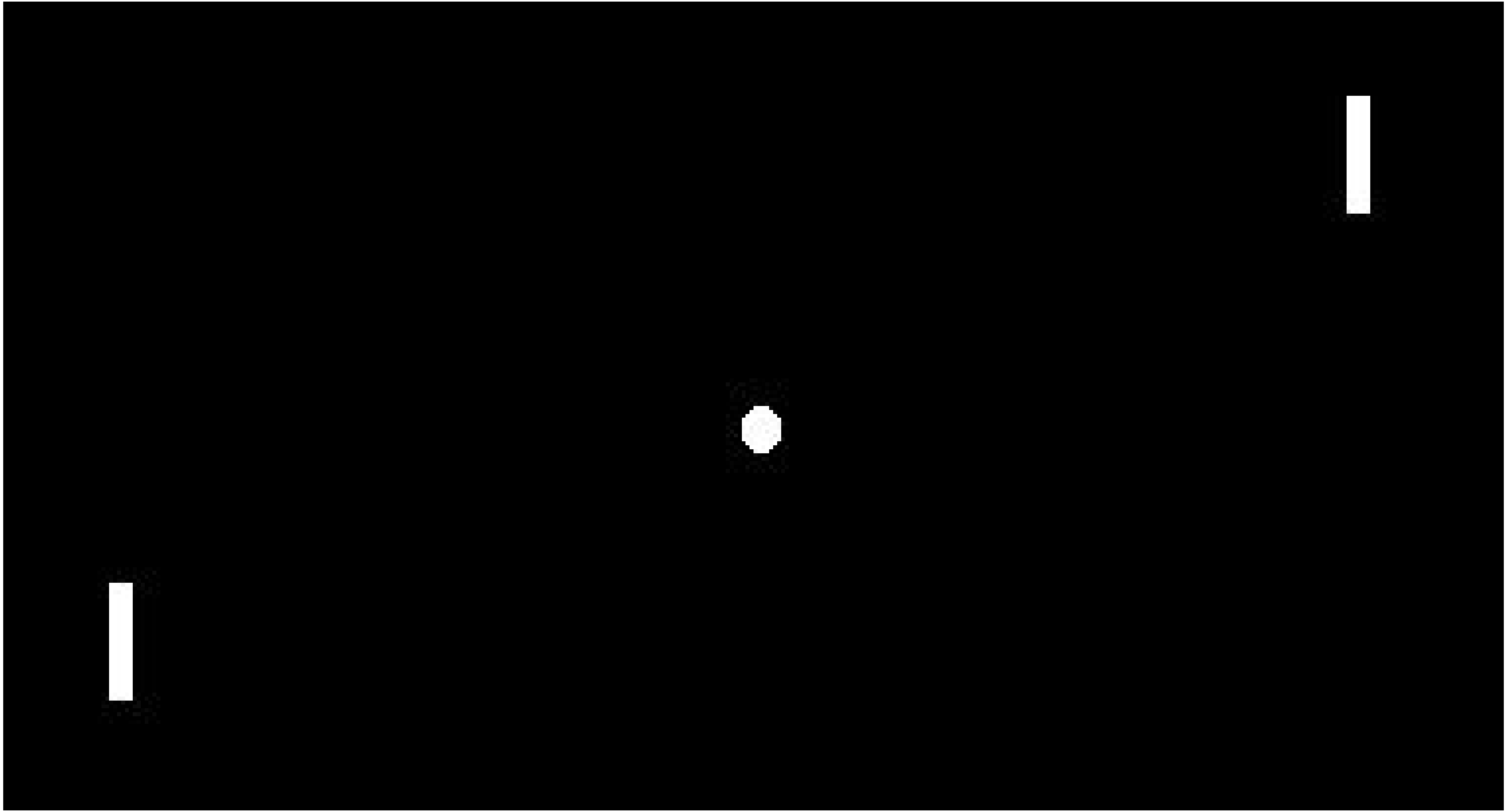
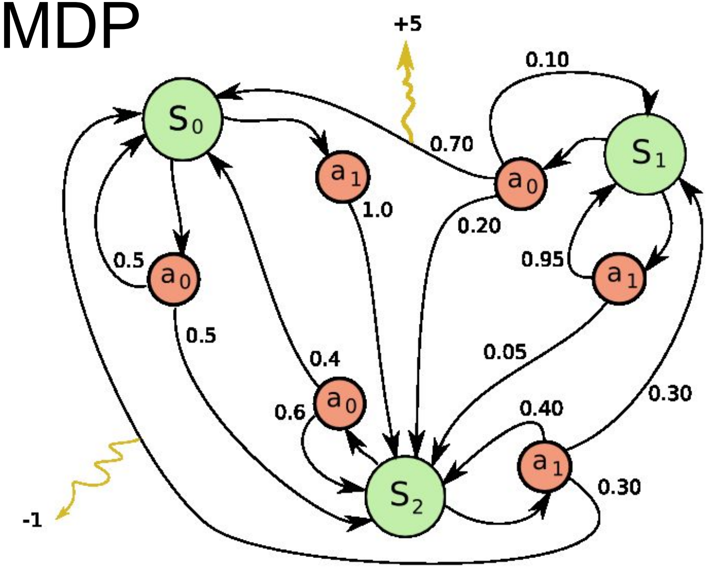
Pong from Pixels

Deep RL Bootcamp

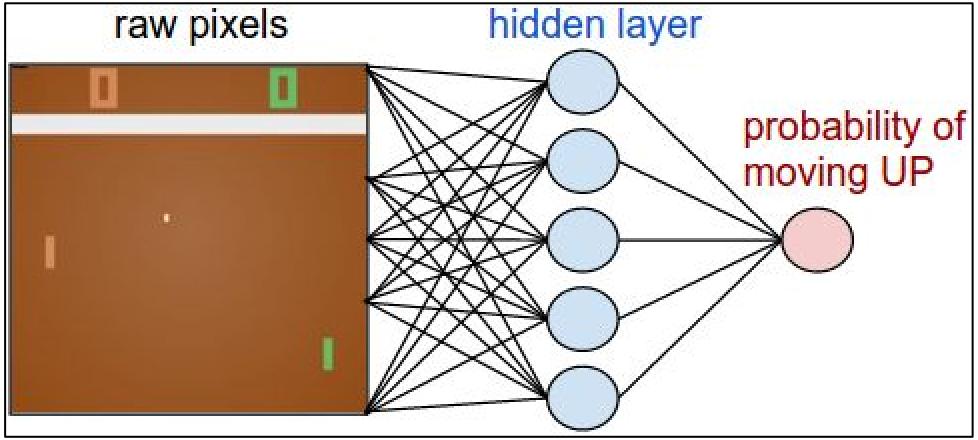
Andrej Karpathy, Aug 26, 2017



MDP


+5
0.10
S0
0.70
S1
a1
a0
1.0
0.20
0.5
a0
0.95
a1
0.5
0.05
0.4
0.30
0.6
a0
0.40
a1
S2
0.30
-1

Policy network

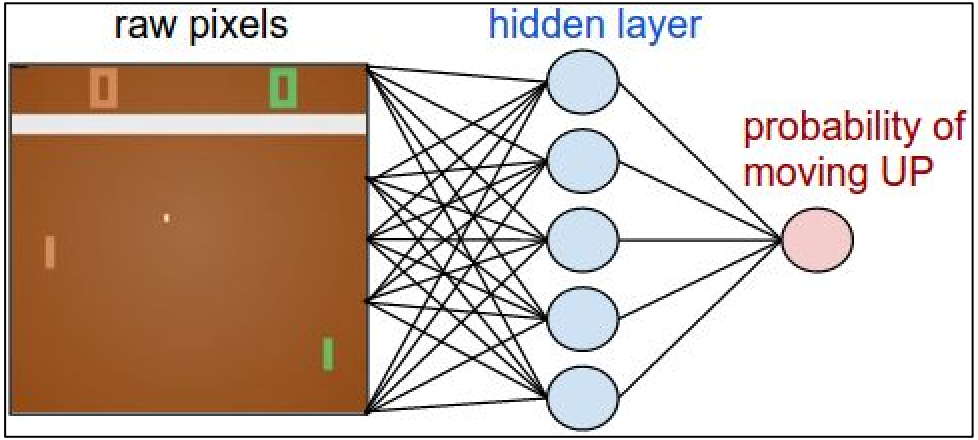


Policy network

e.g.,

height width

[80 x 80]
array of



Policy network

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[80 x 80]
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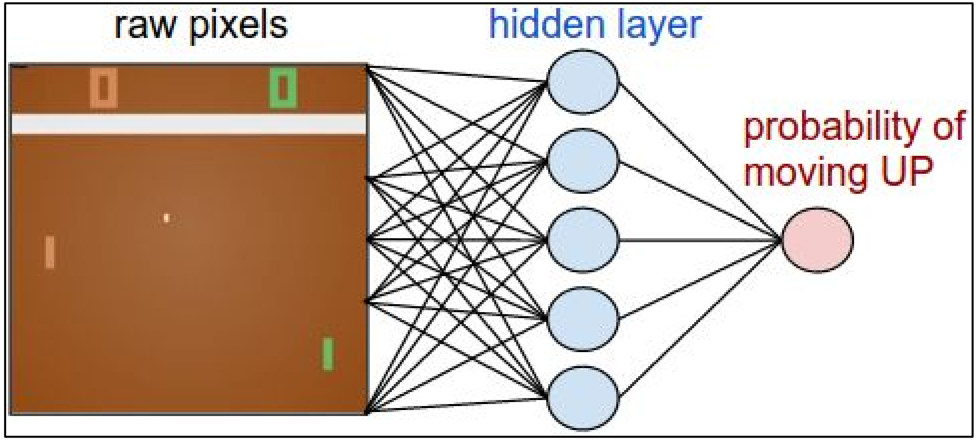
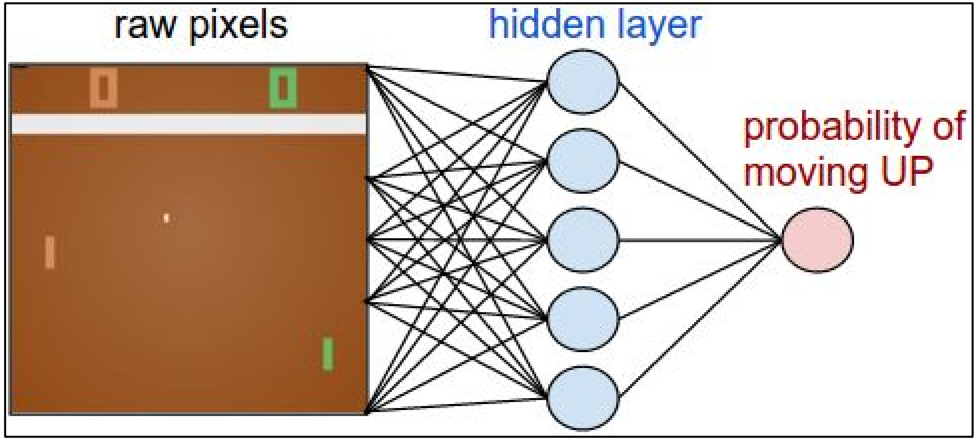



```
h = np.dot(W1, x) # compute hidden layer neuron activations
h[h<0] = 0 # ReLU nonlinearity: threshold at zero
logp = np.dot(W2, h) # compute log probability of going up
p = 1.0 / (1.0 + np.exp(-logp)) # sigmoid function (gives probability of going up)
```

Policy network

height width

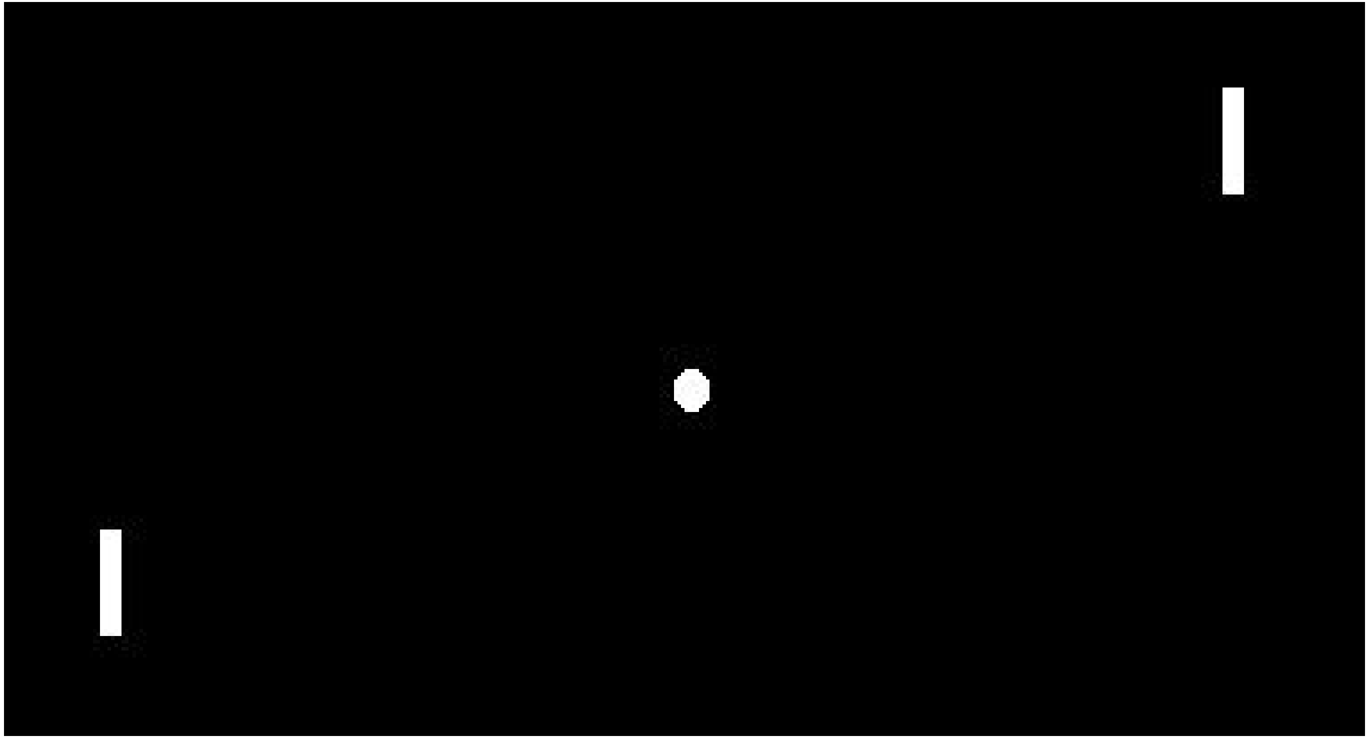
[80 x 80]
array



E.g. 200 nodes in the hidden network, so:

[(80*80)*200 + 200] + [200*1 + 1] = **~1.3M parameters**

Layer 1 Layer 2



Network does not see this. Network sees 80*80 = 6,400 numbers.
It gets a reward of +1 or -1, some of the time.
Q: How do we efficiently find a good setting of the 1.3M parameters?

Problem is easy if you want to be inefficient...

1. **Repeat Forever:**
2. Sample 1.3M random numbers
3. Run the policy for a while
4. If the performance is best so far, save it
5. Return the best policy

Problem is easy if you want to be inefficient...

1. **Repe**
2. Sa
3. Ru
4. If th
5. Retur

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Policy Gradients

Suppose we had the training labels…
(we know what to do in any state)

(x1,UP)
(x2,DOWN)
(x3,UP)
...

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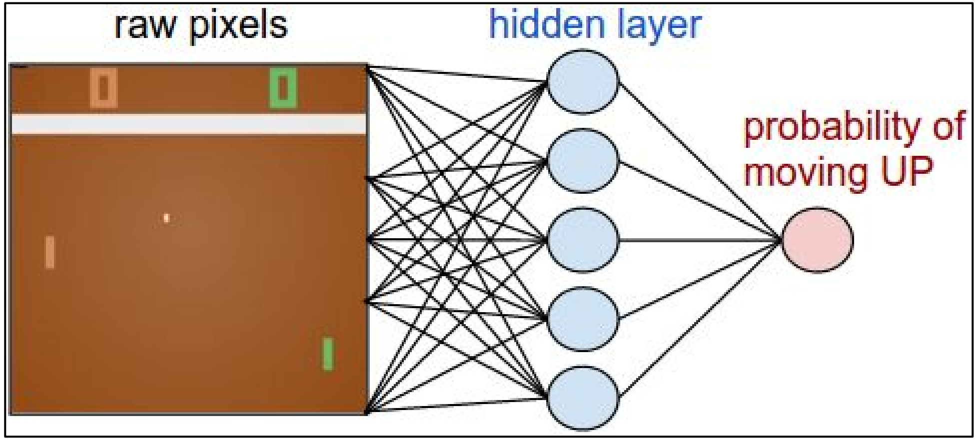
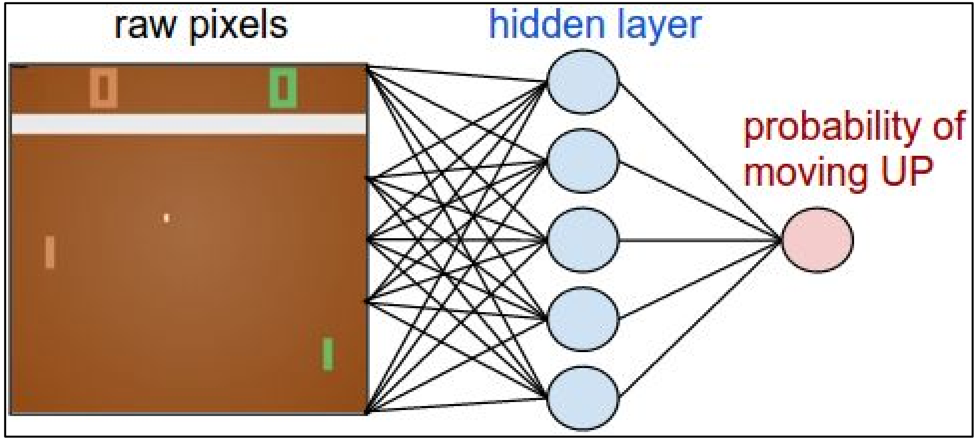


Suppose we had the training labels…
(we know what to do in any state)

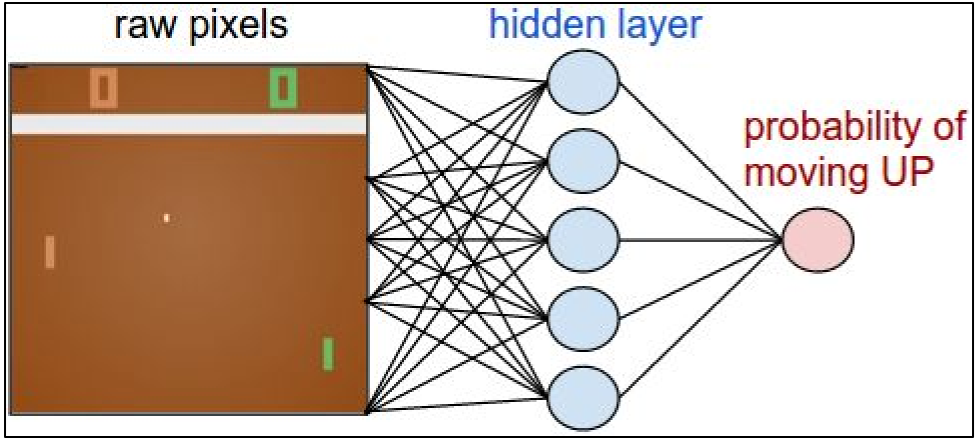
(x1,UP)
(x2,DOWN)
(x3,UP)
...

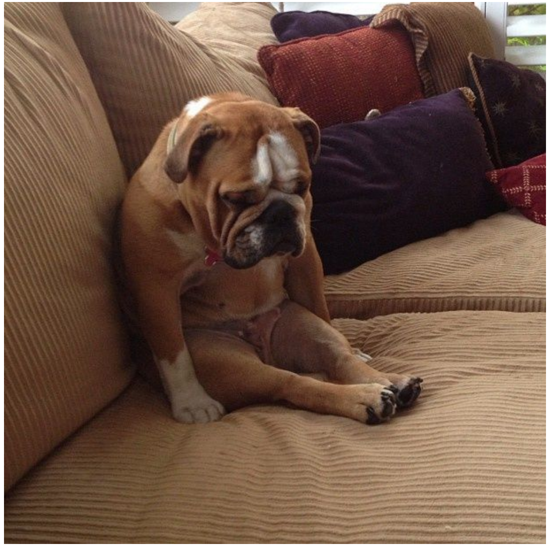
maximize:

$$\boxed{\sum_i \log p(y_i \mid x_i)}$$



Except, we don't have labels...





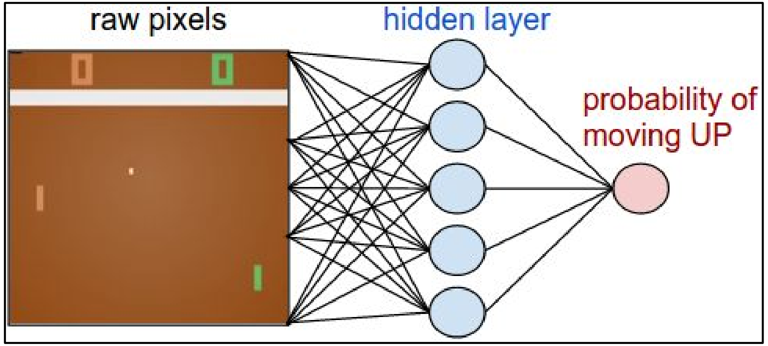
Should we go UP or DOWN?

Except, we don’t have labels...

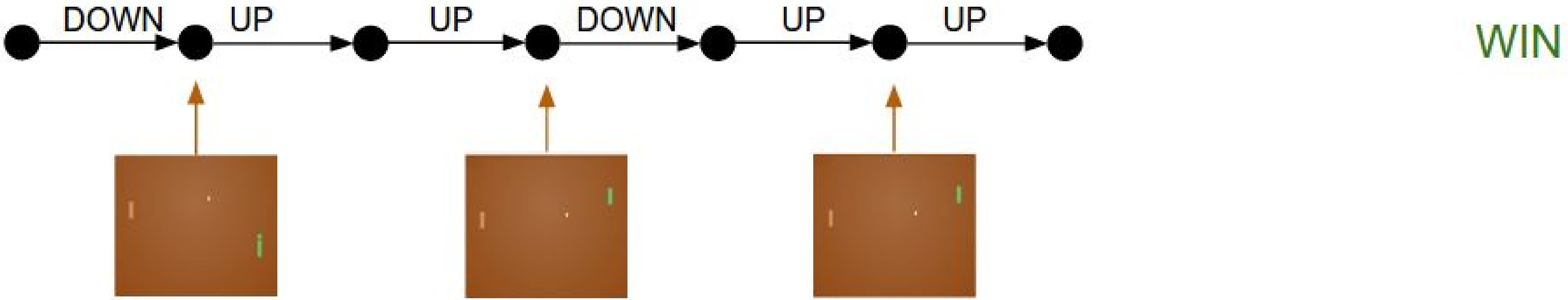
“Try a bunch of stuff and see what happens. Do more of the stuff that worked in the future.”

-RL

Let’s just act according to our current policy...

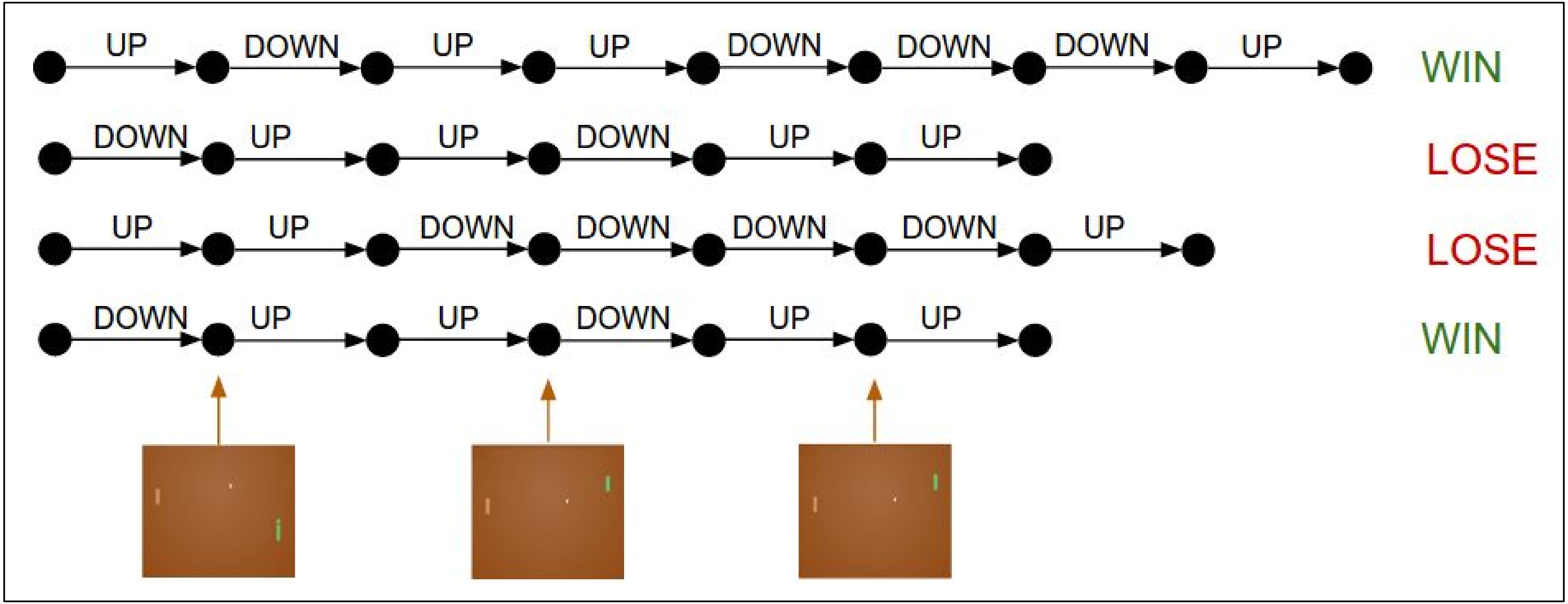


Rollout the policy and collect an episode

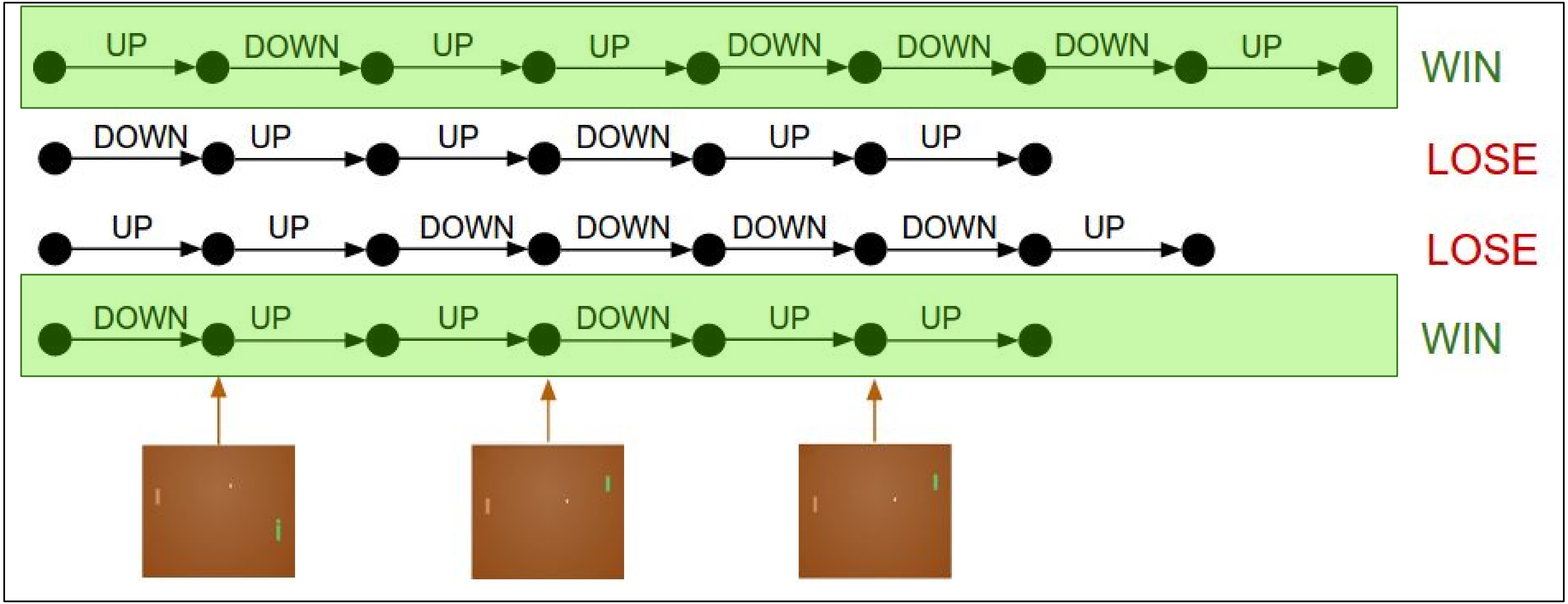


Collect many rollouts...

4 rollouts:



Not sure whatever we did here, but apparently it was good.



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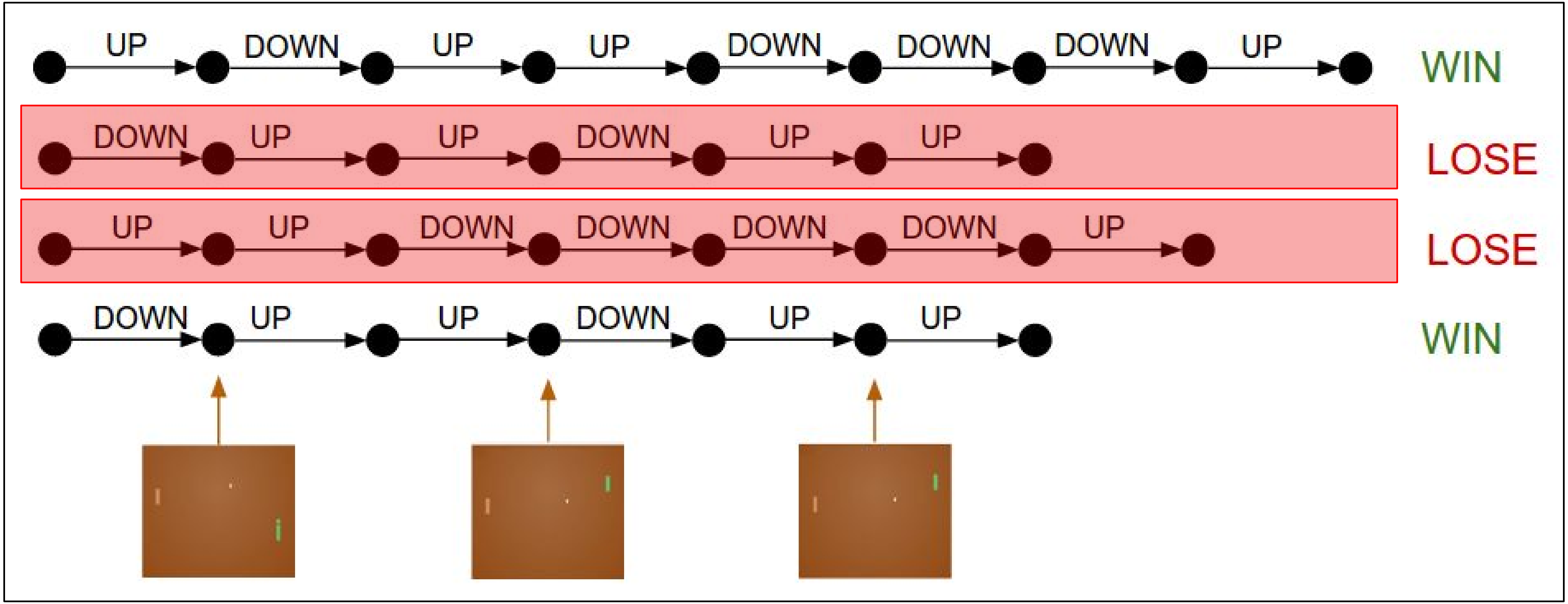
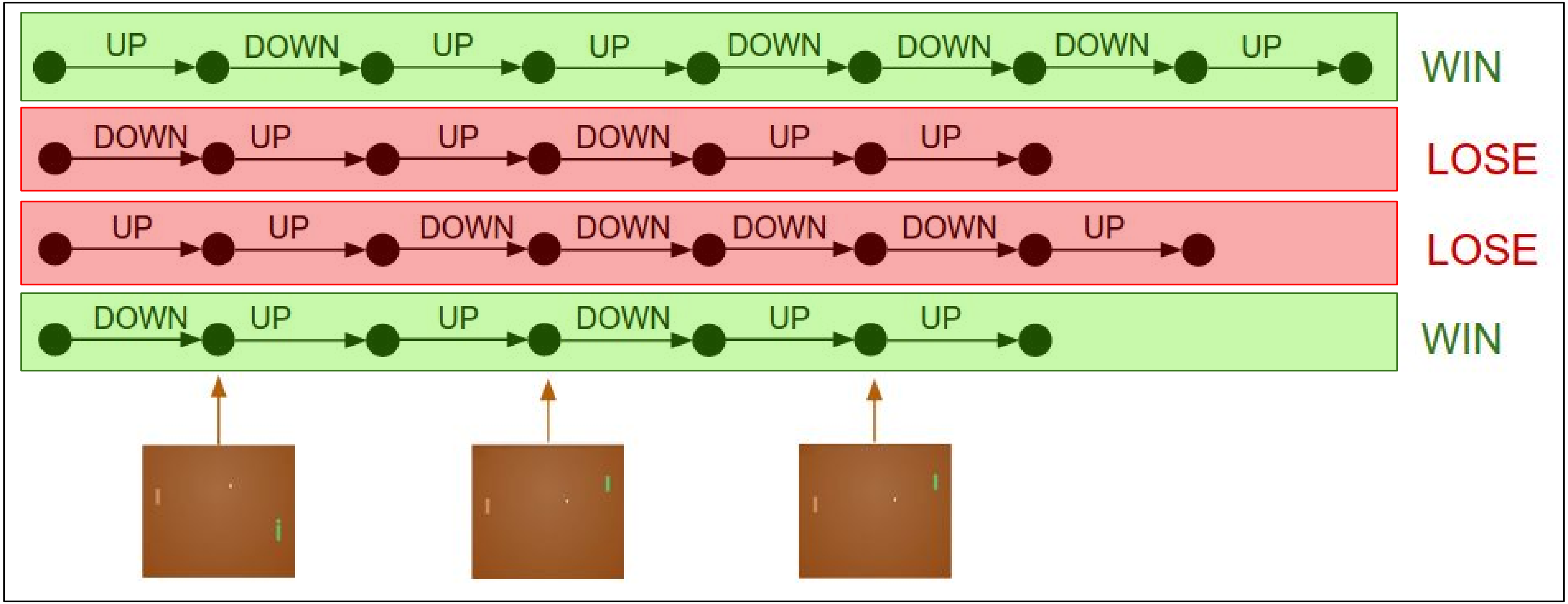


Pretend every action we took here was the correct label.

maximize: $\log p(y_i \mid x_i)$

Pretend every action we took here was the wrong label.

maximize: $(-1) * \log p(y_i \mid x_i)$



Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

Supervised Learning

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Reinforcement Learning

Supervised Learning

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For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot \mid x_i)}$$

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot | x_i)}$$

2) once we collect a batch of rollouts:

maximize:

$$\boxed{\sum_i A_i * \log p(y_i | x_i)}$$

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i \mid x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

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2) once we collect a batch of rollouts:

maximize:

$$\boxed{\sum_i A_i * \log p(y_i \mid x_i)}$$

We call this the **advantage**, it's a number, like +1.0 or -1.0 based on how this action eventually turned out.

Supervised Learning

maximize:

$$\boxed{\sum_i \log p(y_i | x_i)}$$

For images x_i and their labels y_i.

Reinforcement Learning

1) we have no labels so we sample:

$$\boxed{y_i \sim p(\cdot | x_i)}$$

2) once we collect a batch of rollouts:

maximize:

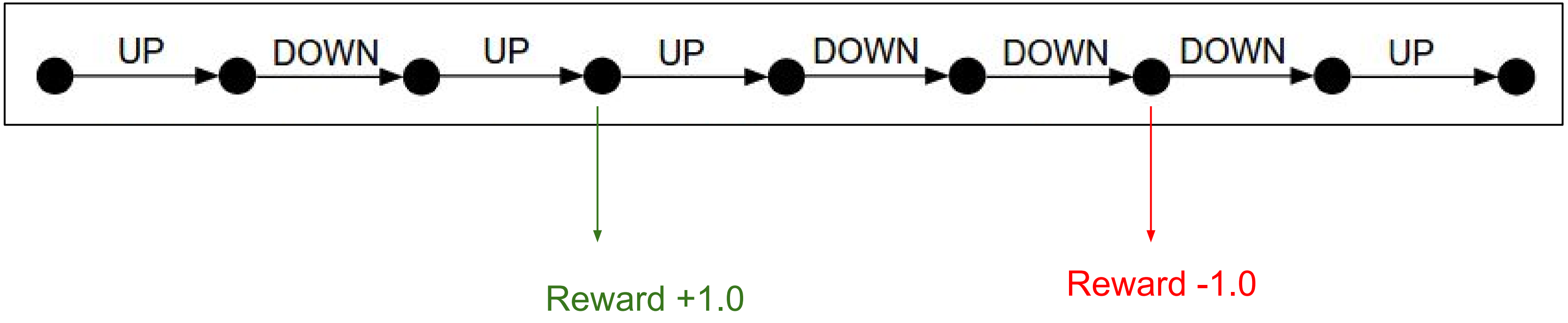
$$\boxed{\sum_i A_i * \log p(y_i | x_i)}$$

+ve advantage will make that action more likely in the future, for that state.

-ve advantage will make that action less likely in the future, for that state.

Discounting

Blame each action assuming that its effects have exponentially decaying impact into the future.



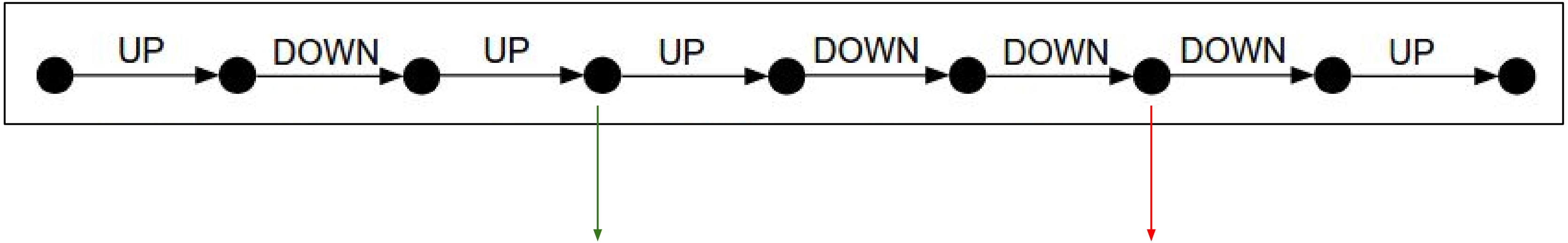
Discounting

Blame each action assuming that its effects have exponentially decaying impact into the future.

$$\sum_i \boxed{A_i} * \log p(y_i|x_i)$$

Discounted rewards

0.21 0.24 0.27 -0.81 -0.9 -1 0 0



Reward +1.0

Reward -1.0

\gamma = 0.9


time
discounted reward
episode start
ball gets past our paddle
-1 reward
we screwed up
somewhere here
this was all hopeless and only
contributes noise to the gradient


YEAH, IF YOU COULD JUST SHOW ME SOME CODE
THAT'D BE GREAT
memegenerator.net

130 line gist, numpy as the only dependency.
https://gist.github.com/karpathy/a4166c7fe253700972fcbc77e4ea32c5

```python
env = gym.make("Pong-v0")
observation = env.reset()
prev_x = None # used in computing the difference frame
xs,hs,dlogps,drs = [],[],[],[]
running_reward = None
reward_sum = 0
episode_number = 0
while True:
  if render: env.render()

  # preprocess the observation, set input to network to be difference image
  cur_x = prepro(observation)
  x = cur_x - prev_x if prev_x is not None else np.zeros(D)
  prev_x = cur_x

  # forward the policy network and sample an action from the returned probability
  aprob, h = policy_forward(x)
  action = 2 if np.random.uniform() < aprob else 3 # roll the dice!

  # record various intermediates (needed later for backprop)
  xs.append(x) # observation
  hs.append(h) # hidden state
  y = 1 if action == 2 else 0 # a "fake label"
  dlogps.append(y - aprob) # grad that encourages the action that was taken to be taken (see http://cs231n.github.io/neural-networks-2/#los

  # step the environment and get new measurements
  observation, reward, done, info = env.step(action)
  reward_sum += reward

  drs.append(reward) # record reward (has to be done after we call step() to get reward for previous action)

  if done: # an episode finished
    episode_number += 1

    # stack together all inputs, hidden states, action gradients, and rewards for this episode
    epx = np.vstack(xs)
    eph = np.vstack(hs)
    epdlogp = np.vstack(dlogps)
    epr = np.vstack(drs)
    xs,hs,dlogps,drs = [],[],[],[] # reset array memory

    # compute the discounted reward backwards through time
    discounted_epr = discount_rewards(epr)
    # standardize the rewards to be unit normal (helps control the gradient estimator variance)
    discounted_epr -= np.mean(discounted_epr)
    discounted_epr /= np.std(discounted_epr)

    epdlogp *= discounted_epr # modulate the gradient with advantage (PG magic happens right here.)
    grad = policy_backward(eph, epdlogp)
    for k in model: grad_buffer[k] += grad[k] # accumulate grad over batch

    # perform rmsprop parameter update every batch_size episodes
    if episode_number % batch_size == 0:
      for k,v in model.iteritems():
        g = grad_buffer[k] # gradient
        rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
        model[k] += learning_rate * g / (np.sqrt(rmsprop_cache[k]) + 1e-5)
        grad_buffer[k] = np.zeros_like(v) # reset batch gradient buffer

    # boring book-keeping
    running_reward = reward_sum if running_reward is None else running_reward * 0.99 + reward_sum * 0.01
    print 'resetting env. episode reward total was %f. running mean: %f' % (reward_sum, running_reward)
    if episode_number % 100 == 0: pickle.dump(model, open('save.p', 'wb'))
    reward_sum = 0
    observation = env.reset() # reset env
    prev_x = None

  if reward != 0: # Pong has either +1 or -1 reward exactly when game ends.
    print ('ep %d: game finished, reward: %f' % (episode_number, reward)) + ('' if reward == -1 else ' !!!!!!!!')
```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```


Nothing too scary over here.

We use OpenAI Gym.
And start the main training loop.

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  # forward the policy network and sample an action from the returned probability
  aprob, h = policy_forward(x)
  action = 2 if np.random.uniform() < aprob else 3 # roll the dice!

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  xs.append(x) # observation
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    epdlogp *= discounted_epr # modulate the gradient with advantage (PG magic happens right here.)
    grad = policy_backward(eph, epdlogp)
    for k in model: grad_buffer[k] += grad[k] # accumulate grad over batch

    # perform rmsprop parameter update every batch_size episodes
    if episode_number % batch_size == 0:
      for k,v in model.iteritems():
        g = grad_buffer[k] # gradient
        rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
        model[k] += learning_rate * g / (np.sqrt(rmsprop_cache[k]) + 1e-5)
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```

```python
def prepro(I):
  """ prepro 210x160x3 uint8 frame into 6400 (80x80) 1D float vector """
  I = I[35:195] # crop
  I = I[::2,::2,0] # downsample by factor of 2
  I[I == 144] = 0 # erase background (background type 1)
  I[I == 109] = 0 # erase background (background type 2)
  I[I != 0] = 1 # everything else (paddles, ball) just set to 1
  return I.astype(np.float).ravel()
```

Get the current image and preprocess it.

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        rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
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```python
def policy_forward(x):
  h = np.dot(model['W1'], x)
  h[h<0] = 0 # ReLU nonlinearity
  logp = np.dot(model['W2'], h)
  p = sigmoid(logp)
  return p, h # return probability of taking action 2, and hidden state
```

```python
def sigmoid(x):
  return 1.0 / (1.0 + np.exp(-x)) # sigmoid "squashing" function to interval [0,1]
```

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        g = grad_buffer[k] # gradient
        rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
        model[k] += learning_rate * g / (np.sqrt(rmsprop_cache[k]) + 1e-5)
        grad_buffer[k] = np.zeros_like(v) # reset batch gradient buffer

    # boring book-keeping
    running_reward = reward_sum if running_reward is None else running_reward * 0.99 + reward_sum * 0.01
    print 'resetting env. episode reward total was %f. running mean: %f' % (reward_sum, running_reward)
    if episode_number % 100 == 0: pickle.dump(model, open('save.p', 'wb'))
    reward_sum = 0
    observation = env.reset() # reset env
    prev_x = None

  if reward != 0: # Pong has either +1 or -1 reward exactly when game ends.
    print ('ep %d: game finished, reward: %f' % (episode_number, reward)) + ('' if reward == -1 else ' !!!!!!!!')
```

```python
# record various intermediates (needed later for backprop)
xs.append(x) # observation
hs.append(h) # hidden state
y = 1 if action == 2 else 0 # a "fake label"
dlogps.append(y - aprob) # grad that encourages the action that was taken to be taken
```

Bookkeeping so that we can do backpropagation later. If you were to use PyTorch or something, this would not be needed.

```python
env = gym.make("Pong-v0")
observation = env.reset()
prev_x = None # used in computing the difference frame
xs,hs,dlogps,drs = [],[],[],[]
running_reward = None
reward_sum = 0
episode_number = 0
while True:
  if render: env.render()

  # preprocess the observation, set input to network to be difference image
  cur_x = prepro(observation)
  x = cur_x - prev_x if prev_x is not None else np.zeros(D)
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  # forward the policy network and sample an action from the returned probability
  aprob, h = policy_forward(x)
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  observation, reward, done, info = env.step(action)
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    episode_number += 1

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    epr = np.vstack(drs)
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    # compute the discounted reward backwards through time
    discounted_epr = discount_rewards(epr)
    # standardize the rewards to be unit normal (helps control the gradient estimator variance)
    discounted_epr -= np.mean(discounted_epr)
    discounted_epr /= np.std(discounted_epr)

    epdlogp *= discounted_epr # modulate the gradient with advantage (PG magic happens right here.)
    grad = policy_backward(eph, epdlogp)
    for k in model: grad_buffer[k] += grad[k] # accumulate grad over batch

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    if episode_number % batch_size == 0:
      for k,v in model.iteritems():
        g = grad_buffer[k] # gradient
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A small piece of backprop:

Derivative of the [log probability of the taken action given this image] with respect to the [output of the network (before sigmoid)]

recall: loss:

$$\boxed{\sum_i A_i * \log p(y_i|x_i)}$$

$$s = W_2 f(W_1 x)$$
$$p = 1/(1 + e^{-s})$$
$$y \sim p$$

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$$s = W_2 f(W_1 x)$$
$$p = 1/(1+e^{-s})$$
$$y \sim p$$

recall: loss:

$$\boxed{\sum_i A_i * \log p(y_i|x_i)}$$

$$\text{if } y = 1, L = \log p, dL/ds = 1 - p$$
$$\text{if } y = 0, L = \log(1-p), dL/ds = -p$$

More compact:

$$L = y\log(p) + (1-y)\log(1-p)$$
$$dL/ds = y - p$$

```python
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observation = env.reset()
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xs,hs,dlogps,drs = [],[],[],[]
running_reward = None
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    episode_number += 1

    # stack together all inputs, hidden states, action gradients, and rewards for this episode
    epx = np.vstack(xs)
    eph = np.vstack(hs)
    epdlogp = np.vstack(dlogps)
    epr = np.vstack(drs)
    xs,hs,dlogps,drs = [],[],[],[] # reset array memory

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    if episode_number % 100 == 0: pickle.dump(model, open('save.p', 'wb'))
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  if reward != 0: # Pong has either +1 or -1 reward exactly when game ends.
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```

```python
# step the environment and get new measurements
observation, reward, done, info = env.step(action)
reward_sum += reward

drs.append(reward) # record reward (has to be done after we call step() to get reward for previous action)
```

Step the environment

(execute the action,
get new state and
record the reward)

```python
env = gym.make("Pong-v0")
observation = env.reset()
prev_x = None # used in computing the difference frame
xs,hs,dlogps,drs = [],[],[],[]
running_reward = None
reward_sum = 0
episode_number = 0
while True:
  if render: env.render()

  # preprocess the observation, set input to network to be difference image
  cur_x = prepro(observation)
  x = cur_x - prev_x if prev_x is not None else np.zeros(D)
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  # forward the policy network and sample an action from the returned probability
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  # step the environment and get new measurements
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  reward_sum += reward

  drs.append(reward) # record reward (has to be done after we call step() to get reward for previous action)

  if done: # an episode finished
    episode_number += 1

    # stack together all inputs, hidden states, action gradients, and rewards for this episode
    epx = np.vstack(xs)
    eph = np.vstack(hs)
    epdlogp = np.vstack(dlogps)
    epr = np.vstack(drs)
    xs,hs,dlogps,drs = [],[],[],[] # reset array memory

    # compute the discounted reward backwards through time
    discounted_epr = discount_rewards(epr)
    # standardize the rewards to be unit normal (helps control the gradient estimator variance)
    discounted_epr -= np.mean(discounted_epr)
    discounted_epr /= np.std(discounted_epr)

    epdlogp *= discounted_epr # modulate the gradient with advantage (PG magic happens right here.)
    grad = policy_backward(eph, epdlogp)
    for k in model: grad_buffer[k] += grad[k] # accumulate grad over batch

    # perform rmsprop parameter update every batch_size episodes
    if episode_number % batch_size == 0:
      for k,v in model.iteritems():
        g = grad_buffer[k] # gradient
        rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
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    running_reward = reward_sum if running_reward is None else running_reward * 0.99 + reward_sum * 0.01
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    if episode_number % 100 == 0: pickle.dump(model, open('save.p', 'wb'))
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    observation = env.reset() # reset env
    prev_x = None

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```

```python
if done: # an episode finished
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  epdlogp = np.vstack(dlogps)
  epr = np.vstack(drs)
  xs,hs,dlogps,drs = [],[],[],[] # reset array memory
```

Once a rollout is done,
Concatenate together all images, hidden states, etc. that were seen in this batch.

Again, if using PyTorch, no need to do this.

```python
env = gym.make("Pong-v0")
observation = env.reset()
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xs,hs,dlogps,drs = [],[],[],[]
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```
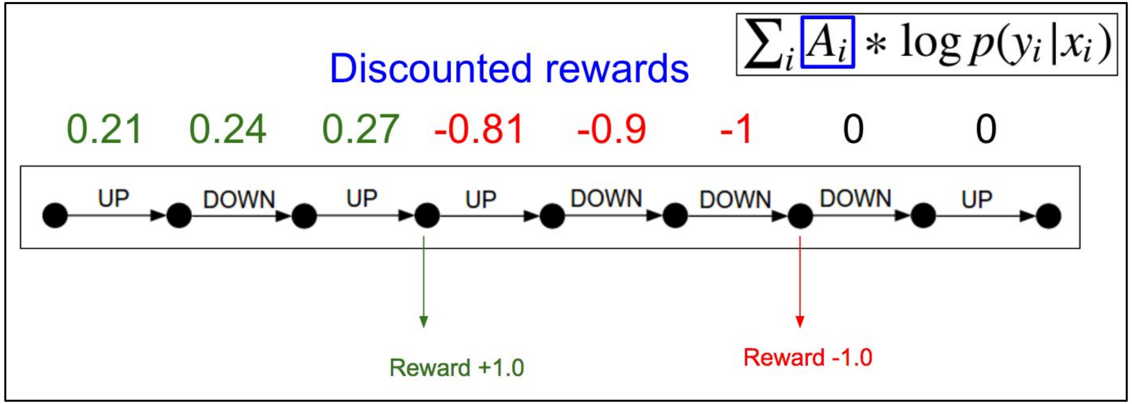

```python
def discount_rewards(r):
  """ take 1D float array of rewards and compute discounted reward """
  discounted_r = np.zeros_like(r)
  running_add = 0
  for t in reversed(xrange(0, r.size)):
    if r[t] != 0: running_add = 0 # reset the sum, since this was a game boundary (pong specific!)
    running_add = running_add * gamma + r[t]
    discounted_r[t] = running_add
  return discounted_r
```



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$$\sum_i \boxed{A_i \ *} \log p(y_i | x_i)$$

Advantage modulation

```python
def policy_backward(eph, epdlogp):
  """ backward pass. (eph is array of intermediate hidden states) """
  dW2 = np.dot(eph.T, epdlogp).ravel()
  dh = np.outer(epdlogp, model['W2'])
  dh[eph <= 0] = 0 # backpro prelu
  dW1 = np.dot(dh.T, epx)
  return {'W1':dW1, 'W2':dW2}
```

backprop!!!!!1

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  hs.append(h) # hidden state
  y = 1 if action == 2 else 0 # a "fake label"
  dlogps.append(y - aprob) # grad that encourages the action that was taken to be taken (see http://cs231n.github.io/neural-networks-2/#los

  # step the environment and get new measurements
  observation, reward, done, info = env.step(action)
  reward_sum += reward

  drs.append(reward) # record reward (has to be done after we call step() to get reward for previous action)

  if done: # an episode finished
    episode_number += 1

    # stack together all inputs, hidden states, action gradients, and rewards for this episode
    epx = np.vstack(xs)
    eph = np.vstack(hs)
    epdlogp = np.vstack(dlogps)
    epr = np.vstack(drs)
    xs,hs,dlogps,drs = [],[],[],[] # reset array memory

    # compute the discounted reward backwards through time
    discounted_epr = discount_rewards(epr)
    # standardize the rewards to be unit normal (helps control the gradient estimator variance)
    discounted_epr -= np.mean(discounted_epr)
    discounted_epr /= np.std(discounted_epr)

    epdlogp *= discounted_epr # modulate the gradient with advantage (PG magic happens right here.)
    grad = policy_backward(eph, epdlogp)
    for k in model: grad_buffer[k] += grad[k] # accumulate grad over batch

    # perform rmsprop parameter update every batch_size episodes
    if episode_number % batch_size == 0:
      for k,v in model.iteritems():
        g = grad_buffer[k] # gradient
        rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
        model[k] += learning_rate * g / (np.sqrt(rmsprop_cache[k]) + 1e-5)
        grad_buffer[k] = np.zeros_like(v) # reset batch gradient buffer

    # boring book-keeping
    running_reward = reward_sum if running_reward is None else running_reward * 0.99 + reward_sum * 0.01
    print 'resetting env. episode reward total was %f. running mean: %f' % (reward_sum, running_reward)
    if episode_number % 100 == 0: pickle.dump(model, open('save.p', 'wb'))
    reward_sum = 0
    observation = env.reset() # reset env
    prev_x = None

  if reward != 0: # Pong has either +1 or -1 reward exactly when game ends.
    print ('ep %d: game finished, reward: %f' % (episode_number, reward)) + ('' if reward == -1 else ' !!!!!!!!')
```

```python
# perform rmsprop parameter update every batch_size episodes
if episode_number % batch_size == 0:
  for k,v in model.iteritems():
    g = grad_buffer[k] # gradient
    rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
    model[k] += learning_rate * g / (np.sqrt(rmsprop_cache[k]) + 1e-5)
    grad_buffer[k] = np.zeros_like(v) # reset batch gradient buffer
```

Use RMSProp for the parameter update.

RMSProp

Update rule:

$$
\begin{aligned}
R_t &= \gamma R_{t-1} + (1-\gamma)\nabla L_t(W_{t-1})^2 \\
W_t &= W_{t-1} - \alpha \frac{\nabla L_t(W_{t-1})}{\sqrt{R_t}}
\end{aligned}
$$

Similar to AdaGrad but with an exponential moving average controlled by $\gamma \in [0, 1)$ (smaller $\gamma \implies$ more emphasis on recent gradients).

```python
env = gym.make("Pong-v0")
observation = env.reset()
prev_x = None # used in computing the difference frame
xs,hs,dlogps,drs = [],[],[],[]
running_reward = None
reward_sum = 0
episode_number = 0
while True:
  if render: env.render()

  # preprocess the observation, set input to network to be difference image
  cur_x = prepro(observation)
  x = cur_x - prev_x if prev_x is not None else np.zeros(D)
  prev_x = cur_x

  # forward the policy network and sample an action from the returned probability
  aprob, h = policy_forward(x)
  action = 2 if np.random.uniform() < aprob else 3 # roll the dice!

  # record various intermediates (needed later for backprop)
  xs.append(x) # observation
  hs.append(h) # hidden state
  y = 1 if action == 2 else 0 # a "fake label"
  dlogps.append(y - aprob) # grad that encourages the action that was taken to be taken (see http://cs231n.github.io/neural-networks-2/#los

  # step the environment and get new measurements
  observation, reward, done, info = env.step(action)
  reward_sum += reward

  drs.append(reward) # record reward (has to be done after we call step() to get reward for previous action)

  if done: # an episode finished
    episode_number += 1

    # stack together all inputs, hidden states, action gradients, and rewards for this episode
    epx = np.vstack(xs)
    eph = np.vstack(hs)
    epdlogp = np.vstack(dlogps)
    epr = np.vstack(drs)
    xs,hs,dlogps,drs = [],[],[],[] # reset array memory

    # compute the discounted reward backwards through time
    discounted_epr = discount_rewards(epr)
    # standardize the rewards to be unit normal (helps control the gradient estimator variance)
    discounted_epr -= np.mean(discounted_epr)
    discounted_epr /= np.std(discounted_epr)

    epdlogp *= discounted_epr # modulate the gradient with advantage (PG magic happens right here.)
    grad = policy_backward(eph, epdlogp)
    for k in model: grad_buffer[k] += grad[k] # accumulate grad over batch

    # perform rmsprop parameter update every batch_size episodes
    if episode_number % batch_size == 0:
      for k,v in model.iteritems():
        g = grad_buffer[k] # gradient
        rmsprop_cache[k] = decay_rate * rmsprop_cache[k] + (1 - decay_rate) * g**2
        model[k] += learning_rate * g / (np.sqrt(rmsprop_cache[k]) + 1e-5)
        grad_buffer[k] = np.zeros_like(v) # reset batch gradient buffer

    # boring book-keeping
    running_reward = reward_sum if running_reward is None else running_reward * 0.99 + reward_sum * 0.01
    print 'resetting env. episode reward total was %f. running mean: %f' % (reward_sum, running_reward)
    if episode_number % 100 == 0: pickle.dump(model, open('save.p', 'wb'))
    reward_sum = 0
    observation = env.reset() # reset env
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    print ('ep %d: game finished, reward: %f' % (episode_number, reward)) + ('' if reward == -1 else ' !!!!!!!!')
```


```python
  # boring book-keeping
  running_reward = reward_sum if running_reward is None else running_reward * 0.99 + reward_sum * 0.01
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if reward != 0: # Pong has either +1 or -1 reward exactly when game ends.
  print ('ep %d: game finished, reward: %f' % (episode_number, reward)) + ('' if reward == -1 else ' !!!!!!!!')
```

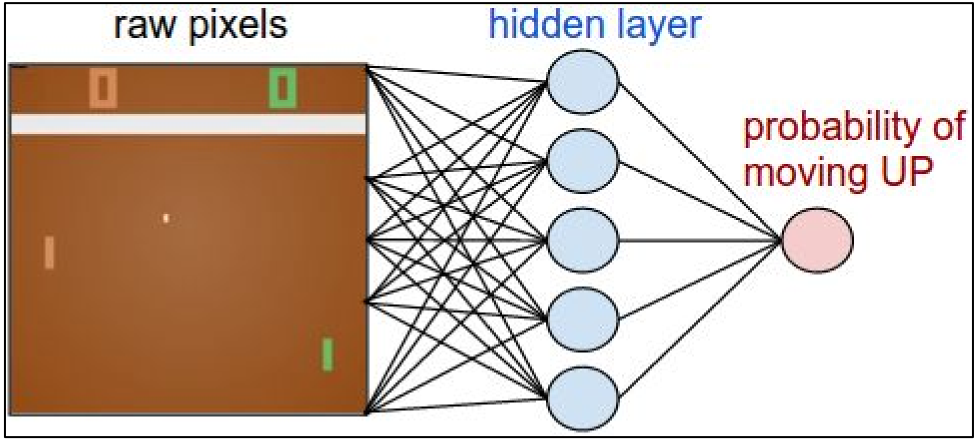

prints etc

In summary

```
1.  Initialize a policy network at random
2.  Repeat Forever:
3.      Collect a bunch of rollouts with the policy
4.      Increase the probability of actions that worked well
5.  ???
6.  Profit.
```


3
10

Thank you! Questions?



$$\sum_i A_i * \log p(y_i | x_i)$$