## Hitting probabilities in 3-player betting games

## Angel Yong He, supervised by Prof. Mark Holmes

 angelh1@student.unimelb.edu.au I GitHub repo: https://github.com/7angel4/3-person-betting-game 2023/2024 Mathematics and Statistics Vacation Scholarships Program, The University of Melbourne
## Introduction

We study two variants of the models examined by Prof. Persi Diaconis ${ }^{[1]}$. Denote the players' fortunes at each round as $\left(X_{n}, Y_{n}, Z_{n}\right) \in \mathbb{N}^{3}$, which evolves as a Markov chain. Write $\left(X_{0}, Y_{0}, Z_{0}\right)=(x, y, z)$.

- 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.
$\boldsymbol{L}_{(x, y, z)}$ : Probability that player 1 loses, given initial state $(x, y, z)$.
The research problem addressed is the difficulty of attaining $\boldsymbol{L}_{(x, y, z)}$ 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)


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
illustrating how the program analyses state $(1,2,3)$.'


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:
i. 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 $2^{-t}$
ii. 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 $\$ 1$ ?

1 The smallest ${ }^{\star}$ such state is $(11,19,48)$ vs. $(10,19,48)$ :
$\left(2\right.$ The smallest ${ }^{*}$ such state is $(4,5,11)$ vs. $(3,5,11)$ :
$L_{(4,5,11)}=\frac{164}{243} \approx 0.6748971193415638$
$L_{(3,5,11)}=\frac{2}{3} \approx 0.6666666666666667$

* 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. $(1,5,5)$ : The smallest such state is $(2,9,10)$ vs. $(1,10,10)$ :

$$
L_{(2,4,5)}=\frac{3529997}{7036351} \approx 0.5016800611566989 \quad L_{(2,9,10)}=\frac{327195}{368089} \approx 0.888901868841503
$$

$L_{(1,5,5)}=\frac{3522116}{7036351} \approx 0.5005600203855664 \quad L_{(1,10,10)}=\frac{8}{9} \approx 0.8888888888888889$
3. Visualisation of $L_{(x, y, z)}$ for varying $x$, fixed $y$ and $z$



Figure 3.1: $L_{(x, y, z)}$ for fixed $x+y+z=\mathbf{2 0 0 0}$ in Game 1.

## 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 $\boldsymbol{x}$ (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:

Players choose at random to give $\min (x, y)$ or $\min (x, y, z)$.
ii. More than 3 players.

- 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
${ }^{[2]}$ 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.

