Autonomous Robotics

Applications: Autonomous Driving

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Announcements

Final project key dates:

April 29: deadline to be included in final tournament.

May 2: final deadline

Course evaluations are now available.

Learning Outcomes

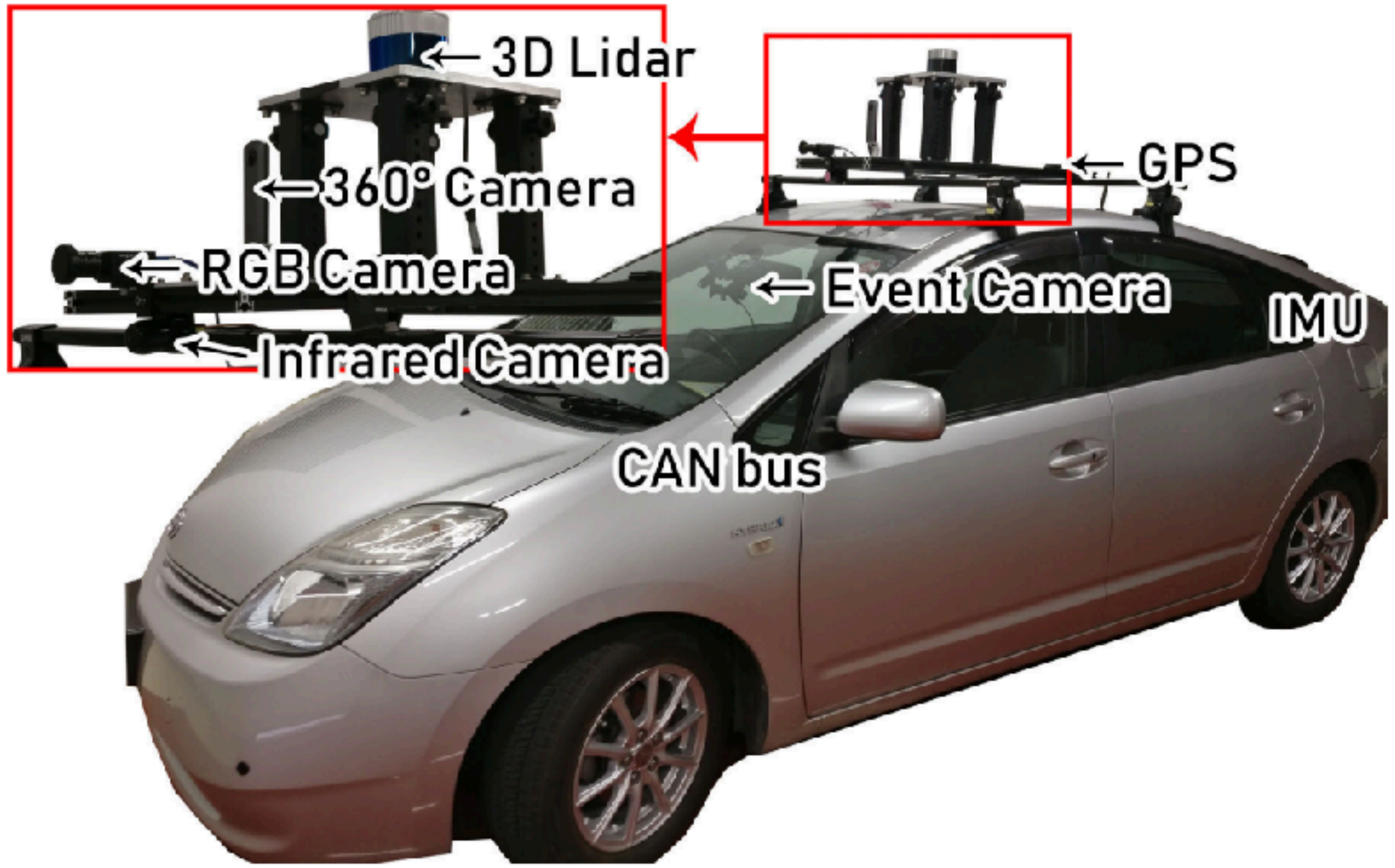
After today's lecture, you will:

- 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

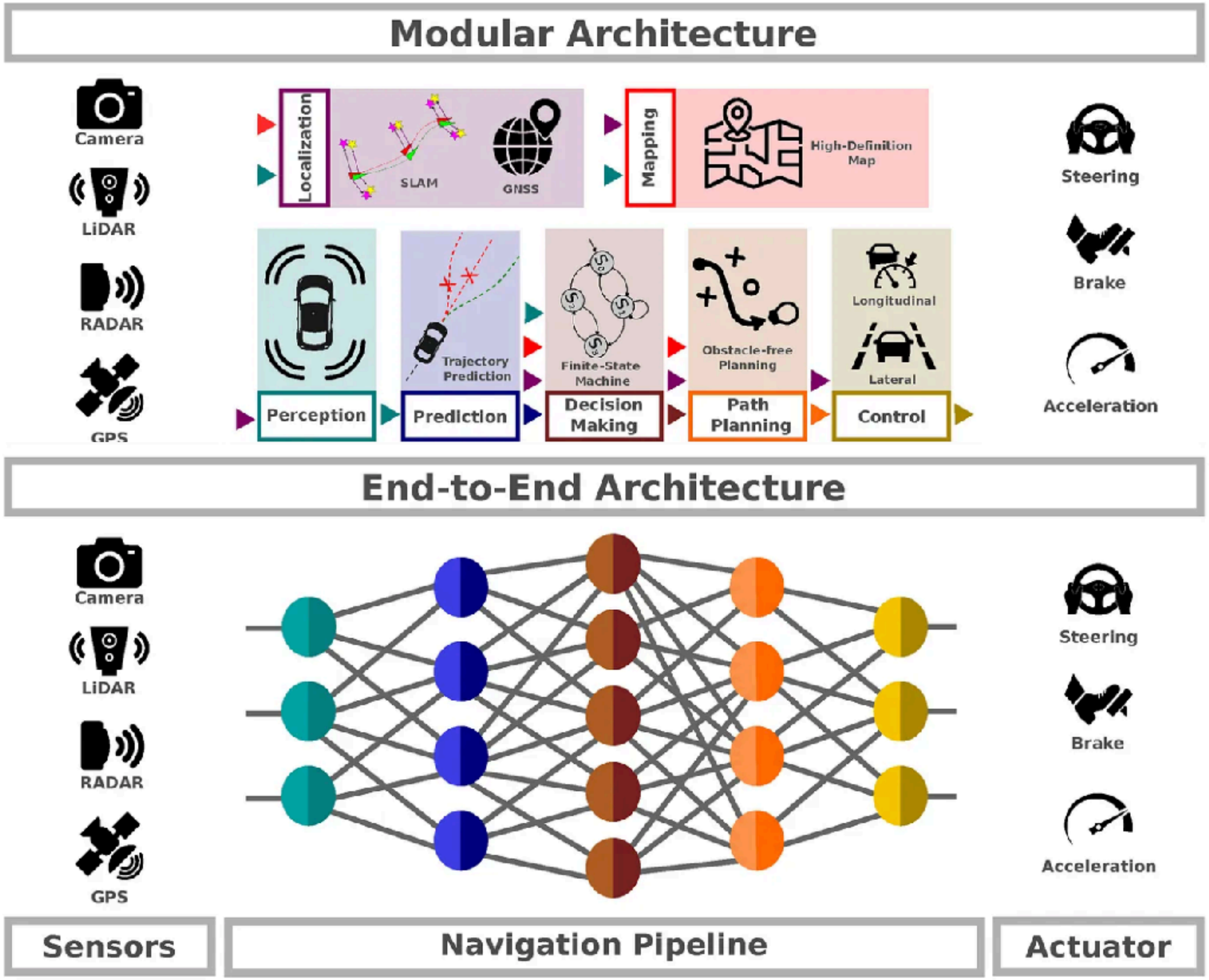
Car equipped with sensors:

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



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

Architecture Choice



https://danieldavenport.medium.com/the-future-of-autonomous-driving-integrating-zero-shot-learning-modular-planning-and-foundation-6eee5ede1bee

Modular

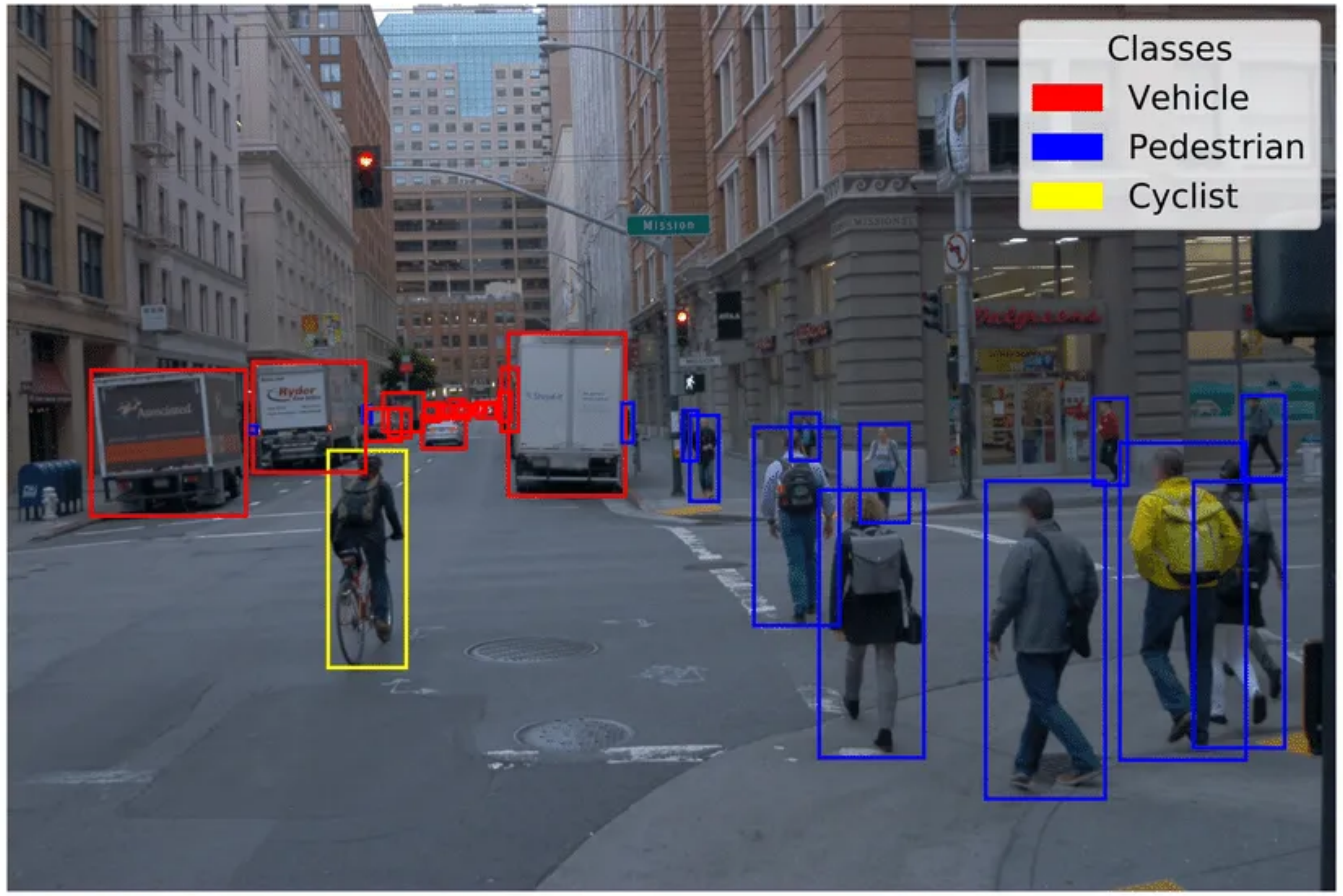
Strengths:

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



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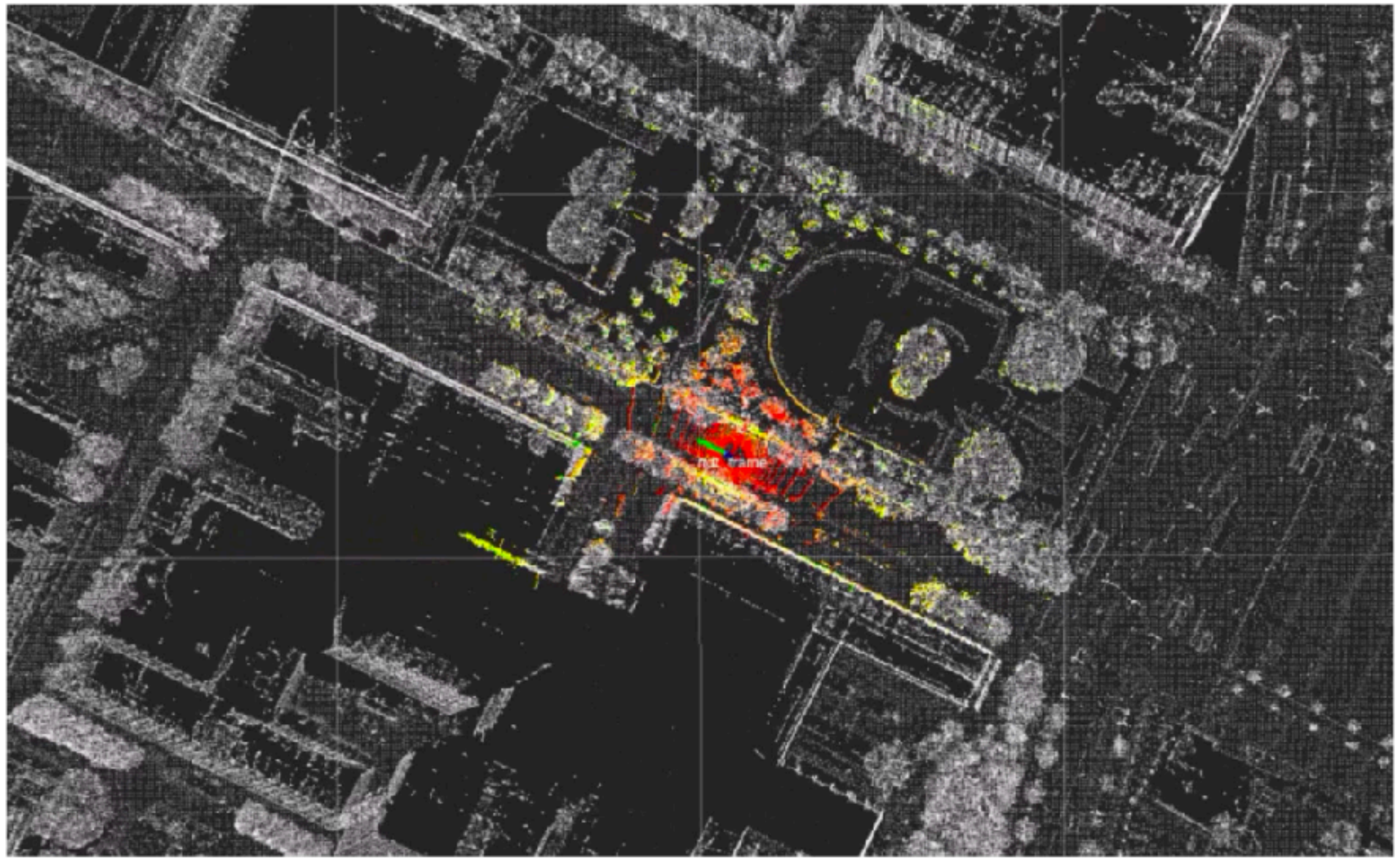
Localization



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

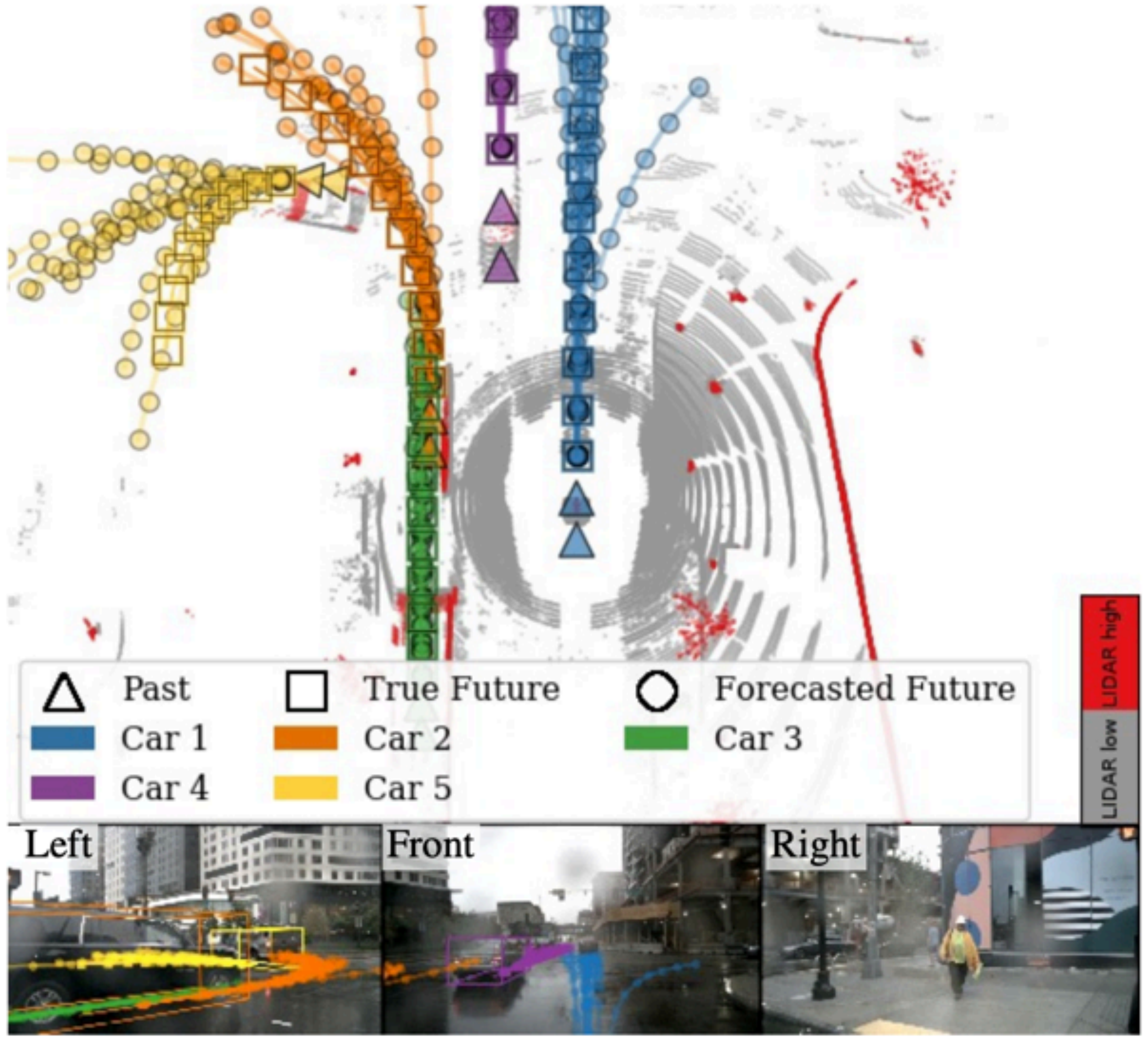
Given the recent history of other agents, determine where they will be at future time instances.

Challenges:

- Need to predict over long time horizons.

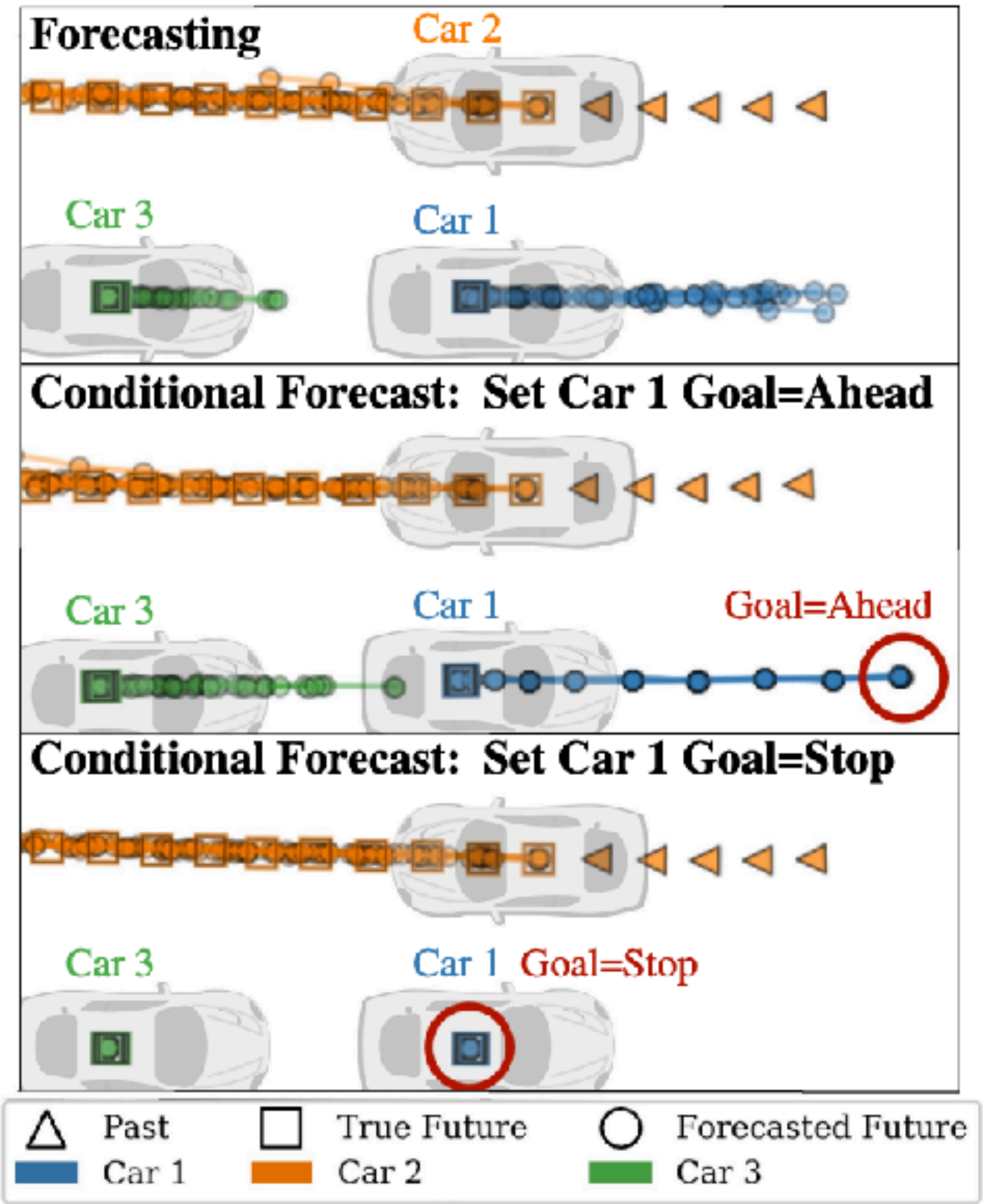
- Need to model how other agents will react to one another.

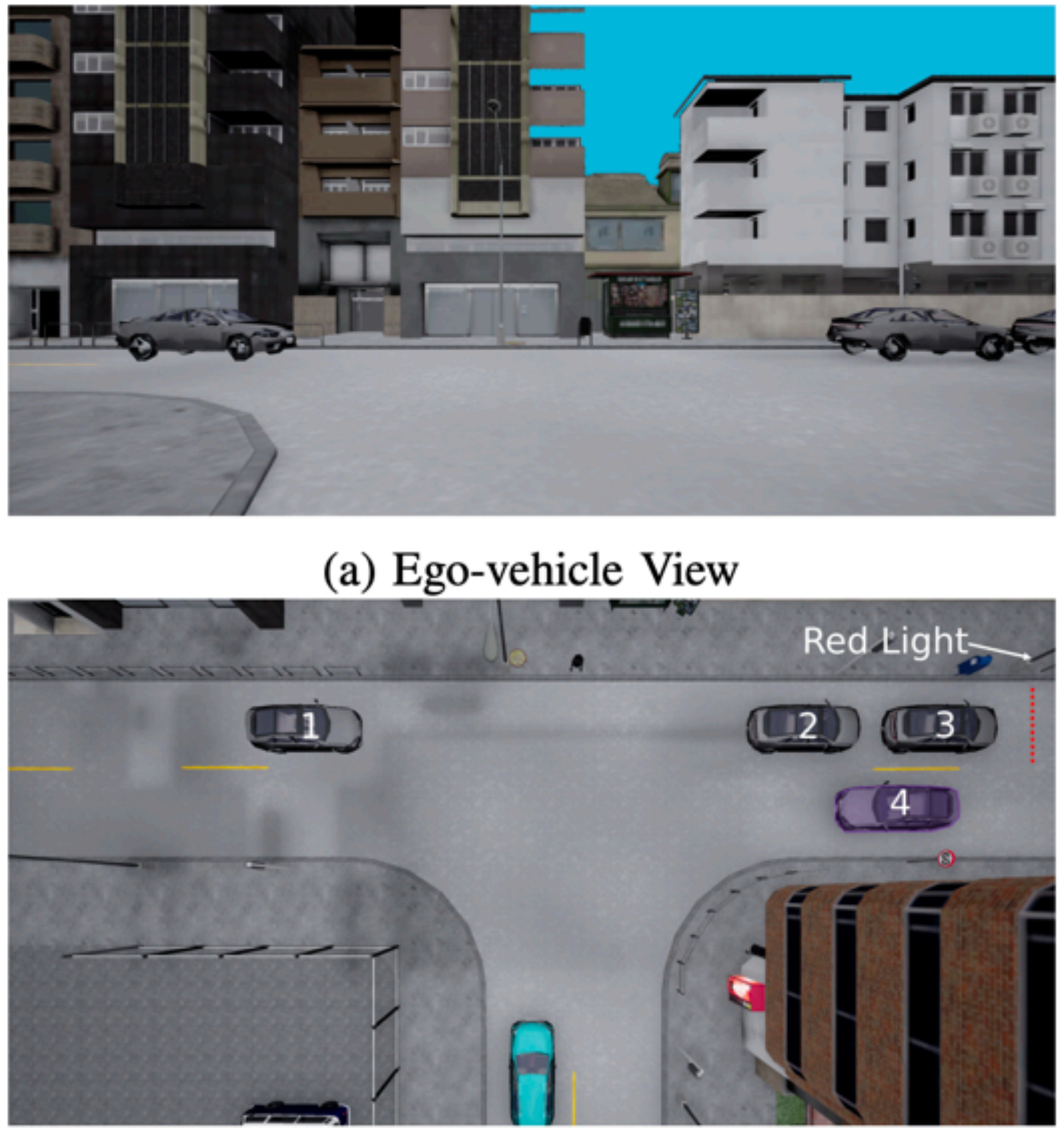
- Ambiguity in the state of the world.

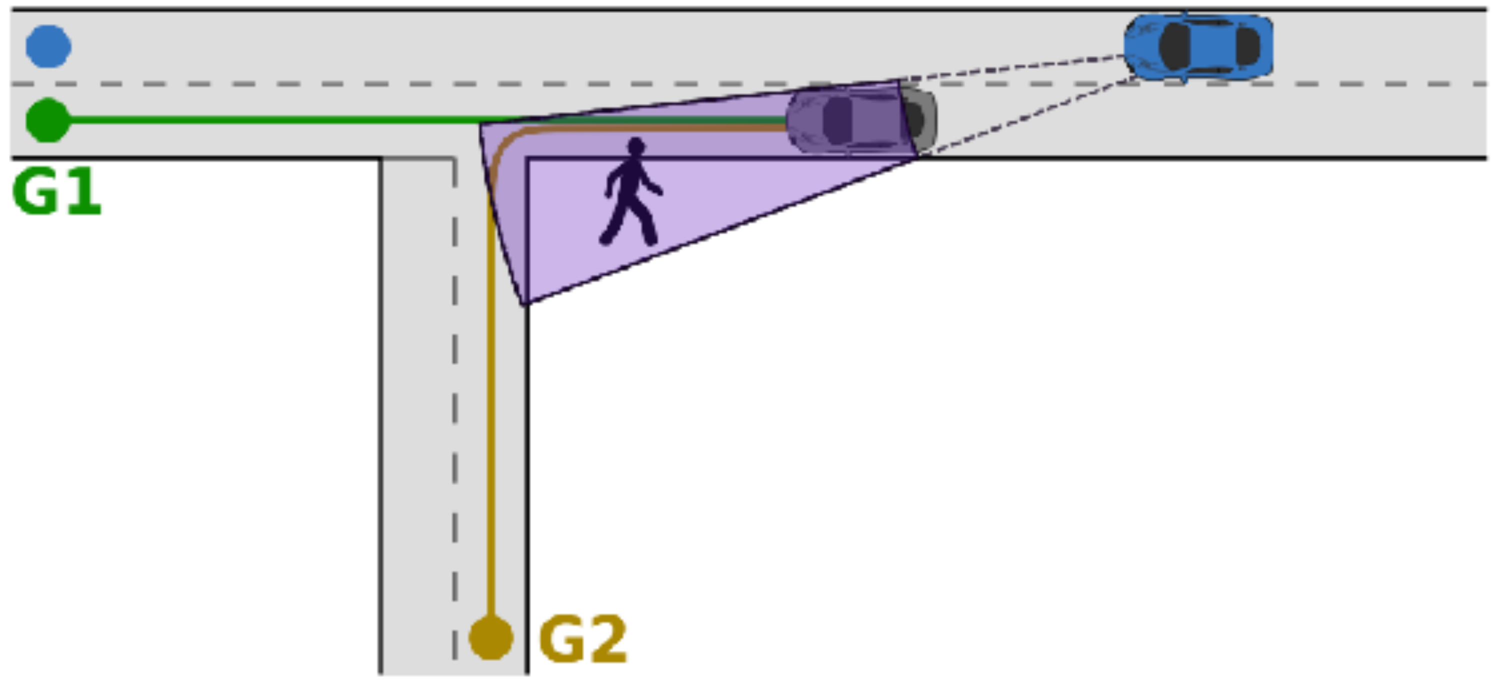


PRECOG: PREdiction Conditioned On Goals in Visual Multi-Agent Settings

Ambiguity in Prediction







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.

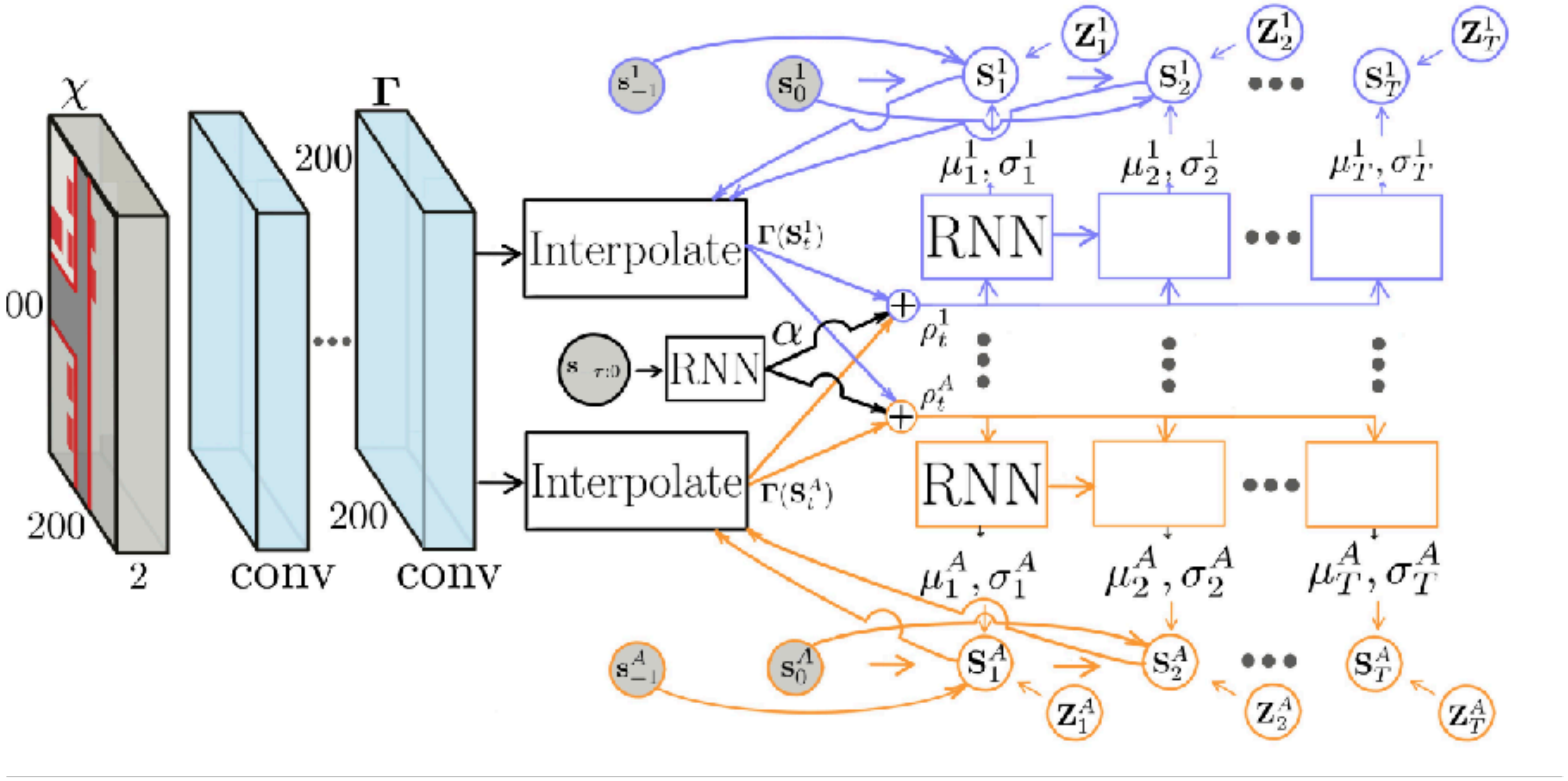
Strengths:

- Scales with data availability.

- Nuanced scene understanding.

Weaknesses:

- Lacks interpretability.



PRECOG: PREdiction Conditioned On Goals in Visual Multi-Agent Settings

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.

Algorithm 1 Goal and Occluded Factor Inference (GOFI)

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

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

Set prior probabilities $p(g^i)$, $p(z)$ (e.g. uniform)
for all $z \in \mathcal{Z}$ **do**
  for all $g^i \in \mathcal{G}^i$ **do**
    $s^{\star i}_{1:T} \leftarrow \text{PLANOPTIMAL}(\hat{s}^i_1, g^i, z)$
    $c^\star \leftarrow \texttt{cost}(s^{\star i}_{1:T}, z)$
    $s^{+i}_{t+1:T} \leftarrow \text{PLANOPTIMAL}(\hat{s}^i_t, g^i, z)$
    $s^{+i}_{1:t} \leftarrow \hat{s}^i_{1:t}$
    $c^+ \leftarrow \texttt{cost}(s^{+i}_{1:T}, z^i)$
    $L(\hat{s}^i_{1:t}|g^i, z) \leftarrow \exp(\beta(c^\star - c^+))$
$\Pr\big(z|\hat{s}^i_{1:t}\big) \propto \sum_g L(\hat{s}^i_{1:t}|g, z)\, p(g)p(z)$
$\Pr\big(g^i|\hat{s}^i_{1:t}, z\big) \leftarrow L(\hat{s}^i_{1:t}|g^i, z)\, p(g^i)p(z)/p(z|\hat{s}^i_{1:t})$
Return $\Pr\big(z|\hat{s}^i_{1:t}\big)$, $\Pr\big(g^i|\hat{s}^i_{1:t}, z\big)$

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 + neuroevoluton are data inefficient; supervised learning requires labelled data.

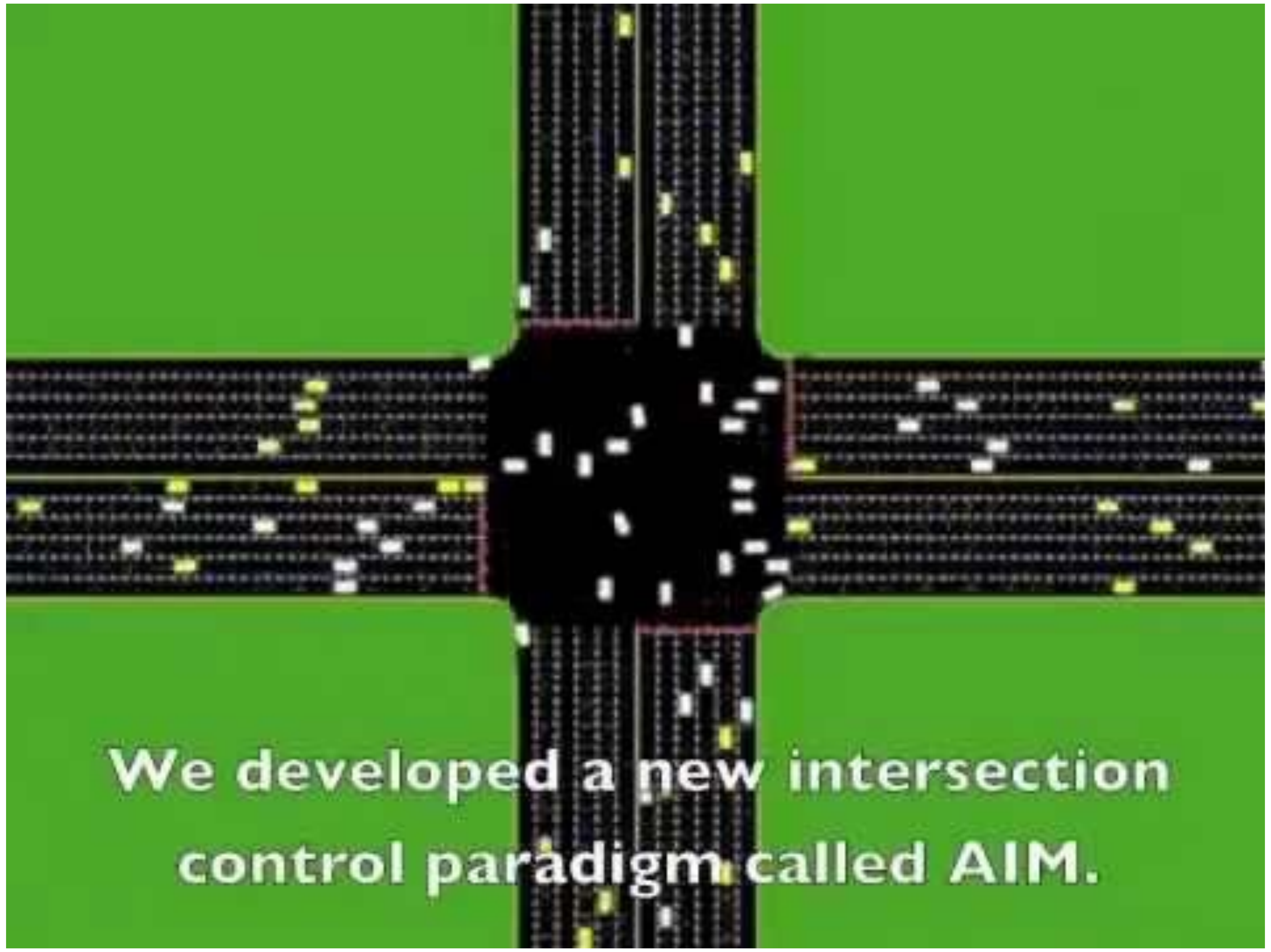
Group Activity: Wisconsin Driving

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?

Undeniably, a lot of progress in the past decade.

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

FORECASTS: 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)*

https://rodneybrooks.com/predictions-scorecard-2025-january-01/

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

Societal impacts reading for next week.

Final project.