Course 2, Module 4
Planning, Learning & Acting

CMPUT 365
Fall 2021

Admin

- We are marking the mini-essay’s now
- Do get started on your project soon
- Practice midterm is on Eclass
  - We will solve it during in class with you

NEW: AI CERTIFICATE
NEW: AI CAPSTONE COURSE

- AI Capstone Course -- Cmput 497/469 (Winter 2022)
  - Taught by Russ Greiner!
  - More info: https://docs.google.com/document/d/1Rk6UO7QNxuyLckvwhZ8qkzWto2Rz5IMgFB_rhIzEDrM/edit
  - prerequisites: (at least) one of CMPUT 267, **365**, or 366

So many algorithms! What is a student to do?

- Introducing the **Course Map**

Can we represent the value function with a **table**?
No
Yes
Are we using **average reward**?
No
Yes
Will we learn on each **timestep**?
Yes
No
Is this a **control** problem?
No
Yes
Semi-Gradient TD
Expected SARSA
Q-Learning
SARSA
Gradient Monte Carlo
Are the actions **continuous**?
Yes
No
Gaussian Actor-Critic
Softmax Actor-Critic
Differential Semi-Gradient SARSA
Do we already have access to a **model**?
Yes
No
Is this a **control** problem?
Yes
No
Value Iteration
Policy Iteration
Iterative Policy Evaluation
Will we learn a **model**?
Yes
No
Q-Planning
Dyna-Q+
Dyna-Q
Will we learn on each **timestep**?
Yes
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Q-Learning
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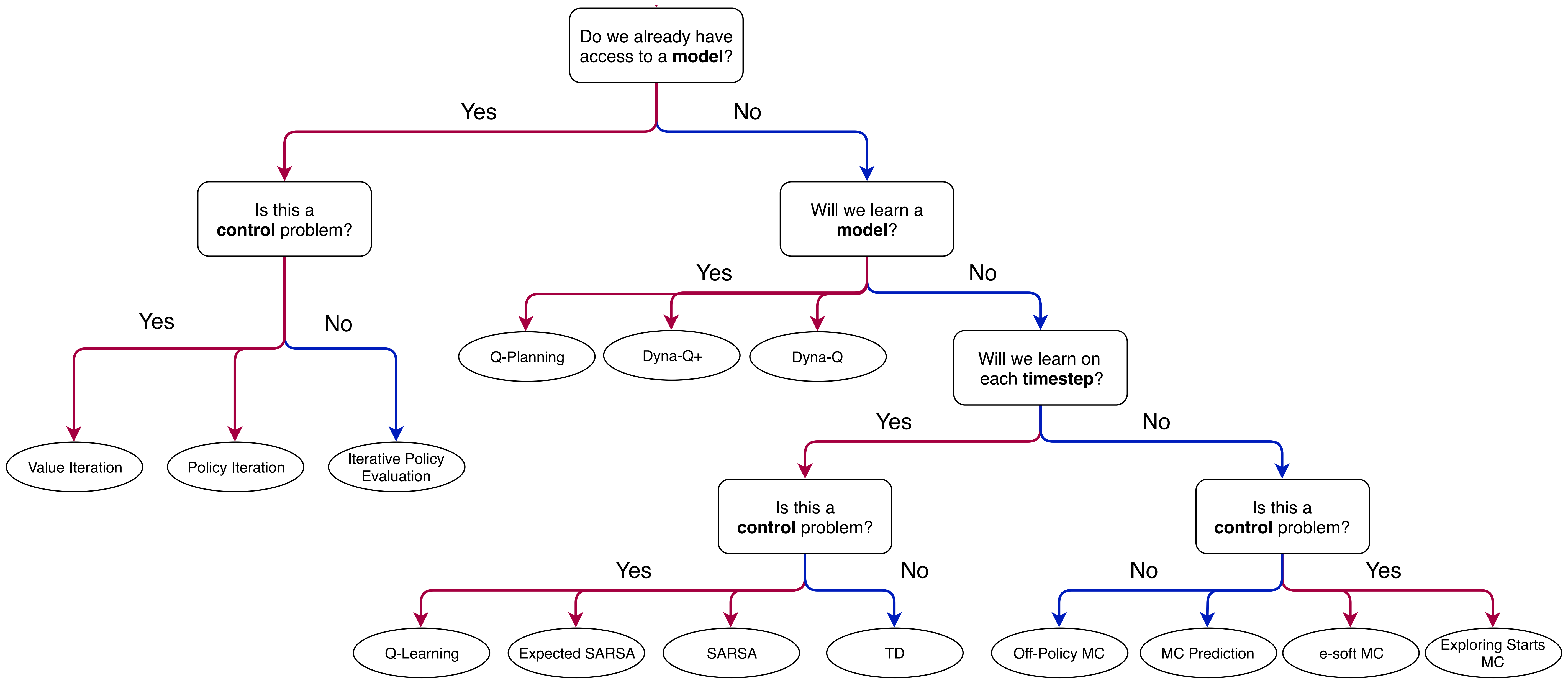
SARSA
TD
Is this a **control** problem?
No
Yes
Off-Policy MC
MC Prediction
e-soft MC
Exploring Starts MC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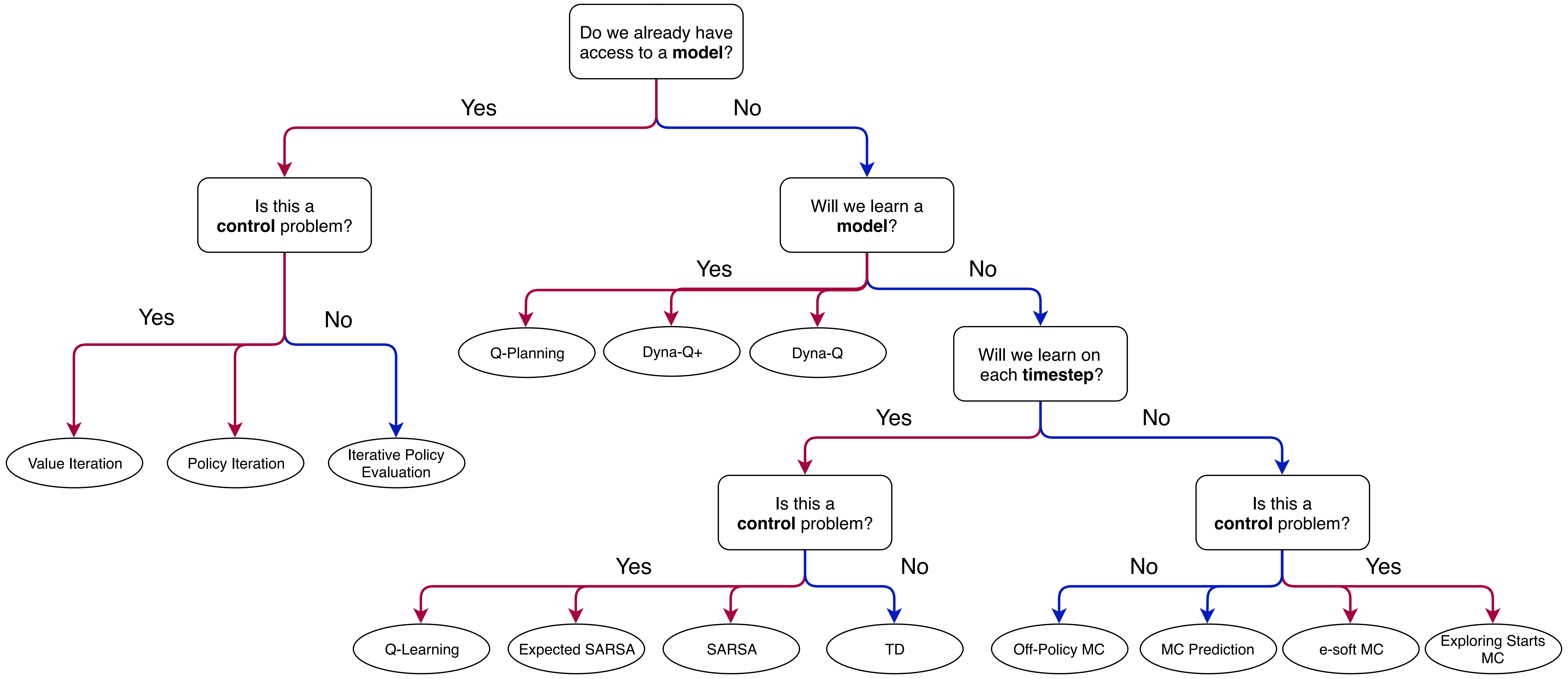
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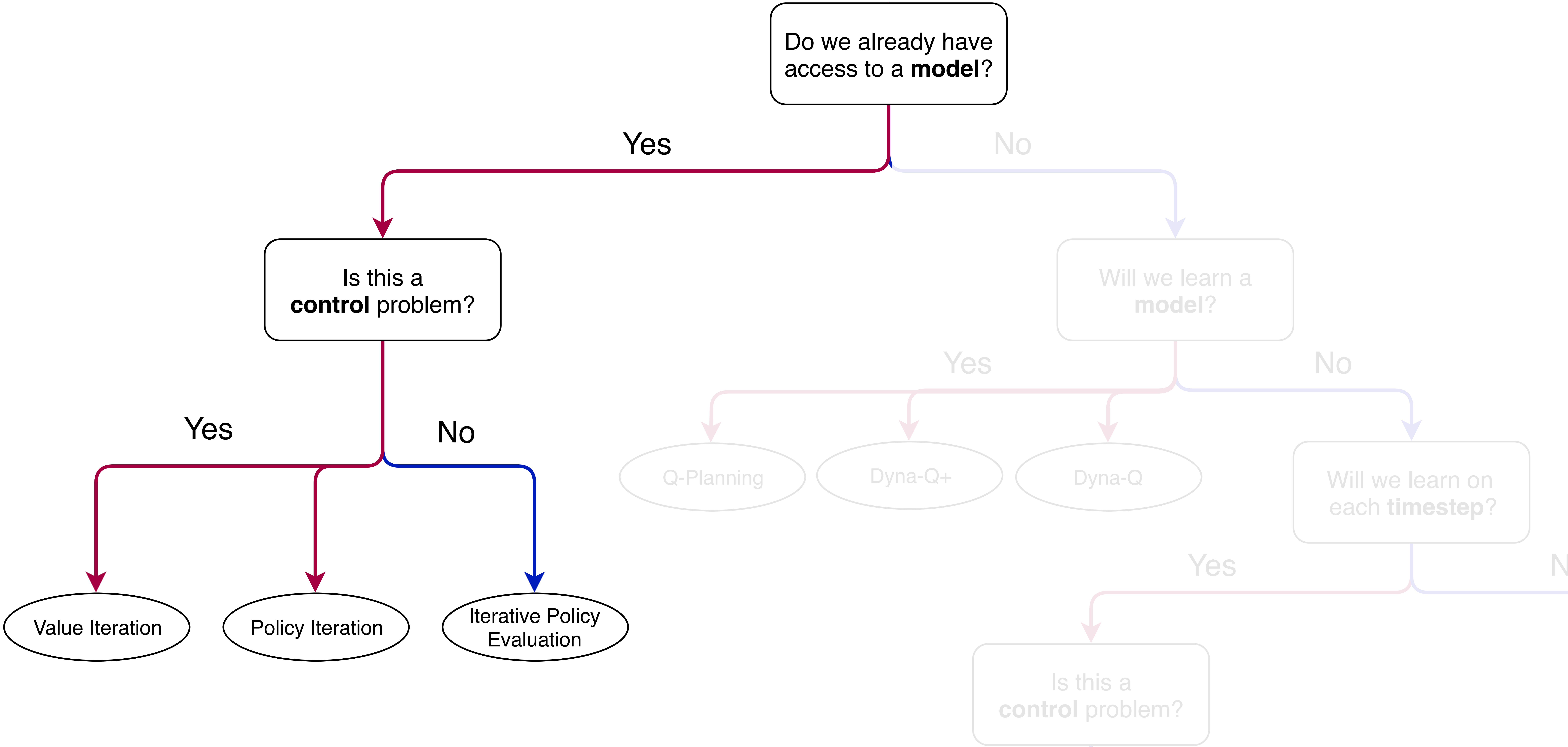

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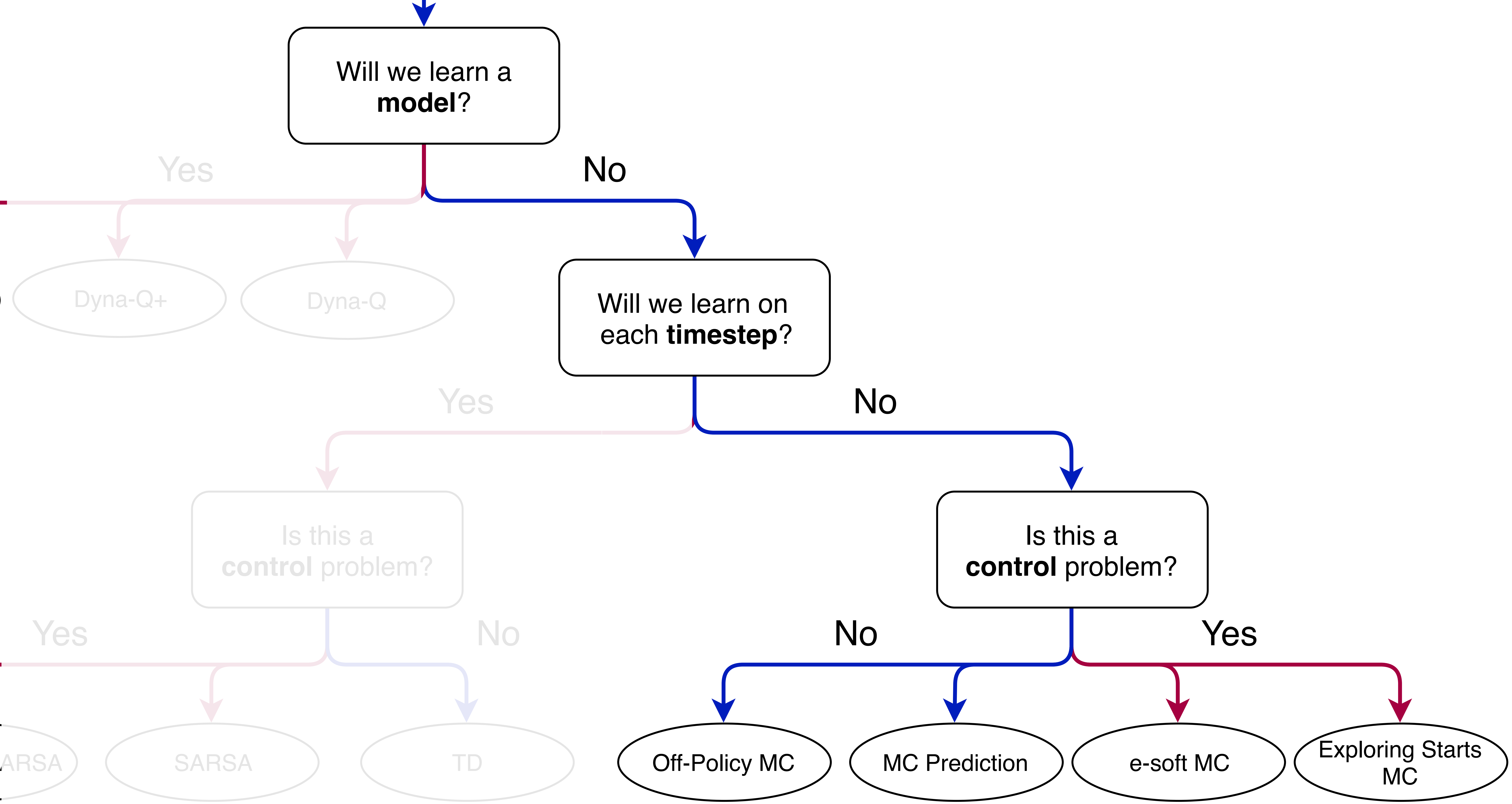

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Dyna-Q+

Dyna-Q

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ARSA

SARSA

TD

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Review of Course 2, Module 4
Learning a Model AND Planning

Video 1: What is a Model?

- **All about models.** What they are? How they might be useful? How would we use one if we had it?
- Goals:
  - Describe a model and how it can be **used**.
  - Know the different model types: **distribution** models or **sample** models
  - identify when to use a distribution model or sample model
- Tell me in simple words what does planning mean in everyday life. Describe how humans plan

Video 2: Comparing Sample and Distribution Models

- If you could have either, which one might you **prefer**? It depends ....
- Goals:
  - Describe the **advantages** and **disadvantages** of sample models and distribution models
  - explain why sample models can be represented more **compactly** than distribution models.
- Which is more general a distribution model or a sample model?

Terminology Review

- **Model:** a model of the environment. Anything that can predict how the environment will respond to the agent's actions: M(S,A) --->S',R

- **Planning**: the computational process that takes the model as input and produces or improves the policy

- **Sample Model**: a model that can produce a possible next state and reward, in agreement with the underlying transition probabilities of the world. We need not store all the probabilities to do this (think about epsilon-greedy)

- **Simulate:** sample a transition from the model. Given an S and A, ask the model for a possible next state S' and reward R

- **Simulated Experience:** samples generated by a sample model. Like dreaming or imagining things that could happen

- **Real Experience:** the states, actions, and rewards that are produced when an agent interacts with the real world.

- **Search Control:** the computational process that selects the state and action in the planning loop

Video 3: Random Tabular, Q-planning

- **A simple planning method.** Assumes access to a sample model. Does Q-learning updates
- Goals:
  - **You will be able to explain how planning is used to improve policies**
  - And describe one-step tabular Q-planning
- What if the model is not correct? What will this algorithm converge to?

One-step Tabular Q-planning

Random-sample one-step tabular Q-planning

```
Loop forever:
    1. Select a state, $S \in \mathcal{S}$, and an action, $A \in \mathcal{A}(S)$, at random
    2. Send $S, A$ to a sample model, and obtain
           a sample next reward, $R$, and a sample next state, $S'$
    3. Apply one-step tabular Q-learning to $S, A, R, S'$:
           $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma \max_a Q(S', a) - Q(S, A)\big]$
```

Question: How does this differ from DP, specifically Value Iteration?

Question: What change makes it more similar to Value Iteration?

Going beyond a given model

- Q-planning does not interact with the world
- It simply computes a policy, by directly querying the given model
- It is an important step since it makes it more clear how to use a sample model
- Next step: do not assume you are given a model

Video 4: The Dyna Architecture

- **Introducing Dyna!** An architecture that mixes (1) learning a model, (2) updating the value function and policy as usual, and (3) planning
- Goals:
  - understand how **simulating experience** from the model **differs** from i**nteracting with the environment.**
  - You will also understand how the **Dyna** architecture **mixes direct RL** updates, and **planning** updates.
- The big idea behind Dyna is that planning and learning are fundamentally similar! What does that mean?

Video 5: The Dyna Algorithm

- The details about one implementation of the Dyna Architecture: **Dyna-Q**
- Goals:
  - Describe how Tabular Dyna-Q works.
  - **Identify** the direct RL, planning, model learning, and search control parts of Dyna-Q.
- Our first nearly complete learning system. It does exploration, fast online reaction, long-term deliberation and planning. What do you think is missing from this agent before we could call it a complete AI system?

Tabular Dyna-Q

Video 6: Dyna & Q-learning in a Simple Maze

- Use a small gridworld to compare Tabular Dyna-Q and model-free Q-learning. **We run an experiment!**

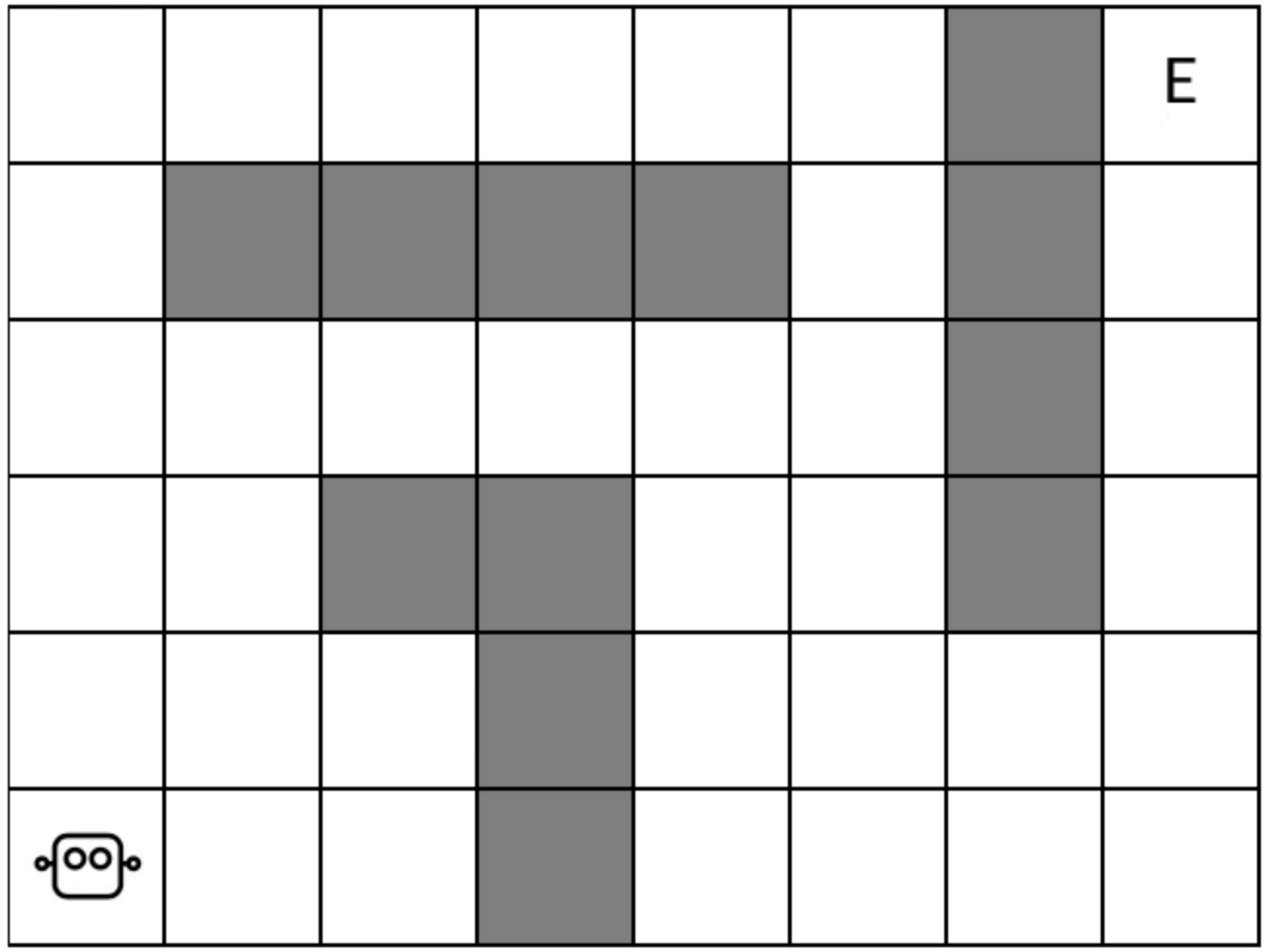
- Goals:

  - describe how learning from both real and model experience impacts performance

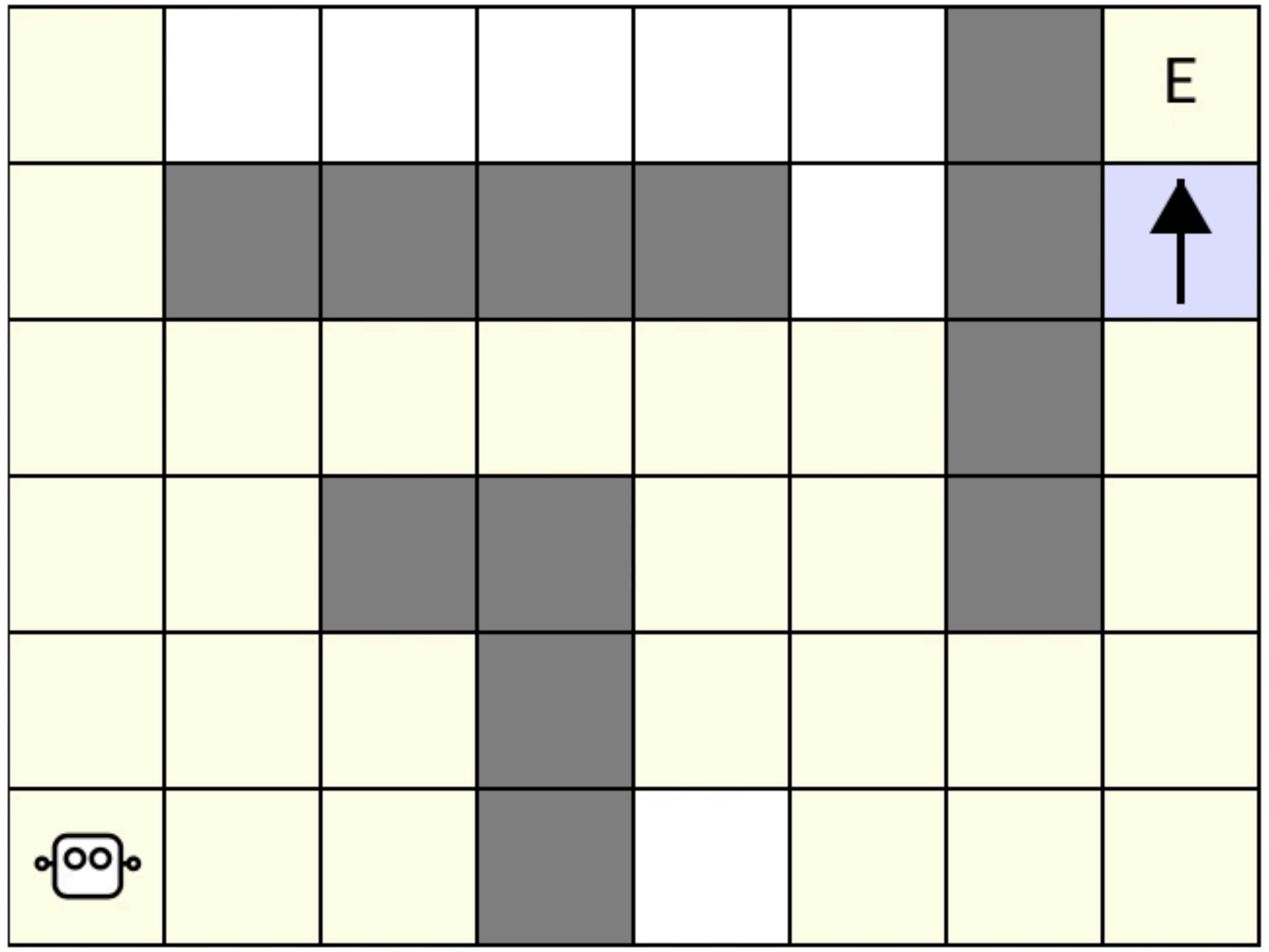
  - explain how a model allows the agent to learn from **fewer interactions** with the environment.

- Is this dramatically faster than Q-learning? Let’s see with a demo! What aspect of the environment/problem-specification contributes to this huge difference?

Number of actions taken: 0

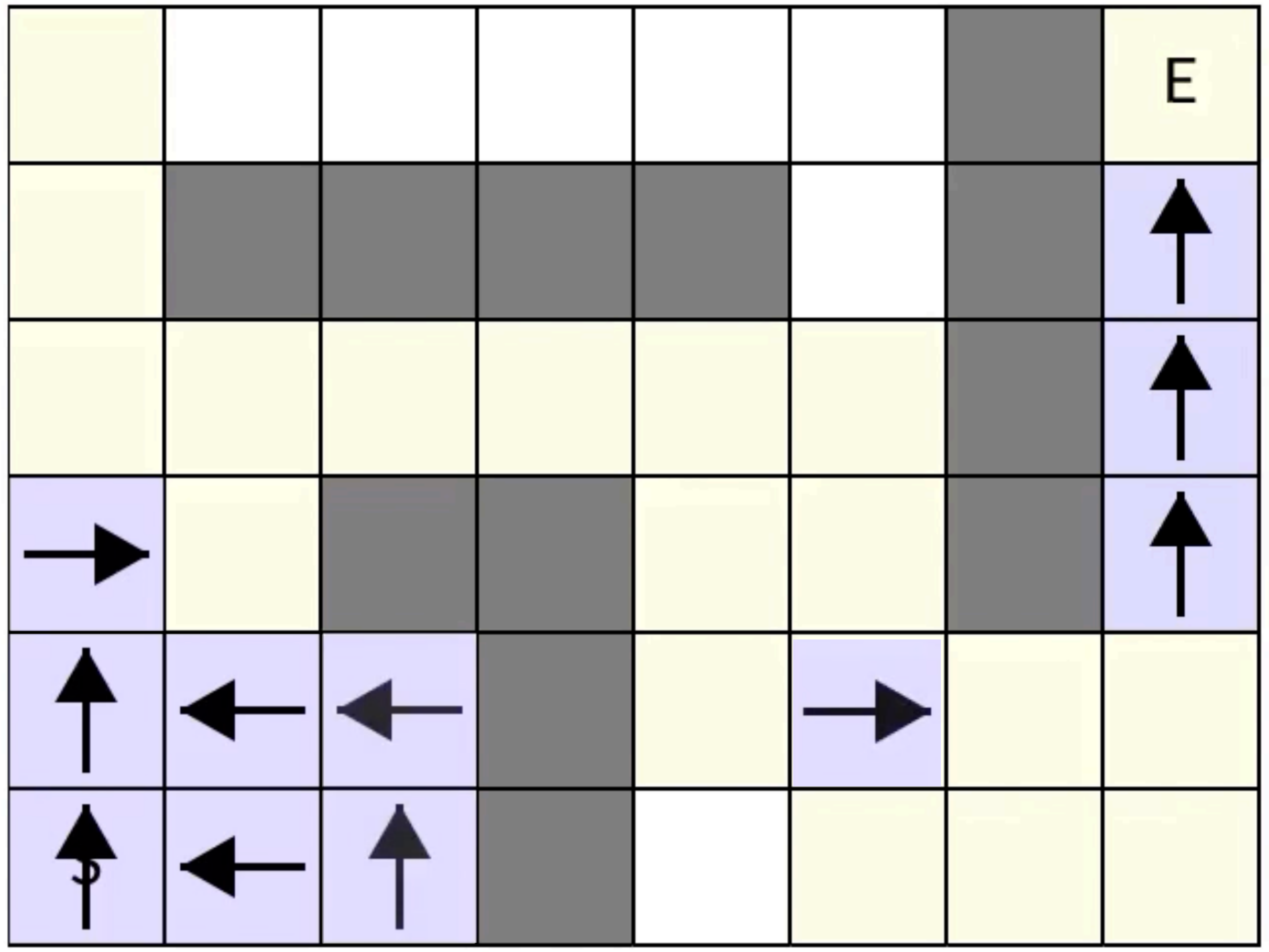


Number of actions taken: 184



Number of steps planned: 100

Number of actions taken: 185



Video 7: What if the model is inaccurate?

- How do we handle if the model is **wrong in some way**? How could that happen? What would be the impact of trying to plan with an inaccurate model?
- Goals:
  - Identify **ways** in which models can be inaccurate,
  - Explain the **effects** of planning with an inaccurate model
  - Describe how Dyna can plan successfully with an incomplete model
- What is the big scary problem about the model being wrong?

Video 8: In-depth with changing environments

- We focus on a specific way the model can be inaccurate: **the world changes** and the model is out of date. **New Algorithm!**

- Goals:

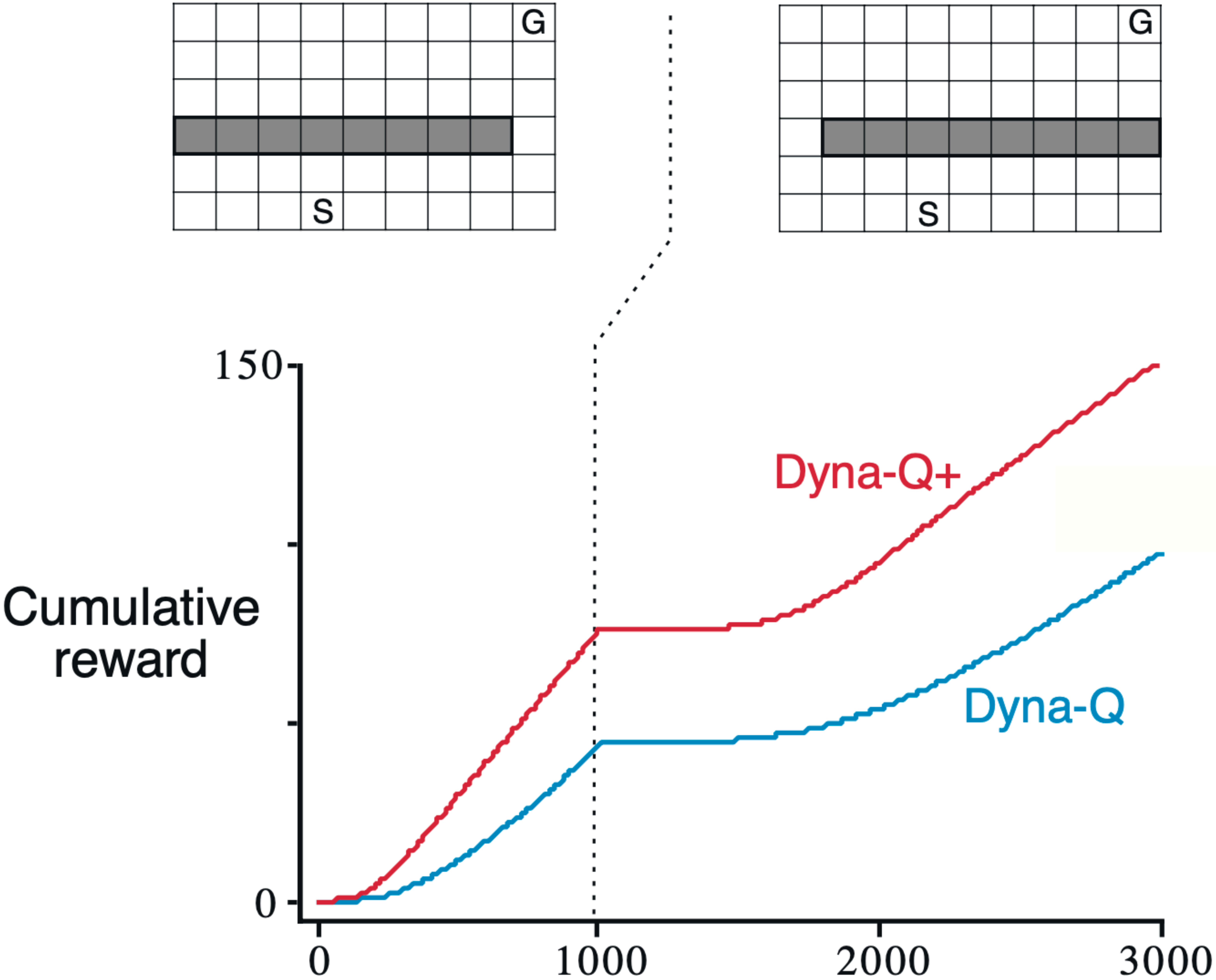
  - Explain how model inaccuracies produce **another exploration-exploitation trade-off**

  - Describe how **Dyna-Q+** addresses this trade-off.

- How does this relate to non-stationarity?

- Is Dyna-Q+ a complete agent?

Changing environments



Quiz review

Algorithm Choices

- “How would we determine the optimal amount of steps to take during the planning phase for a given problem?”
  - Related: “In practical applications what usually limits the amount of planning steps that an agent can take? Is the number of planning steps usually preset or does it just go until the agent performs it's next action?”

Problem Setting

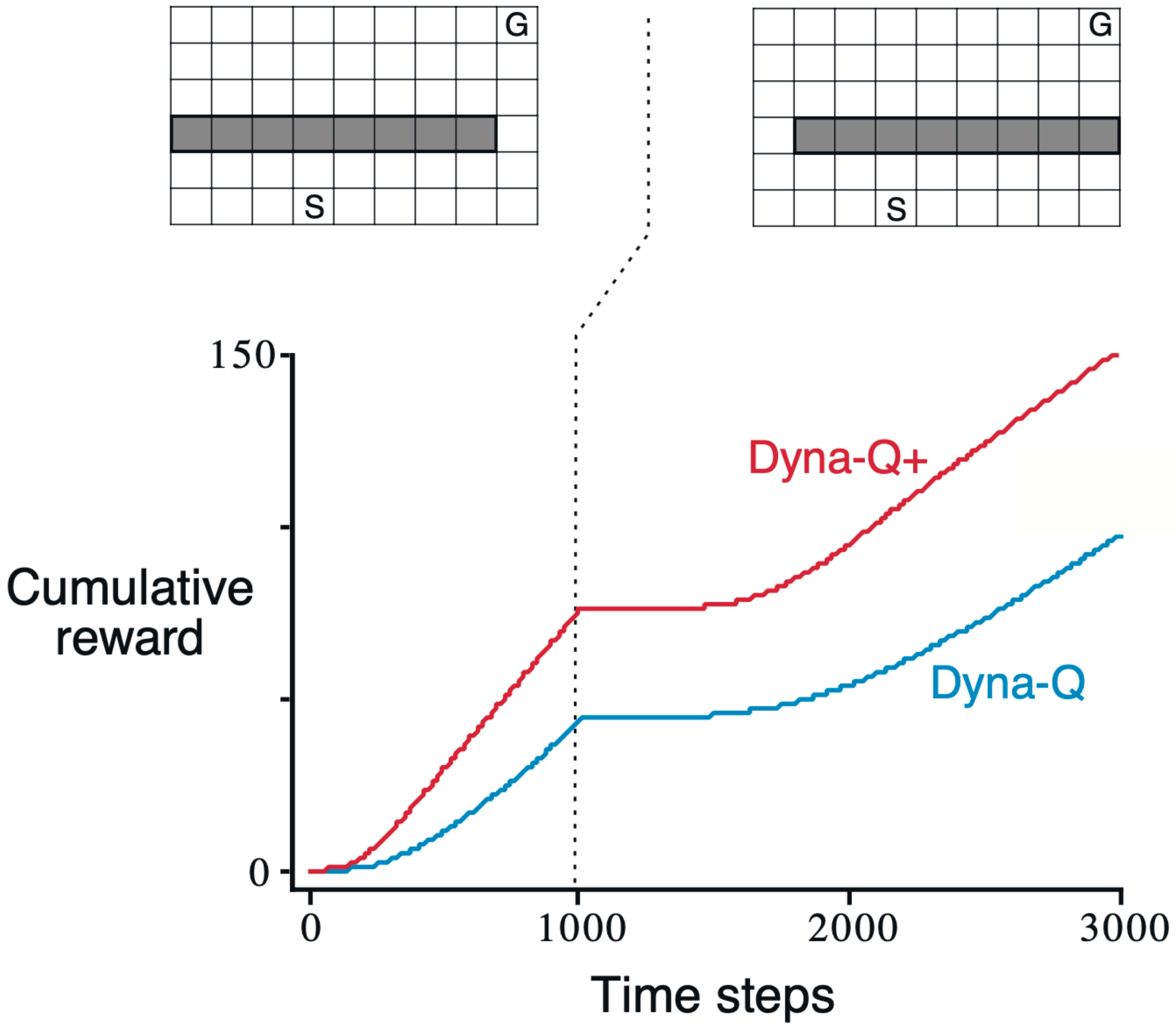
- “Dyna-Q is shown with episodic problems. Can we use it with continuous problems?”
- “How can we modify the tabular Dyna-Q to solve the stochastic problem?”
- “When an environment exists entirely within our computer (so we're not limited by slow "real world" actions), is there any benefit to Dyna-Q over Q-Learning? I'm thinking it could be more computationally efficient to simply generate another episode.”
  - —> This comes down to computational efficiency due to search control

Dyna-Q vs Dyna-Q+

- “Does Dyna-Q+ always have better performance than Dyna-Q?”

- “Can you go over how the bonus reward encourages the agent to return to previous states?”

- “What is the benefit of Dyna-Q+ trying transitions that have not been done in a long time if they are **only being tested on simulated experiences**? How does this allow the model to improve if the transition is not tested on real experience and can not capture changes in the real environment?”



Dyna Q+

- “Why we use kappa*sqrt(tau) in Dyna-Q+ instead of simply using kappa*tau? In other word, what is the advantage of using square root in it?”

Search control

- “For the maze example, our method of search control was randomly selecting a state-action pair. Would it not be more efficient to focus on state-action pairs near those where there was a nonzero reward?”
    - Check out section 8.4