TAXI GAME (Reinforcement Learning)

Importing essential libraires

we will be using OpenAi gym for using Taxi environment

```
import gym
import numpy as np
from IPython.display import clear output
import matplotlib.pyplot as plt
from time import sleep
#environment initialisation
env = gym.make("Taxi-v3")
print("Environment states----->",env.observation space)
print("Environment actions----->",env.action space)
Environment states-----> Discrete(500)
Environment actions-----> Discrete(6)
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed cell` argument and any exception that happen 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 default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/wrappers/step api compatib
ility.py:39: DeprecationWarning: WARN: Initializing environment 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 default
behaviour in future.
  deprecation(
#particular instance analysis
state = 123
action = 1
print("Instant stats",env.P[state][action][0]) #
(probability of step, resulting state, reward, done)
Instant stats (1.0, 23, -1, False)
```

Comparision between random play and playing using Q learning algorithm

Creating a random agent for random play and analyse the statistics

```
class Random_Agent:
    def __init__(self,env):
        self.env = env
    def get_action(self,state):
        return self.env.action_space.sample()

agent = Random_Agent(env)
```

Collecting frames and displaying them as a gameplay

```
def collect info (env,state):
 env.reset()
 env.s = state
  frames = []
  penalties, epochs = 0,0
  done = False
 while not done :
    action = agent.get action(state)
    new state,reward,done,info = env.step(action)
    if reward == -10:
      penalties+=1
    frames.append({
        "frames" : env.render(mode="ansi"),
        "state" : new state,
        "action" : action,
        "reward" : reward,
        "done" : done,
        "penalties" : penalties
    })
    state = new state
    epochs += 1
  return frames, epochs
def display frames list(frames):
  for i,frame in enumerate(frames):
    clear_output(wait=True)
    print(frame["frames"])
    print(f"State : {frame['state']}")
    print(f"Action : {frame['action']}")
    print(f"Reward : {frame['reward']}")
    print(f"Done : {frame['done']}")
```

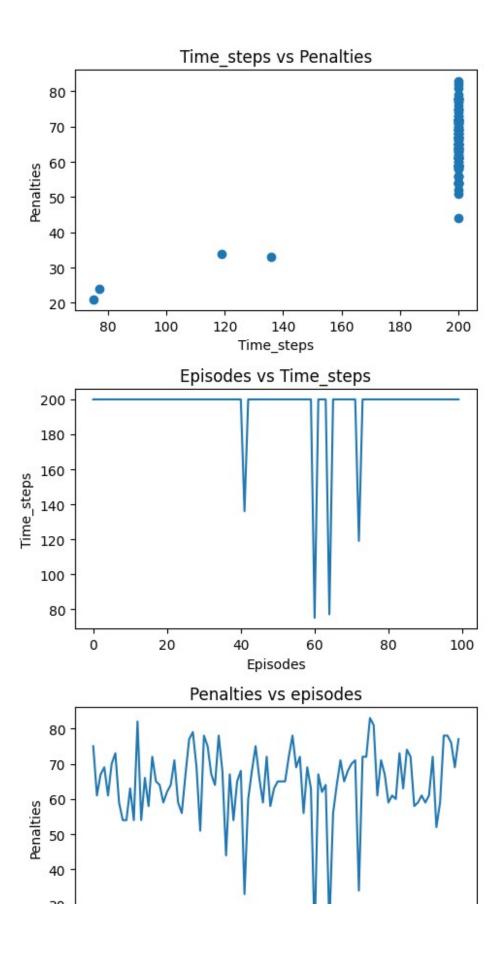
last frame of the gameplay

```
# Looking at stats
episodes = 100
time steps required = []
penalties = []
for in range (episodes):
  frames, epochs = collect info(env, 120)
  time steps required.append(epochs)
  penalties.append(frames[-1]["penalties"])
print(len(time steps required))
print(len(penalties))
fig.ax = plt.subplots(3,1,figsize=(5,10))
ax[0].plot(time_steps_required,penalties,"o")
ax[0].set_title("Time_steps vs Penalties")
ax[0].set xlabel("Time steps")
ax[0].set_ylabel("Penalties")
ax[1].plot(time steps required)
ax[1].set title("Episodes vs Time steps")
ax[1].set xlabel("Episodes")
ax[1].set ylabel("Time steps")
ax[2].plot(penalties)
ax[2].set title("Penalties vs episodes")
ax[2].set xlabel("Episodes")
ax[2].set ylabel("Penalties")
```

```
plt.tight_layout()
plt.show()

print("Average_time_required_to_complete", sum(time_steps_required)/
episodes)
print("Average_penalties", sum(penalties)/episodes )

100
100
```



```
Average_time_required_to_complete 196.07
Average_penalties 64.56
```

It is quite a charm of luck , So let us dive into some mindful steps rather than chances

Creating an agent that follows Q learning algorithm to optimise gameplay

```
class QAgent :
  def init (self,env,alpha,gamma):
    self.env = env
    self.alpha = alpha
    self.gamma = gamma
    self.q table =
np.zeros([env.observation space.n,env.action space.n])
  def get action(self, state):
    return np.argmax(self.q table[state])
  def update parameters(self, state, action, reward, new state):
    old_value =self.q_table[state,action]
    next max = np.max(self.q table[new state])
    new value = old value + self.alpha *(reward + self.gamma *
next max - old value)
    self.q table[state,action] = new value
agent 1 = QAgent(env, 0.5, 0.6)
def collect info 1 (env, state, epsilon):
 env.reset()
 env.s = state
  frames = []
  penalties, epochs = 0,0
  done = False
 while not done :
    if epsilon > np.random.uniform(0,1):
      action = env.action space.sample()
    else:
      action = agent 1.get action(state)
    new state,reward,done,info = env.step(action)
    agent 1.update parameters(state,action,reward,new state)
    if reward == -10:
      penalties+=1
    frames.append({
        "frames" : env.render(mode="ansi"),
        "state" : new state,
        "action" : action,
        "reward" : reward,
```

```
"done" : done,
        "penalties" : penalties
   })
    state = new state
   epochs += 1
  return frames, epochs
def display frames list(frames):
  for i,frame in enumerate(frames):
   clear output(wait=True)
   print(frame["frames"])
   print(f"State : {frame['state']}")
   print(f"Action : {frame['action']}")
   print(f"Reward : {frame['reward']}")
   print(f"Done : {frame['done']}")
   print(f"Penalties : {frame['penalties']}")
   sleep(.1)
display frames list(collect info 1(env, 123, 0.2)[0])
+----+
|R: | : :G|
| : | : : |
| : : : : |
 |Y| : |B: |
(South)
State: 383
Action: 0
Reward: -1
Done : True
Penalties: 39
```

last frame of the gameplay

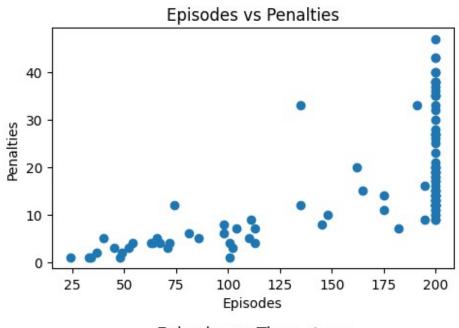
```
# Looking at stats
episodes = 100

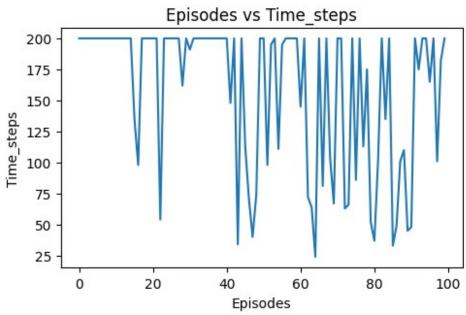
time_steps_required = []
penalties = []
for _ in range (episodes):
    frames,epochs = collect_info_1(env,120,0.2)
    time_steps_required.append(epochs)
    penalties.append(frames[-1]["penalties"])

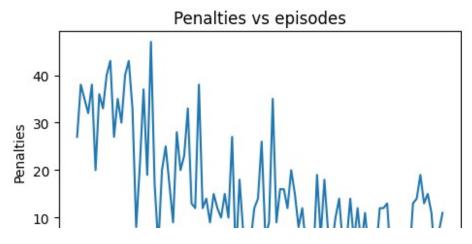
print(len(time_steps_required))
print(len(penalties))

fig,ax = plt.subplots(3,1,figsize=(5,10))
```

```
ax[0].plot(time steps required, penalties, "o")
ax[0].set title("Episodes vs Penalties")
ax[0].set_xlabel("Episodes")
ax[0].set ylabel("Penalties")
ax[1].plot(time steps required)
ax[1].set_title("Episodes vs Time_steps")
ax[1].set xlabel("Episodes")
ax[1].set ylabel("Time steps")
ax[2].plot(penalties)
ax[2].set_title("Penalties vs episodes")
ax[2].set_xlabel("Episodes")
ax[2].set_ylabel("Penalties")
plt.tight_layout()
plt.show()
print("Average time required to complete", sum(time steps required)/
episodes)
print("Average_penalties", sum(penalties)/episodes )
100
100
```



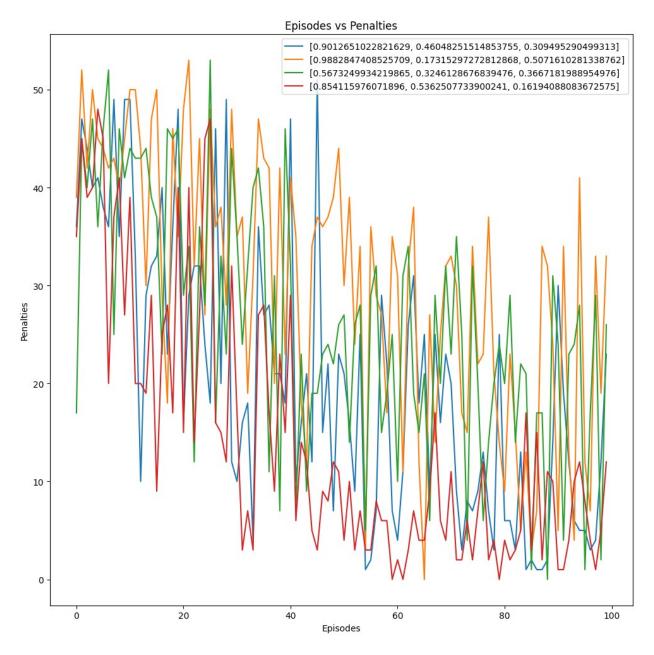




```
Average_time_required_to_complete 159.14
Average_penalties 16.16
```

Generating random series of hyperparameters and analysing the gameplay through penalty stats

```
series = 4
hyperparameters = []
final_penalties = []
for i in range (series):
  alpha = np.random.uniform(0,1)
 gamma = np.random.uniform(0,1)
  epsilon = np.random.uniform(0,1)
  hyperparameters.append([alpha,gamma,epsilon])
  agent 1 = QAgent(env,alpha,gamma)
 episodes = 100
  time steps required = []
  penalties = []
  for _ in range (episodes):
    frames, epochs = collect info 1(env, 120, epsilon)
    time steps required.append(epochs)
    penalties.append(frames[-1]["penalties"])
  final penalties.append(penalties)
plt.figure(figsize=(10,10))
for i in range(series):
  plt.plot(final penalties[i])
  plt.title("Episodes vs Penalties")
  plt.xlabel("Episodes")
  plt.vlabel("Penalties")
  plt.legend(hyperparameters)
plt.tight layout()
plt.show()
```



Hence , we are completed through the full walkthrough analysing how an agent learns to play basic games using Q learning