ICE-Score: Instructing Large Language Models to Evaluate Code

Anonymous ACL submission

Abstract

Recent advancements in the field of natural language generation have facilitated the use of large language models to assess the quality of generated text. Although these models have shown promising results in tasks such as machine translation and summarization, their applicability in code intelligence tasks remains limited without human involvement. The complexity of programming concepts required for such tasks makes it difficult to develop evaluation metrics that align with human judgment. Token-matching-based metrics, such as BLEU, have demonstrated weak correlations with human practitioners in code intelligence tasks. Moreover, utilizing human-written test suites to evaluate functional correctness can be challenging in domains with low resources. To overcome these obstacles, we propose `ICE-Score`, a new evaluation metric via instructing large language models (LLMs) for code assessments. Our metric addresses the limitations of existing approaches by achieving superior correlations with functional correctness and human preferences, without the need for test oracles or references. We evaluate the efficacy of our metric on two different aspects (*human preference* and *execution success*) and four programming languages. Our results demonstrate that our metric surpasses state-of-the-art metrics for code generation, delivering high levels of accuracy and consistency across various programming languages and tasks. We also make our evaluation metric and datasets available to the public[1], encouraging further research in evaluating code intelligence tasks.

1 Introduction

Natural language generation (NLG) systems have seen significant progress in developing large language models (LLMs). These models have shown great promise in generating high-quality and diverse texts that can be difficult to distinguish from human-written texts (Ouyang et al., 2022). However, evaluating the quality of NLG systems remains a challenging task, primarily due to the limitations of traditional evaluation metrics. Token-matching-based metrics, such as BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004), have been widely used to evaluate NLG systems but have demonstrated poor correlation with human judgment and a lack of ability to capture semantic meanings (Kocmi et al., 2021). Furthermore, these metrics require reference output, which can be challenging to obtain for new tasks and low-resource domains (Liu et al., 2023).

In recent years, the use of LLMs as reference-free evaluators for Natural Language Generation (NLG) tasks has gained attention among researchers. This approach is strongly aligned with human preferences, even when reference texts are unavailable (Liu et al., 2023; Fu et al., 2023). The underlying assumption behind this approach is that LLMs possess a profound understanding of human-generated text and task instructions, enabling them to evaluate various NLG tasks through prompts. The exceptional performance of LLMs in contextual understanding and natural language generation, as evidenced by studies (Brown et al., 2020), further supports this assumption. Moreover, LLMs trained on both textual and code-based data have showcased remarkable capabilities in diverse downstream tasks related to source code, including code generation (OpenAI, 2023; Allal et al., 2023; Li et al., 2023). While a performance gap still exists between LLMs and human developers in code-related tasks, recent research has illustrated that LLMs can be enhanced to handle various source code tasks with appropriate guidance (Chen et al., 2023; Madaan et al., 2023). This indicates the significant potential of LLMs in comprehending and working with source code.

Code evaluation presents unique challenges, requiring a deeper understanding of programming

[1] https://anonymous.4open.science/r/ICE-Score

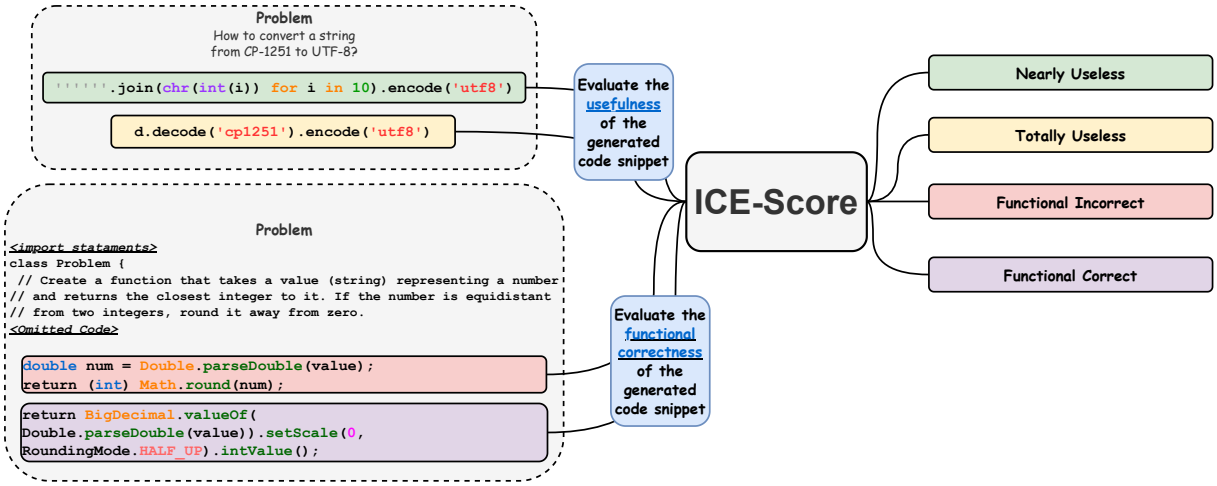

Figure 1: An illustration of `ICE-Score`. On the left-hand side, we input the task problems and corresponding generated code snippets. On the right-hand side, `ICE-Score` outputs the corresponding assessments.

concepts and more complex syntax than natural language generation (Hindle et al., 2016). Traditional reference-based evaluation metrics for code generation, such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), and chrF (Popović, 2015), rely on token matching to assess performance automatically. However, these metrics have demonstrated poor correlation with human evaluation (Evtikhiev et al., 2023) since they often underestimate the variety of outputs with the same semantic logic. While some studies have incorporated programming features to improve these metrics, they have shown limited gains and poor correlation with functional correctness (Eghbali and Pradel, 2022; Tran et al., 2019). Alternatively, researchers have proposed using well-designed test suites to objectively evaluate code generation performance at the function level (Chen et al., 2021; Zheng et al., 2023; Cassano et al., 2023). However, developing these test suites requires programming expertise, which can be impractical and costly in low-resource scenarios. Additionally, executing model-generated code poses a security risk and must be run in an isolated sandbox, which is technically cumbersome.

More recently, CodeBERTScore (Zhou et al., 2023), a neural-model-based evaluation metric, has been proposed, showing a higher correlation with functional correctness and human preferences by capturing the semantic information of reference code and generated code. However, CodeBERTScore still relies on high-quality references that can be difficult and expensive to obtain. Moreover, the limited performance of the CodeBERT (Feng et al., 2020) backbone suggests that it has not yet reached a human-level understanding of source code, limiting the effectiveness of CodeBERTScore. Therefore, more advanced evaluation metrics are needed that can better capture the complex syntax and semantics of code intelligence tasks.

To address these challenges, we propose a novel evaluation metric based on LLMs trained on both text and code, shown in Figure 1. Specifically, we Instruct LLMs to perform human-like multi-dimensional Code Evaluation, where the metric is denoted as `ICE-Score`. Our metric leverages the recent NLG metric, G-EVAL (Liu et al., 2023), but achieves superior correlations with subjective human preferences and objective functional correctness, both at the example and corpus levels. Different from G-EVAL, `ICE-Score` only relies on assessment criteria and evaluation step template, without the need for instruction generation and weighted scoring function.

Based on our extensive evaluation, we have summarized our contributions as follows:

- We designed the first multi-dimensional and reference-free automatic evaluation metric for code intelligence tasks via large language models.

- We conducted extensive experiments to demonstrate the efficacy of `ICE-Score` on four programming languages (Java, Python, C, C++, and JavaScript) from two aspects (*human-based usefulness* and *execution-based functional correctness*).

- We further discussed several aspects that can improve the performance of `ICE-Score`, including the backbone model performance and reasoning capability.

2 Method

Our evaluation metric `ICE-Score`, inspired by G-EVAL (Liu et al., 2023), consists of two main components: 1) task definition, evaluation criteria, and detailed evaluation steps, and 2) a given problem and generated code snippet for evaluation. Different from G-EVAL, we only require the input of evaluation criteria and template-based evaluation steps, without the need for generation from LLMs. In addition, our metric does not need a weighted scoring function after iterative score generation. These two differences suggest that `ICE-Score` is more cost-friendly and efficient.

2.1 Instructions for Code Evaluation

The evaluation of code quality involves two main aspects: 1) human judgment of code usefulness and 2) execution-based functional correctness. To provide a comprehensive evaluation, we adopt the design of G-EVAL for the general task instruction, as follows:

> *You will be given the code snippet for a problem. Your task is to rate the code snippet only on one metric. Please make sure you read and understand these instructions carefully. Please keep this document open while reviewing, and refer to it as needed.*

Regarding the task-agnostic prompt, we have designed the evaluation criteria for assessing **code usefulness**, as shown in Appendix A.1. These criteria are aligned with previous human evaluations of code quality (Evtikhiev et al., 2023). To evaluate **functional correctness**, we emphasize the importance of considering unit tests during the evaluation process. We present the following criteria for evaluating functional correctness, as provided in Appendix A.2.

For the instruction of evaluation steps, we provide a template-based prompt:

> *Evaluation Steps:*
> *1. Read the problem carefully and identify the required functionalities of the implementation.*
> *2. Read the code snippet and compare it to the problem. Check if the code snippet covers all required functionalities of the problem, and if it aligns with the Evaluation Criteria.*
> *3. Assign a score for **[Evaluation Aspect]** on a scale of 0 to 4, where 0 is the lowest and 4 is the highest based on the Evaluation Criteria.*

Here, we define **[Evaluation Aspect]** as any aspects that are emphasized during the evaluation. In our paper, we consider **code usefulness** and **functional correctness**.

2.2 Inputs of Code Evaluation

It is worth noting that most code generative models do not take formatting into account, resulting in unformatted code that requires post-processing of code formatting to be understood, compiled, and executed (Zheng et al., 2023). Additionally, automatic evaluation metrics for code generation, such as CodeBLEU (Ren et al., 2020) and RUBY (Tran et al., 2019), still rely on language-specific program parsers [2]. However, based on prior findings that LLMs can robustly understand input data (Huang et al., 2022; Zhuo et al., 2023; Zhu et al., 2023), we hypothesize that LLMs can also understand programming context without proper formatting. Therefore, for evaluation, we input the problems and generated code (and reference code, if provided). When the reference code is provided, we slightly modify the evaluation steps in the prompt to incorporate it.

3 Experiment Setup

We evaluate the effectiveness of `ICE-Score` using GPT-3.5 (`GPT-3.5-turbo`[3]) as the backbone across multiple datasets and programming languages. We conduct two experiments to investigate the correlation between `ICE-Score` and human preference and functional correctness, respectively. We compare the performance of LLM-based evaluations against 7 predominant automatic evaluation metrics, including the state-of-the-art CodeBERTScore (Zhou et al., 2023). To measure the correlation with human preference, we use the CoNaLa dataset (Yin et al., 2018) and corresponding human annotation on the generated code from

[2] https://tree-sitter.github.io/
[3] https://platform.openai.com/docs/models/gpt-3-5

various models trained on the dataset (Evtikhiev et al., 2023). To measure the correlation with functional correctness, we use the HumanEval-X dataset (Zheng et al., 2023). We do not consider **distinguishability** as an evaluation option, as prior work (Zhou et al., 2023) has shown it to be an unreliable meta-metric that cannot substitute for execution-based or human-based ratings.

3.1 Automatic Evaluation Metric Baselines

The baseline metrics we include can be classified into two groups: **string-based** and **neural-model-based** evaluation.

String-based Evaluation Most evaluation metrics in code generation have been adapted from natural language generation (NLG) and rely on comparing the generated code to reference code. The most commonly used metric is BLEU (Papineni et al., 2002), which computes the overlaps of n-grams in the generated output with those in the reference, where the n-grams are tokenized using a language-specific tokenizer (Post, 2018). Other metrics include ROUGE-L (Lin, 2004), a recall-oriented metric that looks for the longest common subsequence between the reference and the generated code, and METEOR (Banerjee and Lavie, 2005), which is based on unigram matching between the generated code and the reference. However, studies have shown that BLEU may yield similar results for models with different quality levels from the perspective of human graders in code generation (Evtikhiev et al., 2023), leading to the proposal of new evaluation metrics such as RUBY (Tran et al., 2019). RUBY takes the code structure into account and compares the program dependency graphs (PDG) of the reference and the candidate. If the PDG is impossible to build, the metric falls back to comparing the abstract syntax tree (AST), and if the AST is also impossible to build, it compares the weighted string edit distance between the tokenized reference and candidate sequence. Another recent metric is CodeBLEU (Ren et al., 2020), which is a composite metric that computes a weighted average of four sub-metrics treating code differently: as a data-flow graph, as an abstract syntax tree, and as text. CodeBLEU is designed to evaluate the quality of generated code for code generation, code translation, and code refinement tasks.

Neural-model-based Evaluation Neural-model-based evaluation is becoming increasingly important for evaluating the quality of code generated by deep learning models. CodeBERTScore (Zhou et al., 2023) is one of the latest approaches that leverages pre-trained code models like CodeBERT (Feng et al., 2020) and best practices from natural language generation evaluation to assess the quality of generated code. CodeBERTScore encodes the generated code and reference code independently and considers the natural language context, contextual information of each token, and implementation diversity. It enables the comparison of code pairs that are lexically different and calculates precision and recall based on the best-matching token vector pairs. This approach provides an effective way to evaluate the effectiveness of deep learning models for code intelligence tasks. Note that the authors of CodeBERTScore provided both F1 and F3 scores, with the optional source input. Therefore, we use these four language-specific variants of CodeBERTScore in our experiments.

Metric	Example			Corpus		
	τ	r_p	r_s	τ	r_p	r_s
BLEU	.439	.522	.488	.423	.572	.542
CodeBLEU	.292	.363	.331	.259	.397	.339
chrF	.458	.570	.515	.449	<u>.592</u>	.578
ROUGE-L	.447	.529	.499	.432	.581	.552
METEOR	.410	.507	.462	.415	.557	.534
RUBY	.331	.397	.371	.339	.493	.439
CodeBERTScore-F1	.500	<u>.609</u>	.556	<u>.464</u>	.579	<u>.595</u>
CodeBERTScore-F3	<u>.505</u>	<u>.609</u>	<u>.563</u>	.437	.549	.564
`ICE-Score`	**.556**	.613	**.594**	**.546**	.649	**.635**
`Ref-ICE-Score`	.554	**.617**	.591	.539	**.661**	.630

Table 1: Example-level and corpus-level Kendall-Tau (τ), Pearson (r_p) and Spearman (r_s) correlations with the human preferred usefulness on CoNaLa. `ICE-Score`: without reference code inputs, or reference-free; `Ref-ICE-Score`: reference-enhanced. The best performance is **bold**. The second-best performance is <u>underlined</u>.

3.2 Datasets and Evaluation Aspects

Human-based Usefulness Experiments Similar to (Zhou et al., 2023), we conduct an evaluation on the CoNaLa benchmark (Yin et al., 2018), which is a widely used dataset for natural language context to Python code generation. To measure the correlation between each evaluation metric and human preference, we utilize the human annotations provided by (Evtikhiev et al., 2023). Specifically, for each example in the dataset, experienced software developers were asked to grade the generated code snippets from five different models. The grading

Metric	Java		C++		Python		JavaScript		Average	
	τ	r_s	τ	r_s	τ	r_s	τ	r_s	τ	r_s
BLEU	.337	.401	.146	.174	.251	.297	.168	.199	.225	.268
CodeBLEU	.355	.421	.157	.187	.272	.323	.226	.267	.253	.299
chrF	.346	.413	.166	.198	.262	.312	.186	.220	.240	.286
ROUGE-L	.327	.389	.143	.171	.240	.284	.151	.179	.215	.256
METEOR	.358	.425	.174	.208	.276	.327	.195	.231	.251	.298
RUBY	.340	.401	.139	.165	.216	.255	.138	.163	.208	.246
CodeBERTScore-F1	.314	.375	.148	.177	.231	.276	.145	.172	.209	.250
CodeBERTScore-F3	.356	.426	.166	.198	.262	.312	.189	.226	.243	.291
`ICE-Score`	**.427**	**.442**	**.320**	**.326**	.279	.282	.316	.321	**.336**	**.343**
`Ref-ICE-Score`	.388	.404	.274	.282	**.318**	**.325**	**.340**	**.348**	.330	.340

Table 2: Example-level Kendall-Tau (τ) and Spearman (r_s) correlations with the execution-based functional correctness on HumanEval. `ICE-Score`: without reference code inputs, or reference-free; `Ref-ICE-Score`: with reference code inputs, or reference-enhanced. The best performance is **bold**. The second-best performance is underlined.

scale ranges from zero to four, with zero indicating that the generated code is irrelevant and unhelpful, and four indicating that the generated code solves the problem accurately. The dataset comprises a total of 2,860 annotated code snippets (5 generations $\times$ 472 examples) with each snippet being graded by 4.5 annotators on average.

Execution-based Functional Correctness Experiments We conduct an evaluation of functional correctness using the HumanEval benchmark (Chen et al., 2021), which provides natural language goals, input-output test cases, and reference solutions written by humans for each example. The benchmark originally consists of 164 coding problems in Python, and has been extended by (Cassano et al., 2023) to 18 other programming languages, including Java, C++, Python, and JavaScript. We chose to evaluate our models on these languages, as they are among the most popular programming languages. The translated examples also include the predictions of `code-davinci-002` and their corresponding functional correctness scores. Inspired by (Zhou et al., 2023), we obtain them from the HumanEval-X dataset (Zheng et al., 2023). As each problem has nearly 200 generated code samples on average, it would be computationally expensive to evaluate them all using LLMs. Therefore, we randomly select 20 samples from each problem, and collect all samples from problems where no more than 20 versions of code were generated.

Correlation Metrics To measure the correlation between each metric's scores and the references, we follow best practices in natural language evaluation and used Kendall-Tau (τ), Pearson (r_p), and Spearman (r_s) coefficients.[4]. To systematically study the efficacy of each automatic evaluation metric, we compute both example-level and corpus-level correlations. The example-level correlation is the average correlation of each problem example, while the corpus-level correlation is the correlation of all aggregated examples in the task.

4 Results

Human-based Usefulness Table 1 shows the correlation between different metrics with human preference. We compare two variants of our evaluation approach, reference-free and reference-enhanced evaluations, with 10 baseline metrics and their variants. We find that `ICE-Score` outperform these metrics by a significant margin, regarding both example- and corpus-level correlations. Our observation is consistent with the work of CodeBERScore, where the variants of CodeBERScore mostly outperform the strong baselines like chrF and ROUGE-L. For example, `ICE-Score` achieves 0.556 and 0.546 measured by Spearman correlation on example level and corpus level, respectively. In contrast, prior evaluation metrics barely reach a score of 0.5. In addition, we find that `Ref-ICE-Score` does not significantly improve the performance, indicating the reference code may not be optimized. Our further analysis of the human rating of CoNaLa reference code complies with this implication, where the average score of the reference code only achieves 3.4 out of 4, suggesting that not all human practitioners consider

[4]We use the implementations from https://scipy.org/

Metric	Java		C++		Python		JavaScript		Average	
	τ	r_s	τ	r_s	τ	r_s	τ	r_s	τ	r_s
BLEU	.267	.326	.225	.276	.281	.344	.220	.270	.248	.304
CodeBLEU	.293	.359	.212	.260	.303	.371	.315	.385	.281	.343
chrF	.290	.355	.266	.325	.328	.402	.279	.342	.291	.356
ROUGE-L	.280	.342	.234	.286	.296	.363	.216	.264	.256	.314
METEOR	.318	.389	.260	.319	.349	.427	.311	.380	.309	.379
RUBY	.276	.337	.219	.268	.279	.341	.219	.268	.248	.303
CodeBERTScore-F1	.244	.298	.219	.268	.264	.324	.214	.262	.235	.288
CodeBERTScore-F3	.281	.344	.243	.297	.313	.384	.261	.320	.275	.336
`ICE-Score`	.330	.345	.313	.321	.294	.298	.315	.323	.313	.322
`Ref-ICE-Score`	**.412**	**.438**	**.367**	**.383**	**.425**	**.446**	**.432**	**.455**	**.409**	**.431**

Table 3: Corpus-level Kendall-Tau (τ) and Spearman (r_s) correlations with the execution-based functional correctness on HumanEval. `ICE-Score`: without reference code inputs, or reference-free; `Ref-ICE-Score`: with reference code inputs, or reference-enhanced. The best performance is **bold**. The second-best performance is underlined.

the reference fully useful.

Execution-based Functional Correctness Table 2 and Table 3 present the results of example- and corpus-level functional correctness, respectively. From Table 2, we observe that both reference-free and reference-enhanced `Ref-ICE-Scores`consistently outperform the other baselines across all four programming languages on the example level. `ICE-Score` even outperforms the reference-enhanced one, suggesting potential bias in some reference code. Additionally, we find that METEOR and CodeBLEU receive better correlations than all variants of CodeBERTScore, indicating that they are still strong baselines compared to the recent neural-model-based evaluators in code generation. In Table 3, we observe that our `Ref-ICE-Score` achieves state-of-the-art performance among all evaluation metrics. When compared to other baselines, `ICE-Score` still achieves comparable results to the source-free CodeBERTScore-F3.

5 Ablation Study

Does reasoning help the code evaluation? Prior work (Wei et al.; Kojima et al.) has demonstrated that the performance of LLMs can be significantly improved via Chain-of-Thought (CoT) and Zero-Shot-Chain-of-Thought (ZS-CoT), where the prompts instruct LLMs to perform the task in a step-by-step manner. Here, we explore the zero-shot reasoning ability of LLMs in evaluating code generation. Specifically, we instruct GPT-3.5 to perform CoT-evaluation by adding "Step-by-step Evaluation:" at the end of the prompt. An example of the zero-shot-CoT prompt is shown in Figure 2.

Metric	Example			Corpus		
	τ	r_p	r_s	τ	r_p	r_s
`ICE-Score`	.556	.613	.594	.546	.649	.635
`CoT-ICE-Score`	**.561**	**.628**	**.600**	**.579**	**.703**	**.665**
`Ref-ICE-Score`	.554	.617	.591	.539	.661	.630
`CoT-Ref-ICE-Score`	**.571**	**.639**	**.607**	**.583**	**.712**	**.667**

Table 4: Example-level and corpus-level Kendall-Tau (τ), Pearson (r_p) and Spearman (r_s) correlations with the human preferred usefulness on CoNaLa. `ICE-Score`: without reference code inputs, or reference-free; `Ref-ICE-Score`: with reference code inputs, or reference-enhanced. `CoT-` indicates the use of ZS-CoT. The best performance is **bold**.

Instead of using LLMs to extract the evaluation score from the reasoning steps, like the original metric of zero-shot-CoT via multiple queries, we design a rule-based parser to extract scores. Due to limited resources, we only evaluate on CoNaLa in Table 4. Our results show that ZS-CoT can significantly improve the reliability of code evaluation. Additionally, we find that `Ref-ICE-Score` can achieve better results than reference-free ones via ZS-CoT, even though their performances are similar without CoT processing. This suggests that LLMs can exploit the use of reference code through reasoning.

Does more-capable backbone LLM yield better performance on code evaluation? As shown in previous studies (OpenAI, 2023; Bubeck et al., 2023), GPT-4 significantly outperforms GPT-3.5 on various tasks. Therefore, we use GPT-4 as the backbone model for `ICE-Score` and evaluate its performance on CoNaLa. The results in Table 5 indicate that GPT-4 consistently surpasses `GPT-3.5-turbo` on evaluating code, suggesting

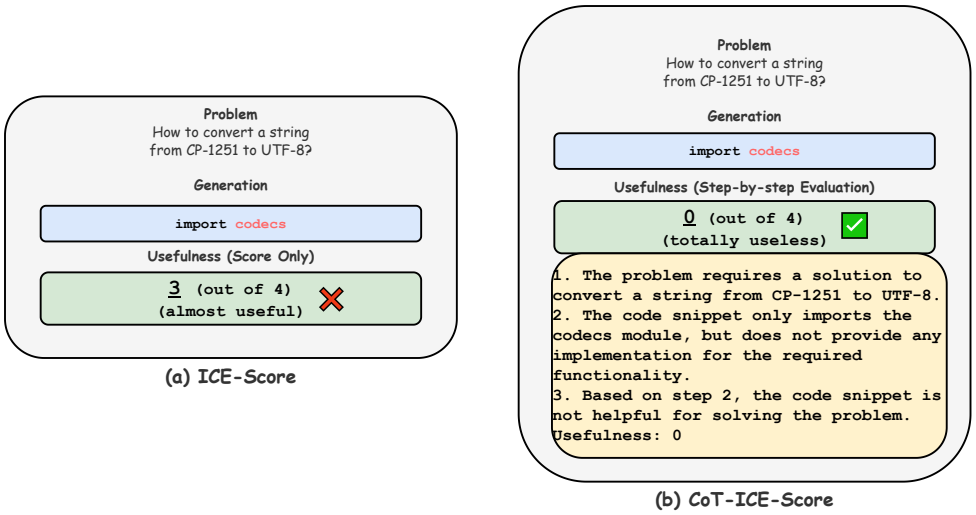

Figure 2: Example inputs and outputs with (a) `ICE-Score`, (b) `ICE-Score` with Zero-Shot Chain-of-Thought. With the step-by-step evaluation, the output assessment is more aligned with human preference.

Metric	Example			Corpus		
	τ	r_p	r_s	τ	r_p	r_s
`ICE-Score-3.5`	.556	.613	.594	.546	.649	.635
`ICE-Score-4`	**.612**	**.658**	**.611**	**.592**	**.720**	**.688**
`Ref-ICE-Score-3.5`	.554	.617	.591	.539	.661	.630
`Ref-ICE-Score-4`	**.592**	**.647**	**.634**	**.632**	**.744**	**.690**

Table 5: Example-level and corpus-level Kendall-Tau (τ), Pearson (r_p) and Spearman (r_s) correlations with the human preferred usefulness on CoNaLa. `ICE-Score`: without reference code inputs, or reference-free; `Ref-ICE-Score`: with reference code inputs, or reference-enhanced. `-3.5` and `-4` suggest the different backbone models. The best performance is **bold**.

it has the superior capability of code comprehension. We also note that using a more capable model like GPT-4 can guarantee even better performance, compared to using ZS-CoT techniques in Table 4.

6 Discussion

Data Contamination Evaluations on recent closed-source LLMs have been criticized for the possibility of data contamination (Aiyappa et al., 2023), where the model may have already seen the evaluation datasets during training, due to the opaque training details of these models. For instance, Kocmi and Federmann (2023) conducted an empirical study on a few closed-source LLMs, including GPT-3.5, and suggested that LLMs are the state-of-the-art evaluators of translation quality, based on the evaluation of the WMT22 Metric Shared Task (Freitag et al., 2022). However, as most of the evaluated models were trained on data prior to 2022[5], it is highly likely that these models have been trained with some human-rated translation quality data. Similarly, G-EVAL(Liu et al., 2023) shows that GPT-3.5 and GPT-4 are the state-of-the-art evaluators of natural language generation (NLG) with the evaluation of three NLG datasets. However, as these human-annotated datasets were released before 2021, it is probable that they were included in the training data of GPT-3.5 and GPT-4. In contrast, our work is minimally impacted by data contamination, as we report the data release year in Table 6. Our analysis suggests that only CoNaL and HumanEval (Python) datasets may have been contaminated, and it is unlikely that GPT-3.5 has seen any human annotation or generated code during training.

Human-aligned Evaluation Beyond Code Generation While our study has shown that LLMs can achieve state-of-the-art performance in evaluating the functional correctness and usefulness of generated source code, the question remains as to whether LLMs can be utilized to evaluate code intelligence tasks beyond code generation. Allamanis et al. (2018) have identified several downstream applications such as code translation, commit message generation, and code summarization. While some studies have investigated the human evaluation of these tasks, none of them have released the annotation data or fully described the human evaluation criteria. This presents a challenge for analyzing if `ICE-Score` can be adapted to these

[5] https://platform.openai.com/docs/model-index-for-researchers

Dataset	Release Year	Likely to be contaminated?
CoNaLa	2018	✓
human-annotated CoNaLa w/ generated code	2023	✗
HumanEval (Python)	2021	✓
HumanEval-X (w/o Python)	2023	✗
human-annotated HumanEval-X w/ generated code	2023	✗

Table 6: Dataset, Release Year and the likelihood of data contamination for each dataset used in our study.

tasks. For example, Hu et al. (2022) proposed a human evaluation metric for code documentation generation quality, which is specifically designed for code comment generation and commit message generation. Their metric includes three aspects: *Language-related*, *Content-related*, and *Effectiveness-related*, with detailed task descriptions and explanations of assigned scores. We propose that the information provided in their metric can be used to create prompts for LLM-based evaluation and enable human-aligned evaluation of code documentation generation.

7 Related Work

Large Language Models for Code. LLMs pretrained on large-scale code data have demonstrated strong capabilities in code intelligence tasks, such as code completion (Li et al., 2023; Luo et al., 2023; Rozière et al., 2023), code summarization (Ahmed and Devanbu, 2022; Sun et al., 2023) and program repair (Surameery and Shakor, 2023; Sobania et al., 2023). However, they remain unreliable, particularly in scenarios that require an understanding of natural language. Recent studies (Muennighoff et al., 2023b; Ma et al.) show that pretraining on both text and code results in the optimal model performance on natural language and code understanding. Furthermore, in order to make LLMs more human-aligned and more capable of performing complex tasks, instruction tuning is proposed to enhance the capability of following natural language requirements. In this work, we utilize such instruction-tuned LLMs to conduct multi-dimensional code evaluation via various instructions.

Automatic Evaluation Metrics for Generation. The quest for reliable and robust automatic evaluation metrics for generated content has been a cornerstone in natural language processing. Traditionally, string-based metrics such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), and METEOR (Banerjee and Lavie, 2005) have dominated the landscape, primarily when assessing machine translation or text summarization outputs. While these metrics provide a quick and cost-effective means of evaluating the quality of the generated text, they often fall short of capturing the nuanced intricacies and semantic richness inherent in natural language. To mitigate such drawbacks, a few neural-based multi-dimensional evaluation metrics have been proposed for text generation, such as UniEval (Zhong et al., 2022), GPTScore (Fu et al., 2023) and G-EVAL (Liu et al., 2023). However, when it comes to code generation, where both syntactical correctness and semantic intent are paramount, there are few attempts to address these challenges. Instead, the most dominant metrics still compute the similarity between generated code and reference code. In this work, we introduce `ICE-Score`, a novel metric that not only addresses the limitations of its predecessors but also harnesses the capabilities of LLMs, setting a new benchmark for the evaluation of code generation tasks.

8 Conclusion

In this paper, we propose a novel evaluation metric based on large language models trained on both text and code, which can better capture the complex syntax and semantics of code intelligence tasks. Our metric achieves superior correlations with subjective human preferences and objective functional correctness, both at the example and corpus levels, without reference and test suites. We conduct an extensive evaluation of four programming languages (Java, Python, C, C++, and JavaScript) and demonstrate the effectiveness of our proposed method on human-based usefulness and execution-based functional correctness. We have publicly released our evaluation metric and datasets to encourage the development of more accurate and effective evaluation metrics for tasks involving source code.

Limitations

Our proposed evaluation metric is based on the assumption that LLMs can follow the instructions to evaluate the code snippets. The backbone models we investigated are closed-source state-of-the-art LLMs from OepnAI. As we noticed that there is a huge performance gap between current closed-source and open-source LLMs, it is possible that `ICE-Score` can be adapted with an open-source LLM trained on code and text, such as WizardCoder (Luo et al., 2023) and OctoPack (Muennighoff et al., 2023a). Hence, we encourage future investigations on open-source LLMs for code evaluation. In addition, as discussed in Section 6, our experiments only focus on two code generation tasks. There are other code intelligence tasks like program repair and code summarization. However, due to the limited study on human evaluation of these tasks, no open-source dataset is publicly available or documented in detail. Finally, `ICE-Score` assumes that either model weights or model APIs are available, which is costly for some users. We, therefore, suggest future work on proposing low-cost evaluation metrics.

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A Prompts for Code Evaluation

A.1 Code Usefulness

Evaluation Criteria:
Usefulness (0-4) Usefulness of the code snippet based on the problem description.
- A score of 0: Snippet is not at all helpful, it is irrelevant to the problem.
- A score of 1: Snippet is slightly helpful, it contains information relevant to the problem, but it is easier to write the solution from scratch.
- A score of 2: Snippet is somewhat helpful, it requires significant changes (compared to the size of the snippet), but is still useful.
- A score of 3: Snippet is helpful, but needs to be slightly changed to solve the problem.
- A score of 4: Snippet is very helpful, it solves the problem.

A.2 Functional Correctness

Evaluation Criteria:
Functional Correctness (0-4) - Execution-based quality of the code snippet combined with the problem. The correctness is measured by all possible unit tests and the comparison of the reference code. The combination of the code snippet and the problem should pass all the possible tests based on your understanding of the reference code. The length of the code snippet can not determine the correctness. You need to assess the logic line by line.
- A score of 0 (failing all possible tests) means that the code snippet is totally incorrect and meaningless.
- A score of 4 (passing all possible tests) means that the code snippet is totally correct and can handle all cases.

B Automatic Evaluation Metric Baselines

Our implementations of the automatic evaluation metric baselines except for CodeBERTScore are based on https://github.com/JetBrains-Research/codegen-metrics. For CodeBERTScore, we adopt the official release at https://github.com/neulab/code-bert-score.

C Correlation Metrics

For all correlation metrics, we use the implementation from https://scipy.org/ and call these APIs with the default settings.

D Rule-based Score Extraction from Zero-shot Chain Of Thought Evaluation

We demonstrate the general implementation of score extraction:

```
import re
TASK_KEY_WORD = "usefulness" # or "functional"
def get_gpt_answer(raw_content):
    try:
```

```
        return int(raw_content)
    except:
        try:
            return process_raw_content(raw_content)
        except:
            return 0

def process_raw_content(content):
    # Clean up and split the content
    splits = content.lower().replace("(", "").replace(")", "").split("\n")

    # Extract relevant lines and clean them up
    ls = [ll.strip(".")
        .replace("out of ", "/")
        .replace("/4", "")
        for l in splits
        for ll in l.lstrip("0123456789.").split(". ")
        if TASK_KEY_WORD in ll or "score" in ll]

    # Extract the scores
    ans = [ll for l in ls for ll in l.split() if ll.isnumeric()]

    # If there are multiple scores, take the most common one
    if len(set(ans)) != 1 and len(ans) > 1:
        return int(Counter(ans).most_common(1)[0][0])

    # If there are no scores or ambiguous scores, return 0 or 1
    if len(set(ans)) != 1:
        if "N/A" in content:
            return 0
        else:
            return 1

    # Otherwise, return the single score
    return int(ans[0])
```

Code Listing 1: Score Extractor Implementation

We note that our extraction process for the evaluation metrics is entirely rule-based and may not be optimized for the best results.