CAREER: Distributionally Robust Learning, Control, and Benefits Analysis of Information Sharing for Connected and Autonomous Vehicles

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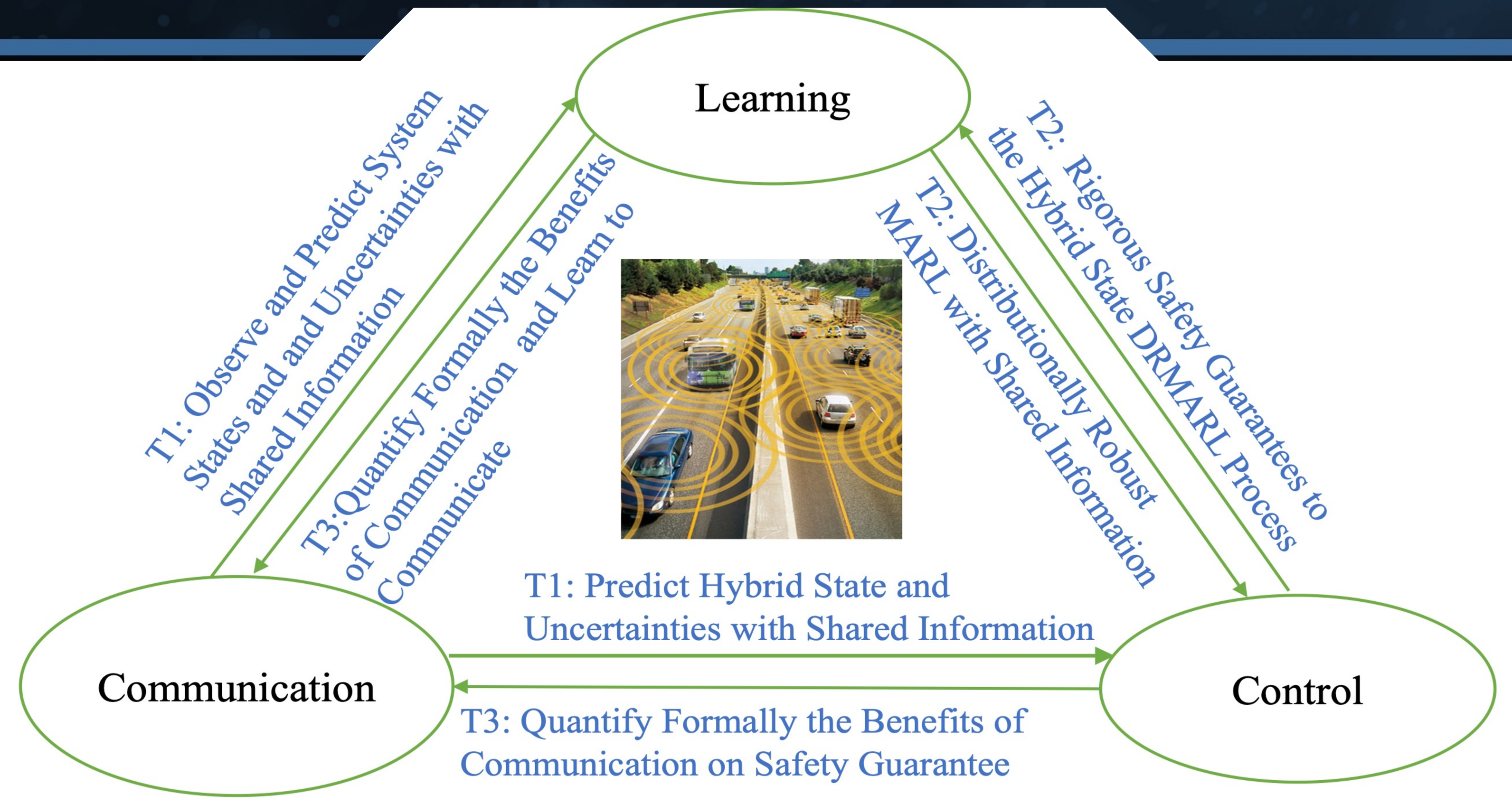
http://feimiao.org/research.html, http://feimiao.org/CAREER_CAV_MARL.html, fei.miao@uconn.edu

	5-Year Career Goals	10-Year Career Goals
Research	Improve CAVs State Prediction with Comm Model CAVs State Uncertainties with Comm DRMARL with Shared Information for CAVs Integrate Learning and Safety Control for CAVs Quantify the Value of Comm Formally for CAVs Learn to Comm for CAVs in Various Scenarios	Networked CPS State Prediction with Comm Networked CPS Model Uncertainties with Comm Robust Cooperative and Competitive Safe MARL Integrated CPS Comm, Learning, and Control Quantify the Value of Comm and Learn to Comm **Security Challenges for Networked CPS**
Education	Educational Tool; K-12 Outreach; Minorities	Education with Research; Increase STEM Minorities



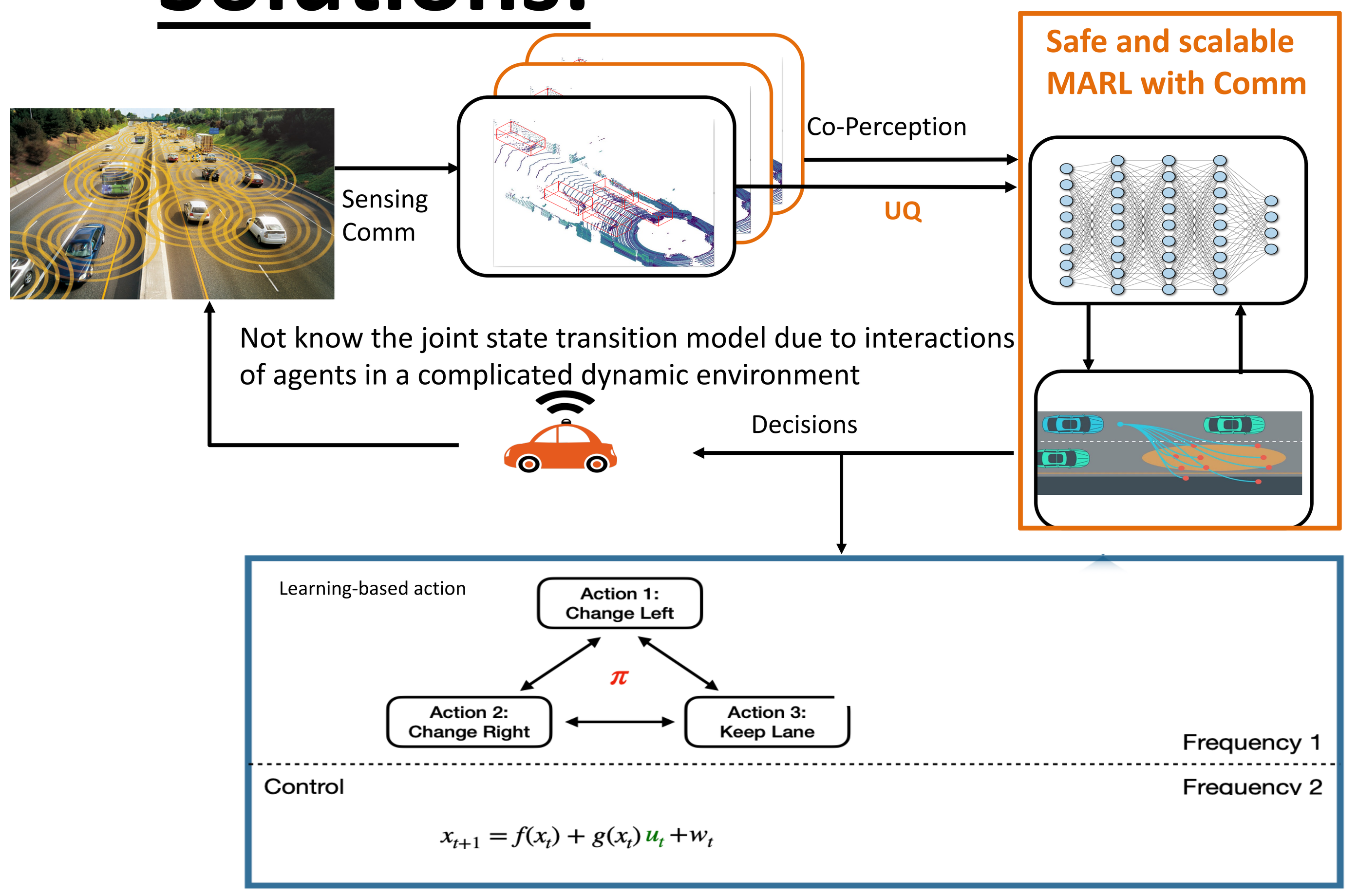
Challenges:

- Understand the tridirectional relationship among communication, learning, and control of networked CPS
- Uncertainty quantification for computer vision tasks
- Safe and robust learning and control decisions with respect to the system model and state uncertainties

Scientific Impact:

Develop integrated communication, learning and control frameworks that are robust to system model uncertainties and improve the performance of ***embodied AI and networked CPS*** by rigorously guaranteeing on their ***safety, efficiency, robustness*** and ***security***

Solutions:



1. Safe and Efficient Multi-Agent Reinforcement Learning (MARL) for Behavior Planning of CAVs

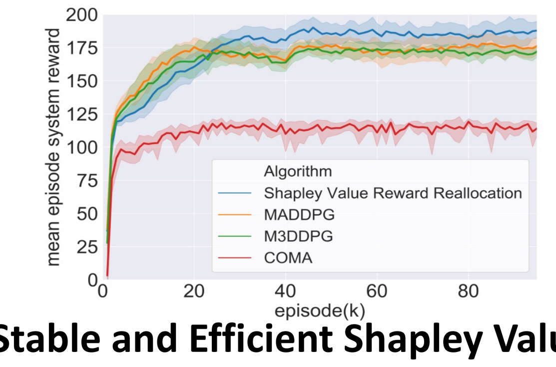
Theorem 1 Truncated Q-function: utilize information sharing, increase scalability, not rely on the global states and global actions: proved approximation error.

Theorem 2 Safe action mapping: map any action in the action space to the safe action set: provably safety guarantee for the actions during training and execution.

Songyang Han and Fei Miao et.al, IEEE Transactions on ITS, Jan. 24

Theorem 1: Shapley value is an efficient reward reallocation

Theorem 2: For a convex game, Shapley value is a stable reward reallocation: all agents (CAVs) will stay within the coalition.



2. Stable and Efficient Shapley Value-Based Reward Reallocation for Multi-Agent Reinforcement Learning of Autonomous Vehicles

S.Han, Fei Miao et.al, ICRA'22

3. What is the Solution for State-Adversarial Multi-Agent Reinforcement Learning?

S. Han, Fei Miao, et.al, Transactions on Machine Learning Research, Jan. 2024

https://openreview.net/pdf?id=HyqSwNhM3x

4. Robust Multi-Agent Reinforcement Learning with Adversarial State Uncertainties

Sihong He, Fei Miao et.al, Transactions on Machine Learning Research, Jun. 2023,

https://openreview.net/forum?id=CqTkapZ6H9

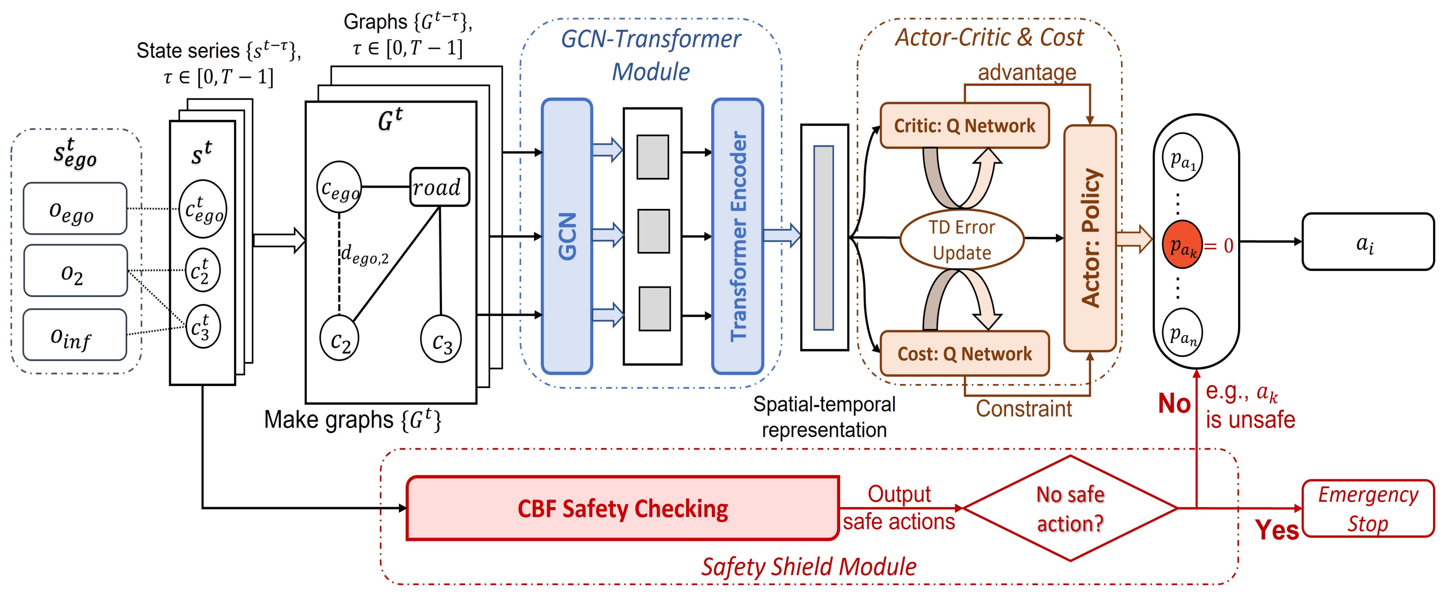
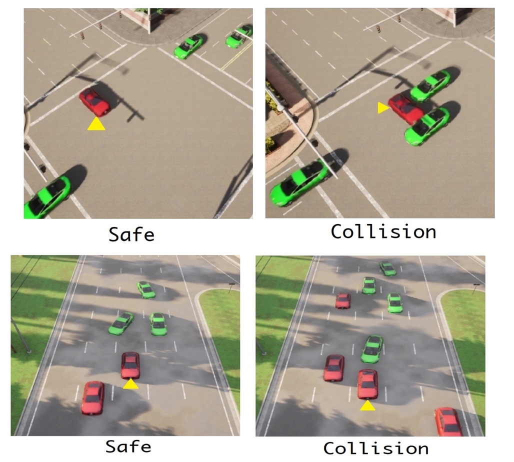


TABLE II
TESTING RESULTS IN THREE SCENARIOS.

Scenario	Baselines		Ours
	w/o SS	FC-CA2C	GT-CA2C
Intersection	20%; 444.8	86%; 579.6	**94%; 586.8**
Highway	2%; 185.3	**90%**; 922.6	**90%; 926.7**
Highway-Hard	0%; 108.6	70%; 706.4	**78%; 724.3**
Intersection w/o Communication	20%; 432.3	44%; 473.7	44%; 513.9
Highway-Hard w/o Communication	0%; 110.8	46%; 567.5	48%; 565.6

Each entry above is (*collision-free rate*; *mean episode return*). Our method **outperforms** baselines in two metrics, proving the improved safety and efficiency with GCN-Transformer and Safety Shield.



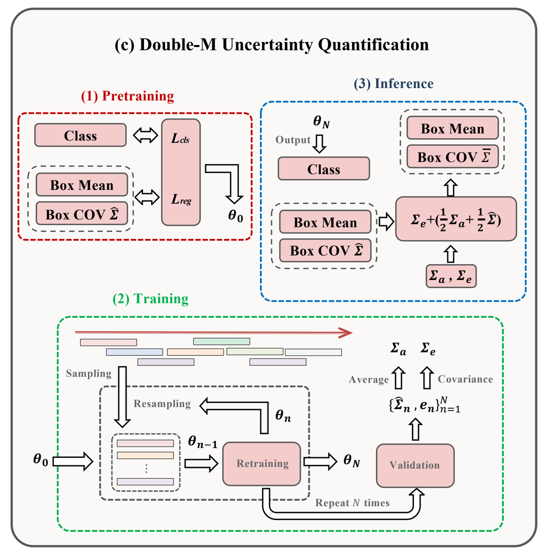
5.Spatial-Temporal-Aware Safe MARL of CAVs in Challenging Scenarios

Zhili Zhang and Fei Miao et.al, ICRA'23, arXiv:2210.02300

6. Safe and Robust Multi-Agent Reinforcement Learning for Connected Autonomous Vehicles under State Perturbations

Z.Zhang, Fei Miao et.al, arxiv:2309.11057.

7.Multi-Agent Reinforcement Learning Guided by Signal Temporal Logic Specifications, under review, J.Wang, Fei Miao et. al, arXiv:2306.06808.



Double-M: Direct Modeling (DM)+ Moving Block Bootstrap (MBB)

	NLL @IoU=0.5 ↓			NLL @IoU=0.7 ↓		
UQ Method	LB	DN	UB	LB	DN	UB
DM [8]	13.222	10.015	14.721	9.009	7.896	13.001
MBB [30]	28.130	13.794	22.958	19.996	9.710	18.077
Double-M (Ours)	**6.871**	**5.084**	**7.974**	**4.889**	**3.851**	**6.696**

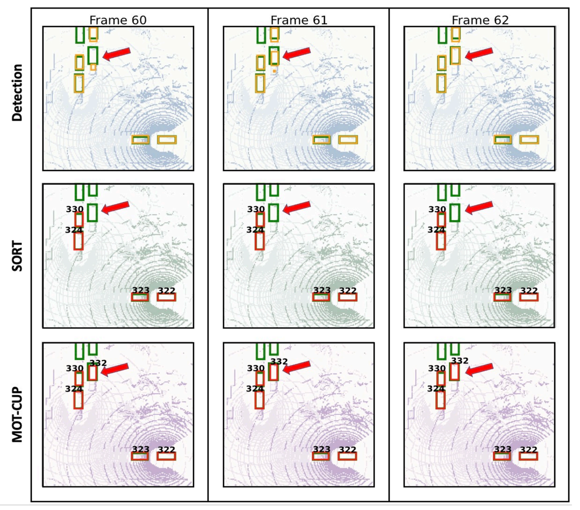
	AP @IoU=0.5 ↑			AP @IoU=0.7 ↑		
UQ Method	LB	DN	UB	LB	DN	UB
None	0.465	0.666	0.698	**0.413**	0.608	0.648
DM [8]	0.433	0.664	0.693	0.392	0.609	0.653
MBB [30]	**0.466**	0.671	**0.704**	0.408	0.610	0.645
Double-M (Ours)	0.438	**0.672**	**0.704**	0.397	**0.627**	**0.664**

- Double-M achieves up to 4x Improvement in uncertainty reduction (NLL)
- Double-M improves up to 3.13% in accuracy (AP)

8. Uncertainty Quantification of Collaborative Object Detection for CAVs

S. Su, F. Miao et al. , ICRA'23, arXiv:2209.08162

Website: https://coperception.github.io/double-m-quantification/



- **MOT-CUP**: UQ in detection input to tracking direct modeling + conformal prediction
- Association: new **NLL similarity** metric with UQ
- Tracklet: UQ on **Kalman Filter**
- Improved accuracy and reduced uncertainty, especially high occlusion cases

9. Collaborative Multi-Object Tracking with Conformal Uncertainty Propagation S.Su, Fei Miao et.al, IEEE Robotics and Automation Letters, Feb.24, DOI: 10.1109/LRA.2024.3364450

Broader Impact:

Award ID#: 2047354

- Full-size CAVs (buses) and the testing ground under development at Uconn with industry partners and DOT
- Opensource code and data; K-12 students and under representative students participate research, F1/10th racing car experiments