Deep Reinforcement Learning with Memory

SERGEY BARTUNOV, HSE, MOSCOW

RL basics

Markov Decision Process

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Environment

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Agent

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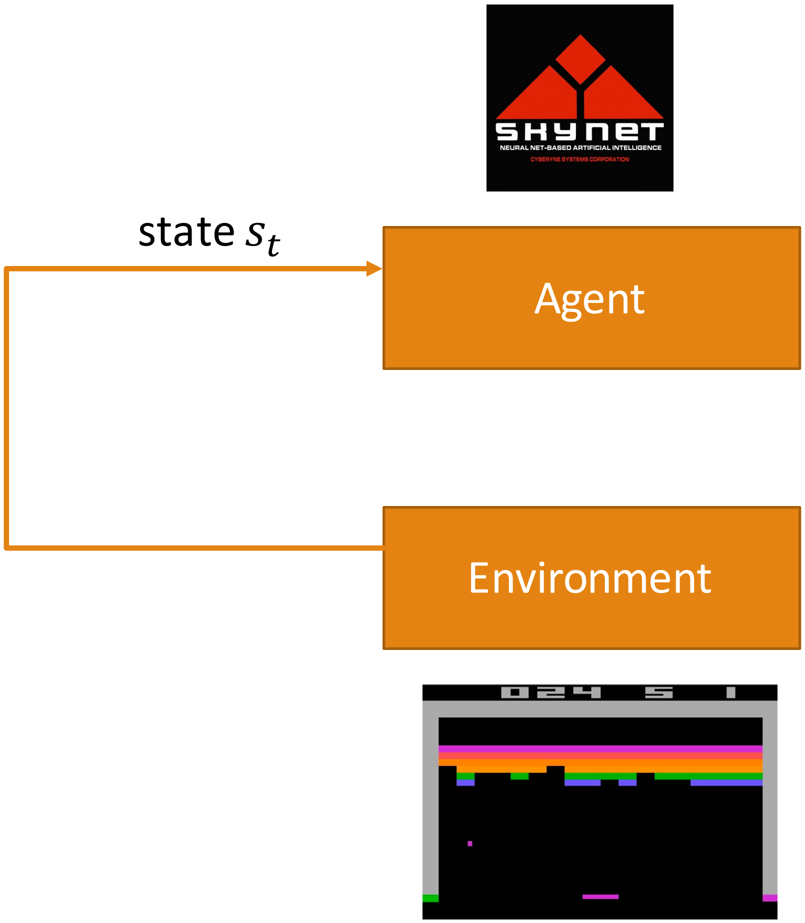

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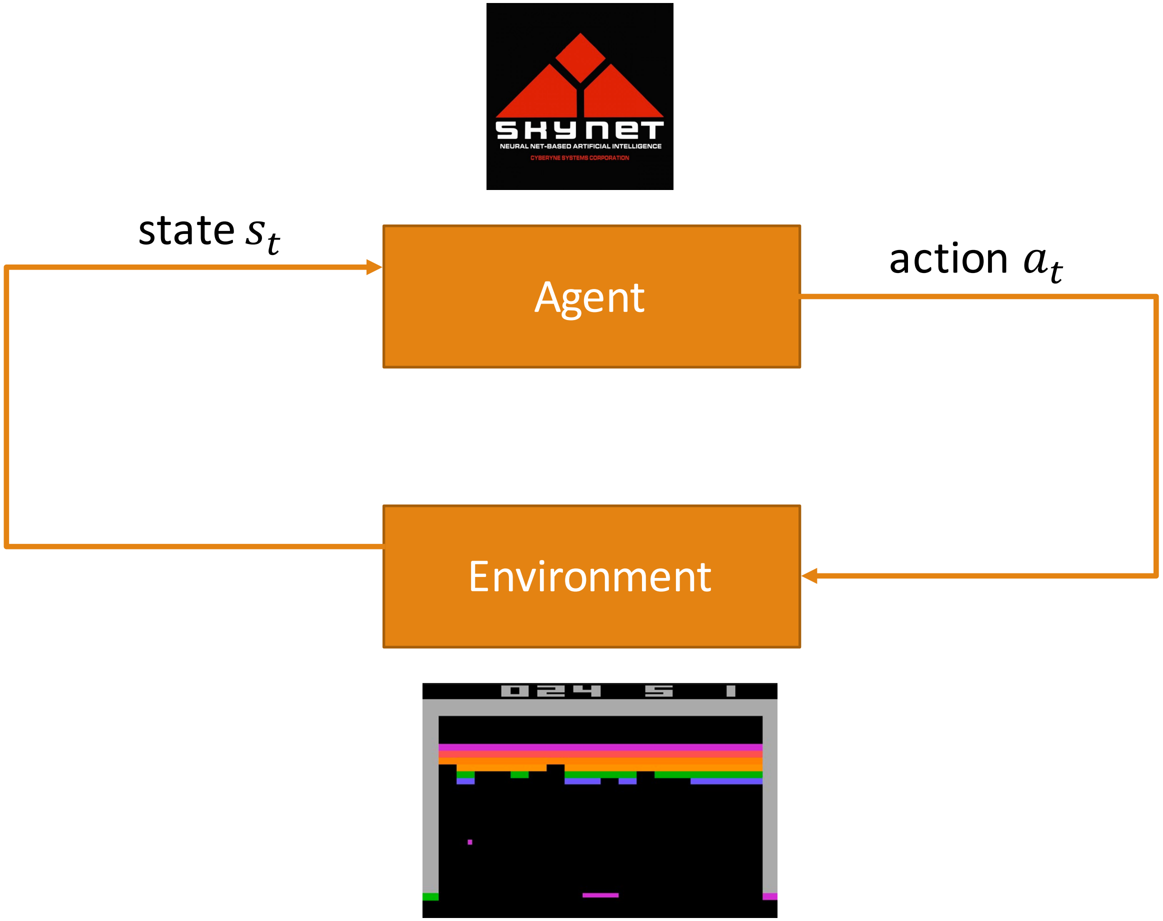

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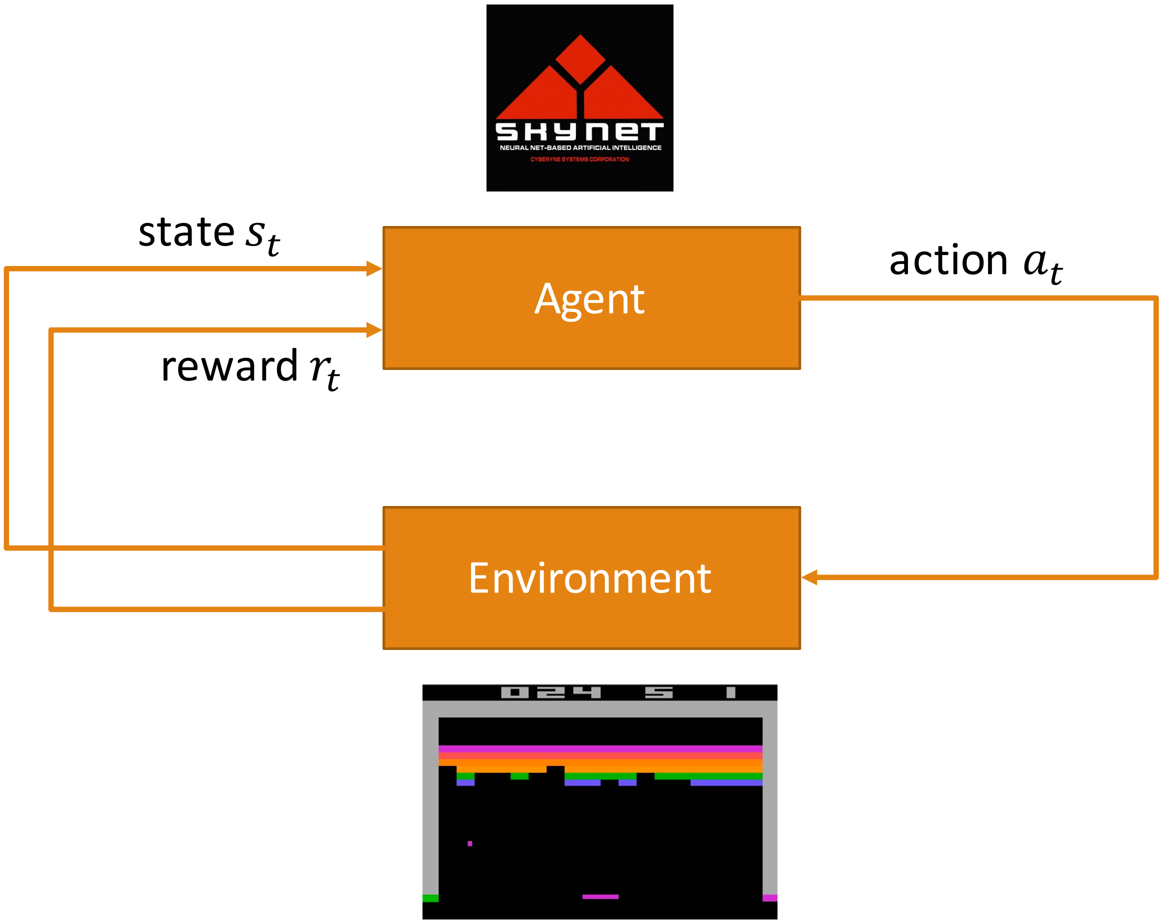

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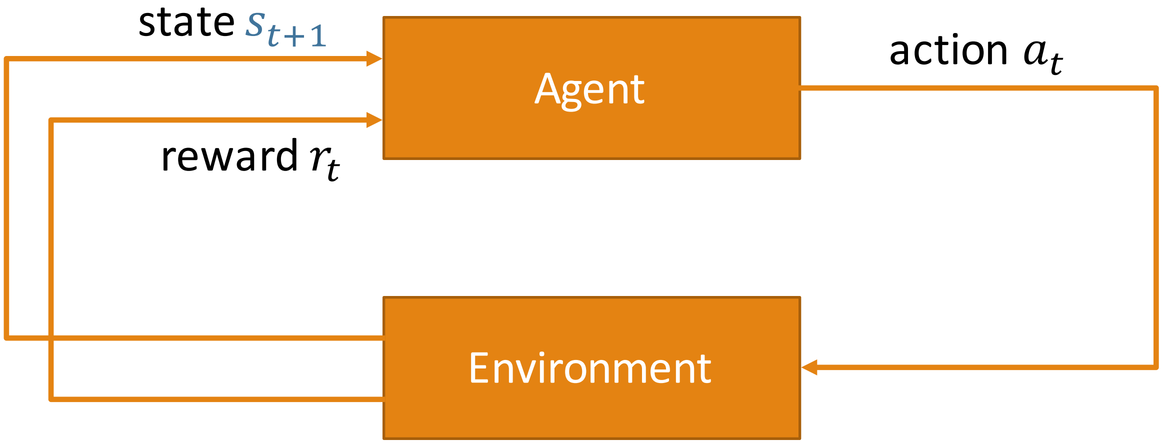
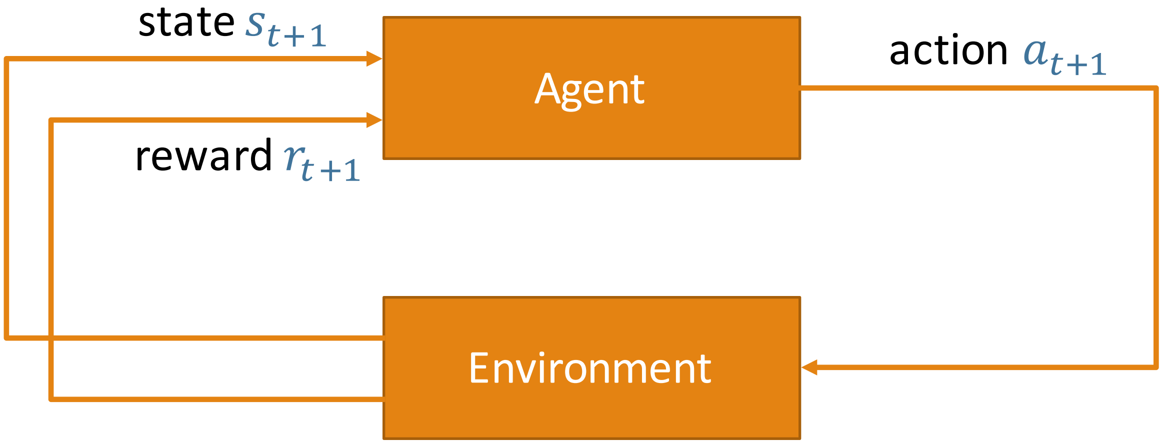


Markov Decision Process

policy
$a_{t+1} \sim \pi(a_{t+1} | s_t)$



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state dynamics
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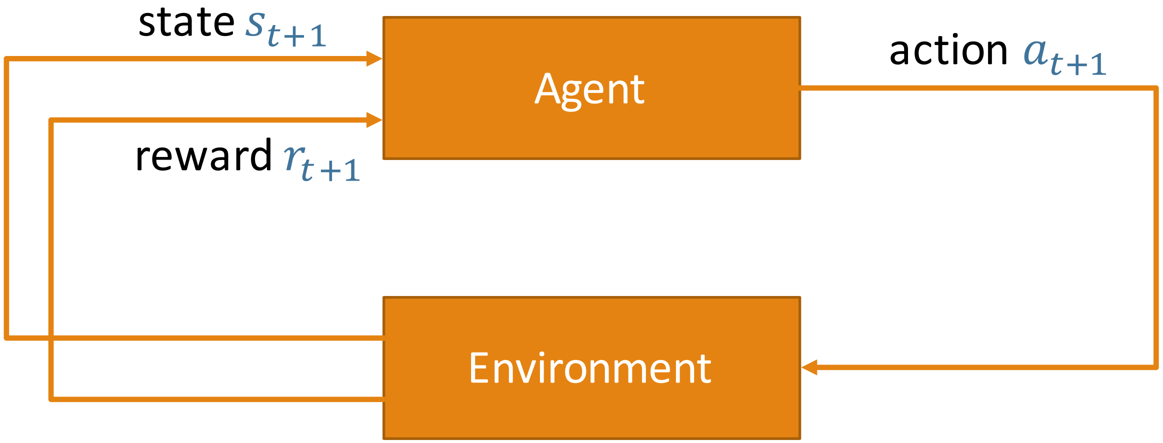

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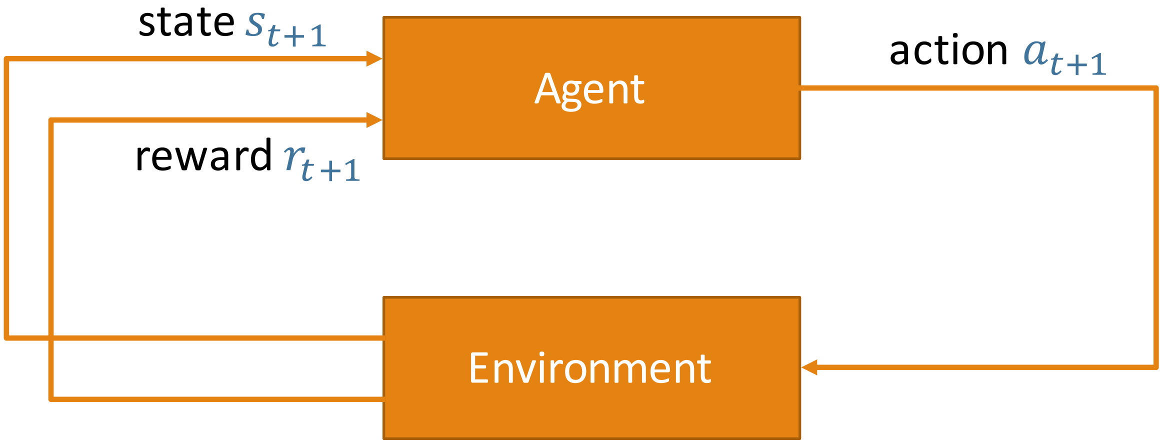

reward structure
$r_t = r(s_t, a_t, s_{t+1})$

Markov Decision Process

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- Action-state function: $Q^\pi(s_t, a_t) = \mathbb{E}_{s_{t:T}, a_{t+1:T}}[\sum_{l=0}^{T} \gamma^l r_{t+l}]$
  - $V^\pi(s_t) = \mathbb{E}_{a_t} Q^\pi(s_t, a_t)$

Bellman equation and Value iteration

- $V^{\pi}(s_t) = r_t + \gamma \mathbb{E}_{s_{t+1}} [V^{\pi}(s_{t+1})]$
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$$\min_{Q} \mathbb{E} \left\| Q(s_t, a_t) - r_t - \gamma Q(s_{t+1}, a_{t+1}) \right\|^2$$

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- Policy gradient can be written as follows:

$$\nabla_\theta R^\pi = \mathbb{E}_{s_{0:T},a_{0:T}} \left[\sum_{t=0}^{T} \gamma^t \sum_{l=0}^{T-t} \gamma^l r_{t+l} \nabla_\theta \log \pi(a_t|s_t;\theta) \right]$$

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- Full gradient:

$$\nabla_\theta R^\pi = \mathbb{E}_{s_{0:T},a_{0:T}}\left[\sum_{t=0}^{T} \gamma^t \Psi_t \nabla_\theta \log \pi(a_t|s_t;\theta)\right]$$

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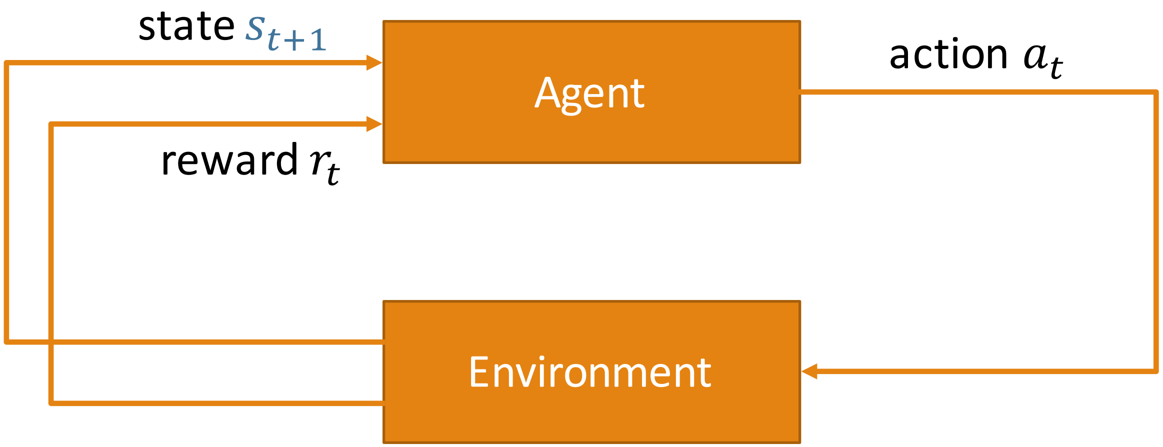
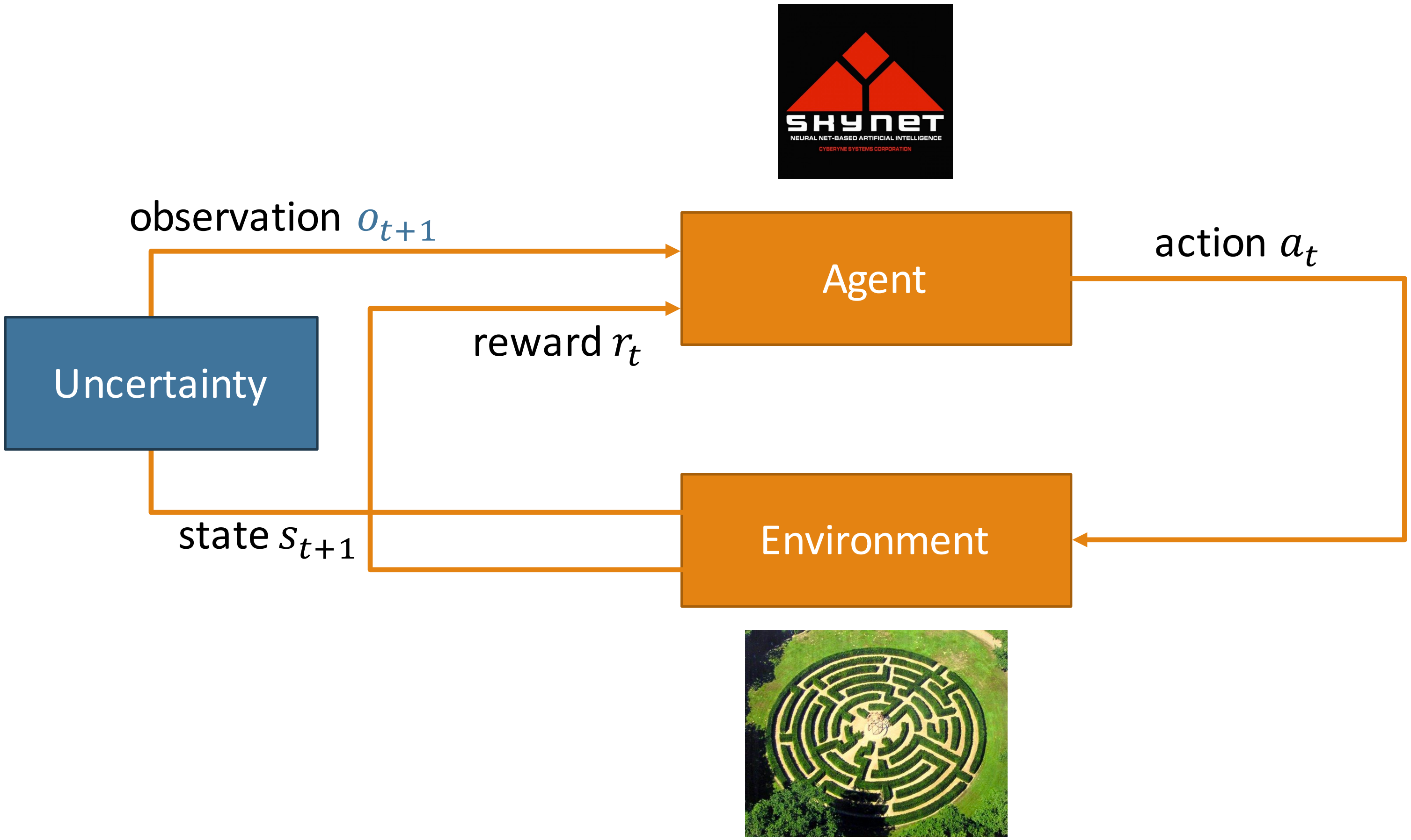
  - $Q^\pi(s_t, a_t) - V^\pi(s_t)$ – advantage function, usually intractable

Memory problems

Markov Decision Process



Partially-observable Markov Decision Process



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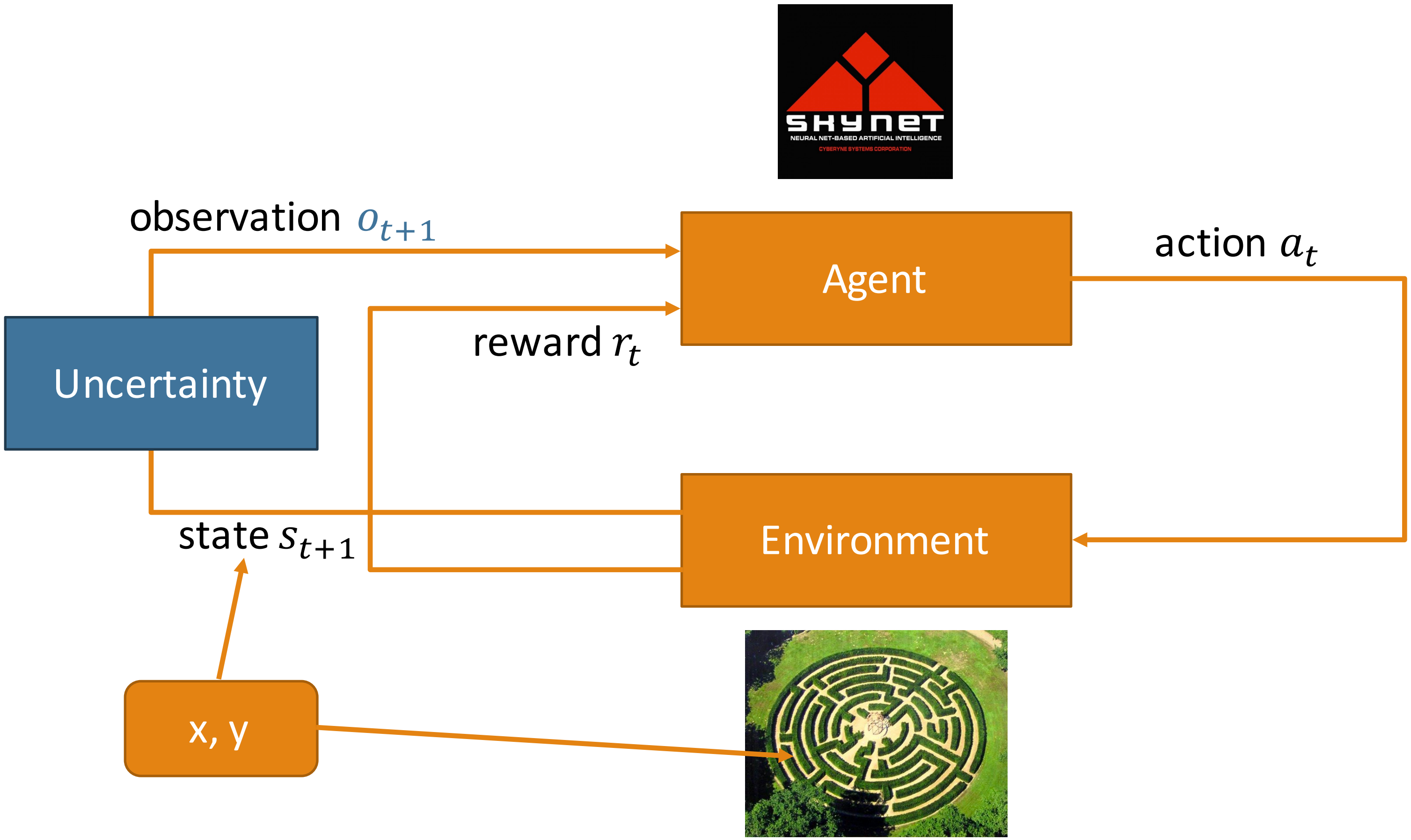

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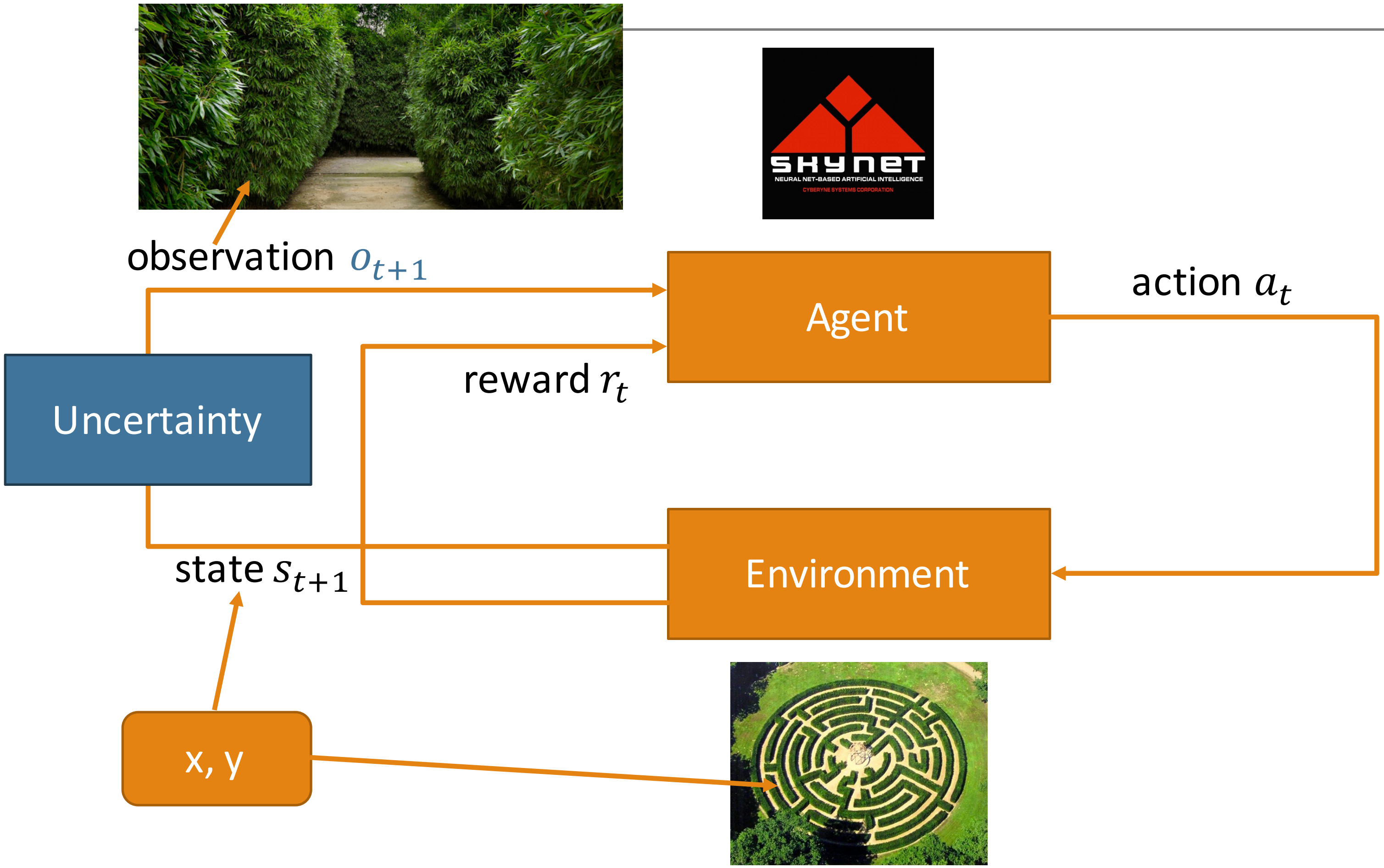

PO-MDP and Memory

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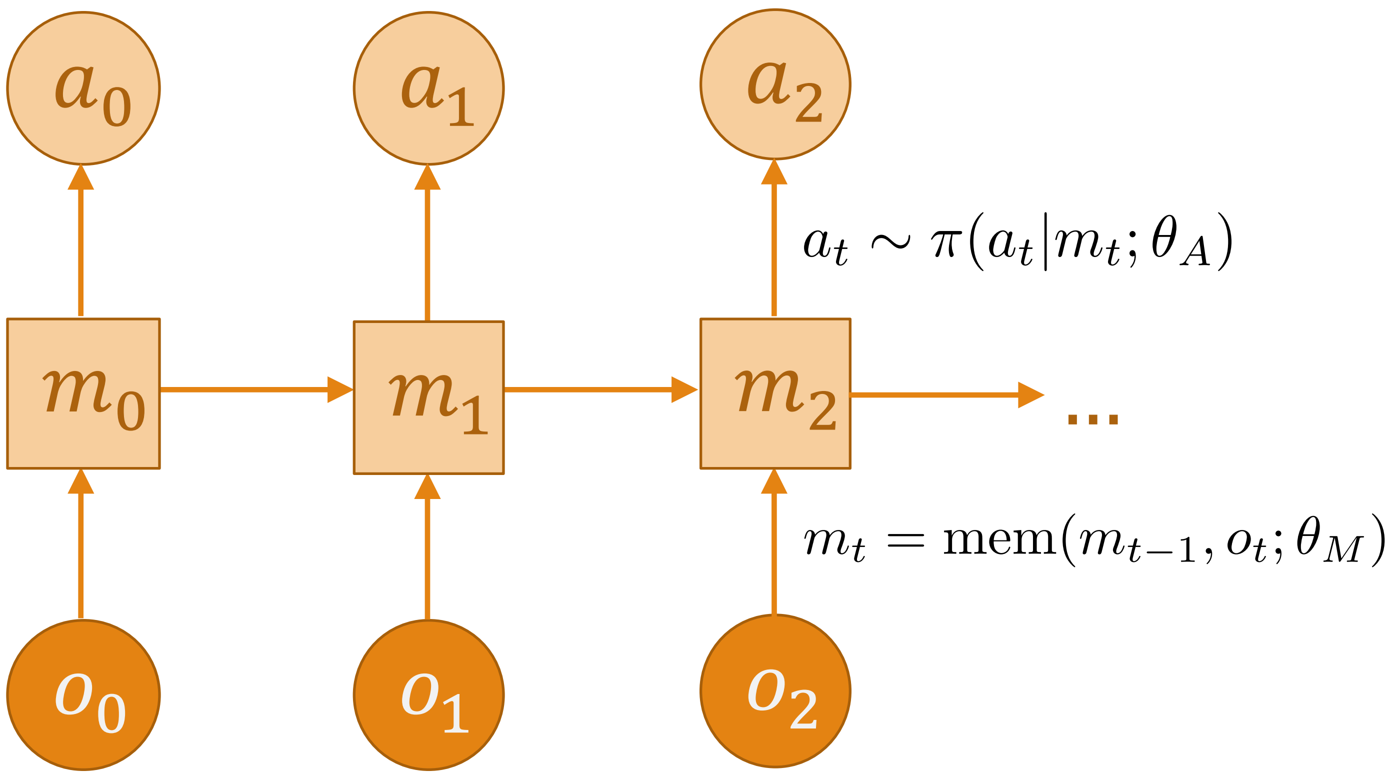
  - $r_t = r(s_t, a_t, s_{t+1})$
- Memory assumption:
  - there exists a memory $m_t = \mathrm{mem}(m_{t-1}, o_{t-1})$
  - such that $s_t \approx f(o_t, m_t)$

LSTM Agent



a_0
a_1
a_2
$a_t \sim \pi(a_t | m_t; \theta_A)$
m_0
m_1
m_2
...
$m_t = \mathrm{mem}(m_{t-1}, o_t; \theta_M)$
o_0
o_1
o_2

Recurrent policy gradients

- Stochastic gradient estimate:

$$\widetilde{\nabla}_\theta R^\pi = \sum_{t=0}^{T} \gamma^t \Psi_t \nabla_\theta \log \pi(a_t|m_t;\theta_A), \quad m_t = \mathrm{mem}(m_{t-1}, o_t; \theta_M)$$

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- Backpropagation through time:

$$\widetilde{\nabla}_{\theta_M} R^\pi = \sum_{t=0}^{T} \gamma^t \Psi_t \frac{\partial \log \pi(a_t|m_t;\theta_A)}{\partial m_t} G_t$$

$$G_t = \frac{\partial m_t}{\partial \theta_M} + \frac{\partial m_t}{\partial m_{t+1}} G_{t+1}$$

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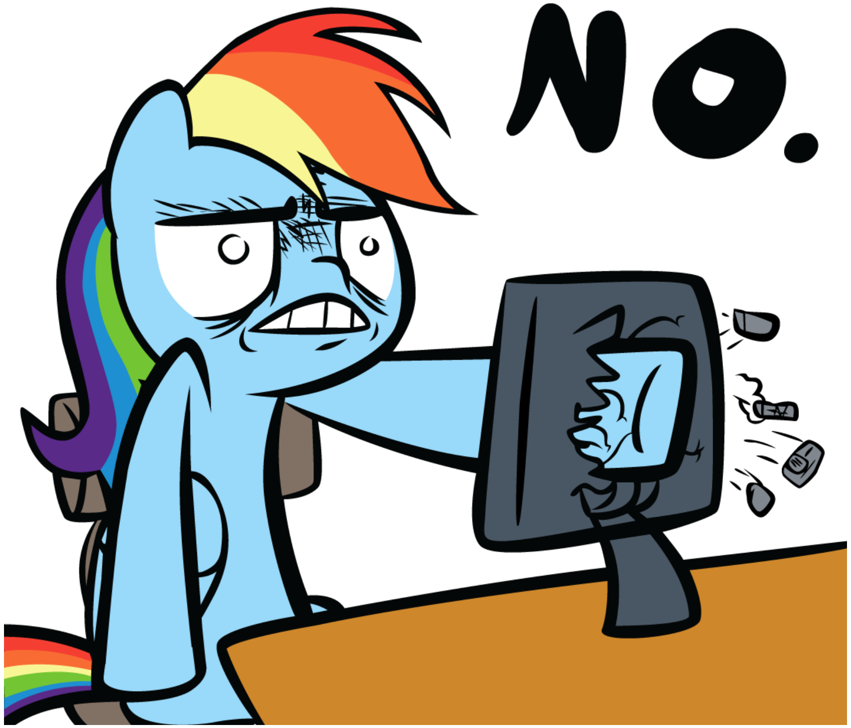

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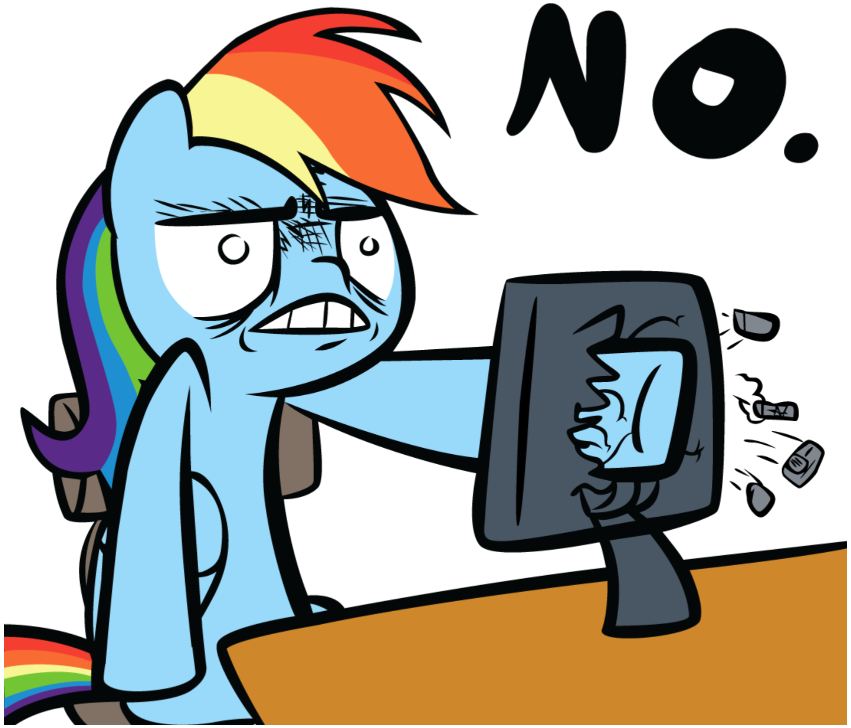


- High variance of gradients
- Usual problems with backpropagation through time
  - Exploding / vanishing gradients
  - Cannot work in a continuous settings

Variance reduction

- Stochastic gradient estimate:

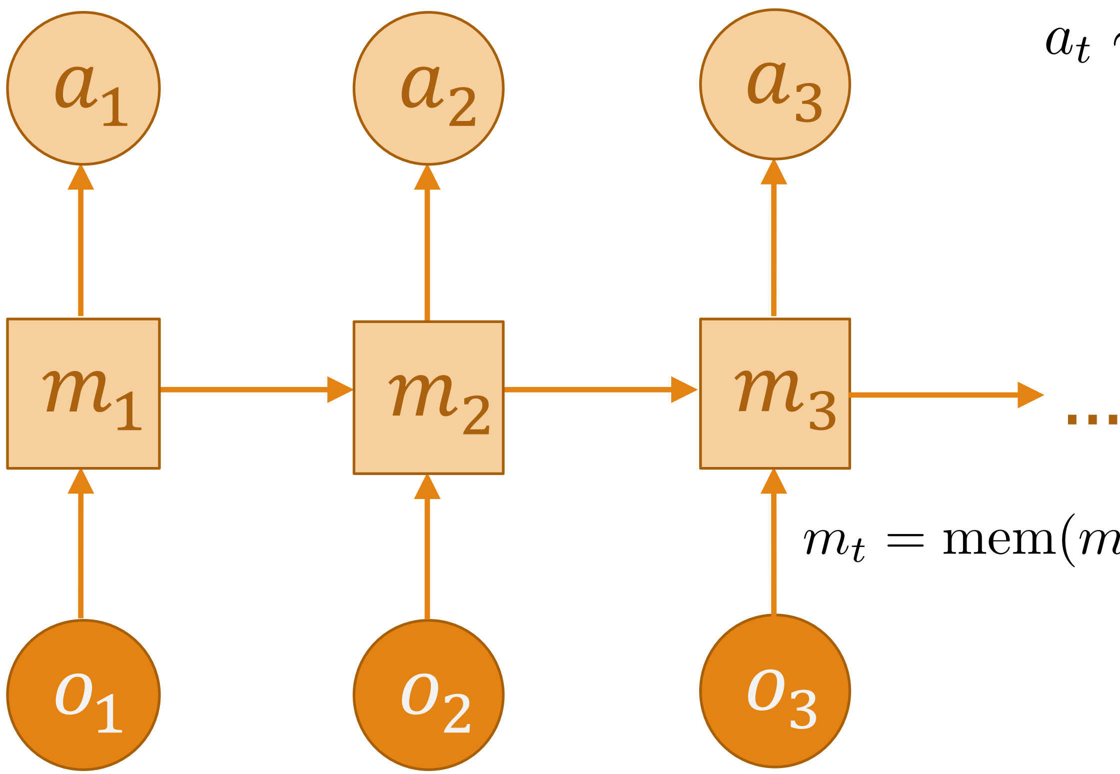
$$\widetilde{\nabla}_\theta R^\pi = \sum_{t=0}^{T} \gamma^t \Psi_t \nabla_\theta \log \pi(a_t|m_t;\theta), \quad m_t = \mathrm{mem}(m_{t-1}, o_t; \theta)$$

  - $\Psi_t = \sum_{l=0}^{T-t} \gamma^l r_{t+l}$ - easy to compute, high variance
  - $\Psi_t = \sum_{l=0}^{T-t} \gamma^l r_{t+l} - b(s_t)$ - baselined estimate

- The optimal baseline is $\dfrac{\mathbb{E}[(\sum_{l=0}^{T-t} \gamma^l r_{t+l})(\nabla_{\theta_j} \log \pi(a_t|m_t))^2]}{\mathbb{E}[(\nabla_{\theta_j} \log \pi(a_t|m_t))^2]}$

- Another important case: $b(s_t) = V^\pi(s_t)$

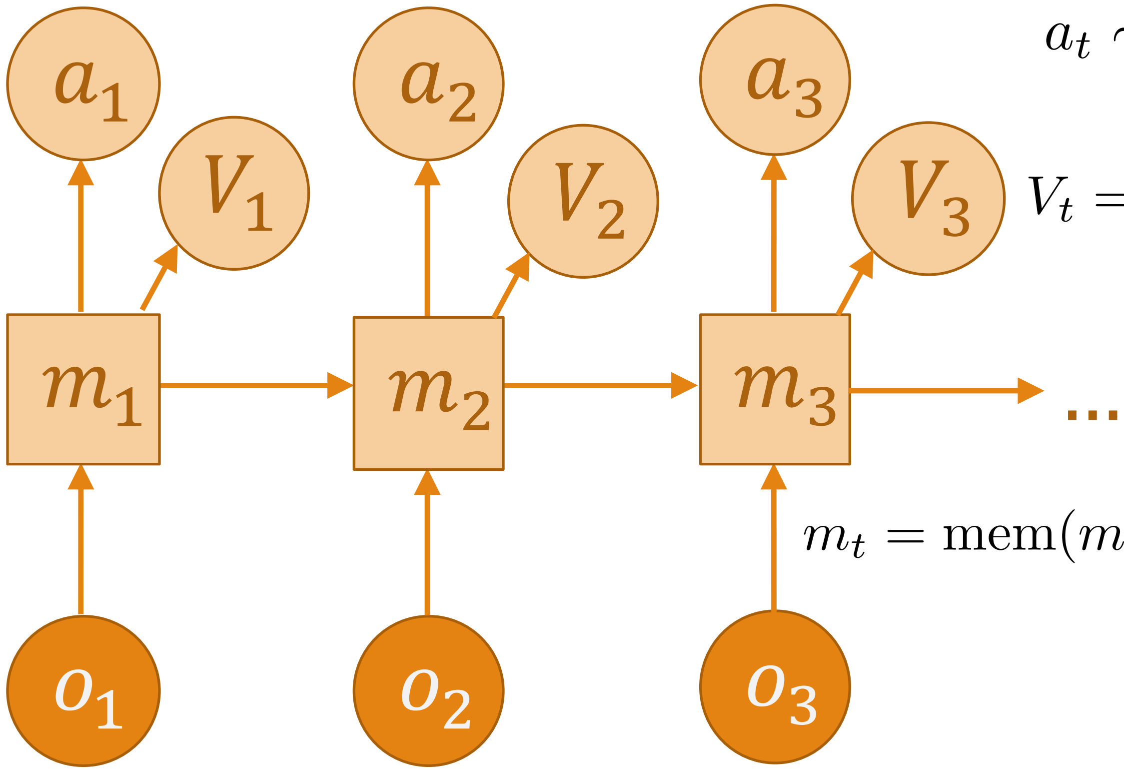
Learning the Value function



$$a_t \sim \pi(a_t | m_t; \theta_A)$$

$$m_t = \mathrm{mem}(m_{t-1}, o_t; \theta_M)$$

Learning the Value function



$$a_t \sim \pi(a_t | m_t; \theta_A)$$

$$V_t = V(m_t; \theta_V)$$

$$m_t = \text{mem}(m_{t-1}, o_t; \theta_M)$$

Final(?) learning algorithm

Repeat until convergence:

1. Collect trajectory $\{(o_t, a_t, r_t)\}_{t=0}^{T}$
2. Update policy parameters using $\widetilde{\nabla}_\theta R = \sum_{t=0}^{T} \gamma^t \Psi_t \nabla_\theta \log \pi(a_t | m_t^\pi; \theta_A)$
3. Update recurrent parameters using BPTT
4. Update baseline parameters using $\nabla_{\theta_V} \sum_{t=0}^{T} (V(m_t^V; \theta_V) - \sum_{l=0}^{T} \gamma^l r_{t+l})^2$

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Actual (wrong) objective:

$$\mathbb{E}\left[\sum_{t=0}^{T} \gamma^t r_t\right] - \mathbb{E}\left[\sum_{t=0}^{T} \sum_{l=0}^{T-t} (r_{t+l} - V(m_t; \theta_V))^2\right]$$

Learning LSTM policies

- Gradients wrt recurrent parameters are bad after K steps
  - For LSTM K is larger than for RNN, but still a finite number
- Continous setting will require large amount of memory
- An obvious solution is to truncate BPTT after K steps
  - This limits the range of learned dependencies
- Gradient estimate:

$$\widetilde{\nabla}_\theta R = \sum_{t=0}^{T} \Psi_t \nabla_\theta \log \pi(a_t | m_t^\pi; \theta_A)$$

- Consider our advantage estimator:

$$\Psi_t = \sum_{l=0}^{T} \gamma^l r_{t+l} - V^\pi(s_t)$$

Eligibility traces

- Gradient estimate:

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- Let's analyze our advantage estimator

$$\Psi_t = \sum_{l=0}^{T} \gamma^l r_{t+l} - V^\pi(s_t)$$

$$= \sum_{l=0}^{K} \gamma^l r_{t+l} + \sum_{l=K+1}^{T} \gamma^l r_{t+l} - V^\pi(s_t)$$

Eligibility traces

- Gradient estimate:

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- Let's analyze our advantage estimator

$$\Psi_t = \sum_{l=0}^{T} \gamma^l r_{t+l} - V^\pi(s_t)$$
$$= \sum_{l=0}^{K} \gamma^l r_{t+l} + \sum_{l=K+1}^{T} \gamma^l r_{t+l} - V^\pi(s_t)$$

- Without changing the expectation of gradient we can use

$$\Psi_t = \sum_{l=0}^{K} \gamma^l r_{t+l} + \gamma^K \underbrace{V^\pi(s_{t+K+1})}_{\approx V(m_{t+K+1}^V; \theta_V)} - V(m_t^V; \theta_V)$$

Bootstrapping the Baseline

- New error function for the Baseline network

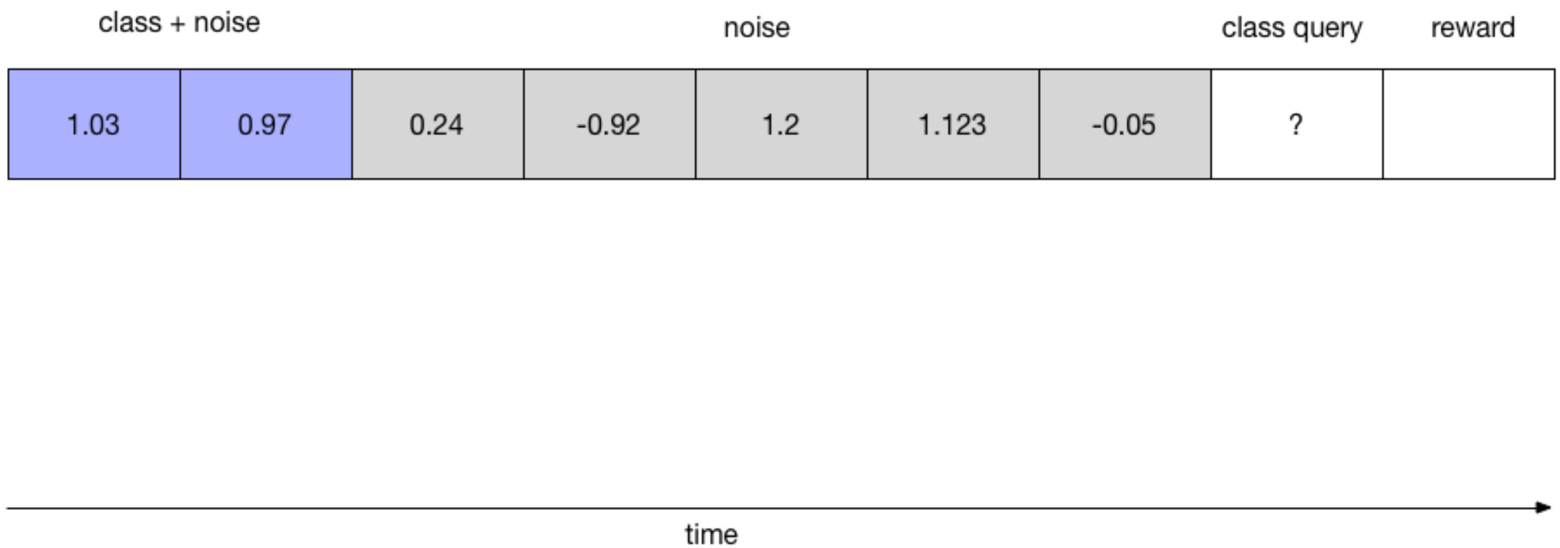
$$\sum_{t=0}^{T}\left(\sum_{l=0}^{K}\gamma^l r_{t+l} + \gamma^K V(m_{t+K+1}^V;\theta_M) - V(m_t^V;\theta_M)\right)^2 \rightarrow \min_{\theta_V}$$

- Memory dynamics is controlled by a second LSTM:

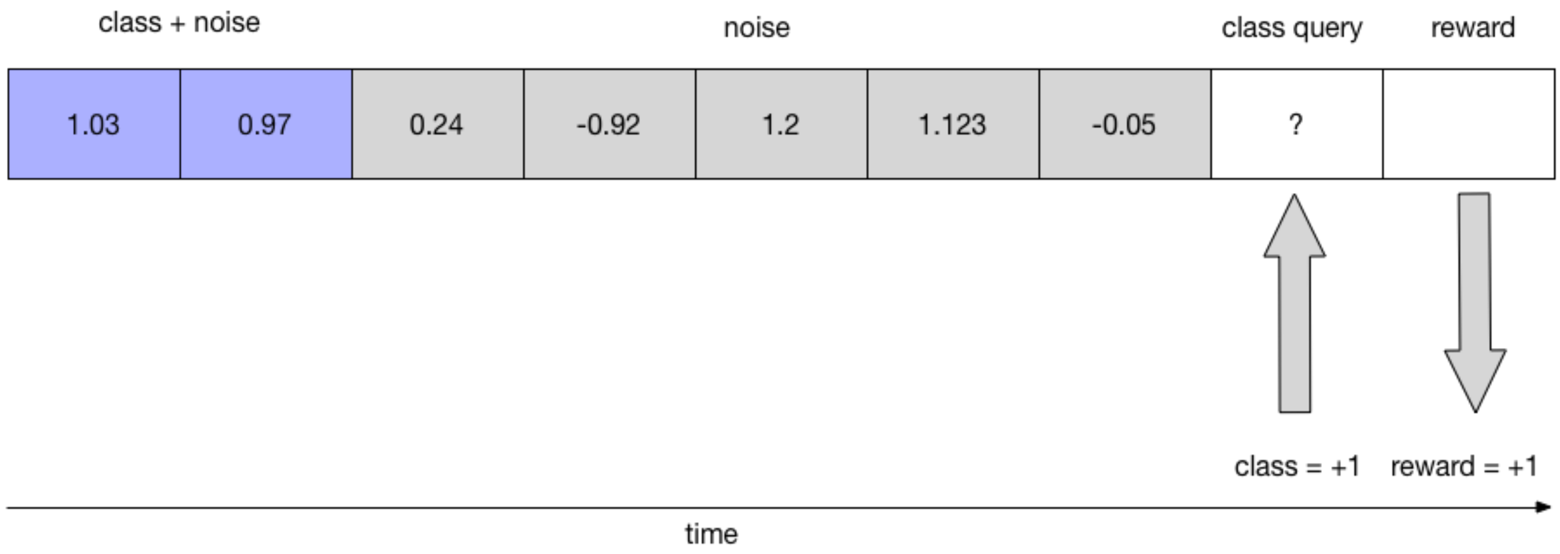
$$m_t^V = \mathrm{mem}(m_{t-1}^V, o_t; \theta_V)$$

Empirical results

Latch task

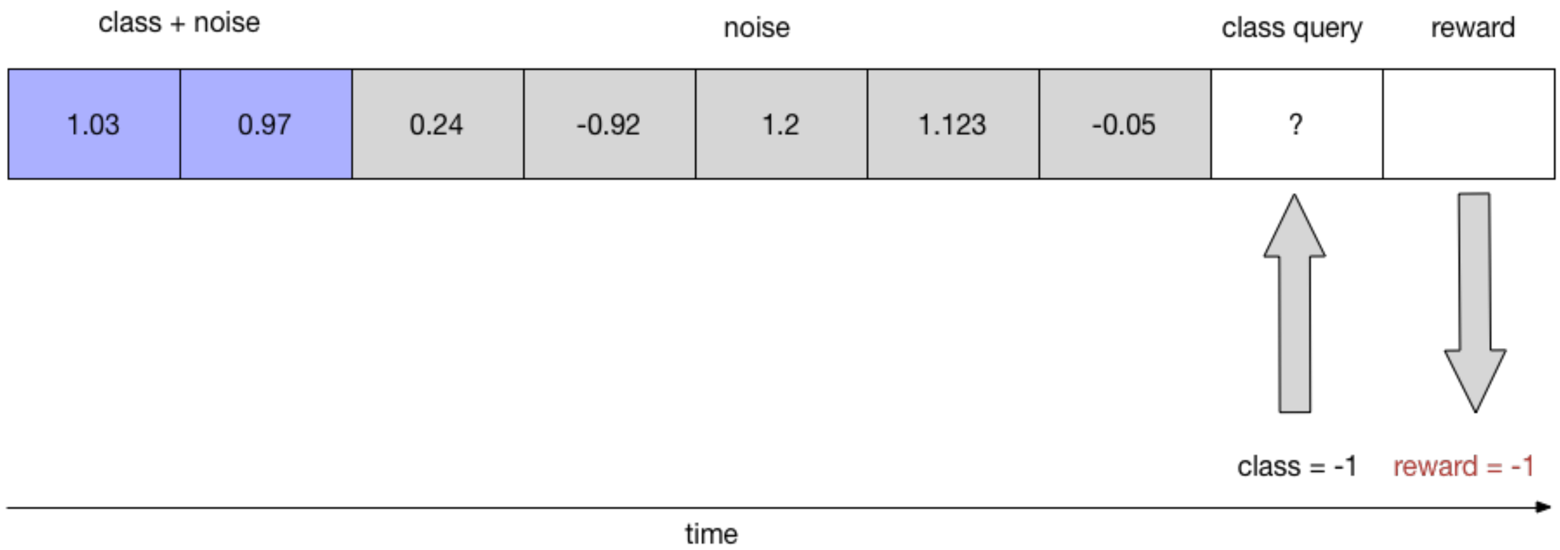

class + noise
noise
class query
reward
1.03
0.97
0.24
-0.92
1.2
1.123
-0.05
?
time

Latch task



class + noise
noise
class query
reward
1.03
0.97
0.24
-0.92
1.2
1.123
-0.05
?
class = +1
reward = +1
time

Latch task



class + noise
noise
class query
reward
1.03
0.97
0.24
-0.92
1.2
1.123
-0.05
?
class = -1
reward = -1
time

Latch task

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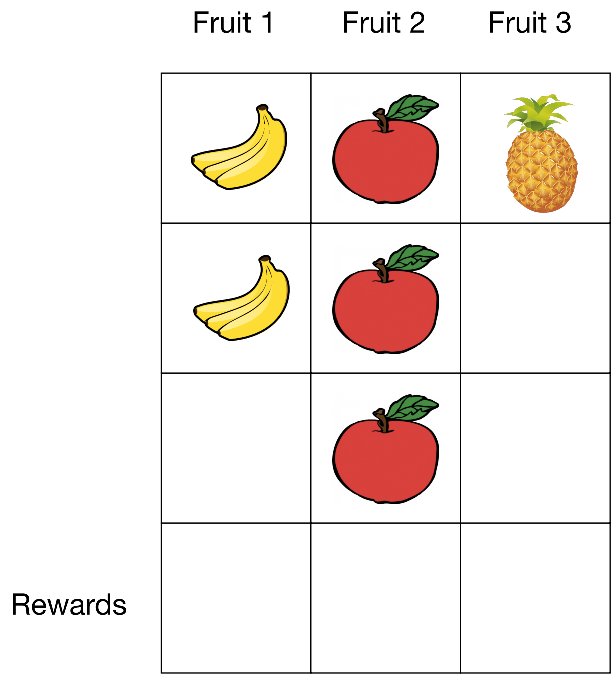
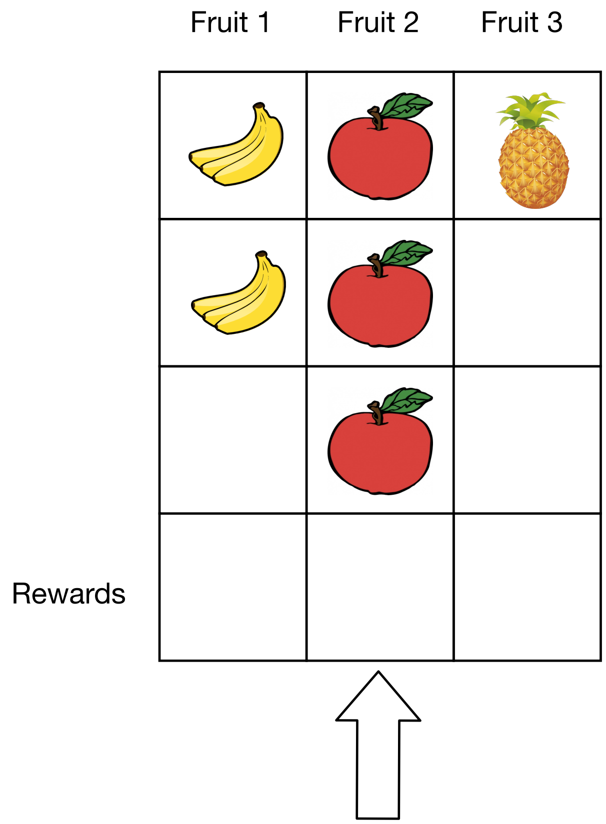
Latch task

- Sequences of length 100 are already hard to learn
- Eliglibility traces work sometimes, but not very stable
- Curriculum learning:
  - Train on shorter sequences
  - Increase sequence length over time
  - Works well even with truncated BPTT, but no guarantees

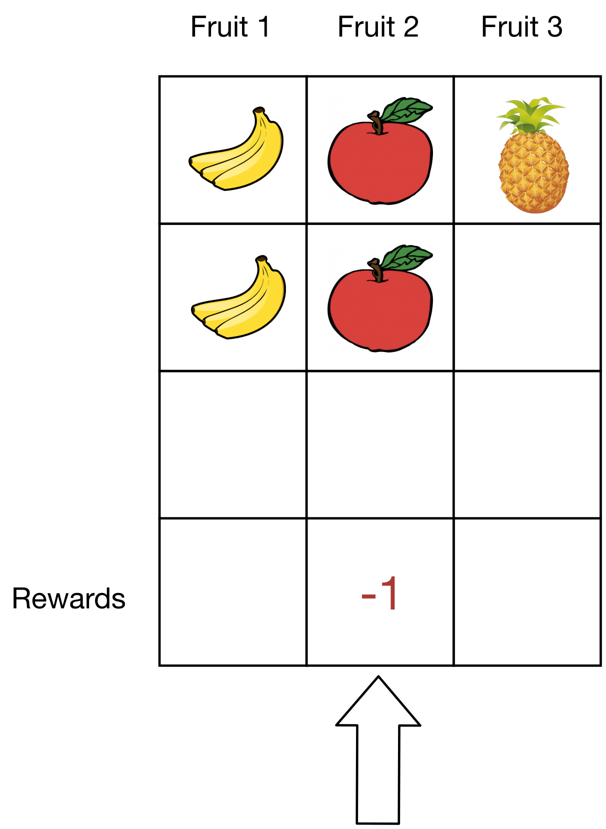
EAT game



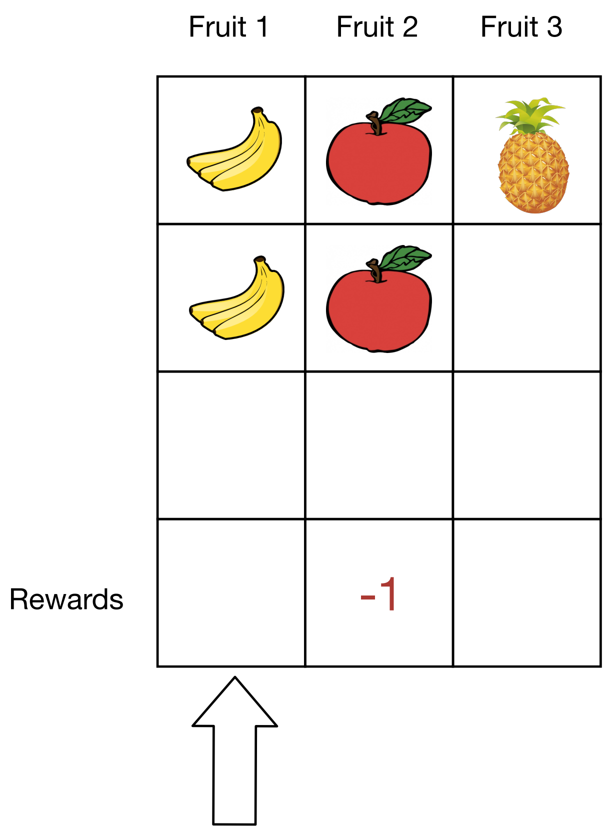
EAT game



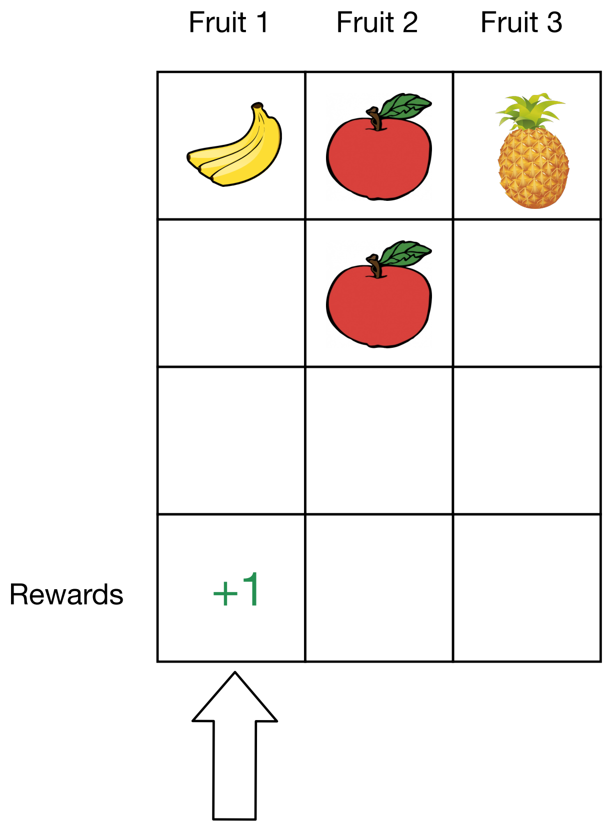
EAT game



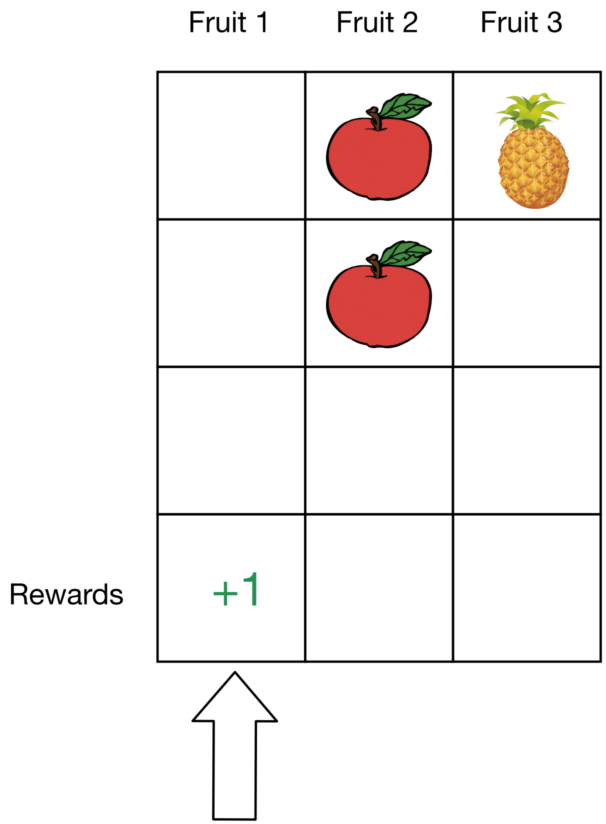
EAT game



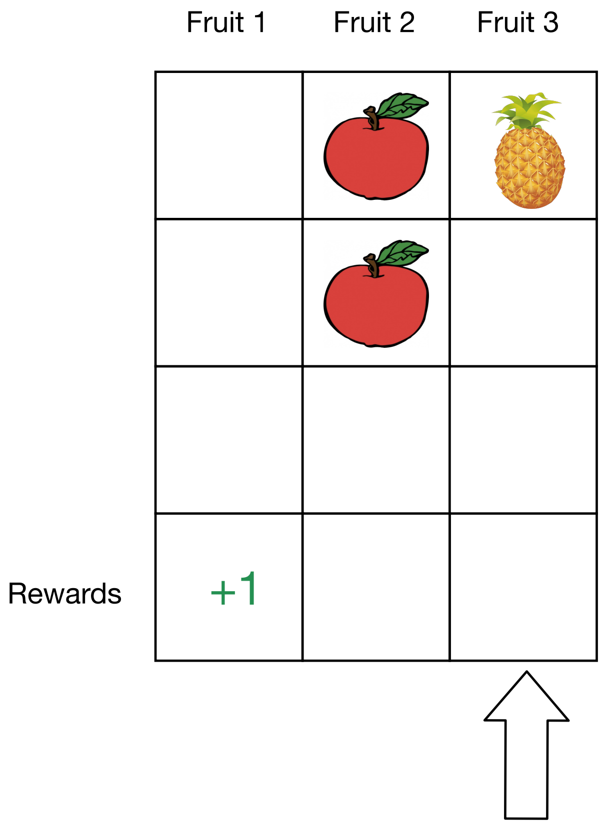
EAT game



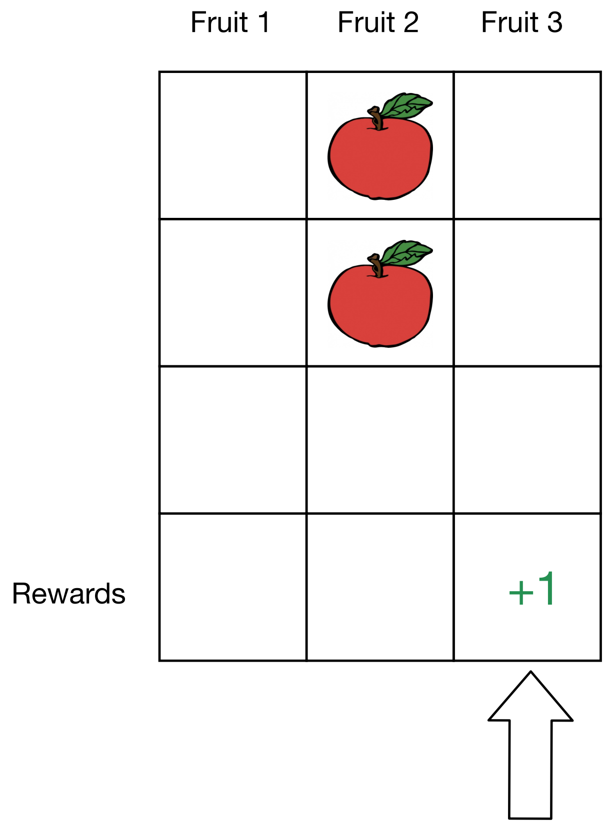
EAT game



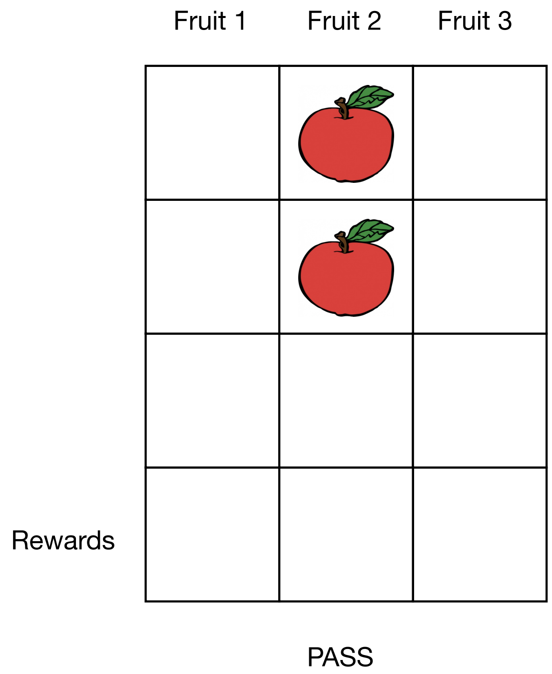
EAT game



EAT game



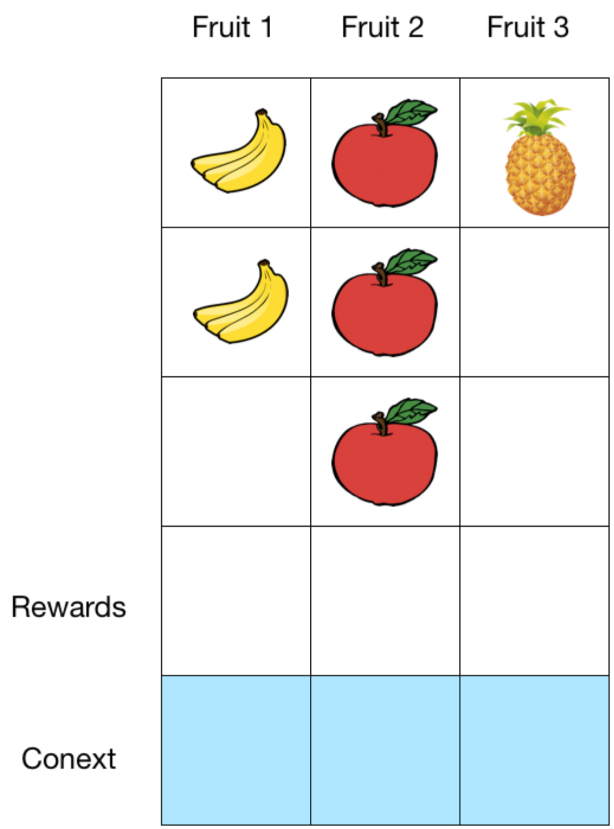
EAT game



Eat game

- Given enough time LSTM can learn the optimal strategy
- Variance reduction techniques and advances optimization methods dramatically improve convergence

Big episode EAT



Big episode EAT

	Fruit 1	Fruit 2	Fruit 3
			
			
			
Rewards	+1	-1	+1
Conext	1	0	0

Big episode EAT

	Fruit 1	Fruit 2	Fruit 3
			
			
Rewards	-1	-1	+1
Conext	0	1	0

Big episode EAT

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  - Couldn't approximate the Value function well
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  - Cannot be handled by curriculum learning directly
- Dirty trick with setting $\Psi_t = r_t$ worked
  - Since our strategy is recurrent future rewards influence gradients at time t
  - Prone to bad value function