

Statistical Inference for Entropy

Karina Marks

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1 Introduction

2 Entropies and Properties

Entropy can be thought of as a representation of the average information content of an observation; sometimes referred to as a measure of unpredictability.

The differential entropy of a random vector X with density function f is given by H ;

$$H = -\mathbb{E}\{\log(f(x))\} \quad (1)$$

$$= - \int_{x:f(x)>0} f(x)\log(f(x))dx \quad (2)$$

3 Estimation of Entropy

3.1 Kozachenko-Leonenko Estimator

We now wish to introduce the Kozachenko-Leonenko estimator of the entropy H . Let X_1, X_2, \dots, X_n , $N \geq 1$ be independent and identically distributed random vectors in \mathbb{R}^d , and denote $\|\cdot\|$ the Euclidean norm on \mathbb{R}^d .

- For $i = 1, 2, \dots, n$, let $X_{(1),i}, X_{(2),i}, \dots, X_{(n-1),i}$ denote an order of the X_k for $k = \{1, 2, \dots, n\} \setminus \{i\}$, such that $\|X_{(1),i} - X_i\| \leq \dots \leq \|X_{(n-1),i} - X_i\|$. Let the metric ρ , defined as;

$$\rho_{(k),i} = \|X_{(k),i} - X_i\| \quad (3)$$

denote the k th nearest neighbour or X_i .

- For dimension d , the volume of the unit d -dimensional Euclidean ball is defined as;

$$V_d = \frac{\pi^{\frac{d}{2}}}{\Gamma(1 + \frac{d}{2})} \quad (4)$$

- For the k th nearest neighbour, the digamma function is defined as;

$$\Psi(k) = -\gamma + \sum_{j=1}^{k-1} \frac{1}{j} \quad (5)$$

where $\gamma = 0.577216$ is the Euler-Mascheroni constant (where the digamma function is chosen so that $\frac{e^{\Psi(k)}}{k} \rightarrow 1$ as $k \rightarrow \infty$).

Then the Kozachenko-Leonenko estimator for entropy, H is given by;

$$\hat{H}_n = \frac{1}{n} \sum_{i=1}^n \log \left[\frac{\rho_{(k),i}^d V_d(n-1)}{e^{\Psi(k)}} \right] \quad (6)$$

This estimator for entropy, when $d \leq 3$, under a wide range of k and some regularity conditions, this estimator satisfies;

$$n\mathbb{E}(\hat{H}_n - H)^2 \rightarrow 0 \quad (n \rightarrow \infty) \quad (7)$$

so \hat{H}_n is efficient in the sense that the asymptotic variance is the best attainable; $n^{\frac{1}{2}}(\hat{H}_n - H) \xrightarrow{d} N(0, Var[\log(f(x))])$.

Later, I will further discuss this estimator for the specific dimensions $d = 1$ and $d = 2$; however, it is important to note that for larger dimensions this estimator is not accurate. When $d = 4$ equation 7, no longer holds but the estimator \hat{H}_n , defined by 6, is still root- n consistent, provided k is bounded. Also, when $d \geq 5$ there is a non trivial bias, regardless of the choice of k .

There is a new proposed estimator, formed as a weighted average of \hat{H}_n for different values of k , explored in Moreover, as this paper only considers $d = 1, 2$, this will not be examined here.

4 Monte-Carlo Simulations