Week 11: Adversarial Reinforcement Learning

COMP90073
Security Analytics

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Semester 2, 2021

Overview

- Background on reinforcement learning
  - Introduction
  - Q-learning
  - Application in defending against DDoS attacks
- Adversarial attacks against RL models
  - Test time attack
  - Training time attack
- Defence

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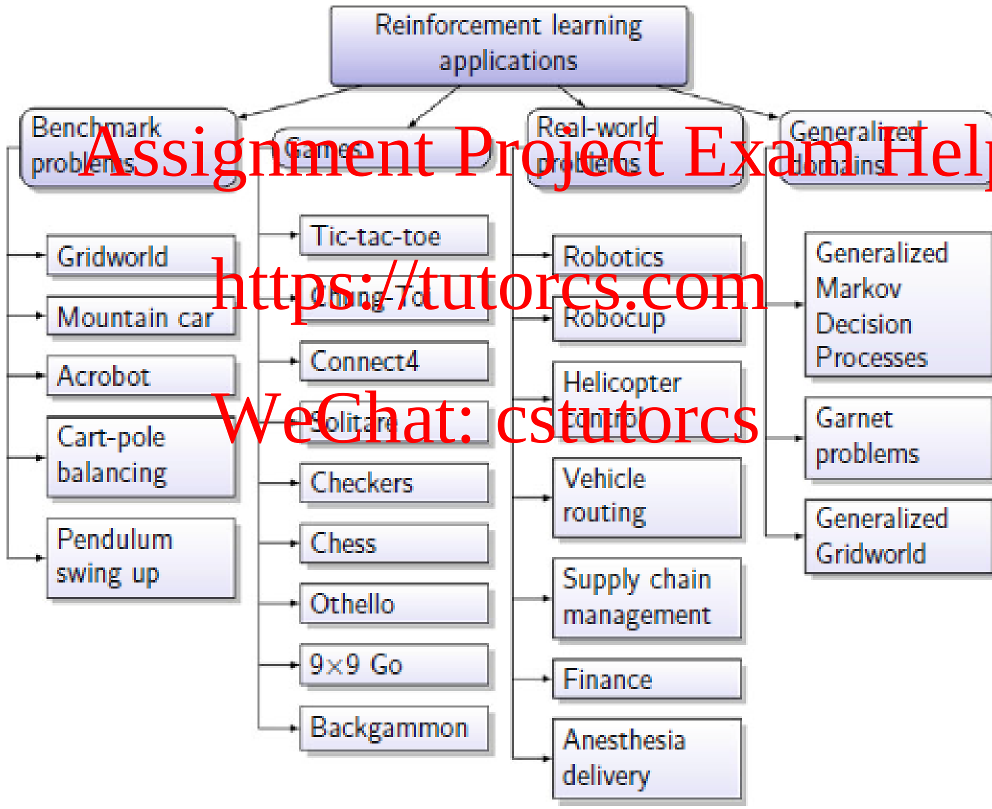
Background on reinforcement learning

- Application



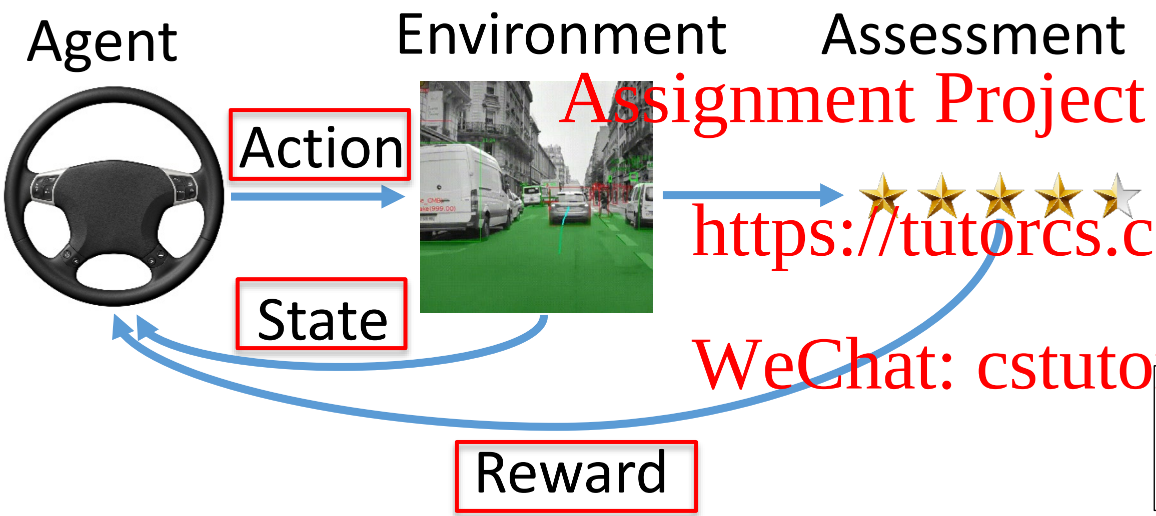
https://www.youtub

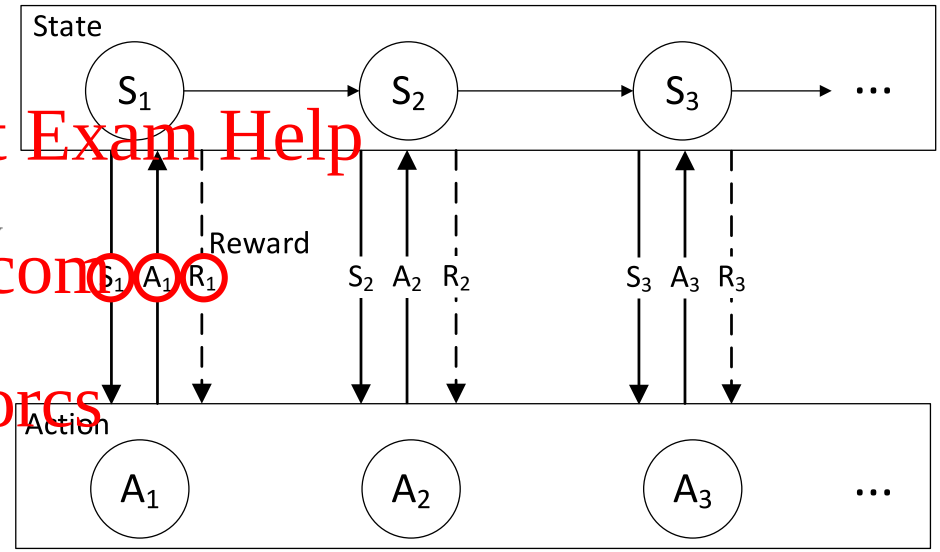
ps/autopilot-self-driving-
ng

https://www.myrealfacts.com/2019/05/applications-of-reinforcement-learning.html

Background on reinforcement learning

- Introduction

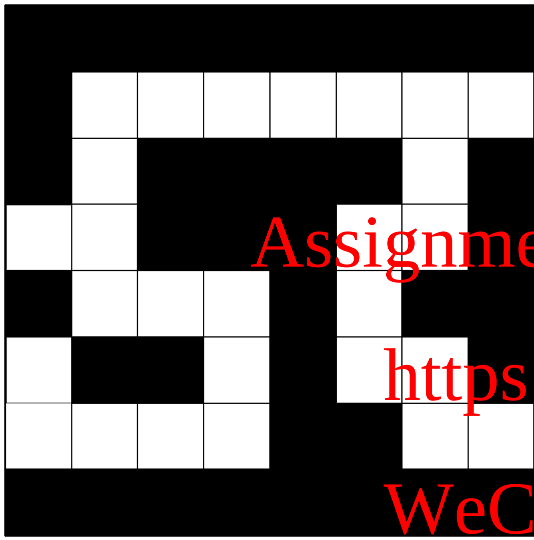


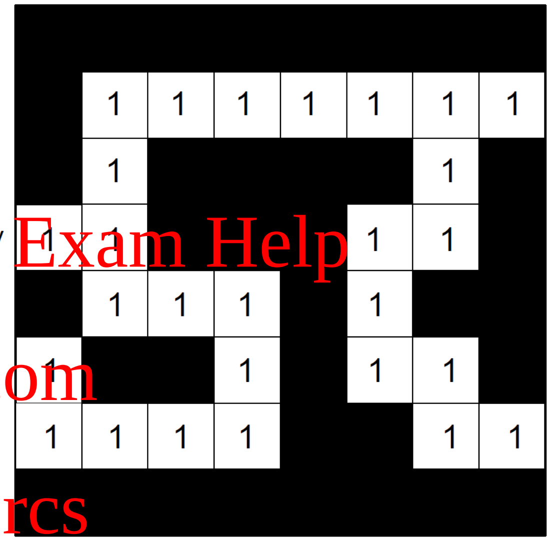


Maximise the discounted cumulative rewards over the long run: $R_t = \sum_{\tau=t}^{\infty} \gamma^{\tau-t} r_\tau , \gamma \in (0, 1]$

Background on reinforcement learning

- State

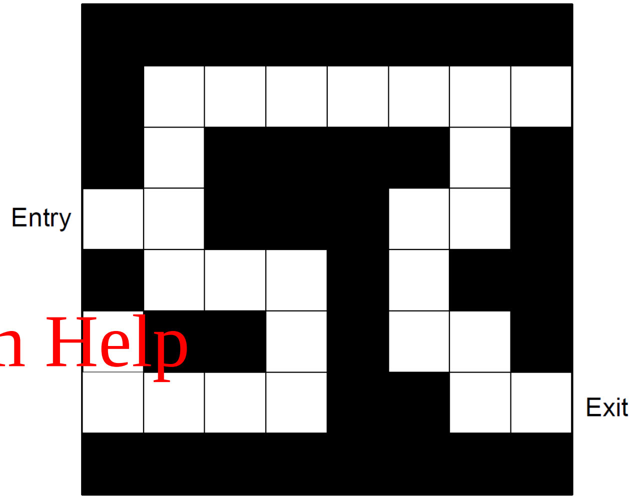




$$\begin{bmatrix} 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 1 & 1 \end{bmatrix} \qquad \begin{bmatrix} 0 & 2 & 1 & 1 & 1 & 1 & 1 & 1 \\ 0 & 2 & 0 & 0 & 0 & 0 & 1 & 0 \\ 2 & 2 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 0 & 0 & 1 & 1 \end{bmatrix}$$

Background on reinforcement learning

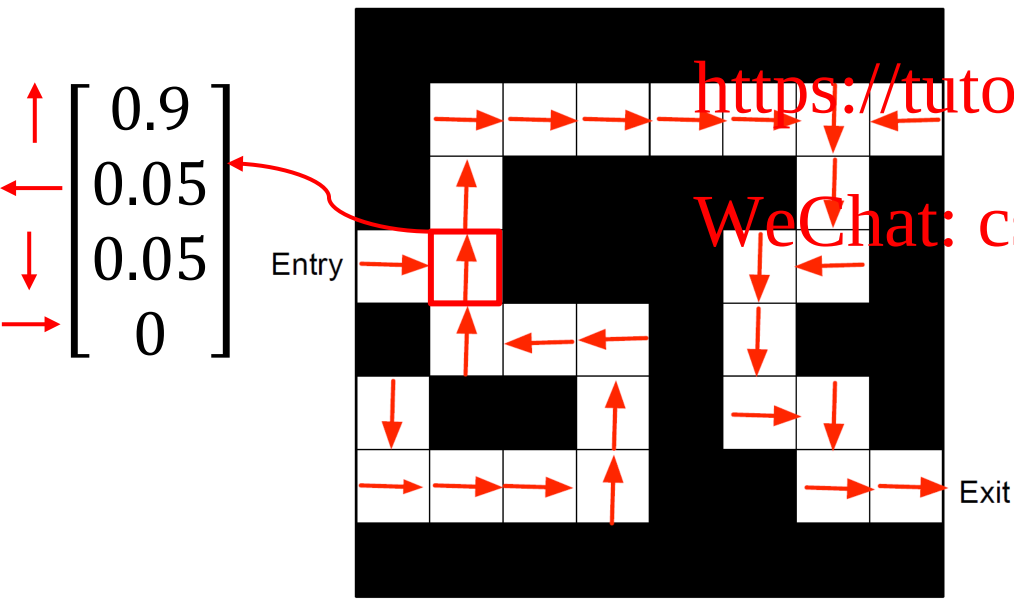
- Action
  - Up
  - Left
  - Down
  - Right

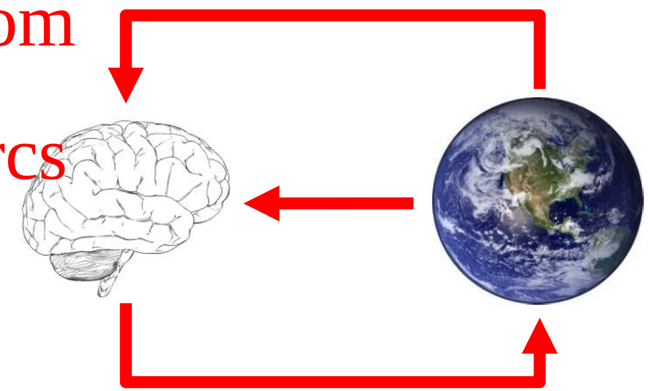


- Reward: an immediate feedback on whether an action is good
  - In the range of [-1, 1]
  - 1: reach the exit
  - -0.8: move to a blocked cell
  - -0.3: move to a visited cell
  - -0.05: move to an adjacent cell

Background on reinforcement learning

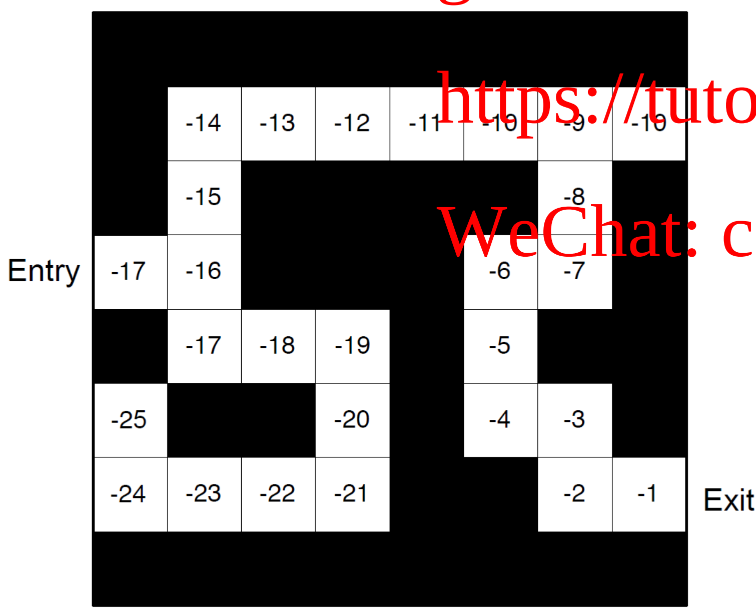
- Policy (π): a mapping from state to action, i.e. $a = \pi(s)$, it tells the agent what to do in a given state

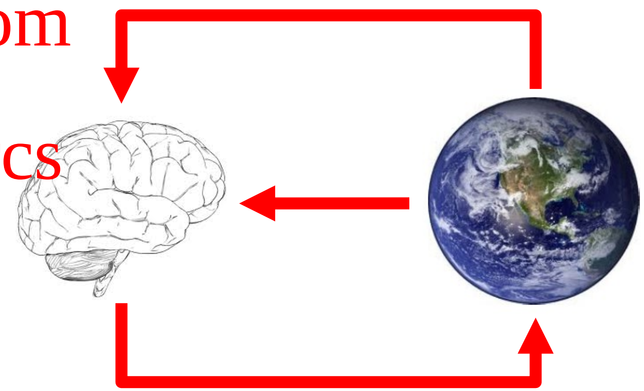




Background on reinforcement learning

- Value function: the future, long term reward of a state
  - Value of state s under policy π: $V^{\pi}(s) = \mathbb{E}\left[\sum_{i=1}^{T} \gamma^{i-1} r_i | S_t = s\right]$
  - Conditional on some policy π
  - Expected value of following policy π starting from state s





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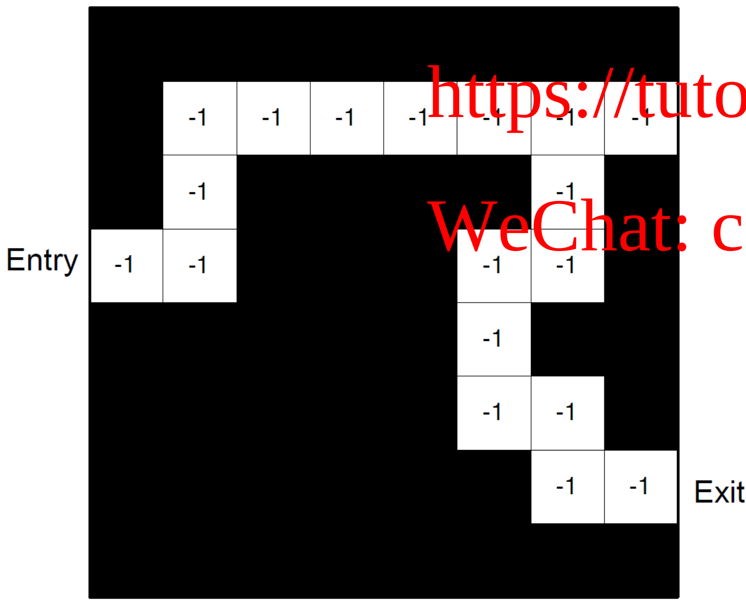
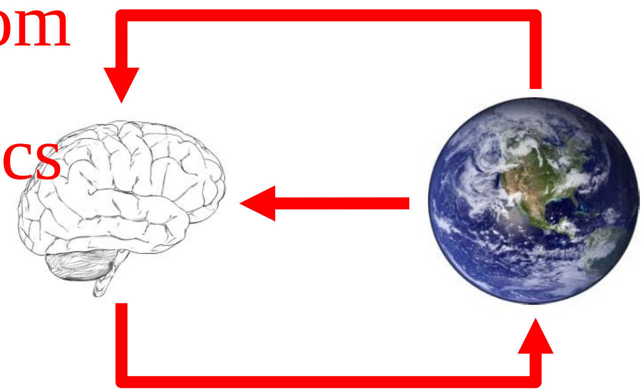
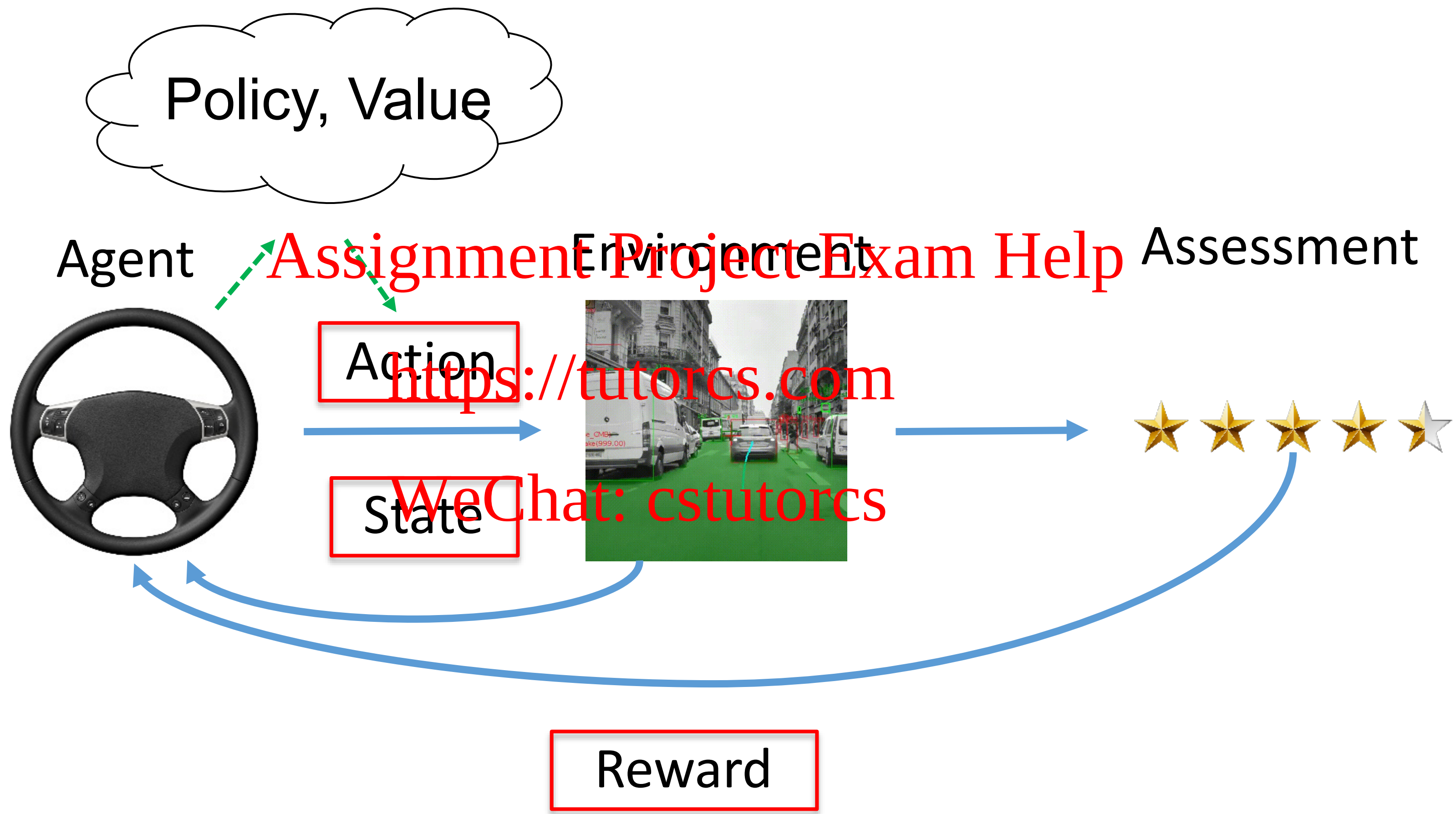
Background on reinforcement learning

- Model of the environment: mimic the behaviour of the environment, e.g., given a state & action, what the next state & reward might be.



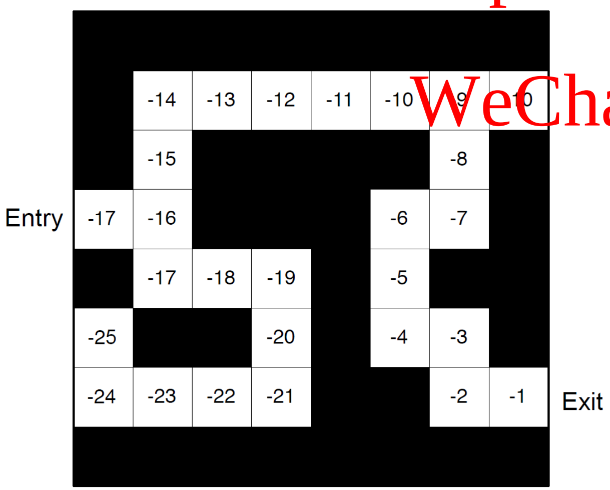


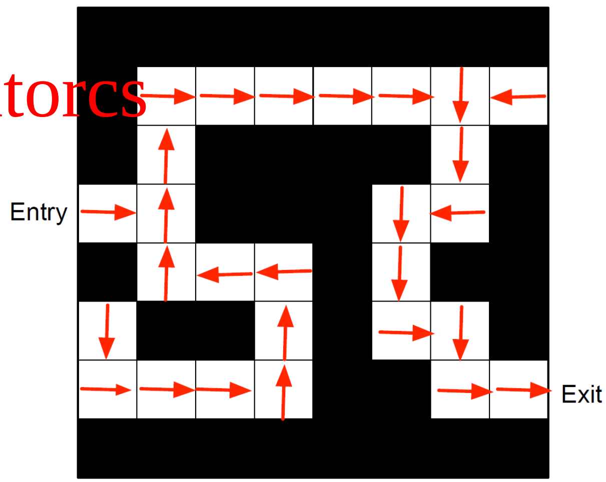
Background on reinforcement learning



Background on reinforcement learning

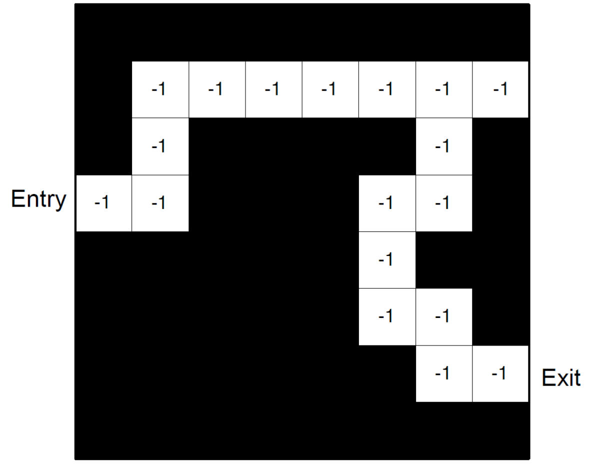
- Classification
  - Value-based algorithm estimates the value function
  - Policy-based algorithm learns the policy directly
  - Actor-critic: critic updates action-value function, actor updates policy





Background on reinforcement learning

- Classification
  - Model free algorithm directly learns the policy and/or the value function
  - Model based algorithm first builds up how the environment works



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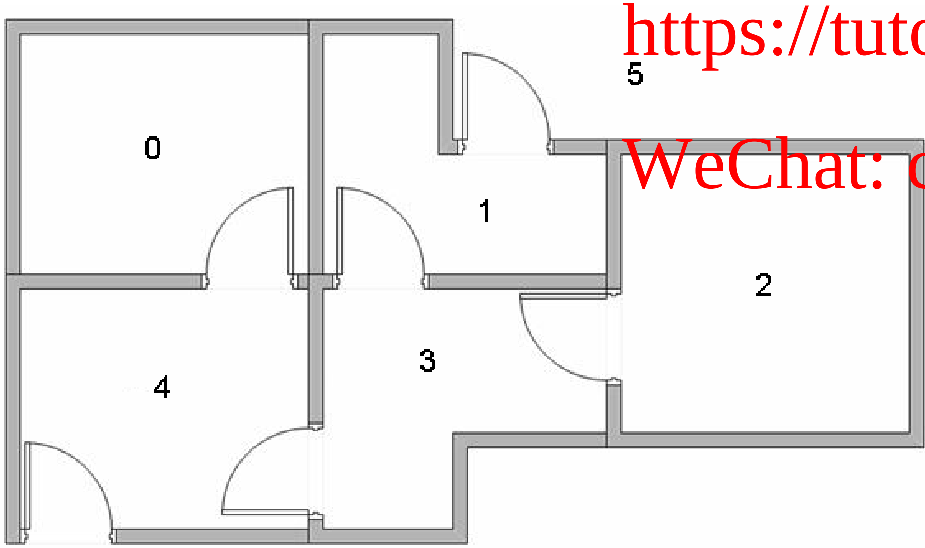
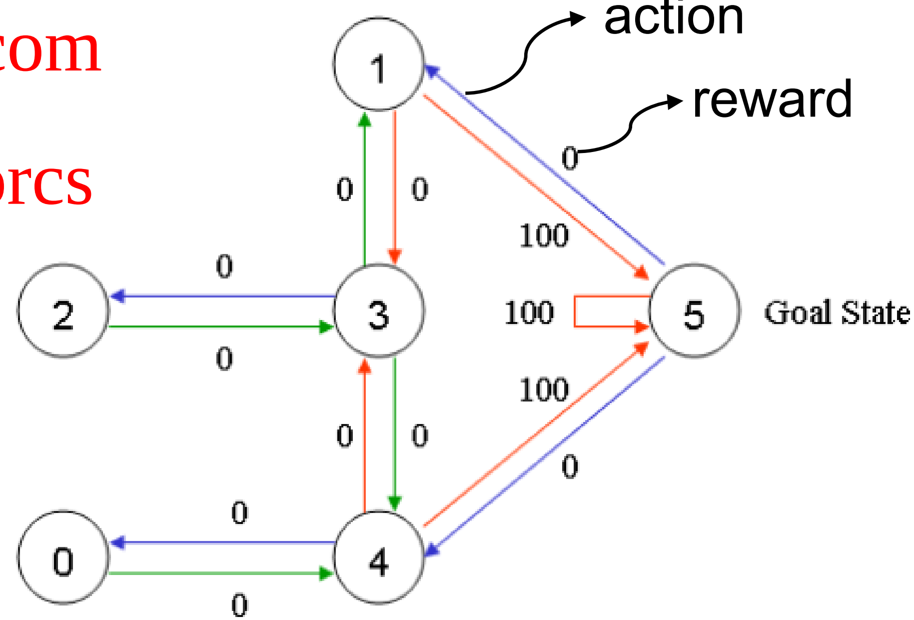
Background on reinforcement learning

- Q-learning: estimate action-value function $Q(s,a)$
  - Expected value of taking action a in state s and then following policy π:

$$Q^{\pi}(s,a) = \mathbb{E}\left[\sum_{i=1}^{T} \gamma^{i-1} r_i \mid S_t = s, A_t = a\right]$$





http://mnemstudio.org/path-finding-q-learning-tutorial.htm

Background on reinforcement learning

- Q-learning

Action

$$
R = \begin{array}{c|cccccc}
\text{State} & 0 & 1 & 2 & 3 & 4 & 5 \\
\hline
0 & -1 & -1 & -1 & -1 & 0 & -1 \\
1 & -1 & -1 & -1 & 0 & -1 & \boxed{100} \\
2 & -1 & -1 & -1 & 0 & -1 & -1 \\
3 & -1 & \boxed{0} & 0 & -1 & 0 & -1 \\
4 & 0 & -1 & -1 & 0 & -1 & 100 \\
5 & -1 & 0 & -1 & -1 & 0 & 100
\end{array}
$$

$$
Q = \begin{array}{c|cccccc}
 & 0 & 1 & 2 & 3 & 4 & 5 \\
\hline
0 & 0 & 0 & 0 & 0 & 400 & 0 \\
1 & 0 & 0 & 0 & 320 & 0 & 500 \\
2 & 0 & 0 & 0 & 320 & 0 & 0 \\
3 & 0 & 400 & 256 & 0 & 400 & 0 \\
4 & 320 & 0 & 0 & 320 & 0 & 500 \\
5 & 0 & 400 & 0 & 0 & 400 & 500
\end{array}
$$

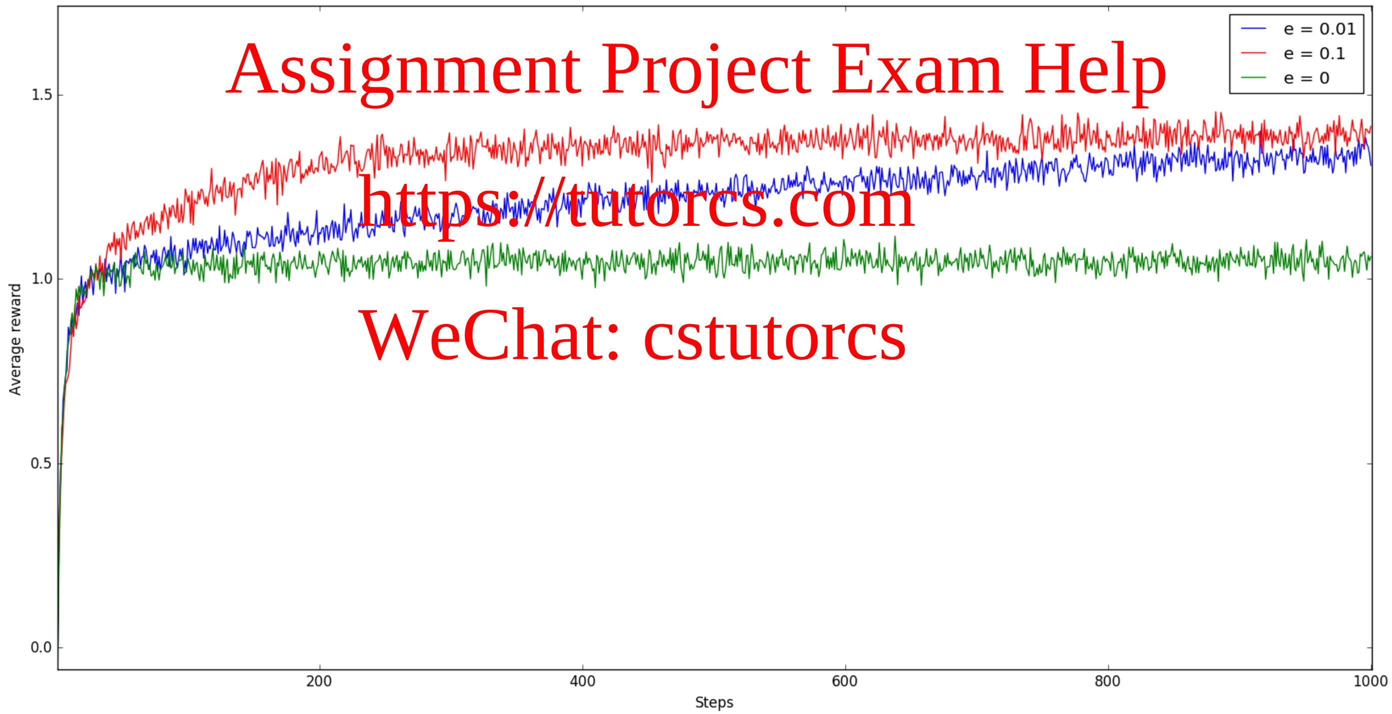
100+0.8*max(0,0,0)

0+0.8*max(0,100)

$$Q(s_t, a_t) \leftarrow \underbrace{r_t}_{\text{reward}} + \underbrace{\gamma}_{\text{discount factor}} \cdot \underbrace{\max_a Q(s_{t+1}, a)}_{\text{estimate of optimal future value}}$$

Background on reinforcement learning

- Exploitation vs. Exploration
  - ε-greedy



Background on reinforcement learning

- The tabular version does not scale with the action/state space
- Classical Q Network [1]
  - Function approximation
  - Approximate $Q(s,a)$ via a neural network: $Q(s,a) \approx Q^*(s,a,\theta)$
  - $L(\theta) = \mathbb{E}\left[\left(\underbrace{r + \gamma \boxed{\max_{a'} Q(s', a'; \theta)}}_{\text{Target Q}} - Q(s, a; \theta)\right)^2\right]$
  - Unstable

Background on reinforcement learning

- Deep Q Network (DQN) [2]
  - Experience replay: draw randomly from a buffer of (*s*, *a*, *s*', *r*)
  - $Q(s,a) \leftarrow r + \gamma max_{a'} Q(s',a',\theta^-)$ (*s*', *a*', *s*'', *r*')
  - $L(\theta) = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s',a';\theta^-) - Q(s,a;\theta)\right)^2\right]$
  - Reward clipped to [-1, 1]
- Double DQN (DDQN) [3]
  - Separate action selection from action evaluation
  - $Q_1(s,a) \leftarrow r + \gamma Q_2(s', argmax_{a'} Q_1(s',a'))$
  - $L(\theta) = \mathbb{E}\left[\left(r + \gamma\, Q_2(s', \arg\max_{a'} Q_1(s',a')) - Q_1(s,a;\theta)\right)^2\right]$

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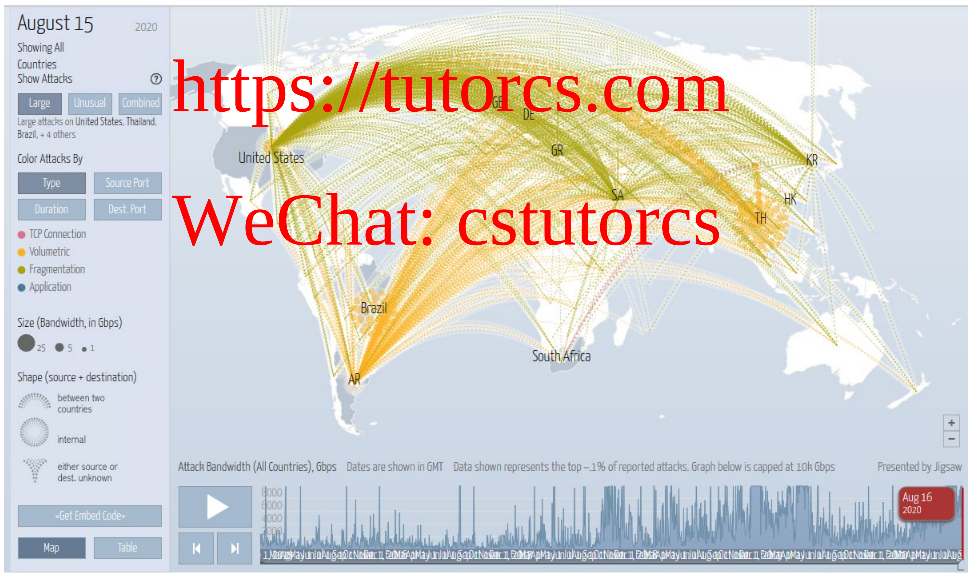
Background on reinforcement learning

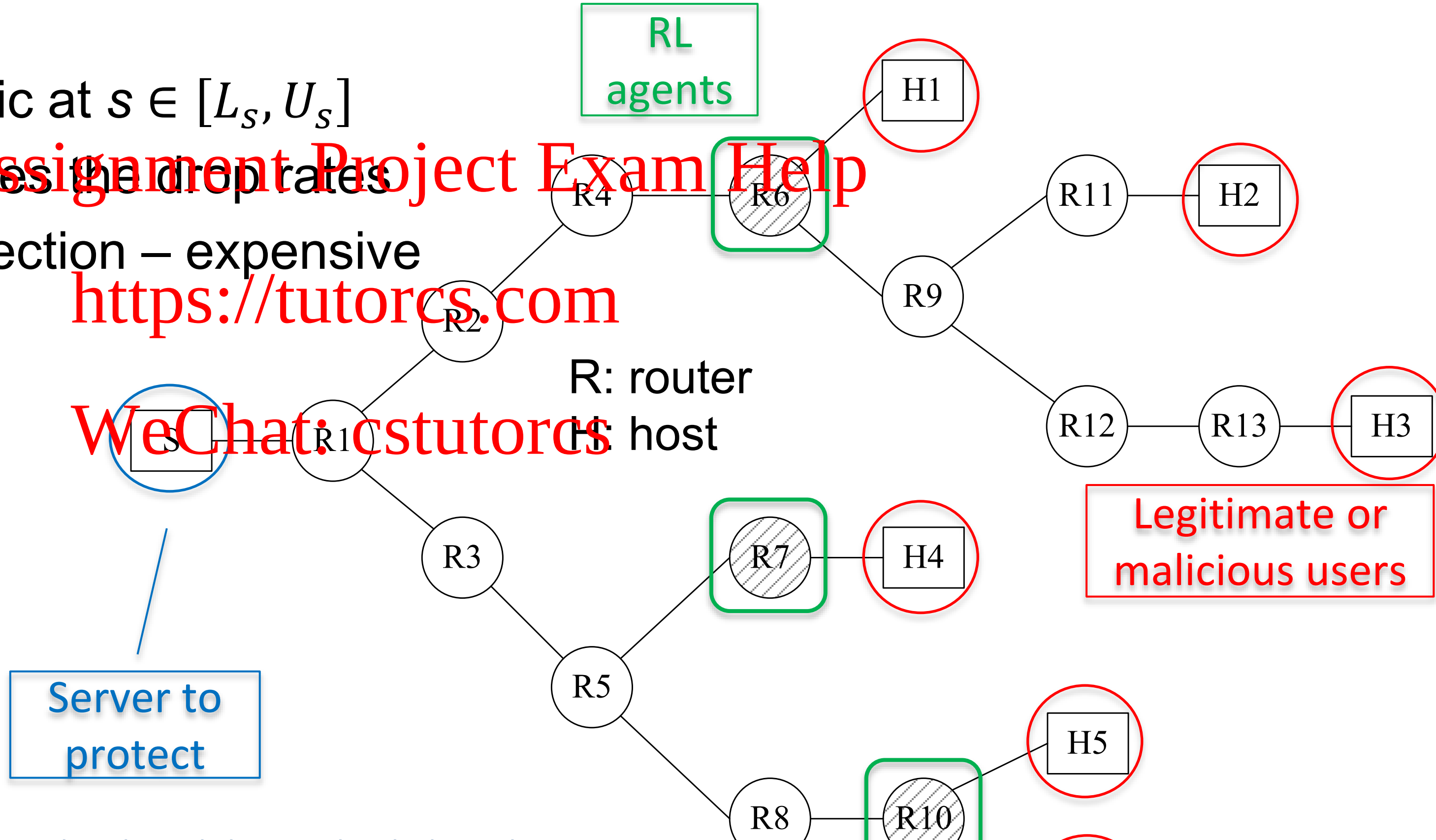
- Distributed Denial-of-Service (DDoS) attacks still occur almost every hour globally
  - http://www.digitalattackmap.com/
  - Statistics are gathered by Arbor’s Active Threat Level Analysis System from 330+ ISP customers with 130Tbps of global traffic



- Can RL be applied to throttle flooding DDoS attacks?

Background on reinforcement learning

- Problem setup [5]
  - A mixed set of legitimate users & attackers
  - Aggregated traffic at $s \in [L_s, U_s]$
  - RL agents decides the drop rates
  - No anomaly detection – expensive



Kleanthis Malialis, Daniel Kudenko, Multiagent Router Throttling: Decentralized Coordinated Response Against DDoS Attacks, In Proc. of AAAI 2013

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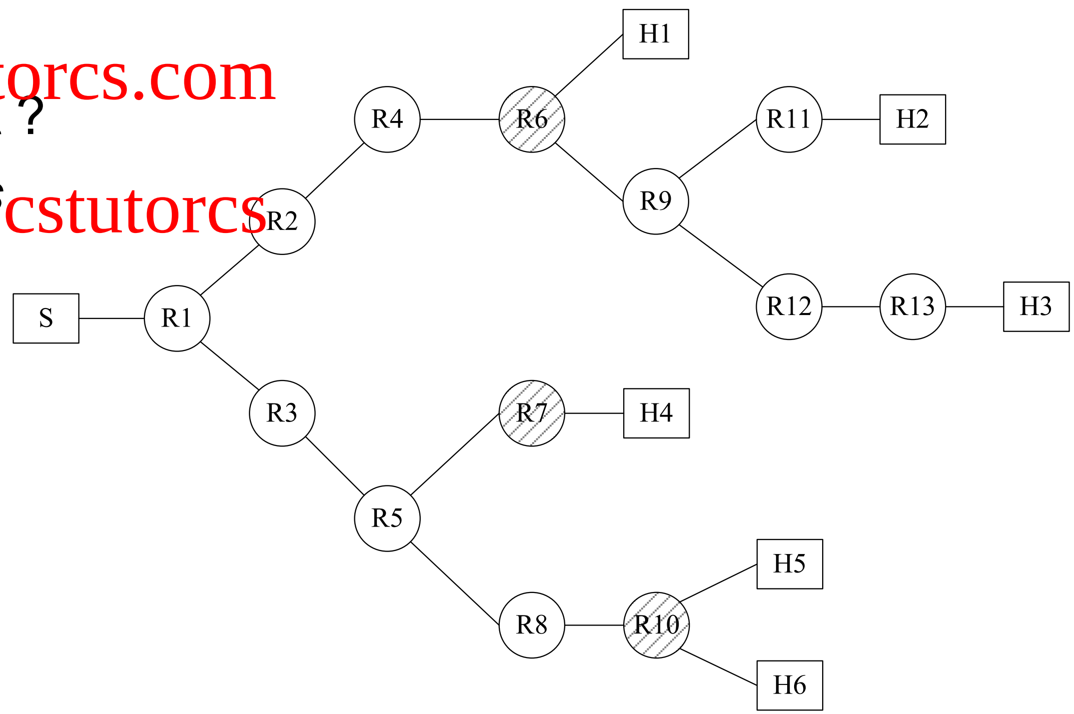
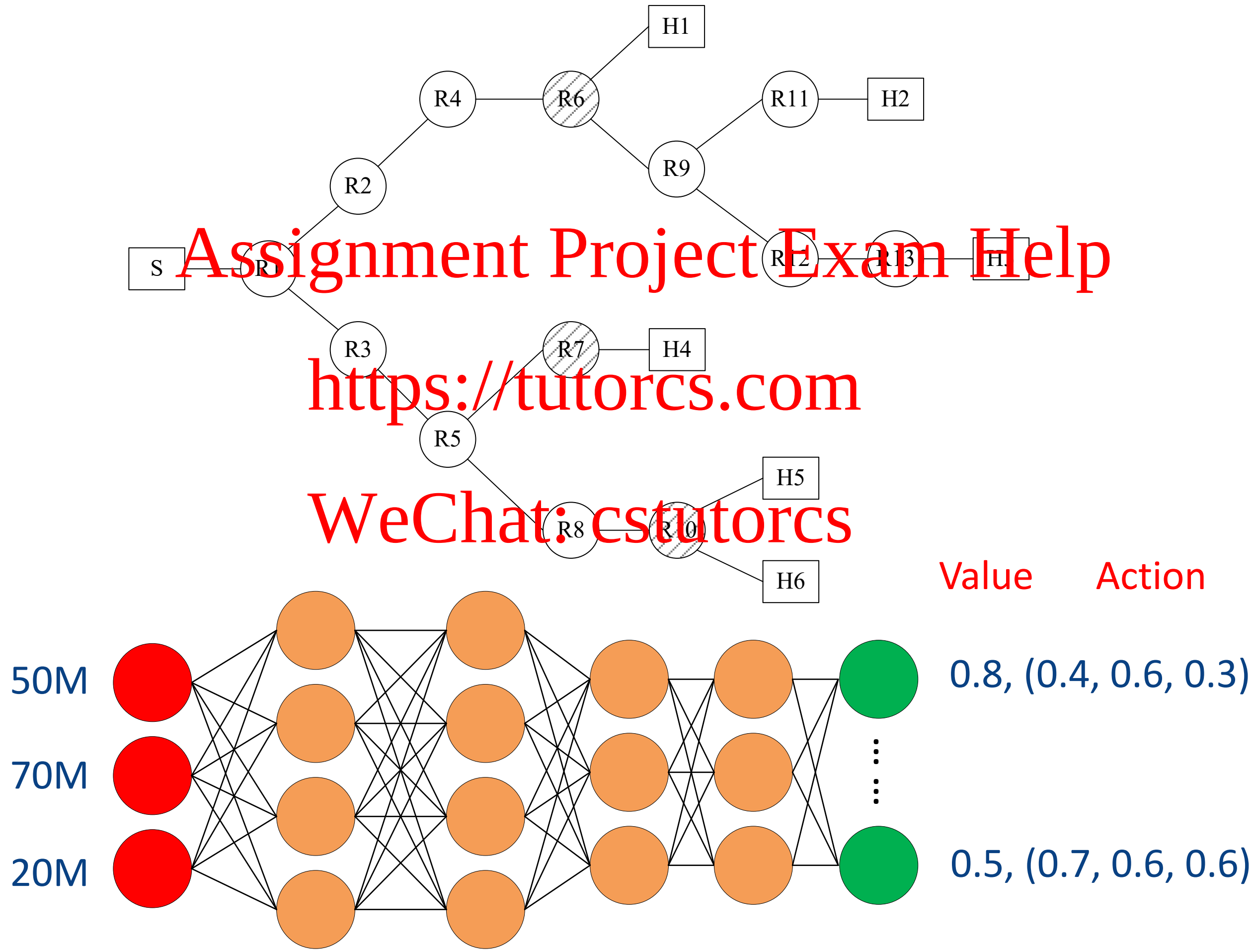
Background on reinforcement learning

- RL problem formalisation
  - State space
    - Aggregated traffic arrived at the router over the last T seconds
  - Action set
    - Percentage of traffic to drop: 0, 10%, 20%, 30%, … 90%
  - Reward
    - Aggregated traffic at $s > U_s$?
    - Legitimate traffic reached s



Background on reinforcement learning

- Training (DDQN)

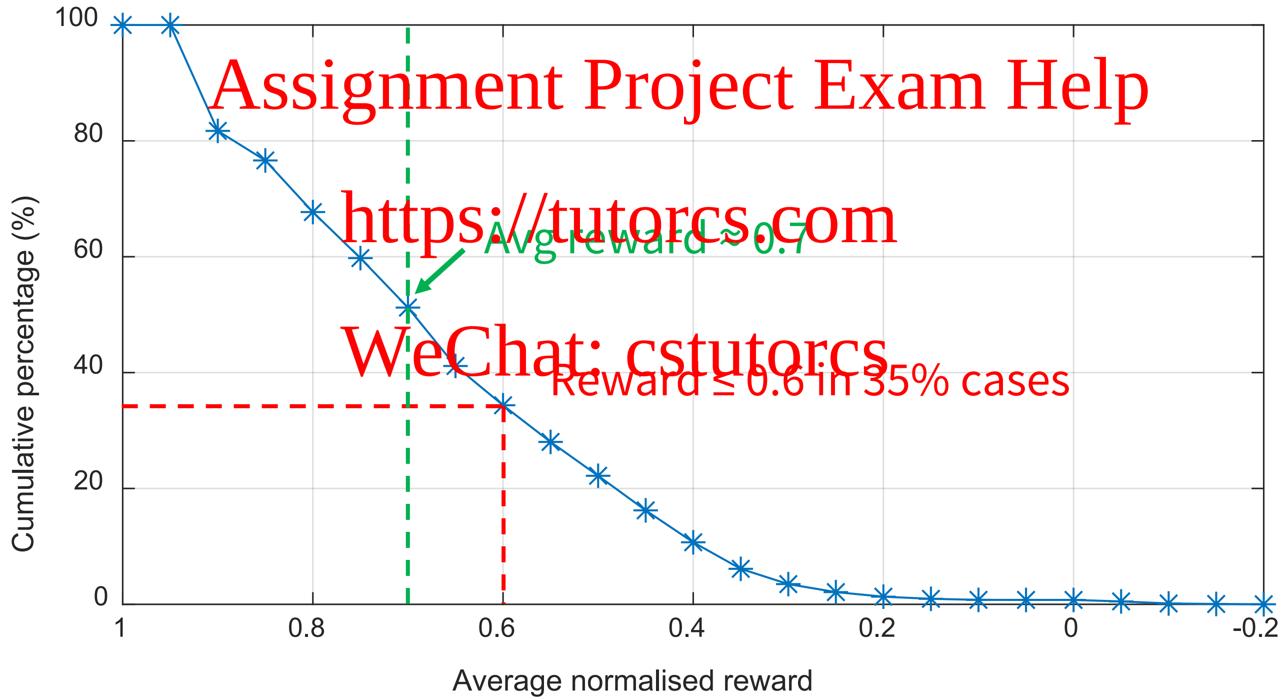


Background on reinforcement learning

$$L(\theta) = \mathbb{E}\left[\left(r + \gamma\, Q_2(s', \arg\max_{a'} Q_1(s', a')) - Q_1(s, a; \theta)\right)^2\right]$$

Background on reinforcement learning

- Test
  - 10000 cases (may not be seen in training)



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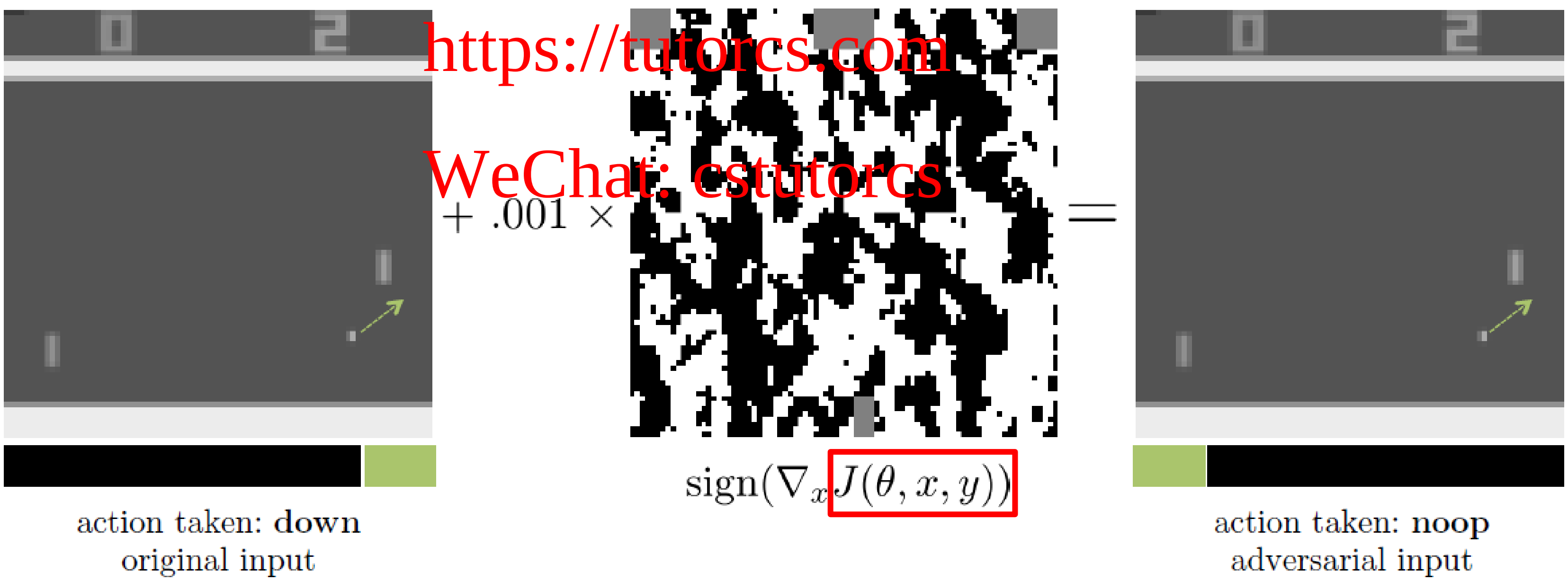
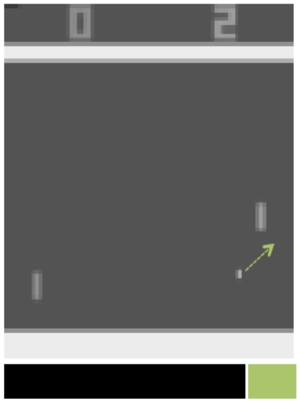
Adversarial attacks against RL models

- Test time attacks
  - Manipulate the environment observed by the agent [5]
  - Without attack: $\ldots, s_t, a_t, r_t, s_{t+1}, a_{t+1}, r_{t+1}, s_{t+2}, \ldots$
  - With attack: $\ldots, s_t + \delta_t, a'_t, r'_t, s_{t+1} + \delta_{t+1}, a'_{t+1}, r'_{t+1}, s_{t+2} + \delta_{t+2}, \ldots$



Adversarial attacks against RL models

- $J(\theta, x, y)$
  - *y*: softmax of the Q-value, i.e., prob. of taking an action



$\rightarrow$ RL agent (θ) $\rightarrow$

$$\begin{pmatrix} 1.5 \\ 2.2 \\ \ldots \\ 0.4 \\ 3.6 \end{pmatrix} \xrightarrow{\text{Softmax}} \begin{pmatrix} 0.07 \\ 0.15 \\ \ldots \\ 0.02 \\ 0.61 \end{pmatrix}$$

$$\pi_i = \frac{e^{Q(s,a_i)}}{\sum_{a_j} e^{Q(s,a_j)}}$$

Q-value for each action

Prob.

  - *J*: cross-entropy loss between *y* and the distribution that places all weight on the action with the highest Q-value

$$y \begin{pmatrix} 0.07 \\ 0.15 \\ \ldots \\ 0.02 \\ \boxed{0.61} \end{pmatrix} \longleftrightarrow \begin{pmatrix} 0 \\ 0 \\ \ldots \\ 0 \\ \boxed{1} \end{pmatrix}$$

similar to the one-hot vector in supervised learning

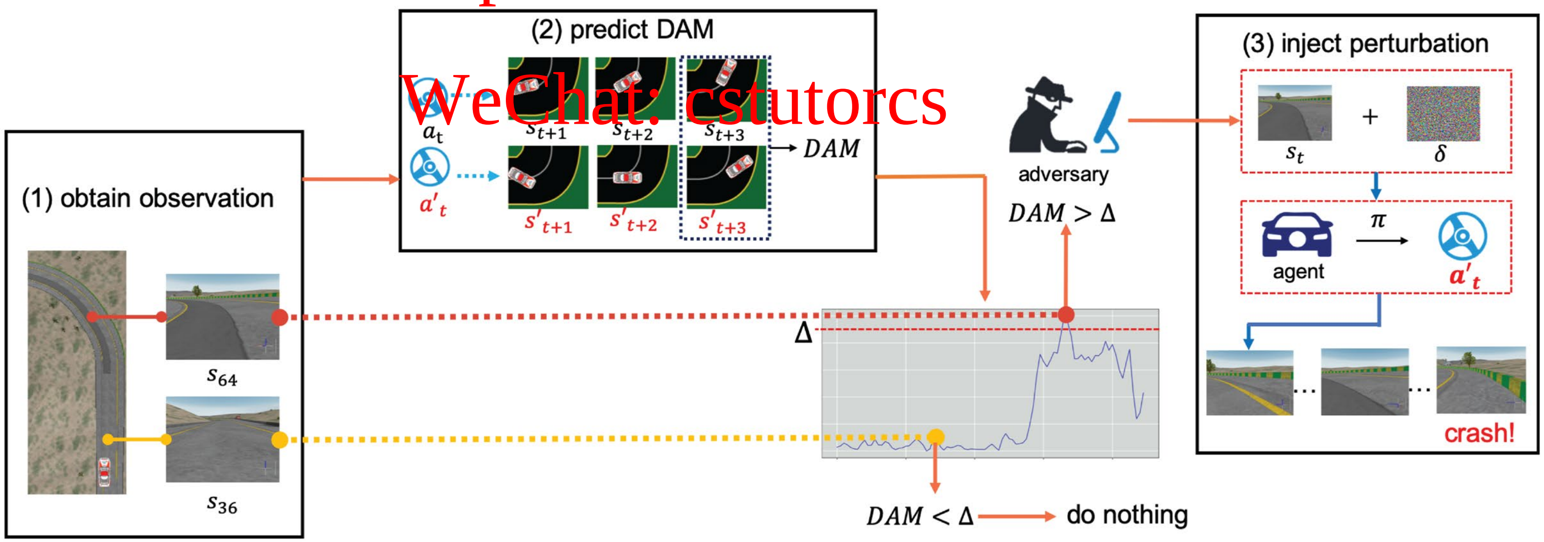
Adversarial attacks against RL models

- Timing of the attack
  - Heuristic method [6]: launch the attack only when

$$c(s) = \max_a \frac{e^{\frac{Q(s,a)}{T}}}{\sum_{a_k} e^{\frac{Q(s,a_k)}{T}}} - \min_a \frac{e^{\frac{Q(s,a)}{T}}}{\sum_{a_k} e^{\frac{Q(s,a_k)}{T}}} > \beta$$

Adversarial attacks against RL models

- Timing of the attack [8]
  - "Brute-force" search
    - Consider all possible *N* consecutive perturbations
    - Evaluate the attack damage at step $t + M$ ($M \geq N$)
    - $s_t, a_t, s_{t+1}, a_{t+1}, \dots, s_{t+N-1}, \dots, s_{t+M}$



Adversarial attacks against RL models

- Timing of the attack [8]
  - "Brute-force" search
    - Train a prediction model: $(s_t, a_t) \rightarrow s_{t+1}$
    - Predict the subsequent states and actions, $\{(s_t, a_t), (s_{t+1}, a_{t+1}), \dots (s_{t+M}, a_{t+M})\}$
    - Assess the potential damage of all possible strategies
      - Danger Awareness Metric (DAM):

        $DAM = |T(s'_{t+M}) - T(s_{t+M})|$

        T: domain-specific definition, e.g., distance between the car and the centre of the road

Adversarial attacks against RL models

- Timing of the attack [8]
  - Train an antagonist model
    - Learn the optimal attack strategy automatically without any domain knowledge
    - Maintain a policy: $s_t \rightarrow (p_t, a'_t)$
      - If $p_t > 0.5$, add the perturbation to trigger a'_t
      - Take the original action a_t
    - Reward: negative of the agent's reward

Adversarial attacks against RL models

- Black-box attack [9]
  - Train a proxy model that learns a task that is *related* to the target agent's policy
  - S threat model
    - Only have access to the states
    - Approximate an expectation of the state transition function
    - $psychic(s_t, \theta_P) \approx \mathbb{E}_{\pi_T}[P(s_{t+1}|s_t)]$
  - SR threat model
    - Have access to the states and reward
    - Estimate the value *V* of a given state under the policy π_T
    - $assessor(s_t, \theta_A) \approx \mathbb{E}_{\pi_T}\left[\sum_{k=0}^{\infty} \gamma_t{}^{(k)}\, r_{t+k+1}\right] = V^{\pi_T}(s_t)$

Adversarial attacks against RL models

- Black-box attack [9]
  - SA threat model
    - Have access to states and actions
    - Approximate the target's policy π_T
    - $imitator(s_t, \theta_I) \approx \pi_T(s_t)$
  - SRA threat model
    - Have access to states, actions and rewards
    - Action-conditioned psychic (AC-psychic): $AC\text{−}psychic(s_t, \theta_P) \approx \mathbb{E}_{\pi_T}[P(s_{t+1}|s_t, a_t)]$
    - Combine $assessor$ and $AC\text{−}psychic$ to decide whether to perturb the state

Adversarial attacks against RL models

- Black-box attack [9]
  - SRA threat model

Algorithm 1: Strategically-timed snooping attack

Input: Trained assessor, trained AC-psychic, trained proxy $\mathcal{M}_\kappa$, trained target agent $\mathcal{T}$, β

$\mathcal{K} \in \{S, SR, SA\}$

for t = *1*, T **do**
    Initialize empty list q;
    foreach $a \in \mathcal{A}$ **do**
        Predict s^H_{t+1} with *AC-psychic*(s_t, a)
        Estimate V^H with *assessor*(s^H_{t+1})
        Append V^H to q;
    end
    $c(s_t) = \max\left[\mathrm{Softmax}(q)\right] - \min\left[\mathrm{Softmax}(q)\right]$
    if $c(s_t) \geq \beta$ **then**
        Perturb s_t using $\nabla_x J_{\mathcal{M}_\kappa}$
    end
    Feed s_t to target $\mathcal{T}$ for action decision;
end

Adversarial attacks against RL models

- Black-box attack [9]
  - Surrogate: assume the adversary has access to the target agent's environment and can train an identical model

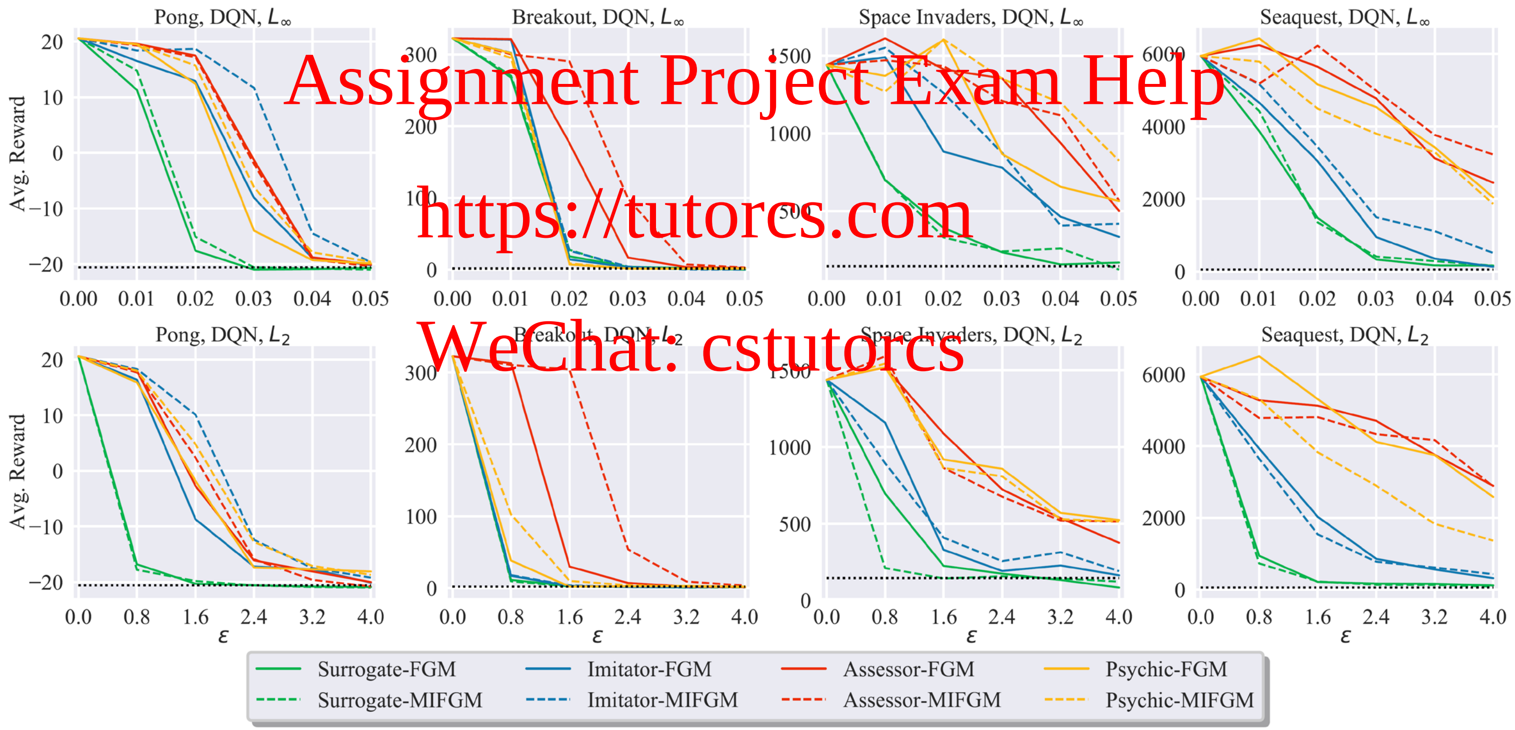


Figure 5: Performance reduction of DQN agents due to L_∞ and L_2 bounded perturbations. The black dotted line represents a random-guess policy.

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Adversarial attacks against RL models

- Training time attack
  - Without attack: ..., $(s_t, a_t, s_{t+1}, r_t), (s_{t+1}, a_{t+1}, s_{t+2}, r_{t+1})$, ...
  - With attack: ..., $(s_t, a_t, s_{t+1} + \delta_{t+1}, r_t'), (s_{t+1} + \delta_{t+1}, a_{t+1}', s_{t+2} + \delta_{t+2}, r_{t+1}')$, ...
  - Purpose: generate δ_{t+1} so that the agent will not take the next action a_{t+1}
  - Cross entropy loss: $J = -\sum_i p_i log \pi_i$
    - $\pi_i = \frac{e^{Q(s,a_i)}}{\sum_{a_j} e^{Q(s,a_j)}}$ → prob. of taking action a_i
    - $p_i = \begin{cases} 1, \text{if } a_i = a_{t+1} \\ 0, \text{otherwise} \end{cases}$
    - Maximise $J = -log\pi_{t+1}$ → minimise the prob. of taking a_{t+1}
  - $\delta = \alpha \cdot Clip_\epsilon\left(\frac{\partial J}{\partial s}\right)$

What about targeted attacks?

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Defence

- Adversarial training [7]
  - Calculate δ using the attacker's strategy: $(s_t, a_t, s_{t+1} + \delta_{t+1}, r'_t)$
  - $a'_{t+1} = \arg\max_a Q(s_{t+1} + \delta_{t+1}, a)$
  - Generate experience $(s_{t+1}, a'_{t+1}, s'_{t+2}, r'_{t+1})$ for the agent to train on

Untampered state

Potentially non-optimal action
→ explore more

Summary

- Reinforcement learning
  - State, action, reward
  - Value function, policy, model
  - Q-learning → Q-network → DQN → DDQN
- Adversarial reinforcement learning
  - Test time attack
    - Timing of the attack
    - Black-box attack
  - Training time attack
- Defence – adversarial training

References

- [1] R. S. Sutton and A. G. Barto, *Introduction to Reinforcement Learning*, First. Cambridge, MA, USA: MIT Press, 1998.
- [2] V. Mnih *et al.*, “Playing Atari with Deep Reinforcement Learning,” *CoRR*, vol. abs/1312.5602, 2013.
- [3] H. V. Hasselt, A. Guez, and D. Silver, “Deep Reinforcement Learning with Double Q-learning,” *eprint arXiv:1509.06461*, Sep. 2015.
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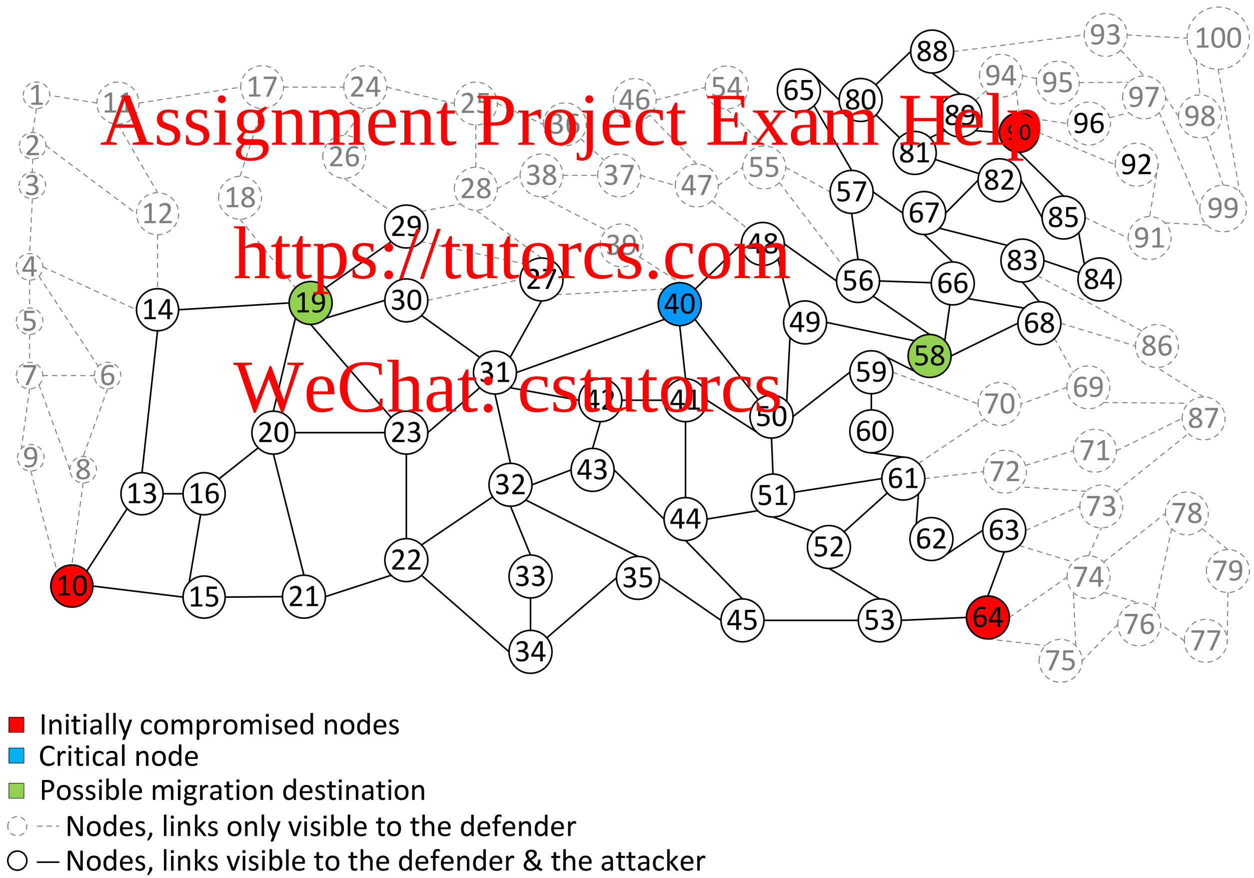
Adversarial Reinforcement Learning in Autonomous Cyber Defence

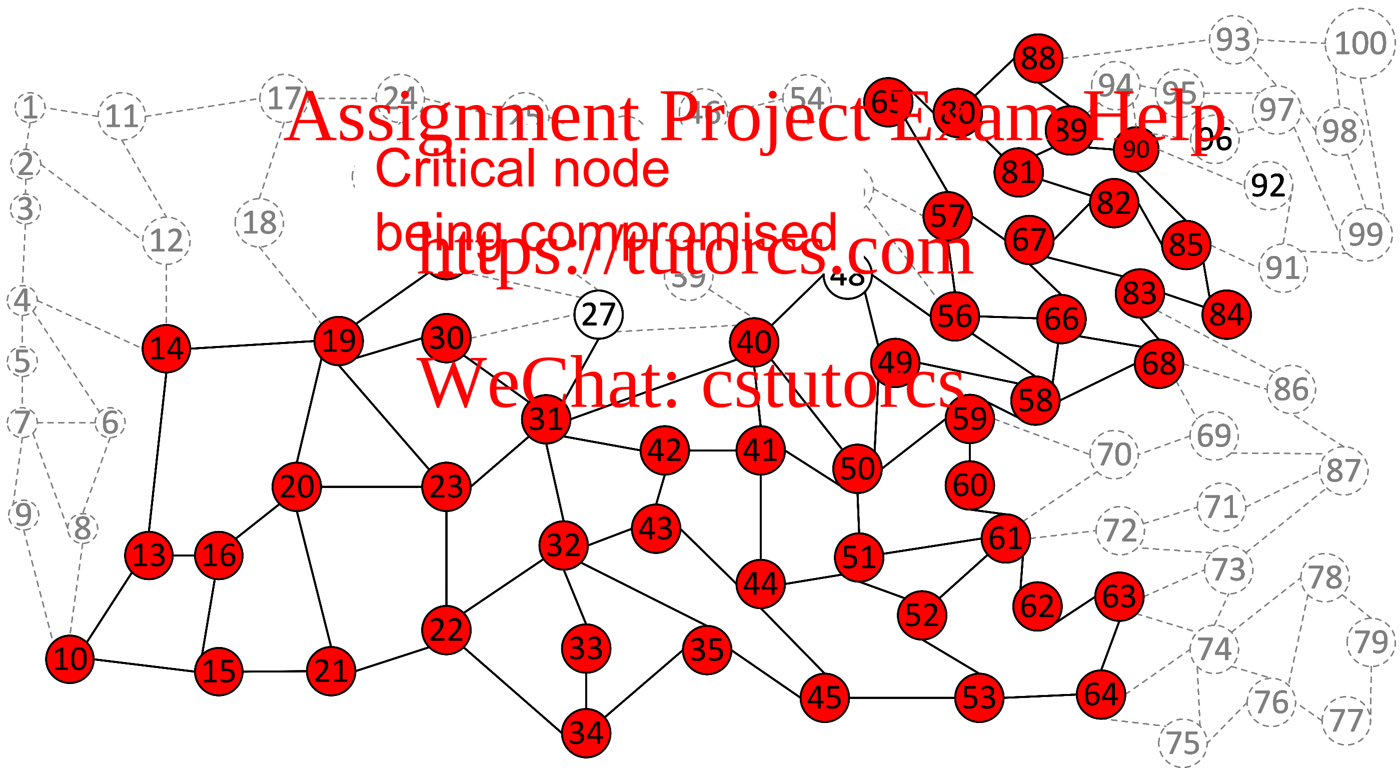
Adversarial attacks against RL models

- Attacker: propagates through the network to compromise the critical server
- The defender applies RL to prevent the critical server from compromise, and preserve as many nodes as possible



Adversarial attacks against RL models

- Attacker: partial observability of the network topology

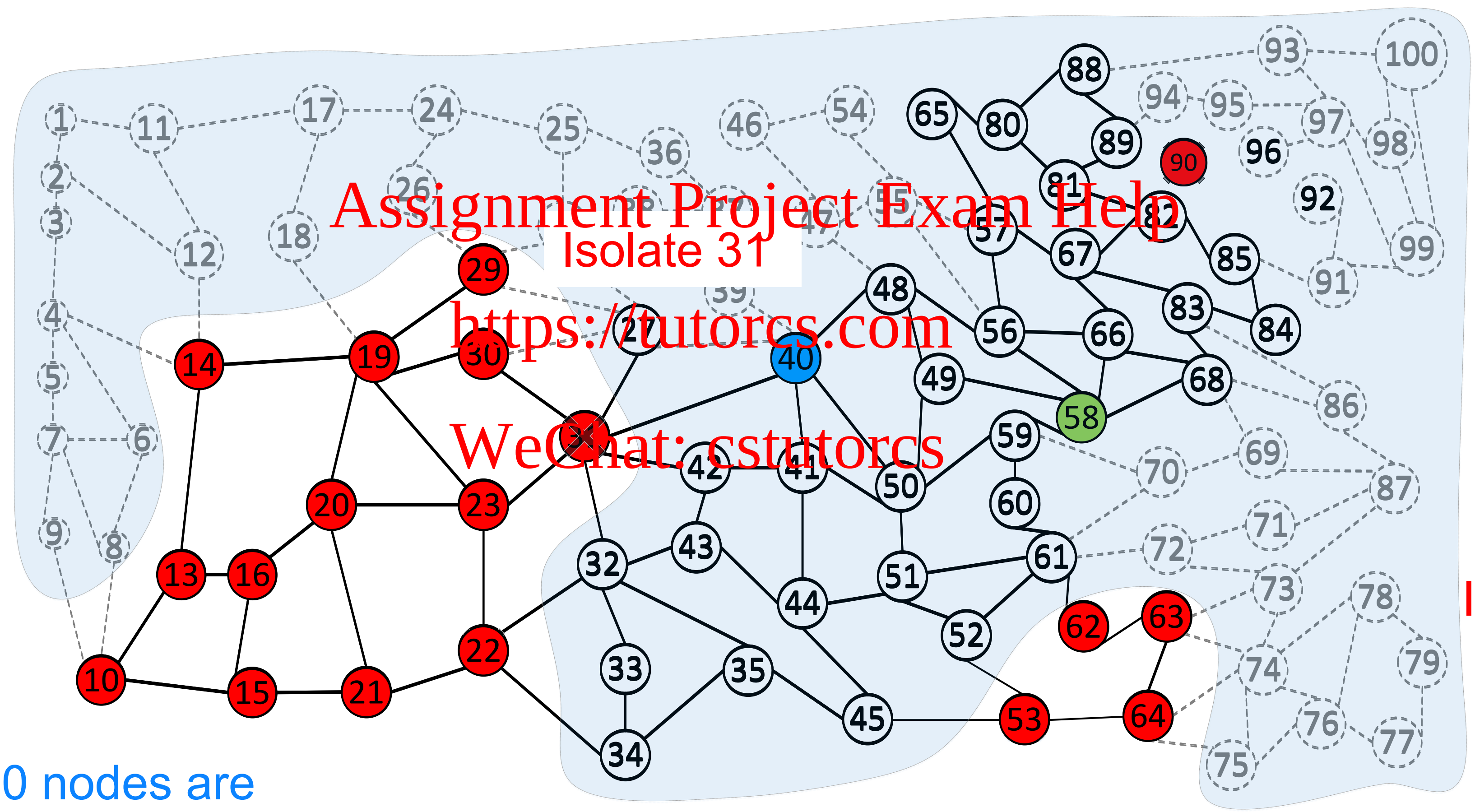


Adversarial attacks against RL models

- Problem definition
  - State: $[\underbrace{0, 0, \ldots, 0}_{\text{State of each node, 0: uncompromised, 1: compromised}}, \overbrace{0, 0, \ldots, 0}^{\text{State of each link, 0: on, 1: off}}]$
  - Action:
    - Action 0~*N*-1: isolate & patch a node $i \in [0, N-1]$
    - Action *N*~2*N*-1: reconnect a node $i \in [0, N-1]$
    - Action 2*N*~2*N*+*M*-1: migrate the critical node to one of the *M* destinations
    - Action 2*N*+*M*: take no action
  - Reward:
    - -1: (1) critical node is compromised or isolated, (2) invalid action
    - Proportional to number of uncompromised nodes that can still reach the critical node
  - Attacker can only compromised a node *x* if there is a visible link between *x* and any compromised node

Adversarial attacks against RL models

- Without training-time attacks



Isolate 90

Isolate 62

82/100 nodes are preserved

Isolate 22

Isolate 53

Adversarial attacks against RL models

- Training-time attack: manipulate states to prevent agents from taking optimal actions
  - $(s_t, a_t, s_{t+1}, r_t) \rightarrow (s_t, a_t, s_{t+1} + \delta_{t+1}, r_t')$
  - Binary state → cannot use gradient-descent based method
  - δ : false positives & false negatives
  - The attacker cannot manipulate the states of all the observable nodes
    - L_{FP}: nodes that can be perturbed as false positive
    - L_{FN}: nodes that can be perturbed as false negative
  - $\min Q(s_{t+1} + \delta_{t+1}, a_{t+1})$, a_{t+1}: the optimal action for s_{t+1} that has been learned so far
    - Loop through L_{FP} (L_{FN}) and flip the state of one node per time
    - Rank all nodes based on ΔQ (decrease of Q-value by flipping state)
    - Flip the states of the top K nodes

Adversarial attacks against RL models

Algorithm 1: Causative attack against DDQN via state perturbation

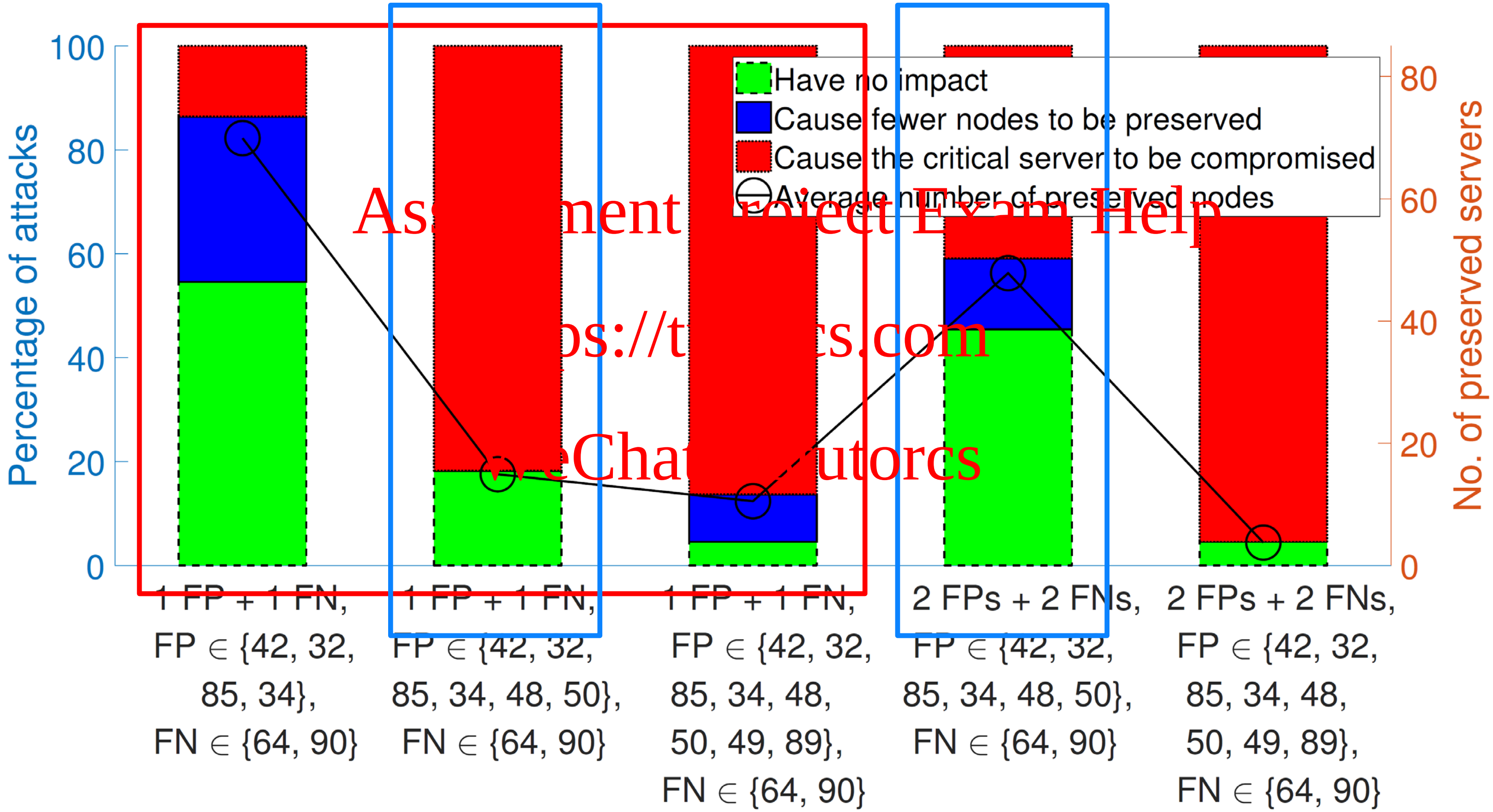
Input : The original experience, (s, a, s', r);
The list of observable nodes, N_O;
The list of nodes that can be perturbed as false positive (false negative) by the attacker, L_{FP} (L_{FN});
The main DQN, Q;
Limit on the number of FPs and FNs per time, LIMIT

Output: The tampered experience $(s, a, s' + \delta, r')$

$FN = FP = \{\}$;
$minQ_{FN} = minQ_{FP} = \{\}$;
$a' = \text{argmax}_{a^*} Q(s', a^*)$;
for *node* n *in* N_O **do**
  if n *is compromised and* n *in* L_{FN} **then**
    mark n as uncompromised;
    if $Q(s' + \delta, a') <$ *any value in* $minQ_{FN}$ **then**
      // δ represents the FP and/or FN readings
      insert n and $Q(s' + \delta, a')$ into appropriate positions in FN and $minQ_{FN}$;
      if $|FN| > LIMIT$ **then**
        remove extra nodes from FN and $minQ_{FN}$;
    restore n as compromised;
  else if n *is uncompromised and* n *in* L_{FP} **then**
    mark n as compromised;
    if $Q(s' + \delta, a') <$ *any value in* $minQ_{FP}$ **then**
      insert n and $Q(s' + \delta, a')$ into appropriate positions in FP and $minQ_{FP}$;
      if $|FP| > LIMIT$ **then**
        remove extra nodes from FP and $minQ_{FP}$;
    restore n as uncompromised;
Change nodes in FN to uncompromised;
Change nodes in FP to compromised;
return $(s, a, s' + \delta, r')$

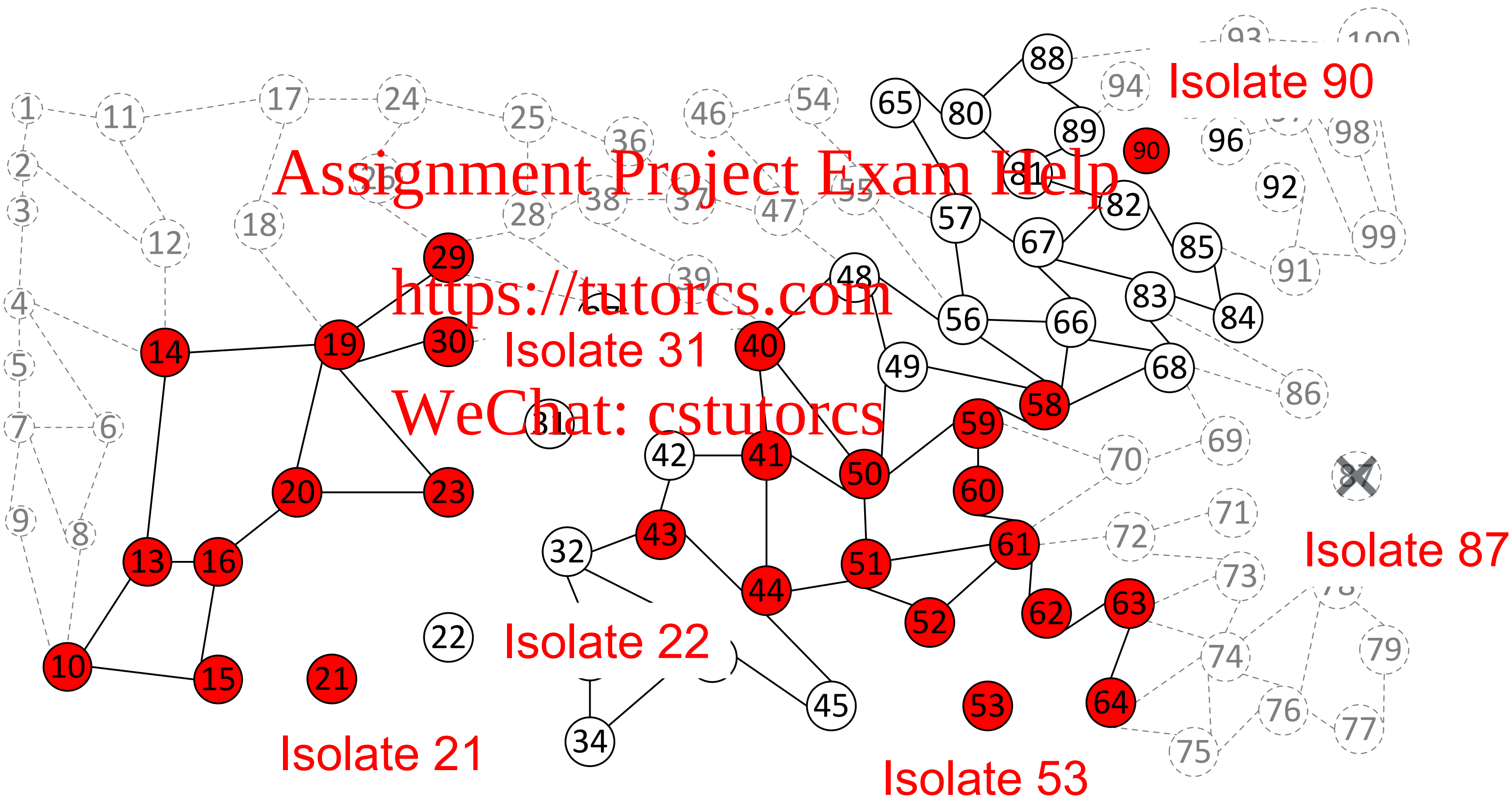
Adversarial attacks against RL models

- Result



Adversarial attacks against RL models

- After training-time attacks



Inversion defence method

- Aim to revert the perturbation/false readings

Attacker	Defender
$s_{t+1} \rightarrow s_{t+1} + \delta_{t+1}$ minimise $Q(s_{t+1} + \delta_{t+1}, a_{t+1})$	$s_{t+1} + \delta_{t+1} \rightarrow s_{t+1} + \delta_{t+1} + \delta'_{t+1}$ maximise $Q(s_{t+1} + \delta_{t+1} + \delta'_{t+1}, a_{t+1})$
Loop through L_{FP} and L_{FN}	Loop through all nodes
Flip K nodes	Flip K' nodes

- Effective even if $K' \neq K$
- Minimum impact on normal training process (i.e., $K = 0$, $K' > 0$)

Inversion defence method

- Before & after the defence method is applied