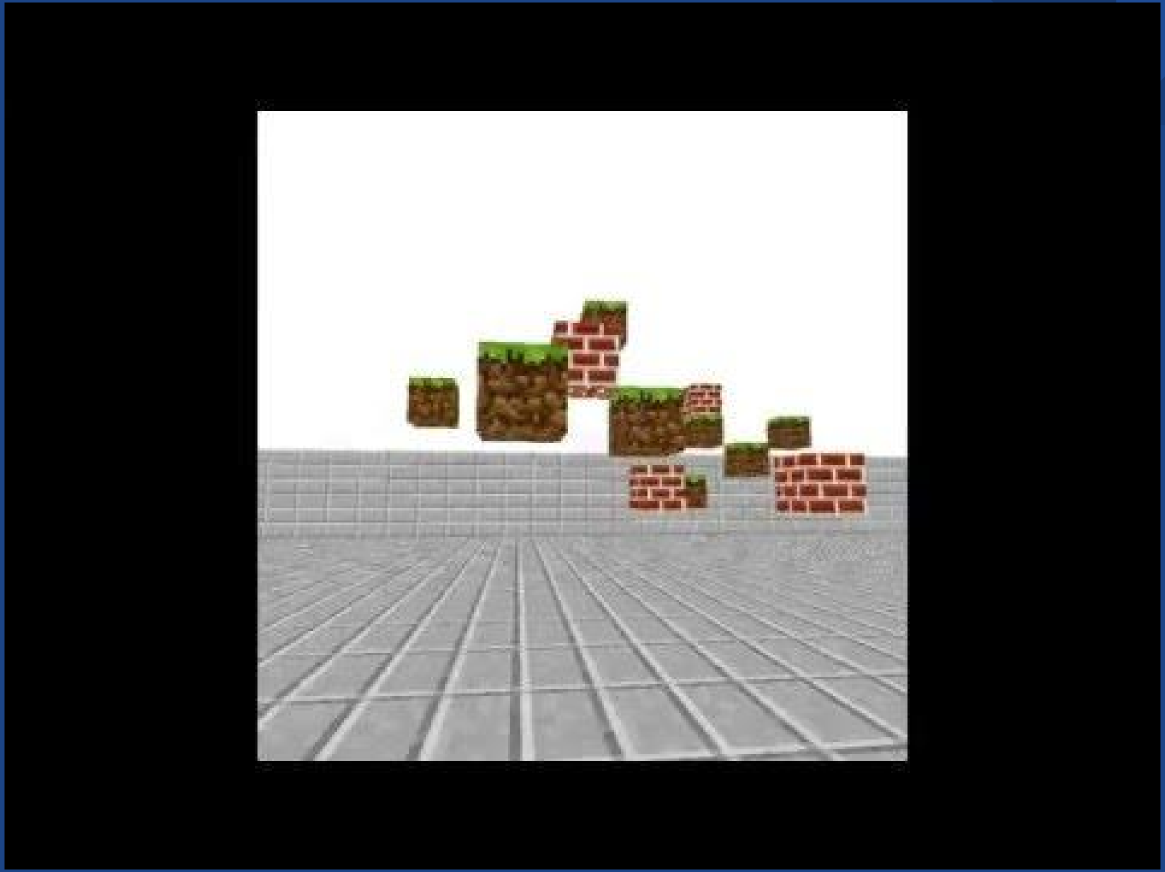
Deep Reinforcement Learning in TensorFlow

Danijar Hafner · Stanford CS 20SI · 2017-03-10

Gu16



Barron16

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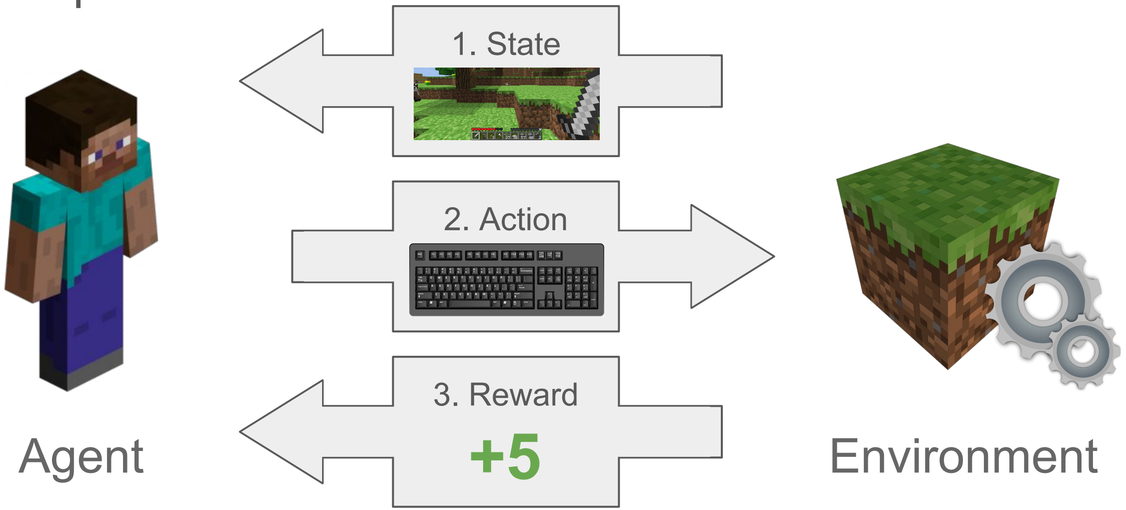
Reinforcement Learning

Repeat until end of episode:



Most methods also work with partial observation instead of state

No perfect example output as in supervised learning

Formalization as Markov Decision Process

Environment:

Markovian states $s \in S$ and actions $a \in A$

Scalar reward function $R(r_t \mid s_t, a_t)$

Transition function $P(s_{t+1} \mid s_t, a_t)$

Agent:

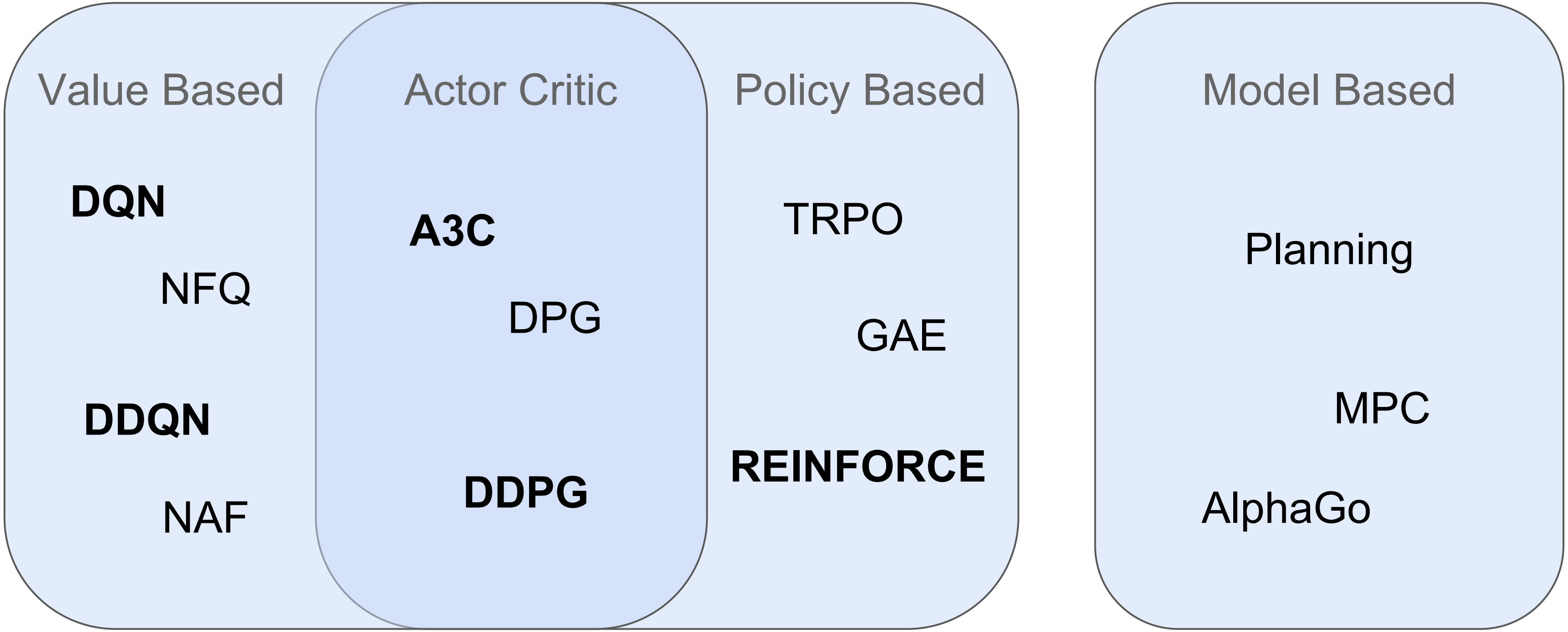
Act according to stochastic policy $\pi(a_t \mid s_0, \ldots, s_t)$

Collects experience tuples (s_t, a_t, r_t, s_{t+1})

Objective:

Maximize expectation of return $R_t = \sum_{i=0, \ldots, \infty} \gamma^i r_{t+i}$ discounted by $0 < \gamma < 1$

Overview of Methods



Value Based Methods

Value Learning

Value function $V(s_t) = E[\, R_t \,] = E[\, \sum_{i=0,\, \ldots,\, \infty} \gamma^i \, r_{t+i} \,]$

Bellman equation $V(s) = r + \gamma \sum_{s' \epsilon S} \{ \, P(s'|s, \pi(a|s)) V(s') \, \}$

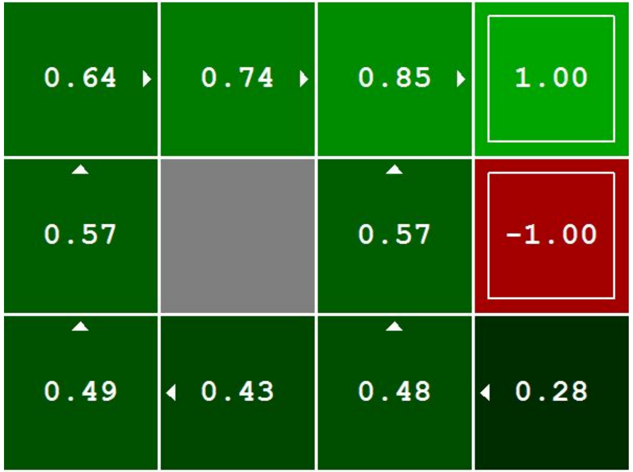
Act according to best V(s'), sometimes randomly

Estimate V(s) using learning rate

$$V'(s) = (1 - \alpha)\, V(s) + \alpha\, (r + V(s'))$$

Converges to true value function and optimal behavior

Problem: Need $P(s'|s)$ to act (as in board games, for example Go)



Andy Zeng (http://www.cs.princeton.edu/~andyz/pacmanRL)

Q Learning (Watkins89)

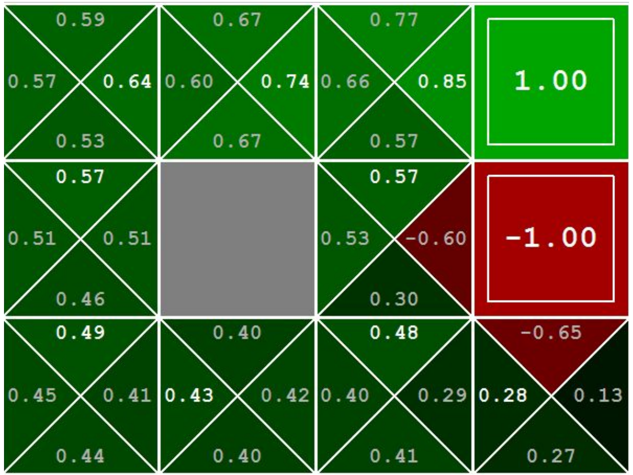
Learn Q function $Q(s_t, a_t) = E[R_t]$ instead

Bellman equation $Q^*(s, a) = r + \gamma \max_{a' \epsilon A} Q^*(s', a')$

Act according to best Q(s, a), sometimes randomly

Estimate $Q^*(s, a)$ using learning rate

$$Q'(s, a) = (1 - \alpha)\, Q(s, a) + \alpha\, (r + \max_{a' \epsilon A} Q(s', a'))$$

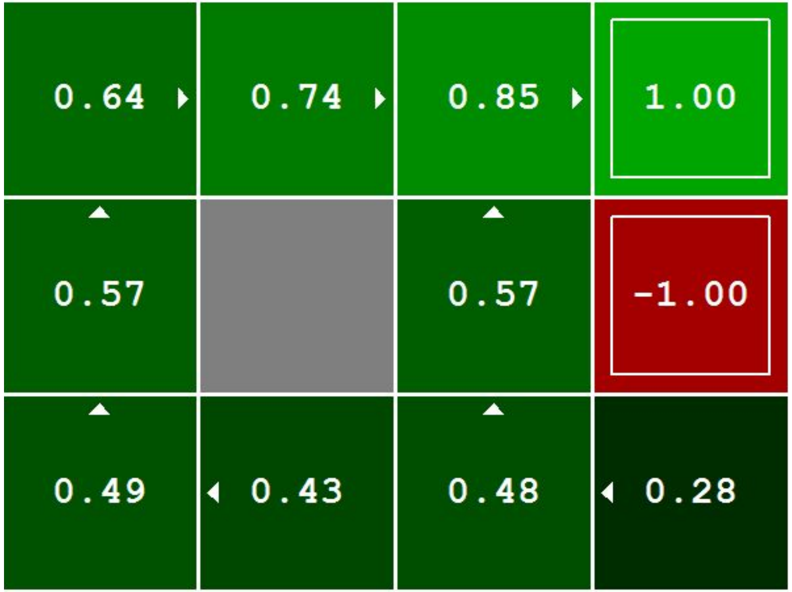


Andy Zeng (http://www.cs.princeton.edu/~andyz/pacmanRL)

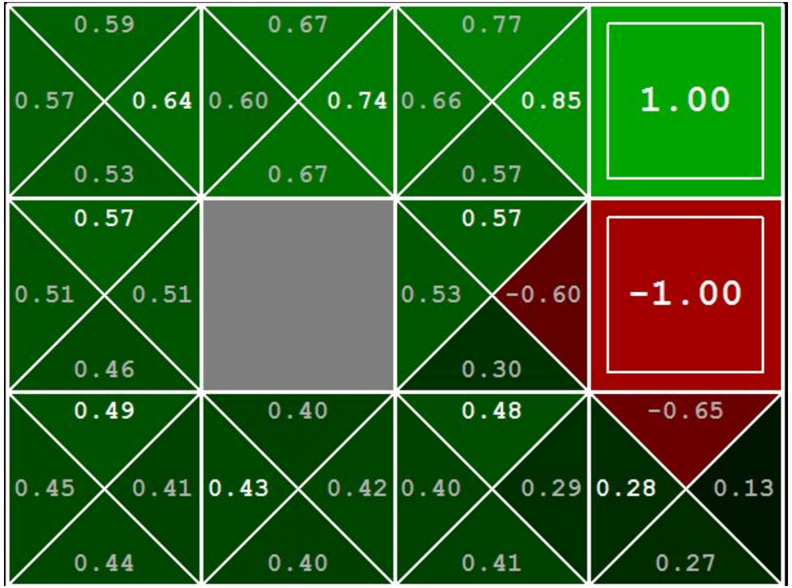
Converges to optimal function $Q^*(s, a)$ and optimal behavior

Doesn't depend on policy, can learn from demonstrations or old experience

Comparison Value Learning and Q-Learning



$\pi(s) = \text{argmax}_{a\epsilon A} \{ \sum_{s'\epsilon S} P(s'|s, a)\, V(s') \}$



$\pi(s) = \text{argmax}_{a\epsilon A}\, Q(s, a)$

Epsilon Greedy Exploration

Convergence and optimality only when visiting each state infinitely often

Exploration is a main challenge in reinforcement learning

Simple approach is acting randomly with probability ε

Will visit each (s, a) infinitely often in the limit

Decay ε exponentially to ensure converge

Right amount of exploration is often critical in practice

```
epsilon = exponential_decay(step, 50000, 1.0, 0.05, rate=0.5)
best_action = tf.arg_max(_qvalues([observ])[0], 0)
random_action = tf.random_uniform((), 0, num_actions, tf.int64)
should_explore = tf.random_uniform((), 0, 1) < epsilon
return tf.cond(should_explore, lambda: random_action, lambda: best_action)

def exponential_decay(step, total, initial, final, rate=1e-4, stairs=None):
  if stairs is not None:
    step = stairs * tf.floor(step / stairs)
  scale, offset = 1. / (1. - rate), 1. - (1. / (1. - rate))
  progress = tf.cast(step, tf.float32) / tf.cast(total, tf.float32)
  value = (initial - final) * scale * rate ** progress + offset + final
  lower, upper = tf.minimum(initial, final), tf.maximum(initial, final)
  return tf.maximum(lower, tf.minimum(value, upper))
```

Deep Neural Networks

Nonlinear Function Approximation

Too many states for a lookup table

We want to approximate Q(s, a) using a deep neural network

Can capture complex dependencies between s, a and Q(s, a)

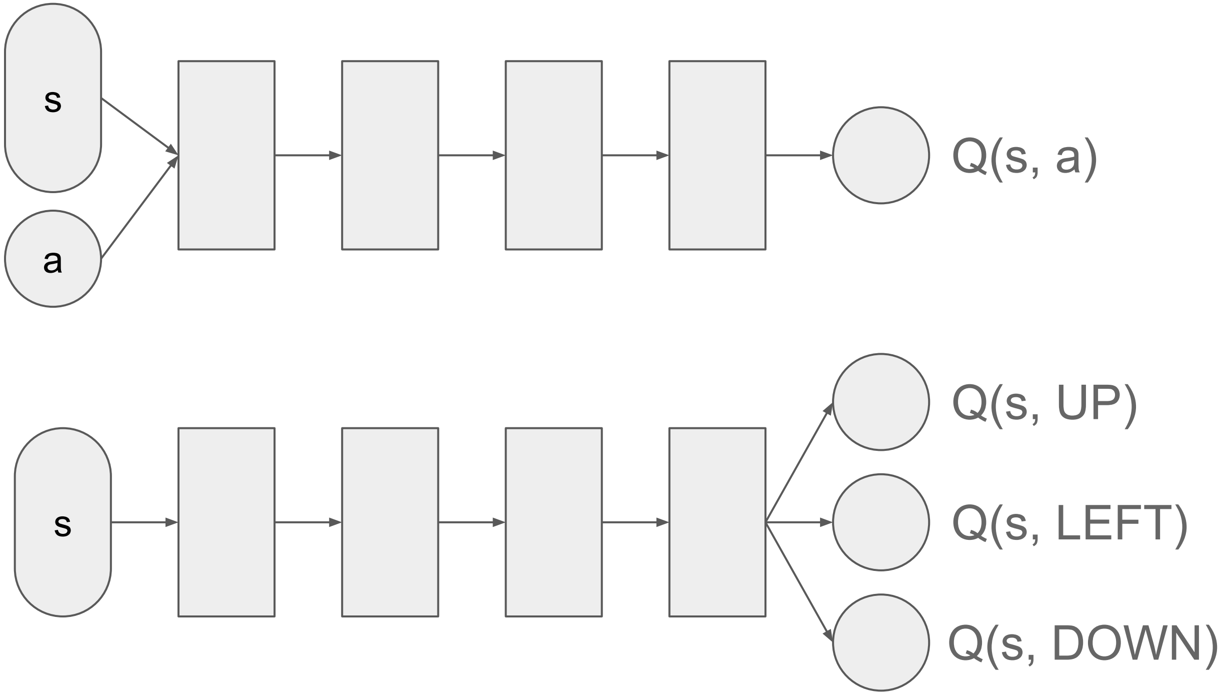
    Agent can learn sophisticated behavior!

Convolutional networks for reinforcement learning from pixels

Share some tricks from papers of the last two years

Sketch out implementations in TensorFlow

Predicting All Q-Values at Once (Mnih13)



Only one forward pass to find the best action!

```python
def _qvalues(observ):
  with tf.variable_scope('qvalues', reuse=True):
    # Network from DQN (Mnih 2015)
    h1 = tf.layers.conv2d(observ, 32, 8, 4, tf.nn.relu)
    h2 = tf.layers.conv2d(h1, 64, 4, 2, tf.nn.relu)
    h3 = tf.layers.conv2d(h2, 64, 3, 1, tf.nn.relu)
    h4 = tf.layers.dense(h3, 512, tf.nn.relu)
    return tf.layers.dense(h4, num_actions, None)

current = tf.gather(_qvalues(observ), action)[:, 0]
target = reward + gamma * tf.reduce_max(_qvalues(nextob), 1)
target = tf.where(done, tf.zeros_like(target), target)
loss = (current - target) ** 2
```

Trick 1: Experience Replay (Mnih13)

Stochastic gradient descent expects independent samples

Agent collects highly correlated experience at a time

Store experience tuples in a large buffer and select random batch for training

Decorrelates training examples!

Even better: Select training examples prioritized by last training cost (Schaul15)

Focuses on rare training examples!

```python
class ReplayBuffer:

  def __init__(self, template, capacity):
    self._capacity = capacity
    self._buffers = self._create_buffers(
        template)
    self._index = tf.Variable(
        0, dtype=tf.int32, trainable=False)

  def size(self):
    return tf.minimum(
        self._index, self._capacity)

  def append(self, tensors):
    position = tf.mod(
        self._index, self._capacity)
    with tf.control_dependencies([
          b[position].assign(t) for b, t in
          zip(self._buffers, tensors)]):
      return self._index.assign_add(1)

  def sample(self, amount):
    positions = tf.random_uniform(
        (amount,), 0, self.size - 1, tf.int32)
    return [tf.gather(b, positions)
                for b in self._buffers]

  def _create_buffers(self, template):
    buffers = []
    for tensor in template:
      shape = tf.TensorShape(
          [self._capacity]).concatenate(
          tensor.get_shape())
      initial = tf.zeros(shape, tensor.dtype)
      buffers.append(tf.Variable(
          initial, trainable=False))
    return buffers
```

```python
class PrioritizedReplayBuffer:

  def __init__(self, template, capacity):
    template = (tf.constant(0.0),) + tuple(template)
    self._buffer = ReplayBuffer(template, capacity)

  def size(self):
    return self._buffer.size

  def append(self, priority, tensors):
    return self._buffer.append((priority,) + tuple(tensors))

  def sample(self, amount, temperature=1):
    priorities = self._buffer._buffers[0].value()[:self._buffer.size()]
    logprobs = tf.log(priorities / tf.reduce_sum(priorities)) / temperature
    positions = tf.multinomial(logprobs[None, ...], amount)[0]
    return [tf.gather(b, positions) for b in self._buffer._buffers[1:]]
```

Trick 2: Target Network (Mnih15, Lillicrap16, ...)

Targets $r + \gamma \max_{a' \epsilon A} Q(s', a')$ depend on own current network $Q(s, a)$

Training towards moving target makes training unstable

Use a moving average $Q^T(s, a)$ of the network to compute the targets

Update network parameters $\theta^T_{t+1} = (1 - \beta)\, \theta^T_t + \beta\, \theta_t$ with $\beta << 1$

Get weights using graph editor and apply tf.train.ExponentialMovingAverage

Use graph editor to copy network graph and bind to averaged variables

```python
def bind(output, inputs):
  for key in inputs:
    if isinstance(inputs[key], tf.Variable):
      inputs[key] = inputs[key].value()
  return tf.contrib.graph_editor.graph_replace(output, inputs)

def moving_average(
    output, decay=0.999, collection=tf.GraphKeys.TRAINABLE_VARIABLES):
  average = tf.train.ExponentialMovingAverage(decay=decay)
  variables = set(v.value() for v in output.graph.get_collection(collection))
  deps = tf.contrib.graph_editor.get_backward_walk_ops(output)
  deps = [t for o in deps for t in o.values()]
  deps = set([t for t in deps if t in variables])
  update_op = average.apply(deps)
  new_output = bind(output, {t: average.average(t) for t in deps})
  return new_output, update_op

current = tf.gather(_qvalues(observ), action)[:, 0]
target_qvalues = moving_average(_qvalues(nextob), 0.999)
target = reward + gamma * tf.reduce_max(target_qvalues, 1)
target = tf.where(done, tf.zeros_like(target), target)
loss = (current - target) ** 2
```

Trick 3: Double Q Learning (Hasselt10, Hasselt15)

Q Learning tends to overestimate Q values

Same network chooses best action and evaluates it

$r + \gamma \max_{a' \epsilon A} Q(s', a') = r + \gamma Q(s', \text{argmax}_{a' \epsilon A} Q(s', a'))$

Learning two Q functions from different experience would be ideal

For efficiency, use target network $Q^T(s, a)$ to evaluate action

Targets become $r + \gamma Q^T(s', \text{argmax}_{a' \epsilon A} Q(s', a'))$

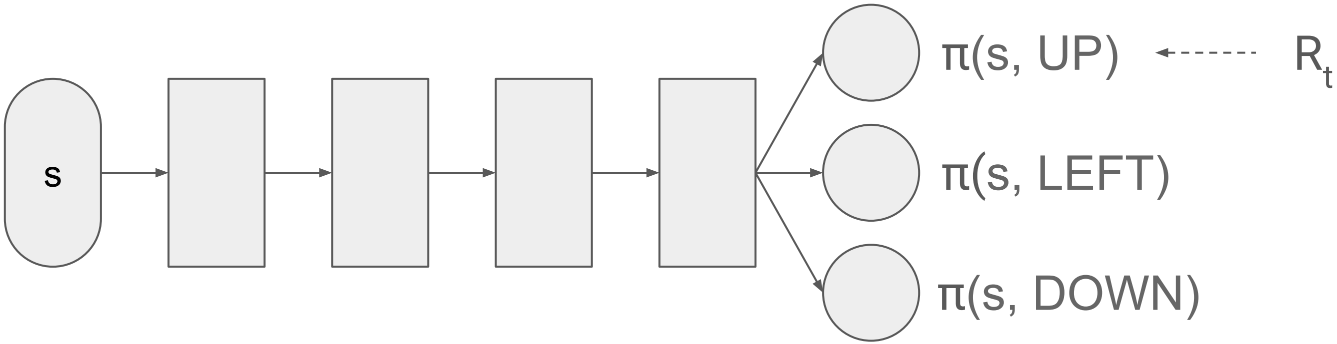
```python
# Q Learning
current = tf.gather(_qvalues(observ), action)[:, 0]
target_qvalues = moving_average(_qvalues(nextob), 0.999)
target = reward + gamma * tf.reduce_max(target_qvalues, 1)
target = tf.where(done, tf.zeros_like(target), target)
loss = (current - target) ** 2

# Double Q Learning
current = tf.gather(_qvalues(observ), action)[:, 0]
target_qvalues = moving_average(_qvalues(nextob), 0.999)
future_action = tf.argmax(_qvalues(nextob), 1)
target = reward + gamma * tf.gather(target_qvalues, future_action)
target = tf.where(done, tf.zeros_like(target), target)
loss = (current - target) ** 2
```

Policy Based Methods

Policy Gradient (Williams92)

Instead of learning value functions, learn policy $\pi(a_t \mid s_0, \ldots, s_t)$ directly

Train network to maximize expected return $E[R_t]$



$R(r \mid s, a)$ is unknown but gradient of expectation still possible: $E[R_t \nabla_\theta \ln \pi(a|s)]$

Can only train on-policy because returns won't match otherwise

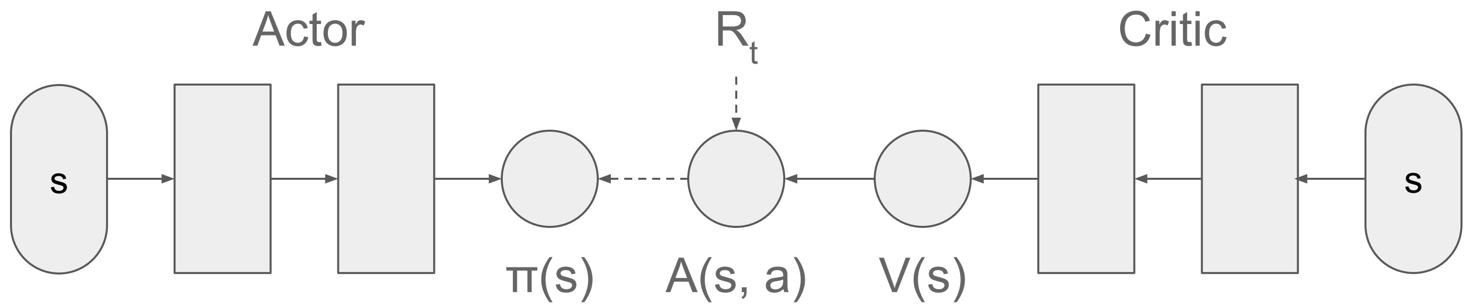
```python
def _policy(observ):
  with tf.variable_scope('policy', reuse=True):
    # Network from A3C (Mnih 2016)
    h1 = tf.layers.conv2d(observ, 16, 8, 4, tf.nn.relu)
    h2 = tf.layers.conv2d(h1, 32, 4, 2, tf.nn.relu)
    h3 = tf.layers.dense(h2, 256, tf.nn.relu)
    cell = tf.contrib.rnn.GRUCell(256)
    h4, _ = tf.nn.dynamic_rnn(cell, h3[None, ...], dtype=tf.float32)
    return tf.layers.dense(h4[0], num_actions, None)

action_mask = tf.one_hot(action, num_actions)
prob_under_policy = tf.reduce_sum(_policy(observ) * action_mask, 1)
loss = -return_ * tf.log(prob_under_policy + 1e-13)
```

Variance Reduction Via Baseline (Williams92, Sutton98)

Learn the best actions and don't care about other parts of reward

Subtract baseline $b(s)$ from return R_t to reduce variance

Advantage actor critic maximizes advantage function $A(s, a) = R_t - V(s)$



In practice, actor and critic often share lower layers

```python
def _shared_network(observ):
  with tf.variable_scope('shared_network', reuse=True):
    # Network from A3C (Mnih 2016)
    h1 = tf.layers.conv2d(observ, 16, 8, 4, tf.nn.relu)
    h2 = tf.layers.conv2d(h1, 32, 4, 2, tf.nn.relu)
    h3 = tf.layers.dense(h2, 256, tf.nn.relu)
    cell = tf.contrib.rnn.GRUCell(256)
    h4, _ = tf.nn.dynamic_rnn(cell, h3[None, ...], dtype=tf.float32)
    return h4[0]

features = _shared_network(observ)
policy = tf.layers.dense(features, num_actions, None)
value = tf.layers.dense(features, 1, None)
advantage = tf.stop_gradient(return_ - value)
action_mask = tf.one_hot(action, num_actions)
prob_under_policy = tf.reduce_sum(_policy(observ) * action_mask, 1)
policy_loss = -advantage * tf.log(prob_under_policy + 1e-13)
value_loss = (return_ - value) ** 2
```

Continuous Control using Policy Gradients

Many control problems are better formulated using continuous actions

For example, control steering angle rather than just left/center/right

Policy gradients don't max over actions as Q Learning does

Well suited for continuous action spaces

Decompose policy into mean and noise $\pi(a \mid s) = \mu(s) + z(s)$

Learn mean and add fixed noise source, or learn both

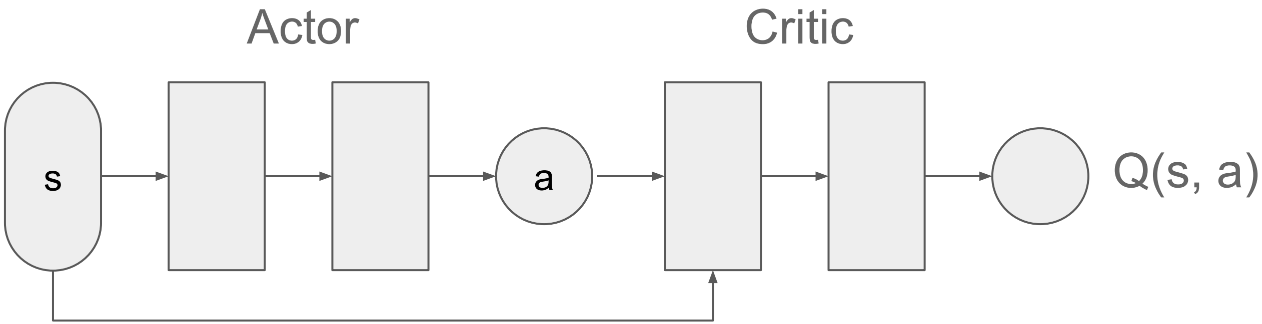
Deterministic Policy Gradient (Silver14, Lillicrap16)

Continuous policy gradient algorithm that can learn off-policy

Evaluate actions using a critic network Q(s, a) rather than the environment

On-policy SARSA doesn't need max over actions!

Backpropagate gradient to the action: $E[\ \nabla_a Q(s, a)\ \nabla_\theta \ln \pi(s)\ ]$



```
features = _shared_network(observ)
action = _policy(features, action_size)
qvalue = _qvalue(features, action)

direction = tf.gradients([qvalue], [action])[0]
if self._clip_q_grad:
  direction = tf.clip_by_value(direction, -1, 1)
target = tf.stop_gradient(action + direction)
policy_loss = tf.reduce_sum((target - action) ** 2, 2)

target_qvalue = _qvalue(_shared_network(nextob))
target_qvalue = moving_average(target_qvalue, 0.999)
target = reward + gamma * target_qvalue
target = tf.where(done, tf.zeros_like(target), target)
loss = (qvalue - target) ** 2
```

Further Resources

Reading:

Richard Sutton	(goo.gl/TCPIwx)
Andrej Karpathy	(goo.gl/UHh7yK)

Lectures:

David Silver	(youtu.be/2pWv7GOvuf0)
John Schulman	(youtu.be/oPGVsoBonLM)

Software:

Gym	(gym.openai.com)
RL Lab	(github.com/openai/rllab)
Modular RL	(github.com/joschu/modular_rl)
Mindpark	(github.com/danijar/mindpark)