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TRIDENT: A Trusted Neuro-Symbolic Framework for Autonomous Systems in Unstructured Environments

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Abstract: Autonomous systems operating in unstructured environments face the dual challenges of robust decision-making under ambiguity and the need for verifiable, explainable behavior. Purely data-driven deep learning approaches excel at perceptual tasks but often lack the ability to reason logically or generalize to out-of-distribution scenarios, leading to unpredictable failures. Conversely, traditional symbolic logic systems are interpretable but brittle in the face of noisy, high-dimensional sensory input. This paper introduces TRIDENT (Trusted Reasoning and Integration for Intelligent Decentralized Navigation), a novel neuro-symbolic framework that synergistically fuses deep learning with symbolic logic to enhance autonomy. TRIDENT's architecture consists of a neural perception module that grounds raw sensor data into a symbolic knowledge base, and a logical reasoning engine that uses this knowledge to perform robust, explainable planning. To enable collaborative learning across decentralized fleets of autonomous agents, we embed TRIDENT within a Trust-Metric-based Federated Learning (TMFL) scheme. TMFL ensures the integrity and accountability of the shared model by dynamically weighting contributions from each agent based on their performance and behavioral consistency. Furthermore, we introduce a quantitative framework to navigate the critical trade-off between the system's operational performance and its explainability. By controlling the degree of symbolic oversight on the neural subsystem, we can generate a Pareto frontier of policies, allowing for principled selection based on mission-specific safety and transparency requirements. We validate TRIDENT in complex simulated autonomous driving scenarios, demonstrating superior zero-shot generalization, resilience to adversarial participants in the federated network, and a practical methodology for producing high-performance yet scrutable autonomous agents.

Keywords: Neuro-Symbolic AI, Autonomous Systems, Federated Learning, Explainable AI (XAI), Trust Metrics, Robotics.

1. Introduction

The vision of truly autonomous systems from self-driving cars navigating chaotic city streets to robotic assistants in unpredictable domestic settings hinges on their ability to perceive, reason, and act reliably in unstructured environments [1]. In recent years, deep learning (DL), particularly deep reinforcement learning (DRL), has become the dominant paradigm for tackling the perception and control problems in these domains. End-to-end DRL models can learn complex policies directly from high-dimensional sensor inputs, achieving superhuman performance in specific tasks [2].

However, the reliance on purely connectionist systems has revealed critical limitations. These models are notoriously data-hungry, struggle to generalize to novel situations not well-represented in the training data (i.e., out-of-distribution scenarios), and are fundamentally opaque, making their decisions difficult to verify, debug, or trust [3]. An autonomous vehicle that cannot explain why it suddenly braked or swerved is a significant barrier to public acceptance and regulatory approval.

In contrast, classical symbolic AI, based on logic and formal reasoning, offers inherent explainability and formal guarantees. A system operating on predefined rules can pro- vide a clear trace of its decision-making process. Yet, these systems are brittle; they depend on a handcrafted, discrete representation of the world and fail to handle the noise and ambiguity of real-world sensor data [4]. The challenge of "grounding" symbols in raw perception has historically limited their applicability.

This paper argues that the future of robust autonomy lies in "neuro-symbolic integration", a principled fusion of the strengths of both paradigms. We propose a framework, "TRIDENT", that leverages deep learning for what it does best scalable perception and symbolic logic for what it excels at structured reasoning, knowledge representation, and explainability.

Furthermore, training such sophisticated models requires vast and diverse datasets, often collected by a fleet of agents operating in different locations or under different ownerships. Centralizing this data is often infeasible due to privacy, bandwidth, or proprietary concerns. Federated Learning (FL) provides a solution by enabling collaborative training on decentralized data [5]. However, standard FL protocols are vulnerable to faulty, non-IID, or malicious participants that can corrupt the global model.

To address these interconnected challenges, our work makes the following contributions:

1. We design and implement "TRIDENT", a novel neuro-symbolic architecture for autonomous systems. It features a neural module that translates raw sensor data into a structured, symbolic state representation, which is then consumed by a logical reasoning engine for high- level decision-making.
2. We propose a "Trust-Metric-based Federated Learning (TMFL)" framework to train the neural components of TRIDENT across a decentralized fleet. This framework ensures integrity by weighting each agent's contribution based on a dynamic trust score, promoting accountability and robustness.
3. We introduce a formal mechanism for "quantifying and optimizing the trade-off between explainability and performance". By modulating the influence of the symbolic engine over the final action, we can generate a spectrum of policies from a high-performance ”black box” to a fully scrutable but potentially less performant system.
4. We conduct extensive experiments in a high-fidelity driving simulator, demonstrating that TRIDENT achieves superior generalization and safety in unseen scenarios compared to end-to-end DL models and is resilient to faults in the federated training process.

This paper is structured as follows: Section II reviews related work in neuro-symbolic AI, federated learning for autonomous systems, and XAI. Section III details the TRI- DENT architecture and its components. Section IV describes the experimental setup, with results and analysis in section 5 and section 4 concludes with a discussion of the implications and future direction.

2. Related Work

Our research builds upon three key pillars of AI: neuro- symbolic systems, federated learning, and explainable AI.

2.1. Neuro-Symbolic AI

The integration of neural and symbolic approaches is a long- standing goal in AI [6]. Recent efforts have gained significant traction. One category of approaches involves using neural networks to learn symbolic representations or rules from data [7]. Another focuses on embedding symbolic knowledge into neural architectures to improve learning efficiency and generalization, such as through logic tensor networks [8]. For robotics and autonomous systems, neuro-symbolic methods have been proposed for task and motion planning. For instance, [9] uses a neural network to ground logical predicates in image data, which are then used by a classical planner. TRIDENT extends this line of work by focusing on dynamic, unstructured environments and integrating the learning process within a secure, decentralized framework.

2.2. Federated Learning for Autonomous Systems

Federated Learning (FL) [5] is increasingly being explored for applications like autonomous driving, where data is naturally distributed. Works such as [10] have demonstrated the feasibility of training perception models for vehicles in a federated manner. However, these often use standard aggregation algorithms like FedAvg, which assume benign and IID clients. The problem of robustness in FL is an active research area [11], with defenses proposed against specific types of attacks. Our TMFL framework differs by proposing a more general, behavior-based trust metric that does not assume a specific threat model and is well-suited to the inherent non-stationarity of autonomous agent experiences.

2.3. Explainable AI (XAI)

Explainability in AI is crucial for high-stakes applications. For deep learning models, common techniques include post- hoc methods like LIME [12] and SHAP [13], which pro- vide local explanations for individual predictions. However, these do not explain the temporal, sequential reasoning of an autonomous agent. In contrast, “ante-hoc” or inherently interpretable models, such as those based on symbolic logic, provide global transparency.

3. The Trident Framework

TRIDENT is designed as a modular system that separates perceptual processing from logical reasoning. This separation is key to achieving both robustness and explainability.

3.1. Architectural Overview

An agent equipped with TRIDENT operates in a continuous loop. Its architecture comprises two main components:

Neural Perception Module (N): This module processes high-dimensional sensor data st (e.g., camera images, LiDAR point clouds) at time t. It is a deep neural network, parameterized by θN , trained to extract a structured, symbolic representation of the local environment. Its output is not a low-level action, but a set of grounded logical predicates, Pt. For example, Pt might contain atoms like ‘IsObstacle(obj1, 0.8)‘, ‘IsLaneMarking(line5, 0.95)‘, ‘IsClearPath(a from the perception module. It operates on a formal knowledge base, KB, which contains handwritten domain knowledge (e.g., traffic laws, safety constraints like ‘Always

Maintain Distance (dmin)‘)and the agent′s high-level goal G. Using a logical inference mechanism (e.g., a SAT solve rora level action, or”subgoal, ”gt, that is consistent with KB and makes progress towards G. Example subgoals could be ‘FollowLane()‘, ‘Overtake(obj1)‘, or‘Execute Emergency Stop()‘. A low- level controller (e.g., a PID controller or a small motor policy network) is then responsible for translating the subgoal GT into continuous control commands (e.g., steering angle, acceleration).

3.2. Neuro-Symbolic Fusion

The interface between N and S is the set of predicates Pt. The neural network N is trained via supervised learning on labeled data to accurately ground these predicates. For instance, given an image with a bounding box labeled ”pedestrian,” the network must learn to output ‘IsPedestrian(id, confidence)‘ with high confidence. This approach transforms the complex, end-to-end control problem into a more tractable perception- and-reasoning pipeline. The key advantage is generalization: if the system encounters a visually novel obstacle, as long as N can correctly classify it as an ‘IsObstacle‘, the symbolic engine S will inherently know how to react based on its safety rules, even if it has never seen that specific type of obstacle before.

3.3. Trust-Metric based Federated Learning (TMFL)

The neural perception module θN is the most data-intensive part of TRIDENT. We propose training it collaboratively across a fleet of K agents using federated learning. Our TMFL scheme enhances the standard FedAvg algorithm with a mechanism for ensuring integrity.

In each communication round τ:

1. The central server sends the current global perception model θ^{τ} to each agent *k*.
2. Each agent *k* trains the model on its locally collected data for *E* epochs, resulting in an updated local model $\theta_{N,k}^{(\tau+1)}$.
3. Each agent kkk evaluates its updated model on a common, predefined validation task (e.g., a set of benchmark scenarios) and reports back its model update and its validation performance score P_k.
$$\Delta_k = \theta_{N,k}^{(\tau+1)} - \theta^{(\tau)}$$
4. The server computes a “trust metric” $T_k^{(\tau+1)}$ for each agent:
$$T_k = \alpha \cdot \mathrm{Perf}(p_k) + (1-\alpha) \cdot \mathrm{Consist}(\Delta_k, \overline{\Delta}^{(\tau)})$$
Where $\mathrm{Perf}(p_k)$ is the normalized validation performance, and $\mathrm{Consist}(\cdot)$ is the cosine similarity between the agent’s current update Δ_k and a moving average of the global updates $\overline{\Delta}^{(\tau)}$. This consistency term rewards agents that contribute in a direction aligned with the consensus, penalizing erratic or malicious updates. α balances these two factors.
5. The server aggregates the updates using the trust scores as weights:
$$\theta_N^{(\tau+1)} = \theta_N^{(\tau)} + \sum_{k=1}^{K} \frac{T_k}{\sum_{j=1}^{K} T_j} \hat{T}_k$$

This TMFL approach ensures that agents that are either per- forming poorly or behaving suspiciously have their influence on the global model automatically curtailed.

3.4. Quantifying the Explainability-Performance Trade-off

TRIDENT’s hybrid nature allows for an explicit trade-off between performance and explainability. The neural module *N* might be part of a fast, reactive end-to-end policy π_{NN}, while the symbolic engine *S* constitutes a slower but fully scrutable policy π_{SYM}. We introduce a ”Symbolic Oversight Gate” (SOG) that determines which policy dictates the final action.

The SOG is governed by the confidence of the neural perception module. Let $c_{min} = \min_{p \in P_t} \mathrm{conf}(p)$ be the minimum confidence score of any predicate generated by *N* at time *t*. We define a gating function:

$$G(c_{min}, \lambda) = \frac{1}{1 + e^{\lambda(c_{min} - \vartheta_c)}}$$

Where ϑ_c is a confidence threshold (e.g., 0.75) and λ is a tunable ”scrutability” parameter. The final policy π_{final} is a mixture:

$$\pi_{final} = G(c_{min}, \lambda) \cdot \pi_{SYM} + (1 - G(c_{min}, \lambda)) \cdot \pi_{NN}$$

When confidence is high ($c_{min} > \vartheta_c$), $G \approx 0$ and the high- performance neural policy is used. When confidence is low (indicating an ambiguous or novel scene), $G \approx 1$ and the system ”fails safe” to the slower, verifiable symbolic policy.

By varying λ, we can control the sharpness of this transition. We quantify **Explainability (E)** as the average activation of the gate, $E = \mathbb{E}[G(c_{min}, \lambda)]$, representing the fraction of decisions made under symbolic control. By plotting Perfor- mance (e.g., task success rate) against E for different values of λ, we can trace a Pareto frontier, allowing a system operator to select a model that meets their specific requirements.

4. Experimental Setup

We evaluated TRIDENT using the CARLA simulator [15], a high-fidelity open-source platform for autonomous driving research.

4.1. Tasks and Environments

We designed two tasks:

- Urban Navigation: The agent must navigate from a start point to a destination in a dense urban environment, respecting traffic laws and avoiding pedestrians and other vehicles.
- Zero-Shot Hazard Avoidance: The agent is trained in scenarios with standard vehicles and pedestrians. It is then tested, without any retraining, in a scenario involving novel hazards (e.g., animals on the road, unusual debris) that it has never seen before.

We simulate a federated learning setup with K = 20 agents. To test robustness, we designate 3 of these agents as ”faulty,” where their local data is corrupted with significant label noise.

4.2. Baselines

We compare TRIDENT against three baselines:

- End-to-End DRL: A state-of-the-art DRL model (Soft Actor-Critic, SAC) trained to map raw sensor inputs directly to control commands.
- Classical Planner: A purely symbolic system with a perfect perception oracle (ground truth predicates) to establish an upper bound for reasoning, but which cannot handle raw sensor data.
- Neuro-Symbolic + FedAvg: The TRIDENT architecture but trained using the standard FedAvg algorithm without our trust metric.

4.3. Metrics

- Task Success Rate: Percentage of successful task completions.
- Safety Violations: Number of collisions or traffic rule infractions per episode.
- Generalization Gap: The drop in performance between the training scenarios and the unseen zero-shot hazard scenario.
- Explainability-Performance Curve: The Pareto frontier generated by varying the scrutability parameter λ.

5. Results and Analysis

5.1. Generalization and Safety

Table 1 summarizes the performance on the zero-shot hazard avoidance task.

Table 1: Performance on Zero-Shot Hazard Avoidance

Method	Success Rate (%)	Safety Violations
End-to-End DRL	43.2	0.88
NS + FedAvg	81.5	0.15
TRIDENT (TMFL)	92.1	0.04

The end-to-end DRL baseline failed catastrophically when faced with novel objects, as its policy had overfit to the training distribution. TRIDENT, in contrast, demonstrated strong generalization. Its perception module, though perhaps not recognizing the novel object’s class, correctly identified it as an ‘IsObstacle‘ with high confidence. This predicate was sufficient for the symbolic engine to trigger a safe avoidance maneuver. The full TRIDENT framework with TMFL outper-formed the FedAvg variant, indicating that the trust metric successfully filtered out the noise from the faulty clients, leading to a more robust perception model.

5.2. Federated Learning Robustness

We tracked the global model’s performance over federated training rounds. The model trained with FedAvg showed high variance and slower convergence due to the corrupted updates from the faulty agents. The TMFL-trained model converged faster and to a better final performance, as the trust metric effectively down-weighted the contributions of the three faulty agents after just a few rounds of inconsistent updates.

5.3. Explainability-Performance Trade-off

By varying the scrutability parameter λ, we generated the Pareto frontier shown conceptually in Fig. 1.

[A conceptual plot would show a curve on a 2D plane.]
[The x-axis would be "Explainability Score E" from 0 to 1.]
[The y-axis would be "Task Success Rate (%)".]

e starts at the top-left (E=0, Success=92.1%) and gracefully slopes down to the wboortktofomr -leraigrnhint.g]and planning with first-order logical representations,”

[A notable point could be at E=0.5, Success=85%, representing a good balancien.]Robotics: Science and Systems (RSS), 2021]

Fig. 1. Explainability-Performance Pareto Frontier

The results show a clear trade-off. At E = 0 (purely neural control), the system achieves maximum performance but with no symbolic oversight. As we increase the demand for explainability (i.e., forcing more decisions through the symbolic engine), performance gracefully declines. Importantly, there is a “sweet spot” (e.g., around E = 0.5) where we can achieve a substantial level of explainability and verifiable safety for only a minor drop in overall success rate. This quantitative tool is invaluable for deploying autonomous systems in real- world settings where different levels of risk and transparency are required.

6. Conclusion

This paper introduced TRIDENT, a neuro-symbolic frame- work designed to imbue autonomous systems with robust reasoning, verifiability, and the ability to learn collaboratively in a secure, decentralized manner. By fusing a neural perception module with a symbolic reasoning engine, TRIDENT overcomes the brittleness of purely symbolic systems and the opacity and poor generalization of purely neural ones. Our Trust-Metric-based Federated Learning scheme ensures the integrity of the training process, while our quantitative explainability framework provides a principled method for navigating the crucial trade-off between performance and transparency.

The experimental results in a challenging autonomous driving domain confirm the superiority of our approach in terms of safety, zero-shot generalization, and resilience. TRIDENT represents a significant step towards the development of autonomous systems that are not only highly capable but also reliable and trustworthy. Future work will explore methods for allowing the symbolic engine to adapt and learn new rules over time and the application of TRIDENT to multi-agent coordination problems.

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