CS 747, Autumn 2022: Lecture 22

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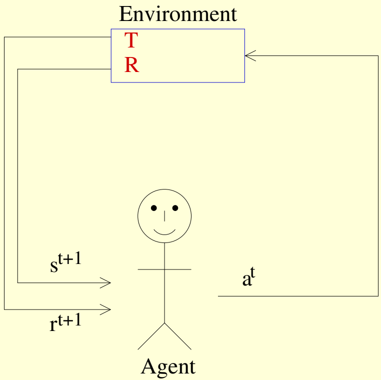
Autumn 2022

Recall What a "Model" is

- MDP (S, A, T, R, γ).



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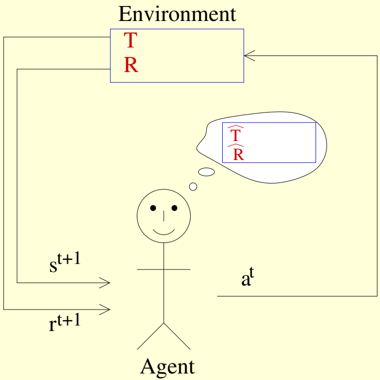

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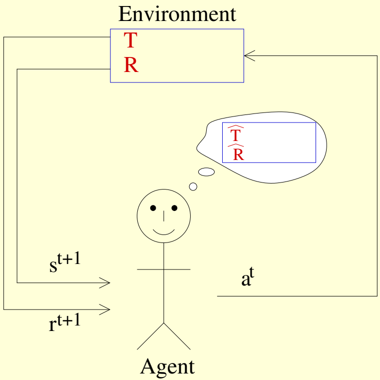

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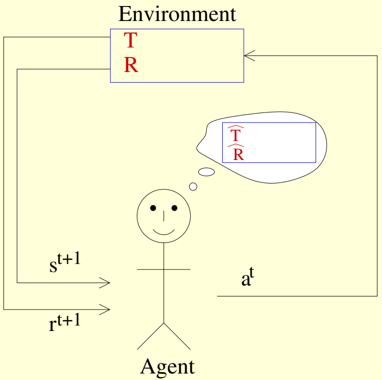

- Model $(\hat{T}, \hat{R})$ is agent's estimate of (T, R).
- Distributional models store $T(s, a, s')$ for $s, s' \in S, a \in A$.
- Sample models generate $s' \sim T(s, a)$ for $s \in S, a \in A$.

Models in RL

1. Dyna-Q algorithm
2. Model-based RL for helicopter control

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Learning and Using Models

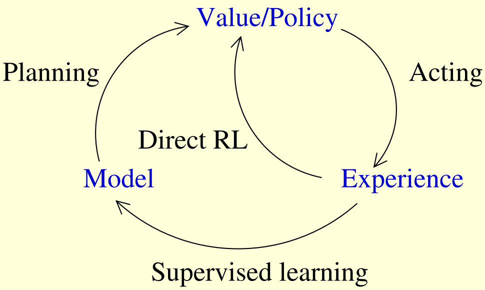

Figure from Section 8.2, Sutton and Barto (2018).

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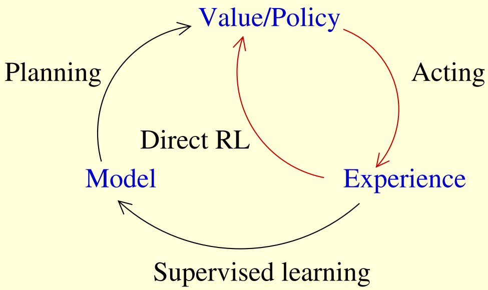

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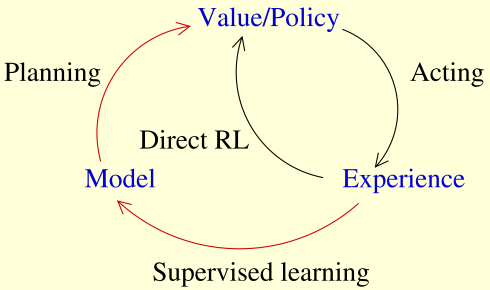

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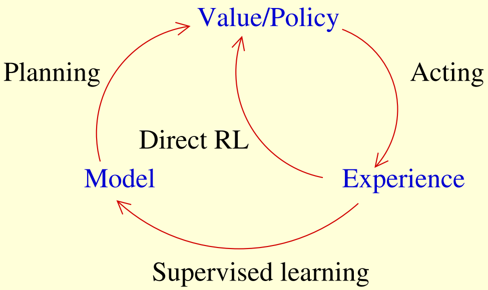

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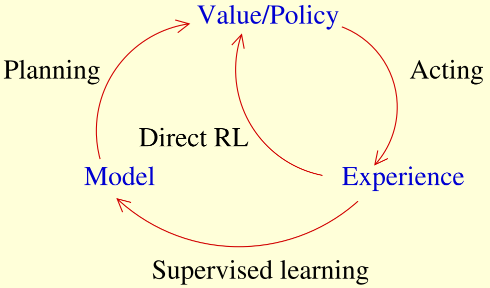

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- What are pluses and minuses of model-based learning?

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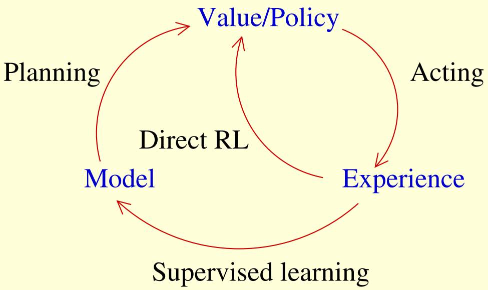

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- What are pluses and minuses of model-based learning?
- \+ Fewer environmental interactions (but more computation).
- \+ Adapting to changes in the environment.
- \- Being misled by an incorrect/biased model.

Dyna-Q Algorithm

Initialise Q, *Model*.
Loop forever:
  $s \leftarrow$ current state.
  $a \leftarrow \epsilon$-greedy(s, Q).
  Take action a; get next state s', reward r.
  $Q(s, a) \leftarrow Q(s, a) + \alpha\{r + \gamma \max_{a' \in A} Q(s', a') - Q(s, a)\}$.
  $UpdateModel(Model, s, a, r, s')$.
  Loop N times:
    $\bar{s} \leftarrow$ Random previously observed state.
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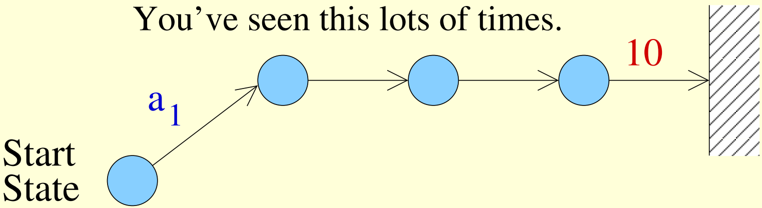
In practice, model and Q implemented using function approximator, rules.

Effect of Model



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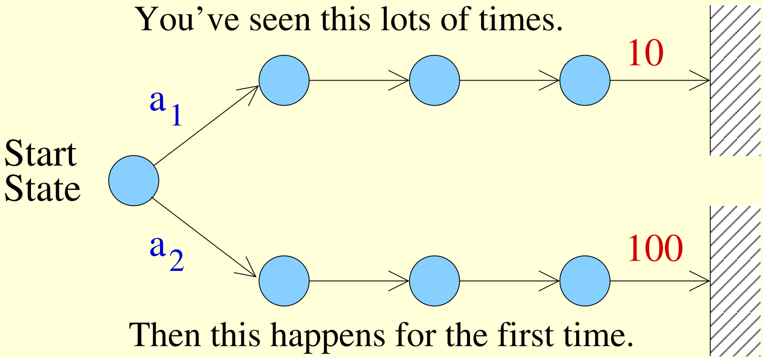

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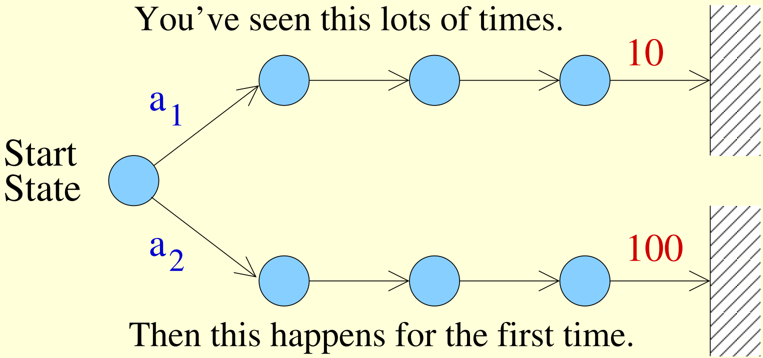

- Models can lead to more efficient exploration.
- Model uncertainties can also be maintained.
- Dyna-Q can be augmented with prioritised sweeping to expedite reconciliation of Q-function with model.

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   Autonomous helicopter flight via Reinforcement Learning.

   Andrew Y. Ng, H. Jin Kim, Michael I. Jordan, and Shankar Sastry, Advances in Neural Information Processing Systems 16, pp. 799-806, MIT Press, 2003.

Controlling a Helicopter

[1]

- State described by position (x, y, z), orientation (ϕ, θ, ω), velocity $(\dot{x}, \dot{y}, \dot{z})$, and angular velocity $(\dot{\phi}, \dot{\theta}, \dot{\omega})$.
- Actions: 4-dimensional control of rotor tilts, speeds.
- Task: hover in place, or follow a trajectory.

1. https://www.publicdomainpictures.net/pictures/20000/velka/police-helicopter-8712919948643Mk.jpg.

Controlling a Helicopter

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- Episodic or continuing? What are T, R, γ?

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Controlling a Helicopter

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- Episodic or continuing? What are T, R, γ?
- How to learn to fly? By trial and error?!

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Approach of Ng et al. (2003)

- Have a human pilot fly the helicopter; record trajectory.
- Learn a model using supervised learning on gathered data.
- Run policy search on the model.
- Evaluate learned policy on (real) helicopter.

Data Gathering

- Human pilot flies helicopter for a few minutes.
- $s^0, a^0, r^0, s^1, a^1, r^1, s^2, \ldots$ trajectory recorded at 50Hz.
- Trajectory split into separate train (339s) and test (140s) segments.
- Domain knowledge applied to simplify model learning (use of body coordinates, accounting for symmetries, etc.).

Learning the Model

- Given query x, output y is computed as a linear function of state features as well as actions:

$$y = \beta x + \eta,$$

  where parameters β and η (noise) are determined mainly by training points in the vicinity of x.

- Example of an instance-based approach yielding a non-linear, distributional model, which is subsequently used as a sample model.

- Some parameters hard-coded based on domain knowledge.

- Design and choices validated by visualising divergence between predicted and actual trajectories.

Policy Search

- Policy template: feed-forward neural networks with state (and derived) features as input, and one output for each of four action dimensions ($[-1, 1]$). Few tens of parameters.
- For given policy π, define $U(\pi)$ to be the expected long-term reward from start state. Need to find

$$\operatorname*{argmax}_{\pi \in \Pi} U(\pi).$$

- Instead find $\operatorname{argmax}_{\pi \in \Pi} \hat{U}(\pi)$, estimated using rollouts of π on model.
- Search based on hill-climbing or gradient ascent.
- "PEGASUS" trick used to reduce variance across rollouts.

Hovering, Trajectory-following

- Hovering at $(x^\star, y^\star, z^\star)$:

$$
\begin{aligned}
R(s, a) &= R(s) + R(a), \text{ where} \\
R(s) &= -[\alpha_x (x - x^\star)^2 + \alpha_y (y - y^\star)^2 + \alpha_z (z - z^\star)^2 + \\
&\qquad \alpha_{\dot{x}} \dot{x}^2 + \alpha_{\dot{y}} \dot{y}^2 + \alpha_{\dot{z}} \dot{z}^2 + \alpha_{\dot{\omega}} \dot{\omega}^2], \\
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- Flying along trajectory $(x_t^\star, y_t^\star, z_t^\star)_{t=0}^{T}$:
  - "Obvious" idea of using $(x_t^\star, y_t^\star, z_t^\star)$ in place of $(x^\star, y^\star, z^\star)$ can be problematic.
  - Instead decouple deviation and progress.
  - Uses more parameters/connections in neural network-based policy than for hovering.

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> *"Essentially, all models are wrong, but some are useful."*
>
> —George Box