A Fast Integrated Planning and Control Framework for Autonomous Driving based on Reinforcement Learning

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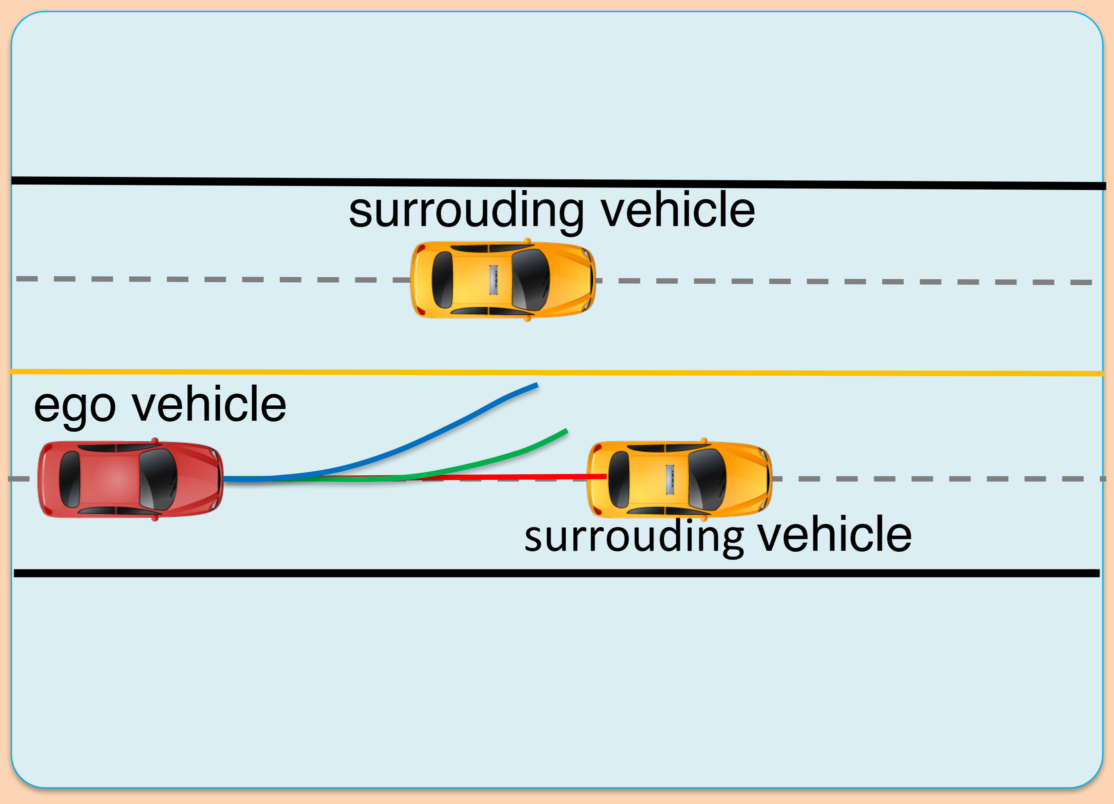
Motivation: Long-term Planning VS Realtimeness? Can we achieve both?

Safe and efficient autonomous driving

- **Long-term** motion planning is desired for safety, feasibility and passengers' comfort
- **Realtime** planning is crucial for autonomous driving due to limited computation time



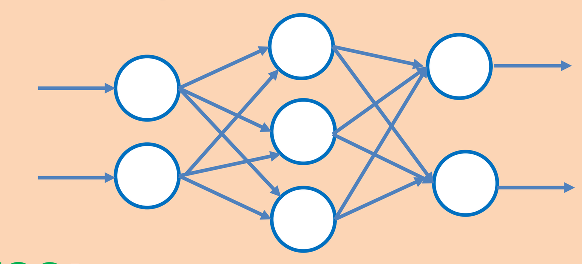
Optimization-based method (eg., MPC)

$$\min_{x \in \mathcal{R}^n} \quad f(x)$$
$$s.t. \quad g(x) \leq 0$$

Pros:
- Guaranteed safety, feasibility
- Intuitive interpretation
- Easy incorporation of different constraints

Cons:
- Nonlinear nonconvex optimization
- Pre-defined objectives
- Exponentially increase of computation load with the planning horizon length

Learning-based method

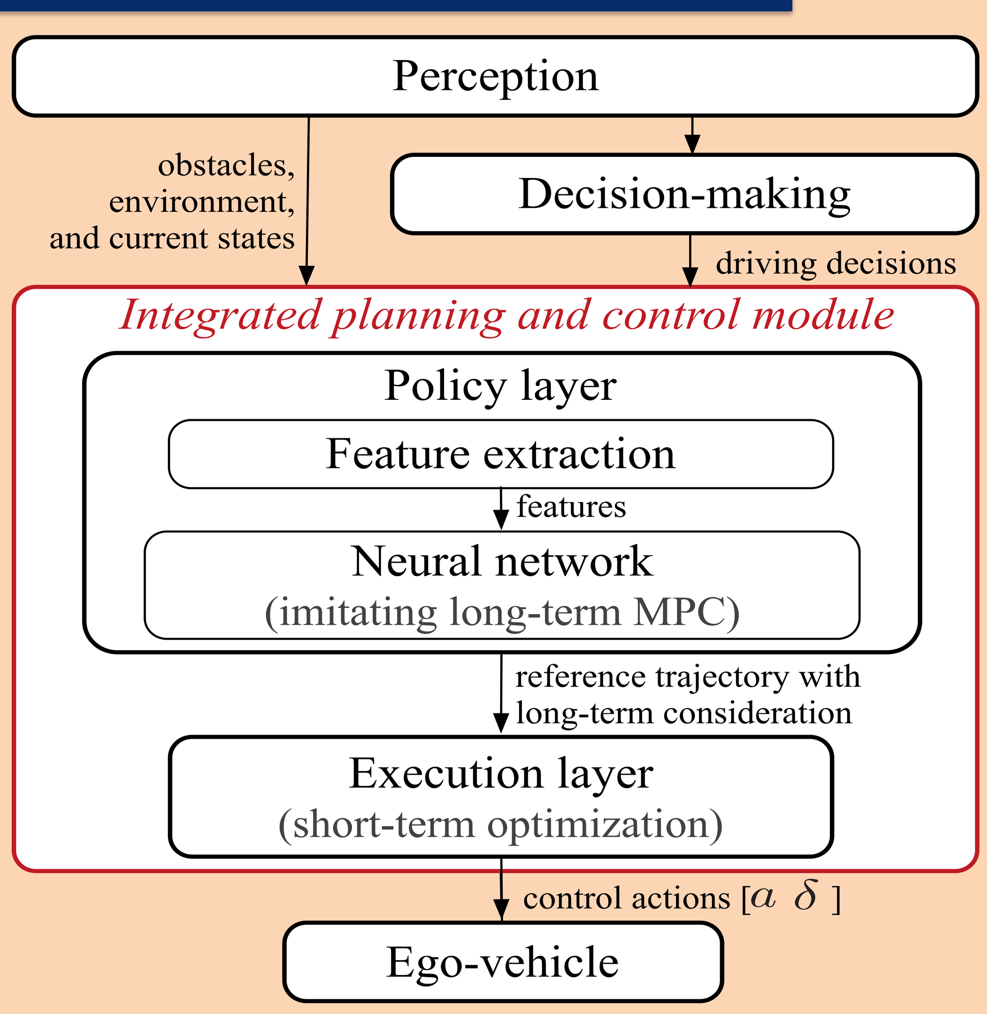


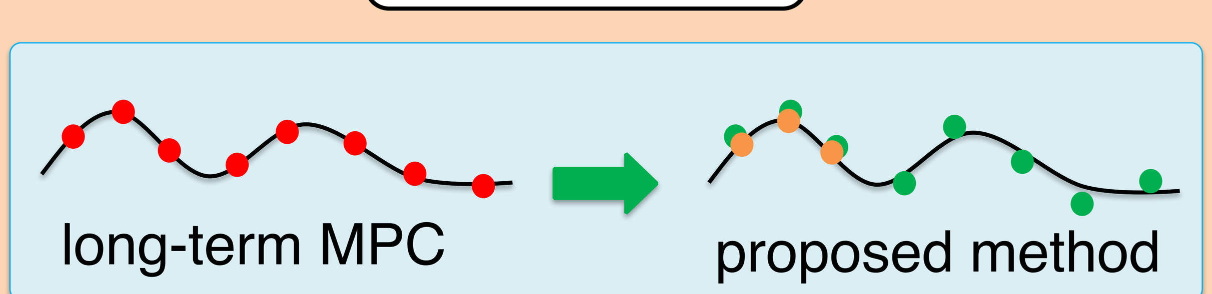
Pros:
- Fast computation
- Mimic human behavior (learn from data)

Cons:
- Non-intuitive interpretation
- Hard to guarantee hard constraints
- Rich data requirement

Long-term rough planning: learning-based
Short-term precise execution: optimization-based

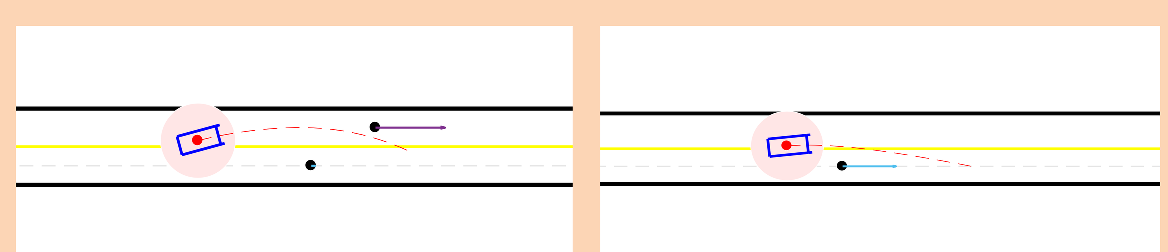
Hierarchical Structure



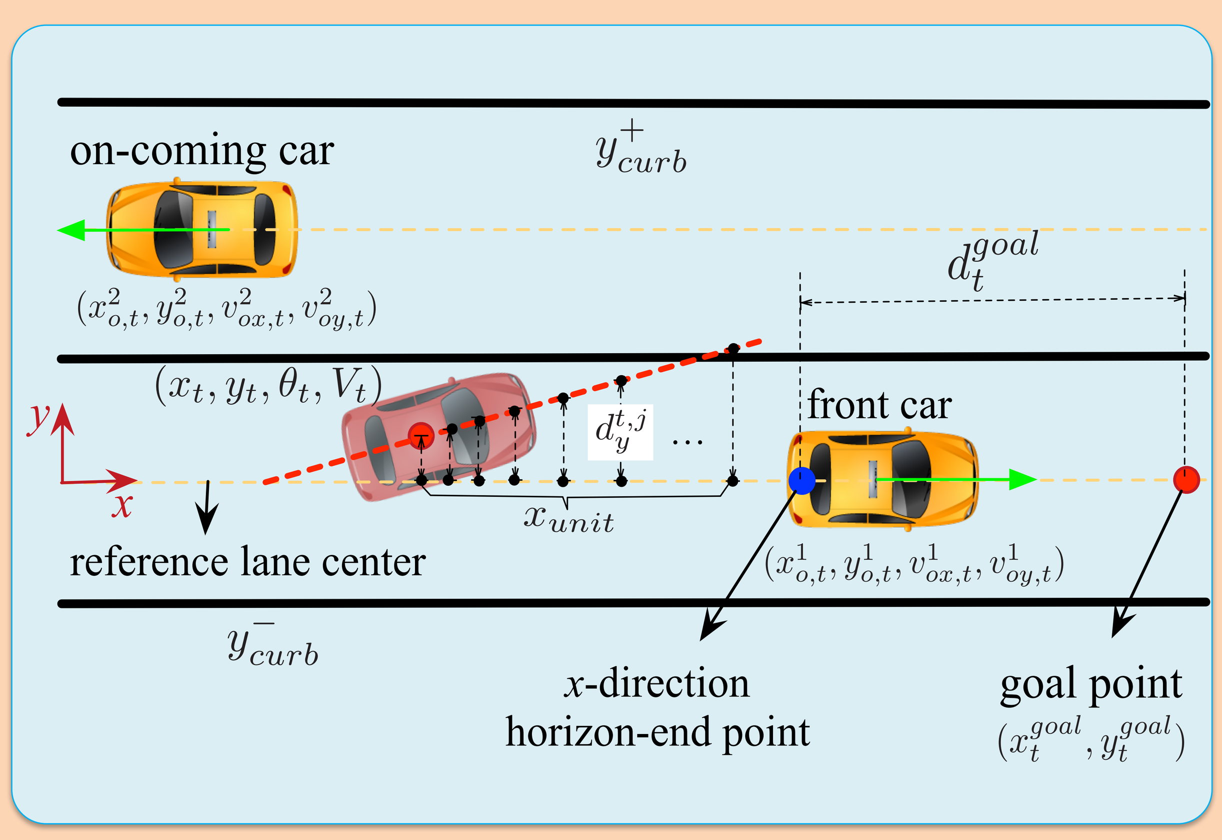


Supervised Learning

Expert policy: long-term MPC

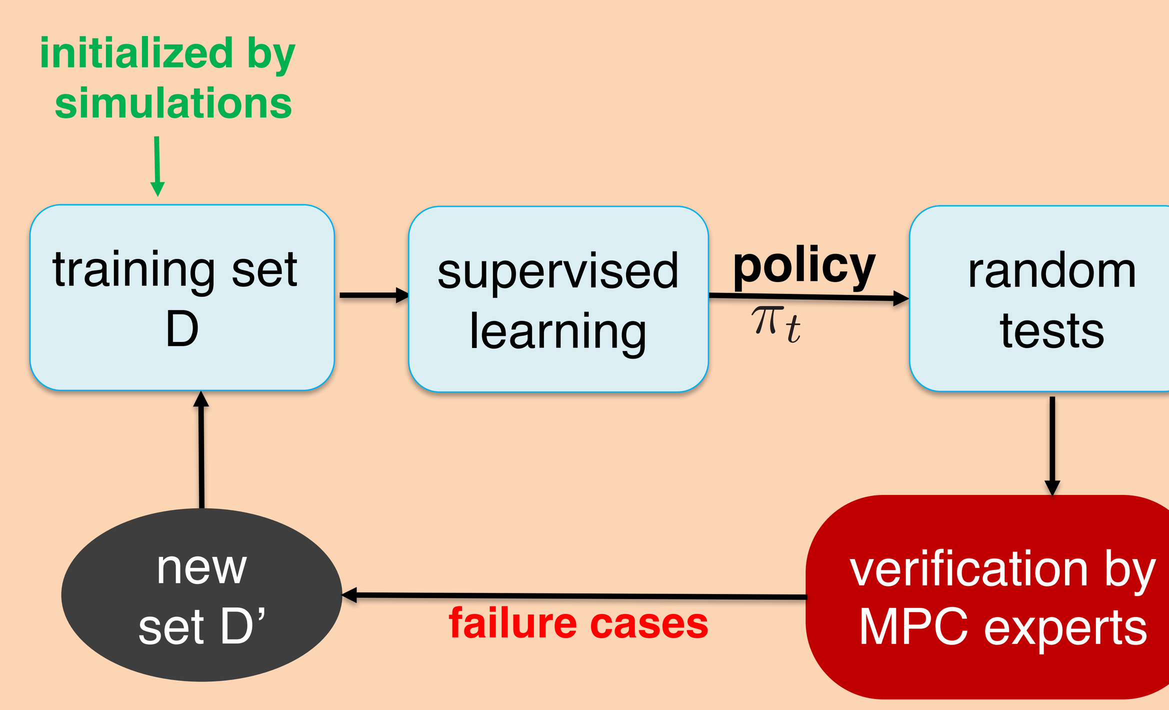


Feature selection:



Imitation Learning with DAgger

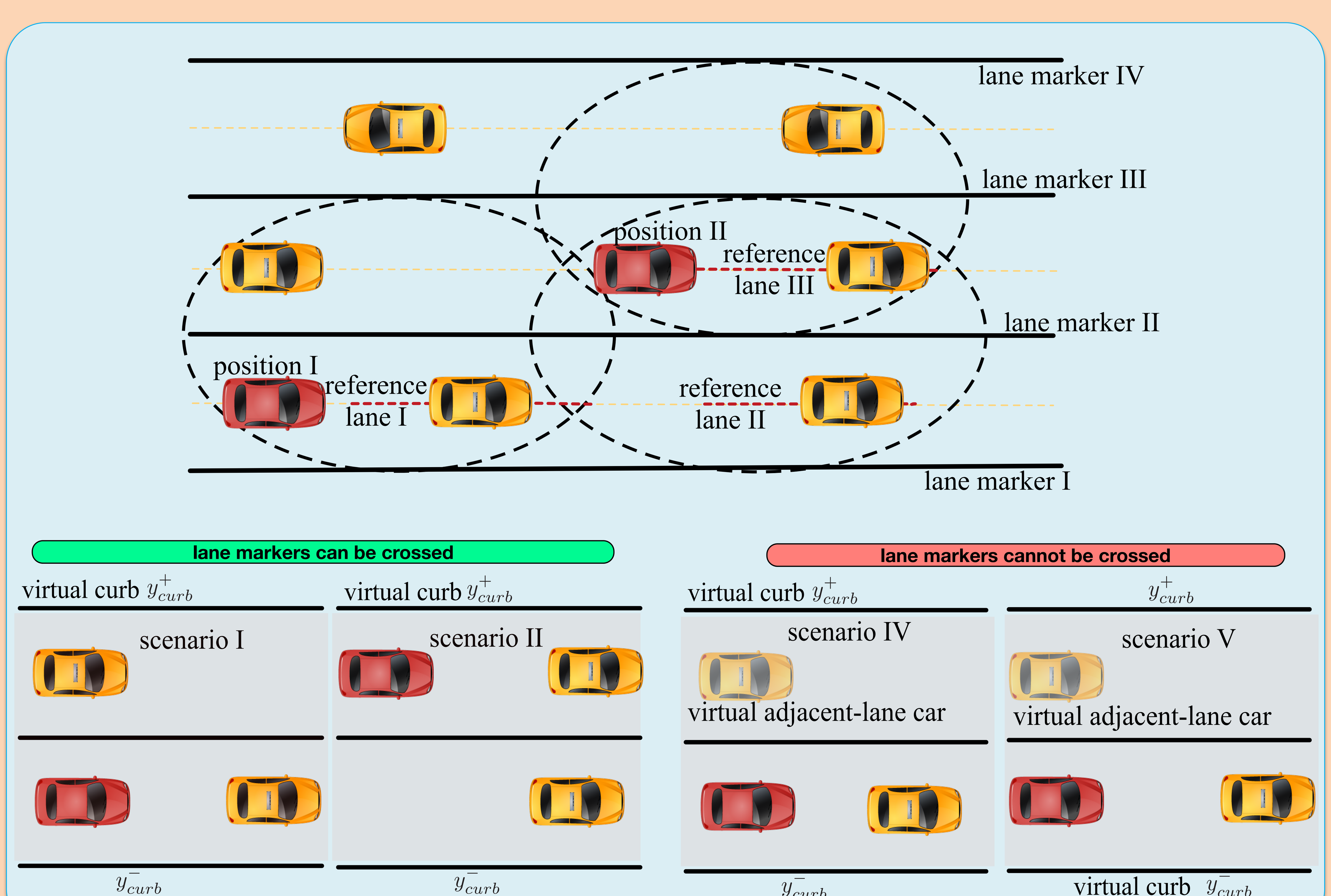
Reinforcement learning:



Advantages:

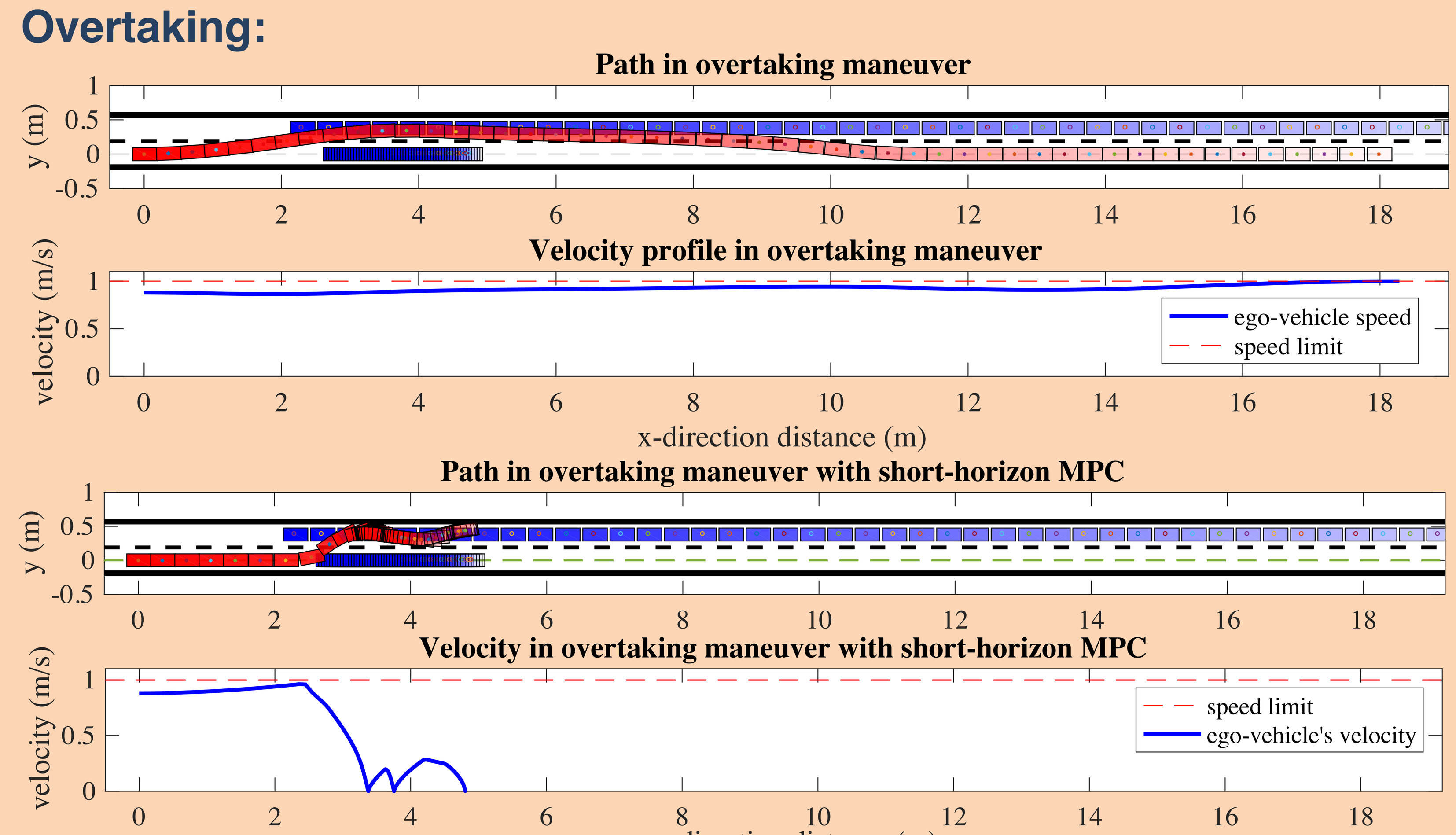
- Short training time (~ 2-3 mins)
- Fast policy updates
- Improved robustness to real world tests

Generalization

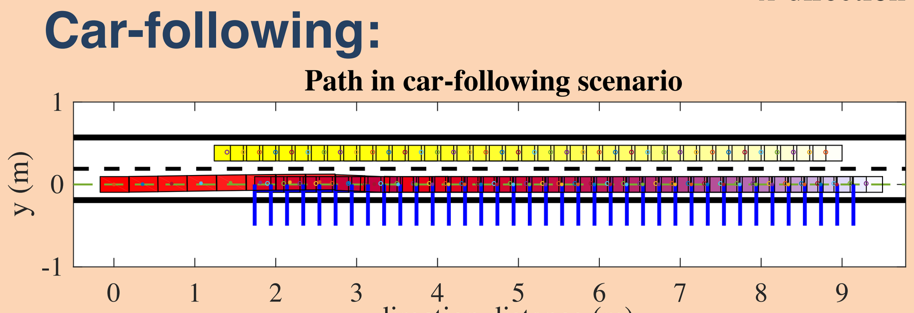


Results

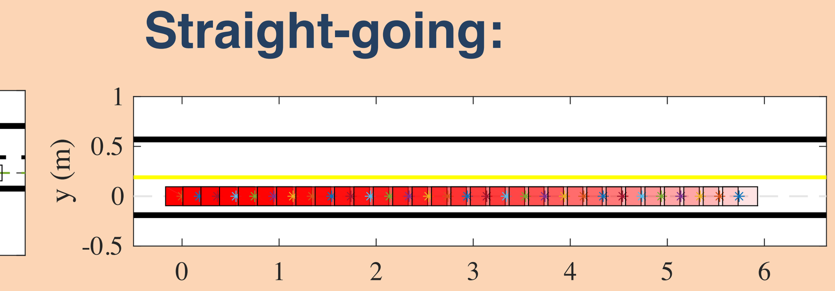
Overtaking:



Car-following:



Straight-going:



L. Sun, C. Peng, W. Zhan, and M. Tomizuka, "A Fast Integrated Planning and Control Framework for Autonomous Driving", submitted to IROS2017.