Language models and formal mathematics

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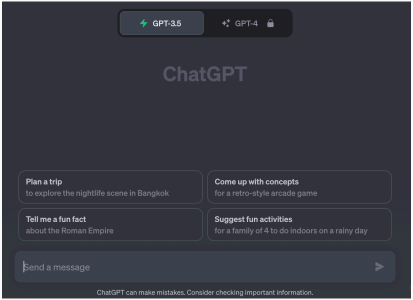
General sequence generation

- Summarize documents
- Generate code from a description
- ...



Language models

Sequence generation in mathematics

- Solve problems
- Open-ended dialogue
- Help generate verified proofs
- ...

[1]See, e.g. Harvard New Technologies in Mathematics: 1/2021 (Christian Szegedy), 3/2022 (Stan Polu), 10/2022 (Guy Gur-Ari), 10/2023 (Alex Gu), 12/2023 (Katherine Collins), ...;

Input:
Let r be a root of $x^2 + 5x + 7 = 0$. Compute $(r-1)(r+2)(r+6)(r+3)$.

Llemma 34B solution:
We have

$$
\begin{aligned}
(r-1)(r+2)(r+6)(r+3) &= (r^2 + r - 2)(r^2 + 9r + 18) \\
&= r^4 + 10r^3 + 25r^2 + 19r - 36 \\
&= r^4 + 5r^3 + 7r^2 + 5r + 7 + 5r^3 + 20r^2 + 14r - 36 \\
&= r^4 + 5r^3 + 25r^2 + 19r - 29 \\
&= (r^2 + 5r + 7)(r^2 + 4r - 5) \\
&= (0)(r^2 + 4r - 5) \\
&= \boxed{0}.
\end{aligned}
$$

Final Answer: The final answer is 0.

Figure 1: A Llemma 34B solution to a MATH [4] problem.

"Informal" mathematics

Input:
Let r be a root of $x^2 + 5x + 7 = 0$. Compute $(r-1)(r+2)(r+6)(r+3)$.

Llemma 34B solution:
We have

$$\begin{aligned}(r-1)(r+2)(r+6)(r+3) &= (r^2+r-2)(r^2+9r+18)\\ &= r^4+10r^3+25r^2+19r-36\\ &= r^4+5r^3+7r^2+5r+7+5r^3+20r^2+14r-36\\ &= r^4+5r^3+25r^2+19r-29\\ &= (r^2+5r+7)(r^2+4r-5)\\ &= (0)(r^2+4r-5)\\ &= \boxed{0}.\end{aligned}$$

Final Answer: The final answer is 0.

Figure 2: No correctness guarantees, errors can be difficult to detect.

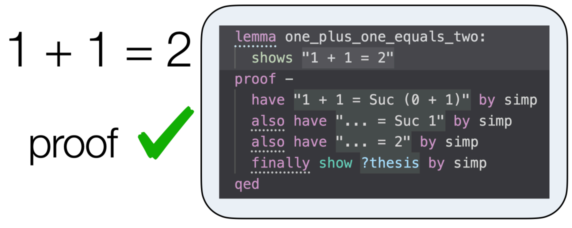


Figure 3: Mathematics as verifiable source code

Formal mathematics (Demo)

If $R \subseteq S$ and $S \subseteq T$ then $R \subseteq T$

LEAN THEOREM PROVER

Formal mathematics

Lean Mathlib

- 1+ million lines of code
- > 300 contributors
- Algebra, Linear Algebra, Topology, Analysis, Probability, Geometry, Combinatorics, . . .

LEAN THEOREM PROVER

Formal mathematics

- **Liquid tensor project**: Lean formalization with Peter Scholze[1]
- **Courses** at CMU, Imperial College London, Fordham, JHU, …[2]
- **eXperimental Lean Lab** at the University of Washington![3]

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[1] *https://www.nature.com/articles/d41586-021-01627-2*
[2] *https://leanprover-community.github.io/teaching/courses.html*
[3] *https://sites.math.washington.edu/~jarod/xll.html*

Formal mathematics

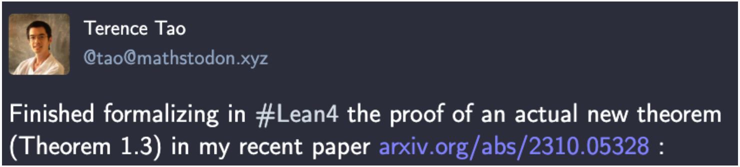

Figure 4: Terence Tao's Lean formalization project (October 2023)

Language models and formal mathematics

Generative Language Modeling for Automated Theorem Proving

Stanislas Polu
OpenAI
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Ilya Sutskever
OpenAI
ilyasu@openai.com

Figure 5: *gpt-f* (2020)

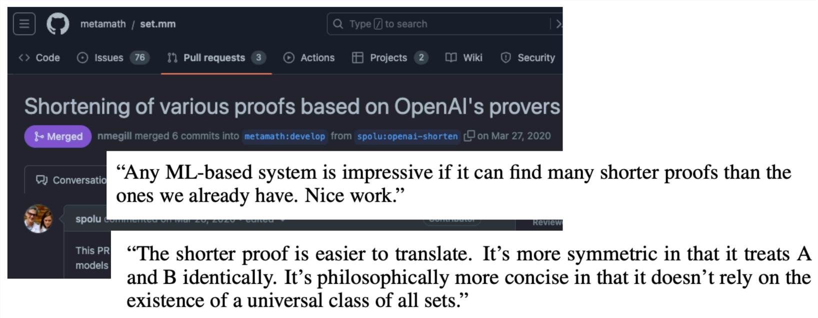


Figure 6: *gpt-f* (2020)

Language models and formal mathematics

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.

Figure 7: Terence Tao's Lean formalization project (October 2023)

This talk: “build your own Lean copilot”

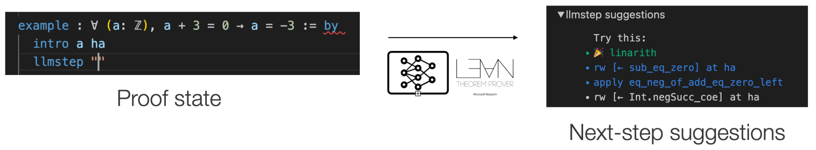
- Part 1: Small models trained to predict the next step of a proof
- Part 2: LLEMMA: foundation model for mathematics

[1] Llemma [2], LLMstep [9]

This talk: “build your own Lean copilot”

- Part 1: Small models trained to predict the next step of a proof
- Part 2: LLEMMA: foundation model for mathematics

LLMSTEP: tool for receiving verified language model suggestions



[1] Llemma [2], LLMstep [9]

Part I:
Next-step prediction

Next-step prediction

Topic	Notebook
0. Intro	notebook
1. Data	notebook
2. Learning	notebook
3. Proof Search	notebook
4. Evaluation	notebook
5. `llmsuggest`	notebook

Interactive notebooks and code:
github.com/wellecks/ntptutorial[4]

[4] From *A tutorial on neural theorem proving*, IJCAI 2023

Next-step prediction

- Language model suggests next-proof-steps
- Generate a full proof via tree search

[1] E.g., [Polu & Sutskever 2020], [Han et al 2021], [Jiang et al 2022], [Yang et al 2023]

Language models

- Model: $p_\theta(\mathrm{y}|\mathrm{x};\mathcal{D})$
    - y : output sequence
    - x : input sequence
    - θ : parameters (e.g., transformer)
    - $\mathcal{D}$: dataset

Language models

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    - y : output sequence
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- Learning:
    - $\arg\max_\theta \sum_{\mathsf{y}\in\mathcal{D}} \log p_\theta(\mathsf{y})$

Language models

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Language models

- Model: $p_\theta(\mathrm{y}|\mathrm{x};\mathcal{D})$
  - y : output sequence
  - x : input sequence
  - θ : parameters (e.g., transformer)
  - $\mathcal{D}$: dataset
- Learning:
  - $\arg\max_\theta \sum_{\mathrm{y}\in\mathcal{D}} \log p_\theta(\mathrm{y})$
- Inference:
  - $\mathrm{y} = f(p_\theta(\cdot|x))$
  - f: e.g., sampling

Problem setup

Proof: sequence of (state, next step)

- $(x_0, y_0), \ldots, (x_t, y_t), \ldots, (x_T, y_T)$
- x_t: proof state from Lean
- y_t: proof step ("tactic")
- x_T: proof complete

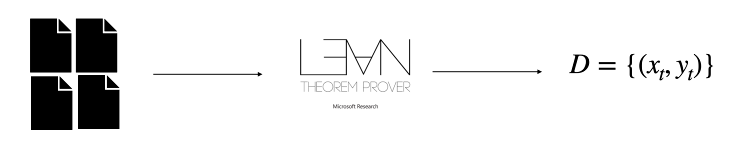
Problem setup

Proof: sequence of (state, next step)

- $(x_0, y_0), \ldots, (x_t, y_t), \ldots, (x_T, y_T)$
- x_t: proof state from Lean
- y_t: proof step ("tactic")
- x_T: proof complete

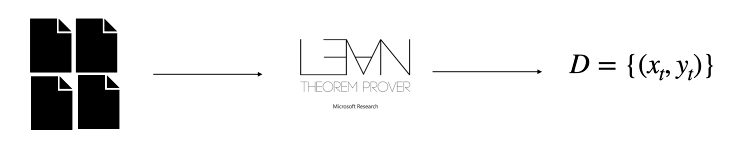
Idea:

- Collect a dataset $\mathcal{D}$ of (state, next step) examples
- Train a language model $p_\theta(y_t|x_t)$ using $\mathcal{D}$



- Extract (state, next step) pairs, e.g. from Mathlib
  - Open-source tooling available[5]

[5] E.g., Lean Dojo [10] and github.com/semorrison/lean-training-data



- Extract (state, next step) pairs, e.g. from Mathlib
  - Open-source tooling available[5]
- Mathlib yields a dataset $\mathcal{D}$ with 170,000 pairs

[5]E.g., Lean Dojo [10] and github.com/semorrison/lean-training-data

Learning

- Standard supervised learning on $\mathcal{D}$:

$$\arg\max_{\theta} \sum_{(x_t, y_t) \in \mathcal{D}} \log p_{\theta}(y_t | x_t)$$

Learning

x_t

```
Input:
[GOAL]ι : Type u_1
I✝ J✝ : Box ι
x y : ι → ℝ
I J : WithBot (Box ι)
⊢ ↑I = ↑J ↔ I = J[PROOFSTEP]
```

y_t

```
Output:
simp only [Subset.antisymm_iff, ← le_antisymm_iff, withBotCoe_subset_iff]<|endoftext|>
```

Proof search

- Use generator $p_\theta(y_t|x_t)$ to generate a full proof $y_1, \ldots, y_T$
- Standard approach: *Best-first search*

Best-first search

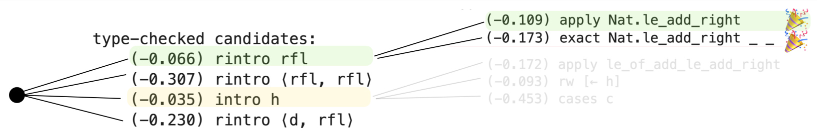
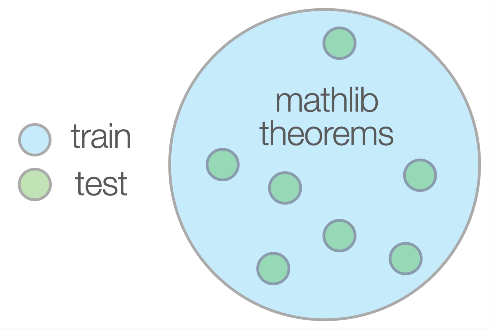


Figure 8: Best-first search[6]

[6] Example scoring function $\frac{1}{Z}\sum_t \log p_\theta(y_t|x_t)$

Evaluation

- Proof search on held-out theorems from the training distribution



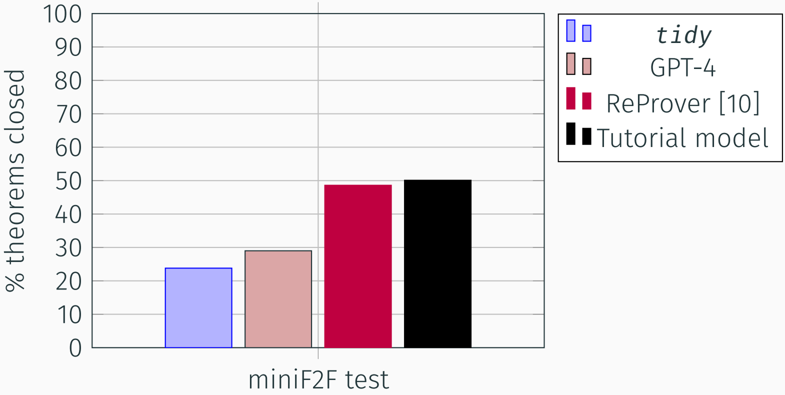


Figure 9: Proof search performance on held-out Mathlib theorems.[7]

[7] *`tidy`* and GPT-4 (Lean 3) from [10]. Tutorial model: llmstep Pythia 2.8b, best-first-search with beam size 32 and a 10 minute timeout.

Evaluation (out of domain)

Benchmarks evaluate problems drawn from a different distribution:

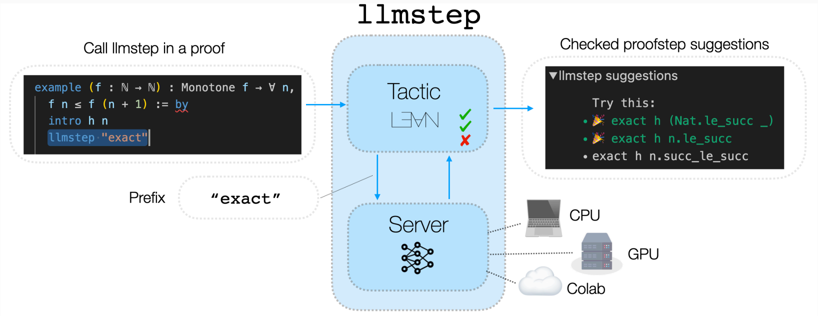
- miniF2F [11]: competition problems (AMC, AIME, IMO)
- ProofNet [1]: undergraduate textbooks (e.g. Analysis, Topology)

```
-- from mathlib:
theorem prod_mono
 {|s₁ s₂ : Subsemiring R|} (hs : s₁ ≤ s₂)
 {|t₁ t₂ : Subsemiring S|} (ht : t₁ ≤ t₂) :
 s₁.prod t₁ ≤ s₂.prod t₂ := by
    intro x hx
    simp_rw [Subsemiring.mem_prod]
    cases' x with x_fst x_snd
    exact ⟨hs hx.1, ht hx.2⟩

-- from miniF2F:
theorem mathd_algebra_159 (b : ℝ) (f : ℝ → ℝ)
 (h₀ : ∀ x, f x = 3*x^4 - 7*x^3 + 2*x^2 - b*x + 1)
 (h₁ : f 1 = 1) : b = -2 := by
    apply eq_neg_of_add_eq_zero_left
    rw [h₀] at h₁
    norm_num at h₁
    linarith
```

Figure 10: Generated proofs on mathlib and miniF2F

Verified Lean copilot: LLMSTEP



LLMSTEP: tool for receiving verified language model suggestions[8]

[8] https://arxiv.org/abs/2310.18457. github.com/wellecks/llmstep.

Verified Lean copilot: LLMSTEP

LLMSTEP: tool for receiving verified language model suggestions

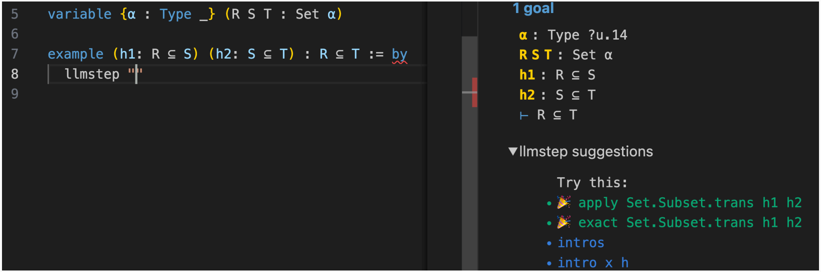


Figure 11: DEMO

Verified Lean copilot: LLMSTEP

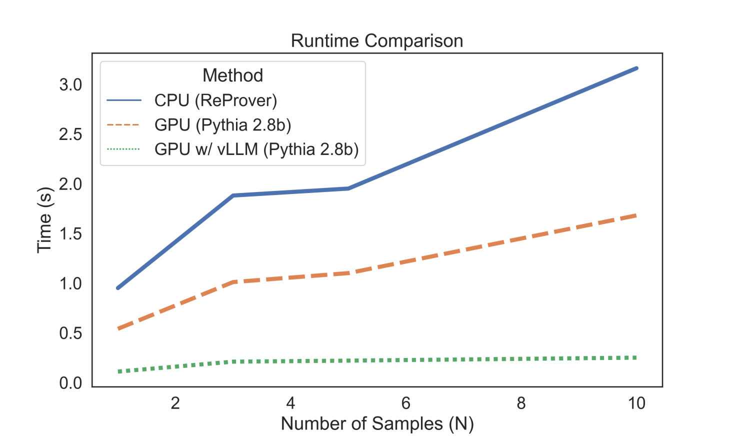


Figure 12: LLMSTEP suggestion latency on CPU and GPU

Try it at *`https://github.com/wellecks/llmstep`*

Part II:
Llemma: foundation model for mathematics

Modeling the distribution of mathematics

- *Previous*: train a model specifically for tactic prediction

Modeling the distribution of mathematics

- *Previous*: train a model specifically for tactic prediction
- *Next*: model a diverse distribution of math-related sequences

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    - Perform a task by prompting with a few (input, output) examples

Modeling the distribution of mathematics

- *Previous*: train a model specifically for tactic prediction
- *Next*: model a diverse distribution of math-related sequences
    - Perform a task by prompting with a few (input, output) examples
    - "*Foundation model*" [3]: train on large quantity of data, adapt to tasks via prompting or further training

Foundation model for mathematics

- Language model learning:

$$\arg\max_{\theta} \sum_{y \in \mathcal{D}} \log p_{\theta}(y)$$

- Equivalent to:

$$\arg\min_{\theta} \mathrm{KL}\left(p_{*}, p_{\theta}\right),$$

$$\text{where } \mathcal{D} \sim p_{*}$$

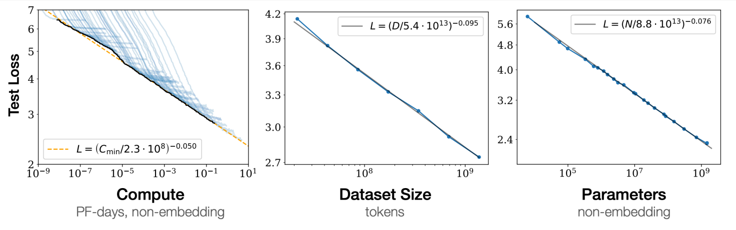

Figure 13: Increasing compute predictably improves language modeling.[9]

[9] Image from [Kaplan et al 2020]. See [5, 8] for more recent scaling laws.

Approach 1: train a good generalist

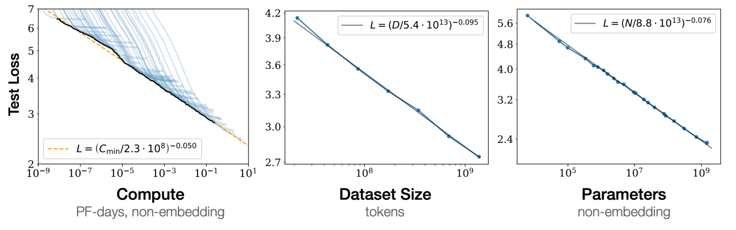

Figure 13: Increasing compute predictably improves language modeling.[9]

- *Idea:* let $\mathcal{D}$ be as general as possible (with math as a subset), increase compute as much as possible ($|\mathcal{D}|$ and $|\theta|$).

[9] Image from [Kaplan et al 2020]. See [5, 8] for more recent scaling laws.

Approach 1: train a good generalist

Example: Llama 2

- θ : 7B parameter transformer
- $\mathcal{D}$: 2 trillion tokens
- *General domain*: CommonCrawl, Github, Wikipedia, Arxiv, ...

Approach 1: train a good generalist

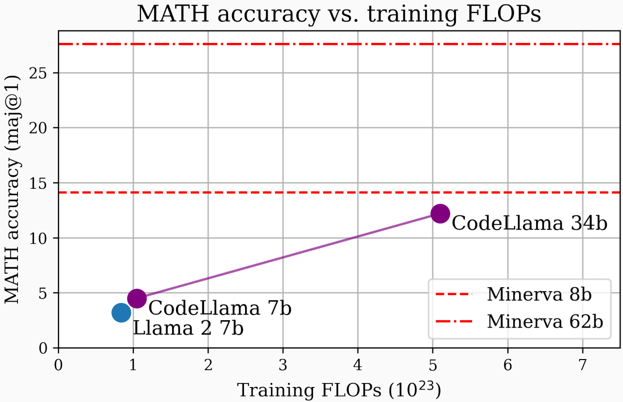

Figure 14: Training a generalist can be inefficient.[10]

[10] Minerva [7]: general language model finetuned on a large mathematical corpus

Approach 2: specialize via transfer

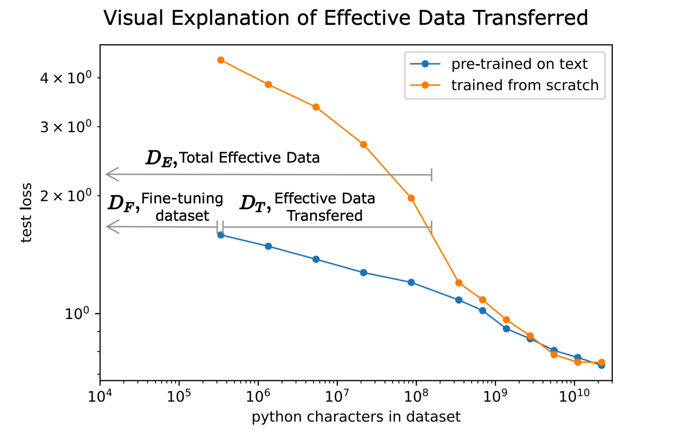

Figure 15: Pretraining on p_1 can make transfer to p_2 more efficient[11]

[11] Image from [Hernandez et al 2020] *Scaling laws for transfer.*

Approach 2: Llemma

Llemma:

Collect high-quality mathematics data $\mathcal{D}'$, transfer to $\mathcal{D}' \sim p_2$

- Initialize with $\theta_{\text{codellama}}$
- Continue training on $\mathcal{D}'$: 55 billion token Proofpile II

Approach 2: Llemma

Llemma:

Collect high-quality mathematics data $\mathcal{D}'$, transfer to $\mathcal{D}' \sim p_2$

- Initialize with $\theta_{\text{codellama}}$
- Continue training on $\mathcal{D}'$: 55 billion token Proofpile II
    - Mathematical code
    - Mathematical web data
    - Scientific papers

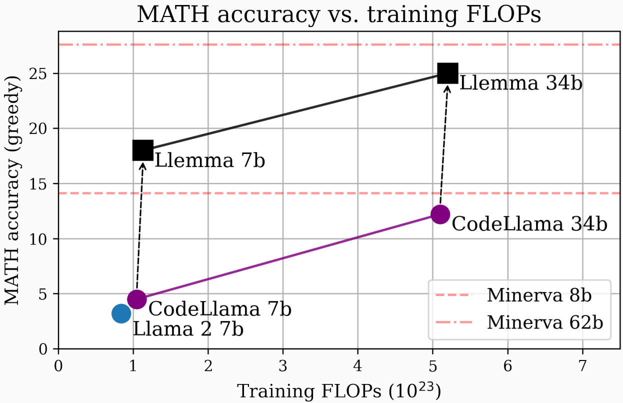

Figure 16: Llemma improves with a modest amount of math-specific compute

Data: Proofpile II

Data: Proofpile II

Proofpile II: 55 billion tokens

- Code: 11B tokens
- Web: 15B tokens
- Papers: 29B tokens

Code: AlgebraicStack

- 11 billion tokens of math-related code
- 17 languages, from the Stack [6], public GitHub repos, proof steps

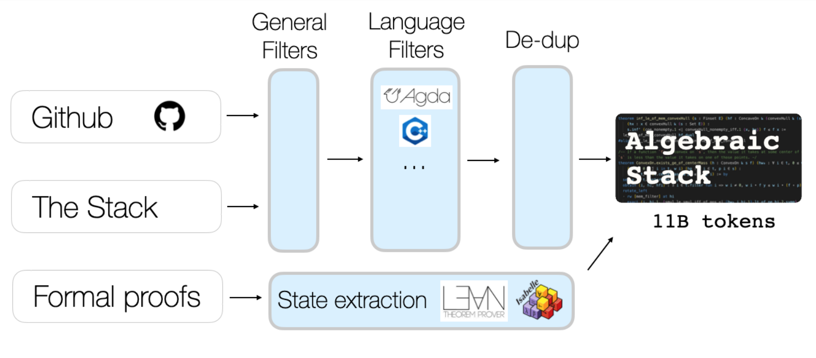

Figure 17: AlgebraicStack pipeline

AlgebraicStack – Formal mathematics

1.5B tokens of formal math: Agda, Coq, Idris, Isabelle, Lean

- Extracted Lean and Isabelle goal states

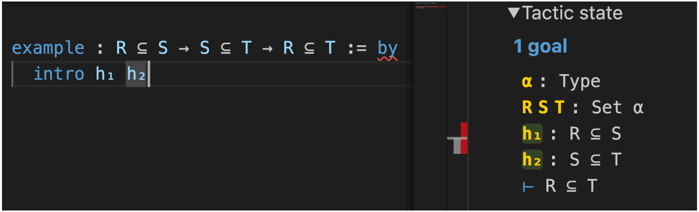

Figure 18: Lean code (left) and goal state (right)

Web: OpenWebMath [Paster et al 2023][12]

- 14.7 billion tokens of math-related web data
- CommonCrawl with math-specific filtering and extraction

[12] *OpenWebMath: An Open Dataset of High-Quality Mathematical Web Text.* Keiran Paster, Marco Dos Santos, Zhangir Azerbayev, Jimmy Ba

Training

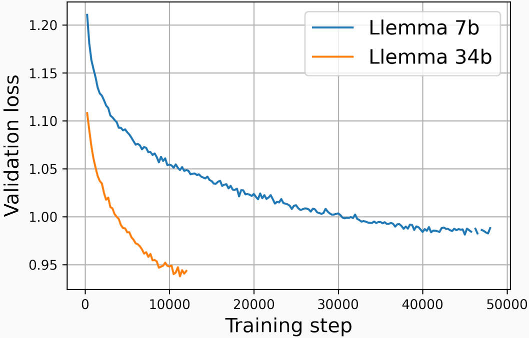

Figure 19: LLEMMA validation loss

Formal theorem proving

Traditional proof search: $p_\theta(\text{next-tactic}|\text{state})$ + best-first search.

- We implement a *few-shot* version by providing Llemma with 3 (*state, next-tactic*) examples in its prompt

Llemma formal-to-formal theorem proving

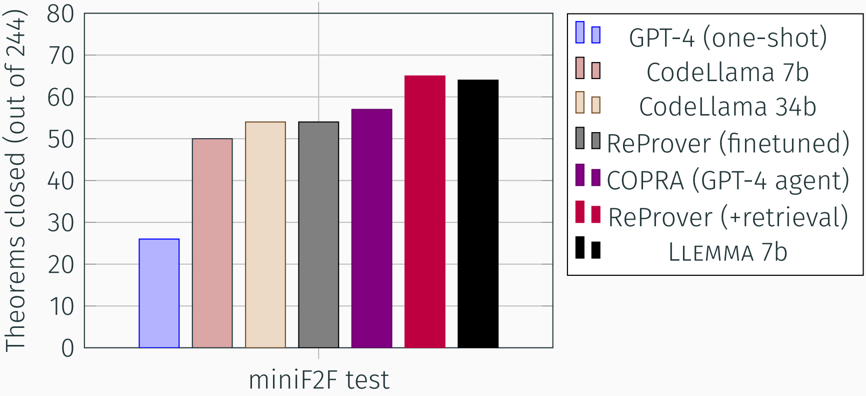

Figure 20: Few-shot proving in Lean with Llemma[13]

[13] CodeLlama and Llemma use best-first-search with beam size 32 and a 10 minute timeout. GPT-4, COPRA and Reprover (no retrieval) from [Thakur et al 2023] (Lean 3)

LLEMMA as a Lean copilot

LLMSTEP + LLEMMA:

- *Part I:* send **proof state** to a tactic prediction model
    - $y_t \sim p_\theta(\cdot|x_t)$
- *Now:* send **file content** and **proof state** to LLEMMA
    - $y_t \sim p_\theta(\cdot|\text{preceding file content})$

Verified Lean copilot: LLMSTEP

Key difference: use new definitions and theorems

```
structure my_object (Ω : Type*)[Fintype Ω] :=
  (f : Ω → ℝ)
  (cool_property : ∀ x : Ω, 0 ≤ f x)

theorem my_object_sum_nonneg (o1 o2: my_object Ω) :
  o1.f + o2.f ≥ 0 := by
  apply add_nonneg
  · apply o1.cool_property
  · llmstep ""
```

```
▼llmstep suggestions

     Try this:
   • 🎉 exact o2.cool_property
   • 🎉 apply o2.cool_property
   • intro hb
   • intro h
```

DEMO

Verified Lean copilot: LLMSTEP

Key difference: use new definitions and theorems

```
-- Probability of any outcome is at most one.
theorem px_le_one (p : pmf Ω) (x : Ω) : p x ≤ 1 := by
  refine' hasSum_le _ (hasSum_ite_eq x (p x)) (hasSum
  intro x
  split_ifs with h
  rw [h]
  llmstep ""
```

```
▼llmstep suggestions
  Try this:
  • 🎉 exact p.my_non_neg _
  • 🎉 exact p.my_non_neg x
  • 🎉 apply p.my_non_neg
  • simp
  • apply le_of_lt
```

DEMO

Beyond formal-to-formal proving

Problem: If $3a + b + c = -3, a + 3b + c = 9, a + b + 3c = 19$, then find abc. Show that it is -56.

Informal Proof (Human-written): Summing all three equations yields that $5a + 5b + 5c = -3 + 9 + 19 = 25$. Thus, $a + b + c = 5$. Subtracting this from each of the given equations, we obtain that $2a = -8, 2b = 4, 2c = 14$. Thus, $a = -4, b = 2, c = 7$, and their product is $abc = -4 \times 2 \times 7 = -56$.

Formal Statement and Proof:

```
theorem mathd_algebra_338:
  fixes a b c :: real
  assumes "3 * a + b + c = -3" and "a + 3 * b + c = 9" and "a + b + 3 * c = 19"
  shows "a * b * c = -56"
proof -
    (* Summing all three equations yields that 5a + 5b + 5c = -3 + 9 + 19 = 25.
    Thus, a + b + c = 5. *)
    have "5 * a + 5 * b + 5 * c = -3 + 9 + 19" using assms <ATP>
    then have "5 * (a + b + c) = 25" <ATP>
    then have "a + b + c = 5" <ATP>
    (* Subtracting this from each of the given equations, we obtain that  2a =
    -8, 2b = 4, 2c = 14. Thus, a = -4, b = 2, c =7, and their product is  abc =
    -4 \times 2 \times 7 = -56. *)
    then have "2 * a = -8" "2 * b = 4" "2 * c = 14" using assms <ATP>
    then have "a = -4" "b = 2" "c = 7" <ATP>
    then show ?thesis <ATP>
qed
```

Few-shot informal-to-formal proving

Setting based on *Draft, Sketch, Prove*; Jiang*, Welleck*, Zhou* et al ICLR 2023

Part II conclusion

- Recipe for specializing a language model to mathematics
  - LLEMMA: 7B and 34B CodeLLama further trained on PROOFPILE II
- Open platform for research:
  - Code/Models/Data: *https://github.com/EleutherAI/math-lm*

Conclusion

Neural theorem proving: language models $\cap$ formal proof assistants

- Next-step predictors: *small/fast*, narrow
- Foundation models: *larger*, flexible
- Both enable new practical tools

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Neural theorem proving: language models $\cap$ formal proof assistants

- Next-step predictors: *small/fast*, narrow
- Foundation models: *larger*, flexible
- Both enable new practical tools

Claim: mathematical foundation models (e.g. LLEMMA) open a new frontier of methods, capabilities, and applications to explore!

Thank you!

- Zhangir Azerbayev (Princeton, Eleuther)
- Hailey Schoelkopf (Eleuther)
- Keiran Paster (Toronto, Vector)
- Marco Dos Santos (Cambridge)
- Stephen McAleer (CMU)
- Albert Jiang (Cambridge)
- Jia Deng (Princeton)
- Stella Biderman (Eleuther)
- Sean Welleck (Washington, CMU)

- Tutorial: *github.com/wellecks/ntptutorial*
- LLMstep: *github.com/wellecks/llmstep*, arXiv:2310.18457
- LLEMMA: *github.com/EleutherAI/math-lm*, arXiv:2310.10631

LLEMMA∎

Appendix

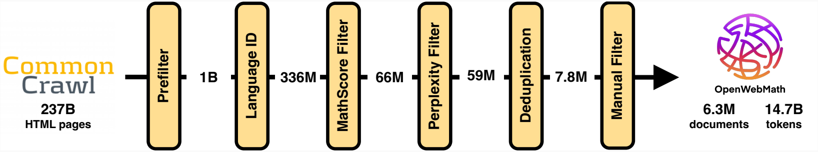

Figure 21: OpenWebMath pipeline.[14]

[14] Image from [Paster et al 2023]

Web: OpenWebMath

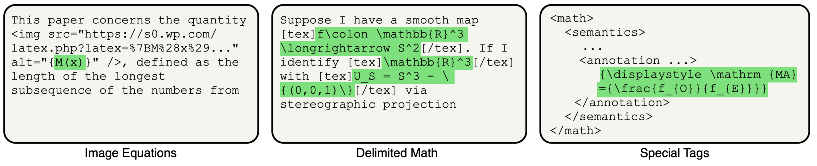

Figure 22: Extraction: OpenWebMath extracts Latex from MathJax and 6 other sources of embedded Latex.[16]

[8] Image from [Paster et al 2023]

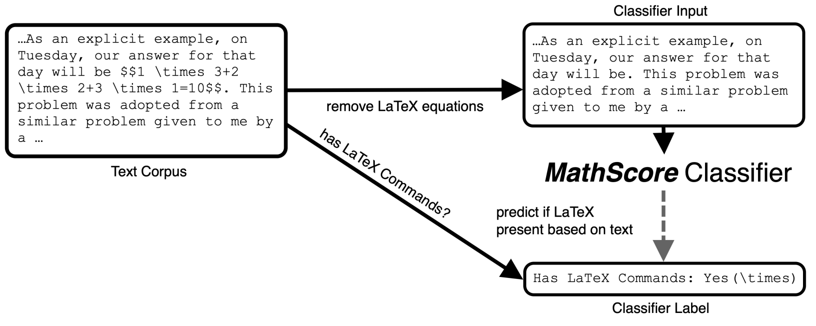

Figure 23: Filtering: the MathScore classifier predicts whether a document contains a popular Latex command given the surrounding words.[18]

[9] Image from [Paster et al 2023]

Scientific Papers

ArXiv papers (29 billion tokens)

- From RedPajama, an open-source replication of Llama data

Llemma as initialization for further fine-tuning

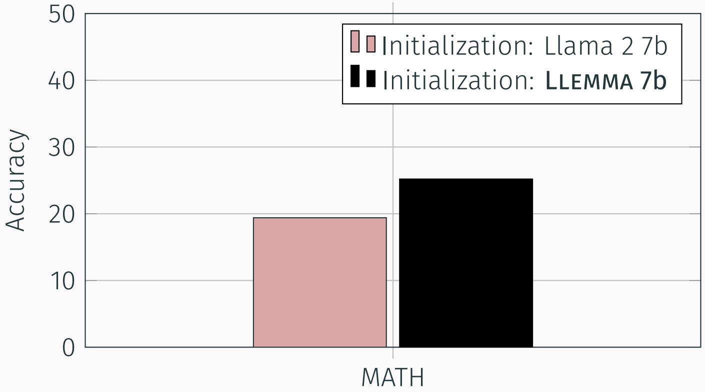

Figure 24: Llemma vs. Llama 2 as initialization for finetuning on MetaMathQA

Not the focus of our work! A lot more to explore with fine-tuning.

LLEMMA's open dataset allows for studying the effects of train/test overlap:[19]

Proof-Pile-2	Test	Problem Example	Problem Docs	Solution Example	Solution Docs
OpenWebMath	MATH	348	717	34	46
AlgebraicStack	MATH	3	3	1	1
OpenWebMath	GSM8k	2	3	0	0
AlgebraicStack	GSM8k	0	0	0	0

Same solution	1
Different solution, same answer	49
Different solution, different answer	9
No solution	41
Different problem	0

Table 6: *Left:* 30-gram hits between MATH test problems or solutions and Proof-Pile-2 documents. *Example* and *Docs* are the numbers of unique test examples and Proof-Pile-2 documents with a hit. *Right:* manual inspection of 100 hits between a problem statement and a Proof-Pile-2 document.

[19] Overlap tool at *https://github.com/wellecks/overlap*

Analysis: memorization

Surprisingly, Llemma did not perform any better on MATH problems that are contained in its training set:

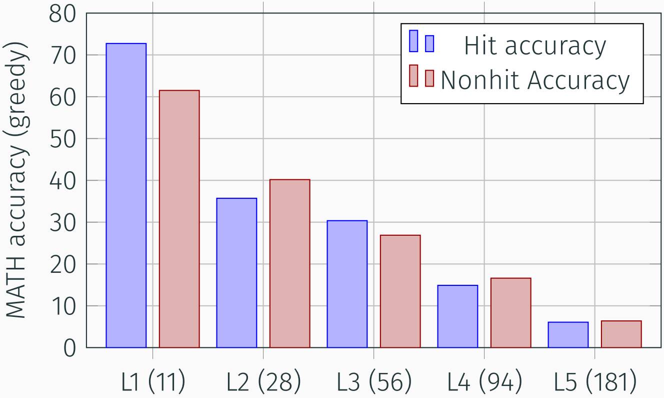

Figure 25: LLEMMA-34b's accuracy on hits and non-hits by MATH level.

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