Deep Reinforcement Learning: Foundations and Practical Environment Setup for Real-World Applications

Franco Terranova

Université de Lorraine, CNRS, Inria, LORIA

franco.terranova@inria.fr

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About Me

Name: Franco Terranova
PhD Student @ Université de Lorraine / INRIA / CNRS / LORIA
Current Project: Deep Reinforcement Learning for Cyber-Attack Paths Prediction
Previous Project: Deep Reinforcement Learning for a Self-driving Telescope
Website: `https://terranovafr.github.io`

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Tutorial Material

https://terranovafr.github.io/teaching/2024-EASSS-Course

Overview

Paradigms of Machine Learning

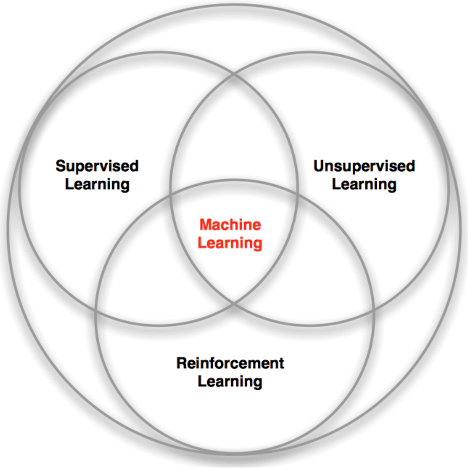


Image Source: `https://medium.com/dataseries/reinforcement-learning-mimics-human-learning-bc701d6ccc08`

Supervised Learning

- **Definition:** Learning from labeled data
- **Label:** The known output or correct answer for a given input
- **Data:** (x, y) — input and label
- **Goal:** Learn a function to map $x \rightarrow y$
- **Applications:** Classification, Regression, etc.

Example:

- Email spam detection: Emails with text labeled as "spam" or "not spam"
- Cat/Dog Image Classification: Images of cats and dogs labeled by type

Unsupervised Learning

- **Definition:** Finding patterns in unlabeled data
- **Data:** x — input data with no labels
- **Goal:** Discover hidden structures or patterns in the data
- **Applications:** Clustering, Dimensionality Reduction, etc.

Example:

- Customer segmentation in marketing: Grouping customers based on purchasing behavior
- Anomaly detection: Identifying unusual patterns in data, such as fraud detection in financial transactions

Reinforcement Learning

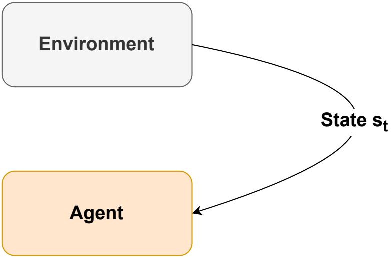
- **Definition:** Learning by interacting through trial and error with an **environment** that provides a **reward signal** (distinct from labels)
- **Goal:** Learn the optimal decision-making strategy in its context $\leftrightarrow$ maximize cumulative expected reward

Example:

- Game Playing: Agents learn strategies for games like Chess
- Drone Navigation: Agent navigating towards a destination by avoiding obstacles

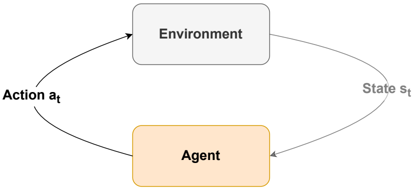
Interaction starts at timestep t

RL Elements - State



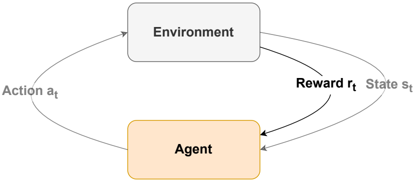
- Input for the agent
- Represents the context where the agent is located
- Agent must learn which elements of the state are relevant
- May not have full visibility of the environment

RL Elements - Action



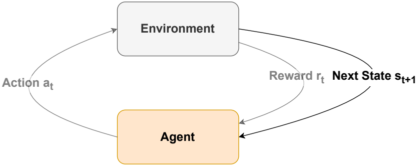
- Output for the agent
- Action produced conditional on the state provided as input $\leftrightarrow$ $a_t | s_t$
- Represents the modification the agent wants to make to the environment state

RL Elements - Reward



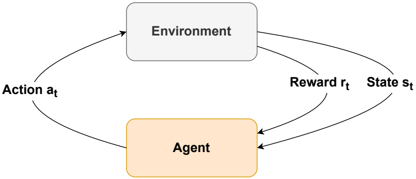
- Evaluation of the action taken in the previous state $\leftrightarrow r_t \mid a_t, s_t$
- Represents a prize or penalty for the action
- Guides the agent in adjusting its behavior for similar future states

RL Elements - Next State



- Resulting outcome of the action taken in the previous state $\leftrightarrow$ $s_{t+1} \mid a_t, s_t$
- Advances the timestep to $t + 1$
- Enables the sequential decision-making

RL Elements - Trial and error



- Agent learns through a loop of trial and error: state $\rightarrow$ action $\rightarrow$ reward, next state
- Sequential decision-making inspired by how humans learn

RL Elements - Simplistic Formulation

- The agent policy maps a state to an action:

$$\text{Action} = \pi(\text{State}) \quad \text{where } \pi \text{ is the policy}$$

- The environment maps an action and state to the next state and reward:

$$\text{Next State}, \text{Reward} = \mathcal{E}(\text{State}, \text{Action})$$

$$\text{where } \mathcal{E} \text{ represents the environment's dynamics}$$

- The overall loop can be summarized as:

$$\text{State}_{t+1}, \text{Reward}_t = \mathcal{E}(\text{State}_t, \pi(\text{State}_t))$$

What Makes RL Different?

- **No Supervisor:** Driven by reward signals, not explicit labeled data
- **Sequential Decision Making:** Optimization of long-term rewards through a series of actions over time
- **Delayed Feedback:** Feedback may be delayed, potentially sacrificing short-term rewards for long-term gains
- **Exploration vs. Exploitation:** Choosing between trying new actions or using known strategies

RL Definitions: Episodes, Trajectory, and Iterations

- **Episode:** A complete sequence of steps from the initial state to a terminal state or goal, after which the process restarts
- **Trajectory** τ **:** A sequence of states, actions, and rewards from the start to the end of an episode

$$\tau = (s_0, a_0, r_0, s_1, a_1, r_1, \ldots, s_T, a_T, r_T)$$

Finite Episode: Episode length $T < \infty$

Infinite Episode: Episode length $T \to \infty$

- **Cutoff or Goal:** The condition or point at which an episode ends

Steps for RL Formulation

- Identify the State (s):
  - Determine what information defines the current situation of the agent
- Define the Actions (a):
  - Specify the possible decisions or moves the agent can take from each state
- Specify the Reward (r):
  - Decide how to quantify the feedback for each action in a given state
- Design the Environment Interaction:
  - Define state transitions and reward assignments based on actions
  - Specify episode structure, including length and termination criteria

Example - Breakout (Atari Game)

Image from https://www.coolmathgames.com/fr/0-atari-breakout

- **State Space:**
  - Raw pixel values from the game screen, 2D array of pixels
- **Action Space:**
  - Discrete actions: moving the paddle left, right, or no action
- **Reward Function:**
  - Positive reward for destroying bricks
  - Negative reward for losing the ball
- **Episode:**
  - Starts with the paddle at the bottom and the ball in motion
  - Ends when the ball falls below the paddle or all bricks are destroyed

AlphaGo (Go Game)

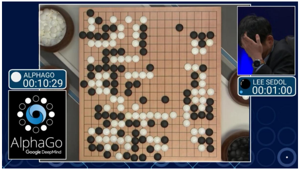


Image from Engadget

- **State Space:**
  - Board configurations, including the positions of black and white stones
- **Action Space:**
  - Placing a stone at any empty intersection on the board
- **Reward Function:**
  - Positive reward for winning the game
  - Negative reward for losing
- **Episode:**
  - Begins with an empty board
  - Ends when a winner is determined

Markov Decision Process (MDP) Formulation

$$
\begin{aligned}
\text{MDP:} \quad & (\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma) \\
\mathcal{S}: \quad & \text{State space} \\
\mathcal{A}: \quad & \text{Action space} \\
\mathcal{P}: \quad & \mathcal{S} \times \mathcal{A} \rightarrow \mathcal{S}, \text{ State transition function} \\
\mathcal{R}: \quad & \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}, \text{ Reward function} \\
\gamma: \quad & \text{Discount factor}
\end{aligned}
$$

Model-based Methods

One approach to finding optimal behavior in an environment involves approximating $\mathcal{P}$ and $\mathcal{R}$:

- **Know $\mathcal{R}$:** Determines the quality of a_t in s_t for each t
- **Know $\mathcal{P}$:** Predicts s_{t+1} based on a_t in s_t. Allows recalculation of $\mathcal{P}$ and $\mathcal{R}$ based on s_{t+1} and a_{t+1}
- **Challenges:** This approach can be impractical for real-world problems

Model-Free Methods

Indirectly approximate environment by approximating the policy:

- **Policy Approximation:** Learn a policy $\pi(s) \rightarrow a$, which maps states s to actions a
- **Objective:** Optimize the policy to maximize the cumulative expected reward (or return) over time

Return

Return (G_t): The total accumulated reward an agent expects to receive starting from time step t

- **Definition:**

$$G_t = r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1}$$

- **Finite Episode:** The sum is limited to a fixed number of steps, T, rather than extending to infinity
- **Components:**
  - $r_{t+1}, r_{t+2}, \ldots$: Rewards received at each time step
  - γ: Discount factor, $0 \leq \gamma \leq 1$

Discounting rewards

Role of Discount Factor (γ):

- **Trade-off Decision:** Determines the trade-off between immediate rewards and future rewards
- $\gamma = 0$**:** Focuses only on immediate reward

$$G_t = r_{t+1}$$

- $\gamma = 1$**:** Values future rewards as much as immediate rewards

$$G_t = r_{t+1} + r_{t+2} + r_{t+3} + \ldots = \sum_{k=0}^{\infty} r_{t+k+1}$$

- **Practical Use:** strictly between 0 and 1

Summary

- RL is a ML paradigm involving a loop of trial and error
- The reward signal guides the learning process
- Environment modeled as MDP
- Model-free methods preferred for real-world problems
- Maximization of $\mathbb{E}_\pi[G_t]$ properly setting γ

Model-Free Methods

We do not approximate $\mathcal{P}$ and $\mathcal{R}$, we approximate them indirectly:

- **Policy-Based:** The policy $\pi(a|s)$
- **Value-Based:** Value functions $V(s)$ or $Q(s, a)$
- **Actor-Critic:** Both policy $\pi(a|s)$ and value functions

Policy-based methods

- **Objective:** Directly learn a policy $\pi(a|s)$ representing the agent
- The policy (π) outputs the probability of taking action a in state s

$$\pi(a|s) = P(a_t = a|s_t = s)$$

- **Optimization Problem:** Train the policy to maximize the cumulative expected reward:

$$J(\pi) = \mathbb{E}_{\pi}[G_t]$$

Value-based methods

- **Objective:** Approximate a function that provides the quality (value) of each action in a given state
- **Potential Options:**
  - **State Value Function ($V(s)$):** Estimates the expected return starting from state s and following a particular policy π:

$$V(s) = \mathbb{E}_\pi[G_t | s_t = s]$$

  - **Action Value Function ($Q(s, a)$):** Estimates the expected return of taking action a in state s and following a particular policy π:

$$Q(s, a) = \mathbb{E}_\pi[G_t | s_t = s, a_t = a]$$

Interconnection of π, V, and Q

- **From Q to π:** Optimal policy can be derived directly by selecting actions with the highest Q-value:

$$\pi(s) = \arg\max_a Q(s, a)$$

- However, we have no direct mapping from V to π
- Same from π to V or Q

Actor-critic methods

- **Objective:** Combine policy-based and value-based methods to improve learning
- **Components:**
  - **Actor:** Learns the policy $\pi(a|s)$ to select actions
  - **Critic:** Estimates the value function $V(s)$ to evaluate the quality of the states
- Leveraging the value estimate to inform the policy updates

RL Intersections

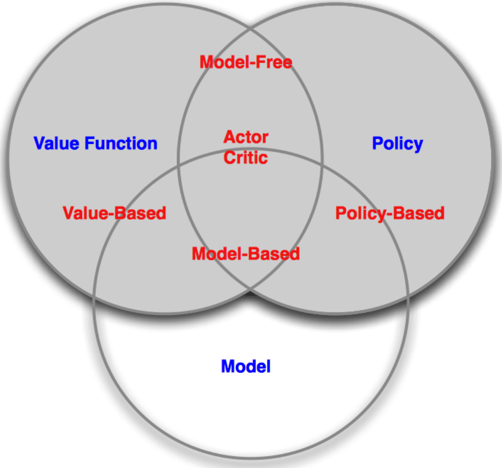


Image Source: Odonkor, Philip & Lewis, Kemper. (2018). Control of Shared Energy Storage Assets Within Building Clusters Using Reinforcement Learning. 10.1115/DETC2018-86094.

Algorithms for Learning

- **Objective:** Find functions that maximize $\mathbb{E}_\pi[G_t]$ using iterative optimization methods
- **Value-Based Methods:**
  - Update Formula: Bellman Equation
- **Policy-Based Methods:**
  - Update Formula: Policy Gradient Theorem, ...
- **Actor-Critic Methods:**
  - Combination of update formulas to reach the approximation of actor and critic

Optimality

Derive Optimal Policy in RL Problems:

- From Policy-Based / Actor-Critic Methods: directly derive the optimal policy (π^*)
- From Value-Based Methods:
  - Approximate the optimal action-value function (Q^*)
  - Derive the optimal policy (π^*) from this function:

$$\pi^*(a|s) = \arg\max_a Q^*(s, a)$$

How to choose?

Choosing the right RL method:

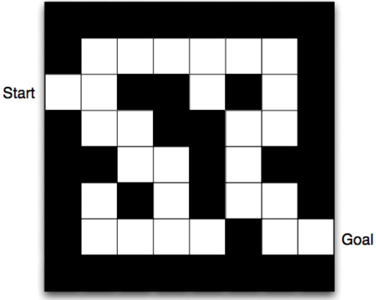
- **Policy-Based / Actor-Critic Methods:**
  - Converge to probabilistic (stochastic) policies
  - Reason: Optimize a policy $\pi(a|s)$, that inherently approximate a probability distribution:

$$\pi^*(a|s) = P(a|s)$$

- **Value-Based Methods:**
  - Converge to deterministic policies
  - Reason: Derive the policy by selecting the unique maximum action in each state:

$$\pi^*(a|s) = \arg\max_a Q^*(s, a)$$

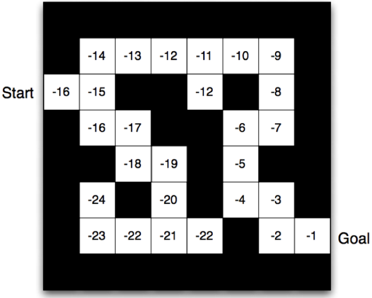
Grid World



Slide credit: D. Silver

- State: (x,y) position
- Action: up, down, left, right
- Rewards: -1 per time-step
- Episode termination: Reach goal

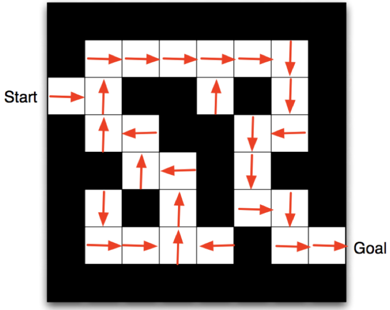
Grid World



Slide credit: D. Silver

- Optimal value function $V_\pi^*(s)$
- Expected return in each state

Grid World



Slide credit: D. Silver

- Optimal policy function $\pi^*(a|s)$
- The optimal policy is deterministic
- Actions that maximize expected return in each state

Tabular RL

Tabular RL Overview:

- **Definition:** Uses tables (arrays) to represent and approximate policies and value functions
- **Tabular Representation:**
  - Value Function Table
  - Action-Value Function Table
  - Policy Function Table

Tabular RL

	Value
State 1	$V^{\pi}(S1)$
State 2	$V^{\pi}(S2)$
....	
State M	$V^{\pi}(SM)$

Tabular representation of the value function

	Action 1	Action 2	....	Action N
State 1	$Q^{\pi}(S1, A1)$	$Q^{\pi}(S1, A2)$		$Q^{\pi}(S1, AN)$
State 2	$Q^{\pi}(S2, A1)$	$Q^{\pi}(S2, A2)$		$Q^{\pi}(S2, AN)$
....				
State M	$Q^{\pi}(SM, A1)$	$Q^{\pi}(SM, A2)$		$Q^{\pi}(SM, AN)$

Tabular representation of the action-value function

	Action 1	Action 2	....	Action N
State 1	$P(A1\|S1)$	$P(A2\|S1)$		$P(AN\|S1)$
State 2	$P(A1\|S2)$	$P(A2\|S2)$		$P(AN\|S2)$
....				
State M	$P(A1\|SM)$	$P(A2\|SM)$		$P(AN\|SM)$

Tabular representation of the policy

Limitations of Tabular RL

Challenges and Limitations:

- **Scalability:**
  - **Optimization:** Slow convergence and inefficient learning in large environments
  - **Memory:** Tables become impractical with large state or action spaces due to memory constraints
- **Generalization:**
  - No ability to generalize across unseen states or actions
- **Continuous Spaces:**
  - Inapplicable for environments with continuous state and action spaces

RL Elements - Discrete vs Continuous

Discrete vs Continuous Spaces:

- **Discrete:**
  - **Definition:** Finite/countable states/actions
  - **Example:** Board games
- **Continuous:**
  - **Definition:** Infinite states/actions
  - **Example:** Robot arm angles
  - **Note:** Requires specialized algorithms
- **Mixed:**
  - **Definition:** Both discrete and continuous elements
  - **Example:** Video games with levels and player control
  - **Note:** May need hybrid approaches

- **Parameterized Models:**
  - Represent the policy $\pi(a|s)$, action-value function $Q(s,a)$, or value function $V(s)$ using a parameterized function:

$$\pi_\theta(a|s) \quad Q_\theta(s,a) \quad V_\theta(s)$$

  - Here, θ represents the parameters of the function to be optimized for the return maximization

Function Approximators

$$\begin{aligned} \pi_\theta :& \quad \mathcal{S} \times \theta \to \mathcal{A} \\ V_\theta^\pi :& \quad \mathcal{S} \times \theta \to \mathbb{R} \\ Q_\theta^\pi :& \quad \mathcal{S} \times \mathcal{A} \times \theta \to \mathbb{R} \\ & \quad \theta \in \Theta, \text{ parameter space} \end{aligned}$$

Function Approximators

$$
\begin{aligned}
\pi_\theta : &\quad \mathcal{S} \times \theta \rightarrow \mathcal{A} \\
V^\pi_\theta : &\quad \mathcal{S} \times \theta \rightarrow \mathbb{R} \\
Q^\pi_\theta : &\quad \mathcal{S} \times \theta \rightarrow \mathbb{R}^{|A|} \\
&\quad \theta \in \Theta, \text{ parameter space}
\end{aligned}
$$

Function Approximators

- **Advantages:**
  - **Generalization:** Handle large or continuous state and action spaces by generalizing across similar states and actions
  - **Efficiency:** Reduce memory usage compared to tabular methods
  - **Optimization:** Efficients algorithms for iterative optimization
- **Deep RL** relies on deep learning, using neural networks (NN) as function approximators

Deep Learning

- **Definition:** A subset of machine learning involving NNs with multiple layers
- **Architecture:** Composed of input, hidden, and output layers
- **Universal Function Approximator:** NNs are capable of approximating any continuous function to a desired level of accuracy, given enough neurons and layers
- Uses **backpropagation** to adjust weights, with **gradients** computed to minimize error through optimization algorithms

Neural Networks as Function Approximators

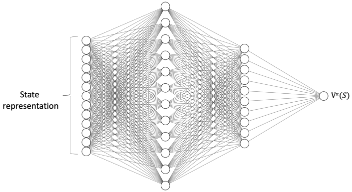
General Update Rule:

$$\theta \leftarrow \theta - \alpha \nabla_\theta J(\theta)$$

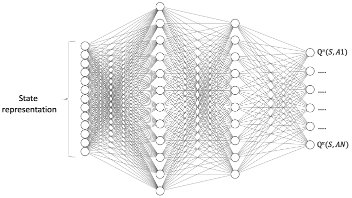
where

- θ denotes the model parameters
- α is the learning rate
- $\nabla_\theta J(\theta)$ represents the gradient of the loss function $J(\theta)$
- Iterative update formulas will be used to define the loss function for updating the function parameters θ

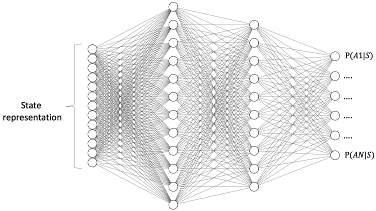
Deep Reinforcement Learning



NN approximating the value function



NN approximating the action-value function



NN approximating the policy function.

Images generated with `https://alexlenail.me/NN-SVG/`

Established DRL Algorithms

- **Value-Based**
  - Deep Q-Network (DQN)
  - ...
- **Policy-Based**
  - Proximal Policy Optimization (PPO)
  - Trust Region Policy Optimization (TRPO)
  - ...
- **Actor-Critic**
  - Advantage Actor Critic (A2C)
  - ...

Deep Q-Network (DQN)

- **What is DQN?**
  - Combines Q-learning with deep NNs
  - Approximates the Q-value function

$$Q(s, a; \theta) \approx Q^*(s, a)$$

  - Uses an experience replay to store and reuse experiences
  - Widely used version incorporates additional strategies to improve learning

DQN Algorithm (Part 1)

1. Initialize Q-network $Q_\theta(s, a)$ with random weights θ
2. Initialize an empty replay buffer
3. Collect experience (s, a, r, s') from the environment using the Q-network and store it in the replay buffer
4. Randomly sample a mini-batch of k transitions (s_i, a_i, r_i, s_i') from the replay buffer

DQN Algorithm (Part 2)

5. Compute target Q-values using the Bellman equation:

$$y_i = r_i + \gamma \max_{a'} Q_\theta(s'_i, a')$$

6. Compute the loss over the mini-batch:

$$L(\theta) = \frac{1}{2k} \sum_{i=1}^{k} (y_i - Q_\theta(s_i, a_i))^2$$

7. Update the Q-network by minimizing the loss:

$$\theta \leftarrow \theta - \eta \nabla_\theta L(\theta)$$

8. Repeat from step 3 until convergence

Target Network

- **Concept:** A target network is a separate Q-network $Q_{\theta^-}(s, a)$ that provides stable Q-value estimates for the Bellman equation
- **Purpose:** Avoid instability in learning due to rapidly changing Q-values
- Periodically update the target network weights to match the online network weights $Q_\theta(s, a)$

DQN Algorithm (Part 1)

1. Initialize Q-network $Q_\theta(s, a)$ with random weights θ
2. **Initialize target network $Q_{\theta^-}(s, a)$ with the same weights as** $Q_\theta(s, a)$
3. Initialize an empty replay buffer
4. Collect experience (s, a, r, s') from the environment using the Q-network and store it in the replay buffer
5. Randomly sample a mini-batch of k transitions (s_i, a_i, r_i, s_i') from the replay buffer

DQN Algorithm (Part 2)

5. **Compute target Q-values using the target network Q_{θ^-}:**

$$y_i = r_i + \gamma \max_{a'} Q_{\theta^-}(s'_i, a')$$

6. Compute the loss over the mini-batch:

$$L(\theta) = \frac{1}{2k} \sum_{i=1}^{k} (y_i - Q_\theta(s_i, a_i))^2$$

7. Update the Q-network by minimizing the loss:

$$\theta \leftarrow \theta - \eta \nabla_\theta L(\theta)$$

8. **Periodically update the target network weights to match the online network weights**
9. Repeat from step 3 until convergence

ϵ-greedy Strategy

- **Concept:** Balances exploration and exploitation in action selection
- **Strategy:**
  - With probability ϵ, select a random action (exploration)
  - With probability $1 - \epsilon$, select the action that maximizes the Q-value (exploitation)
- **Equation:**

$$a_t = \begin{cases} \text{random action} & \text{with probability } \epsilon \\ \arg\max_a Q_\theta(s_t, a) & \text{with probability } 1 - \epsilon \end{cases}$$

ϵ Decay in ϵ-Greedy Strategy

- **Purpose of Epsilon Decay:**
  - Start with high exploration to gather diverse experiences
  - Gradually shift towards exploitation to refine the policy
- **Epsilon Linear Decay Function:**

$$\epsilon_t = \max(\epsilon_{\min}, \epsilon_0 \cdot \text{decay\_rate}^t)$$

  - ϵ_t: Epsilon value at time t
  - ϵ_0: Initial epsilon value
  - decay_rate: Rate at which epsilon decreases
  - $\epsilon_{\min}$: Minimum value epsilon can decay to

DQN Algorithm (Part 1)

1. Initialize Q-network $Q_\theta(s, a)$ with random weights θ
2. Initialize target network $Q_{\theta^-}(s, a)$ with the same weights as $Q_\theta(s, a)$
3. Initialize an empty replay buffer
4. Collect experience (s, a, r, s') from the environment
    - **with probability ϵ, select a random action**
    - **otherwise, select the action that maximizes $Q_\theta(s, a)$**
5. Randomly sample a mini-batch of k transitions (s_i, a_i, r_i, s_i') from the replay buffer

DQN Algorithm (Part 2)

5. Compute target Q-values using the target network Q_{θ^-}:

$$y_i = r_i + \gamma \max_{a'} Q_{\theta^-}(s'_i, a')$$

6. Compute the loss over the mini-batch:

$$L(\theta) = \frac{1}{2k} \sum_{i=1}^{k} (y_i - Q_\theta(s_i, a_i))^2$$

7. Update the Q-network by minimizing the loss:

$$\theta \leftarrow \theta - \eta \nabla_\theta L(\theta)$$

8. Periodically update the target network weights to match the online network weights
9. Repeat from step 3 until convergence

DQN Improvements

- **Dueling DQN:** Improve value estimation
- **Double DQN:** Reduces overestimation bias
- **Prioritized Replay:** Changes sampling strategy
- **Noisy DQN:** Noisy networks instead of ϵ-greedy
- **Distributional DQN:** From expected Q-value to distribution

Proximal Policy Optimization (PPO)

- **What is PPO?**
  - An optimization algorithm aimed to approximate a policy function

$$\pi_\theta(a|s) \approx \text{Optimal Policy Distribution}$$

  - Optimizes the policy using a clipped surrogate objective (here simplified):

$$L(\theta) = \mathbb{E}_t \left[\text{clip}\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}, 1-\epsilon, 1+\epsilon \right) \hat{A}_t \right]$$

  - Uses clipping to ensure stable and reliable updates by preventing large policy changes
  - Uses the advantage of the action $\hat{A}_t$ for the update

PPO Algorithm

1. Initialize the policy network π_θ with random weights
2. Collect data by interacting with the environment using the current policy
3. Compute the advantage $\hat{A}(s, a)$ for each time step
4. Update the policy network by maximizing the PPO objective (simplified):

$$L(\theta) = \mathbb{E}_t \left[\text{clip}\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{\text{old}}}(a_t|s_t)}, 1-\epsilon, 1+\epsilon \right) \hat{A}_t \right]$$

5. Repeat steps 2 to 4 until convergence

Recap

- **Model-Free Methods:**
  - Do not require a model of the environment
  - Suited for real-world complexities
- **Classes of Methods:**
  - Value-Based (e.g., DQN), Policy-Based (e.g., PPO), and Actor-Critic
- **Tabular RL Limitations:**
  - Struggle with large or continuous state/action spaces
- **Deep NNs:**
  - Address scalability issues by approximating functions in complex environments

Extra

Best Practices for RL Experiments

Reporting and Analysis

- Plot reward versus steps/episodes to visualize learning progress and convergence
- Use relevant metrics, such as reward or domain-specific measures, for evaluation
- Document experimental settings and results for reproducibility and future reference

Generalization and Robustness

- Assess how well the policy generalizes to new or unseen environments
- Evaluate the algorithm's robustness to different conditions or noise

Best Practices for RL Experiments

Comparison

- Compare multiple RL algorithms to identify the most effective approach
- Explore hyper-parameters or use hyperparameter optimization techniques
- Conduct multiple runs with different random seeds to ensure result robustness and reproducibility
- Report confidence intervals (CIs) to improve reliability with few runs

Best Practices for RL Experiments

Others

- Consider normalization of the observation space and reward signal
- Consider the sample efficiency of algorithms
- Consider the NN size or function approximator used
- Determine which environment parameters affect learning and how

Partially Observable Markov Decision Process

$$
\begin{aligned}
\text{POMDP:} \quad & (S, A, T, R, \Omega, O) \\
S: \quad & \text{State space (hidden states)} \\
A: \quad & \text{Action space} \\
\Omega: \quad & \text{Observation space} \\
O: \quad & S \times \Omega \to [0,1], \text{ Observation function} \\
P: \quad & S \times A \to S, \text{ State transition function} \\
R: \quad & S \times A \to \mathbb{R}, \text{ Reward function}
\end{aligned}
$$

Challenges and Algorithms for POMDPs

- More suited for modeling realistic scenarios
- Some information may not be available at deployment phase
- **Challenges:**
  - Incomplete or noisy information
  - Hidden states complicate decision-making
- Need DRL to converge also in front of partial observability

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See you soon at the lab session!

Installation Toolkit

- **Installation Toolkit:**
  - **Conda Environment:** Anaconda or Miniconda
  - **IDE:** Install an Integrated Development Environment (IDE) like PyCharm or VSCode for coding
  - **Requirements File:** Download the `environment.yml` file from `https://terranovafr.github.io/teaching/2024-EASSS-Course`.
    - Use the command: `conda env create -f environment.yml` to install the necessary libraries