Bipedal walking using deep reinforcement learning and proximal policy optimization

Jhon Charaja[1] and Luca Borgonovi[1]

[1]Universidade de São Paulo, Brasil

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Outline

Motivation

Bipedal walking is difficult activity to describe due to nonlinear relationships.

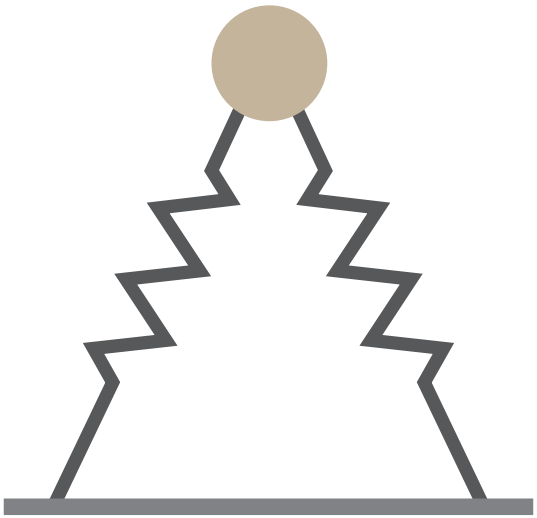

Figure: Spring-loaded inverted pendulum

- Physical representation of legs as springs [1]
- Motion of the trunk with center of mass[1]
- Recent works perform bipedal walking with machine learning methods[2,3]
- Deep reinforcement learning (DRL) does not require mathematical model or control formulation[4]
- DRL with proximal policy optimization is simple and efficient[4]

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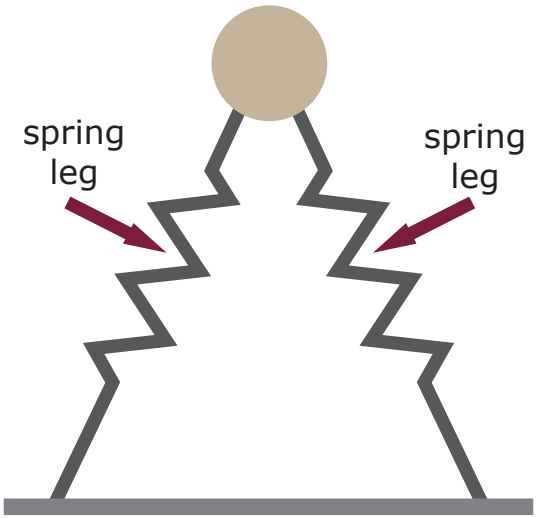

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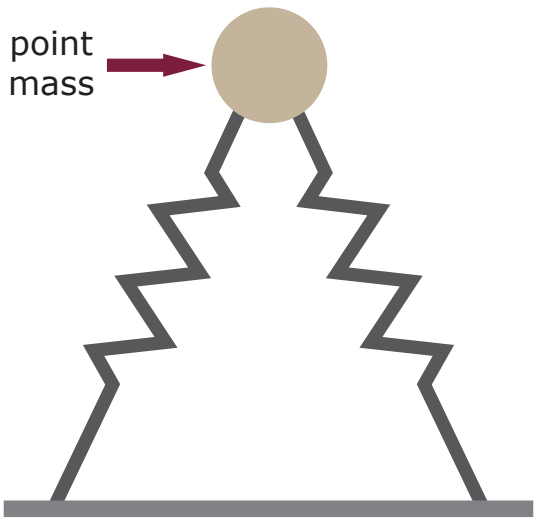

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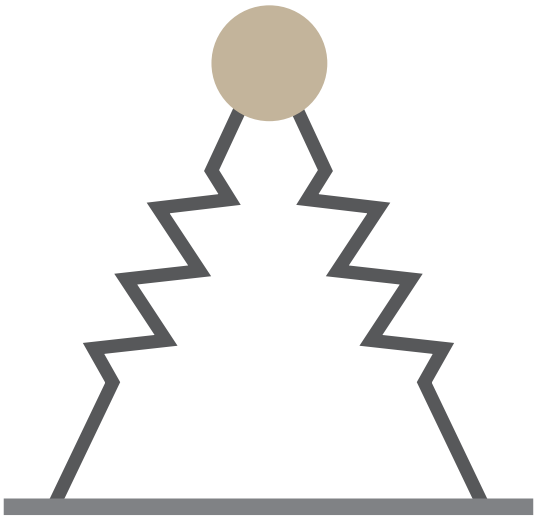

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Objective

Perform bipedal walking using deep reinforcement learning with proximal policy optimization algorithm

Outline

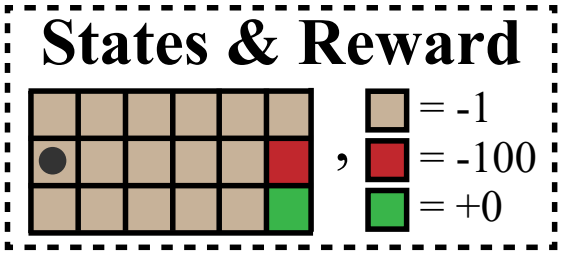
Scopes

- The algorithm is focused on making the robot walk, but not on controlling the way it walks.
- Likewise, the algorithm is not focused on optimizing energy during walking.

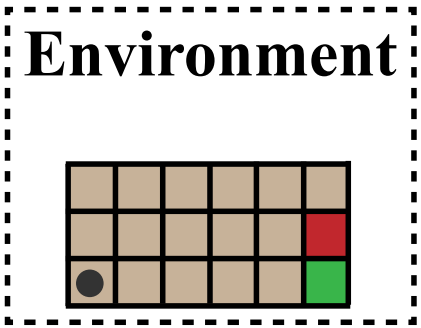
Outline

What is reinforcement learning?

Reinforcement learning is a training technique of machine learning to teach models (agents) to make good (optimal) sequences of decisions under uncertainty [1].

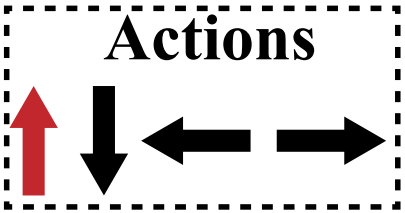


- takes decision (action) based on the reward and punishment.
- gets information throught experience.



- is the agent´s world in which it lives and interact.

: fail
: goal



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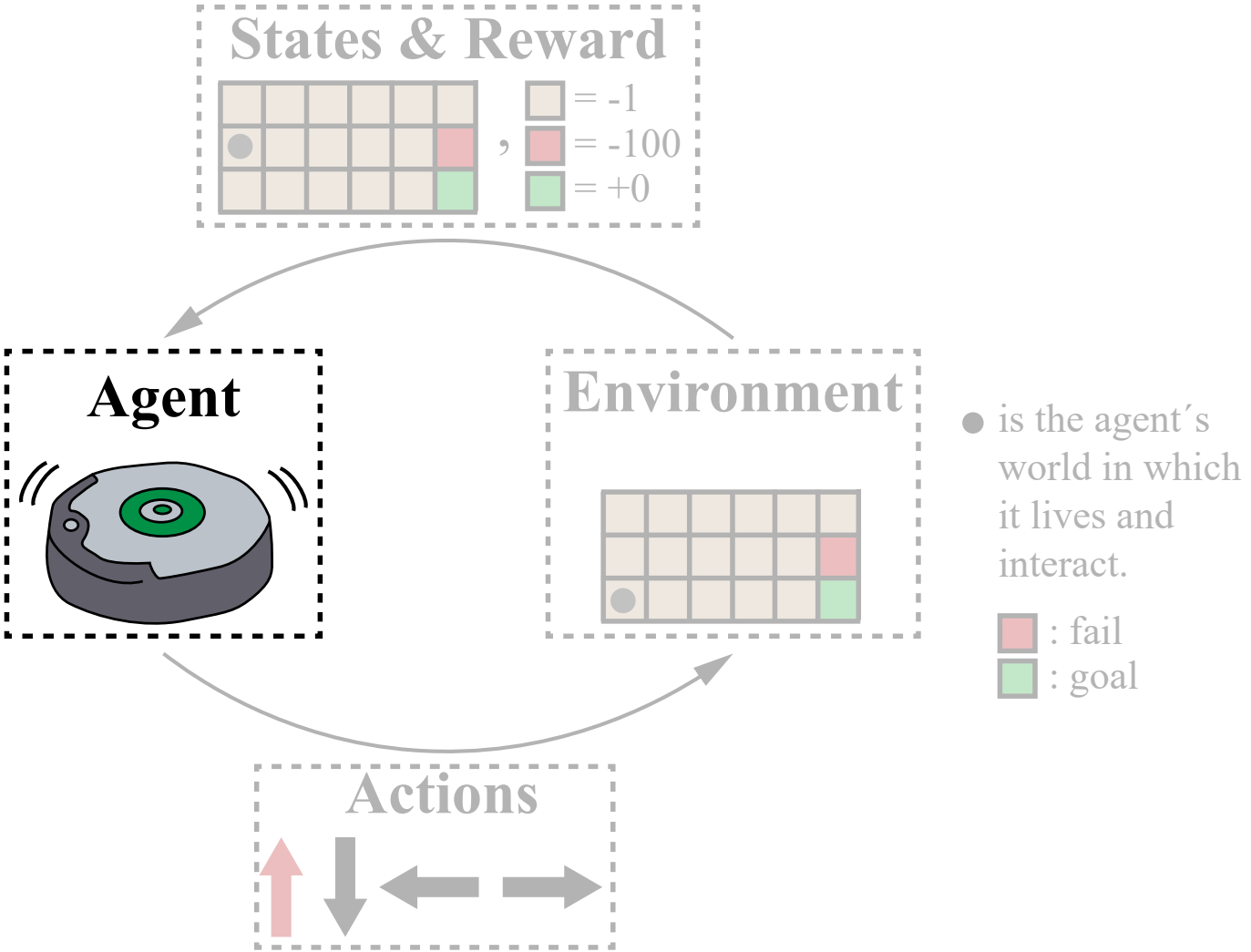

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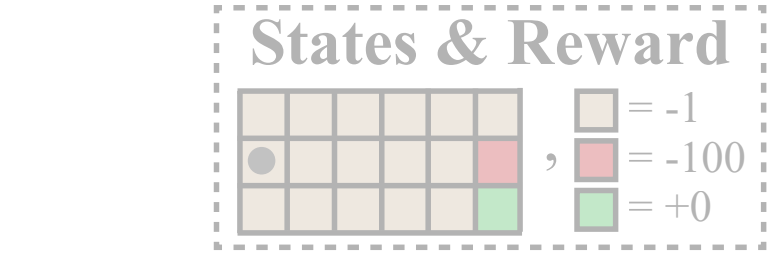

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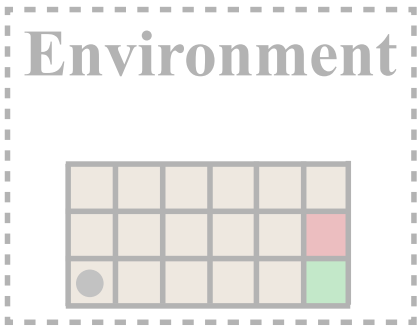

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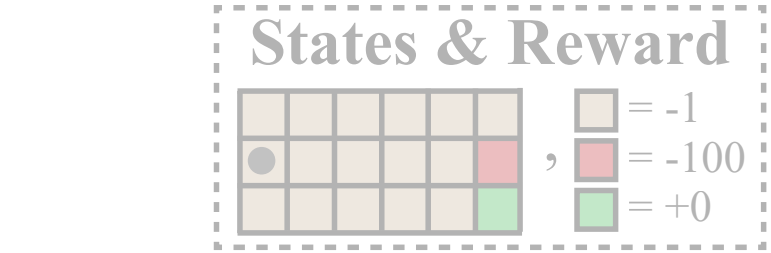

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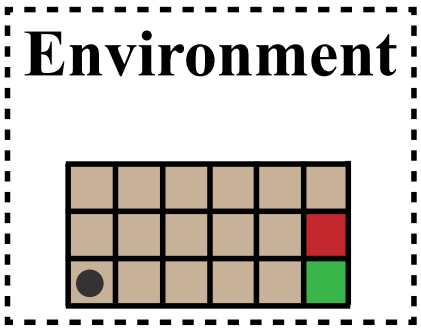

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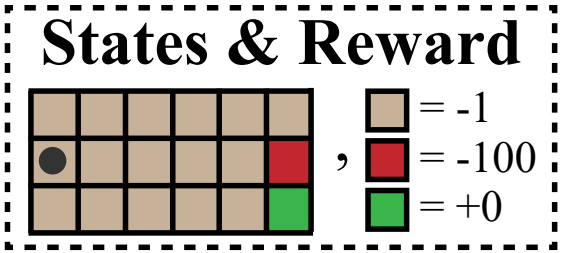

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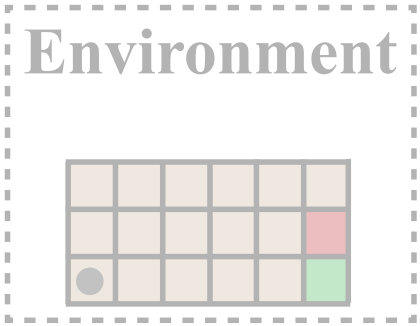

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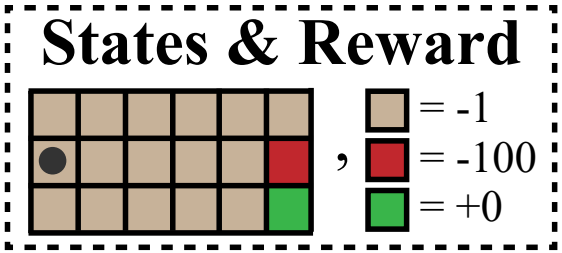

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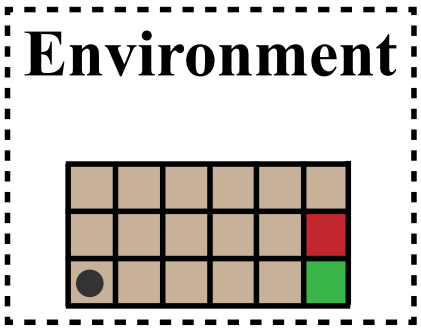

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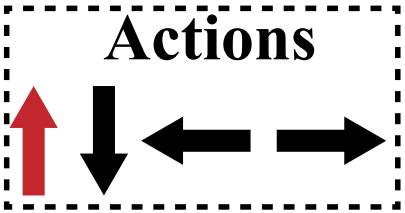

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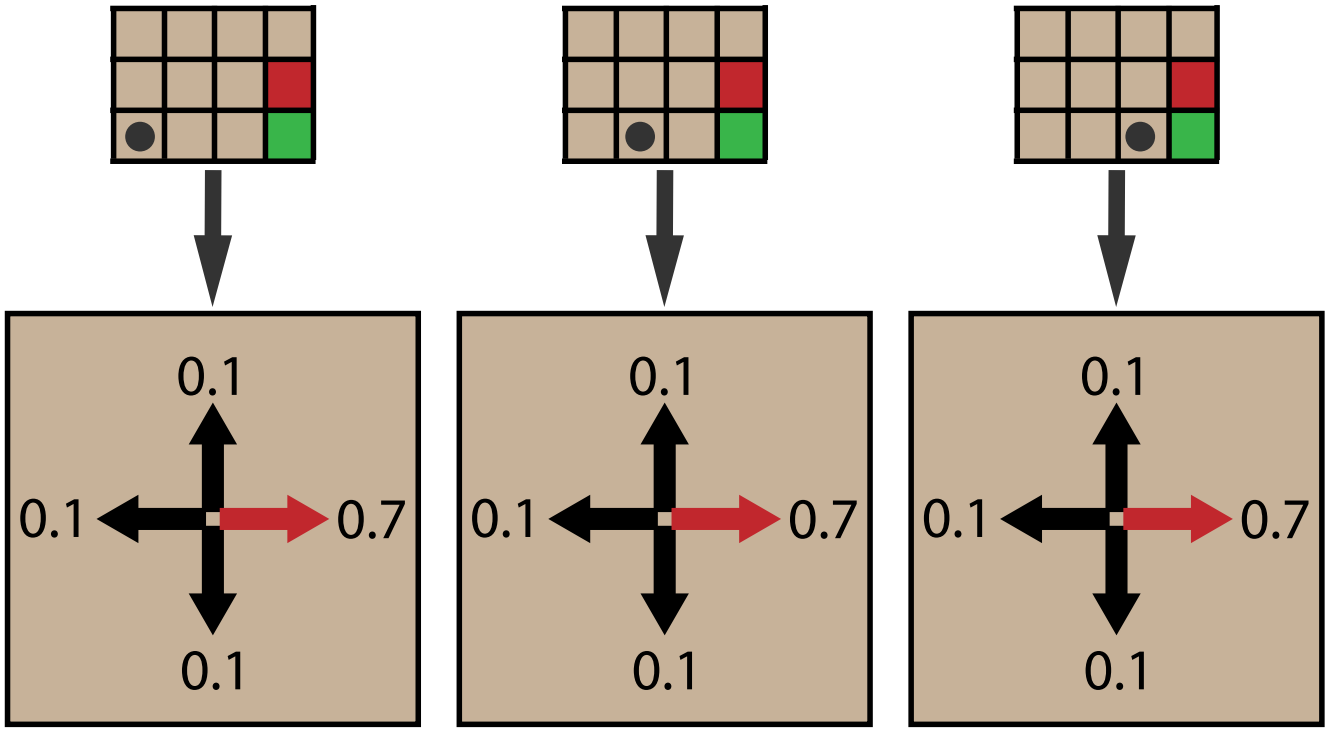
Policy

A policy (π) indicates the decision (action) that the agent should take as a function of the agent's state to accomplish the task[1].



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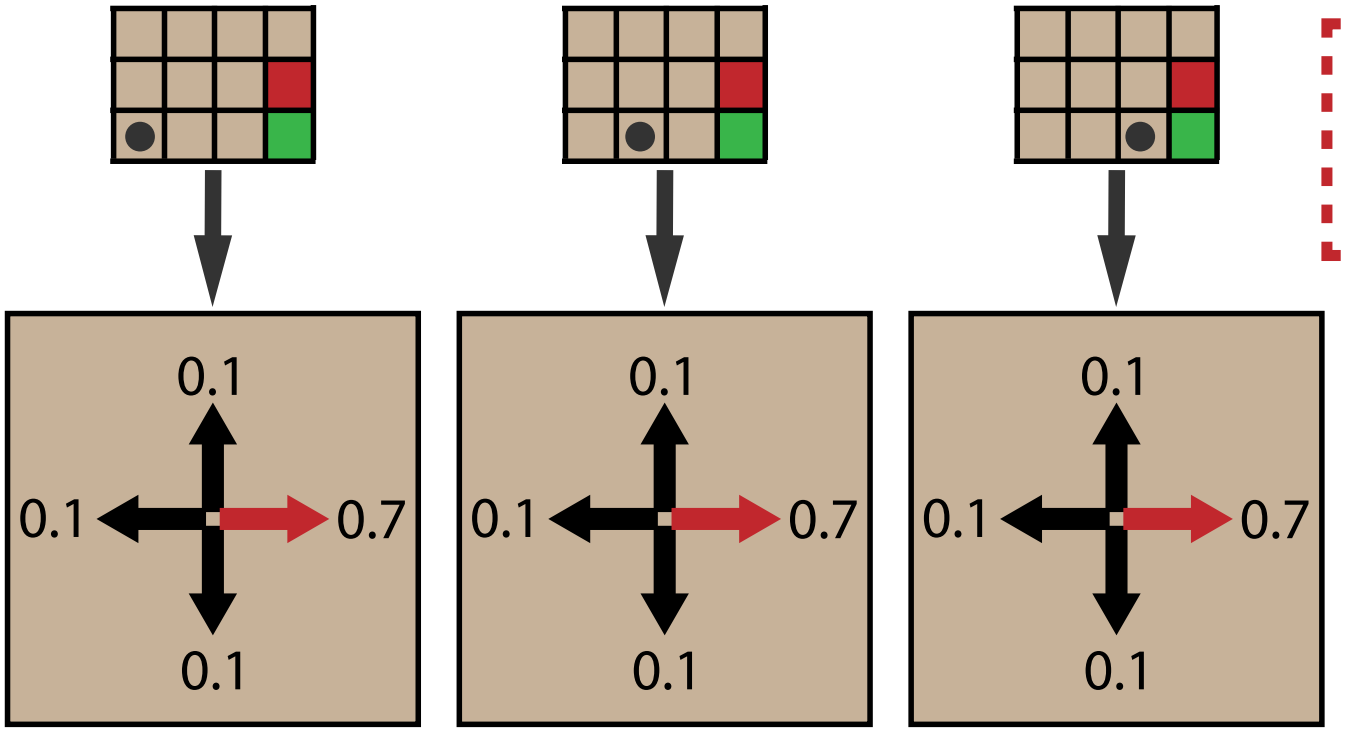


The objective is find the optimal policy (π) that maxime the reward

How quantify the performance of a policy (π)?

[1] R. S. Sutton (2018).

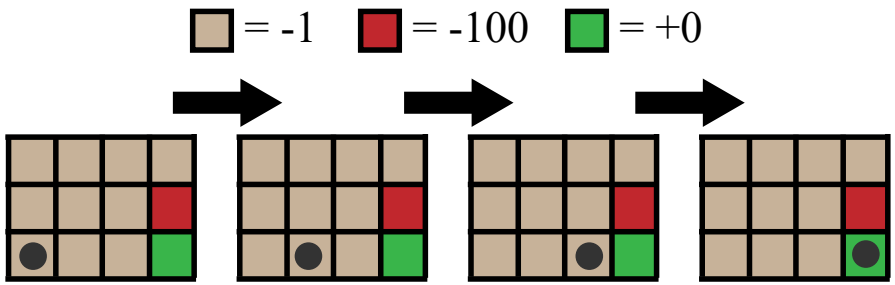
Policy evaluation: value function

The value function ($V^{\pi}(s)$) indicates the final return from being in a state when following a particular policy (π)[1]. It is given by

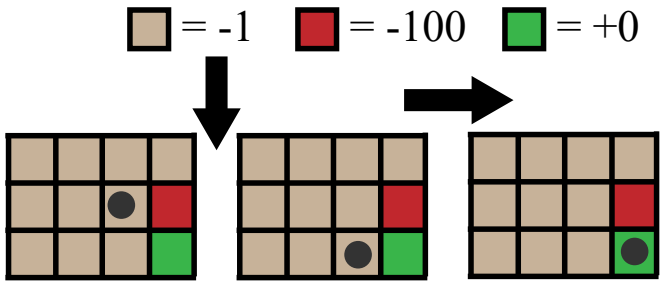
$$V^{\pi}(s_t = s) = E_{\pi}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + ... | s_t = s\right],$$

where γ is a discount factor and s_t is initial state.

Policy (π): Considering:γ=1



$V^{\pi}(s_1)$: -2



$V^{\pi}(s_6)$: -1

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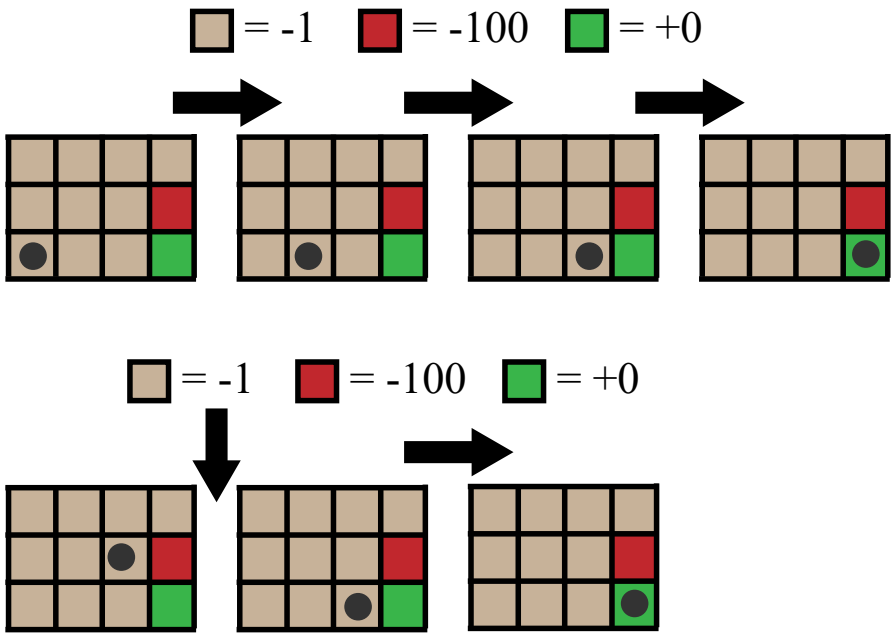


$V^{\pi}(s_1)$: -2

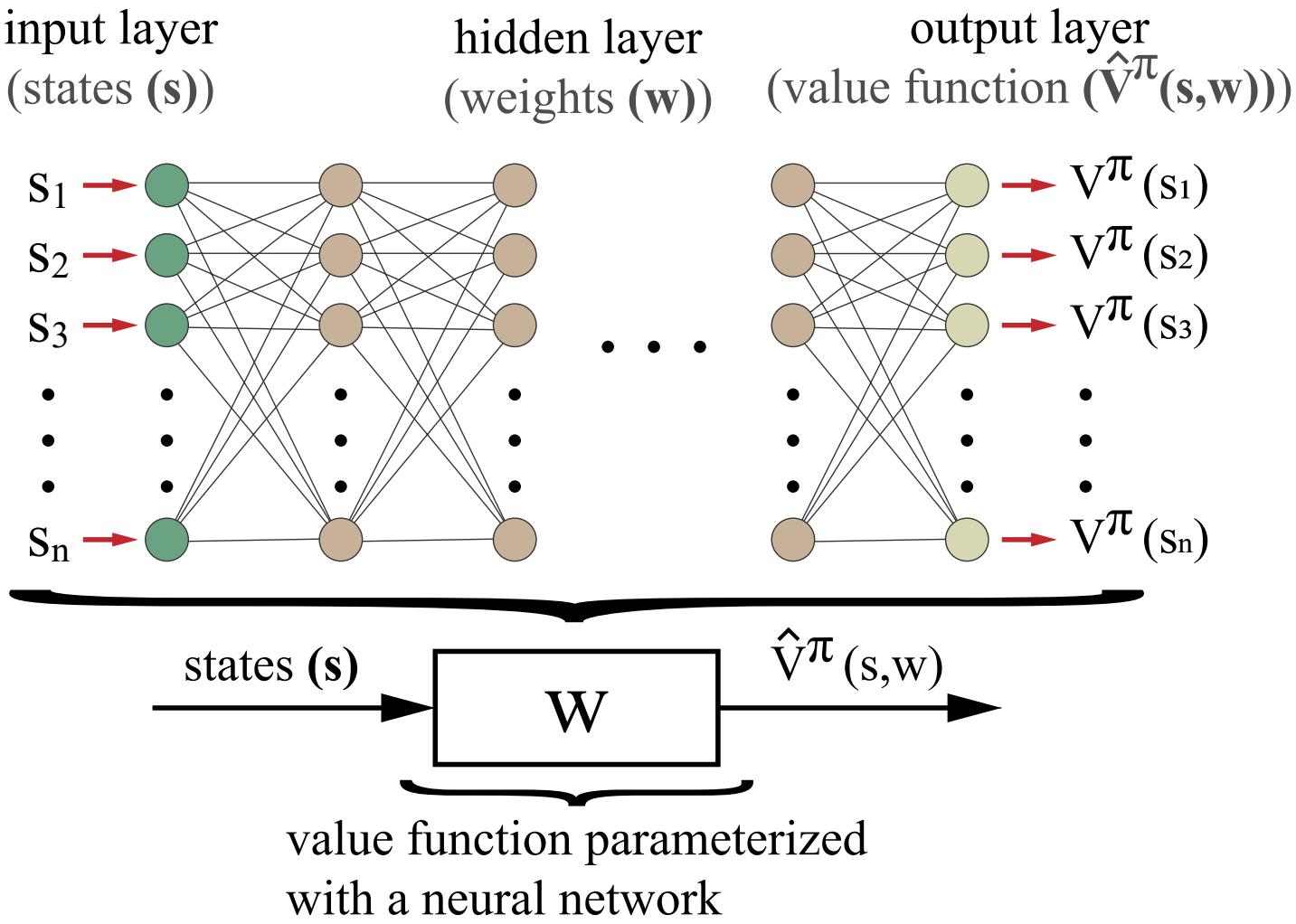
$V^{\pi}(s_6)$: -1

- $V^{\pi}(s)$ depens of policy (π) and initial state (s_t).
- Agent needs to start in ($s_{3,4,5,7,8,9,10}$) to know its value $V^{\pi}(s)$.

[1] R. S. Sutton (2018).

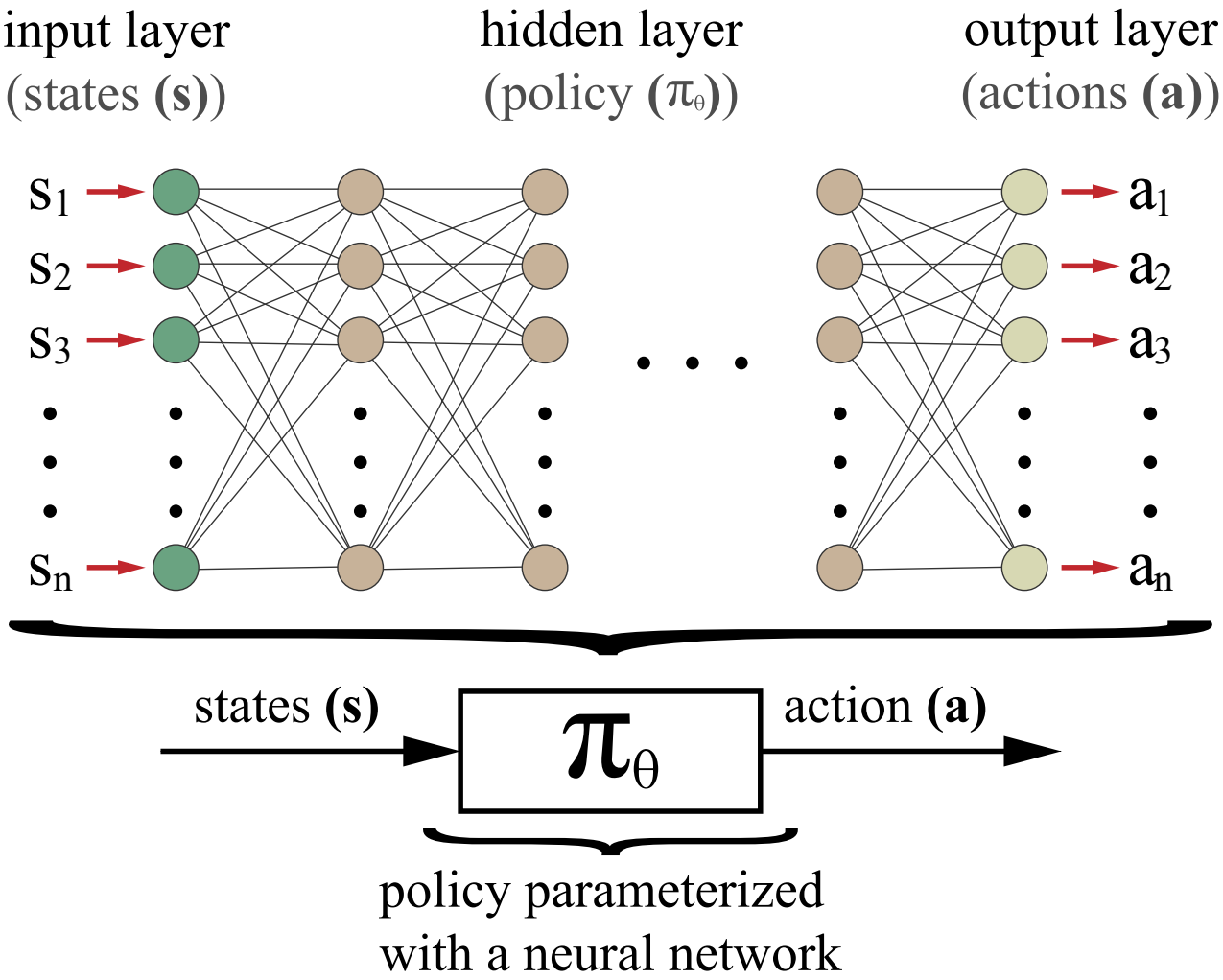
Value function approximation

The value function could be approximated by a neural network



Policy and neural networks

The policy could be represented by a neural network



Policy gradient method

This method is focused on modify the neural network parameters (θ) to get a optimal (local) policy[1].

The objective function (reward) is formulated as[1]

$$L(\theta) = \hat{\mathbb{E}}_t \left[\log \pi_\theta(a|s) \hat{A}_t \right],$$

with,

$$\hat{A}_t = V_t^{\pi_\theta} - \hat{V}_t,$$

where,

- $\hat{A}_t$ advantage function
- $V_t^{\pi_\theta}$ final reward following policy (π_θ)
- $\hat{V}_t$ expected final reward (baseline)

[1] R. S. Sutton (2018).

Proximal policy optimization

PPO is one of the best algorithms for reinforcement learning due to simplicity and high performance[1].

The main objective function (reward) is given by

$$L^{\mathrm{CLIP}}(\theta) = \hat{\mathbb{E}}_t \left[\min \left(r_t(\theta)\hat{A}_t, \mathrm{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t \right) \right],$$

with,

$$r_t(\theta) = \frac{\pi_\theta(a|s)}{\pi_{\theta,\mathrm{old}}(a|s)},$$

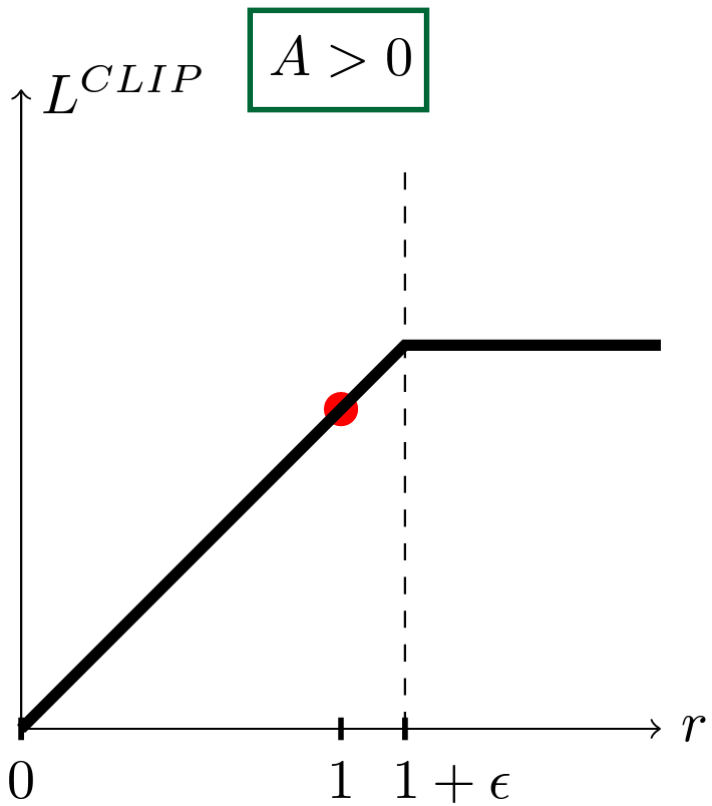
where,

- $r_t(\theta)$ probability ratio between policies
- ϵ hyperparameter

[1] J. Schulman (2017).

Proximal policy optimization

the new action yielded
better than expected return



the new action yielded
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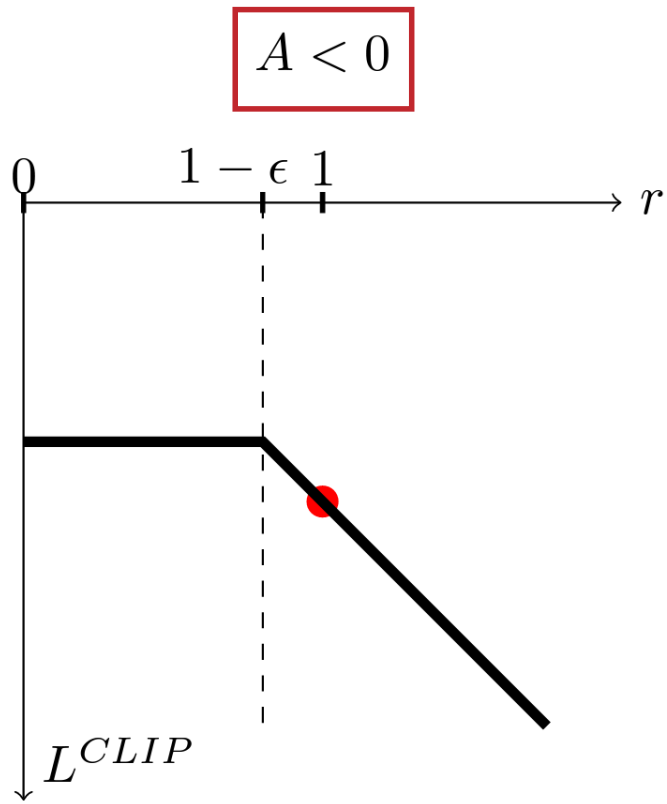

Figure: Image adapted from J. Schulman (2017)

Proximal policy optimization

The final objective function (reward and exploration) is given by[1]

$$L^{\mathrm{PPO}}(\theta) = \hat{\mathbb{E}}_t \left[L^{\mathrm{CLIP}}(\theta) - c_1 L^{\mathrm{VF}}(\theta) + c_2 S[\pi_\theta](s_t) \right],$$

with,

$$L^{\mathrm{VF}}(\theta) = \left(V_\theta(s_t) - V_t^{\mathrm{target}} \right)^2,$$

where,

- c_1, c_2 weighting coefficients
- S entropy bonus (exploration)
- $L^{\mathrm{VF}}(\theta)$ square-error loss
- V_t^{target} objective final reward

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Simulation environment and libraries

MuJoCo

Advanced physics simulation

OpenAI

TensorFlow

Bipedal robot: algorithm configuration

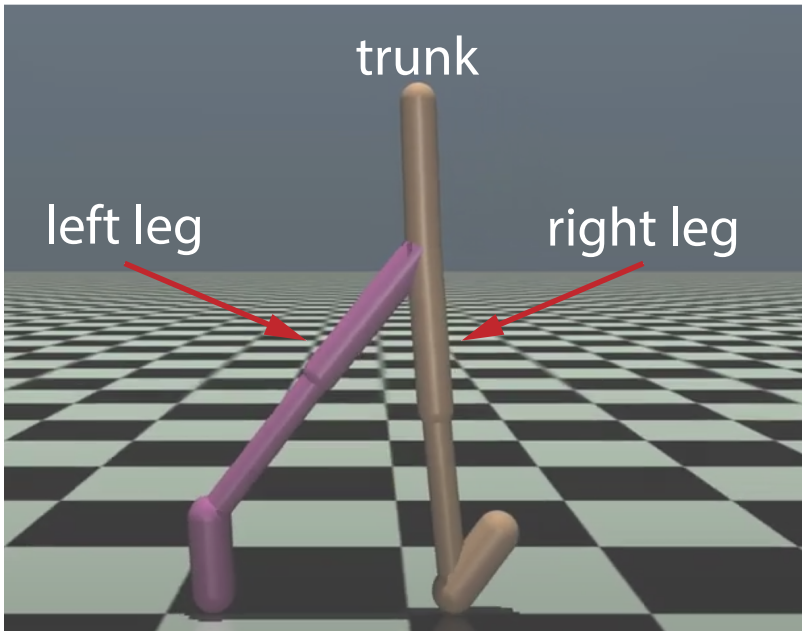


Figure: Bipedal robot in simulation environment

States

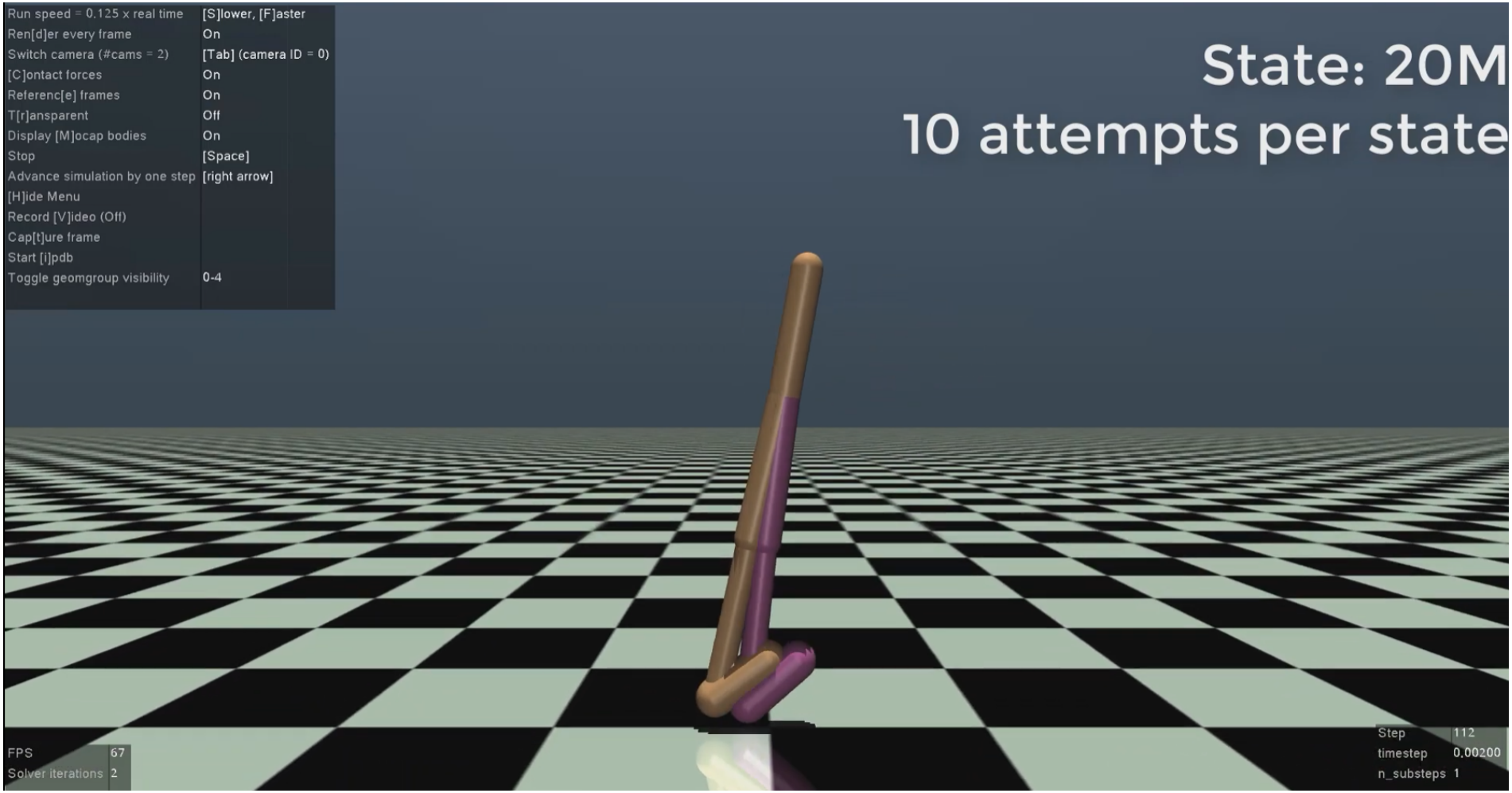
- position: 6 (left, right) + 1 (trunk)
- velocity: 6 (left, right) + 1 (trunk)
- total: 14 states

Reward

- fail when trunk angle $> 50°$
- $+1$ for each iteration alive
- $+$ linear velocity

Outline

Results


Run speed = 0.125 x real time [S]lower, [F]aster
Ren[d]er every frame On
Switch camera (#cams = 2) [Tab] (camera ID = 0)
[C]ontact forces On
Referenc[e] frames On
T[r]ansparent Off
Display [M]ocap bodies On
Stop [Space]
Advance simulation by one step [right arrow]
[H]ide Menu
Record [V]ideo (Off)
Cap[t]ure frame
Start [i]pdb
Toggle geomgroup visibility 0-4
State: 20M
10 attempts per state
FPS 67
Solver iterations 2
Step 112
timestep 0.00200
n_substeps 1

Outline

Conclusions

- We perform bipedal walking without a mathematical model and complex control formulation.
- The strange way of walking of the robot is related to the reward system that was established in this work.
- Finally, it was observed that during training, the robot made movements that removed its center of mass from the support polygon.
- As work in the future, it will be considered to keep the center mass within the support polygon to increase the stability of the system, as well as the possibility of adding muscles to achieve natural movements.