

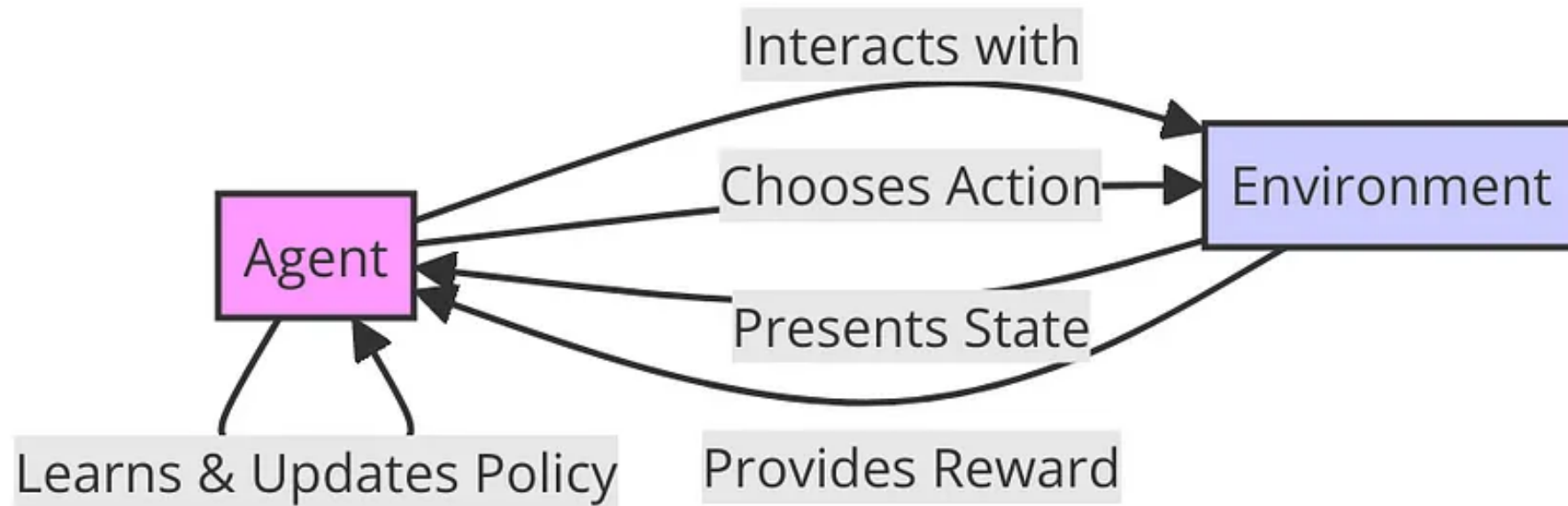
# Reinforcement Learning

Lecture 14

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3<sup>rd</sup> June, 2024

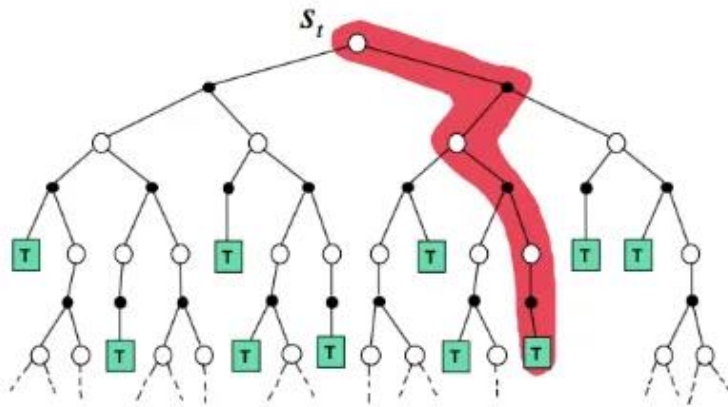
# Reinforcement Learning



# Basic Approaches of RL Algorithms

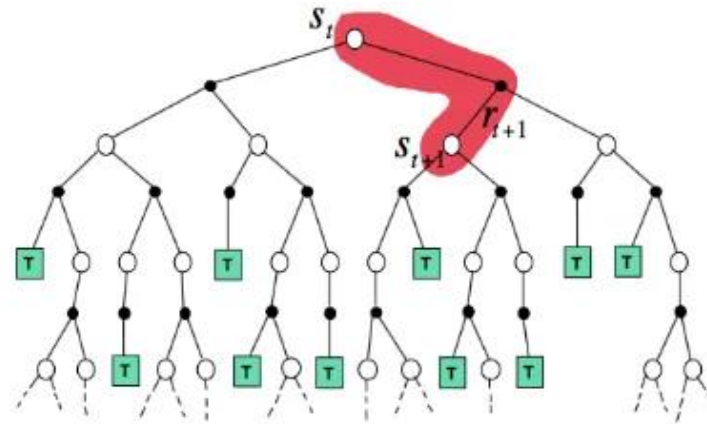
Monte-Carlo

$$V(S_t) \leftarrow V(S_t) + \alpha (G_t - V(S_t))$$



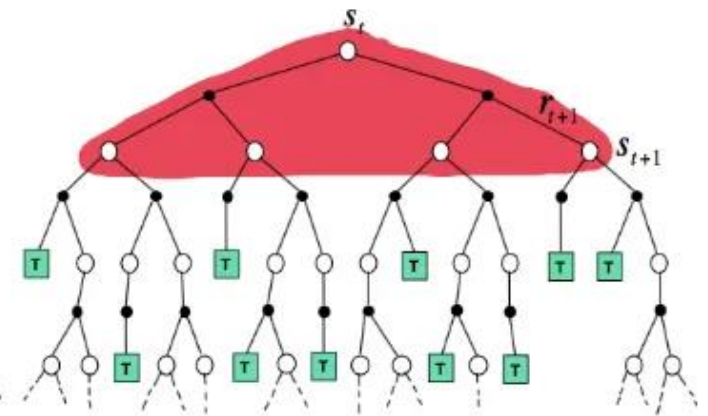
Temporal-Difference

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



Dynamic Programming

$$V(S_t) \leftarrow \mathbb{E}_{\pi} [R_{t+1} + \gamma V(S_{t+1})]$$



# Policy-Based Reinforcement Learning

- The goal is to directly learn the optimal policy ( $\pi^*$ ).
- The policy defines the agent's behavior → which action to take in each possible state
- The policy is modeled and updated directly without consulting a value function

# Value-Based Reinforcement Learning

- The focus is on learning optimal value function ( $V^*$ ).
- The value function estimates expected cumulative future rewards for being in a given state and following the current policy.
- Finding the optimal value function allows deriving the optimal policy.

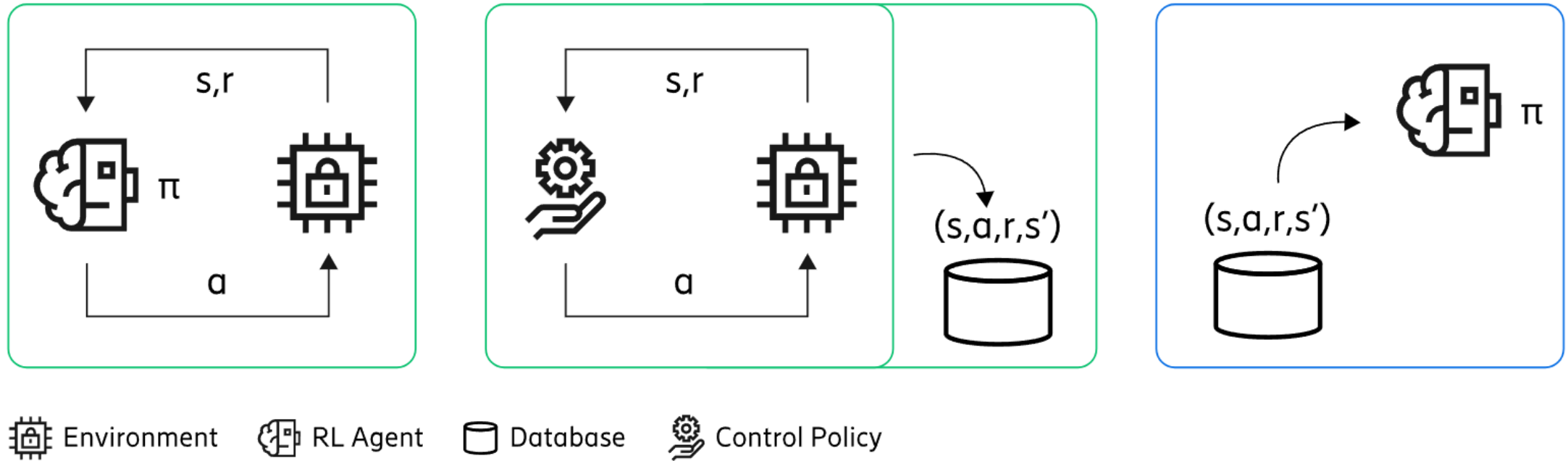
# Policy-based methods are Better?

- More effective in complex environments
- Better for stochastic tasks
- Stable training

# Off-policy vs. On-policy

- In the **off**-policy, the algorithm evaluates and updates a policy that differs from the policy used to take an action.
- The **on**-policy algorithm evaluates and improves the same policy used to take an action.
- **Continuous exploration?**

# Online and offline Reinforcement Learning





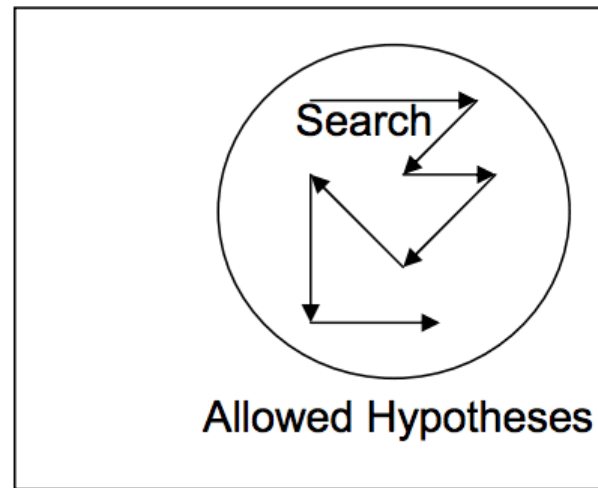
# Model-based and Model-free RL

- Planning OR Learning
- Model-based RL requires less data to learn a policy → why?

# Transfer Learning in Reinforcement Learning

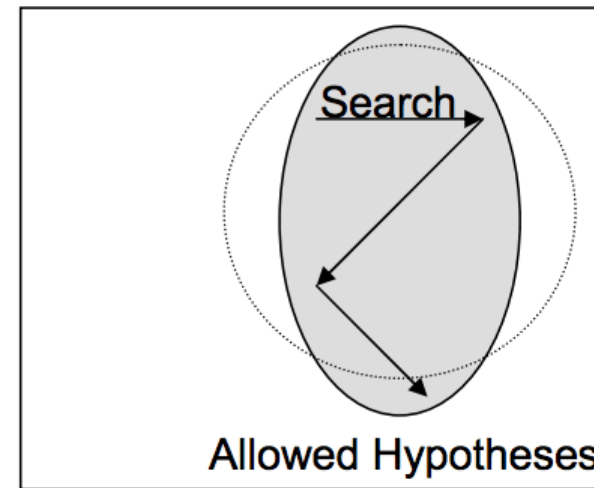
- What is Transfer Learning?
  - A machine learning technique where a model trained on one task is re-purposed on a second related task.

Inductive Learning



All Hypotheses

Inductive Transfer



All Hypotheses

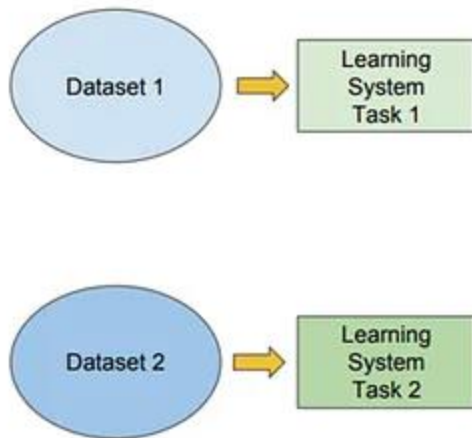
# Transfer Learning

## Traditional ML

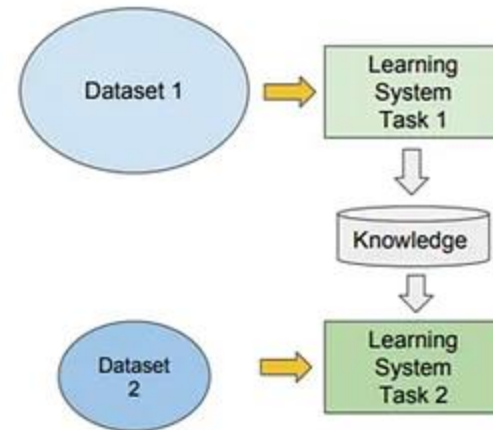
vs

## Transfer Learning

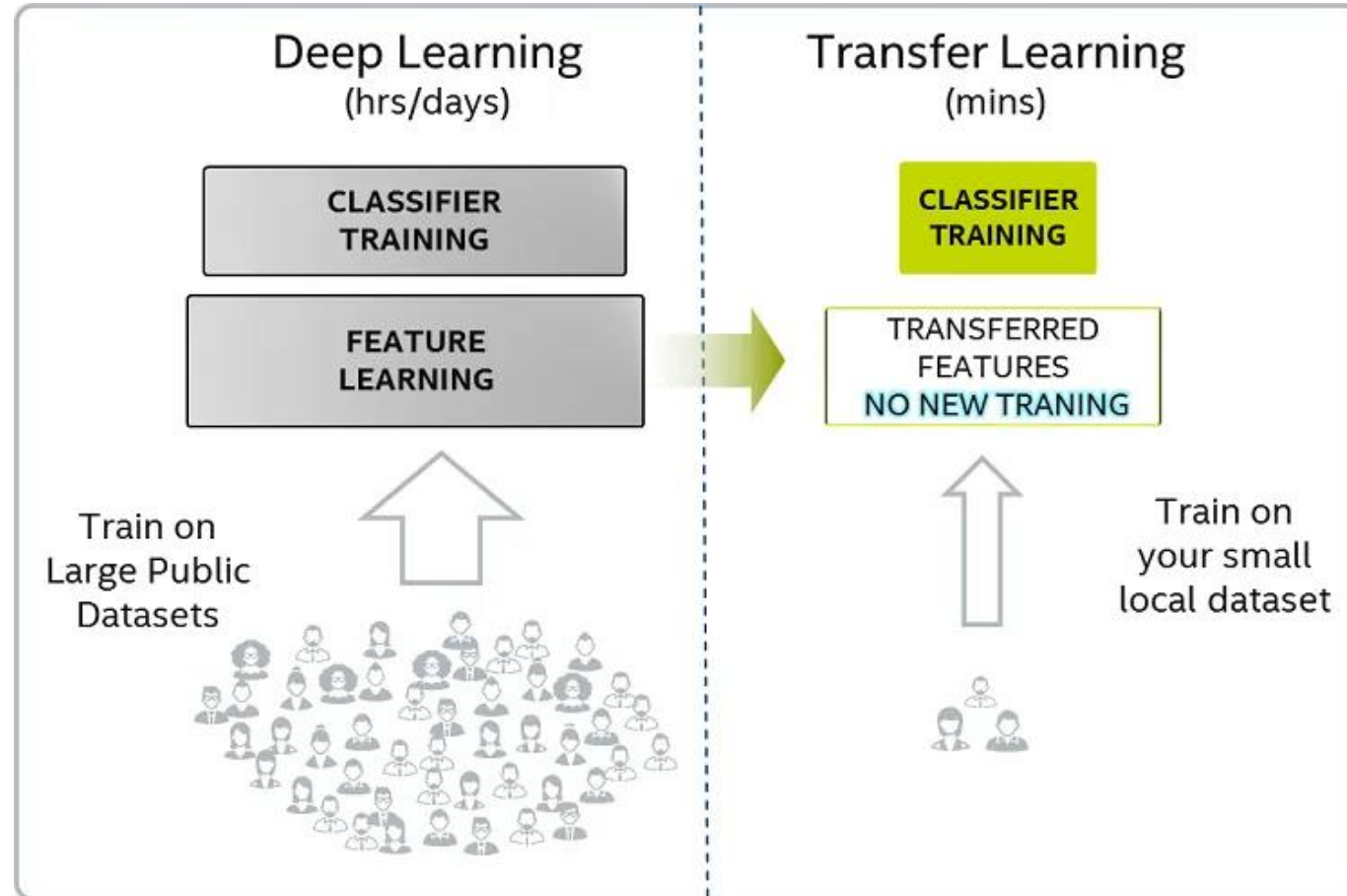
- Isolated, single task learning:
  - Knowledge is not retained or accumulated. Learning is performed w.o. considering past learned knowledge in other tasks



- Learning of a new tasks relies on the previous learned tasks:
  - Learning process can be faster, more accurate and/or need less training data



# Transfer Learning



# Fine Tuning vs. Transfer Learning

Fine-Tuning	Transfer Learning
Adapt pre-trained model to a specific new task	Leverage knowledge from a pre-trained model to enhance performance on a related task
Train the entire model with new data	Often freeze some layers of pre-trained model and train specific layers on the new task
Typically requires more data specific to the new task	Can be effective with smaller datasets due to leveraging pre-trained knowledge
When task-specific data is available and computational resources allow full retraining	When limited labeled data or computational resources are available, and tasks share similarities
More complex as it involves retraining the entire model	Less complex as it often involves freezing some layers and training only specific layers

# Approaches to Transfer Learning in Reinforcement Learning

- Policy Transfer
- Value Function Transfer
- Model Transfer

# Transfer Learning in Reinforcement Learning

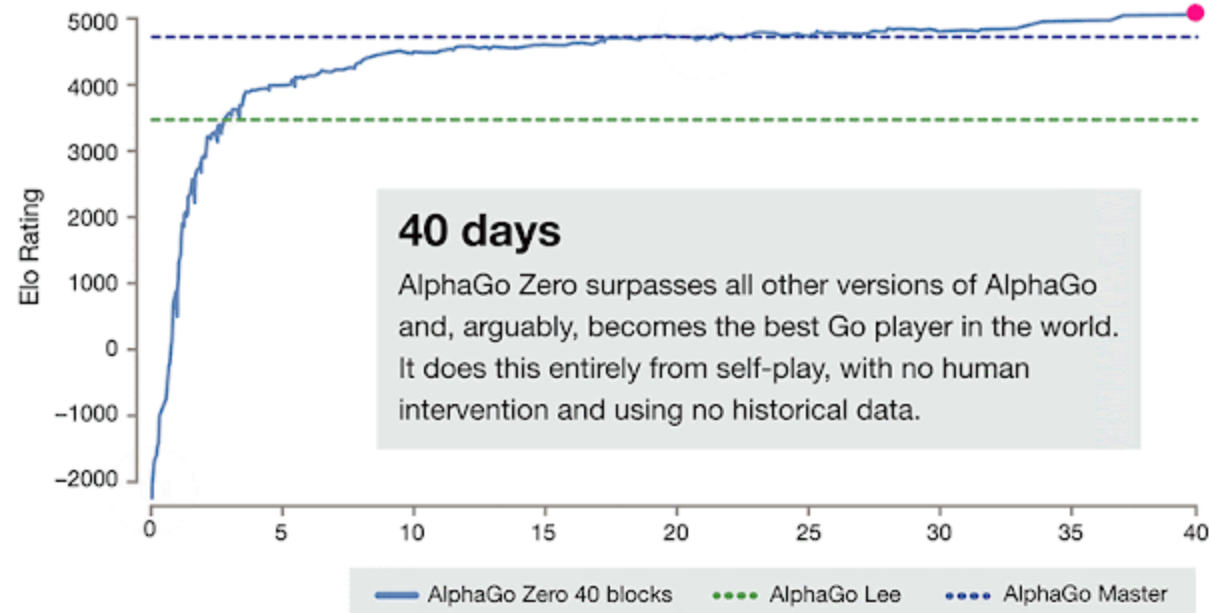
- Issues
  - Exploration
  - Speed up the initial training but degrades learning over the long period.

# Self-Play in Reinforcement Learning





# Self-Play in Reinforcement Learning



# Epoch vs Batch Size vs Iterations

- Epoch: Entire dataset is passed forward and backward through the neural network.
- Batch: divide dataset into number sets or parts.
- Iteration: The number of batches needed to complete one epoch.