

Ishaan Taneja

**Grading:**

30 marks- Complete submission of Problem 1,5  
 70 marks- Problem 1

From Probability and Statistics with Examples Using R

1. The following result is a Berry-Eseen Type bound.

**Theorem:** Let  $X_n \sim \text{Binomial}(n, p)$ , then there exists  $C > 0$  such that

$$\sup_{x \in R} \left| P\left(\frac{X_n - np}{\sqrt{np(1-p)}} \leq x\right) - \int_{-\infty}^x \frac{\exp(-\frac{t^2}{2})}{\sqrt{2\pi}} dt \right| \leq \frac{(p^2 + (1-p)^2)}{2\sqrt{np(1-p)}}$$

We shall prove it by simulation by the below algorithm.

```

For x = -2,-1.9,-1,8,...0,...,1.9,2
  using inbuilt pnorm find z[x]:- pnorm(x)
Set p
For m = 1,50,100,150,...,1000
  For x = -2,-1.9,-1,8,...0,...,1.9,2
    1)Generate B: 1000 Samples of Binomial (m,p) using inbuilt rbinom function
      Compute SB: (B-m*p)/((m*p*(1-p))^(0.5))
    2)Compute y[x] : the proportion of samples in SB less than equal to x
    3)Repeat steps 1) and 2) 100 times and compute average -- my[x] over each trial.
    4)Calculate diff[m]= max(abs(my[x]- z[x]))
For m = 1,50,100,150,...,1000
  Calculate error(m)= [p^2+(1-p)^2]/[2*(m*p*(1-p))^0.5]
Plot diff and error.
  
```

See if result is verified by picture. Can you do anything additional to verify the Theorem?

**Solution: 1**

```

> x=seq(-2,2,0.1)
> z.x=pnorm(x)
> p=runif(1)
> p
  
```

```
[1] 0.6253851
```

```
> my.x=c()
> diff.m=c()
> l=c()
> m=c(1,seq.int(50,1000,50))
> itr=1:100
> for (i in m){
+   for (j in x){
+     prop=c()
+     for (k in itr){
+       c=0
+       B=rbinom(1000,i,p)
+       SB=(B-i*p)/((i*p*(1-p))^0.5)
+       for (s in SB){
+         if(s<= j){
+           c=c+1
+         }
+       }
+       prop=append(prop,c/1000)
+     }
+     my.x=append(my.x,mean(prop))
+
+   }
+ }
> d=abs(my.x-z.x)
> max=41
> r= seq_along(d)
> diff=split(d,ceiling(r/max))
> diff.m=c()
> for (i in 1:21){
+   diff.m=append(diff.m,max(diff[[i]]))
+ }
> error=c()
> for (i in m) {
+   error= append(error,(p^2+(1-p)^2)/(2*(i*p*(1-p))^0.5))
+ }
> library(ggplot2)
> data=data.frame(m,diff.m,error)
> C=ggplot(data, aes(x=m)) +
+   geom_line(aes(y = diff.m, color = "darkred")) +
+   geom_line(aes(y = error, color="steelblue"))+
+   labs(y='Difference and Error',title = 'Error and diff',
+   subtitle = 'Verifies the bound')+
+   labs(color = 'Y series')+ theme(
+     legend.position = c(.95, .95),
+     legend.justification = c("right", "top"),
```

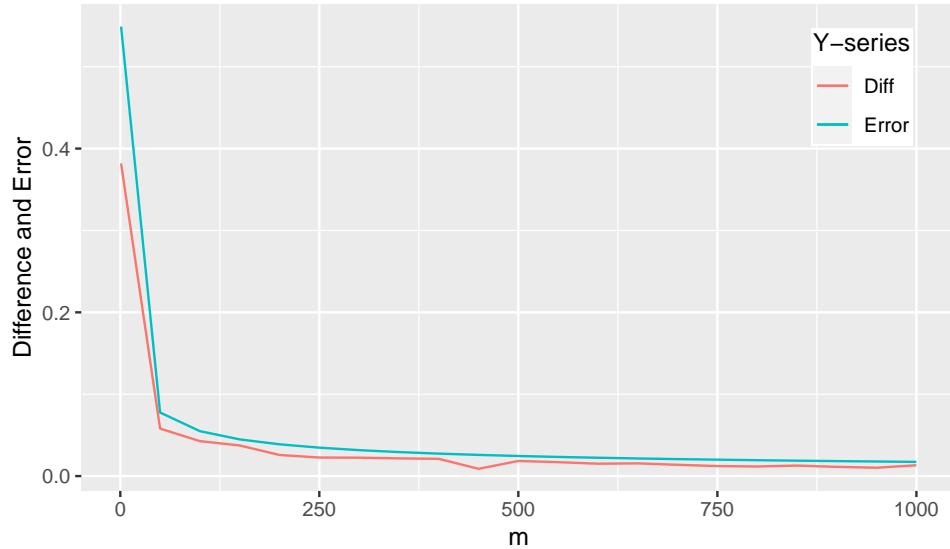
```

+     legend.box.just = "right",
+     legend.margin = margin(1, 1, 1, 1)
+ )+ scale_color_discrete(name="Y-series",labels=c("Diff", "Error"))
> C

```

### Error and diff

Verifies the bound



Additionally, we can increase the number of samples which will increase the accuracy of our result.

## 2. Ex 5.2.10 (c)

**Solution: 2**

$$Z \sim \text{Normal}(\mu, \sigma^2)$$

Let the median of  $Z$  be ' $m$ '.

i.e.

$$\begin{aligned} P(Z < m) &= \frac{1}{2} \\ \implies P\left(\frac{Z - \mu}{\sigma} < \frac{m - \mu}{\sigma}\right) &= \frac{1}{2} \\ \implies P\left(X < \frac{m - \mu}{\sigma}\right) &= \frac{1}{2} \end{aligned}$$

where,  $X \sim \text{Normal}(0,1)$

Therefore,

$$\int_{-\infty}^{\frac{m-\mu}{\sigma}} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx = \frac{1}{2} \quad \dots \dots \dots (1)$$

Using R, we get:

```
> qnorm(1/2)
```

```
[1] 0
```

$$P(X < 0) = \int_{-\infty}^0 \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx = \frac{1}{2} \quad \dots \dots \dots (2)$$

From (1) and (2):

$$\frac{m - \mu}{\sigma} = 0 \implies m = \mu$$

Hence, median of Z is  $\mu$ .

### 3. Ex 5.2.11

**Solution: 3**

$$X \sim \text{Normal}(\mu, \sigma^2)$$

$$\begin{aligned} P(|X - \mu| < k\sigma) &= P(-k\sigma < X - \mu < k\sigma) \\ &= P(-k < \frac{X - \mu}{\sigma} < k) \\ &= P(-k < Z < k) \end{aligned}$$

where,  $Z \sim \text{Normal}(0,1)$

Therefore,

$$\begin{aligned} P(|X - \mu| < k\sigma) &= P(-k < Z < k) \\ P(|X - \mu| < k\sigma) &= \int_{-k}^k \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \end{aligned}$$

which depends only on the value of  $k$  and is independent of  $\mu$  and  $\sigma$ .  
Hence,  $P(|X - \mu| < k\sigma)$  does not depend on the values of  $\mu$  or  $\sigma$ .

### 4. Example 5.2.11

**Solution: 4**

$$X \sim \text{Normal}(0,1)$$

$$E(X) = \mu = 0 \text{ and } \sigma = 1$$

Therefore,

$$\begin{aligned} P(E(X) - \sigma < X < E(X) + \sigma) &= P(-1 < X < 1) \\ &= \int_{-1}^1 \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \\ &= \int_{-\infty}^1 \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx - \int_{-\infty}^{-1} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \\ &= P(X \leq 1) - P(X \leq -1) \end{aligned}$$

Using R, we get:

```
> pnorm(1)-pnorm(-1)
```

```
[1] 0.6826895
```

Therefore,  $P(-1 \leq X \leq 1) \approx 0.68$

i.e. There is roughly 68% chance that a standardized normal random variable will produce a value within one standard deviation of expected value.

##### 5. Example 5.2.12

**Solution: 5**

Let, Y be the random variable representing the weight (in grams) of cashews in the bag filled by machine.

$$Y \sim \text{Normal}(200, 4^2)$$

The probability that a bag filled by machine will have fewer than 195 grams of cashew is given by:

$$\begin{aligned} P(Y < 195) &= P\left(\frac{Y - 200}{4} < \frac{195 - 200}{4}\right) \\ &= P(X < -1.25) \end{aligned}$$

where,  $X \sim \text{Normal}(0,1)$

Using R, we get:

```
> pnorm(-1.25)
```

```
[1] 0.1056498
```

Therefore,

$$P(X < -1.25) = \int_{-\infty}^{-1.25} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} dx \approx 0.106$$

Hence, there is slightly more than a 10% chance of a bag this light being produced by the machine.