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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This work of this thesis was developed at EURECOM (Sophia Antipolis, France)
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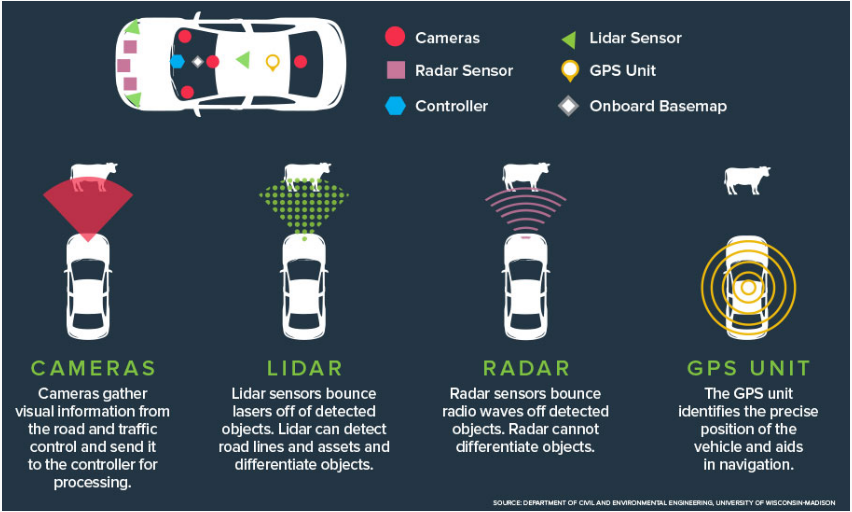
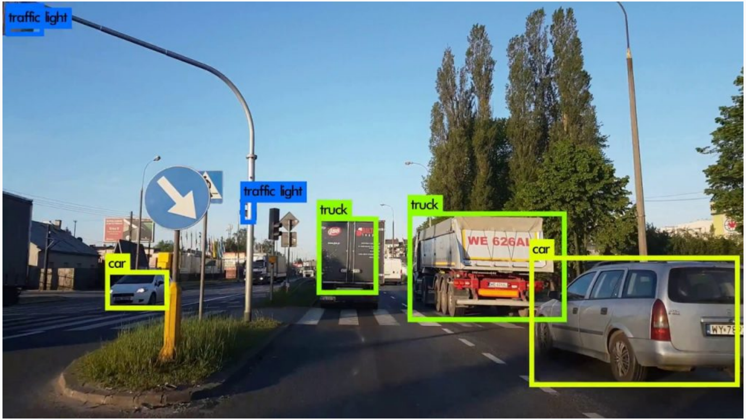
Background

State-of-the-art Autonomous Driving Systems



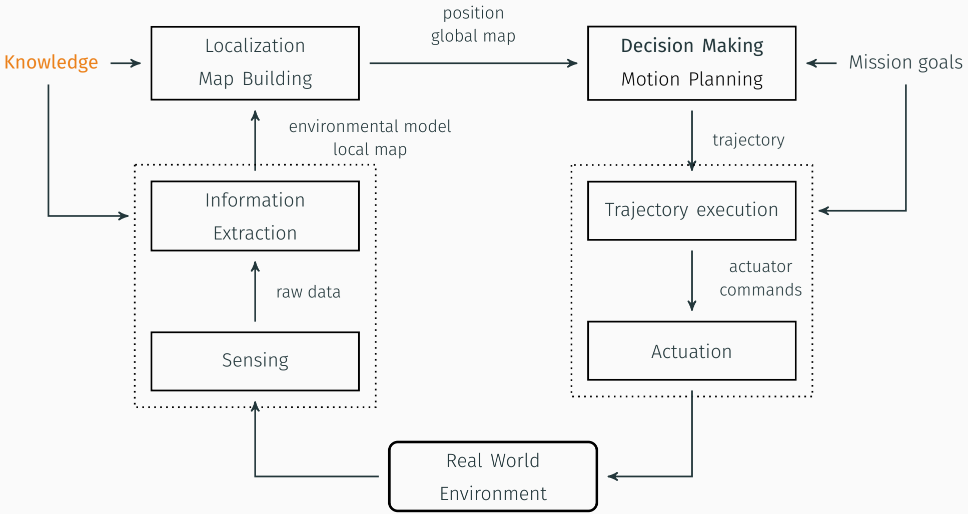
GovTech: Government Technology, *Autonomous Vehicles: Coming to a Road Near You*.

State-of-the-art Autonomous Driving Systems



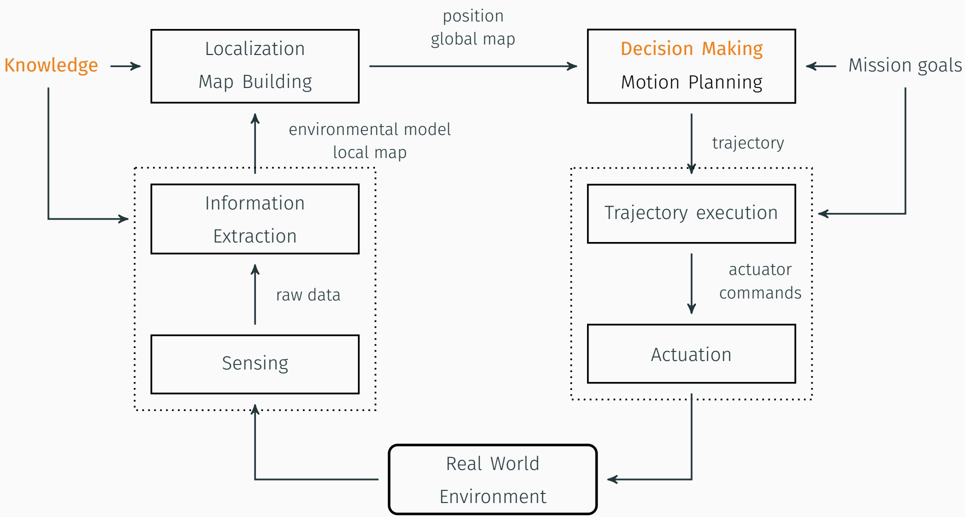
Deep Learning and **Machine Learning** are mainly exploited in object detection and recognition.

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

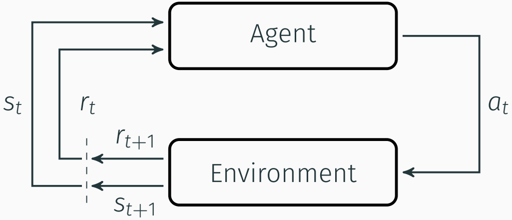


Pavone, *Veicoli a guida autonoma: a che punto siamo e cosa ci aspetta?*

Reinforcement Learning

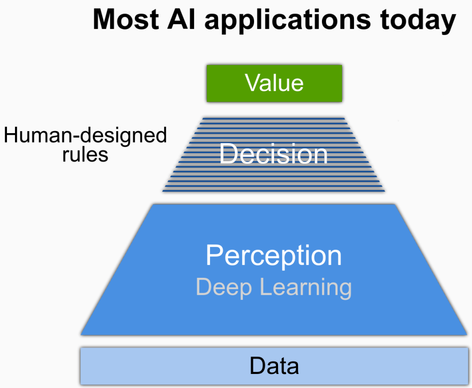
Problems involving an **agent** interacting with an **environment**, which provides numeric **reward signals**.

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



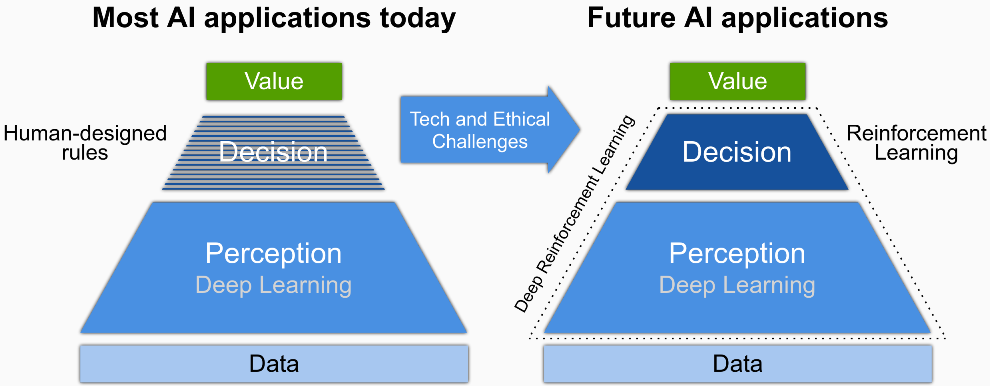
Sutton and Barto, *Reinforcement learning: An introduction*.

From Data to Value



Charafeddine, *Reinforcement Learning in the Wild and Lessons Learned*.

From Data to Value



Charafeddine, *Reinforcement Learning in the Wild and Lessons Learned.*

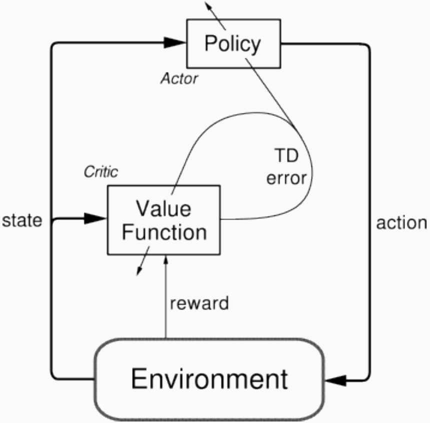
Model-Free Actor Critic methods

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).



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

Deep Deterministic Policy Gradient (DDPG)

- **Off-Policy**:
    - **Experience Replay Memory** of $(s_t, a_t, r_t, s_t + 1, d_t)$ tuples
- **Action space**: Countinuous
- **Policy**: **Deterministic**
- **Exploration**:
    - **Ornstein–Uhlenbeck** process noise
    - Noise regulation with **ϵ-decay function**

<u>Needs accurate hyper-parameters fine-tuning</u>

Lillicrap et al., "Continuous control with deep reinforcement learning".

Soft Actor-Critic (SAC)

- Off-Policy:
  - Experience Replay Memory of $(s_t, a_t, r_t, s_t + 1, d_t)$ tuples
- Action space: Countinuous
- Policy: Stochastic
- Exploration:
  - Temperature Parameter
  - Auto-tuning

Suitable for Real-World Experiments

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

Design of the control system

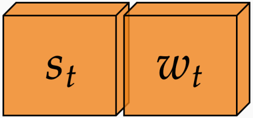
MDP Formalisation - Observation

- **Raw image size**: 64×64 pixels

MDP Formalisation - Observation

- **Raw image size**: 64×64 pixels
- **Stack size**: 2

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

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

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

MDP Formalisation - Reward

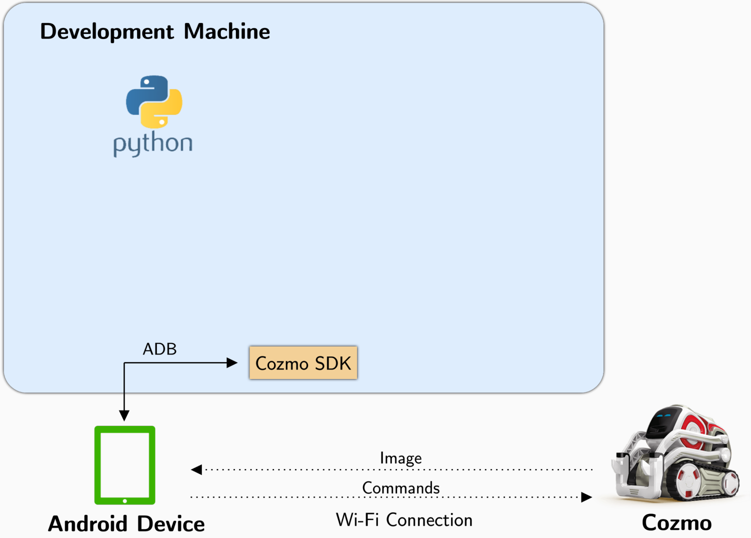
TODO

Outline of the control system

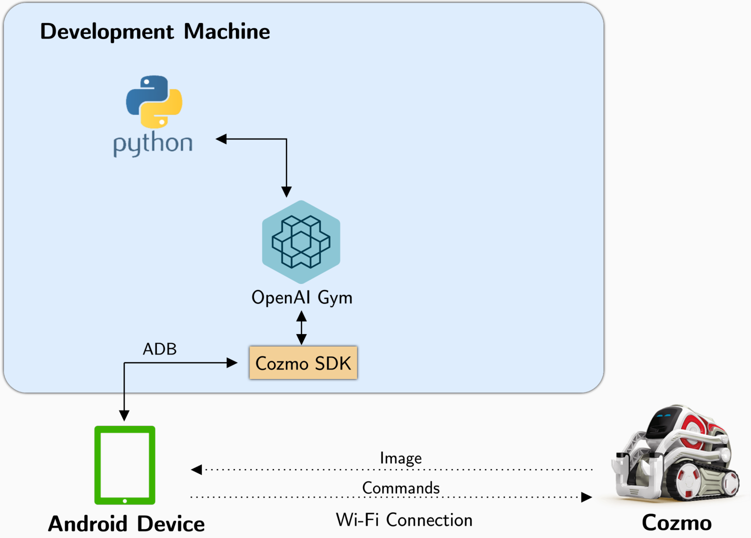
Development Machine

Cozmo

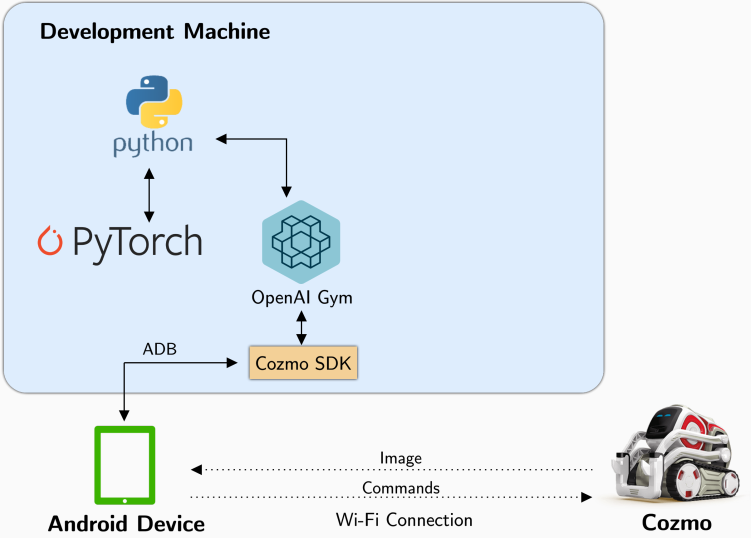
Outline of the control system



Outline of the control system



Outline of the control system



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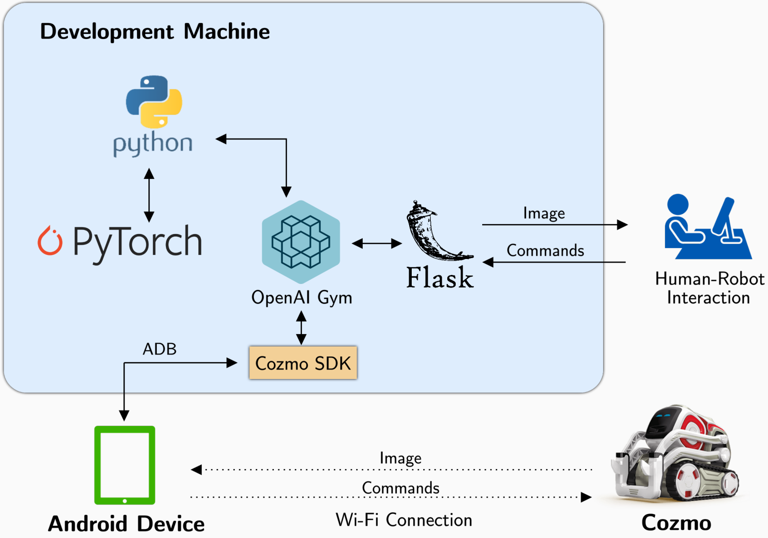
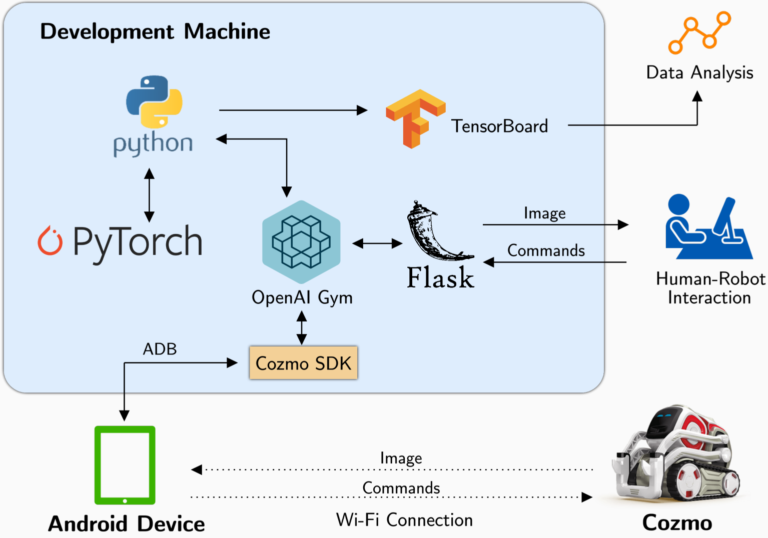
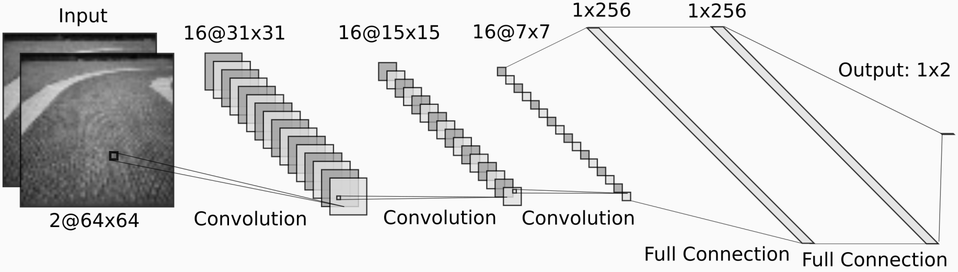


Outline of the control system



Convolutional Neural Network Architecture



System Features

- TODO 1
- TODO 2

Experimental methodology and results

Pendulum-v0 Results

TODO

CozmoDriver-v0 Results

TODO

Conclusions and future work

Conclusions

TODO

Future Work

TODO

Questions?

Thank you!

References

- Charafeddine, Mohamad. *Reinforcement Learning in the Wild and Lessons Learned*. 2018. URL: `https://link.medium.com/SRUZ24Itx4` (visited on 10/26/2018).
- GovTech: Government Technology. *Autonomous Vehicles: Coming to a Road Near You*. 2018. URL: `https://www.govtech.com/transportation/Autonomous-Vehicles-Coming-to-a-Road-Near-You.html`.
- Haarnoja, Tuomas et al. "Soft actor-critic algorithms and applications". In: *arXiv preprint arXiv:1812.05905* (2018).

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- Pavone, Marco. *Veicoli a guida autonoma: a che punto siamo e cosa ci aspetta?* Festival della Tecnologia Conference. 2019.
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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".