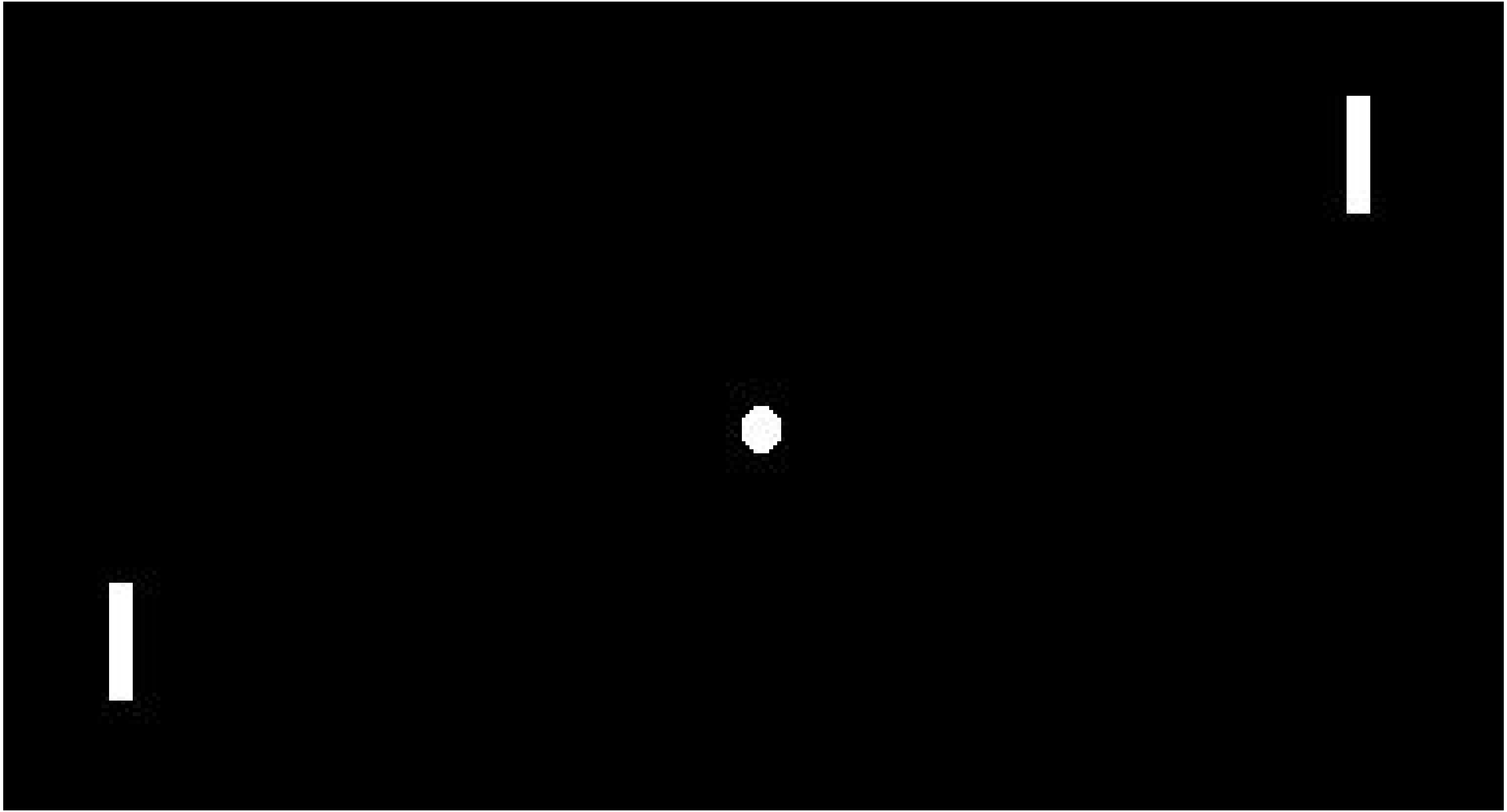
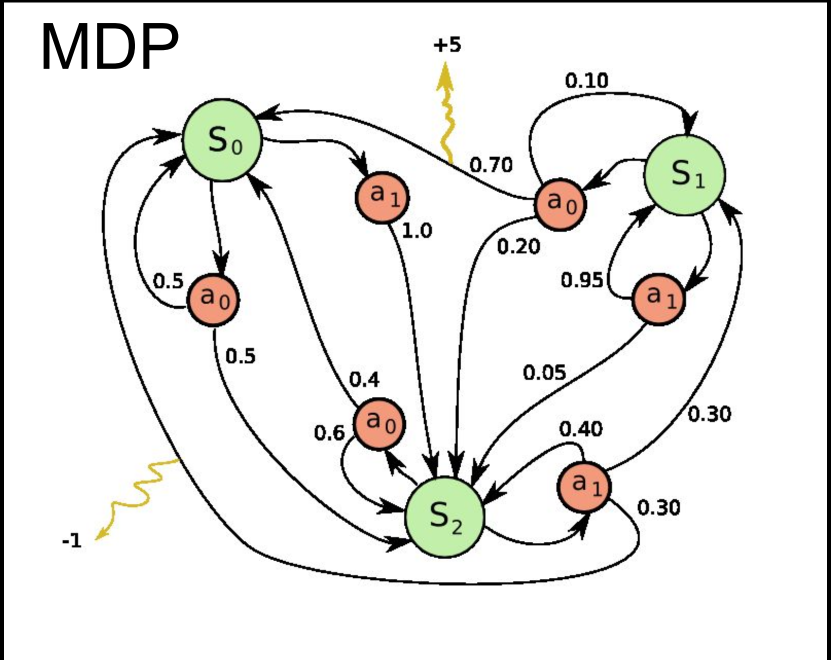
Pong from Pixels

Deep RL Bootcamp

Andrej Karpathy, Aug 26, 2017

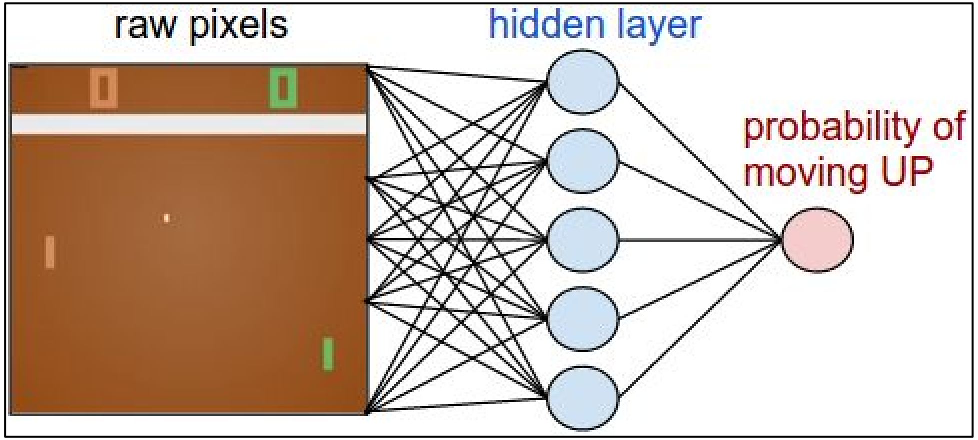


MDP:
- Reward: +1 if we get the ball past the opponent, -1 if they get it past us
- State: 1) location of ball, 2) location of our paddle, 3) location of opponent's paddle
- Actions: 1) Move paddle up, 2) Move paddle down



Policy network

- single-layer MLP
- we predict the probability of moving up

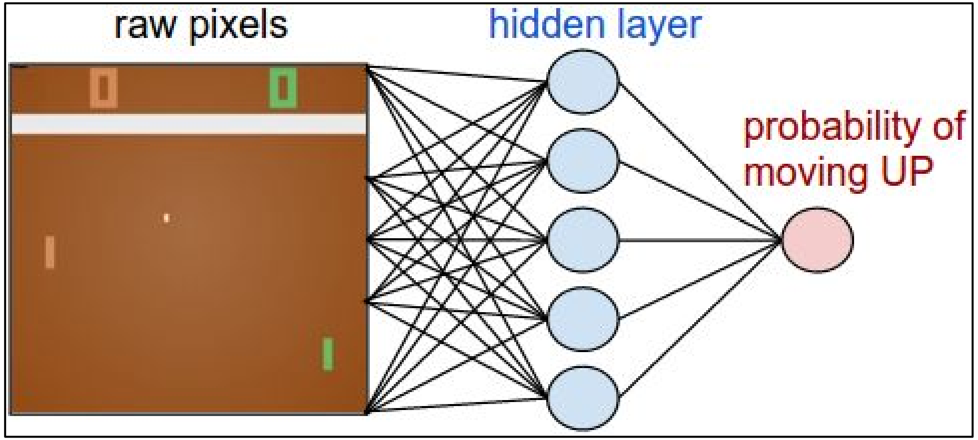


Policy network

e.g.,

height width

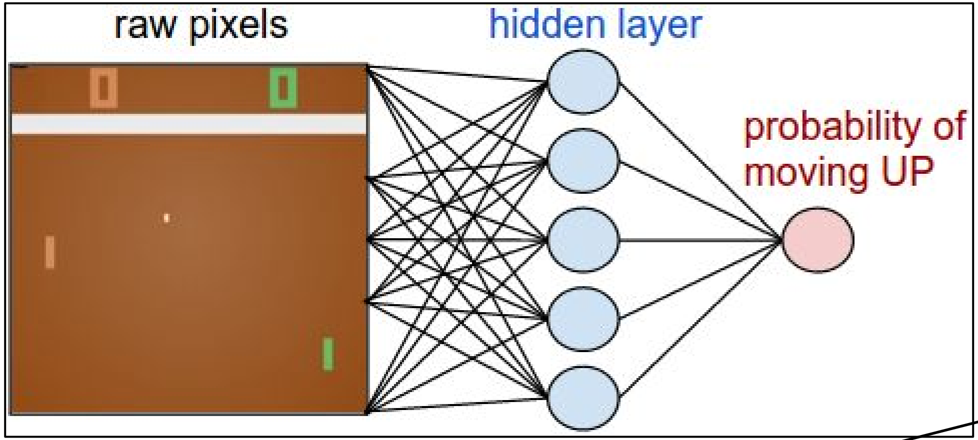
[**80** x **80**]
array of
Grey-scale



Policy network

height width

[80 x 80]
array



input layer is 80*80

get the logit

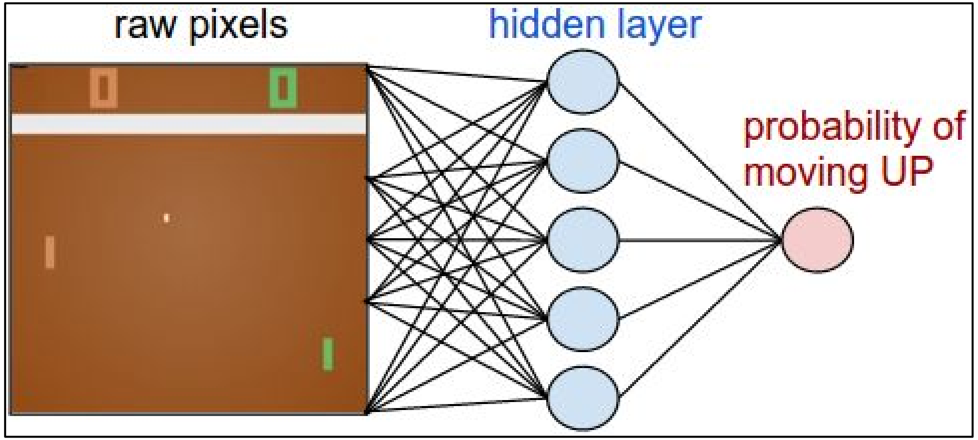
```
h = np.dot(W1, x) # compute hidden layer neuron activations
h[h<0] = 0 # ReLU nonlinearity: threshold at zero
logp = np.dot(W2, h) # compute log probability of going up
p = 1.0 / (1.0 + np.exp(-logp)) # sigmoid function (gives probability of going up)
```

apply sigmoid to squash this between 0 and 1

Policy network

height width

[80 x 80]
array



biases

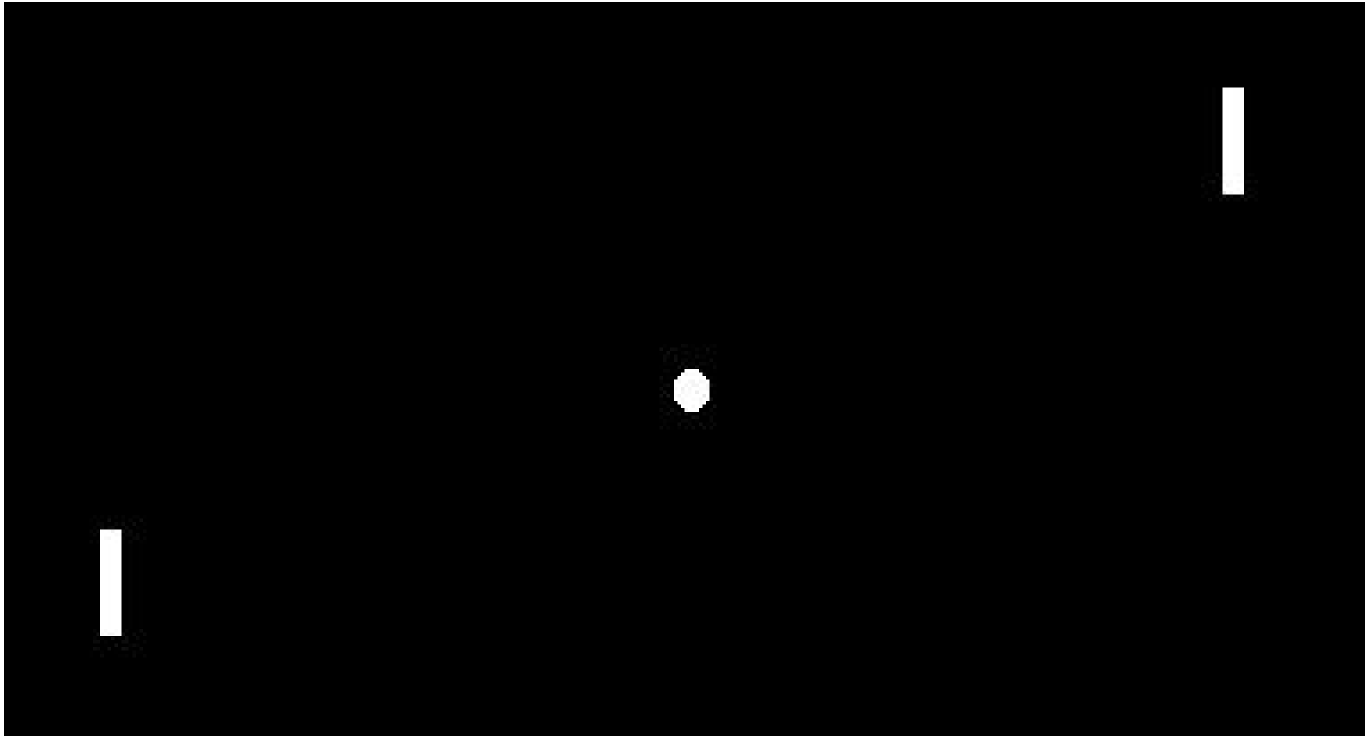
E.g. 200 nodes in the hidden network, so:

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

Layer 1 Layer 2

Note that we can't just take in a single frame because that would only be a static input and the game is dynamic.

Instead we could 1) concatenate/stack multiple frames in the input, or 2) take the difference between two frames as the input



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...

random search

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

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

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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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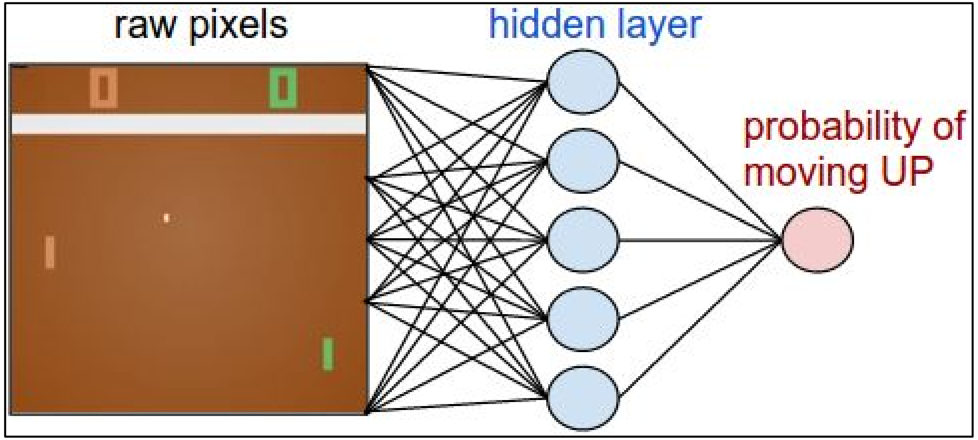


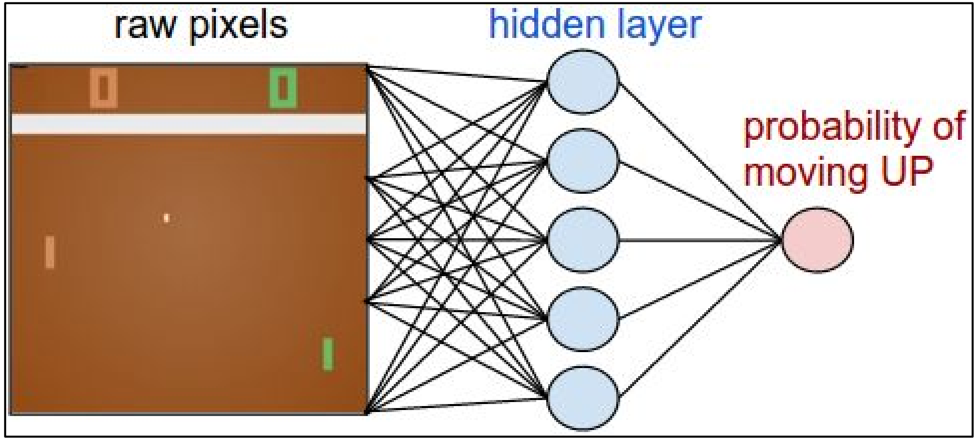
Suppose we had the training labels…
(we know what to do in any state)

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

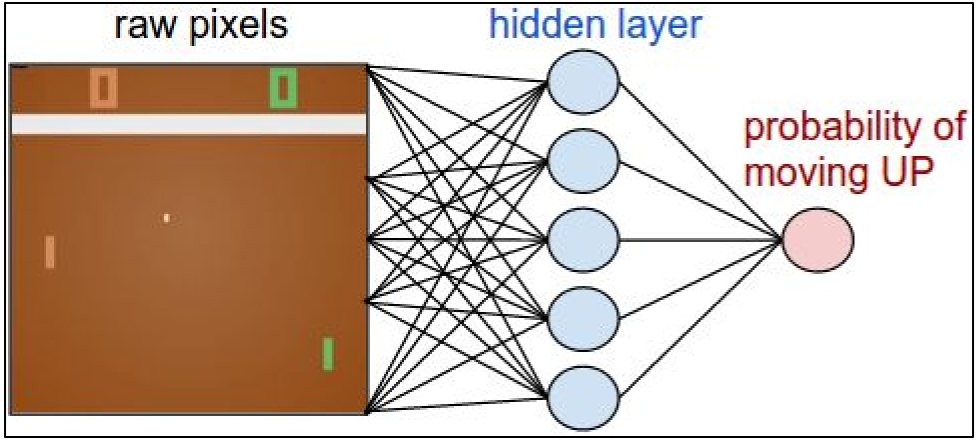
so if we were told what to do at every state, we could just train a NN and this becomes a supervised learning problem where we try to maximize the log probability of getting the answer correct

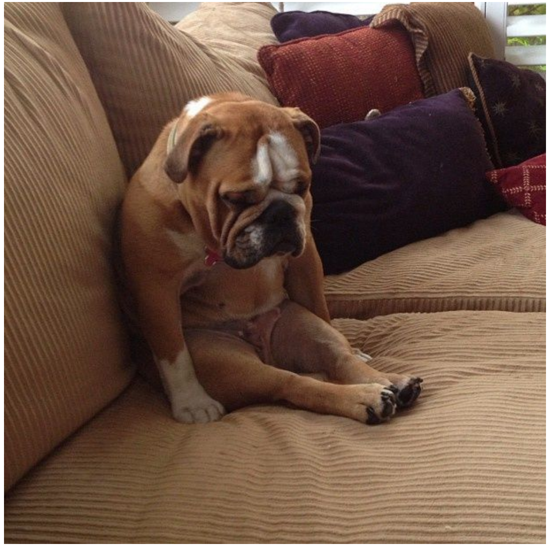
maximize:

$$\sum_i \log p(y_i \mid x_i)$$



Except, we don't have labels...





Should we go UP or DOWN?

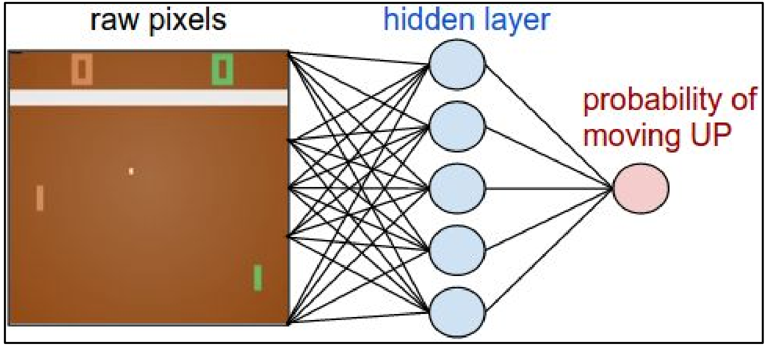
Except, we don’t have labels...

“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...

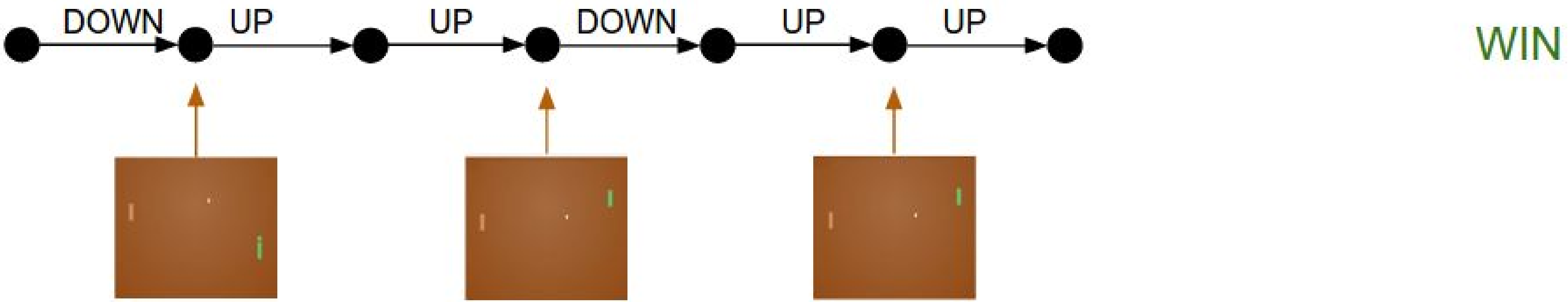
A rollout is a single run/episode of the game with the current policy.



Rollout the policy and collect an episode

Start with a randomly intialized policy, then take actions for each state

So this is what actions we end up doing...At first this is pretty much just random actions

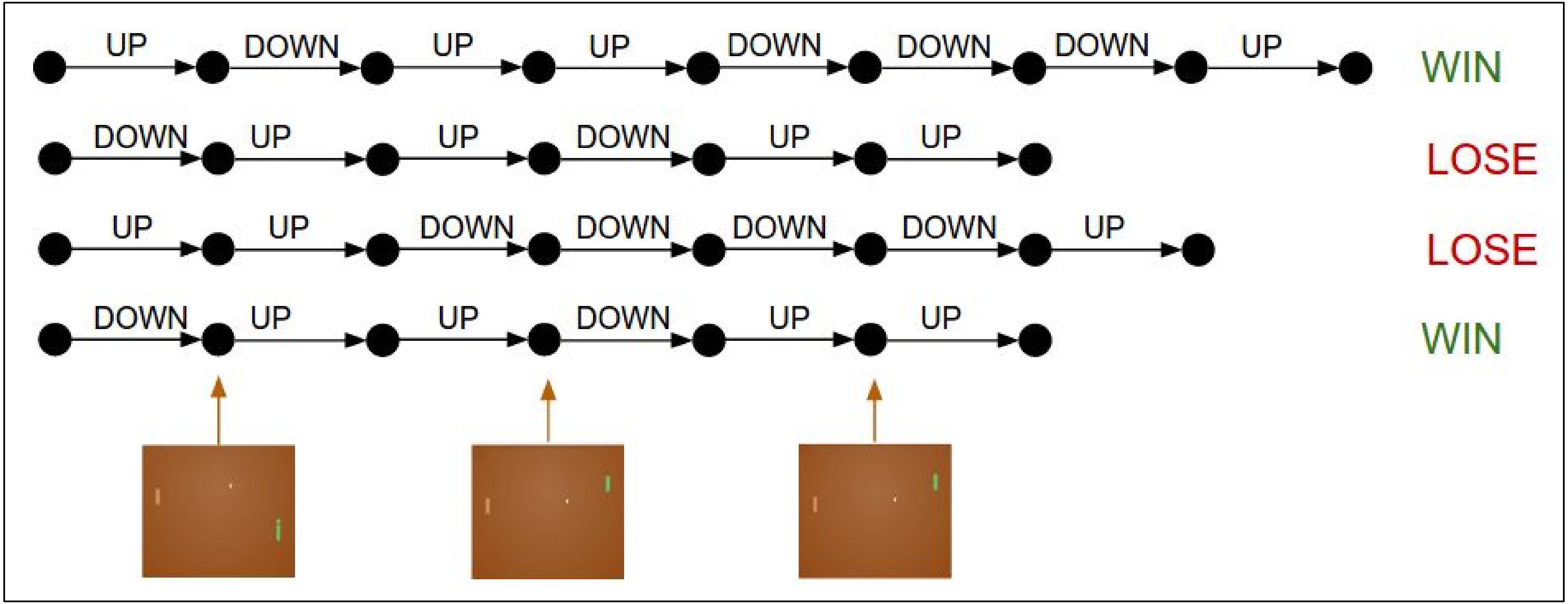


Collect many rollouts...

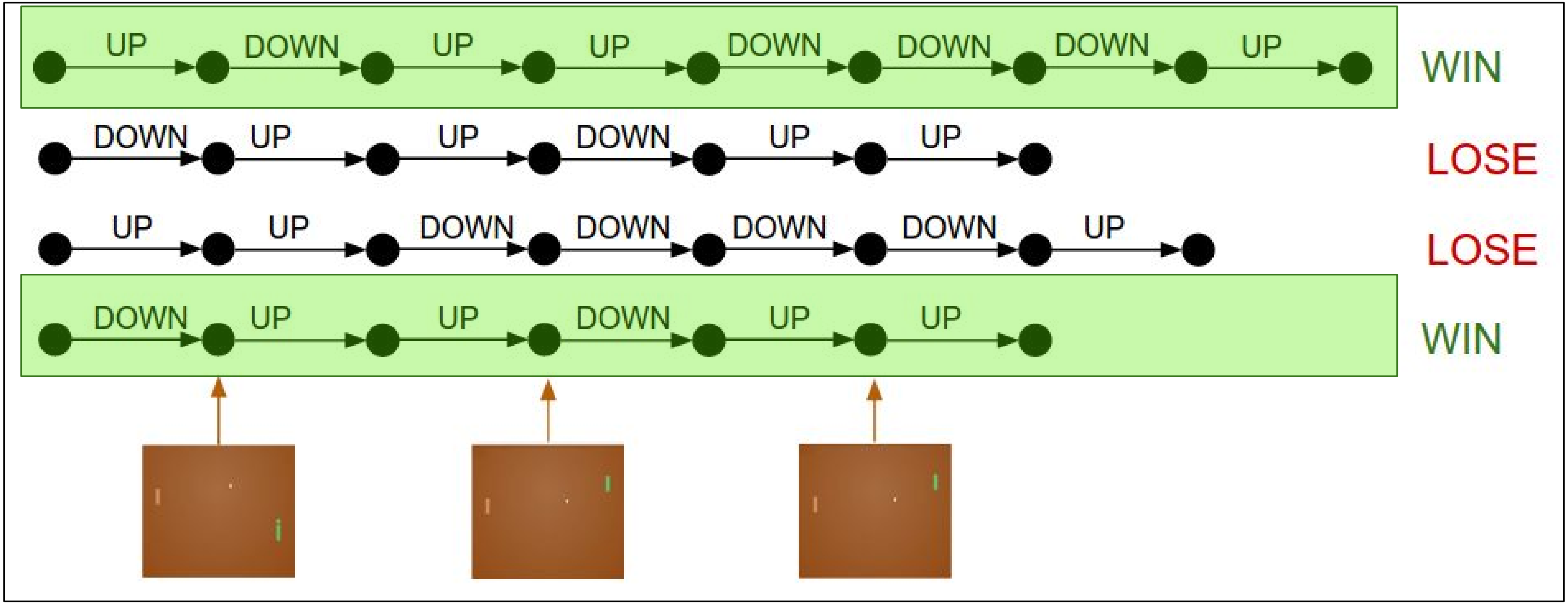
4 rollouts:

So this becomes our dataset

The labels are the actions that we happened to do



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



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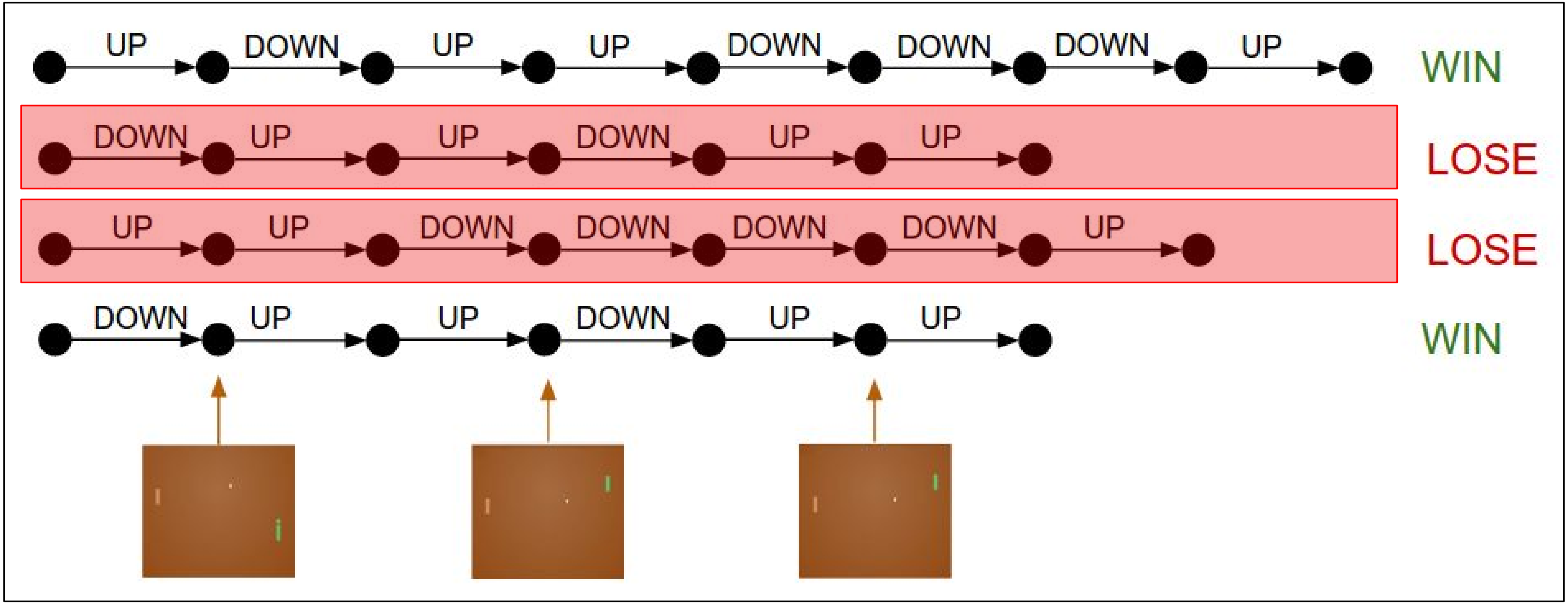
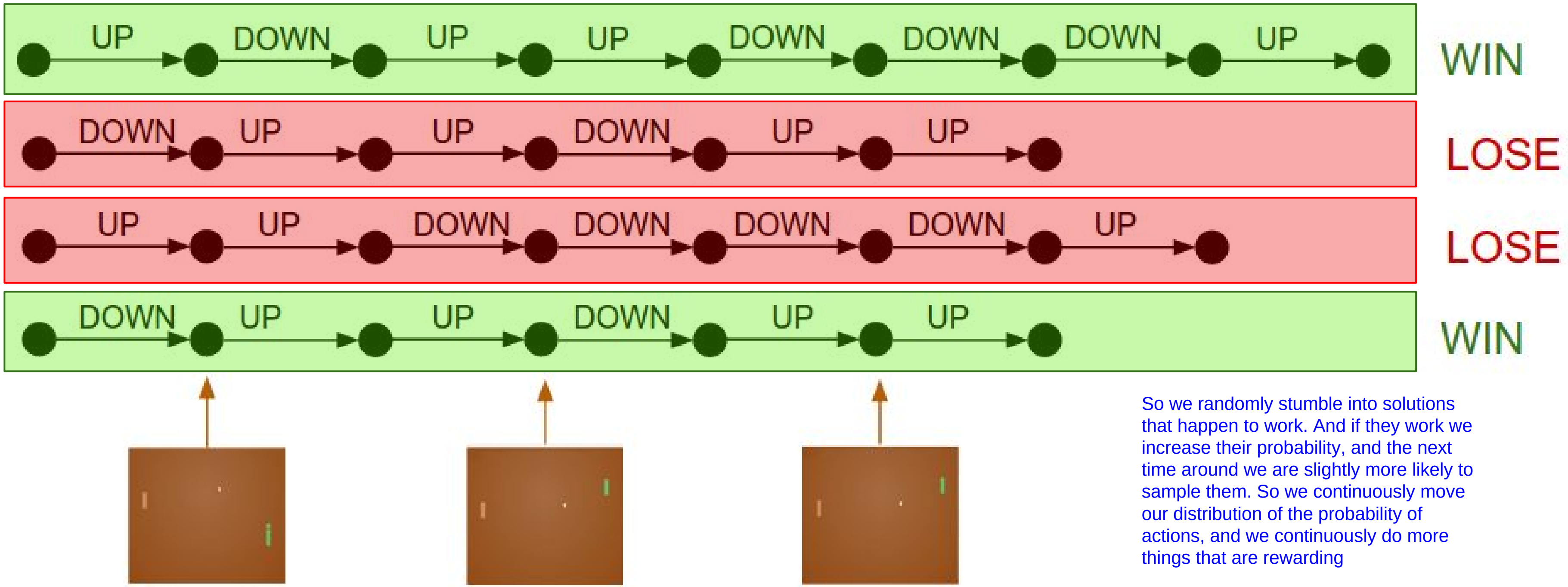


Pretend every action we took here was the correct label.

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

Pretend every action we took here was the wrong label.

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



So we randomly stumble into solutions that happen to work. And if they work we increase their probability, and the next time around we are slightly more likely to sample them. So we continuously move our distribution of the probability of actions, and we continuously do more things that are rewarding

Supervised Learning

maximize:

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

For images x_i and their labels y_i.

Supervised Learning

maximize:

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

For images x_i and their labels y_i.

Reinforcement Learning

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:

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

we rollout our policy and the actions we happen to take become our data

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:

we want this scalar to be high if we want to encourage that action in the future, and we want it to be small if we want to discourage that action in the futre

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

Supervised Learning

maximize:

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

For images x_i and their labels y_i.

So at each state/frame,
1) Pass state into NN as input
2) NN produces probability of 1 (i.e. going up).
   So for example, it could output 0.8
3) Pick a random number between 0-1. If it's > than 0.8, take that action (i.e. go up), and otherwise go down.
4) That action becomes our y_i

Once the game is over,
5) Find the advantage. If you won, A=1, if you lost A=-1.
6) Apply this action to all of the state/actions in that rollout/trajectory. So now we have (s, a, A) for each step in a rollout. Based on this advantage, we'll either increase or decrease the probability of doing that action
7) Now we want to alter our policy to maximize the sum of A * logp(y|x) for everything we did in our batch of rollouts.

Reinforcement Learning

1) we have no labels so we sample:

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

the labels are the actions we happened to take

given an action

2) once we collect a batch of rollouts:

maximize:

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

we want to increase the logprob of actions if it turned out good, and decrease it if it turned out bad

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

so Ai will be the same for all actions/data within the same rollout. So we equally blame all the actions.

Supervised Learning

maximize:

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

For images x_i and their labels y_i.

So the only difference between RL and supervised learning is that we have the Advantage factor, which might be negative. In supervised learning, the "advantage" is always 1.

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:

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

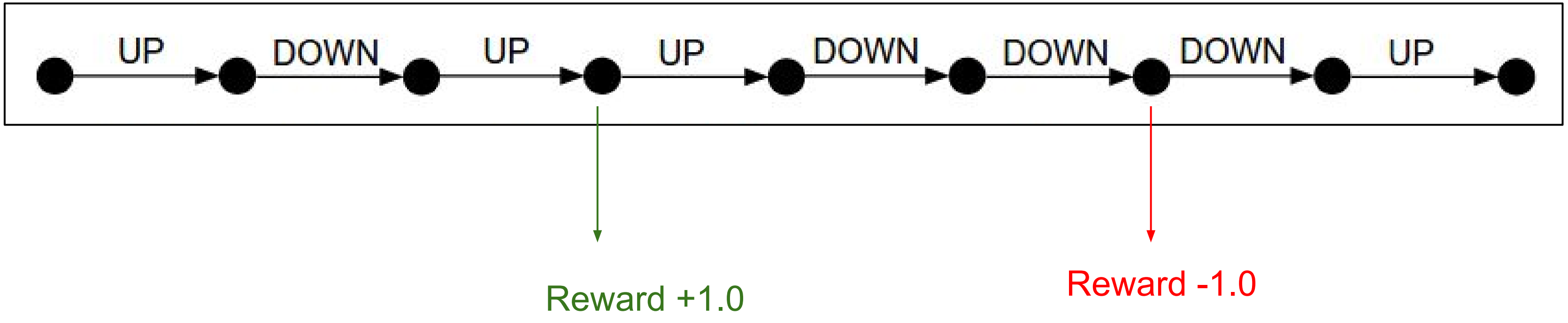
the advantage is a scalar that tells you whether or not you want to encourage or discourage the action to happened to take

+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.

It's kind of odd to assign equal blame to every single action in the rollout, because some of them could have actually been good, while others could have been really bad. So in practice, we discount to module the blame. We blame each action in an exponentially decreasing action. The further away the action was from the reward, the less it's blamed



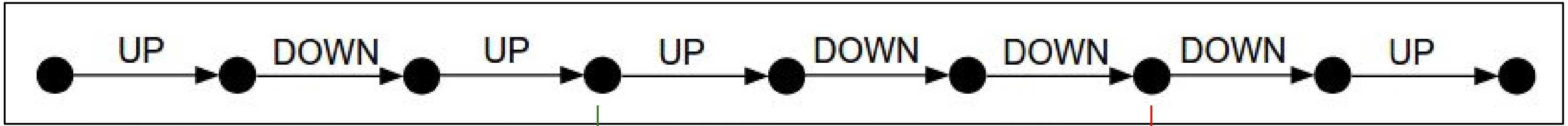
Discounting

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

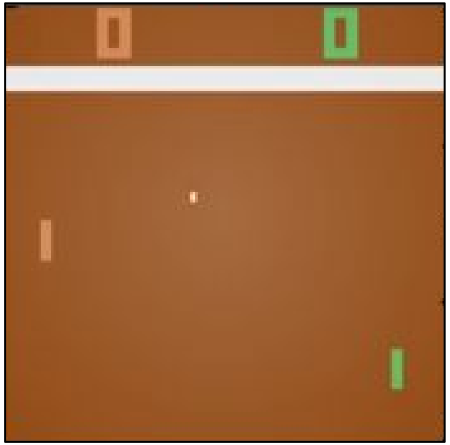
0.21 0.24 0.27 -0.81 -0.9 -1 0 0



Reward +1.0

Reward -1.0

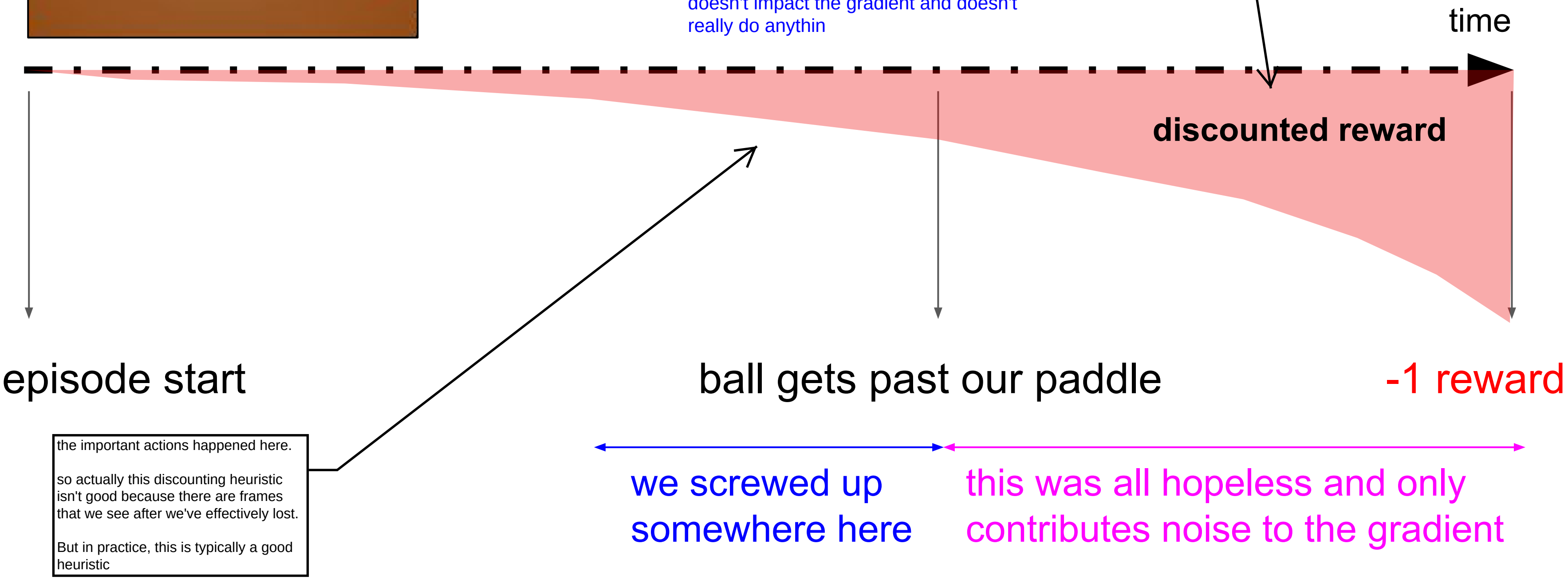
\gamma = 0.9



if you were to use a Value Function, and you have a Value Function estimator, it could learn that when the ball is past you, it knows you're about to lose. So it learns that the expected return is -1. So the baseline would become -1. So in this case the Advantage is return minus baseline. So then the empirical return minus the baseline is 0, so it doesn't contribute the gradient.

This is would be good because the actions after the ball gets past you doesn't impact the gradient and doesn't really do anythin

there's several frames where the ball is past us, but there's nothing we can do




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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```


training loop
- we iterate through the learning algorithm

Nothing too scary over here.

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

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```

To get temporal difference, we subtract the previous preprocessed image from the current reprocessed image. We then pass this difference to the NN so we have some inherent motion in the network. If we instead passed the raw frame, then we wouldn't have any temporal information in the NN

```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()
```

Preprocessing:
- Take a frame from gym (i.e. observation)
- Crop out unimportant stuff
- Downsample by only taking every even pixel
- Make pixels binary
- Then return its float

Get the current image and preprocess it.

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        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
# 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!
```

```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
```

We pass in the difference image to the NN
We return the probability of going up, and the hidden state so we can cache this and do back prop later. This is because we aren't using any NN library.

in the gym environment action 2 = up and action 3 = down

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

```
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
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```
# 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
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while True:
  if render: env.render()

  # preprocess the observation, set input to network to be difference image
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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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dlogps.append(y - aprob) # grad that encourages the action that was taken to be taken
```

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:

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

output of network before the sigmoid

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

KL divergence!

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

More compact:

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

```python
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)
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  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
# 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)
  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)
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    # 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
if done: # an episode finished
  episode_number += 1

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  epx = np.vstack(xs)
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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()
prev_x = None # used in computing the difference frame
xs,hs,dlogps,drs = [],[],[],[]
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while True:
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discounted_epr /= np.std(discounted_epr)
```

epr = episode rewards

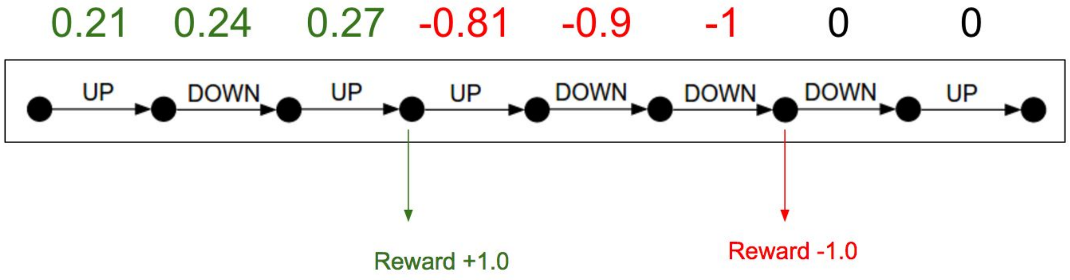
We want to compute an Advantage. We want to the discounted reward to be the Advantage.

```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
```

But to reduce the variance in the Advantage we will get it into zero-mean unit variance. So we are going to subtract the mean and divide by the standard deviation. This will center and scale our rewards. This will allow us to encourage half the actions and discourage half the actions. And we also make sure that the Advantage is on the same scale across rollouts/episodes. So we do this over a batch of rollouts

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

Discounted rewards



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

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  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 ' !!!!!!!!')
```

here we get the weight matrix for W1 and W2. We can then update the network. By doing this the network will be more likely to take actions that increase reward, and less likely to take actions that decrease reward

```python
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
```

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

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

```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
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  # 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
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    # stack together all inputs, hidden states, action gradients, and rewards for this episode
    epx = np.vstack(xs)
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    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)
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    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)
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```

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).

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  if done: # an episode finished
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  print ('ep %d: game finished, reward: %f' % (episode_number, reward)) + ('' if reward == -1 else ' !!!!!!!!')
```

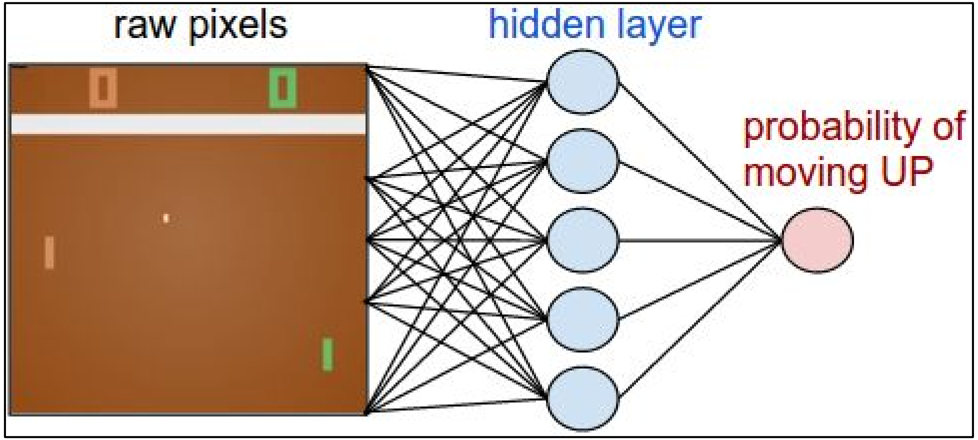

prints etc

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?



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