Lecture 10: Deep Q Learning

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Today's Plan

1. Review on value function approximation
2. Deep Q Networks (DQNs)
3. Code example and the extension of DQNs

4. Project proposal review session
5. Homework 1 review session

Scaling up RL

1. Generalization of RL to tackle practical problems such as self-driving cars, Atari, consumer marketing, healthcare, education
2. Most of these practical problems have enormous state and/or action spaces
3. It requires the representations of models/values/policies that can generalize across states and/or actions

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1. Generalization of RL to tackle practical problems such as self-driving cars, Atari, consumer marketing, healthcare, education
2. Most of these practical problems have enormous state and/or action spaces
3. It requires the representations of models/values/policies that can generalize across states and/or actions
4. Solution: to represent a value function with a parameterized function instead of a lookup table

$$\hat{v}(s, \mathbf{w}) \approx v_\pi(s)$$
$$\hat{q}(s, a, \mathbf{w}) \approx q_\pi(s, a)$$

Review on Stochastic Gradient Descend for Function Approximation

1. Goal: Find the parameter vector $\mathbf{w}$ that minimizes the loss between a true value function $v_\pi(s)$ and its approximation $\hat{v}_\pi(s, \mathbf{w})$ as represented with a particular function approximator parameterized by $\mathbf{w}$
2. The mean square error loss function is as

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

3. Follow the gradient descend to find a local minimum

$$\begin{aligned}\Delta \mathbf{w} =& -\frac{1}{2}\alpha \nabla_{\mathbf{w}} J(\mathbf{w}) \\ \mathbf{w}_{t+1} =& \mathbf{w}_t + \Delta \mathbf{w}\end{aligned}$$

Linear Function Approximation

1. Represent value function by a linear combination of features

$$\hat{v}(S, \mathbf{w}) = \mathbf{x}(S)^T \mathbf{w} = \sum_{j=1}^{n} x_j(S) w_j$$

2. Objective function is $J(\mathbf{w}) = \mathbb{E}_\pi \left[(v_\pi(S) - \mathbf{x}(S)^T \mathbf{w})^2 \right]$
3. Update is as simple as $\Delta \mathbf{w} = \alpha (v_\pi(S) - \hat{v}(S, \mathbf{w})) \mathbf{x}(S)$

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4. But there is no oracle for the true value $v_\pi(S)$, we substitute with the target from MC or TD
   1. for MC policy evaluation,

$$\Delta \mathbf{w} = \alpha \Big(G_t - \hat{v}(S_t, \mathbf{w}) \Big) \mathbf{x}(S_t)$$

   2. for TD policy evaluation,

$$\Delta \mathbf{w} = \alpha \Big(R_{t+1} + \gamma \hat{v}(S_{t+1}, \mathbf{w}) - \hat{v}(S_t, \mathbf{w}) \Big) \mathbf{x}(S_t)$$

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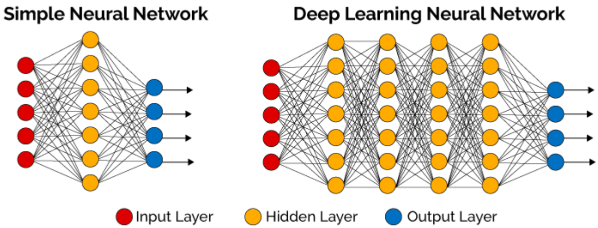
1. Linear VFA often works well given the right set of features
2. But it requires manual designing of the feature set
3. Alternative is to use a much richer function approximator that is able to directly learn from states without requiring the feature design
4. Nonlinear function approximator: Deep neural networks

Deep Neural Networks



1. Multiple layers of linear functions, with non-linear operators between layers

$$f(\mathbf{x};\theta) = \mathbf{W}_{L+1}^T\sigma(\mathbf{W}_L^T\sigma(...\sigma(\mathbf{W}_1^T\mathbf{x}+\mathbf{b}_1)+...+\mathbf{b}_{L-1})+\mathbf{b}_L)+\mathbf{b}_{L+1}$$

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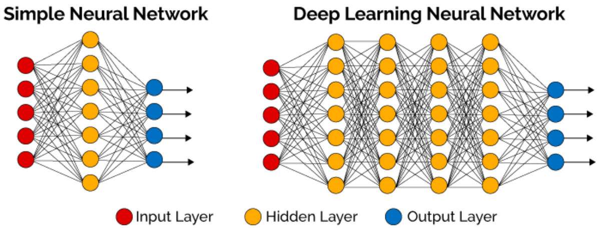

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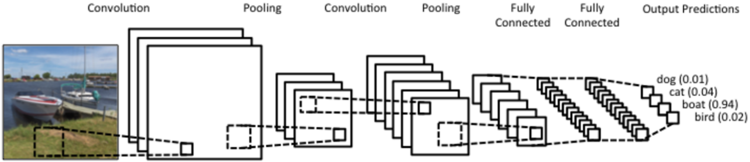
2. The chain rule to backpropagate the gradient to update the weights using the loss function $L(\theta) = \frac{1}{n}\sum_{i=1}^{n}\left(y^{(i)} - f(\mathbf{x};\theta)\right)^2$

Convolutional Neural Networks



1. Convolution encodes the local information in 2D feature map
2. Layers of convolution, reLU, batch normalization, etc.
3. CNNs are widely used in computer vision (more than 70% top conference papers using CNNs)
4. A detailed introduction on CNNs: `http://cs231n.github.io/convolutional-networks/`

Deep Reinforcement Learning

1. Frontier in machine learning and artificial intelligence
2. Deep neural networks are used to represent
   1. Value function
   2. Policy function (policy gradient methods to be introduced)
   3. World model
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3. Loss function is optimized by stochastic gradient descent (SGD)
4. Challenges
    1. Efficiency: too many model parameters to optimize
    2. The Deadly Triad for the danger of instability and divergence in training
        1. Nonlinear function approximation
        2. Bootstrapping
        3. Off-policy training

Deep Q-Networks (DQN)

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2. DQN represents the action value function with neural network approximator
3. DQN reaches a professional human gaming level across many Atari games using the same network and hyperparameters

4 Atari Games: Breakout, Pong, Montezuma's Revenge, Private Eye

Recall: Action-Value Function Approximation

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$$J(\mathbf{w}) = \mathbb{E}_\pi[(q_\pi(S, A) - \hat{q}(S, A, \mathbf{w}))^2]$$

3. Stochastic gradient descend to find a local minimum

$$\Delta\mathbf{w} = \alpha(q_\pi(S, A) - \hat{q}(S, A, \mathbf{w}))\nabla_{\mathbf{w}}\hat{q}(S, A, \mathbf{w})$$

Recall: Incremental Control Algorithm

Same to the prediction, there is no oracle for the true value $q_\pi(S, A)$, so we substitute a target

1. For MC, the target is the return G_t

$$\Delta \mathbf{w} = \alpha\big(G_t - \hat{q}(S_t, A_t, \mathbf{w})\big)\nabla_{\mathbf{w}}\hat{q}(S_t, A_t, \mathbf{w})$$

2. For Sarsa, the target is the TD target $R_{t+1} + \gamma\hat{q}(S_{t+1}, A_{t+1}, \mathbf{w})$

$$\Delta \mathbf{w} = \alpha\big(R_{t+1} + \gamma\hat{q}(S_{t+1}, A_{t+1}, \mathbf{w}) - \hat{q}(S_t, A_t, \mathbf{w})\big)\nabla_{\mathbf{w}}\hat{q}(S_t, A_t, \mathbf{w})$$

3. For Q-learning, the target is the TD target $R_{t+1} + \gamma \max_a \hat{q}(S_{t+1}, a, \mathbf{w})$

$$\Delta \mathbf{w} = \alpha\big(R_{t+1} + \gamma \max_a \hat{q}(S_{t+1}, a, \mathbf{w}) - \hat{q}(S_t, A_t, \mathbf{w})\big)\nabla_{\mathbf{w}}\hat{q}(S_t, A_t, \mathbf{w})$$

DQN for Playing Atari Games

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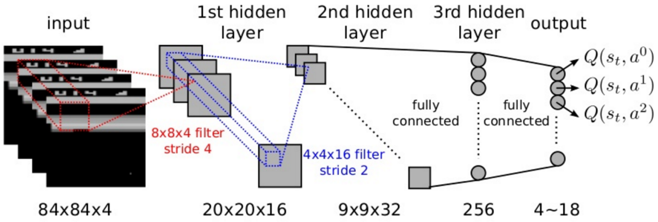
5. Network architecture and hyperparameters fixed across all games



Q-Learning with Value Function Approximation

1. Two of the issues causing problems:
   1. Correlations between samples
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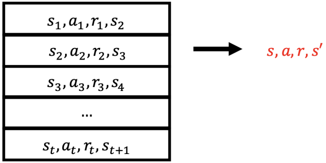
Q-Learning with Value Function Approximation

1. Two of the issues causing problems:
    1. Correlations between samples
    2. Non-stationary targets
2. Deep Q-learning (DQN) addresses both of these challenges by
    1. Experience replay
    2. Fixed Q targets

DQNs: Experience Replay

1. To reduce the correlations among samples, store transition (s_t, a_t, r_t, s_{t+1}) in replay memory $\mathcal{D}$



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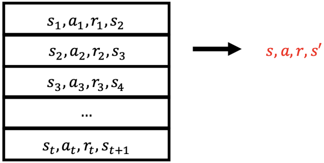

2. To perform experience replay, repeat the following
   1. sample an experience tuple from the dataset: $(s, a, r, s') \sim \mathcal{D}$
   2. compute the target value for the sampled tuple: $r + \gamma \max_{a'} \hat{Q}(s', a', \mathbf{w})$
   3. use stochastic gradient descent to update the network weights

$$\Delta \mathbf{w} = \alpha \Big(r + \gamma \max_{a'} \hat{Q}(s', a', \mathbf{w}) - Q(s, a, \mathbf{w}) \Big) \nabla_{\mathbf{w}} \hat{Q}(s, a, \mathbf{w})$$

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1. To help improve stability, fix the target weights used in the target calculation for multiple updates
2. Let a different set of parameter $\mathbf{w}^-$ be the set of weights used in the target, and $\mathbf{w}$ be the weights that are being updated
3. To perform experience replay with fixed target, repeat the following
    1. sample an experience tuple from the dataset: $(s, a, r, s') \sim \mathcal{D}$
    2. compute the target value for the sampled tuple: $r + \gamma \max_{a'} \hat{Q}(s', a', \mathbf{w}^-)$
    3. use stochastic gradient descent to update the network weights

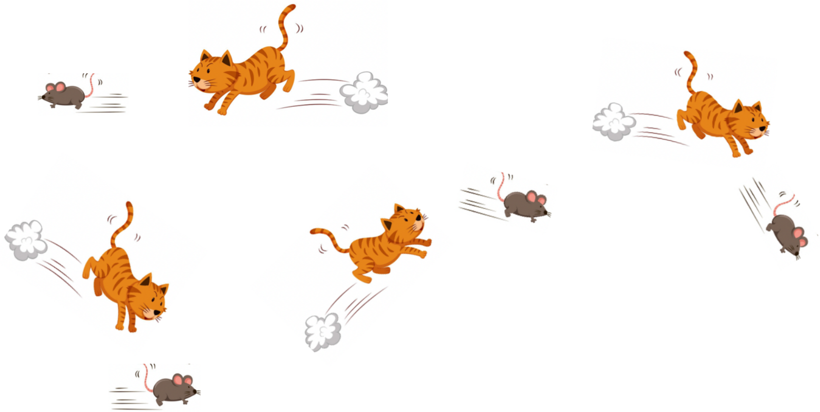
$$\Delta \mathbf{w} = \alpha \Big(r + \gamma \max_{a'} \hat{Q}(s', a', \mathbf{w}^-) - Q(s, a, \mathbf{w}) \Big) \nabla_{\mathbf{w}} \hat{Q}(s, a, \mathbf{w})$$

Why fixed target

1. In the original update, both Q estimation and Q target shifts at each time step
2. Imagine a cat (Q estimation) is chasing after a mouse (Q target)
3. The cat must reduce the distance to the mouse

Why fixed target

1. Both the cat and mouse are moving,



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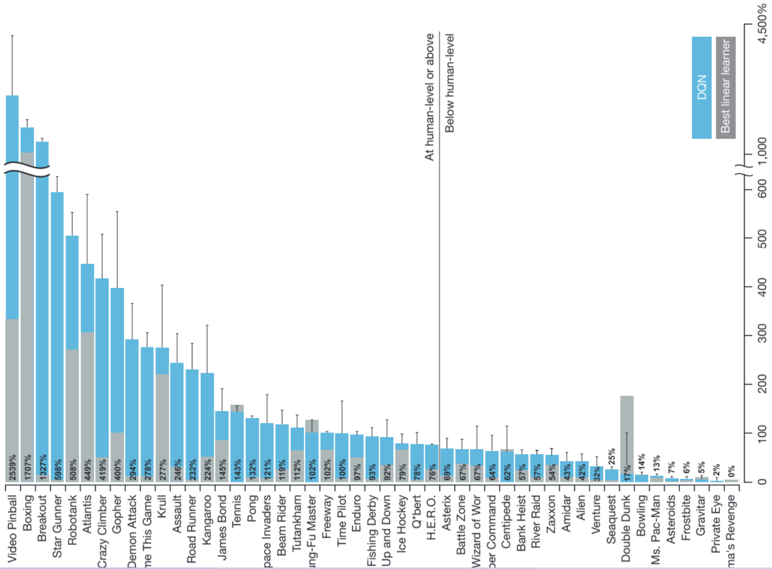
2. Solution: fix the target for a period of time during the training

Performance of DQNs on Atari



Abalation Study on DQNs

1. Game score under difference conditions

	Replay Fixed-Q	Replay Q-learning	No replay Fixed-Q	No replay Q-learning
Breakout	316.81	240.73	10.16	3.17
Enduro	1006.3	831.25	141.89	29.1
River Raid	7446.62	4102.81	2867.66	1453.02
Seaquest	2894.4	822.55	1003	275.81
Space Invaders	1088.94	826.33	373.22	301.99

Demo of DQNs

1. Demo of deep q-learning for Breakout: `https://www.youtube.com/watch?v=V1eYniJ0Rnk`
2. Demo of Flappy Bird by DQN: `https://www.youtube.com/watch?v=xM62SpKAZHU`
3. Code of DQN in PyTorch: `https://github.com/cuhkrlcourse/DeepRL-Tutorials/blob/master/01.DQN.ipynb`
4. Code of Flappy Bird: `https://github.com/xmfbit/DQN-FlappyBird`

Summary of DQNs

1. DQN uses experience replay and fixed Q-targets
2. Store transition $(s_t, a_t, r_{t+1}, s_{t+1})$ in replay memory $\mathcal{D}$
3. Sample random mini-batch of transitions (s, a, r, s') from $\mathcal{D}$
4. Compute Q-learning targets w.r.t. old, fixed parameters $\mathbf{w}^-$
5. Optimizes MSE between Q-network and Q-learning targets using stochastic gradient descent

Improving DQN

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2. Many follow-up works on improving DQNs
    1. **Double DQN**: Deep Reinforcement Learning with Double Q-Learning. Van Hasselt et al, AAAI 2016
    2. **Dueling DQN**: Dueling Network Architectures for Deep Reinforcement Learning. Wang et al, best paper ICML 2016
    3. **Prioritized Replay**: Prioritized Experience Replay. Schaul et al, ICLR 2016
3. A nice tutorial on the relevant algorithms: `https://github.com/cuhkrlcourse/DeepRL-Tutorials`

Improving DQN: Double DQN

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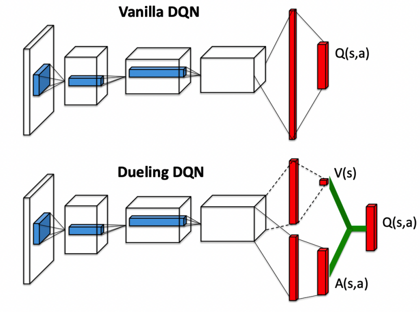
5. Code: `https://github.com/cuhkrlcourse/DeepRL-Tutorials/blob/master/03.Double_DQN.ipynb`

Improving DQN: Dueling DQN

1. One branch estimates $V(s)$, other branch estimates the advantage for each action $A(s,a)$. Then $Q(s,a) = A(s,a) + V(s)$



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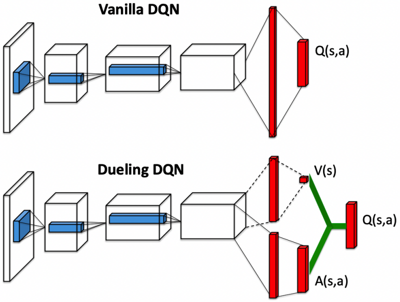
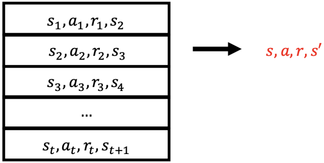


2. By decoupling the estimation, intuitively the DuelingDQN can learn which states are (or are not) valuable without having to learn the effect of each action at each state
3. Code: `https://github.com/cuhkrlcourse/DeepRL-Tutorials/blob/master/04.Dueling_DQN.ipynb`

Improving DQN: Prioritized Experience Replay

1. Transition $(s_t, a_t, r_{t+1}, s_{t+1})$ is stored in and sampled from the replay memory $\mathcal{D}$



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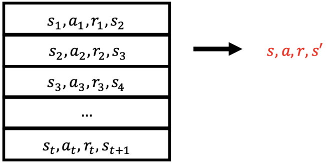

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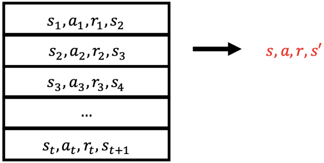


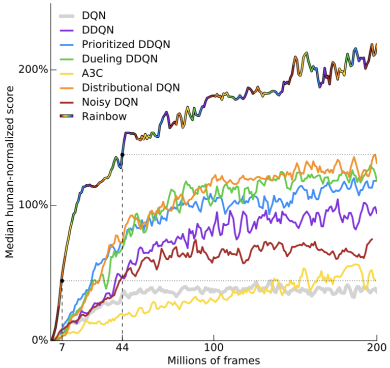
2. Priority is on the experience where there is a big difference between our prediction and the TD target, since it means that we have a lot to learn about it.
3. Define a a priority score for each tuple i

$$p_i = |r + \gamma \max_{a'} Q(s_{i+1}, a', \mathbf{w}^-) - Q(s_i, a_i, \mathbf{w})|$$

4. Code: `https://github.com/cuhkrlcourse/DeepRL-Tutorials/blob/master/06.DQN_PriorityReplay.ipynb`

Improving over the DQN

1. Rainbow: Combining Improvements in Deep Reinforcement Learning. Matteo Hessel et al. AAAI 2018. https://arxiv.org/pdf/1710.02298.pdf
2. It examines six extensions to the DQN algorithm and empirically studies their combination



Homework

1. Go through the Jupytor tutorial and training your own gaming agent: https://github.com/cuhkrlcourse/DeepRL-Tutorials
2. Good resource for your course project
   1. Make sure it works for simple environment such as Pong
3. Homework 2 comes out: https://github.com/cuhkrlcourse/ierg6130-assignment
4. Next week: Policy-based RL