

Towards Large Language Models as Copilots for Theorem Proving in Lean

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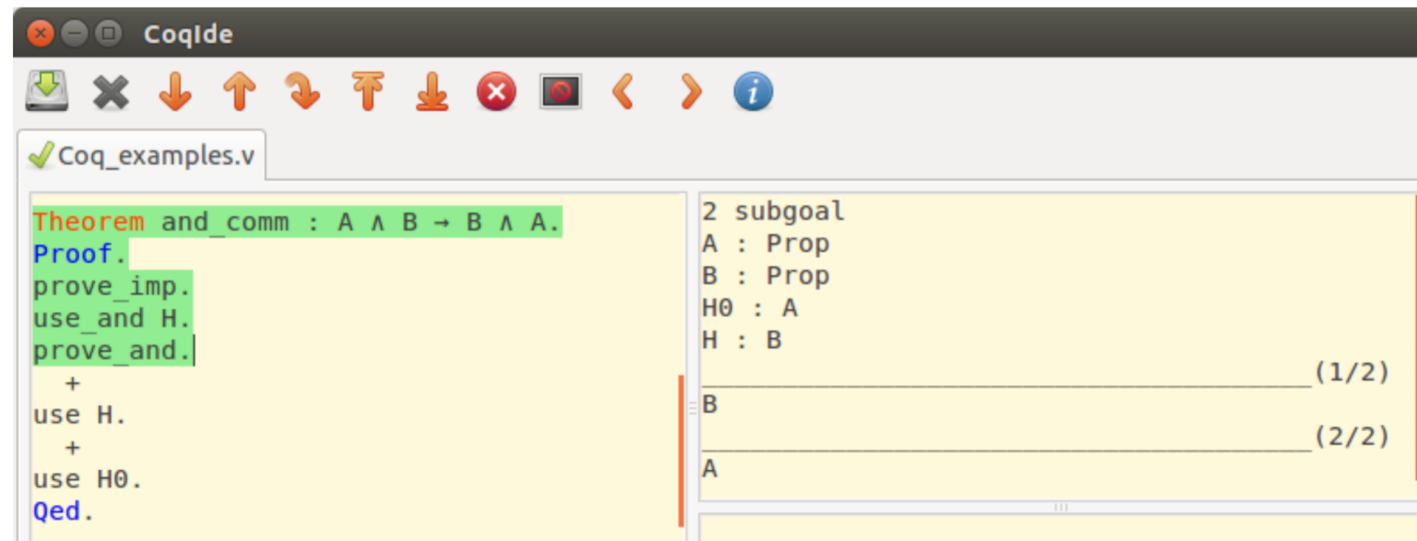
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Background

- Proof assistants (interactive theorem provers)
 - : software for mathematicians to write formal proofs
- ➡ Use them with machine learning (LLMs), to prove theorems automatically.



The screenshot shows the CoqIDE window with a file named 'Coq_examples.v'. The left pane contains the following code:

```
Theorem and_comm : A ∧ B → B ∧ A.  
Proof.  
  prove_imp.  
  use_and H.  
  prove_and.  
    +  
    use H.  
    +  
    use H0.  
Qed.
```

The right pane shows the proof state with two subgoals:

```
2 subgoal  
A : Prop  
B : Prop  
H0 : A  
H : B  
----- (1/2)  
B  
----- (2/2)  
A
```

Learning how to Prove: From the Coq Proof Assistant to Textbook Style – Figure 3 : The complete proof of $A \wedge B \rightarrow B \wedge A$.

Background

- **Previous aim** : to prove theorems fully autonomously without human intervention.

➡ Often fail to prove theorems

- **Present aim** :

Instead of proving theorems by itself, AI can also assist human mathematicians in theorem proving.

Lean

: A functional programming language that makes it easy to write correct and maintainable code.

- Starting from the theorem as the initial goal, tactics repeatedly transform the current goal into simpler sub-goals, until all goals are solved.
- **Tactics** : commands, or instructions, that describe how to build such a proof.
 - ex) $\text{rfl} : X = X, x+37 = 37+x$

$a + (b + 0) + (c + 0) = a + b + c.$ ➡ **Goal**

```
example (a b c : ℕ) : a + (b + 0) + (c + 0) = a + b + c := by
```

```
1 rw [add_zero]
2 rw [add_zero]
3 rfl
```

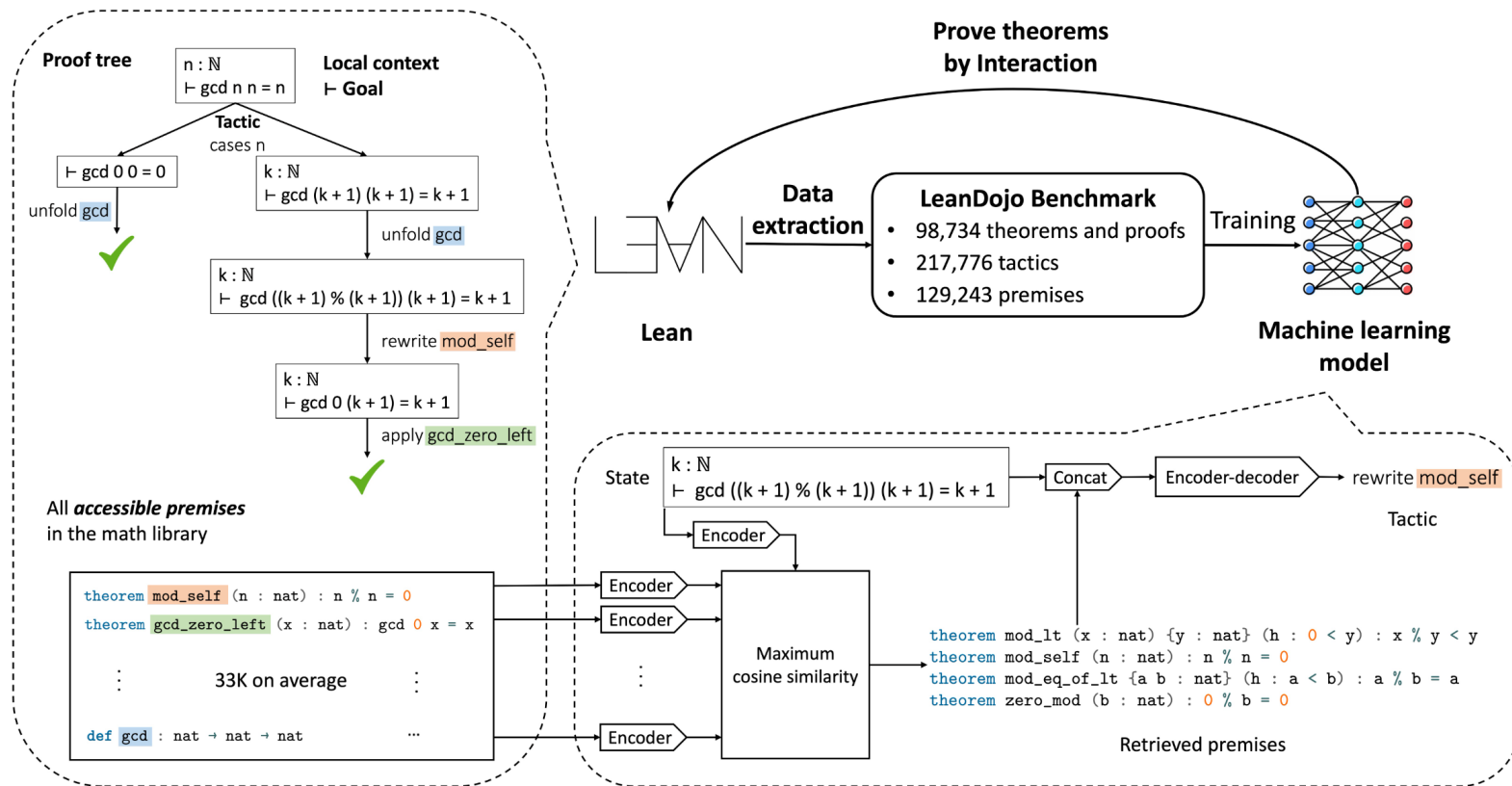
Lean Theorem Proving Tutorial website : <https://adam.math.hhu.de/-/g/leanprover-community/NNG4>

Lean Copilot

: A framework for developing LLM-based proof automation in Lean

- Works out of the box
- LeanDojo
- The model is small and efficient enough to run on most hardware

Overview of LeanDojo



<https://leandojo.org/>

Lean Copilot

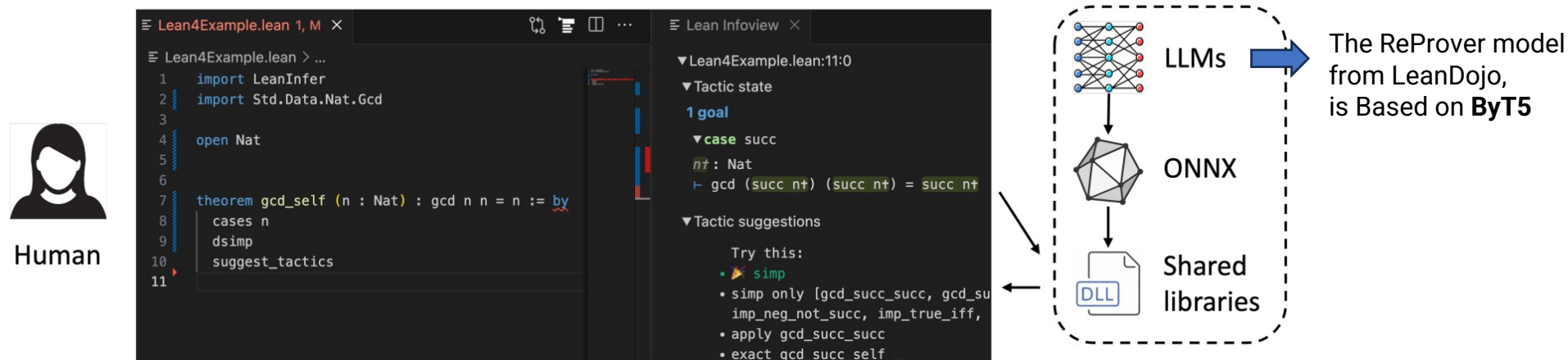


Figure 1: Large language models (LLMs) can assist humans in proving theorems. To prove the theorem `gcd_self` in Lean, the user enters two tactics manually (`cases n` and `dsimp`) and then calls `suggest_tactics`, which uses an LLM to generate four tactic suggestions, displayed in the infoview panel (Right). The LLM-generated tactic suggestion `simp` successfully proves the theorem.

- Convert the model into a platform-independent format, ONNX (Open Neural Network Exchange)
- Run it as a shared library through Lean's foreign function interface (FFI)

LLM-based proof automation

Use Lean Copilot to build two **tools** for **assisting** humans in theorem proving

1. ***suggest_tactic***

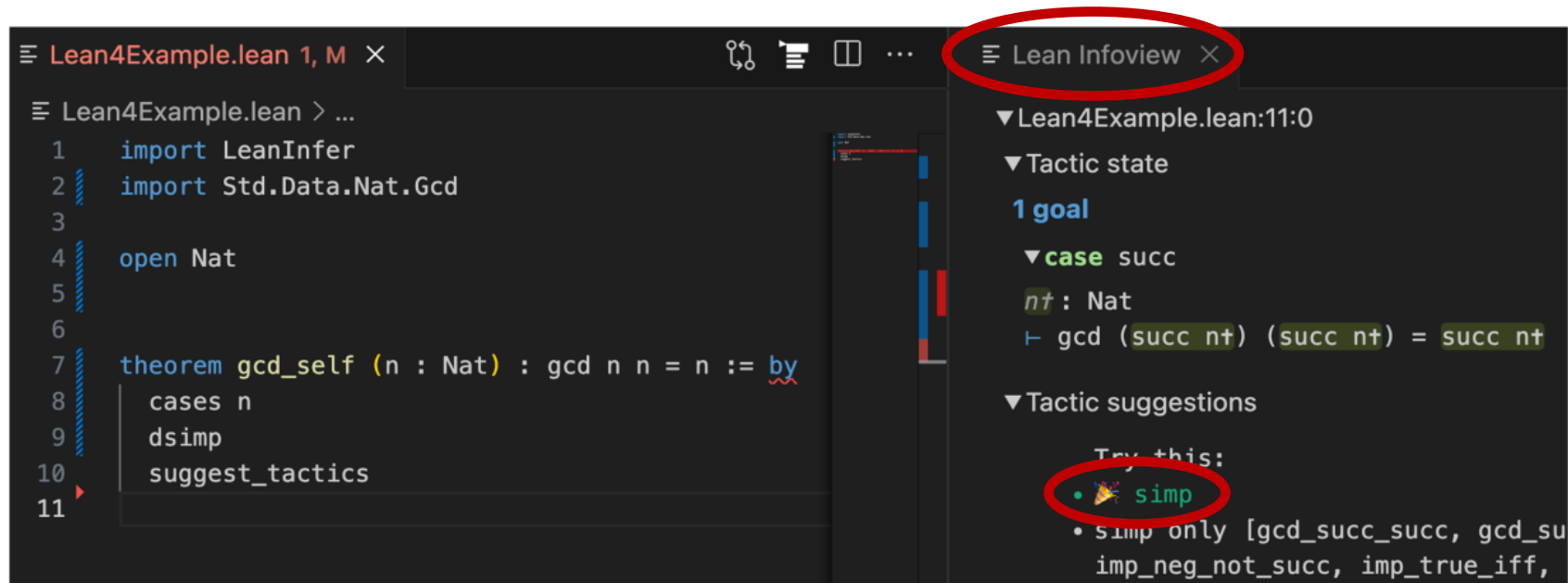
: a tactic that uses LLMs to suggest proof steps

2. **LLM-aesop**

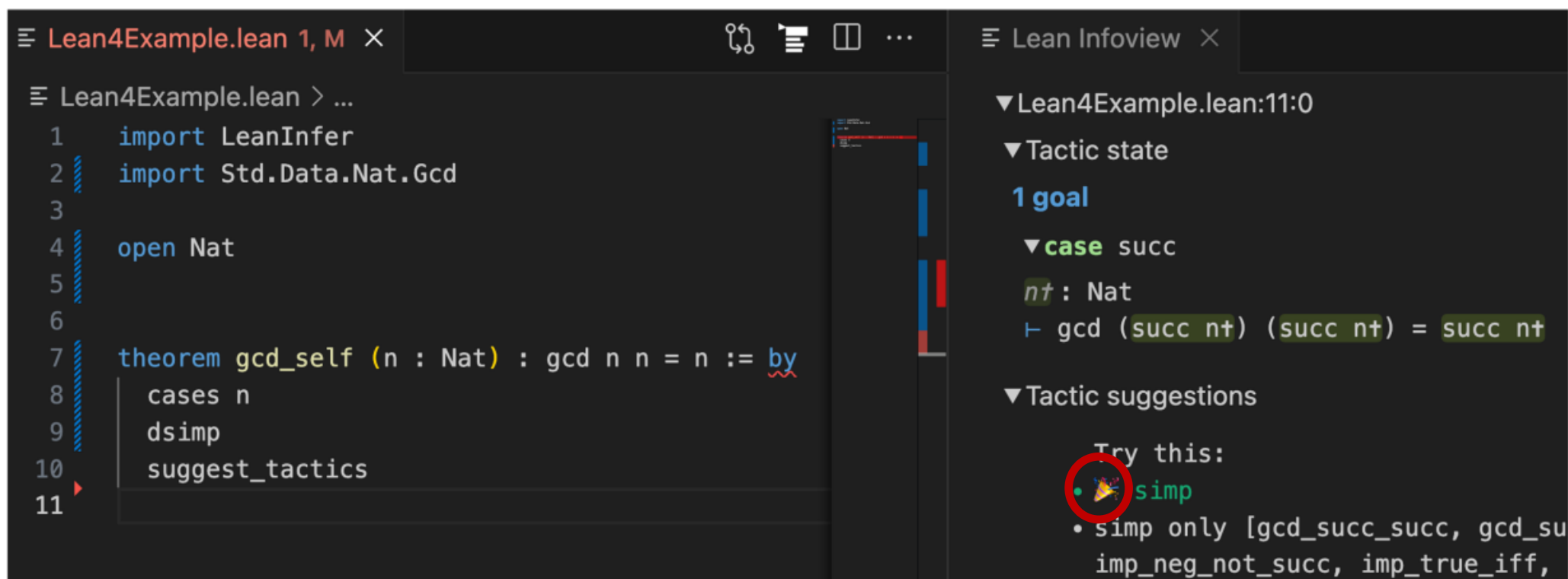
: a proof search tactic that combines LLM-generated proof steps with *aesop*

Suggest_tactic

- It feeds the current goal into an LLM and displays the generated tactics in the 'infoview panel'
- The user can choose whether to accept one of the suggestions by clicking on it
- Our frontend for displaying tactics is based on an existing tactic suggestion tool, *llmstep*
 - *llmstep* : A Lean 4 tactic for suggesting proof steps using a language model




Suggest_tactic



The screenshot shows the Lean4 IDE interface. On the left, the editor displays the file `Lean4Example.lean` with the following code:

```
1 import LeanInfer
2 import Std.Data.Nat.Gcd
3
4 open Nat
5
6
7 theorem gcd_self (n : Nat) : gcd n n = n := by
8   cases n
9   dsimp
10  suggest_tactics
11
```

On the right, the `Lean Infoview` panel shows the current state of the proof at line 11:

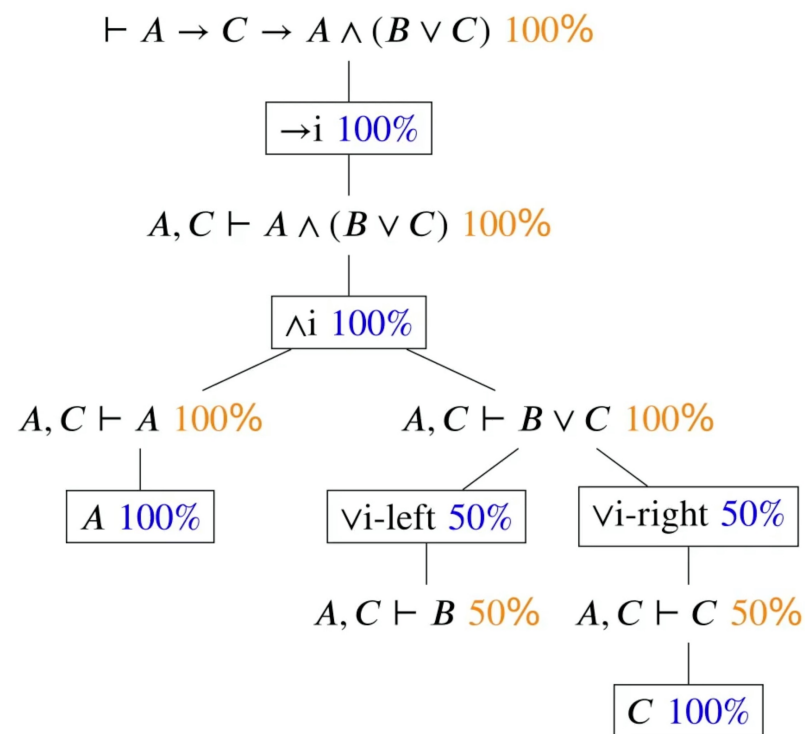
- ▼ Lean4Example.lean:11:0
- ▼ Tactic state
- 1 goal
- ▼ case succ
- $n+1 : \text{Nat}$
- $\vdash \text{gcd} (\text{succ } n+) (\text{succ } n+) = \text{succ } n+$
- ▼ Tactic suggestions
- Try this:
-  `simp`
- `simp only [gcd_succ_succ, gcd_su`
- `imp_neg_not_succ, imp_true_iff,`

- If a suggestion can directly solve the current goal, it is marked by a party popper emoji 🎉

LLM-aesop

- ***Suggest_tactics*** only generates tactics for the current step, without the capability to search for multi-tactic proofs.
- ➡ Combine it with ***aesop*** to build an LLM-based proof search tool named **LLM-aesop**.
- ***Aesop*** : Implements best-first search and allows users to configure how the search tree gets expanded.

Best-First Search



<https://url.kr/rduyo1>

LLM-aesop

- Aesop's performance depends critically on problem ➡ **LLM-aesop**
- Augments aesop's tactic set with goal-dependent tactics generated by ***suggest_tactics***.
- Allow tactics to be customized for each goal, which makes aesop substantially more flexible.
- A drop-in replacement of *aesop*
 - : Users can easily switch between LLM-aesop and the original aesop by activating/deactivating the LLM-generated tactics.

Experiments

To validate the effectiveness of **LLM-aesop** compared to *aesop* and *suggest_tactics* in two settings:

- (1) proving theorems autonomously
- (2) assisting humans in theorem proving.
- **Dataset** : Randomly selected 50 theorems in “[Mathematics in Lean](#)”
 - their proofs have 5.52 tactics on average
 - Data example

```
example : (a + b) * (a + b) = a * a + 2 * (a * b) + b * b := by
  rw [mul_add, add_mul, add_mul]
  rw [← add_assoc, add_assoc (a * a)]
  rw [mul_comm b a, ← two_mul]
```

Experiments

- **Setup**

- 1) To mimic a human user, we enter the ground truth tactics one by one.
- 2) After each tactic, we try to prove the remaining goals using an automated tool
: LLM-aesop, aesop, or suggest_tactics.
- 3) Record the number of tactics entered manually before the tool succeeds,
and the number is zero if it can prove the original theorem fully autonomously
without requiring human-entered tactics.

Experiments

- Results

Table 1: Performance of `suggest_tactics`, `aesop` and LLM-`aesop` on proving 50 theorems selected from “Mathematics in Lean” [20]. LLM-`aesop` outperforms both baselines in proving theorems autonomously and in assisting human users, requiring fewer tactics entered by humans. More detailed results can be found in Appendix B.

Method	Avg. # human-entered tactics (↓)	% Theorems proved autonomously (↑)
<code>aesop</code>	3.62	12%
<code>suggest_tactics</code>	2.72	34%
LLM- <code>aesop</code>	1.02	64%

➡ LLM-`aesop` can prove **64%** (32 out of 50) theorems autonomously,

which is significantly higher than `aesop` and `suggest_tactics`.

➡ When used to assist humans, LLM-`aesop` only requires an average of **1.02** manually-entered tactics, which also compares favorably to `aesop` (3.62) and `suggest_tactics` (2.72)

Conclusion

- Introduced Lean Copilot: a framework for running neural network inference in Lean through FFI.
 - Using Lean Copilot, have built LLM-based proof automation for generating tactic suggestions (`suggest_tactics`) and searching for proofs (LLM-aesop).
 - Lean Copilot provides an extendable interface between LLMs and Lean.
 - This work has explored how it enables LLMs to assist Lean users.
- ⇒ In the future, we hope to see LLM-based proof automation help us formalize mathematics and ultimately enhance LLMs' capability in mathematical reasoning.**

Reference:

Lean - <https://leanprover.github.io/lean4/doc/whatIsLean.html>

Tactic - https://leanprover-community.github.io/mathlib_docs/tactics.html#dsimp

Lean Theorem Probing Tutorial website : <https://adam.math.hhu.de/-/g/leanprover-community/NNG4>

Leandojo - <https://leandojo.org/>

Leancopilot - <https://github.com/lean-dojo/LeanCopilot>

ByT5 - <https://arxiv.org/abs/2105.13626>

Llmstep - <https://github.com/wellecks/llmstep?tab=readme-ov-file>

Pythia - <https://github.com/EleutherAI/pythia>

Aesop best-first search - <https://url.kr/rduyo1>

Mathematics in Lean - https://leanprovercommunity.github.io/mathematics_in_lean/