Carnegie Mellon

School of Computer Science

Deep Reinforcement Learning and Control

Imitation Learning with Behavior Cloning

Fall 2021, CMU 10-703

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Limitations of Learning by Interaction

- The agent should have the chance to try (and fail) MANY times
- This is hard when safety is a concern: we cannot afford to fail
- This is also quite hard in general in real life where each interaction takes time (in contrast to simulation)

Crusher robot

Learning from Demonstration for Autonomous Navigation in Complex Unstructured Terrain, Silver et al. 2010

Imitation Learning (a.k.a. Learning from Demonstrations)

visual imitation

The actions of the teacher need to be inferred from visual sensory input and mapped to the action space of the agent.

Two challenges:

1) visual understanding
2) action mapping, especially when the agent and the teacher do not have the same action space

(later lecture)

kinesthetic imitation

- The teacher takes over the end-effectors of the agent.
- Demonstrated actions are in the action space of the imitator and can be imitated directly)

this lecture

Notation

Richard Bellman

Lev Pontryagin

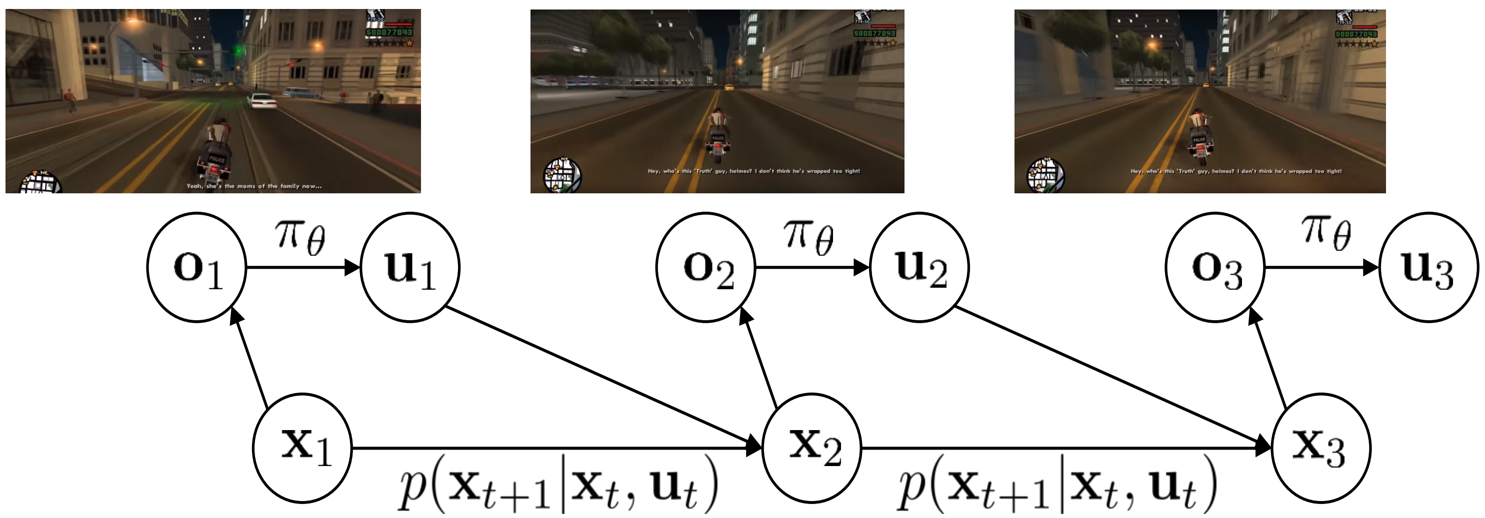
actions a_t
states s_t
rewards r_t
dynamics $p(s_{t+1} \mid s_t, a_t)$
observations o_t

actions u_t
states x_t
costs $c(x_t, u_t)$
dynamics $p(x_{t+1} \mid x_t, u_t)$

Diagram from Sergey Levine

Imitation learning VS Sequence labelling

Imitation learning



Training data:

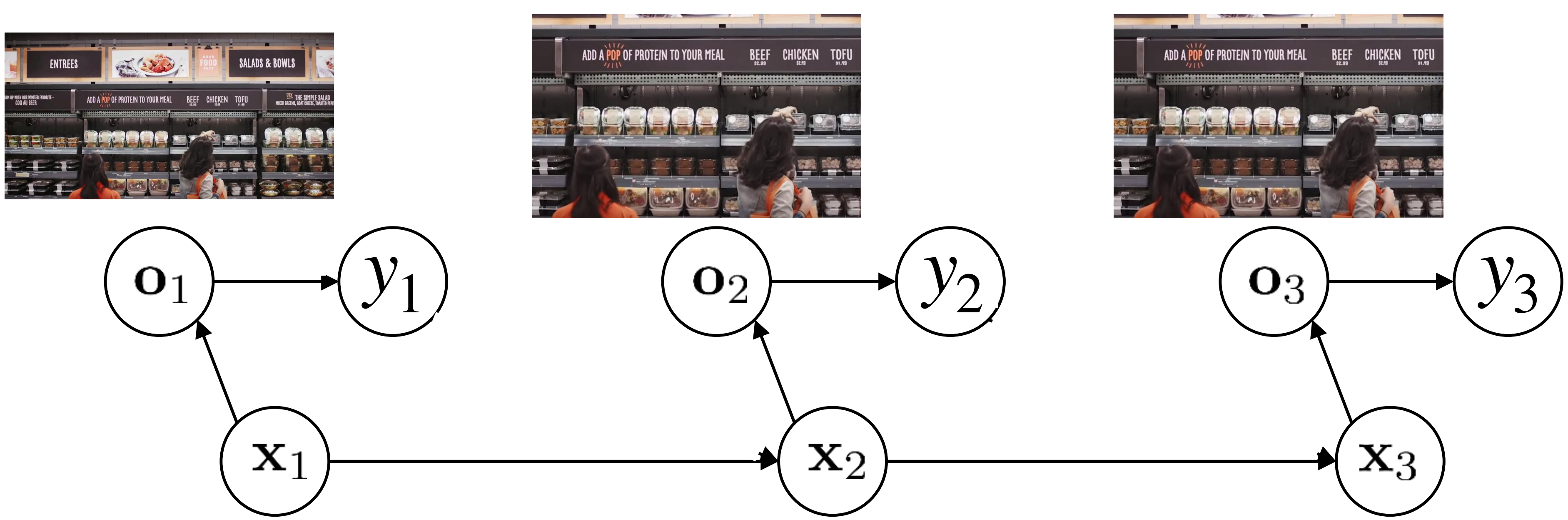
$o_1^1, u_1^1, o_2^1, u_2^1, o_3^1, u_3^1, \ldots$

$o_1^2, u_1^2, o_2^2, u_2^2, o_3^2, u_3^2, \ldots$

$o_1^3, u_1^3, o_2^3, u_2^3, o_3^3, u_3^3, \ldots$

$\mathbf{u}_t$:the action at time t $\mathbf{o}_t$:the observation at time t $\mathbf{x}_t$:the state at time t

Sequence labelling



Training data:

$o_1^1, y_1^1, o_2^1, y_2^1, o_3^1, y_3^1, \ldots$

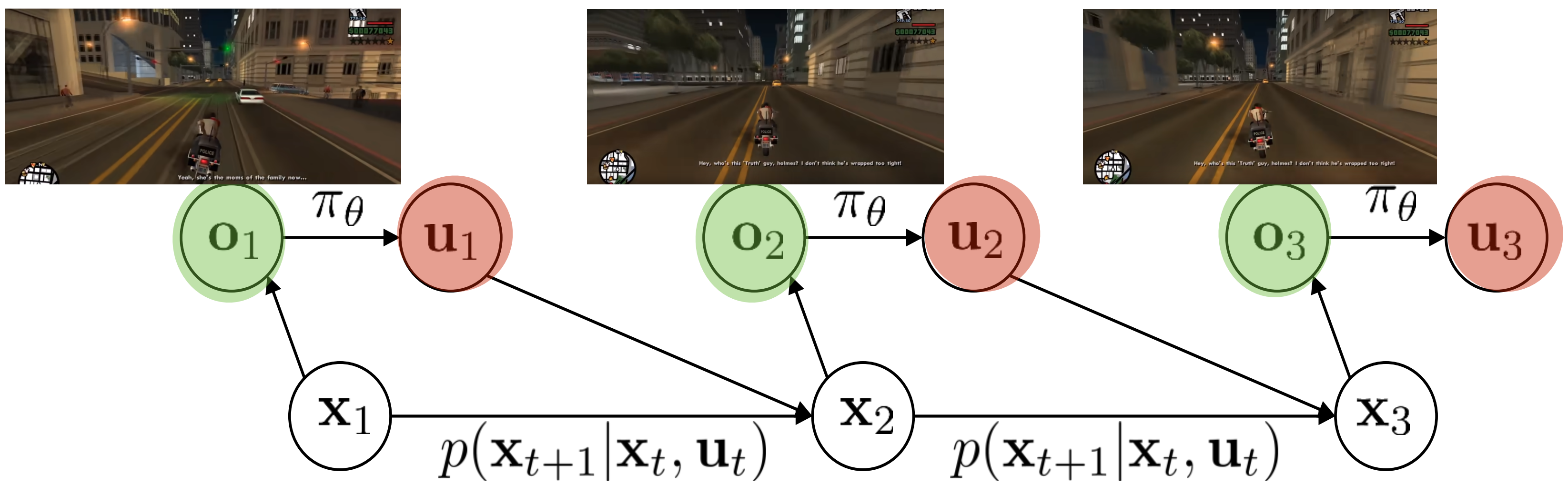
$o_1^2, y_1^2, o_2^2, y_2^2, o_3^2, y_3^2, \ldots$

$o_1^3, y_1^3, o_2^3, y_2^3, o_3^3, y_3^3, \ldots$

y_t : which product was purchased at frame t (if any) $\mathbf{o}_t$:the observation at time t $\mathbf{x}_t$:the state at time t

Imitation learning VS Sequence labelling

Imitation learning



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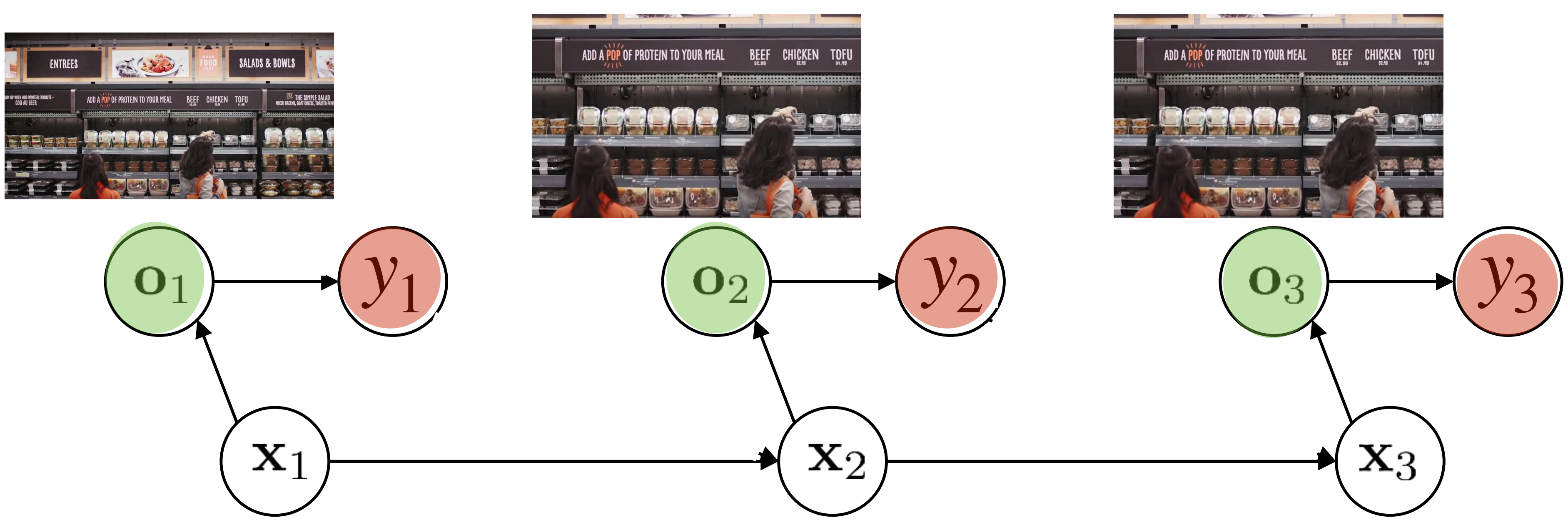

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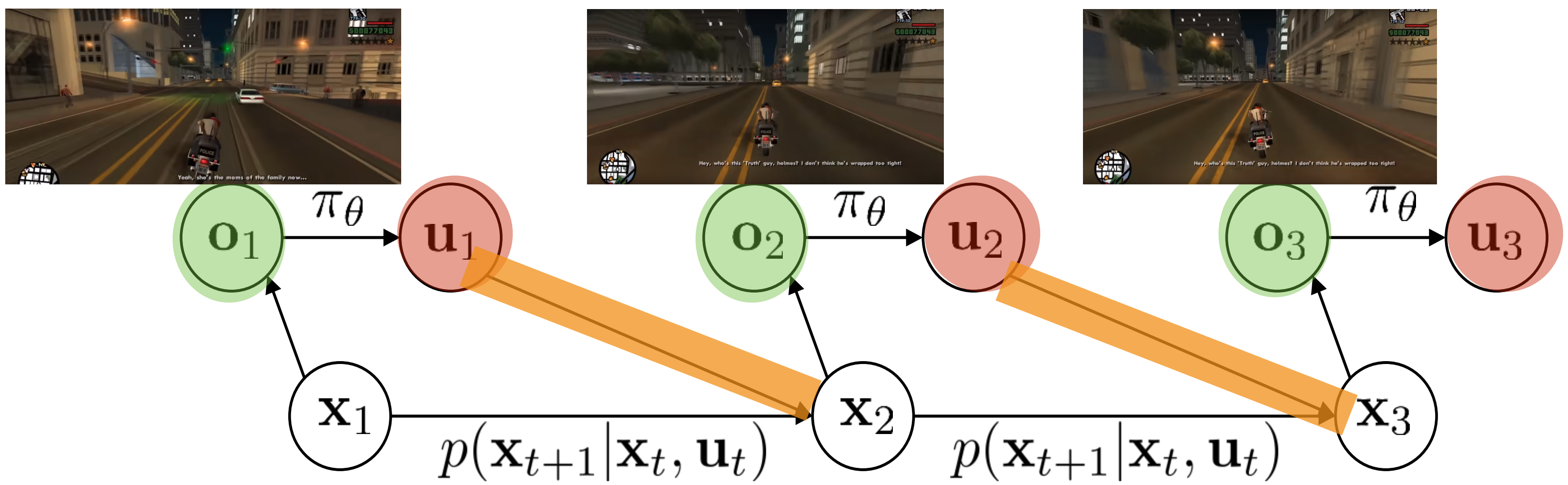
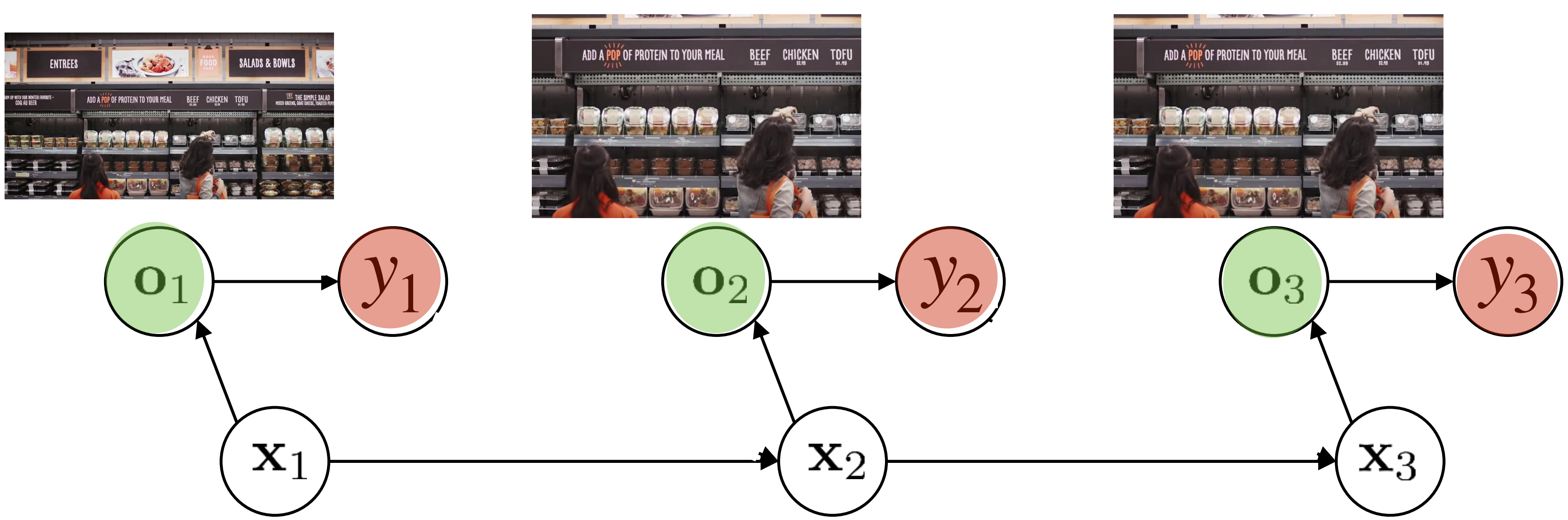


$\mathbf{u}_t$:the action at time t $\mathbf{o}_t$:the observation at time t $\mathbf{x}_t$:the stat

- In RL, our actions will influence our future state, and thus our future data.
- In sequence labelling, our labels won't influence the future frames.

Sequence labelling



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$$o_1^3, y_1^3, o_2^3, y_2^3, o_3^3, y_3^3, \ldots.$$

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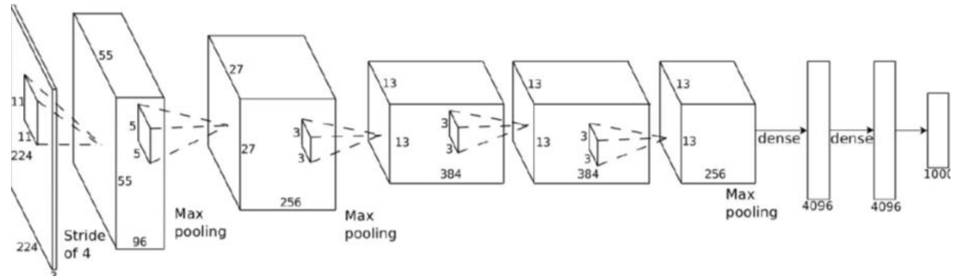
Video sequence labelling

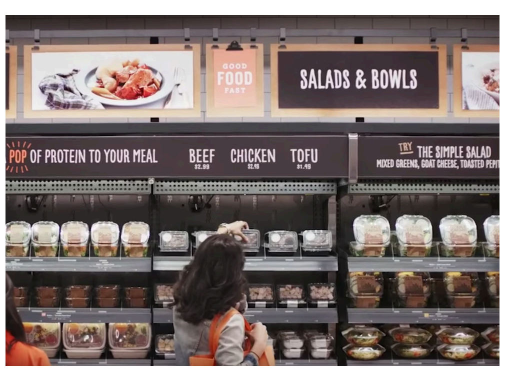
Action labelling: a mapping from states/observations to action labels



"picking up chicken A"

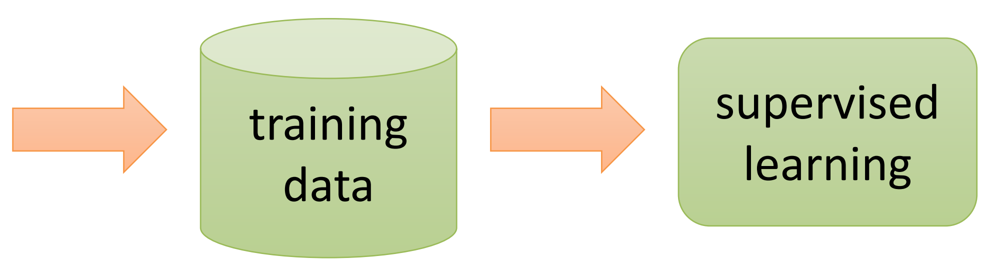
$f_\theta(y_t \mid \mathbf{o}_t)$

- Assume action labels in an annotated video are i.i.d. (independent and identically distributed).
- Train a classifier to map observations to labels at each time step of the trajectory



$\mathbf{o}_t$

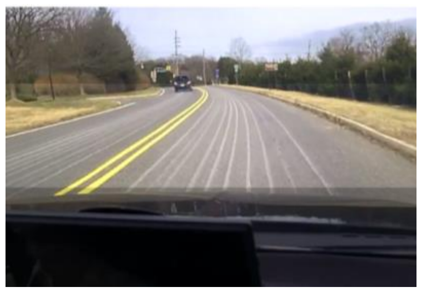
y_t

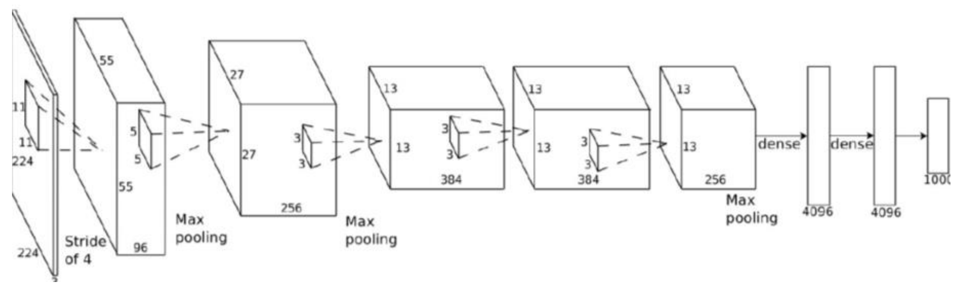


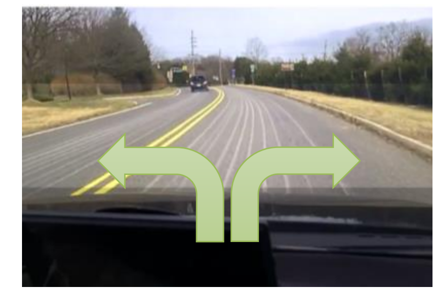
$f_\theta(y_t \mid \mathbf{o}_t)$

Imitation Learning

Policy: a mapping from observations to actions

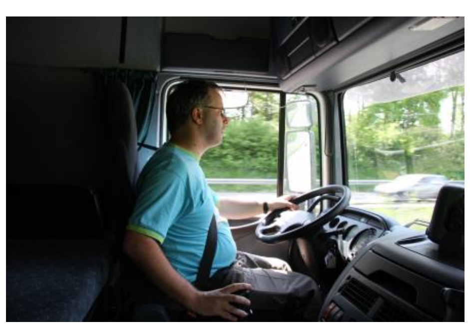




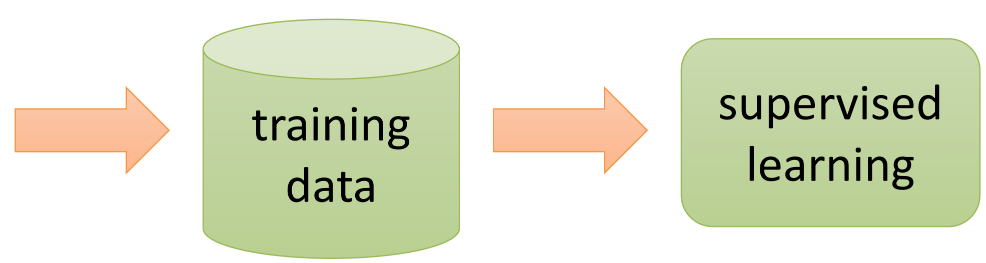


$\mathbf{o}_t$ $\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$ $\mathbf{u}_t$

- Assume actions in the expert trajectories are i.i.d. (independent and identically distributed)
- Train a function to map observations/states to actions at each time step of the trajectory



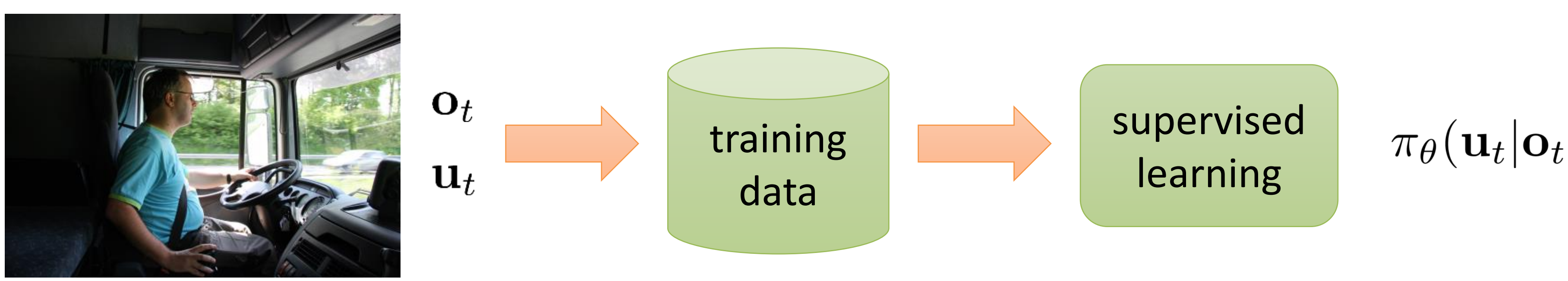
$\mathbf{o}_t$
$\mathbf{u}_t$

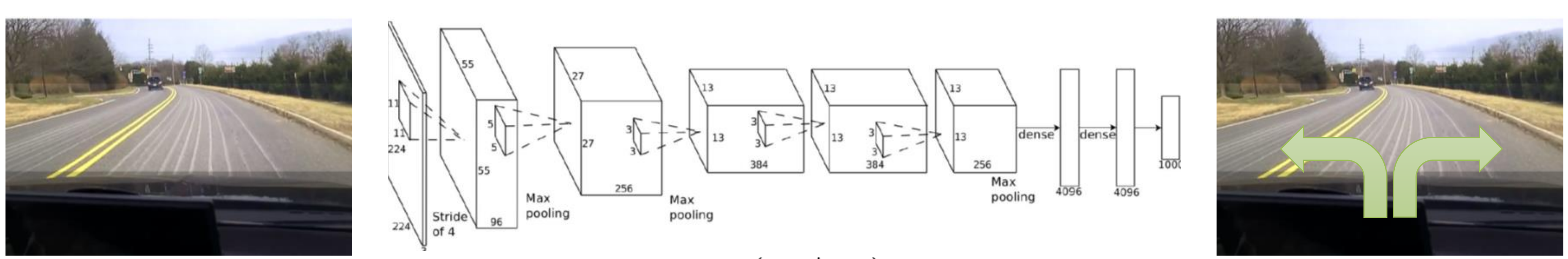


$\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$

Imitation learning - Challenges

- Compounding errors
  Fix: data augmentation
- Non-Markovian observations
  Fix: observation concatenation or recurrent models
- Lack of generalization
  Fix: Self-supervised visual feature learning





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Imitation learning - Challenges

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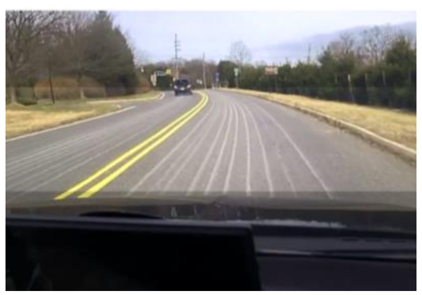
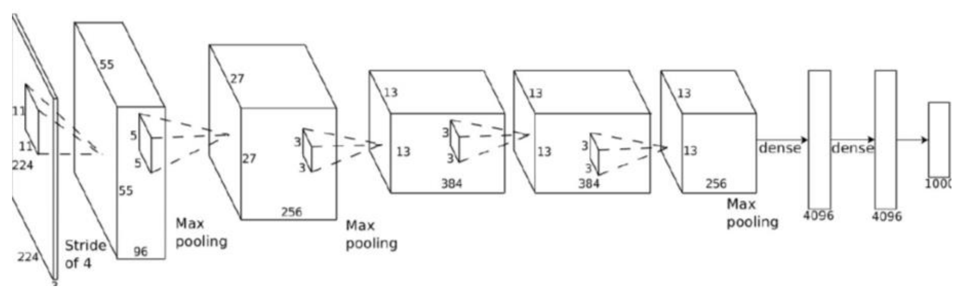
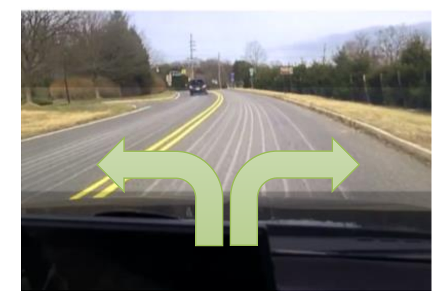
  Fix: data augmentation



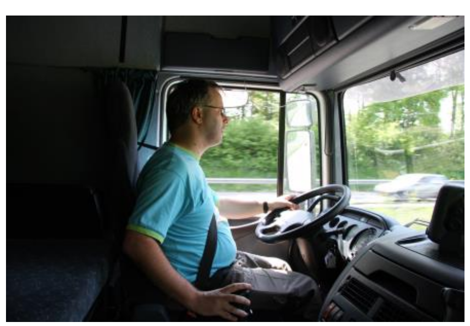
$\mathbf{o}_t$



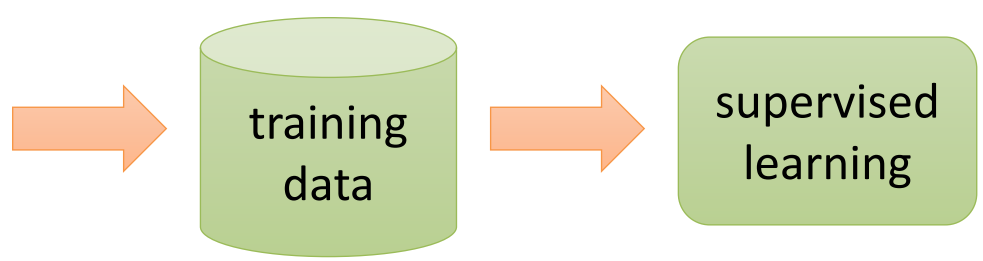
$\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$



$\mathbf{u}_t$



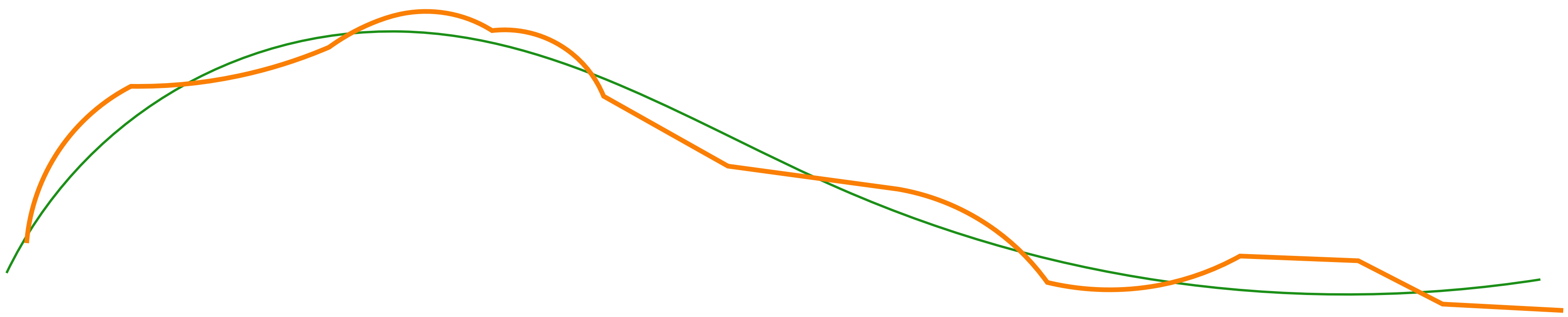
$\mathbf{o}_t$
$\mathbf{u}_t$



$\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$

Independent in time errors

This means that at each time step t, the agent wakes up on a state drawn from the state distribution of the expert trajectories, and executes an action.

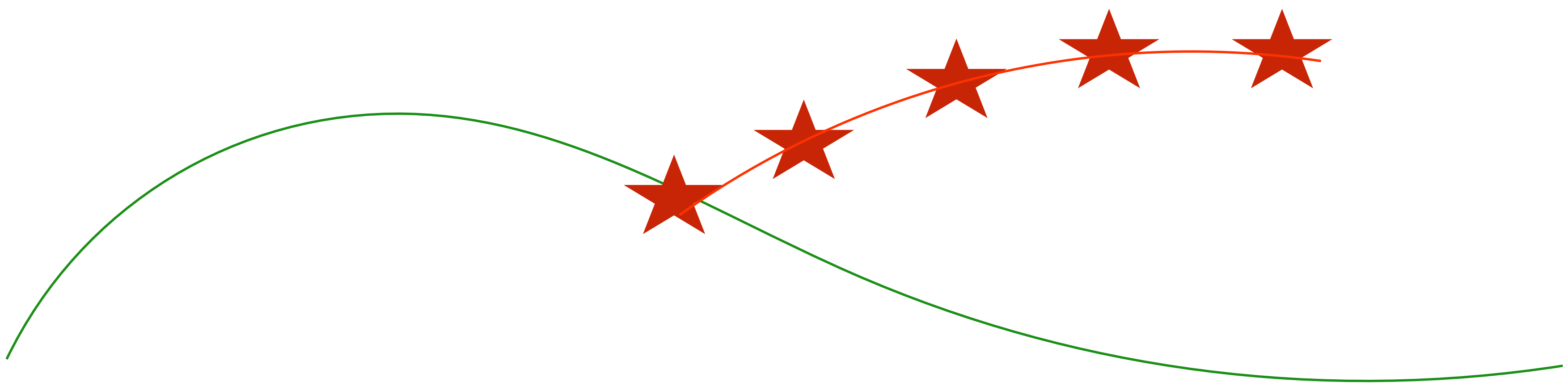


error at time t with probability ε

E[Total errors] ≲ εT, T the length of the trajectory

Compounding Errors

This means that at each time step t, the agent wakes up on a state drawn from the state distribution resulting from executing the action the learned policy suggested in the previous time step.



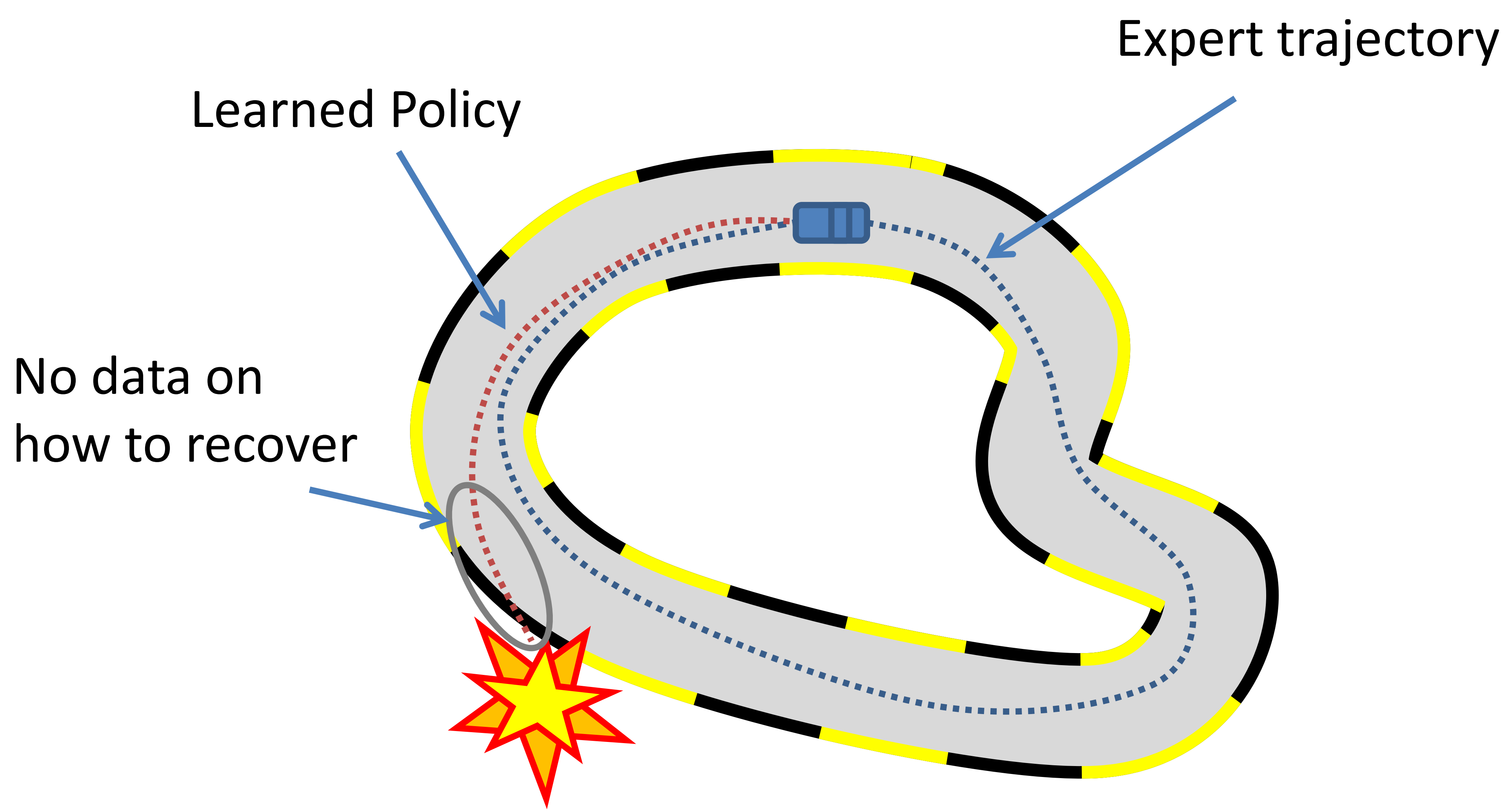
error at time t with probability ε

$$E[\text{Total errors}] \lesssim \varepsilon(T + (T-1) + (T-2) + \ldots + 1) \propto \varepsilon T^2$$

A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning, Ross et al. 2011

Distribution mismatch (distribution shift)

$$P_{\pi^*}(\mathbf{o}_t) \neq P_{\pi_\theta}(\mathbf{o}_t)$$



Distribution mismatch (distribution shift)

	supervised learning	supervised learning + control (NAIVE)
train	(x,y) ~ D	$\mathbf{o}_t \sim P_{\pi^*}(\mathbf{o}_t)$
test	(x,y) ~ D	$\mathbf{o}_t \sim P_{\pi_\theta}(\mathbf{o}_t)$

Supervised learning succeeds when training and test data distributions match, that is a fundamental assumption.

Solution: data augmentations

Change $P_{\pi*}(\mathbf{o}_t)$ by augmenting the expert demonstration trajectories.
This means: add examples in expert demonstration trajectories to cover the states/observations points where the agent will land when trying out its own policy. How?

1. By generating synthetic data in simulation
2. By collecting additional data via clever hardware
3. By interactively querying the experts in additional datapoints

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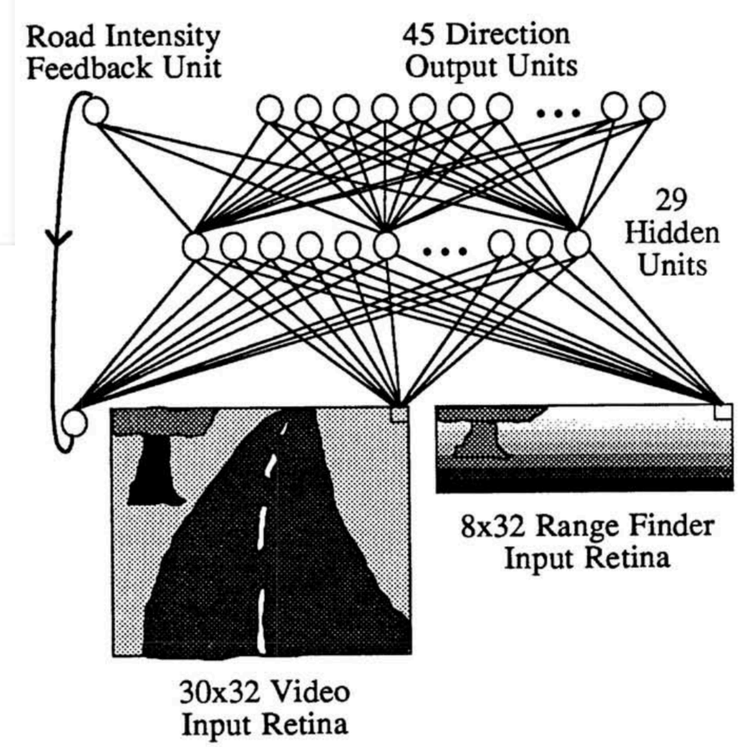
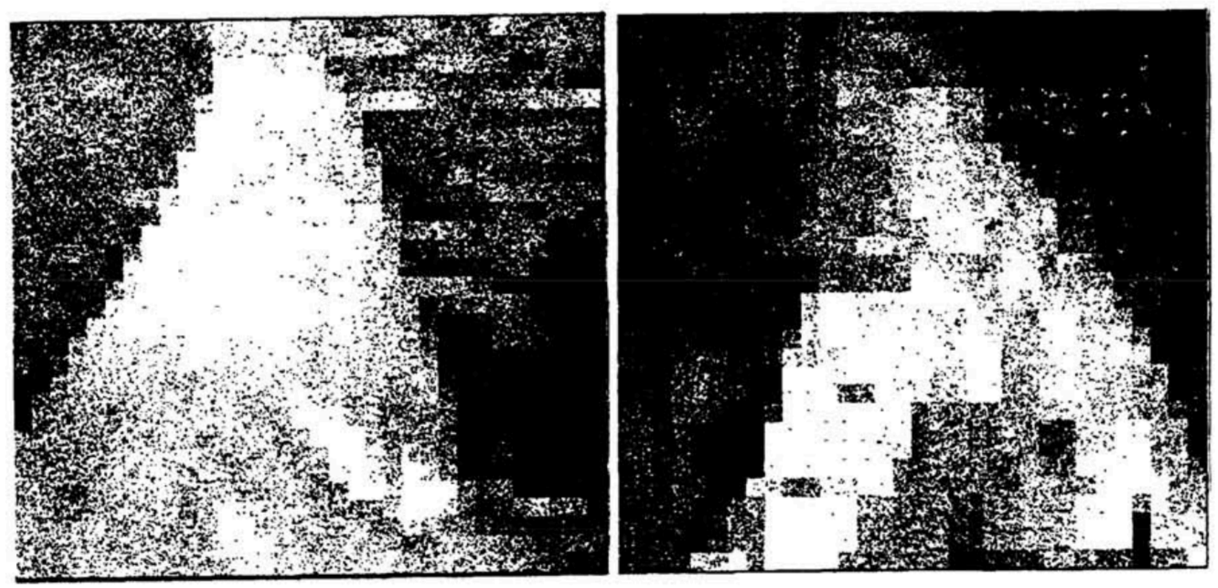
Demonstration Augmentation: ALVINN 1989



Demonstration Augmentation: ALVINN 1989

"In addition, the network must not solely be shown examples of accurate driving, but also how to recover (i.e. return to the road center) once a mistake has been made. Partial initial training on a variety of simulated road images should help eliminate these difficulties and facilitate better performance."
ALVINN: An autonomous Land vehicle in a neural Network", Pomerleau 1989

Demonstration Augmentation: ALVINN 1989



Real Road Image Simulated Road Image

- Use of image simulator to generate images of how the road looks like when the vehicle deviates slightly from its trajectory.
- Simulating the images too longer than training the network

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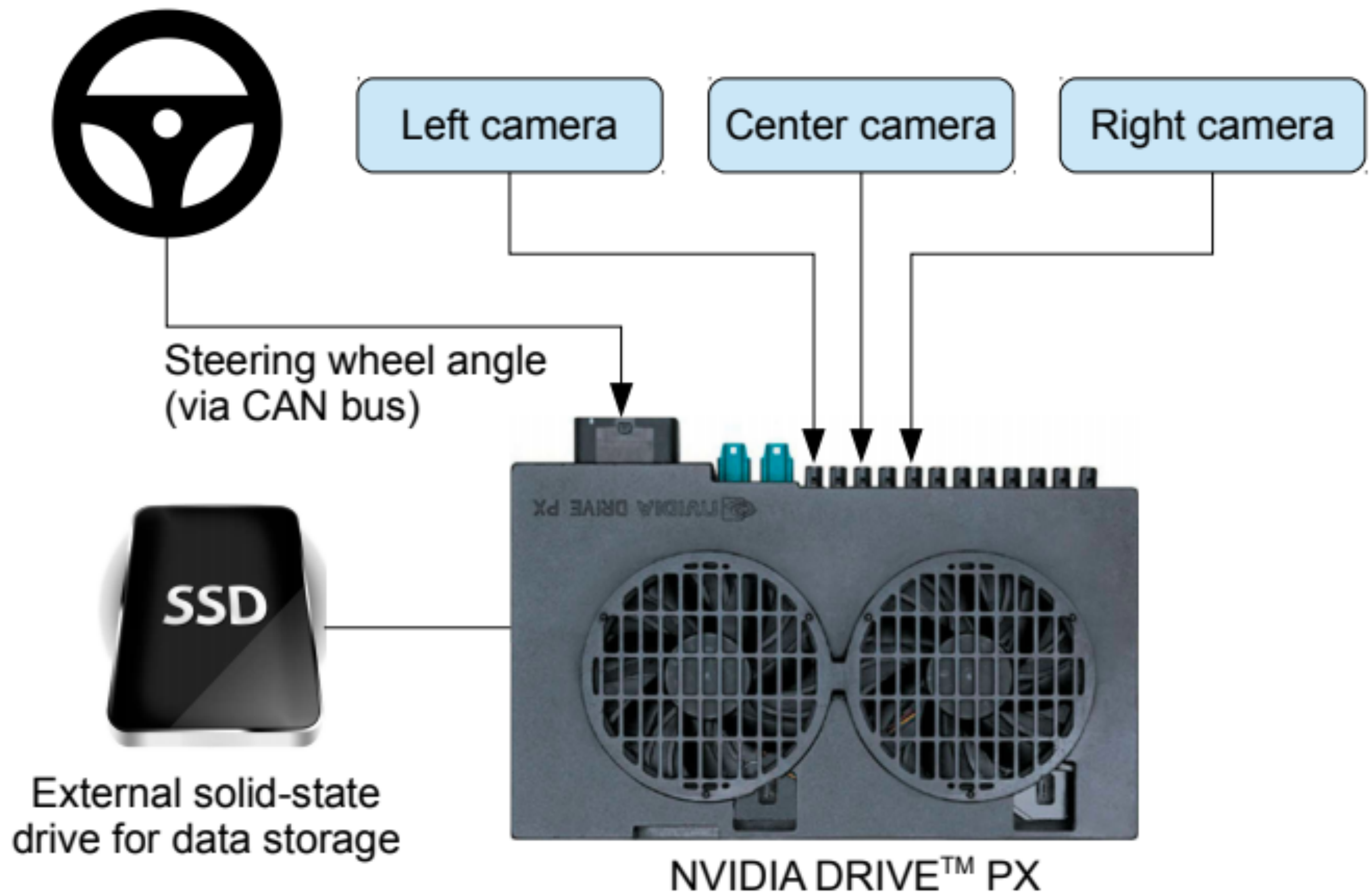
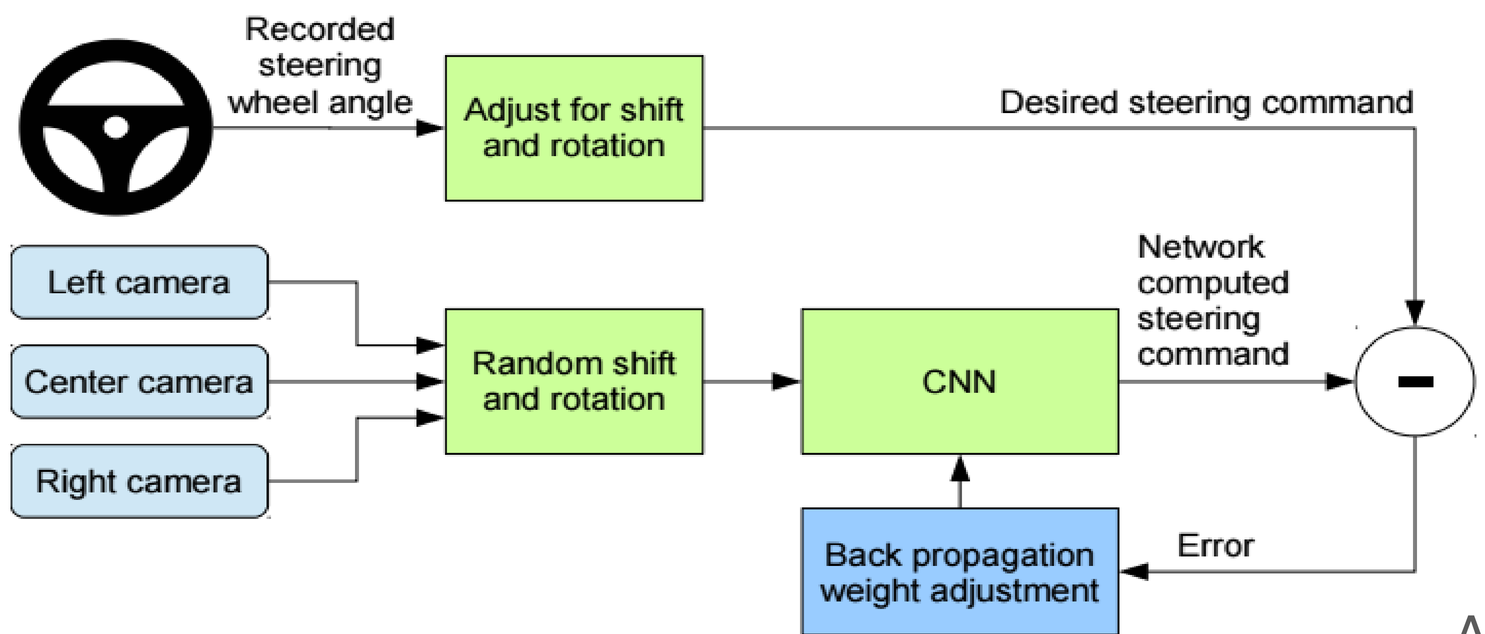
Learning to Drive a Car: Supervised Learning

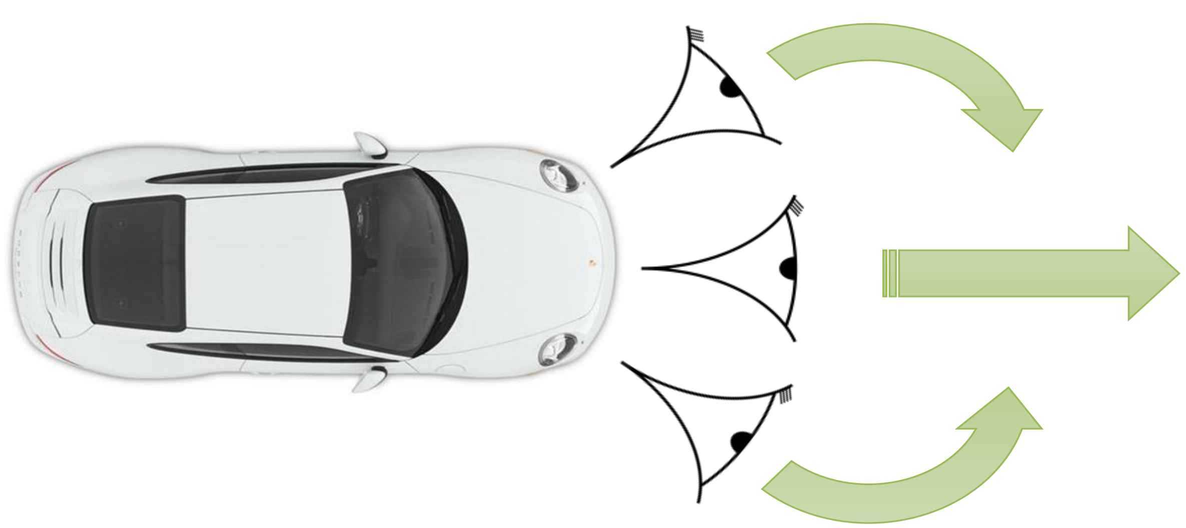


End to End Learning for Self-Driving Cars, NVIDIA, 2016

Demonstration Augmentation: NVIDIA 2016



Additional, left and right cameras with automatic ground-truth labels to recover from mistakes



“DAVE-2 was inspired by the pioneering work of Pomerleau [6] who in 1989 built the Autonomous Land Vehicle in a Neural Network (ALVINN) system. Training with data from only the human driver is not sufficient. The network must learn how to recover from mistakes. …”

End to End Learning for Self-Driving Cars , Bojarski et al. 2016

Data Augmentation (2): NVIDIA 2016

DAVE 2 Driving a Lincoln

- A convolutional neural network
- Trained by human drivers
- Learns perception, path planning, and control
  "pixel in, action out"
- Front-facing camera is the only sensor

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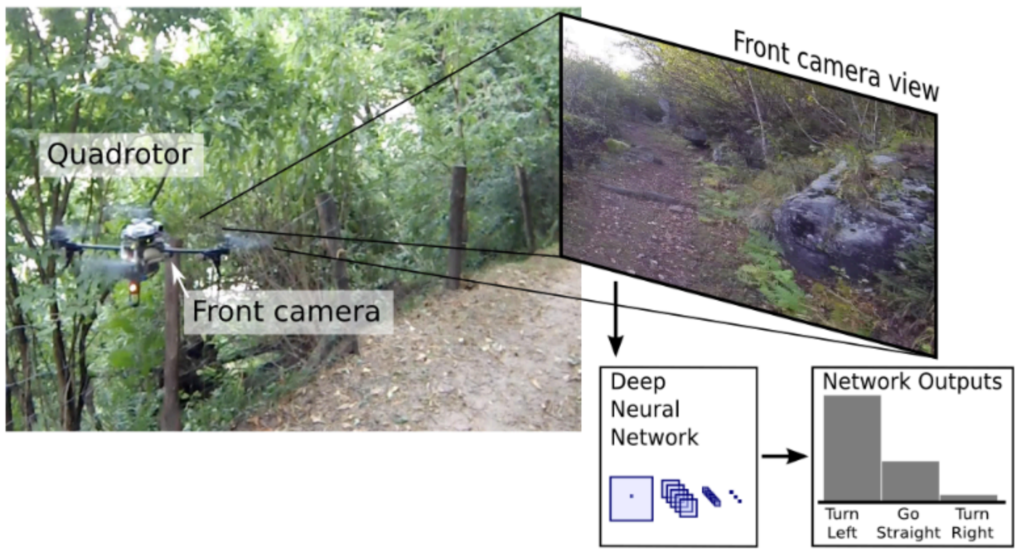
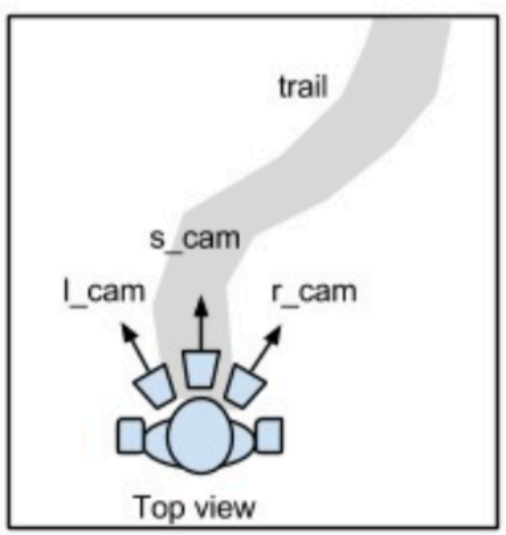
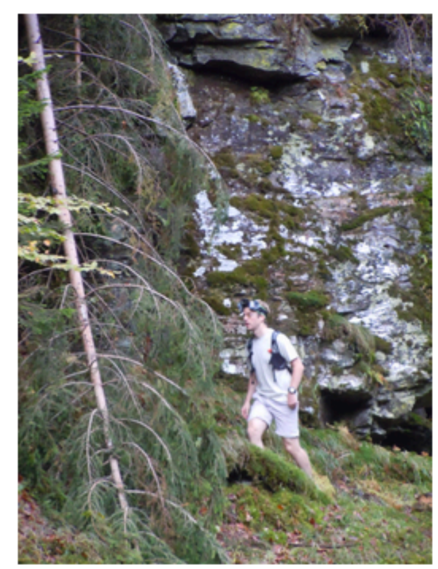
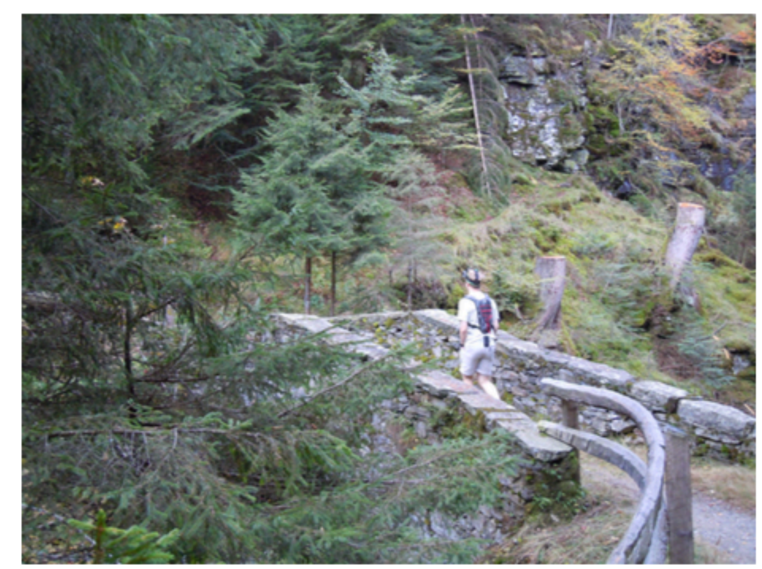
Data Augmentation (3): Trails 2015









A Machine Learning Approach to Visual Perception of Forest Trails for Mobile Robots. Giusti et al.

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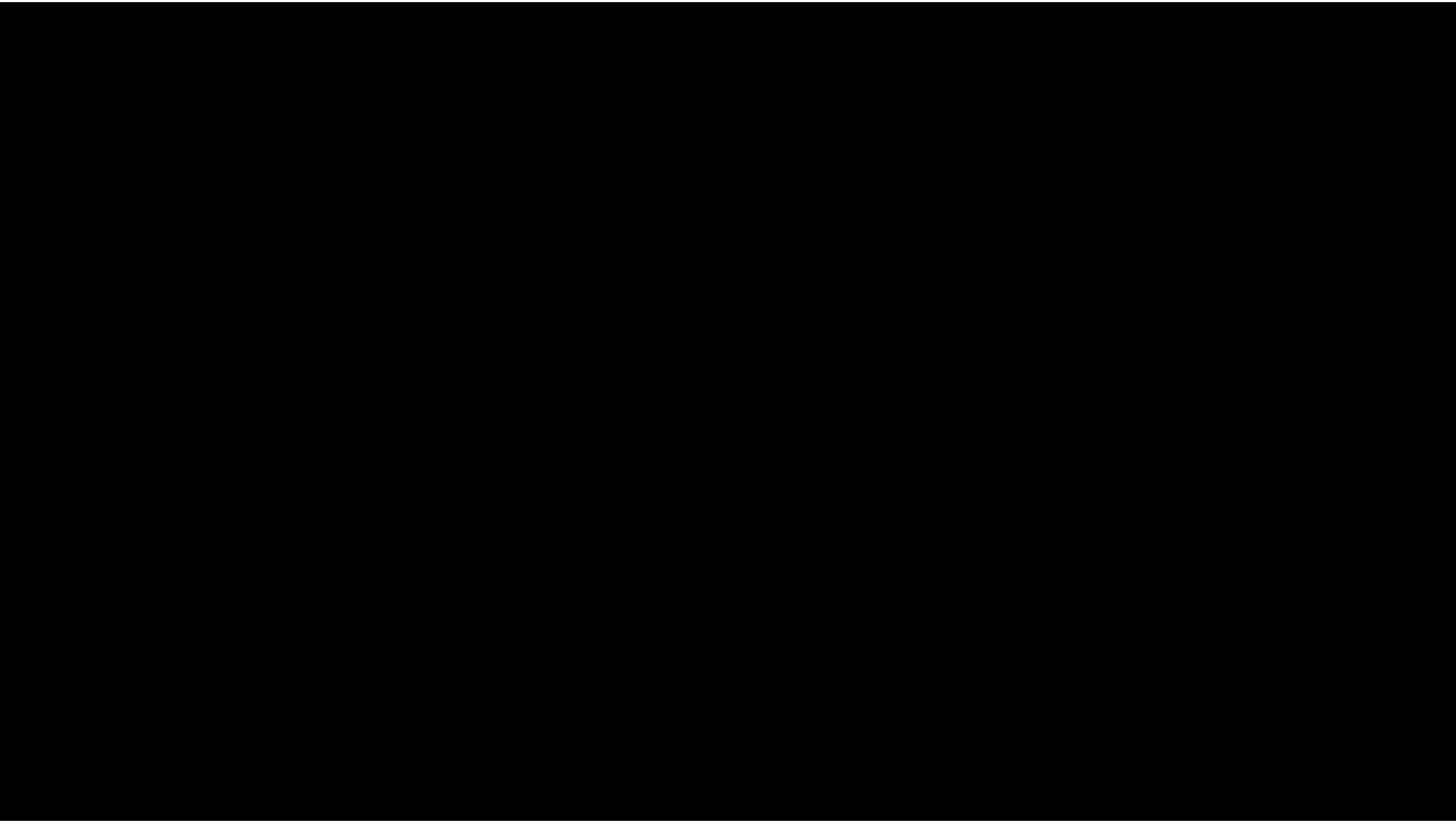

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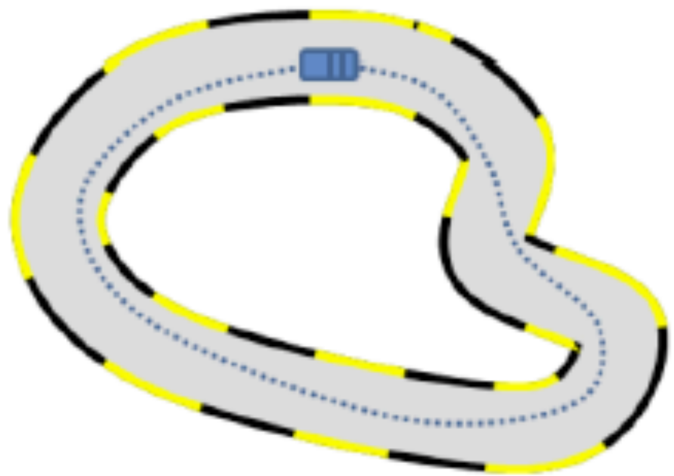
Learning to Drive a Car: Supervised Learning

Expert Trajectories



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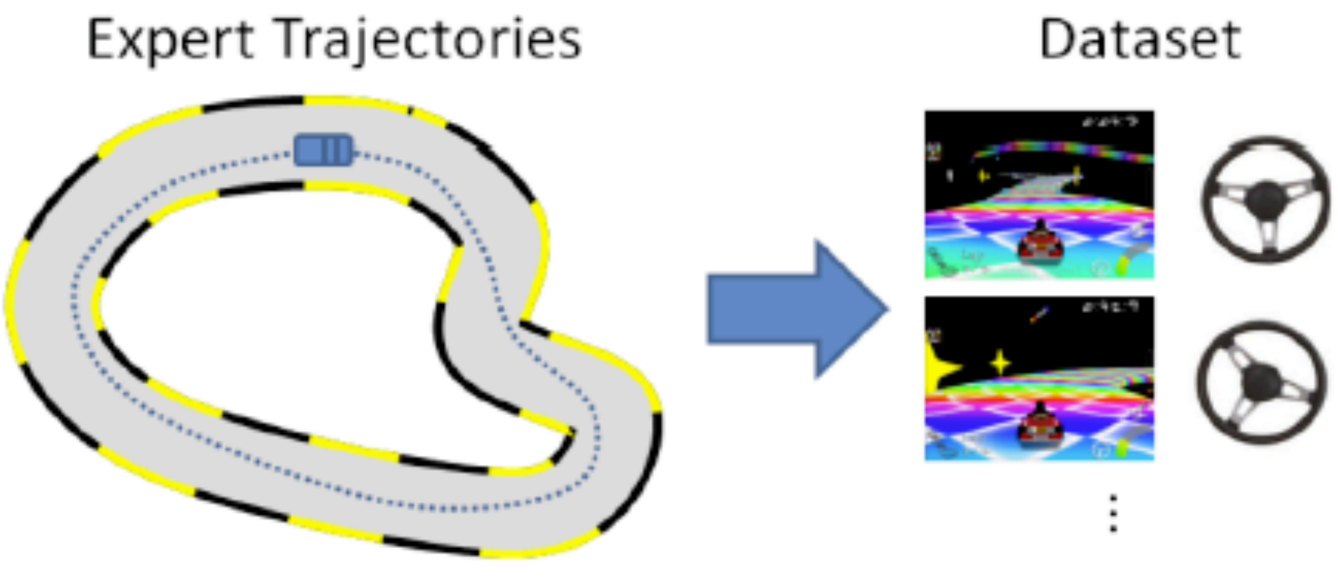
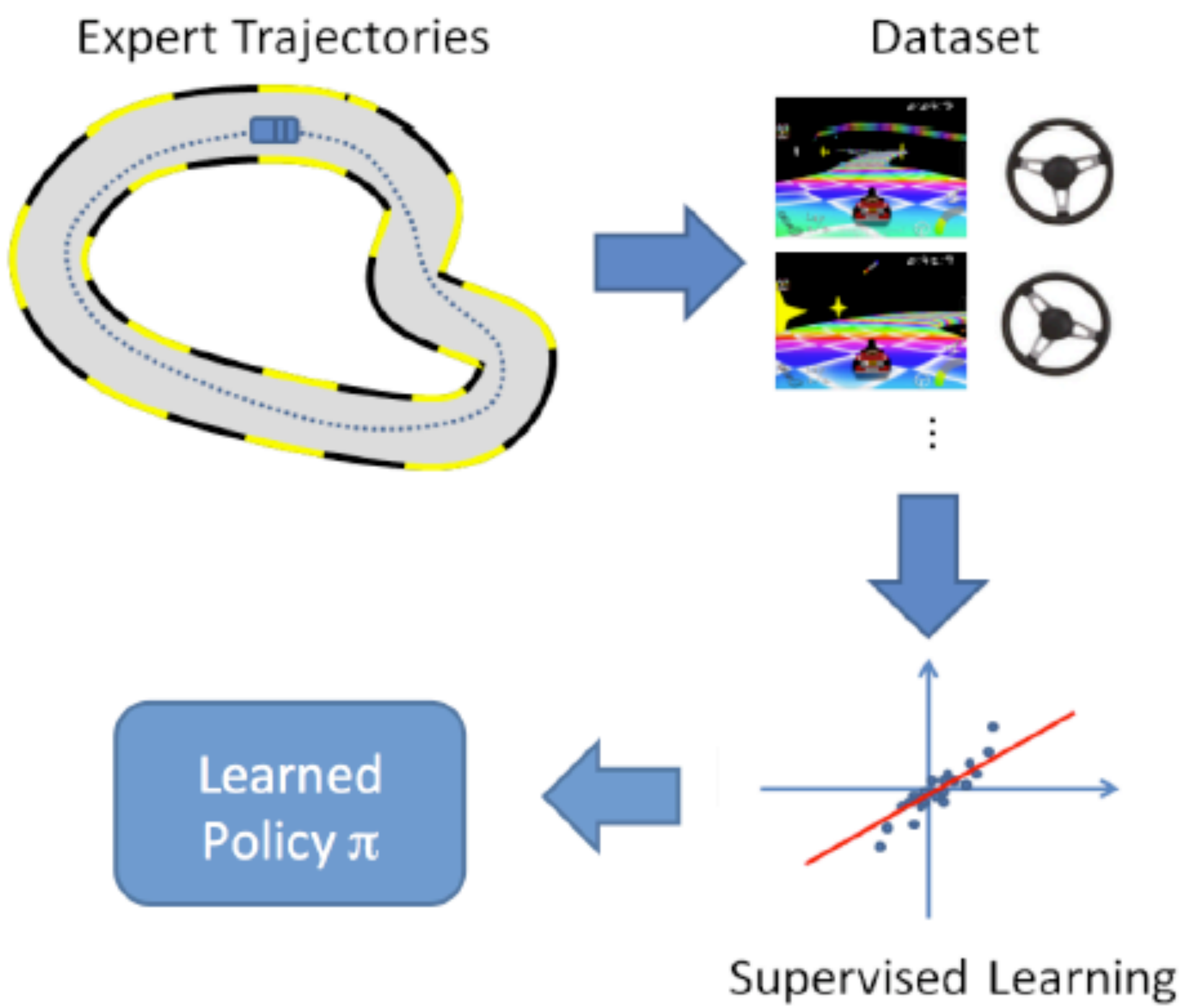


Learning to Drive a Car: Supervised Learning



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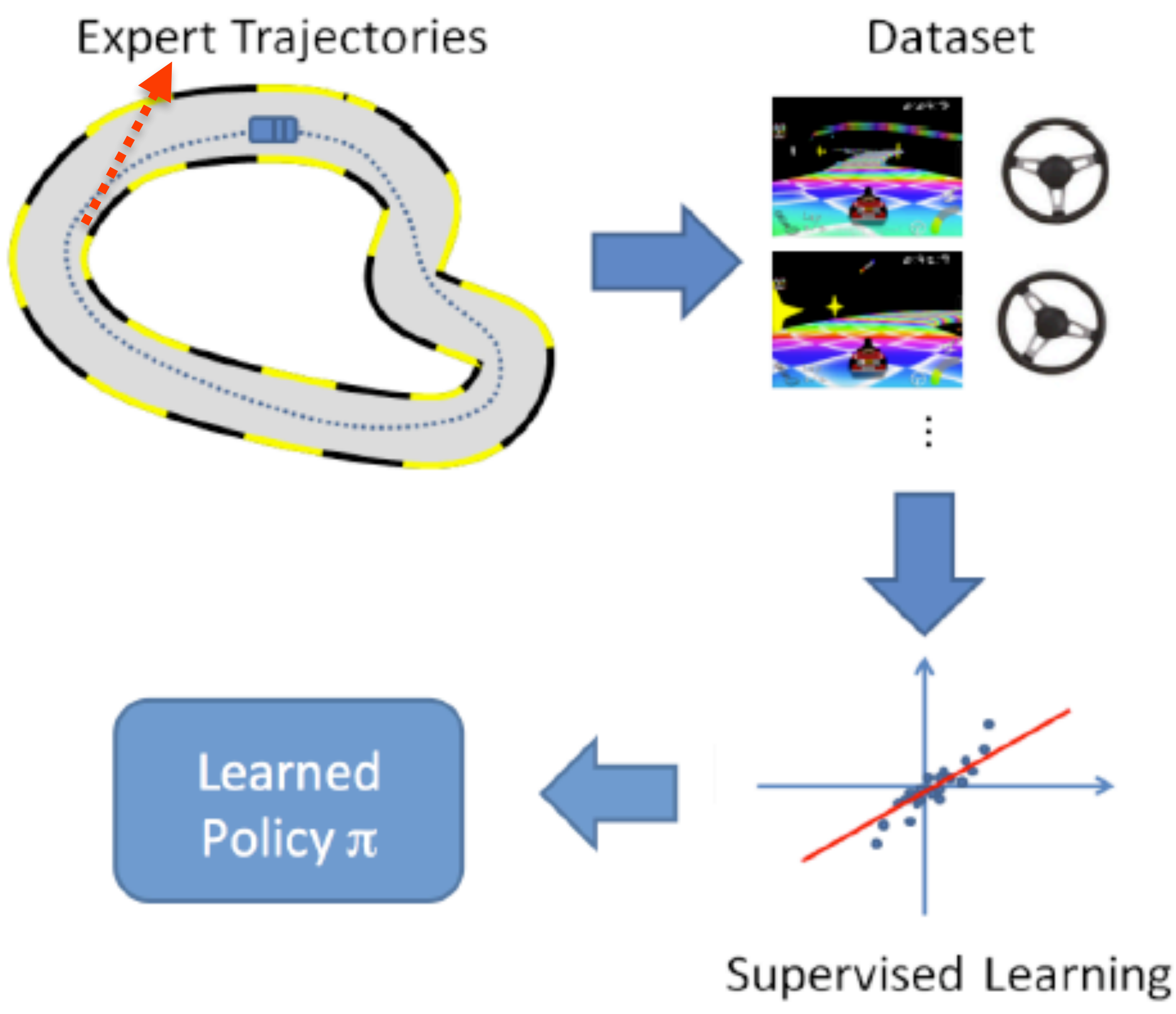

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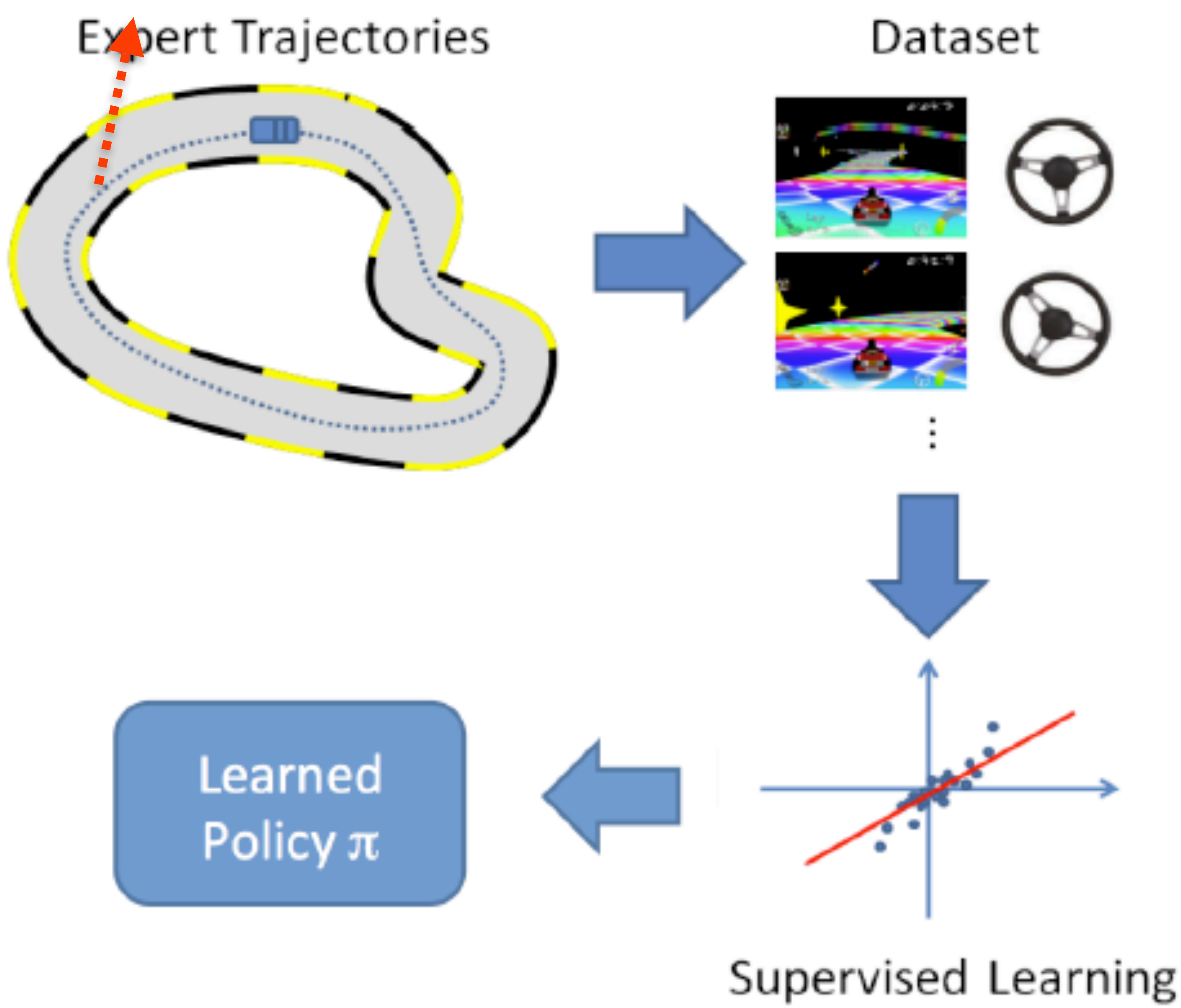

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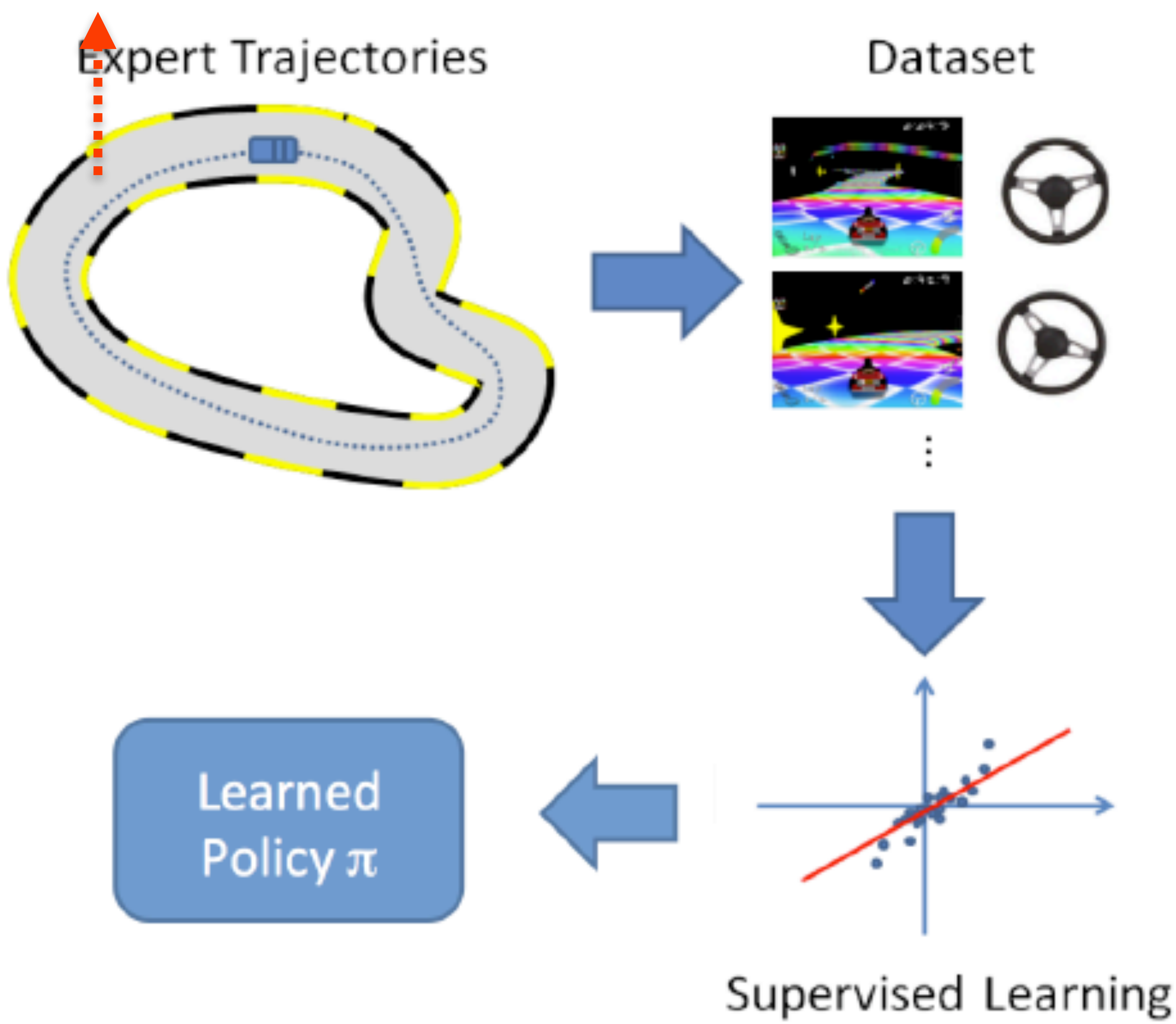
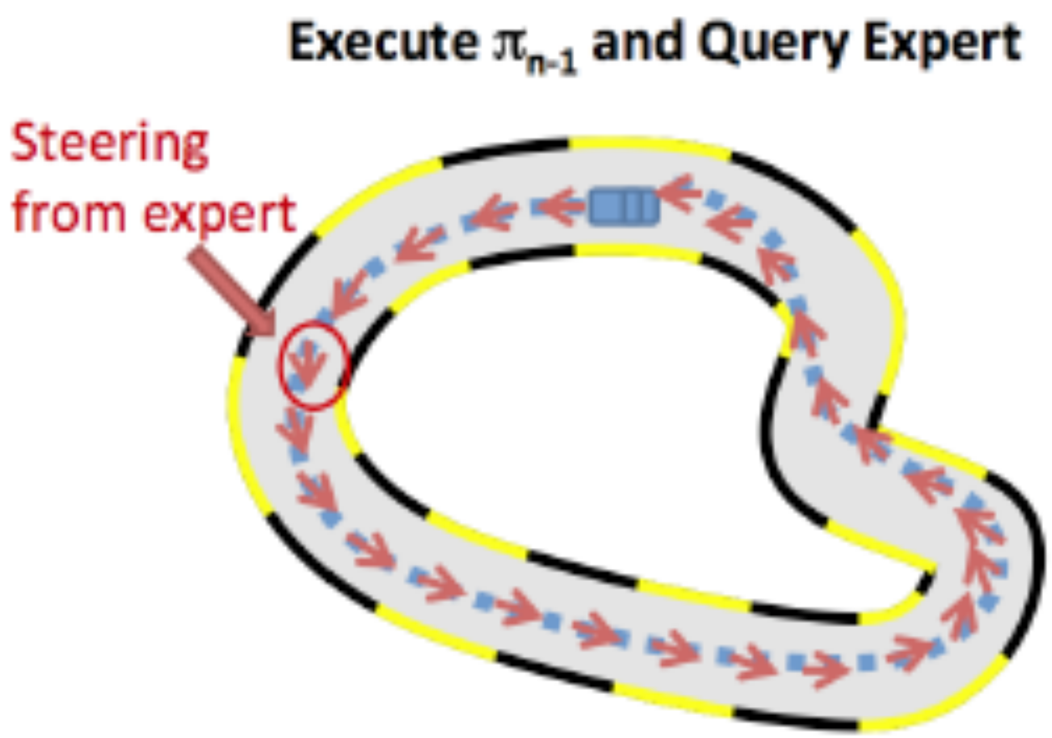


Learning to Race a Car : Interactive learning-DAGGer



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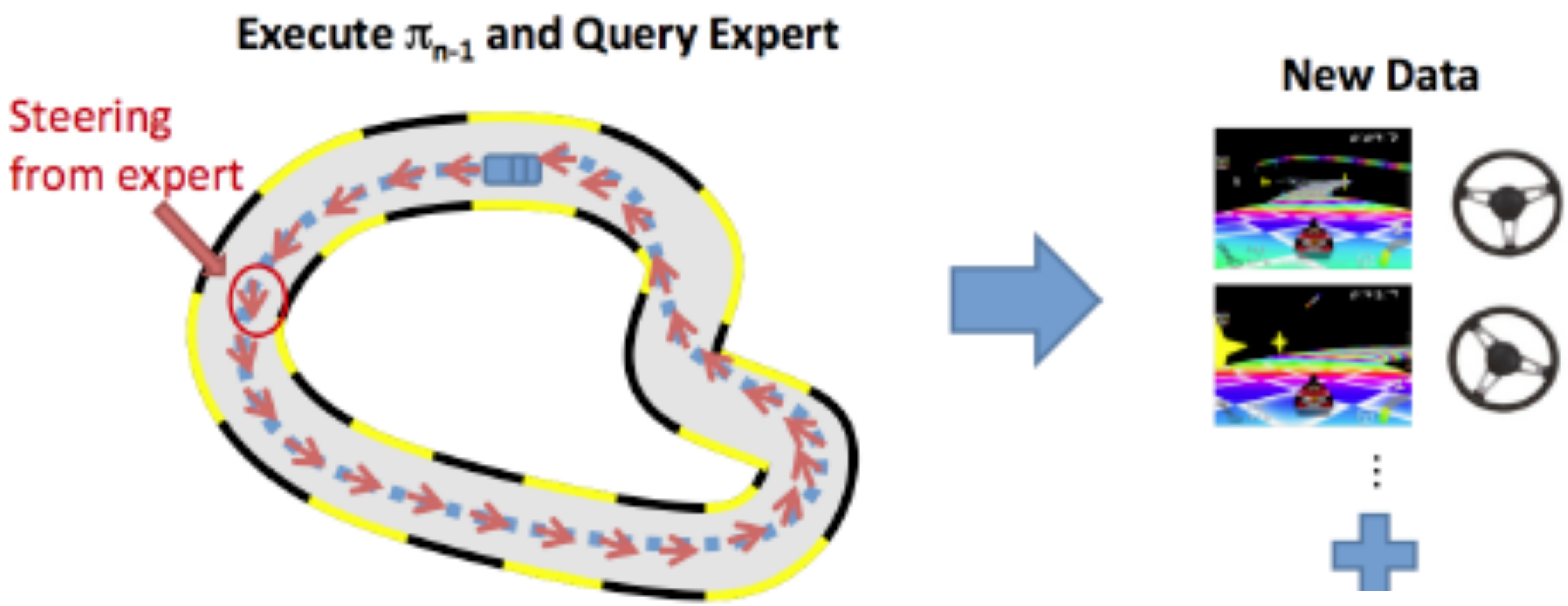

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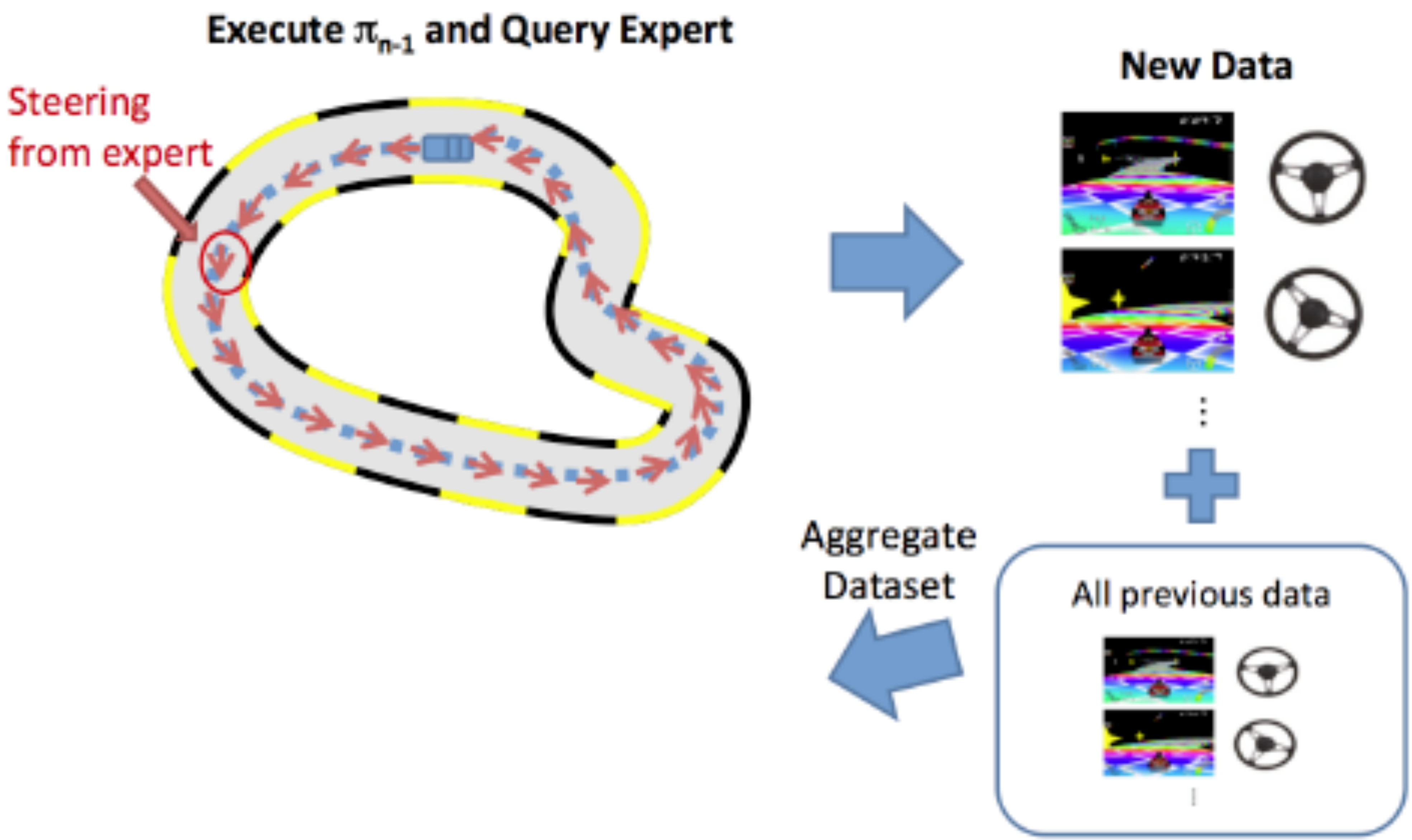

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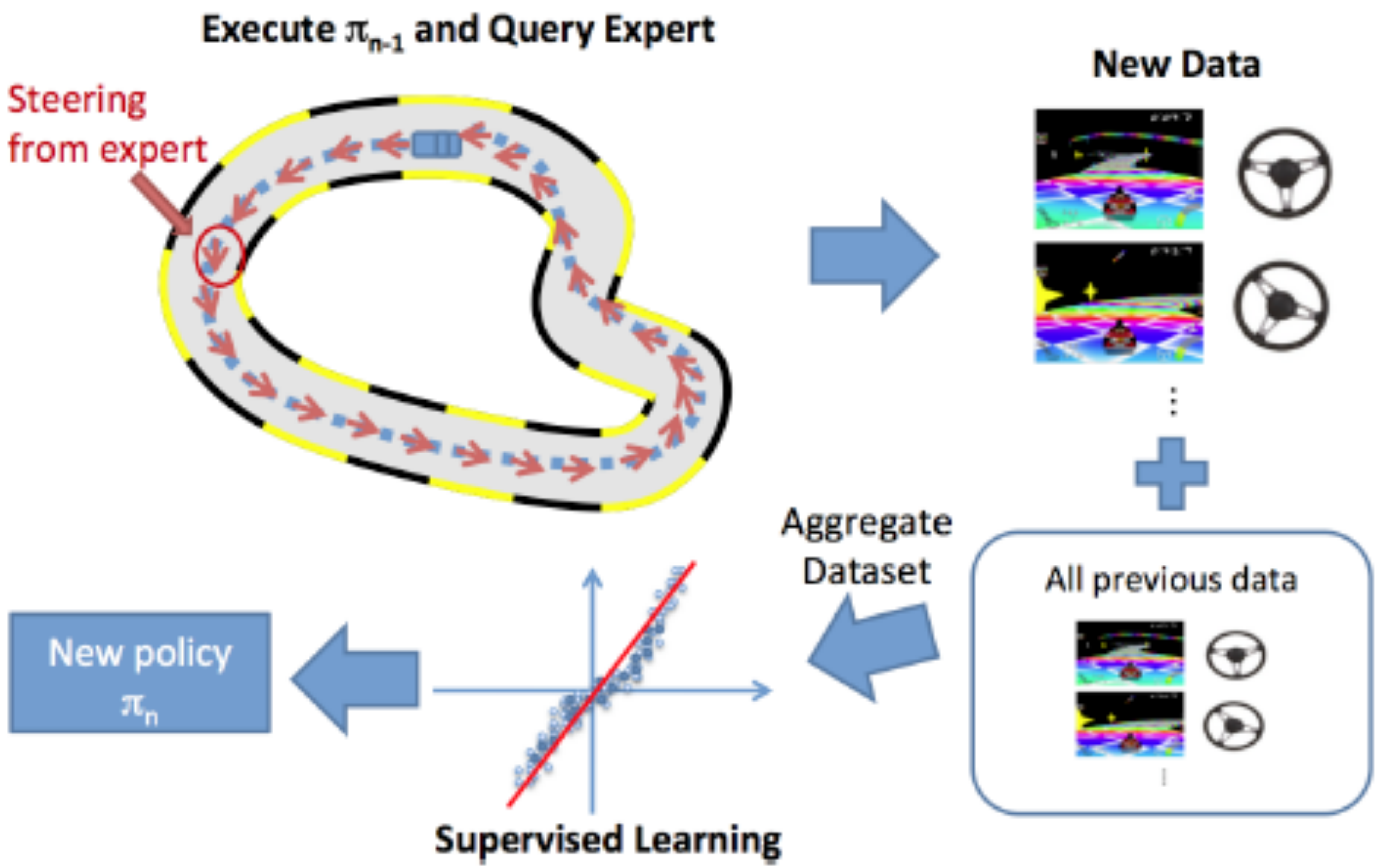
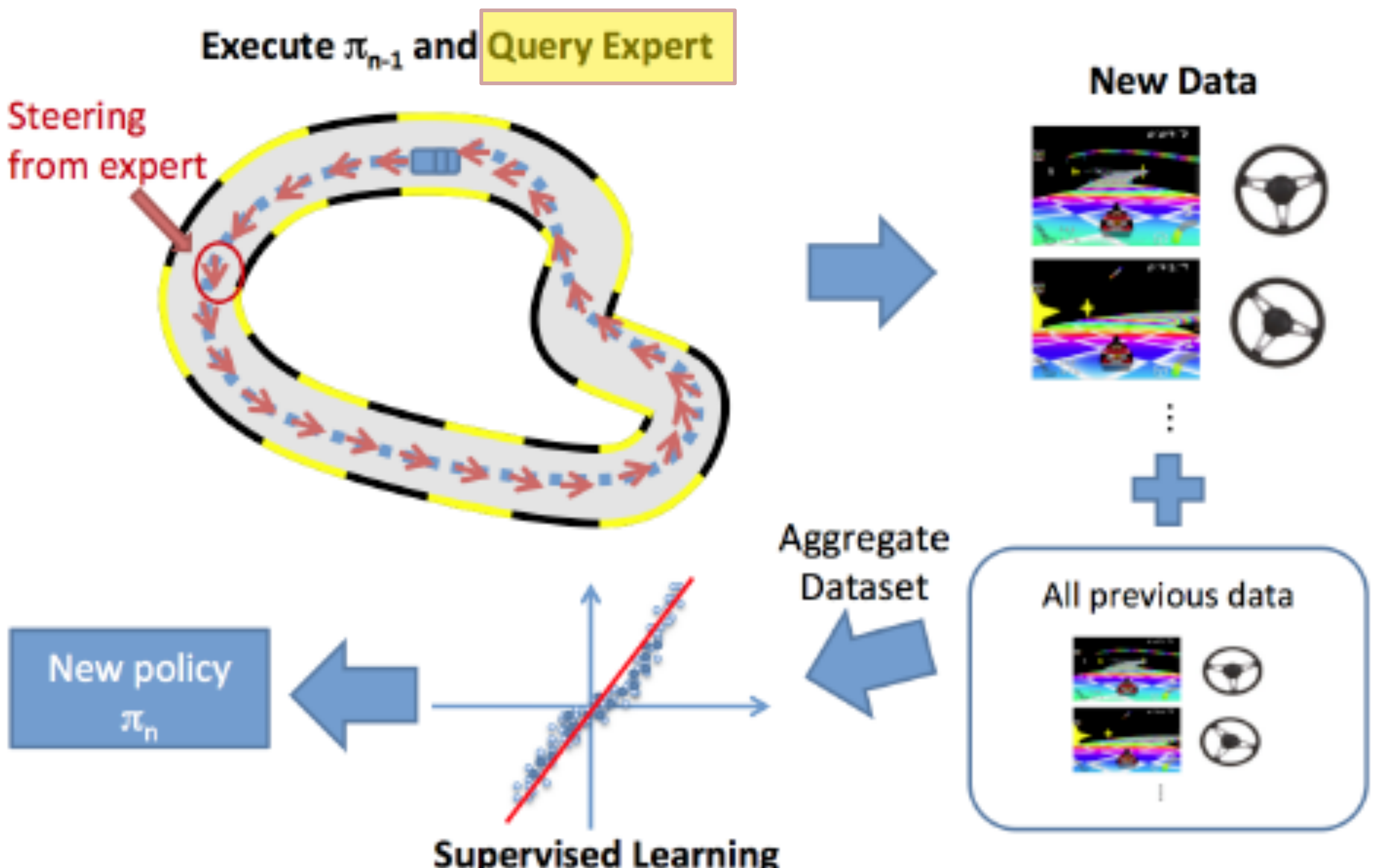


Learning to Race a Car : Interactive learning-DAGGer

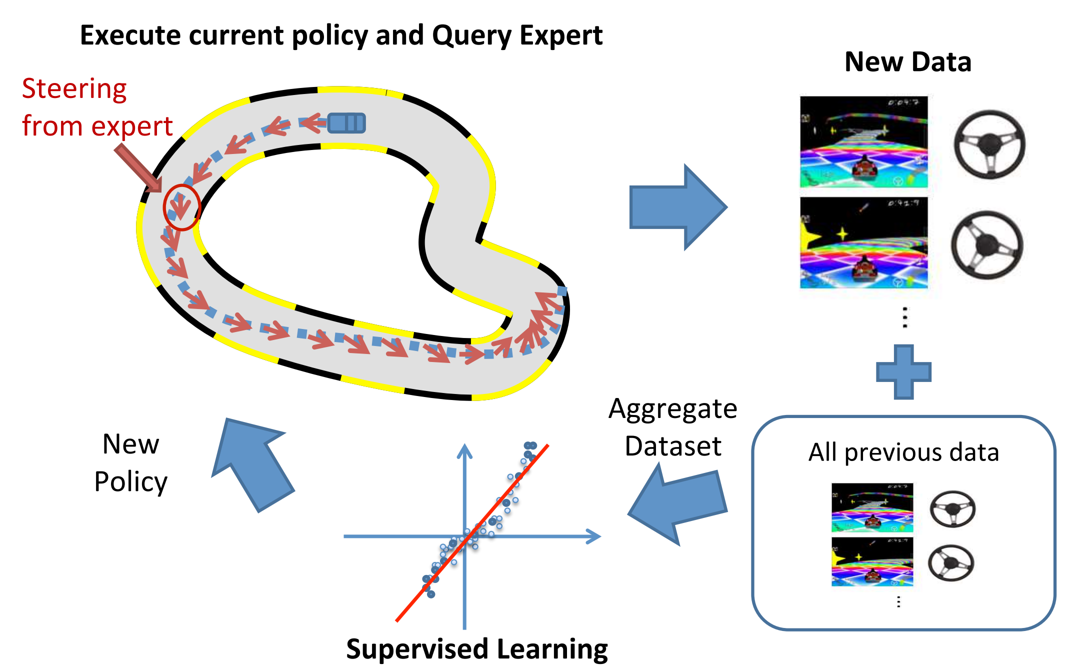
This assumes you can actively access an expert during training!



A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning Stephane Ross, Geoffrey J. Gordon, J. Andrew Bagnell

DAGGER (in simulation)

Dataset AGGregation: bring learner's and expert's trajectory distributions closer by labelling additional data points resulting from applying the current policy.

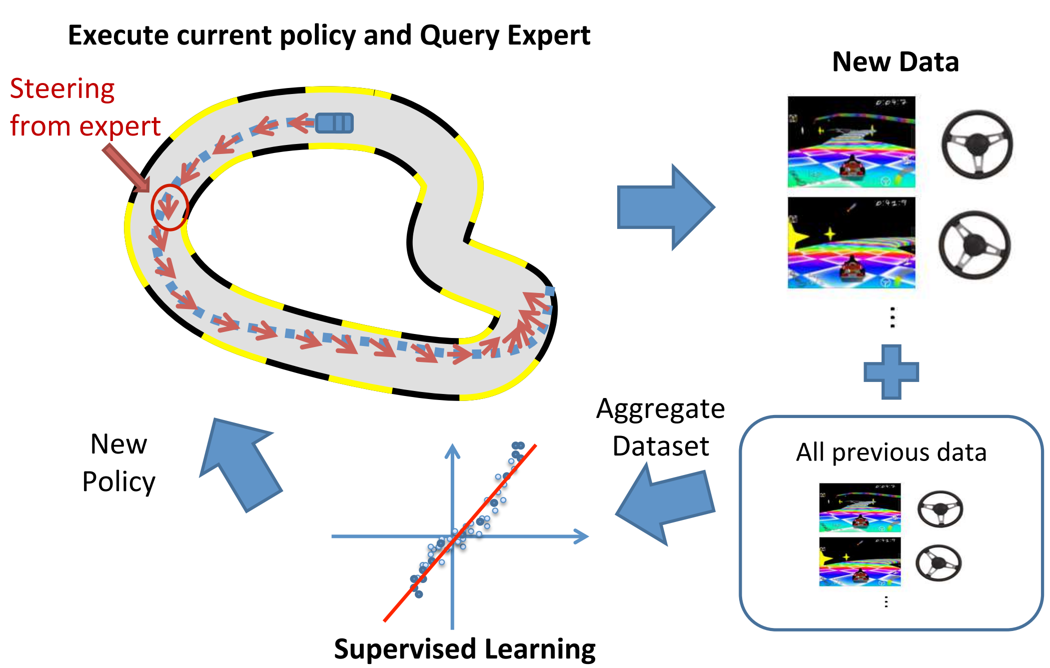


A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning, Ross et al. 2011

DAGGER (in simulation)

Dataset AGGregation: bring learner's and expert's trajectory distributions closer by (asking human experts to provide) labelling additional data points resulting from applying the current policy

1. Train $\pi_\theta(u_t \mid o_t)$ from human data $\mathcal{D}_{\pi^*} = \{o_1, u_1, \ldots o_N, u_N\}$
2. Run $\pi_\theta(u_t \mid o_t)$ to get dataset $\mathcal{D}_\pi = \{o_1, \ldots, o_M\}$
3. Ask human to label $\mathcal{D}_\pi$ with actions u_t
4. Aggregate: $\mathcal{D}_{\pi^*} \leftarrow \mathcal{D}_{\pi^*} \cup \mathcal{D}_\pi$
5. GOTO step 1.



Problems:

- execute an unsafe/partially trained policy
- repeatedly query the expert

A Reduction of Imitation Learning and Structured Prediction to No-Regret Online Learning, Ross et al. 2011

DAGGER (on a real platform)

Application on drones: given RGB from the drone camera predict steering angles

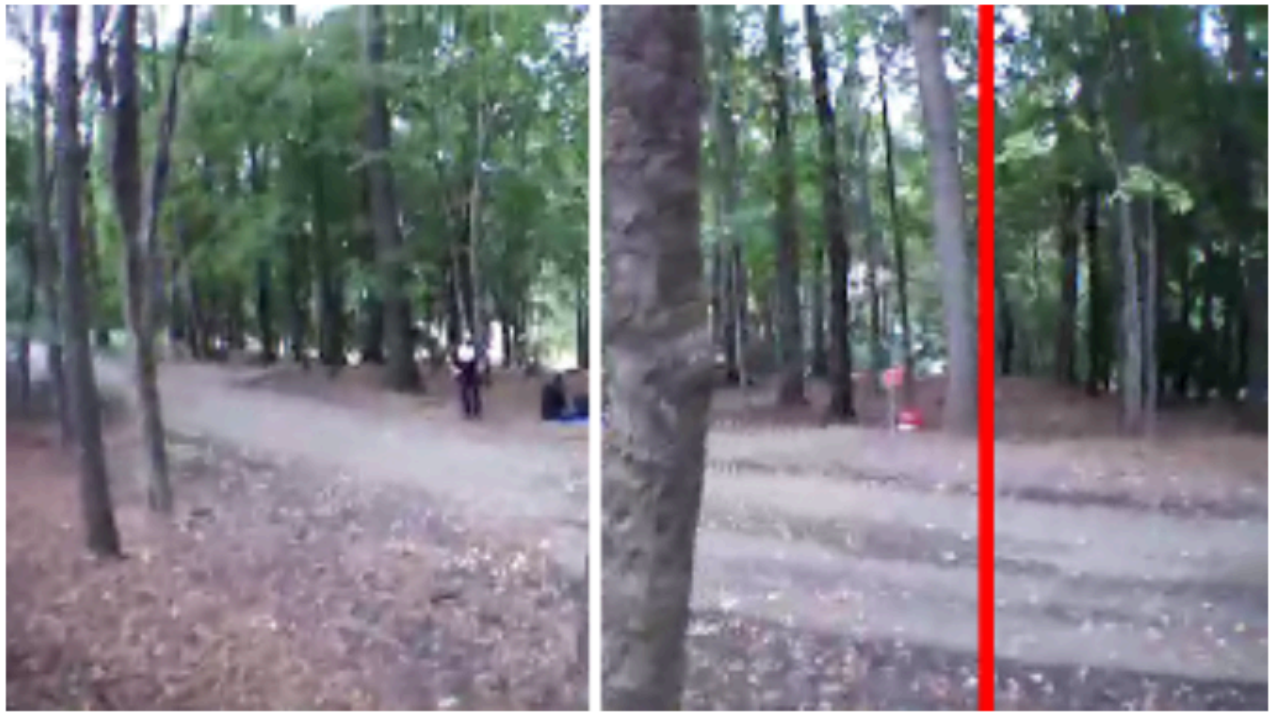
Learning monocular reactive UAV control in cluttered natural environments, Ross et al. 2013

DAGGER (on a real platform)

Application on drones : given RGB from the drone camera predict steering angle

Caveats:

1. It is hard for the expert to provide the right magnitude for the turn without feedback of his own actions! Solution: provide him with visual feedback



Learning monocular reactive UAV control in cluttered natural environments, Ross et al. 2013

DAGGER (on a real platform)

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1. Is hard for the expert to provide the right magnitude for the turn without feedback of his own actions! Solution: provide him with his visual feedback

2. The expert's reaction time to the drone's behavior is large, this causes imperfect actions to be commanded. Solution: play-back in slow motion offline and record their actions.

3. Executing an imperfect policy causes accidents, crashes into obstacles. Solution: safety measures which make again the data distribution matching imperfect between train and test, but good enough..

Learning monocular reactive UAV control in cluttered natural environments, Ross et al. 2013

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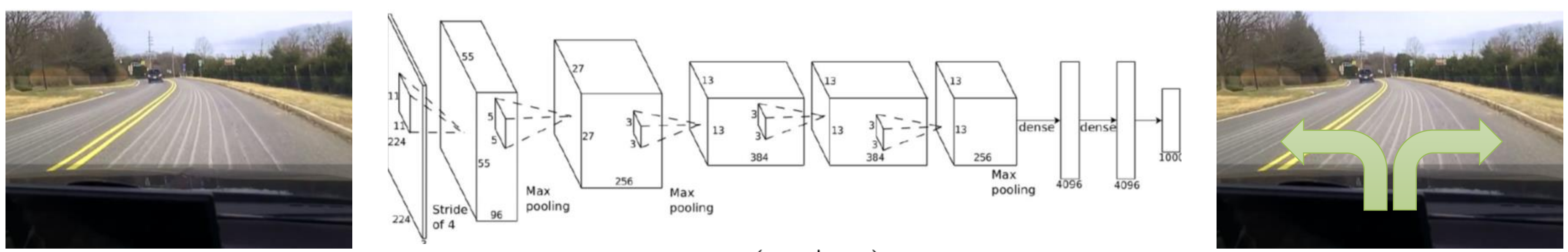
- Experts do not need to be humans.
- Machinery that we develop in this lecture can be used for imitating expert policies found through (easier) optimization in a constrained smaller part of the state space.
- Imitation then means distilling knowledge of expert constrained policies into a general policy that can do well in all scenarios the simpler policies do well.

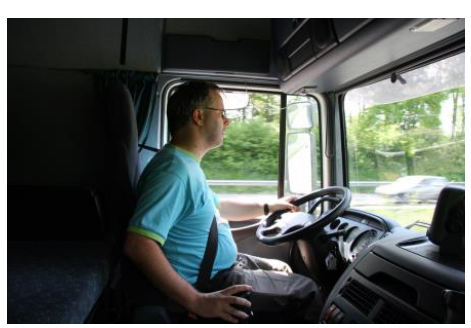
Learning monocular reactive UAV control in cluttered natural environments, Ross et al. 2013

Imitation learning - Challenges

- Non-markovian observations
  - Fix: observation concatenation or recurrent models

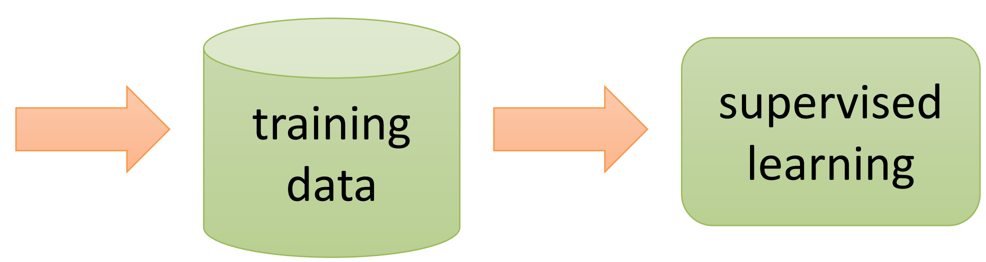


$\mathbf{o}_t$ $\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$ $\mathbf{u}_t$



$\mathbf{o}_t$

$\mathbf{u}_t$



$\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$

End to End Learning for Self-Driving Cars, Bojarski et al. 2016

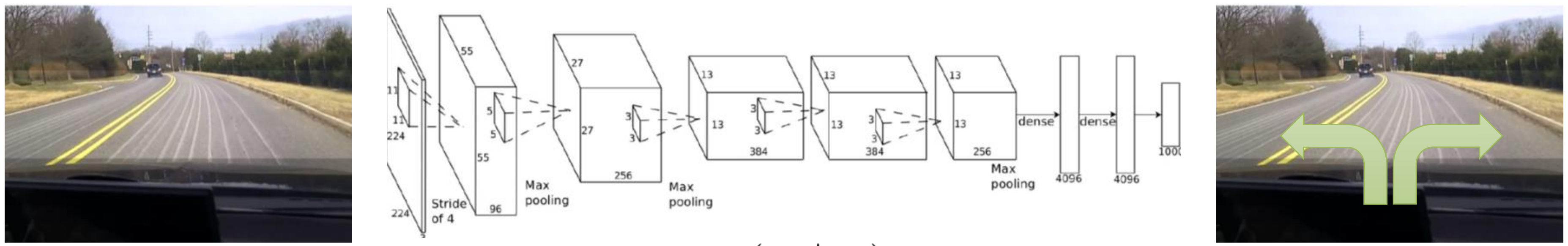
Markov property

A stochastic process has the Markov property if the conditional probability distribution of future states of the process (conditional on both past and present states) depends only upon the present state, not on the sequence of events that preceded it

$$\mathbb{P}[R_{t+1} = r, S_{t+1} = s' | S_0, A_0, R_1, ..., S_{t-1}, A_{t-1}, R_t, S_t, A_t] = \mathbb{P}[R_{t+1} = r, S_{t+1} = s' | S_t, A_t]$$

for all $s' \in \mathcal{S}, r \in \mathscr{R}$ and all histories

Non-Markovian observations



$\mathbf{o}_t$ $\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$ $\mathbf{u}_t$

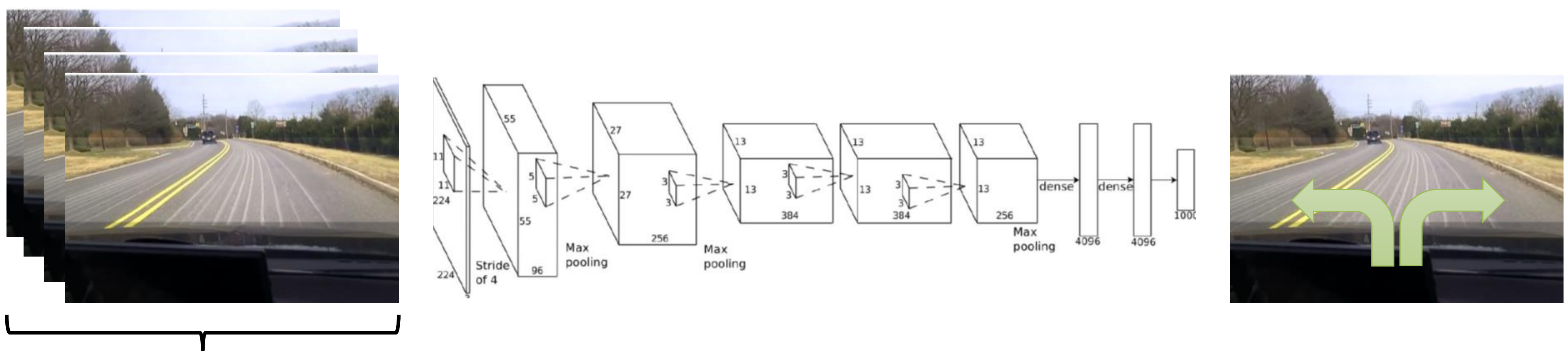
$$\pi_\theta(\mathbf{u}_t|\mathbf{o}_t)$$

behavior depends only
on current observation

$$\pi_\theta(\mathbf{u}_t|\mathbf{o}_1, \ldots, \mathbf{o}_t)$$

behavior depends on
all past observations

Fix 1: concatenate observations



Fix 2: use recurrent networks

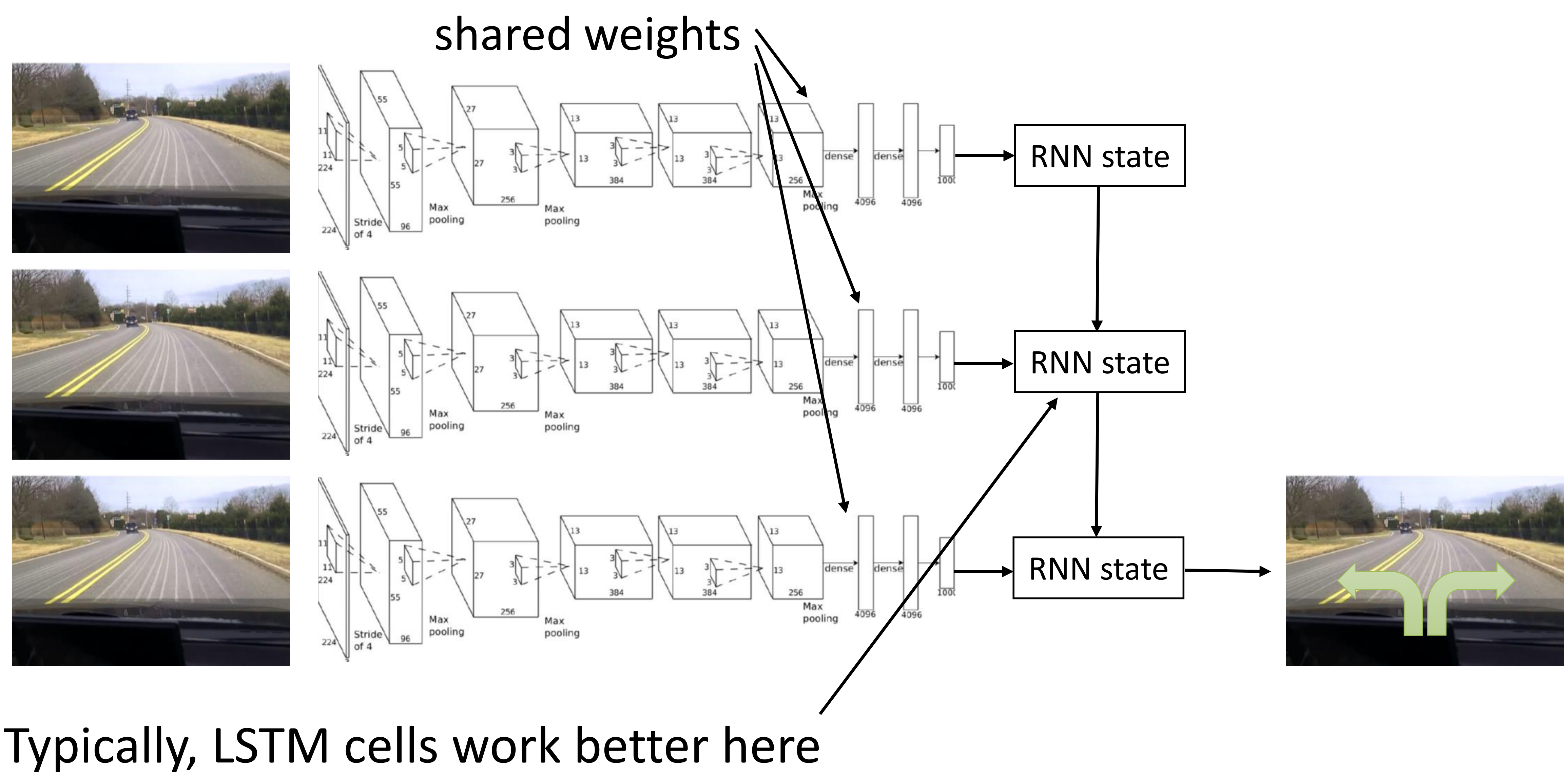


Diagram from Sergey Levine

Recurrent Neural Networks (RNNs)

- RNNs tie the weights at each time step
- Condition the neural network on all previous inputs

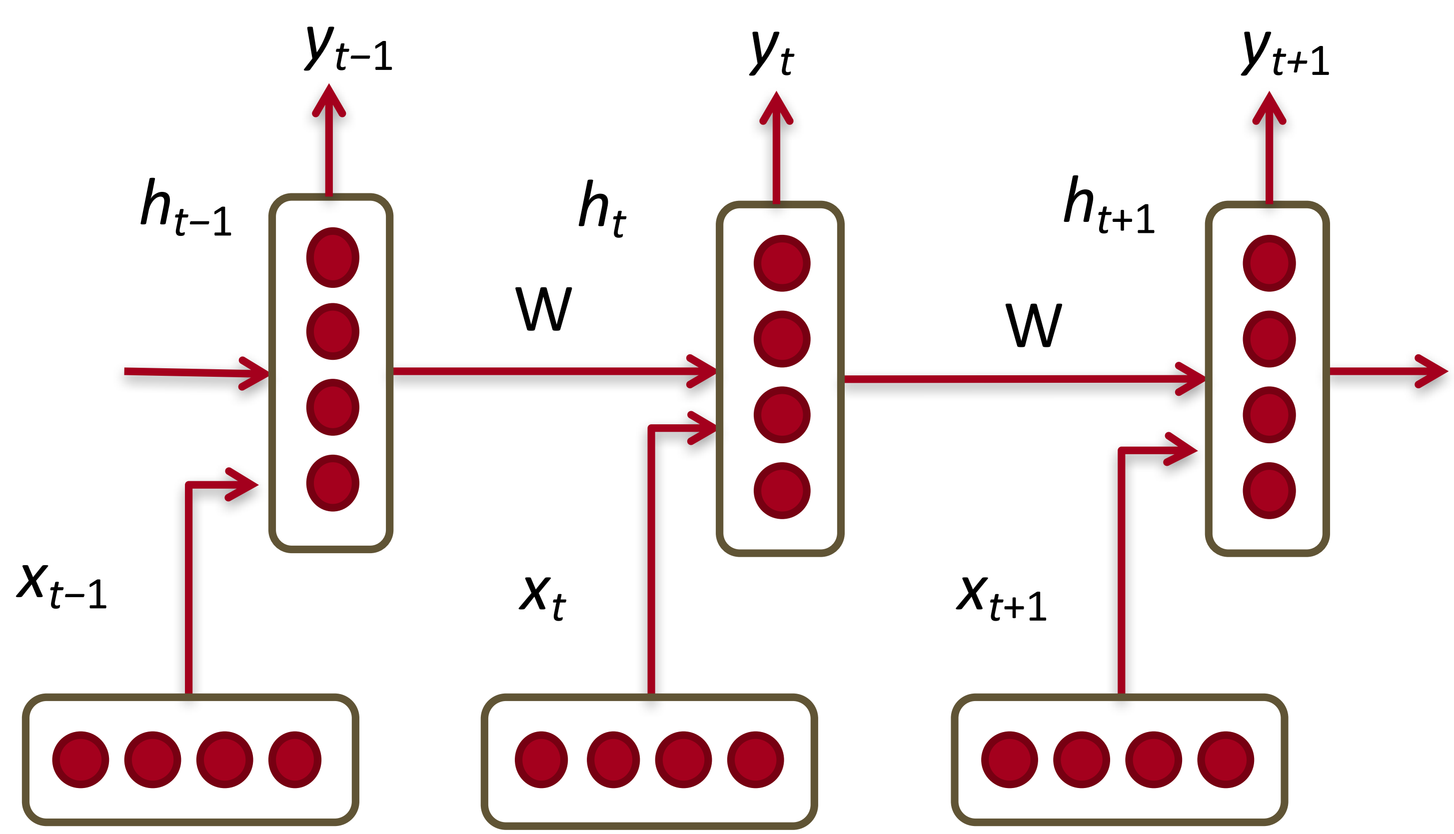


Diagram from Richard Socher

Recurrent Neural Network (single hidden layer)

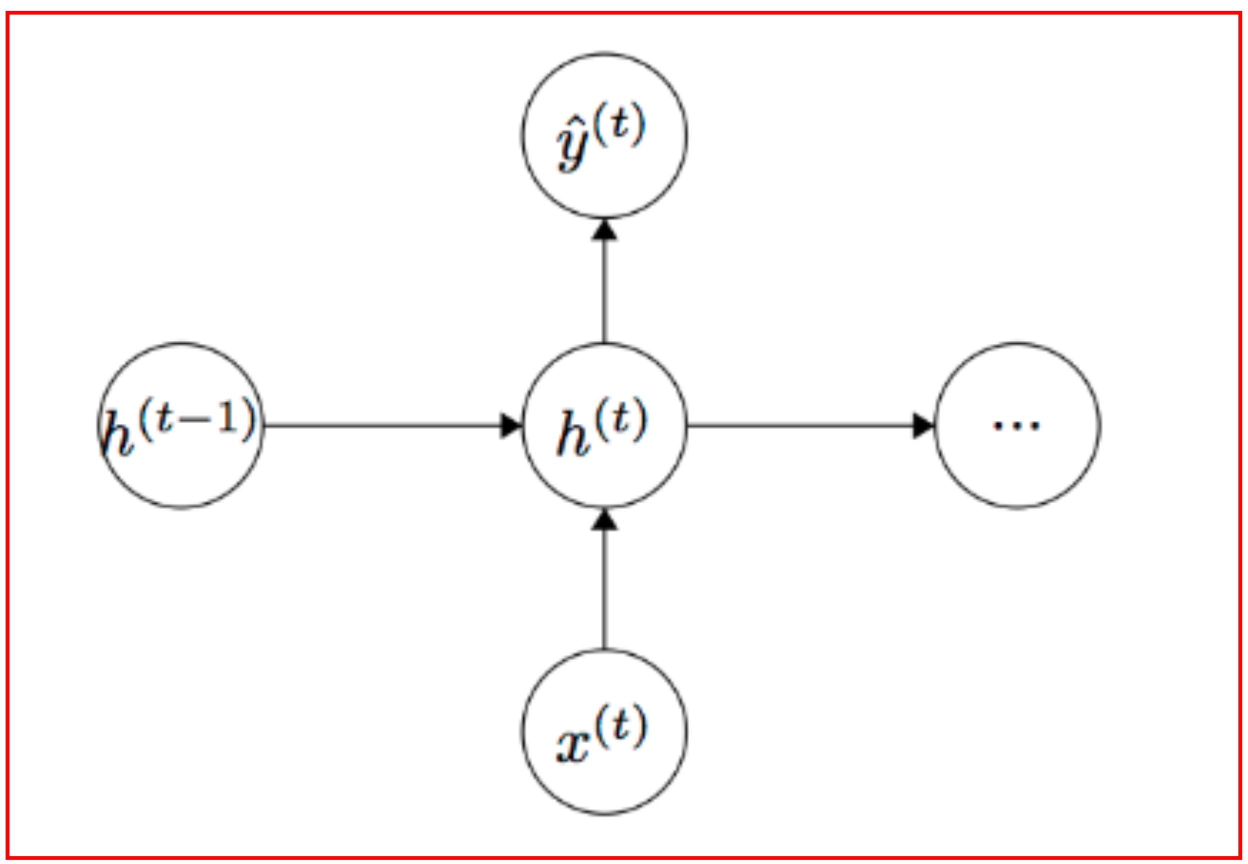
Given list of vectors: $x_1, ..., x_{t-1}, x_t, x_{t+1}, ..., x_T$

At a single time step:

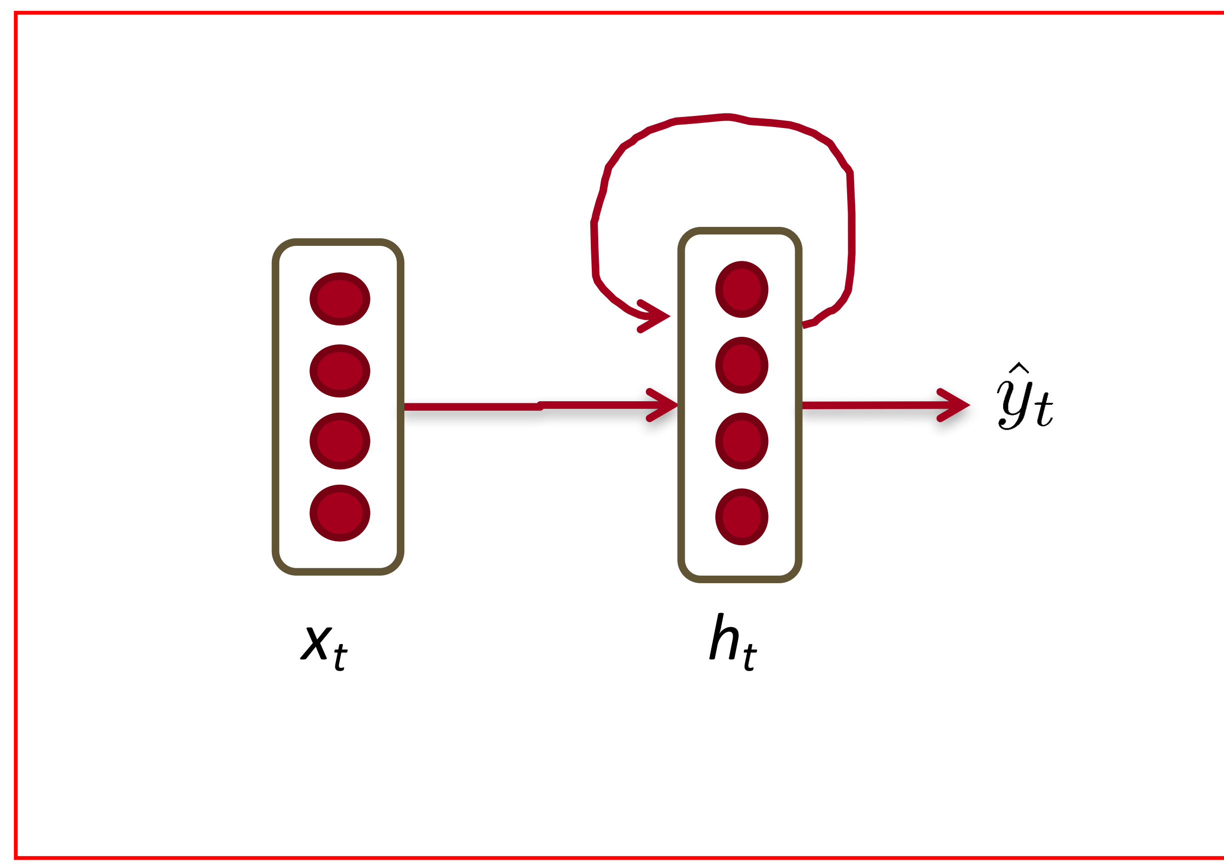
$$h_t = \sigma\left(W^{(hh)} h_{t-1} + W^{(hx)} x_{[t]}\right)$$

$$\hat{y}_t = \text{softmax}\left(W^{(S)} h_t\right)$$

(in case of discrete labels)



$\leftrightarrow$



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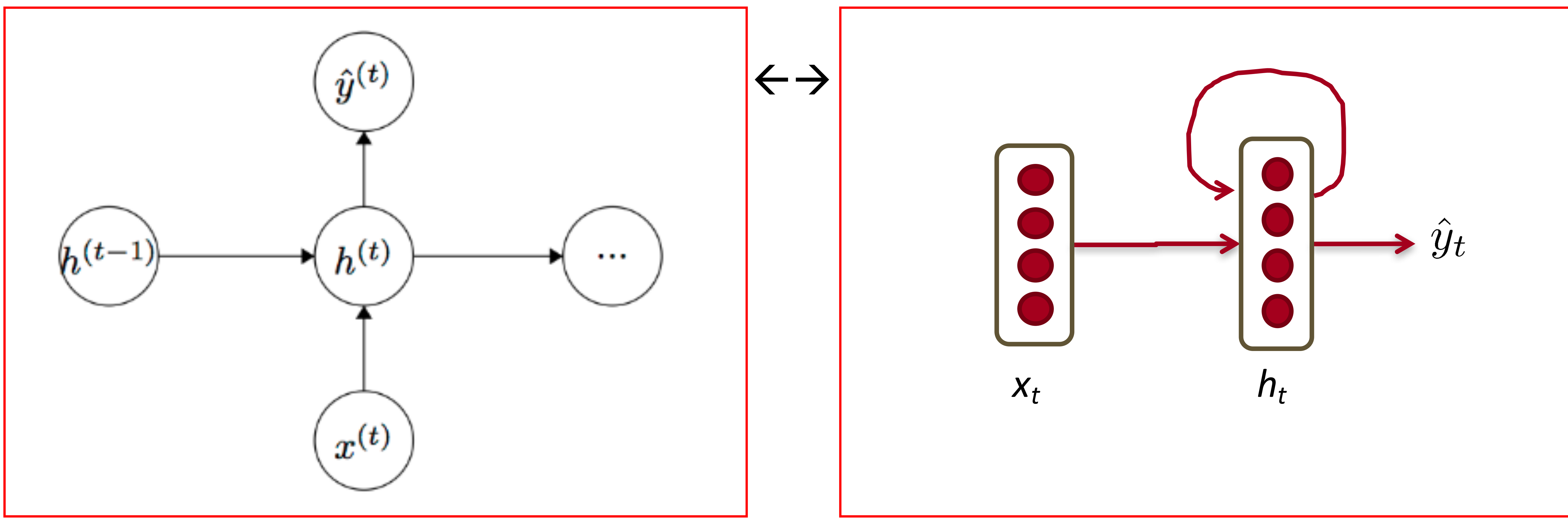


Diagram from Richard Socher

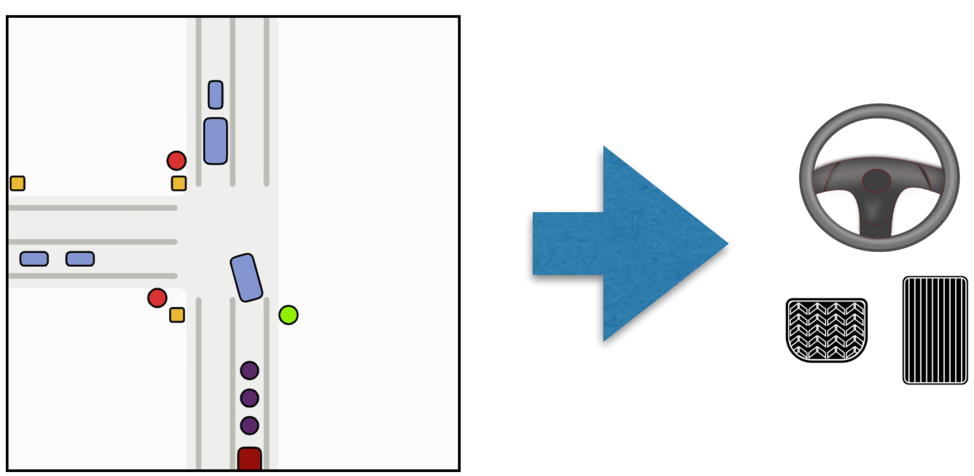
Fix 2: use recurrent networks

- Usually much more structure is needed in the latent state than a vanilla LSTM can provide, e.g., detections and trackless of objects.
- We will discuss later in the course structured recurrent neural networks for video perception.

Learning by Cheating

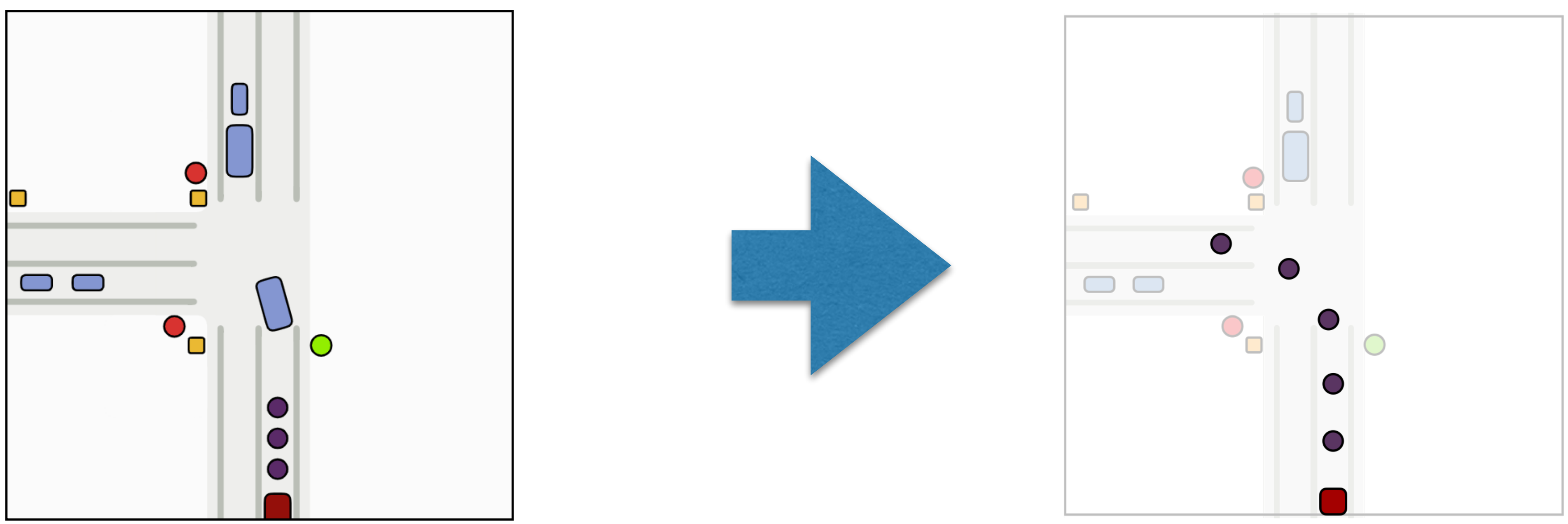
DAGGER: from a privileged teaching agent to an agent that drives from images.

privileged agent



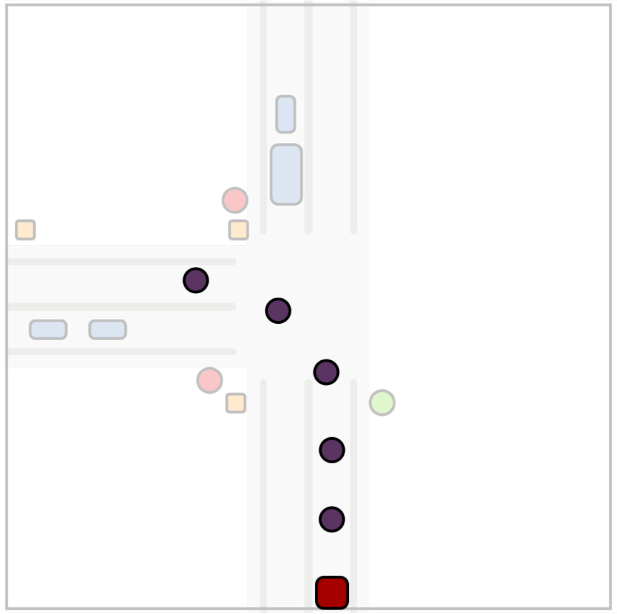
sensorimotor agent

Privileged Agent cheats: drives with the internal state of the simulator



it predicts future waypoints for the car to follow

Sensorimotor Agent drives from images



it predicts future waypoints for the car to follow

Waypoints are translated to steering commands with a low-level controller

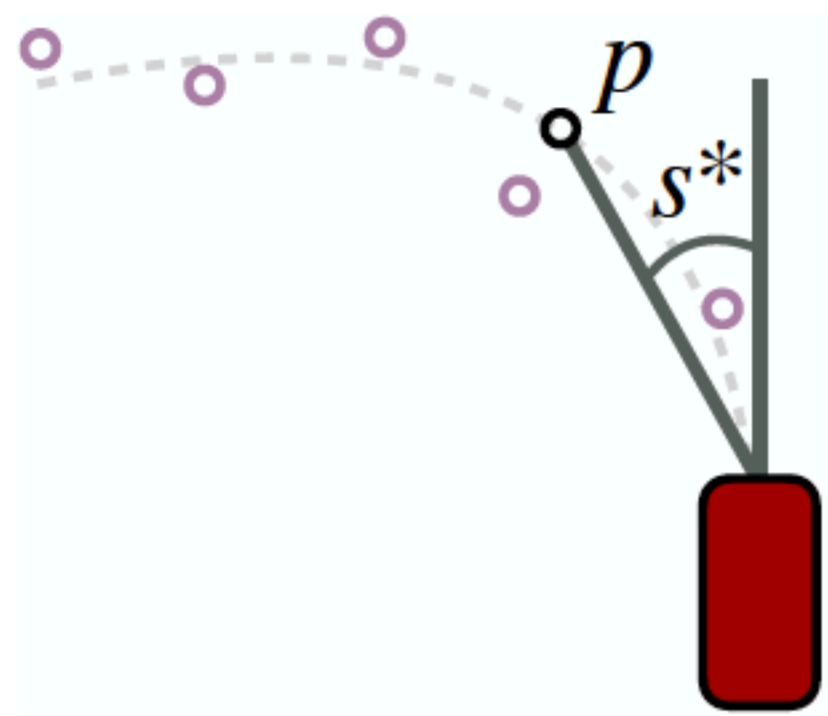
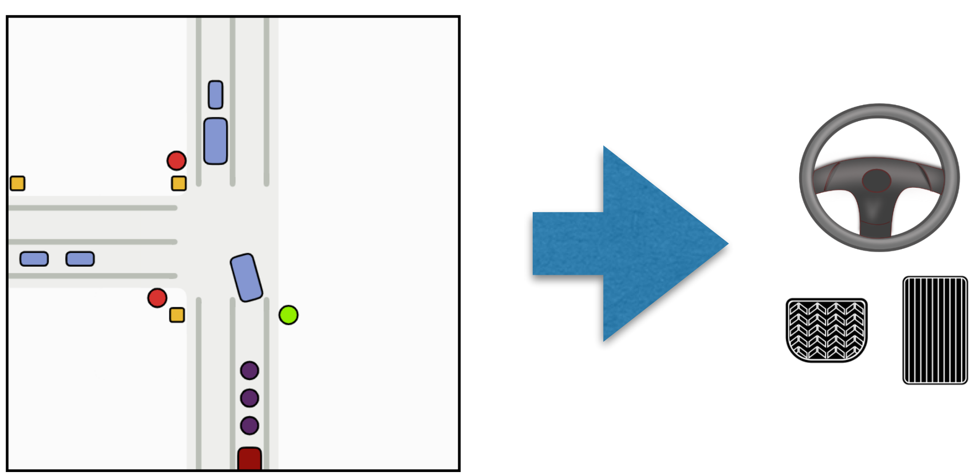


Figure 4: Lateral PID controller. Here the agent aims at the projection of the second waypoint onto the fitted arc. s^* denotes the angle between the vehicle and the target point p.

Learning by Cheating

DAGGER: from a privileged teaching agent to an agent that drives from images.

privileged agent



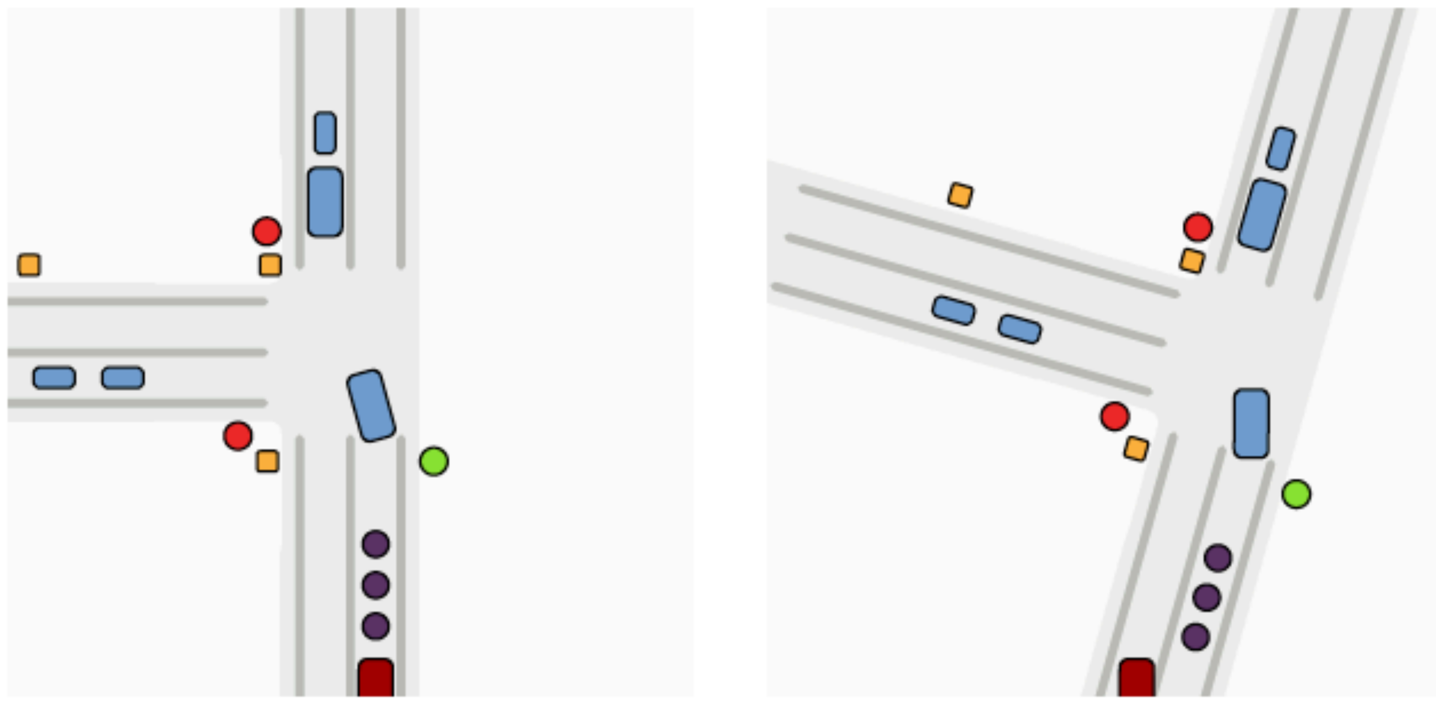
trained with imitation learning
from human experts

sensorimotor agent

trained with imitation learning
from the privileged agent

But why learning from simplified input helps?
It is the same supervised learning problem!

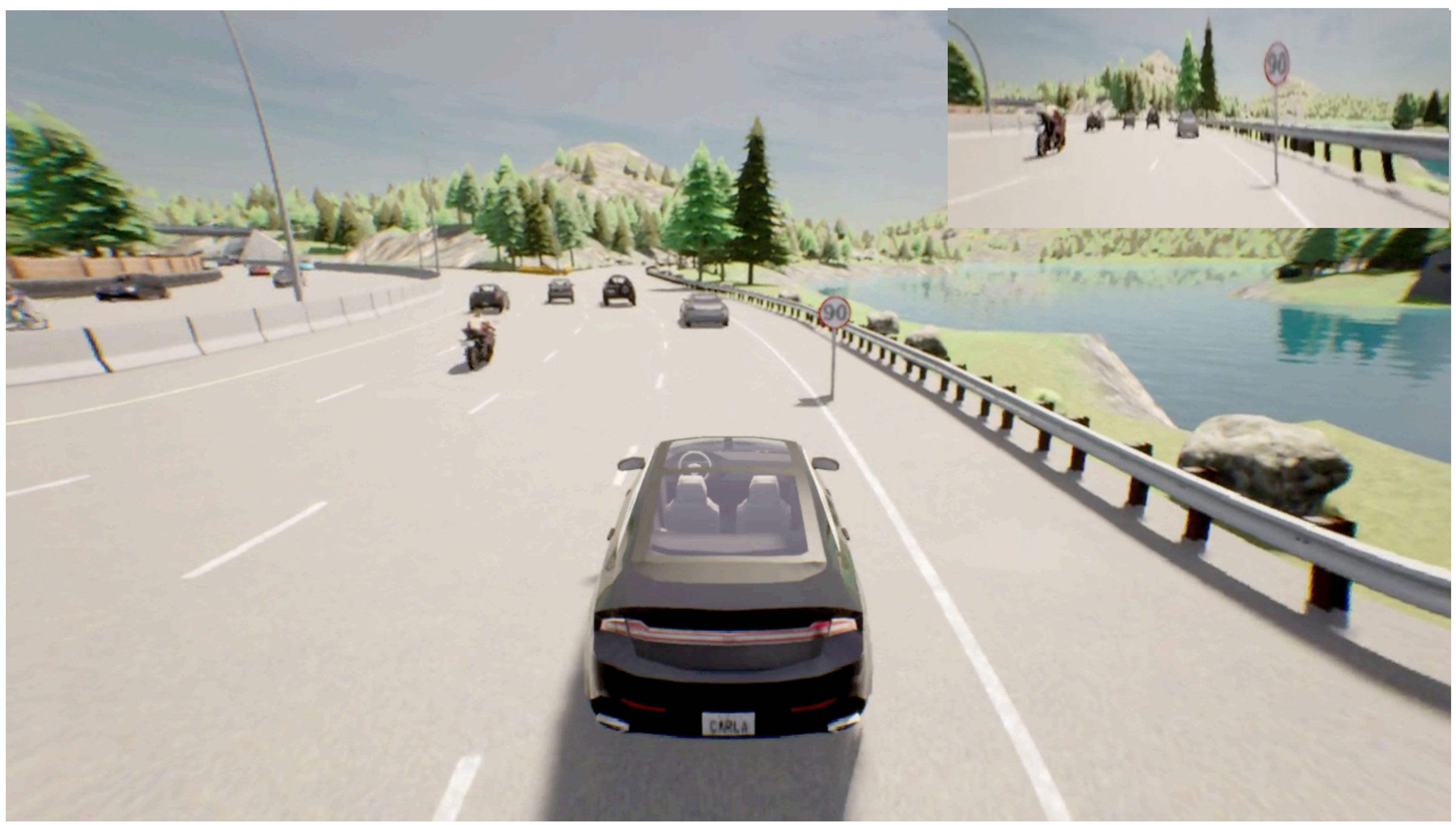
The privileged agent can augment its data!



(a) Road map (b) Rotation and shift aug.

Figure 3: **(a)** Map M provided to the privileged agent. One channel each for road (light grey), lane boundaries (grey), vehicles (blue), pedestrians (orange), and traffic lights (green, yellow, and red). The agent is centered at the bottom of the map. The agent's vehicle (dark red) and predicted waypoints (purple) are shown for visualization only and are not provided to the network. **(b)** The map representation affords simple and effective data augmentation via rotation and shifting.

Results



- high level command
- controller error
- lack of temporal reasoning