Notably, for problems not fully solved, our generator typically identifies the genuine issues in its proofs, while fully solved problems pass all 64 verification attempts. This demonstrates that we can successfully train LLM-based verifiers to assess proofs previously considered difficult to verify automatically. By scaling test-time compute under verifier guidance, our model solves problems that require hours of effort from human competitors.

4. Related Work

Reasoning models (OpenAI, 2024; Guo et al., 2025) have saturated quantitative reasoning benchmarks like AIME and HMMT within one year. This rapid advancement is partly attributed to the well-defined evaluation criterion: if we care only about final answers, then quantitative reasoning is easy to verify. However, this final answer metric is inapplicable to theorem proving, which often requires no numerical answers but demands rigorous step-by-step derivation. Informal mathematical proofs have long been considered hard to verify automatically, lacking reliable approaches to assess proof correctness. Recent developments suggest this barrier may be surmountable. Models like Gemini-2.5 Pro already demonstrate a certain level of self-verification capabilities, which can refine their own solutions to improve quality (Huang and Yang, 2025). More significantly, DeepMind's internal DeepThink variant (Luong and Lockhart, 2025) achieved gold medal performance at IMO 2025 using pure natural language reasoning – serving as an existence proof that LLM-based verification of complex proofs is achievable. Recent research has begun exploring whether reasoning models can evaluate proofs, both with and without reference solutions (Dekoninck et al., 2025; Luong et al., 2025), showing promising results. In this work, we open source DeepSeekMath-V2 and our training methodology as concrete steps toward self-verifiable mathematical reasoning, showing how models can learn to verify and improve their own proofs.

Proof assistants like Lean (de Moura et al., 2015) and Isabelle (Paulson, 1994) offer a reliable approach to verify proofs – proofs must be written in formal language, but once compiled, correctness is guaranteed. AlphaProof (AlphaProof and teams, 2024; Trinh et al., 2024; Chervonyi et al., 2025), a system specialized for formal proof search, achieved silver-level performance at IMO 2024 but required intensive computation. While using informal reasoning to guide formal proof generation has been explored extensively (Jiang et al., 2023), recent reasoning models have dramatically improved informal reasoning quality, making this guidance far more effective. Systems like DeepSeek-Prover-V2 (Ren et al., 2025) and Seed-Prover (Chen et al., 2025) can now produce substantially more valid formal proofs within the same computational budget, with Seed-Prover solving 5 of 6 problems at IMO 2025. Notably, these results were achieved without specifically optimizing the informal reasoning components for theorem proving tasks. We believe advancing natural language theorem proving will significantly benefit formal reasoning. We hope to contribute toward truly reliable mathematical reasoning systems that leverage both informal insights and formal guarantees to advance mathematical research.

5. Conclusion

We presented DeepSeekMath-V2, a model capable of both generating and verifying mathematical proofs. By training models to identify issues in their own reasoning and incentivizing them to address these issues before finalizing outputs, we move beyond the limitations of final-answer-based rewards toward self-verifiable mathematical reasoning. Our iterative training process – alternating between improving verification capabilities and using these to enhance generation – creates a sustainable cycle where each component drives the other forward. Our