Autonomous Teams: Where Learning Meets Control

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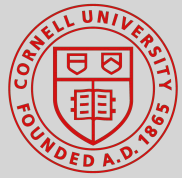
IEEE CSS TC on Smart Cities Tutorial Session: Challenges and Opportunities for Control in Smart Cities

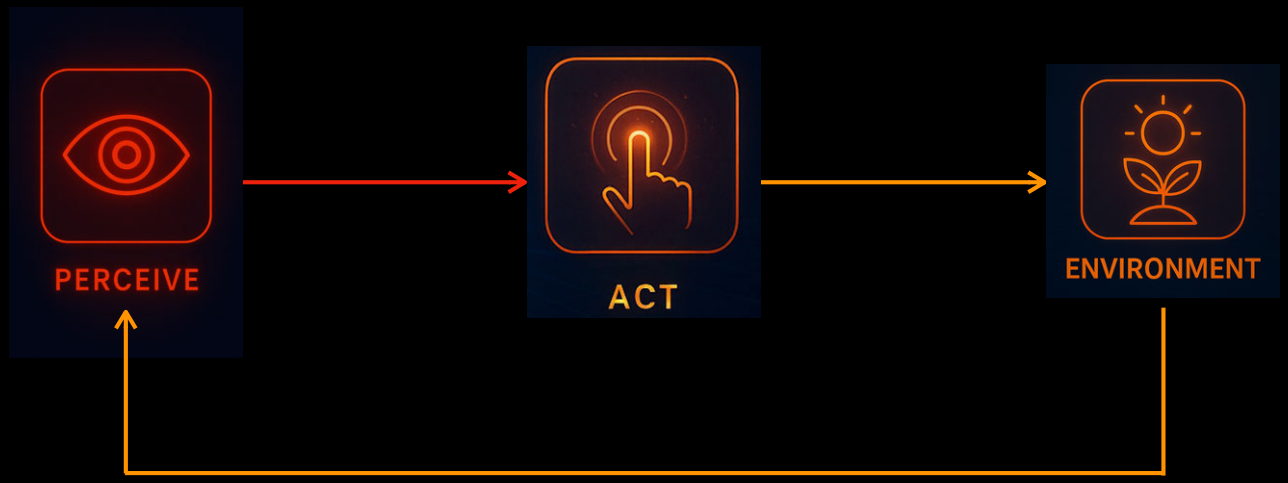
2025 64th IEEE Conference on Decision and Control (CDC)

December 12, 2025

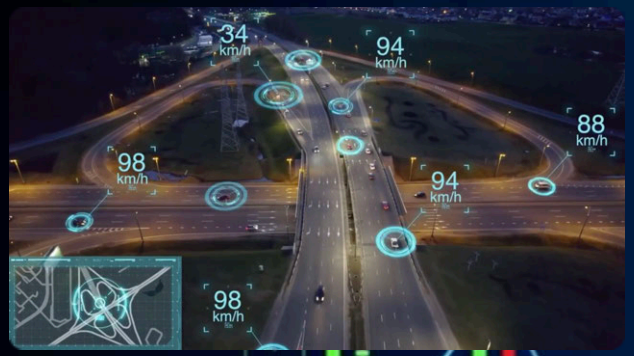


autonomy

operate without human supervision



…we are heading to enhanced autonomy…


34
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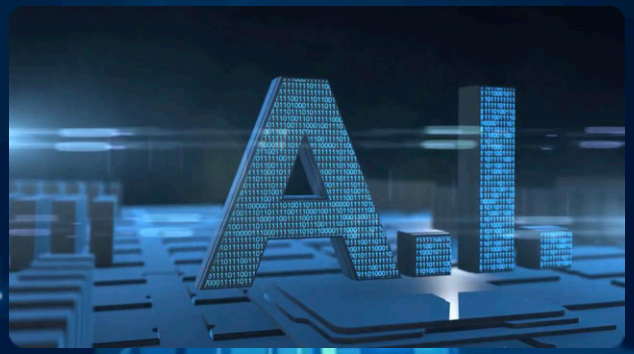
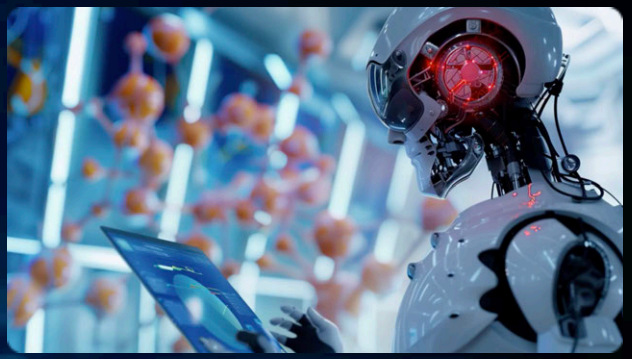
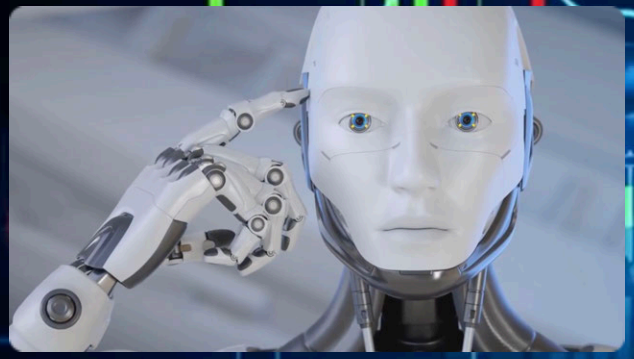
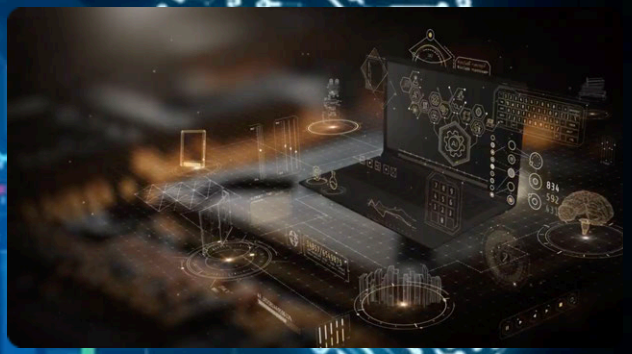
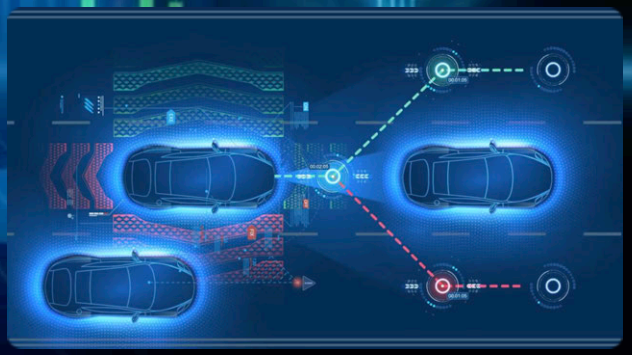

A.I.

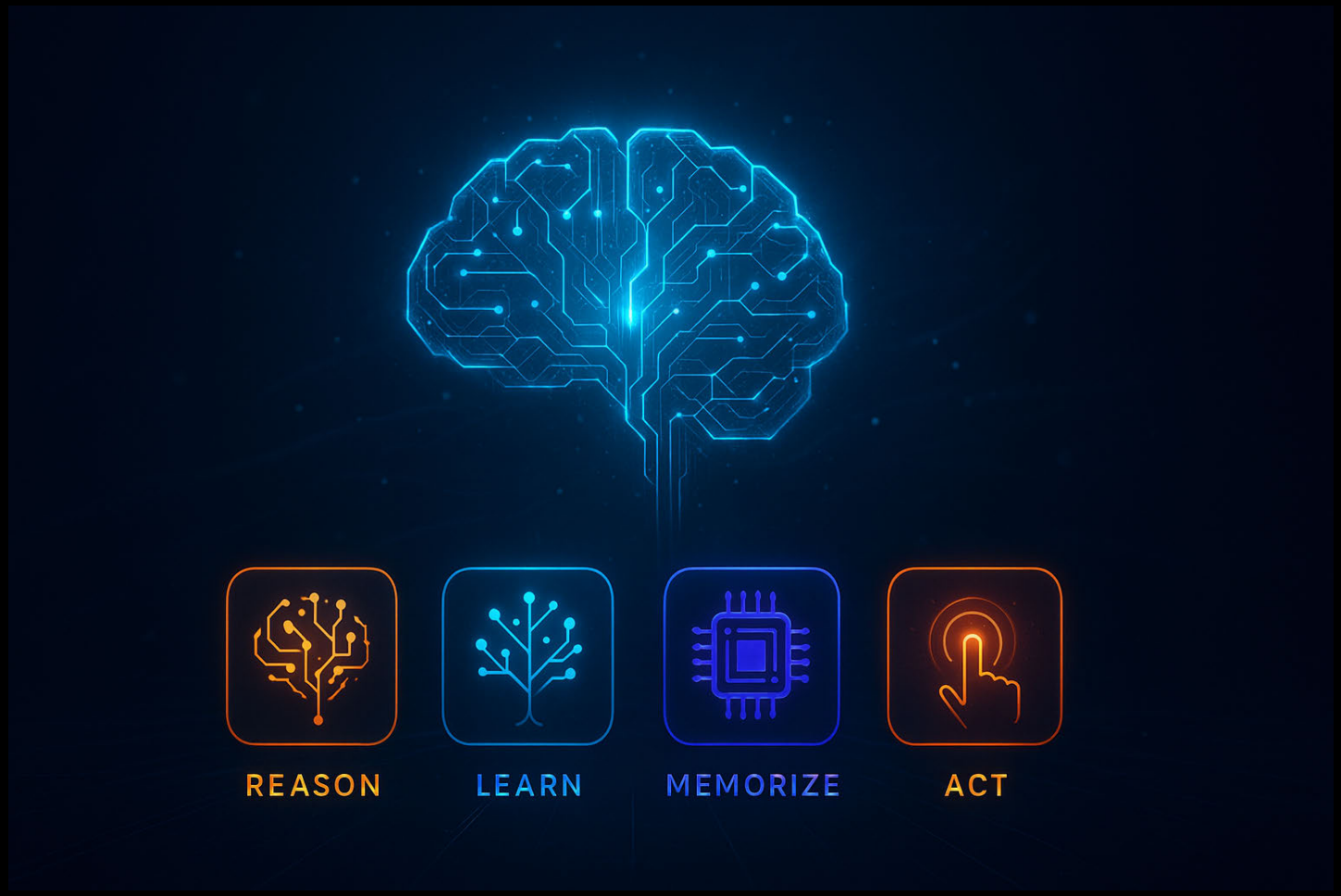








agentic ai



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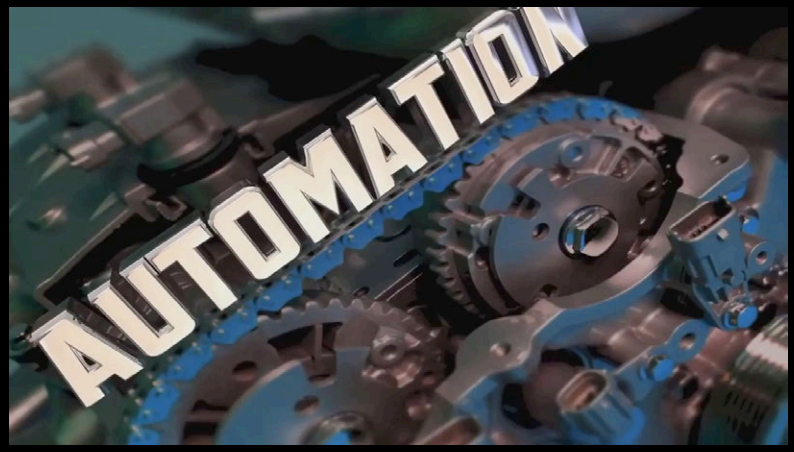
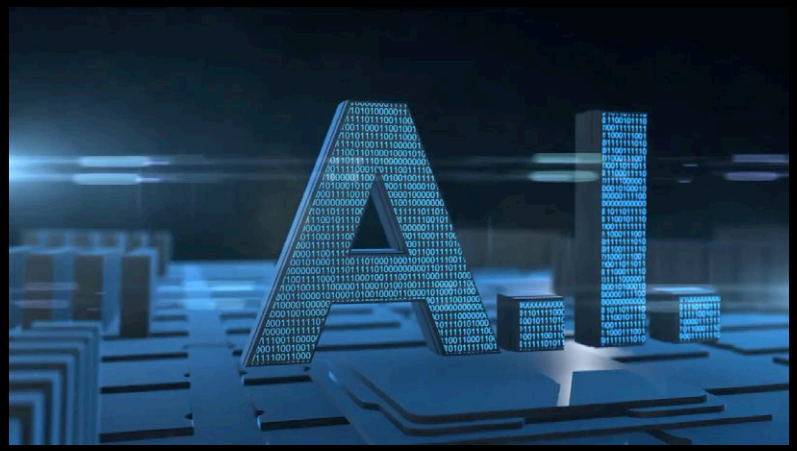
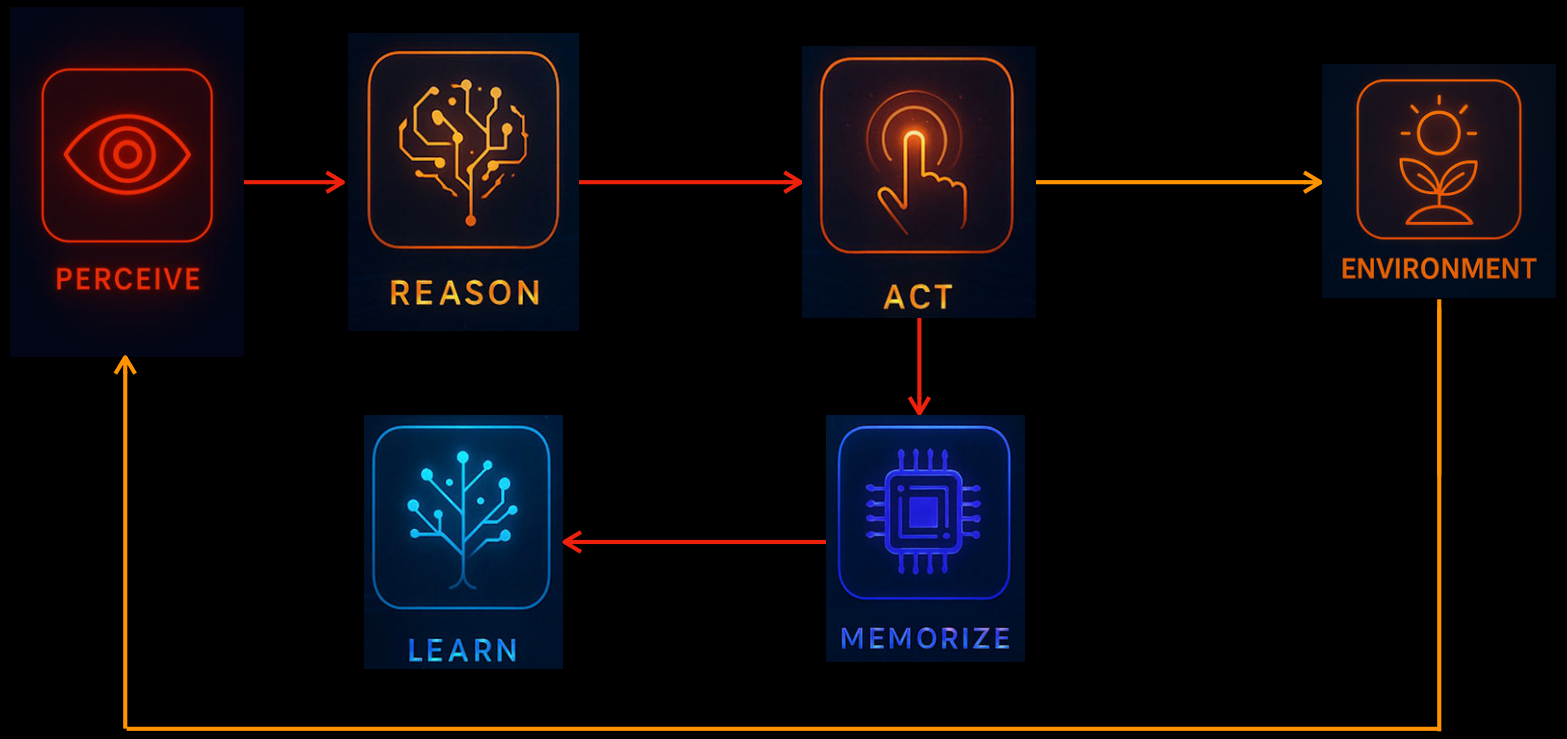


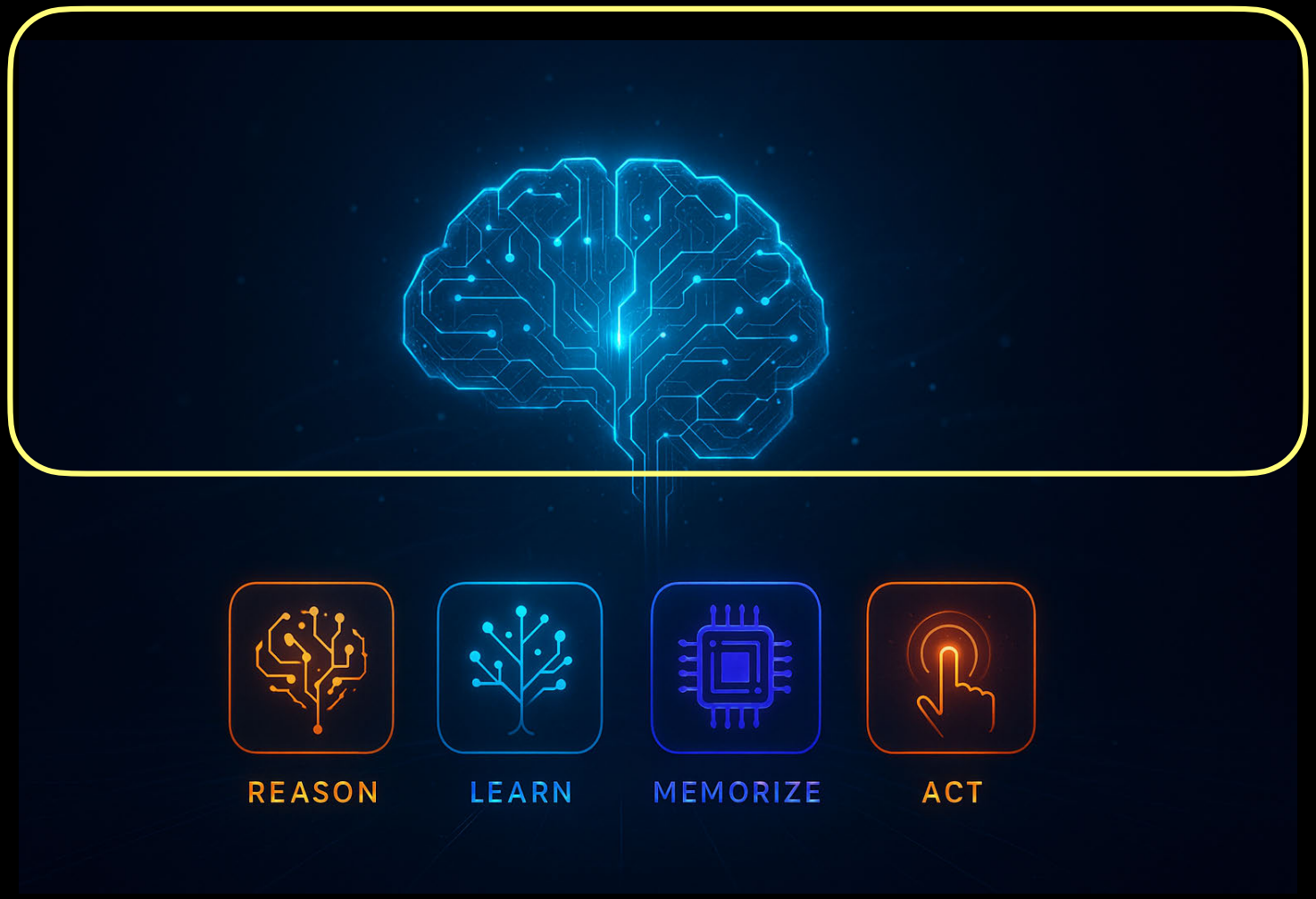


agentic ai

operate without human supervision



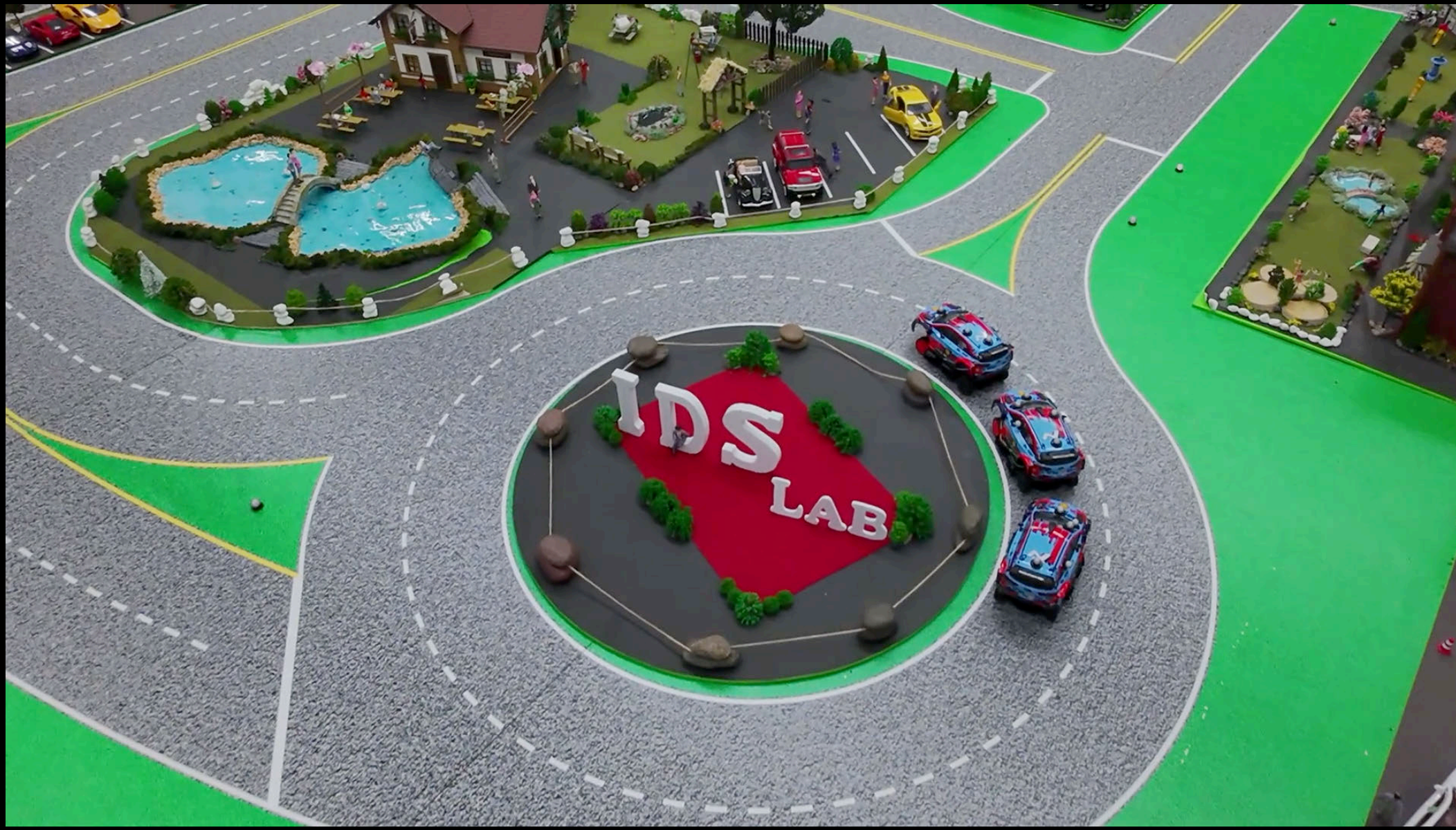
information and decision science (IDS) lab



information and decision science (IDS) lab

The overarching goal of the IDS Lab is to develop rigorous theories and data-driven system approaches at the intersection of learning and control to enable systems—whether vehicles, robots, or large-scale infrastructures—to operate autonomously while safely interacting with dynamic environments. Our work integrates decision-theoretic foundations with learning-based methods to endow engineered systems with the capability to reason, learn, and act in real time.

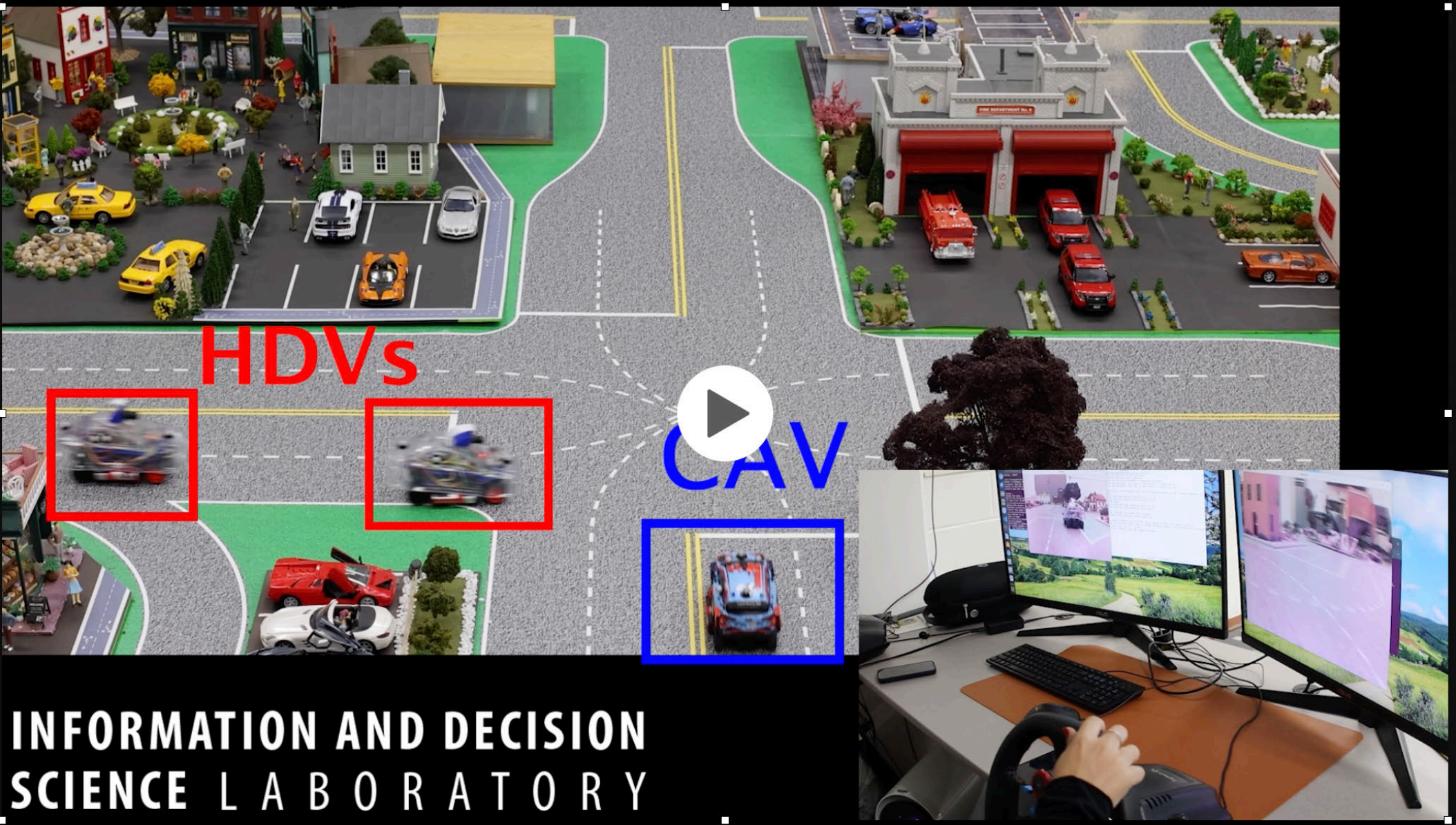
information and decision science (IDS) lab



information and decision science (IDS) lab

INFORMATION AND DECISION SCIENCE LABORATORY

information and decision science (IDS) lab



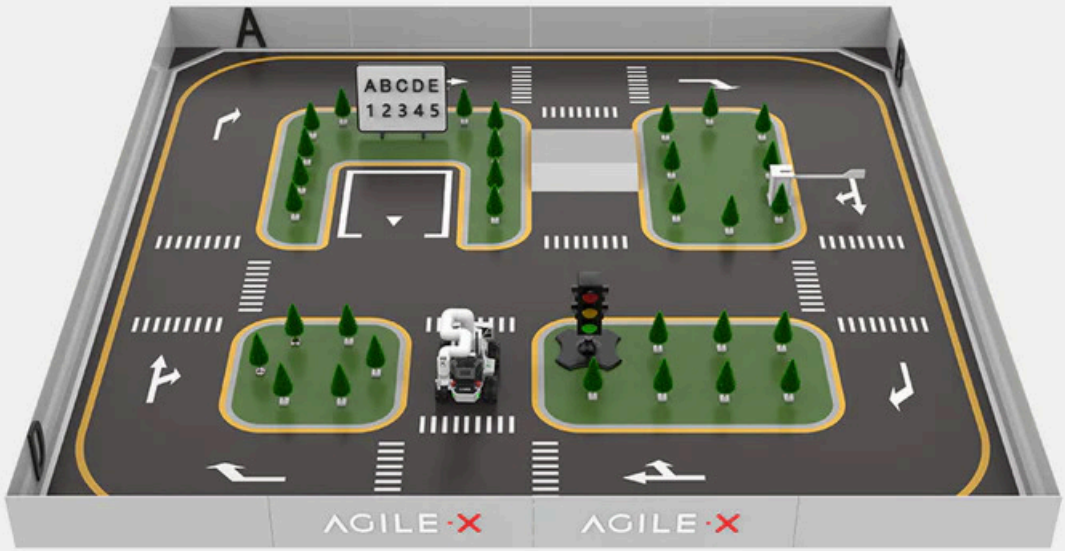
information and decision science (IDS) lab

INFORMATION AND DECISION SCIENCE LABORATORY

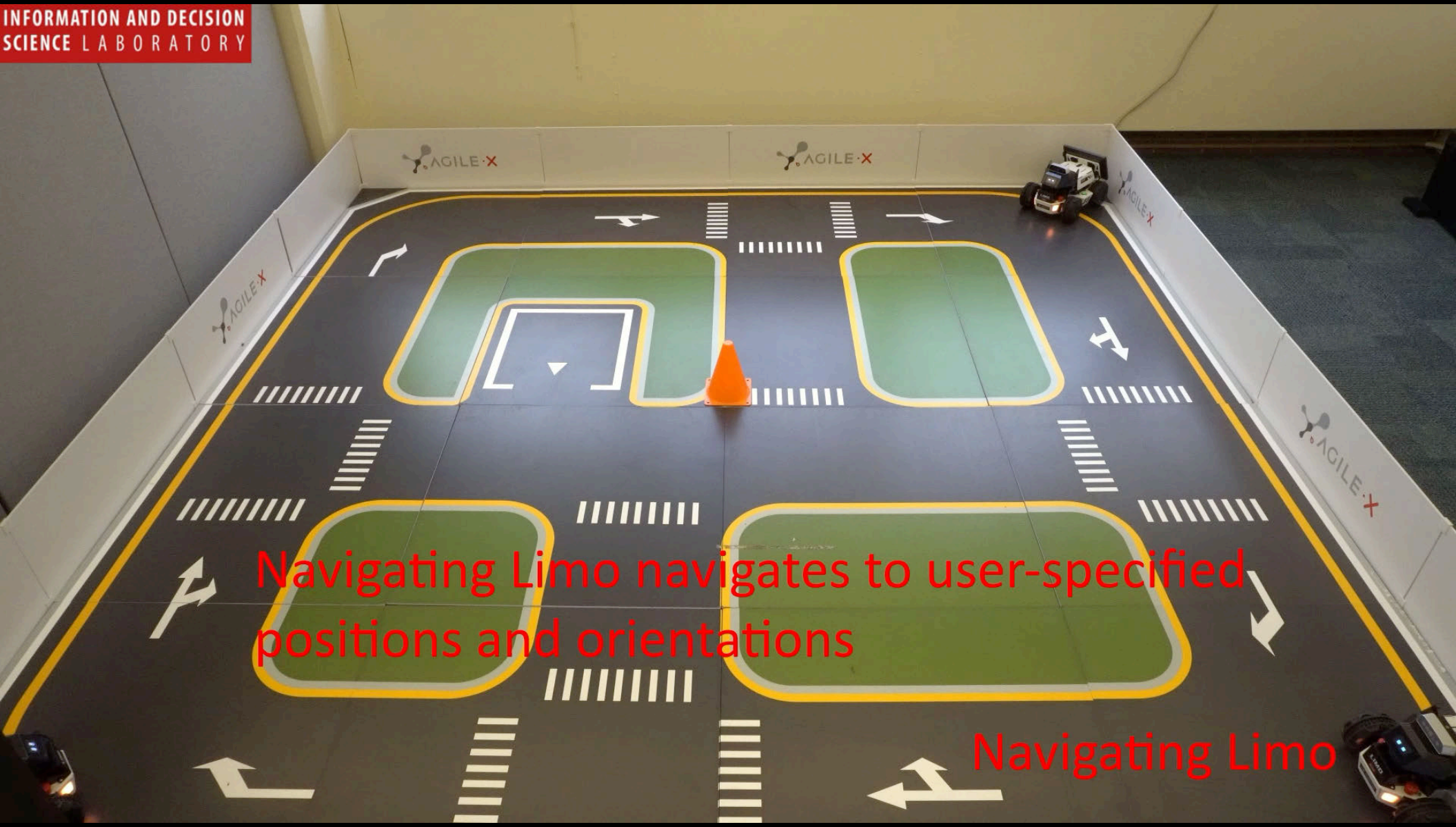
virtual reality driver simulation testbed

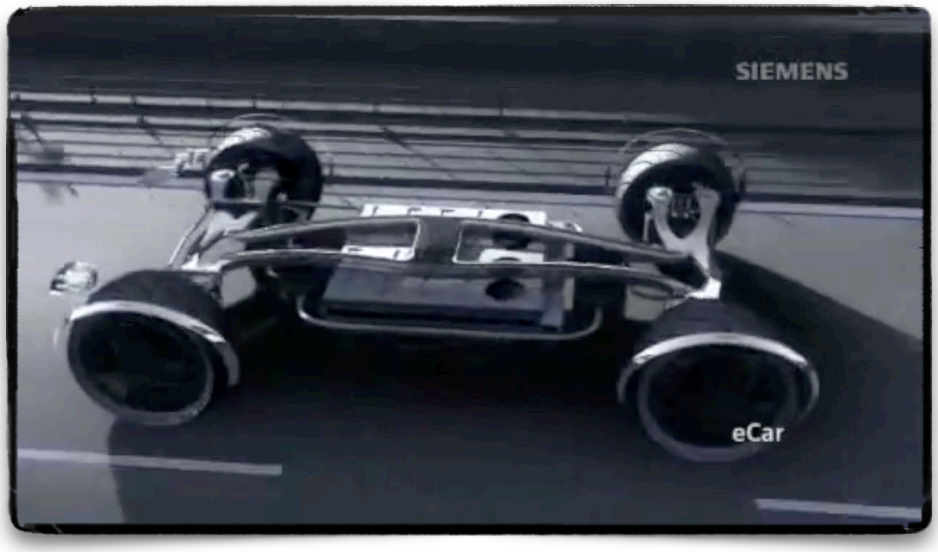
INFORMATION AND DECISION SCIENCE LABORATORY

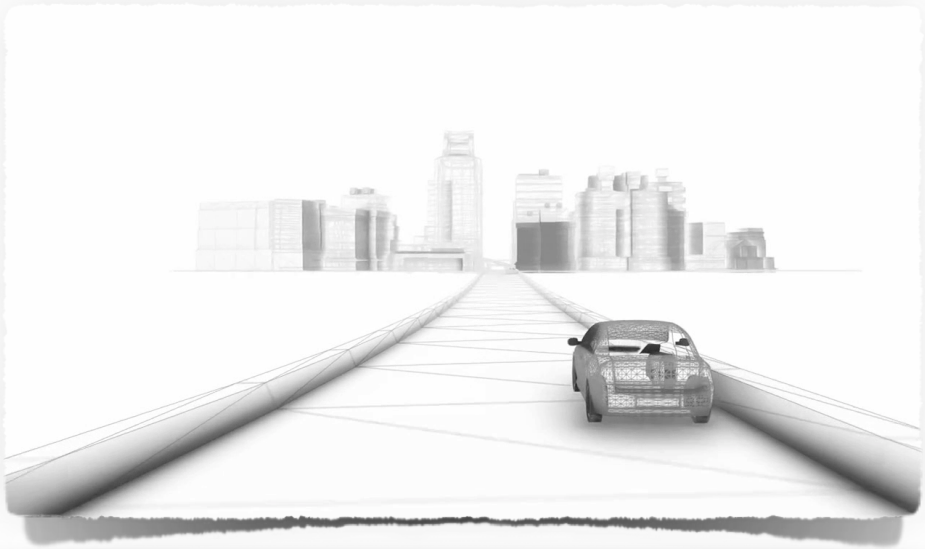
Limos

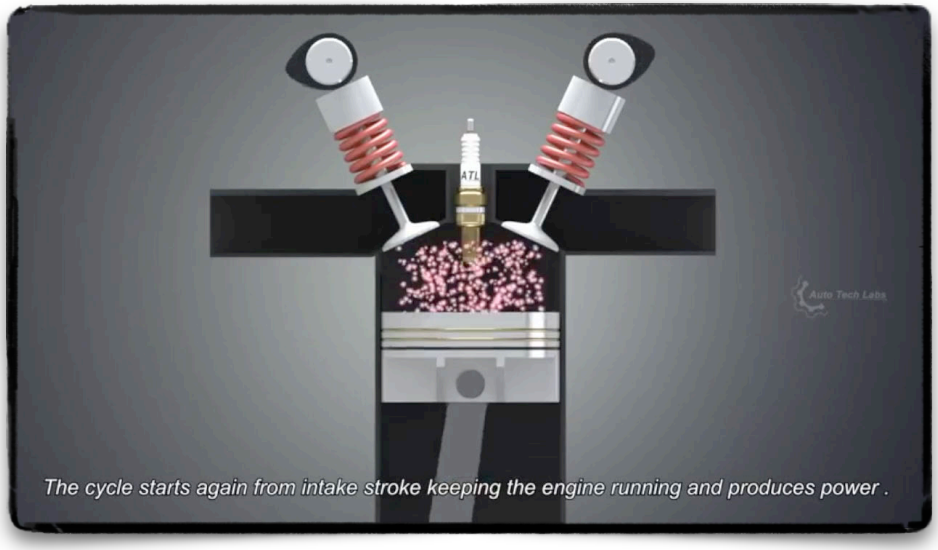


Limos

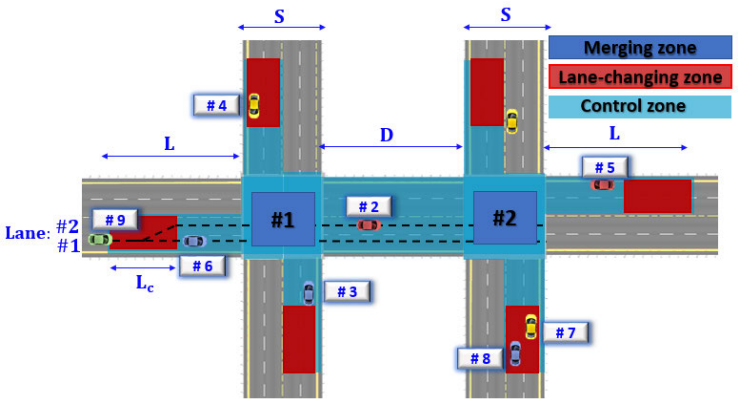

INFORMATION AND DECISION SCIENCE LABORATORY
AGILE·X
Navigating Limo navigates to user-specified positions and orientations
Navigating Limo

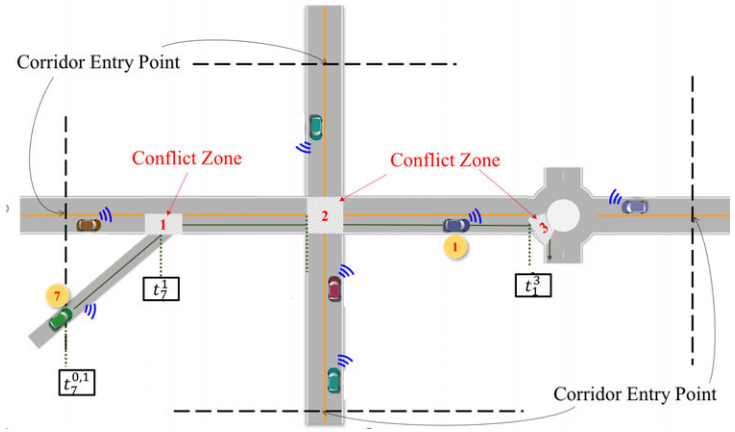

SIEMENS
eCar

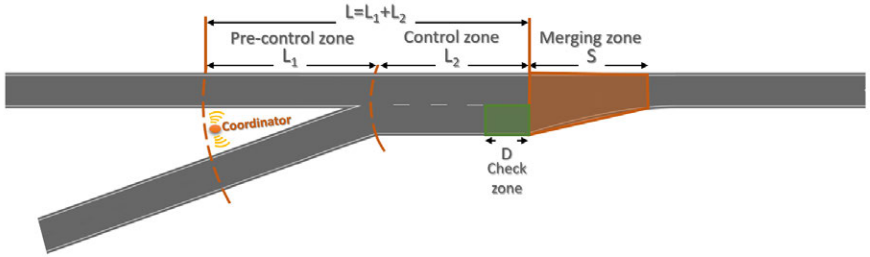


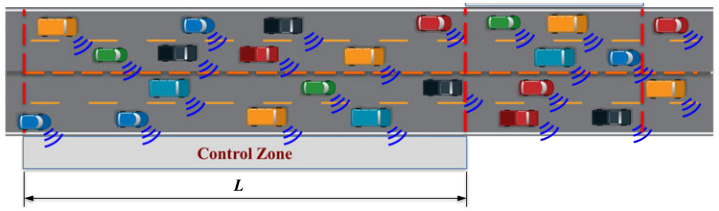

ATL
Auto Tech Labs
The cycle starts again from intake stroke keeping the engine running and produces power .

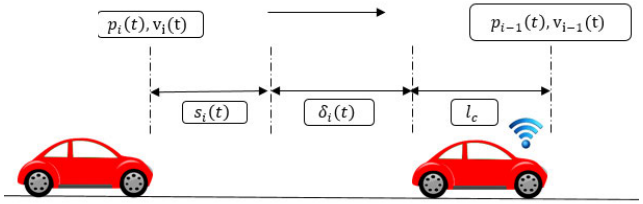
multiple scenarios[1]-[6]

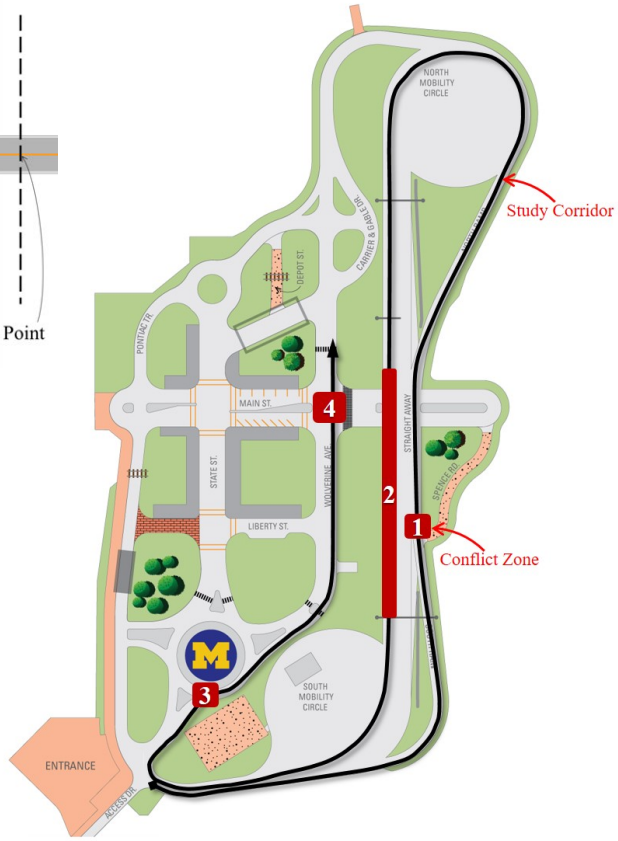






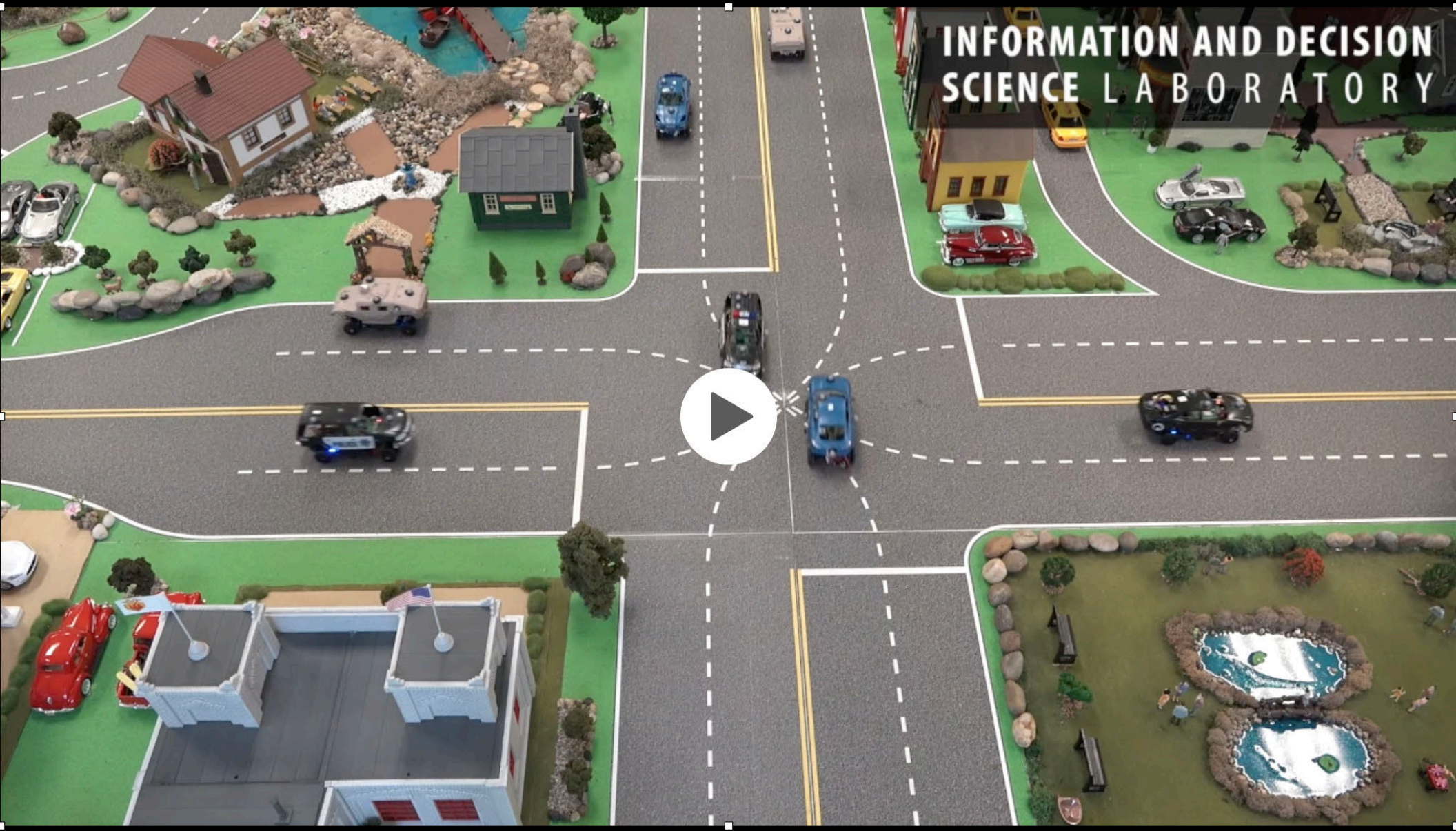






[1] Mahbub, A M. I., and Malikopoulos, A.A., "A Platoon Formation Framework in a Mixed Traffic Environment," IEEE Control Systems Letters, 6, 1370–1375, 2022.
[2] Chalaki, B., and Malikopoulos, A.A., "Optimal Control of Connected and Automated Vehicles at Multiple Adjacent Intersections," IEEE Trans. on Control Systems Tech., 2021.
[3] Chalaki, B., and Malikopoulos, A.A., "Time-Optimal Coordination for Connected and Automated Vehicles at Adjacent Intersections," IEEE Trans. Intell. Transp. Syst., 2021.
[4] Kumaravel, S.D., Malikopoulos, A. A., and Ayyagari, R., "Optimal Coordination of Platoons of Connected and Automated Vehicles at Signal-Free Intersections," IEEE Trans. Intell. Veh., 2021.
[5] Mahbub, A M. I., Malikopoulos, A.A., and Zhao, L., "Decentralized Optimal Coordination of Connected and Automated Vehicles for Multiple Traffic Scenarios," Automatica, 117, 108958, 2020.
[6] Malikopoulos, A. A., Hong, S., Park, B., Lee, J., and Ryu, S. "Optimal Control for Speed Harmonization of Automated Vehicles," IEEE Trans. Intell. Transp. Syst., 20, 7, 2405–2417, 2019.

experimental results in IDS^{3}C

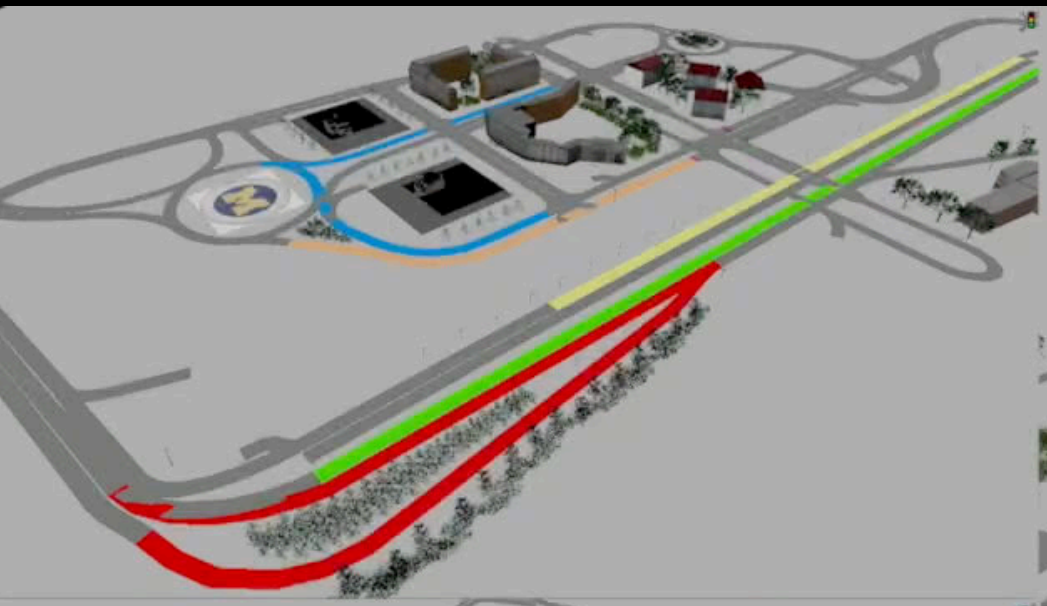


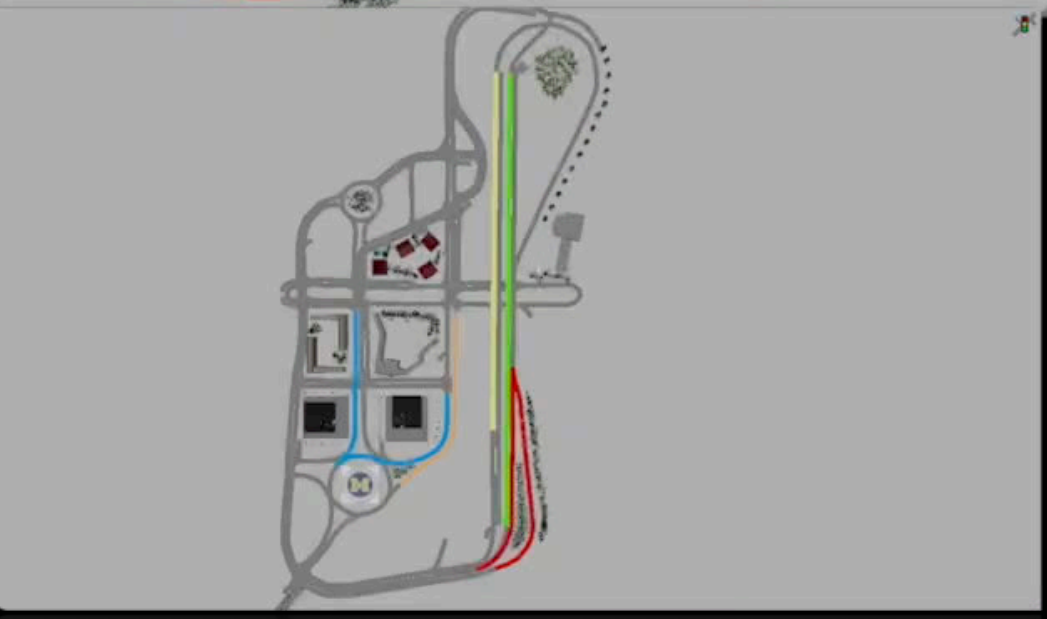
coordination of CAVs

ARPAE NEXTCAR —field test in Mcity

field tests in Mcity

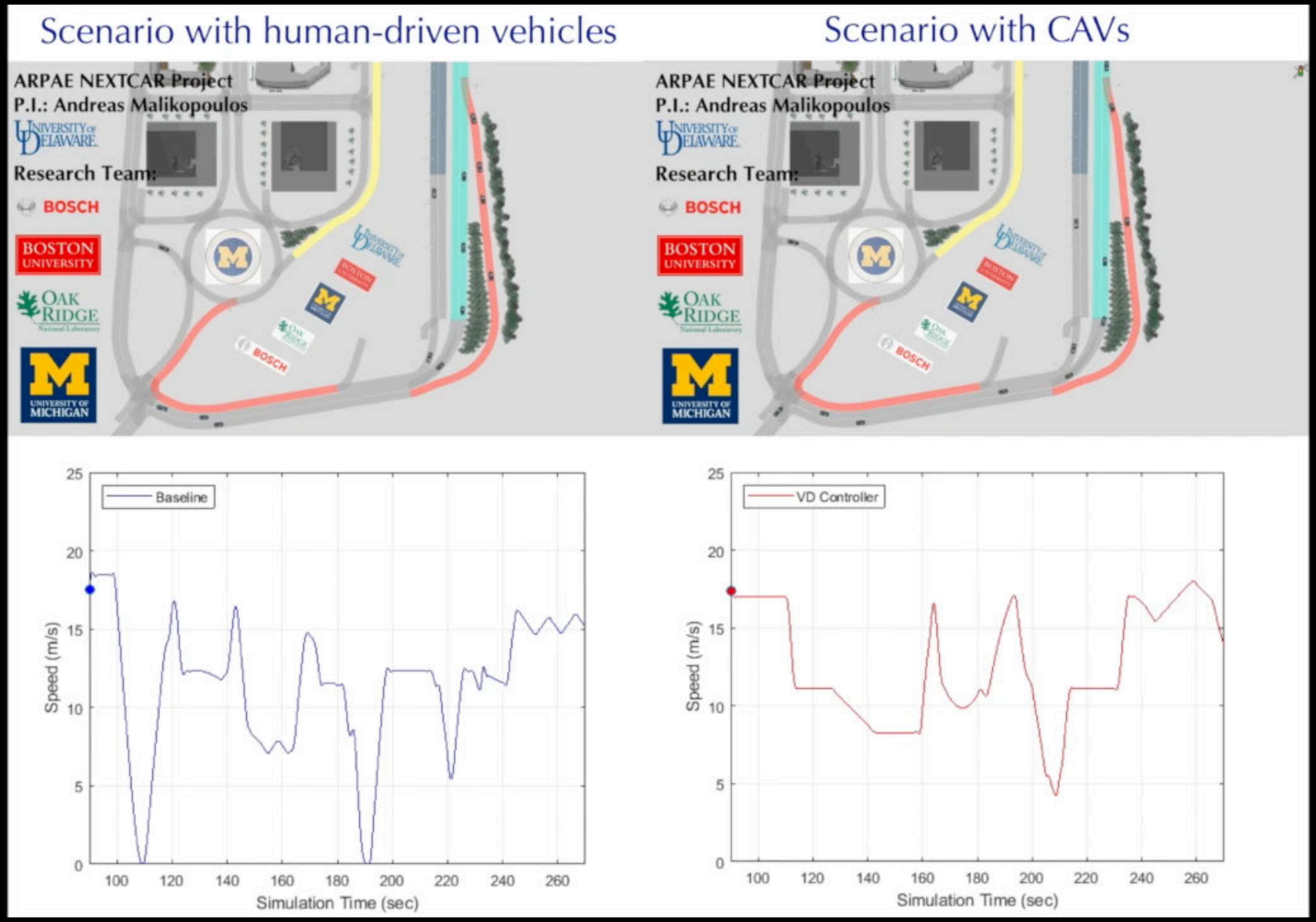
Speed x 20



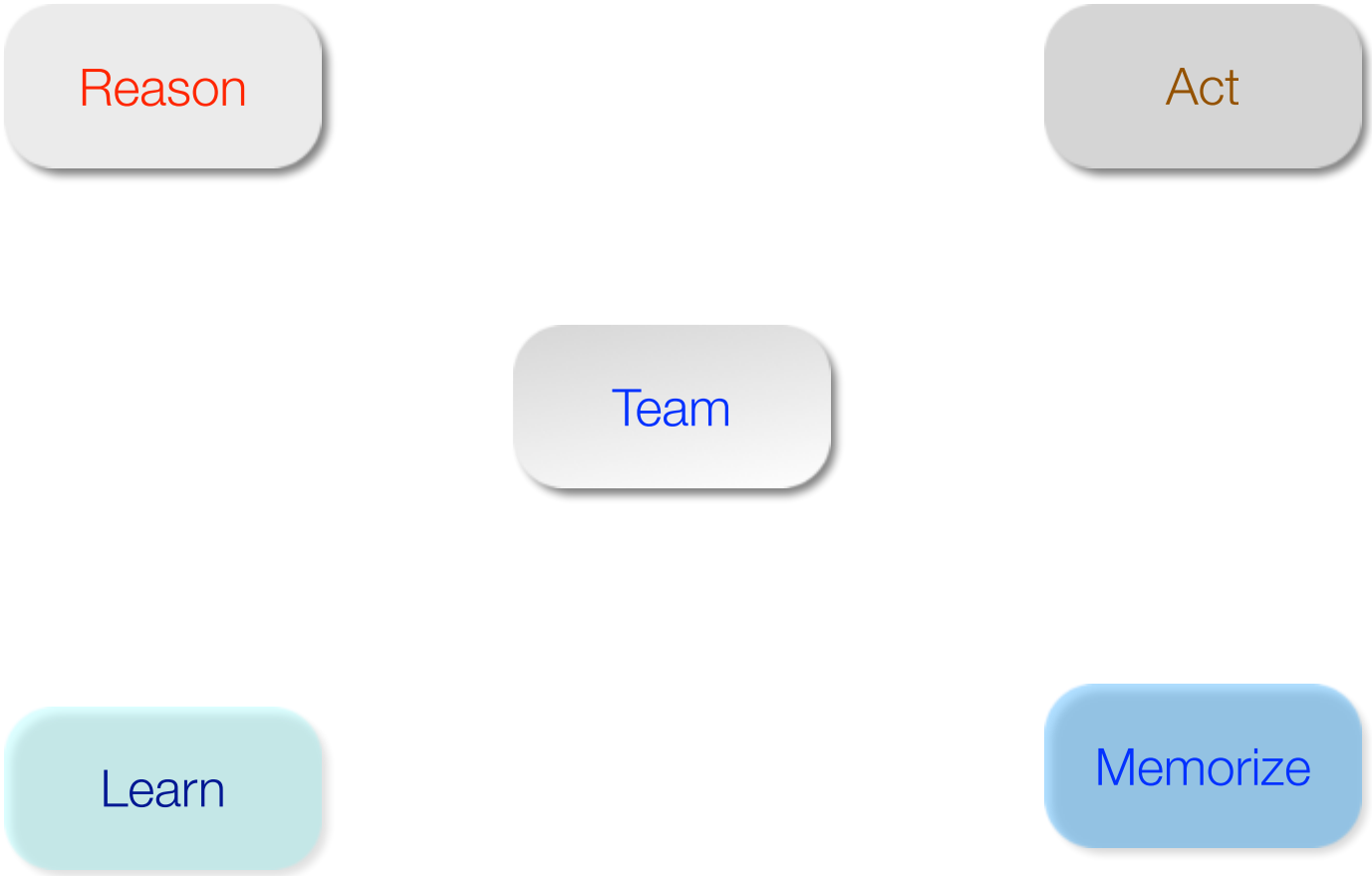


Coordination at Ramp Merging

vehicle in the loop in Bosch facilities



agentic ai: autonomous teams



agentic ai: autonomous teams

Team

- Team of $K \in \mathbb{N}$ members
- State: $X_t \colon (\Omega, \mathcal{F}) \to (\mathrm{X}_t, \mathcal{X}_t)$ defined on $(\Omega, \mathcal{F}, \mathbb{P})$
- Control: $U_t^{1:K} = (U_t^1, \ldots, U_t^K)$
- Disturbance: $W_t \colon (\Omega, \mathcal{F}) \to (\mathrm{X}_t, \mathcal{W}_t)$
- $X_{t+1} = f_{t+1}(X_t, U_t^{1:K}, W_t),\ t = 0, \ldots, T-1$
- For each team member k, $Y_t^k = h_t^k(X_t, Z_t^k),\ t = 0, \ldots, T$
- Noise: $Z_t^k \colon (\Omega, \mathcal{F}) \to (\mathrm{X}_t, \mathcal{Z}_t^k)$
- Information structure
- $\Delta_t \colon = (Y_{0:t}, U_{0:t}^{1:K})$ and $\Lambda_t^k \colon = (Y_{t-n+1:t}^k, U_{t-n+1:t-1}^k)$

optimal strategy

Reason

Theorem[1]

- Let

$$V_T(\pi_T) := \mathbb{E}^g\left[C_T(X_T) \mid \Pi_T = \pi_T\right],$$

$$V_t(\pi_t) := \inf_{u_t^{1:K} \in \mathrm{U}_t} \mathbb{E}^g\left[C_t(X_t, u_t) + V_{t+1}\left(\theta_t\left[\pi_t, Y_{t+1}^{1:K}, u_t^{1:K}\right]\right) \mid \Pi_t = \pi_t, U_t^{1:K} = u_t^{1:K}\right]$$

and let $g \in \mathscr{G}^s$ be a separated control strategy that achieves the infimum. Then, g is optimal.

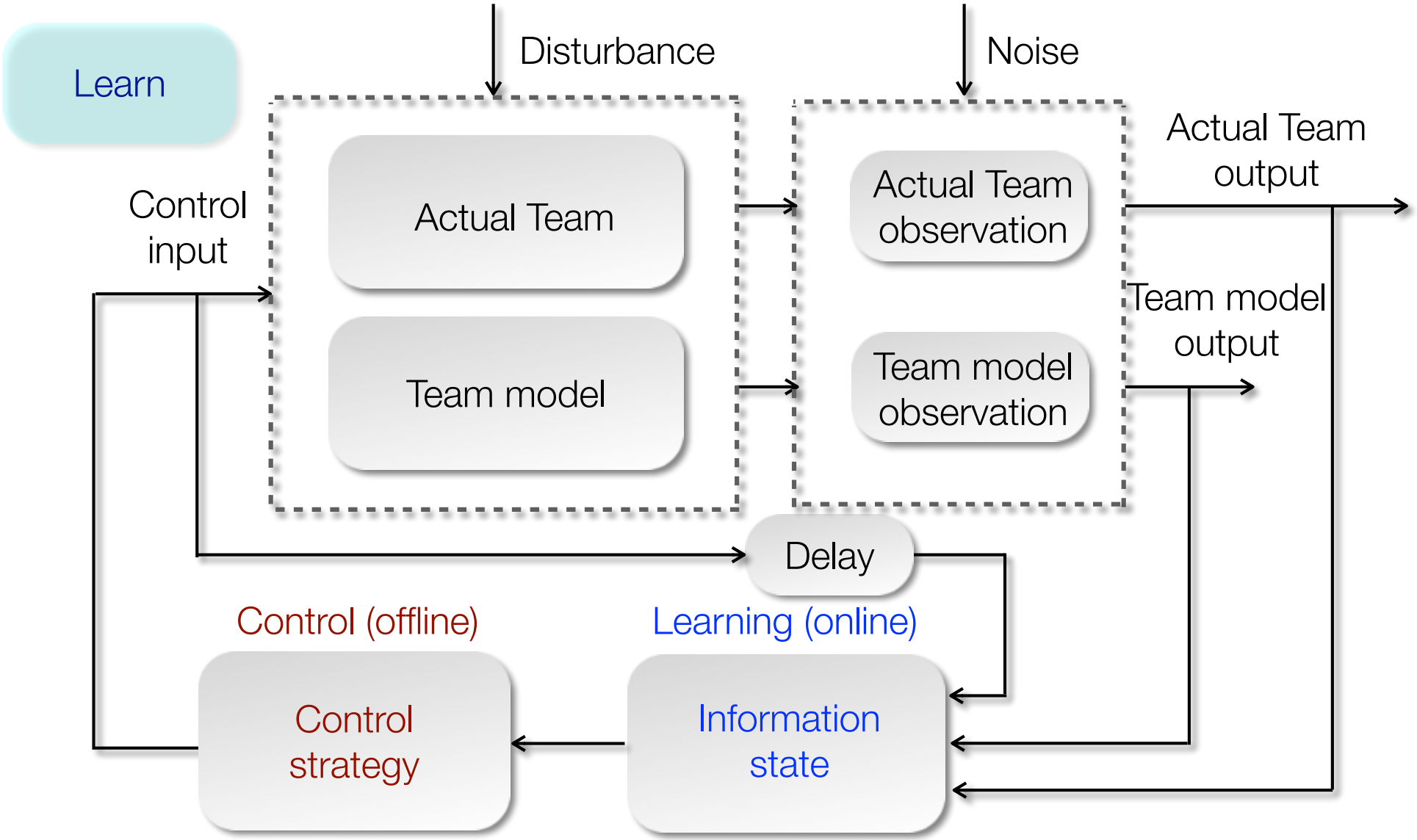
[1] Malikopoulos, A.A., "On Team Decision Problems with Nonclassical Information Structures," *IEEE Trans. Autom. Control, Vol. 68, 7, pp. 3915–3930, 2023.*

optimal decisions

- Control strategy: $\mathbf{g} = \{\mathbf{g}_1, \ldots, \mathbf{g}_{T-1}\}$
- Decision: $U_t^{1:K} = g_t(\Pi_t) = g_t\left[\mathbb{P}(X_t \mid \Delta_t, \Lambda_t^{1:K})\right]$
- Update: $\Pi_{t+1} = \theta_t\left[\mathbb{P}(X_t \mid \Delta_t, \Lambda_t^{1:K}), Y_{t+1}^{1:K}, U_t^{1:K}\right]$

Act

learning the information state[1]-[3]



[1] Malikopoulos, A.A., "Separation of Learning and Control for Cyber-Physical Systems," *Automatica*, 151, 110912, 2023.
[2] Malikopoulos, A.A. "Combining Learning and Control in Linear Systems," European Journal of Control, Vol. 80, Part A, 101043, 2024.
[3] Kounatidis, P., and Malikopoulos, A.A., "Combined Learning and Control: A New Paradigm for Optimal Control with Unknown Dynamics," arXiv:2510.00308, 2025.

storing information

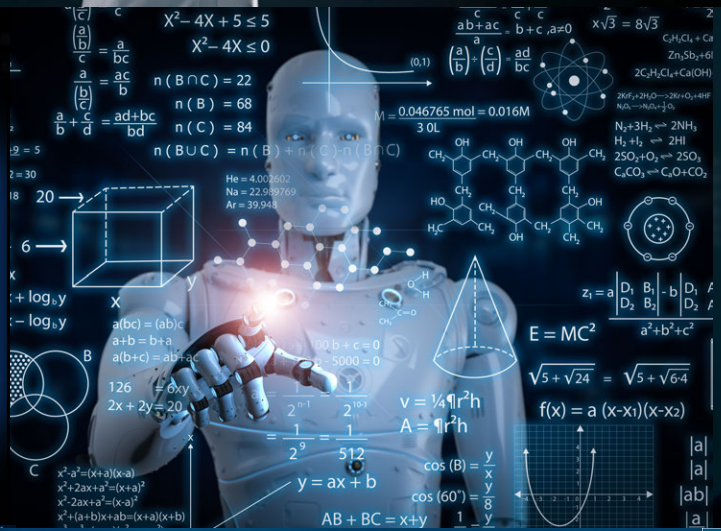
- Decision: $U_t^{1:K} = g_t(\Pi_t) = g_t\left[\mathbb{P}(X_t \mid \Delta_t, \Lambda_t^{1:K})\right]$

  instead of $U_t^k = g_t(\Delta_t, \Lambda_t^k) = g_t(Y_{0:t-n}^{1:K}, U_{0:t-n}^{1:K}, Y_{t-n+1:t}^k, U_{t-n+1:t-1}^k)$

Memorize


medical
infographic
LOREM IPSUM DOLOR
01INFOGRAPHIC
02INFOGRAPHIC
25%
28%


AI


X²−4X+5≤5
X²−4X≤0
n(B∩C) = 22
n(B) = 68
n(C) = 84
n(B∪C) = n(B) + n(C)−n(B∩C)
E = MC²
f(x) = a (x-x₁)(x-x₂)
y = ax + b
AB + BC = x+y
V = ¼¶r²h
A = ¶r²h


SELF-DRIVING
SEARCH
75 Km


IDEA
27 18

acknowledgements

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Thank you for your attention!

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