VeHICaL: Verified Human Interfaces, Control, and Learning for Semi-Autonomous Systems

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http://vehical.org







Annual Meeting September 19, 2017

Human Cyber-Physical Systems (h-CPS)

CPS that operate in concert with humans



Driver Assistance in Cars



Robotic Surgery & Medicine



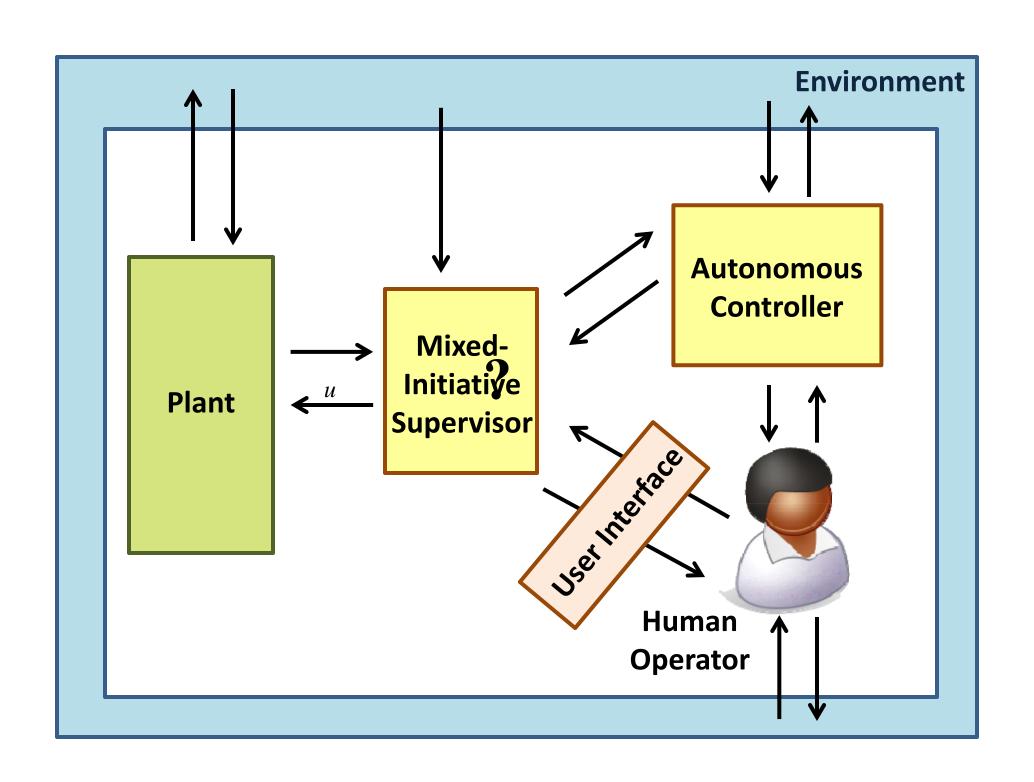
Fly-by-wire Cockpit
Interfaces



UAVs with Human Operators



Semi-Autonomous Manufacturing



Overall Project Objective of VeHICaL

To develop a science of verified co-design of controllers for semi-autonomous cyber-physical systems and interfaces between humans and cyber-physical components

Motivating Applications

Semi-Autonomous Automobiles

TECHNOLOGY

The New York Times

The 15-Point Federal Checklist for Self-Driving Cars

By CECILIA KANG SEPT. 20, 2016

A Lesson of Tesla Crashes? Computer Vision Can't Do It All Yet

Semi-Autonomous UAVs

FAA Expects 600,000 Commercial Drones In The Air Within A Year





HOW TO ACE THE FAA'S NEW TEST AND BECOME A PRO DRONE PILOT



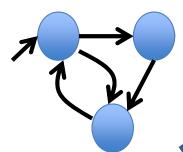
Sensing & HMI Design







Security & Privacy







Control





VeHi Cal

System-level Integration & **Validation**



Learning Models

from Data











Four Project Thrusts

1. Specification and Modeling

2. Learning, Verification, and Control

3. Human-Machine Interface Design & Verification

4. Testbed and Evaluation

Quick Overview of Year 1 Results

- Characterizing Behavior of Bounded Agents [Griffiths]
- Interaction-Aware Control [Sastry, Seshia]
- Computing Approximately-Optimal Controls for Stochastic Systems [Tomlin]
- FaSTrack: Fast and Safe Tracking for High Dimensional Systems [Tomlin]
- aDOBO: Dynamics Optimization via Bayesian Optimization [Tomlin]
- Verification of Learning-based CPS [Seshia]
- User Interfaces that Convey Internal and External Awareness [Bajcsy, Sastry, Seshia]
- Optimizing the Information-Performance Tradeoff between Humans and Autonomy [Bajcsy]
- Privacy Preserving Drowsiness Detection [Sturton]

Recent Graduates and New Additions

- Katherine Driggs-Campbell
 - Ph.D. UC Berkeley 2017
 - Currently Postdoctoral Researcher,
 Stanford
- Dorsa Sadigh
 - Ph.D. UC Berkeley 2017
 - Currently Asst. Professor, Stanford
- Mark Ho
 - Joining as VeHICaL postdoctoral researcher in Jan. 2018
 - Currently finishing Ph.D. at Brown University







Education and Outreach

- New course on "Reimagining Mobility" at the Jacobs Insitute of Design Innovation (Bjoern Hartmann)
- New undergraduate course on "Robotic Manipulation and Interaction" (Ruzena Bajcsy)
 - first undergraduate robotics course that emphasizes design and human-robot interactions, and applications
- Girls in Engineering summer outreach program (Claire Tomlin)
- Two Industry Workshops (Nov. 9, 2016 and May 9, 2017)
- NHTSA Engagement (ongoing) on defining a testing methodology for autonomous vehicles

S. A. Seshia

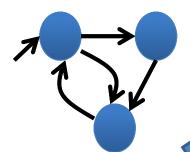
Sensing & HMI Design







Security & Privacy







Control |





System-level Integration & Validation









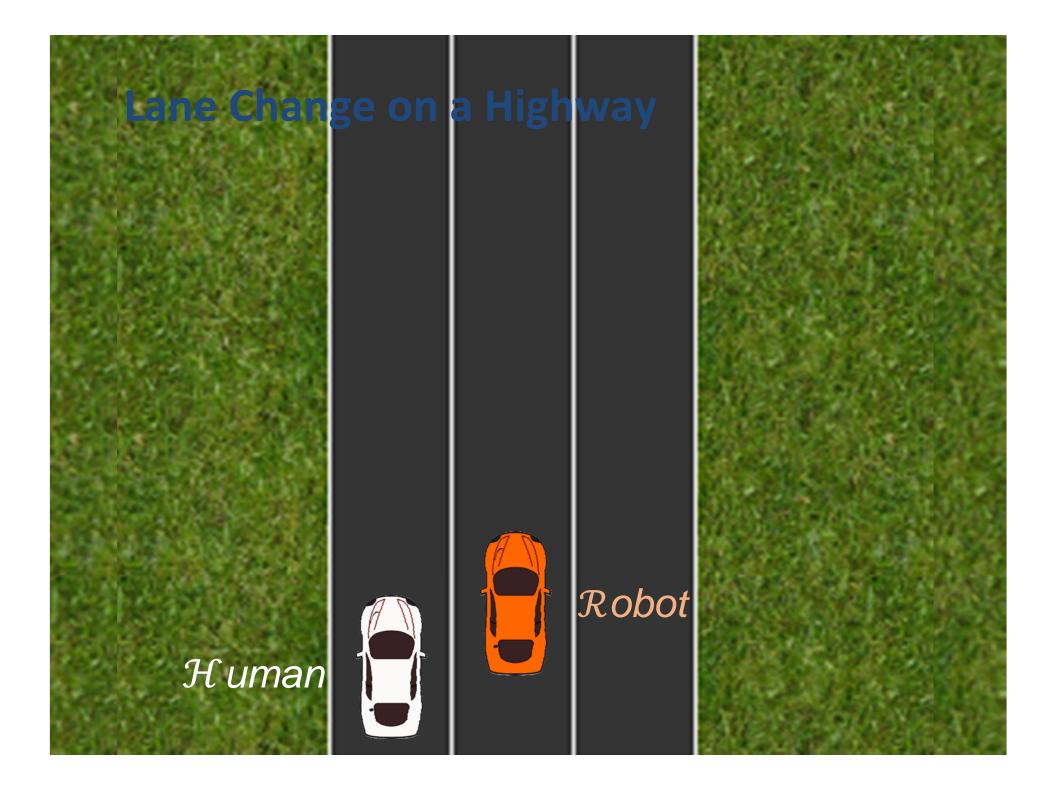


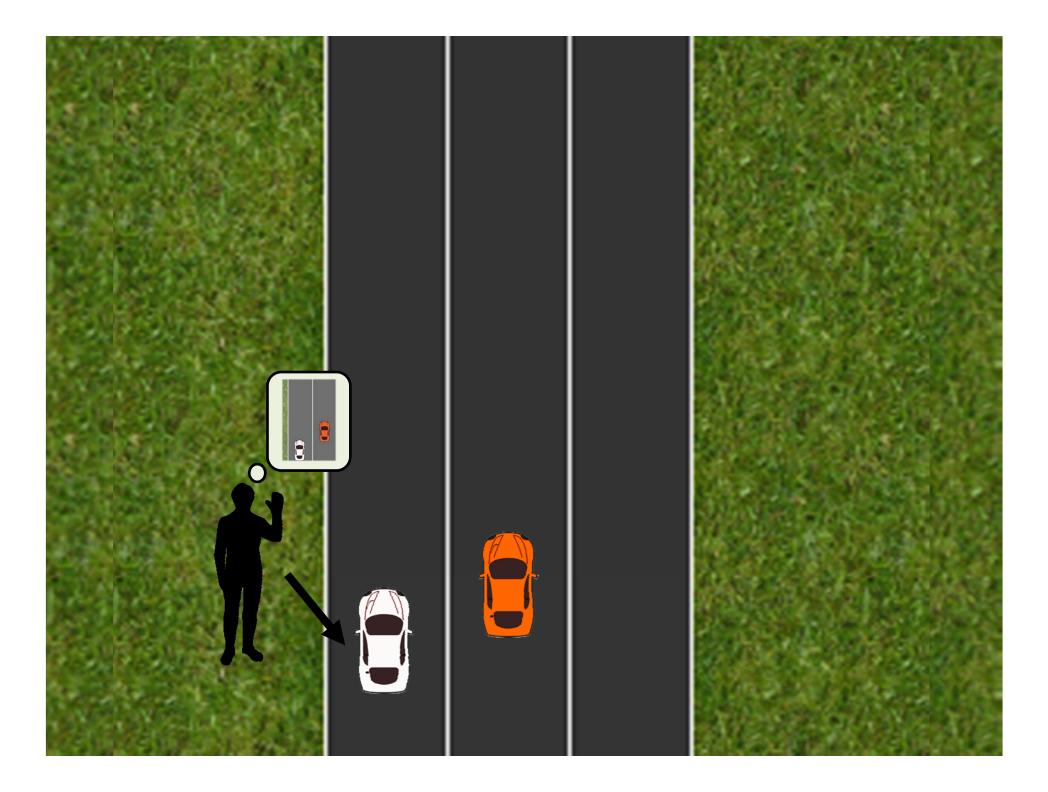


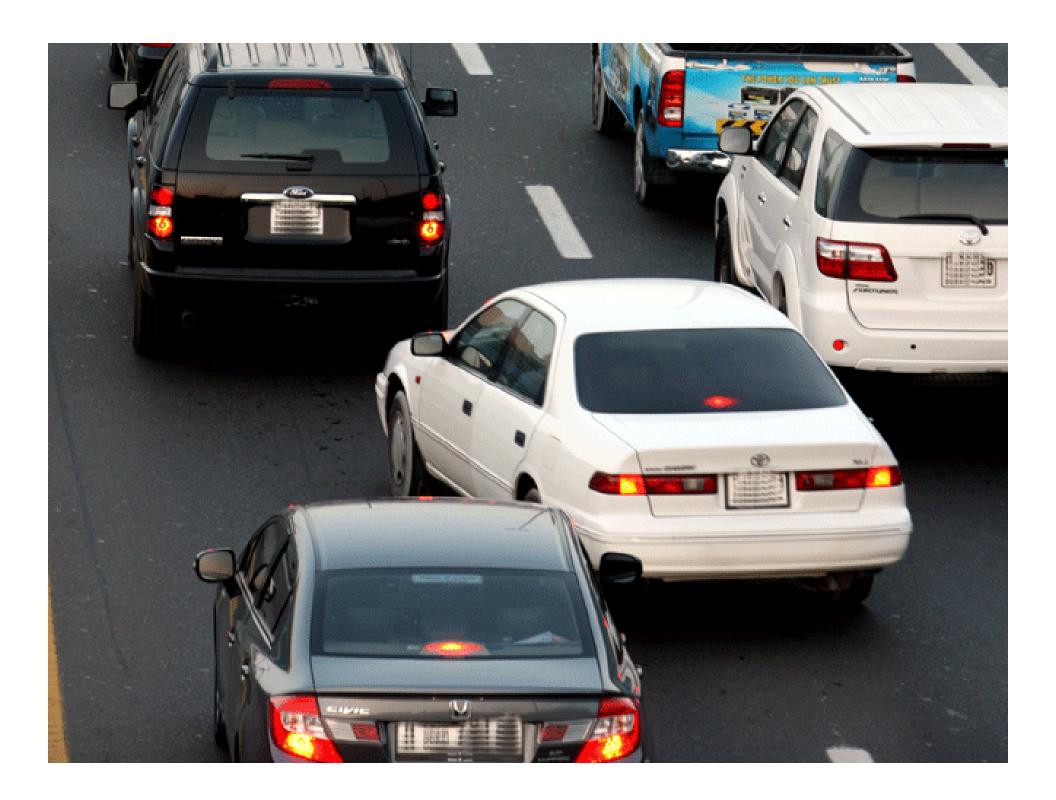


Interaction-Aware Control

- D. Sadigh, S. Sastry, S. Seshia, A. Dragan. Information Gathering Actions over Internal Human State. In IROS, 2016.
- D. Sadigh, S. Sastry, S. Seshia, A. Dragan. Planning for Autonomous Cars that Leverages Effects on Human Actions. In RSS, 2016.



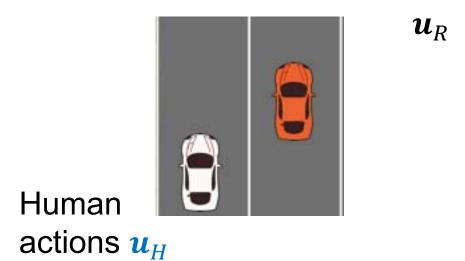




Interaction as a Dynamical System

$$x^{t+1} = f_{\mathcal{H}}(f_{\mathcal{R}}(x^t, u_{\mathcal{R}}^t), u_{\mathcal{H}}^t)$$

Robot actions



Model the problem as a *Stackelberg (turn-based) Game*. Robot moves first.

Assumptions/Simplifications

Model Predictive (Receding Horizon) Control:

Optimize over short time horizon N, replan at every step t.

$$R_{\mathcal{R}}(x, \mathbf{u}_{\mathcal{R}}, u_{\mathcal{H}}) = \sum_{t=1}^{N} r_{\mathcal{R}}(x^t, \mathbf{u}_{\mathcal{R}}^t, u_{\mathcal{H}}^t) \qquad R_{\mathcal{H}}(x, \mathbf{u}_{\mathcal{R}}, u_{\mathcal{H}}) = \sum_{t=1}^{N} r_{\mathcal{H}}(x^t, \mathbf{u}_{\mathcal{R}}^t, u_{\mathcal{H}}^t)$$

Assume *deterministic "rational"* human model, human optimizes reward function which is a linear combination of "features".

Human has full access to u_R for the short time horizon.

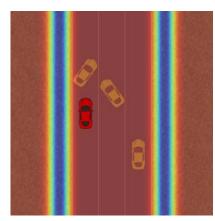
$$\boldsymbol{u}_{H}^{*}(x_{0}, \boldsymbol{u}_{R}) = \underset{\boldsymbol{u}_{H}}{\operatorname{argmax}} R_{H}(x_{0}, \boldsymbol{u}_{R}, \boldsymbol{u}_{H})$$

Learning (Human) Driver Models

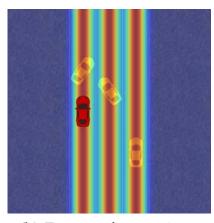
Learn Human's reward function based on Inverse Reinforcement Learning [Ziebart et al, AAAI'08; Levine & Koltun, 2012].

Assume structure of human reward function:

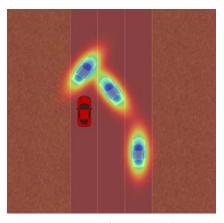
$$r_H(x^t, u_R^t, u_H^t) = w^\top \phi(x^t, u_R^t, u_H^t)$$



(a) Features for the boundaries of the road



(b) Feature for staying inside the lanes.

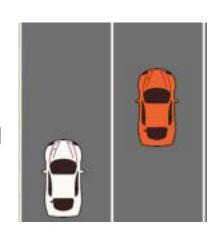


(c) Features for avoiding other vehicles.

Interaction as a Dynamical System

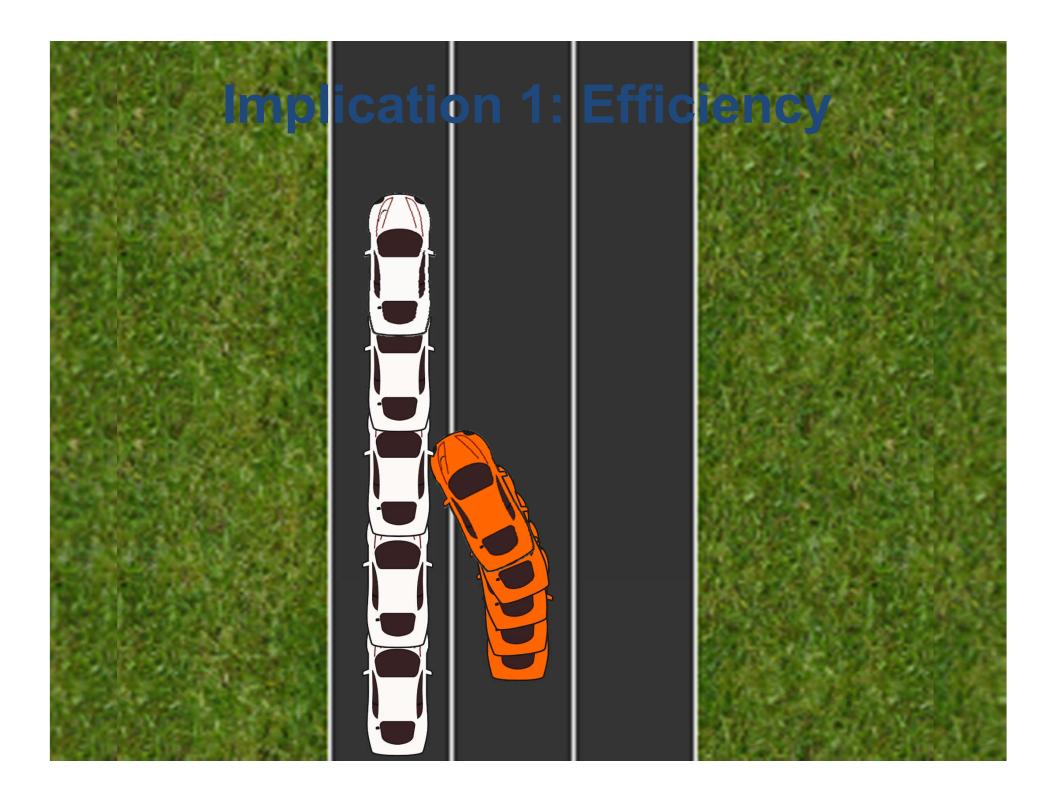
$$\boldsymbol{u}_{R}^{*} = \underset{\boldsymbol{u}_{R}}{\operatorname{argmax}} R_{R}(x_{0}, \boldsymbol{u}_{R}, \boldsymbol{u}_{H}^{*}(x_{0}, \boldsymbol{u}_{R}))$$

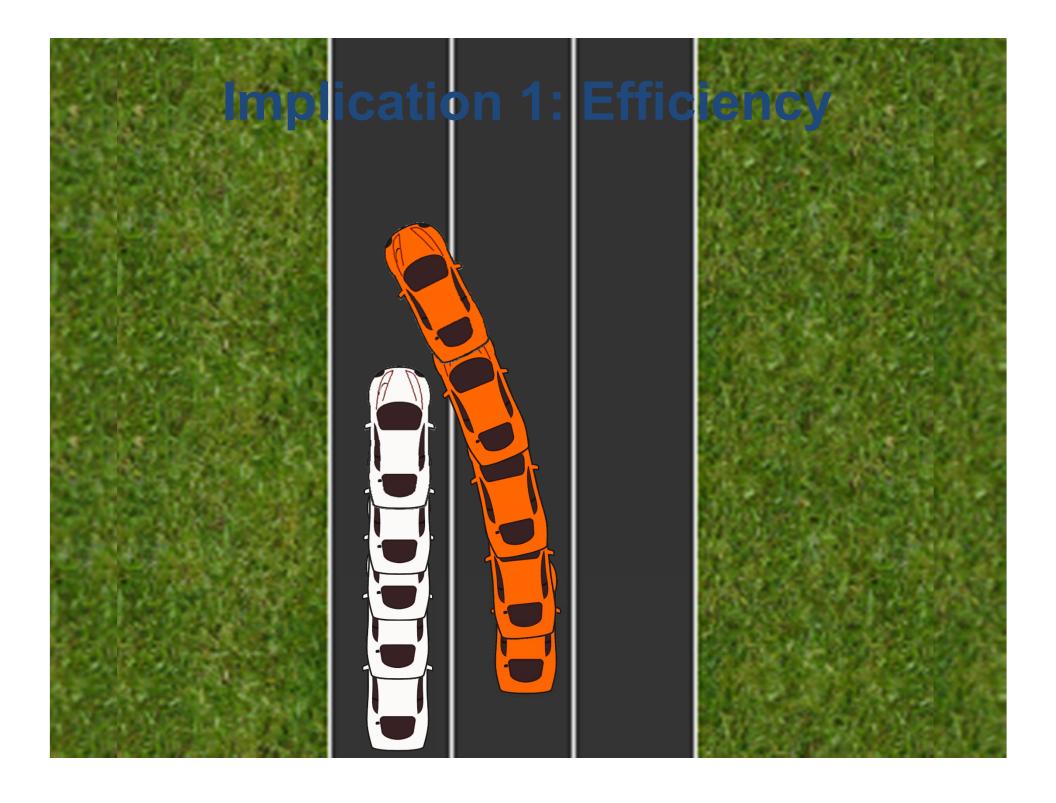
Model u_H^* as optimizing the human reward function R_H .

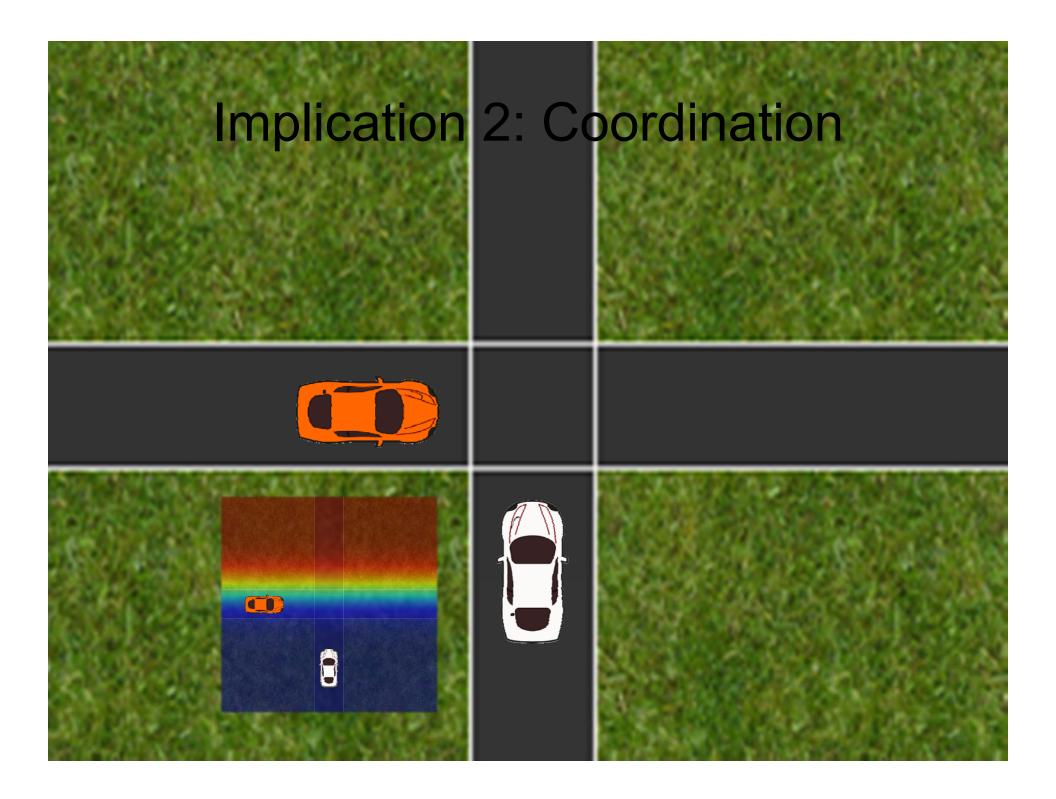


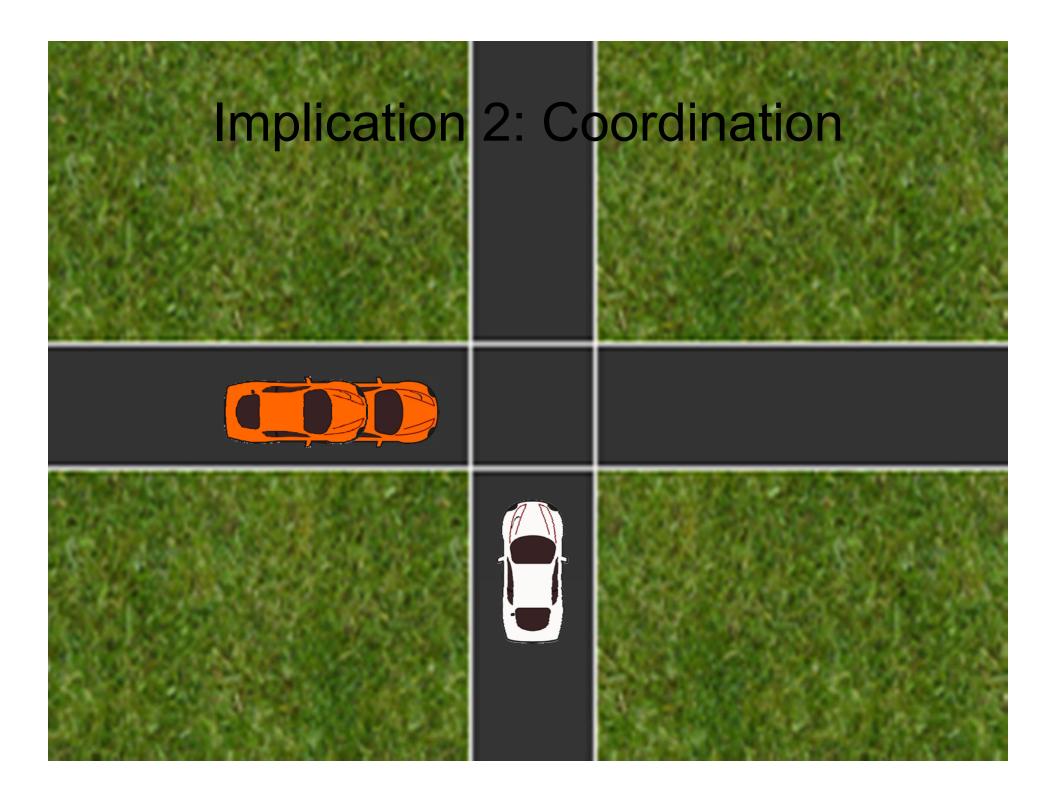
Find optimal actions for the autonomous vehicle while accounting for the human response u_H^* .

$$\mathbf{u}_H^*(x_0, \mathbf{u}_R) = \underset{\mathbf{u}_H}{\operatorname{argmax}} R_H(x_0, \mathbf{u}_R, \mathbf{u}_H)$$

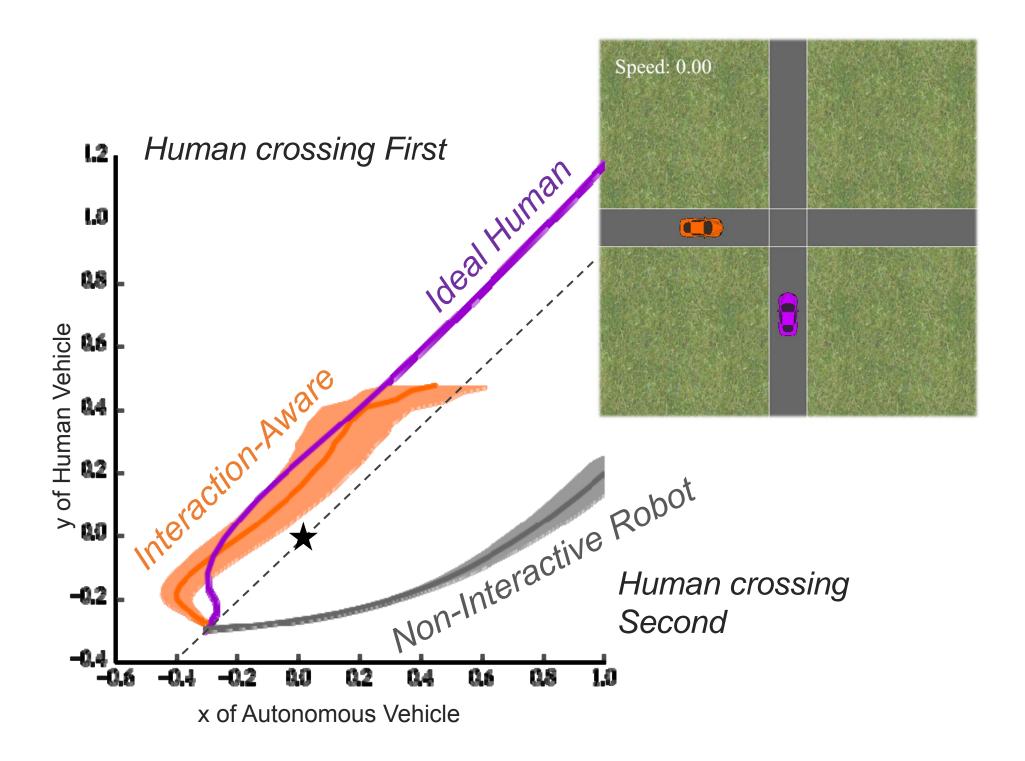












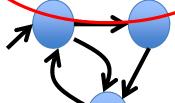








Security & Privacy



Verification



Control



System-level Integration & Validation

Learning Models from Data







Evaluation & User Studies





Questions for the Meeting

- Human Modeling:
 - Multiple approaches/formalisms: what are the pros and cons of each?
- Learning Systems:
 - What are the unique specification, verification, and control problems that arise?
- Interfaces:
 - How do we best integrate control design with interface design?
- Challenge Problems:
 - What are the best integrative challenge problems to tackle (from our target domains)?

S. A. Seshia