The basic idea of this project is to apply simulation techniques to understand the expected number of cycles in the Dice Roll Game and explore its distribution details. Simulation, using a random number generator to replicate the roll of a dice, is useful to easily run a large number of random experiments to discover relationships. While we did not pursue the following analysis within the scope of this project, we could also consider translating the dice roll probabilities into a transition matrix of an absorptive Markov chain and using a technique called first step analysis. More information can be found here. The Dice Roll Game includes two players using 6-sided die tosses to win coins. The game starts with the initial setup of both players having 4 coins, with 2 coins in the common "pot". Players take turn rolling the die, and act on the die outcome based on the following mapping: • 1: then the player does nothing. • 2: then the player takes all coins in the pot. • 3: then the player takes half of the coins in the pot (rounded down). • 4,5,6: then the player puts a coin in the pot. A player loses, and the game concludes, when they are unable to perform the task of putting a coin in the pot. We have not interpreted the pot being empty as a player being unable to perform the task of drawing from the pot - the player would simply draw 0 coins in this case, and the game continues on. In the remainder of this report, we will build a simulation (developed using python) to explore the following: 1. Expected number of cycles the game will last for 2. The distribution of the expected number of cycles 3. Further exploration - how tweaks to the game's rules can impact these results Core code has been kept in the body of the implementation, below. After the conclusion, you can find additional code used primarily for the exploration of rule tweaks. **Implementation & Main Findings** import random In [1]: import time import matplotlib.pyplot as plt import numpy as np random.seed(998877) Above, we import python's 'random' library. The library gives access to, among other functionality not used here, methods that can be used to generate random numbers. The module uses the Mersenne Twister pseudorandom number generator. While not without its drawbacks, the PRNG is widely accepted across software implentations as a fast, well-implemented PRNG. Mathematical details on the underlying algorithm can be found here. After importing the library, we set the seed for reproducibility. In [2]: class DiceGame: Our python implementation of the Dice Roll Game.

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small tweaks to the game's rule can have a large impact on the expected number of cycles.

The goal of this report is to explore the Dice Roll Game, which is described below in the Background & Description. Due to the nature of the game's rules, there is no predetermined number of "cycles" for which the game will last. Instead, the game ends when one of two players cannot perform a required action. Using python, we were able to create a simulation of the Dice Roll Game, which allowed us to replicate the playing of thousands of rounds of the games in a short amount of time. The result of this programmatic approach to the problem gave us the ability to answer many questions about the game, including the expected number of cycles in the Dice Roll Game. Using the rules as described, we found that the expected number of cycles for the Dice Roll Game is roughly **17.52**. We also found that

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**Background & Description** 

The \_\_init\_\_ method starts the game off as

self.players = {'a':self.player a,

self.current\_player = self.first

return random.randrange(6) + 1

self.cycles +=1
outcome = self.\_\_roll()
if self.cycles == 1:

if outcome == 1:
 continue
elif outcome == 2:

= simulate n games(DiceGame, 10000)

1200

1000

800

self.pot = 0
elif outcome == 3:

if self.current\_player == 'a':

self.first = outcome

half pot = self.pot // 2

self.pot -= half\_pot

'b':self.player b}

demanded by the most recent roll.

def \_\_init\_\_(self, first='a'):
 self.player\_a = 4
 self.player\_b = 4
 self.pot = 2
 self.cycles = 0
 self.first = first

self.winner = None

to a dice roll number.

roll(self):

def play\_game(self):
 while True:

def

The play\_game method executes the playing of a full game while tracking the number of cycles, winner, and pot amounts. It runs until the breaking condition, defined as the current player being unable to perform the task

random's randrange function is used to generate a random integer between

self.players[self.current player] += self.pot

self.players[self.current player] += half pot

0 and 5, inclusive. A 1 is added to this number to make the number equivalent

defined in the prompt.

Abstract

else: if self.players[self.current player] == 0: self.winner = 'a' if self.current player == 'b' else 'b' self.players[self.current player] -= 1 self.pot += 1self.current player = 'a' if self.current player == 'b' else 'b' **Expected Value** In order to ascertain the Expected Value of the number of cycles required to complete a game of Dice Roll, we simulate the game 10,000 times below. The number for n, 10,000, was chosen somewhat arbitrarily - it gives us the ability to feel confident that the number of iterations is sufficient to approach the true Expected Value and avoid overweighting of outliers, while not being overly computationally and time intensive. In [3]: def simulate n games(game object, n=10000, plot=True): This helper function is used to execute the DiceGame class n times. After running n times, the function produces a histogram of cycle frequencies, noting the mean value of the cycles from the n iterations of the game. This is taken to represent the expected value, or how long, on average, a game of Dice Roll will last. number of cycles = [] for i in range(n): game = game\_object() game.play game() number of cycles.append(game.cycles) mean cycles = np.mean(number of cycles) std cycles = np.std(number of cycles) if plot: fig = plt.figure(figsize=(20, 10)) ax = fig.add subplot(111)ax.hist(number of cycles, bins = len(set(number of cycles)), color='green' if game object == DiceGame else 'orange', alpha=.5); ax.set\_title(str(n) + " Simulations of Dice Game"); plt.grid(True, alpha=.5) ax.set xlabel('Cycles'); ax.set ylabel('Frequency'); plt.axvline(mean cycles, color='red', ls='--', lw='3') print("Mean # of cycles per game: " + str(round(mean cycles,2))) print("Standard Deviation of # of cycles per game: " + str(round(std cycles,2))) return mean cycles

10000 Simulations of Dice Game

400 Cycles Mean # of cycles per game: 17.52 Standard Deviation of # of cycles per game: 12.71 The result of our simulation shows that the average game, across 10,000 games, lasted 17.52 cycles. We take this value to represent the Expected Value of the number of cycles in the Dice Roll Game. We also note that the distribution is Geometric in appearance. We can also see that the distribution shows that no game lasted fewer than 5 cycles. This makes sense, since, to lose a game, a player would have to give a coin in each of their first four turns, before being unable to give a coin on their fifth turn. There are some games that last for over 100 cycles, and the standard deviation, relative to the mean, is quite high at 12.71. **Distribution of Errors** Since we are simulating the game 10,000 times, it would be interesting to see how the Expected Value of the number of cycles varies across multiple simulations. Our hypothesis prior to running this analysis is that the EV should be roughly the same (17.52), but have variance that forms a normal distribution. To test this, we can run n simulations k times and plot the resulting Expected Values. This also helps us validate the EV number from the above single simulation of 10,000 iterations. Code for this has been provided in the appendix as get\_mean\_cycle\_k\_times. In [9]: get\_mean\_cycles\_k\_times() note that the default values of k and n are used. n is 100, not 10,000, for speed purposes. Average # of Cycles for 1000 Simulations of 100 Games 50 40 30 20 10 17 As expected, the errors (distribution of the EVs of 1000 simulations, each of 100 iterations) appear to follow a normal distribution, with the mean centered at roughly 17.5. **Further Exploration** Below, we have conducted additional simulations with slight modifications to the data collection and rules. Code for the modified DiceRoll classes can be found in the appendix. Exploring inherent bias in game design Is a player's winning percentage improved based on if they get to go first? In [10]: def simulate n games winner(n=1000, plot=True, first='a'): winner = []for i in range(n): game = DiceGame(first=first)

game.play game()

In [12]: from scipy.stats import binom test

binom test(4973, 10000, .5)

In [11]:

In [13]:

In [14]:

Out[11]: 0.4973

Out[12]: 0.5961141332886245

winner.append(game.winner)

return len([i for i in winner if i == first])/n

simulate n games winner(10000, 'a') # says that when 'a' goes first, they win 49.73% of matches

```
The null hypothesis here is that getting the first turn does not increase the likelihood of winning the game. Winning is defined as not being
the player who is unable to perform the required action.
Above, Player 'a' is arbitrarily chosen to go first. We can treat n=10000 iterations of the game as 10000 Bernoulli trials. Then, using a
Binomial Distribution to compare the result (Player 'a' won 49.7% of games) to the expected winning percentage (50%), we can see that
the resulting p-value is .596, which is far above the .05 we desire in order to reject the null at the 95% confidence level. Therefore, we
cannot reject the null hypothesis that going first does not increase the likelihood of winning.
Exploring changes in rules to determine flexibility in game design
What if we change the rules so that if a player rolls a 1, they have to give up a coin?
This modification raises the probability from 3/6 to 4/6 that a player would have to give up a coin. Code is available in the appendix in the
ModifiedDiceGame1 class.
  = simulate n games (ModifiedDiceGame1, 10000)
                                                          10000 Simulations of Dice Game
  2500
  2000
  1500
   500
                                                                   Cycles
Mean # of cycles per game: 11.21
Standard Deviation of # of cycles per game: 7.4
The result above is expected. Since the odds that a player has to give up a coin are increased (by ~17%), players run out of coins faster,
shrinking the Expected Value of the number of cycles from 17.52 to only 11.21.
On the other hand, what if instead, rolling a 2 means a player gets twice as many coins as are currently in the pot?
Code is in the appendix as the ModifiedDiceGame2x class.
   = simulate n games (ModifiedDiceGame2x, 100)
                                                          100 Simulations of Dice Game
  50
```

400 Cycles Mean # of cycles per game: 362.0 Standard Deviation of # of cycles per game: 468.35 The result above is jarring and shows how well-designed the game must be to avoid these 'blowups'. The EV for the number of cycles skyrocketed to 362, and that actually isn't even the true number. Since new coins were being added to the game, in some cases (roughly 30% of the time, as seen above), players kept increasing their pot sizes exponentially, essentially growing so large that going 'bankrupt' no longer was realistically possible. To avoid having the simulation run forver, I had to cap such games at 1000 cycles, so the EV is truly much higher. The high standard deviation confirms the extreme (infinite) upside in the number of cycles. Conclusion Using the Mersenne Twister PRNG and other built-in python tools, we are very easily able to design and execute a simulation to assess expectations, rules, and strategies for games of chance. The Dice Roll Game simulated here shows that a delicate balance must be struck in the rules of the game to avoid creating a game that does not end, or one that ends too quickly. Through this simulation design, we were able to determine the Expected Value of the number of cycles in the game (17.52) and visualize its distribution. We found simulation to be a nimble, quick, and robust way to learn more about the game. **Appendix** In [6]: def get\_mean\_cycles\_k\_times(k=1000, n=100): This function calls the simulate\_n\_games function k times in order to determine the distribution of the expected values. 11 11 11 means = []for i in range(k): means.append(simulate\_n\_games(DiceGame, n, plot=False)) fig = plt.figure(figsize=(10, 10)) ax = fig.add\_subplot(111) ax.hist(means, color='darkorchid', alpha=.5, bins=min(k//10,50)); ax.set\_title("Average # of Cycles for " + str(k) + " Simulations of " + str(n) + " Games"); mean\_of\_means = np.mean(means) std\_of\_means = np.std(means) plt.xlim((mean\_of\_means-3\*std\_of\_means, mean\_of\_means+3\*std\_of\_means)) plt.axvline(mean\_of\_means, color='red', ls='--', lw='3') plt.grid(True, alpha=.5) In [7]: class ModifiedDiceGame1: def \_\_init\_\_(self, first='a'):  $self.player_a = 4$ self.player b = 4self.pot = 2self.cycles = 0self.first = first self.players = {'a':self.player a, 'b':self.player\_b} self.current\_player = self.first self.winner = None def roll(self): return random.randrange(6) + 1 def play\_game(self): while True: if self.current\_player == 'a': self.cycles +=1 outcome = self. roll() if self.cycles == 1: self.first = outcome if outcome == 2: self.players[self.current\_player] += self.pot self.pot = 0elif outcome == 3: half pot = self.pot // 2 self.players[self.current\_player] += half\_pot self.pot -= half pot else: # now also includes 1, in addition to 4-6 if self.players[self.current player] == 0:

self.winner = 'a' if self.current\_player == 'b' else 'b'

self.players[self.current player] += 2\*self.pot # 2x coins instead of just 1x

self.winner = 'a' if self.current player == 'b' else 'b'

self.current player = 'a' if self.current player == 'b' else 'b'

self.current player = 'a' if self.current player == 'b' else 'b'

break

self.pot += 1

self.players = {'a':self.player a,

self.current\_player = self.first

return random.randrange(6) + 1

if self.cycles == 1000:
 self.winner = 'draw'

self.cycles +=1
outcome = self.\_\_roll()
if self.cycles == 1:

if self.current player == 'a':

self.first = outcome

half pot = self.pot // 2

self.pot -= half pot

self.players[self.current player] += half pot

if self.players[self.current player] == 0:

self.players[self.current player] -= 1

return

if outcome == 1:
 continue
elif outcome == 2:

self.pot = 0
elif outcome == 3:

self.pot += 1

def init (self, first='a'):

self.player\_a = 4
self.player\_b = 4
self.pot = 2
self.cycles = 0
self.first = first

self.winner = None

def roll(self):

def play\_game(self):
 while True:

else:

In [8]: class ModifiedDiceGame2x:

self.players[self.current player] -= 1

'b':self.player\_b}