Lecture 6: CNNs and Deep Q Learning [2]

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CS234 Reinforcement Learning.

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[2] 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/

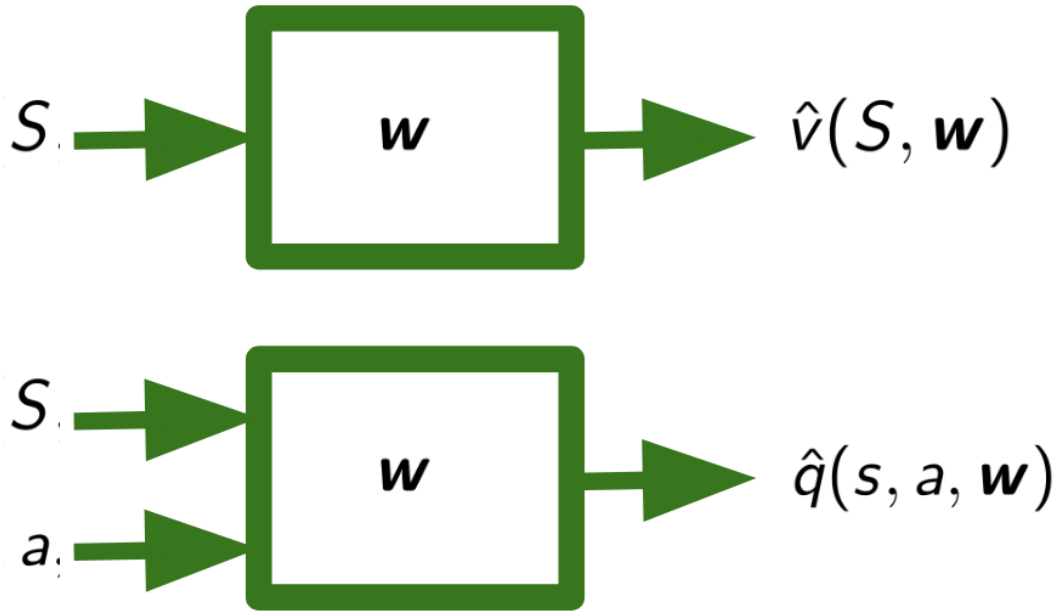
Table of Contents

Class Structure

- Last time: Value function approximation and deep learning
- This time: Convolutional neural networks and deep RL
- Next time: Imitation learning

Generalization

- Want to be able use reinforcement learning to tackle self-driving cars, Atari, consumer marketing, healthcare, education
- Most of these domains have enormous state and/or action spaces
- Requires representations (of models / state-action values / values / policies) that can generalize across states and/or actions
- Represent a (state-action/state) value function with a parameterized function instead of a table



Recall: The Benefit of Deep Neural Network Approximators

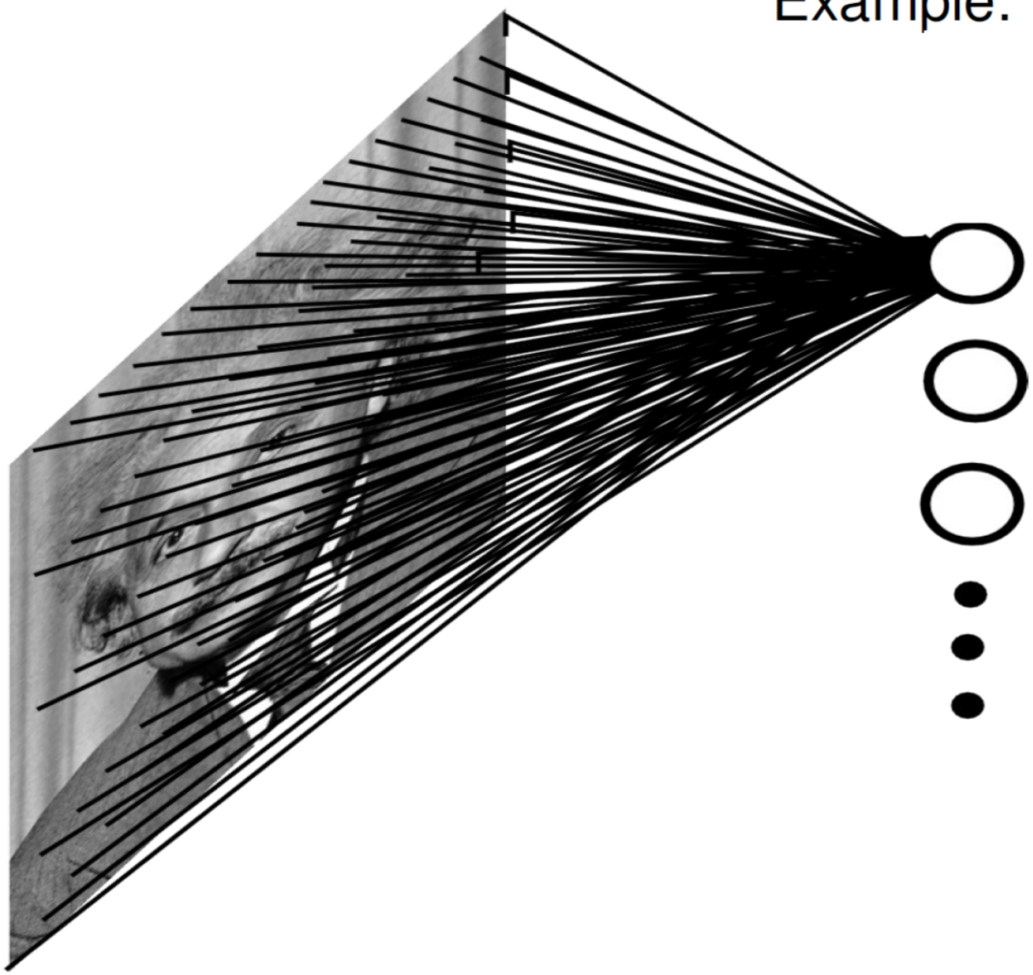
- Linear value function approximators assume value function is a weighted combination of a set of features, where each feature a function of the state
- Linear VFA often work well given the right set of features
- But can require carefully hand designing that feature set
- An alternative is to use a 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: use 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
- Last time discussed basic feedforward deep networks

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

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

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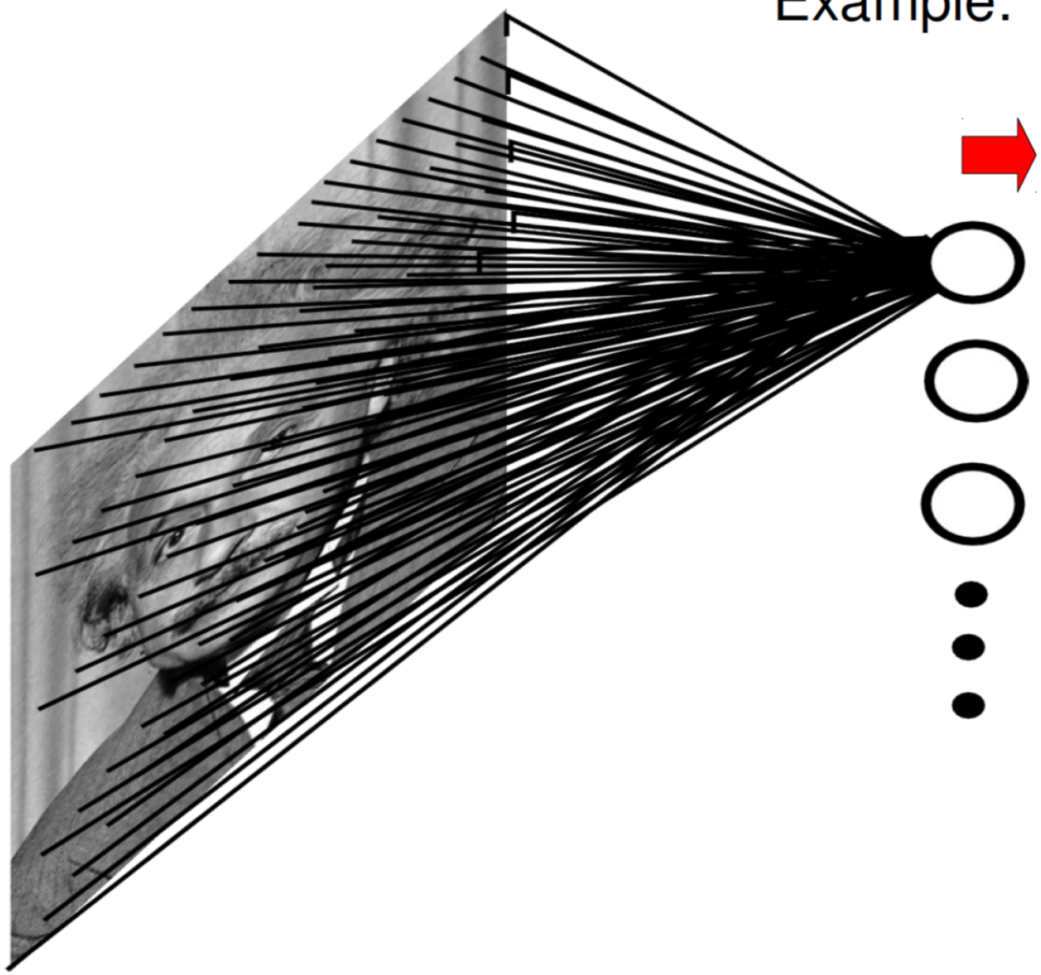
Fully Connected Neural Net



Example: 1000x1000 image

1M hidden units

10^12 parameters!!!

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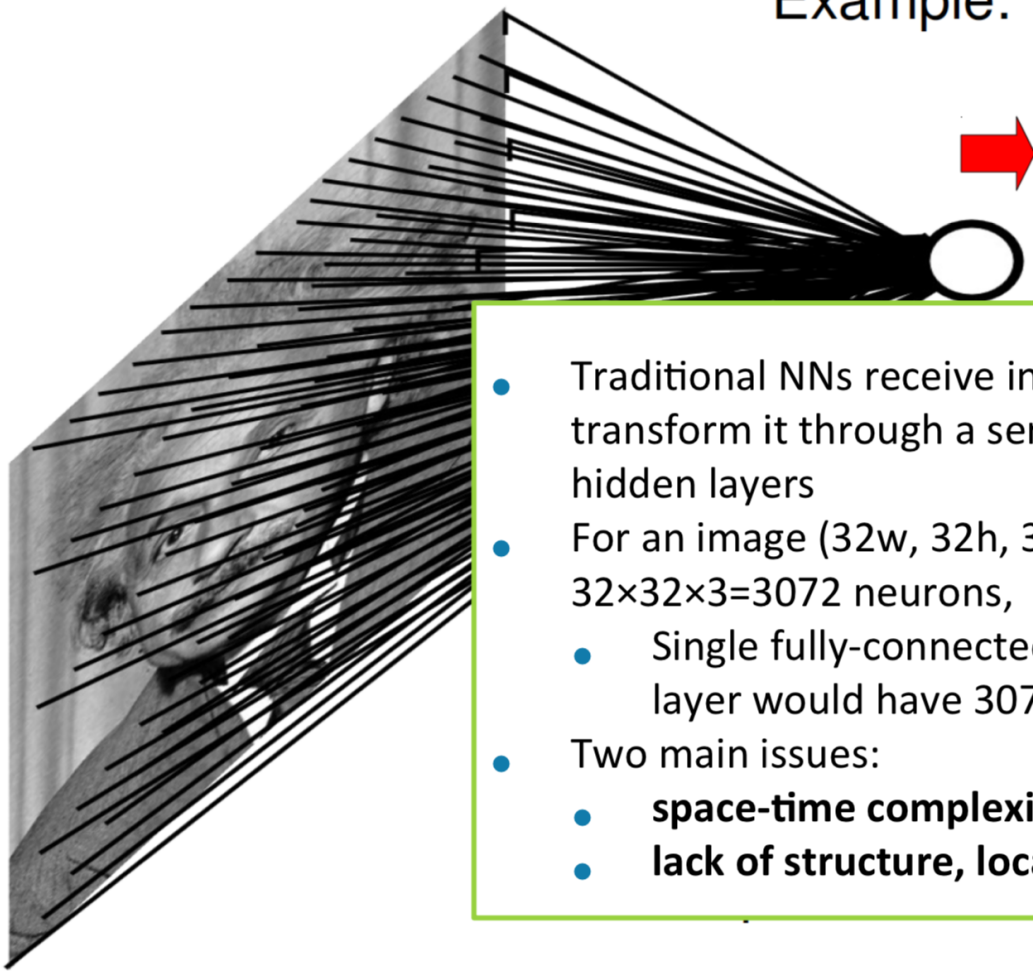
Fully Connected Neural Net



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

Image Features

- Want uniqueness
- Want invariance
- Geometric invariance: translation, rotation, scale
- Photometric invariance: brightness, exposure, ...
- Leads to unambiguous matches in other images or w.r.t. to known entities of interest
- Look for "interest points": image regions that are unusual
- Coming up with these is nontrivial

Convolutional NN

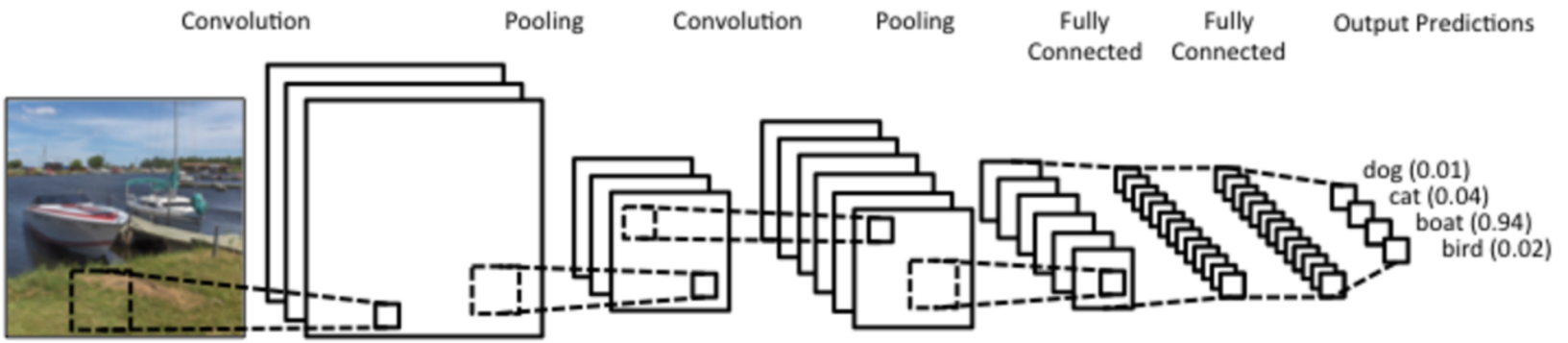
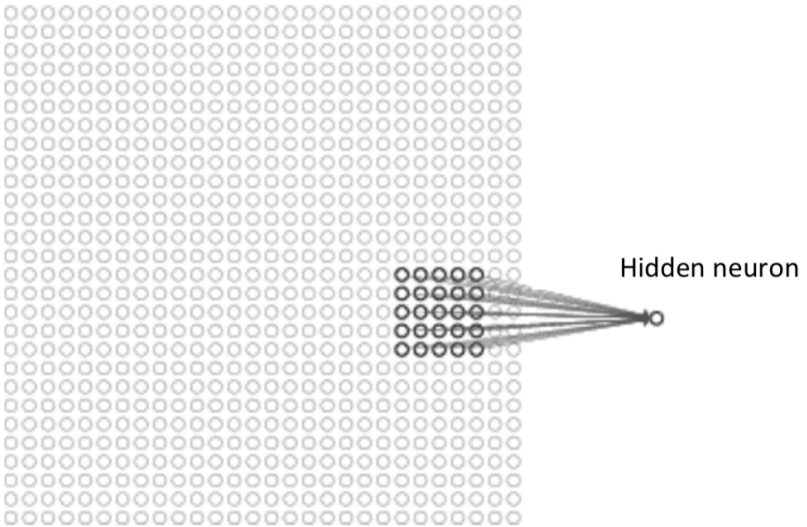
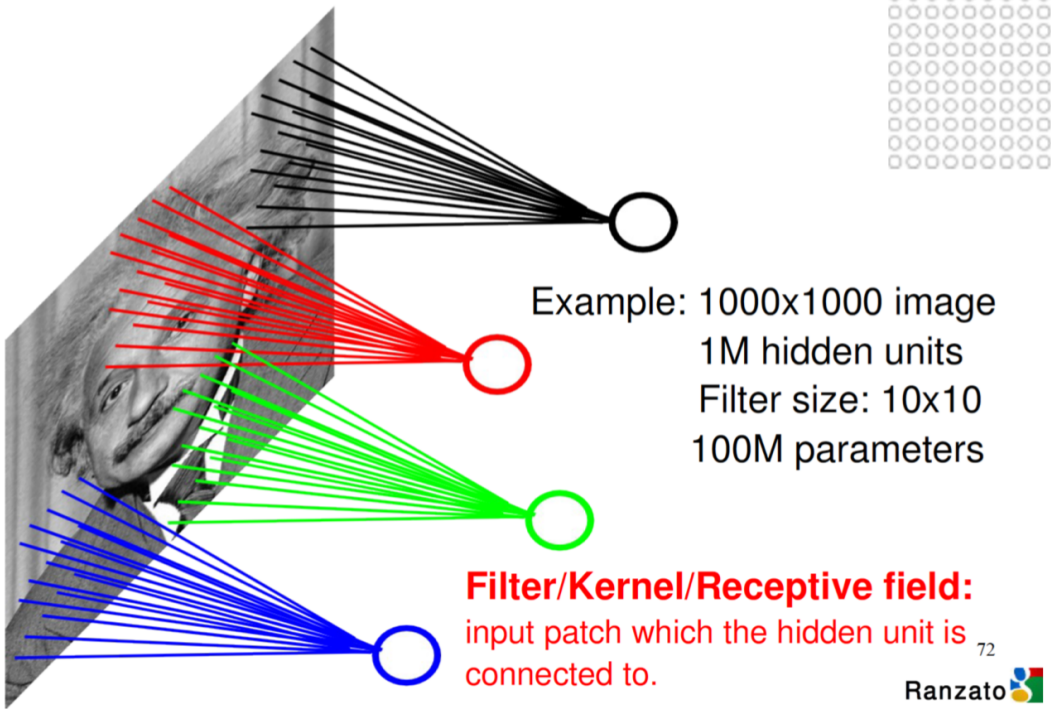


Image: http://d3kbpzbmcynnmx.cloudfront.net/wp-content/uploads/2015/11/Screen-Shot-2015-11-07-at-7.26.20-AM.png

- 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

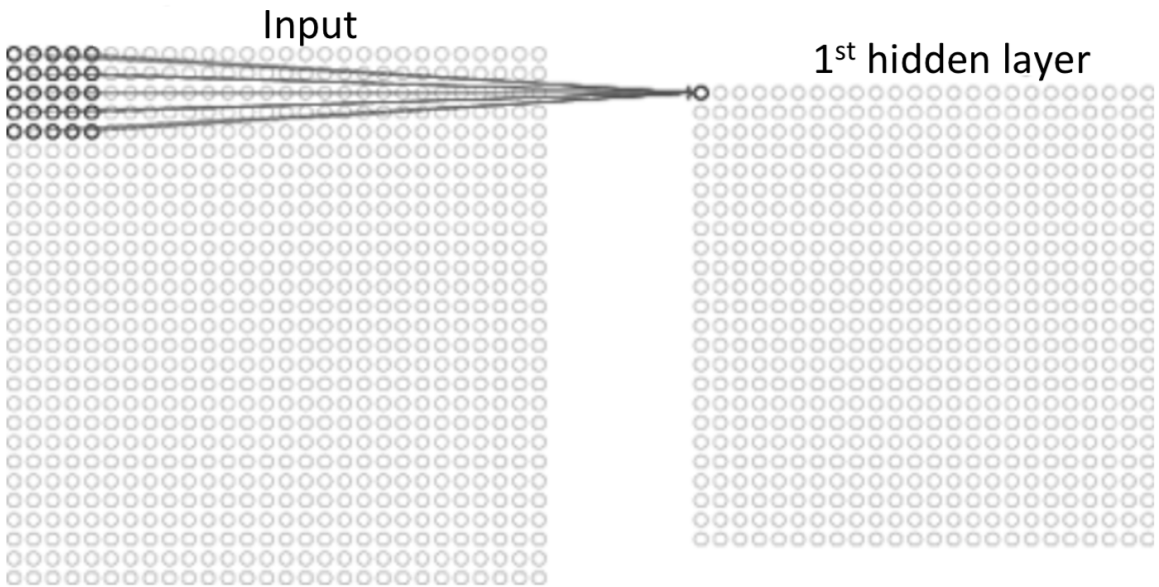
Locality of Information: Receptive Fields



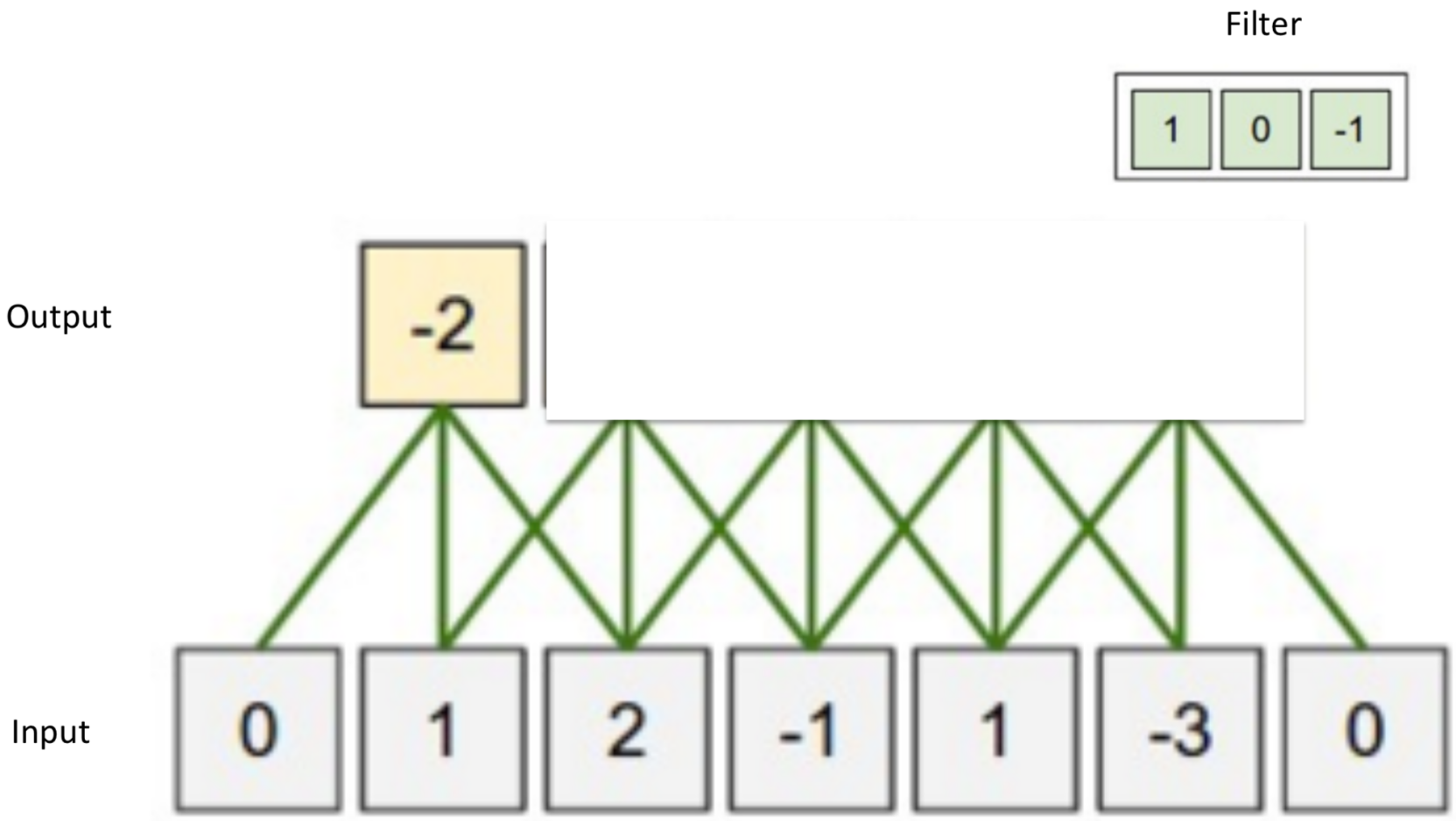


(Filter) Stride

- 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?

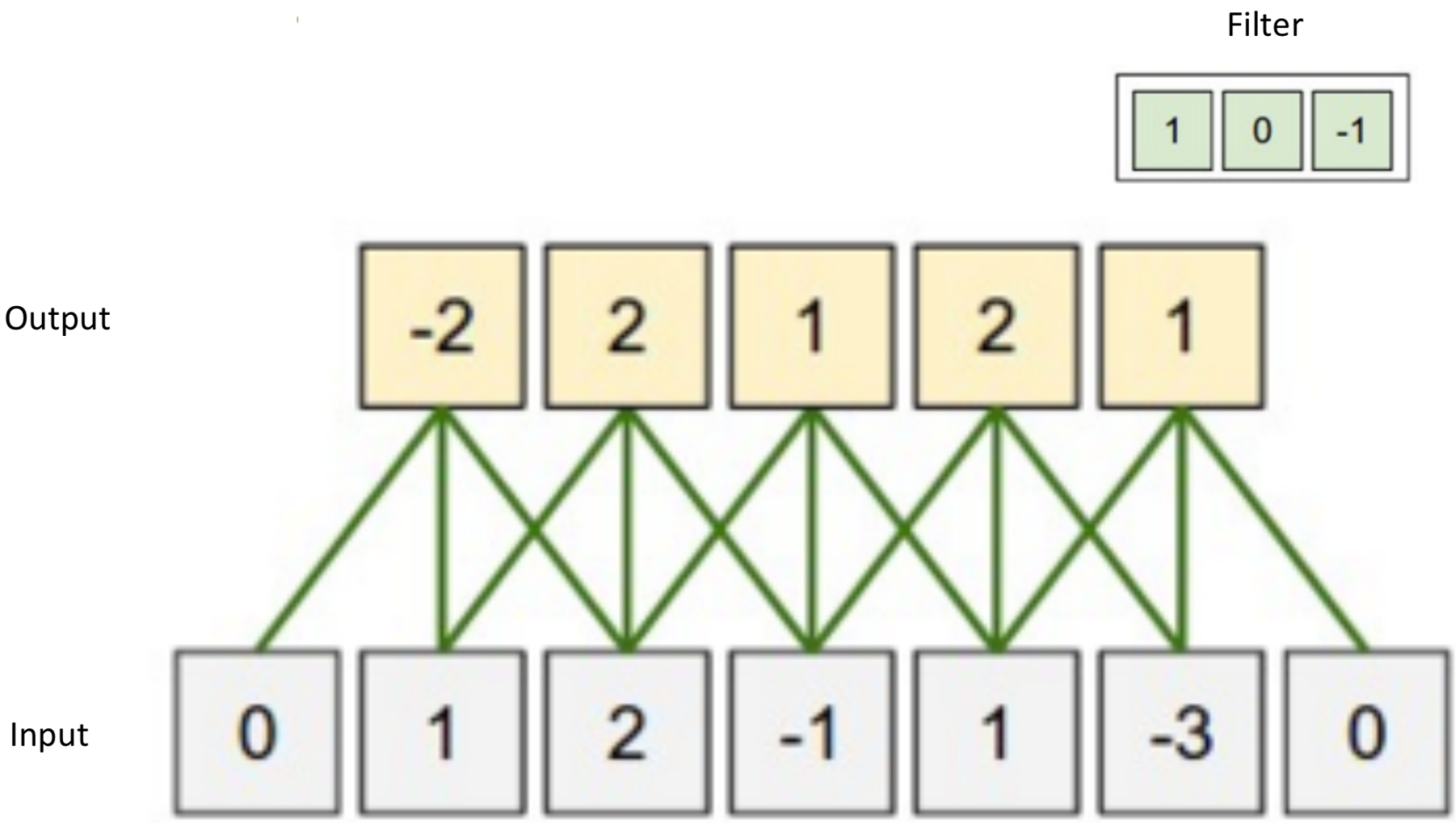


Stride and Zero Padding



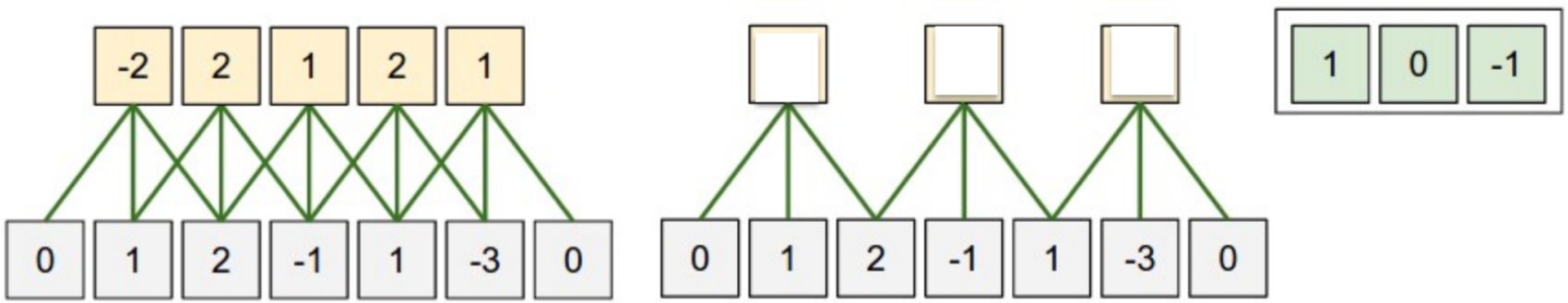
- Stride: how far (spatially) move over filter
- Zero padding: how many 0s to add to either side of input layer

Stride and Zero Padding

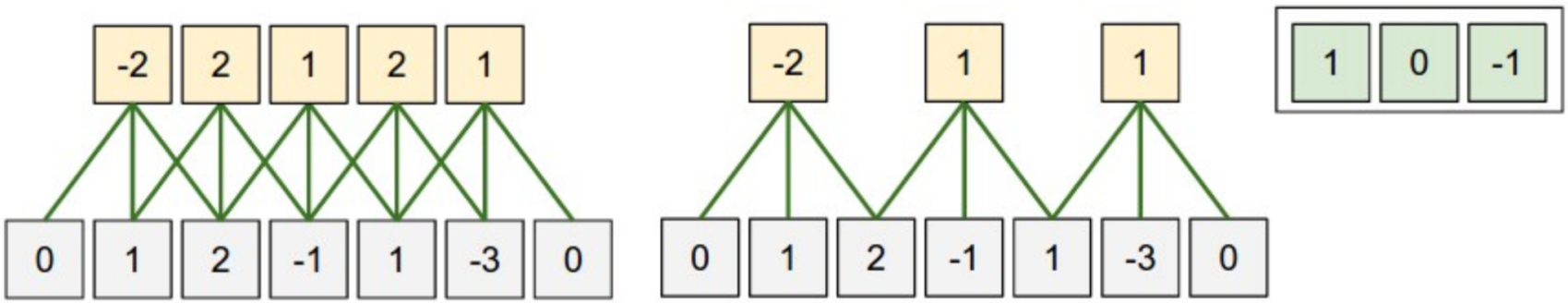


- Stride: how far (spatially) move over filter
- Zero padding: how many 0s to add to either side of input layer

What is the Stride and the Values in the Second Example?



Stride is 2



Shared Weights

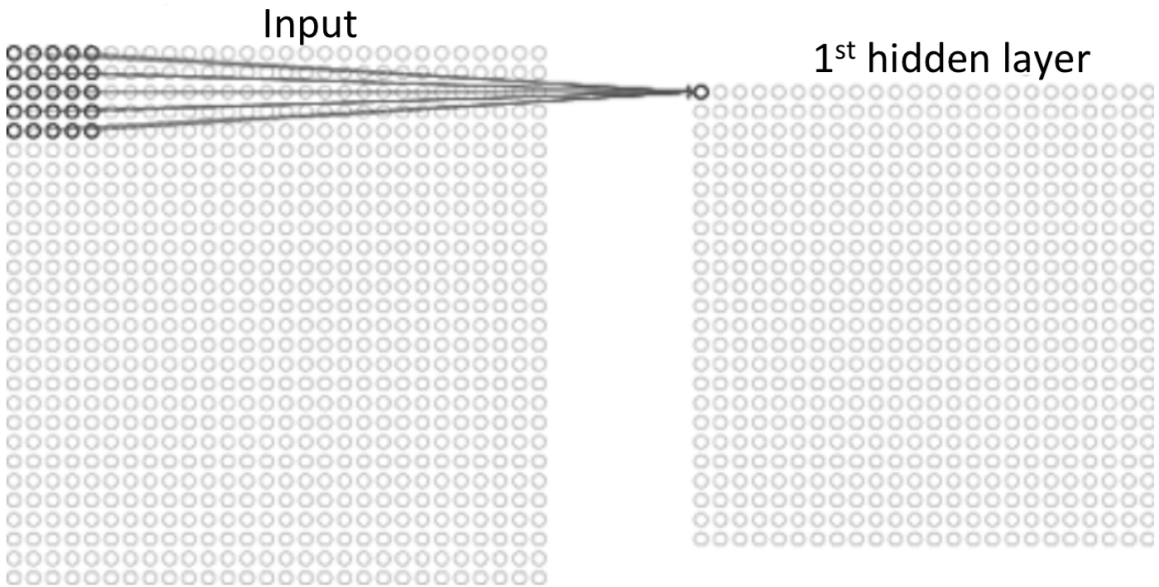
- What is the precise relationship between the neurons in the receptive field and that in the hidden layer?
- What is the *activation value* of the hidden layer neuron?

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

- 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

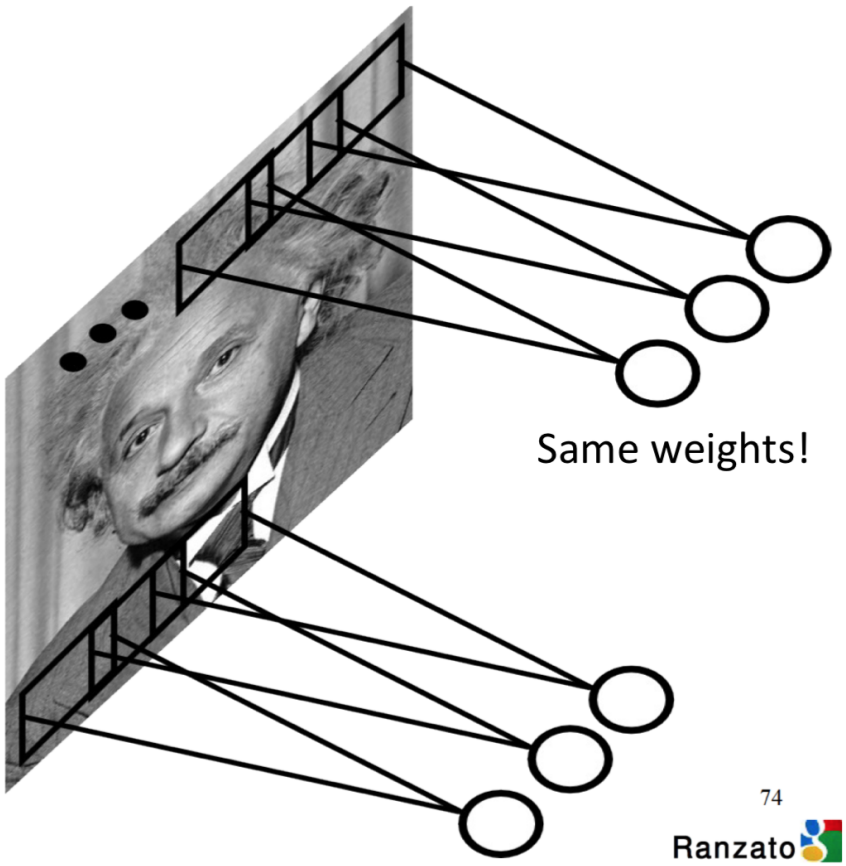


- Receptive field is 5x5
- Number of parameters for 1st hidden neuron?
- Number of parameters for entire layer of hidden neurons?

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 Image Filters

1	1	1
1	1	1
1	1	1

Unweighted 3x3 smoothing kernel

0	1	0
1	4	1
0	1	0

Weighted 3x3 smoothing kernel with Gaussian blur

0	-1	0
-1	5	-1
0	-1	0

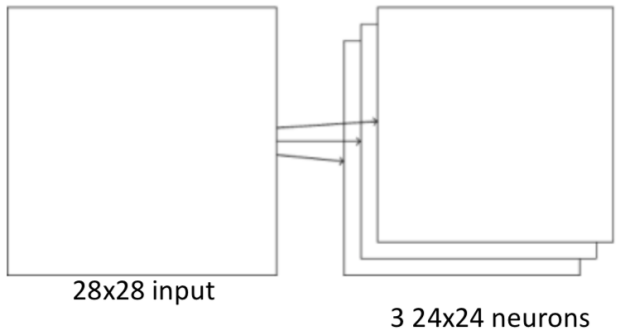
Kernel to make image sharper

-1	-1	-1
-1	9	-1
-1	-1	-1

Intensified sharper image

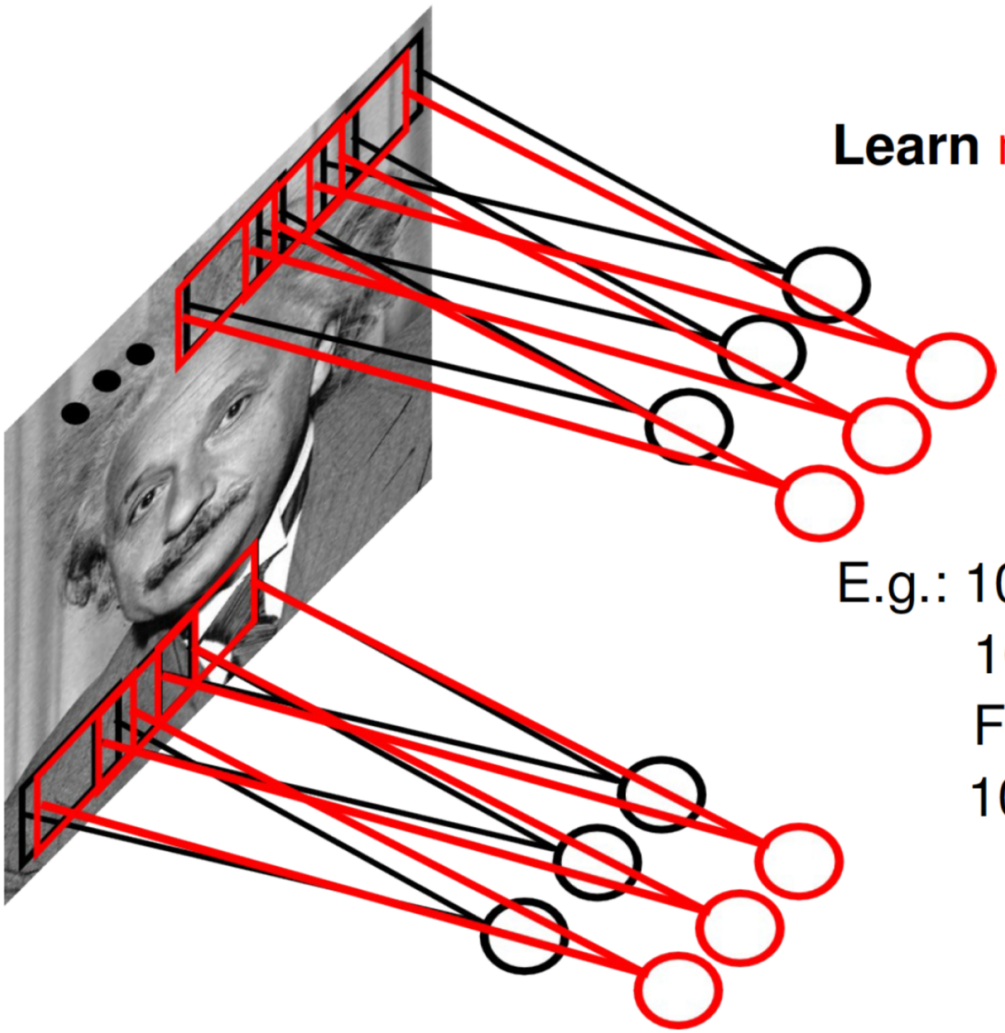
Why Only 1 Filter?

- At the i-th hidden layer n filters can be active in parallel
- A **bank of convolutional filters**, each learning a different feature (different weights and bias)



- 3 feature maps, each defined by a set of 5×5 shared weights & 1 bias
- Network detects 3 different kinds of features, with each feature being detectable across the entire image

Convolutional Net



Learn multiple filters.

E.g.: 1000x1000 image
100 Filters
Filter size: 10x10
10K parameters

75

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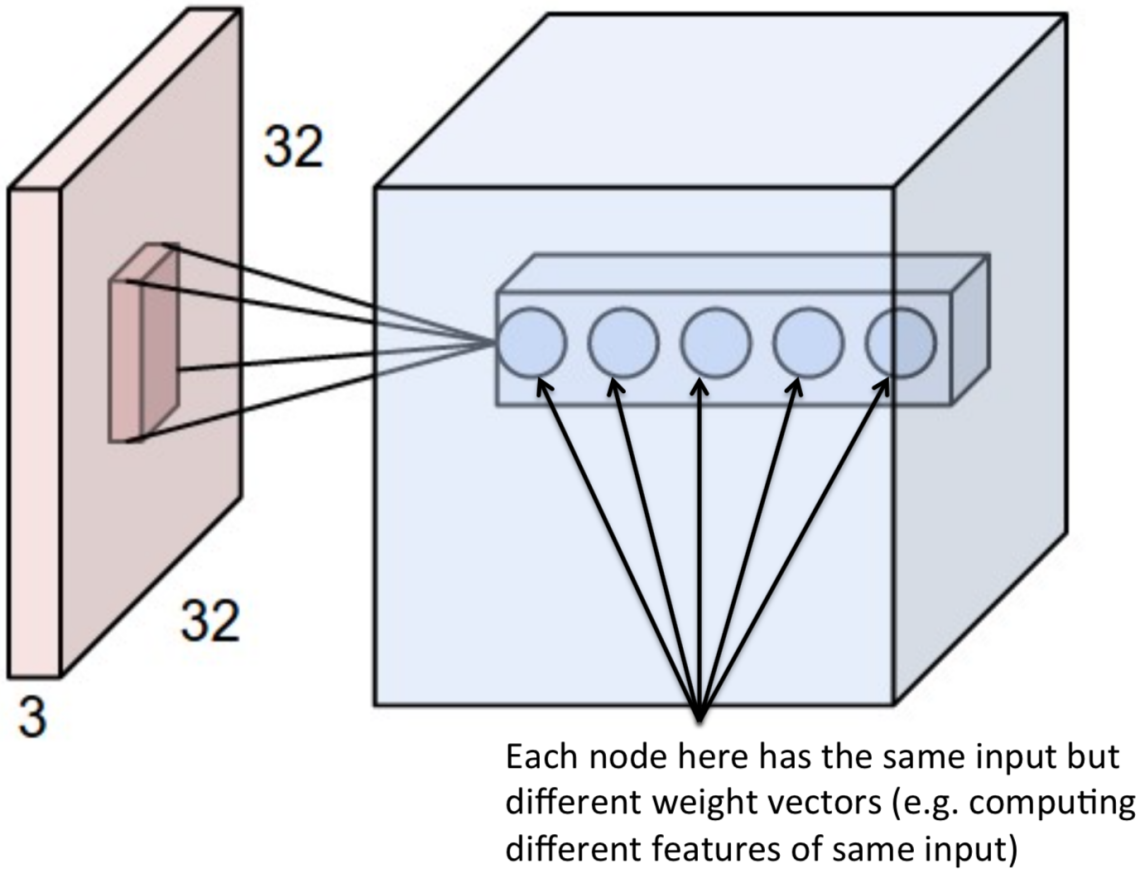
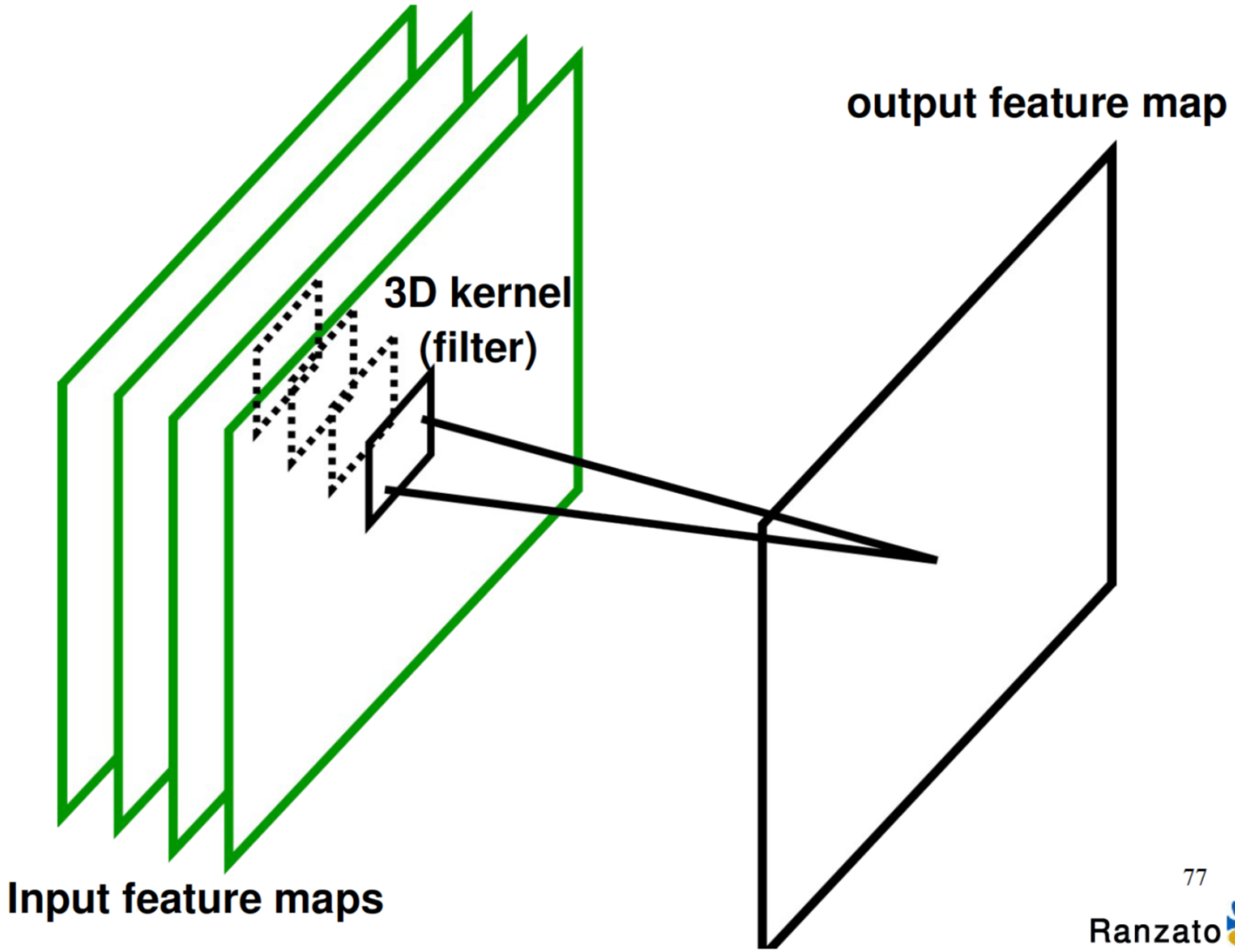
Volumes and Depths

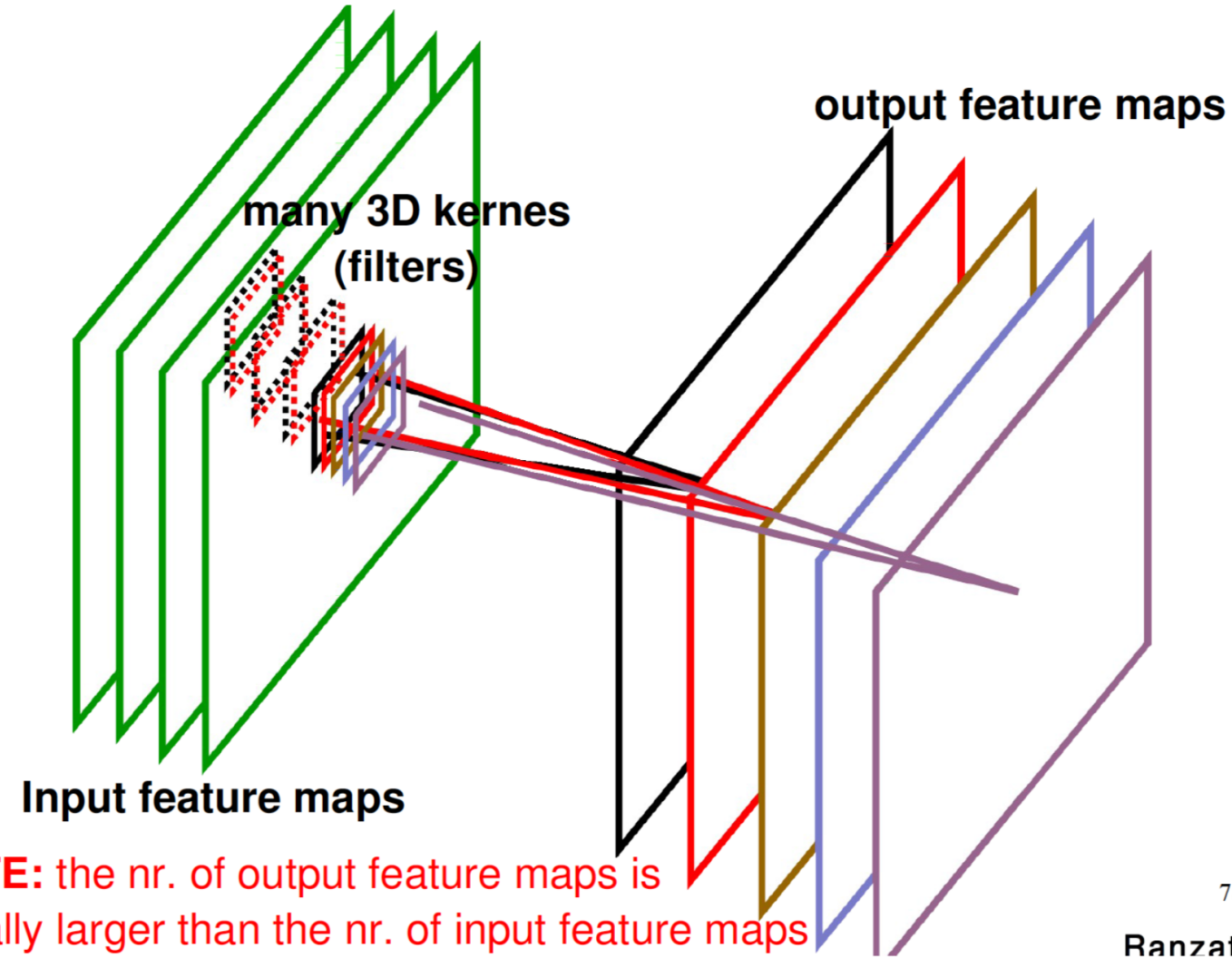


- Equivalent to applying different filters to the input, and then stacking the result of each of those filters

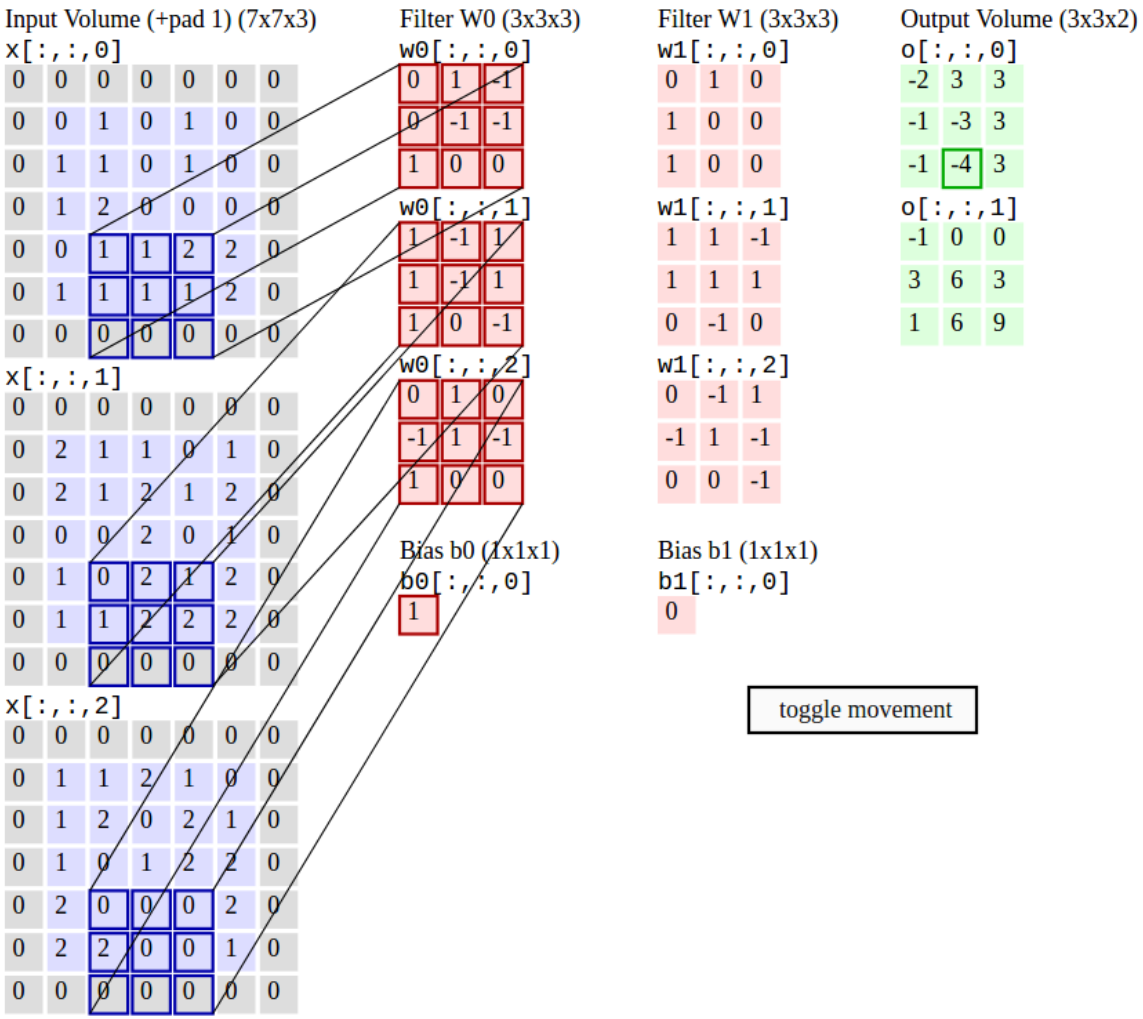
Convolutional Layer



Convolutional Layer



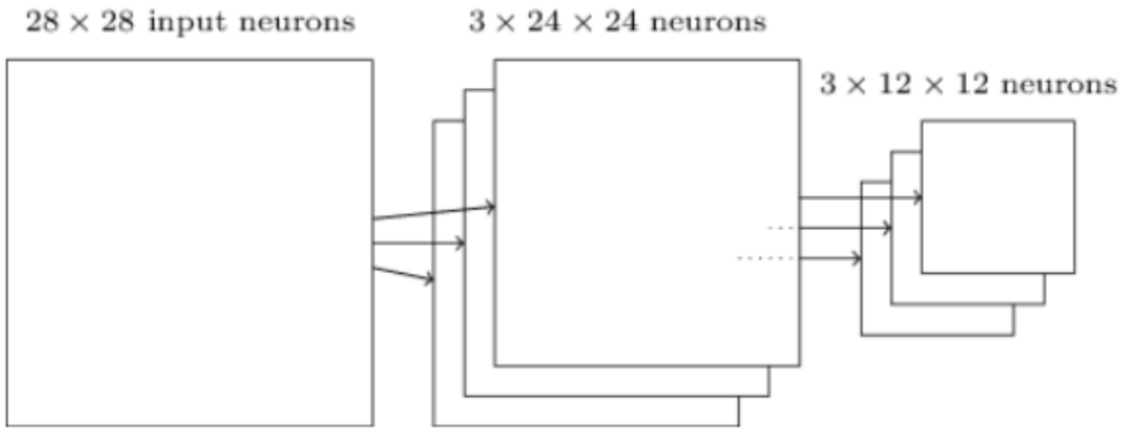
Computing the next layer[32]



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

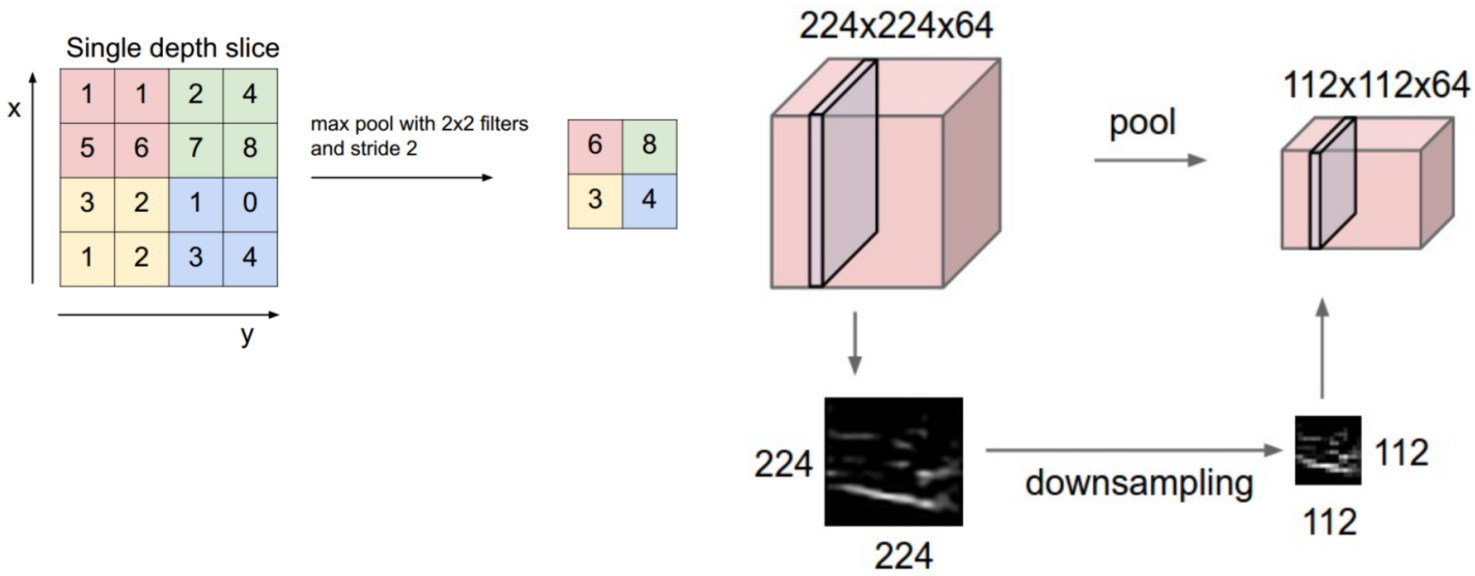
Pooling Layers

- 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



Max Pooling

- Max-pooling: a pooling unit simply outputs the max activation in the input region



Max-Pooling Benefits

- Max-pooling is a way for the network to ask whether a given feature is found anywhere in a region of the image. It then throws away the exact positional information.
  - Pooling and stride length are both ways to perform downsampling:

- Once a feature has been found, its exact location isn't as important as its rough location relative to other features.
- A big benefit is that there are many fewer pooled features, and so this helps reduce the number of parameters needed in later layers.
  - Convolutional layers can also significantly reduce the number of output features

Final Layer Typically Fully Connected

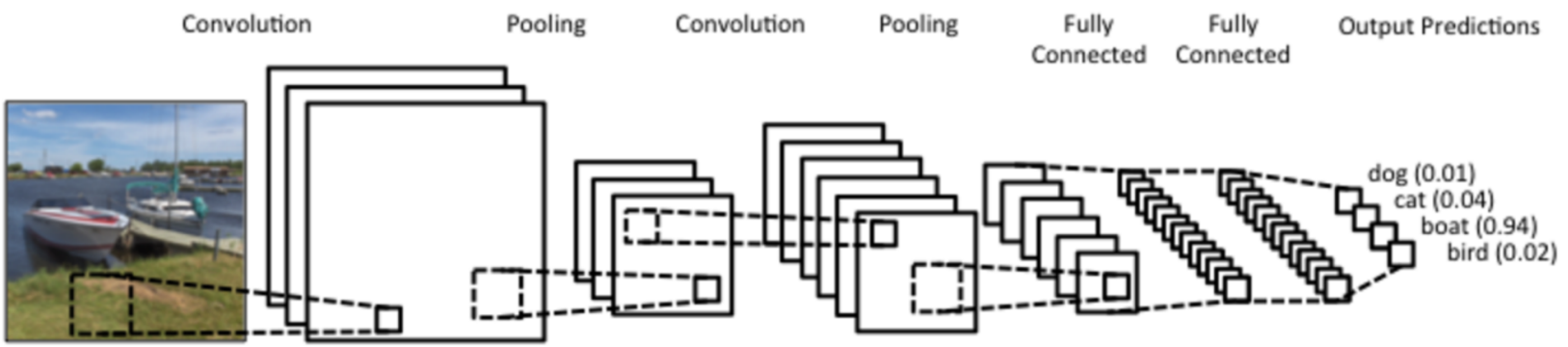


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Table of Contents

Generalization

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

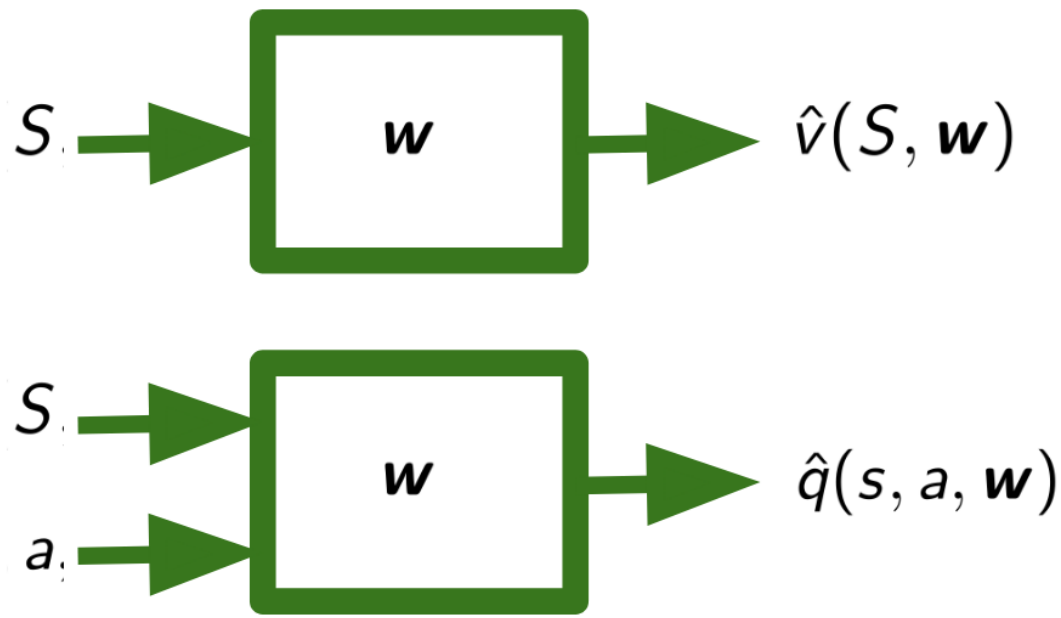
Deep Reinforcement Learning

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

Deep Q-Networks (DQNs)

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

$$\hat{q}(s, a, \boldsymbol{w}) \approx q(s, a) \tag{1}$$



Recall: Action-Value Function Approximation with an Oracle

- $\hat{q}^{\pi}(s, a, w) \approx q^{\pi}$
- Minimize the mean-squared error between the true action-value function $q^{\pi}(s, a)$ and the approximate action-value function:

$$J(w) = \mathbb{E}_{\pi}[(q^{\pi}(s, a) - \hat{q}^{\pi}(s, a, w))^2] \tag{2}$$

- Use stochastic gradient descent to find a local minimum

$$-\frac{1}{2} \bigtriangledown w \, J(w) = \mathbb{E}\left[(q^{\pi}(s, a) - \hat{q}^{\pi}(s, a, w)) \bigtriangledown_w \hat{q}^{\pi}(s, a, w)\right] \tag{3}$$

$$\Delta(w) = -\frac{1}{2}\alpha \bigtriangledown_w J(w) \tag{4}$$

- Stochastic gradient descent (SGD) samples the gradient

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

$$\Delta w = \alpha(G_t - \hat{q}(s_t, a_t, w)) \bigtriangledown_w \hat{q}(s_t, a_t, w) \tag{5}$$

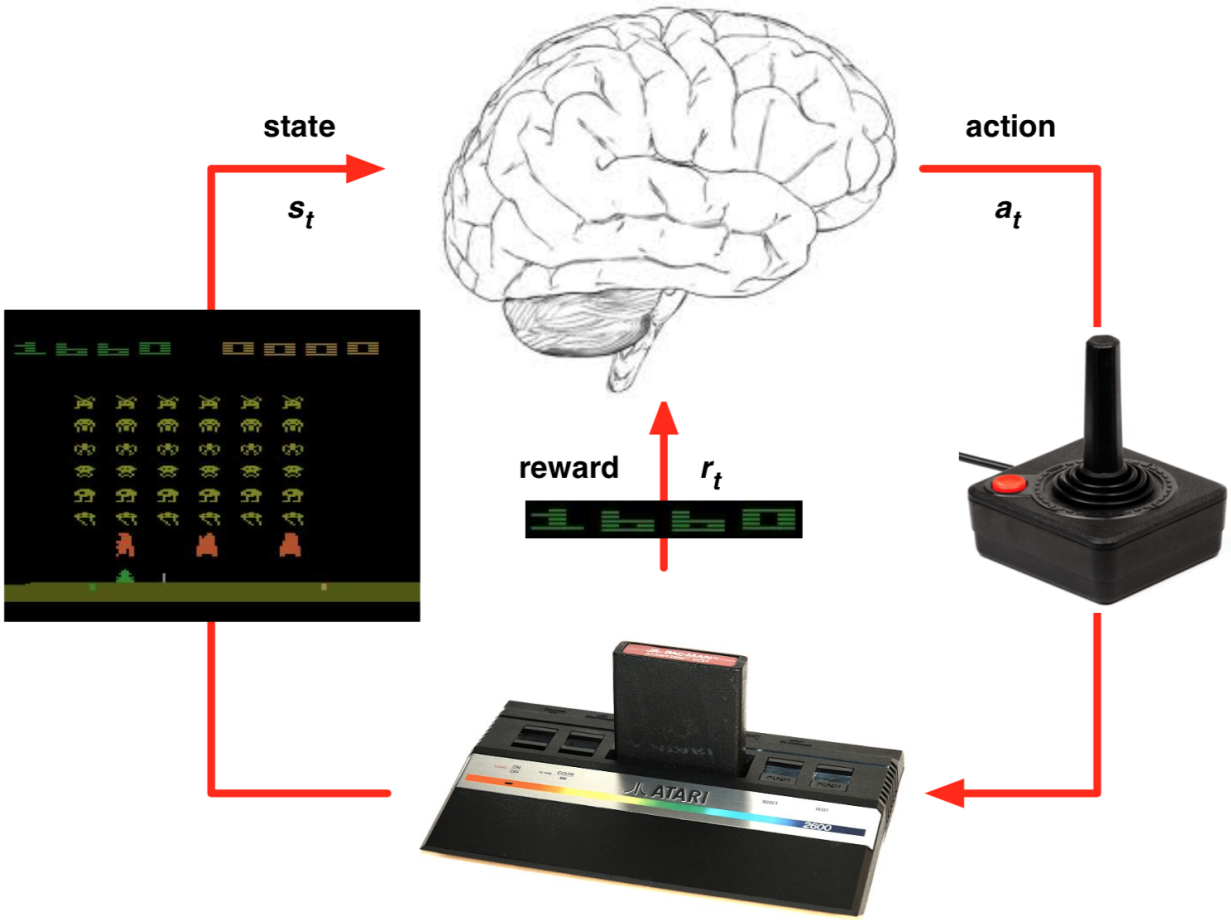
- For SARSA instead use a TD target $r + \gamma \hat{q}(s', a', w)$ which leverages the current function approximation value

$$\Delta w = \alpha(r + \gamma \hat{q}(s', a', w) - \hat{q}(s, a, w)) \bigtriangledown_w \hat{q}(s, a, w) \tag{6}$$

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

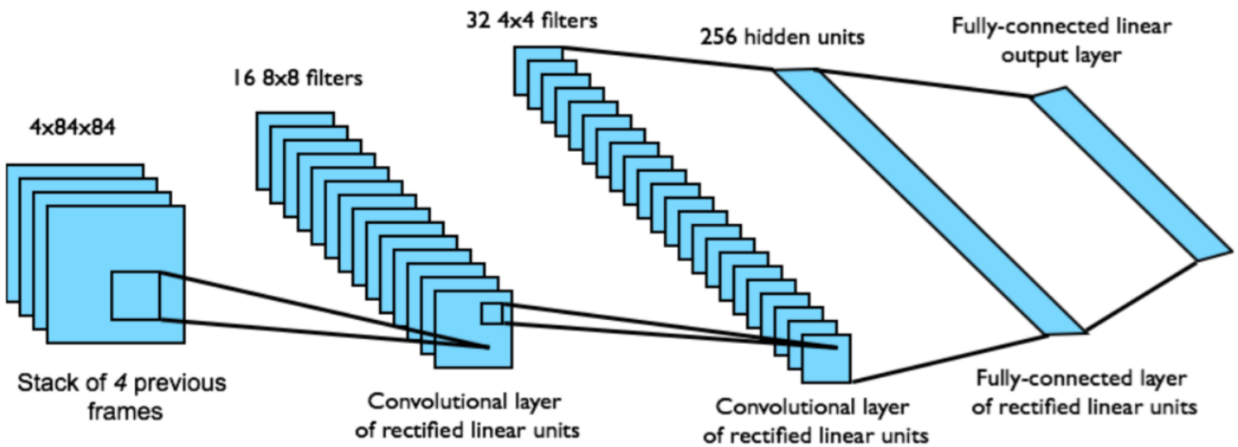
$$\Delta w = \alpha(r + \gamma \max_{a'} \hat{q}(s', a', w) - \hat{q}(s, a, w)) \bigtriangledown_w \hat{q}(s, a, w) \tag{7}$$

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



Mnih et.al., Nature, 2014

- Network architecture and hyperparameters fixed across all games

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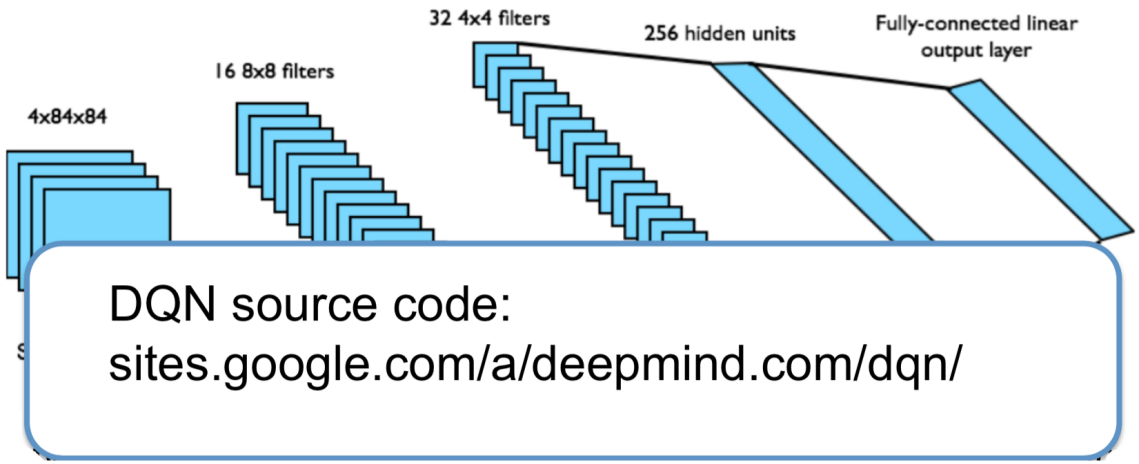

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Q-Learning with Value Function Approximation

- Minimize MSE loss by stochastic gradient descent
- Converges to optimal q 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

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

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \max_{a'} \hat{q}(s', a', \boldsymbol{w}) - \hat{q}(s, a, \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{q}(s, a, \boldsymbol{w}) \quad (8)$$

DQNs: Experience Replay

- To help remove correlations, store dataset $\mathcal{D}$ from prior experience

s_1, a_1, r_2, s_2
s_2, a_2, r_3, s_3
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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 network** 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

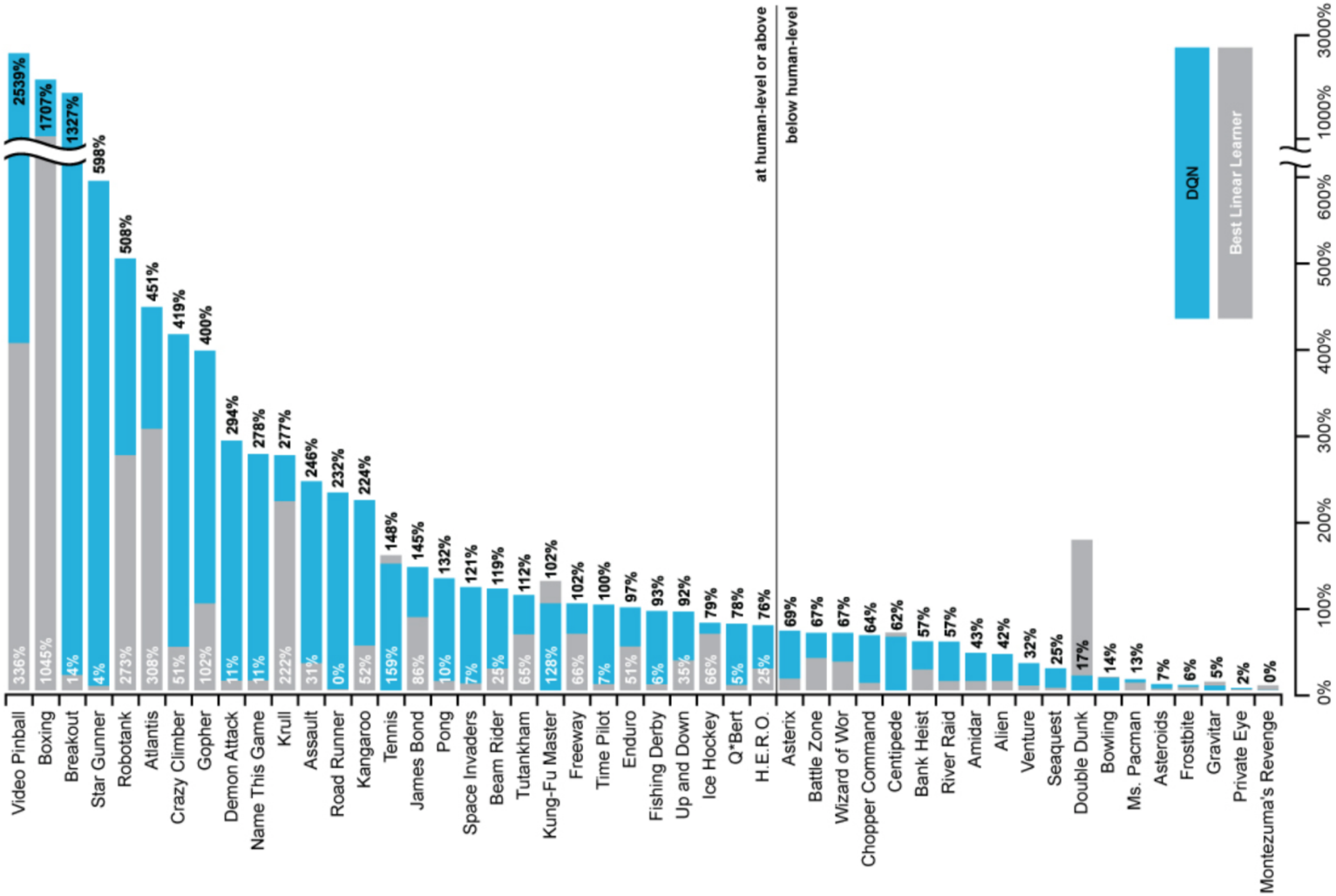
$$\Delta \boldsymbol{w} = \alpha(r + \gamma \max_{a'} \hat{q}(s', a', \boldsymbol{w}^-) - \hat{q}(s, a, \boldsymbol{w}))\nabla_{\boldsymbol{w}} \hat{q}(s, a, \boldsymbol{w}) \quad (10)$$

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

Demo

DQN Results in Atari



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 item Why? Beyond helping with correlation between samples, what does replaying do?

Deep RL

- Success in Atari has lead to huge excitement in using deep neural networks to do value function approximation in RL
- Some immediate improvements (many others!)
  - Double DQN
  - Dueling DQN (best paper ICML 2016)

Double DQN

- Recall maximization bias challenge
  - Max of the estimated state-action values can be a biased estimate of the max
- Double Q-learning

Recall: Double Q-Learning

1: Initialize $Q_1(s,a)$ and $Q_2(s,a), \forall s \in S, a \in A$ $t=0$, initial state $s_t = s_0$
2: **loop**
3: Select a_t using ϵ-greedy $\pi(s) = \arg\max_a Q_1(s_t,a) + Q_2(s_t,a)$
4: Observe (r_t, s_{t+1})
5: **if** (with 0.5 probability) **then**

$$Q_1(s_t,a_t) \leftarrow Q_1(s_t,a_t) + \alpha(r_t + Q_1(s_{t+1}, \arg\max_{a'} Q_2(s_{t+1},a')) - Q_1(s_t,a_t)) \tag{11}$$

6: **else**

$$Q_2(s_t,a_t) \leftarrow Q_2(s_t,a_t) + \alpha(r_t + Q_2(s_{t+1}, \arg\max_{a'} Q_1(s_{t+1},a')) - Q_2(s_t,a_t))$$

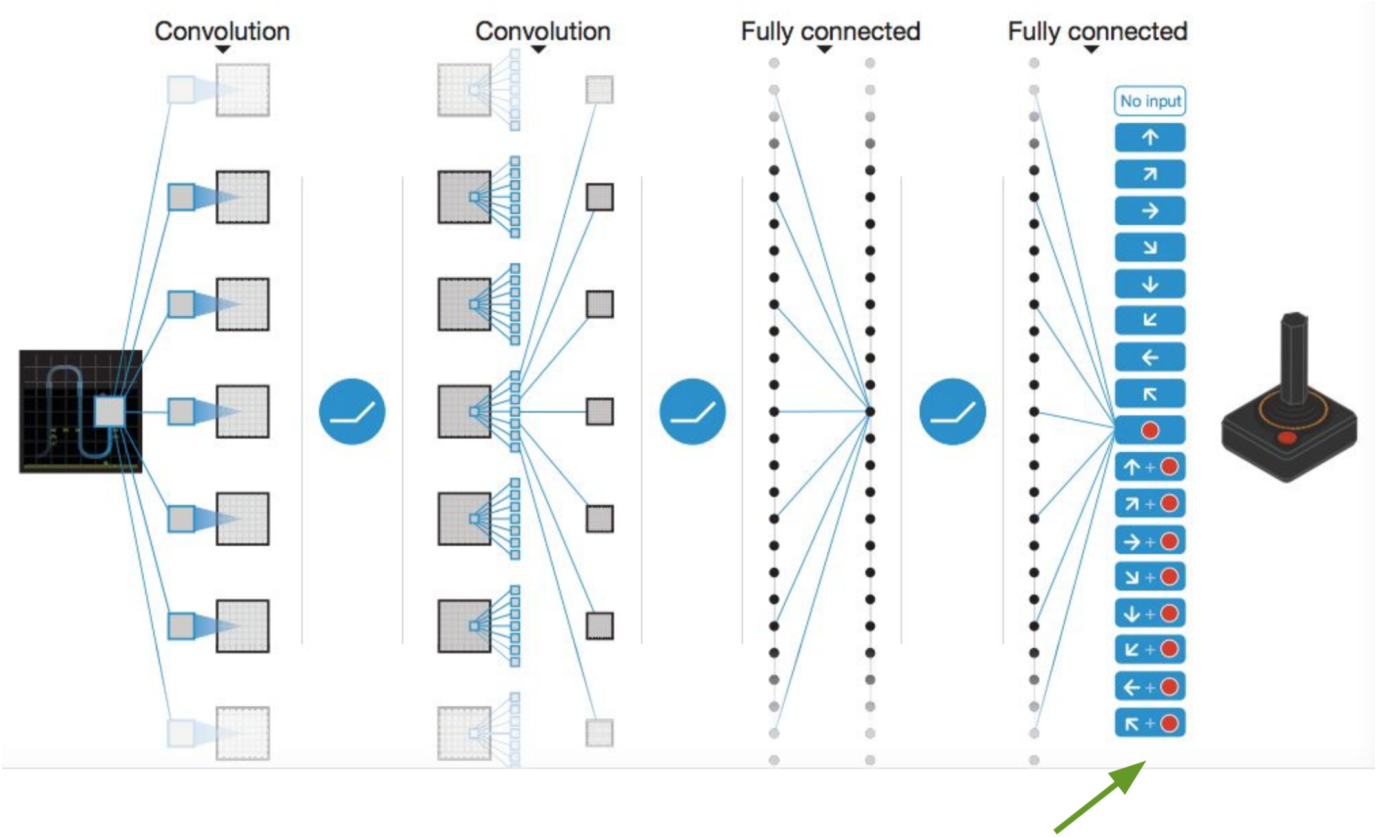
7: **end if**
8: $t = t+1$
9: **end loop**

Double DQN

- Extend this idea to DQN
- Current Q-network $\boldsymbol{w}$ is used to select actions
- Older Q-network $\boldsymbol{w}^-$ is used to evaluate actions

$$\Delta \boldsymbol{w} = \alpha(r + \gamma \overbrace{\hat{q}(\underbrace{\arg\max_{a'} \hat{q}(s', a', \boldsymbol{w})}_{\text{Action selection: } \boldsymbol{w}}, \boldsymbol{w}^-)}^{\text{Action evaluation: } \boldsymbol{w}^-} - \hat{q}(s, a, \boldsymbol{w})) \tag{12}$$

Double DQN


Convolution
Convolution
Fully connected
Fully connected
No input
1 network, outputs Q value for each action

Double DQN

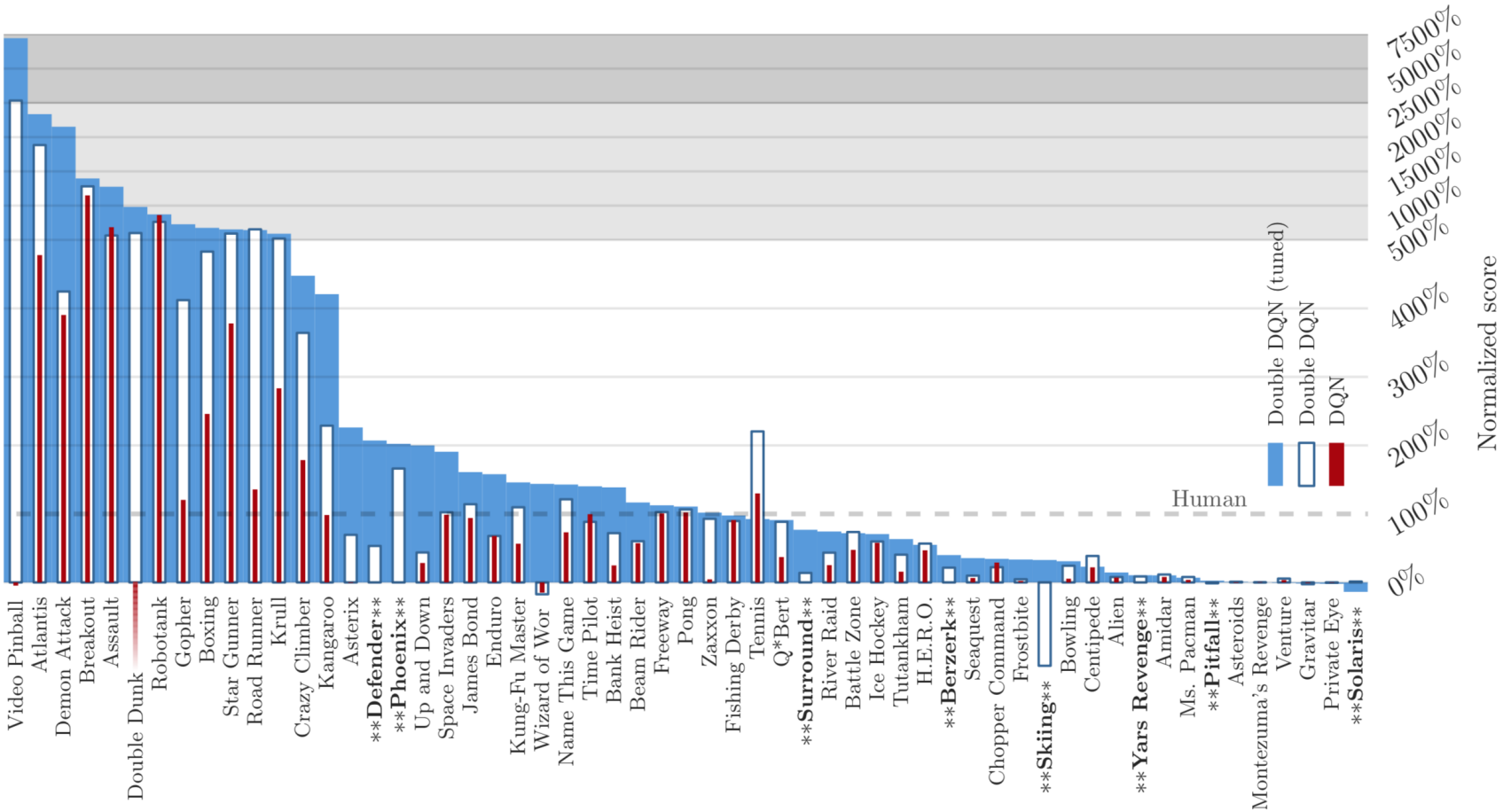


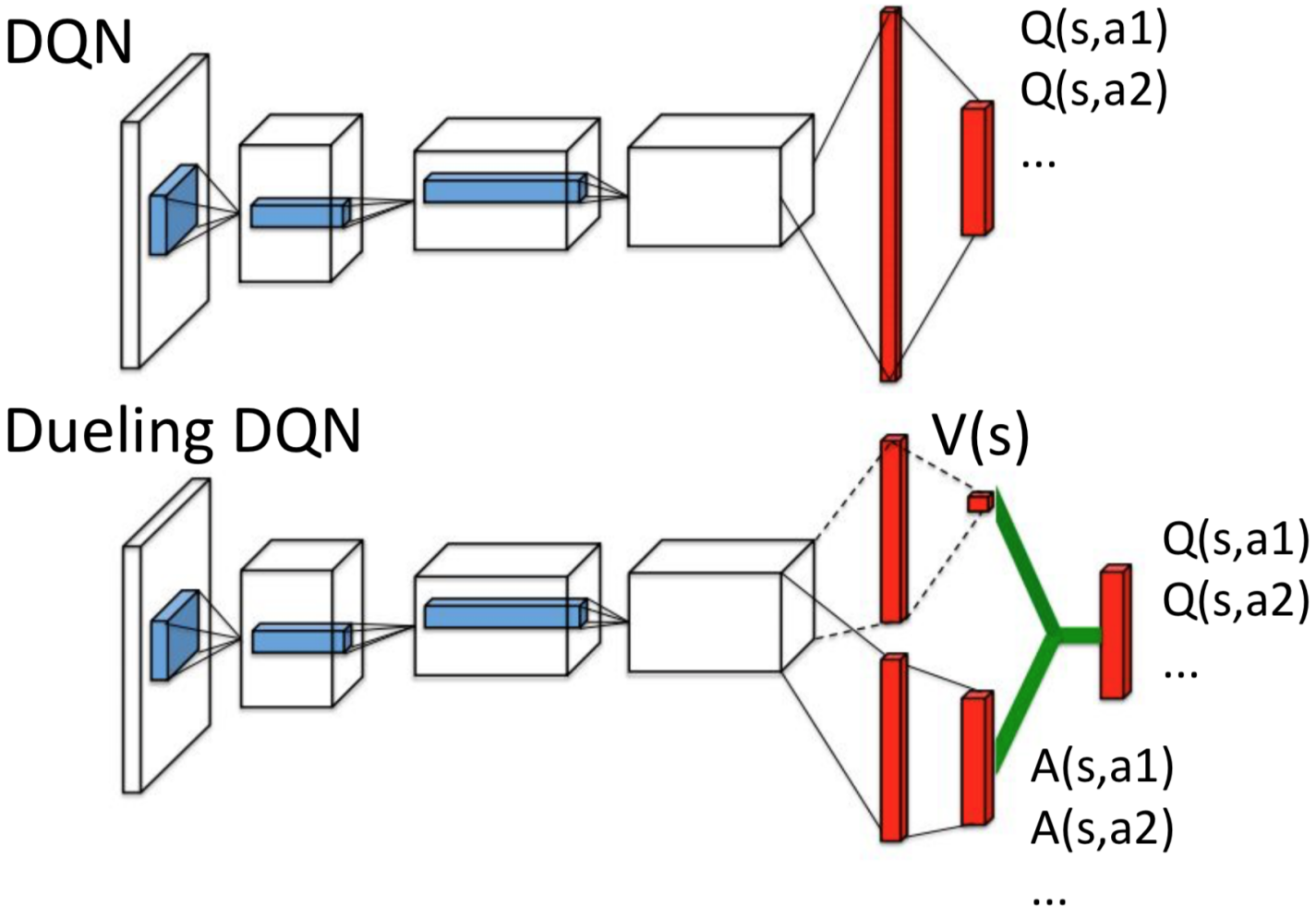
Figure: van Hasselt, Guez, Silver, 2015

Value & Advantage Function

- Intuition: Features need to pay attention to determine value may be different than those need to determine action benefit
- E.g.
  - Game score may be relevant to predicting $V(s)$
  - But not necessarily in indicating relative action values
- Advantage function (Baird 1993)

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$

Dueling DQN



Wang et.al., ICML, 2016

Identifiability

- Advantage function

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$

- Identifiable?

Identifiability

- Advantage function

$$A^{\pi}(s,a) = Q^{\pi}(s,a) - V^{\pi}(s)$$

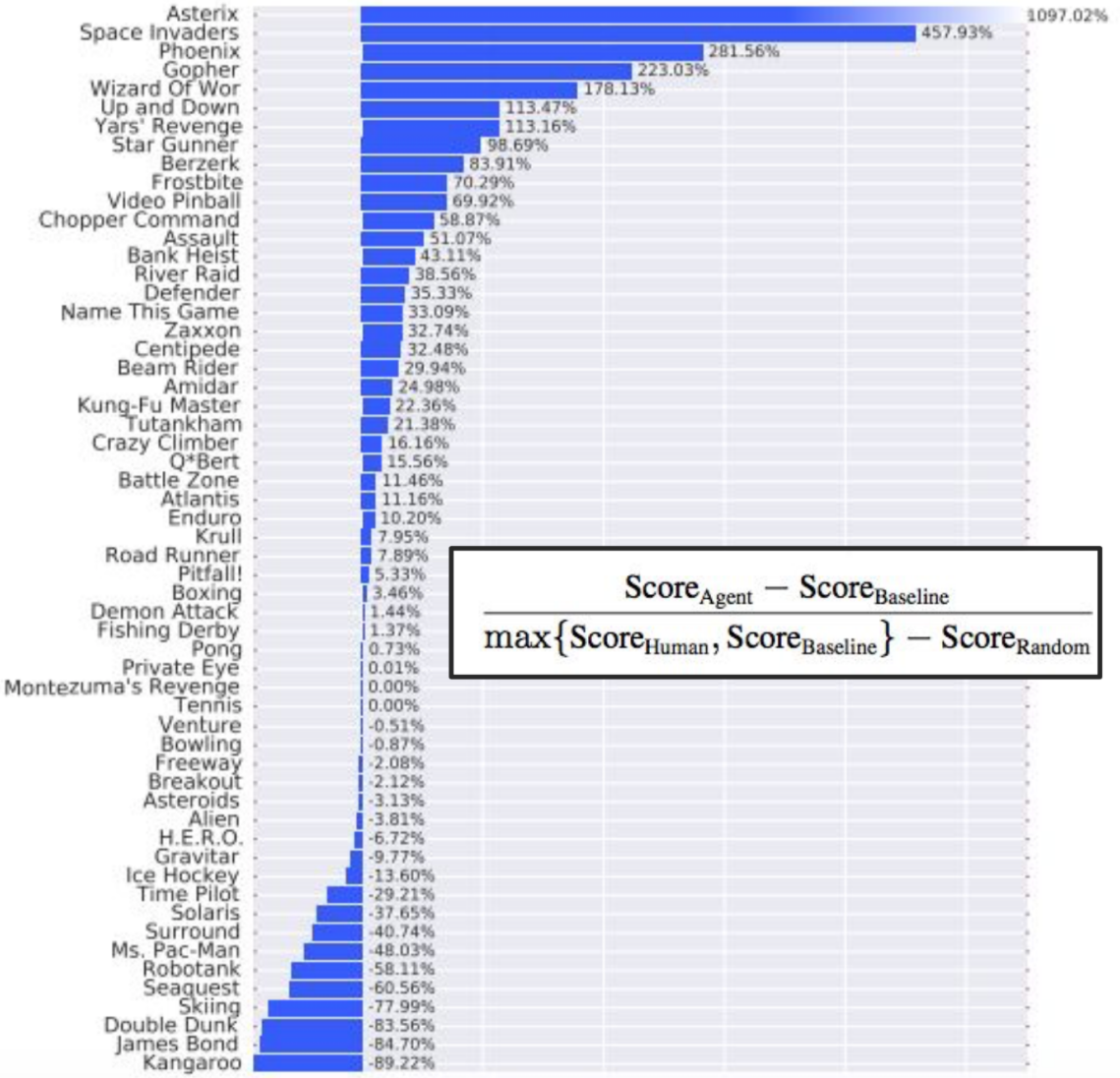
- Unidentifiable
- Option 1: Force $A(s,a) = 0$ if a is action taken

$$\hat{q}(s,a;\boldsymbol{w}) = \hat{v}(s;\boldsymbol{w}) + \left(A(s,a;\boldsymbol{w}) - \max_{a' \in \mathcal{A}} A(s,a';\boldsymbol{w}) \right)$$

- Option 2: Use mean as baseline (more stable)

$$\hat{q}(s,a;\boldsymbol{w}) = \hat{v}(s;\boldsymbol{w}) + \left(A(s,a;\boldsymbol{w}) - \frac{1}{|\mathcal{A}|} \sum_{a'} A(s,a';\boldsymbol{w}) \right)$$

V.S. DDQN with Prioritized Replay



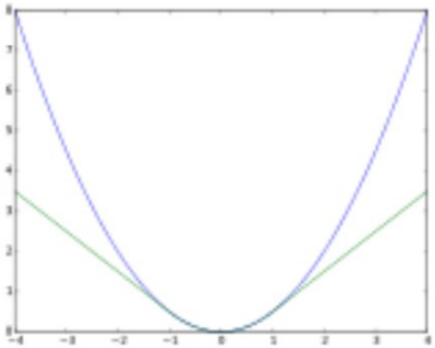
Practical Tips for DQN on Atari (from J. Schulman)

- DQN is more reliable on some Atari tasks than others. Pong is a reliable task: if it doesn't achieve good scores, something is wrong
- Large replay buffers improve robustness of DQN, and memory efficiency is key
  - Use uint8 images, don't duplicate data
- Be patient. DQN converges slowly—for ATARI it's often necessary to wait for 10-40M frames (couple of hours to a day of training on GPU) to see results significantly better than random policy
- In our Stanford class: Debug implementation on small test environment

Practical Tips for DQN on Atari (from J. Schulman) cont.

- Try Huber loss on Bellman error

$$L(x) = \begin{cases} \frac{x^2}{2} & \text{if } |x| \leq \delta \\ \delta|x| - \frac{\delta^2}{2} & \text{otherwise} \end{cases}$$



Practical Tips for DQN on Atari (from J. Schulman) cont.

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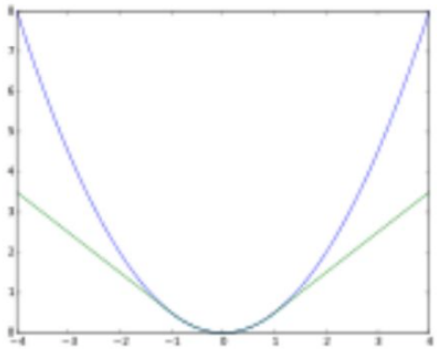

- Consider trying Double DQN—significant improvement from 3-line change in Tensorflow.
- To test out your data pre-processing, try your own skills at navigating the environment based on processed frames
- Always run at least two different seeds when experimenting
- Learning rate scheduling is beneficial. Try high learning rates in initial exploration period
- Try non-standard exploration schedules

Table of Contents

Class Structure

- Last time: Value function approximation and deep learning
- This time: Convolutional neural networks and deep RL
- Next time: Imitation learning