UNIVERSITY OF TECHNOLOGY
IN THE EUROPEAN CAPITAL OF CULTURE
CHEMNITZ

Deep Reinforcement Learning

Model-based RL

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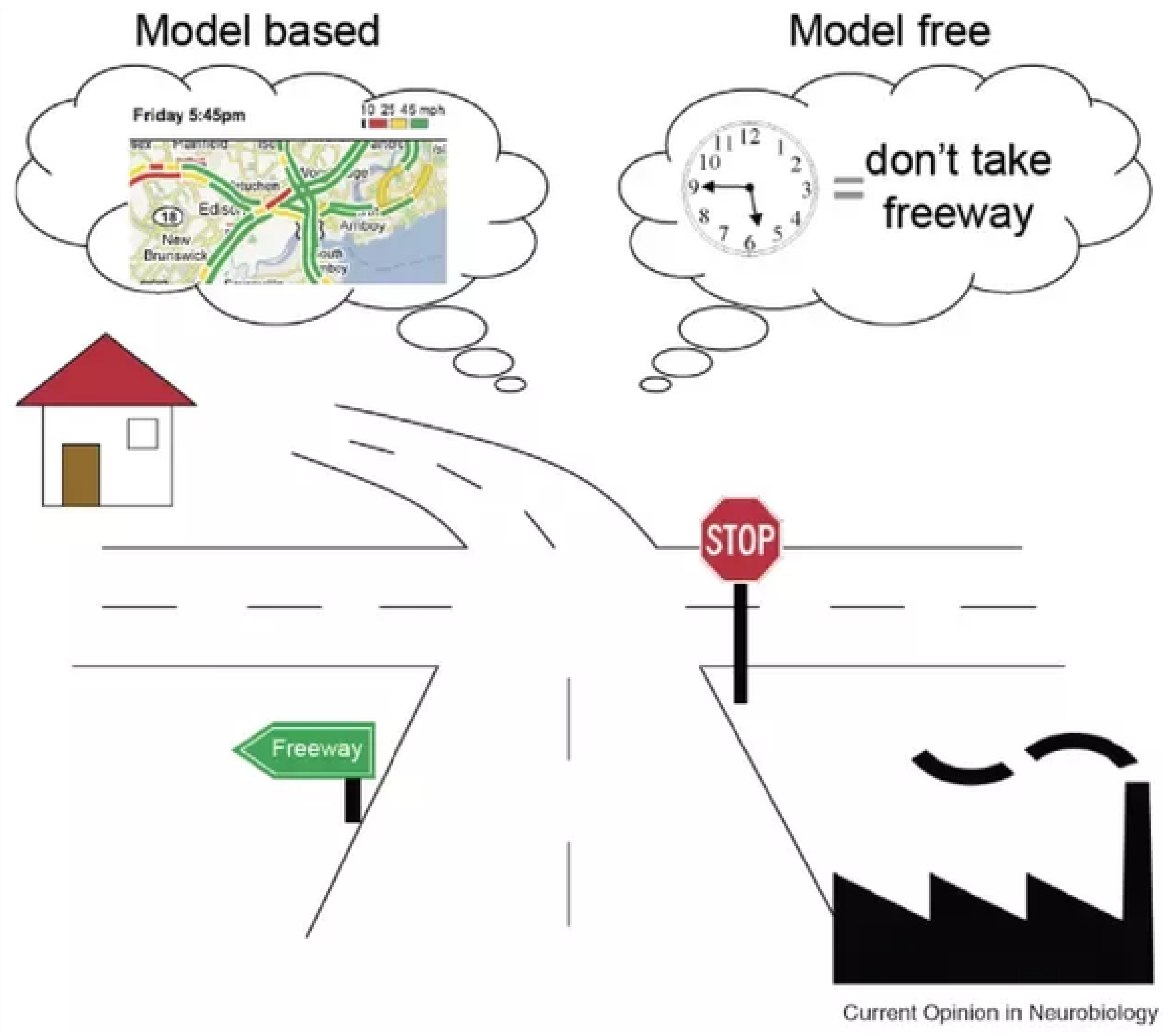
1 - Model-based RL

Model-free vs. model-based RL



Source: Dayan P, Niv Y. (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.

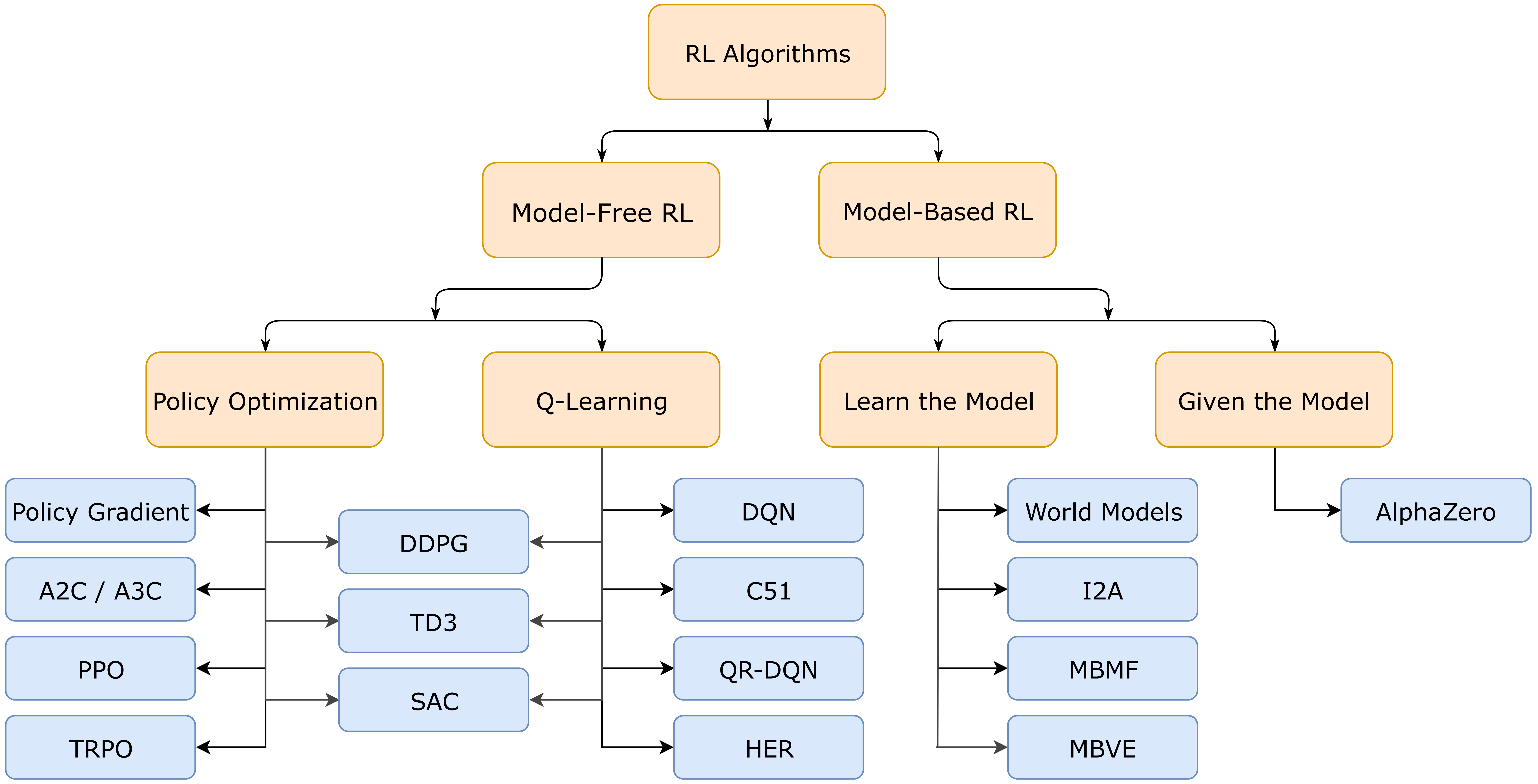
Source: https://www.chess.com/article/view/announcing-the-chess-com-gif-maker

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

Click to select this military unit.
Scout Cavalry
Celts
SNap
wikiHow to Win in Wonder Race in Age of Empires 2

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

Two families of deep RL algorithms

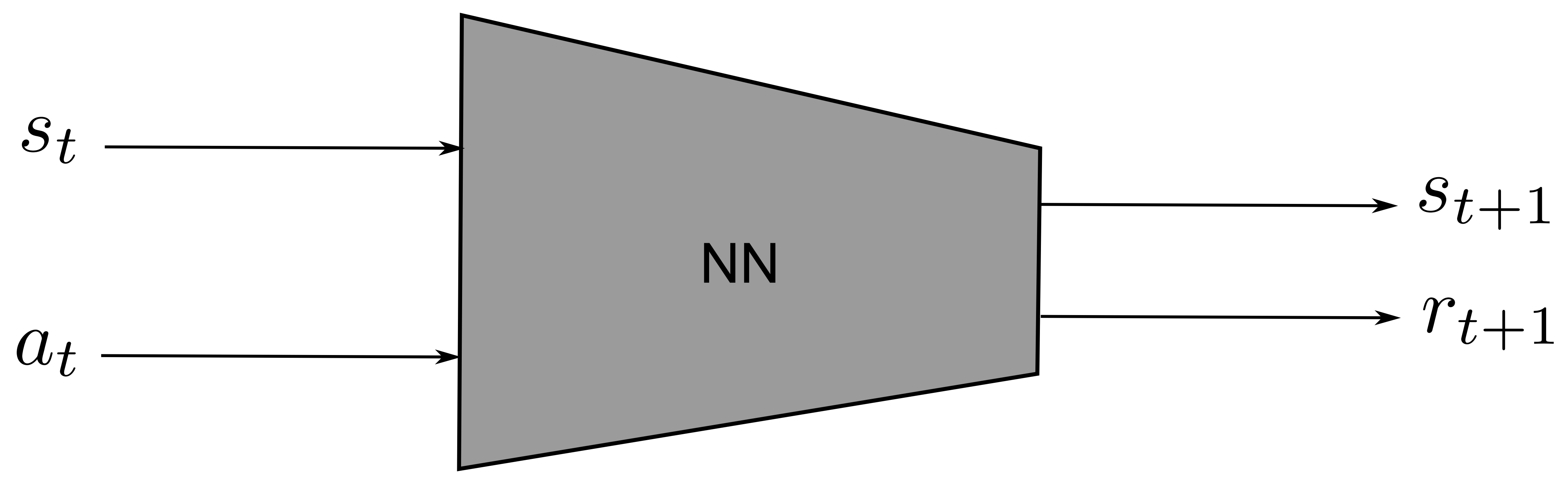


Source: https://github.com/avillemin/RL-Personnal-Notebook

2 - Model Predictive Control

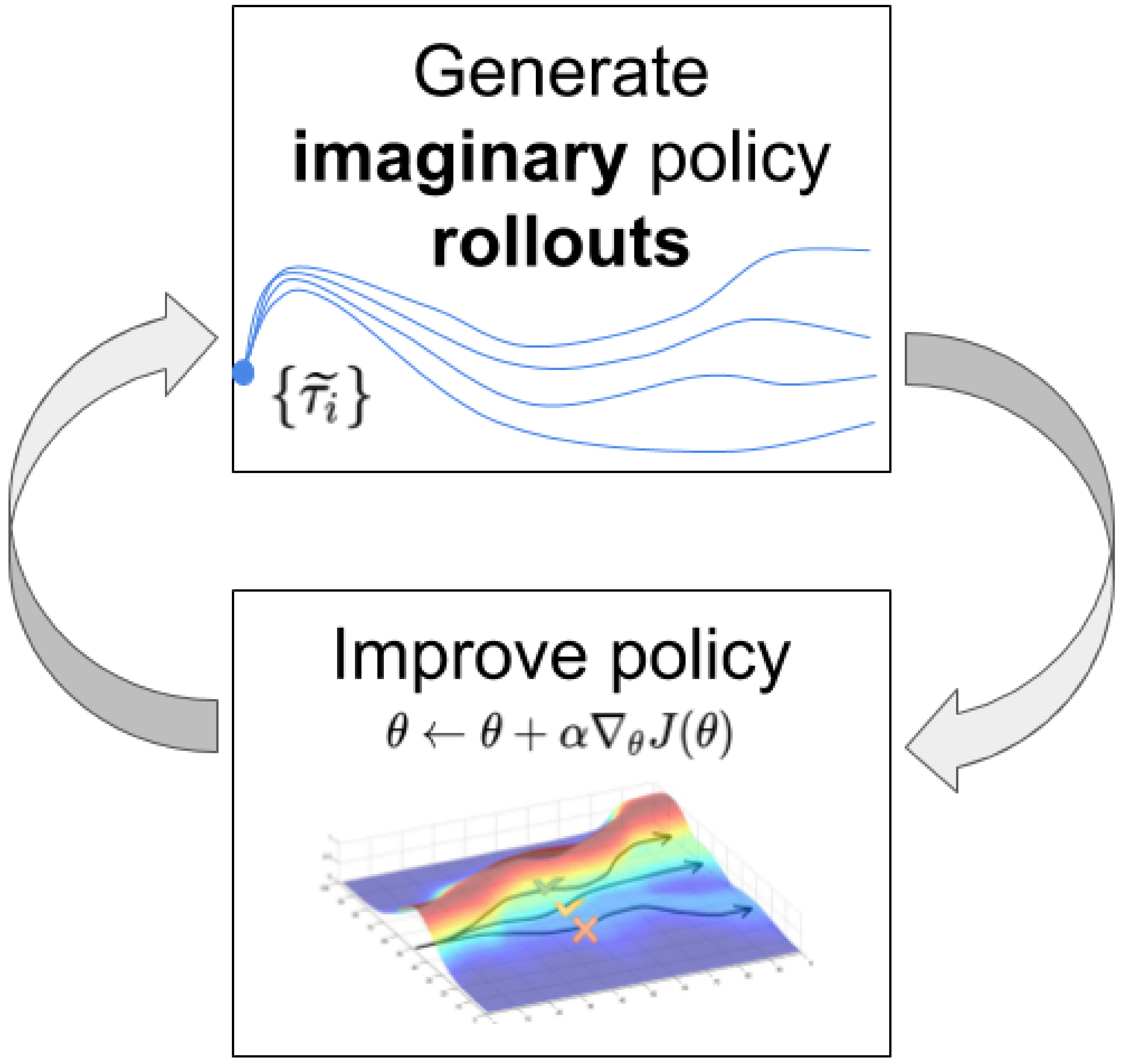
Learning the world model

- 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


Generate **imaginary** policy **rollouts**
$\{\tilde{\tau}_i\}$
Improve policy
$\theta \leftarrow \theta + \alpha \nabla_\theta J(\theta)$

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

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

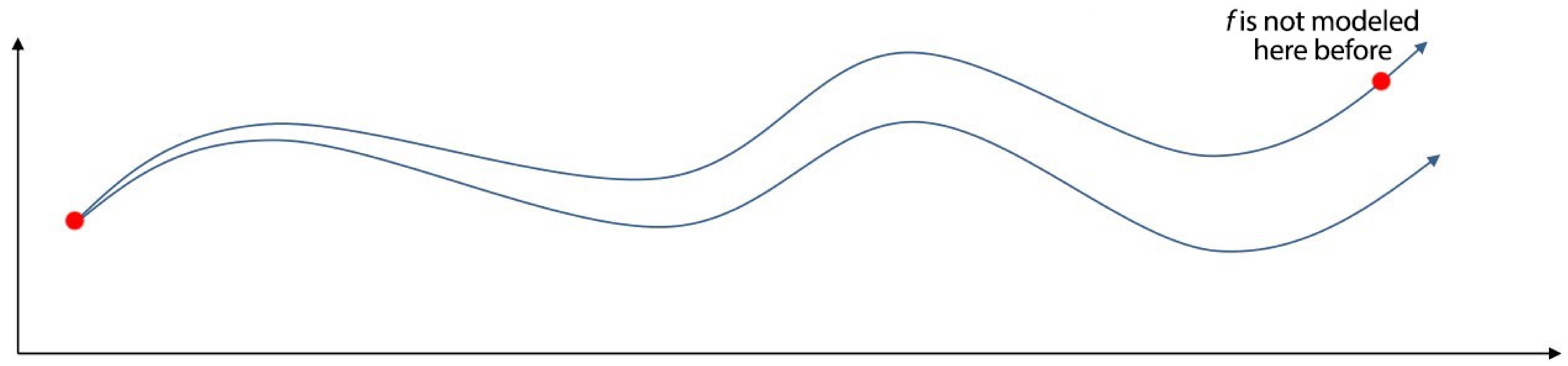
- You can then feed these trajectories to any model-free algorithm (value-based, policy-gradient) that will learn to maximize the returns.

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

- 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.

Imperfect model

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

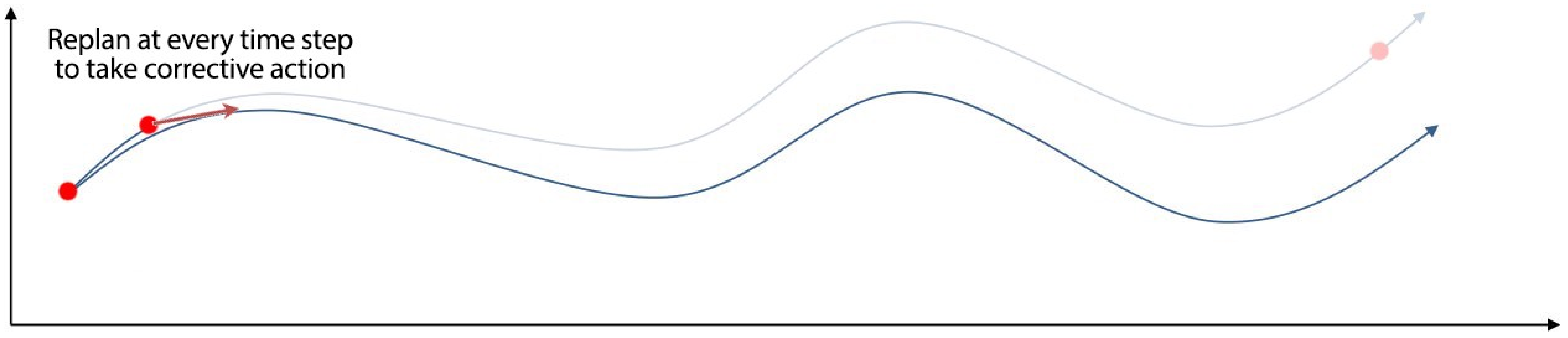


Source: https://medium.com/@jonathan_hui/rl-model-based-reinforcement-learning-3c2b6f0aa323

- 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 the first planned action **in the real environment**.



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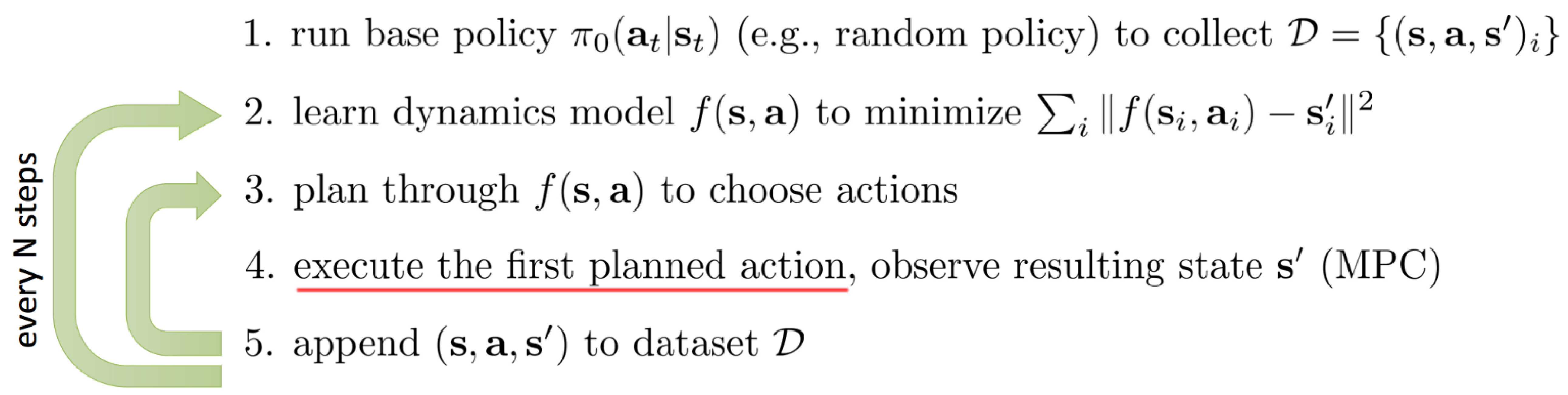
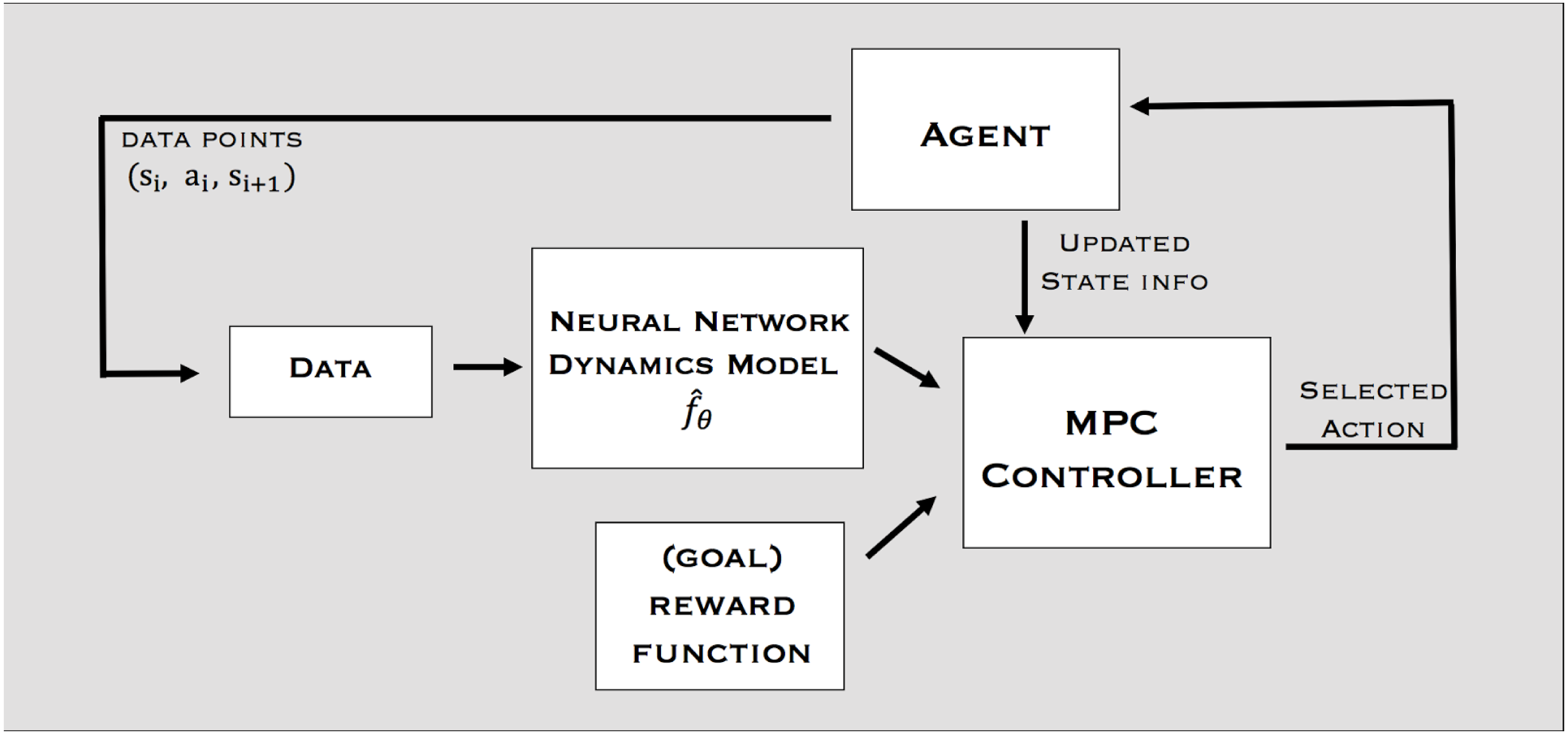
- **Model Predictive Control** iteratively plans complete trajectories, but only selects the first action.


every N steps

1. run base policy $\pi_0(\mathbf{a}_t|\mathbf{s}_t)$ (e.g., random policy) to collect $\mathcal{D} = \{(\mathbf{s}, \mathbf{a}, \mathbf{s}')_i\}$
2. learn dynamics model $f(\mathbf{s}, \mathbf{a})$ to minimize $\sum_i \|f(\mathbf{s}_i, \mathbf{a}_i) - \mathbf{s}'_i\|^2$
3. plan through $f(\mathbf{s}, \mathbf{a})$ to choose actions
4. execute the first planned action, observe resulting state $\mathbf{s}'$ (MPC)
5. append $(\mathbf{s}, \mathbf{a}, \mathbf{s}')$ to dataset $\mathcal{D}$

Source: http://rail.eecs.berkeley.edu/deeprlcourse-fa17/f17docs/lecture_9_model_based_rl.pdf

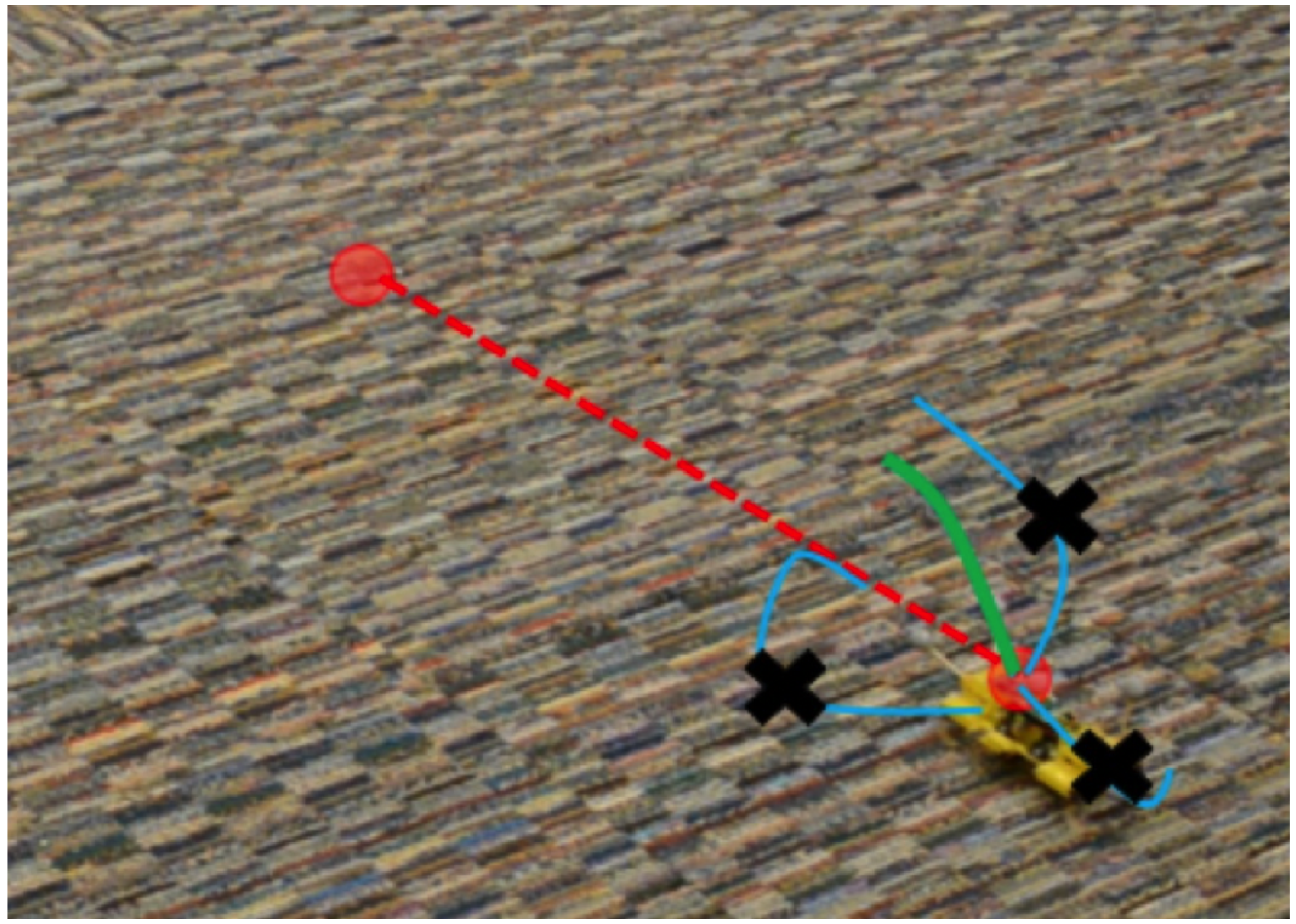
MPC - Model Predictive Control



MPC - Model Predictive Control

- 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.

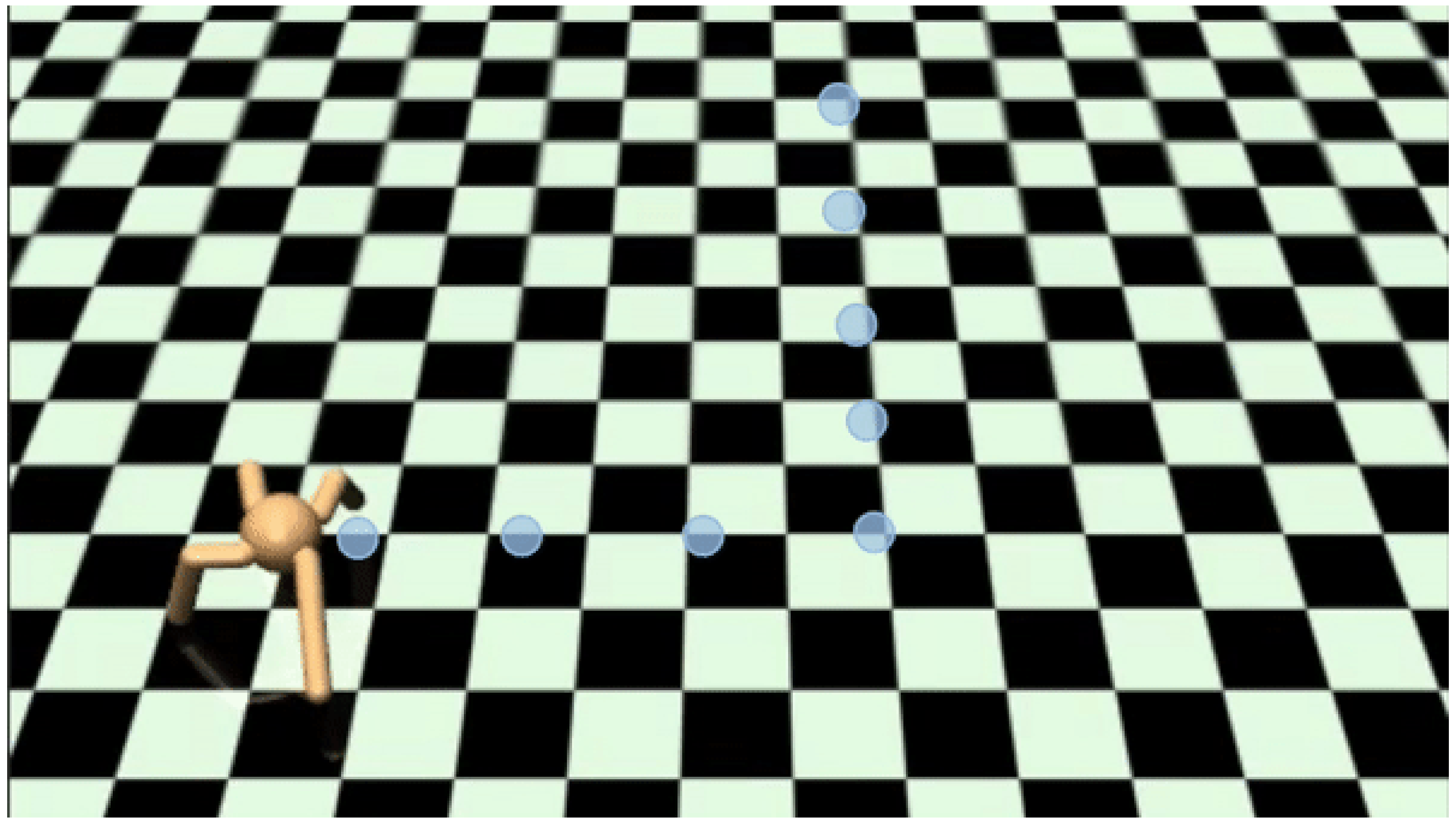


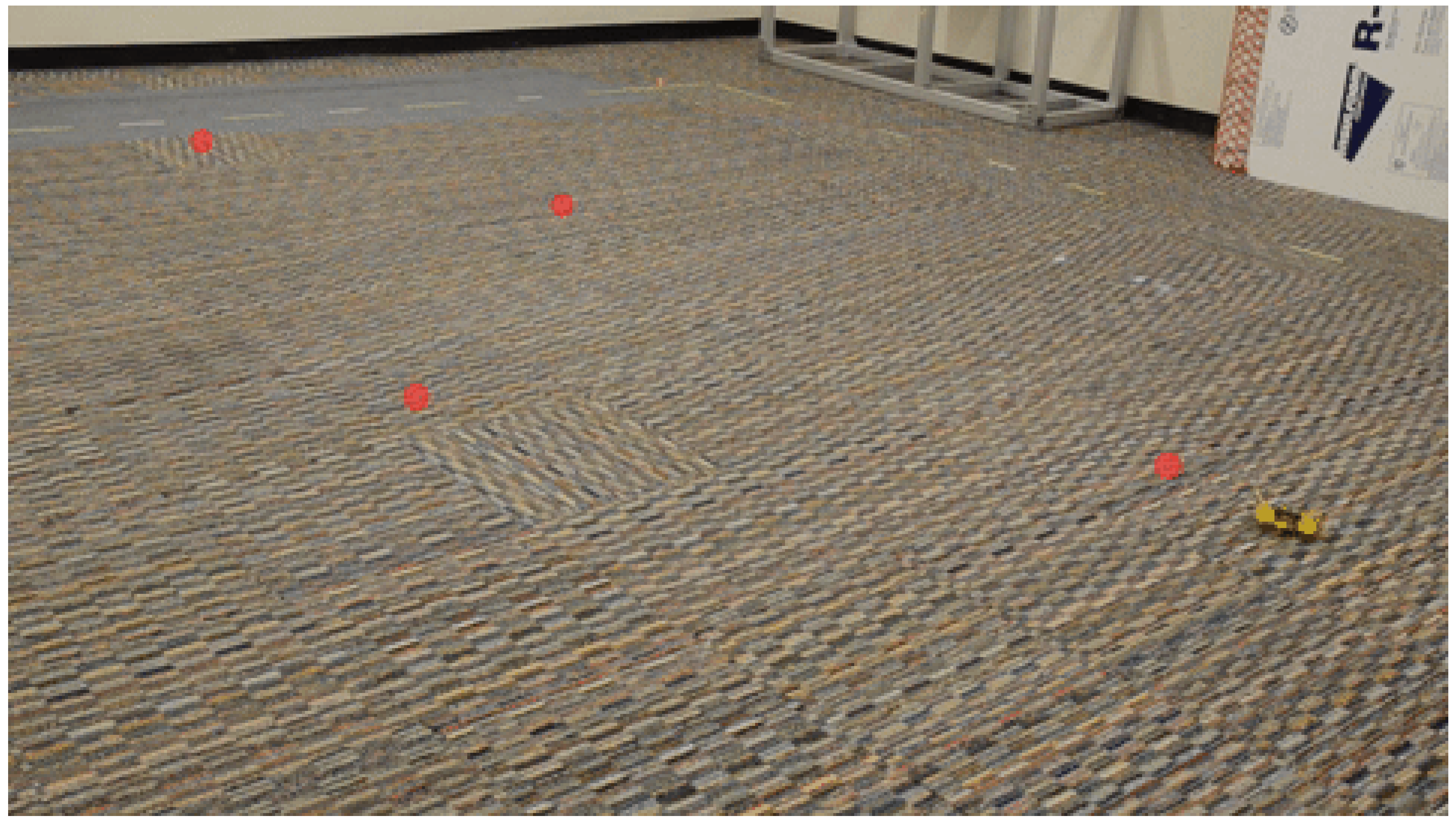
- Alternatively, one can use **random-sampling shooting**:
  1. in the current state, select a set of possible actions.
  2. generate rollouts with these action and compute their returns using the model.
  3. select the action whose rollout has the highest return.

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

MPC - Model Predictive Control

- 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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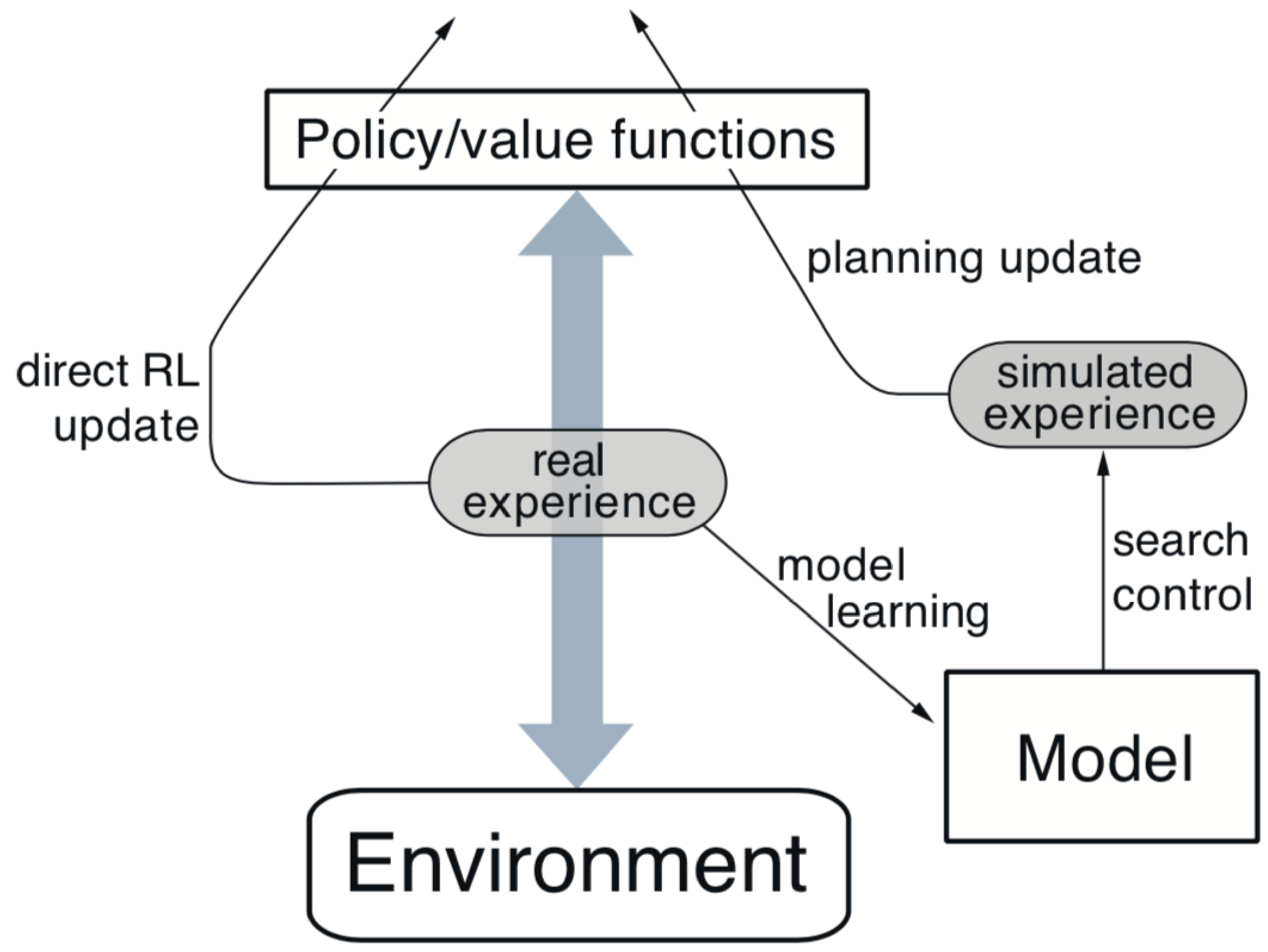
3 - Dyna-Q

Dyna-Q



Source: https://towardsdatascience.com/reinforcement-learning-model-based-planning-methods-5e99cae0abb8

- 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.

Sutton, R. S. (1990). Integrated Architectures for Learning, Planning, and Reacting Based on Approximating Dynamic Programming. Machine Learning Proceedings.

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:

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

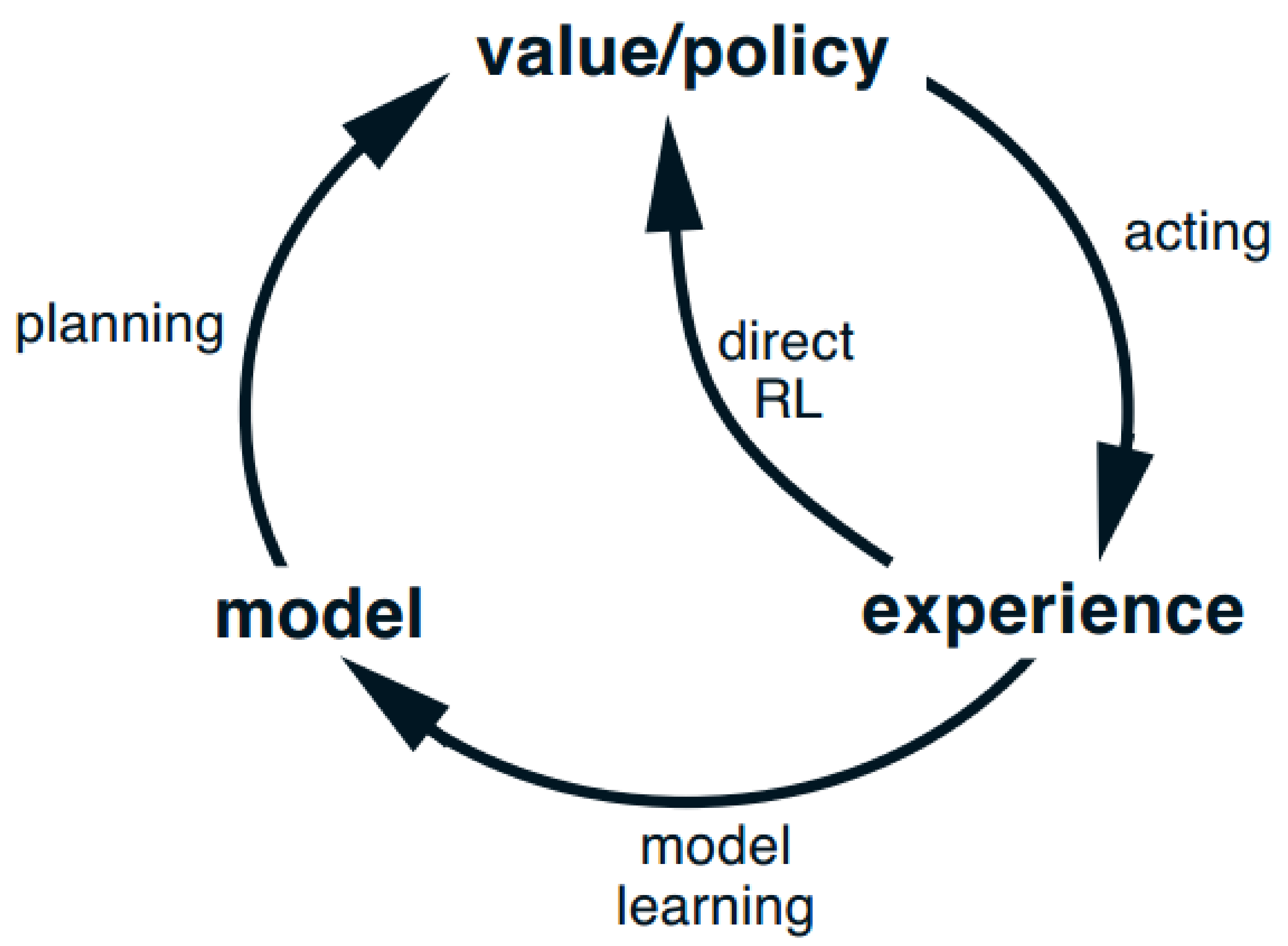
    - Update the model:

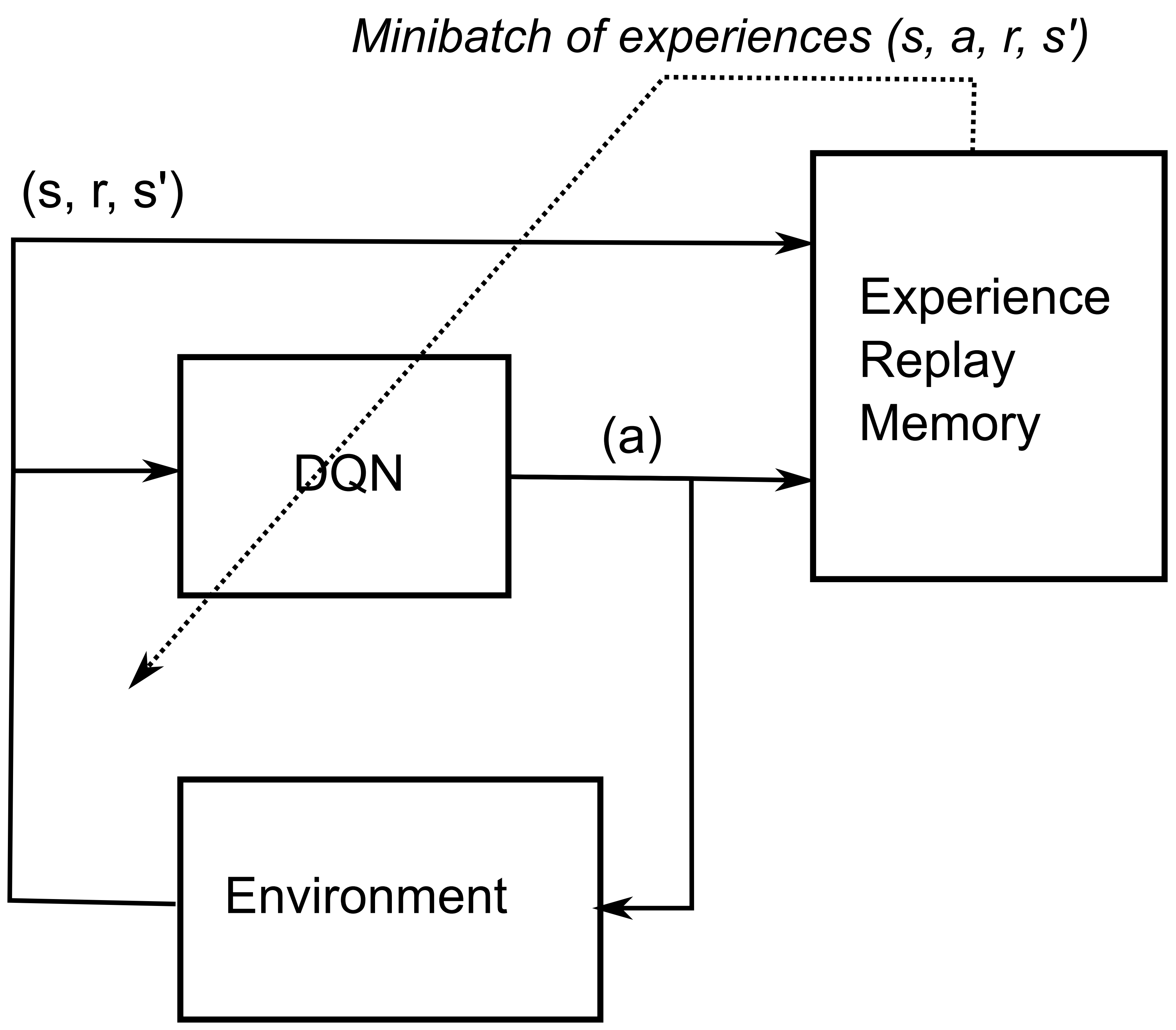
$$M(s, a) \leftarrow (s_{t+1}, r_{t+1})$$

    - **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:

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

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.