Learning for Autonomous Vehicles

– introduction

TSFS12: Autonomous Vehicles – planning, control, and learning systems

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Course announcements

- Industrial guest lecturers from Scania, Thursday October 5, 13:15.

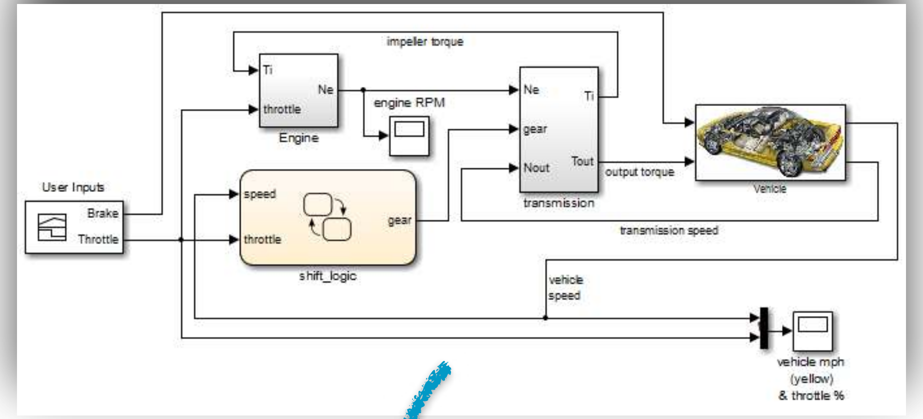
  “*Motion planning and control for autonomous heavy-duty trucks: Mining and Hub to Hub use cases*”

- Hand-ins progressing. To help us:
  - Remove matlab directory of you’ve solved in python and vice versa.
  - In python, please indicate in your submission which file we should run (main.ipynb, main.py, or some other file?)
- Introduction to mini-projects on Tuesday, September 26, 13:15. Important that you participate.

Learning, models, and data

Q: What is (machine) learning?

A: using data to build models that can predict and/or act upon the world



predictive/control models

Learning and Autonomous Vehicles

- This is not a course in machine learning
- Objectives of this part of the course
  - Discuss learning in the context of autonomous vehicles
  - Identify key areas of ML that is interesting
  - Get some basic, hands-on, experience with basic methods
- In particular, two methods/areas will be discussed in some detail
  - Neural Networks
  - Reinforcement learning

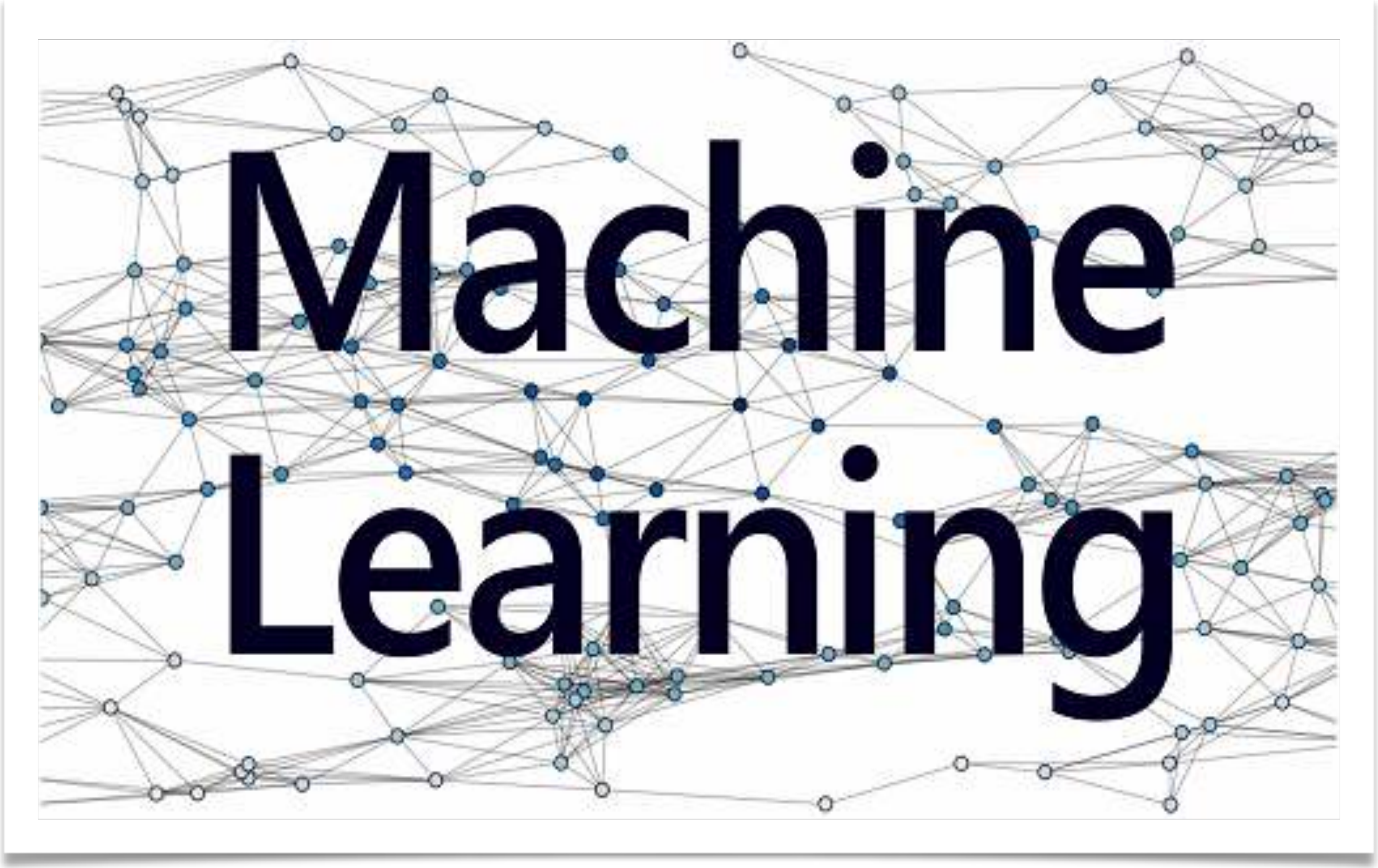
Reflections on the Learning-to-Control Renaissance

https://youtu.be/IEZFwh8sw8s

- Plenary Talk from the June 2020 IFAC World Congress (IFAC - International Federation of Automatic Control)
- Benjamin Recht - UC Berkley
- Slightly advanced — but highly recommended 45 minutes
- Modern discussion on learning, control, when they apply and how they can fit together
- A critical eye on RL and some constructive ideas forward
- As you'll see, I borrowed from this lecture a little

Rough characterization of machine learning tasks

- Supervised learning
  - Learn by examples
- Unsupervised learning
  - No labeled data
- Reinforcement learning
  - Learn with a reward function

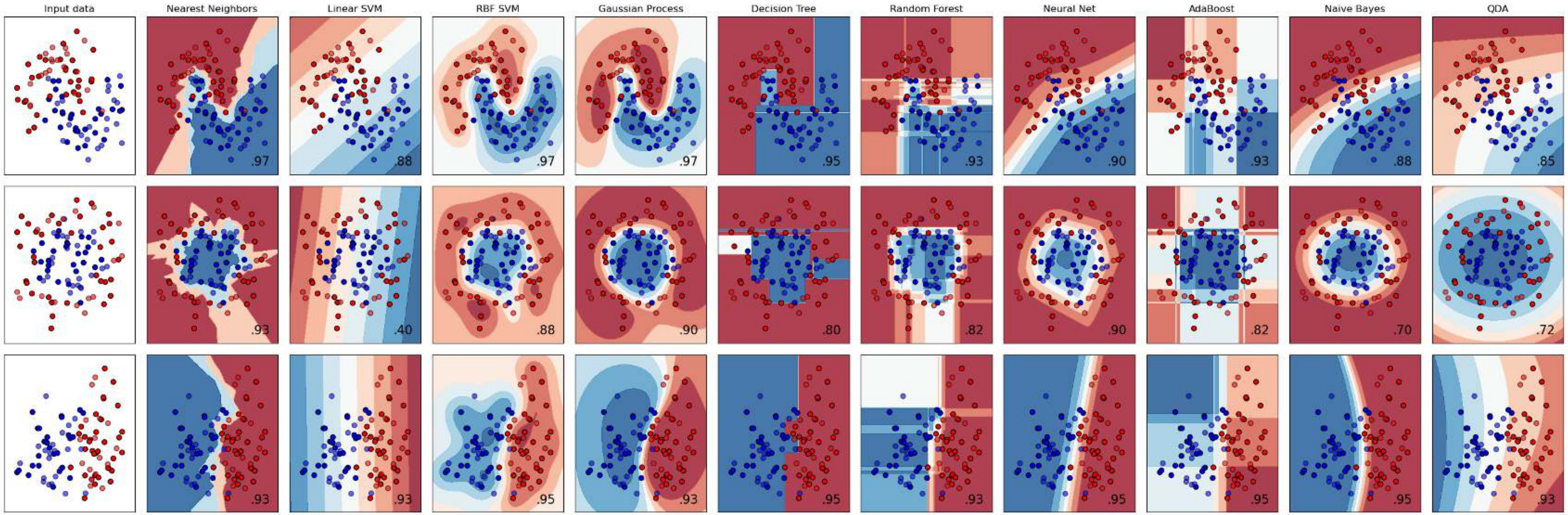


Learning and Autonomous Vehicles

- From the start, it became important to know where you are in the world
  ➠ Localization and mapping
- Then it became important to know more about surroundings
  ➠ Perception
  - Computer Vision
  - Sensor development, Lidar technology, …
- A current hot topic is how to model and *predict* behavior of the environment
- Modeling camera inputs and agent behavior in an uncertain and complex world is difficult

data and learning an exciting possibility going forward

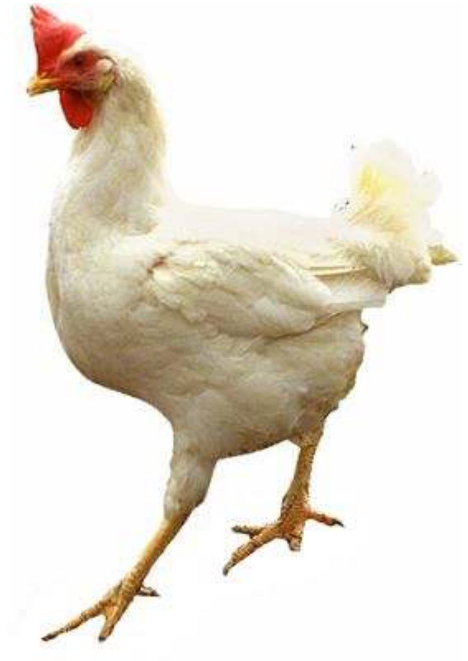
Learning - some basics



- Methods look for patterns/features in data to make classifiers or predictors
- Models often opaque — be careful what your model predicts
- Can be *very* sensitive when extrapolating into areas not covered by data

Edge cases are surprising and rare

This is not a human



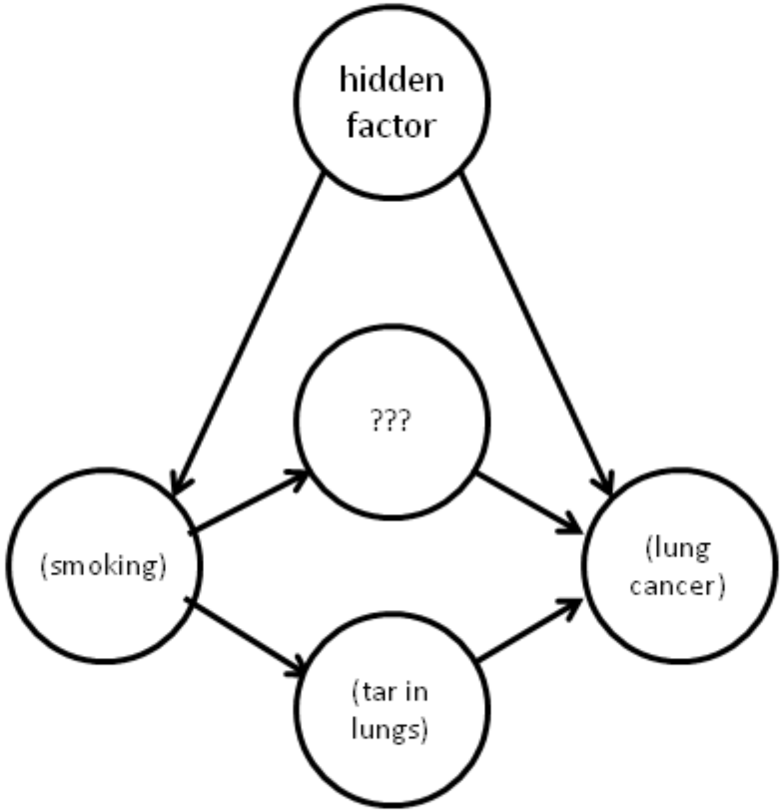
or is it …

- You won't see them in testing; things no-one thought about
- Typical solution — an on-line system supervising methods and algorithms that are difficult to monitor, e.g.,

  Wabersich, Kim Peter, and Melanie N. Zeilinger. "*A predictive safety filter for learning-based control of constrained nonlinear dynamical systems*." Automatica 129 (2021)

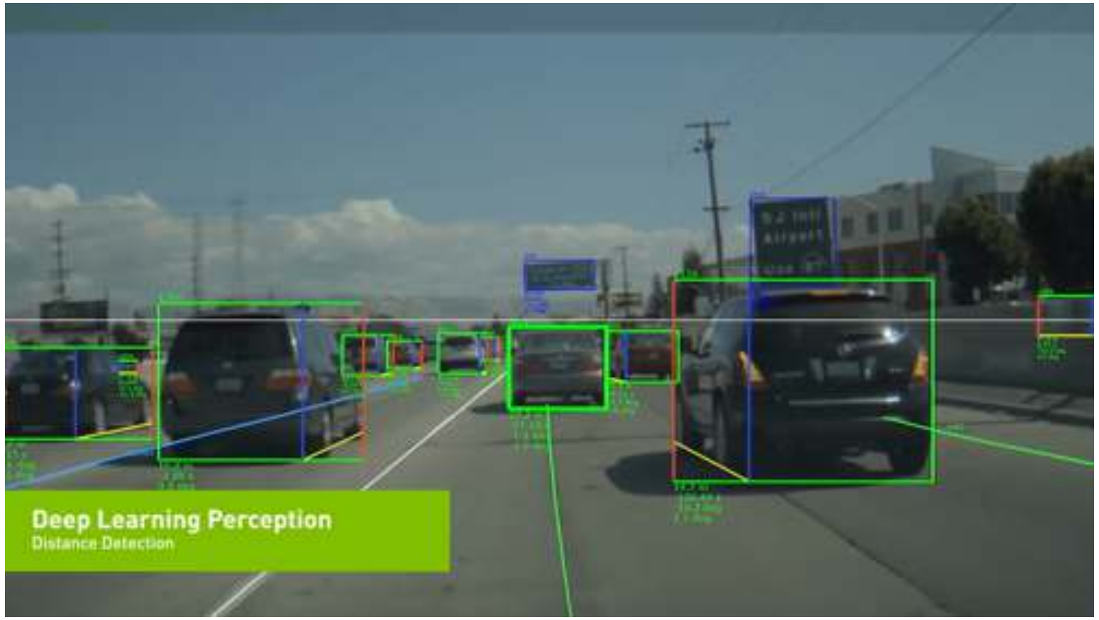
Learning - some basics

- Basic machine learning looks for patterns in data
    - Correlation models
    - It does not find cause and effect
- Extrapolation becomes brittle
- Models are only as good as your data
    - You need a lot of information (not the same as many data points)
- Look out for biased models (mathematically, socially, ethically, …)



AI and machine learning

- Many current systems are hand-crafted and are heavily based on advanced sensor techniques
- Learning systems have the potential to make high-level autonomy a reality



- Probable components where deep-learning systems will be core
  - computer vision, situation awareness
  - model-based reinforcement learning for decision making
- ML will most likely be an important part of the solution (but most likely not *the only* solution)

Learning for Autonomous Vehicles

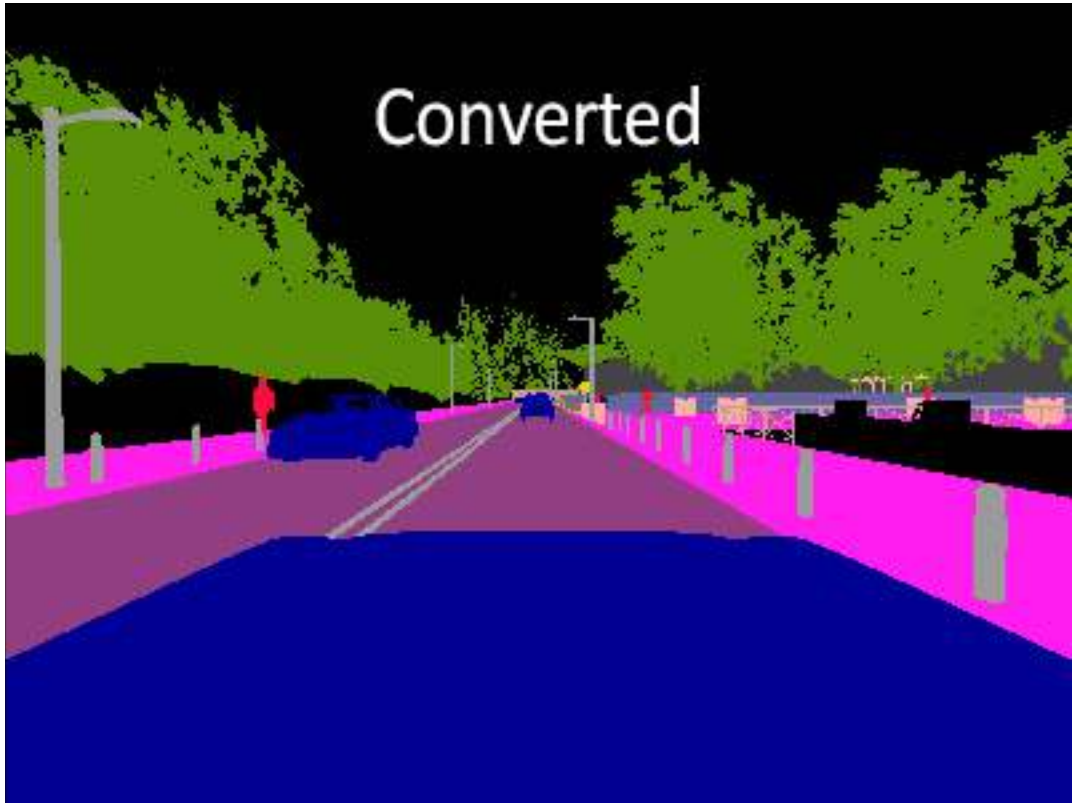
Where are we now and where are we learning?

Boston Dynamics

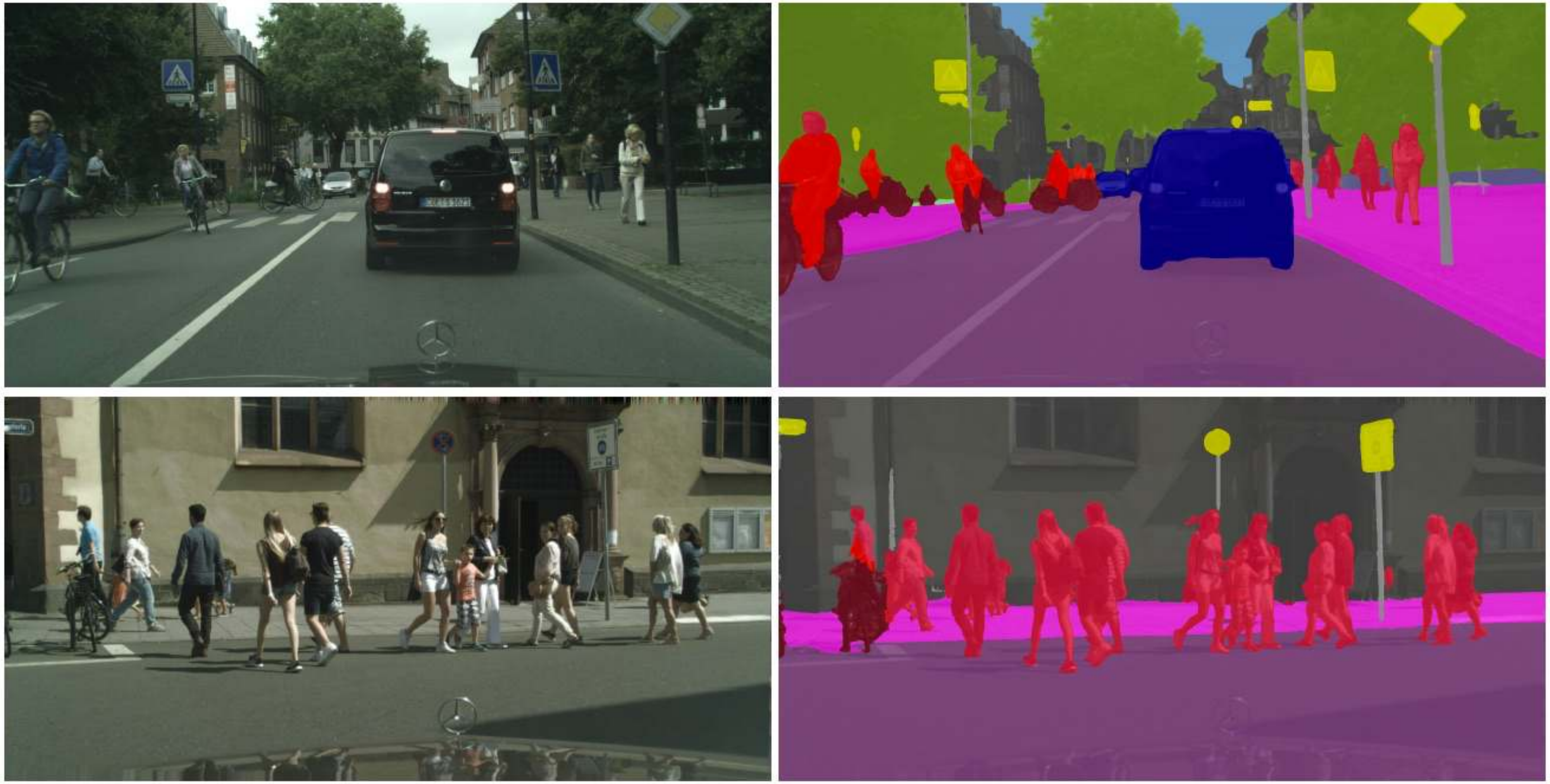
ETH Zürich

Waymo, Tesla, …

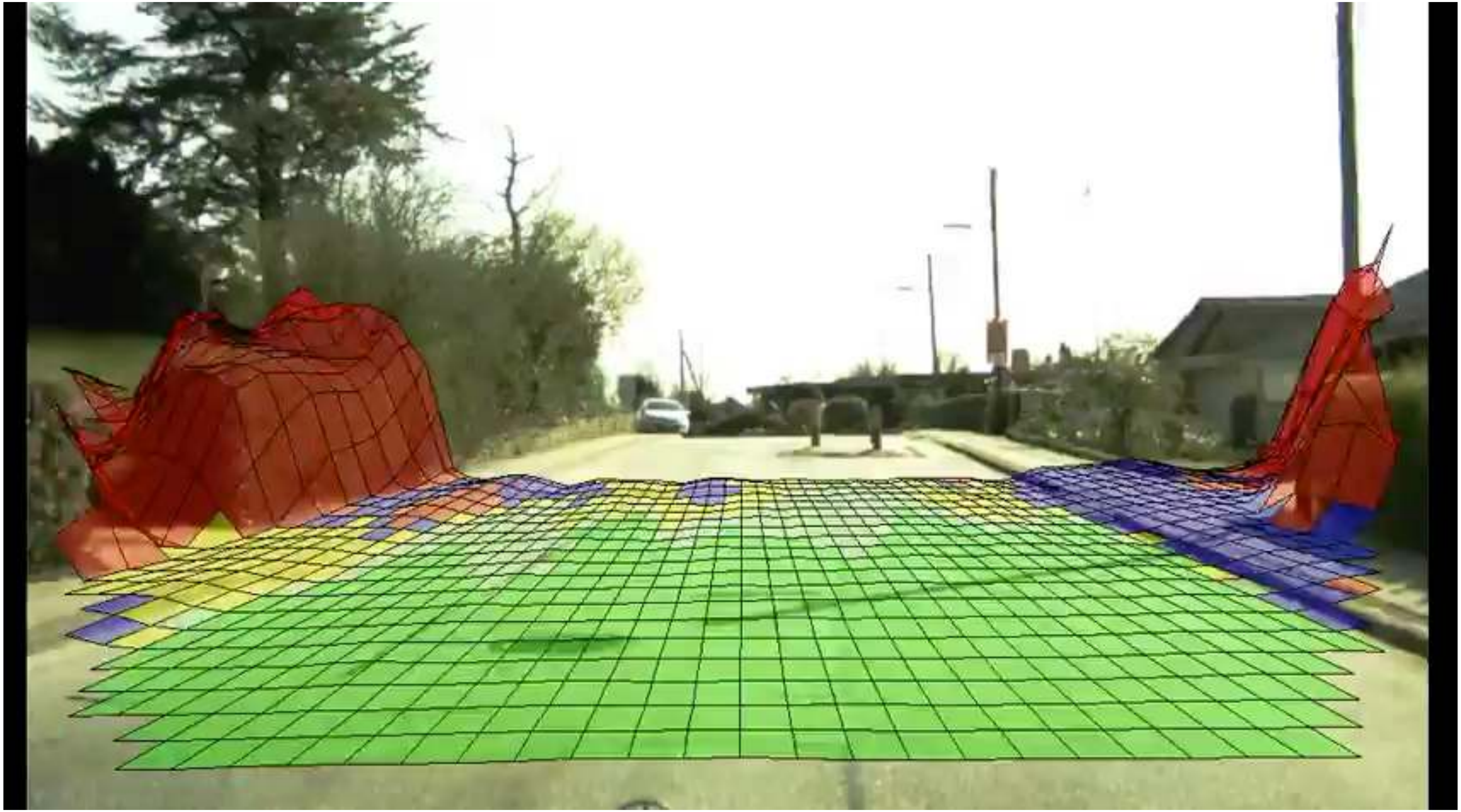
Semantic segmentation in the CARLA simulator



Semantic segmentation for real-world data



"Feature Space Optimization for Semantic Video Segmentation", Abhijit Kundu, Vibhav Vineet, and Vladlen Koltun, Computer Vision and Pattern Recognition (CVPR), 2016



Excerpt from Veoneer video: https://youtu.be/d6d38b-G2NI

Vision based systems

- Maps are good; but need detailed information about environment that is not included in maps,
  - Detection of other vehicles, pedestrians, cyclists,
  - Road boundaries, road condition, rain, free space …
  - Traffic lights, signs, …
  - Detection of people in a search and rescue mission
- Vision systems and cameras are (currently) cost-effective compared to, e.g., Lidar systems
  - Are Lidars essential or can they be replaced by learning-powered Vision systems?
- Learning techniques are core in these tasks

Vision based systems

- Machine learning methods have enhanced the field tremendously during the last years, but still a long way to go
  - Robustness
  - Reduce need for labeled data
  - Verification of function based on ML models
- Big area for autonomous vehicles that is not covered in this course: recommend courses from computer vision laboratory:

  TSBB19 - Machine Learning for Computer Vision

Perception yes, but can we learn how to act?

- Reinforcement Learning (RL) is one possibility
- RL is learning what to do by *maximizing a reward* without being told what to do.
- Instead perform actions and evaluate the results and improve the policy/controller
- Discover actions on its own, by exploring and evaluating the outcome.
- Learn
  - policy/controller, $u_t = f(x_t)$
  - cost-to-go

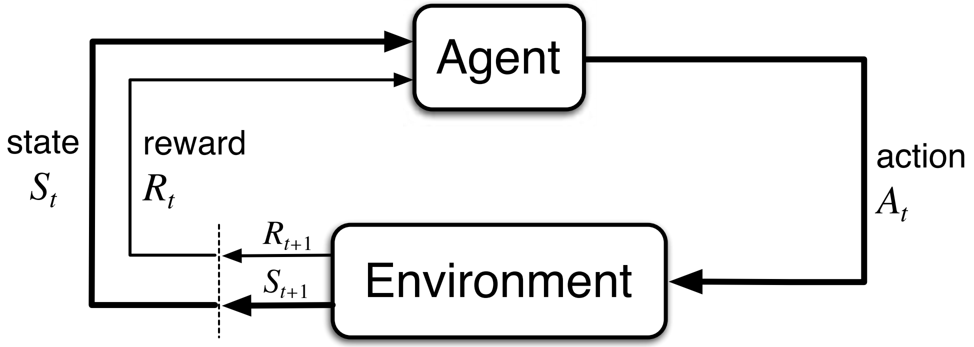
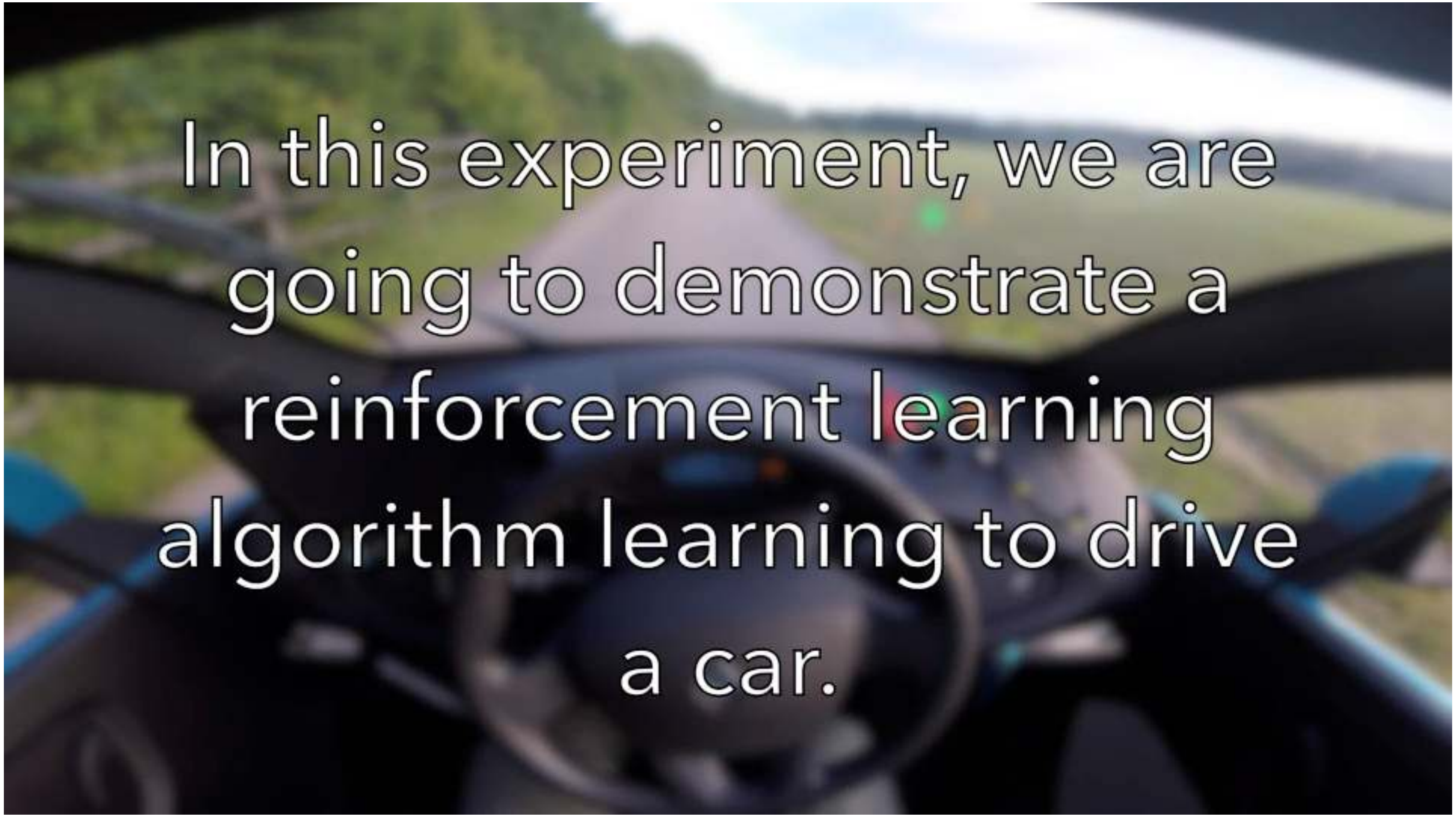


Figure 3.1: The agent–environment interaction in a Markov decision process.

"Reinforcement Learning: An Introduction"
Richard S. Sutton and Andrew G. Barto

End-to-end (camera-to-control) learning



https://youtu.be/eRwTbRtnT1I

Kendall, Alex, et al. "*Learning to drive in a day*." *2019* International Conference on Robotics and Automation (ICRA). IEEE, 2019.

Currently a hot topic ...

IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, VOL. 23, NO. 6, JUNE 2022

Deep Reinforcement Learning for
Autonomou

IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, VOL. 23, NO. 6, JUNE 2022

ment Learning for
Driving: A Survey

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIV.2022.3167271, IEEE Transactions on Intelligent Vehicles

JOURNAL OF LaTeX CLASS FILES 1

A Receding Horizon Reinforcement Learning
Approach f

Xinglong Zhang,

Abstract—Kinodynamic motion
tonomous vehicles with high ma

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIV.2022.3165178, IEEE Transactions on Intelligent Vehicles

IEEE TRANSACTIONS ON INTELLIGENT VEHICLES 1

Robust Lane Change Decision Making for Autonomous Vehicles: An Observation Adversarial Reinforcement Learning Approach

Xiangkun He, *Member, IEEE*, Haohan Yang, Zhongxu Hu, and Chen Lv, *Senior Member, IEEE*

End-to-end learning, deep reinforcement learning

- The result from the last video is kind of nice, but is it a good idea for real-life autonomous vehicles? It highlights some striking problems.
- If perception can give us road boundaries, do we need to learn how to drive at the center of the road?
- There are plenty of arguments
  - Learn to adapt to uncertainty
  - Model the world is too difficult, measure instead
  - Why should we learn things we already know
  - Use RL for high-level reasoning
  - …
- Fair to say the jury is still out on this one.
- I highly recommend the Ben Recht plenary talk video for a deeper discussion

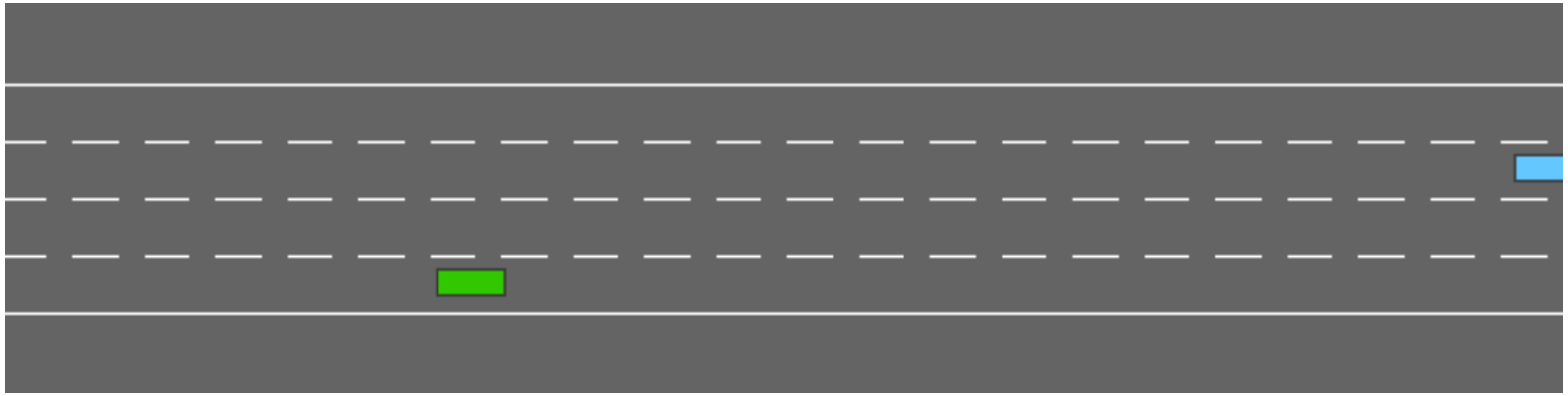
Why is this so difficult in practice?

- Uncertainty, robustness, humans, …
- Worlds like Go, chess follow simple rules (although succeeding in these games is certainly not simple …).
  - Closed-world assumption holds true.
- CWA not true for real driving/flying environments; Anything can happen
- Modeling the real world is difficult; significant model errors inevitable
- How do you ensure safety? Humans are fragile and unpredictable.
- A main challenge — introduce robustness, safety, and resilience

Most likely, performant systems will consist of learning systems and advanced control, (and …)

HI – Learning and autonomous vehicles

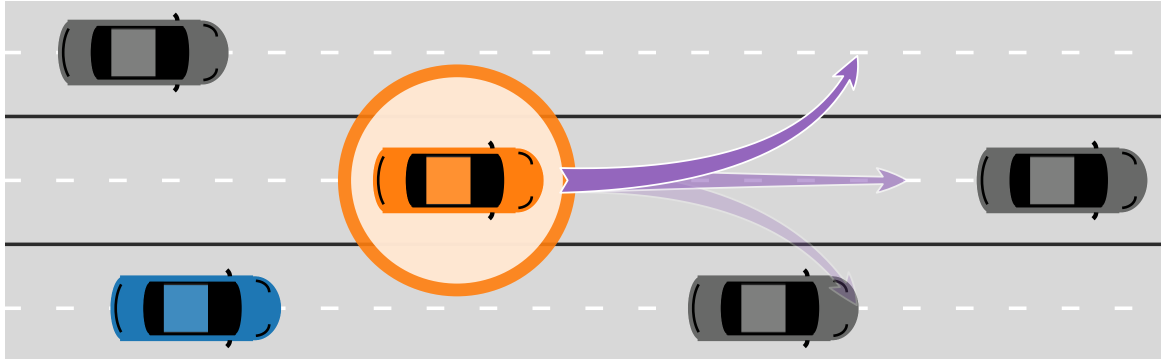
- The HI for learning in this course is aimed to get initial understanding of the two techniques
- Basic HI
  1. Basic RL understanding, small academic example
  2. Neural networks for behavior prediction
- Extra assignment — Deep Q-learning for (reckless) highway driving

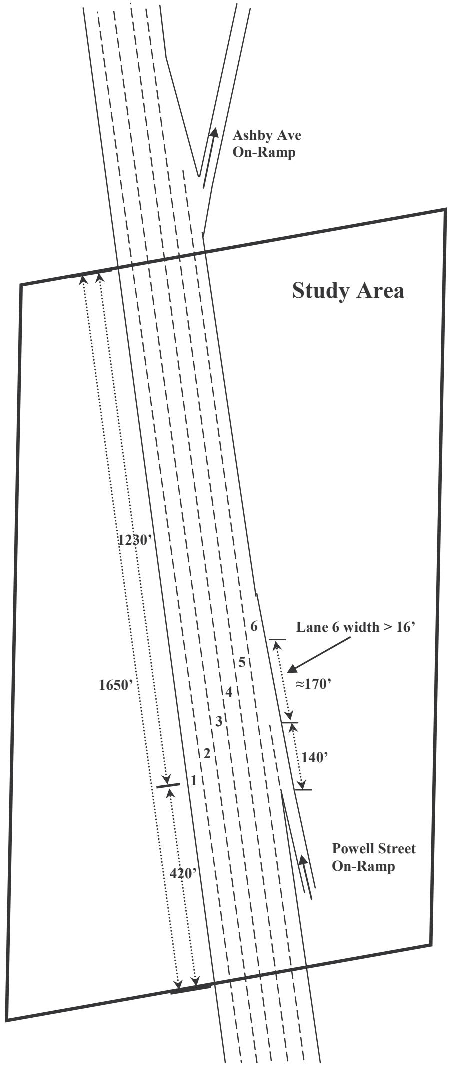


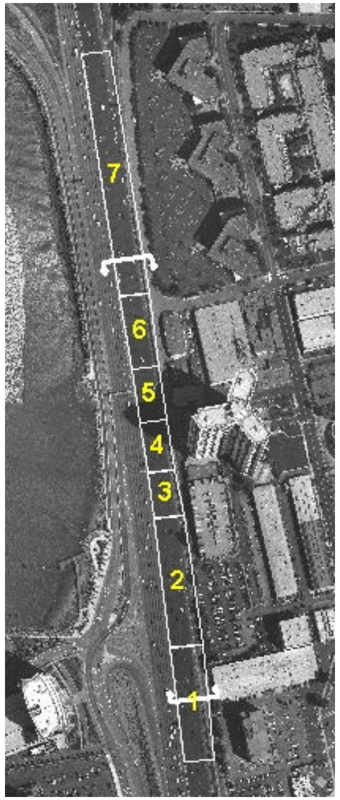
A possible use-case - driver prediction

Example - behavioral models of drivers

- Physical models are very useful, they can be understood, and they extrapolate well.
- We know how to model basic mechanics; but how do we model human behavior?
- Consider the 6 lane highway, a section of the I-80 in Emeryville outside Oakland
- To plan safe motion in high density traffic, it would be good to have predictions what surrounding drivers will do next

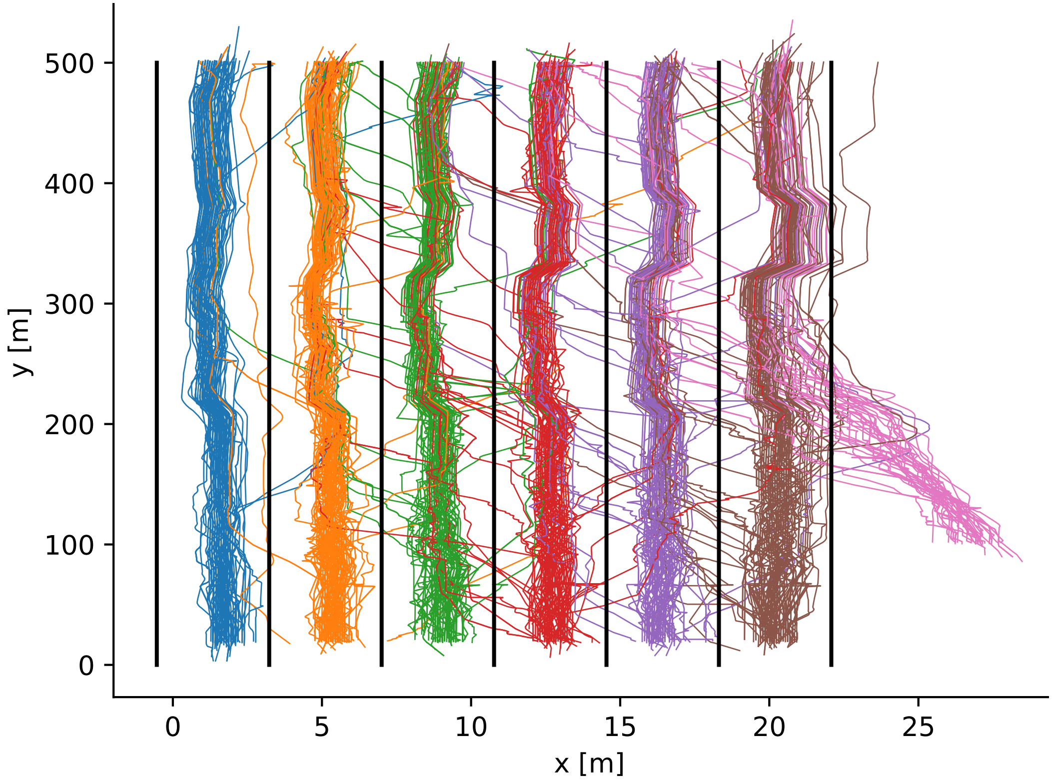






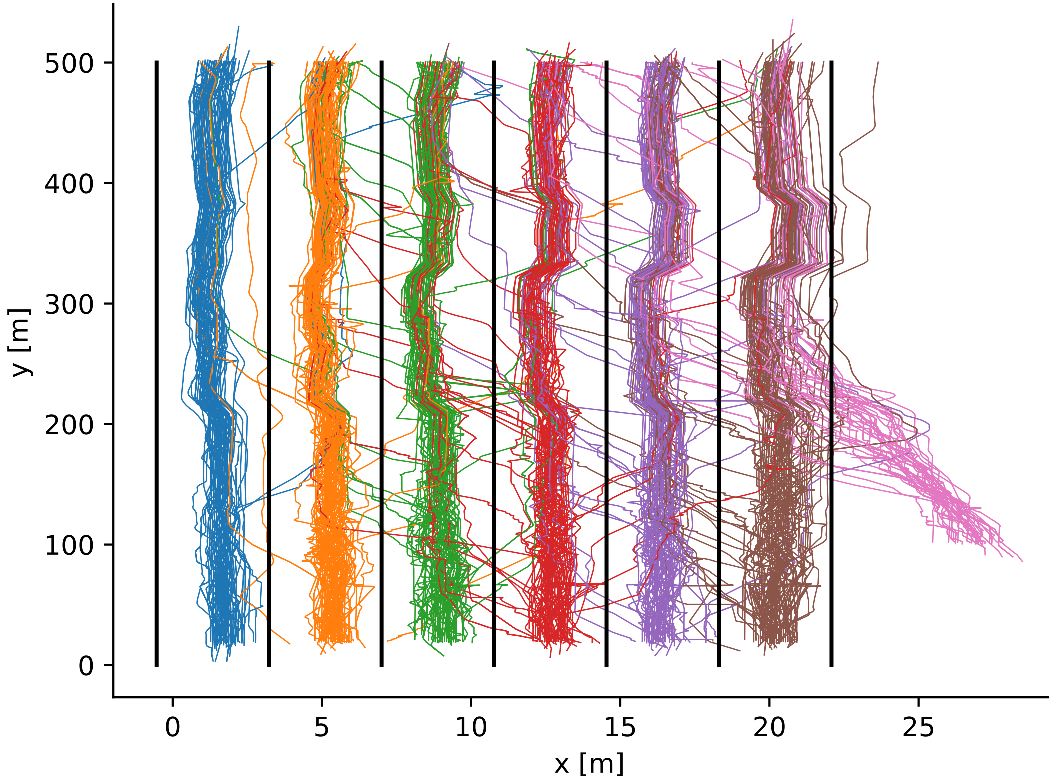
What could influence a driver? (1/2)

- The (unknown) long-term plan
- Surrounding traffic - positions, velocities, accelerations
- Many aim for high speed lanes to the left, i.e., lane shifts to the left more common than the opposite
- Could depend on mean velocity and density, in lanes
- … and then some



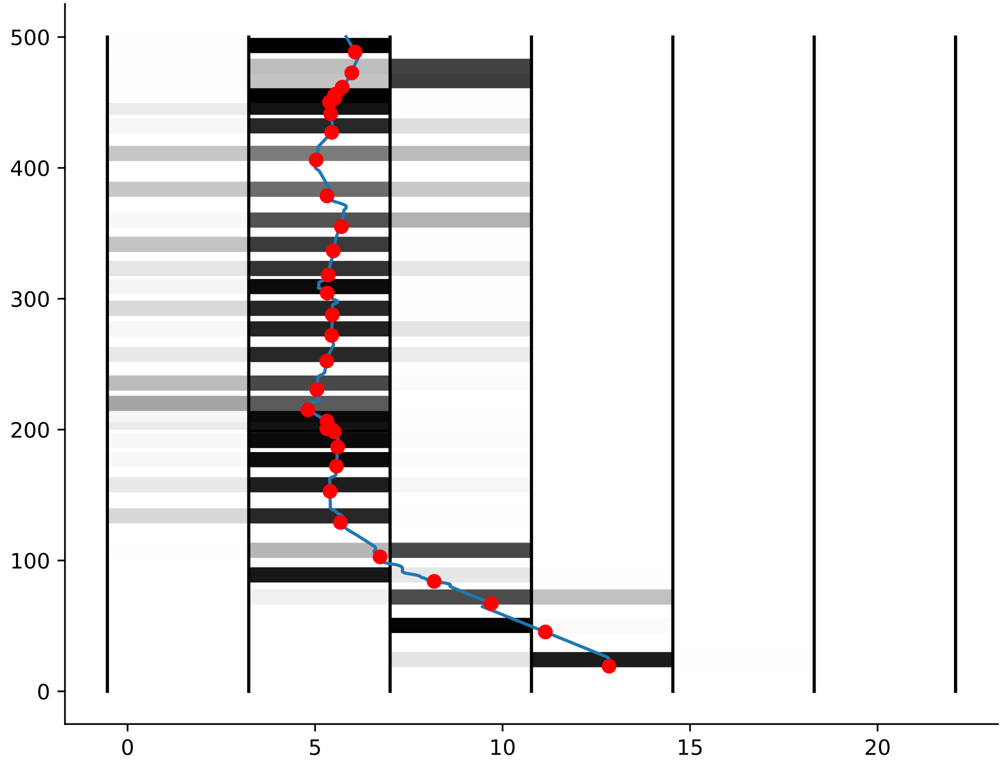
What could influence a driver? (2/2)

- Predicting what a driver will do short-term (less than a second), look at the velocity vector
- On a medium time-scale 1-3 seconds, drivers start to interact and act with the environment
- Long-term, then strategic driver plans
- Building a rule-based model for driver behavior will be difficult



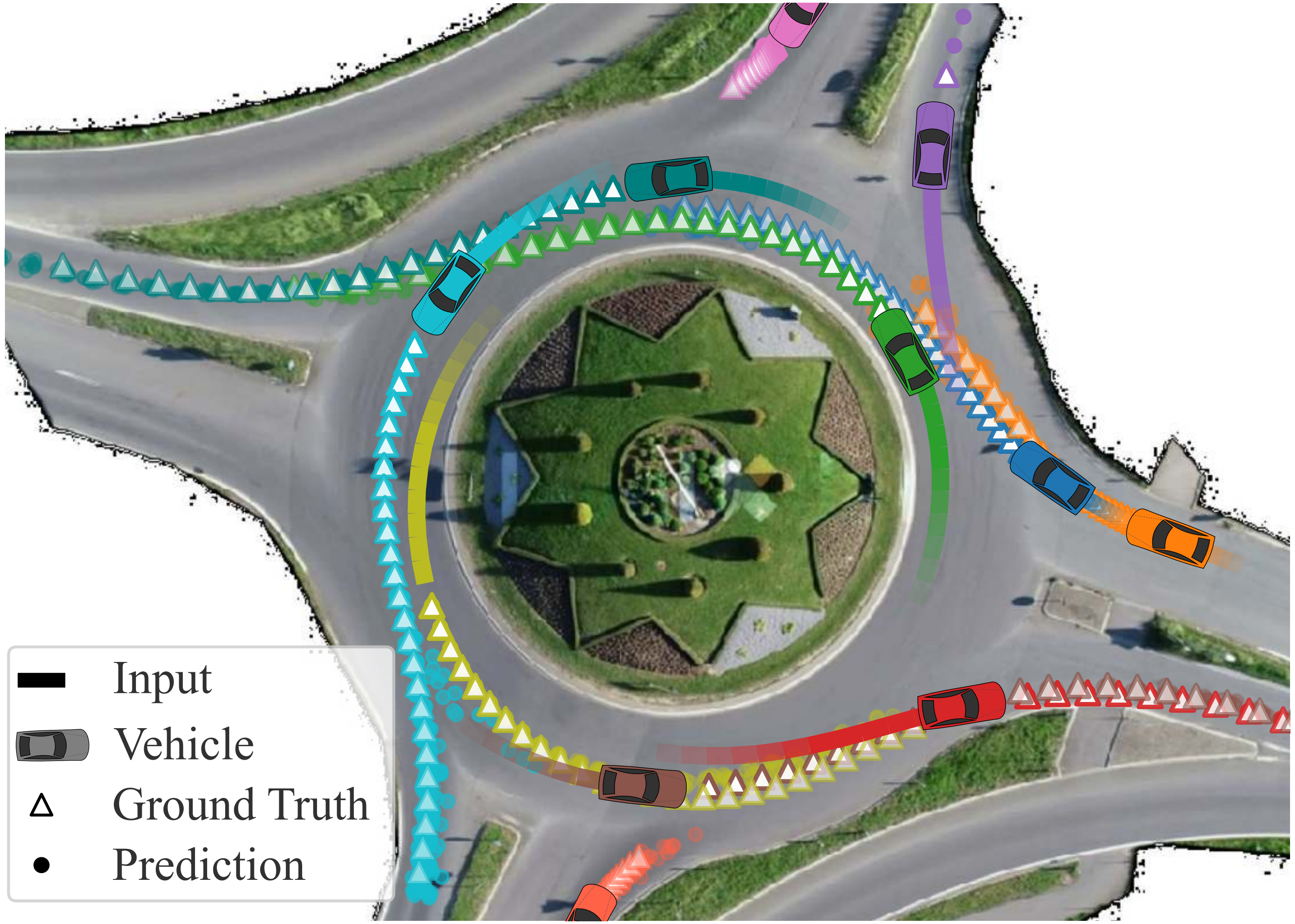
A simple approach

- Maybe using recorded data to build ML models can be used to predict driving behavior
- Find features x, data about the current situation and try to predict if a driver will change lanes within the next 3 seconds
- Model
  $\hat{y} = f(x) \in \{\text{left, stay, right}\}$
- What is a good feature vector x?



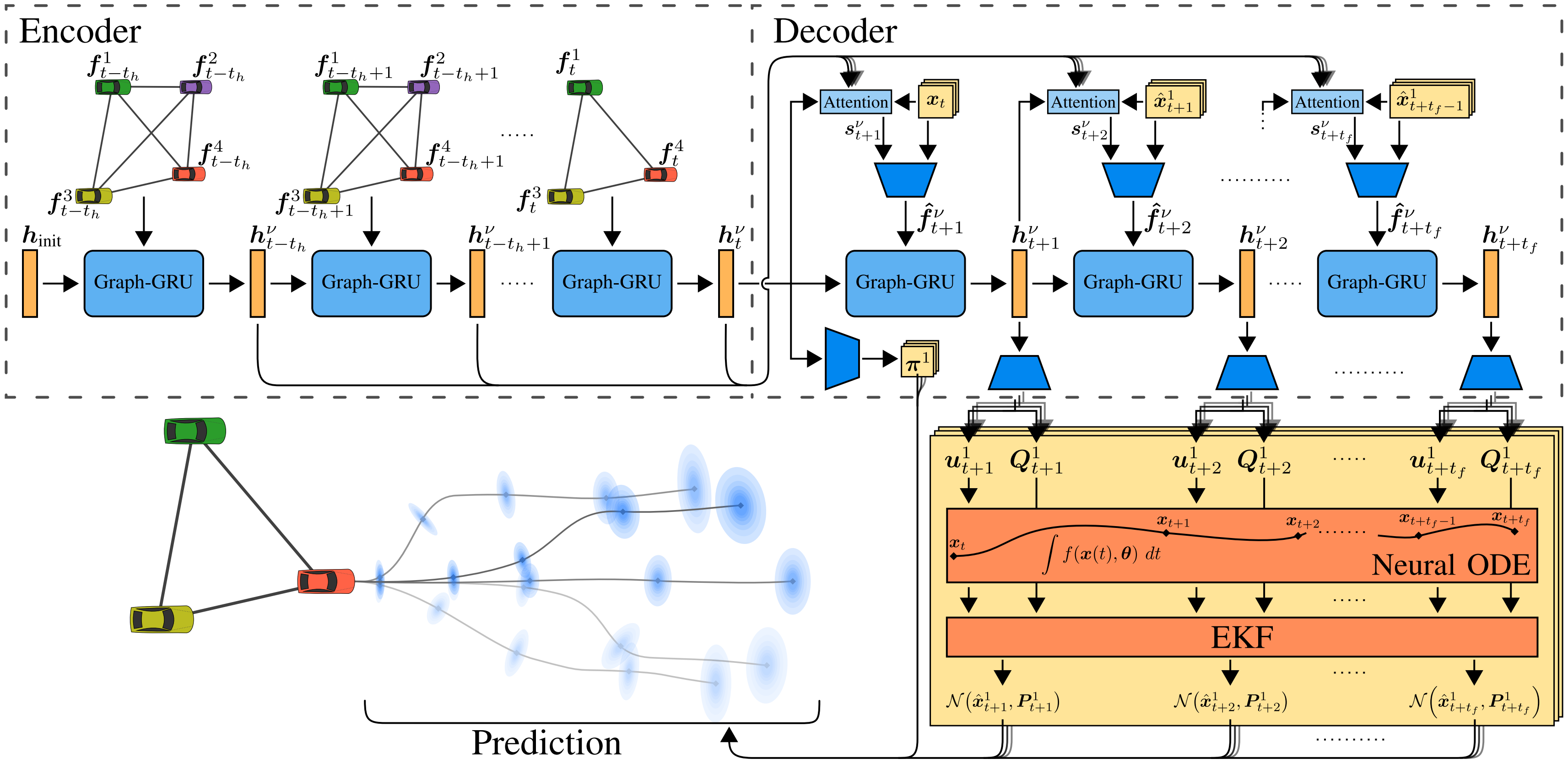
In hand-in 5-extra, you will build a neural-network model $f(x)$

A more state-of-the-art approach (1/2)



Westny, Theodor, et al. "*MTP-GO: Graph-Based Probabilistic Multi-Agent Trajectory Prediction with Neural ODEs*." IEEE Transactions on Intelligent Vehicles (2023).

A more state-of-the-art approach (2/2)



≈200.000 - 300.000 parameters (not small but not big)

Westny, Theodor, et al. "*MTP-GO: Graph-Based Probabilistic Multi-Agent Trajectory Prediction with Neural ODEs*." IEEE Transactions on Intelligent Vehicles (2023).

Summary of introduction

- Learning for autonomous vehicles is still very much an active research area
- Computer vision, detection and classification of objects in images, semantic segmentation of the world
  - areas where learning techniques are already important (essential)
- We are dealing with mechatronic systems, classical control will be important
  - Model Predictive Control is an especially interesting branch of control
- A basic research question for learning and control;
  how, where, and when they can collaborate to realize safe, robust, and resilient autonomous systems

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