```
import gym
import numpy as np
import matplotlib.pyplot as plt
import sys
```

## **Semi-Gradient Sarsa(0)**

```
In [2]: # Create the Mountain Car environment
        env = gym.make('MountainCar-v0')
        # Set up the action and observation space
        action_space = env.action_space.n
        observation_space = env.observation_space.shape[0]
        # Define the weight vector for linear function approximation
        weights_sarsa = np.random.rand(observation_space + 1) # Add 1 for the action
        # Define the hyperparameters
        alpha = 0.1 # Learning rate
        gamma = 0.99 # discount factor
        epsilon = 0.1 # exploration rate
        episodes = 100 # number of episodes
        steps_per_episode = 200 # maximum number of steps per episode
        # Define the epsilon-greedy policy function
        def epsilon_greedy(weights, state, epsilon):
            if np.random.rand() < epsilon:</pre>
                return np.random.randint(action_space)
            else:
                q_values = [np.dot(weights, get_features(state, a)) for a in range(action_
                return np.argmax(q_values)
        # Define the feature extraction function
        def get_features(state, action=None):
            if action is None:
                return np.append(state, 1) # Append 1 for the action
                return np.append(state, action)
        # Initialize lists to store rewards and steps
        rewards sarsa = []
        # Implement the Semi-Gradient Sarsa(0) algorithm with linear function approximation
        for episode in range(episodes):
            state = env.reset()
            action_sarsa = epsilon_greedy(weights_sarsa, state, epsilon)
            episode_reward = 0
            for step in range(steps_per_episode):
                # Take action and observe the next state and reward
                next_state, reward, done, _ = env.step(action_sarsa)
                # Choose next action using epsilon-greedy policy for Sarsa(0)
                next_action_sarsa = epsilon_greedy(weights_sarsa, next_state, epsilon)
                # Compute the TD error for Sarsa(0)
                td_error = reward + gamma * np.dot(weights_sarsa, get_features(next_state,
                # Update the weight vector for Sarsa(0) using the gradient descent update
                weights_sarsa += alpha * td_error * get_features(state, action_sarsa)
```

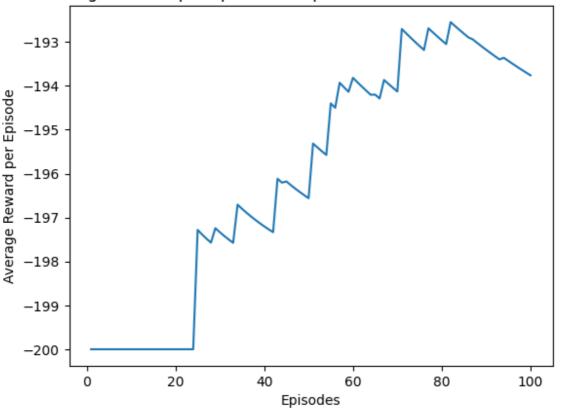
```
# Update the state and action for Sarsa(0)
        state = next_state
        action_sarsa = next_action_sarsa
        episode reward += reward
        if done:
            break
    # Store the total reward for the current episode
    rewards_sarsa.append(episode_reward)
    # Print the current state during training
    print("Episode:", episode + 1, "Steps:", step + 1, "State:", state, "Average Ro
# Test the learned policy
total_reward = 0
state = env.reset()
for step in range(steps_per_episode):
    action = epsilon_greedy(weights_sarsa, state, 0) # Set exploration rate to 0;
    state, reward, done, _ = env.step(action)
    total_reward += reward
    if done:
        break
print("Total reward:", total_reward)
# Plot the average reward per episode vs episodes
avg_rewards_sarsa = [np.mean(rewards_sarsa[max(0, i-99):i+1]) for i in range(len(re
plt.plot(range(1, episodes + 1), avg_rewards_sarsa)
plt.xlabel('Episodes')
plt.ylabel('Average Reward per Episode')
plt.title('Average Reward per Episode vs Episodes - Semi-Gradient Sarsa(0)')
plt.show()
# Close the environment
env.close()
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarn
ing: `should_run_async` will not call `transform_cell` automatically in the futur
e. Please pass the result to `transformed_cell` argument and any exception that ha
ppen during thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
 and should_run_async(code)
/usr/local/lib/python3.10/dist-packages/gym/core.py:317: DeprecationWarning: WARN:
Initializing wrapper in old step API which returns one bool instead of two. It is
recommended to set `new step api=True` to use new step API. This will be the defau
It behaviour in future.
 deprecation(
/usr/local/lib/python3.10/dist-packages/gym/wrappers/step_api_compatibility.py:39:
DeprecationWarning: WARN: Initializing environment in old step API which returns o
ne bool instead of two. It is recommended to set `new_step_api=True` to use new st
ep API. This will be the default behaviour in future.
```

deprecation(

```
Episode: 1 Steps: 200 State: [-8.4259486e-01 -2.6320363e-04] Average Reward: -200.
Episode: 2 Steps: 200 State: [-0.6806075
                                 0.01010762] Average Reward: -200.0
Episode: 3 Steps: 200 State: [-1.0174215
                                 0.00299919] Average Reward: -200.0
Episode: 4 Steps: 200 State: [-0.8358097
                                 0.00302388] Average Reward: -200.0
Episode: 6 Steps: 200 State: [-9.235712e-01 8.131184e-04] Average Reward: -200.0
Episode: 7 Steps: 200 State: [-0.72480965 0.00979286] Average Reward: -200.0
Episode: 10 Steps: 200 State: [-0.734279 -0.04016607] Average Reward: -200.0
Episode: 12 Steps: 200 State: [-0.60650396 -0.03249706] Average Reward: -200.0
Episode: 14 Steps: 200 State: [-0.6643349 -0.03597895] Average Reward: -200.0
Episode: 15 Steps: 200 State: [-0.7352178  0.0021055] Average Reward: -200.0
Episode: 16 Steps: 200 State: [-0.92205733 -0.02568693] Average Reward: -200.0
Episode: 17 Steps: 200 State: [-6.7989928e-01 -6.0048847e-06] Average Reward: -20
0.0
Episode: 18 Steps: 200 State: [-0.69207263  0.00095853] Average Reward: -200.0
Episode: 19 Steps: 200 State: [-0.8629312 -0.02998947] Average Reward: -200.0
Episode: 20 Steps: 200 State: [-0.7410086 0.0016352] Average Reward: -200.0
Episode: 21 Steps: 200 State: [-0.3933155 -0.02485566] Average Reward: -200.0
Episode: 22 Steps: 200 State: [-0.7146811 -0.04508664] Average Reward: -200.0
Episode: 23 Steps: 200 State: [-1.1465876 0.01498606] Average Reward: -200.0
Episode: 25 Steps: 132 State: [0.51488835 0.03676482] Average Reward: -132.0
Episode: 26 Steps: 200 State: [-1.1149721 -0.02395261] Average Reward: -200.0
Episode: 27 Steps: 200 State: [-0.51093775 -0.03158752] Average Reward: -200.0
Episode: 28 Steps: 200 State: [-0.8242753 -0.03257569] Average Reward: -200.0
Episode: 29 Steps: 188 State: [0.51015043 0.03766095] Average Reward: -188.0
Episode: 31 Steps: 200 State: [0.41605997 0.02835641] Average Reward: -200.0
Episode: 32 Steps: 200 State: [-1.1000296 0.0175474] Average Reward: -200.0
Episode: 33 Steps: 200 State: [-0.48996037 -0.02559725] Average Reward: -200.0
Episode: 34 Steps: 168 State: [0.50676763 0.02170159] Average Reward: -168.0
Episode: 35 Steps: 200 State: [-1.1907398 -0.01330119] Average Reward: -200.0
Episode: 38 Steps: 200 State: [-0.71396494  0.0063156 ] Average Reward: -200.0
Episode: 39 Steps: 200 State: [-0.81217724 0.00679169] Average Reward: -200.0
Episode: 40 Steps: 200 State: [0.31388873 0.02309423] Average Reward: -200.0
Episode: 42 Steps: 200 State: [-0.00240222 -0.00829094] Average Reward: -200.0
Episode: 43 Steps: 145 State: [0.5076362 0.02036635] Average Reward: -145.0
Episode: 44 Steps: 200 State: [-0.46902502 0.0206257 ] Average Reward: -200.0
Episode: 45 Steps: 195 State: [0.52178204 0.03640092] Average Reward: -195.0
Episode: 46 Steps: 200 State: [0.1879756 0.042589 ] Average Reward: -200.0
Episode: 47 Steps: 200 State: [-0.004007
                                 0.03010839] Average Reward: -200.0
Episode: 49 Steps: 200 State: [-0.8802302
                                 0.00091193] Average Reward: -200.0
Episode: 50 Steps: 200 State: [0.23687948 0.01489573] Average Reward: -200.0
Episode: 51 Steps: 133 State: [0.5044651 0.03174096] Average Reward: -133.0
Episode: 52 Steps: 200 State: [0.13448797 0.0427868 ] Average Reward: -200.0
Episode: 53 Steps: 200 State: [0.47189558 0.00875743] Average Reward: -200.0
Episode: 54 Steps: 200 State: [-0.54675424 0.02320059] Average Reward: -200.0
Episode: 55 Steps: 131 State: [0.5211556 0.03957938] Average Reward: -131.0
Episode: 56 Steps: 200 State: [-0.6469838 0.0180815] Average Reward: -200.0
Episode: 57 Steps: 162 State: [0.50427556 0.01491424] Average Reward: -162.0
Episode: 58 Steps: 200 State: [-0.33361968 0.02923066] Average Reward: -200.0
Episode: 60 Steps: 175 State: [0.5289303 0.04546462] Average Reward: -175.0
Episode: 62 Steps: 200 State: [-1.1969926 -0.04883662] Average Reward: -200.0
```

```
Episode: 63 Steps: 200 State: [-0.7507747 0.0038181] Average Reward: -200.0
Episode: 64 Steps: 200 State: [-0.88045454 -0.03203848] Average Reward: -200.0
Episode: 65 Steps: 194 State: [0.5230265 0.02667838] Average Reward: -194.0
Episode: 66 Steps: 200 State: [-0.3646996     0.05281581] Average Reward: -200.0
Episode: 67 Steps: 166 State: [0.5073271  0.01907358] Average Reward: -166.0
Episode: 69 Steps: 200 State: [-1.18752
                                     0.00500816] Average Reward: -200.0
Episode: 70 Steps: 200 State: [-0.47701612 -0.02751889] Average Reward: -200.0
Episode: 71 Steps: 93 State: [0.50371903 0.01831982] Average Reward: -93.0
Episode: 72 Steps: 200 State: [-0.23867162 0.04318878] Average Reward: -200.0
Episode: 73 Steps: 200 State: [-0.1609821 0.0418838] Average Reward: -200.0
Episode: 74 Steps: 200 State: [ 0.30889738 -0.00580547] Average Reward: -200.0
Episode: 75 Steps: 200 State: [-0.91103005 -0.02858634] Average Reward: -200.0
Episode: 76 Steps: 200 State: [0.26154855 0.03212797] Average Reward: -200.0
Episode: 77 Steps: 155 State: [0.51786655 0.01841644] Average Reward: -155.0
Episode: 78 Steps: 200 State: [-1.1987581 0.0012419] Average Reward: -200.0
Episode: 79 Steps: 200 State: [-1.0555344 -0.02109323] Average Reward: -200.0
Episode: 80 Steps: 200 State: [-0.43440753 -0.02904705] Average Reward: -200.0
Episode: 81 Steps: 200 State: [ 0.03229128 -0.00863347] Average Reward: -200.0
Episode: 82 Steps: 152 State: [0.5035765 0.01753113] Average Reward: -152.0
Episode: 83 Steps: 200 State: [-1.0811756 -0.00946005] Average Reward: -200.0
Episode: 84 Steps: 200 State: [-0.3751748 -0.01593433] Average Reward: -200.0
Episode: 85 Steps: 200 State: [-0.22679679 -0.02833044] Average Reward: -200.0
Episode: 87 Steps: 197 State: [0.51475066 0.02153336] Average Reward: -197.0
Episode: 88 Steps: 200 State: [-0.7023657 0.0136055] Average Reward: -200.0
Episode: 89 Steps: 200 State: [-0.07260948 -0.00314452] Average Reward: -200.0
Episode: 90 Steps: 200 State: [-0.48694718     0.03973457] Average Reward: -200.0
Episode: 91 Steps: 200 State: [-1.0918249 0.0147572] Average Reward: -200.0
Episode: 92 Steps: 200 State: [-0.654301 -0.04968017] Average Reward: -200.0
Episode: 93 Steps: 200 State: [-0.597553 -0.0441918] Average Reward: -200.0
Episode: 94 Steps: 190 State: [0.5273151  0.03047346] Average Reward: -190.0
Episode: 95 Steps: 200 State: [-0.40278888 0.03766304] Average Reward: -200.0
Episode: 97 Steps: 200 State: [-0.54112226 -0.03886005] Average Reward: -200.0
Episode: 98 Steps: 200 State: [0.4761966 0.03388999] Average Reward: -200.0
Episode: 100 Steps: 200 State: [-0.11698714 -0.01035212] Average Reward: -200.0
Total reward: -200.0
```

## Average Reward per Episode vs Episodes - Semi-Gradient Sarsa(0)



## Semi-Gradient TD(λ)

```
# Set up the action and observation space
action_space = env.action_space.n
observation_space = env.observation_space.shape[0]
# Define the weight vector for linear function approximation
weights_td = np.random.rand(observation_space + 1) # Add 1 for the action
# Define the hyperparameters
alpha = 0.1 # Learning rate
gamma = 0.99 # discount factor
epsilon = 0.1 # exploration rate
episodes = 100 # number of episodes
steps_per_episode = 200 # maximum number of steps per episode
lambda_ = 0.5 # eligibility trace parameter
# Define the epsilon-greedy policy function
def epsilon_greedy(weights, state, epsilon):
    if np.random.rand() < epsilon:</pre>
        return np.random.randint(action space)
    else:
        q_values = [np.dot(weights, get_features(state, a)) for a in range(action_
        return np.argmax(q_values)
# Define the feature extraction function
def get_features(state, action=None):
    if action is None:
        return np.append(state, 1) # Append 1 for the action
    else:
        return np.append(state, action)
# Initialize lists to store rewards and steps
rewards_td = []
```

```
# Initialize lists to store average rewards and steps
avg_rewards_td = []
episode_steps = []
# Implement the Semi-Gradient TD(\lambda) algorithm with linear function approximation
for episode in range(episodes):
    state = env.reset()
    action_td = epsilon_greedy(weights_td, state, epsilon)
    eligibility_trace_td = np.zeros_like(weights_td) # Initialize eligibility trace
    episode_reward = 0 # Track the total reward in each episode
    for step in range(steps per episode):
        # Take action and observe the next state and reward
        next_state, reward, done, _ = env.step(action_td)
        # Choose next action using epsilon-greedy policy for TD(\lambda)
        next_action_td = epsilon_greedy(weights_td, next_state, epsilon)
        # Compute the TD error for TD(\lambda)
        td_error_td = reward + gamma * np.dot(weights_td, get_features(next_state)
        # Update the eligibility trace for TD(\lambda)
        eligibility_trace_td = gamma * lambda_ * eligibility_trace_td + get_feature
        # Update the weight vector for TD(\lambda) using the gradient descent update rule
        weights_td += alpha * td_error_td * eligibility_trace_td
        # Update the state and action for TD(\lambda)
        state = next state
        action_td = next_action_td
        episode_reward += reward # Accumulate the reward
        if done:
            break
    # Store the total reward for the current episode
    rewards_td.append(episode_reward)
    # Calculate the average reward per episode
    if len(rewards td) >= 100:
        avg_reward = sum(rewards_td[-100:]) / 100
    else:
        avg_reward = sum(rewards_td) / len(rewards_td)
    avg rewards td.append(avg reward)
    # Store the number of steps in the episode
    episode steps.append(step + 1)
    # Print the current state during training
    print("Episode:", episode + 1, "Steps:", step + 1, "State:", state, "Average Right")
# Test the learned policy
total reward = 0
state = env.reset()
for step in range(steps per episode):
    action = epsilon_greedy(weights_td, state, 0) # Set exploration rate to 0 for
    state, reward, done, _ = env.step(action)
    total reward += reward
```

```
if done:
    break

print("Total reward:", total_reward)

# Plot the average reward per episode vs. episodes
plt.plot(range(1, episodes + 1), avg_rewards_td)
plt.xlabel('Episodes')
plt.ylabel('Average Reward per Episode')
plt.title('Average Reward per Episode vs. Episodes - Semi-Gradient TD(λ)')
plt.show()

# Close the environment
env.close()
```

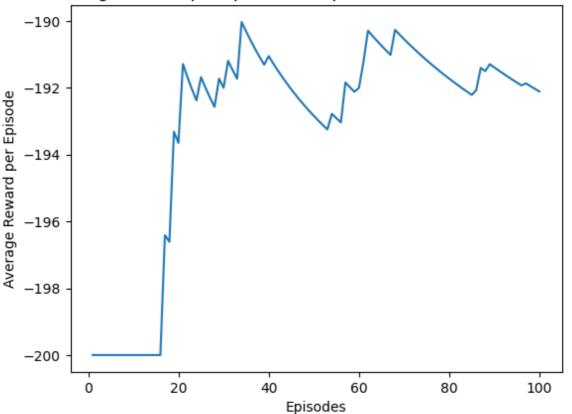
```
Episode: 1 Steps: 200 State: [-0.92463166 -0.00286642] Average Reward: -200.0
Episode: 2 Steps: 200 State: [-0.74627227 0.00914829] Average Reward: -200.0
Episode: 4 Steps: 200 State: [0.2611268  0.01088297] Average Reward: -200.0
Episode: 7 Steps: 200 State: [-0.82883275    0.00811999] Average Reward: -200.0
Episode: 9 Steps: 200 State: [-0.45200142 -0.05459183] Average Reward: -200.0
Episode: 10 Steps: 200 State: [-0.9599345 -0.05304709] Average Reward: -200.0
Episode: 11 Steps: 200 State: [-0.64362967 -0.03579873] Average Reward: -200.0
Episode: 12 Steps: 200 State: [-1.182204 -0.03403521] Average Reward: -200.0
Episode: 13 Steps: 200 State: [0.43392906 0.00911236] Average Reward: -200.0
Episode: 15 Steps: 200 State: [-4.1128936e-01 -2.5509340e-05] Average Reward: -20
0.0
Episode: 16 Steps: 200 State: [-0.4247219
                                       0.00428661] Average Reward: -200.0
Episode: 17 Steps: 139 State: [0.52490693 0.03002022] Average Reward: -196.4117647
0588235
Episode: 18 Steps: 200 State: [-0.48762628 0.02103901] Average Reward: -196.61111
111111111
Episode: 19 Steps: 134 State: [0.5068088 0.0310818] Average Reward: -193.315789473
68422
Episode: 20 Steps: 200 State: [-0.40814114 0.00262107] Average Reward: -193.65
Episode: 21 Steps: 144 State: [0.5055911 0.02501375] Average Reward: -191.2857142
Episode: 22 Steps: 200 State: [-0.4345183 -0.00149484] Average Reward: -191.68181
81818182
Episode: 23 Steps: 200 State: [-0.45787796  0.0464466 ] Average Reward: -192.04347
826086956
Episode: 24 Steps: 200 State: [-0.9982282 -0.00192826] Average Reward: -192.375
Episode: 25 Steps: 175 State: [0.53817767 0.04194646] Average Reward: -191.68
Episode: 26 Steps: 200 State: [-0.51387686 0.03065731] Average Reward: -192.0
Episode: 27 Steps: 200 State: [-0.73576796 -0.0350589 ] Average Reward: -192.29629
62962963
Episode: 28 Steps: 200 State: [-0.83635
                                      -0.03243763] Average Reward: -192.57142
857142858
Episode: 29 Steps: 168 State: [0.502831 0.04043475] Average Reward: -191.7241379
3103448
Episode: 30 Steps: 200 State: [-0.54176843 -0.02201995] Average Reward: -192.0
Episode: 31 Steps: 167 State: [0.5296794 0.03839257] Average Reward: -191.1935483
Episode: 32 Steps: 200 State: [-0.7962345
                                       0.03228319] Average Reward: -191.46875
Episode: 33 Steps: 200 State: [-0.7004834
                                       0.00938237] Average Reward: -191.72727
272727272
Episode: 34 Steps: 134 State: [0.5144252 0.02964413] Average Reward: -190.0294117
6470588
Episode: 35 Steps: 200 State: [-1.0942681 -0.06088854] Average Reward: -190.31428
571428572
Episode: 36 Steps: 200 State: [-0.73905456 0.00362168] Average Reward: -190.58333
Episode: 37 Steps: 200 State: [-1.2 0.] Average Reward: -190.83783783783784
Episode: 38 Steps: 200 State: [-0.01024785 -0.03653956] Average Reward: -191.07894
736842104
Episode: 39 Steps: 200 State: [-0.6647864 -0.04176928] Average Reward: -191.30769
230769232
Episode: 40 Steps: 181 State: [0.50571036 0.03368236] Average Reward: -191.05
Episode: 41 Steps: 200 State: [-0.37446812 0.00410289] Average Reward: -191.26829
268292684
Episode: 42 Steps: 200 State: [-0.616329
                                     0.0369092] Average Reward: -191.4761904
7619048
Episode: 43 Steps: 200 State: [-0.23150732 0.00171207] Average Reward: -191.67441
860465115
Episode: 44 Steps: 200 State: [-0.80081314  0.03307518] Average Reward: -191.86363
```

```
636363637
Episode: 45 Steps: 200 State: [-1.0291226
                                         0.02147224] Average Reward: -192.04444
44444445
Episode: 46 Steps: 200 State: [-0.46976477 -0.04257053] Average Reward: -192.21739
13043478
Episode: 47 Steps: 200 State: [-0.24228156 -0.01111466] Average Reward: -192.38297
872340425
Episode: 48 Steps: 200 State: [-0.9382387 -0.02536759] Average Reward: -192.54166
66666666
Episode: 49 Steps: 200 State: [-0.3388645 -0.00561276] Average Reward: -192.69387
755102042
Episode: 50 Steps: 200 State: [-0.85473037 -0.02868152] Average Reward: -192.84
Episode: 51 Steps: 200 State: [-0.5842732 -0.03126747] Average Reward: -192.98039
Episode: 52 Steps: 200 State: [0.4167754 0.0294074] Average Reward: -193.115384615
3846
Episode: 53 Steps: 200 State: [-0.46721974 -0.01517898] Average Reward: -193.24528
301886792
Episode: 54 Steps: 168 State: [0.5171817  0.03260274] Average Reward: -192.7777777
777777
Episode: 55 Steps: 200 State: [-1.1450701 -0.00434856] Average Reward: -192.90909
09090909
428571428
Episode: 57 Steps: 125 State: [0.5355561 0.04260675] Average Reward: -191.8421052
631579
Episode: 58 Steps: 200 State: [-0.5937683
                                          0.04714421] Average Reward: -191.98275
862068965
Episode: 59 Steps: 200 State: [-1.0440333
                                          0.02191837] Average Reward: -192.11864
406779662
Episode: 60 Steps: 185 State: [0.53325003 0.04860929] Average Reward: -192.0
Episode: 61 Steps: 145 State: [0.5021369 0.01725516] Average Reward: -191.2295081
967213
Episode: 62 Steps: 133 State: [0.51274043 0.02787882] Average Reward: -190.2903225
8064515
Episode: 63 Steps: 200 State: [-0.36717895     0.00085132] Average Reward: -190.44444
44444446
Episode: 64 Steps: 200 State: [-0.8998434 0.0286513] Average Reward: -190.59375
Episode: 65 Steps: 200 State: [-1.1388116
                                          0.01264561] Average Reward: -190.73846
153846154
Episode: 66 Steps: 200 State: [-0.66062456 0.0120718 ] Average Reward: -190.87878
787878788
Episode: 67 Steps: 200 State: [-0.22668093 0.03656664] Average Reward: -191.01492
537313433
Episode: 68 Steps: 140 State: [0.5008336 0.0265551] Average Reward: -190.264705882
35293
Episode: 69 Steps: 200 State: [-0.8544397
                                           0.00975345] Average Reward: -190.40579
710144928
Episode: 70 Steps: 200 State: [-0.94659704 -0.02338161] Average Reward: -190.54285
714285714
Episode: 71 Steps: 200 State: [-0.7262785
                                           0.00801378] Average Reward: -190.67605
633802816
Episode: 72 Steps: 200 State: [-0.20947197
                                          0.02346583] Average Reward: -190.80555
55555554
Episode: 73 Steps: 200 State: [-0.70176494 0.03506107] Average Reward: -190.93150
684931507
Episode: 74 Steps: 200 State: [-0.5608737
                                         -0.06749154] Average Reward: -191.05405
405405406
Episode: 75 Steps: 200 State: [-1.0653682 -0.03941942] Average Reward: -191.17333
33333335
Episode: 76 Steps: 200 State: [-0.7973031
                                          0.00229879] Average Reward: -191.28947
368421052
Episode: 77 Steps: 200 State: [-0.25568175 -0.05383581] Average Reward: -191.40259
```

74025974

```
Episode: 78 Steps: 200 State: [-7.1491307e-01 -7.0210337e-04] Average Reward: -19
1.51282051282053
Episode: 79 Steps: 200 State: [-0.93798643 -0.02775243] Average Reward: -191.62025
316455697
Episode: 80 Steps: 200 State: [-1.127172
                                          -0.04335022] Average Reward: -191.725
Episode: 81 Steps: 200 State: [-0.9738132 -0.03864793] Average Reward: -191.82716
049382717
Episode: 82 Steps: 200 State: [-0.86410034 -0.03052386] Average Reward: -191.92682
92682927
Episode: 83 Steps: 200 State: [-1.1925281
                                           0.00374203] Average Reward: -192.02409
638554218
Episode: 84 Steps: 200 State: [-0.7424698
                                           0.00447596] Average Reward: -192.11904
761904762
Episode: 85 Steps: 200 State: [-0.811014 -0.0345521] Average Reward: -192.2117647
0588236
Episode: 86 Steps: 180 State: [0.5126368 0.01680115] Average Reward: -192.0697674
4186048
Episode: 87 Steps: 134 State: [0.5206378  0.03228648] Average Reward: -191.4022988
505747
Episode: 88 Steps: 200 State: [-0.65177345 0.03238655] Average Reward: -191.5
Episode: 89 Steps: 173 State: [0.5159471 0.03352075] Average Reward: -191.2921348
314607
Episode: 90 Steps: 200 State: [-0.37552056 -0.00290903] Average Reward: -191.38888
88888889
Episode: 91 Steps: 200 State: [-0.9386321
                                           0.02823923] Average Reward: -191.48351
64835165
Episode: 92 Steps: 200 State: [-0.8567966
                                           0.01189915] Average Reward: -191.57608
695652175
Episode: 93 Steps: 200 State: [-1.018026
                                           0.02285265] Average Reward: -191.66666
66666666
Episode: 94 Steps: 200 State: [-0.7698058 -0.03107499] Average Reward: -191.75531
914893617
Episode: 95 Steps: 200 State: [-1.1812301 0.0062899] Average Reward: -191.8421052
631579
Episode: 96 Steps: 200 State: [-0.49724802 -0.02242005] Average Reward: -191.92708
33333334
Episode: 97 Steps: 186 State: [0.5136781 0.03999509] Average Reward: -191.8659793
814433
Episode: 98 Steps: 200 State: [-0.99768156  0.02334484] Average Reward: -191.94897
959183675
Episode: 99 Steps: 200 State: [-0.7664023
                                           0.00768417] Average Reward: -192.03030
303030303
Episode: 100 Steps: 200 State: [-1.1962702 0.0024879] Average Reward: -192.11
Total reward: -200.0
```

## Average Reward per Episode vs. Episodes - Semi-Gradient $TD(\lambda)$



```
In [4]: # Comparison
# Plot the average reward per episode vs. episodes for TD(λ)
plt.plot(range(1, episodes + 1), avg_rewards_td, color='red', label='TD(λ)')

# Plot the average reward per episode vs. episodes for SARSA(θ)
avg_rewards_sarsa = [np.mean(rewards_sarsa[max(θ, i-99):i+1]) for i in range(len(replt.plot(range(1, episodes + 1), avg_rewards_sarsa, color='blue', label='SARSA(θ)'

plt.xlabel('Episodes')
plt.ylabel('Average Reward per Episode')
plt.title('Average Reward per Episode vs. Episodes')
plt.legend()
plt.show()
```

