

Motivation & Societal Impact

- **Higher Autonomy** is a primary goal for transportation systems of future cities.
- **Problem:** Most autonomy systems rely on **AI models** for critical **perception tasks**.
- **AI in Transportation Trade-off:**

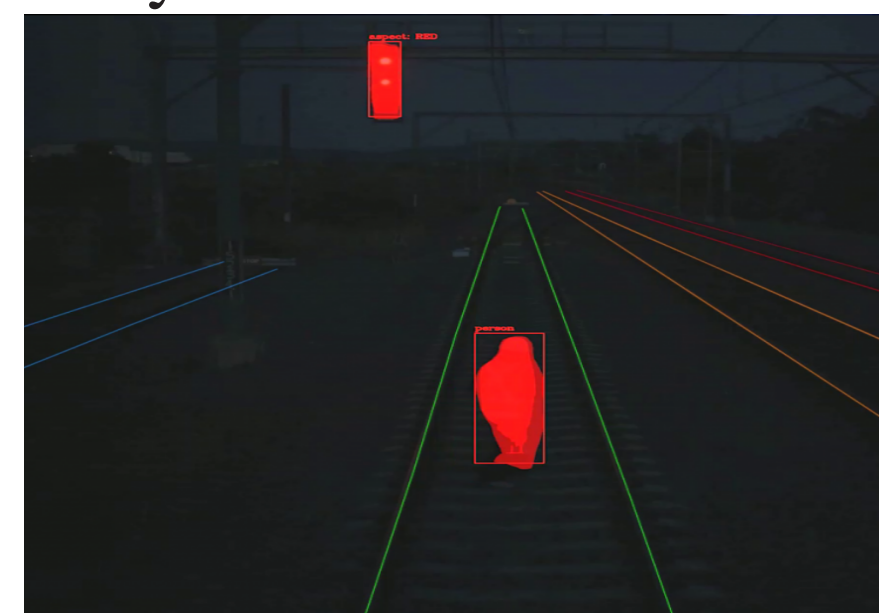
Promises of AI Perception

- ✓ High performance in complex urban settings.
- ✓ Superior recognition of signs & signals.



Risks of Deployment

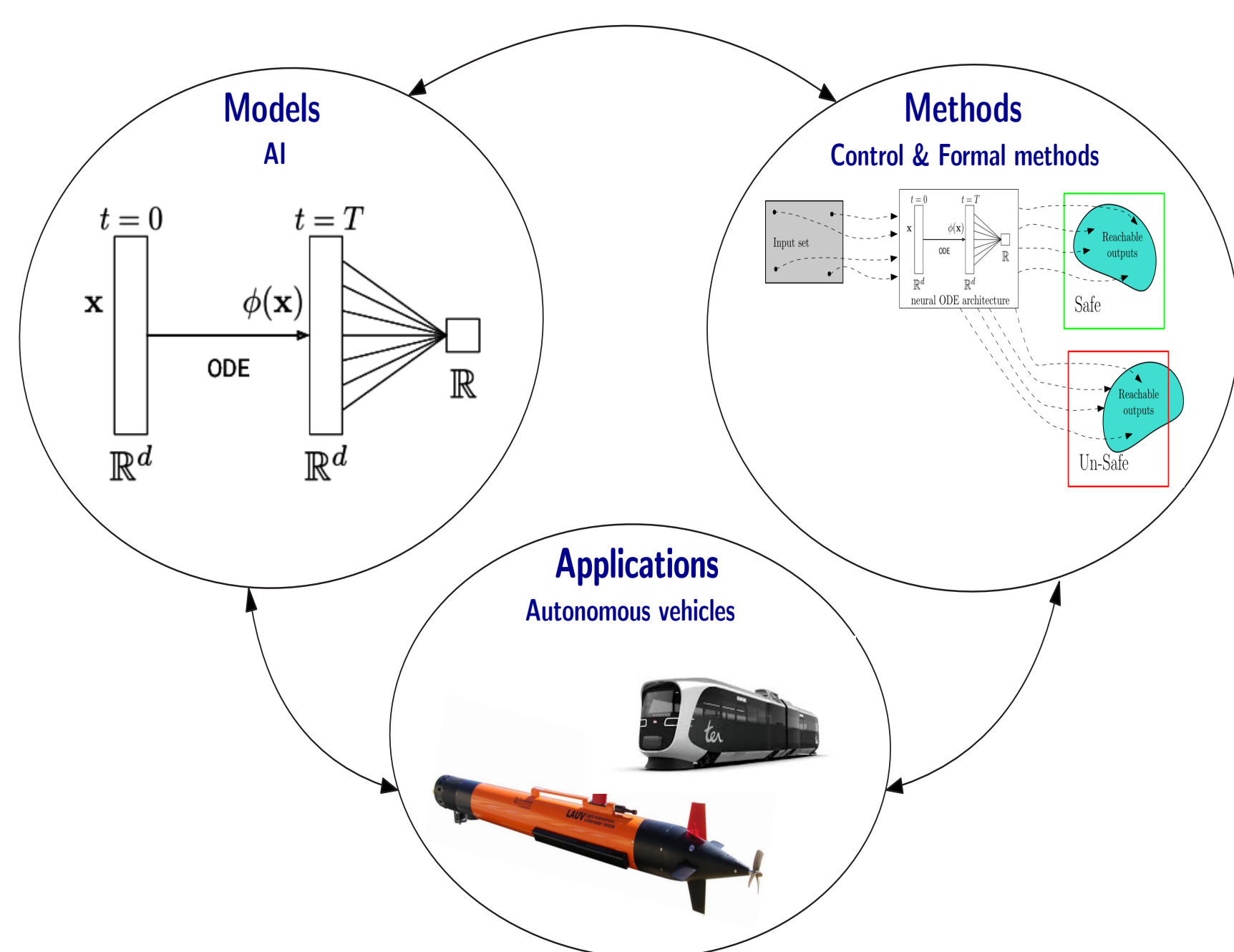
- ⚠️ Unpredictability in edge-cases.
- ⚠️ lack of of formal verification.
- ⚠️ Major risks for deployment on safety-critical systems.



My research is motivated by the critical need to bridge the gap between AI-based perception modules and their safety verification when deployed in autonomous vehicles.

- **Neural ODE** (*Chen et al. 2018*) are commonly described as a **continuous-depth** generalization (*Sayed et al. 2025a*) of a discrete **ResNet** (*He et al. 2016*).
- **Neural ODE** have gained prominence in **time-series** modeling over discrete neural networks (*kidger, 2021*).
- **Neural ODE Verification Gap:** Current methods are **underdeveloped** (*Lopez et al. 2022*), and existing methods are **computationally intensive** (*Sayed et al. 2025b*).

- We provide novel methods and light weight tools based on reachability analysis to **analyze and verify safety properties of neural ODE**.
- We combine **continuous AI/neural ODE** models, **reachability analysis** methods to analyze such models, with the final objective of **verifying safety of AI mdoels utilized by autonomous vehicles**.



Future Research Directions

- **Scalability to other architectures** Extending the framework in **R.D 1** to handle more neural network architectures (e.g., **RNN** and **CNN**).
- **Uncertainty quantification** Moving from deterministic ODEs to **Stochastic Differential Equations (SDEs)** to model sensor noise and environmental unpredictability.
- **Closed-loop verification** Verifying the safety of the entire autonomous loop by integrating the neural ODE perception module with the vehicle's control policy.
- **Real-time verification** Optimizing verification algorithms to run efficiently on embedded hardware for **adaptive mission planning**.

References

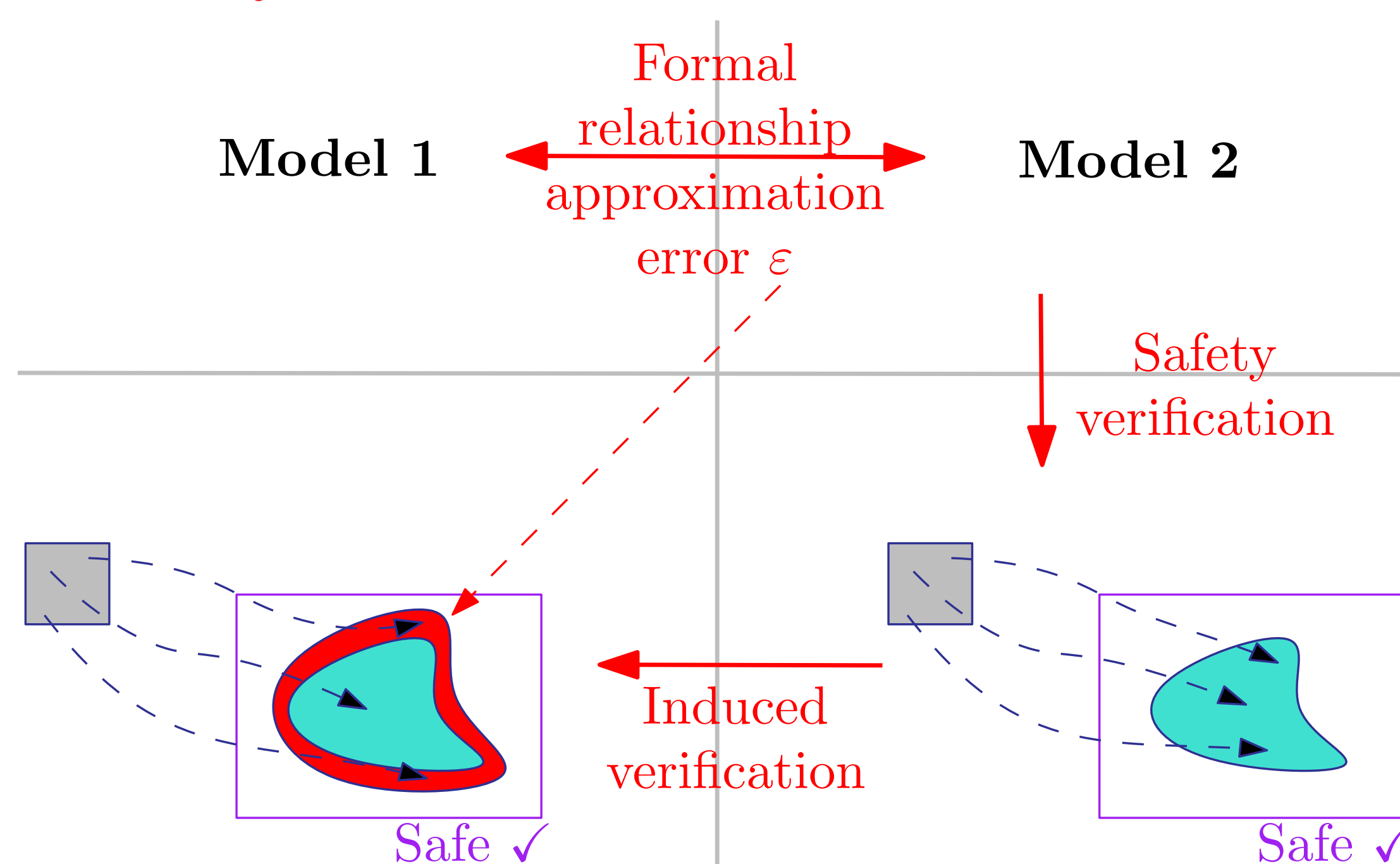
- [1] Sayed, A.S., Meyer, P.J., Ghazel, M.: Bridging neural ode and resnet: A formal error bound for safety verification. In: International Symposium on AI Verification. pp. 97–114. Springer (2025)
- [2] Sayed, A.S., Meyer, P.J., Ghazel, M.: Mixed monotonicity reachability analysis of neural ode: A trade-off between tightness and efficiency. In: NeurIPS 2025 Workshop on Symmetry and Geometry in Neural Representations (2025)

Thesis Contributions

1. R.D 1: Formal relationships between neural networks and neural ODE

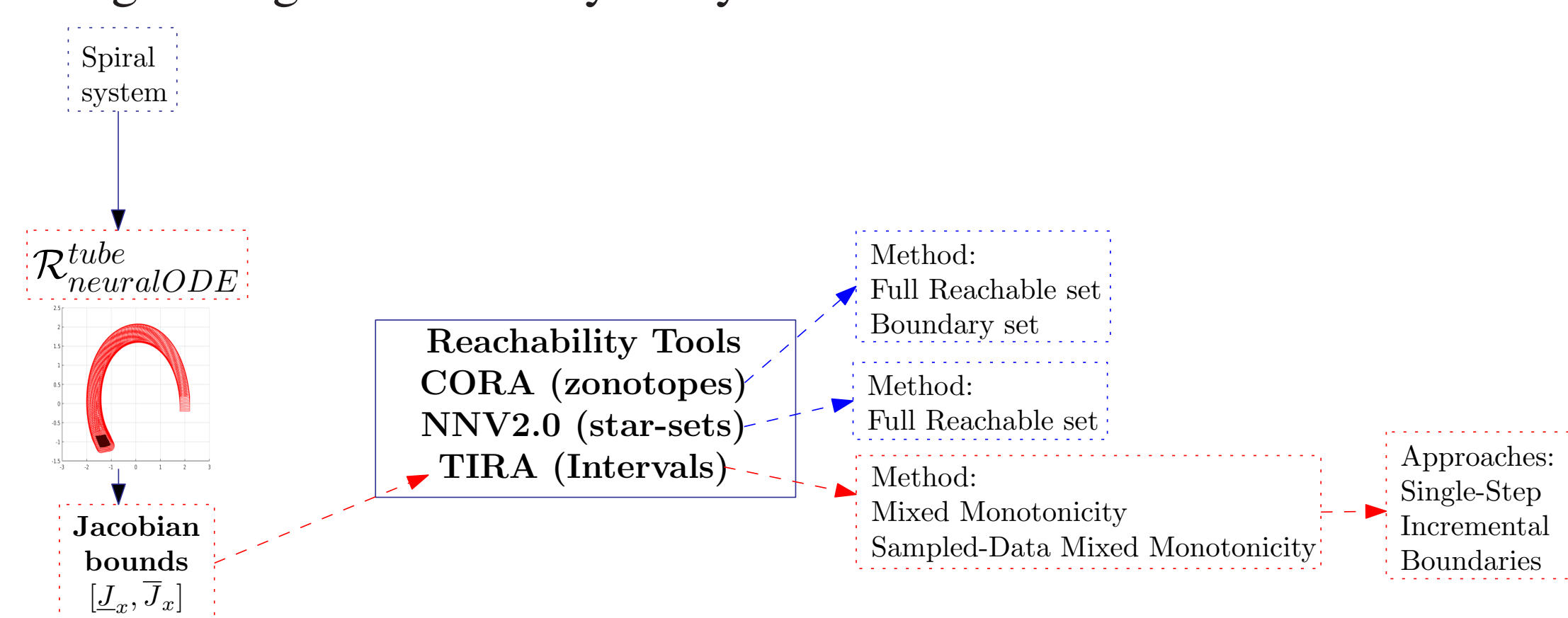
(Sayed et al. 2025a)

- Rigorous error bound (ε) on the approximation error between neural ODE and ResNet.
- Tighter Ω_ε over-approximation $< \mathbf{16\ million\ times} \times \mathbf{SOTA}$ (Sander et al. 2022).
- Verification proxy to verify one model based on the reachable set of the other $\pm \Omega_\varepsilon$.



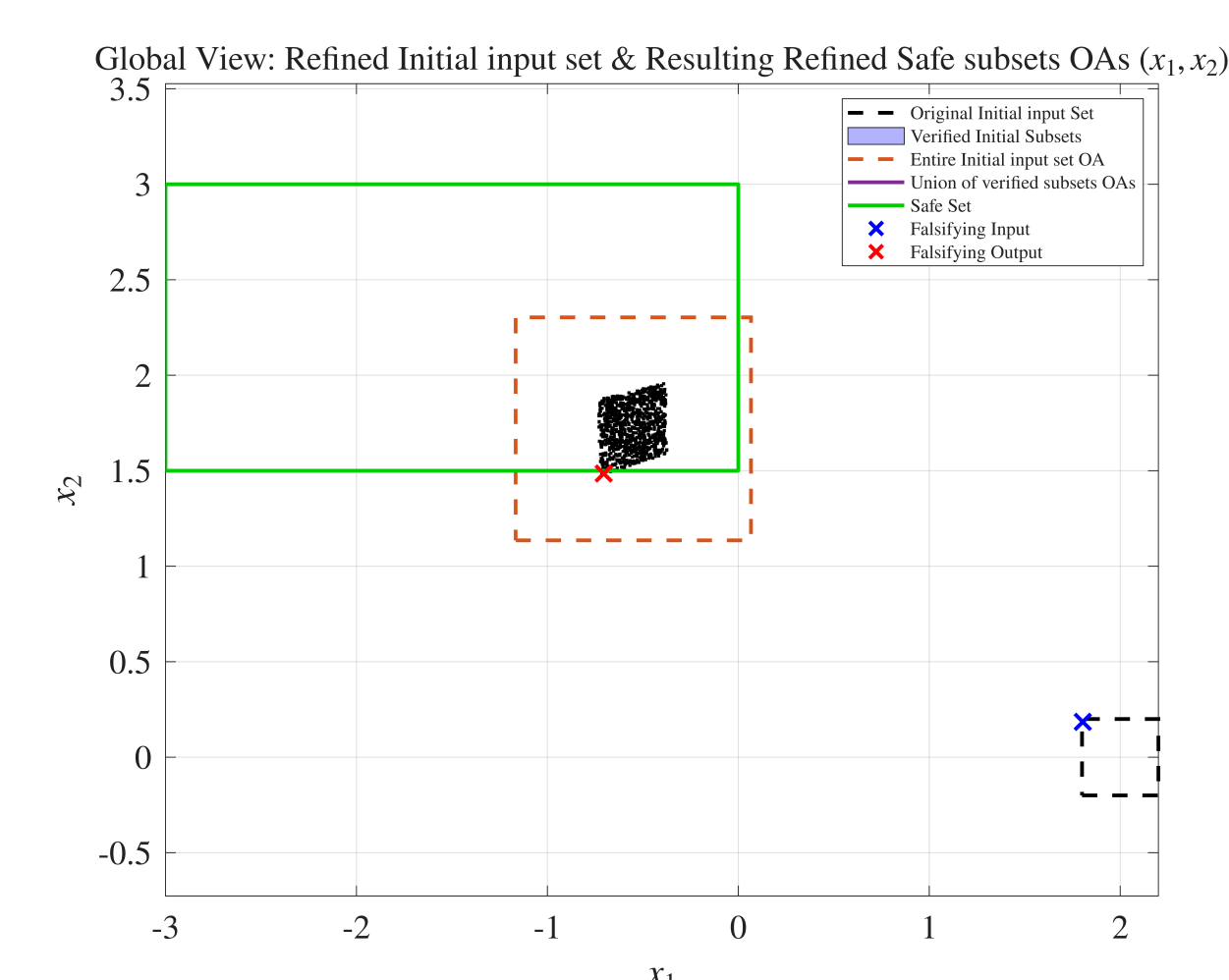
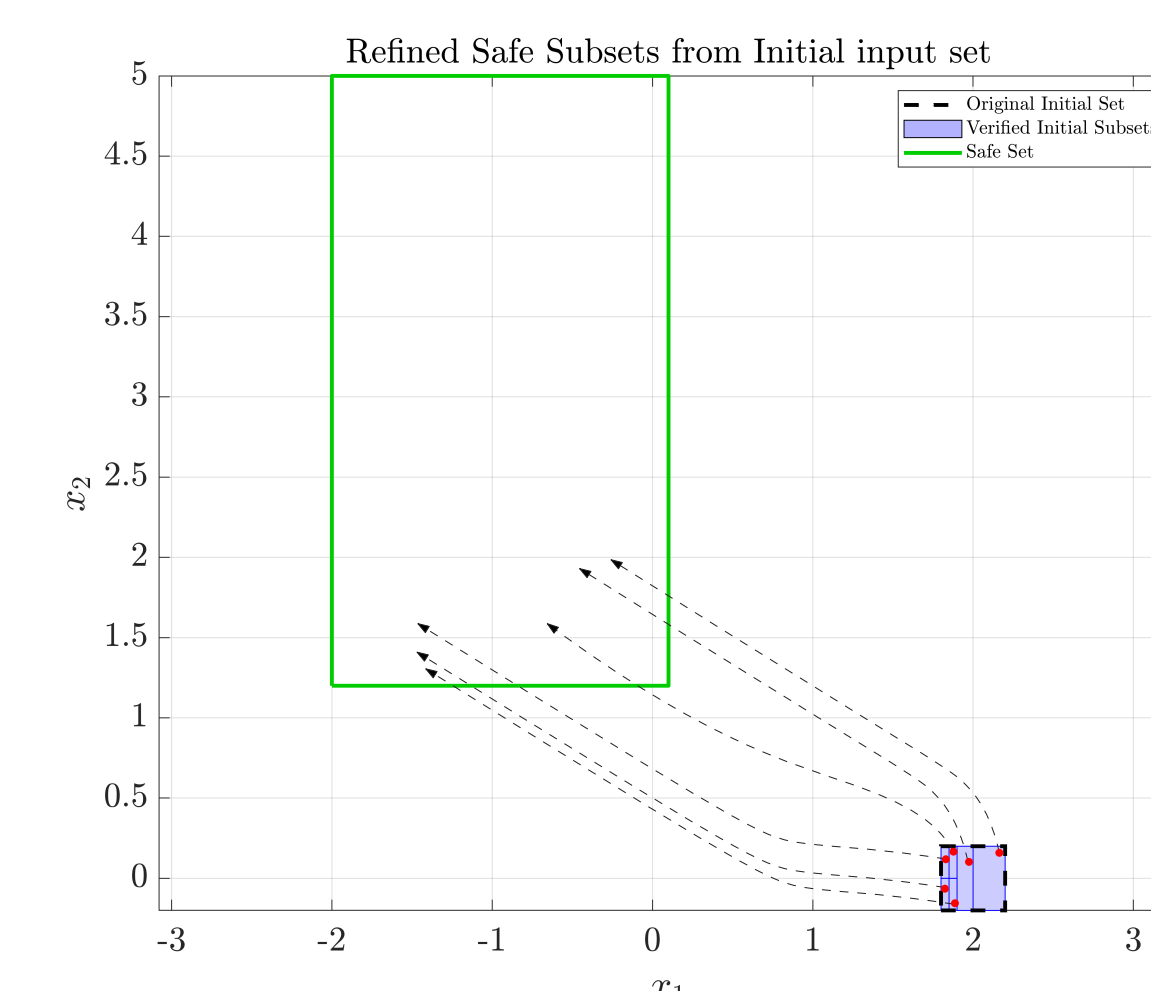
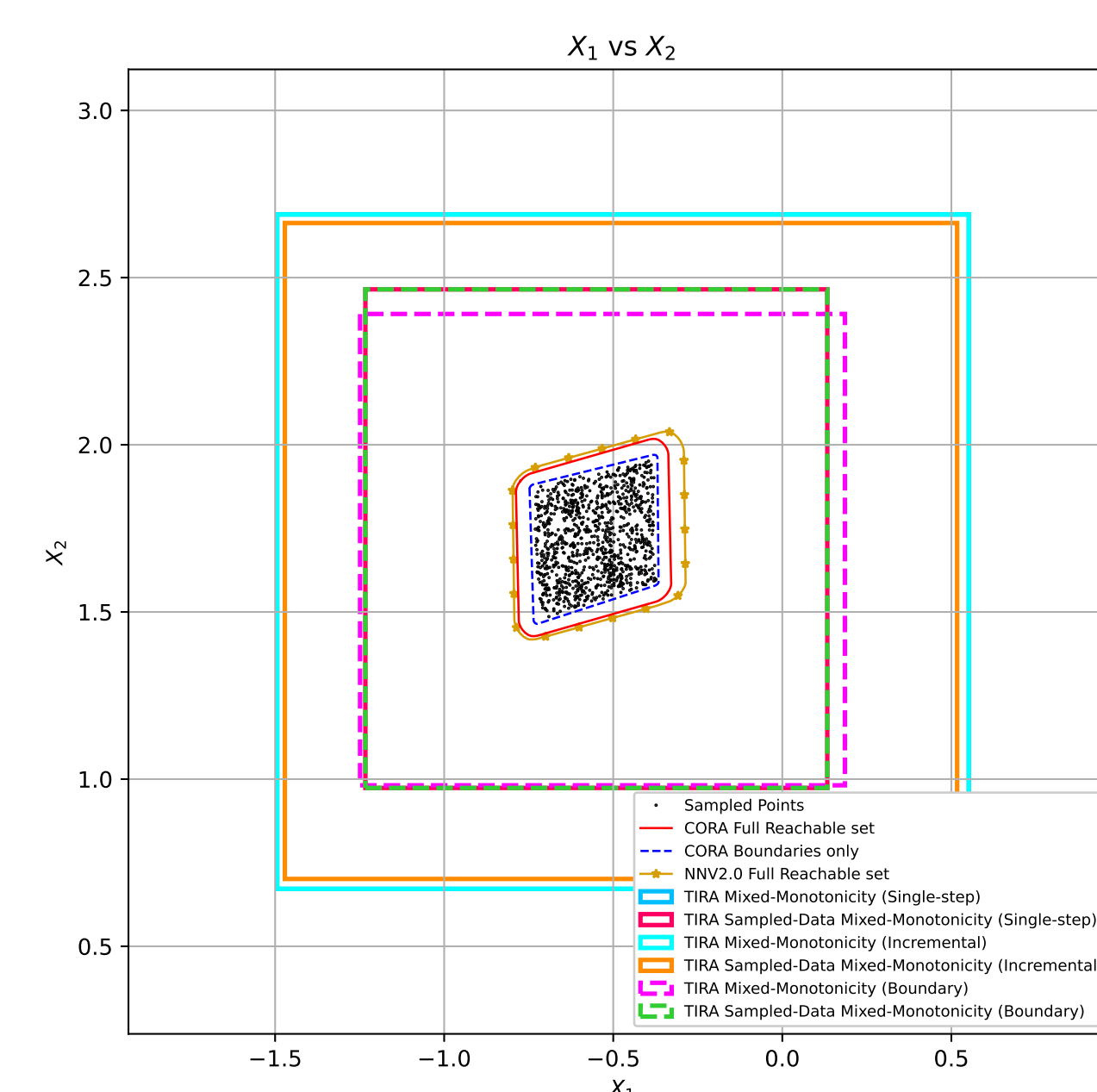
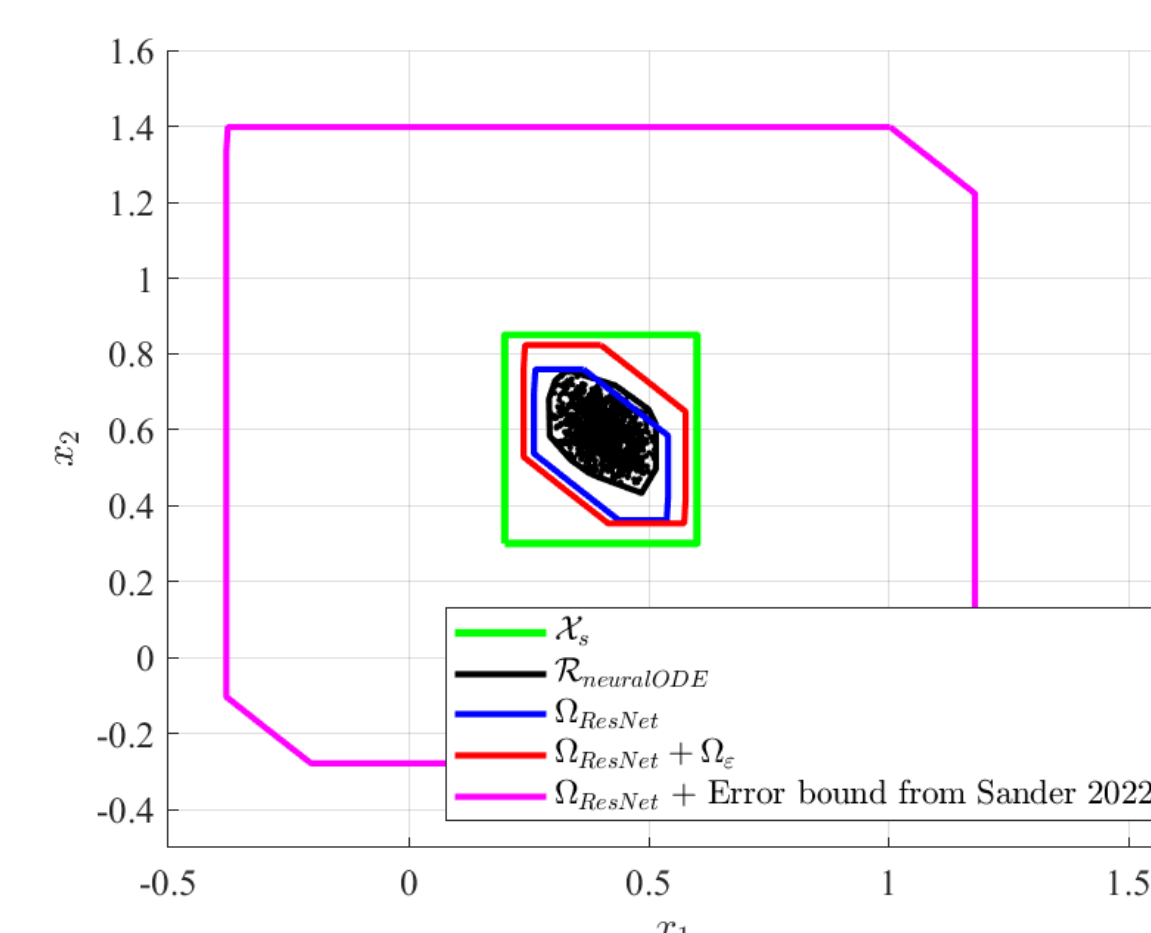
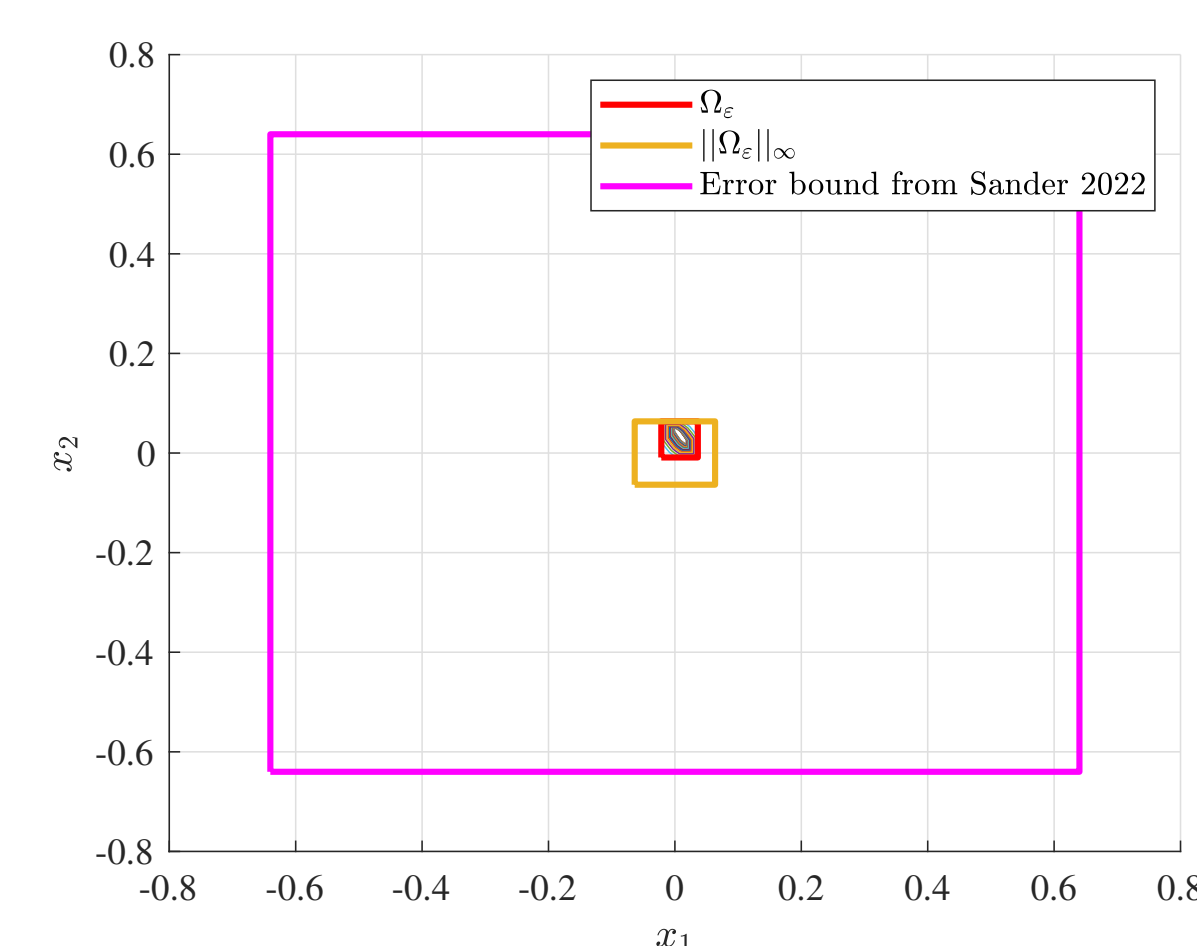
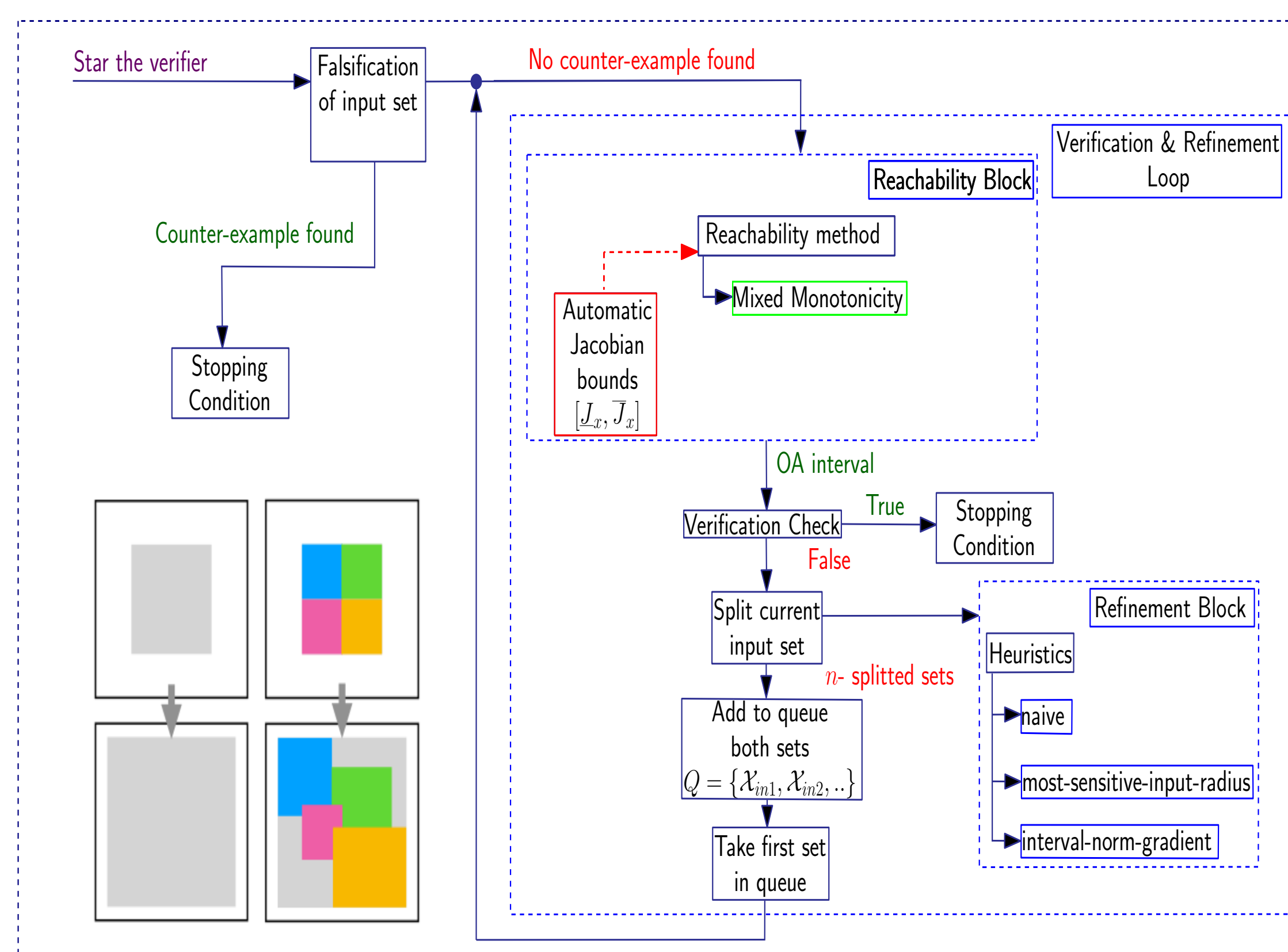
2. R.D 2: Safety verification of neural ODE based on reachability analysis methods (Sayed et al. 2025b)

- Reachability analysis of neural ODE based on continuous-time mixed monotonicity.
- Light weight reachability analysis methods for scalable verification.



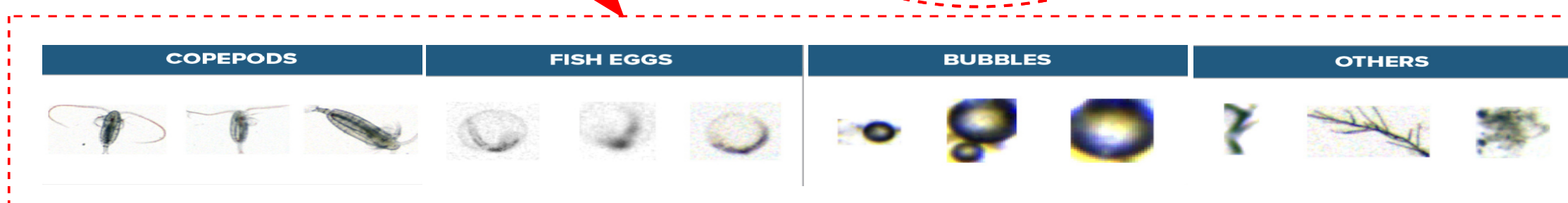
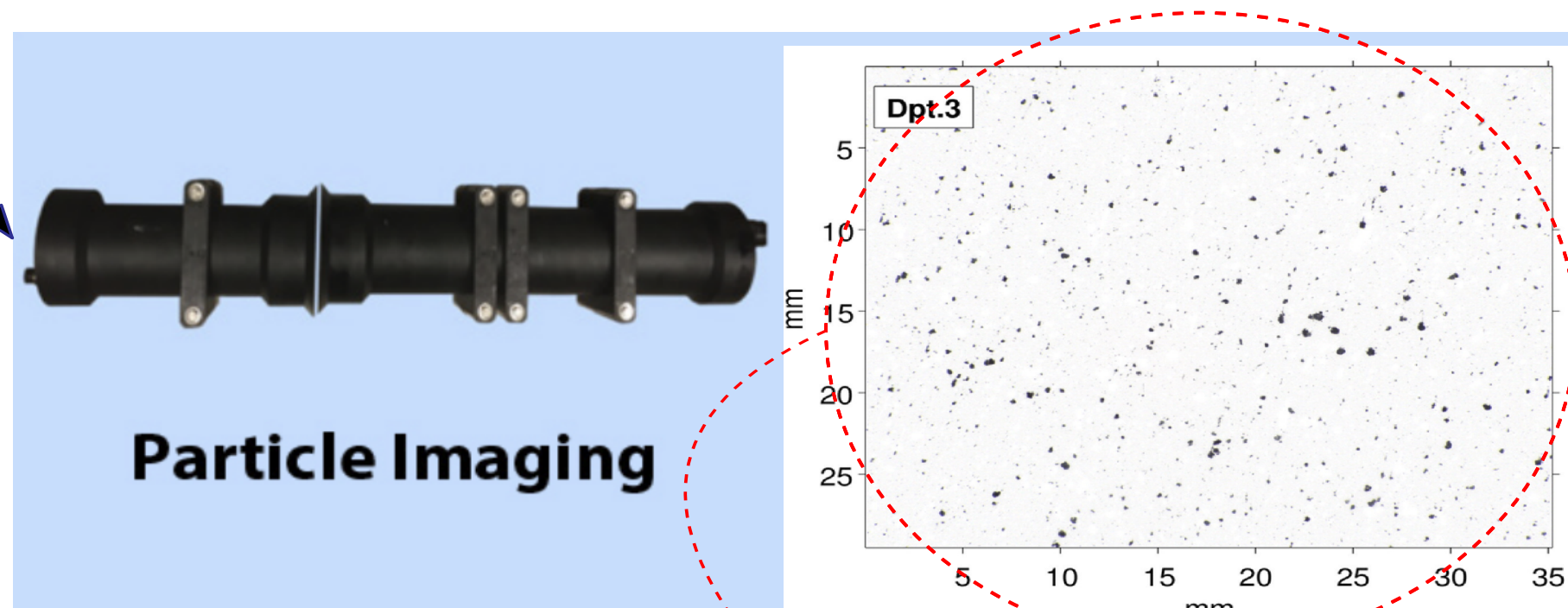
3. R.D 3: Verification toolbox for neural ODE

- Iterative refinement approach for neural ODE input set.
- Benchmarking with other neural ODE verification tools.



4. Verification and testing on autonomous underwater vehicles (AUVs)

- Robustness verification for ROI from in situ images.



neural ODE

