Interactive Code Generation via Test-Driven User-Intent Formalization

Shuvendu K. Lahiri†, Sarah Fakhoury†, Aaditya Naik‡, Georgios Sakkas§
Saikat Chakraborty†, Madanlal Musuvathi†, Jeevana Priya Inala†, Piali Choudhury†
Curtis von Veh†, Chenglong Wang†, Jianfeng Gao†

1Microsoft Research
{shuvendu, sfakhoury, saikatc, madanm, jinala, pialic, curtissv, chenwang, jfgao}@microsoft.com
2University of Pennsylvania
asnaik@seas.upenn.edu
3University of California, San Diego
gsakkas@eng.ucsd.edu

Abstract—Large language models (LLMs) have shown great potential in automating significant aspects of coding by producing natural code from informal natural language (NL) intent. However, when interacting with LLMs, users have no guarantees that the code suggestions produced correctly satisfy the intent they provided. In fact, it is hard to define a notion of correctness since natural language can be ambiguous and lacks a formal semantics.

In this paper, we propose the workflow of interactive test-driven code generation (ITDCG), which leverages lightweight user feedback to (a) formalize the user intent using generated tests that can be useful for debugging, and (b) produce an improved set of code suggestions by pruning and ranking candidate code suggestions.

We describe a language-agnostic abstract algorithm for ITDCG, and a concrete implementation TiCODER. We perform an automated evaluation of TiCODER on the MBPP and HumanEval code generation benchmarks.

Our results are promising with using the OpenAI Codex LLM: our best algorithm improves the passeg code generation accuracy (in absolute percentages) between 22.49% to 37.71% for MBPP and between 24.79% to 53.98% for HumanEval using between 1 to 5 simulated user queries.

I. INTRODUCTION

Large Language Models (LLMs) have shown tremendous potential in generating natural-looking programs from informal intent expressed in natural language. There has been surge in research on training large language models over programming language artifacts in just the last couple of years [1], [2], [3], [4], [5]. Commercial offerings such as Copilot [6] are now available, and are already known to generate non-trivial fraction of code in real-world developer scenarios [7].

However, the rise of code synthesis from natural language poses new challenges for generating correct code. First, natural language is ambiguous, unlike formal specifications, to express the user intent. Consider the following docstring, taken from MBPP [8], a popular Python programming tasks benchmark:

```python
1  def text_lowercase_underscore(text):
2    """Write a function that returns true if the input string contains sequences of lowercase letters joined with an underscore and false otherwise""
```

This docstring is inherently ambiguous as 1) it does not specify how many sequences of lowercase letters joined by underscores are expected, and 2) if the input string must consist entirely of the sequence described, or can be a substring. An LLM may interpret the docstring in a number of ways, and generate several plausible programs with different behaviours. More importantly, the lack of a precise semantics of natural language means that one cannot even articulate the correctness of the code generated by a LLM. Research has shown that users struggle to understand LLM generated code suggestions presented to them, unless relying on the ability to run or debug the code to internalize program behaviour [9]. Otherwise, users may accept buggy code, or reject correct code that are too difficult to understand. Finally, when presented with a long list of plausible suggestions from LLMs, often sorted by some naturalness of the answer [10], a user often has to linearly scan each code suggestion, identify, and reject the incorrect ones.

While these issues are nascent to the LLM-based code generation space, the problem of disambiguation of user intent has been a long standing challenge in Programming by Example (PBE) paradigm [11], where users provide a set of input-output examples to express intended program behavior. However, prior research has shown that it can be difficult for users to manually provide a sufficient number of examples [12] and for those examples to sufficiently cover the hypothetical input space [13]. An augmented set of examples (or inputs) that cover a wider range of the input space can not only help to better guide synthesis techniques by pruning away more plausible programs, but also helps to reduce the mental load of understanding and validating synthesized programs [14] [15].

Although the benefits of intent disambiguation through example generation has been studied in the context of specific DSLs in PBE (such as regular expressions), such techniques do not readily apply to the problem of code generation in arbitrary

---

†Equal Contribution.
‡Work done while interning at Microsoft.
In this paper, we contribute by studying the ITDCG workflow through the following steps:

1) First, we describe an abstract algorithm InteractiveTestDrivenCodeGen for ITDCG that can (a) leverage off-the-shelf LLMs for generating seed tests, and (b) is parameterized by various well-specified components for pruning, mutating and ranking tests. Our approach is both domain-agnostic and programming-language agnostic by leveraging off-the-shelf LLMs for generating tests and rely only on runtime feedback to prune, mutate and rank tests and code.

2) Next, we implement InteractiveTestDrivenCodeGen in a tool TiCODER and evaluate several heuristics across our metrics on two Python programming datasets: MBPP and HumanEval.

3) Finally, we demonstrate empirically that each component of InteractiveTestDrivenCodeGen (namely, interaction, prompts, mutation, ranking) contributes to improving the effectiveness of the approach over a purely LLM-based baseline approach. Our best algorithm improves the pass@1 code generation accuracy metric by 22.49% with a single user query, and by 37.71% with 5 user queries for MBPP, and by 24.79% with one user query, and by 53.98% with 5 user queries for HumanEval. Second, we can generate a unit test consistent with the user intent within an average of 1.7 user queries for 87.12% of the examples in MBPP and 1.5 user queries for 95.73% of HumanEval.

II. WORKFLOW AND PROBLEM FORMULATION

In this section, we first provide some background on Large Language Models and outline the workflow for leveraging test generation and user feedback to disambiguate and refine user intent. Next we define intuitive metrics to evaluate different approaches that implement the workflow. Finally, we provide an algorithm to describe the workflow.

A. Background: Large Language Models for Code

Autoregressive language models based on the GPT-3 architecture [20] such as Codex [11] and PolyCoder [5], predict the probability of a token given the previous tokens, i.e. the input string (or prompt) of restricted length that is passed to the LLM. The left-to-right nature of these models makes them useful for program generation tasks, such as code completion. Given a code prompt, that may include a natural language description and/or input-output examples along with any other relevant context, a LLM generates a set of candidate completions that can be used for code completions.

B. High-level Workflow

Figure 1 describes the high-level workflow of Interactive Test-Driven Code Generation (ITDCG).

1) The human user requests the agent for completing a function body given the prefix in a file, a natural language description and the function header/signature containing method name, parameters and returns.
2) The agent generates a set of candidate code and test suggestions by prompting (possibly different) LLMs and possibly mutating them using purely runtime techniques.

3) The agent chooses a test and queries the user asking if a test is consistent with the user intent.

4) The user responds either YES, NO, or UNDEFINED to each of the queries from the agent.

5) The agent leverages the user response to prune, rank and mutate the existing set of code and test suggestions.

6) Once the interaction terminates, the agent outputs (a) a set of tests that the user has approved, and (b) a ranked list of code suggestions that are consistent with the user responses.

We note a few aspects of the workflow: First, the proposed workflow is language and domain agnostic, as it only relies on LLMs that are increasingly capable of generating code and test suggestions in multiple popular programming languages. It only relies on runtime execution feedback to prune, rank and mutate suggestions that are not language-specific.

Second, we allow a 3-valued possible user responses, including UNDEFINED, since there are many cases when a test outcome is ill-defined in the context of the intended functionality. For example, when presented with a test that violates the precondition of the desired function (e.g., \( \text{assert} \left( \text{Sqrt}(-4) == -2 \right) \)) for a square-root function that is undefined on negative numbers, it is desirable to respond UNDEFINED. As another example, if the test has parse errors (e.g., \( \text{assert} \left( \text{foo}() \right) \)), the question of the test being consistent with the user intent is not well defined. Finally, a flaky test that depends on non-determinism within a function may not have a unique answer (e.g., \( \text{assert} \left( \text{CurrentDayOfWeek}() == \text{Sunday} \right) \)).

Finally, note that our framework seeks only 1 of 3 possible user responses instead of richer feedback where, for example, the agent prompts the user to provide the desired output for a given input value.\(^1\) We believe this is not only more lightweight even when a test consists of an input-output example, but the framework also generalizes well for richer tests and specifications. For example, tests of stateful APIs comprises of a test-prefix as input and the output oracle consists of a non-trivial predicate (e.g., checking non-emptiness of a stack). Similarly, our framework generalizes to richer symbolic postconditions where a formula tightly couples the input and the output state (e.g., saying that the output array is a permutation of the input array for a sorting function).

### C. Metrics

| Metric      | Meaning                                                                 |
|-------------|--------------------------------------------------------------------------|
| pass@k@m    | Syntactic sugar for (possibly ranked) pass@k metric after m user queries |
| accept@m    | At least one of the proposed tests is consistent with the user-intent after m queries |

Table I describes two intuitive metrics to evaluate and compare the effectiveness of different approaches to ITDCG over a benchmark set. For evaluating the correctness of the generated code suggestions, we appeal to the popular metric pass@k for evaluating the quality of code-generation by LLMs with respect to hidden tests. A code suggestion is correct if it passes all the hidden tests, and pass@k determines the expected value of choosing at least one correct code suggestion within all possible samples of size k. We define the syntactic sugar pass@k@m to denote the pass@k for the code suggestions after m user queries (where pass@k is the same as pass@k@0).

For evaluating the correctness of the generated test suggestions, we introduce the metric accept@m, where m denotes the number of test queries to the user. For a given example, the metric accept@m equals 1 if at least one of the m suggested test queries is consistent with the user intent, and equals 0 otherwise.

Observe that the pass@k@m metric also indirectly serves to measure the quality of generated tests, by favoring tests that better prune incorrect codes.

### D. Abstract Algorithm

Although the workflow is general enough to apply to any program and test framework, we make the workflow ITDCG precise in the setting of a class of simple programs containing a single function to be completed. We also restrict a test to be an input-output pair \((i, o)\). A function \(f\) satisfies a test \((i, o)\) if and only if the result of executing \(f\) on \(i\) terminates with a unique value \(o\), i.e., \(f(i) = o\).

**Definition II.1.** A program \(p\) is a tuple \(\langle \text{prfx}_p, s_p, h_p, b_p, T_p \rangle\), where \(\text{prfx}_p\) is a prefix that may contain definitions of other global variables and imports, \(s_p\) is a natural language string description, \(h_p\) is the function header or signature, \(b_p\) is the body of the function and \(T_p\) is a set of unit tests.

**Figure 2** gives an example of such a program \(p\) expanding our running example.
Algorithm 1 InteractiveTestDrivenCodeGen

Input: Prefix prfx, description s, header h of a function f
Output: A ranked (possibly empty) list of candidate implementations for f

1: Output: A (possibly empty) set of user-approved tests T+

2: Output: f(i) == o for each f’ ∈ G and (i, o) in T+

3: G ← QueryLLM(M, CodePrompt(prfx, s, h)) ▷ Query LLM for codes

4: U ← SyntacticMutateTests(U) ▷ Mutate tests statically

5: U ← DynMutateTests(U, G) ▷ Mutate tests using dynamic execution

6: while k ≤ MaxRounds and |U| > 0 do

7: U ← RankTests(U, G) ▷ Rank the test suggestions

8: (i, o) ← U.pop() ▷ Remove the top ranked test

9: k ← k + 1 ▷ Number of user queries

10: r ← SatisfiesUserIntent(i, o, f) ▷ Query user for intent

11: if r == Yes then

12: T+ ← T+ ∪ {(i, o)} ▷ Prune codes that fail the accepted test

13: G ← G \ {c | c(i) ≠ o} ▷ Prune codes that pass the rejected test

14: else if r == No then

15: G ← G \ {c | c(i) == o} ▷ Prune codes that fail the accepted test

16: end if

17: G ← RankCodes(G, U) ▷ Rank the code suggestions

18: end while

19: return G, T+

Algorithm 1 describes the workflow informally sketched previously in Figure 1. The abstract algorithm is parameterized by a number of components that are underlined. It takes as inputs the prefix prfx in a file containing imports and other global variables, the natural language description of intent s, the signature/header of a function h including the function name and parameters.

The algorithm also takes a threshold MaxRounds for the number of user interaction rounds. Once terminated, the algorithm returns a set of tests approved by the user T+ as well as a ranked list G of candidate implementations of f that satisfies all the tests in T+.

The algorithm starts off by generating sets of code and test suggestions in to the variables G (line 1) and U (line 2) respectively. The quality of these sets will depend on the choice of the large language model M as well as the code and test prompts constructed from the problem description.2

We allow the test generation prompt to take the set of generated codes in G, to possibly improve the prompt. The algorithm maintains the invariant that the final set of code suggestions returned to the user is always a (possibly empty) subset of the initial set of suggestions in G, and never prunes a correct (as defined by the hidden tests) code suggestion. On the other hand, we allow the set of tests in U to be modified or augmented through both syntactic (line 3) and dynamic mutation (line 4) techniques using SyntacticMutateTests and DynMutateTests components respectively. Notice the dynamic mutation technique DynMutateTests takes the set of code suggestions in G as an input (in addition to U).

Finally, iterating in a loop (lines 6 to 18) until the stopping criteria is satisfied or the set of candidate tests in U is empty, ranking the tests in U using the method RankTests (line 7) and queries the user with the top-ranked test (line 10). If the user accepts the test, the set T+ is updated (line 12), and any code suggestion in G that disagrees with the test is pruned away (line 15). No action is taken if the user responds with UNDEFINED. Finally, the code suggestions in G are re-ranked with the remaining test suggestions in U (line 17) after the pruning.

III. TiCODER

In this section, we describe TiCODER (Test-driven Interactive Coder), a tool that implements the various components that are underlined in Algorithm 1. For each component (such as CodePrompt, RankTests), we provide several possible alternate implementations to define the space of solutions.

A. Code and Test Generation Prompts

It is well-known that the choice of prompts that determine the actual string that is fed to an LLM has a substantial impact on the quality of output [24]. In this section, we outline several choices for implementing the prompt generation routines CodePrompt and TestPrompt for generating code and test suggestions from the problem description consisting of (prfx, s, h).

Figure 3 presents a possible code prompt (in the gray boxes) that is generated by CodePrompt(prfx, s, h) and can be passed to an LLM to produce code suggestions for the given problem in Figure 2. Querying a LLM (e.g. Codex) with the code generation prompt in Figure 3 will result in a set of code suggestions as shown in Figure 4. Code suggestion c3 is a valid solution to the problem, while c1 is an incorrect code suggestion (since it allows the first substring to start with an uppercase letter) and c2 is also incorrect (since it allows more than one sequence of lowercase letters joined with an underscore).
There are several interesting choices for generating the test prompts for TestPrompt. Given that we wish to generate a test for a function without an implementation, the problem of TestPrompt in our setting boils down to completing the method body of $f$. The green boxes in Figure 3 show the “Prompt Body” and the subsequent “Test Body” that, together with the code prompt, constitute the test prompt. We use the statement pass as the method body, corresponding to a placeholder implementation in Python. The generated test suggestions (Figure 4) present the user with a set of tests. Some of these are consistent with the user intent ($t_3$), while others are inconsistent with the user intent ($t_1$ and $t_2$).

However, there are several other interesting possibilities for designing TestPrompt. For instance, we can sample a code completion $b'_p$ from the set of generated code suggestions $G$ and use it as definition of $f$. We therefore explore two options for $b_p$ in this work:

- pass: We can instantiate $b_p$ to simply be pass to keep the prompt for the test generation syntactically correct, as illustrated in Figure 3
- choose: Alternatively, we can sample a definition from a set of code suggestions $G$ and use it to instantiate the body of $f$.

In our experiment, we choose the code suggestion that appears first in the set of code suggestions in $G$ returned by the LLM.

**B. Static mutation of tests with SyntacticMutateTests**

Given an initial set of candidate tests in $U$, one can perform various syntactic mutations of a given test $t$ to yield new test cases. For each test $t \in U$, we consider two options for statically mutating it:

- In case a test has a parsing error, we consider the longest prefix of $t$ that parses.
- We consider the prefix of $t$ up to the first assertion; since each assertion is a point of failure, considering only one assertion maximizes the chance of a test passing. We refer to this technique as single-assert.

However, note that some of these decisions (such as single-assert) may also adversely impact the performance as it weakens the checks in the tests.

**C. Dynamic mutation of tests with DynMutateTests**

In addition to statically mutating tests, one can also exploit the ability to execute the tests, using the execution feedback to obtain new tests.

Given a test $(i,o)$ and a candidate implementation $f' \in G$, we can generate an alternate test $(i,f'(i))$ by modifying the output value observed by executing $f'$ (if any). The intuition behind this is that if $f'$ happens to be a correct solution, then we generate at least one test that is consistent with $f'$. We have implemented assert-rewrite-all, where we augment $U$ with all the tests obtained by rewriting each $(i,o) \in U$ with $(i,f'(i))$ for each $f' \in G$.

Consider a simple example, where we rewrite the test $t_2$ to $t'_2$ in Figure 4, where we mutate the test $t_2$ ("aa_bb_cc", True) to ("aa_bb_cc", False) by executing the input of $t_2$ through suggestion $c_3$ to obtain a new test $t'_2$. Now $t'_2$ is consistent (i.e. passes) with the correct suggestion $c_3$. Although in this particular case (given the Boolean valued function) both $t_2$ and $t'_2$ have the same pruning ability on the current code suggestions that have a Boolean return value, accepting $t'_2$ will prune any (hypothetical) code suggestion $c_n$ that incorrectly returns an integer as output. The mutation is more effective when the output value comes from a large space of values (e.g., strings, lists or integers).

**D. Ranking test suggestions using RankTests**

After obtaining the set of tests $U$, the user is presented with a test $t \in U$, which the user answers, thus pruning away code suggestions that are inconsistent with the user’s suggestions.

Therefore, to minimize the overhead of number of user interactions, it is necessary to present tests to the user that would result in the most number of incorrect code suggestions being pruned away [22], [15]. We describe various test ranking strategies starting with the performance of an optimal ranker.

1) **Ideal:** (ideal) Given the set of tests $U$, we first define the optimal (yet unrealizable) ranking policy. This option simulates the effect of choosing each test $t \in U$ to present to the user, and the number of incorrect code suggestions that will be pruned for such a choice by executing lines 10 to 15 of Algorithm 1. Since the Algorithm only prunes incorrect code suggestions, the above simulation would identify the test in $U$ that would maximize the pruning of incorrect suggestions, and establish an upper bound. However, this strategy is not realizable, as it requires the labeling of code suggestions as correct or incorrect.

We now discuss several alternative realizable approaches to implementing RankTests.

2) **Random:** (random) In this policy, we present the user with a test $t$ randomly chosen from $U$. This serves as a baseline where the user is simply presented with a test suggestion without any estimate of how useful presenting that test to the user would actually be.

3) **Discriminative:** (discriminative) In this policy, we rank the tests from $U$ based on how well they discriminate the set of code suggestions in $G$. If a test $t$ can discriminate between code suggestions well (i.e., splits the set of code
Fig. 4: Code and test suggestions for the running example in Figure 2 generated from a LLM. Code suggestion $c_3$ and test suggestion $t_3$ are both correct, while code suggestions $c_1$, $c_2$ and test suggestions $t_1$, $t_2$ are incorrect (appear shaded), i.e. they don’t satisfy the problem prompts in Figure 3.

suggestions into roughly equal halves), then it would prune away a substantial fraction of the code suggestions irrespective of the user response. Under the assumption that each code suggestion is equally likely to be correct or incorrect, this heuristic is likely going to yield a good test ranking strategy.

More precisely, for each test $t \in U$, we split the set of code suggestions $G$ into the sets $G^+_t$ and $G^-_t$ of code suggestions that pass and fail the assertions in $t$, respectively. We then prioritize tests where the ratio of the sizes of these two set is closest to 1. In other words, we rank the tests in decreasing order using the following scoring metric $s_{discr}$:

$$
min = \min(|G^+_t|, |G^-_t|) \\
max = \max(|G^+_t|, |G^-_t|) \\
s_{discr}(t) = \begin{cases} 
0 & \text{if max is 0} \\
\frac{\min}{\max} & \text{otherwise}
\end{cases}
$$

Note that we do not consider runtime exceptions and precondition failures as part of $G^-_t$. Our reasoning is similar to how we define the $\text{SatisfiesUserIntent}$ predicate, where we expect the user would likely respond with $\text{UNDEFINED}$ to such tests.

Consider the example in Figure 4. Consider the two tests $t_1$ and $t_2$: Two code suggestions $\{c_2, c_3\}$ fail on test suggestion $t_1$ while one suggestion $\{c_1\}$ passes, making $s_{discr}(t_1) = \min(1, 2)/\max(1, 2) = 1/2$. Similarly, two code suggestions $\{c_1, c_2\}$ pass on test suggestion $t_2$ while one suggestion $\{c_3\}$ fails and $s_{discr}(t_2) = 1/2$. Both tests $t_1$ and $t_2$ have equal discriminative ranking, although ideal ranking would choose to show $t_2$ as it prunes more incorrect code. All code suggestions in this example pass on test $t_3$ making $s_{discr}(t) = 0$. In this example, it is clear that showing $t_3$ would prune away the least number of incorrect code suggestions, and would not be chosen.

E. Ranking code suggestions using RankCodes

Finally, our goal is to present the user with a ranked list of code suggestions in $G$. We currently define a single code ranking strategy (passing-tests) that uses the tests in $U$ to determine an ordering on $G$ as follows:

- Each generated code $c \in G$ is executed with each test $t \in U$ and gets assigned as a score the number of passing tests $d_c$. The codes are then ranked based on the decreasing order of $d_c$.

Other variations of clustering and ranking code suggestions using tests have also been previously explored in recent works [25], [26], but currently not implemented in TiCODER.

Following from the example in the previous section, represented in Figure 4, code suggestion $c_1$ passes on all tests $\{t_1, t_2, t_3\}$, code suggestion $c_2$ passes on $\{t_2, t_3\}$ and code suggestion $c_3$ passes on $\{t_3\}$. Our ranking would therefore rank $c_1$ highest initially in the absence of any feedback from the user.

IV. EXPERIMENTAL EVALUATION

In this section, we start with our main research questions to evaluate different approaches and techniques for the test-driven interactive code generation problem. We next describe the experimental setup including datasets and how we automate the experimental setup. In Section V we describe our results.

A. Research Questions

1) RQ1: How does the interactive workflow improve the accuracy of code suggestions?
2) **RQ2**: How does the correctness of generated code and tests improve with the number of user queries?

3) **RQ3**: How do each of the design decisions affect the metrics (ablation study)?

### B. Dataset

We use two Python programming datasets for our evaluation, including the sanitized version of the MBPP dataset \[27\], dataset from Google, and the HumanEval dataset, introduced in the Codex paper \[1\], to answer the research questions. MBPP consists of 427 \([prfx, sp, hp, bp, T_p]\) tuples and HumanEval of 164 tuples as per Definition \[11\], where \(bp\) is the ground truth definition of the corresponding function. One example of such a tuple has been discussed in Figure 2.

We modify the original HumanEval dataset to remove any (non-hidden) input-output examples that are included in the docstring; in the presence of such examples in the docstring, one can write simple rules to propose a test that is guaranteed to satisfy the user intent as well as prune many incorrect code suggestions.

### C. Experimental setup and tools

For all experiments, we use OpenAI’s Codex code-davinci-002 model for inference only exposed through APIs. In each case, we query the Codex model for 100 code suggestions, with a temperature of 0.8 and a top \(p\) of 0.95. Intuitively, a temperature closer to 1 allows LLMs to provide more diverse sets of solutions, whereas a temperature closer to 0 forces LLMs to only generate fewer solutions with the highest confidence. The maximum code generation length is 300 tokens. Additionally, we query the Codex model for 50 test suggestions using the same parameters as before. Results are reported using the expected values of either pass@m or accept@m metrics described in Section \[1-B\] over all examples in each dataset. Further, in order to account for the non-determinism of Codex, we only query Codex once to generate the initial code and test suggestions into a cache of Codex responses and refer to the same cache for all experiments.

We have implemented our approach in TiCODER and we compare the performance of our approach with the Codex’s standard code generation, without including any user interaction. We also consider a Baseline version of TiCODER, where the tests to be presented to the user are generated by Codex with TestGenPrompt = pass with no further mutation, pruning or ranking while also disabling code ranking. Finally, we also compare against our implementation of a recent related work CodeT \[25\], which also exploits LLM-generated tests to improve the quality of code generation without any user interaction. In a nutshell, CodeT ranks a code (respectively, a test) by the number of tests (respectively, codes) it satisfies.

We also consider a few settings that help us establish an upper bound on the performance of any solution:

\[3\] Access to this model was removed to the public by OpenAI in March 2023.

### D. Automated evaluation

In practice, our proposed workflow requires real-time user response to determine if a generated test is consistent with the

![Image](image_url)
user's intent (i.e., SatisfiesUserIntent in Algorithm 1). Therefore, evaluating TiCODER offline with large-scale benchmark datasets is largely impractical. This is a common challenge faced by various tools and interaction models that require user input. To address this issue, and inspired by the framework of Oracle-Guided Inductive Synthesis (OGIS) [22], [15], [28], we propose the use of the oracle, i.e., the reference code implementation in each benchmark dataset, as a proxy for the user response. We use the reference implementation \( b_p \) as an oracle to answer if a test \((i, o)\) is consistent with the user intent. In other words, we assume that the intent of the user is precisely the semantics of the (hidden) reference implementation \( f_p \) for all terminating executions of \( f_p \).

We define the use of the oracle as a proxy for the user response as follows:

**Definition IV.1.** For a deterministic function \( f \) in a program \( p \) with a reference implementation \( f_p \) (comprising of \( h_p \) as header and \( b_p \) as the body) of \( f \), and a test (or an input/output example) \((i, o)\), SatisfiesUserIntent\((i, o, f)\) returns

1) YES, if \( f_p(i) \) terminates and produces the output \( o \).
2) NO, if \( f_p(i) \) terminates and produces an output \( o' \neq o \).
3) UNDEFINED, denoting syntax errors, runtime exceptions, or infinite loops.

V. Results

A. RQ1: Code suggestion accuracy

To answer RQ1, we compare the accuracies of Baseline, IdealTests, IdealRanking, and TiCODER (default option) restricted to the case of a single user query. We use the \( \text{pass}@k@m \) metric, where \( k \in \{1, 2, 5, 10\} \) and \( m = 1 \). We also compare the tools with Codex without any user interaction (\( m = 0 \)). Additionally, to get the best possible result from Codex, we also show Codex\(_{x=0}\), where we query Codex for 1 suggestion with temperature 0. We do not show results for Codex\(_{x=k}\) for \( k \geq 1 \) since we query for only one suggestion. Finally, recall that CodeT doesn’t include user interaction [25] and therefore we only report \( \text{pass}@k@0 \) numbers here, after applying their code and test ranking strategies.

Figure 5a presents the results for MBPP and Figure 5b the results for HumanEval. We observe that TiCODER has a \( \text{pass}@1@1 \) of 70.73% for MBPP, improving over the baseline Codex (48.24%) by non-trivial percentage. It also outperforms other baselines such as Codex\(_{x=0}\) (61.59%), Baseline (52.69%) and CodeT (63.70%). Similarly, Figure 5b also shows that TiCODER has a \( \text{pass}@1@1 \) of 55.28% for HumanEval, again improving over Codex baseline (30.49%). It also outperforms Codex\(_{x=0}\) (44.02%) and Baseline (37.80%), but falls a bit behind CodeT (58.54%). In Table III we do note that an alternate non-default configuration of TiCODER with \( \text{pass}@1@1 \) of 59.62% outperforms CodeT as well. TiCODER continues outperforming Baseline and Codex for \( k \in \{2, 5, 10\} \) for both datasets and additionally outperforms CodeT for all these metrics.

However, as expected, it falls short of the optimal IdealTests, with the \( \text{pass}@1@1 \) metric trailing by 16.62% and 35.57% behind for MBPP and HumanEval respectively.

The comparison with IdealRanking illustrates that there is room to improve the test ranking option itself, showing up to 13.58% and 14.29% potential improvement for \( \text{pass}@1@1 \) for the two benchmarks.

Finally, note that the performance of IdealTests and IdealRanking are comparable for MBPP as well as HumanEval for larger values of \( m \), but IdealRanking is always slightly lower (as expected). This shows that our test generation strategies that include tests generated by Codex along with the static/dynamic mutations can for the most part generate high-quality disambiguating tests.
B. RQ2: Impact of user interaction

To answer RQ2, we evaluate the four configurations along with CodeT as a baseline. In addition, we also evaluate a new configuration BaselineIdeald that we discuss later.

We show the results for pass@1@m in Figure 6a for MBPP and Figure 6b for HumanEval. In all cases, increasing the limit of the maximum number of queries increases the performance. However, this increase is very slight for the Baseline, while it is considerable for TiCODER. Note that IdealTests achieves the highest possible performance matching the pass@100 value after using all the hidden tests (3 tests for MBPP and 1 test HumanEval), while IdealRanking closely follows it. With 5 interactions, the accuracy of TiCODER approaches the accuracy of the IdealRanking, signifying that there is a good benefit to offset the interaction cost. Improvements to the ranking policy can result in further improvements for TiCODER and can require fewer user interactions.

To understand if our test mutation techniques improve the pool of tests over the pool of purely LLM-generated tests, we also apply optimal ranking to only the tests generated by the Baseline approach (reported as BaselineIdeald). Both Figures 6a and 6b demonstrate that our test mutation improves the accuracy by 10.72% and 13.74% respectively for MBPP and HumanEval after 5 interactions.

We additionally observe that CodeT consistently outperforms the simple Baseline, even though it includes no user interactions. However, TiCODER outperforms CodeT with only 1 user interaction in MBPP and with 2 user interactions in HumanEval.

Figure 7 shows the cumulative fraction of examples that produced a user-accepted test within m user queries, i.e. the expected value of accept@m for a given m. Additionally, it takes an average of 1.7 and 1.5 interactions with TiCODER to find a test satisfying user intent for MBPP and HumanEval respectively, with 1 being the minimum, and 10 being the maximum number of interactions (we cap the maximum number of user interactions to 10).

We observe that TiCODER is able to propose a test that is consistent with the user intent for 87.12% of the examples within 10 queries for MBPP and 95.73% for HumanEval, whereas the first query provides such a consistent test for 61.12% and 73.17% of examples respectively.

The results demonstrate that TiCODER is able to propose a consistent test (that can serve as a unit test accompanying the code) in a large fraction of cases within a small number of trials. Moreover, these test cases are non-vacuous (i.e., not assert true) and have good discriminative power as they prune the incorrect code suggestions and improves the pass@1@m for m ≥ 1.

C. RQ3: Ablation study

In order to examine the effects of various TiCODER components, we conduct ablation studies for each component individually. Specifically, we evaluate the performance of TiCODER with pass@k@m for k ∈ {1, 2, 5}, as well as pass@1@m for m ∈ {2, 5}. We consider the following ablations:

- TiCODER: This is the default configuration as described in Section IV-C.
- Code Prompt: TestGenPrompt = choose(G), where we choose one of the suggested code suggestions in the prompt instead of pass.
- Single Assert: StaticMutateTests = none, where we do not perform any pruning of assertions.
- Dynamic Mutation: DynMutateTests = none.
- Test Ranking: TestRanking = random.
- Code Ranking: CodeRanking = none, where we use the standard (unranked) pass@k metric over an unordered set of code suggestions.

Table II and Table III present the result of ablation for the two benchmarks. For each metric, the cell corresponding to the highest-performing configuration is marked in bold. Each configuration contributes differently to the evaluation, as we can see from the different metrics. The default configuration was chosen to be the configuration that performed best on the
pass@1@1 metric for the MBPP dataset. We prioritize the pass@1@1 metric since it is perhaps the most natural metric for code generation in an interactive setting since it relies on at most one user interaction and produces only one code suggestion as the final output. Note that the default configuration also performs best on pass@1@2 and pass@1@5 for MBPP. We observe, however, that for the HumanEval dataset a different code prompt than pass yields higher numbers, performing the best for pass@1@1, and pass@2@1. Finding the optimal configuration that performs best on both benchmarks is subject of future work.

Although we do not find a configuration that performs well for all the metrics across the two different benchmarks, it is clear that most of the components have a non-trivial impact on the performance overall metrics. Presenting the user with randomly picked tests from the set of test suggestions, rather than the top-ranked test, performs uniformly worse than the default configuration for both datasets. This indicates the importance of the test-ranking policy as a component. Similarly, another component that is helpful for the default configuration is dynamic test mutation; removing it results in a dip in performance as shown in Table II for MBPP. However, for HumanEval in Table I, pass@5@1 is higher without dynamically mutated tests. This could be the case that the generation of many tests can adversely impact the rule-based test ranking.

Code ranking is clearly useful in the default configuration for the pass@1@m metrics for MBPP but performs worse for the pass@k@1 metrics for k ≥ 2. For HumanEval, we observe again that code ranking can be important for 1 code suggestion, i.e. high pass@1@1 and pass@1@2 with a non-pass prompt, but can have adverse effects for more.

The ablations also demonstrate that other components have a non-trivial effect on the evaluation metrics. For example, disabling the static test mutation heuristic improves pass@2@1, while using the code suggestions in the test generation prompt improves performance on pass@1@2. However, these configurations were not chosen to be the default since they all perform worse on the pass@1@1 metric.

VI. Threats

Generalization of findings. We evaluate TiCODER using two popular and state-of-the-art research Python benchmarks for code generation tasks: MBPP and HumanEval. While both benchmarks exercise common programming patterns, they may not be representative of real-world software development. Our findings may not generalize to a different set of programs across different languages and problem domains.

Stability of model output. As we have used OpenAI API to access the Codex model, we cannot control the stochasticity of the output by the model, and the model endpoints themselves are often updated or even discontinued. This poses a threat to the replicability of our study. We aim to mitigate this by releasing model generated output in the near future used in this study to improve reproducibility of our results.

Interaction simulation. To enable a large scale evaluation of the potential of TiCODER to improve correctness of generated code, we simulate user interaction by using the oracle of reference code implementations as common in interactive synthesis literature. However, our automated evaluation assumes the user is able to answer the generated tests, and cannot account for the cognitive effort of users undertaking the coding tasks. We plan to conduct a user study to evaluate such metrics in practice similar to prior works in PBE [14].

VII. Related Work

AlphaCode [26] and CodeT [25] improve the pass@k metric by generating tests using LLMs (AlphaCode trains a new test-generation model) and then groups code suggestions by the set of tests they satisfy. When suggesting code suggestions, only a single suggestion from each group is reported. CodeT [25] refines the approach by scoring tests and code suggestions simultaneously by prioritizing tests that satisfy many code suggestions and prioritizing codes that satisfy many tests. Unlike ITDCG, these approaches still pass@k metric and do not account for user interaction or provide any guarantees on suggested code. On the other hand, our test and code ranking components can benefit from the algorithms in CodeT — we leave it as future work.

Scalable test generation for software has a rich history, and comprehensive coverage is outside the scope of this work. The dominating approaches for real-world code are based on variants of feedback-driven random testing [23] or on genetic programming [29]. These approaches are optimized for maximizing code coverage and finding runtime crashes. However, these approaches are not directly applicable in ITDCG scenario for two primary reasons (a) we do not start with an implementation of the method under test, and (b) it is critical to generate test oracles (expected output) without access to the method definition. Neural approaches have shown promise recently in either synthesizing test oracles [30], [18] or high-coverage tests [17] or generating an entire test [31]. We expect to harness these approaches to generate the seed tests that can be further mutated and ranked using suitable extensions to the algorithms presented in this work.

Finally, work on program synthesis [32], [33] generates code that satisfies a formal specification either expressed as a logical specification or input-output examples [34]. Unlike program synthesis, LLMs generate code from informal specifications (our setup) and evaluate it through hidden tests or specifications. However, it would be interesting for future work to leverage user-provided tests to improve the quality of code generation, as explored in recent works [35], [36].

Our work is closest to prior works in oracle-guided inductive synthesis [22], [28] and interactive program synthesis [15], [37] in querying an oracle (reference implementation or users) for distinguishing examples in addition to initial set. However, our work differs in several respects. First, most prior works appeal to an automatic symbolic engine (such as a constraint solver [37] or automata construction [14]) to generate distinguishing example inputs for a pair of programs, which is
inconceivable for general purpose imperative programming languages such as Python. Second, unlike classical uses of OGIS [22], we only require the user to provide a 3-valued output instead of asking for output for a given input. This requires less effort on the part of a user, making our queries closer in spirit to membership queries in Angluin’s classical automata learning algorithm [38]. Finally, unlike most program synthesis approaches that start with a handful of examples to express the intent, our formulation only starts with a natural language intent. Therefore, the augmented test cases are not only valuable to arrive at the correct code, but also serve as regression unit tests for maintaining the code.

VIII. CONCLUSIONS

In this work, we study the workflow of test-driven interactive code generation using LLMs. We explore various dynamic approaches for improving the effectiveness of a purely baseline LLM-based solution, and illustrate non-trivial improvements on code and test generation accuracy with different components for mutating, pruning and ranking test and code suggestions.

In future works, we plan to collect and evaluate our approach on real-world benchmarks such as CoderEval [39] and nl2fix [40]. We also leave as future work a user study on TiCODER to complement our findings from the simulated quantitative evaluation. Finally, we plan to explore how our approach can be extended to richer forms of formal specifications given a scalable generator and checker of such forms of specifications.

REFERENCES

[1] M. Chen, J. Tvorek, H. Jun, Q. Yuan, H. P. d. O. Pinto, J. Kaplan, H. Edwards, Y. Burda, N. Joseph, G. Brockman, A. Ray, R. Puri, G. Krueger, M. Petrov, H. Khlaaf, G. Sastry, P. Mishkin, B. Chan, S. Gray, N. Ryder, M. Pavlov, A. Power, L. Kaiser, M. Bavarian, C. Winter, P. Tillet, F. P. Such, D. Cummins, M. Plappert, F. Chantzi, E. Barnes, A. Herbert-Voss, W. H. Guss, A. Nichol, A. Paino, N. Tezak, J. Tang, I. Babuschkin, S. Balaji, S. Jain, W. Saunders, C. Hesse, A. N. Carr, J. Leike, J. Achiam, V. Misra, E. Morikawa, A. Radford, M. Knight, M. Brundage, M. Murati, K. Mayer, P. Welinder, B. McGrew, D. Amodei, S. McCandlish, I. Sutskever, and W. Zaremba, “Evaluating large language models trained on code,” 2021.

[2] A. Chowdhery, S. Narang, J. Devlin, M. Bosma, G. Mishra, A. Roberts, P. Barham, W. H. Chung, C. Sutton, S. Gehrmann, P. Schuh, K. Shi, S. Tsvyashchenko, J. Maynez, A. Rao, P. Barnes, Y. Tay, N. Shazeer, P. Brabakaran, E. Reif, N. Du, B. Hutchinson, R. Pope, J. Bradbury, J. Austin, M. Isard, G. Gur-Ari, P. Yin, T. Duke, A. Levskaya, S. Ghemawat, S. Dev, H. Michalewski, X. Garcia, V. Misra, K. Robinson, L. Fedus, D. Zhou, D. Ippolito, D. Luan, H. Lim, B. Zoph, A. Spiridonov, R. Sepassi, D. Doohan, S. Agrawal, M. Omernick, A. M. Dai, T. S. Pillai, M. Pellat, A. Lewkowycz, E. Moreira, R. Child, O. Polozov, K. Lee, Z. Zhou, X. Wang, B. Saeta, M. Diaz, O. Firat, M. Catasta, J. Wei, K. Meier-Hellstern, D. Eck, J. Dean, S. Petrov, and N. Fiedel, “Palm: Scaling language modeling with pathways,” 2022.

[3] E. Nijkamp, B. Pang, H. Hayashi, L. Tu, H. Wang, Y. Zhou, S. Savarese, and C. Xiong, “A conversational paradigm for program synthesis,” 2022.

[4] D. Fried, A. Aghajanian, J. Lin, S. Wang, E. Wallace, F. Shi, R. Zhong, W.-t. Yih, L. Zettlemoyer, and M. Lewis, “Indcoder: A generative model for code infilling and synthesis,” 2022.

[5] F. F. Xu, U. Alon, G. Neubig, and Y. J. Hellelloord, “A systematic evaluation of large language models of code,” in Proceedings of the 6th ACM SIGPLAN International Symposium on Machine Programming, MAPS 2022, (New York, NY, USA), p. 1–10, Association for Computing Machinery, 2022.

[6] GitHub, “Github copilot,” 2022. Accessed August 5, 2022. https://github.com/features/copilot/

[7] A. Ziegler, E. Kalliamvakou, X. A. Li, A. Rice, D. Riffkin, S. Simister, G. Sirtapatapam, and E. Aftandilian, “Production assessment of neural code completion,” in MAPS@PLDI 2022: 6th ACM SIGPLAN International Symposium on Machine Programming, San Diego, CA, USA, 13 June 2022 (S. Chaudhuri and C. Sutton, eds.), pp. 21–29, ACM, 2022.

[8] J. Austin, A. Odena, M. Nye, M. Bosma, H. Michalewski, D. Dohan, E. Jiang, C. Cai, M. Terry, Q. Le, et al., “Program synthesis with large language models,” arXiv preprint arXiv:2108.07732, 2021.

[9] P. Vaitilingam, T. Zhang, and E. L. Glassman, “Expectation vs. experience: Evaluating the usability of code generation tools powered by large language models,” in Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems, CHI EA ’22, (New York, NY, USA), Association for Computing Machinery, 2022.

[10] A. Hindle, E. T. Barr, M. Gabel, Z. Su, and P. Devanbu, “On the naturalness of software,” Communications of the ACM, vol. 59, no. 5, pp. 122–131, 2016.

[11] S. Gulwani, “Programming by examples: Applications, algorithms, and ambiguity resolution,” in Automated Reasoning - 8th International Joint Conference, IJCAR 2016, Coimbra, Portugal, June 27 - July 2, 2016, Proceedings (N. Olivetti and A. Tiwari, eds.), vol. 9706 of Lecture Notes in Computer Science, pp. 9–14, Springer, 2016.

[12] T. Lau, “Why program-writing-by-demonstration systems fail: Lessons learned for usable ai,” AI Magazine, vol. 30, no. 4, pp. 65–65, 2009.

[13] T. Y. Lee, C. Dugan, and B. B. Bederson, “Towards understanding human mistakes of programming by example: an online user study,” in Proceedings of the 22Nd International Conference on Intelligent User Interfaces, pp. 257–261, 2017.

[14] T. Zhang, L. Lowmanstone, X. Wang, and E. L. Glassman, “Interactive program synthesis by augmented examples,” in Proceedings of the 33rd Annual ACM Symposium on User Interface Software and Technology, pp. 627–648, 2020.

[15] V. Le, D. Perelman, O. Polozov, M. Raza, A. Udupa, and S. Gulwani, “Interactive program synthesis,” arXiv preprint arXiv:1703.03539, 2017.

[16] N. Perry, M. Srivastava, D. Kumar, and D. Boneh, “Do users write more insecure code with ai assistants?”, arXiv preprint arXiv:2211.03622, 2022.

[17] C. Lemieux, J. P. Inala, S. K. Lahiri, and S. Sen, “Codamosa: Escaping coverage plateaus in test generation with pre-trained large language models,” in 45th International Conference on Software Engineering, ser. ICSE, 2023.

[18] E. Dinella, G. Ryan, T. Mytkowicz, and S. Lahiri, “Toga: A neural method for test oracle generation,” in ICSE 2022, ACM, May 2022.

[19] M. Schäfer, S. Nadi, A. Eghbalii, and F. Tip, “Adaptive test generation using a large language model,” arXiv preprint arXiv:2302.06527, 2023.

[20] T. B. Brown, B. Mann, N. Ryder, M. Subbiah, J. Kaplan, P. Dhariwal, A. Neelakantan, P. Shyam, G. Sastry, A. Askell, S. Agarwal, A. Herbert-Voss, G. Krueger, T. Henighan, R. Child, A. Ramesh, D. M. Ziegler, J. Wu, C. Winter, C. Hesse, M. Chen, E. Sigler, M. Litwin, S. Gray, B. Chess, J. Clark, C. Berner, S. McCandlish, A. Radford, I. Sutskever, and D. Amodei, “Language models are few-shot learners,” 2020.

[21] Q. Luo, F. Hariri, L. Eloussi, and D. Marinov, “An empirical analysis ofaky tests,” in Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering, (FSE-22), Hong Kong, China, November 16 - 22, 2014 (S. Cheung, A. Orso, and M. D. Storey, eds.), pp. 643–653, ACM, 2014.

[22] S. Jha, S. Gulwani, S. A. Seshia, and A. Tiwari, “Oracle-guided component-based program synthesis,” in Proceedings of the 32nd ACM/IEEE International Conference on Software Engineering - Volume 1, ICSE 2010, Cape Town, South Africa, 1-8 May 2010 (J. Kramer, J. Bishop, P. T. Devanbu, and S. Uchitel, eds.), pp. 215–224, ACM, 2010.

[23] C. Pacheco, S. K. Lahiri, M. D. Ernst, and T. Ball, “Feedback-directed random test generation,” in ICSE 2007, Proceedings of the 29th International Conference on Software Engineering, (Minneapolis, MN, USA), pp. 75–84, May 2007.

[24] L. Reynolds and K. McDonell, “Prompt programming for large language models: Beyond the few-shot paradigm,” 2021.
B. Chen, F. Zhang, A. Nguyen, D. Zan, Z. Lin, J.-G. Lou, and W. Chen, “Codet: Code generation with generated tests,” 2022.

Y. Li, D. Choi, J. Chung, N. Kushman, J. Schrittwieser, R. Leblond, T. Eccles, J. Keeling, F. Gimeno, A. D. Lago, T. Hubert, P. Choy, C. d. M. d’Autume, I. Babuschkin, X. Chen, P.-S. Huang, J. Welbl, S. Goyal, A. Cherepanov, J. Molloy, D. J. Mankowitz, E. S. Robson, P. Kohli, N. de Freitas, K. Kavukcuoglu, and O. Vinyals, “Competition-level code generation with alphacode,” 2022.

J. Austin, A. Odena, M. Nye, M. Bosma, H. Michalewski, D. Dohan, E. Jiang, C. Cai, M. Terry, Q. Le, and C. Sutton, “Program synthesis with large language models,” 2021.

S. Jha and S. A. Seshia, “A theory of formal synthesis via inductive learning,” *Acta Informatica*, vol. 54, no. 7, pp. 693–726, 2017.

G. Fraser and A. Arcuri, “Evolutionary generation of whole test suites,” in *International Conference On Quality Software (QSIC)*, (Los Alamitos, CA, USA), pp. 31–40, IEEE Computer Society, 2011.

M. Tufano, D. Drain, A. Svyatkovskiy, and N. Sundaresan, “Generating accurate assert statements for unit test cases using pretrained transformers,” in *IEEE/ACM International Conference on Automation of Software Test, AST@ICSE 2022*, Pittsburgh, PA, USA, May 21-22, 2022, pp. 54–64, ACM/IEEE, 2022.

M. Tufano, D. Drain, A. Svyatkovskiy, S. K. Deng, and N. Sundaresan, “Unit test case generation with transformers and focal context,” 2020.

S. Gulwani, O. Polozov, and R. Singh, “Program synthesis,” *Found. Trends Program. Lang.*, vol. 4, no. 1-2, pp. 1–119, 2017.

A. Solar-Lezama, “The sketching approach to program synthesis,” in *Programming Languages and Systems (Z. Hu, ed.),* (Berlin, Heidelberg), pp. 4–13, Springer Berlin Heidelberg, 2009.

S. Gulwani, “Automating string processing in spreadsheets using input-output examples,” in *PoPL’11*, January 26-28, 2011, Austin, Texas, USA, January 2011.

N. Jain, S. Vaidyanath, A. Iyer, N. Natarajan, S. Parthasarathy, S. Rajamani, and R. Sharma, “Jigsaw: Large language models meet program synthesis,” in *International Conference on Software Engineering (ICSE)*, May 2022.

K. Rahmani, M. Raza, S. Gulwani, V. Le, D. Morris, A. Radhakrishna, G. Soares, and A. Tiwari, “Multi-modal program inference: a marriage of pre-trained language models and component-based synthesis,” *Proc. ACM Program. Lang.*, vol. 5, no. OOPSLA, pp. 1–29, 2021.

R. Ji, J. Liang, Y. Xiong, L. Zhang, and Z. Hu, “Question selection for interactive program synthesis,” in *Proceedings of the 41st ACM SIGPLAN Conference on Programming Language Design and Implementation*, PLDI 2020, (New York, NY, USA), p. 1143–1158, Association for Computing Machinery, 2020.

D. Angluin, “Learning regular sets from queries and counterexamples,” *Inf. Comput.*, vol. 75, no. 2, pp. 87–106, 1987.

H. Yu, B. Shen, D. Ran, J. Zhang, Q. Zhang, Y. Ma, G. Liang, Y. Li, T. Xie, and Q. Wang, “Codereval: A benchmark of pragmatic code generation with generative pre-trained models,” arXiv preprint arXiv:2302.00288, 2023.

S. Fakhoury, S. Chakraborty, M. Musuvathi, and S. K. Lahiri, “Towards generating functionally correct code edits from natural language issue descriptions,” arXiv preprint arXiv:2304.03816, 2023.