Part 2 - Reinforcement Learning

November 11, 2018

```
In [56]: %load_ext autoreload

         from gridworld import GridWorld1
         import RL
         import gridrender as gui
         import matplotlib.pyplot as plt
         import numpy as np
         import time
         %autoreload 2
```

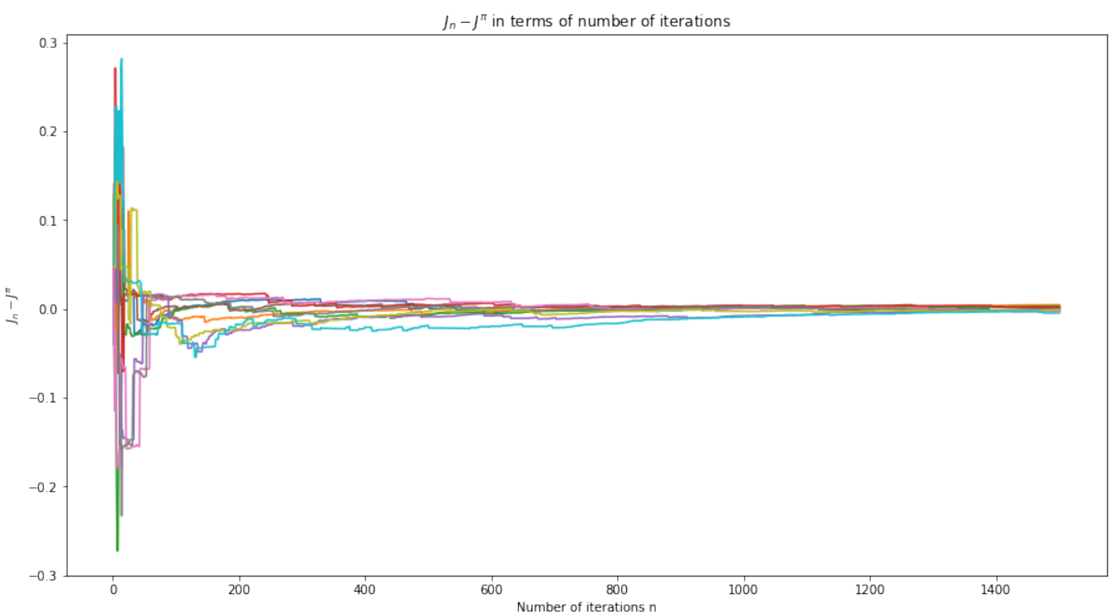
```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

```
In [57]: ################################################################################
         # Initialization
         ################################################################################

         env = GridWorld1
         n_states = env.n_states
         n_actions = len(env.action_names)

         model = RL.RL(env)
```

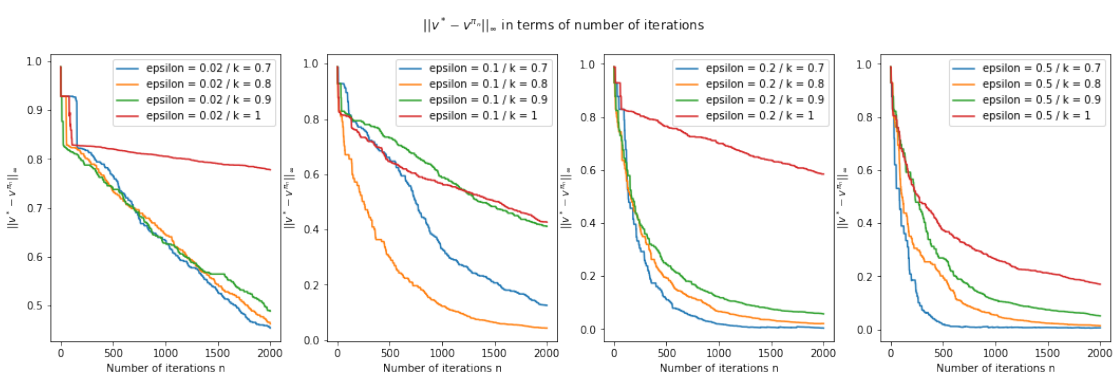
```
In [58]: # Estimating initial state distribution
         n_start = 10000
         model.estimate_start_distribution(n_start)
         print(f'Estimated start state distribution is {model.mu} after {n_start} throws')

         # Tmax st the discounted truncated sum of rewards is delta-closed to the infinite sum
         delta = 0.01
         tmax = -int(np.log(delta)/(1-env.gamma))
         print(f'Tmax (max number of iterations in an episode) is chosen as : {tmax}')
```

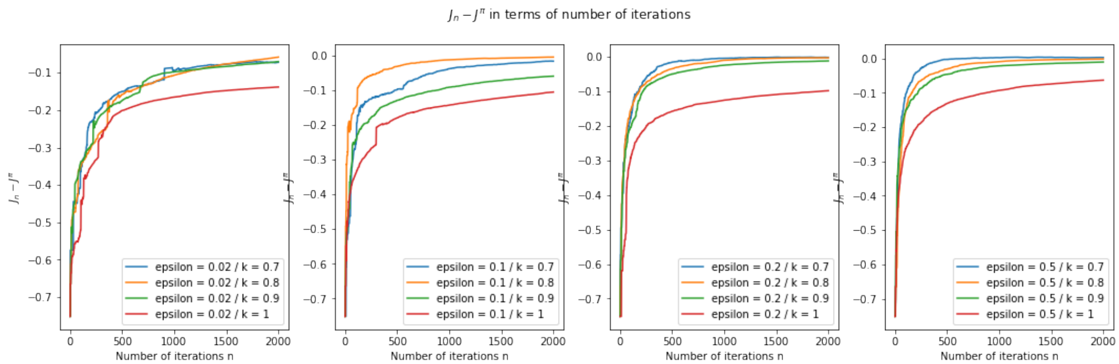
```
Estimated start state distribution is [ 0.1439  0.0954  0.0867  0.0462  0.0905  0.0914  0.0931
  0.0871  0.0905] after 10000 throws
Tmax (max number of iterations in an episode) is chosen as : 92
```

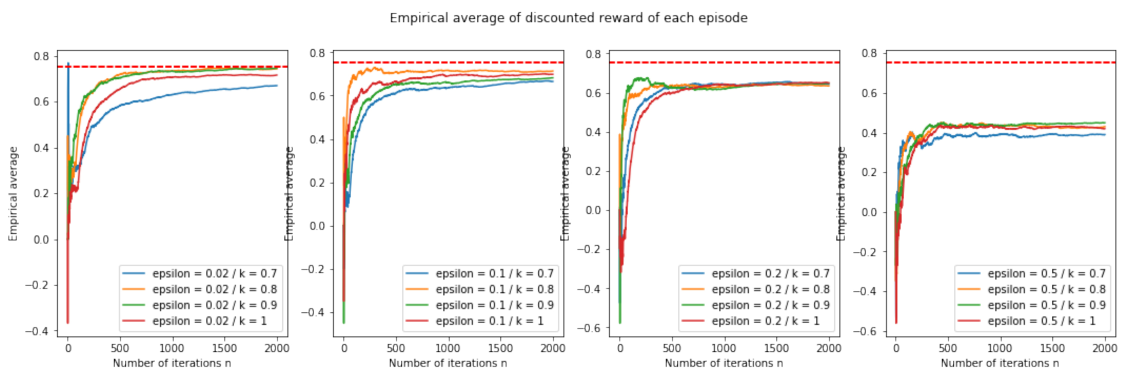
In [79]:
```
#################################################################################
# Q4: Policy evaluation
#################################################################################

# Deterministic policy: always go right when available, otherwise up
policy = np.zeros(n_states)
for i, el in enumerate(env.state_actions):
        if 0 in el:
                policy[i] = 0
        else:
                policy[i] = 3
model.set_policy(policy)

f, ax = plt.subplots(1, figsize= (15,8))

# Policy estimation using Monte-Carlo estimation on trajectories:
# one trajectory = one sample for initial state
for i in range(10):
        model.estimate_value_MC(1500, tmax)

        v_q4 = np.array([0.87691855, 0.92820033, 0.98817903, 0.00000000,
                         0.67106071, -0.99447514, 0.00000000, -0.82847001,
                         -0.87691855, -0.93358351, -0.99447514])
        model.plot_avg_value_approximation(v_q4, ax = ax)



plt.show()
```



```
In [87]: #################################################################################
         # Q5: Policy optimization
         #################################################################################
         ks = [0.7, 0.8, 0.9, 1]
         epss = [0.02, 0.1, 0.2, 0.5]
         f1, ax1 = plt.subplots(1,len(epss), figsize = (18,5))
         f2, ax2 = plt.subplots(1,len(epss), figsize = (18,5))
         f3, ax3 = plt.subplots(1, len(epss), figsize = (18,5))

         v_opt = np.array([0.87691855, 0.92820033, 0.98817903, 0.00000000, 0.82369294,
                           0.92820033, 0.00000000, 0.77818504, 0.82369294, 0.87691855,
                           0.82847001])

         for k in ks:
             for i,eps in enumerate(epss):
                 alpha = lambda x: 1/(x**k)
                 learning_rates = np.full((n_states, n_actions), alpha)
                 model.learn_q(2000, tmax, eps, learning_rates)

                 label = f'epsilon = {eps} / k = {k}'
                 model.plot_value_error(v_opt, label = label, ax = ax1[i])
                 model.plot_avg_value_approximation(v_opt, label = label, ax = ax2[i])
                 model.plot_reward(discounted = True, yline = model.avg_value_infty, \
                                   label = label, ax = ax3[i])


         for i in range(len(epss)):
             ax1[i].set_title('')
             ax2[i].set_title('')
             ax3[i].set_title('')

         f1.suptitle(r'$||v^* - v^{\pi_n}||_{\infty}$ in terms of number of iterations')
         f2.suptitle(r'$J_n - J^\pi$ in terms of number of iterations')
         f3.suptitle('Empirical average of discounted reward of each episode')
         plt.show()
```







In [90]:
```
# Optimal policy render
alpha = lambda x: 1 / (x ** 0.7)
learning_rates = np.full((n_states, n_actions), alpha)
model.learn_q(10000, tmax, 0.2, learning_rates)

pol = model.policy_n[:,-1]
gui.render_policy(env, pol)

q_formatted = [model.Q_n[state, :, -1][model.Q_n[state, :, -1] != -np.inf] \
               for state in range(n_states)]
gui.render_q(env, q_formatted)
```