Lecture 6: CNNs and Deep Q Learning [1]

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CS234 Reinforcement Learning.

Winter 2022

[1] 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/

Lecture 6: Refresh Your Knowledge

- In TD learning with linear VFA (select all):
  1. $\boldsymbol{w} = \boldsymbol{w} + \alpha(r(s_t) + \gamma \boldsymbol{x}(s_{t+1})^T \boldsymbol{w} - \boldsymbol{x}(s_t)^T \boldsymbol{w})\boldsymbol{x}(s_t)$
  2. $V(s) = \boldsymbol{w}(s)\boldsymbol{x}(s)$
  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

Lecture 6: Refresh Your Knowledge **Solutions**

- In TD learning with linear VFA (select all):
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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

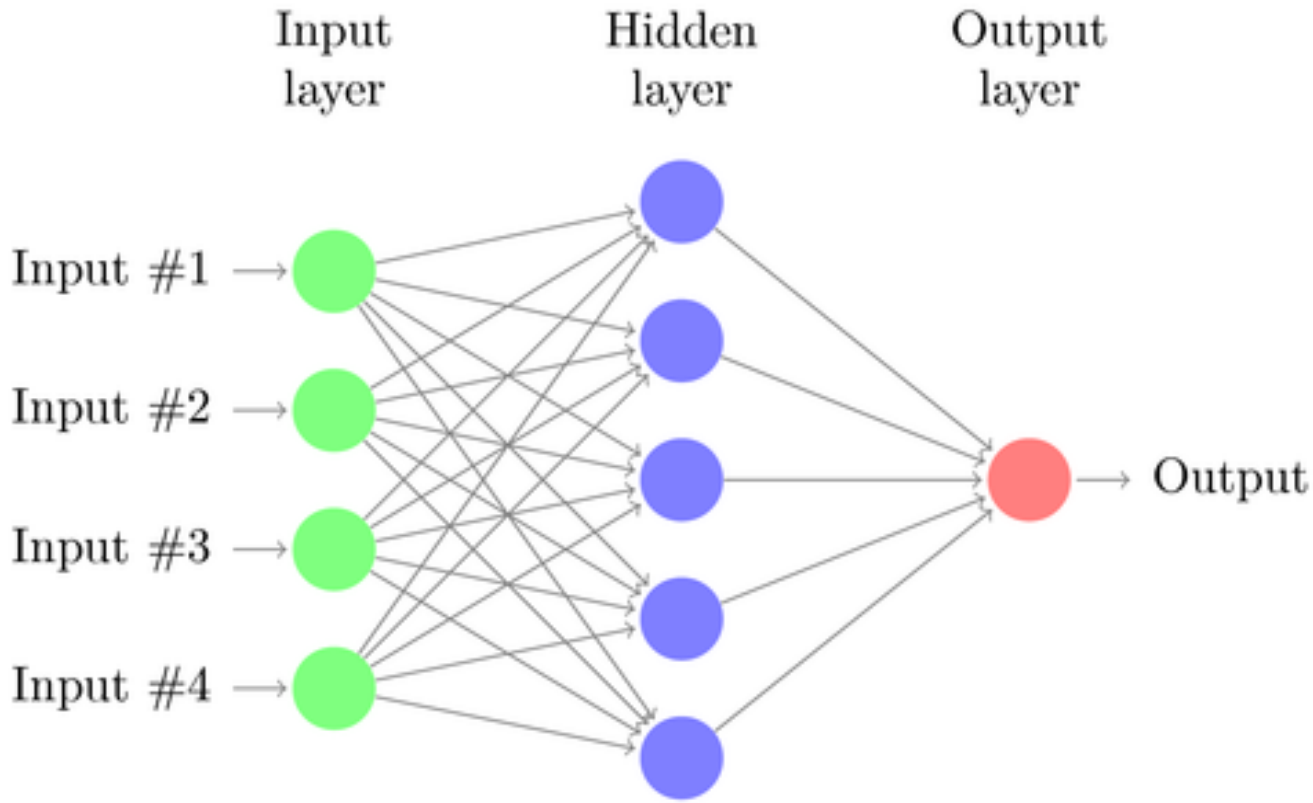
Control using Value Function Approximation

- Use value function approximation to represent state-action values $\hat{Q}^{\pi}(s, a; \boldsymbol{w}) \approx Q^{\pi}$
- Interleave
  - Approximate policy evaluation using value function approximation
  - Perform ϵ-greedy policy improvement
- Can be unstable. Generally involves intersection of the following:
  - Function approximation
  - Bootstrapping
  - **Off-policy learning**

RL with Function Approximation

- 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 [1]



[1] Figure by Kjell Magne Fauske

Deep Neural Networks (DNN)

- Composition of multiple functions
- Can use the chain rule to backpropagate the gradient
- 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:
  - Non-linear:
- 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

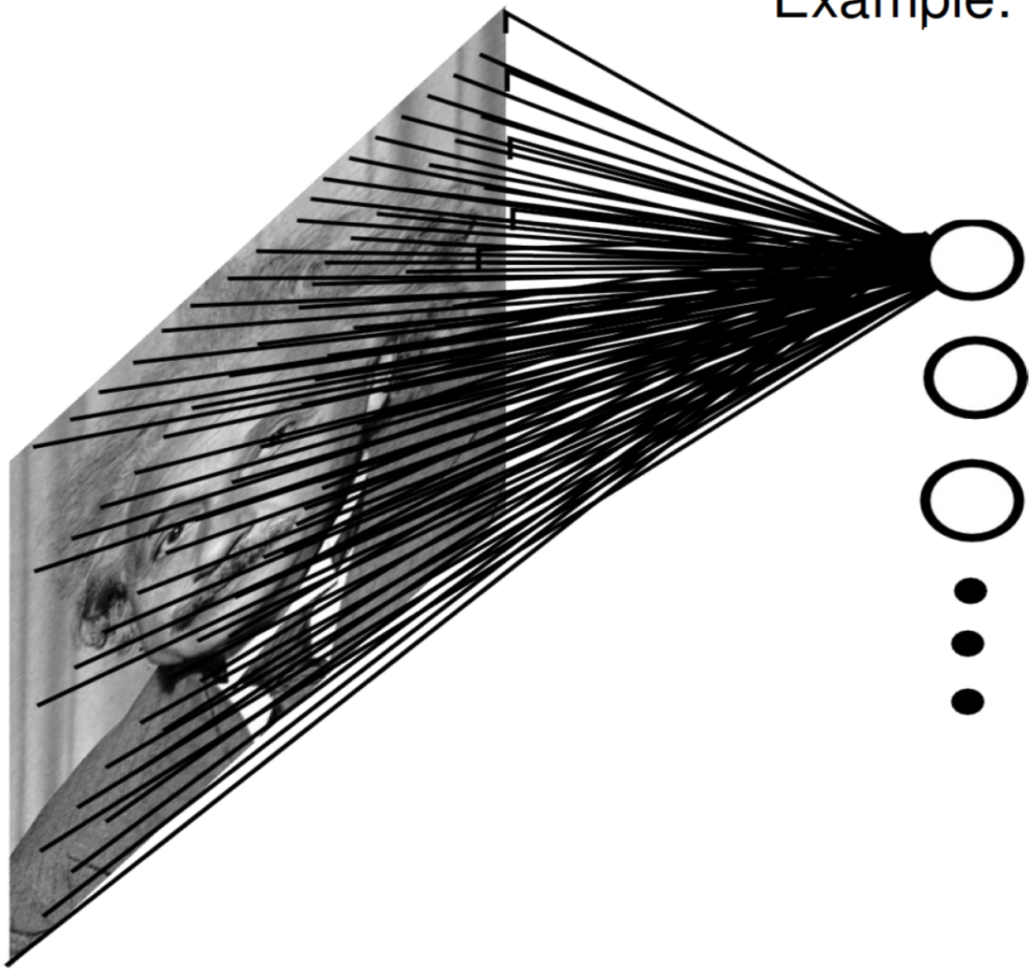
Today

- Value function approximation
- Deep neural networks
- **CNNs**
- DQN

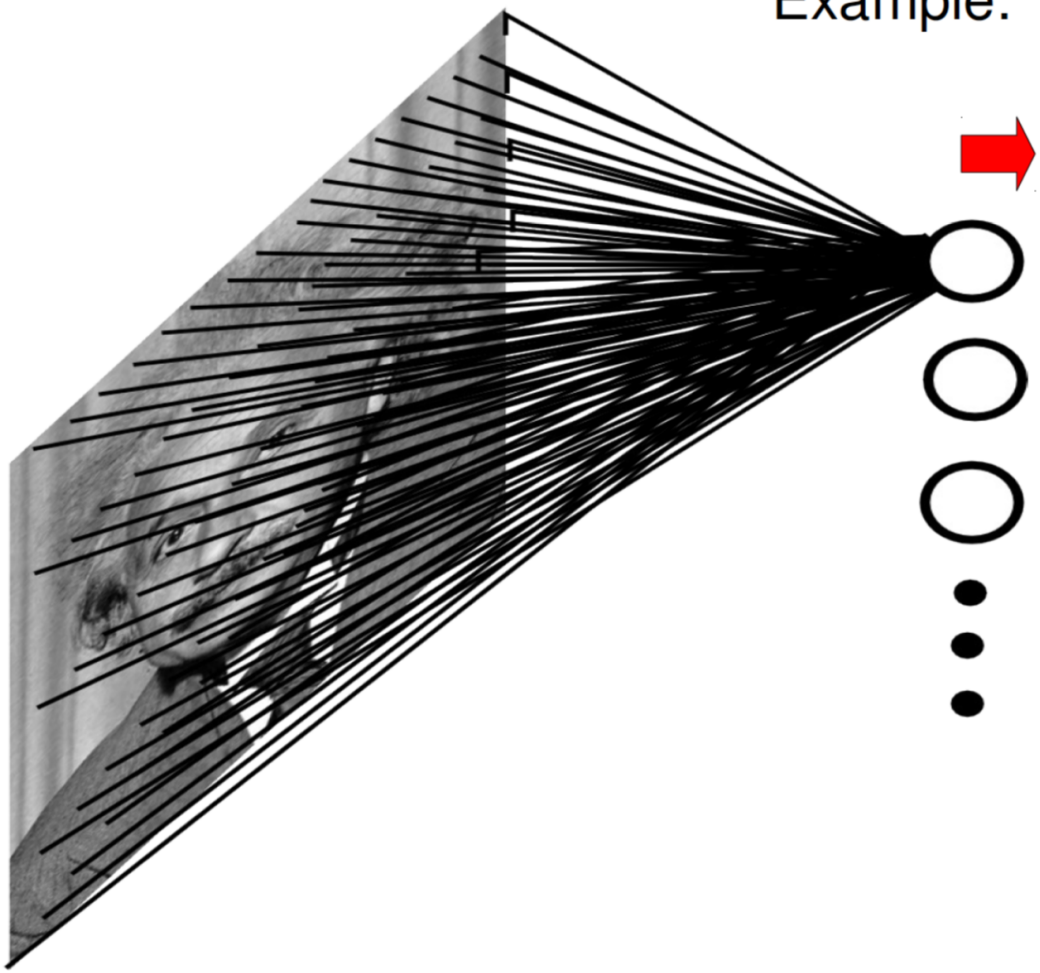
Why Do We Care About CNNs?

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

Fully Connected Neural Net



Fully Connected Neural Net



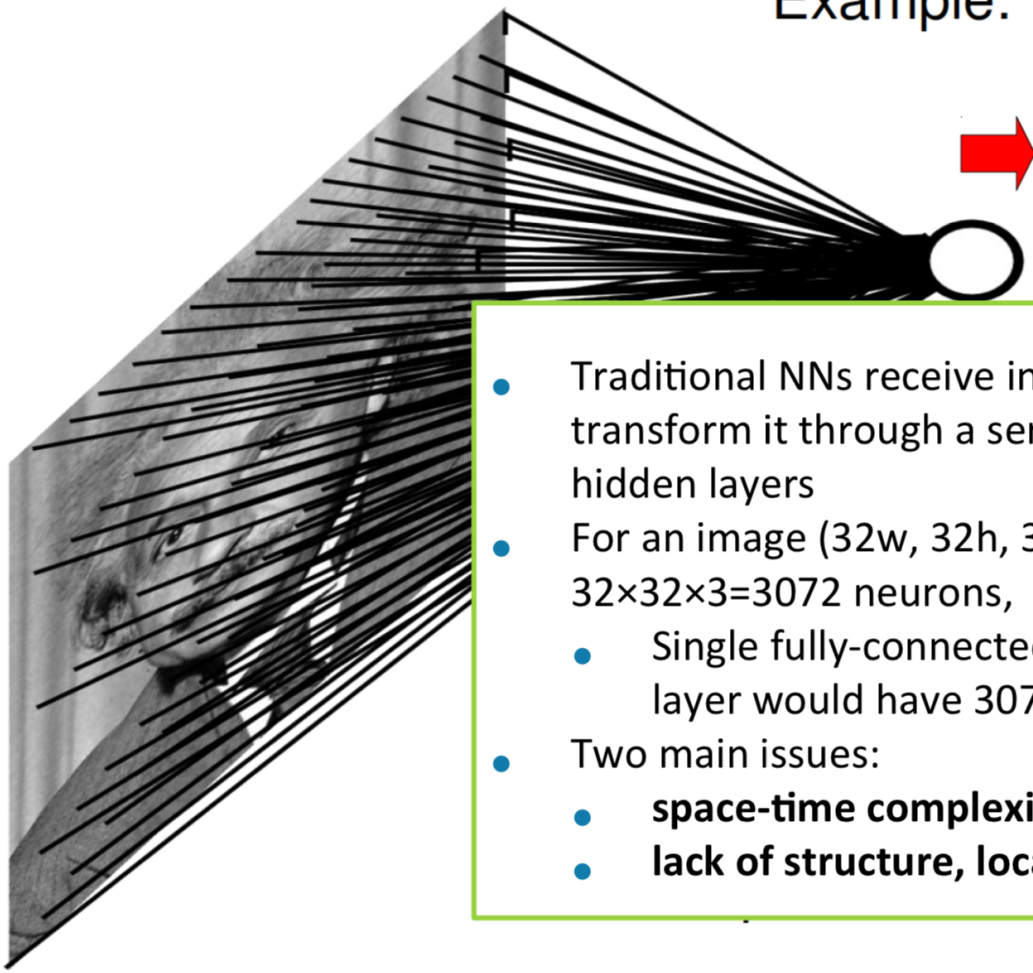
Example: 1000x1000 image

1M hidden units

10^12 parameters!!!

Ranzato

Fully Connected Neural Net



Example: 1000x1000 image
1M hidden units
10^12 parameters!!!

- Traditional NNs receive input as single vector & transform it through a series of (fully connected) hidden layers
- For an image (32w, 32h, 3c), the input layer has 32×32×3=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**

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Images Have Structure

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

Convolutional NN

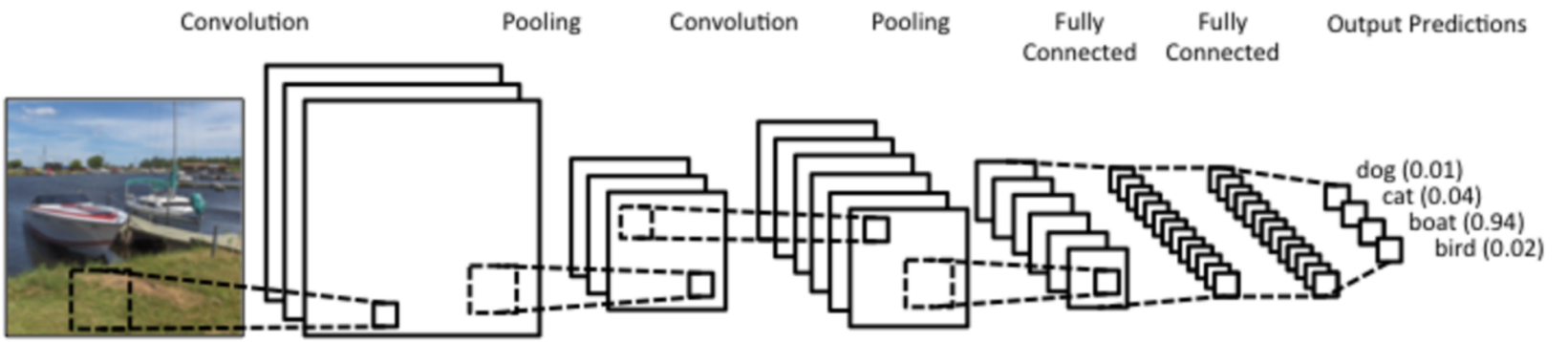
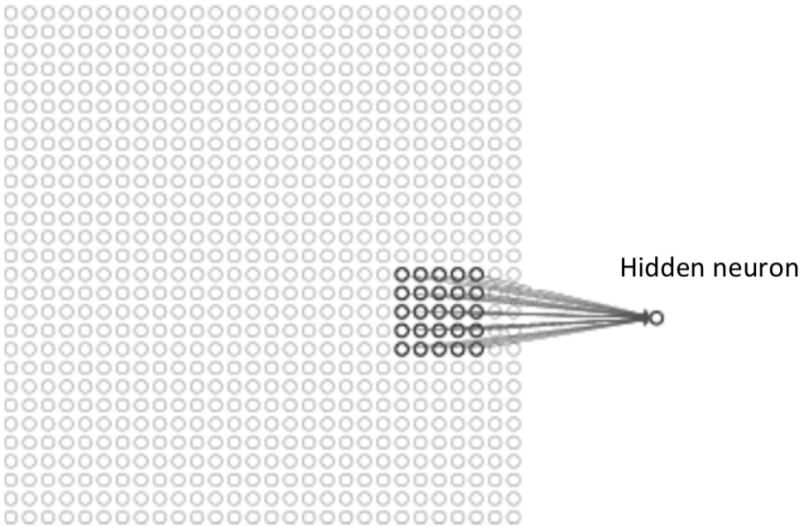
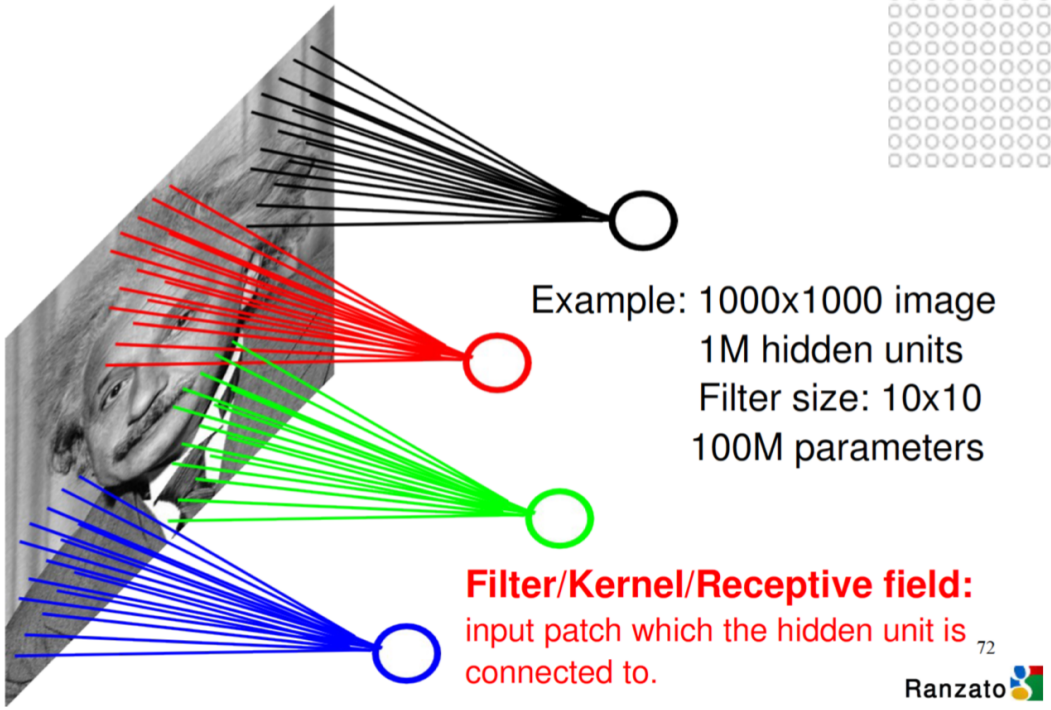


Image: http://d3kbpzbmcynnmx.cloudfront.net/wp-content/uploads/2015/11/Screen-Shot-2015-11-07-at-7.26.20-AM.png

- 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

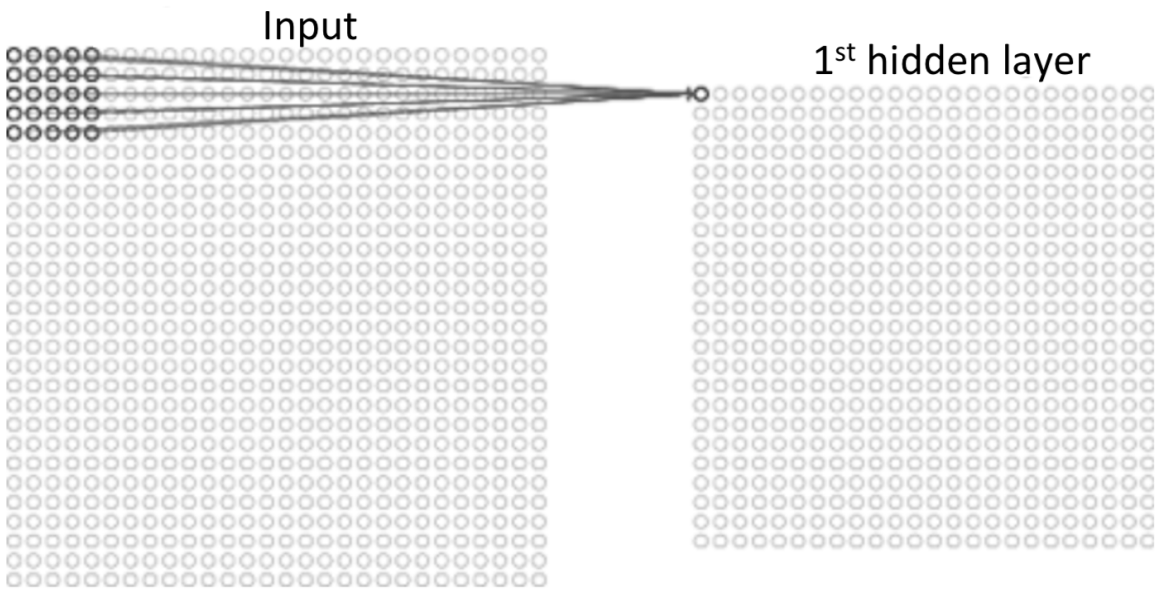
Locality of Information: Receptive Fields





(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

Shared Weights

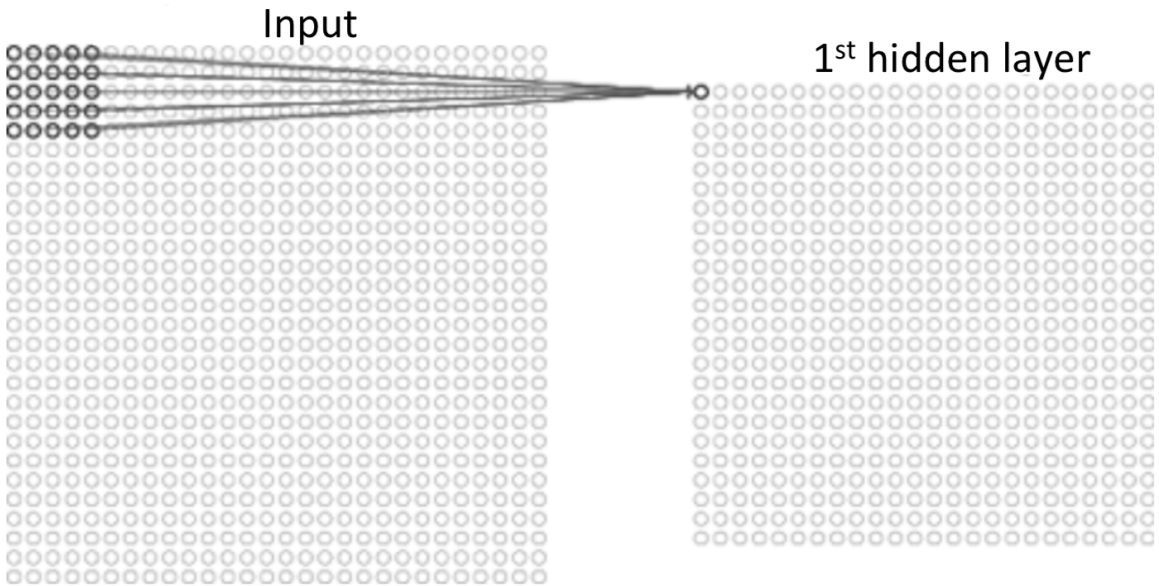
- What is the precise relationship between the neurons in the receptive field and that in the hidden layer?
- What is the *activation value* of the hidden layer neuron?

$$g(b + \sum_i w_i x_i)$$

- Sum over i is *only over the neurons in the receptive field* of the hidden layer neuron
- *The same weights w and bias b* are used for each of the hidden neurons
  - In this example, 24×24 hidden neurons

Ex. Shared Weights, Restricted Field

- Consider 28x28 input image
- 24x24 hidden layer

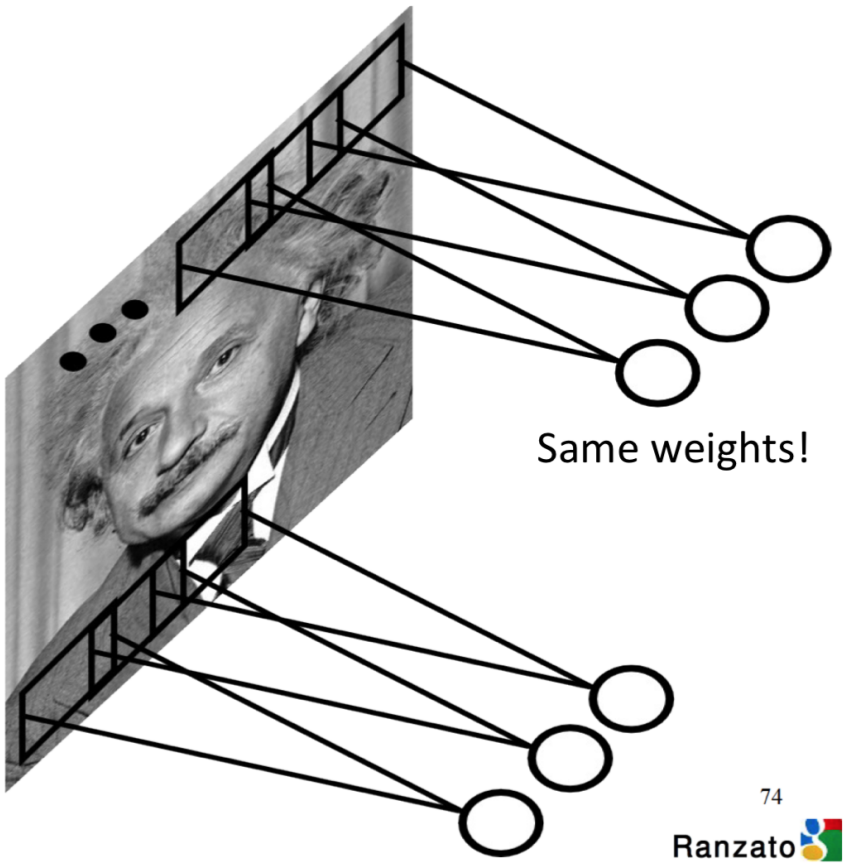


- Receptive field is 5x5

Feature Map

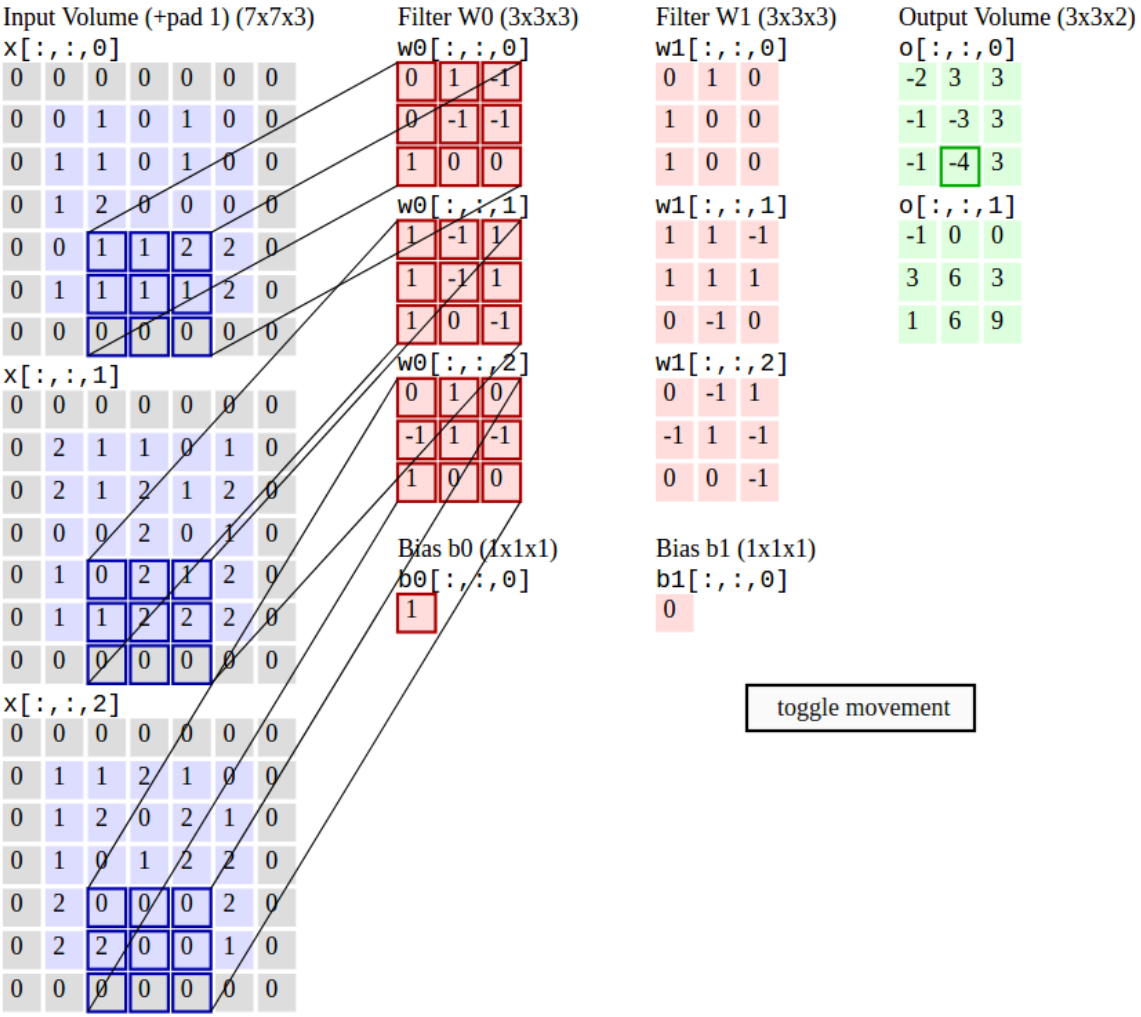
- All the neurons in the first hidden layer *detect exactly the same feature, just at different locations* in the input image.
- **Feature**: the kind of input pattern (e.g., a local edge) that makes the neuron produce a certain response level
- Why does this makes sense?
  - Suppose the weights and 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

Feature Map



- 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

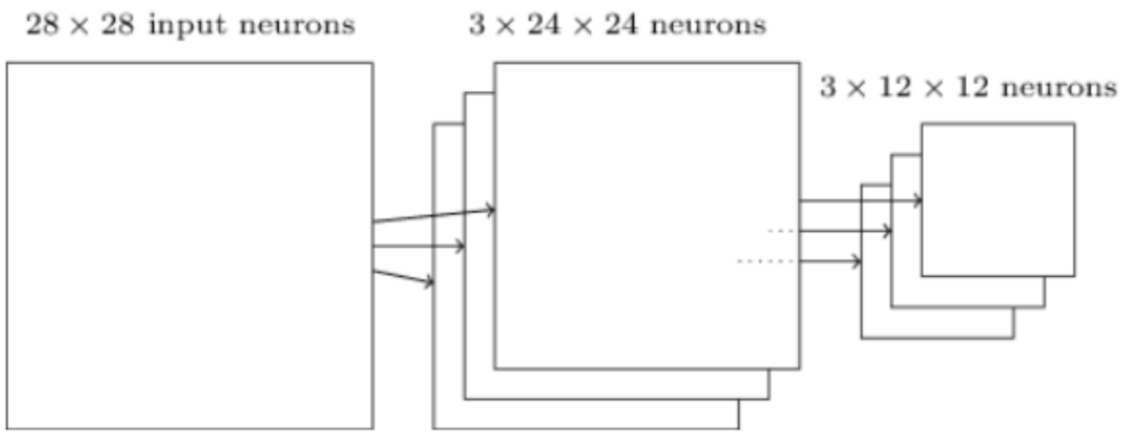
Convolutional Layer: Multiple Filters Ex.[2]



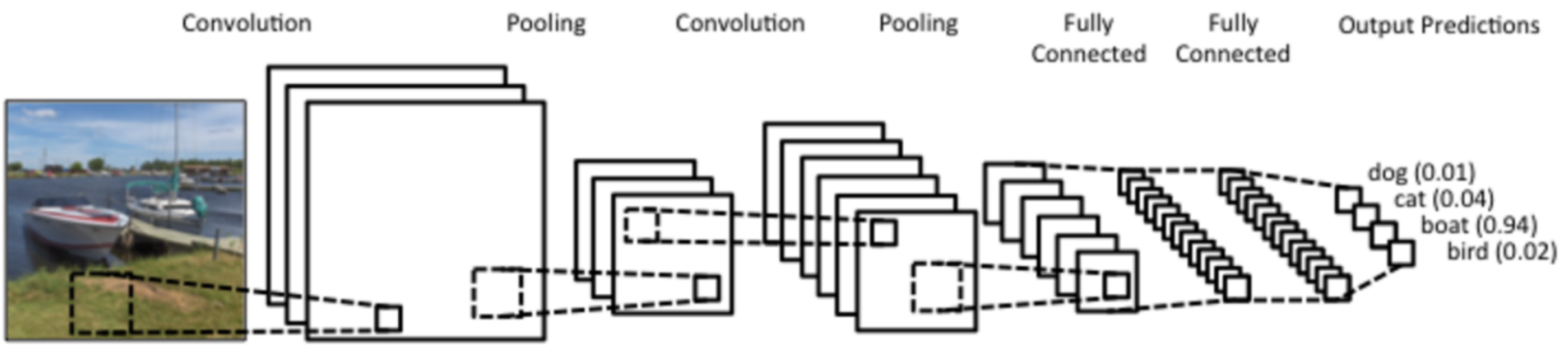
[2] http://cs231n.github.io/convolutional-networks/

Pooling 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



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Today

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- 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

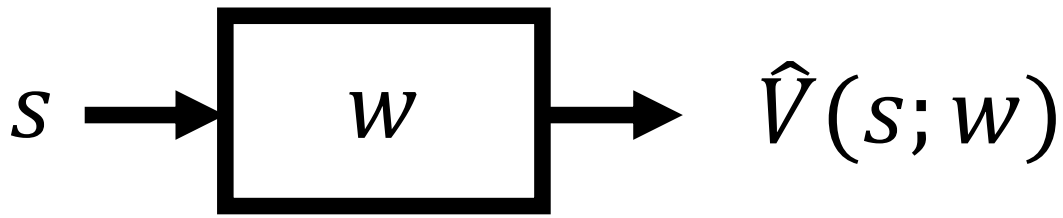
Deep Reinforcement Learning

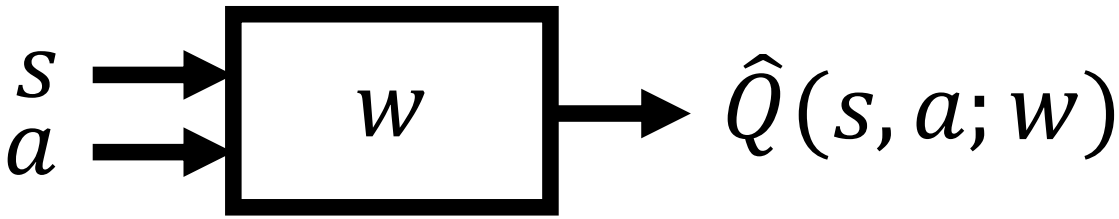
- Use deep neural networks to represent
  - Value, Q function
  - Policy
  - Model
- Optimize loss function by stochastic gradient descent (SGD)

Deep Q-Networks (DQNs)

- Represent state-action value function by Q-network with weights $\boldsymbol{w}$

$$\hat{Q}(s, a; \boldsymbol{w}) \approx Q(s, a)$$





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

$$\Delta \boldsymbol{w} = \alpha(G_t - \hat{Q}(s_t, a_t; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_t, a_t; \boldsymbol{w})$$

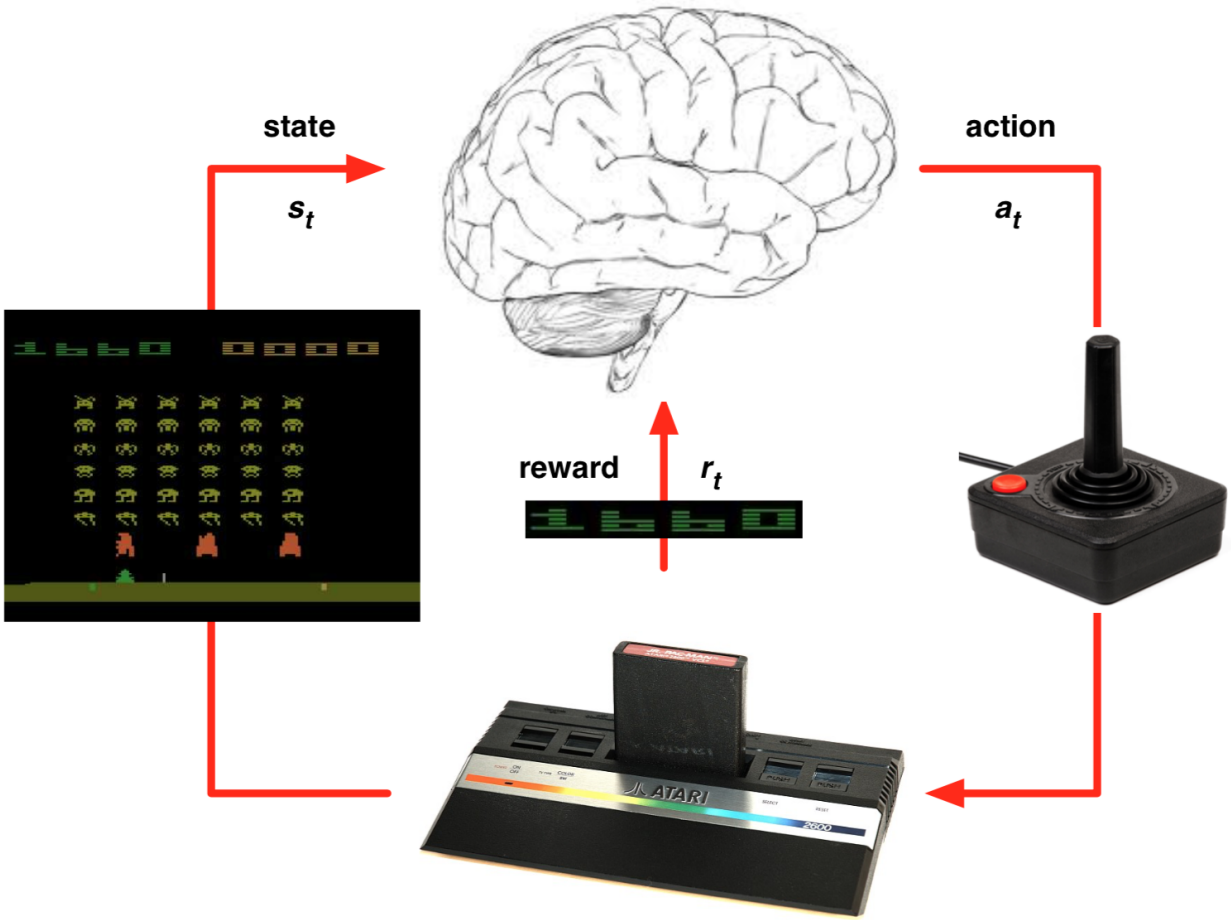
- For SARSA instead use a TD target $r + \gamma \hat{Q}(s_{t+1}, a_{t+1}; \boldsymbol{w})$ which leverages the current function approximation value

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \hat{Q}(s_{t+1}, a_{t+1}; \boldsymbol{w}) - \hat{Q}(s_t, a_t; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_t, a_t; \boldsymbol{w})$$

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

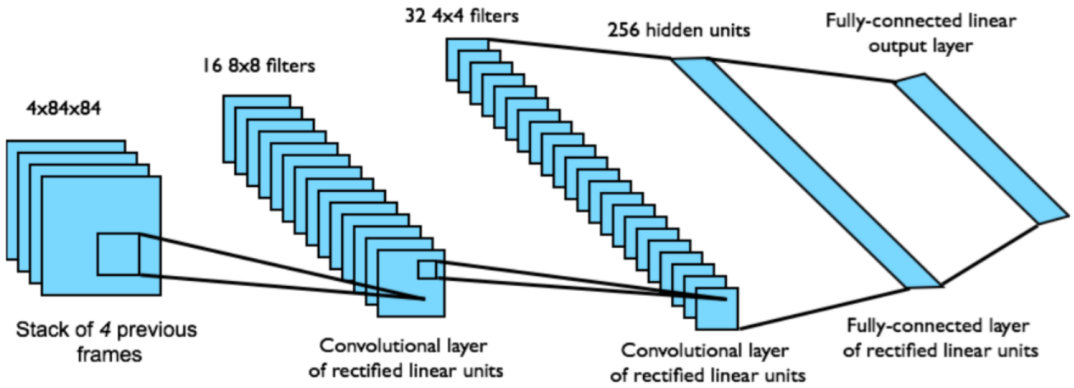
$$\Delta \boldsymbol{w} = \alpha(r + \gamma \max_a \hat{Q}(s_{t+1}, a; \boldsymbol{w}) - \hat{Q}(s_t, a_t; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_t, a_t; \boldsymbol{w})$$

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

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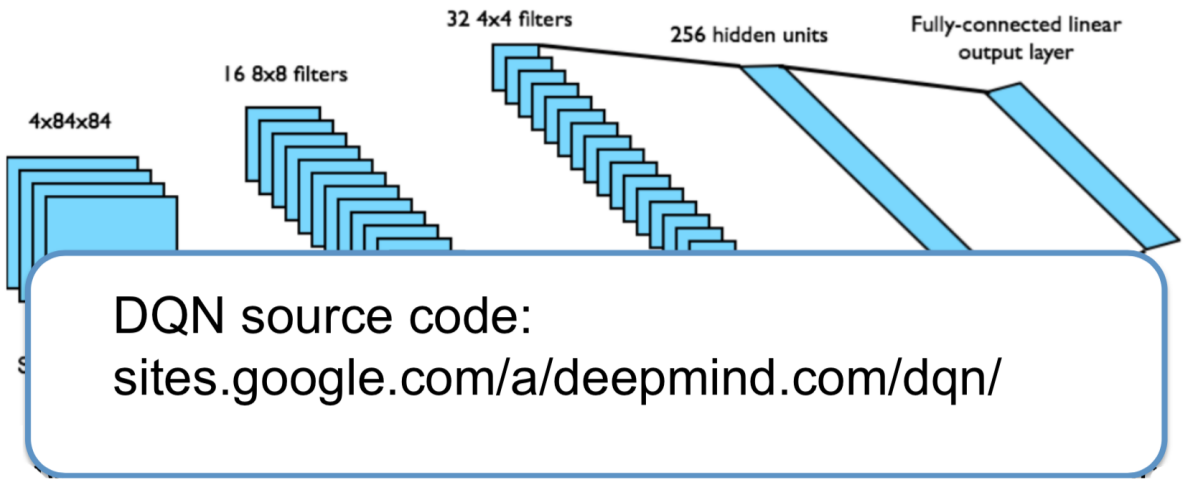

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Q-Learning with Value Function Approximation

- 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

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

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

- 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: $r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w})$
  - Use stochastic gradient descent to update the network weights

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

DQNs: Experience Replay

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- **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 $\boldsymbol{w}^-$ be the set of weights used in the target, and $\boldsymbol{w}$ be the weights that are being updated
- Slight change to computation of target value:
  - $(s, a, r, s') \sim \mathcal{D}$: sample an experience tuple from the dataset
  - Compute the target value for the sampled s: $r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}^-)$
  - Use stochastic gradient descent to update the network weights

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

DQN Pseudocode

Input C, α, $D = \{\}$, Initialize $\boldsymbol{w}$, $\boldsymbol{w}^- = \boldsymbol{w}$, $t = 0$
Get initial state s_0
loop
    Sample action a_t given ϵ-greedy policy for current $\hat{Q}(s_t, a; \boldsymbol{w})$
    Observe reward r_t and next state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in replay buffer D
    Sample random minibatch of tuples (s_i, a_i, r_i, s_{i+1}) from D
    for j in minibatch **do**
        if episode terminated at step $i + 1$ **then**
            $y_i = r_i$
        else
            $y_i = r_i + \gamma \max_{a'} \hat{Q}(s_{i+1}, a'; \boldsymbol{w}^-)$
        end if
        Do gradient descent step on $(y_i - \hat{Q}(s_i, a_i; \boldsymbol{w}))^2$ for parameters $\boldsymbol{w}$: $\Delta \boldsymbol{w} = \alpha(y_i - \hat{Q}(s_i, a_i; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_i, a_i; \boldsymbol{w})$
    end for
    $t = t + 1$
    if mod(t,C) == 0 **then**
        $\boldsymbol{w}^- \leftarrow \boldsymbol{w}$
    end if
end loop

DQN Pseudocode Hyperparameters

Input $\boldsymbol{C}$, $\boldsymbol{\alpha}$, $D = \{\}$, Initialize $\boldsymbol{w}$, $\boldsymbol{w}^- = \boldsymbol{w}$, $t = 0$
Get initial state s_0
loop
    Sample action a_t given ϵ-greedy policy for current $\hat{Q}(s_t, a; \boldsymbol{w})$
    Observe reward r_t and next state s_{t+1}
    Store transition (s_t, a_t, r_t, s_{t+1}) in replay buffer D
    Sample random minibatch of tuples (s_i, a_i, r_i, s_{i+1}) from D
    for j in minibatch **do**
        if episode terminated at step $i + 1$ **then**
            $y_i = r_i$
        else
            $y_i = r_i + \gamma \max_{a'} \hat{Q}(s_{i+1}, a'; \boldsymbol{w}^-)$
        end if
        Do gradient descent step on $(y_i - \hat{Q}(s_i, a_i; \boldsymbol{w}))^2$ for parameters $\boldsymbol{w}$: $\Delta \boldsymbol{w} = \alpha(y_i - \hat{Q}(s_i, a_i; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s_i, a_i; \boldsymbol{w})$
    end for
    $t = t + 1$
    if mod(t,C) == 0 **then**
        $\boldsymbol{w}^- \leftarrow \boldsymbol{w}$
    end if
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: $r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}^-)$
- 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: $r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}^-)$
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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 $\boldsymbol{w}^-$
- Optimizes MSE between Q-network and Q-learning targets
- Uses stochastic gradient descent

DQN

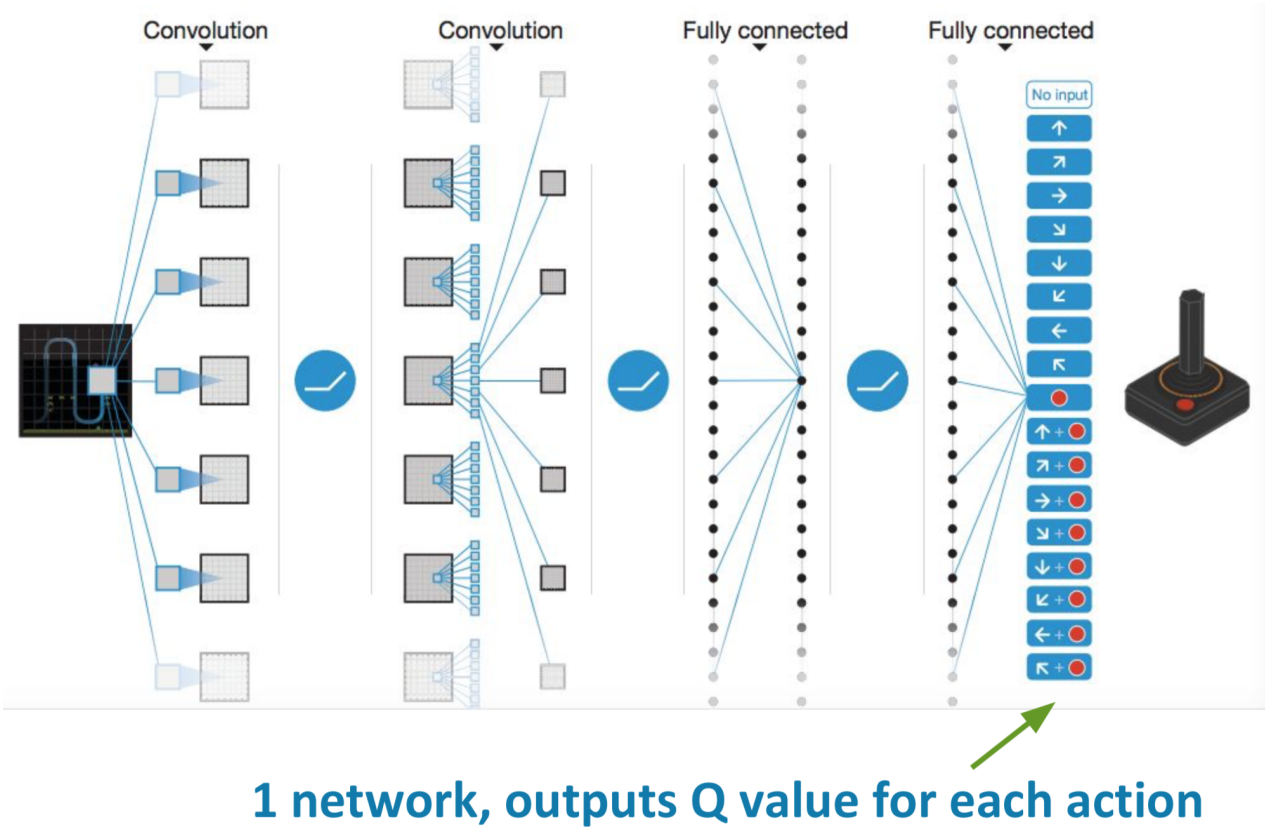

Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015

Demo

DQN Results in Atari

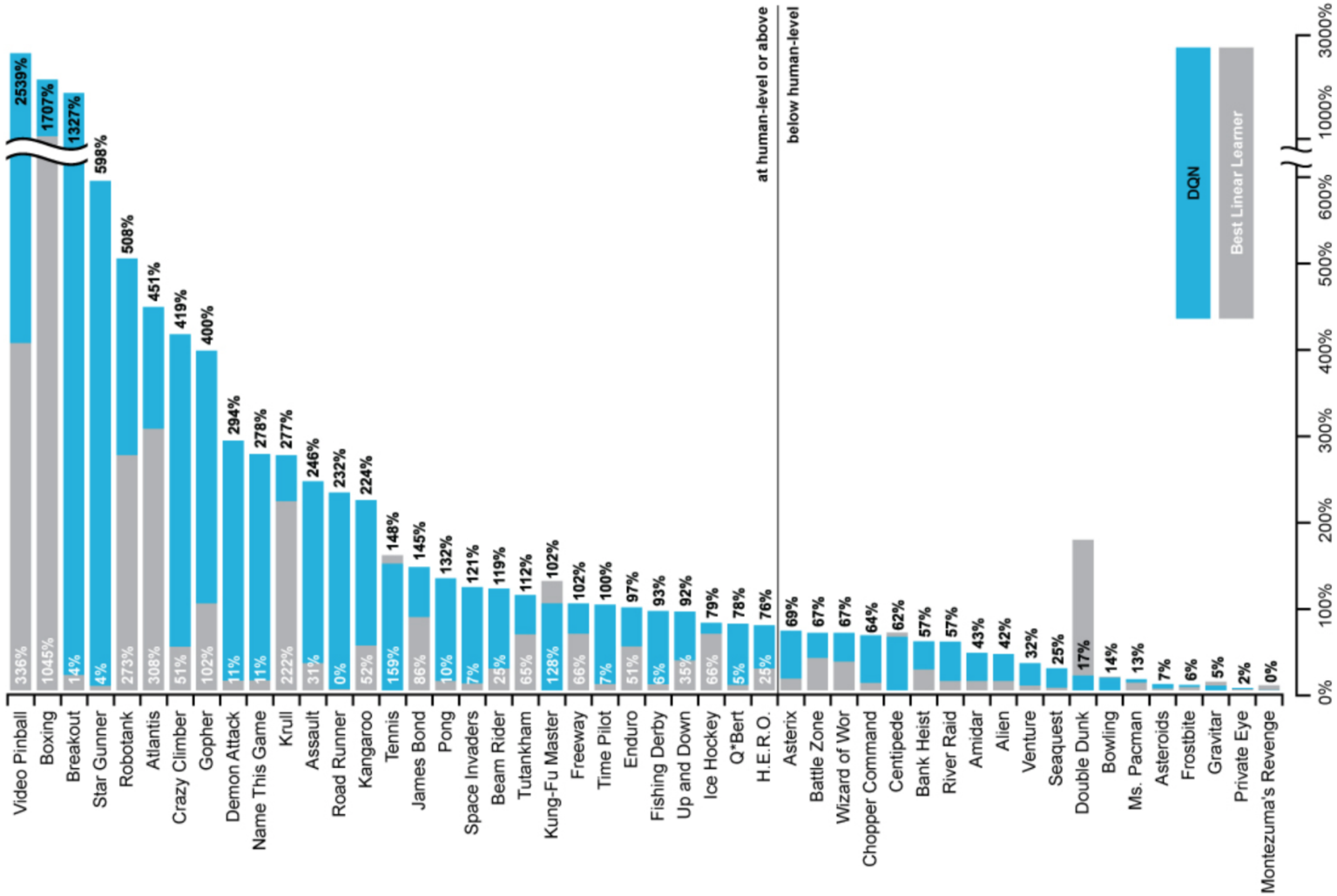

Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015

Which Aspects of DQN were Important for Success?

Game	Linear	Deep Network
Breakout	3	3
Enduro	62	29
River Raid	2345	1453
Seaquest	656	275
Space Invaders	301	302

Note: just using a deep NN actually hurt performance sometimes!

Which Aspects of DQN were Important for Success?

Game	Linear	Deep Network	DQN w/ fixed Q
Breakout	3	3	10
Enduro	62	29	141
River Raid	2345	1453	2868
Seaquest	656	275	1003
Space Invaders	301	302	373

Which Aspects of DQN were Important for Success?

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

- Replay is **hugely** important
- Why? Beyond helping with correlation between samples, what does replaying do?

Deep RL

- 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)
  - Dueling DQN (best paper ICML 2016) (Dueling Network Architectures for Deep Reinforcement Learning, Wang et al, ICML 2016)

Class Structure

- 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