# Autonomous Driving and Reinforcement Learning – an Introduction

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# Outline

# Next in Line...

# Self-Driving I

## Goals

- Reach the destination
- Avoid dangerous states
- Provide comfort to passengers (e.g. avoid oscillations, sudden moves)

## Settings

- Multi-agent problem
  - One have to consider others
- Interaction is both
  - Cooperative, all the agents desire safety
  - Competitive, each agent has its own goal
- Environment
  - Non-deterministic
  - Partially observable
  - Dynamic

# Self-Driving II

## Three sub-problems

**Recognition** Identify environment's components

**Prediction** Predict the evolution of the surrounding

**Decision making** Take decisions and act to pursue the goal

## Two approaches

- Single task handling
  - Use human ingenuity to inject knowledge about the domain
- End-to-end
  - Let the algorithm optimize towards the final goal without constrains

# Self-Driving III

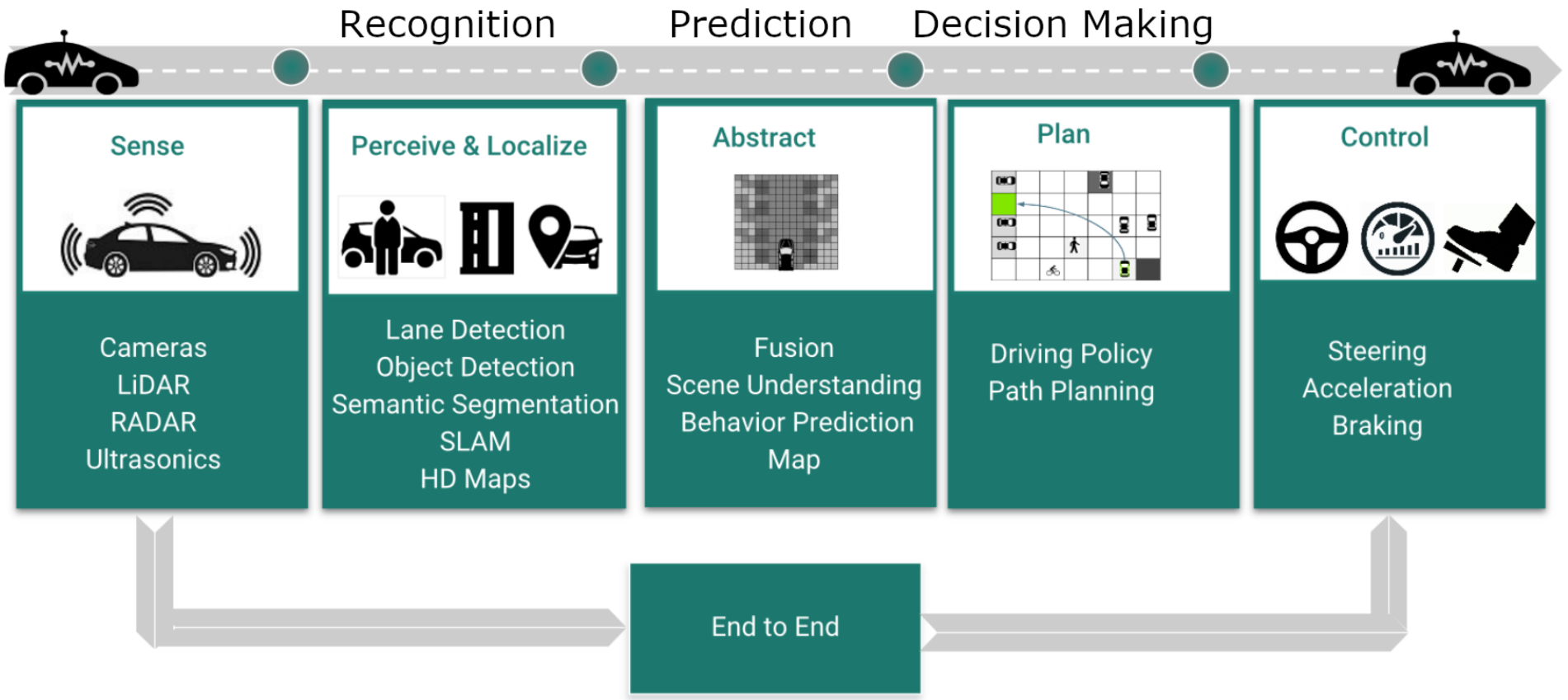



Figure: Modules of autonomous driving systems (source [Talpaert et al., 2019] - modified)

# Sensing & Control

## Sensing

- Which sensors?
- Single/multiple
- Sensor expense
- Operating conditions

## Control

- Continuous – steering, acceleration, braking
- Discrete – forward, right, left, brake

# Recognition

- Convolutional Neural Networks (CNNs)
  - YOLO [Redmon et al., 2015]
- Computer Vision techniques for object detection
  - Feature based
  - Local descriptor based
- Mixed

# Prediction

- Model-based
  - Physics-based
  - Maneuver-based
  - Interaction-aware
- Data-driven
  - Recurrent NN (like Long-Short Term Memory LSTM)

# Decision Making

- Planning/Tree Search/Optimization
- Agent-oriented programming (like the BDI model)
- Deep Learning (DL)
- Reinforcement Learning (RL)

# End-to-end

## Supervised Learning

- Based on imitation
- Current approach by major car manufacturer
- **Robotic drivers are expected to be perfect**

### Drawbacks

**Training data** Huge amounts of labeled data or human effort

**Covering all possible driving scenarios** is very hard

## Unsupervised Learning

- Learns behaviors by trial-and-error
  - like a young human driving student

- Does not require explicit supervision from humans.

- Mainly used on simulated environment
  - to avoid consequences in real-life

# Simulations

## Keep in mind

- An agent trained in a virtual environment will not perform well in the real setting
  - For cameras: different visual appearance, especially for textures
  - You need some kind of transfer learning or conversion of images/data
- Always enable noises of sensors/actuators
- Some “grand truth” sensors present in some simulators aren’t available in real life
  - For example, in TORCS (a circuit simulator popular in the ML field) you can have exact distances from other cars and from the borders. Too easy...

# Next in Line...

# Agent-environment interaction

- In RL, an agent learns how to fulfill a task by interacting with its environment
- The interaction between the agent and the environment can be reduced to:

| | |
|---|---|
| State | Every information about the environment useful to predict the future |
| Action | What the agent do |
| Reward | A real number that Indicates how well the agent is doing |

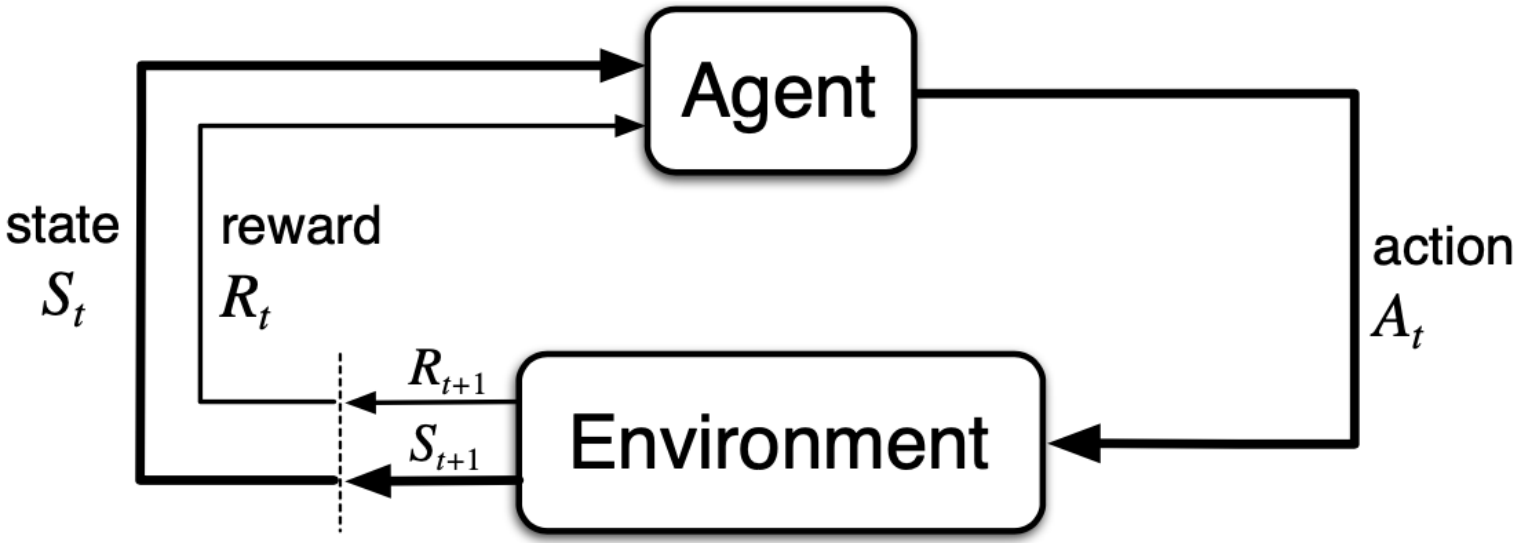



Figure: At each ***time step*** $t$ the agent perform an action $A_t$ and receives the couple $S_{t+1}, R_{t+1}$ (source [Sutton and Barto, 2018])

# Terminology

## Episode

- A complete run from a starting state to a final state

**Episodic task** A task that has an end

**Continuing task** A task that goes on without limit

- We can split it e.g. by setting a maximum number of steps

# Markov Decision Process (MDP)

A RL problem can be formalized as a MDP. The 4-tuple:

- $S$ set of states
- $A_s$ set of actions available in state $s$
- $P(s'|s,a)$ state-transition probabilities (probability to reach $s'$ given $s$ and $a$)
- $R(s,s')$ reward distribution associate to state transitions

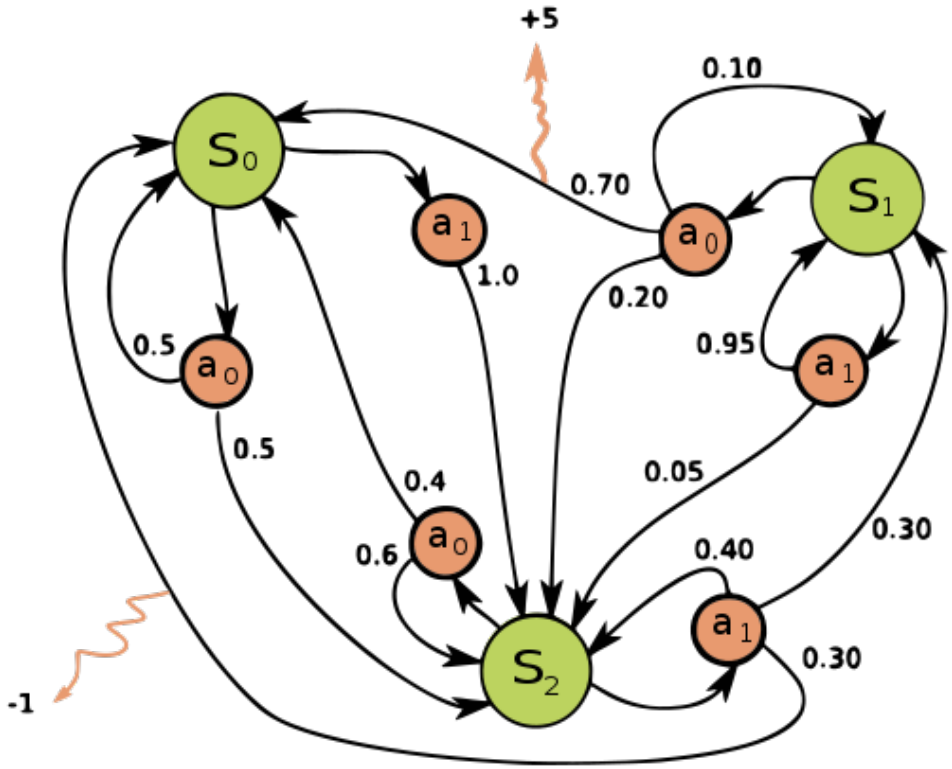



Figure: Example of a simple MDP (source Wikipedia)

# Environment features

- MDPs can deal with non-deterministic environments (because they have probability distributions)
- But we need to cope with observability

## Markov Property – Full observability

- Classical RL algorithms rely on the Markov property
- A state satisfy the property if it includes information about all aspects of the (past) agent-environment interaction that make a difference for the future

## From states to *observations* – Partial observability

- Sometimes, an agent has only a partial view of the world state
- The agent gets information (observations) about some aspects of the environment
- Abusing the language, observations/history are called "state" and symbolized $S_t$

## How to deal with partial observability?

- Approximation methods (e.g. NN) doesn't rely on the Markov property
- Sometimes we can reconstruct a Markov state using a history
  - Stacking the last n states
  - Using a RNN (e.g. LSTM)

# Learning a Policy I

We want the agent to learn a strategy i.e. a policy

## Policy $\pi$

A map from states to actions used by the agent to choose the next action

In particular, we are searching for the optimal policy
$\rightarrow$ The policy that maximize the cumulative reward

## Cumulative reward

The discounted sum of rewards *over time*

$$R = \sum_{t=0}^{n} \gamma^t r_{t+1} \mid 0 \leq \gamma \leq 1$$

For larger values of $\gamma$, the agent focuses more about the long term rewards
For smaller values of $\gamma$, the agent focuses more about the immediate rewards

## What does this mean?

- The actions of the agent affect its possibilities later in time
- It could be better to choose an action that led to a better state than an action that gives you a greater reward but led to a worse state

# Learning a Policy II

## Problem

we don't know the MDP model (state transition probabilities and reward distribution)

## Solution

Monte Carlo approach: let's make estimations based on experience

- A way to produce a policy is to estimate the value (or action-value) function
  - given the function, the agent needs only to perform the action with the greatest value

## Expected return $\mathbb{E}[G_t]$

The expectation of cumulative reward i.e. our current estimation

## Value function $V_\pi(s) = \mathbb{E}[G_t|S_t = s]$

- (state) $\rightarrow$ expected return when starting in $s$ and following $\pi$ thereafter

## Action-value function $Q_\pi(s, a) = \mathbb{E}[G_t|S_t = s, A_t = a]$

- (state, action) $\rightarrow$ expected return performing $a$ and following $\pi$ thereafter

# Learning a Policy III

## SARSA and Q-learning

- They are algorithms that approximate the action-value function
- At every iteration the estimation is refined thanks to the new experience.
- Every time the evaluation becomes more precise, the policy gets closer to the optimal one.

## Generalized Policy Iteration (GPI)

- Almost all RL methods could be described as GPI
  - They all have identifiable policies and value functions
- Learning consist of two interacting processes

  Policy evaluation Compute the value function
  Policy improvement Make the policy greedy

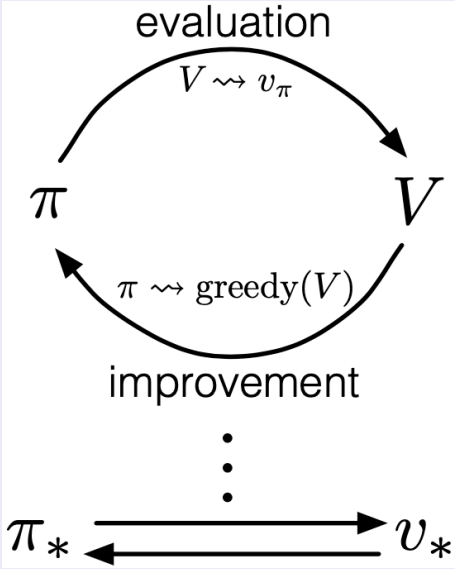



Figure: [Sutton and Barto, 2018]

# Learning a policy IV

## The exploration/exploitation dilemma

- The agent seeks to learn action values of optimal behavior, but it needs to behave non-optimally in order to explore all actions (to find the optimal actions)
- $\varepsilon$-greedy policy: the agent behave greedily but there is a (small) $\varepsilon$ probability to select a random action.

## On-policy learning

- The agent learns action values of the policy that produces its own behavior ($q_\pi$)
- It learns about a near-optimal policy ($\varepsilon$-greedy)
- Target policy and behavior policy correspond

## Off-policy learning

- The agent learns action values of the optimal policy ($q_*$)
- There are two policies: target and behavior
- Every $n$ steps the target policy is copied into the behavior one
  - If $n = 1$ there is only one action-value function
  - But it's not the same of on-policy (the target and behavior policy still not correspond)

# How to estimate the value function?

- A table that associate state (or state-action pairs) to a value
- Randomly initialized

## Temporal Difference (TD) update

$$V(S_t) \leftarrow V(S_t) + \alpha[R_{t+1} + \gamma V(S_{t+1}) - V(S_t)]$$

## TD error

$$\delta_t = R_{t+1} + \gamma V(S_{t+1}) - V(S_t)$$

- $R_{t+1} + \gamma V(S_{t+1})$ is a better estimation of $V(S_t)$
  - The actual reward obtained plus the expected rewards for the next state
- By subtracting the old estimate we get the error made at time $t$

## Sarsa (on-policy)

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma Q(S_{t+1}, A_{t+1}) - Q(S_t, A_t)]$$

## Q-learning (off-policy)

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)]$$

# Next in Line...

# Deep Q-Network

## DQN

- When the number of states increases, it becomes impossible to use a table to store the Q-function (alias for action-value function)
- A neural network can approximate the Q-function
- We also get better generalization and the ability to deal with non-Markovian envs

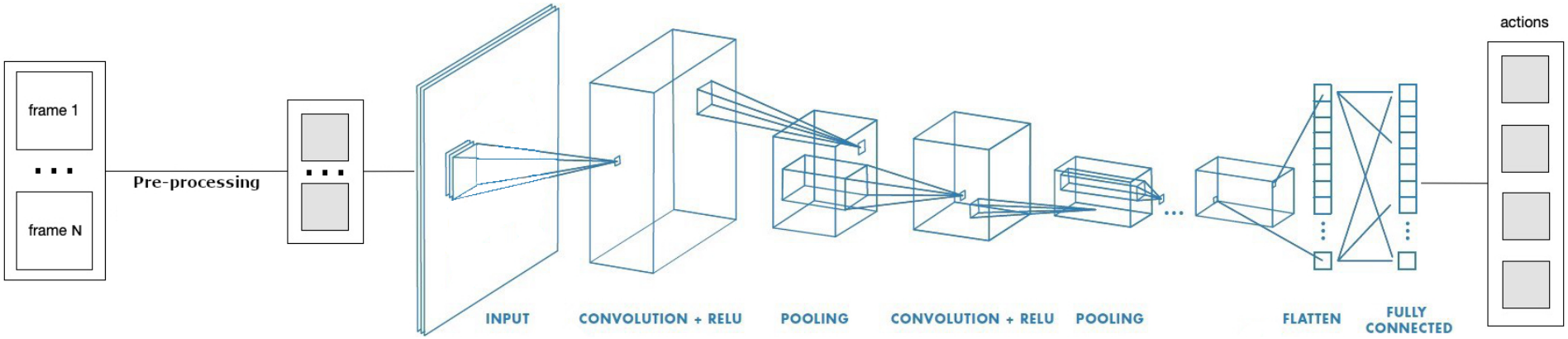
## How to represent the action-value function in a NN?

1. Input: the state (as a vector) $\rightarrow$ Output: the values of each action
2. Input: the state and an action $\rightarrow$ Output: the value for that action

## Design the driver agent

- Environment: states and actions, reward function
- Neural network
- Training cycle

# Neural Network



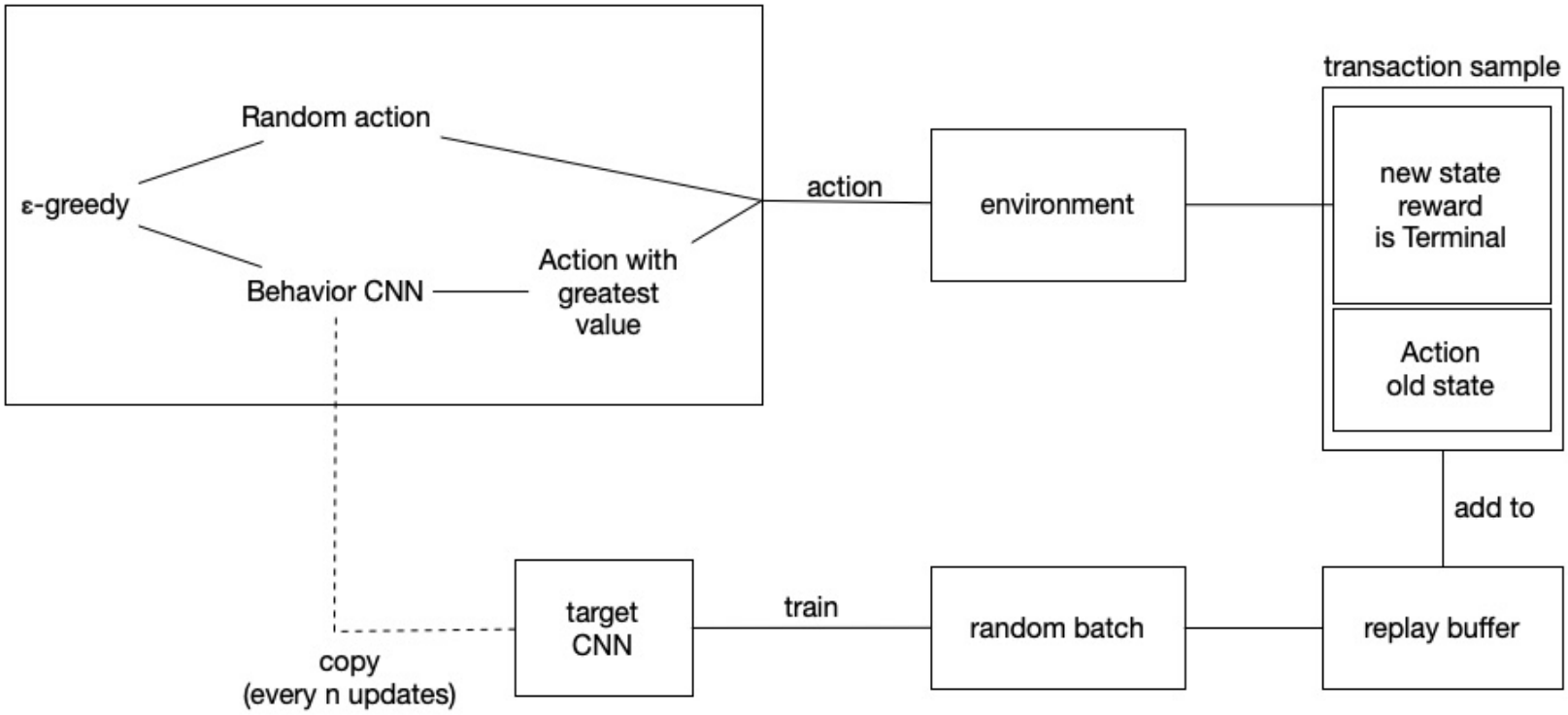

## Pre-processing

- It's important how we present the data to the network
- Let's take images as an example
  - Resize to small images (e.g. 84x84)
  - If colors are not discriminatory, use grayscale
  - How many frames to stack?
  - Remember: the larger the input vector, the larger the searching space

## Convolutional Neural Networks

- A good idea for structured/spatially local data
  - e.g. images, lidar data ...

# Training Cycle




- Transaction samples are used to compute the target update
- Training use a gradient form of Q-learning ([Mnih et al., 2013] and [Sutton and Barto, 2018] for details)

# DQN Issues and Solutions I

Each of these features significantly improve performance

## Experience Replay

- We put samples in a buffer and we take random batches from it for training
- When full, oldest samples are discarded
- Why? Experience replay is needed to break temporal relation
  - In supervised learning, inputs should be independent and identically distributed (i.i.d.) i.e. the generative process have no memory of past generated samples
- Other advantages:
  - More efficient use of experience (samples are used several times)
  - Avoid catastrophic forgetting (by presenting again old samples)

## Double DQN

- We have two networks, one behavior NN and one target NN
- We train the target NN
- Every N steps we copy the target NN into the behavior one
- Why? To reduce target instability
  - Supervised learning to perform well requires that for the same input a label does not change over time
  - In RL, the target change constantly (as we refine the estimations)

# DQN Issues and Solutions II

## Rewards scaling

Scaling rewards in the range $[-1; 1]$ dramatically improves efficiency [Mnih et al., 2013]

## Frame skipping

- Consequent frames are very similar $\rightarrow$ we can skip frames without loosing much information and speed up training by N times
- The selected action is repeated for N frames

## Initial sampling

It could be useful to save K samples in the replay buffer before start training

## So many parameters...

- [Mnih et al., 2015] is a good place to start
  - The table of hyperparameters used in their work is in the next slide
- More recent works and experiments could provide better suggestions

# Hyperparameters used in [Mnih et al., 2015]

**Extended Data Table 1 | List of hyperparameters and their values**

| Hyperparameter | Value | Description |
|---|---|---|
| minibatch size | 32 | Number of training cases over which each stochastic gradient descent (SGD) update is computed. |
| replay memory size | 1000000 | SGD updates are sampled from this number of most recent frames. |
| agent history length | 4 | The number of most recent frames experienced by the agent that are given as input to the Q network. |
| target network update frequency | 10000 | The frequency (measured in the number of parameter updates) with which the target network is updated (this corresponds to the parameter *C* from Algorithm 1). |
| discount factor | 0.99 | Discount factor gamma used in the Q-learning update. |
| action repeat | 4 | Repeat each action selected by the agent this many times. Using a value of 4 results in the agent seeing only every 4th input frame. |
| update frequency | 4 | The number of actions selected by the agent between successive SGD updates. Using a value of 4 results in the agent selecting 4 actions between each pair of successive updates. |
| learning rate | 0.00025 | The learning rate used by RMSProp. |
| gradient momentum | 0.95 | Gradient momentum used by RMSProp. |
| squared gradient momentum | 0.95 | Squared gradient (denominator) momentum used by RMSProp. |
| min squared gradient | 0.01 | Constant added to the squared gradient in the denominator of the RMSProp update. |
| initial exploration | 1 | Initial value of $\varepsilon$ in $\varepsilon$-greedy exploration. |
| final exploration | 0.1 | Final value of $\varepsilon$ in $\varepsilon$-greedy exploration. |
| final exploration frame | 1000000 | The number of frames over which the initial value of $\varepsilon$ is linearly annealed to its final value. |
| replay start size | 50000 | A uniform random policy is run for this number of frames before learning starts and the resulting experience is used to populate the replay memory. |
| no-op max | 30 | Maximum number of "do nothing" actions to be performed by the agent at the start of an episode. |

The values of all the hyperparameters were selected by performing an informal search on the games Pong, Breakout, Seaquest, Space Invaders and Beam Rider. We did not perform a systematic grid search owing to the high computational cost, although it is conceivable that even better results could be obtained by systematically tuning the hyperparameter values.

# Last things

## Reward function

- Designing a reward function is not an easy task
- It could severely affect learning
- In the case of a driving agent (like in RL for robotics), the rewards are internal and doesn't come from the environment
- You should give rewards also for intermediate steps to direct the agent (i.e. not only $+1$ when successful and $-1$ when it fails)
- Some naive hints
  - Reach target $+1$
  - Crash $-1$
  - Car goes forward $+0.4$ (if too big it will inhibit crash penalty)
  - Car turns $+0.1$ (if too big it will keep circle around)
  - $-0.2$ instead of the positive reward if the agent turns to a direction and just after it turns to the opposite one (i.e. right-left or left-right) to reduce car oscillations

## Exploration/exploitation

- Start with a big $\varepsilon$
- Gradually reduce it with an $\varepsilon$-decay (e.g. 0.999)
- $\varepsilon_{t+1} = \varepsilon_t * decay$

# Appendix: Reading Suggestions

# Reading Suggestions: Access to Resources

- Books and papers are available through the university proxy
- Search engine: `https://sba-unibo-it.ezproxy.unibo.it/AlmaStart`
- If you want to access an article by link
  converts dots in scores and add .ezproxy.unibo.it at the end of the url e.g:
  `https://www.nature.com/articles/nature14236`
  ↓
  `https://www-nature-com.ezproxy.unibo.it/articles/nature14236`

# Reading Suggestions: Driving Problem

- Extended review of autonomous driving approaches [Leon and Gavrilescu, 2019]
- Overview of RL for autonomous driving and its challenges [Talpaert et al., 2019]
- Tutorial of RL with CARLA simulator `https://pythonprogramming.net/introduction-self-driving-autonomous-cars-carla-python`

## End-to-end approach examples

- CNN to steering on a real car [Bojarski et al., 2016]
- DQN car control [Yu et al., 2016]

## Single task approach example

- NN for recognition + RL for control [Li et al., 2018]

## Converting virtual images to real one

- [Pan et al., 2017]

# Reading Suggestions: RL & DL

## In depth (books)

- [Sutton and Barto, 2018] is the bible of RL – the second version (2018) contains also recent breakthroughs
- [Goodfellow et al., 2016] for Deep Learning

## Compact introductions

- Briefly explanation of RL basics and DQN: `https://rubenfiszel.github.io/posts/rl4j/2016-08-24-Reinforcement-Learning-and-DQN`
- CNN: `https://cs231n.github.io/convolutional-networks/`
  - Even more compact: `https://pathmind.com/wiki/convolutional-network`

## DQN

- [Mnih et al., 2015] Revised version (better)
- [Mnih et al., 2013] Original version
- [van Hasselt et al., 2015] Double Q-learning

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