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# Hide and Seek Game: Technical Analysis Report

# Game Concept Overview:

- The implementation represents a strategic "Hide and Seek" game using game theory principles. In this two-player zero-sum game:
  - Game World: A grid of cells (rows × columns) or Linear with the size only.
  - Players: Hider and Seeker
  - **Difficulty Levels**: Each cell has a random difficulty level (easy, medium, hard).
  - Payoffs: Values determined by difficulty levels that represent the scoring outcomes
  - Modes:
    - Human vs. Computer: Player chooses to be either the Hider or Seeker.
    - Computer Simulation: Both roles played by computer using optimal strategies

The core objective is to apply game theory to determine optimal strategies for both players, creating an Al opponent that makes rational decisions based on mathematical principles.

# Game Theory Fundamentals:

#### Zero-Sum Game Structure:

This implementation models a classic zero-sum game where one player's gain exactly equals the other player's loss. Key game theory concepts applied include:

#### 1. Payoff Matrix:

- A mathematical representation of all possible outcomes.
- Each cell (i,j) represents the outcome when Hider chooses position i and Seeker chooses position j.
- Positive values benefit the Hider; negative values benefit the Seeker.

#### 2. Mixed Strategy:

- The game uses probabilistic strategies rather than pure strategies.
- Each player chooses locations according to probability distributions.

#### 3. Minimax Principle:

- Hider aims to maximize their minimum payoff.
- Seeker aims to minimize Hider's maximum payoff.
- The value of the game represents the expected outcome with optimal play.

# Linear Programming Solution:

The game's probabilities is calculated using linear programming (LP), a mathematical optimization technique:

1. For the Hider (Maximizing Player):

- Maximize v subject to:
- For each Seeker position j: -p·A[:,j] + v ≤ 0
- Sum of probabilities equals 1
- 2. For the Seeker (Minimizing Player):
  - Minimize v subject to:
  - For each Hider position i: p·A[i,:] v ≤ 0
  - Sum of probabilities equals 1

#### Where:

- p represents the probability distribution over positions
- v represents the value of the game
- A is the payoff matrix

### Data structures Used:

The implementation leverages several key data structures to represent and process the game state:

1. 2D Grid Arrays:

```
self.world = [[0 for _ in range(world_cols)] for _ in range(world_rows)]
self.difficulty = [[0 for _ in range(self.world_cols)] for _ in range(self.world_rows)]
```

- Purpose: Represent the game board and difficulty levels.
- **Benefit**: Direct mapping to the visual grid for intuitive understanding.

### 2. Payoff Matrix:

```
self.payoff = [[0 for _ in range(self.world_size)] for _ in range(self.world_size)]
```

- Purpose: Core mathematical representation of game outcomes
- Structure: Row i represents Hider position, column j represents Seeker position

- Values: Positive values favor Hider, negative values favor Seeker
- 3. Linear Programming Arrays:

```
A = [] # Coefficient matrix for constraints
b = [] # Right-hand side values
c = [] # Objective function coefficients
```

- **Purpose**: Represent the minimax optimization problem
- **Usage**: Fed into scipy's linprog solver to find optimal strategies
- 4. Probability Vectors:

```
computer_strategy = result.x[:-1] # Extract probabilities from LP solution
```

- Purpose: Represent mixed strategies from game theory
- **Usage**: Probabilities for selecting each position
- Implementation: Used with numpy's random.choice for stochastic decisions

# ♦ Code Architecture and Implementation :

The codebase is structured into three main components:

1. Flask Web Server (main.py):

This file implements the game's API endpoints using Flask:

```
@app.route('/api/start-game', methods=['POST'])
def start_game():
    # Initialize a new game with specified parameters

@app.route('/api/play-round', methods=['POST'])
def play_round():
    # Process a single round of gameplay

@app.route('/api/simulate', methods=['POST'])
def simulate_game():
    # Run a computer vs. computer simulation
```

### The server handles three primary operations:

- Game initialization with customizable parameters
- Individual round processing for human vs. computer mode
- Game simulation for computer vs. computer mode
- 2. Game Logic Helper (helperMethods.py) :

This intermediate layer coordinates between the API and core game logic:

```
def initialize_game(rows, cols, game_mode_str, player_role_str):
    # Convert parameters and initialize game state

def get_computer_move():
    # Calculate optimal computer move using game theory

def process_round(player_role, player_move):
    # Process player and computer moves and return results

def run_simulation(total_rounds):
    # Run multiple rounds of computer vs. computer simulation
```

This module handles:

- Parameter conversion between API and game engine
- Computer move calculation using the game theory solver
- Round processing logic
- Simulation execution and results aggregation

#### 3. Core Game Engine (startUp.py):

The GameState class implements the fundamental game mechanics:

```
def start(self, world_rows, world_cols, game_mode, human_player_mode):
    # Initialize the game world and parameters

def generate_random_world(self):
    # Create a random game world with difficulty levels

def hider_plays(self, i, j):
    # Process the Hider's move

def seeker_plays(self, i, j):
    # Process the Seeker's move and calculate scores

def formulate_game(self):
    # Set up the game matrix for solving

def solve_game_as_LP(self):
    # Find the optimal strategy using linear programming
```

#### This class manages:

- Game state initialization
- Random world generation with difficulty levels
- Move processing for both players
- Score calculation
- Game matrix formulation
- Linear programming solution for optimal strategies

# Algorithm Analysis :

1. World Generation Algorithm:

The game world is generated with random difficulty levels (easy, medium, hard) that affect the payoff values:

```
def generate_random_world(self):
    level = [0] * self.world_size
    world_matrix = [[0 for _ in range(self.world_size)] for _ in range(self.world_size)]

# Generate difficulty level for each position
for i in range(self.world_size):
    level[i] = random.randint(0, 2) # 0: easy, 1: medium, 2: hard

# Set payoff values based on difficulty level
# ...
```

### **Key features:**

- Each position is assigned a random difficulty (0, 1, or 2)
- Payoff values are determined by difficulty level
- Nearby positions have adjusted payoffs to create strategic depth

# 2. Linear Programming Solution:

The core algorithmic component is the linear programming solver that calculates optimal mixed strategies:

```
def solve_game_as_LP(self):
    # Set up bounds for all variables
    bounds = [(0, 1)] * self.world_size + [(None, None)]

A = [] # Coefficient matrix for inequality constraints
b = [] # Right-hand side of inequality constraints
c = [] # Objective function coefficients

if self.human_player_mode == 0: # Human is hider (maximize minimum)
    # ...
else: # Human is seeker (minimize maximum)
    # ...

# Solve the linear program using scipy
result = linprog(
    c=c, A_ub=A, b_ub=b, A_eq=eq_constraint, b_eq=eq_value,
    bounds=bounds, method='highs'
)
```

### The algorithm:

- 1. Sets up the linear programming problem based on player role
- 2. Constructs constraints that enforce game theory principles
- 3. Uses the high-performance 'highs' solver from scipy
- 4. Returns probability distributions representing optimal strategies

#### 3. Simulation Procedure:

The simulation mode runs multiple rounds with both players using optimal strategies:

```
def run_simulation(total_rounds):
    # Initialize tracking variables

# Run simulation for specified number of rounds
for _ in range(total_rounds):
    # Get optimal strategies for both players
    game.formulate_game()
    result = game.solve_game_as_LP()
    computer_strategy = result.x[:-1]

# Choose moves for both players based on optimal strategy
    player_move = np.random.choice(len(computer_strategy), p=computer_strategy)
# ...
    computer_move = np.random.choice(len(computer_strategy), p=computer_strategy)
# ...
```

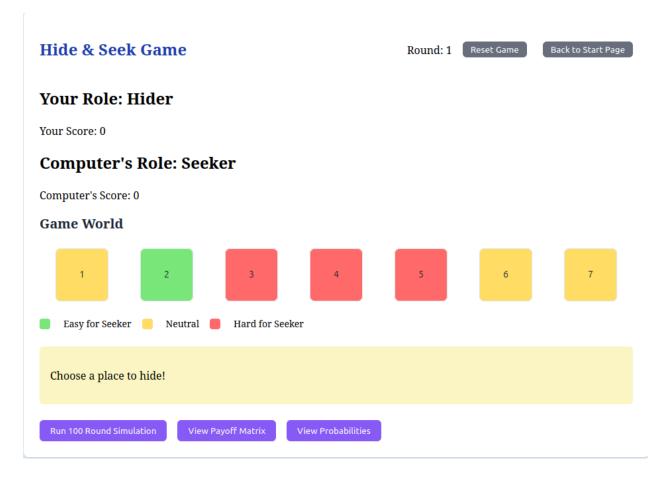
#### This process:

- 1. Calculates optimal mixed strategies using LP
- 2. Samples move from these probability distributions
- 3. Processes moves and updates scores
- 4. Tracks statistics across all rounds

- ♦ Test Case Scenarios:
- Test 1:

This test for linear grid (7 cells) and Hider player, Seeker computer

→ Grid shape and difficulties :



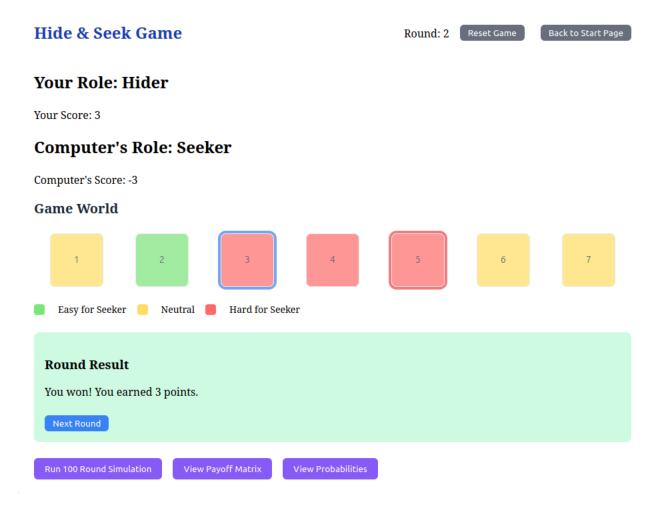
# → Payoff matrix :

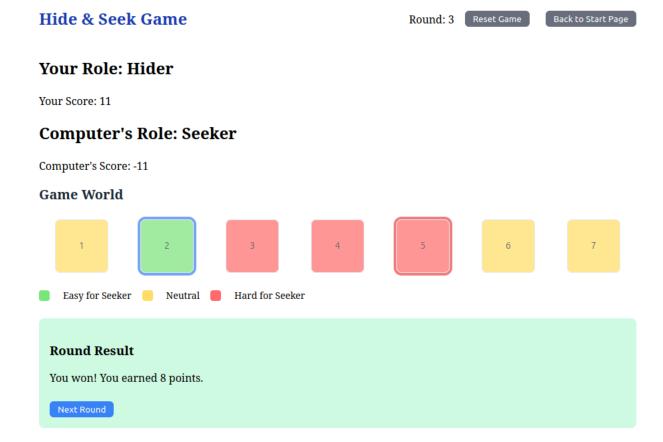
	Payoff Matrix										
	<b>C1</b>	C2	С3	C4	C5	C6	С7				
R1	-1	0.5	0.75	1	1	1	1				
R2	1	-1	1	1.5	2	2	2				
R3	0.75	0.5	-3	0.5	0.75	1	1				
R4	1	0.75	0.5	-3	0.5	0.75	1				
R5	1	1	0.75	0.5	-3	0.5	0.75				
R6	1	1	1	0.75	0.5	-1	0.5				
R7	1	1	1	1	0.75	0.5	-1				

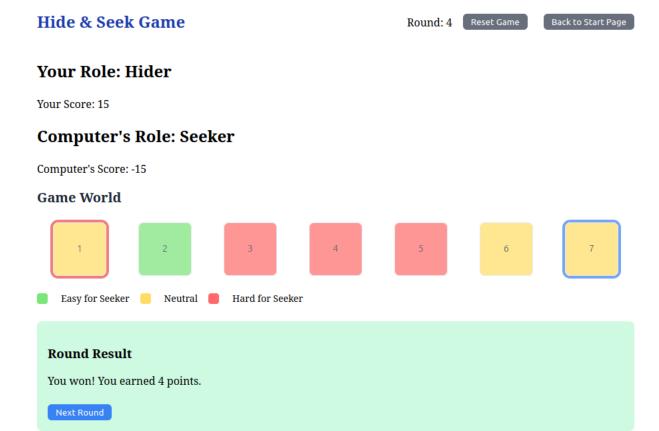
# → Probabilities for every cell :

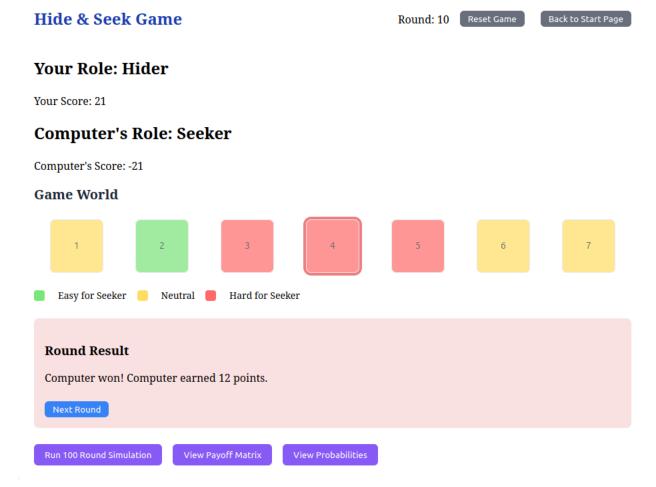
Computer Probabilities	
P1	0.203448
P2	0.131605
Р3	0.077139
P4	0.090710
Р5	0.085630
Р6	0.191039
Р7	0.220429

#### → Some choices with scores :





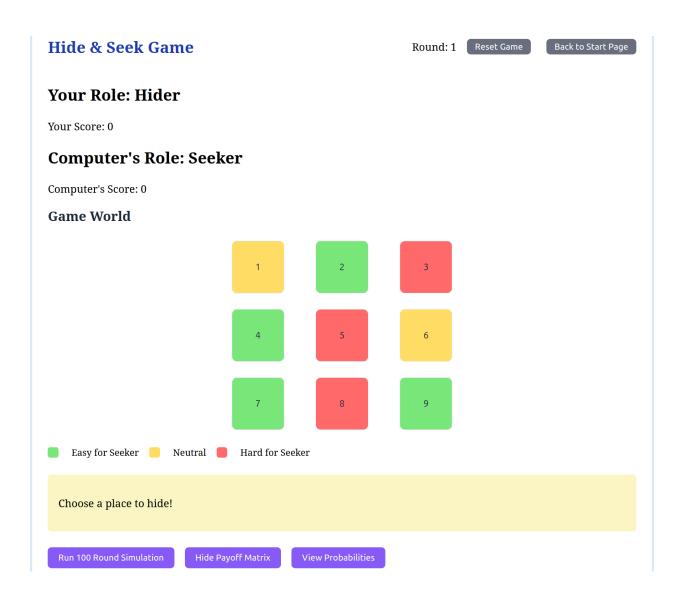




### • Test 2 :

This test for 2D grid and Hider player, Seeker computer

→ Grid shape and difficulties :



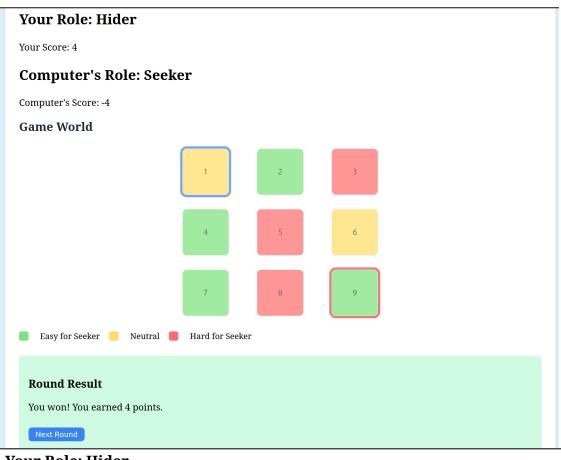
# → Payoff matrix :

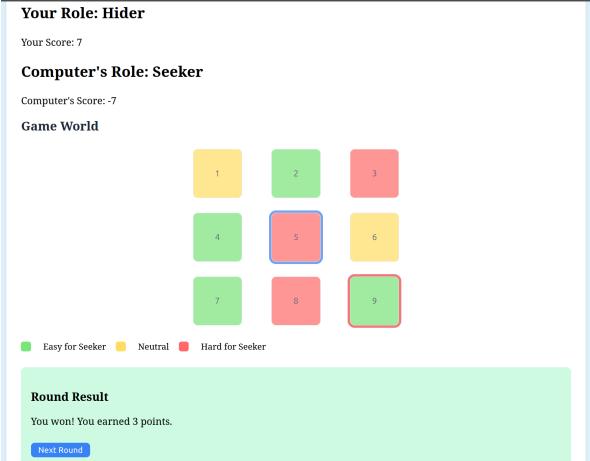
Payoff Matrix											
	<b>C1</b>	C2	С3	<b>C4</b>	<b>C</b> 5	C6	<b>C7</b>	C8	С9		
R1	-1	0.5	0.75	0.5	0.75	1	0.75	1	1		
R2	1	-1	1	1.5	1	1.5	2	1.5	2		
R3	0.75	0.5	-3	1	0.75	0.5	1	1	0.75		
R4	1	1.5	2	-1	1	1.5	1	1.5	2		
R5	0.75	0.5	0.75	0.5	-3	0.5	0.75	0.5	0.75		
R6	1	0.75	0.5	0.75	0.5	-1	1	0.75	0.5		
R7	1.5	2	2	1	1.5	2	-1	1	1.5		
R8	1	0.75	1	0.75	0.5	0.75	0.5	-3	0.5		
R9	2	2	1.5	2	1.5	1	1.5	1	-1		

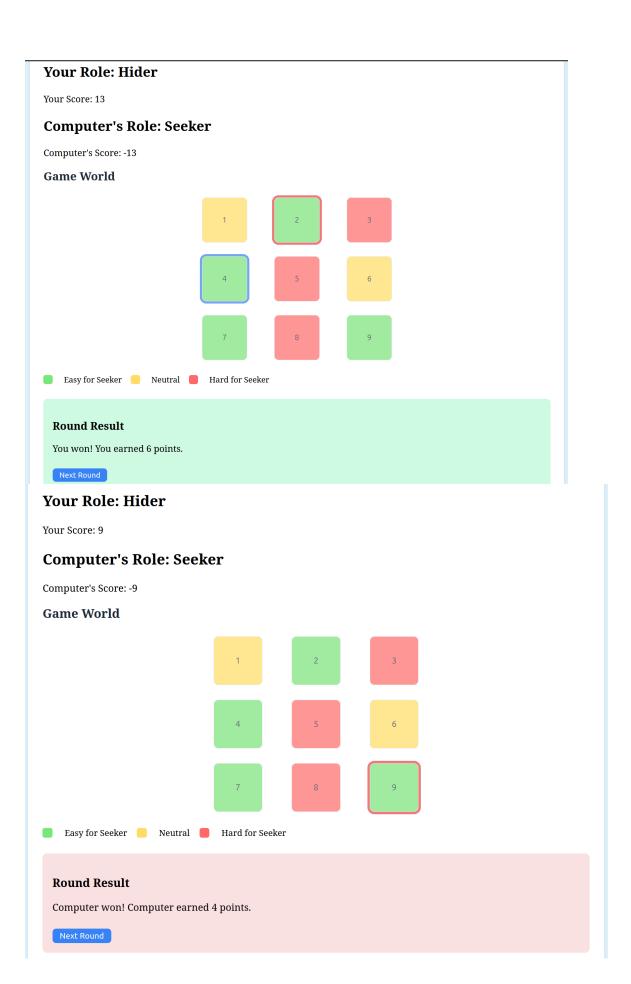
# → Probabilities for every cell :

Computer Probabilities	
P1	0
P2	0.291667
Р3	0
P4	0.208333
P5	0
P6	0
P7	0.208333
P8	0
Р9	0.291667

#### Some choices with scores:



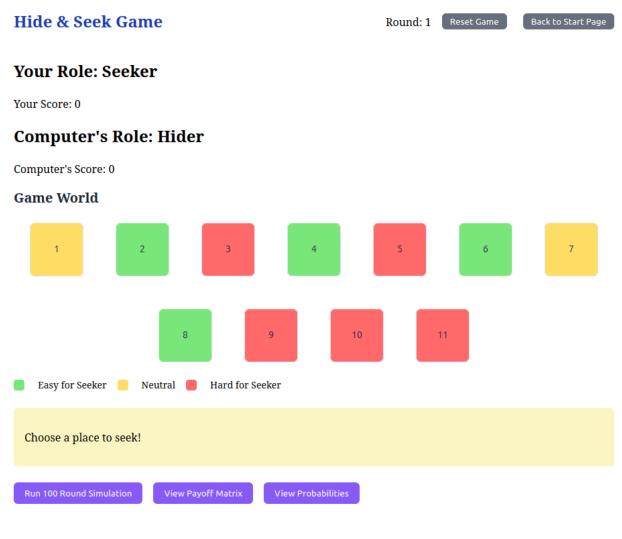




### • Test 3:

This test for linear grid (11 cells) and Seeker player, Hider computer

→ Grid shape and difficulties :



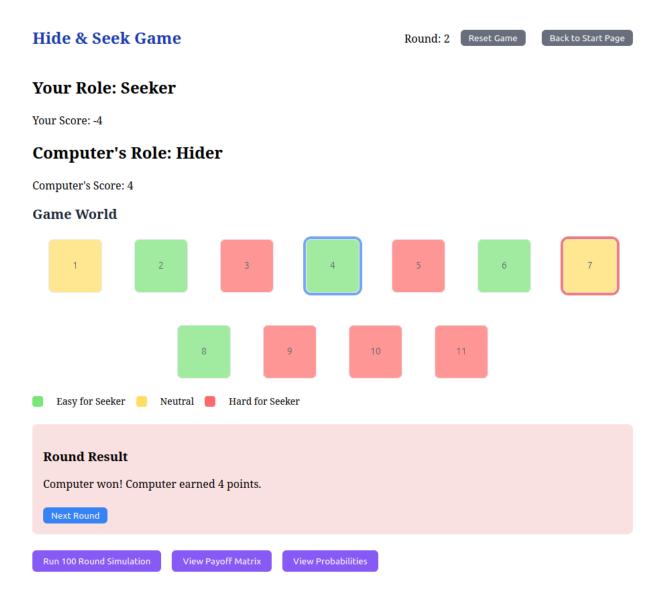
### → Payoff Matrix:

	Payoff Matrix											
	<b>C1</b>	<b>C2</b>	C3	<b>C4</b>	<b>C</b> 5	<b>C6</b>	<b>C7</b>	C8	<b>C</b> 9	C10	C11	
R1	-1	0.5	0.75	1	1	1	1	1	1	1	1	
R2	1	-1	1	1.5	2	2	2	2	2	2	2	
R3	0.75	0.5	-3	0.5	0.75	1	1	1	1	1	1	
R4	2	1.5	1	-1	1	1.5	2	2	2	2	2	
R5	1	1	0.75	0.5	-3	0.5	0.75	1	1	1	1	
R6	2	2	2	1.5	1	-1	1	1.5	2	2	2	
R7	1	1	1	1	0.75	0.5	-1	0.5	0.75	1	1	
R8	2	2	2	2	2	1.5	1	-1	1	1.5	2	
R9	1	1	1	1	1	1	0.75	0.5	-3	0.5	0.75	
R10	1	1	1	1	1	1	1	0.75	0.5	-3	0.5	
R11	1	1	1	1	1	1	1	1	0.75	0.5	-3	

# → Probabilities :

Computer Probabilities	
P1	0.059889
P2	0
Р3	0.390788
P4	0
P5	0.044161
P6	0
P7	0.390788
P8	0
P9	0.021263
P10	0.045796
P11	0.047315

#### → some choices with scores :



Round: 4 Reset Game

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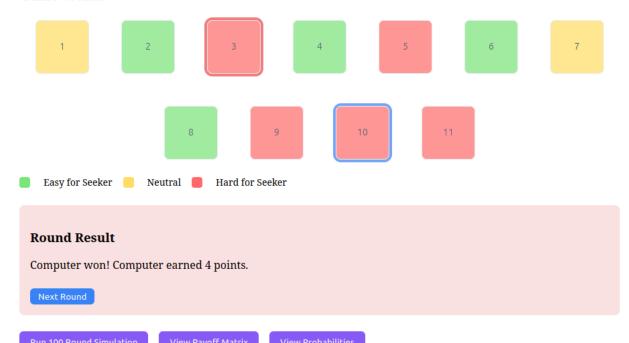
### Your Role: Seeker

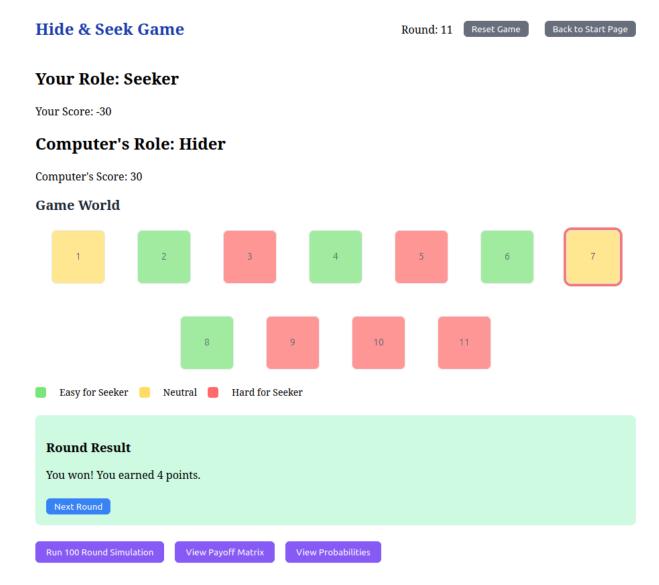
Your Score: -12

# Computer's Role: Hider

Computer's Score: 12

#### **Game World**





### • Test 4:

This test for 2D grid (5x5) and Hider computer, Seeker player

→ Grid shape and difficulties :

Round: 1 Reset Game

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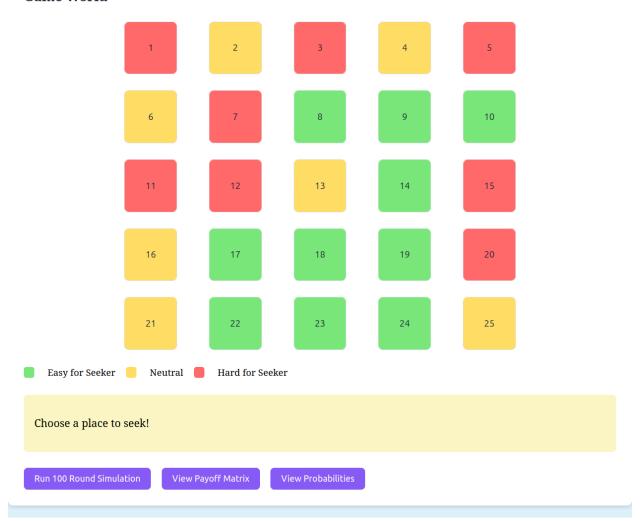
Your Role: Seeker

Your Score: 0

Computer's Role: Hider

Computer's Score: 0

#### **Game World**



# → Payoff Matrix :

С3	C4	C5	C6	<b>C7</b>	<b>C8</b>	<b>C</b> 9	C10	C11	C12	C13	C14	C15	C16	C17	C18
0.75	1	1	0.5	0.75	1	1	1	0.75	1	1	1	1	1	1	1
0.5	0.75	1	0.75	0.5	0.75	1	1	1	0.75	1	1	1	1	1	1
-3	0.5	0.75	1	0.75	0.5	0.75	1	1	1	0.75	1	1	1	1	1
0.5	-1	0.5	1	1	0.75	0.5	0.75	1	1	1	0.75	1	1	1	1
0.75	0.5	-3	1	1	1	0.75	0.5	1	1	1	1	0.75	1	1	1
1	1	1	-1	0.5	0.75	1	1	0.5	0.75	1	1	1	0.75	1	1
0.75	1	1	0.5	-3	0.5	0.75	1	0.75	0.5	0.75	1	1	1	0.75	1
1	1.5	2	1.5	1	-1	1	1.5	2	1.5	1	1.5	2	2	2	1.5
1.5	1	1.5	2	1.5	1	-1	1	2	2	1.5	1	1.5	2	2	2
2	1.5	1	2	2	1.5	1	-1	2	2	2	1.5	1	2	2	2
1	1	1	0.5	0.75	1	1	1	-3	0.5	0.75	1	1	0.5	0.75	1
1	1	1	0.75	0.5	0.75	1	1	0.5	-3	0.5	0.75	1	0.75	0.5	0.75
0.75	1	1	1	0.75	0.5	0.75	1	0.75	0.5	-1	0.5	0.75	1	0.75	0.5
2	1.5	2	2	2	1.5	1	1.5	2	1.5	1	-1	1	2	2	1.5
1	1	0.75	1	1	1	0.75	0.5	1	1	0.75	0.5	-3	1	1	1
1	1	1	0.75	1	1	1	1	0.5	0.75	1	1	1	-1	0.5	0.75
2	2	2	2	1.5	2	2	2	1.5	1	1.5	2	2	1	-1	1
2	2	2	2	2	1.5	2	2	2	1.5	1	1.5	2	1.5	1	-1
2	2	2	2	2	2	1.5	2	2	2	1.5	1	1.5	2	1.5	1
1	1	1	1	1	1	1	0.75	1	1	1	0.75	0.5	1	1	0.75
1	1	1	1	1	1	1	1	0.75	1	1	1	1	0.5	0.75	1
2	2	2	2	2	2	2	2	2	1.5	2	2	2	1.5	1	1.5
2	2	2	2	2	2	2	2	2	2	1.5	2	2	2	1.5	1
2	2	2	2	2	2	2	2	2	2	2	1.5	2	2	2	1.5
1	1	1	1	1	1	1	1	1	1	1	1	0.75	1	1	1

# → Probabilities :

Computer Probabilities	
P1	0.021135
P2	0.021614
Р3	0
P4	0.127504
P5	0.025565
P6	0.039829
P7	0.003374
P8	0
Р9	0
P10	0
P11	0
P12	0.075153
P13	0.116103
P14	0
P15	0.064362
P16	0
P17	0
P18	0
P19	0
P20	0.157053
P21	0.194630
P22	0
P23	0
P24	0
P25	0.153679

### → some choices :

Round: 2 Reset Game

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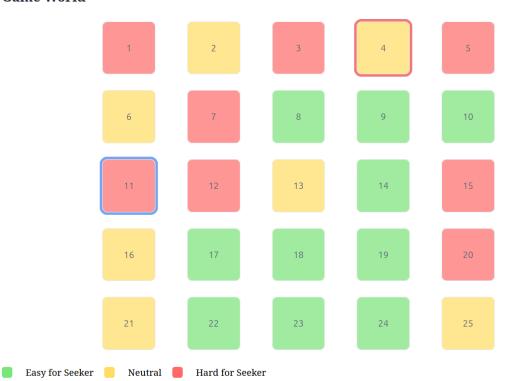
Your Role: Seeker

Your Score: -4

Computer's Role: Hider

Computer's Score: 4

#### **Game World**



#### **Round Result**

Computer won! Computer earned 4 points.

Next Round

Round: 3 Reset Game

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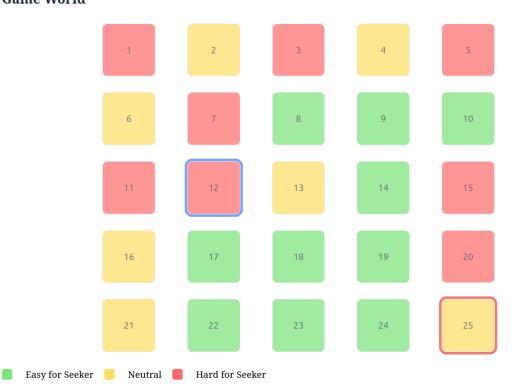
Your Role: Seeker

Your Score: -8

Computer's Role: Hider

Computer's Score: 8

#### **Game World**



#### **Round Result**

Computer won! Computer earned 4 points.

Next Round

Round: 5 Reset Game

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Your Role: Seeker

Your Score: -8

Computer's Role: Hider

Computer's Score: 8

#### **Game World**



#### **Round Result**

You won! You earned 4 points.

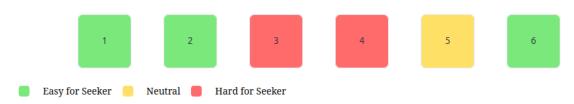
Next Round

### • Test 5:

This test for Simulation linear grid (6 cells) and  $\underline{\text{Seeker}}$  player ,  $\underline{\text{Hider}}$  computer

# → Grid shape and difficulties :

#### **Game World**



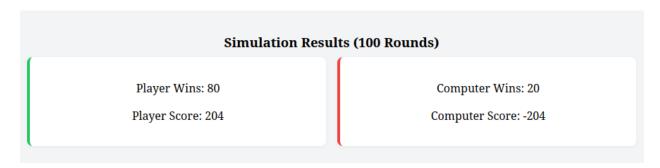
### → Payoff Matrix :

	Payoff Matrix									
	C1	C2	С3	C4	C5	C6				
R1	-1	1	1.5	2	2	2				
R2	1	-1	1	1.5	2	2				
R3	0.75	0.5	-3	0.5	0.75	1				
R4	1	0.75	0.5	-3	0.5	0.75				
R5	1	1	0.75	0.5	-1	0.5				
R6	2	2	2	1.5	1	-1				

### → Probabilities :

Hider Probabilities (Simulation)								
P1	0.258760							
P2	0.235849							
Р3	0							
P4	0.183288							
P5	0							
Р6	0.322102							
Seeker Probabilities (Simula	tion)							
P1	0.088710							
P2	0							
Р3	0.709677							
P4	0							
Р5	0.064516							
Р6	0.137097							

### → results of simulation :



And if you want to see Rounds details , we showed all rounds like :

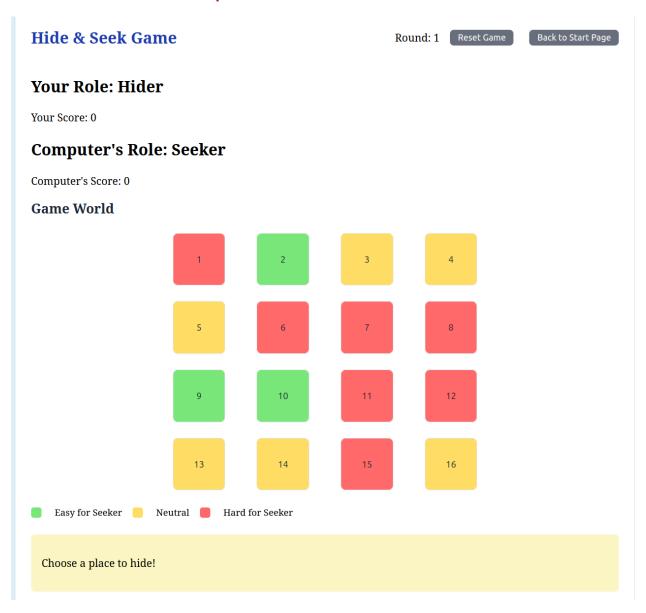
Rounds Deta	ils				
Round	Winner	Hider Move	Seeker Move	Hider Score	Seeker Score
1	player	3	2	2	-2
2	player	0	5	8	-8
3	player	0	2	6	-6
4	player	3	2	2	-2
5	player	1	2	4	-4
6	player	5	2	8	-8
7	player	0	5	8	-8
8	player	0	2	6	-6
9	player	1	2	4	-4
10	player	1	2	4	-4
11	player	1	0	4	-4
12	player	3	2	2	-2
13	player	1	2	4	-4
14	player	1	2	4	-4
15	player	1	2	4	-4
16	player	0	2	6	-6
17	player	5	2	8	-8
18	player	0	5	8	-8
19	player	3	2	2	-2
20	player	1	5	8	-8

And all rounds like this....

### • Test 6:

This test for Simulation 2D grid (4x4) and Seeker computer, Hider player

→ Grid shape and difficulties :



### → Payoff Matrix :

						Pa	yoff M	Iatrix							
	<b>C1</b>	C2	C3	C4	C5	C6	С7	C8	С9	C10	C11	C12	C13	C14	<b>C1</b>
R1	-3	0.5	0.75	1	0.5	0.75	1	1	0.75	1	1	1	1	1	1
R2	1	-1	1	1.5	1.5	1	1.5	2	2	1.5	2	2	2	2	2
R3	0.75	0.5	-1	0.5	1	0.75	0.5	0.75	1	1	0.75	1	1	1	1
R4	1	0.75	0.5	-1	1	1	0.75	0.5	1	1	1	0.75	1	1	1
R5	0.5	0.75	1	1	-1	0.5	0.75	1	0.5	0.75	1	1	0.75	1	1
R6	0.75	0.5	0.75	1	0.5	-3	0.5	0.75	0.75	0.5	0.75	1	1	0.75	1
<b>R7</b>	1	0.75	0.5	0.75	0.75	0.5	-3	0.5	1	0.75	0.5	0.75	1	1	0.7
R8	1	1	0.75	0.5	1	0.75	0.5	-3	1	1	0.75	0.5	1	1	1
R9	1.5	2	2	2	1	1.5	2	2	-1	1	1.5	2	1	1.5	2
R10	2	1.5	2	2	1.5	1	1.5	2	1	-1	1	1.5	1.5	1	1.
R11	1	1	0.75	1	1	0.75	0.5	0.75	0.75	0.5	-3	0.5	1	0.75	0.
R12	1	1	1	0.75	1	1	0.75	0.5	1	0.75	0.5	-3	1	1	0.7
R13	1	1	1	1	0.75	1	1	1	0.5	0.75	1	1	-1	0.5	0.7
R14	1	1	1	1	1	0.75	1	1	0.75	0.5	0.75	1	0.5	-1	0.
R15	1	1	1	1	1	1	0.75	1	1	0.75	0.5	0.75	0.75	0.5	-3
R16	1	1	1	1	1	1	1	0.75	1	1	0.75	0.5	1	0.75	0.

# → Probabilities :

Hider Probabilities (Simulation)					
P1	0				
P2	0.139632				
Р3	0				
P4	0.191783				
P5	0				
P6	0				
P7	0				
P8	0.082821				
Р9	0.141047				
P10	0.087407				
P11	0				
P12	0.063012				
P13	0				
P14	0				
P15	0.086840				

# Seeker Probabilities (Simulation)

P1	0.010818
P2	0
Р3	0.061352
P4	0.098745
P5	0.253227
P6	0.244576
P7	0
P8	0.018233
Р9	0
P9 P10	0
P10	0
P10 P11	<b>0</b> 0.023529
P10 P11 P12	0 0.023529 0.036334
P10 P11 P12 P13	0 0.023529 0.036334 0.074617
P10 P11 P12 P13 P14	0 0.023529 0.036334 0.074617 0.050851

→ result of simulation :

# Simulation Results (100 Rounds)

Player Wins: 89

Player Score: 324

Computer Wins: 11

Computer Score: -324

#### **Rounds Details**

Round	Winner	Hider Move	Seeker Move	Hider Score	Seeker Score
1	player	1	5	4	-4
2	player	8	4	4	-4
3	player	1	3	6	-6
4	player	1	5	4	-4
5	player	1	13	8	-8
6	player	3	4	4	-4
7	player	1	4	6	-6
8	player	3	5	4	-4
9	player	11	4	4	-4
10	player	15	4	4	-4
11	computer	3	3	-4	4
12	player	9	5	4	-4
13	player	3	12	4	-4
14	player	1	4	6	-6
15	computer	15	15	-4	4
16	player	15	12	4	-4
17	computer	3	3	-4	4
18	player	3	13	4	-4
19	player	1	3	6	-6
20	player	15	11	2	-2
21	player	3	5	4	-4
22	computer	11	11	-12	12
23	computer	11	11	-12	12

# Bonus Requirements:

To further enhance the strategic depth and realism of the game, two optional bonus features were implemented and tested:

#### 1. Proximity:

To make the game more dynamic and fairer, a proximity-based scoring system was introduced. This system penalizes the hider based on how close the seeker's chosen position is to their hiding spot. Specifically:

- If the seeker's choice is 1 cell away, the hider's score is multiplied by 0.5.
- If the seeker is 2 cells away, the hider's score is multiplied by 0.75.
- If the seeker is farther than 2 cells, the hider's score remains unchanged.

Our implementation to handle it:

```
def _adjust_nearby_payoffs(self, matrix, position, base_value):
    """Helper method to adjust payoffs for nearby positions."""
    # Adjust +/-1 positions
    if position + 1 < self.world_size:
        matrix[position][position + 1] = base_value * 0.5
    if position - 1 >= 0:
        matrix[position][position - 1] = base_value * 0.5

# Adjust +/-2 positions
    if position + 2 < self.world_size:
        matrix[position][position + 2] = base_value * 0.75
    if position - 2 >= 0:
        matrix[position][position - 2] = base_value * 0.75
```

This modification encouraged more careful decision-making by the hider and made the seeking process more rewarding and challenging.

#### 2. 2D array:

We add in welcome page when the User want to add the grid size, we add 2 choices:

- 1. Linear grid
- 2. 2D grid

This allowed for more intricate hide-and-seek dynamics, especially when applying proximity scoring in two dimensions. Movement and payoff calculations were adapted accordingly, and visualization was updated to reflect the new grid-based interface.

These bonus features added an extra layer of engagement and analytical depth to the game, demonstrating the versatility of game-theoretic models when combined with algorithmic strategies and user-centered design.

# **♦** Assumptions:

### 1. Reset Button:

**Hide & Seek Game** 

Round: 1 Reset Game Back to Start Page

will reset the difficulty level of each cell which will change the payoff matrix causing the probabilities to change but the size of the grid has <u>not changed</u>.

#### 2. Scores calculation:

we assume that the scoring unit is 4 to eliminate the fractions of proximity so:

- in hard place for seeker
  - catching a hider will bring to the seeker 4\*3 = 12
     points
  - failing in catching the hider will bring to him 4\*1 = 4
     points
- in neutral place for seeker
  - catching a hider will bring to the seeker 4\*1 = 4 points
  - failing in catching the hider will bring to him 4\*1 = 4 points
- in easy place for seeker
  - catching a hider will bring to the seeker 4\*1 = 4 points
  - failing in catching the hider will bring to him 4\*2 = 8
     points

### 3. Back to Start page:

**Hide & Seek Game** 

Round: 1 Reset Game Back to Start Page

this will make everything null and return you to the welcome page to start a new game with a new grid.

### Conclusion:

In this lab, we successfully implemented a Hide and Seek game grounded in game theory principles and linear programming strategies. By modeling the interaction between the hider and seeker using a payoff matrix, we analyzed optimal strategies and applied the simplex method to solve for the computer's decisions. The game dynamically adapts to a linear world of size N, with various place types influencing scoring, and includes both interactive and simulation models for comprehensive testing. Additional features such as proximity scoring and a 2D grid layout were explored to enhance realism and strategic complexity. This assignment reinforced our understanding of zero-sum games, optimization techniques, and the practical application of operations research in game-based scenarios.