

# Autonomous Robotics

Applications: Autonomous Driving

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# Announcements

Final project:

For tournament: due tonight, must score 100% to be included in the tournament.

May 1: final deadline

Complete course evaluation

Check your grades on Canvas

# Learning Outcomes

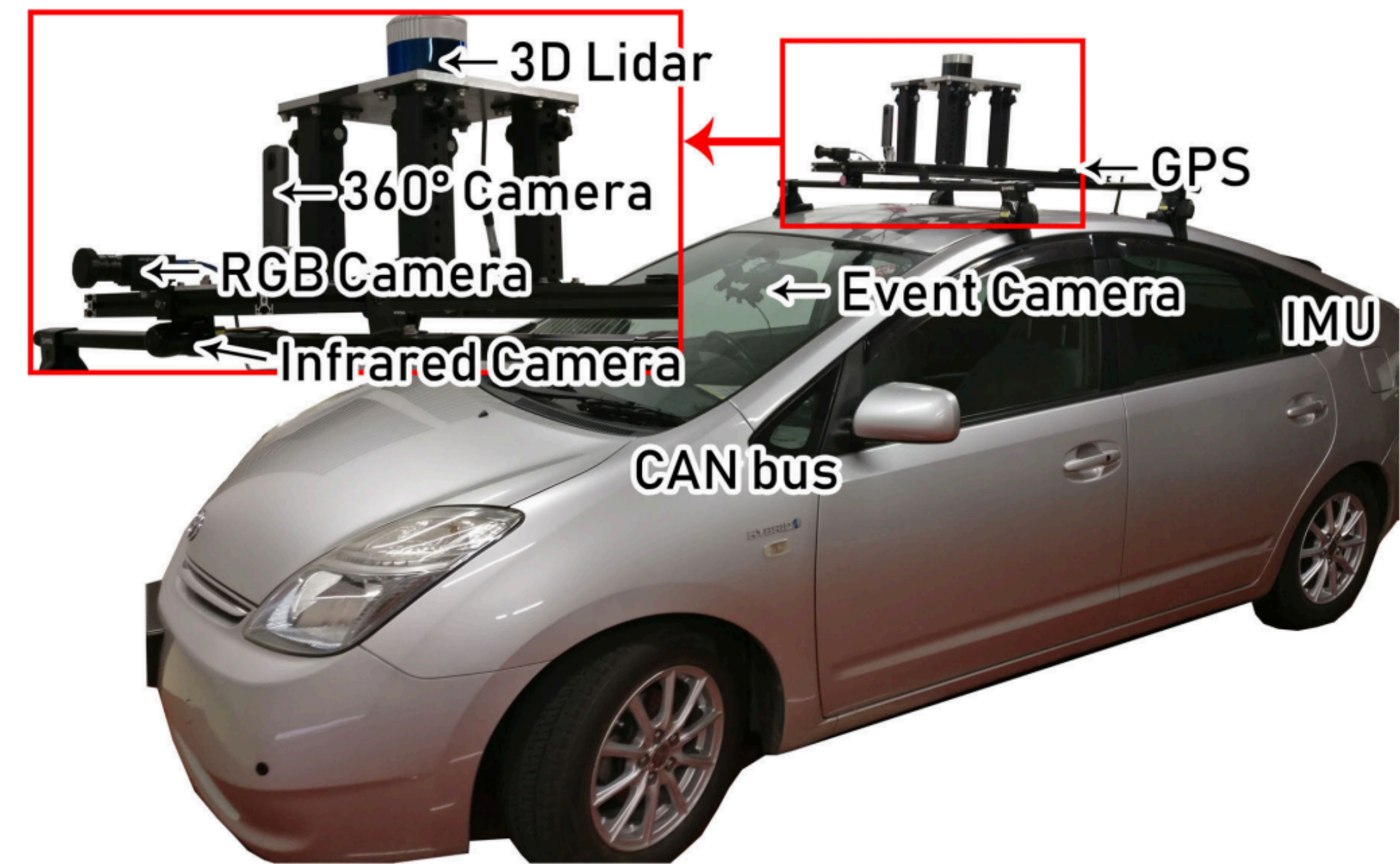
After today's lecture, you will:

- Have applied your robotics knowledge to design an autonomous vehicle.
- Have learned about the prediction problem in autonomous driving.
- Be able to compare and contrast modular vs end-to-end approaches to autonomous driving.

# Autonomous Driving

Car equipped with sensors:

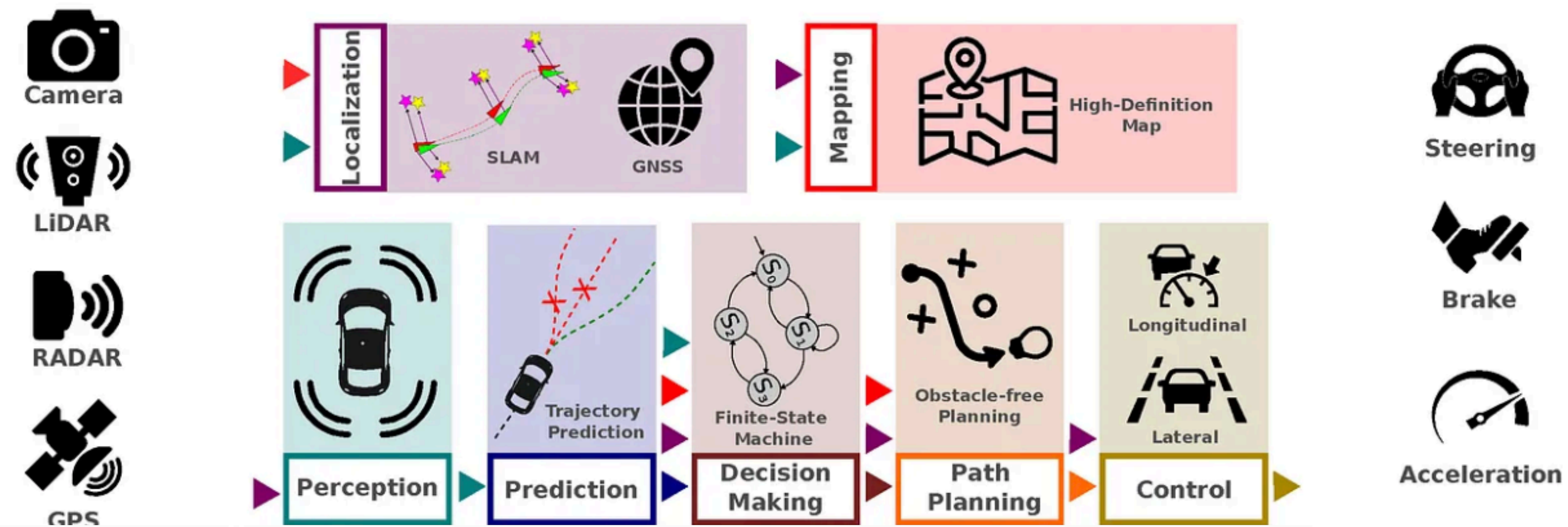
- Camera
- Lidar
- Radar
- GPS
- IMU
- Proprioception



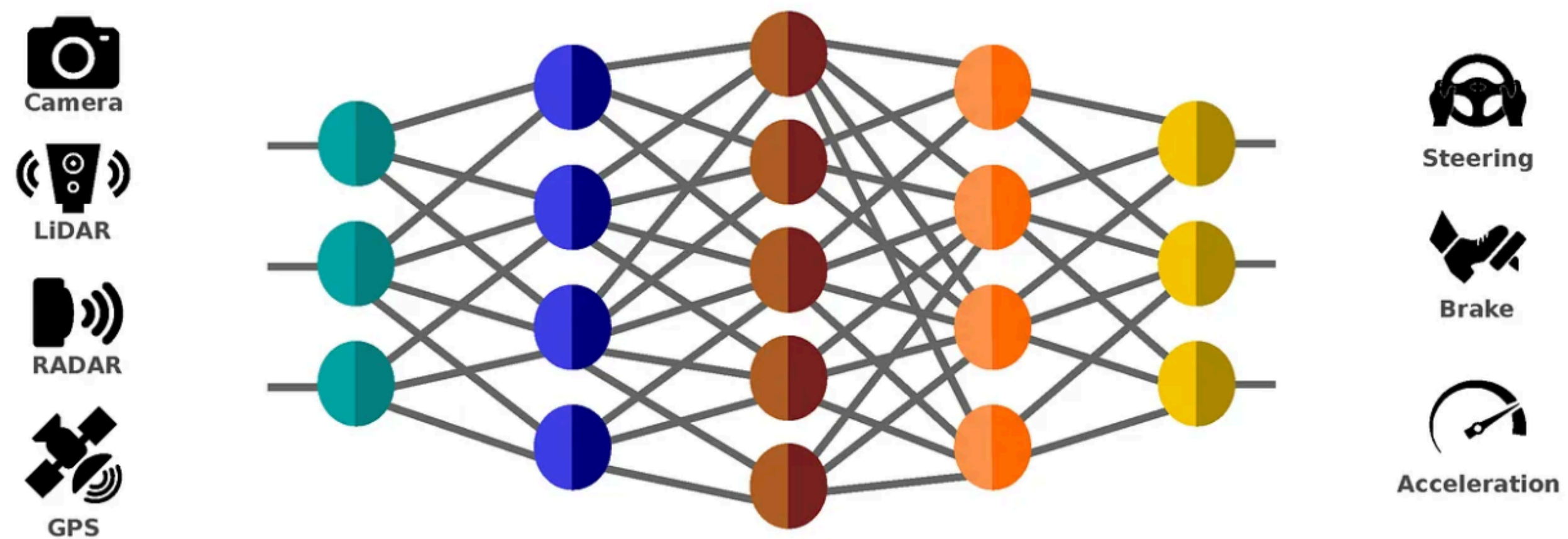
Standard control interface (steering wheel, accelerator, brake).

# Architecture Choice

## Modular Architecture



## End-to-End Architecture



## Sensors Navigation Pipeline Actuator

# Modular

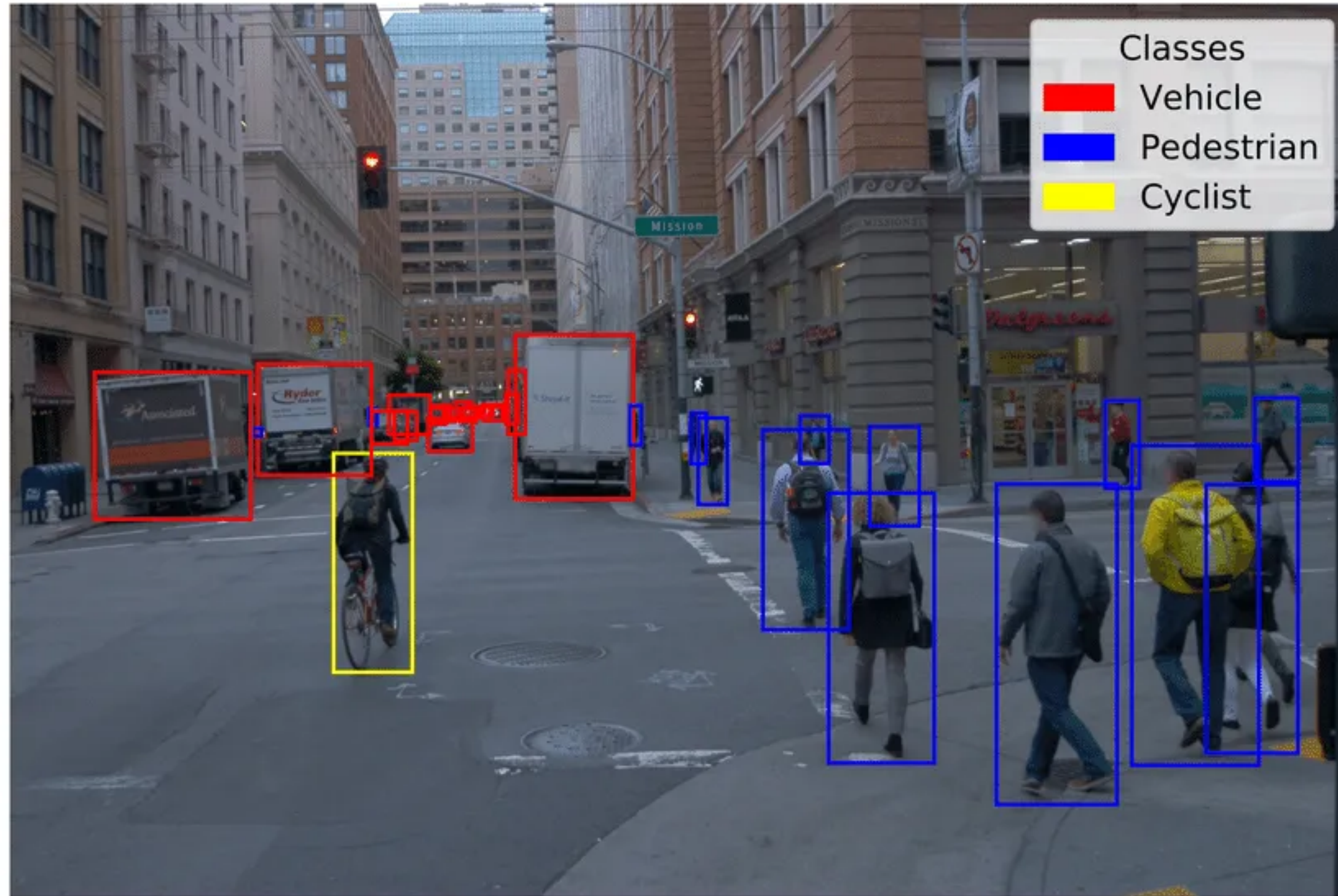
## Strengths:

1. Decomposition of complex problem into well understood sub-parts.
2. Interpretable
3. Debuggable

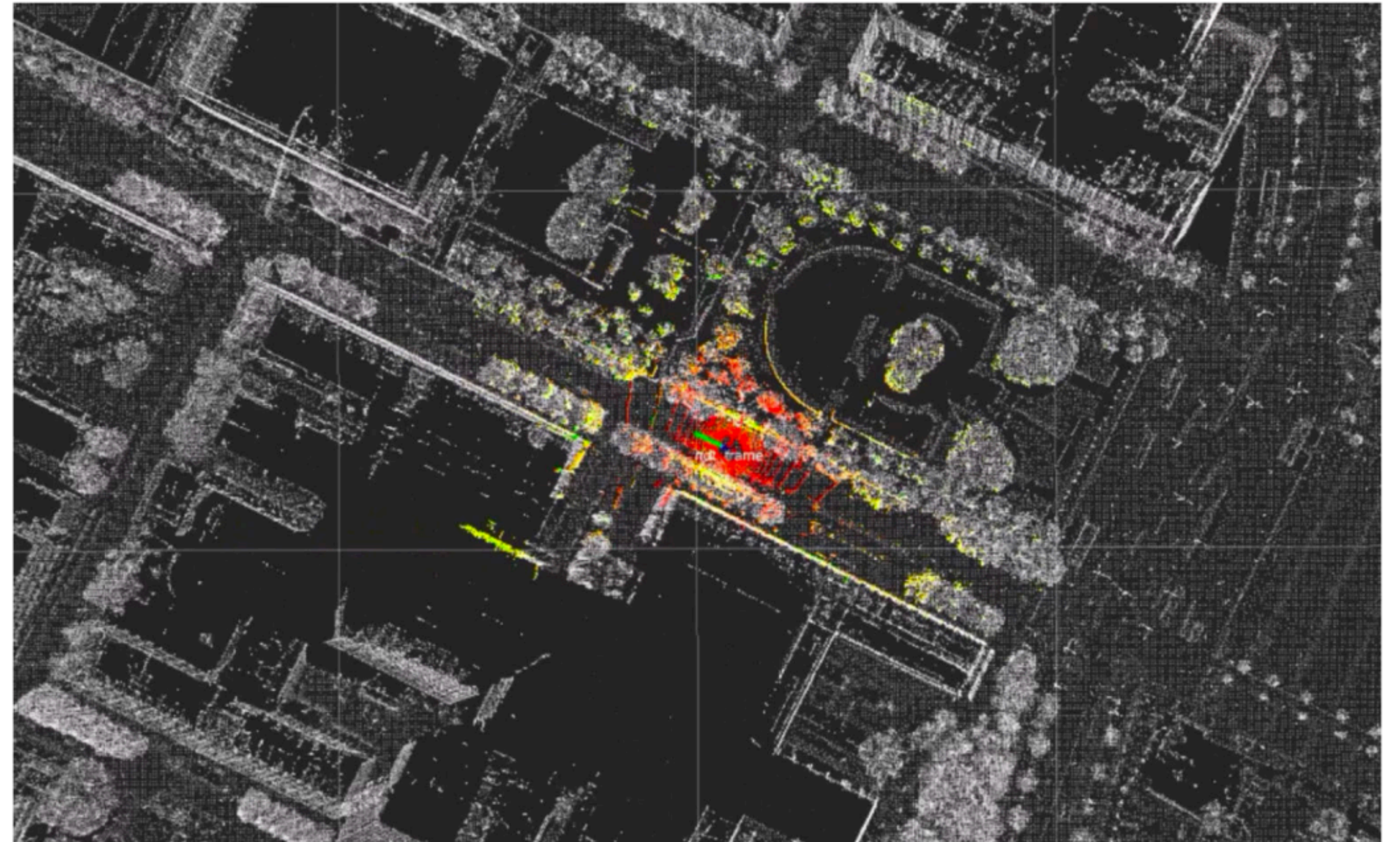
## Weaknesses:

1. Components are tuned in isolation; not as one unified whole.
2. Error in one component propagates to the next one.

# Perception



# Localization



# Group Activity: Wisconsin Driving

Design an autonomous driving system that can drive around UW — Madison's campus in a snow storm.

First, discuss how your vehicle will represent and identify state:

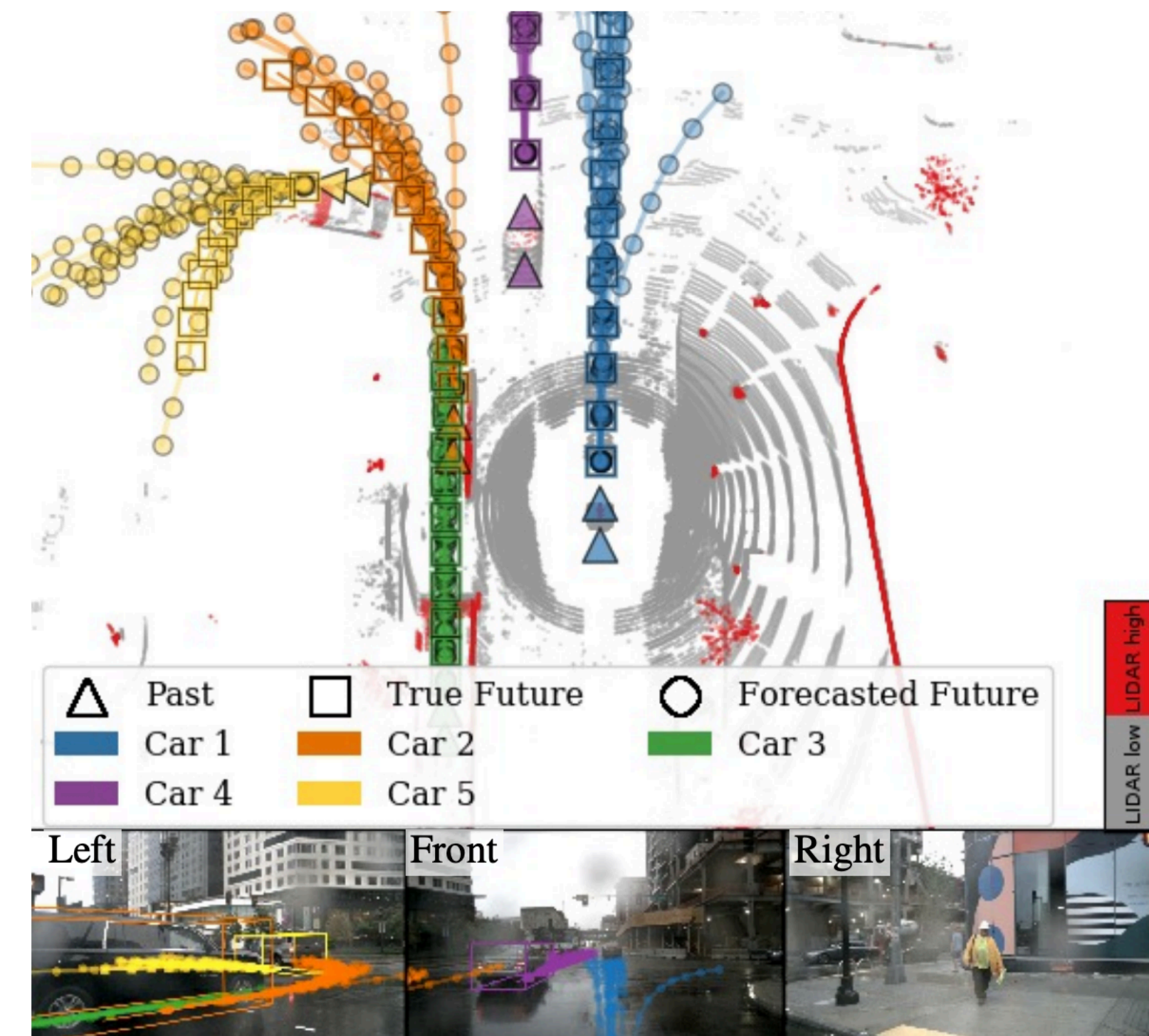
- What variables will be included in your state representation?
- What sensors will you need to identify this state?
- What state estimation techniques do you expect to be useful here?

# Prediction

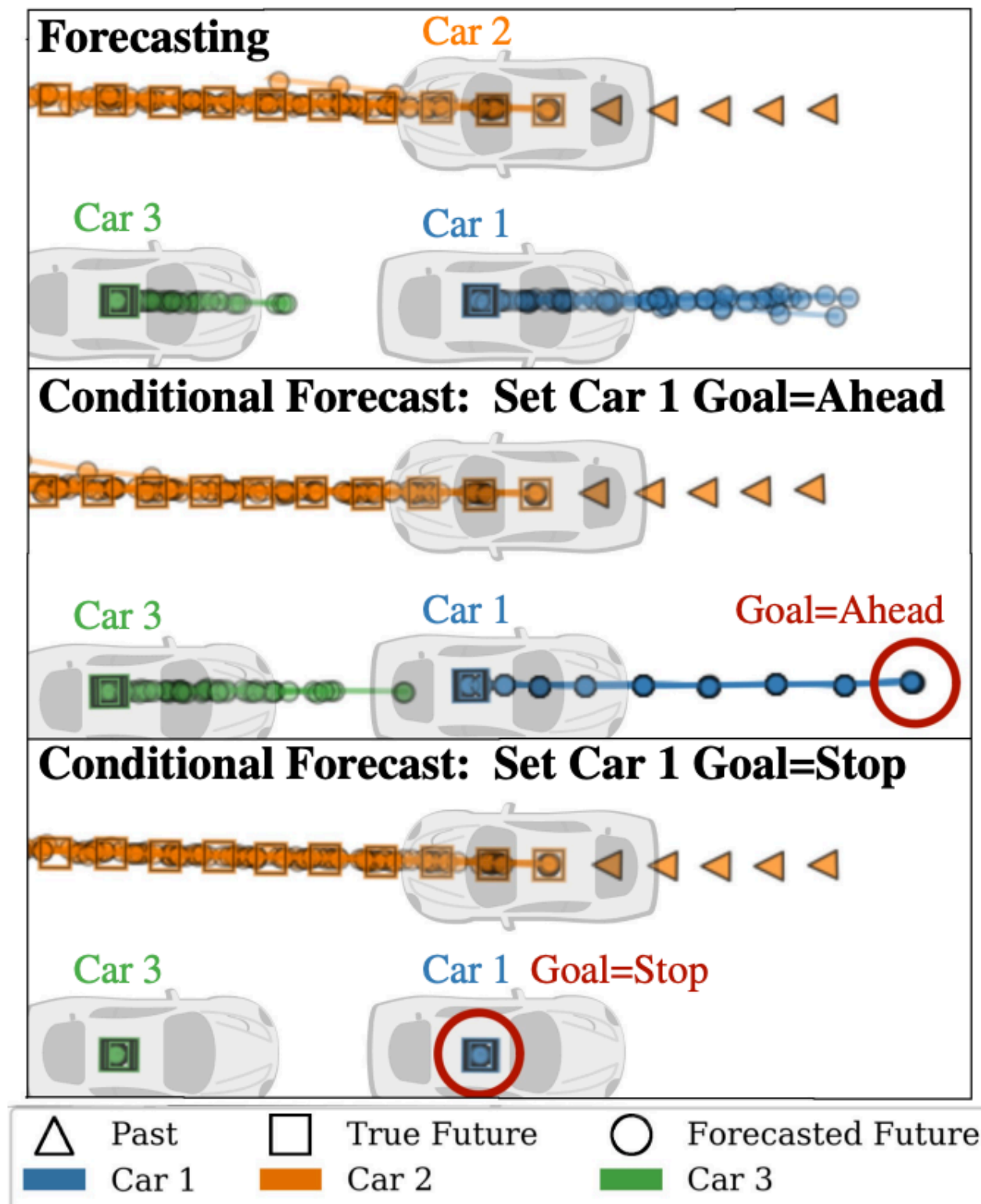
Given the recent history of other agents, determine where they will be at future time instances.

Challenges:

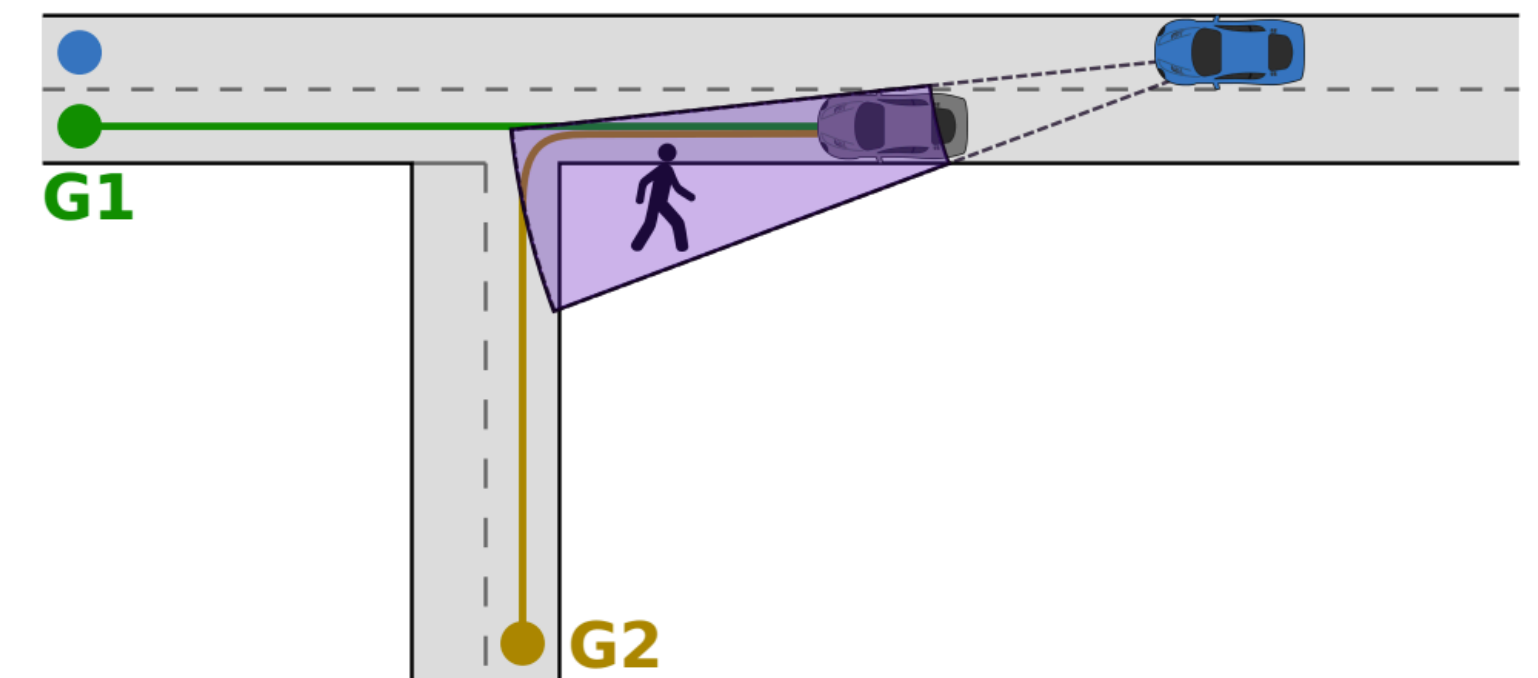
- Need to predict over long time horizons.
- Need to model how other agents will react to one another.
- Ambiguity in the state of the world.



# Ambiguity in Prediction



(a) Ego-vehicle View



# Prediction via Deep Learning

Collect a dataset of scenes with other agents.

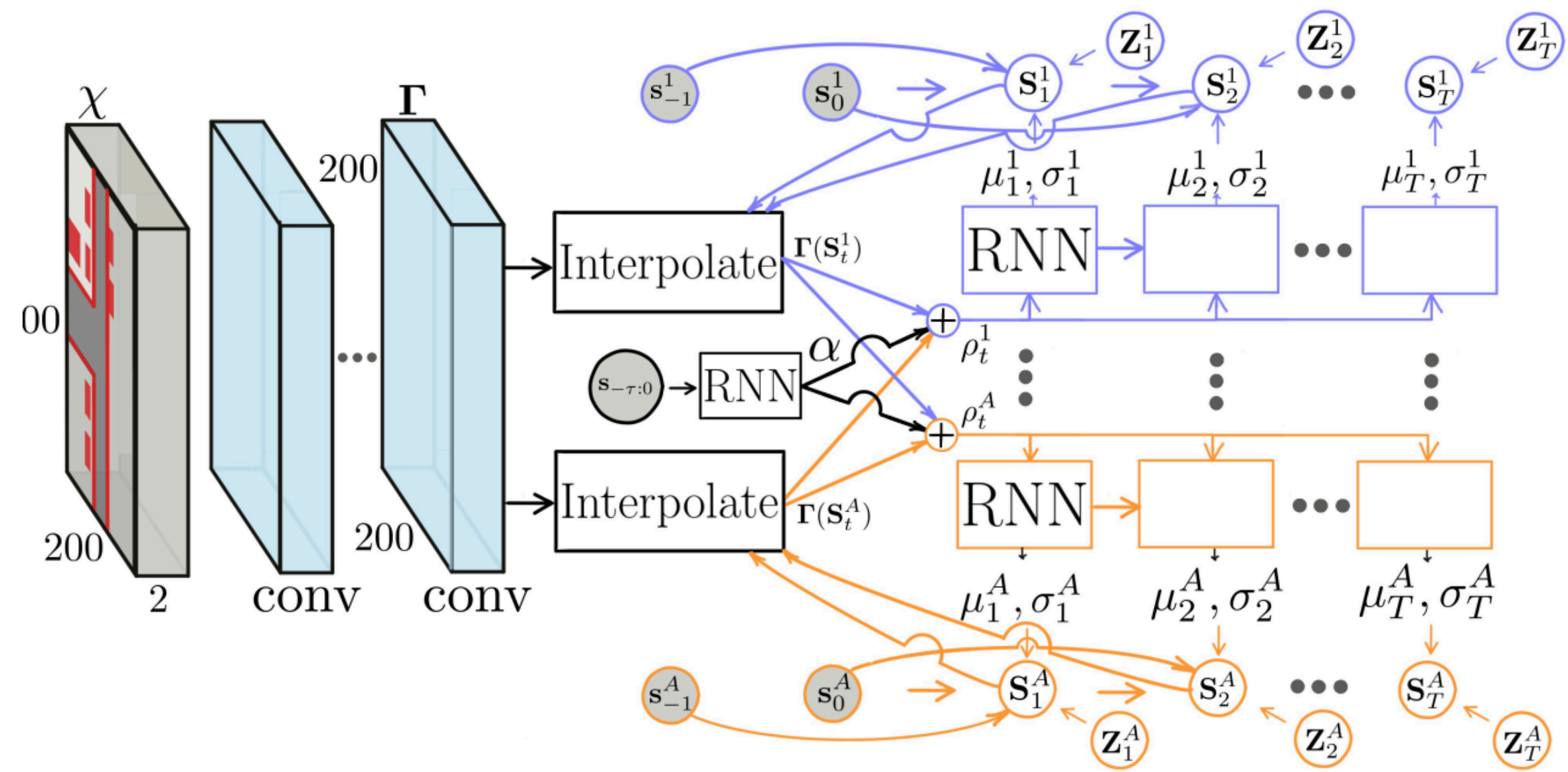
Train a neural network to predict where all agents will go based on where you've seen them drive so far.

Strengths:

- Scales with data availability.
- Nuanced scene understanding.

Weaknesses:

- Lacks interpretability.



# Prediction via Inverse Planning

Assume that agents behave approximately rationally.

Future trajectories are more likely if they match optimal behavior.

Strengths:

- Interpretable.

Weaknesses:

- Sensitive to how optimality is defined.
- Optimality assumption may be strong.

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**Algorithm 1** Goal and Occluded Factor Inference (GOFI)

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**Input:** vehicle  $i$ , state estimates  $\hat{s}_{1:t}$ , possible goals  $\mathcal{G}^i$ , set of occluded factor  $\mathcal{Z}$

**Returns:** occluded factor probabilities  $\Pr(z|\hat{s}_{1:t}^i)$  and goal probabilities  $p(g^i|\hat{s}_{1:t}^i, z)$

- 1: Set prior probabilities  $p(g^i)$ ,  $p(z)$  (e.g. uniform)
  - 2: **for all**  $z \in \mathcal{Z}$  **do**
  - 3:   **for all**  $g^i \in \mathcal{G}^i$  **do**
  - 4:      $s_{1:T}^{*i} \leftarrow \text{PLANOPTIMAL}(\hat{s}_1^i, g^i, z)$
  - 5:      $c^* \leftarrow \text{cost}(s_{1:T}^{*i}, z)$
  - 6:      $s_{t+1:T}^{+i} \leftarrow \text{PLANOPTIMAL}(\hat{s}_t^i, g^i, z)$
  - 7:      $s_{1:t}^{+i} \leftarrow \hat{s}_{1:t}^i$
  - 8:      $c^+ \leftarrow \text{cost}(s_{1:T}^{+i}, z)$
  - 9:      $L(\hat{s}_{1:t}^i|g^i, z) \leftarrow \exp(\beta(c^* - c^+))$
  - 10:  $\Pr(z|\hat{s}_{1:t}^i) \propto \sum_g L(\hat{s}_{1:t}^i|g, z) p(g)p(z)$
  - 11:  $\Pr(g^i|\hat{s}_{1:t}^i, z) \leftarrow L(\hat{s}_{1:t}^i|g^i, z) p(g^i)p(z)/p(z|\hat{s}_{1:t}^i)$
  - 12: **Return**  $\Pr(z|\hat{s}_{1:t}^i)$ ,  $\Pr(g^i|\hat{s}_{1:t}^i, z)$
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# Planning

Control is performed over multiple time-scales.

Route planner determines the vehicle's route.

Motion planner determines an initial path for completing each step of the route.

Trajectory optimization provides a smooth and collision-free path.

Trajectory tracking (e.g., PD control) to select final commands.

# End-to-end Approaches

## Strengths:

1. The entire system is optimized toward the goal of the system.
2. In theory, more robust to the effect of error propagation.
3. Potentially more robust to misspecified world representations.

## Weaknesses:

1. Lacks interpretability, debuggability
2. Difficult to develop: RL is data inefficient (or sim2real gap); imitation learning requires labelled data.

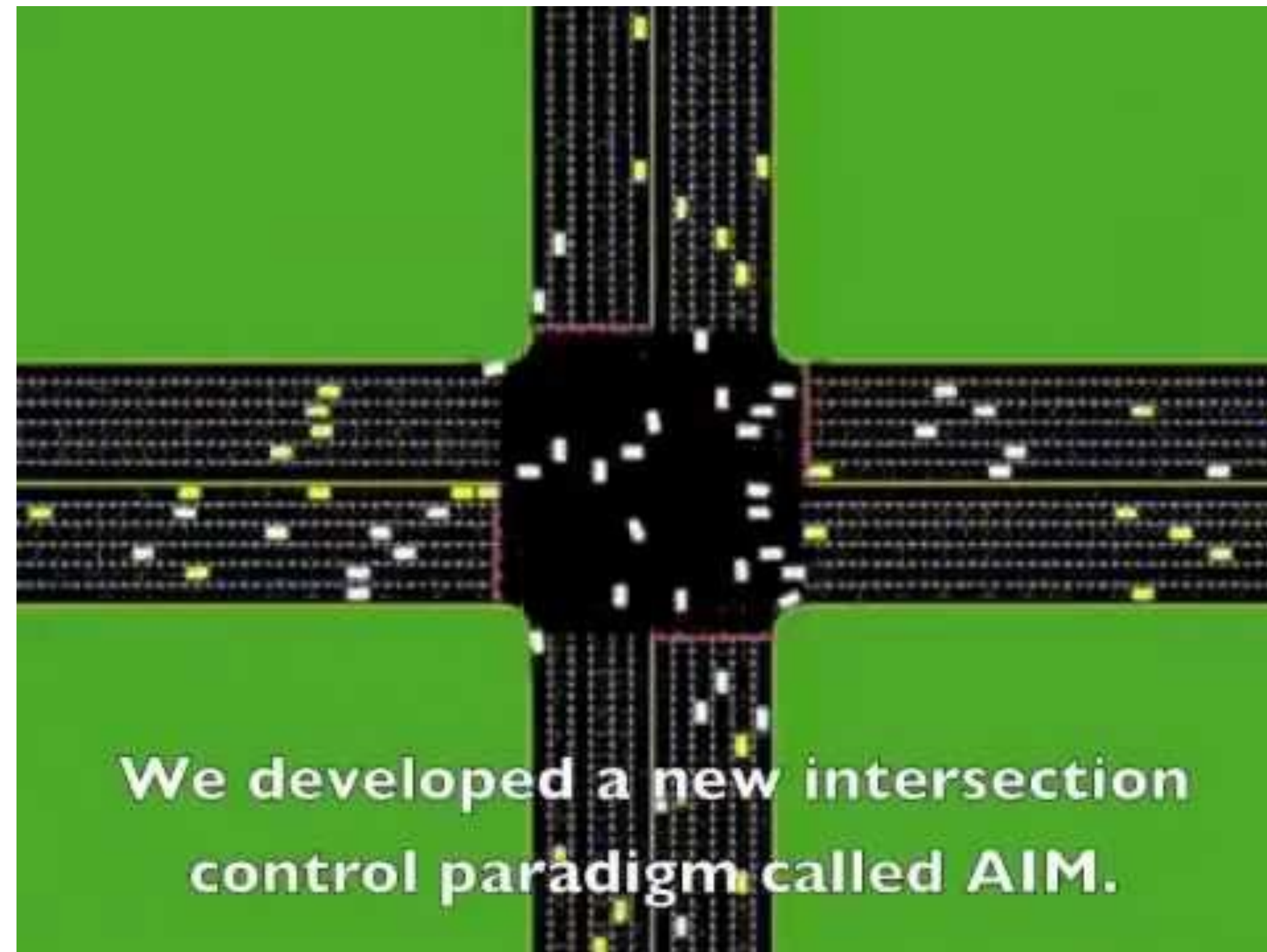
# Group Activity: Wisconsin Driving

Design an autonomous driving system that can drive around UW — Madison's campus in a snow storm.

Now, discuss how your vehicle will make decisions:

- Hierarchical planning? End-to-end? Hybrid?
- If hierarchical planning, what levels will you have in the hierarchy.
- If end-to-end, how will you train decision-making?
- For all methods, when will you be confident that decision-making is performant?

# Connected Vehicles



# Autonomous Driving: where are we?

A lot of progress in the past decade.

Still debate on how close the field is to level 5 autonomy.

FORECASTS: [http://www.driverless-future.com/?page\\_id=384](http://www.driverless-future.com/?page_id=384) March 27, 2017

NVIDIA to introduce level-4 enabling system by **2018** (2017)  
NuTonomy to provide self-driving taxi services in Singapore by **2018**, expand to 10 cities around world by **2020** (2016)  
Delphi and MobilEye to provide off-the-shelf self-driving system by **2019** (2016)  
Ford CEO announces fully autonomous vehicles for mobility services by **2021** (2016) ←  
Volkswagen expects first self driving cars on the market by **2019** (2016)  
GM: Autonomous cars could be deployed by **2020** or sooner (2016) ←  
BMW to launch autonomous iNext in **2021** (2016) ←  
Ford's head of product development: autonomous vehicle on the market by **2020** (2016) ←  
Baidu's Chief Scientist expects large number of self-driving cars on the road by **2019** (2016)  
First autonomous Toyota to be available in **2020** (2015) ←  
Elon Musk now expects first fully autonomous Tesla by **2018**, approved by **2021** (2015)  
US Sec Trans: Driverless cars will be in use all over the world by **2025** (2015)  
Uber fleet to be driverless by **2030** (2015) ←  
Ford CEO expects fully autonomous cars by **2020** (2015) ←  
Next generation Audi A8 capable of fully autonomous driving in **2017** (2014)  
Jaguar and Land-Rover to provide fully autonomous cars by **2024** says Director of Research and Technology (2014)  
Fully autonomous vehicles could be ready by **2025**, predicts Daimler chairman (2014) ←  
Nissan to provide fully autonomous vehicles by **2020** (2013) ←  
Truly autonomous cars to populate roads by **2028-2032** estimates insurance think tank executive (2013)  
Continental to make fully autonomous driving a reality by **2025** (2012)

# Can humans just supervise?

One potential approach is to let the vehicle do most of the driving and just let the human intervene as needed.

- Potentially have a person in a call center intervene remotely.

What challenges do you see happening here?

# Summary

Today we covered:

1. Architectures for autonomous driving.
2. Discussed the prediction problem in autonomous driving.
3. Designed systems for autonomous driving.

# Action Items

Final project.

Check your grades.

Course evaluation (email confirmation needed for extra credit).