

# Exploratory Data Analysis (S670): Assignment 6

Created by Krishna Mahajan, 0003572903

## Q1

Show that the jackknife estimate and the jackknife SE are exactly the same as sample mean  $\bar{x}$  and standard error  $se(\bar{x}) = s/\sqrt{n}$  when  $\hat{\theta} = \bar{x}$  (sample mean).

(sol)

We know that jackknife estimate is similar to the bootstrap in that it involves resampling, but instead of sampling with replacement, the method samples without replacement.

### Definition

The  $i_{th}$  jackknife replication of  $\hat{\theta}_{(i)}$  of the statistic  $\hat{\theta} = s(x)$  is  $\hat{\theta}_{(i)} = s(x_i)$ ,  $\forall i = 1, \dots, n$

### Jackknife estimation of mean

$$\begin{aligned} s(x_{(i)}) &= \frac{1}{n-1} \sum_{j \neq i} x_j \\ &= \frac{n\bar{x} - x_i}{n-1} \\ &= \bar{x}_i \end{aligned}$$

now,

$$\bar{x}_{(\cdot)} = \frac{1}{n} \sum_{i=1}^n \bar{x}_i = \bar{x}$$

Thus Jackknife estimate of sample mean is same as  $\bar{x}$ .

### Jackknife estimate of the standard error of the mean

For  $\hat{\theta} = \bar{x}$ , it is easy to show that:

$$\begin{aligned} \bar{x}_i &= \frac{1}{n-1} \sum_{j \neq i} x_j \\ &= \frac{n\bar{x} - x_i}{n-1} \\ &= \bar{x}_i \end{aligned}$$

$$\bar{x}_{(\cdot)} = \frac{1}{n} \sum_{i=1}^n \bar{x}_i = \bar{x}$$

Therefore:

$$\begin{aligned} se_{jack}(\bar{x}) &= \left( \sum_{i=1}^n \frac{x_i - \bar{x}}{(n-1)n} \right)^{1/2} \\ &= \frac{\bar{s}}{\sqrt{(n)}} \\ &= \frac{s}{\sqrt{(n)}} \end{aligned}$$

## Q2

Show that the standard error of the pseudo-values (jackknife SE) is the same as the standard deviation of the "leave-out-one" values multiplied by  $(n-1)/\sqrt{(n)}$  i.e. that the standard error of the pseudo-values (jackknife SE) is the same as the standard error of the "leave-out-one" values multiplied by  $(n-1)$ .

(sol)

To Prove :  $SE(PV's) = \frac{(n-1)}{\sqrt{(n)}} . SD(y_{(-i)})$  Here,

$$y_{(-i)} = \text{mean}(x \text{ without } x_i) = \sum_{k \neq i} x_k / (n-1)$$

$$PV's = n \cdot \text{mean}(y) - (n-1)y_{(-i)} \text{ (as Taught in Class)}$$

so,

$$var(PV's) = var(n \cdot \text{mean}(y) - (n-1)y_{(-i)})$$

$$var(PV's) = var(n \cdot \text{mean}(y)) + var((n-1)y_{(-i)})$$

$$var(PV's) = n^2 var(\text{mean}(y)) + (n-1)^2 var(y_{(-i)})$$

$$Sd(PV's) = n * sd(\text{mean}(y)) + (n-1) * sd(y_{(-i)}) \text{ (i.e Taking root on both the sides to get standard deviation)}$$

$$SE(Pv's) = \frac{sd(mean(y))}{\sqrt{(n)}} + \frac{n-1sd(y_{(-i)})}{\sqrt{(n)}} \text{ (i,e dividing by } n^1/2 \text{ on both sides to get SE)}$$

Now,  $\frac{sd(mean(y))}{\sqrt{(n)}} = 0$  as  $mean(y)$  is true population mean and it wont have any variance.

Thus,

$$SE(Pv's) = \frac{n-1sd(y_{(-i)})}{\sqrt{(n)}}$$