- HuggingFace Deep RL course (https://huggingface.co/deep-rl-course/unit0/introduction?fw=pt)
- HuggingFace Deep RL course github (https://github.com/huggingface/deep-rl-class)
- Reinforcement Learning book: Sutton (http://incompleteideas.net/book/RLbook2020.pdf)

Introduction: What is Reinforcement Learning (RL) ?

We have previously learned a form of learning called *Supervised Learning*

- learning a function from examples/demonstrations of the input/output relationship

We will now consider another form of learning called *Reinforcement Learning*.

Reinforcement Learning is the process whereby an *Agent* (the learner)

- learns a function by trial and error

In contrast to Supervised Learning

- where the learner learns from labeled examples
    - mappings from input to output

in Reinforcement Learning, the learner gathers information by interacting with the world

- The Agent is able to partially observe information (the *State*) about the world
- Given the State, the Agent has an available set of *Actions* that can be performed.
- the Agent's function (the *Policy*) guides its behavior: mapping the current State to an Action to perform
- the Agent performs the action
- The *Environment* responds to the action
    - with a *Reward*
    - and a new State

It is the Reward that serves as feedback for the Agent and guides it toward a solution

- the Agent's goal is maximization of Reward
- rather than minimization of Loss as in Supervised Learning

This interaction between Agent and Environment may continue for multiple steps

- multi-step sequence of State/Action/Reward/New State is called an *episode* or *trajectory*

The Agent's goal in formulating its Policy is maximization of reward received over the trajectory

- *Return* is the cumulative Reward (received over the sequence of chosen actions)

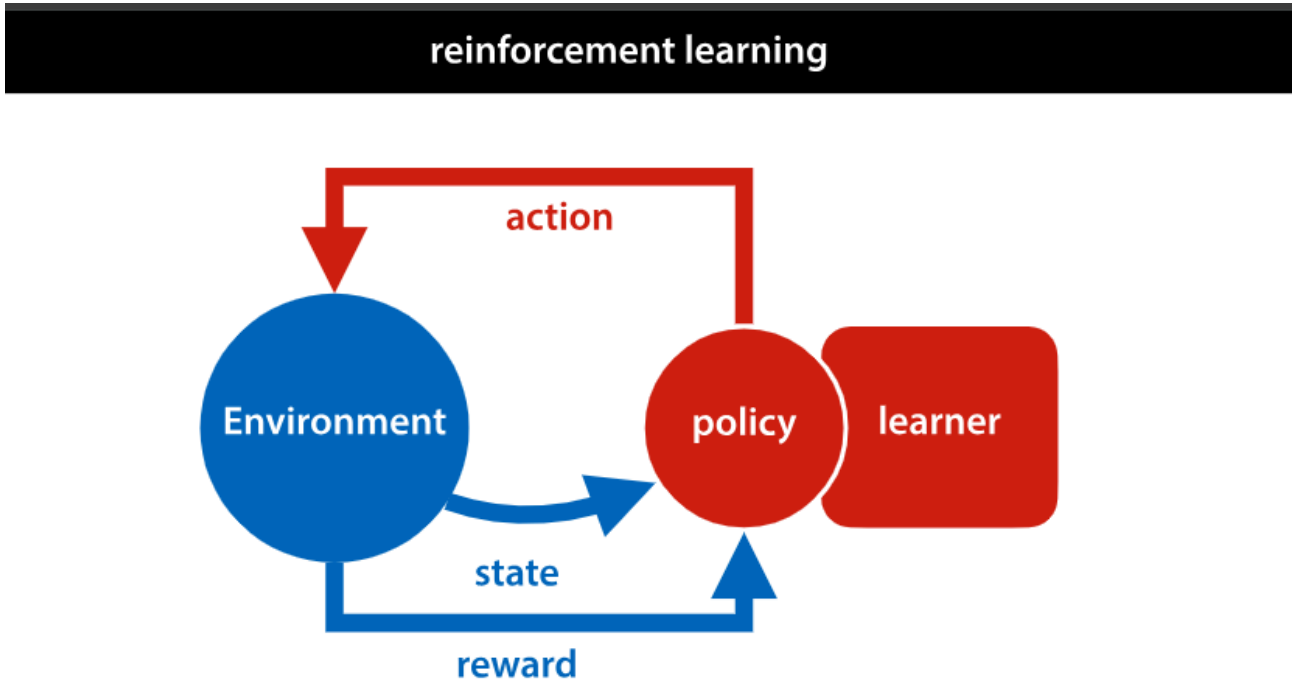
So Rewards are used by the Agent as a form of feedback

- evaluating the chosen Action
- guidance used to learn an optimal Policy.

Each episode/trajectory in analogous to an example

- deriving an optimal policy may require many episodes
- until an episode yield Maximum Return is achieved

Reinforcement Learning: information flow



Attribution: https://mlvu.github.io/lecture13/71.ReinforcementLearning.key-stage-0003.svg

Example: Frozen Lake

Here is an example: Frozen Lake

- the goal is for the character who starts in the upper left corner of a grid
- to learn a path to the gift in the lower right corner
- while traversing a grid on a frozen lake
- without falling into holes in the ice

Each element of the grid is a State.

The Action space for the character is

- Move: { Left, Right, Up, Down }

The Environment responds to an Action

- by moving the character to a new state
- potentially giving a Reward
    - large positive reward for reaching the state with the gift
    - large negative reward for falling into a hole
    - optional intermediate rewards
        - for getting closer to the goal

The Agent plays the game for multiple episodes

- until it learns how to safely navigate to the gift

Comparison with Supervised Learning

There is an important difference between Reinforcement Learning and Supervised Learning.

In Supervised Learning, we have a *target*

- Loss is minimized when the Agent reproduces the target **exactly**
- it is a form of imitation

In Reinforcement Learning

- we can give a reward for the *quality* of an answer, not just its syntactic form

Consider Frozen Lake.

Using SFT

- we create examples
    - each is a sequence of (State,Action) pairs that eventually lead to the gift
- train a model to start from an empty sequence and predict the next state

The Agent learns to imitate successful paths

- without explicit guidance to the *principles* that lead to success
    - avoid falling in holes

Using Reinforcement Learning

- we give a large negative reward for falling into a hole
    - demonstrating the principle to avoid danger

Continuous versus discrete

Continuing the comparison

- Supervised Learning's optimization is: Loss Minimization
    - Loss is continuous, differentiable
- Reinforcement Learning's optimization is: Return Maximization
    - Rewards may be discrete, rather than continuous

Reinforcement Learning to post-train an LLM to become an AI Assistant

Another example

- reflecting the particular interest in this class to training AI Assistants.

Consider how a model might learn to answer the question

```
How are you today ?
```

In Supervised Learning, there is a single Target

```
I feel fine, thank you
```

But there may be an equally acceptable response

```
Great, thanks for asking
```

Yet, this *semantically similar* response

- results in a Loss

as does a completely inappropriate response

The sky is blue

In Reinforcement Learning, we can acknowledge multiple answers and rank them (via reward)

- the Return can be a measure of the *quality* of the response
- rather than how *syntactically similar* it is to the target

```
Fine.

Fine thank you.

Fine, thank you, and how are you feeling ?
```

Comment

Imitation feels "shallow", overly quantitative

- emphasizing syntactic equivalence with the target
- the "what" rather than the "why"

Learning from experience feels "deeper", qualitative

- emphasizing the result (semantics) rather than the exact path to the result

Comparison: Reinforcement Learning vs Supervised Learning

Aspect	Reinforcement Learning (RL)	Supervised Learning (SL)
Learning Signal	Reward signal potentially delayed and sparse	Direct feedback with labeled input-output pairs
Data Acquisition	Data collected through interaction with environment	Data typically fixed and pre-collected
Goal	Learn a policy to maximize cumulative future reward	Learn a function mapping inputs to outputs
Feedback Type	Scalar reward signal, often sparse and delayed	Exact target labels for each input
Training Setup	Trial-and-error interaction, sequential data	Independent and identically distributed (i.i.d.) samples
Exploration	Critical to discover effective actions	Usually not required, data is given
Optimization Target	Maximize expected cumulative reward (possibly stochastic)	Minimize empirical loss over dataset
Environment Model	May be unknown or partially known, learning from experience	Typically no environment dynamics involved

Challenges of RL

State

- The "full State" (all relevant information) may not be visible
    - The State available to the agent is *partially observable*

For example, suppose you (the Agent) are playing a game against a computer (the Environment)

- Chess/Go: full state is visible to Agent
- Poker: opponent (Environment) cards are not visible to Agent

Rewards

Sparse rewards

- rewards may *not be received at every step*
- in the limit
    - single reward at end of trajectory
    - e.g., your assignment grade is received when you complete the assignment, not at every partial solution

Consider Frozen Lake

- harder for Agent to learn
- when the *only reward* is received in a terminal state
    - fall into hole/receive gift
- versus a per-step reward
    - "hot"/"cold": closer/farther from gift

Environment

- state transition may be stochastic rather than deterministic

In Frozen Lake

- the surface of the lake is covered in ice
- an Agent trying to move in one direction may slip
    - and not wind up where expected

The Environment

- with some non-zero probability
- **will move it to a state in the *opposite* direction**

Policy

- action choice may be stochastic
- Policy is based only on State, not the trajectory
    - *Partially Observable Markov Decision Process (POMDP)*

Given the possible stochastic nature of the trajectory

- goal is maximization of *Expected Reward*

Challenges in finding an optimal policy

The Agent learns to update the policy through experience.

The quality of the experience matters

- you can't become an expert by only playing against weak opponents
- the agent may never achieve true optimal policy
    - for games where the optimal opponent strategy is not known (or is intractable computationally)
    - the agent can become the best *current* player of the game of Go
        - without a truly optimal policy

Exploration versus Exploitation

The agent's policy evolves with experience.

- accumulates more information about rewards and the environment through new episodes
- in the interim, it only has partial knowledge

Thus, if the agent

- chooses the same action $\act$ every time it visits state $\state$
    - when the policy has not changed since the last visit
- it will never gain knowledge about other possible continuations of the trajectory

For example

- choosing alternate action act' may lead to a trajectory with higher return

The dilemma is called *exploration versus exploitation*

- *exploitation*: always choose the action with highest forward return
    - based on current limited knowledge
- *exploration*: take a new action, in order to explore alternate possible forward returns

Notation

Term	Definition
$\States$	**Set** of possible states
$\Actions$	**Set** of possible actions
$\Rewards$	**function** $\States \times \Actions \to \Reals$
	maps state and action to a reward
$\disc$	discount factor for reward one step in future
\stateseq_\tt	The state at beginning of time step
\actseq_\tt	The action performed at time step
$\rewseq_{+1}$	The reward resulting form the action performed at time step
$\transp$	**Function** $\States \times \Actions \to \States \times \Rewards$
	Transition probability: maps state and chosen action
	to new state and reward received

We can begin to develop some notation to describe what is happening.

An *episode* (or *trajectory*) is a sequence that records the events as agent follows its policy in making decisions.

Here is a timeline of an episode

- column labeled "Agent": actions chosen by the Agent
- column labeled "Environment": the responses generated in reaction to the decision

Step	Agent	Environment	Notes
0		$\stateseq_0$	Environment chooses initial state
	$\pi(\stateseq_0)$	$\rewseq_1, \stateseq_1$	Agent observes $\stateseq_0$
			chooses action $\pi(\stateseq_0)$ according to policy π
			receiving reward $\rewseq_1$
			environment updates state to $\stateseq_1$
1	$\pi(\stateseq_1)$	$\rewseq_2, \stateseq_2$	Agent continues to follow policy π

$\vdots$ | $\pi(\stateseq_)$ | $\rewseq_{+1}, \stateseq_{+1}$ | Agent follows policy to choose action $\pi(\stateseq_)$ | | | Environment responds to action by giving reward $\rewseq_{+1}$ and changing state to $\stateseq_{+1}$ $\vdots$

Notes on episode notation

The triple of elements corresponding to experience number

- is
  $\stateseq, \actseq, \rewseq_{+1}$
- **not**
  \stateseq_\tt, \actseq_\tt, \rewseq_\tt

following the notational standard of the Sutton and Barto book (http://incompleteideas.net/book/RLbook2020.pdf).

The latter notation is also used, but less common.

We also develop notation to describe the behavior of

- the Agent: policy
- the Environment: transition probability to reward and successor state

Definitions relative to an episode

$$
\begin{array}[lll]\\
\stateseq_0, \actseq_0, \rewseq_1, \ldots \stateseq_\tt, \actseq_\tt, \rewseq_{\tt+1}, \ldots
 & \textbf{sequence}: \text{Episode/Trajectory} \\
& \text{sequence of states, action performed, reward received} \\
\transp({ \state', \rew | \state, \act }) & \textbf{Transition probability} \text{ (rules of the game)} \\
& = \transp({\stateseq_\tt = \state', \rewseq_\tt = \rew | \stateseq_{\tt-1} = \state, \actseq_{\tt-1} = \a
 & \textbf{Markov Decision Process} \text{: depends only on } \stateseq_{\tt-1} \\
 & \text{and not on history } \stateseq_0, \ldots, \stateseq_{\tt-1} \\
\pi(\act | \state) & \text{Policy (decision process for agent)} \\
& \textbf{probability distribution over } \Actions \\
\pi(\state) & \text{the action } \act \text{ chosen by the policy from state } \state \\
& \text{abuse of notation: } \pi(\state) \text{ is a probability distribution over } \Actions \\
G_\tt & \text{return/return to go} \\
& \text{cumulative rewards (discounted by } \gamma \text{) in the episode starting from ste
& = \sum_{k=0}^\tt { \gamma^k * \rewseq_{\tt+k+1} } \\
& = \rew_{\tt+1} + \gamma * G_{\tt+1} \\
& & \text{ where } \gamma \text{ is a factor for discounting future returns.}\\
\end{array}
$$

Reinforcement Learning: information flow (with labels)

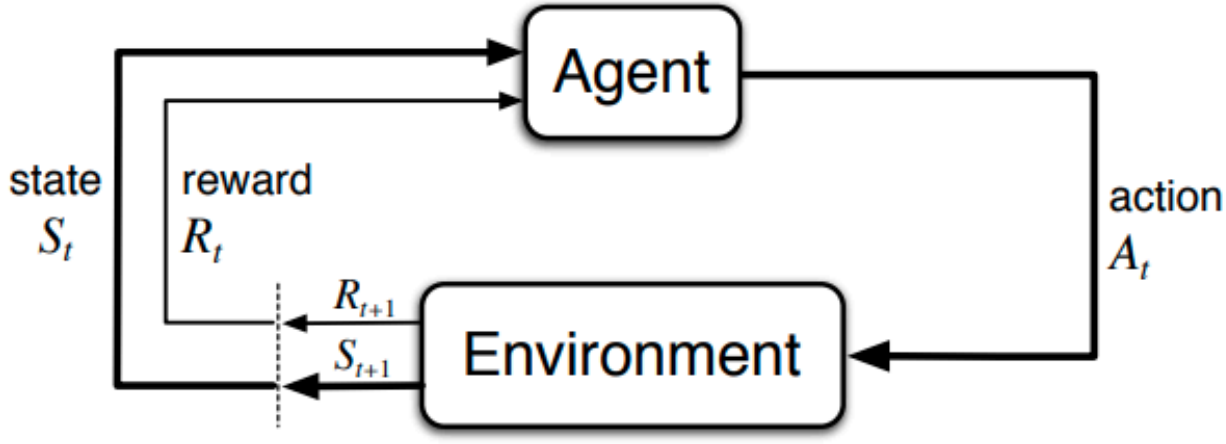


Figure 3.1: The agent–environment interaction in a Markov decision process.

Attribution: completeideas.net/book/RLbook2020.pdf#page=70

Finding an optimal Policy: Solving an RL system

A policy π is a function mapping a state to an action.

It is the "algorithm" that guides the actions behavior.

The "solution" to an RL system is the optimal policy π^* that maximizes *return* from the initial state

- return is sum of discounted rewards accumulated by following the policy from a given state $$ \begin{array}\ G*tt* & = & *sum*{k=0}^\tt { \gamma^k * \rewseq_{\tt+k+1}}\
  ```
  & = & \rew_{\tt+1}  + \gamma * G_{\tt+1} \\
  ```
  \end{array} $$ where $\gamma \leq 1$ is a factor for discounting future returns.

Note on the discount factor

What is the purpose of the discount factor ?

Given two trajectories with *equal* return

- we sometimes want to favor the *shorter* trajectory
    - favor direct path over indirect path
    - favor immediate rewards to deferred rewards
- the discount factor is a way of expressing our preference

For simplicity of presentation, we often assume

$$\gamma = 1$$

How do we find the optimal policy π ?

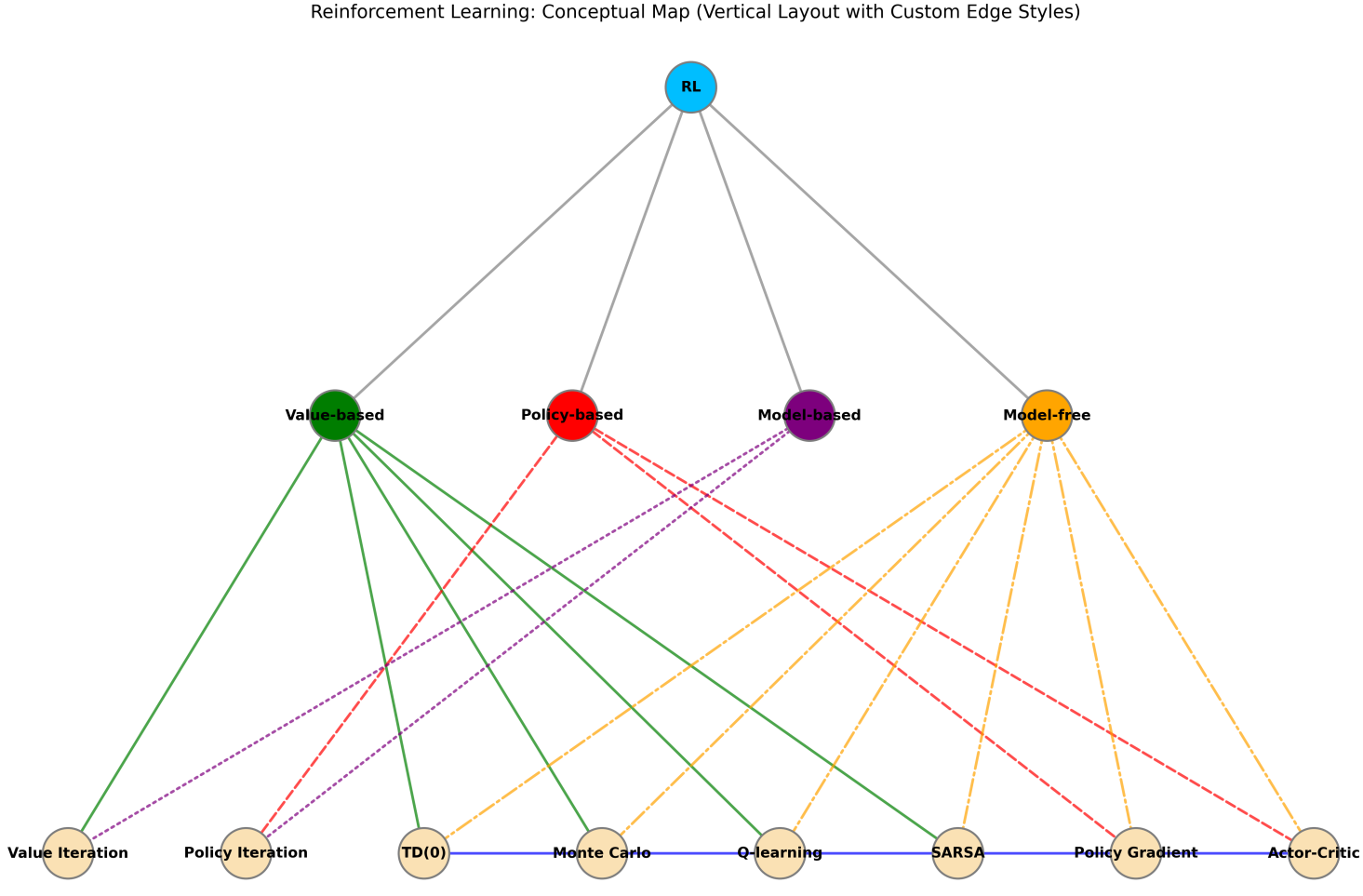
The way we find the optimal policy is typically via an iterative process

- We construct a sequence of improving policies
  $$\pi_0, \ldots, \pi_p, \ldots$$
  that hopefully converges to π^*.

For simplification, let us assume for the moment that

- the sets of states, actions and rewards be *finite*.

RL Methods Landscape



Graph Edge Explanations

This graph illustrates the conceptual relationships and classifications within Reinforcement Learning methods.

General Arrows:

- Arrows represent a hierarchical or conceptual relationship, indicating that a method or family falls under another category, or that one method incorporates another.

Colored Arrows from Family Nodes (Depth 1): These arrows indicate the primary classification of the methods into different RL families:

- **Green (Solid, from 'Value-based'):** Methods primarily focused on estimating and optimizing value functions.
- **Red (Dashed, from 'Policy-based'):** Methods focused on directly learning and optimizing a policy.
- **Purple (Dotted, from 'Model-based'):** Methods that build or use a model of the environment.
- **Orange (Dashdot, from 'Model-free'):** Methods that learn directly from experience without needing an explicit model of the environment.

Specific Blue Arrow:

- **Blue (Solid, from 'Actor-Critic' to 'TD(0)'):** This specific connection highlights that the 'Critic' component of many Actor-Critic algorithms typically uses Temporal Difference (TD) learning, often `TD(0)` or similar TD updates, to estimate the value function.

Model-Based vs Model-Free RL

There are two main approaches to solving an RL system.

A *model-based* approach uses a model of the environment in forming a solution.

The model defines the response of the Environment to an action of the Agent

- $\transp(\state', \rew | \state, \act)$

The model can be either

- given
- learned

The advantage of having a model is that

- the Agent can explore the consequences of an action without having to perform an episode.

A *model-free* approach does not rely on a pre-defined model

- it learns from interacting with the environment

- Model-Based RL: Learns or uses the dynamics model $ P(s'|s,a) $.
    - Example methods: Dynamic Programming, Dyna, Monte Carlo Tree Search.
- Model-Free RL: Learns policies or value functions without modeling $ P $.
    - Example methods: Q-Learning, SARSA, Policy Gradient.

To illustrate with Frozen Lake:

Model-based:

The character has

- has a global view of the grid
- knowledge of the results of its actions

It can find an optimal policy (route)

- without "playing the game" (interacting with the Environment)
    - optimization problem with no unknowns other than the route
    - search by simulating the consequences of its action by calling the model

Model-free:

The character has **no** initial knowledge

- of the layout of the grid, location of gift/holes
- consequence of its actions (what is successor state)

It must "play the game" in order to accumulate experience and formulate policy.

Value-Based vs Policy-Based Methods

There are several major approaches to solving an RL problem

- Value-Based Methods
    - Learn function to either
        - map state $\state$ to an expected return $\statevalfun(\state)$
        - map state-action pair to an expected return $\actvalfun_{\pi}(\state, \act)$
    - Derive policies indirectly from these functions
    - Examples: Q-learning, DQN.
- Policy-Based Methods
    - Learn the policy $ \pi(\act \; | \; \state)$ directly.
    - Examples: REINFORCE, Actor-Critic, PPO.
- Actor-Critic
    - Hybrid methods combining policy and value learning.

On-Policy vs Off-Policy Methods

Some methods involve two potentially distinct choices for actions.

- the *behavior policy*: the one that choose an action *while learning*
- the *target policy*: the one that we are trying to learn; reflected in the update

An *On-Policy* method

- Behavior and Target policies are the same
- Learn from the policy used to generate data ($ \pi $).
    - Examples: SARSA, REINFORCE.

An *Off-policy* method

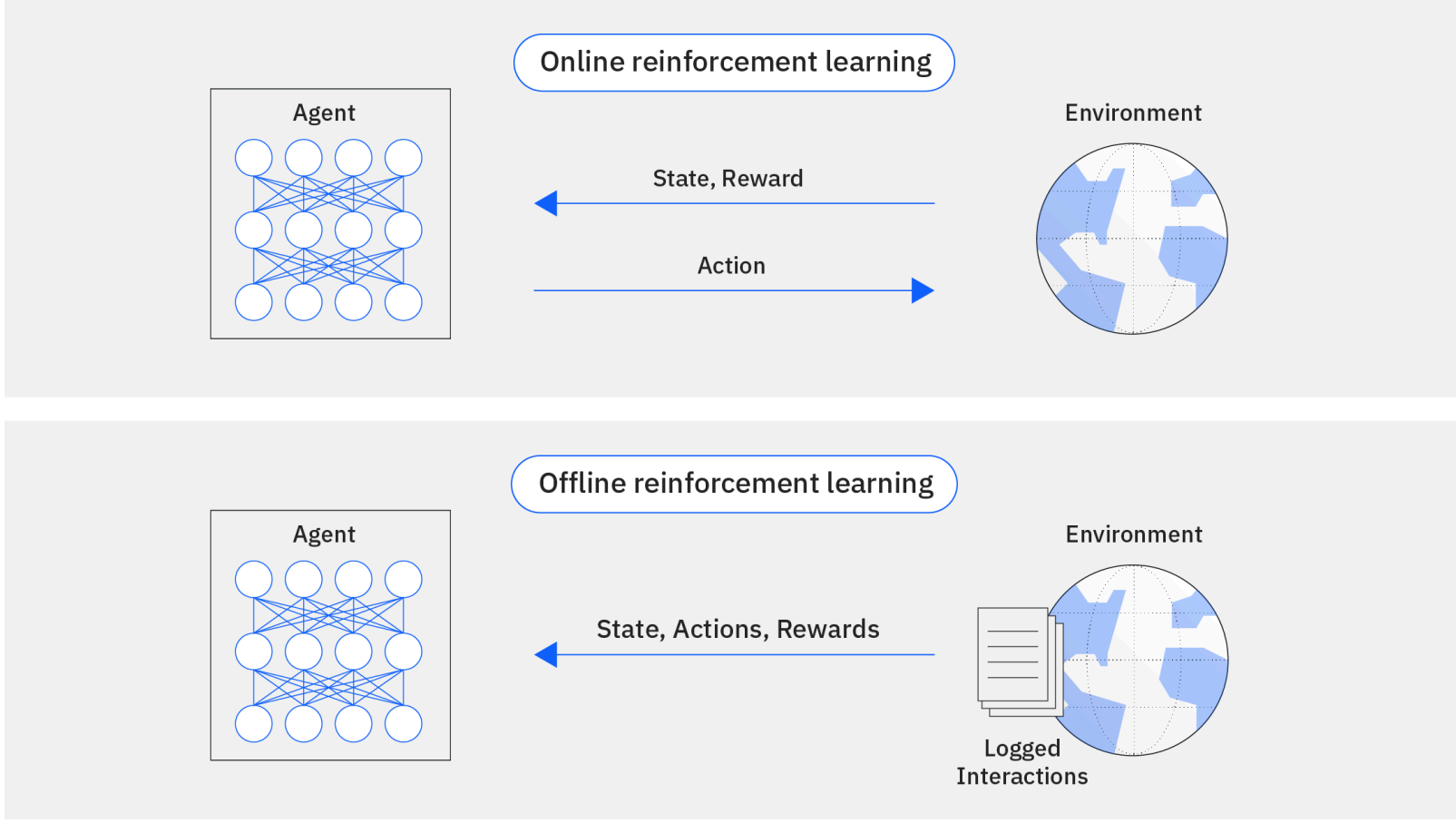
- Behavior and Target policies are different
- Learn about a target policy $ \pi $ different from behavior policy $ \mu $.
    - Examples: Q-learning, DQN.

On-Line vs Off-Line RL

The experience could be gained either

- *On-line*: playing the game
- *Off-line*: replaying the experiences of prior attempts
- On-Line RL: Updates and learns from interaction with environment in real time.
- Off-Line RL: Learns from a fixed dataset without further interaction.
    - Applications: healthcare, robotics.

Reinforcement Learning: Online vs Offline



Attribution: https://www.ibm.com/think/topics/reinforcement-learning

Core RL Algorithms and Their Categories

Algorithm	Model-Based	Model-Free	Value-Based	Policy-Based	On-Policy	Off-Policy	On-Line	Off-Line
Value Iteration	✓		✓					
Policy Iteration	✓		✓	✓				
SARSA		✓	✓		✓		✓	
Q-learning		✓	✓			✓	✓	
REINFORCE		✓		✓	✓		✓	
Actor-Critic		✓	✓	✓	✓	Some	✓	
Deep Q-Networks (DQN)		✓	✓			✓	✓	✓
PPO, A2C/A3C		✓	✓	✓	✓		✓	
Batch RL		✓	✓			✓		✓

Deep Reinforcement Learning

Deep Reinforcement Learning refers to the special case of Reinforcement Learning where

- the *policy* is a parameterized (by θ) function mapping states $\backslash\mathrm{stateseq}$ to (a probability distribution) actions

$$\pi_\theta(\backslash\mathrm{actseq}|\backslash\mathrm{stateseq})$$

- implemented as a Neural Network

Our initial presentation will be of fixed (non-parameterized) policies.

- We will subsequently introduce parameterized Neural Networks to implement the functions we define

In [2]:
```
print("Done")
```

```
Done
```