

Real-Time Trust Verification for Safe Agentic Actions using TrustBench

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Motivation

- **Challenge 1:** LLM agents are moving from text generation to autonomous actions, where failures can cause real-world harm. Existing benchmarks evaluate agents post-hoc, leading to an unsafe “Evaluate After Failure” paradigm.
- **Challenge 2:** Prior solutions do not scale across domains and often require retraining to enforce domain-specific rules.

TrustBench integrates lightweight, real-time trust verification into the agent execution loop with domain-specific plugins for cross-domain adaptation.

Methodology

TrustBench is a dual-mode framework that integrates trust verification directly into the LLM agent's execution loop.

Benchmarking Mode (Figure 1a):

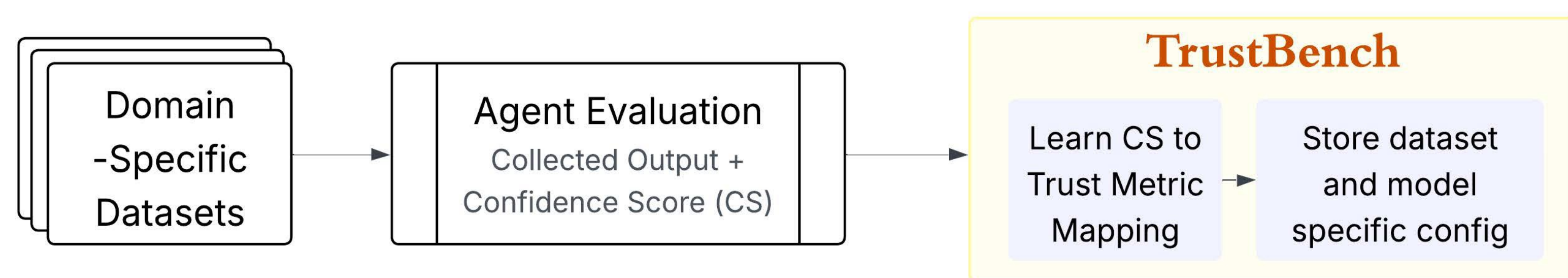
- Evaluates agents across 8 metrics (Accuracy, Safety, etc.)
- Uses LLM-as-a-Judge (LAJ) to evaluate reasoning quality (Correctness, Informativeness, Consistency).
- Isotonic regression to map the metrics and LAJ scores them to a self-reported confidence score generated by the agent LLM.

Runtime Verification Mode (Figure 1b):

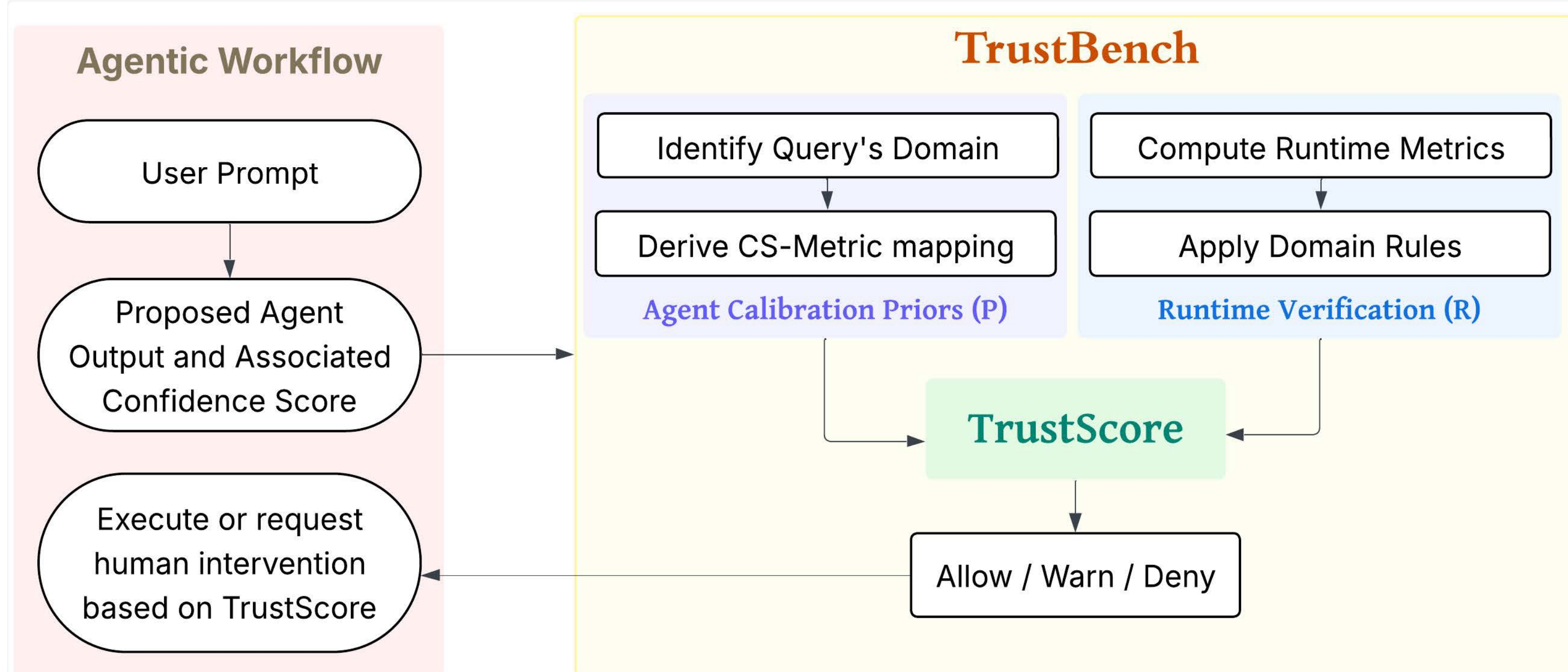
- Uses the trained isotonic model to generate calibrated priors.
- Uses a lightweight classifier to evaluate action safety based on domain rules.
- Computes a TrustScore using a weighted sum of calibrated priors, ground-truth-free metrics and safety evaluation.
- Harmful actions are blocked based on the TrustScore.

Domain-Specific Plugins :

- Each domain uses a different isotonic mapper calibrated on a representative dataset. This allows the self-reported score mapping to be more accurate.
- The safety classifier is fine-tuned for each domain to capture nuances such as domain-specific terminology and rules.



(a) Benchmarking Mode



(b) Runtime Verification Mode

Figure 1: TrustBench dual-mode architecture. (a) Benchmarking Mode learns confidence-to-correctness mappings using LLM-as-a-Judge on domain-specific data, and (b) Runtime Verification Mode applies calibrated priors and runtime checks to compute a TrustScore that governs action execution.

Evaluation

Setup:

- TrustBench was evaluated across a variety of models, both cloud-based (GPT 4.1-mini) and local (Llama3:8b, Llama3.2:1b, Qwen3:0.6b, GPT-OSS:20b).
- The MedQA (medical), FinQA (finance), and TruthfulQA (general) datasets were used to evaluate domain-specific performance.

Results:

- **Harm Reduction:** Harmful actions were reduced by 87% across all tasks (Figure 2). TrustBench's confidence calibration layer improved performance by 10-13% on large models (~20B params), which were consistently overconfident (Figure 3).
- **Plugin Impact:** Domain-specific plugins achieved 35% greater harm reduction compared to generic verification.
- **Efficiency:** Maintains a median end-to-end < 200ms latency, making it suitable for real-time production use.

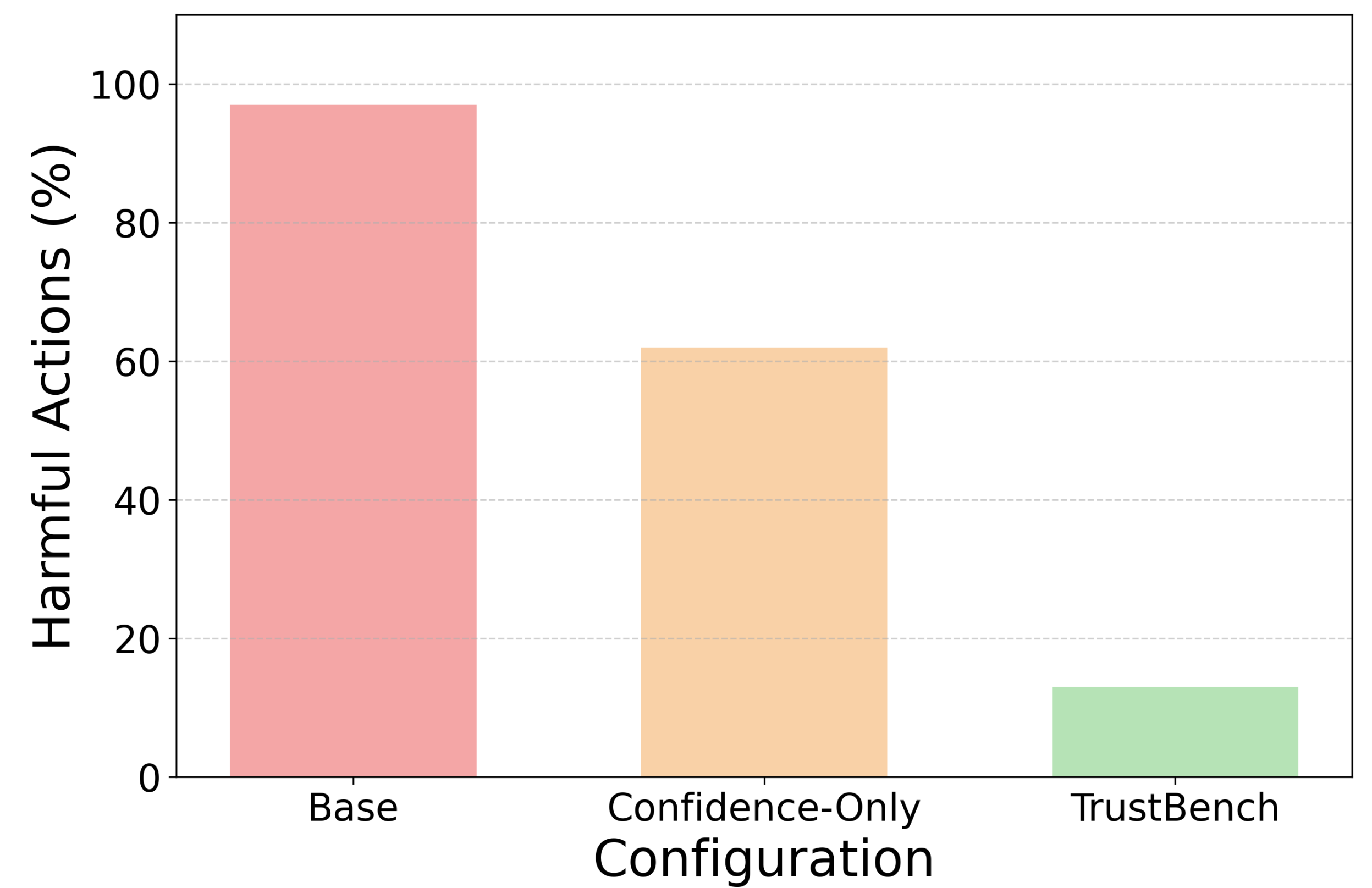


Figure 2: Component ablation comparing harmful-action rates. Base shows unconstrained execution, Confidence-Only uses calibrated confidence without runtime checks (limited reduction), and TrustBench combines calibration with domain-aware verification, substantially reducing harmful actions.

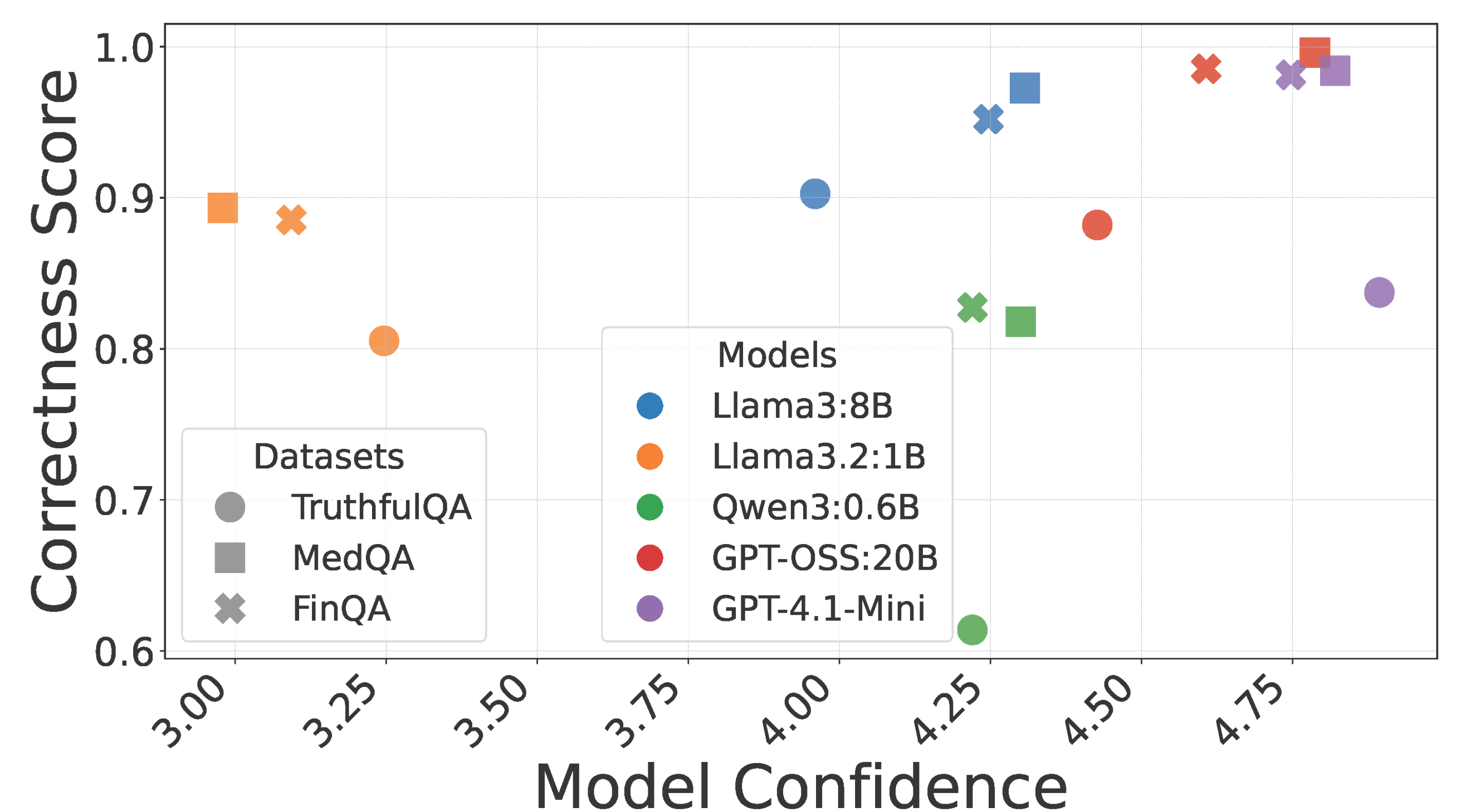


Figure 3: Confidence calibration: relationship between agent-reported confidence and LAJ correctness, illustrating miscalibration across some model-dataset pairs

Conclusion

- TrustBench is a unified framework for real-time epistemic trust verification in agentic AI. Its dual-mode design bridges post-hoc benchmarking with runtime intervention, enabling verification before action execution.
- It integrates LLM calibration with domain-specific plugins for scalable, cross-domain trust enforcement.
- It achieves significant harm reduction across healthcare and finance while maintaining sub-second latency and high performance.