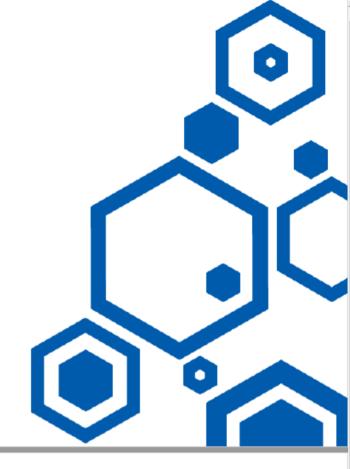


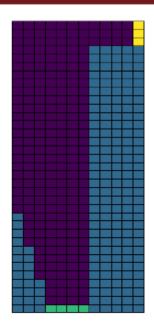
## 第7章作业解析





## Homework





Grid Map

- ②  $X_I = \{\text{green grids}\}\$  $X_F = \{\text{yellow grids}\}\$
- **3**  $U = \{(\ddot{x}, \ddot{y}) | \ddot{x} \in \{0, 1\}, \ddot{y} \in \{0, 1\}\}$
- $\Theta = \{\theta_1, \theta_2\}$ 
  - $\theta_1$ :  $f(\mathbf{x}_{k+1}, \mathbf{x}_k, \mathbf{u}_k) = \mathbf{x}_k \quad p_1 = 0.1$
  - $\theta_2$ :  $f(\mathbf{x}_{k+1}, \mathbf{x}_k, \mathbf{u}_k) = \mathbf{x}_{k+1}$   $p_1 = 0.9$
- **6**  $l(\mathbf{x}_k, \mathbf{x}_k, \theta_k) = -1$
- **6** Find an optimal plan from  $X_I$  to  $X_F$



## DP & RTDP



```
Initialize G values of all states to finite values;

while not converge do

for all the states x do

G(x_F) = 0;
G_k(x_k) = \min_{u_k \in U(x_k)} \{E_{\theta_k} [l(x_k, u_k, \theta_k) + G_{k+1}(x_{k+1})]\},
if x_k \neq x_F;

end
```

Initialize G values of all states to admissible values;

- Follow greedy policy picking outcomes at random until goal is reached;
- Backup all states visited on the way;
- 4 Reset to  $x_s$  and repeat 2-4 until all states on the current greedy policy have Bellman errors  $< \Delta$ , where  $\Delta(x_k) = ||G(x_k) G(x_{k+1})||$ ;

DP

RTDP



## Initialize G values



```
def Init_G_value(node):
    min_dis = 100000000.0
    for pnt in FINISH_LINE:
        (target_px, target_py) = (pnt[0], pnt[1])
        dis = ((target_px - node.px)**2 + (target_py - node.py)**2)**0.5
        if dis < min_dis:
            min_dis = dis
        return min_dis
```

```
for key in graph.keys():

state = graph[key]

if state.is_goal:

state.g_value = 0

else:

if state.px == 32 or state.px == 33 or state.px == 34:

state.g_value = 11 - state.py

else:

state.g_value = (32 - state.px) + (11 - state.py)
```

# greedy\_policy



```
rand_start = np.random.randint(low=0, high=3, size=1)[0]
greedy_plan = greedy_policy(idx=rand_start)
```

```
def greedy policy(idx=0, explore=True):
    start_node = Node(START_LINE[idx][0], START_LINE[idx][1], 0, 0)
    start_key = start_node.key
    state = graph[start_key]
    trajectory = [state.key]
    while not state.is goal:
        value uk = []
        for child idx in range(len(ACTION SPACE)):
            child_key_9 = state.next_prob_9[child_idx]
            child 9 = graph[child key 9]
            value uk.append(child 9.g value)
        action idx = np.argmin(value uk)
        if explore:
            action idx = explore action(action idx)
        child_key = state.next_prob_9[action_idx]
        trajectory.append(child key)
        state = graph[child_key]
        # if [state.px, state.py] in START LINE:
              trajectory = [state.key]
        print('finding feasible path: {}, {}'.format(state.px, state.py))
    # print('found trajectory: {}'.format(trajectory))
    return trajectory
```

```
def explore_action(u_idx, epsilon=0.2):
    if np.random.uniform(0, 1) < epsilon:
        return np.random.randint(0, len(ACTION_SPACE))
    else:
        return u_idx</pre>
```

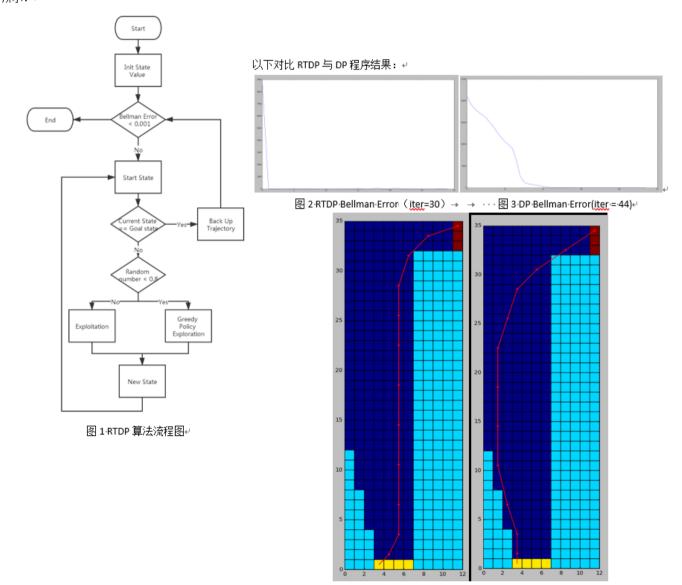
### 运动规划第七章作业。

#### •1、用 Python 实现 Real time dynamic programming

下面简要介绍程序所实现的算法: ↩

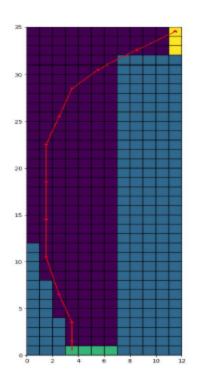
- (1)→初始化 State 的 g value,在这里我们用 State 到所有终点的最短距离作为初始值。↔
- (2)→然后选择某个 Start State 作为搜寻路径的开始点。↩
- (3)→随机进行 Exploitation 和 Greedy-Policy-Exploration 操作得到新的状态(这里我们设置 进行 Exploitation 的概率是 0.2,Exploration 的概率是 0.8)。↩
- (4)→当搜寻到完整的一条路径的时候,我们进行 BackUp 相关操作,在更新路径上 State 的 g value 的同时,计算整条路径的 Bellman-Error,直到 Bellman-Error 收敛,从而得到 RTDP 结果。↩

算法流程图如下所示: ↩



## Motion Planning for Mobile Robots 第七次作业

本次作业完成了 RTDP(real time dynamic programming), 下面比较了 RTDP 和 MDP 两种方法产生的结果差异。



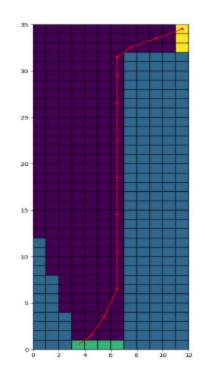


FIG 1: MDP

FIG 2: RTDP

	ITR_NUM	TIME	POINT_NUM
MDP	52	143	1020580
RTDP	172	37	2320

FIG 3: MDP 和 RTDP 比较

从实验结果看,虽然 RTDP 的迭代总数大于 MDP,但是在总时间上 RTDP 是小于 MDP 的,从节点数量上看,MDP 是远大于 RTDP,所以从而增大了 MDP 的时间。原因是 MDP 需要计算所有 state 的值,而 RTDP 只是计算与其 state 相关的值。