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 $6787 \approx 0.5333426632230114$ 

### Introduction

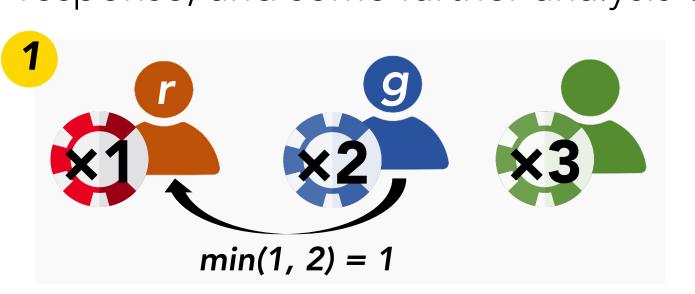
We study two variants of the models examined by Prof. Persi Diaconis [1]. Denote the players' fortunes at each round as  $(X_n, Y_n, Z_n) \in \mathbb{N}^3$ , which evolves as a Markov chain. Write  $(X_0, Y_0, Z_0) = (x, y, z)$ .

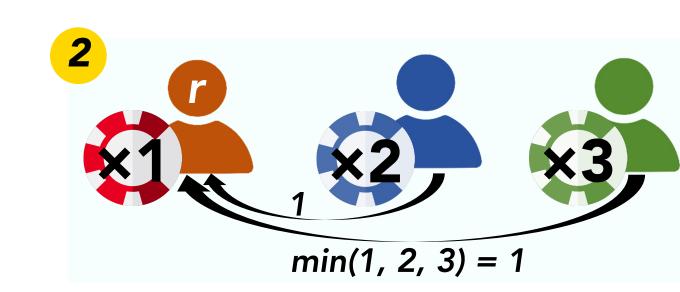
- Game 1: At each round, a giver and receiver are chosen at random. The giver transfers the minimum of their fortunes to the receiver.
- Game 2: Only a receiver is chosen each round to receive min(x, y, z).

Define the following terminology / representations:

- Loser: First player to reach 0 (if tied in Game 2, pick one randomly).
- Winner: First player to have all the money.
- $L_{(x,y,z)}$ : Probability that player 1 loses, given initial state (x,y,z).

The research problem addressed is the difficulty of attaining  $L_{(x,y,z)}$  by hand. This poster presents an overview of the program I produced in response, and some further analysis on the first-hand data.





# Problem Specification

While P(winner = player 1) is simply  $\frac{x}{x+y+z}$  [2], determining their losing probability is much more difficult. E.g. Consider the initial state (1, 2, 3):

$$L_{(1,2,3)} = \frac{1}{6} (L_{(0,3,3)} + L_{(0,2,4)} + L_{(2,1,3)} + L_{(1,0,5)} + L_{(1,0,5)} + L_{(1,2,2)} + L_{(1,4,1)})$$

$$= \frac{1}{6} \left( 1 + 1 + L_{(2,1,3)} + 0 + \frac{1}{3} + L_{(1,4,1)} \right)$$

$$= \frac{7}{18} + \frac{1}{6} \left( L_{(2,1,3)} + L_{(1,4,1)} \right)$$

One step of the analysis has already introduced 6 intermediate states (but some can be 'pruned' early).

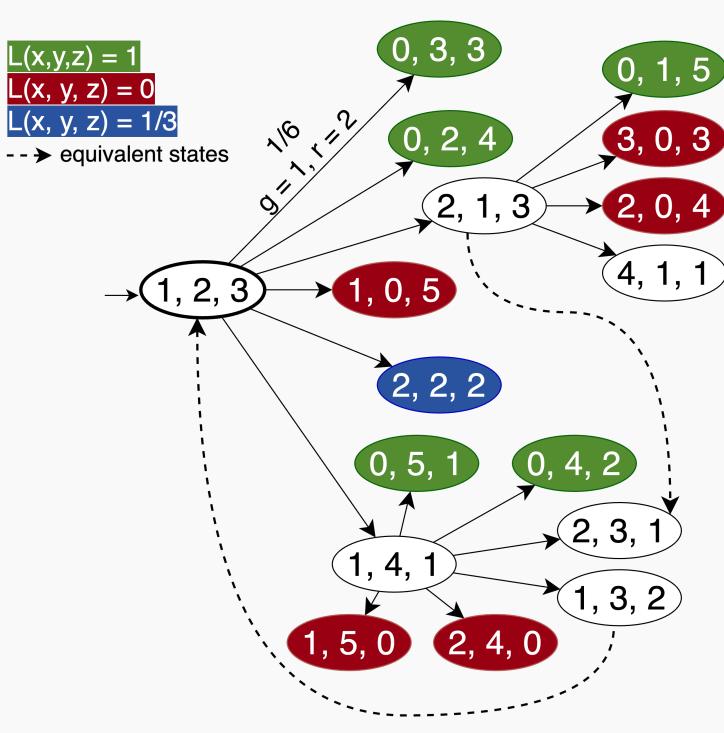


Figure 1.1: Modified transition diagram for Game 1, illustrating how the program analyses state (1, 2, 3).

 $L_{(1,2,3)} = \frac{1}{3} \left( L_{(3,1,2)} + L_{(0,4,2)} + L_{(0,1,5)} \right)$   $= \frac{1}{3} \left( L_{(3,1,2)} + 1 + 1 \right)$ 

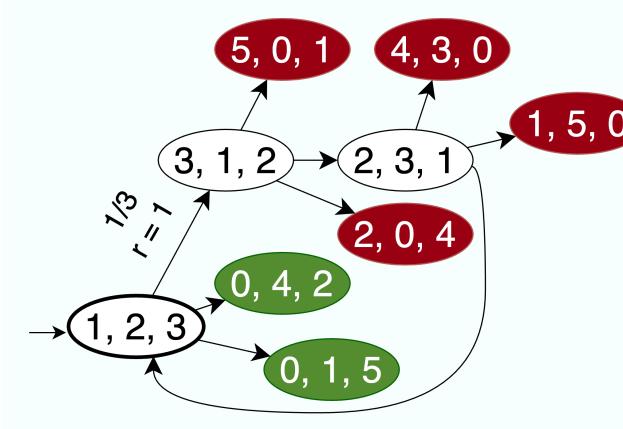


Figure 1.2: Modified transition diagram for Game 2.

Due to the 'depth' of the analysis, as the states become larger, it quickly becomes intractable to calculate by hand. Thus, I wrote a Python program to automate the analysis (with guaranteed termination) and produce the exact  $L_{(x,y,z)}$ 's in fraction form.

## Program Functionalities

Given the initial state as input, the program can:

- Generate and solve the first step analysis equations;
- Generate  $L_{(x,y,z)}$  for the initial and intermediate states. Export the equations and probabilities to a text file.

These are combined into the LoserAnalysis class.

Analysis in the "Selected Results" section is also automated.

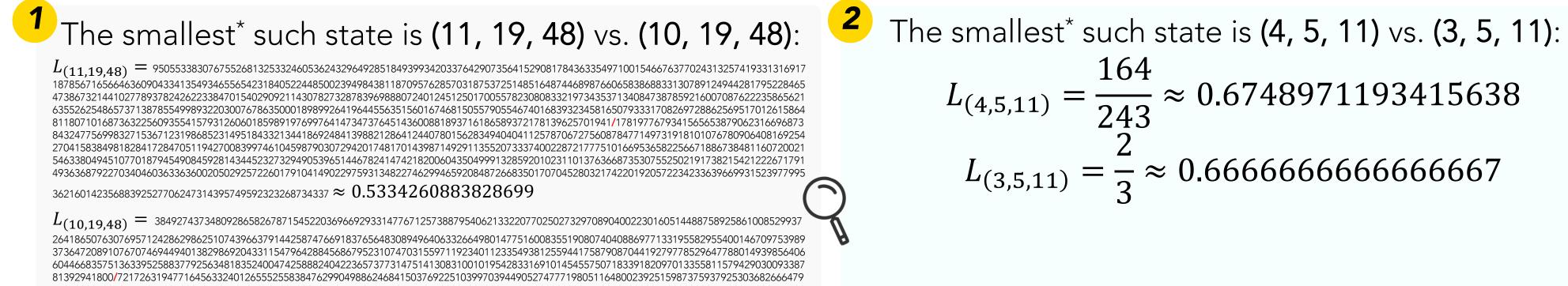
# Implementation Details

- The program uses the **sympy** library to solve equations.
- $L_{(x,y,z)} = L_{(x,z,y)}$ . Our convention is to store the smaller stack at front.
- To accommodate for slow execution large inputs, the program offers:
- Fallback option: Approximates  $L_{(x,y,z)}$ , by enumerating the game up to a fixed number of rounds (t), using memoisation to optimise efficiency. The result is accurate to  $2^{-t}$ .
- Exception-handling: If the maximum recursion depth or time limit is hit, the program throws and catches an exception, then skips the current state / uses the fallback method.

### Selected Results

The probabilities generated are stored as CSV files in the project's GitHub repository. We only present some remarkable results here.

1. If player 1's objective is not to lose, when are they better off giving away \$1?

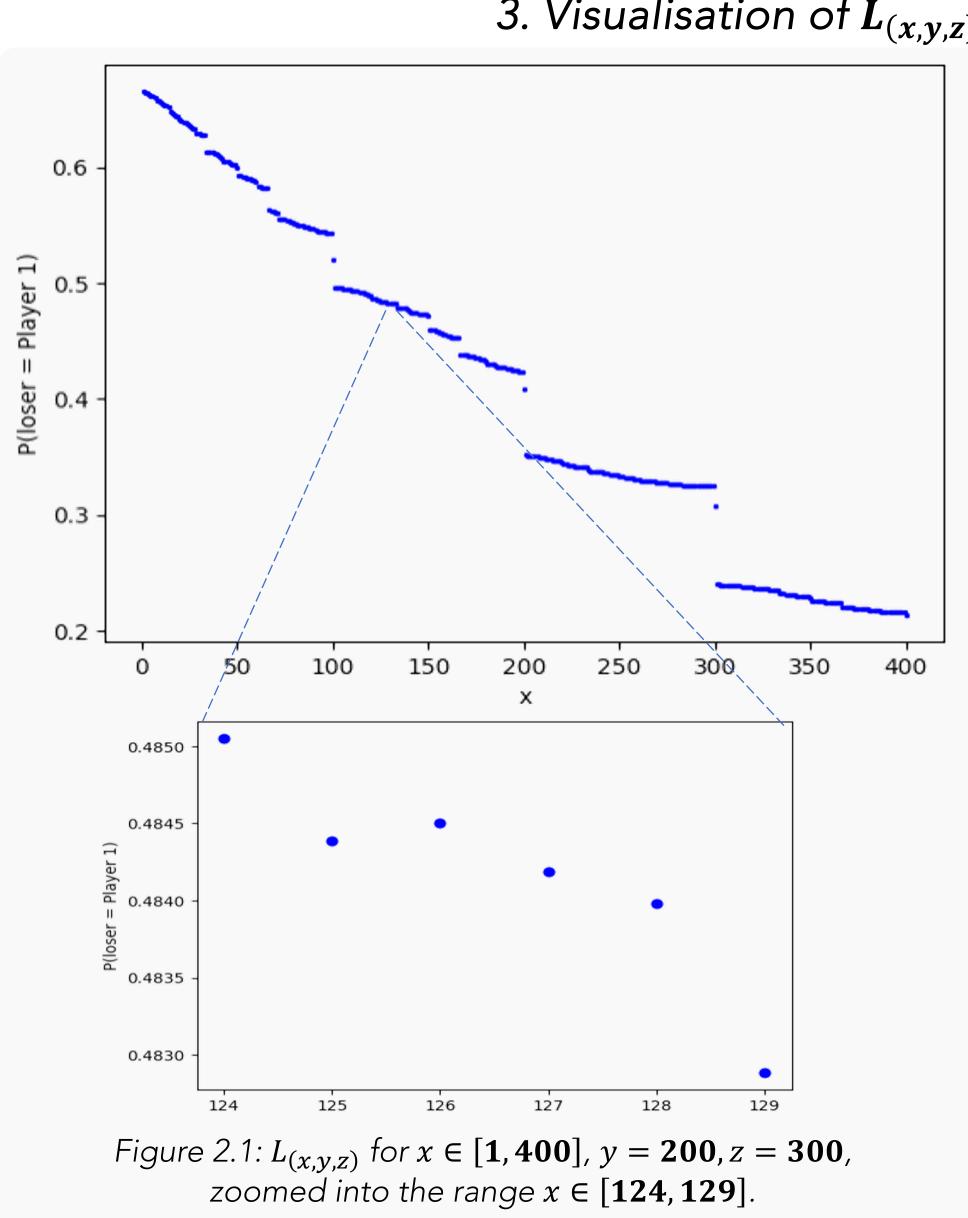


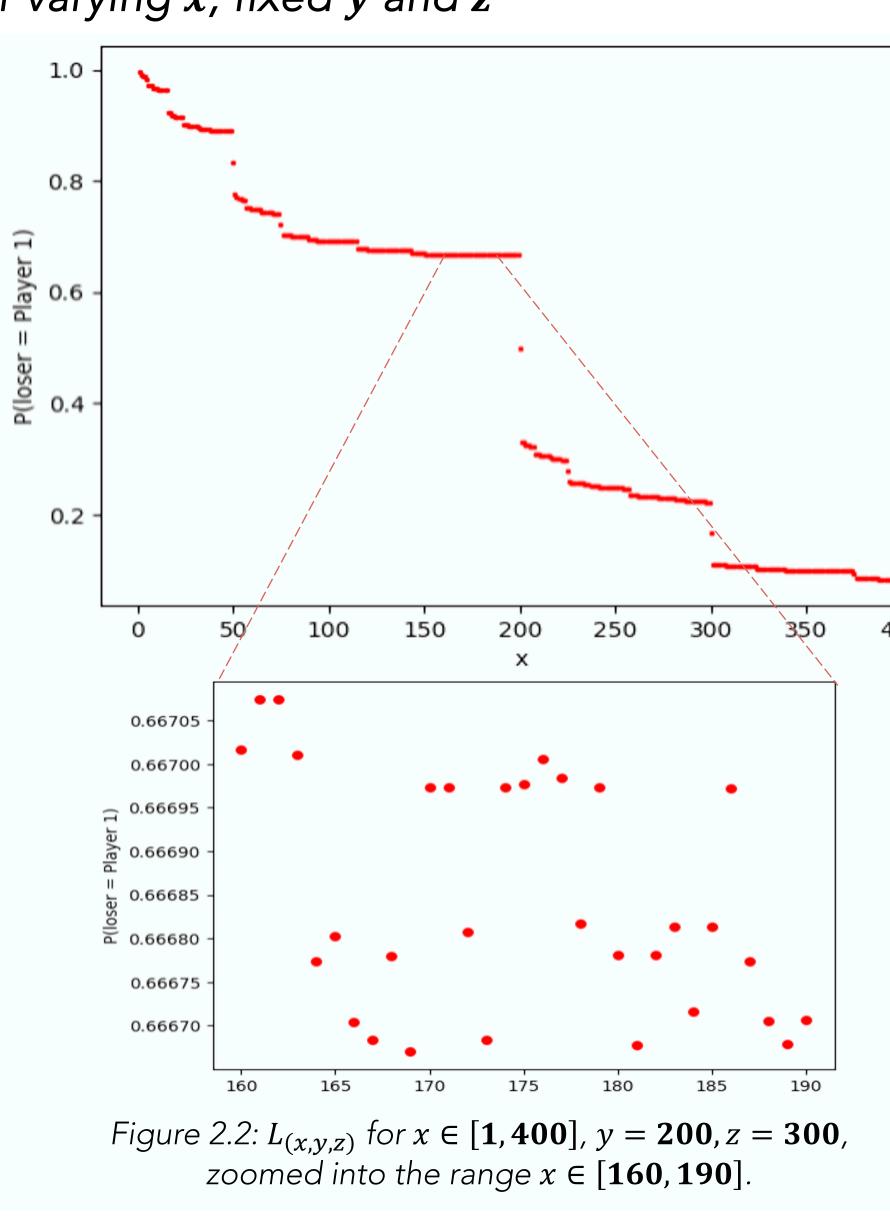
\* by lexicographical ordering

#### 2. Similarly, when is player 1 better off giving away \$1 to another player?

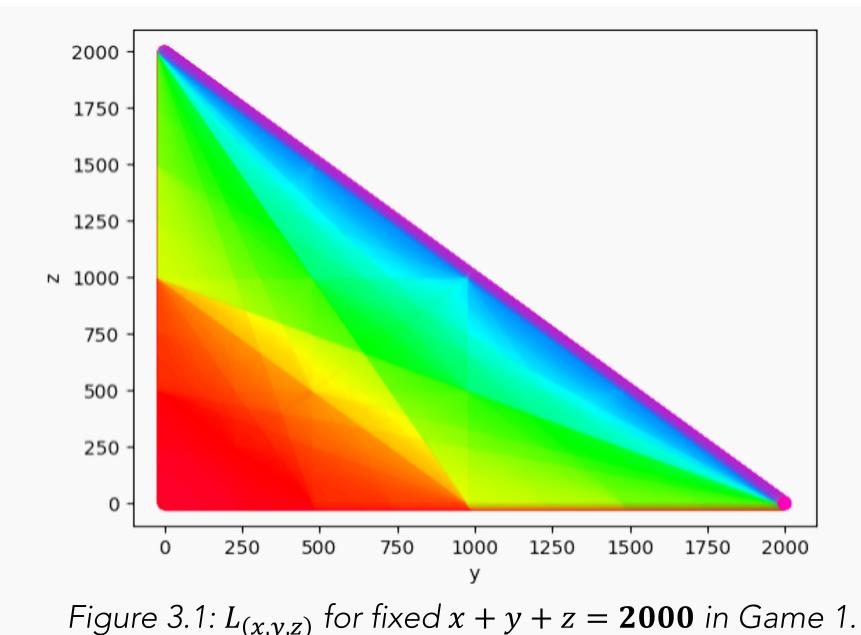
The smallest such state is (2, 4, 5) vs. (1, 5, 5):  $L_{(2,4,5)} = \frac{1}{7036351} \approx 0.5016800611566989$ 3522116  $L_{(1,5,5)} = \frac{1}{7036351} \approx 0.5005600203855664$  The smallest such state is (2, 9, 10) vs. (1, 10, 10):  $L_{(2,9,10)} = \frac{327195}{368089} \approx 0.888901868841503$ 

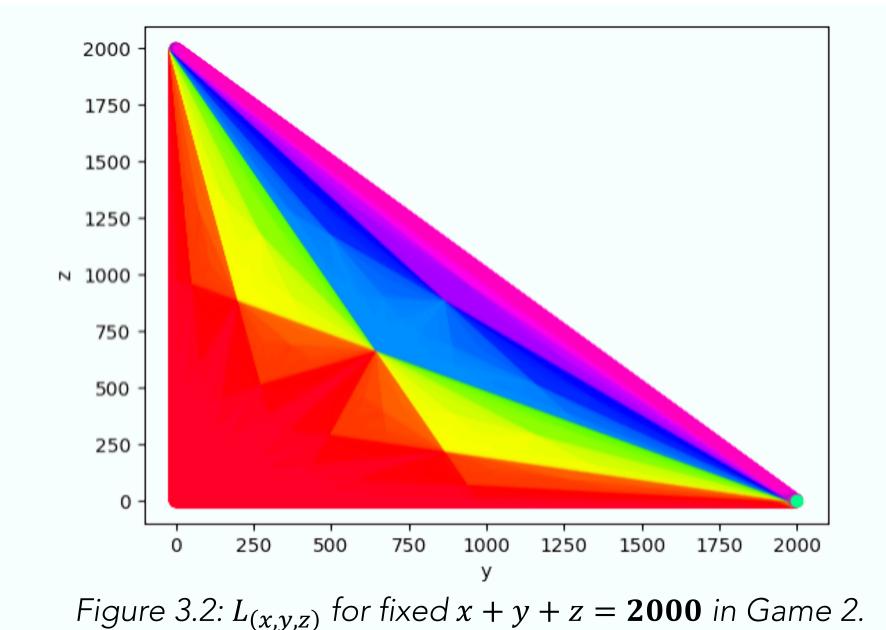
## 3. Visualisation of $L_{(x,y,z)}$ for varying x, fixed y and z





#### 4. Visualisation of $L_{(x,y,z)}$ for fixed sum, x + y + z





Key Observations

- The big jumps happen when player 1's fortune is tied with another player's fortune.
- The function  $L_{(x,y,z)}$  is **not monotonic decreasing in x** (visible when we zoom into a flat segment).
- Given the same (x, y, z), the program executes **faster on Game 2** than Game 1 (no. of intermediate states grows exponentially with base 6 in Game 1, but with base 3 in Game 2).
- Game 2 has more states where player 1 is not better off with an extra \$1 (more flat segments).
- For both models,  $L_{(x,y,z)}$  is fractal-like!

## Future extensions

Variants of the model:

ii. More than 3 players.

- . Players choose at random to give  $\min(x, y)$  or  $\min(x, y, z)$ .
- Optimise program's efficiency for large inputs.

# Acknowledgement

#### This project has really taught me how to effectively integrate theory with practice, computing techniques with mathematical analysis, to conduct research. I am glad that my computing skills can be incorporated to produce some concrete results. Many thanks to my supervisor, Prof. Mark Holmes, for his insightful guidance and support throughout this project.

### References

- [1] Diaconis, P. & Ethier, S. (2020). Gambler's Ruin and the ICM. Statistical Science, Statist. Sci. 37(3), 289-305. https://doi.org/10.1214/21-STS826
- <sup>[2]</sup> Grinstead, C. M. & Snell, J. L. (2006). 12.2: Gambler's Ruin. In Doyle, P. G (Ed.), Introductory Probability (pp. 487-490). American Mathematical Society.