Game theoretic simulation for verification and validation of autonomous vehicles

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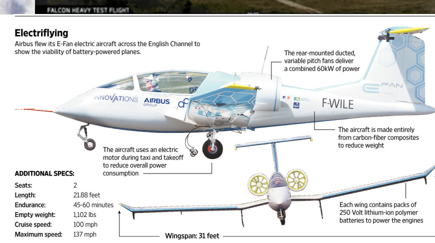
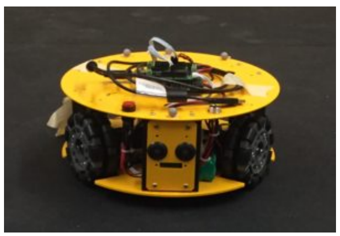
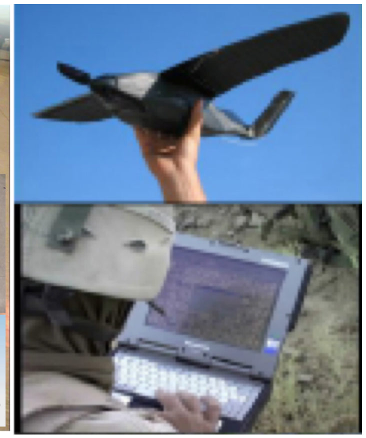


Collaborators/Funding/Thanks





- **Vehicle Optimization, Dynamics, Control and Autonomy Laboratory:** Dynamics, control and optimization of advanced, increasingly autonomous vehicles operating in the space, air, ground or marine domains.

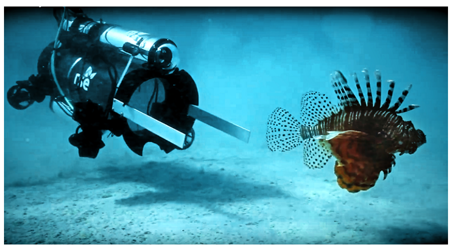
- **Collaborators:** I. Kolmanovsky, A. Berning, W. Dunham, N. Li, R. Sutherland, R. Tian

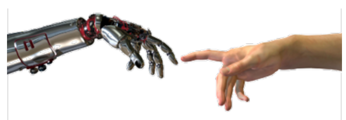
- **Funding Sources:** AFRL, AFOSR, NASA, NSF, ONR, TARDEC, Boeing, Luna Rossa, Oracle, and the automotive industry.

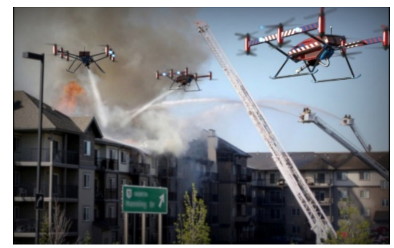
- **Website:** vodca.engin.umich.edu

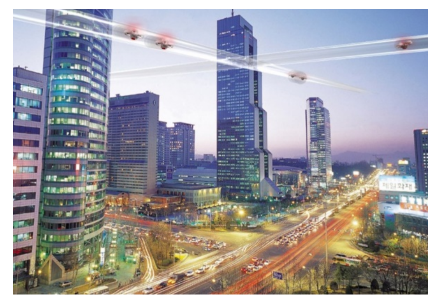
Robots are increasingly capable and prevalent

Robots, including collaborative robots, are becoming more capable, better accepted, and more commonplace.



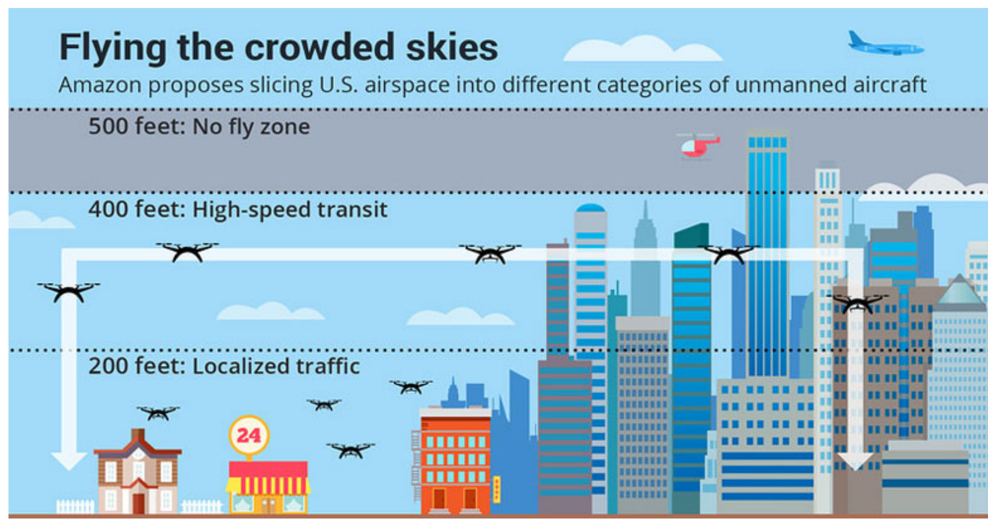






Unmanned Air Vehicles are here

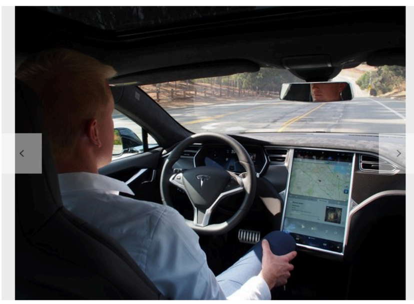
- ❑ Estimated number of UAVs shipped in 2017: almost 3 million
- ❑ Projected number of UAVs in US by 2020: 7 million
- ❑ Estimated number of commercial UAVs in the air by 2018: 600,000
- ❑ Number of UAVs registered with the FAA: 770,000
- ❑ Estimated value of UAV industry: $ 3.3 billion
- ❑ Projected value of UAV industry in 2025: $ 90 billion
- ❑ Percentage of Americans who own a "drone:" 8%



Self-driving cars are being tested

MOLLY MCHUGH GEAR 10.14.15 05:19 PM

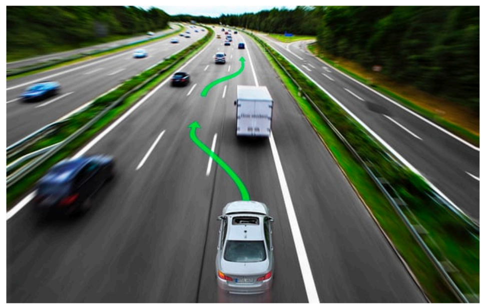
TESLA'S CARS NOW DRIVE THEMSELVES, KINDA



1 / 7 Technically, it's advised to keep hands resting on the wheel---but you can go hands-free.
MOLLY MCHUGH/WIRED

Self-driving cars: from 2020 you will become a permanent backseat driver

Driverless cars will revolutionise motoring, claim the manufacturers. But is the greatest danger that they will be too safe?



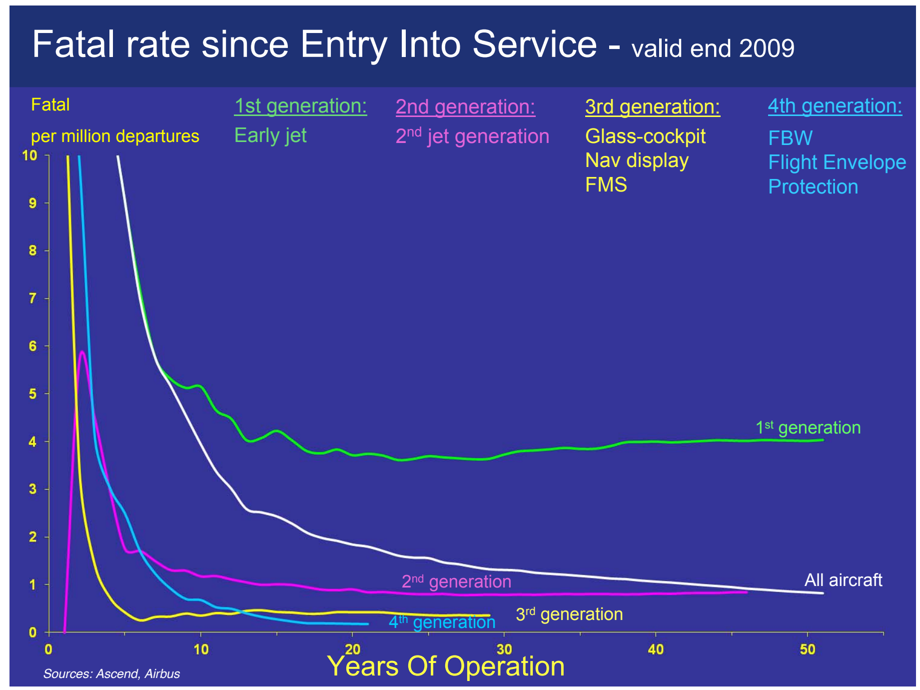
▲ A BMW 'highly automated' prototype on the German autobahn. Photograph: PR

Self-driving cars: it's only a matter of time until they take over

Nicholas Tucker, Staff Reporter
April 11, 2018
Filed under Opinion

Self-driving trucks are coming—and this law just made things even worse for truckers

Safety/validation concerns are relevant



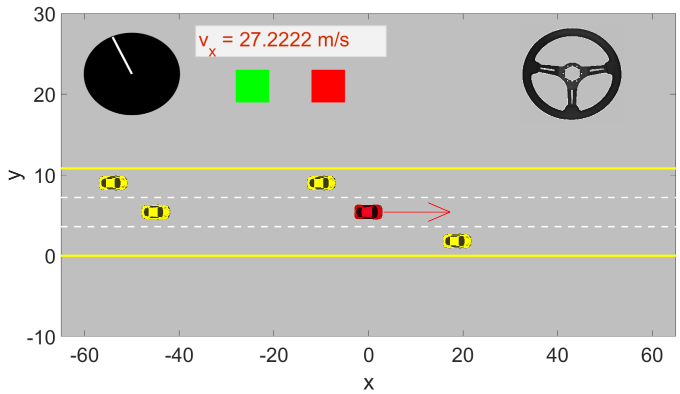
D. Chatrenet, Air transport safety technology and training, ETP 2010

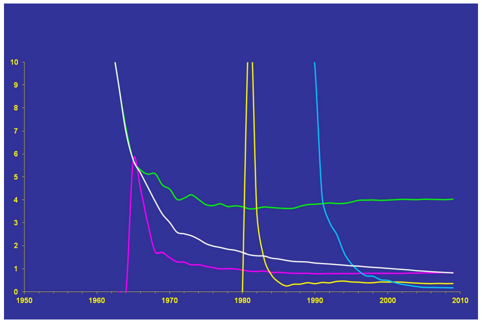
Traffic Simulation

Why do we need traffic simulation?

- ❑ Estimated that one must drive **>100 million kilometers** to validate autonomous driving software

- ❑ Use traffic simulators to:
  - ❑ Create a pool of traffic scenarios, trajectories, inputs,
  - ❑ Evaluate the performance of control algorithms in different scenarios,
  - ❑ Compare vehicle control algorithms,
  - ❑ Detect "faults" in the algorithms, e.g., conditions under which the algorithm may cause unsafe driving behavior.





Fatality rates with introduction of new technology (Aircraft data)

In extreme situations, traffic modeling is easy

At **very low traffic densities**, everyone travels their desired speed. The interaction between vehicles is negligible.

At **very high traffic densities**, we have (almost) complete stoppage. The traffic dynamics are irrelevant, and queueing theory is a good model.

Important, and challenging, traffic modeling

If the **traffic is dense but moving**:

- ❑ Microscopic traffic models: how do vehicles interact with each other?
- ❑ Macroscopic traffic models: temporal evolution of traffic density? Traffic waves?

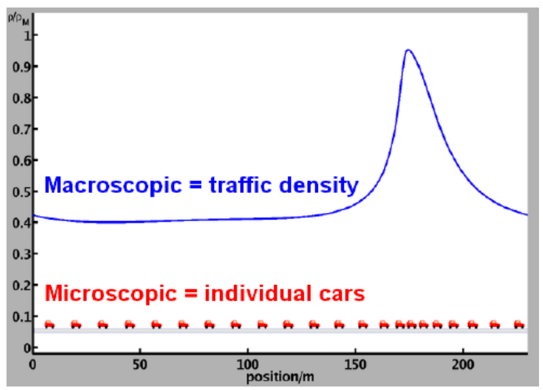
Micro vs. macro traffic models

Microscopic traffic models:

- ❑ Track individual vehicle trajectories
- ❑ Quantities of interest: vehicle position, speed, acceleration
- ❑ Popular framework: car-following models
- ❑ Small number of vehicles (as low as 2)

Macroscopic traffic models:

- ❑ Track field quantities, defined everywhere
- ❑ Quantities of interest: vehicle density, velocity field, flow rate field
- ❑ Popular frameworks: LWR, ARZ
- ❑ Large number of vehicles (thousands)



Opportunity and Challenge:
Intermediate models that consider interactions between 10-50 vehicles

Intermediate traffic models

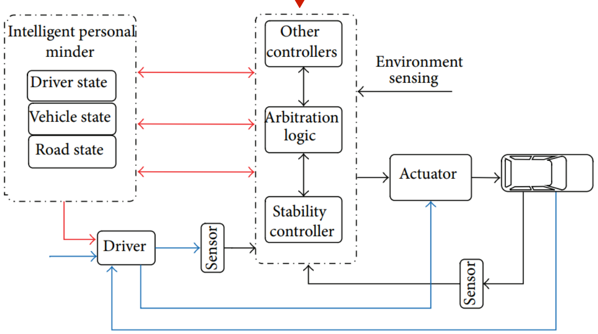
To study *microscopic phenomena*:
predicting driver intent, driving maneuvers, vehicle and driver states, to improve driving safety and experience [1].

To study *macroscopic phenomena*:
analyzing statistical properties of traffic flow, transportation capacity, traffic jams, to improve transportation system effectiveness and efficiency [2].

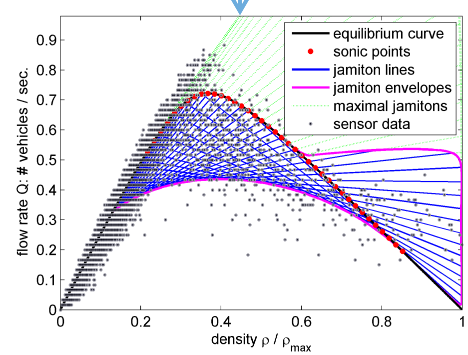
Driver behavior modeling

Our game-theoretic vehicle interaction modeling

Traffic modeling

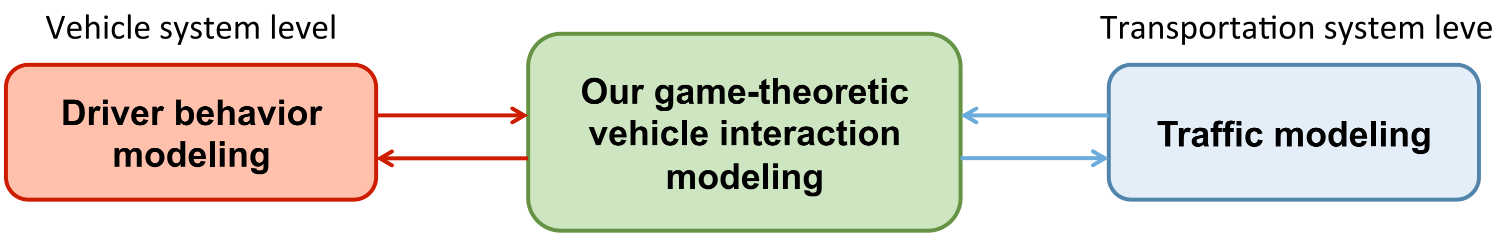


A driver behavior model example [3]



A fundamental diagram of traffic example [4]

Modeling vehicle interactions is important



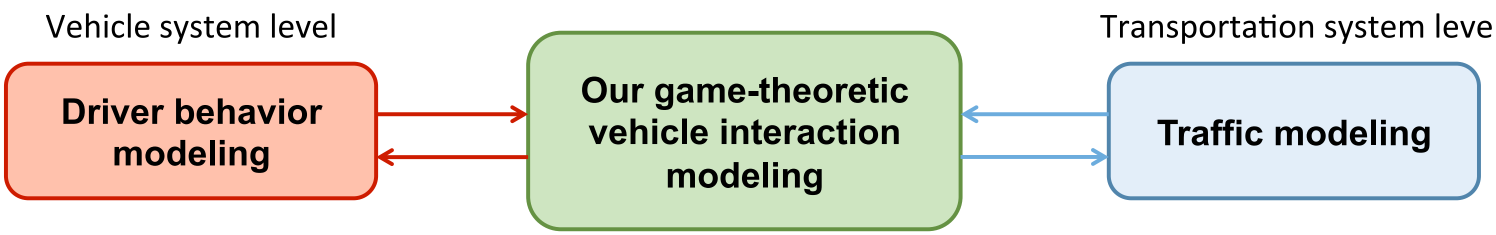
Top five contributing factors to collisions [5]:

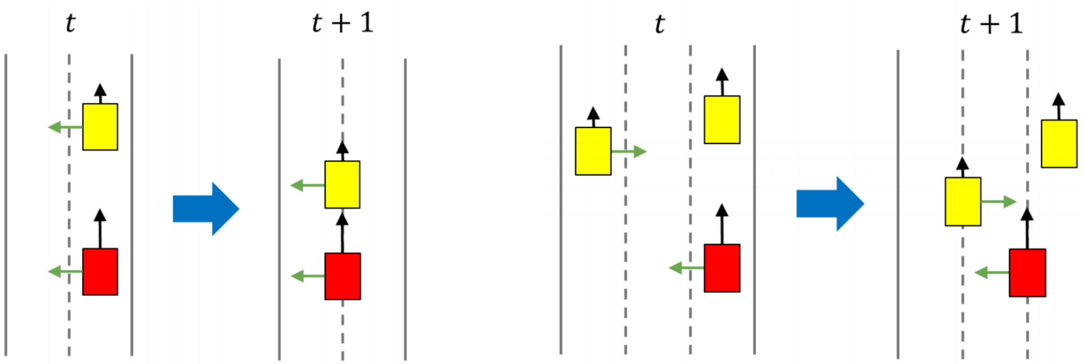
Driver failed to look properly, 41%;
Driver failed to judge other person's path or speed, 22%;
Driver careless, reckless or in a hurry, 15%;
Poor turn or maneuver, 14%;
Loss of control, 12%.

related to ***vehicle interactions***

Real traffic scenarios include ***complex interactions among road users***. Modeling and handling interactions with other road users is necessary to provide safety, and remains an ***unsolved problem*** for autonomous driving [6].

Intermediate models capture corner cases



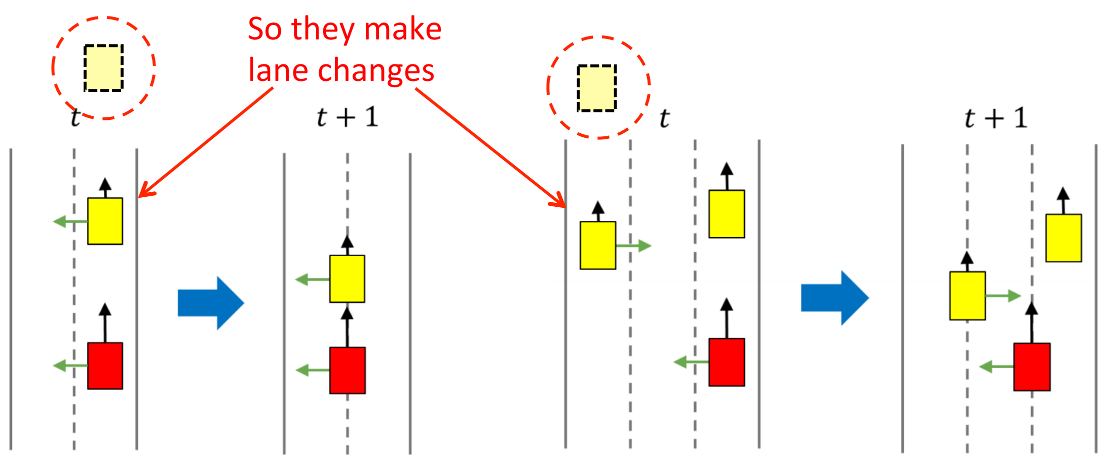


These two scenarios involve more vehicles than shown in the diagram!

Two *conflict scenarios* involving the interaction among multiple vehicles detected by our model [7]

A traffic conflict is a situation where two or more road users approach each other in time and space to such an extent that a collision is imminent if their movements remain unchanged [8].

Intermediate models capture corner cases



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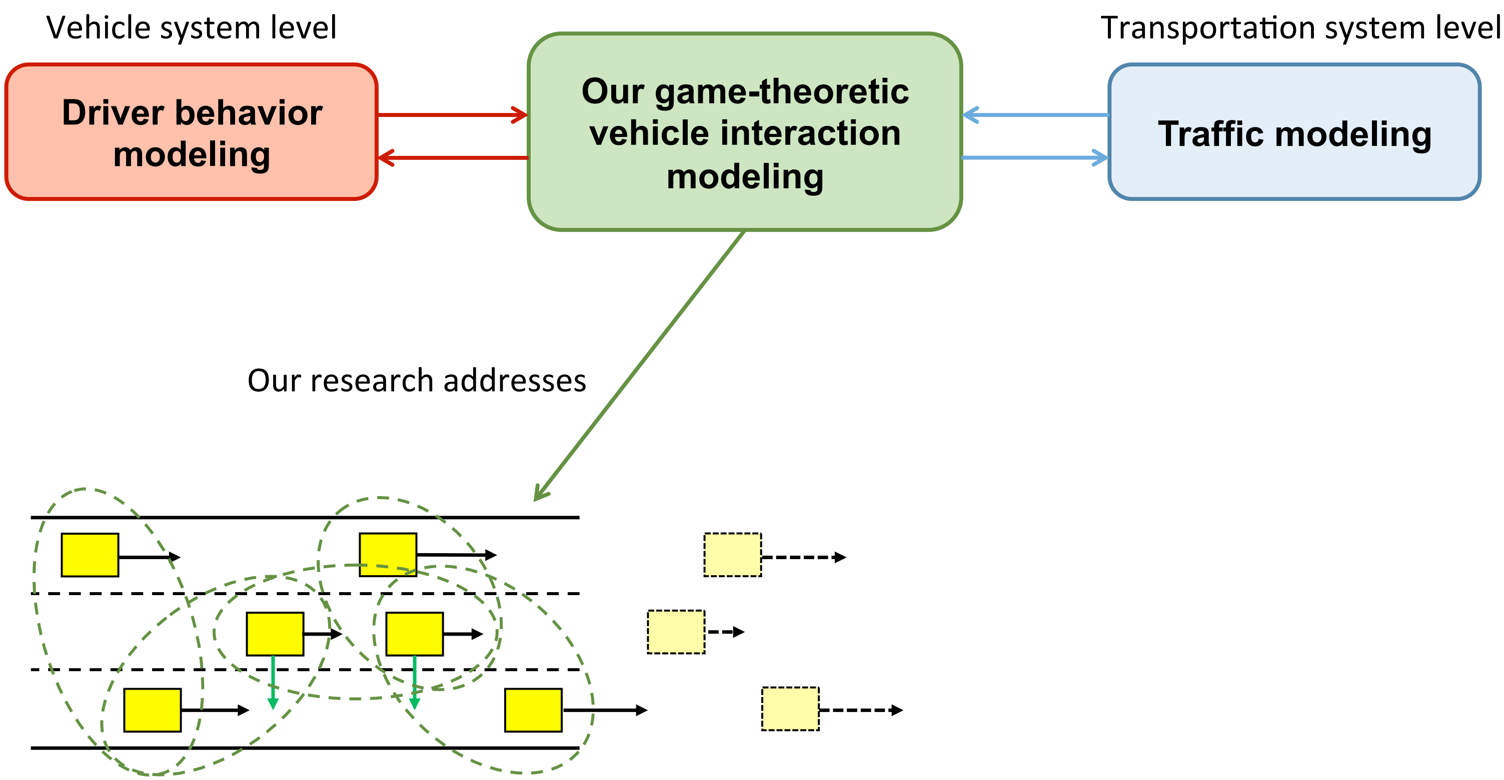
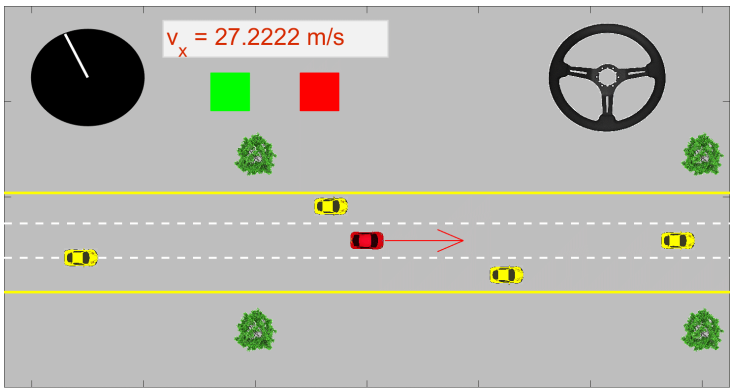
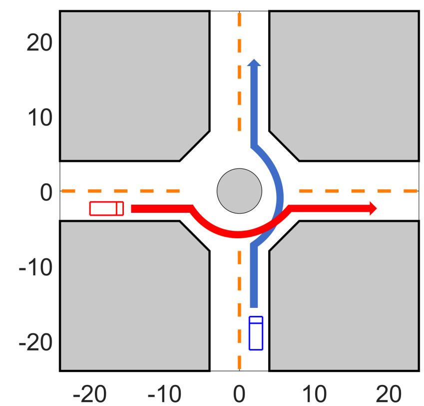


Real traffic scenarios include ***complex interactions among road users***.

Game Theoretic Traffic Simulation

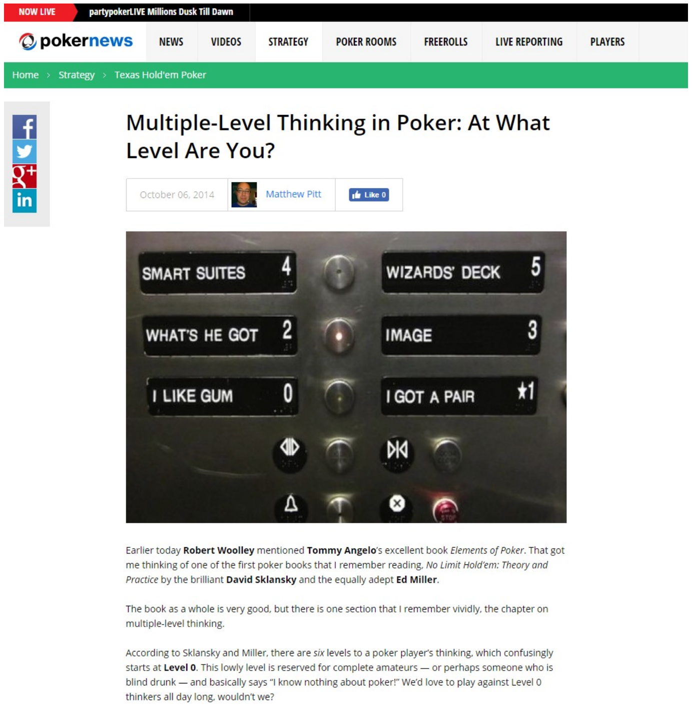




Main Collaborators: Ilya Kolmanovsky, Yildiray Yildiz, Nan Li, Ran Tian.

Hierarchical reasoning game theory

- **Modeling humans precisely is difficult** (Variability, small data sets).
- **Hierarchical reasoning game theory (level-k game theory)** attempts to describe human thought processes in strategic games. Assumes that players base their decisions on their predictions of the likely actions of other players.
- Players in strategic games can be categorized by the "depth" of their strategic thought. Players have bounded rationality.
- Level-k theory **predicts human decisions better than equilibrium-based models** in a range of games.



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Multiple-Level Thinking in Poker: At What Level Are You?

October 06, 2014 | Matthew Pitt | Like 0

Earlier today **Robert Woolley** mentioned **Tommy Angelo**'s excellent book *Elements of Poker*. That got me thinking of one of the first poker books that I remember reading, *No Limit Hold'em: Theory and Practice* by the brilliant **David Sklansky** and the equally adept **Ed Miller**.

The book as a whole is very good, but there is one section that I remember vividly, the chapter on multiple-level thinking.

According to Sklansky and Miller, there are *six* levels to a poker player's thinking, which confusingly starts at **Level 0**. This lowly level is reserved for complete amateurs — or perhaps someone who is blind drunk — and basically says "I know nothing about poker!" We'd love to play against Level 0 thinkers all day long, wouldn't we?

An example: the Keynesian “beauty” contest

- **Keynesian beauty contest:** Pick a number between 0 and 100. Winner is the person whose number is the closest to half of the average of all the (many) participants' guesses.

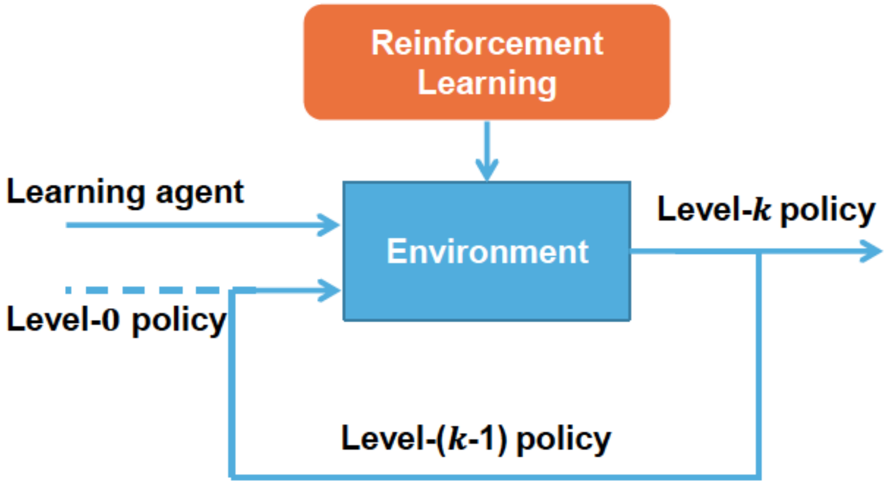
- **Level zero players:** choose a number non-strategically (at random, 42 for Doug Adams, birthday, etc.)

- **Level one players:** choose their number consistent with the belief that all other players are level zero. If all other players in the game are level zero, the average of those guesses would be about 50. Therefore, a level one player chooses 25.

- **Level two players:** choose their number consistent with the belief that all other players are level one. Since a level one player will choose 25, a level two player should choose 13. This process repeats for higher-level players.

- Studies from other domains show **humans are usually level 0, 1 or 2, rarely 3**.

Level-k reasoning and reinforcement learning



- Level-**0** agent makes instinctive decisions and does not take into account the interactions.
- Level-**1** agent assumes all of the other agents are Level-**0** and makes optimal responses based on this assumption.

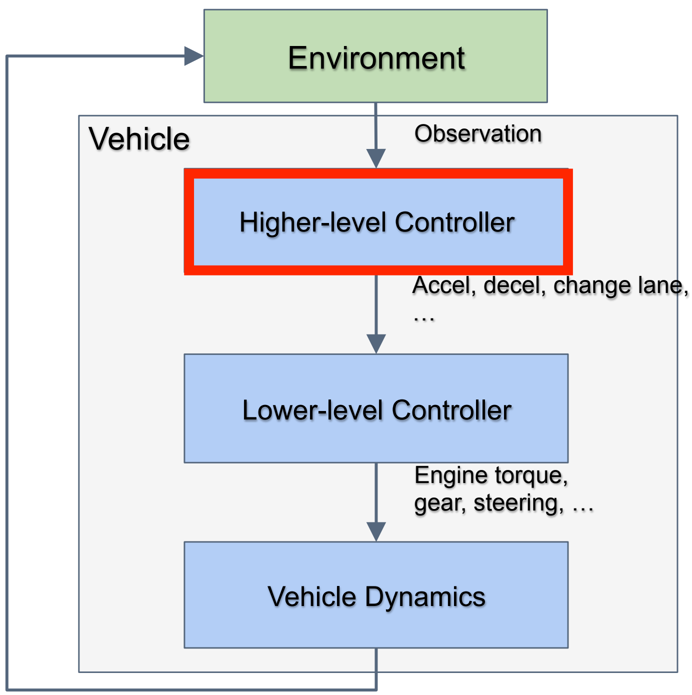
⋮

- Level-**k** agent assumes all of the other agents are Level-(**k**-1) and makes optimal responses based on this assumption.

- To obtain the level-k policy, we put a learner in traffic consisting of level-(k-1) drivers, and use reinforcement learning to train the learner. In other domains, humans have been shown to usually be levels 0, 1 or 2 decision makers.

MDP for highway driving

❑ Control Hierarchy. Focus: Higher-level Controller



- **Set of states:**
  - 3 states per vehicle, longitudinal position and velocity, lateral position
  - 30-50 vehicles in simulation

- **Set of actions: 7 dimensional**
  - Maintain
  - Change lane left/right
  - Accelerate/decelerate (regular maneuver)
  - Emergency Accelerate/decelerate

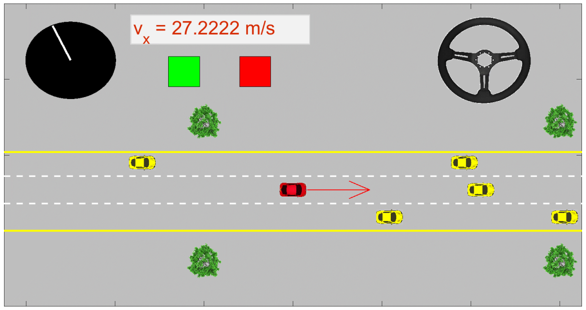
- **Reward/Penalty:** (safe distance) constraint violation, vehicle speed, maneuver effort, headway

$$R = w_1 c + w_2 v + w_3 e + w_4 h$$

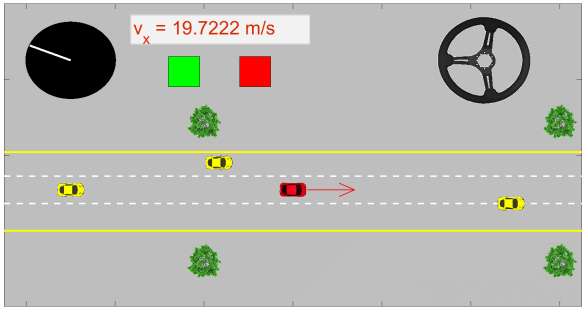
- **Observation space (POMDP): 18-dimensional**
  - Observe states of 5 neighboring vehicles + self

Game theoretic traffic modeling results

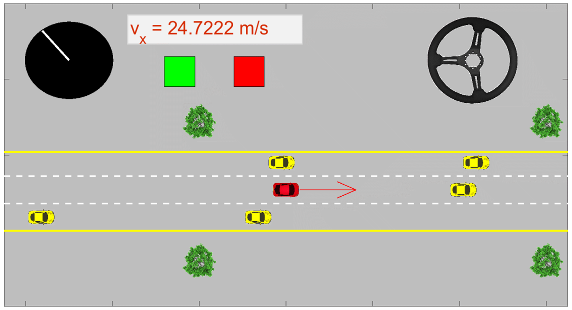
Level-1 vs Level-0



Level-2 vs Level-1



Mixed traffic (10% Level-0, 60% Level-1 and 30% Level-2)



Un-signalized Intersections

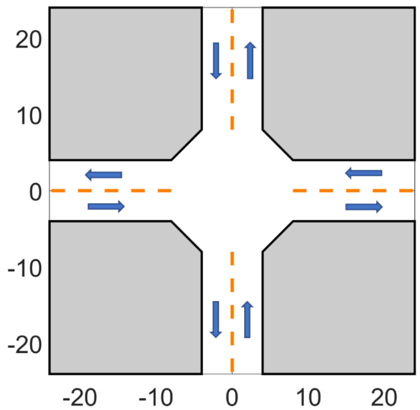
Four-way intersection

Roundabout

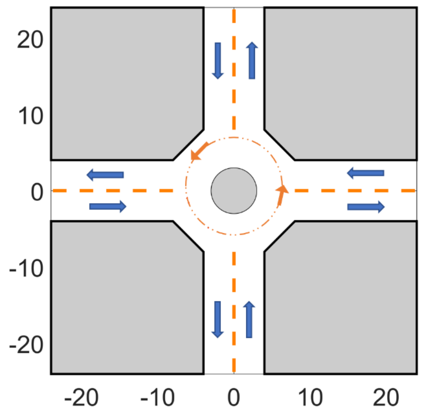
- ❑ Represent roughly **50% of intersection crashes** in the US
- ❑ Require a balance between overly aggressive actions (that do not take into account behavior of others) and overly conservative actions (deadlock)
- ❑ Challenges: predict other drivers' actions (interactive), take optimal decision corresponding to the prediction

Un-signalized intersections: Scenarios

2-vehicle interactions at:

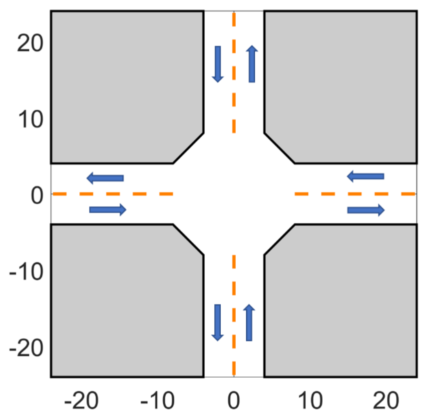


Unsignalized four-way intersection



Roundabout

MDP for intersections



- **Set of states (MDP, not POMDP):**
  - 4 states per vehicle, longitudinal and lateral positions, speed, yaw angle
  - 2-vehicle interactions at first
- **Set of actions: 6 possible combinations**
  - Acceleration
  - Yaw rate
- **Reward/Penalty:** (safe distance) constraint violation, vehicle speed, maneuver effort, headway

penalty for collision, penalty for being too close, penalty for driving off road, penalty for driving in wrong lane, reward for approaching objective lane

Un-signalized intersections: Results

L0 driver treats the other car as a stationary obstacle and does not take into account her potential actions → aggressive

L2 driver predicts that the other car will yield the right of way, thus decides to pass first.

When predictions are incorrect…

Fail

Fail

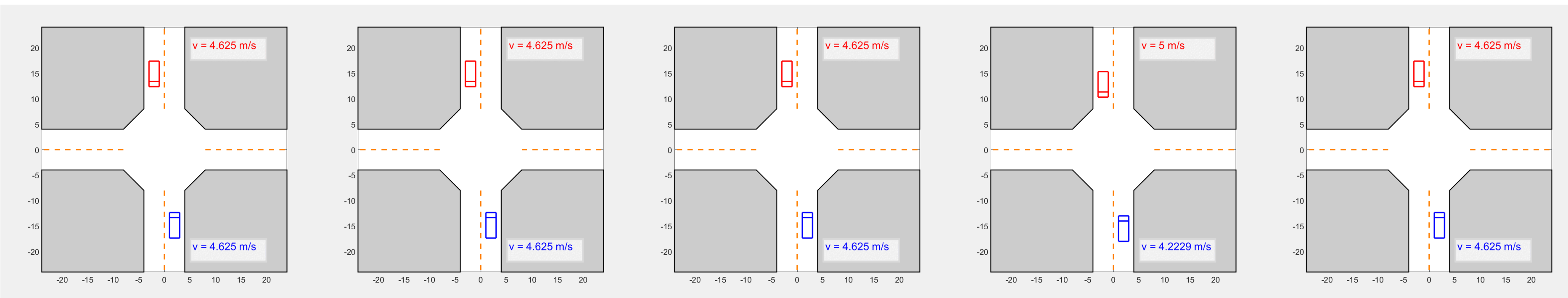
L1 vs L0

L2 vs L1

L1 vs L1

L0 vs L0

L2 vs L2



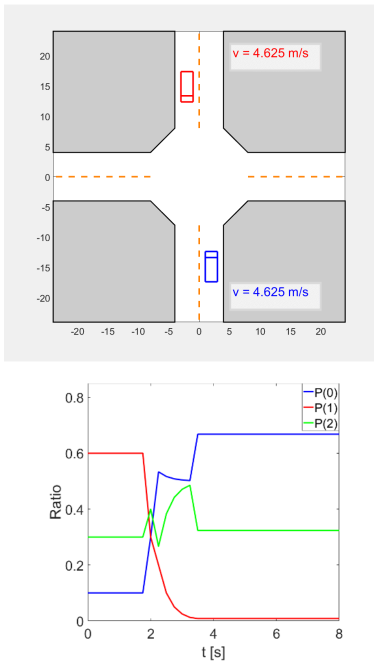
L1 driver predicts the other car to be aggressive, thus yield the right of way.

Both cars yield the right of way at the beginning, then reach an agreement.

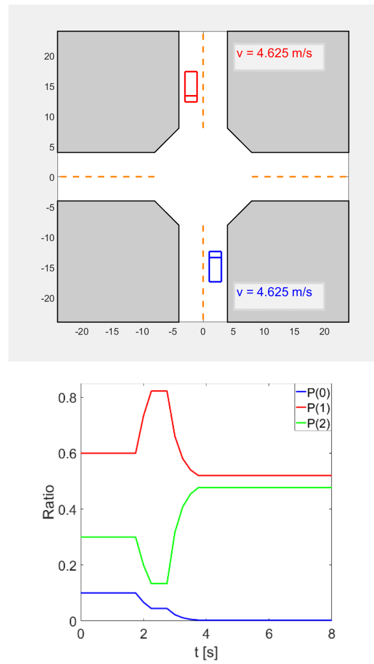
Humans are usually level-0, 1 and 2 reasoners in their interactions (Costa-Gomes, M. A., & Crawford, V. P. (2006). Cognition and behavior in two-person guessing games: An experimental study. American Economic Review, 96(5), 1737-1768).

Controller $\mathcal{D}$ versus level-k drivers

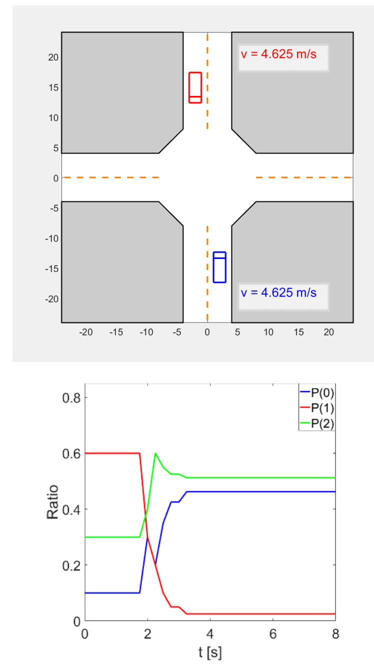
D vs L0



D vs L1



D vs L2

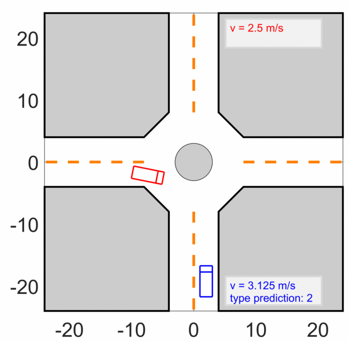


Controller $\mathcal{D}$ versus level-k and human drivers

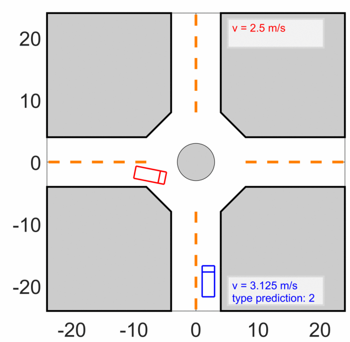
Roundabout scenario:

We let a human operator control the red car using the keyboard.

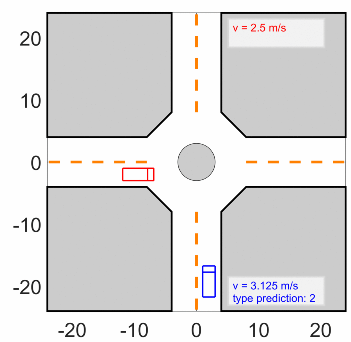
D vs L1



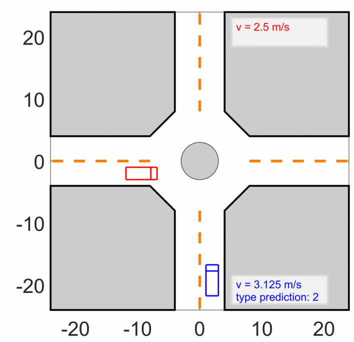
D vs L2



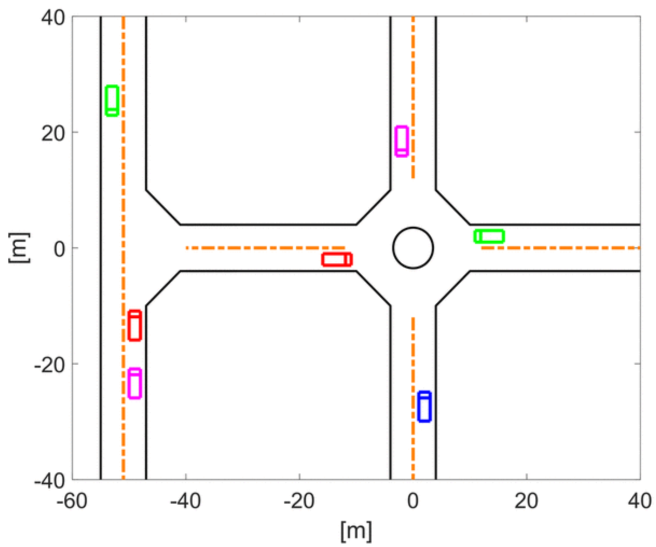
D vs Human 1



D vs Human 2

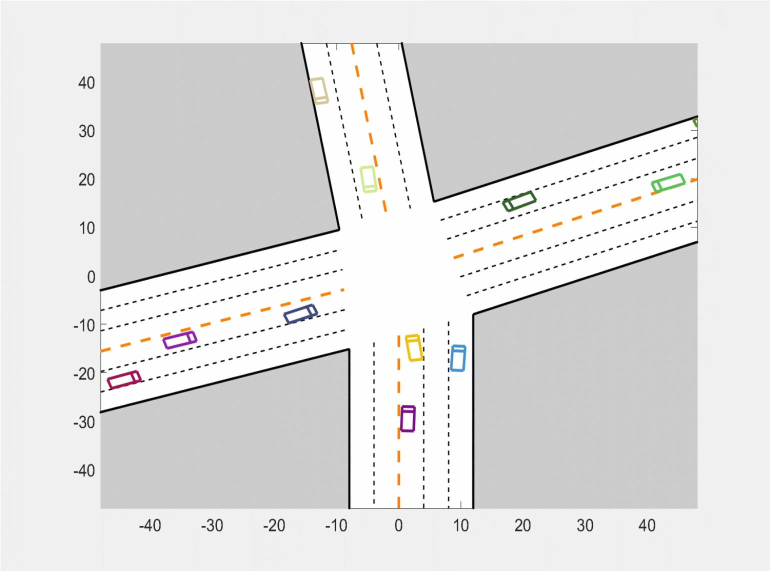


Generalization to n–vehicle scenarios

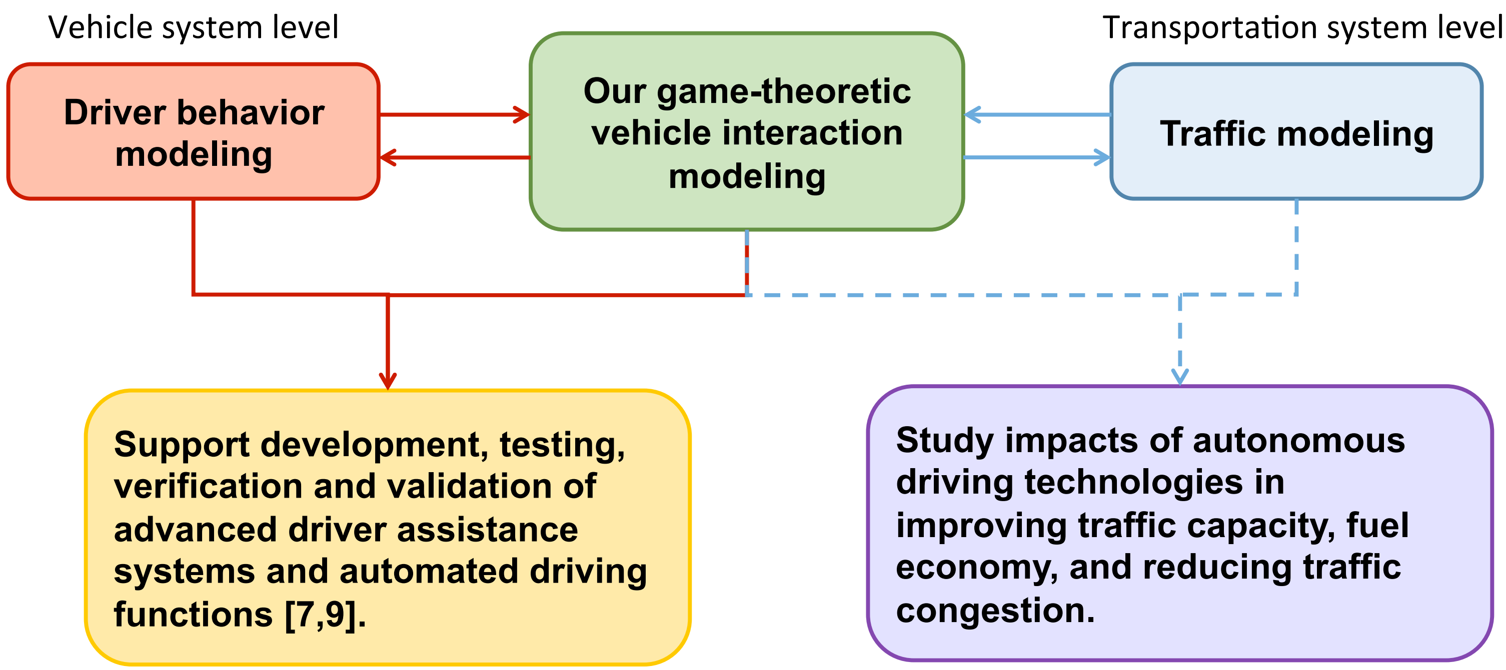


- **POMDP:**
  - The ego car considers its interactions with its two nearest neighbors

Generalization to arbitrary road geometries



Intermediate models can be used to…



About the speaker

Anouck R. Girard received the Ph.D. degree in ocean engineering from the University of California, Berkeley, CA, USA, in 2002. She has been with the University of Michigan, Ann Arbor, MI, USA, since 2006, where she is currently an Associate Professor of Aerospace Engineering.

She has co-authored the book Fundamentals of Aerospace Navigation and Guidance (Cambridge University Press, 2014). Her current research interests include flight dynamics and control systems. Dr. Girard was a recipient of the Silver Shaft Teaching Award from the University of Michigan and a Best Student Paper Award from the American Society of Mechanical Engineers.

Background

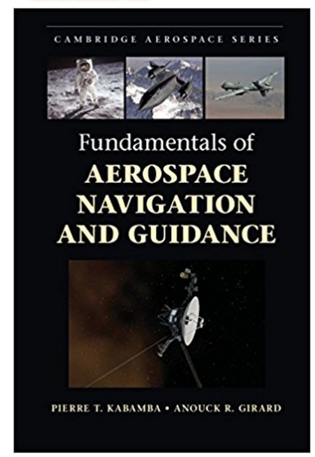
- 2006 – Current: Assistant/Associate Professor, Aerospace Engineering, University of Michigan
- 2004 – 2006: Assistant Professor, Mechanical Engineering, Columbia University
- 2002 – 2004: Post-Doctoral Researcher/Lecturer, UC Berkeley
- 1998 – 2002: PhD, UC Berkeley, Karl Hedrick's group

- **Research Interests:** Controlling advanced and increasingly autonomous vehicles and vehicle systems operating in the air, space, ground and marine domains. These vehicles / systems exhibit complex nonlinear dynamics, and must function in uncertain environments with limited resources, while satisfying stringent constraints and counteracting the effects of disturbances.

- **Publications:** 1 textbook (navigation and guidance), 46 journal papers, 130+ conference papers

- **Center Experience:** PI for the MACCCS Center, 2007-2016

- **Teaching Experience:** Undergraduate: Aircraft Performance, Spacecraft Dynamics, Aircraft Dynamics and Control, Classical Control; Graduate: Linear Systems, Nonlinear Systems, Navigation and Guidance, Spacecraft Dynamics and Control, Predictive and Nonlinear Control, Autonomy.



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