# Deep Reinforcement Learning for Autonomous Systems

Designing a control system to exploit model-free deep reinforcement learning algorithms to solve a real-world autonomous driving task of a small robot.

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**Supervisors**: Prof. Pietro Michiardi, EURECOM, France
Prof. Elena Baralis, Politecnico di Torino, Italy

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POLITECNICO
DI TORINO

This work of this thesis was developed at EURECOM (Sophia Antipolis, France) in collaboration with

Prof. Pietro Michiardi (EURECOM)
Prof. Elena Baralis (Politecnico di Torino)

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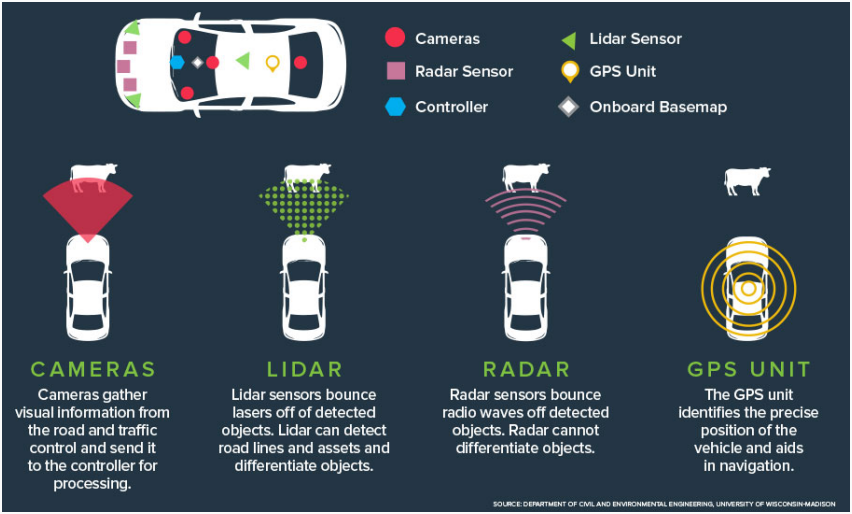
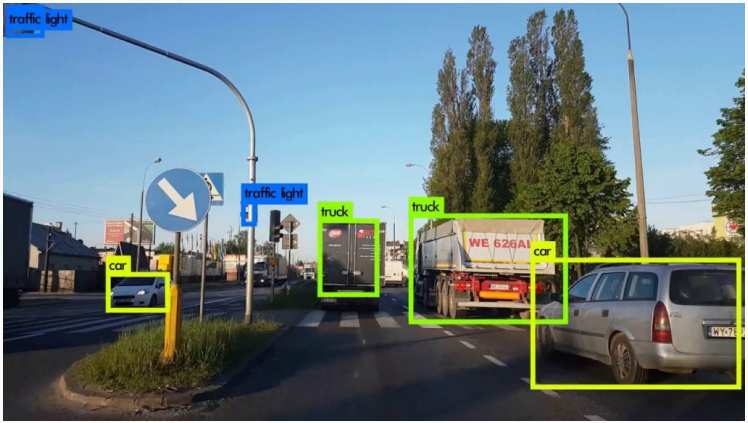
# Background

# State-of-the-art Autonomous Driving Systems



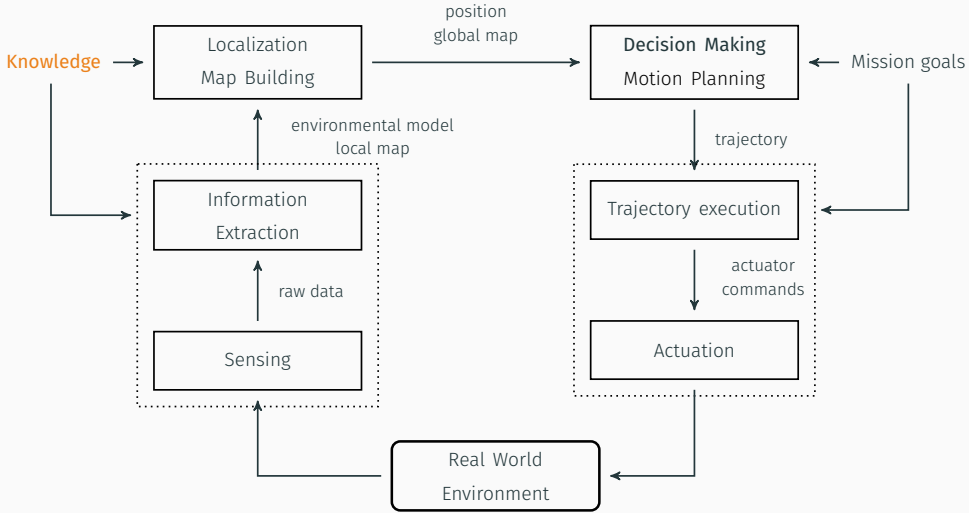

GovTech: Government Technology, *Autonomous Vehicles: Coming to a Road Near You.*

# State-of-the-art Autonomous Driving Systems



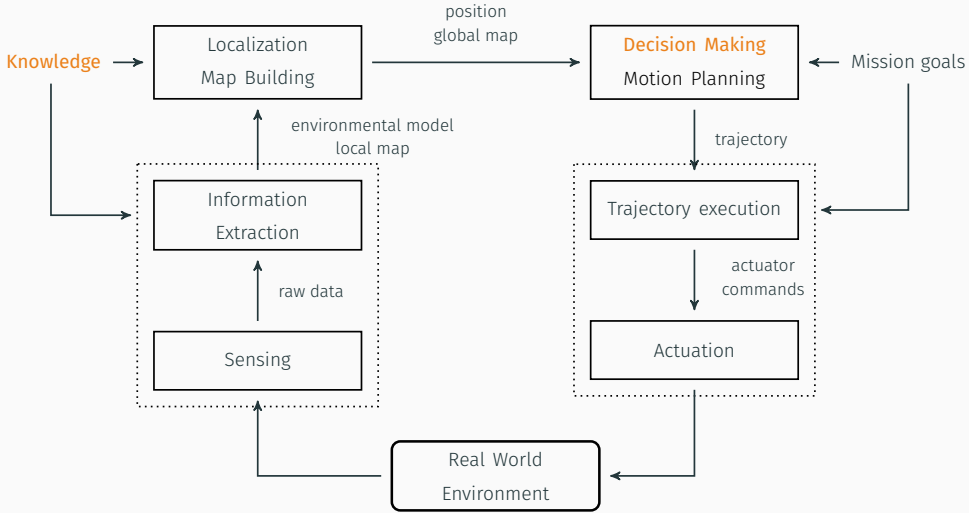

**Deep Learning** and **Machine Learning** are mainly exploited in object detection and recognition.

# State-of-the-art Autonomous Driving Systems




Pavone, *Veicoli a guida autonoma: a che punto siamo e cosa ci aspetta?*

# State-of-the-art Autonomous Driving Systems

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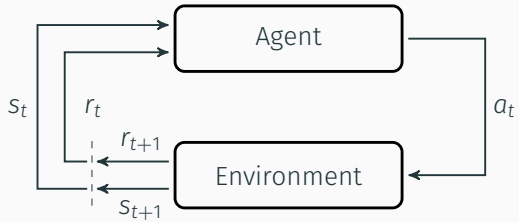
# Reinforcement Learning

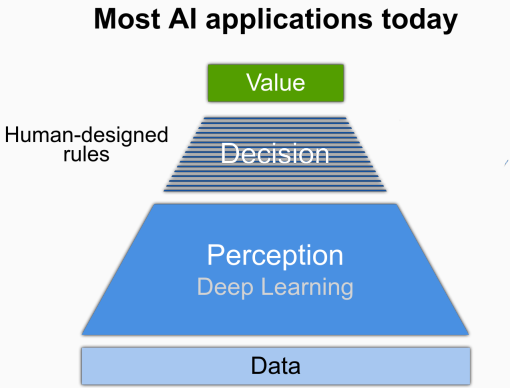
Problems involving an agent interacting with an environment, which provides numeric reward signals.

**Goal**: Learn how to take actions in order to maximize a reward function.




Sutton and Barto, *Reinforcement learning: An introduction*.

# From Data to Value

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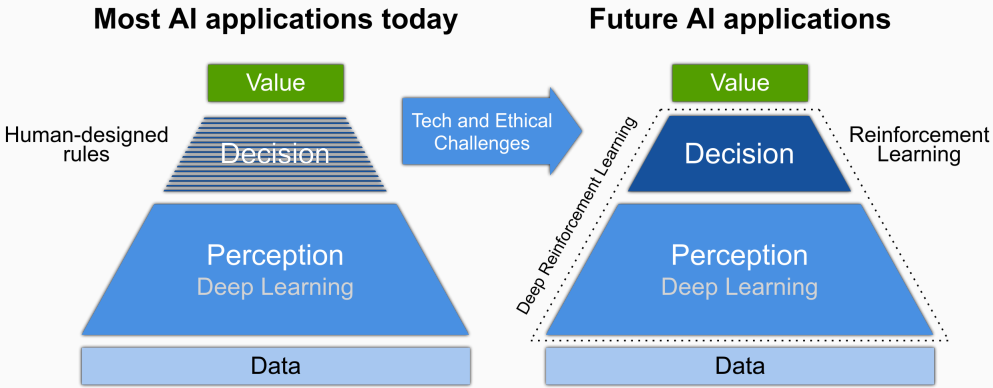


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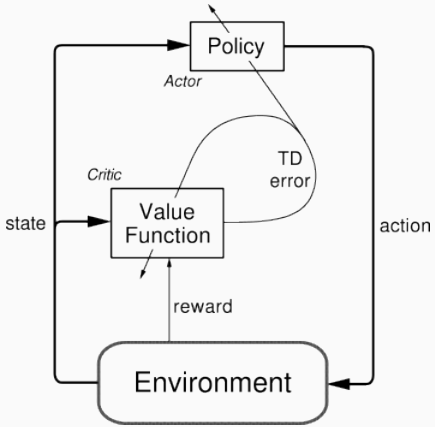
# Model-Free Actor Critic methods

**Critic Network**

Estimates the value function. This could be the action value $Q$ or state value $V$.

**Actor Network**

Updates the policy distribution in the direction suggested by the Critic (such as with policy gradients).

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# Deep Deterministic Policy Gradient (DDPG)

- Off-Policy:

Lillicrap et al., “Continuous control with deep reinforcement learning”.

# Deep Deterministic Policy Gradient (DDPG)

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  - Experience Replay Memory of $(s_t, a_t, r_t, s_t + 1, d_t)$ tuples

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Needs accurate hyper-parameters fine-tuning

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# Soft Actor-Critic (SAC)

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- **Off-Policy**:
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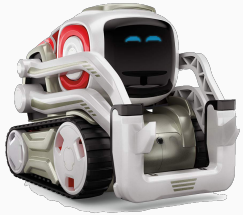
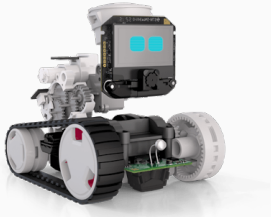
Suitable for Real-World Experiments

Haarnoja et al., “Soft actor-critic algorithms and applications”.

# Design of the control system

# Anki Cozmo - Not just a toy robot

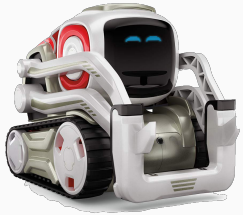


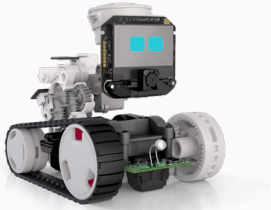


Why Anki Cozmo?

- Small and portable

# Anki Cozmo - Not just a toy robot





## Why Anki Cozmo?

- Small and portable
- 30fps VGA Camera

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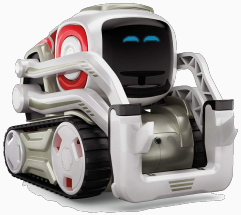

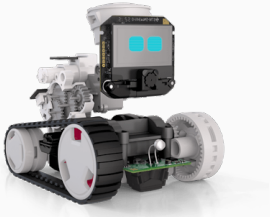

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- Powerful mechanics

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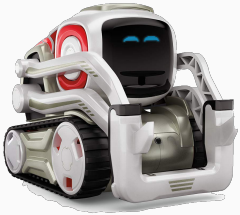

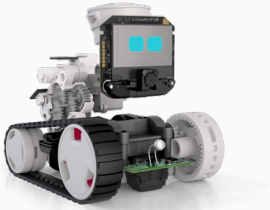

## Why Anki Cozmo?

- Small and portable
- 30fps VGA Camera
- Powerful mechanics
- Python SDK and interfaces

# Track Design

Features:

- Portable

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- Low-reflections

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- Scaled Reality

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- Low-reflections
- Scaled Reality
- Reproducible

# Main Goals

- Building a **control system** and an **interface** between Cozmo robot and algorithms using OpenAI Gym.

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# Main Goals

- Building a **control system** and an **interface** between Cozmo robot and algorithms using OpenAI Gym.
- **Real World** Reinforcement Learning experiments analysis.
  - **No model** of the environment.
  - **No preliminary simulation** to tune hyper-parameters

# MDP Formalisation - Observation

Configuration:

- Gray-scale image

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- Frame Rate: $\sim 15 fps$

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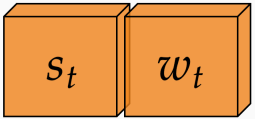
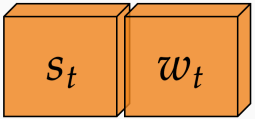
# MDP Formalisation - Actions




$s_t \in \{x \in \mathbb{R} \mid 0 \leq x \leq 1\}$ $\quad$ $w_t \in \{x \in \mathbb{R} \mid -1 \leq x \leq 1\}$

# MDP Formalisation - Actions

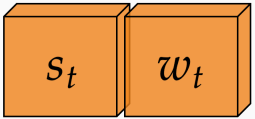



$$s_t \in \{x \in \mathbb{R} \mid 0 \leq x \leq 1\} \qquad w_t \in \{x \in \mathbb{R} \mid -1 \leq x \leq 1\}$$

**Maximum forward speed** $\rightarrow s_{\text{forward\_max}} = 150\text{mm/s}$

**Maximum turning speed** $\rightarrow s_{\text{turning\_max}} = 100\text{mm/s}$

# MDP Formalisation - Actions

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$$\text{Maximum forward speed} \rightarrow s_{\text{forward\_max}} = 150\text{mm/s}$$
$$\text{Maximum turning speed} \rightarrow s_{\text{turning\_max}} = 100\text{mm/s}$$

$$\text{Left tread speed} \leftarrow s_t \cdot s_{\text{forward\_max}} + w_t \cdot s_{\text{turning\_max}}$$
$$\text{Right tread speed} \leftarrow s_t \cdot s_{\text{forward\_max}} - w_t \cdot s_{\text{turning\_max}}$$

# MDP Formalisation - Reward

Distance Covered

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$$R_t = s_t \cdot T_t$$

# MDP Formalisation - Reward

**Distance Covered**

**Fixed timing between actions**: $T_t$ [s] $\leftarrow \frac{1}{15 \text{ fps}}$

**Desired Speed**: $s_t$ [mm/s]

$$R_t = s_t \cdot T_t$$

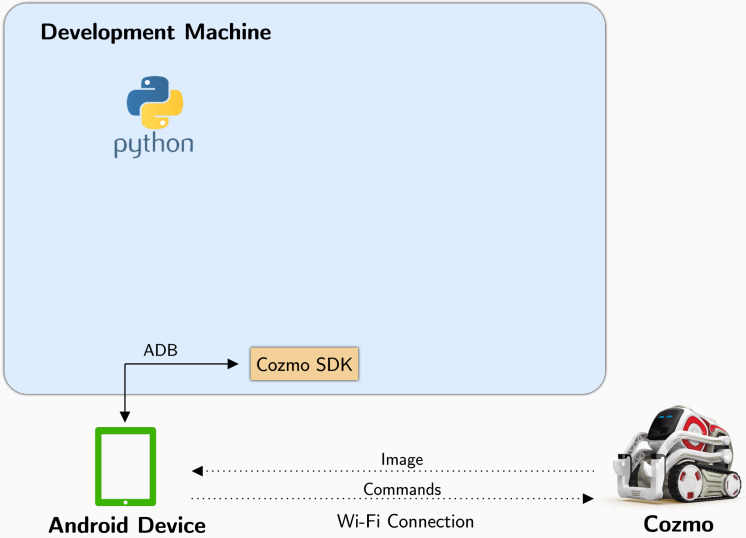
if $t$ is terminal $\rightarrow R_t = 0$

# Outline of the control system

**Development Machine**


**Cozmo**

# Outline of the control system



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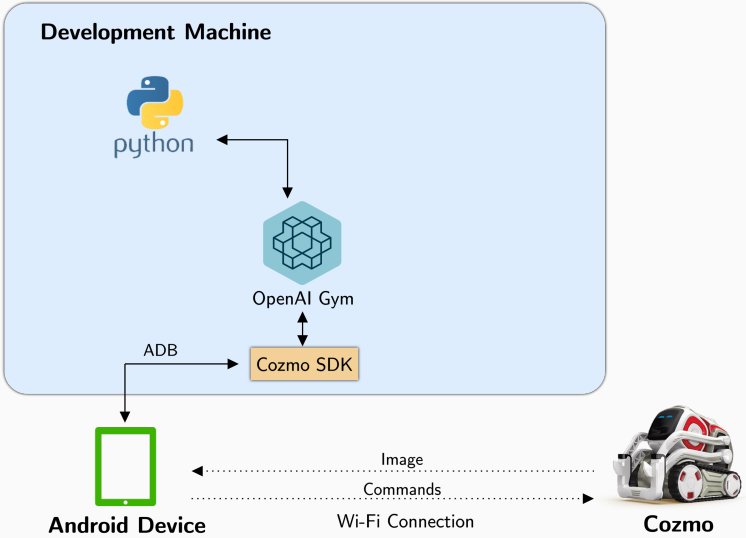

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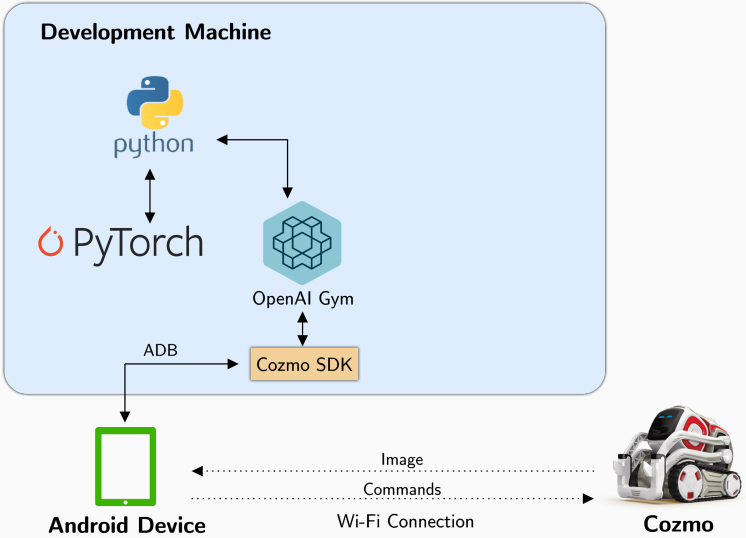

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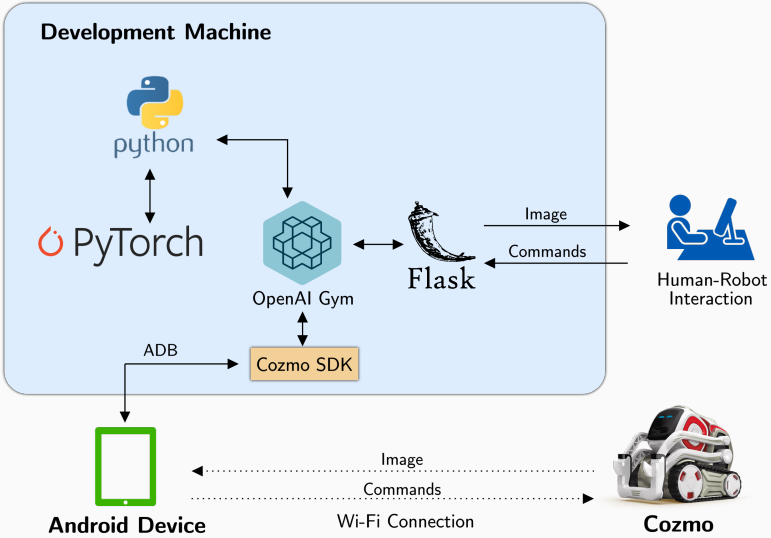

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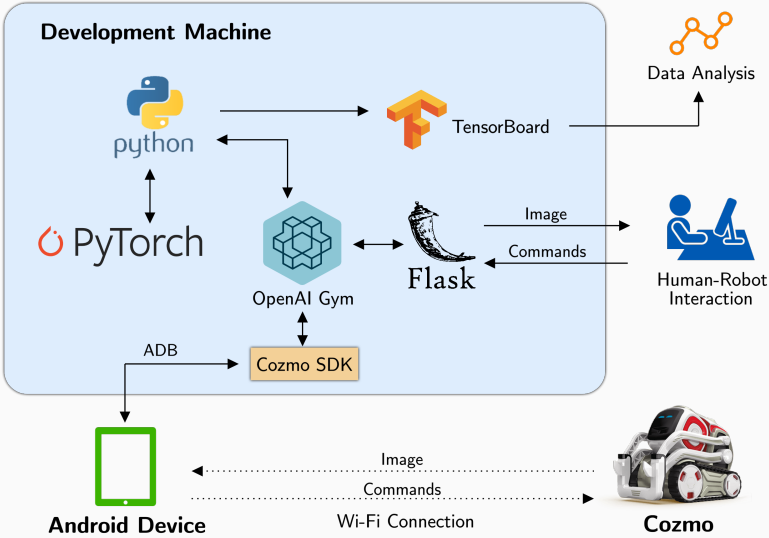
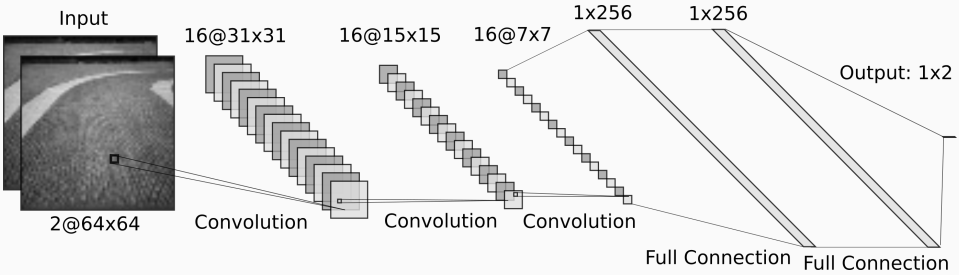
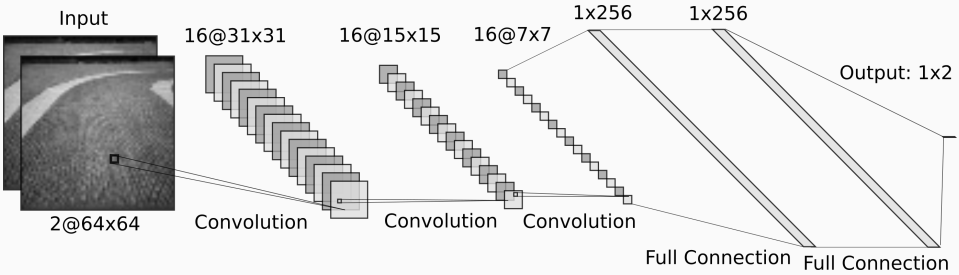


# Convolutional Neural Network Architecture




- 3 Convolutional Layers: 16 features ($3 \times 3$), Stride 2, Padding 0

# Convolutional Neural Network Architecture




- 3 Convolutional Layers: 16 features ($3 \times 3$), Stride 2, Padding 0
- 2 Fully Connected Layer with hidden size = 256

# System Features

- Backup/Restore feature:

# System Features

- Backup/Restore feature:
  - Episode restore

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- Backup/Restore feature:
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- Playground Recording

# Experimental methodology and results

# Pendulum-v0 Results

TODO

# CozmoDriver-v0 Results

TODO

# Episode Showcase - 1

# Episode Showcase - 2

# Conclusions and future work

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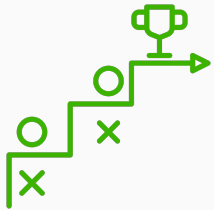
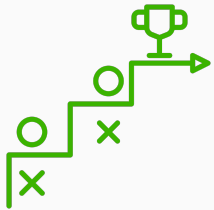
  - Visible improvements during experiments
- Unstable for concrete application:
  - **Average reward reached**: $\sim$ 1 meter
  - Visible improvements during experiments
  - It needs time to improve

# Future Work



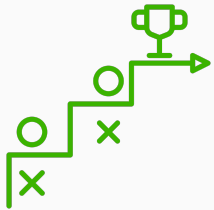
- Improving Sensors

# Future Work



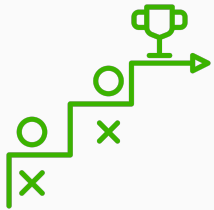
- Improving Sensors
  - Custom RC car (e.g. Donkey Car)

# Future Work



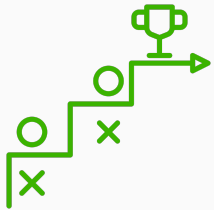
- Improving Sensors
  - Custom RC car (e.g. Donkey Car)
  - Anki Vector

# Future Work



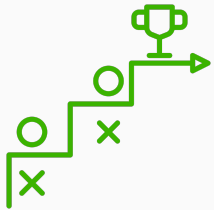
- Improving Sensors
  - Custom RC car (e.g. Donkey Car)
  - Anki Vector
- Feature Extraction

# Future Work



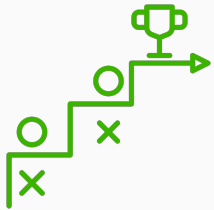
- Improving Sensors
  - Custom RC car (e.g. Donkey Car)
  - Anki Vector
- Feature Extraction
  - Variational Auto-Encoder (VAE)

# Future Work



- Improving Sensors
  - Custom RC car (e.g. Donkey Car)
  - Anki Vector
- Feature Extraction
  - Variational Auto-Encoder (VAE)
- Data fusion

# Future Work



- Improving Sensors
  - Custom RC car (e.g. Donkey Car)
  - Anki Vector
- Feature Extraction
  - Variational Auto-Encoder (VAE)
- Data fusion
- Model-based approach

Questions?

Thank you!

# References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# Appendix - Background

# Components of the Agent

- **Policy**: agent's behaviour function

$$\textbf{Deterministic}: \pi(s) = a$$

$$\textbf{Stochastic}: \pi(a|s) = \mathbb{P}[A_t = a|S_t = s]$$

- **Value Function**: policy evaluation function

$$\textbf{State Value}: V^{\pi}(s) = \mathbb{E}\left[\sum_{t\geq 0} \gamma^k r_t | s_0 = s, \pi\right]$$

$$\textbf{Action Value}: Q^{\pi}(s,a) = \mathbb{E}\left[\sum_{t\geq 0} \gamma^k r_t \big| s_0 = s, a_0 = a, \pi\right]$$

- **Model**: agent's representation of the environment

# Categorizing Reinforcement Learning agents

- Value Based
  - No Policy (implicit)
  - Value Function
- Policy Based
  - Policy
  - No value function
- Actor Critic
  - Policy
  - Value function

- Model Free
  - Policy and/or value function
  - No Model
- Model Based
  - Policy and/or value function
  - Model

# Deep Deterministic Policy Gradient (DDPG) - Neural Networks

It uses **Target Networks** to minimise the instability MSBE loss

**2 Local Neural Networks:**

- Actor $\pi(s \mid \theta)$
- Critic $Q(s, a \mid \phi)$

**2 Target Neural Networks:**

- Actor $\pi'(s \mid \bar{\theta})$
- Critic $Q'(s, a \mid \bar{\phi})$

# Deep Deterministic Policy Gradient (DDPG) - Learning Equations

$$
\begin{aligned}
L(\phi) &= \mathbb{E}_{s_t \sim \rho^{\beta}, a_t \sim \beta, r_t \sim E}[(Q(s_t, a_t|\phi) - y_t)^2] \\
y_t &= r(s_t, a_t) + \gamma(1 - d_t)Q'(s_{t+1}, \pi'(s_t + 1|\bar{\theta})|\bar{\phi})
\end{aligned}
\tag{1}
$$

Lillicrap et al., “Continuous control with deep reinforcement learning”.