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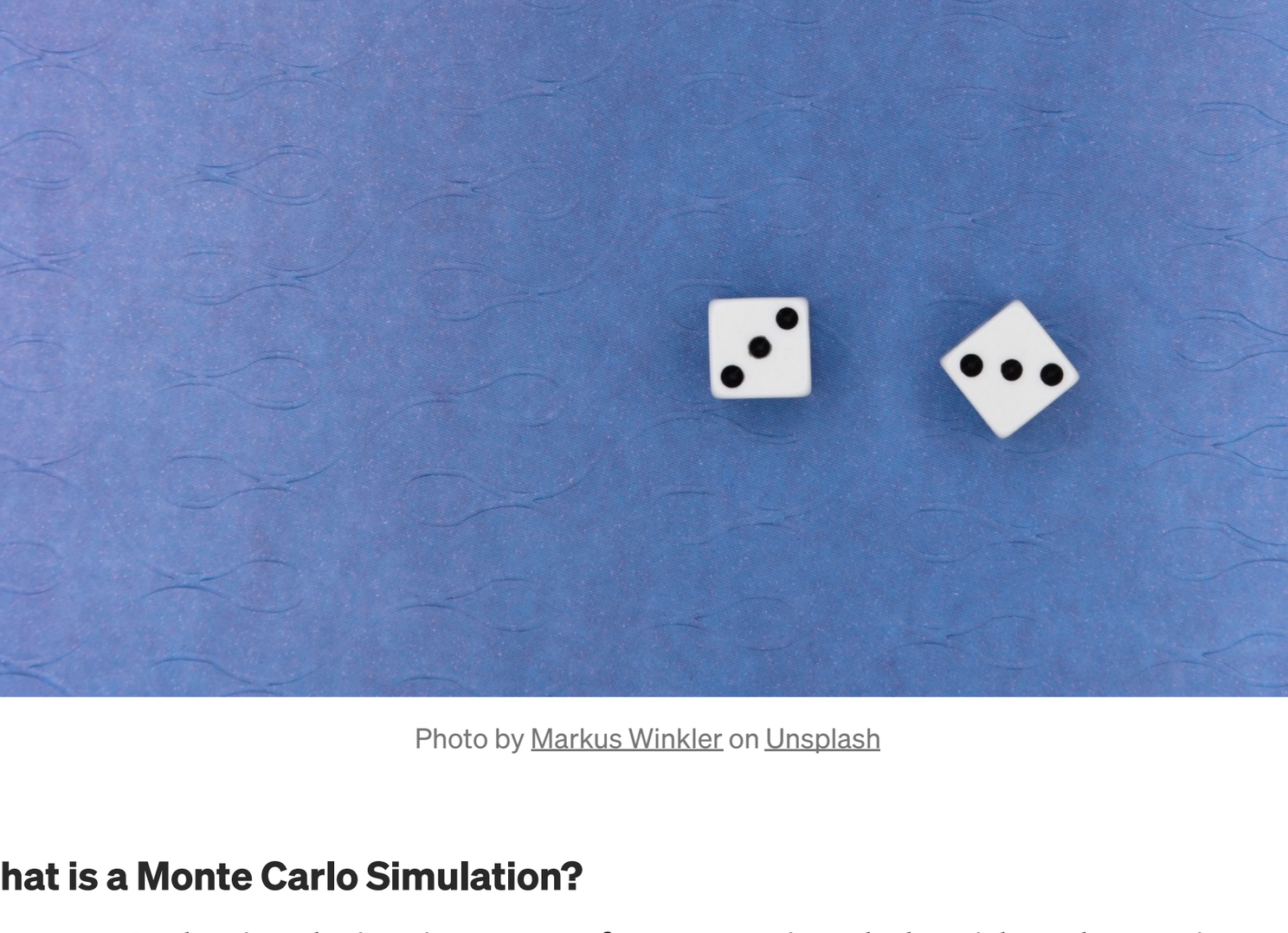
How to Create a Monte Carlo Simulation using Python

Walkthrough an example to learn what a Monte Carlo simulation is and how it can be used to predict probabilities



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What is a Monte Carlo Simulation?

A Monte Carlo simulation is a type of computational algorithm that estimates the probability of occurrence of an undeterminable event due to the involvement of random variables. The algorithm relies on repeated random sampling in an attempt to determine the probability. This means simulating an event with random inputs a large number of times to obtain your estimation. You can determine other factors as well, and we will see that in the example. Monte Carlo simulations can be utilized in a broad range of fields spanning from economics, gambling, engineering, energy, and anything in-between. So, no matter what career field you are in, it's an excellent thing to know about.

When learning how to build Monte Carlo simulations, it's best to start with a basic model to understand the fundamentals. The easiest and most common way to do that is with simple games, so we will make use of a dice game in this article. You've probably heard the saying, "the house always wins," so for this example, the house (typically a casino) will have an advantage, and we will show what that means for the player's possible earnings.

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The Dice Game

Our simple game will involve two six-sided dice. In order to win, the player needs to roll the same number on both dice. A six-sided die has six possible outcomes (1, 2, 3, 4, 5, and 6). With two dice, there is now 36 possible outcomes (1 and 1, 1 and 2, 1 and 3, etc., or 6 x 6 = 36 possibilities). In this game, the house has more opportunities to win (30 outcomes vs. the player's 6 outcomes), meaning the house has the quite the advantage.

Let's say our player starts with a balance of $1,000 and is prepared to lose it all, so they bet $1 on every roll (meaning both dice are rolled) and decide to play 1,000 rolls. Because the house is so generous, they offer to payout 4 times the player's bet when the player wins. For example, if the player wins the first roll, their balance increases by $4, and they end the round with a balance of $1,004. If they miraculously went on a 1,000 roll win-streak, they could go home with $5,000. If they lost every round, they could go home with nothing. Not a bad risk-reward ratio… or maybe it is.

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Importing Python Packages

Let's simulate our game to find out if the player made the right choice to play. We start our code by importing our necessary Python packages: *Pyplot* from *Matplotlib* and *random*. We will be using *Pyplot* for visualizing our results and *random* to simulate a normal six-sided dice roll.

```
# Importing Packages
import matplotlib.pyplot as plt
import random
```

Dice Roll Function

Next, we can define a function that will randomize an integer from 1 to 6 for both dice (simulating a roll). The function will also compare the two dice to see if they are the same. The function will return a Boolean variable, *same_num*, to store if the rolls are the same or not. We will use this value later to determine actions in our code.

```
# Creating Roll Dice Function
def roll_dice():
    die_1 = random.randint(1, 6)
    die_2 = random.randint(1, 6)

    # Determining if the dice are the same number
    if die_1 == die_2:
        same_num = True
    else:
        same_num = False
    return same_num
```

Inputs and Tracking Variables

Every Monte Carlo simulation will require you to know what your inputs are and what information you are looking to obtain. We already defined what our inputs are when we described the game. We said our number of rolls per game is 1,000, and the amount the player will be betting each roll is $1. In addition to our input variables, we need to define how many times we want to simulate the game. We can use the *num_simulations* variable as our Monte Carlo simulation count. The higher we make this number, the more accurate the predicted probability is to its true value.

The number of variables we can track usually scales with the complexity of a project, so nailing down what you want information on is important. For this example, we will track the win probability (wins per game divided by the total number of rolls) and ending balance for each simulation (or game). These are initialized as lists and will be updated at the end of each game.

```
# Inputs
num_simulations = 10000
max_num_rolls = 1000
bet = 1

# Tracking
win_probability = []
end_balance = []
```

Setting up Figure

The next step is setting up our figure before running through the simulation. By doing this prior to the simulation, it allows us to add lines to our figure after each game. Then, once we have run all of the simulations, we can display the plot to show our results.

```
# Creating Figure for Simulation Balances
fig = plt.figure()
plt.title("Monte Carlo Dice Game [" + str(num_simulations) + "
          simulations]")
plt.xlabel("Roll Number")
plt.ylabel("Balance [$]")
plt.xlim([0, max_num_rolls])
```

Monte Carlo Simulation

In the code below, we have an outer *for* loop that iterates through our pre-defined number of simulations (10,000 simulations) and a nested *while* loop that runs each game (1,000 rolls). Before we start each *while* loop, we initialize the player's balance as $1,000 (as a list for plotting purposes) and a count for rolls and wins.

Our *while* loop will simulate the game for 1,000 rolls. Inside this loop, we roll the dice and use the Boolean variable returned from *roll_dice()* to determine the outcome. If the dice are the same number, we add 4 times the bet to the *balance* list and add a win to the win count. If the dice are different, we subtract the bet from the *balance* list. At the end of each roll, we add a count to our *num_rolls* list.

Once the number of rolls hits 1,000, we can calculate the player's win probability as the number of wins divided by the total number of rolls. We can also store the ending balance for the completed game in the tracking variable *end_balance*. Finally, we can plot the *num_rolls* and *balance* variables to add a line to the figure we defined earlier.

```
# For loop to run for the number of simulations desired
for i in range(num_simulations):
    balance = [1000]
    num_rolls = [0]
    num_wins = 0

    # Run until the player has rolled 1,000 times
    while num_rolls[-1] < max_num_rolls:
        same = roll_dice()

        # Result if the dice are the same number
        if same:
            balance.append(balance[-1] + 4 * bet)
            num_wins += 1
        # Result if the dice are different numbers
        else:
            balance.append(balance[-1] - bet)

        num_rolls.append(num_rolls[-1] + 1)

# Store tracking variables and add line to figure
    win_probability.append(num_wins/num_rolls[-1])
    end_balance.append(balance[-1])
    plt.plot(num_rolls, balance)
```

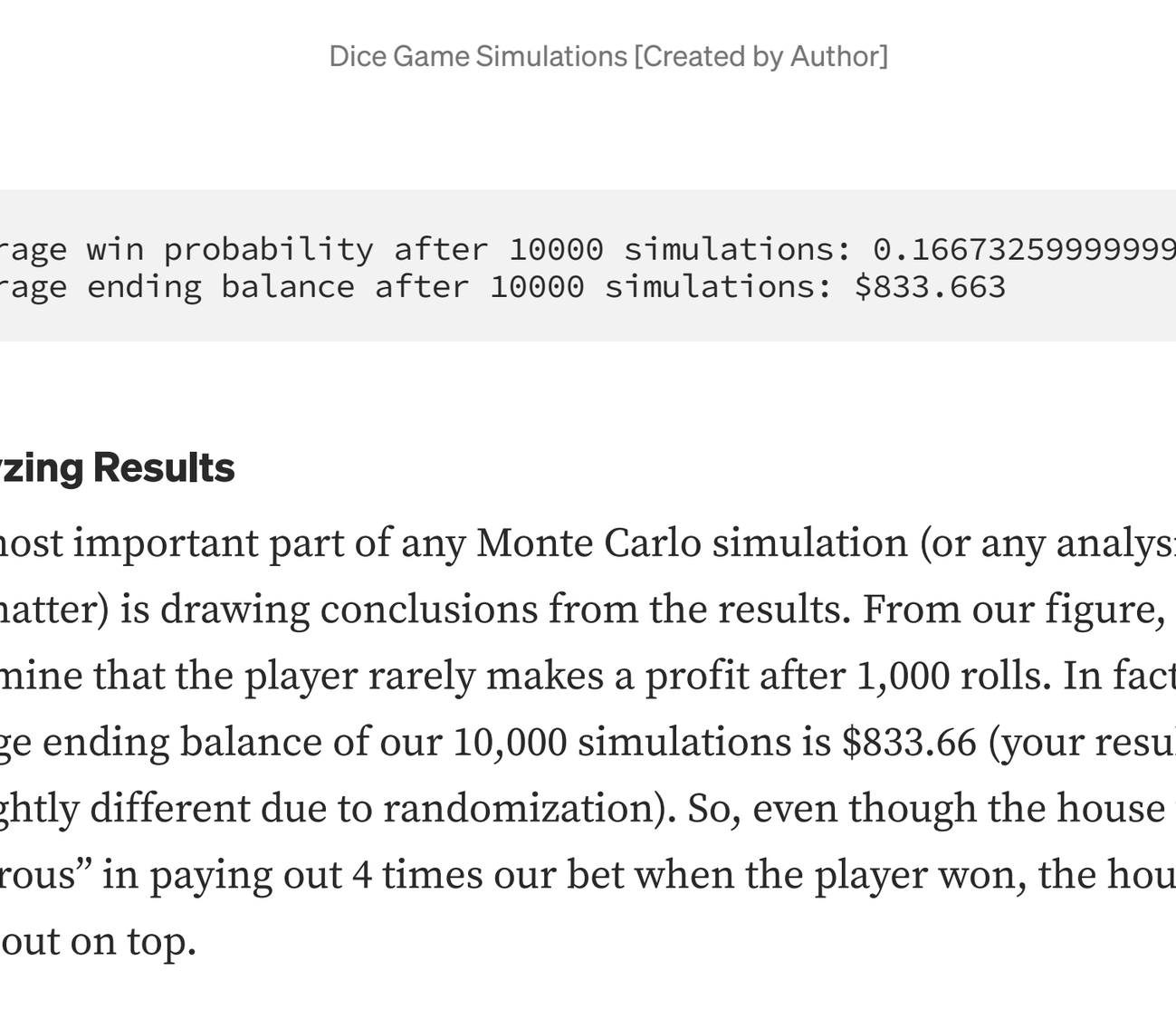
Obtaining Results

The last step is displaying meaningful data from our tracking variables. We can display our figure (shown below) that we created in our *for* loop. Also, we can calculate and display (shown below) our overall win probability and ending balance by averaging our *win_probability* and *end_balance* lists.

```
# Showing the plot after the simulations are finished
plt.show()

# Averaging win probability and end balance
overall_win_probability = sum(win_probability)/len(win_probability)
overall_end_balance = sum(end_balance)/len(end_balance)

# Displaying the averages
print("Average win probability after " + str(num_simulations) + "
       runs: " + str(overall_win_probability))
print("Average ending balance after " + str(num_simulations) + "
       runs: $" + str(overall_end_balance))
```



Dice Game Simulations [Created by Author]

```
Average win probability after 10000 simulations: 0.1667325999999987
Average ending balance after 10000 simulations: $833.663
```

Analyzing Results

The most important part of any Monte Carlo simulation (or any analysis for that matter) is drawing conclusions from the results. From our figure, we can determine that the player rarely makes a profit after 1,000 rolls. In fact, the average ending balance of our 10,000 simulations is $833.66 (your results may be slightly different due to randomization). So, even though the house was "generous" in paying out 4 times our bet when the player won, the house still came out on top.

We also notice that our win probability is about 0.1667, or approximately 1/6. Let's think about why that might be. Returning back to one of the earlier paragraphs, we noted that the player had 6 outcomes in which they could win. We also noted there are 36 possible rolls. Using these two numbers, we would expect that the player would win 6 out of 36 rolls, or 1/6 rolls, which matches our Monte Carlo prediction. Pretty cool!

Conclusion

You can use this example to be creative and try different bets, different dice rolls, etc. You could also track some other variables if you wanted. Use this example to get comfortable with Monte Carlo simulations and really make it into your own. On a more interesting note, if the house paid out 5 times the bet, the player would break even with the house on average. Furthermore, if they paid out anything greater than 5 times the bet, the house would likely go bankrupt eventually. If you want to see those results, let me know in the comments! This simple example shows why Monte Carlo simulations and probabilities are so important.

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Thank you for reading the article! I hope this helps in your journey to creating a solid Monte Carlo simulation! Give me a follow for more Python related articles, and check out the other articles I've written!