On the Cheating of Offline RL

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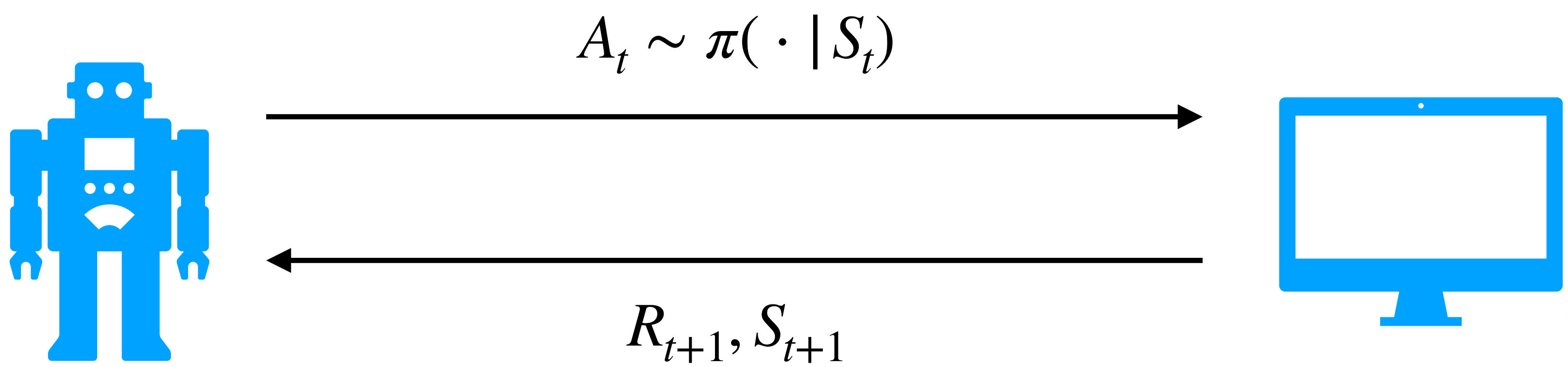
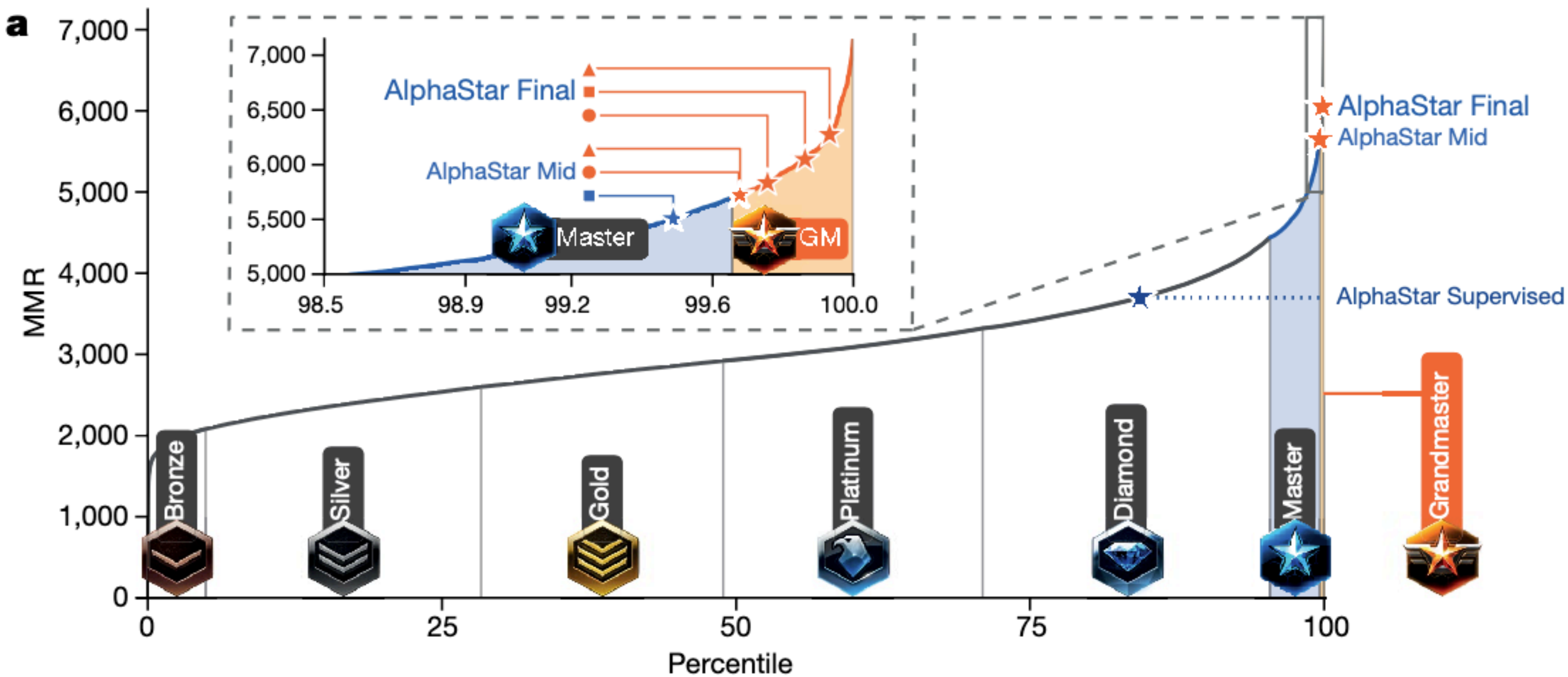
Canonical RL relies on agent-env interaction



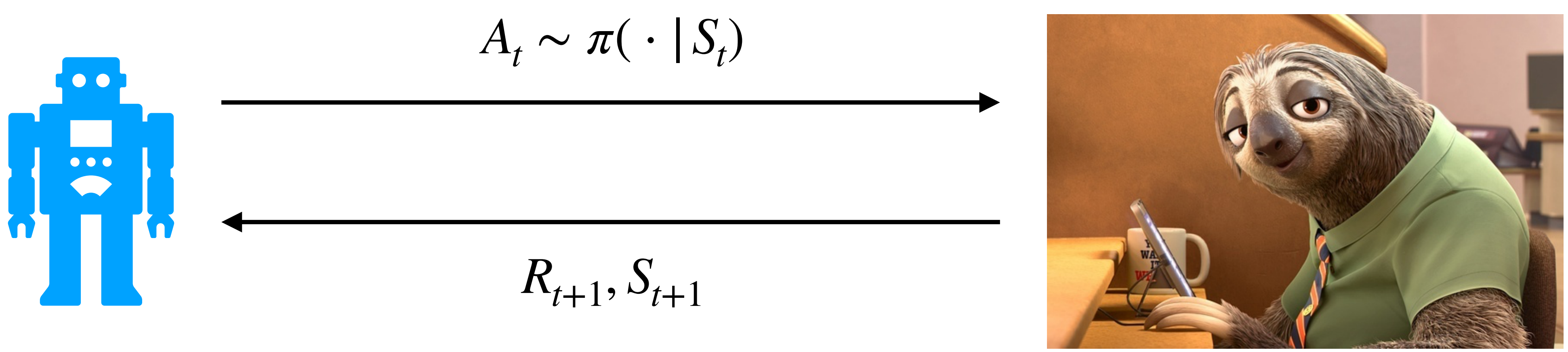
Case study: AlphaStar



(Vinyals et al. 2019)

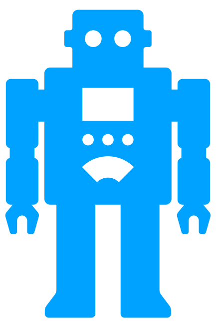
Trillions of interactions with SCII simulator!

Online interaction can be slow



DMV

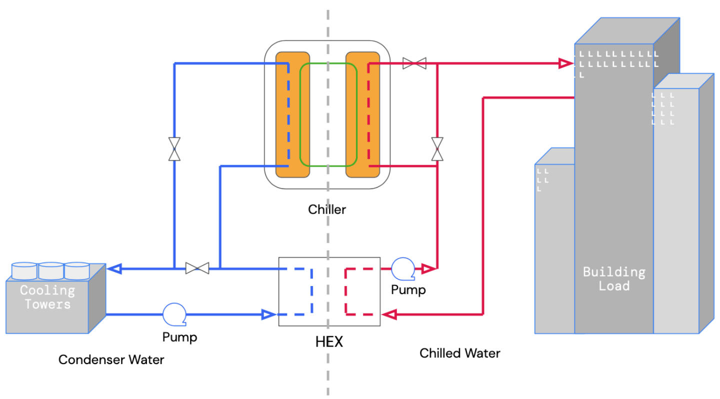
Case study: industrial cooling system



$A_t \sim \pi(\cdot \mid S_t)$

5 mins - 1 hour

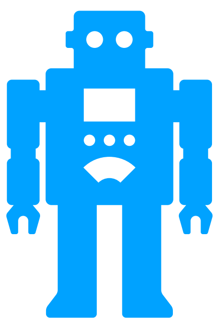
R_{t+1}, S_{t+1}



(Chervonyi et al. 2022)

1M training steps is nothing in RL

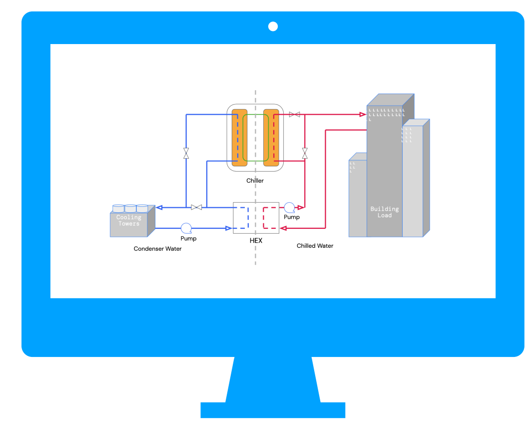
Case study: industrial cooling system



$A_t \sim \pi(\cdot \mid S_t)$

10 seconds

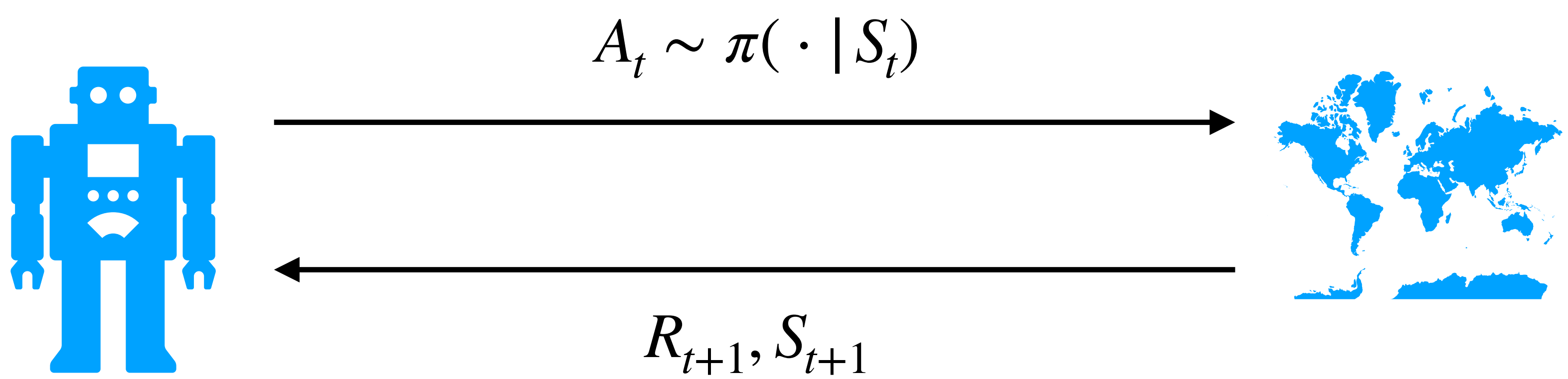
R_{t+1}, S_{t+1}



(Chervonyi et al. 2022)

$10 \times 10^6 \div 3600 \div 24 \approx 116$ **days**

Online interaction can be dangerous

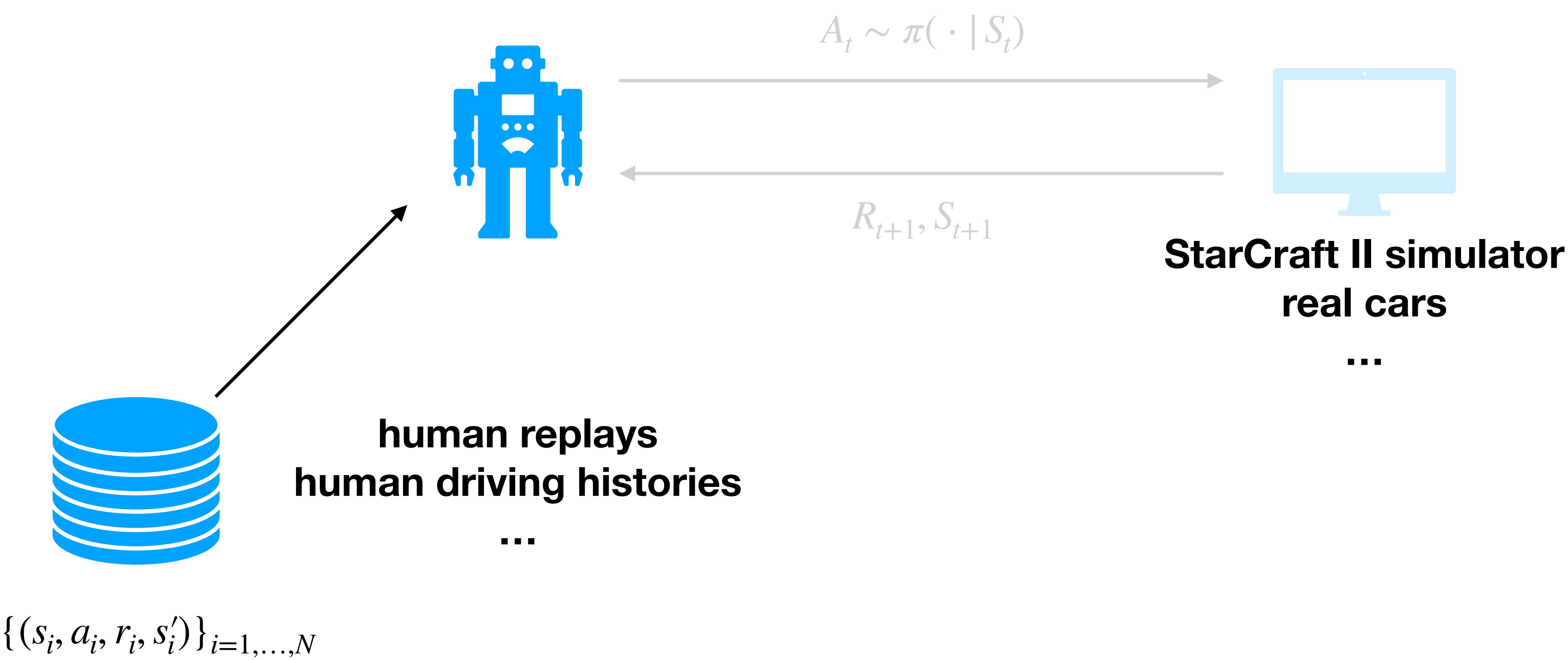


TECH NEWS

Self-driving Uber car that hit and killed woman did not recognize that pedestrians jaywalk

The automated car lacked "the capability to classify an object as a pedestrian unless that object was near a crosswalk," an NTSB report said.

Offline RL uses previously logged data



Case study: Offline AlphaStar

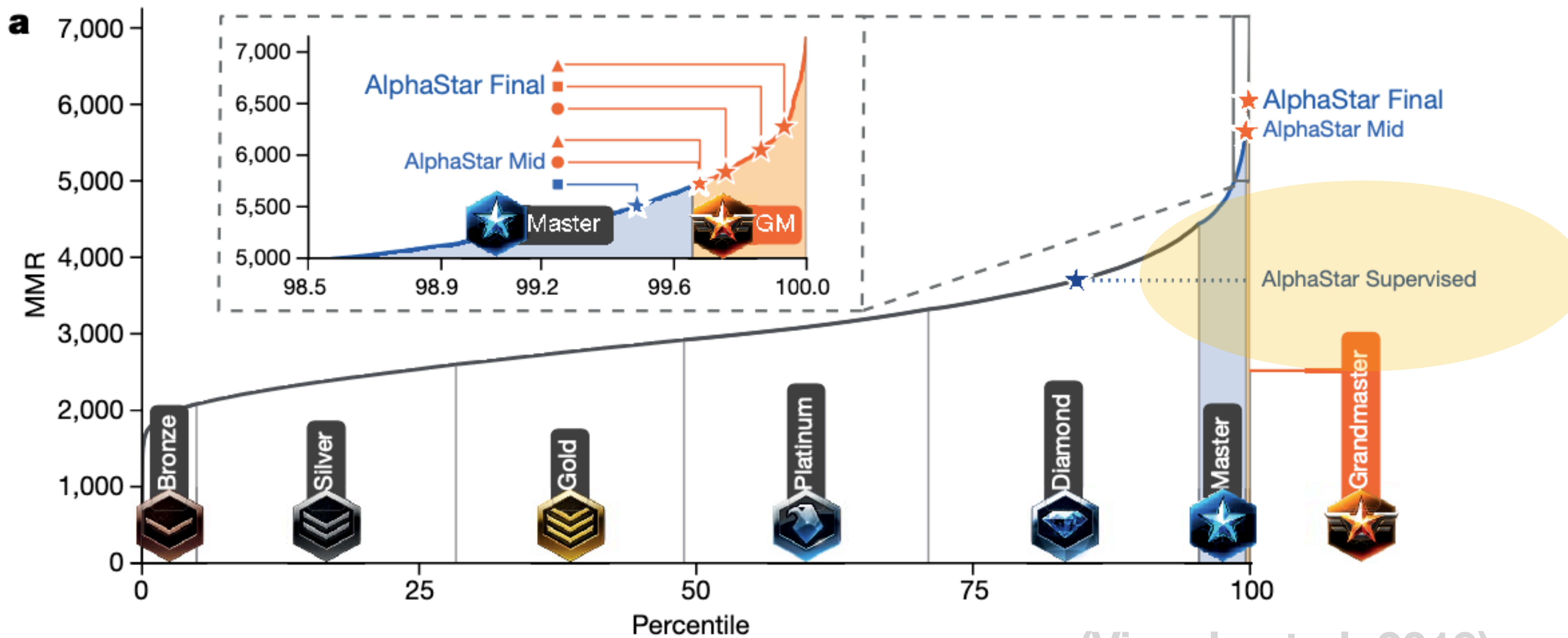
DeepMind

2023-8-8

AlphaStar Unplugged: Large-Scale Offline Reinforcement Learning

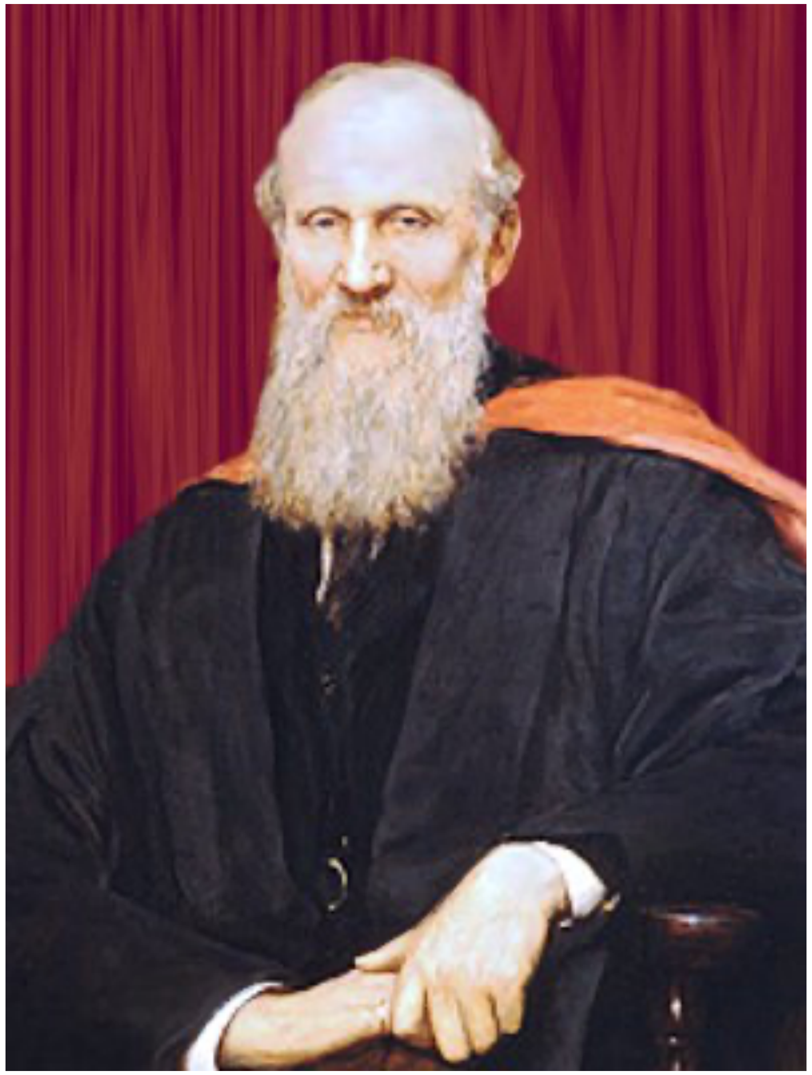
Michaël Mathieu[*,1], Sherjil Ozair[*,1], Srivatsan Srinivasan[*,1], Caglar Gulcehre[*,1], Shangtong Zhang[*,2], Ray Jiang[*,1], Tom Le Paine[*,1], Richard Powell[1], Konrad Żołna[1], Julian Schrittwieser[1], David Choi[1], Petko Georgiev[1], Daniel Toyama[1], Aja Huang[1], Roman Ring[1], Igor Babuschkin[1], Timo Ewalds[1], Mahyar Bordbar[1], Sarah Henderson[1], Sergio Gómez Colmenarejo[1], Aäron van den Oord[1], Wojciech Marian Czarnecki[1], Nando de Freitas[1] and Oriol Vinyals[1]

Case study: Offline AlphaStar



(Vinyals et al. 2019)

Offline AlphaStar has more than 90% win-rate against AlphaStar Supervised.



William Thomson, Lord Kelvin
1824 - 1907

Only two small clouds remained on the horizon of knowledge in ~~physics~~ offline RL.

Kyunghyun Cho
@kchonyc

how do people tune hyperparameters in offline reinforcement learning???

3:26 PM · Jun 23, 2023 · **105.2K** Views

Kyunghyun Cho

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Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation K Cho, B van Merrienboer, C Gulcehre, F Bougares, H Schwenk, ... Conference on Empirical Methods in Natural Language Processing (EMNLP 2014)	28511	2014
Empirical evaluation of gated recurrent neural networks on sequence modeling J Chung, C Gulcehre, KH Cho, Y Bengio arXiv preprint arXiv:1412.3555	15084	2014

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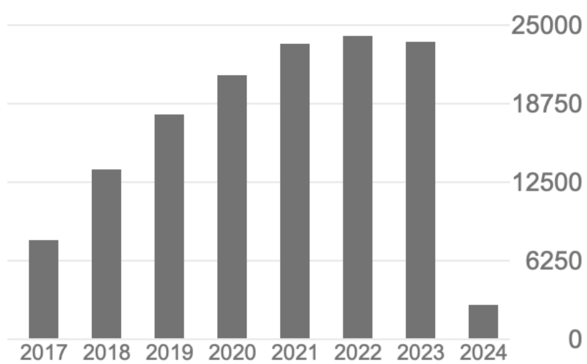

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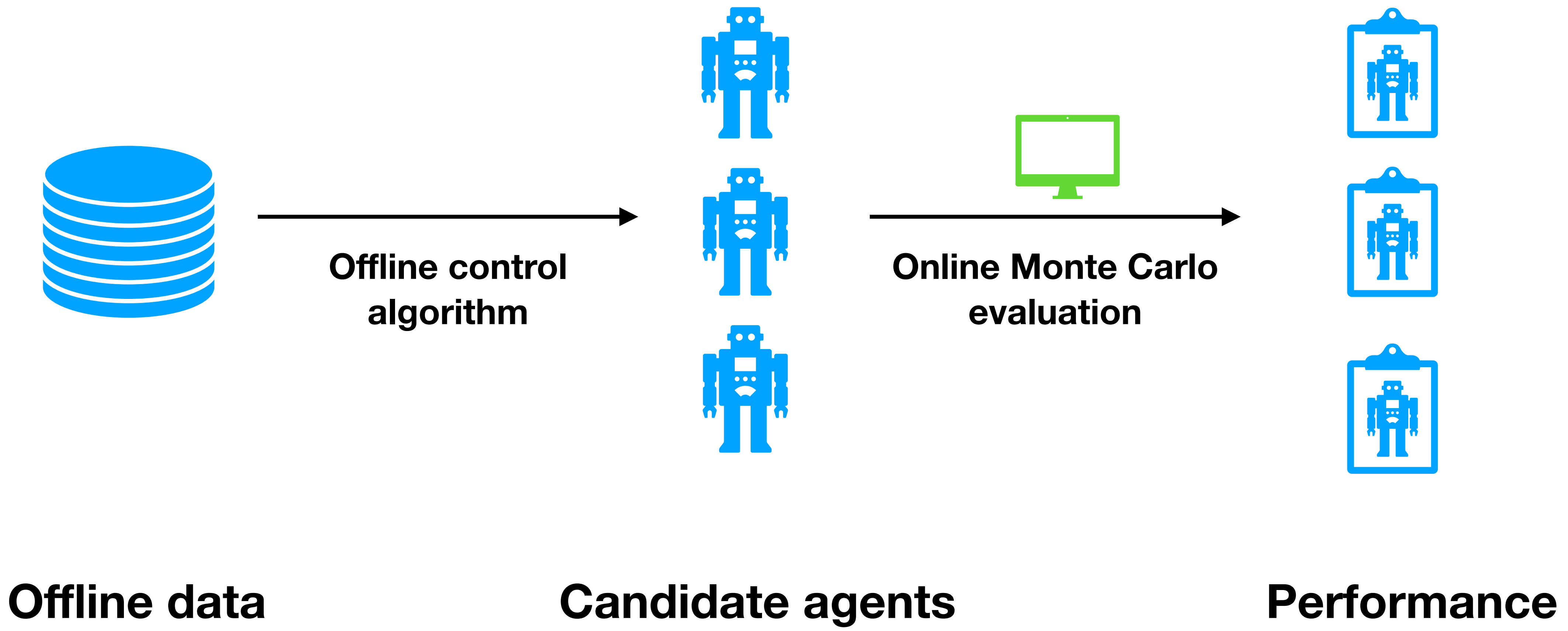
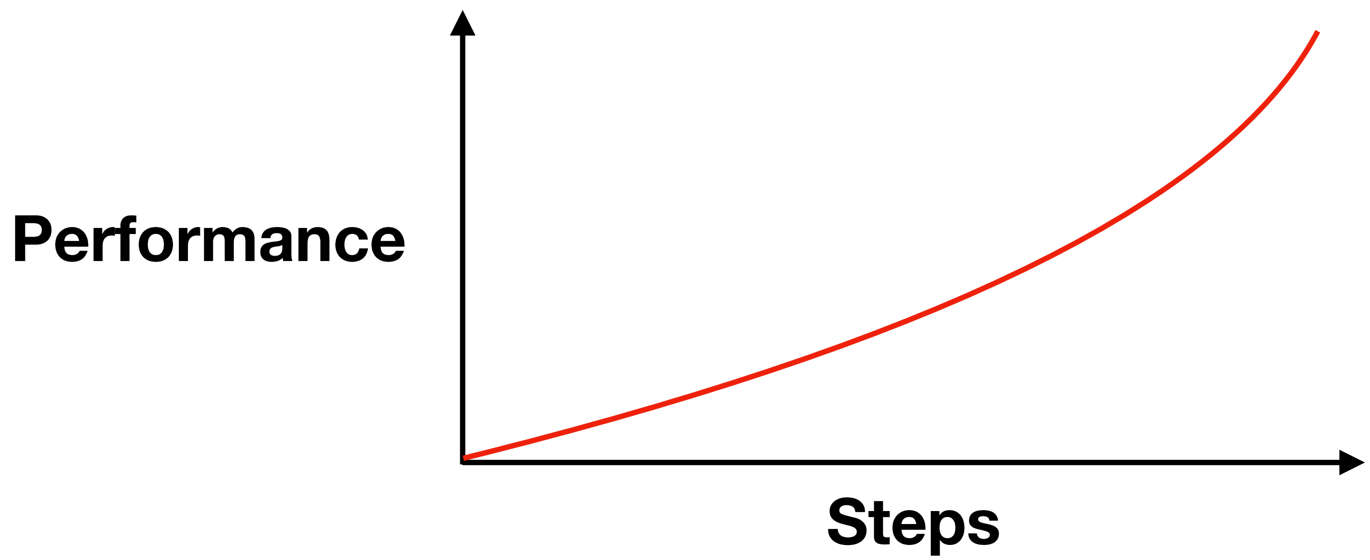
Offline RL uses simulator for model selection

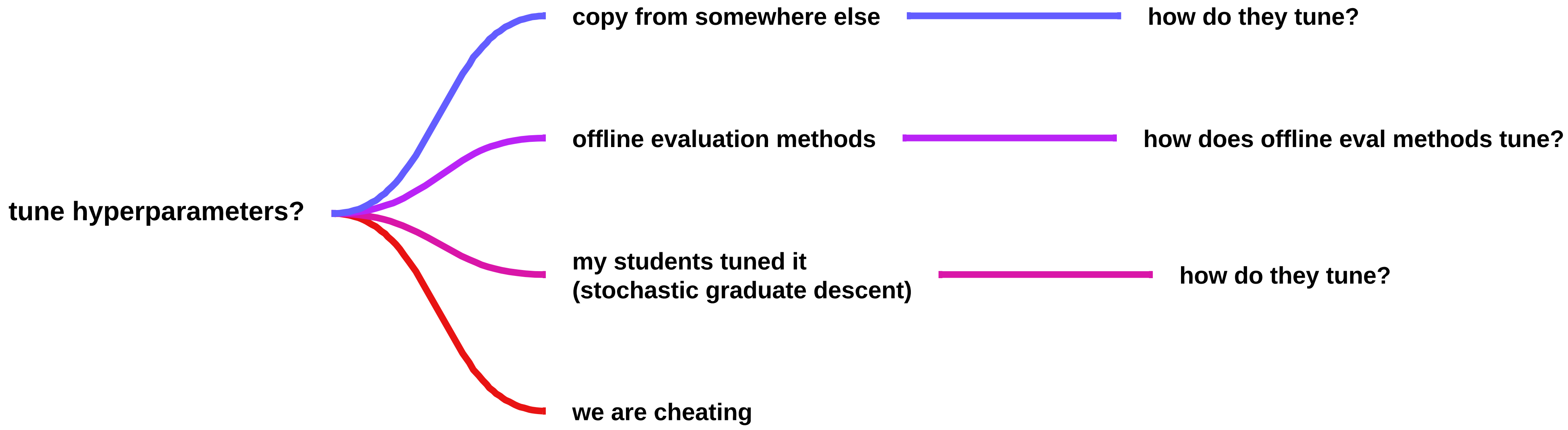


Monte Carlo dominates RL evaluation



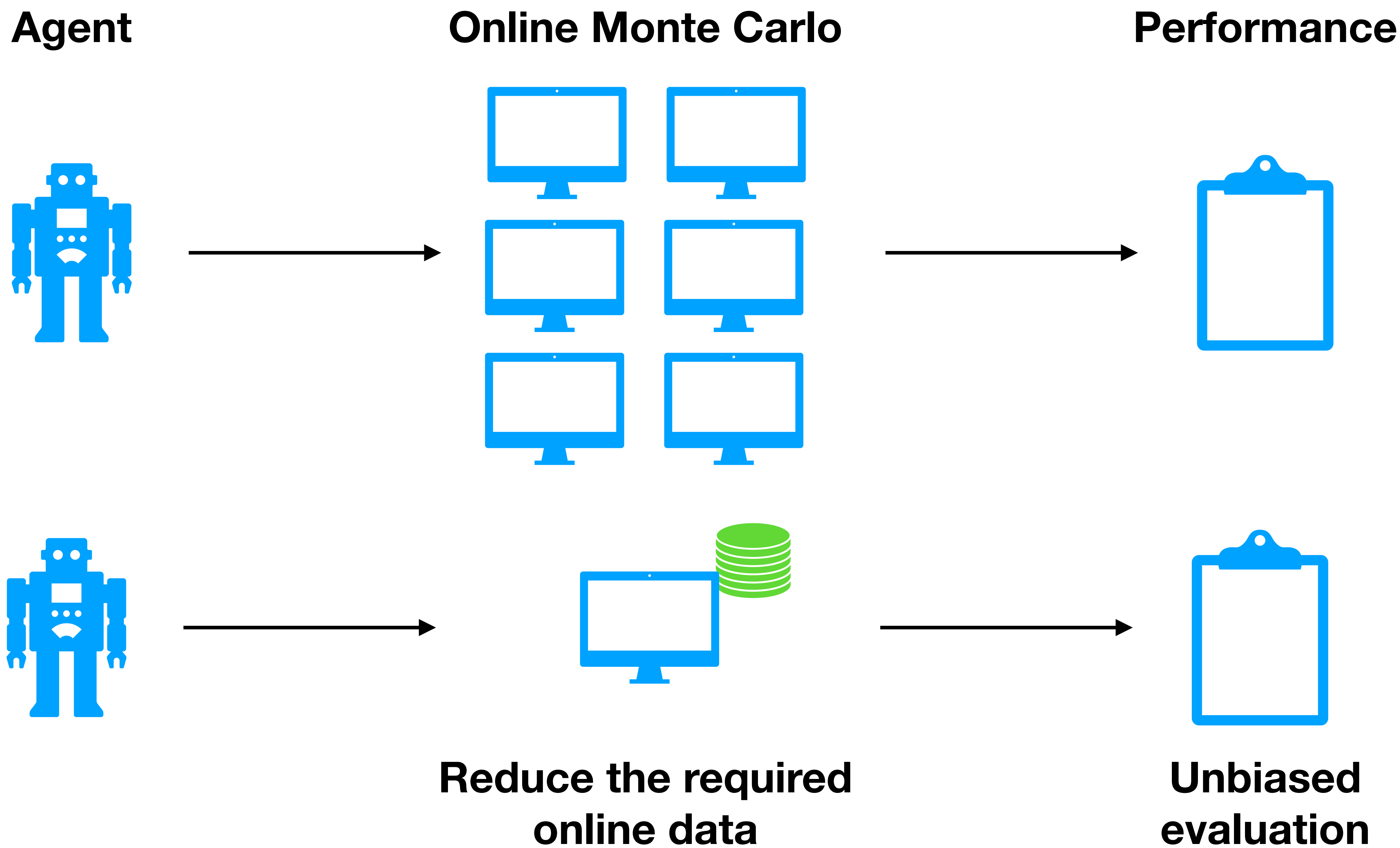
99% of such curves in RL papers are generated by online Monte Carlo

Guideline for attending offline RL talks / posters



Simulator!!!

Our approach: admit that we have to use Monte Carlo but try to use Monte Carlo smartly



Improving Monte Carlo Evaluation with Offline Data.
Shuze Liu, Shangtong Zhang. arXiv:2301.13734, 2023.

Thanks & Questions

Build intuition with STAT 101

- Estimating an expectation $\mathbb{E}_{X \sim p}[f(X)]$
- Monte Carlo $\frac{1}{N}\sum_{i=1}^{N} f(X_i), \quad X_i \sim p$
- Importance sampling

$$\mathbb{E}_{X \sim p}\left[f(X)\right] = \mathbb{E}_{X \sim q}\left[\frac{p(X)}{q(X)} f(X)\right] \qquad \frac{1}{N}\sum_{i=1}^{N} \frac{p(X_i)}{q(X_i)} f(X_i), \quad X_i \sim q$$

- Optimal sampling distribution minimizing the variance

$$q(x) = \frac{p(x)\,|\,f(x)\,|}{\sum_y p(y)\,|\,f(y)\,|}$$

From STAT 101 to RL 999

- Data in RL $\{S_0, A_0, R_1, S_1, A_1, R_2, \ldots, R_T\} \sim \mu$

- Per-decision importance sampling ratio Monte Carlo estimator

$$\sum_{t=1}^{T} \left(\prod_{i=0}^{t-1} \frac{\pi(A_i \mid S_i)}{\mu(A_i \mid S_i)} \right) R_t$$

"Improving Monte Carlo Evaluation with Offline Data."
Shuze Liu, Shangtong Zhang
arXiv:2301.13734, 2023.

- A **provably** variance reducing behavior policy for the per-decision MC estimator

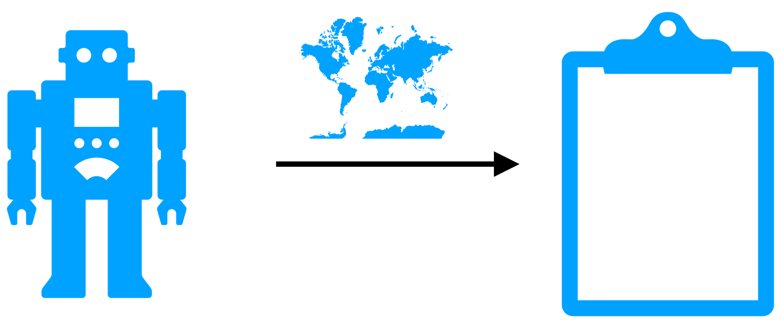
$$\sum_{t=1}^{T} \left(\prod_{i=0}^{t-1} \frac{\pi(A_i \,|\, S_i)}{\mu(A_i \,|\, S_i)} \right) R_t$$

- A computationally efficient and model-free method to learn this behavior policy from offline data

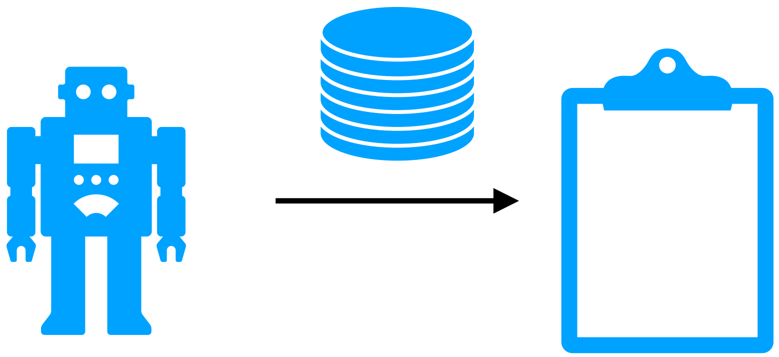
Searching good behavior policies for off-policy MC is not new

- Some cannot exploit offline data and require new online data
- Some assume special structure of the MDP and need to learn a model

It is desired to do evaluation with offline data

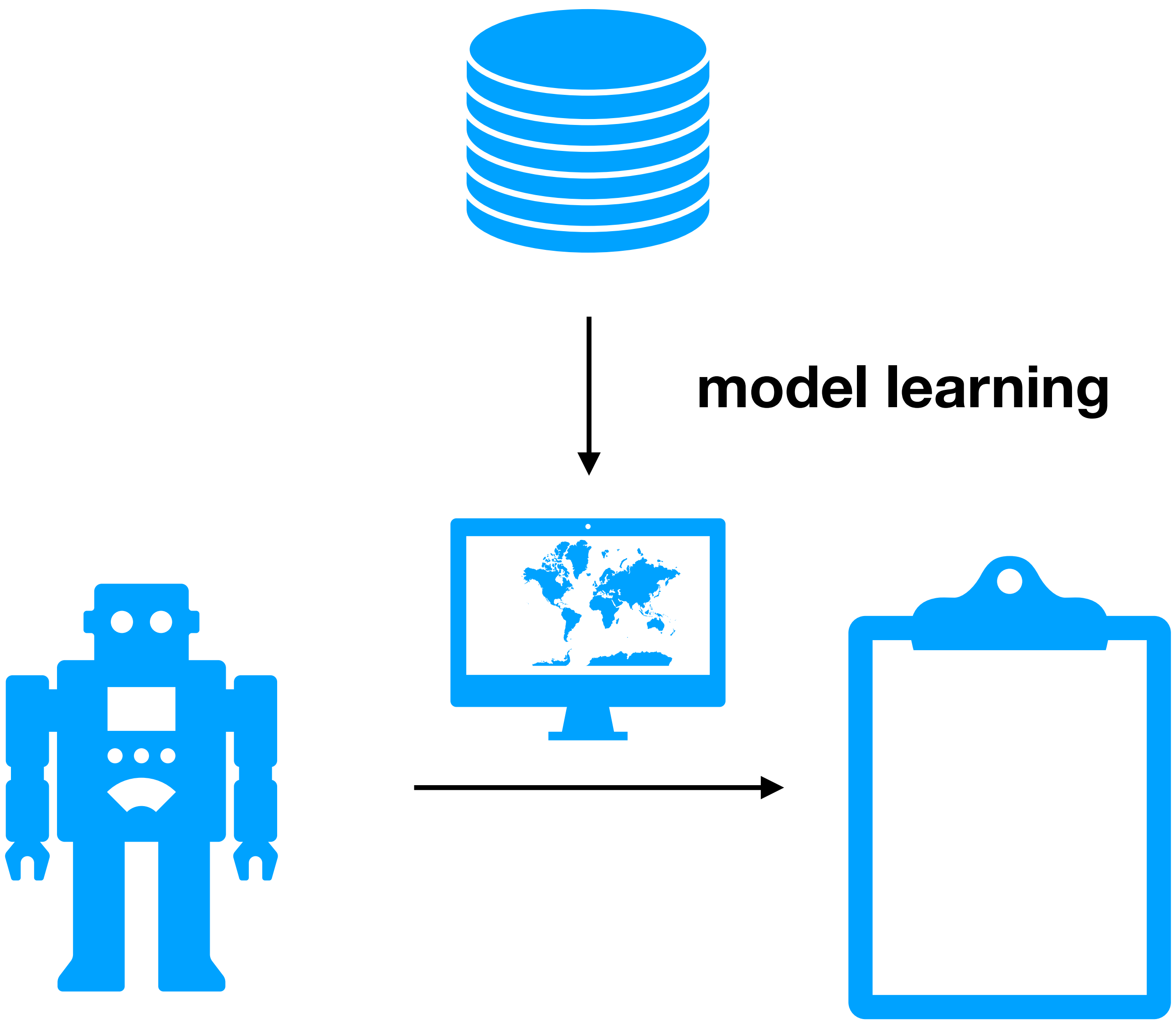


Online Monte Carlo

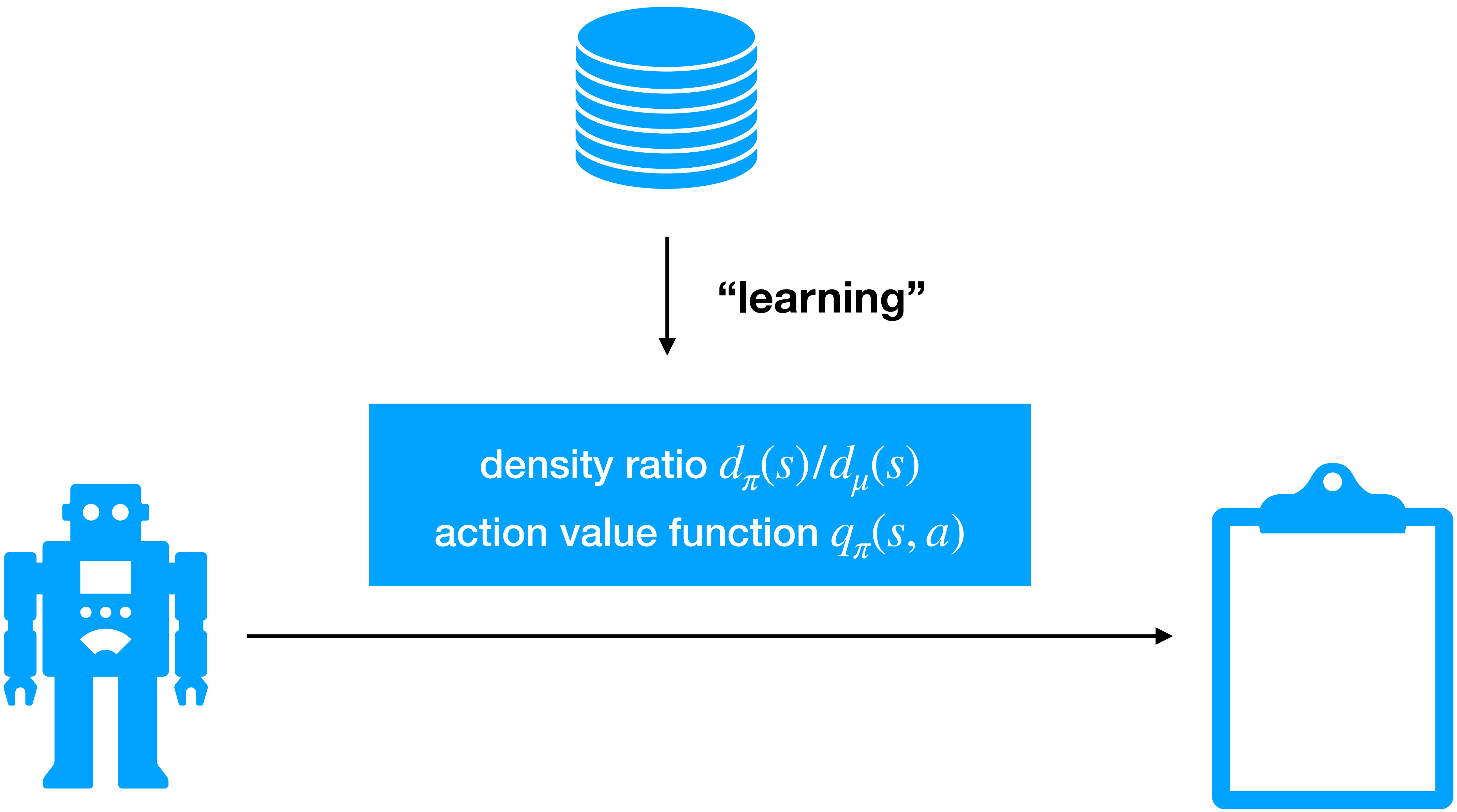


Offline data

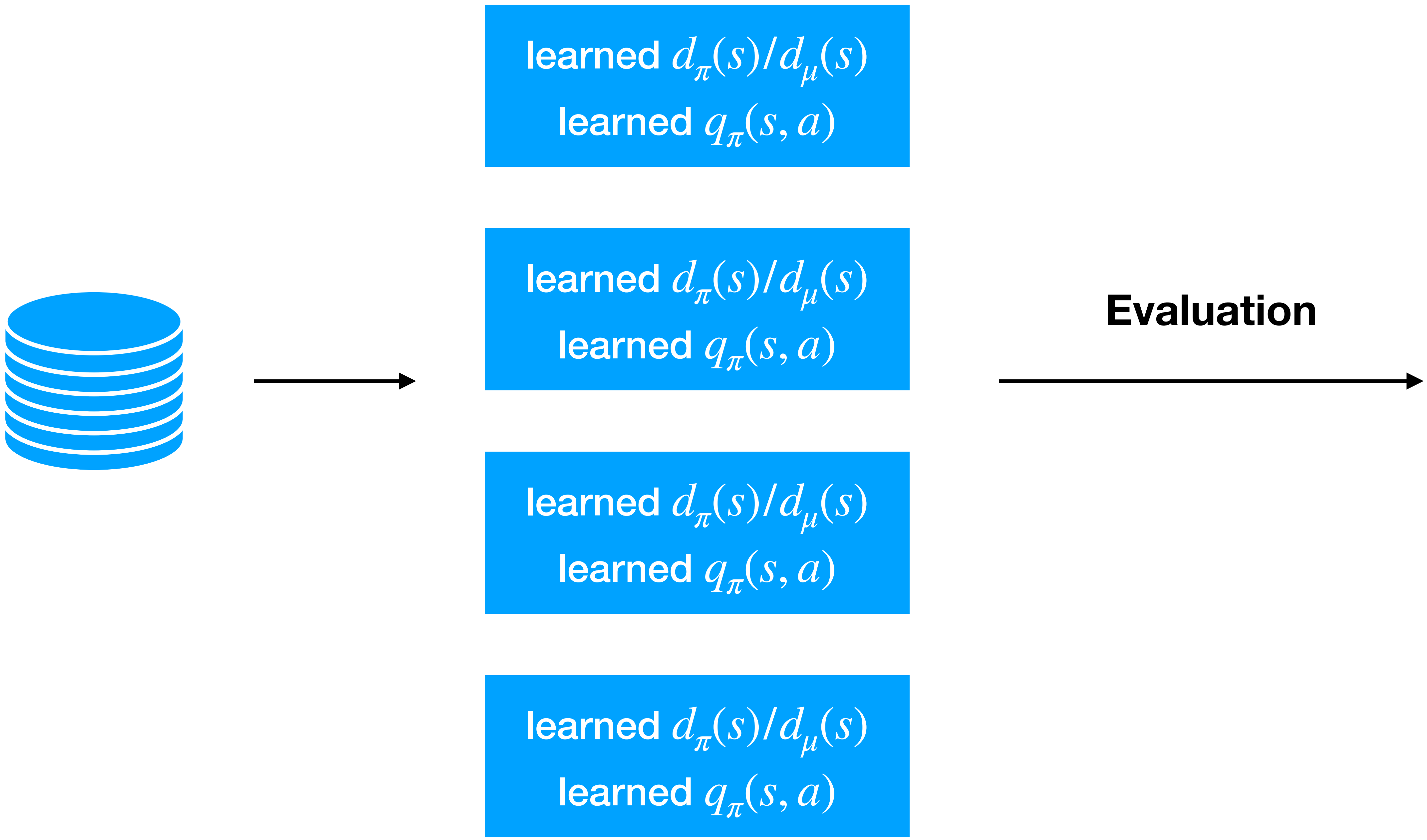
Model-based offline evaluation reduces to simulator



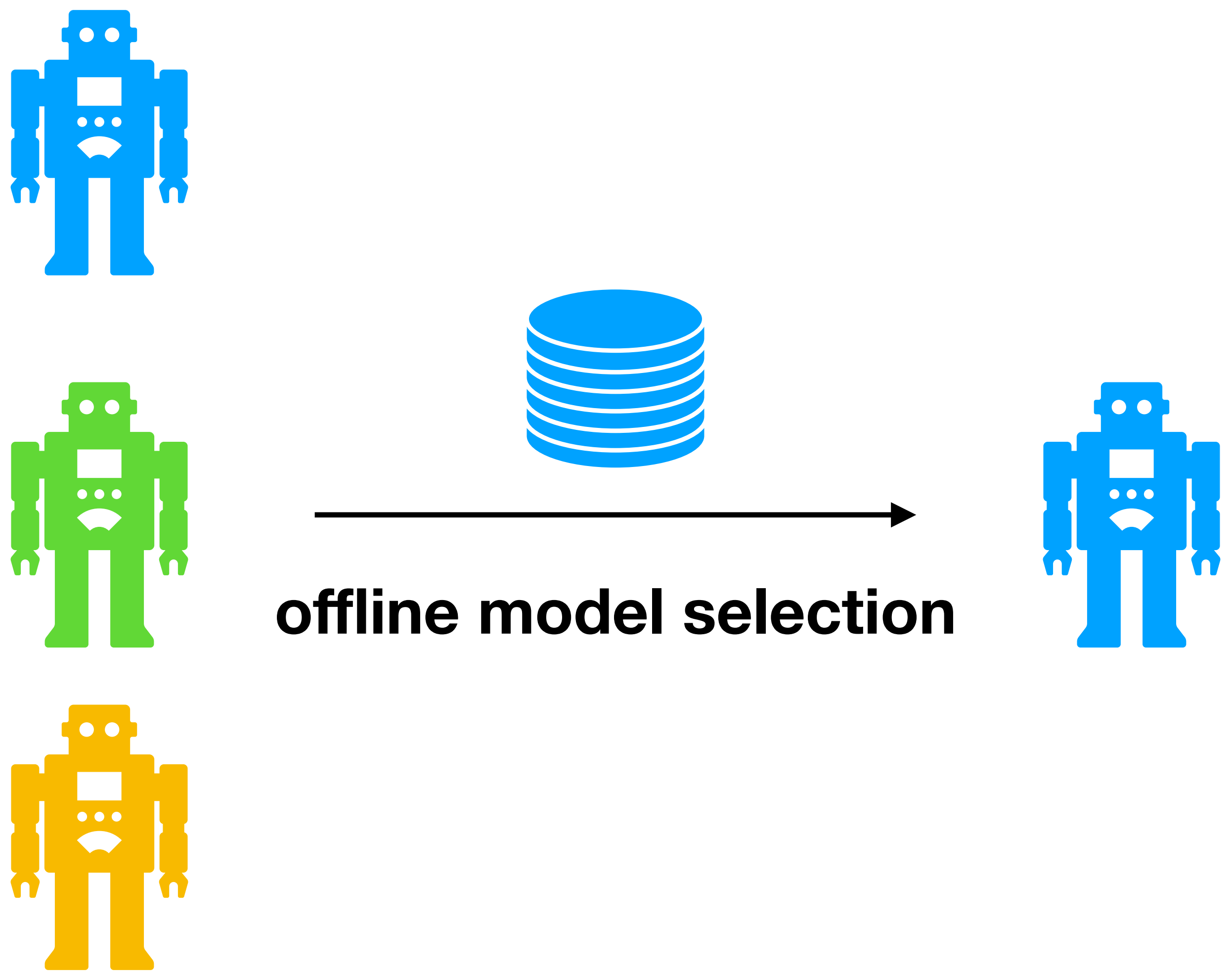
Model-free offline evaluation reduces to model-selection



Model-free offline evaluation reduces to model-selection

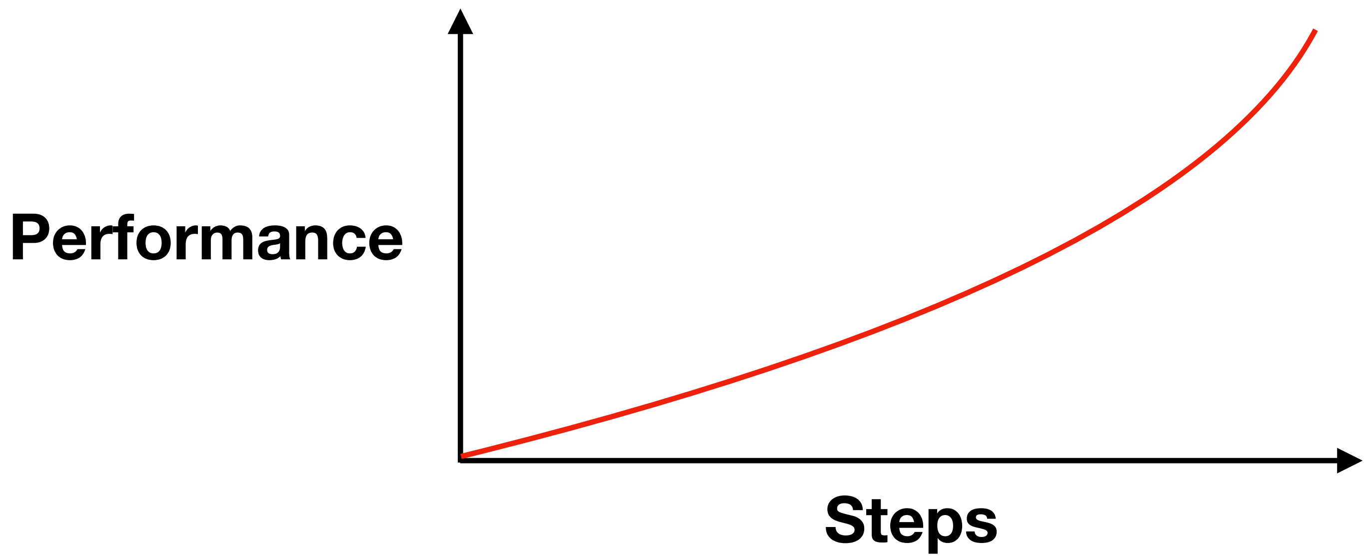


Offline model selection hardly has correctness guarantee



Pitfalls of offline evaluation methods

Bias! Bias! Bias!



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