Playing Atari with Deep Reinforcement Learning

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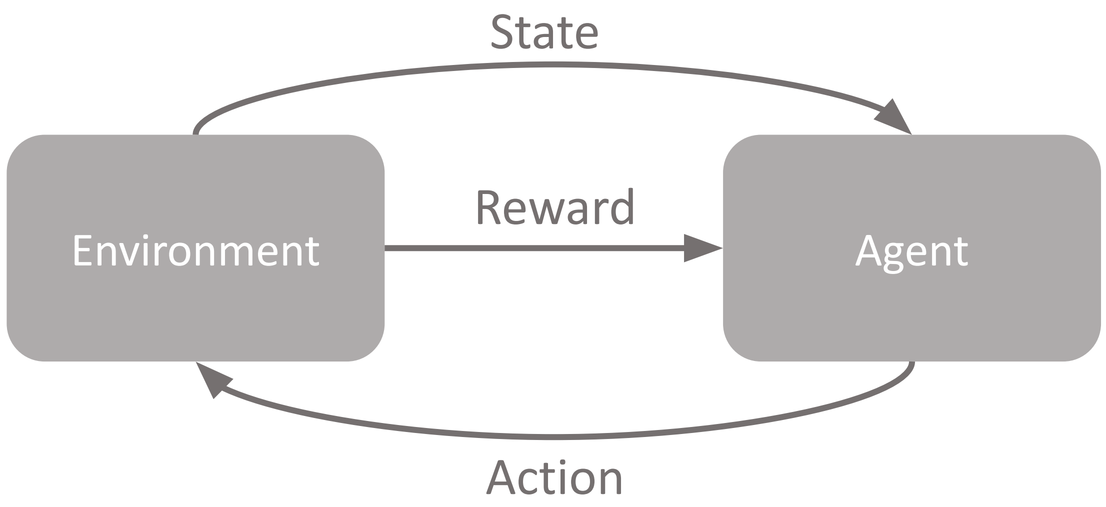
Basic Knowledge
Reinforcement Learning

- Like the way people learn by themselves by interacting with the environment.
- Applies to the problem of making decisions sequentially
- Goal : Finding optimal policy (maximize sum of rewards)



Basic Knowledge
MDP & Action Value Function

- Markov Decision Processes : Mathematical definition of information about the environment
  - State $\boldsymbol{S}$, Action $\boldsymbol{A}$: finite set of possible states or actions
  - Reward function $\boldsymbol{R}$: $R_s^a = E[R_{t+1}|S_t = s, A_t = a]$, expected value of R_{t+1} which is result of state and action in time t
  - State transition probability $\boldsymbol{P}$: $P_{ss'}^a = P[S_{t+1} = s'|S_t = s, A_t = a]$ probability to go s to s' by action a
  - Discount factor $\boldsymbol{\gamma}$: make future reward less valuable
- Action value function $Q(s,a)$: which action is more valuable

$$Q(s,a) = E[\underbrace{R_{t+1} + \gamma R_{t+2} + \ldots}_{\text{Sum of future rewards}}|S_t = s, A_t = a] = E[\sum_{k=0}^{\infty} \gamma^k R_{t+k+1}|S_t = s, A_t = a]$$

Basic Knowledge
Q-Learning

- Algorithm which learn action value function Q
- Model-free : don't need model information(State transition probability, Reward function)
- Update Q

$$Q(s_t, a_t) \leftarrow R_{t+1} + \gamma Q(s_{t+1}, a')$$

- Off-policy : Use two policy
  - ε-greedy to choose action a_t to do
  - greedy to choose action a' used as update goal

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

Deep Reinforcement Learning
DQN & Policy Gradient

Deep Q Network

Policy Gradient

Play Atari with Deep Reinforcement Learning

DQN
Challenges, Goal, Introduction

- What we want : Learning to control agents directly from high-dimensional sensory inputs like vision and speech
  - Deep Learning can make it possible! -> DL could also be beneficial for RL with sensory data?
- Challenges

	Deep Learning	Reinforcement Learning
Training data	Labeled training data	Reward Signal (sparse, noisy, delayed)
Data dependency	Independent	Dependent
About data distribution	Assume a fixed underlying distribution	The data distribution changes as the algorithm learns new behaviors

DQN
Can solve these!

- CNN can overcome these challenges to learn successful control policies from raw video data in complex RL environments
- Model : CNN(Convolutional Neural Network)
- Trained with variant of Q-learning
  - Input : raw pixels
  - Output : value of function estimating future rewards
- Stochastic Gradient Descent
- Experience Replay Memory
- Apply method to many games with no adjustment of the architecture or learning algorithm

DQN
Q-Network

$$R_t = \sum_{t'=t}^{T} r^{t'-t} r_{t'}$$

$$Q^*(s,a) = max_\pi E[R_t | s_t = s, a_t = \alpha, \boxed{\pi}]$$

Policy function

$$Q^*(s,a) = \mathbb{E}_{s' \sim \mathcal{E}}\left[r + \gamma max_{a'} Q^*(s',a') \,\middle|\, s,a\right].$$

- Iteratively update Bellman equation to estimate Q. So Value Iteration algorithm iteratively do this procedure

$$Q_{i+1}(s,a) = \mathbb{E}\left[r + \gamma Q_i(s',a') \,\middle|\, s,a\right] \qquad \boxed{Q_i \rightarrow Q^* \text{ as } i \rightarrow \infty}$$

- But it is impractical!

  ->action-value function is estimated separately for each sequence, without any generalization.

DQN
Q-Network

- Q-network : Q-learning + neural network function approximator with weights θ

$$Q(s, a; \theta) \simeq Q^*(s, a).$$

- Loss function

Target value for iteration i

$$L_i(\theta_i) = \mathbb{E}_{s,a\sim \boxed{\rho(\cdot)}}\left[\left(\boxed{y_i} - Q(s, a; \theta_i)\right)^2\right], \text{where, } y_i = \mathbb{E}_{s'\sim\mathcal{E}}\left[r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) \,\middle|\, s, a\right]$$

Behavior distribution

$\rho(s, a)$: probability distribution over sequences s and actions a

- The parameters from the previous iteration θ_{i-1} are held fixed when optimizing the loss function $L_i(\theta_i)$
- Gradient

$$\nabla_{\theta_i} L_i(\theta_i) = \mathbb{E}_{s,a\sim\rho(\cdot);s'\sim\mathcal{E}}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta_{i-1}) - Q(s, a; \theta_i)\right)\nabla_{\theta_i} Q(s, a; \theta_i)\right]$$

DQN

Preprocessing with CNN(Convolution Neural Network)

- Why?

  Raw Atari frames : 210 × 160 pixel images with a 128 color palette

  -> computationally demanding

- Convert their RGB representation to gray-scale & Down-sample it to a 110×84 image.
- Crop an 84 × 84 region of the image that roughly captures the playing area
- Preprocess function φ
  - applies this preprocessing to the last 4 frames of a history
  - stacks them to produce the input to the Q-function

DQN
Algorithm

Algorithm 1 Deep Q-learning with Experience Replay

Initialize replay memory $\mathcal{D}$ to capacity N
Initialize action-value function Q with random weights
for episode $= 1, M$ **do**
  Initialise sequence $s_1 = \{x_1\}$ and preprocessed sequenced $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ϵ select a random action a_t
    otherwise select $a_t = \max_a Q^*(\phi(s_t), a; \theta)$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$
    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in $\mathcal{D}$
    Sample random minibatch of transitions $(\phi_j, a_j, r_j, \phi_{j+1})$ from $\mathcal{D}$
    Set $y_j = \begin{cases} r_j & \text{for terminal } \phi_{j+1} \\ r_j + \gamma \max_{a'} Q(\phi_{j+1}, a'; \theta) & \text{for non-terminal } \phi_{j+1} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ according to equation $\boxed{3}$
  end for
end for

Deep Reinforcement Learning
Result

Close to Human Performance

Better than other algorithms

	B. Rider	Breakout	Enduro	Pong	Q*bert	Seaquest	S. Invaders
Random	354	1.2	0	−20.4	157	110	179
Sarsa	996	5.2	129	−19	614	665	271
Contingency	1743	6	159	−17	960	723	268
DQN	**4092**	**168**	**470**	**20**	**1952**	**1705**	**581**
Human	7456	31	368	−3	18900	28010	3690

Better than Human Performance

Far from Human Performance

	B. Rider	Breakout	Enduro	Pong	Q*bert	Seaquest	S. Invaders
HNeat Best	3616	52	106	19	1800	920	**1720**
HNeat Pixel	1332	4	91	−16	1325	800	1145
DQN Best	**5184**	**225**	**661**	**21**	**4500**	**1740**	1075

HNeat : produce deterministic policies that always get the same score

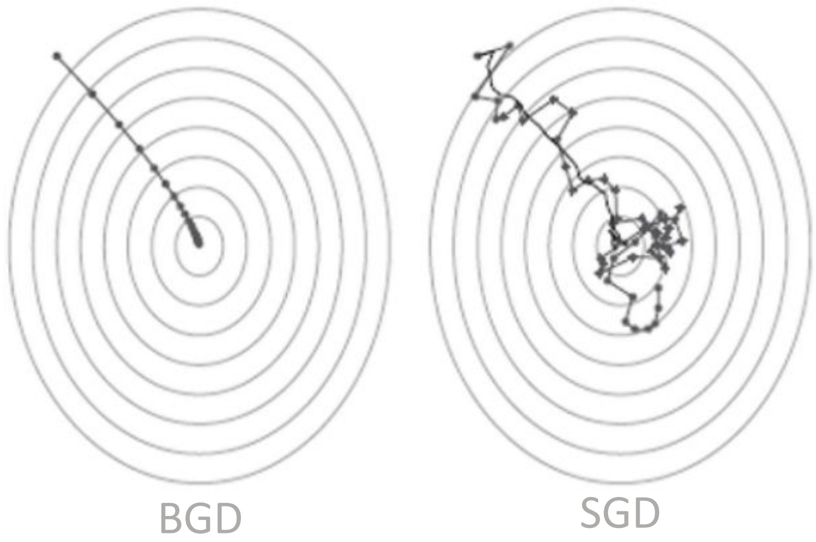
- Best : hand-engineered object detector algorithm (outputs the locations and types of objects on the Atari screen)

- Pixel : the special 8 color channel representation of the Atari emulator (represents an object label map at each channel)

DQN : ε-greedy policy with ε = 0.05.

DQN
Characteristic of DQN - 1

- SGD(Stochastic Gradient Descent)
  - If we use batch update(BGD, Batch Gradient Descent), it will be proportional to the size of data set
  - SGD have low constant cost per iteration and scale to large data-sets
- Advantage of using SGD
  - More steps can be made at the same time
  - If repeated several times, converge as a result of batch processing.
  - High possibility of converging in a better direction without falling into Local Minima(BGD can fall)



DQN
Characteristic of DQN - 2

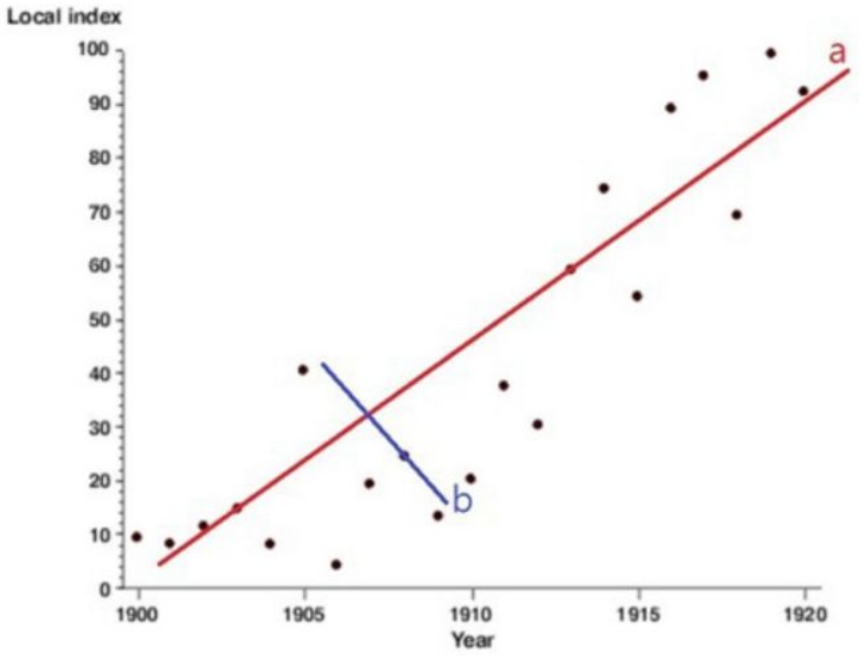
- Approximate Q with neural network
  - Can use image pixel information, not hand-craft feature
  - If it implemented by array, It would have been difficult to achieve correlated results under similar states
  - Because CNN automatically extracts important information from the game and then calculates each Q value again based on those features, you can also expect robust calculations for small state changes.

DQN

Characteristic of DQN - 3

- Experience Replay
  - store the agent's experiences at each time-step, pooled over many episodes into a replay memory

    $e_t = (s_t, a_t, r_t, s_{t+1})$ **in a data-set** $\mathcal{D} = e_1, \ldots, e_N$
  - During the inner loop of the algorithm, we apply Q-learning updates, or minibatch updates, to samples of experience, $e \sim \mathcal{D}$, drawn at random from the pool of stored samples
  - a is the correct answer in the whole, but b can be the answer in the vicinity of b. Experience Replay prevents this situation in the RL environment.



Deep Reinforcement Learning

Conclusion(In my opinion)

- Learn with raw data, not processed data.
- learn anything compared to the previous algorithm.

DQN means a lot.

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Thank You