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# TLA-Verus: Generating and Solving Temporal Proof Obligations with LLM Agents

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## Abstract

The TLA+ (temporal logic of actions) formal specification toolkit has seen widespread adoption in modeling modern distributed software systems including databases, storage systems, ledgers and coordination protocols. This popularity is despite its two significant limitations for software verification: Firstly, TLA+ offers no way to detect drift between software implementation and mathematical specification; secondly, TLC and TLAPS cannot provide satisfactory proofs of arbitrary temporal logic properties. We take a step towards addressing these shortcomings by translating TLA+ specifications into Verus, an auto-active verifier built for Rust, via both a deterministic transpiler and an agentic translator. We demonstrate that our LLM-based pipeline is able to generate proof obligations from TLA+ specifications at scale, and to produce fully machine checkable proofs of both safety and liveness properties. Since temporal logic reasoning in Verus is a largely new task for LLMs, our work yields a valuable evaluation dataset, which we use to map out current generation model capabilities in Verus theorem proving.

## 1 Introduction

Frontier coding agents show remarkable success in automating complex proof search, solving one of the most challenging technical problems in software verification. However, mainstream adoption of formal verification in modern software is not exclusively a technical capability question: it depends on how well verification integrates into the workflows developers already use, and on finding repeatable ways of specifying system properties — general enough languages in which idiosyncratic correctness properties of many different systems can be expressed compactly.

TLA+ is a successful example of a formal modeling toolkit that ticks these boxes. It is widely deployed in modern, mainstream distributed systems engineering, see e. g. MongoDB [8], Amazon Web Services [22, 20], Kafka’s KRaft protocol [31], or Datadog [26], etc. In the modern context TLA+ is dated technology, and suffers from two main weaknesses:

- there is no way to prove that the implementation refines the mathematical specification, often leading to implementation - specification drift,
- limited support for proofs especially of liveness properties for large, complex systems.

Temporal logic reasoning has more recently been embedded directly into auto-active deductive verifiers, allowing liveness proofs to live alongside safety proofs in the same verified codebase rather than in a separate model. Microsoft’s IronFleet project pioneered this for a Paxos-based replication protocol [12], and more recently, Anvil embedded temporal logic reasoning in Verus to verify liveness of Kubernetes cluster management controllers [29, 3].

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This work builds directly on Anvil, and significantly extends the number of temporal logic proofs carried out in this style. It addresses the second weakness and takes a step towards the first: we bring specifications into Verus, where an implementation can later be proved to match them.

Beyond the value this provides to users of temporal logic directly, it also provides value for the development of better vericoding agents: it yields a new dataset of safety and liveness proofs that is not academic in size or focus, but practically motivated — and, critically, one whose solutions do not already appear in the training data of existing systems.

The contributions of this work are:

- we describe and compare two approaches for translating TLA+ specifications to Verus: a purely algorithmic transpiler, and one based on an agentic workflow (Section 3.1)
- we describe a multi-turn, prover-reviewer pipeline for writing proofs of TLA properties (Section 3.2)
- we successfully prove 3,094 tasks’ algorithmic translations, and 492 tasks’ agentic translations using Anthropic’s Opus. Moreover, we select 40 tasks and build two datasets from them: `tlaverus_algo` from their algorithmic translations and `tlaverus_llm` from their agentic ones (Section 3.3)
- we compare proof search across the two encodings by running the prover–reviewer pipeline on the same 500 (specification, property) pairs, translated both algorithmically and agenticallly (Section 4.1)
- we evaluate a range of state-of-the-art language models on three datasets: `tlaverus_algo`, `tlaverus_llm` and `verusbench` ([33]) (Section 4.2).

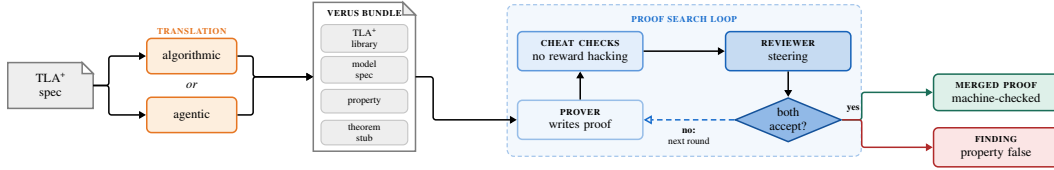


Figure 1: The pipeline end to end. A TLA+ specification becomes a Verus bundle with one property to prove; the merge gate turns the bundle into either a merged, machine-checked proof or a finding about the specification itself.

## 2 Background

### 2.1 Temporal logic and TLA+

Software systems change their state in response to various events. Claims about the system’s safe or correct behavior can be formalized as predicates over execution traces, sequences of states hypothetically visited by the system. Temporal logic of actions [27], a variant of linear temporal logic, allows us to reason about such temporal predicates, and provides a language to describe behavioural properties of interest. In TLA+ we use three operators to construct temporal properties:  $\Box P$  (always,  $P$  holds in every state visited),  $\Diamond P$  (eventually,  $P$  holds in some state) and  $P \leadsto Q \equiv \Box(P \Rightarrow \Diamond Q)$  ( $P$  leads to  $Q$ , whenever  $P$  holds, eventually  $Q$  will hold at some point in the future). In this language one can express a range of properties, the most typical ones can be categorised as:

**safety** ( $\Box$ –**Something Bad**): undesired states (incorrect, inconsistent, deadlocked, etc) are avoided.

**liveness** ( $\Diamond$ **Something Good**): a desired state is eventually reached.

TLA+ [14, 15] describes a system as a temporal formula that holds for all executions that the system can produce:

$$Spec \equiv Init \wedge \Box[Next]_{vars} \wedge F$$

*Init* declares what is true at initialisation. *Next* is a binary relation between a previous and next state, which defines the state transitions possible. *Next* itself is defined as a union of named relations called actions. Grouping transitions to named actions serve easier interpretation and play a role in defining fairness, as explained below. The  $\Box[Next]_{vars}$  notation means that every step either satisfies *Next* or keeps all variables *vars* unchanged, called a stutter step. Stutter steps allow the composition of multiple TLA+ modules: steps where variables don’t change allow variables in other components of a large system to change asynchronously.

These two conjuncts (*Init* and *Next*) define what the system *can* do, but not what it is *likely* to do or what it *must* do to make progress. In this sense they are too weak to imply correct behaviour. To reason about liveness properties, we want to rule out "degenerate" execution traces where nothing happens, or where only irrelevant and uninteresting events keep happening in a loop. This is why we include fairness assumptions *F*. These are individually defined over actions and require that if an action *A* stays enabled, then it is eventually taken. Specs differ in whether they assume weak WF(*A*) or strong (SF(*A*)) on actions that make progress.

TLA+ is widely used in industry to this day [see e. g. 16, 21, 8, 26] but has two major drawbacks:

**specification-implementation drift:** The specification and the implementation are separate artifacts in different languages, and the correspondence between them itself is not checkable. If the code changes, there is no obligation to revise the model, so a specification's guarantees might not hold for the code that implements it. In this sense, TLA+ is used only for model checking, rather than software verification.

**limited proof support:** Properties declared in TLA+ can be checked either by TLC [36], an explicit state model checker, or TLAPS [7] an interactive theorem prover. Both have limitations: TLC cannot handle state space blow-up, thus its use is restricted to small configurations of systems, potentially missing errors that occur as systems are scaled up. TLAPS avoids explicit state-space exploration, but its support for liveness proofs is limited.

## 2.2 Verus

Verus is an auto-active verifier that unites specification, implementation, and proof in one language built on Rust [17]. While primarily designed to support contracts for methods, its rich ghost code support allows reasoning about abstract models of behaviour, so long as the mathematical content remains within the capabilities of an SMT solver.

In our context, Verus thus promises a fully end-to-end environment for verified code synthesis, addressing the specification-implementation gap in temporal logic: the TLA specification can be tied directly to the actual implementation by a refinement proof, as demonstrated for Kubernetes controllers in the Anvil library [29]. Furthermore, Verus supports fully machine checkable proofs for both safety and liveness properties.

In this paper, we focus on translating system specifications written in TLA+ to Verus (Section 3.1), and then using an agentic workflow to produce Verus-checked proofs of system properties (Section 3.2). Connecting implementations to the specifications via refinement proofs is left for future work.

| TLA                                                 | Verus (Anvil encoding)                                                                 |
|-----------------------------------------------------|----------------------------------------------------------------------------------------|
| execution trace                                     | <code>Execution&lt;State&gt; = <math>\mathbb{N} \rightarrow \text{State}</math></code> |
| state predicate                                     | <code>State <math>\rightarrow</math> Bool</code>                                       |
| action relation                                     | <code>State <math>\times</math> State <math>\rightarrow</math> Bool</code>             |
| temporal predicate                                  | <code>Execution&lt;State&gt; <math>\rightarrow</math> Bool</code>                      |
| state predicate <i>P</i> holds at state <i>l</i>    | <code>lift_state(p)</code>                                                             |
| action predicate <i>A</i> holds at first transition | <code>lift_action(a)</code>                                                            |
| $\text{WF}_{\text{vars}}(A), \text{ENABLED } A$     | <code>weak_fairness(a), enabled(a)</code>                                              |
| $\text{Init} \wedge \Box[\text{Next}]$              | <code>and(lift_state(init), always(lift_action(next)))</code>                          |
| $\Box P, \Diamond P$                                | <code>always(p), eventually(p)</code>                                                  |
| $P \rightsquigarrow Q$                              | <code>p.leads_to(q)</code>                                                             |
| $\text{Spec} \Rightarrow \Phi$                      | <code>spec().entails(phi)</code>                                                       |

Table 1: TLA+ concepts and operators used in specifying models and properties (*left*) and their Verus encoding (*right*), adapted from Anvil [29]. An execution trace is modeled as a Verus spec function mapping natural numbers to a state while predicates are encoded as functions returning a Boolean value. The operators ‘always’ and ‘eventually’ are implemented as Verus spec functions with ‘forall’ and ‘exists’ constructs, with control over SMT trigger selection. The temporal library also includes proven lemmas, such as the transitivity of  $\rightsquigarrow$  and Lamport’s WF1 rule [14] for reasoning under a weak fairness assumption.

### 3 The pipeline

#### 3.1 Translation

The first step in our pipeline is to embed a TLA+ spec of an arbitrary system into Verus. For this embedding we use a temporal logic library based on that of Anvil [29]. Table 1 summarises the main code constructs used in this embedding.

This translation step is non-trivial because of the semantic gap between TLA+ and Verus. We developed two approaches to this problem which make different trade-offs: an algorithmic transpiler written in Rust we call *TranSpec*; and an agentic translation loop that uses an LLM agent paired with an LLM judge.

##### 3.1.1 Algorithmic Transpilation (*TranSpec*)

In this section we provide an overview of the key challenges our transpiler program *TranSpec* has to overcome to translate TLA+ to valid Verus specifications.

**Type System:** The transpiler has to bridge the gap between untyped TLA+ and strongly typed Verus and Rust. *TranSpec* performs constraint solving, synthesizes enums, records, maps and sequences. The transpiler uses `Optional` types to handle TLA+’s untyped `CONSTANT NULL`, and ‘Sum’ types to encode TLA+ variables that hold different types depending on system state.

**Verus specific: termination measures, SMT triggers:** The transpiler has to produce valid Verus code, and that is a high bar. Recursive function calls in Verus require a termination measure (via decreases annotations), which have to be inferred by *TranSpec*. Every quantifier expression in the program (`forall`, `exists` or `choose`) should also include trigger annotations [17] which control how the SMT solver instantiates quantified variables. These triggers do not impact the semantics but determine the search space the solver explores: incorrect trigger annotations may lead to infinite loops or out-of-memory errors. Determining the correct placement of trigger annotations remains the most challenging task of this transpiler.

**Ambiguous and unusual syntax:** TLA+ writes `f[x]` for functions, sequences and maps, and it is not always clear from the context where this appears which of these the creator of the spec intended. *TranSpec* delays this decision until further information is available. TLA+ includes other elements of unusual syntax that don’t map cleanly to modern programming language syntax.

##### 3.1.2 Agentic Translation

Even after solving the aforementioned challenges of mechanistic transpilation, an important problem remains: Some specs may contain false properties, or, more commonly, properties whose truth value is contingent on implicit assumptions not captured in the TLA+ spec. Implicit assumptions may lurk in a TLC config file or the way the model checker interprets specs and explores the state space.

To allow greater flexibility in *creatively* fixing these issues, and to handle the long tail of TLA+ syntax, we also leverage LLM agents to perform the translation. The faithfulness of the translation is then checked by a reviewer LLM, resulting in a translator-reviewer loop similar to the prover-reviewer loop explained in Section 3.2. We ran experiments with both translation approaches, see quantitative comparison in Section 4.1.

#### 3.2 Proof search

We propose a prover–reviewer setup for automatic proof generation on Rust/Verus systems (Figure 2).

Our setup has three components.

1. **The prover.** A long-running LLM session that writes the proof files, running Verus locally for quick feedback and committing as it goes.
2. **The reviewer.** An LLM session with clean context, called on request by the prover. The reviewer reads an incremental addition from the prover and returns a verdict with a list of blockers.
3. **Anti-cheating checks.** We ensure that the prover cannot edit system specification or insert statements (e.g., `assume(false)`) that would make the proof vacuously true, passing the Verus verifier. We extend *lynette* [33] with a wider class of anti-cheating checks, see Appendix A for details.

**Motivation for the reviewer.** The reviewer allows the prover to seek feedback incrementally. In long-horizon tasks, such as in complex systems, this means the prover can break down the proof into smaller pieces and change course early if it chooses an unfruitful proof strategy. Moreover, the Verus

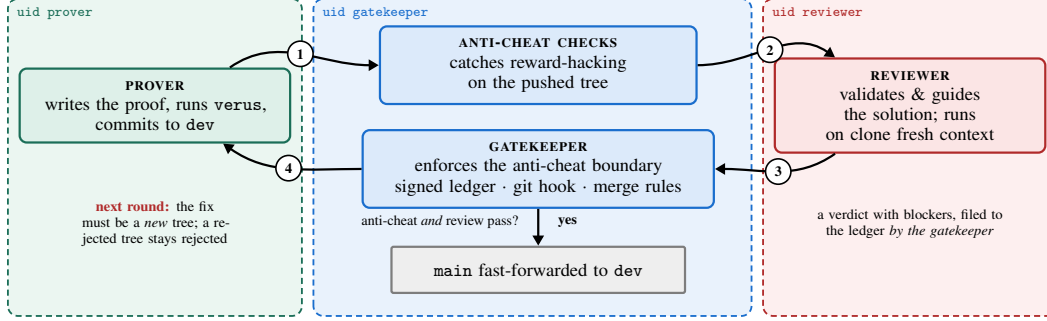


Figure 2: One cycle of the merge gate. The prover and the reviewer are LLM agents; the gatekeeper is a set of scripts that orchestrate the pipeline. Three entities run as three Unix accounts. Only the gatekeeper’s account can merge: it does so at the prover’s request, and only once the anti-cheat checks and the reviewer have both accepted.

verifier is limited: it only shows which assertion or postcondition failed, but no counterexample. The reviewer provides semantic feedback and can point out why and how to fix the solution.

**Technical setup.** The two agents work in a local git repository, initialised with a Verus bundle of the system and one property to prove about it. The bundle also contains a supporting temporal layer: the Verus encoding of temporal logic from Anvil [29], for the prover to use out-of-the-box. The prover works incrementally on a dev branch, proving subsets of lemmas. To merge dev into main, we want to ensure the proof is sound: all anti-cheat checks pass, and the reviewer has accepted the head commit on dev. If the prover could merge into main on its own, it could breach these criteria. A set of programs we call the gatekeeper creates a deterministic boundary between the agents and the code. We describe how this is enforced in Appendix B. One cycle of operation is shown in Figure 2.

**Review.** The reviewer is a second agentic LLM session that starts with a fresh context. The prover requests a review periodically. It has two main roles:

**Validate or reject unprovability claims.** The prover may declare that a property is false. We use this escape hatch to identify errors in specifications, but the prover can misuse it to escape from a hard proof. This is why the reviewer is told to push back hard, retrace the counterexample on its own, and pragmatically stress-test the unprovability argument. In Appendix C.2, we show a run where the reviewer refused an unprovability claim from the prover, and the prover went on to prove the theorem. This is significant for formal verification to be used in production: false alarms waste time in repairing a system that wasn’t broken to start with.

**Guide the proof.** Steer the prover towards a cleaner proof. For example, instead of copy-pasting lemmas for mirror cases (left/right), the prover is advised to use a parameterised interface. This can lead to shorter and more human-maintainable proof code.

After the mechanical checks and the reviewer have run, the prover either requests a merge into main if they both accept, or continues iterating.

### 3.3 From translations to an evaluation set

**A single file with three regions.** After the two pipelines produced the algorithmic and agentic translations, both are normalised to the same three-region layout so models see identical input structure. Region 1 is a frozen scaffold of temporal-logic definitions and proof rules—755 lines, 30,780 characters, byte-identical across tasks and never edited. Region 2 contains the problem: the state type, state machine, property predicates, and theorem statement. Region 3 is an *empty* proof `fn` that the model must fill.

**Corpus.** We ran both pipelines over the same 16,459 (specification, property) pairs; Table 3 summarizes the results. A reference proof, where available, must verify without errors and be a pure addition to the task, identical in regions 1 and 2, so it cannot restate the problem. Since well-posedness only means the verifier can parse the problem, we also ran proof search. At scale, the algorithmic pipeline found proofs for **3,094** out of 5,160. For the agentic pipeline, from the 12,352 well-posed translations, we ran a 500-task sample drawn from problems already proved algorithmically, obtaining **492** proofs. This enables a paired comparison: both encodings are provable, so failures reflect the

|                           | count       |                                  | count      |
|---------------------------|-------------|----------------------------------|------------|
| Pairs attempted           | 16,459      | Pairs attempted                  | 16,459     |
| Not translated            | 10,389      | Judged unprovable                | 2,851      |
| Translated                | 6,070       | Judged provable                  | 13,608     |
| → trivial / vacuous       | 145         | → trivial / vacuous              | 1,235      |
| → Verus rejected output   | 765         | → property type: unknown         | 21         |
| → well-posed translations | 5,160       | → well-posed translations        | 12,352     |
| → <b>proven</b>           | <b>3094</b> | → <b>proven</b> (of 500 sampled) | <b>492</b> |

(a) Algorithmic (TranSpec)
(b) Agentic (LLM)

Table 3: Translating the same 16,459 TLA<sup>+</sup> (spec, property) pairs to Verus, as a funnel. A *well-posed* translations verifies at exactly one error—the open proof obligation; a *trivial* one already verifies with an empty stub. The pipelines lose tasks at different stages: the algorithmic one cannot translate them, the agentic one judges them false. All the ‘Judged provable’ tasks verifies by Verus.

encoding rather than an unprovable goal. Dataset statistics are given in Section D.1: task counts by property type over all well-posed translations (Section D.1.2), and counts and mean task lengths over the proven subset (Section D.1.3).

**Selecting the 40 evaluation tasks.** The evaluation set is 40 tasks, 10 from each of the four property types (*safety*, *TypeOK*, *invariance*, *liveness* – see Table 2), each present in both encodings. Candidates were filtered on seven criteria: (1) both translations exist; (2) the task is known provable; (3) the two translations state the same theorem; (4) the source repository carries a permissive licence; (5) the specification is not from a TLA<sup>+</sup> tutorial or benchmark repository, which a model has likely seen in training; (6) no near-duplicate specifications; and (7) specification and repository diversity, applied when sampling rather than as an exclusion.

| Category             | Form                                                       | Meaning                              |
|----------------------|------------------------------------------------------------|--------------------------------------|
| <i>safety</i>        | $\Box[A]_{vars}, \Box(P \Rightarrow \Box Q)$ , and similar | nothing bad ever happens             |
| <i>safety_typeOK</i> | $\Box TypeOK$                                              | the variables stay of the right type |
| <i>invariance</i>    | $\Box P$ , $P$ a state predicate other than <i>TypeOK</i>  | $P$ holds in every reachable state   |
| <i>liveness</i>      | $P \rightsquigarrow Q$ or $\Diamond P$                     | something good eventually happens    |

Table 2: The four property categories every (specification, property) pair is classified into.

### 3.4 Experimental setup

**Datasets.** We evaluate off-the-shelf large language models on three datasets: `tlaverus_algo` and `tlaverus_llm`, the two encodings of the 40 paired tasks built in Section 3.3, and `verusbench` ([33]), an existing benchmark of 150 short, self-contained Verus functions. Table 4 gives their sizes. The contrast is the point of including `verusbench`: a `tlaverus` task is roughly 80× longer, because the model must prove a property inside a whole translated specification rather than about a single function. The two `tlaverus` rows are the same 40 (spec, property) pairs translated two ways, so their difference, 7,421 characters, is the cost of the translation style alone. Table 5 reports the same 40 tasks net of the 30,780-character scaffold both task shares, leaving the problem text alone, and shows that the gap is not concentrated in one property type: it holds at 1.35–1.55× across all four.

| Dataset                    | Tasks | Mean chars |
|----------------------------|-------|------------|
| <code>verusbench</code>    | 150   | 619        |
| <code>tlaverus_algo</code> | 40    | 47,379     |
| <code>tlaverus_llm</code>  | 40    | 54,800     |

Table 4: **Size of the three evaluated datasets.** Both include the frozen scaffold of 30,780 characters shared by every `tlaverus` task; net of it the means are 16,599 and 24,020.

**Evaluation.** We evaluate eleven models, from frontier closed-weight systems down to open-weight models of 35B–120B parameters; Section E gives the full list with parameter counts where published, decoding parameters, toolchain versions and more.

The evaluation harness differs from the prover–reviewer setup. Every `tlaverus` task is presented the same way: the model receives the task file and returns region 3 alone, the body of the open proof `fn`, and the harness re-attaches regions 1 and 2 before verification. This is cost efficient, and a model cannot alter the problem by rewriting the file around it. `verusbench` tasks are much shorter, have no

separate regions, and the model returns the whole file. Verus is the oracle: a submission passes only if the whole file verifies with zero errors. Otherwise the verifier’s error output is fed back for revision, up to  $V = 10$  verification attempts per sample. We draw  $k = 3$  independent samples per task and report  $\text{pass}@k$ , the fraction of tasks solved by at least one sample, alongside the per-sample pass rate. Passing files are additionally checked for cheating (Section 3.2, Section A).

## 4 Results

In this section, we compare proof search across the two encodings by running the prover–reviewer pipeline on the same 500 (specification, property) pairs. Moreover, we evaluate a range of state-of-the-art language models on three datasets.

### 4.1 Agentic vs algorithmic translation comparison

To compare the two translations we ran the same prover on the 500 pairs twice: once from the TRANSPEC translation and once from the agentic one. The 500 were drawn from pairs already proven algorithmically, so every algorithmic side is proven by construction; on the agentic side the prover closed 492 and exhausted its budget on 8. All paired statistics below are over the 492 pairs proven in both encodings.

**The LLM translation costs 19% more to prove.** It is the more expensive one in 71% of pairs, and the median ratio is  $1.19 \times [1.15, 1.23]$ : \$2.07 against \$1.67 per proof (Figure 8). Proofs are the same length ( $1.05 \times$ ), and Z3 does less work on the LLM side,  $0.86 \times$  the rlimit and  $0.73 \times$  the quantifier instantiations (Figure 9). The extra API cost goes into turns:  $1.38 \times$  prover turns,  $2.00 \times$  verus runs and  $1.88 \times$  input tokens per proof (Figure 12).

**The extra verus runs are mostly compile errors.** Figure 7b splits the runs by outcome. Both sides need 1.62 successful runs per proof, and the LLM side has fewer failed verifications (0.32 against 0.64). The main difference is trigger errors, 1.19 runs per proof against 0.13, and name-resolution errors, 0.26 against 0.07. Two thirds of LLM proofs hit at least one trigger error; only 8% of algorithmic proofs do.

**The algorithmic translation leaves more triggers to Verus, yet causes fewer trigger errors.** TRANSPEC emits three times as many forall quantifiers as the LLM translator and annotates fewer of them: in 47% of algorithmic bundles Verus had to pick triggers for six or more quantifiers, while 80% of LLM bundles have none (Figure 11).

### 4.2 Model evaluations

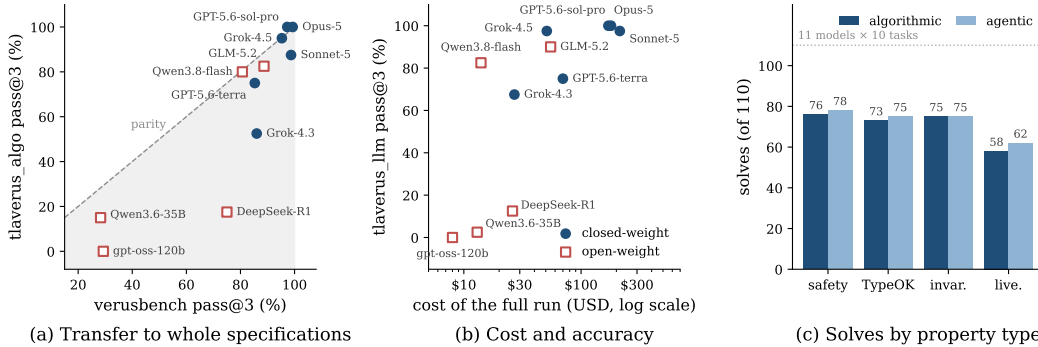


Figure 3: (a) verusbench against tlaverus\_algo pass@3; dashed line is parity, shading is where a model does worse on tlaverus. (b) Cost of the full tlaverus\_llm run against pass@3. (c) Tasks solved by property type, summed over all 11 models: each bar is out of 110 (11 models  $\times$  10 tasks of that type).

We evaluate eleven models on all three datasets. Table 11 to Table 14 in Section F shows all numbers used for creating Figure 3 and Table 6. The main measure of accuracy is pass@3.

**TLA-Verus is harder than Verusbench for every model but the strongest ones.** Nine of the eleven models score lower on `tlaverus_algo`, and only Opus-5 and GPT-5.6-sol-pro, the best ones gain; Grok-4.5 and Qwen3.8-flash are the boundary cases at  $-0.3$  and  $-0.7$ . The rest lose heavily: 33.5 points for Grok-4.3, 57.2 for DeepSeek-R1, and 29.3 for gpt-oss-120b, which reaches zero (Figure 3a).

**tlaverus\_algo is not easier than tlaverus\_llm despite consisting shorter tasks.** The two datasets have the same 40 pairs, so this comparison is controlled. For nine of eleven models, the agentic translation is solved as well as or better than the algorithmic translation, despite the tasks in `tlaverus_llm` being  $1.45\times$  longer on average. (Table 5), the opposite of what length alone would predict. The only two models which lose on `tlaverus_llm` (DeepSeek-R1 and Qwen3.6-35B) are among the weakest. The ordering of the models remains the same for two TLA-Verus datasets (Table 6), with rank changes confined to ties. We hypothesize that `tlaverus_llm` is easier for the models, because the agentic translation of the tasks may contain additional comments helping in proof generation.

**Liveness is the hardest type, and not because these tasks are the longest.** Summed over all eleven models, safety, TypeOK and invariance are solved 76, 73 and 75 times out of 110 on `tlaverus_algo`, while liveness reaches only 58 (Figure 3c). `tlaverus_llm` behaves the same way: 78, 75 and 75 against 62 for liveness. Liveness is where strong models break first: Sonnet-5 holds 10/10 on safety and invariance on `tlaverus_algo` and drops to 7/10 on liveness, GPT-5.6-terra goes 10/10 to 4/10. Length does not explain it — safety and liveness differ by under 2% in problem-text length (Table 5), and TypeOK, the shortest type, is not the easiest.

**Three attempts reach well beyond one.** Opus-5 is the only model that solves tasks with no gap on either dataset. gpt-oss-120b has no gap on `tlaverus_algo` and `tlaverus_llm` since it does not solve anything. For every other model, pass@3 exceeds the per-sample rate, and often by a lot (Table 6): e.g. GPT-5.6-sol-pro solves every task on `tlaverus_llm` but passes only 83.3% of samples, and GPT-5.6-terra reads 75.0 against 52.5. The two numbers answer different questions — what a model can reach when allowed to retry, and how often a single attempt succeeds — so we report both throughout.

**The weakest models spend the budget without getting closer.** Every model below 20% uses all ten verification attempts on nearly every sample and passes almost none of them. Turns track strength almost perfectly in the other direction too: Opus-5 needs only 1.1 per sample on `tlaverus_algo`, and the count climbs down the table until the budget is exhausted (Table 6).

**Price is an unreliable guide to accuracy, and reasoning volume is no guide at all.** Stronger models are generally the more expensive ones on both `tlaverus` datasets (Figure 3b, Figure 6a). The interesting cases are the models that sit well off that line, and they are the same on both datasets. Grok-4.5 is the clearest: it reaches 97.5% on `tlaverus_llm` for \$51, the same score Sonnet-5 reaches for \$214, at a quarter of the price. Qwen3.8-flash is among the cheapest at \$14 and still lands mid-field at 82.5%, ahead of GPT-5.6-terra at \$70. Reasoning volume, meanwhile, carries no signal at all (Figure 6b, c).

## 5 Related works

**TLA<sup>+</sup>, its tooling, and the gap to code.** TLA<sup>+</sup> [14, 15] is written by engineers, not only by verification researchers: AWS reports using it on S3, DynamoDB and EBS [22], and MongoDB on replication and reconfiguration [28]. TLC [36] and Apache [13] check bounded instances and return counterexamples, not proofs; TLAPS proves and is effective on safety [7, 4], but liveness must be reduced to a propositional fragment and system-scale temporal proofs stay rare. Nor is there a refinement path to an implementation: PGo compiles Modular PlusCal to Go [11], trace validation checks a running system against its specification [6], and IronFleet [12] and Verdi [32] close the gap by construction, at the price of writing the system inside the framework. We keep the specification and change the prover, moving existing TLA<sup>+</sup> into Verus [17, 18], an auto-active Rust verifier, so that specification and implementation can share a language and liveness is discharged by the same deduction as safety, at a scale hand-written TLAPS proofs have not reached.

**Liveness proofs.** Temporal reasoning is not native to auto-active verifiers but can be embedded: Anvil defines a TLA-style temporal logic as a Verus library and proves liveness of Kubernetes

| Model           | verusbench |      | tlaverus_algo |       |       |        | tlaverus_llm |       |       |        | $\Delta(\%)$ |
|-----------------|------------|------|---------------|-------|-------|--------|--------------|-------|-------|--------|--------------|
|                 | p@3        | p@1  | p@3↓          | p@1   | turns | reas.  | p@3↓         | p@1   | turns | reas.  |              |
| Opus-5          | 99.3       | 99.3 | <b>100.0</b>  | 100.0 | 1.1   | 36.0k  | <b>100.0</b> | 100.0 | 1.6   | 38.3k  | 0.0          |
| GPT-5.6-sol-pro | 97.3       | 93.3 | <b>100.0</b>  | 92.5  | 3.5   | 16.8k  | <b>100.0</b> | 83.3  | 5.5   | 18.2k  | 0.0          |
| Grok-4.5        | 95.3       | 90.4 | 95.0          | 90.8  | 4.2   | 6.6k   | 97.5         | 90.0  | 5.0   | 4.6k   | +2.5         |
| Sonnet-5        | 98.7       | 94.2 | 87.5          | 82.5  | 3.4   | 196.9k | 97.5         | 87.5  | 4.6   | 115.2k | +10.0        |
| GLM-5.2°        | 88.7       | 75.6 | 82.5          | 70.8  | 5.7   | 101.6k | 90.0         | 78.3  | 5.6   | 72.5k  | +7.5         |
| Qwen3.8-flash   | 80.7       | 58.2 | 80.0          | 68.3  | 6.4   | 217.9k | 82.5         | 60.0  | 7.3   | 169.6k | +2.5         |
| GPT-5.6-terra   | 85.3       | 73.1 | 75.0          | 60.8  | 6.8   | 5.9k   | 75.0         | 52.5  | 7.5   | 4.7k   | 0.0          |
| Grok-4.3        | 86.0       | 78.2 | 52.5          | 40.8  | 8.0   | 46.7k  | 67.5         | 52.5  | 7.6   | 36.7k  | +15.0        |
| DeepSeek-R1°    | 74.7       | 57.6 | 17.5          | 10.8  | 9.6   | 32.4k  | 12.5         | 7.5   | 9.8   | 29.8k  | -5.0         |
| Qwen3.6-35B°    | 28.3       | 14.4 | 15.0          | 5.0   | 9.9   | 64.3k  | 2.5          | 0.8   | 10.0  | 69.0k  | -12.5        |
| gpt-oss-120b°   | 29.3       | 13.1 | 0.0           | 0.0   | 10.0  | 26.6k  | 0.0          | 0.0   | 10.0  | 27.2k  | 0.0          |

Table 6: **Model results.**  $p@3$  and  $p@1$  (%): tasks solved by at least one of  $k = 3$  samples out of 40, and all samples passed (120). *turns* and *reas.*: mean model calls and reasoning tokens per sample.  $\Delta$ : `tlaverus_llm` minus `tlaverus_algo`  $p@3$ . ° open-weight. Remaining cols in Tables 11 to 13.

controllers [29], and our encoding builds on it. In the first-order setting, Ivy [23] and liveness-to-safety make liveness decidable in a restricted fragment, at the cost of manual prophecy and fairness encodings [25, 24]. Each such proof is a bespoke expert artifact; we generate them automatically over a corpus nobody wrote proofs for.

**LLMs for Verus.** AutoVerus orchestrates agents that mimic the phases of human proof construction [33]; SAFE and VeruSyn bootstrap Verus-capable models by self-evolution, the latter scaling to 6.9M synthesised verified programs [5, 9], on which supervised fine-tuning lifts a mid-size open-weight model to near-parity with a  $\sim 50\times$  larger frontier model [30]; RagVerus retrieves same-project proofs [37]; and AlphaVerus translates Dafny to Verus [1], where ours is formal-to-formal and accepted only when Verus compiles the bundle to exactly one open obligation. All target functional correctness of Rust code, whereas our obligations are temporal claims about infinite behaviours. They also share our scaffold shape — verifier errors fed back to the model, with cheat detection on top: VeruSAGE runs a cheat-checker [34] and AlphaVerus pairs a rule-based detector with a filtering model. We keep both parts (section 3.2, section A), run under a different user than the prover so it cannot write its own verdict, and record every verdict in a signed ledger.

**Verification benchmarks.** Verus benchmarks have grown from 150 self-contained functions in `verusbench` [33] to 383 repository-level tasks in `RepoVBench` [37] and 849 across eight projects in `VeruSAGE-Bench` [34], with comparable suites for Dafny and Lean [19, 10, 35, 2]. Ours is generated rather than curated, and it is the first whose tasks are temporal — including liveness, whose fairness and well-foundedness arguments have no analogue in functional verification. The specifications come from deployed systems and the Verus encodings did not exist before this work, so the solutions are in no model’s training data.

## 6 Discussion

We have created a pipeline to translate  $\text{TLA}^+$  system specifications to Verus, and create fully machine-checkable proofs of safety and liveness properties. From over 16,000 (specification, property) pairs, our pipeline produces over 3,000 fully machine-checked proofs. Evaluating eleven models on a paired evaluation set shows that proof search on `tlaverus` is already saturated for the strongest frontier models — Opus-5 and GPT-5.6-sol-pro both solve every task — but the benchmark remains sharply discriminating further down the field, where scores span from 97.5% (Grok-4.5) down to 0% (gpt-oss-120b).

Our pipeline’s main limitation today is the inability to reliably differentiate between false statements and true statements for which finding a proof is too difficult. In some cases, properties require additional assumptions to be added to the Verus specification, and determining when an assumption is a *fair* addition, similarly remains a challenge. Porting temporal logic models to Verus opens the door to closing the implementation–specification gap itself: expanding the pipeline to produce fully end-to-end verified implementations of real systems, where safety and liveness proofs live alongside the implementation rather than in a separate  $\text{TLA}^+$  model.

## References

- [1] Pranjal Aggarwal, Bryan Parno, and Sean Welleck. AlphaVerus: Bootstrapping formally verified code generation through self-improving translation and tree refinement. *arXiv preprint arXiv:2412.06176*, 2024.
- [2] Sergiu Bursuc, Theodore Ehrenborg, Shaowei Lin, Lacramioara Astefanoaei, Ionel Emilian Chiosa, Jure Kukovec, Alok Singh, Oliver Butterley, Adem Bizid, Quinn Dougherty, Miranda Zhao, Max Tan, and Max Tegmark. A benchmark for vericoding: Formally verified program synthesis. *arXiv preprint arXiv:2509.22908*, 2025.
- [3] Zhizhen Cathy Cai, Nikhil Date, Jiawei Tyler Gu, Cody Rivera, Tej Chajed, Oded Padon, Tianyin Xu, and Xudong Sun. Welder: Compositional Liveness Verification of Cluster Control Planes. In *Proceedings of the 32nd ACM Symposium on Operating Systems Principles (SOSP’26)*, September 2026.
- [4] Kaustuv Chaudhuri, Damien Doligez, Leslie Lamport, and Stephan Merz. Verifying safety properties with the TLA+ proof system. In *International Joint Conference on Automated Reasoning (IJCAR)*, 2010.
- [5] Tianyu Chen, Shuai Lu, Shan Lu, Yeyun Gong, Chenyuan Yang, Xuheng Li, Md Rakib Hossain Misu, Hao Yu, Nan Duan, Peng Cheng, Fan Yang, Shuvendu K. Lahiri, Tao Xie, and Lidong Zhou. Automated proof generation for Rust code via self-evolution. In *International Conference on Learning Representations (ICLR)*, 2025. arXiv:2410.15756.
- [6] Horatiu Cîrstea, Markus A. Kuppe, Benjamin Loillier, and Stephan Merz. Validating traces of distributed programs against TLA+ specifications. In *Software Engineering and Formal Methods (SEFM)*, 2024.
- [7] Denis Cousineau, Damien Doligez, Leslie Lamport, Stephan Merz, Daniel Ricketts, and Hernán Vanzetto. TLA+ proofs. In *FM 2012: Formal Methods*, pages 147–154, 2012.
- [8] A. Jesse Jiryu Davis, Max Hirschhorn, and Judah Schvimer. extreme modelling in practice. *Proceedings of the VLDB Endowment*, 13(9):1346–1358, 2020. doi: 10.14778/3397230.3397233. URL <https://doi.org/10.14778/3397230.3397233>.
- [9] Nongyu Di, Tianyu Chen, Shan Lu, Shuai Lu, Yeyun Gong, Peng Cheng, Jacob R. Lorch, Yuan Yao, and Xiaoxing Ma. Reducing the costs of proof synthesis on Rust systems by scaling up a seed training set. *arXiv preprint arXiv:2602.04910*, 2026.
- [10] Quinn Dougherty and Ronak Mehta. Proving the coding interview: A benchmark for formally verified code generation. *arXiv preprint arXiv:2502.05714*, 2025.
- [11] Finn Hackett, Shayan Hosseini, Renato Costa, Matthew Do, and Ivan Beschastnikh. Compiling distributed system models with PGo. In *Architectural Support for Programming Languages and Operating Systems (ASPLOS)*, 2023.
- [12] Chris Hawblitzel, Jon Howell, Manos Kapritsos, Jacob R. Lorch, Bryan Parno, Michael L. Roberts, Srinath Setty, and Brian Zill. IronFleet: Proving practical distributed systems correct. In *Symposium on Operating Systems Principles (SOSP)*, 2015.
- [13] Igor Konnov, Jure Kukovec, and Thanh-Hai Tran. TLA+ model checking made symbolic. *Proceedings of the ACM on Programming Languages*, 3(OOPSLA), 2019.
- [14] Leslie Lamport. The temporal logic of actions. *ACM Transactions on Programming Languages and Systems*, 16(3):872–923, 1994.
- [15] Leslie Lamport. *Specifying Systems*. Addison-Wesley, 2002.
- [16] Leslie Lamport. Industrial use of TLA+. <https://lamport.azurewebsites.net/tla/industrial-use.html>, 2025. Last modified 13 October 2025. Accessed October 14, 2026.
- [17] Andrea Lattuada, Travis Hance, Chanhee Cho, Matthias Brun, Isitha Subasinghe, Yi Zhou, Jon Howell, Bryan Parno, and Chris Hawblitzel. Verus: Verifying Rust programs using linear ghost types. *Proceedings of the ACM on Programming Languages (OOPSLA)*, 7, 2023.

- [18] Andrea Lattuada, Travis Hance, Jay Bosamiya, Matthias Brun, Chanhee Cho, Hayley LeBlanc, Pranav Srinivasan, Reto Achermann, Tej Chajed, Chris Hawblitzel, Jon Howell, Jay Lorch, Oded Padon, and Bryan Parno. Verus: A practical foundation for systems verification. In *Proceedings of the 30th ACM Symposium on Operating Systems Principles (SOSP)*, 2024.
- [19] Chloe Loughridge, Qinyi Sun, Seth Ahrenbach, Federico Cassano, Chuyue Sun, Ying Sheng, Anish Mudide, Md Rakib Hossain Misu, Nada Amin, and Max Tegmark. DafnyBench: A benchmark for formal software verification. *Transactions on Machine Learning Research*, 2025.
- [20] Chris Newcombe. Why Amazon chose TLA+. In *Abstract State Machines, Alloy, B, TLA, VDM, and Z (ABZ)*, 2014.
- [21] Chris Newcombe, Tim Rath, Fan Zhang, Bogdan Munteanu, Marc Brooker, and Michael Deardeuff. How Amazon web services uses formal methods. *Communications of the ACM*, 58(4):66–73, April 2015. URL <https://cacm.acm.org/research/how-amazon-web-services-uses-formal-methods/>. Accessed October 14, 2026.
- [22] Chris Newcombe, Tim Rath, Fan Zhang, Bogdan Munteanu, Marc Brooker, and Michael Deardeuff. How Amazon Web Services uses formal methods. *Communications of the ACM*, 58(4):66–73, 2015.
- [23] Oded Padon, Kenneth L. McMillan, Aurojit Panda, Mooly Sagiv, and Sharon Shoham. Ivy: Safety verification by interactive generalization. In *Programming Language Design and Implementation (PLDI)*, 2016.
- [24] Oded Padon, Giuliano Losa, Mooly Sagiv, and Sharon Shoham. Paxos made EPR: Decidable reasoning about distributed protocols. *Proceedings of the ACM on Programming Languages*, 1(OOPSLA), 2017.
- [25] Oded Padon, Jochen Hoenicke, Giuliano Losa, Andreas Podelski, Mooly Sagiv, and Sharon Shoham. Reducing liveness to safety in first-order logic. *Proceedings of the ACM on Programming Languages*, 2(POPL), 2018.
- [26] Arun Parthiban, Sesh Nalla, and Cecilia Wat-Kim. How we use formal modeling, lightweight simulations, and chaos testing to design reliable distributed systems. <https://www.datadoghq.com/blog/engineering/formal-modeling-and-simulation/>, November 2024. Datadog Engineering Blog. Published November 20, 2024. Accessed October 14, 2026.
- [27] Amir Pnueli. The temporal logic of programs. In *18th Annual Symposium on Foundations of Computer Science (FOCS)*, pages 46–57, 1977.
- [28] William Schultz, Ian Dardik, and Stavros Tripakis. Formal verification of a distributed dynamic reconfiguration protocol. In *Certified Programs and Proofs (CPP)*, 2022.
- [29] Xudong Sun, Wenjie Ma, Jiawei Tyler Gu, Zicheng Ma, Tej Chajed, Jon Howell, Andrea Lattuada, Oded Padon, Lalith Suresh, Adriana Szekeres, and Tianyin Xu. Anvil: Verifying liveness of cluster management controllers. In *18th USENIX Symposium on Operating Systems Design and Implementation (OSDI)*, 2024.
- [30] Szilvia Ujváry, Beatrix Benkő, and Csongor Horváth. Verification at lightning speed. <https://reasonable.io/blog/verification-at-lightning-speed/>, August 2026. Reasonable blog post, accessed October 14, 2026.
- [31] Jack Vanlightly. KRaft: TLA+ specification of the Kafka KRaft protocol. <https://github.com/Vanlightly/raft-tlaplus/blob/main/specifications/pull-raft/KRaft.tla>, 2024. GitHub repository, accessed October 14, 2026.
- [32] James R. Wilcox, Doug Woos, Pavel Panchekha, Zachary Tatlock, Xi Wang, Michael D. Ernst, and Thomas Anderson. Verdi: A framework for implementing and formally verifying distributed systems. In *Programming Language Design and Implementation (PLDI)*, 2015.
- [33] Chenyuan Yang, Chris Hawblitzel, Jacob R. Lorch, Shan Lu, et al. Automated proof generation for Rust code. *Proc. ACM Program. Lang. (OOPSLA)*, 2025. arXiv:2409.13082.

- [34] Chenyuan Yang, Nicolae Neamtu, Chris Hawblitzel, Jacob R. Lorch, and Shan Lu. VeruSAGE: A study of agent-based verification for Rust systems. *arXiv preprint arXiv:2512.18436*, 2025.
- [35] Zhe Ye et al. Verina: Benchmarking verifiable code generation. *arXiv preprint arXiv:2505.23135*, 2025.
- [36] Yuan Yu, Panagiotis Manolios, and Leslie Lamport. Model checking TLA+ specifications. In *Correct Hardware Design and Verification Methods (CHARME)*, pages 54–66, 1999.
- [37] Sicheng Zhong and Xujie Si. RagVerus: Repository-level program verification with LLMs using retrieval augmented generation. *arXiv preprint arXiv:2502.05344*, 2025.

## A Anti-cheat checks

The Verus verifier certifies that a proof is accepted, not that it is trustworthy. Like every practical proof assistant, Verus provides *escape hatches* that let an author declare a fact instead of proving it. For instance, `assume(P)` adds  $P$  as a hypothesis, and a function marked `external_body` has its `ensures` taken as true without its body being checked. They exist to state trusted facts about hardware, libraries and the environment, which lie outside the verified code. Used inside a proof, they make it *vacuous*: Verus reports *N verified, 0 errors* while the proof assumes the program is correct rather than proving it. An agent whose goal is to pass verification can misuse them, so in our setup a proof counts as a solution only if it also passes the two deterministic checks below, one for each way of making a task easier: changing the task, or faking the proof.

**The task is unchanged.** `lynette` [33] is the structural diff from `AutoVerus`: it parses the task file and the candidate and requires that everything defining the problem statement is identical (function signatures, `requires/ensures` clauses, `spec fn` bodies and executable bodies – with proof annotations removed). It allows only new proof or `spec` items to be added and nothing to be deleted. A candidate that passes `lynette` has solved the original problem rather than a weaker one.

**The proof is not faked.** `lynette` deliberately does not check proof bodies, so that the agent can prove lemmas any way it likes. Escape hatches inside proof code, such as `proof { admit(); }`, would therefore pass it. We extend `lynette` with anti-cheating checks that reject any trust marker that is *net-new*, that is, appearing in the candidate but not in the task, ignoring comments. Table 7 shows examples of cheating patterns that our checks flag.

| Cheat form                 | Example                                                                                          | Effect                                                                    |
|----------------------------|--------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------|
| <code>admit</code>         | <code>proof { admit(); }<br/>use vstd::pervasive::admit as shh;</code>                           | the current goal is accepted without proof                                |
| <code>assume</code>        | <code>assume(false)<br/>macro_rules! m { () =&gt; { assume(false) } }<br/>proof { m!(); }</code> | the stated fact is accepted without proof                                 |
| <code>external_body</code> | <code>#[verifier::external_body]<br/>proof fn any_fact() ensures false {}</code>                 | the function’s <code>ensures</code> is accepted without checking its body |
| <code>axiom</code>         | <code>axiom fn any_fact() ensures false;</code>                                                  | the lemma is accepted without a proof                                     |

Table 7: Net-new escape hatches that our anti-cheating checks reject in the proof.

## B Enforcing the boundary

Our requirement for merging `dev` into `main` is for both the mechanical checks and the reviewer to accept. An autonomous prover is normally given `sudo` permissions, which means it could merge into the repository directly, bypassing our criteria for a sound proof. To mitigate this, our setup sandboxes the agents and implements safe communication between them. We explain four key components: Linux UIDs, MCP tools, a signed ledger, and git management.

**MCP tools.** Model Context Protocol (MCP) is a standard released by Anthropic for setting up communication between AI models and tools. Our prover agent has access to five tools:

1. `run_mechanical(sha?)` – run mechanical checks on a commit, receiving the full report;
2. `run_review(sha?)` – request a review of a commit, receiving the full review;
3. `request_merge(sha?)` – request to fast-forward `main` to `dev`. The merge is allowed if the head commit carries an accepted review and mechanical checks; the head commit never carried rejected verdicts; the signed ledger is consistent, among other rules.

4. `merge_status(sha?)` – request the pass/fail status for every merge rule for the given commit, including reasons for failing each rule;
5. `push_status()` – report what commit is head for `dev` and `main` in the canonical repository, how many commits `dev` is ahead, and the most recent pushes the git hook refused.

The tools run under the prover’s Linux UID and only give the request to the gatekeeper through `sudo`. Using these tools, the prover can contribute to the git repo without having direct access to it.

**Git management.** The prover’s clone reaches the repository only over git’s `ext` transport. The remote’s command is a root-owned helper that runs as the prover with no privileges and accepts only the `upload-pack` and `receive-pack` service names. It sends the request through `sudo` to the gatekeeper’s server, which runs the git service. The prover therefore has no filesystem access to the repository and fetches and pushes through the gatekeeper’s uid. A root-owned `pre-receive` hook accepts pushes to `dev`, refuses deletion of either branch and any other ref, and moves `main` only by fast-forward to a commit that passes the same merge decision function as `request_merge()`.

**Signed ledger.** All mechanical checks, reviews, and merges are recorded in an append-only ledger owned by the gatekeeper, signed with an Ed25519 key. The prover is denied read of the key, as it is stored under a ‘deny to everyone else’ 0600 mode owned by the gatekeeper. It is also denied write of the ledger, as that is a gatekeeper-owned directory under 0755 permission, and each record is written once with 0444 permission. Each record contains the hash of the previous one. Deleting a record would be detected by a check inside the merge decision function on each tool call.

**Linux UIDs.** The prover, the gatekeeper and the reviewer are three unprivileged accounts with no shared group. The canonical repository is gatekeeper-owned and unreadable to the prover. The ledger directory is gatekeeper-owned and world-readable, so the prover can audit it but cannot write it. The signing key is gatekeeper-owned with mode 0600. The gatekeeper’s programs live in a root-owned directory. The prover’s `sudoers` entry lets it run, as the gatekeeper and with a reset environment, exactly eight argument lists: the five MCP tool back-ends and three transport verbs (`upload-pack`, `receive-pack`, `log-refusal`). The prover sends its data over `stdin`. The reviewer has no `sudo` entry. This ensures the prover cannot approve its own work or tamper with the ledger, but can deliver its work to the repository.

## C The reviewer in action

### C.1 Steering towards a shorter proof

The reviewer steers the prover towards a shorter, quicker solution. On a liveness obligation, the prover had begun proving each step of a WF1 chain as its own lemma.

#### REVIEWER, ROUND 1 — VERBATIM

Per-step WF1 pattern is about to be replicated  $\sim 15\times$ ; require a single parameterised `wf1_link` helper now, before duplication compounds.

#### REVIEWER, ROUND 2 — VERBATIM

Resolved and done well. RM-008 delivers exactly this... Do not re-raise.

### C.2 A refuted disproof

We used our pipeline to prove *Agreement*, the central safety property of a Raft-style consensus protocol taken from a public repository.<sup>2</sup> Agreement states that no two nodes are leaders in the same election term.

<sup>2</sup>From a public GitHub repository, since removed by its owner. We quote only the operators needed here; the full specification is available to reviewers on request.

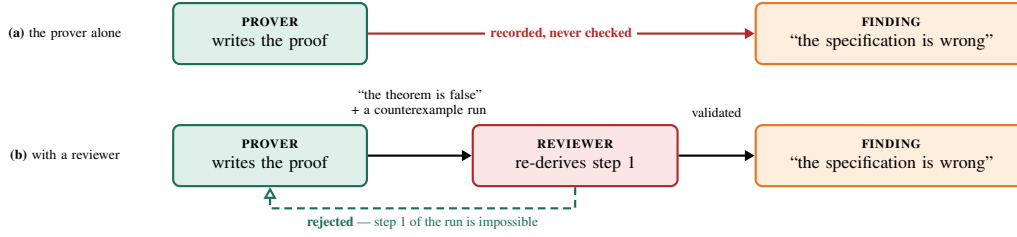


Figure 4: What the second agent adds. Without it, an unprovability claim is recorded unchecked.

```

Agreement  $\triangleq \forall n1, n2 \in \text{Nodes} :$ 
  (role[n1] = "Leader"  $\wedge$  role[n2] = "Leader"
    $\wedge$  currentTerm[n1] = currentTerm[n2])  $\Rightarrow$  n1 = n2

```

The prover declined to prove and argued that the property was false. It supplied a ten-step execution on a three-node cluster which resulted in two leaders in term 1. The prover traced the error to the `AppendEntries` handler, which allows one node to vote twice in a single term (Figure 5).

#### PROVER, ITERATION 1 — PARAPHRASED

Agreement is not inductive and no strengthening rescues it: `votedFor` is reset at equal term, so a node can grant two candidates in one term. Here is a reachable execution in which *a* and *b* both become leader...

The reviewer retraced the execution itself and found that step 1 is not a transition of `Next`.

```

Send(m)  $\triangleq$  messages' = messages  $\cup$  {m}

StartPreVote(n)  $\triangleq$ 
  ...
   $\wedge \forall m \in \text{Nodes} \setminus \{n\} : \text{Send}(\text{type} \mapsto \text{"PreVote"}, \dots, \text{dest} \mapsto m)$ 

```

`Send` requires `messages'` to equal `messages  $\cup$  {PreVote  $\mapsto$  b}` and `messages  $\cup$  {PreVote  $\mapsto$  c}` at once, so for any cluster of three or more nodes `StartPreVote` is unsatisfiable and the specification cannot leave its initial state.

#### REVIEWER, ROUND 1 — PARAPHRASED

Give-up rejected. Your first step is not a transition of `Next`: two exact assignments to `messages'` cannot both hold, so the counterexample is not an execution of this specification.

After the review the prover proved `Agreement` in one further iteration, with the invariant that any node which is `Candidate` or `Leader` is the only node in the cluster. The invariant holds for a second reason of the same shape: the only action that makes a node a `Candidate` conjoins `Send`, which adds a `RequestVote` to `messages'`, with `Discard`, which removes the handled response from it. Whenever another node exists, the two cannot agree. In any cluster of two or more nodes no node ever becomes a `Candidate`, and `Agreement` is vacuous.

The reviewer rejected a disproof that was plausible, and steered the prover to prove both the theorem and the vacuity of the protocol as written. Claiming that a true property is unprovable is a failure mode we could catch in our pipeline only with a second, sceptical agent. The two defects it surfaced are both repairs to the specification rather than to the pipeline: an exact assignment to `messages'` composed under a quantifier, a pattern that recurs in our corpus, and a vote reset at equal term that departs from Raft.<sup>3</sup>

<sup>3</sup>The specification does not parse as published (two operators are used before their definitions) and, once repaired, violates its own liveness property `EventualLeader == <>(\E n \in Nodes : role[n] = "Leader")` by every behaviour in a cluster with three or more nodes.

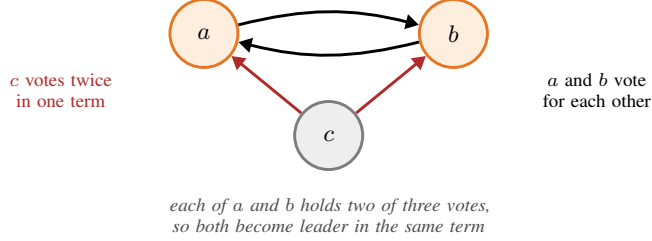


Figure 5: The prover’s claimed counterexample to Agreement.

## D Dataset creation details

### D.1 Dataset statistics

The two halves of this subsection describe two different populations, and the difference matters for how each table should be read. Section D.1.2 covers *every well-posed translation*, i.e. the corpus as released. Section D.1.3 covers only the *proven* subset: those translations the prover closed. Nothing in the second half is a statement about the corpus as a whole, and nothing in the first is conditioned on provability.

#### D.1.1 Flattening

The two pipelines produce different artifacts: the algorithmic translator produces one self-contained Verus file per property, while the agentic pipeline produces a Cargo crate with specifications, state machines, and properties across modules. The translations of the agentic pipeline were flattened into a single file, then separated to 3 regions described in Section 3.3.

#### D.1.2 All well-posed translations

**Composition.** Table 8 gives the well-posed task counts — every translation that passed the well-posedness filter, whether or not a proof was later found for it. The agentic encoding yields the larger corpus in every property type, 12,352 tasks against 5,160. The two are otherwise balanced similarly — invariance is about two thirds of each, TypeOK a sixth — with one exception: safety is 1% of the algorithmic corpus and 5% of the agentic one.

| Property type | Algorithmic | Agentic |
|---------------|-------------|---------|
| safety        | 50          | 630     |
| TypeOK        | 858         | 2,286   |
| invariance    | 3,440       | 7,993   |
| liveness      | 809         | 1,443   |
| Total         | 5,160       | 12,352  |

Table 8: **All well-posed translations**, by property type: every translation that passed the well-posedness filter, proven or not. The proven subset is counted separately in Table 9.

#### D.1.3 The proven subset

Everything below is restricted to translations the prover closed. On the algorithmic side that is 3,094 of the 5,160 well-posed tasks in Table 8. The agentic side is not the corresponding subset of its own column: it is a 500-task sample drawn from pairs whose *algorithmic* translation was already proven, of which 492 were themselves proven. The two  $n$  columns of Table 9 therefore support comparisons down a column but not across.

**Task length by property type.** Every task opens with the same frozen scaffold, so 30,780 characters of any length figure is a shared constant that compresses the difference between the two encodings. Table 9 therefore reports both the whole file, which is the length a model actually receives, and the problem text with the scaffold subtracted. Read on the problem text, three things follow.

First, the agentic encoding is the longer one overall, by 22%, which is consistent with a translator that elaborates rather than one working from a fixed set of templates. Second, the gap is not constant across property types: it is widest on safety and narrows monotonically to liveness, where the two encodings are the same length to within 1% and the algorithmic encoding is in fact the marginally longer of the two. Third, length and difficulty move together here without being the same thing.

Liveness gives the longest problems under both encodings and is the type models solve least often; safety gives the shortest and is the type they solve most often; yet the algorithmic encoding, which is the shorter of the two on every type but liveness, is not the easier one.

The safety rows are thin — 24 proven tasks algorithmic, 2 agentic — so the  $1.51\times$  at the top of the ratio column carries the least weight of any row.

| Property type | Algorithmic |            |         | Agentic |            |         | Ratio        |
|---------------|-------------|------------|---------|---------|------------|---------|--------------|
|               | $n$         | whole file | problem | $n$     | whole file | problem |              |
| safety        | 24          | 47,475     | 16,695  | 2       | 56,062     | 25,282  | $1.51\times$ |
| TypeOK        | 521         | 47,627     | 16,847  | 77      | 52,509     | 21,729  | $1.29\times$ |
| invariance    | 2,245       | 52,788     | 22,008  | 367     | 57,941     | 27,161  | $1.23\times$ |
| liveness      | 304         | 54,296     | 23,516  | 46      | 53,977     | 23,197  | $0.99\times$ |
| All           | 3,094       | 52,026     | 21,246  | 492     | 56,712     | 25,932  | $1.22\times$ |

Table 9: **Proven translations only:** counts and mean length, in characters, by property type. Not a subset relationship with Table 8 on the agentic side — see Section D.1.3. “Whole file” is what a model receives; “problem” subtracts the frozen scaffold that opens every task (region 1: 755 lines, 30,780 characters, identical corpus-wide). “Ratio” is agentic problem length over algorithmic. Dividing by 2.14 gives an approximate token count; the ratio was measured over the whole corpus and is tokenizer-dependent, so any such figure is an estimate.

## D.2 Selecting the 40 evaluation tasks

**Criterion 3** is three independent checks. *Assumptions*: the generated assumptions() must match the source ASSUME with no invented preconditions, since an added hypothesis makes the theorem strictly weaker and lets a model pass without proving what the specification asks. *Predicate and polarity*: the same temporal predicate with the same sign, which caught a pair proving opposite claims about a deliberately buggy specification. *State space*: the same enumerated vocabulary, retained as metadata rather than used as a filter, because it compares the two translations to each other when the correct reference is the TLA<sup>+</sup> source, and every pair it excluded turned out to be one where the algorithmic side had under-modelled.

**Criterion 2** binds hardest on safety: of 630 safety properties with an agentic translation, 578 have no usable algorithmic bundle, leaving 42, of which 24 are proved. Applying criteria 1–6 strictly leaves six safety tasks, so criterion 5 was relaxed for that arm and the affected tasks carry a flag. The other three arms are unconstrained and were sampled for specification and repository diversity. Because two properties of one specification may both be selected, the 40 tasks draw on fewer than 40 distinct specifications, and within the safety arm on nine. Selection never looks at how either encoding is written, only at whether the algorithmic side was proved and the two agree, so the encoding differences we go on to measure are not themselves a selection criterion.

## D.3 Sources and licensing

The 40 evaluation tasks are drawn from 32 TLA<sup>+</sup> specifications in 24 public GitHub repositories; we record the repository, commit and SPDX licence of every source file. All are permissively licensed: 27 tasks come from MIT sources, 12 from Apache-2.0 and one from BSD-2-Clause. Two repositories are retained despite a contamination flag, because the *safety* arm cannot be filled otherwise: `tlapplus/tlapplus`, the canonical TLA<sup>+</sup> distribution, and `LUC-AI4FM/FormaLLM`, an LLM-formalisation research repository, both of which may appear in model training data alongside published proofs of the properties we ask for. Beyond the specifications, the work builds on three third-party assets. The frozen scaffold that opens every `tlaverus` task derives from the Anvil verifier (<https://github.com/anvil-verifier/anvil>, Copyright 2022 VMware, Inc., MIT), and its notice is preserved verbatim inside every task file. Verification uses Verus at the pinned release `0.2026.04.19.6f7d4de` on Rust `1.95.0`. `verusbench` is an existing benchmark cited in the main text. The evaluated models are accessed through the OpenRouter gateway under the providers’ terms of use. We redistribute none of these assets: the paper reports evaluation results, and neither the

| Model            | Developer | Params      | Pinned provider<br>( <code>tlaverus</code> ) | $T$ | max_tokens |          | Effort |
|------------------|-----------|-------------|----------------------------------------------|-----|------------|----------|--------|
|                  |           |             |                                              |     | verusbench | tlaverus |        |
| Claude Opus 5    | Anthropic | undisclosed | —                                            | 1.0 | 32,768     | 128,000  | —      |
| Claude Sonnet 5  | Anthropic | undisclosed | —                                            | 1.0 | 32,768     | 128,000  | —      |
| GPT-5.6-sol-pro  | OpenAI    | undisclosed | —                                            | 1.0 | 32,768     | 128,000  | —      |
| GPT-5.6-terra    | OpenAI    | undisclosed | —                                            | 1.0 | 32,768     | 128,000  | —      |
| Grok-4.5         | xAI       | undisclosed | —                                            | 1.0 | 32,768     | 128,000  | —      |
| Grok-4.3         | xAI       | undisclosed | —                                            | 1.0 | 32,768     | 128,000  | high   |
| GLM-5.2          | Z.ai      | 744B/40B    | Baseten, FP8                                 | 1.0 | 32,768     | 128,000  | —      |
| DeepSeek-R1-0528 | DeepSeek  | 671B/37B    | DeepInfra, FP4                               | 1.0 | 32,768     | 32,768   | —      |
| Qwen3.8-flash    | Alibaba   | undisclosed | —                                            | 1.0 | 98,304     | 128,000  | —      |
| Qwen3.6-35B-a3b  | Alibaba   | 35B/3B      | —                                            | 1.0 | 32,768     | 128,000  | —      |
| gpt-oss-120b     | OpenAI    | 120B/5.1B   | Nebius, FP4                                  | 1.0 | 32,768     | 49,152   | —      |

Table 10: **Per-model configuration.** All models are called through OpenRouter. For the `tlaverus` runs we pin a specific upstream provider and precision for some open-weight models, as listed; everywhere else (all `verusbench` runs, and other model on the `tlaverus` dataset) we use OpenRouter’s default routing at its default precision. Parameter counts are total/active. A dash is a provider we do not pin or an effort level we do not set. Grok-4.3’s default reasoning effort is low, so we set it high to match the default reasoning effort of Grok-4.5. DeepSeek-R1 and gpt-oss-120b run below the `max_token` = 128000 ceiling on `tlaverus` because their pinned providers advertise a smaller one. We set `max_token` to 98,304 for Qwen3.8-flash on `verusbench`, since we empirically saw that 32,768 would not be enough for this model.

source specifications nor the translated tasks are released with it, so the permissive licences impose no obligation beyond the attribution given here.

## E Experimental details

**Models and configuration.** We evaluate eleven models spanning proprietary and open-weight families. Table 10 gives, for each, the parameter count where the developer discloses one, the endpoint it was served from, and the full decoding configuration. All models are served through a single API gateway so that prompting, retry and accounting are identical across vendors, and where an endpoint is named we pin it for the whole run so that samples of one arm are never split across providers or precisions.

The configuration is uniform by design with only a few places where a model departs from it. Every run uses temperature 1.0,  $k = 3$  samples per task and  $V = 10$  verification attempts, and no run sets `top_p`, a seed or a chat-template argument. The two `tlaverus` datasets always share a model’s settings, so the table needs no column to separate them.

**Budgets.** The budgets differ by dataset rather than by model, since a `tlaverus` task asks for a whole proof region rather than a short function: the completion limit is 32,768 tokens on `verusbench` against 128,000 on `tlaverus`, the request timeout 600 s against 1800 s, and the verifier timeout 60 s against 300 s, the last because a wrong but plausible proof can send the SMT solver far past the time a correct one takes. A few models depart where an endpoint forces it, e.g. DeepSeek-R1 and gpt-oss-120b run below the `max_token` = 128,000 ceiling because their pinned endpoints advertise a smaller one. ; where a model id names a provider and quantisation we hold that endpoint for the whole run, so the samples of one arm are never split across backends.

**What the configuration guarantees.** These are the values we *send*. Whether a provider honours them is not observable from the client: a request that sets a temperature the model ignores returns no indication that it did so, so we report the configuration rather than claim an effect. The one parameter we can check is reasoning effort, since the provider returns a chain-of-thought token count. Every model with the parameter unset still reports a non-zero count. The setting therefore scales how much a model reasons rather than switching the behaviour on.

**The verification loop.** A sample proceeds as: render the prompt, take the model’s region 3, splice it onto regions 1 and 2, run Verus. On success the sample ends. On failure the verifier’s diagnostics are appended to the conversation and the model is asked again, to a maximum of  $V = 10$  verification attempts. A sample that exhausts the budget is recorded as `verif_cap` and scored a failure. Since each attempt is one model call, a sample costs up to  $V + 1$  calls, and mean turns per sample is reported alongside accuracy as a measure of how quickly a model converges.

**Verifier and toolchain.** All datasets are graded with Verus at a single pinned release, 0.2026.04.19.6f7d4de, on Rust 1.95.0, inside a container image built once per dataset. The pin matters: Verus changes the accepted surface syntax between releases, and a later toolchain fails every task in this corpus at compile time regardless of the proof. Pinning also makes a score reproducible, since the same submission can change verdict under a different prover version.

**Ground-truth separation.** Model-facing jobs read a mirror of the dataset from which the reference proofs have been removed, and run under a credential that is denied access to the prefix holding them. A job that tried to read the reference proofs would fail with a permission error rather than silently succeed, so a leak cannot occur unobserved.

**Reporting.** We report  $\text{pass}@k$  at  $k = 3$ , the per-sample pass rate over all samples drawn, mean model calls per sample, and mean reasoning and answer tokens per sample. Reasoning tokens are the part of the provider’s completion count reported separately as chain of thought; where an endpoint does not report them the split is marked unavailable rather than assumed to be zero. Cost is the provider’s own billed figure summed over the run.

## F Further evaluation results

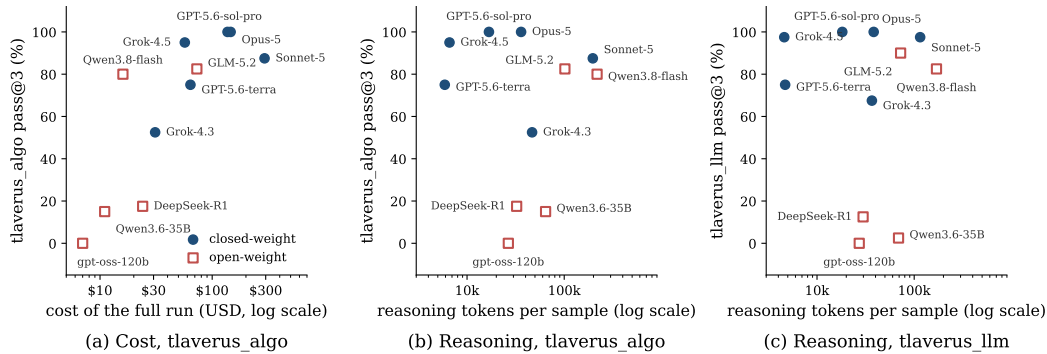


Figure 6: **(a)** Cost of the full `tlaverus_algo` run against  $\text{pass}@3$ ; a run is 40 tasks  $\times$  3 samples. **(b), c)** Reasoning tokens per sample against  $\text{pass}@3$  on the two `tlaverus` datasets. All axes but  $\text{pass}@3$  are logarithmic.

**Cost and reasoning in full.** Figure 6 gives the two views the main text draws on. Panel a is the cost plot for `tlaverus_algo`, the dataset omitted from Figure 3b; it shows the same picture, with the same models off the line. Grok-4.5 beats Sonnet-5 outright here, 95.0% for \$57 against 87.5% for \$293, a sharper version of the tie it reaches on `tlaverus_llm`. Per solved task the field spans \$0.50 for Qwen3.8-flash and \$1.50 for Grok-4.5 against \$3.65 for Opus-5 and \$8.37 for Sonnet-5.

Panels b and c plot reasoning tokens against  $\text{pass}@3$  on the two datasets. The two are uncorrelated on both (Spearman  $\rho = -0.06$  on `tlaverus_algo`,  $\rho = 0.00$  on `tlaverus_llm`; 11 models each), so the finding holds across two encodings of the same 40 (spec, property) pairs. Sonnet-5 spends 196.9k reasoning tokens per sample on `tlaverus_algo` and scores below Grok-4.5 at 6.6k; Qwen3.8-flash spends more than any other model, 217.9k, to land mid-field at 80.0%; gpt-oss-120b spends 26.6k to solve nothing. Reasoning and cost are uncorrelated with each other as well, so the models deliberating most are neither the priciest nor the most accurate.

| Model           | p@3  | p@1  | turns | reas.  | ans. | cost  |
|-----------------|------|------|-------|--------|------|-------|
| Opus-5          | 99.3 | 99.3 | 1.4   | 3.4k   | 1.1k | \$54  |
| Sonnet-5        | 98.7 | 94.2 | 2.6   | 10.6k  | 2.0k | \$67  |
| GPT-5.6-sol-pro | 97.3 | 93.3 | 3.3   | 10.9k  | 7.8k | \$167 |
| Grok-4.5        | 95.3 | 90.4 | 2.6   | 3.7k   | 1.9k | \$17  |
| GLM-5.2         | 88.7 | 75.6 | 5.6   | 23.7k  | 5.9k | \$53  |
| Grok-4.3        | 86.0 | 78.2 | 4.7   | 22.9k  | 2.5k | \$31  |
| GPT-5.6-terra   | 85.3 | 73.1 | 5.6   | 3.8k   | 4.5k | \$55  |
| Qwen3.8-flash   | 80.7 | 58.2 | 6.7   | 353.9k | 9.4k | \$77  |
| DeepSeek-R1     | 74.7 | 57.6 | 6.3   | 24.3k  | 5.7k | \$31  |
| gpt-oss-120b    | 29.3 | 13.1 | 9.2   | 9.0k   | 4.3k | \$3   |
| Qwen3.6-35B     | 28.3 | 14.4 | 4.4   | 18.9k  | 6.3k | \$23  |

Table 11: verusbench, 150 tasks. Rows ordered by p@3.

| Model           | p@3   | p@1   | turns | reas.  | ans.  | cost  |
|-----------------|-------|-------|-------|--------|-------|-------|
| Opus-5          | 100.0 | 100.0 | 1.1   | 36.0k  | 7.8k  | \$146 |
| GPT-5.6-sol-pro | 100.0 | 92.5  | 3.5   | 16.8k  | 46.1k | \$137 |
| Grok-4.5        | 95.0  | 90.8  | 4.2   | 6.6k   | 44.7k | \$57  |
| Sonnet-5        | 87.5  | 82.5  | 3.4   | 196.9k | 18.8k | \$293 |
| GLM-5.2         | 82.5  | 70.8  | 5.7   | 101.6k | 26.0k | \$73  |
| Qwen3.8-flash   | 80.0  | 68.3  | 6.4   | 217.9k | 49.8k | \$16  |
| GPT-5.6-terra   | 75.0  | 60.8  | 6.8   | 5.9k   | 15.5k | \$64  |
| Grok-4.3        | 52.5  | 40.8  | 8.0   | 46.7k  | 20.1k | \$31  |
| DeepSeek-R1     | 17.5  | 10.8  | 9.6   | 32.4k  | 13.5k | \$24  |
| Qwen3.6-35B     | 15.0  | 5.0   | 9.9   | 64.3k  | 16.9k | \$11  |
| gpt-oss-120b    | 0.0   | 0.0   | 10.0  | 26.6k  | 8.4k  | \$7   |

Table 12: tlaverus\_algo, 40 tasks. Rows ordered by p@3.

**Full per-model results.** Tables 11 to 13 give every measured quantity for the three datasets, one table each. The accuracy columns are those of Table 6; what follows concerns the rest.

*Answer length is the quantity that changes most between benchmarks.* A verusbench answer averages 1.1k to 9.4k tokens per sample; a tlaverus answer 7.4k to 51.5k. The increase is not uniform, and it is largest for the models that do best: on tlaverus\_algo Grok-4.5 grows 24 $\times$  (1.9k to 44.7k) and Sonnet-5 9 $\times$ , while gpt-oss-120b grows 2 $\times$  and DeepSeek-R1 2.4 $\times$ ; Opus-5 (7 $\times$ , 1.1k to 7.8k) is the exception, writing the shortest tlaverus answers of any model. That is the proof body getting longer rather than the search for it getting harder — a weak model cannot write a long proof it has not found, so its answers stay short no matter how many attempts it makes.

*The split between reasoning and answer is a property of the model, not of the task.* The share of the completion reported as reasoning is nearly identical on the two tlaverus datasets for every model — Sonnet-5 at 91% and 86%, Qwen3.8-flash at 81% and 81%, Grok-4.5 at 13% and 11%, GPT-5.6-terra at 28% and 22%. A model that deliberates before writing does so on both encodings, in about the same proportion, which is why reasoning volume carries no information about either dataset.

*Turns rise almost everywhere, and cost rises for all but one model once normalised.* Every model needs more model calls per sample on tlaverus than on verusbench on at least one dataset; on tlaverus\_algo Opus-5 (1.1 against 1.4) and Qwen3.8-flash (6.4 against 6.7) need marginally fewer, and GLM-5.2 stays at 5.6–5.7 throughout. The cost column is not comparable across datasets as printed, since a verusbench run covers 450 samples and a tlaverus run 120; per sample the price rises for every model except Qwen3.8-flash, whose tlaverus runs cost 0.8 $\times$  and 0.7 $\times$  its verusbench rate, from 1.8 $\times$  for Qwen3.6-35B to 16 $\times$  for Sonnet-5 on tlaverus\_algo. That factor tracks the 77–89 $\times$  difference in prompt length only loosely, because the prompt is re-sent on each turn and the turn counts differ.

**Property type per model.** Table 14 gives the cells behind the aggregate in Figure 3c. Two patterns survive at the level of individual models. First, liveness is the type that separates the field: it is strictly

| Model           | p@3   | p@1   | turns | reas.  | ans.  | cost  |
|-----------------|-------|-------|-------|--------|-------|-------|
| Opus-5          | 100.0 | 100.0 | 1.6   | 38.3k  | 7.4k  | \$171 |
| GPT-5.6-sol-pro | 100.0 | 83.3  | 5.5   | 18.2k  | 51.5k | \$180 |
| Grok-4.5        | 97.5  | 90.0  | 5.0   | 4.6k   | 36.8k | \$51  |
| Sonnet-5        | 97.5  | 87.5  | 4.6   | 115.2k | 19.4k | \$214 |
| GLM-5.2         | 90.0  | 78.3  | 5.6   | 72.5k  | 18.9k | \$55  |
| Qwen3.8-flash   | 82.5  | 60.0  | 7.3   | 169.6k | 40.8k | \$14  |
| GPT-5.6-terra   | 75.0  | 52.5  | 7.5   | 4.7k   | 16.4k | \$70  |
| Grok-4.3        | 67.5  | 52.5  | 7.6   | 36.7k  | 12.6k | \$27  |
| DeepSeek-R1     | 12.5  | 7.5   | 9.8   | 29.8k  | 15.6k | \$26  |
| Qwen3.6-35B     | 2.5   | 0.8   | 10.0  | 69.0k  | 20.1k | \$13  |
| gpt-oss-120b    | 0.0   | 0.0   | 10.0  | 27.2k  | 10.2k | \$8   |

Table 13: `tlaverus_11m`, 40 tasks. Rows ordered by  $p@3$ .  $p@3$  is the share of tasks solved by at least one of  $k = 3$  samples,  $p@1$  the share of all samples that passed, *turns* the mean model calls per sample, *reas.* and *ans.* the mean disjoint reasoning and answer tokens per sample, and *cost* the price of the whole run. The same columns appear in Tables 11 and 12.

| Model           | tlaverus_algo |        |     |      | tlaverus_11m |        |     |      |
|-----------------|---------------|--------|-----|------|--------------|--------|-----|------|
|                 | safe          | TypeOK | inv | live | safe         | TypeOK | inv | live |
| Opus-5          | 10            | 10     | 10  | 10   | 10           | 10     | 10  | 10   |
| GPT-5.6-sol-pro | 10            | 10     | 10  | 10   | 10           | 10     | 10  | 10   |
| Grok-4.5        | 10            | 8      | 10  | 10   | 10           | 10     | 10  | 9    |
| Sonnet-5        | 10            | 8      | 10  | 7    | 10           | 9      | 10  | 10   |
| GLM-5.2         | 10            | 8      | 9   | 6    | 10           | 10     | 9   | 7    |
| Qwen3.8-flash   | 8             | 8      | 8   | 8    | 9            | 7      | 9   | 8    |
| GPT-5.6-terra   | 8             | 8      | 10  | 4    | 8            | 8      | 9   | 5    |
| Grok-4.3        | 7             | 8      | 4   | 2    | 9            | 9      | 7   | 2    |
| DeepSeek-R1     | 0             | 4      | 3   | 0    | 1            | 2      | 1   | 1    |
| Qwen3.6-35B     | 3             | 1      | 1   | 1    | 1            | 0      | 0   | 0    |
| gpt-oss-120b    | 0             | 0      | 0   | 0    | 0            | 0      | 0   | 0    |
| All             | 76            | 73     | 75  | 58   | 78           | 75     | 75  | 62   |

Table 14: **Tasks solved by property type**, out of 10 per cell; the bottom row is out of 110 model–task pairs. The two datasets hold the same 40 pairs and are comparable cell by cell.

the worst type for four models on each dataset, and the only other strict minima are on TypeOK, by one or two tasks (Grok-4.5 on `tlaverus_algo`; Sonnet-5 and Qwen3.8-flash on `tlaverus_11m`). The break is not confined to weak models — Sonnet-5 holds 10/10 on safety and invariance on `tlaverus_algo` and drops to 7/10 on liveness, and GPT-5.6-terra goes 10/10 to 4/10.

Second, liveness is where the two encodings diverge least. Grok-4.3 gains on three types under the agentic translation, safety 7 to 9, TypeOK 8 to 9 and invariance 4 to 7, and stays at 2/10 on liveness; GPT-5.6-terra moves by one task there and by at most one elsewhere. Sonnet-5 is the exception, going 7 to 10, which accounts for most of its four-task gain. Whatever makes liveness hard is therefore largely a property of what is being proved rather than of how the specification was translated, which is consistent with the two datasets differing by under 2% in problem-text length on this type (Table 5).

## G Compute resources

Dataset construction consumed approximately \$16,200 of Claude tokens for agentic translation and \$13,300 for proof search across both pipelines, so approximately \$29,500 total, valued at list API prices; the work was run under a Claude subscription, so this is a measure of compute used rather than an amount billed. The algorithmic transpiler itself uses no model calls. Evaluation costs are reported per model in Section F, making it approximately \$2,500 in total.

## H LLM versus algorithmic translations

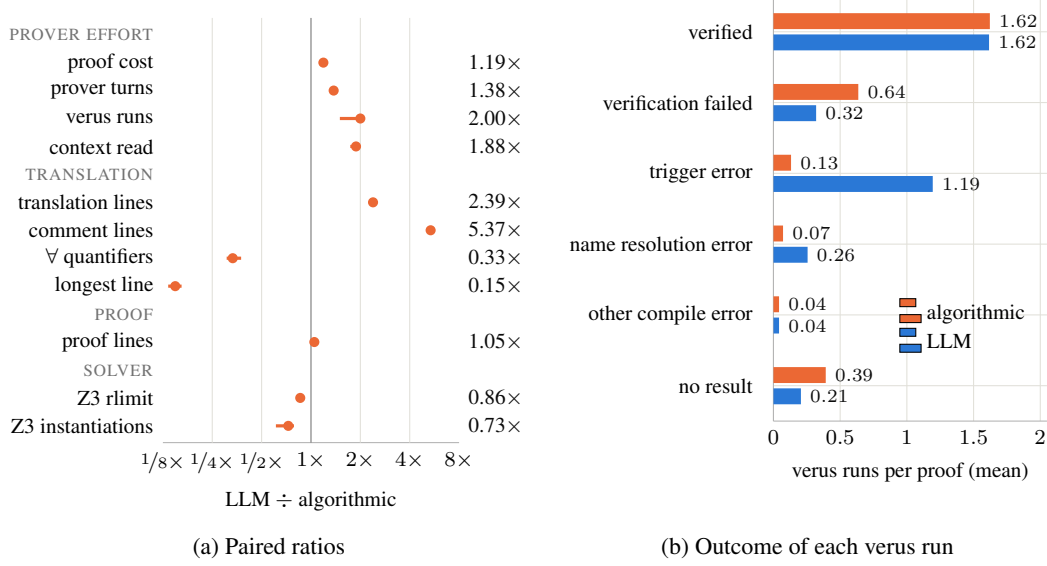


Figure 7: **(a)** Median of per-pair ratios, LLM translation over algorithmic, with 95% bootstrap intervals. **(b)** Mean number of verus runs per proof, grouped by result.

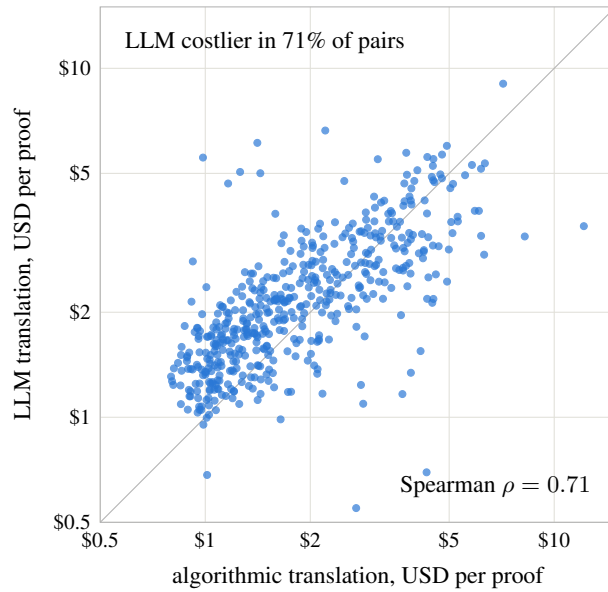


Figure 8: Proof cost per problem, paired. Each point is one (specification, property) pair.

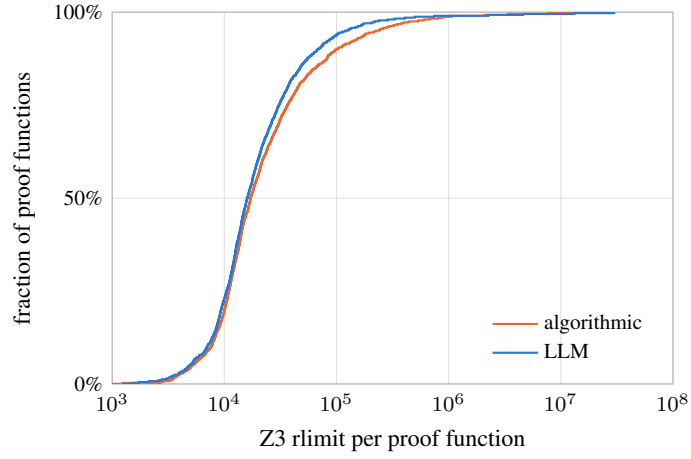


Figure 9: Z3 resource use per proof function.

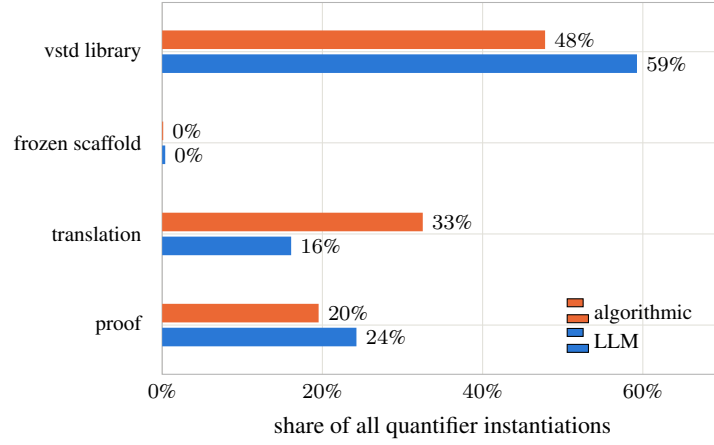


Figure 10: Share of all Z3 instantiations by the location of the quantifier.

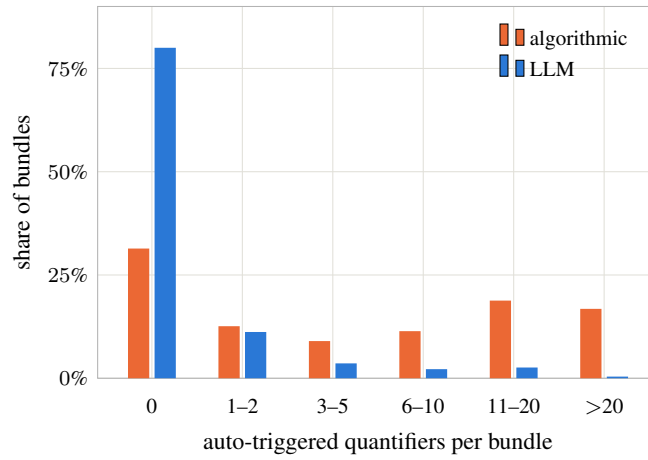


Figure 11: Quantifiers for which Verus auto-triggered quantifiers, excluding the six in the frozen scaffold.

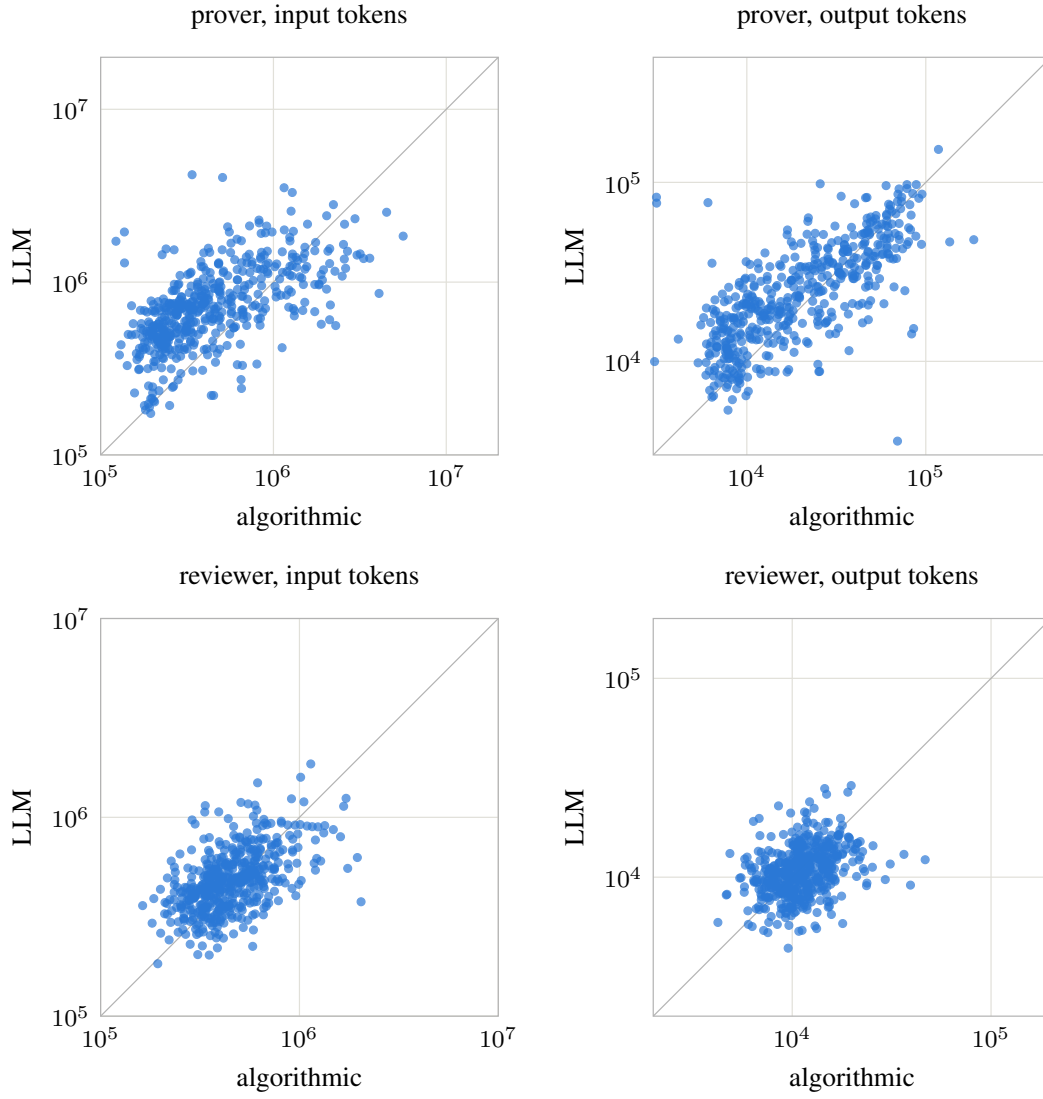


Figure 12: Tokens per proof, paired. Input counts cache reads and cache writes.

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