Simulation and Probabilistic Analysis of Terraria's Loot System Based on Combinatorics

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***Abstract*—The loot system in Terraria is chance-based mechanism to determine the items players are obtaining. This system reflects an application of discrete mathematics, specifically combinatorics and probabilities. This paper aims to use combinatorial principles and simulations to verifies theoretical of drop-chances. Simulated results displayed that the theoretical expectations approach the simulated results, with normal deviation. Simulations are iterated 100000 times using a python program. This study concludes that a combinatorial and probabilistic approach can be used in order to understand and evaluate loot systems scientifically.**

***Keywords*— Combinatorics, Discrete Probabilities, Loot Ssytem, Terraria, Simulation.**

I. Introduction

Most video games are designed for the player's entertainment. This seemingly simple task usually has deep layers of mechanics each interacting with another to form the gaming experience. One of the interesting aspects of this is the surprisingly complex loot system. A loot system is a mechanism where players obtain rewards in different forms, and is meant as a reward for progressing in-game. Loots for progression usually exceeds the caliber of anything currently being used by the player, hence the sense of progression. The methods of obtaining said loots are variative, ranging from regular exploration, enemy combats, or simple gambling. All of these systems are structured around combinatorics principles along with discrete probability.

The sandbox-action-adventure game Terraria, released by Re-Logic, the loot system purposes not just as cosmetics, but is integral to the progression of the game itself. Players often obtains new items out of necessity to progress. Stronger weapons to beat stronger enemies, special items to access specific regions of the map required to progress in-game are examples of loots for progression. Consequently, understanding how loots are generated is an important aspect for not just for players who wanted an efficient way of play, but for game developers to ensure a balanced, fair, and a challenging yet engaging experience.

Discrete mathematics, especially the branch of combinatorics and probabilities, provides a pragmatic approach of modeling loot systems. The amount of possible combination of items are calculated using combinatorics, and probabilities is used to manage expectations, calculate cumulative chances, and variance of item drops. The implementation of said concepts is practical when designing a computer-based simulation to validate theoretical models.

This paper looks closely on the Wall of Flesh, one of Terraria's main bosses, which has a simple yet representative loot table of its treasure bag. Having a clear loot structure and documented loot table making it a good candidate for analysis. By focusing on it, a probabilistic model can be formed, and a detailed numerical simulation to study the dynamics of the loot system can be attained.

Approaching the problem like this not only is convenient to understand loot systems in-game, but to illustrate how discrete math can be applied in random systems that commonly appear in real-life. By using video games, the study of discrete mathematics is more appealing and applicable to other real-life problems.

II. Theoritical Foundation

A. Combinatorics

Combinatorics is a branch of mathematics that study counting, arranging, and choosing elements of a set. In the context of loot system such in Terraria, combinatorics is applied to understand how many ways an item appears from a specific loot table.

1. Permutation and Combination

   The act of arranging elements of a set into a sequence or order, with taking into consideration its order. A permutation of N elements from a set R are represented as follow:

$$_{N}P_{R} = \frac{R!}{(R-N)!}$$

Combination is a selection of set where the order of elements chosen doesn't matter, unlike permutation. A combination of N elements from a set R are represented as follow:

$$_{N}C_{R} = \frac{R!}{N!\,(R-N)!}$$

Both representation assuming each element of R are distinct.

When using combinatorics to analyze loot systems in Terraria, most of the loot generation doesn't take into consideration of which order the loot is generated. This implication is that permutation is severely unused when compared to combination.

2. Discrete Probabilities and Expectation

Discrete probabilities are related tightly to combinatorics and is used for calculating how likely a combination or an event can occur. In loot systems, each loot has a constant chance to generate for each attempt, e.g., an item that has a drop chance of 25% has a probability of 0.25 to generate, and a probability of 0.75 to not generate. Probabilities are represented as follow:

$$P(N) = \frac{\text{number of possibilities resulting N}}{\text{number of all possibilities}}$$

With the probability of P(N) not happening is the complement of P(N).

$$P^{-1}(N) = 1 - P(N)$$

The Bernoulli model is the simplest in this case, with only a binary result, successfully generated and unsuccessfully generated. For a series of independent attempts, a binomial model can be applied to calculate the probability of obtaining a certain amount of loot. In the other hand, the expectation value ($E = 1/P$) is used to calculate the average attempts needed to obtain a certain amount of loot, with P as the probability of said event happening.

3. Coupon Collector's Problem

If a player wanted to obtain every loot dropped by a certain enemy, the probabilistic approach turns more complex. The Coupon Collector's Problem is a classic problem in probabilities that estimates how many attempts needed to obtain all types of different coupons. Of K distinct items, and each has the same probabilities, the expectation value of obtaining all different types of items is approximately:

$$k \times H_k$$

with H_k is the k-th harmonic number.

B. Terraria Loot System

The 2D sandbox action-adventure game Terraria a union of exploration, building, and importantly, combat. In each combat interaction, especially fighting bosses or opening chests, lie a loot mechanic that determine what items and how many are generated. This system is not deterministic, rather it relies on a predetermined loot table.

1. Loot Table

A loot table is predetermined set of items that is possible to generate when a specific event—the player winning against the Wall of Flesh—is triggered. Imagine a scale of 1 to 100, where when said specific event is triggered, a random number in the scale is generated. The loot table already has a predetermined set of items which corresponds to a subset of the scale itself. E.g., 1-10 nothing drops, 11-40 drops a common loot, and 41-100 drops a rare item. The type of item dropped relies on the number randomly generated by the game when said specific event is triggered. This number is generated using a PRNG (Pseudo Random Number Generator), but this paper assumes a purely random system for modelling purposes.

2. Loot Category and Chance Variance

Terraria categorize loot generation into a few types:

a. guaranteed drop, loot will always drop after an event trigger.

b. chance-based drop, loot drops based on a predetermined chance

c. pool selection drop, loot is selected from a pool of predetermined set, where each item of the set has a chance of dropping, and the loot which is generated is selected randomly with respect for each item probability of generating. This results in a generated item being completely exclusive from other items, while not directly interacting with other types of loot. E.g., a 1 in 4 chance of item A generating, 2 in 4 chance of item B generating, and 1 in 4 chance of item C generating.

3. Case Study: Wall of Flesh

Wall of Flesh is the final boss of the pre-hardmode phase in terraria, and is focal point of this paper due to a relatively simple and well-defined loot structure. In expert or master mode, the Wall of Flesh drops a Wall of Flesh treasure bag. The treasure bag incentivizes the players to play on harder difficulties, by increasing the rewards. This increases player retention at the cost of a more complex implementation.

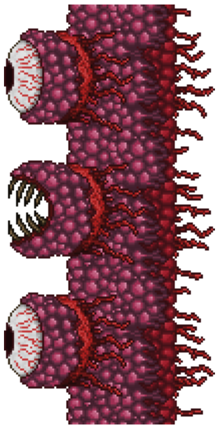

Fig. 1. The Wall of Flesh [6]

This treasure bag contains a few items; the Demon Heart, a one in seven chance of the Wall of Flesh mask, the Pwnhammer, gold coins, a one in four chance of getting a:

- Warrior emblem,
- Ranger emblem,
- Sorcerer emblem or a;
- Summoner emblem [6]

and a one in four chance of getting a

- Breaker Blade,
- Clockwork Assault Rifle,
- Laser Rifle, or a
- Firecracker. [6]

For modelling purposes, this analysis is focused on the emblems and weapons.

Fig. 2. The Wall of Flesh Treasure Bag loot table [6]

III. IMPLEMENTATION

A. Model Assumptions and Simplification

For the mathematical analysis and simulation which will be discussed in this chapter, a few assumptions—some of which are documented game mechanic—are agreed upon with the purpose of simplification.

1. Each attempt is independent of each other, the results of one treasure bag has no effect on any other treasure bag contents.

2. The results take into account the number of players, since when playing in multiplayer, when a boss is defeated, the amount of treasure bag corresponds to how many players contributed in defeating said boss. Loot sharing is also disabled, this implies that each loot generation are independent of each other, e.g., two players can get the same emblem and/or weapon after the same combat.

3. Few of the items that can be generated from treasure bag—the Pwnhammer, gold coins, and the mask—are omitted to retain the focus of studying the main emblems and weapons.

B. Basic Probability Model

Assume a player opened a treasure bag, the chances of the player getting a specific emblem is 25%, equivalent to the weapon chances. Since the generation of an emblem and a weapon are independent of each other, then the probability of obtaining a specific combination of a weapon and an emblem, e.g., a Summoner Emblem and a Laser Rifle, is:

$$P(Summoner\ Emblem\ and\ Laser\ Rifle) = P(Summoner\ Emblem) \times P(Laser\ Rifle)$$

$$P(Summoner\ Emblem\ and\ Laser\ Rifle) = 0.25 \times 0.25$$

$$P(Summoner\ Emblem\ and\ Laser\ Rifle) = 0.0625$$

Since there are 4 distinct emblems and 4 distinct weapons that are able to generate. The number of combination available is $4 \times 4 = 16$ distinct combinations.

C. Collective Model

When a player opens more than one treasure bags—say from multiple fights—questions start to appear; How many treasure bags are needed to obtain each emblem? Or each weapon? Or both!

These problems have similarity to the Generalized Coupon Collector's Problem, such that finding the expected values for emblems:

$$E_4 = 4 \cdot \left(1 + \frac{1}{2} + \frac{1}{3} + \frac{1}{4}\right) \approx 4 \ \cdot \ 2.083 \ \approx 8.33$$

It takes approximately 8-9 bags—since .33 bag is not possible, we're discussing discrete math here—to obtain either each of the four emblems or each of the four weapons.

In the other hand, the expected value of obtaining each of the four emblems and each of the four weapons are:

$$E_8 = 8 \cdot \left(1 + \frac{1}{2} + \frac{1}{3} + \cdots + \frac{1}{8}\right) \approx 8 \cdot 2.718 \approx 21.74$$

So around approximately 22 treasure bags are needed in order to obtain each of the 8 unique items at least once.

D. Unique Probability Simulation with Multiple Players

For N players contributing to the defeat of the Wall of Flesh, N treasure bags are generated. Assuming each players shares loot, the amount of loot gained is much greater compared to only a single player in the same span of time. Assuming there are 10 players, the chances of getting at least one specific weapon or emblem—in this case a Warrior emblem— is as follow:

$$P(No\, Warrior\ Emblem) = \left(\frac{3}{4}\right)^{10} \approx 0.0563$$

$$P(At\ Least\ 1\ Warrior\ Emblem) = 1 - \ P(No\, Warrior\ Emblem)$$

$$P(At\ Least\ 1\ Warrior\ Emblem) = 1 - \left(\frac{3}{4}\right)^{10} \approx 0.9437$$

This applies to all different types of combination of loot. The inclusion-exclusion principle or Monte Carlo simulation can be used to calculate more accurate approximation.

E. Double-Drop Interaction Effect

In treasure bags, there is a mechanic where two different items are generated by opening the same treasure bag. This results in a not fully independent trials, even without any one generation affecting the other. This event results in the Coupon Collector's Problem not being able to accurately approximate the theoretical expectation.

IV. SIMULATION AND EXPERIMENT

A. Simulation Goals and Variables

The goal of the simulation is to approximate the average amount of fights needed to collect any amount of each item from the Wall of Flash loot table—the 4 emblems—with taking into consideration the number of active players, which effect the numbers of treasure bag generated each fight.

With all the variables and assumptions mentioned, we can start the simulation, keeping in mind the following goals:

1. Calculating the average amount of treasure bags needed to obtain on of each emblem.
2. Calculating the average amount of treasure bags needed to obtain on of each weapon.
3. Calculating the average amount of treasure bags needed to obtain on of each emblem and weapon.

All simulations are run with 100.000 iterations.

B. Simulation Algorithm

The algorithm is created using python due to its ability for understandable syntax and ease of access.

```python
def simulate_with_players(target_collection, group, players=1, trials=10000):
  results = []

  for trial in range(1, trials+1):
    seen = collections.Counter()
    fights = 0
    while any(seen[item] < count for item, count in target_collection.items()):
      fights += 1
      for _ in range(players):
        emblem = random.choice(group["emblem"])
        weapon = random.choice(group["weapon"])
        seen[emblem] += 1
        seen[weapon] += 1
    results.append(fights)
  return results
```

Fig. 3. Python code to simulate treasure bag drops

The algorithm works by taking a target collection—in this case map of each possible loot and the desired amount for each item—a group of possible loots, number of players, and how many trials are being run. Each iteration, the program simulates the opening of a fresh treasure bag, and keeps opening treasure bags until the target collection is fulfilled, and continues to the next iteration.

C. Simulation Results

Item Targets	theoretical Expectation (Number of Bags)	Average Fights
4 Emblems	8.33	8.33
4 Weapons	8.33	8.33
4 Emblems and 4 Weapons	21.74	10.30

Fig. 4. Simulation results on an individual player per boss fights

Number of Players	Theoretical Expectation (Bags per Player)	Average Fights	Average Total Bags
2	4.17	4.42	8.83
3	2.78	3.12	9.36
4	2.08	2.46	9.86
8	1.04	1.42	11.39

Fig. 5. Simulation results of many player per boss fights with a collection target of emblems

Number of Players	Theoretical Expectation (Bags per Player)	Average Fights	Average Total Bags
2	4.17	4.40	8.79
3	2.78	3.12	9.35
4	2.08	2.47	9.87
8	1.04	1.42	11.36

Fig. 6. Simulation results of many player per boss fights with a collection target of weapons

Number of Players	Theoretical Expectation (Bags per Player)	Average Fights	Average Total Bags
2	10.87	5.40	10.79
3	7.24	3.76	11.29
4	5.43	2.95	11.78
8	2.71	1.70	13.59

Fig. 7. Simulation results of many player per boss fights with a collection target of emblems and weapons

D. Interpretation and Implication

Results of the simulation exhibited the average total bags remained relatively static $(E \pm 2)$, the number of average fights dropped drastically. This implies that defeating the boss in a group manner rather than individually speeds up collective progress in obtaining the desired items.

In spite of the drop in number of average fights, the approximation of holds no value if each of the players decided to keep their own loot, despite the amount of collective loot—the total owned by everyone—increases faster.

V. RESULTS ANALYSIS

A. Simulated and Theoritical Comparisson

Simulation proofed that this approach is an accurate method of predicting the number of fights needed to the expected loot for getting the 4 distinct emblems or weapons. However, when simulating with the target collection of both weapons and emblems, the theoretical expectation is not accurate to the simulated average fights. This phenomenon is caused by the fact that the generation of emblems and weapons, despite independent of each other, is triggered by the same—opening the treasure bag—event.

The accuracy of theoretical expectation compared to the average fights with multiple players also follows the same fate. Where results are accurate until the target collection is a combination of both emblems and weapons.

Regardless, this approach—and the accuracy of the results—of using the coupon collector's problem is proof that approximating the number of bosses needed to be fought in order to obtain a desired amount of loot has some merit.

B. Number of Players and its Effect in Efficiency

Results of the simulation displayed in Fig.2. and Fig.3. presented that in spite of the relatively regular average bags obtained, the average fights abated significantly. This reduction implies that in the context of playtime, cooperative farming increases time efficiency. Assuming the time taken for each fight is relatively equal.

C. Strategical Implication for Players

The outcome of the simulation rises a few implications that can be used by players strategize ways of loot collection, such as:

1. Farming in a group gives an advantage compared to individually from a timewise manner.

2. The amount of loot per player changed insignificantly if the loot is not shared between players.

3. If loot sharing is done by each player, the process of obtaining them became more efficient in the context of how many fights needed.

For playing individually, opening 10-11 bags is the average result for obtaining each of the loot available.

D. Correctness and Limitations

Even with a decent accuracy of the results compared to the theoretical expectations, the model found a few limitations by using this approach. Such as a not fully accommodating expectation value calculation, lack of expandability for other loot tables, and modularity for other loot system mechanics—player luck and difficulties—which left room for improvements.

VI. CONCLUSION

This paper aims to study the loot system of Terraria, specifically of the Wall of Flesh, through a combinatorics and discrete probabilistic approach. By analyzing treasure bags—where players can obtain one emblems and weapons each from a pool of for distinct items—a probabilistic model is built to approximate the amount of treasure bags needed to obtain each unique item.

Theoretically, the expectation for obtaining all 8 distinct items with their own respective distribution chances using the coupon collector's problem, with the result of around 21.74 bags, despite the simulated result of 10.30 which is a result of a not fully independent triggers.

The addition of a new dimension in the form of number of players displayed a positive result in efficiency when obtaining loots. An increase of players corresponds positively with the amount of loot being obtained.

From an academic standpoint, this study exhibits that discrete mathematics, specifically combinatorics and probabilities, has an appealing real-world application in the context of video games analysis and design. The current model can be built upon to accommodate more complex loot systems, such as uneven probability distribution, pity systems, chained drop logic, or even a loot economy based on in-game exchange rates. The implementations of the aforementioned subjects can improve a player experience when playing a game by reducing grinding, increases engagement, or even adding a new layer of depth into these games.

As a follow-up, this study can be expanded to compare efficiencies of loot systems between different games, develop a strategic interface for players based in probabilities, or a web-based simulation tool for the gaming community. In a world full chance-based mechanisms, a quantitative approach in dealing with such problems provides a rational solution and increases our understanding in random systems.

Other than that, this simulation can also be extended to other branches of mathematics such as graph theory or Markov Chains to model item ownerships or optimal crafting path. Value weighting can also be added to accommodate a more accurate and nuanced in-game economy to present the most efficient money-making method. This approach may not only be beneficial to players by showing the most efficient path of obtaining loot or displaying the most efficient investing route in a probabilistic manner, but also to developers to ensure a balanced and fair system.

VII. Appendix

The full code of the program can be found in the following link:
https://gist.github.com/PikaProgram/1491b491d21f2971f27425c087978fc3

VIII. Acknowledgment

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PERNYATAAN

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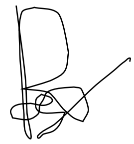
Bandung, 20 Juni 2025



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