AlphaGeometry: Solving olympiad geometry without human demonstrations

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IMO 2004 P1:

"Let ABC be an acute-angled triangle with AB ≠ AC.
The circle with diameter BC intersects the sides AB and AC at
M and N respectively. Denote by O the midpoint of the side
BC. The bisectors of the angles ∠BAC and ∠MON intersect
at R. Prove that the circumcircles of the triangles BMR and
CNR have a common point lying on the side BC."

```
Translate
A B C O M N R P : Points
mid_point(0,B,C)
                   [00] OM=OB [01
same_line(B, M, A)
-same_line(N,C,A) [02] ON=OB [03]
∠BAR=∠RAC [04] ∠MOR=∠RON [05]
circle(B,M,R,P) [06] circle(C,N,R,P) [07]
                                                                        Generalize
same_line(P, B, C)
[01][03] ⇒ ∠ONM=∠NMO [08]
[01][03][05] ⇒ RN=RM [09]
[01][03][09] ⇒ NM ⊥ OR [10]
AUXILIARY POINT K : KM = KN
[01][03] KM = KN ⇒ MN ⊥ KO [12]
AUXILIARY POINT L : KL = KA, OL = OA
KL = KA, OL = OA \Rightarrow KO \perp AL [15] \angle AKO = \angle OKL [16]
[15][12][10][16][13] \Rightarrow RA=RL [17]
OL = OA \Rightarrow \angle OAL = \angle ALO [18]
angle-chase:[12][15][08][18]⇒∠NOA=∠LOM [19]
[01][03]OL = OA[19] \Rightarrow AN=LM [21]
[17][21][09] \Rightarrow \angle NAR = \angle RLM [22]
[02][04][00][22] \Rightarrow circle(L,M,A,R) [23]
similar ⇒ circle(R,L,N,A) [24]
[23][24] \Rightarrow \angle RMA = \angle RNA [25]
     ⇒ ∠BPR=∠BMR [26]
 07] ⇒ ∠NCP=∠NRP [27]
[00][02][25][26][27] ⇒ PC // BP
⇒ same_line(B,P,C)
```

ABC Unused premises

ABC Used premises

ABC Neural net output

ABC Symbolic solver output

AlphaGeometry overview

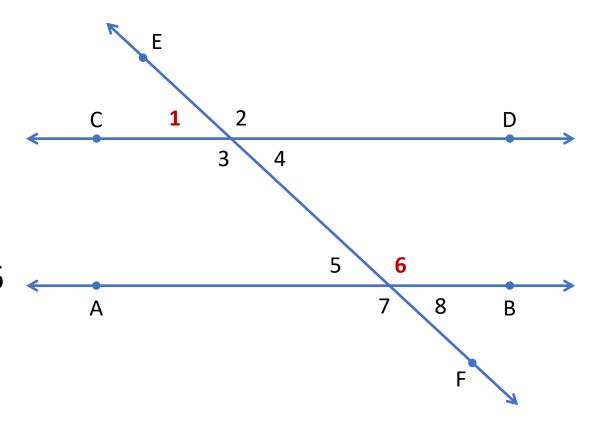
- Solves Euclidean plane geometry proofs from International Mathematical Olympiad contest problems, achieving SOTA
- Combines off the shelf symbolic deduction engine with an LLM
 - Symbolic engine expands list of facts by matching thousands of theorem premises with existing facts, calculating the closure
 - LLM suggests new objects to construct, allowing further deduction
 - The space of auxiliary construction is huge, so LLM must reason well
- They solved the training data problem by generating synthetic proofs
- LLM was pretrained on full proofs, then fine-tuned on subset requiring auxiliary construction

Symbolic deduction engine

- Symbolic deduction engine has a database of geometric rules
 - They added algebraic rules
- Rules are Horn clauses of the form $Q(x) \leftarrow P_1(x_1), P_2(x_2), ..., P_k(x_k)$
 - Each P_i or Q is a predicate such as "equal segments" or "collinear"
 - Each x is a set of one or more point objects
- If all of the needed P's are matched, then Q(x) is added to the list of known facts
- The symbolic engine alone will solve simpler proofs that don't require constructing additional objects, but it won't construct new objects
- Existing techniques and code generally ran in seconds

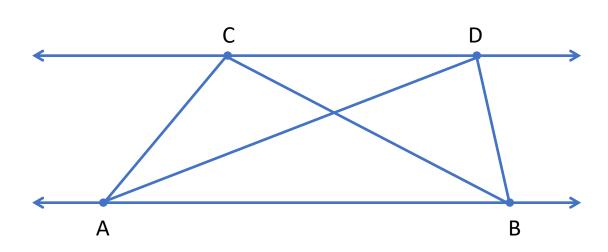
Deduction example

- We want to prove that angle 1 and angle 6 are supplementary, given parallel lines AB and CD
- First, symbolic engine might prove that angle 1 equals angles 4, 5, and 8
- Then, it might prove that angle 6 and angle 8 are supplementary
- Combining the above two, we have shown that angle 1 and angle 6 are supplementary



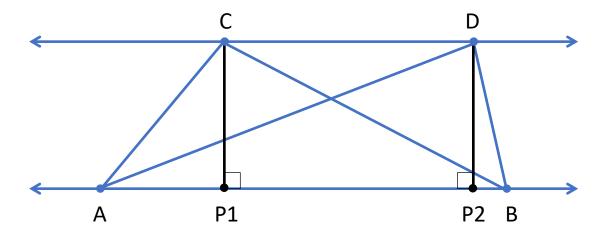
Deduction insufficiency example [1]

 We want to prove that triangle ABC and triangle ABD have the same area, given parallel lines AB and CD



Deduction insufficiency example [2]

- We want to prove that triangle ABC and triangle ABD have the same area, given parallel lines AB and CD
- Adding two points P1 and P2 allows us to show the heights of both triangles are the same
- Since both share the same base, the areas are the same



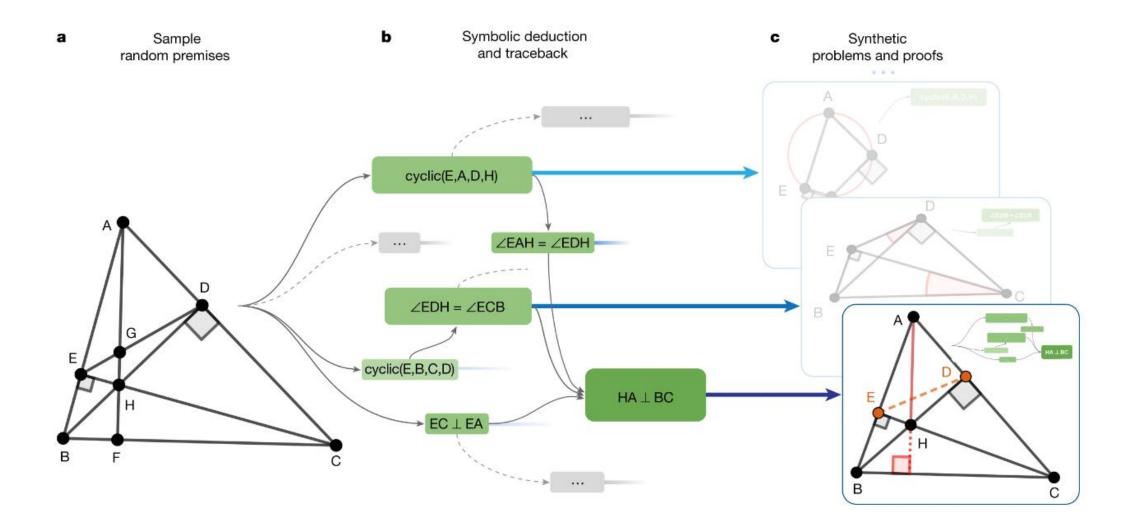
Training data

- Arguably the biggest problem was needing a very large set of training data
- Very few geometry proofs available to train on
 - Geometry can be difficult to translate into general purpose mathematical languages such as Lean
 - Geometry-specific languages exist, but each can only express a subset of concepts needed for proofs
- Decided against using any human proofs
- Instead, created their own set of synthetic theorems and proofs

Synthetic data

- Start by sampling random theorem premises
- Use symbolic deduction engine to expand to deduction closure
 - Track each deduction step, forming a DAG
- For each node N, trace backward along DAG for minimal set of premises P and deductions in a subgraph G(N)
- This forms a training example:
 - Premises P
 - Conclusion N
 - Proof G(N)

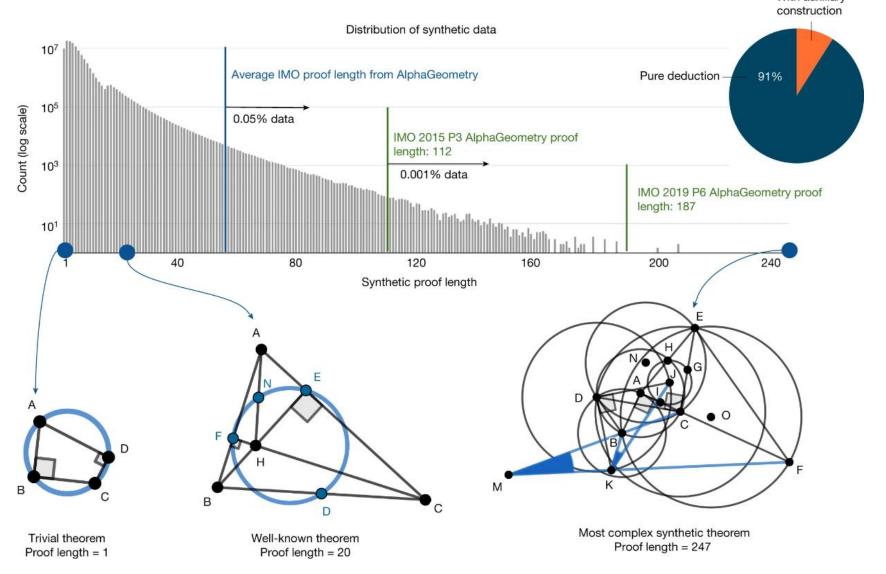
Synthetic data process



Synthetic auxiliary construction

- Start with a proof:
 - Premises P
 - Conclusion N
 - Proof G(N)
- The subset of P that N is independent of can be removed from P and added to the proof as auxiliary construction steps
 - Consider our points P1 and P2 from the triangle area example
- We now have harder proof(s) that require auxiliary construction
 - Footnote: they perform exhaustive testing with all subsets of auxiliary points to ensure all of them are really needed

Synthetic proof length and type



LLM and Training

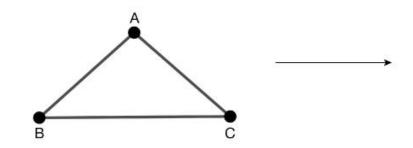
- GPT style decoder only LLM
 - 12 layers, model dimension 1024, 8 attention heads, 4x MLP expansion, ReLU
 - Max sequence length 1024
 - 151 million parameters
 - T5-style relative position embeddings
 - Custom tokenizer, vocab size 757
- Convert each proof into a text string of the form ""conclusion>conclusion>"
- Pretraining usual next token prediction with cross-entropy loss
 - Over 100 million synthetic proofs in training set
- Fine-tune on just the 9 million proofs requiring auxiliary construction

Proof Solving with LLM Inference

- Alternate between the symbolic engine and LLM
- Start the LLM with the prompt "conclusion" and have it generate one auxiliary construction such as "construct point X so that ABCX is a parallelogram"
 - Use beam search keeping top k completions (default was k=512, max depth=16)
- Each symbolic engine turn, expand the deduction closure for all k new constructions
 - If the conclusion is reached, the proof is complete
- On subsequent LLM turns, append prior constructions to the prompt and have the LLM generate one additional auxiliary construction
 - Note that the LLM doesn't get to see the symbolic engine's deduction closure

Proof solving workflow

a A simple problem

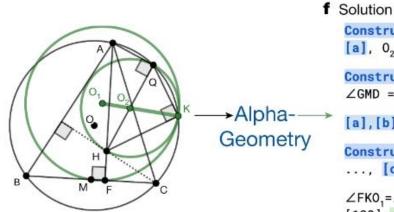


"Let ABC be any triangle with AB = AC. Prove that \angle ABC = \angle BCA."

Symbolic deduce Solved! Construct D: midpoint BC, AB=AC, BD = DC, AD=AD ⇒ ∠ABD=∠DCA [1]

e IMO 2015 P3

"Let ABC be an acute triangle. Let (O) be its circumcircle, H its orthocenter, and F the foot of the altitude from A. Let M be the midpoint of BC. Let Q be the point on (O) such that QH \perp QA and let K be the point on (O) such that KH \perp KQ. Prove that the circumcircles (O₁) and (O₂) of triangles FKM and KQH are tangent to each other."



c Language model

Construct D: midpoint BH [a]
[a], O₂ midpoint HQ ⇒ BQ // O₂D [20]

Construct G: midpoint HC [b] ...

∠GMD = ∠GO₂D ⇒ M O₂ G D cyclic [26]

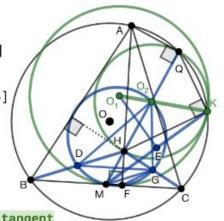
...

[a], [b] ⇒ BC // DG [30]

Construct E: midpoint MK [c]

[c] ⇒ ∠KEC = ∠KO E [104]

Construct E: midpoint MK [c] ..., [c] $\Rightarrow \angle KFC = \angle KO_1E$ [104] $\angle FKO_1 = \angle FKO_2 \Rightarrow KO_1 // KO_2$ [109] [109] $\Rightarrow O_1O_2K$ collinear $\Rightarrow (O_1)(O_2)$ tangent



[1], B C D collinear ⇒ ∠ABC=∠BCA

Results

- 30 IMO proofs since 2000 were this kind of geometry
- AlphaGeometry beat existing computer algebra and search methods, including their attempts to boost DD and GPT-4 with techniques used here

Method		Problems solved (out of 30)
Computer algebra	Wu's method (previous state of the art)	10
	Gröbner basis	4
Search (human- like)	GPT-4	0
	Full-angle method	2
	Deductive database (DD)	7
	DD + human-designed heuristics	9
	DD + AR (ours)	14
	DD + AR + GPT-4 auxiliary constructions	15
	DD + AR + human-designed heuristics	18
	AlphaGeometry	25
	Without pretraining	21
	Without fine-tuning	23
	 Only 20% of training data 	21
	• Beam search <i>k</i> =8	21

AlphaGeometry conclusion

- AlphaGeometry solves Euclidean plane geometry problems better than any computer baseline, and at the level of top IMO competitors
 - AlphaGeometry solved 25/30 and silver medalist avg. 22.9; gold avg. 25.9
- Data-scarcity was solved by synthetically generating training data
 - Key factor was generating proofs with auxiliary construction
- Final solution uses symbolic engine for deduction and LLM for suggestions for auxiliary construction
 - They call this combination a "neuro-symbolic" system
- These search-style proofs can be made human-readable, unlike the computer algebra techniques which just output True

References

- AlphaGeometry blog post: <u>https://deepmind.google/discover/blog/alphageometry-an-olympiad-level-ai-system-for-geometry/</u>
- AlphaGeometry GitHub repo: https://github.com/google-deepmind/alphageometry
- Generative language modeling for automated theorem proving Polu, S. and Sutskever, I. (2020) https://arxiv.org/abs/2009.03393
- Llemma: An Open Language Model For Mathematics Azerbayev, Z. et al. (2023) https://arxiv.org/abs/2310.10631