

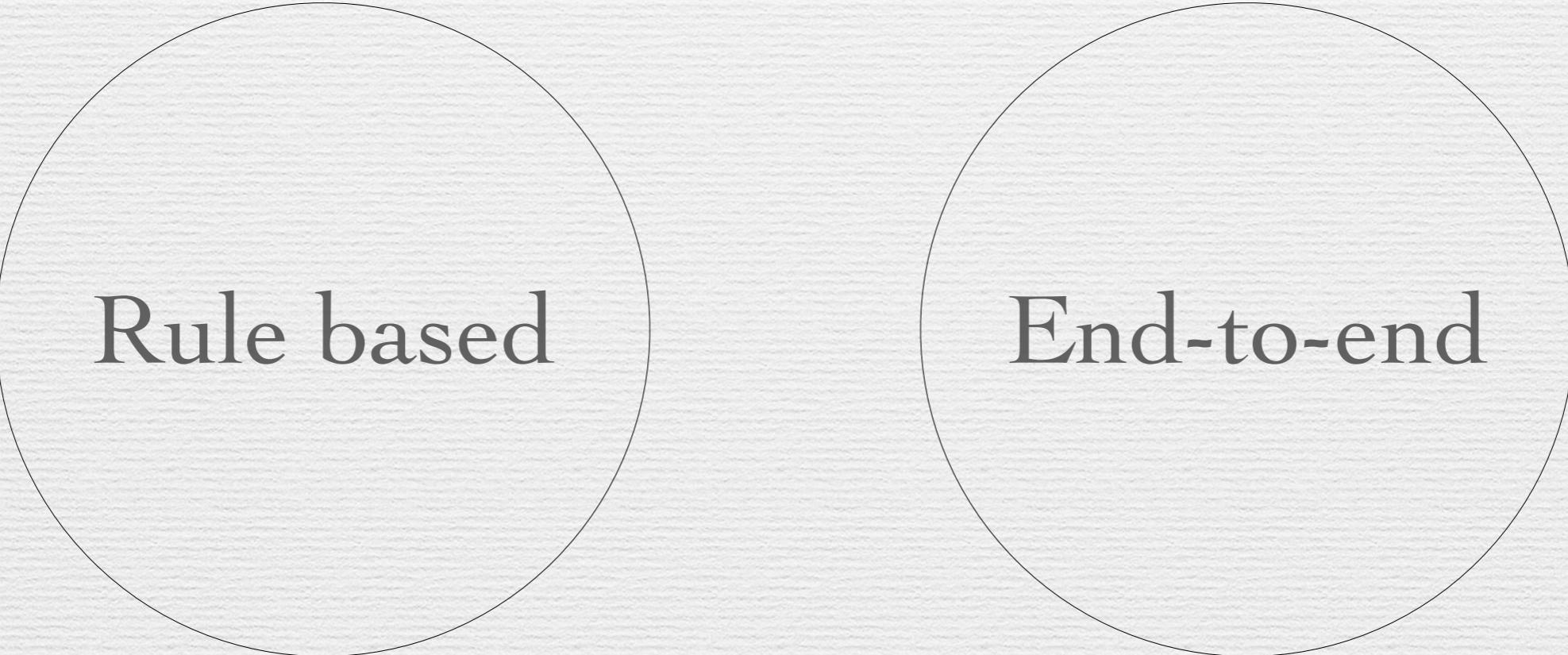
媒体智能实验室
Media Intelligence Lab



End-to-end Deep Models For Self-driving Car

Yuchu Luo
Intelligent Agent Group
26 November, 2017

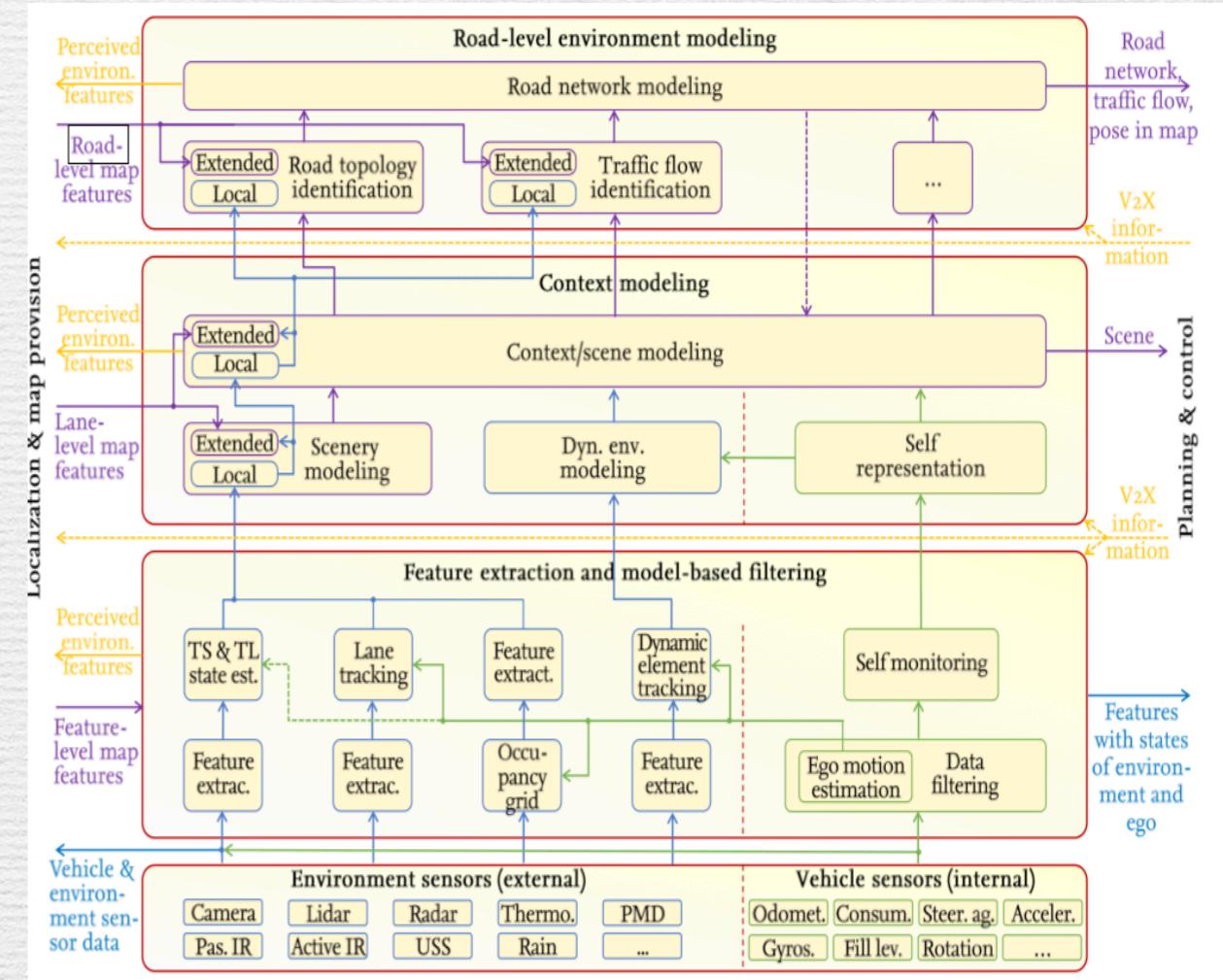
Categories of driving systems



Rule based

End-to-end

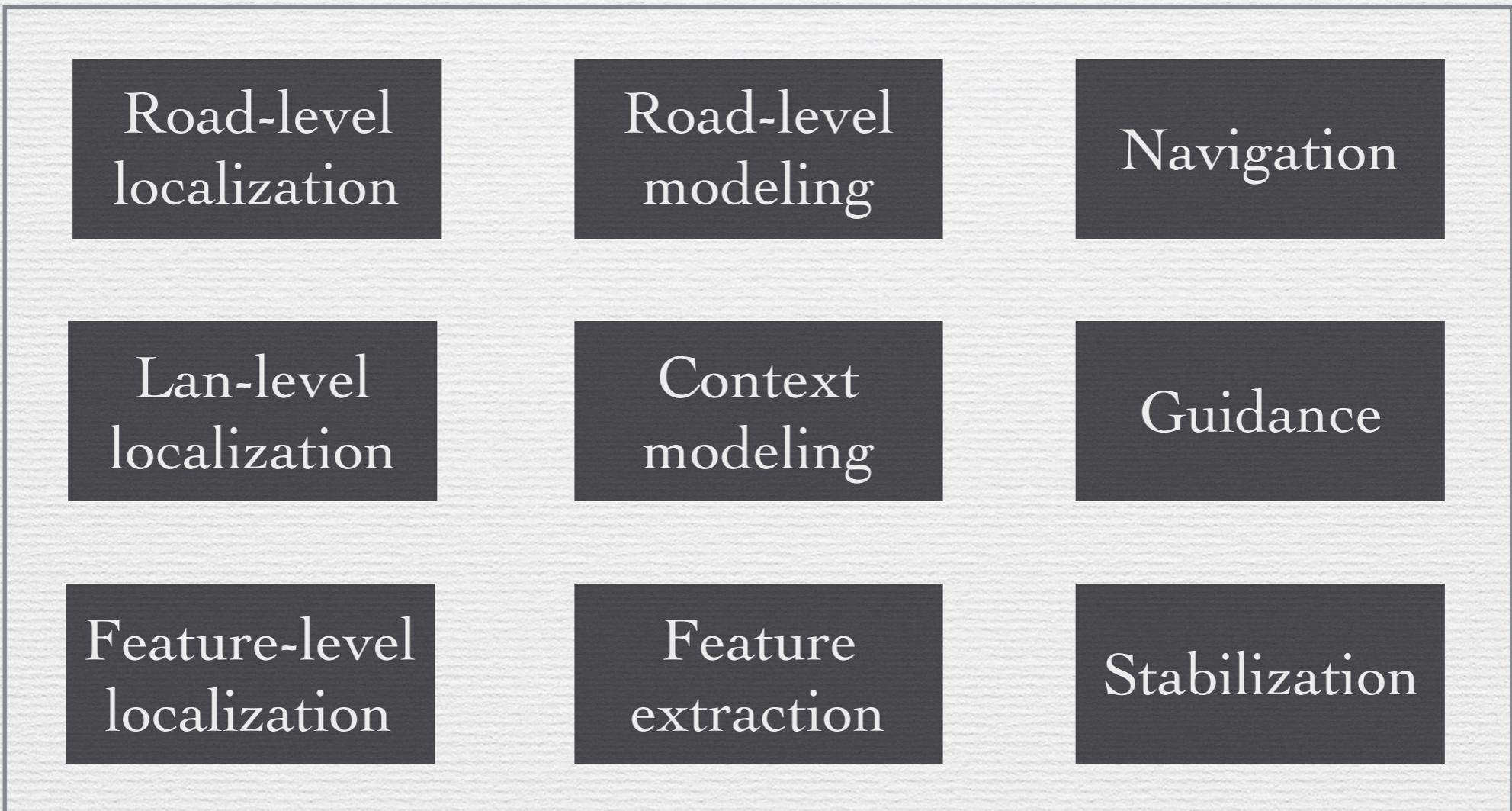
Rule based



Huval, Brody, et al. "An empirical evaluation of deep learning on highway driving." arXiv preprint arXiv:1504.01716 (2015).

Ulbrich, Simon, et al. "Towards a Functional System Architecture for Automated Vehicles." arXiv preprint arXiv:1703.08557 (2017).

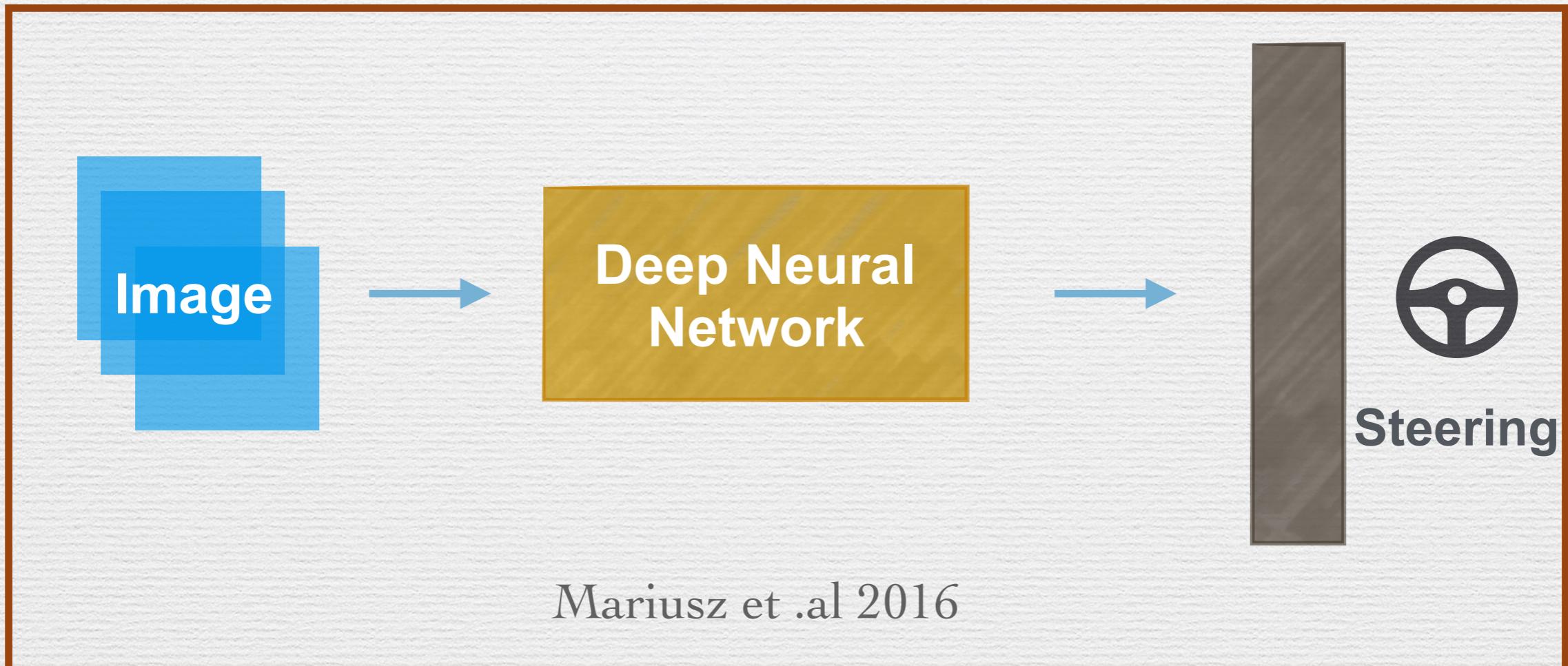
Rule based



Rule based vs End-to-end

		Rule based	End-to-end
function	reactive control (边打电话边开车)		
	proactive planning (思考判断怎么开)		
system complexity		very high	very low
interpretability		high	low
scale costs		high (HD Map)	low
sensor costs		very high	low
computing power (on board)		very high	low

End-to-end



End-to-end

ALVINN - 1989

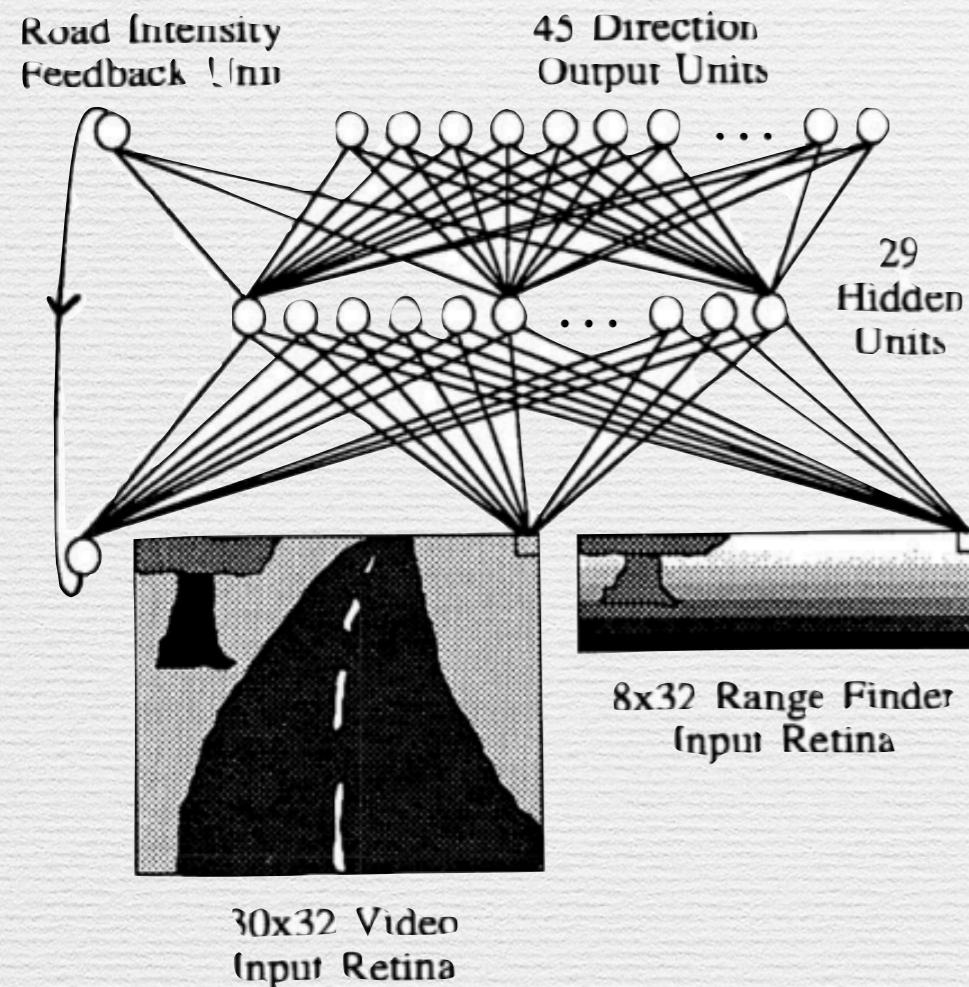
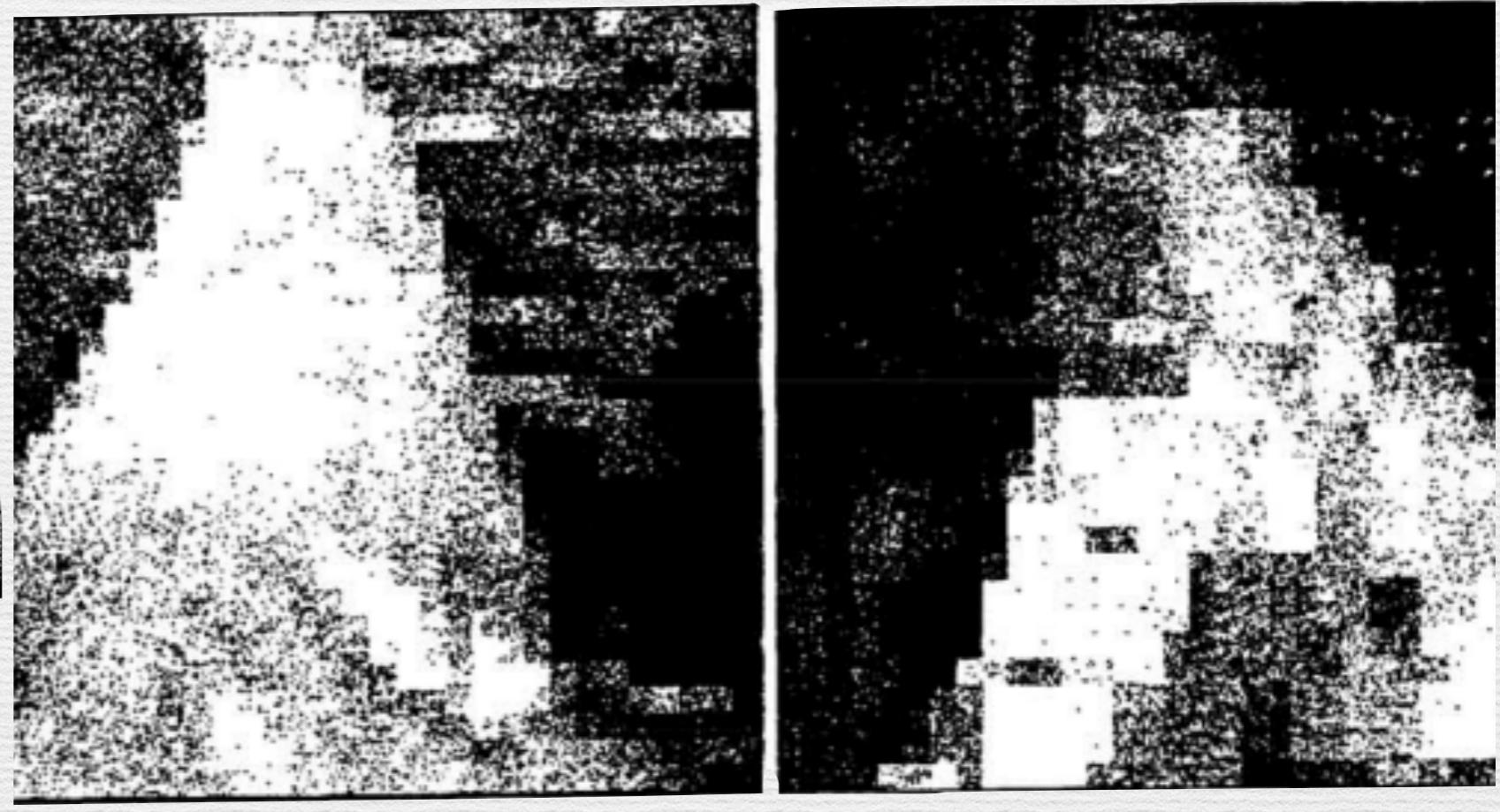


Figure 1. ALVINN Architecture



Real Road Image

Simulated Road Image

Figure 2. Real and simulated road images

Pomerleau, Dean A. "Alvinn: An autonomous land vehicle in a neural network." Advances in neural information processing systems. 1989.

End-to-end

DAVE - 2006

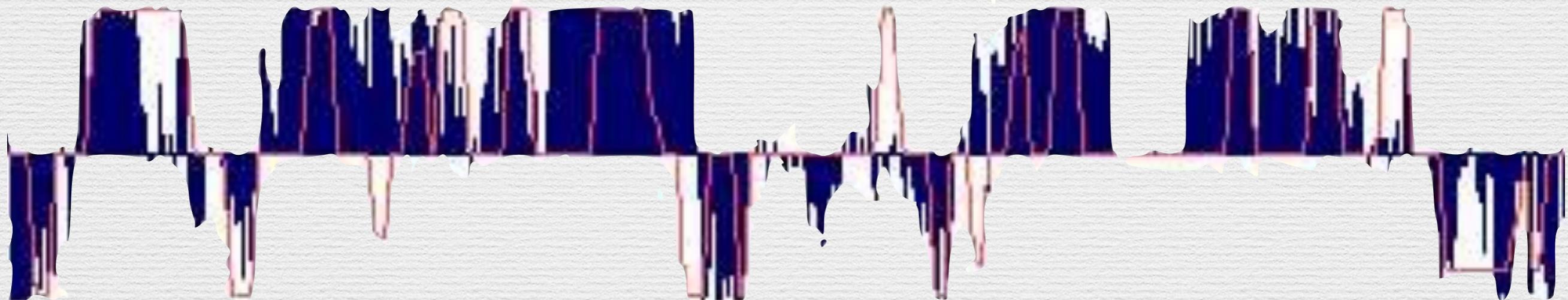


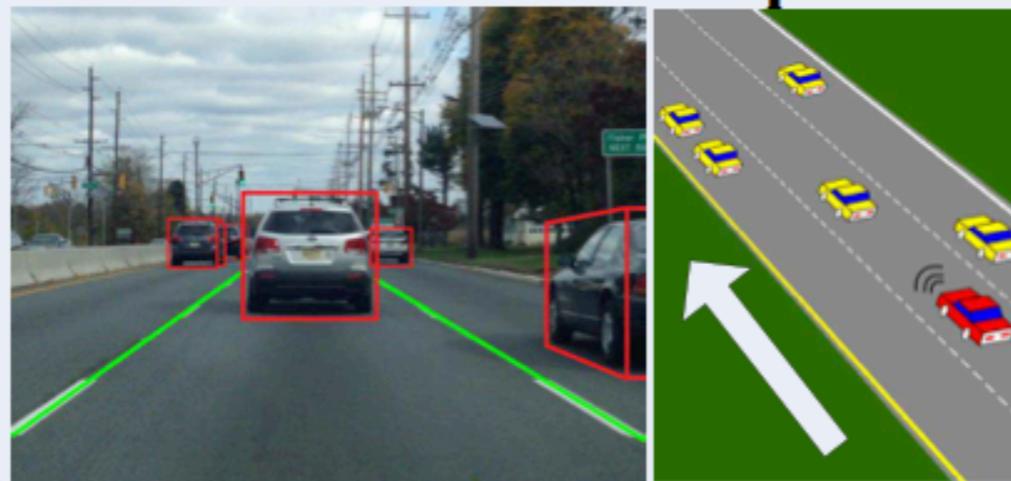
Figure: The steering angle produced by the system (black) compared to the steering angle provided by the human operator (red line) for 8000 frames from the test set. Very few obstacles would not have been avoided by the system.

Muller, Urs, et al. "Off-road obstacle avoidance through end-to-end learning.
" Advances in neural information processing systems. 2006.APA

End-to-end (Intermediate Approach)

DeepDriving - 2015

Mediated Perception

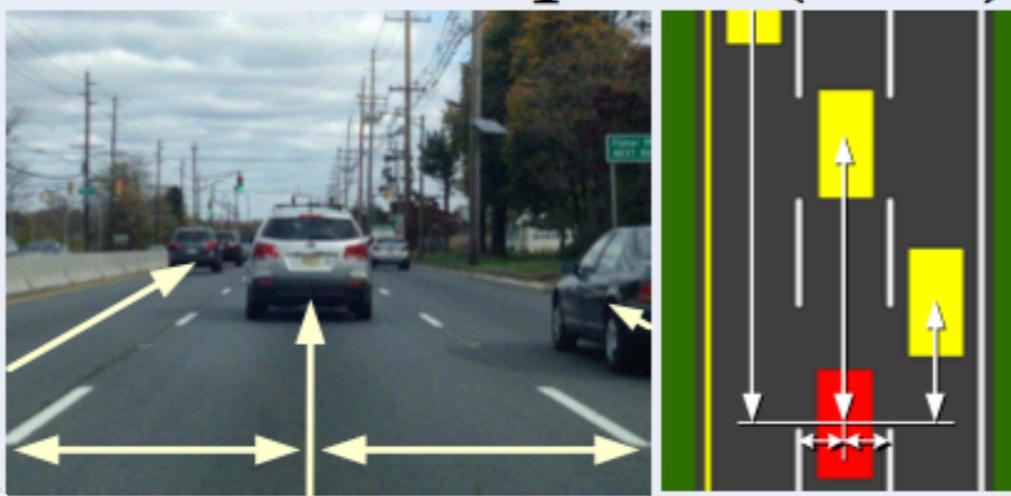


Input Image



Behavior Reflex

Direct Perception (ours)



Driving Control

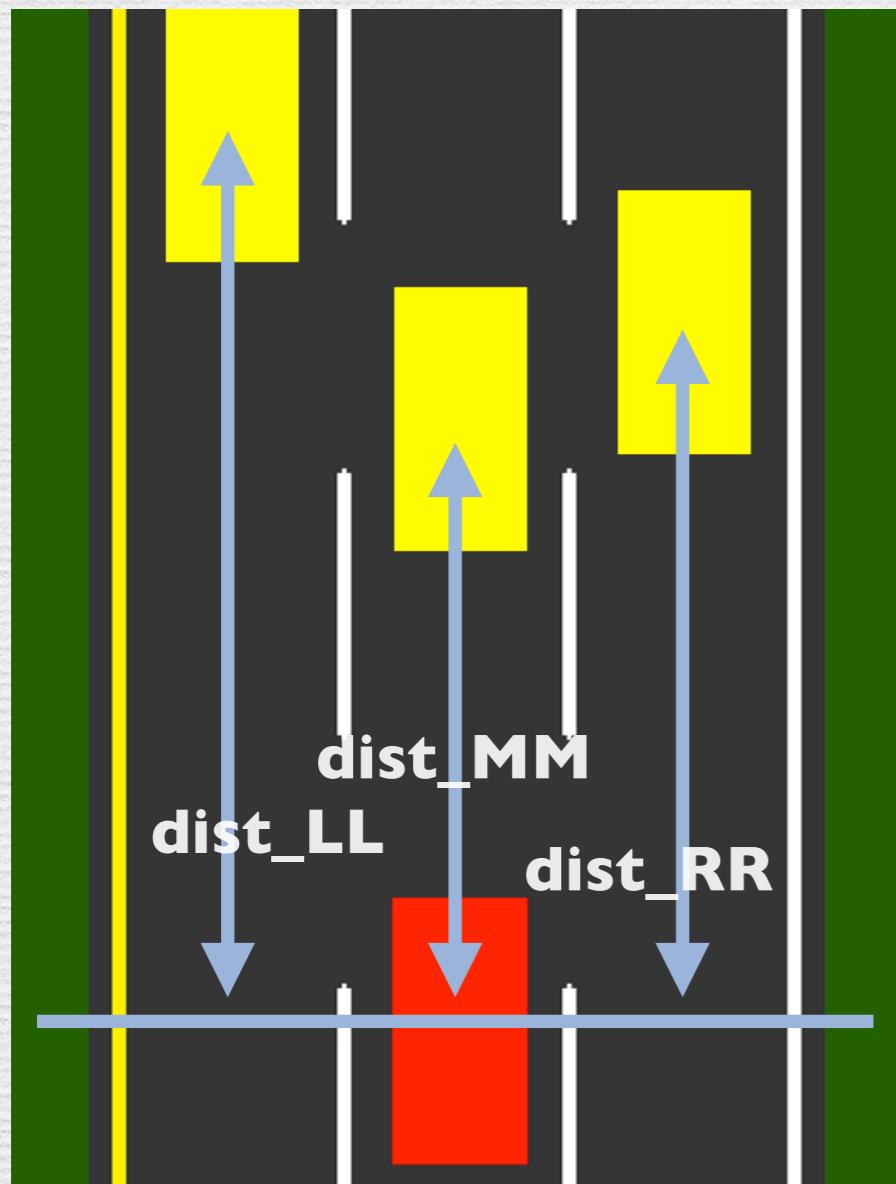


Chen, Chenyi, et al. "Deepdriving: Learning affordance for direct perception in autonomous driving." Proceedings of the IEEE International Conference on Computer Vision. 2015.

End-to-end (Intermediate Approach)

DeepDriving - 2015

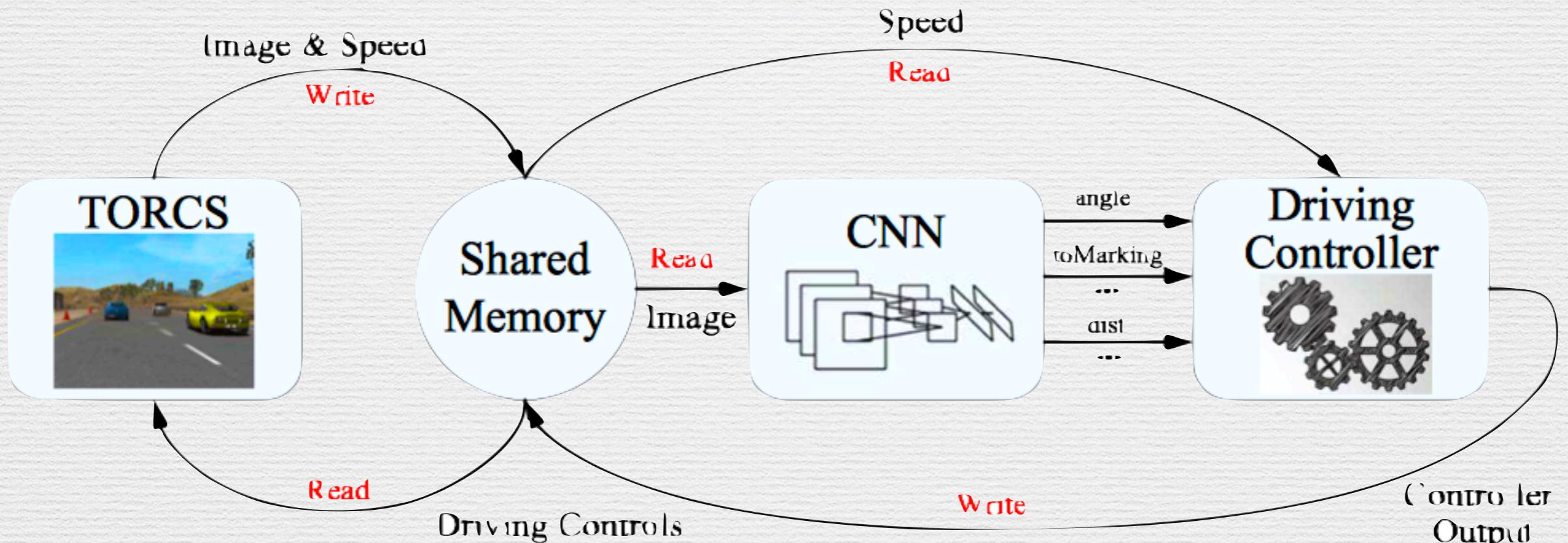
Learn the traffic representation



- 1) **angle**: angle between the car's heading and the tangent of the road "in lane system", when driving in the lane:
- 2) **toMarking LL**: distance to the left lane marking of the left lane
- 3) **toMarking ML**: distance to the left lane marking of the current lane
- 4) **toMarking MR**: distance to the right lane marking of the current lane
- 5) **toMarking RR**: distance to the right lane marking of the right lane
- 6) **dist LL**: distance to the preceding car in the left lane
- 7) ...

End-to-end (Intermediate Approach)

DeepDriving - 2015



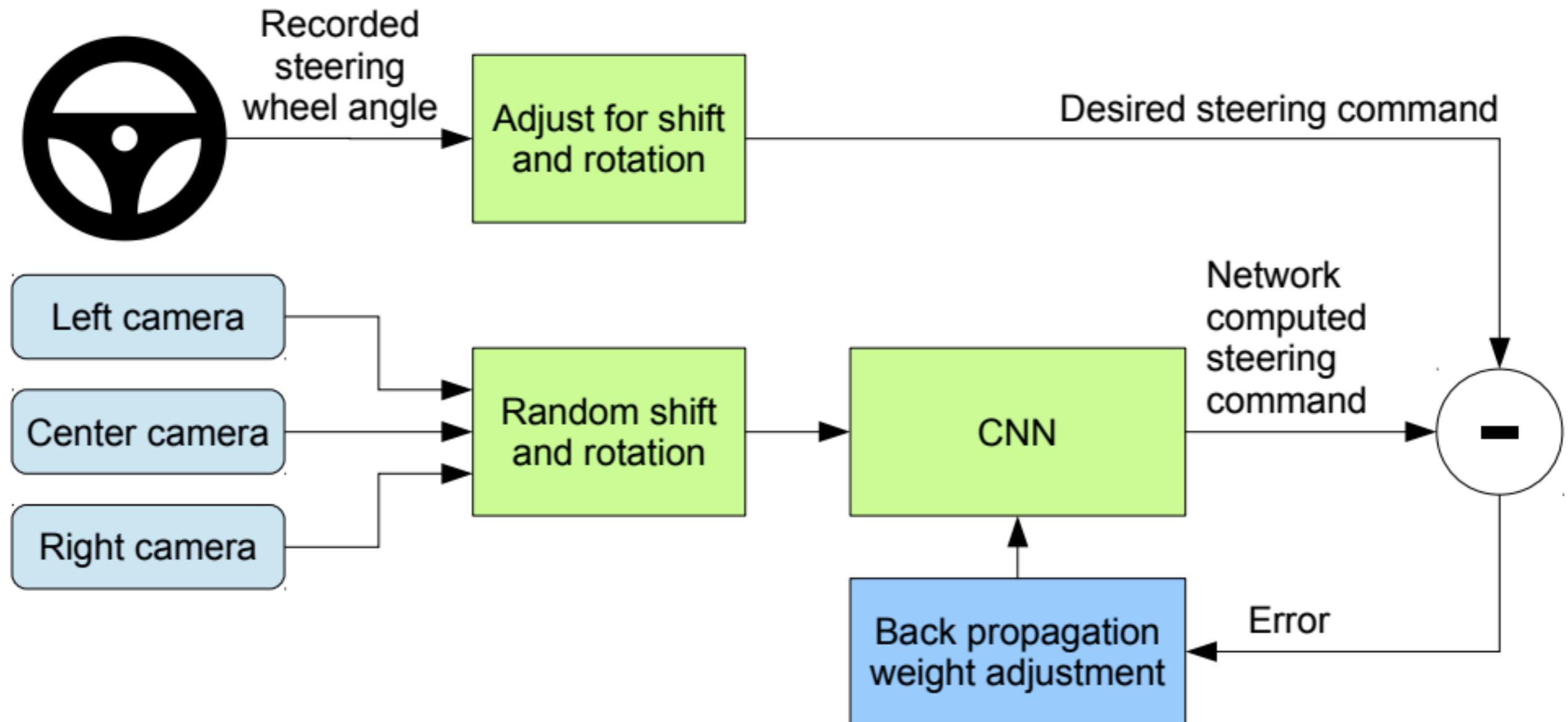
The ConvNet processes the TORCS image and estimates 13 indicators for driving. Based on the indicators and the current speed of the car, a controller computes the driving commands which will be sent back to TORCS to drive the host car in it.

End-to-end (Intermediate Approach)

- Better interpretability
- Less human-design modules
- Can't cover all the corner cases

End-to-end

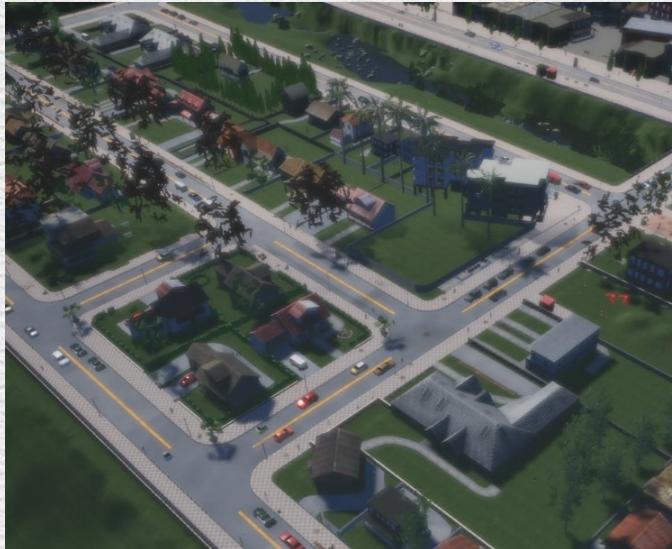
Self-driving Car - 2016



仿真实验中，90% 的情况下 CNN 可以自动驾驶
路测表明，不同路况自动驾驶的概率为 98%

End-to-end

Conditional Imitation Learning - 2017



The vehicle was given the command
“turn right at the next intersection”

Codevilla, Felipe, et al. "End-to-end driving via conditional imitation learning."
arXiv preprint arXiv:1710.02410 (2017).

Dataset

Real data

- Udacity
- Oxford
- Comma.ai
- **Berkeley**
- **Baidu Apollo**

Simulation data

- OpenAI
- Universal
- DeepMind
- TORCS
- Virtual KITTI

Berkeley Data Drive



30 fps
720 p

Over 400 hours of HD video sequences across many different times in the day, weather conditions, and driving scenarios. Our video sequences also include GPS locations, IMU data, and timestamps.

How to apply these dataset
to a real driving task?

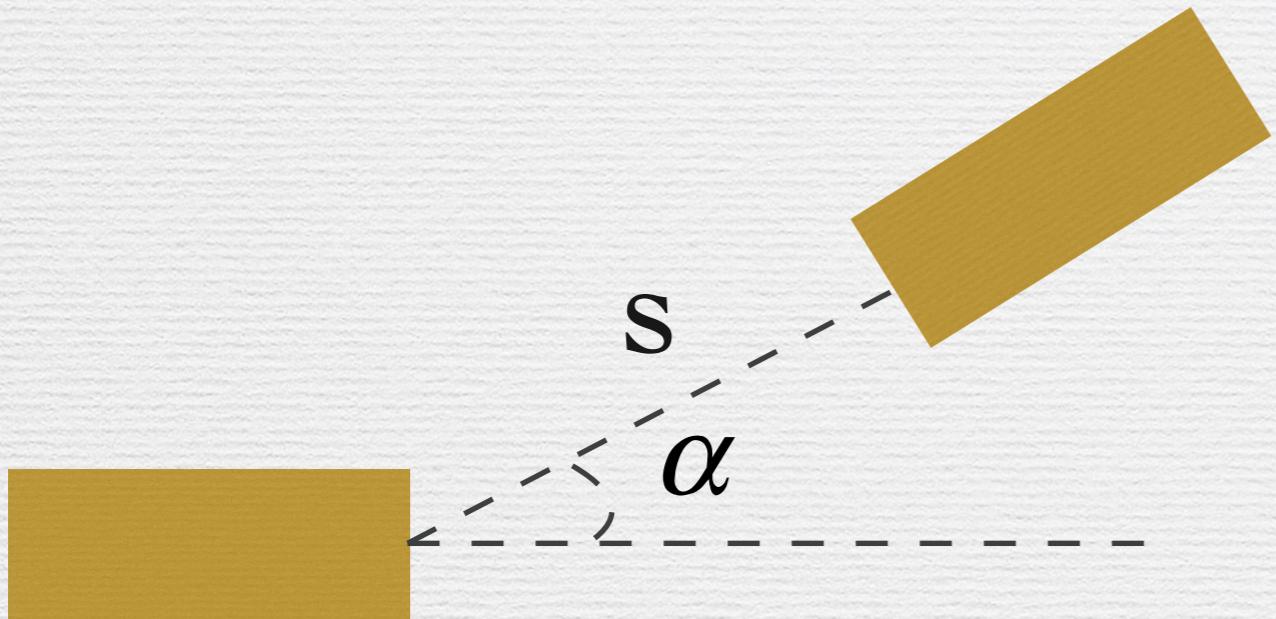
Imitation Learning - Behavior Cloning



(state_0, action_0, state_1, action_1, ..., state_n)

state: images from 3 camera
action: steering angle

Self-driving Formulation - Egomotion Prediction



$$F(s,a) : S \times A \rightarrow \mathbb{R}$$

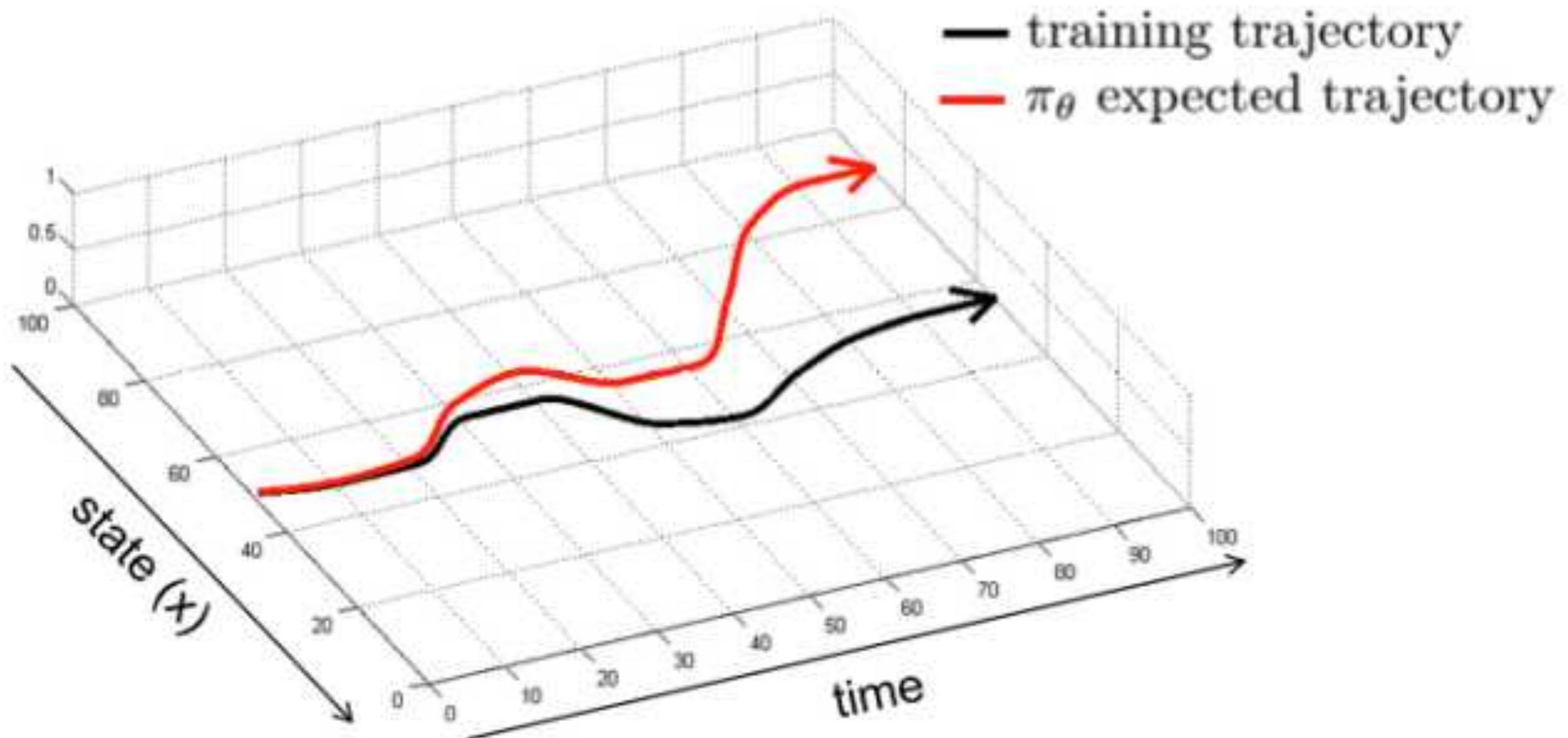
- State s :
 - visual information
 - vehicle dynamic state estimation
- Action a :
 - discrete: GO, STOP, LEFT, RIGHT
 - continuous: turning angle and acceleration next 0.1s
 - 6 DOF motions

**Not be affected
by vehicle
parameters**

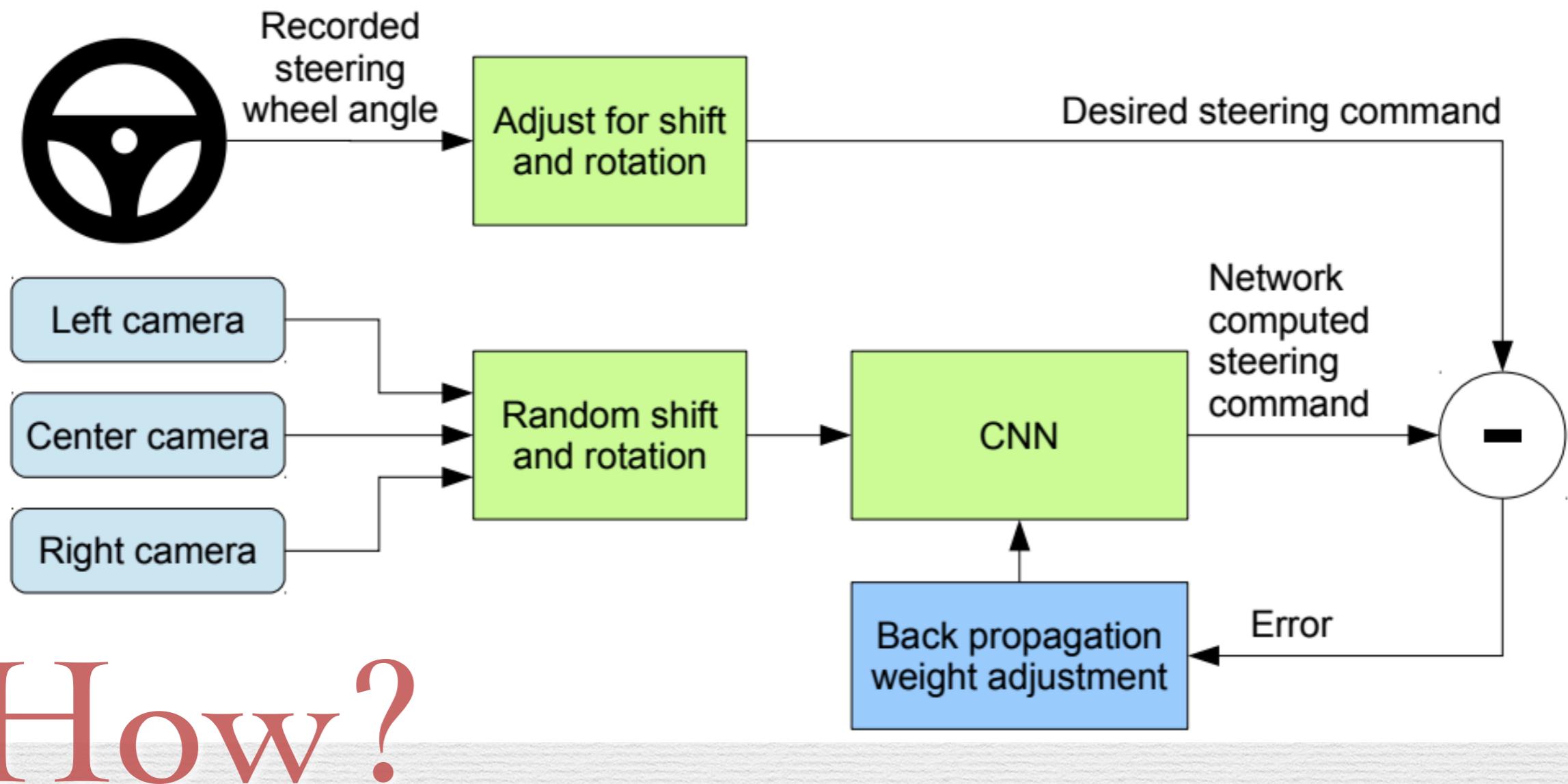
Problem: Compounding errors

$$E[\text{errors}] \leq \varepsilon(T + (T - 1) + (T - 2) + \dots + 1) \propto \varepsilon T^2$$

Distribution mismatch



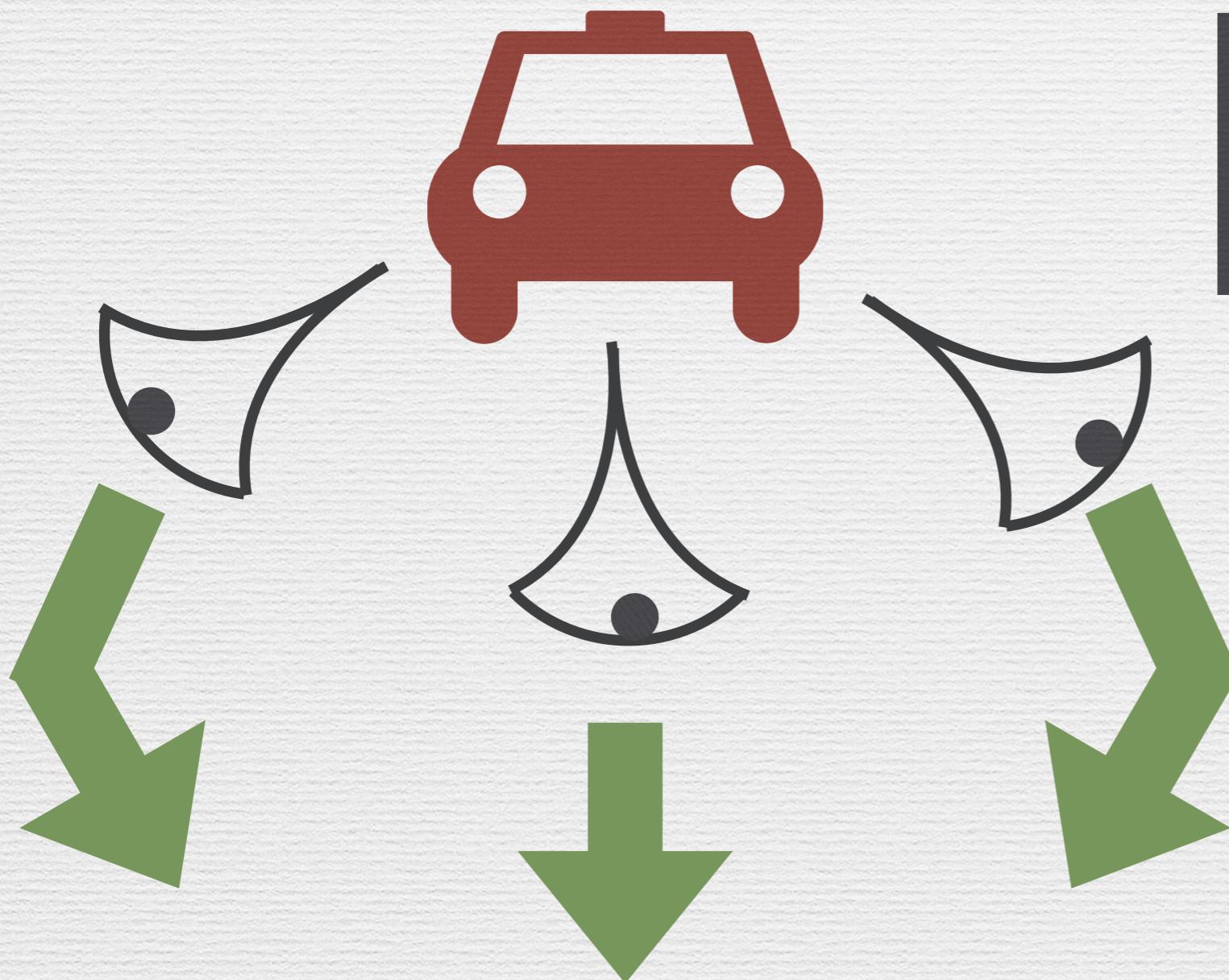
Self-driving Car - 2016



How?

仿真实验中，90% 的情况下 CNN 可以自动驾驶
路测表明，不同路况自动驾驶的概率为 98%

Self-driving Car - 2016



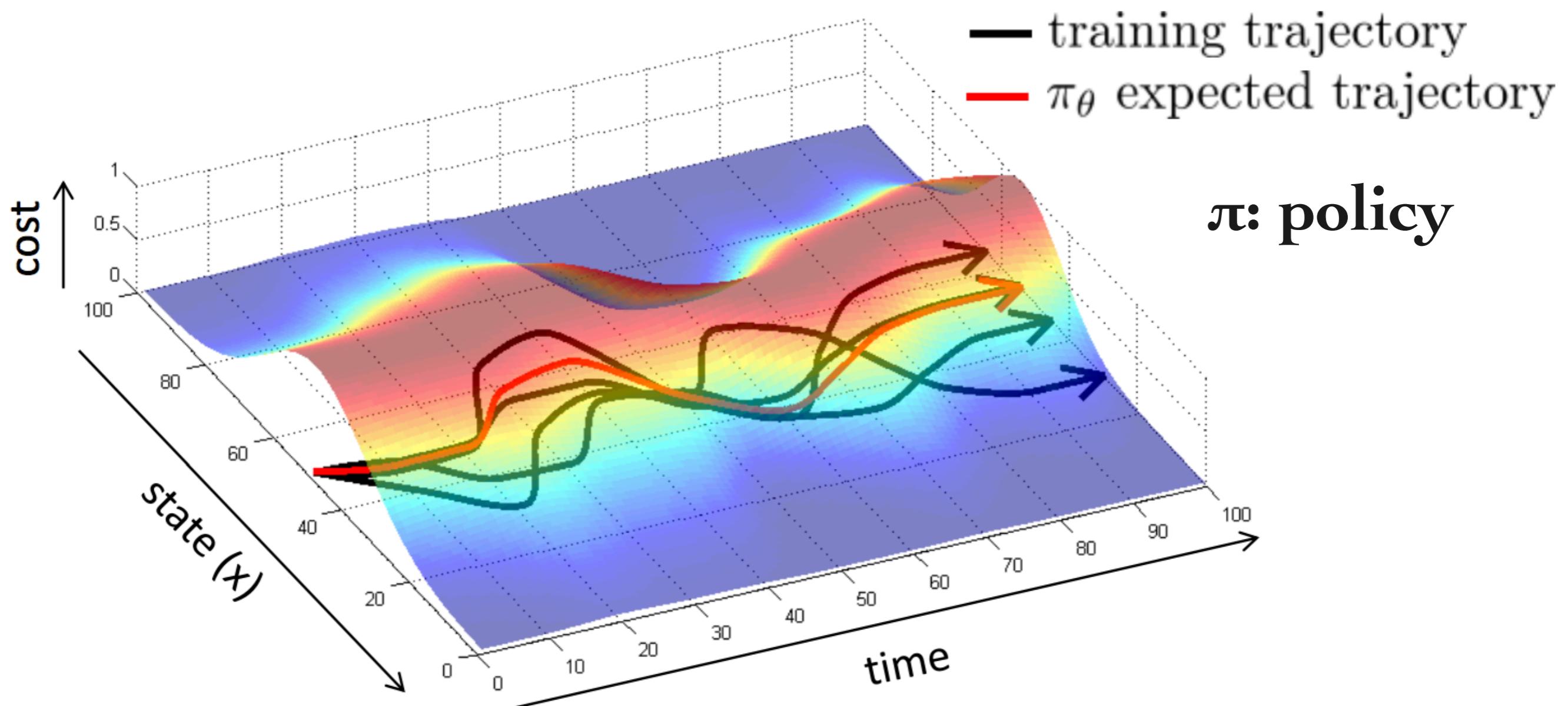
左右摄像头可以令无人车
从部分糟糕的状态中恢复

self-stability

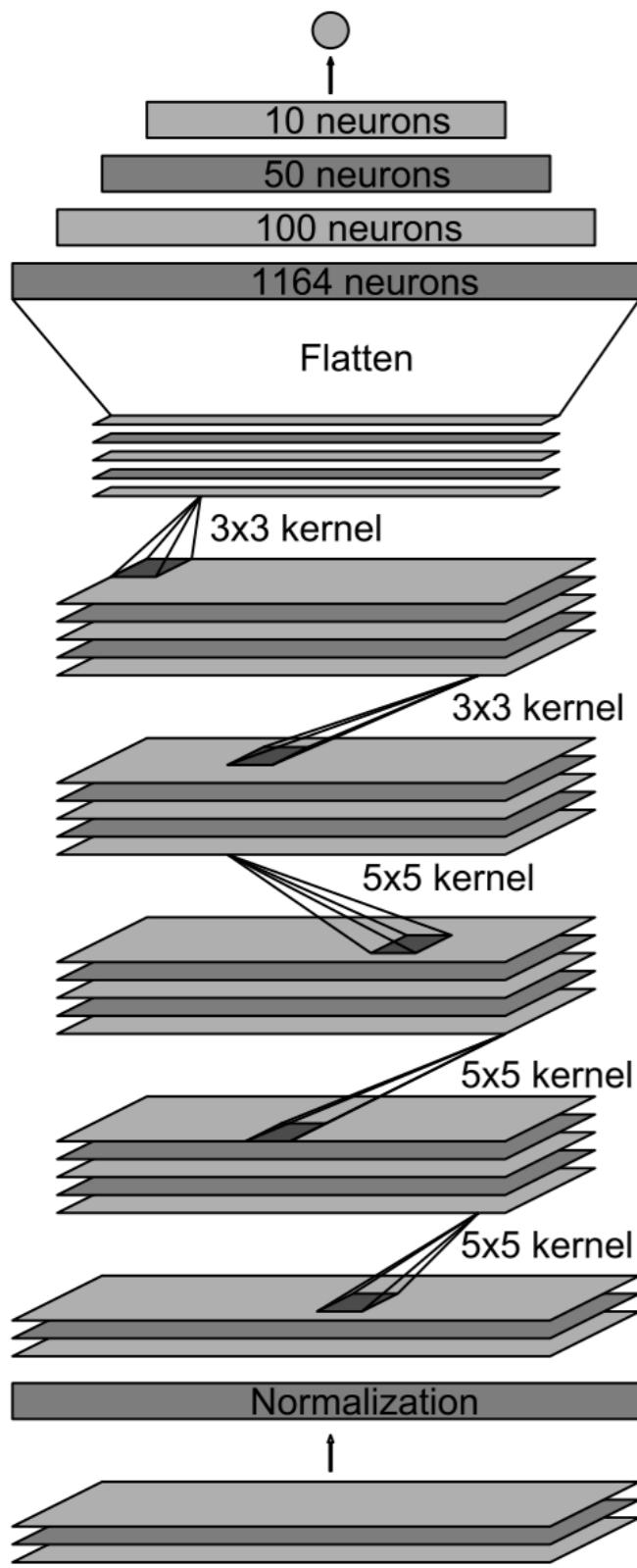
Recover from bad case.

The better way...

make $P_{data}(O_t) = P_\pi(O_t)$



Experiments



Output: vehicle control

Fully-connected layer

Fully-connected layer

Fully-connected layer

Convolutional
feature map
64@1x18

Convolutional
feature map
64@3x20

Convolutional
feature map
48@5x22

Convolutional
feature map
36@14x47

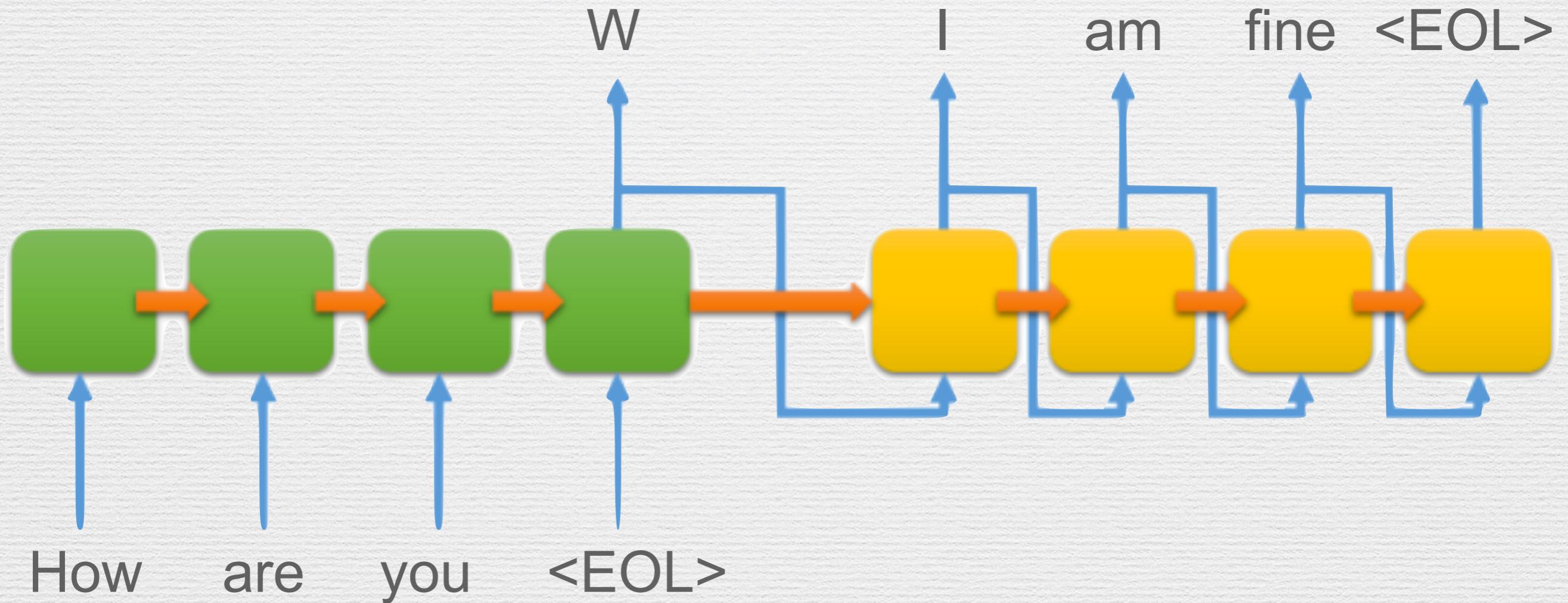
Convolutional
feature map
24@31x98

Normalized
input planes
3@66x200

Input planes
3@66x200

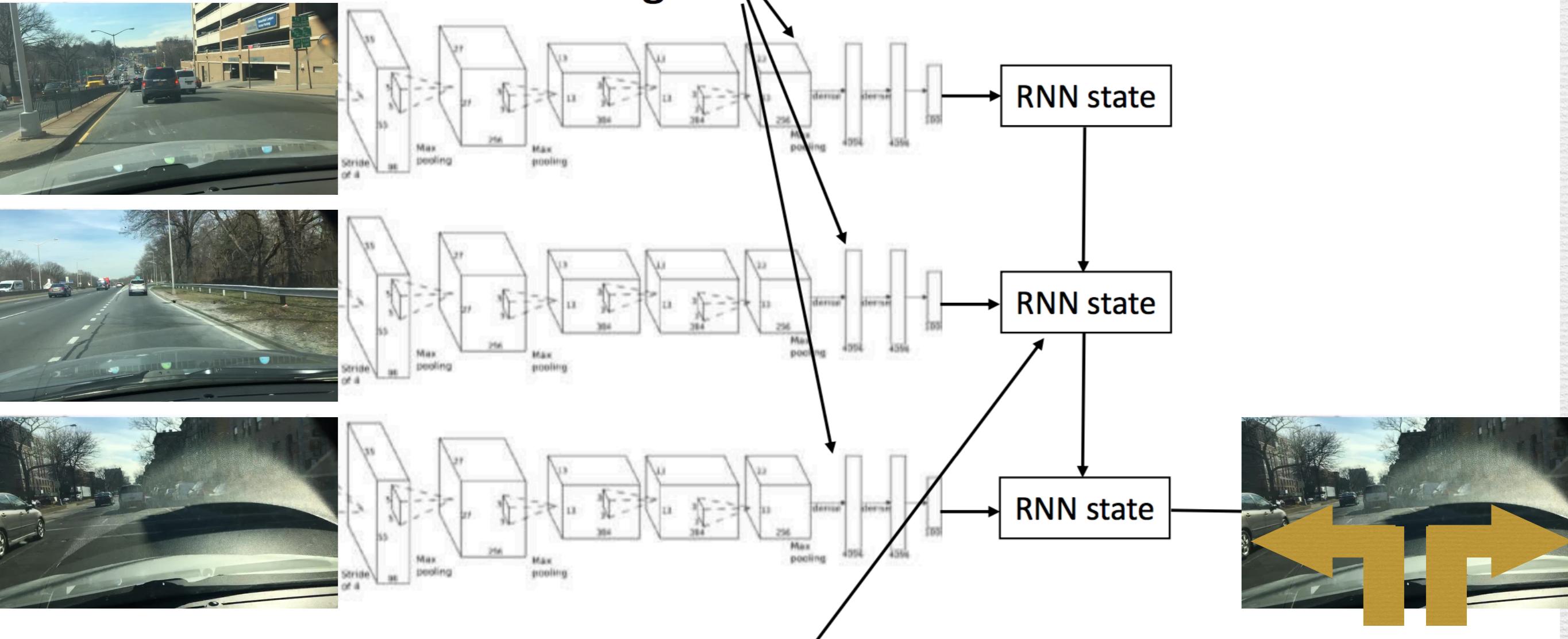


How to model historical information

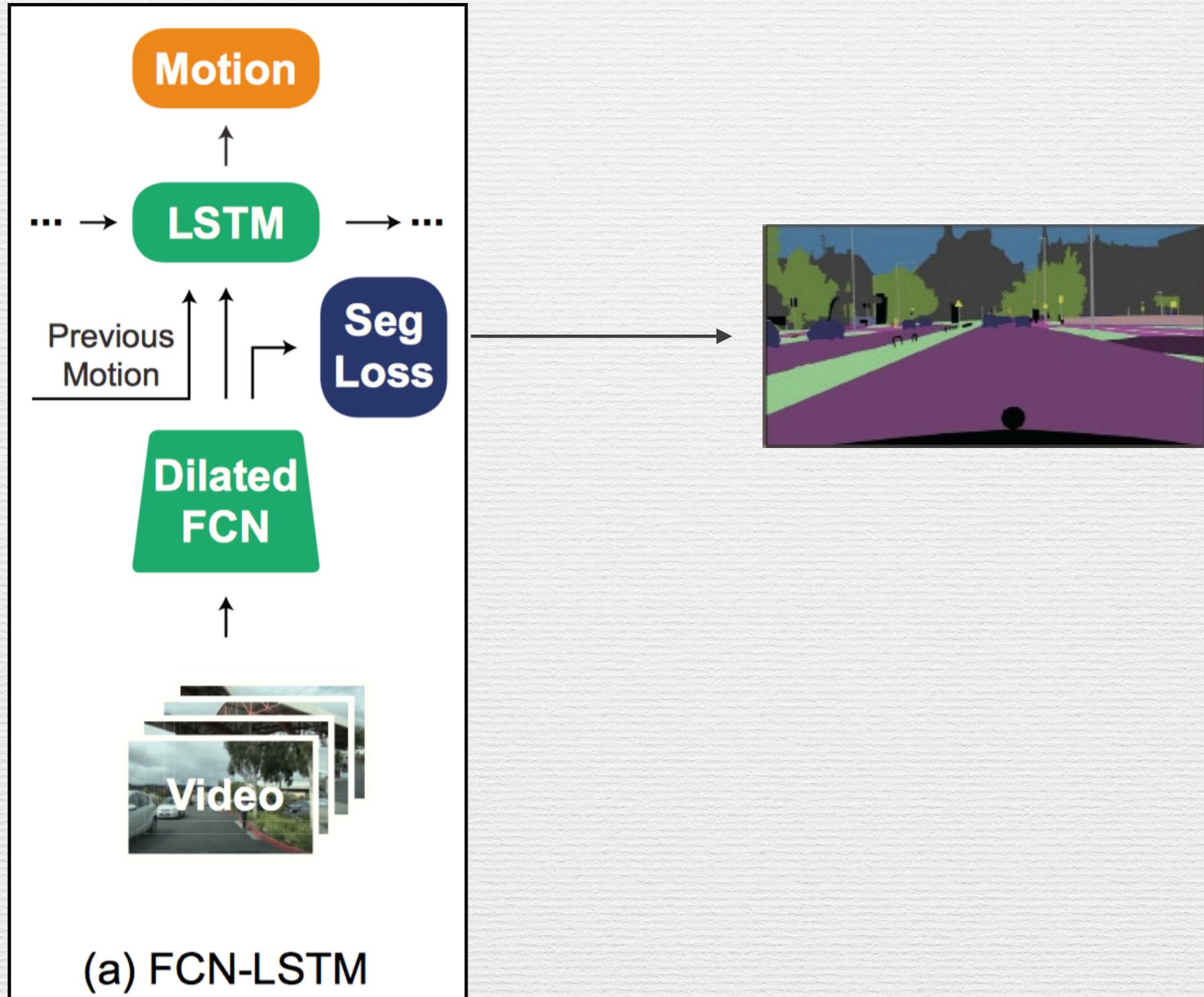


Seq2Seq Model (RNN)

RNN based architecture

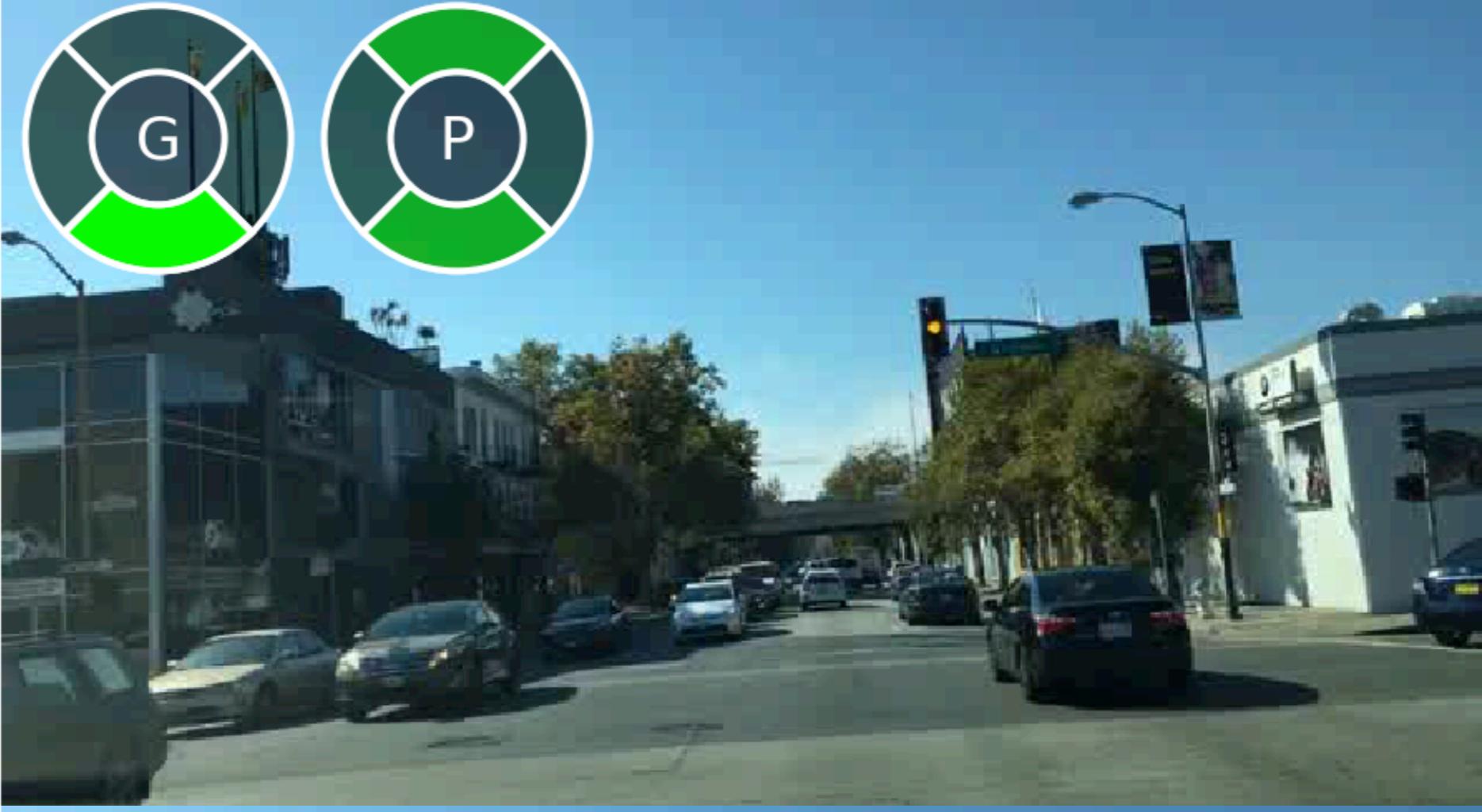


Typically, LSTM cells work better here



Xu, Huazhe, et al. "End-to-end learning of driving models from large-scale video datasets."
arXiv preprint arXiv:1612.01079(2016).

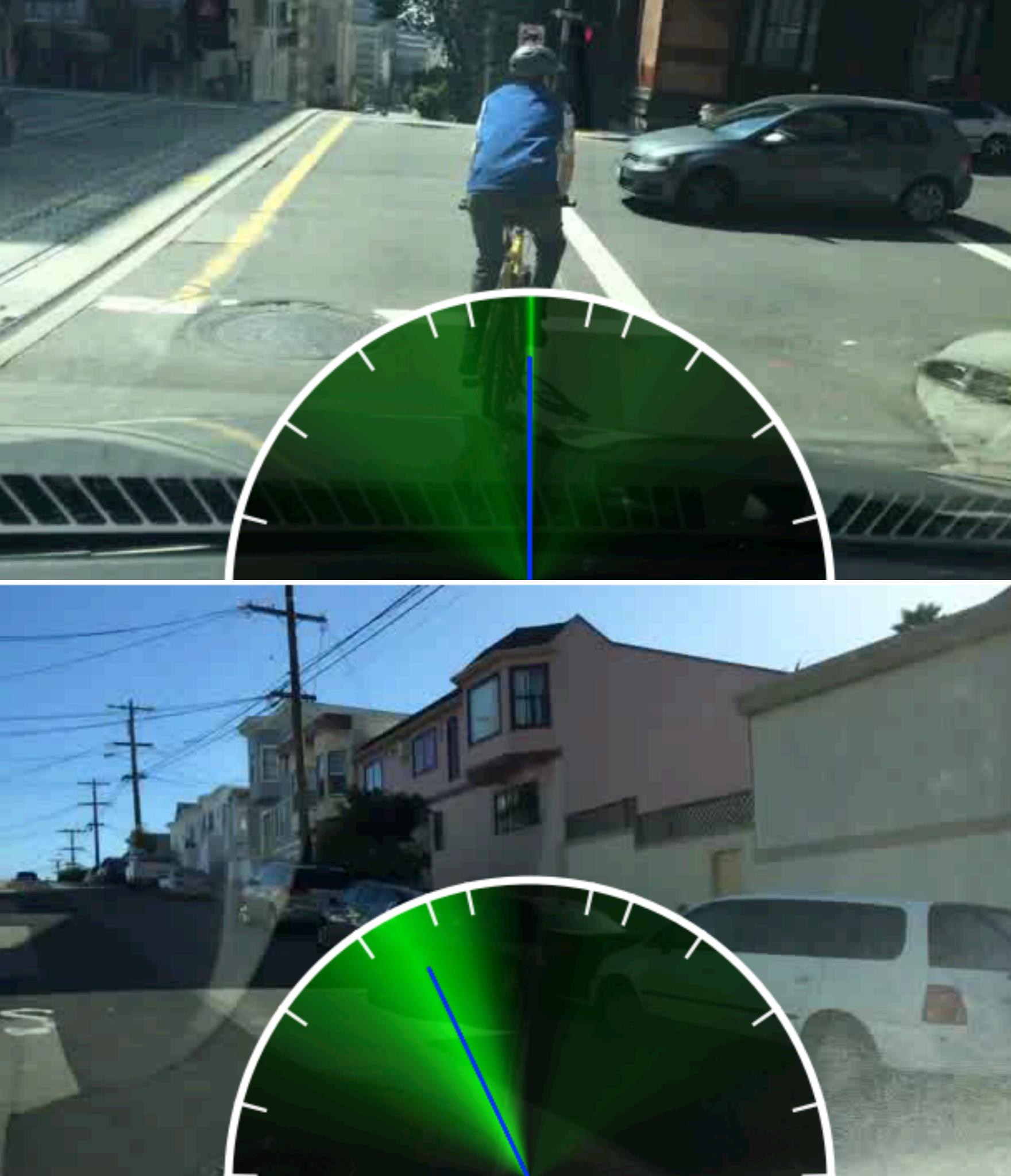
Discrete Action Driving Model

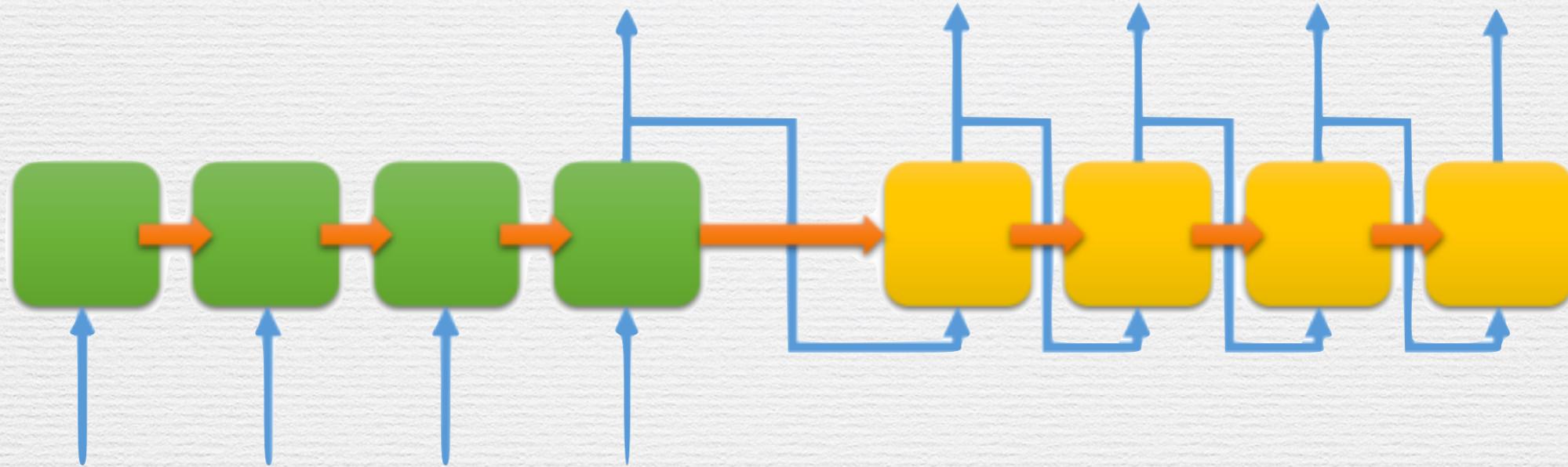


Xu, Huazhe, et al. "End-to-end learning of driving models from large-scale video datasets."
arXiv preprint arXiv:
1612.01079(2016).

Continuous Action Driving Model

Xu, Huazhe, et al. "End-to-end learning of driving models from large-scale video datasets."
arXiv preprint arXiv: 1612.01079(2016).



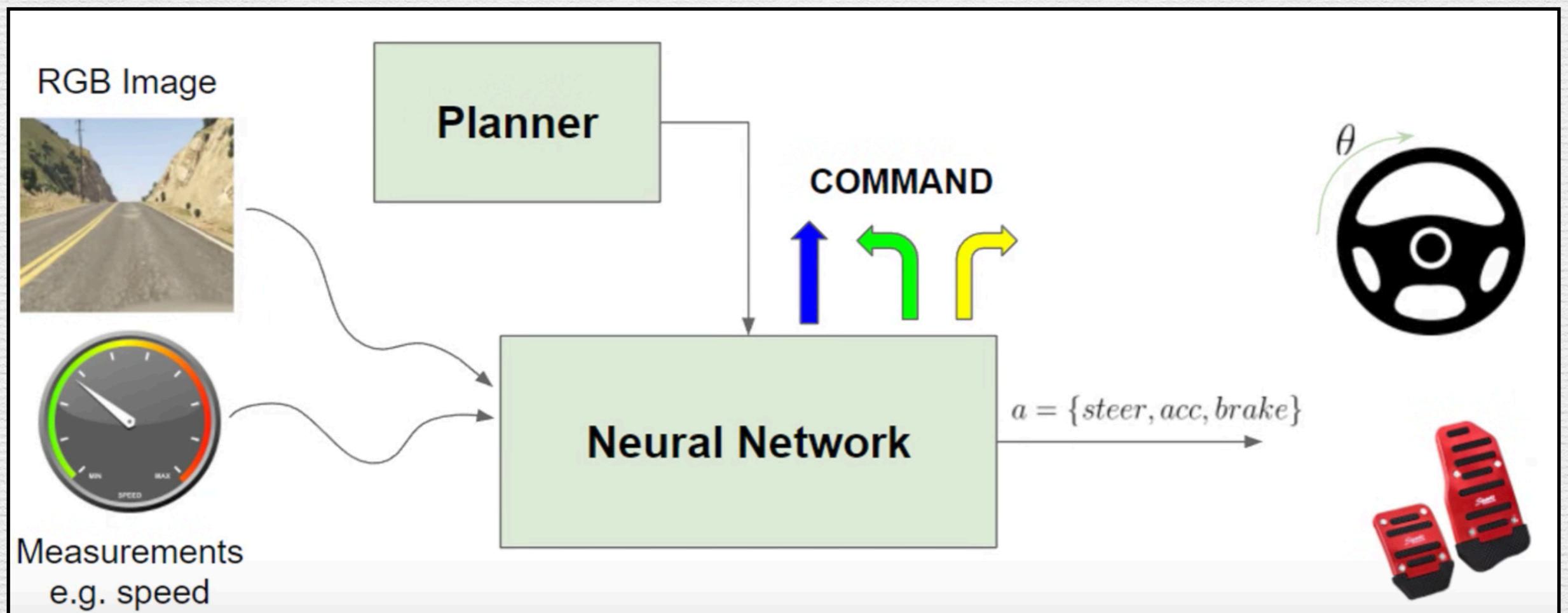


Advanced ideas:

- Attention mechanism
- 横纵向关联关系
- time-series
- ...

Conditional Imitation Learning - 2017

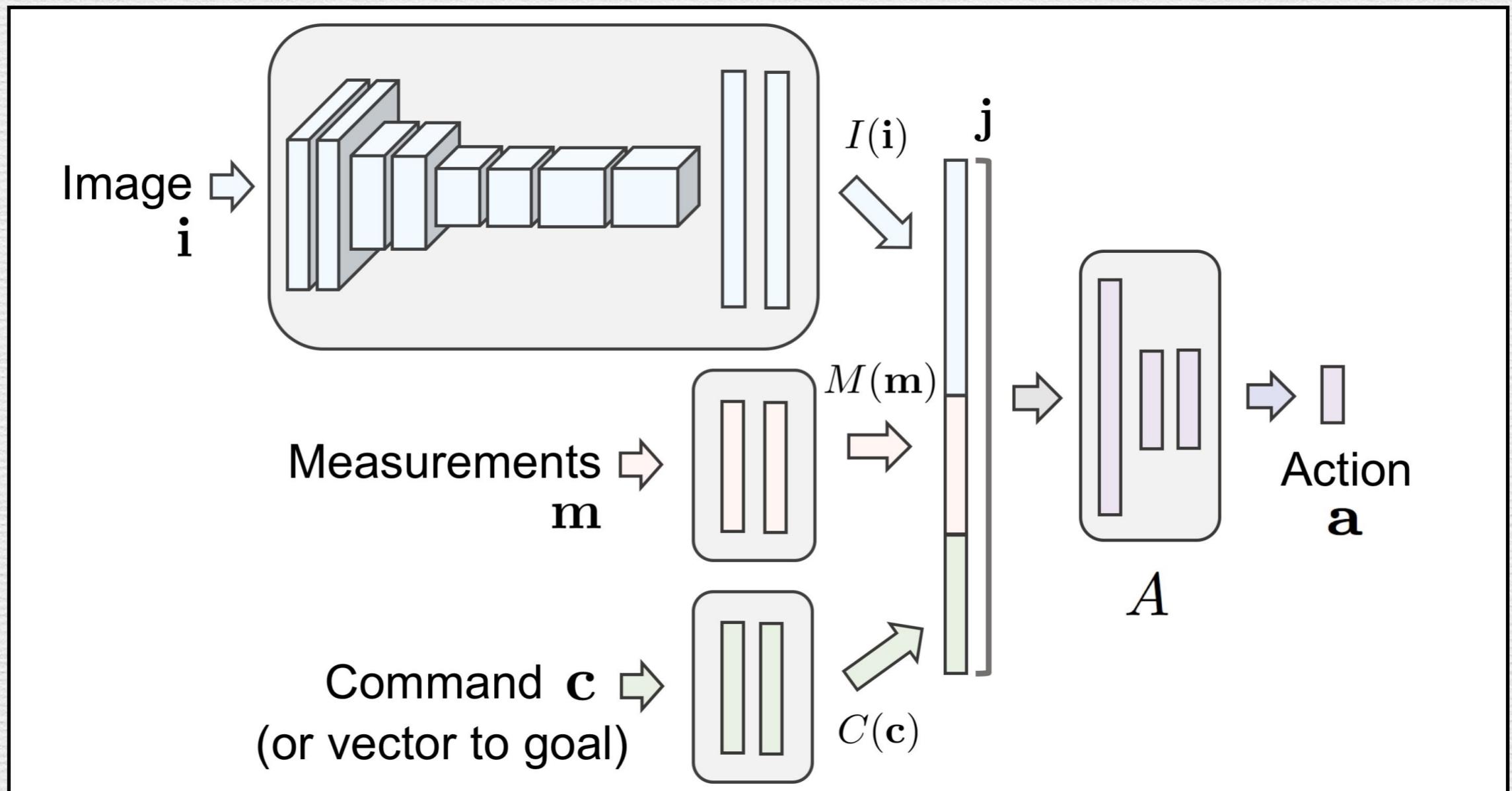
High-level overview



Codevilla, Felipe, et al. "End-to-end driving via conditional imitation learning."
arXiv preprint arXiv:1710.02410 (2017).

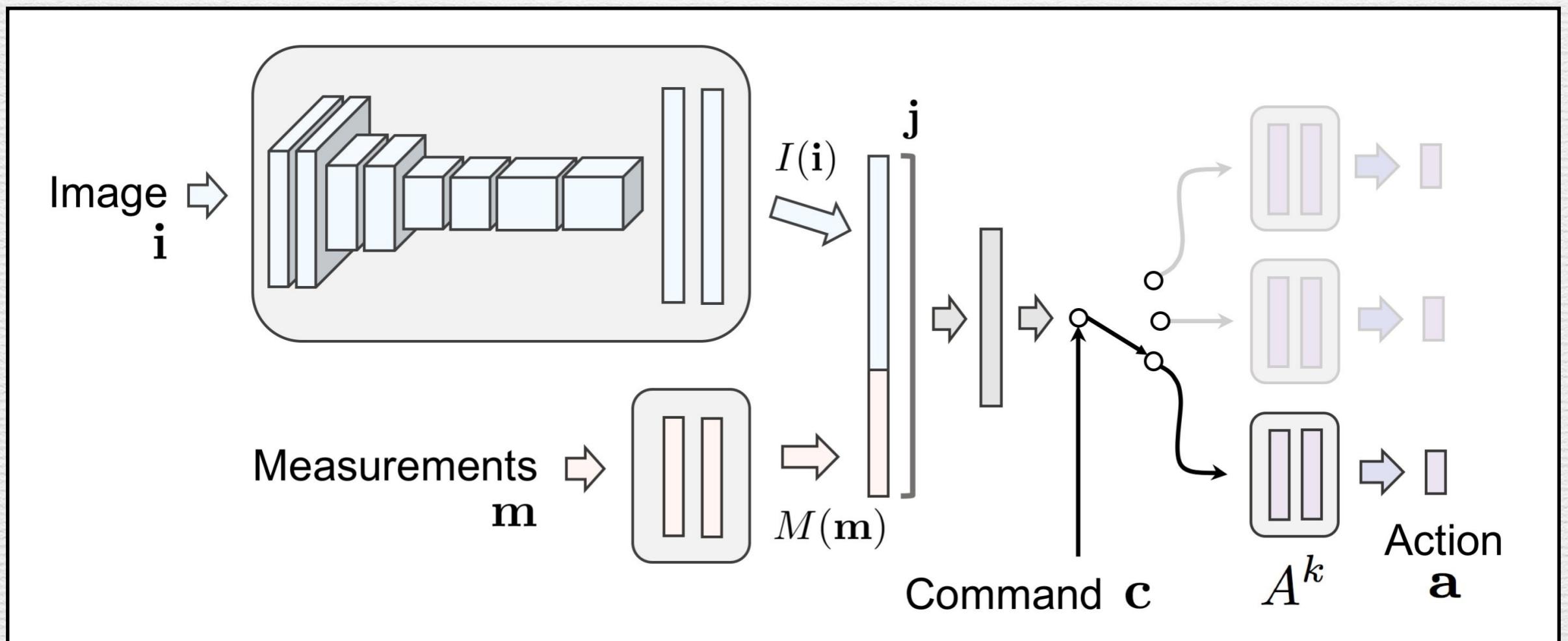
Conditional Imitation Learning - 2017

Network architecture I: command input

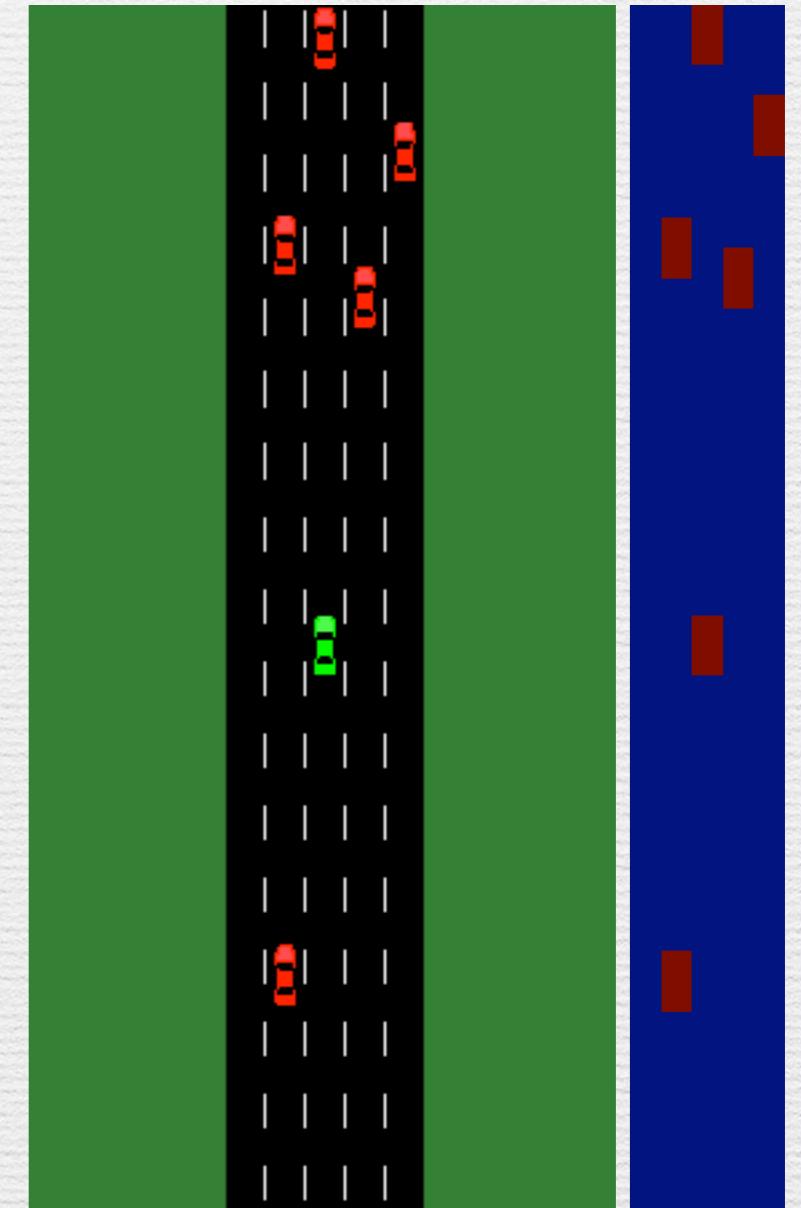


Conditional Imitation Learning - 2017

Network architecture II: branched



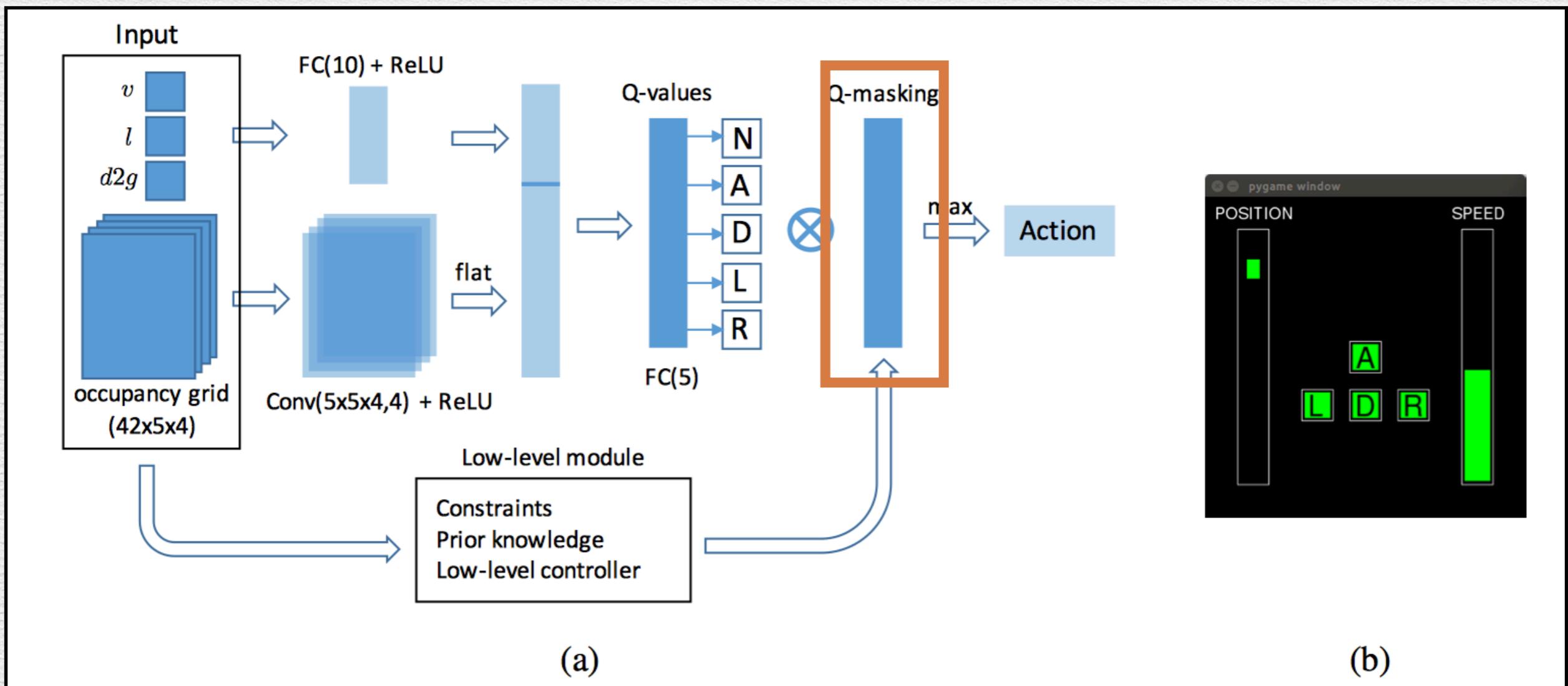
Lane Changing with Reinforcement Learning - 2017



Mukadam, Mustafa, et al.

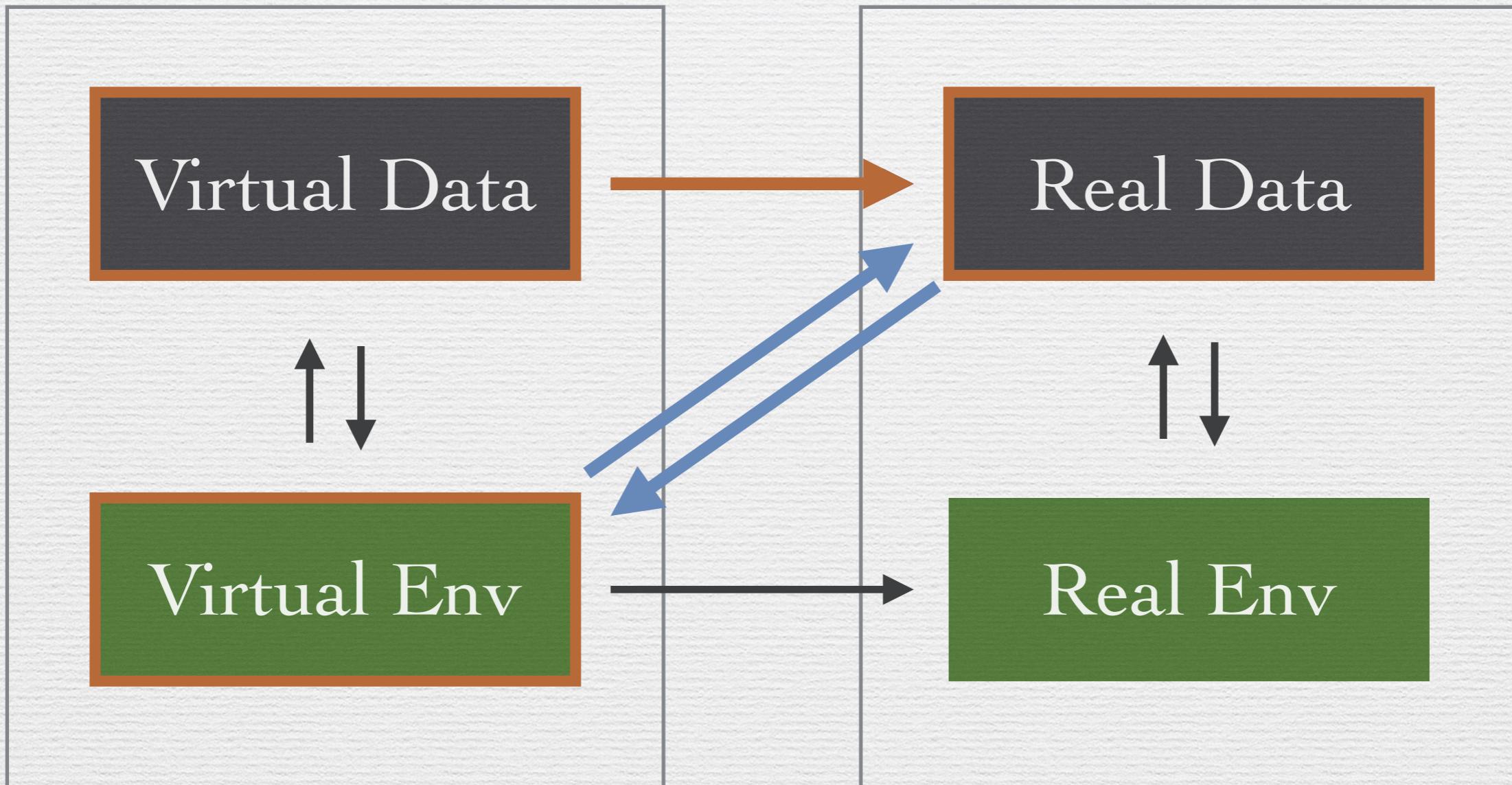
"Tactical Decision Making for Lane Changing with Deep Reinforcement Learning." (2017).

Framework



Our work

Task Doing: From Real to Virtual and From Virtual to Real



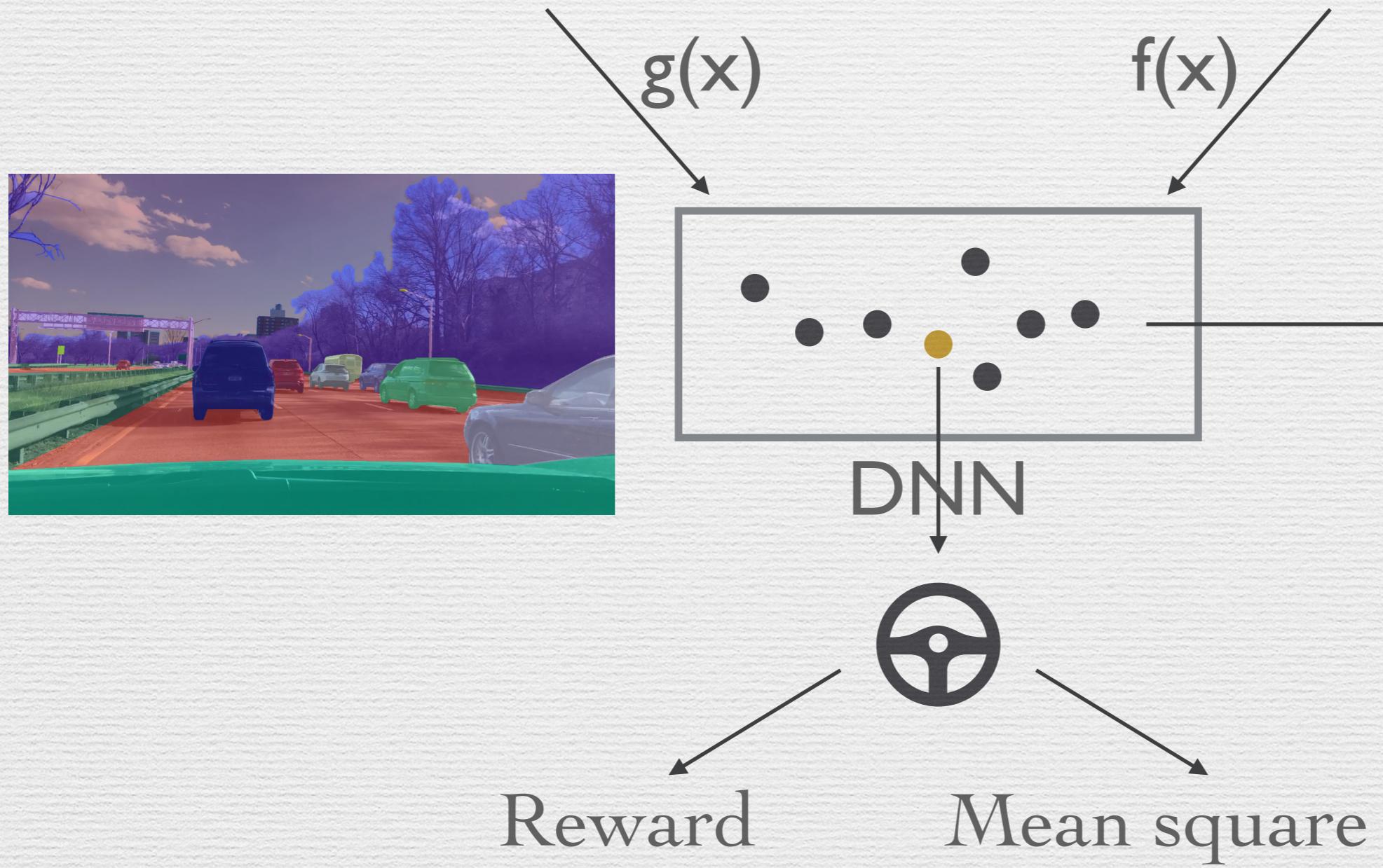
**Deep Reinforcement Learning
Generative Adversarial Network**



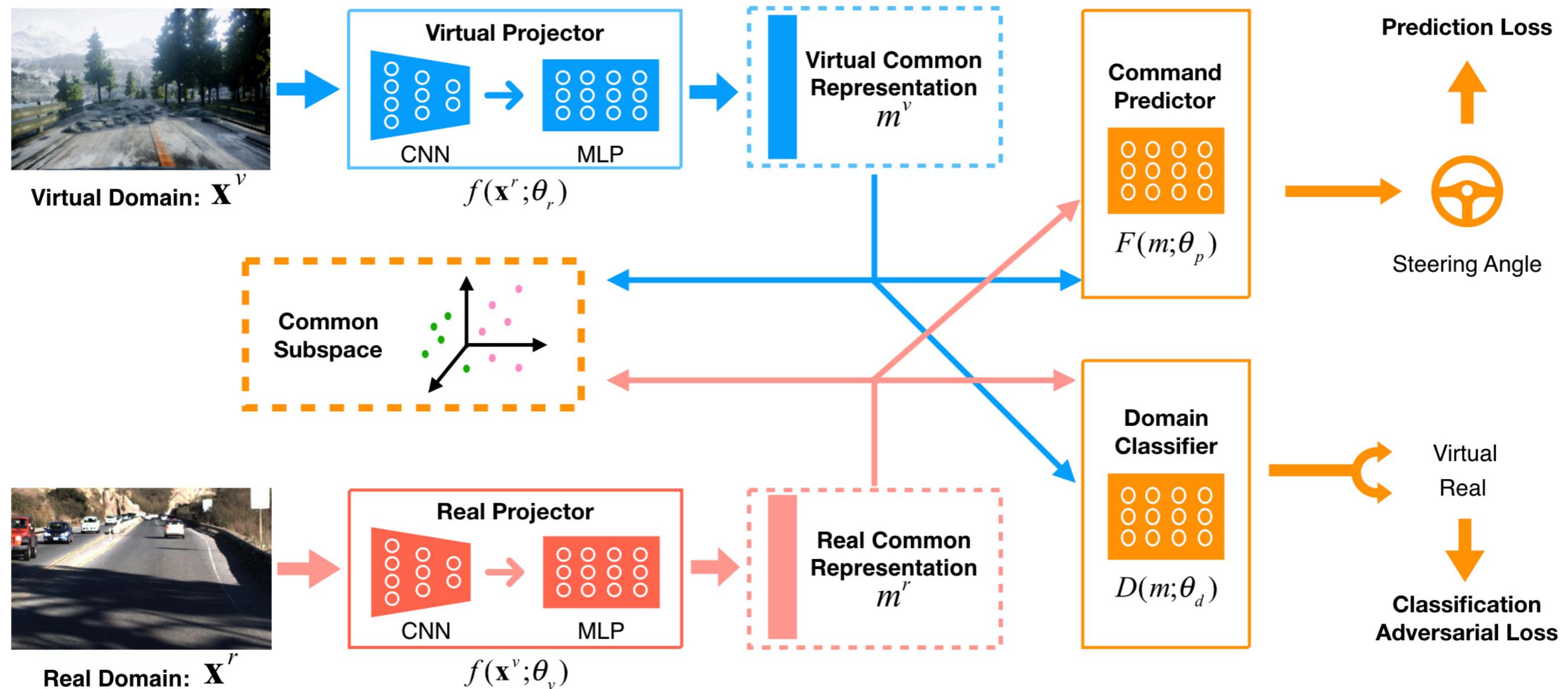
Virtual Data



Real Data



Adversarial End-to-end Self-driving on Both of Virtual and Real Worlds

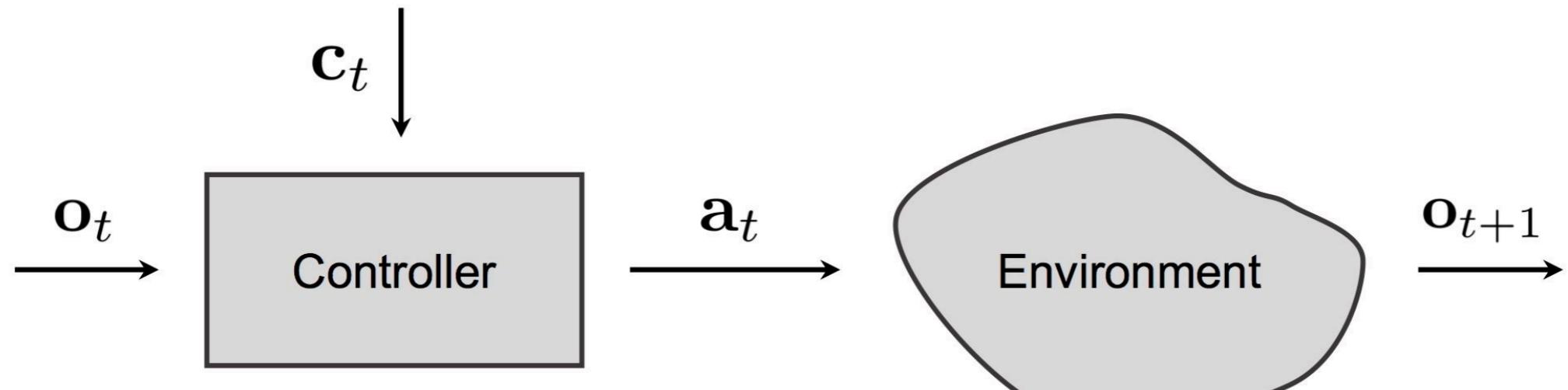


Experiments

Dataset	Model	MAE
Udacity [24]	PilotNet [1]	4.81
	DU-Drive [26]	4.52
	PilotNet-ADAED-UC	4.13
	PilotNet-ADAED-UA	3.88
	PilotNet-ADAED-w/oAL-UA	4.27
AirSim [16]	PilotNet-JT-UA	13.19
	PilotNet [1]	1.89
	PilotNet-ADAED-UA	1.87
	PilotNet-ADAED-w/oAL-UA	1.92
CARLA [5]	PilotNet-JT-UA	8.65
	PilotNet [1]	5.09
	PilotNet-ADAED-UC	5.32
CARLA [5]	PilotNet-ADAED-w/oAL-UC	5.38
	PilotNet-JT-UC	15.22

Table 2. Comparison of the steering angle prediction performance in terms of mean absolute error (MAE).

Task TODO: Conditional Imitation Learning for Real Cars



Furthermore...

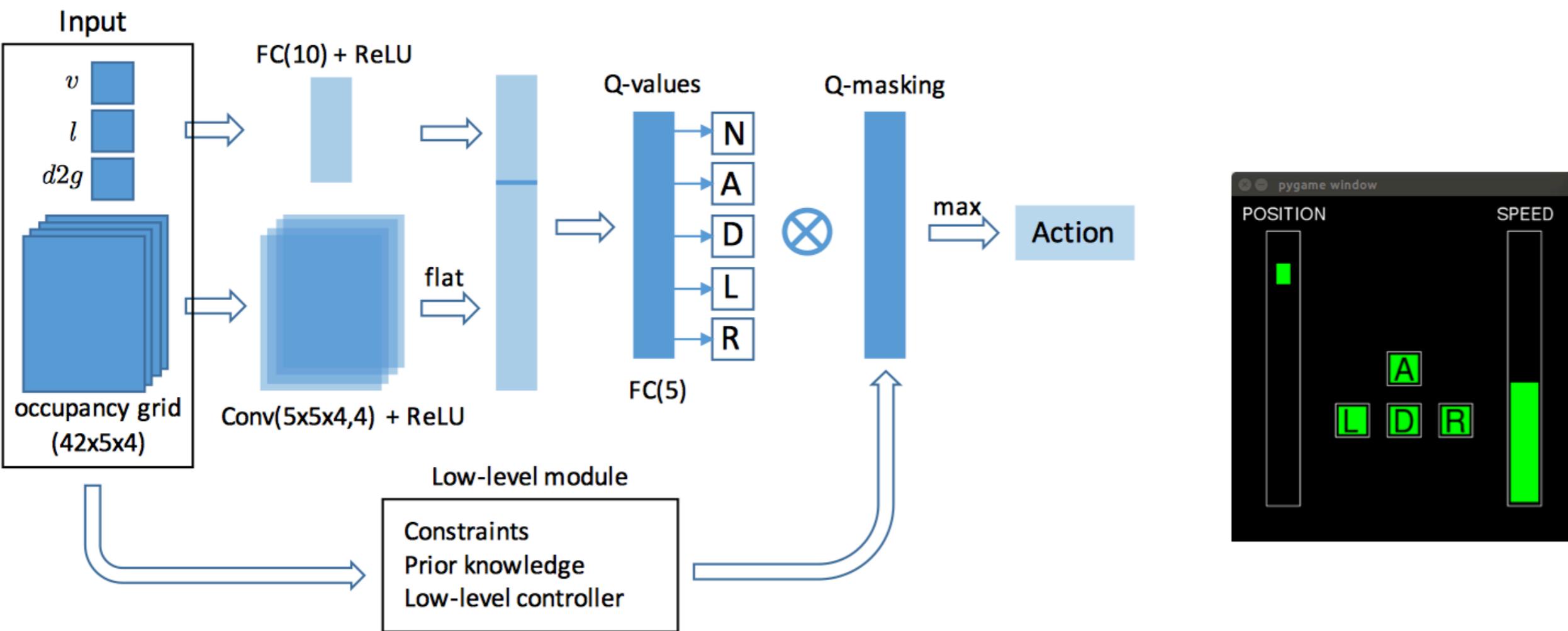
Use **reinforcement learning** for high-level control
conditional imitation learning for low-level control

VIDEO

End-to-end Driving via Conditional Imitation Learning

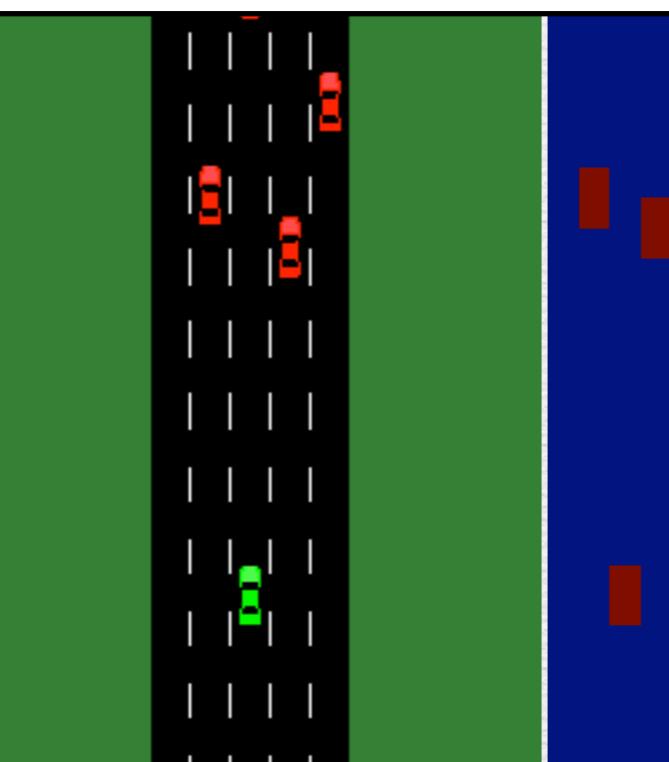
Felipe Codevilla, Matthias Mueller, Alexey Dosovitskiy, Antonio Lopez, Vladlen Koltun

Submitted to ICRA 2018



(a)

(b)



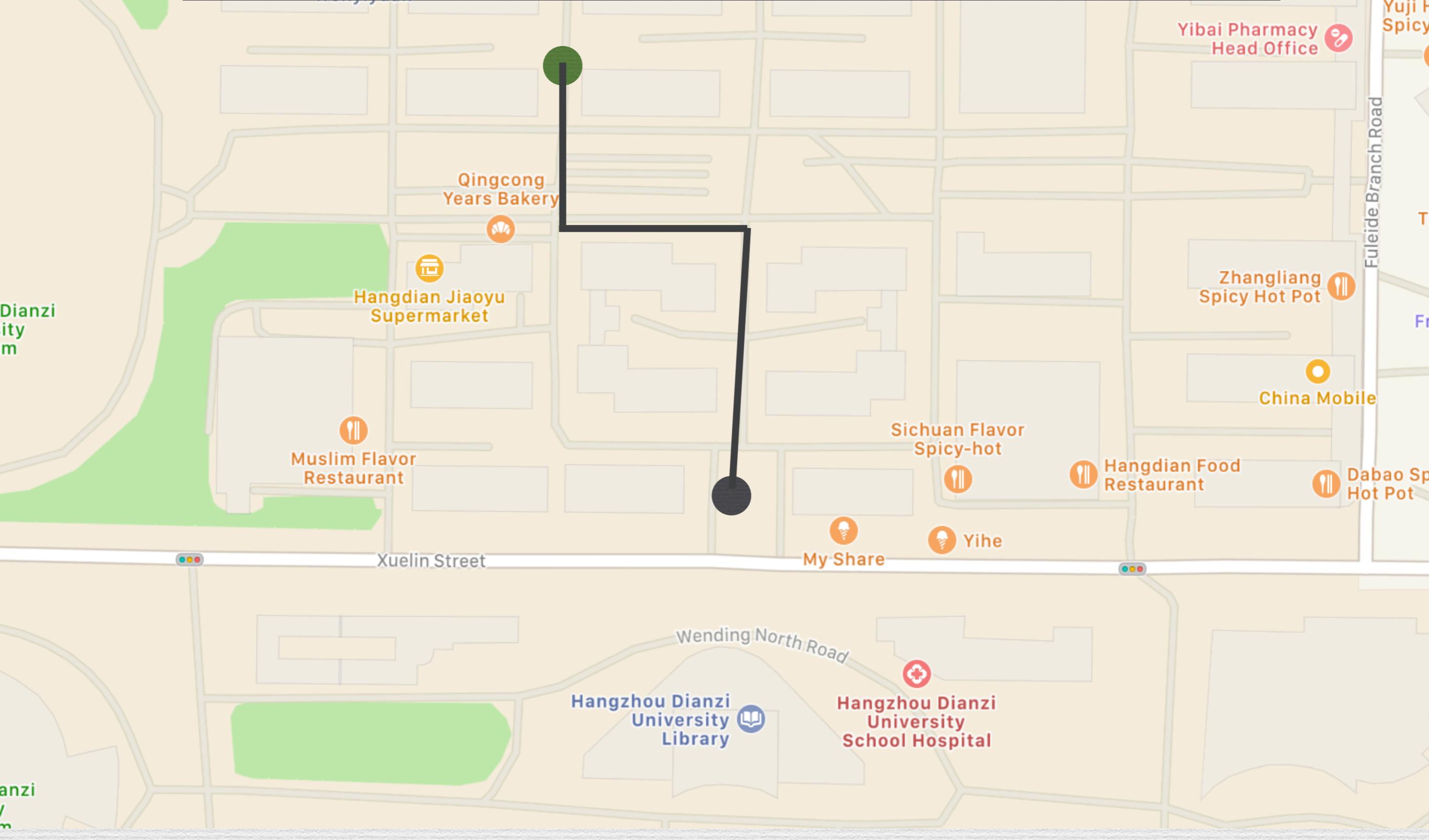
Xueyuan Street

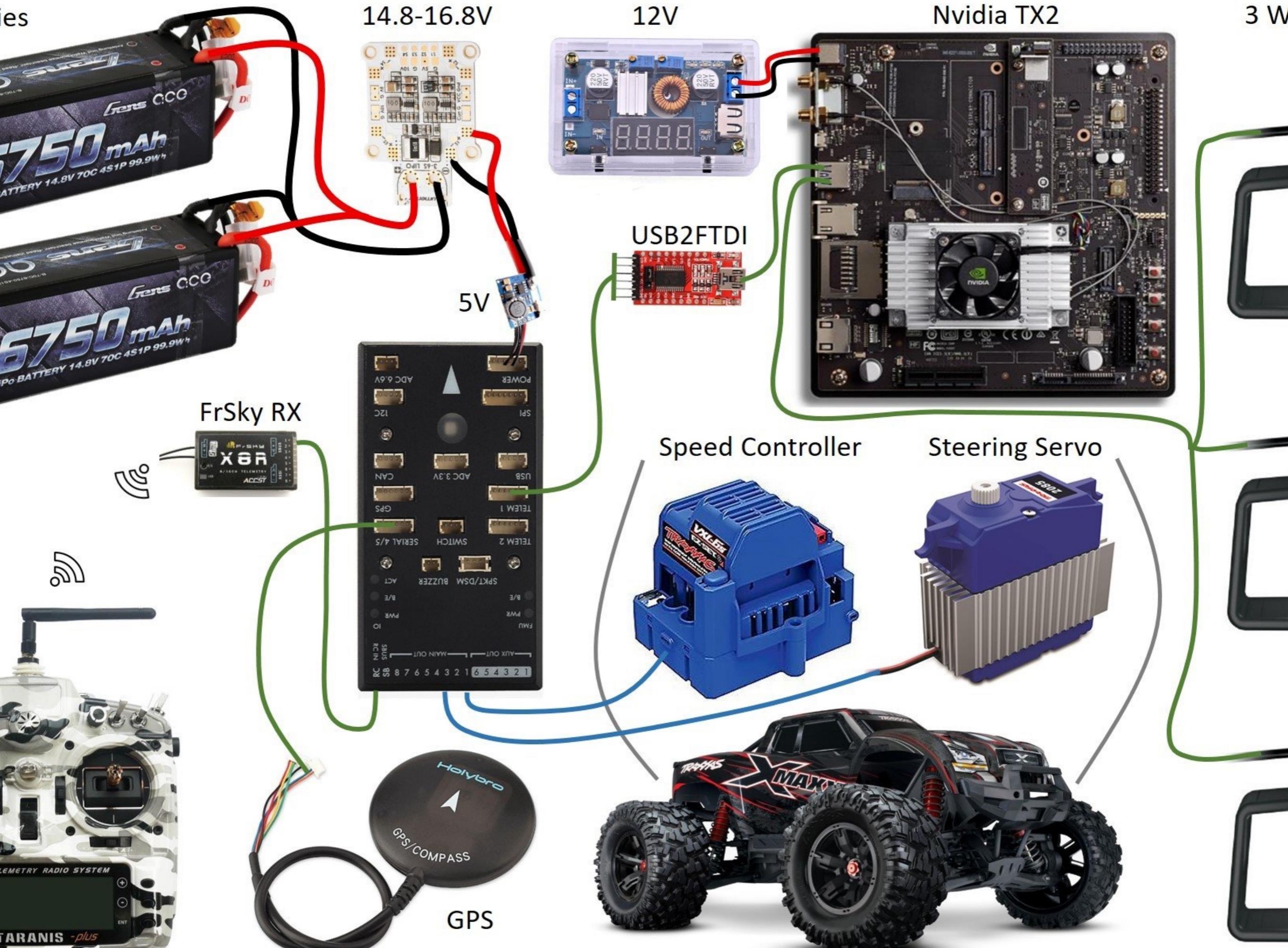
Minxin Supermarket

Zhejiang University of Media and Communications International

Maoxi Guochuar

Goal: give a GPS coordinate, then get there





Thanks.