Multiagent (Deep) Reinforcement Learning

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Reinforcement learning

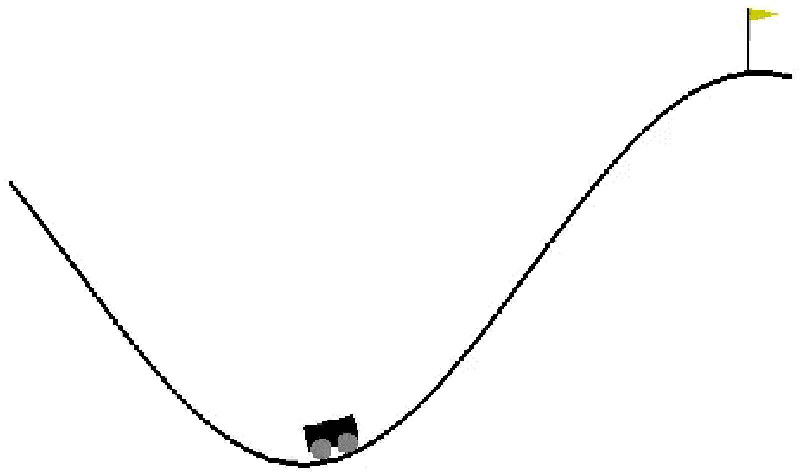
The agent needs to learn to perform tasks in environment

No prior knowledge about the effects of tasks

Maximized its utility

Mountain Car problem →

- Typical RL toy problem
- Agent (car) has three actions – left, right, none
- Goal – get up the mountain (yellow flag)
- Weak engine – cannot just go to the right, needs to gain speed by going downhill first



Reinforcement learning

Formally defined using a Markov Decision Process (MDP) (S, A, R, p)

- $s_t \in S$ – state space
- $a_t \in A$ – action space
- $r_t \in R$ – reward space
- $p(s', r|s, a)$ – probability that performing action a in state s leads to state s' and gives reward r

Agent's goal: maximize discounted returns $G_t = R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} \ldots = R_{t+1} + \gamma G_{t+1}$

Agent learns its policy: $\pi(A_t = a|S_t = s)$

- Gives a probability to use action a in state s

State value function: $V^\pi(s) = E_\pi[G_t|S_t = s]$

Action value function: $Q^\pi(s, a) = E_\pi[G_t|S_t = s, A_t = a]$

Q-Learning

Learns the Q function directly using the Bellman's equations

$$Q(s_t, a_t) \leftarrow (1-\alpha)Q(s_t, a_t) + \alpha(r_t + \gamma \max_a Q(s_{t+1}, a))$$

During learning – sampling policy is used (e.g. the ϵ-greedy policy – use a random action with probability ϵ, otherwise choose the best action)

Traditionally, Q is represented as a (sparse) matrix

Problems

- In many problems, state space (or action space) is continuous → must perform some kind of discretization
- Can be unstable

Watkins, Christopher JCH, and Peter Dayan. "Q-learning." Machine learning 8, no. 3-4 (1992): 279-292.

Deep Q-Learning

Q function represented as a deep neural network

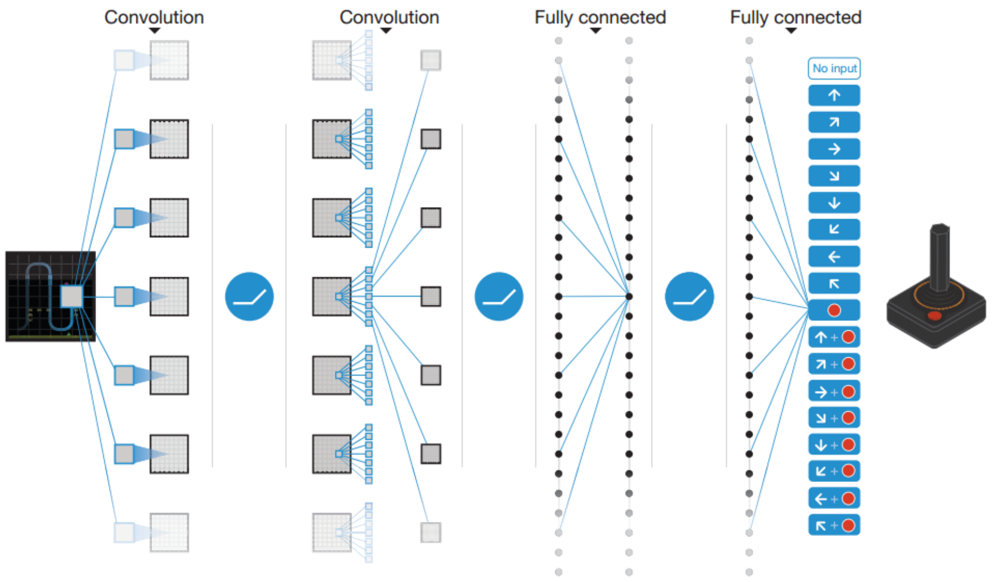
Experience replay
- stores previous experience (state, action, new state, reward) in a replay buffer – used for training

Target network
- Separate network that is rarely updated

Optimizes loss function

$$L(\theta) = E\left[\left(r + \gamma \max_{a'} Q(s, a; \theta_i^-) - Q(s, a; \theta)\right)^2\right]$$

- θ, θ^- - parameters of the network and target network



Mnih, Volodymyr, Koray Kavukcuoglu, David Silver, Andrei A. Rusu, Joel Veness, Marc G. Bellemare, Alex Graves, et al. "Human-Level Control through Deep Reinforcement Learning." *Nature* 518, no. 7540 (February 2015): 529–33. https://doi.org/10.1038/nature14236.

Deep Q-Learning

Successfully used to play single player Atari games

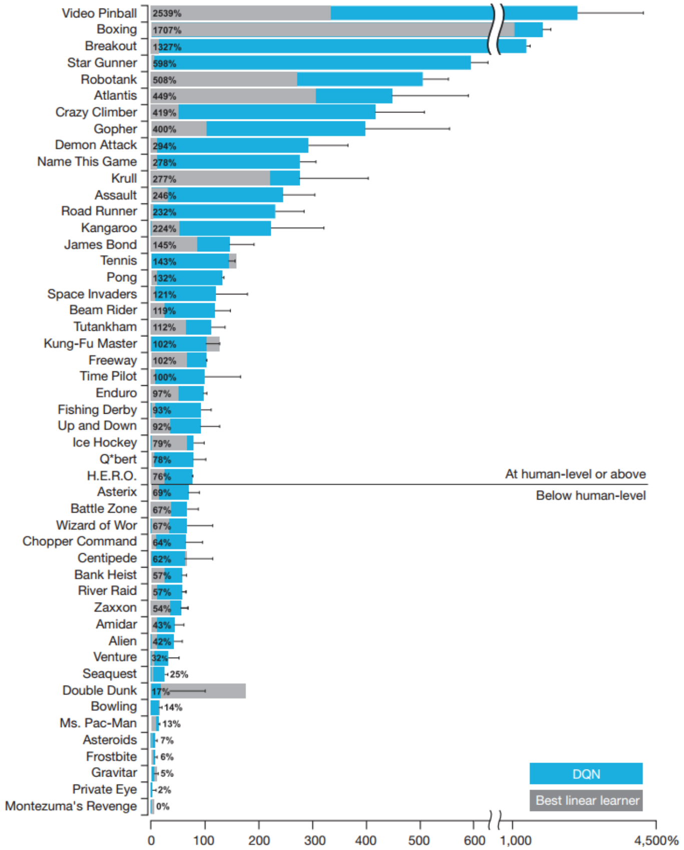
Complex input states – video of the game

Action space quite simple – discrete

Rewards – changes in game score

Better than human-level performance

- Human-level measured against “expert” who played the game for around 20 episodes of max. 5 minutes after 2 hours of practice for each game.



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Actor-Critic Methods

The actor (policy) is trained using a gradient that depends on a critic (estimate of value function)

Critic is a value function

- After each action checks if things have gone better or worse than expected
- Evaluation is the error $\delta_t = r_{t+1} + \gamma V(s_{t+1}) - V(s_t)$
- Is used to evaluate the action selected by actor
  - If δ is positive (outcome was better than expected) – probability of selecting a_t should be strengthened (otherwise lowered)

Both actor and critic can be approximated using NN

- Policy ($\pi(s,a)$) update - $\Delta\theta = \alpha \nabla_\theta (\log \pi_\theta(s,a)) q(s,a)$
- Value ($q(s,a)$) update - $\Delta w = \beta\big(R(s,a) + \gamma q(s_{t+1}, a_{t+1}) - q(s_t, a_t)\big) \nabla_\mathrm{w} \mathrm{q}(\mathrm{s_t}, \mathrm{a_t})$

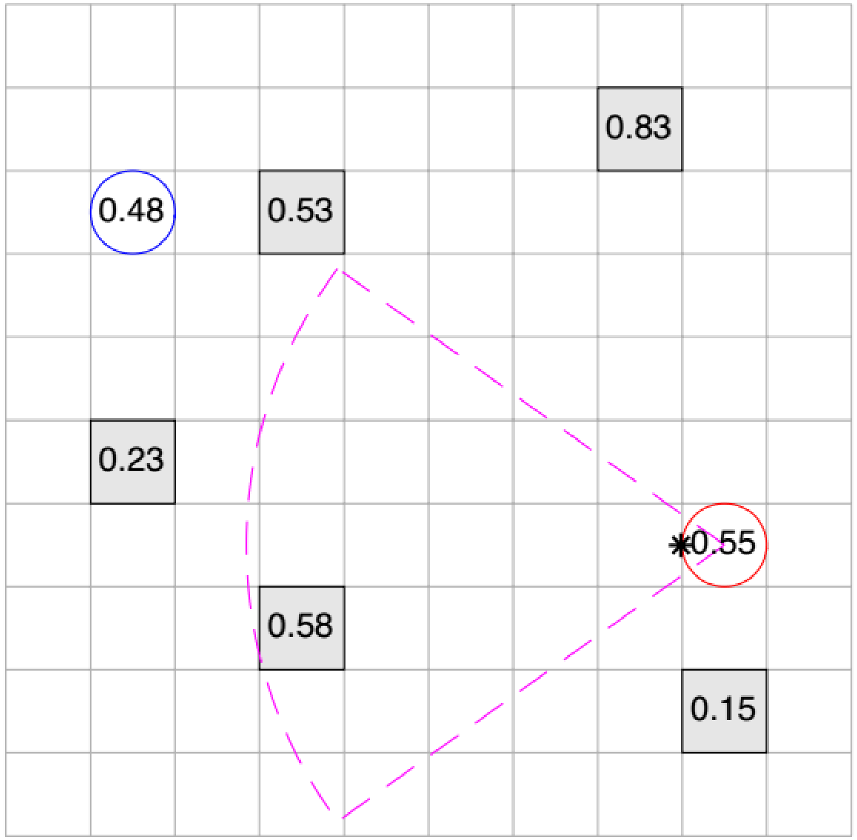
Works in continuous action spaces

Multiagent Learning

Learning in multi-agent environments more complex – need to coordinate with other agents

Example – level-based foraging (→)

- Goal is to collect all items as fast as possible
- Can collect item, if sum of agent levels is greater than item level



Goals of Learning

Minmax profile

- For zero-sum games – (π_i, π_j) is minimax profile if $U_i(\pi_i, \pi_j) = -U_j(\pi_i, \pi_j)$
  - Guaranteed utility against worst-case opponent

Nash equilibrium

- Profile $(\pi_1, \dots, \pi_n)$ is Nash equilibrium if $\forall i \forall \pi_i' : U_i(\pi_i', \pi_{-i}) \leq U_i(\pi)$
  - No agent can improve utility unilaterally deviating from profile (every agent plays best-response to other agents)

Correlated equilibrium

- Agents observe signal x_i with joint distribution $\xi(x_1, \dots, x_n)$ (e.g. recommended action)
- Profile $(\pi_1, \dots, \pi_n)$ is correlated equilibrium if no agent can improve its expected utility by deviating from recommended actions
- NE is special type of CE – no correlation

Goals of Learning

Pareto optimum

- Profile $(\pi_1, \dots, \pi_n)$ is Pareto-optimal if there is not other profile π' such that $\forall i: U_i(\pi') \geq U\_i(\pi)$ and $\exists i: U_i(\pi') > U_i(\pi)$
- Cannot improve one agent without making other agent worse

Social Welfare & Fairness

- Welfare of profile is sum of utilities of agents, fairness is product of utilities
- Profile is welfare or fairness optimal if it has the maximum possible welfare/fairness

No-Regret

- Given history $\mathrm{H}^{\mathrm{t}} = (a_0, \dots, a_{t-1})$ agent i's regret for not having taken action a_i is

$$R_i(a_i) = \sum_t u_{i(a_i, a_{-i}^t)} - u_i(\, a_i^t, a_{-i}^t)$$

- Policy π_i achieves no-regret if $\forall a_i: \lim_{t\to\infty} \frac{1}{t} R_i(a_i | H^t) \leq 0.$

Joint Action Learning

Learns Q-values for joint actions $a \in A$

- joint action of all agents $a = (a_1, \dots, a_n)$, where a_i is the action of agent i

$Q^{t+1}(a_t, s_t) = (1 - \alpha)Q^t(a_t, s_t) + \alpha u_i^t$

- u_i^t - utility received after joint action a_t

Uses opponent model to compute expected utilities of action

- $E(a_i) = \sum_{a_{-i}} P(a_{-i}) Q^{t+1}((a_i, a_{-i}), s_{t+1})$ – joint action learning
- $E(a_i) = \sum_{a_{-i}} P(a_{-i}|a_i) Q^{t+1}\left((a_i, a_{-i}), s_{t+1}\right)$ – conditional joint action learning

Opponent models predicted from history as relative frequencies of action played (conditional frequencies in CJAL)

ϵ – greedy sampling

Policy Hill Climbing

Learn policy π_i directly

Hill-climbing in policy space

- $\pi_i^{t+1} = \pi_i^t\left(s_i^t, a_i^t\right) + \delta$ if a_i^t is the best action according to $Q(s^t, a_i^t)$
- $\pi_i^{t+1} = \pi_i^t\left(s_i^t, a_i^t\right) - \frac{1}{|A_i|-1}$ otherwise

Parameter δ is adaptive – larger if winning and lower if losing

Counterfactual Multi-agent Policy Gradients

Centralized training and de-centralized execution (more information available in training)

Critic conditions on the current observed state and the actions of all agents

Actors condition on their observed state

Credit assignment – based on difference rewards

- Reward of agent $i \sim$ the difference between the reward received by the system if joint action a was used, and reward received if agent i would have used a default action
  - Requires assignment of default actions to agents
- COMA – marginalize over all possible actions of agent i

Used to train micro-management of units in StarCraft

Foerster, Jakob, Gregory Farquhar, Triantafyllos Afouras, Nantas Nardelli, and Shimon Whiteson. "Counterfactual Multi-Agent Policy Gradients." *ArXiv:1705.08926 [Cs]*, May 24, 2017. http://arxiv.org/abs/1705.08926.

Counterfactual Multi-agent Policy Gradients

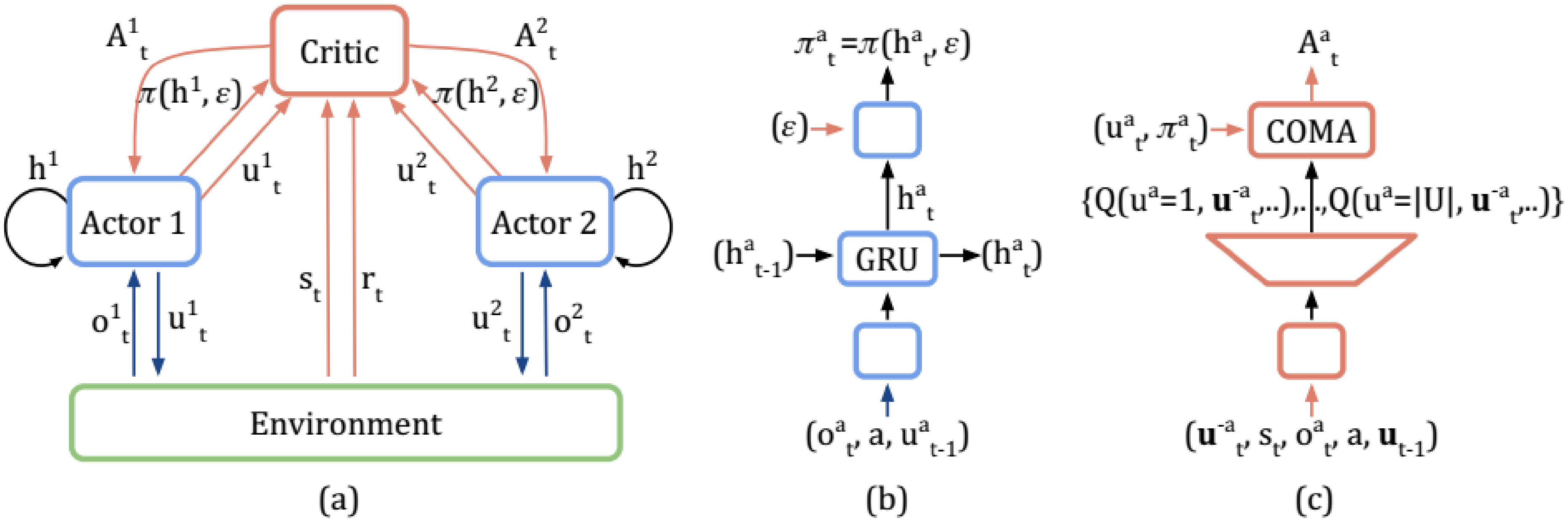


Figure 1: In (a), information flow between the decentralised actors, the environment and the centralised critic in COMA; red arrows and components are only required during centralised learning. In (b) and (c), architectures of the actor and critic.

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Ad hoc Teamwork

Typically whole team of agents provided by single organization/team.

- There is some pre-coordination (communication, coordination, …)

Ad hoc teamwork

- Team of agents provided by different organization need to cooperate
  - RoboCup Drop-In Competition – mixed players from different teams
- Many algorithms not suitable for ad hoc teamwork
  - Need many iterations of game – typically limited amount of time
  - Designed for self-play (all agents use the same strategy) – no control over other agents in ad hoc teamwork

Ad hoc Teamwork

Type-based methods

- Assume different types of agents
- Based on interaction history – compute belief over types of other agents
- Play own actions based on beliefs
- Can also add parameters to types

Other problems in MAL

Analysis of emergent behaviors

- Typically no new learning algorithms, but single-agent learning algorithms evaluated in multi-agent environment
- Emergent language
  - Learn agents to use some language
  - E.g. signaling game – two agents are show two images, one of them (sender) is told the target and can send a message (from fixed vocabulary) to the receiver; both agents receive a positive reward if the receiver identifies the correct image

Learning communication

- Agent can typically exchange vectors of numbers for communication
- Maximization of shared utility by means of communication in partially observable environment

Learning cooperation

Agent modelling agents

References and Further Reading

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