

The Penney Ante Problem

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1 Introduction

Imagine a two player game where each player is assigned a sequence, for example THTH and HTHH, and a coin is flipped until either player sees their sequence. The first player to see their sequence appear wins. Given two sequences, which sequence is expected to come first in the sequence of coin flips? What is the probability of a certain player winning? Although these two questions sound similar, the result is that in our example, the expected number of turns for sequence A to appear is 20 and for B it is 18. However, surprisingly, the probability of A winning is $9/14$ while the probability of B winning is $5/14$. Additionally the game has the property that for any sequence A chooses, B can always find a sequence that has a higher probability of winning. These counterintuitive results are the core of the Penney Ante problem, discovered by Walter Penney [3]. My thesis will study this problem through three approaches based in Markov chains, martingales, and a counting approach.

2 Conway's Algorithm

Let X_t be a random variable for $t \geq 1$, and let (X_t) be a stochastic process of letters chosen uniformly and randomly from a q -letter alphabet. In the case of a coin, $q = 2$ and (X_t) represents the sequence of coin flips. Let $A = a_1a_2\dots a_n$ and $B = b_1b_2\dots b_n$ be sequences of n letters chosen from the q -letter alphabet. We say sequence A or B wins if it is the first sequence to appear within (X_t) or more precisely, A or B wins if it is the lowest i such that $A = a_1a_2\dots a_n = X_iX_{i+1}\dots X_n$ or $B = b_1b_2\dots b_n = X_iX_{i+1}\dots X_n$. Let τ_A and τ_B be random variables denoting the number of turns required for A or B to appear. We denote the probability of A winning as $P(\tau_A < \tau_B)$ and we denote the expected time for sequence A and B to appear as $E(\tau_A)$ and $E(\tau_B)$. This notation will be used throughout of the paper.

We can use Conway's algorithm to find $P(\tau_A < \tau_B)$ and $E(\tau_A)$. Conway devised an algorithm for computing these two values which has been described as an algorithm that "cranks out the answer as if by magic" [3]. The algorithm is as follows,

Theorem 2.1. (*Conway's Algorithm [3]*) *Given two sequences of length n , A and B , we find the correlation in base 2, AB_2 , by the following algorithm:*

1. *loop through integers 1, 2, ..., n ,*
2. *At every i th iteration we look at the i th through n th digits of A and compare it to the 1st through the $(n-i)$ th digits of B .*
3. *If these subsequences are equal, the i th digit in the binary representation is 1 but 0 otherwise.*

The binary number of AB_2 is then converted to a decimal number, AB . Once we find AA , AB , BA , and BB , the probability that A precedes B is

$$P(\tau_A < \tau_B) = \frac{AA - AB}{(BB - BA) + (AA - AB)}$$

Furthermore,

$$E(\tau_A) = AA$$

The goal of this paper is to demystify the magic algorithm by providing three methods for computing these values. We will use martingales, Markov chains, and generating functions to verify that the algorithm works.

Throughout the paper we will use $A = HTHT$ and $B = HTHH$ as an example. If we plug this example into Conway's formula we get that $E(\tau_A) = 20$ and $E(\tau_B) = 18$. Pictured is the calculation for $E(\tau_A)$.

Finally, we define nontransitivity. In this context, a game is nontransitive if for any sequence A , player B can choose a sequence B such that $P(\tau_A < \tau_B)$. In later sections we will see that the Penney ante game is nontransitive for $n \geq 4$. In general nontransitivity is....

3 Martingales

3.1 Introduction

We can study the Penney ante problem using a mathematical object called a martingale. A martingale is a stochastic process such that at any time, the expected value of the

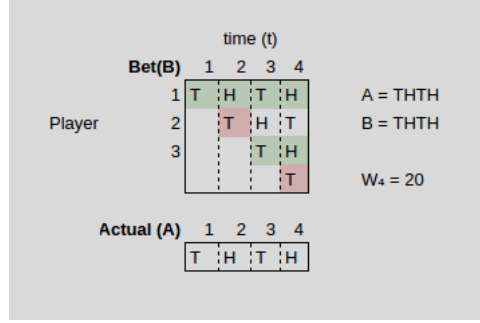


Figure 1: Calculation of AA. $E(\tau_A) = 20$.

random variable is the same. We call a martingale with an expected value of 0 a fair game. More precisely,

Definition 3.1 ([6]). A martingale is a stochastic process (X_t) such that for any integer k and for any finite expected value $E(|X_k|)$,

$$E(X_{k+1} | X_1, \dots, X_k) = X_k$$

Let's define a martingale representing the Penney Ante game. Given a stochastic process of coin flips (X_t) , and for each t , define W_t , assuming $W_0 = 0$,

$$W_{t+1} = \begin{cases} W_t + 2^t & \text{if } X_t = \text{some value that we are betting on} \\ 0 & \text{otherwise} \end{cases}$$

We can reformulate the Penney ante problem into a game found in Grinstead [4]. Grinstead and Snell devised a game based on making side bets on the Penney Ante game to determine the expected waiting times and the probability of a player winning. We will see that the sequence representing the winnings at each turn, W_t , is a martingale [4]. We can then find $E_\varnothing(\tau_B)$ with the help of Doob's convergence theorem, and then $E_A(\tau_B)$. Finally, using some probability we find that $P(\tau_B < \tau_A)$. This side betting game will reveal the inner workings of Conway's algorithm.

Given sequences A and B , imagine at each turn t , a player joins the game and bets 1 choosing to play double or nothing until either they lose or the sequence B is found. On a player's i th turn, the player bets on the i th letter of B appearing while in fact the t th letter of A actually appears. The number of turns in the game is equal to the length of A . We will denote this betting strategy, betting on B while A appears, AB . At each

turn if the player's bet matches the actual outcome, they double their money, otherwise they lose all of their money and stop playing. On each subsequent turn, another player joins the game and also bets AB . At each turn, W_t is the earnings of all the players for time t . Note in this game the case where B is a substring of A is trivial because... [4]

3.2 Example

Consider $A = B = HTH$ as an example. Figure 2 demonstrates the game in a table. At each turn, a new player enters the game and bets on B . Player i 's bet at time t is denoted by the i th row in the t th column in the table. The actual letter appearing is in the 'Actual' table below. The green denotes a match while red denotes a mismatch and thus the stopping of betting for that player.

		time (t)					
		Bet(B)	1	2	3	4	
Player	1	H	T	H	H		A = THTH B = HTHH W ₄ = 10
	2		H	T	H		
	3				H	T	
						H	
		Actual (A)	1	2	3	4	
			T	H	T	H	

Figure 2: Calculation of W_3 for $A = B = HTH$.

Note the repetitive pattern of the table. A table very similar to this will be generated in Conway's algorithm for determining the expected waiting times.

3.3 Expected Winning Times and Probability of B Winning

To prove that $E(\tau_B) = BB$, we must first show that W_t is a martingale.

Claim 3.2. W_t is a martingale.

Proof: From our earlier definition of a martingale we know that W_t is martingale if for each k , $E(W_{k+1}|W_1, W_2, \dots, W_k) = W_k$. Informally, we can see at each time t , the value of each of the gambler's winnings double or go to zero with a .5 chance each way. That means the expected value of each gambler's winnings at time $t + 1$ is the value of their winnings at time t . This seems to indicate that the expected value of W_{t+1} is just the

value of W_t , making it a martingale. More formally, given a stochastic process of coin flips (X_t) , and for $t > 0$, we can define W_t as,

$$W_{t+1} = \begin{cases} W_t + 2^t & \text{if } X_t = \text{some value that we are betting on} \\ 0 & \text{otherwise} \end{cases}$$

Once we choose an X_t to bet on, there is a .5 chance of the bet winning. So $E(W_{t+1}) = \frac{1}{2}(W_t + 2^t) + \frac{1}{2}(0)$. Find the right formula for W_t so this part works out***

□

Now we can find $E_\varnothing(\tau_B)$. Note that the final payout of the game occurs at time $t = \tau_B$, when sequence B fully appears. The random variable τ_B is a stopping time. (Should I prove that τ_B is a stopping time?). First we need Doob's Martingale Convergence Theorem which states that if SOME QUANTITY INVOLVING A RANDOM VARIABLE*** converges to zero then the expected value of the random variable at time $t = \tau_B$ is equal to it's expected value at the stopping time. Formally,

Theorem 3.3. (Doob's Martingale Convergence Theorem) Let W_t be a martingale and τ_B a stopping time. If,

$$\liminf_{k \rightarrow \infty} \int_{\tau_B > k} |W_k| dP = 0$$

then $\{W_1, W_{\tau_B}\}$ is a martingale and $E(W_{\tau_B}) = E(W_1)$.

As stated earlier, W_t is indeed a martingale and τ_B is a stopping time. So we need to show $\liminf_{k \rightarrow \infty} \int_{\tau_B > k} |W_k| dP = 0$. Because XXX we know that $W_{\tau_{AB}} = BB - \tau_{AB}$.

$$E(W_{\tau_{AB}}) \leq BB + E(\tau_{AB}) < \infty$$

Let $Aw_k B$ represent the sequence XXX followed by XXX. Then for $\tau_{AB} > k$,

$$\begin{aligned} W_k &\leq (Aw_k B) + k \\ &\leq BB + \tau_{AB} \end{aligned} \tag{1}$$

This implies that,

$$\lim_{k \rightarrow \infty} \int_{\tau_{AB}} |W_k| dP \leq \lim_{k \rightarrow \infty} \int_{\tau_{AB}} (BB + \tau_{AB}) dP = 0$$

So now we are able to use Doob's convergence theorem to find that,

$$E(W_{\tau_{AB}}) = E(W_0) = AB$$

From the fact that $W_{\tau_{AB}} = BB - \tau_{AB}$, it's true that,

$$E(\tau_{AB}) = BB - AB$$

***Remember τ_{AB} is the random variable representing the time it takes for B to appear starting with A .

***The payout at this time, W_{τ_B} is equal to BB , the amount won from betting on B while sequence B appears. So $E_{\varnothing}(\tau_B) = BB$. Now for AB , the first k tosses (where k is the length of A), the gamblers collectively make AB , ie $W_k = AB$. The total amount the gamblers make at $t = \tau_B$ is thus $BB - BA$ so $E_A(\tau_B) = BB - BA$. [4].

Now what is $P(\tau_B < \tau_A)$? Note that for two random variables, X, Y , $P(X > Y) = \frac{E(X)}{E(X) + E(Y)}$ [4]. So,

$$P(\tau_B < \tau_A) = \frac{E_A(\tau_B)}{E_A(\tau_B) + E_B(\tau_A)} = \frac{AA - AB}{(BB - BA) + (AA - AB)}$$

4 Markov Chains

As stated earlier, $E(\tau_A) < E(\tau_B)$ does not imply $P(\tau_A < \tau_B) > \frac{1}{2}$. To prove and understand this result, we will construct a Markov chain. A Markov chain is a stochastic process (X_t) that has the probability that each state of the chain occurs – ie each X_k – is based solely on the previous state, X_{k-1} for all $k > 1$. Markov chains allow the sequence to be represented by a graph with all the possible states of the sequence as vertices. Edges connecting vertices denote probabilities between that a state will occur after another state. More formally,

Definition 4.1 ([8]). A Markov chain is a stochastic process such that

$$P(X_{k+1} = x | X_1, X_2, \dots, X_k) = P(X_{k+1} = x | X_k)$$

That is, the probability that each $x \in \Omega$ occurs given the entire history of previous states is only dependent on the most recent event. Denote the probability that $P(X_{k+1} = y | X_k = x)$ as $P(x, y)$. The matrix $P = P(x, y)$ for all $x, y \in \Omega$ is called the transition matrix of (X_t) .

The Penney ante game can be represented as a Markov chain because each sequence of coin flips, for example $X_4 = HTHT$, depends only on the previous state X_3 and not the entire history of states. We can use Markov chains to find $E(\tau_A)$ and $P(\tau_A < \tau_B)$

by writing a system of equations for the probability and expected value of each state which will be done next section.

Using Markov chains, we can construct a system of equations for the expected waiting time to win and probability of a sequence winning. Let p_x denote the probability sequence A of length n wins given that $x \in \Omega$ has occurred. To find p_\emptyset , the probability of A winning given nothing has happened, we can construct a system of $n + 1$ equations for each X_i composed of probabilities times of reaching x from y . Assuming $x - y$ means $P(x, y) > 0$,

$$p_x = \sum_{y-x} P(x, y) p_y$$

In this game where $q = 2$, each sum will have two terms since there will only be at most two states x that are reachable from each state y . Similarly, we can find the expected value with this method but with a small change. Let E_x denote the time to win given x has occurred. Then we can write a system of $n + 1$ equations,

$$E_x = \sum_{y-x} P(x, y) (1 + E_y)$$

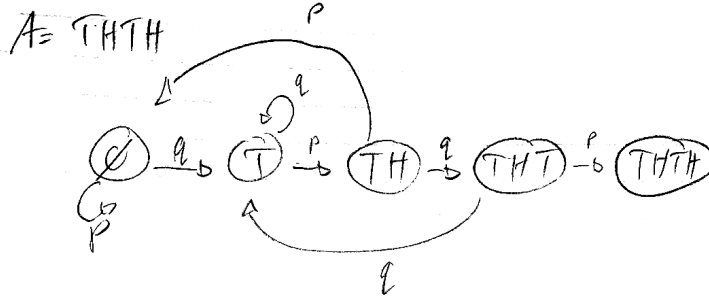


Figure 3: The graph of Ω_A

As an example, let $A = THTH$ and $B = HTHH$. Although not all possible sequences have the property that, $E(\tau_A) < E(\tau_B)$ while $P(\tau_A < \tau_B) > \frac{1}{2}$, this particular example goes against our intuition so it is worthwhile to look at. As stated in the introduction, $E(\tau_A)$ is 20, $E(\tau_B)$ is 18, and $P(\tau_A > \tau_B) = \frac{9}{14}$. As a sanity check, we should check that the three methods described in the previous section give the same answer for $P(\tau_A > \tau_B)$ and $E(\tau_B)$.

With the Markov chain approach, we can directly construct the transition matrix P .

value we have,

$$\begin{aligned}
E_{\emptyset} &= \frac{1}{2}(1 + E_{THT}) \\
E_T &= \frac{1}{2}(1 + E_{TH}) + \frac{1}{2}(1 + E_{\emptyset}) \\
E_{TH} &= \frac{1}{2}(1 + E_{THT}) + \frac{1}{2}(1 + E_{THTH}) \\
E_{THT} &= \frac{1}{2}(1 + E_{THTH}) + \frac{1}{2}(1 + E_{TH}) \\
E_{THTH} &= 1
\end{aligned} \tag{4}$$

The calculation for B is omitted because it is essentially the same. Using the same Mathematica code we find that $E_{THTHT} = 20$. Thus concludes the calculation using the Markov chain approach. Conway's algorithm gives us the same result.

Consider $A = THTH$. The calculation AA is as follows,

```

1010
THTH
THTH
THTH
THTH
THTH
THTH

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The binary number 1010 in decimal is 9 so $E(\tau_{THTH}) = 18$ and $P(\tau_A < \tau_B) = \frac{9}{14}$.

5 Generating Function

For the final method of proving Conway's algorithm, we will be using a combinatoric method for finding $E(\tau_A)$ based around finding the generating function for the number of possible X_t , for a given t , which do not contain A as a substring. Once we have this generating function, denoted $F(z)$, we can count XXXX. Then we will see that this method exemplifies Conway's algorithm. First, let's define a generating function.

Definition 5.1 ([9]). *Given any sequence $(X_t) = f(0), f(1), f(2), \dots$, we define the generating function $F(z)$ as*

$$F(z) = \sum_{n=0}^{\infty} f(n)z^{-n}$$

where $z \in \{0, 1, 2, \dots\}$.

Recall the value AB from Conway's algorithm. This value, which Odlyzko defines

as the correlation of strings A and B , represents the amount of overlap between two strings [9], and so it will be used in the generating function.

Claim 5.2. ([9] [3]) *Assuming AA_z represents the correlation of A with A expressed in base z , then the generating function for a string of length z that contains no occurrences of string A of length q is,*

$$F(z) = \frac{zAA_z}{1 + (z - q)AA_z}$$

Proof: ([9]) Let $f_A(n)$ be the number of strings of length n such that only the last (rightmost) q letters are A . Let,

$$F_A(z) = \sum_{n=0}^{\infty} f_A(n)z^{-n}$$

Then it follows both that (****Why does this follow? I really need to explain the jumps between these steps)

$$(z - q)F(z) + zF_A(z) = z$$

$$F(z) = zAA_zF_A(z)$$

Finally we can see that

$$F(z) = \frac{zAA_z}{1 + (z - q)AA_z}$$

□

We can get that $F(2) = AA$. The probability that A does not appear in the first n coin tosses is $f(n)2^{-n}$. The expected number of coin tosses until A appears is,

$$F(2) = \sum_{n=0}^{\infty} f(n)2^{-n}$$

The probability that A does not appear in the first n coin tosses is $f(n)2^{-n}$ [9]. The expected number of coin tosses can be derived from these facts and will involve a number called the correlation of two strings, denoted AB . The correlation AB will be better defined later when outlining Conway's algorithm. Conway devised a "magic algorithm" which let us compute AB which will be used to find the expected winning time and the probability of A winning. This operation AB has a careful connection to the AB defined in the betting strategy. The correlation will give us the expected number of coin tosses until A appears and it is also used to model the above gambling game. The connection between the two AB 's will come in a later section.

6 Conclusion

***Add conclusion

7 Other

References

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