## Final Project: Gomoku AI Game

Minerva University

CS152 - Harnessing Artificial Intelligence Algorithms

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#### I. Problem Definition

Gomoku (also known as five in a row) is an abstract strategy board game that is normally played on a 15x15 grid board. The game is played by two players with one player using black and the other using white stones. However, there might be certain variations (such as it can be played on a 19x19 grid with other pieces and by more than two players). While starting the same, the board would be empty. Each player then takes turns placing their stone on the board. The player who win is the person who manages to place a sequence of five stones either in a row, horizontally, vertically, or diagonally line. If the board is full (meaning there are 225 stones on the board), but there is no sequence of length five, then it would be a draw.

Even though the rule of the game is relatively simple, it has a high branching factor meaning that for each turn there are many next possible moves that the other player can make (we can think that if the board state for each turn represents a node there are many child nodes that can be generated). To avoid losing, each player must be able to balance defense and offense efficiently. Or in other words, the player needs to make sure they are creating a sequence of five stones to win while blocking the opponent from doing so to prevent losing. To effectively do so, the players must be able to think ahead and explore all the next possible moves and outcomes to determine which move they would play next to optimize their chances of winning.

However, keeping track of their moves and predicting their opponent's moves to combat and play optimally is a challenging task. Therefore, in this project, I will create a Gomoku AI using a minimax alpha-beta pruning algorithm to help humans determine the best possible moves given a board state and can also play against humans to challenge them out. The game has been tested to be able to beat humans or give a draw in the game. The details of the algorithm implementation will be carried out below.

#### **II. Solution Specification.**

#### a. Minimax Search Algorithm

The game's characteristics is multiagent (2 agents specifically who take turns), deterministic, zero-sum, and fully observable (perfect information), which makes it suitable for the minimax algorithm.

The optimal solution is determined through the utility value of the final state of the game. The minimax search algorithm (using depth-first search) would try to find the optimal move for the max player by testing all possible paths and choosing the path that would result in the largest utility value in the terminal node assuming both players play optimally. On the other hand, the min player would want to get to a state with the lowest utility. We can see that it is a recursive algorithm, as for each state, it will continue to call the search function to go down one depth in the tree until it reaches way down the terminal nodes and backs up the minimax values with recursion. The recursive nature of the minimax algorithm becomes apparent as it traverses the game tree by repeatedly calling the search function to explore one level deeper until it reaches the terminal nodes. Once it goes to the end of the game, the algorithm backtracks up the tree, passing along values to determine the optimal move for the current player. The code for using the minimax algorithm (with alpha-beta pruning) and building the AI agent in the game is commented on thoroughly in the appendix.

#### b. Implementing alpha-beta pruning and depth cut-off.

However, as the search space and the number of game states increase exponentially with depth, it would be nearly impossible to develop the whole search tree. Therefore, we will implement several techniques to limit the scope of examining every state. First, we will use alpha-beta pruning to eliminate irrelevant subtrees that make no difference to the final outcome. However, due to computation time and space constraints, even with alpha-beta pruning, we can not fully compute the utility in the terminal nodes (states where the game ends). Therefore, we would need to cut off the search early by giving the game tree max depth and using a heuristic evaluation function to estimate the expected utility. The heuristic function I used is a linear weighted sum function in which the coefficients are derived from testing out the game given a fixed depth. The max depth I used to cut off the search is also derived from testing out the game to guarantee the move generated by AI doesn't take long but can still give a somewhat optimal move. An explanation of how I constructed the heuristic will be detailed below.

Another additional heuristic to limit the search space is to only generate successor nodes (positions) that are near the pre-existing stones on the board. This is implemented by defining a function that generates successor nodes only for positions that are within a certain distance of existing stones. This is reasonable given an isolated square cannot lead to immediate loss/win and add less value to the game. I also used the heuristic to create a random computer moves

generator. The constraints make the moves less random since it limits the positions the stone lands on and makes it slightly more effective than a pure random moves generator.

## c. Explanation of heuristic function

Given S(i,j) denotes a sequence of length i (where i is an integer ranging from 2 to 5), with j being the number of openings (ranging from 0 to 2). If S(i,j) belongs to the current player (max player), its score is given by weight\_i \* j, where weight\_i is a coefficient (which value is derived from tests) that depends on the length of the sequence i. On the other hand, if S(i,j) belongs to the opponent, its score is -weight\_i \* j. The heuristic score is obtained through summing up the scores of all sequences. The longer the sequence (i) is, the larger the coefficient is. This is because we want the game board to prioritize a long sequence of our stones as it leads to a better chance of winning and is also heavily penalized when the opponent is forming a long sequence to prevent us from losing. The weight (or coefficients) is determined through constant tests. The number of openings (j) is also an important variable, as a sequence with more openings has a higher chance of extending. If a sequence is closed (no opening), it cannot develop into a sequence of five. Therefore, moves that would lead to a sequence with the same length but have more empty cells (openings) around it would be more prioritized.

## III. Testing

I will conduct several tests that would confirm that the AI Gomoku Player is operating rationally and have relevant results. Further evidence and details will be listed in Appendix, along with snapshots of the game.

- 1) Human versus AI: The human player (me) is the white player, and the AI player is the black player. I tested three games, and the AI beat me in all games as I may have made mistakes and performed suboptimal moves. This result is expected as AI is behaving (nearly) optimally, so it should be able to win. We can see when I'm nearing 3 or 4 sequences, the AI player always manages to make defensive moves to block me while also making offensive moves to win. The demo video and screenshots of the game are illustrated in Appendix A.
- agent, I tried to test 100 games and plot graphs. The graph shows that the AI agent wins all 100 games, meaning that the moves the AI player made are more informed. However, I observed the AI agent made a lot of suboptimal decisions which prevented it from

making a much earlier win. This made sense as the minimax search algorithm assumes that the opponent is playing optimally, which isn't true for the non-AI agent. The bar graph (illustrating the result of the testing of 100 games) and screenshots of the game are illustrated in Appendix B.

3) AI vs AI: With AI vs AI, the result shows a tie ( it took almost an hour for the game to finish fully). We can see that there are a lot of sequences of three and four in the game made by both players but were never completed to five. This means the AI manages to balance defensive moves and offensive moves. As both players presumably are playing optimally, it made sense that the game resulted in a tie.

To conclude, various test cases show that the AI agent made an informed decision before taking action and could compete to win the game against humans. Their decision is certainly more informed than the Non-AI agent's as the test shows it won against them in 100 rounds. However, it's worth noticing that the AI assumes that the opponent is making optimal decisions to choose their next move (which isn't always true for humans and random moves generator). This can be a potential explanation for why at the beginning of the game the AI was making suboptimal moves against the non-AI agent (but not against humans). However, when playing against a human who is trying to win the game or another AI agent, the moves are always (nearly) optimal. Furthermore, the depth level is quite small, therefore, sometimes making suboptimal decisions are expected.

#### IV. AI Use

I only used Chat-GPT to initially understand more about how the game works. However, I read and used other sources to write my paper.

#### References

- Codeofcarson. (n.d.). *Checkers/board.py at master · Codeofcarson/Checkers*. GitHub. Retrieved April 20, 2023, from https://github.com/codeofcarson/Checkers/blob/master/board.py
- Luzgabriel. (n.d.). *Luzgabriel/Pymoku: Gomoku Terminal based game written in Python*. GitHub. Retrieved April 20, 2023, from https://github.com/luzgabriel/pymoku
- Wikimedia Foundation. (2023, March 19). *Gomoku*. Wikipedia. Retrieved April 20, 2023, from https://en.wikipedia.org/wiki/Gomoku
- Russell, S. J., Norvig, P., & Davis, E. (2022). *Artificial Intelligence: A modern approach*. Pearson Educación.

## APPENDIX A: TESTING HUMAN VS AI

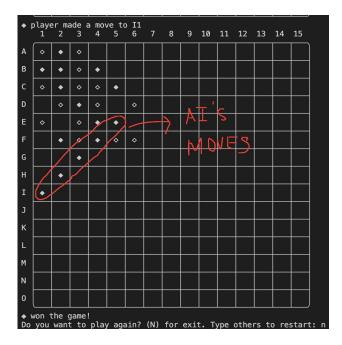
## Simply go to the file directory and run through the terminal command:

python3 -m venv venv source venv/bin/activate pip3 install -r requirements.txt python3 gomoku\_game.py

00000	GOMOKU	GAME	000000
	Random vs AI Computer Random		

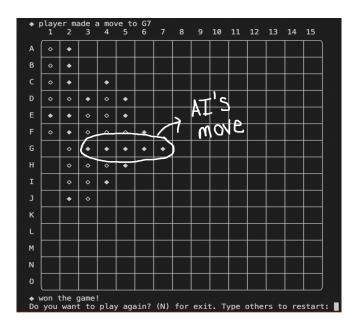
Demo game link: <a href="https://www.loom.com/share/2a157d98764d44a29d56f30a8d0c9ccf">https://www.loom.com/share/2a157d98764d44a29d56f30a8d0c9ccf</a>

## 1. Round 1: AI wins



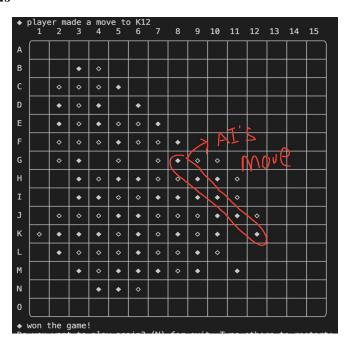
**Figure 1:** Screenshot showing the result of the first round, where the AI won against the human player. The sequence of five was made diagonally from I1 to E5.

## 2. Round 2: AI wins



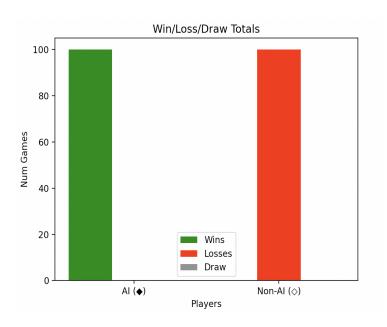
**Figure 2:** Screenshot showing the second round result, where the AI won against the human player. The sequence of five was made horizontally from G3 to G7.

## 3. Round 3: AI wins

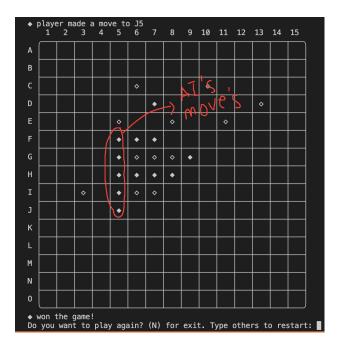


**Figure 3**: Screenshot showing the result of the third round, where the AI won over the human player again. The sequence of five was made diagonally from G7 to G12.

## APPENDIX B: TESTING AI VS NON-AI PLAYER

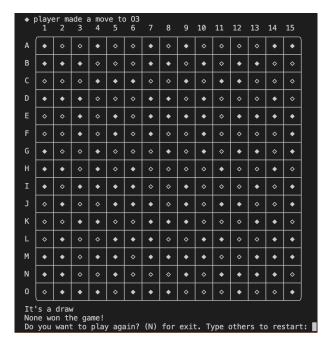


**Figure 4:** Bar graph showing the number of Wins, Losses, Draw of the AI and Non-AI players who have played 100 rounds of games.



**Figure 5:** Screenshot showing the result of a game in which the AI won after making a sequence of five vertically from F5 to J5.

## APPENDIX C: TESTING AI PLAYER VS AI PLAYER



**Figure 6:** Screenshot showing the game resulting in a draw when they played against each other

**APPENDIX D: Proposal Form** 

## Thanks for filling out CS152 Final Project Proposal

Here's what was received.

# CS152 Final Project Proposal

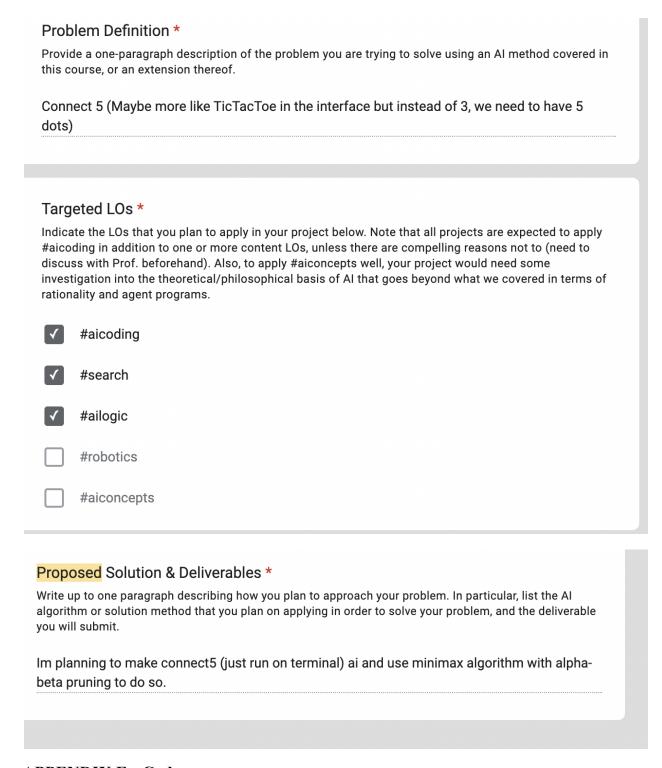
Fill out the details below. Please note that it may take up to a week to get a response to your proposal, so it is in your interest to submit it with adequate time prior to the end of week 15.

Your email (trinhnguyen@uni.minerva.edu) was recorded when you submitted this form.

Name \*
Trinh Nguyen

#### Problem Definition \*

Provide a one-paragraph description of the problem you are trying to solve using an AI method covered in this course, or an extension thereof.



#### **APPENDIX E: Code**

I. gomoku game.py

```
import numpy as np
code logic inspired by https://github.com/luzgabriel/pymoku/blob/master/pymokugame/pymokugame.py#
 printing board function slightly inspired by game of checker https://github.com/codeofcarson/Checkers/blob/master/board.py
class GomokuGame():
 Class Gomoku Game: A class to create structure for Gomoku Game with four modes Human vs AI, Humans vs Non-AI agent
 ,Non-AI vs AI (for testing purpose) and AI vs AI (for testing purpose). To start the game,
 ,we method play game
 Attribute:
 - width (int): Default to 15. The width of the Gomoku board
 - height (int): Default to 15. The height of the Gomoku board
 - max_depth(int): Default to 2. The cut off depth of the tree (works well with the weight given in the heuristic functions)
 BLACK = "♦"
 WHITE = "◇"
 EMPTY = ''
 def __init__(self, width=15, height=15,max_depth=2):
   self.width = width
   self.height = height
   self.board state = [[self.EMPTY for j in range(self.width)] for i in range(self.height)]
    self.game over = False
    self.winner = None
    self.maxdepth = max_depth
    self.all moves =[] #all moves that have been generated by both opponents
    self.all moves comp = [] #all moves that have been generated by the AI Agent
 def check valid move(self,row,column):
    This function checks whether the move is valid given the current board of the state
      - row(int): the row number that the position in
      - column(int): the column number that the position in
      - bool: return True if the position is valid else False
```

```
if row >= 0 and row <= self.height -1:
      if column >= 0 and column <= self.width- 1:
        if self.board_state[row][column] == self.EMPTY:
           return True
 def available_bounded_pos(self,bound=5):
    This function returns a list of empty positions within a region of bounded box size
    from pre-existing stones:
      - bound(int): default to five. Width/Height of the bounded box size.
   Output:
      - available_pos(list): return a list of available poisitons that the player can move to
    available pos = []
    for pos in self.all moves:
      pos_x = pos[0]
      pos_y = pos[1]
      for i in range(0,bound):
        for j in range(0,bound):
           new pos x = pos x + (i - bound//2)
           new_pos_y = pos_y + (j - bound//2)
           if (new pos x \ge 0) and (new pos y \ge 0) and self.check valid move(new pos x,new pos y):
             if ([new_pos_x, new_pos_y] not in available_pos) and (self.board_state[new_pos_x][new_pos_y] ==
self.EMPTY):
                available_pos.append([new_pos_x,new_pos_y])
   return available_pos
 def empty positions(self):
    This function checks whether the position is empty
```

```
- row(int): the row number that the position in
    - column(int): the column number that the position in
  Output:
     - bool: return True if the position is empty else False
  for row in self.board state:
     for pos in row:
       if pos == self.EMPTY:
  return False
def mark_position(self,position,player,do_print:bool):
  This function mark the position of the position on the board
    - position(list): the position of the move in row,column
    - player(str) : the symbol of the player
    - do_print(bool) : print out string showing the player's moves
  Output:
     - bool: return True if the position is marked else return False
    row = position[0]
    column = position[1]
    if self.check valid move(row,column):
       self.board\_state[row][column] = player
       if do_print:
         print(f'{player} player made a move to {chr(row+65)} {column+1}')
       return True
       if do_print:
         print("Board game position is invalid try again")
     print("Board game position is invalid try again")
```

```
def get_row(self, position):
  This function returns the array which is a row (horizontal line) of where the position is at
  Input:
     - position(list): the position of the move is at
  Output:
     - list: the array which is a row (horizontal line) of where the position is at
  state = np.array(self.board_state)
  return state[position[0],:]
def get_column(self,position):
  This function returns the array which is a row (horizontal line) of where the position is at
  Input:
    - position(list): the position of the move is at
  Output:
    - list: the array which is a column (vertical line) of where the position is at
  state = np.array(self.board state)
  return state[:,position[1]]
def horizontal_vertical_sequences(self):
  sequences =[]
  visited_pos =[]
  for pos in self.all moves:
     #check if we have already got the sequences of column containing that pos
     if pos[1] not in visited_pos:
       column = self.get_column(pos)
       sequence = self.get sequences in array(column)
       visited_pos.append(pos[1])
       if len(sequence) > 0:
          sequences.extend(sequence)
```

```
#check if we have already got the sequences of row containing that pos
     if pos[0] + 15 not in visited pos:
       row = self.get_row(pos)
       sequence = self.get sequences in array(row)
       visited pos.append(pos[0]+15)
       if len(sequence) > 0:
         sequences.extend(sequence)
  return sequences
def get sequences in array(self,array):
  Get a list of sequences in the given array.
    - array(list): A list representing the array we want to get the sequence of.
     list: A list of sequences. Each element of the list is a list containing information about a sequence,
    including the player symbol, the number of open ends, and the length of the sequence.
  sequences = []
  temp_seq = []
  temp open = 0
  for idx, val in enumerate(array):
     #skip the first element as there is no prev item we can compare
    if idx == 0:
       prev val = array[idx-1]
       # if current value is occupied by either player
       if val != self.EMPTY:
          if prev_val != val:
```

```
if prev_val == self.EMPTY:
              temp_open = 1
              temp_seq.append(val)
              if len(temp\_seq) > 1:
                sequences.append([temp_seq[0],temp_open, len(temp_seq)])
              temp seq = []
              temp_open = 0
           if(len(temp\_seq)) < 1:
              temp_seq.append(val)
           temp_seq.append(val)
      #check the end of a sequence
      elif prev_val != val:
         if len(temp\_seq) > 1:
           sequences.append([temp seq[0], temp open+1, len(temp seq)])
         temp seq = []
         temp open = 0
  if len(temp_seq) > 1:
    sequences.append([temp\_seq[0], temp\_open, len(temp\_seq)])
  sequences = [sequence for sequence in sequences if sequence[0] != self.EMPTY]
  return sequences
def diagonal_line(self):
```

```
Get a list of diagonal line in a board
  Output:
     list: A list of all diagonal lines in the board (represented as list).
  sequences = []
  matrix = np.array(self.board state)
  diagonal lines = []
  for i in range(-matrix.shape[0] + 1, matrix.shape[1]):
     diagonal_lines.append(matrix[::-1,:].diagonal(i))
  for i in range(matrix.shape[1] - 1, -matrix.shape[0], -1):
     diagonal_lines.append(matrix.diagonal(i))
  for diagonal in diagonal_lines:
     sequences += self.get_sequences_in_array(list(diagonal))
  #make sure that only get sequences that are from bklack or white player
  sequences = [sequence for sequence in sequences if sequence[0] != self.EMPTY]
  return sequences
def get_total_sequences(self):
  Get all the total sequences in the board
     list: A list of all diagonal lines in the board (represented as list).
  total_sequences = []
  vertical_horizontal_sequences = self.horizontal_vertical_sequences()
```

```
#print(f"vertical_horizontal{vertical_horizontal_sequences}")
  diagonal_sequences = self.diagonal_line()
  total_sequences.extend(vertical_horizontal_sequences)
  total sequences.extend(diagonal sequences)
  return total_sequences
def win_game(self):
  check to see if someone has won a game given the state
  return the winner if so
  Output:
    str: The winner of the game (if there is)
  total sequences = self.get total sequences()
  for sequence in total_sequences:
    if len(sequence) > 0:
       if sequence [2] \ge 5:
         self.winner = sequence[0]
         return sequence[0]
def get_score(self,length):
  getting the weight of the sequence given a length
  Input:
    int: the weight of the sequence given a length
```

```
if length == 2:
  elif length == 3:
     return 800
  elif length == 4:
     return 60000
  elif length >= 5:
     return 4000000000
def undo_move(self,position):
     pos(list): position of a move we want to undo
  Output:
  self.board_state[position[0]][position[1]] = self.EMPTY
def calculate_heuristic_score(self, player, depth):
  calculate heuristic score of the board configuration
     - player(str): the current player
  Output:
  total_sequences = self.get_total_sequences()
  #initialize the heuristic score
  heuristic_score = 0
  for sequence in total_sequences:
```

```
if len(sequence) > 0:
       player_val = sequence[0]
       opening = sequence[1]
       #get the length of the sequence
       length_seq = sequence[2]
       if length seq in range(2, 5):
         seq score = self.get score(length seq) * opening
         #penalize if it belongs to the opponent
         if player val == player:
            heuristic_score += seq_score
            heuristic_score -= seq_score
       elif length_seq >= 5:
         #as the num openings doesn't matter (since you would lose/win anyway); sequence score = score(5)
         seq_score = self.get_score(5)
         if player_val == player:
            heuristic_score += seq_score
            heuristic score -= seq score
  return heuristic score
  #return (heuristic score*225)/depth
def minimax_with_pruning(self, player, alpha=float('-inf'), beta=float('inf'), count_depth=0, positions_list=None):
  implement the minimax algorithm with alpha-beta pruning to determine the optimal move.
    player (str): the current player
    alpha (float): the alpha value for alpha-beta pruning, initialized as negative infinity.
    beta (float): the beta value for alpha-beta pruning, initialized as positive infinity.
    count_depth (int): the current depth of the recursive search, default as 0.
    positions list (list): The list of all previous moves, default = None
```

```
output:
  list: return a list containing the optimal score and move.
next_positions = self.available_bounded_pos()
if positions list is None:
  positions list = self.all moves.copy()
# initialize the optimal move and score
opt move = [-1,-1]
# check if the game is over or if the maximum depth has been reached
if not self.empty positions() or count depth >= self.maxdepth:
  # if the game is over or the maximum depth has been reached, calculate the heuristic score for the current board state
  heuristic score = self.calculate heuristic score(player, count depth)
  return (heuristic_score, opt_move)
  # loop through the possible next positions
  for position in next positions:
    self.mark position(position, player, do print=False)
    positions_list.append(position)
     next_player = self.WHITE if player == self.BLACK_else self.BLACK
    heuristic score = self.minimax_with_pruning(next_player, alpha, beta, count_depth+1, positions_list.copy())[0]
    self.undo_move(position)
    positions_list.pop()
     # update the alpha-beta values and optimal move
     # if the current player is the maximizer, update the alpha value if the heuristic score > larger
     #as we find better move
     if player == self.WHITE:
```

```
if heuristic_score > alpha:
            alpha = heuristic_score
            opt_move = position
       #as the minimizer find better move
         if heuristic_score < beta:
            beta = heuristic_score
            opt_move = position
       if alpha >= beta:
         return [alpha if player == self.WHITE else beta, opt_move]
    return [alpha if player == self.WHITE else beta, opt_move]
def get_opt_move(self):
  get optimal move for a player
  Input:
  Output:
    return optimal move
  _, opt_move = self.minimax_with_pruning(self.WHITE, alpha=float('-inf'), beta=float('inf'), count_depth=0)
  return opt_move
def print_board(self):
  print out the board game
```

```
Output:
    str: Print out the state if the board game
  board line = []
  board line.append(" 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 ")
  board\_line.append(f' \ \ \ \cap \{"-------- " \ * (self.width-1)\}-------- ')
  for num, row in enumerate(self.board state[:-1]):
    board_line.append(f'{chr(num+65)} | {" | ".join(row)} | ')
    board\_line.append(f \ \ | + ("-------|" * (self.width-1)) --------|")
  board_line.append(f {chr(self.height+64)} | {" | ".join(self.board_state[-1])} | ')
  print('\n'.join(board_line))
def play_game(self, black_player, white_player, board_print=True):
  Set the game to start
    - black_player(str): symbol of first player
    - black_player(str): symbol of second player
    - board_print(bool): whether to print out the board or not
    - A game that we can play
  while True:
    turn = self.WHITE
    print(" ===
    print(" 00000
    print(" ======
    if board_print:
      self.print board()
    black turn = False
    self.winner = None # reset the winner for each game
    while self.winner != self.BLACK and self.winner != self.WHITE:
       if not self.empty_positions():
```

```
print("It's a draw")
        if black_turn:
           filled_pos = black_player.get_move(self)
           if board print:
             self.print_board()
           black_turn = False
           filled_pos = white_player.get_move(self)
           if board_print:
             self.print board()
           black_turn = True
        self.winner = self.win_game()
      print(f"{self.winner} won the game!")
      play_again = input("Do you want to play again? (N) for exit. Type others to restart: ").lower()
      if play_again == "n":
        self.__init__(15,15,2)
        self.play_game
if __name__ == '__main__':
 print(" ===
 print(" 00000
                        GOMOKU GAME
                                                        000000")
 print(" ====
 print("1. Human vs AI")
 print("2. Computer Random vs AI")
 print("3. Human vs Computer Random")
 print("4. AI vs AI ")
 choice = input("Enter your choice: ")
   #setting up the mode for human vs ai
   if int(choice) == 1:
      black player = ComputerPlayAI("♦")
      white player = SelfPlayer('\diamondsuit')
      game = GomokuGame()
      game.play_game(black_player,white_player,board_print=True)
```

```
elif int(choice) == 2:
    black_player = ComputerPlayAI("◆")
    white player = ComputerPlayerEasy(\langle \rangle)
    game = GomokuGame()
    game.play_game(black_player,white_player,board_print=True)
  elif int(choice) == 3:
    black player = SelfPlayer(' • ')
    white player = ComputerPlayerEasy(\langle \rangle)
    game = GomokuGame()
    game.play_game(black_player,white_player,board_print=True)
  #setting up the mode for AI vs AI
  elif int(choice) == 4:
    black_player = ComputerPlayAI('◆')
    white_player = ComputerPlayAI('\circ\circ\circ\)
    game = GomokuGame()
    game.play_game(black_player,white_player,board_print=True)
    raise ValueError("Invalid choice")
except ValueError as e:
  print(f"Error: {e}")
```

## 2. player.py

```
Attribute:
   - player(str): The player's symbol
 def __init__(self,player):
   self.player = player
 def get_move(self, game):
class ComputerPlayerEasy(Player):
 A child class of the Player class representing a random moves generator
   - player(str): The player's symbol
 def __init__(self, player):
    super().__init__(player)
 def get_move(self, game):
    if len(game.available_bounded_pos()) == 0:
      move = [6,6]
      move = random.choice(game.available_bounded_pos())
    game.mark_position(move, player=self.player, do_print=True)
    game.all_moves_comp.append(move)
    game.all_moves.append(move)
    return move
class SelfPlayer(Player):
 A child class of the Player class representing a human player.
 Attribute:
   - player(str): The player's symbol
```

```
def __init__(self, player):
    super().__init__(player)
 def get_move(self, game):
    input_val = None
   valid move = False
   while not valid_move:
      player_input = input(f"It's {self.player}'s turn. Enter the game position in row/column form (eg: A4):")
      player_input = player_input.strip()
      input_val = self.parse_input(player_input)
      valid move = game.mark position(input val, player=self.player, do print=True)
    game.all moves.append(input val)
    return input_val
 def parse input(self,player input):
      row = player_input[0].upper()
      row = ord(row.upper()) - 65
      column = int(player_input[1:])-1
      return [int(row), column]
      return False, False
class ComputerPlayAI(Player):
 A child class of the Player class representing a computer AI agent.
   - player(str): The player's symbol
 def init (self, player):
   super().__init__(player)
 def get_move(self, game):
   move = game.get_opt_move()
   game.mark_position(move, player=self.player, do_print=True)
    game.all_moves_comp.append(move)
    game.all moves.append(move)
    return move
```

## 3. graph.py

```
f name == ' main ':
 #set up game
black_player = ComputerPlayAI("◆")
 white player = ComputerPlayerEasy(\langle \rangle)
 game = GomokuGame(15, 15, 2)
 #https://realpython.com/python-matplotlib-guide/#bar-charts
resultss =[]
results = {'Wins': [0, 0], 'Loss': [0, 0], 'Draw': [0, 0]}
 for i in range(100):
   result = game.play_game(black_player, white_player, board_print=False)
   if result == ' \diamondsuit':
     results['Wins'][0] += 1
     results['Loss'][1] += 1
   elif result == '\diamondsuit':
      results['Wins'][1] += 1
     results['Loss'][0] += 1
     results['Draw'][0] += 1
     results['Draw'][1] += 1
   resultss.append(result)
 print(results)
 x = range(2)
 fig, ax = plt.subplots()
bar width = 0.3
#plot bars showing win/lose/draw
ax.bar(x, results['Wins'], width=bar_width, color='green', label='Wins')
 ax.bar([i + bar_width for i in x], results['Loss'], width=bar_width, color='red', label='Losses')
ax.bar([i + 2*bar_width for i in x], results['Draw'], width=bar_width, color='gray', label='Draw')
ax.set_xlabel('Players')
ax.set_ylabel('Num Games')
ax.set_title('Win/Loss/Draw Totals')
ax.set_xticks([i + bar_width for i in x])
 ax.set_xticklabels(['AI (♦)', 'Non-AI (♦)'])
```

ax.legend()
# show plots
plt.show()