

Program Synthesis via Test-Time Transduction

Kang-il Lee¹ Jahyun Koo² Seunghyun Yoon³ Minbeom Kim²
 Hyukhun Koh² Dongryeol Lee¹ Kyomin Jung^{1,2*}

¹Dept. of ECE, Seoul National University ²IPAI, Seoul National University

³Adobe Research

{4bkang,kjung}@snu.ac.kr

Abstract

We introduce transductive program synthesis, a new formulation of the program synthesis task that explicitly leverages test inputs during synthesis. While prior approaches to program synthesis—whether based on natural language descriptions or input-output examples—typically aim to generalize from training examples, they often struggle with robustness, especially in real-world settings where training examples are limited and test inputs involve various edge cases. To address this, we propose a novel framework that improves robustness by treating synthesis as an active learning over a finite hypothesis class defined by programs’ outputs. We use an LLM to predict outputs for selected test inputs and eliminate inconsistent hypotheses, where the inputs are chosen via a greedy maximin algorithm to minimize the number of LLM queries required. We evaluate our approach on four benchmarks: Playgol, MBPP+, 1D-ARC, and programmatic world modeling on MiniGrid. We demonstrate that our method significantly improves program synthesis in both accuracy and efficiency. We release our code at <https://github.com/klee972/SYNTRA>.

1 Introduction

Program synthesis is the task of generating programs from a given specification, where the format of the specification can vary widely depending on the problem setting. Recent approaches to program synthesis using large language models [47, 30] rely on a natural language description, usually accompanied by a few test cases, to produce a program. In inductive program synthesis, the model operates without a natural language description, using only a set of input-output examples [48, 38, 19]. A common strategy in both lines of work involves sampling or enumerating multiple candidate programs and selecting those that satisfy the specification by executing them on the provided training examples. However, relatively little attention has been paid to settings where test inputs are available at synthesis time, i.e., the transductive learning scenario.

Vapnik famously advocated for transductive inference [45] with the principle: “*When solving a problem of interest, do not solve a more general problem as an intermediate step.*” In the context of program synthesis, this suggests that full generalization through induction may not be necessary if the goal is to predict outputs for a fixed set of test inputs. Such transductive scenarios are common in real-world applications such as spreadsheet automation or data transformation, where the goal is to synthesize a *one-off* program that correctly completes a given set of test inputs (Figure 1). In these settings, the number of training examples is often limited, as they are typically filled manually by users. As a result, programs synthesized from few examples may lack robustness when applied to the test inputs, especially if those inputs include edge cases (i.e., inputs that are atypical compared to the training examples or expose corner-case bugs in program logic). This limitation arises from

*Corresponding authors.

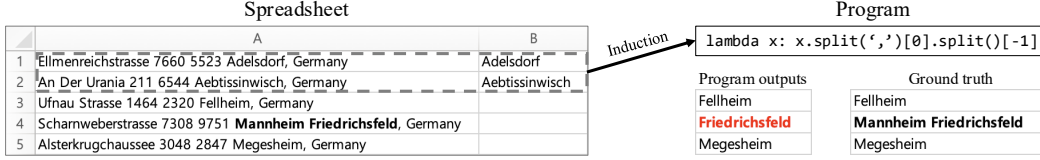


Figure 1: An example of spreadsheet auto-completion. Given the training examples (rows 1 and 2) as input, the inductive program synthesizer generates a program that satisfies these examples. However, this program produces an **incorrect output** for the test input in row 4, which represents an **edge case**.

epistemic uncertainty; the model is uncertain about what kinds of inputs will appear at test time. To address this, we introduce **transductive program synthesis**: an approach that explicitly leverages the available test inputs during synthesis to reduce uncertainty and produce more robust programs.

In this work, we formalize transductive program synthesis and propose **SYNTRA** (**SYNthesis-by-TRANsduction**) framework to improve the robustness of programs. The input to transductive program synthesis consists of a program specification and a set of N test inputs, and the goal is to synthesize a program that produces correct outputs on those test inputs. A straightforward approach to this problem might be to feed an LLM with the specification and test inputs and then either ask the model to (1) generate a program that satisfies them, or (2) directly predict the test outputs. However, both approaches suffer from poor scalability; their efficiency and performance degrade rapidly as the number of test inputs increases.

Alternatively, we approach this problem as a learning over a finite hypothesis class. The hypothesis class \mathcal{H} is defined as a set of N -tuples, consisting of program outputs on the test inputs, where the programs are generated by a **program synthesis model** based on the given specification. In our work, we implement the model using an LLM for its capability to generate code in general-purpose languages (e.g., Python). The programs' outputs on test inputs are collected and deduplicated to construct \mathcal{H} . We assume a realizable setting, in which there exists at least one hypothesis $h^* \in \mathcal{H}$ that matches all ground truth outputs. The objective is to identify this correct hypothesis h^* .

To achieve this, we leverage a **transduction model** that observes a test input and program outputs as candidates, and selects one output as a pseudo-label. Hypotheses inconsistent with this pseudo-label are eliminated from the current version of the hypothesis class. This process of transductive prediction and hypothesis elimination is repeated iteratively until a single hypothesis remains. Here, the number of queries to the transduction model depends on which inputs are queried and in what order. To minimize this cost, we propose a greedy maximin algorithm, which selects the test input that eliminates the largest number of hypotheses in the worst case. We instantiate the transduction model using an LLM, leveraging its reasoning abilities and world knowledge to produce high-accuracy pseudo-labels. As a result, our framework offers the best of both worlds: program synthesis (precision, efficiency and interpretability) and LLMs (common sense and world knowledge).

We evaluate our method on four program synthesis datasets: Playgol [9], an inductive programming benchmark for string transformation, MBPP+ [31], a benchmark for generating code from a natural language description, 1D-ARC [49], a visual reasoning benchmark, and programmatic world modeling on MiniGrid [7] environment. On these benchmarks, our algorithm significantly outperforms purely inductive [26] or transductive [33] methods. Moreover, by choosing test inputs according to the maximin criterion, we achieve comparable accuracy with substantially fewer LLM calls (halving the extra LLM calls above the lower bound) than when selecting inputs at random. We also empirically show that the number of required query increases sublinearly with the number of inputs, making it scalable to large test sets.

Our contributions are as follows:

- We formulate **transductive program synthesis** as a new task.
- We propose **SYNTRA**, a general framework that significantly improves the robustness of program synthesis on edge cases, by leveraging test inputs through a transduction model.
- We instantiate this framework using large language models and evaluate it on four datasets, showing up to 196% improvements in task accuracy.

2 Related Work

2.1 Program Synthesis with LLMs

Large language models have recently emerged as powerful tools for program synthesis, significantly advancing the automation of software development tasks. Models such as Codex [3] and Code Llama [39] have demonstrated strong performance on benchmarks like HumanEval [3] and MBPP [1].

Several works have explored enhancing program synthesis by using execution feedback to iteratively refine candidate programs [38, 23, 43], and by generating diverse solutions and selecting the best candidate based on test case results [29, 30, 47, 32] or functional consensus [25, 2, 42]. Despite these advances, the reliability of generated programs remains a challenge, particularly in the presence of edge cases or under-specified tasks [31, 4]. Our work seeks to improve robustness in such settings by leveraging available test inputs and the LLM’s transductive prediction capability.

2.2 Inductive Program Synthesis

Our work on transductive program synthesis is closely related to the extensively studied area of inductive program synthesis. It aims to generate a program from input-output examples, with the synthesized program expected to generalize to unseen inputs. Applications of inductive synthesis include string transformation [17, 11, 22], spreadsheet automation [6], list processing [40], visual reasoning [8, 28], symbolic regression [16], and graphics generation [13].

Early approaches to inductive program synthesis mostly relied on hand-crafted domain-specific languages (DSLs) to limit the space of possible programs [5, 35]. Recently, LLMs have emerged as powerful tools for inductive synthesis tasks, due to their ability to leverage extensive pre-trained knowledge and code generation capabilities in general-purpose languages such as Python [48, 27, 46].

Most of the mentioned works assume scenarios in which the number of training examples is sufficient to uniquely determine a single program. Some studies have explored designing optimal inputs for induction [37, 15] and using direct transductive prediction when program induction fails [28]. While researchers adopt Bayesian program learning [21, 12, 36] to address uncertainty and learning from few examples, its primary focus is learning a prior from training data rather than leveraging multiple test inputs during inference. Our work explicitly makes use of test inputs and proposes an effective methodology for addressing them.

3 Transductive Program Synthesis and SYNTRA Framework

We begin by formally defining the task of transductive program synthesis. We then describe the most general form of the Synthesis-by-Transduction (SYNTRA) framework, followed by a detailed explanation in Section 4 of how we instantiate this framework using large language models.

3.1 Problem Definition

Our problem formulation closely resembles that of transductive inference. Given an input set \mathcal{X} and an output set \mathcal{Y} , consider a function $f^* : \mathcal{X} \rightarrow \mathcal{Y}$ with a specification S . S includes M train input-output pairs $\{(x_i, y_i)\}_{i=1}^M \in (\mathcal{X} \times \mathcal{Y})^M$ where $f^*(x_i) = y_i$ for all $i \in [M]$, and (optionally) a natural language task description t . Also, there is a set of N test inputs $\{\tilde{x}_i\}_{i=1}^N$ visible to the system. The goal of the task is to predict the test outputs $\{\tilde{y}_i\}_{i=1}^N = \{f^*(\tilde{x}_i)\}_{i=1}^N$, given S and $\{\tilde{x}_i\}_{i=1}^N$.

In transductive program synthesis, predictions for the outputs are made by first synthesizing a program f , and then applying it to the test inputs. We expect f to produce correct outputs for the given test inputs; the primary concern here is not the overall correctness or generality of f , but rather its accuracy on the specific test set. Nevertheless, producing a predictive model in the form of an executable program offers several advantages, as will be discussed further in Section 6.

3.2 Synthesis-by-Transduction (SYNTRA)

We frame the above problem as an active learning problem over a finite hypothesis class.

Algorithm 1: SYNTRA

Input: Specification S with training examples $\{(x_j, y_j)\}_{j=1}^M$; Test inputs $\{\tilde{x}_i\}_{i=1}^N$; Program synthesis model σ ; Transduction model τ

Output: Hypothesis h^*

```
1 Function  $\mathbf{Y}(i, \mathcal{V})$ :  
2   return  $\{h[i] | h \in \mathcal{V}\}$   
3  $\mathcal{P} \leftarrow \sigma(S)$  // Generate programs  
4  $\mathcal{P}' \leftarrow \{f \in \mathcal{P} | f(x_j) = y_j, \forall j \in [M]\}$  // Filter by training examples  
5  $\mathcal{H} \leftarrow \text{exe\_dedup}(\mathcal{P}', \{\tilde{x}_i\}_{i=1}^N)$  // Get execution results and deduplicate  
6  $\mathcal{V}_0 \leftarrow \mathcal{H}$  // Initial version space  
7  $t \leftarrow 0$   
8 while  $|\mathcal{V}_t| > 1$  do  
9    $\mathcal{I} \leftarrow \arg \max_{i \in [N]} \min_{y \in \mathbf{Y}(i, \mathcal{V}_t)} |\{h \in \mathcal{V}_t | h[i] \neq y\}|$  // A set of maxes of mins  
10   $i^* \leftarrow \arg \min_{i \in \mathcal{I}} \sum_{y \in \mathbf{Y}(i, \mathcal{V}_t)} \text{len}(y)$  // Tie-break by shorter outputs  
11   $\hat{y} \leftarrow \tau(S, \tilde{x}_{i^*}, \mathbf{Y}(i^*, \mathcal{V}_t))$  // Transductive prediction  
12   $\mathcal{V}_{t+1} \leftarrow \{h \in \mathcal{V}_t | h[i^*] = \hat{y}\}$  // Eliminate inconsistent hypotheses  
13   $t \leftarrow t + 1$   
14 end  
15 return  $h^* \in \mathcal{V}_t$ 
```

Hypothesis class The construction of the hypothesis class \mathcal{H} (Alg. 1 L3~L6) follows these steps:

1. Generate a set of K candidate programs \mathcal{P} using a program synthesis model σ .
2. Filter the programs to retain only those that satisfy all M provided training input-output pairs.
This step yields $\mathcal{P}' = \left\{ f \in \mathcal{P} \mid \bigwedge_{i=1}^M f(x_i) = y_i \right\}$.
3. Execute the programs in \mathcal{P}' on the N test inputs and deduplicate the execution results to construct our hypothesis class $\mathcal{H} = \{(f(\tilde{x}_1), f(\tilde{x}_2), \dots, f(\tilde{x}_N)) | f \in \mathcal{P}'\}$. Note that the elements of \mathcal{H} are not programs themselves, but the outputs of those programs.

Since the hypothesis class defined above is only verified against the training input-output pairs, we must select a hypothesis that robustly generalizes the diverse cases that may appear in the test inputs. To this end, we iteratively repeat the process of input query selection, transductive prediction, and hypothesis elimination until only a single hypothesis remains.

Input query selection To leverage the power of the transduction model, we must decide which input to query for a prediction. The number of queries required to eliminate all but one hypothesis depends on which inputs are selected and in what order, making this choice a critical component of the method. We select an input based on a criterion that greedily maximizes the number of hypotheses eliminated in the worst case (Alg. 1 L9~L10).

To describe what our maximin criterion does: for each input, we first consider the worst-case prediction by the transduction model—that is, the scenario in which the prediction eliminates the fewest hypotheses (as illustrated in the “min” column of Figure 2). We then select the input for which this minimum number of eliminated hypotheses is maximized (\tilde{x}_1 in Figure 2).

Let us denote the i -th element of h as $h[i]$, and the deduplicated output set for input \tilde{x}_i and hypothesis class \mathcal{H} as $\mathcal{Y}_{i, \mathcal{H}}$. In other words, $\mathcal{Y}_{i, \mathcal{H}} = \{h[i] | h \in \mathcal{H}\}$. Then our proposed criterion to select the input index i^* can be represented as follows.

$$i^* = \arg \max_{i \in [N]} \min_{y \in \mathcal{Y}_{i, \mathcal{H}}} |\{h \in \mathcal{H} | h[i] \neq y\}| \quad (1)$$

	h_1	h_2	h_3	h_4	min
\tilde{x}_1	A	A	B	C	2
\tilde{x}_2	D	D	D	E	1
\tilde{x}_3	F	G	G	G	1

Figure 2: An example of the maximin algorithm. The numbers of eliminated hypotheses in the worst case are shown in the “min” column.

While this approach does not guarantee a globally optimal solution, it can be seen as a greedy algorithm that makes a locally optimal decision at each iteration. If we can assume that each query eliminates at least a certain fixed proportion of hypotheses, then this approach requires $O(\log |\mathcal{H}|)$ queries. Similar query selection mechanisms are widely used in the active learning literature [10, 34], where it is well understood that outperforming such greedy algorithms is often provably hard [18] in the absence of additional information.

When a tie occurs in the maximin value, we break ties by selecting the input whose set of possible output candidates has the shortest total length. This reduces the length of the input passed to the transduction model in the next step, helping to reduce computational cost and alleviate reasoning burden.

Transductive prediction The next step is to use the transduction model τ to predict the output for the selected input (Alg. 1 L11). Presumably, the transduction model is implemented using an LLM, due to its extensive world knowledge acquired from vast corpora and strong reasoning capabilities. The model’s input consists of the specification S , selected test input \tilde{x}_{i^*} for which the output is to be predicted, and the set of candidate outputs $\mathcal{Y}_{i^*, \mathcal{H}}$. The model’s output \hat{y} is one of the elements from the candidate output set.

$$\hat{y} = \tau(S, \tilde{x}_{i^*}, \mathcal{Y}_{i^*, \mathcal{H}}) \quad (2)$$

Hypothesis elimination As the final step of each iteration, we eliminate all hypotheses that are inconsistent with the output predicted by the transduction model (Alg. 1 L12). We define the **version space** at iteration t , denoted as \mathcal{V}_t , as the set of hypotheses consistent with all training and test observations collected up to iteration t .

$$\mathcal{V}_t = \{h \in \mathcal{V}_{t-1} | h[i^*] = \hat{y}\}, \mathcal{V}_0 = \mathcal{H} \quad (3)$$

4 LLM-Based Instantiation

So far, we have described the most general form of the SYNTRA framework. In this section, we provide details on how we instantiate this framework using an LLM, focusing on the implementation of the program synthesis model σ and the transduction model τ .

4.1 Program Synthesis Model

In our work, the program synthesis model σ is a function that takes program information as input and generates a set of candidate programs. We implement this model by prompting an LLM. The simplest approach is providing the LLM with a natural language instruction and program specification, and then obtaining multiple candidate programs through repeated IID sampling. A crucial consideration here is the *semantic diversity of the generated programs*, as diversity directly influences the expressiveness of the hypothesis space and thus significantly impacts the final system performance. However, IID sampling from the most powerful LLMs available today often results in programs with limited semantic diversity [24].

To overcome this limitation, we prompt the LLM to first generate distinct algorithms (implementations) for solving the given programming task. Subsequently, we prompt the LLM to translate each algorithm into executable Python code. By generating algorithm lists of length c through s rounds of IID sampling, we ultimately obtain a total of cs candidate programs as \mathcal{P} . In Appendix C.2, we observe that this approach indeed boosts diversity, leading to an increased number of tasks for which at least one correct program is generated. Henceforth, we refer to this approach as **AGA** (Autoregressively Generated Algorithms).

4.2 Transduction Model

In our framework, the role of the transduction model τ is to predict the output corresponding to a given input. The choice of LLM for implementing the transduction model is presumed to be more capable than the one used for the program synthesis model. This is because the program synthesis model needs to generate multiple candidate programs, making computation the main bottleneck. In contrast, the transduction model is expected to be called fewer times, but each prediction must be highly accurate. We instantiate this model using two types of LLMs (gpt-4.1-2025-04-14 or

gpt-4o-mini-2024-07-18) and compare their performance in Section 5.2. Specifically, the LLM is instructed to predict the correct output for a given test input, conditioned on the specification and candidate outputs. Additionally, we use zero-shot chain-of-thought prompting [20] to encourage explicit reasoning by the LLM. Since the LLM’s output is not guaranteed to exactly match one of the candidate outputs, we use fuzzy string matching to select the candidate that is most similar to the LLM’s prediction. We set the temperature of the program synthesis model to 1 and that of the transduction model to 0.7. Detailed prompts for both models are in Appendix B.

5 Experiment

5.1 Dataset

Playgol	MBPP+	1D-ARC	MiniGrid
"Conger, Minnesota(MN)" ↓ "State: Minnesota"	Write a function to check whether a list contains the given sublist or not. [[3, 5, 7], [3, 7]] → False	[0,0,1,0,0,0,1,0] ↓ [0,0,1,1,1,1,1,0]	Wall(0,0); Goal(1,0); Wall(0,1); Agent(1,1,direction=(1, 0)) ↓ action: turn left
"Princeton, New Jersey(NJ)" ↓ "State: New Jersey"	[[4, 3], [4, 3]] → True [['r'], []] → True	[0,1,0,0,1,0,0,0,0] ↓ [0,1,1,1,1,0,0,0,0]	Wall(0,0); Goal(1,0); Wall(0,1); Agent(1,1,direction=(0, -1))

Figure 3: Examples of Playgol, MBPP+, 1D-ARC and MiniGrid domain. Test outputs are highlighted in green.

We apply transductive program synthesis to four domains: string transformation, Python programming, visual reasoning, and programmatic world modeling (Figure 3). The string transformation domain is central to spreadsheet automation technologies, such as FlashFill [17] and Smart Fill [14]. Among the available datasets, we select Playgol² [9], a real-world dataset originally designed for inductive programming, as our benchmark.³ In Playgol, the original task is to generate a program consistent with a set of given input-output examples. Each task in Playgol provides five input-output examples; to simulate realistic conditions involving epistemic uncertainty, we use only one example as a training example and treat the remaining four examples as test inputs.

For the Python programming domain, we use the MBPP+ dataset [31] to evaluate our methodology. Compared to MBPP [1], MBPP+ provides significantly more diverse and numerous test cases, making it especially suitable for evaluating our framework, which assumes many available test inputs and potential edge cases. Furthermore, MBPP+ provides natural language instructions describing the desired functionality for each task. This setting mirrors realistic scenarios where a user provides input data along with an instruction specifying the task to be performed. MBPP+ provides at least 52 input-output pairs for every task; we utilize one example as training data and between 5 and 50 examples as test cases.

In the visual reasoning domain, we use 1D-ARC [49]. 1D-ARC is a 1D version of the challenging 2D grid visual reasoning benchmark, ARC [8], and it includes a variety of visual concepts (e.g., fill, flip, mirror, denoise, etc.). In this benchmark, we use 1 example as the training set and 3 examples as the test set.

Finally, we validate SYNTRA’s ability on programmatic world modeling (e.g. WorldCoder [44])—a complex task that requires modeling interaction mechanisms between different entities and actions. We used two MiniGrid [7] environments (DoorKey, UnlockPickup), and focused on generating a transition function that, given the current state and action, outputs the next state. In our experiment, the synthesis model receives the current state, action list, and natural language mission as input, and generates the world models. The transduction model’s role is to select the most plausible next state candidate among multiple world model predictions. For evaluation, given a state and an action, the world model selected by SYNTRA predicts the next state, which we then compare to the ground truth next state. The state and action pairs for evaluation are collected from human play. This task is well-suited for transductive program synthesis, as the action space is typically known beforehand and can serve as a visible test input. Since programmatic world modeling differs in nature from the three domains discussed earlier, we present it separately in Section 5.4.

²The name “Playgol” originally refers to an inductive logic programming system [9]. We use the name here to refer to the string transformation dataset introduced in that work.

³We manually corrected some mislabeled tasks of the dataset.

5.2 Main Results

Our primary focus in this section is the learning over the hypothesis class defined earlier. Therefore, we filter out tasks where learning is trivial. Specifically, we only retain tasks where the hypothesis class \mathcal{H} constructed by σ contains both correct and incorrect candidate hypotheses. After this filtering, we obtain 119 tasks with 4 test inputs from Playgol, 149 tasks with 50 test inputs from MBPP+, and 124 tasks with 3 test inputs from 1D-ARC for our evaluation.

Table 1: Comparison of different approaches on the filtered Playgol and MBPP+ datasets. Filtering is based on the 32 programs generated using AGA ($c = 4, s = 8$) with gpt-4o-mini-2024-07-18.

Approach	Playgol (1 train / 4 test)			MBPP+ (1 train / 10 test)		
	Task Acc.	Example Acc.	# τ Calls	Task Acc.	Example Acc.	# τ Calls
Random program $f \in \mathcal{P}'$	66.6	79.9	-	70.6	88.2	-
Random hypothesis $h \in \mathcal{V}_0$	37.6	62.7	-	43.4	76.8	-
<i>gpt-4.1 for τ</i>						
LLM direct transduction [33]	85.7	93.7	476	59.7	87.2	1490
SYNTRA w/ random query	93.3	96.0	144	84.6	94.1	198
SYNTRA w/ maximin	93.3	96.3	131	85.9	95.6	164
<i>gpt-4o-mini for τ</i>						
LLM direct transduction [33]	72.3	87.4	476	35.6	75.0	1490
SYNTRA w/ random query	91.6	95.5	140	75.2	90.4	190
SYNTRA w/ maximin	93.3	96.3	132	73.2	89.5	163

In Table 1 and 2, we evaluate our proposed methodology against several baselines. In this experiment, we use 10 test inputs out of 50 for MBPP+. We report two primary accuracy metrics: task-level accuracy, defined as the percentage of tasks for which all test outputs are predicted correctly, and example-level accuracy, defined as the proportion of correctly predicted test outputs. Additionally, we report the number of transduction model calls as a measure of efficiency (see Section 6 for more detailed discussion on computational cost). We compare SYNTRA with the following ablations.

Table 2: Comparison of different approaches on the filtered 1D-ARC dataset. Filtering is based on the 128 programs generated using MoC [26] with gpt-4.1-mini-2025-04-14.

Approach	1D-ARC (1 train / 3 test)		
	Task Acc.	Example Acc.	# τ Calls
Random program $f \in \mathcal{P}'$	24.0	28.7	-
<i>gpt-4.1 for τ</i>			
LLM direct transduction [33]	41.9	68.1	372
SYNTRA w/ random query	71.8	82.1	179
SYNTRA w/ maximin	71.8	80.8	159

- **Random program** selects a program uniformly at random from the set of candidates that are consistent with the training example (i.e., from \mathcal{P}' in our algorithm).
- **Random hypothesis** first deduplicates the outputs of the programs to form a hypothesis class, then samples a single hypothesis uniformly at random from this set. This baseline performs significantly worse than the random program baseline, suggesting that correct programs are sampled more frequently before output-based deduplication.
- **LLM direct transduction** bypasses program synthesis entirely and instead asks the LLM to directly predict test outputs given the training example and test inputs. The prompt explicitly instructs the LLM to reason step-by-step. Interestingly, this approach outperforms the synthesis baseline (random program) on Playgol and 1D-ARC but underperforms on MBPP+. We attribute this to the fact that Playgol and 1D-ARC tasks often benefit from world knowledge and pattern recognition (a strength of LLMs), whereas MBPP+ tasks tend to be more algorithmic in nature (a strength of programs). A key limitation of direct LLM transduction is that the number of LLM calls scales linearly with the number of test inputs, making the method computationally impractical when the test set is large.
- **SYNTRA with random query** is a variant of SYNTRA, which randomly selects the input query (from those with at least two possible output candidates) as an ablation of the maximin criterion. As shown in the table, this approach already yields significant improvements over all baselines in both domains and with both models. The performance gain is especially pronounced when using a more capable model like gpt-4.1.

- **SYNTRA with maximin criterion** is the full version of our method, including the maximin input selection criterion. Compared to the random query variant, this method substantially reduces the number of transduction model calls, particularly in MBPP+, where the number of test inputs is larger. This result highlights the efficiency and scalability of our SYNTRA framework.

Appendix C.1 presents additional experimental results using smaller open-source LLMs. Additionally, Appendix D provides examples where our methodology succeeds and fails, along with an analysis of its strengths and weaknesses.

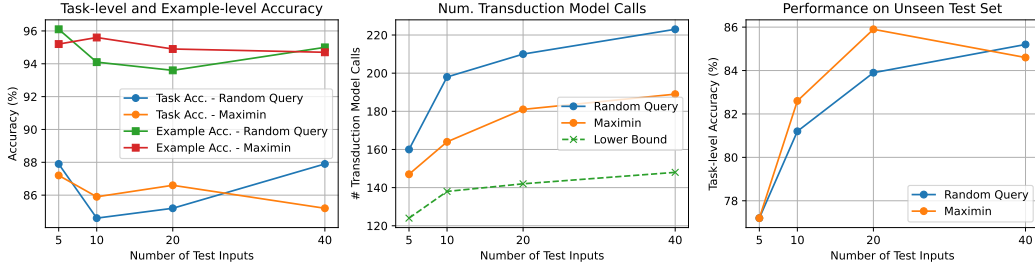


Figure 4: Experimental results on test input scaling and the unseen test set.

Scaling test set size In real-world applications, program synthesis is especially valuable when the number of test inputs is so large that manual processing is cumbersome. To simulate such conditions, we leverage the abundant test cases in MBPP+. Specifically, we vary the number of visible test inputs provided to the system: 5, 10, 20, and 40. For each setting, we measure accuracy and the number of transduction model calls.

In Figure 4, we observe that task-level and example-level accuracy remain relatively stable regardless of the number of test inputs. In terms of transductive model call counts, the number of calls increases **sub-linearly** with the number of test inputs, demonstrating the scalability of our framework. Notably, the gap between the maximin and random query methods also widens as the test set grows. In addition, we indicate a “lower bound,” the number of tasks where the initial hypothesis class \mathcal{V}_0 contains at least two distinct hypotheses. This value serves as a rather conservative lower bound on the number of necessary LLM calls, since at least one query is needed to resolve any ambiguity (the true minimum number of calls is likely higher). When comparing the number of LLM calls to this lower bound, we find that the maximin criterion approaches roughly twice the efficiency of the random query strategy. These results indicate that the maximin algorithm significantly improves the efficiency of the SYNTRA framework.

Performance on unseen test set Next, we investigate how well the programs synthesized via SYNTRA generalize to an unseen test set. The unseen test set is constructed by selecting 10 test inputs from the 50 available in MBPP+, while the remaining 40 are used as test inputs visible to the system. We run SYNTRA using 5, 10, 20, or 40 of these visible test inputs and measure the task-level accuracy of the resulting program on the unseen test set.

The results in Figure 4 show a general trend: as the number of visible test inputs increases, the accuracy on the unseen test set also improves. When using 20 or more visible test inputs, the accuracy on the unseen test set approaches the task accuracy reported in Table 1. This suggests that programs synthesized via SYNTRA from a sufficiently large number of test inputs can be expected to perform comparably well even on new, unseen inputs.

5.3 Variations on Program Synthesis Model

Up to this point, we have focused on how efficiently and robustly our method can select a correct program from fixed hypothesis class constructed by particular synthesis model. However, when considering expected performance over all tasks, the choice of synthesis model becomes critically important. In this section, we examine how the choice of synthesis model affects overall performance on the full, unfiltered datasets. In this experiment, we use 4 test inputs for Playgol, 50 test inputs for MBPP+, and 3 test inputs for 1D-ARC.

IID sampling The AGA approach we use first generates algorithms autoregressively and then translates each into Python code. As a result, the resulting programs do not strictly follow the LLM’s output distribution. This deliberate “flattening” of the output probability boosts diversity, which benefits in more challenging tasks [26, 47, 30]. However, it may reduce the likelihood of sampling a correct program in easier tasks, where the correct solution is already highly probable under the model’s natural distribution. To investigate this phenomenon in the context of our work, we consider a more standard approach for the synthesis model: IID sampling of programs from a fixed prompt. We evaluate how this affects end-to-end performance.

Table 3 (IID) shows the performance of randomly selecting a program from those obtained via IID sampling. On Playgol and 1D-ARC, IID slightly outperforms AGA. However, in MBPP+, performance drops significantly. This suggests that MBPP+ tasks benefit more from the diversity encouraged by AGA, which increases the chance of synthesizing a robust program.

Table 3: Task accuracies (%) of various approaches.

Approach	Playgol	MBPP+	1D-ARC
AGA	72.7	64.8	23.9
AGA + SYNTRA	82.5	72.4	37.8
IID	76.9	56.9	25.0
IID + SYNTRA	82.5	59.1	38.9
MoC [26]	78.1	71.4	16.7
MoC + SYNTRA	83.7	74.0	49.4
AGA + test inputs as prompt	80.4	63.5	-
AGA + test inputs as prompt + SYNTRA	84.6	70.3	-
IID + test inputs as prompt	83.2	49.3	-

Interestingly, the performance gap between AGA and IID on Playgol disappears when we apply SYNTRA (AGA + SYNTRA v.s. IID + SYNTRA). This indicates that AGA did generate the correct program, but it was underrepresented in the overall program pool and thus unlikely to be selected—SYNTRA was able to recover it. In contrast, on MBPP+, applying SYNTRA does not close the gap between AGA and IID, implying that IID sampling failed to generate the correct program at all, leaving no opportunity for SYNTRA to recover it. These observations underscore the value of diversity-enhancing strategies like AGA, especially when combined with effective verification mechanisms like SYNTRA.

Advanced model We also examine the impact on final performance when SYNTRA is applied to state-of-the-art program synthesis model. We use Mixture of Concepts (MoC) [26], a recent inductive program synthesis approach based on LLMs. MoC first generates distinct elementary concepts that may help solve the problem, then produces natural language hypotheses based on these concepts, and synthesizes Python programs based on the hypotheses. For MBPP+, we made a minor modification by including the natural language task description in the prompt.

The results in the table show that MoC alone yields mixed outcomes depending on the benchmark. However, when combined with SYNTRA, performance improves even further, outperforming all other approaches we compared. This demonstrates that the SYNTRA framework can be layered on top of existing strong program synthesis models to push performance beyond current limits.

Test inputs as prompt A straightforward way to directly improve the output distribution of an LLM-based program synthesis model is to include test inputs in the prompt, explicitly instructing the model to generate a program that generalizes to those inputs. While intuitive, this approach is not scalable, as the prompt length increases proportionally with the number of test inputs.

As shown in Table 3 (test inputs as prompt), this method can indeed be beneficial in cases like Playgol, where the number of test inputs is relatively small. However, for MBPP+, including test inputs in the prompt leads to a performance drop for both AGA and IID. This likely results from the excessive prompt length—incorporating all 50 test inputs may overwhelm the LLM and hinder its reasoning ability. These limitations further highlight the importance of scalable alternatives such as SYNTRA, which can robustly select correct programs without overloading the prompt.

5.4 Programmatic World Modeling on MiniGrid

Finally, we apply SYNTRA to programmatic world modeling on MiniGrid. Both the synthesis and transduction models are `gpt-4.1-mini-2025-04-14`. We sample 16 IID programs per state, and used example-level accuracy to compute transition function accuracy. In Table 4, SYNTRA shows substantial benefit for the world model synthesis task as well. SYNTRA enables learning a more accurate world model, which would likely result in more efficient planning or policy learning.

Table 4: Task accuracies (%) on MiniGrid.

Approach	DoorKey	UnlockPickup
IID	57.1	62.9
IID + SYNTRA	68.8	67.6

A good example that illustrates how SYNTRA helps in this task is coordinate notation. In the MiniGrid state representation we used, the positive directions are to the right and downward, and this sign convention can be inferred from the coordinates of surrounding objects. Since this convention is not obvious at the outset, actions such as `turn left` or `turn right` are not always implemented correctly during the synthesis stage. However, the transduction model, by directly observing the candidate output states, was able to identify the correct one.

6 Discussion

Extension to online learning and human-in-the-loop Our methodology naturally extends to online or human-in-the-loop settings. After identifying a final hypothesis through SYNTRA, we can retain the corresponding program and, when a new input arrives, detect behavioral divergence across candidate programs. In such cases, the system can invoke the transduction model to update the version space accordingly. Moreover, in situations where the transduction model’s confidence is low, the system can selectively ask the user for label, enabling interactive program synthesis with minimal human intervention.

Transductive program synthesis v.s. LLM direct transduction In our experiments, we compared transductive program synthesis and LLM direct transduction primarily by measuring the number of transduction model calls. When considering the full pipeline, the program synthesis method includes a preliminary step of generating 32 candidate programs. In such cases, direct LLM prediction may result in fewer total calls. However, in our experimental setup, we used a smaller model for synthesis and a larger model for transduction, prioritizing prediction quality over generation cost. SYNTRA typically required no more than three calls per task, making the overall cost lower for SYNTRA despite the initial synthesis step. Furthermore, as the number of test inputs increases, the cost of direct transduction increases linearly, whereas our method remains more stable.

Beyond efficiency, transductive program synthesis offers significant advantages over direct transduction in terms of performance, interpretability, and extensibility to online or human-in-the-loop workflows. In domains where some tasks are inherently difficult to express through code, a hybrid approach that ensembles program synthesis with direct prediction may be more effective [28].

Probabilistic perspective Rather than performing probabilistic inference over programs directly, our approach constructs a hypothesis class by deduplicating execution results and eliminates hypotheses based on transductive predictions. This design choice is intended to ensure broad applicability, even to models where program probabilities are difficult to estimate, such as black-box LLMs or synthesis models based on enumerative search. If such probabilities were available, our framework could incorporate probabilistic strategies. For instance, instead of maximin criteria, we could adopt uncertainty-based strategies or more sophisticated methods like query-by-committee [41]. These directions offer promising extensions for future work.

7 Conclusion

We introduced transductive program synthesis, a new framework that leverages test inputs during synthesis to improve the robustness and efficiency of program generation. By combining LLM-based program synthesis with transductive prediction and hypothesis elimination, our SYNTRA framework significantly outperforms baselines in terms of accuracy and efficiency. This framework is scalable, interpretable, and extensible; offering a promising direction for robust real-world program synthesis.

References

- [1] Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. Program synthesis with large language models. *arXiv preprint arXiv:2108.07732*, 2021.
- [2] Jingchang Chen, Hongxuan Tang, Zheng Chu, Qianglong Chen, Zekun Wang, Ming Liu, and Bing Qin. Divide-and-conquer meets consensus: Unleashing the power of functions in code generation. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL <https://openreview.net/forum?id=cFqAANINGW>.
- [3] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde De Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*, 2021.
- [4] QiHong Chen, Jiachen Yu, Jiawei Li, Jiecheng Deng, Justin Tian Jin Chen, and Iftekhar Ahmed. A deep dive into large language model code generation mistakes: What and why? *arXiv preprint arXiv:2411.01414*, 2024.
- [5] Xinyun Chen, Chang Liu, and Dawn Song. Execution-guided neural program synthesis. In *International Conference on Learning Representations*, 2019. URL <https://openreview.net/forum?id=H1gf0iAqYm>.
- [6] Xinyun Chen, Petros Maniatis, Rishabh Singh, Charles Sutton, Hanjun Dai, Max Lin, and Denny Zhou. Spreadsheetcoder: Formula prediction from semi-structured context. In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 1661–1672. PMLR, 18–24 Jul 2021. URL <https://proceedings.mlr.press/v139/chen21m.html>.
- [7] Maxime Chevalier-Boisvert, Bolun Dai, Mark Towers, Rodrigo De Lazcano Perez-Vicente, Lucas Willems, Salem Lahlou, Suman Pal, Pablo Samuel Castro, and J K Terry. Minigrid & miniworld: Modular & customizable reinforcement learning environments for goal-oriented tasks. In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023. URL <https://openreview.net/forum?id=PFfmfspm28>.
- [8] François Chollet. On the measure of intelligence. *arXiv preprint arXiv:1911.01547*, 2019.
- [9] Andrew Cropper. Playgol: Learning programs through play. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19*, pages 6074–6080. International Joint Conferences on Artificial Intelligence Organization, 7 2019. doi: 10.24963/ijcai.2019/841. URL <https://doi.org/10.24963/ijcai.2019/841>.
- [10] Sanjoy Dasgupta. Analysis of a greedy active learning strategy. In L. Saul, Y. Weiss, and L. Bottou, editors, *Advances in Neural Information Processing Systems*, volume 17. MIT Press, 2004. URL https://proceedings.neurips.cc/paper_files/paper/2004/file/c61fbef63df5ff317aecdc3670094472-Paper.pdf.
- [11] Jacob Devlin, Jonathan Uesato, Surya Bhupatiraju, Rishabh Singh, Abdel rahman Mohamed, and Pushmeet Kohli. RobustFill: Neural program learning under noisy I/O. In Doina Precup and Yee Whye Teh, editors, *Proceedings of the 34th International Conference on Machine Learning*, volume 70 of *Proceedings of Machine Learning Research*, pages 990–998. PMLR, 06–11 Aug 2017. URL <https://proceedings.mlr.press/v70/devlin17a.html>.
- [12] Kevin Ellis. Human-like few-shot learning via bayesian reasoning over natural language. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL <https://openreview.net/forum?id=dVnhdm9MIg>.
- [13] Kevin Ellis, Catherine Wong, Maxwell Nye, Mathias Sablé-Meyer, Lucas Morales, Luke Hewitt, Luc Cary, Armando Solar-Lezama, and Joshua B. Tenenbaum. Dreamcoder: bootstrapping inductive program synthesis with wake-sleep library learning. In *Proceedings of the 42nd ACM SIGPLAN International Conference on Programming Language Design and Implementation, PLDI 2021*, page 835–850, New York, NY, USA, 2021. Association for Computing Machinery. ISBN 9781450383912. doi: 10.1145/3453483.3454080. URL <https://doi.org/10.1145/3453483.3454080>.
- [14] Google. Use smart fill in sheets to automate data entry. URL <https://support.google.com/docs/answer/9914525?hl=en>.
- [15] Gabriel Grand, Valerio Pepe, Jacob Andreas, and Joshua B Tenenbaum. Loose lips sink ships: Asking questions in battleship with language-informed program sampling. *arXiv preprint arXiv:2402.19471*, 2024.

- [16] Arya Grayeli, Atharva Sehgal, Omar Costilla Reyes, Miles Cranmer, and Swarat Chaudhuri. Symbolic regression with a learned concept library. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL <https://openreview.net/forum?id=B7S4jJG1v1>.
- [17] Sumit Gulwani. Automating string processing in spreadsheets using input-output examples. *SIGPLAN Not.*, 46(1):317–330, January 2011. ISSN 0362-1340. doi: 10.1145/1925844.1926423. URL <https://doi.org/10.1145/1925844.1926423>.
- [18] Laurent Hyafil and Ronald L. Rivest. Constructing optimal binary decision trees is np-complete. *Information Processing Letters*, 5(1):15–17, 1976. ISSN 0020-0190. doi: [https://doi.org/10.1016/0020-0190\(76\)90095-8](https://doi.org/10.1016/0020-0190(76)90095-8). URL <https://www.sciencedirect.com/science/article/pii/0020019076900958>.
- [19] Ruhma Khan, Sumit Gulwani, Vu Le, Arjun Radhakrishna, Ashish Tiwari, and Gust Verbruggen. Llm-guided compositional program synthesis. *arXiv preprint arXiv:2503.15540*, 2025.
- [20] Takeshi Kojima, Shixiang Shane Gu, Machel Reid, Yutaka Matsuo, and Yusuke Iwasawa. Large language models are zero-shot reasoners. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho, editors, *Advances in Neural Information Processing Systems*, 2022. URL <https://openreview.net/forum?id=e2TBb5y0yFf>.
- [21] Brenden M. Lake, Ruslan Salakhutdinov, and Joshua B. Tenenbaum. Human-level concept learning through probabilistic program induction. *Science*, 350(6266):1332–1338, 2015. doi: 10.1126/science.aab3050. URL <https://www.science.org/doi/abs/10.1126/science.aab3050>.
- [22] Tessa Lau, Steven A Wolfman, Pedro Domingos, and Daniel S Weld. Programming by demonstration using version space algebra. *Machine Learning*, 53:111–156, 2003.
- [23] Hung Le, Yue Wang, Akhilesh Deepak Gotmare, Silvio Savarese, and Steven Hoi. CodeRL: Mastering code generation through pretrained models and deep reinforcement learning. In Alice H. Oh, Alekh Agarwal, Danielle Belgrave, and Kyunghyun Cho, editors, *Advances in Neural Information Processing Systems*, 2022. URL <https://openreview.net/forum?id=WaGvb7OzySA>.
- [24] Florian Le Bronnec, Alexandre Verine, Benjamin Negrevergne, Yann Chevalere, and Alexandre Allauzen. Exploring precision and recall to assess the quality and diversity of LLMs. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 11418–11441, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.616. URL <https://aclanthology.org/2024.acl-long.616/>.
- [25] Kang-il Lee, Segwang Kim, and Kyomin Jung. Weakly supervised semantic parsing with execution-based spurious program filtering. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 6884–6894, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.425. URL <https://aclanthology.org/2023.emnlp-main.425/>.
- [26] Kang-il Lee, Hyukhun Koh, Dongryeol Lee, Seunghyun Yoon, Minsung Kim, and Kyomin Jung. Generating diverse hypotheses for inductive reasoning. In Luis Chiruzzo, Alan Ritter, and Lu Wang, editors, *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 8461–8474, Albuquerque, New Mexico, April 2025. Association for Computational Linguistics. ISBN 979-8-89176-189-6. URL <https://aclanthology.org/2025.naacl-long.429/>.
- [27] Wen-Ding Li and Kevin Ellis. Is programming by example solved by LLMs? In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL <https://openreview.net/forum?id=xqc8yyhScL>.
- [28] Wen-Ding Li, Keya Hu, Carter Larsen, Yuqing Wu, Simon Alford, Caleb Woo, Spencer M. Dunn, Hao Tang, Wei-Long Zheng, Yewen Pu, and Kevin Ellis. Combining induction and transduction for abstract reasoning. In *The Thirteenth International Conference on Learning Representations*, 2025. URL <https://openreview.net/forum?id=UmdotAAVDe>.
- [29] Yujia Li, David Choi, Junyoung Chung, Nate Kushman, Julian Schrittwieser, Rémi Leblond, Tom Eccles, James Keeling, Felix Gimeno, Agustín Dal Lago, et al. Competition-level code generation with alphacode. *Science*, 378(6624):1092–1097, 2022.
- [30] Jonathan Light, Yue Wu, Yiyu Sun, Wenchao Yu, Yanchi Liu, Xujiang Zhao, Ziniu Hu, Haifeng Chen, and Wei Cheng. SFS: Smarter code space search improves LLM inference scaling. In *The Thirteenth International Conference on Learning Representations*, 2025. URL <https://openreview.net/forum?id=MCHuGOkExF>.

- [31] Jiawei Liu, Chunqiu Steven Xia, Yuyao Wang, and Lingming Zhang. Is your code generated by chatGPT really correct? rigorous evaluation of large language models for code generation. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023. URL <https://openreview.net/forum?id=1qv610Cu7>.
- [32] Noble Saji Mathews and Meiyappan Nagappan. Test-driven development for code generation. *arXiv preprint arXiv:2402.13521*, 2024.
- [33] Suvir Mirchandani, Fei Xia, Pete Florence, brian ichter, Danny Driess, Montserrat Gonzalez Arenas, Kanishka Rao, Dorsa Sadigh, and Andy Zeng. Large language models as general pattern machines. In *7th Annual Conference on Robot Learning*, 2023. URL <https://openreview.net/forum?id=RcZMI8MSyE>.
- [34] Robert Nowak. Noisy generalized binary search. In Y. Bengio, D. Schuurmans, J. Lafferty, C. Williams, and A. Culotta, editors, *Advances in Neural Information Processing Systems*, volume 22. Curran Associates, Inc., 2009. URL https://proceedings.neurips.cc/paper_files/paper/2009/file/556f391937dfd4398cbac35e050a2177-Paper.pdf.
- [35] Augustus Odena and Charles Sutton. Learning to represent programs with property signatures. In *International Conference on Learning Representations*, 2020. URL <https://openreview.net/forum?id=rylHspEKPr>.
- [36] Alessandro B. Palmarini, Christopher G. Lucas, and Siddharth N. Bayesian program learning by decompiling amortized knowledge. In Ruslan Salakhutdinov, Zico Kolter, Katherine Heller, Adrian Weller, Nuria Oliver, Jonathan Scarlett, and Felix Berkenkamp, editors, *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *Proceedings of Machine Learning Research*, pages 39042–39055. PMLR, 21–27 Jul 2024. URL <https://proceedings.mlr.press/v235/palmarini24a.html>.
- [37] Wasu Top Piriyakulkij, Cassidy Langenfeld, Tuan Anh Le, and Kevin Ellis. Doing experiments and revising rules with natural language and probabilistic reasoning. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL <https://openreview.net/forum?id=HXdAfK488A>.
- [38] Linlu Qiu, Liwei Jiang, Ximing Lu, Melanie Sclar, Valentina Pyatkin, Chandra Bhagavatula, Bailin Wang, Yoon Kim, Yejin Choi, Nouha Dziri, and Xiang Ren. Phenomenal yet puzzling: Testing inductive reasoning capabilities of language models with hypothesis refinement. In *The Twelfth International Conference on Learning Representations*, 2024. URL <https://openreview.net/forum?id=bNt7oajl2a>.
- [39] Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Romain Sauvestre, Tal Remez, et al. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950*, 2023.
- [40] Joshua Stewart Rule. *The child as hacker : building more human-like models of learning*. PhD thesis, Massachusetts Institute of Technology, 2020.
- [41] H. S. Seung, M. Oppen, and H. Sompolinsky. Query by committee. In *Proceedings of the Fifth Annual Workshop on Computational Learning Theory, COLT '92*, page 287–294, New York, NY, USA, 1992. Association for Computing Machinery. ISBN 089791497X. doi: 10.1145/130385.130417. URL <https://doi.org/10.1145/130385.130417>.
- [42] Freda Shi, Daniel Fried, Marjan Ghazvininejad, Luke Zettlemoyer, and Sida I. Wang. Natural language to code translation with execution. In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 3533–3546, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. URL <https://preview.acanthology.org/emnlp-22-ingestion/2022.emnlp-main.231>.
- [43] Hao Tang, Keya Hu, Jin Peng Zhou, Si Cheng Zhong, Wei-Long Zheng, Xujie Si, and Kevin Ellis. Code repair with LLMs gives an exploration-exploitation tradeoff. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL <https://openreview.net/forum?id=o863gX6DxA>.
- [44] Hao Tang, Darren Yan Key, and Kevin Ellis. Worldcoder, a model-based LLM agent: Building world models by writing code and interacting with the environment. In *The Thirty-eighth Annual Conference on Neural Information Processing Systems*, 2024. URL <https://openreview.net/forum?id=QGJSXMhVaL>.
- [45] Vladimir N. Vapnik. *Statistical Learning Theory*. Wiley, 1998.
- [46] Gust Verbruggen, Ashish Tiwari, Mukul Singh, Vu Le, and Sumit Gulwani. Execution-guided within-prompt search for programming-by-example. In *The Thirteenth International Conference on Learning Representations*, 2025. URL <https://openreview.net/forum?id=PY56Wur7S0>.

- [47] Evan Z Wang, Federico Cassano, Catherine Wu, Yunfeng Bai, William Song, Vaskar Nath, Ziwen Han, Sean M. Hendryx, Summer Yue, and Hugh Zhang. Planning in natural language improves LLM search for code generation. In *The Thirteenth International Conference on Learning Representations*, 2025. URL <https://openreview.net/forum?id=48WAZhwHHw>.
- [48] Ruocheng Wang, Eric Zelikman, Gabriel Poesia, Yewen Pu, Nick Haber, and Noah Goodman. Hypothesis search: Inductive reasoning with language models. In *The Twelfth International Conference on Learning Representations*, 2024. URL <https://openreview.net/forum?id=G7UtIGQmjm>.
- [49] Yudong Xu, Wenhao Li, Pashootan Vaezipoor, Scott Sanner, and Elias Boutros Khalil. LLMs and the abstraction and reasoning corpus: Successes, failures, and the importance of object-based representations. *Transactions on Machine Learning Research*, 2024. ISSN 2835-8856. URL <https://openreview.net/forum?id=E8m8oySvPJ>.

A Limitation

While SYNTRA demonstrates strong performance, scalability, and explainability across multiple domains, it is important to recognize its limitations.

First, our approach relies on the assumption that visible test inputs exist. This assumption is critical for enabling the transduction model to evaluate and filter candidate programs. In domains where such inputs are absent or unobservable, the method becomes less applicable. However, this limitation can be partially addressed by generating test inputs with the LLM.

Second, SYNTRA is less effective in settings where inputs are semantically meaningless. In such cases, the LLM cannot effectively exploit its prior world knowledge, limiting the benefits of our framework.

Third, although SYNTRA can select the optimal program from a mixture of correct and incorrect candidates, it does not inherently improve the synthesis of highly complex programs. For problems that require deep search or reasoning, the synthesis step remains a bottleneck.

Finally, because LLMs are used as transduction models, undesirable biases present in the models may propagate to the final outputs. This raises concerns about fairness, safety, and robustness.

B Prompts

Here, we present the prompts used for our program synthesis and transduction models. The prompts below are all designed for use on Playgol. For MBPP+, we additionally prepended the natural language task description directly before the input-output examples.

Prompt for Program Synthesis Model - Algorithm Generation

```
You will be given a list of input-output pairs. There are
multiple algorithms that transform each input to the
corresponding output.
Generate 4 algorithms for the transformation in natural language
form.
These algorithms should be distinct; they map the given input to
the output but implemented in various ways.

Please format your algorithms as follows:

{{
1: "algorithm",
2: "algorithm",
...
}}

Input-output pairs:
{INPUT_OUTPUT_PAIRS}

Algorithms:
```

Prompt for Program Synthesis Model - Code Generation

You will be given a list of input-output pairs and an algorithm described in natural language.

Implement the given algorithm in a Python function 'fn' that maps the following inputs to their corresponding outputs.

Please format your Python function as follows:

```
'''python
def fn(x):
    # x is {INPUT_FORMAT}
    # Your code here
    return y # y is {OUTPUT_FORMAT}
'''
```

Input-output pairs:
{INPUT_OUTPUT_PAIRS}

Algorithm:
{ALGORITHM}

Python function:

Prompt for Transduction Model

Based on given input-output pairs, select which of the outputs is most plausible for given test input.

Think step-by-step and enclose your answer with ''' at the end of your response.

Input-output pairs:
{INPUT_OUTPUT_PAIRS}

Test input:
{TEST_INPUT}

Test output candidates:
{TEST_OUTPUT_CANDIDATES}

C Additional Results

C.1 Results with Additional LLMs

In this section, we present experimental results on Playgol using more smaller open-source models. Specifically, we used Llama-3.1-8B-Instruct as the program synthesis model and Llama-3.1-70B-Instruct as the transduction model.

Table 5: Comparison of different approaches on the filtered Playgol dataset consisting of 124 tasks. Filtering is based on the programs generated using AGA.

Approach	Playgol (1 train / 4 test)		
	Task Acc.	Example Acc.	# τ Calls
Random program $f \in \mathcal{P}'$	62.5	74.8	-
Random hypothesis $h \in \mathcal{V}_0$	34.9	56.0	-
<i>Llama-3.1-70B-Instruct for τ</i>			
LLM direct transduction [33]	58.1	84.3	476
SYNTRA w/ random query	71.0	81.5	140
SYNTRA w/ maximin	78.2	84.8	128

While the overall performance is low compared to GPT-based models, the trend of improvements achieved by SYNTRA remains consistent (Table 5).

We also evaluate performance on the unfiltered Playgol dataset using a wider range of LLMs, including gemma-3-27b-it, Claude Sonnet 4, and DeepSeek-V3-0324. In this setting, we use the same LLM as both the synthesis model and the transductive model.

Table 6: Task accuracies (%) of different approaches and LLMs on the unfiltered Playgol dataset.

Approach	gemma-3-27b-it	Claude Sonnet 4	DeepSeek-V3-0324
AGA	66.5	82.8	80.0
AGA + SYNTRA	72.0	89.8	90.2

While absolute accuracy varied across model types, we consistently observed that SYNTRA improves performance.

C.2 Program Diversity

Table 7: Comparison of program diversity.

Approach	Playgol	MBPP+
IID (Section 5.3)	4.32	3.29
AGA	6.65	7.20

Here, we demonstrate the semantic diversity of the programs generated by the IID and AGA methods. We define semantic diversity in terms of behavioral equivalence. The numbers in Table 7 represent the average number of programs, out of the 32 generated, that produce unique execution results on the training and test inputs. As shown, AGA significantly boosts diversity compared to IID sampling. This increased diversity raises the likelihood that a correct program is included in the program pool, thereby offering more opportunities for SYNTRA to improve final performance.

C.3 Comparison with Majority Vote

We compared the performance of majority vote (MV) and SYNTRA. For MV, a majority vote was taken over outputs of generated programs, so there may not be a program exactly matching all the submitted outputs. In our experiment, MV does provide some improvement, but it’s smaller than SYNTRA.

Table 8: Task accuracies (%) of majority vote (MV) and SYNTRA on unfiltered dataset.

Approach	Playgol	MBPP+	1D-ARC
IID	76.9	56.9	25.0
IID + MV	77.5	55.7	28.9
IID + SYNTRA	82.5	59.1	38.9

C.4 Scaling Compute

Below are results when using MoC on the MBPP+ dataset with sample counts of 32, 64, and 128. In our experiments, MoC alone did not show a clear compute scaling effect, likely because (1) with as many as 128 concepts, the relevance of newly generated concepts diminished, and (2) as the number of programs increased, the ratio of incorrect programs also increased, raising the chance of a wrong guess when randomly selecting outputs. However, with SYNTRA, at least the second issue is mitigated, resulting in compute scaling benefits.

Table 9: Task accuracies (%) by the number of generated programs on unfiltered MBPP+ dataset.

Approach	32	64	128
MoC	78.1	80.9	77.8
MoC + SYNTRA	83.7	84.3	85.5

D Case Study

D.1 Successful Cases

Example 1 The task is to extract the country name. The edge case here lies in the test input selected during the first iteration, where the state name appears between the city and country names. As a result, some programs extract the state name ("OR") instead of the country ("USA"). In this case, the transduction model correctly selected the ground truth "USA", effectively eliminating the hypotheses that extracted the state name.

Dataset: Playgol

Input-output pairs:

Input: "ILP 2009, Leuven, Belgium, July 02-04, 2009"

Output: "Belgium"

Iteration 1

Test input: "ILP 2007, Corvallis, OR, USA, June 19-21, 2007"

Output candidates: ["OR", "USA", ""]

Transduction model prediction: "USA"

GT output: "USA"

Change in the number of hypotheses: 6 → 2

Iteration 2

Test input: "ILP 2012, Dubrovnik, Croatia, September 17-19, 2012"

Output candidates: ["Croatia", ""]

Transduction model prediction: "Croatia"

GT output: "Croatia"

Change in the number of hypotheses: 2 → 1

Example 2 In this task, the edge case arises in Iteration 2, where the challenge is how to handle situations with only one occurrence of the character to be removed. The transduction model chose to remove the single occurrence rather than leave it unchanged, which aligned with the ground truth output.

Dataset: MBPP+

Task description: Write a Python function to remove the first and last occurrence of a given character from the string.

```

Input-output pairs:
  Input: ["hello", "l"]
  Output: "heo"
Iteration 1
  Test input: ["xxx", "x"]
  Output candidates: ["x", ""]
  Transduction model prediction: "x"
  GT output: "x"
  Change in the number of hypotheses: 8 → 4
Iteration 2
  Test input: ["xrworlaaada", "x"]
  Output candidates: ["rworlaaada", "xrworlaaada", "worlaaada"]
  Transduction model prediction: "rworlaaada"
  GT output: "rworlaaada"
  Change in the number of hypotheses: 4 → 2
Iteration 3
  Test input: ["lo", "a"]
  Output candidates: ["ValueError('substring not found')", "lo"]
  Transduction model prediction: "lo"
  GT output: "lo"
  Change in the number of hypotheses: 2 → 1

```

D.2 Failed Cases

Example 1 In this problem, it is difficult to use world knowledge to resolve uncertainty. The correct program logic is to output the substring up to (but not including) the first uppercase letter. However, based on the given training example alone, a program that outputs the first three characters of the input string could also satisfy it. Since the input strings in this problem are meaningless and arbitrary, there is little information available to determine which of the two programs is correct. In such cases, it would be preferable to query the user in order to generate a program that aligns with their intent.

```

Dataset: Playgol
Input-output pairs:
  Input: "worCiqshrbgrplzaaBirqvwic"
  Output: "wor"
Iteration 1
  Test input: "htvpAsgrwbsoeigjvtryhtfp"
  Output candidates: ["htv", "", "htvp"]
  Transduction model prediction: "htv"
  GT output: "htvp"
  Change in the number of hypotheses: 3 → 1

```

Example 2 This is a case where the ambiguity present in the task description is reflected in the hypothesis class.

```

Dataset: MBPP+
Task description: Write a function that checks whether a string contains
  the "a" character followed by two or three "b" characters.
Input-output pairs:
  Input: "ac"
  Output: False
Iteration 1
  Test input: ""
  Output candidates: [True, False, None]
  Transduction model prediction: False
  GT output: False
  Change in the number of hypotheses: 5 → 2
Iteration 2
  Test input: "abbbba"

```

Output candidates: [False, True]
Transduction model prediction: False
GT output: True
Change in the number of hypotheses: 2 -> 1

NeurIPS Paper Checklist

1. Claims

Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

Answer: [\[Yes\]](#)

Justification: The abstract and introduction provide an overview of the paper's contributions, assumptions, and key ideas.

Guidelines:

- The answer NA means that the abstract and introduction do not include the claims made in the paper.
- The abstract and/or introduction should clearly state the claims made, including the contributions made in the paper and important assumptions and limitations. A No or NA answer to this question will not be perceived well by the reviewers.
- The claims made should match theoretical and experimental results, and reflect how much the results can be expected to generalize to other settings.
- It is fine to include aspirational goals as motivation as long as it is clear that these goals are not attained by the paper.

2. Limitations

Question: Does the paper discuss the limitations of the work performed by the authors?

Answer: [\[Yes\]](#)

Justification: In Section 6, we explain that our approach may incur higher costs compared to direct LLM transduction. We state the weaknesses of our framework in the Section 5.2 and Appendix D.

Guidelines:

- The answer NA means that the paper has no limitation while the answer No means that the paper has limitations, but those are not discussed in the paper.
- The authors are encouraged to create a separate "Limitations" section in their paper.
- The paper should point out any strong assumptions and how robust the results are to violations of these assumptions (e.g., independence assumptions, noiseless settings, model well-specification, asymptotic approximations only holding locally). The authors should reflect on how these assumptions might be violated in practice and what the implications would be.
- The authors should reflect on the scope of the claims made, e.g., if the approach was only tested on a few datasets or with a few runs. In general, empirical results often depend on implicit assumptions, which should be articulated.
- The authors should reflect on the factors that influence the performance of the approach. For example, a facial recognition algorithm may perform poorly when image resolution is low or images are taken in low lighting. Or a speech-to-text system might not be used reliably to provide closed captions for online lectures because it fails to handle technical jargon.
- The authors should discuss the computational efficiency of the proposed algorithms and how they scale with dataset size.
- If applicable, the authors should discuss possible limitations of their approach to address problems of privacy and fairness.
- While the authors might fear that complete honesty about limitations might be used by reviewers as grounds for rejection, a worse outcome might be that reviewers discover limitations that aren't acknowledged in the paper. The authors should use their best judgment and recognize that individual actions in favor of transparency play an important role in developing norms that preserve the integrity of the community. Reviewers will be specifically instructed to not penalize honesty concerning limitations.

3. Theory assumptions and proofs

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: This paper does not include theoretical results.

Guidelines:

- The answer NA means that the paper does not include theoretical results.
- All the theorems, formulas, and proofs in the paper should be numbered and cross-referenced.
- All assumptions should be clearly stated or referenced in the statement of any theorems.
- The proofs can either appear in the main paper or the supplemental material, but if they appear in the supplemental material, the authors are encouraged to provide a short proof sketch to provide intuition.
- Inversely, any informal proof provided in the core of the paper should be complemented by formal proofs provided in appendix or supplemental material.
- Theorems and Lemmas that the proof relies upon should be properly referenced.

4. Experimental result reproducibility

Question: Does the paper fully disclose all the information needed to reproduce the main experimental results of the paper to the extent that it affects the main claims and/or conclusions of the paper (regardless of whether the code and data are provided or not)?

Answer: [Yes]

Justification: We presented the algorithm of our methodology (Algorithm 1), and in Section 5, we provided comprehensive details on the dataset, hyperparameters, and prompts used.

Guidelines:

- The answer NA means that the paper does not include experiments.
- If the paper includes experiments, a No answer to this question will not be perceived well by the reviewers: Making the paper reproducible is important, regardless of whether the code and data are provided or not.
- If the contribution is a dataset and/or model, the authors should describe the steps taken to make their results reproducible or verifiable.
- Depending on the contribution, reproducibility can be accomplished in various ways. For example, if the contribution is a novel architecture, describing the architecture fully might suffice, or if the contribution is a specific model and empirical evaluation, it may be necessary to either make it possible for others to replicate the model with the same dataset, or provide access to the model. In general, releasing code and data is often one good way to accomplish this, but reproducibility can also be provided via detailed instructions for how to replicate the results, access to a hosted model (e.g., in the case of a large language model), releasing of a model checkpoint, or other means that are appropriate to the research performed.
- While NeurIPS does not require releasing code, the conference does require all submissions to provide some reasonable avenue for reproducibility, which may depend on the nature of the contribution. For example
 - (a) If the contribution is primarily a new algorithm, the paper should make it clear how to reproduce that algorithm.
 - (b) If the contribution is primarily a new model architecture, the paper should describe the architecture clearly and fully.
 - (c) If the contribution is a new model (e.g., a large language model), then there should either be a way to access this model for reproducing the results or a way to reproduce the model (e.g., with an open-source dataset or instructions for how to construct the dataset).
 - (d) We recognize that reproducibility may be tricky in some cases, in which case authors are welcome to describe the particular way they provide for reproducibility. In the case of closed-source models, it may be that access to the model is limited in some way (e.g., to registered users), but it should be possible for other researchers to have some path to reproducing or verifying the results.

5. Open access to data and code

Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

Answer: [No]

Justification: We plan to release the code and data after the paper is accepted.

Guidelines:

- The answer NA means that paper does not include experiments requiring code.
- Please see the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- While we encourage the release of code and data, we understand that this might not be possible, so “No” is an acceptable answer. Papers cannot be rejected simply for not including code, unless this is central to the contribution (e.g., for a new open-source benchmark).
- The instructions should contain the exact command and environment needed to run to reproduce the results. See the NeurIPS code and data submission guidelines (<https://nips.cc/public/guides/CodeSubmissionPolicy>) for more details.
- The authors should provide instructions on data access and preparation, including how to access the raw data, preprocessed data, intermediate data, and generated data, etc.
- The authors should provide scripts to reproduce all experimental results for the new proposed method and baselines. If only a subset of experiments are reproducible, they should state which ones are omitted from the script and why.
- At submission time, to preserve anonymity, the authors should release anonymized versions (if applicable).
- Providing as much information as possible in supplemental material (appended to the paper) is recommended, but including URLs to data and code is permitted.

6. Experimental setting/details

Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

Answer: [Yes]

Justification: See Section 5.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The experimental setting should be presented in the core of the paper to a level of detail that is necessary to appreciate the results and make sense of them.
- The full details can be provided either with the code, in appendix, or as supplemental material.

7. Experiment statistical significance

Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

Answer: [No]

Justification: Due to the high computational cost of using LLMs in our experiments, we conducted only a single run.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The authors should answer "Yes" if the results are accompanied by error bars, confidence intervals, or statistical significance tests, at least for the experiments that support the main claims of the paper.
- The factors of variability that the error bars are capturing should be clearly stated (for example, train/test split, initialization, random drawing of some parameter, or overall run with given experimental conditions).

- The method for calculating the error bars should be explained (closed form formula, call to a library function, bootstrap, etc.)
- The assumptions made should be given (e.g., Normally distributed errors).
- It should be clear whether the error bar is the standard deviation or the standard error of the mean.
- It is OK to report 1-sigma error bars, but one should state it. The authors should preferably report a 2-sigma error bar than state that they have a 96% CI, if the hypothesis of Normality of errors is not verified.
- For asymmetric distributions, the authors should be careful not to show in tables or figures symmetric error bars that would yield results that are out of range (e.g. negative error rates).
- If error bars are reported in tables or plots, The authors should explain in the text how they were calculated and reference the corresponding figures or tables in the text.

8. Experiments compute resources

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [Yes]

Justification: Since we primarily used APIs, there is no specific environment to report. The computational cost is discussed in detail in Section 6.

Guidelines:

- The answer NA means that the paper does not include experiments.
- The paper should indicate the type of compute workers CPU or GPU, internal cluster, or cloud provider, including relevant memory and storage.
- The paper should provide the amount of compute required for each of the individual experimental runs as well as estimate the total compute.
- The paper should disclose whether the full research project required more compute than the experiments reported in the paper (e.g., preliminary or failed experiments that didn't make it into the paper).

9. Code of ethics

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics <https://neurips.cc/public/EthicsGuidelines>?

Answer: [Yes]

Justification: We checked NeurIPS Code of Ethics.

Guidelines:

- The answer NA means that the authors have not reviewed the NeurIPS Code of Ethics.
- If the authors answer No, they should explain the special circumstances that require a deviation from the Code of Ethics.
- The authors should make sure to preserve anonymity (e.g., if there is a special consideration due to laws or regulations in their jurisdiction).

10. Broader impacts

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [NA]

Justification: Our work focuses on program synthesis and we do not expect any direct societal impact.

Guidelines:

- The answer NA means that there is no societal impact of the work performed.
- If the authors answer NA or No, they should explain why their work has no societal impact or why the paper does not address societal impact.

- Examples of negative societal impacts include potential malicious or unintended uses (e.g., disinformation, generating fake profiles, surveillance), fairness considerations (e.g., deployment of technologies that could make decisions that unfairly impact specific groups), privacy considerations, and security considerations.
- The conference expects that many papers will be foundational research and not tied to particular applications, let alone deployments. However, if there is a direct path to any negative applications, the authors should point it out. For example, it is legitimate to point out that an improvement in the quality of generative models could be used to generate deepfakes for disinformation. On the other hand, it is not needed to point out that a generic algorithm for optimizing neural networks could enable people to train models that generate Deepfakes faster.
- The authors should consider possible harms that could arise when the technology is being used as intended and functioning correctly, harms that could arise when the technology is being used as intended but gives incorrect results, and harms following from (intentional or unintentional) misuse of the technology.
- If there are negative societal impacts, the authors could also discuss possible mitigation strategies (e.g., gated release of models, providing defenses in addition to attacks, mechanisms for monitoring misuse, mechanisms to monitor how a system learns from feedback over time, improving the efficiency and accessibility of ML).

11. Safeguards

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [NA]

Justification: We do not release any data or models.

Guidelines:

- The answer NA means that the paper poses no such risks.
- Released models that have a high risk for misuse or dual-use should be released with necessary safeguards to allow for controlled use of the model, for example by requiring that users adhere to usage guidelines or restrictions to access the model or implementing safety filters.
- Datasets that have been scraped from the Internet could pose safety risks. The authors should describe how they avoided releasing unsafe images.
- We recognize that providing effective safeguards is challenging, and many papers do not require this, but we encourage authors to take this into account and make a best faith effort.

12. Licenses for existing assets

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: We cited the papers for datasets we used.

Guidelines:

- The answer NA means that the paper does not use existing assets.
- The authors should cite the original paper that produced the code package or dataset.
- The authors should state which version of the asset is used and, if possible, include a URL.
- The name of the license (e.g., CC-BY 4.0) should be included for each asset.
- For scraped data from a particular source (e.g., website), the copyright and terms of service of that source should be provided.
- If assets are released, the license, copyright information, and terms of use in the package should be provided. For popular datasets, paperswithcode.com/datasets has curated licenses for some datasets. Their licensing guide can help determine the license of a dataset.

- For existing datasets that are re-packaged, both the original license and the license of the derived asset (if it has changed) should be provided.
- If this information is not available online, the authors are encouraged to reach out to the asset’s creators.

13. **New assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: This paper does not release new assets.

Guidelines:

- The answer NA means that the paper does not release new assets.
- Researchers should communicate the details of the dataset/code/model as part of their submissions via structured templates. This includes details about training, license, limitations, etc.
- The paper should discuss whether and how consent was obtained from people whose asset is used.
- At submission time, remember to anonymize your assets (if applicable). You can either create an anonymized URL or include an anonymized zip file.

14. **Crowdsourcing and research with human subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: This paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Including this information in the supplemental material is fine, but if the main contribution of the paper involves human subjects, then as much detail as possible should be included in the main paper.
- According to the NeurIPS Code of Ethics, workers involved in data collection, curation, or other labor should be paid at least the minimum wage in the country of the data collector.

15. **Institutional review board (IRB) approvals or equivalent for research with human subjects**

Question: Does the paper describe potential risks incurred by study participants, whether such risks were disclosed to the subjects, and whether Institutional Review Board (IRB) approvals (or an equivalent approval/review based on the requirements of your country or institution) were obtained?

Answer: [NA]

Justification: This paper does not involve crowdsourcing nor research with human subjects.

Guidelines:

- The answer NA means that the paper does not involve crowdsourcing nor research with human subjects.
- Depending on the country in which research is conducted, IRB approval (or equivalent) may be required for any human subjects research. If you obtained IRB approval, you should clearly state this in the paper.
- We recognize that the procedures for this may vary significantly between institutions and locations, and we expect authors to adhere to the NeurIPS Code of Ethics and the guidelines for their institution.
- For initial submissions, do not include any information that would break anonymity (if applicable), such as the institution conducting the review.

16. Declaration of LLM usage

Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does not impact the core methodology, scientific rigorousness, or originality of the research, declaration is not required.

Answer: [Yes]

Justification: We have explained how LLMs are utilized in both the methodology and the experiments.

Guidelines:

- The answer NA means that the core method development in this research does not involve LLMs as any important, original, or non-standard components.
- Please refer to our LLM policy (<https://neurips.cc/Conferences/2025/LLM>) for what should or should not be described.