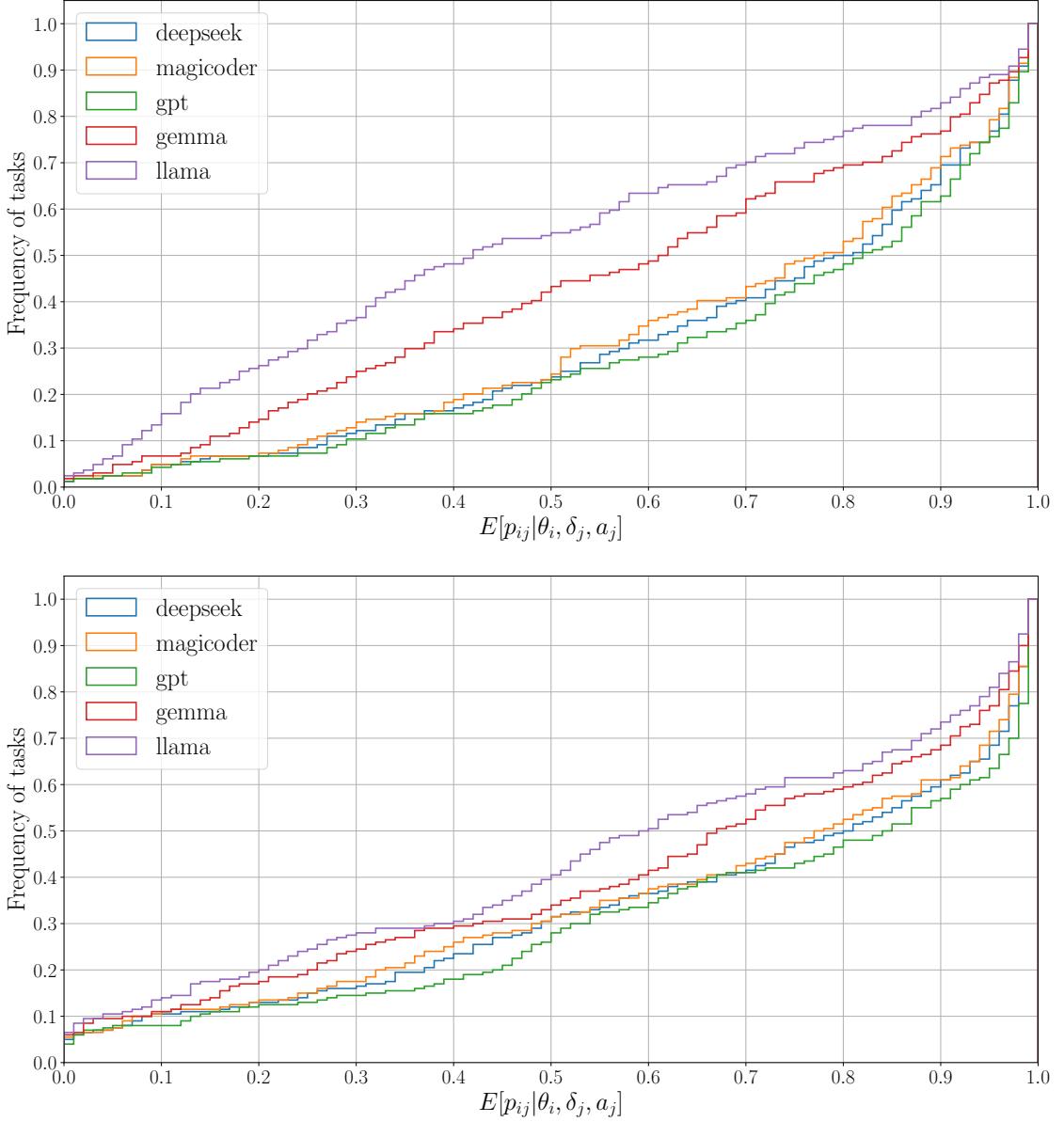


Fig. 4. Proportion of tasks in *HumanEval+* (**Top**) and *ClassEval* (**Bottom**) with a given expected probability of response for each CodeLLM.

though the trend is more pronounced for *HumanEval+*: the most discriminative tasks, in the sense allowing to tell which CodeLLMs are better, are more likely to be the middle of the range of difficulty. Indeed, for hard tasks or easy tasks, either all CodeLLMs fail or all CodeLLMs manage in a similar proportion, which makes it difficult to discriminate

between them. This echoes what we observed with the cumulative distribution of the expected probability of answer in Figure 4 with a wider discrepancy between CodeLLMs.

We note however an inverse pattern in terms of difficulty / expected probability when we reach the tasks with a negative discriminant. It should be noted, from Figure 2, that a negative discriminant means that less capable CodeLLMs are more likely to have a correct answer than more capable CodeLLMs. We make the distinctions between two parts of this side of the diagram: the tasks with high difficulty and low difficulty as symbolized by the 0.5 threshold. For tasks with negative discriminant and high difficulty, we also note that CodeLLMs tend to also have a relatively high expected probability on these tasks. In that case, this can be explained by both non-determinism in the prompts and the small number of CodeLLMs used. For instance, in the green curve in Figure 2, if all CodeLLMs have abilities between 0.3 and 0.5, the difference between expected probability would be small but the IRT models would yield a negative discriminant with a high difficulty. In that case, it is even possible that, by adding more CodeLLMs, that the slope could be rectified or even inverted. The second part of this half of the diagrams have tasks with low difficulty and negative discriminant. In that case, most CodeLLMs will fail such tasks. This is generally symptomatic of possible annotation errors as less capable CodeLLM do better than more capable ones but all CodeLLMs are generally not good. We thus manually investigated these tasks. Among the 9 tasks from *ClassEval* and 3 tasks from *HumanEval+*, we found issues in the way the original prompts (and so our prompts generated from them) were formulated for 7 of them in *ClassEval* and 1 in *HumanEval+*. For instance, in *ClassEval*, one task consists in implementing the cosine function using a taylor approximation. We give in Listing 4 an excerpt with relevant information. From the excerpt, the CodeLLMs have access to the signature of the function implementing the ‘taylor’ function but not the actual implementation. The oracle implementation contains codes to convert x into radians before returning the approximation. This poses an issue as without this information, most CodeLLMs will generate codes in the ‘cos’ that convert x into radian before using the ‘taylor’ function, leading to an error. *Code LLama* and *Code Gemma* tend not to follow this approach as much, hence why the negative discriminant and low expected probability.

```

1 from math import pi, fabs
2 class TriCalculator:
3     """
4         The class allows to calculate trigonometric values, including cosine, sine, and tangent, using
5             Taylor series approximations.
6     """
7     def __init__(self):
8         pass
9     ...
10    def taylor(self, x, n):
11        pass # Implementation not given, but oracle function converts x into radian
12    ...
13    def cos(self, x):
14        """
15            Calculate the cos value of the x-degree angle
16        :param x:float
17        :return:float
18        >>> tricalculator = TriCalculator()
19        >>> tricalculator.cos(60)
20        0.5

```

20

'''

Listing 4. Excerpt from the ‘cos’ task of *ClassEval* following the original prompt

On the other hand, for the tasks we investigated where no issues were detected, we observed behaviors that may reveal specific characteristics of CodeLLMs, possibly influenced by their training data. Given in Listing 5 is the original prompt for a task of *HumanEval+* where the goal is to filter a list to retain only integers. While relatively simple, more able CodeLLMs like *GPT3.5* fail several times on it when *Code Llama* is better at managing it. Looking at the answers provided, the codes generated are similar, except that *GPT3.5* generally relies on ‘`isinstance`’ while *Code Llama* relies on ‘`type`’ to check for integers. While ‘`isinstance`’ is generally more useful as it accounts for inheritance, however, in that case, ‘`type`’ should be used. Indeed, if the list would, for instance, contain boolean ‘True’ or ‘False’, ‘`isinstance`’ would consider them as integer (as boolean type inherits from integer in Python) while ‘`type`’ will not. This can be indicative of specificity of the training dataset or, in the worst case, some form of memorization.

```

1 from typing import List, Any
2
3 def filter_integers(values: List[Any]) -> List[int]:
4     """
5         Filter given list of any python values only for integers
6     >>> filter_integers(['a', 3.14, 5])
7     [5]
8     >>> filter_integers([1, 2, 3, 'abc', {}, []])
9     [1, 2, 3]
10    """

```

Listing 5. Excerpt from the ‘filter_integers’ task of *HumanEval+* following the original prompt

Findings 1: IRT allows us to map tasks in terms of difficulty and discriminant and to contrast benchmarks. CodeLLMs have varying behavior within and between benchmarks: *ClassEval* tends to have more extreme (very easy/difficult) tasks while *HumanEval+* have more medium tasks in terms of difficulty for the CodeLLMs under study, with more discrepancies in terms of expected answers in *HumanEval+*. Most discriminant tasks in both benchmarks generally have a difficulty between 0.2 and 0.4, which thus are better at separating CodeLLMs. Few tasks have negative discriminant, symptomatic of small differences due to non-determinism or annotation errors.

5.2 RQ2: Do tasks’ topics affect their characteristics?

In this section, we proceed with the exploration of the topics. Results are given in Figure 5. Starting with *HumanEval+*, we see that most topics have a mean difficulty in the easy-medium range (0.3 – 0.5). Only the last three topics show a high variation from the rest of the topics, however it might be explained by the lower number of individual tasks in these topics making them particularly specialized. Out of the other topics, three of them have a mean difficulty above 0.45: *Nested parentheses/brackets* (12), *Sequences* (8), and *Strings to number* (5). *Sequences* (e.g., Fibonacci) also have a high positive discriminant, pointing out that less capable CodeLLMs such as *Code Llama* tend to have a hard time processing those tasks. Such tasks can be interesting to distinguish between different CodeLLMs. On the contrary, *Strings to number* (e.g., converting roman numeral to numbers) has a mean discriminant lower than 1, showing that CodeLLMs perform somewhat similarly on such tasks. The mean accuracy of the CodeLLMs varies from topic to topic,

but *GPT3.5* is generally the model with the highest mean accuracy and *Code Llama* the one with the lowest. Most topics have a mean discriminant around 1 and no topics have a negative mean discriminant. Such topics are more likely to distinguish between more/less capable CodeLLMs, though there can be some variability between similarly capable CodeLLMs such as *MagiCoder* and *Deepseek* or *Code Llama* and *Code Gemma*.

Regarding *ClassEval*, we see that contrary to *HumanEval+* most topics are fairly easy with 48% of the topics with a mean difficulty below 0.3 and most CodeLLMs achieving a higher mean accuracy compared to *HumanEval+*. As such, *Statistics* (7) (e.g., calculating a mean), *Files reading* (13) (e.g., opening a JSON file and returning the content), and *Data Structure information retrieval* (17) (e.g., finding data in a dictionary) are relatively trivial for all CodeLLMs. On the contrary, besides *Temperature processing* (18), which might have a very high difficulty due to a low number of very specialized tasks (dealing with classes with functions related to ambient temperature control), four topics have a mean difficulty above 0.45: *Data structure calculations* (3) (e.g., computing Pearson correlations between two lists), *SQL requests* (8) (see the example in Listing 1, Section 2), *Text encryption/decryption* (14) (e.g., implementing Caesar cipher), and *Strings replacements* (16) (e.g., replacing a character by another in a string). Compared to *HumanEval+*, there are more low discriminant topics (discriminant < 1 or even < 0.75) which highlights that *ClassEval* contains more tasks where CodeLLMs tend to obtain similar results. As we mentioned in Section 5.1, there were fewer discrepancies between CodeLLMs in terms of the expected probability of answer in *ClassEval* than *HumanEval+*. Within these topics, we can even see some of them for which less capable CodeLLMs (*Code Gemma* and *Code Llama*) achieve a higher mean accuracy than more capable ones: it is the case for *String processing* (4) (e.g., removing stop-words from a text with NLTK), *Data structure items additions* (15), and to a lesser degree *SQL requests* (8). The case of *Data structure items additions* (15) is interesting as it is the only topic for which *Code Llama* and *Code Gemma* are on average better than even *GPT3.5*, as highlighted by the average negative discriminant. Analyzing the tasks within the topic, we observe that more capable models often infer additional assumptions about the task, leading to unnecessarily complex generated code. As an example, we give the generated codes for one such task of *GPT3.5* and *Code Llama* along with the original prompt in Listing 6.

```

1 # Original prompt
2 from datetime import datetime
3 class Classroom:
4     """
5         This is a class representing a classroom, capable of adding and removing courses, checking
6             availability at a given time, and detecting conflicts when scheduling new courses.
7     """
8     def __init__(self, id):
9         """
10            Initialize the classroom management system.
11            :param id: int, the id of classroom
12        """
13        self.id = id
14        self.courses = []
15
16    def check_course_conflict(self, course):
17        pass
18
19    ... # Some other class functions

```

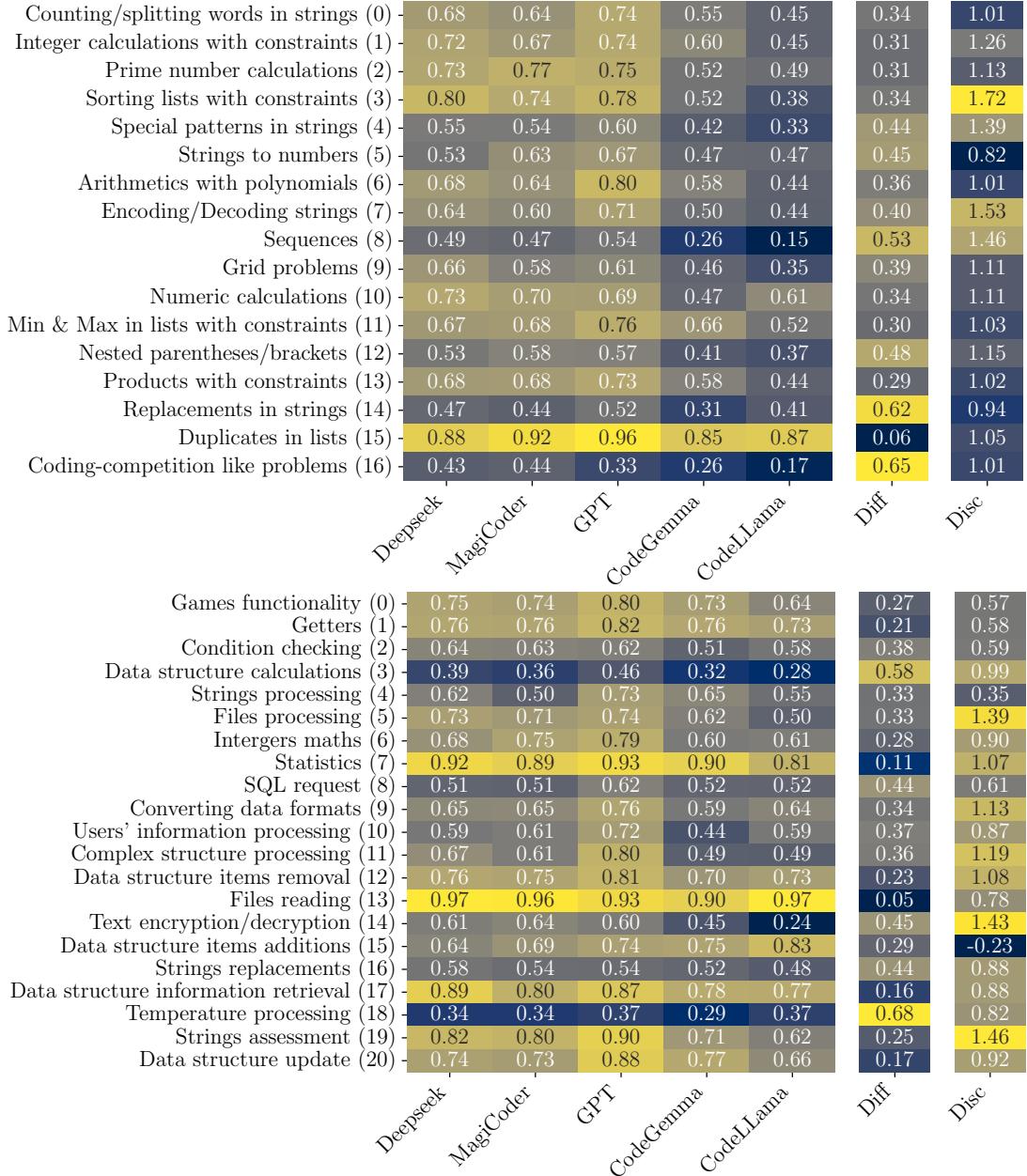


Fig. 5. Mean per topic of: 1) the accuracy on the tasks' prompts for each CodeLLM, 2) the tasks' difficulty (*Diff*), 3) the tasks' discriminant (*Disc*). **(Top)** *HumanEval+*, **(Bottom)** *ClassEval*.

```

20
21     def add_course(self, course):
22         """Add a course to the "self.courses" list if the course is not already in it.

```

```

23     :param course: dict, information of the course, including 'start_time', 'end_time' and 'name'
24     """
25 # GPT3.5 code
26 def add_course(self, course):
27     if course not in self.courses and not self.check_course_conflict(course):
28         self.courses.append(course)
29
30 # Code Llama code
31 def add_course(self, course):
32     if course not in self.courses:
33         self.courses.append(course)

```

Listing 6. Example of discrepancy on a task from Topic 15. We give first one of our prompt for the task, then generated code by GPT3.5, and CodeLlama.

As one can see, *GPT3.5* assumes there is a need to check for some conflicts, possibly due to the ‘course’ parameter containing information such as ‘start_time’ and the function ‘self.check_course_conflict’ being available as a class function from the prompt. However, this is not requested at all in the prompt (and in the task), which is quite straightforward. On the contrary, *Code Llama* manages the task by following exactly the instructions mentioned in the prompt. We observe a similar phenomenon for other generated code on the same task. This behaviour explains the negative discriminant on the task: less capable CodeLLMs such as *Code Llama* end up having better performance than more able CodeLLMs which tend to overdo it when addressing the task.

Findings 2: Analyzing topics can reveal variations in how CodeLLMs handle different types of tasks. Some topics are notably harder for CodeLLMs in both benchmarks (e.g., *Sequences* and *Nested parentheses/brackets* in *HumanEval+* and *SQL requests* in *ClassEval*) while some are trivial (e.g., *Statistics* in *ClassEval*). Discriminant information gives us clues on some topics of interest, highlighting tasks where CodeLLMs behave singularly.

5.3 RQ3: Do programming constructs affect tasks’ characteristics?

Results of the correlations between node types extracted and tasks’ characteristics as well as AD test are given in Table 1 and Table 2. To facilitate interpretation, we regrouped node types into semantically similar categories before calculating the categories. Hence, *Op* includes all nodes related to math operations such as addition, subtraction or even boolean operations, *Loop* includes both *For* and *While* node types, *DataStruct* contains all *List*, *Set*, *Dict* or *Tuple* node types etc. All details on the grouping process are available in our replication package [8].

Observing the results, we distinguish several patterns that can be intra-dataset (across CodeLLMs) or inter-dataset (between *HumanEval+* and *ClassEval*). First, looking at the comparison with tasks’ difficulty (Table 1), several node types such as *If* and *Op* are present across CodeLLMs and benchmarks, highlighting a commonality in the programming constructs that CodeLLMs use to address harder/easier tasks. While harder tasks could result in longer code which might bias the outcome, as we controlled for the size of the code fragments, it points out that it is not simply about more absolute processing but that to tackle harder tasks CodeLLMs rely on a higher level of processing. As such, the harder the tasks, the more the CodeLLMs need conditions and variable assignments/operations, independently of the number of lines of code to solve the task. In turn, this might increase their chance of producing erroneous code as they get lost in the logic flow. Note that this highlights how CodeLLMs attempt to solve the task, rather than what is *required* to solve the task. There are various ways to approach each task, and optimizing the code was not a requirement for

CodeLLMs. As a result, programming constructs such as *If*, *Op*, *Assign*, and *Loop* show positive correlations, along with significant statistical differences between the distributions of programming constructs for the top 50% easiest and hardest tasks, despite fluctuations in the strength of these correlations and significance. In contrast, some differences emerge between the two benchmarks, highlighted by stronger correlations and/or more significant results from the AD test for CodeLLMs. For *HumanEval+*, CodeLLMs tend to utilize more *FunctionDef* (defining additional sub-functions) and *Comparison* (e.g., *Compare*) constructs when tackling harder tasks. For *ClassEval*, CodeLLMs make more use of index manipulation (*Subscript*) or structure comprehension (*comprehension* such as list comprehension, and dict comprehension). In that last case, we find non-significant correlations for this same node type for *HumanEval+*, despite said node type being used in *HumanEval+* tasks. In that case, it means that this is not a property of tasks in general but it is a property of the tasks of *ClassEval*. Correlations are mostly *weak* (> 0.06), with only the correlations with the *If* node in *HumanEval+* being *moderate* (> 0.26) [24, 60]. It should be noted that it is possible to have, for most CodeLLMs, significant AD test without significant correlations (e.g., *Subscript* in *HumanEval+*) or the invert (e.g., *DataStruct* in *ClassEval*): Certain node types may be more prevalent in harder tasks, but since the AD test measures the difference between the top and bottom 50%, and the median is relatively low, this can result in a nonsignificant difference.

Regarding CodeLLMs, we observe that *GPT-3.5* exhibits generally fewer significant correlations between task difficulty and the programming constructs used. On the contrary, correlations seem more numerous overall for *Code Llama* and *Code Gemma*. Moreover, in terms of AD test, *GPT3.5* has the lowest number of statistical differences between 50% easiest/hardest tasks in *HumanEval+* and is tied in *ClassEval*. Moreover, we observe that for some node types, some CodeLLMs do or do not exhibit a correlations/AD difference while the other CodeLLMs exhibit the opposite. For instance, in *HumanEval+*, *Raise* and *Subscript* nodes exhibit a positive correlation for all CodeLLMs except *GPT3.5*. This highlights that CodeLLMs will deal with tasks within the benchmark differently, based on their understanding of the prompt, their training dataset, and their architecture. While this can lead to errors, as we saw for instance in Listing 6 in the previous Section 5.2, it can also be harmless but emphasize particularity in how the prompts are processed. For instance, for the *Raise* node type in *HumanEval+*, we note that they are most often used by CodeLLMs to handle constraints in the prompts that are informative (e.g., “the numbers will be between 0 and 1000”). These constraints are not enforced in the tests (and so with or without, the code is correct) but are phrased in the prompts which will be reflected in how the CodeLLMs will generate a code. In this case, for several tasks, *GPT3.5* will return a message as a string rather than raising an exception. The correlation tends to be positive as tasks with these informative constraints tend to be harder.

Regarding now the comparison with the tasks’ discriminant, we note that they are no cross CodeLLMs’ patterns for *HumanEval+* and so tasks’ discriminant does not seem to influence the type of program constructs used. However, for *ClassEval*, we note a few intra-benchmarks patterns. First, both AD and correlations are significant for all CodeLLMs when it comes to *Assign* node type. Given that the correlations are negative, this points towards CodeLLMs using variable assignments less on high discriminant tasks compared to low discriminant tasks (i.e., where CodeLLMs have a similar probability of being correct). This might be a contributing factor to why such tasks are less discriminant. That is, the higher number of assignments needed (or at least used by CodeLLMs) can increase the logic and so the likelihood of the CodeLLMs making a mistake, with more capable CodeLLMs being less likely to make a mistake compared to less capable ones as per the high discriminant. We also found that most CodeLLMs feature significant correlations/AD on *comprehension* and *DataStruct* node types with *GPT3.5* being the only one not featuring such behavior in both cases.

Table 1. Top program construct (node type) for each CodeLLM with regard to the tasks’ difficulty. τ gives the Kendall– τ correlations between the program constructs used in each CodeLLM and the tasks’ difficulty. AD gives the result of the Anderson-Darling test between the programming constructs of tasks with difficulty $< x$ and $\geq x$ (top 50% easiest tasks vs top 50% hardest tasks), where $x = 0.19$ for *HumanEval+* and $x = 0.15$ for *ClassEval*. Significance of the p -value is given by the number of stars ($*** \rightarrow p < 0.01$, $** \rightarrow p < 0.05$, $* \rightarrow p < 0.1$ and $- \rightarrow p > 0.1$).

Benchmark	Node	Deepseek		MagiCoder		GPT3.5		CodeGemma		CodeLLama	
		τ	AD	τ	AD	τ	AD	τ	AD	τ	AD
HumanEval+	<i>If</i>	0.284***	***	0.283***	***	0.294***	***	0.289***	***	0.270***	***
	<i>FunctionDef</i>	0.180***	***	0.123*	***	0.135**	***	0.111*	***	0.119*	***
	<i>Compare</i>	0.180***	***	0.181***	***	0.195***	***	0.189***	***	0.169***	***
	<i>Assign</i>	0.176***	***	0.164***	**	0.151**	**	0.144**	**	0.189***	***
	<i>Raise</i>	0.160**	***	0.232***	***	-	-	0.139**	-	0.173**	**
	<i>Op</i>	0.157***	***	0.160***	***	0.156***	***	0.180***	***	0.145**	**
	<i>Loop</i>	0.149**	**	0.171***	***	0.154**	***	0.140**	*	0.174***	***
	<i>DataStruct</i>	0.129**	**	0.142**	**	0.124**	-	0.182***	**	0.177***	***
	<i>Subscript</i>	0.101*	-	0.120**	*	-	-	0.102*	-	0.107*	**
	<i>Try-Catch</i>	-	-	0.117*	-	-	-	0.125*	**	-	-
ClassEval	<i>Op</i>	0.230***	***	0.209***	***	0.207***	***	0.254***	***	0.250***	***
	<i>comprehension</i>	0.225***	***	0.195***	***	0.217***	***	0.192***	***	0.169***	***
	<i>If</i>	0.206***	***	0.207***	***	0.180***	**	0.221***	***	0.191***	***
	<i>Subscript</i>	0.181***	***	0.177***	***	0.148***	***	0.194***	***	0.175***	***
	<i>Assign</i>	0.140***	**	0.177***	***	0.179***	***	0.141***	**	0.157***	***
	<i>Loop</i>	0.126**	***	0.141**	***	0.132**	***	0.135**	***	0.145**	***
	<i>Compare</i>	0.112**	-	0.133**	*	0.103*	-	0.138***	-	0.103*	-
	<i>Call</i>	0.094*	*	0.125**	**	-	*	0.089*	*	-	*
	<i>FunctionDef</i>	-	**	0.163***	***	0.119*	-	0.104*	-	0.133**	***
	<i>DataStruct</i>	-	***	0.110**	***	-	***	0.138**	***	0.114**	***
	<i>Import</i>	-	-	-	-	-	-	-	-	0.107*	***

Findings 3: Cross-checking AST of generated codes with tasks’ characteristics points towards specific program constructs used by CodeLLMs to address a task. Conditions, variables assignments, and loop are generally used more in harder tasks, independently of the code length, and some node types are more specific to a particular benchmark (e.g., *Subscript* in *ClassEval* and *Compare* in *HumanEval+*). We do not find any particular patterns when using the discriminant of the tasks for both benchmarks.

5.4 RQ4: Do human annotators and CodeLLMs rate tasks’ difficulty similarly?

As detailed in Section 4.5, estimating difficulty of tasks has been conducted in several iterative rounds. After the first round, only 6 tasks did not reach the aimed agreement. In the second round, we thus redid one questionnaire with these 6 tasks, following the same template, except we added the minimum/median/maximum time/difficulty estimations of the previous round, as well as comments provided by previous participants. We obtained again 5 answers and computed the agreement resulting in only 1 tasks not reaching the threshold. Analysis of this task revealed that all but one participant judged the task long (40 minutes or more) and one participant judged it quick (5 minutes), which resulted in an agreement below 0.6 because of the metric used in Alhamed et al. [9], the same as the first round. Given this observation, even with a lower agreement, we accepted the task as most participants agreed on the time effort.

Table 2. Top program construct (node type) for each CodeLLM with regard to the tasks’ difficulty. τ gives the Kendall– τ correlations between the program constructs used in each CodeLLM and the tasks’ absolute discriminant. AD gives the result of the Anderson-Darling test between the programming constructs of tasks with absolute discriminant $< x$ and $\geq x$ (top 50% least discriminant tasks vs top 50% most discriminant tasks), where $x = 1.17$ for *HumanEval+* and $x = 0.98$ for *ClassEval*. Significance of the p-value is given by the number of stars (* → $p < 0.01$, ** → $p < 0.05$, * → $p < 0.1$ and – → $p > 0.1$).

CodeLLM	Node	Deepseek		MagiCoder		GPT3.5		CodeGemma		CodeLLama	
		τ	AD	τ	AD	τ	AD	τ	AD	τ	AD
HumanEval+	<i>Lambda</i>	-	-	-	-	0.119*	-	0.117*	-	0.122*	-
	<i>Op</i>	-	-	-	-	-0.104*	-	-	-	-	-
	<i>Import</i>	-	-	-	-	-	-	0.129*	*	0.117*	***
	<i>comprehension</i>	-	*	-	*	-	-	0.119*	**	-	-
	<i>Attribute</i>	-	-	-	-	-	-	0.102*	-	-	-
ClassEval	<i>comprehension</i>	-0.147**	**	-0.140**	**	-	-	-0.115**	**	-0.111*	**
	<i>Assign</i>	-0.114**	***	-0.134**	***	-0.143***	***	-0.089*	**	-0.144***	***
	<i>Op</i>	-0.099*	**	-0.092*	-	-	-	-	-	-	-
	<i>DataStruct</i>	-0.096*	***	-0.100*	***	-	***	-0.094*	***	-0.103*	**
	<i>Compare</i>	-0.093*	-	-0.092*	-	-	-	-	-	-	-
	<i>Try-Catch</i>	-	-	-	-	0.109*	-	0.125**	-	0.111*	-
	<i>Import</i>	-	-	-	-	-	-	-	-	-0.122*	-

To analyze the results, we first compare the human annotators’ difficulty assessment between *HumanEval+* and *ClassEval*. The AD test between both distributions reveal a $p\text{-value} < 0.01$ showing a significant difference between the two distributions. When examining the distributions, we found that annotators tended to rate tasks from *ClassEval* more difficult than *HumanEval+*: 40% of *ClassEval* were labeled as taking 20 minutes or more, while only 17% of *HumanEval+* were labeled as requiring the same time. This contrasts with the assessment made by CodeLLMs as we saw in RQ1 and RQ2 that *HumanEval+* tended to have a higher number of medium-difficult tasks for the CodeLLMs compared to *ClassEval*. While this could be attributed to a bias in our sampled tasks, we found no significant difference between the difficulty distributions of our sampled tasks and those of the entire set of tasks.

We then compared the human annotators’ difficulty assessment and the CodeLLMs’ assessment. Given that we have two types of rating on the same items, we can use the Cohen- κ to measure the agreement between the two raters (i.e., the human annotators median and the IRT based difficulty). The agreement is weighted using a linear scheme that is, for instance, rating a task as 0 and 1 will be considered as a better agreement than 0 and 2. This results in a $\kappa = 0.21$ for *HumanEval+* and a $\kappa = 0.14$ for *ClassEval*, resulting in respectively a Slight and Fair agreement [53], which is a relatively low agreement. As such this points toward human annotators not being a reliable proxy for the difficulty as estimated by CodeLLMs, as there exists a non-trivial number of tasks on which both sides disagree. While Alhamed et al. [9] showed that annotators tend to underestimate the real difficulty of the tasks, we found that this does not affect our result. Indeed, even if we were to increase the difficulty reported by human annotators by one category (i.e., accounting for the human annotators underestimating the real difficulty), the κ coefficient of agreement between the human annotators and the CodeLLMs’ assessment would remain unchanged. We found a similar results if we consider that human annotators overestimate the difficulty.

Thus, this shows that the estimation by human annotators can, at least in several cases, drastically differ from CodeLLMs. For instance, in *HumanEval+*, several of the easiest tasks for CodeLLMs that were assessed as harder by participants are mathematical/logical in nature, for example sorting tasks based on a condition (like binary representation

Table 3. Examples of difficulty ratings between humans and LLMs for some tasks of *HumanEval+* (**Left**) and *ClassEval* (**Right**). Numbers represent the reported difficulty on the scale used by our human assessors. We discretize the difficulty evaluated for our LLMs on the same scale for comparison.

Task Description (<i>HumanEval+</i>)	Judgment		Task Description (<i>ClassEval</i>)	Judgment	
	LLMs	Humans		LLMs	Humans
Convert String to MD5	0	2	Convert Snake Game component	0	3
Encoding by shifting characters	4	2	Hexadecimal conversion	0	2
Prime factors of an integer	1	3	XML files write	0	3
Triplet under conditions	2	4	SQL requests on age	4	1
List with sentences as elements	5	2	Convert Unicodes in HTML	5	3

of the numbers and prime numbers). In this case, while the tasks themselves are not inherently difficult, they become more complex due to additional concepts that human annotators perceive as increasing the difficulty. This might, of course, differ depending on the annotators, yet the ratings we aim to capture is a general assessment. In contrast, tasks with convoluted prompts or multiple conditions, which were challenging for CodeLLMs, tended to be rated simpler by humans. We give examples of such tasks in Table 3.

In that case, CodeLLMs might struggle to keep track of all conditions. We give an example in Listing 7. In that example, CodeLLMs' difficulty is high (0.96) while human-annotators' median announced time is 5 min (low difficulty). Human-annotators point out that the task is easy, as it is a basic string manipulation with a simple edge case. Observing CodeLLMs' codes, it is clear that the CodeLLMs struggle handling the two conditions, especially the last one. Indeed, the CodeLLMs' code generally messes the two conditions up by merging them together (e.g., “Example 1” should be “Example-1”, but the generated code generally returns “Example-__1”).

```

1 def fix_spaces(s: str) -> str:
2     """Write a function named 'fix_spaces' that modifies a given string by replacing all spaces with
       underscores. If a string contains more than two consecutive spaces, these spaces should be
       replaced with a single dash."""

```

Listing 7. Example of a task, represented here by a single prompt, difficult for CodeLLMs but judged simple by human-annotators.

Findings 4: Human-annotators assessment differ in both case to CodeLLMs' difficulty assessment, emphasizing that using human judgement to assess CodeLLMs' tasks difficulty might not be a valid proxy. This motivates the usage of approach like ours that rely directly on CodeLLMs' assessments to establish characteristics of the tasks.

6 Discussion

Echoing previous studies, our paper highlights that multiple prompts is a necessity to properly assess and evaluate CodeLLMs [10]. Indeed, variation in the prompts can drastically alter the output as we saw, for instance, in the motivating examples in Section 2. In our case, it is even more important as we aimed to evaluate concepts at the *task*-level, i.e., as independent of the formulation of the prompt as possible. Similarly, we showed that difficulty as assessed by humans might not be a valid proxy for CodeLLMs. Thus, using difficulty as reported in code-games benchmarks, such as CodeContest [41] might not apply when evaluating CodeLLMs. Beyond evaluation, from a user perspective, extra care needs to be taken when prompting a CodeLLM, especially if the output of a single generation will be used. Using prompt

tuning methods can help eliminate some biases [21], but it may not completely address them. As such, a trade-off should be reached between using the output of a single prompt and using too many to be leveraged effectively by a user. In that regard, the use of differential testing or partial oracles [72] could be a promising venue of improvement.

In our study, analyzing tasks through the prism of IRT allows for some insights into the benchmark under study. Identifying tasks with varying difficulty helps reveal potential shortcomings of CodeLLMs, especially when this concerns a whole topic as we saw in RQ2. From there, further analysis can be conducted to understand why a difficulty is present. For instance, we saw in Section 2, from Listing 1, the impact that (the lack of) example could have on CodeLLMs generating a correct output in this SQL task. This could potentially be automated to provide a streamlined process of identifying shortcomings or hard topics. Then, the shortcomings should be addressed, potentially by fine-tuning the CodeLLMs on similar tasks/certain prompt templates or exploiting in-context learning (such as few-shot learning). To further train CodeLLMs, one can generate new tasks using the extracted information with the help of an approach such as Self-Instruct [73] which allows generating new tasks based on a subset of sampled tasks through a generator LLM. This subset of tasks can be, for instance, the identified topics, as the prompt similarity between tasks can ease the generation. However, only giving a list of tasks marked as easy/hard is likely not to allow us to generate new hard/easy tasks accurately. Indeed, the limited number of tasks as well as the lack of explanation on why a given task is hard/easy would mean LLM tasked with generating new tasks will tend to struggle to identify what makes a task hard/easy just from the prompt. Instead, using a combinatory approach where one asks the generator LLM to augment a hard task by adding a constraint, or by adding a constraint from a hard task to an easy one (i.e., some form of fuzzing), could provide better results. This would ultimately reduce the diversity of generated tasks, but increase the likelihood that the generated tasks are hard.

On the other hand, discriminant can be used to further select tasks to distinguish between CodeLLMs. Indeed, if the goal is, for a given benchmark, to differentiate between CodeLLMs, only the most discriminant tasks are required, as these tasks are the ones for which there are the most differences between CodeLLMs. On the contrary, focusing on low discriminant tasks can also highlight shortcomings but of a different nature. In that case, different CodeLLMs will perform similarly to each other. If all CodeLLMs also struggle on these tasks, it can emphasize particular tasks for which CodeLLMs under study are not adequately aligned. For instance, in RQ2, from Figure 5, we saw that the tasks in the *SQL request* topic of *ClassEval* had an average difficulty of 0.44 and an average discriminant of 0.61. Since all models struggle with tasks on this topic, regardless of their capability, this underscores that SQL-based tasks can still pose significant challenges for CodeLLMs.

7 Related Works

Evaluating CodeLLMs: Evaluation of CodeLLMs in the most simple form involves using a benchmark and having a CodeLLMs under test generates code for each prompt in the benchmark. Then, an aggregated metric can be calculated to evaluate the performance of the CodeLLMs on the benchmark. Several benchmarks for code have been proposed over the years, each with some particularity: besides *HumanEval+* and *ClassEval* used in this work, *APPS* [30] is a benchmark based on coding competition code fragments, *CodeXGlue* [47] contains additional tasks beyond code generation such as code completion or code translation or *BigCodeBench* [4] which contains more complex instructions. The difference between those benchmarks mainly stem from the different levels of dependency needed to solve the task (e.g., simple function for *HumanEval+* or class level for *ClassEval*), yet the evaluation mainly relies on aggregation over the whole benchmark using accuracy or pass@k. More recently, multiple benchmarks are being proposed to measure a particular property of the CodeLLMs by collecting/crafting in a particular way: Coignion et al. [18] evaluated the speed

of generated code based on LeetCode, Liu et al. [44] created *HallucCode* to evaluate CodeLLMs attitude towards different types of hallucination or Jain et al. [33] introducing LiveCode bench to measure contamination in CodeLLMs. However, the properties evaluated are generally at the benchmark level and the possible impact of the rephrasing is not evaluated. Moreover, when it comes to difficulty, most benchmarks make use of human judgment, for instance in the case of APPS, by using the subjective score given by code game contestants. We showed in RQ4 that this assessment might not translate to the actual difficulty of realizing the task for CodeLLMs. This result echoes to similar observations in other studies: Ouyang et al. [55] showed that the test pass rate does not necessarily correlate with difficulty, as aggregated by human participants in a coding contest, and Kou et al. [37] highlighted major differences when comparing how a human developer and CodeLLMs process codes' instruction.

Item Response Theory to evaluate NLP models: IRT [12] has been used extensively to evaluate NLP models. Sedoc et al. [62] used IRT to compare chatbots' proficiency by leveraging human annotators' judgment on the chatbots' output as observations. They notably show that the IRT model can be used to further streamline evaluations by selecting the most discriminative examples. Rodriguez et al. [58] propose to leverage IRT to redefine leaderboards in NLP model evaluation by defining the Difficulty and Ability Discriminating (DAD) approach. They show that IRT models offer greater reliability in assessing the ranking stability of questions both within and across benchmarks and can provide valuable qualitative insights into the evaluated leaderboards. Similarly, Vania et al. [69] uses a unique IRT model to analyze 29 NLP datasets and 18 Transformers, producing insights into which dataset contains more difficult examples or which is more effective at distinguishing strong models. Zhuang et al. [83] explain how IRT can be used for adaptive testing of CodeLLMs highlighting the limitations of traditional metrics such as Accuracy. First, compared to those studies, we focus on coding tasks and, more particularly, code generation. Secondly, these studies consider an analysis of the benchmark prompts. On the contrary, we aim at measuring the difficulty of the *task* itself, as previous studies showed that prompt formulation has a drastic impact on the models' output [51, 71, 75].

8 Threats to Validity

Construct validity: To derive the characteristics of the tasks we rely on IRT which has been extensively used in education measurement [81], as well as in assessing LLM in classical NLP settings [38, 57]. As such, the backbone of our approach is grounded in theory. We used a multi-prompted approach as previous studies highlighted the importance of multiple phrasing. To avoid potential local dependence effect (i.e., measure a score using multiple prompts referring to the same tasks), we aggregate results of prompts for a same task, effectively building polytomous super-items or "testlets" [70]. We rely on three levels of prompts to model the effect of information on how the CodeLLMs handle the task. The choice of three levels was made based on our observations. So, while we limited our study to three levels of prompts, we do not expect providing more information in prompts affects our results drastically. Another threat might come from the generation of the prompts. The transformations used are motivated based on existing works. Moreover, while we have made use of state-of-the-art GPT-4 to generate them, we manually checked the prompts to make sure that the generative process did not alter semantics. Finally, another threat to validity comes from the fact that we did not consider examples in the prompts. This, as we mentioned, can decrease the performance of the models and so add artificially hard tasks. This was nonetheless necessary to make the comparison fair across tasks as not all examples contain the same information, as we gave some examples in Section 2. However, beyond modifying some tasks' characteristics, it does not affect the applicability of *TaskEval*.

Internal validity: The CodeLLMs and benchmarks selected could be a threat to validity. We made sure to select different architectures through 5 different CodeLLMs to encompass different models. We used the implementation

and models' weights as present on HuggingFace [31] by the original authors of each model or the web API in the case of GPT3.5. For the benchmarks, we selected two different datasets, both acting at different levels (functional for *HumanEval+* and class for *ClassEval*). Regarding our experiments, the modeled topics as well as the human-annotations data could be a limitation. For the topics, we used BerTopics to automatically label the tasks, with noisy tasks being discarded. This could reduce our potential topics list, but this allowed for an automatic process. We still obtained over 15 topics with at least 3 tasks each. We manually reviewed the obtained topics. Regarding human annotations, the data primarily reflect how difficult annotators perceive each task to be. As detailed in RQ4, we did not ask crowd-workers to code the tasks, as this could introduce biases due to the uncontrolled use of CodeLLMs. Instead we followed an existing approach [9] based on effort estimation which mitigates this issue. Although the difficulty is then assessed based on developers' subjective judgment, the used approach allows to obtain an estimation of a consensus which limits potential outliers due to different experience, relative estimation etc. Moreover, even under variations due to human judgment, participants' experience etc. we still show there is a delta between human's and LLM's perception of the difficulty, which further motivate proposing an approach that is LLM-centric.

External validity: Our selection of tasks from the chosen benchmarks may pose a threat to validity, as the collection might not fully represent real-world programming tasks for assessing LLMs' capabilities. To mitigate this, we used two benchmarks, each focusing on different aspects. Moreover, both *HumanEval+* and *ClassEval* have been used to evaluate CodeLLM performance [5, 6] in previous studies. Finally, this study aimed to establish a foundation for assessing task characteristics rather than focusing on their practical implementation. We believe that using tasks from these two benchmarks offers a diverse set of use cases for evaluating code generation in CodeLLMs. The approach should not be affected by more practical benchmarks, and we leave to future works the application of the method to said benchmarks.

Reliability validity: We provide a detailed description of our methodology and make our code and data publicly available to facilitate reproducibility and further research [8].

9 Conclusion

In this paper, we present a method for analyzing the characteristics of code generation tasks for CodeLLMs. Specifically, we introduce *TaskEval*, a novel framework designed to assess and explore task characteristics in depth. We evaluated *TaskEval* on two well-known benchmarks for CodeLLM-based code generation: *HumanEval+* and *ClassEval*. A set of diverse prompts is crafted for each task including different levels of contextual information about the task and various rephrasings, accounting for the impact of prompts variations on the generation. Then, five state-of-the-art CodeLLMs were used to solve coding tasks using the set of prompts. *TaskEval* is based on Item Response Theory and allows to compute difficulty (i.e., how hard is a given task for CodeLLMs) and discriminant (i.e., how do CodeLLMs compare to each other on a given task) of each task within a benchmark. Using our method, we conducted multiple analyses on the tasks, namely topic-wise, program construct-wise, as well as a comparison with human annotators. Based on thematic similarities, we clustered tasks from both benchmarks into respectively 17 and 21 topics to inspect their characteristics, revealing topics with high difficulty and high discriminant for CodeLLMs (e.g., *Sequences*). Similarly, we assess program construct (e.g., conditions, variable assignment etc.) used given the tasks' difficulty/discriminant and highlighted discrepancy/similarity between benchmarks. Finally, we compared the difficulty assessment between CodeLLMs and human annotators, revealing stark differences in the assessment. In future work, we plan to extend the evaluation of *TaskEval* to additional domains, such as code completion and summarization. Furthermore, we aim to build on our analysis to enhance task selection (e.g., based on discriminative features) and facilitate task generation (e.g., using topic modeling).

References

- [1] 2023. GPT-3.5 Turbo. <https://platform.openai.com/docs/models/gpt-3-5-turbo>.
- [2] 2023. GPT-4. <https://platform.openai.com/docs/models/gpt-4-turbo-and-gpt-4>.
- [3] 2024. Big Code Leaderboard. <https://huggingface.co/spaces/bigcode/bigcode-models-leaderboard>.
- [4] 2024. BigCodeBench: Benchmarking Code Generation with Diverse Function Calls and Complex Instructions. arXiv:2406.15877 [cs.SE] <https://arxiv.org/abs/2406.15877>
- [5] 2024. ClassEval Leaderboard. <https://fudanselab-classeval.github.io/leaderboard.html>.
- [6] 2024. EvalPlus Leaderboard. <https://evalplus.github.io/leaderboard.html>.
- [7] 2024. Models on Hugging Face. <https://huggingface.co/models>.
- [8] 2024. Rep-Package. <https://github.com/FlowSs/TaskEval>.
- [9] Mohammed Alhamed and Tim Storer. 2021. Playing planning poker in crowds: human computation of software effort estimates. In *2021 IEEE/ACM 43rd International Conference on Software Engineering (ICSE)*. IEEE, 1–12.
- [10] Usman Anwar, Abulhair Saparov, Javier Rando, Daniel Paleka, Miles Turpin, Peter Hase, Ekdeep Singh Lubana, Erik Jenner, Stephen Casper, Oliver Sourbut, Benjamin L. Edelman, Zhaowei Zhang, Mario Günther, Anton Korinek, Jose Hernandez-Orallo, Lewis Hammond, Eric Bigelow, Alexander Pan, Lauro Langosco, Tomasz Korbak, Heidi Zhang, Ruiqi Zhong, Séan Ó hÉigearthaigh, Gabriel Recchia, Giulio Corsi, Alan Chan, Markus Anderljung, Lilian Edwards, Aleksandar Petrov, Christian Schroeder de Witt, Sumeet Ramesh Motwan, Yoshua Bengio, Danqi Chen, Philip H. S. Torr, Samuel Albanie, Tegan Maharaj, Jakob Foerster, Florian Tramer, He He, Atoosa Kasirzadeh, Yejin Choi, and David Krueger. 2024. Foundational Challenges in Assuring Alignment and Safety of Large Language Models. arXiv:2404.09932 [cs.LG] <https://arxiv.org/abs/2404.09932>
- [11] Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, and Charles Sutton. 2021. Program Synthesis with Large Language Models. arXiv:2108.07732 [cs.PL]
- [12] Frank B Baker. 2001. *The basics of item response theory*. ERIC.
- [13] Matthew Byrd and Shashank Srivastava. 2022. Predicting Difficulty and Discrimination of Natural Language Questions. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, Smaranda Muresan, Preslav Nakov, and Aline Villavicencio (Eds.). Association for Computational Linguistics, Dublin, Ireland, 119–130. <https://doi.org/10.18653/v1/2022.acl-short.15>
- [14] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. 2021. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374* (2021).
- [15] Tsong Yueh Chen, Fei-Ching Kuo, Huai Liu, Pak-Lok Poon, Dave Towey, TH Tse, and Zhi Quan Zhou. 2018. Metamorphic testing: A review of challenges and opportunities. *ACM Computing Surveys (CSUR)* 51, 1 (2018), 1–27.
- [16] Xinyun Chen, Maxwell Lin, Nathanael Schärlí, and Denny Zhou. 2023. Teaching large language models to self-debug. *arXiv preprint arXiv:2304.05128* (2023).
- [17] Yu Chen, Telmo Silva Filho, Ricardo B Prudencio, Tom Diethe, and Peter Flach. 2019. β^3 -IRT: A New Item Response Model and its Applications. In *The 22nd International Conference on Artificial Intelligence and Statistics*. PMLR, 1013–1021.
- [18] Tristan Coignion, Clément Quinton, and Romain Rouvoy. 2024. A Performance Study of LLM-Generated Code on Leetcode. In *Proceedings of the 28th International Conference on Evaluation and Assessment in Software Engineering* (Salerno, Italy) (EASE '24). Association for Computing Machinery, New York, NY, USA, 79–89. <https://doi.org/10.1145/3661167.3661221>
- [19] Yihe Deng, Weitong Zhang, Zixiang Chen, and Quanquan Gu. 2023. Rephrase and respond: Let large language models ask better questions for themselves. *arXiv preprint arXiv:2311.04205* (2023).
- [20] Xueying Du, Mingwei Liu, Kaixin Wang, Hanlin Wang, Junwei Liu, Yixuan Chen, Jiayi Feng, Chaofeng Sha, Xin Peng, and Yiling Lou. 2023. Classeeval: A manually-crafted benchmark for evaluating llms on class-level code generation. *arXiv preprint arXiv:2308.01861* (2023).
- [21] Chrisantha Fernando, Dylan Banarse, Henryk Michalewski, Simon Osindero, and Tim Rocktäschel. 2023. Promptbreeder: Self-Referential Self-Improvement Via Prompt Evolution. arXiv:2309.16797 [cs.CL] <https://arxiv.org/abs/2309.16797>
- [22] Manuel Ferreira-Junior, Jessica T. S. Reinaldo, Telmo M. Silva Filho, Eufrasio A. Lima Neto, and Ricardo B. C. Prudencio. 2023. β^4 -IRT: A New β^3 -IRT with Enhanced Discrimination Estimation. arXiv:2303.17731 [cs.LG] <https://arxiv.org/abs/2303.17731>
- [23] Tim Füllerer, Christian Fischer, Anastasiia Alekseeva, Xiaobin Chen, Tamara Tate, Mark Warschauer, and Peter Gerjets. 2023. ChatGPT in education: global reactions to AI innovations. *Scientific reports* 13, 1 (2023), 15310.
- [24] Andrew R Gilpin. 1993. Table for conversion of Kendall's Tau to Spearman's Rho within the context of measures of magnitude of effect for meta-analysis. *Educational and psychological measurement* 53, 1 (1993), 87–92.
- [25] Hila Gonen, Srinivas Iyer, Terra Blevins, Noah A Smith, and Luke Zettlemoyer. 2022. Demystifying prompts in language models via perplexity estimation. *arXiv preprint arXiv:2212.04037* (2022).
- [26] James Grenning. 2002. Planning poker or how to avoid analysis paralysis while release planning. *Hawthorn Woods: Renaissance Software Consulting* 3 (2002), 22–23.
- [27] Maarten Grootendorst. 2022. BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv preprint arXiv:2203.05794* (2022).
- [28] Daya Guo, Qihao Zhu, Dejian Yang, Zhenda Xie, Kai Dong, Wentao Zhang, Guanting Chen, Xiao Bi, Y Wu, YK Li, et al. 2024. DeepSeek-Coder: When the Large Language Model Meets Programming—The Rise of Code Intelligence. *arXiv preprint arXiv:2401.14196* (2024).

- [29] Perttu Hämäläinen, Mikke Tavast, and Anton Kunnari. 2023. Evaluating Large Language Models in Generating Synthetic HCI Research Data: a Case Study. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (<conf-loc>, <city>Hamburg</city>, <country>Germany</country>, </conf-loc>) (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 433, 19 pages. <https://doi.org/10.1145/3544548.3580688>
- [30] Dan Hendrycks, Steven Basart, Saurav Kadavath, Mantas Mazeika, Akul Arora, Ethan Guo, Collin Burns, Samir Puranik, Horace He, Dawn Song, et al. 2021. Measuring coding challenge competence with apps. *arXiv preprint arXiv:2105.09938* (2021).
- [31] HuggingFace [n. d.]. *Hugging Face – huggingface.co*. Retrieved May 27, 2024 from <https://huggingface.co/>
- [32] Naman Jain, King Han, Alex Gu, Wen-Ding Li, Fanjie Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica. 2024. LiveCodeBench: Holistic and Contamination Free Evaluation of Large Language Models for Code. *arXiv:2403.07974* [cs.SE]
- [33] Naman Jain, King Han, Alex Gu, Wen-Ding Li, Fanjie Yan, Tianjun Zhang, Sida Wang, Armando Solar-Lezama, Koushik Sen, and Ion Stoica. 2024. Livecodebench: Holistic and contamination free evaluation of large language models for code. *arXiv preprint arXiv:2403.07974* (2024).
- [34] Matthew Jin, Syed Shahriar, Michele Tufano, Xin Shi, Shuai Lu, Neel Sundaresan, and Alexey Svyatkovskiy. 2023. InferFix: End-to-End Program Repair with LLMs. In *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE 2023)*. Association for Computing Machinery, New York, NY, USA, 1646–1656. <https://doi.org/10.1145/3611643.3613892>
- [35] Maurice G Kendall. 1938. A new measure of rank correlation. *Biometrika* 30, 1-2 (1938), 81–93.
- [36] Jan H Klemmer, Stefan Albert Horstmann, Nikhil Patnaik, Cordelia Ludden, Cordell Burton Jr, Carson Powers, Fabio Massacci, Akond Rahman, Daniel Votipka, Heather Richter Lipford, et al. 2024. Using AI Assistants in Software Development: A Qualitative Study on Security Practices and Concerns. *arXiv preprint arXiv:2405.06371* (2024).
- [37] Bonan Kou, Shengmai Chen, Zhijie Wang, Lei Ma, and Tianyi Zhang. 2023. Is model attention aligned with human attention? an empirical study on large language models for code generation. *arXiv preprint arXiv:2306.01220* (2023).
- [38] John P Lalor, Hao Wu, and Hong Yu. 2016. Building an evaluation scale using item response theory. In *Proceedings of the Conference on Empirical Methods in Natural Language Processing. Conference on Empirical Methods in Natural Language Processing*, Vol. 2016. NIH Public Access, 648.
- [39] Md Tahmid Rahman Laskar, Sawsan Alqahtani, M Saiful Bari, Mizanur Rahman, Mohammad Abdullah Matin Khan, Haidar Khan, Israt Jahan, Amran Bhuiyan, Chee Wei Tan, Md Rizwan Parvez, Enamul Hoque, Shafiq Joty, and Jimmy Huang. 2024. A Systematic Survey and Critical Review on Evaluating Large Language Models: Challenges, Limitations, and Recommendations. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (Eds.). Association for Computational Linguistics, Miami, Florida, USA, 13785–13816. <https://doi.org/10.18653/v1/2024.emnlp-main.764>
- [40] Caroline Lemieux, Jeevana Priya Inala, Shuvendu K Lahiri, and Siddhartha Sen. 2023. CODAMOSA: Escaping Coverage Plateaus in Test Generation with Pre-trained Large Language Models. In *Accepted by 45th International Conference on Software Engineering (ICSE)*.
- [41] Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittweiser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustin Dal Lago, et al. 2022. Competition-level code generation with alphacode. *Science* 378, 6624 (2022), 1092–1097.
- [42] Changshu Liu, Shizhuo Zhang, Ali Reza Ibrahimzada, and Reyhaneh Jabbarvand. [n. d.]. Can Large Language Models Reason About Code? ([n. d.]).
- [43] Fang Liu, Yang Liu, Lin Shi, Houkun Huang, Ruifeng Wang, Zhen Yang, and Li Zhang. 2024. Exploring and Evaluating Hallucinations in LLM-Powered Code Generation. *arXiv preprint arXiv:2404.00971* (2024).
- [44] Fang Liu, Yang Liu, Lin Shi, Houkun Huang, Ruifeng Wang, Zhen Yang, Li Zhang, Zhongqi Li, and Yuchi Ma. 2024. Exploring and Evaluating Hallucinations in LLM-Powered Code Generation. *arXiv:2404.00971* [cs.SE] <https://arxiv.org/abs/2404.00971>
- [45] Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and LINGMING ZHANG. 2023. Is Your Code Generated by ChatGPT Really Correct? Rigorous Evaluation of Large Language Models for Code Generation. In *Advances in Neural Information Processing Systems*, A. Oh, T. Naumann, A. Globerson, K. Saenko, M. Hardt, and S. Levine (Eds.), Vol. 36. Curran Associates, Inc., 21558–21572. https://proceedings.neurips.cc/paper_files/paper/2023/file/43e9d647cc3e4b7b5baab53f0368686-Paper-Conference.pdf
- [46] Anton Lozhkov, Raymond Li, Loubna Ben Allal, Federico Cassano, Joel Lamy-Poirier, Nouamane Tazi, Ao Tang, Dmytro Pykhtar, et al. 2024. StarCoder 2 and The Stack v2: The Next Generation. *arXiv:2402.19173* [cs.SE]
- [47] Shuai Lu, Daya Guo, Shuo Ren, Junjie Huang, Alexey Svyatkovskiy, Ambrosio Blanco, Colin B. Clement, Dawn Drain, et al. 2021. CodeXGLUE: A Machine Learning Benchmark Dataset for Code Understanding and Generation. *CoRR* abs/2102.04664 (2021).
- [48] Vahid Majdinasab, Michael Joshua Bishop, Shawn Rasheed, Arghavan Moradidakhel, Amjad Tahir, and Foutse Khomh. 2023. Assessing the Security of GitHub Copilot Generated Code—A Targeted Replication Study. *arXiv preprint arXiv:2311.11177* (2023).
- [49] Antonio Mastropolo, Luca Pasarella, Emanuela Guglielmi, Matteo Ciniselli, Simone Scalabrino, Rocco Oliveto, and Gabriele Bavota. 2023. On the Robustness of Code Generation Techniques: An Empirical Study on GitHub Copilot. In *2023 IEEE/ACM 45th International Conference on Software Engineering (ICSE)*. 2149–2160. <https://doi.org/10.1109/ICSE48619.2023.00181>
- [50] Timothy R. McIntosh, Teo Susnjak, Nalin Arachchilage, Tong Liu, Paul Watters, and Malka N. Halgamuge. 2024. Inadequacies of Large Language Model Benchmarks in the Era of Generative Artificial Intelligence. *arXiv:2402.09880* [cs.AI] <https://arxiv.org/abs/2402.09880>
- [51] Moran Mizrahi, Guy Kaplan, Dan Malkin, Rotem Dror, Dafna Shahaf, and Gabriel Stanovsky. 2024. State of What Art? A Call for Multi-Prompt LLM Evaluation. *arXiv:2401.00595* [cs.CL]
- [52] Arghavan Moradi Dakhel, Vahid Majdinasab, Amin Nikanjam, Foutse Khomh, Michel C. Desmarais, and Zhen Ming (Jack) Jiang. 2023. GitHub Copilot AI pair programmer: Asset or Liability? *Journal of Systems and Software* 203 (2023), 111734. <https://doi.org/10.1016/j.jss.2023.111734>

- [53] Sergio R Munoz and Shrikant I Bangdiwala. 1997. Interpretation of Kappa and B statistics measures of agreement. *Journal of Applied Statistics* 24, 1 (1997), 105–112.
- [54] Nhan Nguyen and Sarah Nadi. 2022. An empirical evaluation of GitHub copilot’s code suggestions. In *Proceedings of the 19th International Conference on Mining Software Repositories*. 1–5.
- [55] Shuyin Ouyang, Jie M. Zhang, Mark Harman, and Meng Wang. 2024. An Empirical Study of the Non-determinism of ChatGPT in Code Generation. *ACM Transactions on Software Engineering and Methodology* (Sept. 2024). <https://doi.org/10.1145/3697010>
- [56] Shuo Ren, Daya Guo, Shuai Lu, Long Zhou, Shujie Liu, Duyu Tang, Neel Sundaresan, Ming Zhou, Ambrosio Blanco, and Shuai Ma. 2020. Codebleu: a method for automatic evaluation of code synthesis. *arXiv preprint arXiv:2009.10297* (2020).
- [57] Pedro Rodriguez, Joe Barrow, Alexander Miseric Hoyle, John P Lalor, Robin Jia, and Jordan Boyd-Graber. 2021. Evaluation examples are not equally informative: How should that change NLP leaderboards?. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*. 4486–4503.
- [58] Pedro Rodriguez, Joe Barrow, Alexander Miseric Hoyle, John P. Lalor, Robin Jia, and Jordan Boyd-Graber. 2021. Evaluation Examples are Not Equally Informative: How should that change NLP Leaderboards?. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli (Eds.). Association for Computational Linguistics, Online, 4486–4503. <https://doi.org/10.18653/v1/2021.acl-long.346>
- [59] Baptiste Roziere, Jonas Gehring, Fabian Gloclekle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémie Rapin, et al. 2023. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950* (2023).
- [60] Patrick Schober, Christa Boer, and Lothar A Schwarte. 2018. Correlation coefficients: appropriate use and interpretation. *Anesthesia & analgesia* 126, 5 (2018), 1763–1768.
- [61] Fritz W Scholz and Michael A Stephens. 1987. K-sample Anderson–Darling tests. *J. Amer. Statist. Assoc.* 82, 399 (1987), 918–924.
- [62] João Sedoc and Lyle Ungar. 2020. Item Response Theory for Efficient Human Evaluation of Chatbots. In *Proceedings of the First Workshop on Evaluation and Comparison of NLP Systems*, Steffen Eger, Yang Gao, Maxime Peyrard, Wei Zhao, and Eduard Hovy (Eds.). Association for Computational Linguistics, Online, 21–33. <https://doi.org/10.18653/v1/2020.eval4nlp-1.3>
- [63] Xinyue Shen, Zeyuan Chen, Michael Backes, and Yang Zhang. 2023. In ChatGPT We Trust? Measuring and Characterizing the Reliability of ChatGPT. *arXiv:2304.08979* [cs.CR]
- [64] Mohammed Latif Siddiq, Simantika Dristi, Joy Saha, and Joanna C. S. Santos. 2024. Quality Assessment of Prompts Used in Code Generation. *arXiv:2404.10155* [cs.SE]
- [65] Florian Tambon, Arghavan Moradi Dakhel, Amin Nikanjam, Foutse Khomh, Michel C Desmarais, and Giuliano Antoniol. 2024. Bugs in large language models generated code. *arXiv preprint arXiv:2403.08937* (2024).
- [66] Gemma Team, Thomas Mesnard, Cassidy Hardin, Robert Dadashi, Surya Bhupatiraju, Shreya Pathak, Laurent Sifre, Morgane Rivière, Mihir Sanjay Kale, Juliette Love, et al. 2024. Gemma: Open models based on gemini research and technology. *arXiv preprint arXiv:2403.08295* (2024).
- [67] Rebeka Tóth, Tamas Bisztray, and László Erdodi. 2024. LLMs in Web-Development: Evaluating LLM-Generated PHP code unveiling vulnerabilities and limitations. *arXiv preprint arXiv:2404.14459* (2024).
- [68] Clara Vania, Phu Mon Htut, William Huang, Dhara Mungra, Richard Yuanzhe Pang, Jason Phang, Haokun Liu, Kyunghyun Cho, and Samuel R Bowman. 2021. Comparing test sets with item response theory. *arXiv preprint arXiv:2106.00840* (2021).
- [69] Clara Vania, Phu Mon Htut, William Huang, Dhara Mungra, Richard Yuanzhe Pang, Jason Phang, Haokun Liu, Kyunghyun Cho, and Samuel R Bowman. 2021. Comparing test sets with item response theory. *arXiv preprint arXiv:2106.00840* (2021).
- [70] Howard Wainer and Gerard L Kiely. 1987. Item clusters and computerized adaptive testing: A case for testlets. *Journal of Educational measurement* 24, 3 (1987), 185–201.
- [71] Shiqi Wang, Zheng Li, Haifeng Qian, Chenghao Yang, Zijian Wang, Mingyue Shang, Varun Kumar, Samson Tan, Baishakhi Ray, Parminder Bhatia, Ramesh Nallapati, Murali Krishna Ramanathan, Dan Roth, and Bing Xiang. 2022. ReCode: Robustness Evaluation of Code Generation Models. *arXiv:2212.10264* [cs.LG]
- [72] Xiaoyin Wang and Dakai Zhu. 2024. Validating LLM-Generated Programs with Metamorphic Prompt Testing. *arXiv:2406.06864* [cs.SE] <https://arxiv.org/abs/2406.06864>
- [73] Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2022. Self-instruct: Aligning language models with self-generated instructions. *arXiv preprint arXiv:2212.10560* (2022).
- [74] Yue Wang, Weishi Wang, Shafiq Joty, and Steven CH Hoi. 2021. Codet5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation. *arXiv preprint arXiv:2109.00859* (2021).
- [75] Lucas Weber, Elia Bruni, and Dieuwke Hupkes. 2023. Mind the instructions: a holistic evaluation of consistency and interactions in prompt-based learning. *arXiv:2310.13486* [cs.CL]
- [76] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems* 35 (2022), 24824–24837.
- [77] Yuxiang Wei, Zhe Wang, Jiawei Liu, Yifeng Ding, and Lingming Zhang. 2023. Magicoder: Source code is all you need. *arXiv preprint arXiv:2312.02120* (2023).
- [78] Chunqiu Steven Xia, Yinlin Deng, and Lingming Zhang. 2024. Top Leaderboard Ranking= Top Coding Proficiency, Always? EvoEval: Evolving Coding Benchmarks via LLM. *arXiv preprint arXiv:2403.19114* (2024).

- [79] Burak Yetiştiren, İşık Özsoy, Miray Ayerdem, and Eray Tüzün. 2023. Evaluating the code quality of ai-assisted code generation tools: An empirical study on github copilot, amazon codewhisperer, and chatgpt. *arXiv preprint arXiv:2304.10778* (2023).
- [80] Hao Yu, Bo Shen, Dezhi Ran, Jiaxin Zhang, Qi Zhang, Yuchi Ma, Guangtai Liang, Ying Li, Tao Xie, and Qianxiang Wang. 2023. CoderEval: A Benchmark of Pragmatic Code Generation with Generative Pre-trained Models. *arXiv preprint arXiv:2302.00288v1* (2023).
- [81] Cristian Zanon, Claudio S Hutz, Hanwook Henry Yoo, and Ronald K Hambleton. 2016. An application of item response theory to psychological test development. *Psicologia: Reflexão e Crítica* 29 (2016).
- [82] Yan Zhuang, Qi Liu, Yuting Ning, Weizhe Huang, Rui Lv, Zhenya Huang, Guanhao Zhao, Zheng Zhang, Qingyang Mao, Shijin Wang, et al. 2023. Efficiently measuring the cognitive ability of llms: An adaptive testing perspective. *arXiv preprint arXiv:2306.10512* (2023).
- [83] Yan Zhuang, Qi Liu, Yuting Ning, Weizhe Huang, Zachary A. Pardos, Patrick C. Kyllonen, Jiyun Zu, Qingyang Mao, Rui Lv, Zhenya Huang, Guanhao Zhao, Zheng Zhang, Shijin Wang, and Enhong Chen. 2024. From Static Benchmarks to Adaptive Testing: Psychometrics in AI Evaluation. *arXiv:2306.10512 [cs.CL]* <https://arxiv.org/abs/2306.10512>
- [84] Cyrine Zid, Fiorella Zampetti, Giuliano Antoniol, and Massimiliano Di Penta. 2024. A Study on the Pythonic Functional Constructs' Understandability. In *Proceedings of the IEEE/ACM 46th International Conference on Software Engineering*. 1–13.

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009