Beyond the Map: Learning to Navigate Unseen Urban Dynamics Using Diffusion-Guided Deep Reinforcement Learning

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IJCAI 2025 MONTREAL

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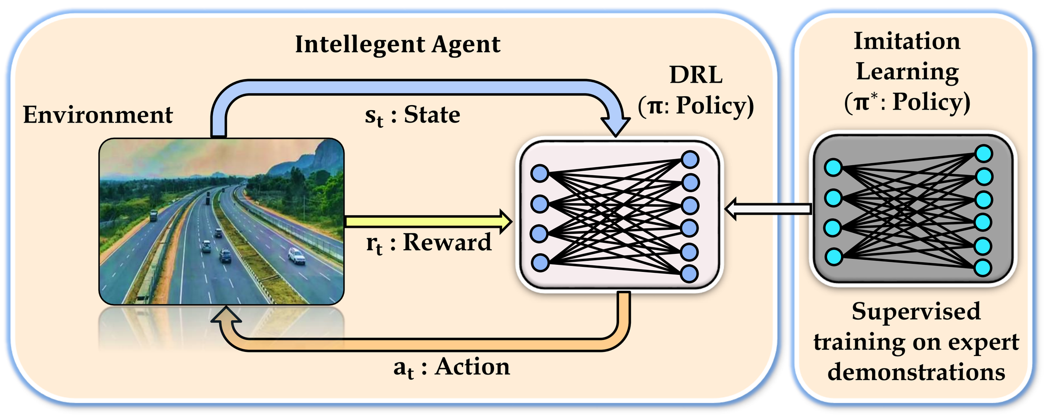
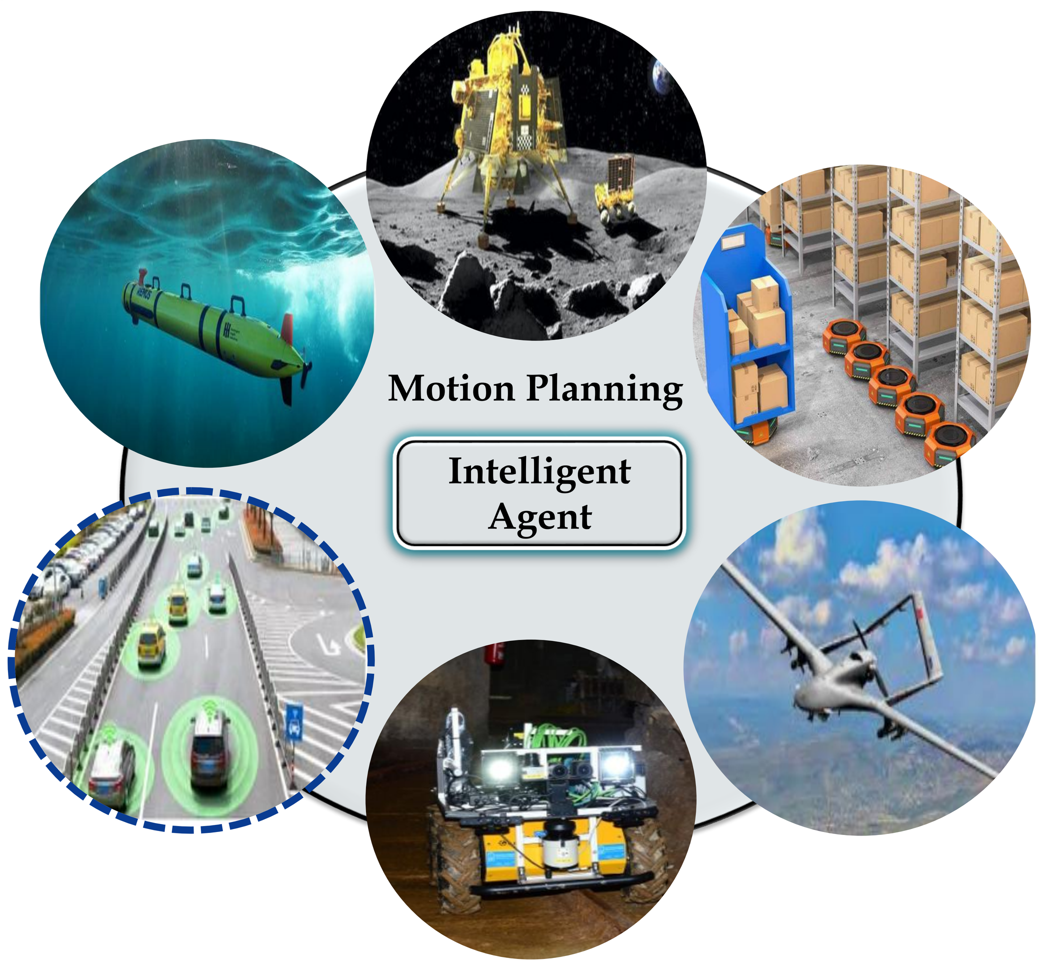
Problem Statement

- Vision-based motion planning is a crucial task for an intelligent agent to effectively learn and adapt to the dynamic characteristics of its environment.



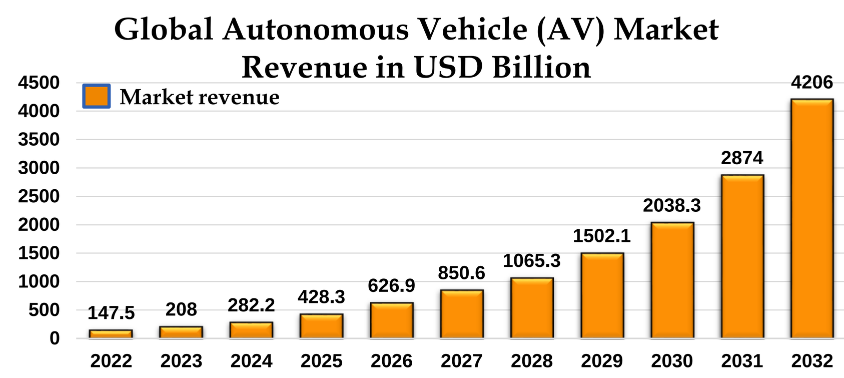
- **Challenges in IL-Based DRL Approaches:**
  - Performance limited by the quality of the expert data.
  - Impossible to collect expert data for all driving scenarios.
  - Distribution mismatch between training and real-world data causes poor generalization to new states.

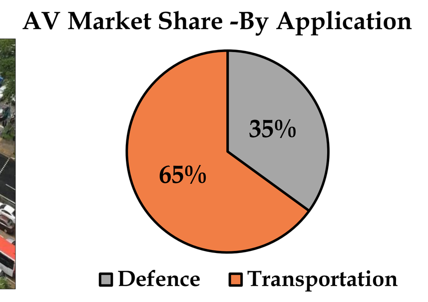
Applications



Motivation

- Greater Road Safety
- Greater Independence
- Reduced Congestion
- Increase Productivity
- Enhanced accessibility





- According to US market reports [5], transportation applications dominate the AV market with 65% share across self-driving cars, trucks, and public transit. This dominance creates significant opportunities for AI-driven solutions in autonomous driving.

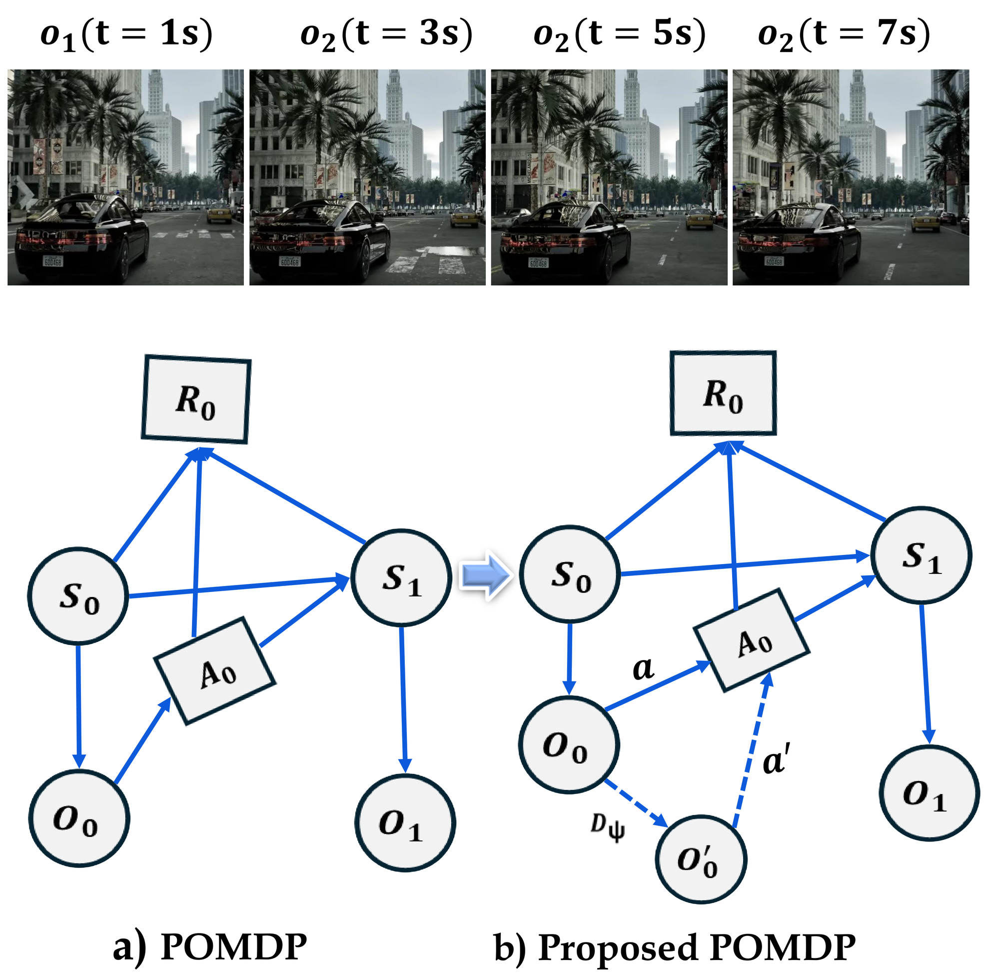
Key Contributions

- We propose a Diffusion-Guided Deep Reinforcement Learning (**DGDRL**) framework, which integrates diffusion models with Soft Actor-Critic to enhance task generalization and reduce dependency on IL.
- We introduce a novel modified Partially Observable Markov Decision Process (**mPOMDP**) to optimize the behavior of the SAC policy for handling uncertainty in dynamic environments.
- We conduct extensive testing across multiple CARLA towns under varying weather conditions and traffic densities (Empty, Regular, and Dense scenarios). where DGDRL achieves 95% task completion success rate with enhanced safety

Actor Network Function (π)

$$L_\phi^\pi = -\mathbb{E}_{o_t\sim D}\left[\mathbb{E}_{\tilde{a}_t\sim\pi_\phi(\cdot|o_t)}\left(\min_{k=1,2} Q_{\theta_k}(o_t,\tilde{a}_t) - \alpha\log\pi_\phi(\tilde{a}_t|o_t)\right)\right] + \lambda\,\mathbb{E}_{o'_t\sim\text{Diffusion}(o_t)}\left[D_{\mathrm{KL}}\left(\pi_\phi(\cdot|o_t)\,\|\,\pi_\phi(\cdot|o'_t)\right)\right]$$

Proposed Method : Diffusion-Guided Deep Reinforcement Learning



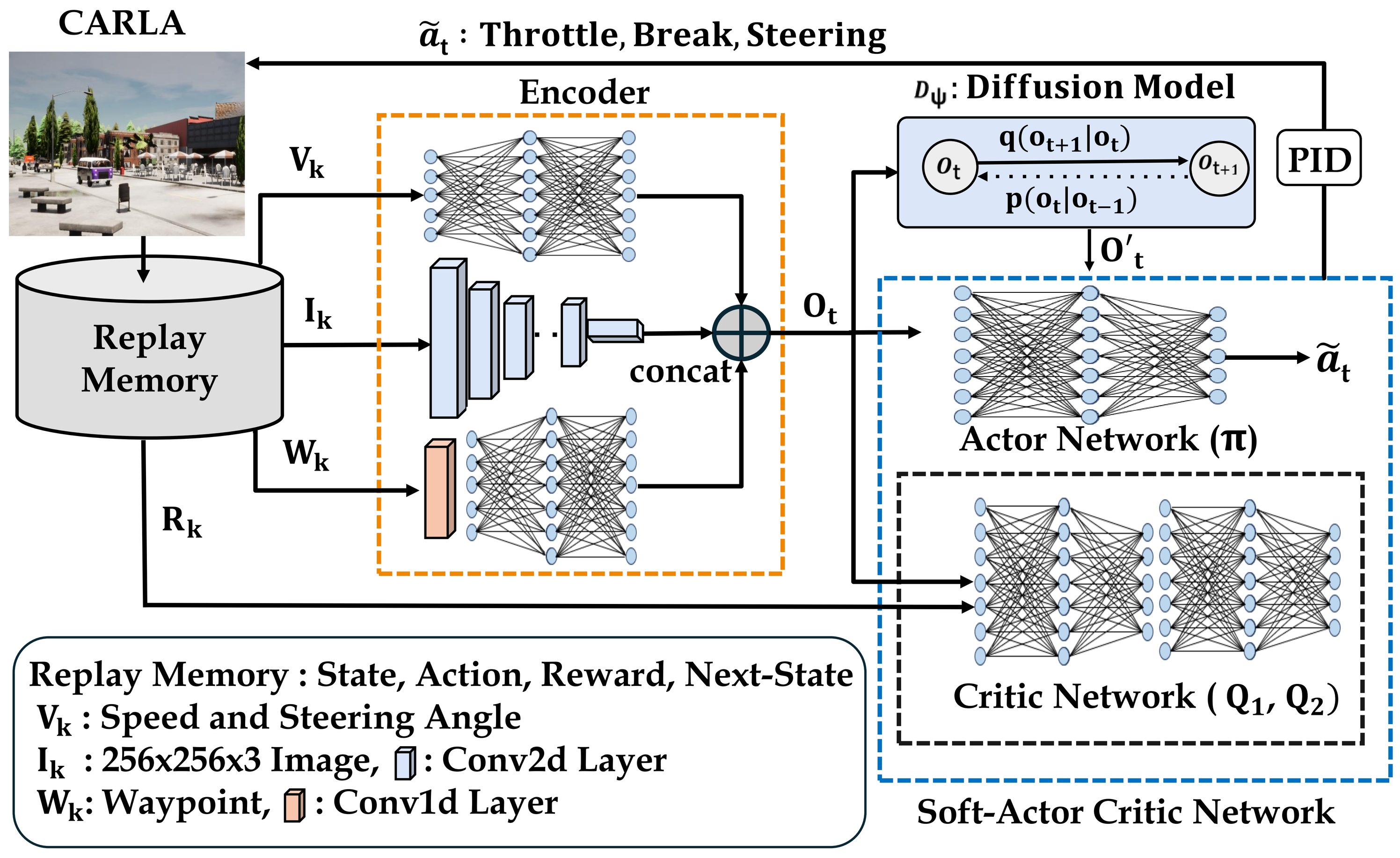


Figure 1: The DGDRL framework integrates encoder blocks, diffusion mode, and Soft Actor-Critic networks to address uncertainty and improve generalization in dynamic environments.

Results

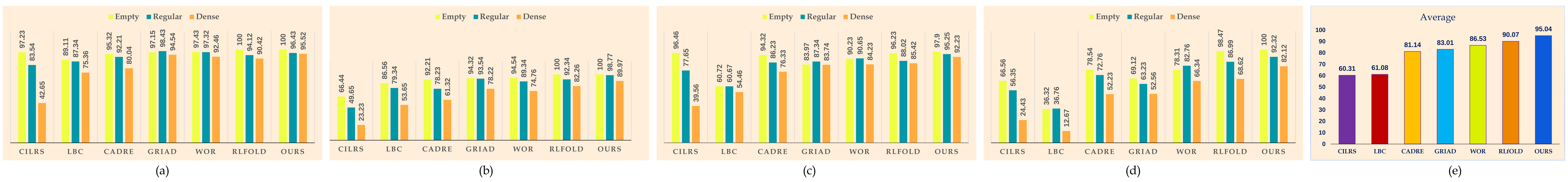


Figure 2: DGDRL performance comparison showing success rates (%) on CARLA NoCrash benchmark across two towns (T01, T02) and weather conditions (W01, W02): (a) T01, W01; (b) T01, W02; (c) T02, W01; (d) T02, W02

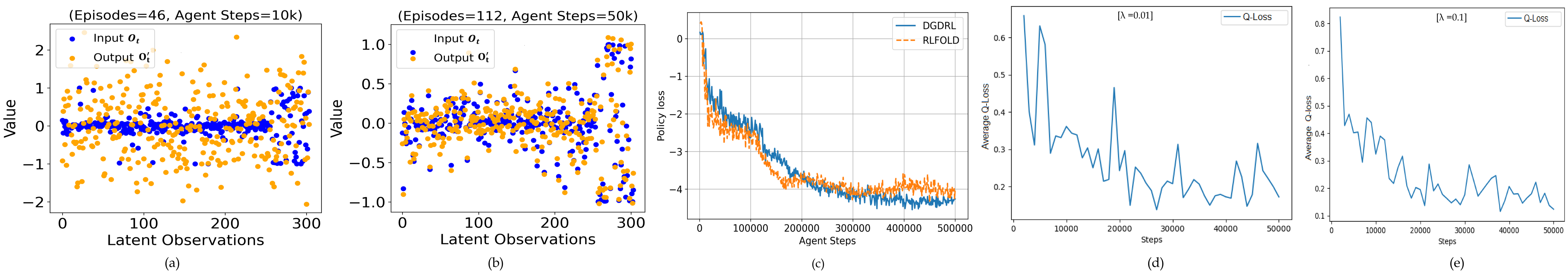


Figure 3: DGDRL training analysis across multiple metrics: (a-b) Latent observation comparison (o_t vs o'_t) at 10K and 50K steps showing diffusion model's progressive enhancement in guiding policy network to handle environmental uncertainties, (c) Policy loss evolution over 500K training steps, and (d-e) Q-network loss curves comparing λ values (0.01 vs 0.1) during initial 50K steps to illustrate hyperparameter impact on learning dynamics.

Figure 4: DGDRL generalization analysis in Town02 dense setup. Rows 1-2: successful navigation through complex scenarios including underpasses. Bottom row: failure case where the model encounters a tunnel and halts, unable to make decisions. These examples highlight both model adaptability and limitations in specific environments.

Conclusion and Future Work

- **Model:** The proposed Diffusion-Guided Deep Reinforcement Learning (DGDRL) model integrates diffusion models with Soft Actor-Critic under a modified POMDP framework.
- **Performance Benchmark:** 95.04% success rate across diverse environments (e.g., new town and weather)
- **Key Improvements:** Enhanced generalization to new task and improve pedestrian safety.
- **Future Work:** Targets complex scenarios such as tunnels, lane change , and broader domain applications.

Acknowledgement

This work is partially supported by the DST-NSF Project and MeitY CPS Project , Govt. of India.

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