## Documentation

## Jerry Wang

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## 1 Introduction

## 1.1 Entropy - Surprise Factor

First we would like to define the concept of the "surprise" of an event E occurring and define entropy based off that. We deem this important since entropy plays a large role in many of the metric developed and implemented. As such, it would be helpful to define a consistent mathematical framework as well as develop intuition for these definitions at a precise mathematical level.

The following methods and definitions are based on Ross's A First Course in Probability [1]. Mathematically, it makes sense that the surprise invoked by an event E occurring should be a function of the probability of event E itself, which we will denote p. Thus we define S(p) as the surprise invoked by an event with a probability of p. Now we will begin by stating some axioms for this definition of surprise.

#### Axiom 1

$$S(1) = 0$$

Intuitively, that just means we should feel no surprise when a event with probability 1 occurs. That is, it is not surprising at all for a sure event to occur.

#### Axiom 2

$$p < q \implies S(p) < S(q)$$

That is, S(p) is a strictly decreasing function of p.

#### Axiom 3

S(p) is a continuous function with respect to p

#### Axiom 4

$$S(pq) = S(p) + S(q)$$

The intuition of this axiom is given when we consider independent events  $E_1$  and  $E_2$  with probabilities of occurring with p and q respectively. Since  $E_1$  and  $E_2$  are independent,  $P(E_1 \cap E_2) = P(E_1) \cdot P(E_2) = pq$ . Thus the surprise invoked by  $E_1 \cap E_2$  should be defined as S(pq). But now, let us consider that we are first told that event  $E_1$  occurred, and then afterwards event  $E_2$  occur. We know the total surprise invoked is simply the surprised invoked by  $E_1 \cap E_2$  which is S(pq), and since we know that S(p) is the surprise invoked by event  $E_1$  alone, it follows that S(pq) - S(p) should represent the initial surprise invoked by  $E_2$ . Due to independence, we know the probability of  $E_2$  is still q and thus the surprise of event  $E_2$  should remain S(q). Thus we have that S(pq) - S(p) = S(q) or that S(pq) = S(p) + S(q).

From the axioms, we can prove that

$$S(p) = -C \log_2 p$$

where C > 0. From Axiom 4, we have that

$$S(p^2) = S(p) + S(p) + 2S(p)$$

From induction, we also have that for  $m \in \mathbb{Z} > 0$ 

$$S(p^m) = mS(p) \tag{1}$$

Also note that for  $n \in \mathbb{Z} > 0$ 

$$S(p) = S\left((p^{\frac{1}{n}})^n\right) = nS(p^{\frac{1}{n}})$$

which implies that

$$S(p^{\frac{1}{n}}) = \frac{S(p)}{n} \tag{2}$$

Combining equations 1 and 2, we can define

$$S(p^x) = xS(p) \tag{3}$$

for  $x \in \mathbb{Q} > 0$ . Now from Axiom 3, we can define equation  $3 \ \forall x \in \mathbb{Q} > 0$ .

Now let us take  $x = -\log_2 p$  which implies  $p = \left(\frac{1}{2}\right)^x$  which allows for the following relation.

$$S(p) = S\left((\frac{1}{2})^x\right) = xS\left(\frac{1}{2}\right) = -S\left(\frac{1}{2}\right) \cdot \log_2 p$$

Now notice  $S\left(\frac{1}{2}\right) = C$  is simply a constant (that is non-zero thanks to Axiom 1 and Axiom 2).

Thus we have shown that

$$S(p) = -C\log_2 p \tag{4}$$

follows from the axioms. Lastly, note that it is standard to let C=1.

### 2 Mathematical Metrics

## 2.1 Shannon Entropy Metric

Now we aim to quantify the expected amount of surprise incurred by a random variable X. Since  $\log_2 p_i$  is the value of the surprise invoked when an event (let's say  $E_i$ ) with probability  $p_i$  occurs, the expected value of  $S(p_i)$  for any outcome of  $E_i$  is  $p_i \cdot \log_2 p_i$ . Now summing over all expectations, we have the expected surprise of a random variable X which takes on n values with probability  $p_1, p_2, ... p_n$  is

$$H(x) = \sum_{i=1}^{n} p_i \log_2 p_i$$

### 2.1.1 Shannon Entropy Ratio

It can be proven using Lagrange Multipliers that the distribution that maximizes entropy such that . Thus we will take a score

$$R = \frac{H(x,n)}{H_{\max}(n)}$$

### 2.2 Password Entropy Metric

# References

 $[1]\,$  Ross, Sheldon M. 2019. A First Course in Probability. 10th ed. Pearson.