项目1--吃豆人代理

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摘要

本项目实现了四个部分,分别是minimax算法,α-β剪枝算法,expectmax期望最大值算法以及evaluation函数,实现了吃豆人对于寻找最佳得分路径并赢得最终胜利的游戏代码.

游戏规则

在有限大小的地图内,你所扮演的pacman需要躲过幽灵代理的追击,避开墙体等障碍物,将所有豆子吃掉以获得胜利.

游戏道具

- **能量豆**:吃掉后获得大量分数;在有限的时间内使幽灵惧怕吃豆人,吃豆人此时接近并吃掉幽灵可以得分,幽灵回到出生点.不同的幽灵有独立的"恐惧时间",恐惧时间可叠加.
- **普通豆**:吃掉获得分数,不被幽灵抓到的情况下吃完场上的豆子将赢得胜利.

任务一:实现minimax函数

1. **实现思路**:实现内置的helper函数,对每一层的游戏状态进行分析,如果是轮到吃豆人代理行动,则选取对吃豆人分数提升最大的行动;如果轮到幽灵代理行动,则选取降低吃豆人分数最大的行动;实现难点在于helper函数的参数设置、结束递归的条件以及从外部进入helper函数时的前置代码.
2. **代码总览**
   以下是 `MinimaxAgent` 类的代码实现:

```python
class MinimaxAgent(MultiAgentSearchAgent):
    def getAction(self, gameState: GameState):
        def helper(depth, game_state, agent_index):
            agent_index = agent_index % game_state.getNumAgents()
            if game_state.isWin() or game_state.isLose() or depth == self.depth * gameState.getNumAgents() - 1:
                return self.evaluationFunction(game_state)
            elif agent_index == 0:
                max_value = -float('inf')
                for i in game_state.getLegalActions(agent_index):
                    value = helper(depth + 1, game_state.generateSuccessor(agent_index, i), agent_index + 1)
                    max_value = max(max_value, value)
                return max_value
            else:
                min_value = float('inf')
                for i in game_state.getLegalActions(agent_index):
                    value = helper(depth + 1, game_state.generateSuccessor(agent_index, i), agent_index + 1)
                    min_value = min(value, min_value)
                return min_value

        max_score = -float('inf')
        best_action = None
        actions = gameState.getLegalActions(0)

        for action in actions:
            score = helper(0, gameState.generateSuccessor(0, action), 1)
            if score > max_score:
                max_score = score
                best_action = action

        return best_action
        util.raiseNotDefined()
```

3. **代码解释:**

- `helper(depth, game_state, agent_index)` : `depth` 是一个整数,表示当前递归的深度, `game_state` 表示游戏状态,以分析游戏当前的情况,返回值是一个 `GameState` 类对象,应该要能够在递归之后追踪代理采取行动后的最新游戏状态; `agent_index` 是一个整数,表示代理的编号,0是吃豆人代理,非0是幽灵代理.
- `agent_index = agent_index % game_state.getNumAgents()` :用取模来模拟代理的循环, `game_state.getNumAgents` 表示全部代理的数量,不使用 `gameState` 而使用 `game_state` 前者表示游戏开始时候的初始游戏状态,它不会随着递归深度的增加而改变,只有**后者是能够随着递归深度增加而改变的最新游戏状态.**
- **递归结束条件:**
  递归要检索当前游戏的输赢状况以及当前递归的深度(从0开始,因此递归的深度最后要在层数和代理数量乘积的基础上-1)返回值是一个评估函数.

```
if game_state.isWin() or game_state.isLose() or depth == self.depth * gameState.getNumAgents() - 1:
    return self.evaluationFunction(game_state)
```

- **非结束条件代码段:**
  `max_value = -float('inf')` 和 `min_value = float('inf')` :表示两边代理最终想要升高or降低分数的分数初始值.接着进入循环,对于当前游戏状态的代理的合法行动进行遍历,将这些行动的值赋值给中间变量value,并利用max或min函数挑选出得分最大/最小值,最终返回最大/最小值.
  `value = helper(depth + 1, game_state.generateSuccessor(agent_index, i), agent_index + 1)` :递归,对于下一个游戏状态(在进行当前代理的行动之后),深度应该+1,游戏状态传参应该传入行动和代理编号,并且代理编号变化.

```
elif agent_index == 0:
        max_value = -float('inf')
        for i in game_state.getLegalActions(agent_index):
            value = helper(depth + 1, game_state.generateSuccessor(agent_index, i), agent_index + 1)
            max_value = max(max_value, value)
        return max_value
    else:
        min_value = float('inf')
        for i in game_state.getLegalActions(agent_index):
            value = helper(depth + 1, game_state.generateSuccessor(agent_index, i), agent_index + 1)
            min_value = min(value, min_value)
        return min_value
```

- **进入helper/前置结束代码段:**
  `max_score` 表示行动的最大得分(可变化),初始值设置为一个非常小的值
  `best_action` 表示最佳行动,是对应于最大得分的行动(可变化)
  `actions` 给 `getLegalActions` 赋值为永远第一个行动的pacman的编号,返回值是一串对应的合法行动列表
  `for action in actions:` 这个for循环的作用和helper函数里面的作用是一样的,只不过添加了一个best_action判断,目的是返回最终的最佳行动.

```
max_score = -float('inf')
best_action = None
actions = gameState.getLegalActions(0)

for action in actions:
    score = helper(0, gameState.generateSuccessor(0, action), 1)
    if score > max_score:
        max_score = score
        best_action = action

return best_action
util.raiseNotDefined()
```

4. **实验结果:**
   运行 `python autograder.py -q q2` 后的结果图:

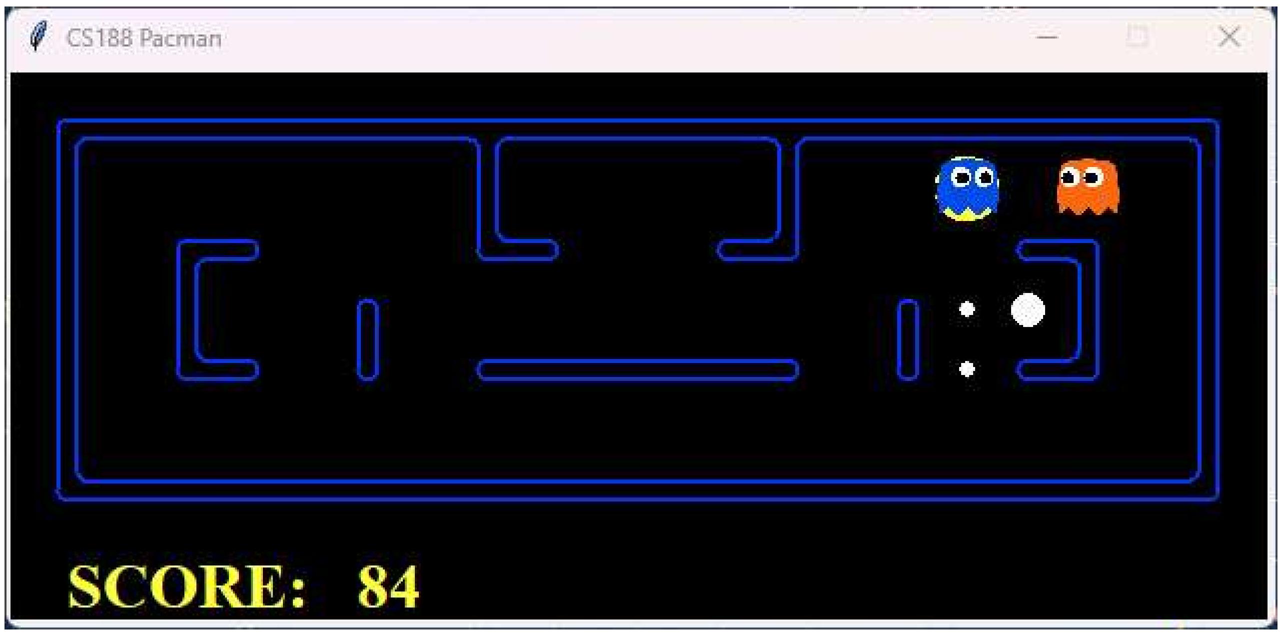
```
Pacman died! Score: 84
Average Score: 84.0
Scores:        84.0
Win Rate:      0/1 (0.00)
Record:        Loss
*** Finished running MinimaxAgent on smallClassic after 13 seconds.
*** Won 0 out of 1 games. Average score: 84.000000 ***
*** PASS: test_cases\q2\8-pacman-game.test

### Question q2: 5/5 ###


Finished at 21:47:52

Provisional grades
==================
Question q2: 5/5
------------------
Total: 5/5
```

游戏的结束截图:



分析:pacman虽然没有获胜,但是通过了所有的测试用例,实验成功.

任务二:实现α-β剪枝算法

1. **实现思路**:本质上,任务二是在任务一的基础上进行剪枝.剪枝原理如下:初始的α值为-∞,表示当前场上的最大可能得分;初始的β值为+∞,表示当前场上的最小可能得分;在吃豆人代理进行结果遍历时,不断获取场上的当前最高分数作为alpha值传入下一小层递归;在幽灵代理进行结果遍历时,不断获取场上最小得分更新β值,一旦发现当前的结果`min_value`小于`alpha`,就进行剪枝,返回`mmin_value`.这是因为**幽灵代理默认吃豆人会进行最佳选择(吃豆人知道选择这个行为会使得比起选择别的行为获得更低的分数),也就没有必要对吃豆人选择的这个行为进行其他分支的检索了**,反之亦然.
2. **代码总览**
   以下是 `AlphaBetaAgent` 类的代码实现:

```python
class AlphaBetaAgent(MultiAgentSearchAgent):


 def getAction(self, gameState: GameState):

     def helper(depth,game_state,agent_index,beta,alpha):
         agent_index=agent_index%game_state.getNumAgents()

         if game_state.isWin() or game_state.isLose() or depth==self.depth*gameState.getNumAgents()-1:
             return self.evaluationFunction(game_state)

         elif agent_index==0:
             max_value=-float('inf')
             for i in game_state.getLegalActions(agent_index):
                 value=helper(depth+1,game_state.generateSuccessor(agent_index,i),agent_index+1,beta,alpha)
                 max_value=max(max_value,value)
                 if max_value>beta:return max_value
                 alpha=max(alpha,max_value)
             return max_value
         else:
             min_value=float('inf')
             for i in game_state.getLegalActions(agent_index):
                 value=helper(depth+1,game_state.generateSuccessor(agent_index,i),agent_index+1,beta,alpha)
                 min_value=min(value,min_value)
                 if min_value<alpha:return min_value
                 beta= min(min_value,beta)
             return min_value

     max_score = -float('inf')
     best_action = None
     actions = gameState.getLegalActions(0)
     beta=float('inf')
     alpha=-float('inf')
     for action in actions:
         score = helper(0, gameState.generateSuccessor(0, action), 1,beta,alpha)
         if score > max_score:
             max_score = score
             best_action = action
         alpha=max(max_score,alpha)

     return best_action
     util.raiseNotDefined()
```

3. **代码解释:**
   - `helper(depth, game_state, agent_index,beta,alpha)` : `alpha` :初始值为-∞.表示幽灵代理能够接受的最小值,如果遍历的分数低于这个值,表明吃豆人代理不会选择这条分路对应的行动. `beta` :初始值为+∞.表示吃豆人代理能够接受的最大值如果再次获得的max_value比这个值大,说明幽灵代理不可能接受吃豆人选择这条能够获得 `beta` 分数的分路.
   - **非结束条件代码段:**
     在任务1的基础上添加了剪枝判断:

```
elif agent_index==0:
        max_value=-float('inf')
        for i in game_state.getLegalActions(agent_index):
            value=helper(depth+1,game_state.generateSuccessor(agent_index,i),agent_index+1,beta,alpha)
            max_value=max(max_value,value)
            if max_value>beta:return max_value
            alpha=max(alpha,max_value)
        return max_value
    else:
        min_value=float('inf')
        for i in game_state.getLegalActions(agent_index):
            value=helper(depth+1,game_state.generateSuccessor(agent_index,i),agent_index+1,beta,alpha)
            min_value=min(value,min_value)
            if min_value<alpha:return min_value
            beta= min(min_value,beta)
        return min_value
```

- **进入helper/前置结束代码段:**
  初始化了 `alpha` 和 `beta` ,第一次for循环不需要剪枝,目的是求出所有存在分路(相对于第一次遍历)的分数,避免偶然误差.

```
max_score = -float('inf')
best_action = None
actions = gameState.getLegalActions(0)
beta=float('inf')
alpha=-float('inf')
for action in actions:
    score = helper(0, gameState.generateSuccessor(0, action), 1,beta,alpha)
    if score > max_score:
        max_score = score
        best_action = action
    alpha=max(max_score,alpha)

return best_action
util.raiseNotDefined()
```

4. **实验结果:**
   运行 `python autograder.py -q q3` 后的结果图:

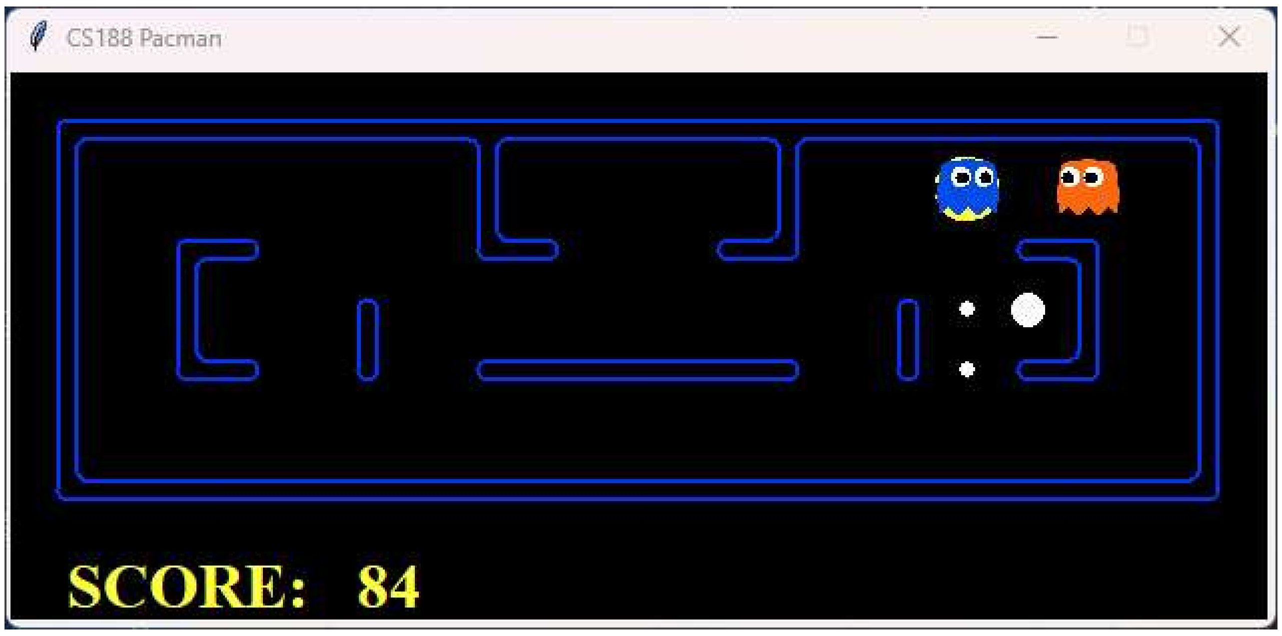
```
Pacman died! Score: 84
Average Score: 84.0
Scores:        84.0
Win Rate:      0/1 (0.00)
Record:        Loss
*** Finished running AlphaBetaAgent on smallClassic after 13 seconds.
*** Won 0 out of 1 games. Average score: 84.000000 ***
*** PASS: test_cases\q3\8-pacman-game.test

### Question q3: 5/5 ###


Finished at 23:18:14

Provisional grades
==================
Question q3: 5/5
------------------
Total: 5/5
```

   游戏的结束截图:

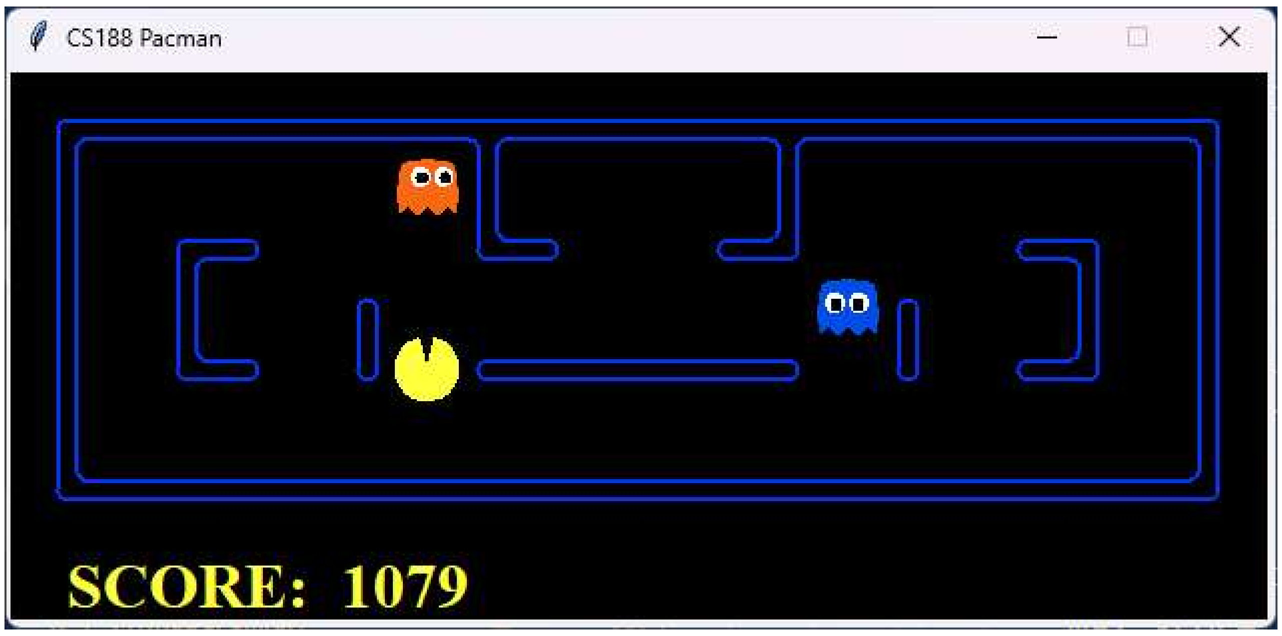


分析:pacman虽然没有获胜,但是通过了所有的测试用例,实验成功.

此外,还进行了剪枝效率测试,相比不添加剪枝的minimax算法效率确实有所提升.以下是效率检测结果图:

```
PS D:\vscode\codes\Python\CS188-Pac-Man\multiagent\multiagent> python pacman.py -p AlphaBetaAgent -a depth=3 -l smallClassic
Pacman emerges victorious! Score: 1079
Average Score: 1079.0
Scores:        1079.0
Win Rate:      1/1 (1.00)
Record:        Win
```

检测结束的截图



任务三:实现期望最大值算法

1. **实现思路**:对于所有潜在的幽灵代理,其行为为不一定是最优选择,那么对于幽灵代理的返回分数,只需要在遍历所有结果之后返回其平均分,也就是"期望值"分数,就能让吃豆人代理获得最合理的应对所有幽灵代理的分数;在初始进入helper函数时再对所有结果取最大值,就能获得"期望最大值"分数了.
2. **代码总览**
   以下是 `ExpectimaxAgent` 类的代码实现:

```python
class ExpectimaxAgent(MultiAgentSearchAgent):

 def getAction(self, gameState: GameState):
     def helper(depth,game_state,agent_index):
         agent_index=agent_index%game_state.getNumAgents()

         if game_state.isWin() or game_state.isLose() or depth==self.depth*gameState.getNumAgents()-1:
             return self.evaluationFunction(game_state)

         elif agent_index==0:
             max_value=-float('inf')
             for i in game_state.getLegalActions(agent_index):
                 value=helper(depth+1,game_state.generateSuccessor(agent_index,i),agent_index+1)
                 max_value=max(max_value,value)
             return max_value
         else:
             sum_score=0
             num=0
             for i in game_state.getLegalActions(agent_index):
                 sum_score+=helper(depth+1,game_state.generateSuccessor(agent_index,i),agent_index+1)
                 num+=1
             return sum_score/num

     max_score = -float('inf')
     best_action = None
     actions = gameState.getLegalActions(0)

     for action in actions:
         score = helper(0, gameState.generateSuccessor(0, action), 1)
         if score > max_score:
             max_score = score
             best_action = action

     return best_action
     util.raiseNotDefined()
```

3. **代码解释:**
   - **非结束条件代码段:**
     在任务1的基础上修改了幽灵代理的逻辑:
     `sum_score`:各种行动返回的总得分
     `num`:行动的数量
     返回值是平均得分.

     ```python
     else:
             sum_score=0
             num=0
             for i in game_state.getLegalActions(agent_index):
                 sum_score+=helper(depth+1,game_state.generateSuccessor(agent_index,i),agent_index+1)
                 num+=1
             return sum_score/num
     ```

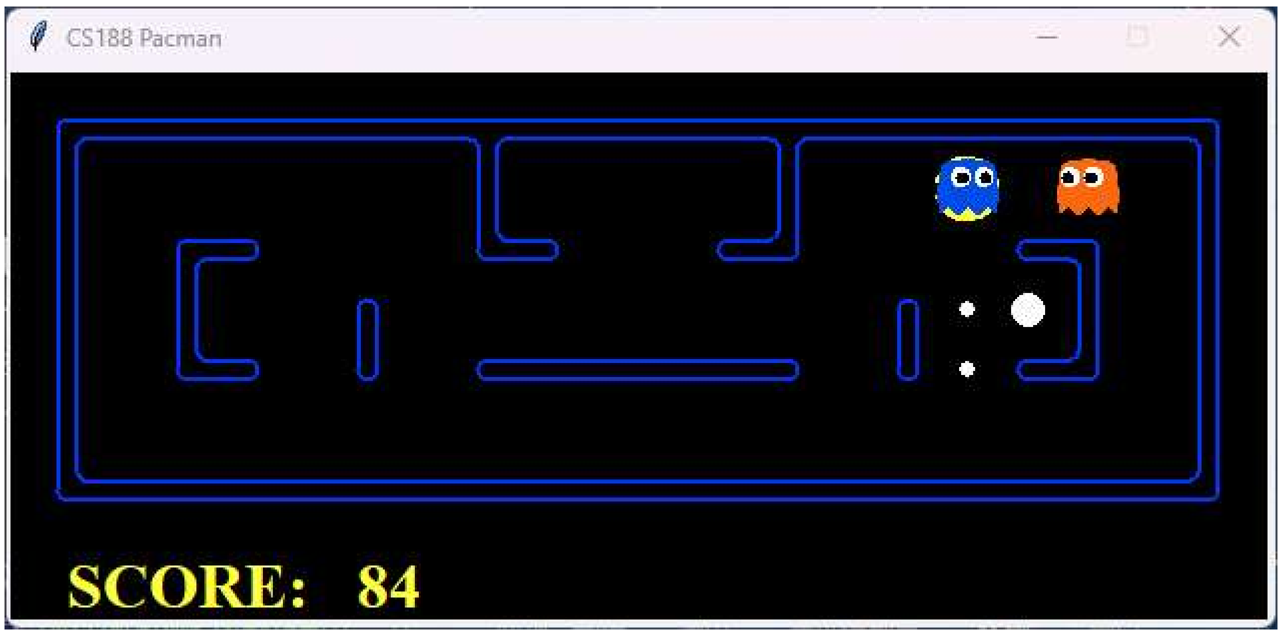
4. **实验结果:**
   运行 `python autograder.py -q q4` 后的结果图:

```
Pacman died! Score: 84
Average Score: 84.0
Scores:        84.0
Win Rate:      0/1 (0.00)
Record:        Loss
*** Finished running ExpectimaxAgent on smallClassic after 12 seconds.
*** Won 0 out of 1 games. Average score: 84.000000 ***
*** PASS: test_cases\q4\7-pacman-game.test

### Question q4: 5/5 ###


Finished at 23:51:07

Provisional grades
==================
Question q4: 5/5
------------------
Total: 5/5
```
游戏的结束截图:



分析:pacman虽然没有获胜,但是通过了所有的测试用例,实验成功.

此外,还观察了最大期望搜索和α-β剪枝在随机幽灵代理的情况下的胜率分析:

```
PS D:\vscode\codes\Python\CS188-Pac-Man\multiagent\multiagent> python pacman.py -p AlphaBetaAgent -l trappedClassic -a depth=3 -q -n 10
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Pacman died! Score: -501
Average Score: -501.0
Scores:        -501.0, -501.0, -501.0, -501.0, -501.0, -501.0, -501.0, -501.0, -501.0, -501.0
Win Rate:      0/10 (0.00)
Record:        Loss, Loss, Loss, Loss, Loss, Loss, Loss, Loss, Loss, Loss
```
α-β算法的胜率为0;

```
PS D:\vscode\codes\Python\CS188-Pac-Man\multiagent\multiagent> python pacman.py -p ExpectimaxAgent -l trappedClassic -a depth=3 -q -n 10
Pacman died! Score: -502
Pacman died! Score: -502
Pacman emerges victorious! Score: 532
Pacman emerges victorious! Score: 532
Pacman died! Score: -502
Pacman emerges victorious! Score: 532
Pacman emerges victorious! Score: 532
Pacman emerges victorious! Score: 532
Pacman emerges victorious! Score: 532
Pacman emerges victorious! Score: 532
Average Score: 221.8
Scores:        -502.0, -502.0, 532.0, 532.0, -502.0, 532.0, 532.0, 532.0, 532.0, 532.0
Win Rate:      7/10 (0.70)
Record:        Loss, Loss, Win, Win, Loss, Win, Win, Win, Win, Win
```
期望最大值的胜率突破了百分之50.

任务四:实现评估函数

1. **实验思路:** 评估函数应该尽可能考虑更多的影响最终评分的因素,如场上存在食物的多少,和幽灵的距离,和食物的距离,能量球的多少和与能量球的距离,还有墙壁因素(没有被添加到最终的代码.),还有幽灵代理的剩余恐惧时间.

2. **代码总览**

以下是 `ExpectimaxAgent` 类的代码实现:

```
def betterEvaluationFunction(currentGameState: GameState):
 Position = currentGameState.getPacmanPosition()
 GhostStates = currentGameState.getGhostStates()
 ScaredTimes = [ghostState.scaredTimer for ghostState in GhostStates]

 score = currentGameState.getScore()
 #walls = currentGameState.getWalls()
 Food = currentGameState.getFood()
 foodList = Food.asList()
 capsules = currentGameState.getCapsules()

 for food in foodList:
     distance = util.manhattanDistance(Position, food)
     score += 6 * math.exp(-distance / 2) + 0.7

 for capsule in capsules:
     distance = util.manhattanDistance(Position, capsule)
     score += 6 * math.exp(-distance / 2) + 0.7
 for i, ghostState in enumerate(GhostStates):
     ghostPos = ghostState.getPosition()
     distance = util.manhattanDistance(Position, ghostPos)
     if ScaredTimes[i] > 5:
         score += 150 + math.exp(3 / distance)
     elif 0 < ScaredTimes[i] <= 5:
         score += 5 + math.exp(3 / distance)
     else:
         if distance <= 2.7:
             score -= 500
         else:
             score -= 7 * math.exp(-distance / 2)

 return score
 util.raiseNotDefined()
```

3. **代码解释:**

- `Position` 和 `GhostStates` :吃豆人和幽灵在地图上的位置.
- `ScaredTimes` :返回一个场上所有幽灵受惊吓的时间列表.
- `score` :吃豆人的评估分数.对于当前的行为,评估分数越高,吃豆人越可能采取这一行为.
- `Food` 和 `foodList` :返回场上的食物列表.
- `capsules` 返回场上的胶囊列表.
- **食物评估得分:**

```
for food in foodList:
distance = util.manhattanDistance(Position, food)
score += 6 * math.exp(-distance / 2) + 0.7
```

- **胶囊评估得分:**

```
for capsule in capsules:
distance = util.manhattanDistance(Position, capsule)
score += 6 * math.exp(-distance / 2) + 0.7
```

- **幽灵评估得分:**

  对每一个幽灵采取曼哈顿距离的判断,越近越危险,当达到阈值2.7之后,瞬间降低评估得分,以让吃豆人逃脱险境;反之,若幽灵处于惊吓阶段,则距离越近得分越高,对于即将结束恐惧的幽灵,提升的分值将偏低,以避免吃豆人在前往恐惧幽灵的路上出现幽灵结束恐惧的情况.

```python
for i, ghostState in enumerate(GhostStates):
ghostPos = ghostState.getPosition()
distance = util.manhattanDistance(Position, ghostPos)
if ScaredTimes[i] > 5:
    score += 150 + math.exp(3 / distance)
elif 0 < ScaredTimes[i] <= 5:
    score += 5 + math.exp(3 / distance)
else:
    if distance <= 2.7:
        score -= 500
    else:
        score -= 7 * math.exp(-distance / 2)
```

- **为什么采取指数函数而不采取简单的一次函数和倒数:** 采取一般的一次函数和倒数来分析距离会对远端的事件分析不敏感,采取指数函数,可以更平滑过渡到远端的事件.实际测试下,采取普通的倒数和一次函数,有一定的机率发生"待机"现象,从而导致白白流失分数.
- **指数函数内部参数的选取:** `math.exp(3 / distance)` 采取3而不是别的数:在有限的测试次数内,选取"3"使得评估分数已经能够达到正确识别恐吓幽灵的级别,不会出现摇摆不定的情况(实测选取2的时候,甚至会输掉游戏)
- **为什么胶囊的评分和普通食物评分一样:**同样避免"摇摆不定"的情况,提高吃豆人代理稳定性.

4. **实验结果:**

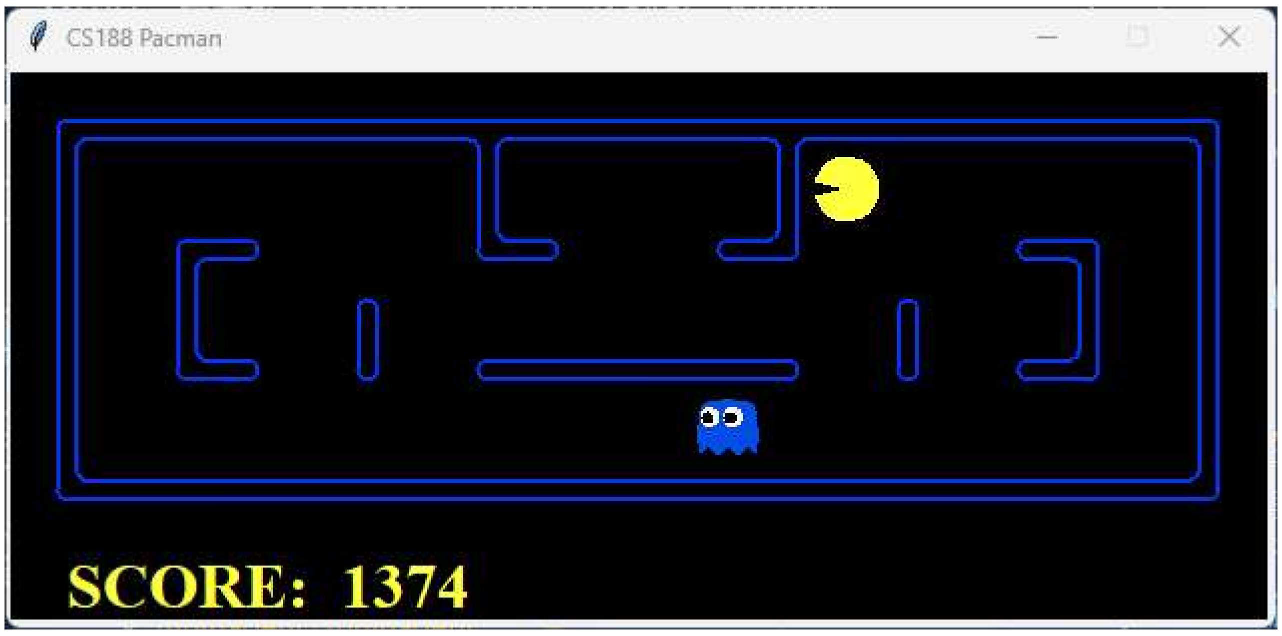
运行 `python autograder.py -q q5` 后的结果图:

```
Question q5
===========

Pacman emerges victorious! Score: 1161
Pacman emerges victorious! Score: 1357
Pacman emerges victorious! Score: 1373
Pacman emerges victorious! Score: 1374
Pacman emerges victorious! Score: 1366
Pacman emerges victorious! Score: 1353
Pacman emerges victorious! Score: 1360
Pacman emerges victorious! Score: 1170
Pacman emerges victorious! Score: 1153
Pacman emerges victorious! Score: 1148
Average Score: 1281.5
Scores:        1161.0, 1357.0, 1373.0, 1374.0, 1366.0, 1353.0, 1360.0, 1170.0, 1153.0, 1148.0
Win Rate:      10/10 (1.00)
Record:        Win, Win, Win, Win, Win, Win, Win, Win, Win, Win
*** PASS: test_cases\q5\grade-agent.test (6 of 6 points)
***     1281.5 average score (2 of 2 points)
***         Grading scheme:
***          < 500:  0 points
***         >= 500:  1 points
***         >= 1000:  2 points
***     10 games not timed out (1 of 1 points)
***         Grading scheme:
***          < 0:  fail
***         >= 0:  0 points
***         >= 10:  1 points
***     10 wins (3 of 3 points)
***         Grading scheme:
***          < 1:  fail
***         >= 1:  1 points
***         >= 5:  2 points
***         >= 10:  3 points

### Question q5: 6/6 ###
```

游戏的结束截图:



基本上远超1000分的要求了,并且得分非常稳定

结束语

本次实验通过吃豆人这个载体,研究了搜索对抗算法中minimax算法,α-β剪枝算法等的应用,以及评估函数的合理编写,对我们在今后的学习中对更高层次的ai构建有着基础性的帮助.