Introduction of Reinforcement Learning

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Reference

1. `David Silver UCL course`
2. `My notebook for RL`
3. `One standard repo for RL agent in PyTorch`
4. Alibaba Reinforcement Learning Application
5. Lots of repos can be found on `GitHub`

Outline

1. Introduction and MDP
2. Planning by DP
3. Model-Free Value-Based
4. Value function approximation
   1. FA and its limiation
   2. DQN and extensions
5. Model-Free Policy-Based
   1. Policy Gradient
   2. Algorithms
6. Model-Based
   1. Integrating Learning
   2. Dyna-Q
7. Application
   1. RL in NLP
   2. Alibaba StarCraft

1. Introduction

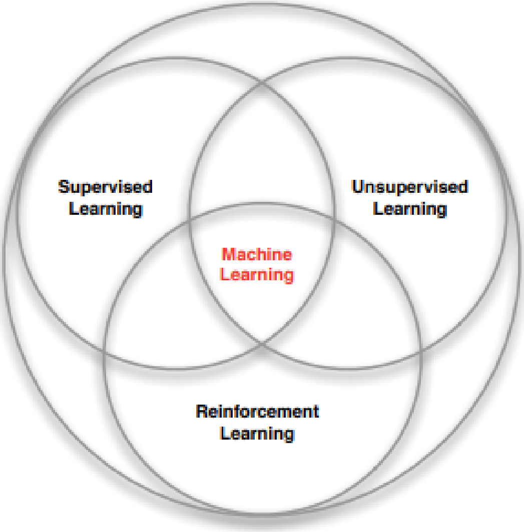


Figure 1: Reinforcement Learning

1. Introduction and MDP

Reinforcement Learning:

Dynamic decision process with delay reward

1. no supervisor, only `reward` signal from environment
2. Feedback is delayed
3. Time really matters
4. Agent's action affect subsequent data it receives

Reward hypothesis:

All goals can be described by `Maximisation of expected cumulative rewards`

RL Task

Prediction and Control

What is MDP and why we need it?

1. `Markov decision processes` formally describe the Environment for RL
   In RL, we only care about `Agent` and `Environment`
2. Current state is known, the history can be thrown away

$$S_t = F(h_{<t})$$

3. Almost all RL problems can be formalised as MDPs

1. Introduction and MDP

1. MDP definition

$$(S, A, R, P, \gamma)$$

$$P^a_{ss'} = \mathbb{P}[S_{t+1} = s' | S_t = s]$$

$$R^a_s = \mathbb{E}[R_{t+1} | S_t = s, A_t = a]$$

$$\gamma \in [0, 1]$$

2. Policy definition
   Define the distribution of the action condition on state

$$\pi(a|s) = \mathbb{P}[A_t = a | S_t = s]$$

3. Return Reward
   Cumulative reward from current state

$$G_t = R_{t+1} + \gamma R_{t+2} + ... = \sum_{k=0}^{\infty} \gamma^k R_{t+1+k}$$

1. Value function
   - State Value function

$$v_\pi(s) = \mathbb{E}[G_t | S_t = s]$$

   - Action Value function

$$q_\pi(s, a) = \mathbb{E}_\pi[G_t | S_t = s, A_t = a]$$

2. Bellman Equation
   - State Value Bellman function

$$v_\pi(s) = \mathbb{E}_\pi[R_{t+1} + \gamma v_\pi(S_{t+1}) | S_t = s]$$

   - Action Value Bellman function

$$q_\pi(s, a) = \mathbb{E}_\pi[R_{t+1} + \gamma q_\pi(S_{t+1}, A_{t+1}) | S_t = a, A_t = a]$$

1. Introduction and MDP

Optimal Bellman Equation

$$v_*(s) = max_a q_*(s, a)$$

$$q_*(s, a) = R_s^a + \gamma \sum_{s' \in S} P_{ss'}^a v_*(s')$$

$$q_*(s, a) = R_s^a + \gamma \sum_{s' \in S} P_{ss'}^a max_{a'} q_*(s', a')$$

Find stable $v_*(s)$, prediction problem solved

Find stable $p_*(s, a)$, control problem solved

Need to use iterate the equation, because the Optimal Bellman Equation is nonlinear.

Dynamic Programming: Optimal method for decision process

- Optimal substructure
  Optimal solution can be decomposed into subproblems
- Overlapping subproblems
  Solutions can be cached and reused
- Markov Decision Process satisfy the properties
  - Bellman equation gives the way to decompose solution
  - Value function store solution

Prediction

- Problem: MDP and policy π given, solve v_π, evaluate policy π
- Solution: iterative application of Bellman equation

$$v_1 \rightarrow v_2 \rightarrow ... \rightarrow v_\pi$$

- Convergence of v_π can be proven

$$v_{k+1}(s) = \sum_{a \in A} \pi(a|s)(R_s^a + \gamma \sum_{s' \in S} P_{ss'}^a v_k(s'))$$

$$v^{k+1} = R^\pi + \gamma P^\pi v^k$$

Control

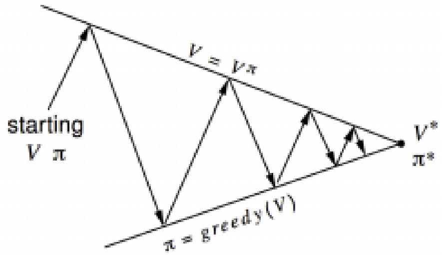
- Problem: MDP and initial policy π given, return best π
- Solution: Policy Iteration
  - Evaluation

$$v_\pi(s) = \mathbb{E}[R_{t+1} + \gamma R_{t+2} + ...|S_t = s]$$

  - Improve policy

$$\pi' = greedy(v_\pi)$$

2. Planning by DP



Policy evaluation Estimate v_π

Iterative policy evaluation

Policy improvement Generate $\pi' \geq \pi$

Greedy policy improvement

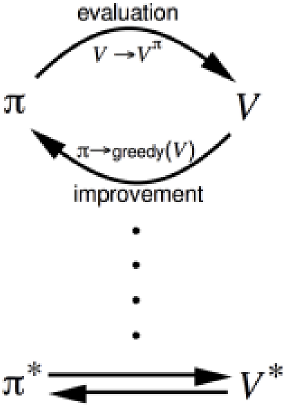


Figure 2: Policy Iteration

- Convergence

$$v_\pi(s) = max_{a \in A} q_\pi(s, a) = v_*(s)$$

$$q_*(s, a) = R_s^a + \gamma \sum_{s' \in S'} P_{ss'}^a v_*(s')$$

$$v_\pi(s) = q_\pi(s, \pi'(s)) = max_{a \in A} q_\pi(s, a) \geq q_\pi(s, \pi(s)) = v_\pi(s)$$

- Optimal Bellman equation satisfy, solve the MDP control problem

2. Planning by DP

- Value Iteration for control problem
  Iterative application of this equation

$$v_*(s) \leftarrow max_{a \in A} R_s^a + \gamma \sum_{s' \in S} P_{ss'}^a v_*(s')$$

  Value Iteration is another way to solve the control and prediction problem
- Constraint for Planning by DP
  MDP must be given, which means that $P_{ss'}^a$ and R_s^a can be accssed.

Definition

1. MDP is unknow, but we still want to solve it. $P_{ss'}^a$ and R_s^a is unkown to us.
2. We can only learn the `value` or `policy` from the experience.
3. Find the optimal V value function, prediction solved.
4. Find the optimal Q value function, control solved.

Monte-Carlo Learning

1. Learn from the episode experience with environment
2. MC is `model-free`: no knowledge of MDP (P, R)
3. MC learns from complete expisode without bootstrapping
4. MC's idea: $value = \mathbb{E}[G]$
5. Constraint: All epsiodes must terminate

Monte-Carlo Learning

1. Goal: learn v_π from episodes of experience under policy π

$$S_1, A_1, R_2, ..., S_k \backsim \pi$$

2. Discounted reward of episode

$$G_t = R_{t+1} + \gamma R_{t+2} + ... + \gamma^{T-1} R_T$$

3. Update $v(s)$ after episode

$$N(S_t) \leftarrow N(S_t) + 1$$

$$V(S_t) \leftarrow V(S_t) + \frac{1}{N(S_t)}(G_t - V(S_t))$$

$$V(S_t) \leftarrow V(S_t) + \alpha(G_t - V(S_t))$$

Temporal-Difference Learning

1. TD methods learn directly from episodes of experience
2. TD is `model-free`: no knowledge of MDP (P,R)
3. TD learns from `incomplete` episode with bootstrapping
4. TD update the value function with the guess from previous iteration

Temporal-Difference Learning

1. Goal: learn v_π online from experience under policy π
2. MC update

$$V(S_t) \leftarrow V(S_t) + \alpha(G_t - V(S_t))$$

3. TD(0)

$$V(S_t) \leftarrow V(S_t) + \alpha(R_{t+1} + \gamma V(S_{t+1}) - V(S_t))$$

- $R_{t+1} + \gamma V(S_{t+1})$ is called `TD target`
- $\delta_t = R_{t+1} + \gamma V(S_{t+1}) - V(S_t)$ is called `TD error`

Comparison

1. TD learns online but MC wait until end of episode
2. MC has high variance and zero bias, TD has low variance and some bias
3. Convergence:
    1. MC converges to solution with MSE

$$\sum_{k=1}^{K}\sum_{t=1}^{T_k}(G_t^k - V(s_t^k))^2$$

    2. TD converges to max likelihood Markov model
       TD is better suited to the Markov environment.

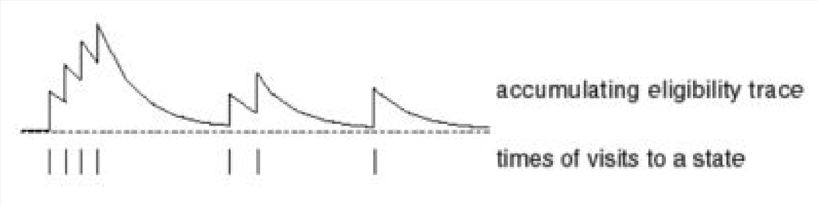
TD(λ)

$$E_0(s) = 0$$

$$E_t(s) = \gamma\lambda E_{t-1}(s) + 1(if\ \ S_t = s)$$

$$\delta_t = R_{t+1} + \gamma V(S_{t+1}) - V(S_t)$$

$$V(s) \leftarrow V(s) + \alpha\delta_t E_t(s)$$



- TD(λ) converges faster than TD(0)
- δ_t define the result of fixing
- E_t define the degree of fixing

Generalised Policy Iteration

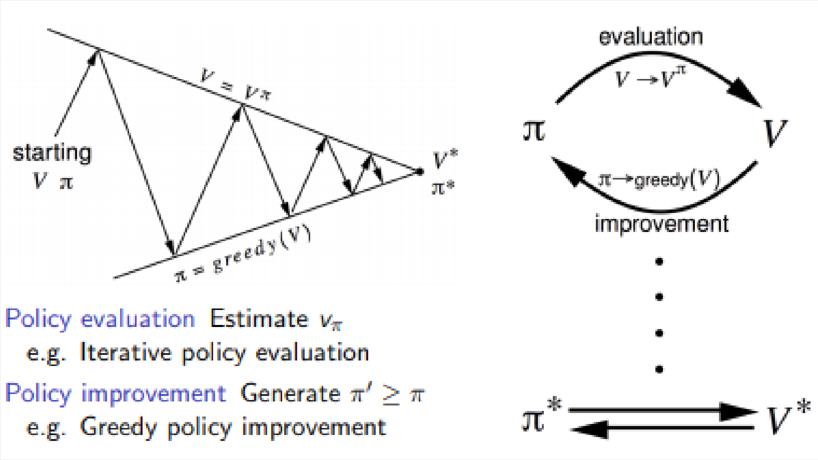


Figure 3: Generalised Policy Iteration

3. Model-Free Control

Sarsa

Initialize $Q(s, a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
    Initialize S
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Repeat (for each step of episode):
        Take action A, observe R, S'
        Choose A' from S' using policy derived from Q (e.g., ε-greedy)
        $Q(S, A) \leftarrow Q(S, A) + \alpha\big[R + \gamma Q(S', A') - Q(S, A)\big]$
        $S \leftarrow S'$; $A \leftarrow A'$;
    until S is terminal

Figure 4: Sarsa Algorithm

Sarsa(λ)

Initialize $Q(s,a)$ arbitrarily, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$
Repeat (for each episode):
  $E(s,a) = 0$, for all $s \in \mathcal{S}, a \in \mathcal{A}(s)$
  Initialize S, A
  Repeat (for each step of episode):
    Take action A, observe R, S'
    Choose A' from S' using policy derived from Q (e.g., ε-greedy)
    $\delta \leftarrow R + \gamma Q(S',A') - Q(S,A)$
    $E(S,A) \leftarrow E(S,A) + 1$
    For all $s \in \mathcal{S}, a \in \mathcal{A}(s)$:
      $Q(s,a) \leftarrow Q(s,a) + \alpha\delta E(s,a)$
      $E(s,a) \leftarrow \gamma\lambda E(s,a)$
    $S \leftarrow S'$; $A \leftarrow A'$
  until S is terminal

Figure 5: Sarsa(λ) Algorithm

Off-Policy and On-Policy

1. On-Policy
   - learn about policy π from experience sampled from π
   - The special case of the Off-Policy
2. Off-Policy
   - learn about policy π from experience sampled from μ
   - Re-use experience generated from other policy (other agent or even human)
   - Balance between Explotition and Exploration though Q-Learning

Q-Leanring

Initialize $Q(s,a), \forall s \in \mathcal{S}, a \in \mathcal{A}(s)$, arbitrarily, and $Q(\textit{terminal-state}, \cdot) = 0$
Repeat (for each episode):
  Initialize S
  Repeat (for each step of episode):
    Choose A from S using policy derived from Q (e.g., ε-greedy)
    Take action A, observe R, S'
    $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$
    $S \leftarrow S'$;
  until S is terminal

Figure 6: Off-Policy TD Learning, Q-Learning

4. Value Function Approximation

1. Reinforcement Learning can be used to solve `large` problem
   - Backgammon: 10^{20} states
   - Game of Go: 10^{170} states
   - Some environment: continuous state space
2. Problem:
   - Tabular method need lots of memory to store Value Function
   - Learn value individually slowly
3. Solution - **Value Function Approximation**
   - Save the memory with approximation parameters w

$$v(s, w) \approx v_\pi(s)$$

$$q(s, a, w) \approx q_\pi(s, a)$$

   - Extension to unseen states

4. Value Function Approximation

1. Approximate model
   - Nonlinear model: Nerual Networks
   - Linear regression
   - Other regression model ...
2. Optimal parameters
   - Gradient descent
   - Batch training

Gradient Descent

1. Goal: Find the parameter vector w minimising MSE betweeen approximate value function $v(s, w)$ and true value function $v_\pi(s)$

$$J(w) = \mathbb{E}_\pi[(v_\pi(s) - v(s, w))^2]$$

2. Gradient descent

$$\delta w = -\frac{1}{2}\alpha \nabla_w J(w) = \alpha \mathbb{E}_\pi[(v_\pi(s) - v(s, w))\nabla_w v(s, w)]$$

$$\delta w = \alpha(v_\pi(s) - v(s, w))\nabla_w v(s, w)$$

3. SGD $\rightarrow$ Expectation

4. Value Function Approximation

Gradient Descent

1. Linear function, $x(S)$ is the feature vector

$$v(s, w) = x(S)^T w$$

2. Object function

$$J(w) = \mathbb{E}_\pi[(v_\pi(s) - x(s)^T w)^2]$$

3. Gradient Descent

$$\delta w = \alpha(v_\pi(s) - v(s, w))x(s)$$

4. Lookup table is the special case of Linear function

$$v(s, w) = x_{one-hot}^T w$$

Gradient Descent

1. MC

$$\delta w = \alpha(G_t - v(s_t, w))\nabla_w v(s_t, w)$$

2. TD(0)

$$\delta w = \alpha(R_{t+1} + \gamma v(s_{t+1}, w) - v(s_t, w))\nabla_w v(s_t, w)$$

3. TD(λ)

$$\delta w = \alpha(G_t^\lambda - v(s, w))\nabla_w v(s_t, w)$$

$$\delta_t = R_{t+1} + \gamma v(s_{t+1}, w) - v(s_t, w)$$

$$E_t = \gamma\lambda E_{t-1} + x(s_t)$$

$$\delta w = \alpha\delta_t E_t$$

4. Value Function Approximation

Limiation

Algorithm	Table Lookup	Linear	Non-Linear
Monte-Carlo Control	✓	(✓)	✗
Sarsa	✓	(✓)	✗
Q-learning	✓	✗	✗
Gradient Q-learning	✓	✓	✗

(✓) = chatters around near-optimal value function

Figure 7: Neural Networks don't work[1]

An analysis of temporal-difference learning with function approximation. IEEE 1997

Batch Methods - DQN

1. DeepMind Nature 2015
   - DRL of DQN
   - integrate the `CNN` and `Q-Learning` to master the games
   - Solve the divergence of nonlinear function approximation `Q-Learning`
2. Idea
   - Experience replay: avoid relevance
   - Fixed Q target Network: Off-Policy

Algorithm 1 Deep Q-learning with experience replay

Initialize replay memory D to capacity N
Initialize action-value function Q with random weights θ
Initialize target action-value function $\hat{Q}$ with weights $\theta^- = \theta$
for episode $1, M$ **do** Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$
  for $t = 1, T$ **do**
    With probability ε select a random action a_t
    otherwise select $a_t = \arg\max_a Q(\phi(s_t), a; \theta)$
    Execute action a_t in the 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 experience $(\phi_t, a_t, r_t, \phi_{t+1})$ in D
    Sample random minibatch of experiences $(\phi_j, a_j, r_j, \phi_{j+1})$ from D
    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step } j+1 \\ r_j + \gamma \max_{a'} \hat{Q}(\phi_{j+1}, a'; \theta^-) & \text{otherwise} \end{cases}$
    Perform a gradient descent step on $(y_j - Q(\phi_j, a_j; \theta))^2$ with respect to the weights θ
    Every C steps reset $\hat{Q} = Q$
  end for
end for

Figure 8: DQN

Extension of DQN

1. Double DQN
   - fix the `overestimation` problem of Q-Learning
   - avoid suboptimal result

$$loss = (r + \gamma Q(s', \arg\max_{a} Q(s', a', w), w^{-}) - Q(s, a, w))^2$$

2. Prioritized Replay DQN
   - When reward is sparse, DQN is hard to train
   - TD error is the weight
3. Dueling DQN
   - For some states, V function is more important
   - spee up

$$A^{\pi}(s, a) = Q^{\pi}(s, a) - V^{\pi}(s)$$

5. Policy Gradient

Value-Based and Policy-Based RL

- Value Based
  - Learn value function
  - implicit policy (such as ϵ-greedy)
- Policy Based
  - No valuse function
  - Learn policy directly
- Actor-Critic
  - `Critic`: Learn Value Function
  - `Actor`: Learn policy with the guidance of `Critic`

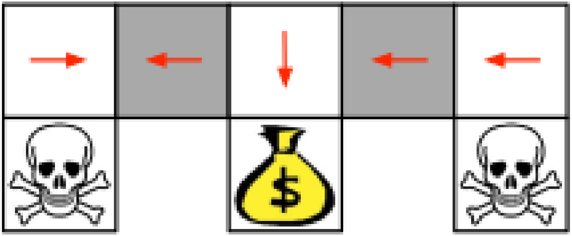


Figure 9: Aliased

Advantage

- Learn policy with probability
- Learn for continous state space, better than Value-Based

5. Policy Gradient

1. Parameterise the **policy**

$$\pi_\theta(s,a) = \mathbb{P}[a|s,\theta]$$

2. Evaluate the policy with object function

$$J(\theta) = \sum \pi_\theta(a|s) Q(s,a;\theta)$$

$$J(\theta) = \mathbb{E}_{\pi_\theta, s \backsim \rho^\pi}[Q(s,a;\theta)]$$

3. Optimize
   1. Gradient Ascent
   2. No Gradient Ascent

5. Policy Gradient

Compute the score function for gradient

1. Discrete environment - **Softmax Policy**

$$\pi_\theta(s,a) \propto e^{\phi(s,a)^T\theta}$$

$$\nabla_\theta \log \pi_\theta(s,a) = \phi(s,a) - \mathbb{E}_\theta[\phi(s,\cdot)]$$

$$\nabla_\theta \pi_\theta(s,a) = \pi_\theta(s,a)\frac{\nabla_\theta \pi_\theta(s,a)}{\pi_\theta(s,a)} = \pi_\theta(s,a)\nabla_\theta \log \pi_\theta(s,a)$$

2. Continuing environment - **Gaussian Policy**

$$\nabla_\theta \log \pi_\theta(s,a) = \frac{(a-\mu(s))\phi(s)}{\sigma^2}$$

5. Policy Gradient

Policy Gradient Theorem

For any policy object function, the **Policy Gradient** is the same[a]

$$\nabla_\theta J(\theta) = \mathbb{E}_{\pi_\theta}[\nabla_\theta \log \pi_\theta(s,a) Q^{\pi_\theta}(s,a)]$$

1. $\nabla_\theta \log \pi_\theta(s,a)$ means the gradient
2. Q means the degree of fixing
3. Used to minimize the $-\log \pi_\theta(s,a) Q^{\pi_\theta}(s,a)$

[a] https://lilianweng.github.io/lil-log/2018/04/08/policy-gradient-algorithms.html

MC Policy Gradient

function REINFORCE
    Initalise θ arbitrarily
    for each spisode $\{s_1, a_1, r_2, ..., \} \backsim \pi_\theta$ do
        for t = 1 to T - 1 do
            $\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(s_t, a_t) v_t$
        end for
    end for
    return θ
end function

5. Policy Gradient Algorithms

TD Policy Gradient

function TD Policy Gradient
    Initalise θ arbitrarily
    for each episode do
        for t = 1 to T - 1 do
            $\theta \leftarrow \theta + \alpha \nabla_\theta \log \pi_\theta(s_t, a_t) v_t$
        end for
    end for
    return θ
end function

Actor-Critic Policy Gradient

1. MC has variance and need to be improved
2. **Actor-Critic**
   1. Critic: parametries $Q_w(s, a)$ for policy evaluation
   2. Acotr: Policy Gradient with the guidance of Critic
   3. Result

$$\nabla_\theta J(\theta) \approx \mathbb{E}_{\pi_\theta}[\nabla_\theta \log \pi_\theta(s, a) Q_w(s, a)]$$

$$\delta\theta = \alpha \nabla_\theta \log \pi_\theta(s, a) Q_w(s, a)$$

Actor-Critic Policy Gradient with Linear function approximation

function QAC
  Initialise s, θ
  Sample $a \backsim \pi_\theta$
  for each step do
    Sample reward $r = R_s^a$ and $s' \backsim P_s^a$
    Sample action $a' \backsim \pi_\theta(s', a')$
    $\delta = r + \gamma Q_w(s', a') - Q_w(s, a)$
    $\theta = \theta + \alpha \nabla_\theta \log \pi_\theta(s, a) Q_w(s, a)$
    $w \leftarrow w + \beta \delta \phi(, sa)$
    $a \leftarrow a', s \leftarrow s'$
  end for
end function

DDPG (Deep Deterministic Policy Gradient)

- DQN can't handle with high-dimension or continous space
- Inspired by DQN, DeepMind propose DDPG
    - Actor-Critic: DQN is Critic and DPG[2] is Actor
    - Fixed Q target Network for policy and value
    - Target Network update slowly

[2] http://proceedings.mlr.press/v32/silver14.pdf

5. Policy Gradient

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ.
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q$, $\theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
  Initialize a random process $\mathcal{N}$ for action exploration
  Receive initial observation state s_1
  for t = 1, T **do**
    Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the current policy and exploration noise
    Execute action a_t and observe reward r_t and observe new state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in R
    Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
    Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
    Update critic by minimizing the loss: $L = \frac{1}{N}\sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
    Update the actor policy using the sampled policy gradient:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N}\sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu}\mu(s|\theta^\mu)|_{s_i}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau\theta^Q + (1-\tau)\theta^{Q'}$$

$$\theta^{\mu'} \leftarrow \tau\theta^\mu + (1-\tau)\theta^{\mu'}$$

  end for
end for

Figure 10: DDPG

Comparation

1. Model-Free
   Learn value function and policy from the experience
2. Model-Based
   Learn MDP from the experience and get the policy and value function by planning.

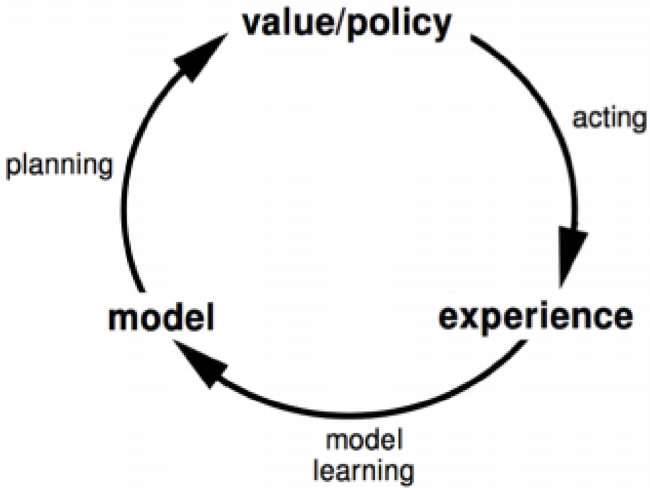


Figure 11: Model-Based method

6. Model-Based

1. Use any `supervised Learning model` to learn the MDP
2. Anything we know now can be used to solve MDP
3. A direct way to solve the MDP but the bias is a disadvantage
4. Model is the agent's impression of environment

6. Model-Based

1. Parameter η represente the MDP

$$P_\eta \approx P$$

$$R_\eta \approx R$$

2. Goal: estimate model MDP from experience $\{s_1, a_1, r_2, ..., s_T\}$
3. Supervised learning problem

$$S_t, A_t \to R_{t+1}, S_{t+1}$$

4. After learning the MDP, solved by
   - Planning (Policy Iteration, Value Iteration)
   - Model-Free (DQN, Policy Gradient)

Dyna

1. Thinking: Use the model to generate infinite samples
   This property is very useful for time-cost environment
2. Simulation: Apply **model-free** RL to evalution the samples and fix the policy

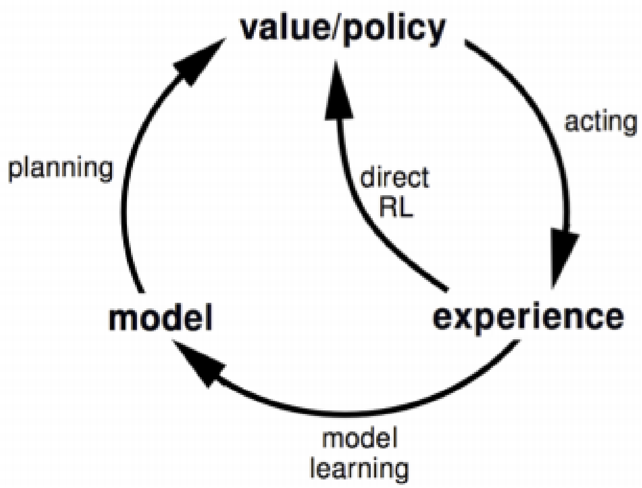


Figure 12: Dyna

Intergrated Architexture for Dyna-Q

Initialize $Q(s,a)$ and $Model(s,a)$ for all $s \in \mathcal{S}$ and $a \in \mathcal{A}(s)$
Do forever:
(a) $S \leftarrow$ current (nonterminal) state
(b) $A \leftarrow \varepsilon$-greedy(S,Q)
(c) Execute action A; observe resultant reward, R, and state, S'
(d) $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$
(e) $Model(S,A) \leftarrow R, S'$ (assuming deterministic environment)
(f) Repeat n times:
  $S \leftarrow$ random previously observed state
  $A \leftarrow$ random action previously taken in S
  $R, S' \leftarrow Model(S,A)$
  $Q(S,A) \leftarrow Q(S,A) + \alpha\big[R + \gamma \max_a Q(S',a) - Q(S,A)\big]$

Figure 13: Dyna-Q, Q-Learning, DQN

7. Application

Conclusion

1. `Reward` is the core for Reinforcenment Learning
2. If the problem can be thought as the MDP / POMDP, RL can be used
3. If the reward is clear, RL can be used
4. Sample data is important, no experience no RL
5. RL is difficult to train, be careful about parameters

RL in NLP

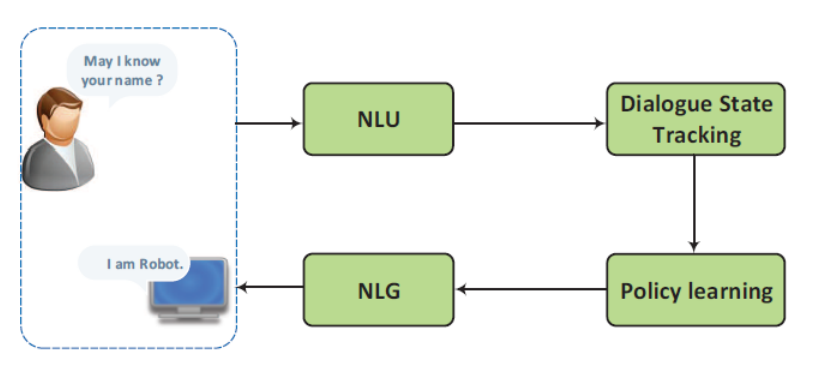


Figure 14: Pipeline Task-oriented dialogue system

7. Application

RL in NLP

For task-oriented dialogue, reward is clear

1. `DQN` for Policy Learning
2. `Deep Dyna-Q` (Dyna-Q + DQN) for Policy Learning
3. `REINFORCE` for Policy Learning

7. Application

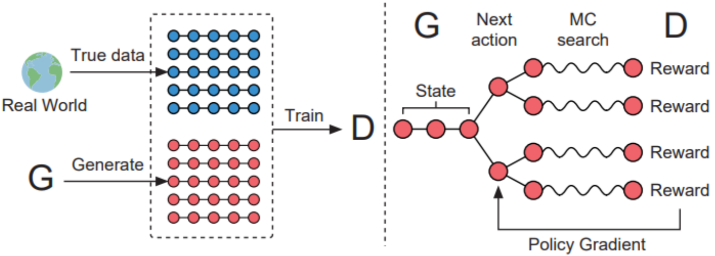


Figure 1: The illustration of SeqGAN. Left: D is trained over the real data and the generated data by G. Right: G is trained by policy gradient where the final reward signal is provided by D and is passed back to the intermediate action value via Monte Carlo search.

Figure 15: SeqGAN

SeqGAN

- Model the sequence generation as MDP
- The first work: integrate GANs with RL to generate discrete elemenets
- Generator is LSTM Policy (RL Agent)
  REINFORCE Algorithm is used for updating G
- Discriminator is CNN with MC Search

Alibaba StarCraft

Figure 16: StarCraft

7. Application

Alibaba StarCraft

1. Alibaba choose the `StarCraft` as the platform for RL research
    - Game is the wonderful platform for RL
    - Experience data is infinite
    - Reward is clear
2. Difficulies
    - `Real-Time strategy`
    - Huge state and action space
    - Incomplete nformation games
    - Inference for spatial and sequential
    - Multi Agent

Alibaba StarCraft

Why `GAMES`?

1. Advertisement in Alimama
2. Search in TaoBao
3. Intelligent agent for task-oriented dialogue (AliMeChat)
4. Alibaba RL sort strategy decision model for 11.11

End

Question and Answer