Order Statistics and Quantiles

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February 13, 2020

Order Statistics

The order statistics of a sample X_1, X_2, \ldots, X_n are the smallest to largest, indicated by $X_{(1)}, X_{(2)}, \ldots, X_{(n)}$.

Distribution of Order Statistics

Suppose X_i are iid for i = 1, ..., n with distribution function (CDF) F. Then, the probability that the smallest order statistics is larger than a certain value x can be expressed using F:

$$P(X_{(1)}>x)=\prod_{i=1}^n P(X_i>x)=(1-F(x))^n.$$

Then,

$$F_{X_{(1)}}(x) = P(X_{(1)} < x) = 1 - (1 - F(x))^n.$$

Similarly,

$$F_{X_{(n)}}(x) = P(X_{(n)} < x) = F(x)^n.$$

And, for a general $1 \leq j \leq n$ the cumulative distribution of $X_{(j)}$ is

$$F_{X_{(j)}}(x) = inom{n}{j} F(x)^j (1-F(x))^{n-j}.$$

Density function of order statistics

Density of $X_{(j)}$. A counting argument: There are n ways to choose which X_i is $X_{(j)}$. There are n-1 left and j-1 are smaller than $X_{(j)}$, so

$$egin{aligned} f_{X_{(j)}}(x) &= nf(x)inom{n-1}{j-1}F(x)^{j-1}(1-F(x))^{n-j} \ &= rac{n!}{(j-1)!(n-j)!}f(x)F(x)^{j-1}(1-F(x))^{n-j} \end{aligned}$$

You can generalize this argument (carry it forward) to find joint densities of 2 or more order statistics.

Example: Uniform

Suppose we have n iid Uniform $\left(0,1\right)$ r.v.'s. Then,

$$egin{aligned} f_{X_{(j)}}(x) &= rac{n!}{(j-1)!(n-j)!} f(x) F(x)^{j-1} (1-F(x))^{n-j} \ f_{X_{(j)}}(x) &= rac{n!}{(j-1)!(n-j)!} imes 1 imes x^{j-1} imes (1-x)^{n-j} \end{aligned}$$

which is a Beta distribution with shape parameters lpha=j and eta=n-j+1 .

Example: Range

The range is $Y_1 = X_{(n)} - X_{(1)}$, and let $Y_2 = X_{(n)}$. The joint density of $\left(X_{(1)}, X_{(n)}\right)$ is

$$f(x_1,x_n)=n(n-1)f(x_1)f(x_n)[F(x_n)-F(x_1)]^{n-2}.$$

The Jacobian from $(X_{(1)},X_{(n)})$ to (Y_1,Y_2) is -1 . Then,

$$f(y_1,y_2)=n(n-1)f(y_2-y_1)f(y_2)[F(y_2)-F(y_2-y_1)]^{n-2}.$$

Suppose the r.v.'s are iid Unif(0,1), then

$$egin{aligned} f(y_1) &= \int_{y_1}^\infty n(n-1)f(y_2-y_1)f(y_2)[F(y_2)-F(y_2-y_1)]^{n-2}dy_2 \ && f(y_1) = \int_{y_1}^1 n(n-1)[y_2-(y_2-y_1)]^{n-2}dy_2 \ && = n(n-1)y_1^{n-2}(1-y_1) \end{aligned}$$

which is Beta(lpha=n-1,eta=2) .

Quantiles and sample quantiles

The p^{th} quantile of a r.v. X with distribution function F is $x_p = F^{-1}(p)$. One estimator is $X_{(k)}$ where $k = \lfloor p(n+1) \rfloor$. Then,

$$EF(X_{(k)})=\int_a^b F(x_k)f_{X_{(k)}}(x_k)dx_k$$

 $EF(X_{(k)}) = \int_a^b F(x_k) rac{n!}{(k-1)!(n-k)!} F(x_k)^{k-1} (1-F(x_k))^{n-k} f(x_k) dx_k$

Let $u=F(x_k)$ with $d_u=f(x_k)dx_k$ so that

$$EF(X_{(k)}) = \int_0^1 u rac{n!}{(k-1)!(n-k)!} u^{k-1} (1-u)^{n-k} du$$

which is the expectation of $Beta(\alpha = k, \beta = n - k + 1)$ which is $\frac{\alpha}{\alpha + \beta} = \frac{k}{n+1}$. Since $p \approx \frac{k}{n+1} X_{(k)}$ is a nearly unbiased estimator.

Nonparametric CI for pop. quantile

We want to find a confidence interval for x_p the p^{th} quantile of the distribution of a continuous r.v. X. Consider the event $X_{(j)} < x_p < X_{(k)}$ for j < p(n+1) < k. Since $F(x_p) = p$ we have

$$P(X_{(j)} < x_p < X_{(k)}) = \sum_{\ell=j}^{k-1} \binom{n}{\ell} p^\ell (1-p)^{n-\ell}.$$

For a given coverage $(1 - \alpha)$ we can compute the above probability and use sample quantiles $(x_{(j)}, x_{(k)})$ as the interval estimate.

```
data <- c(2, 3, 4, 6, 10, 13, 17, 22, 39, 43)
p <- 1/2
n<-10
binom.int <- function(n,j,k,p){
    s.seq <- seq(from = j, to = k-1, by = 1)
    return(sum(dbinom(s.seq,n,p)))
}
binom.int(10,2,8,1/2)</pre>
```

[1] 0.9345703

binom.int(10,3,9,1/2)

[1] 0.9345703

binom.int(10,4,9,1/2)

[1] 0.8173828

binom.int(10,3,8,1/2)

[1] 0.890625

c(data[2], data[8])

[1] 3 22

c(data[3], data[9])

[1] 4 39