

Distributed Synchronous Value Iteration

The goal of this assignment is to implement both single-core and distributed versions of synchronous value iteration (VI). In particular, VI will be applied to Markov Decision Processes (MDPs) in order to compute policies that optimize expected infinite horizon discounted cumulative reward.

The relevant content about MDPs and VI are in the following course notes from CS533.

<https://oregonstate.instructure.com/courses/1765131/files/79109644/download?wrap=1>
<https://oregonstate.instructure.com/courses/1765131/files/79109644/download?wrap=1>
<https://oregonstate.instructure.com/courses/1765131/files/78928721/download?wrap=1>
<https://oregonstate.instructure.com/courses/1765131/files/78928721/download?wrap=1>

Synchronous Value Iteration Recap

Below is a review of the synchronous value iteration algorithm. The algorithm is iterative and each iteration produces a newly updated value function V_{new} based on the value function from the previous iteration V_{curr} . This is done by applying the Bellman backup operator to V_{curr} at each state. That is,

$$V_{new}(s) = \max_{a \in A} R(s, a) + \beta \sum_{s' \in S} T(s, a, s') V_{curr}(s')$$

where $\beta \in [0, 1]$ is the discount factor, R is the reward function, and T is the transition function.

The algorithm also maintains the greedy policy π at each iteration, which is based on a one-step look ahead operator:

$$\pi_{curr}(s) = \arg \max_{a \in A} R(s, a) + \beta \sum_{s' \in S} T(s, a, s') V_{curr}(s')$$

After an update we define the Bellman error of that iteration as $\max_s |V_{new}(s) - V_{curr}(s)|$. In the notes, it is shown that this error allows us to bound the difference between the value function of π_{curr} and the optimal value function V^* . Thus, a typical stopping condition for VI is to iterate until the Bellman error is below a specified threshold ϵ . Putting everything together, the overall algorithm is as follows:

- Start with $V_{curr}(s) = 0$ for all s
- error = ∞
- While error $> \epsilon$
 - For each state s
 - $V_{new}(s) = \max_{a \in A} R(s, a) + \beta \sum_{s' \in S} T(s, a, s') V_{curr}(s')$

- $\pi_{curr}(s) = \arg \max_{a \in A} R(s, a) + \beta \sum_{s' \in S} T(s, a, s') V_{curr}(s')$
- $\text{error} = \max_s |V_{new}(s) - V_{curr}(s)|$;; could do this incrementally
- $V_{curr} = V_{new}$

The reason we refer to this version of VI as synchronous is because it maintains both a current and new value function, where all values of the new value function are computed based on the fixed current value function. That is, each iteration updates all states based on the value function of the previous iteration.

To simplify this first assignment, we have decided to focus on Synchronous VI and to investigate how to best create a distributed implementation using the Ray framework. In particular, a distributed version of Synchronous VI should still produce a sequence of value functions and policies that are equivalent to those that would be produced by a single-core version, but ideally do so much faster. The remainder of this notebook guides you through some of the MDP mechanics and algorithm implementations. The grand finale of this first assignment is a competition where you will try to develop the fastest distributed implementation that you can.

```
In [ ]: # You will need to uncomment the following pip commands if the libraries need to be installed.
# You may get some errors related to readchar, but they should not break the project.

#!pip install --user readchar
#!pip install --user gym
```

```
In [ ]: import ray
import time
from copy import deepcopy
import matplotlib.pyplot as plt
from random import randint, choice
%matplotlib inline
import pickle
```

FrozenLake

We will use the FrozenLake environment as the MDP environment for this experiment. This is a type of gridworld environment, whose size (number of states) can be controlled by adjusting the grid dimensions. The environment is intended to model the process of navigating a frozen lake, while avoiding falling into holes with the objective of reaching a goal location.

The environment is defined as follows:

- The environment is a rectangular grid of states/cells. There are four different types of cells as indicated by the following cell labels:

- S labels the starting/initial cell, always in the top left corner
- F labels frozen cells that are safe to step on
- H labels holes and if the agent enters a hole cell there is a penalty of -1000 and the episode ends
- G labels the goal cell and when reached gives a reward of 1000 and the episode ends
- There are four possible actions (Left, Right, Down, Up).
- The transition function moves the agent in the expected direction with 0.7 probability, and there is a 0.3 probability of transitioning to one of the other randomly selected directions.
- There is a reward of -1 for each action taken by the agent, which is intended to encourage the agent to reach the goal as fast as possible.
- Episodes end whenever the agent falls in a hole or reaches the goal. An end-of-episode is modeled by transitioning to a zero-reward terminal state (all actions lead to that state).

Below is the code for the FrozenLake environment class, which has the following functions that will be used in this assignment:

- FrozenLake.GetSuccessors() : Take a state and an action as input, and return a list of pairs, where each pair (s', p) is a successor state s' with non-zero probability and p is the probability of transitioning to p .
- FrozenLake.GetTransitionProb() : Take a state, an action, a next state as input, and return the probability of the transition
- FrozenLake.GetReward() : Take a state and an action as input, and return the reward of that.

The version we are using for the assignment 2 is a modified version of the environment at the following location.

Source: https://github.com/openai/gym/blob/master/gym/envs/toy_text/frozen_lake.py
(https://github.com/openai/gym/blob/master/gym/envs/toy_text/frozen_lake.py)

Execute the following cell to initialize the MDP environments. (You do not need to change the code in this part.)

```

In [ ]: import sys
        from contextlib import closing

import numpy as np
from six import StringIO, b

from gym import utils
from gym.envs.toy_text import discrete

LEFT = 0
DOWN = 1
RIGHT = 2
UP = 3

np.set_printoptions(threshold=sys.maxsize, linewidth=sys.maxsize, precision = 2)
TransitionProb = [0.7, 0.1, 0.1, 0.1]
def generate_row(length, h_prob):
    row = np.random.choice(2, length, p=[1.0 - h_prob, h_prob])
    row = ''.join(list(map(lambda z: 'F' if z == 0 else 'H', row)))
    return row

def generate_map(shape):
    """
    :param shape: Width x Height
    :return: List of text based map
    """
    h_prob = 0.1
    grid_map = []

    for h in range(shape[1]):

        if h == 0:
            row = 'SF'
            row += generate_row(shape[0] - 2, h_prob)
        elif h == 1:
            row = 'FF'
            row += generate_row(shape[0] - 2, h_prob)

        elif h == shape[1] - 1:
            row = generate_row(shape[0] - 2, h_prob)
            row += 'FG'

```

```
MAPS = {
    "4x4": [
        "SFFF",
        "FHFH",
        "FFFH",
        "HFFG"
    ],
    "8x8": [
        "SFFFFFFFF",
        "FFFFFFFF",
        "FFFHFFFF",
        "FFFFFFFF",
        "FFFHFFFF",
        "FHHFFHF",
        "FHFFHFHF",
        "FFFHFFFG"
    ],
    "16x16": [
        "SFFFFFFFFFHFFFHF",
        "FFFFFFFFFFFFFFFFHF",
        "FFFHFFFFFFFFFFFFFF",
        "FFFFFFFFFHFFFFFFFF",
        "FFFFFFFFFFFFFFFFFFFF",
        "FFHHFFFFFFFFFHFFFH",
        "FFFFFFFFFFFFFFFFFFFF",
        "FFFFFFHFFFFFFFFHFFF",
        "FFFFFFFFHFFFFFFFFFH",
        "FFFFFFFFHFFFFFFFFFFF",
        "FFFFFFFFFFFFFFFFHFFF"
    ]
}
```

[illegible]

```

def generate_random_map(size=8, p=0.8):
    """Generates a random valid map (one that has a path from start to goal)
    :param size: size of each side of the grid
    :param p: probability that a tile is frozen
    """
    valid = False

    # BFS to check that it's a valid path.
    def is_valid(arr, r=0, c=0):
        if arr[r][c] == 'G':
            return True

        tmp = arr[r][c]
        arr[r][c] = "#"

        # Recursively check in all four directions.
        directions = [(1, 0), (0, 1), (-1, 0), (0, -1)]
        for x, y in directions:
            r_new = r + x
            c_new = c + y
            if r_new < 0 or r_new >= size or c_new < 0 or c_new >= size:
                continue

            if arr[r_new][c_new] not in '#H':
                if is_valid(arr, r_new, c_new):
                    arr[r][c] = tmp
                    return True

        arr[r][c] = tmp
        return False

    while not valid:
        p = min(1, p)
        res = np.random.choice(['F', 'H'], (size, size), p=[p, 1-p])
        res[0][0] = 'S'
        res[-1][-1] = 'G'
        valid = is_valid(res)
    return [" ".join(x) for x in res]

class FrozenLakeEnv(discrete.DiscreteEnv):
    """

```

Winter is here. You and your friends were tossing around a frisbee at the park when you made a wild throw that left the frisbee out in the middle of the lake. The water is mostly frozen, but there are a few holes where the ice has melted. If you step into one of those holes, you'll fall into the freezing water. At this time, there's an international frisbee shortage, so it's absolutely imperative that you navigate across the lake and retrieve the disc. However, the ice is slippery, so you won't always move in the direction you intend. The surface is described using a grid like the following

```
SFFF
FHFH
FFFH
HFFG
```

S : starting point, safe
 F : frozen surface, safe
 H : hole, fall to your doom
 G : goal, where the frisbee is located

The episode ends when you reach the goal or fall in a hole.
 You receive a reward of 1 if you reach the goal, and zero otherwise.

```
"""
```

```
metadata = {'render.modes': ['human', 'ansi']}
```

```
def __init__(self, desc=None, map_name="4x4", is_slippery=True):
    if desc is None and map_name is None:
        desc = generate_random_map()
    elif desc is None:
        desc = MAPS[map_name]
    self.desc = desc = np.asarray(desc, dtype='c')
    self.nrow, self.ncol = nrow, ncol = desc.shape
    self.reward_range = (0, 1)

    nA = 4
    nS = nrow * ncol

    isd = np.array(desc == b'S').astype('float64').ravel()
    isd /= isd.sum()

    rew_hole = -1000
    rew_goal = 1000
```



```

rew_step = -1

P = {s : {a : [] for a in range(nA)} for s in range(nS)}
self.TransitProb = np.zeros((nA, nS + 1, nS + 1))
self.TransitReward = np.zeros((nS + 1, nA))

def to_s(row, col):
    return row*ncol + col

def inc(row, col, a):
    if a == LEFT:
        col = max(col-1,0)
    elif a == DOWN:
        row = min(row+1,nrow-1)
    elif a == RIGHT:
        col = min(col+1,ncol-1)
    elif a == UP:
        row = max(row-1,0)
    return (row, col)

for row in range(nrow):
    for col in range(ncol):
        s = to_s(row, col)
        for a in range(4):
            li = P[s][a]
            letter = desc[row, col]
            if letter in b'H':
                li.append((1.0, s, 0, True))
                self.TransitProb[a, s, nS] = 1.0
                self.TransitReward[s, a] = rew_hole
            elif letter in b'G':
                li.append((1.0, s, 0, True))
                self.TransitProb[a, s, nS] = 1.0
                self.TransitReward[s, a] = rew_goal
            else:
                if is_slippery:
                    #for b in [(a-1)%4, a, (a+1)%4]:
                    for b, p in zip([a, (a+1)%4, (a+2)%4, (a+3)%4], TransitionProb):
                        newrow, newcol = inc(row, col, b)
                        newstate = to_s(newrow, newcol)
                        newletter = desc[newrow, newcol]
                        done = bytes(newletter) in b'GH'
                        #rew = float(newletter == b'G')

```

```

        #li.append((1.0/10.0, newstate, rew, done))
        if newletter == b'G':
            rew = rew_goal
        elif newletter == b'H':
            rew = rew_hole
        else:
            rew = rew_step
        li.append((p, newstate, rew, done))
        self.TransitProb[a, s, newstate] += p
        self.TransitReward[s, a] = rew_step
    else:
        newrow, newcol = inc(row, col, a)
        newstate = to_s(newrow, newcol)
        newletter = desc[newrow, newcol]
        done = bytes(newletter) in b'GH'
        rew = float(newletter == b'G')
        li.append((1.0, newstate, rew, done))

super(FrozenLakeEnv, self).__init__(nS, nA, P, isd)

def render(self, mode='human'):
    outfile = StringIO() if mode == 'ansi' else sys.stdout

    row, col = self.s // self.ncol, self.s % self.ncol
    desc = self.desc.tolist()
    desc = [[c.decode('utf-8') for c in line] for line in desc]
    desc[row][col] = utils.colorize(desc[row][col], "red", highlight=True)
    if self.lastaction is not None:
        outfile.write("  ({})\n".format(["Left", "Down", "Right", "Up"][self.lastaction]))
    else:
        outfile.write("\n")
    outfile.write("\n".join(''.join(line) for line in desc)+"\n")

    if mode != 'human':
        with closing(outfile):
            return outfile.getvalue()

def GetSuccessors(self, s, a):
    next_states = np.nonzero(self.TransitProb[a, s, :])
    probs = self.TransitProb[a, s, next_states]
    return [(s,p) for s,p in zip(next_states[0], probs[0])]

def GetTransitionProb(self, s, a, ns):

```

```
        return self.TransitProb[a, s, ns]

    def GetReward(self, s, a):
        return self.TransitReward[s, a]

    def GetStateSpace(self):
        return self.TransitProb.shape[1]

    def GetActionSpace(self):
        return self.TransitProb.shape[0]
```

Play Game

Have Fun! (You don't have to do this part, but if you do make sure to use quite using "q" so that you can continue.)

```

In [ ]: print("-----actions-----")
print("a: Left\ns: Down\nd: Right\nw: Up\n(q: quit)")
env = FrozenLakeEnv(map_name="16x16")
env.render()
rew = 0
for _ in range(1000):
    a = input("input action: ")
    if a == 'a':
        a = 0
    elif a == 's':
        a = 1
    elif a == 'd':
        a = 2
    elif a == 'w':
        a = 3
    elif a == 'q':
        break
    else:
        print('illegal input')
        continue
    observation, reward, done, info = env.step(a)
    rew += reward
    print(chr(27) + "[2J")
    print("-----actions-----")
    print("a: Left\ns: Down\nd: Right\nw: Up\n(q: quit)")
    print()
    print("current state:" + str(observation))
    if info['prob'] == TransitionProb[0] or info['prob'] == 1:
        print('move to expected direstion')
    else:
        print('move to unexpected direstion')
    print("probabilty: " + str(info['prob']))
    print("current reward:" + str(rew))
    print()
    env.render()
    print()
    if done:
        print('end')
        break

```

Initializations

Run the following cell to initialize maps of different sizes.

```
In [ ]: map_8 = (MAPS["8x8"], 8)
map_16 = (MAPS["16x16"], 16)
map_32 = (MAPS["32x32"], 32)
#map_50 = (generate_map((50,50)), 50)
#map_110 = (generate_map((110,110)), 110)

MAP = map_8
map_size = MAP[1]
run_time = {}
```

Empirical Policy Evaluation

As a warm up we are going to get experience running a policy in an MDP to empirically evaluate the performance of the policy.

Run the following cell to define the policy evaluation function, which allows us to run a specified policy in a specified environment for a specified number of trials. The function assumes that the trials will terminate for any policy, which is indicated by the "done" variable returned by the environment. This version of the function measures performance by total cumulative reward. Since the environment is stochastic each trial may return a different total reward. This function returns the average cumulative reward across the trials.

```
In [ ]: def evaluate_policy(env, policy, trials = 1000):
    total_reward = 0
    for _ in range(trials):
        env.reset()
        done = False
        observation, reward, done, info = env.step(policy[0])
        total_reward += reward
        while not done:
            observation, reward, done, info = env.step(policy[observation])
            total_reward += reward
    return total_reward / trials
```

Discounted Policy Evaluation

Create a modified version of the above evaluation function that measure the discounted total reward rather than just the total reward as above. The discount factor is specified via a parameter to the function. Specifically, if a trial results in a sequence of rewards: r_0, r_1, r_2, r_3 the discounted total reward would be $r_0 + \beta r_1 + \beta^2 r_2 + \beta^3 r_3$, where β is the discount factor.

```
In [ ]: def evaluate_policy_discounted(env, policy, discount_factor, trials = 1000):
        total_reward = 0
        #INSERT YOUR CODE HERE
        return total_reward / trials
```

Helper Function

Execute the following cell to define the print function. This function shows the policy and state values and saves them to disk. We will use this later in the assignment.

```
In [ ]: def print_results(v, pi, map_size, env, beta, name):
        v_np, pi_np = np.array(v), np.array(pi)
        print("\nState Value:\n")
        print(np.array(v_np[:-1]).reshape((map_size, map_size)))
        print("\nPolicy:\n")
        print(np.array(pi_np[:-1]).reshape((map_size, map_size)))
        print("\nAverage reward: {}\n".format(evaluate_policy(env, pi)))
        print("Avereage discounted reward: {}\n".format(evaluate_policy_discounted(env, pi, discount_factor)))
        print("State Value image view:\n")
        plt.imshow(np.array(v_np[:-1]).reshape((map_size, map_size)))

        pickle.dump(v, open(name + "_" + str(map_size) + "_v.pkl", "wb"))
        pickle.dump(pi, open(name + "_" + str(map_size) + "_pi.pkl", "wb"))
```

Random policy

To provide a reference point for policy performance the following cell defines a random policy (selects actions uniformly at random) and evaluates it. Execute the cell and observe the results.

```
In [ ]: env = FrozenLakeEnv(desc = MAP[0], is_slippery = True)
env.render()
pi = [0] * map_size * map_size
for i in range(map_size * map_size):
    pi[i] = randint(0, 3)
print("Average reward:", evaluate_policy(env, pi))
print("Average discounted reward:",
      evaluate_policy_discounted(env, pi, discount_factor = 0.999))
```

Synchronous Value Iteration with full transition function

In this section, you should implement the synchronous value iteration algorithm. A code skeleton is provided below. Complete the given code by implementing the Bellman backup operator. Recall that the Bellman backup for a state assuming the current value function is V is given by:

$$V_{new}(s) = \max_{a \in A} R(s, a) + \beta \sum_{s' \in S} T(s, a, s') V(s')$$

For this part of the assignment you should implement this Bellman backup operator in a way that performs the sum over all possible next states $s' \in S$. You will want to use the functions `env.GetTransitionProb()` to get the transition probabilities and `env.GetReward()` to get the rewards. In each iteration you need to do the following:

1. Apply the Bellman backup to all state.
2. Compute and update the Bellman error (see first part of document).
3. Update the value and policy accordingly.

```
In [ ]: def sync_value_iteration_v1(env, beta = 0.999, epsilon = 0.0001):

    A = env.GetActionSpace()
    S = env.GetStateSpace()

    pi = [0] * S
    v = [0] * S

    pi_new = [0] * S
    v_new = [0] * S

    bellman_error = float('inf')
    while(bellman_error > epsilon):
        bellman_error = 0
        for state in range(S):
            max_v = float('-inf')
            max_a = 0
            for action in range(A):
                #INSERT YOUR CODE HERE

        v = deepcopy(v_new)
        pi = deepcopy(pi_new)

    return v, pi
```

Run the following cell to see the output of your function and store the value and policy matrices to file.


```
In [ ]: beta = 0.999
env = FrozenLakeEnv(desc = MAP[0], is_slippery = True)
print("Game Map:")
env.render()

start_time = time.time()
v, pi = sync_value_iteration_v1(env, beta = beta)
v_np, pi_np = np.array(v), np.array(pi)
end_time = time.time()
run_time['Sync Value Iteration v1'] = end_time - start_time
print("time:", run_time['Sync Value Iteration v1'])

print_results(v, pi, map_size, env, beta, 'sync_vi')
```

Synchronous Value Iteration Using GetSuccessors()

The above version of value iteration can be very inefficient when the number of states is large because it iterates over all next states. In practice, it is usually the case that for any state s and action a most states have zero probability of being successors. We can exploit that fact to make value iteration more efficient.

The goal of this part is to use `GetSuccessors()` function to decrease the running time. This function takes a state and an action as input and returns the possible next states (with non-zero transition probability) and their transition probabilities. this allows us to ignore all states with zero transition probability. Implement value iteration in the following cell following the previous implementation. But, here, use the `env.GetSuccessors()` function to limit the Bellman backup to only consider non-zero probability states in the summation over next states. Using this function you will not need the `GetTransitionProb` function.

```
In [1]: def sync_value_iteration_v2(env, beta = 0.999, epsilon = 0.0001):

    A = env.GetActionSpace()
    S = env.GetStateSpace()

    pi = [0] * S
    v = [0] * S

    pi_new = [0] * S
    v_new = [0] * S

    error = float('inf')

    #INSERT YOUR CODE HERE

    return v, pi
```

Run the following cell to see the output of your function and store the value and policy matrices to file. Note the time taken for this version versus the previous version of value iteration. The computation time should be significantly smaller for this later version that uses GetSuccessors. Because of this time savings, for the remainder of this assignment you should implement Bellman backups using GetSuccessors.

```
In [ ]: beta = 0.999
env = FrozenLakeEnv(desc = MAP[0], is_slippery = True)
print("Game Map:")
env.render()

start_time = time.time()
v, pi = sync_value_iteration_v2(env, beta = beta)
v_np, pi_np = np.array(v), np.array(pi)
end_time = time.time()
run_time['Sync Value Iteration v2'] = end_time - start_time
print("time:", run_time['Sync Value Iteration v2'])

print_results(v, pi, map_size, env, beta, 'sync_vi_gs')
```

Initialize Ray

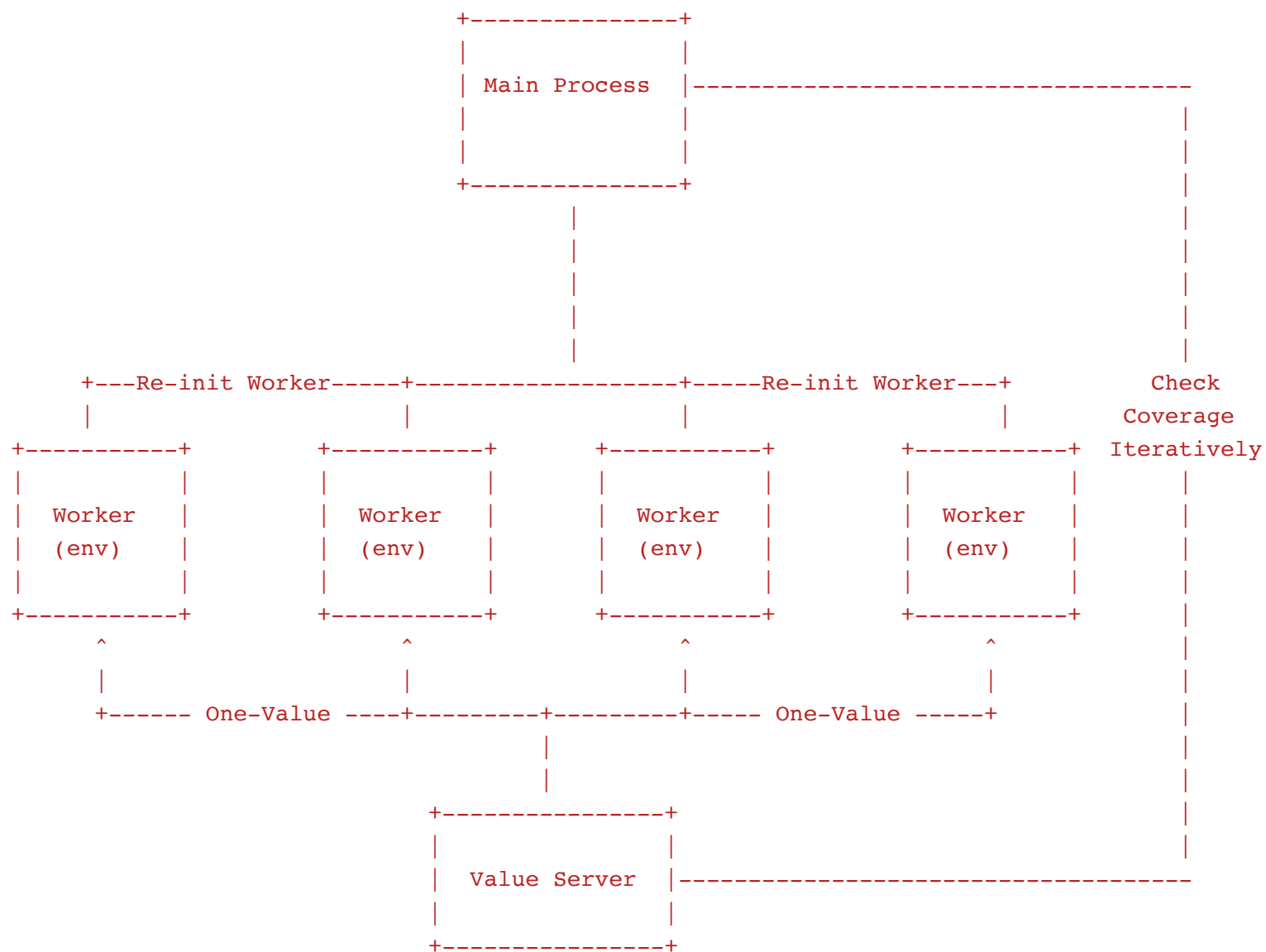
Now we are going to use Ray to develop distributed versions of the above value iteration algorithm. The first step of course is to initialize Ray.

```
In [ ]: ray.shutdown()  
ray.init(include_webui=False, ignore_reinit_error=True, redis_max_memory=500000000, object_store_memory=
```

Distributed Synchronous Value Iteration -- Version 1

A simple way to distribute Value Iteration would be to implement each iteration by having a each state updated by a distinct worker. That is each state is updated by creating a work to do the Bellman backup for that state and then recording the result. In order to avoid creating an enormous number of workers, the first implementation will only allow a specified number of workers to be active at any time. After each iteration, the main process checks the Bellman error and if it is less than the specified epsilon it terminates. The following diagram demonstrates the architecture of such a system.

```
"""
```



```
"""
```

A key part of this implementation is the Value Server, which is a Ray actor that workers interface with to update the value function at each iteration. In order to avoid

You need to complete the following code by adding the Bellman backup operator to it. Once you implemented the function, run the following cell to test it and to store the value and policy matrices to file. Note that this implementation should replicate the results of the non-distributed version of synchronous value iteration.

Importantly you should see that this version is significantly slower than the above non-distributed version. Think about why this might be the case.

```

In [ ]: @ray.remote
class VI_server_v1(object):
    def __init__(self, size):
        self.v_current = [0] * size
        self.pi = [0] * size
        self.v_new = [0] * size

    def get_value_and_policy(self):
        return self.v_current, self.pi

    def update(self, update_index, update_v, update_pi):
        self.v_new[update_index] = update_v
        self.pi[update_index] = update_pi

    def get_error_and_update(self):
        max_error = 0
        for i in range(len(self.v_current)):
            error = abs(self.v_new[i] - self.v_current[i])
            if error > max_error:
                max_error = error
            self.v_current[i] = self.v_new[i]

        return max_error

@ray.remote
def VI_worker_v1(VI_server, data, worker_id, update_state):
    env, workers_num, beta, epsilon = data
    A = env.GetActionSpace()
    S = env.GetStateSpace()

    # get shared variable
    V, _ = ray.get(VI_server.get_value_and_policy.remote())

    # bellman backup

    #INSERT YOUR CODE HERE

    VI_server.update.remote(update_state, max_v, max_a)

    # return ith worker
    return worker_id

```

```
def sync_value_iteration_distributed_v1(env, beta = 0.999, epsilon = 0.01, workers_num = 4, stop_steps = 1000000):
    S = env.GetStateSpace()
    VI_server = VI_server_v1.remote(S)
    workers_list = []
    data_id = ray.put((env, workers_num, beta, epsilon))

    start = 0
    # start the all worker, store their id in a list
    for i in range(workers_num):
        w_id = VI_worker_v1.remote(VI_server, data_id, i, start)
        workers_list.append(w_id)
        start += 1

    error = float('inf')
    while error > epsilon:
        for update_state in range(start, S):
            # Wait for one worker finishing, get its result, and delete it from list
            finished_worker_id = ray.wait(workers_list, num_returns = 1, timeout = None)[0][0]
            finish_worker = ray.get(finished_worker_id)
            workers_list.remove(finished_worker_id)

            # start a new worker, and add it to the list
            w_id = VI_worker_v1.remote(VI_server, data_id, finish_worker, update_state)
            workers_list.append(w_id)

        start = 0
        error = ray.get(VI_server.get_error_and_update.remote())

    v, pi = ray.get(VI_server.get_value_and_policy.remote())
    return v, pi
```

```
In [ ]: beta = 0.999
env = FrozenLakeEnv(desc = MAP[0], is_slippery = True)
print("Game Map:")
env.render()

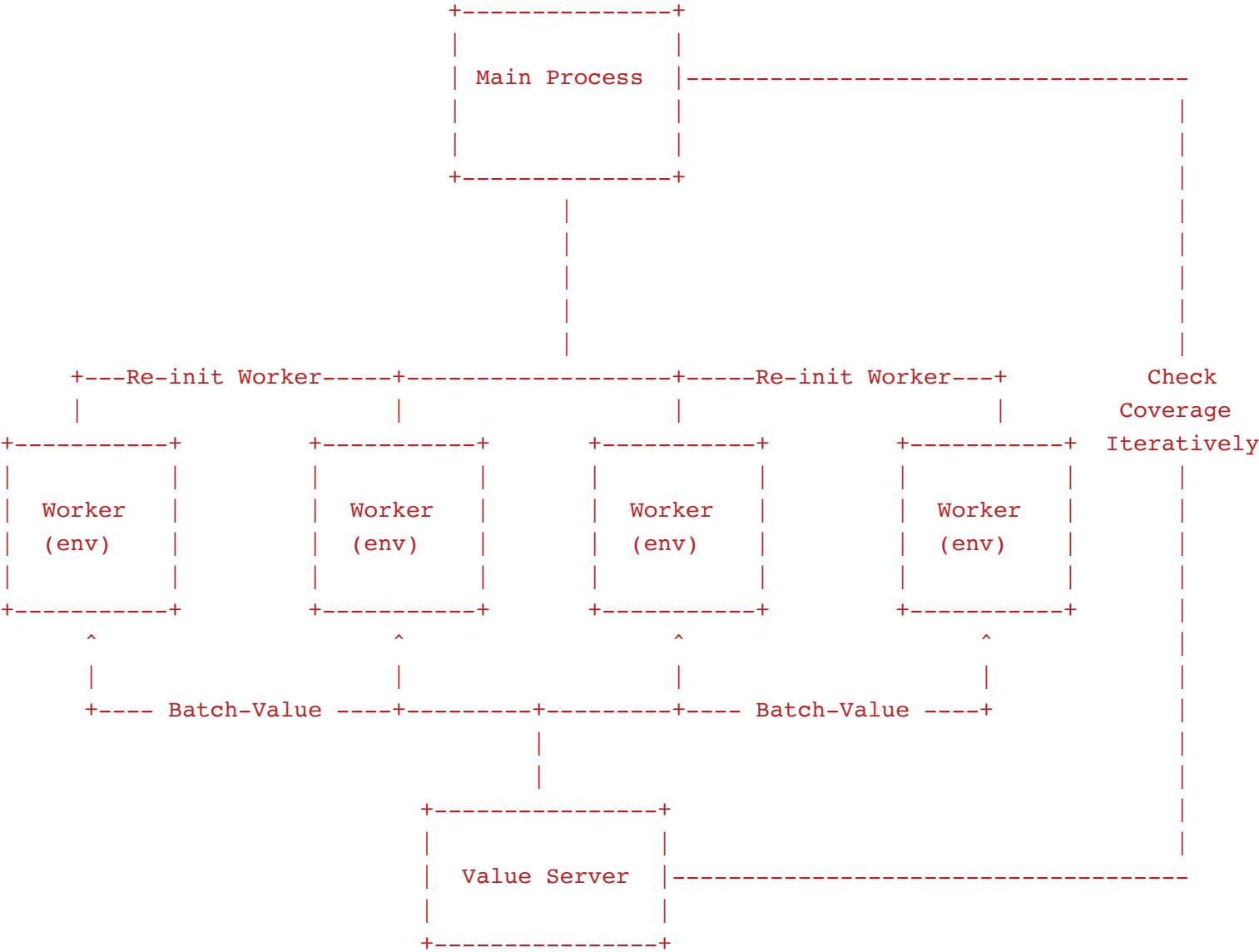
start_time = time.time()
v, pi = sync_value_iteration_distributed_v1(env, beta = beta, workers_num = 4)
v_np, pi_np = np.array(v), np.array(pi)
end_time = time.time()
run_time['Sync distributed v1'] = end_time - start_time
print("time:", run_time['Sync distributed v1'])

print_results(v, pi, map_size, env, beta, 'dist_vi_v1')
```

Distributed Synchronous Value Iteration -- Version 2

One way to improve the above approach is to create a limited number of workers and have each worker perform backups on a batch of states. Effectively, this approach partitions the state space and uses a worker to handle each state subset of the partition. The following diagram demonstrates the architecture of such a system.

"""



"""

In this section, you should implement the idea described above.

- Partition the states into batches. The number of batches should be equal to the number of the workers.
- Create workers to handle each batch and run them
- Terminate the workers once the error is less than the given epsilon

Again, this implementation should exactly emulate the result of each iteration of non-distributed value iteration.

```
In [ ]: @ray.remote
class VI_server_v2(object):
    #INSERT YOUR CODE HERE

@ray.remote
def VI_worker_v2(VI_server, data, start_state, end_state):
    env, workers_num, beta, epsilon = data
    A = env.GetActionSpace()
    S = env.GetStateSpace()

    #INSERT YOUR CODE HERE

def sync_value_iteration_distributed_v2(env, beta = 0.999, epsilon = 0.01, workers_num = 4, stop_steps = 10000):
    S = env.GetStateSpace()
    VI_server = VI_server_v2.remote(S)
    workers_list = []
    data_id = ray.put((env, workers_num, beta, epsilon))
    #INSERT YOUR CODE HERE

    error = float('inf')
    while error > epsilon:
        #INSERT YOUR CODE HERE

    return v, pi
```

Run the following code to see the running time of your code. This code stores the policy and state values to disk.

```
In [ ]: beta = 0.999
env = FrozenLakeEnv(desc = MAP[0], is_slippery = True)
print("Game Map:")
env.render()

start_time = time.time()
v, pi = sync_value_iteration_distributed_v2(env, beta = beta, workers_num = 4)
v_np, pi_np = np.array(v), np.array(pi)
end_time = time.time()
run_time['Sync distributed v2'] = end_time - start_time
print("time:", run_time['Sync distributed v2'])
print_results(v, pi, map_size, env, beta, 'dist_vi_v2')
```

Comparison of different approaches

Run the following cell to compare the running time of different approaches.

```
In [ ]: from copy import deepcopy
temp_dict = deepcopy(run_time)
print("All:")
for _ in range(len(temp_dict)):
    min_v = float('inf')
    for k, v in temp_dict.items():
        if v is None:
            continue
        if v < min_v:
            min_v = v
            name = k
    temp_dict[name] = float('inf')
    print(name + ": " + str(min_v))
    print()
```

Report

Write a report that includes the following:

- A plot that shows the running time of the above 4 approaches against the map sizes f 8, 16 and 32.
- A plot that shows the running time of both distributed approaches against the number of the workers with 2, 4 and 8 workers.

- Briefly explain why the second distributed method is faster than the first one?
- Compare the best distributed method with the best non-distributed approach. Which one is better? Briefly explain why.

Distributed Synchronous VI Competition

In this part, you should design and implement your own distributed synchronous VI method based on what you have learned in the previous parts. Your implementation has the following constraints:

- It must terminate and return a value function (and corresponding greedy policy) that satisfies the specified Bellman error threshold
- It must be iterative in the sense that it produces the same sequence of value functions as non-distributed synchronous value iteration

For this part, you should create a stand alone python file named `competition.py`. You can copy the needed functions from this notebook to your file. Your code should contain a main function called `fast_value_iteration` with the following exact signature:

```
def fast_value_iteration(env, beta = 0.999, epsilon = 0.01, workers_num = 4)
```

Here epsilon is the Bellman error threshold and worker_num is the maximum number of workers. This function should return policy and value vectors that satisfy the Bellman error constraint.

To test your code, you should use an exclusive computation node of DevCloud. You can use the `qsub -I -lselect=1` command to connect to a computation node and run your code on it. We may test your programs on problems as large as 100x100 FrozenLake environments.

Some possible ideas to consider

- How should the number of workers be selected and how should states be partitioned across workers?
- Are there alternative protocols between the server and workers?
- Where are the communication bottlenecks in the system and how might they be improved?

Deliverables

Submit a zip file to Canvas that contains:

- completed version of this notebook
- the .pkl files generated by print_results function for your runs on map of size 8x8
- a python file for distributed VI competition
- your PDF report file

In []: