

# Verification Meets Uncertainty: Enabling Next-Generation Robotics, Logistics, and Compliance

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Alvaro Velasquez,  
Professor, University of Colorado Boulder,  
Former PM, DARPA,  
CEO, NSI  
[alvaro.velasquez@colorado.edu](mailto:alvaro.velasquez@colorado.edu)

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University of Colorado  
Boulder



# Neural vs. Neurosymbolic

## THE STATE OF AI

Today's AI learns patterns *implicitly*—through massive data, models, and compute—making it inefficient and hard to trust.

## OUR NEUROSYMBOLIC VISION

By *explicitly* embedding symbolic structures like physics and logic, AI can learn faster, generalize better, and be *mathematically verifiable* for trust.

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NEWS | 18 September 2026

## AI cracked the Navier–Stokes challenge. What does that mean for physics?

Physicists and mathematicians are going beyond the classic equations of fluid dynamics to understand turbulence – often with the help of AI.

By [Nicola Jones](#)

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NEWS | 22 May 2026

## AI cracks 80-year-old mathematics challenge – researchers are astonished

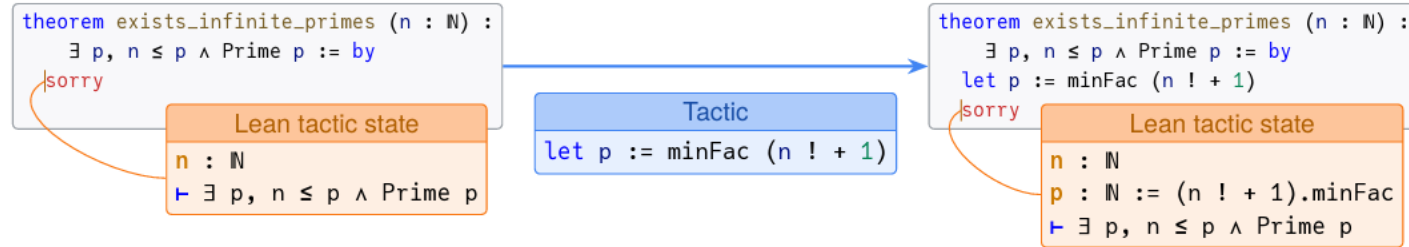
The late Hungarian mathematician Paul Erdős thought he had the last word on a geometry problem. Now an OpenAI chatbot has proved him wrong.

By [Davide Castelvecchi](#)

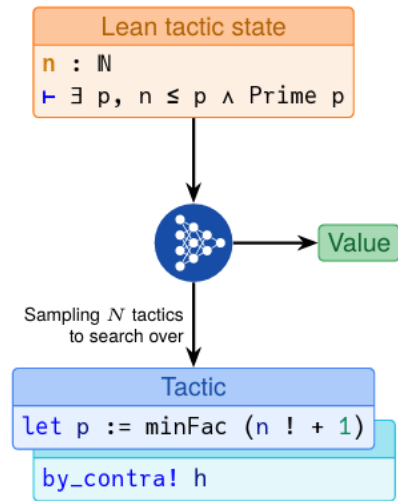
# Verification: the next frontier revolutionizing AI4Math

- Example: DeepMind's AlphaProof.

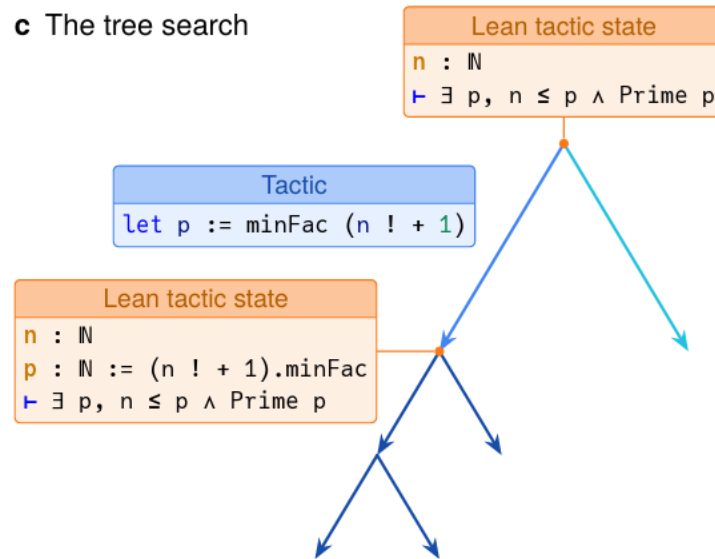
## a Lean environment



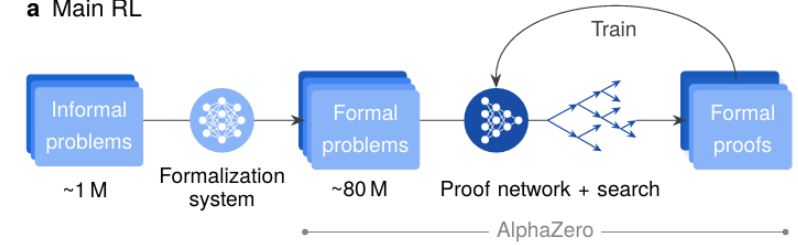
## b The proof network



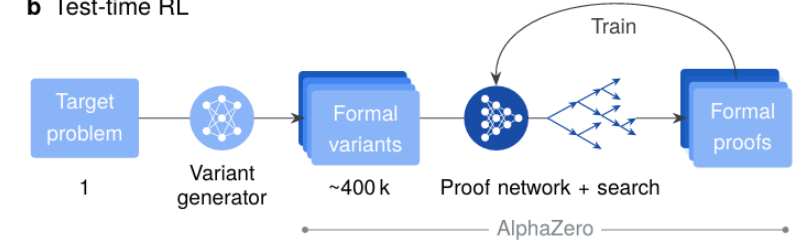
## c The tree search



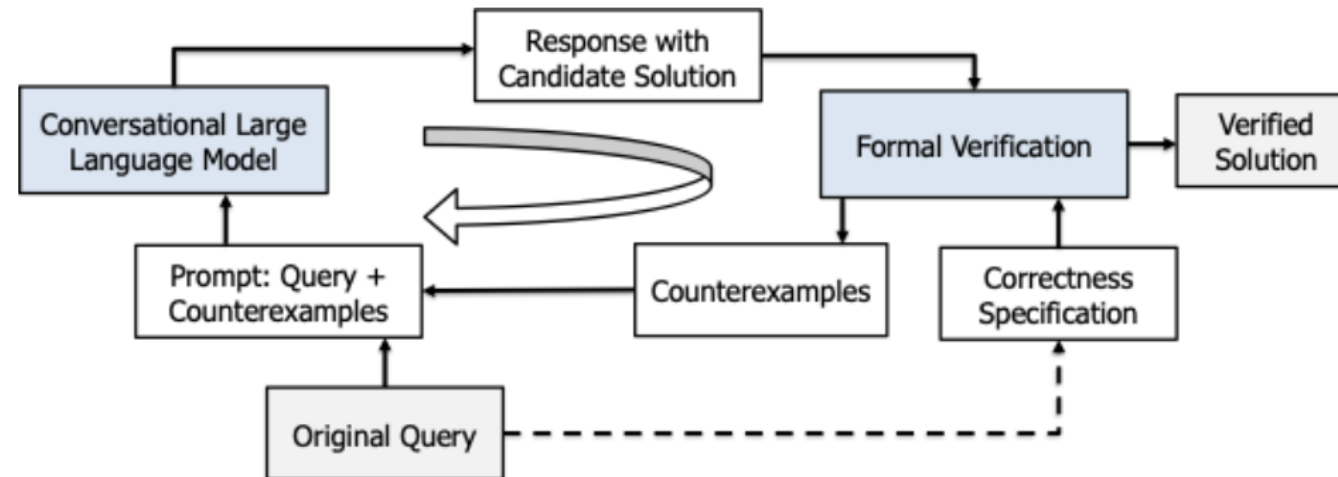
## a Main RL



## b Test-time RL



# Verification also works on AI4Code!



Jha, Susmit, Sumit Kumar Jha, Patrick Lincoln, Nathaniel D. Bastian, Alvaro Velasquez, and Sandeep Neema.  
"Dehallucinating large language models using formal methods guided iterative prompting." In *2023 IEEE International Conference on Assured Autonomy (ICAA)*, pp. 149-152. IEEE, 2023.

# But what about verification for systems subject to uncertainty?

## Verification in the real world is subject to:

- Unknown models.
- Incomplete and small data.
- Limited operating picture.
- Ever changing requirements.



contested logistics



DDIL military systems



safety-critical robotics

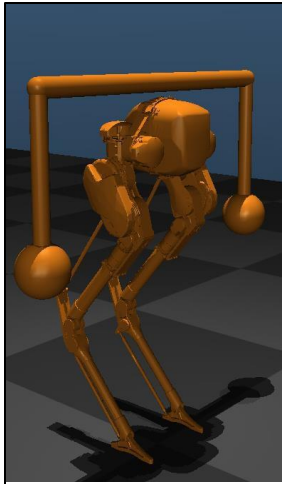


molecular discovery



# How bad can uncertainty be?

Containers



*Simulation*



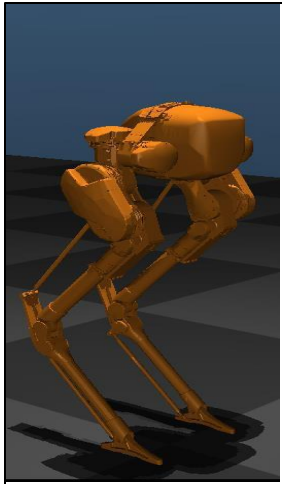
*Real*

Containers

## **Low uncertainty: small sim-to-real gap**

- Precise models for robot
- Precise models for containers
- Result: 96% success rate for achieving task

No  
containers



*Simulation*



*Real*

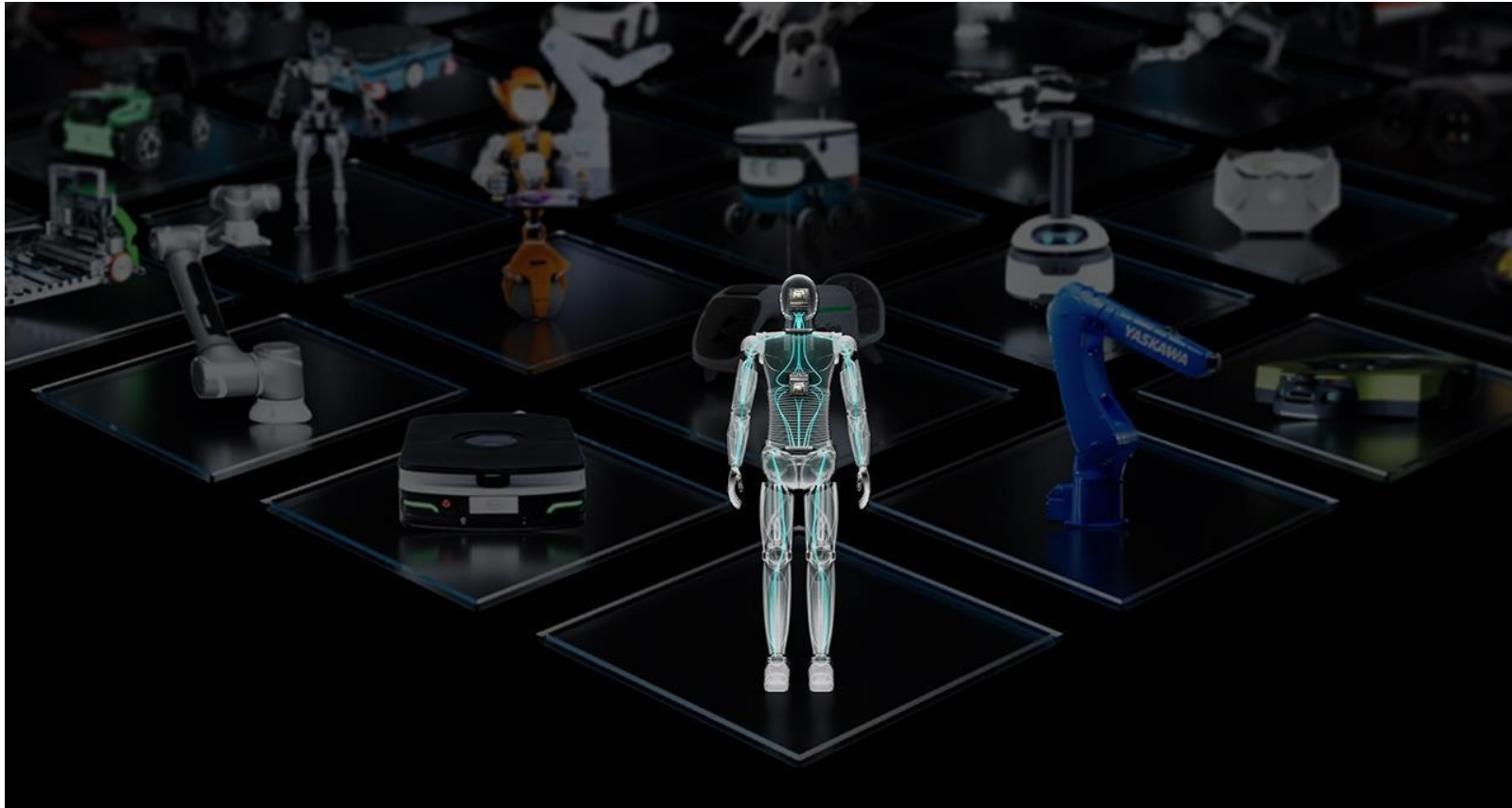
Containers

## **High uncertainty: moderate sim-to-real gap**

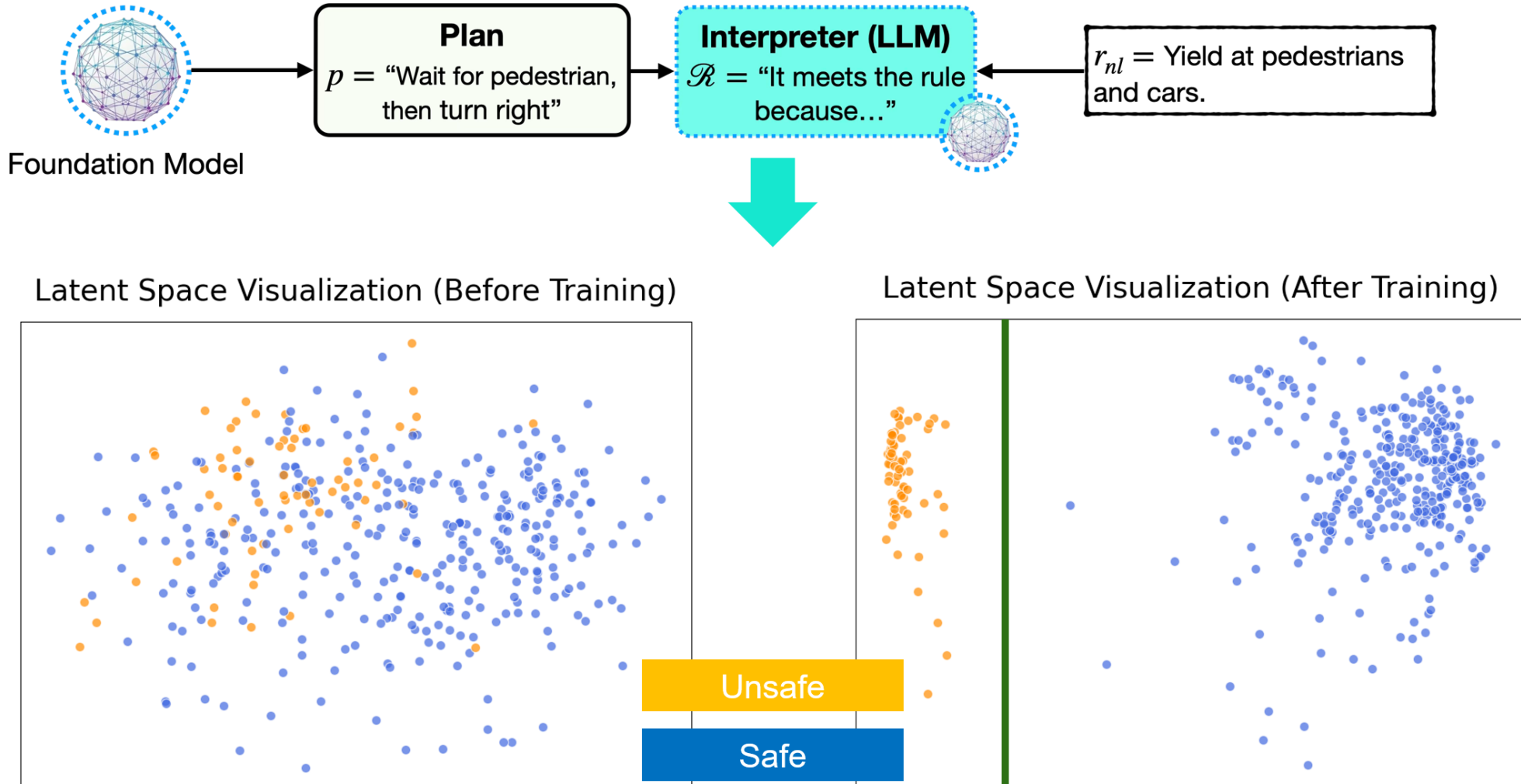
- Precise models for robot
- No models for containers
- Result: 0.1% success rate for achieving task

# Conventional wisdom: scale up compute, parameters, data, etc.

- NVIDIA Project GR00T, Waymo autonomous driving, etc.



# Verification under uncertainty is possible with a shared geometry





# Verification under uncertainty is possible with a shared geometry

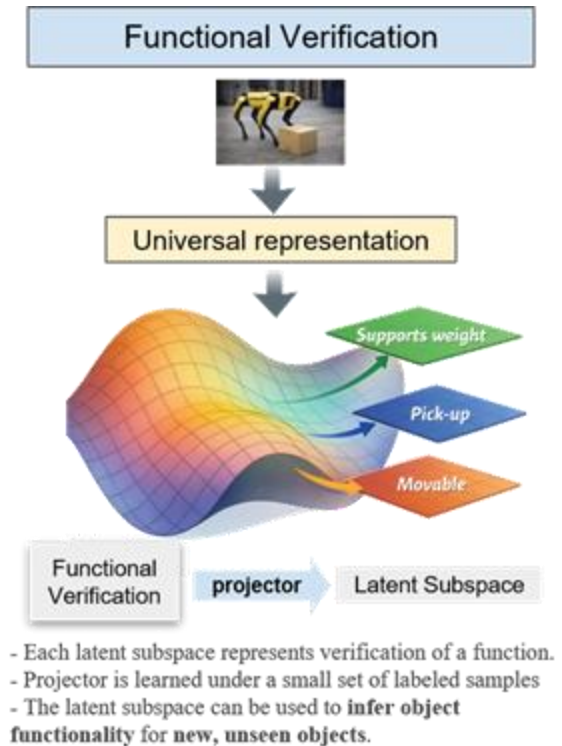
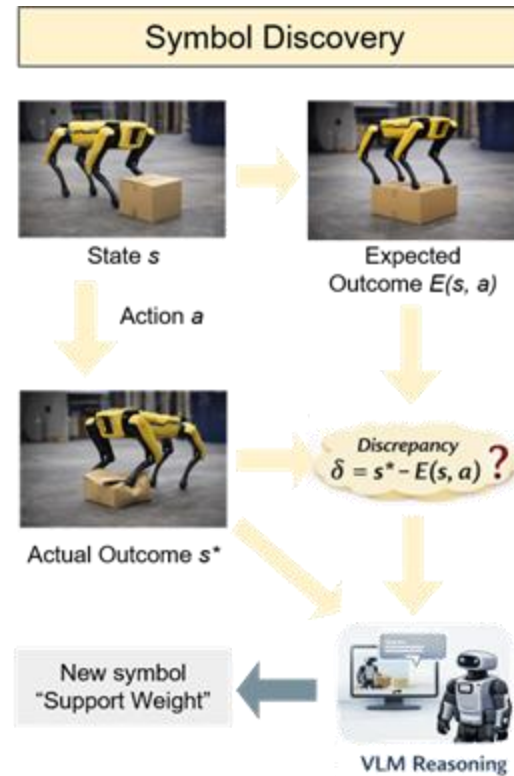
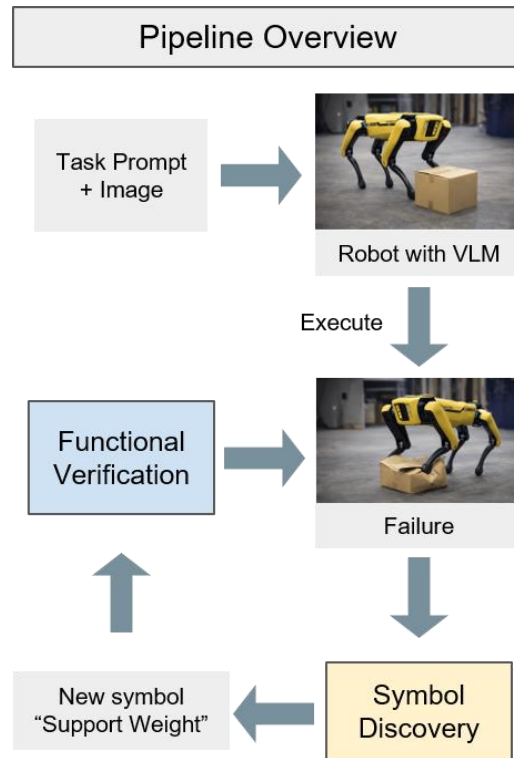
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- Our methods enable verification under uncertainty for self-improving AI in settings where there is scarce and noisy data.
- We transform the verification problem into a prediction over the geometry of shared learned representations, enabling the successes of verification to scale to new verticals.
  - In robotics, uncertainty comes from our inability to model the real world and verification is transformed into prediction over learned robot sensor representations and the rules that should be satisfied.
  - In logistics, uncertainty comes from unforeseen supply chain issues and verification is transformed into prediction over learned representations of logistics plans and the routing constraints of the logistics problem.
  - In compliance, uncertainty comes from natural language interpretation of guidelines and verification is transformed into prediction over learned representations of a given system description (e.g., insurance claim) and the rules extracted from the guidelines (e.g., the Affordable Care Act).

## Use case: home robotics

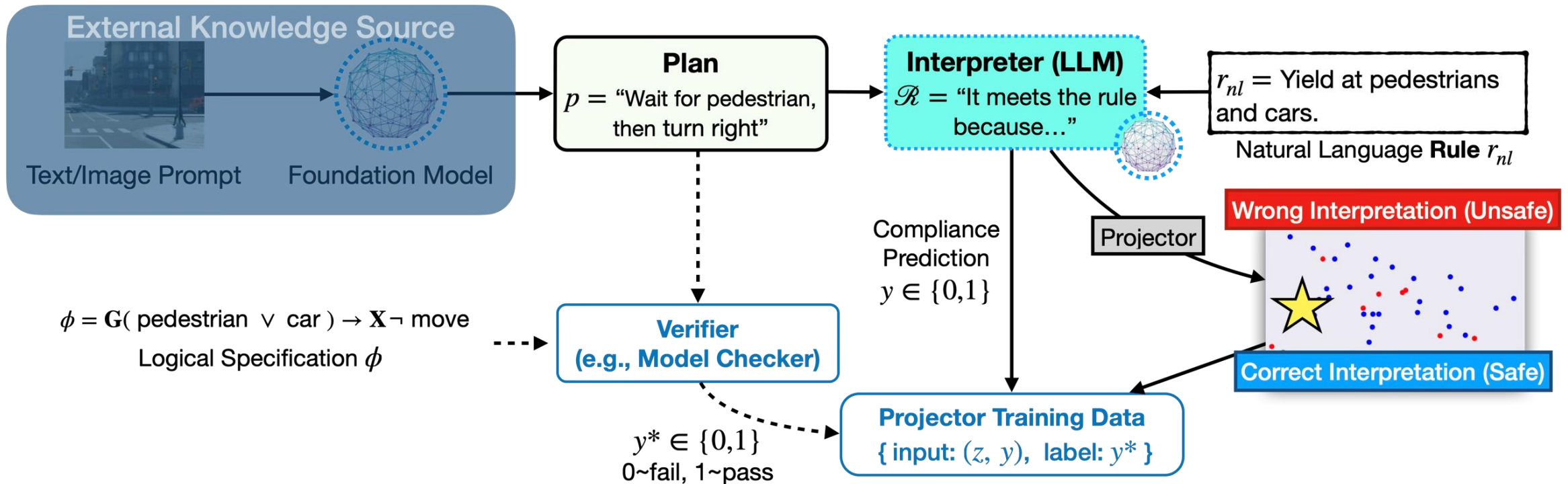


# Verification under uncertainty for the edge



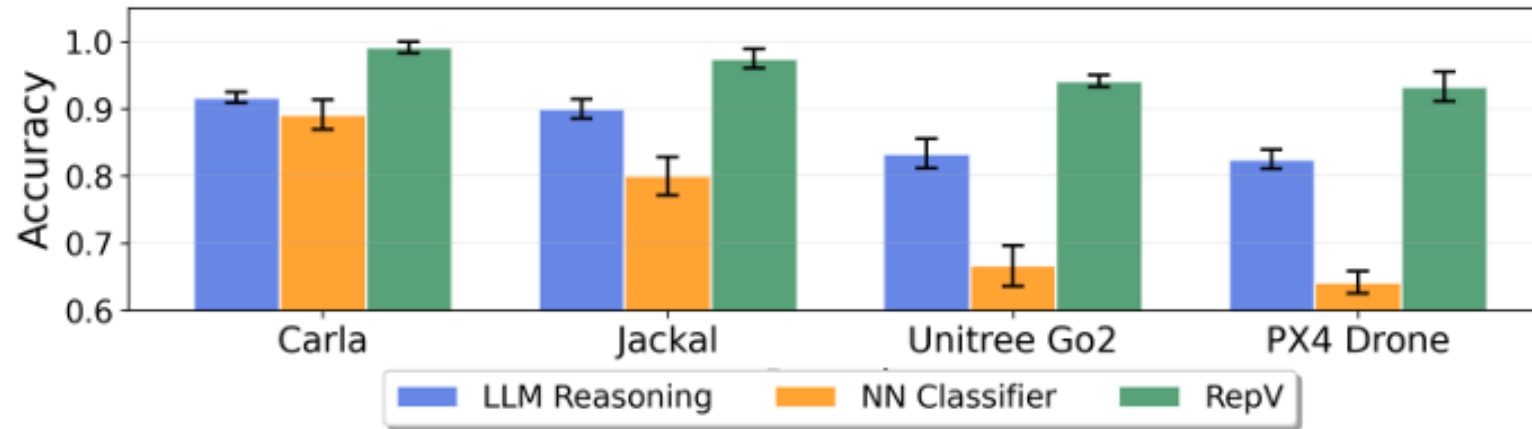
# Natural language verification under uncertainty

The projector constructs a safety-separable latent space, and predicting plan compliance against natural language rules is simply based on the spatial location of the projector's output representation for the natural language plan and constraints.



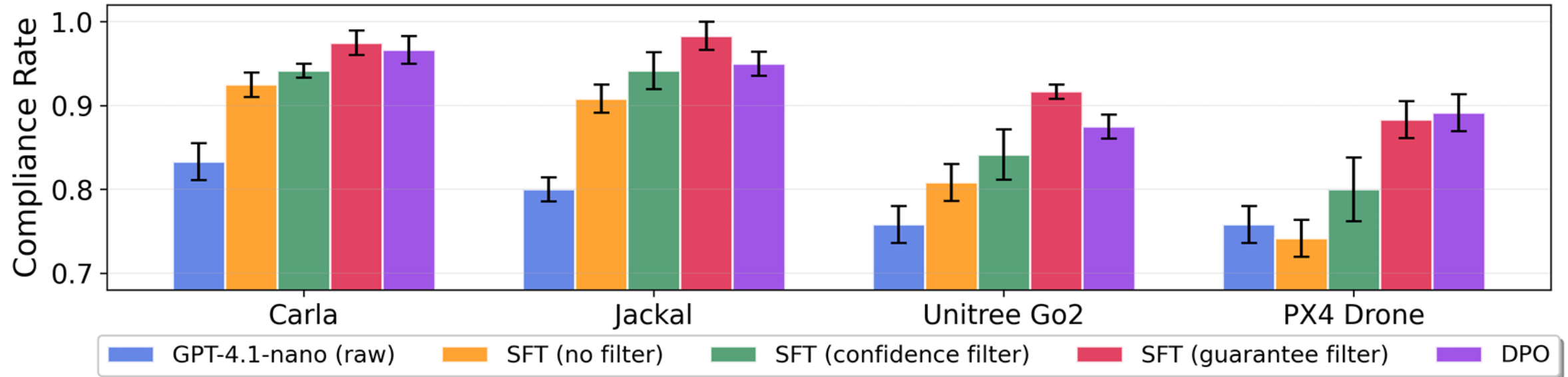
# Natural language verification improves reasoning

Our approach outperforms powerful LLM reasoning baselines.



OpenAI GPT-4.1-nano

# Using predictive verification for self-improving models

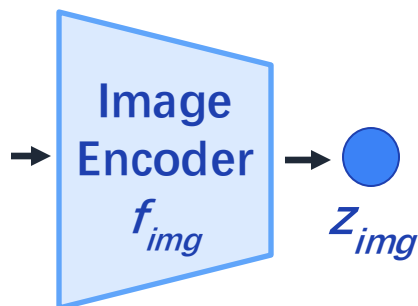


- SFT via Guarantee Filter (Ours): Fine-tuning restricted to samples satisfying the rules with probabilistic guarantee  $p(y \mid z) \geq \tau = 0.8$ .
- DPO (Ours): DPO using the probabilistic guarantee as a ranking signal between alternative plans.

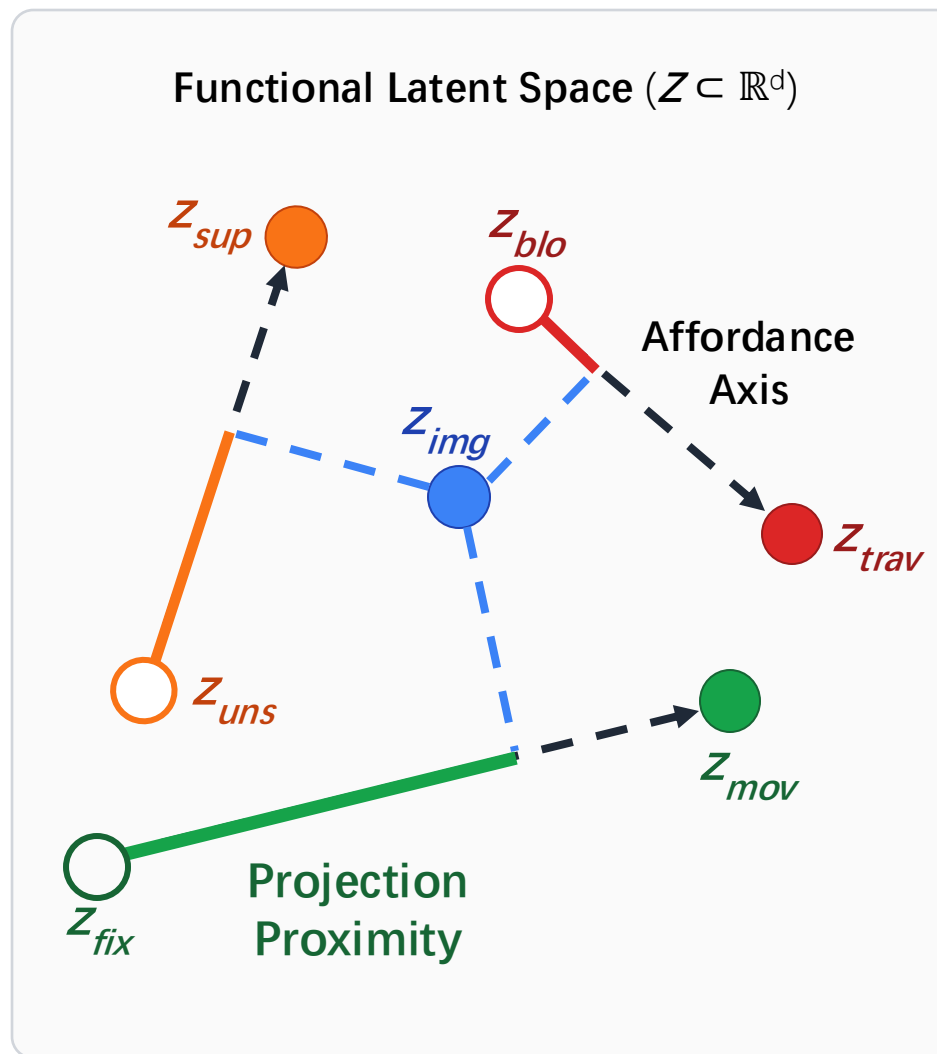
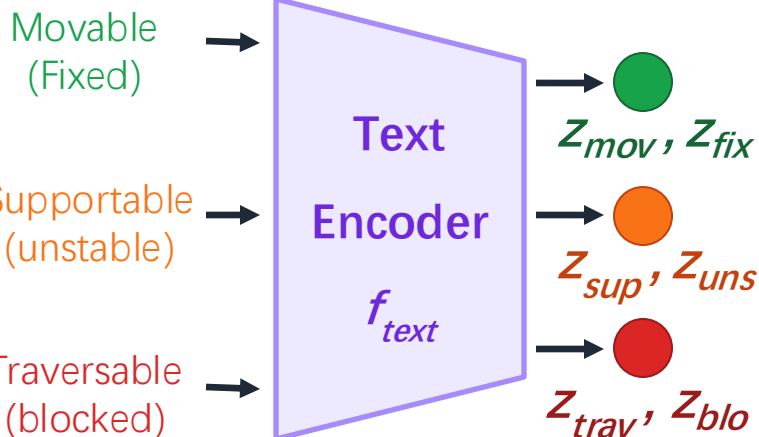
# Using the shared geometry of uncertainty to discover function



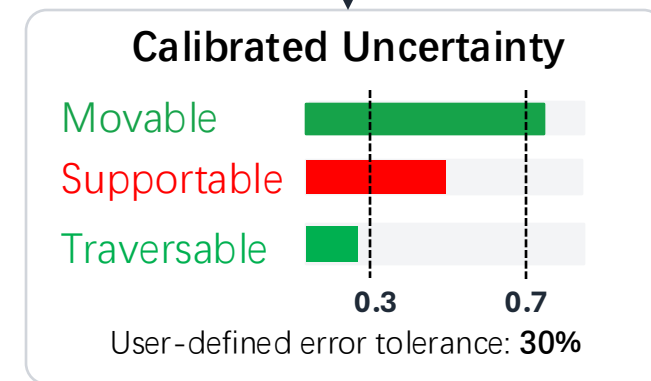
## Visual Observation



## Affordance Vocabulary (Antonym)



| Projection Proximity                    |      |   |
|-----------------------------------------|------|---|
| Distance b/w proj. & affordance antonym |      |   |
| Movable                                 | 2.38 | ✓ |
| Supportable                             | 2.32 | ✓ |
| Traversable                             | 2.24 | ✗ |



$$0.3 < \text{Supportable} < 1 - 0.3$$

## Decision

Trigger Oracle VLM  
to label **Supportable**

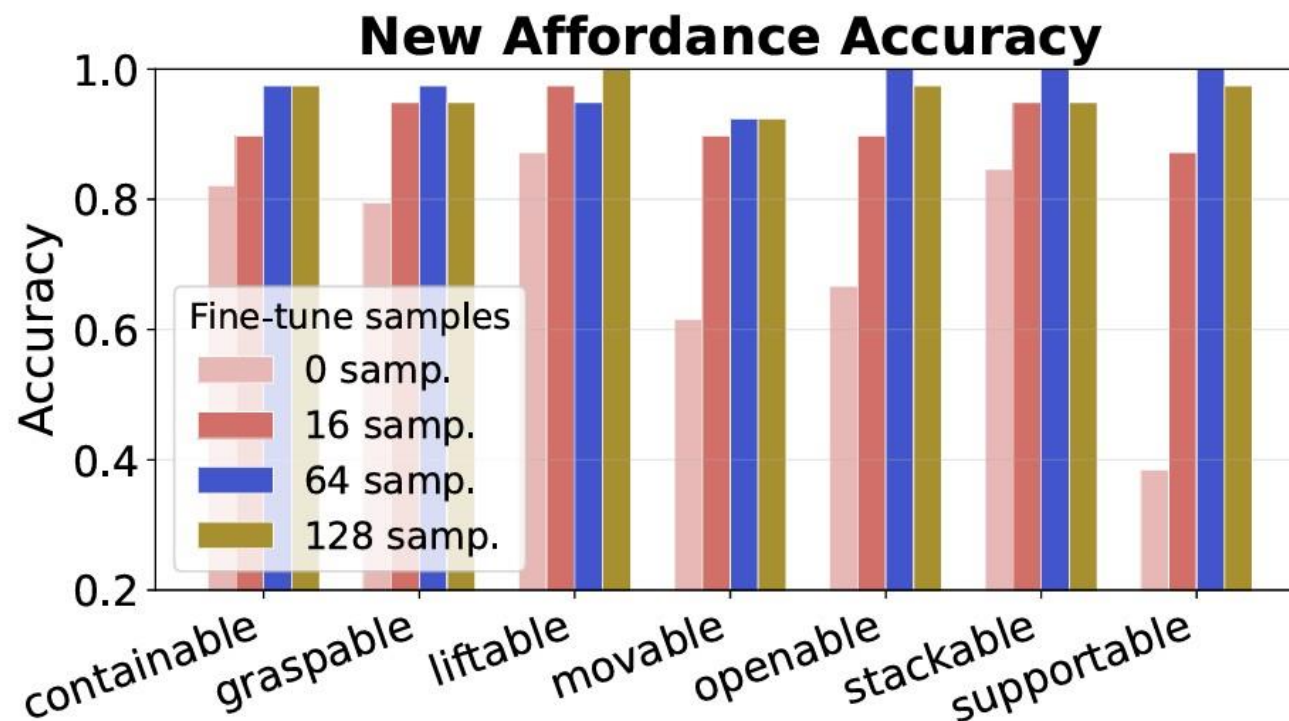


# Using the shared geometry of uncertainty to discover function

Given input image and task prompt, **infer** object affordances relevant to the task and estimate associated inference **uncertainty** in **real time** while **discovering** new affordances when required.

**Proof of concept:** Cloudless low-power edge robotics.

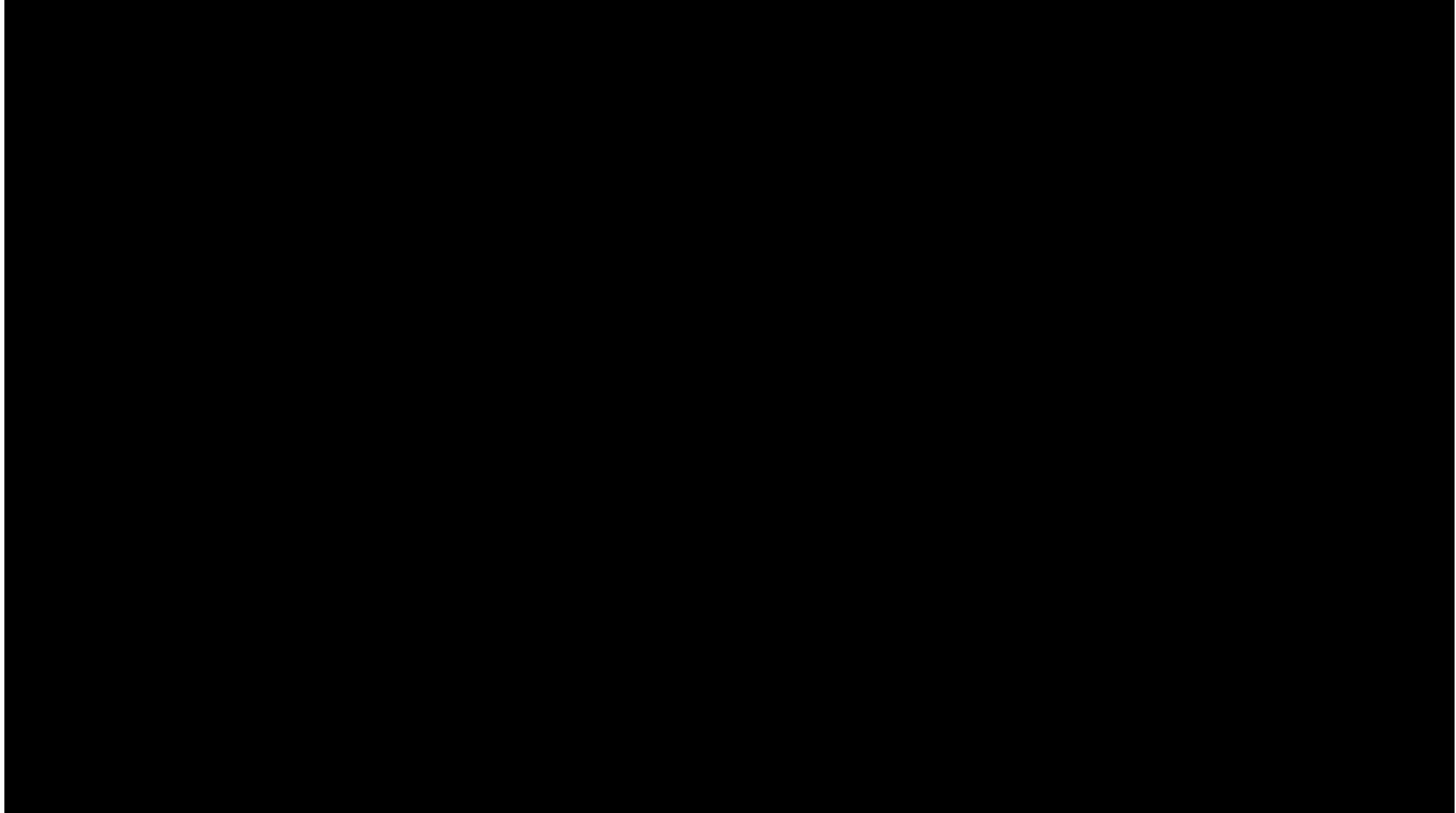
- **Small data:** <200 data points required to learn and reason about the function of objects with greater accuracy than GPT-5.4 (94% versus 79%).
- **Real-time inference:** 100x faster inference when compared to GPT-5.4 (22ms vs. 2.6s)
- **Lightweight:** 150M parameters compared to 2.2T parameters in GPT-5.4, 20B in GPT-OSS.
- **Improved loitering time:** 15% longer duration compared to a GPT-OSS-20B model running on a SPOT robot.





# Use case: crater exploration for lunar prospecting

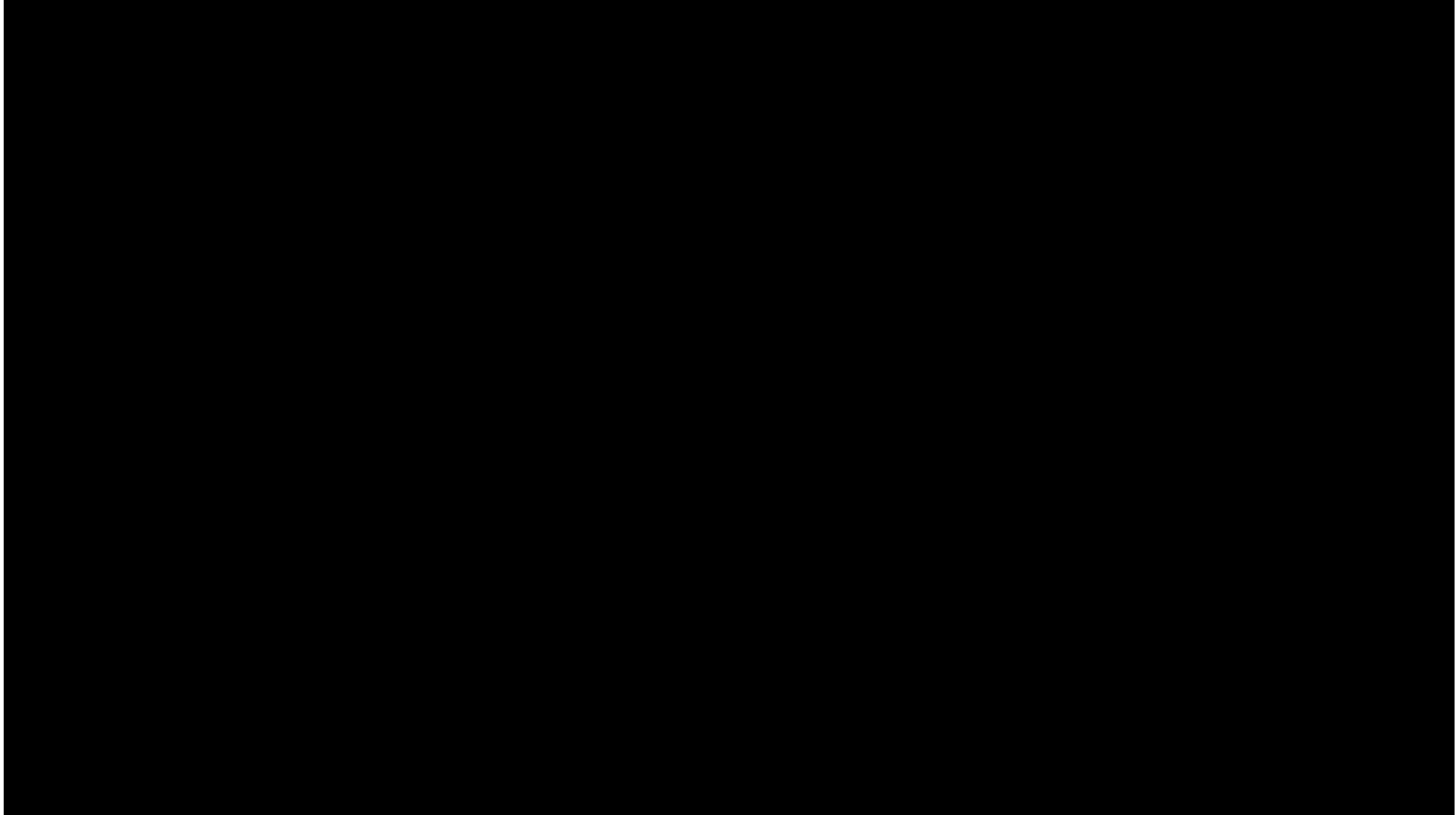
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# Use case: crater exploration for lunar prospecting

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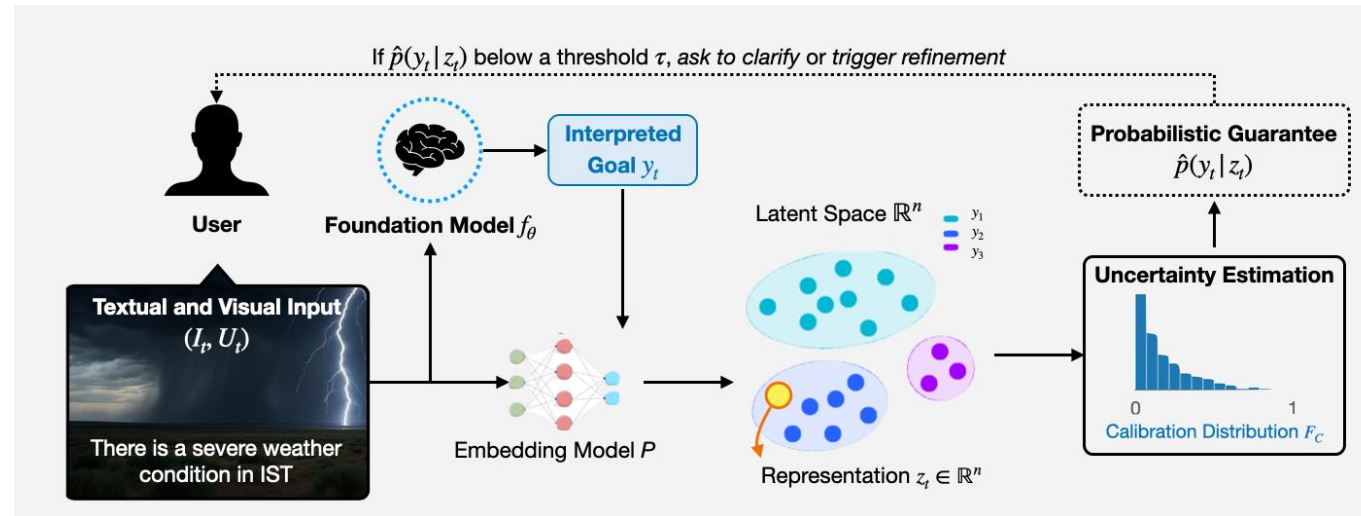
Other applications: logistics and compliance under uncertainty

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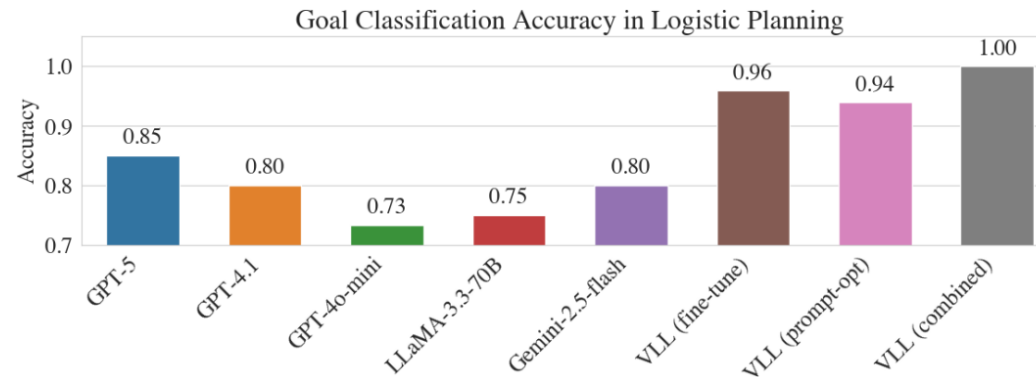


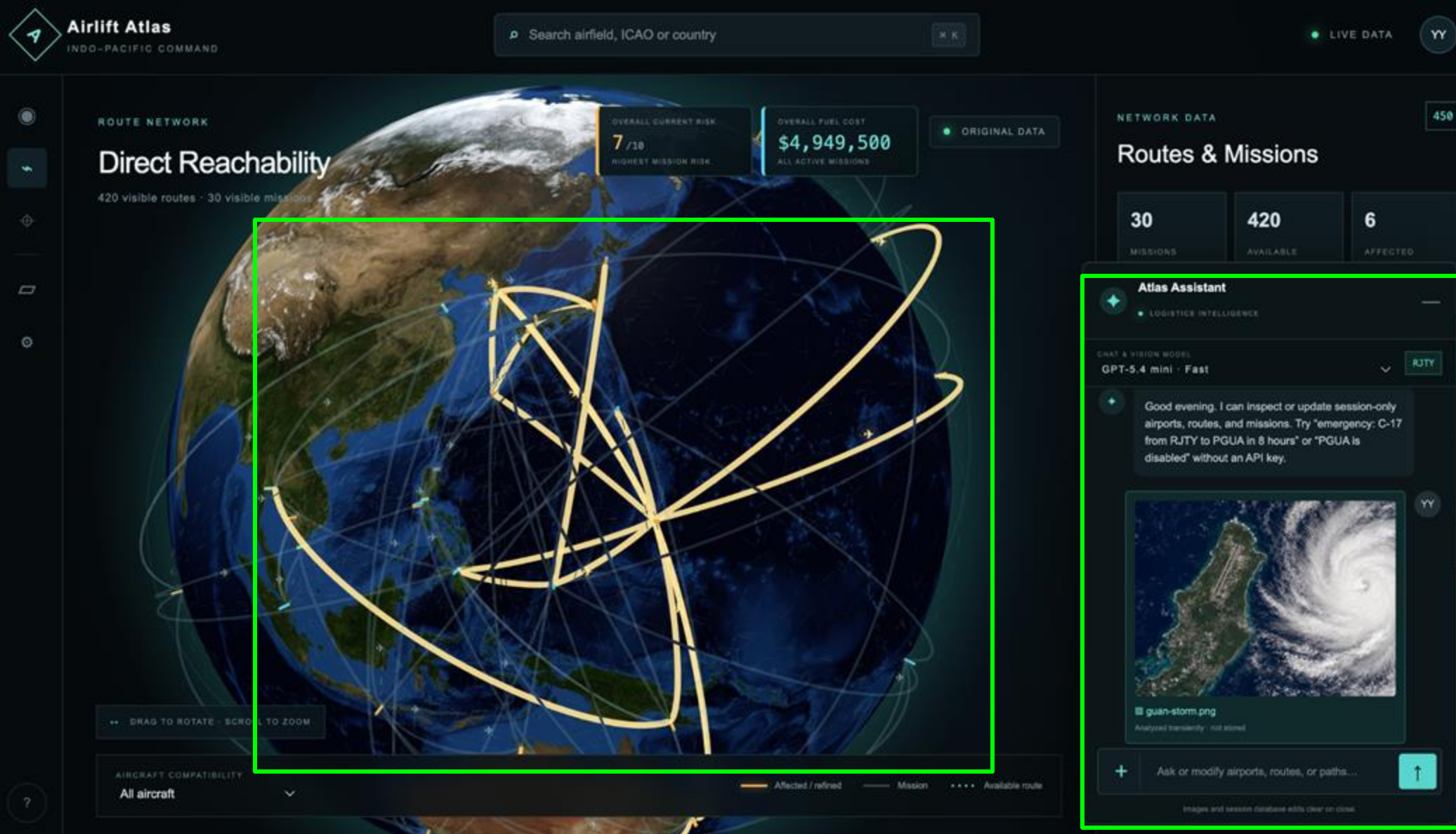
# Logistics under uncertainty

- We have developed an architecture that outperforms GPT-5 for military logistics that satisfies constraints from natural language and visual data.
- Inputs are converted into structured goals and dispatched to symbolic planners. Predictive verification under uncertainty is performed on the plans produced.



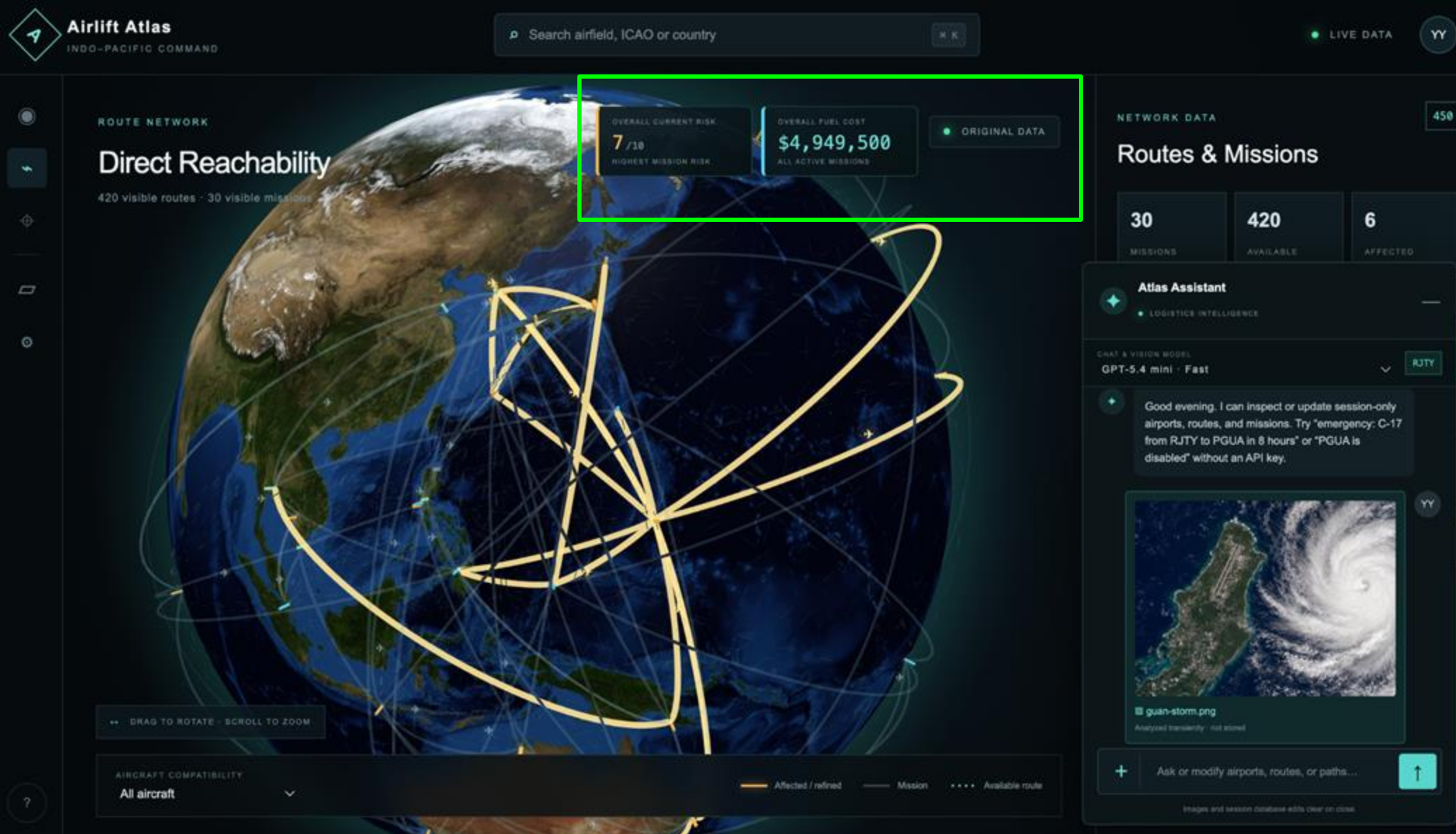
Yang, Yunhao, Neel P. Bhatt, Christian Ellis, Alvaro Velasquez, Zhangyang Wang, and Ufuk Topcu. "Foundation Models for Logistics: Toward Certifiable, Conversational Planning Interfaces." NeuS 2026.



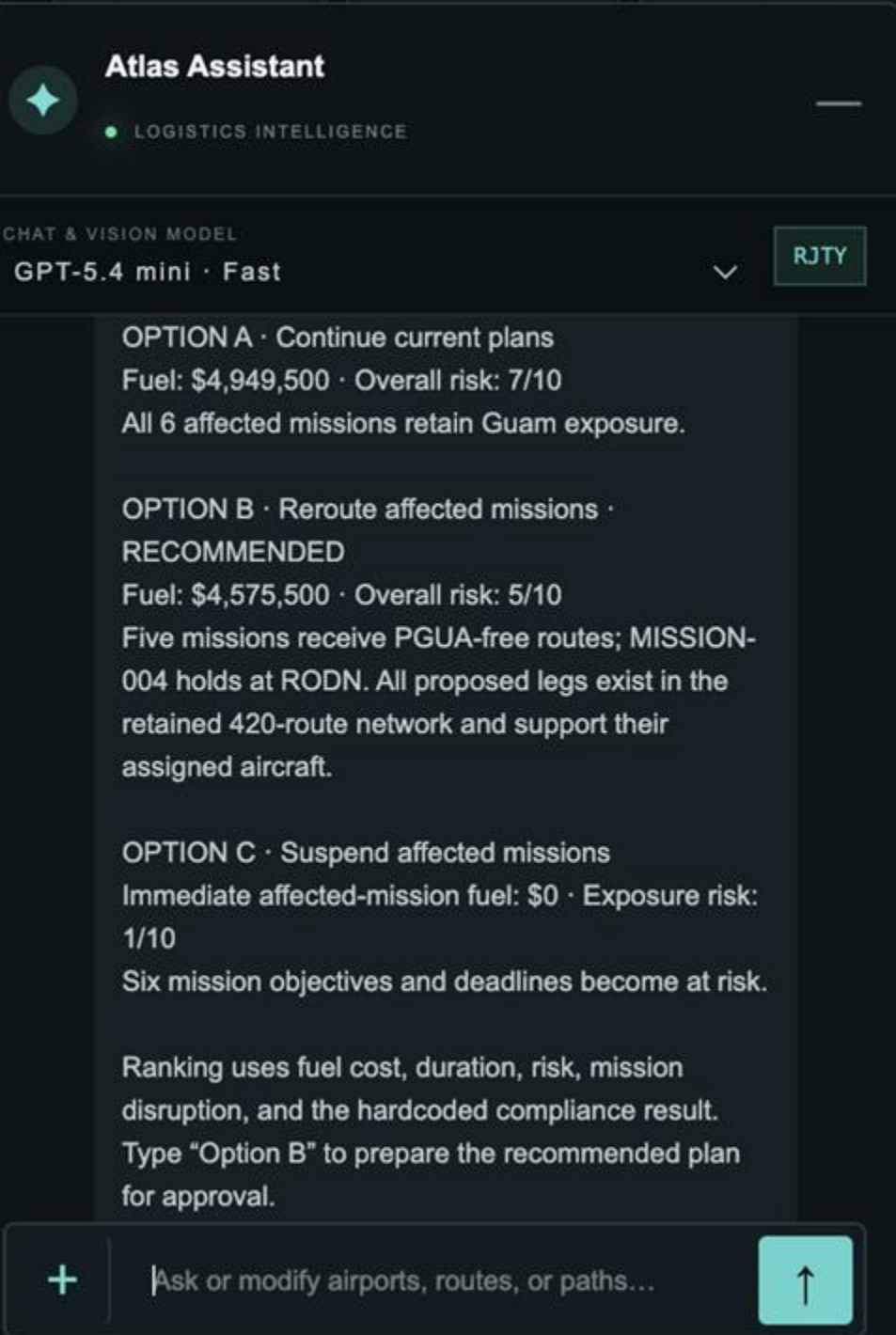


user upload  
image to the  
chat

The VLL determine which  
agents (paths) will be affected

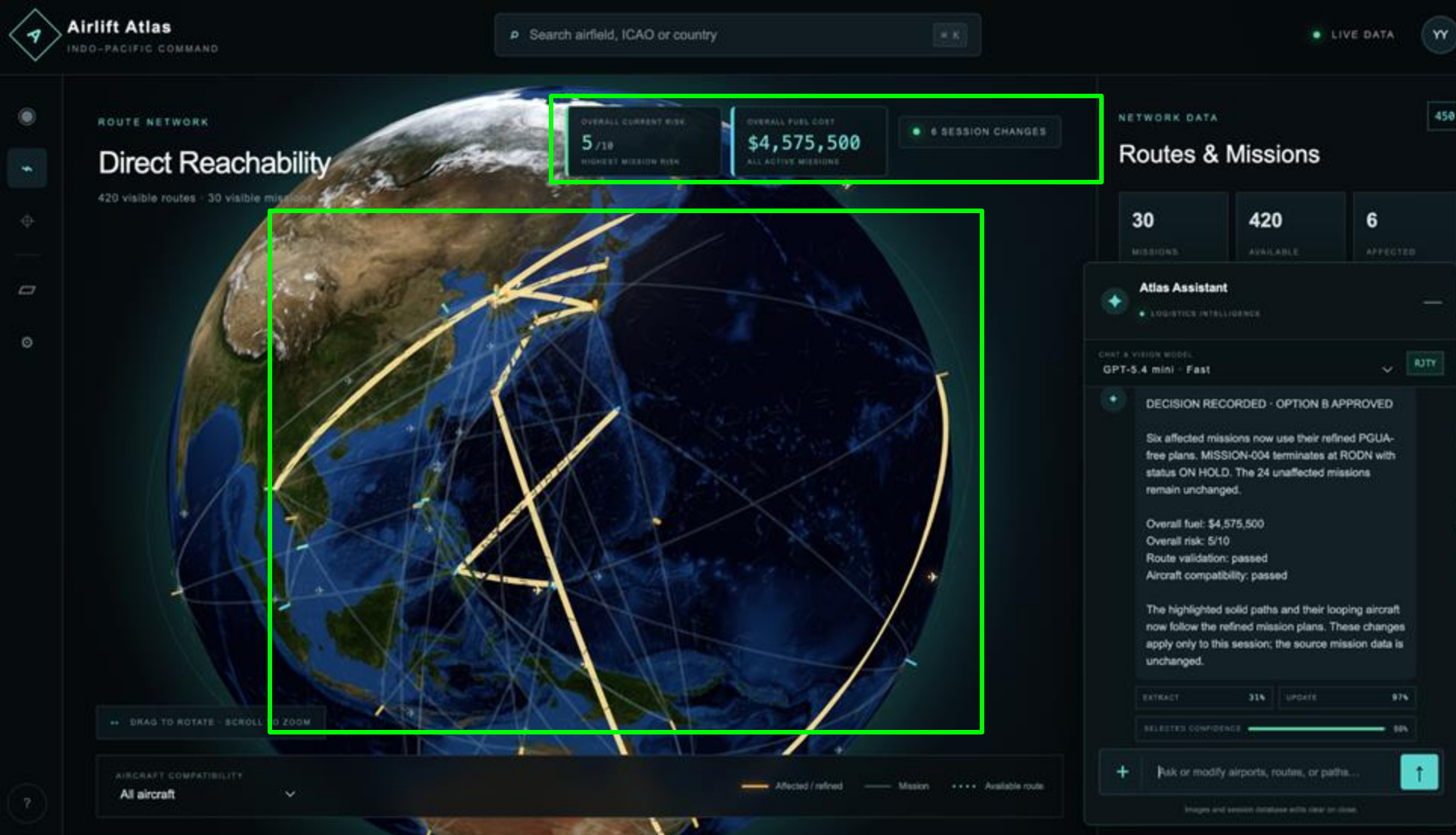


Keep track of the fuel costs and risks (calibrated probability of compliance)



The VLL applies multi-agent path planning to the impacted paths and provide three options with **explanations**

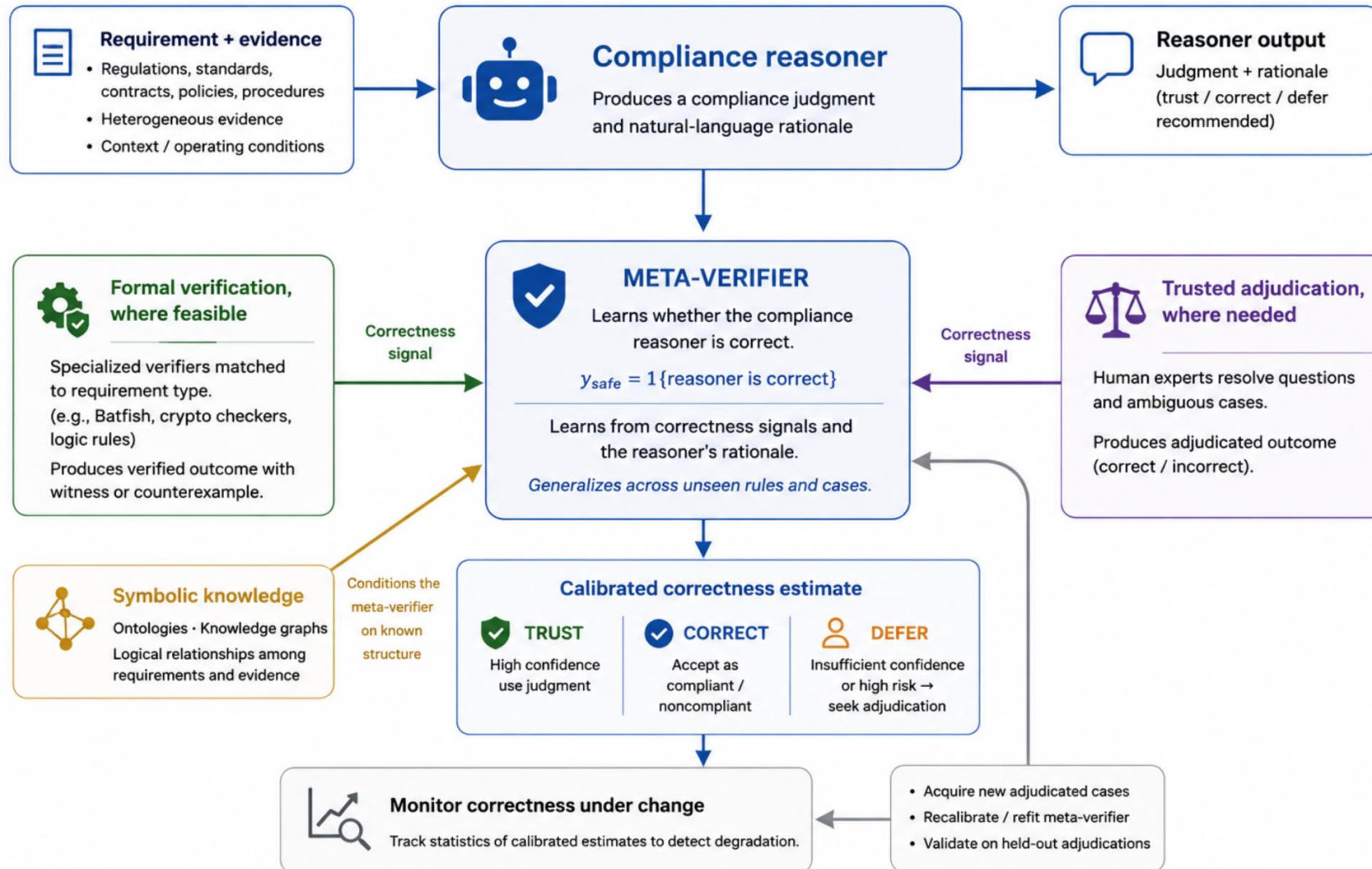
It then **ranks the options** based on the costs, risks, mission completion rate, etc and gives user a recommendation



Risk and cost are updated accordingly

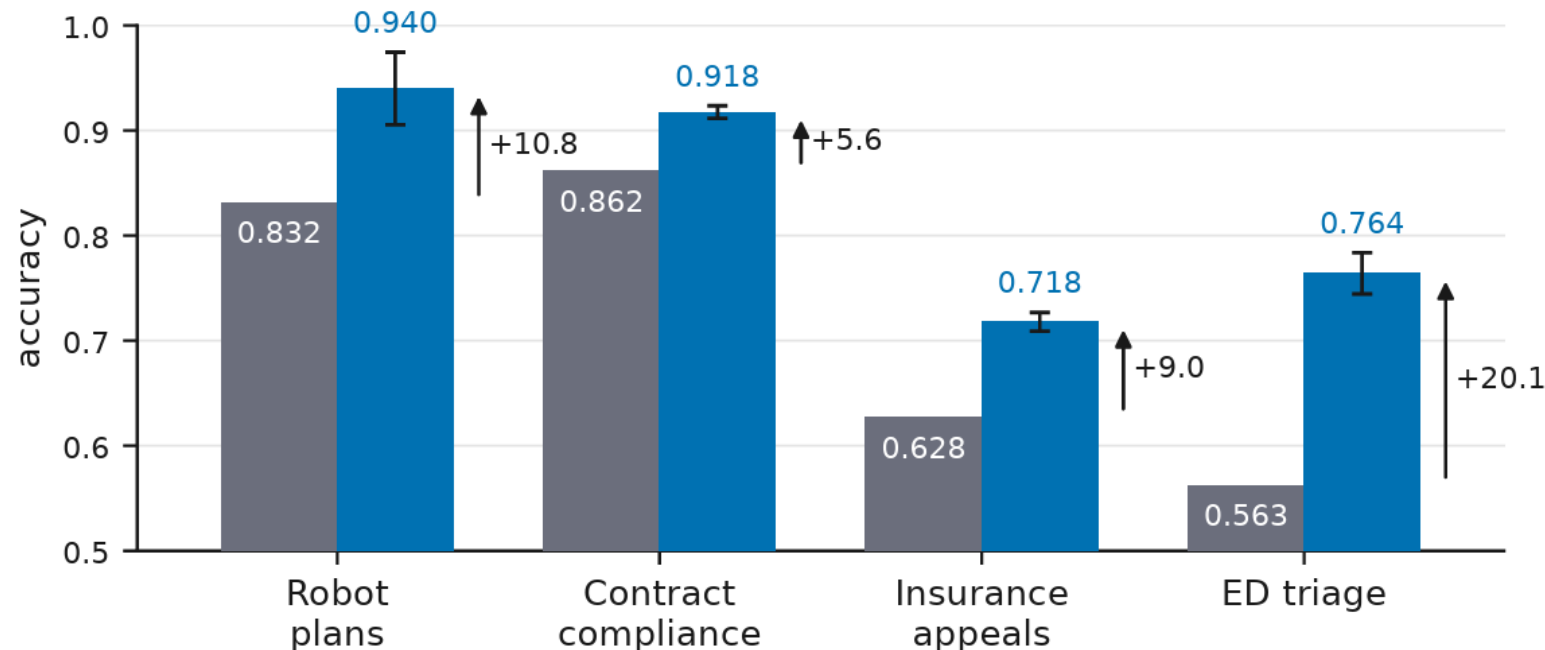
The VLL update paths once user makes the decision

# Compliance under uncertainty



## Compliance under uncertainty: medical use case

Insurers deny roughly 17% of in-network claims — about 48 million a year in the ACA marketplace alone — and fewer than 2000 denials are ever appealed. Yet when someone does appeal, about 41% of denials get overturned. Nobody re-examines the other 99.8% — not patients, and not the hospitals sitting on the money. That informs the market opportunity: California publishes 42,000+ adjudicated appeal decisions, so we can rank a hospital's denial pile by calibrated probability of overturn and have the same appeals staff file the winnable, high-dollar ones first.





## Conclusion

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- Verification is revolutionizing AI4Math
- For verification to do the same for robotics, logistics, compliance, and other domains, it must handle uncertainty
- We achieve verification under uncertainty by mapping systems and uncertainty to a shared geometry where we can compute confidence of prediction and the amount of additional data required to achieve a threshold of confidence

# Thanks!

[alvaro.velasquez@colorado.edu](mailto:alvaro.velasquez@colorado.edu)