Reinforcement learning

Episode -1

Miscellaneous cool stuff

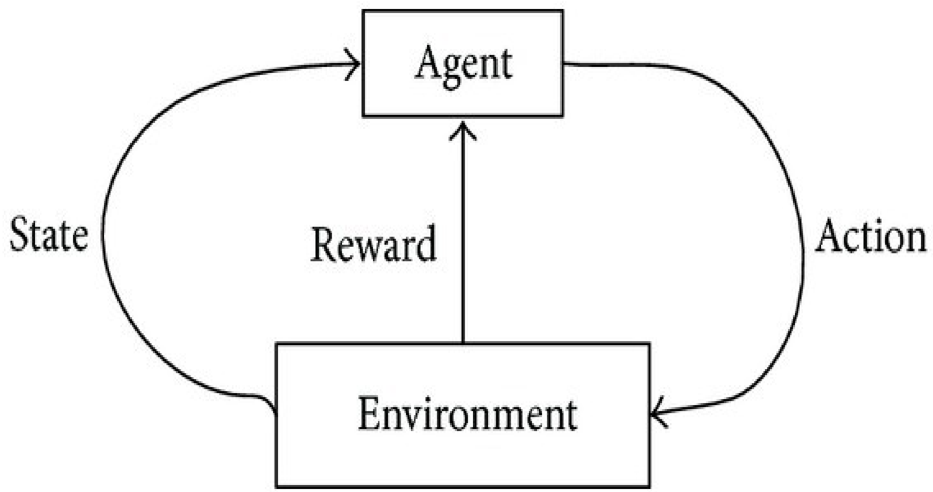
Yandex
Data Factory

LAMBDA

British Hedgehog
Preservation Society

Part 1: Continuous action spaces

- Regular MDP
- $a \in \mathbb{R}^n$



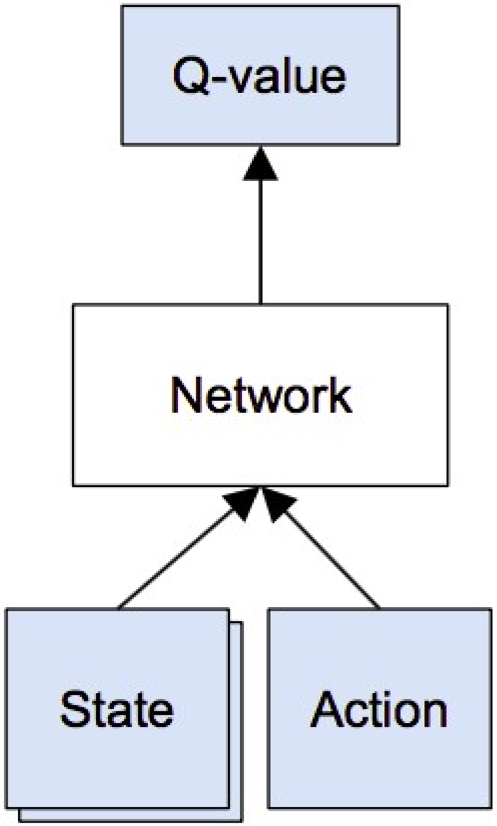
Which methods can we use?

Continuous action spaces

- We can learn critic easily

- The problem is finding

$$a_{opt}(s) = \underset{a}{argmax}\, Q(s,a)$$



Worst case: optimize over neural net!

Normalized advantage functions

Idea 1: restrict Q(s,a) so that optimization becomes trivial

For example, parabola (for 1d action space)

$$Q(s,a)=V(s)+A(s,a)$$

$$A(s,a)=-k_\theta(s)\cdot(a-\mu_\theta(s))^2$$

How to find optimal a?

Normalized advantage functions

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$$Q(s,a)=V(s)+A(s,a)$$

$$A(s,a)=-k_\theta(s)\cdot(a-\mu_\theta(s))^2$$

How to find optimal a? - a_opt = mu(s)

Normalized advantage functions

Idea 1: restrict Q(s,a) so that optimization becomes trivial

For example, parabola (for 1d action space)

$$Q(s,a) = V(s) + A(s,a)$$

$$A(s,a) = -k_\theta(s) \cdot (a - \mu_\theta(s))^2$$

How does it generalize for n-dimensional **a**?

Normalized advantage functions

Idea 1: restrict Q(s,a) so that optimization becomes trivial

For example, parabola (for 1d action space)

$$Q(s,a)=V(s)+A(s,a)$$

$$A(s,a)=-0.5\cdot(a-\mu_\theta(s))^T\cdot L(s)\cdot L(s)^T(a-\mu_\theta(s))$$

Where L(s) is a lower-triangular matrix

Normalized advantage functions

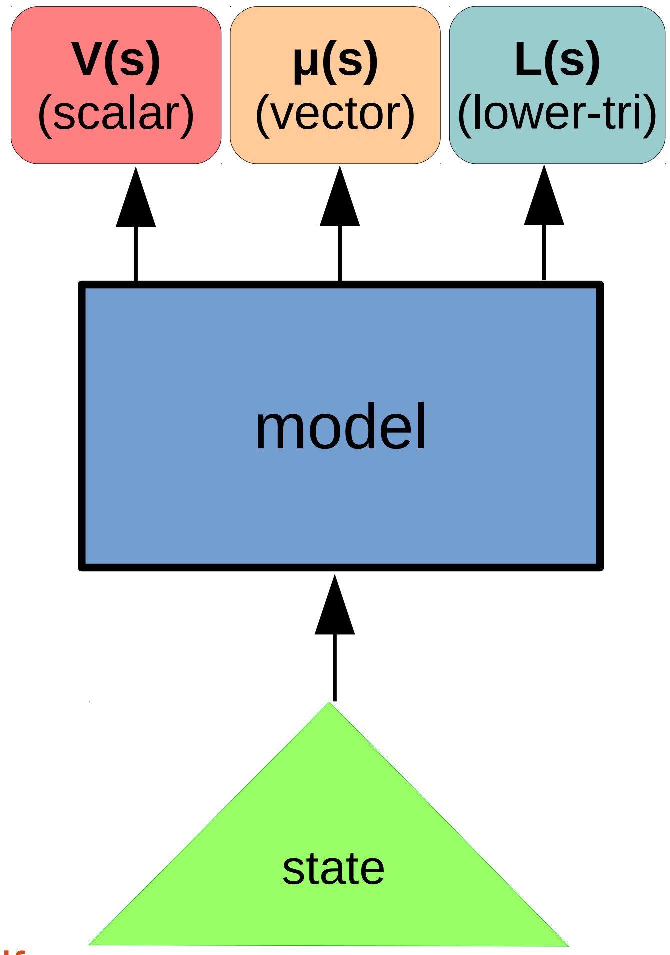
Network:

(trains end-to-end)

$$Q(s,a) = V(s) + A(s,a)$$

$$A(s,a) = \dots$$

$$\underset{\theta}{argmin}\left(Q(s_t,a_t) - [r + \gamma \cdot V(s_{t+1})]\right)^2$$



https://arxiv.org/pdf/1603.00748.pdf

Deterministic policy gradient

- Idea2: learn a separate network to find a_opt

- Train critic $Q_\theta(s, a)$

$$\underset{\theta}{argmin}\left(Q(s_t, a_t) - [r + \gamma \cdot V(s_{t+1})]\right)^2$$

- Train actor $a_{opt}(s) \approx \mu_\theta(s)$

$$\nabla_\theta J = \frac{\partial Q^\theta(s,a)}{\partial a} \frac{\partial \mu(s|\theta)}{\partial \theta}$$

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How do we get V(s')?

- Train actor $a_{opt}(s) \approx \mu_\theta(s)$

$$\nabla_\theta J = \frac{\partial Q^\theta(s,a)}{\partial a} \frac{\partial \mu(s|\theta)}{\partial \theta}$$

Deterministic policy gradient

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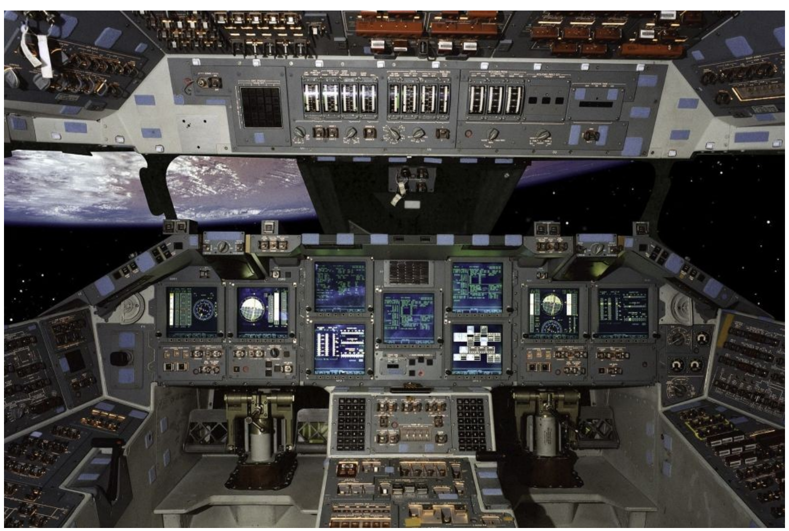
Deterministic policy gradient

Demo with torcs http://bit.ly/2pXwdKa

Ugly action spaces

- Keyboard
- Aircraft control
- ~Any strategy game



Exploiting action space structure

- Imagine a large discrete action space, 10^90

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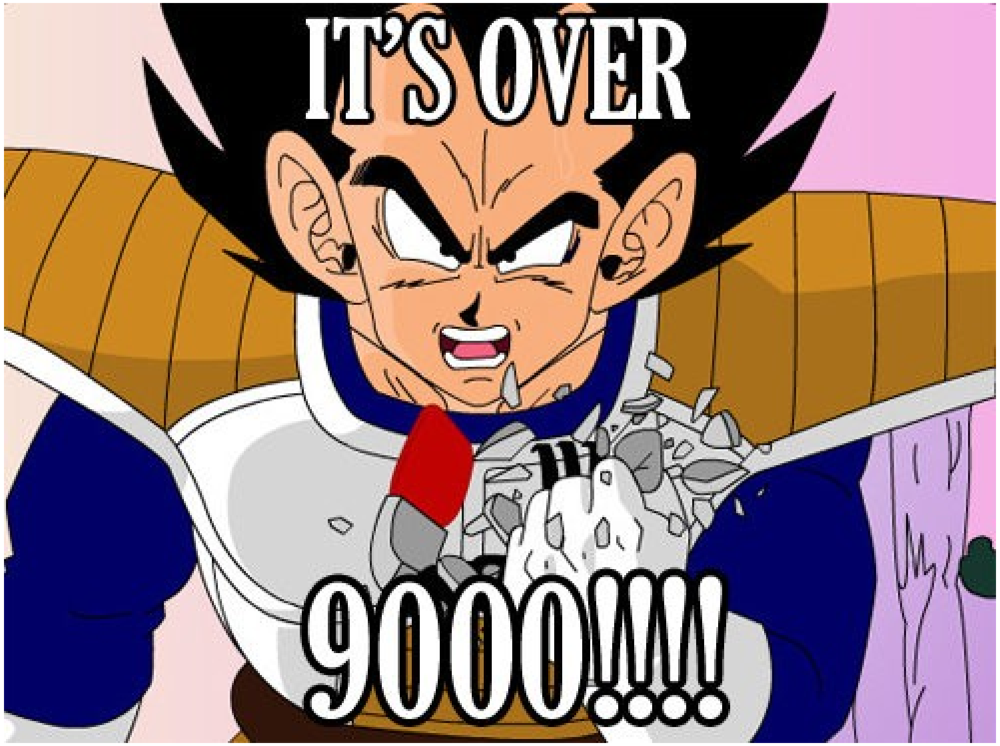

Like, way over 9000

Exploiting action space structure

- Imagine a large discrete action space, 10^90
  - We worked with such spaces before!

$$a = \langle a_0, a_1, a_2, \ldots, a_{50} \rangle$$

$$|a_i| = 60 \qquad\qquad |a| = 60^{50} \approx 10^{90}$$

Does it remind you of anything?

Exploiting action space structure

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$$|a_i| = 60 \qquad\qquad |a| = 60^{50} \approx 10^{90}$$

a_i is a single letter, a is full translation

How did we deal with 10^90 actions?

Structured action space: sequential

- Action space

$$a=\langle a_0, a_1, a_2, \ldots, a_{60}\rangle$$

- Straightforward $\pi(a|s)$ $|s|\times|a|$

- Sequential

$$\pi(a|s)=\pi(a_0|s)\cdot\pi(a_1|s,a_0)\cdot\ldots\cdot\pi(a_i|s,a_{0:i-1})$$

Structured action space: sequential

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How did we approximate this distribution?
With RNNs/HMMs!

Recommender systems

- Typical bandit
- One action per item, 10^5 items (still over 9000)
- Even worse: new items arrive over time!
- Similar items have similar audiences

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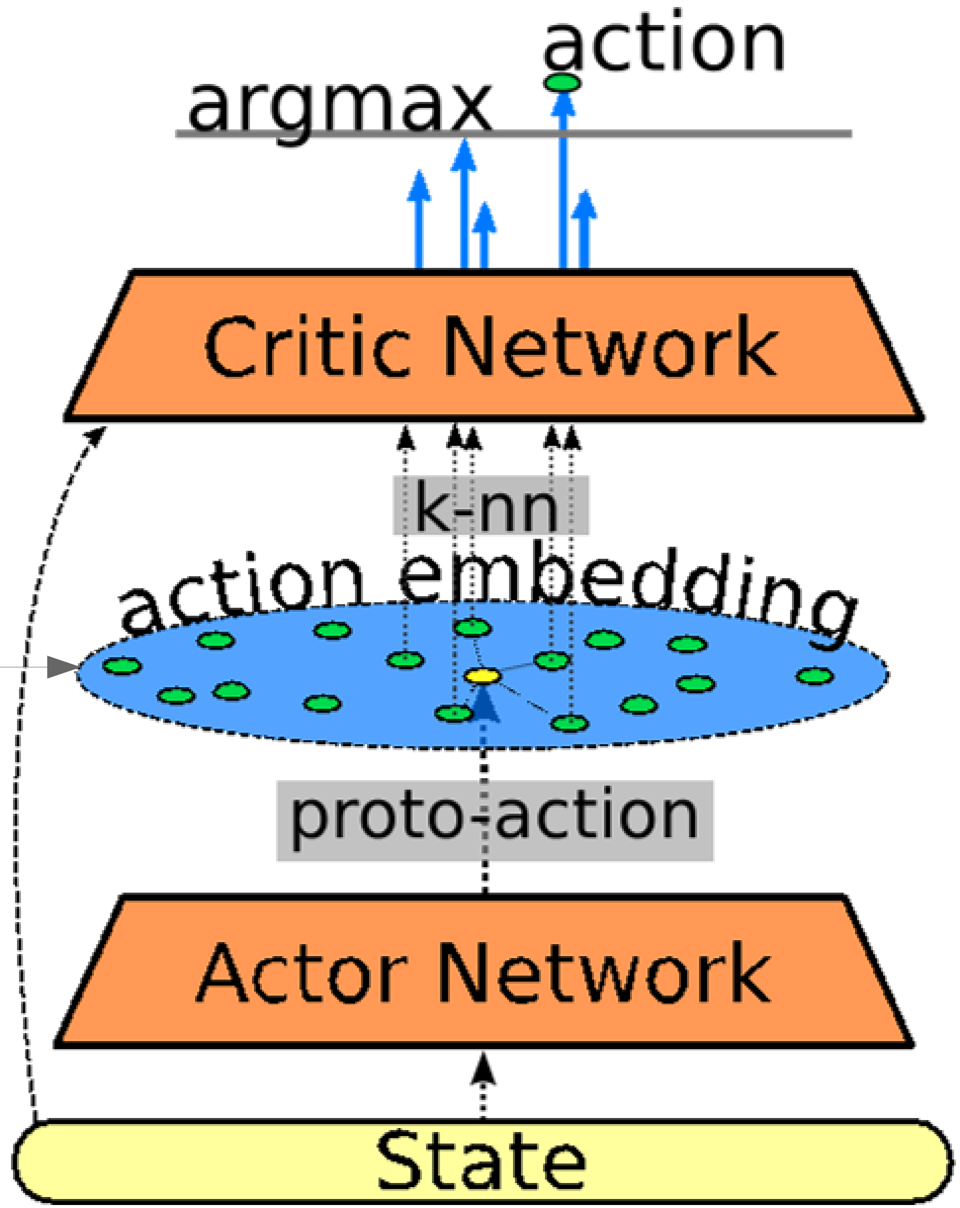
Action embedding

Map actions into some continuous space

How to do that for films?



Action embedding

- Map actions into some continuous space

  (hand-crafted / tsne / emb)

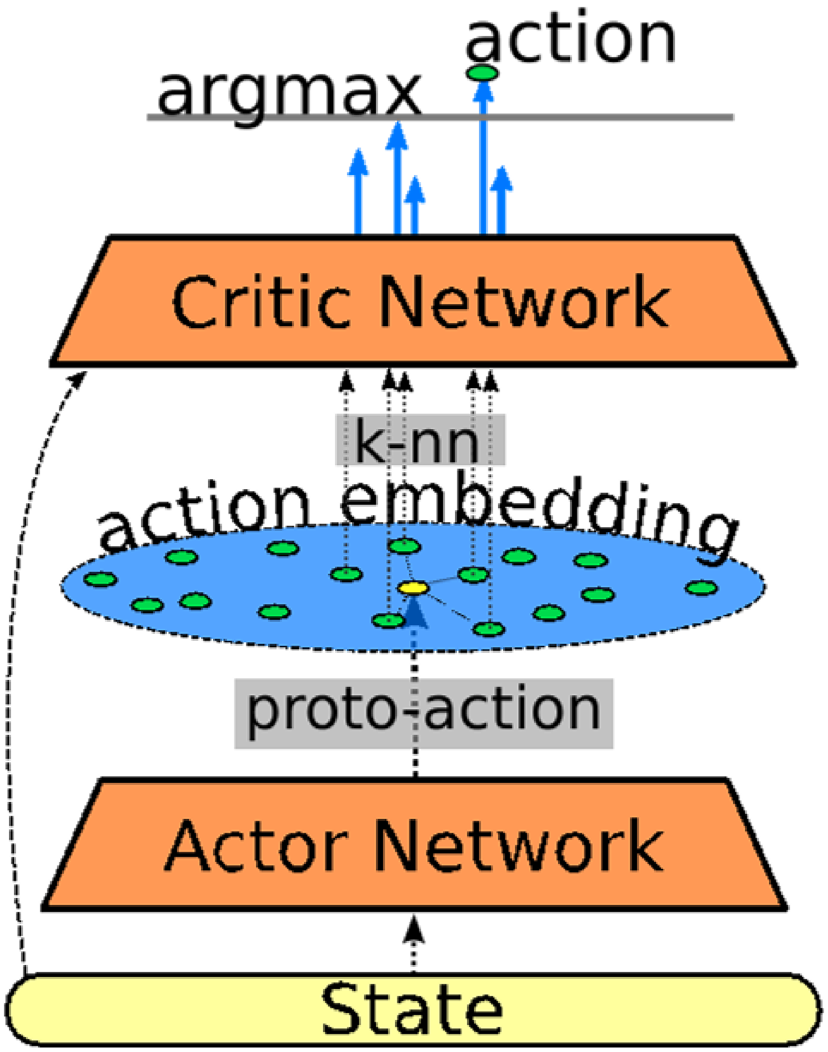
- Predict continuous “action”

  (aka proto-action)

- Pick closest discrete action

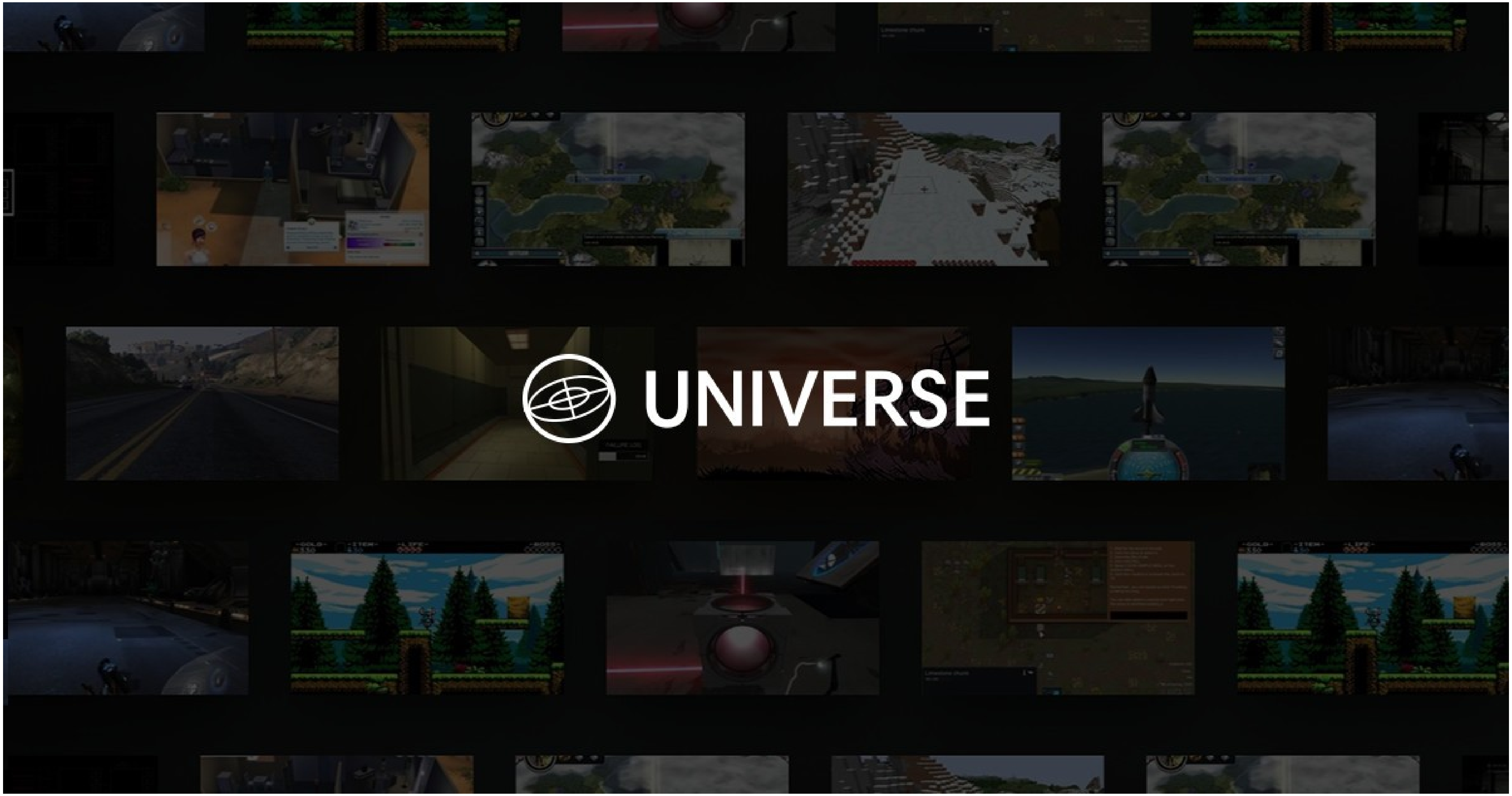
  e.g. with (LSH)

  (locally sensitive hashes)



https://arxiv.org/abs/1512.07679

Let's figure it out!



http://universe.openai.com

Let's figure it out!

- Emulate human PC user
  - Actions: keyboard and mouse

How do we define $\pi(a|s)$?

OpenAI

Part 2: hierarchical RL

Problem: Rewards are usually sparse (temporally rare) and delayed.

It takes exponentially more random exploration to learn optimal policy in case of rare rewards.

Humans:

- Don't seem to follow epsilon-greedy exploration policy (see lecture 9)

- Think in several layers of abstraction
  - “Contract leg muscles”
  - “Push gas pedal (while driving)”
  - “Take left turn in 15 meters”
  - “Drive to school”,
  - “Give my children education”

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  - “Contract leg muscles”
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We want hierarchical decision-making!

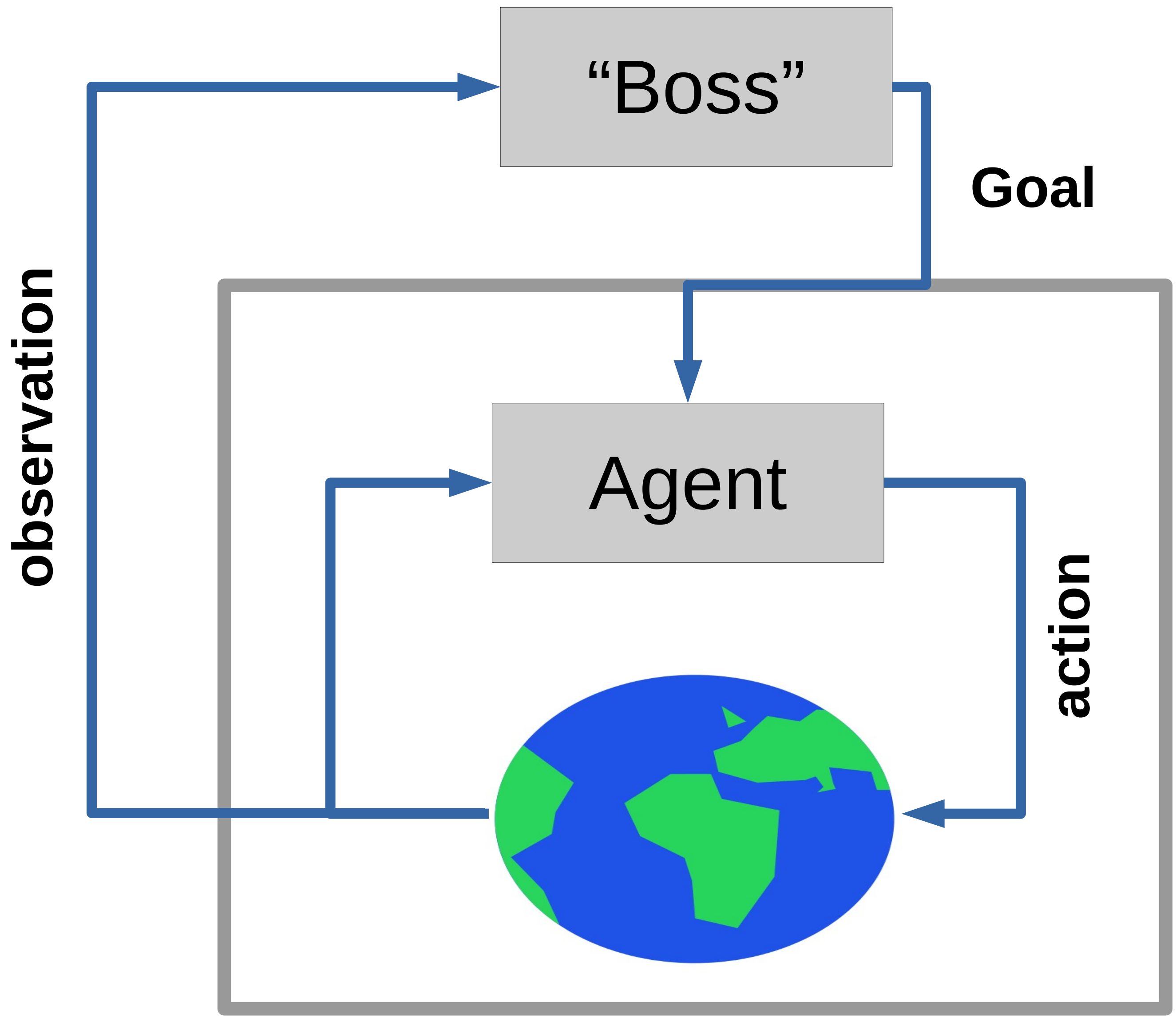
So what is hierarchy, again?

Suggestions?

So what is hierarchy, again?

- I know, I know! It's about operating in term of more abstract states!
- No! It's about acting on a longer time scale!
- No! it's about decomposing reward into short-term and long-term

Hierarchical MDP



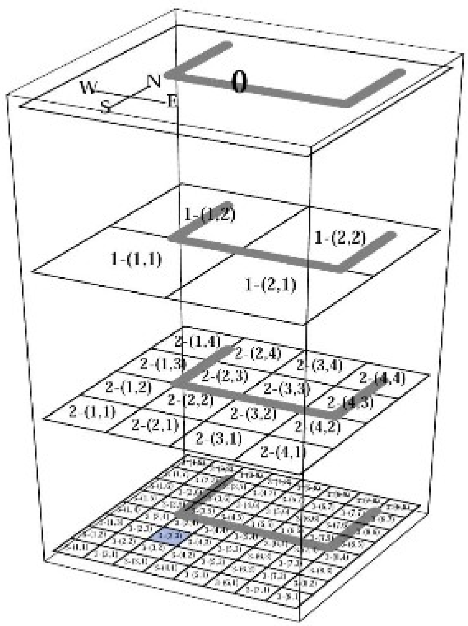
Feudal RL

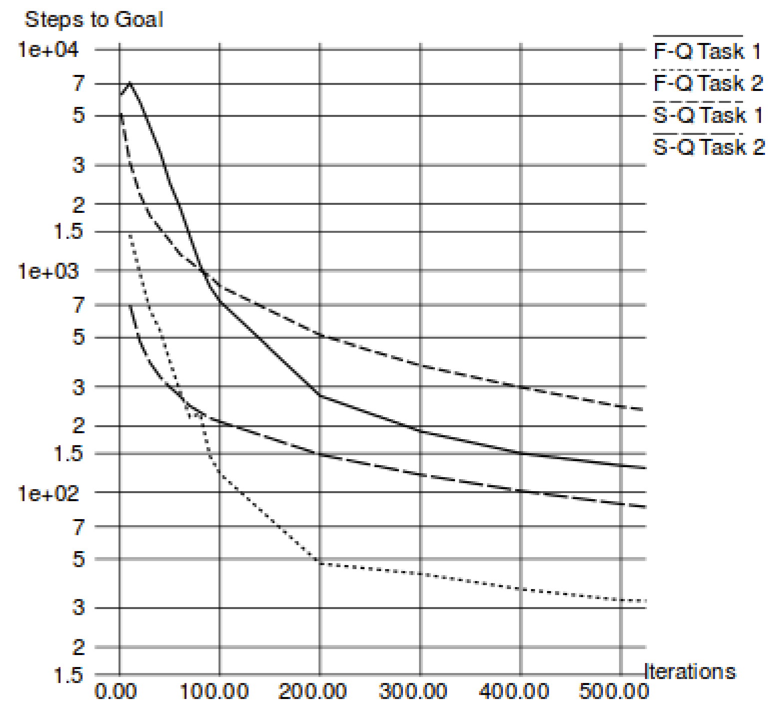
- Idea:
  - At the bottom, there's regular agent that operates on raw states and takes actual actions. He also receives goals from above.
  - Above him, there's a 'manager' agent that operates on more abstract states and issues goals to bottom agent. He also may receive higher-order goals from above him.

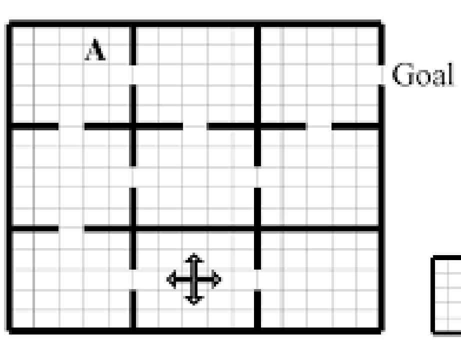
- Manager doesn't care whether his goal is actually beneficial to his super.
- Neither he does care about what orders does his sub-manager issue.

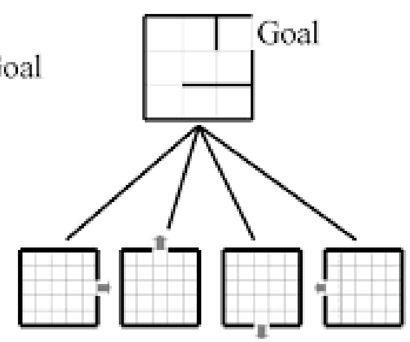
Feudal RL

- Idea:

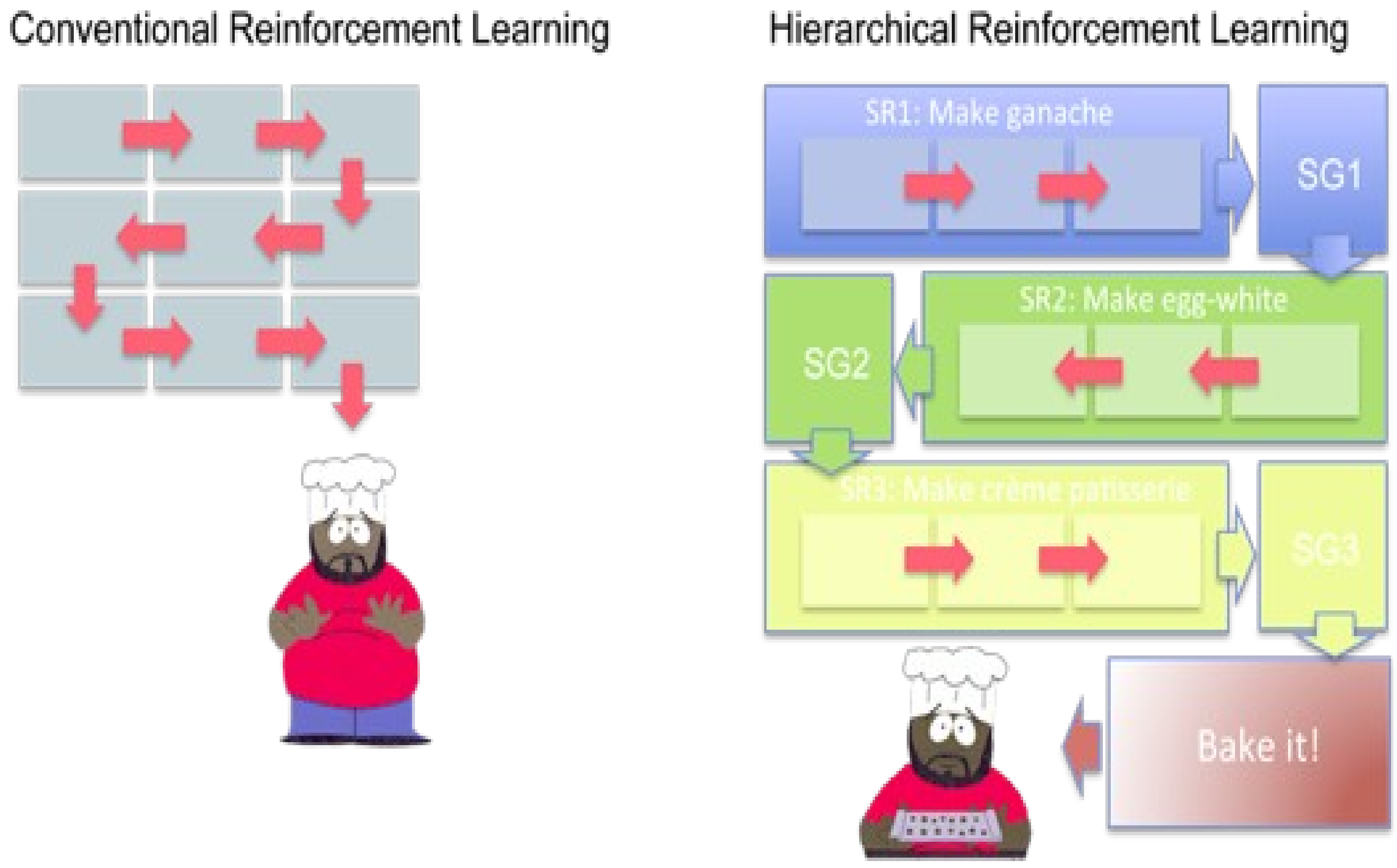






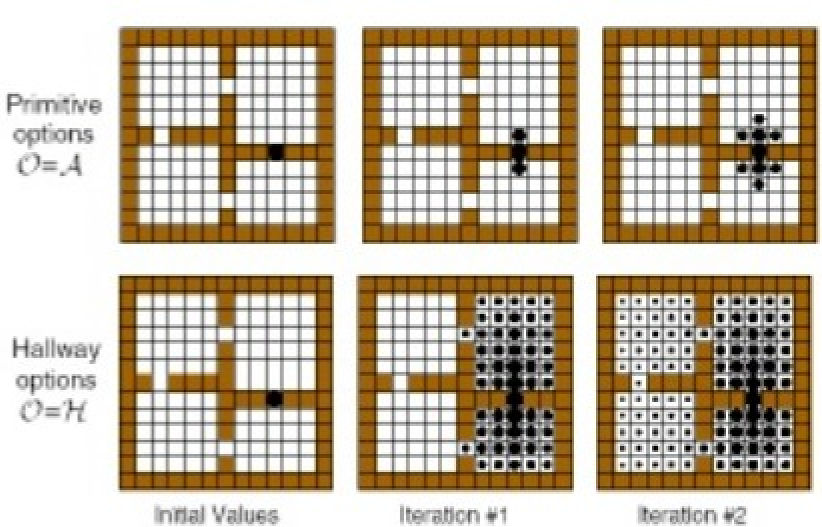


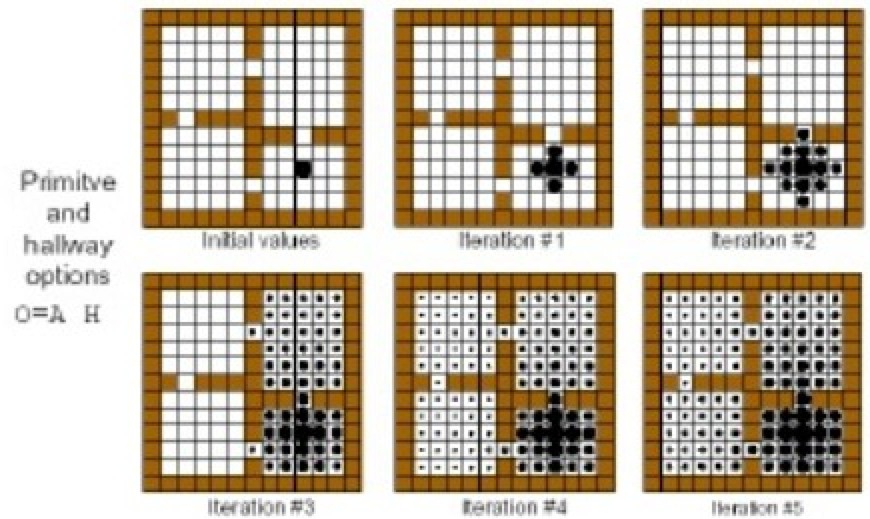
Temporal abstraction RL



The “option" method by Sutton, Precup, and Singh 1998

Temporal abstraction RL





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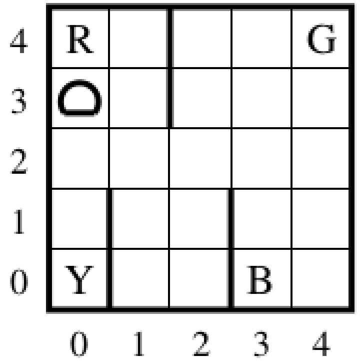
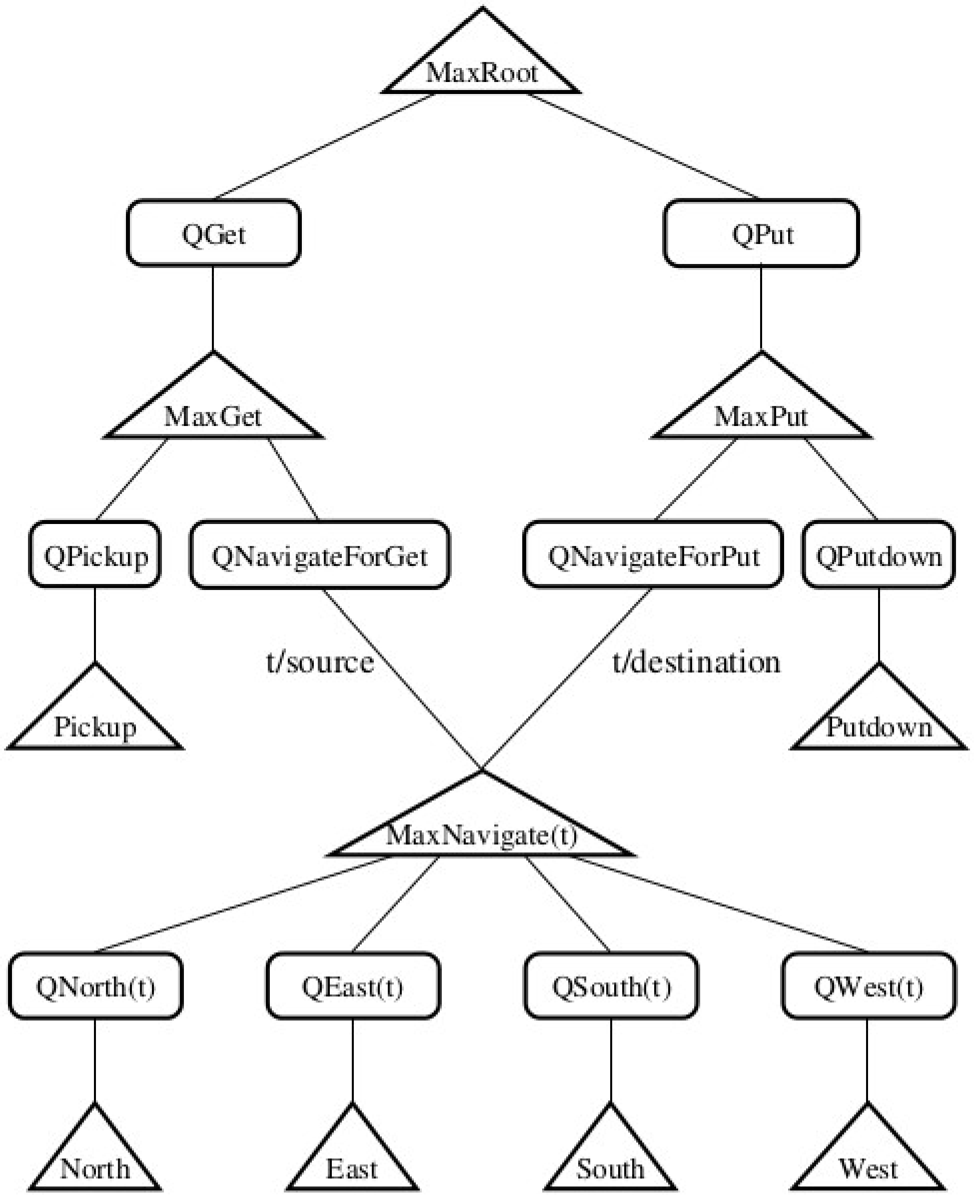
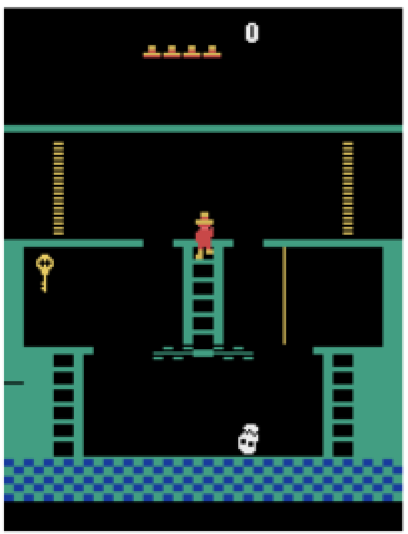
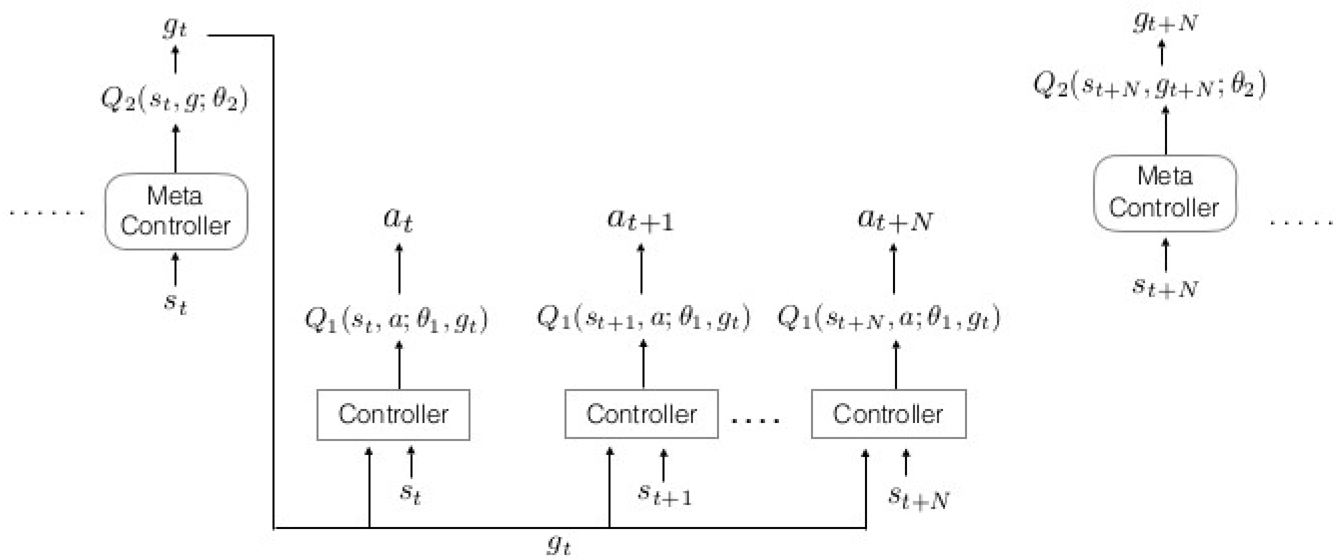
MDP decomposition





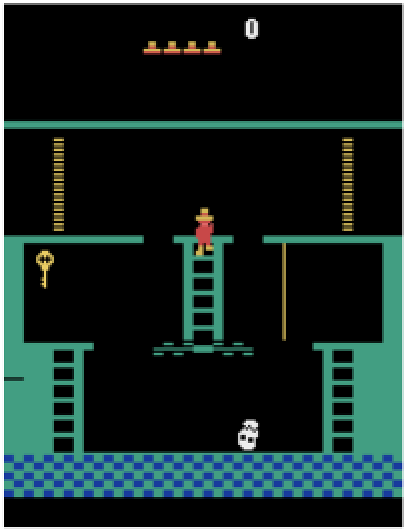
Hierarchical deep RL

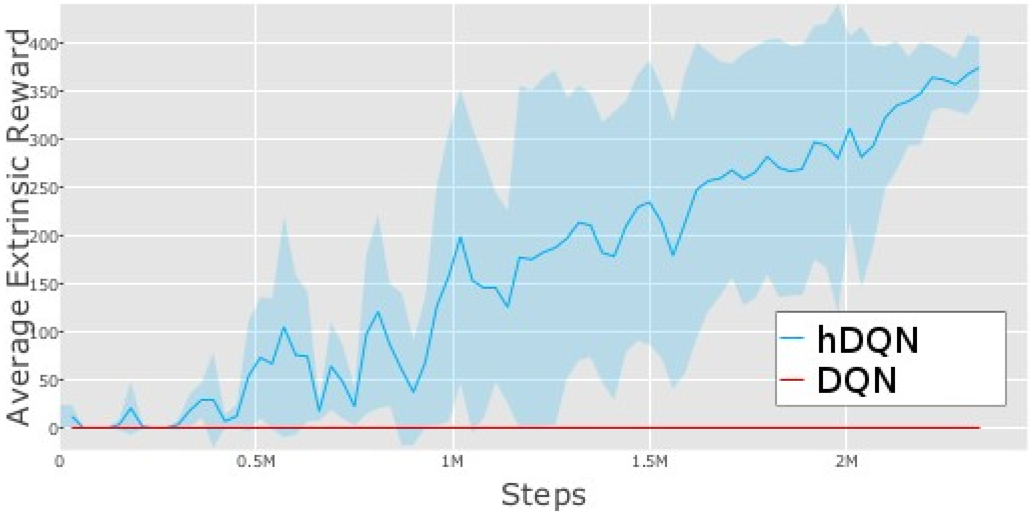




Tenenbaum et al. https://arxiv.org/abs/1604.06057v1

Hierarchical deep RL





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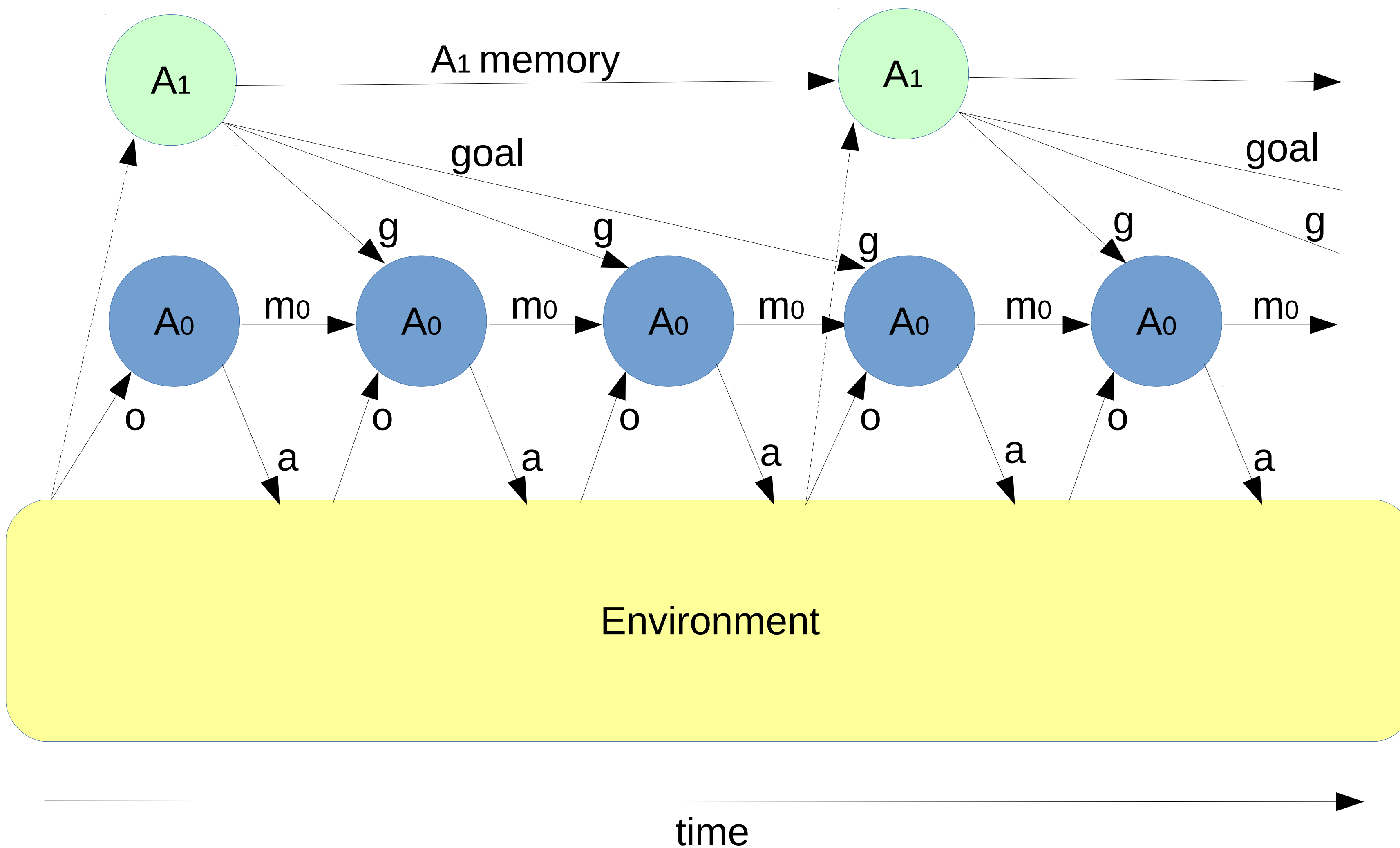
Hierarchical RL



Model-free hierarchical RL

- Upper-level agent actions (goals for lower-level) are just arbitrary numbers without any model knowledge
- Lower-level agent uses goal embedding as a part of his state vector

$$A_1 : g \in N \pi\left(g \middle| s, m_1\right) : argmax\, R$$

Model-free hierarchical RL

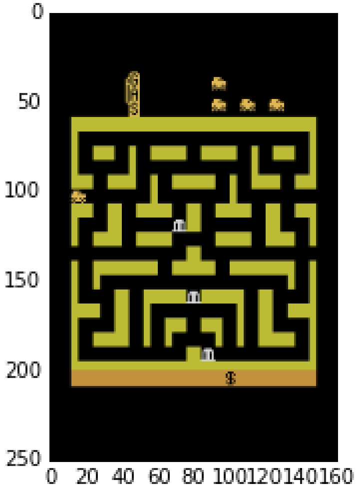
- Upper-level agent actions (goals for lower-level) are just arbitrary numbers without any model knowledge $g \in N$
- Lower-level agent uses goal embedding as a part of his state vector

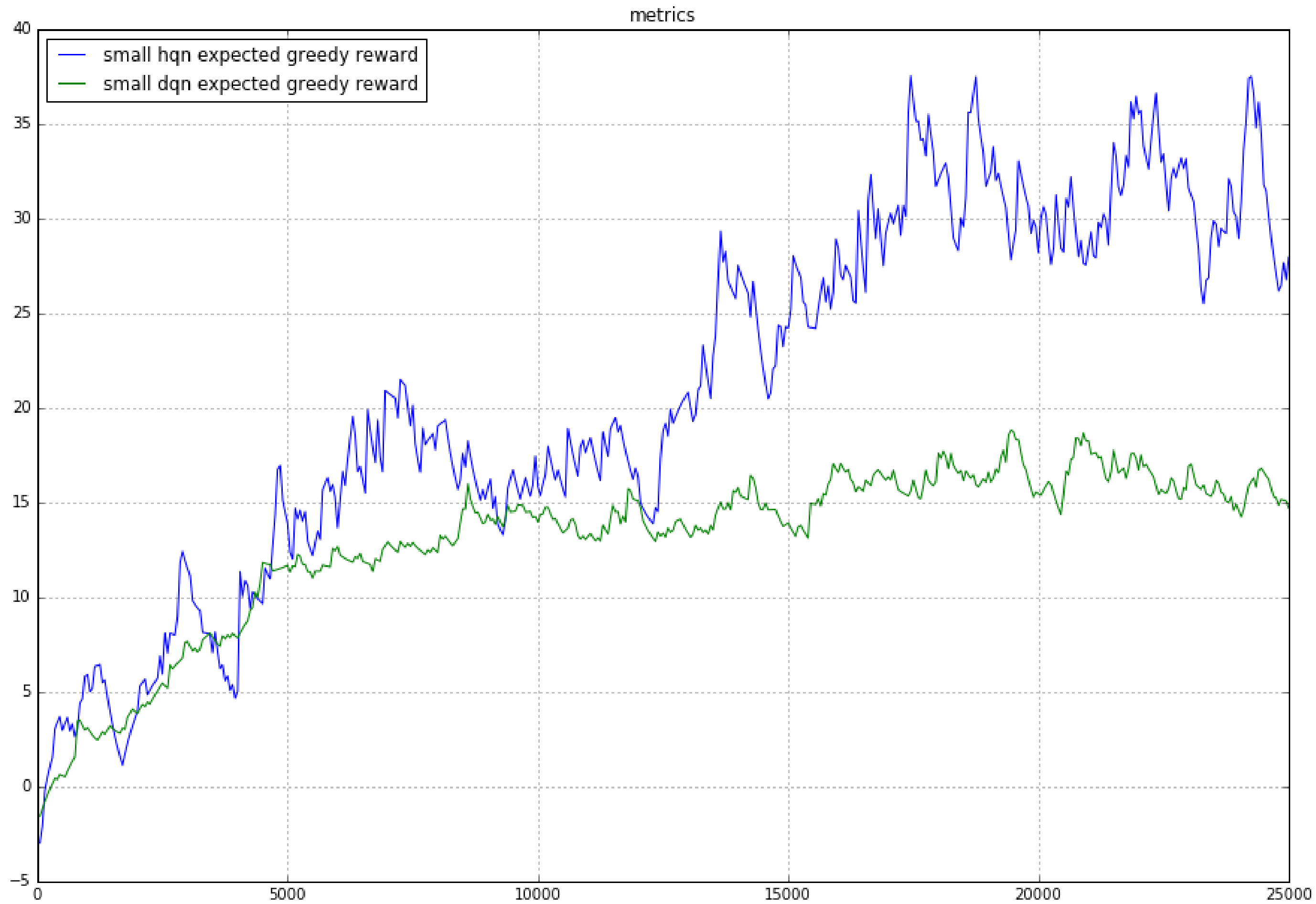
$$\pi(g|s, m_1) : argmax\, R$$

$$R_i = V_{A1}(s|m_1)$$

$$\pi(a|s, m_0) : R_i \rightarrow max$$

Learning curves





What's left behind

- Learning from human experience
- Inverse RL – learn **r** given near-optimal policy
- Model-based methods
- Whatever new stuff comes out '17

Course outro

This is almost the end...

Probably not too late to send homeworks.

Gonna be binge-checking on 19-20

Please tell us how to improve the course
http://bit.ly/2qwZSwN

Course outro