



# MATP-BENCH: Can MLLM Be a Good Automated Theorem Prover for Multimodal Problems?

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## Abstract

Numerous theorems, such as those in geometry, are often presented in multimodal forms (e.g., diagrams). Humans benefit from visual reasoning in such settings, using diagrams to gain intuition and guide the proof process. Modern Multimodal Large Language Models (MLLMs) have demonstrated remarkable capabilities in solving a wide range of mathematical problems. However, the potential of MLLMs as Automated Theorem Provers (ATPs), specifically in the multimodal domain, remains underexplored. In this paper, we introduce the **Multimodal Automated Theorem Proving benchmark (MATP-Bench)**, a new Multimodal, Multi-level, and Multi-language benchmark designed to evaluate MLLMs in this role as multimodal automated theorem provers. MATP-BENCH consists of 1056 multimodal theorems drawn from high school, university, and competition-level mathematics. All these multimodal problems are accompanied by formalizations in Lean 4, Coq and Isabelle, thus making the benchmark compatible with a wide range of theorem-proving frameworks. MATP-BENCH requires models to integrate sophisticated visual understanding with mastery of a broad spectrum of mathematical knowledge and rigorous symbolic reasoning to generate formal proofs. We use MATP-BENCH to evaluate a variety of advanced multimodal language models. Existing methods can only solve a limited number of the MATP-BENCH problems, indicating that this benchmark poses an open challenge for research on automated theorem proving. The benchmark is publicly available at <https://matpbench.github.io>.

## 1 Introduction

In recent years, with the rapid advancement of large language models (LLMs), increasing attention has been devoted to their applications in automated theorem proving (ATP) [3; 22; 49; 53; 57; 55; 61]. LLMs is trained to generate rigorous formal proofs, which are then verified by systems such as Lean 4 [31], Isabelle [54], and Coq [9] to ensure the logical soundness of the reasoning process.

Although substantial progress has been made in automating the theorem proving, existing studies are generally limited to text-based inputs, and their potential for handling a wide range of theorems involving multimodal information has not yet been fully explored. Many mathematical problems require presentation and solution through multimodal information, such as geometric proofs, where non-textual elements like diagrams are crucial for problem understanding and reasoning, and mere textual descriptions are often insufficient. Current mainstream datasets, such as MiniF2F [61] and ProofNet [3], mainly consist of textual theorems and lack support for multimodal theorem proving and multilingual proof verification. While LeanEuclid [32] includes multimodal Euclidean geometry theorems, it primarily focuses on automatic formalization rather than proof. AlphaGeometry [42], on

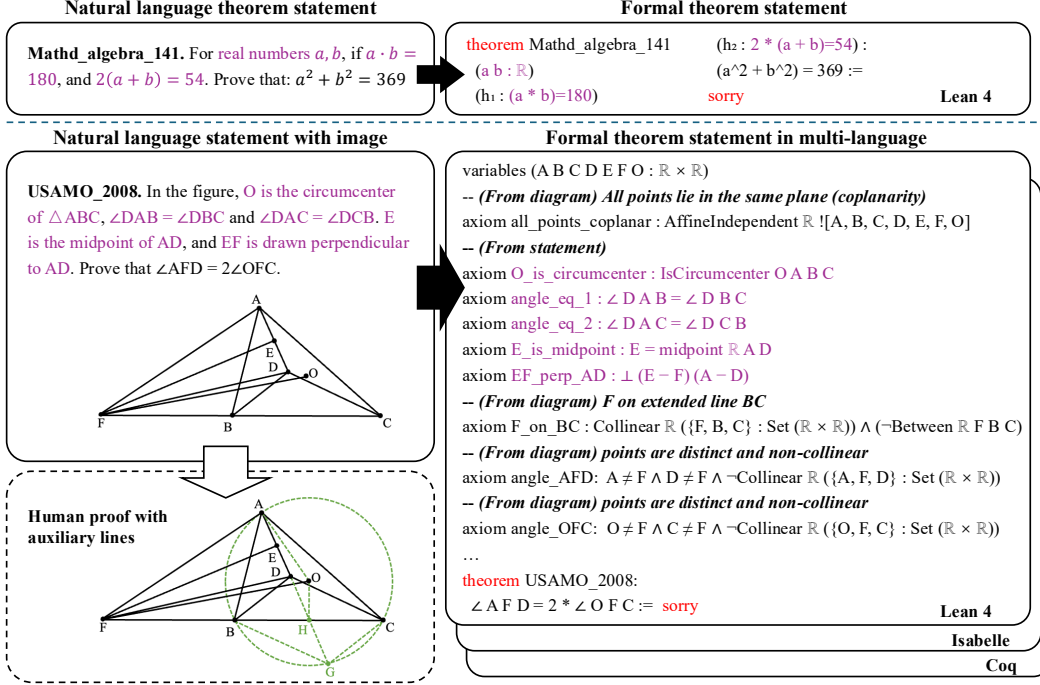


Figure 1: We illustrate the differences between traditional ATP and MATP through examples from miniF2F (above) and MATPBench (below). Multimodal theorems consist of an image paired with a natural language theorem statement, which complement each other to convey complete theorem information. Furthermore, additional auxiliary constructions are often essential for their proof (as shown in the bottom left subfigure). In traditional ATP, theorem formalization relies solely on textual statements (we use purple to indicate premises derived from the original statement), whereas MATP requires the model to extract critical premises not explicitly expressed in the text by analyzing accompanying diagrams (see *From diagram* on the right). We provide formalized versions of all multimodal theorems in Lean4, Coq, and Isabelle.

the other hand, can solve complex Olympiad geometry problems but is not multimodal and does not support verification in systems like Lean4.

Humans often rely on diagrams and visual structures to support mathematical reasoning. With the rapid progress of multimodal large language models (MLLMs), they have shown great potential in handling a wide range of mathematical problems [28; 51; 44; 43], even those at Olympiad competition levels [37; 48; 41]. However, the exploration of MLLMs as automated theorem provers for multimodal problems remains underexamined. Given their proficiency in multimodal comprehension, investigating their application in automated theorem proving could enable the handling of intricate proofs that rely on visual information, thereby pushing the boundaries of formal verification.

To this end, we present **Multimodal Automated Theorem Proving benchmark (MATP-Bench)**, a multimodal, multi-level, and multi-language benchmark for multimodal automated theorem proving (MATP). Our benchmark consists of 1056 multimodal theorems drawn from high school, university, and competition-level mathematics. Each theorem is accompanied by formal theorems in Lean 4 [31], Isabelle [54], and Coq [9], making the benchmark compatible with a wide range of theorem-proving frameworks. As shown in Figure 1, each data sample in MATP-BENCH consists of an image, a natural language theorem statement, and formal theorem statements in three different languages. Compared to traditional ATP, MATP requires the integration of reasoning across both language and visual modalities. This is particularly crucial in geometry-related mathematical problems, which often rely on mathematical structures conveyed through images, such as topological relations, that are typically difficult to express precisely in natural language. For humans, the reasoning process in such tasks involves not only drawing intuitive insights from visual representations but also constructing auxiliary diagrams and identifying implicit structural relations.

We use MATP-BENCH to evaluate a variety of multimodal language models. Our findings indicate that even current state-of-the-art models can only solve a limited number of problems, particularly when generating proofs in the Lean 4 language, where they perform poorly even for problems of only

high school difficulty. Detailed analysis further reveals that: (1) All evaluated models commonly exhibit issues with incomplete understanding of problem information and the generation of invalid formal proof steps, indicating deficiencies in their visual-symbolic joint reasoning capabilities; (2) While models demonstrate some ability in converting natural language questions and geometric figures into formal statements, they still face significant challenges in subsequent complex logical reasoning and the construction of correct formal proofs; (3) Models can introduce steps or concepts involving auxiliary constructions (e.g., auxiliary lines) in proofs, but they fail to effectively utilize these constructions to substantively advance the proof process. **In summary, our key contributions are as follows:**

(1) We introduce the Multimodal Automated Theorem Proving benchmark (MATP-Bench), which contains 1056 multimodal theorems drawn from high school, university, and competition-level mathematics. All these multimodal problems are accompanied by formalizations in Lean 4, Coq and Isabelle, thus making the benchmark compatible with a wide range of theorem-proving frameworks.

(2) We conduct extensive experiments on MATP-BENCH with six advanced multimodal language models of varying sizes. The experimental results show that even current state-of-the-art models can only solve a limited number of problems, particularly when generating proofs in the Lean 4 language, where they perform poorly even for problems of only high school difficulty.

(3) Our detailed analysis indicates that the primary bottleneck in current MATP task lies in symbolic reasoning and the construction of correct formal proofs. Although models have demonstrated an initial ability to introduce auxiliary constructions (e.g., auxiliary lines), they fail to effectively utilize these constructions to substantively advance the proof process. These findings offer valuable insights for future research. We release our datasets and code publicly at <https://matpbench.github.io>.

## 2 Related Work

**Automated Theorem Proving.** Automated theorem proving (ATP) has been a long-standing challenge in symbolic reasoning [40; 5; 61; 24], with substantial progress made in developing automated theorem provers [35; 36; 20; 47; 4; 18; 50]. In recent years, multiple benchmarks [19; 11; 58; 22] have been proposed for formal mathematical proof. MINIF2F [61] features a diverse collection of 488 problems, each formalized in languages including Lean 3, Metamath, Isabelle, and HOL Light. ProofNet [3] comprises 371 parallel formal and natural language theorem statements with proofs, designed to evaluate autoformalization and theorem proving. PutnamBench [49] is a multilingual benchmark for theorem provers, featuring 1,692 formalizations of 640 Putnam Competition problems. All problems are manually formalized in Lean 4 and Isabelle, with many in Coq. FIMO [24] contains 149 IMO Shortlisted Problems formalized in Lean, designed to advance automated theorem proving at the Olympiad level. LeanDojo [57] Benchmark is a large-scale theorem-proving dataset sourced from mathlib, featuring a evaluation split that requires generalization to unseen premises. Unlike existing benchmarks that focus exclusively on text-based theorem proving in single formal languages, MATP-BENCH establishes the exploration of multimodal automated theorem proving with multi-language formalization proofs.

**Multimodal Math Benchmarks.** Various benchmarks have been created to assess the mathematical reasoning capabilities of LLMs [1; 10; 30; 13; 15; 16; 23], with a growing number of specialized evaluations for MLLMs [27; 29; 28; 51]. GeoQA+ [6], UniGeo [7], GEOS [42], and Geometry3K [27] provide standardized benchmarks focused on plane geometry problem-solving. MMMU [59] offers a multi-disciplinary benchmark, incorporating a small subset of mathematical problems in multiple-choice format. MATHVERSE [60] is a visual math benchmark with 2,612 core problems, generating 15K test samples across plane geometry, solid geometry, and functions. MATHVISTA [28] includes 6,141 examples to assess mathematical and visual reasoning across diverse tasks. MATH-Vision [51] consists of 3,040 carefully selected problems with visual contexts, drawn from 19 real-world math competitions and spanning 12 grade levels. CMM-Math [26] is a Chinese multimodal math dataset with over 28,000 high-quality samples across 12 grades, covering diverse problem types and providing detailed solutions. MV-MATH [52] is a multimodal benchmark featuring 2,009 multi-image questions (up to 8 images per question), categorized into three question types and 11 K-12 math subjects at three difficulty levels. Although significant progress has been made in multimodal mathematical benchmarking, the exploration of automated theorem proving in multimodal settings remains limited. To address this gap, we propose MATP-BENCH, a benchmark that evaluates the

Table 1: Comparison of existing related benchmarks. MATP-BENCH is a **Multimodal, Multi-level, and Multi-language** benchmark designed to evaluate MLLMs as automated theorem provers.

Benchmark	Size	Verifiable	Theorem Proving	Theorem formalization	Multi-modal	Multi-level	Lean	Isabelle	Coq
miniF2F [61]	488	✓	✓			✓	✓	✓	
ProofNet [3]	371	✓	✓				✓		
Fimo [24]	149	✓	✓				✓		
Geometry3K-test [27]	601	✓			✓				
LeanEuclid [32]	173	✓		✓	✓	✓	✓		
PutnamBench [49]	640	✓	✓				✓	✓	✓
AlphaGeometry-test [48]	30	✓	✓		✓				
ProverBench [39]	325	✓	✓				✓		
GeoTrust-test [14]	240	✓			✓	✓			
MATPBench	1056	✓	✓	✓	✓	✓	✓	✓	✓

ability of MLLMs to integrate visual perception, mathematical reasoning, and symbolic manipulation to construct rigorous formal proofs. The detailed comparison between related benchmarks and MATPBENCH is shown in Table 1.

### 3 Problem Formulation

**Automated Theorem Proving (ATP).** In the ATP task [61; 3; 49; 24], the system takes a **formalized theorem statement**  $T$  as input, as shown in the upper part of Figure 1. The goal is to generate a formal proof  $P$  such that:

$$\text{Prover}_{ATP}(T) \rightarrow P, \quad \text{where } \text{Check}(T, P) = \text{True}.$$

Here, Check denotes the built-in proof verifier of the formal system (such as Lean, Coq, or Isabelle), which ensures that the generated proof  $P$  is a valid derivation of theorem  $T$ .

**Multimodal Automated Theorem Proving (MATP).** In the MATP task, the input to the MATP system is a pair  $(I, S)$ , where:

- $I$  is a **multimodal input** (e.g., geometric figure);
- $S$  is a **natural language statement of the theorem** (not formalized).

As shown in the bottom part of Figure 1, the natural language statement  $S$  and the information from the multimodal input  $I$  are complementary, together forming a complete theorem. Hence, the model must first generate the complete formal theorem  $T$ . Then, generates a valid formal proof  $P$ . The entire MATP task can be summarized as:

$$\text{Prover}_{MATP}(I, S) \rightarrow (T, P), \quad \text{where } \text{Check}(T, P) = \text{True}.$$

**Preventing Modality Leakage.** To avoid modality leakage, where the model could ignore visual inputs, we provide only natural language  $S$  and image  $I$ , without the formalized theorem  $T$ . This encourages the model to interpret and reason over multimodal inputs, as humans do when proving multimodal theorems. Furthermore, we incorporate a **formal theorem verification** task in the experimental setup to ensure that the formal theorems automatically generated by the multimodal model are consistent with the problem statement, rather than fabricating simple theorems arbitrarily.

### 4 MATP-BENCH

MATP-BENCH is a new Multimodal, Multi-level, and Multi-language benchmark designed to evaluate MLLMs as automated theorem provers. MATP-BENCH consists of 1056 multimodal theorems drawn from high school, university, and competition-level mathematics. Each theorem is accompanied by formalization in Lean 4, Isabelle, and Coq, making the benchmark compatible with a wide range of theorem-proving frameworks.

**Multimodal Context and Multi-language Theorem.** Compared to previous automated theorem proving datasets, which typically contain only plain-text theorems, MATP-BENCH introduces

concrete multimodal contexts to jointly evaluate models on visual understanding, mathematical reasoning, and symbolic manipulation. As shown in the lower part of Figure 1, each theorem consists of an image and a corresponding natural language description, which complement each other to form a complete statement. MATP-BENCH provides formalizations of these multimodal theorems in Lean 4, Isabelle, and Coq. To the best of our knowledge, MATP-BENCH is the first multimodal automated theorem proving benchmark covering all three of these languages. MATP-BENCH presents the following challenges: (1) **Visual Understanding**: The model must accurately extract key information from theorem-related images, akin to human perception, to construct formal theorem statements; (2) **Mathematical Reasoning**: It requires rigorous mathematical reasoning to derive complete proofs based on the provided natural language descriptions and images; (3) **Neural-Symbol Proof Generation**: The model must be proficient in these formal languages and capable of strictly translating the mathematical reasoning process into verifiable formal proof.

**Hierarchy and Diversity.** To comprehensively evaluate the potential of multimodal large language models (MLLMs) as automated theorem provers, MATP-BENCH has been meticulously designed to feature both clear hierarchy and rich diversity. Existing widely used benchmarks such as ProofNet [3] mainly focus on basic mathematical problems from early undergraduate courses, FIMO [24] is limited to high school mathematics, while PutnamBench [49] targets advanced mathematical reasoning at the undergraduate level. In contrast, as shown in Table 2, The problems in MATP-BENCH span three distinct educational stages—high school, university, and competitions—systematically

Table 2: Statistics summary of MATP-BENCH. Counts and percentages are provided for each category.

	Category	Count	Percentage
Level	High School	472	44.7%
	College	468	44.3%
	Competition	116	11.0%
Type	Plane Geometry	937	88.7%
	3D Geometry	73	6.9%
	Analytic Geometry	46	4.4%
Topic	Segment Relationships	355	33.6%
	Angle Relationships	282	26.7%
	Area Relationships	222	21.0%
	Circles and Tangents	86	8.1%
	Parallel and Perpendicular Lines	38	3.6%
	Similarity and Proportionality	25	2.4%
	Cyclic Quads & Common Points	20	1.9%
	Other	28	2.7%

covering a wide range of difficulty levels from elementary to advanced. Specifically, the high school and university problems are collected from publicly available multimodal math problem datasets [28; 51; 52; 27], while the competition problems are sourced from public Mathematical Olympiad examinations. Furthermore, we manually annotate the formal statements of each problem in three formal languages. This design ensures a thorough examination of models’ reasoning capabilities across different levels of complexity and mathematics problems. Moreover, the multimodal theorems in MATP-BENCH are primarily centered around the domain of geometry, spanning plane geometry, 3D geometry, analytic geometry. These theorems not only require models to demonstrate a solid grasp of fundamental geometric knowledge but also emphasize cross-modal understanding, complex reasoning, spatial modeling, and multi-step logical deduction, aiming to systematically evaluate models’ overall performance and depth of reasoning in structured mathematical tasks.

**Task Formulation.** As we mentioned in Section 3, we aim to achieve end-to-end multimodal automated theorem proving (Task 1), where the input is a natural language theorem and an image, and the output is a formal theorem and its proof, i.e.  $\text{Prover}_{\text{MATP}}(I, S) \rightarrow (T, P)$ . Furthermore, to prevent the model from generating formal theorems that do not align with original problems, we separately set up multimodal theorem formalization (Task 2) for verification, which aligns with LeanEuclid [32]. Thus, we divide the task into two progressively challenging sub-tasks:

- **Task 1: Multimodal Automated Theorem Proving**: This task aims to achieve end-to-end multimodal automated theorem proving similar to human provers, by directly generating a formalized theorem  $T$  and its proof  $P$  from multimodal informal input, i.e.  $\text{Prover}_{\text{Task1}}(I, S) \rightarrow (T, P)$ .
- **Task 2: Multimodal Theorem Formalization**: The prover receives the multimodal question, and is required to formalize it into a precise theorem  $T$ , formally denoted as

$\text{Prover}_{\text{Task1}}(I, S) \rightarrow T$ . This task evaluates the model’s ability to correctly understand and formalize information from both textual and visual modalities.

**Formalization Effort and Challenges.** Our formalization team consists of two doctoral students and several undergraduate students with backgrounds in advanced mathematics, computer science, and prior experience with formal proof assistants. The problems covers various question formats that we manually formalized on a case-by-case basis. Specifically: (1) Multiple-choice questions: we formalize these by using the correct answer and incorporating key information extracted from the accompanying image, reformulating the problem as a concrete theorem; (2) Fill-in-the-blank questions: the correct answer is directly filled into the problem statement, and the theorem is formalized by integrating relevant information present in the image; (3) Open-ended solution questions: we transform interrogative formulations into declarative statements based on the provided answer and combine them with visual cues from the image to construct a complete formal theorem. On average, fully formalizing a high school problem, a university problem, and a competition problem takes approximately 25, 30, and 15 minutes respectively (in one language). Among these, the descriptions of high school and university problem are relatively concise, with rich information contained in the images requiring preprocessing, while competition problems are more detailed and thus easier to formalize. Each formalization is reviewed by at least one other team member. In contrast to prior formalization tasks based solely on textual theorems, a central challenge in our setting lies in the incompleteness of the original natural language descriptions. Many essential assumptions are conveyed exclusively through diagrams. As a result, the formalization process requires manual identification and extraction of such visual information, such as geometric structures, to reconstruct a complete and rigorous formal statement.

## 5 Experiments

### 5.1 Experimental settings

**Methods:** we conduct extensive experiments on a wide variety of advanced multimodal large language models with different sizes. Specifically, the reasoning models [21; 38; 8] include OpenAI-o1 (o1 for short) [34], Claude-3.7-Sonnet-Thinking (Claude-3.7 for short) [2], and Gemini-2.0-Flash-Thinking (Gemini-2.0 for short) [12]; while the non-reasoning models include GPT-4.1 (GPT-4.1 for short) [33], Qwen2.5-VL-Instruct-70B (Qwen2.5-VL for short) [46], and Llama3.2-Vision-Instruct-11B (Llama3.2-V for short) [25].

**Metrics:** For **Task 1**, requires the model to generate both a correct formal theorem and its proof, we follow prior studies [61; 49; 24] and adopt  $\text{pass}@n$  ( $n=10$ ) as the evaluation metric. This metric evaluates whether the prover can successfully complete a valid proof within  $n$  attempts in the formal proof environment. For **Task 2**, which requires the model to formalize the multimodal theorem, we use GPT-4o as the judge to assess whether the theorem generated by the model is consistent with the our annotated ground truth. We also adopt  $\text{pass}@n$  as the evaluation metric. Details of the prompts for different tasks and evaluation can be found in Appendix F.

### 5.2 Main results

**Lean 4.** End-to-end complete multimodal theorem formalization and proof generation (Task 1) is an extremely challenging task. The overall performance of the models significantly declines with increasing theorem difficulty, dropping from 6.96% at the high school level to 3.12% at the university level and 2.08% at the competition level, highlighting the models’ shortcomings in handling complex geometric reasoning and generating rigorous formal proofs. Even for the currently strongest model, o1, its overall success rate ( $\text{pass}@10$ ) is only 5.68%. In contrast, Task 2 only required models to generate Lean 4 formal theorems based on multimodal input, and its overall success rate reached 46.81%. The significantly higher success rate of Task 2 indicates that the models’ ability to understand and convert natural language descriptions and geometric figures into Lean 4 formal statements .

**Coq.** In the Coq language tests, the overall success rate ( $\text{pass}@10$ ) for the end-to-end complete multimodal theorem formalization and proof generation (Task 1) task is 12.86%. Compared to the overall Task 1 success rate in Lean 4 (4.68%), the models demonstrate stronger proof generation capability in Coq. Nevertheless, the success rate still decreases with increasing theorem difficulty, although the drop appears less severe than in Lean 4. The o1 model ranks first with an overall success

Table 3: Experimental results of **Multimodal Automated Theorem Proving** (Task 1), which requires model to generate both formalized theorem and proof. We adopt *pass@10* as the evaluation metric. We further present the experimental results of *pass@n* (n=1, n=5) in Table 5 and 6.

Task 1	Method						Avg.
	OpenAI-o1	Claude-3.7	Gemini-2.0	GPT-4.1	Qwen2.5-VL	Llama3.2-V	
Lean 4 (pass@10)							
High school	7.63	7.20	8.47	<b>9.32</b>	2.12	3.58	6.39
University	<b>4.70</b>	3.85	2.14	2.99	1.50	1.92	2.85
Competition	1.72	1.72	0.86	<b>3.45</b>	0.00	0.00	1.29
Overall	5.68	5.11	4.82	<b>5.87</b>	1.61	2.46	4.62
Coq (pass@10)							
High school	<b>28.37</b>	22.47	14.76	28.27	7.59	6.96	18.07
University	11.75	<b>12.39</b>	4.27	6.62	5.34	4.91	7.55
Competition	5.45	4.31	1.72	<b>9.48</b>	0.86	0.17	3.67
Overall	<b>19.43</b>	16.92	8.71	16.64	3.59	7.37	12.15
Isabelle (pass@10)							
High school	<b>10.17</b>	8.90	7.84	11.23	4.03	3.60	7.63
University	<b>7.48</b>	5.34	3.63	4.49	2.78	3.21	4.49
Competition	0.86	<b>1.72</b>	0.00	2.59	0.00	0.00	0.86
Overall	<b>6.75</b>	5.9	4.11	6.39	2.27	2.45	4.65

Table 4: Experimental results of **Multimodal Theorem Formalization** (Task 2), which only require model to generate formalized theorem. We use GPT-4o as the judge and adopt *pass@10* as the evaluation metric. We present the experimental results of *pass@n* (n=1, n=5) in Table 7 and 8.

Task 2	Method						Avg.
	OpenAI-o1	Claude-3.7	Gemini-2.0	GPT-4.1	Qwen2.5-VL	Llama3.2-V	
Lean 4 (pass@10)							
High school	53.12	55.07	44.02	47.58	26.84	15.50	40.36
University	61.28	60.42	56.11	58.19	33.33	21.81	48.52
Competition	63.32	61.64	59.40	56.03	38.66	28.58	51.27
Overall	58.24	57.26	51.05	53.20	31.46	19.72	45.16
Coq (pass@10)							
High school	42.65	39.07	27.15	37.03	16.73	11.79	29.07
University	45.64	51.22	30.00	43.89	20.14	16.39	34.56
Competition	63.37	65.20	54.17	68.35	38.66	31.38	55.54
Overall	41.31	49.65	31.76	43.13	20.64	15.97	33.74
Isabelle (pass@10)							
High school	51.88	49.78	35.79	42.10	21.94	17.42	36.49
University	63.50	62.22	54.86	65.73	31.81	23.89	50.34
Competition	63.08	58.28	42.59	44.27	25.63	19.61	42.58
Overall	60.14	56.21	44.97	52.56	26.66	20.52	43.51

rate of 19.43%, performing particularly well at the high school level (28.37%). Task 2 (formalization only) in Coq has an overall success rate of 35.25%, far higher than Coq’s. Simultaneously, the models’ overall performance in generating proofs within the Coq environment is superior to that in Lean 4.

**Isabelle.** The overall success rate of Task 1 (4.71%) is comparable to that of Lean 4, but significantly lower than the overall success rate of Coq, indicating that models face similarly high challenges in performing end-to-end proof generation in the Isabelle environment as they do in Lean 4. The o1 model ranks first at the university difficulty level (7.48%). The performance of the Qwen2.5 and Llama3.2 models in Task 1 under the Isabelle environment remains at the lower end. Models’ ability

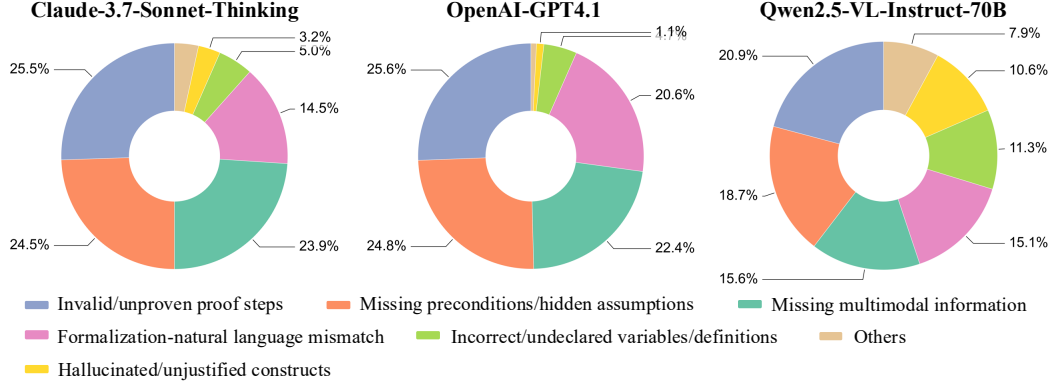


Figure 2: We perform an error analysis on the results of three different models (Lean 4), with the figure illustrating the seven most frequent error types.

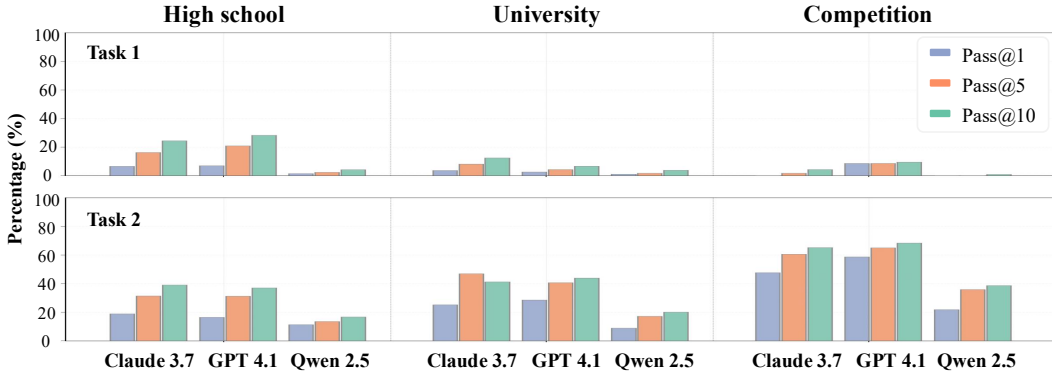


Figure 3: We present the performance of different MLLMs (Gemini-2.0-flash-thinking, OpenAI-GPT4.1, and Qwen2.5-VL-Instruct-70B) on multimodal theorem automated proving (Task 1) and theorem formalization (Task 2) across varying difficulty levels, evaluated using *Pass@1*, *Pass@5*, and *Pass@10* metrics.

to convert multimodal information into Isabelle formal statements is relatively good, similar to Lean 4, and superior to Coq.

### 5.3 Analysis of Error Distribution in Multimodal Automated Theorem Proving

We analyze the types of errors generated by multimodal models in theorem proving. As shown in Figure 2, the results indicate that different models exhibit both common errors and specific issues. For the Claude model, the most significant errors are concentrated in invalid/unproven proof steps (24.9%), missing preconditions/hidden assumptions (23.8%), and missing unformalized information (underutilizing multimodal information, 23.3%); these three categories collectively account for approximately 72% of its total errors. Similarly, the error distribution of the GPT-4.1 model is very similar. This suggests that even for relatively better-performing models, the core challenges lie in complex logical reasoning and identifying and utilizing all implicit and explicit information required by the theorem. The error distribution of the Qwen2.5 model, however, differs. While missing unformalized information (20.9%) and missing preconditions/hidden assumptions (18.7%) are also major errors, the proportion of invalid/unproven proof steps is relatively lower (15.6%), while more fundamental formalization errors such as missing/incorrect library imports (11.3%) and incorrect/undeclared variables/definitions (10.6%) are more prominent. This might indicate that while Qwen struggles with proof step errors, it also faces significant issues in generating basic code that conforms to the formal language specification. Overall, all models commonly exhibit problems with incomplete information understanding and broken reasoning chains.



## 5.4 Main Bottleneck in Multimodal Automated Theorem Proving

As shown in Figure 3, the analysis of the pass@n performance of multimodal models in the Coq language shows that for both complete theorem formalization and proof generation (Task 1) and formalization only (Task 2), allowing models to generate more candidates (from pass@1 to pass@10) generally increases the success rate. However, the pass@n success rate for Task 1 is significantly lower than the pass@n success rate for Task 2 across all difficulty levels and models. For example, at the high school difficulty level, the highest pass@10 for Task 1 reaches 28.27% for GPT-4.1, while the pass@10 for Task 2 for the same model reaches 37.03%. Notably, the pass@n values for Task 2, especially at the competition difficulty level, can even remain at a relatively high level (68.35% for GPT-4.1’s pass@10). This may be attributed to the fact that the problem descriptions for competition-level theorems are often more complete and precise, providing clearer formalization basis for the models, even if the proof process heavily relies on complex steps like constructing auxiliary lines (which is precisely why the Task 1 success rate is extremely low at this difficulty). This large performance gap between Task 1 and Task 2 is consistent across all pass@n settings, demonstrating that models have shown a certain ability in converting natural language descriptions and geometric figures into Coq formal statements (Task 2 pass@n is relatively high), but still face significant challenges in the subsequent complex logical reasoning and constructing formal proofs.

## 5.5 Model Capability in Generating Auxiliary Constructions for Multimodal Theorems

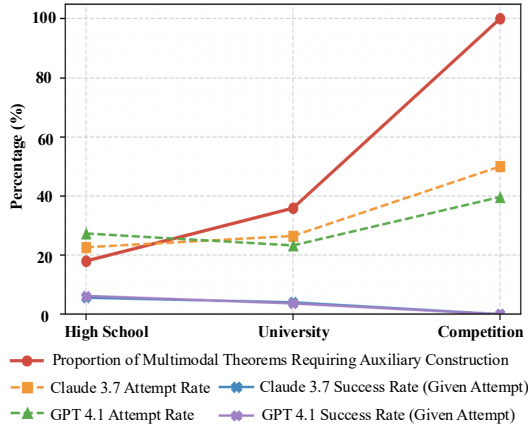


Figure 4: Auxiliary construction analysis by question difficulty level and model, evaluated using *Pass@10*.

A characteristic distinguishing multimodal theorem proving from pure text theorem proving is that many theorems require the construction of auxiliary lines to aid thinking, especially problems at the competition level. Therefore, we further investigate the models’ ability to construct auxiliary lines during the proof process. As shown in Figure 4, with the increase in theorem difficulty, the proportion of problems requiring auxiliary construction significantly rises, confirming the importance of auxiliary construction for solving high-difficulty geometric theorems. Claude 3.7 and GPT 4.1, which perform best in Task 1 and Task 2, attempt to perform auxiliary constructions when generating proofs, and this attempt rate also increases with difficulty, which indicates that the models possess a certain degree of autonomous auxiliary construction capability and awareness. However, the success rate of these proofs containing auxiliary construction

(Figure 4 blue and purple solid lines) is very low. This prominently indicates that while models can introduce steps or concepts involving auxiliary constructions in proofs, they cannot effectively utilize these constructions to advance the proof process. However, recent research shows that multimodal models can be augmented by visual prompts [17; 45; 56]. For example, Visual Sketchpad [17] demonstrates this potential by providing MLLMs with a visual sketchpad and drawing tools, which offers a promising direction for multimodal theorem proving.

## 6 Conclusion

In this paper, we introduce **Multimodal Automated Theorem Proving benchmark (MATP-Bench)**, a new multimodal, multi-level, and multi-language benchmark designed to evaluate MLLMs as automated theorem provers. MATP-BENCH consists of 1056 multimodal theorems drawn from high school, university, and competition-level mathematics. All these multimodal problems are accompanied by formalizations in Lean 4, Coq and Isabelle. Our experimental results demonstrate significant variability in the performance of various mainstream MLLMs. Our findings highlight the current capabilities and limitations of state-of-the-art MLLMs in automated theorem proving, and indicate that the primary bottleneck in current MATP task lies in the construction of correct formal proofs. These findings offer valuable insights for future research.

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Table 5: Experimental results of **Multimodal Automated Theorem Proving** (Task 1), which requires model to generate both formalized theorem and proof. We adopt *pass@5* as the evaluation metric.

Task 1	Method						Avg.
	OpenAI-o1	Claude-3.7	Gemini-2.0	GPT-4.1	Qwen2.5-VL	Llama3.2-V	
Lean 4 (pass@5)							
High school	4.03	3.39	5.51	5.08	1.48	2.54	4.06
University	2.78	1.71	1.50	3.38	0.86	1.72	2.12
Competition	0.00	0.86	0.00	1.72	0.00	0.00	0.74
Overall	3.03	2.27	3.12	3.69	1.04	1.61	2.78
Coq (pass@5)							
High school	18.78	16.24	8.65	20.89	3.58	4.43	13.62
University	6.84	8.12	3.85	4.27	2.56	3.21	4.98
Competition	1.72	1.72	0.86	8.62	0.00	0.00	2.95
Overall	11.63	11.08	5.67	12.19	2.65	3.40	8.62
Isabelle (pass@5)							
High school	6.78	5.30	4.45	7.84	2.54	1.91	5.27
University	4.70	3.42	2.14	3.82	1.92	2.35	3.17
Competition	0.86	1.72	0.00	2.59	0.00	0.00	0.99
Overall	4.11	3.48	2.2	4.97	1.49	1.42	3.14

Table 6: Experimental results of **Multimodal Automated Theorem Proving** (Task 1), which requires model to generate both formalized theorem and proof. We adopt *pass@1* as the evaluation metric.

Task 1	Method						Avg.
	OpenAI-o1	Claude-3.7	Gemini-2.0	GPT-4.1	Qwen2.5-VL	Llama3.2-V	
Lean 4 (pass@1)							
High school	2.75	2.54	3.18	<b>3.39</b>	0.85	1.48	2.60
University	1.50	0.85	0.43	<b>2.85</b>	0.43	0.64	1.32
Competition	0.00	<b>0.86</b>	0.00	0.00	0.00	0.00	0.00
Overall	1.89	1.52	1.61	<b>2.56</b>	0.57	0.95	1.73
Coq (pass@1)							
High school	<b>10.13</b>	6.54	3.59	6.96	1.48	3.16	5.71
University	<b>4.91</b>	3.63	1.28	2.56	1.07	1.44	2.68
Competition	0.00	0.00	0.86	<b>7.62</b>	0.00	0.00	2.20
Overall	<b>6.72</b>	4.54	2.27	5.20	1.13	2.08	3.95
Isabelle (pass@1)							
High school	<b>4.24</b>	3.60	2.97	4.87	1.27	0.85	3.24
University	<b>3.28</b>	2.14	0.85	2.14	1.07	1.28	1.86
Competition	0.00	<b>1.72</b>	0.00	0.86	0.00	0.00	0.25
Overall	<b>3.18</b>	1.91	1.27	2.62	0.78	0.71	1.78

## A Examples of questions at different levels

In Figure 6 and Figure 7, we show high school and university-level problems respectively, with Figure 1 featuring competition-level questions.

## B Multimodal Automated Theorem Proving

Tables 5 and 6 present the experimental results for Task 1, evaluating multimodal automated theorem proving using *pass@5* and *pass@1* metrics, respectively, across Lean 4, Coq, and Isabelle formal languages and three difficulty levels. Comparing the two tables, it is evident that providing models

Table 7: Experimental results of **Multimodal Theorem Formalization** (Task 2), which only requires model to generate formalized theorem. We adopt *pass@5* as the evaluation metric.

Task 2	Method						Avg.
	OpenAI-o1	Claude-3.7	Gemini-2.0	GPT-4.1	Qwen2.5-VL	Llama3.2-V	
Lean 4 (pass@5)							
High school	49.64	47.58	39.36	42.92	24.70	13.58	38.17
University	60.14	58.89	52.36	55.00	30.83	21.27	48.06
Competition	60.52	58.84	55.47	52.11	36.42	25.90	50.45
Overall	55.48	53.82	46.88	49.27	28.38	55.17	41.93
Coq (pass@5)							
High school	38.95	31.40	23.45	31.27	13.54	9.87	26.34
University	45.83	46.89	25.83	40.69	17.22	14.31	32.48
Competition	63.58	60.52	53.23	65.04	35.86	30.26	53.39
Overall	44.85	39.91	27.77	39.14	18.06	14.07	32.08
Isabelle (pass@5)							
High school	43.16	42.37	30.44	45.52	19.34	15.63	33.42
University	61.67	60.83	48.61	57.36	29.03	21.67	48.73
Competition	57.72	54.91	37.54	38.10	21.45	16.81	40.77
Overall	52.39	50.91	39.26	45.46	23.96	18.43	41.03

with more attempts (*pass@5* vs *pass@1*) generally leads to higher success rates across all models, formal languages, and difficulty levels, highlighting the benefit of multiple decoding attempts in this task. Analyzing the *pass@5* results in Table 5, among the individual models, GPT-4.1 consistently ranks among the top performers under *pass@5*, showing notable strength in handling higher difficulty levels. Gemini-2.0, Qwen2.5-VL, and Llama3.2 generally achieve lower pass rates across most tasks and difficulty levels under *pass@5*.

The *pass@1* results in Table 6, which assesses the model’s ability to generate a correct proof on the very first attempt, are considerably lower across the board. The relative ranking of models shifts for some languages under this stricter metric. GPT-4.1 still demonstrates relative strength at the competition level even at *pass@1* in Coq (7.62%) and Isabelle (0.86%), suggesting some capability for direct high-difficulty solutions. The performance difference between *pass@5* and *pass@1* highlights that while all models benefit from retries, some models, appear to leverage multiple attempts more effectively to find a successful proof compared to their initial attempt performance, whereas others, like o1 in Coq and Isabelle, are relatively stronger at generating a correct proof on the first try.

## C Multimodal Theorem Formalization

Tables 7 and 8 present the experimental results for Multimodal Theorem Formalization (Task 2), which evaluates models on generating formalized theorems using *pass@5* and *pass@1* metrics across Lean 4, Coq, and Isabelle. As expected, *pass@5* scores consistently exceed *pass@1* scores, indicating that multiple attempts improve formalization accuracy. However, compared to full proof generation (Task 1), the relative increase from *pass@1* to *pass@5* appears less dramatic for Task 2, suggesting that models capable of formalizing a theorem often do so successfully on earlier attempts. Overall, for theorem formalization, models achieve considerably higher pass rates than for proof generation, highlighting that generating the correct theorem statement is a less challenging task than generating the complete proof.

Analyzing the results, o1 demonstrates particular strength in first-attempt formalization (*pass@1*), frequently leading in Coq and Isabelle. Models like Claude-3.7 and GPT-4.1 show competitive performance in specific languages or difficulty tiers, while others generally trail. These results indicate that while current models are significantly better at theorem formalization than full proof generation, their ability to accurately formalize theorems still varies depending on the specific formal language and problem complexity, with o1 showing notable capabilities in this task.

Table 8: Experimental results of **Multimodal Theorem Formalization** (Task 2), which only requires model to generate formalized theorem. We adopt *pass@1* as the evaluation metric.

Task 2	Method						Avg.
	OpenAI-o1	Claude-3.7	Gemini-2.0	GPT-4.1	Qwen2.5-VL	Llama3.2-V	
Lean 4 (pass@5)							
High school	33.05	30.72	24.14	26.19	13.71	7.68	24.80
University	45.61	45.82	35.14	37.22	20.56	13.8	35.07
Competition	43.15	39.78	36.98	33.06	24.66	19.05	35.16
Overall	40.24	38.21	30.41	31.82	17.94	11.67	30.52
Coq (pass@1)							
High school	27.66	18.92	18.10	16.46	11.38	8.68	17.73
University	35.49	25.28	12.92	28.61	8.89	5.36	21.94
Competition	57.26	47.63	34.18	58.72	21.85	12.61	41.72
Overall	34.62	24.88	17.57	26.36	11.43	8.35	22.13
Isabelle (pass@1)							
High school	23.68	26.31	15.77	16.73	10.97	8.78	18.29
University	51.19	49.86	27.36	53.33	18.19	13.47	36.35
Competition	35.66	31.70	21.85	26.34	12.89	8.95	25.46
Overall	37.18	39.76	21.56	29.55	14.38	10.87	26.97

## D Performance Comparison Across Formal Languages

Figure 5 and the associated data illustrate the performance of Claude 3.7, GPT 4.1, and Qwen 2.5 on multimodal theorem proving tasks across Lean 4, Coq, and Isabelle, evaluated by Pass@1, Pass@5, and Pass@10 metrics across varying difficulty levels. The results consistently demonstrate that model performance significantly decreases with increasing task difficulty and improves with a greater number of allowed attempts, with Pass@10 achieving the highest pass rates. Among the evaluated models, GPT 4.1 generally exhibits the strongest performance across most formal languages and difficulty levels, particularly excelling in challenging scenarios. Claude 3.7 typically ranks as the second-best performer, while Qwen 2.5 consistently shows the lowest pass rates. Performance also varies by formal language, with models often achieving higher success rates in Coq compared to Lean 4 and Isabelle. The substantial difference between Pass@1 and Pass@10 highlights the models’ ability to find correct proofs with multiple tries, although overall performance remains low on complex competition-level problems for all evaluated models.

## E Limitations

This paper evaluates the capabilities of various mainstream language models in multimodal automated theorem proving. We select three different formal languages—Lean 4, Coq, and Isabelle—for testing, and compare the performance (primarily using pass@10 as the metric) of general language models including o1, Claude-3.7, Gemini-2.0, GPT-4.1, Qwen2.5-VL, and Llama3.2-Vision on problems of varying difficulty levels. Although this study provides a exploration into the application of language models in the domain of formal proof, it also has several limitations. Firstly, the testing of language models in this paper primarily involves one-shot generation of formal theorems and proofs, and does not explore multi-step or interactive proof generation capabilities. Secondly, the analysis of the model is primarily based on its final results, without delving into its internal mechanisms or the specific impact of different reasoning steps on performance. Future work could consider employing more comprehensive datasets, exploring richer evaluation scenarios such as multi-step and interactive proof generation, and conducting a more in-depth mechanistic analysis of the models’ proof generation process.



## F Prompts

We present prompts for different tasks in Figure 8 and Figure 10 respectively.

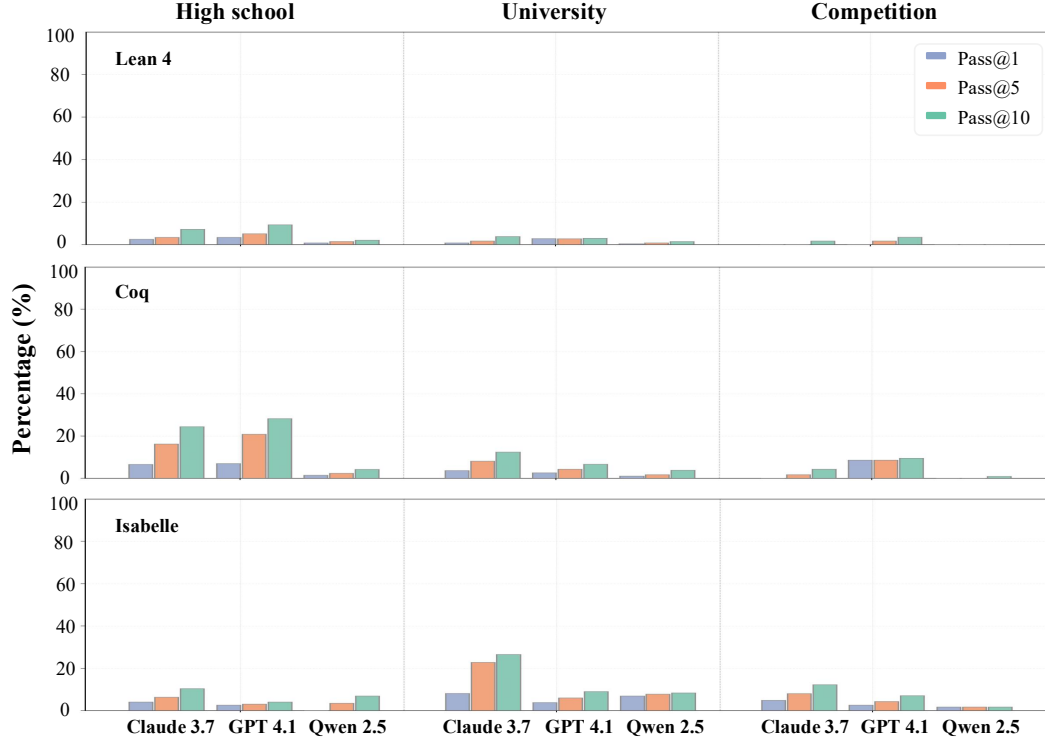


Figure 5: We present the performance of different MLLMs (Gemini-2.0-flash-thinking, OpenAI-GPT4.1, and Qwen2.5-VL-Instruct-70B) on multimodal automated theorem proving task across varying difficulty levels, evaluated using *Pass@1*, *Pass@5*, and *Pass@10* metrics.

### Example Question of High School Level

Proof Coplanar squares  $ABGH$  and  $BCDF$  are adjacent, with  $CD = 10$  units and  $AH = 5$  units. Point  $E$  is on segments  $AD$  and  $GB$ . The area of triangle  $ABE$ , in square units, is  $\frac{25}{3}$ .

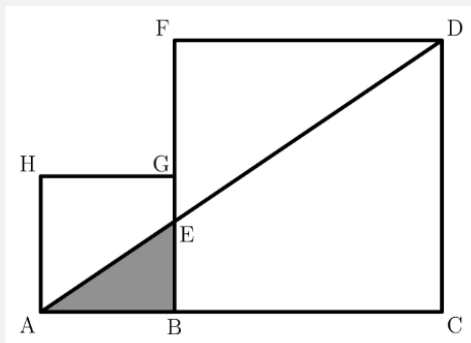


Figure 6: Examples question of high school level.

### Example Question of University Level

Proof A regular icosahedron is a 20-faced solid where each face is an equilateral triangle and five triangles meet at every vertex. The regular icosahedron shown below has one vertex at the top, one vertex at the bottom, an upper pentagon of five vertices all adjacent to the top vertex and all in the same horizontal plane, and a lower pentagon of five vertices all adjacent to the bottom vertex and all in another horizontal plane. Find the number of paths from the top vertex to the bottom vertex such that each part of a path goes downward or horizontally along an edge of the icosahedron, and no vertex is repeated is 810.

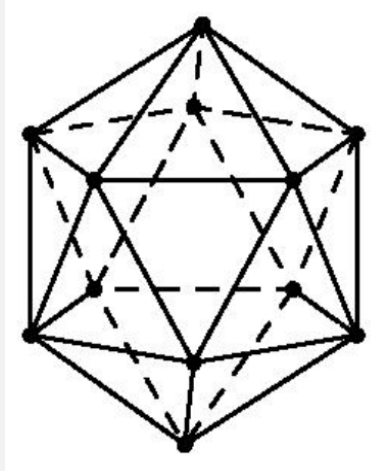


Figure 7: Examples question of university level.

### Prompt for Multimodal Automated Theorem Proving

You are a formal mathematical assistant. Given a natural language description of a theorem and an accompanying diagram, your task is to generate a formal, unambiguous, and complete version of the theorem using Lean 4 formal language, without providing any proof. Note: This is a multimodal theorem formalization task. The natural language description alone may be incomplete or ambiguous, and the diagram contains essential geometric, positional, or structural information required to construct the full formal statement. You must carefully extract and integrate information from both the text and the diagram to ensure the resulting formal theorem is correct, complete, and self-contained. Your output should only include the Lean 4 code block defining the theorem, and follow the style of the following examples (with appropriate imports, variable declarations, hypotheses, and theorem statement):

Here are a few complete form theorem examples:

Example 1:

**Image:** (image1)

**Natural language theorem statement:** Let  $\triangle ABC$  satisfy  $\angle CAB < \angle BCA < \frac{\pi}{2} < \angle ABC$ . If the bisector of the external angle at  $A$  meets line  $BC$  at  $P$ , the bisector of the external angle at  $B$  meets line  $CA$  at  $Q$ , and  $AP = BQ = AB$ , find  $\angle CAB$ .

**Output (Formal theorem using Lean4 language):**

```
import Mathlib

open MeasureTheory

theorem example
  (A B C X Y : EuclideanSpace ℝ (Fin 2))
  (hABC : Collinear ℝ {A, B, C})
  (hangles :  $\angle C A B < \angle B C A \wedge \angle B C A < \pi/2 \wedge \pi/2 < \angle A B C$ )
  (hX : Collinear ℝ {X, B, C}  $\wedge \angle X A B = (\pi - \angle C A B)/2 \wedge \text{dist } A X = \text{dist } A B$ )
  (hY : Collinear ℝ {Y, C, A}  $\wedge \angle Y B C = (\pi - \angle A B C)/2 \wedge \text{dist } B Y = \text{dist } A B$ )
  :  $\angle C A B = \text{example} :=$ 
sorry
```

Figure 8: Prompt for multimodal automated theorem proving task (part1).

### Prompt for Multimodal Automated Theorem Proving

Example 2:

**Image:** (image2)

**Natural language theorem statement:** Let  $a$ ,  $b$ , and  $c$  be the side lengths of a triangle with inradius  $r$ . If  $p = \frac{a+b+c}{2}$ , show that

$$\frac{1}{(p-a)^2} + \frac{1}{(p-b)^2} + \frac{1}{(p-c)^2} \geq \frac{1}{r^2}.$$

**Output (Formal theorem using Lean4 language):**

```
import Mathlib

theorem putnam_a2
(r : ℝ)
(A B C : EuclideanSpace ℝ (Fin 2))
(hABC : Collinear ℝ {A, B, C})
(a b c p : ℝ)
(ha : a = dist B C)
(hb : b = dist C A)
(hc : c = dist A B)
(hp : p = (dist B C + dist C A + dist A B)/2)
(hr : ∃ I : EuclideanSpace ℝ (Fin 2),
  (∃! P : EuclideanSpace ℝ (Fin 2), dist I P = r ∧ Collinear ℝ {P,
    ↪ B, C}) ∧
  (∃! Q : EuclideanSpace ℝ (Fin 2), dist I Q = r ∧ Collinear ℝ {Q,
    ↪ C, A}) ∧
  (∃! R : EuclideanSpace ℝ (Fin 2), dist I R = r ∧ Collinear ℝ {R,
    ↪ A, B}) ∧
  (∀ Z : EuclideanSpace ℝ (Fin 2), dist I Z ≤ r → Z ∈ convexHull
    ↪ ℝ {A, B, C}))
: 1/(p - a)^2 + 1/(p - b)^2 + 1/(p - c)^2 ≥ 1/r^2 :=
sorry
```

Strict Instructions:

- Only output the formal theorem in Lean 4, including all necessary imports, variable declarations, hypotheses, and the theorem statement.
- Do NOT include any proof or attempt to prove the theorem.
- Explicitly indicate that this is an unproven theorem by ending the statement with `:= sorry`.
- Do not use `by`, `exact`, or any other proof-related keywords.

Figure 9: Prompt for multimodal automated theorem proving task (part2).

### Prompt for Multimodal Theorem Formalization

You are a formal mathematical assistant specializing in **multimodal theorem proving**. Given a natural language description of a mathematical theorem and a related diagram, your task is to:

- **Jointly interpret both the text and the image**, extracting all relevant mathematical information, including geometric or algebraic configurations, object relationships, and any labeled points, angles, lines, circles, or symbols present in the diagram.
- When the **natural language description is incomplete or ambiguous**, you must infer and complete the necessary assumptions or details based on the visual content of the image.
- Formulate a **precise, unambiguous, and self-contained formal statement** of the theorem in the **Lean 4 proof assistant language**, including all necessary variable declarations and hypotheses.
- Construct a **complete, rigorous, and correct formal proof** of the theorem in Lean 4, ensuring that it passes verification in the Lean 4 environment.
- The formalization must be **independent and fully self-contained**, requiring no reference to the original natural language or image once generated.

Your output must consist of **Lean 4 code only**, and include the following components:

- All required `import` statements.
- Declarations of all relevant variables, structures, and assumptions derived from both the text and the image.
- A clear and precise formal statement of the theorem.
- A complete and logically sound proof written in Lean 4, suitable for direct verification.

Follow the conventions and style used in the **Lean 4 mathlib** library to ensure correctness, consistency, and readability.

Now, the output must follow the exact style of the examples:

**Image:** (image upload)

**Natural language theorem statement:** row["NL\_statement"]

**Output (Lean 4 code only):**

Figure 10: Prompt for multimodal theorem formalization task.

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