Lecture 6: CNNs and Deep Q Learning [1]

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CS234 Reinforcement Learning.

Winter 2020

[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/

Refresh Your Knowledge 5

- 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. $V(s) = w(s)x(s)$ $V(s) = w^T x(s)$
  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

X

TD is best MSE $\frac{1}{1-\gamma}$

Class Structure

- Last time: Value function approximation
- This time: RL with function approximation, deep RL

Table of Contents

linear

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**

Linear State Action Value Function Approximation

- Use features to represent both the state and action

$$\boldsymbol{x}(s,a) = \begin{pmatrix} x_1(s,a) \\ x_2(s,a) \\ \ldots \\ x_n(s,a) \end{pmatrix}$$

- Represent state-action value function with a weighted linear combination of features

$$\hat{Q}(s,a;\boldsymbol{w}) = \boldsymbol{x}(s,a)^T \boldsymbol{w} = \sum_{j=1}^{d} x_j(s,a) w_j$$

- Gradient descent update:

$$\nabla_{\boldsymbol{w}} J(\boldsymbol{w}) = \nabla_{\boldsymbol{w}} \mathbb{E}_\pi[(Q^\pi(s,a) - \hat{Q}^\pi(s,a;\boldsymbol{w}))^2]$$

Incremental Model-Free Control Approaches w/Linear VFA

- 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

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

(s, a, r, s', a')

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

$$\begin{aligned} \Delta \boldsymbol{w} &= \alpha(r + \gamma \hat{Q}(s', a'; \boldsymbol{w}) - \hat{Q}(s, a; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s, a; \boldsymbol{w}) \\ &= \alpha(r + \gamma \boldsymbol{x}(s', a')^T \boldsymbol{w} - \boldsymbol{x}(s, a)^T \boldsymbol{w})\boldsymbol{x}(s, a) \end{aligned}$$

Incremental Model-Free Control Approaches

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

$$\begin{aligned} \Delta \boldsymbol{w} &= \alpha(r + \gamma \max_{a'} \hat{Q}(s', a'; \boldsymbol{w}) - \hat{Q}(s, a; \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{Q}(s, a; \boldsymbol{w}) \\ &= \alpha(r + \gamma \max_{a'} \boldsymbol{x}(s', a')^T \boldsymbol{w} - \boldsymbol{x}(s, a)^T \boldsymbol{w})\boldsymbol{x}(s, a) \end{aligned}$$

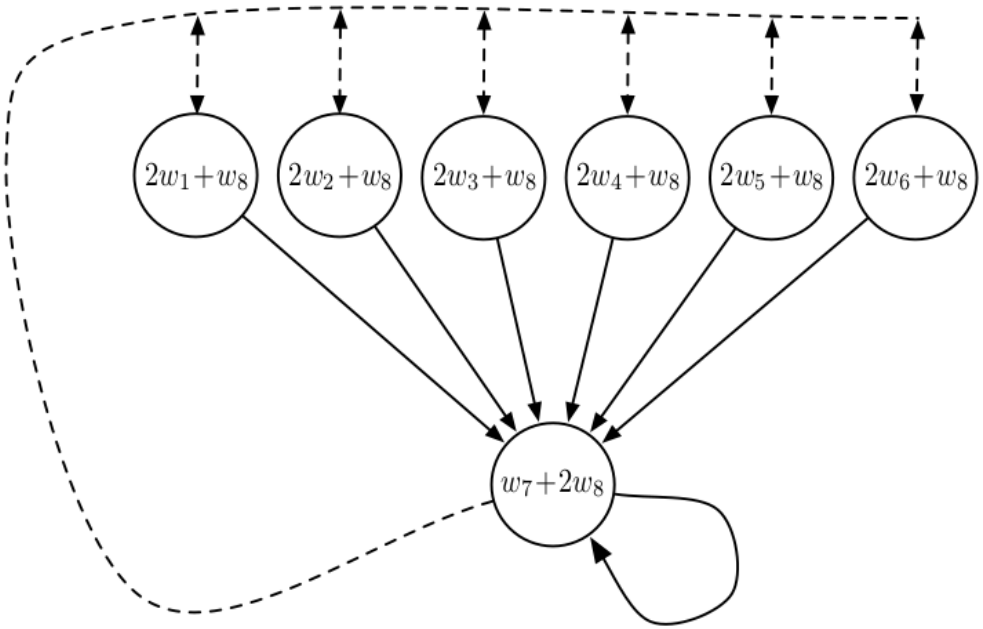
Convergence of TD Methods with VFA

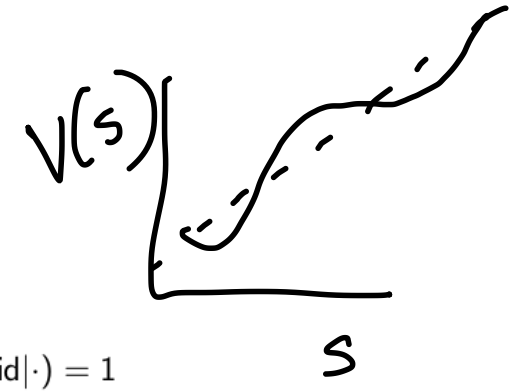
- Informally, updates involve doing an (approximate) Bellman backup followed by best trying to fit underlying value function to a particular feature representation
- Bellman operators are contractions, but value function approximation fitting can be an expansion

$$\|\check{\beta}V - \tilde{\beta}V'\| \not\leq \|V - V'\|$$

1995
Gordon

Challenges of Off Policy Control: Baird Example [1]



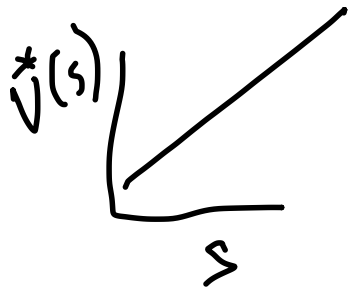


$\pi(\text{solid}|\cdot) = 1$

$\mu(\text{dashed}|\cdot) = 6/7$

$\mu(\text{solid}|\cdot) = 1/7$

$\gamma = 0.99$



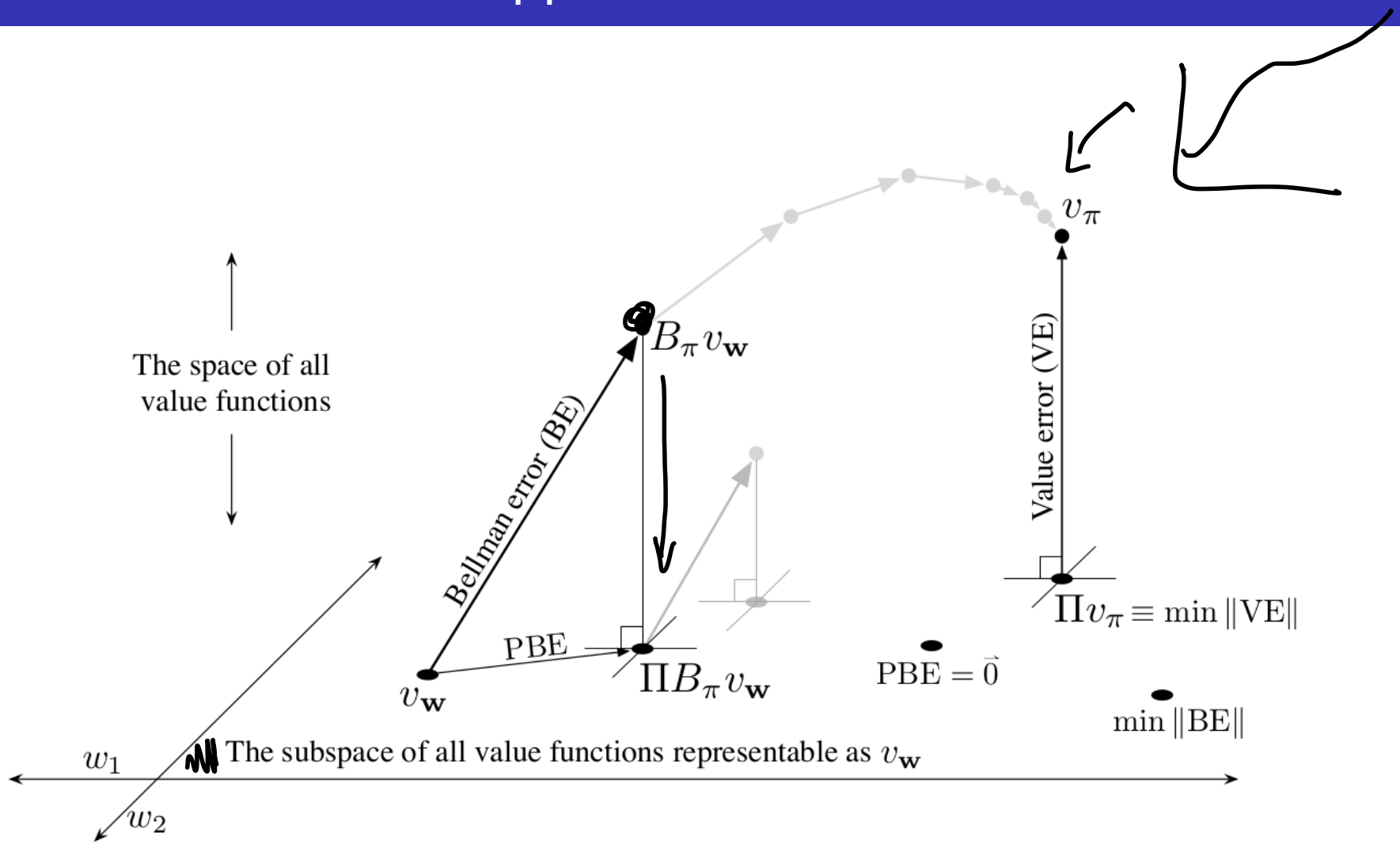
- Behavior policy and target policy are not identical
- Value can diverge

Convergence of Control Methods with VFA

Algorithm	Tabular	Linear VFA	Nonlinear VFA
Monte-Carlo Control	✓	✓	?
Sarsa	✓	✓	
Q-learning	✓	✗	

- This is an active area of research
- An important issue is not just whether the algorithm converges, but **what** solution it converges too
- Critical choices: **objective function and feature representation**
- Chp 11 SB has a good discussion of some efforts in this direction

Linear Value Function Approximation[1]



[1] Figure from Sutton and Barto 2018

What You Should Understand

linear VFA

- Be able to implement TD(0) and MC on policy evaluation with linear value function approximation
- Be able to define what TD(0) and MC on policy evaluation with linear VFA are converging to and when this solution has 0 error and non-zero error.
- Be able to implement Q-learning and SARSA and MC control algorithms
- List the 3 issues that can cause instability and describe the problems qualitatively: function approximation, bootstrapping and off policy learning

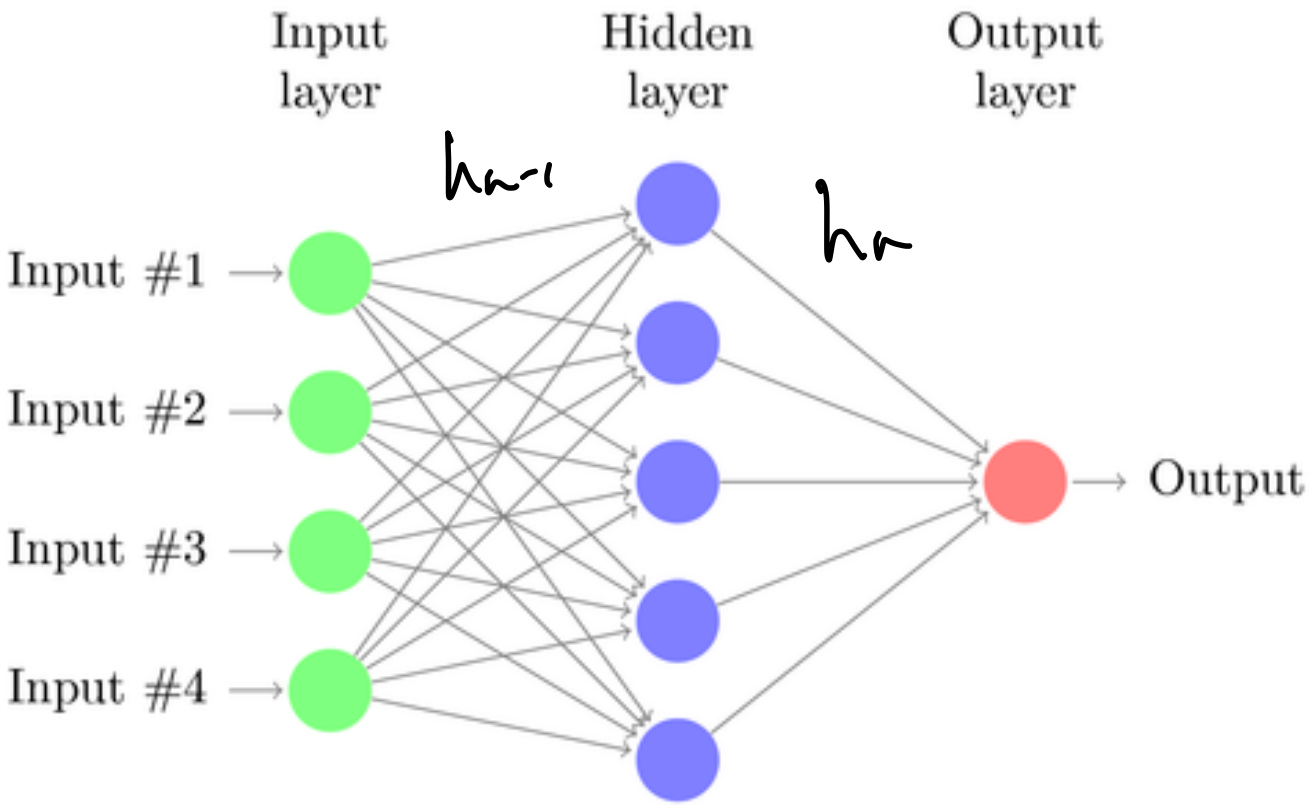
Class Structure

- 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

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 [2]

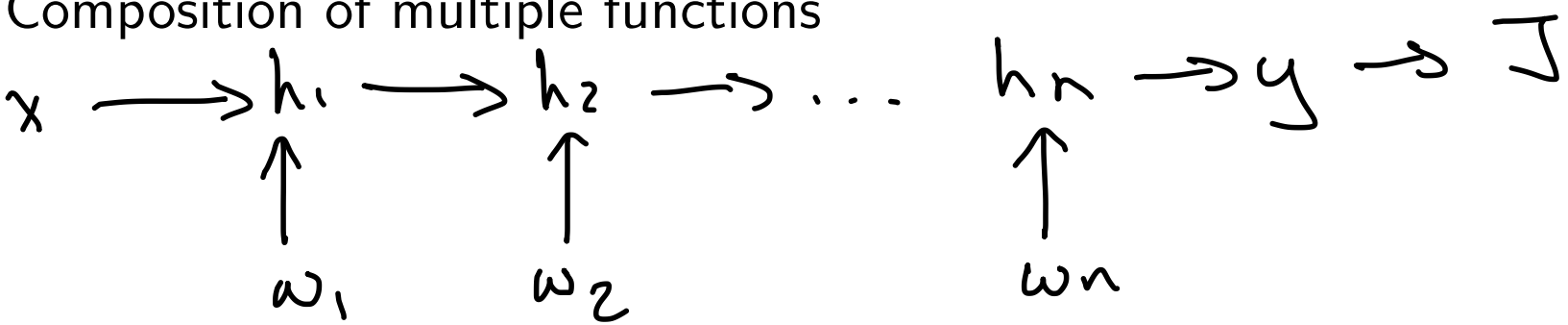


[2] Figure by Kjell Magne Fauske

Deep Neural Networks (DNN)

$$y = h_n(h_{n-1}(\dots(\vec{x})))$$

- Composition of multiple functions



- Can use the chain rule to backpropagate the gradient

$$dJ/dw_1 \quad dJ/dh_n \; dh_n/dh_{n-1} \dots dh_1/dw_1$$

- 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: $h_n = W h_{n-1}$
  - Non-linear: 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
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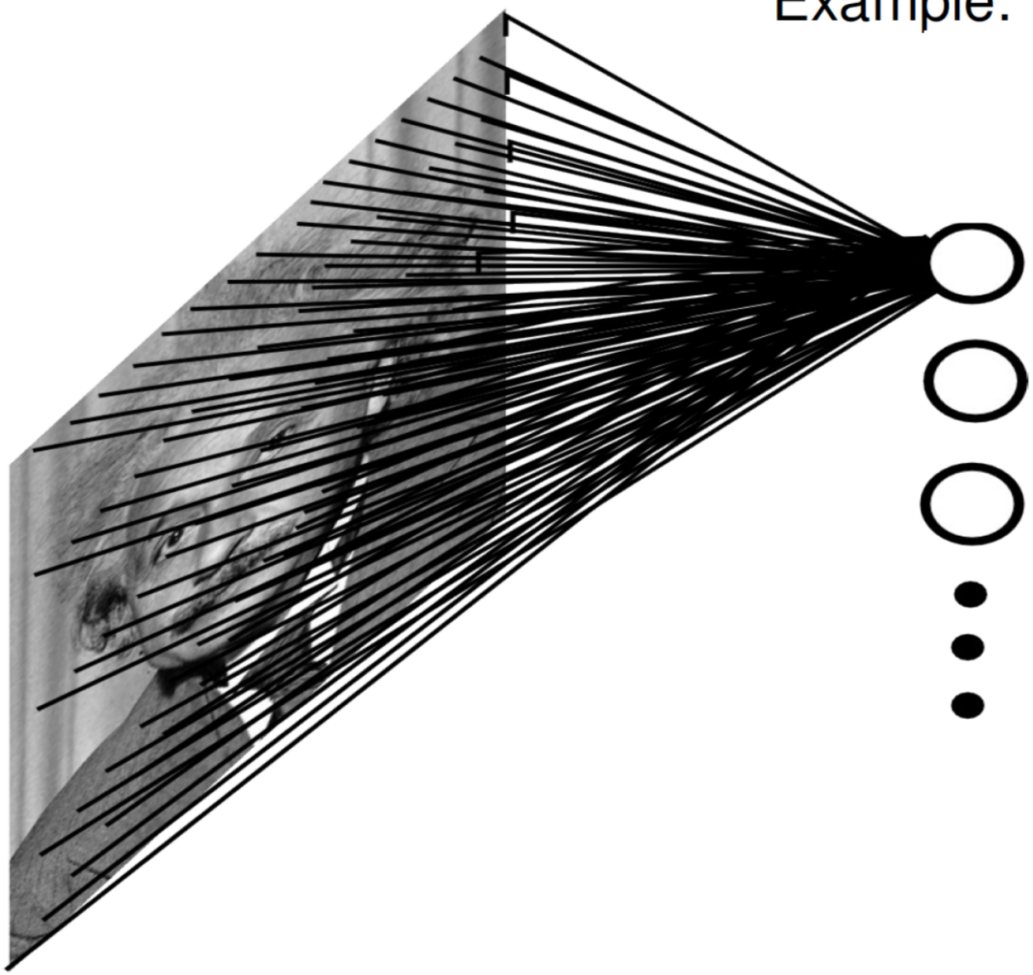
- But can require carefully hand designing that feature set
- An alternative is to use a much richer function approximation class that is able to directly go from states without requiring an explicit specification of features
- Local representations including Kernel based approaches have some appealing 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

Table of Contents

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



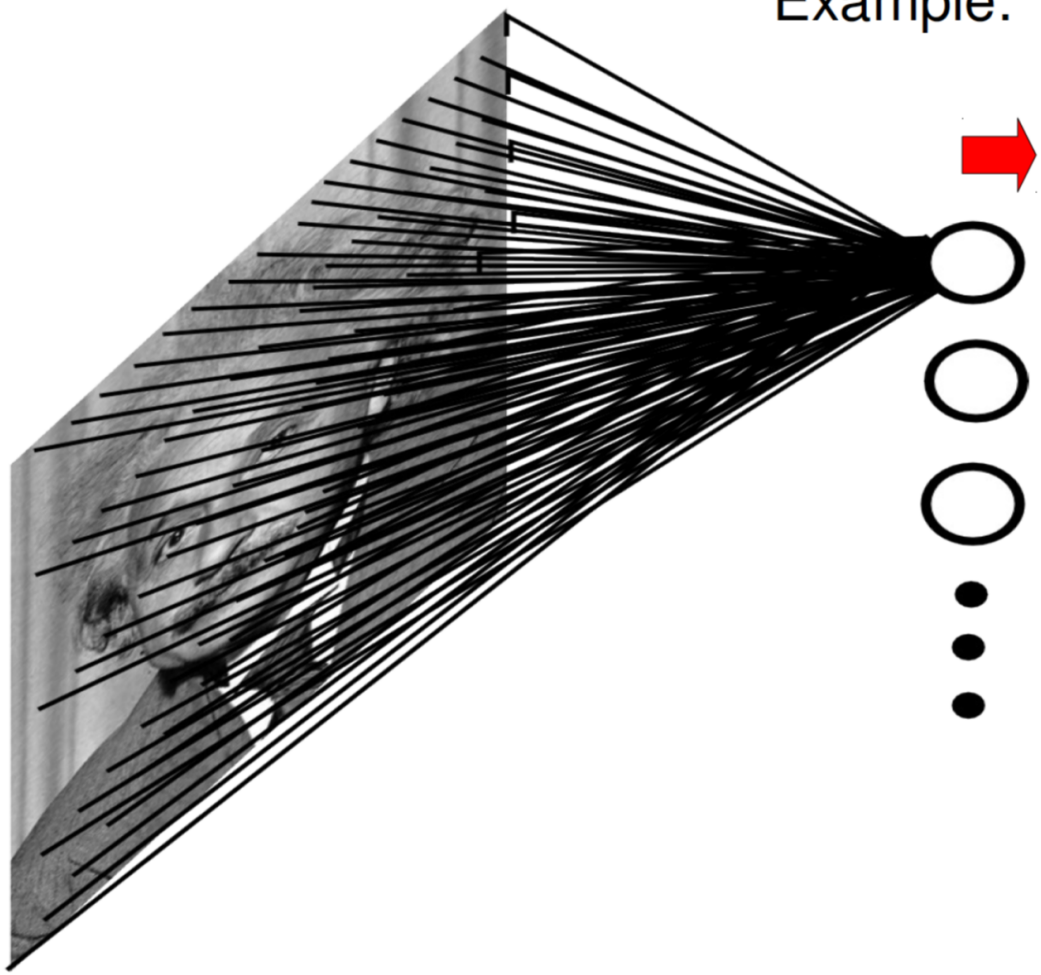
Example: 1000x1000 image

10^6

How many weight parameters for a single node which is a linear combination of input?

Ranzato

Fully Connected Neural Net



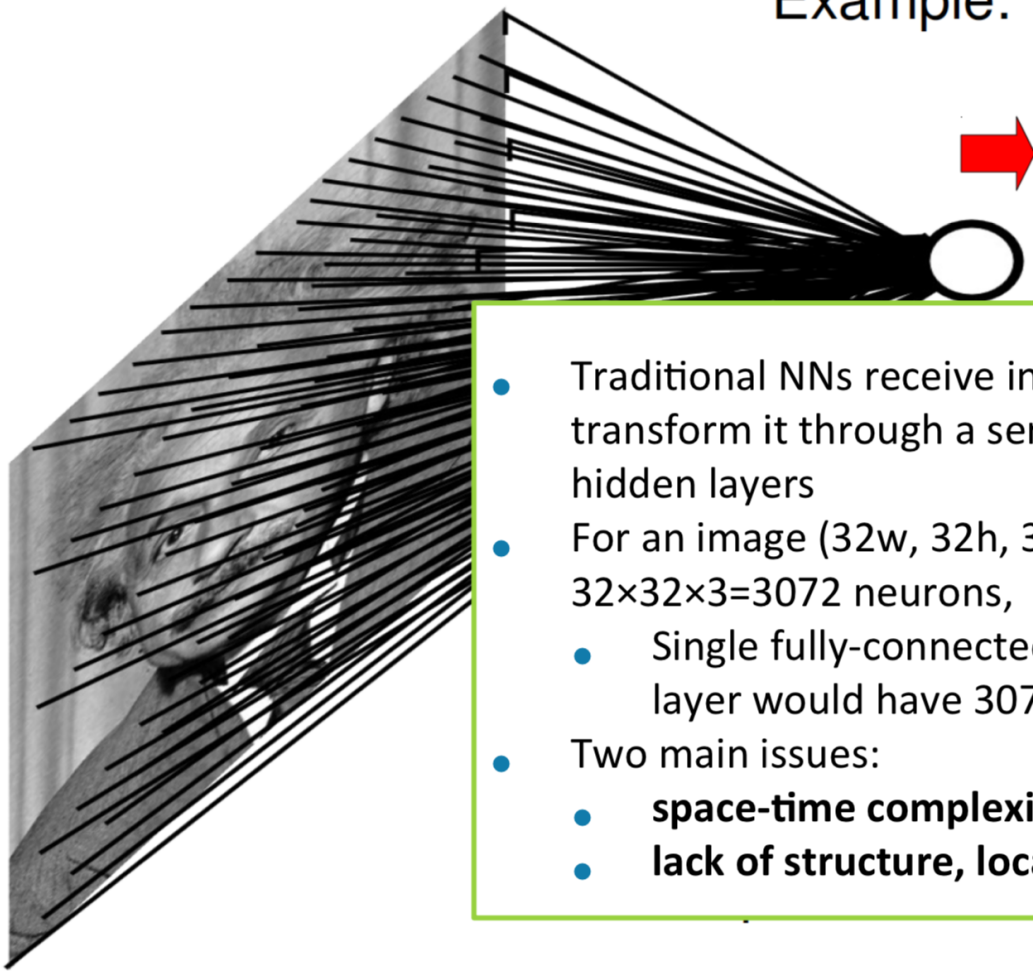
Example: 1000x1000 image

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**

Ranzato

Images Have Structure

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

Convolutional NN

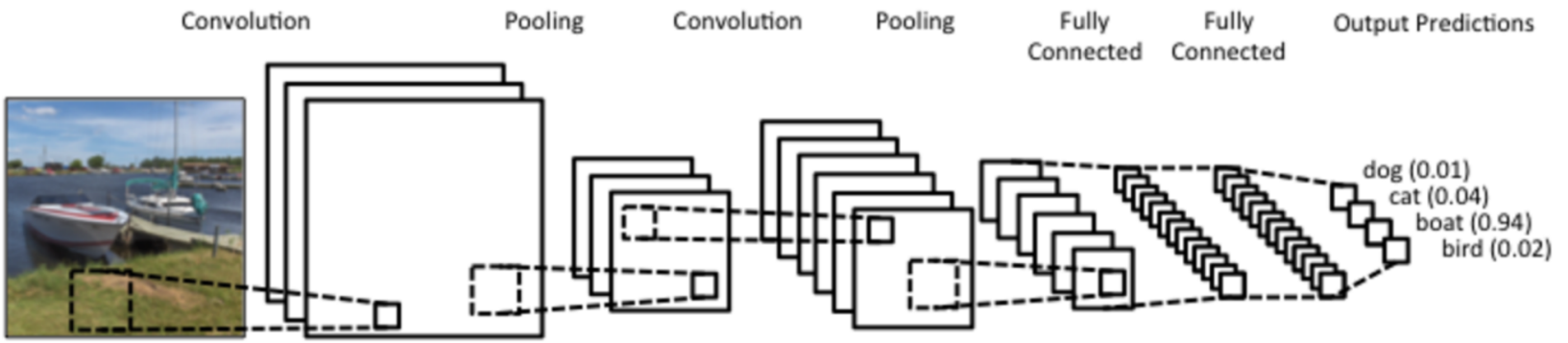
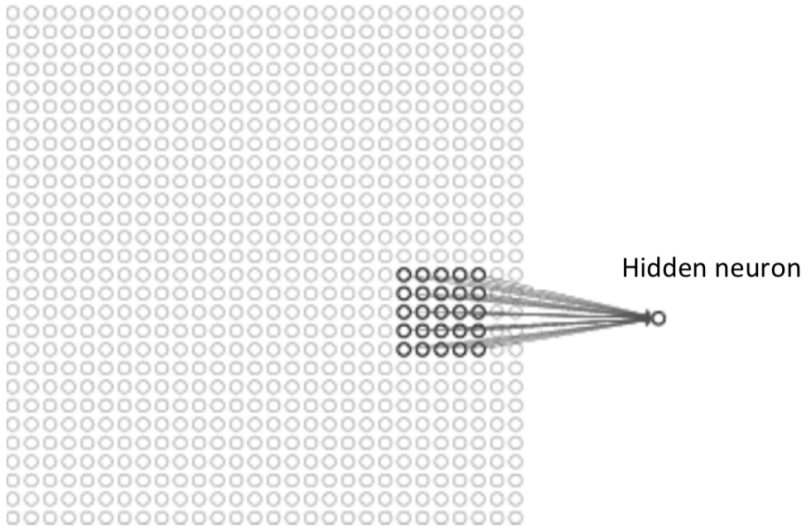
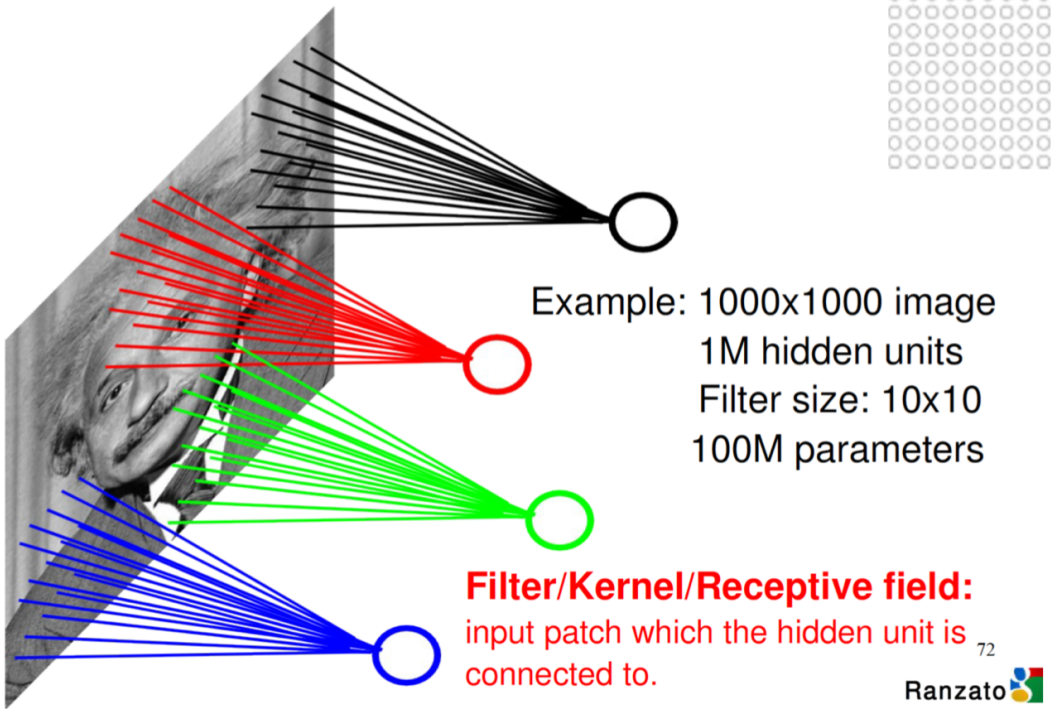


Image: http://d3kbpzbmcynnmx.cloudfront.net/wp-content/uploads/2015/11/Screen-Shot-2015-11-07-at-7.26.20-AM.png

- 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

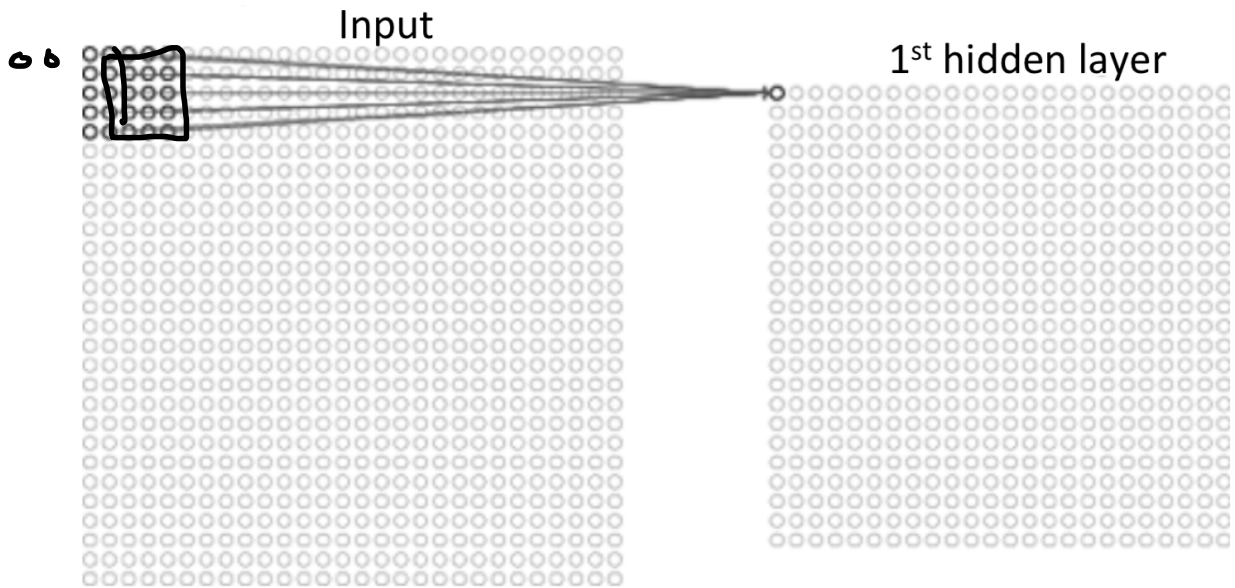
Locality of Information: Receptive Fields





(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? 24×24



- Zero padding: how many 0s to add to either side of input layer

Shared Weights

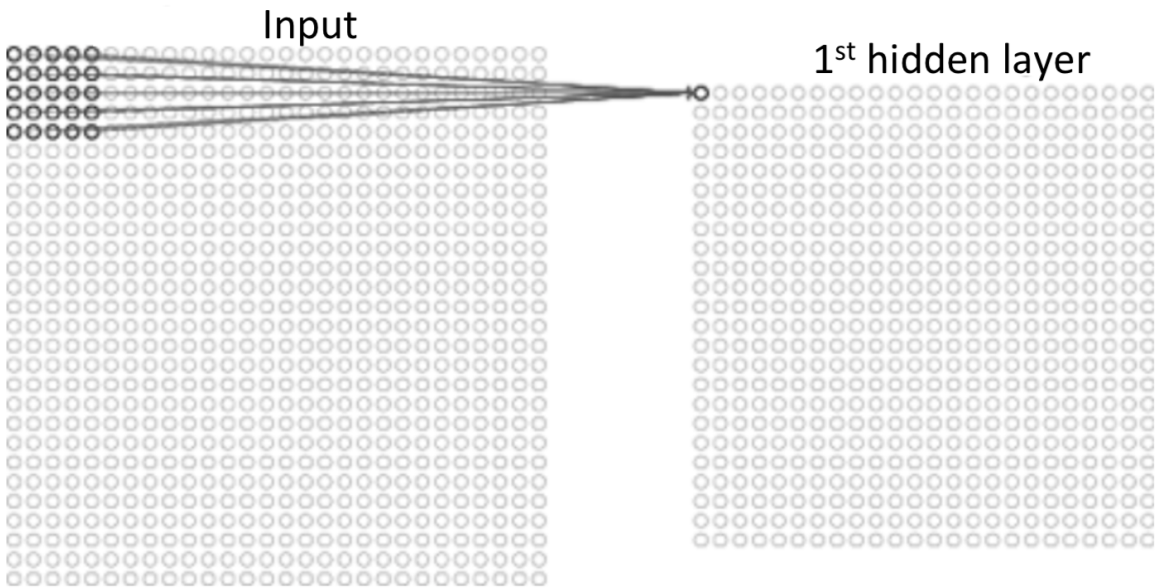
- What is the precise relationship between the neurons in the receptive field and that in the hidden layer?
- What is the *activation value* of the hidden layer neuron?

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

- 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

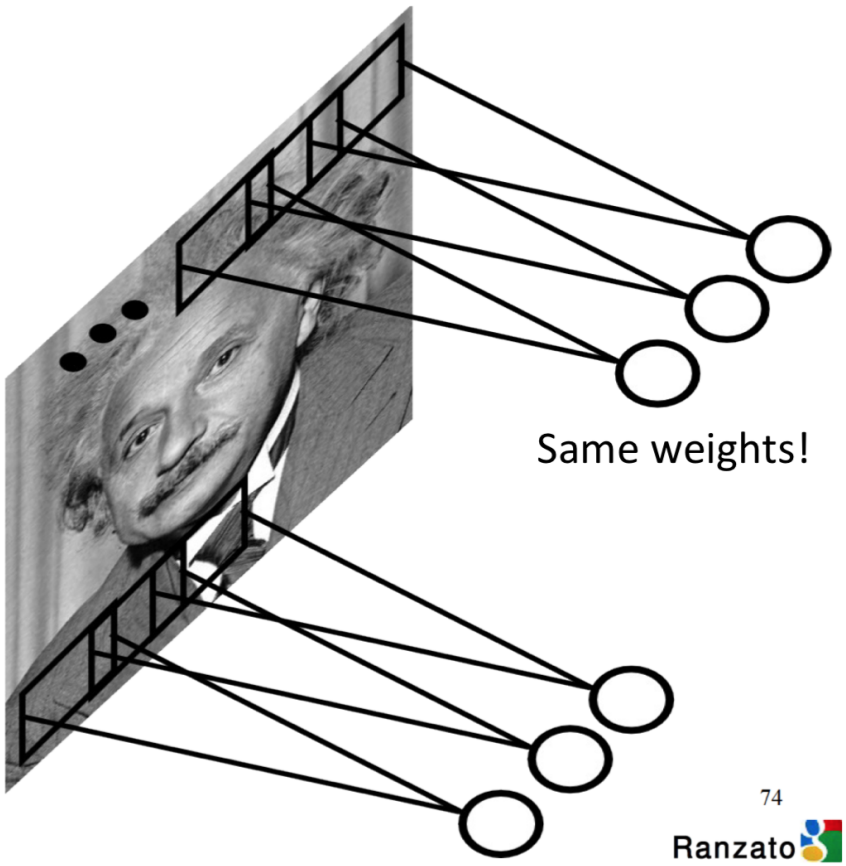


- Receptive field is 5x5

Feature Map

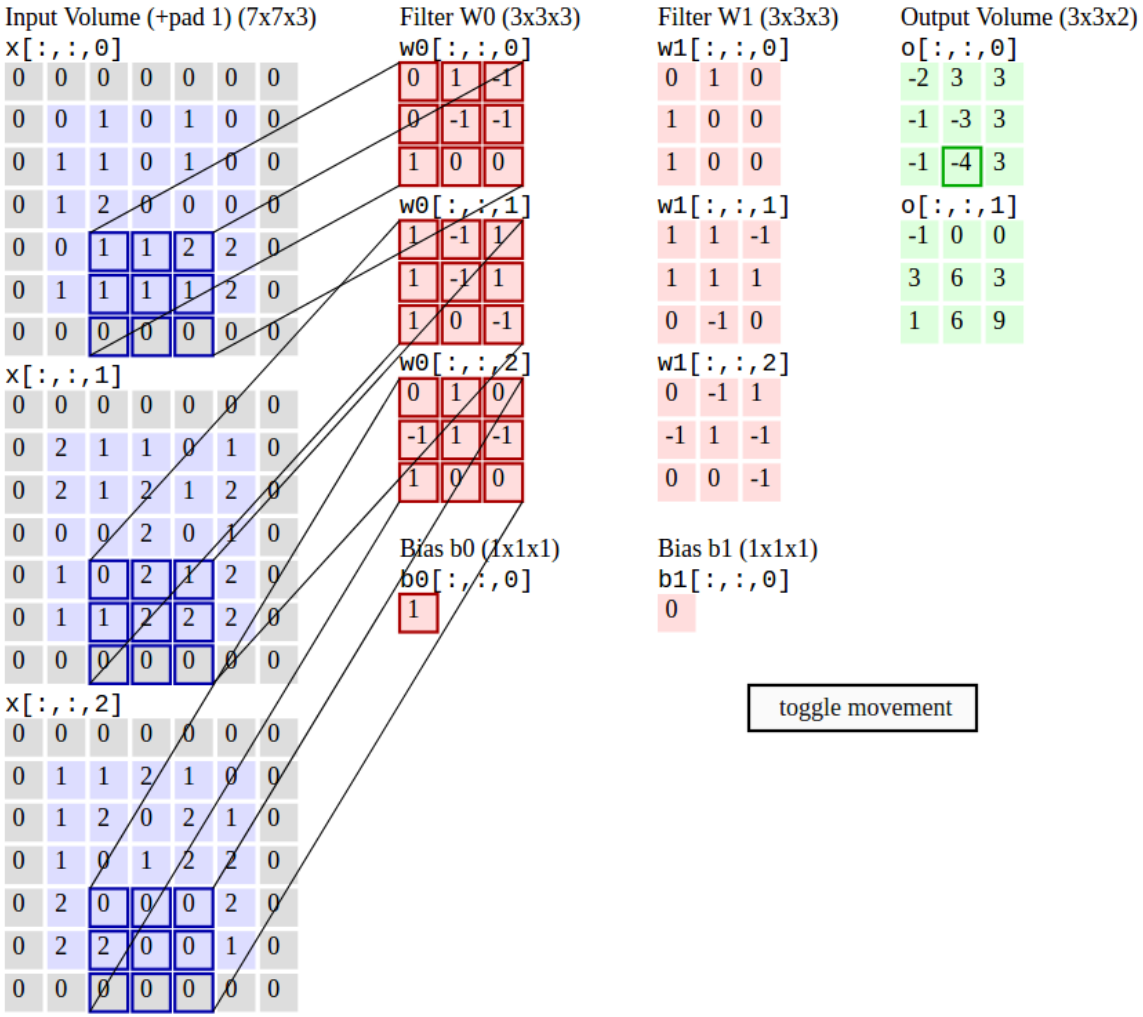
- All the neurons in the first hidden layer *detect exactly the same feature, just at different locations* in the input image.
- **Feature**: the kind of input pattern (e.g., a local edge) that makes the neuron produce a certain response level
- Why does this makes sense?
  - Suppose the weights and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

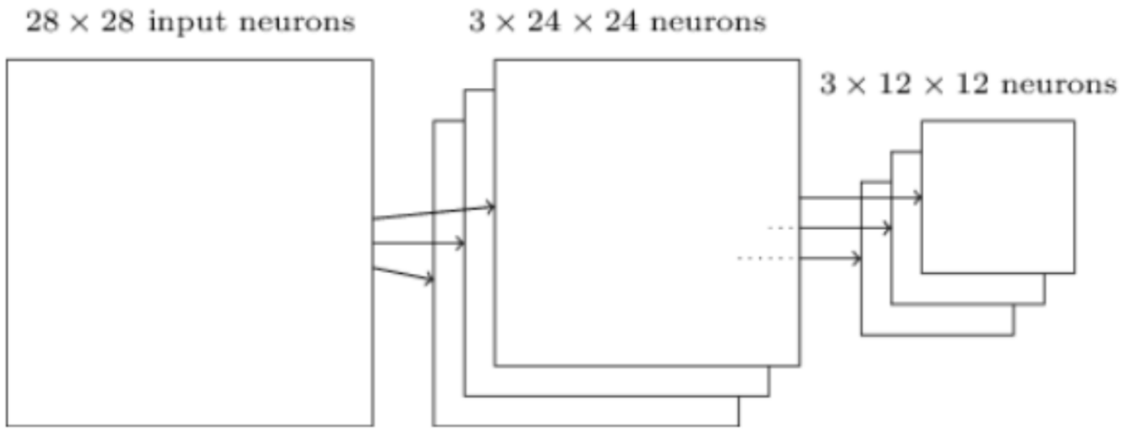
Convolutional Layer: Multiple Filters Ex.[3]



[3] 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

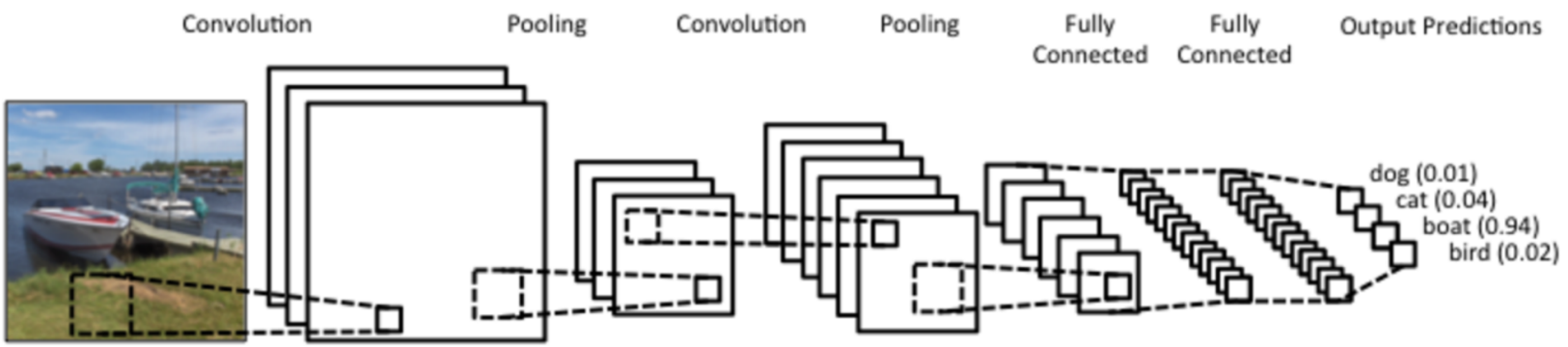


Image: http://d3kbpzbmcynnmx.cloudfront.net/wp-content/uploads/2015/11/Screen-Shot-2015-11-07-at-7.26.20-AM.png

Table of Contents

Generalization

- Using function approximation to help scale up to making decisions in really large domains

1994 backgammon
RL + NN

1995 - 1998
neg examples?
theory for
IVG

mid 2005-now
DNN

~2013/2014 deepmind
Atari

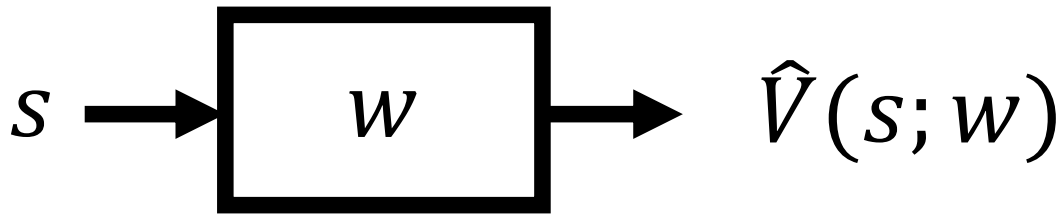
Deep Reinforcement Learning

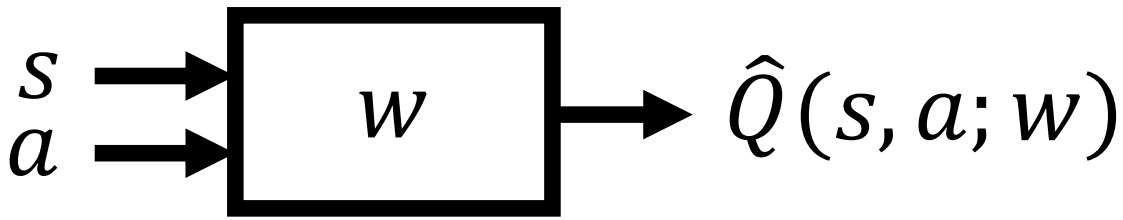
- Use deep neural networks to represent
  - Value, Q function
  - Policy
  - Model
- Optimize loss function by stochastic gradient descent (SGD)

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
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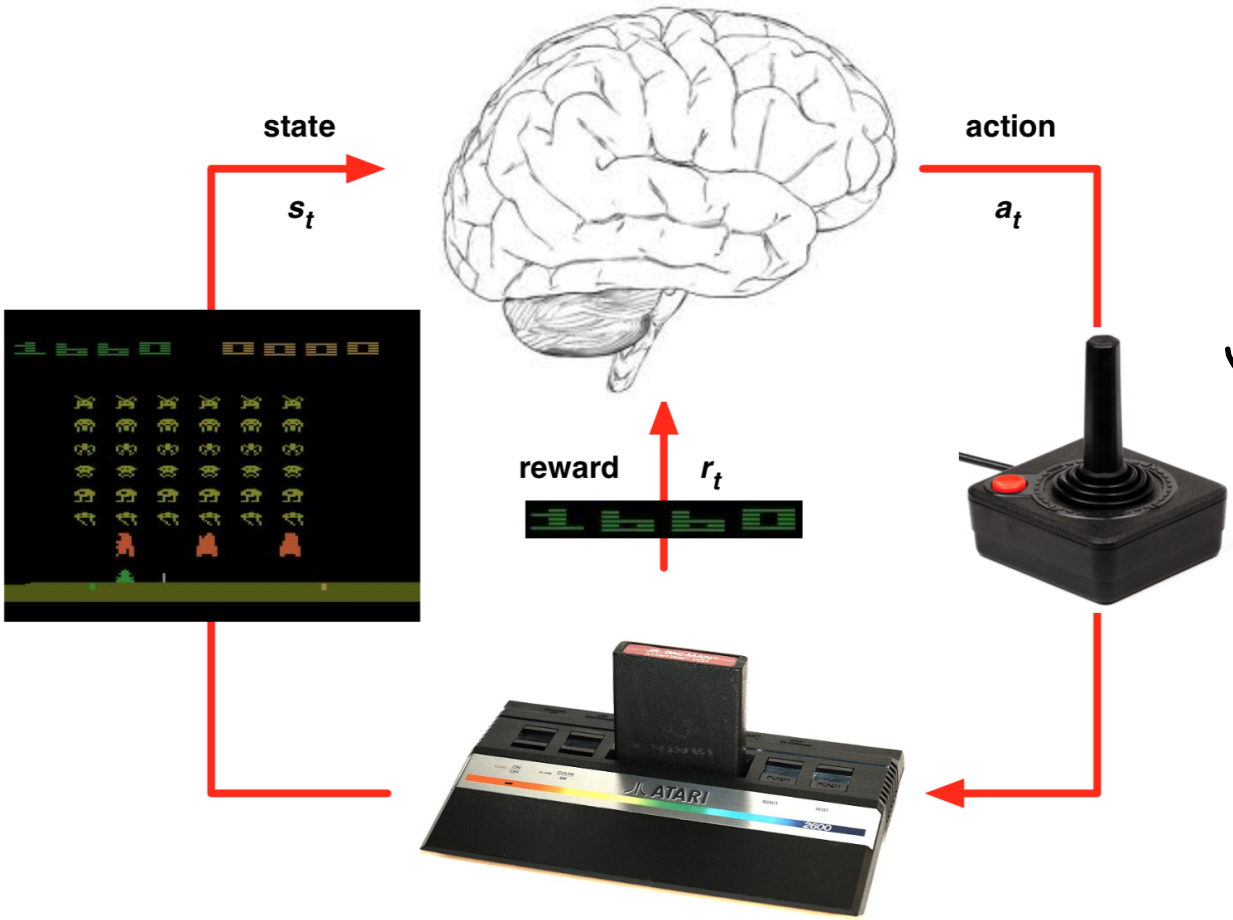
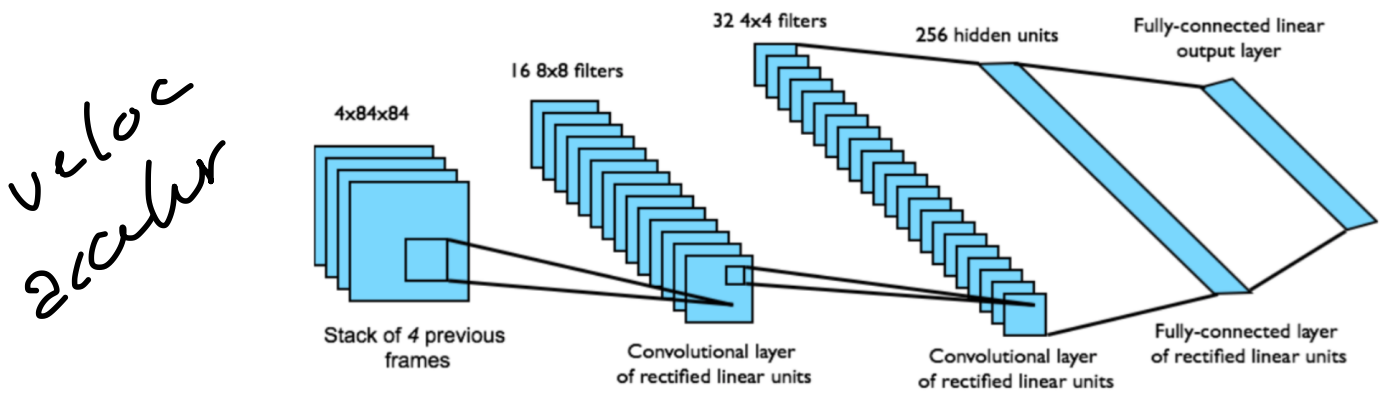
Using these ideas to do Deep RL in Atari



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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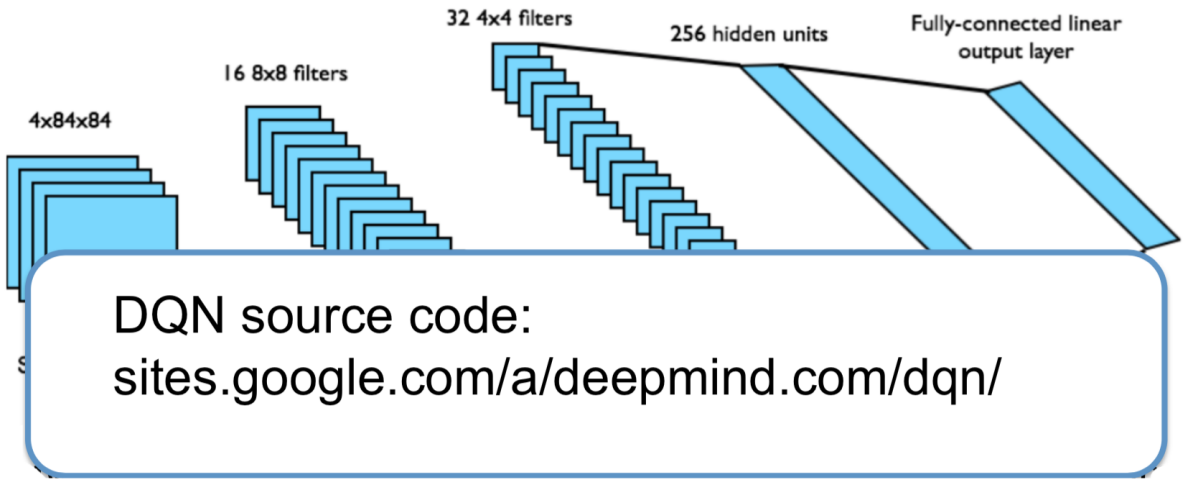


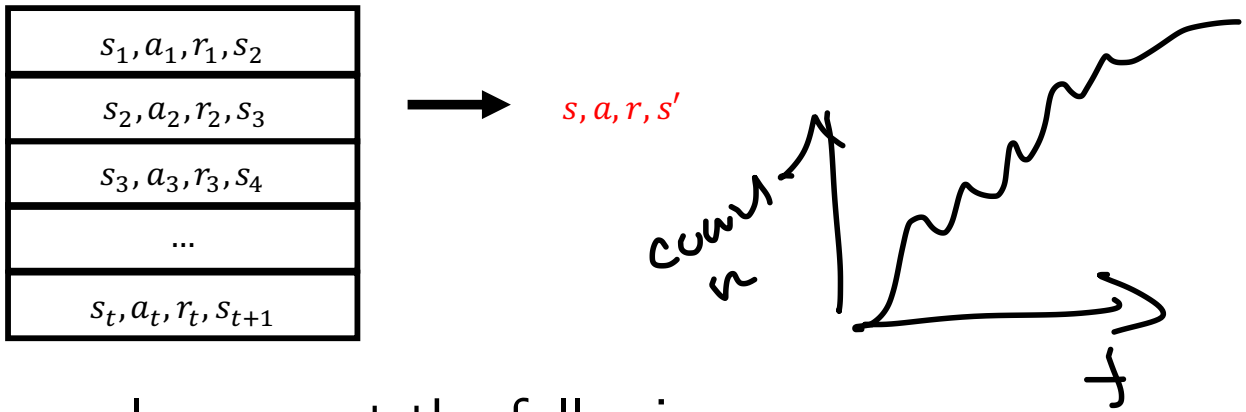
- Network architecture and hyperparameters fixed across all games

Q-Learning with Value Function Approximation

- Minimize MSE loss by stochastic gradient descent
- Converges to the optimal $Q^*(s, a)$ using table lookup representation
- But Q-learning with VFA can diverge
- Two of the issues causing problems:
  - Correlations between samples
  - Non-stationary targets
- Deep Q-learning (DQN) addresses both of 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



- 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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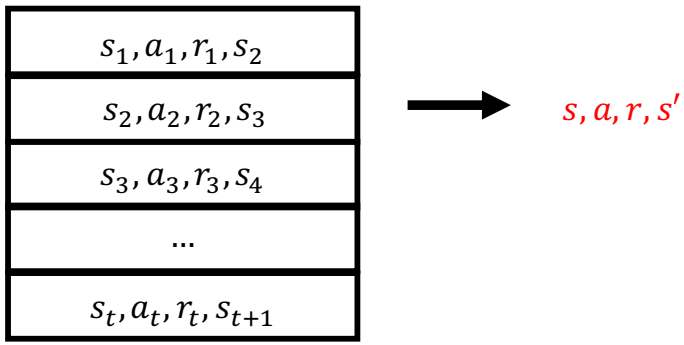

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- **Can treat the target as a scalar, but the weights will get updated on the next round, changing the target value**

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

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

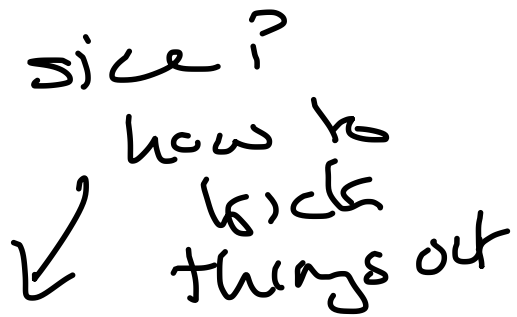
$Q^*(s,a)$

Check Your Understanding: Fixed Targets

- In DQN we compute the target value for the sampled 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

$r + \gamma Q_1(s, \underset{a}{\operatorname{argmax}} Q_2(s, a_2))$

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

Periodically we update w^-

Set $w^- \leftarrow w$

DQN

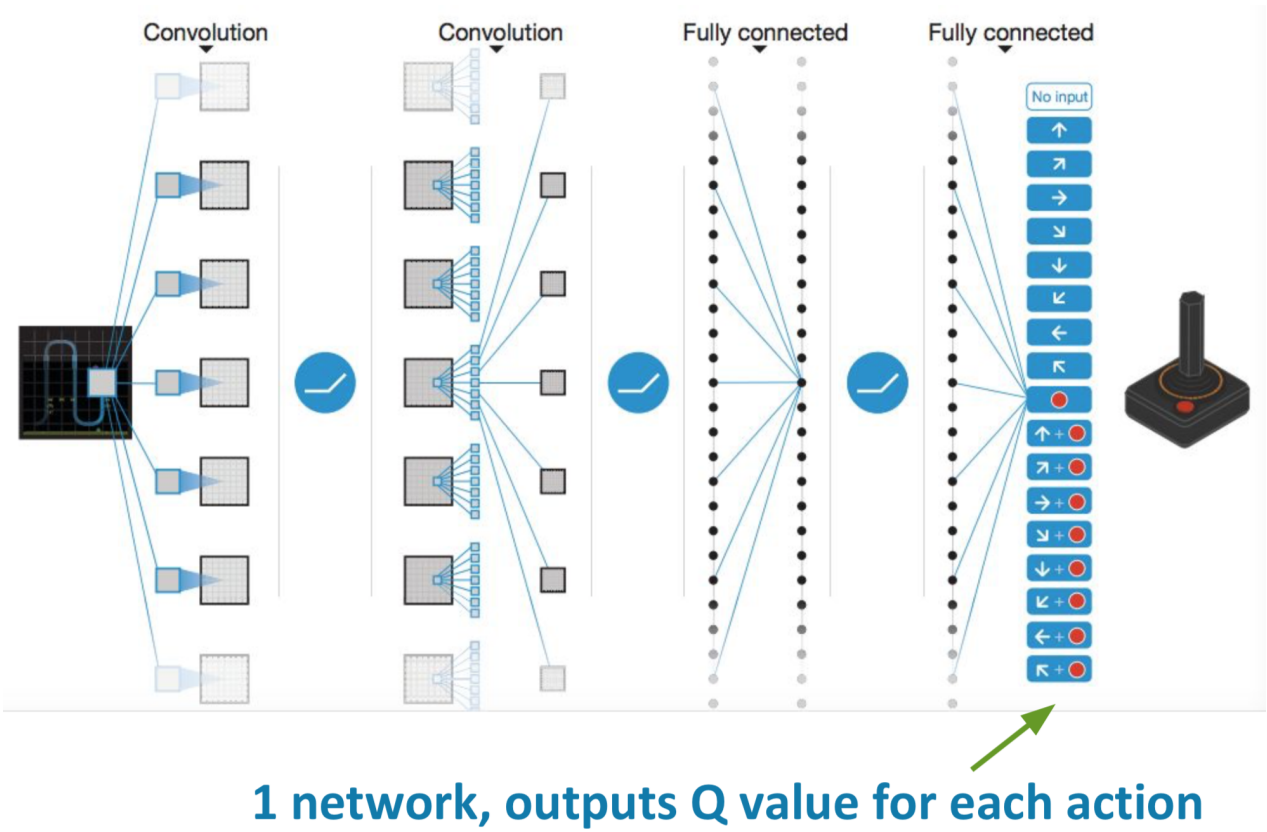


Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015

Demo

DQN Results in Atari

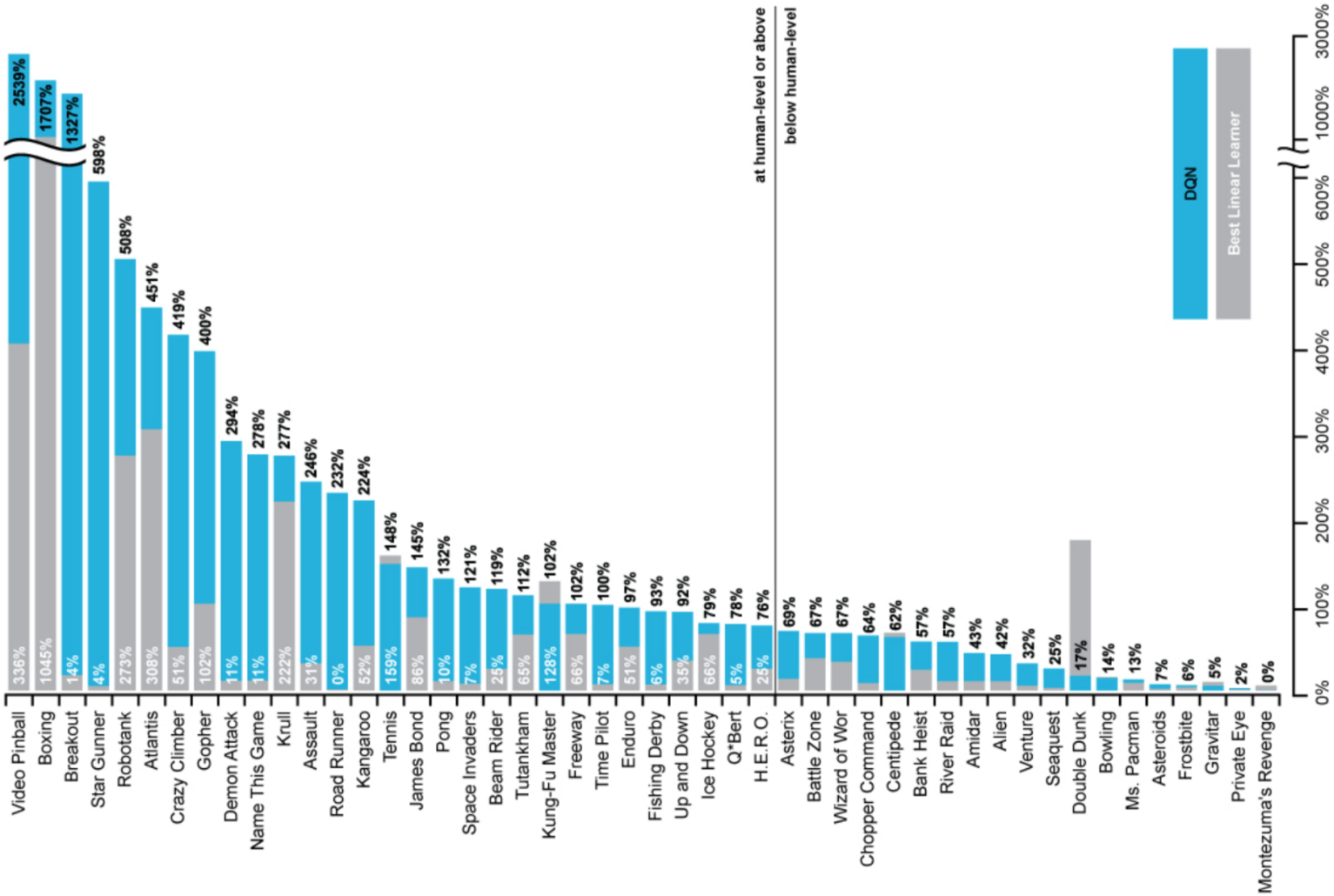


Figure: Human-level control through deep reinforcement learning, Mnih et al, 2015

Which Aspects of DQN were Important for Success?

Game	Linear	Deep Network	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