

ThinknCheck

Grounded Claim Verification with Compact, Reasoning-Driven, and Interpretable Models

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TL;DR

- **Research Question:** How can we activate strong scientific claim verification in a small language model?
- **The Problem**
 - **Model:** Direct CoT prompting does not work reliably, and straightforward input–output fine-tuning gives only limited gains for 1B-scale models.
 - **Data:** Existing benchmarks mostly reward span matching, not multi-sentence or numerical reasoning.
- **Our Solution:**
 - **Data:** Create **LLMAggreFact-Think**, a 24.1K reasoning-augmented dataset; Construct **GSMClaims**, a new dataset for arithmetic claim verification.
 - **Model:** Build **ThinknCheck**, a 4-bit Gemma3-1B model fine-tuned to reason first, then decide; Build **ThinknCheck-Science**, a science-focused variant for real multi-step and numerical reasoning.
- **The Impact:** ThinknCheck-1B reaches 78.1 BAcc on LLMAggreFact (in-domain) and 64.7 BAcc on SciFact (out-of-domain), surpassing the larger SOTA MiniCheck-7B.

MOTIVATION

Claim verification sits at the core of **science, medicine, and public policy**: we rely on it to decide which findings to trust, which treatments to recommend, and which reports to act on. In these settings, we need systems that are not only **accurate** but also **grounded in evidence** and **easy to interpret**.

But today:

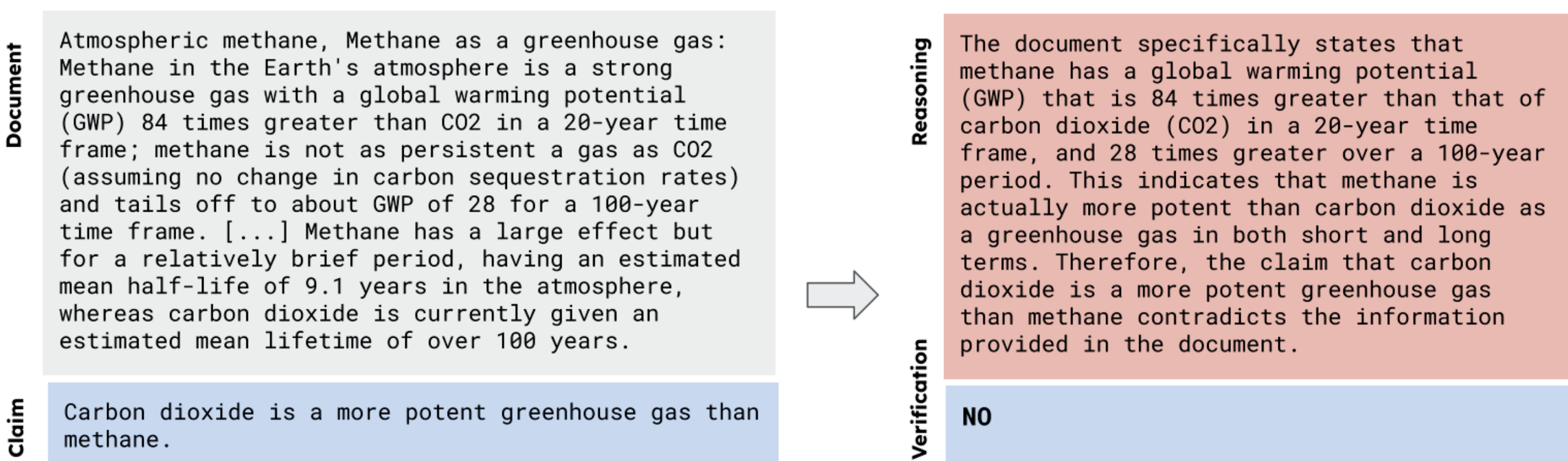
- Models: LLM-based verifiers are often large, closed, and expensive, limiting real-world deployment.
- Data: Common benchmarks over-reward span matching and under-test multi-sentence, scientific, and numerical reasoning.
- Small LMs: Naïve “make it think” methods (zero-shot CoT, simple GRPO rewards) can hurt 1B models, reinforcing lexical shortcuts instead of genuine reasoning.

👉 **Our work asks:** can a small model become a strong, interpretable claim verifier if we redesign both its training signals and evaluation benchmarks?

OUR METHOD

Key Intuition:

“Reason first, then decide” — even a 1B model can be a strong verifier if we train it to produce concise, task-specific rationales instead of raw labels or uncontrolled CoT.



Data & Benchmarks

1. **LLMAggreFact-Think** = LLMAggreFact + GPT-4o-mini reasoning chains + filter → 24.1K (document, claim, rationale, YES/NO) pairs
2. **GSMClaims** = GSM8K problems → GPT-4o rewrites as document + GPT-4o generates positive/negative claims + reasoning chains → arithmetic claim verification benchmark

Models

1. **ThinknCheck-1B** = 4-bit Gemma3-1B + SFT on LLMAggreFact-Think → <REASONING> concise rationale </REASONING> <SOLUTION> YES / NO </SOLUTION>
2. **ThinknCheck-Science** = ThinknCheck-1B + extra SFT on SciFact and GSMClaims → stronger scientific & numerical claim verification

KEY RESULTS

BAcc = $\frac{1}{2} \left(\frac{TP}{TP + FN} + \frac{TN}{TN + FP} \right)$				
Model	BAcc	Model	LLMAggre Fact	SciFact (dev) GSM Claims
GPT-4 (zero-shot)	75.3	MiniCheck-7B	77.4	50.0 51.3
GPT-4o (zero-shot)	75.9	ThinknCheck-nothink-1B	57.5	21.7 49.4
Claude-Sonnet-3.5 (zero-shot)	77.2	ThinknCheck-1B	78.1	64.7 52.2
AlignScore (355M/fp16)	70.4	ThinknCheck-Science-1B	79.2	66.4 61.0
MiniCheck (7B/fp16)	77.4			
Gemma3 (1B/fp4) (“base”)	55.7	Method (Gemma3-1B, fp4)		BAcc
Gemma3 + CoT (1B/fp4)	51.4	GRPO on Gemma3 (“base”)		52.6
ThinknCheck-nothink (1B/fp4)	57.5	GRPO on Gemma3-SFT-400 (“warm start”)		74.2
ThinknCheck (1B/fp4)	78.1			

Claim: Momentum $P \approx 10.0 \pm 1.1 \text{ kg} \cdot \text{m/s}$
Document: Mass $M = 5.0 \pm 0.1 \text{ kg}$. Velocity $V = 2.0 \pm 0.2 \text{ m/s}$.

MiniCheck-7B verification result:

DOES NOT SUPPORT

ThinknCheck-Science-1B verification result:

SUPPORTS

ThinknCheck-Science-1B reasoning:

The momentum is calculated by multiplying the mass and the velocity: $5.0 \text{ kg} \times 2.0 \text{ m/s} = 10.0 \text{ kg} \cdot \text{m/s}$. The relative uncertainty in the mass is $0.1/5.0 = 2\%$ and in the velocity is $0.2/2.0 = 10\%$. When uncertainties are combined for multiplication, they add in quadrature: $\sqrt{((2\%)^2 + (10\%)^2)} = \sqrt{(0.0004 + 0.01)} = \sqrt{(0.0104)} \approx 10.2\%$. This results in an uncertainty of about $10.2\% \times 10.0 \text{ kg} \cdot \text{m/s} \approx 1.0 \text{ kg} \cdot \text{m/s}$. A better calculation using maximum and minimum values yields $P_{\max} = 5.1 \text{ kg} \times 2.2 \text{ m/s} = 11.22 \text{ kg} \cdot \text{m/s}$ and $P_{\min} = 4.9 \text{ kg} \times 1.8 \text{ m/s} = 8.82 \text{ kg} \cdot \text{m/s}$. The range between P_{\max} and P_{\min} is $11.22 - 8.82 = 2.4 \text{ kg} \cdot \text{m/s}$, implying an uncertainty of approximately $\pm 1.2 \text{ kg} \cdot \text{m/s}$. Since both approaches yield an uncertainty around ± 1.0 to $\pm 1.2 \text{ kg} \cdot \text{m/s}$, the claim of $10.0 \pm 1.1 \text{ kg} \cdot \text{m/s}$ is consistent with the uncertainties derived from the document.

TAKE AWAYS

1. **Small but smart:** A 1B, 4-bit verifier with supervised reasoning can match or beat 7B and closed models, while being cheap and deployable.
2. **Reasoning matters:** Explicit, supervised reasoning is far more effective than naïve CoT or simple RL at the 1B scale.
3. **Benchmarks must evolve:** Current benchmarks under-test multi-step and numerical reasoning—we need better tasks and rationales to assess claim verification truly.