

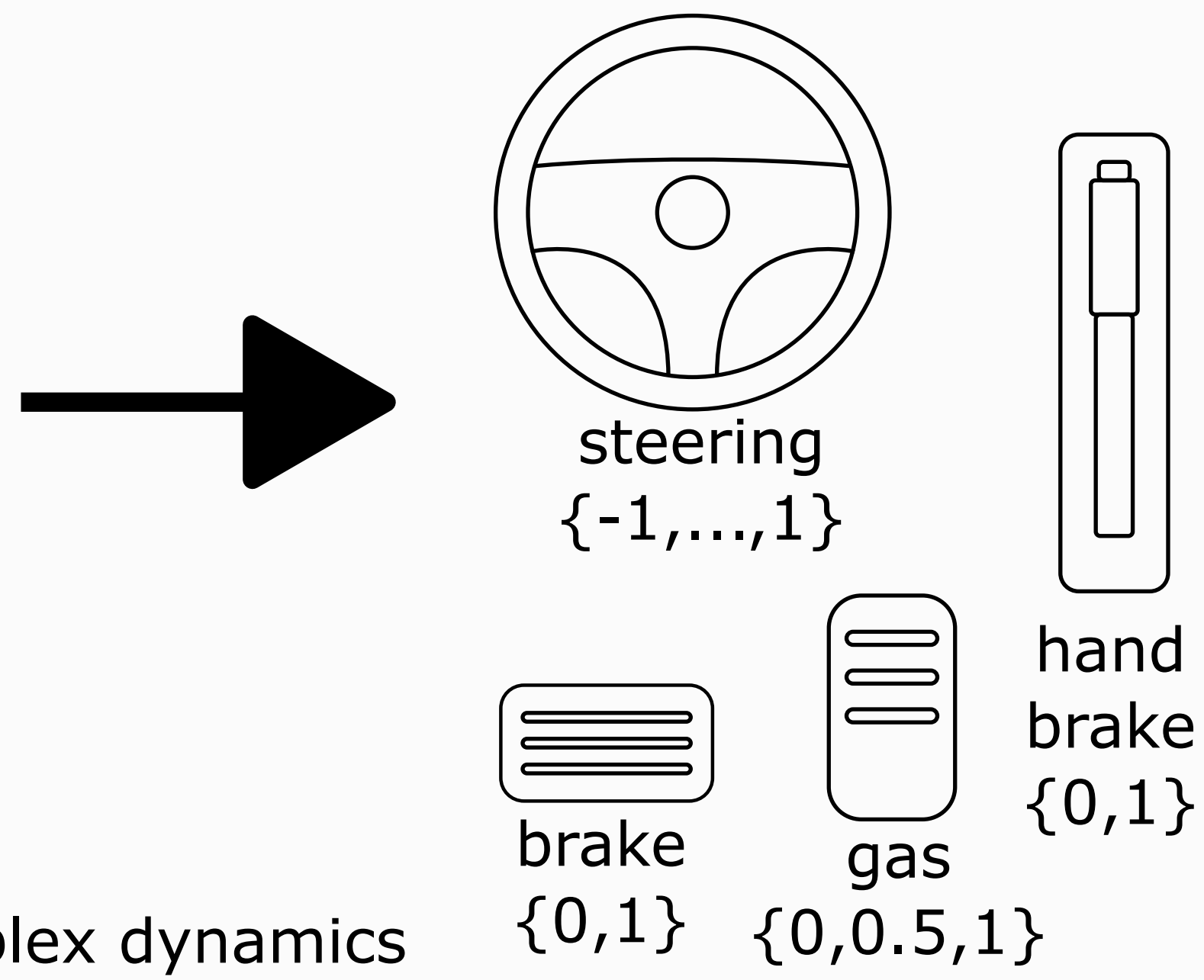
Etienne Perot<sup>1</sup>

Maximilian Jaritz<sup>1,2</sup>

Marin Toromanoff<sup>1</sup>

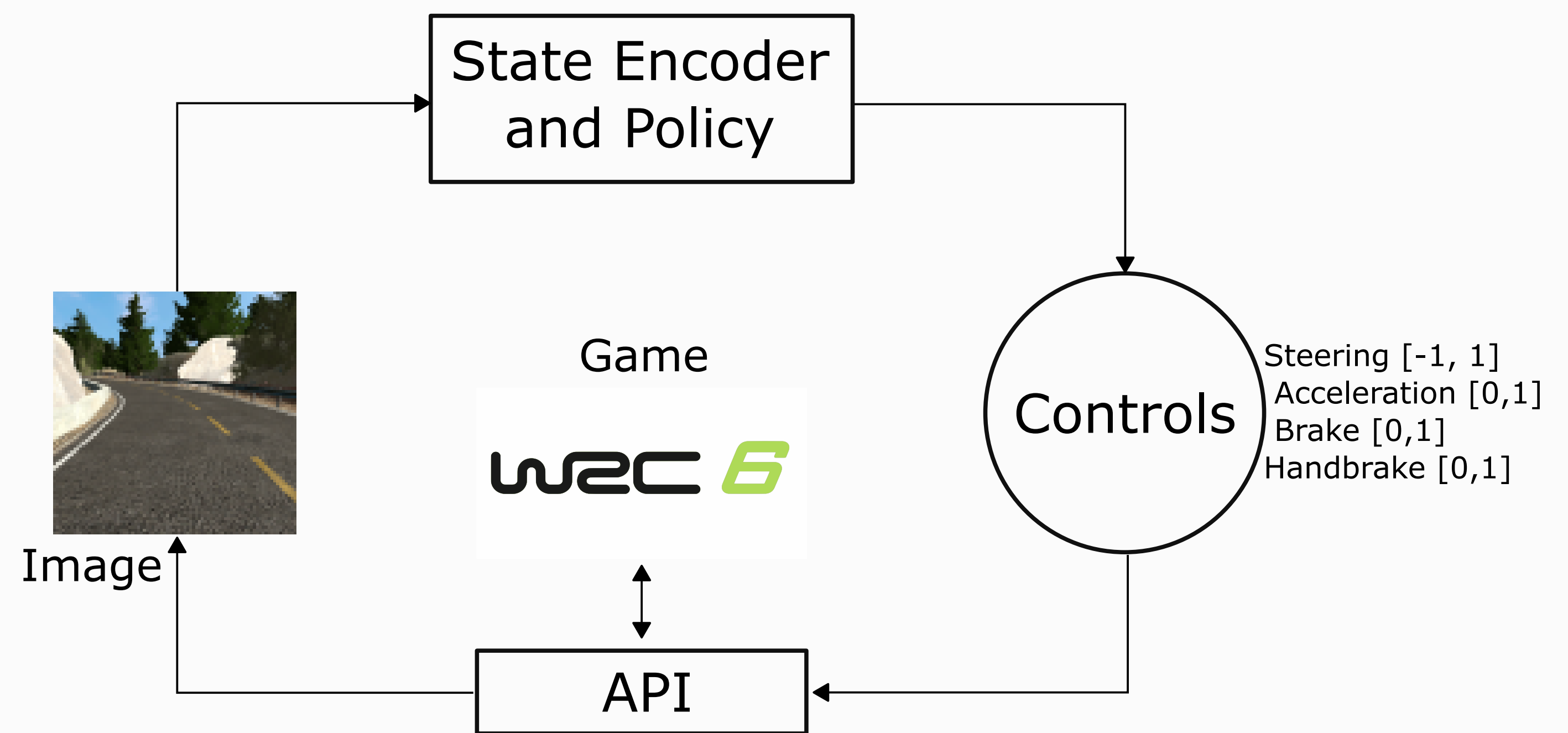
Raoul de Charette<sup>2</sup>

## Learning direct control from image



### Challenges

- Full control
- Realistic graphics, complex dynamics
- Racing setup: fast driving, drifting

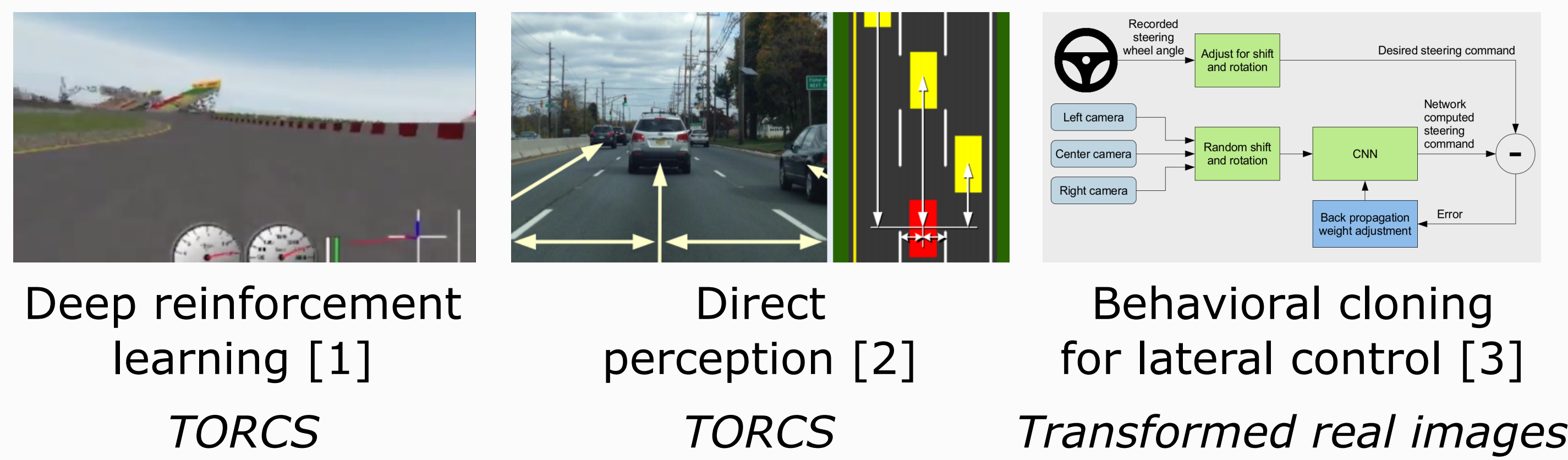


### Dedicated API

- Receive image, speed and angle, send controls

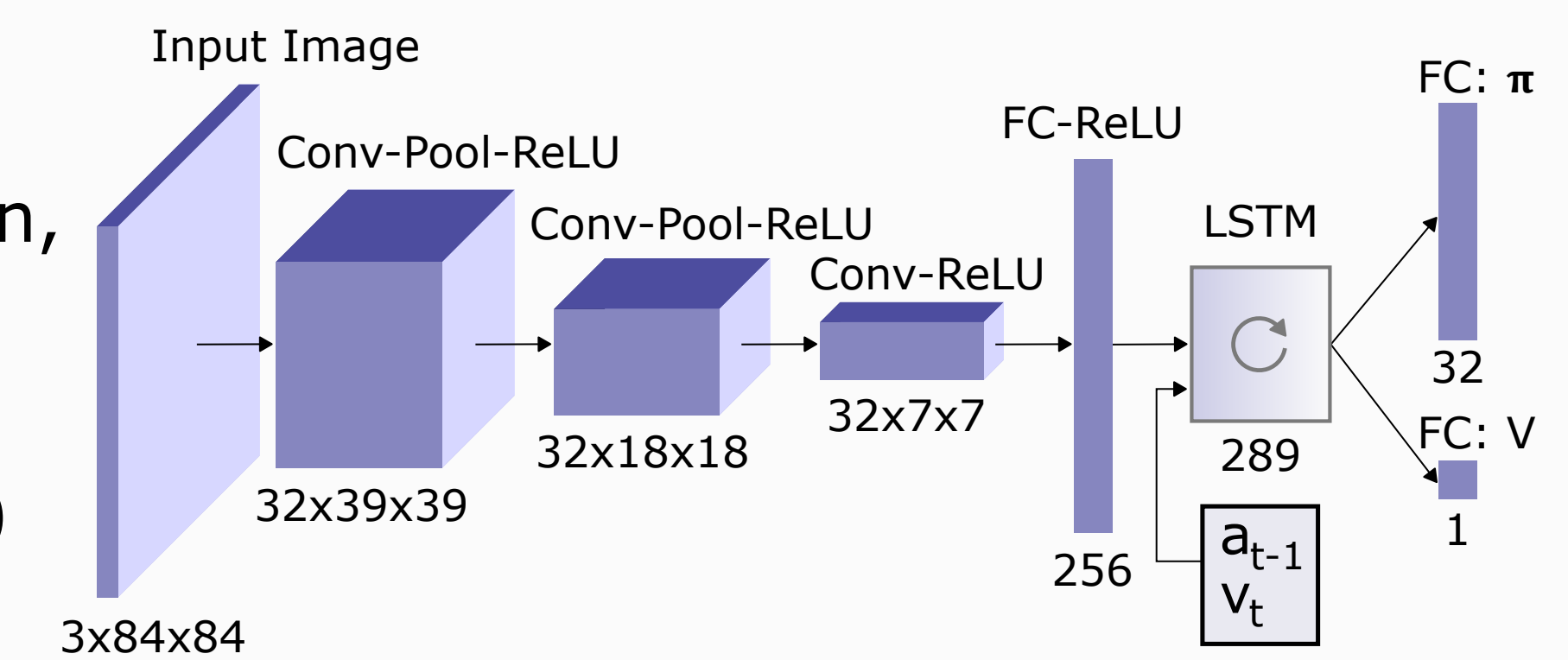
OVERVIEW

## Related works



## State Encoder

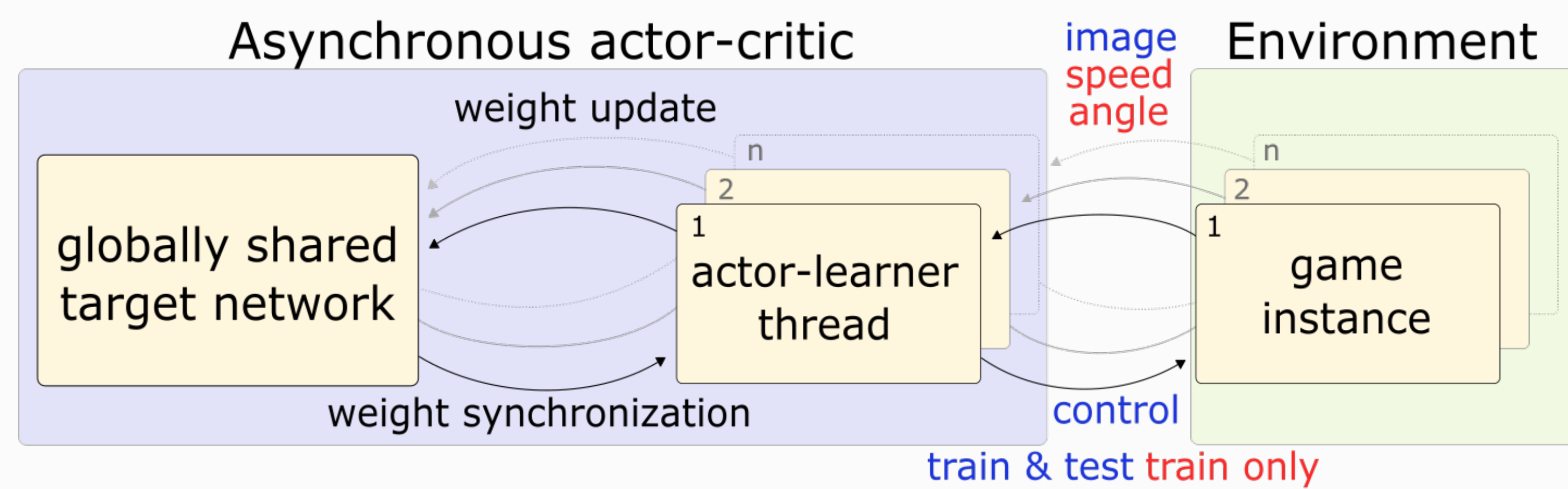
- LSTM takes additional inputs (previous action, current speed)
- Outputs action probabilities (softmax)



METHODOLOGY

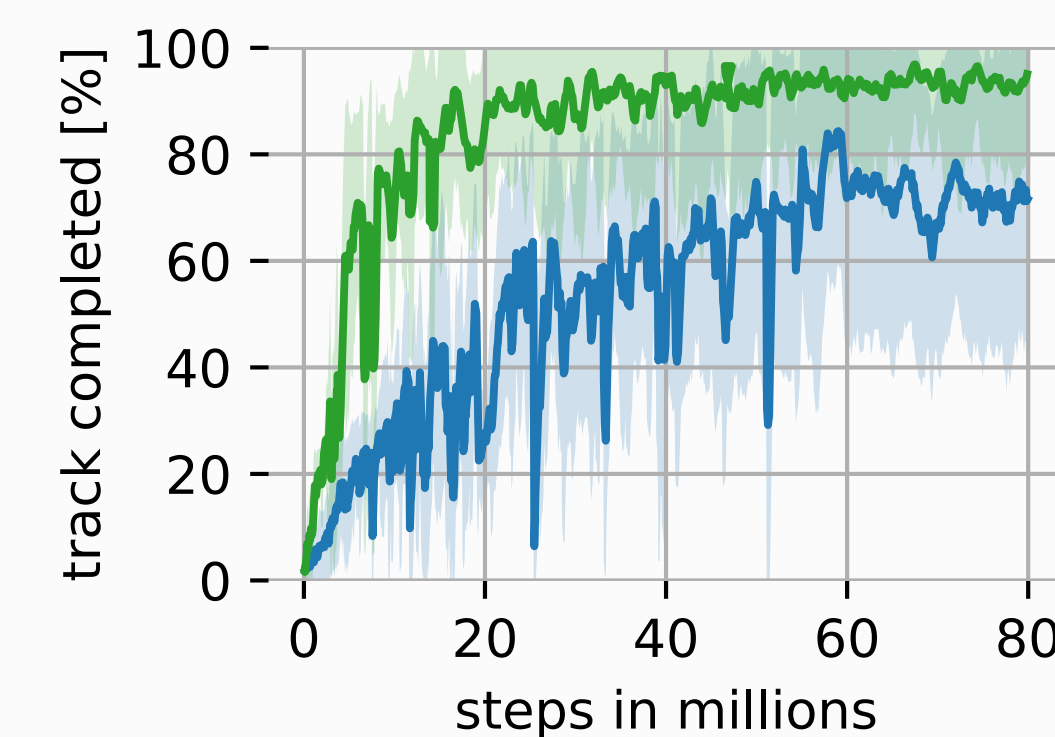
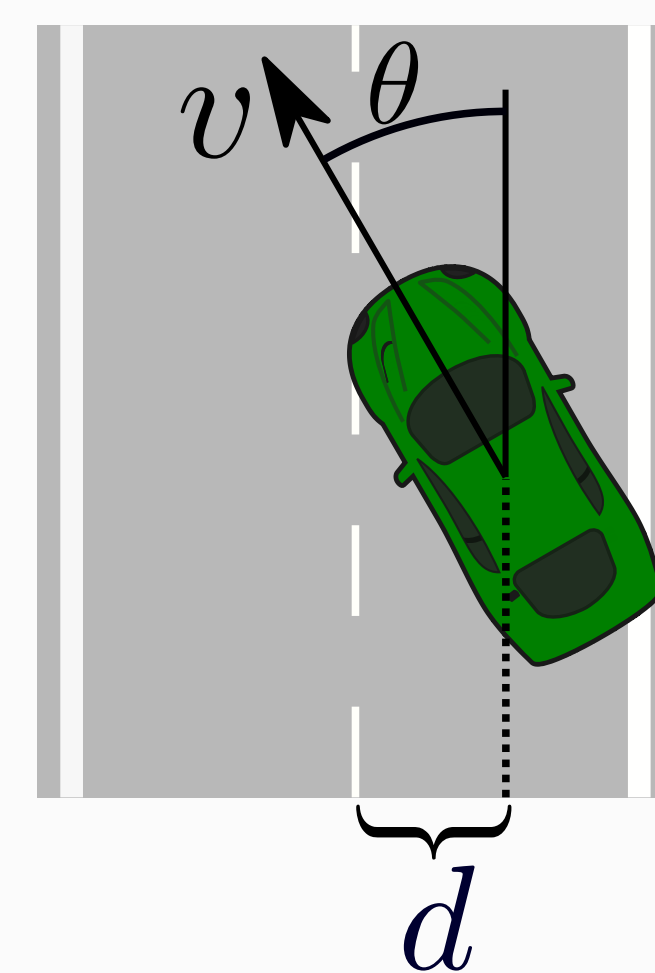
## A3C Algorithm [1]

- Asynchronous: No experience replay needed
- Multi-agent: Parallel computing



## Reward

- Frame-wise, function of speed and angle
- New: add distance from the middle of the track as penalty



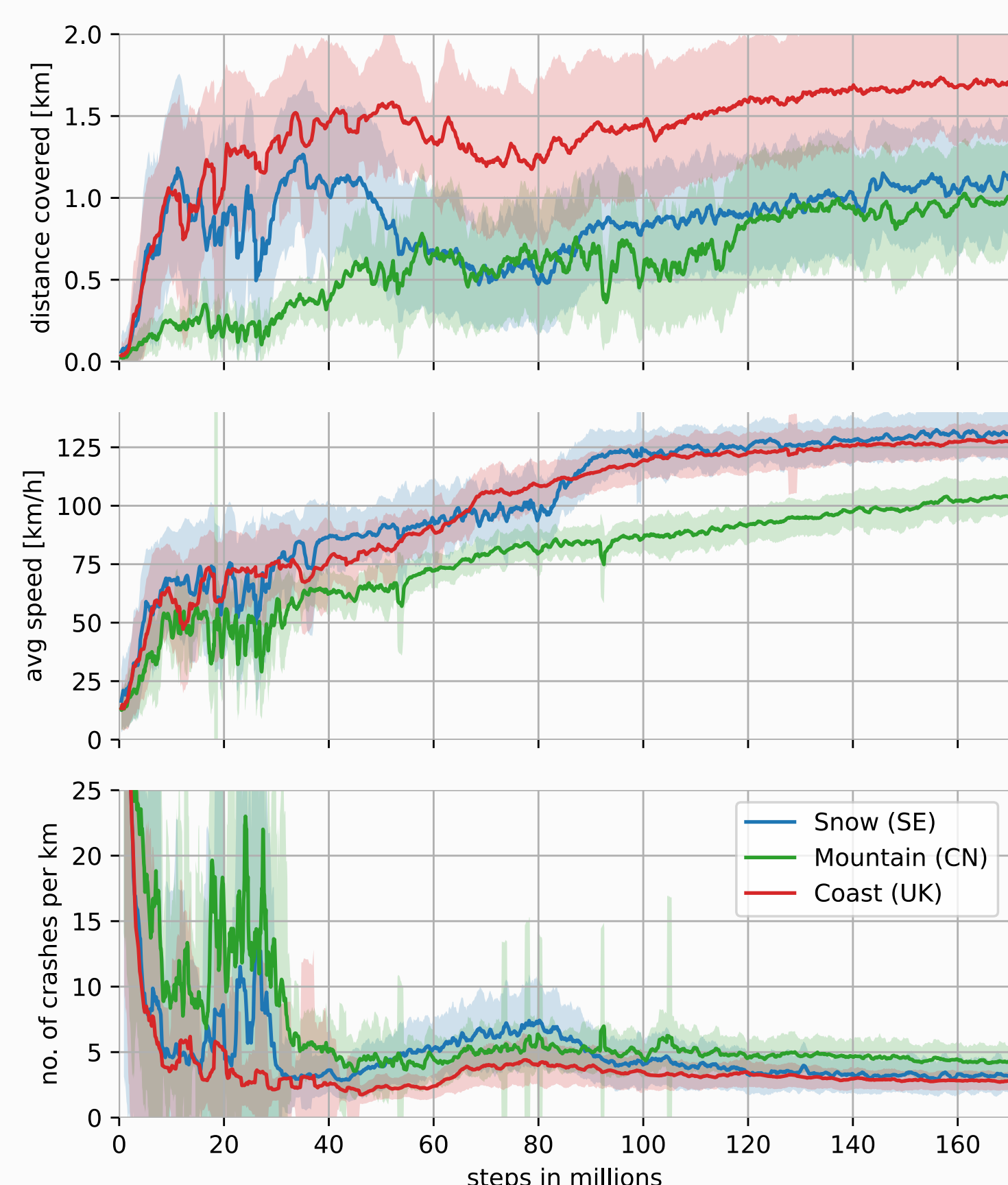
Reward used  
 $R = v(\cos \theta - d)$   
 VS  
 Mnih et al. [1]  
 $R = v \cos \theta$

EXPERIMENTS

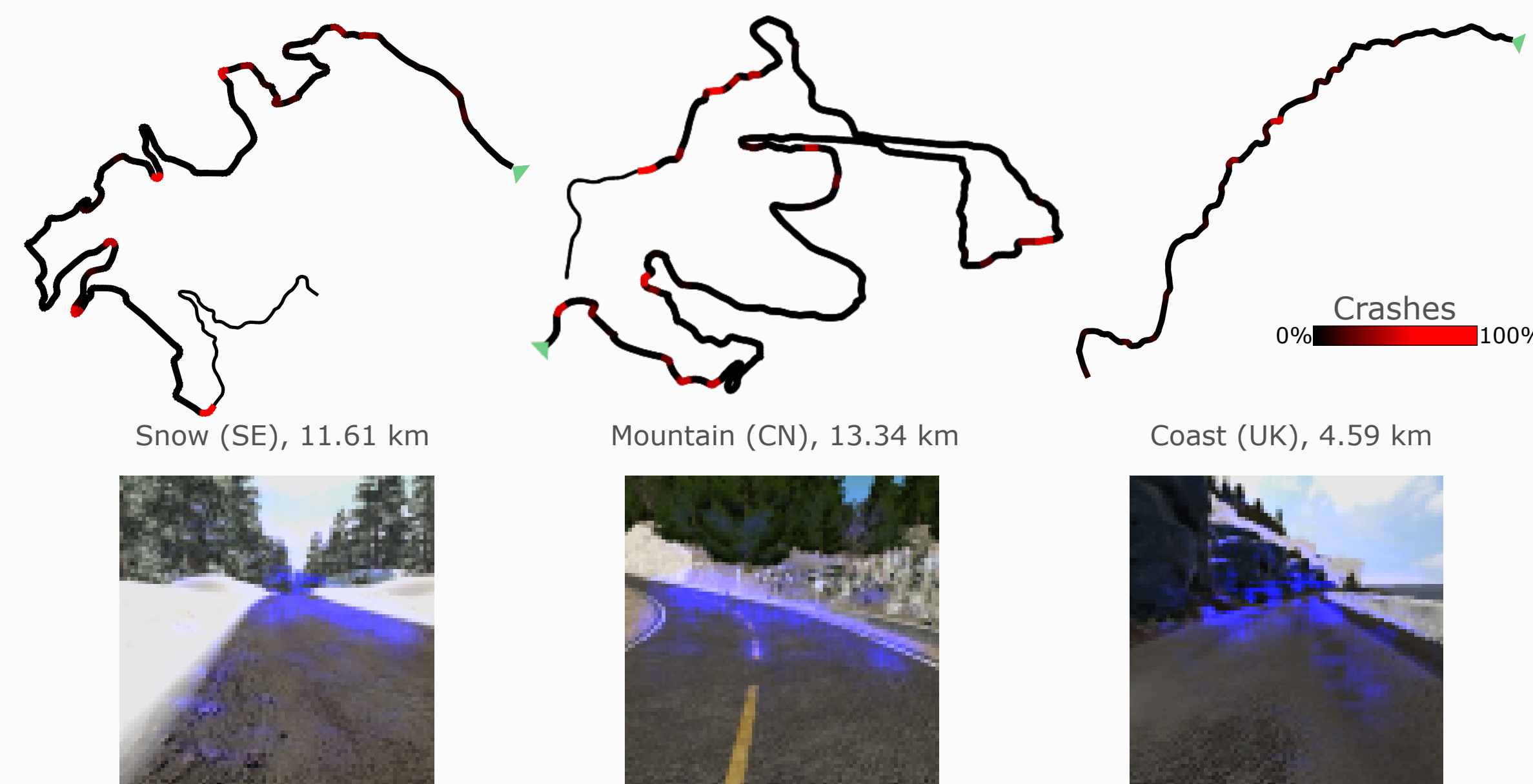
## Joint training on 3 tracks with different graphics and physics

## Test on unseen track

### Task specific evaluation metrics

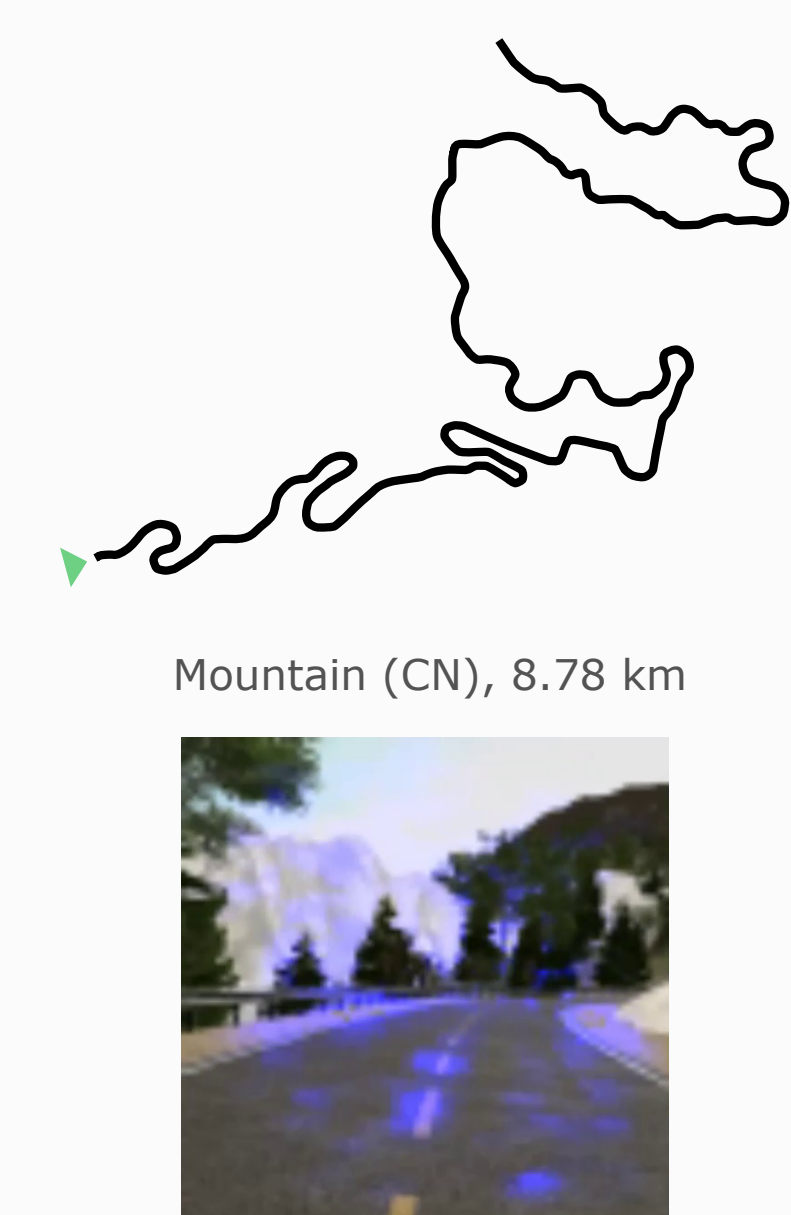


### Performance after 170 million steps

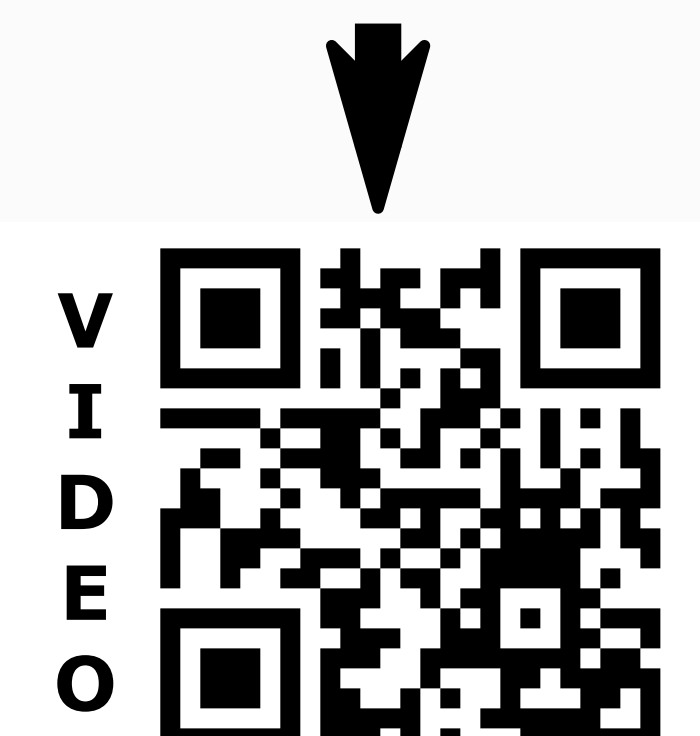


- Trained with 15 agents (5 per track)
- Average run: 121 km/h, 1.29 km, 2.5 crashes/km

### Generalization



- Qualitative performance in video



<https://youtu.be/e9jk-IBWFlw>

[1] Mnih et al., Asynchronous methods for deep reinforcement learning, ICML 2016

[2] Chen et al., DeepDriving: Learning affordance for direct perception in autonomous driving, ICCV 2015

[3] Bojarski et al., End to end learning for self-driving cars, arxiv 2016