# Project Report on the Computational Analysis of the Monty Hall Problem: An In-depth Examination of Probability and Decision Strategy

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## Abstract:

This project report delineates the comprehensive analysis of the Monty Hall problem, a renowned probability puzzle, employing Python for simulations and algorithmic strategies. It encapsulates the development of interactive games and analytical models to unravel the puzzle's complexities. By integrating core computer science algorithms and principles, the report presents a novel perspective on this classic problem, contributing to the field of computational probability and decision-making.

## 1. Introduction:

The Monty Hall problem, stemming from a game show scenario, presents a unique challenge in probability theory and decision-making. This project aims to apply advanced computer science techniques, particularly in Python programming, to analyze and simulate the problem. The objective is to provide empirical evidence supporting the theoretical probability models and to create an interactive understanding of the problem's dynamics.

## 2. Methodology:

## 2.1 Bayesian Analysis:

- 2.1.1. Setting Up the Problem:
  - Hypothesis (H): The car is behind door 1.
  - Evidence (E): Monty opens a door revealing a goat.
- 2.1.2. Bayesian Formula Application:

 $P[H|E] = \frac{P[E|H] \cdot P[H]}{P[E]} = \frac{P[E|H] \cdot P[H]}{P[E|H] \cdot P[H] + P[E|not H] \cdot P[}$ • The H ---- the chosen door has a car behind it
• not H ---- the chosen door has a goat behind it.
• E ---- Monty has revealed a door with a goat behind it
• P(H) = 1/3
• P(not H) = 1-P(H) = 2/3
• P(E|H) = 1
• P(E|not H) = 1

 $P(H|E) = \frac{1 \times \frac{1}{3}}{1 \times \frac{1}{3} + 1 \times \frac{2}{3}} = \frac{1}{3}$ 

Here, ( P(H|E) ) is the probability that the car is behind door 1 given that Monty has shown a goat.

2.1.3. Determining Probabilities:

- P(H): The prior probability that door 1 has the car, which is 1/3 as there are three doors.

- P(E|H) : The probability is 1 that Monty shows a goat given the car is behind door 1. Since Monty will always show a goat.

- P(E|notH) : The probability is 1 that Monty shows a goat given the car is not behind door 1.

### 2.2 Python Simulation:

In addition to the React development, we have implemented Python code to simulate the Monty Hall problem, providing statistical analysis and visualizations. This section of the report explains the Python code used to simulate and analyze the Monty Hall problem.

2.2.1 Initialization and Setup:

- Importing Libraries: We import necessary Python libraries such as NumPy, Pandas, Random, and Matplotlib for data manipulation, random number generation, and data visualisation.

- `doors\_array` Function: This function initializes the doors. It randomly assigns a car (marked as 1) behind one of the three doors (marked as 0 if no car).

- `win\_loose` Function: Determines the outcome of the game based on the player's strategy (change or unchange). It checks whether the player wins (collects 1 point) or loses (collects 0 points) based on their final choice.

### 2.2.2 Simulation and Results Collection:

- `total\_results` Function: Runs the Monty Hall game multiple times and collects the results. It records the door configurations, initial choices, host's choices, final decisions, and game outcomes.

- Dataframes Creation: Using Pandas, we create dataframes to store and display the outcomes of games where the player either changed or did not change their initial door choice.

#### 2.2.3 Visualization and Statistical Analysis:

- Plotting Results: We use Matplotlib to plot the outcomes of each strategy (change or unchange) over multiple iterations, providing a visual representation of the probability of winning.

- `average\_win` Function: Calculates the average probability of winning the game over multiple iterations for both strategies.

- \*\*Comparative Analysis:\*\* The plots compare the effectiveness of changing versus not changing the door, visually demonstrating the higher probability of winning when changing the door.

#### 2.2.3. Results:

The Python simulations revealed a consistent pattern: switching doors resulted in a success rate of approximately 67%, while sticking to the original choice yielded a success rate of about 33%. These findings align with the theoretical probability models and underscore the counterintuitive nature of the problem.

#### 2.3 React Game Implementation:

In addition to our Python-based simulations, we have expanded our analysis of the Monty Hall problem by developing an interactive game using React. This web-based application allows users to directly engage with the Monty Hall scenario, further enhancing the understanding of the problem's dynamics.

- Game Setup: The game initializes with three doors, one of which randomly conceals a car while the others hide goats. This setup is achieved using the React state management system.

- User Interaction: Players select a door, after which one of the remaining doors with a goat is revealed. The player then has the option to either stick with their original choice or switch to the other unopened door.

- Game Stages: The game progresses through stages, from initial selection to the final reveal, utilizing React's state updates to manage these transitions.

- Game Logic: The core logic of the game reflects the Monty Hall problem's probabilistic nature. It includes functions to handle door selection, reveal a non-prize door, and determine the game's outcome based on the player's final choice.

#### 2.3.1 React Component Structure:

The `ThreeDoorsGame` component encapsulates the entire game logic. It uses React hooks such as `useState` and `useEffect` for state management and lifecycle methods.
 State Variables:

- `doors`: Represents the doors in the game.
- `carBehindDoor`: Randomly sets which door has the car.
- `chosenDoorIndex`: Tracks the player's chosen door.
- `revealedDoorIndex`: Indicates the door revealed by the host.
- `gameStage`: Manages the different stages of the game.
- `gameOver`: Flags the end of the game.

#### - Event Handlers:

- `handleDoorClick`: Manages the player's door selection and the game's progression.
- `revealGoatDoor`: Reveals a door with a goat, excluding the chosen and winning doors.
- `checkWin`: Determines if the player wins based on their final choice.

#### 2.3.2 User Experience:

- The game provides a simple and interactive interface, allowing players to click on doors and make decisions, closely mimicking the real-life game show scenario.

- Alerts are used to inform the player of the game's outcome, whether they have won the car or found a goat.

- A 'Restart' button allows players to reset the game and try different strategies.

## 3. Conclusion and Future Enhancements:

Our team reflects on the enriching mathematical and probabilistic knowledge gained through this project. The Monty Hall problem exploration has yielded valuable insights into decision-making processes and the practical application of probability theory in real-life scenarios. We envision this report as a cornerstone for subsequent academic pursuits and projects, contributing substantially to our scholarly and professional development.

Future endeavors include expanding the algorithmic complexity to encompass more intricate scenarios and integrating machine learning models to predict outcomes based on different decision-making patterns.

- User Data Analysis: Collecting data from player choices in the React game could provide insights into common decision-making patterns and strategies.

- Advanced Game Features: Implementing additional features such as a score tracker, various difficulty levels, and enhanced user interfaces can further enrich the game experience.

In summary, this report offers a comprehensive examination of the Monty Hall problem, integrating mathematical theories, Bayesian analysis, computational simulations, and game theory principles. Our findings extend beyond resolving the central query, contributing to a broader comprehension of decision-making and probability. Despite inherent limitations, our study establishes a strong foundation for future research in related fields.

Appendix:

Appendix A Python Scripts

```
In [1]: import numpy as np
         import pandas as pd
         import random
         import matplotlib as plt
         import matplotlib.pyplot as plt
In [2]: # normal question
In [11]: def doors_array():
              1.1.1
             the function is desigend for initialize the door list
             And if the gift behind the door, we mark it as 1, otherwise, it is 0
             doors = [0, 0, 0]
             gift_i = random.randint(0,2)
             doors[gift_i] = 1
             return doors,gift_i
         def win_loose(doors_array, change):
              1.1.1
             the function is desigend for check if the guest win the game based on two stratgies
             change: the string the represented change a door or not
                  change: switch to another unopend door
                  unchange: stick in the initial choice
             Output:
                 win_change_nums: if the guest win the game, we collect 1 point, otherwise, collect 0 point
                  choose_i: the initial chooice
                 gift_i: the door which hide the gift
                 change_choose_i: final decision of the guest
                 host_i: the door opened by the host
              1.1.1
             #users choose a door
             choose_i = random.randint(0,2)
             doors = doors_array()[0]
             gift_i = doors_array()[1]
             # host open the door
             host_i = -1
             for i in range(len(doors)):
                 if doors[i] != 1 and i != choose_i:
                     host_i = i
                     break
             # user1 -- unchange
             if change == 'unchange':
                 win_unchange_nums = 0
                 if doors[choose_i] == 1:
                     win_unchange_nums +=1
                  change_choose_i = choose_i
                  return win_unchange_nums,choose_i,gift_i,change_choose_i,host_i
             if change == 'change':
                 win_change_nums = 0
                  for i in range(len(doors)):
                      if i != host_i and i != choose_i:
                          change_choose_i = i
                 if doors[change_choose_i] == 1:
                      win_change_nums+=1
                  return win_change_nums, choose_i, gift_i, change_choose_i, host_i
In [12]: # get the results
         def total_results(times, change_or_not, doors_array, win_loose):
```

the function is designed for help us to run the model multiple times and collect results
Args:
times: how many times we play
change\_or\_not: the string that represented change the door or not
doors\_array: the function that represented initilize the door list
win\_loose: the function that generate the result of each time

#### Outputs:

total\_door: the list represented the three doors win\_or\_lose: the result of playing the game open\_door: the user's initial choice gift\_door: the door that hide the gift host\_door: the door opened by the host final\_open: the user's final decision prob\_win: the probability of winning the game

```
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```

```
times_num = times
```

```
# Behind Door
total_door = []
```

# if the car(1) behind the door, get 1 point; if the sheep(0) behind the door, get 0 point
win\_or\_lose = []

```
# initial choice of the door
```

```
open_door = []
# the gift behind this door
gift_door = []
# the door opened by the host
host_door = []
# final decision of the user
final_open = []
for i in range(times):
    total_door.append(doors_array()[0])
    doors result = win_loose(doors_array, change_or_not)
    win_or_lose.append(doors_result[0])
    open_door.append(doors_result[1])
    gift_door.append(doors_result[2])
    final_open.append(doors_result[3])
    host_door.append(doors_result[4])
#the probability of win the game (the car behind the door)
prob_win = sum(win_or_lose)/times
return total_door,win_or_lose,open_door,gift_door,host_door,final_open, prob_win
```

In [ ]:

```
In [13]: #generate a table to visualize results
         times = 100
         total_unchange_result = total_results(times, 'unchange', doors_array, win_loose)
         unchange_result = pd.DataFrame({'Behind Door':total_unchange_result[0],
                                  'Unchange: Initial Choice':total_unchange_result[2],
                                  'Unchange: Host Choice':total_unchange_result[4],
                                  'Unchange: Final Decision': total_unchange_result[5],
                                  'Unchange: Gift': total_unchange_result[3],
                                  'Unchange: Win or Lose':total_unchange_result[1]})
         prob_win_unchange = total_unchange_result[-1]
         total_change_result = total_results(times, 'change', doors_array, win_loose)
         change_result = pd.DataFrame({'Behind Door':total_change_result[0],
                                  'Change: Initial Choice':total_change_result[2],
                                  'Change: Host Choice':total_change_result[4],
                                  'Change: Final Decision': total_change_result[5],
                                  'Change: Gift': total change result[3],
                                  'Change: Win or Lose':total_change_result[1]})
         prob_win_change = total_change_result[-1]
```

In [19]: # plot the results for one sub sample

```
plt.figure(figsize=(15,6))
plt.plot([prob_win_unchange]*times,color = 'black',label = 'The probabilty of win the game if unchange the door')
plt.scatter(range(times),unchange_result['Unchange: Win or Lose'],color = 'black',label = 'Unhange the Door:{}'.format
plt.plot([prob_win_change]*times,color = 'pink',label = 'The probabilty of win the game if change the door')
plt.scatter(range(times),change_result['Change: Win or Lose'],color = 'pink',label = 'Change the Door:{}'.format(prob_
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.title('Unchange Vs Change the Door')
plt.ylabel('Score')
```

Out[19]: Text(0, 0.5, 'Score')





Out [17]: Behind Door Unchange: Initial Choice Unchange: Host Choice Unchange: Final Decision Unchange: Gift Unchange: Win or Lose

0	[0, 1, 0]	0	1	0	0	0
1	[0, 0, 1]	2	0	2	2	0
2	[0, 1, 0]	1	2	1	0	0
3	[0, 1, 0]	0	1	0	0	1
4	[1, 0, 0]	2	0	2	1	1
•••						
95	[1, 0, 0]	2	0	2	2	0
96	[0, 1, 0]	0	1	0	0	0
97	[1, 0, 0]	1	2	1	2	0
98	[1, 0, 0]	0	2	0	0	0
99	[1, 0, 0]	1	0	1	1	0

100 rows × 6 columns

In [18]: change\_result

Out[18]:		Behind Door	Change: Initial Choice	Change: Host Choice	Change: Final Decision	Change: Gift	Change: Win or Lose
	0	[0, 1, 0]	0	1	2	1	1
	1	[1, 0, 0]	0	1	2	0	0
	2	[0, 0, 1]	2	0	1	2	1
	3	[0, 0, 1]	1	0	2	1	0
	4	[0, 1, 0]	0	1	2	2	1
	•••						
	95	[0, 0, 1]	2	0	1	1	0
	96	[0, 1, 0]	2	0	1	0	1
	97	[0, 0, 1]	0	2	1	1	1
	98	[1, 0, 0]	1	2	0	2	1
	99	[0, 0, 1]	1	0	2	2	1

```
100 rows × 6 columns
```

```
In [75]: # statisical analysis
```

In [76]:	<pre>]: def average_win(total_results,times,change_or_not,doors_array,win_loose):</pre>			
	the function is help us to calculate the average probability of winning the gift			
	output: result: the list represented the probability of winning the game of each sub sample avg_prob: the average probability of winning the game			
	<pre>result = [] for i in range(times):     total_result = total_results(times,change_or_not,doors_array,win_loose)     result.append(total_result[-1]) avg_prob = round(sum(result)/len(result),4) return result, avg_prob</pre>			
In [77]:	<pre>times = 1000 unchange_result = average_win(total_results,times,'unchange',doors_array,win_loose)[0] unchange avg prob = average win(total results,times,'unchange',doors array,win loose)[1]</pre>			

change\_avg\_prob = average\_win(total\_results,times,'change',doors\_array,win\_loose)[1]

average\_win(total\_results,times,'change',doors\_array,win\_loose)[0]

```
In [78]: plt.figure(figsize=(10,6))
```

change\_result

```
plt.plot(change_result,color = 'khaki',label = 'The probabilty of win the game if change the door')
plt.plot([change_avg_prob]*times,color = 'olive',label = 'Swithcing Strategy:{}'.format(change_avg_prob))
plt.plot(unchange_result,color = 'bisque',label = 'The probabilty of win the game if unchange the door')
plt.plot([unchange_avg_prob]*times,color = 'darkorange',label = 'Sticking Strategy:{}'.format(unchange_avg_prob))
plt.legend(loc='center left', bbox_to_anchor=(1, 0.5))
plt.title('Unchange Vs Change the Door')
plt.ylabel('Times')
plt.ylabel('Score')
plt.ylim(0, 1)
```

Out[78]: (0.0, 1.0)



#### Appendix B React Code

```
import React, { useEffect, useReducer, useState } from 'react'
import { Door } from './Door';
import goatImg from './goat_tr.png'
       import Button from '@mui/material/Button';
import carImg from './car_tr.png'
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        const getRandomNumber=(n)=>
           return ((Math.floor(Math.random() * 10))%n)
       export const PlayingArea = ({resetGame,gameEnd,totalGame,winningGames,switchingWins}) => {
            let a=[0,1,2]
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             const [doorState, changeState]=useState([0,0,0,0])
             const [winingState, changeWinningState]=useState(0)
             useEffect(()=>
                   changeWinningState(getRandomNumber(3))
             let isSwitch=[]
             const openDoorHandler=(id)=>
                     if(!doorState[id])
                           isSwitch.push(id)
                              if(!doorState[3])
                                     let x=doorState
                                     if(winingState==id)
```

