Deep Q-learning Network

* With some material from David Silver (UCL), Emma Brunskill (Standford), Jiehan Chen (NCKU)

RL with Function Approximator

- 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

The Benefit of Deep Neural Network Approximators

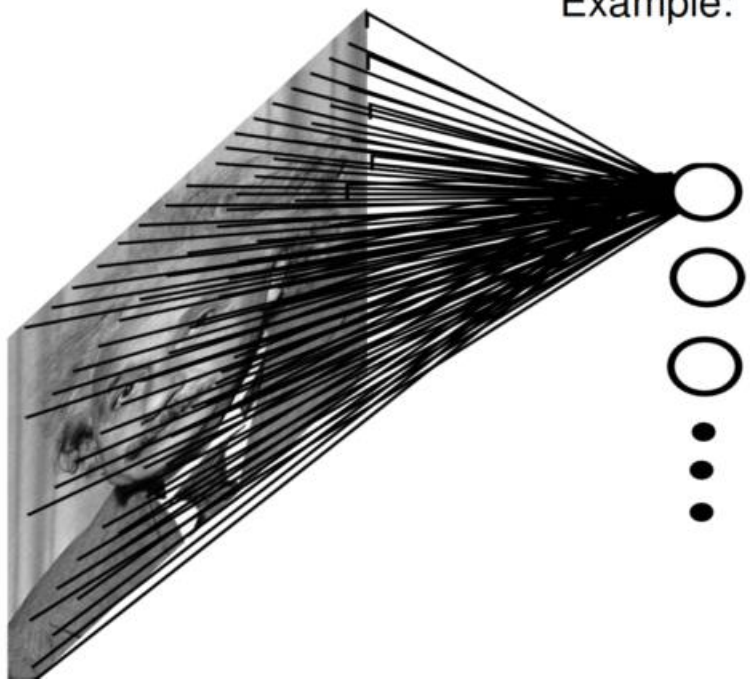
- Uses distributed representations instead of local representations
- Universal function approximator
- Can potentially need exponentially less nodes/parameters (compared to a shallow net) to represent the same function
- Can learn the parameters using stochastic gradient descent

Convolutional Neural Nets (CNNs)

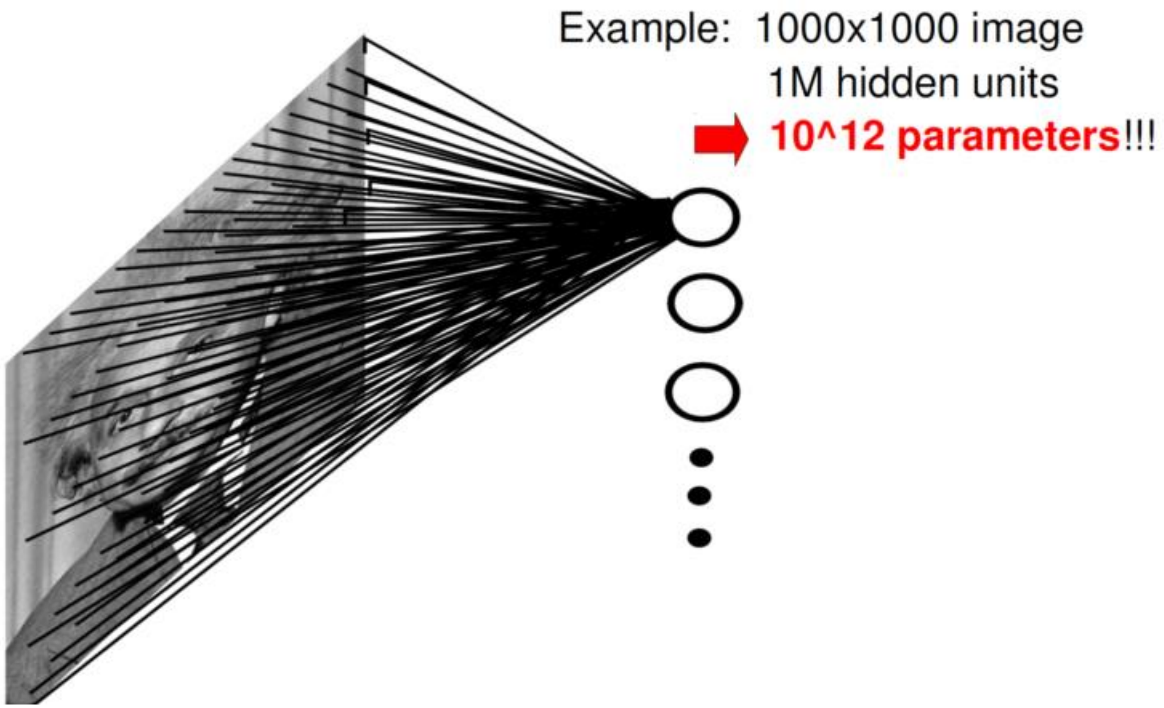
- CNNs extensively used in computer vision
- If we want to go from pixels to decisions, likely useful to leverage insights for visual input

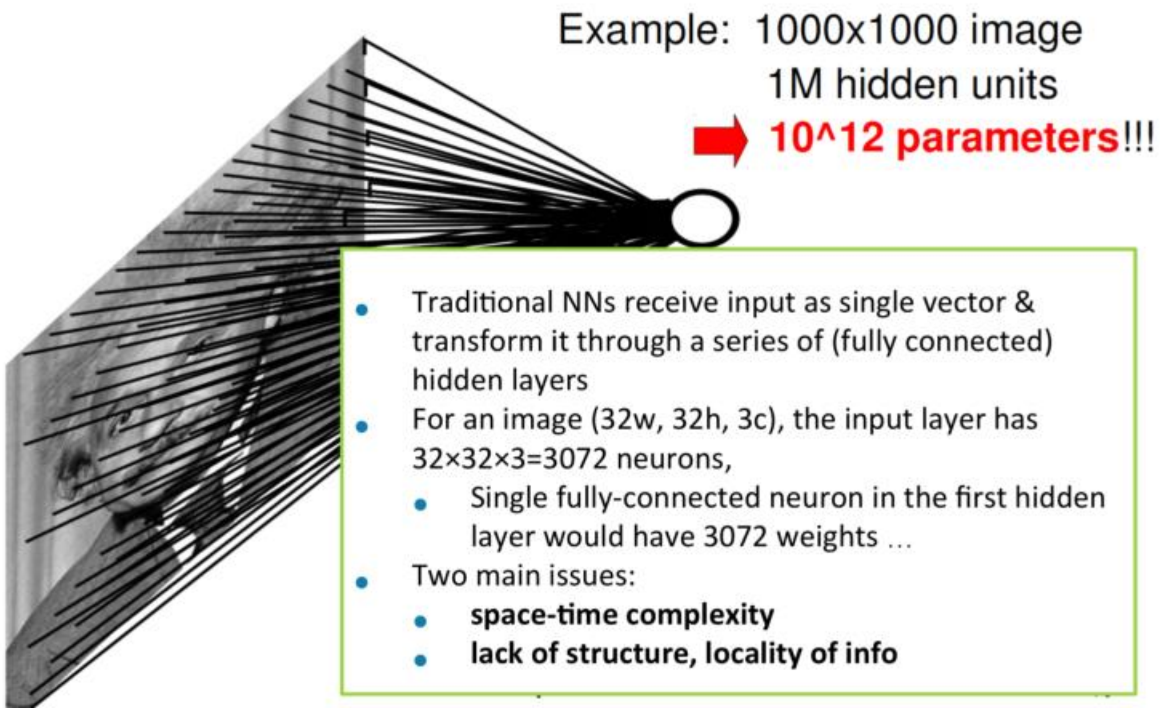
Fully Connected Neural Net

Example: 1000x1000 image



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


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


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

Images Have Structure

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

Convolutional NN

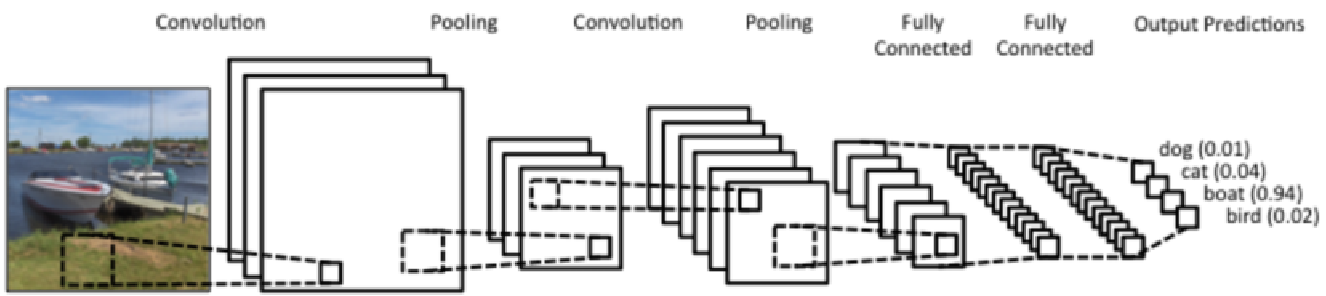
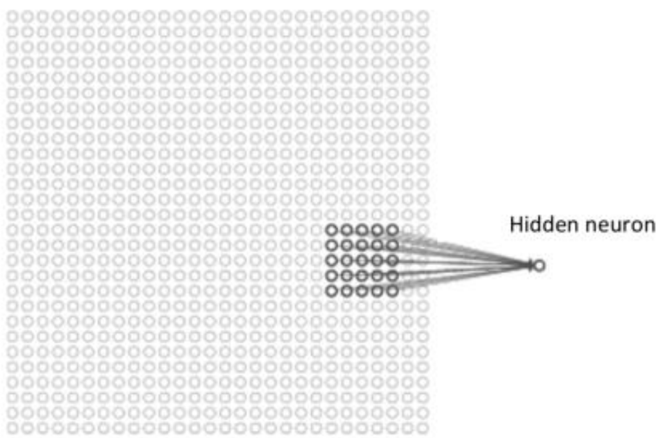
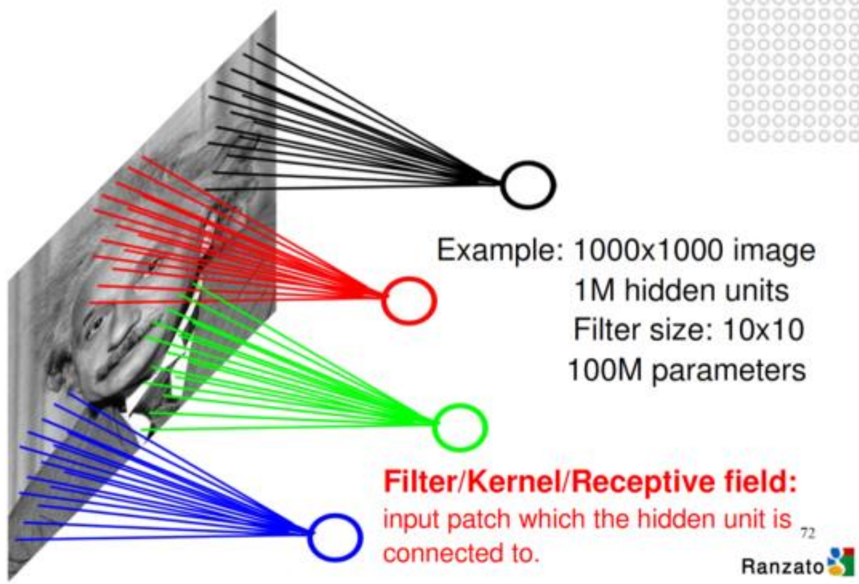


Image: http://d3kbpzbmcynnmx.cloudfront.net/wp-content/uploads/2015/11/Screen-Shot-2015-11-07-at-7.26.20-AM.png

- 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

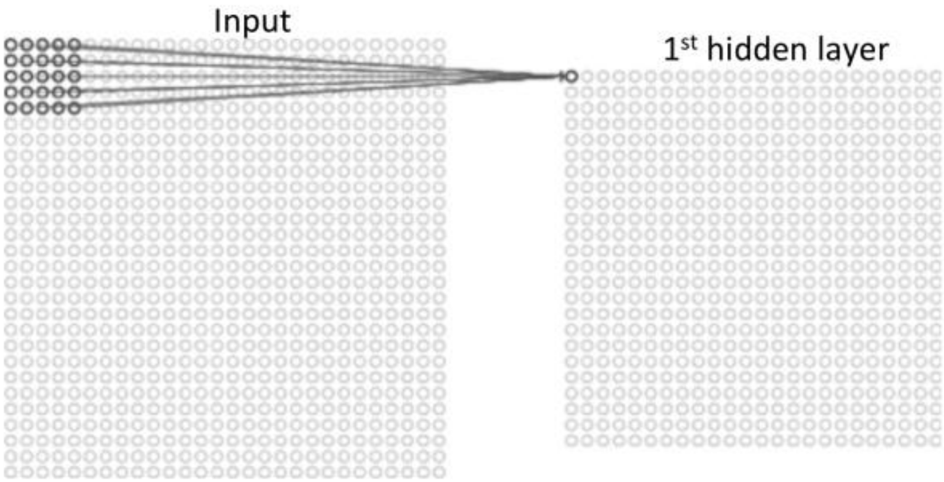
Locality of Information: Receptive Fields





(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

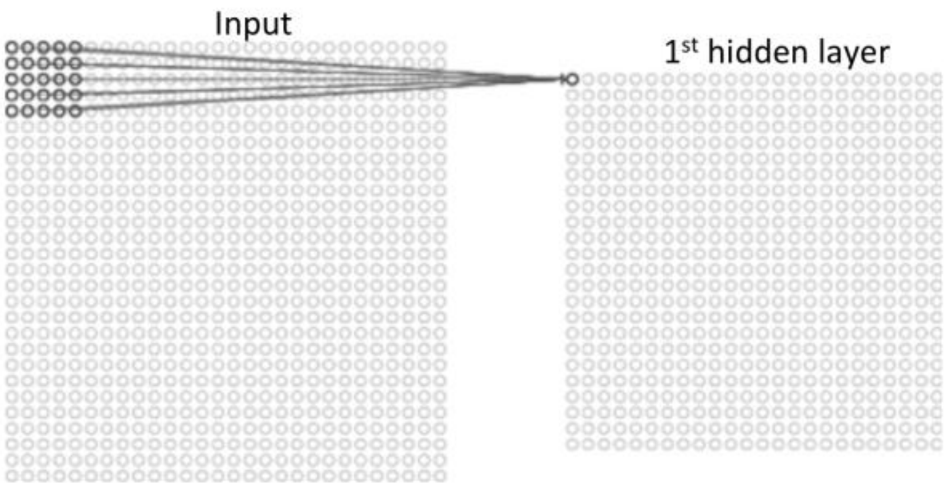
- What is the precise relationship between the neurons in the receptive field and that in the hidden layer?
- What is the *activation value* of the hidden layer neuron?

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

- 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

Shared Weights, Restricted Field

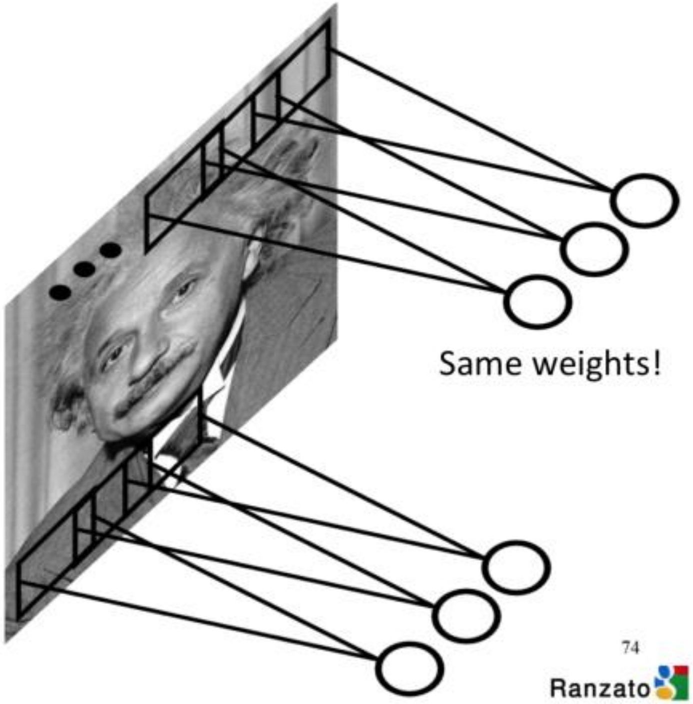
- Consider 28x28 input image
- 24x24 hidden layer



- Receptive field is 5x5

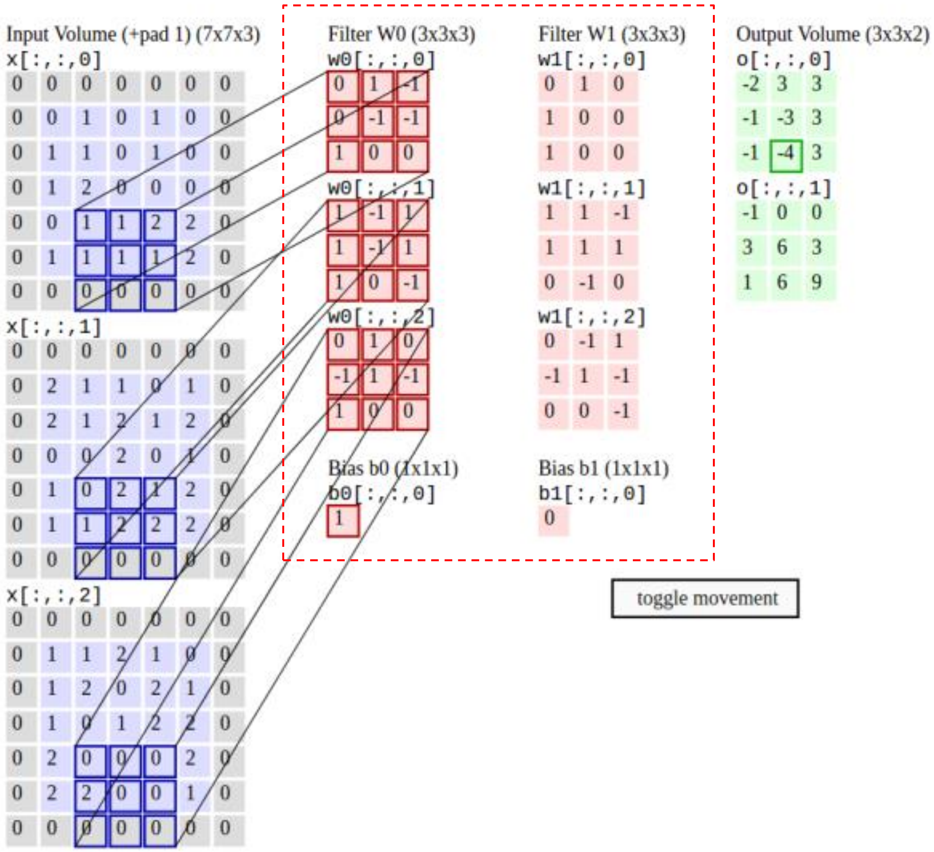
Feature Map

- 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



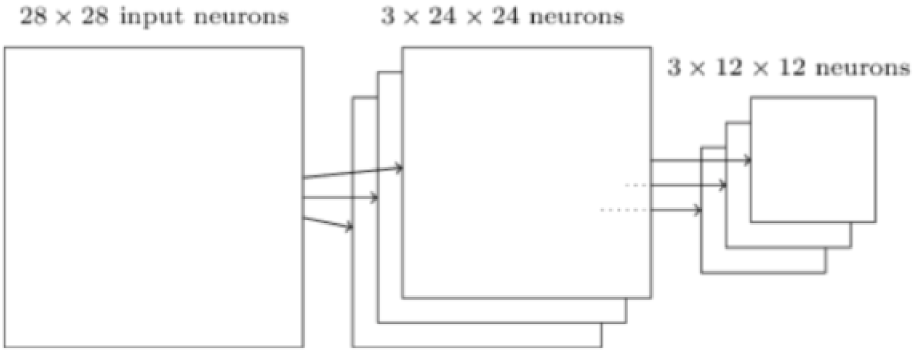
- The map from the input layer to the hidden layer is therefore a feature map: all nodes detect the same feature in different parts
- The map is defined by the shared weights and bias
- The shared map is the result of the application of a convolutional filter (defined by weights and bias), also known as convolution with learned kernels

Convolutional Layer: Multiple Filters

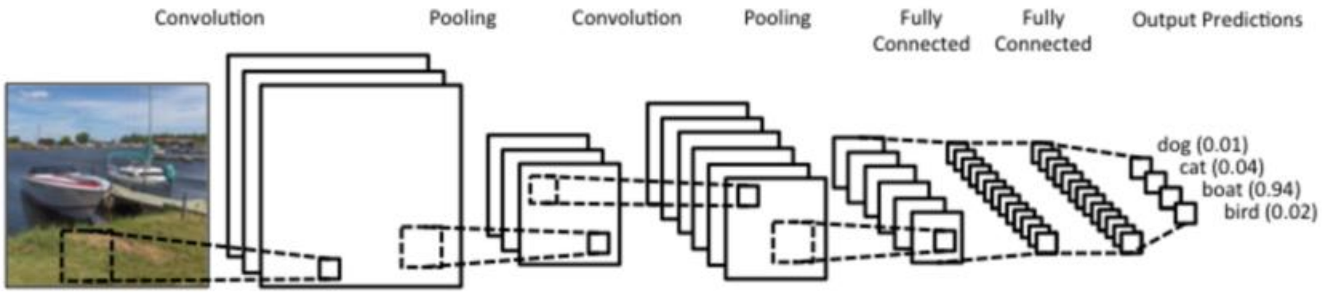


Pooling Layers

- 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



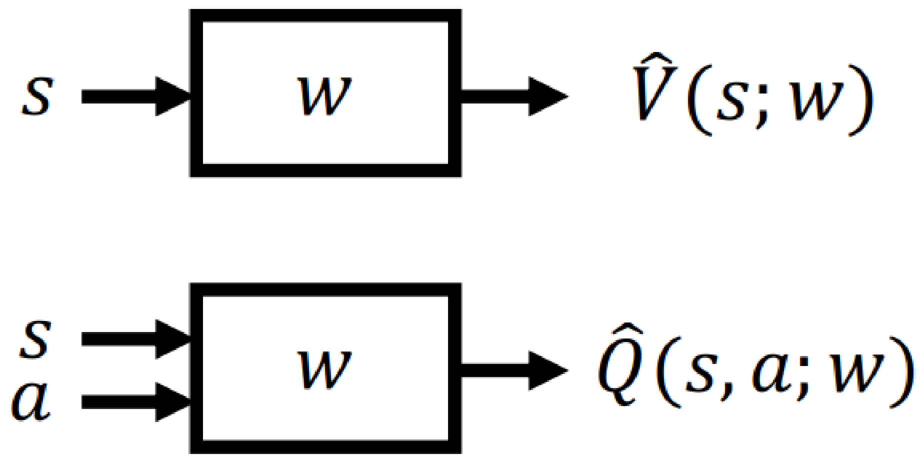
Deep Q-Learning

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

Deep Q-Networks (DQNs)

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

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



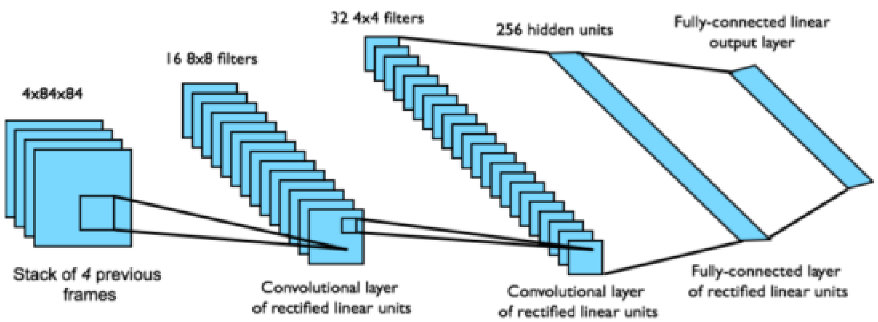
Deep Q-Networks (DQNs)

1. proposed by V Mnih, K Kavukcuoglu, **David Silver** et al., DeepMind [1][2]
2. use neural network as **non-linear** function approximator
3. DQN = Deep Learning + Q-Learning
4. use Atari Game as their testbed

[1]V Mnih et al., Playing Atari with Deep Reinforcement Learning
[2]V Mnih et al., Human-level control through deep reinforcement learning (2015 Nature)

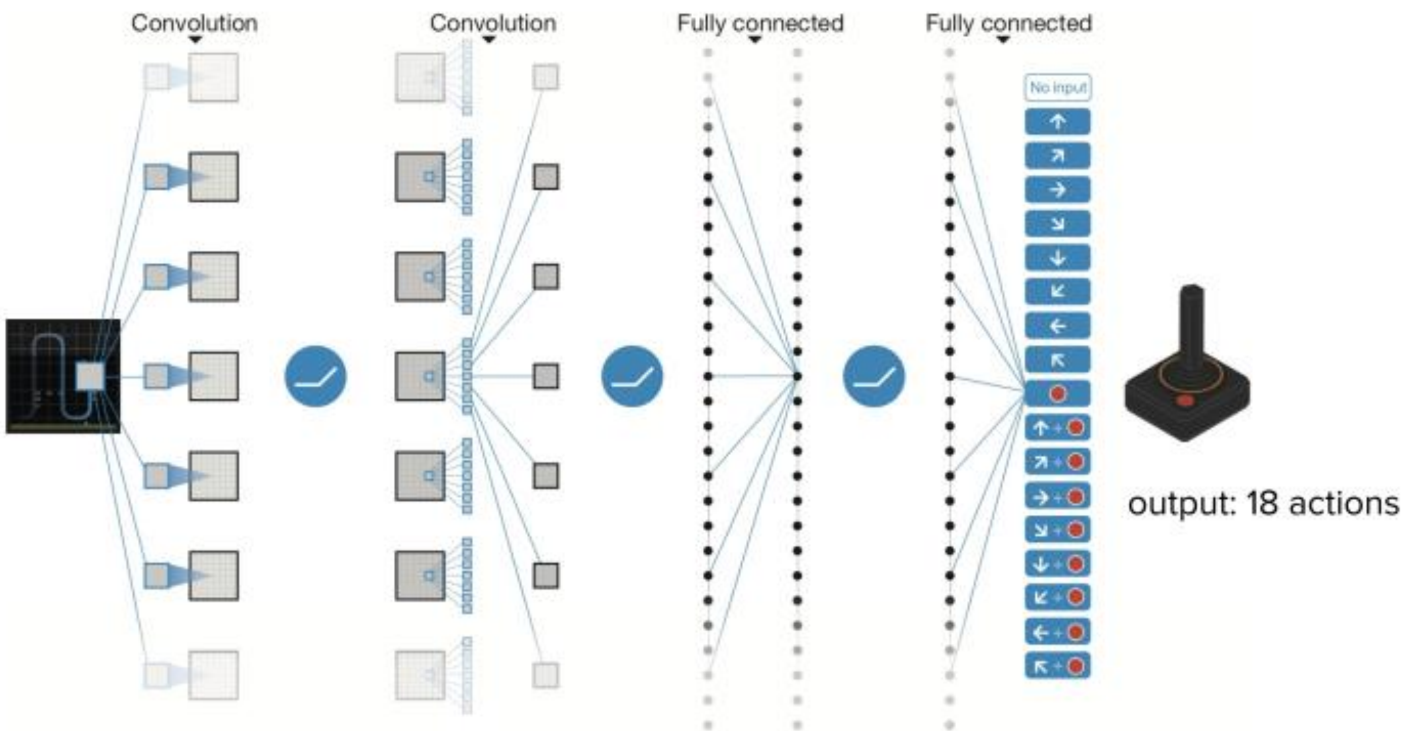
DQNs in Atari

- 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



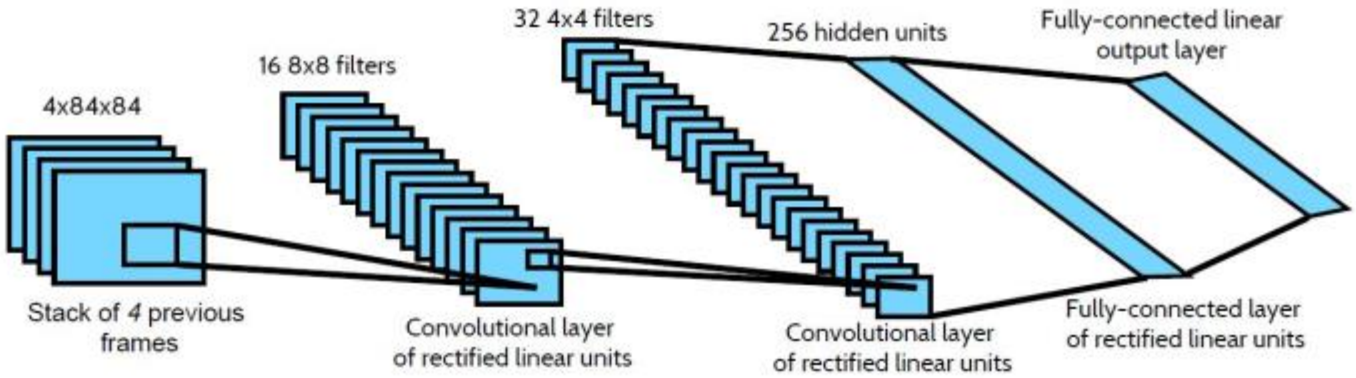
- Network architecture and hyperparameters fixed across all games

DQN – Network Structure



DQN – Network Structure(2013)

1. 2 Convolutional neural network
   a. 16 filters, 8x8 each with 4 stride
   b. 32 filters, 4x4 each with 2 stride
2. 2 Fully Connected network
   a. flatten to 256 neurons
   b. 256 to # of actions (output layer)
3. Without:
   a. pooling
   b. batch normalization
   c. dropout



DQN – Network Structure(Nature 2015)

DQN - Network Architecture (Nature 2015)

1. 3 Convolutional neural network
   a. 32 filters, 8x8 each with 4 stride
   b. 64 filters, 4x4 each with 2 stride
   c. 64 filters, 3x3 each with 1 stride
2. 2 Fully Connected network
   a. flatten to 512 neurons
   b. 512 to # of actions (output layer)
3. Again without:
   a. pooling
   b. batch normalization
   c. dropout

DQN algorithm

We use online-learning in DQN, just like Q-learning:

step1: we observe the environement, get observation

step2: we take the action according to current observation

step3: update the neural weights

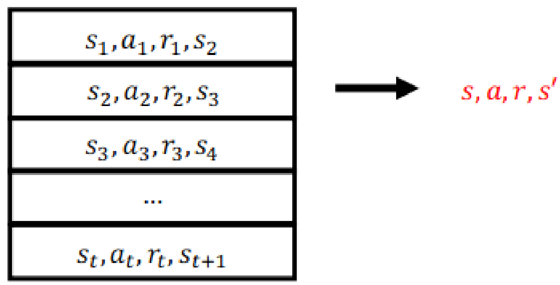
This part is called **sampling**, sample experience (s, a, r, s')

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

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

DQNs: Fixed Q-Targets

- To help improve stability, fix the **target weights** used in the target calculation for multiple updates
- Use a different set of weights to compute target than is 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

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

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

Algorithm 1: deep Q-learning with experience replay.

Initialize replay memory D to capacity N

Initialize action-value function Q with random weights θ

Initialize target action-value function $\hat{Q}$ with weights $\theta^{-} = \theta$

For episode = 1, M **do**

  Initialize sequence $s_1 = \{x_1\}$ and preprocessed sequence $\phi_1 = \phi(s_1)$

  For t = 1,T **do**

    With probability ε select a random action a_t

    otherwise select $a_t = \text{argmax}_a Q(\phi(s_t), a; \theta)$

    Execute action a_t in emulator and observe reward r_t and image x_{t+1}

    Set $s_{t+1} = s_t, a_t, x_{t+1}$ and preprocess $\phi_{t+1} = \phi(s_{t+1})$

    Store transition $(\phi_t, a_t, r_t, \phi_{t+1})$ in D

    Sample random minibatch of transitions $\left(\phi_j, a_j, r_j, \phi_{j+1}\right)$ from D

    Set $y_j = \begin{cases} r_j & \text{if episode terminates at step j+1} \\ r_j + \gamma \max_{a'} \hat{Q}\left(\phi_{j+1}, a'; \theta^{-}\right) & \text{otherwise} \end{cases}$

    Perform a gradient descent step on $\left(y_j - Q\left(\phi_j, a_j; \theta\right)\right)^2$ with respect to the network parameters θ

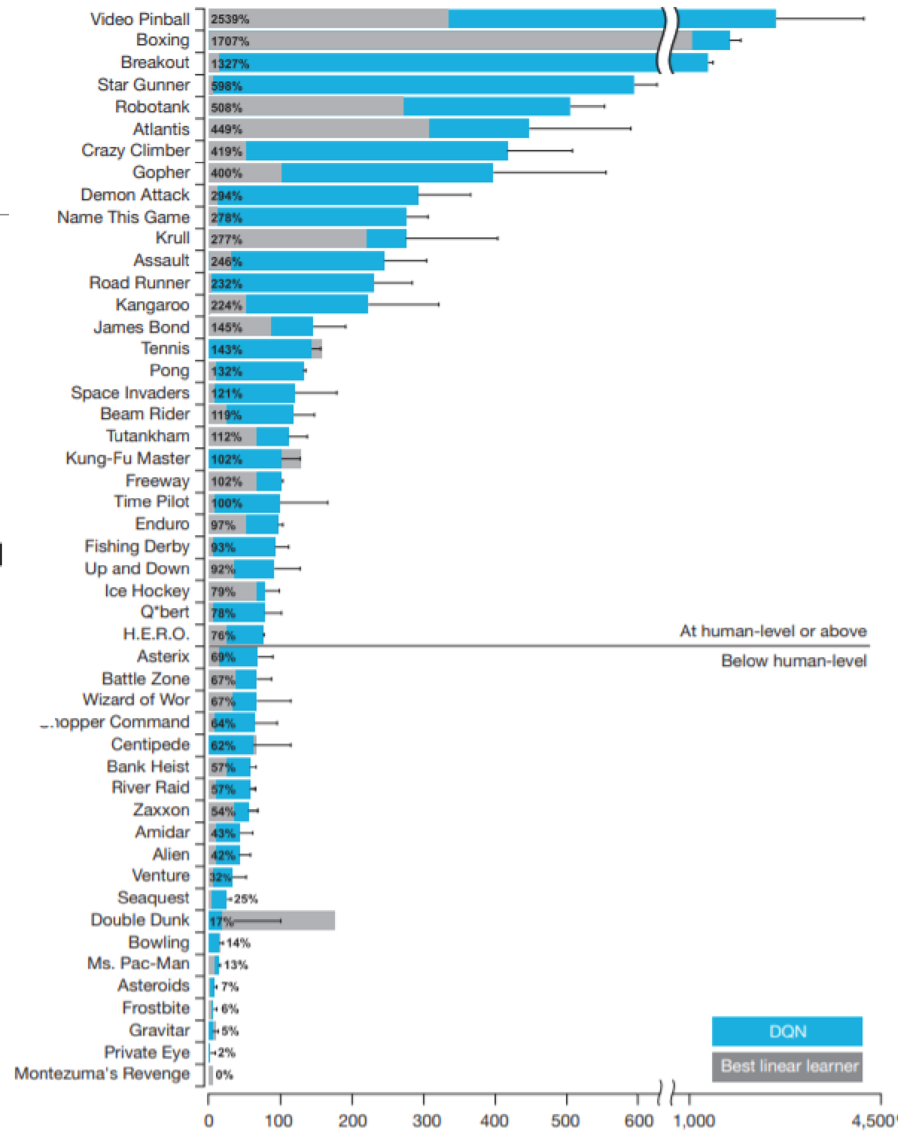
    Every C steps reset $\hat{Q} = Q$

  End For

End For

Results

The human performance is the average reward achieved from around 20 episodes of each game lasting a maximum of 5 min each, following around 2 hrs of practice playing each game.



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

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)