Homework 3: Multi-Agent Search

Please keep the title of each section and delete examples.

Part I. Implementation (5%):

Part1

```
# Begin your code (Part 1)

"""

Using recursion to compute the minimax values of each state. The minimax function takes state, depth, agent index as arguments, and returns minimax value of the state. If the state is a terminal state or the maximum depth has been reached, the function returns the evaluation of the state. Otherwise, the function computes the minimax value for the current agent by either maximizing or minimizing the values of the next agent's actions, depending on the current agent is Pacman or a ghost.

Finally, the function returns the computed minimax value.

"""

def minimax(state, depth, agentIndex):
    if state.isWin() or state.isLose() or depth == self.depth:
        return self.evaluationfunction(state)
    if agentIndex == 0: # maximize for pacman
    v = max(v, minimax)

v = minimize for ghost

v = minimixe for ghost

v = minimixe for gentledex);

for action in state.getLegalActions(agentIndex);

v = minimixe for gentledex for gentledex);

for action in state.getLegalActions(agentIndex, action), depth, agentIndex + 1))

else: #move to next ghost

v = minimixe for gentledex for gentledex for gentledex, action), depth + 1

v = minimixe for gentledex f
```

Part2:

```
# Begin your code (Part 2)
              maxValue function returns the maximum value achievable by the current agent in the current state,
              while minValue function returns the minimum value achievable by the next agent.
              The main loop iterates through all legal actions of the current agent and calculates the value
              of each action using the minValue function, and updates the best action accordingly. It uses
              alpha-beta pruning to avoid exploring paths that will not lead to a better outcome.
              Finally, return the best action.
              def maxValue(state, agentIndex, depth, alpha, beta):
                  v = float("-inf")
                  legalActions = state.getLegalActions(agentIndex)
                  if not legalActions or depth == self.depth:
                      return self.evaluationFunction(state)
                  for action in legalActions:
                      nextState = state.getNextState(agentIndex, action)
                      v = max(v, minValue(nextState, agentIndex + 1, depth, alpha, beta))
                       if v > beta:
                          return v
                      alpha = max(alpha, v)
                  return v
              def minValue(state, agentIndex, depth, alpha, beta):
                  v = float("inf")
                  legalActions = state.getLegalActions(agentIndex)
                  if not legalActions or depth == self.depth:
                      return self.evaluationFunction(state)
                   for action in legalActions:
                      nextState = state.getNextState(agentIndex, action)
                      if agentIndex == state.getNumAgents() - 1:
                          v = min(v, maxValue(nextState, 0, depth + 1, alpha, beta))
                          v = min(v, minValue(nextState, agentIndex + 1, depth, alpha, beta))
                       if v < alpha:</pre>
                          return v
                      beta = min(beta, v)
                  return v
217
              legalActions = gameState.getLegalActions()
              bestAction = None
              v = float("-inf")
              alpha = float("-inf")
              beta = float("inf")
              for action in legalActions:
                  nextState = gameState.getNextState(0, action)
                  nextValue = minValue(nextState, 1, 0, alpha, beta)
                  if nextValue > v:
                      v = nextValue
                      bestAction = action
                   if v > beta:
                      return bestAction
                  alpha = max(alpha, v)
              return bestAction
              # End your code (Part 2)
```

Part3:

```
# Begin your code (Part 3)
              maxValue function recursively calculates the maximum value of a given state by iterating over
              all legal actions of the pacman player and calling the expectValue function on the resulting next state.
              The expectValue function calculates the expected value of a given state by iterating over all legal
              actions of the current agent and recursively calling either maxValue or expectValue on the resulting next state.
              And returns the average of the resulting values, weighted by probability of each action.
              Finally, the agent selects the action with the highest expected score and returns.
256
              def maxValue(state, depth):
    if state.isWin() or state.isLose() or depth == self.depth:
                      return self.evaluationFunction(state)
                  for action in state.getLegalActions(0):
                     v = max(v, expectValue(state.getNextState(0, action), depth, 1))
              def expectValue(state, depth, agentIndex):
                  if state.isWin() or state.isLose() or depth == self.depth:
                     return self.evaluationFunction(state)
                  legalActions = state.getLegalActions(agentIndex)
                  p = 1.0 / len(legalActions)
                   for action in legalActions:
                      if agentIndex == state.getNumAgents() - 1:
                         v += p * maxValue(state.getNextState(agentIndex, action), depth + 1)
                         v += p * expectValue(state.getNextState(agentIndex, action), depth, agentIndex + 1)
                  return v
              legalMoves = gameState.getLegalActions()
              scores = []
              for action in legalMoves:
                  score = expectValue(gameState.getNextState(0, action), 0, 1)
                  scores.append(score)
              bestScore = max(scores)
              bestIndices = [index for index in range(len(scores)) if scores[index] == bestScore]
              chosenIndex = random.choice(bestIndices)
              return legalMoves[chosenIndex]
              # End your code (Part 3)
```

Part4:

```
# Begin your code (Part 4)
          The function calculates a score for a pacman game state based on the distance and proximity of ghosts to pacman,
          the distance to the closest remaining food, and the number of remaining capsules.
          The function prioritizes getting closer to food while avoiding ghosts, while also
          taking into account the remaining capsules on the board.
          pPos = currentGameState.getPacmanPosition()
          gDist = 0
303
          gProximity = 0
          for gState in currentGameState.getGhostPositions():
              dist = util.manhattanDistance(pPos, gState)
              gDist += dist
              if dist <= 1:</pre>
                  gProximity += 1
          foodList = currentGameState.getFood().asList()
          minfoodList = min([util.manhattanDistance(pPos, foodPos) for foodPos in foodList], default=0)
          capsuleNum = len(currentGameState.getCapsules())
          return currentGameState.getScore() - (1 / (gDist+1)) - gProximity + (1 / (minfoodList+1)) - capsuleNum
```

Part II. Results & Analysis (5%):

```
Provisional grades
Question part1: 20/20
Question part2: 25/25
Question part3: 25/25
Question part4: 10/10
Parman energes victorious! Score: 1159
Parman energes victorious! Score: 1158
Parman energes victorious! Score: 1174
Question part4: 10/10
Parman energes victorious! Score: 1174
Parman energes victorious! Score: 1179
Parman energes victorious! Score: 1169
Average Score: 1169.5
Parman energes victorious! Score: 1169
Parman energes victorio
```

During the evaluation of the pacman game state, the distance between pacman and ghosts, food, the proximity of ghosts around pacman, and the number of capsules are taken into consideration. Among these factors, the distance between pacman and food has the most significant impact on the score. This makes sense since the ultimate objective of the game is to gain more points, and getting closer to food is the key to achieving this objective. However, the other factors such as the proximity of ghosts and the number of capsules also influence the outcome since they are essential for survival and successful completion of the game.