Introduction to Probability

Lecture 10: Estimators (Part I)

Mateja Jamnik, Thomas Sauerwald

University of Cambridge, Department of Computer Science and Technology
email: {mateja.jamnik,thomas.sauerwald}@cl.cam.ac.uk

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Outline

Introduction

Setting: We can take random samples in the form of i.i.d. random variables $X_1, X_2, \ldots, X_n$ from an unknown distribution.

- Taking enough samples allows us to estimate the mean (WLLN, CLT)
- Using indicator variables, we can estimate $\mathbf{P}[X \leq a]$ for any $a \in \mathbb{R}$
  $\rightsquigarrow$ in principle we can reconstruct the entire distribution

???

- How can we directly estimate the variance or other parameters?
  $\rightsquigarrow$ estimator
- How can we measure the accuracy of an estimator?
  $\rightsquigarrow$ bias (this lecture) and mean squared error (next lecture)

expectation

variance

Physical Experiments:

$$\text{Measurement} = \text{Quantity of Interest} + \text{Measurement Error}$$

Empirical Distribution Functions

Definition of Empirical Distribution Function (Empirical CDF)

Let $X_1, X_2, \ldots, X_n$ be i.i.d. samples, and F be the corresponding distribution function. For any $a \in \mathbb{R}$, define

$$F_n(a) := \frac{\text{number of } X_i \in (-\infty, a]}{n}.$$

Remark

The Weak Law of Large Numbers implies that for any $\epsilon > 0$ and $a \in \mathbb{R}$,

$$\lim_{n \to \infty} \mathbf{P}\left[\,|F_n(a) - F(a)| > \epsilon\,\right] = 0.$$

Thus by taking enough samples, we can estimate the entire distribution (including its expectation and variance).

Empirical Distribution Functions (Example 1/2)

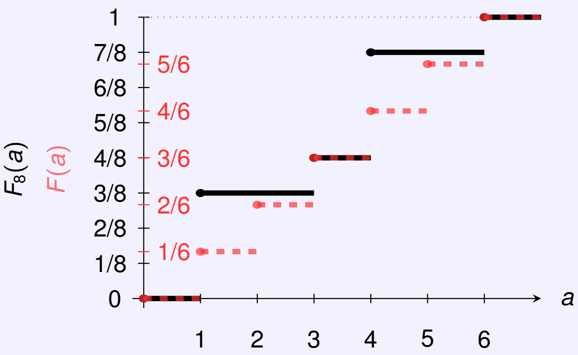
Example 1

Consider throwing an unbiased dice 8 times, and let the realisation be:

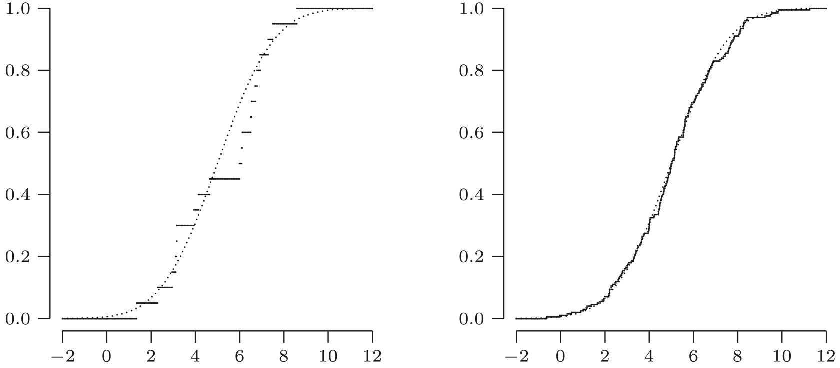
$$(x_1, x_2, \ldots, x_8) = (4, 1, 4, 3, 1, 6, 4, 1).$$

What is the Empirical Distribution Function $F_8(a)$?

Answer



Empirical Distribution Functions (Example 2/2)



Source: Modern Introduction to Statistics

Figure: Empirical Distribution Functions of samples from a Normal Distribution $\mathcal{N}(5, 4)$ ($n = 20$ left, $n = 200$ right)

An Example of an Estimation Problem

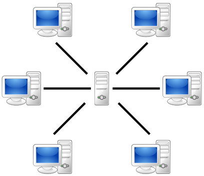
Scenario

Consider the packages arriving at a network server.

- We might be interested in:
  1. number of packets that arrive within a "typical" minute
  2. percentage of minutes during which no packets arrive
- If arrivals occur at random time $\rightsquigarrow$ number of arrivals during one minute follows a Poisson distribution with **unknown** parameter λ

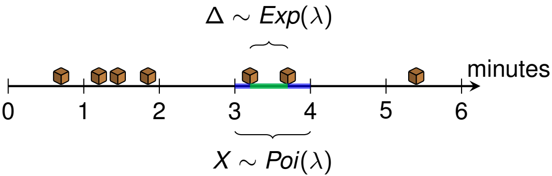
Estimator for λ

Estimator for $e^{-\lambda}$



Source: Wikipedia

Waiting Time (Lecture 5, Slide 22)



$$\mathbf{P}[X = k] = e^{-\lambda} \cdot \frac{\lambda^k}{k!}$$

Estimator

Definition of Estimator

An estimate is a value t that only depends on the dataset $x_1, x_2, \dots, x_n$, i.e.,

$$t = h(x_1, x_2, \dots, x_n).$$

Then t is a realisation of the random variable

$$T = h(X_1, X_2, \dots, X_n),$$

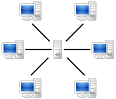
which is called estimator.

Questions:

- What makes an estimator suitable? unbiased (later: mean squared error)
- Does an unbiased estimator always exist? How to compute it?
- If there are several unbiased estimators, which one to choose?

Outline

Example: Arrival of Packets (1/3)



- Samples: Given $X_1, X_2, \dots, X_n$ i.i.d., $X_i \sim Pois(\lambda)$
- Meaning: X_i is the number of packets arriving in minute i

Example 2

Estimate λ by using the sample mean $\overline{X}_n$.

Answer

We have

$$\overline{X}_n := \frac{X_1 + X_2 + \cdots + X_n}{n},$$

and $\mathbf{E}\left[\overline{X}_n\right] = \mathbf{E}[X_1] = \lambda$. This suggests the estimator:

$$h(X_1, X_2, \dots, X_n) := \overline{X}_n.$$

Applying the Weak Law of Large Numbers:

$$\lim_{n\to\infty} \mathbf{P}\left[\left|\overline{X}_n - \lambda\right| > \epsilon\right] = 0 \qquad \text{for any } \epsilon > 0.$$

Example: Arrival of Packets (2/3)

Example 3a

Define an estimator h_1 for the probability of zero arrivals, $e^{-\lambda}$.

Answer

Let $X_1, X_2, \ldots, X_n$ be the n samples. Let

$$Y_i := \mathbf{1}_{X_i=0}.$$

Then

$$\mathbf{E}[\, Y_i \,] = \mathbf{P}[\, X_i = 0 \,] = e^{-\lambda},$$

and thus we can define an estimator by

$$h_1(X_1, X_2, \ldots, X_n) := \frac{Y_1 + Y_2 + \cdots + Y_n}{n} = \overline{Y_n}.$$

Example: Arrival of Packets (3/3)

- Suppose we get the samples $(x_1, x_2, x_3) = (50, 100, 0)$
- Then $(y_1, y_2, y_3) = (0, 0, 1)$, and $h_1(x_1, x_2, x_3) = \frac{1}{3}$
- This seems too large! Also note that for the samples $(x_1, x_2, x_3) = (1, 1, 0)$, our estimator would give the same estimate

Example 3b

Define an estimator h_2 for $e^{-\lambda}$ based on $\overline{X}_n$.

Answer

We saw that $\overline{X}_n = \frac{\sum_{i=1}^{n} X_i}{n}$ satisfies $\mathbf{E}\left[\,\overline{X}_n\,\right] = \mathbf{E}\left[\,X_1\,\right] = \lambda$.
Recall by the Weak Law of Large Numbers:

$$\lim_{n\to\infty} \mathbf{P}\left[\,\left|\overline{X}_n - \lambda\right| > \epsilon\,\right] = 0 \qquad \text{for any } \epsilon > 0.$$

This suggests to estimate $e^{-\lambda}$ by $e^{-\overline{X}_n}$. Hence our estimator is

$$h_2(X_1, X_2, \ldots, X_n) := e^{-\overline{X}_n}.$$

Behaviour of the Estimators

- Suppose we have $n = 30$ and we want to estimate $e^{-\lambda}$
- Consider the two estimators $h_1(X_1, \ldots, X_n)$ and $h_2(X_1, \ldots, X_n)$.

How **good** are these two estimators?

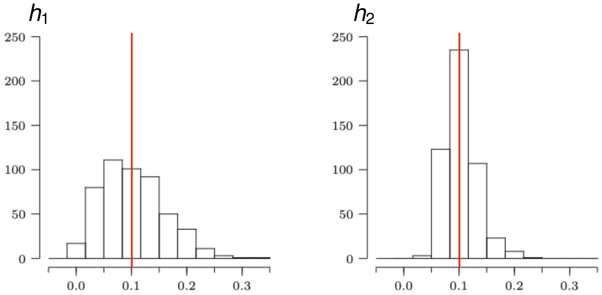
$\Rightarrow$ The first estimator can only attain values $0, \frac{1}{30}, \frac{2}{30}, \ldots, 1$

$\Rightarrow$ The second estimator can only attain values $1, e^{-1/30}, e^{-2/30}, \ldots$

For most values of λ, both estimators will never return the exact value of $e^{-\lambda}$ on the basis of 30 observations.

Simulation of the two Estimators

- The unknown parameter is $p = e^{-\lambda} = 0.1$ (i.e., $\lambda = \ln 10 \approx 2.30\ldots$)
- We consider $n = 30$ minutes and compute h_1 and h_2
- We repeat this 500 times and draw a frequency histogram ($h_1 = \overline{Y}_n$ left, $h_2 = e^{-\overline{X}_n}$ right)



Source: Modern Introduction to Statistics

Both estimators concentrate around the true value 0.1, but the second estimator appears to be more concentrated.

Unbiased Estimators and Bias

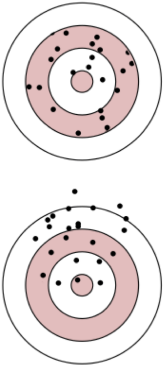
Definition

An estimator T is called an unbiased estimator for the parameter θ if

$$\mathbf{E}\left[T \right] = \theta,$$

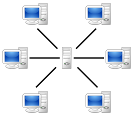
irrespective of the value θ. The bias is defined as

$$\mathbf{E}\left[T \right] - \theta = \mathbf{E}\left[T - \theta \right].$$



Source: Edwin Leuven (Point Estimation)

Which of the two estimators h_1, h_2 are unbiased?



Analysis of the Bias of the First Estimator

Example 4a

Is $h_1(X_1, X_2, \ldots, X_n) = \frac{Y_1 + Y_2 + \cdots + Y_n}{n}$ an unbiased estimator for $e^{-\lambda}$?

Answer

Recall we defined $Y_i := \mathbf{1}_{X_i = 0}$. **Yes**, because:

$$\begin{aligned} \mathbf{E}[\, h_1(X_1, X_2, \ldots, X_n) \,] &= \frac{n \cdot \mathbf{E}[\, Y_1 \,]}{n} \\ &= \mathbf{P}[\, X_1 = 0 \,] \\ &= e^{-\lambda}. \end{aligned}$$

Bias of the Second Estimator (and Jensen's Inequality)

Example 4b

Is $h_2(X_1, X_2, \ldots, X_n) = e^{-\overline{X}_n}$ an unbiased estimator for $e^{-\lambda}$?

Answer

No! (recall: $\mathbf{E}\left[X^2\right] \geq \mathbf{E}\left[X\right]^2$)

- We have

$$\mathbf{E}\left[e^{-\overline{X}_n}\right] > e^{-\mathbf{E}\left[\overline{X}_n\right]} = e^{-\lambda}$$

- This follows by Jensen's inequality, and the inequality is strict since $g : z \mapsto e^{-z}$ is strictly convex and $\overline{X}_n$ is not constant.
- Thus $h_2(X_1, X_2, \ldots, X_n)$ is not unbiased – it has positive bias.

$$\lambda g(a) + (1-\lambda)g(b) \;\geq\; g(\lambda a + (1-\lambda)b)$$

Jensen's Inequality

For any random variable X, and any convex function $g : \mathbb{R} \to \mathbb{R}$, we have

$$\mathbf{E}\left[g(X)\right] \geq g(\mathbf{E}\left[X\right]).$$

If g is strictly convex and X is not constant, then the inequality is strict.

Asymptotic Bias of the Second Estimator (non-examinable)

Example 4c

$\mathbf{E}[\, h_2(X_1,\ldots,X_n)\,] \overset{n\to\infty}{\longrightarrow} e^{-\lambda}$ (hence it is asymptotically unbiased).

Answer

- Recall $h_2(X_1,\ldots,X_n) = e^{-\overline{X}_n}$. For any $0 \le k \le n$,

$$\mathbf{P}\left[\, h_2(X_1,\ldots,X_n) = e^{-k/n}\,\right] = \mathbf{P}\left[\,\sum_{i=1}^{n} X_i = k\,\right] = \mathbf{P}[\, Z = k\,],$$

where $Z \sim Pois(n\cdot\lambda)$ (since $Pois(\lambda_1) + Pois(\lambda_2) = Pois(\lambda_1+\lambda_2)$)

$$\Rightarrow \qquad \mathbf{P}\left[\, h_2(X_1,\ldots,X_n) = e^{-k/n}\,\right] = \frac{e^{-n\lambda}\cdot(n\lambda)^k}{k!}$$

$$\Rightarrow \qquad \mathbf{E}[\, h_2(X_1,\ldots,X_n)\,] = \sum_{k=0}^{\infty} e^{-n\lambda}\cdot\frac{(n\lambda^k)}{k!}\cdot e^{-k/n}$$

By LOTUS

$$= e^{-n\lambda}\cdot e^{n\lambda e^{-1/n}} \sum_{k=0}^{\infty} e^{-n\lambda e^{-1/n}}\cdot\frac{(n\lambda e^{-1/n})^k}{k!}$$

$$= e^{-n\lambda\cdot(1-e^{-1/n})}\cdot 1$$

$$\overset{n\to\infty}{\approx} e^{-n\lambda\cdot(1-1+1/n+O(1/n^2))} = e^{-\lambda+O(\lambda/n)}.$$

since $e^x = 1 + x + O(x^2)$ for small x

Hence in the limit, the positive bias of h_2 diminishes.

Outline

Unbiased Estimator for Expectation and Variance

Unbiased Estimators for Expectation and Variance

Let $X_1, X_2, \ldots, X_n$ be identically distributed samples from a distribution with finite expectation μ and finite variance σ^2.

- Then

$$\overline{X}_n := \frac{X_1 + X_2 + \cdots + X_n}{n}$$

  is an unbiased estimator for μ.

- Furthermore, for $n \geq 2$,

$$S_n = S_n(X_1, \ldots, X_n) := \frac{1}{n-1} \cdot \sum_{i=1}^{n} \left(X_i - \overline{X}_n \right)^2$$

  is an unbiased estimator for σ^2.

Example 5

We need to prove: $\mathbf{E}[S_n] = \sigma^2$.

Answer

Multiplying by $n-1$ yields:

$$
\begin{aligned}
(n-1)\cdot S_n &= \sum_{i=1}^{n}\left(X_i - \overline{X}_n\right)^2 \\
&= \sum_{i=1}^{n}\left(X_i - \mu + \mu - \overline{X}_n\right)^2 \\
&= \sum_{i=1}^{n}(X_i-\mu)^2 + \sum_{i=1}^{n}\left(\overline{X}_n - \mu\right)^2 - 2\sum_{i=1}^{n}(X_i-\mu)\left(\overline{X}_n-\mu\right) \\
&= \sum_{i=1}^{n}(X_i-\mu)^2 + n\left(\overline{X}_n - \mu\right)^2 - 2\left(\overline{X}_n-\mu\right)\cdot n\cdot\left(\overline{X}_n-\mu\right) \\
&= \sum_{i=1}^{n}(X_i-\mu)^2 - n\left(\overline{X}_n - \mu\right)^2.
\end{aligned}
$$

By Lec. 8, Slide 21: $\mathbf{E}\left[(\overline{X}_n-\mu)^2\right] = \mathbf{V}\left[\overline{X}_n\right] = \sigma^2/n$

Let us now take expectations:

$$
\begin{aligned}
(n-1)\cdot\mathbf{E}[S_n] &= \sum_{i=1}^{n}\mathbf{E}\left[(X_i-\mu)^2\right] - n\cdot\mathbf{E}\left[\left(\overline{X}_n-\mu\right)^2\right] \\
&= n\cdot\sigma^2 - n\cdot\sigma^2/n \\
&= (n-1)\cdot\sigma^2.
\end{aligned}
$$

An Unbiased Estimator may not always exist

Example 6

Suppose that we have one sample $X \sim Bin(n, p)$, where $0 < p < 1$ is unknown but n is known. Prove there is no unbiased estimator for $1/p$.

Answer

- First a simpler proof which exploits that p might be arbitrarily small
- Intuition: By making p smaller and smaller, we force $\max_{0 \leq k \leq n} T(k)$, $k \in \{0, 1, \ldots, n\}$ to become bigger and bigger
- Formal Argument:
  - Fix any estimator $T(X)$
  - Define $M := \max_{0 \leq k \leq n} T(k)$. Then,

$$\begin{aligned} \mathbf{E}[\,T(X)\,] &= \sum_{k=0}^{n} \binom{n}{k} p^k (1-p)^{n-k} \cdot T(k) \\ &\leq M \cdot \sum_{k=0}^{n} \binom{n}{k} p^k (1-p)^{n-k} = M. \end{aligned}$$

  - Hence this estimator does not work for $p < \frac{1}{M}$, since then $\mathbf{E}[\,T(X)\,] \leq M < \frac{1}{p}$ (negative bias!)
- The next proof will work even if $p \in [a, b]$ for $0 < a < b \leq 1$.

An Unbiased Estimator may not always exist (cntd. - non-examinable)

Example 6 (cntd.)

Suppose that we have one sample $X \sim Bin(n, p)$, where $0 < p < 1$ is unknown but n is known. Prove there is no unbiased estimator for $1/p$.

Answer

- Suppose there exists an unbiased estimator with $\mathbf{E}[\,T(X)\,] = 1/p$.
- Then

$$1 = p \cdot \mathbf{E}[\,T(X)\,] = p \cdot \sum_{k=0}^{n} \mathbf{P}[\,X = k\,] \cdot T(k) = p \cdot \sum_{k=0}^{n} \binom{n}{k} p^k \cdot (1-p)^{n-k} \cdot T(k)$$

- Last term is a polynomial of degree $n+1$ with constant term zero

$\Rightarrow p \cdot \mathbf{E}[\,T(X)\,] - 1$ is a (non-zero) polynomial of degree $\leq n+1$

$\Rightarrow$ this polynomial has at most $n+1$ roots

$\Rightarrow \mathbf{E}[\,T(X)\,]$ can be equal to $1/p$ for at most $n+1$ values of p, and thus cannot be an unbiased.