Lecture 6: CNNs and Deep Q Learning

Emma Brunskill

CS234 Reinforcement Learning.

Winter 2022

---

With many slides for DQN from David Silver and Ruslan Salakhutdinov and some vision slides from Gianni Di Caro and images from Stanford CS231n, http://cs231n.github.io/convolutional-networks/
In TD learning with linear VFA (select all):

1. \( \mathbf{w} = \mathbf{w} + \alpha (r(s_t) + \gamma \mathbf{x}(s_{t+1})^T \mathbf{w} - \mathbf{x}(s_t)^T \mathbf{w}) \mathbf{x}(s_t) \)
2. \( V(s) = \mathbf{w}(s) \mathbf{x}(s) \)
3. Asymptotic convergence to the true best minimum MSE linear representable \( V(s) \) is guaranteed for \( \alpha \in (0, 1), \gamma < 1. \)
4. Not sure
In TD learning with linear VFA (select all):

1. \[ w = w + \alpha (r(s_t) + \gamma x(s_{t+1})^T w - x(s_t)^T w) x(s_t) \]
2. \[ V(s) = w(s)x(s) \]
3. Asymptotic convergence to the true best minimum MSE linear representable \( V(s) \) is guaranteed for \( \alpha \in (0, 1), \gamma < 1 \).
4. Not sure

Answer: 1 is true. Convergence is not guaranteed to the best, the resulting one may still be worse than the best MSE solution by a factor of \( \frac{1}{1-\gamma} \). It is also important to know that this is with respect to the stationary distribution \( d(s) \). Also note the weights do not depend on the state.
Class Structure

- Last time: Value function approximation
- This time: RL with function approximation, deep RL
- Next time: Deep RL continued
Today

- Value function approximation
- Deep neural networks
- CNNs
- DQN
Use value function approximation to represent state-action values
\[ \hat{Q}^{\pi}(s, a; w) \approx Q^{\pi} \]

Interleave
- Approximate policy evaluation using value function approximation
- Perform \( \epsilon \)-greedy policy improvement

Can be unstable. Generally involves intersection of the following:
- Function approximation
- Bootstrapping
- Off-policy learning
Linear value function approximators assume value function is a weighted combination of a set of features, where each feature a function of the state.

Linear VFA often work well given the right set of features.

But can require carefully hand designing that feature set.

An alternative is to use a much richer function approximation class that is able to directly go from states without requiring an explicit specification of features.

Local representations including Kernel based approaches have some appealing properties (including convergence results under certain cases) but can’t typically scale well to enormous spaces and datasets.
Neural Networks

Figure by Kjell Magne Fauske
Deep Neural Networks (DNN)

\[ y = h_n(h_{n-1}(\ldots h_1(x)\ldots)) \]

- Composition of multiple functions

\[ \hat{x} \rightarrow h_1 \rightarrow h_2 \rightarrow h_3 \ldots \rightarrow h_n \rightarrow y \rightarrow J \]

\[ w_1 \quad w_2 \quad w_3 \quad w_n \]

- Can use the chain rule to backpropagate the gradient

\[ \frac{dJ}{dw_r} = \frac{dJ}{dh_n} \frac{d|h_n|}{dh_{n-1}} \ldots \frac{d|h_1|}{dx} \]

- Major innovation: tools to automatically compute gradients for a DNN
Deep Neural Networks (DNN) Specification and Fitting

- Generally combines both linear and non-linear transformations
  - Linear: \( h_n = \omega h_{n-1} \)
  - Non-linear: \( \text{relu, softmax} \)
- To fit the parameters, require a loss function (MSE, log likelihood etc)
The Benefit of Deep Neural Network Approximators

- Linear value function approximators assume value function is a weighted combination of a set of features, where each feature a function of the state
- Linear VFA often work well given the right set of features
- But can require carefully hand designing that feature set
- An alternative is to use a much richer function approximation class that is able to directly go from states without requiring an explicit specification of features
- Local representations including Kernel based approaches have some appealing properties (including convergence results under certain cases) but can’t typically scale well to enormous spaces and datasets
- Alternative: Deep neural networks
  - Uses distributed representations instead of local representations
  - Universal function approximator
  - Can potentially need exponentially less nodes/parameters (compared to a shallow net) to represent the same function
  - Can learn the parameters using stochastic gradient descent
Today

- Value function approximation
- Deep neural networks
- CNNs
- DQN
Why Do We Care About CNNs?

- CNNs extensively used in computer vision
- If we want to go from pixels to decisions, likely useful to leverage insights for visual input
Example: 1000x1000 image

How many weight parameters for a single node which is a linear combination of input?
Example: 1000x1000 image
1M hidden units
10^12 parameters!!!
Fully Connected Neural Net

- Traditional NNs receive input as a single vector & transform it through a series of (fully connected) hidden layers.
- For an image (32w, 32h, 3c), the input layer has $32 \times 32 \times 3 = 3072$ neurons,
  - Single fully-connected neuron in the first hidden layer would have 3072 weights ...
- Two main issues:
  - space-time complexity
  - lack of structure, locality of info
Images Have Structure

- Have local structure and correlation
- Have distinctive features in space & frequency domains
Convolutional NN

- Consider local structure and common extraction of features
- Not fully connected
- Locality of processing
- Weight sharing for parameter reduction
- Learn the parameters of multiple convolutional filter banks
- Compress to extract salient features & favor generalization
Locality of Information: Receptive Fields

Example: 1000x1000 image
1M hidden units
Filter size: 10x10
100M parameters

Filter/Kernel/Receptive field:
input patch which the hidden unit is connected to.

Hidden neuron
(Filter) Stride

- Slide the 5x5 mask over all the input pixels
- Stride length = 1
  - Can use other stride lengths
- Assume input is 28x28, how many neurons in 1st hidden layer?

Zero padding: how many 0s to add to either side of input layer
What is the precise relationship between the neurons in the receptive field and that in the hidden layer?

What is the \textit{activation value} of the hidden layer neuron?

\[
g(b + \sum_i w_i x_i)
\]

- Sum over \(i\) is \textit{only over the neurons in the receptive field} of the hidden layer neuron.
- \textit{The same weights} \(w\) \textit{and bias} \(b\) are used for each of the hidden neurons.
  - In this example, \(24 \times 24\) hidden neurons.
Consider 28x28 input image

24x24 hidden layer

Receptive field is 5x5
All the neurons in the first hidden layer detect exactly the same feature, just at different locations in the input image.

**Feature**: the kind of input pattern (e.g., a local edge) that makes the neuron produce a certain response level.

Why does this makes sense?

- Suppose the weights and bias are (learned) such that the hidden neuron can pick out, a vertical edge in a particular local receptive field.
- That ability is also likely to be useful at other places in the image.
- Useful to apply the same feature detector everywhere in the image. Yields translation (spatial) invariance (try to detect feature at any part of the image).
- Inspired by visual system

*not preprogrammed features*
The map from the input layer to the hidden layer is therefore a feature map: all nodes detect the same feature in different parts.

The map is defined by the shared weights and bias.

The shared map is the result of the application of a convolutional filter (defined by weights and bias), also known as convolution with learned kernels.
Convolutional Layer: Multiple Filters Ex.\(^2\)

\[\text{Input Volume (\text{pad 1}) (7x7x3)} \]
\[\begin{array}{cccccc}
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 1 & 0 & 0 \\
0 & 1 & 1 & 0 & 1 & 0 \\
0 & 1 & 2 & 0 & 0 & 0 \\
0 & 1 & 1 & 2 & 2 & 0 \\
0 & 1 & 1 & 1 & 2 & 2 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{array}\]

\[\text{Filter } W_0 (3x3x3) \]
\[\begin{array}{cccc}
1 & 1 & 0 & 0 \\
1 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 \\
\end{array}\]

\[\text{Filter } W_1 (3x3x3) \]
\[\begin{array}{cccc}
2 & 1 & -1 & -1 \\
1 & -1 & 1 & 1 \\
1 & 1 & 1 & 0 \\
\end{array}\]

\[\text{Output Volume (3x3x2)} \]
\[\begin{array}{cccc}
-2 & 3 & 3 \\
-1 & -3 & 3 \\
-1 & -4 & 3 \\
\end{array}\]

\[\text{Input Volume (\text{pad 1}) (7x7x3)} \]
\[\begin{array}{cccccc}
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 2 & 1 & 1 & 0 & 1 \\
0 & 2 & 1 & 2 & 1 & 2 \\
0 & 0 & 0 & 2 & 0 & 1 \\
0 & 1 & 0 & 2 & 1 & 2 \\
0 & 1 & 1 & 2 & 2 & 2 \\
0 & 0 & 0 & 0 & 0 & 0 \\
\end{array}\]

\[\text{Filter } W_0 (3x3x3) \]
\[\begin{array}{cccc}
1 & 0 & 1 & 0 \\
1 & 1 & -1 & -1 \\
0 & -1 & 0 & 0 \\
\end{array}\]

\[\text{Filter } W_1 (3x3x3) \]
\[\begin{array}{cccc}
0 & -1 & 1 & -1 \\
-1 & -1 & 1 & 1 \\
0 & 0 & 0 & -1 \\
\end{array}\]

\[\text{Output Volume (3x3x2)} \]
\[\begin{array}{cccc}
0 & -1 & 0 & 0 \\
3 & 6 & 3 & 1 \\
6 & 9 & 0 & 0 \\
\end{array}\]

\[\text{Bias } b_0 (1x1x1) \]
\[1\]

\[\text{Bias } b_1 (1x1x1) \]
\[0\]

\[\text{toggle movement}\]

\(^2\)http://cs231n.github.io/convolutional-networks/
Poolign Layers

- Pooling layers are usually used immediately after convolutional layers.
- Pooling layers simplify / subsample / compress the information in the output from convolutional layer
- A pooling layer takes each feature map output from the convolutional layer and prepares a condensed feature map
Final Layer Typically Fully Connected

Today

- Value function approximation
- Deep neural networks
- CNNs
- DQN
DeepMind Atari Breakout

- https://www.youtube.com/watch?v=Q70ulPJW3Gk
Generalization

- Using function approximation to help scale up to making decisions in really large domains
Use deep neural networks to represent
- Value, Q function
- Policy
- Model

Optimize loss function by stochastic gradient descent (SGD)
Deep Q-Networks (DQNs)

- Represent state-action value function by Q-network with weights $w$
  \[ \hat{Q}(s, a; w) \approx Q(s, a) \]

![Diagram]

\( S \xrightarrow{w} \hat{V}(s; w) \)

\( S \xrightarrow{a} w \xrightarrow{\hat{Q}(s, a; w)} \)
Recall: Incremental Model-Free Control Approaches

- Similar to policy evaluation, true state-action value function for a state is unknown and so substitute a target value.
- In Monte Carlo methods, use a return $G_t$ as a substitute target.

\[
\Delta w = \alpha \left( G_t - \hat{Q}(s_t, a_t; w) \right) \nabla_w \hat{Q}(s_t, a_t; w)
\]

- For SARSA instead use a TD target $r + \gamma \hat{Q}(s_{t+1}, a_{t+1}; w)$ which leverages the current function approximation value.

\[
\Delta w = \alpha \left( r + \gamma \hat{Q}(s_{t+1}, a_{t+1}; w) - \hat{Q}(s_t, a_t; w) \right) \nabla_w \hat{Q}(s_t, a_t; w)
\]

- For Q-learning instead use a TD target $r + \gamma \max_a \hat{Q}(s_{t+1}, a; w)$ which leverages the max of the current function approximation value.

\[
\Delta w = \alpha \left( r + \gamma \max_a \hat{Q}(s_{t+1}, a; w) - \hat{Q}(s_t, a_t; w) \right) \nabla_w \hat{Q}(s_t, a_t; w)
\]
Using these ideas to do Deep RL in Atari
DQNs in Atari

- End-to-end learning of values $Q(s, a)$ from pixels $s$
- Input state $s$ is stack of raw pixels from last 4 frames
- Output is $Q(s, a)$ for 18 joystick/button positions
- Reward is change in score for that step

- Network architecture and hyperparameters fixed across all games
DQNs in Atari

- End-to-end learning of values $Q(s, a)$ from pixels $s$
- Input state $s$ is stack of raw pixels from last 4 frames
- Output is $Q(s, a)$ for 18 joystick/button positions
- Reward is change in score for that step

DQN source code:
sites.google.com/a/deepmind.com/dqn/

- Network architecture and hyperparameters fixed across all games
Q-Learning with Value Function Approximation

- Q-learning converges to the optimal $Q^*(s, a)$ using table lookup representation.
- In value function approximation Q-learning we can minimize MSE loss by stochastic gradient descent using a target Q estimate instead of true Q (as we saw with linear VFA).
- But Q-learning with VFA can diverge.
- Two of the issues causing problems:
  - Correlations between samples
  - Non-stationary targets
- Deep Q-learning (DQN) addresses these challenges by
  - Experience replay
  - Fixed Q-targets
DQNs: Experience Replay

- To help remove correlations, store dataset (called a **replay buffer**) $\mathcal{D}$ from prior experience

<table>
<thead>
<tr>
<th>$s_1, a_1, r_2, s_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$s_2, a_2, r_3, s_3$</td>
</tr>
<tr>
<td>$s_3, a_3, r_4, s_4$</td>
</tr>
<tr>
<td>...</td>
</tr>
<tr>
<td>$s_t, a_t, r_{t+1}, s_{t+1}$</td>
</tr>
</tbody>
</table>

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

$$\Delta w = \alpha (r + \gamma \max_{a'} \hat{Q}(s', a'; w) - \hat{Q}(s, a; w)) \nabla_w \hat{Q}(s, a; w)$$
DQNs: Experience Replay

- To help remove correlations, store dataset $D$ from prior experience

$$ s_1, a_1, r_2, s_2 \\ s_2, a_2, r_3, s_3 \\ s_3, a_3, r_4, s_4 \\ \vdots \\ s_t, a_t, r_{t+1}, s_{t+1} $$

$\rightarrow s, a, r, s'$

- To perform experience replay, repeat the following:
  - $(s, a, r, s') \sim D$: sample an experience tuple from the dataset
  - Compute the target value for the sampled $s$: $r + \gamma \max_{a'} \hat{Q}(s', a'; w)$
  - Use stochastic gradient descent to update the network weights

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

- Can treat the target as a scalar, but the weights will get updated on the next round, changing the target value
DQNs: Fixed Q-Targets

- To help improve stability, fix the **target weights** used in the target calculation for multiple updates.
- Target network uses a different set of weights than the weights being updated.
- Let parameters $w^−$ be the set of weights used in the target, and $w$ be the weights that are being updated.
- Slight change to computation of target value:
  - $(s, a, r, s') \sim D$: sample an experience tuple from the dataset.
  - Compute the target value for the sampled $s$: $r + \gamma \max_{a'} \hat{Q}(s', a'; w^-)$.
  - Use stochastic gradient descent to update the network weights.

\[
\Delta w = \alpha (r + \gamma \max_{a'} \hat{Q}(s', a'; w^-)) - \hat{Q}(s, a; w) \nabla_w \hat{Q}(s, a; w)
\]
DQN Pseudocode

1: Input $C$, $\alpha$, $D = \{\}$, Initialize $w$, $w^{-} = w$, $t = 0$
2: Get initial state $s_0$
3: loop
4: Sample action $a_t$ given $\epsilon$-greedy policy for current $\hat{Q}(s_t, a; w)$
5: Observe reward $r_t$ and next state $s_{t+1}$
6: Store transition $(s_t, a_t, r_t, s_{t+1})$ in replay buffer $D$
7: Sample random minibatch of tuples $(s_i, a_i, r_i, s_{i+1})$ from $D$
8: for $j$ in minibatch do
9: if episode terminated at step $i + 1$ then
10: $y_i = r_i$
11: else
12: $y_i = r_i + \gamma \max_{a'} \hat{Q}(s_{i+1}, a'; w^{-})$
13: end if
14: Do gradient descent step on $(y_i - \hat{Q}(s_i, a_i; w))^2$ for parameters $w$: $\Delta w = \alpha (y_i - \hat{Q}(s_i, a_i; w)) \nabla_w \hat{Q}(s_i, a_i; w)$
15: end for
16: $t = t + 1$
17: if mod($t, C$) == 0 then
18: $w^{-} \leftarrow w$
19: end if
20: end loop
DQN Pseudocode Hyperparameters

1: Input $C, \alpha, D = \{\}$, Initialize $w, w^- = w, t = 0$
2: Get initial state $s_0$
3: loop
4: Sample action $a_t$ given $\epsilon$-greedy policy for current $\hat{Q}(s_t, a; w)$
5: Observe reward $r_t$ and next state $s_{t+1}$
6: Store transition $(s_t, a_t, r_t, s_{t+1})$ in replay buffer $D$
7: Sample random minibatch of tuples $(s, a, r, s_{i+1})$ from $D$
8: for $j$ in minibatch do
9: if episode terminated at step $i + 1$ then
10: $y_i = r_i$
11: else
12: $y_i = r_i + \gamma \max_{a'} \hat{Q}(s_{i+1}, a'; w^-)$
13: end if
14: Do gradient descent step on $(y_i - \hat{Q}(s_i, a_i; w))^2$ for parameters $w$: $\Delta w = \alpha (y_i - \hat{Q}(s_i, a_i; w)) \nabla_w \hat{Q}(s_i, a_i; w)$
15: end for
16: $t = t + 1$
17: if $\text{mod}(t, C) == 0$ then
18: $w^- \leftarrow w$
19: end if
20: end loop

Note there are several hyperparameters and algorithm choices. One needs to choose the neural network architecture, the learning rate, and how often to update the target network. Often a fixed size replay buffer is used for experience replay, which introduces a parameter to control the size, and the need to decide how to populate it.
Check Your Understanding: Fixed Targets

- In DQN we compute the target value for the sampled \((s, a, r, s')\) using a separate set of target weights: 
  \[ r + \gamma \max_{a'} \hat{Q}(s', a'; w^-) \]

Select all that are true

- If the target network is trained on other data, this might help with the maximization bias
- This doubles the computation time compared to a method that does not have a separate set of weights
- This doubles the memory requirements compared to a method that does not have a separate set of weights
- Not sure
Check Your Understanding: Fixed Targets Solutions

- In DQN we compute the target value for the sampled \((s, a, r, s')\) using a separate set of target weights: \(r + \gamma \max_{a'} \hat{Q}(s', a'; w^-)\)

Select all that are true

- If the target network is trained on other data, this might help with the maximization bias
- This doubles the computation time compared to a method that does not have a separate set of weights
- This doubles the memory requirements compared to a method that does not have a separate set of weights
- Not sure

Answer: If the target network is trained on other data, this might help with the maximization bias (False). Doubles the computation time (False). It doubles the memory requirements. (True)
DQNs Summary

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

1 network, outputs Q value for each action

Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015
Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015
Which Aspects of DQN were Important for Success?

<table>
<thead>
<tr>
<th>Game</th>
<th>Linear</th>
<th>Deep Network</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breakout</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Enduro</td>
<td>62</td>
<td>29</td>
</tr>
<tr>
<td>River Raid</td>
<td>2345</td>
<td>1453</td>
</tr>
<tr>
<td>Seaquest</td>
<td>656</td>
<td>275</td>
</tr>
<tr>
<td>Space Invaders</td>
<td>301</td>
<td>302</td>
</tr>
</tbody>
</table>

Note: just using a deep NN actually hurt performance sometimes!
Which Aspects of DQN were Important for Success?

<table>
<thead>
<tr>
<th>Game</th>
<th>Linear</th>
<th>Deep Network</th>
<th>DQN w/ fixed Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breakout</td>
<td>3</td>
<td>3</td>
<td>10</td>
</tr>
<tr>
<td>Enduro</td>
<td>62</td>
<td>29</td>
<td>141</td>
</tr>
<tr>
<td>River Raid</td>
<td>2345</td>
<td>1453</td>
<td>2868</td>
</tr>
<tr>
<td>Seaquest</td>
<td>656</td>
<td>275</td>
<td>1003</td>
</tr>
<tr>
<td>Space Invaders</td>
<td>301</td>
<td>302</td>
<td>373</td>
</tr>
</tbody>
</table>
Which Aspects of DQN were Important for Success?

<table>
<thead>
<tr>
<th>Game</th>
<th>Linear</th>
<th>Deep Network</th>
<th>DQN w/ fixed Q</th>
<th>DQN w/ replay</th>
<th>DQN w/replay and fixed Q</th>
</tr>
</thead>
<tbody>
<tr>
<td>Breakout</td>
<td>3</td>
<td>3</td>
<td>10</td>
<td>241</td>
<td>317</td>
</tr>
<tr>
<td>Enduro</td>
<td>62</td>
<td>29</td>
<td>141</td>
<td>831</td>
<td>1006</td>
</tr>
<tr>
<td>River Raid</td>
<td>2345</td>
<td>1453</td>
<td>2868</td>
<td>4102</td>
<td>7447</td>
</tr>
<tr>
<td>Seaquest</td>
<td>656</td>
<td>275</td>
<td>1003</td>
<td>823</td>
<td>2894</td>
</tr>
<tr>
<td>Space Invaders</td>
<td>301</td>
<td>302</td>
<td>373</td>
<td>826</td>
<td>1089</td>
</tr>
</tbody>
</table>

- Replay is **hugely** important
- Why? Beyond helping with correlation between samples, what does replaying do?
Success in Atari has led to huge excitement in using deep neural networks to do value function approximation in RL

Some immediate improvements (many others!)

- **Double DQN** (Deep Reinforcement Learning with Double Q-Learning, Van Hasselt et al, AAAI 2016)
- Prioritized Replay (Prioritized Experience Replay, Schaul et al, ICLR 2016)
Last time and start of this time: Control (making decisions) without a model of how the world works
Rest of today: Deep reinforcement learning
Next time: Deep RL continued