

# Sequential Decision Making and Reinforcement Learning

(SDMRL)

Model-Based RL

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# Acknowledgments

- David Sliver's course on RL:  
*<https://www.deepmind.com/learning-resources/introduction-to-reinforcement-learning-with-david-sliver>*
- Slides by Malte Helmert, Carmel Domshlak, Erez Karpas and Alexander Shleyfman.

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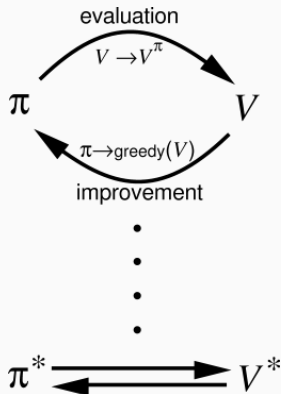
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## Recap

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# Anatomy of RL Algorithms



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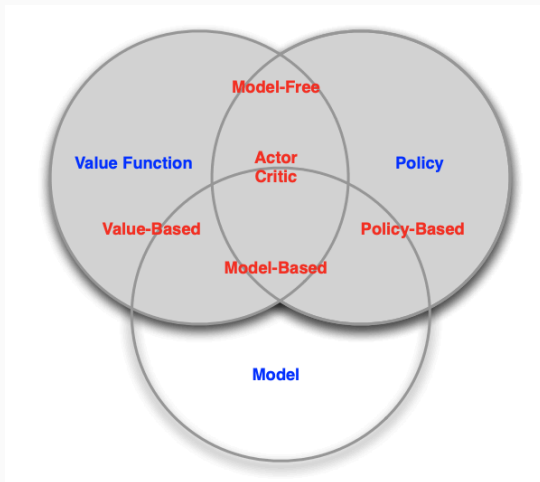
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# RL Approaches



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# Model-Free vs. Model-Based RL

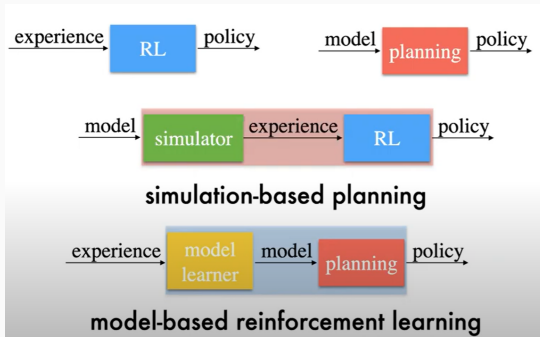


Figure 1: By Michael Littman

<https://www.youtube.com/watch?v=45FKxa3qPHo>

# Model-Free vs. Model-Based RL

There is no clear distinction. Can be viewed as a spectrum.



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# From Model-Free to Model-Based RL

- We have so far explored two **model-free value-based** approaches:

- Monte-Carlo methods:

$$V_{\pi}(S_t) \leftarrow V_{\pi}(S_t) + \alpha(G_t - V_{\pi}(S_t))$$

- Temporal Difference methods:

$$V_{\pi}(S_t) \leftarrow V_{\pi}(S_t) + \alpha(\mathcal{R}(S_t) + \gamma V_{\pi}(S_{t+1}) - V_{\pi}(S_t))$$

- We have also explored policy based methods.
- In **model-based RL** the agent uses a transition and reward model to make decisions about how to act.
  - The model may be initially known (e.g., chess) or unknown (e.g., robot manipulator).

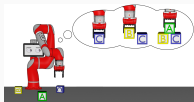


# Model-Based RL Intro

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# Model-Based RL

- Reinforcement learning systems can make decisions in one of two ways.
  - In the model-based approach, a system uses a predictive model of the world to ask questions of the form **“what will happen if I do x?”** to choose the best action.
  - In the alternative model-free approach, the modeling step is bypassed altogether in favor of **learning a control policy directly**. **“how much reward will I get if I do x?”**
- Although in practice the line between these two techniques can become blurred, as a coarse guide it is useful for dividing up the space of algorithmic possibilities.



BAIR blog by Michael Janner

<https://bair.berkeley.edu/blog/2019/12/12/mbpo/>

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# Advantages and disadvantages of Model-Based RL

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# Advantages and disadvantages of Model-Based RL

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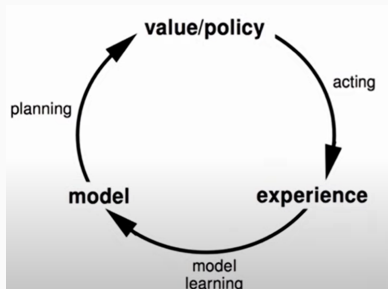
## Advantages:

- Can efficiently learn model by supervised learning methods
- Can reason about model uncertainty
- Explainability

## Disadvantages:

- First learn a model, then construct a value function  $\Rightarrow$  two sources of approximation error

# Model-Based RL



By Emma Brunskill

<https://www.youtube.com/watch?v=vDF1BYWhqL8>

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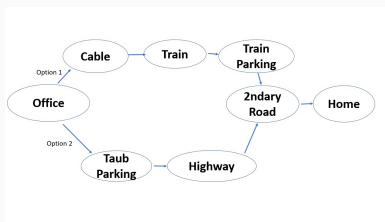
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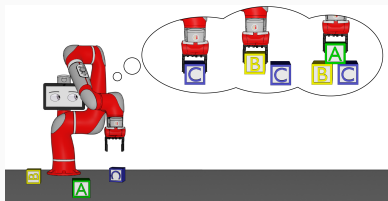
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## Model-Based RL for the Going Home Example ?





Ideas for model-based evaluation ?

Ideas for model-based control ?

# Learning a Model

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# What is a Model?

- A model  $\mathcal{M}$  is a representation of an MDP  $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R} \rangle$  parameterized by  $\eta$
- Typically,  $\mathcal{S}$  and  $\mathcal{A}$  are assumed to be known
- So a model  $\mathcal{M}_\eta = \langle \mathcal{P}_\eta, \mathcal{R}_\eta \rangle$  represents state transitions  $\mathcal{P}_\eta \approx \mathcal{P}$  and rewards  $\mathcal{R}_\eta \approx \mathcal{R}$

$$S_{t+1} \sim \mathcal{P}_\eta(S_{t+1} | S_t, A_t)$$

$$R_{t+1} \sim \mathcal{R}_\eta(R_{t+1} | S_t, A_t)$$

- Typically assume conditional independence between state transitions and rewards

$$\mathbb{P}[S_{t+1}, R_{t+1} | S_t, A_t] = \mathbb{P}[S_{t+1} | S_t, A_t] \mathbb{P}[R_{t+1} | S_t, A_t]$$

# Model Learning

- Goal: estimate model  $\mathcal{M}_\eta$  from experience collected by interacting with the environment  $\{S_1, A_1, R_2, \dots, S_T\}$
- This is a supervised learning problem

$$S_1, A_1 \rightarrow R_2, S_2$$

$$S_2, A_2 \rightarrow R_3, S_3$$

.

.

.

$$S_{T-1}, A_{T-1} \rightarrow R_T, S_T$$

- Learning  $s, a \rightarrow r$  is a regression problem
- Learning  $s, a \rightarrow s'$  is a density estimation problem
- Pick loss function, e.g. mean-squared error, KL divergence, ...
- Find parameters  $\eta$  that minimise empirical loss

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## Examples of Models

- Table Lookup Model
- Linear Expectation Model
- Linear Gaussian Model
- Gaussian Process Model
- Deep Belief Network Model
- ...

- Model is an explicit MDP with estimated transition function  $\hat{\mathcal{P}}$  and estimated reward function  $\hat{\mathcal{R}}$
- Count visits  $N(s, a)$  to each state action pair

$$\hat{\mathcal{P}}_{s,s'}^a = \frac{1}{N(s, a)} \sum_{t=1}^T \mathbf{1}(S_t, A_t, S_{t+1} = s, a, s')$$

$$\hat{\mathcal{R}}_s^a = \frac{1}{N(s, a)} \sum_{t=1}^T \mathbf{1}(S_t, A_t = s, a) R_t$$

- Alternatively
  - At each time-step  $t$ , record experience tuple  $\langle S_t, A_t, R_{t+1}, S_{t+1} \rangle$
  - To sample model, randomly pick tuple matching  $\langle s, a, \cdot, \cdot \rangle$

# Model-Based Evaluation

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# Model-based Evaluation: Adaptive Dynamic Programming (ADP)

## Adaptive Dynamic Programming (ADP)

- Follow the policy for a while
- Estimate transition model based on observations
- Learn reward function
- Use estimated model to compute utility of policy

$$V_{\pi}(s) = \mathcal{R}(s) + \gamma \sum_{s'} \mathcal{P}(s'|s, \pi(s)) \cdot V_{\pi}(s')$$

How can we estimate transition model  $\mathcal{P}$  and  $\mathcal{R}$ ?

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# Model-based Evaluation: Adaptive Dynamic Programming (ADP)

## Adaptive Dynamic Programming (ADP)

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- Estimate transition model based on observations
- Learn reward function
- Use estimated model to compute utility of policy

$$V_{\pi}(s) = \mathcal{R}(s) + \gamma \sum_{s'} \mathcal{P}(s'|s, \pi(s)) \cdot V_{\pi}(s')$$

## How can we estimate transition model $\mathcal{P}$ and $\mathcal{R}$ ?

Compute the fraction of times we see  $s'$  after taking  $a$  in state  $s$  (similarly for the reward function).

Chernoff bounds can be used to quantify the confidence in these estimates by providing high-probability bounds on the deviation of the estimated probabilities from the true probabilities.

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# Model-based Control

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- A simple but powerful approach to planning
- Use the model only to generate samples
- **Sample** experience from model

$$S_{t+1} \sim \mathcal{P}_\eta(S_{t+1}|S_t, A_t)$$

$$R_{t+1} \sim \mathcal{R}_\eta(R_{t+1}|S_t, A_t)$$

- Apply model-free RL to samples, e.g.: Monte-Carlo control, Sarsa, Q-learning
- Sample-based planning methods are often more efficient

# Sample-Based Planning: Back to the AB Example

- Construct a table-lookup model from real experience
- Apply model-free RL to sampled experience

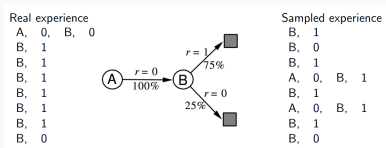


Figure 2: e.g., Monte-Carlo learning:  $\mathcal{V}(A) = 1, \mathcal{V}(B) = 0.75$

- Given a model  $\mathcal{M}_\eta = \langle \mathcal{P}_\eta, \mathcal{R}_\eta \rangle$
- Solve the MDP  $\langle \mathcal{S}, \mathcal{AP}_\eta, \mathcal{R}_\eta \rangle$  using favourite planning algorithm
  - Value iteration
  - Policy iteration
  - Tree search
  - Heuristic search

# Naïve Approach To Model-Based Control

## Model-based approach to RL

- 1 Act randomly for a (long) time
- 2 Learn transition function and reward function
- 3 Solve resulting MDP using value iteration, policy iteration, LAO\*, MCTS etc.
- 4 Follow resulting policy thereafter.

Will this work ?

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Will this work ?

Yes, if we do step 1 long enough and there are no “dead-ends”.

Any problems?

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- 4 Follow resulting policy thereafter.

Will this work ?

Yes, if we do step 1 long enough and there are no “dead-ends”.

Any problems?

We will act randomly for a long time before exploiting what we know

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## Model-based approach to RL

- 1 Start with initial (uninformed) model
- 2 Solve for optimal policy given current model (using value or policy iteration)
- 3 Execute action suggested by policy in current state
- 4 Update estimated model based on observed transition
- 5 Goto 2

## Model-based approach to RL

- 1 Start with initial (uninformed) model
- 2 Solve for optimal policy given current model (using value or policy iteration)
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This is just ADP but we follow the greedy policy suggested by current value estimate

Will this work ?



# Revision of Naïve Approach

## Model-based approach to RL

- 1 Start with initial (uninformed) model
- 2 Solve for optimal policy given current model (using value or policy iteration)
- 3 Execute action suggested by policy in current state
- 4 Update estimated model based on observed transition
- 5 Goto 2

This is just ADP but we follow the greedy policy suggested by current value estimate

Will this work ? No. Can get stuck in local optimum

What can be done ?

# Reminder: Exploration versus Exploitation

- Two reasons to take an action in RL
  - **Exploitation:** We exploit our current knowledge to get a payoff.
  - **Exploration:** Get more information about the world. How do we know if there is not a pot of gold around the corner?
- To explore we typically need to take actions that do not seem best according to our current model.
- Managing the trade-off between exploration and exploitation is a critical issue in RL.
- Basic **intuition** behind most approaches:

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# Reminder: Exploration versus Exploitation

- Two reasons to take an action in RL
  - **Exploitation:** We exploit our current knowledge to get a payoff.
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- To explore we typically need to take actions that do not seem best according to our current model.
- Managing the trade-off between exploration and exploitation is a critical issue in RL.
- Basic **intuition** behind most approaches:
  - Explore more when knowledge is weak
  - Exploit more as agent gains knowledge

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## ADP-based RL

- 1 Start with initial model
- 2 Solve for optimal policy given current model (using value or policy iteration)
- 3 Execute action suggested by an explore/exploit policy (explores more early on and gradually uses policy from 2)
- 4 Update estimated model based on observed transition
- 5 Goto 2

This is just ADP but we follow the explore/exploit policy  
Will this work?

## ADP-based RL

- 1 Start with initial model
- 2 Solve for optimal policy given current model (using value or policy iteration)
- 3 Execute action suggested by an explore/exploit policy (explores more early on and gradually uses policy from 2)
- 4 Update estimated model based on observed transition
- 5 Goto 2

This is just ADP but we follow the explore/exploit policy

Will this work? Depends on the explore/exploit policy

Any ideas?

- **Greedy action** is action maximizing estimated **Q-value**

$$Q(s, a) = \mathcal{R}(s) + \gamma \sum_{s'} \mathcal{P}(s'|s, a) \cdot V_{\pi}(s')$$

- where  $V$  is current optimal value function estimate (based on current model), and  $\mathcal{R}$  and  $\mathcal{P}$  are current estimates of the model
- $Q(s, a)$  is the expected value of taking action  $a$  in state  $s$  and then getting the estimated value  $V(s')$  of the next state  $s'$ .
- We want an exploration policy that is GLIE (greedy in the limit of infinite exploration).

- GLIE policy 1:
  - On time step  $t$  select random action with probability  $p(t)$  (i.e.,  $\epsilon$ ) and greedy action with probability  $1 - p(t)$
  - $p(t) = \frac{1}{t}$  (will lead to convergence, but is slow.)
  - Greedy action is the one that maximizes the Q value.
- GLIE policy 2: **Boltzmann Exploration** <sup>1</sup>
  - Select action  $a$  with probability  $\mathcal{P}(a|s) = \frac{\exp(Q(s,a)/T)}{\sum_{a' \in \mathcal{A}} \exp(Q(s,a')/T)}$
  - $T$  is the “**temperature**”: Large  $T$  means that each action has about the same probability. Small  $T$  leads to more greedy behavior.
  - Typically: start with large  $T$  and decrease with time.

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<sup>1</sup>according to wikipedia - a Boltzmann distribution (also called Gibbs distribution) is a probability distribution or probability measure that gives the probability that a system will be in a certain state as a function of that state's energy and the temperature of the system.

$$\mathcal{P}(a|s) = \frac{\exp(Q(s, a)/T)}{\sum_{a' \in \mathcal{A}} \exp(Q(s, a')/T)}$$

Suppose we have just two actions and that  $Q(s, a_1) = 1$ , and  $Q(s, a_2) = 2$ . Which action will higher probability?

❶  $T = 10$ :



$$\mathcal{P}(a|s) = \frac{\exp(Q(s, a)/T)}{\sum_{a' \in \mathcal{A}} \exp(Q(s, a')/T)}$$

Suppose we have just two actions and that  $Q(s, a_1) = 1$ , and  $Q(s, a_2) = 2$ . Which action will higher probability?

- 1  $T = 10$ :  $\mathcal{P}(a_1|s) = 0.48$ ,  $\mathcal{P}(a_2|s) = 0.52$   
Almost equal probability, and so explore
- 2  $T = 1$ :

$$\mathcal{P}(a|s) = \frac{\exp(Q(s, a)/T)}{\sum_{a' \in \mathcal{A}} \exp(Q(s, a')/T)}$$

Suppose we have just two actions and that  $Q(s, a_1) = 1$ , and  $Q(s, a_2) = 2$ . Which action will higher probability?

- ❶  $T = 10$ :  $\mathcal{P}(a_1|s) = 0.48$ ,  $\mathcal{P}(a_2|s) = 0.52$   
Almost equal probability, and so explore
- ❷  $T = 1$ :  $\mathcal{P}(a_1|s) = 0.27$ ,  $\mathcal{P}(a_2|s) = 0.73$   
Probabilities more skewed, so explore  $a_1$  less
- ❸  $T = .25$ :

$$\mathcal{P}(a|s) = \frac{\exp(Q(s, a)/T)}{\sum_{a' \in \mathcal{A}} \exp(Q(s, a')/T)}$$

Suppose we have just two actions and that  $Q(s, a_1) = 1$ , and  $Q(s, a_2) = 2$ . Which action will higher probability?

- ❶  $T = 10$ :  $\mathcal{P}(a_1|s) = 0.48$ ,  $\mathcal{P}(a_2|s) = 0.52$   
Almost equal probability, and so explore
- ❷  $T = 1$ :  $\mathcal{P}(a_1|s) = 0.27$ ,  $\mathcal{P}(a_2|s) = 0.73$   
Probabilities more skewed, so explore  $a_1$  less
- ❸  $T = .25$ :  $\mathcal{P}(a_1|s) = 0.02$ ,  $\mathcal{P}(a_2|s) = 0.98$   
Almost always exploit  $a_2$

# Alternative Approach: Optimistic Exploration

## Model-based approach to RL

- 1 Start with initial model
- 2 Solve for **optimistic policy** given current model using optimistic value iteration - that inflates value of actions leading to unexplored regions.
- 3 Execute **greedy** action suggested by the **optimistic policy** (explores more early on and gradually uses policy from 2)
- 4 Update estimated model based on observed transition
- 5 Goto 2

Basically act as if all “unexplored” state-action pairs are maximally rewarding

# Optimistic Exploration

- Recall that value iteration iteratively performs the following update at all states:

$$V(s) := \mathcal{R}(s) + \gamma \max_a \sum_{s'} \mathcal{P}(s'|s, a) \cdot V_{\pi}(s')$$

- Optimistic variant -

What do we mean by “explored enough”?

- Recall that value iteration iteratively performs the following update at all states:

$$V(s) := \mathcal{R}(s) + \gamma \max_a \sum_{s'} \mathcal{P}(s'|s, a) \cdot V_{\pi}(s')$$

- Optimistic variant - adjusts update to make actions that lead to unexplored regions look promising
- Implement variant of VI that assigns the highest possible value  $V^{max}$  to any state-action pair that has not been explored enough
  - Maximum value is when we get maximum reward forever

$$V^{max} = \sum_{t=0}^{\infty} \gamma^t \cdot R^{max} = \frac{R^{max}}{1 - \gamma}$$

What do we mean by “explored enough”?

# Optimistic Exploration

- What do we mean by “explored enough”?
  - $N(s, a) > N_e$ , where  $N(s, a)$  is number of times action  $a$  has been tried in state  $s$  and  $N_e$  is a user selected parameter.
  - While the standard update rule is:

$$V^{max} := \sum_{t=0}^{\infty} \gamma^t \cdot R^{max} = \frac{R^{max}}{1-\gamma}$$

- Optimistic value iteration computes an optimistic value function  $V^+$  using updates:

$$V^+ := \mathcal{R}(s) + \gamma \max_a \begin{cases} V^{max}, & N(s, a) < N_e \\ \sum_{s'} \mathcal{P}(s'|s, a) \cdot V_{\pi}(s'), & \text{otherwise} \end{cases}$$

- The agent will behave initially as if there were wonderful rewards scattered all over around (-> optimistic)
- But after actions are tried enough times, we will perform standard “non-optimistic” value updates

For more details: R-max – A General Polynomial Time Algorithm for Near-Optimal

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# Planning with an Inaccurate Model

- Given an imperfect model  $\langle \mathcal{P}_\eta, \mathcal{R}_\eta \rangle \neq \langle \mathcal{P}, \mathcal{R} \rangle$
- Performance of model-based RL is limited to optimal policy for approximate MDP  $\langle \mathcal{S}, \mathcal{AP}_\eta, \mathcal{R}_\eta \rangle$
- i.e. Just like model-free RL is only as good as the data that is collected, model-based RL is only as good as the estimated model
- When the model is inaccurate, planning process will compute a suboptimal policy
- Solution 1: when model is wrong, use model-free RL
- Solution 2: reason explicitly about model uncertainty

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# Integrated Architectures

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We consider two sources of experience:

- Real experience Sampled from environment (true MDP)

$$S' \sim \mathcal{P}_{s,s'}^a$$

$$R' \sim \mathcal{R}_s^a$$

- Simulated experience Sampled from model (approximate MDP)

$$S' \sim \mathcal{P}_\eta(S'|S, A)$$

$$R \sim \mathcal{R}_\eta(R|S, A)$$

# Integrating Learning and Planning

- Model-Free RL
  - No model
  - **Learn** value function (and/or policy) from real experience

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# Integrating Learning and Planning

- Model-Free RL
  - No model
  - **Learn** value function (and/or policy) from real experience
- Model-Based RL
  - Learn a model from real experience
    - Using Sample-Based Planning: Plan value function (and/or policy) from simulated experience
    - **Plan** using estimated model
- Dyna
  - Learn a model from real experience
  - **Learn and plan** value function (and/or policy) from real and simulated experience

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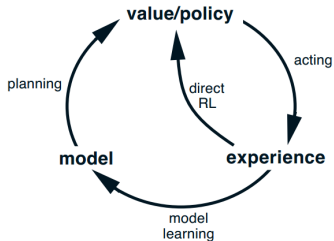


Figure 8.1: Relationships among learning, planning, and acting.

Initialize  $Q(s, a)$  and  $Model(s, a)$  for all  $s \in \mathcal{S}$  and  $a \in \mathcal{A}(s)$

Do forever:

- (a)  $S \leftarrow$  current (nonterminal) state
- (b)  $A \leftarrow \varepsilon$ -greedy( $S, Q$ )
- (c) Execute action  $A$ ; observe resultant reward,  $R$ , and state,  $S'$
- (d)  $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_a Q(S', a) - Q(S, A)]$
- (e)  $Model(S, A) \leftarrow R, S'$  (assuming deterministic environment)
- (f) Repeat  $n$  times:
  - $S \leftarrow$  random previously observed state
  - $A \leftarrow$  random action previously taken in  $S$
  - $R, S' \leftarrow Model(S, A)$
  - $Q(S, A) \leftarrow Q(S, A) + \alpha [R + \gamma \max_a Q(S', a) - Q(S, A)]$

## SOTA(ish) Examples

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# Approaches to Models-Based RL

- **Analytic gradient computation:**

- Based on assumptions about the form of the dynamics and cost function (e.g., Gaussian processes)
- Can yield locally optimal control (e.g. Linear-quadratic regulator ).
- Even when these assumptions are not valid, can account for small errors introduced by approximated dynamics.
- Linear (simplified) models, can also be used to provide guiding samples for training more complex nonlinear policies.

- **Sampling-based planning:**

- Typically, for nonlinear dynamics models we resort to sampling action sequences (e.g., via random shooting). More sophisticated variants iteratively adjust the sampling distribution.
- In discrete-action settings, however we can search over tree structures than to iteratively refine a single trajectory of waypoints.
  - **Monte-Carlo Tree Search (MCTS)**- has underpinned recent impressive results in games playing, and iterated width search.
- In both continuous and discrete domains, can be combined with structured physics-based, object-centric priors.

- **Model-based data generation**

- Many machine learning success stories rely on artificially increasing the size of a training set.
- It is difficult to define a manual data augmentation procedure for policy optimization, but we can view a predictive model analogously as a learned

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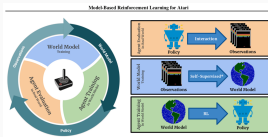


# Model-Based RL: State-of-the-Art

*“In this paper, we explore how video prediction models can similarly enable agents to solve Atari games with orders of magnitude fewer interactions than model-free methods. We describe Simulated Policy Learning (SimPLe), a complete model-based deep RL algorithm based on video prediction models and present a comparison of several model architectures, including a novel architecture that yields the best results in our setting.” (arXiv)*

Paper by Kaiser et al 2020 <https://arxiv.org/abs/1903.00374>  
<https://medium.com/syncedreview/>

[google-brain-simple-complete-model-based-reinforcement-learning-for-atari](#)



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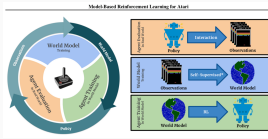
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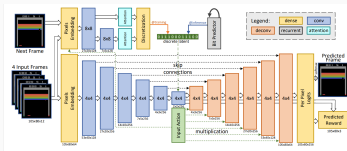
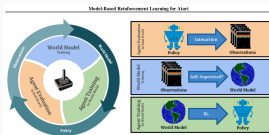
# Model-Based RL: Example

- SimPLE is a complete model-based deep RL algorithm that utilizes video prediction techniques and can train a policy to play a game within the learned model.
- SimPLE outperforms model-free algorithms in terms of learning speed on nearly all of the games, and in the case of a few games, does so by over an order of magnitude.
- The best model-free reinforcement learning algorithms require tens or hundreds of millions of time steps — equivalent to several weeks. SimPLE has obtained competitive results with only 100K interactions between the agent and the environment on Atari games, which corresponds to about two hours of real-time play.



# Model-Based RL: Example

- Agent starts interacting with the real environment following the latest policy (initialized to random).
- Collected observations used to train (update) current world model.
- Agent updates the policy by acting inside the world model. The new policy will be evaluated to measure performance and collect more data (back to 1).



<https://bair.berkeley.edu/blog/2019/12/12/mbpo/>

Benchmarking Model-Based Reinforcement Learning by Wang et al. 2019 <https://arxiv.org/abs/1907.02057> When to Trust Your Model: Model-Based Policy Optimization Janner et al. 2021 <https://arxiv.org/abs/1906.08253>

<https://www.natolambert.com/writing/debugging-mbrl>  
<https://bair.berkeley.edu/blog/2019/12/12/mbpo/>

## Conclusion

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# Model-Free vs. Model-Based RL

- Adaptive Dynamic Programming (model based)
- Monte-Carlo Direct Estimation (model free)
- Temporal Difference Learning (model free)

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# Model-Free vs. Model-Based RL

- Adaptive Dynamic Programming (model based)
  - Harder to implement
  - Each update is a full policy evaluation (expensive)
  - Fully exploits Bellman constraints
  - Fast convergence (in terms of updates)
- Monte-Carlo Direct Estimation (model free)
  - Simple to implement
  - Each update is fast
  - Does not exploit Bellman constraints
  - Converges slowly
- Temporal Difference Learning (model free)
  - Update speed and implementation similar to direct estimation
  - Partially exploits Bellman constraints—adjusts state to “agree” with observed successor (not all possible successors)
  - Convergence in between direct estimation and ADP

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# What Next ?

## Large State Spaces

- When a problem has a large state space we can not longer represent the  $V$  or  $Q$  functions as explicit tables
- Even if we had enough memory
  - Never enough training data!
  - Learning takes too long

What to do?

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