AI for (Formal) Mathematics

Sean Welleck April 15, 2025

Carnegie Mellon University

AI agents in expert domains

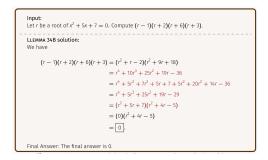
- Finance
- Medicine
- Mathematics

AI agents in expert domains

- Finance
- Medicine
- Mathematics
 - Open-ended dialogue
 - Come up with counterexamples
 - Help write proofs
 - ...

Math as raw data (text, images, ...)

- Flexible
- Widely used
- Difficult to check



Language model solution.

Math as source code

- Write a specification (e.g., 1+1=2)
- Write a proof
- Automatically checked
 - $\bullet \ \ {\sf Code \ compiles} \equiv {\sf correct \ proof}$



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 - $\bullet \ \ Code \ \ compiles \equiv correct \ \ proof$

Lean

Isabelle

Coq

Theorem proving languages

If $R \subseteq S$ and $S \subseteq T$ then $R \subseteq T$ $\lim_{T \to OREM \ PROVER}$

Growing use in mathematics:



@tao@mathstodon.xyz

Finished formalizing in #Lean4 the proof of an actual new theorem (Theorem 1.3) in my recent paper arxiv.org/abs/2310.05328 :

Terence Tao's Lean formalization project (October 2023)

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Terence Tao's Lean formalization project (October 2023)

• Lean Mathlib project: 1+ million lines of code, 300+ contributors

- Break down a big problem into multiple pieces
- Anyone can submit code to solve a piece
- We know we can trust the code since it is automatically checked!

¹See e.g., Mathematics and the formal turn, AFM Aims and Scope

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- Guaranteed correctness

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- ...

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Formal math for AI

- Verifiable
 - Prevent incorrect math and code generation
 - Feedback signal for learning

Formal math for AI

- Verifiable
 - Prevent incorrect math and code generation
 - Feedback signal for learning
- Tests reasoning
 - From easy: 1+1 = 2
 - To hard: Fermat's Last Theorem

Generative Language Modeling for Automated Theorem Proving

Stanislas Polu OpenAI spolu@openai.com Ilya Sutskever OpenAI ilyasu@openai.com

gpt-f (2020)

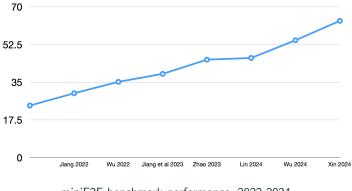
This PR models



"The shorter proof is easier to translate. It's more symmetric in that it treats A and B identically. It's philosophically more concise in that it doesn't rely on the existence of a universal class of all sets."

gpt-f (2020)

Rapid progress in methods based on language models:



$LLMs \cap formal math$

```
theorem imo 1960 p2 (x : R) (h<sub>0</sub> : 0 \le 1 + 2 * x) (h<sub>1</sub> : (1 - Real.sort (1 + 2 *
    x)) 2 \neq 0
    (h_2: 4 * x^2 / (1 - \text{Real.sqrt} (1 + 2 * x))^2 < 2 * x + 9): -(1 / 2)
   \leq x \wedge x < 45 / 8 := bv
 norm num at h0 h1 h2
 have h_3: 0 \le 1 + 2 * x := by linarith
 have h_4: 0 < 1 + Real.sqrt (1 + 2 * x) := by
    nlinarith [Real.sqrt nonneg (1 + 2 * x)]
 have h_5: 4 * x ^ 2 / (1 - Real.sqrt (1 + 2 * x)) ^ 2 < 2 * x + 9 := by
   linarith
 have h_6 : 1 - Real.sort (1 + 2 * x) \neq 0 := by
   intro h
   apply h<sub>1</sub>
    nlinarith
 have h_7: 4 * x ^ 2 / (1 - Real.sart (1 + 2 * x)) ^ 2 = (1 + Real.sart (1 +
   (2 * x))^2 := bv
   field simp [h<sub>6</sub>]
    nlinarith [sq sqrt (show 0 \le 1 + 2 * x by linarith)]
 rw [h7] at h5
 constructor <;> nlinarith [sq_sqrt (show 0 ≤ 1 + 2 * x by linarith)]
```

Generated International Math Olympiad solution in Lean (DeepSeek Prover-1.5B, Xin et al 2024)



Terence Tao @tao@mathstodon.xyz

Finished formalizing in #Lean4 the proof of an actual new theorem (Theorem 1.3) in my recent paper arxiv.org/abs/2310.05328 :

The ability of Github copilot to correctly anticipate multiple lines of code for various routine verifications, and inferring the direction I want to go in from clues such as the names I am giving the theorems, continues to be uncanny.

Terence Tao's Lean formalization project (October 2023)



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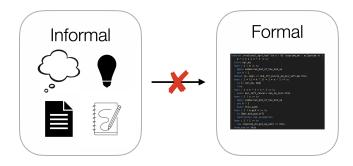
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Terence Tao's Lean formalization project (October 2023)

So...why don't people and AI always use formal math?

Informal ideas, intuitions, and even proofs are difficult to express formally:



- Each step of reasoning needs to be specified in detail
- Requires a deep knowledge of the formal system



This talk: Bridging Informal and Formal Mathematical Reasoning with AI

1. Informal thoughts

2. Informal provers

3. Research-level mathematics

This talk: Bridging Informal and Formal

- 1. Informal thoughts
 - Training models to think informally
 - Lean-STaR
- 2. Informal provers

3. Research-level mathematics

This talk: Bridging Informal and Formal

- 1. Informal thoughts
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 - Sketching proofs and filling in the gaps
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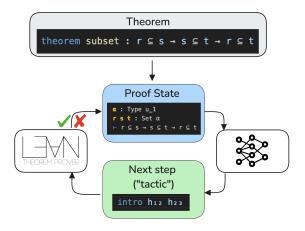
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- 1. Informal thoughts
 - Training models to think informally
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- 2. Informal provers
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- 3. Research-level mathematics
 - Assisting in research-level projects
 - Practical tools
 - MiniCTX

I: Informal thoughts

Lean-STaR: Learning to Interleave Thinking and Proving Haohan Lin, Zhiqing Sun, Yiming Yang, Sean Welleck *ICLR 2025* (Spotlight)

Neural theorem proving



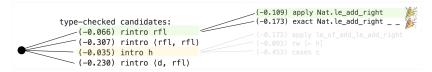
- Math as checkable code
- Proof: sequence of (state, step)

Language model-based proving:

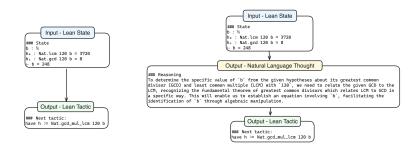
- Train a model $p_{\theta}(y|x)$ on a dataset $\mathcal{D} = \{(x, y)\}$, e.g.,
 - x: proof state
 - y: next tactic (next "step")
 - $\bullet~\mathcal{D}:$ extracted from theorems and proofs

Language model-based proving:

- Train a model $p_{\theta}(y|x)$ on a dataset $\mathcal{D} = \{(x, y)\}$, e.g.,
 - x: proof state
 - y: next tactic (next "step")
 - $\mathcal{D}:$ extracted from theorems and proofs
- Generate proofs:

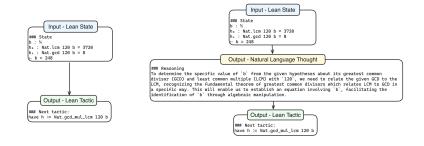


Best-first search



Can we train a model to "think" before each step of formal reasoning?

1. Training models to "think" — Lean-STaR



Why?

- Plan proof steps
- Diversify search space
- More tokens can give more computational capacity

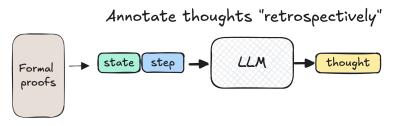
Lean-STaR (Self-taught reasoner²)

Learn to generate thoughts via reinforcement learning

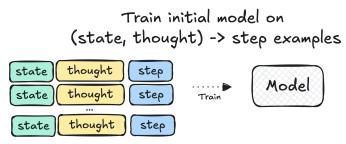
- 1. Initialization
- 2. Reinforcement learning

²Inspired by STaR: Bootstrapping Reasoning with Reasoning, Zelikman et al 2022

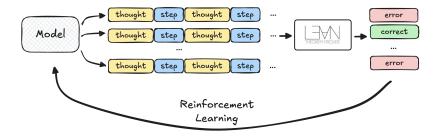
1. Initialization



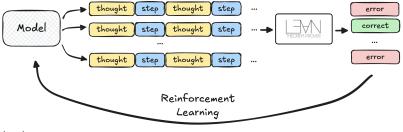
1. Initialization



2: Reinforcement learning

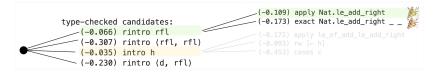


2: Reinforcement learning

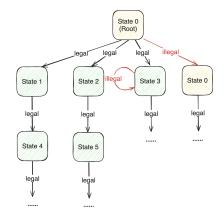


Need:

- Method to generate proofs
- Learning algorithm



Best-first search: difficult to score (thought, tactic) candidates



New sampling method

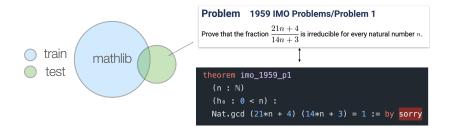
Algorithm: train on the successful proofs, and repeat:³

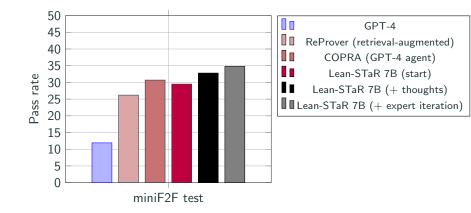
- Collect (state, thought, tactic) from successful proofs
- Train a new model $p^1_{\theta}(thought, tactic|state)$
- Generate proofs

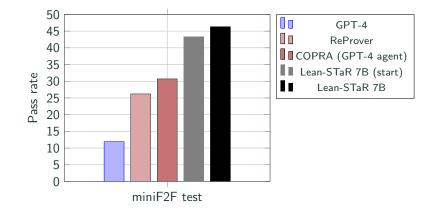
• ...

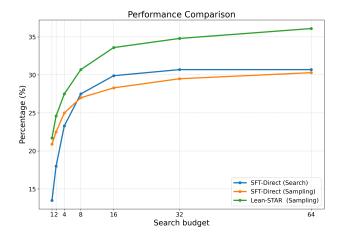
³I.e. Expert Iteration [Polu et al 2022], Rest-EM [Singh et al 2024]

• miniF2F: competition problems (AMC, AIME, IMO)









Increasing the search budget is more effective with thoughts

```
theorem amc12a_2002_p6 (n : N) (h<sub>0</sub> : 0 < n)

: \exists m, m > n \land \exists p, m * p \leq m + p :=

use n + 1, by linarith only [h<sub>0</sub>] -- Reasoning: To demonstrate the existence of

such an 'm' and 'p' that satisfy the given inequalities, we leverage the

property of natural numbers that ensures an increase in 'n' from '0' leads to

the possibility of finding such 'm' and 'p'. This approach is supported by the

fundamental property of natural numbers and their arithmetic operations,

suggesting that for a given 'n' greater than '0', there exists a successor 'm'

and a number 'p' that satisfy the conditions outlined.

exact (0, by simp) -- Reasoning: To demonstrate that there exists an \(n \in N

\) such that \((n + 1) * p \leq n + 1 + p\) holds for some \(p \in N\), we

recognize that setting \(p = 0\) satisfies the inequality by the properties of

zero in arithmetic. This is because \(n + 1 > 0\) by assumption, ensuring the

left-hand side is non-negative and the right-hand side simplifies to \(n +

1\).
```

Example generated thoughts and proof from Lean-STaR

theorem aime_1983_p2 (x p : R) (f : R \rightarrow R) (h₀ : 0 \land p < 15) (h₁ : p < x \land x < 15)

(h2 : f x = abs (x - p) + abs (x - 15) + abs (x - p - 15)) : 15 < f x :=

cases' h: with h: h: -- Reasoning: Given a function \(f)) defined over the real numbers, where l(f(x)) equals the sum of the absolute values of the differences \(z - p|), \(z - 15|), and \(x - p - 15)), along with conditions on |(p|) and |(a)) that ensure |(a)) lies between |(p|) and |(15)) and |(p)) is positive, we aim to show that \(f(m) \geq 15\). To demonstrate this, we consider all possible cases for the position of \(m)) relative to \(p)) and \(15)), specifically at \(p)) stself, between \(p)) and \(15)), and at \(15)). By evaluating |(f(x)|) for each case, we can establish a lower bound of \(f(x))) that is greater than or equal to \(15)).

simp [h1, abs of nonneg (sub nonneg, 2 h1), abs of nonneg (sub nonneg, 2 h2), *] -- Reasoning: The objective is to show that |(f(x))) is at least 15 for \(x)) within the bounds | (p \le z |le 15\), where | (p)) is positive but less than 15. The provided expression for \(f(x))) suggests using properties of absolute values and inequalities to simplify and analyze $\backslash (f(\alpha))$. By applying simplification rules for absolute values and inequalities, along with the given bounds, we aim to demonstrate the desired inequality \(f(a) | ae 15\). simp only [abs of nonneg] at * -- Reasoning: The objective is to establish an inequality involuting an expression with absolute values and a sum, where all terms are functions of \(m)). By recognizing that the absolute value functions are always non-negative, we can simplify the given expression by removing the absolute value symbols, thus focusing on the arithmetic manipulation of the terms to demonstrate the inequality.

simp only [abs of nonneg, sub add en add sub] at . -- Reasoning: The objective is to demonstrate that the expression ' $15 \le x - p + |x - 15| + |x - p - 15|$ ' holds given the conditions on 'p', 'z', and the function 'f'. Since the expression in question involves absolute values which inherently involve non-negativity, manipulating these expressions to highlight their non-negativity or equality is a logical initial step. This involves recognising that the absolute value of a difference can be rewritten as the difference of absolute values, which simplifies the manipulation of the expression to prove the inequality.

congr 1 -- Reasoning: To establish the inequality $15 \le n + |n - 15| + |n - n|$ - 15/ - p', we recognize that the left-hand side of the inequality involves a min of additions and subtractions of real numbers. By introducing a congruence transformation that simplifies operations involving absolute values, we aim to align both sides of the inequality in a form that directly reflects the properties of real numbers under these operations.

simp only [abs_of_nonpos (sub_nonpos_of_le h_), abs_of_nonneg (sub_nonneg_of_le h.)] -- Reasoning: The objective is to prove an inequality involving absolute values and subtractions that aligns the given conditions and constraints. Simplification using the properties of absolute values and the provided bounds can directly lead to the desired conclusion by eppressing the absolute values in terms of their underlying expressions and applying the given constraints.

simp [abs_of_pos, +] -- Reasoning: To prove the given inequality involving absolute values, simplification using algebraic properties and given hupotheses will directly lead us to the desired inequality by recooniging the algebraic manipulation and application of the known bounds 'h1' and 'h2', as well as the non-negativity of 'p'

rw [abs_of_nonpos] -- Reasoning: The objective is to demonstrate that '16 \leq 15 + /x - p - 15/ - p' under the given constraints on 'p' and 'x'. Given 'p < 15' and 'p ≤ a ≤ 15', it's apparent that 'p - 15' is non-positive. This observation allows us to apply the property that the absolute value of a non-positive number is equal to its negative value, thereby simplifying the expression on the right-hand side of the inequality.

all goals linarith -- Reasoning: The goal involves demonstrating a relationship between expressions involving inequalities and subtraction. The simplification of these eppressions into a form that directly compares their numerical values can lead to a straightforward application of known inequalities and algebraic properties, demonstrating the inequality's validity under the given conditions.

Example generated thoughts and proof from Lean-STaR

Output:

After Lean-STaR, incorporating thoughts became a widely-used component of LLM-based theorem proving:

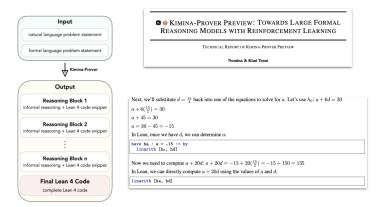


left-hand side can be rewritten as a perfect square $(3x \sin x - 2)^2$. -- We use the fact that $(3x\sin x - 2)^2$ is non-negative to establish this. nlinarith [sq_nonneg (3 * x * Real.sin x - 2)] ...

generating theorem proof code. Similar to Lean-STaR (Lin et al., 2024), which performs isolated chain-of-thought reasoning (Wei et al., 2022; Feng et al., 2023) before each proof step, our method integrates this reasoning directly as comments within the proof code. We use the DeepSeek-

Informal thoughts in DeepSeek Prover 1.5

After Lean-STaR, incorporating thoughts became a widely-used component of LLM-based theorem proving:



Informal thoughts in Kimina Prover (April 14 2025)

More broadly, *reasoning models* that generate long chains-of-thought have subsequently begun to revolutionize LLM reasoning:

September 12, 2024 Release

Learning to reason with LLMs

We are introducing OpenAl of, a new large language model trained with reinforcement learning to perform complex reasoning, of thinks before it answers —it can produce a long internal chain of thought before responding to the user.

OpenAl o1 reasoning model

Wdeepseek

DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning

DeepSeek-AI

research@deepseek.com

DeepSeek R1 reasoning model

Recap: Lean-STaR

- Training on formal code may be insufficient to learn the underlying thought process needed to produce the code
- Learn to generate thoughts via reinforcement learning

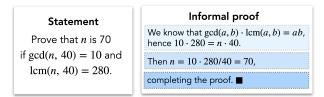
1. Informal thoughts

2. Informal provers

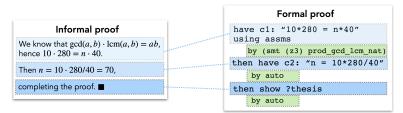
- Sketching proofs and filling in the gaps
 - Draft, Sketch, Prove
 - LeanHammer
- 3. Research-level mathematics

II: Informal and formal provers

Overall goal: combine high-level reasoning and low-level reasoning



How would we write this as a formal proof?





A proof with a high-level sketch and low-level proof steps.

Low-level provers: Sledgehammer



Sledgehammer [Paulson 2010] calls out to external automated provers.

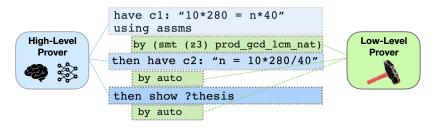
• First-order logic, higher-order logic, SMT

Low-level provers: Sledgehammer



Struggles due to the large search space of possible proofs

Idea: combine high-level and low-level proving



Idea: combine high-level (human, LLM) and low-level proving

Draft, Sketch, Prove: Guiding Formal Theorem Provers with Informal Proofs

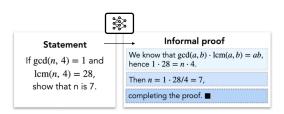
Albert Q. Jiang, Sean Welleck, Jin Peng Zhou Jiacheng Liu, Wenda Li, Mateja Jamnik Guillaume Lample, Yuhuai Wu *ICLR 2023* (Oral)

Idea:

Draft an informal proof, translate it into a formal **sketch**, then use a low-level **prover** to fill in the gaps.

Given informal theorem x_I , formal theorem x_F

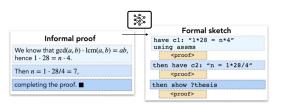
1. Draft $y_l \sim p(\cdot|x_l)$



Human-written or LLM-generated draft

Given informal theorem x_I , formal theorem x_F

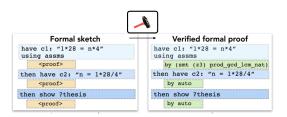
- 1. Draft $y_l \sim p(\cdot|x_l)$
- 2. Sketch $z_F \sim p(\cdot|x_F, x_I, y_I)$



LLM-generated sketch

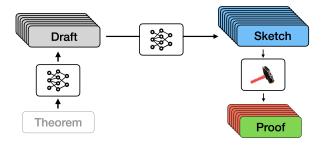
Given informal theorem x_I , formal theorem x_F

- 1. Draft $y_l \sim p(\cdot|x_l)$
- 2. Sketch $z_F \sim p(\cdot|x_F, x_I, y_I)$
- 3. **Prove** $y_F = f(x_F, z_F)$

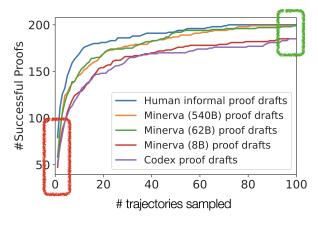


Low-level prover (Sledgehammer) fills in the gaps

Proof search



Draft-sketch-prove



Inference-time proof search scaling

Draft-sketch-prove







Statement: Prove that the fraction $\frac{21n+4}{14n+3}$ is irreducible for every natural number <i>n</i> .
Informal Proof (Minerva 62B): We must show that $gcd(21n + 4, 14n + 3) = 1$. The Euclidean algorithm gives
$21n + 4 = 1 \cdot (14n + 3) + 7n + 1$ $14n + 3 = 2 \cdot (7n + 1) + 1.$
Since $gcd(7n + 1, 1) = 1$, we have $gcd(21n + 4, 14n + 3) = 1$.
Formal Proof: theorem imo_1959_p1: fixes n::nat shows "rock (21*n + 4) (14*n + 3) = 1" proof -
$ \begin{array}{l} (* \mbox{ The Excludean algorithm gives} \\ 21n+4+10x0(14n+3)+7n+1 \\ 14n+3=2)x00x(14n+3)+1*) \\ have c0; "21n + 4 = 1*(14n + 3) + 7n+1" \\ by auto (1/P) \\ (have c1; "14n + 3 = 2*(7n+1) + 1" using c0 \\ by auto (1/P) \\ \end{array} $
<pre>(+ Since \gcd(7n+1,1)=1, we have \gcd(2in+4,14n+3)=1. *) then have "gcd (7*n + 1) 1 = 1" by auto [ATP] then have "gcd (21*n + 4) (14*n + 3) = 1" using c1 by (smt (z3) BitL_plus_one ab_semigroup_add_class.add_ac(1) add.assoc 0 gcd.commute gcd_add_gcd_add_mult mult_numeral_1 numeral_One numeral_eq_Suc numerals(1) semiring_norm(3)) [ATP] then ahow Tchesis using c1 by last [ATP] ged</pre>

International Math Olympiad problem



Demo notebook: github.com/cmu-l3/ntptutorial-II

Recap:

- Draft-Sketch-Prove: generate high-level sketches and fill in gaps
- Isabelle's Sledgehammer calls out to external provers to fill in gaps

Recap:

- Draft-Sketch-Prove: generate high-level sketches and fill in gaps
- Isabelle's Sledgehammer calls out to external provers to fill in gaps

Next: can we build a Sledgehammer for Lean?

Premise Selection for a Lean Hammer

Thomas Zhu, Joshua Clune Jeremy Avigad, Albert Q. Jiang, Sean Welleck *Under Review 2025* A **hammer** integrates an automated theorem prover into an interactive theorem prover

A **hammer** integrates an automated theorem prover into an interactive theorem prover

- Interactive theorem prover: Lean, Isabelle, Coq
 - A programming language that checks proofs

A **hammer** integrates an automated theorem prover into an interactive theorem prover

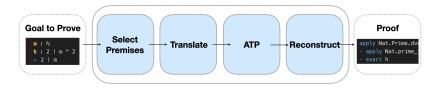
- Interactive theorem prover: Lean, Isabelle, Coq
 - A programming language that checks proofs
- Automated theorem prover: higher-order logic provers, SMT solvers
 - Tries to automatically find proofs

Automated theorem provers (ATPs) struggle with the large search space of possible proofs.

- **Premise selection**: select a small subset of theorems and definitions that are likely to be useful for proving a given theorem.
 - Around 250,000 premises in Lean's Mathlib
 - Cuts down the prover's search space

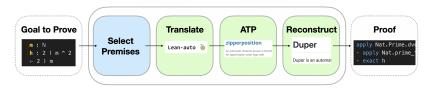
A hammer pipeline

A standard hammer pipeline:



A hammer pipeline

A standard hammer pipeline:



Pre-existing components:

- Translation: LeanAuto [Qian et al 2025]
- ATP: Zipperposition [Cruanes et al 2015]
- Reconstruction: Duper [Clune et al 2024]

A hammer pipeline

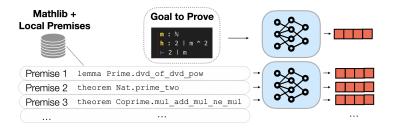
A standard hammer pipeline:



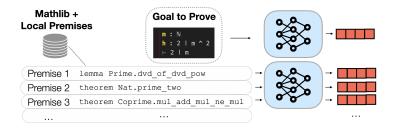
Our challenge:

- Premise selection
- Put it all together to create LeanHammer

Idea: frame premise selection as retrieval with a neural language model

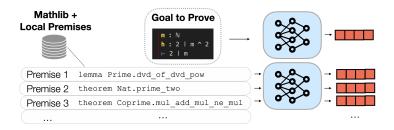


Idea: frame premise selection as retrieval with a neural language model



• Transformer encoder embeds the state and candidate premises

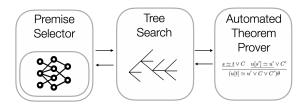
Idea: frame premise selection as retrieval with a neural language model



- Transformer encoder embeds the state and candidate premises
- Contrastive loss on (state, {premise⁺}, {premise⁻}) examples
 - Nuance in how to collect and format examples

LeanHammer — Putting it all together

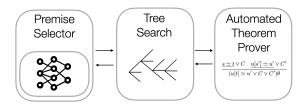
Idea: combine the premise selector and ATP with a tree search



Tree search: Aesop [Limperg & From 2023]

LeanHammer — Putting it all together

Idea: combine the premise selector and ATP with a tree search

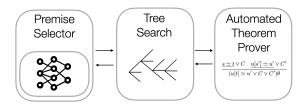


Tree search: Aesop [Limperg & From 2023]

- 1. Queries the automated theorem prover using the premises
- 2. Applies tactics (e.g. apply, simp_all) using the premises

LeanHammer — Putting it all together

Idea: combine the premise selector and ATP with a tree search



Tree search: Aesop [Limperg & From 2023]

- 1. Queries the automated theorem prover using the premises
- 2. Applies tactics (e.g. apply, simp_all) using the premises

Goes beyond the standard hammer pipeline!

As a user, simply issue hammer at any step of a proof:



LeanHammer in action

LeanHammer — Demo

Demo: start with human-written proof sketch (from Mathematics in Lean)

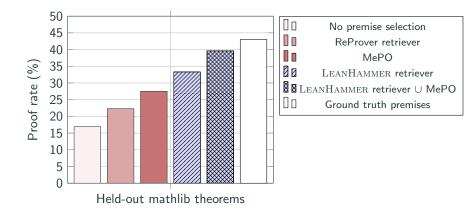
```
/-- Theorem taken from Mathematics in Lean -/
theorem irrational_sqrt_two {m n : N} (coprime_mn : m.Coprime n) :
    m^{2} \neq 2 \neq n^{2} := by
 intro sqr eq
 have : 2 \mid m := by
  sorry
  obtain (k, meq) := dvd_iff_exists_eq_mul_left.mp this
  have : 2 * (2 * k^2) = 2 * n^2 := by
  sorrv
  have : 2 * k^2 = n^2 := by
  sorry
 have : 2 \mid n := by
   sorry
  have : 2 \mid m.qcd n := by
   sorry
 have : 2 | 1 := by
  sorry
  sorry
```

LeanHammer — Demo

Demo: fill in the gaps (sorrys) with LeanHammer



Varying the premise selector within LEANHAMMER:



- Draft-Sketch-Prove (DSP)
 - LLM drafts informal proof, generates formal sketch
 - Low-level prover (Sledgehammer) fills in low-level details

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• LeanHammer

- Brings hammer functionality to Lean
- Neural premise selection + tree search + automated theorem proving
- Enables filling in proof sketches with hammer command

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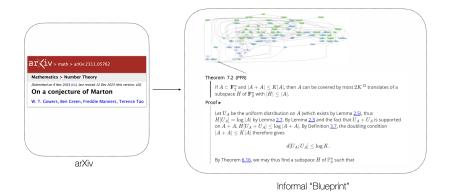
Even small neural networks are powerful! (retriever: < 100M params)

- 1. Informal thoughts
- 2. Informal provers

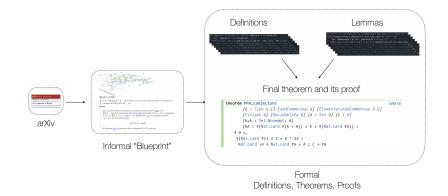
3. Research-level mathematics

- Assisting in research-level projects
- Practical tools
- MiniCTX

III: Research-level mathematics



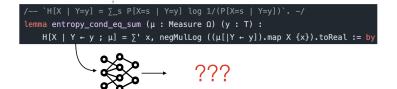
⁴ Formalizing the proof of PFR in Lean4 using Blueprint: a short tour by Terence Tao



⁴ Formalizing the proof of PFR in Lean4 using Blueprint: a short tour by Terence Tao

As a start, can AI help with filling in small parts of the blueprint?





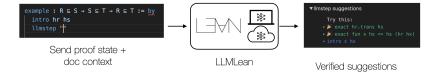
Accessibility gap:

- Some methods are hard to integrate into tools
 - Not open-source (AlphaProof, ...)
 - Expensive to run (MCTS, ...)

Accessibility gap:

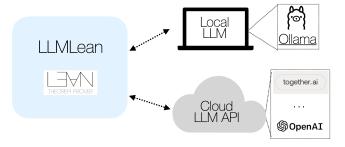
- Some methods are hard to integrate into tools
 - Not open-source (AlphaProof, ...)
 - Expensive to run (MCTS, ...)

However, there are already tools available!



LLMLean: https://github.com/cmu-l3/llmlean

Where can AI help? — Existing tools



LLMLean: https://github.com/cmu-l3/llmlean



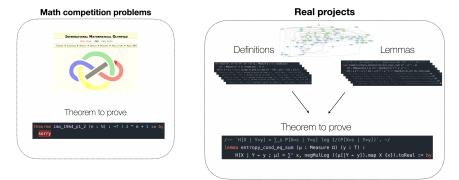
LLMLean example on Polynomial Freiman Rusza Conjecture project

Math competition problems

1		
1	INTERNATIONAL MATHEMATICAL OLYMPIAD	
	DHO 2024 🧐 THO 2825	
	Theorem to prove	
theorem <mark>sorry</mark>	imo_1964_p1_2 (n : N) : ¬7 2 ^ n + :	:= by

- Self-contained
- Uses standard results

Where can AI help? — Benchmarking gap



- Self-contained
- Uses standard results

- Part of a project
- Uses new definitions and lemmas

miniCTX: Neural Theorem Proving with (Long-)Contexts

Jiewen Hu, Thomas Zhu, Sean Welleck *ICLR 2025* (Oral)

Research-level theorems depend on newly-formalized context

- (context, theorem) ightarrow proof
 - Context: repository of code, new definitions, auxiliary lemmas

miniCTX:

Test models on real Lean projects:5

- "Future mathlib": theorems added after a time cutoff
- Recent projects: PFR, PrimeNumberTheorem, ...

 $^{^5+}$ tools for easily adding new projects: https://github.com/cmu-l3/ntp-toolkit

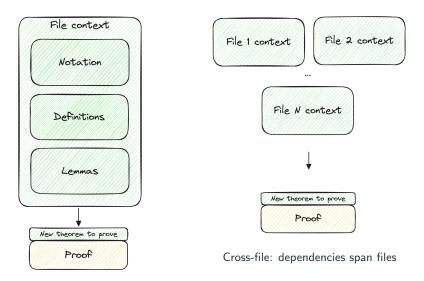
miniCTX:

Test models on real Lean projects:5

- "Future mathlib": theorems added after a time cutoff
- Recent projects: PFR, PrimeNumberTheorem, ...

Periodically updated with new projects to stay ahead of LLM training cutoffs.

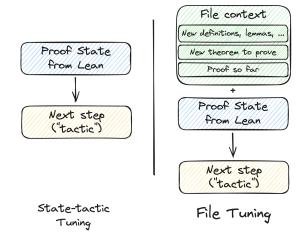
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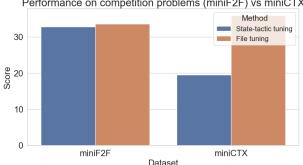
In-file: dependencies appear in the file

miniCTX — preceding code context

Does context actually matter? A simple experiment.

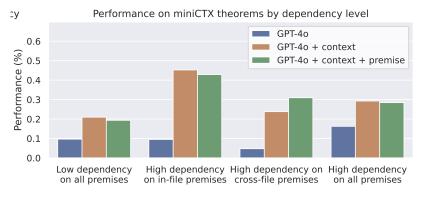


"File tuning": train on (preceding code, state, next-tactic) examples



Performance on competition problems (miniF2F) vs miniCTX

Two methods can have similar performance on competition problems, but vastly difference performance on actual projects



Premise selection helps with cross-file dependencies.

File-tuned model is deployed in LLMLean:

LLM on your laptop:		
	1. Install <u>ollama</u> .	
	2. Pull a language model:	
	ollama pull wellecks/ntpctx-llama3-8b	Q

https://github.com/cmu-l3/llmlean

Benchmark, models, code are open-source:

- Data/models: https://huggingface.co/l3lab
- Data extraction: https://github.com/cmu-13/ntp-toolkit
- Evaluation: https://github.com/cmu-13/minictx-eval

Formalizing research-level math has unique challenges

- Accessibility gap exists between AI advances and real-world formalization
 - But we have some tools available!
- Benchmarking gap exists between competition problems and real-world formalization
 - miniCTX tests the ability to generalize to new, real-world projects

- 1. Informal thoughts
 - Training models to think informally
 - Lean-STaR
- 2. Informal provers
 - Sketching proofs and filling in the gaps
 - Draft, Sketch, Prove
 - LeanHammer
- 3. Research-level mathematics
 - Assisting in research-level projects
 - Practical tools
 - MiniCTX

Thank you!

Collaborators on works in this talk (alphabetical by last name):

- Jeremy Avigad (CMU)
- Joshua Clune (CMU)
- Jiewen Hu (CMU)
- Mateja Jamnik (Cambridge)
- Albert Q. Jiang (Cambridge, Mistral)
- Timothee Lacroix (Meta, Mistral)
- Guillaume Lample (Meta, Mistral)
- Haohan Lin (Tsinghua)

- Wenda Li (Edinburgh)
- Jiacheng Liu (Washington)
- Zhiqing Sun (CMU, OpenAI)
- Yuhuai (Tony) Wu (Google, X.ai)
- Yiming Yang (CMU)
- Jin Peng Zhou (Cornell)
- Thomas Zhu (CMU)

Sean Welleck CMU School of Computer Science Learning, Language, and Logic (L3) Lab wellecks@cmu.edu