

1. Let X_1, \dots, X_n be i.i.d. $\text{Ber}(p)$, a Bernoulli random variable with parameter p . Let $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$ be the sample average.

- What is the expected value $\mathbb{E}(\bar{X}_n)$? What is the variance $\text{Var}(\bar{X}_n)$?
- Explain what is meant by a *consistent* estimator of p , and show that \bar{X}_n a consistent estimator of p ?
- Explain why $\sqrt{n}(\bar{X}_n - p)$ can be approximated by a $N(0, p(1-p))$ distribution when n is large.

$$(a) E(\bar{X}_n) = E\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n} E\left(\sum_{i=1}^n X_i\right) = \frac{1}{n} [np + 0 \times (n-p)] = p$$

$$\begin{aligned} \text{Var}(\bar{X}_n) &= \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) \\ &= \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right) \\ &= \frac{1}{n^2} np(1-p) \\ &= \frac{1}{n} p(1-p) \end{aligned}$$

(b) A consistent estimator means that as the sample size gets large the estimate gets closer and closer to the true value of the parameter.

$$\lim_{n \rightarrow \infty} P(|\bar{X}_n - p| > \alpha) = 0, \quad \alpha > 0$$

$$(c) Y_n = \sqrt{n}(\bar{X}_n - p)$$

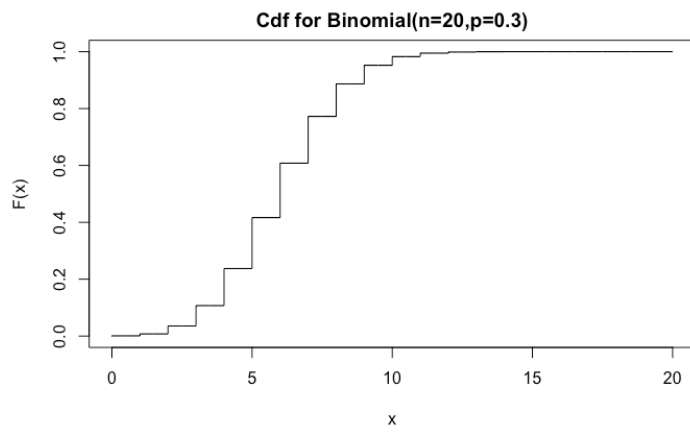
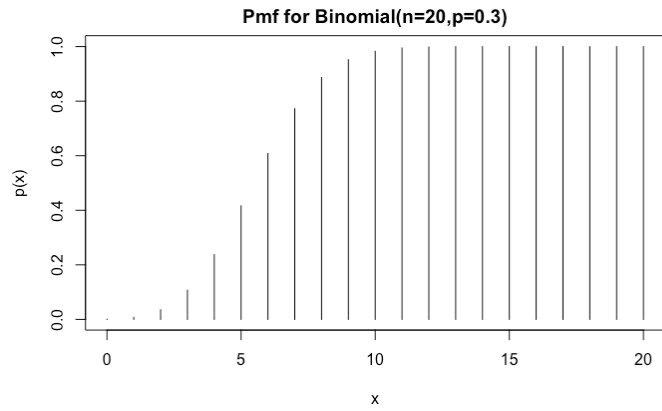
$$E(Y_n) = 0$$

$$\text{Var}(Y_n) = \text{Var}(\sqrt{n}(\bar{X}_n - p)) = (\sqrt{n})^2 \times p(1-p) = np(1-p)$$

According to the central limit theorem, when n gets larger, $Y_n \sim N(0, p(1-p))$.

2. Use the R-functions `dbinom()`, `dnorm()` and/or `pbinom()`, `pnorm()` to complete this question.

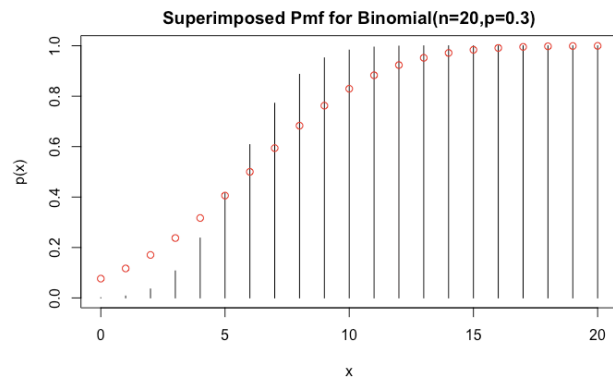
- Plot the probability mass function and cumulative distribution function (cdf) of a Binomial random variable $Y \sim \text{Bin}(n, p)$ when $n = 20$ and $p = 0.3$.
- What Normal distribution might approximate the distribution of Y ?
- Superimpose on your plots the probability density function and cdf of this Normal distribution (in a contrasting color such as blue or red)

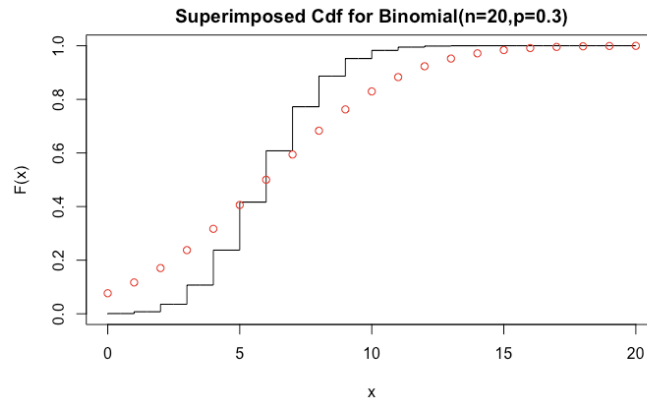


(b) we can use $N(np, npq)$ to approximate the distribution .

$$n=20, \quad p=0.3, \quad q=1-0.3=0.7$$

$$N(6, 4.2)$$





3. Let X_1, \dots, X_n be i.i.d from $Exp(1/\beta)$, with pdf $f(x) = \frac{1}{\beta}e^{-x/\beta}$ on $x \geq 0$.
Let $\bar{X}_n = \frac{1}{n} \sum_{i=1}^n X_i$ be the sample average.
- What are the bias and variance of \bar{X}_n as an estimator of β ?
 - What is the mean square error of using \bar{X}_n as the estimator of β ? Does \bar{X}_n converge to β ? Why?
 - Now consider a new estimator $\tilde{\beta} = a \bar{X}_n$, where $a \in \mathbb{R}$ is a real number. Show that the mean square error of $\tilde{\beta}$ is $[n(a-1)^2 + a^2]\beta^2/n$.
 - Find the value of a that minimizes this MSE and show that the resulting MSE is smaller than the MSE of \bar{X}_n .
(Note: this new estimator is related to the *Stein's Shrinkage estimator*.)

$$3.(a) E(x) = \int_0^{\infty} x \frac{1}{\beta} e^{-x/\beta} = \beta$$

$$\text{Bias}(x) = E(x) - \bar{x}_n = \beta - \frac{1}{n} \sum_{i=1}^n x_i$$

$$\text{Var}(x) = E(x^2) - (E(x))^2 = \beta^2$$

$$\begin{aligned} (b) \text{MSE} &= \frac{1}{n} \sum_{i=1}^n (\bar{x}_n - x_i)^2 \\ &= \frac{1}{n} \sum_{i=1}^n (\bar{x}_n^2 + x_i^2 - 2\bar{x}_n x_i) \\ &= \bar{x}_n^2 - 2\bar{x}_n^2 + \frac{1}{n} \sum_{i=1}^n x_i^2 \\ &= \text{Var}(\bar{x}_n) + (E(\bar{x}_n) - \beta)^2 \end{aligned}$$

$$\begin{aligned} E(\bar{x}_n) &= E\left(\frac{1}{n} \sum_{i=1}^n x_i\right) \\ &= \frac{1}{n} \sum_{i=1}^n E(x_i) \\ &= \frac{1}{n} \cdot n \cdot E(x) \\ &= \beta \end{aligned}$$

So it does converge to β

$$(c) E(a\bar{x}_n) = a\beta$$

$$\text{var}(a\bar{x}_n) = a^2 \frac{\beta^2}{n}$$

$$\text{MSE}(a\bar{x}_n)$$

$$\begin{aligned}
 &= E[(a\bar{x}_n - E(a\bar{x}_n)) + E(a\bar{x}_n) - a\beta] \\
 &= \text{var}(a\bar{x}_n) + (E(a\bar{x}_n) - a\beta)^2 \\
 &= [n(a-1)^2 + a^2] \frac{\beta^2}{n}
 \end{aligned}$$

$$(d) \text{MSE}' = [2n(a-1) + 2a] \frac{\beta^2}{n} = 0 \quad \Rightarrow \quad a = \frac{n}{n+1}$$

$a \in (-\infty, \frac{n}{n+1})$, $\text{MSE}' < 0$, MSE decreases

$a \in (\frac{n}{n+1}, \infty)$, $\text{MSE}' > 0$, MSE increases.

So when $a = \frac{n}{n+1}$, MSE has the smallest value.

4. Let $X_1, X_2 \sim \text{Uni}[2, 4]$. Let $Y = (X_1 + X_2)/2$.

(a) Use the R-function **runif()** to generate at least 10000 realizations of Y and plot the corresponding histogram.

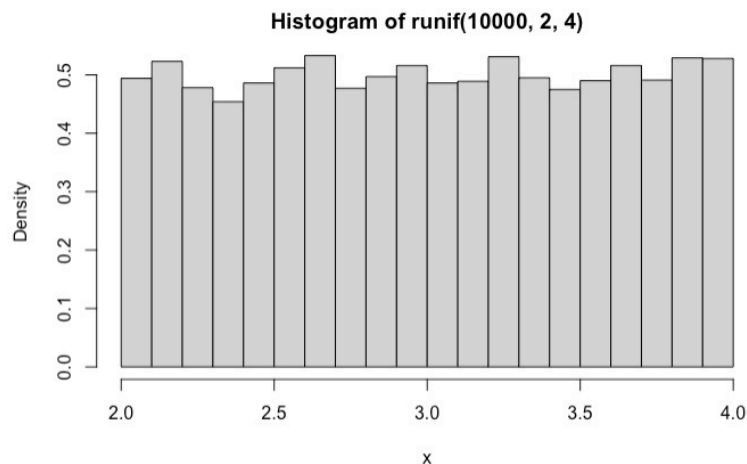
(b) The density curve of Y is

$$f_Y(x) = \begin{cases} x-2, & \text{when } 2 \leq x \leq 3 \\ 4-x, & \text{when } 3 < x \leq 4 \\ 0, & \text{otherwise} \end{cases}$$

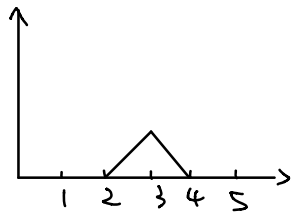
Verify that $f_Y(x)$ is a density function (pdf).

(c) Superimpose the $f_Y(x)$ density curve on your histogram (in a contrasting color).

(a)



$$(b) \quad f_X(x) = \begin{cases} x-2 & 2 \leq x \leq 3 \\ 4-x & 3 < x \leq 4 \\ 0 & \text{otherwise} \end{cases}$$



$$\begin{aligned} & \int_2^4 f_X(x) dx \\ &= \int_2^3 (x-2) dx + \int_3^4 (4-x) dx \\ &= \left(\frac{x^2}{2} - 2x \right) \Big|_2^3 + \left(4x - \frac{x^2}{2} \right) \Big|_3^4 \\ &= \frac{9}{2} - 6 - \frac{4}{2} + 4 + 16 - \frac{16}{2} - 12 + \frac{9}{2} \\ &= \frac{1}{2} + \frac{1}{2} \\ &= 1 \end{aligned}$$

It integrates to 1, so it's a density function.

(c)

