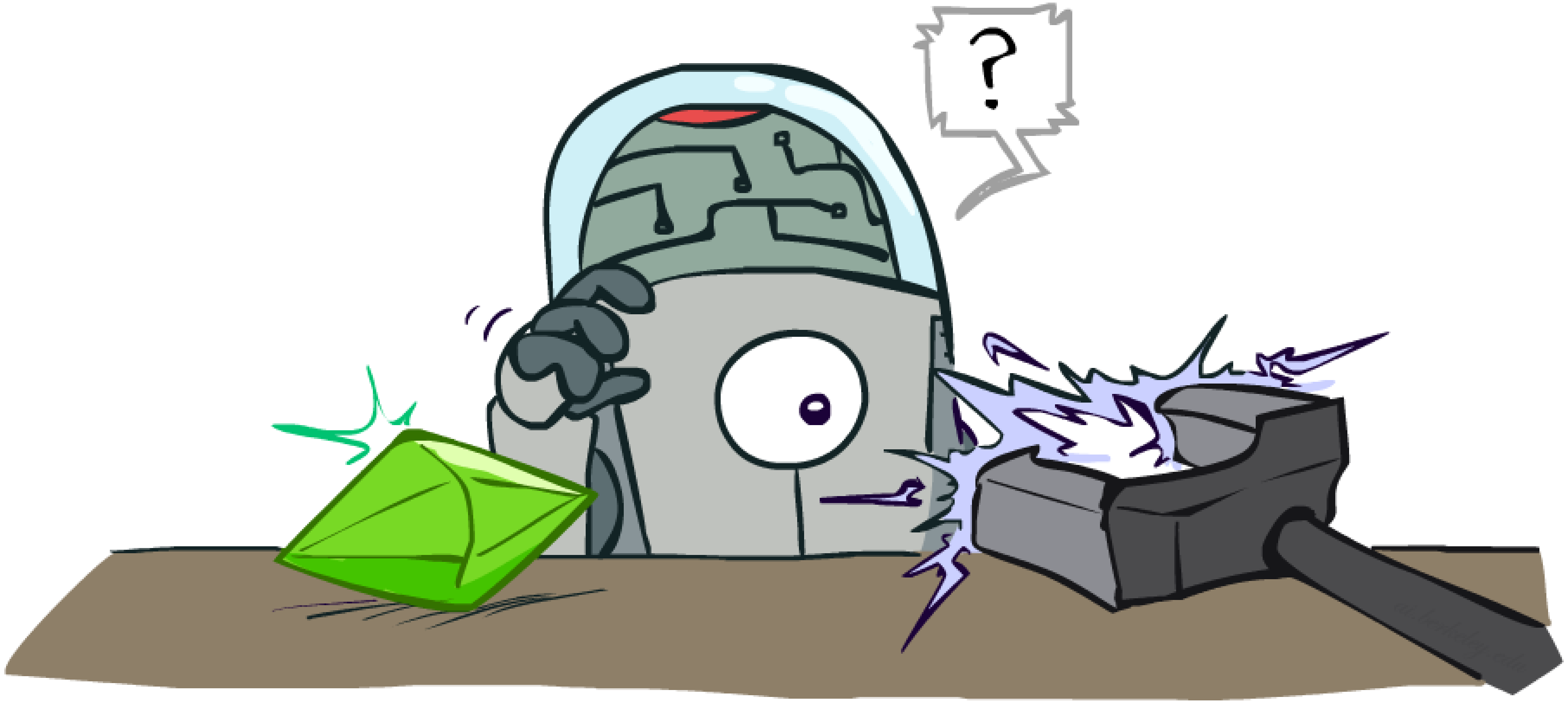
CS 188: Artificial Intelligence

Reinforcement Learning Continued



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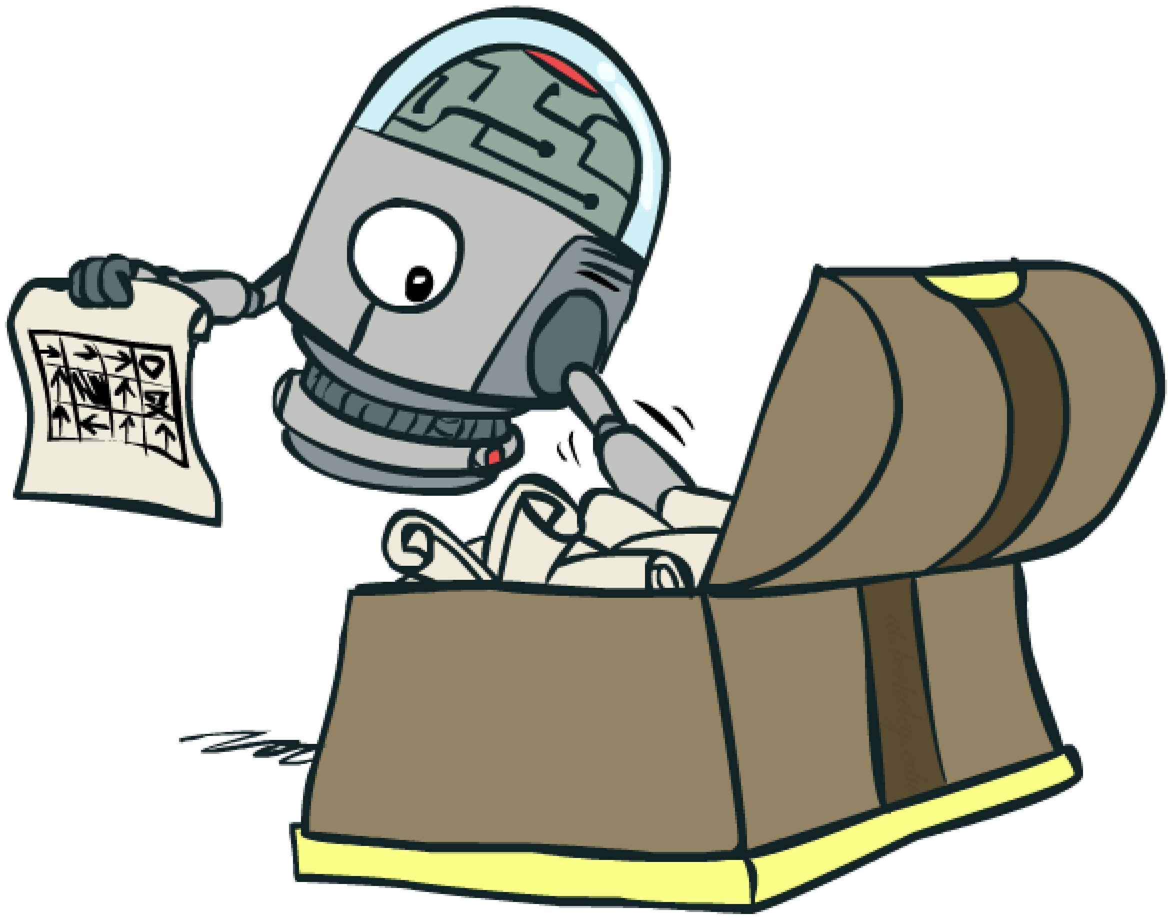
[These slides were created by Dan Klein and Pieter Abbeel for CS188 Intro to AI at UC Berkeley. All CS188 materials are available at http://ai.berkeley.edu.]

Policy Search



Policy Search

- Problem: often the feature-based policies that work well (win games, maximize utilities) aren't the ones that approximate V / Q best
  - E.g. your value functions from project 2 were probably horrible estimates of future rewards, but they still produced good decisions
  - Q-learning's priority: get Q-values close (modeling)
  - Action selection priority: get ordering of Q-values right (prediction)
  - We'll see this distinction between modeling and prediction again later in the course

- Solution: learn policies that maximize rewards, not the values that predict them

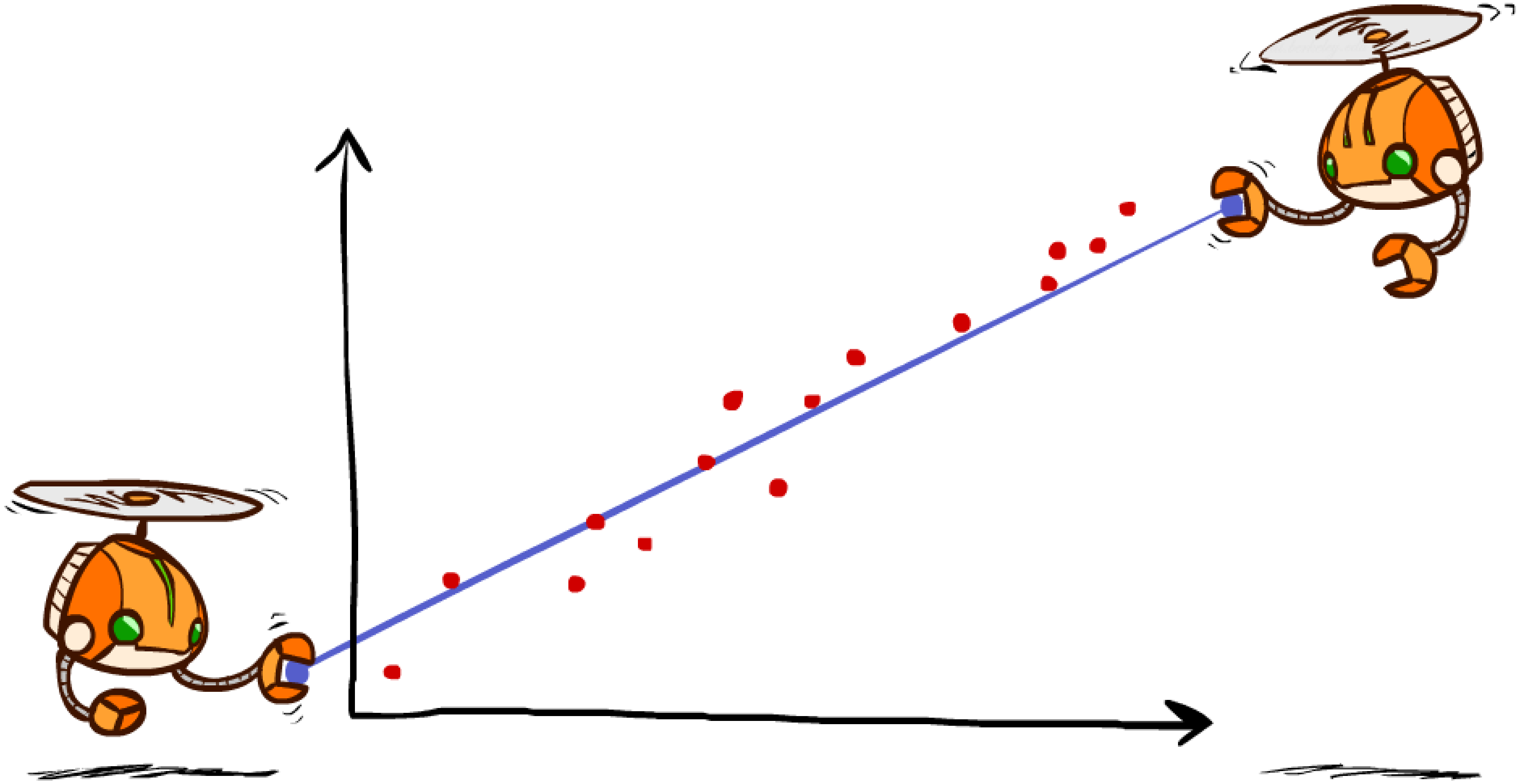
- Policy search: start with an ok solution (e.g. Q-learning) then fine-tune by hill climbing on feature weights

Policy Search

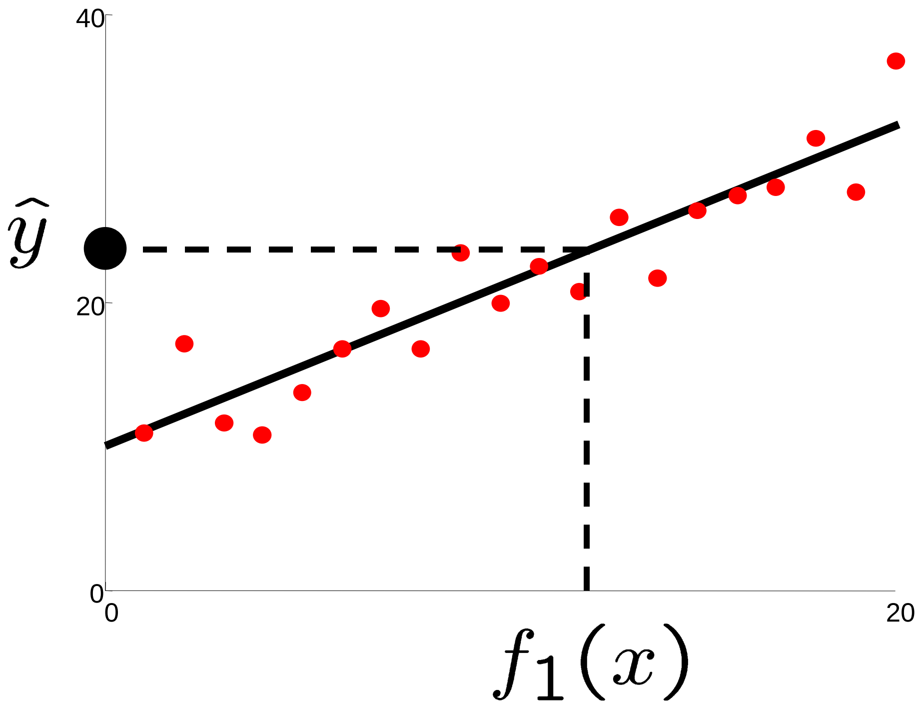
- Simplest policy search:
  - Start with an initial linear value function or Q-function
  - Nudge each feature weight up and down and see if your policy is better than before
- Problems:
  - How do we tell the policy got better?
  - Need to run many sample episodes!
  - If there are a lot of features, this can be impractical
- Better methods exploit lookahead structure, sample wisely, change multiple parameters…

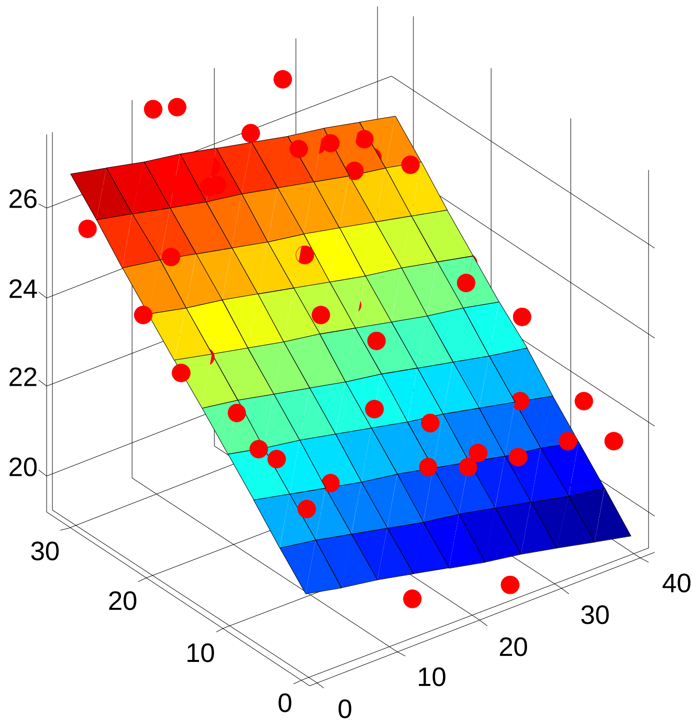
[Video: HELICOPTER]

Q-Learning and Least Squares



Linear Approximation: Regression





Prediction:

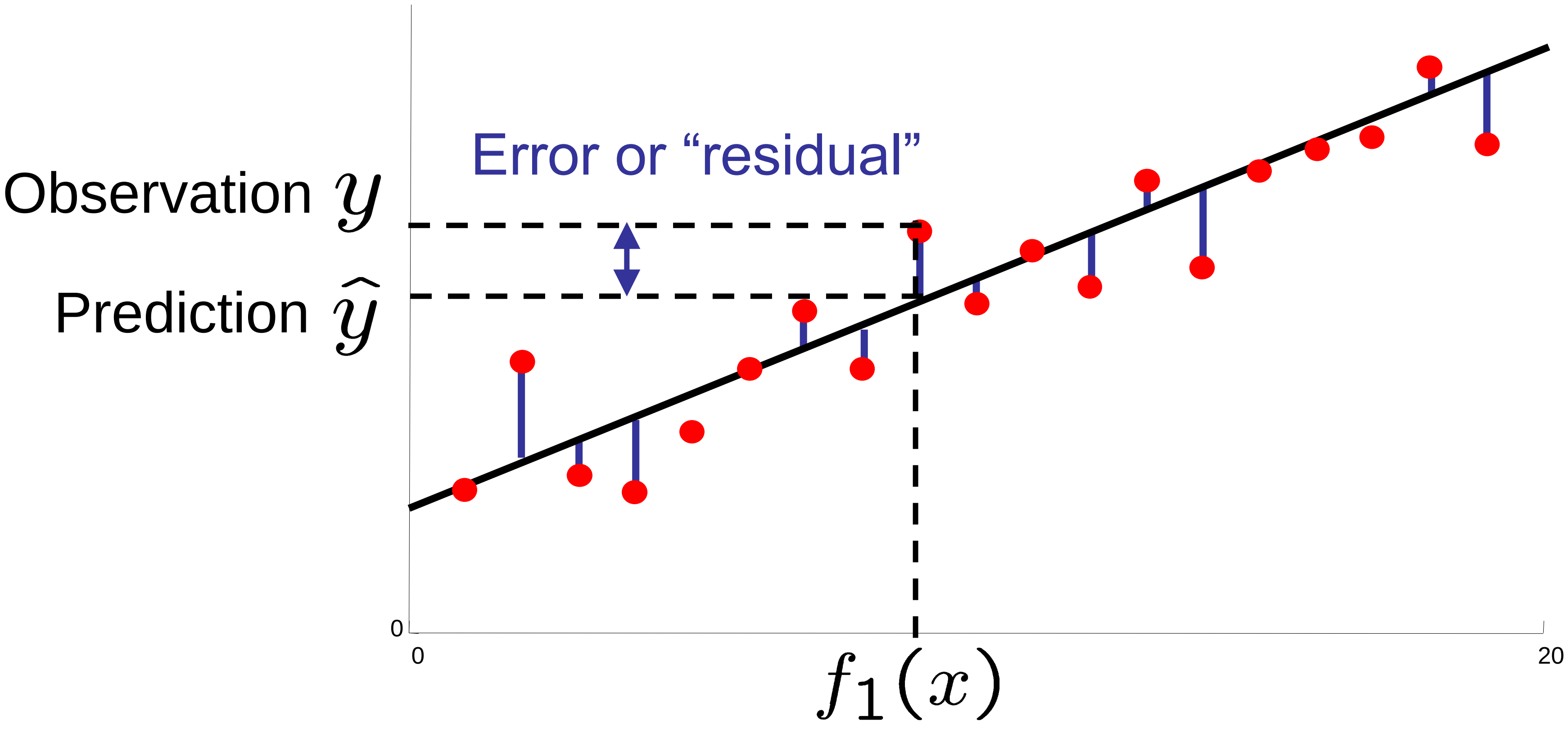
$$\hat{y} = w_0 + w_1 f_1(x)$$

Prediction:

$$\hat{y}_i = w_0 + w_1 f_1(x) + w_2 f_2(x)$$

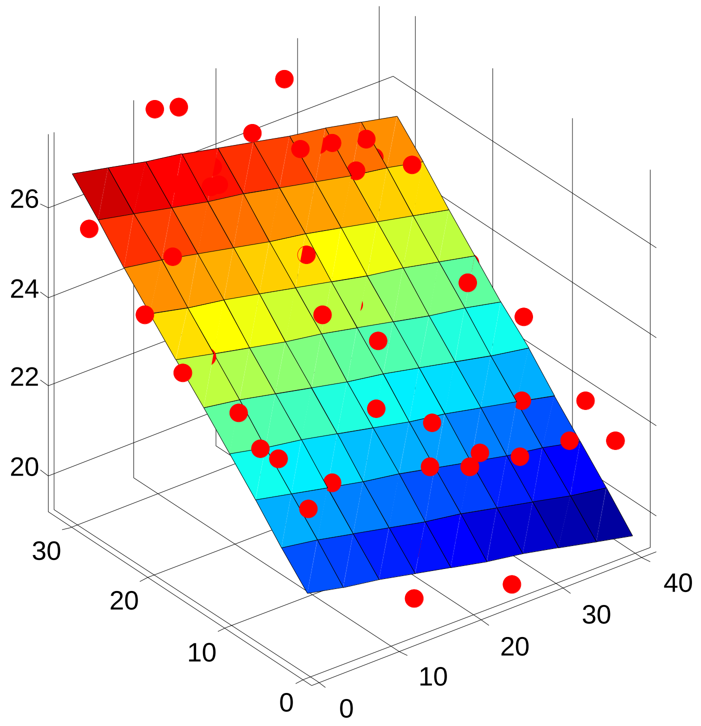
Optimization: Least Squares

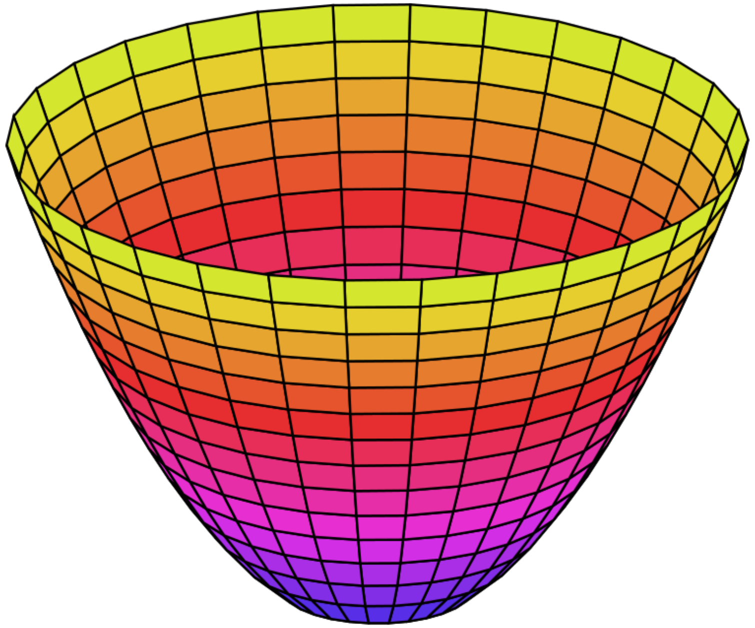
$$\text{total error} = \sum_i (y_i - \hat{y}_i)^2 = \sum_i \left(y_i - \sum_k w_k f_k(x_i) \right)^2$$



Loss Function

$$\text{total error} = \sum_i (y_i - \hat{y}_i)^2 = \sum_i \left(y_i - \sum_k w_k f_k(x_i) \right)^2$$





Gradients

$$y = x_1^2 + x_2^2$$

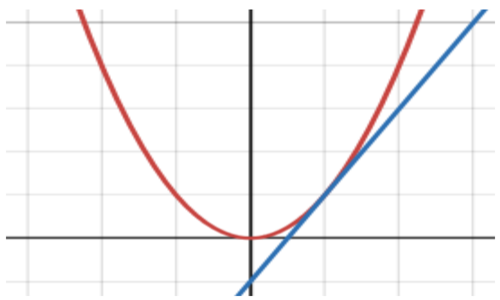
$$\frac{dy}{dx} = \lim_{\Delta x \to 0} \frac{\Delta y}{\Delta x}$$

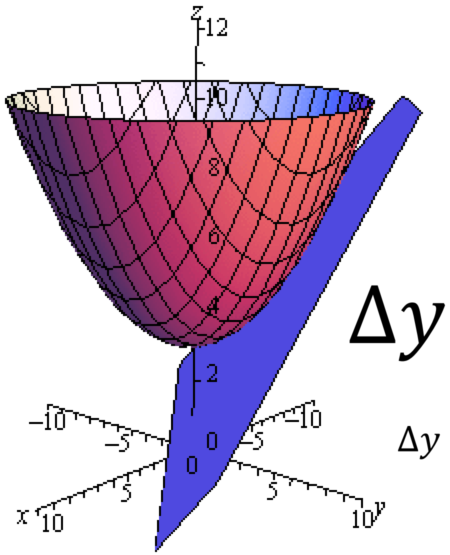
$$\frac{\partial y}{\partial x_1} = 2x_1$$

$$\frac{\partial y}{\partial x_2} = 2x_2$$

$$\nabla y = \begin{bmatrix} \frac{\partial y}{\partial x_1} \\ \frac{\partial y}{\partial x_2} \end{bmatrix}$$

- Partial derivative: the immediate change of output for a change of input, or slope, or rate.
- Gradient: vector of partial derivatives, one per input scalar.
- Defines tangent plane.
- Gradient points in the direction of fastest increase.
  - Actually, on the tangent plane, so only in a region around the dot for the actual function.

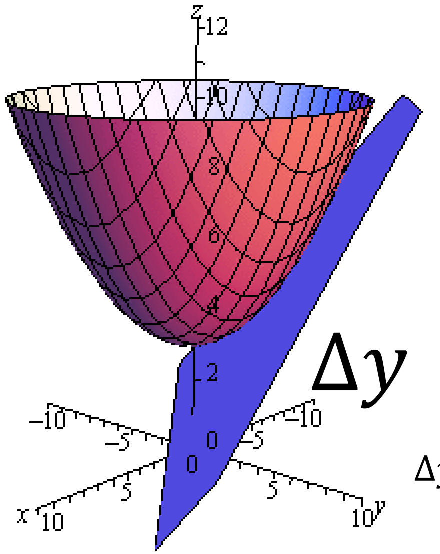




$$\Delta y = \nabla y \ * \Delta x$$

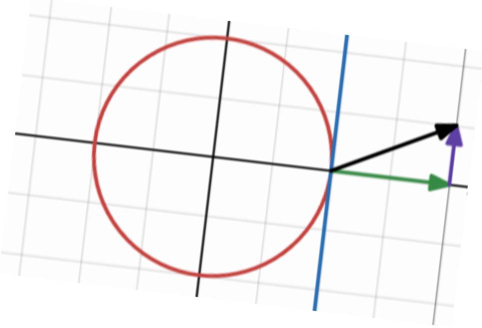
$$\Delta y = \begin{bmatrix} \frac{\partial y}{\partial x_1} \\ \frac{\partial y}{\partial x_2} \end{bmatrix} * \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \end{bmatrix} = \frac{\partial y}{\partial x_1} * \Delta x_1 + \frac{\partial y}{\partial x_2} * \Delta x_2$$

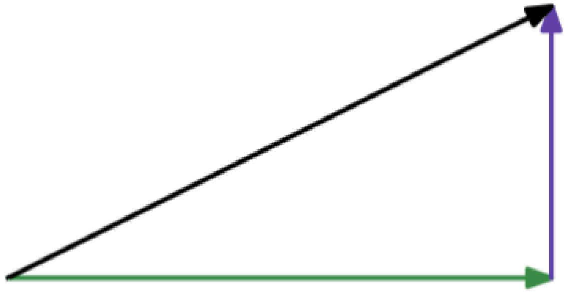
Gradients



$$\Delta y = \nabla y \; * \Delta x$$

$$\Delta y = \begin{bmatrix} \frac{\partial y}{\partial x_1} \\ \frac{\partial y}{\partial x_2} \end{bmatrix} * \begin{bmatrix} \Delta x_1 \\ \Delta x_2 \end{bmatrix}$$





$$\Delta y = \nabla y \; * (\Delta_1 x + \Delta_2 x)$$

$$\Delta y = \nabla y \; * \Delta_1 x + \nabla y \; * \Delta_2 x$$

$$\Delta y = \nabla y \; * \Delta_1 x + 0$$

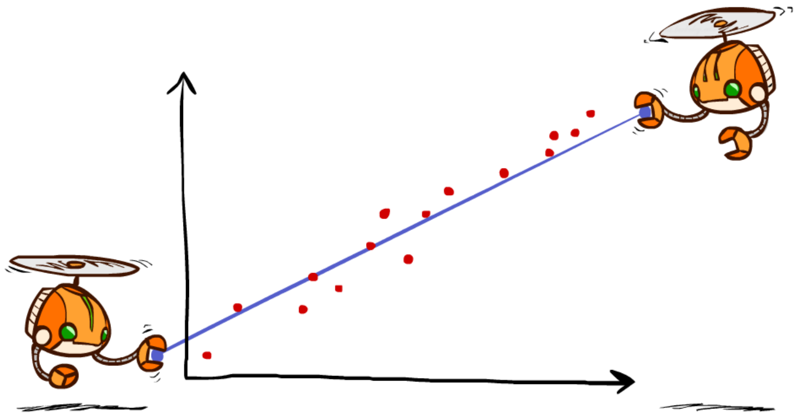
Minimizing Error

Imagine we had only one point x, with features f(x), target value y, and weights w:

$$\text{error}(w) = \frac{1}{2}\left(y - \sum_k w_k f_k(x)\right)^2$$

$$\frac{\partial\, \text{error}(w)}{\partial w_m} = -\left(y - \sum_k w_k f_k(x)\right) f_m(x)$$

$$w_m \leftarrow w_m + \alpha \left(y - \sum_k w_k f_k(x)\right) f_m(x)$$

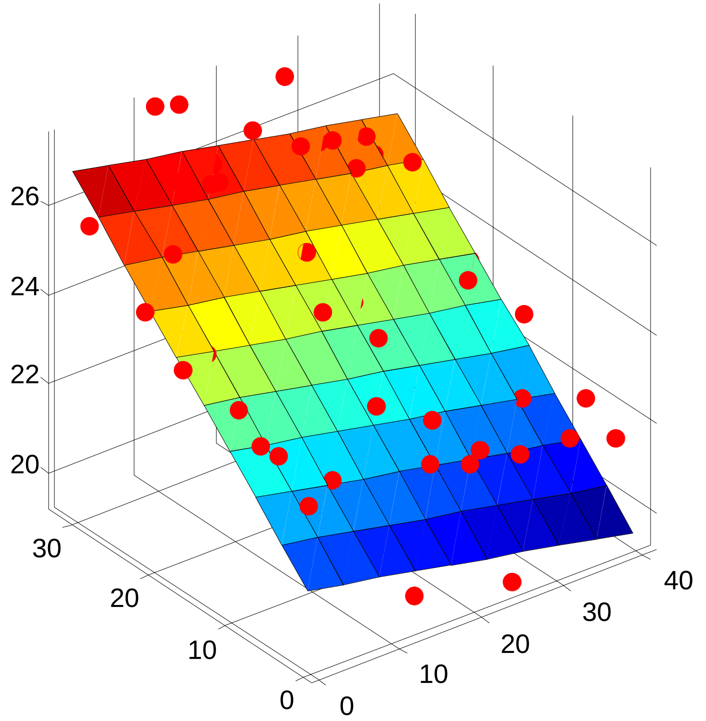


Approximate q update explained:

$$w_m \leftarrow w_m + \alpha \left[r + \gamma \max_a Q(s', a') - Q(s,a) \right] f_m(s,a)$$

“target” “prediction”

Updating w

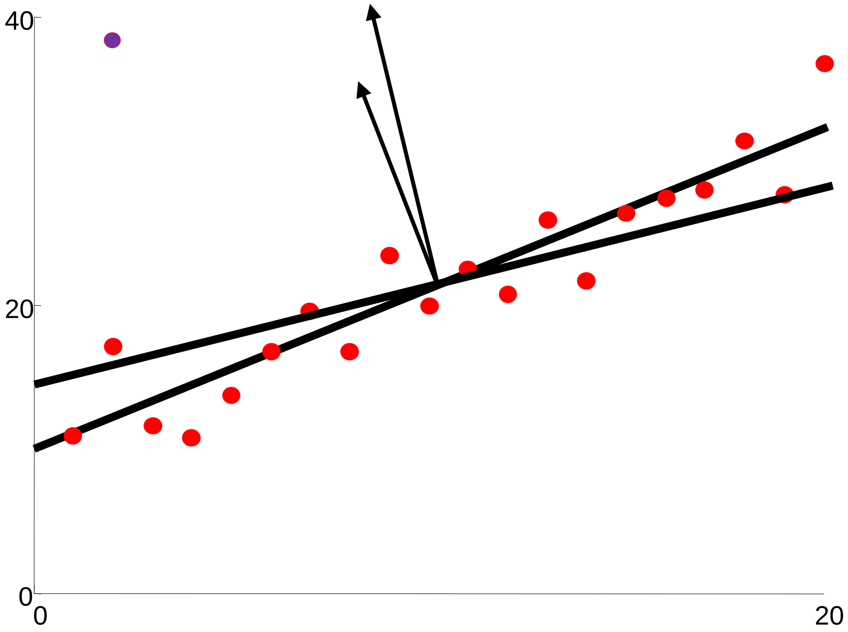


Prediction:

$$\widehat{y}_i = w_0 + w_1 f_1(x) + w_2 f_2(x)$$

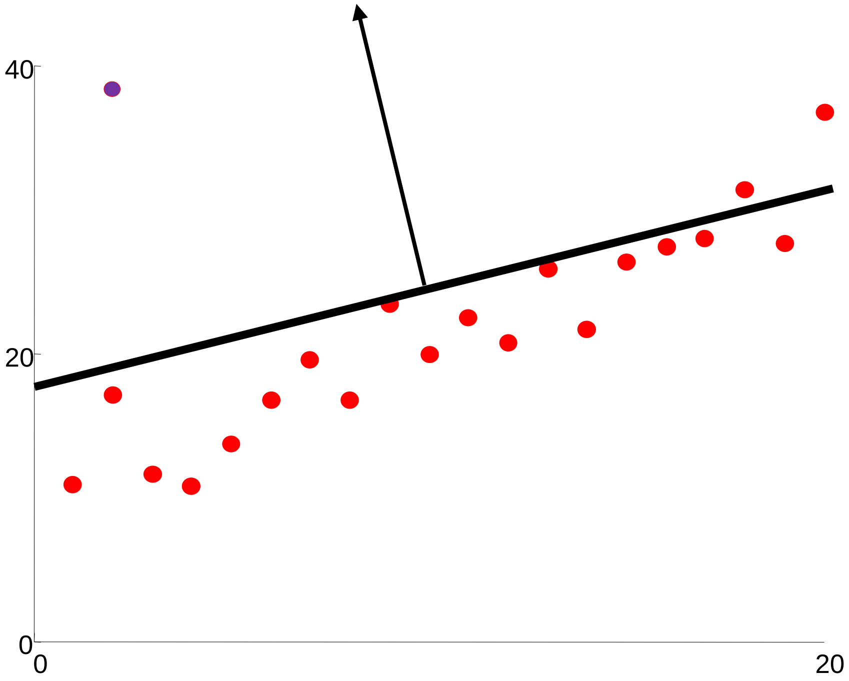
Updating w

- "Rotating" w



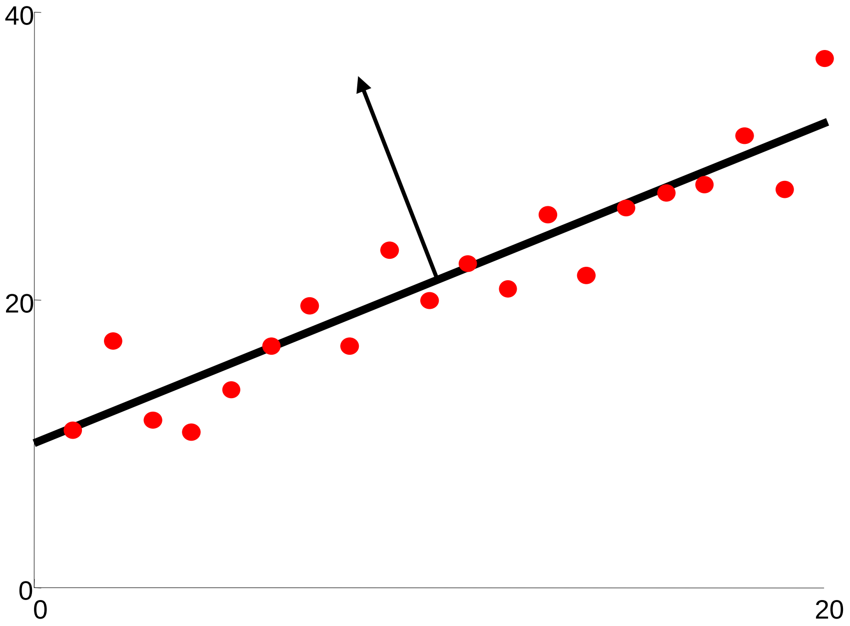
Prediction:

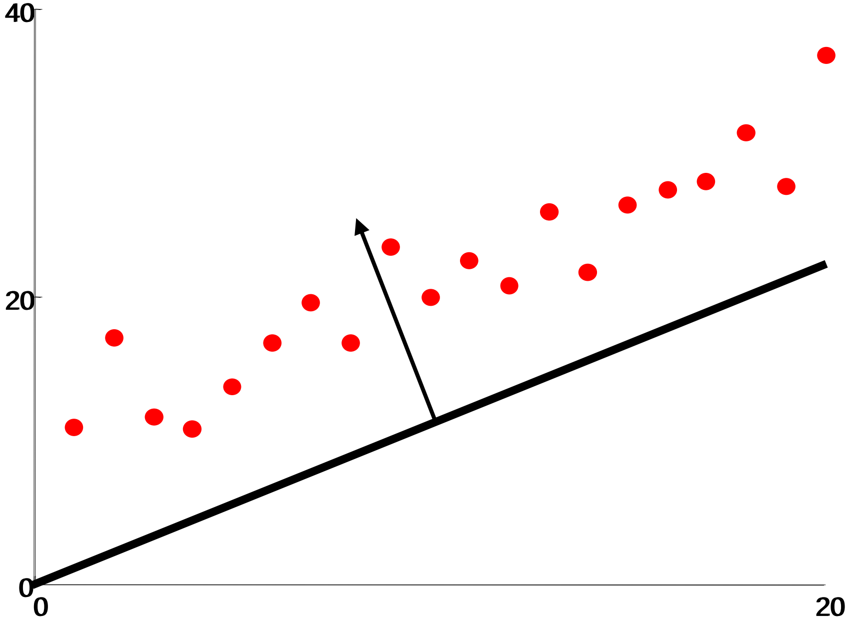
$$\hat{y}_i = w_0 + w_1 f_1(x) + w_2 f_2(x)$$



Updating w

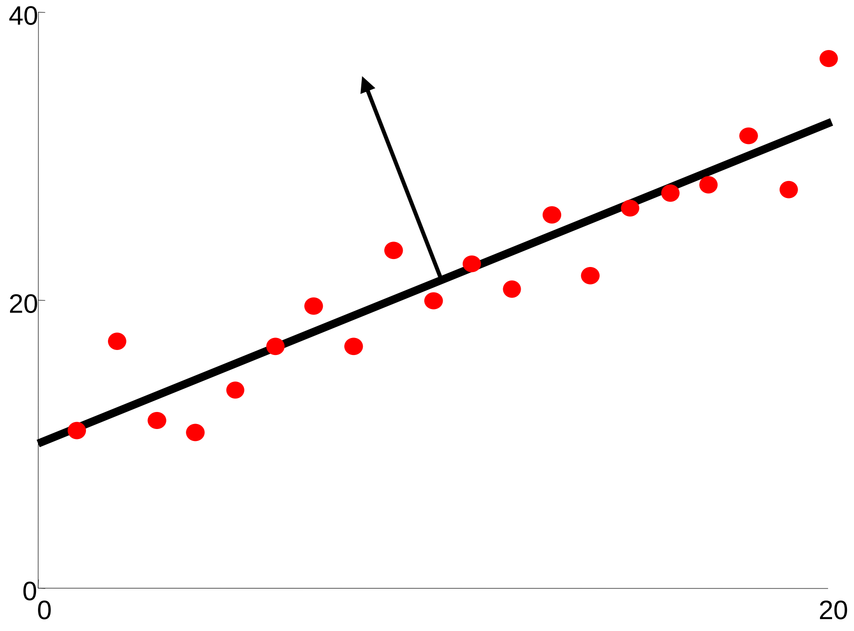
- Bias

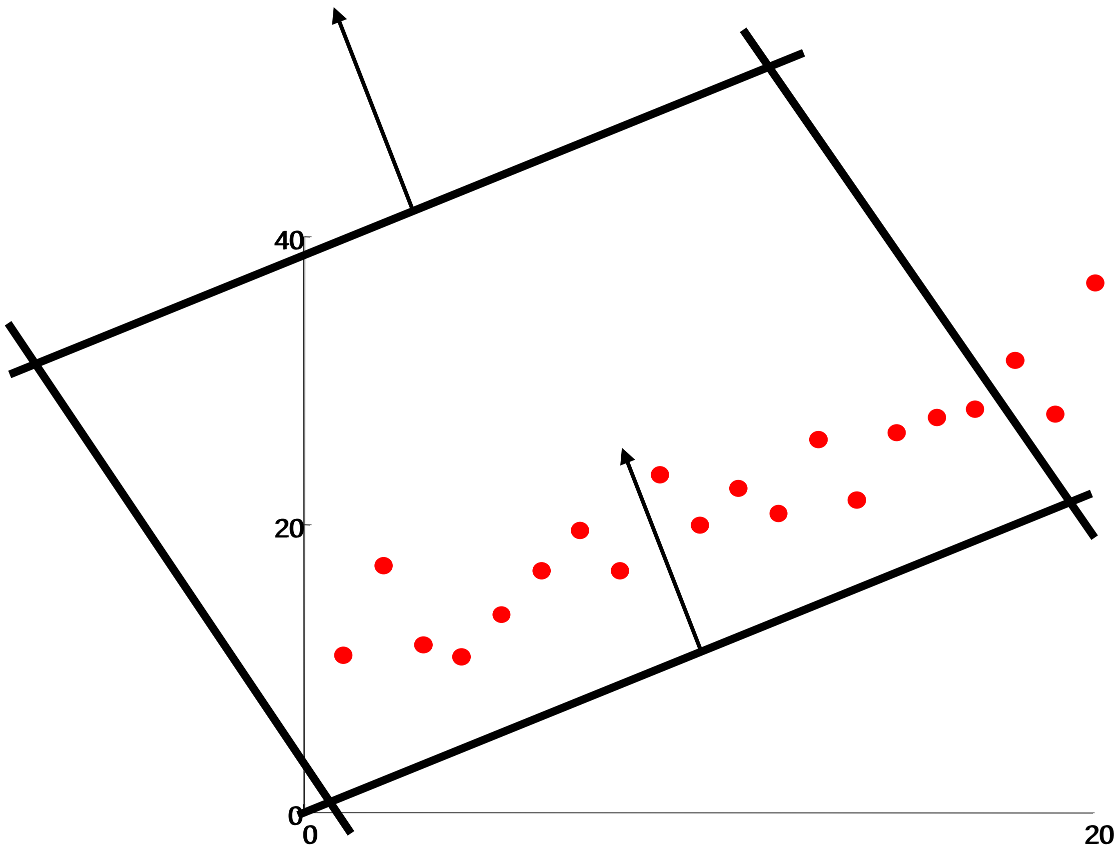




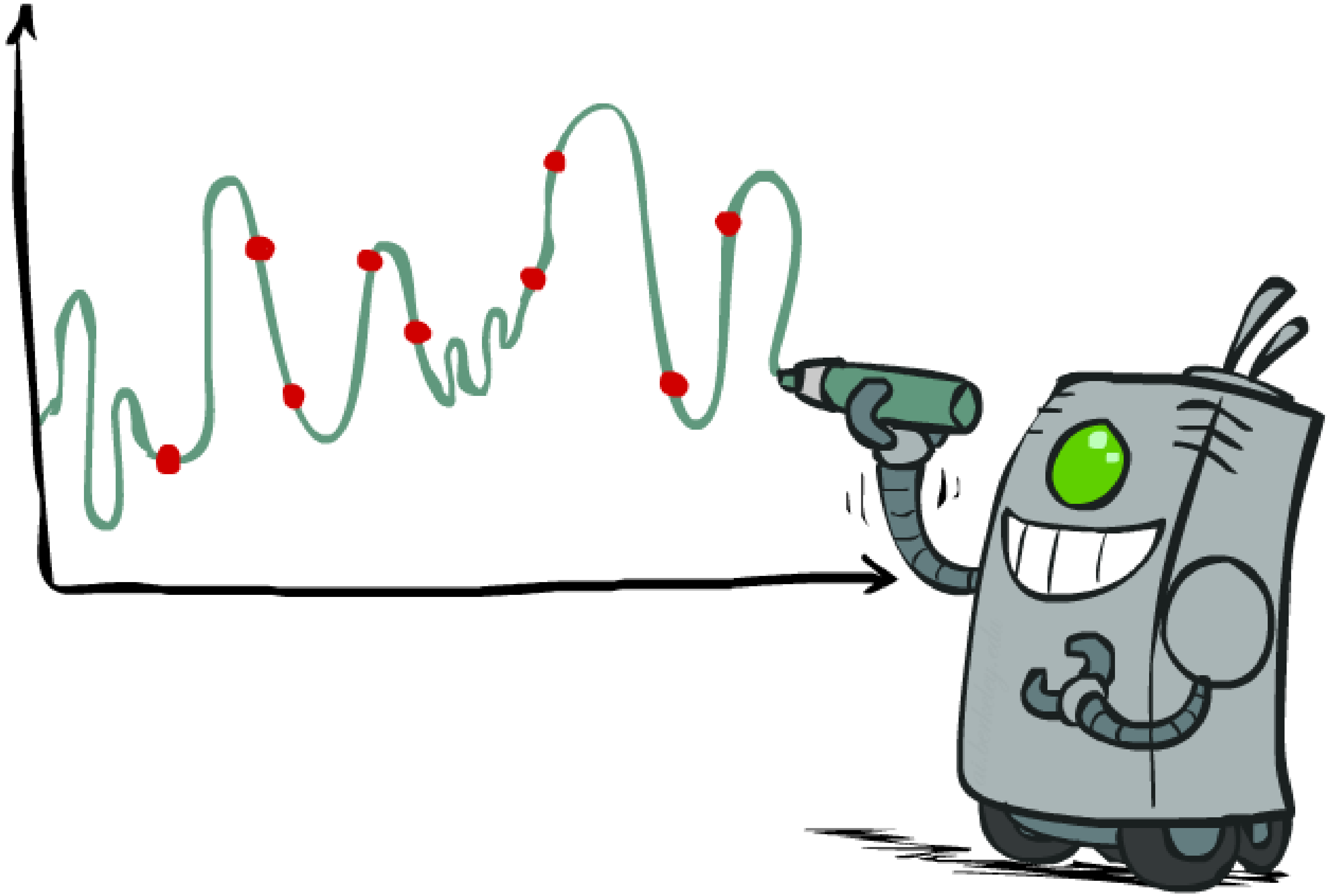
Updating w

- Bias





Overfitting: Why Limiting Capacity Can Help*

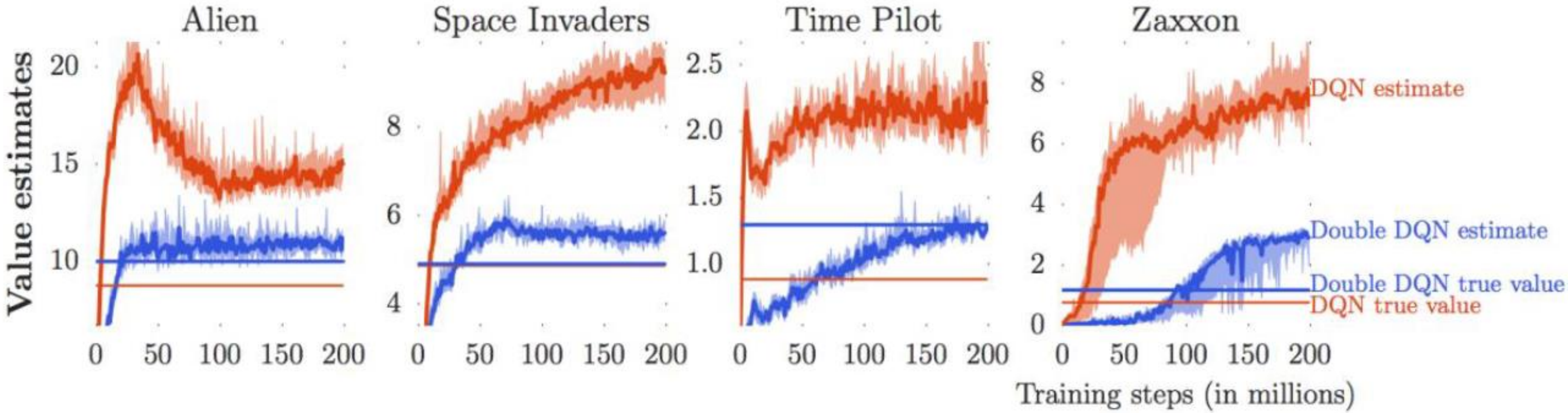


Actor-Critic Algorithms

- Analogous to Policy Iteration, we will have V^{π} and π.
- π is no longer deterministic. Policy is now $P(a|s)$.

1. take action a based on $\pi(a|s)$, get (s, a, s', r)
2. update V^{π} based on $r + \gamma V^{\pi}(s')$
3. update π based on $r + \gamma V^{\pi}(s') - V^{\pi}(s)$ weighted by $\nabla \log \pi(a|s)$
    1. pretend it's weighted by features of $\pi(a|s)$

Optimism



Alien
Space Invaders
Time Pilot
Zaxxon
Value estimates
20
15
10
8
6
4
2.5
2.0
1.5
1.0
8
6
4
2
0
0 50 100 150 200
0 50 100 150 200
0 50 100 150 200
0 50 100 150 200
Training steps (in millions)
DQN estimate
Double DQN estimate
Double DQN true value
DQN true value

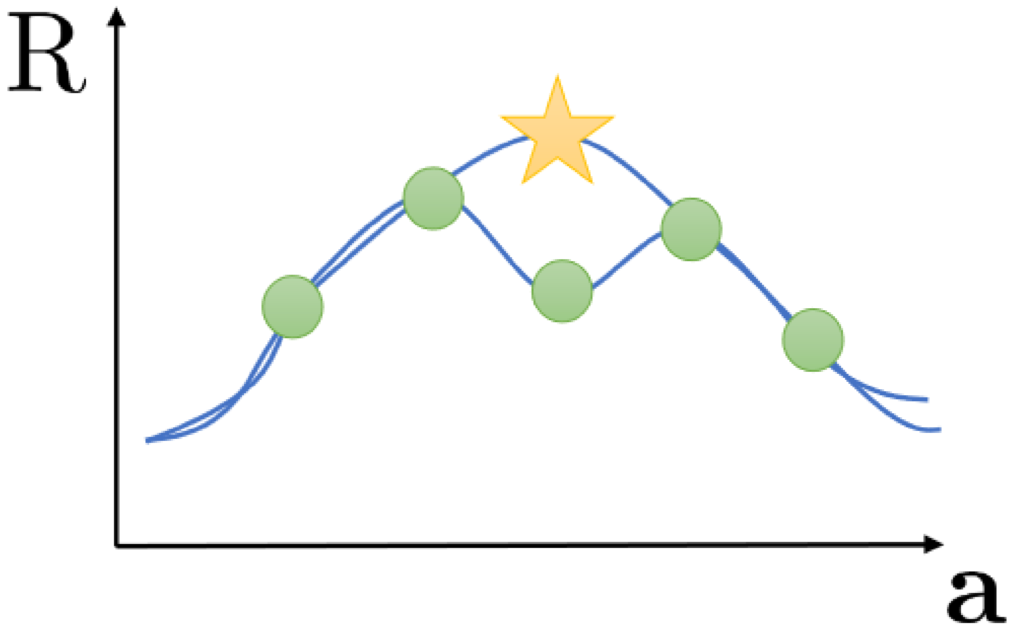
Double Deep Q-Network

- Deep Q-Network = Deep Neural Network estimating Q values.

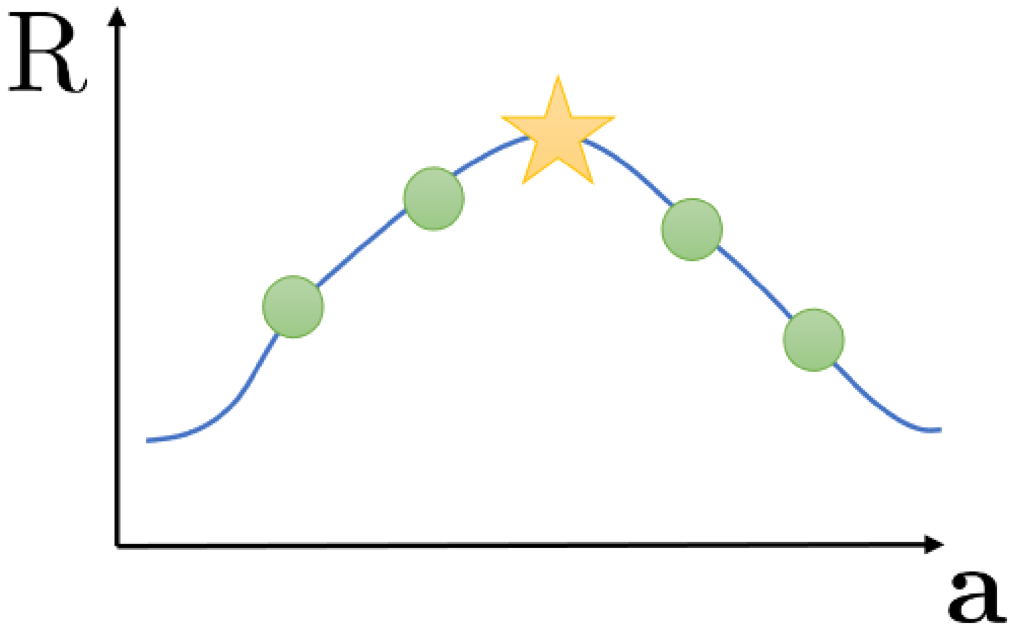
1. checkpoint DQN into Q’
2. iterate:
    1. collect samples (s, a, s', r)
        1. ideally, some are based on Q
    2. update Q based on $r + \gamma Q(s', a = argmax\ Q') - Q(s, a)$

Generalization

online RL setting

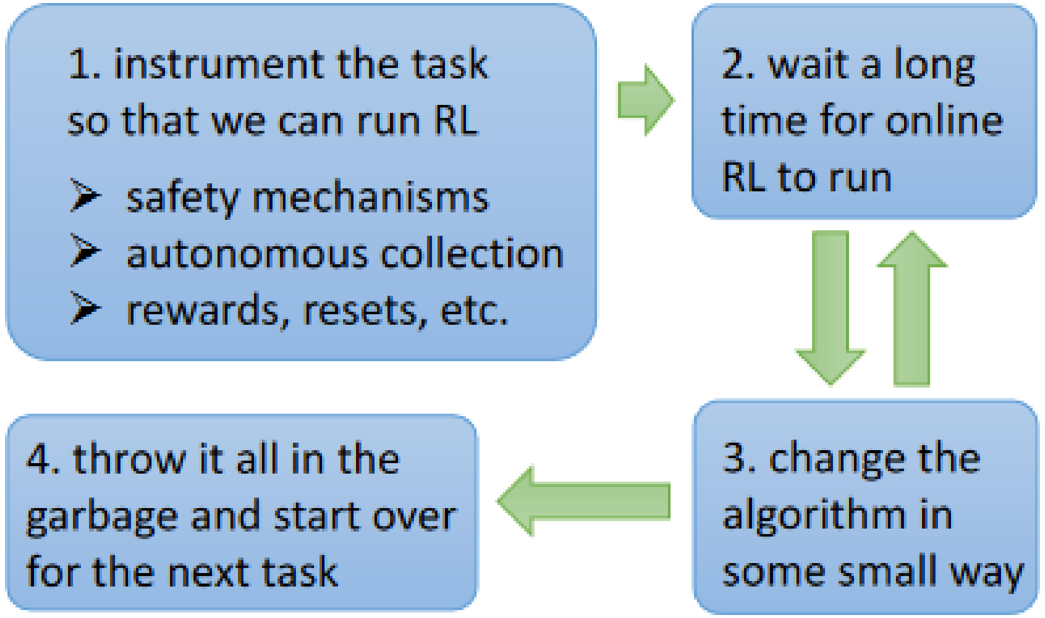


offline RL setting

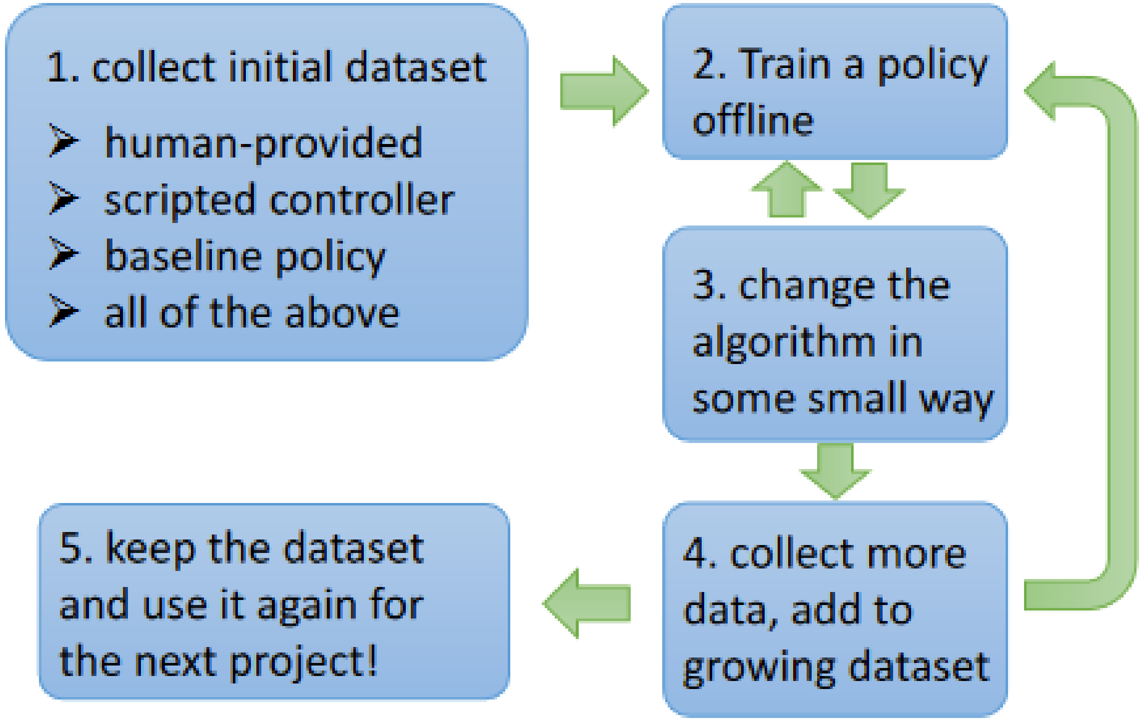


Why Off-Policy

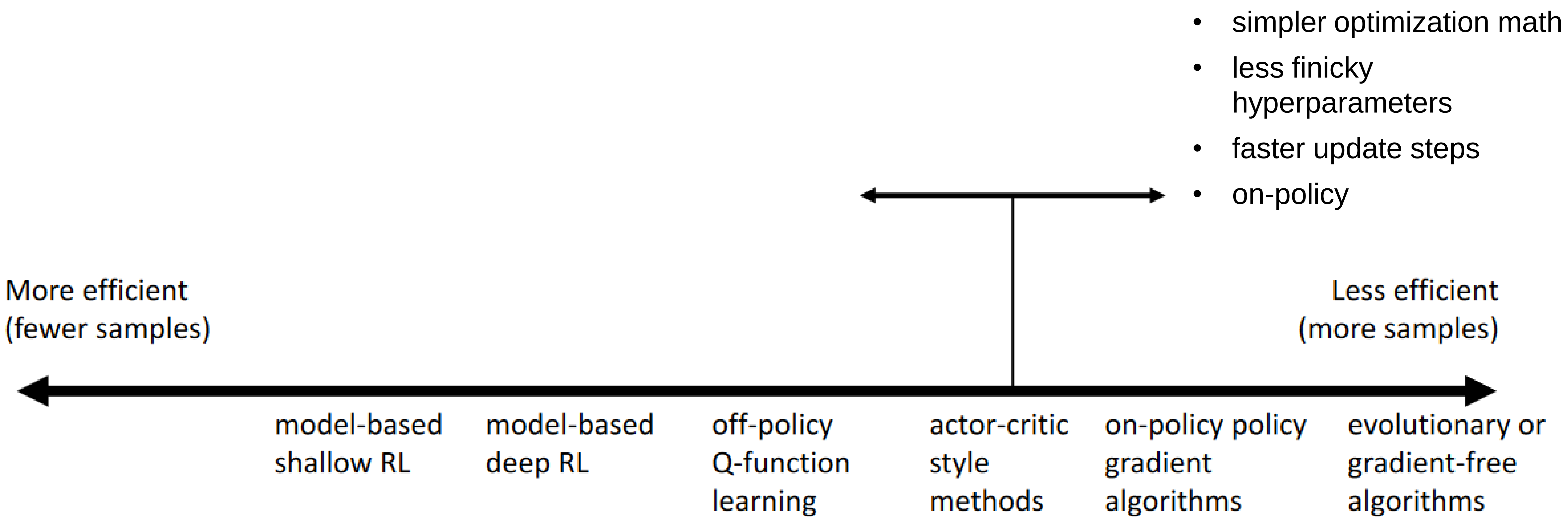
standard real-world RL process



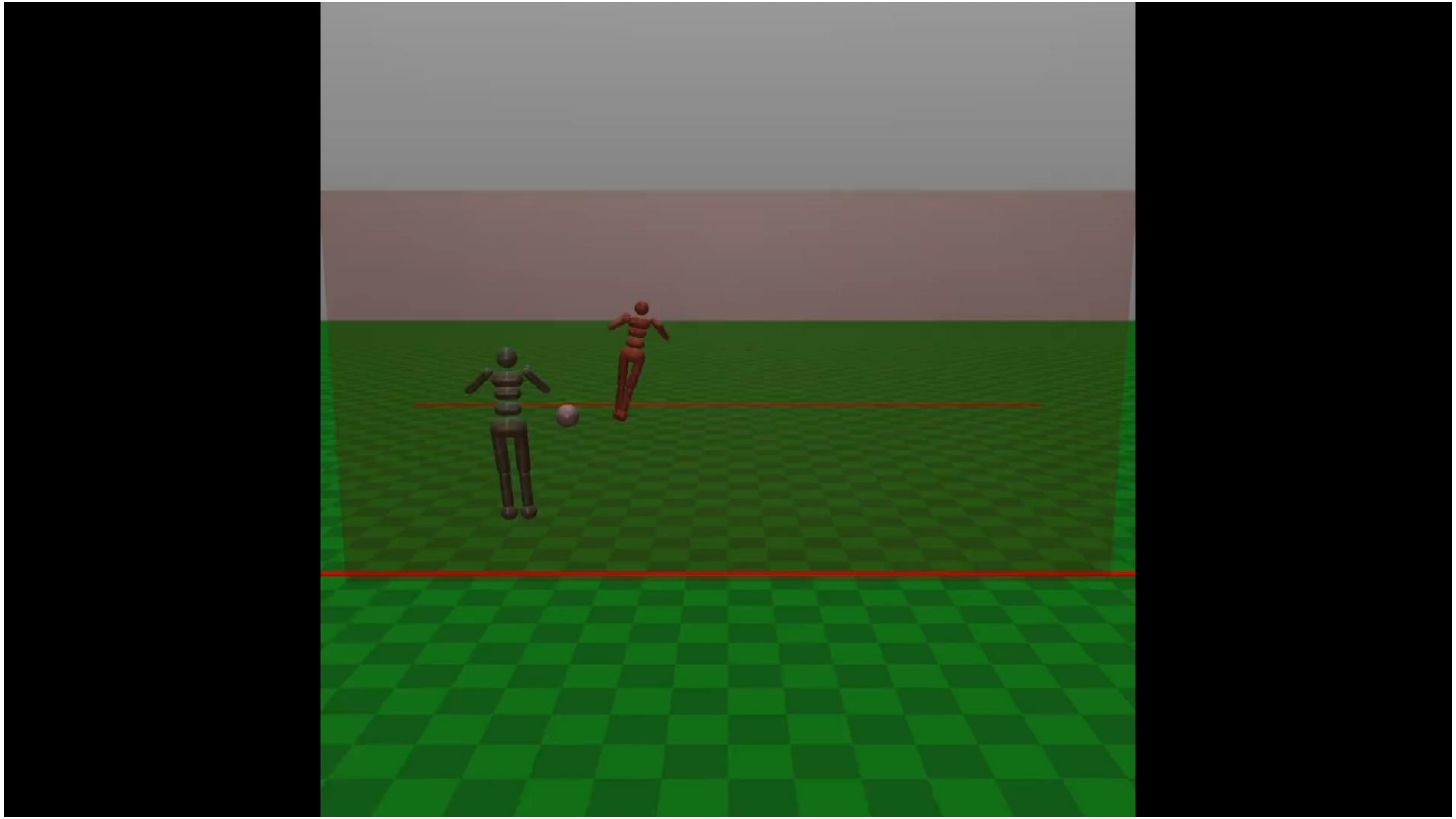
offline RL process

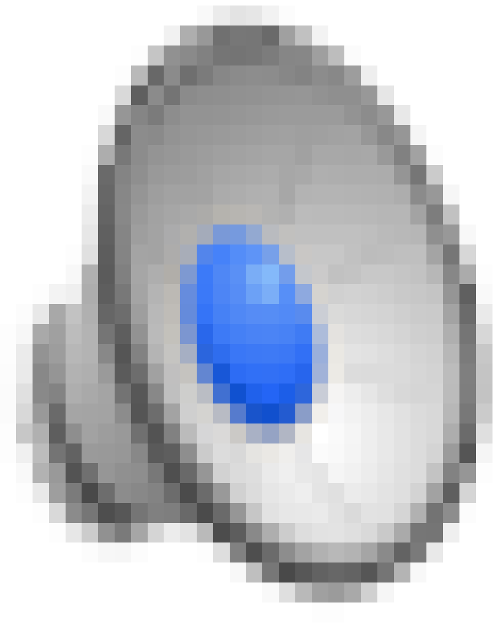


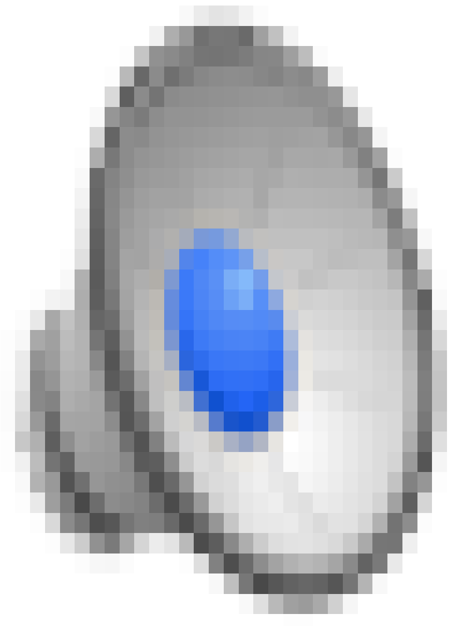
Why Multiple Algorithms

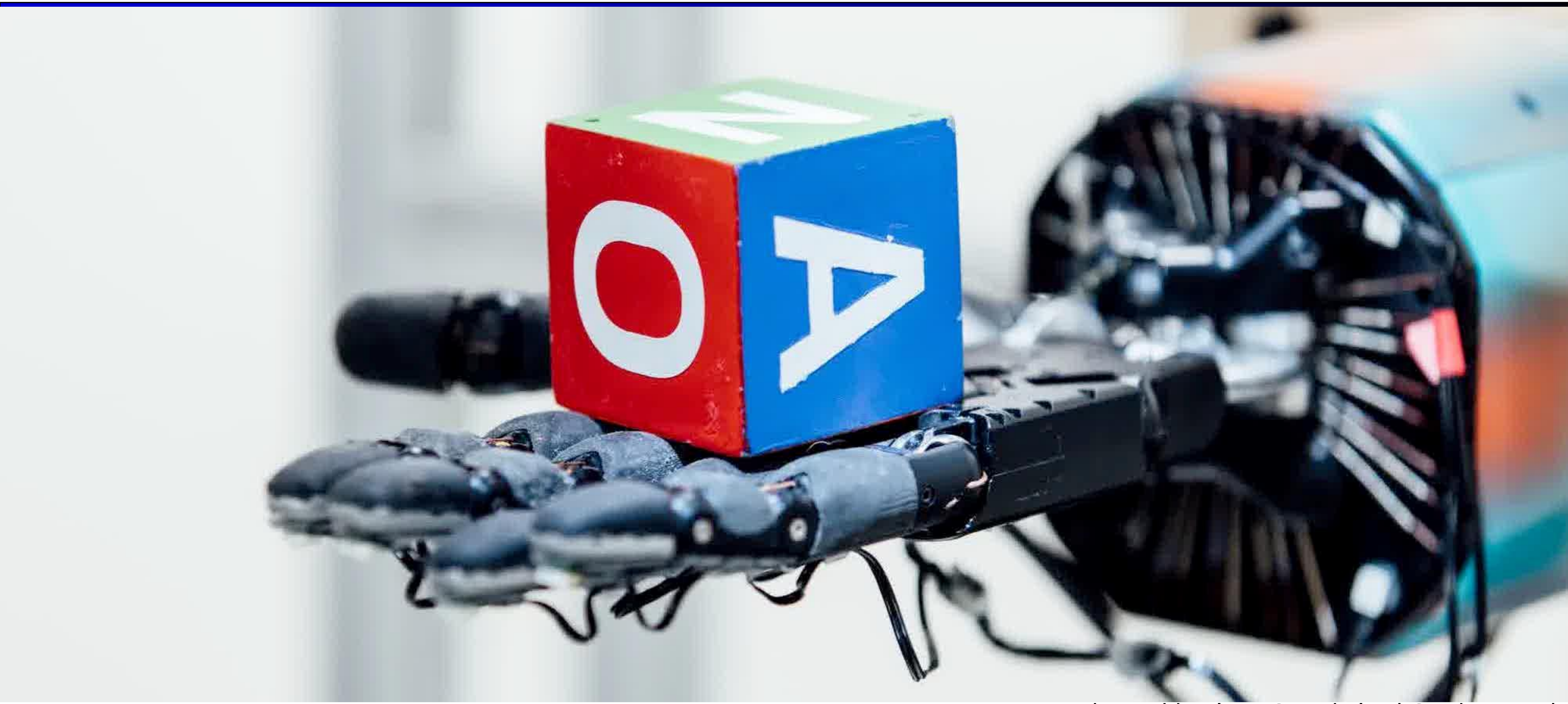


[Video: GAE]





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