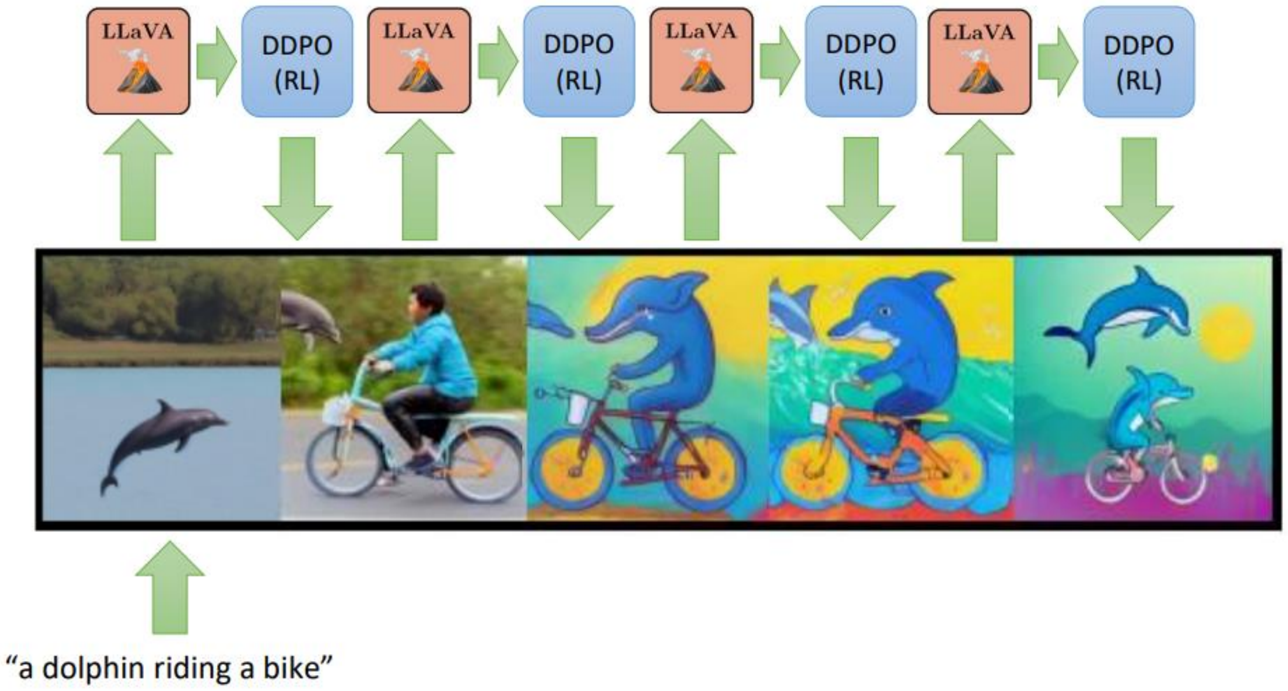
Introduction To Reinforcement Learning



Lancaster AI Reading Group – 22nd January 2025

Based on CS285 Berkeley Course

Machine Learning

A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E.

By Tom Mitchell (Prof. Carnegie Mellon University):

Experience

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$$\{(x_1, y_1), \ldots, (x_N,\ y_N)\}$$

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$$\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N\}$$

Experience

$$\{(x_1, y_1), \ldots, (x_N,\ y_N)\}$$

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That is not always the case!

The 3 ML Settings

Supervised Learning

Unsupervised Learning

Reinforcement Learning

The 3 ML Settings

Supervised Learning	Unsupervised Learning	Reinforcement Learning
$\{(x_1, y_1), \ldots, (x_N, y_N)\}$	$\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N\}$	?
Learn p(y|x)	Learn p(x)	

The 3 ML Settings

Supervised Learning

$$\{(x_1, y_1), \ldots, (x_N,\ y_N)\}$$

Learn p(y|x)

Unsupervised Learning

$$\{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N\}$$

Learn p(x)

Reinforcement Learning

- Environment

The 3 ML Settings

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Reinforcement Learning

- Environment
- Agent
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Reinforcement Learning

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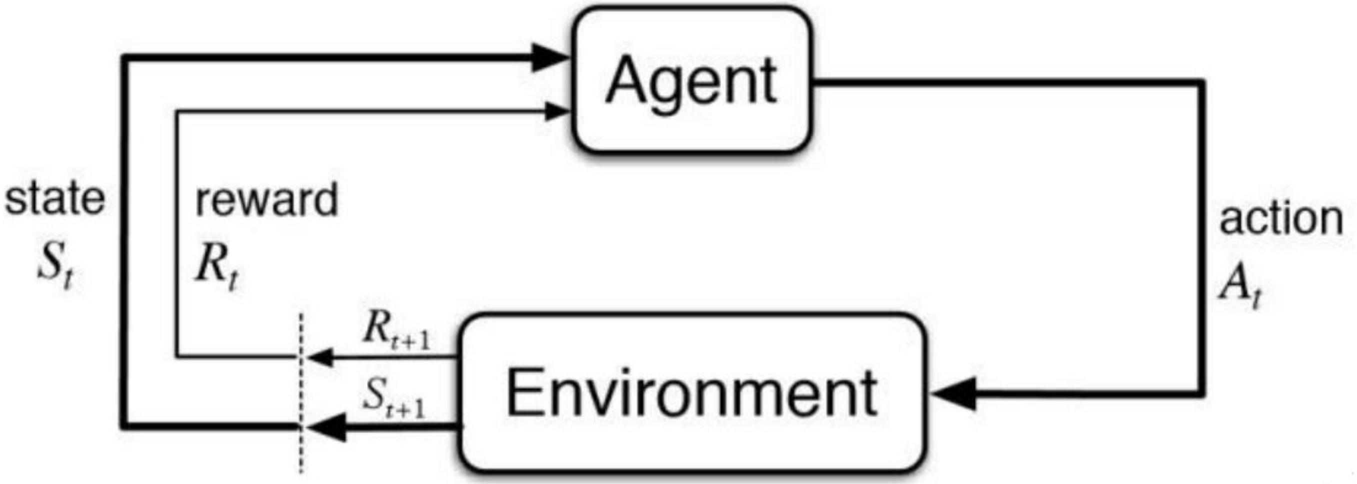
How to learn a policy that maximise the cumulative reward?

The RL Framework



Reinforcement Learning

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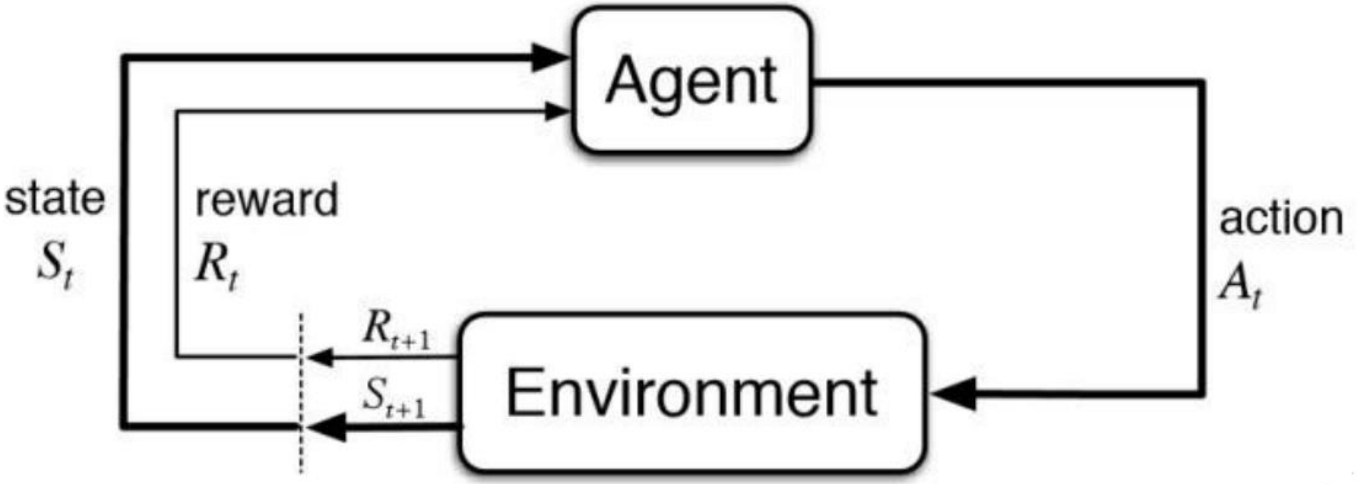

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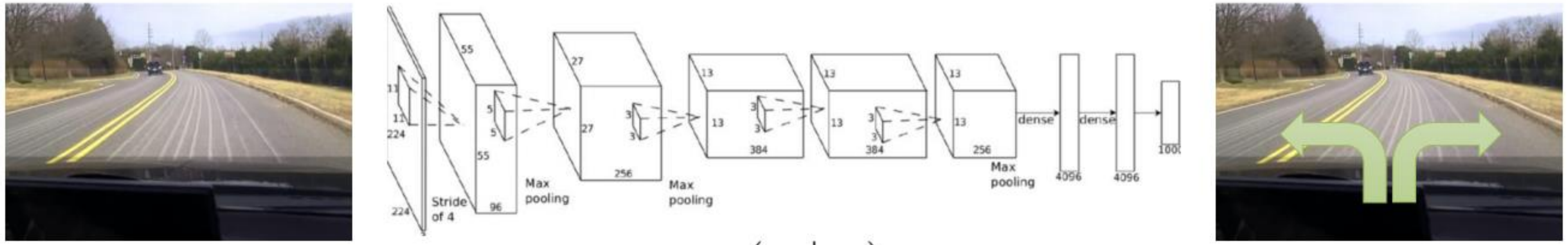


$\mathbf{o}_t$ $\pi_\theta(\mathbf{a}_t|\mathbf{o}_t)$ $\mathbf{a}_t$

RL Examples

RL Examples

Actions: muscle contractions
Observations: sight, smell
Rewards: food

Actions: motor current or torque
Observations: camera images
Rewards: task success measure (e.g., running speed)

Actions: what to purchase
Observations: inventory levels
Rewards: profit

What about the environments?

What about the environments?

OpenAI Gym

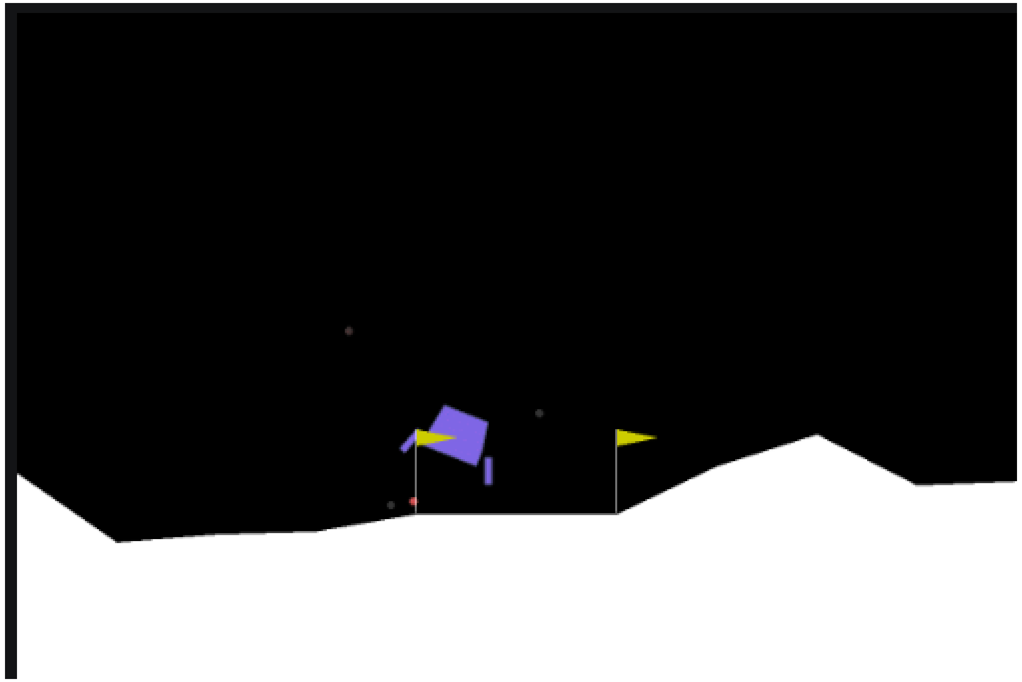
BRAX

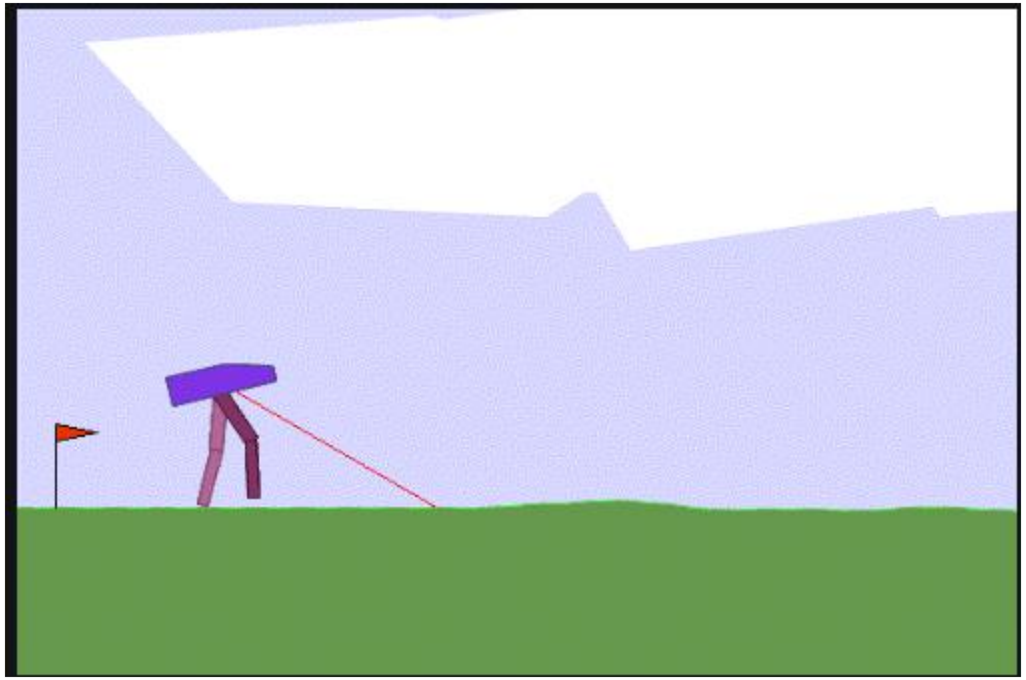
What about the environments?

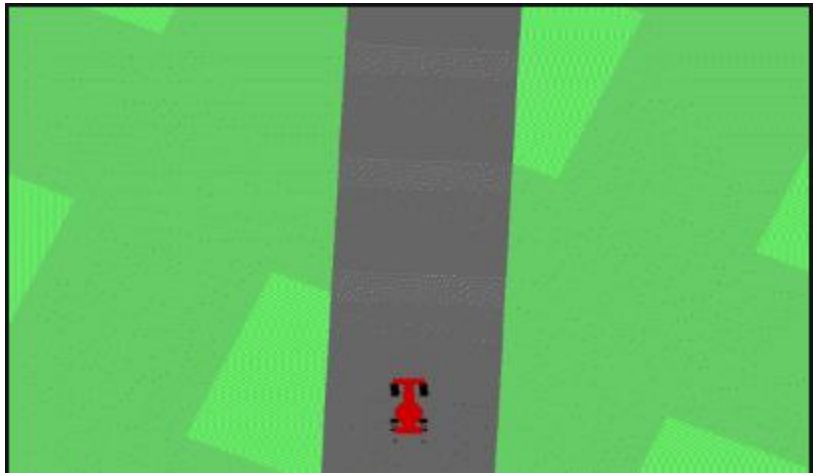
OpenAI Gym

```
import gym

# Create an environment
env = gym.make("Ant-v4", new_step_api=True)
# Reset the environment to an initial state
obs = env.reset()
# Take a random action
action = env.action_space.sample()
# Update the environment according to the action
obs, reward, done, info = env.step(action)

env.close()
```

Example Environments







How to learn a “good” policy?

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A simple RL algorithm: **REINFORCE**

How to learn a “good” policy?

A simple RL algorithm: **REINFORCE**

- Sample a trajectory from the current policy.

How to learn a “good” policy?

A simple RL algorithm: **REINFORCE**

$$\nabla_{\boldsymbol{\theta}} \mathbb{E}_{\tau \sim p_{\boldsymbol{\theta}}(\tau)} \left[\sum_t r(\mathbf{s}_t, \mathbf{a}_t) \right] \approx \frac{1}{N} \sum_{i=1}^{N} \left(\sum_{t=1}^{T} \nabla_{\boldsymbol{\theta}} \log \pi_{\boldsymbol{\theta}}(\mathbf{a}_{i,t} | \mathbf{s}_{i,t}) \right) \left(\sum_{i=1}^{T} r(\mathbf{s}_{i,t}, \mathbf{a}_{i,t}) \right)$$

- Sample a trajectory from the current policy.
- Estimate the gradient of the objective (use backpropagation in the case of Neural Networks).

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- Sample a trajectory from the current policy.
- Estimate the gradient of the objective (use backpropagation in the case of Neural Networks).
- Update the policy using a gradient based optimization algorithm.

The necessity of RL

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- Some tasks are hard to get supervised pairs from (e.g. movements of a robot).
- Supervised learning is not ideal for sequential decision making.
- RL allows for novel solutions.

Imitation Learning

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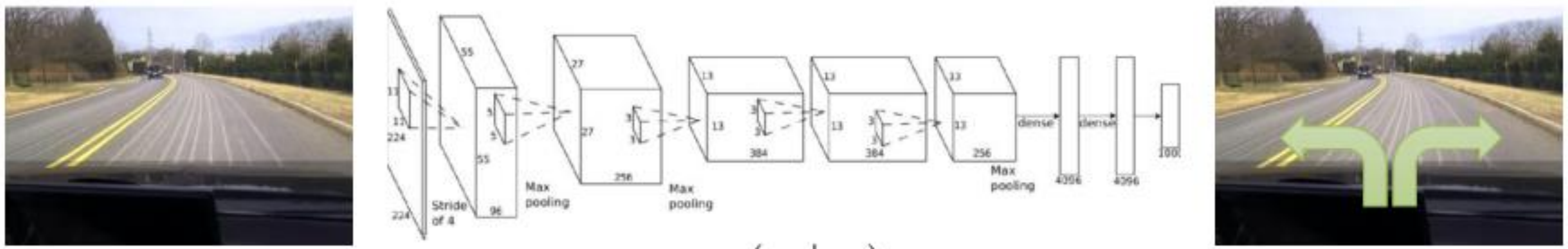

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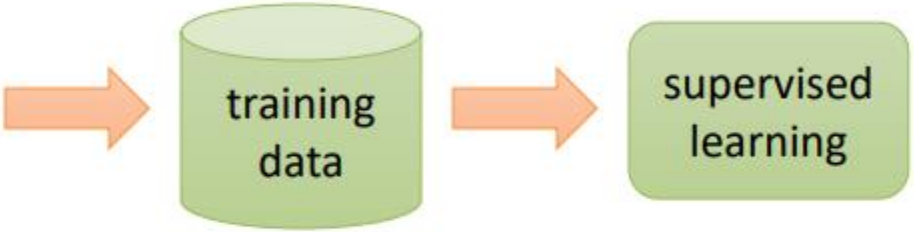

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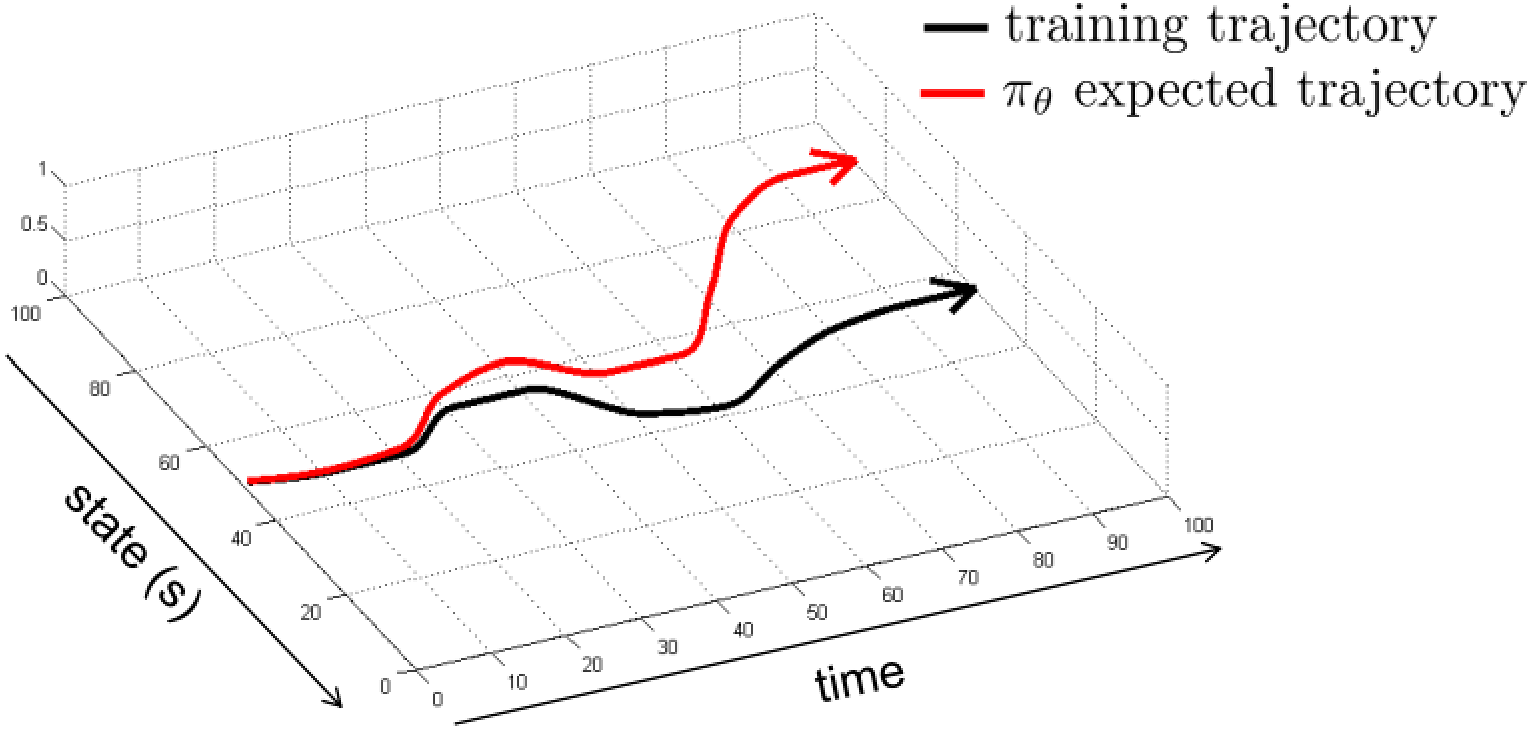

Data is not iid!

Recent advances in DL vs RL

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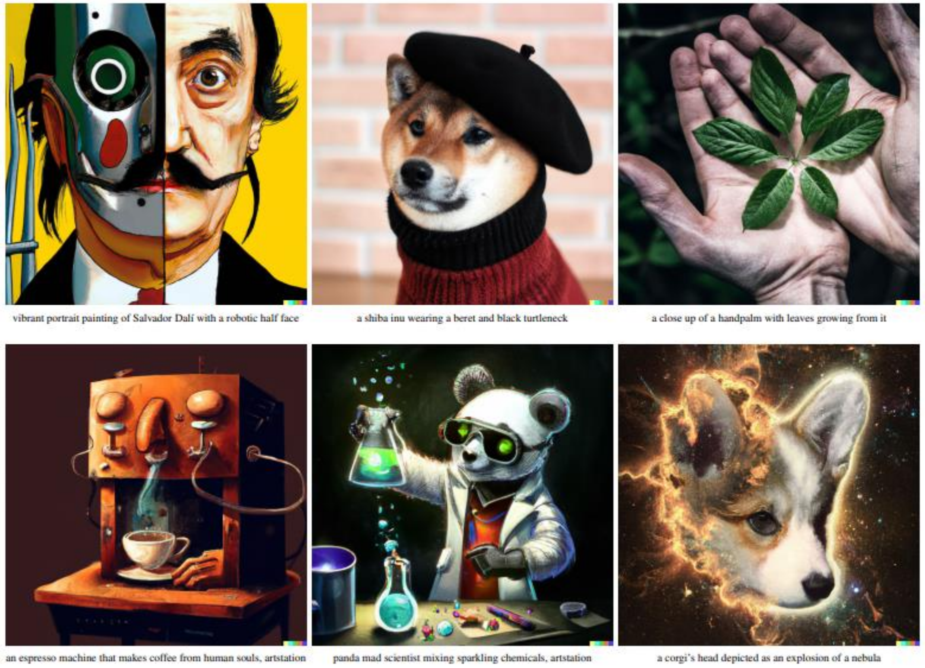

ChatGPT

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$p(x)$ $p(x|c)$ $p(y_n|y_{1:n-1})$

vibrant portrait painting of Salvador Dalí with a robotic half face
a shiba inu wearing a beret and black turtleneck
a close up of a handpalm with leaves growing from it
an espresso machine that makes coffee from human souls, artstation
panda mad scientist mixing sparkling chemicals, artstation
a corgi's head depicted as an explosion of a nebula

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Image/Video

$$p(x)$$

Text

$$p(x|c)$$

Next token

Prev tokens

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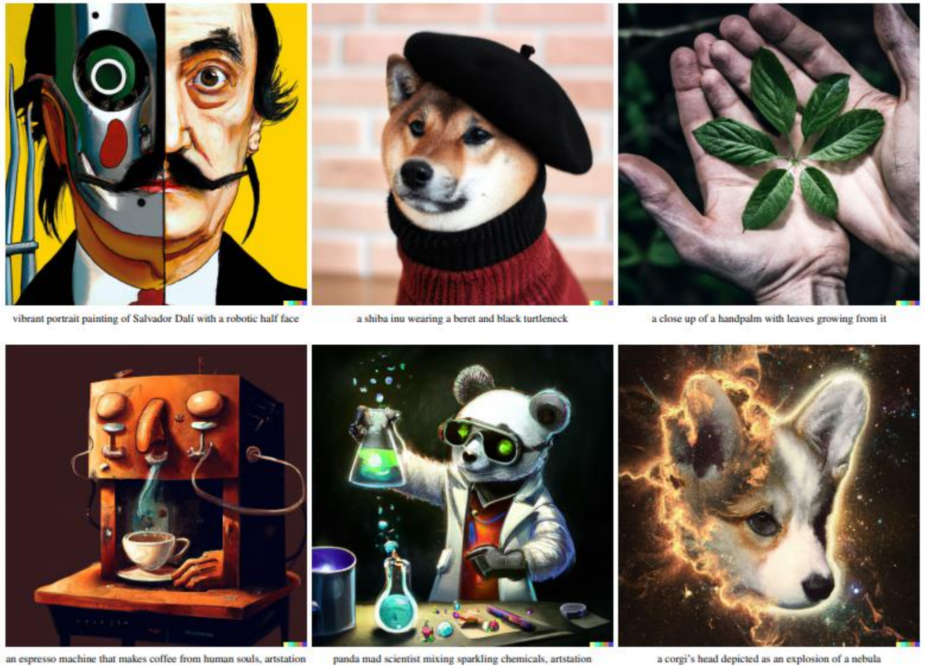

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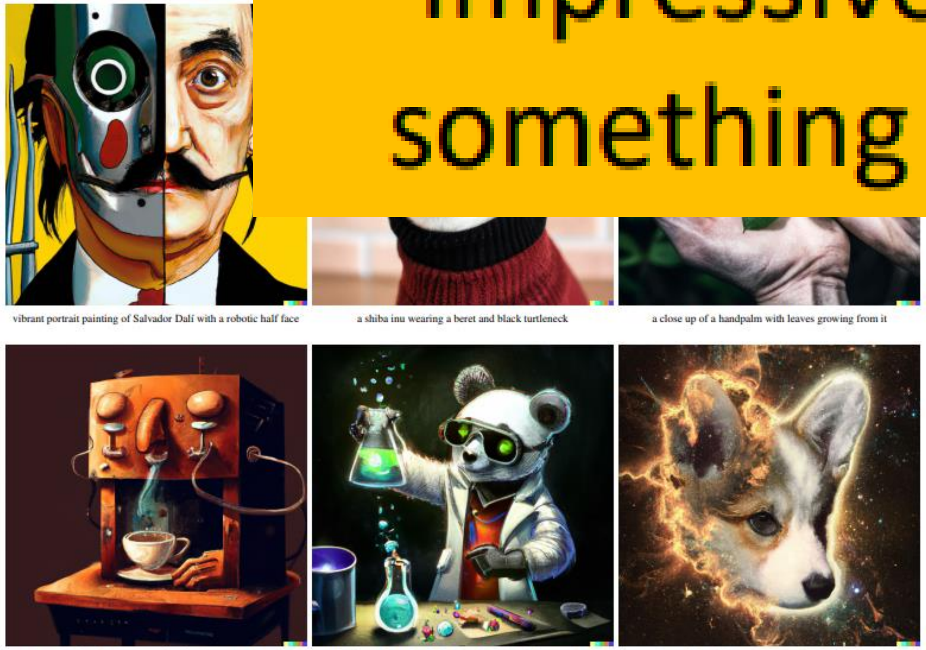
Impressive because it looks like something a person might draw!



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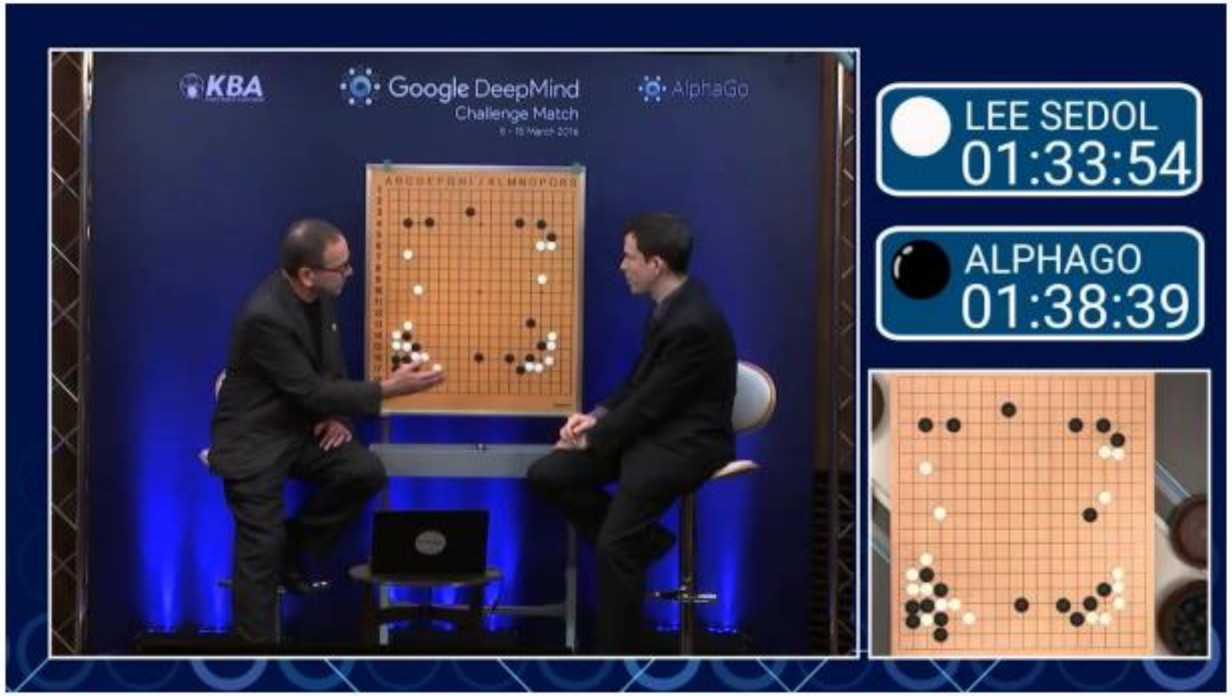

"Move 37" in Lee Sedol AlphaGo match: reinforcement learning "discovers" a move that surprises everyone

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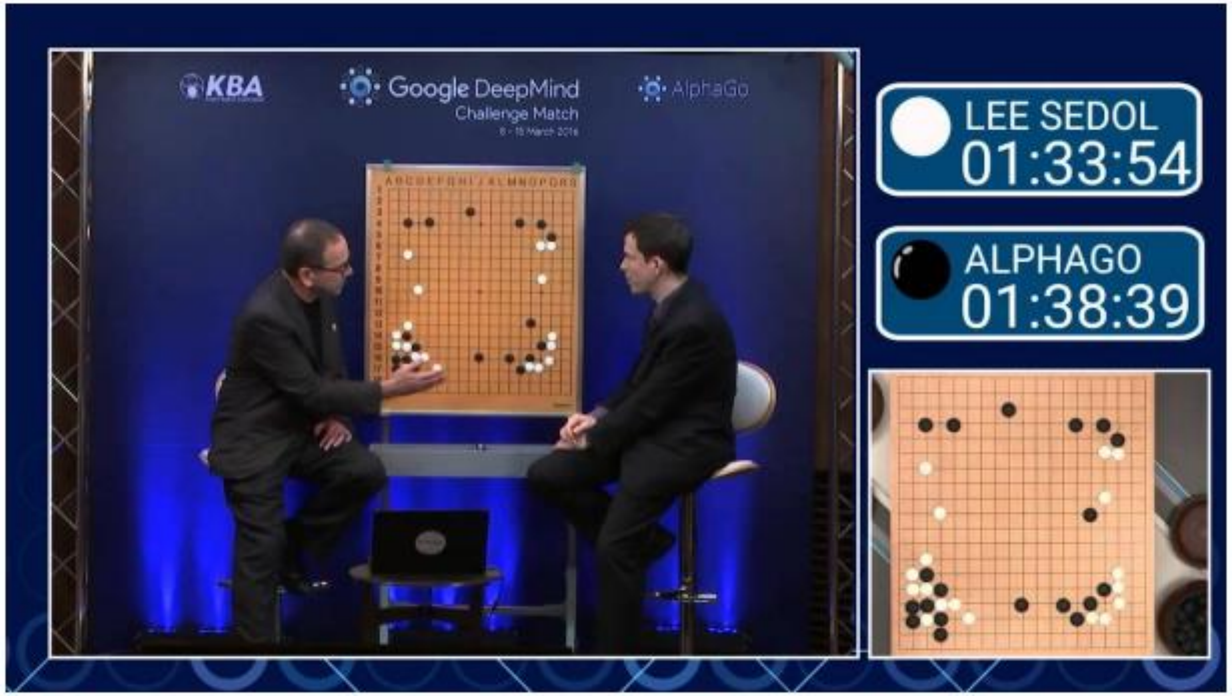

"Move 37" in Lee Sedol AlphaGo match: reinforcement learning "discovers" a move that surprises everyone

Impressive because no person had thought of it!

Q and Value Functions

- State at time t: s_t
- Action at time t: a_t
- Reward function: $r(s_t, a_t)$

Q and Value Functions

The Q-Function is the **total reward from taking action** a_t in state s_t :

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$$Q^\pi(\boldsymbol{s}_t, \boldsymbol{a}_t) = \sum_{t'=t}^{T} \mathbb{E}_{\pi_{\boldsymbol{\theta}}}[r(\boldsymbol{s}_{t'}, \boldsymbol{a}_{t'})|\boldsymbol{s}_t, \boldsymbol{a}_t]$$

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Idea 2:

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If we have a policy π and we know the Q-Function we can improve the policy by setting:

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$$\pi'(\boldsymbol{a}|\boldsymbol{s}) = 1 \text{ if } \boldsymbol{a} = \arg\max_{\boldsymbol{a}} Q^{\pi}(\boldsymbol{s}, \boldsymbol{a})$$

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If $Q^{\pi}(\boldsymbol{s}, \boldsymbol{a}) > V^{\pi}(\boldsymbol{s})$

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If $Q^{\pi}(s, \boldsymbol{a}) > V^{\pi}(s)$ then a is better than average and we can increase $\pi(\boldsymbol{a}|\boldsymbol{s})$.

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Type of RL Algorithms

- **Policy Gradients:**
- **Value Based:**
- **Actor Critic:**
- **Model-Based:**

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- **Actor Critic**: Estimate the Value or Q Function of the **current** policy. Use it to improve policy.
- **Model-Based**: Estimate the transition model and use it for planning/improving policy/other.

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Online vs Offline RL

- **Online RL:** The agent **interacts with the environment** during training.

Online vs Offline RL

- **Online RL:** The agent **interacts with the environment** during training.
- **Offline RL:** The agent **uses a fixed dataset** of previously collected experiences without further interaction with the environment during the training phase.

On-Policy vs Off-Policy RL

- **On-Policy RL:** The agent improves **the policy currently being used** to make decisions.

On-Policy vs Off-Policy RL

- **On-Policy RL:** The agent improves **the policy currently being used** to make decisions.
- **Off-Policy RL:** The agent improves **a different policy than the one it is using**.

Exploration vs. Exploitation

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- **Exploration:** Try a new restaurant.

Exploration vs. Exploitation

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Exploration vs. Exploitation

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How much should I explore?

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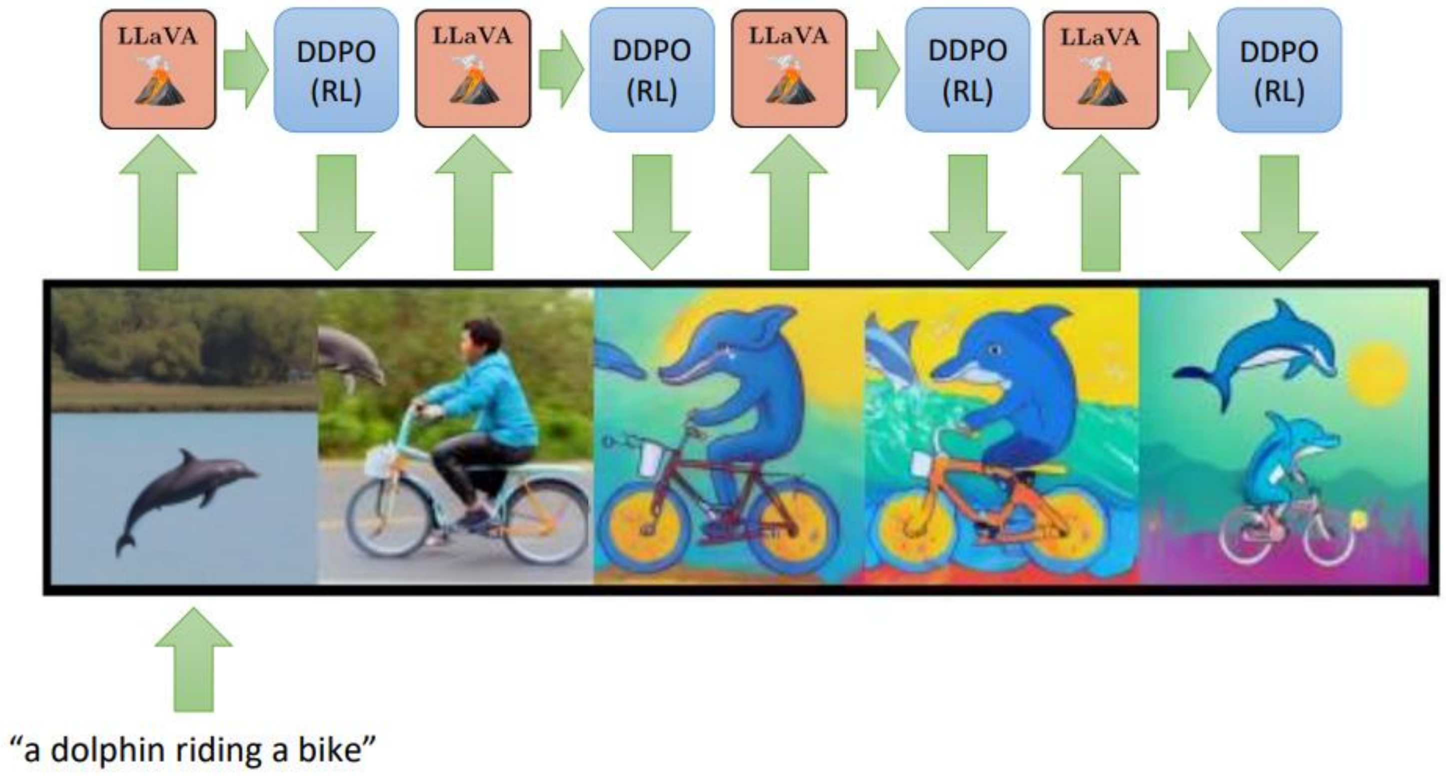
Applications of RL



Kevin Black, Michael Janner, Yilun Du, Ilya Kostrikov, Sergey Levine. Training Diffusion Models with Reinforcement Learning. 2023.

Applications of RL

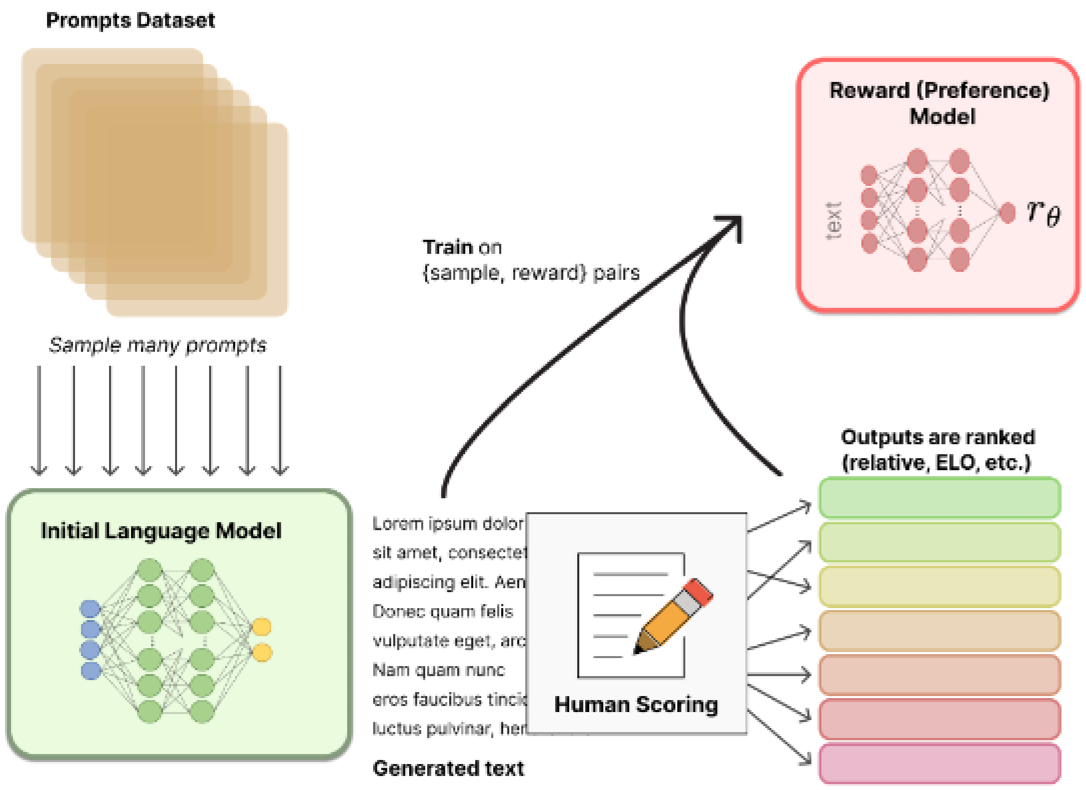
Imitation-based policies can be sensitive

source policy (motion imitation)

Smith et al., "Learning and Adapting Agility Skills by Transferring Experience." 2022.

Applications of RL

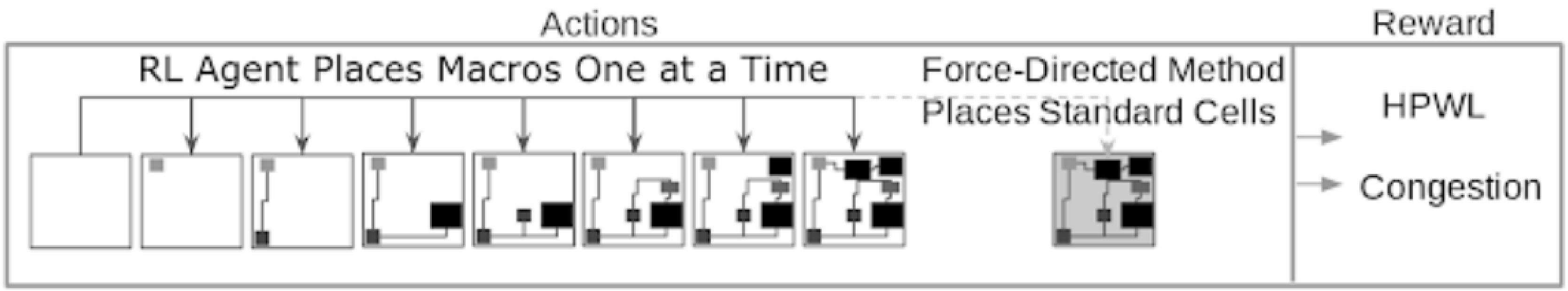
RL for fine-tuning LLMs

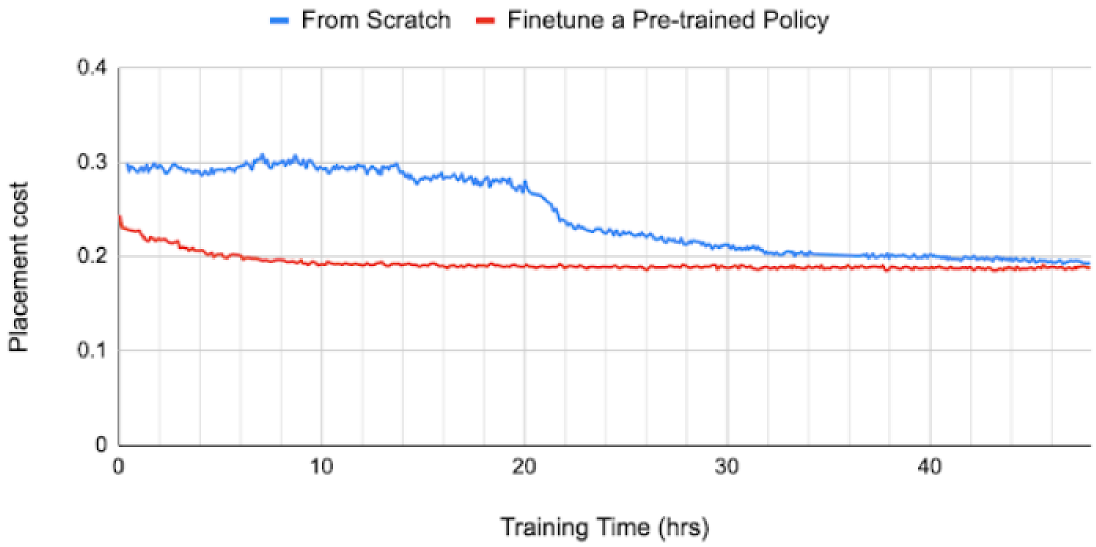


Source: https://huggingface.co/blog/rlhf

Applications of RL

RL for Chip Design

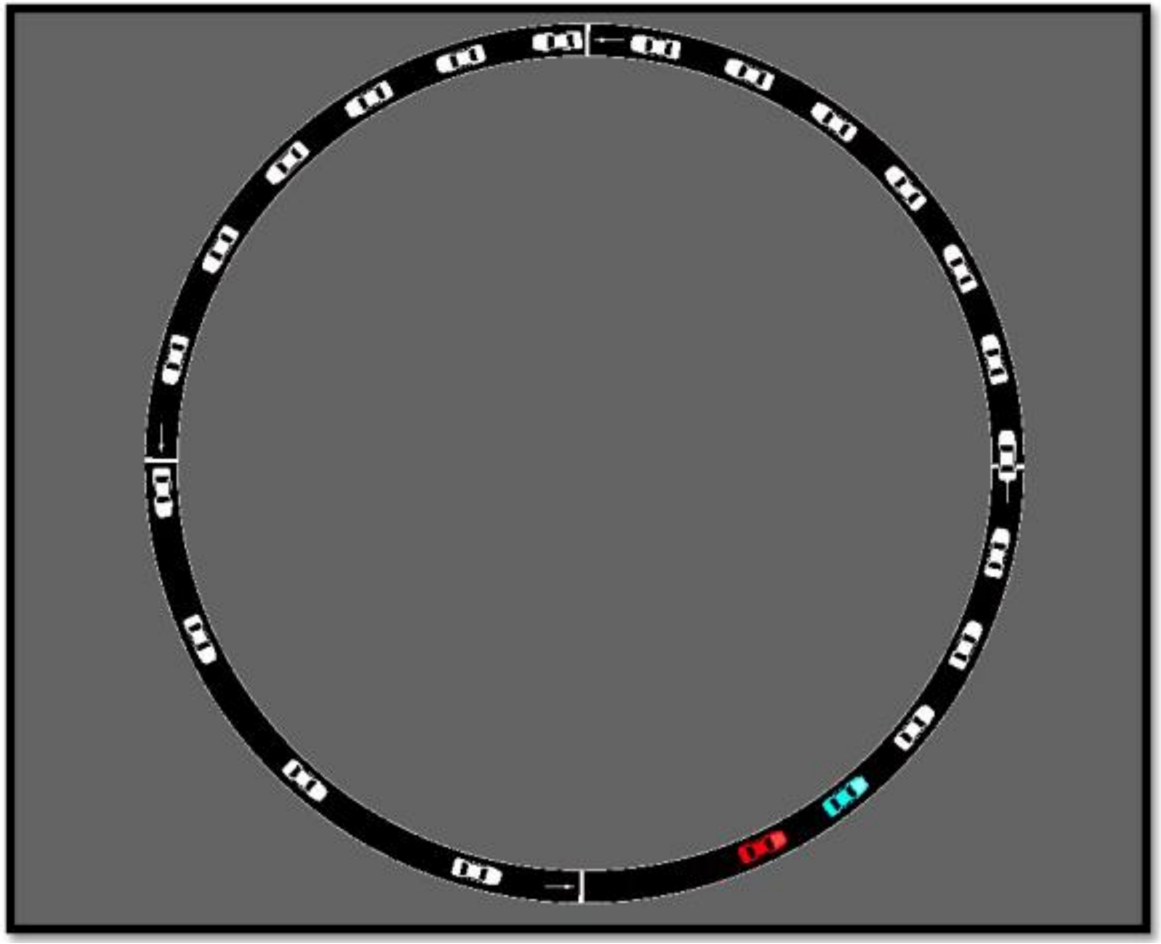


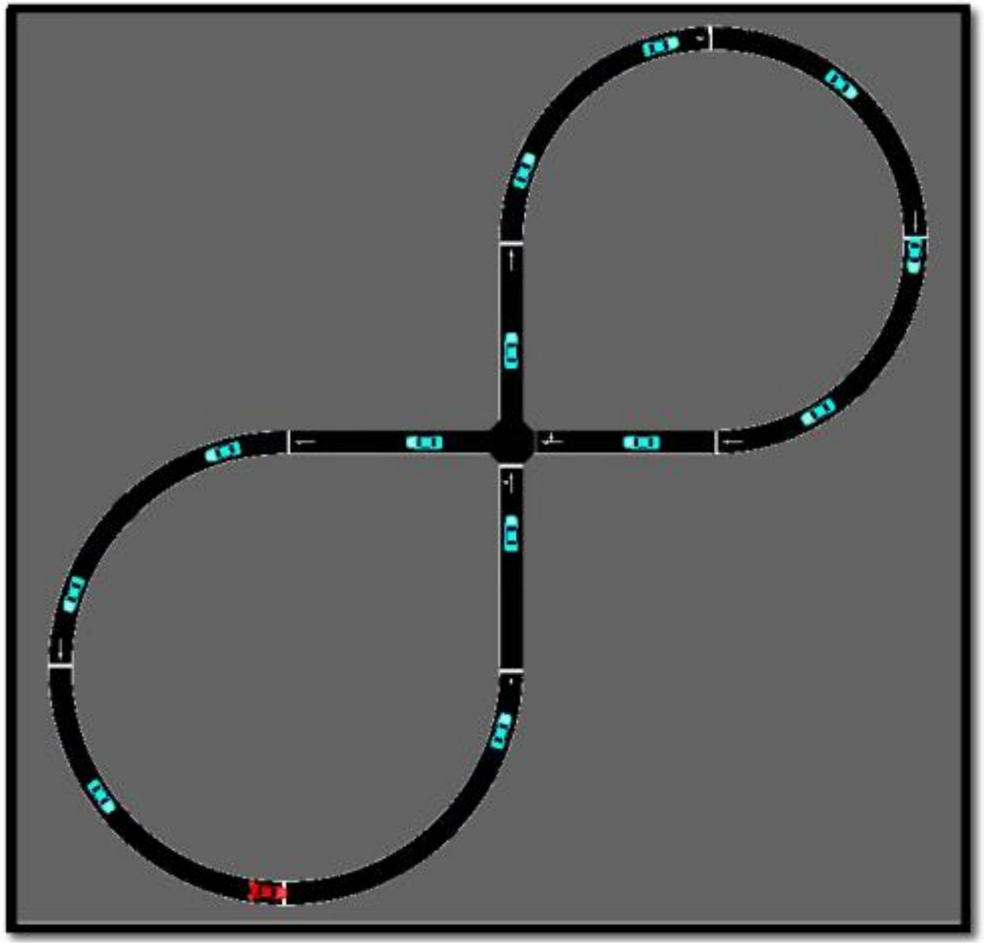


Source: https://ai.googleblog.com/2020/04/chip-design-with-deep-reinforcement.html

Applications of RL

RL for Controlling Traffic





Wu Cathy et al., Emergent Behaviors in Mixed-Autonomy Traffic, 2017