Learning for Autonomous Vehicles

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

Lecture 10: Erik Frisk <erik.frisk@liu.se>

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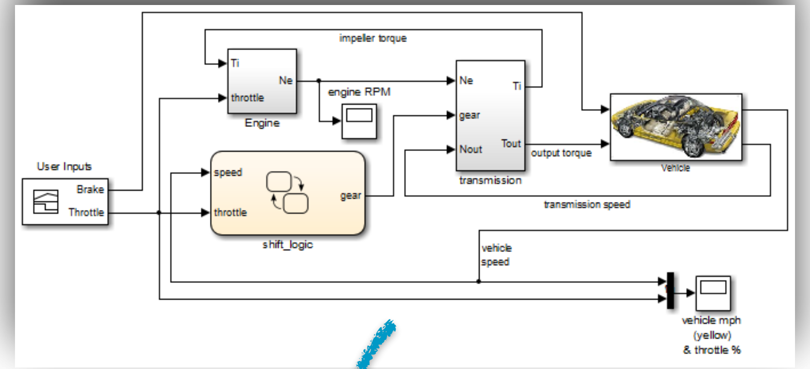
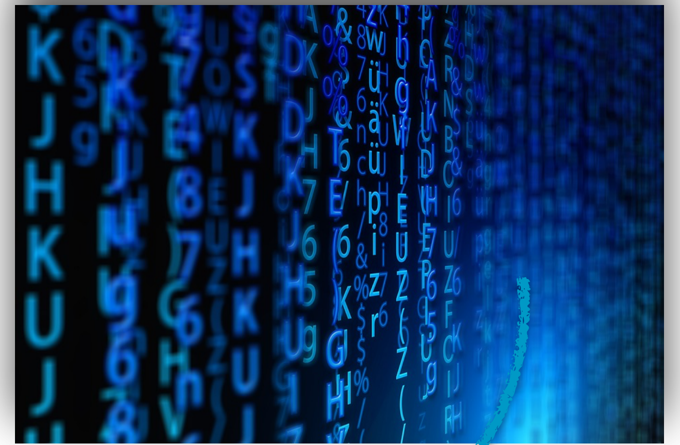
Learning, models, and data

Q: What is (machine) learning?

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

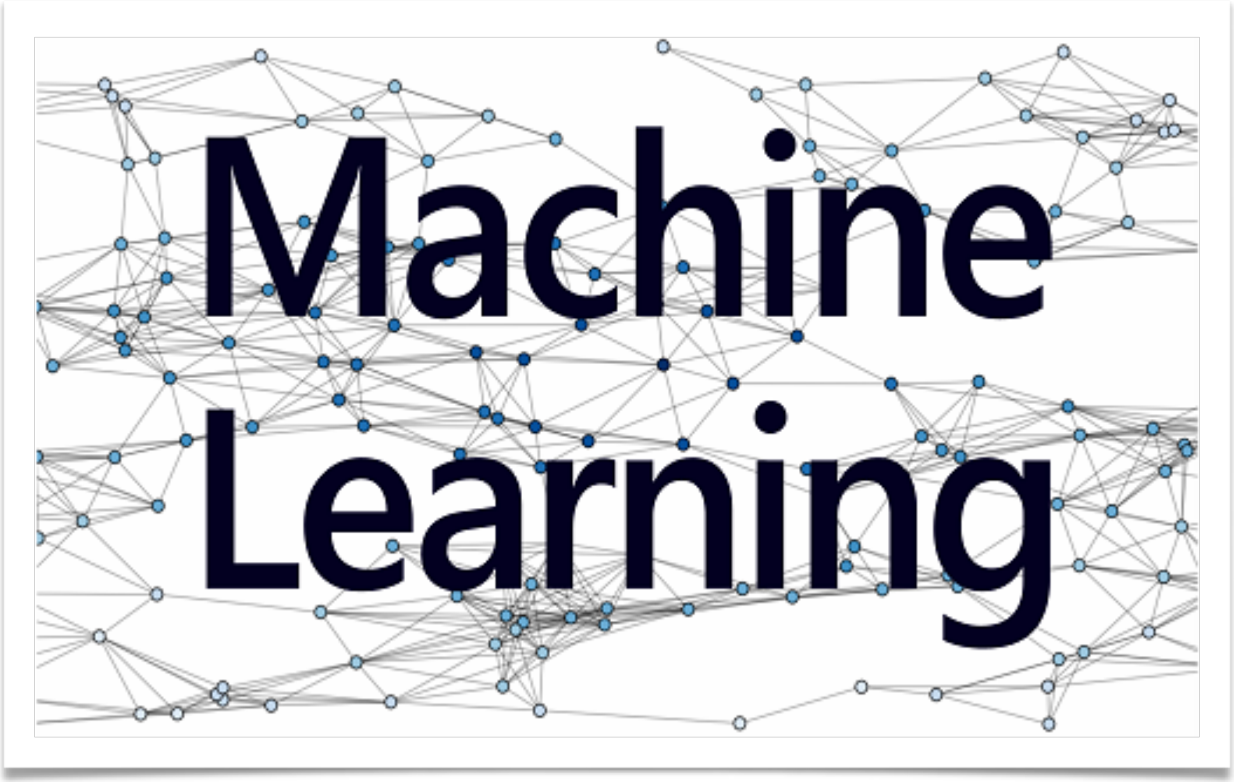




predictive/control models

Rough characterization of machine learning tasks

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

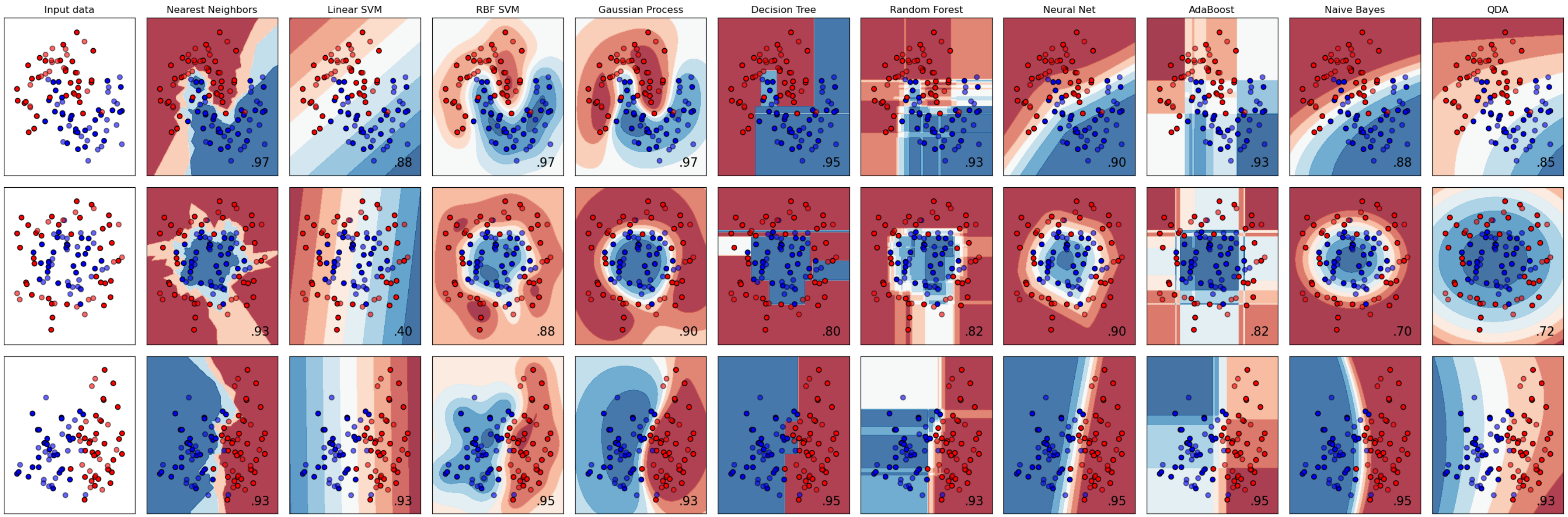


Learning and Autonomous Vehicles

- 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

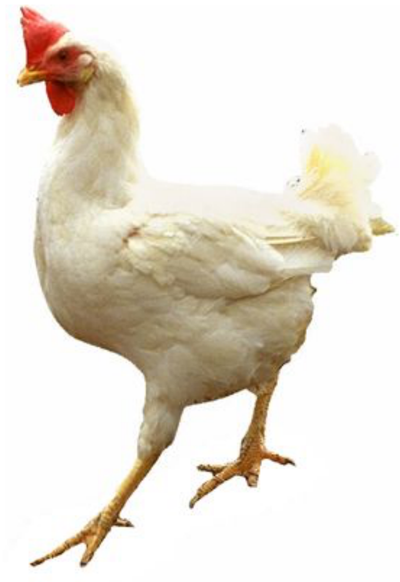
Learning - some basics



- Methods look for patterns in data
- 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



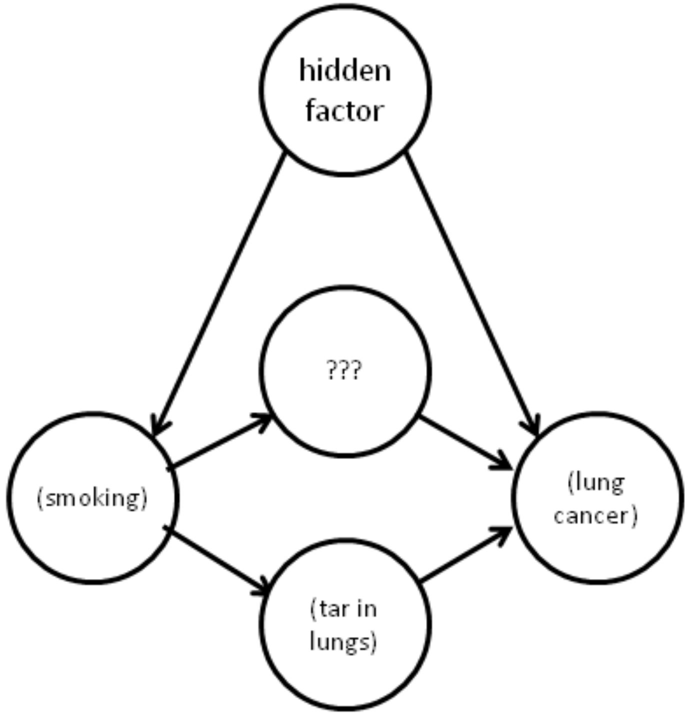
or is it …

- You won't see them in testing; things no-one thought about
- You need on-line system supervision of methods and algorithms that are difficult to monitor

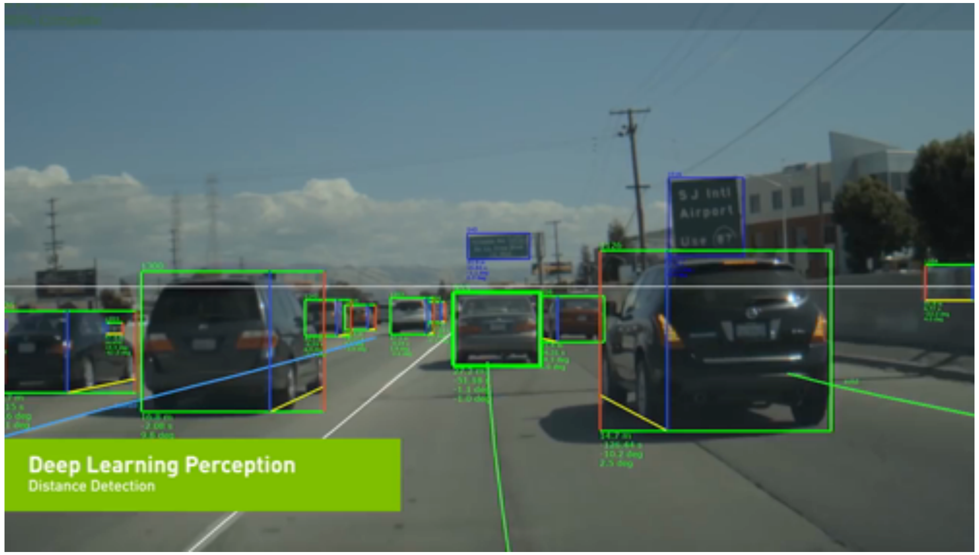
Source: *"Autonomous Vehicle Safety Technical and Social Issues"*, *P. Koopman, Carnegie Mellon, 2018*

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, …)



Machine learning, and autonomous vehicles



- Learning systems have the potential to make high-level autonomy a reality — but we're not there yet
- Many current systems are hand-crafted and are heavily based on advanced sensor techniques
- 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 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 methods
- In particular, three methods/areas will be discussed in some detail
  - Reinforcement learning
  - Gaussian Processes
  - Neural Networks

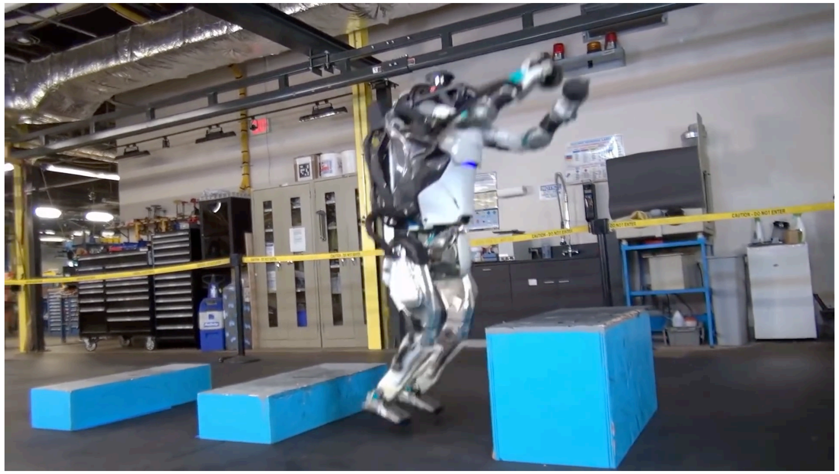
Reflections on the Learning-to-Control Renaissance

- 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
- As you'll see, I borrowed some of his insights into this lecture

https://youtu.be/IEZFwh8sw8s

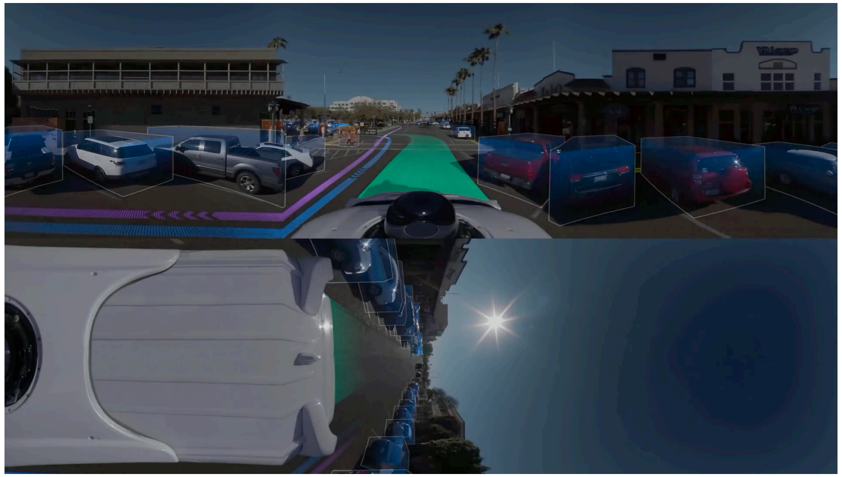
Learning for Autonomous Vehicles

Where are we now and where are we learning?



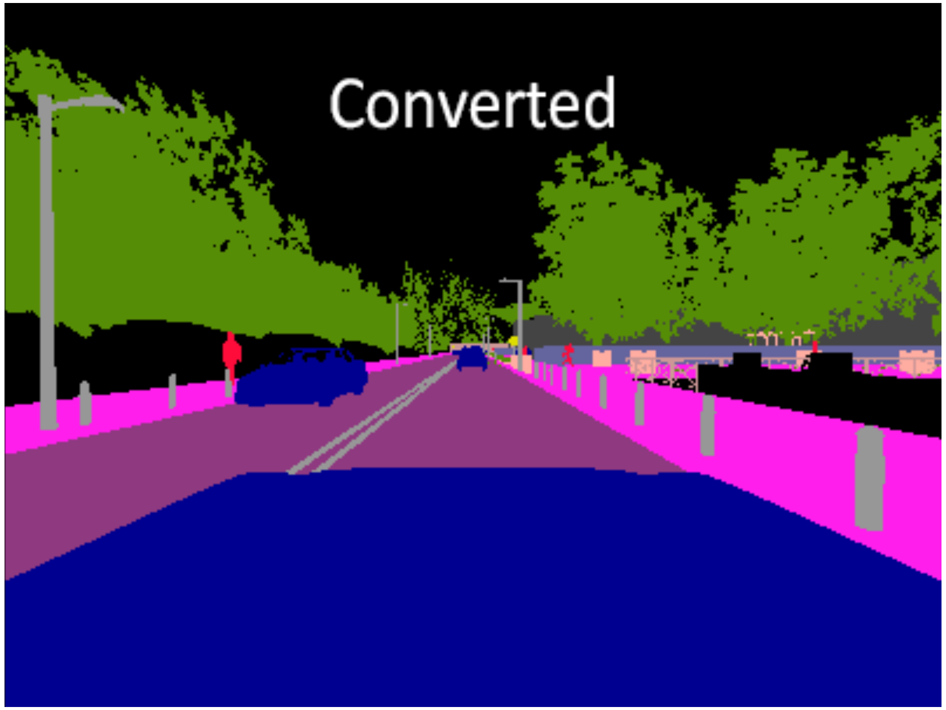
Boston Dynamics

ETH Zürich

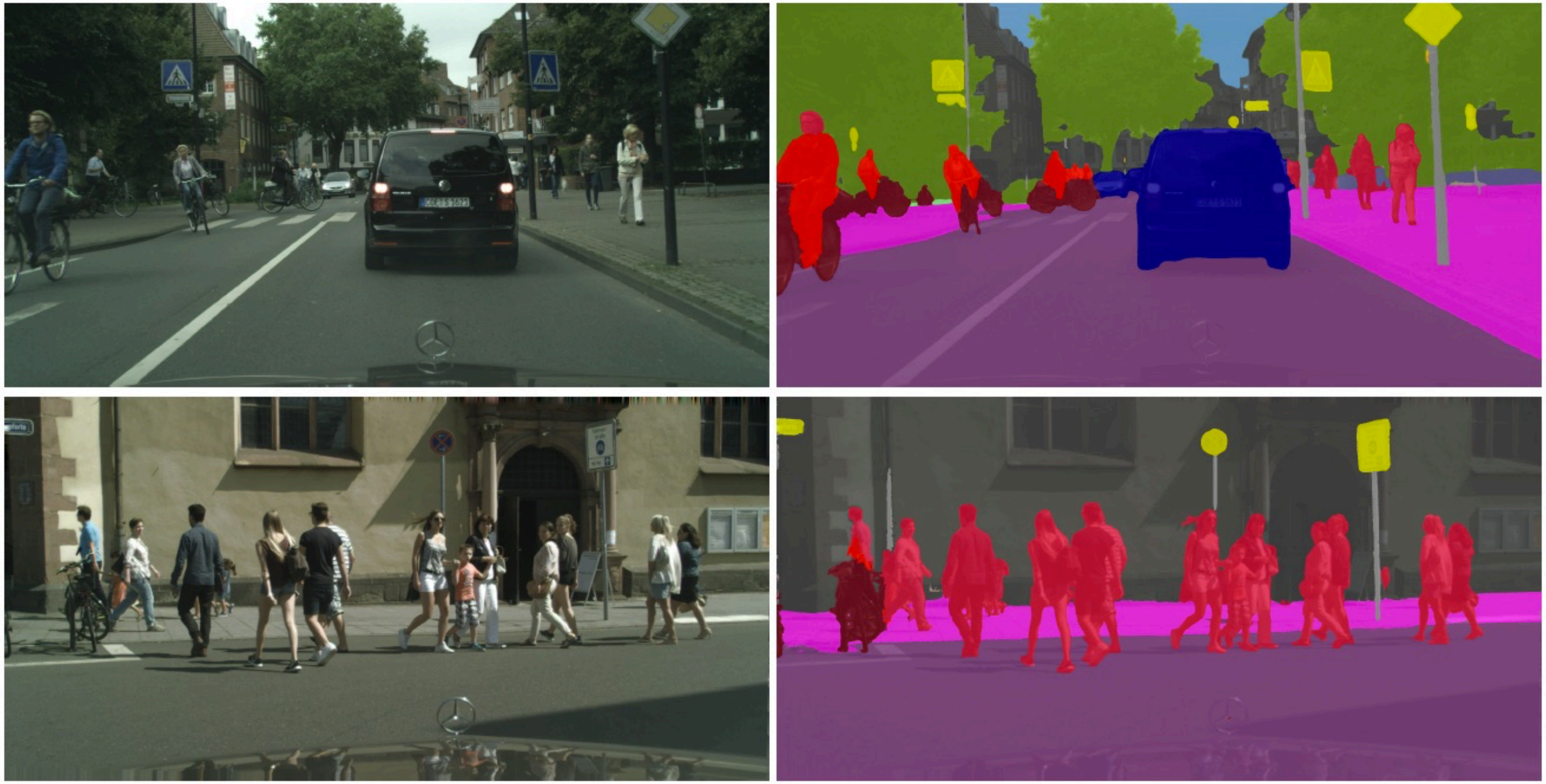


Waymo, Tesla, …

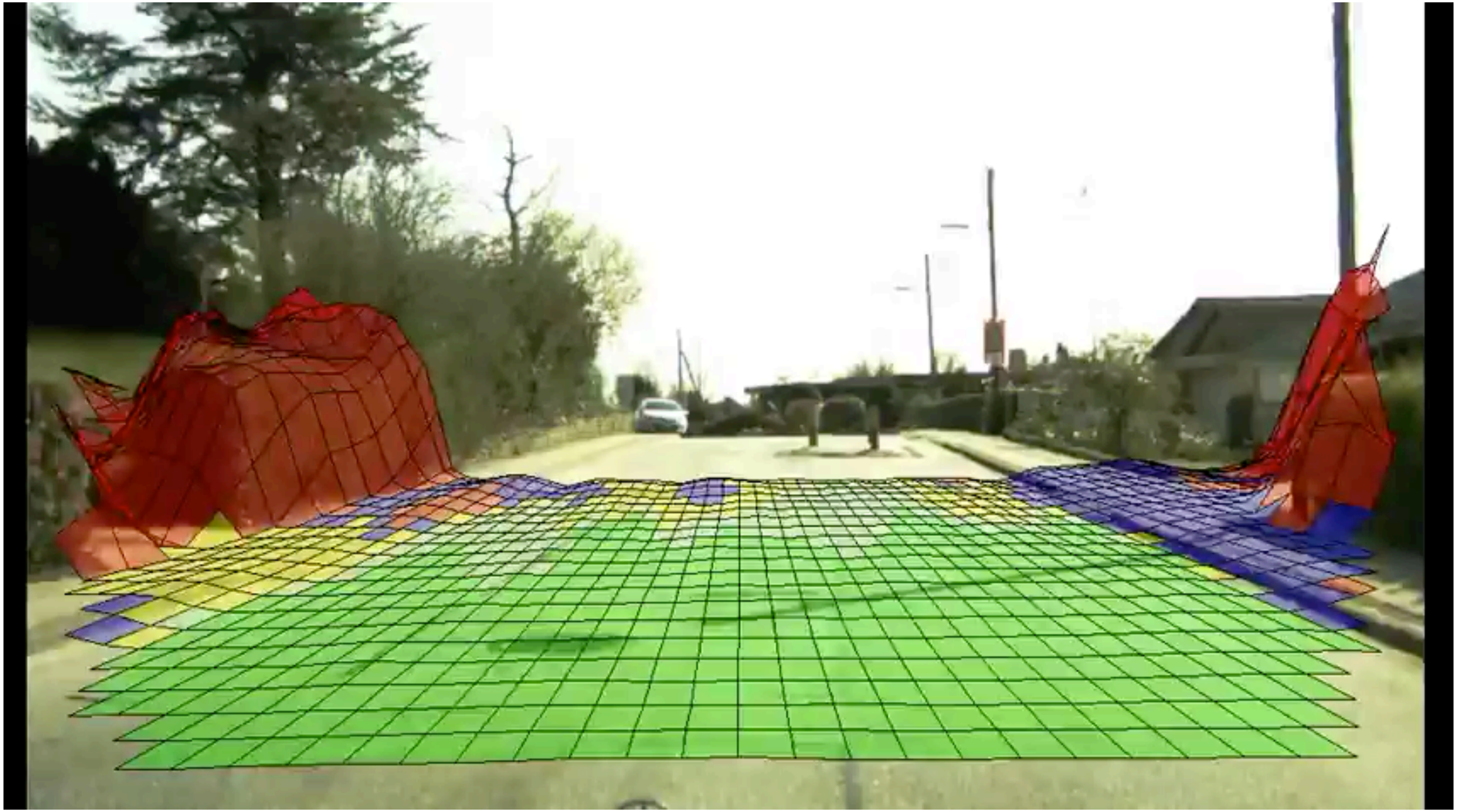
Semantic segmentation in the CARLA simulator



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:

  TSBB17 - Visual Object Recognition and Detection

Perception yes, but can we learn how to act?

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

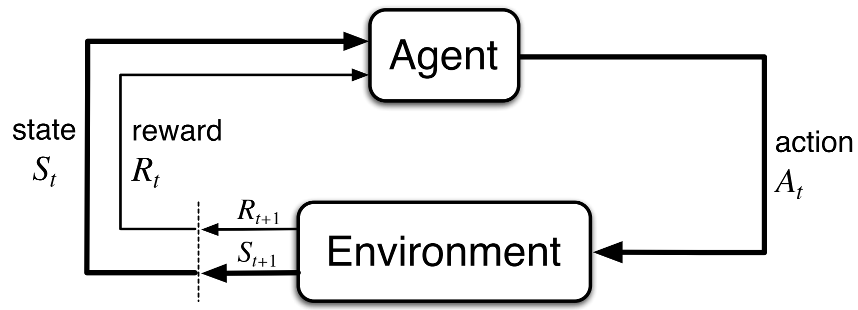
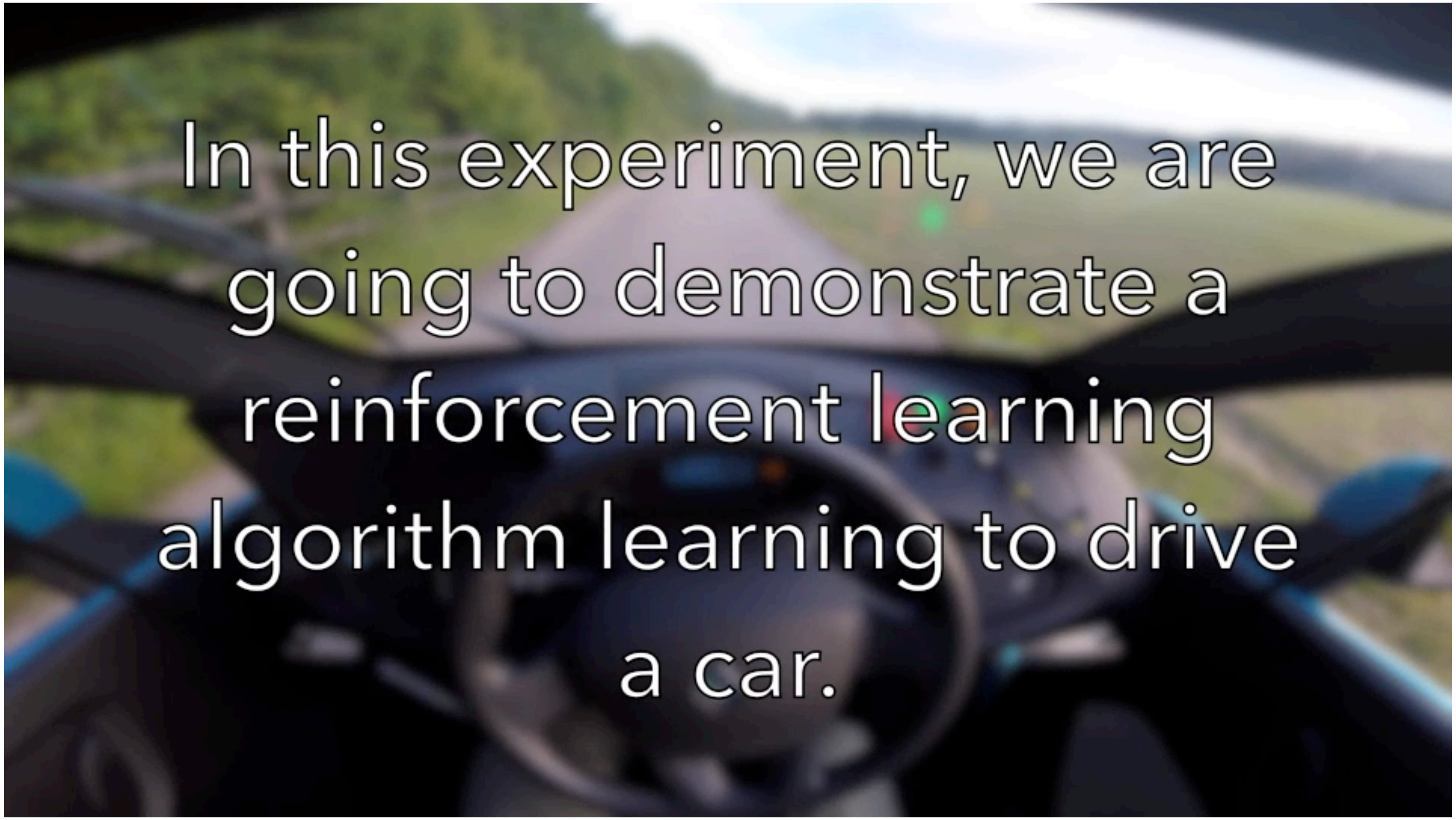


Figure 3.1: The agent–environment interaction in a Markov decision process.

"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.

End-to-end learning, deep reinforcement learning

- The result from the last video is impressive, 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
  - …
- Fair to say the jury is still out on this one

Why is this so difficult in practice?

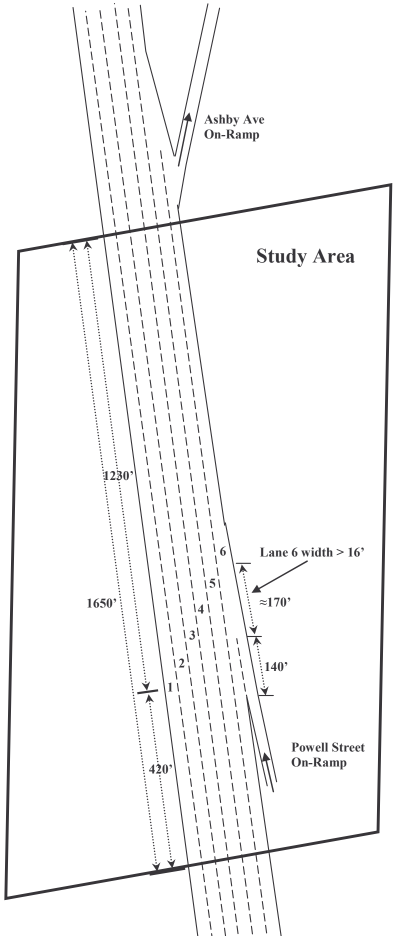
- Uncertainty, robustness, humans, …
- Worlds like Go, chess follow simple rules (although succeeding in these games is certainly not simple …).
  - Closed-world assumption holds true.
- CWA not true for real driving/flying environments; Anything can happen
- Modeling the real world is difficult; significant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

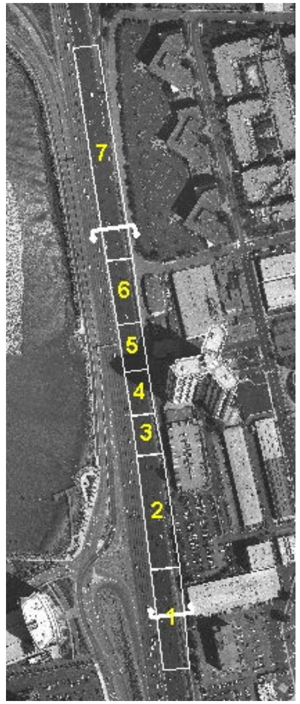
Most likely, performant systems will consist of learning systems and advanced control, (and …)

A possible use-case - driver prediction

Example - behavioral models of drivers

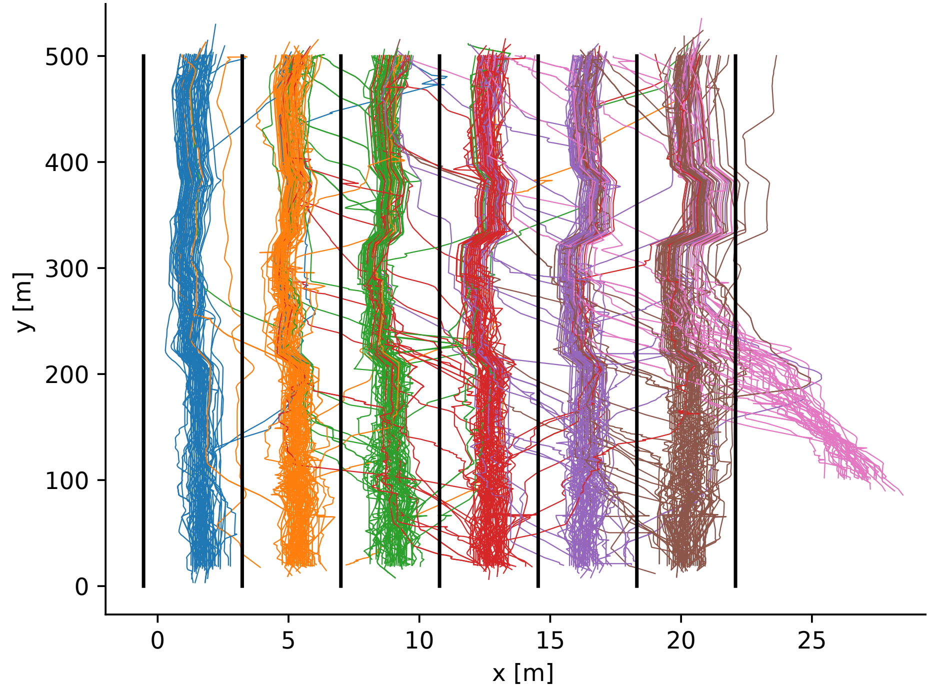
- Physical models are very useful, they can be understood, and they extrapolate well.
- We know how to model basic mechanics; but how do we model human behavior?
- Consider the 6 lane highway, a section of the I-80 in Emeryville outside Oakland
- To plan safe motion in high density traffic, it would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





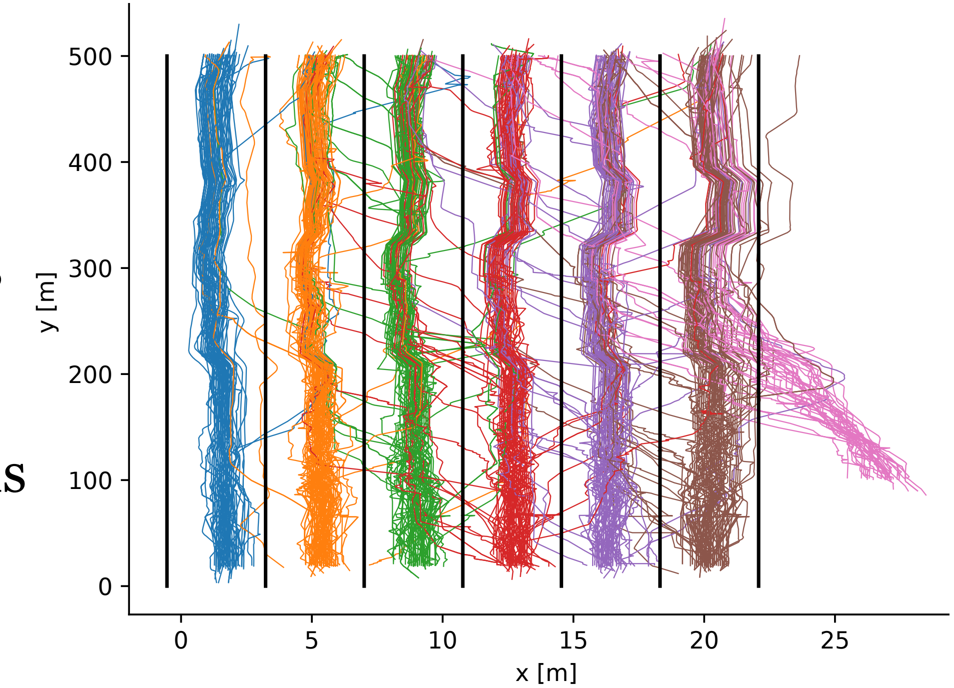
What could influence a driver? (1/2)

- 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



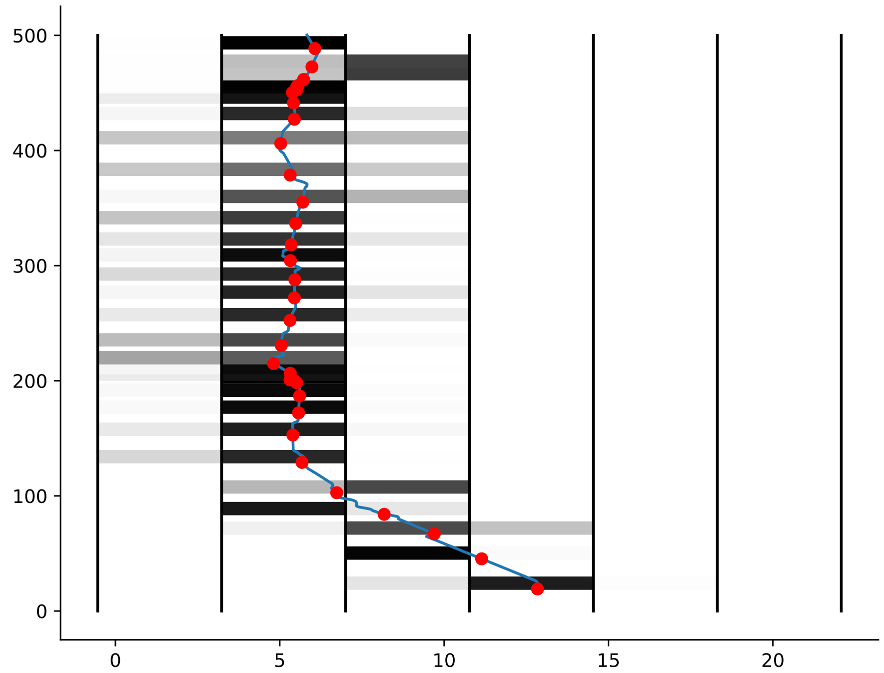
What could influence a driver? (2/2)

- 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
  $\hat{y} = f(x) \in \{\text{left}, \text{stay}, \text{right}\}$
- What is a good feature vector x?



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

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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