

# Information Theory, Part II

Manan Shah  
manan.shah.777@gmail.com  
The Harker School

January 20, 2017

This document contains lecture notes from Harker's Advanced Topics in Mathematics class in Information Theory II, taught by Dr. Anuradha Aiyer. This course is the second part of a two part offering that explores the basic concepts of Information Theory, as initially described by Claude Elwood Shannon at Bell Labs in 1948. In Part 2 of the course, we explore other applications of Information Theory to the disciplines of Gambling, Statistics, Physics, Computer science, Economics and Philosophy. These notes were taken using TeXShop and  $\text{\LaTeX}2\epsilon$  and will be updated for each class. The reader is advised to note any errata at the source control repository <https://github.com/mananshah99/infotheory>.

## Contents

<b>1 Unit 1: Gambling</b>	<b>2</b>
1.1 Repeated Gambling . . . . .	2

# 1 Unit 1: Gambling

We'll discuss the duality between the growth rate of investment (i.e. a horse race) and the entropy rate of the horse race and how the side information's financial value is tied to mutual information.

**Definition 1** (Horse Race). We have  $m$  horses in a race in which the  $i$ th horse wins with probability  $p_i$ . If horse  $i$  wins, the payoff is  $o_i$  for  $1^1$ . We'll assume that the gambler invests his wealth across all horses and doesn't hold on to any of his money. Specifically,  $b_i$  is the fraction of wealth invested in horse  $i$  where  $b_i \geq 0$  and  $\sum b_i = 1$ . If horse  $i$  wins, the gambler wins  $o_i b_i$ ; this case occurs with probability  $p_i$ . The wealth at the end of the race is a random variable which we will attempt to maximize.

## 1.1 Repeated Gambling

Define  $S_n$  as the total growth in the gambler's wealth after  $n$  races. We have

$$S_n = \prod_{j=1}^n S(X_j) \quad \text{and} \quad S(X_j) = b(X_j) o(X_j)$$

with  $X$  representing the horse that wins (this changes between races). Here,  $S(X_i)$  represents the factor by which the gambler's wealth grows. We can define the doubling rate of a race  $W$  as

$$E(\log S(X)) = \sum_{k=1}^m p_k \log(b_k o_k) = W(b, p)$$

**Theorem 1.** Let race outcomes  $X_1, X_2, X_3, \dots, X_n$  be identically and independently distributed  $\sim p(x)$ . The wealth of a gambler using betting strategy  $b$  grows exponentially at the rate  $W(b, p)$  such that  $S_n = 2^{nW(b, p)}$ .

*Proof.* Functions of independent random variables are also independent, so  $\log S(X_1), \dots, \log S(X_n)$  are i.i.d. From our earlier definition of  $S_n$  we have

$$\frac{1}{n} \log S_n = \frac{1}{n} \sum \log S(X_i)$$

By the weak law of large numbers<sup>2</sup>, this equates to  $E(\log S(X)) = W(b, p)$ . So we can conclude that  $S_n = 2^{nW(b, p)}$  and the proof is complete. So if to maximize  $S_n$ , we'll need to maximize  $W$ .  $\square$

**Definition 2.** The optimum doubling rate over all choices of  $b_i$  is

$$W^*(p) = \max_b W(b, p) = \max_{b: b_i \geq 0, \sum b_i = 1} \sum_i p_i \log b_i o_i$$

We must formally maximize  $W(b, p)$  such that  $\sum b_i = 1$ . To do this, we'll apply Lagrange optimization. We have

$$J(b) = \sum p_i \log b_i o_i + \lambda \sum b_i$$

<sup>1</sup>There are two ways to describe a bet: either  $a$  for 1 or  $b$  to 1. The first notation indicates an exchange that happens prior to the race, and the latter indicates an exchange that happens post-race (although in both cases the horses are picked before the race). More concretely,  $a$  for 1 indicates that if one places \$1 on a particular horse before the race, the payoff is \$ $a$  iff the horse wins and \$0 if the horse loses.  $b$  to 1 indicates that one would pay \$1 after the race if a particular horse loses and win \$ $b$  if the horse wins. The equivalency between these scenarios is  $b = a - 1$ .

<sup>2</sup>See <http://mathworld.wolfram.com/WeakLawofLargeNumbers.html> for more information.

Taking the partial with respect to  $b_i$  and setting it equal to 0,

$$\frac{\partial J}{\partial b_i} = \frac{p_i}{b_i} + \lambda$$

where  $i \in \{1 \dots m\}$ .  $\sum b_i = 1$  results in  $b_i = p_i$ . Technically, we'd have to take the second derivative to prove that this is a maximum; this verification is left to the reader.

**Theorem 2.**  $W^* = \sum p_i \log o_i - H(p)$

## Appendix A—Quotes

- “I have a problem. It’s called gambling.” (Dr. Aiyer)
- “What’s  $E$ ? Entropy?” (David Zhu)
- “So is it the strong law of weak numbers?” (Jerry Chen)
- “It’s like a half life... but it’s a double life” (Steven Cao)