Aligning Offline Metrics and Human Judgments of Value of AI-Pair Programmers

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Abstract—Large language models trained on massive amounts of natural language data and code have shown impressive capabilities in automatic code generation scenarios. Development and evaluation of these models has largely been driven by offline functional correctness metrics, which consider a task to be solved if the generated code passes corresponding unit tests. While functional correctness is clearly an important property of a code generation model, we argue that it may not fully capture what programmers value when collaborating with their AI pair programmers. For example, while a nearly correct suggestion that does not consider edge cases may fail a unit test, it may still provide a substantial starting point or hint to the programmer, thereby reducing total needed effort to complete a coding task. To investigate this, we conduct a user study with \(N = 49\) experienced programmers, and find that while both correctness and effort correlate with value, the association is strongest for effort. We argue that effort should be considered as an important dimension of evaluation in code generation scenarios.

We then revisit *syntactic similarity-based offline metrics*, such as normalized edit similarity, hypothesizing that they better capture effort. We find that functional correctness remains better at identifying the highest-value generations; but, as expected, participants still saw considerable value in code that failed unit tests. Conversely, similarity-based metrics are very good at identifying the lowest-value generations among those that fail unit tests. Based on these findings, we propose a simple hybrid metric, which combines functional correctness and similarity-based metrics to capture different dimensions of what programmers might value and show that this hybrid metric more strongly correlates with both value and effort. Our findings emphasize the importance of designing human-centered metrics that capture what programmers need from and value in their AI pair programmers.

I. INTRODUCTION

Large language models trained on code (e.g., Codex [7], AlphaCode [18], CodeGen [22], InCoder [10]) have shown impressive capabilities on automatic code generation tasks. One important application for such models is *Human-AI pair programming*, where a model works together with a programmer-in-the-loop and suggests its generations as code completions (e.g., within an IDE) that programmers can choose to ignore, accept, or edit as needed. Early studies suggest that this paradigm may dramatically boost programmer productivity and potentially transform the practice of software development [16, 32].

As with most AI model development, in practice, the development of such code-generation models is largely driven by *offline metrics* that AI developers can efficiently and automatically compute on held out evaluation data. *Functional correctness* metrics such as *pass@k* [7] currently represent the state-of-best-practice (e.g., [5, 7, 8, 10, 14, 17, 22]). Functional correctness metrics evaluate an AI’s generation by executing the generation against a series of unit tests and and then computing whether the completed code passes or fails the tests. While functional correctness is clearly an important property of useful AI code generations, correctness alone may not fully capture all properties that make AI pair programmers useful. For example, what if a code generation that fails unit tests provides critical hints to solve a programming task (see example in Fig 1) or serves as boilerplate that can be adapted with minimal effort and modifications? Further, what if functionally correct code is difficult to read or maintain, or contains vulnerabilities not captured by unit-tests? In both these cases, functional correctness will fail to accurately assess the usefulness of AI code generations for human-AI pair programming because it does not assign partial credit to generations and does not consider the effort it would take to review and edit these generations. Thus, we argue that another important property of useful AI code generations should be their ability to increase a programmer’s productivity [9].

In this paper, we revisit offline metrics based on *syntactic similarity* such as Edit Similarity [8, 27] and BLEU [23], and examine how they may complement functional correctness, e.g., by capturing the effort programmers spend modifying code generations to solve programming tasks. Similarity-based metrics typically compute how similar (or different) a generation is to reference or ground truth code that solves the coding task. We compare functional correctness and similarity metrics to *perceived* value, an important dimension of programmer
productivity [9].

of code generations through a user study involving experienced programmers. Specifically, we examine the following key research questions: 1) **For a given programming task, which AI generations do programmers rate as most valuable?** For instance, do programmers rate generations that (they think) accurately solve the task as most valuable? Or do they rate generations that require the least effort to edit and adapt for solving the task as most valuable? 2) **How well do existing offline metrics for evaluating generations align with programmers’ rating of value?** Does functional correctness account for all generations that programmers find valuable? 3) **Can similarity-based offline metrics help capture the most valuable code generations?** And can we combine functional correctness and similarity metrics to develop metrics that even better align with programmers’ perceived value?

To answer these questions we conducted a user study with n=49 experienced programmers to understand how functional testing and similarity-based metrics align with what programmers perceive as valuable in practice. Our studies show that:

1) While, in general, programmers find generations that they perceive as correct as valuable, perceived accuracy failed to explain and account for all high-value generations. Surprisingly, the new effort-based factor that we considered – effort required to edit and adapt code generations – was highly correlated with value. In fact, on our user study sample, effort was significantly more correlated with value than perceived accuracy was.

2) While generations that passed unit tests were often rated as valuable, a large number of generations that failed unit tests (almost 42%) were also rated as valuable, again indicating that functional correctness can severely underestimate which generations programmers find most valuable.

3) While similarity-based metrics were less correlated with perceived value and effort than functional correctness, they still complemented functional correctness by helping differentiate between high- and low-value inaccurate generations. In fact, a simple combination of the two offline metrics improved the correlation with perceived value by 14%.

In summary, we contribute a user study to evaluate alignment between offline metrics and human judgements for code generation models, provide an empirical evidence for limitations of functional correctness, and develop a new combined metric to improve alignment with human judgements of value.

II. RELATED WORK

Large language models trained on massive amounts of natural language data and code have recently been applied to a range of software engineering tasks including code generation, translation, summarization, and search. In this work we study large language-based code generation models used to support developers in collaborative pair-programming tasks.

For AI-based systems that are intended to work collaboratively with people, “online” evaluations (such as A/B testing or user studies) can provide the best insights about how well those systems work with people-in-the-loop. However,
because online evaluations require fully functional systems and human subjects, they can be prohibitively expensive to apply in routine practice, let alone after every model or system update or availability. As a result, the AI community has turned to “offline” evaluations of AI models as isolated components by running models over one or more benchmark datasets and computing aggregate model scores such as accuracy, AUC, and precision/recall.

While offline metrics enable at-scale and less expensive evaluations, it is critical to validate that they reflect what people need and value in practice [11, 13, 15, 24, 28]. Indeed, existing research such as [6, 31] suggest that what is considered “effective” using offline metrics, may not always translate to more “value” for users in the real world. This metric-value mismatch may be due to a lack of justification or validation of metrics [31] or re-purposing datasets or metrics from scenarios that may not match the underlying socio-technical system that includes people (i.e., seeking to complement users rather than working in isolation and replacing them) [31].

To this end, we consider two of the most commonly used families of offline metrics for evaluating code generation models: functional correctness and similarity-based and investigate the extent to which they capture the actual usage scenario and what programmers value.

Functional correctness metrics seek to evaluate the generated code against known objective properties such as passing unit tests [5, 7, 18, 26]. Following the release of Codex and the HumanEval dataset [7]—which is a dataset of 164 handwritten problems in python with associated unit tests—the functional correctness metric of pass@k (where k code samples are generated per problem and a problem is considered solved if any of the k generations passes the corresponding unit tests) has emerged as the dominant method for evaluating code generation models (e.g., [5, 10, 18, 30]). Advocates of these metrics argue for their resemblance to programming best practices (e.g. test-driven development) and fidelity to capturing functional behaviour [7]. Evaluating models based on functional correctness, however, has some practical limitations including reliance on comprehensive unit tests that may be challenging to obtain [18] and language specific infrastructure to run automatically generated code and tests (e.g., inferring and installing appropriate libraries) which may pose security risks and can be resource intensive to run at-scale on large datasets.

Similarity-based metrics compare the tokens from generated code to tokens of known solutions and the generated code that are more similar to the solution(s) are considered to be more effective. Existing studies have applied multiple similarity-based metrics in evaluating code generation models: these include exact match [20], edit distance [8, 27], BLEU [23], CodeBLEU [25], and ROGUE [19]. Critics of similarity-based metrics argue that they may poorly account for the large and complex space of programs that may be functionally equivalent to a reference solution [7]. Moreover, correlation analysis of similarity-based metrics and other measures of code quality have been mixed (e.g., [25] vs Austin et al. [5]).

We argue that while similarity-based metrics are less commonly used compared to metrics approximating functional correctness, these metrics may be particularly relevant for programming over other natural language tasks, because “developers prefer to write and read code that is conventional, idiomatic, and familiar, because it helps in understanding and maintaining software systems” [4]. Furthermore, while similarity-based metrics may be insufficient for approximating functional correctness, we posit that what developers value about code generation models may go beyond correctness only. This is inline with findings from [29] that programmers might still find imperfect and erroneous generations useful and Forsgren et al. [9] who argue that developer productivity is multi-faceted and should be measured comprehensively including by considering code-quality as well as subjective perceptions of efficiency, flow, and satisfaction. As such and aligned with Svyatkovskiy et al. [27] and Lu et al. [20], we hypothesize that similarity-based metrics may be an important proxy for the effort it takes for programmers to edit and fix generated code and get to a state which is valuable to keep, and therefore are worth-while to do more research investigation on.

In this work we focus on pass@k as a proxy for functional correctness and we experiment with two similarity-based metrics, namely, normalized edit similarity [8, 20, 27] (which measures how many single-character edits—including insertion, substitution, or deletion—are required to convert generated code to some reference code) and BLEU (which measures the token overlap between the generated and reference text) to investigate how these metrics approximate different facets of what programmers value in practice.

III. USER STUDY

We designed a user study to evaluate how well functional correctness- and similarity-based offline metrics approximate value of code generations for programmers. At a high-level, the study showed experienced programmers various programming tasks, code generations for those tasks from popular code generation models, and reference solutions to the problems. Programmers then rated the generations in terms of perceived accuracy, effort to modify, and overall value.

A. Dataset for Programming Tasks

We selected programming tasks from the HumanEval dataset [7], which consists of 164 hand-crafted programming tasks and solutions written in python. Each task in HumanEval includes a task description (i.e., a function header followed by a comment describing the task and some sample test cases (115 – 1360 characters)), a canonical hand-written solution, and a set of associated unit tests. HumanEval has been extensively used to evaluate code generation systems (e.g., [7, 8, 10, 22, 30]) particularly because it includes hand-crafted coding tasks released as a compressed binary file making them less likely to be represented in the large data sets used for training code generation models [7]. On top of this, the simplicity of HumanEval tasks made it a good candidate for
our user study given there was no need to train participants in advance.

B. Offline Metrics for Code Generation

We experimented with three offline metrics, one of which served as a proxy for functional correctness and the other two served as a proxy for a programmer’s effort.

- **Pass**: As a proxy for functional correctness, we computed the pass@k metric [7]. pass@k takes k generations for a problem and considers the problem solved by a model if any generation in the set passes accompanying unit tests (in our case the unit tests provided in the HumanEval dataset). While related work has presented pass@k results for values of k including 1, 10, and even up to 1M [7, 18], we focus our analysis on k = 1 which most closely resembles the real-world scenario where a programmer sees a single generation inline within a coding editor.

- **Edit-Sim**: As one proxy for effort, we computed normalized edit similarity [27] as follows:

\[
\text{Edit-Sim} = 1 - \frac{\text{lev}(\text{gen}, \text{ref})}{\text{max}(\text{len}(\text{gen}), \text{len}(\text{ref}))}
\]

where gen is code generated by a model for a problem in the HumanEval dataset, ref is the hand-written reference solution to the problem and lev is the character Levenshtein edit distance.

- **BLEU**: As another proxy for effort, we computed BLEU using the formulation introduced by Papineni et al. [23] (generated code compared with a single reference), and based on the implementation in the Tensorflow library [1].

C. Code Generation Models

We selected a set of publicly available autoregressive large language models trained on code, varied mostly by the parameter size of each model. The first two models are variants of the CodeGen model introduced by Nijkamp et al. [22] - autoregressive transformers with the regular next-token prediction language modeling as the learning objective trained on a natural language corpus and programming language data curated from GitHub. In our work we use the CodeGen350 Multi (CG350M, 350M parameters) and CodeGen2B Multi (CG2B, 2B parameters) variants trained on code in six programming languages: C, C++, Go, Java, JavaScript, and Python. Our work also include the three publicly available variants of the Codex model [7], a GPT language model fine-tuned on publicly available code from GitHub (Cushman: CodexC1, Davinci1: CodexD1, Davinci2: CodexD2). Note that the goal of this work is to compare code-generation metrics and not to assess the performance of models. We used models of different sizes to help ensure our findings on how metrics behave translate across a range of model qualities. Following guidance from Chen et al. [7] who demonstrate the importance of optimizing sampling temperature for particular values of k, we used a low temperature value of t = 0.2 for k = 1 so that each model generates the most likely code tokens.

D. Tasks

We used programming tasks from the HumanEval dataset, where for each task, participants were shown the task description (function header and docstring describing the task along with sample test cases), the corresponding unit tests, and two code snippets — the reference solution from the HumanEval dataset and a generation for that task from one of the models — shown in a random order. Each snippet was randomly assigned a name - Code Snippet A or Code Snippet B for easy reference in the subsequent questions. All parts of the interface showing code were syntax highlighted to improve readability.

For each task, participants answered questions designed to collect their judgements along three dimensions of interest: overall value, accuracy, and effort which we hypothesized would impact value. Each question used 5-point Likert scales and were shown sequentially only after the previous question had been answered. The questions were as follows:

- **Accuracy**: The first question asked participants to judge whether both snippets were functionally equivalent. Since the reference solution is correct, functional equivalence can be used to infer perceived accuracy of a generation (complete equivalence indicates the participant believes the generation would produce the same outputs for all the same inputs as the reference solution which passes the provided unit tests). We used this equivalence question-based approach to assess perceived accuracy because our pilots suggested that judging equivalence is easier than solving the coding task from scratch, and also because it enabled us to design a simpler, consistent survey – the other two survey questions (as described next) also compared the generation to the reference. At this point in the task, participants were not told which snippet corresponded to the generation and which was written by a human programmer to minimize the impact of any existing biases about the capabilities of AI models.

- **Value**: Once participants advanced to the second question, the interface disclosed which snippet (A or B) was AI generated and which was a reference solution. They were then asked how useful the generated snippet would be assuming they were a programmer attempting to solve the task themselves. We described usefulness in terms of whether participants believed the generation provided a useful starting point, ranging from Extremely useful (they ”would definitely accept it and use it as a starting point”) to Not at all useful (they ”would not even want to see the generation” let alone accept and use it as a starting point).

- **Effort**: The final question asked participants how much effort they believed it would require them to modify the AI generated solution into a correct solution similar to the snippet written by a human programmer, if any.
Are the code snippets A and B above functionally equivalent?

- Completely equivalent (they would produce the same output for all of the same input)
- Mostly equivalent (they would produce the same output for most of the same input)
- Somewhat equivalent (they would produce the same output for some of the same input)
- Slightly equivalent (they would produce the same output for a few of the same input)
- Not equivalent (they would not produce the same output for any of the same input)

Assuming you were a programmer writing a solution to the task, and you received code snippet A (AI model) as a starting point, how useful will this be to you?

- Extremely useful (I would definitely accept and use it as a starting point)
- Very useful (I would likely accept it as a starting point)
- Somewhat useful (I might or might not accept it as a starting point)
- Not very useful (I would likely not accept it as a starting point)
- Not at all useful (I would not even want to see this suggestion)

How much effort would it take to modify Solution B (AI model) into a correct solution similar to Solution A (human programmer)?

- No effort (it completely solved the problem, I don't need to modify it)
- Little effort (it solved parts of the problem but I would have to make a few modifications to get it to work)
- Average effort (I would have to discard half of the code and write the other half from scratch)
- Some effort (it gave me some idea about how to solve the problem, but I would have had to rewrite most of the function)
- A lot of effort (it was way off and would have wasted my time)

Fig. 2: (a) Screenshot of a section in the main study task. For each task, participants were shown a pair of code snippets.

(b) 3 likert-type style questions that participants responded to - accuracy (framed as program equivalence to a known correct ground truth), value of generated code and effort.

Figure 2 shows screenshots of the user interface.

E. Study Protocol and Participants

The study consisted of four sections: consent form, instructions, main study, and a brief post-study feedback section. The instructions section was a sample task designed to familiarize participants with the mechanics of the study interface (e.g., they will be shown problems and asked to provide ratings, they will not be allowed to go back and revise previous responses) and to anchor them to pair programming scenario.

The main study was made up of 12 tasks. We chose 12 because our pilot studies showed that participants could complete 12 tasks within an hour. For each task, participants were shown a generation from one randomly chosen model from our set of 5 models.

A key goal of our study was to assess how well our offline metrics of interest align with what programmers value. We were particularly interested in understanding the tradeoffs between functional correctness and similarity as they relate to value and so we wanted to probe cases where these metrics disagreed. Therefore, to select study tasks, we first considered taking a random sample from HumanEval. However, the number of generations falling into regions where these metrics agreed on the largest model (Davinci2) was over-represented compared to the disagreement region (70% agreement vs 30% disagreement). Therefore, we chose a stratified sampling
method where we first assigned each HumanEval problem into one of three buckets: PASS = 1 and EDIT-SIM is low, PASS = 0 and EDIT-SIM is high, PASS and EDIT-SIM agree. Then, we sampled equally across each bucket aiming to annotate 20 problems per bucket for this study.

Because we intended to recruit professional programmers, we aimed to obtain up to 2 annotations per problem-model pair. With 60 problems (20 per bucket), 5 models, and 2 annotations per task and a budget of 12 problems per participant, this required us to recruit 50 participants for this study. We assigned annotation tasks to participants by randomly sampling a problem from our sample of 60 and then randomly sampling a generation for that problem, without repeating a problem for any participant, until each problem-model pair was assigned 2 annotations.

We recruited professional programmers from a large technology company for this study and recruitment emails were sent out to a randomly sampled subset of software engineers. Participants were required to have at least 1-2 years of programming experience with Python and to program in Python at least a few times a year. 61% of respondents indicated they had worked on a python project in the last month and 59% had never used a pair programming AI assistant like GitHub Copilot.

The study was deployed as a web application. Participants were given five days to complete the study, and could pause and resume using their personalized study link. At the end of the study, participants were given a $50 online gift card. As an additional incentive, we awarded the top 5 performers an additional $50 gift card. We determined top performers based on the rate at which participants correctly indicated a generation was equivalent to the reference code when it passed vs when it failed the given unit tests. This experiment was approved by our organization’s internal IRB process.

### IV. Study Results

At the end of the study period, we obtained responses from 49 participants. We then applied the following criteria to evaluate the quality of responses: First, we computed the median response time per task for all participants and also computed a performance rating on the code equivalence task in the same way we determined top performers in our study. Data from three participants who fell within the bottom 10th percentile of the median task completion times and their performance was worse than the probability of random chance (given the questions they responded to) was excluded from the data analysis. The final dataset includes data from 46 participants with 552 annotations across 290 unique tasks and 1.96 annotation per task. Finally, across tasks where we obtained multiple annotations, we verified that there was agreement between annotators and then computed the mean annotation per task for use in our analysis. In this section, we present the main findings based on this data.

#### A. Accuracy is Valuable, But Effort Matters Too

Our first finding is that the VALUE of a generation is nearly perfectly correlated with the perceived EFFORT needed to correct a generation (Pearson \( r = 0.94\); 95%-confidence interval [0.92–0.95]). Recall that EFFORT is reverse-coded such that a score of 5 indicates “no effort” is needed. ACCURACY is also highly correlated (Pearson \( r = 0.87\); 95%-confidence interval [0.84 – 0.90]), but significantly less so – we note that their confidence intervals do not overlap. From this we conclude that ACCURACY isn’t everything, and EFFORT is at least as important a signal for capturing VALUE. We will return to this theme throughout the paper. Correlations between these dimensions are presented in the top-left quadrant of Figure 3.

#### B. Offline Metrics Highly Correlate with Programmers’ Judgements, But There is Room for Improvement

Our second finding confirms that the metrics used in practice (PASS, EDIT-SIM, and BLEU) are indeed positively correlated with VALUE, but there are important differences (Fig. 3, bottom-left quadrant). As an example, PASS shows the strongest association with ACCURACY of the three metrics \( (r = 0.66; p < 0.001) \). This is unsurprising, given that PASS is a direct measure of functional correctness. More surprising to us, however, is that PASS is also the most strongly correlated metric to both EFFORT and VALUE \( (r = 0.62; p < 0.001, \text{ and } r = 0.62; p < 0.001 \text{ respectively}) \). This was unexpected since EDIT-SIM is a direct measure of the number of changes needed to correct a suggestion, and yet shows weaker correlation to EFFORT \( (r = 0.48; p < 0.001) \). With a correlation of \( r = 0.36; p < 0.001 \), BLEU under-performs all other metrics. Finally, given that none of the metrics correlate better than \( r = 0.66 \), there is significant opportunity to develop improved metrics.

\(^1\)According to Davinci2 and where similarity was thresholded along the median similarity value for that model.

\(^2\)In 50% of cases, annotators are in perfect agreement; 75% differ by at most one point in valence (on a rating scale of 1-5) and the mean difference is 0.89.

| Human Judgement | Offline Metrics |
|-----------------|-----------------|
| Value | Accuracy | Effort | Pass | Edit Sim | bleu | Combined |
| Value | 1.00 | 0.61 | 0.48 | 0.38 | 0.70 |
| Accuracy | 0.61 | 0.48 | 0.38 | 0.70 |
| Effort | 0.48 | 0.38 | 0.70 |

| Pass | 0.61 | 0.61 | 0.61 | 1.00 |
| Edit Sim | 0.48 | 0.46 | 0.33 | 1.00 |
| bleu | 0.38 | 0.34 | 0.19 | 0.68 | 1.00 |
| Combined | 0.70 | 0.71 | 0.72 | 0.89 | 0.61 | 0.38 | 1.00 |

Fig. 3: Correlation (Pearson) between human judgements (perceived value, accuracy and effort) and offline metrics (functional correctness, edit similarity and a combined metric (see section IV-D)). All correlations are significant with \( p < 0.001 \).
we find that when (\textsc{pass} = 1), the \textit{value} tends to be high (blue outlined regions). However, we also find that when a generation both fails the unit test and has low \textsc{edit-sim} (i.e., \textsc{pass} = 0; \textsc{edit-sim} = low), it tends to be judged to have low \textit{value} (red outlined region). Conversely, in the final region (\textsc{pass} = 0; \textsc{edit-sim} = high), \textit{value} is distributed more uniformly, and the signal is less clear. This strongly suggests that if human labeling is limited by budget, it may be worthwhile oversampling this region to maximally recover some of the missing \textit{value} signal.

This also suggests that there is an opportunity to combine metrics because \textsc{pass} = 1 is good at spotting high-value generations, while \textsc{pass} = 0; \textsc{edit-sim} = high is good at spotting low-value generations. To investigate this further, we formally define a simple combined metric as follows:

\[ \text{Combined} = \min(1.0, \text{pass} + \text{edit-sim}) \]  

Figure 3, row 7, shows some merit to this approach: The combined metric correlates better with human judgments of value \((r = 0.70; p < 0.001)\) than \textsc{pass} \((r = 0.61; p < 0.001)\) and \textsc{edit-sim} \((r = 0.48; p < 0.001)\) for \textsc{edit-sim}. This is an extremely promising result, but was also only our first attempt at combining metrics. Future work is needed to explore other potential combinations.

V. Discussion & Future Work

A. What Do Programmers Value from Their AI Pair Programmers?

Much of the current research evaluating code generation models aims to approximate overall value via some notion of correctness [5, 7, 8, 10, 14, 17, 22]. Even research exploring similarity-based metrics have tended to validate these against some general notion of code quality (e.g., Mathur et al. [21] consider “adequacy” while Ren et al. [25] consider “good vs bad”). In this work, we aim to tease out distinct aspects of value to better understand how they contribute what programmers want from their AI-pair programmers. In this study, we examine the impact of correctness and effort. Our findings show that effort indeed matters to programmers. Accuracy also matters but, interestingly, our findings suggest that effort savings may be even more valuable to programmers than accuracy.

In general, we take the position that value is a multi-dimensional theoretical construct [28]. As such, while our findings showed effort as more valuable to programmers than accuracy, because both are still highly correlated with value, we recommend considering both when assessing the impact of human-AI pair programming. Moreover, there are likely many other properties of AI-pair programmers that developers find valuable [9] and future work warrants investigating how these may also be captured in offline evaluations.

B. How Can Developers Approximate Value Offline?

Our results show that when developers have access to evaluation data containing high quality unit tests (as in HumanEval),
Fig. 5: Distributions of VALUE judgments, in the four possible combinations of PASS outcomes and low/high EDIT-SIM scores. The top and bottom rows indicate cases where EDIT-SIM falls below and above the 50th percentile, respectively. The left and right columns indicate cases where PASS = 0 and PASS = 1 respectively. When PASS = 1, generations are likely to be high value (blue regions). When both PASS = 0 and EDIT-SIM = low, generations are likely to be low value (red region). The VALUE is more uniformly distributed in the remaining region where both PASS = 0 and EDIT-SIM = high.

generations that pass unit tests are highly likely to be valuable to programmers. This suggests that PASS could be used as a reasonable filter in high precision scenarios (e.g., if an AI-pair programmer was tuned to limit distractions by only showing generations when they most likely to be valuable).

That said, however, PASS alone may miss a significant fraction of generations that programmers might find valuable. Our findings show that another offline metric – EDIT-SIM can help overcome this issue when we combine it with PASS according to Equation 1. This new metric is similar in spirit to hinge-loss in support vector machines. In that setting, misclassifications are penalized based on their distance to the hyperplane decision boundary. Conversely, correct classifications all receive a fixed loss of 0, following the intuition that they don’t become more correct the further they move from the hyperplane. In our setting, we expect VALUE to increase as generations become more similar to a reference solution, but once it reaches functional correctness it doesn’t become more correct the closer it gets (syntactically) to the reference solution.

We emphasize, however, that metrics can have varying implications on model development decisions and therefore the choice of when or if to combine them is important. For example, when developers are seeking to make deployment decisions between models, selecting models that rank highest in terms of the overall value they may provide to programmers seems reasonable. In this case, the theoretical construct being approximated is perceived VALUE and our COMBINED metric is better at estimating this than PASS or EDIT-SIM alone. However, when developers are diagnosing issues during model development (e.g., via error analyses) we recommend that PASS and EDIT-SIM be applied independently to get a clearer picture of model behavior [28] and to ensure appropriate mitigation strategies are used for different issues. For example, PASS failing on certain types of problems (e.g., recursive problems) or code blocks (e.g., conditional statements, error handling) may suggest additional data is needed in fine tuning. Whereas, EDIT-SIM failures may warrant new user interface techniques to help programmers focus attention to parts of the code most likely needing edits.

C. How Can Developers Approximate Accuracy and Effort Offline?

Our results show that programmers value both accuracy and effort savings when it comes to their AI pair programmers.
We demonstrate that **PASS** is a reasonable proxy for accuracy. Surprisingly, however, we found that **EDIT-SIM** is only moderately correlated with effort and in fact is less correlated with effort than **PASS**. This is somewhat counter-intuitive since **EDIT-SIM** directly measures the number of characters that need to be changed to convert a generation to the reference solution [20, 27].

This, along with our finding that programmers value effort reduction from their AI pair-programmers, suggests that an important area for future work is to experiment with alternative ways to operationalize effort for offline evaluation. This also, emphasizes the importance of validating that metrics faithfully capture the theoretical constructs they are trying to measure [15].

**D. When Should Developers Use EDIT-SIM?**

Our findings show that **EDIT-SIM** is moderately correlated with **PASS**. This is important because there are many situations where computing **PASS** may be undesirable. For example, **PASS** requires executing arbitrary generated code which can be resource intensive and may pose security risks [7]. **PASS** and other functional evaluation metrics also require the availability of comprehensive, high-quality unit tests as well as language-specific test infrastructure, assumptions which may not hold in some evaluation scenarios (e.g., testing functions in the wild). Therefore, while we recommend **PASS** when it is appropriate because it is more strongly correlated with value than **EDIT-SIM**, our findings suggest that **EDIT-SIM** may be a reasonable alternative when it is desirable to avoid limitations of functional evaluation.

Of course, limitations of similarity metrics should also be weighed against their benefits. For example, similarity metrics can fail when tasks have multiple syntactically divergent solutions - e.g. an algorithm may have an iterative vs recursive implementation with low token overlap, leading to noisy similarity metric. However, we intuit that this scenario is relatively infrequent given the structured nature of programming languages and existing research on developer behaviour e.g., Allamanis et al. [4] who mention that developers prefer to write [3] and read code [12] that is conventional, idiomatic, and familiar, because it helps in understanding and maintaining software systems. A convergence towards idiomatic solutions make it more likely the solutions and patterns learned by large language models of code coincide with ground truth solutions, limiting the scenario where generated code is syntactically different from but functionally equivalent to ground truth.

**E. Do These Findings Generalize?**

In this work, we focused on problems posed in the handcrafted **HumanEval** dataset [7]. A potential pitfall of a curated dataset such as **HumanEval** is that the results may not generalize to real-world scenarios where developers often deal with more complex problems and code bases (e.g., code with multiple dependencies across multiple files). To address this limitation, we originally explored the use of datasets mined from GitHub. However, our experiments indicated memorization issues (e.g., verbatim generation of solutions to niche problem), potentially due to the sample code already being included in the model training set. In practice, high quality code deduplication required to avoid this specific limitation is challenging. Work by Allamanis [2] find that the impact of duplicate code can be severe, sometimes inflating model performance scores by up to 100%. Furthermore, in our early pilot tests, functions extracted in the wild were found to contain insufficient context (e.g. absence of docstring) for even expert human annotators and isolating functional tests is challenging without heavy curation. Further research is therefore needed to understand how our findings might generalize to a wider variety of deployment settings as well as research on designing diverse evaluation datasets.

**VI. Conclusion**

We studied how well two types of offline metrics for evaluating code generation models (i.e., functional correctness such as **pass@k** based on unit tests and similarity-based metrics such as edit similarity) align with human judgements of value when used for human-AI pair programming. Our user study with 49 experienced programmers suggests that while programmers find functionally correct code generations valuable, the effort to edit and adapt generations also matters. Existing offline metrics show high correlation with human judgements of value, but there is room for improvement. One reason is that while code that passes unit tests is very likely to be rated high-value, code that fails unit tests is often still considered valuable by programmers. Based on this observation, we propose a combined offline metric inspired by hinge-loss in support vector machines that allows for partial credit by combining strengths of functional correctness and similarity-based metrics. Our analysis shows that this combined metric aligns better with human judgements of value in code generations than functional correctness or similarity alone. Overall our work highlights the importance of validating that offline metrics in AI capture what people value and that human-centered metrics, inspired by what people value, can provide better estimates of what people want from their AI-pair programmers.

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