On combining Reinforcement Learning with Random Forests

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INTRODUCTION

THEORETICAL BACKGROUND

Reinforcement Learning

Type of machine learning

Agent learns to make decisions by performing actions in an environment to maximize cumulative reward

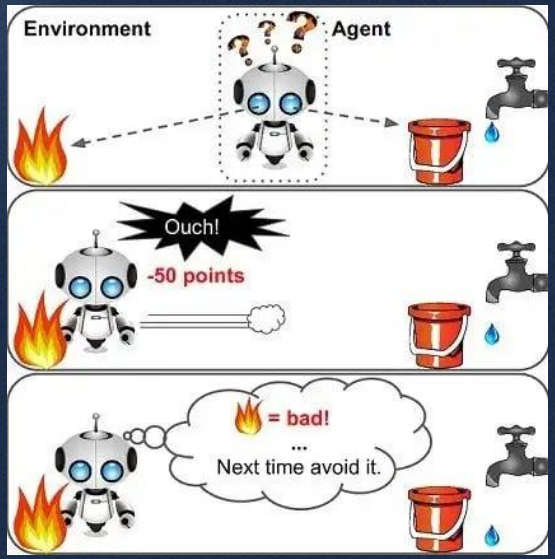
Random Forests

Machine learning method that falls under the category of ensemble learning

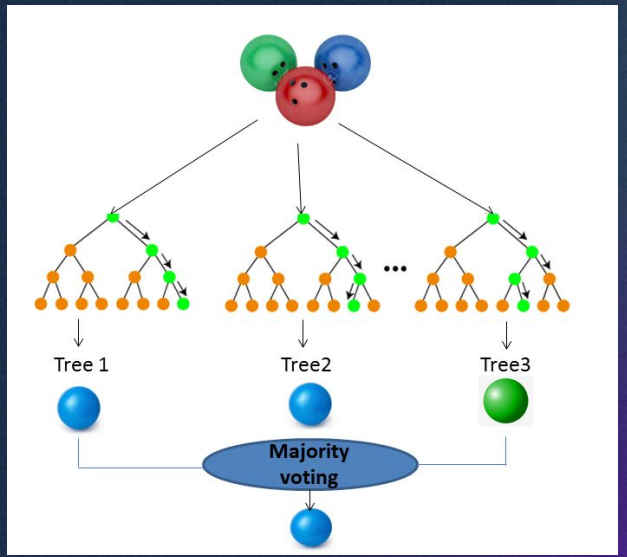
Used for classification, regression, and other tasks by constructing multiple decision trees during training and combining their outputs to improve accuracy and robustness

A MORE VISUAL APPROACH...

Reinforcement Learning



Random Forests



WHAT IF WE COMBINED THEM?

Improved Generalization

DRL uses NNs for function approximation → overfitting

RFs can generalize better to unseen data, thus improving the reliability of the learned policies

Sample Efficiency

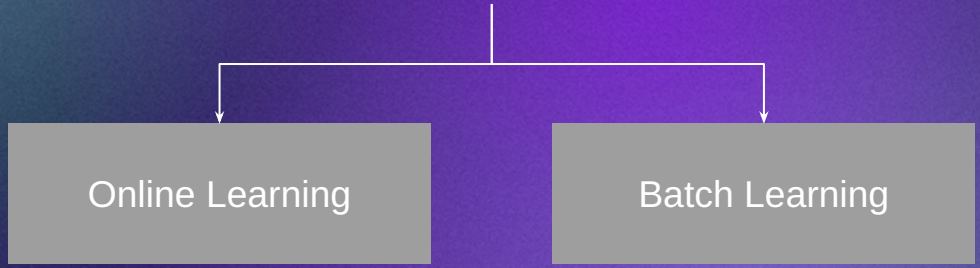
Training RL agents requires a large number of interactions with the environment

RFs reduce complexity by approximating the value function or policy

02

MAIN PROBLEM

LIES IN THEIR NATURE...



- Machine learning approach → model is updated incrementally as new data becomes available.

- “Offline learning”.
- Machine learning approach → model is trained on a fixed dataset all at once.

03

RELATED RESEARCH

RELEVANT INVESTIGATIONS

1

Q-Learning with Online Random Forests

- ORFs for approximating the Q-function in RL.
- Performance improvements over DQNs.

2

Random Forest Q-Learning for Feedback Stabilization of Probabilistic Boolean Control Networks

- Hybrid algorithm → Random Forests + Q-learning to stabilize PBCNs.
- Computational advantages over neural network-based approaches in controlling large-scale systems.

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PROPOSALS

BUT FIRST...

We need to be specific

1. Any environment/application?
2. Provide a clearer direction
3. Identify the most suitable methods for combining RL and RF

POSSIBLE INTEGRATION METHODS

Value Function Approximation

A

RF to approximate the value function in RL.

Helps the agent evaluate the long-term benefits of actions.

Policy Approximation

B

RF to approximate the policy, guiding the agent's action selection.

Environment Modeling

C

Train RF to model the environment's dynamics.

Provides the RL agent with accurate predictions of future states and rewards.