Assignment 1 - Policy iteration and Value iteration for grid example

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Course: AI for Multiagent system

How to run the code

The code is located on Github https://github.com/supreethms1809/multiagent.git.

```
python assignment1_main.py [-h] \\
    [--task {policy_iteration,value_iteration}] \\
    [--gamma GAMMA] [--epsilon EPSILON] \\
    [--max_iterations MAX_ITERATIONS] \\
    [--grid_size grid_size] [--stepReward STEPREWARD] \\
    [--goalReward GOALREWARD] \\
    [--valueFunctionInit {V,Q}] \\
    [--randomValueFunctionInit] \\
    [--uniformPolicyInit] \\
    [--problem {1,2,3,4}] [--plotTable] \\
    [--goalStates GOALSTATES] \\
    [--splStates SPECIALSTATES] \\
    [--splReward SPLREWARD]

    options:
    -h, --help            show this help message and exit
    --task {policy_iteration,value_iteration}
    --gamma GAMMA                          Gamma for the value
       iteration
    --epsilon EPSILON                      Epsilon for the value
       iteration
    --max_iterations MAX_ITERATIONS        Maximum number of
       iterations
                                           for the value iteration and
                                           policy iteration
    --grid_size grid_size                  Size of the grid N
    --stepReward STEPREWARD                Step reward
    --goalReward GOALREWARD                Goal reward
    --valueFunctionInit {V,Q}              Type of value function used
                                           V or Q
    --randomValueFunctionInit              Initialize the value
       function
                                           with random values
    --uniformPolicyInit                    Initialize the policy
                                           with uniform distribution
    --problem {1,2,3,4}                    Problem number
    --plotTable                            Plot the value function
```

```
                                                and policy
      --goalStates GOALSTATES                   Goal states list. Format
                                                list of tuples
                                                [(x, y), (x, y), ...]
      --splStates SPECIALSTATES                 Spl states list. Format
                                                list of tuples
                                                [(x, y), (x, y), ...]
      --splReward SPLREWARD                     Special state reward
```

The configurations for the four problems given in the assignment is hardcoded in the source code for convinience. Alternatively, you can also pass the configurations as the command line options. The usage is shown above. The code is modular and well commented for description. The code should be able to handle bigger square grid as well.

To run problem 1 use

```
python assignment1_main.py --problem 1

# Problem 1 sets the following options
# config.stepReward = -1
# config.goalReward = 0
# config.gamma = 0.9
# config.epsilon = 1e-6
# config.max_iterations = 150
# config.grid_size = 4
# config.valueFunctionInit = "V"
# config.randomValueFunctionInit = False
# config.uniformPolicyInit = True
# config.task = "policy_iteration"
# config.plotTable = True
# config.goalStates = [(0, 0), (3, 3)]
# config.splStates = None
# config.splReward = None
```

To run problem 2,3,4

```
python assignment1_main.py --problem 2
python assignment1_main.py --problem 3
python assignment1_main.py --problem 4
```

Problem description

- Grid map problem, one agent moves on the grid map.
- The terminal states are (0,0) --> 0 and (3,3) --> 15.
- Reward for going to the terminal state 0.

Problem 1 - Policy Iteration

- Policy iteration
- Policy is uniform distribution policy
- every step generates reward of -1
- Goal reward is 0
- gamma $\gamma = 0.9$
- Goal state (0,0) and (3,3)
- Evaluate the policy iteratively
- Plot the value of each state after the policy evaluation is complete(One plot)
- Tips: 1. run more than 150 iterations. 2. set the convergence threshold less than 1e-6

Policy iteration consists of two parts. First is the policy evaluation and the policy improvement. In this phase, we calculate the value function using the Bellman expectation equation under the current policy

$V^\pi(s) = \sum_a \pi(a|s) \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^\pi(s')]$

We run this update for all states until the values converge (i.e., they stop changing between successive iterations) or until a maximum number of iterations is reached. During this process, the policy remains fixed.

Once we have an updated value function, we improve the policy by making it greedy with respect to the current value estimates:

$\pi'(s) = \arg\max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V^\pi(s')]$

If the policy changes, we repeat the evaluation and improvement steps. If the policy remains unchanged (i.e., stable), then we have reached convergence.

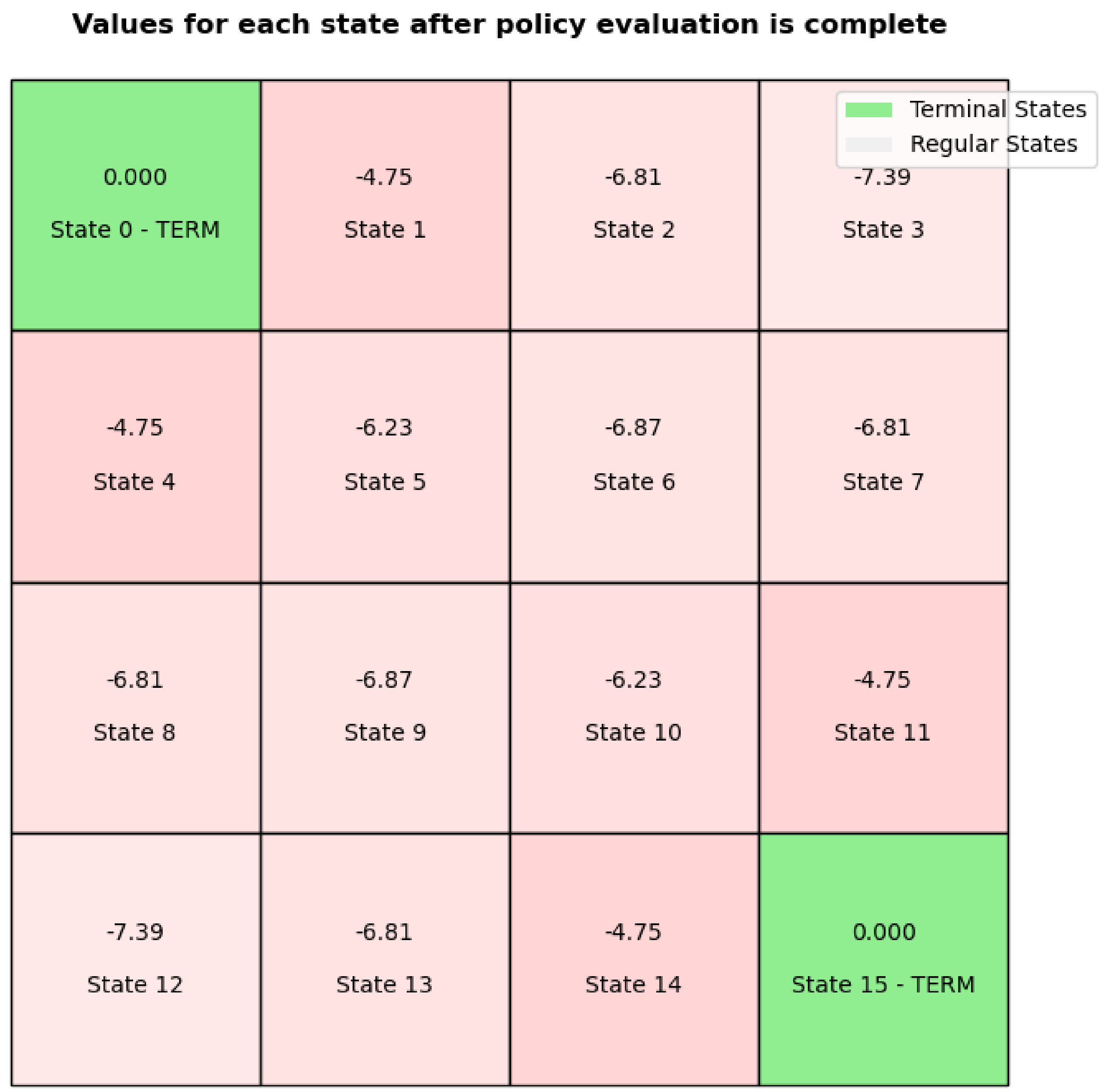
Run `python assignment1_main.py --problem 1`

```
# Problem 1 sets the following options
# config.stepReward = -1
# config.goalReward = 0
# config.gamma = 0.9
# config.epsilon = 1e-6
# config.max_iterations = 200
# config.grid_size = 4
# config.valueFunctionInit = "V"
# config.randomValueFunctionInit = True
# config.uniformPolicyInit = True
# config.task = "policy_iteration"
# config.plotTable = True
# config.goalStates = [(0, 0), (3, 3)]
# config.splStates = None
# config.splReward = None
```

Running problem 1

```
INFO:__main__:Performing calculations for Prob 1: policy_iteration with
    V value function and uniform distribution for policy initialization
INFO:__main__:Using V value function with random initialization
INFO:__main__:Using uniform policy initialization
INFO:__main__:Starting policy iteration with 200 max iterations
INFO:__main__:Value function converged after 62 evaluation iterations
INFO:__main__:Plotting value function
INFO:__main__:Value function converged after 4 evaluation iterations
INFO:__main__:Value function converged after 1 evaluation iterations
INFO:__main__:Policy converged after 3 iterations
INFO:__main__:Policy iteration converged successfully
```

Plot the value of each state after the policy evaluation is complete: Value and action of each state after the policy evaluation is complete



Problem 2 - Policy Iteration

- Policy iteration
- Policy is uniform distribution policy

- every step generates reward of -4
- Goal state reward 0
- gamma $\gamma = 0.9$
- Special state reward -1
- Special state (2,2) --> state 10,
- Goal state (0,0) and (3,3)
- Evaluate the policy iteratively
- Plot the value of each state after the policy evaluation is complete(One plot)

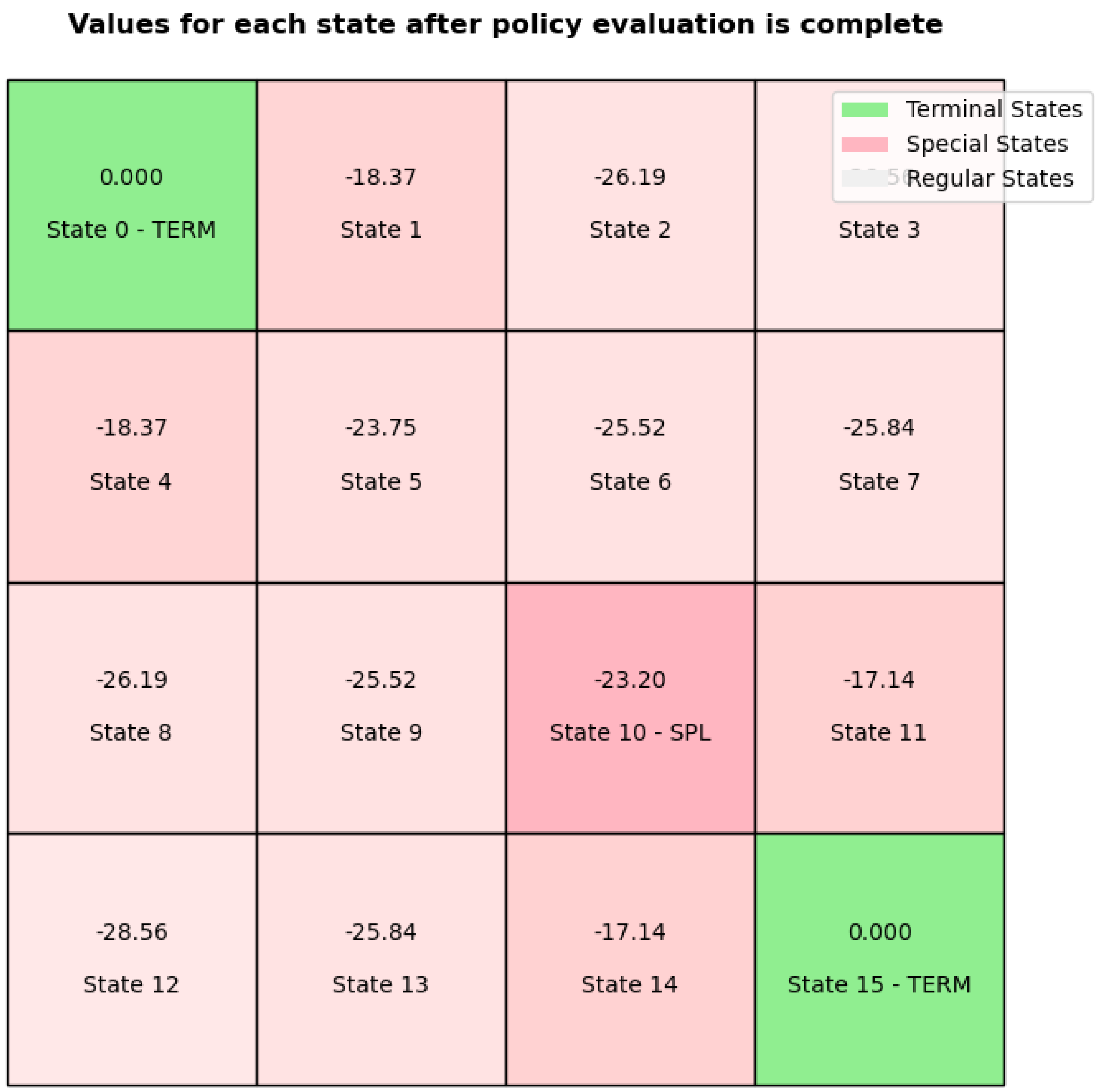
Run `python assignment1_main.py --problem 2`

```
# Problem 2 sets the following options
# config.stepReward = -4
# config.goalReward = 0
# config.gamma = 0.9
# config.epsilon = 1e-6
# config.max_iterations = 200
# config.grid_size = 4
# config.valueFunctionInit = "V"
# config.randomValueFunctionInit = True
# config.uniformPolicyInit = True
# config.task = "policy_iteration"
# config.plotTable = True
# config.goalStates = [(0, 0), (3, 3)]
# config.splStates = [(2,2)]
# config.splReward = -1
```

Running problem 2

```
INFO:__main__:Performing calculations for Prob 2: policy_iteration with
    V value function and uniform distribution for policy initialization
INFO:__main__:Using V value function with random initialization
INFO:__main__:Using uniform policy initialization
INFO:__main__:Starting policy iteration with 200 max iterations
INFO:__main__:Value function converged after 62 evaluation iterations
INFO:__main__:Plotting value function
INFO:__main__:Value function converged after 4 evaluation iterations
INFO:__main__:Value function converged after 1 evaluation iterations
INFO:__main__:Policy converged after 3 iterations
INFO:__main__:Policy iteration converged successfully
```

Plot the value of each state after the policy evaluation is complete: Value and action of each state after the policy evaluation is complete



Problem 3 - Policy Iteration

- Policy iteration
- Policy is uniform distribution policy

- every step generates reward -4
- Goal state reward 0
- gamma $\gamma = 0.9$
- Special state reward -1
- Special state (2,2) --> state 10
- Goal state (0,0) and (3,3)
- Evaluate the policy iteratively

Run `python assignment1_main.py --problem 3`

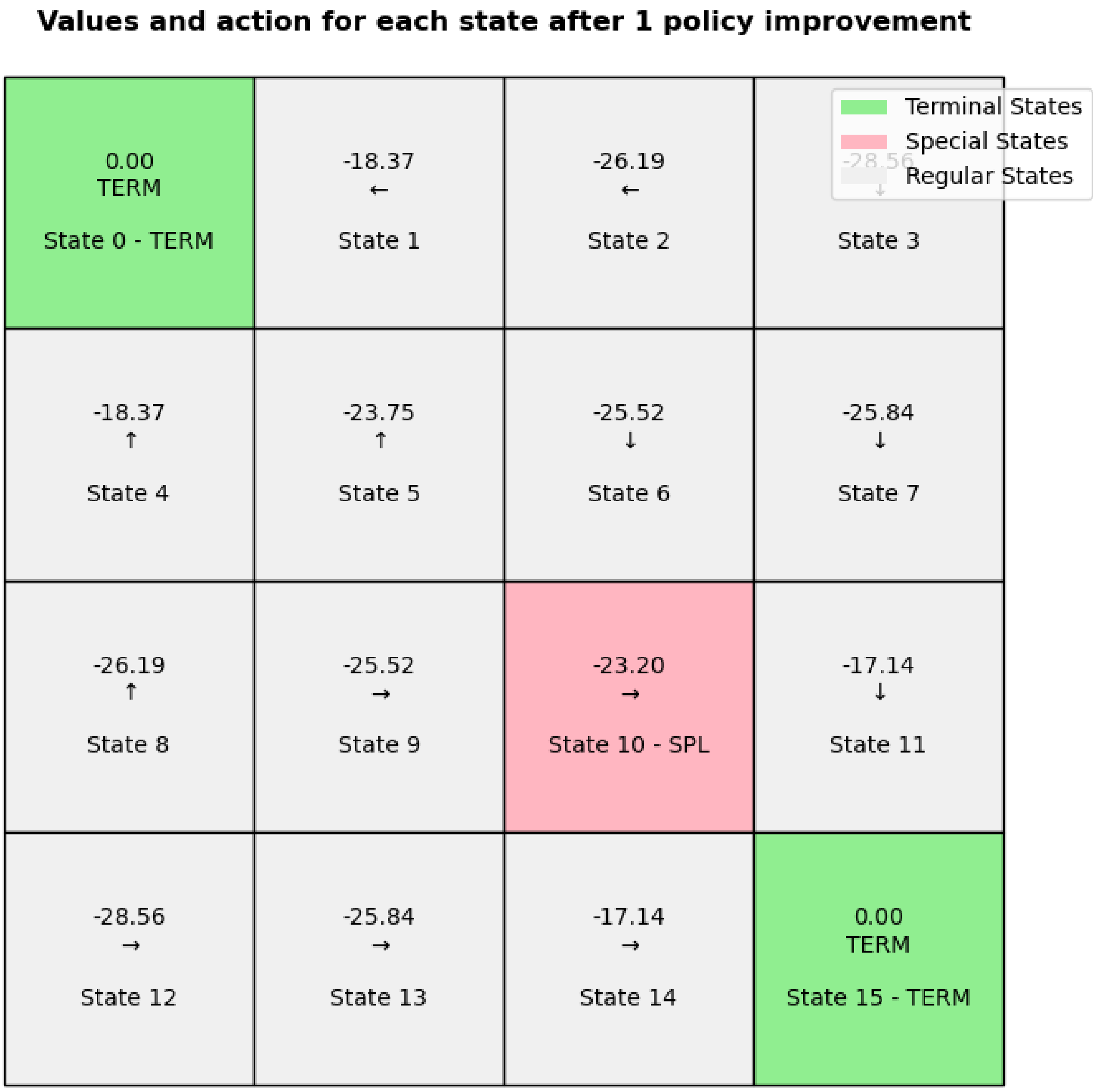
```
# Problem 3 sets the following options
# config.stepReward = -4
# config.goalReward = 0
# config.gamma = 0.9
# config.epsilon = 1e-6
# config.max_iterations = 200
# config.grid_size = 4
# config.valueFunctionInit = "V"
# config.randomValueFunctionInit = True
# config.uniformPolicyInit = True
# config.task = "policy_iteration"
# config.plotTable = True
# config.goalStates = [(0, 0), (3, 3)]
# config.splStates = [(2,2)]
# config.splReward = -1
```

Running problem 3

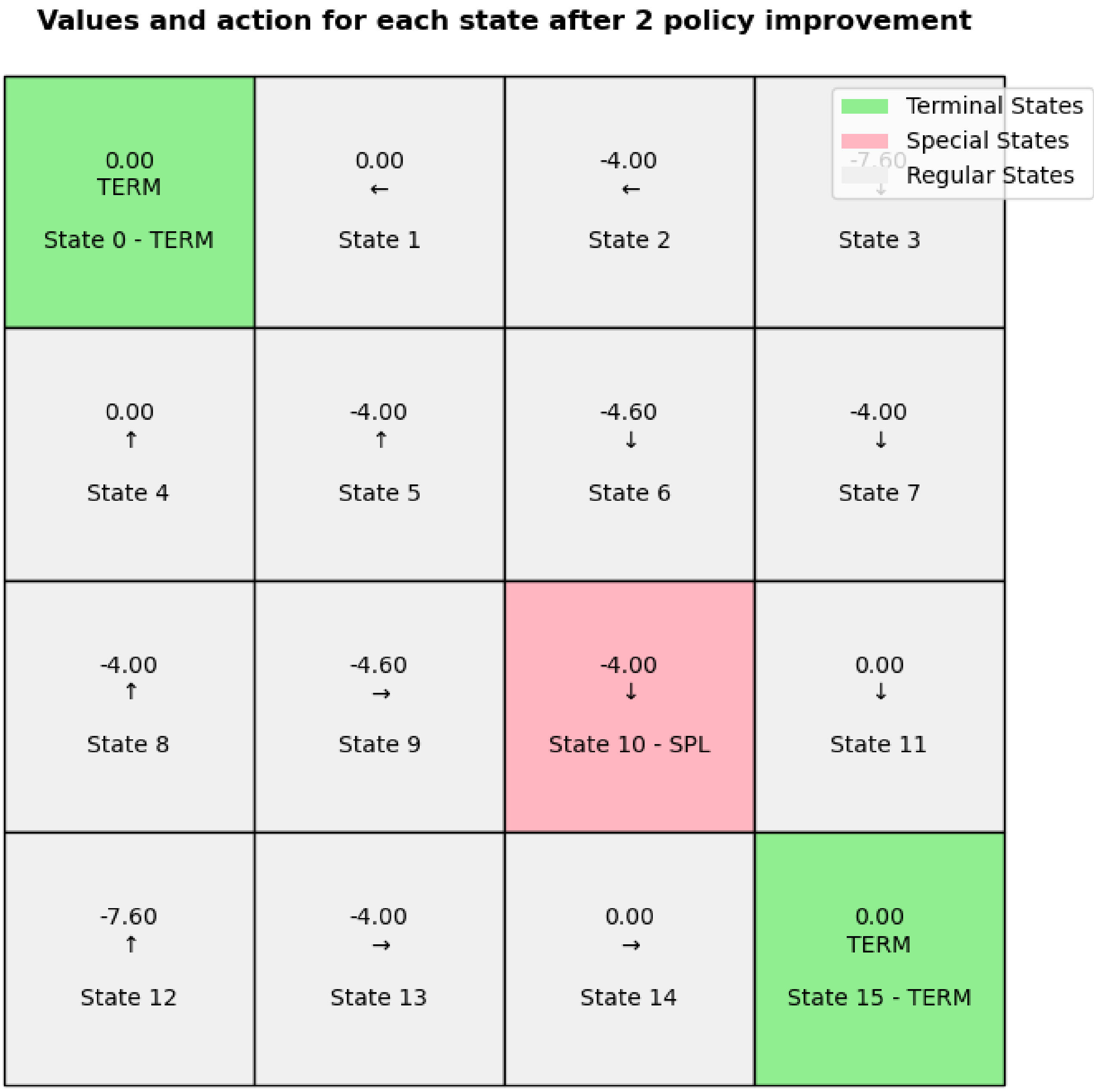
```
INFO:__main__:Performing calculations for Prob 3: policy_iteration with
    V value function and uniform distribution for policy initialization
INFO:__main__:Using V value function with random initialization
INFO:__main__:Using uniform policy initialization
INFO:__main__:Starting policy iteration with 200 max iterations
INFO:__main__:Value function converged after 62 evaluation iterations
INFO:__main__:Plotting optimal policy with values and actions
INFO:__main__:Value function converged after 4 evaluation iterations
INFO:__main__:Plotting optimal policy with values and actions
INFO:__main__:Value function converged after 1 evaluation iterations
INFO:__main__:Plotting optimal policy with values and actions
INFO:__main__:Policy converged after 3 iterations
INFO:__main__:Policy iteration converged successfully
INFO:__main__:Plotting value function
INFO:__main__:Plotting optimal policy with values and actions
```

Plot the comparison of value and optimal action of each state after each policy improvement (similar to the slides). As many plots as the number of policy improvement goes

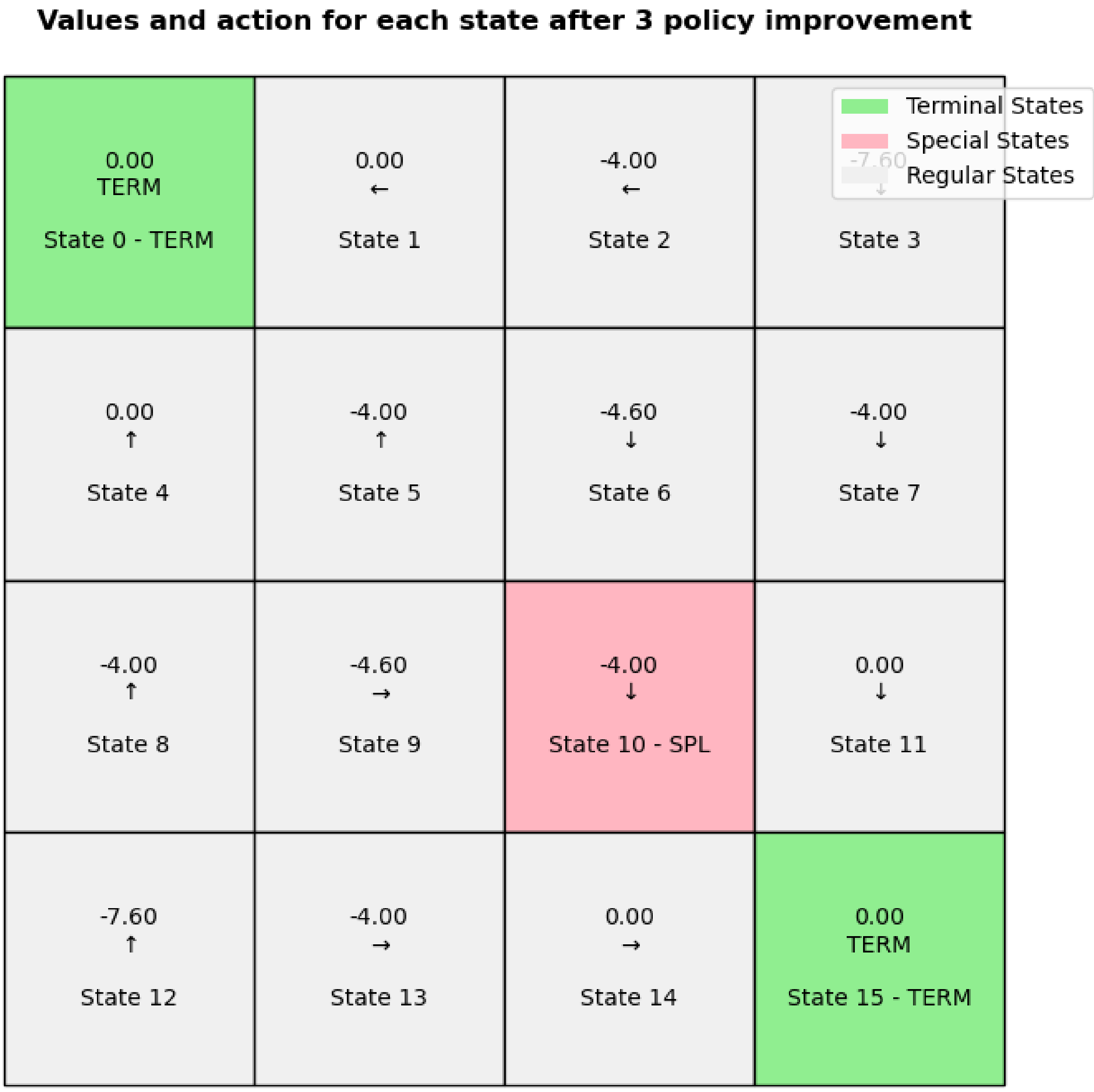
Value and action of each state after the 1st policy improvement



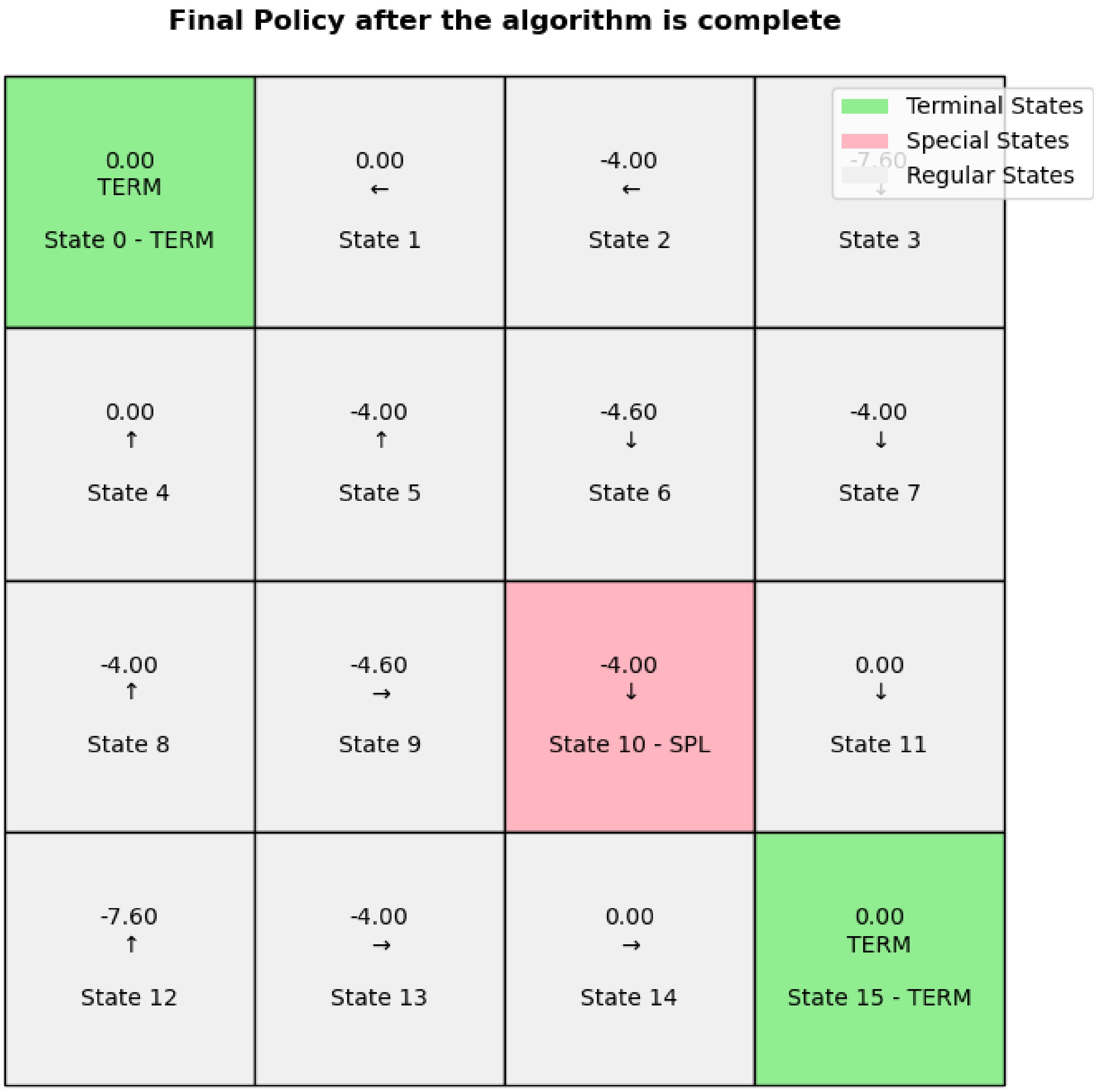
Value and action of each state after the 2nd policy improvement



Value and action of each state after the 3rd policy improvement



Final Optimal policy



Comment: The states 1, 4, 11, 14 has the value 0 at the end. If the reward for going to the terminal state were to positive in the problem, these states would have some values other than 0. When the value is 0, the agent has no incentive to reach the goal. So, the decision to choose reward is important.

Problem 4 - Value Iteration

- Value iteration
- every step generates reward -4
- Goal state reward 0
- gamma $\gamma = 0.9$
- Special state reward -1
- Special state (2,2) --> state 10
- Goal state (0,0) and (3,3)
- Run value iteration and generate a policy based on the values

Here we are using value iteration. Value iteration has only one update. we directly update the value function using the Bellman optimality equation.

$V_{k+1}(s) = \max_a \sum_{s'} P(s'|s,a)[R(s,a,s') + \gamma V_k(s')]$

We repeat this update across all states until the value function converges (the difference between successive iterations is below some threshold ϵ)

Run `python assignment1_main.py --problem 4`

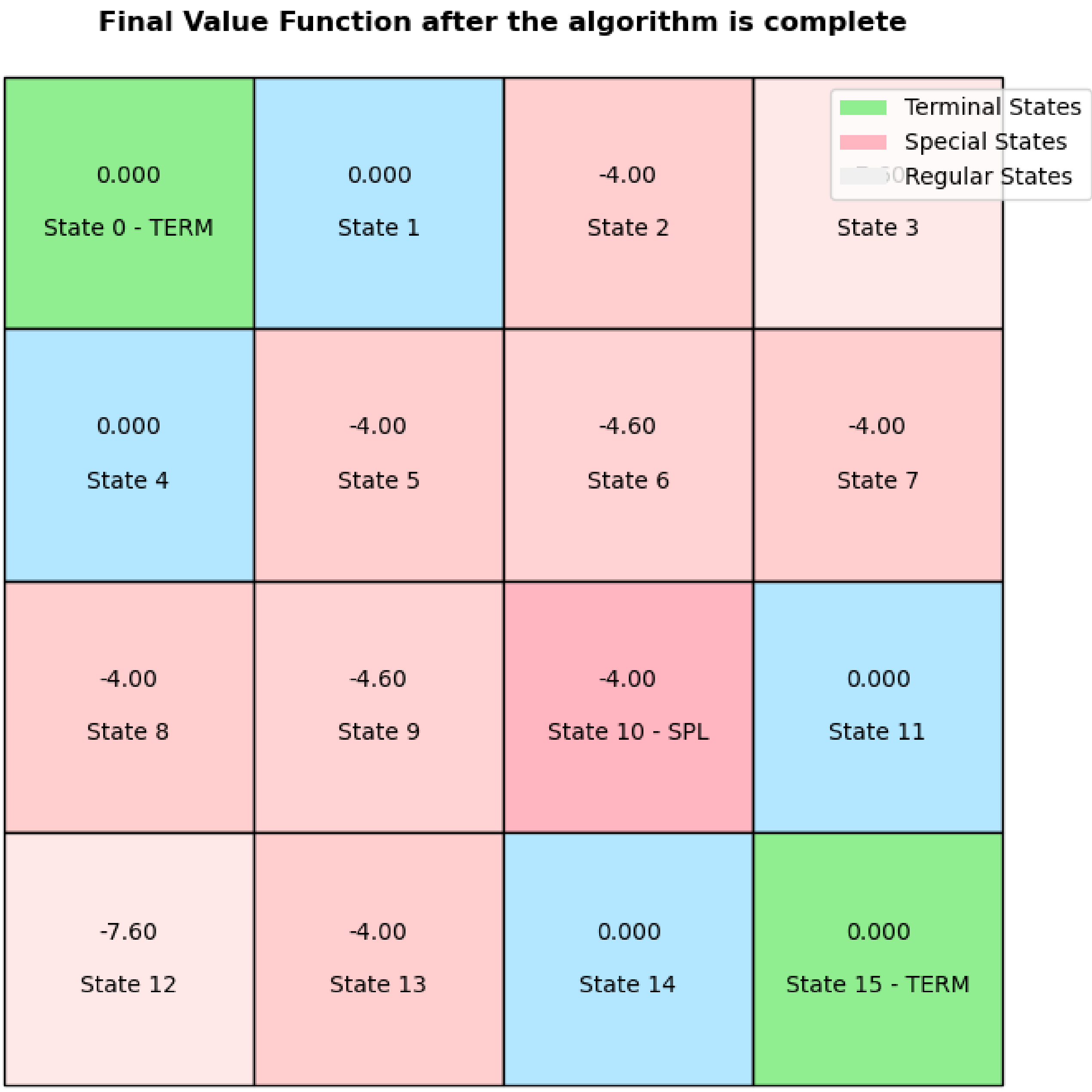
```
# Problem 4 sets the following options
# config.stepReward = -4
# config.goalReward = 0
# config.gamma = 0.9
# config.epsilon = 1e-6
# config.max_iterations = 200
# config.grid_size = 4
# config.valueFunctionInit = "V"
# config.randomValueFunctionInit = True
# config.uniformPolicyInit = True
# config.task = "value_iteration"
# config.plotTable = True
# config.goalStates = [(0, 0), (3, 3)]
# config.splStates = [(2,2)]
# config.splReward = -1
```

Running problem 4

```
INFO:__main__:Performing calculations for Prob 4: policy_iteration with V value function and uniform distribution for policy initialization
INFO:__main__:Using V value function with random initialization
INFO:__main__:Value iteration converged after 4 iterations
INFO:__main__:Value iteration converged successfully
INFO:__main__:Plotting value function
INFO:__main__:Plotting optimal policy with values and actions
```

Plot the comparison of value and optimal action of each state after the algorithm is completed (similar to the slides). One plot for value, one plot for policy.

Value after the algorithm is complete



Policy after the algorithm is complete