LLM-Assisted Synthesis of High-Assurance C Programs

Prasita Mukherjee
Department of Computer Science
Purdue University
West Lafayette, USA
mukher39@purdue.edu

Minghai Lu
Department of Computer Science
Purdue University
West Lafayette, USA
lu1074@purdue.edu

Benjamin Delaware
Department of Computer Science
Purdue University
West Lafayette, USA
bendy@purdue.edu

***Abstract*—We present SynVer — a novel, general purpose synthesizer for C programs equipped with machine-checked proofs of correctness using the Verified Software Toolchain. To do so, SynVer employs two Large Language Models (LLMs): the first generates candidate programs from user-provided specifications, and the second helps automatically construct formal proofs of their correctness in the Rocq proof assistant. To facilitate verification, SynVer places a set of syntactic restrictions on candidate programs that make them amenable to automated reasoning. SynVer uses a hybrid verification strategy that combines symbolic reasoning with LLM-powered proof generation to discharge proof obligations that the symbolic engine cannot handle on its own. We demonstrate the applicability of SynVer using a diverse set of benchmarks drawn from the program synthesis and verification literature.**

***Index Terms*—Formal Verification, Automatic Programming, and Large Language Models**

I. Introduction

The goal of *program synthesis* is to automatically generate a program from a high-level specification of its intended behavior [1]. While the form of these specifications can vary, e.g., input-output examples that describe a subset of the target program's functionality, or a logical formula that fully captures the desired behavior, traditional program synthesis techniques typically guarantee that generated programs satisfy the input specification. *Deductive synthesis* techniques in particular aim to provide strong guarantees by framing synthesis as a deductive inference problem, and employ a rule-based search to find a program that meets the target specification. These systems often repurpose program *verification* rules to ensure that each step is justified, resulting in programs that are *correct by construction*. Deductive techniques have been successfully applied to a diverse set of domains, including SQL-style queries [2], heap-manipulating programs [3], [4], serializers and deserializers [5], clients of APIs with strong specifications [6], and concurrent garbage collectors [7]. These rigorous guarantees come at a cost, however: to keep this search tractable, fully automated tools are forced to limit the class of specifications and programs they can handle.

More recently, large language models (LLMs) have shown a remarkable ability to automatically generate programs from natural language descriptions, and have quickly become part of the modern software development toolbox. Unlike traditional program synthesis techniques, however, LLM-powered code generation tools do not provide any guarantees about the behaviors of the programs they produce, leaving that task entirely to the user. In response, several recent works have investigated how to provide more assurance about LLM-generated programs, e.g., by targeting verification-oriented languages like Dafny [8] and F* [9]. In the case of tools that target mainstream languages such as C and Rust, several works have proposed adding annotations to programs that can then be statically checked by existing automated verifiers [10], [11], [12]. Unfortunately, these annotation-based approaches target assertion logics that are not expressive enough to capture the full range of specifications used by prior deductive synthesizers, including properties of heap manipulating programs expressed in separation logic [13].

This work proposes SynVer , a framework that fills this gap by combining LLM-powered code and proof generation with deductive verification. SynVer synthesizes C programs from semantically rich specifications, with machine-checked guarantees about their correctness. Unlike prior deductive synthesis engines, which are typically domain-specific, our tool is expressive enough to support multiple application domains. To do so, we leverage two key insights from prior deductive synthesis approaches: first, we constrain the space of candidate solutions by automated verification. Second, we develop custom proof automation procedures, or *tactics*, tailored to programs meeting this bias, enabling automated verification using an existing (interactive) verification framework [14] implemented in the Rocq/Coq proof assistant [15]. Due to the richness of our specification language, our tactic-based automation is necessarily incomplete; we address this limitation by introducing a novel LLM-powered proof synthesis technique [16], [17] that discharges proof obligations that our tactic cannot resolve on its own.

We evaluate SynVer on three synthesis problems drawn from three distinct application domains previously targeted by separate deductive synthesis engines. While each of those tools can only handle problems from their particular domain, our tool is flexible enough to synthesize high-assurance C programs for all three domains. Our experiments also show that our combination of custom proof automation and LLM-based proof synthesis outperforms existing LLM-based proof

```
1   /* {h1 ↦ l1 * h2 ↦ l2} */
2   struct sll* append(struct sll* h1, struct sll* h2)
3   {
4     struct sll *current = h1;
5     if (h1 == NULL) {
6         return h2;
7     }
8     while (current->next != NULL) {
9         current = current->next;
10    }
11    current->next = h2;
12    return h1;
13  }
14  /* {h ↦ (l1 ++ l2)} /*
```

Fig. 1: C function that concatenates two singly-linked lists

```
1   Theorem append_correct :
2     ⊢ - {SEP(listrep l1 h1; listrep l2 h2)} append
3     {Exists h: val, SEP(listrep (l1 ++ l2) h)}.
4
5   forward_if. forward.
6   assert (l1 = @nil z). apply H0. reflexivity.
7   subst. Exists h2.
8   entailer!!. simpl. entailer!!
9   rewrite (listrep_nonnull _ h1) by auto. Intros h hs y.
10  forward.
11  forward_loop
12    (EX sla: list Z, EX b: Z, EX sic: list Z,
13     EX t: val, EX u: val,
14     PROP (Int.min_signed <= b <= Int.max_signed;
15                l1 = sla ++ b :: s1c)
16     LOCAL (temp _h1 h1; temp_h2 h2; temp_head t)
17     SEP (lseg sla pl t;
18           data_at Ish t_list (Vint (Int. repr b), u) t;
19           listrep sic u; listrep 12 h2))%assert
```

Fig. 2: A partial proof of correctness of `append` in VST

automation techniques when reasoning about the correctness of programs generated by SYNVER.

In summary, this paper presents the following contributions:

- We propose a novel LLM-powered program synthesis framework that generates high-assurance C programs from rich logical specifications, with machine-checked proofs of their correctness in the Rocq proof assistant.
- We show that by biasing the space of candidate programs and combining custom proof automation and LLM-based proof synthesis, we can repurpose an existing interactive program verification framework to automatically verify LLM-generated programs.
- We demonstrate the flexibility of our framework by evaluating it on a suite of benchmarks drawn from three distinct domains from the deductive synthesis literature, and show that our hybrid proof automation approach outperforms prior LLM-based proof techniques when reasoning about these programs. An artifact containing the source code of SYNVER and our experiments is publicly available [18].

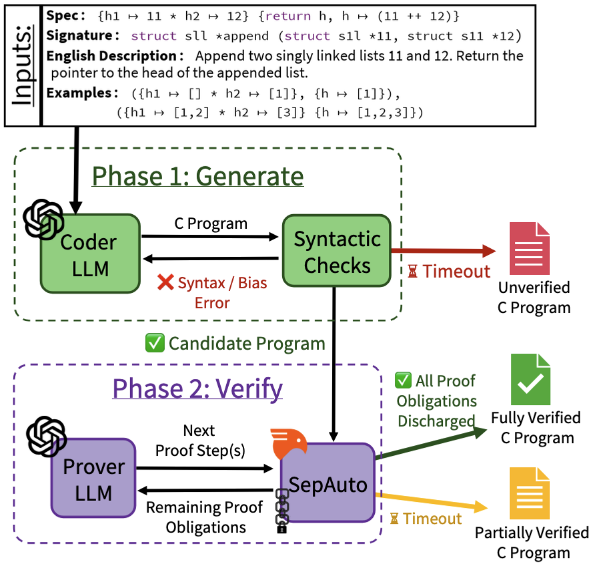
II. BACKGROUND

We begin by briefly reviewing the Verification Software Toolchain (VST) [14], the Rocq/Coq-based program verification framework that SYNVER uses to reason about the C programs it generates. In VST, program properties are expressed using Hoare triples [19] of the form $\vdash \{P\}$ `c` $\{Q\}$ which claims that when the program `c` is executed in a state satisfying the precondition P, it will either run forever or terminate in a state satisfying the postcondition Q. VST is equipped with a separation logic for proving that such triples are valid. It also includes a set of *tactics* [20] that developers can use to interactively build up proofs of program correctness using the rules of the underlying separation logic.

To illustrate this process, consider the `append` function shown in Fig. 1. When given pointers to two valid singly linked lists, `append` concatenates them together and returns a pointer to the head of the resulting (singly linked) list. The comments on lines 1 and 14 give pre- and post-conditions that specify this behavior. To verify that `append` meets this specification using VST, a user first defines a *theorem* stating a Hoare triple with these pre- (P) and postconditions (Q), as shown on lines 2-3 of Fig. 2. Processing this definition causes Rocq to enter its interactive proof mode, displaying an initial *goal*, or proof obligation— in this case, the top-level correctness statement for `append`. The user then writes a *proof script*, a sequence of tactics that explain how to build a proof of this goal; lines 5-19 of Fig. 2 show the first part of a proof script for `append_correct`. Processing a tactic replaces the current goal with a (possibly empty) set of new subgoals, again shown to the user; the proof is complete when no subgoals remain.

The proof script in Fig. 2 includes both VST-specific and Rocq's built-in tactics, which are highlighted in purple and green, respectively. Some tactics take arguments: **`rewrite`** on line 9, for example, takes a fact of the form `x = y`, and replaces all occurrences of `x` in the current goal with `y`. VST-provided tactics often require richer inputs: the **`forward_loop`** tactic on line 11, for example, takes an inductive *loop invariant* that specifies the behavior of each iteration of the loop on lines 8-10 of `append`. Automatically coming up with loop invariants is one of the most challenging problems in program verification [21], and VST thus expects users to supply them manually. Tactics can fail if applied to goals that do not have the expected shape. Oftentimes, users will apply tactics to change a goal into one that a specific tactic can handle: the tactics on lines 5-7, for instance, transform the goal into a form supported by `entailer!!`. The tactics on line 9 similarly produce a goal which `forward` can process.

As this example illustrates, VST is a powerful tool for constructing a formal proof about rich behaviors of C programs. The framework is designed to be used interactively, with a user inspecting the current goal and supplying a tactic that moves the proof forward, e.g., by providing loop invariants or transforming goals into a form that VST-supplied tactics can automatically discharge. SYNVER builds on top of the foundation provided by VST to verify generated programs, but attempts to remove the user from the loop. The next section describes how SYNVER constrains the shape of generated programs to make them amenable to automated verification, uses custom proof automation to discharge many of the resulting proof obligations, and deploys LLM-guided proof synthesis to handle the rest.



```
Spec: {h1 ↦ 11 * h2 ↦ 12} {return h, h ↦ (11 ++ 12)}
Signature: struct sll *append (struct s1l *11, struct s11 *12)
English Description: Append two singly linked lists 11 and 12. Return the
 pointer to the head of the appended list.
Examples: ({h1 ↦ [] * h2 ↦ [1]}, {h ↦ [1]}),
          ({h1 ↦ [1,2] * h2 ↦ [3]} {h ↦ [1,2,3]})
```

Fig. 3: Overview of our approach

III. Approach

Fig. 3 depicts the high-level workflow of our synthesis pipeline, which is divided into two phases: generation and verification. Our system takes four inputs that describe the target function: its signature, its separation logic specification, a natural language description of its behavior, and a couple of input-output examples. In the first phase, these inputs are used to prompt a *coder LLM* to synthesize a candidate program. The candidate program is then checked for syntax errors and conformance with our syntactic biases. If either check fails, the coder LLM is re-prompted upto a threshold.

Otherwise, our pipeline proceeds to the second phase, which attempts to verify that the candidate program meets its separation logic specification using VST. This phase works by iteratively attempting to discharge a set of outstanding proof obligations; this set initially consists of only the top-level statement of correctness for the candidate. Each iteration of this phase first applies SepAuto, our custom automation proof tactic, to the current set of proof obligations, producing a new (possibly empty) set of obligations. If all obligations are satisfied, the system returns the verified program and the complete proof script. Otherwise, a *prover LLM* is asked to either a) suggest tactics that will make progress on the remaining obligations or b) identify a goal as unsolvable. These suggestions are used to further refine the current proof script, and the loop continues. To ensure termination, this phase places an upper bound on the number of iterations; if this threshold is reached, the candidate program and the current (incomplete) proof script are returned.

The remainder of this section describes the generation and verification phases of our pipeline in more detail, using the input from Fig. 3 as a running example.

A. Phase 1: Program Generation

SynVer generates an initial candidate C program by querying the coder LLM using the prompt template shown in Fig. 4. This prompt includes a few examples of input specifications along with their expected output C programs. The placeholders in the prompt, e.g., ⟨**Spec**⟩ and ⟨**Name**⟩ are then instantiated with the arguments provided to SynVer. The top of Fig. 3 includes example inputs for synthesizing a C function that appends two singly linked lists. SynVer first checks if the program is a valid C program by attempting to compile it. If compilation fails, SynVer re-prompts the coder LLM using the first template in Fig. 5, instantiating its placeholder with the compilation error.

Translate the given specification to a C program. Only include the C program in the content. No need to include a main function in the translated C program. There should not be loops in the program. All loops must be replaced by recursion. The only helper functions permitted are the ones provided under 'Helper functions:'. There should not be any novel helper functions used in the program. Generate recursive code if and only if non-loopy code generation is not possible. The code must compile using *CLightGen*. The user provides the specification,followed by the function name, signature, English description, and two input output examples of the function behaviour.

Here are a couple of examples of how generated C
programs look given the input specifications:
[swap-spec, void swap(int *a, int *b) {..},..] (elided for spaces)

Please provide the specifications as asked below:
Specification: ⟨**Spec**⟩
Function Name: ⟨**Name**⟩
Function Signature: ⟨**Signature**⟩
English Description: ⟨**English**⟩
Input Output Examples: ⟨**Example1**⟩⟨**Example2**⟩
Helper Functions: ⟨**Signature, English, Spec**⟩

Fig. 4: The initial prompt template for the coder LLM

The program generated has the syntax error: ⟨**Error**⟩. Please re-generate the program such that it compiles with *CLightGen*.

The program generated violated the syntactic bias: ⟨**Bias-Type**⟩. Please re-generate the program adhering to the syntactic biases.

Fig. 5: Templates used to re-prompt the coder LLM

As Section II discussed, in VST (and Rocq more broadly) proofs of program correctness are typically constructed *interactively*. VST provides a set of specialized tactics for working with the proof obligations that arise when reasoning about C programs in its logic, some of which, e.g. `forward_if`, and `forward_loop`, can require additional input from the user driving the process. To limit the need for user interaction when reasoning about the programs it synthesizes, SynVer places two key restrictions, or *biases*, on the syntax of candidate programs.

a) No calls to functions without specifications: VST requires logical specifications for any functions used by the program being verified. Function specifications are stored in a context; if a function is missing from the context, a user must manually supply its specification. To avoid this situation, the initial generator prompt (Fig. 4) instructs the LLM to not to introduce any intermediate helper functions, and SynVer checks that a candidate program only calls functions whose specifications are included in the global context. As an example, swap in Fig. 6, is not a candidate for verification, as it introduces and calls the helper function add, which lacks a corresponding specification. When this occurs, SynVer re-prompts the coder LLM using the second template in Fig. 5, filling in the ⟨**Bias-Type**⟩ placeholder instantiated with a message noting that add lacks a specification.

b) No loops: As is standard in program logics, reasoning about loops in VST requires users to supply a *loop invariant*. When dealing with separation logic assertions, such invariants can be quite involved, often requiring complex operators like the separating implication [22]. Recursive function calls, in contrast, can reuse the function's top-level specification and do not require additional user input. Thus, the prompt used by SynVer stipulates that the generated program should avoid loops and use recursion instead. Including this restriction in the prompt causes the coder LLM to generate the program on the left of Fig. 6: while semantically equivalent to the function in Fig. 1, reasoning about this version does not require any logical specifications on top of the one in Fig. 1. When the coder LLM generates a program with loops, SynVer will re-prompt it using the second template in Fig. 5, filling in the ⟨**Bias-Type**⟩ placeholder with a message to instructing the LLM to avoid using loops.

```
sll *append (sll *h1,
             sll *h2)
{
 if (h1 == NULL)  {
  return h2;
 } else {
  h1->next =
   append (h1->next, h2);
 }
 return h1;
}
```

```
void add (int *x){
  *x= *x + 1;
}
void swap (int *x,
           int *y){
 int a = *x;
 int b = *y;
 if(a < b){
  *x= b;
  *y = a;
 } else {
  *y = a;
 }
 add (x);
}
```

Fig. 6: A recursive (i.e., bias-correct) version of append, and a bias-incorrect swap program which calls a helper function without a specification

B. Phase 2: Program Verification

After it has generated a candidate program that meets these two restrictions, SynVer attempts to verify that program is correct via GenProof (Algorithm 1). This algorithm takes as input a candidate program p, target pre- and postconditions P and Q, and a bound on the number of interactions with the prover LLM *limit*. GenProof either returns a complete proof script showing that $\vdash \{P\}\ p\ \{Q\}$ in VST, or as much of the proof it was able to complete within the interaction bound. At a high level, GenProof mimics the standard proof development process in which a developer examines the current goal to decide the next proof step, tells the theorem prover to process the corresponding tactic, and then repeats this loop until no subgoals remain. Alongside the current proof script, GenProof maintains a set of unsolved proof obligations as a tree, *ptree*, where each node represents a goal and its children correspond to subgoals generated by a tactic application. Intuitively, the leaves of *ptree* represent the goals remaining after processing the current proof script; the proof is completed when *ptree* is empty.

Algorithm 1: Proof Generation

```
1  Procedure GenProof($C_p, P, Q, limit$)
     Inputs  : $C_p$: candidate C program
               $P, Q$: target pre- and postconditions
     Output  : Complete Proof or Partial Proof
2    $ptree \leftarrow$ initProofTree(SepAuto($\{\vdash \{P\}\ C_p\ \{Q\}\}$))
3    $curGoal \leftarrow$ nextGoal($ptree$)
4    $curPrompt \leftarrow$ initialStepsPrompt($C_p$, $P$, $Q$, $curGoal$)
5    for $1 \ldots limit$ do
6      if $curGoal = \bot$ then return $ptree$        /* Complete proof */
7
8      switch GenNxtStep($curPrompt$) do
9        case Unsolvable do
10         $curPrompt \leftarrow$ nextStepsPrompt($curGoal$)
11         $curGoal \leftarrow$ Parent($curGoal$)
12         DeleteAllChildren($curGoal$)
13       case Try $C_{tac}$ do
14         $resp \leftarrow \emptyset$
15         while $C_{tac} \neq \emptyset$ do
16           $curTactic \leftarrow$ Pop($C_{tac}$)
17           switch takeStep($g$, $curTactic$) do
18             case Progress $subGoals$ do
19               $subGoals' \leftarrow$ SepAuto($subGoals$)
20               if $subGoals' \neq \emptyset$ then
21                 $curGoal \leftarrow$AddGoals($ptree$, $subGoals'$)
22               else
23                 $curGoal \leftarrow$ RemoveGoal($ptree$, $curGoal$)
24               $curPrompt \leftarrow$ nextStepsPrompt($curGoal$)
25               break
26             case Fail $msg$ do
27               $resp \leftarrow resp \cup \{(curTactic, msg)\}$
28               if $C_{tac} = \emptyset$ then
29               $curPrompt \leftarrow$
                  nextStepsAfterFailurePrompt($curGoal$, $resp$)
30   return $ptree$                                  /* Partial proof */
```

GenProof first uses SepAuto (Algorithm 2), a custom tactic that simplifies and discharges VST-specific proof obligations, to simplify the top-level goal. It then uses any subgoals generated by SepAuto to construct an initial proof tree (line 2) and chooses one of these goals to work on next (line 3). GenProof uses the selected subgoal to construct the initial prompt for the prover LLM (line 4). This prompt uses the template shown in Fig. 7 to suggest a prioritized list of five tactics that could help resolve this goal. This template begins with a set of helper definitions and lemmas and some example proofs in VST; its placeholders are instantiated with the candidate program and its CompCert AST (⟨**Cand-Prog**⟩ and ⟨**C-AST**⟩), its formal specification and top-level statement of correctness (⟨**VST-Spec**⟩ and ⟨**Thm-Stmnt**⟩), and the current proof obligation (⟨**Cur-Goal**⟩).

GenProof next enters a loop that attempts to iteratively verify the candidate program meets its specification. This loop continues until all proof obligations are discharged or the interaction limit with the prover LLM has been reached. In the latter case, GenProof returns the partial proof up to that point (line 30). If no goals remain, GenProof returns the

You are an expert in Coq, specifically in Separation Logic and the Verified Software Toolchain module. Please help me prove the correctness of CompCert C programs in VST (version 2.14) and Coq (version 8.19.2), against the specification in VST. It is recommended to use VST Floyd tactics like forward, forward_if, entailer!! etc. to advance most of the proofs in this setting. Here are some additional definitions and lemmas you may need to use that are not included in the VST codebase:
[Definition t_list := .., Lemma nullBST := BST E ,..] (elided for spaces)

Here are 4 examples of how VST proofs look like given the CompCert AST and specification:
[Definition swap_spec : ident * funspec := .., Definition f_swap := .. ,..] (elided for spaces)

Given the C-code: ⟨**Cand-Prog**⟩, corresponding CompCert AST: ⟨**C-AST**⟩ and VST specification: ⟨**VST-Spec**⟩, your task is to prove the lemma: ⟨**Thm-Stmnt**⟩ by specifying a set of up to 5 tactics to advance the current goal, in order of highest probability of success. The interpreted state would then be returned back to you, and you will predict the next set of tactics, till a fixpoint is reached, or the proof is completed. All tactics you predict, must be only relevant to the current goal.

Current Goal: ⟨**Cur-Goal**⟩

Fig. 7: Template used to construct initial prompt to the prover LLM

complete proof (line 6). Each iteration of the loop first queries the prover LLM with the current prompt. The prover LLM may flag the current goal as unsolvable, which can happen when an earlier iteration chose the wrong tactic, e.g., applying a lemma whose assumptions are not provable from the current set of hypotheses. When this occurs, GenProof backtracks to the parent of the current goal in *ptree*, i.e., the goal that spawned the current (unsolvable) proof obligation (lines 10-12), and attempts a different proof strategy.

Given the goal: ⟨**current-goal**⟩, predict the next set of tactics to advance the goal.You must predict at most five tactics, all of whom only advance this goal by one step, in order of highest probability of success. If the goal cannot be solved, please respond with *Unsolvable*.

Fig. 8: Prompt template used after a successful tactic application, or after backtracking one level up the proof tree

Alternatively, GenProof calls the `takeStep` subroutine to each tactic proposed by `GenNxtStep` (line 17). This subroutine decides whether to apply the current tactic *curTactic* to *curGoal*. First, `takeStep` checks if the current tactic has been tried before. If not, it then asks Rocq to apply *curTactic* to *curGoal*; if Rocq reports an error or the goal is unchanged, the tactic is rejected. Otherwise, `takeStep` examines the subgoals that result from applying *curTactic*. If any of the new subgoals are equivalent to an unsolved goal in *ptree*, there is a cycle in the current proof, and `takeStep` rejects *curTactic*. Next, if the conclusion of any of the new subgoals is more than twice the size of the conclusion of *curGoal*, *curTactic* is rejected. When neither of these situations occur, GenProof accepts the current tactic, and adds the resulting subgoals to *ptree* (line 21). If no subgoals have been generated, the current proof obligation has been discharged and it is removed from *ptree*, as are any of its ancestors that have been solved (line 23). In both cases, the prompt for the prover LLM is updated using the template in Fig. 8 instantiated with a new subgoal (line 24), and the main loop continues. If all proposed tactics are rejected, the prover LLM is prompted again using the fallback template in Fig. 9 (line 29), which includes information about the failing tactics.

Algorithm 2: SepAuto - Proof automation for VST

```
1  Procedure SepAuto($G_o$)
     Inputs  : $G_o$: Initial set of outstanding goals
     Output  : Set of unresolved goals
2    $G_u \leftarrow \emptyset$                                  /* Unresolved goals */
3    while $G_o \neq \emptyset$ do
4      $g \leftarrow$ firstGoal($G_o$)
5      $G_o \leftarrow G_o \setminus \{g\}$
6      switch $g$ do
7        case $H \vdash \{P\}$ if $b$ then $c_1$ else $c_2$ $\{Q\}$ do
8          $G_o \leftarrow G_o \cup \{$forward_if(g)$\}$

9        case $H \vdash \{P\}$ (if $b$ then $c_1$ else $c_2$);$c_3$ $\{Q\}$ do
10         $g \leftarrow$ H ⊢ {P} if b then $c_1$;$c_3$ else $c_2$;$c_3$ {Q}
11         $G_o \leftarrow G_o \cup \{$forward_if($g$)$\}$

12       case $H \vdash \{P\}$ $f$($x_1$, $x_2$, ..., $x_n$) $\{Q\}$ do
13         $f_p \leftarrow$ inferCallParams($g$)
14         $g' \leftarrow \{$forward_call($g, f_p$)$\}$
15         if $g' \neq g$ then $G_o \leftarrow G_o \cup \{g'\}$              /* Progress */
16         else $G_u \leftarrow G_u \cup \{g'\}$

17       case $H \vdash \{P\}$ $c$ $\{Q\}$ do
18         $g' \leftarrow$ forward_withauto($g$)
19         if $g' \neq g$ then $G_o \leftarrow G_o \cup \{g'\}$              /* Progress */
20         else $G_u \leftarrow G_u \cup \{g'\}$

21       case $H \vdash$ _                                   /* Side Condition */
22        do
23         $g' \leftarrow$ resolve_withauto($g$)
24         if $g' \neq g$ then $G_o \leftarrow G_o \cup \{g'\}$              /* Progress */
25         else $G_u \leftarrow G_u \cup \{g'\}$

26   return $G_u$
```

The tactics: ⟨**tactic1,..,tactic5**⟩ failed because of the following reasons: ⟨**reason1,...,reason5**⟩. Please re-generate the tactics for the current goal: ⟨**current-goal**⟩. If the goal cannot be solved, please respond with *Unsolvable*.

The proof generated by you so far is: ⟨**all-tactics-tried**⟩. The correct proof generated so far is: ⟨**current-proof**⟩.

Fig. 9: Prompt template used after application of all predicted tactics resulted in failure

Algorithm 2 presents SepAuto, the symbolic reasoning subroutine that GenProof uses to simplify and solve VST-specific proof obligations. This function maintains sets of outstanding and unresolved goals, G_o and G_u respectively. SepAuto attempts to iteratively simplify or solve each goal in G_o using a combination of custom and VST-provided tactics. Goals that cannot be simplified or solved are added to G_u, which SepAuto returns when no goals remain in G_o. In each iteration its main loop, SepAuto identifies the current goal as either a Hoare triple (lines 7-20) or a side condition (lines 21-25). In the former case, SepAuto uses the shape of the program in the triple to decide how to proceed.

If the goal is a hoare triple involving a conditional statement (lines 7-8), SepAuto applies VST's built-in `forward_if` tactic, creating new subgoals for the `then` and `else` branches. If the conditional is sequenced with another statement, i.e., `(if b then c1 else c2); c3`, however, applying `forward_if` would create a third goal for the trailing statement c3. In this case, the tactic expects the user to provide a precondition capturing the program state after the conditional is executed. Since SEPAUTO is meant to be fully automatic, it first rewrites a goal of this form into an equivalent one by moving c3 inside each of the branches. This allows forward_if to be applied as before, without any additional input (lines 10-11).

The built-in VST tactic for function calls, forward_call, expects users to explicitly provide arguments for each parameter of the called function. To automate this step, SEPAUTO uses a custom subroutine inferCallParams that extract these arguments from the current goal (lines 13-14). Alternatively, when the current goal is a Hoare triple that is not covered by one of these three cases, e.g. it is c_1; c_2 or $x := a$, SEPAUTO applies forward_withauto, an enhanced version of VST's forward tactic. This custom tactic tries to automatically discharge side conditions related to memory safety, e.g., ensuring that a pointer is not null before it is dereferenced. To discharge these sorts of side conditions, forward_withauto combines the current set of assumptions with a custom library of helper lemmas. As a simple example, when reasoning about line 11 of Fig. 1, SEPAUTO needs to ensure that current is non-null, which it does by rewriting the goal using the lemma listrep_nonnull. Applying this lemma generates a new subgoal, similar to the proof on line 9 of Fig. 2, which SEPAUTO attempts to solve automatically. If forward_withauto cannot make progress, the current goal is added to G_u. Finally, SEPAUTO uses a custom resolve_withauto tactic to resolve goals that are side conditions (line 23) using a combination of standard, e.g., list_solve and rep_lia, and VST-specific tactics, e.g., entailer. Any goals that are not completely solved by resolve_withauto are added to G_u (line 25).

In summary, SYNVER implements a two-phase approach to synthesizing formally verified C programs from high-level specifications. The first phase uses a coder LLM to generate a program whose shape facilitates automated verification. The second phase then attempts to build a formal proof that the program satisfies a user-provided separation logic specification using VST. To automate this proof, SYNVER uses a complementary combination of symbolic reasoning (SEPAUTO) and LLM-aided proof generation (GenNxtStep). The former handles proof obligations generated by VST, while the latter handles goals that SEPAUTO cannot.

IV. EVALUATION

Our evaluation investigates three key research questions about our approach:

- **RQ1**: How effective is SYNVER? Is it able to automatically generate fully verified C programs for a diverse set of synthesis tasks?
- **RQ2**: How much does each component of our prompt contribute to its ability to generate bias-correct programs that satisfy their separation logic specification?
- **RQ3**: How does GENPROOF compare to other proof automation approaches?

All of our experiments were carried out on an Apple M2 Max Macbook Pro with 32GB RAM, except for our Rango evaluation [23], which was carried out on a NVIDIA 5500 GPU with 24GB RAM. SYNVER uses GPT-5mini for both its coder and prover LLMs, and limits the number of LLM interactions in the first and second phases to 10 and 50, respectively.

A. Benchmark Construction

To evaluate our approach, we developed a suite of specifications for a set of programs of varying complexity. Each of the benchmarks used in our evaluation falls into three distinct categories. The first category (**Basic**) consists of programs that only use simple built-in datatypes, e.g., **int** and **char**, and arrays. This category includes 19 programs of varying complexity that were adapted from a collection of formally verified Dafny programs [8]. The second set of benchmarks (**Heap**) includes 24 programs that manipulate heap-allocated data structures like singly linked lists and trees; these were drawn from the evaluation suite of a prior deductive synthesizer [4]. The final class (**API**) consists of adaptations of standard textbook algorithms [24], and is made up of 5 programs that make function calls and use structured datatypes, e.g., arrays, lists, and trees. To ensure that programs in this class can be automatically verified, each callable function is equipped with a formal specification. The specifications for the API manipulating programs were derived from their textbook specification by a verification expert.

B. RQ1: Effectiveness of SYNVER

Table I and II presents the results of SYNVER for each of the input specifications in our benchmark suite. SYNVER was able to successfully generate programs of varying lengths, ranging from 3 to 31 lines of code, with an average length of 10 lines. On average, it took GPT-5mini 11.23 seconds to produce a candidate program. In all cases, GPT-5mini was able to generate a syntactically valid candidate program meeting our biases on the first try— reprompting was never needed.

Table I shows the results for the 70% (34/48) of our benchmarks that GENPROOF was able to fully and automatically verify. These include both simple programs (e.g., mulTwo simply multiplies two integers) and more complex ones (e.g., insertBST is a recursive function that inserts an element into a binary search tree and has a complex specification). Of these 34 programs, GENPROOF was able to automatically verify 10 programs with just its initial call to SEPAUTO. Since it did not have to query the prover LLM, the time needed to verify each of these benchmarks was quite short, under 5 seconds. For the remaining 24 programs, GENPROOF produced proof scripts of varying lengths, ranging from 2 to 35 proof lines, with an average length of 9, where each line consists of a tactic suggested by GPT-5mini followed by a call to SEPAUTO. When generating 11 of these 24 proofs, GENPROOF did not discard any tactics or backtrack; for the remaining 13, GENPROOF did one of these actions an average 38.7% of the time. The total time needed to generate these proofs corresponds to the number of tactics tried by GENPROOF, and ranged from 1.2

TABLE I: The results of SynVer on the benchmarks it was able to completely verify. The three groups of rows correspond to the **Basic**, **Heap**, and **API** categories, respectively. The **Rec** column indicates whether the target program makes a recursive call, and **LoC** gives the length of the generated program. **GP** reports the number of proof obligations generated by the initial call to SepAuto — a value of 0 means SepAuto was able to fully verify the candidate program. **LoP** is the number of lines in the generated proof script. **PT** and **GT** report the time needed to fully verify and generate a program, respectively. **MS** gives the number of tactics discarded and the number of times GenProof backtracked. **TE** gives the total number of tactics `takeStep` evaluated.

Benchmark	Rec	LoC	GP	LoP	PT	GT	MS	TE
isEven	✖	7	2	5	2m 54s	9.29s	0	4
getElement	✖	11	3	12	10m	9.08s	15	26
isDivBy11	✖	7	2	3	1m 36s	7.05s	2	4
minTwo	✖	7	0	1	1.8s	3.67s	0	0
mulTwo	✖	3	0	1	1.2s	4.24s	0	0
minThree	✖	9	0	1	4.4s	8.20s	0	0
lastDigit	✖	3	0	1	1.5s	5.65s	0	0
nIsGreater	✔	12	3	26	53m	17.02s	53	78
arrayModify	✔	9	0	1	3.6s	7.95s	0	0
addBy1	✔	9	1	2	29.40s	8.70s	0	4
allSame	✔	11	3	21	14m 48s	15.86s	7	27
swap	✖	5	0	1	2.6s	5.26s	0	0
swapdAdd	✖	7	0	1	2.3s	5.80s	0	0
swapIf	✖	11	2	7	4m	13.70s	4	10
assignX	✖	3	0	1	2s	4.85s	0	0
assignYAdd	✖	3	0	1	3.5s	6.66s	0	0
listLength	✔	8	2	6	2m	8.92s	0	5
listFree	✔	9	1	3	43.1s	8.61s	0	2
isListEmpty	✖	11	2	10	4m 30s	7.77s	2	11
listAppend	✔	11	2	7	2m 54s	7.70s	0	6
listInsBeg	✖	6	1	4	59s	10.36s	0	3
listDelEnd	✔	12	4	15	32m 30s	11.45s	13	27
listLookup	✔	9	3	24	10m 54s	11.20s	2	25
listCopy	✔	10	2	9	3m 42s	10.19s	0	8
listInsEnd	✔	11	2	9	3m 48s	12.00s	0	8
listFilter	✔	15	3	14	6m 24s	14.55s	0	13
listAdd1	✔	9	2	5	1m 36s	7.72s	0	4
listDelBeg	✖	13	2	20	29m 54s	12.65s	41	60
bstFree	✔	8	0	1	3.6s	6.70s	0	0
bstLookup	✔	15	3	35	32m 12s	14.19s	20	54
bstInsert	✔	24	4	22	17m 24s	16.81s	7	28
bstMinValue	✔	7	3	11	6m 36s	7.90s	0	10
bstSkewed	✖	3	2	12	7m	22.77s	6	17
popHighest	✖	5	3	8	3m 24s	18.87s	2	9

TABLE II: The results for the benchmarks SynVer was only able to partially verify. **SP** reports how many of the initial subgoals from SepAuto that GenProof completely solved.

Benchmark	Rec	LoC	GP	SP	LoP	PT	GT	MS	TE
checkSorted	✔	19	3	2	34	1h 18m	19.23s	80	115
checkZ	✔	11	4	1	17	1h	9.54s	100	117
consecNums	✔	11	4	3	26	1h 18m	18.02s	108	134
firstOddIndex	✔	11	4	3	33	1h 24m	9.98s	76	109
arrayMember	✔	9	3	1	12	1h 6m	7.75s	167	180
OddAtOdd	✔	14	5	1	13	1h 6m	22.93s	134	152
lastPosition	✔	11	2	1	5	40m 48s	14.87s	200	204
compArrays	✔	11	4	3	41	2h 36m	15.69s	68	108
listArrayEq	✔	16	4	1	31	1h 30m	13.78s	86	119
bstMinNode	✔	10	3	0	34	4h 18m	10.35s	119	154
bstMinKey	✔	7	3	2	42	1h 36m	6.15s	70	113
countValue	✖	10	5	0	27	1h 42m	12.51s	138	164
bstDel	✔	31	6	1	30	4h 24m	20.55s	127	156
addLast	✖	12	3	0	28	2h	15.76s	106	133

seconds to 53 minutes, with an average time of roughly 7.5 minutes.

Based on a manual analysis, SynVer generated correct programs for each of the remaining benchmarks, even though GenProof was only able to partially verify these programs within its interaction limit. These programs tend to be longer and have more complex specifications than those GenProof was able to fully verify. Table II shows the results for these 14 benchmarks. As the table shows, `takeStep` discards many more tactics and backtracks more often in these benchmarks, on average 80% of the time. This suggests that GenProof spent much of its time on these benchmarks exploring unproductive proof directions. As a consequence, the proof generation time for these benchmarks was considerably slower than the for the fully verified benchmarks, with an average time of nearly 2 hours. Note that our current implementation of GenProof asks Rocq to reprocess the current proof script in its entirety each time `takeStep` tries a new tactic— thus, the overall proving time increases substantially with the number of tactics `takeStep` evaluates. This overhead could be substantially reduced by implementing via a more incremental interaction loop with the theorem prover.

A manual inspection of the proof scripts generated by GenProof suggests that `GPT-5mini` can effectively compensate for gaps in SepAuto's automation. As one example, SepAuto does not attempt to instantiate existential variables, a key part of correctness proofs in VST for functions with a non-`void` return type. `GPT-5mini` was able to identify the right instantiation in all but three of our benchmarks. This investigation also indicates that `GPT-5mini` was able to effectively identify and apply lemmas that help the proof make progress.

We also performed a manual analysis of the 14 proofs GenProof could only partially complete. Based on this analysis, we categorized each program into one of four categories:

- **Faulty Suggestions**: The partial proofs for `checkZ`, `OddAtOdd` and `lastPosition` feature a large number of tactics (86%, 88% and 98%) that were discarded due to Rocq-reported errors or failure to make progress.
- **Cyclic Reasoning**: The partial proofs for `consecNums`, `checkSorted`, and `lastPosition` all repeatedly try sequences of tactics that modify the goal in some way before eventually arriving at the original goal, effectively not making progress. Incorporating better cycle detection in `takeStep` could help ameliorate these sorts of failures.
- **Superfluous Tactic Suggestions**: The partial proofs for `firstOddIndex`, `listArrayEq`, `bstMinNode`, `countValue`, and `bstDel` repeated call unnecessary tactics that, e.g., perform superfluous case analysis or induction.
- **Backtracking Failure**: The partial proofs for the three remaining benchmarks all incorrectly instantiate an existential variable at some point, but GenProof is unable to either detect this, in the case of `addLast`, or it detects the

TABLE III: The result of using different variations of the coder prompt with `GPT-5mini`. The first column (**Var**) lists the prompt variant, followed by five columns indicating which components of the prompt were included. The first four of these indicate whether the prompt includes explicit instructions to follow the syntactic biases (**Bias**), a separation logic specification (**Spec**), a natural language description (**Desc**), and input-output examples (**Ex**). The next column lists the kind of function name that was included in the prompt: Original uses the name from Tables I and II; Verbose uses a long but meaningful function name; and Arbitrary is a random name with no relation to the function's intent. The next two groups of columns list the number of programs meeting the syntactic bias (**B**) and the number of correct programs (**C**) generated in response to each prompt variations for the (**Basic**) and (**Heap**) benchmark categories.

Var	**Bias**	**Spec**	**Desc**	**Ex**	**Name**	**Basic** (19)		**Heap** (24)	
						B	**C**	**B**	**C**
P1	✖	✔	✔	✔	Original	7	9	11	24
P2	✔	✖	✖	✖	Verbose	19	18	24	22
P3	✔	✔	✖	✖	Verbose	19	19	24	24
P4	✔	✖	✔	✖	Arbitrary	19	19	24	24
P5	✔	✔	✖	✖	Arbitrary	19	19	24	20

problem much further later in the proof script and is unable to quickly revert to the point at which the flawed reasoning occured, in the case of `arrayMember` and `bstMinKey`. For these last two benchmarks, allowing GENPROOF to revert to an arbitrary earlier point in the proof could help lead to better results.

C. RQ2: Composition of the coder LLM Prompt

As discussed in Section III, GENPROOF is designed to be applied to semantically correct programs that conform to a set of syntactic biases. This section presents an ablation study of how much the individual components of the prompt given to the coder LLM contributes to the ability of SYNVER to generate programs meeting those biases. For this experiment, we have constructed five variants of the prompt from Fig. 4 and use these to prompt `GPT-5mini` for programs for the 43 specifications belonging to the first two benchmark categories. The API benchmark is omitted from this experiment because their prompt includes additional information in the form of the additional functions (with specifications) that the synthesized program is allowed to call.

Table III reports the results of manually checking whether the resulting programs were correct and conformed to our biases. Each of these variations investigates a different aspect of the coder prompt:

- **P1**: This variation investigates the shape of the programs that the coder LLM generates without additional instructions. Without explicit guidance, `GPT-5mini` generates programs following our syntactic bias less than half of the time, using loops instead of recursion in all but 4 cases; of these, 3 are tree programs that naturally admit recursive solutions.
- **P2 and P3**: When provided with only a descriptive function name and instructions about our biases, `GPT-5mini` responds with a correct program for all but three of our specifications, suggesting that `GPT-5mini` is particularly sensitive to this prompt component. The programs in the three failing cases— `consecNumbers`, `assignX` and `assignYAdd`— had ambiguous names, further supporting this hypotheses. Providing additional semantic information in the form of separation logic specifications (**P3**), enables `GPT-5mini` to generate all correct programs, suggesting that including specifications can help the LLM when only part of the target functionality is encoded in the function name.
- **P4**: This variant probes how well the LLM responds to informal specifications. In contrast to **P2** and **P3**, however, all of the natural language descriptions used in this experiment are able to completely capture the behavior of the target program. `GPT-5mini` is able to generate correct programs for all our benchmarks with this variant, suggesting that it can effectively interpret mathematically imprecise specifications.
- **P5**: This final prompt variant tests how well `GPT-5mini` is able to interpret mathematically rigorous specifications written in separation logic. `GPT-5mini` was less effective when provided with just these sorts of specifications, however, failing to generate correct programs for four of our benchmarks using this prompt. Three of these— `listAdd1`, `listAppend`, and `listDelEnd`— make a copy of the input list, which is inconsistent with the target specification. The last incorrect program generated by `GPT-5mini`, `bstFree`, fails to properly deallocate the target list, simply returning `null` instead.

Taken together, these results suggest that it is important to include explicit instructions about our syntactic biases. In addition, while `GPT-5mini` can effectively interpret natural language components, it is less effective at interpreting more formal specifications of target program behaviors.

D. RQ3: Alternative Proof Automation Strategies

To evaluate the effectiveness of SYNVER's approach to proof automation, we have conducted a comparative study of GENPROOF with other proof automation approaches. Our set of alternative approaches includes two state-of-the art learning-based theorem provers, Tactician [25] and Rango [23], three simplified variants of GENPROOF, and SA++, an enhanced version of SEPAUTO equipped with additional tactic-based proof automation. SA++ is meant to serve as a roofline for how well purely symbolic proof automation can work for VST-style proofs of program correctness. This tactic was developed by a verification expert who first manual wrote proof scripts for a subset of our benchmarks, and then generalized the high-level proof strategies used into a `crush`-style tactic [26], a process that took about 100 person-hours.

We divide the benchmarks used in these experiments into two groups. The first group consists of 42 benchmarks and admits a total ordering based on the number of proofs each approach

TABLE IV: The results of using alternative proof automation approaches to verify a subset of candidate programs. **Framework** lists the prover, and the remaining columns report the number of benchmarks from the **Basic**, **Heap**, and **API** categories each framework was able to completely verify. SA only applies SepAuto to the top-level theorem. GP-SA-H is a limited version of GenProof that only calls SepAuto on the top-level theorem, and tries to discharge all subsequent proof obligations using just the prover LLM, does not backtrack, and uses a version of `takeStep` that does not filter tactics based on the size of the goals they generate. GP+SA-H is a variant of GP-SA-H that also applies SepAuto to new subgoals. SA++ is an enhanced version of SepAuto that is equipped with additional tactic-based automation.

Framework	**Basic (18)**	**Heap (22)**	**API (2)**
Rango	0	3	0
Tactician	2	4	0
SA	5	5	0
GP-SA-H	9	14	0
GP+SA-H	9	18	0
GenProof	11	19	0
SA++	14	21	1

was able to completely solve (shown in Table IV): Rango ⊂ Tactician ⊂ SA ⊂ GP-SA-H ⊂ GP+SA-H ⊂ GenProof ⊂ SA++.

In general, the two learning-based proof automation approaches performed quite poorly, with Tactician finishing slightly more (6) proofs than Rango (3). We attribute this to the specialized nature of proofs of program correctness in VST: there are not many publicly available examples of such proofs, and the training data for both provers is thus unlikely to include such proofs; Tactician supports on-the-fly learning, and is thus able to perform better. We provide the four examples of VST proofs used in our prompt to the prover LLM when evaluating both tools, and Tactician seems to learn from these examples.

Of the 42 benchmarks that admit a total order on approaches, the three limited variants of GenProof all perform better than Rango and Tactician, but are only able to solve a subset of the proofs that GenProof and SA++ can. The proofs that only SA++ is able to solve completely, all feature specifications with nested quantifiers and boolean predicates; showing the corresponding programs correct requires correctly instantiating these quantifiers. The other proof generation approaches struggle with this task, generating a large number of discarded tactics and repeatedly backtracking. We also note there are 6 programs that none of the approaches are able to completely verify; all of these have particularly complex specifications, e.g., combination of nested quantifiers and boolean operators, and the separating implication operator.

Table V presents the results of each approach for the 6 benchmarks that violate our total ordering. The verification failures on these benchmarks can be divided into two categories. First, some approaches failed to correctly instantiate an existential variable, as discussed in Section IV-B (`arrayMember`, `addLast`, `bstSkewed`). Second, the remaining failures were due to an inability to identify and apply the helper lemma (`listDelBeg`, `listDelEnd` and `popHighest`). The failures of SA++ are due to its reliance on a fixed set of heuristics to perform both of these tasks — in the case of `popHighest`, for example, the tactic did not include a necessary helper lemma in its built-in database of auxiliary facts. The LLM-based approaches, in contrast, were able to identify the lemma needed to completely verify this program. On the other hand, these approaches were less effective at supplying the right existential witnesses in some cases. Interestingly, in some cases the simpler approaches were able to find witnesses that the more powerful GenProof could not. This is most likely due to the nondeterministic nature of LLMs, causing `GPT-5mini` to occasionally fail to find the right witness.

TABLE V: The results of verifying the 6 benchmarks not included in Table IV. Results for Rango, Tactician, and SA are omitted, as all three are unable to completely verify any of these programs. The columns after **Framework** correspond to these 6 benchmarks: `arrayMember`, `listDelEnd`, `listDelBeg`, `addLast`, `bstSkewed`, `popHighest`.

Framework	**arMem**	**addL**	**bstS**	**lDelE**	**lDelB**	**popH**
GP-SA-H	✖	✔	✖	✔	✖	✔
GP+SA-H	✔	✖	✖	✔	✔	✔
GenProof	✖	✖	✔	✔	✔	✔
SA++	✔	✔	✖	✖	✖	✖

E. Discussion

1) Performance of Generated Code: As with most deductive synthesizers, SynVer prioritizes verifiability over performance when generating candidate programs, and our experiments suggest that it achieves this goal. That said, the performance of synthesized programs remains an important concern. To better understand the performance of the programs generated by SynVer, we investigated the impact of our requirement that candidate programs use recursion instead of loops. For the 21 specifications that admit tail recursive implementations, we found that SynVer consistently generated tail recursive programs. Manual inspection of the compiled programs indicates that GCC [27] was able to optimize all of these into versions that were equivalent to those produced by an implementation using loops. This suggests that modern compilers can be effective at mitigating the performance impact of SynVer's preference for recursive programs.

2) Comparison with SUSLik: SUSLik [3] is a state-of-the-art deductive synthesizer for generating heap-manipulating C-like programs. SUSLik takes as input the signature and separation-logic pre- and post-conditions of the target program, written as $\{pre\} \rightsquigarrow \{post\}$, and searches for a corresponding implementation. This search is carried out by applying a series of deductive synthesis rules which decompose the current synthesis task into subtasks. At each search step, the synthesizer examines the current goal and uses heuristics to select the next rule to apply. The space of programs that SUSLik considers is thus constrained both by its set of synthesis rules and the heuristics used to apply those rules. To compare these two approaches, we applied SUSLik on our basic and heap-manipulating benchmarks— SUSLik does not include rules for reasoning about functions calls and thus can not handle any program from the API benchmark. Of these benchmarks, SUSLik was able successfully synthesize implementations of 9 of our basic and 22 of our heap-manipulating benchmarks.[1]

To illustrate some of the differences between SUSLik and SYNVER, we highlight two of the programs that SUSLik was not able to solve:

a) Allocate a block of n elements: The following specification describes a function that allocates a set of n blocks.

$$\{0 \leq n\} \rightsquigarrow \{0 \leq n\,; ret \mapsto x * sll(x, n)\}$$

Solving this goal requires performing case analysis on n, but SUSLik's rule for case splitting requires the precondition to include at least one heap predicate. Since the precondition here only contains pure predicates, SUSLik cannot apply its case analysis rule, and fails to synthesize a solution.

b) List membership: When attempting to synthesize a program that checks whether a set s with n elements contains the integer mem, SUSLik will encounter the following subgoal:

$$\begin{aligned}&\{mem = v \wedge 0 \leq n1 \wedge n = 1 + n1 \wedge x \neq null \wedge s = v1 \cup s1;\\ &\quad ret \mapsto a * x \mapsto v * x \mapsto nxt * list\_mem(nxt, mem, n1, s1)\}\\ \rightsquigarrow\ &\{ret \mapsto (1 + n1 = 0\,?\,0 : 1) * list\_mem(nxt, mem, n, v \cup s1)\}\end{aligned}$$

Here, SUSLik fails to infer that the function should return 1, as $(1 + n1 = 0)$ must be false. SUSLik has limited support for reasoning about the pure fragment of specifications, and tries to heuristically instantiate the return value of the function with either a constant drawn from a predetermined set or one of the variables in scope, e.g., mem and v. None of these are the correct choice, and SUSLik fails to solve the synthesis goal.

3) Threats to Validity:

a) Internal validity: We cannot guarantee the absence of **data leak** - i.e., the training set `GPT-5mini` used by SYNVER excludes the target implementation (specifically the programs) of our benchmark specifications. In fact, many of our data points are based on standard and widely used data structure implementations; therefore resulting in all the programs being generated correctly on the first try.

SYNVER uses LLMs to generate and verify programs that are inherently **non-deterministic**. Although our evaluation uses fixed seeds to support reproducibility, we cannot guarantee that our results are robust to changes in those seeds. This contrasts with traditional program synthesizers, which typically produce deterministic results.

b) External validity: SYNVER uses VST to verify generated programs. Thus, both SEPAUTO and the tactics predicted by the prover LLM are geared to VST specifically and Rocq more broadly. Alternative Rocq-based verification frameworks for C programs also exist, e.g., Iris [28] and RefinedC [29]. Since proofs in these frameworks are similar to those in VST, our approach should naturally generalize to those settings, although the prompts for the prover LLM and SEPAUTO would need to be adapted to account for proof idioms and the custom tactics provided by those frameworks.

4) Limitations: VST has built-in support for basic types, arrays, and pointers to a single memory location. Reasoning about data structures that reside in non-contiguous memory locations requires manual effort to encode the data type in separation logic and to prove helper lemmas for reasoning about values of that type. At present, we have manually encoded and verified Singly Linked Lists (SLL) and Binary Search Trees (BST); SEPAUTO is equipped with helper lemmas for discharging obligations related to those data structures. In order to support other data structures, SYNVER would need to be extended with the required specifications and helper lemmas. Similar helper lemmas would be needed to reason about composite data types, e.g., a graph data structure that uses adjacency list implemented as an array of singly linked lists.

V. RELATED WORK

A. Machine Learning for Interactive Theorem Proving

Many of the initial learning-based proof automation techniques for interactive theorem provers focused on the problems of *premise selection* [30], [31], [32], [33], i.e., identifying lemmas that are relevant to a given theorem or proof state, and *tactic prediction*, i.e., choosing the best tactic to apply in a given proof state. Early tactic predication works explored different neural encodings of an in-progress proof, including GNNs [25] RNNs [34], [35] and Tree-LSTMs [36], [37], [38], as well as how to enhance the proof state with additional information, e.g., the current partial proof [37], the identifiers currently appearing in a goal [39], and recent proof scripts [25].

More recent works have also explored the use of LLMs for tactic prediction: Copra [40], for example, asks GPT-4 to predict the next tactic in a Rocq proof script, given the current proof state, previous proof steps, and any relevant error messages. LeanDojo [16] similarly queries an LLM to suggest the next step in a proof in Lean [41]; both approaches attempt to generate complete proofs by combining tactic prediction with a heuristic search that explores different proof directions. Other LLM-based approaches attempt to generate a complete proof by first generating a candidate proof script and then repairing any errors reported by the proof assistant [17], [42]. Prior LLM-based approaches also leverage purely symbolic automation [43], [42] when generating proofs, although these works rely on hammers [43], [44], tactics that attempt to completely discharge subgoals in the proof assistant by calling out to external automated theorem provers. Unlike SEPAUTO, which is designed to handle VST-specific goals, hammers are general-purpose tools meant to discharge arbitrary proof conditions. Similarly, all of these prior works are trained and evaluated on corpuses of generic theorems [36], [45], [46] drawn from a diverse set of problem domains, including pure mathematics, programming language metatheory, and verification of pure functional programs.

[1] These results use slightly weaker specifications for the `insert` and `delete` programs than SYNVER, as they do not guarantee the order of the elements in the resulting list.

B. Machine Learning for Program Verification

Learning-based approaches for program verification have primarily targeted frameworks that rely on explicit annotations, e.g., loop invariants, to enable automated reasoning, e.g., Dafny [47], Frama C [48], VeriFast [49], and Verus [50]. These annotations are used to generate *verification conditions*— formulas in a decidable logic whose validity guarantees the correctness of the original program— that can be discharged by a automated theorem prover like Z3. A key challenge when using these tools is identifying the right set of annotations needed to verify a program. This task has traditionally fallen to the user, but a number of tools have recently been proposed for automatically generating these annotations. Code2Inv [51], for example, combines Graph Representation Learning and reinforcement learning to automatically infer loop invariants for C programs. In the past few years, several tools have relied on LLMs to generate annotations for program written in both C [12], [11] and Rust [10], [52]. A recent study suggests that LLMs struggle with inferring specifications in full separation logic [53], resulting in hundreds of compilation and verification errors across different prompts. As a consequence, most of these tools use simpler assertion languages than separation logic, preventing them from reasoning about the full range of specifications that SynVer currently supports — Frama C, for example, cannot handle the separating implication operator, and requires increasingly complex annotations for non-contiguous heap allocated structures. A verification case study [54] of the linked list module of Contiki [55] in Frama C, for example, required 1400 lines of annotations to verify 176 lines of C code.

C. Program Synthesis

Like SynVer, traditional deductive synthesizers also generate correct-by-construction from formal specifications [56], [7], [57], [2], [5], [3], [6], but unlike SynVer, these works either target specific application domains to achieve automation or rely on user guidance to synthesize a program. Recent work has shown that LLMs are effective at synthesizing programs with less rigorous specifications, e.g., input-output examples [58], [59]. LLMs have also shown potential to simultaneously generate programs and their specifications in solver-aided languages from natural language descriptions [8], [9], although the LLM-generated specifications tend to be weaker than those used by SynVer, however. Even when the resulting programs can be verified against their generated specifications there is no guarantee that those specifications accurately capture the user's intent.

VI. Conclusion

We have presented SynVer, a program synthesis framework that is capable of generating high-assurance C programs for a diverse range of problem domains. Each synthesized program is accompanied by a formal proof— built using the Rocq-based VST framework— that ensures it satisfies its target separation logic specification. To accomplish this, SynVer employs two LLMs: a coder LLM which generates candidate programs from user-provided specifications, and a prover LLM which helps automatically verify the correctness of candidate programs. To facilitate verification, SynVer places a set of syntactic biases on generated programs that make them amenable to automated reasoning. SynVer verifies programs using a hybrid strategy that combines symbolic reasoning with LLM-assisted proof generation, causing it to discharge proof obligations that neither approach can handle on its own. We have demonstrated the applicability of SynVer on a diverse set of benchmarks drawn from the program synthesis and verification literature.

Acknowledgements

The authors thank the anonymous reviewers for their valuable suggestions and feedback. The authors thank Andrew Appel for his help with VST and his insights on tail call optimization in GCC. The authors also thank Robert Thompson for helping us set up the Rango evaluations. This work was partially supported by the National Science Foundation under Grant CCF-SHF 2321680 and by a grant from the Purdue Research Foundation.

References

[1] Z. Manna and R. Waldinger, "Synthesis: Dreams ⇒ programs," *IEEE Trans. Softw. Eng.*, vol. 5, no. 4, p. 294–328, Jul. 1979. [Online]. Available: https://doi.org/10.1109/TSE.1979.234198

[2] B. Delaware, C. Pit-Claudel, J. Gross, and A. Chlipala, "Fiat: Deductive synthesis of abstract data types in a proof assistant," *SIGPLAN Not.*, vol. 50, no. 1, p. 689–700, jan 2015. [Online]. Available: https://doi.org/10.1145/2775051.2677006

[3] N. Polikarpova, "Suslik: Synthesis of safe pointer-manipulating programs (invited tutorial)," in *2019 Formal Methods in Computer Aided Design (FMCAD)*, 2019, pp. 1–1.

[4] Y. Watanabe, K. Gopinathan, G. Pîrlea, N. Polikarpova, and I. Sergey, "Certifying the synthesis of heap-manipulating programs," *Proc. ACM Program. Lang.*, vol. 5, no. ICFP, aug 2021. [Online]. Available: https://doi.org/10.1145/3473589

[5] B. Delaware, S. Suriyakarn, C. Pit-Claudel, Q. Ye, and A. Chlipala, "Narcissus: correct-by-construction derivation of decoders and encoders from binary formats," *Proc. ACM Program. Lang.*, vol. 3, no. ICFP, jul 2019. [Online]. Available: https://doi.org/10.1145/3341686

[6] A. Mishra and S. Jagannathan, "Specification-guided component-based synthesis from effectful libraries," *Proc. ACM Program. Lang.*, vol. 6, no. OOPSLA2, oct 2022. [Online]. Available: https://doi.org/10.1145/3563310

[7] D. Pavlovic, P. Pepper, and D. R. Smith, "Formal derivation of concurrent garbage collectors," in *Mathematics of Program Construction*. Springer Berlin Heidelberg, 2010, pp. 353–376.

[8] M. R. H. Misu, C. V. Lopes, I. Ma, and J. Noble, "Towards ai-assisted synthesis of verified dafny methods," *Proc. ACM Softw. Eng.*, vol. 1, no. FSE, pp. 812–835, 2024. [Online]. Available: https://doi.org/10.1145/3643763

[9] S. Chakraborty, G. Ebner, S. Bhat, S. Fakhoury, S. Fatima, S. K. Lahiri, and N. Swamy, "Towards neural synthesis for smt-assisted proof-oriented programming," in *47th IEEE/ACM International Conference on Software Engineering, ICSE 2025, Ottawa, ON, Canada, April 26 - May 6, 2025*. IEEE, 2025, pp. 1755–1767. [Online]. Available: https://doi.org/10.1109/ICSE55347.2025.00002

[10] C. Yang, X. Li, M. R. H. Misu, J. Yao, W. Cui, Y. Gong, C. Hawblitzel, S. K. Lahiri, J. R. Lorch, S. Lu, F. Yang, Z. Zhou, and S. Lu, "Autoverus: Automated proof generation for rust code," *CoRR*, vol. abs/2409.13082, 2024. [Online]. Available: https://doi.org/10.48550/arXiv.2409.13082

[11] M. Sevenhuijsen, K. Etemadi, and M. Nyberg, "Vecogen: Automating generation of formally verified c code with large language models," 2025. [Online]. Available: https://arxiv.org/abs/2411.19275

[12] C. Wen, J. Cao, J. Su, Z. Xu, S. Qin, M. He, H. Li, S.-C. Cheung, and C. Tian, "Enchanting program specification synthesis by large language models using static analysis and program verification," in *Computer Aided Verification*, A. Gurfinkel and V. Ganesh, Eds. Cham: Springer Nature Switzerland, 2024, pp. 302–328.

[13] J. Reynolds, "Separation logic: a logic for shared mutable data structures," in *Proceedings 17th Annual IEEE Symposium on Logic in Computer Science*, 2002, pp. 55–74.

[14] Q. Cao, L. Beringer, S. Gruetter, J. Dodds, and A. W. Appel, "Vst-floyd: A separation logic tool to verify correctness of C programs," *J. Autom. Reason.*, vol. 61, no. 1-4, pp. 367–422, 2018. [Online]. Available: https://doi.org/10.1007/s10817-018-9457-5

[15] The Coq Development Team, "The Coq reference manual – release 8.19.0," https://coq.inria.fr/doc/V8.19.0/refman, 2024.

[16] K. Yang, A. Swope, A. Gu, R. Chalamala, P. Song, S. Yu, S. Godil, R. Prenger, and A. Anandkumar, "LeanDojo: Theorem proving with retrieval-augmented language models," in *Neural Information Processing Systems (NeurIPS)*, 2023.

[17] E. First, M. N. Rabe, T. Ringer, and Y. Brun, "Baldur: Whole-proof generation and repair with large language models," in *Proceedings of the 31st ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, ESEC/FSE 2023, San Francisco, CA, USA, December 3-9, 2023*, S. Chandra, K. Blincoe, and P. Tonella, Eds. ACM, 2023, pp. 1229–1241. [Online]. Available: https://doi.org/10.1145/3611643.3616243

[18] P. Mukherjee, M. Lu, and B. Delaware, "LLM-Assisted Synthesis of High-Assurance C Programs," sep 2025. [Online]. Available: https://doi.org/10.5281/zenodo.17219749

[19] C. A. R. Hoare, "An axiomatic basis for computer programming," *Commun. ACM*, vol. 12, no. 10, p. 576–580, Oct. 1969.

[20] Q. Cao, L. Beringer, S. Gruetter, J. Dodds, and A. W. Appel, "Vst-floyd: A separation logic tool to verify correctness of c programs," *Journal of Automated Reasoning*, vol. 61, pp. 367–422, 2018.

[21] C. A. Furia, B. Meyer, and S. Velder, "Loop invariants: Analysis, classification, and examples," *ACM Computing Surveys (CSUR)*, vol. 46, no. 3, pp. 1–51, 2014.

[22] Y. Xiao, "Hyperwand: Extending the magic wand operator in separation logic," *j*, 2023.

[23] K. Thompson, N. Saavedra, P. Carrott, K. Fisher, A. Sanchez-Stern, Y. Brun, J. F. Ferreira, S. Lerner, and E. First, "Rango: Adaptive retrieval-augmented proving for automated software verification," *ICSE*, 2025. [Online]. Available: https://people.cs.umass.edu/∼brun/pubs/pubs/Thompson25icse.pdf

[24] T. H. Cormen, C. E. Leiserson, R. L. Rivest, and C. Stein, *Introduction to Algorithms, Third Edition*, 3rd ed. The MIT Press, 2009.

[25] L. Blaauwbroek, J. Urban, and H. Geuvers, "The tactician: A seamless, interactive tactic learner and prover for coq," in *International Conference on Intelligent Computer Mathematics*. Springer, 2020, pp. 271–277.

[26] A. Chlipala, *Certified Programming with Dependent Types: A Pragmatic Introduction to the Coq Proof Assistant*. The MIT Press, 2013.

[27] B. J. Gough and R. Stallman, *An Introduction to GCC*. Network Theory Limited Bristol, UK, 2004.

[28] R. Jung, R. Krebbers, J.-H. Jourdan, A. Bizjak, L. Birkedal, and D. Dreyer, "Iris from the ground up: A modular foundation for higher-order concurrent separation logic," *Journal of Functional Programming*, vol. 28, p. e20, 2018.

[29] M. Sammler, R. Lepigre, R. Krebbers, K. Memarian, D. Dreyer, and D. Garg, "Refinedc: automating the foundational verification of c code with refined ownership types," in *Proceedings of the 42nd ACM SIGPLAN International Conference on Programming Language Design and Implementation*, 2021, pp. 158–174.

[30] J. Alama, T. Heskes, D. Kühlwein, E. Tsivtsivadze, and J. Urban, "Premise selection for mathematics by corpus analysis and kernel methods," *J. Autom. Reason.*, vol. 52, no. 2, p. 191–213, Feb. 2014. [Online]. Available: https://doi.org/10.1007/s10817-013-9286-5

[31] T. Gauthier and C. Kaliszyk, "Premise selection and external provers for hol4," in *Proceedings of the 2015 Conference on Certified Programs and Proofs*, ser. CPP '15. New York, NY, USA: Association for Computing Machinery, 2015, p. 49–57. [Online]. Available: https://doi.org/10.1145/2676724.2693173

[32] M. Wang, Y. Tang, J. Wang, and J. Deng, "Premise selection for theorem proving by deep graph embedding," in *Proceedings of the 31st International Conference on Neural Information Processing Systems*, ser. NIPS'17. Red Hook, NY, USA: Curran Associates Inc., 2017, p. 2783–2793.

[33] B. Piotrowski, R. F. Mir, and E. Ayers, "Machine-learned premise selection for lean," in *Automated Reasoning with Analytic Tableaux and Related Methods: 32nd International Conference, TABLEAUX 2023, Prague, Czech Republic, September 18–21, 2023, Proceedings*. Berlin, Heidelberg: Springer-Verlag, 2023, p. 175–186. [Online]. Available: https://doi.org/10.1007/978-3-031-43513-3_10

[34] D. Huang, P. Dhariwal, D. Song, and I. Sutskever, "Gamepad: A learning environment for theorem proving," *arXiv preprint arXiv:1806.00608*, 2018.

[35] A. Sanchez-Stern, Y. Alhessi, L. Saul, and S. Lerner, "Generating correctness proofs with neural networks," in *Proceedings of the 4th ACM SIGPLAN International Workshop on Machine Learning and Programming Languages*, ser. MAPL 2020. New York, NY, USA: Association for Computing Machinery, 2020, p. 1–10. [Online]. Available: https://doi.org/10.1145/3394450.3397466

[36] K. Yang and J. Deng, "Learning to prove theorems via interacting with proof assistants," in *International Conference on Machine Learning (ICML)*, 2019.

[37] E. First, Y. Brun, and A. Guha, "Tactok: semantics-aware proof synthesis," *Proc. ACM Program. Lang.*, vol. 4, no. OOPSLA, pp. 231:1–231:31, 2020. [Online]. Available: https://doi.org/10.1145/3428299

[38] E. First and Y. Brun, "Diversity-driven automated formal verification," in *Proceedings of the 44th International Conference on Software Engineering*, ser. ICSE '22. New York, NY, USA: Association for Computing Machinery, 2022, p. 749–761. [Online]. Available: https://doi.org/10.1145/3510003.3510138

[39] A. Sanchez-Stern, E. First, T. Zhou, Z. Kaufman, Y. Brun, and T. Ringer, "Passport: Improving automated formal verification using identifiers," *ACM Trans. Program. Lang. Syst.*, vol. 45, no. 2, pp. 12:1–12:30, 2023. [Online]. Available: https://doi.org/10.1145/3593374

[40] A. Thakur, G. Tsoukalas, Y. Wen, J. Xin, and S. Chaudhuri, "An in-context learning agent for formal theorem-proving," 2024. [Online]. Available: https://arxiv.org/abs/2310.04353

[41] L. De Moura, S. Kong, J. Avigad, F. Van Doorn, and J. von Raumer, "The Lean theorem prover (system description)," in *Automated Deduction-CADE-25: 25th International Conference on Automated Deduction, Berlin, Germany, August 1-7, 2015, Proceedings 25*. Springer, 2015, pp. 378–388.

[42] M. Lu, B. Delaware, and T. Zhang, "Proof automation with large language models," in *Proceedings of the 39th IEEE/ACM International Conference on Automated Software Engineering*, ser. ASE '24. New York, NY, USA: Association for Computing Machinery, 2024, p. 1509–1520. [Online]. Available: https://doi.org/10.1145/3691620.3695521

[43] A. Jiang, K. Czechowski, M. Jamnik, P. Milos, S. Tworkowski, W. Li, and Y. T. Wu, "Thor: Wielding hammers to integrate language models and automated theorem provers," in *NeurIPS*, 2022.

[44] z. Czajka and C. Kaliszyk, "Hammer for coq: Automation for dependent type theory," *J. Autom. Reason.*, vol. 61, no. 1–4, p. 423–453, Jun. 2018. [Online]. Available: https://doi.org/10.1007/s10817-018-9458-4

[45] K. Zheng, J. M. Han, and S. Polu, "Minif2f: a cross-system benchmark for formal olympiad-level mathematics," *arXiv preprint arXiv:2109.00110*, 2021.

[46] G. Tsoukalas, J. Lee, J. Jennings, J. Xin, M. Ding, M. Jennings, A. Thakur, and S. Chaudhuri, "Putnambench: evaluating neural theorem-provers on the putnam mathematical competition," in *Proceedings of the 38th International Conference on Neural Information Processing Systems*, ser. NIPS '24. Red Hook, NY, USA: Curran Associates Inc., 2025.

[47] K. R. M. Leino, "Dafny: an automatic program verifier for functional correctness," in *Proceedings of the 16th International Conference on Logic for Programming, Artificial Intelligence, and Reasoning*, ser. LPAR'10. Berlin, Heidelberg: Springer-Verlag, 2010, p. 348–370.

[48] F. Kirchner, N. Kosmatov, V. Prevosto, J. Signoles, and B. Yakobowski, "Frama-c: A software analysis perspective," *Formal aspects of computing*, vol. 27, no. 3, pp. 573–609, 2015.

[49] B. Jacobs, J. Smans, P. Philippaerts, F. Vogels, W. Penninckx, and F. Piessens, "Verifast: A powerful, sound, predictable, fast verifier for c and java," in *NASA formal methods symposium*. Springer, 2011, pp. 41–55.

[50] A. Lattuada, T. Hance, C. Cho, M. Brun, I. Subasinghe, Y. Zhou, J. Howell, B. Parno, and C. Hawblitzel, "Verus: Verifying rust programs using linear ghost types," *Proceedings of the ACM on Programming Languages*, vol. 7, no. OOPSLA1, pp. 286–315, 2023.

[51] X. Si, A. Naik, H. Dai, M. Naik, and L. Song, "Code2inv: A deep learning framework for program verification," in *Computer Aided Verification: 32nd International Conference, CAV 2020, Los Angeles, CA, USA, July 21–24, 2020, Proceedings, Part II 32*. Springer, 2020, pp. 151–164.

[52] T. Chen, S. Lu, S. Lu, Y. Gong, C. Yang, X. Li, M. R. H. Misu, H. Yu, N. Duan, P. Cheng, F. Yang, S. K. Lahiri, T. Xie, and L. Zhou,

"Automated proof generation for rust code via self-evolution," in *The Thirteenth International Conference on Learning Representations, ICLR 2025, Singapore, April 24-28, 2025*. OpenReview.net, 2025. [Online]. Available: https://openreview.net/forum?id=2NqssmiXLu

[53] M. Rego, W. Fan, X. Hu, S. Dod, Z. Ni, D. Xie, J. DiVincenzo, and L. Tan, "Evaluating the ability of gpt-4o to generate verifiable specifications in verifast," in *2025 IEEE/ACM Second International Conference on AI Foundation Models and Software Engineering (Forge)*. IEEE, 2025, pp. 246–251.

[54] A. Blanchard, N. Kosmatov, and F. Loulergue, "Ghosts for lists: A critical module of contiki verified in frama-c," in *NASA Formal Methods*, A. Dutle, C. Muñoz, and A. Narkawicz, Eds. Cham: Springer International Publishing, 2018, pp. 37–53.

[55] A. Dunkels, B. Gronvall, and T. Voigt, "Contiki-a lightweight and flexible operating system for tiny networked sensors," in *29th annual IEEE international conference on local computer networks*. IEEE, 2004, pp. 455–462.

[56] D. Smith, "Kids: a semiautomatic program development system," *IEEE Transactions on Software Engineering*, vol. 16, no. 9, pp. 1024–1043, 1990.

[57] F. Franchetti, T.-M. Low, T. Popovici, R. Veras, D. G. Spampinato, J. Johnson, M. Püschel, J. C. Hoe, and J. M. F. Moura, "SPIRAL: Extreme performance portability," *Proceedings of the IEEE, special issue on "From High Level Specification to High Performance Code"*, vol. 106, no. 11, 2018.

[58] 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.

[59] S. Fakhoury, A. Naik, G. Sakkas, S. Chakraborty, and S. K. Lahiri, "Llm-based test-driven interactive code generation: User study and empirical evaluation," *IEEE Trans. Software Eng.*, vol. 50, no. 9, pp. 2254–2268, 2024. [Online]. Available: https://doi.org/10.1109/TSE.2024.3428972