Lab4

Exercises

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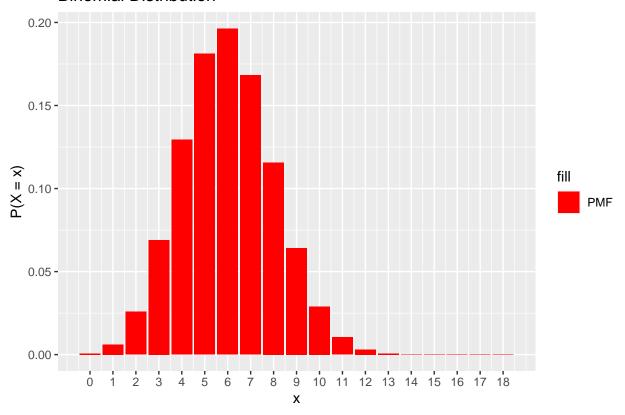
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Exercise 1
\mathbf{A}
Plot the Probability Mass Function for the Binomial distribution with $n=18$ and $p=\frac{1}{3}$. Calculate:
1. $P(X=3)$
dbinom(3, 18, 1 / 3) ## [1] 0.06901723
2. $P(X \ge 3)$
<pre>1 - pbinom(2, 18, 1 / 3) ## [1] 0.9673521 # or pbinom(2, 18, 1 / 3, lower.tail = FALSE) ## [1] 0.9673521</pre>
3. $P(1 \le X > 5)$
pbinom(4, 18, 1 / 3) - pbinom(0, 18, 1 / 3) ## [1] 0.2303957
4. $P(X \ge 15)$
<pre>pbinom(14, 18, 1 / 3, lower.tail = FALSE) ## [1] 1.852509e-05</pre>
library(ggplot2) df (- data frame(y - 0.18 y - dbinom(0.18 18 1 / 3))

```
ggplot(df, aes(x = x, y = y, fill = "PMF")) +
  geom_col() +
  scale_x_continuous(breaks = 0:18) +
  scale_fill_manual(values = "red") +
  labs(
    title = "Binomial Distribution",
    x = "x",
    y = "P(X = x)"
)
```

Binomial Distribution



\mathbf{B}

Plot the Cumulative Distribution Function for the Poisson distribution with $\lambda=3$. Calculate:

```
1. P(X = 3)
lambda <- 3
dpois(3, lambda)
## [1] 0.2240418

2. P(X \ge 3)
ppois(2, lambda, lower.tail = FALSE)
## [1] 0.5768099

3. P(1 \le X > 5)
ppois(4, lambda) - ppois(0, lambda)
## [1] 0.7654762
```

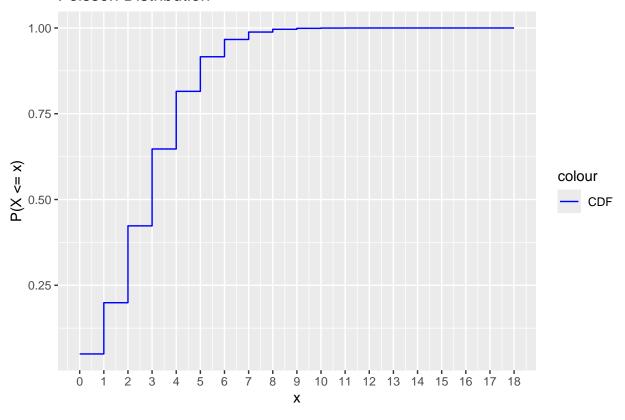
```
4. P(X \ge 15)
```

```
ppois(14, lambda, lower.tail = FALSE)
## [1] 6.703859e-07

df <- data.frame(x = 0:18, y = ppois(0:18, lambda))

ggplot(df, aes(x = x, y = y, color = "CDF")) +
    geom_step() +
    scale_x_continuous(breaks = 0:18) +
    scale_color_manual(values = "blue") +
    labs(
        title = "Poisson Distribution",
        x = "x",
        y = "P(X <= x)"
    )
</pre>
```

Poisson Distribution



Exercise 2

Demonstrate that a Poisson r.v. may be used as an approximation for a binomial r.v.

\mathbf{A}

```
n <- c(20, 30, 40, 100)
p <- c(1 / 4, 1 / 6, 1 / 8, 1 / 20)

pmf <- matrix(NA, nrow = 21, ncol = 4)</pre>
```

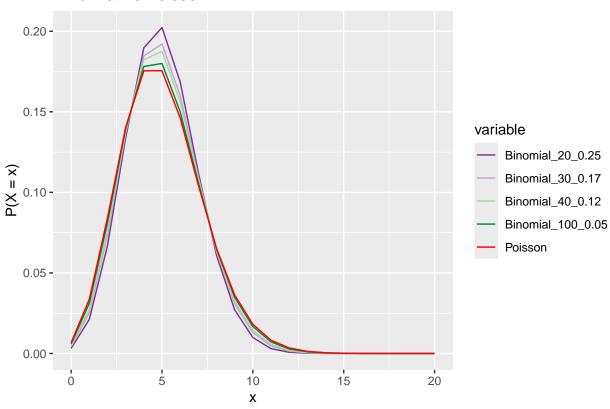
```
for (i in 1:4) {
  pmf[, i] <- dbinom(0:20, n[i], p[i])</pre>
pmf <- as.data.frame(pmf)</pre>
colnames(pmf) <- paste("Binomial", n, round(p, 2), sep = "_")</pre>
pmf$Poisson <- dpois(0:20, n * p)</pre>
pmf$X <- 0:20
```

```
В
library(reshape2)
df_plot <- melt(pmf, id.vars = "X")</pre>
df_plot
##
                   variable
                                   value
## 1
        O Binomial_20_0.25 3.171212e-03
## 2
        1 Binomial_20_0.25 2.114141e-02
## 3
        2 Binomial_20_0.25 6.694781e-02
        3 Binomial_20_0.25 1.338956e-01
## 4
## 5
        4 Binomial 20 0.25 1.896855e-01
## 6
        5 Binomial_20_0.25 2.023312e-01
## 7
        6 Binomial_20_0.25 1.686093e-01
## 8
           Binomial_20_0.25 1.124062e-01
## 9
           Binomial_20_0.25 6.088669e-02
## 10
        9 Binomial_20_0.25 2.706075e-02
       10 Binomial_20_0.25 9.922275e-03
## 11
## 12
           Binomial_20_0.25 3.006750e-03
       11
## 13
           Binomial_20_0.25 7.516875e-04
           Binomial_20_0.25 1.541923e-04
## 14
      13
## 15
       14
           Binomial_20_0.25 2.569872e-05
## 16
       15 Binomial_20_0.25 3.426496e-06
## 17
           Binomial 20 0.25 3.569266e-07
## 18
      17
           Binomial_20_0.25 2.799425e-08
## 19
       18
           Binomial_20_0.25 1.555236e-09
## 20
           Binomial_20_0.25 5.456968e-11
## 21
           Binomial_20_0.25 9.094947e-13
           Binomial_30_0.17 4.212720e-03
## 22
## 23
        1 Binomial_30_0.17 2.527632e-02
## 24
        2 Binomial_30_0.17 7.330133e-02
## 25
        3 Binomial_30_0.17 1.368292e-01
## 26
        4 Binomial_30_0.17 1.847194e-01
## 27
           Binomial_30_0.17 1.921081e-01
## 28
        6 Binomial_30_0.17 1.600901e-01
## 29
        7
           Binomial_30_0.17 1.097761e-01
## 30
           Binomial_30_0.17 6.312124e-02
## 31
        9
           Binomial_30_0.17 3.085927e-02
## 32
           Binomial_30_0.17 1.296090e-02
       11 Binomial_30_0.17 4.713053e-03
## 33
```

```
34
       12
           Binomial_30_0.17 1.492467e-03
##
  35
       13
           Binomial_30_0.17 4.132985e-04
##
   36
           Binomial 30 0.17 1.003725e-04
##
  37
       15
           Binomial_30_0.17 2.141280e-05
##
   38
       16
           Binomial_30_0.17 4.014899e-06
   39
       17
##
           Binomial 30 0.17 6.612776e-07
       18
  40
           Binomial 30 0.17 9.551787e-08
## 41
       19
           Binomial_30_0.17 1.206542e-08
##
   42
       20
           Binomial_30_0.17 1.327196e-09
##
  43
        0
           Binomial_40_0.12 4.789852e-03
   44
           Binomial_40_0.12 2.737058e-02
        1
   45
##
           Binomial_40_0.12 7.624663e-02
##
   46
           Binomial_40_0.12 1.379701e-01
##
   47
           Binomial_40_0.12 1.823176e-01
## 48
        5
           Binomial_40_0.12 1.875267e-01
##
   49
        6
           Binomial_40_0.12 1.562722e-01
        7
##
  50
           Binomial_40_0.12 1.084338e-01
##
   51
           Binomial 40 0.12 6.389849e-02
##
  52
        9
           Binomial_40_0.12 3.245638e-02
##
   53
       10
           Binomial 40 0.12 1.437354e-02
##
   54
       11
           Binomial_40_0.12 5.600080e-03
   55
       12
##
           Binomial 40 0.12 1.933361e-03
       13
## 56
           Binomial 40 0.12 5.948803e-04
##
   57
       14
           Binomial 40 0.12 1.638956e-04
##
   58
       15
           Binomial 40 0.12 4.058367e-05
   59
       16
           Binomial_40_0.12 9.058855e-06
   60
       17
           Binomial_40_0.12 1.826996e-06
##
##
   61
       18
           Binomial_40_0.12 3.334992e-07
   62
       19
##
           Binomial_40_0.12 5.516529e-08
##
   63
       20
           Binomial_40_0.12 8.274793e-09
##
   64
        O Binomial_100_0.05 5.920529e-03
##
   65
        1 Binomial_100_0.05 3.116068e-02
##
   66
        2 Binomial_100_0.05 8.118177e-02
   67
##
        3 Binomial_100_0.05 1.395757e-01
##
   68
        4 Binomial_100_0.05 1.781426e-01
##
  69
        5 Binomial_100_0.05 1.800178e-01
## 70
        6 Binomial 100 0.05 1.500149e-01
## 71
        7 Binomial_100_0.05 1.060255e-01
## 72
        8 Binomial_100_0.05 6.487089e-02
##
  73
        9 Binomial_100_0.05 3.490130e-02
   74
       10 Binomial 100 0.05 1.671588e-02
       11 Binomial_100_0.05 7.198228e-03
##
  75
##
   76
       12 Binomial_100_0.05 2.809834e-03
##
  77
       13 Binomial_100_0.05 1.001075e-03
  78
       14 Binomial_100_0.05 3.274191e-04
## 79
       15 Binomial_100_0.05 9.880016e-05
##
  80
       16 Binomial_100_0.05 2.762505e-05
##
   81
       17 Binomial_100_0.05 7.184222e-06
##
  82
       18 Binomial_100_0.05 1.743539e-06
##
  83
       19 Binomial_100_0.05 3.960394e-07
   84
       20 Binomial_100_0.05 8.441893e-08
##
## 85
        0
                    Poisson 6.737947e-03
## 86
        1
                    Poisson 3.368973e-02
## 87
                    Poisson 8.422434e-02
```

```
Poisson 1.403739e-01
## 88
## 89
        4
                    Poisson 1.754674e-01
## 90
                    Poisson 1.754674e-01
## 91
                    Poisson 1.462228e-01
        6
## 92
        7
                    Poisson 1.044449e-01
## 93
        8
                    Poisson 6.527804e-02
## 94
        9
                    Poisson 3.626558e-02
## 95
                    Poisson 1.813279e-02
       10
## 96
       11
                    Poisson 8.242177e-03
## 97
                    Poisson 3.434240e-03
       12
## 98
     13
                    Poisson 1.320862e-03
                    Poisson 4.717363e-04
## 99
       14
## 100 15
                    Poisson 1.572454e-04
## 101 16
                    Poisson 4.913920e-05
## 102 17
                    Poisson 1.445271e-05
## 103 18
                    Poisson 4.014640e-06
## 104 19
                    Poisson 1.056484e-06
## 105 20
                    Poisson 2.641211e-07
library(ggplot2)
library(RColorBrewer) # Color palettes
ggplot(df_plot, aes(x = X, y = value, color = variable)) +
  geom_line() +
  scale_color_manual(values = c(brewer.pal(4, "PRGn"), "red")) +
 labs(
   title = "Binomial vs Poisson PMF",
    x = "x"
    y = "P(X = x)"
```

Binomial vs Poisson PMF



Exercise 3

\mathbf{A}

Generate N=1000 random numbers from a binomial distribution with n=9 trials and p=0.8. Thus each of the 1000 random numbers will be an integer between 0 and 9.

```
set.seed(123)
n <- 9
p < -0.8
t <- 1000
rbinom(t, n, p)
                              \begin{smallmatrix} 1 \end{smallmatrix} \begin{smallmatrix} 1 \end{smallmatrix} \begin{smallmatrix} 3 \end{smallmatrix} \begin{smallmatrix} 6 \end{smallmatrix} \begin{smallmatrix} 8 \end{smallmatrix} \begin{smallmatrix} 6 \end{smallmatrix} \begin{smallmatrix} 5 \end{smallmatrix} \begin{smallmatrix} 9 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 6 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 5 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 9 \end{smallmatrix} \begin{smallmatrix} 6 \end{smallmatrix} \begin{smallmatrix} 8 \end{smallmatrix} \begin{smallmatrix} 8 \end{smallmatrix} \begin{smallmatrix} 8 \end{smallmatrix} \begin{smallmatrix} 5 \end{smallmatrix} \begin{smallmatrix} 6 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 4 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix} \begin{smallmatrix} 8 \end{smallmatrix} \end{smallmatrix} \begin{smallmatrix} 8 \end{smallmatrix} \begin{smallmatrix} 5 \end{smallmatrix} \begin{smallmatrix} 6 \end{smallmatrix} \begin{smallmatrix} 7 \end{smallmatrix}
##
                        [34] 6 9 7 6 8 8 8 8 8 8 8 8 8 8 8 7 8 6 9 7 6 9 7 8 9 6 6 8 7 9 8 8 6 7
##
                        [67] \ 6 \ 6 \ 6 \ 7 \ 6 \ 7 \ 7 \ 9 \ 7 \ 8 \ 8 \ 7 \ 8 \ 9 \ 8 \ 7 \ 8 \ 6 \ 9 \ 8 \ 4 \ 6 \ 6 \ 8 \ 9 \ 7 \ 8 \ 7 \ 8 \ 8 \ 6 \ 9 \ 7
##
                    ##
##
                     [166] \ 7 \ 6 \ 8 \ 8 \ 8 \ 7 \ 8 \ 6 \ 6 \ 7 \ 7 \ 8 \ 7 \ 6 \ 7 \ 8 \ 7 \ 8 \ 7 \ 8 \ 7 \ 6 \ 6 \ 8 \ 8 \ 4 \ 7 \ 5 \ 7 \ 8 \ 7 
##
                     [199] \  \, 8 \  \, 7 \  \, 8 \  \, 6 \  \, 8 \  \, 8 \  \, 8 \  \, 8 \  \, 7 \  \, 8 \  \, 8 \  \, 7 \  \, 9 \  \, 8 \  \, 6 \  \, 5 \  \, 8 \  \, 5 \  \, 7 \  \, 7 \  \, 9 \  \, 8 \  \, 7 \  \, 7 \  \, 5 \  \, 7 
##
                    ##
                     [265] \ 7 \ 7 \ 8 \ 8 \ 9 \ 7 \ 6 \ 9 \ 9 \ 8 \ 6 \ 7 \ 5 \ 7 \ 9 \ 7 \ 6 \ 8 \ 8 \ 8 \ 9 \ 8 \ 9 \ 8 \ 9 \ 7 \ 8 \ 9 \ 9 \ 6 \ 6 \ 6 \ 4 
##
                     [298] \ 9 \ 9 \ 6 \ 6 \ 9 \ 6 \ 7 \ 7 \ 8 \ 9 \ 7 \ 7 \ 8 \ 7 \ 7 \ 9 \ 8 \ 6 \ 6 \ 8 \ 8 \ 6 \ 6 \ 8 \ 8 \ 7 \ 9 \ 9 \ 3 \ 9 \ 8 \ 5 
                     [331] \ 7 \ 8 \ 7 \ 6 \ 8 \ 7 \ 7 \ 7 \ 5 \ 8 \ 9 \ 7 \ 8 \ 4 \ 8 \ 8 \ 7 \ 8 \ 5 \ 7 \ 8 \ 7 \ 4 \ 7 \ 8 \ 8 \ 6 \ 8 \ 8 \ 6 
##
                     [ 364 ] \  \, 8 \  \, 8 \  \, 6 \  \, 8 \  \, 9 \  \, 8 \  \, 7 \  \, 8 \  \, 8 \  \, 6 \  \, 7 \  \, 6 \  \, 8 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 8 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 8 \  \, 6 \  \, 7 \  \, 6 \  \, 8 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 5 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 7 \  \, 6 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \ \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, \, 8 \  \, \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \  \, 9 \  \, 8 \ 
##
                     [397] \ 8 \ 9 \ 9 \ 4 \ 4 \ 8 \ 6 \ 7 \ 8 \ 7 \ 7 \ 9 \ 8 \ 7 \ 8 \ 6 \ 8 \ 7 \ 8 \ 8 \ 5 \ 8 \ 7 \ 9 \ 7 \ 7 \ 7 \ 8 \ 6 \ 7 \ 8 \ 8 \ 8
```

```
[430] 6 5 7 8 4 8 7 9 7 9 8 8 7 7 8 6 7 6 8 8 7 7 8 8 9 8 6 6 6 8 9 5 8
##
    [463] \ 7 \ 8 \ 7 \ 8 \ 8 \ 7 \ 8 \ 6 \ 9 \ 6 \ 8 \ 6 \ 7 \ 7 \ 7 \ 9 \ 8 \ 7 \ 8 \ 6 \ 8 \ 7 \ 5 \ 9 \ 9 \ 7 \ 8 \ 6 \ 5 \ 9 \ 7 \ 7 \ 9
##
    [496] 4 8 9 7 6 8 8 8 9 8 8 7 7 5 8 7 9 6 8 7 8 7 6 9 6 8 8 8 9 7 7 6 9
    [529] 4 8 5 7 7 6 9 6 8 6 7 8 6 9 6 8 6 5 9 6 6 8 8 8 7 6 7 7 7 7 7 9 9
##
##
    [562] 5 6 8 7 7 8 6 7 6 7 6 7 8 5 7 8 9 7 7 6 6 6 8 8 8 7 5 7 7 9 5 9
    [595] 9 6 7 8 6 9 8 7 8 8 8 6 8 6 8 8 7 9 9 4 7 6 6 6 5 9 6 6 6 8 9 8 8
##
    [628] 6 8 8 6 6 7 7 9 8 5 6 6 8 7 6 6 8 9 7 6 9 8 7 6 5 7 7 7 6 6 9 7 8
    ##
##
    [727] 6 7 6 9 8 6 7 5 8 8 6 4 8 9 4 8 9 7 8 7 6 9 7 5 8 8 8 9 7 7 7 6 9
##
    [760] 8 7 8 7 7 7 8 8 8 7 7 5 6 7 6 9 8 8 8 7 6 8 6 9 7 6 7 8 9 8 5 5 7
    [793] \ 8 \ 7 \ 6 \ 8 \ 9 \ 8 \ 8 \ 7 \ 8 \ 9 \ 9 \ 8 \ 5 \ 7 \ 7 \ 6 \ 7 \ 9 \ 7 \ 8 \ 6 \ 6 \ 8 \ 8 \ 9 \ 7 \ 7 \ 7 \ 8 \ 7 \ 4 \ 6
##
    [826] \ 9 \ 7 \ 9 \ 8 \ 7 \ 9 \ 6 \ 7 \ 7 \ 7 \ 7 \ 7 \ 8 \ 9 \ 5 \ 7 \ 7 \ 9 \ 7 \ 8 \ 6 \ 9 \ 8 \ 9 \ 8 \ 7 \ 4 \ 7 \ 7 \ 8 \ 5 \ 9
##
    [859] 9 6 8 9 7 7 7 8 8 9 7 7 8 8 6 7 6 7 9 7 6 7 9 5 7 8 6 5 8 8 8 8 7
##
##
    [892] 6 7 7 6 6 9 8 9 6 5 7 6 7 7 7 6 6 6 9 9 9 6 7 8 5 7 7 8 8 6 9 8 6
##
     [925] \ 7 \ 7 \ 8 \ 7 \ 8 \ 6 \ 6 \ 8 \ 6 \ 7 \ 5 \ 8 \ 7 \ 6 \ 6 \ 9 \ 5 \ 7 \ 8 \ 8 \ 9 \ 8 \ 8 \ 8 \ 8 \ 7 \ 8 \ 5 \ 9 \ 8 \ 5 \ 7 
##
    [958] \ 9 \ 8 \ 8 \ 7 \ 7 \ 8 \ 6 \ 7 \ 7 \ 9 \ 6 \ 7 \ 6 \ 9 \ 6 \ 8 \ 8 \ 7 \ 5 \ 9 \ 8 \ 8 \ 7 \ 7 \ 5 \ 7 \ 6 \ 6 \ 8 \ 8 \ 8 \ 8
    [991] 9 8 7 8 7 6 7 8 7 9
```

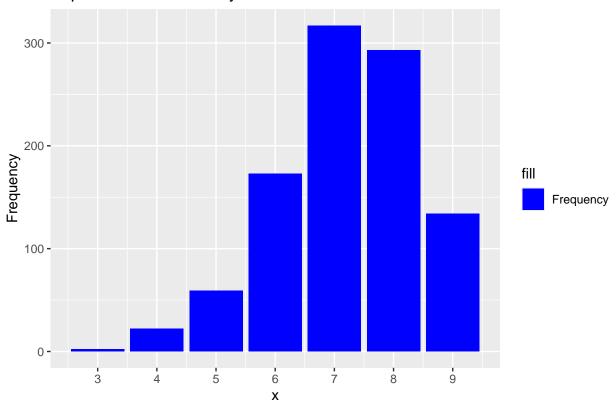
\mathbf{B}

Plot the experimental probability using the geom_bar() function.

```
df <- data.frame(x = rbinom(t, n, p))

ggplot(df, aes(x = x, fill = "Frequency")) +
    geom_bar() +
    scale_x_continuous(breaks = 0:9) +
    scale_fill_manual(values = "blue") +
    labs(
        title = "Experimental Probability",
        x = "x",
        y = "Frequency"
)</pre>
```

Experimental Probability



\mathbf{C}

For each value of the x-axis obtained in the previous plot, compute the real probability mass function and add it in the plot as red dots using geom_point().

```
ggplot(df, aes(x = x, fill = "Frequency")) +
  geom_bar() +
  geom_point(
    aes(x = x, y = dbinom(x, n, p)),
    color = "red",
    size = 2
) +
  scale_x_continuous(breaks = 0:9) +
  scale_fill_manual(values = "blue") +
  labs(
    title = "Experimental vs Real Probability",
    x = "Successes",
    y = "Frequency"
)
```

Experimental vs Real Probability

