CS-866 Deep Reinforcement Learning

Learned Model-Based Learning

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From Model-Free to Model-Based RL

The previous chapters discussed model-*free* methods, and we saw their success in video games and simulated robotics.

In model-free methods:

- the agent updates a policy directly from the feedback that the environment provides,
- the environment performs the state transitions and calculates the reward.

A disadvantage of deep model-free methods:

- they can be slow to train,
- millions of environment samples are often needed for stable convergence or low variance.

Basic Idea of Model-Based RL

In contrast, with model-*based* methods the agent first builds its own internal transition model from the environment feedback.

Using this local transition model, the agent can:

- reason about the effect of actions on states and rewards,
- use a planning algorithm to play *what-if* games,
- generate policy updates without causing any state changes in the environment.

Generating policy updates from the internal model is called:

planning or **imagination**.

Indirect Policy Learning

Model-based methods update the policy *indirectly*:

1. first learn a local transition model from the environment,
2. then use this learned model to update the policy.

Two consequences of indirect learning:

Positive side

As soon as the agent has its own transition model, it can:

- learn the best policy for free,
- avoid further acting in the environment,
- achieve much lower sample complexity.

The Downside: Model Error

The downside is that the learned transition model may be inaccurate.

If the agent learns the policy from a **bad model**:

- the resulting policy may be of low quality,
- the policy may fail in the real environment,
- even infinite planning samples cannot fix a biased model.

Thus:

model bias and uncertainty are central challenges in model-based RL.

Historical Context and Model Types

The idea of learning an internal transition function is very old.

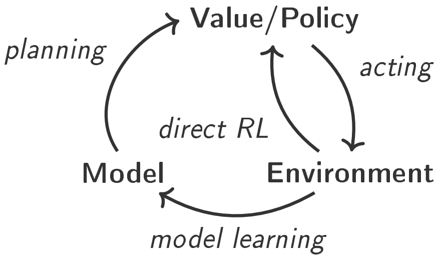
Transition models have been implemented in many ways:

- **Tabular models**
- **Deep neural network models**
- hybrids and structured models

Modern deep RL often uses:

- convolutional or recurrent predictors,
- latent dynamics models,
- multi-step world models and learned simulators.

Direct and Indirect Reinforcement Learning[1]



[1] Richard S Sutton and Andrew G Barto. *Reinforcement learning, An Introduction, Second Edition*. MIT Press, 2018.

Tabular Imagination

- **Dyna**: Classic approach[2] popularizing model-based RL.
- Environment samples used to:
  - train transition model,
  - plan to improve policy,
  - update policy directly.
- Hence: hybrid of model-free + model-based learning.
- "Imagination": agent looks ahead using its own dynamics model.
- Imagined samples augment real samples at no cost.

[2] Richard S Sutton. 'Integrated architectures for learning, planning, and reacting based on approximating dynamic programming'. In: *Machine Learning Proceedings 1990*. Elsevier, 1990, pp. 216–224.

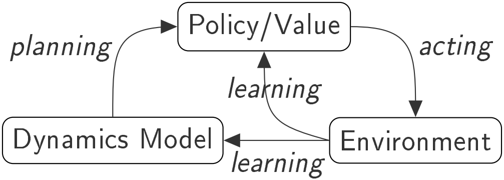
Why Hybrid?

- In strict model-based approach, policy is updated only from learned model.
- In Dyna, real samples *also* update policy directly.
- Hybrid = model-free updates + planning updates.
- Imagination $\Rightarrow$ planning inside the agent's "mind".
- Real + imagined samples used together.

Strict Learned Dynamics Model

repeat
  Sample env E to get $D = (s, a, r', s')$
  Learn model $M = T_a(s, s'), R_a(s, s')$
  for $n = 1 \dots N$ **do**
    Update policy $\pi(s, a)$ using M ▷ planning
  end for
until π converges

Hybrid Model-Based Imagination



repeat
  Sample env E to get $D = (s, a, r', s')$
  Update policy $\pi(s, a)$ directly ▷ learning
  Learn model $M = T_a(s, s'), R_a(s, s')$
  for $n = 1 \dots N$ **do**
    Update policy $\pi(s, a)$ using M ▷ planning
  end for
until π converges

How Imagination Uses Feedback

- Real samples:
  - update policy,
  - update dynamics model.
- Model:
  - generates imagined transitions,
  - provides extra policy updates.
- Greatly increases number of updates without extra environment cost.

Dyna-Q Algorithm

Initialize $Q(s, a) \to \mathbb{R}$ randomly
Initialize $M(s, a) \to \mathbb{R} \times S$ randomly $\triangleright$ Model
repeat
  Select $s \in S$ randomly
  $a \leftarrow \pi(s)$ $\triangleright$ $\pi(s)$ can be ϵ-greedy(s) based on Q
  $(s', r) \leftarrow E(s, a)$ $\triangleright$ Learn new state and reward from environment
  $Q(s, a) \leftarrow Q(s, a) + \alpha \cdot [r + \gamma \cdot \max_{a'} Q(s', a') - Q(s, a)]$
  $M(s, a) \leftarrow (s', r)$
  for $n = 1, \ldots, N$ **do**
    Select $\hat{s}$ and $\hat{a}$ randomly
    $(s', r) \leftarrow M(\hat{s}, \hat{a})$ $\triangleright$ Plan imagined state and reward from model
    $Q(\hat{s}, \hat{a}) \leftarrow Q(\hat{s}, \hat{a}) + \alpha \cdot [r + \gamma \cdot \max_{a'} Q(s', a') - Q(\hat{s}, \hat{a})]$
  end for
until Q converges

Remarks on Dyna-Q

- Uses Q-function as behavior policy (ϵ-greedy).
- Each real sample:
  - updates Q-values (model-free),
  - updates model M.
- Each planning step:
  - samples M using random actions,
  - updates Q-values.
- N controls ratio: real vs. model updates.
- Typical large-scale settings: $1 : 1000$ (env:model).

Reversible Planning vs. Irreversible Learning

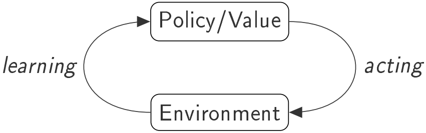
Model-Free vs. Model-Based (High-Level)

- Model-free:
  - Sample the environment directly
  - Update policy $\pi(s, a)$ in one step
  - No explicit transition model
- Model-based:
  - Learn dynamics model $\{T_a, R_a\}$ from samples
  - Update policy *indirectly* using the learned model
  - Planning replaces many real environment interactions

Key motivation: reduce environment samples while keeping/improving policy quality.

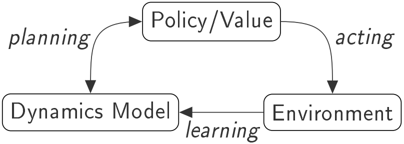
Model-Based vs. Model-Free

Model-Free Learning



- Update policy directly from real experience

Model-Based Learning and Planning



- Learn model $\{T_a, R_a\}$
- Plan with model to update policy

Learning vs. Planning: Big Picture

Planning:

- Uses an internal transition model
- Local state lives *inside the agent*
- Actions can be undone
- Enables search, backtracking, tree expansion
- Synonyms: imagination, simulation

Learning:

- No internal transition model
- Must act in the real environment
- Actions are irreversible
- No backtracking; only forward progression
- Synonyms: sampling, rollout

Why Planning is Reversible

- Planning uses the agent's internal model
- Local state is stored in memory
- Agent can:
  - Try an action
  - Observe predicted next state
  - Undo action and return to previous state
  - Explore alternative branches
- Enables tree search methods and "what-if" reasoning
- Similar to dreaming: we can undo actions in imagination[3].

[3] Thomas M Moerland, Joost Broekens, and Catholijn M Jonker. 'A Framework for Reinforcement Learning and Planning'. In: *arXiv preprint arXiv:2006.15009* (2020).

Why Learning is Irreversible

- Real actions applied to real environment
- Next state cannot be undone by the agent
- Environment transitions are one-way
- Learning must follow environment trajectory (a path)
- Policy learned by repeated real sampling
- No ability to backtrack or explore alternate realities

Comparing Planning and Learning

	Planning	Learning
Transition model in:	Agent	Environment
Undo possible?	Yes	No
State:	Reversible	Irreversible
Dynamics:	Backtracking	Forward-only
Structure:	Tree	Path
New state from:	Agent model	Env. samples
Reward from:	Agent model	Env. samples
Synonyms:	Imagination, simulation	Sampling, rollout

Similarity Between Planning and Learning

- Both collect (s, a, r, s') samples
- Both update the policy $\pi(s, a)$
- Difference is *source of samples*:
  - Learning: real environment
  - Planning: internal model
- Model-based RL learns both:
  - Policy $\pi(s, a)$
  - Dynamics $\{T_a(s, s'), R_a(s, s')\}$

Learning the Model

- In model-based RL, the transition model is learned from sampled interactions.
- Planning quality depends critically on model accuracy.
- If the model is inaccurate:
  - Planning does not improve the value or policy functions.
  - Performance may become worse than model-free RL.
- When the learning/planning ratio is large (e.g., 1/1000), even small model errors quickly degrade performance.
- Two major strategies to increase transition-model accuracy:
  1. **Uncertainty Modeling**
  2. **Latent Models**

Uncertainty Modeling: Motivation

- Transition variance can be reduced with more samples, but this is expensive.
- Goal: Explicitly estimate and propagate model uncertainty.
- Benefits:
  - More reliable long-horizon predictions.
  - Improved policy learning under model errors.

Gaussian Processes for Dynamics

- A popular approach for small or low-dimensional problems.
- Gaussian Processes learn:
  - A predictive function for the next state.
  - A covariance matrix representing uncertainty.
- Advantages:
  - Strong uncertainty estimates.
  - Very sample-efficient.
- Limitations:
  - Poor scalability to high-dimensional environments.
  - Computationally expensive for large datasets.
- Example: **PILCO** (Probabilistic Inference for Learning Control).

Example: PILCO

- Uses Gaussian Processes to model probabilistic dynamics.
- Learns policies by propagating uncertainty through predictions.
- Demonstrated strong sample efficiency on:
  - Cartpole
  - Mountain Car
- Limitation: Does not scale to high-dimensional inputs (e.g., raw pixels).

Trajectory Distribution Approaches

- Another method: sample trajectories optimized for cost.
- These trajectories are then used to train a policy.
- Uses locally linear models + stochastic trajectory optimization.
- Example: **Guided Policy Search (GPS)**
- GPS can efficiently train high-dimensional policies (hundreds–thousands of parameters).

Ensemble Methods

- Ensembles combine multiple models to reduce variance.
- Widely used in supervised ML (e.g., Random Forests).
- In model-based RL:
  - Each model provides a prediction.
  - The ensemble variance serves as an uncertainty estimate.
- Applications show strong performance on continuous-control tasks.

PETS: Probabilistic Ensembles with Trajectory Sampling

- Introduced by Chua et al. (2018).
- Uses:
  - An ensemble of probabilistic neural networks.
  - Stochastic trajectory sampling.
- Achieves excellent performance in:
  - Half-Cheetah
  - Reacher
  - Other MuJoCo tasks
- Improves sample efficiency vs. model-free baselines.

ME-TRPO: Ensembles + TRPO

- Proposed by Kurutach et al. (2018).
- Method:
  - Train an ensemble of neural network dynamics models.
  - During planning, each imaginary transition is sampled from a random ensemble member.
  - Use TRPO to optimize policy.
- Reported strong sample efficiency on:
  - Snake
  - Swimmer
  - Hopper
  - Half-Cheetah

Summary: Uncertainty Modeling

- Explicitly captures model uncertainty.
- Methods include:
  - Gaussian Processes
  - Trajectory-distribution methods (e.g., GPS)
  - Ensembles (e.g., PETS, ME-TRPO)
- Works well for:
  - Low-dimensional problems (GP methods)
  - Moderate-dimensional problems (ensembles)
- Next: A complementary approach — **Latent Models**.

Latent Models: Key Idea

- High-dimensional environments (e.g., images) contain many irrelevant details.
- Latent models compress observations into a smaller representation.
- Planning and learning occur entirely in this low-dimensional **latent space**.
- Benefits:
  - Reduced sample complexity.
  - More robust prediction.
  - Focus on task-relevant features only.

Why Latent Models?

- Raw observations often contain:
  - Background objects
  - Unchanging elements
  - Visual artifacts unrelated to reward
- Latent models:
  - Learn compact abstract states.
  - Remove irrelevant information.
  - Enable long-horizon planning in latent space.

Examples of Latent Model Approaches

- Many recent successes rely on latent-space planning:
  - World Models (Ha and Schmidhuber, 2018)
  - Dreamer / DreamerV2 / DreamerV3 (Hafner et al.)
  - Value Prediction Networks (VPN)
  - Mastering Atari with Discrete World Models (Hafner, 2020)
  - PlaNet (Hafner, 2019)
- All share the principle: **Plan and learn in a reduced latent space**.

Value Prediction Network (VPN)

- Proposed by Oh et al. (2017).
- Key idea: **Predict values and rewards without predicting observations**.
- Uses four differentiable latent-space functions:
  1. Encoding function $f_{\theta_e}^{enc}$
  2. Reward function $f_{\theta_r}^{reward}$
  3. Value function $f_{\theta_v}^{value}$
  4. Transition function $f_{\theta_t}^{trans}$
- Planning occurs on latent abstract states.

VPN: Latent-Space Functions

- **Encoding**:

$$f_{\theta_e}^{enc} : s_{actual} \to s_{latent}$$

  Maps raw observations (e.g., images) to latent states.
- **Transition**: Predicts next latent state given action.
- **Reward**: Predicts expected reward in latent space.
- **Value**: Predicts the expected future return from a latent state.

VPN: Why It Works

- Latent states contain only task-relevant features.
- No need to model high-dimensional observations.
- Planning becomes:
  - Faster
  - Lower variance
  - Less computationally expensive
- Enables multi-step lookahead and imagination-based planning.

From Learning Models to Using Models

- So far we focused on improving the *accuracy* of learned internal models.
- We now shift from model *construction* to model *usage*.
- We study two planning approaches designed to tolerate model inaccuracies:
  - Trajectory rollouts with limited horizon
  - Model-predictive control (MPC)
- Goal: reduce the effect of model errors by limiting planning horizon and continuously re-planning.

Trajectory Rollouts

- At each planning step, the learned transition model

$$T_a(s) \to s'$$

  predicts next states and rewards.
- Long rollouts accumulate large model errors.
- Therefore: avoid deep planning horizons.

Example: Gu et al. (2016)

- Use locally linear models.
- Rollout depth: 5–10 steps.
- Effective on MuJoCo tasks (Gripper, Reacher).

Model-Based Value Expansion (MVE)

- Feinberg et al. (2018): limit look-ahead to depth H, then combine:
  - Near future: model-based predictions
  - Far future: model-free value estimates
- Horizons tried: 1, 2, 10.
- Horizon 10 performs best on Swimmer, Walker, Half-Cheetah.
- Sample complexity improves over DDPG.

Other works:

- Janner et al. (2019), Kalweit & Boedecker (2017)
- All find that effective model horizons are much shorter than full task horizons.

Model-Predictive Control (MPC)

- Also known as *decision-time planning*.
- Standard technique in process engineering.
- Key idea:
  - Optimize a model-based plan over a short horizon.
  - Execute *only the first action*.
  - Re-learn and re-plan at every time-step.
- Why it works:
  - Many real processes are locally linear over small ranges.
  - Frequent re-planning prevents large error accumulation.

MPC in Real Systems

- Applied in automotive and aerospace domains:
  - Terrain-following
  - Obstacle avoidance
  - Complex process control
- Works well with inaccurate models due to short horizon updates.

Deep RL examples:

- Finn et al. (2017) and Ebert et al. (2018):
  - Visual foresight for robotic manipulation.
  - Model predicts future frames.
  - MPC selects lowest-cost action sequence.
- Capabilities:
  - Multi-object manipulation
  - Pushing, grasping, placing
  - Cloth folding

MPC with Ensemble Models: PETS

- PETS (Chua et al. 2018):
  - Uses probabilistic ensembles for dynamics learning.
  - Uses CEM (Cross-Entropy Method) for planning.
  - In MPC style: execute first action only; re-plan at every step.
- Common trend:
  - Ensemble dynamics models + MPC = robust planning.

Planning by a Neural Network?

- Traditionally:
  - Learn transition model with backprop.
  - Use hand-crafted algorithm for planning (e.g., limited-horizon search).
- Trend in ML:
  - Replace hand-coded algorithms with differentiable, learnable modules.
  - Train them end-to-end.
- Question:

> Can we make the *planning* stage differentiable and learnable?

Why Might Planning-by-Network Work?

- Neural networks typically do:
  - Transformations
  - Filtering
  - Classification / selection
- Planning consists of:
  - Action selection
  - State unrolling
- RNNs and LSTMs *do* maintain state internally.
- Therefore: planning might be implementable using deep networks.

Value Iteration Networks (VIN)

- Tamar et al. (2016) introduced VIN:
  - A differentiable neural network that performs value iteration.
  - Designed for Grid world planning.
  - CNN layers emulate dynamic programming steps.
- Core idea:
  - Value iteration = repeated convolution + max-pooling.
  - Each CNN channel corresponds to an action's Q-value.
  - Stacking K convolution layers K value-iteration updates.

Value Iteration Computation in CNN Form

Value iteration update:

$$V(s) = \max_a \sum_{s'} T_a(s, s')(R_a(s, s') + \gamma V(s'))$$

- Double loop over states and actions.
- CNN implementation:
  - Convolution implements local transition and reward propagation.
  - Max-pooling implements action maximization.
- The VIN module becomes a differentiable planner.
- Training via backprop learns:
  - Transition dynamics
  - Embedded planning behavior