UNIVERSITY OF TECHNOLOGY
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CHEMNITZ

Deep Reinforcement Learning

Model-based RL

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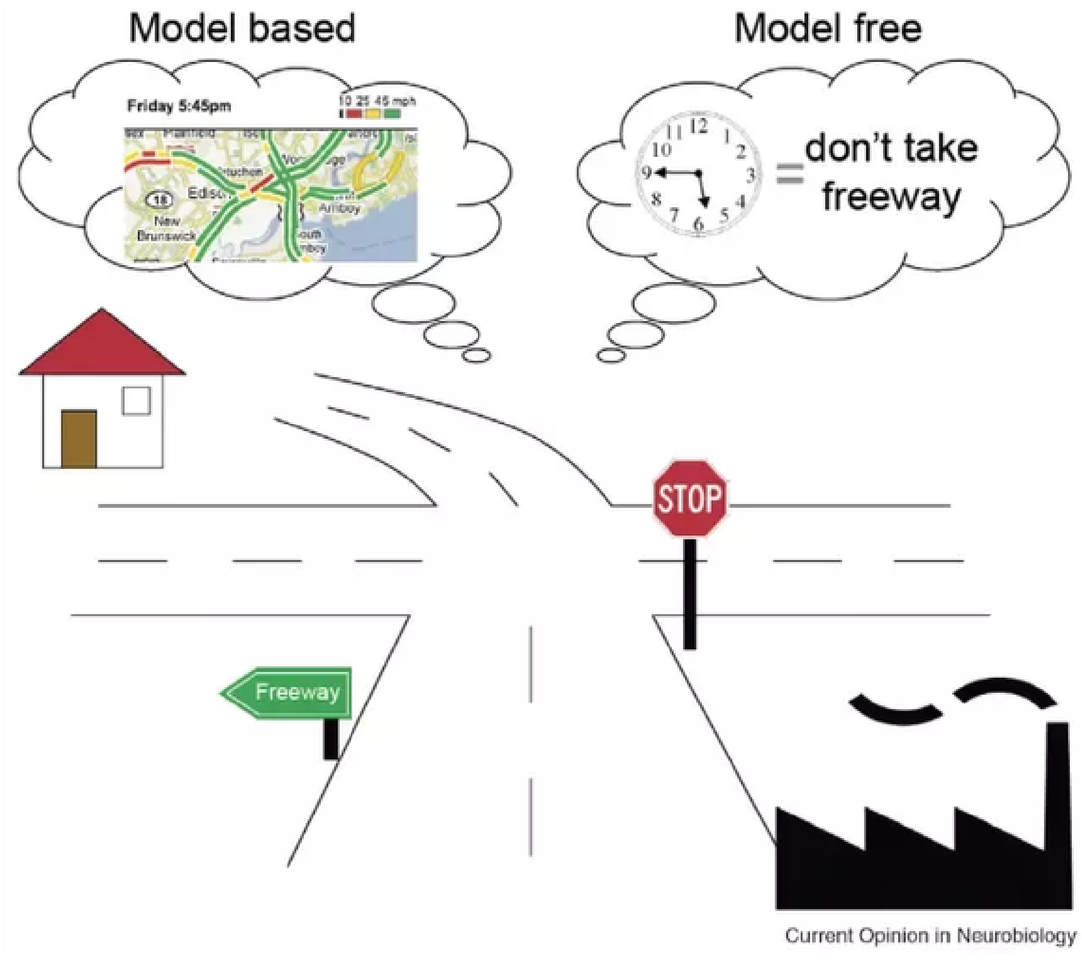
1 - Model-based RL

Model-free vs. model-based RL



Source: Dayan and Niv (2008) Reinforcement learning: The Good, The Bad and The Ugly. Current Opinion in Neurobiology, Cognitive neuroscience 18:185–196. doi:10.1016/j.conb.2008.08.003

- In **model-free RL** (MF) methods, we do not need to know anything about the dynamics of the environment to start learning a policy:

$$p(s_{t+1}|s_t, a_t) \quad r(s_t, a_t, s_{t+1})$$

- We just sample transitions (s, a, r, s') and update Q-values or a policy network.
- The main advantage is that the agent does not need to "think" when acting: just select the action with highest Q-value (**reflexive behavior**).
- The other advantage is that you can use MF methods on **any** MDP: you do not need to know anything about them.

- But MF methods are very slow (sample complexity): as they make no assumption, they have to learn everything by trial-and-error from scratch.

Model-free vs. model-based RL

- If you had a **model** of the environment, you could plan ahead (what would happen if I did that?) and speed up learning (do not explore stupid ideas): **model-based RL** (MB).

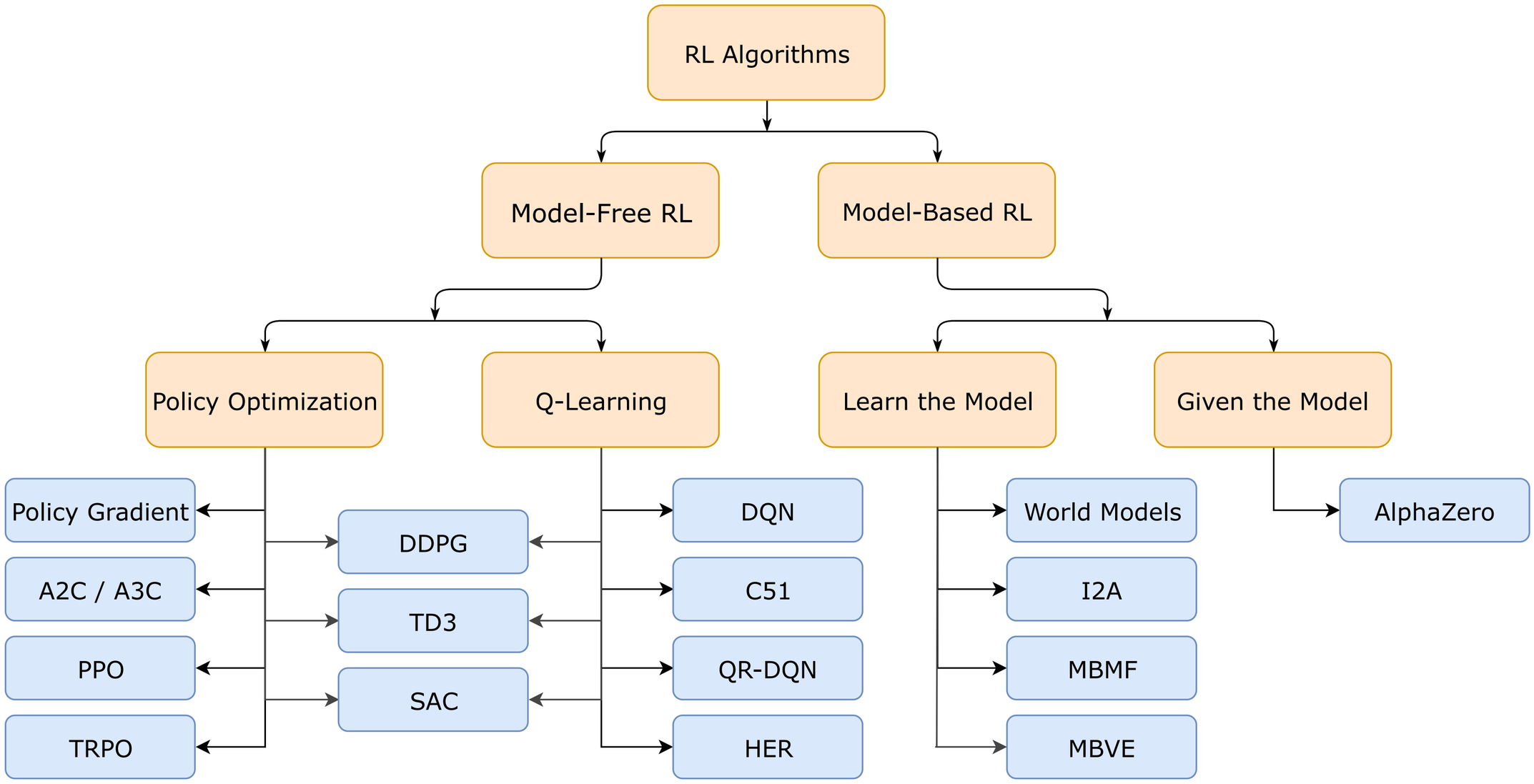
- In chess, players **plan** ahead the possible moves up to a certain horizon and evaluate moves based on their emulated consequences.

Source: https://www.chess.com/article/view/announcing-the-chess-com-gif-maker

- In real-time strategy games, learning the environment (**world model**) is part of the strategy: you do not attack right away.

Source: https://towardsdatascience.com/model-based-reinforcement-learning-cb9e41ff1f0d

Two families of deep RL algorithms

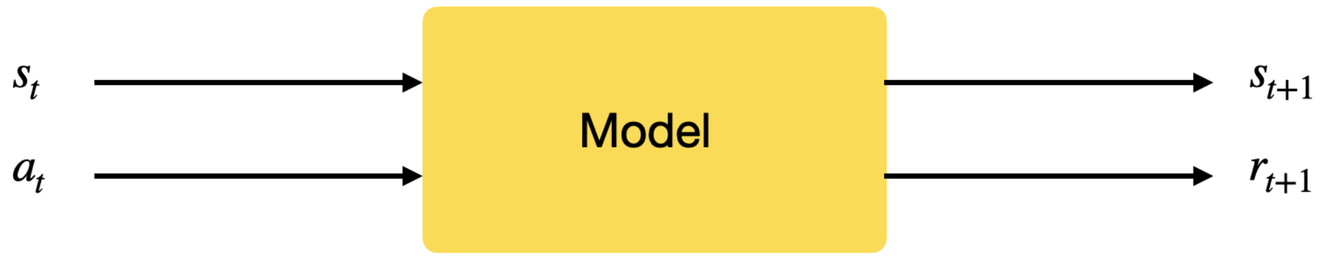


Source: https://github.com/avillemin/RL-Personnal-Notebook

2 - Model Predictive Control

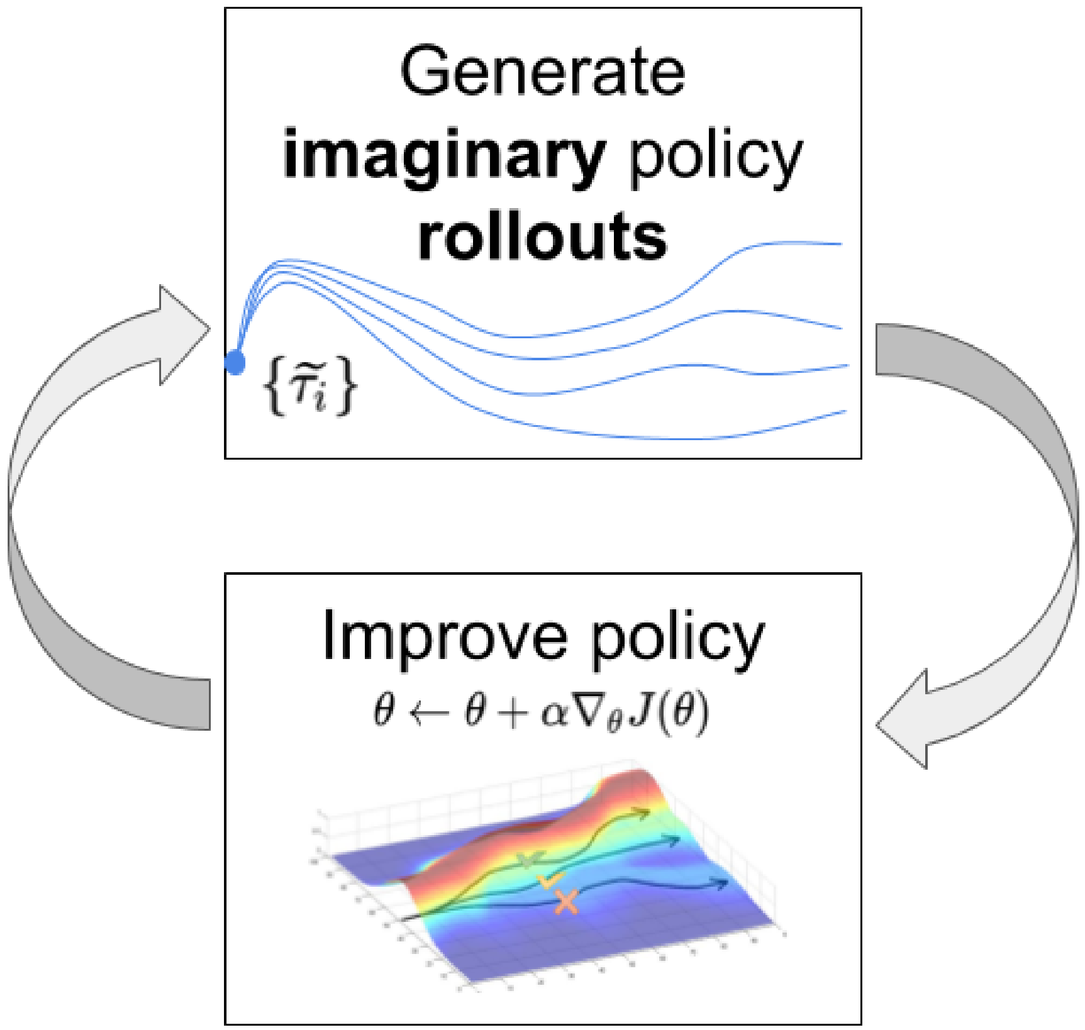
Learning the world model

- Learning the world model is not complicated in theory.
- We just need to collect *enough* transitions $s_t, a_t, s_{t+1}, r_{t+1}$ using a random agent (or during learning) and train a **supervised** model to predict the next state and reward.



- Such a model is called the **dynamics model**, the **transition model** or the **forward model**.
  - **What happens if I do that?**
- The model can be deterministic (use neural networks) or stochastic (use Gaussian Processes).
- Given an initial state s_0 and a policy π, you can unroll the future using the local model.

Learning from imaginary rollouts



- Once you have a good transition model, you can generate **rollouts**, i.e. imaginary trajectories / episodes using the model.

$$\tau = (s_o, a_o, r_1, s_1, a_1, \ldots, s_T)$$

- You can then feed these trajectories to any model-free algorithm (value-based, policy-gradient) that will learn to maximize the returns.

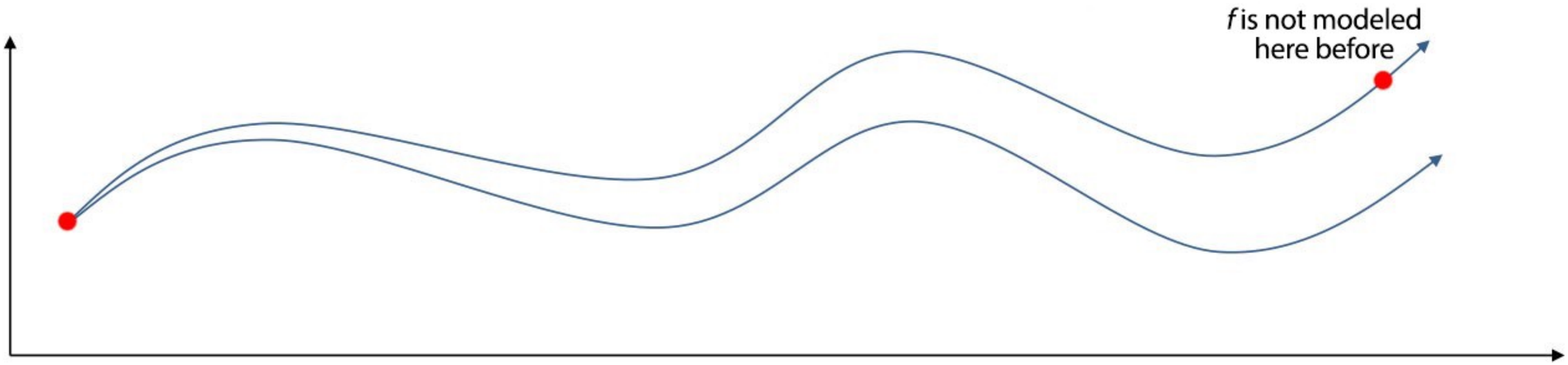
$$\mathcal{J}(\theta) = \mathbb{E}_\tau[R(\tau)]$$

- The only sample complexity is the one needed to train the model: the rest is **emulated**.
- Drawback: This can only work when the model is close to perfect, especially for long trajectories or probabilistic MDPs.

Kurutach et al. (2018) Model-Ensemble Trust-Region Policy Optimization. arXiv:1802.10592.

Imperfect model

- For long horizons, the slightest imperfection in the model can accumulate (**drift**) and lead to completely wrong trajectories.

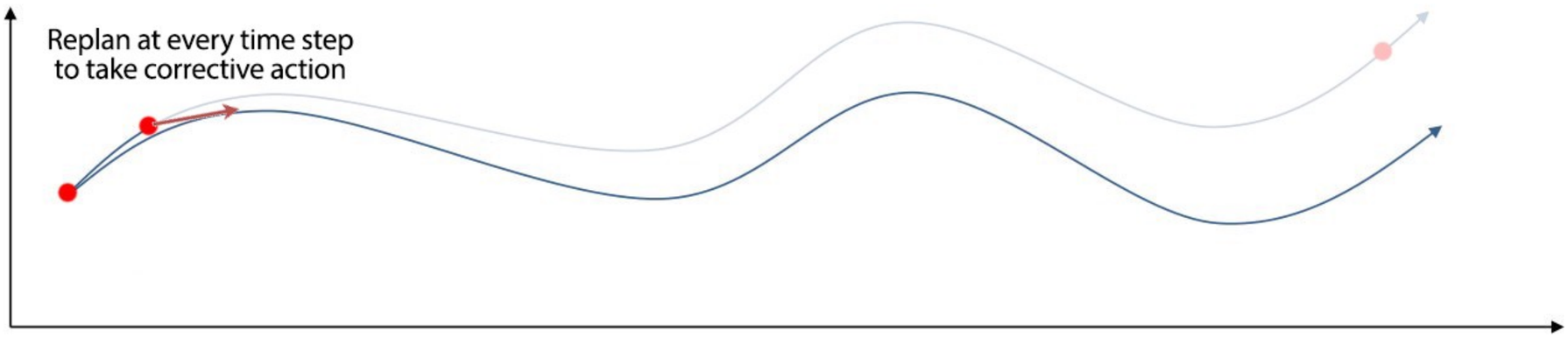


Source: https://medium.com/@jonathan_hui/rl-model-based-reinforcement-learning-3c2b6f0aa323

- The emulated trajectory will have a biased return, the algorithm does not converge to the optimal policy.
- If you have a perfect model, you should not be using RL anyway, as classical control methods would be much faster (but see AlphaGo).

MPC - Model Predictive Control

- The solution is to **replan** at each time step and execute only the first planned action **in the real environment**.



Source: https://medium.com/@jonathan_hui/rl-model-based-reinforcement-learning-3c2b6f0aa323

- Replanning avoids accumulating errors over long horizons.

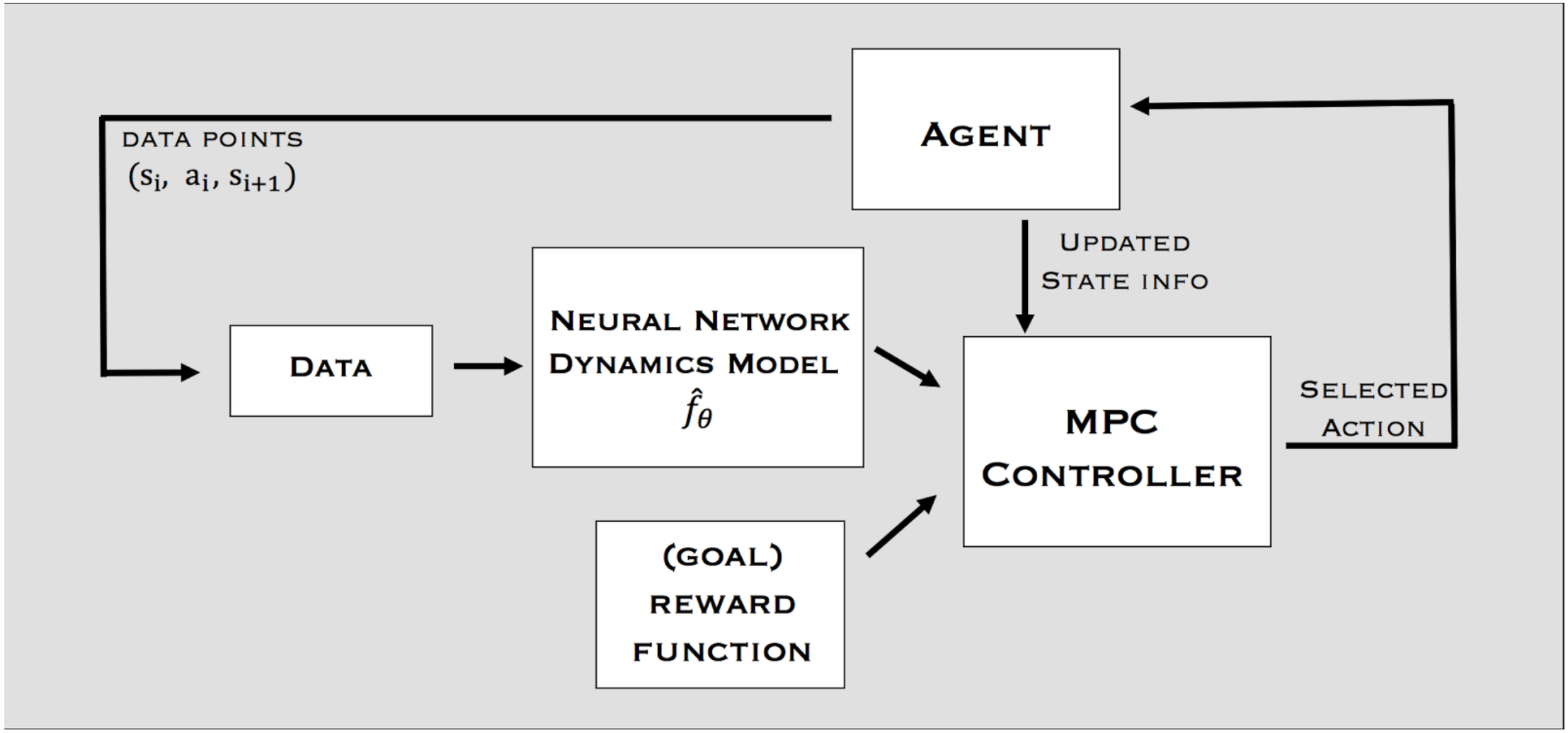
MPC - Model Predictive Control

- Collect transitions (s, a, r, s') using a (random/expert) policy b and create an initial dataset $\mathcal{D} = \{(s_k, a_k, r_, s'_k\}_k$.
- **while** not converged:
  - (Re)Train the dynamics model $M(s, a) = (s', r)$ on $\mathcal{D}$ using supervised learning.
  - **foreach** step t in the trajectory:
    - Plan a trajectory from the current state s_t using the model M, returning a sequence of planned actions:

$$a_t, a_{t+1}, \ldots, a_T$$

    - Take the first action a_t, observe the next state s_{t+1}.
    - Append the transition (s_t, a_t, s_{t+1}) to the dataset.

MPC - Example with a neural model

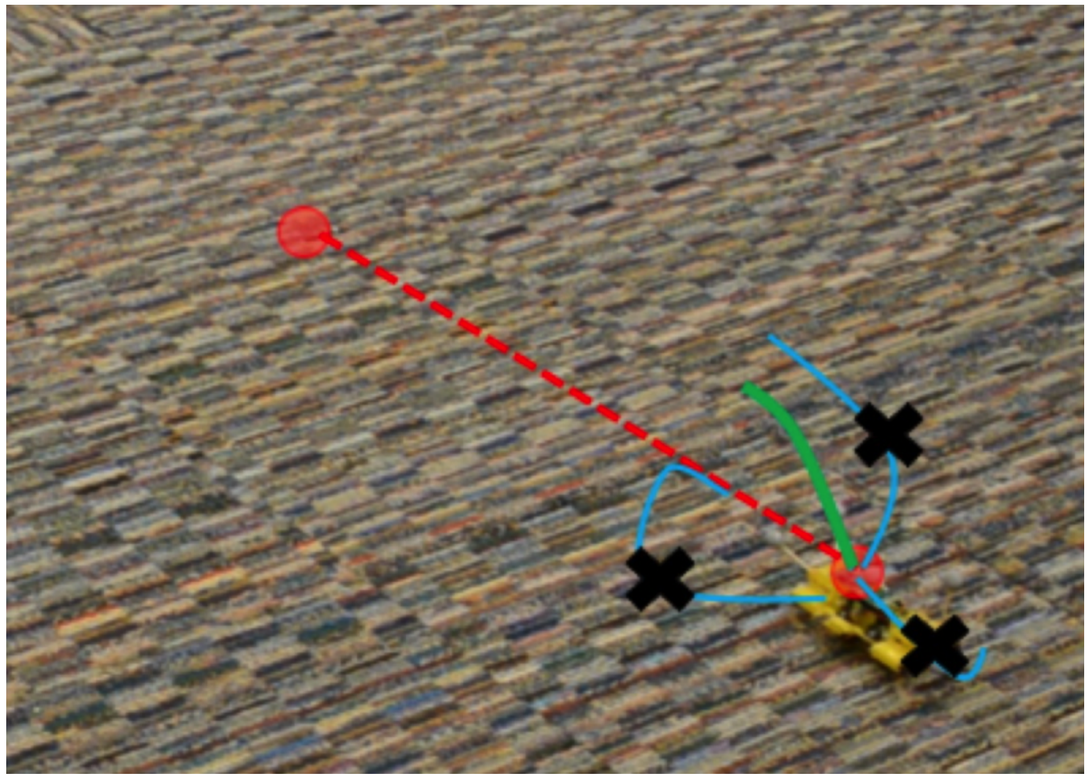


Nagabandi et al. (2017). Neural Network Dynamics for Model-Based Deep Reinforcement Learning with Model-Free Fine-Tuning. arXiv:1708.02596.

MPC - Example with a neural model

- The planner can actually be anything, it does not have to be a RL algorithm.
- For example, it can be iLQR (Iterative Linear Quadratic Regulator), a non-linear optimization method.

https://jonathan-hui.medium.com/rl-lqr-ilqr-linear-quadratic-regulator-a5de5104c750.

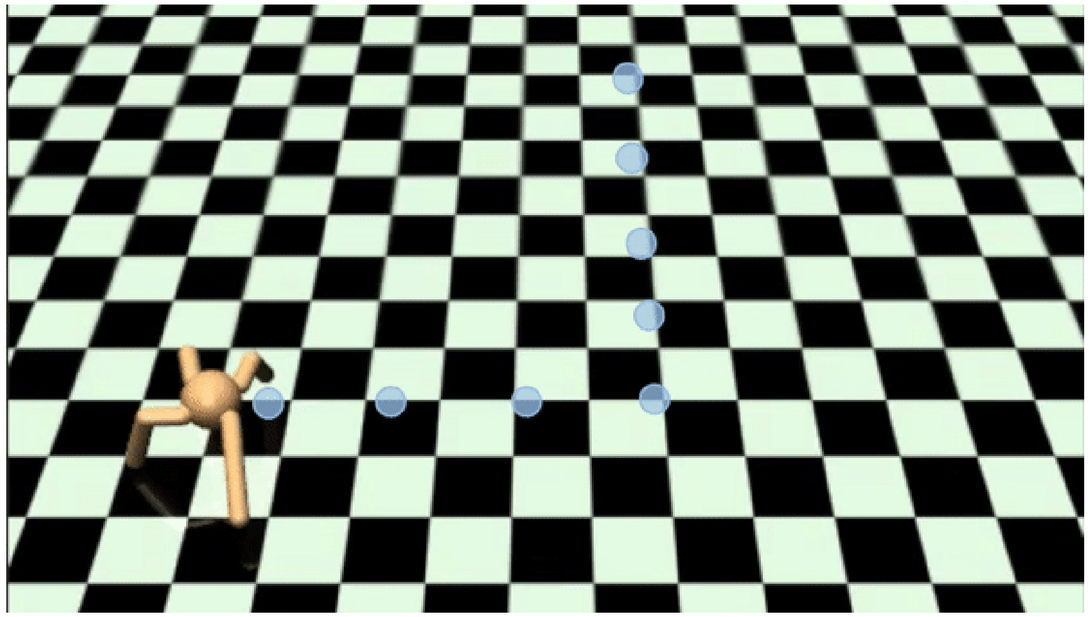


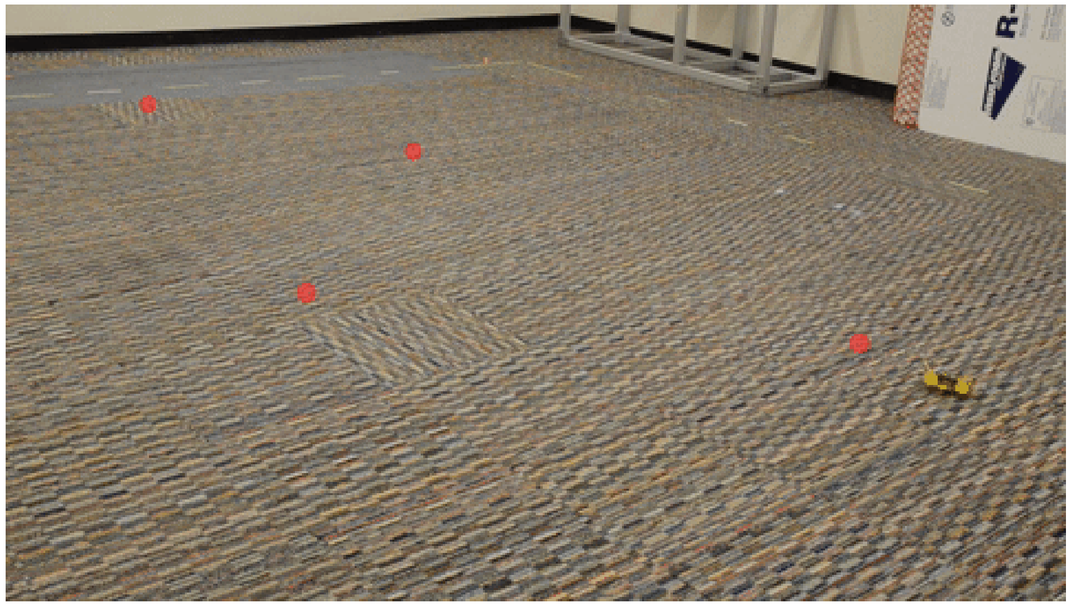
Source: https://bair.berkeley.edu/blog/2017/11/30/model-based-rl/

- Alternatively, one can use **random-sampling shooting**:
  1. in the current state, select a set of possible actions.
  2. generate rollouts with these actions and compute their returns using the model.
  3. select the action whose rollout has the highest return.

MPC - Example with a neural model

- The main advantage of MPC is that you can change the reward function (the **goal**) on the fly: what you learn is the model, but planning is just an optimization procedure.
- You can set intermediary goals to the agent very flexibly: no need for a well-defined reward function.
- Model imperfection is not a problem as you replan all the time. The model can adapt to changes in the environment (slippery terrain, simulation to real-world).





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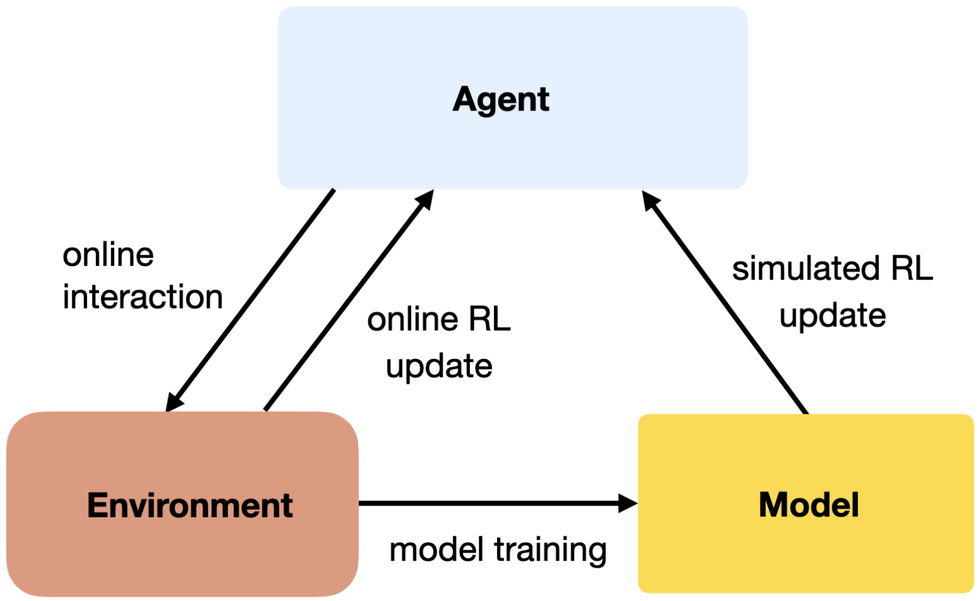
3 - Dyna-Q

Dyna-Q



- Another approach to MB RL is to **augment** MF methods with MB rollouts.
- The MF algorithm (e.g. Q-learning) learns from transitions (s, a, r, s') sampled either with:
  - **real experience**: interaction with the environment.
  - **simulated experience**: simulation by the model.
- If the simulated transitions are good enough, the MF algorithm can converge using much less **real transitions**, thereby reducing its **sample complexity**.

- The **Dyna-Q** algorithm is an extension of Q-learning to integrate a model $M(s, a) = (s', r')$.
- The model can be tabular or approximated with a NN.

Dyna-Q

- Initialize values $Q(s, a)$ and model $M(s, a)$.
- **for** $t \in [0, T_{\text{total}}]$:
  - Select a_t using Q, take it on the **real environment** and observe s_{t+1} and r_{t+1}.
  - Update the Q-value of the **real** action:

$$\Delta Q(s_t, a_t) = \alpha \left(r_{t+1} + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right)$$

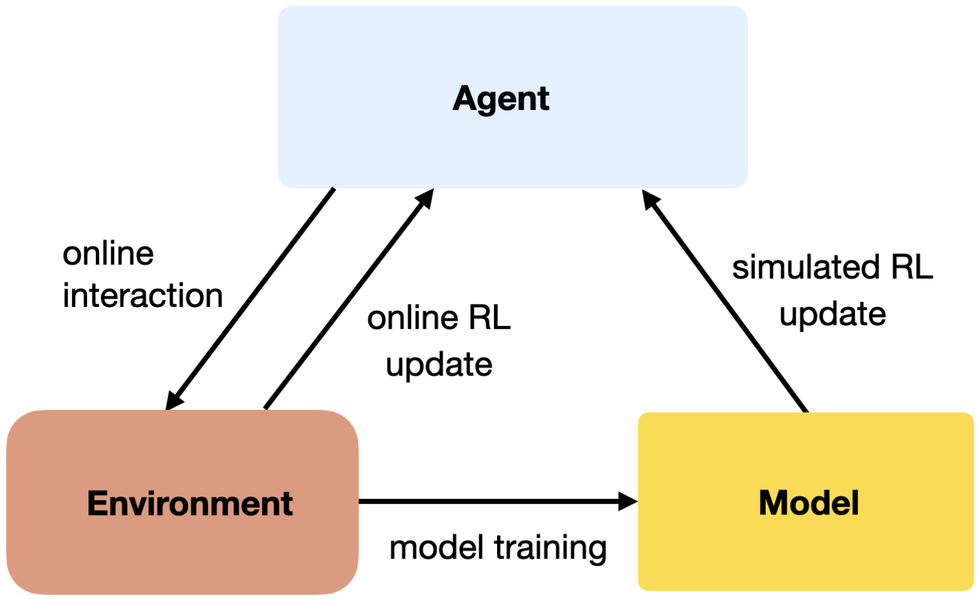
  - Update the model:

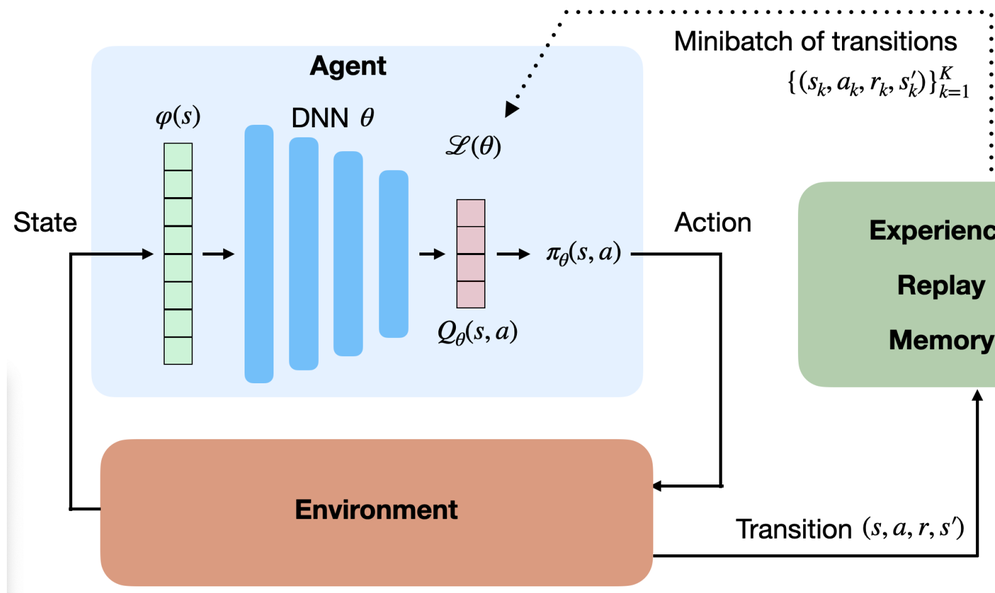
$$M(s_t, a_t) \leftarrow (s_{t+1}, r_{t+1})$$

  - **for** K steps:
    - Sample a state s_k from a list of visited states.
    - Select a_k using Q, predict s_{k+1} and r_{k+1} using the **model** $M(s_k, a_k)$.
    - Update the Q-value of the **imagined** action:

$$\Delta Q(s_k, a_k) = \alpha \left(r_{k+1} + \gamma \max_a Q(s_{k+1}, a) - Q(s_k, a_k) \right)$$

Dyna-Q





- It is interesting to notice that Dyna-Q is very similar to DQN and its **experience replay memory**.
- In DQN, the ERM stores **real transitions** generated in the past.
- In Dyna-Q, the model generates **imagined transitions** based on past real transitions.

References

Dayan, P., and Niv, Y. (2008). Reinforcement learning: The Good, The Bad and The Ugly. *Current Opinion in Neurobiology* 18, 185–196. doi:10.1016/j.conb.2008.08.003.

Kurutach, T., Clavera, I., Duan, Y., Tamar, A., and Abbeel, P. (2018). Model-Ensemble Trust-Region Policy Optimization. http://arxiv.org/abs/1802.10592.

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