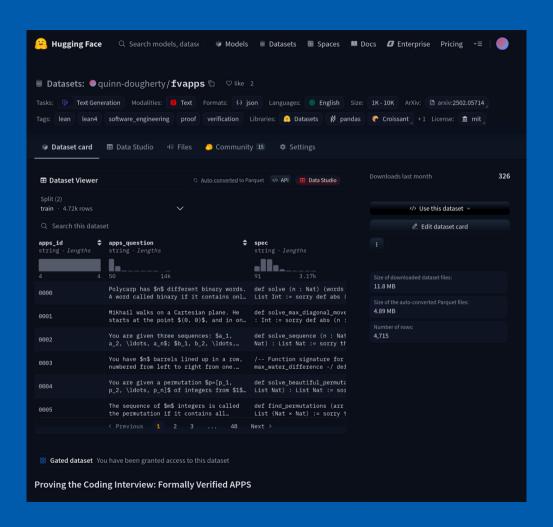
Proving the Coding Interview: A Benchmark for Formally Verified Code Generation

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Motivation

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- [1] D. Hendrycks *et al.*, "Measuring Coding Challenge Competence With APPS," *ArXiv*, 2021, [Online]. Available: https://api.semanticscholar.org/CorpusID:234790100

Formal verification and proof assistants: quality assurance

QA Process	Blindspot		
Unit tests	What did I forget to test?		
Fuzzing/property-based tests	Cases are non-exhaustive		
Formal verification	The "world-spec gap" (i.e. sidechannels)		

Formal verification and proof assistants: quality assurance

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Formal verification	The "world-spec gap" (i.e. sidechannels)		

Proof assistants accomplish this degree of assurance by *exploiting inductive structure*.

Formal verification and proof assistants: compile time knowledge

- ▶ Python is ruled by *runtime knowledge*: the absence of an initial error message is tiny evidence that your program is correct
- A dependent type theory like Lean is ruled by *compiletime knowledge*: the absence of an error message is strong evidence that your program is correct.

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Formal verification and proof assistants: out with math, in with software

- Most formal proof automation effort is invested into mathematics (i.e. MiniF2F)
- Instead, we could focus on **software** to bring the assurances of type theory to the real world
- ▶ This benchmark is a babystep in that direction

Benchmark Generation

Scaffold

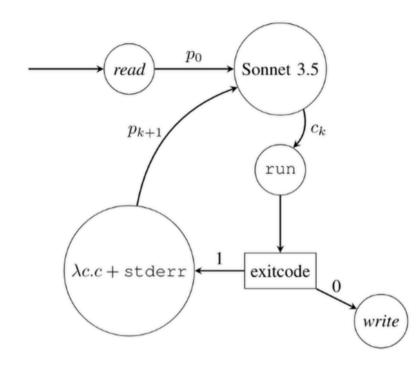


Fig. 3. Our generic scaffolding loop used at various stages of our pipeline. The run element is replaced with the python, pytest, lean, or lake build executable respectively.

• A *scaffold* or *agent* is an architecture involving LLM calls and observations (*tool use*).

Scaffold

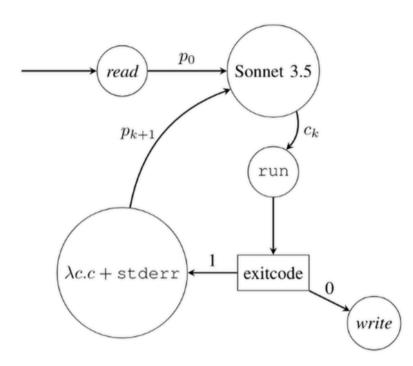


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- A *scaffold* or *agent* is an architecture involving LLM calls and observations (*tool use*).
- ► The simplest possible architecture, which is all we need, is a **loop**.

Benchmark Generation Pipeline

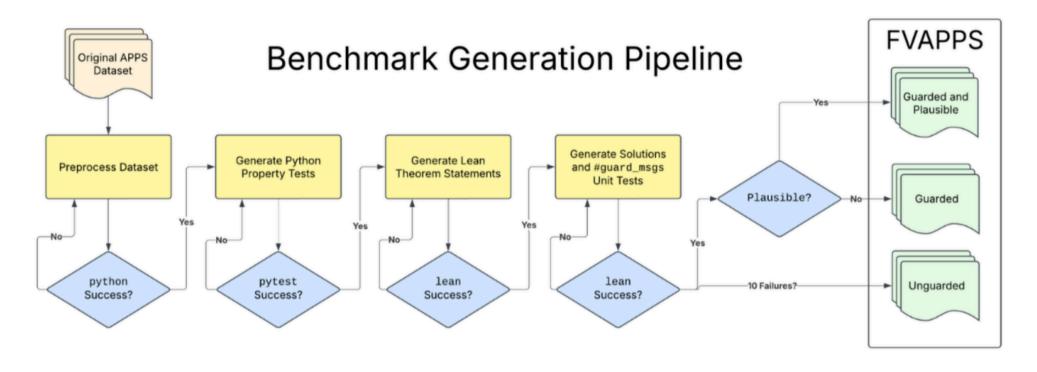


Fig. 1. Benchmark generation pipeline for creating coding interview theorem statements in Lean from APPS questions and solutions.

Example Sample

```
def solve_elections (n : Nat) (voters : List (Nat × Nat)) : Nat := sorry

theorem solve_elections_nonnegative (n : Nat) (voters : List (Nat × Nat)) : solve_elections n
    voters >= 0 := sorry

theorem solve_elections_upper_bound (n : Nat) (voters : List (Nat × Nat)) : solve_elections n
    voters <= List.foldl (λ acc (pair : Nat × Nat) => acc + pair.2) 0 voters := sorry

theorem solve_elections_zero_votes (n : Nat) (voters : List (Nat × Nat)) : (List.all voters
        (fun pair => pair.1 = 0)) -> solve_elections n voters = 0 := sorry

theorem solve_elections_single_zero_vote : solve_elections 1 [(0, 5)] = 0 := sorry
```

Fig. 2. FVAPPS sample 23, derived from train sample 23 of APPS source. The def is where the solver implements the function, each theorem is a correctness specification.

Theorems per sample

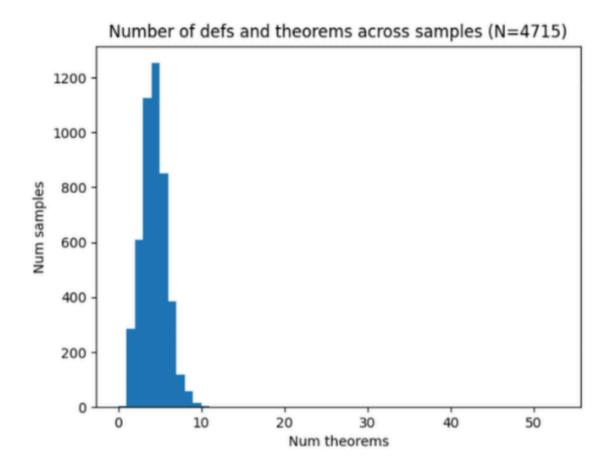


Fig. 4. Total number of defs and theorems across FVAPPS samples.

Baselines

What did we test?

LLMs were given a loop scaffold similar to that in the generation.

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- ▶ We measured Sonnet 3.5 (October 2024) and Gemini 1.5 Pro (retrieved November 2024)

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What did we test?

- LLMs were given a loop scaffold similar to that in the generation.
- ▶ We measured Sonnet 3.5 (October 2024) and Gemini 1.5 Pro (retrieved November 2024)
- ▶ A human baseliner attempted one sample for 10 hours

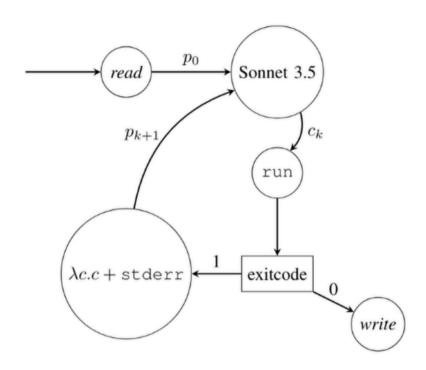


Fig. 3. Our generic scaffolding loop used at various stages of our pipeline. The run element is replaced with the python, pytest, lean, or lake build executable respectively.

406 theorems were attempted across 101 randomly selected samples

Each sample requires a function definition to be filled in before theorems can be attempted

On these, Sonnet proved 30% and Gemini proved 18%

	Baseline	Sonnet	Gemini
	Counts	Successes	Successes
Unguarded	69	41	28
Guarded	18	12	11
Guarded and Plausible	14	7	4
Total	101	60	43

TABLE II

BASELINE RESULTS SPLIT ACROSS QUALITY ASSURANCE STAGES OF OUR GENERATION PIPELINE.

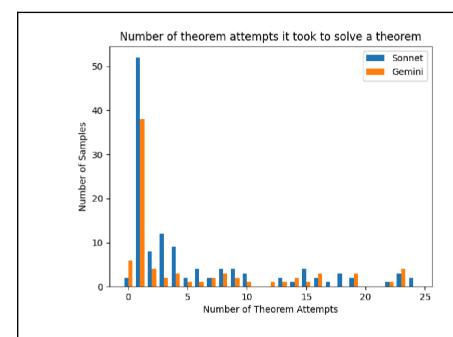


Fig. 7. Number of theorem attempts it took to solve a theorem, conditional on that theorem succeeding.

Of the theorems that got eventually completed, roughly 20% of each model's were done in zero or one iteration of the loop.

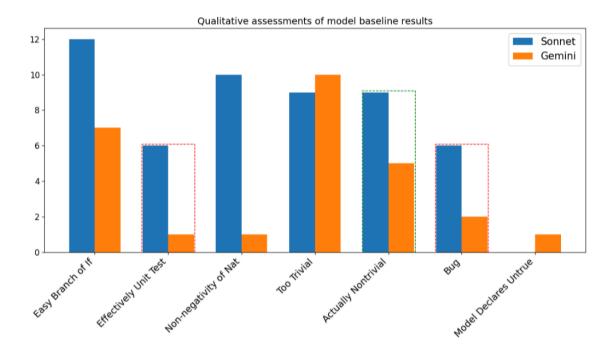


Fig. 6. Qualitative categories of theorem solutions in the 100 samples, first two theorems each sample. The red box shows completely spurious results, either bugs or a substitution of a quantified variable with a single value. The green box shows the most nontrivial results. The other categories are neither spurious nor impressive, though they require some syntactic fluency that many language models would fail at.

Future

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• Quality control for **soundness** (no false positives) could be improved

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- Quality control for soundness (no false positives) could be improved
- Harvesting property tests from the real world and turning them into Lean theorems (go from job interview code to real code)



References

[1] D. Hendrycks *et al.*, "Measuring Coding Challenge Competence With APPS," *ArXiv*, 2021, [Online]. Available: https://api.semanticscholar.org/CorpusID:234790100