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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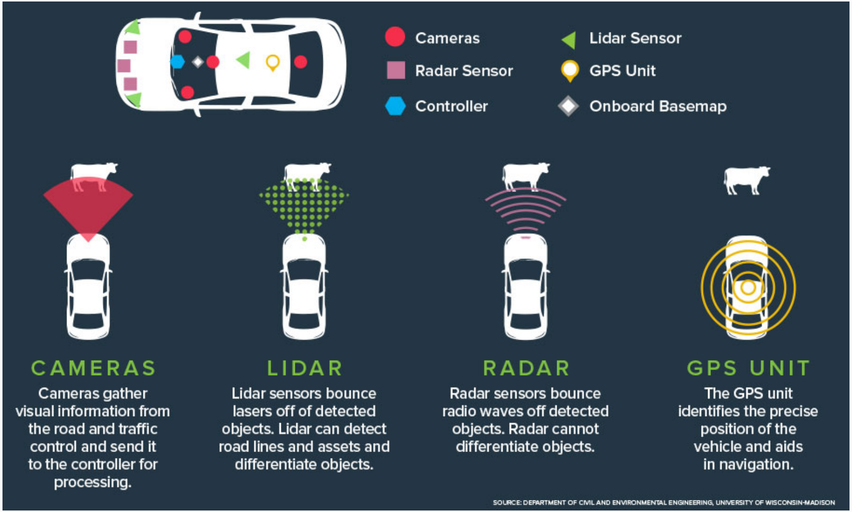
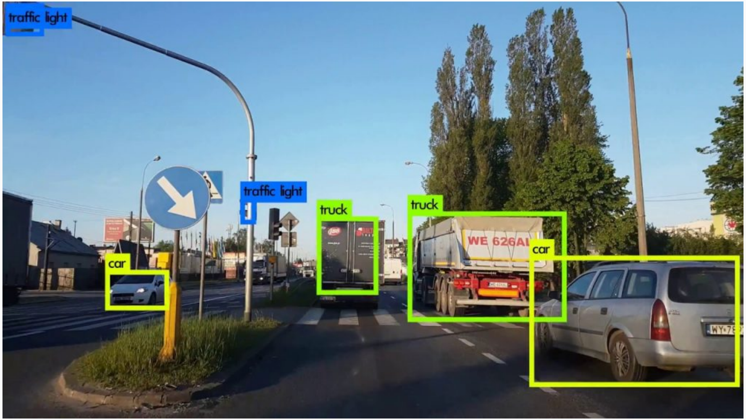
Background

State-of-the-art Autonomous Driving Systems



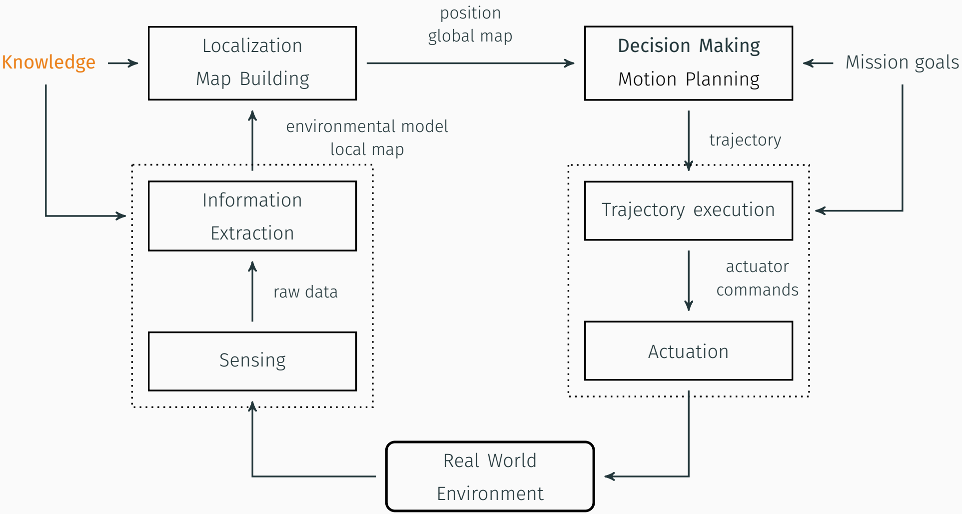
GovTech: Government Technology, *Autonomous Vehicles: Coming to a Road Near You*.

State-of-the-art Autonomous Driving Systems



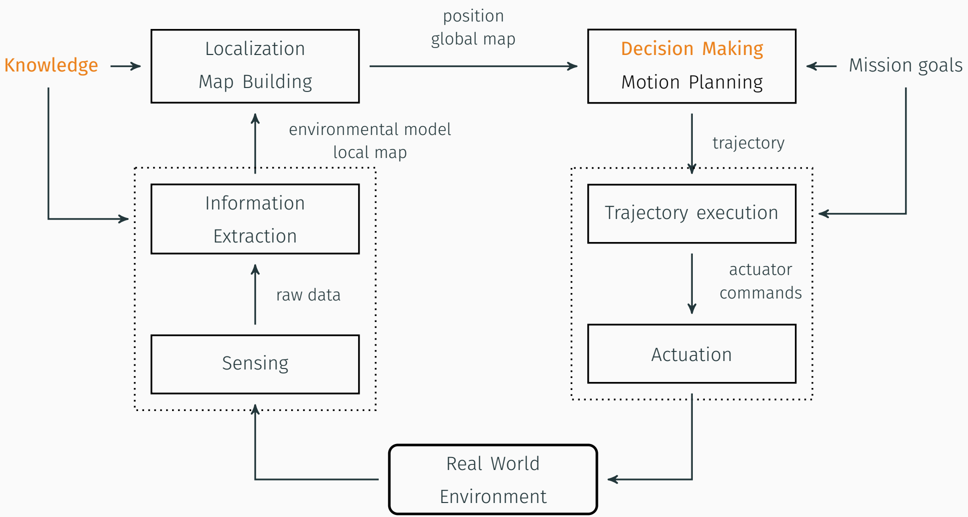
Deep Learning and **Machine Learning** are mainly exploited in **object detection** and **recognition**.

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

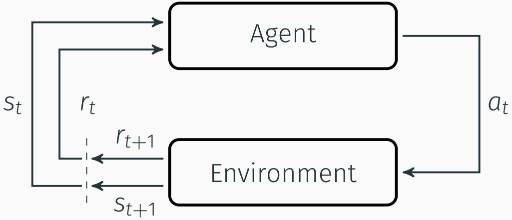


Pavone, *Veicoli a guida autonoma: a che punto siamo e cosa ci aspetta?*

Reinforcement Learning

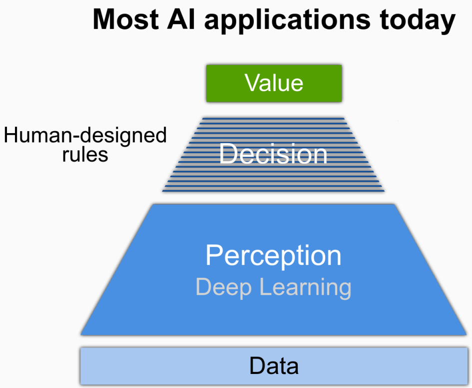
Problems involving an **agent** interacting with an **environment**, which provides numeric **reward signals**.

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



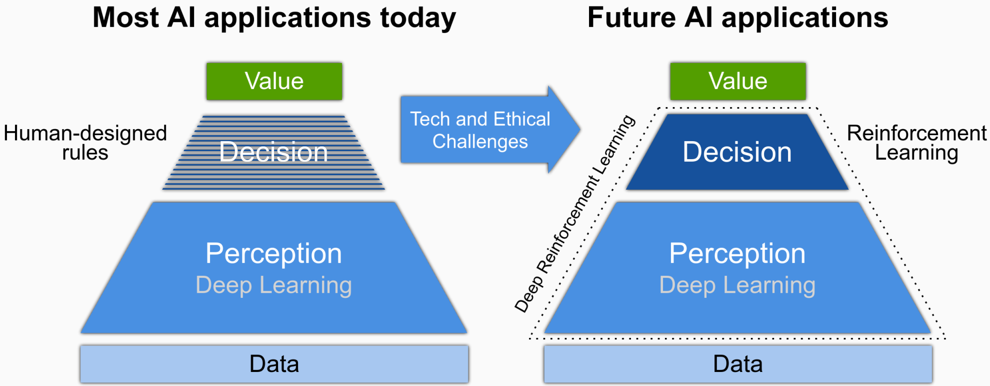
Sutton and Barto, *Reinforcement learning: An introduction*.

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.*

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

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

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

- **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

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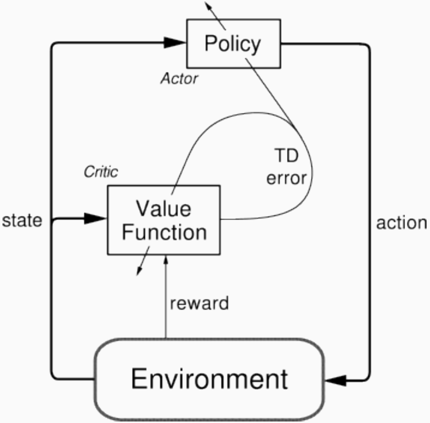
Model-Free Actor Critic methods

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).



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

Needs accurate hyper-parameters fine-tuning

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

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".

Soft Actor-Critic (SAC)

- **Off-Policy**
- **Action space**: Countinuous
- **Policy**: **Stochastic**
- **Exploration**: **Temperature** Parameter
- SAC is an off-policy algorithm which exploits entropy-regularized reinforcement learning
- Auto-tune parameters: Less hyper-parameters, less tuning
- Suitable for Real-World Experiments

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

Design of the control system

Experimental methodology and results

Conclusions and future work

Questions?

Thank you!

References

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