

Lab 1

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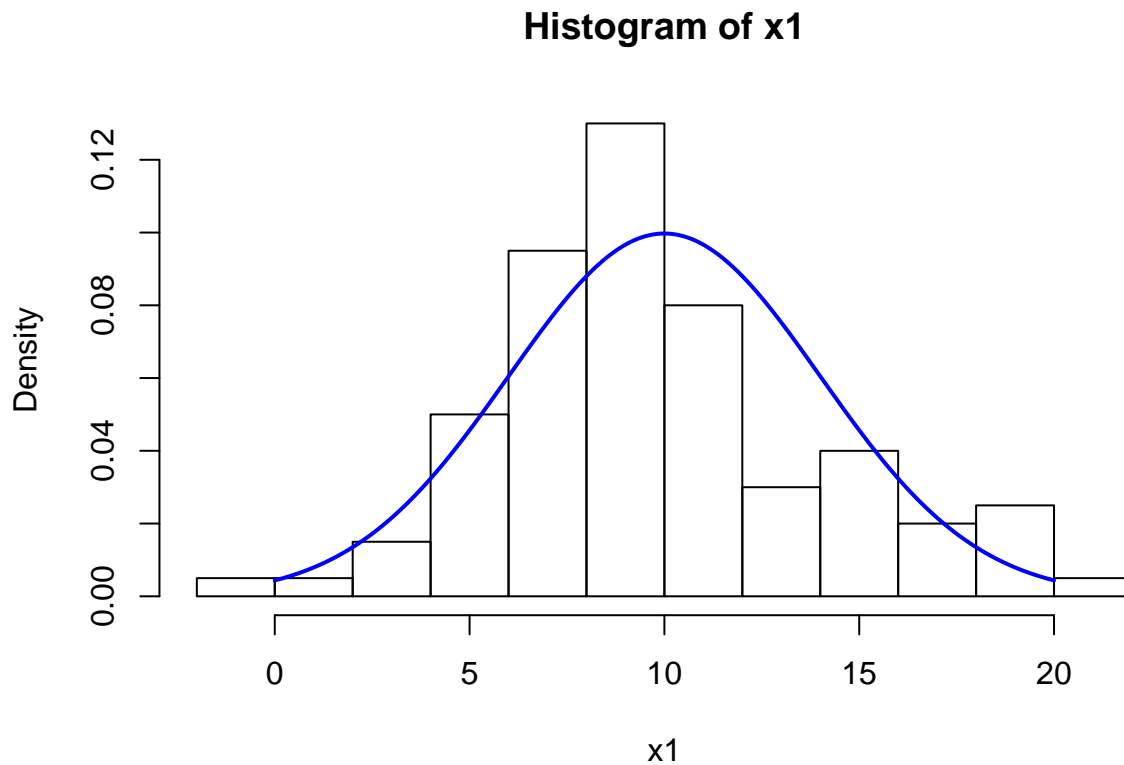
Uppgift 1 Simulering av normalfördelning

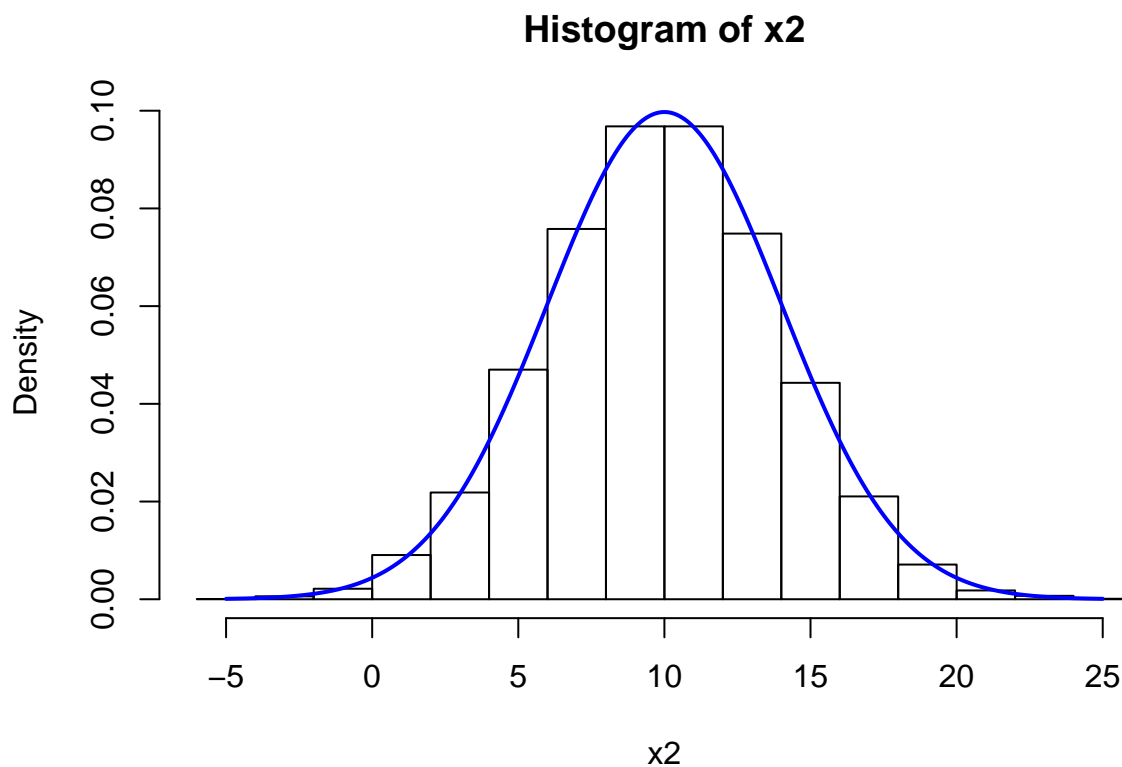
a) Visualisera fördelningarna i två histogram. Visualisera fördelningens pdf i samma graf.

Nedan simuleras normalfördelningen med olika antalet dragningar.

```
x1 <- rnorm(100, mean = 10, sd = 4)
x2 <- rnorm(10000, mean = 10, sd = 4)
```

I figurerna nedan visas resultatet av dragningarna som ett histogram tillsammans med täthetsfunktionen.





b) Beskriv skillnaden mellan de olika graferna.

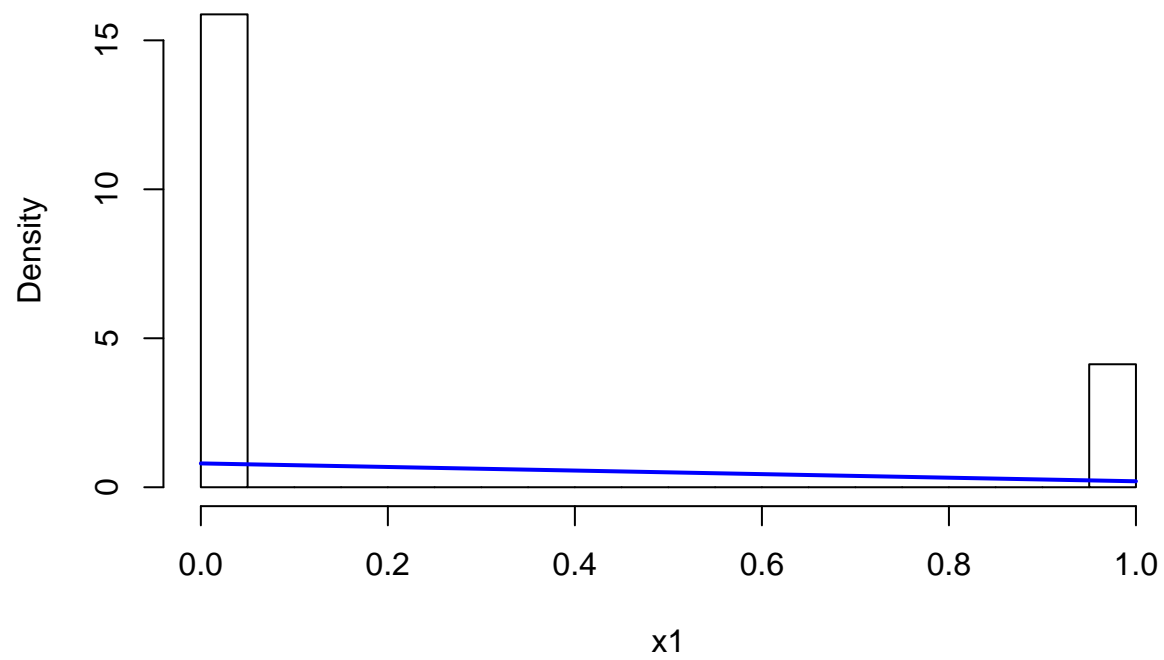
Vi kan tydligare se normalfördelningsformen om vi gör fler dragningar/simuleringar.

3.1.2

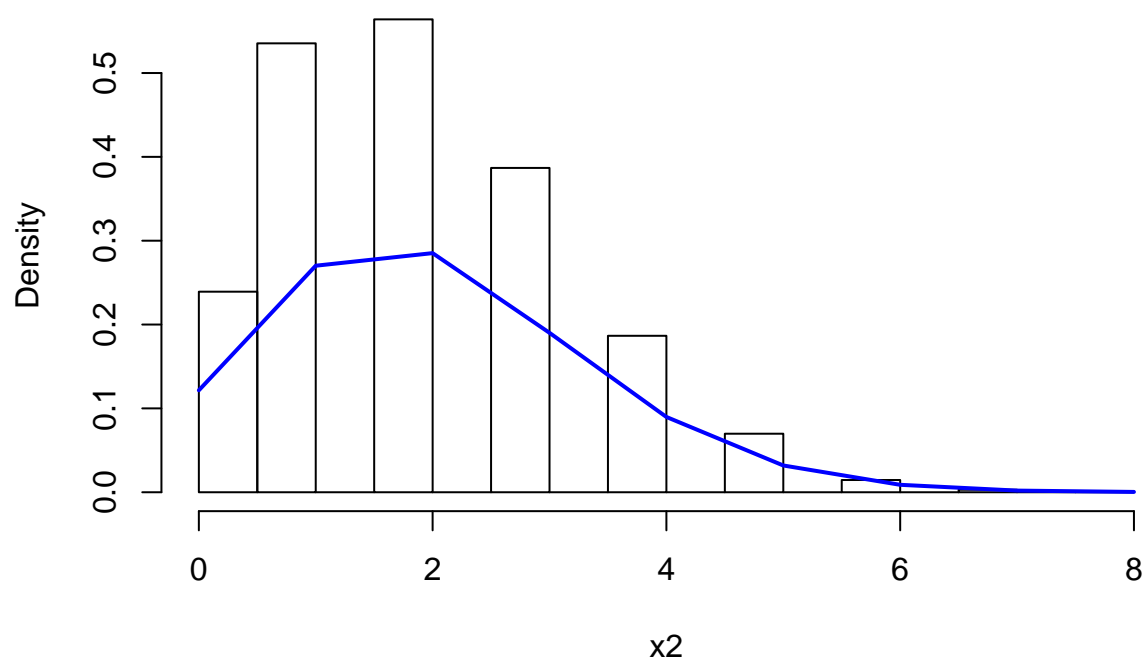
```
n <- 10000
x1 <- rbinom(n, 1, 0.2)
x2 <- rbinom(n, 20, 0.1)
x3 <- rbinom(n, 20, 0.5)
x4 <- rgeom(n, 0.1)
x5 <- rpois(n, 10)

y1 <- runif(n, min = 0, max = 1)
y2 <- rexp(n, 3)
y3 <- rgamma(n, 2, 1)
y4 <- rt(n, 3)
y5 <- rbeta(n, 0.1, 0.1)
y6 <- rbeta(n, 1, 1)
y7 <- rbeta(n, 10, 5)
```

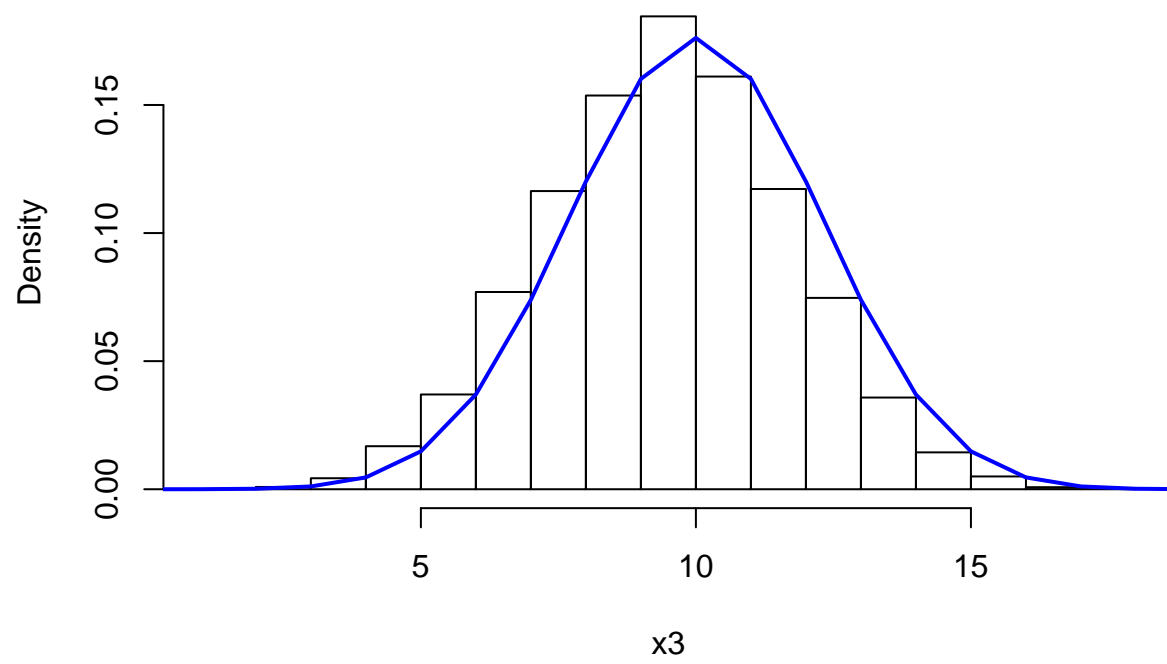
Histogram of x1



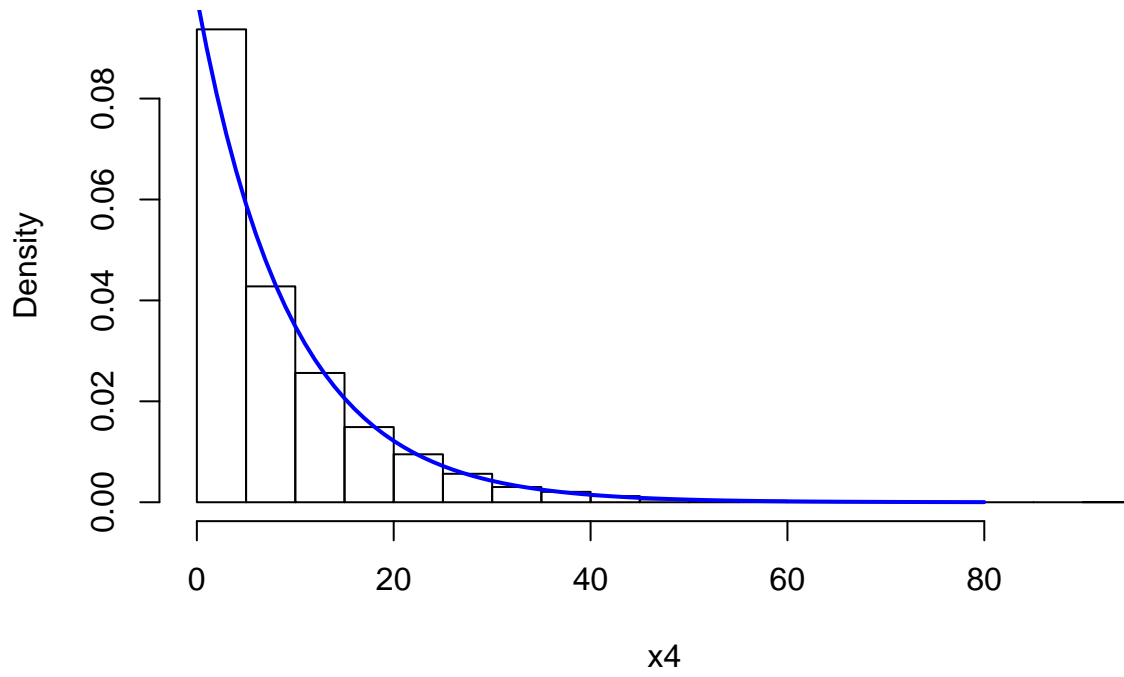
Histogram of x2



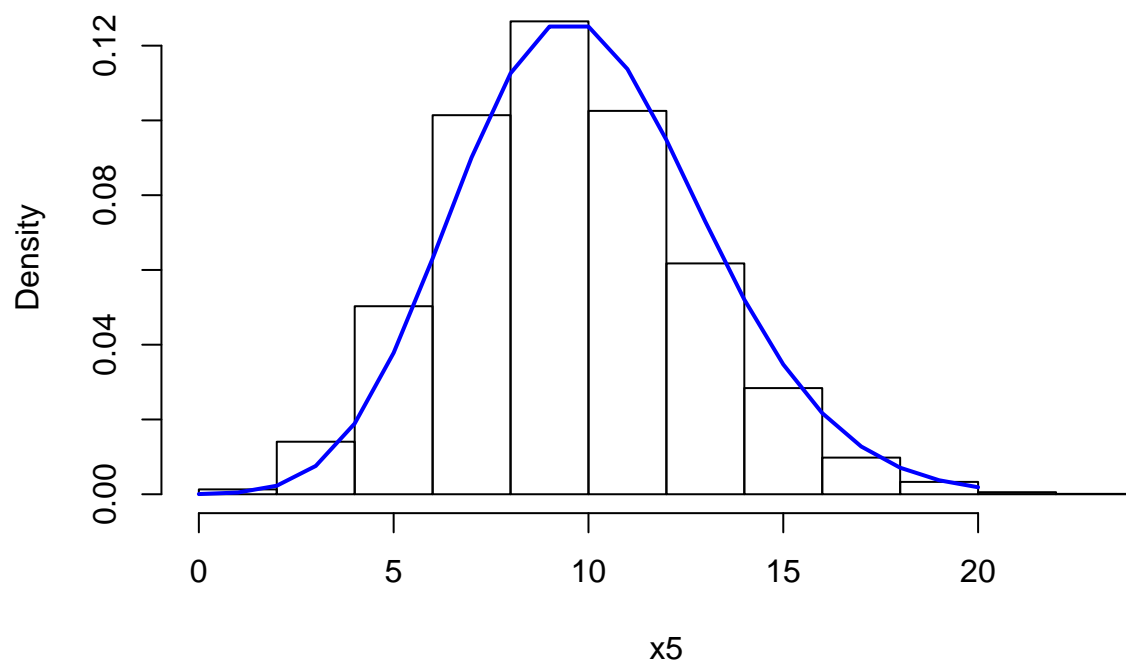
Histogram of x3



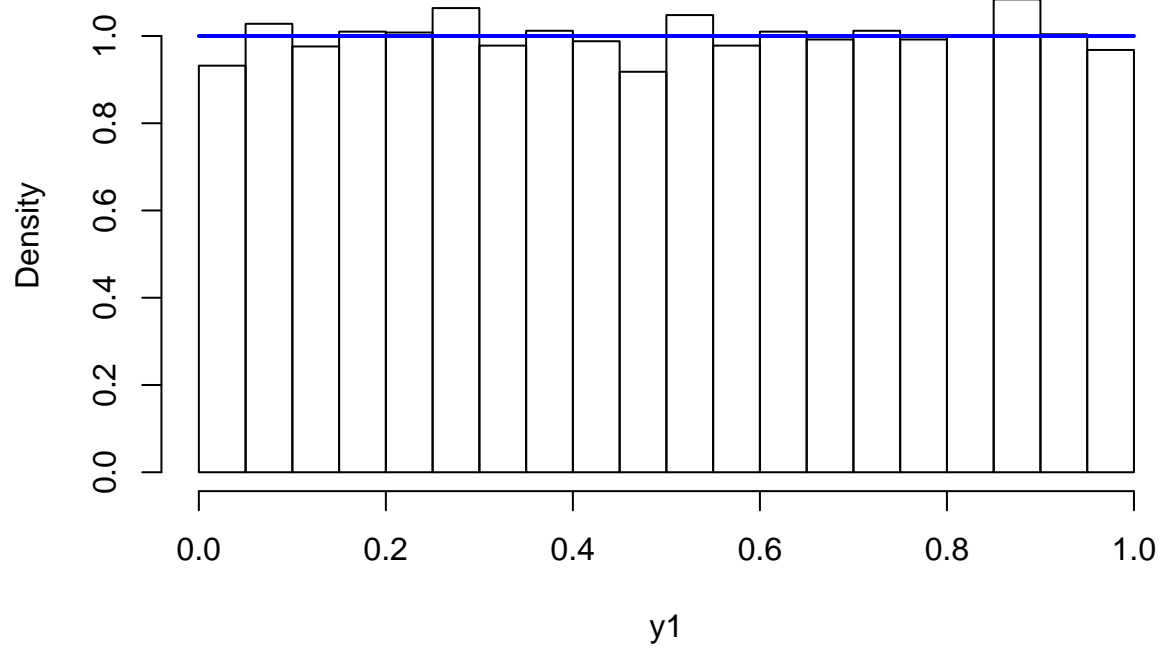
Histogram of x4



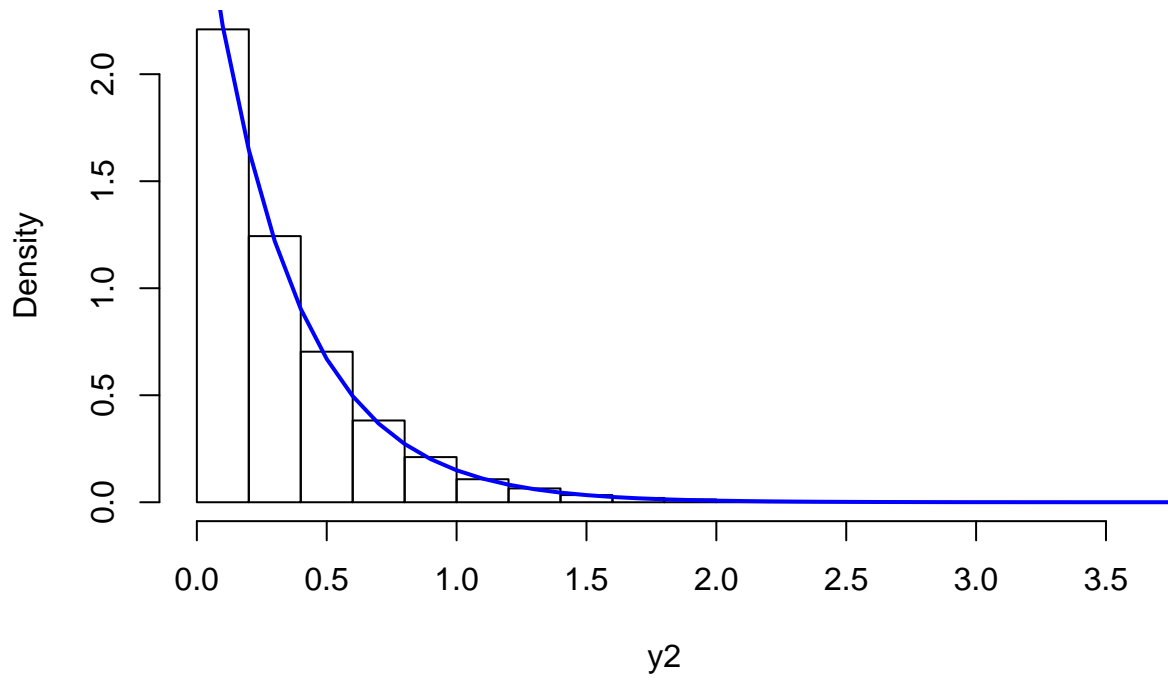
Histogram of x5



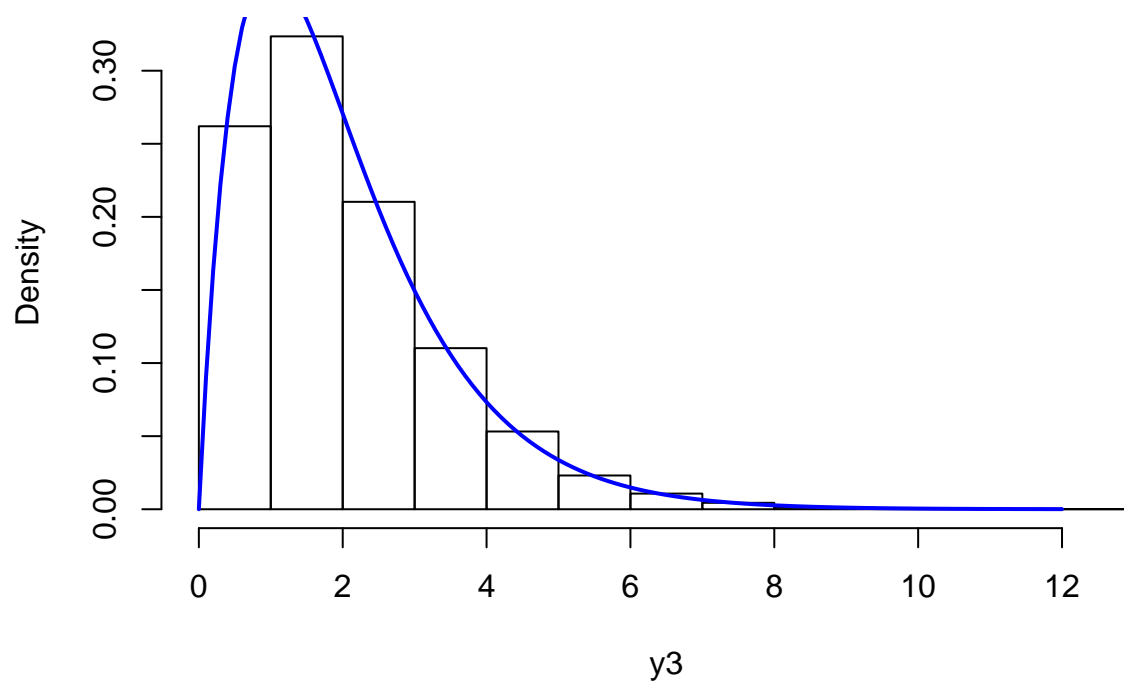
Histogram of y1

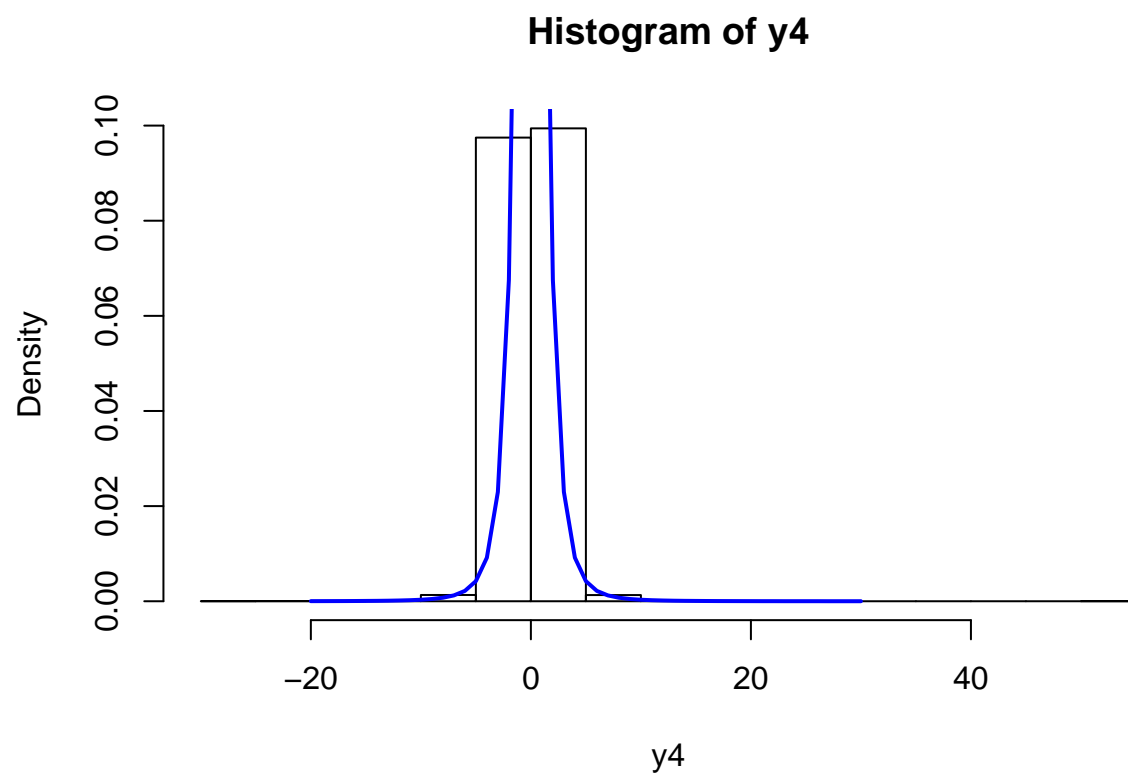


Histogram of y2

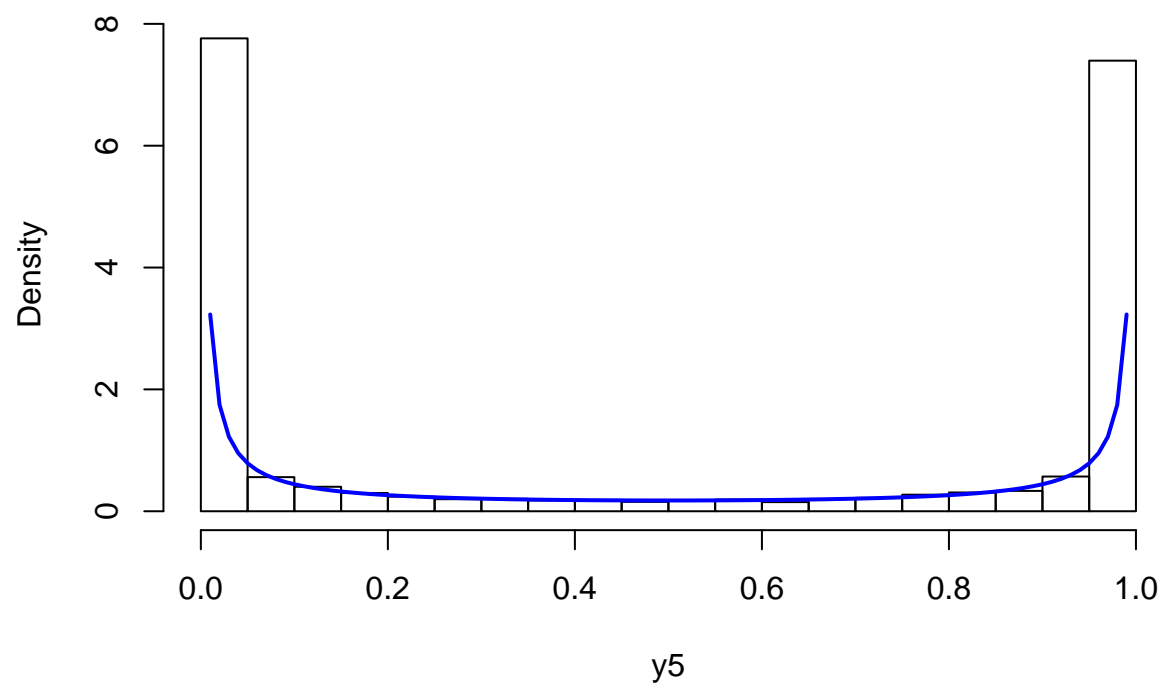


Histogram of y3

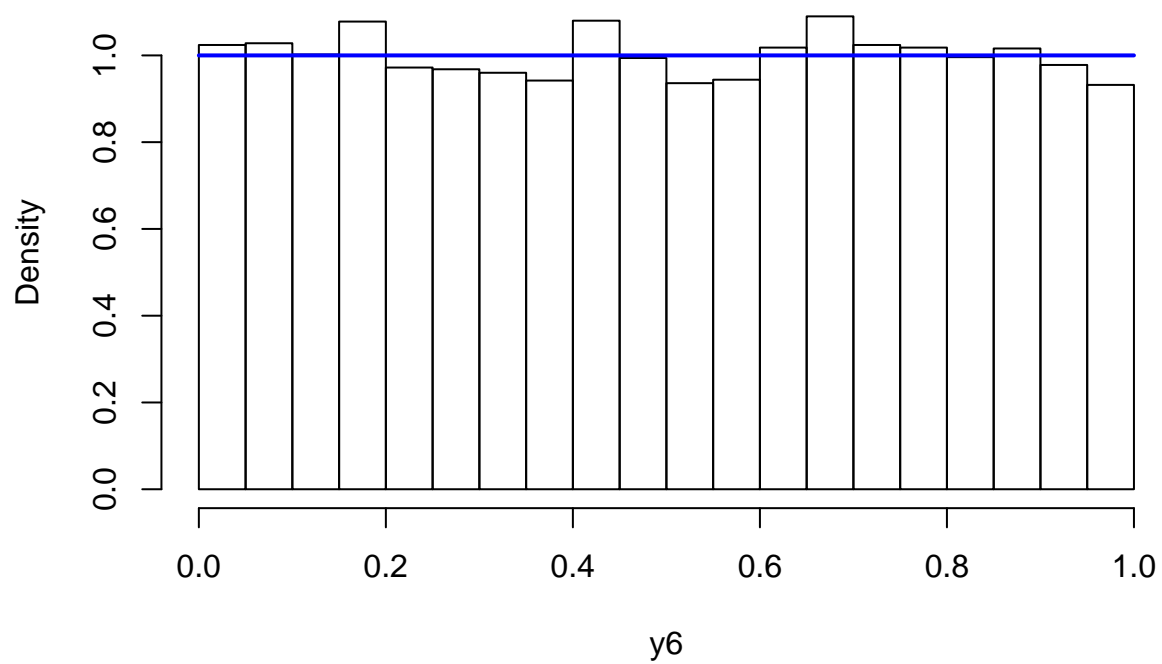


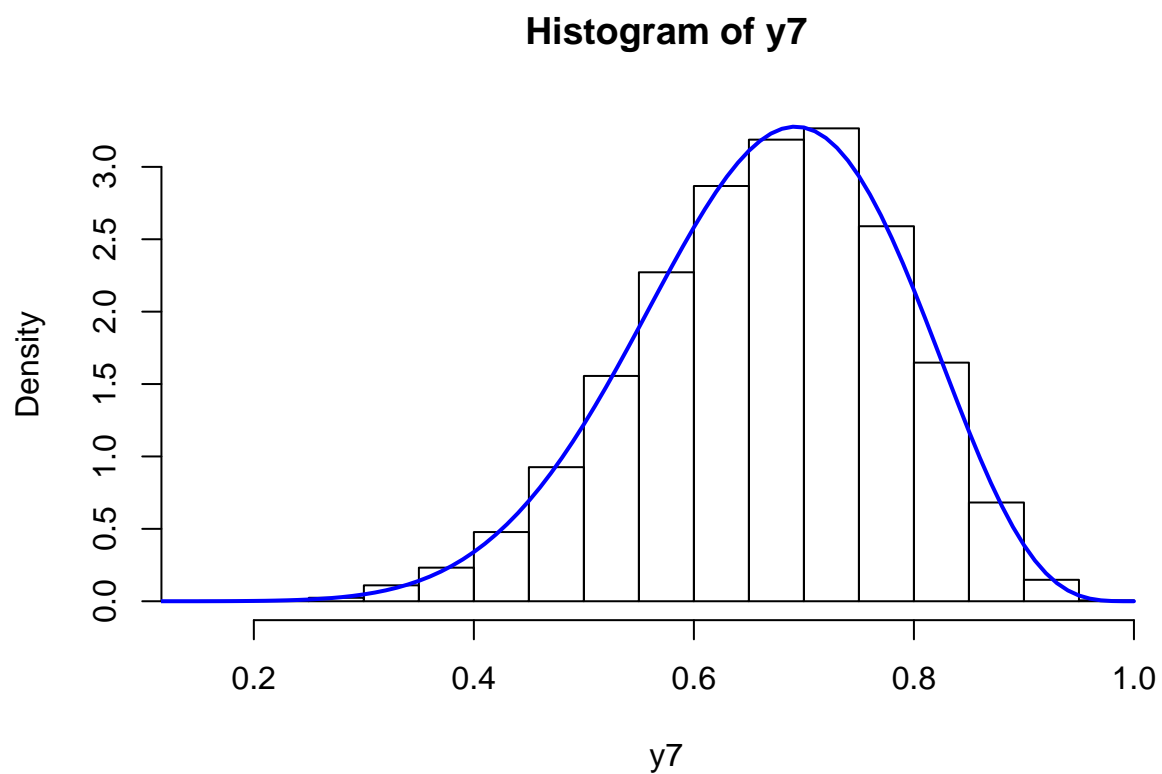


Histogram of y5



Histogram of y6

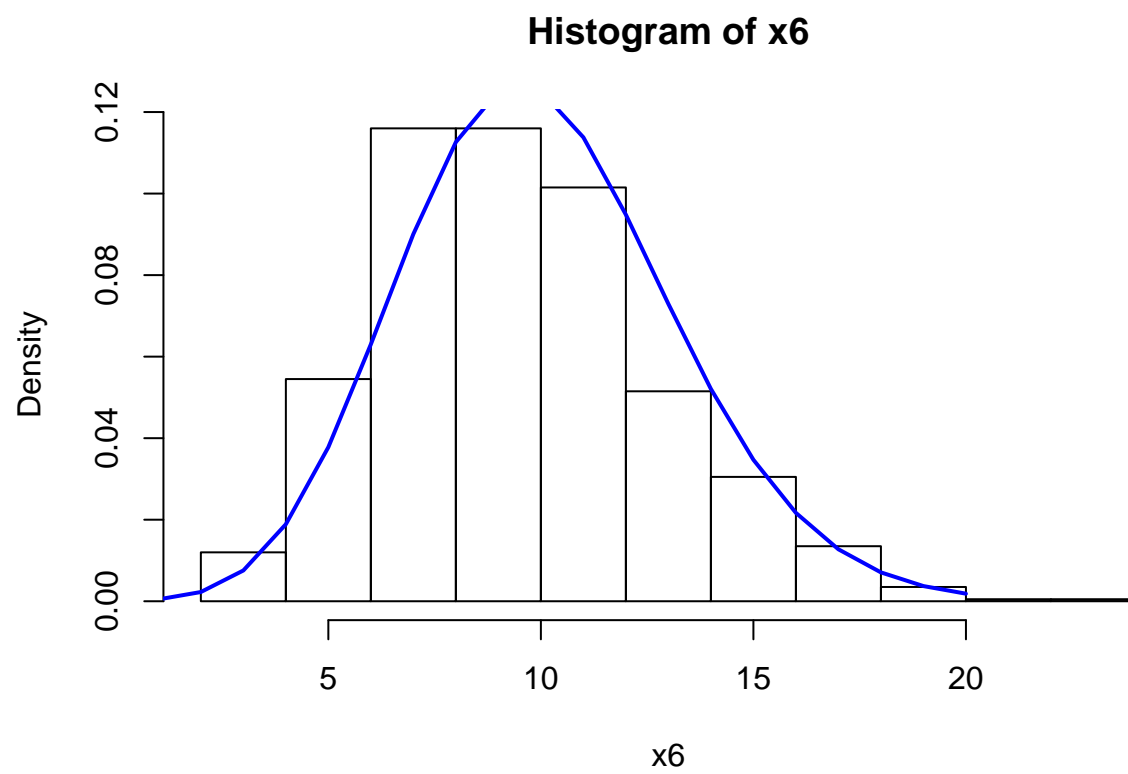




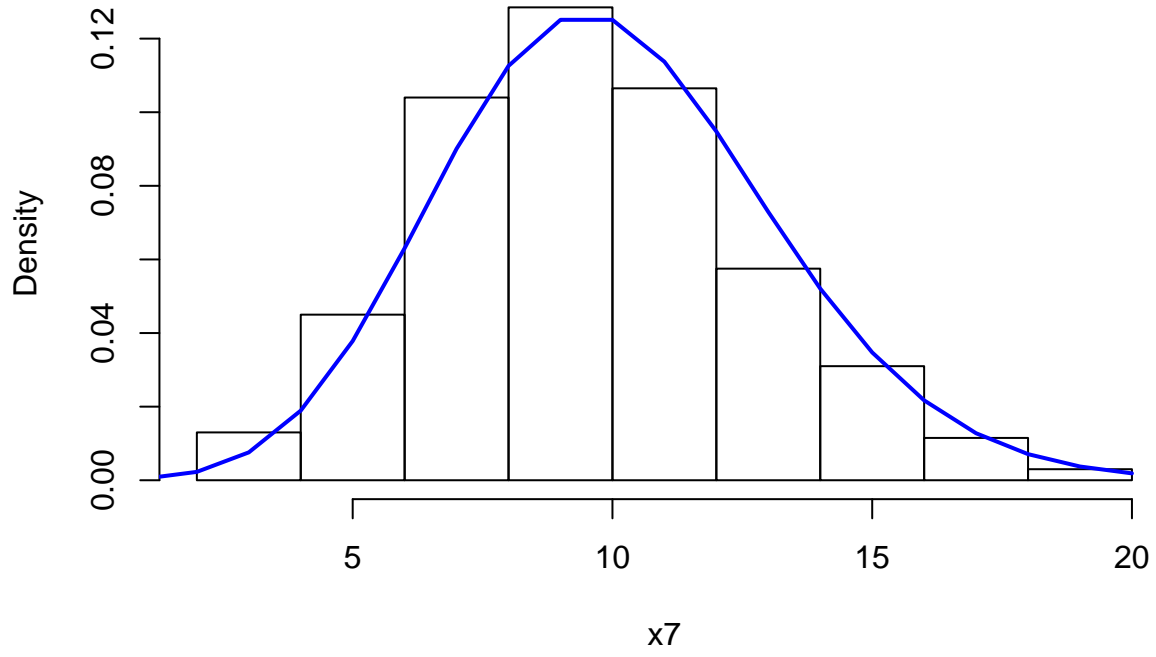
3.1.3

(1) Simulera 1000 dragningar från varje fördelning.

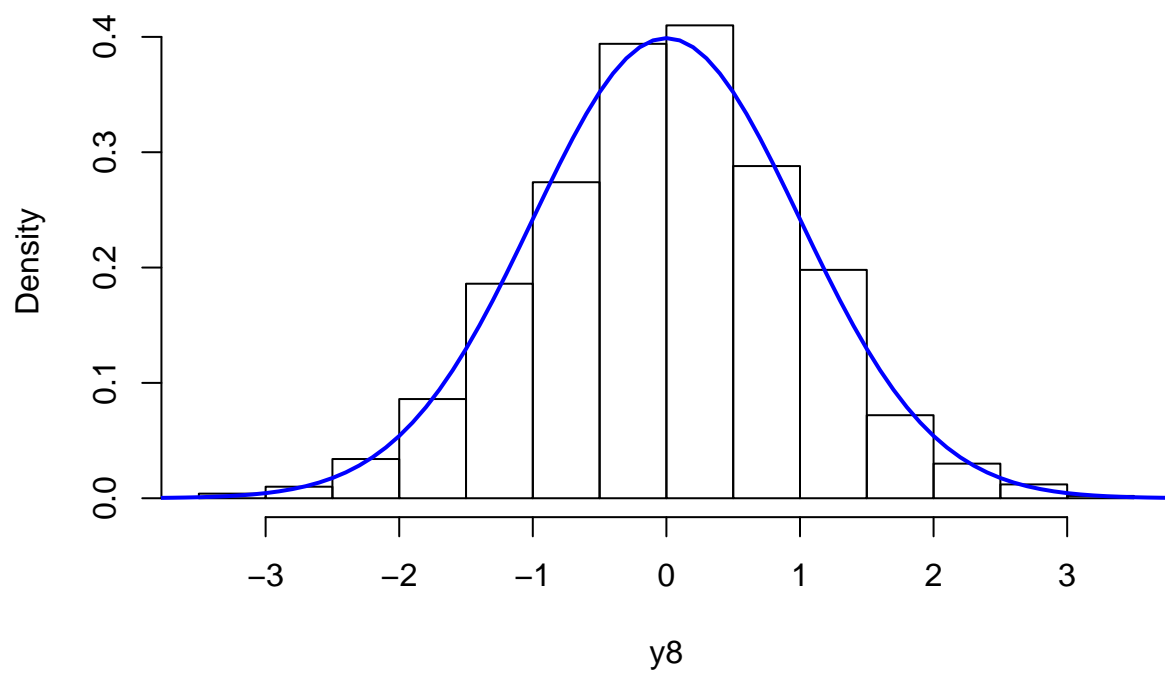
```
n <- 1000
x6 <- rbinom(n, 10000, 0.001)
y8 <- rt(n, 10000)
x7 <- rpois(n, 10000*0.001)
y9 <- rnorm(n, 10000, 1)
```

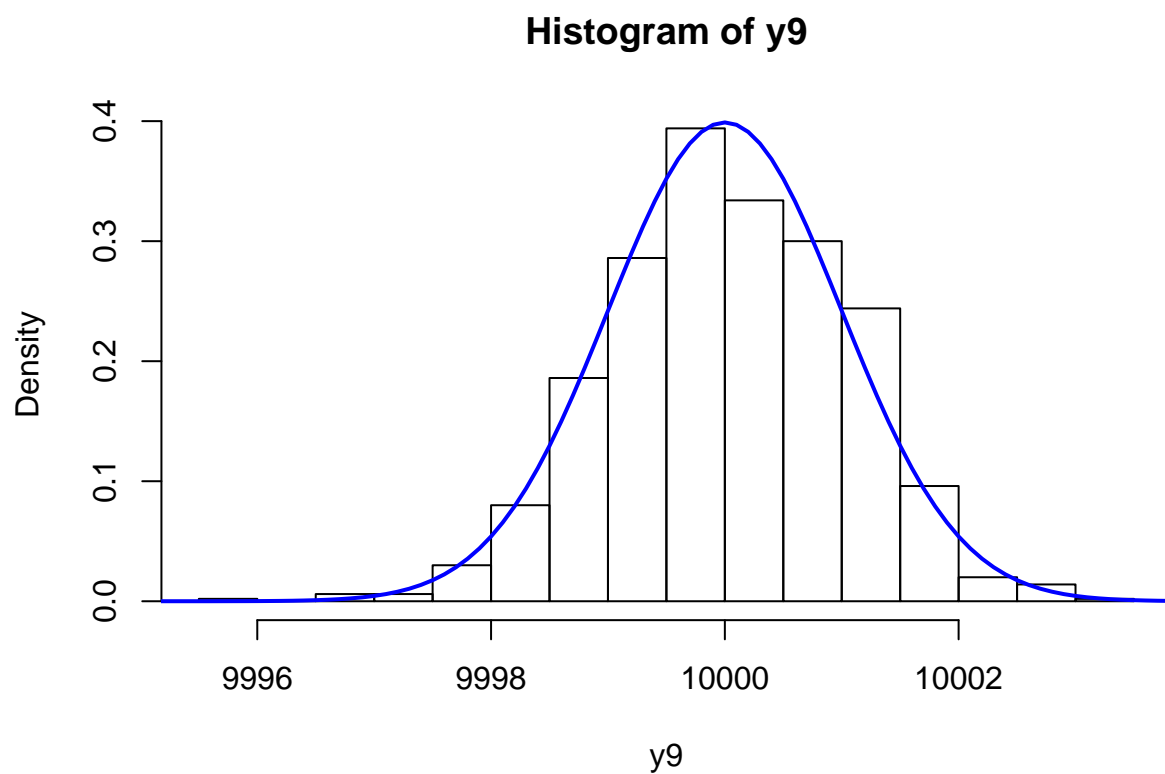


Histogram of x7



Histogram of y8





3.1.4

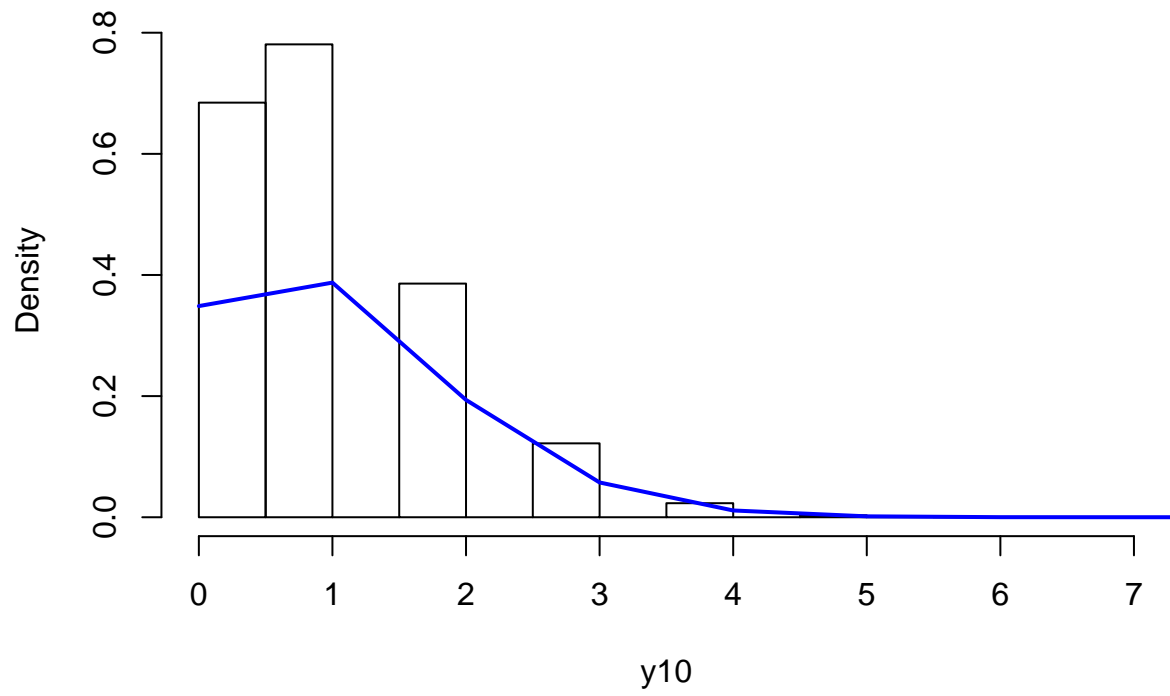
(1) simulera 10000 dragningar från varje fördelning och skriv ut sannolikheten att en dragning är lika med 0

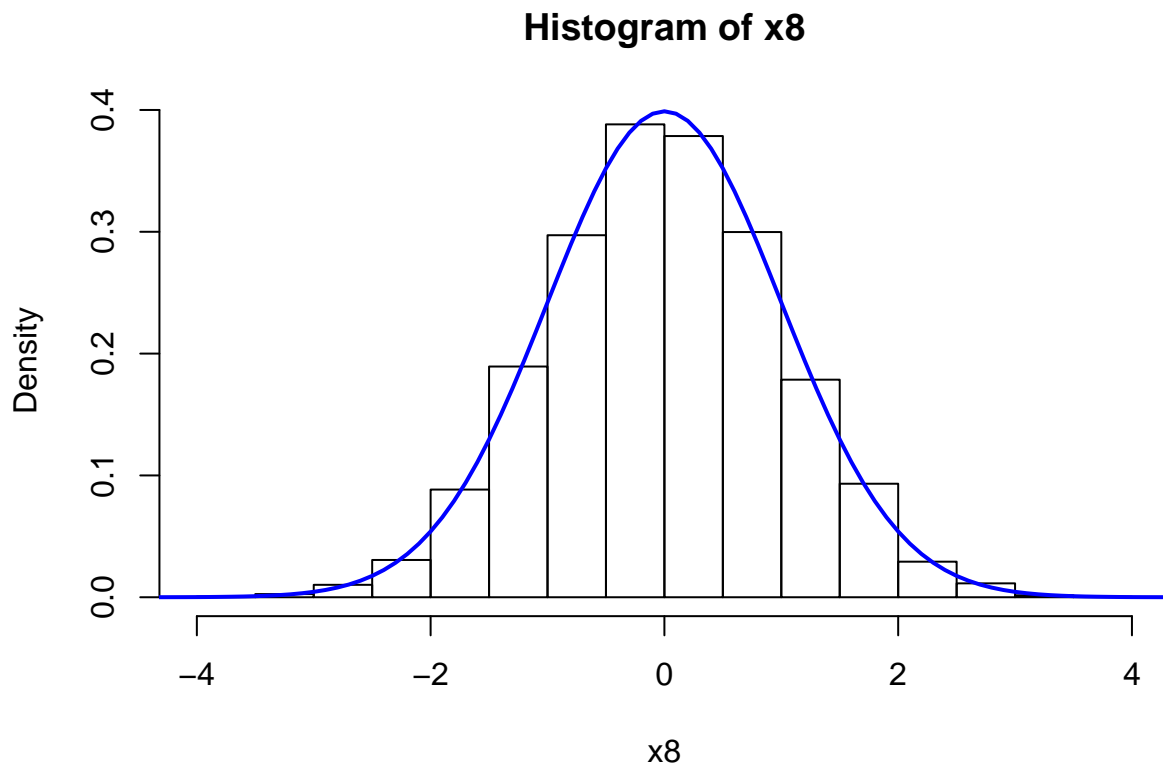
```
y10 <- rbinom(10000, 10, 0.1)
x8 <- rnorm(10000, 0, 1)

p <- dbinom(0, 10, 0.1)
print(p)
```

```
## [1] 0.3486784
```

Histogram of y10





(2) Använd den kumulativa fördelningsfunktionen för att beräkna sannolikheterna

```
p1 <- pnorm(0, 0, 1)
print(p1)
```

```
## [1] 0.5
```

```
p2 <- pnorm(1, 0, 1) - pnorm(-1, 0, 1)
print(p2)
```

```
## [1] 0.6826895
```

```
p3 <- 1 - pnorm(1.96, 0, 1)
print(p3)
```

```
## [1] 0.0249979
```

```
p4 <- pbinom(10, 10, 0.1) - pbinom(0, 10, 0.1)
print(p4)
```

```
## [1] 0.6513216
```

```
eps <- 0.0001
p5 <- pbinom(0 + eps, 10, 0.1) - pbinom(0 - eps, 10, 0.1)
print(p5)
```

```
## [1] 0.3486784
```

```
p6 <- p4 + p5
print(p6)
```

```
## [1] 1
```

(3) Simuleringar för att beräkna samma sannolikheten som i (2)

```
p1s <- sum(x8 < 0) / 10000  
print(p1s)
```

```
## [1] 0.5036
```

```
p2s <- (sum(x8 < 1) - sum(x8 <= -1)) / 10000  
print(p2s)
```

```
## [1] 0.6819
```

```
p3s <- sum(x8 > 1.96) / 10000  
print(p3s)
```

```
## [1] 0.0245
```

```
p4s <- (sum(y10 < 10) - sum(y10 <= 0)) / 10000  
print(p4s)
```

```
## [1] 0.6577
```

```
p5s <- sum(y10 == 0) / 10000  
print(p5s)
```

```
## [1] 0.3423
```

```
p6s <- (sum(y10 <= 10) - sum(y10 < 0)) / 10000  
print(p6s)
```

```
## [1] 1
```

3.1.5

(1) Beräkna antalet förväntade fel.

```
old <- rbinom(n = 10000, size = 337, p = 0.1)  
print(sum(old)/10000)
```

```
## [1] 33.6597
```

```
prob <- sum(runif(n = 10000, min = 0.02, max = 0.16))/10000  
new <- rbinom(n = 10000, size = 337, p = prob)  
print(sum(new)/10000)
```

```
## [1] 30.09
```

(2) Beräkna sannolikheten att vi får mindre fel i den nya jämfört med den gamla.

```
print(sum(new < old)/10000)
```

```
## [1] 0.6577
```

(3) Beräkna sannolikheten att vi får mer än 50 fel.

```
sum(old > 50)/10000
```

```
## [1] 0.0018
```

```
sum(new > 50)/10000
```

```
## [1] 3e-04
```

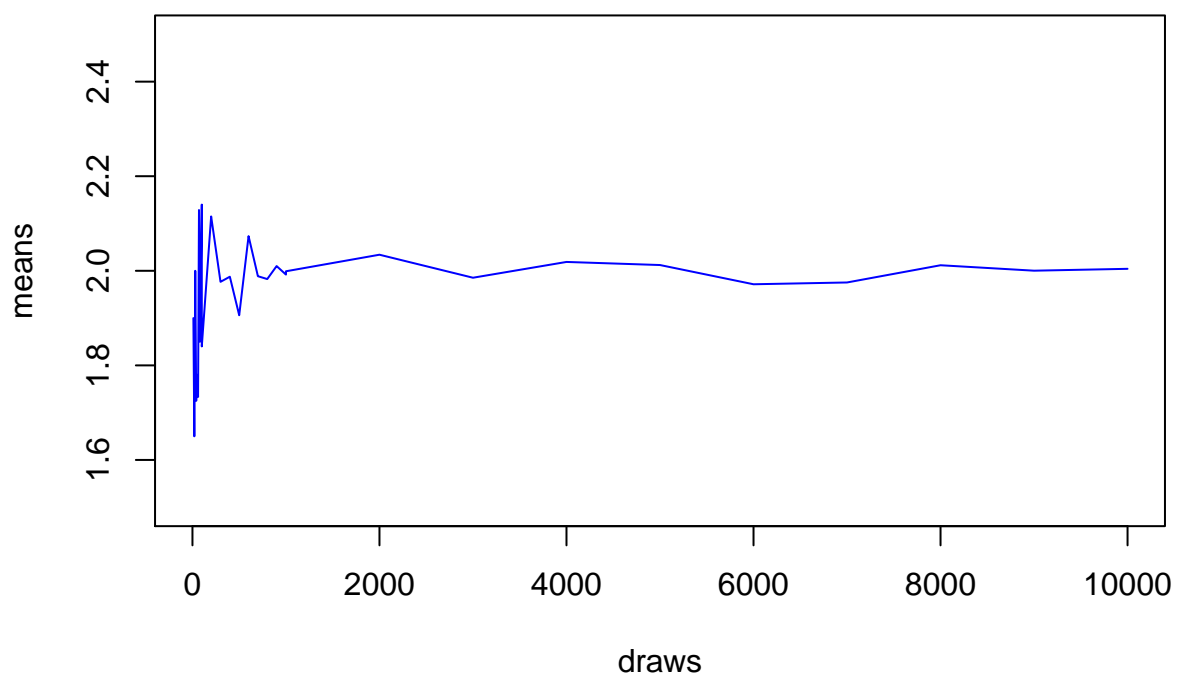
3.2.1

(1) $E(X) = 10 * 0.2 = 2$

$E(Y) = 2 / 2 = 1$

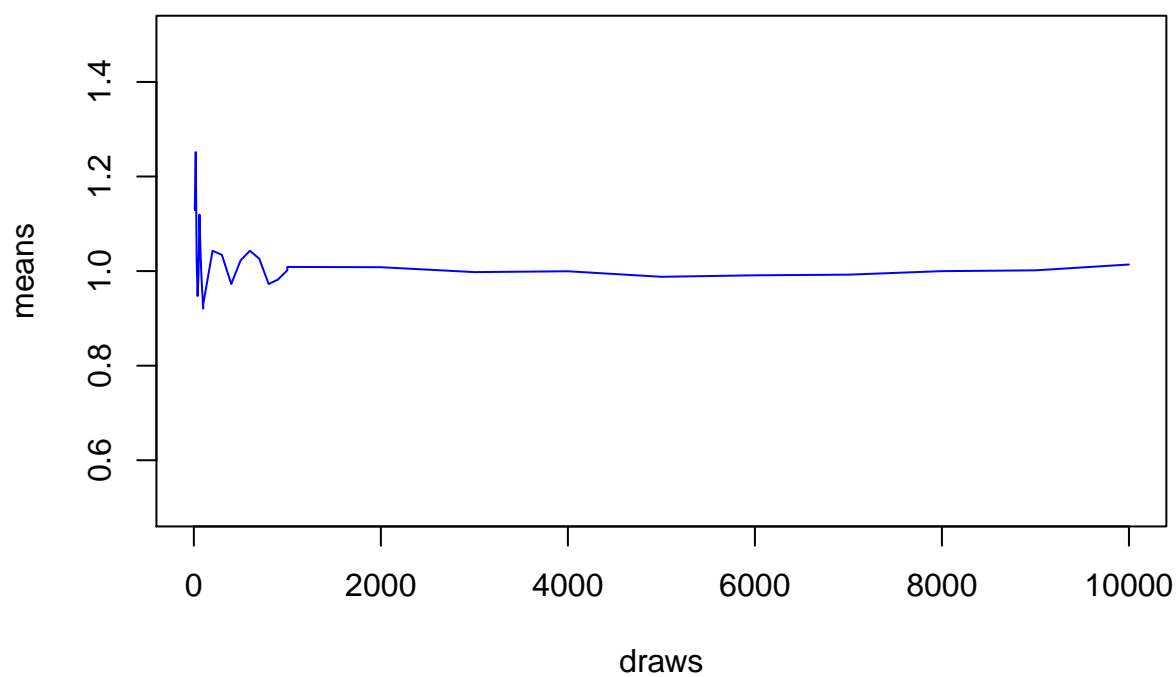
```
draws <- c(seq(10, 100, 10), seq(100, 1000, 100), seq(1000, 10000, 1000))
binomMeans <- numeric(length(draws))
gammaMeans <- numeric(length(draws))
for (i in 1:length(draws)) {
  n <- draws[i]
  binomMeans[i] <- mean(rbinom(n, 10, 0.2))
  gammaMeans[i] <- mean(rgamma(n, 2, 2))
}
```

binom means as a function of draws



(2)

gamma means as a function of draws



3.3.1

(1) $E(X) = 1 / 10 = 0.1$

$\text{Var}(X) = 1 / (10^2) = 0.01$

$E(Y) = 3$

$\text{Var}(Y) = 3$

(2) Använd simuleringarna för att beräkna medelvärdet och variansen.

```
x <- rexp(10000, 10)
print(mean(x))
```

```
## [1] 0.1008502
```

```
print(var(x))
```

```
## [1] 0.01000535
```

```
y <- rpois(10000, 3)
print(mean(y))
```

```
## [1] 2.9795
```

```
print(var(y))
```

```
## [1] 3.009381
```

(3) $E(3) = 3$

$E(3X + 2) = E(3X) + E(2) = 3 * E(X) + 2 = 0.3 + 2 = 2.3$

$E(X + Y) = E(X) + E(Y) = 0.1 + 3 = 3.1$

$E(X * Y) = E(X) * E(Y) = 0.1 * 3 = 0.3$

$E(3X + 2Y - 3) = 3E(X) + 2E(Y) - 3 = 0.3 + 6 - 3 = 3.3$

$\text{Var}(2X - 5) = 2^2 * \text{Var}(X) = 4 * 0.01 = 0.04$

$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) = 0.01 + 3 = 3.01$

(4) Använd simulering för att beräkna värdena i 3.

```
print(mean(3))
```

```
## [1] 3
```

```
print(mean(3*x + 2))
```

```
## [1] 2.302551
```

```
print(mean(x + y))
```

```
## [1] 3.08035
```

```
print(mean(x * y))
```

```
## [1] 0.3022441
```

```
print(mean(3*x + 2*y - 3))
```

```
## [1] 3.261551
```



```
print(var(2*x - 5))
```

```
## [1] 0.0400214
```

```
print(var(x + y))
```

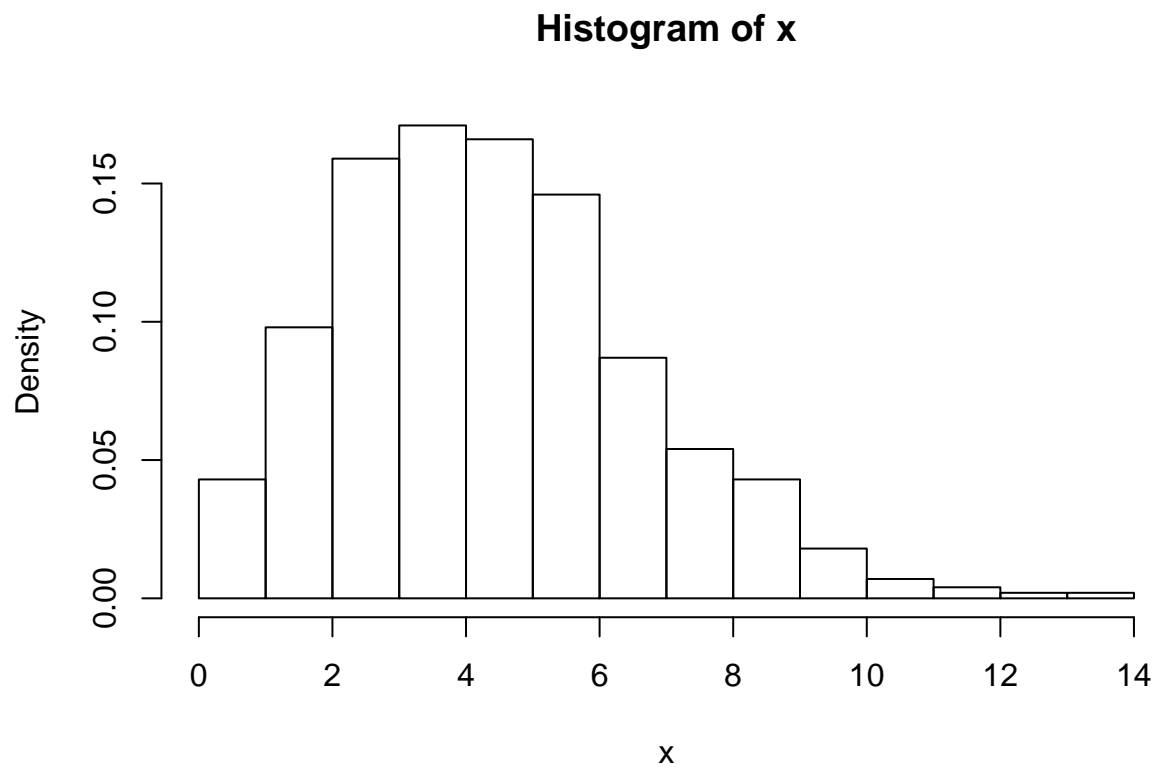
```
## [1] 3.022908
```

3.4.1

(1) Kör 1000 dragningar och visualisera med histogram.

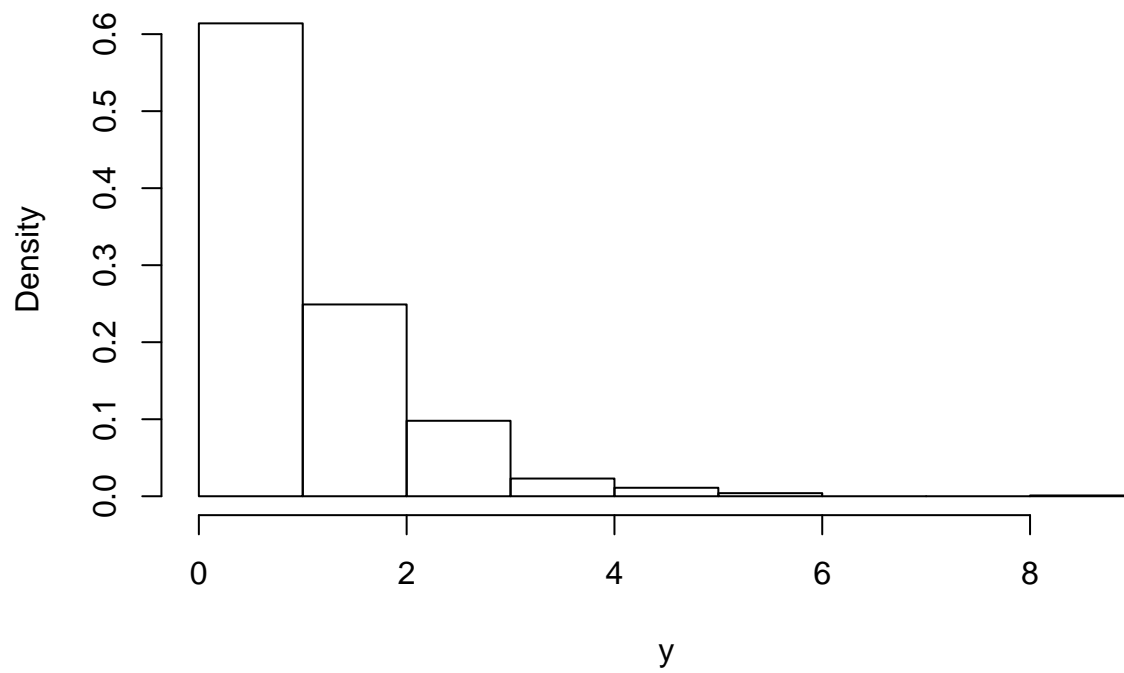
```
x <- rpois(1000, 5)
y <- rexp(1000, 1)
z <- rbinom(1000, 10, 0.01)

hist(x, probability = TRUE)
```



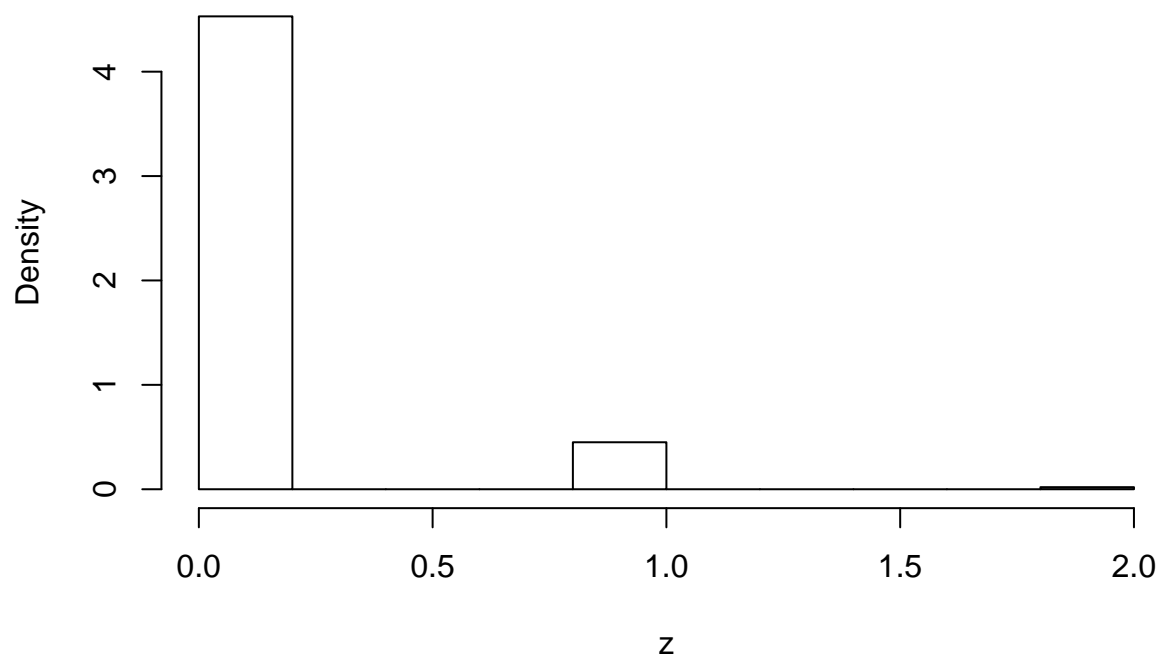
```
hist(y, probability = TRUE)
```

Histogram of y



```
hist(z, probability = TRUE)
```

Histogram of z

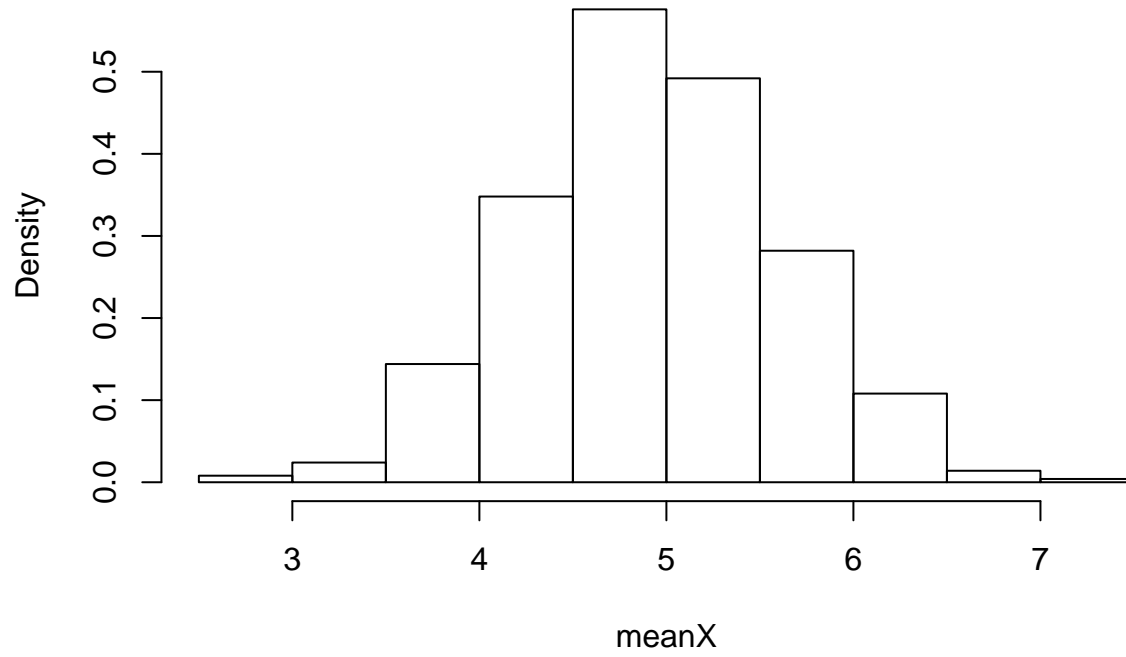


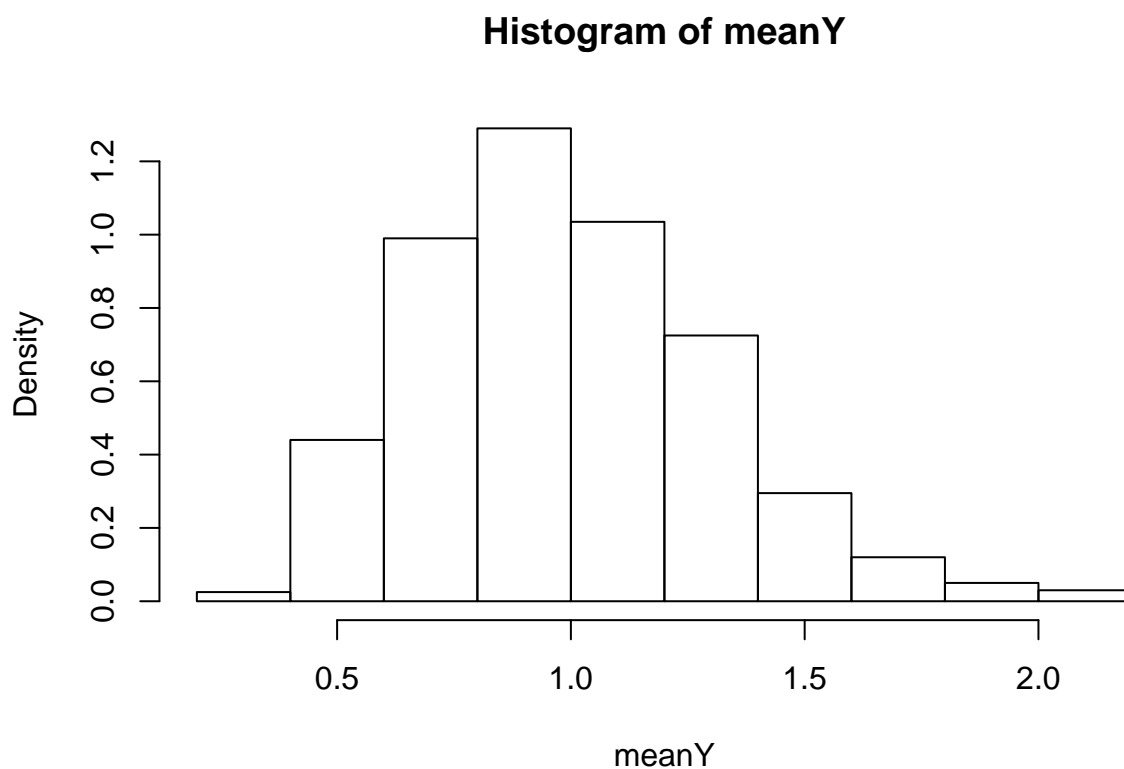
(2) kör 10 dragningar 1000 gånger och beräkna medelvärdet för varje 10 dragningar.

Sen visas medelvärdena som histogram.

```
meanX <- numeric(0)
meanY <- numeric(0)
for (i in 1:1000) {
  meanX <- c(meanX, mean(rpois(10, 5)))
  meanY <- c(meanY, mean(rexp(10, 1)))
}
```

Histogram of meanX

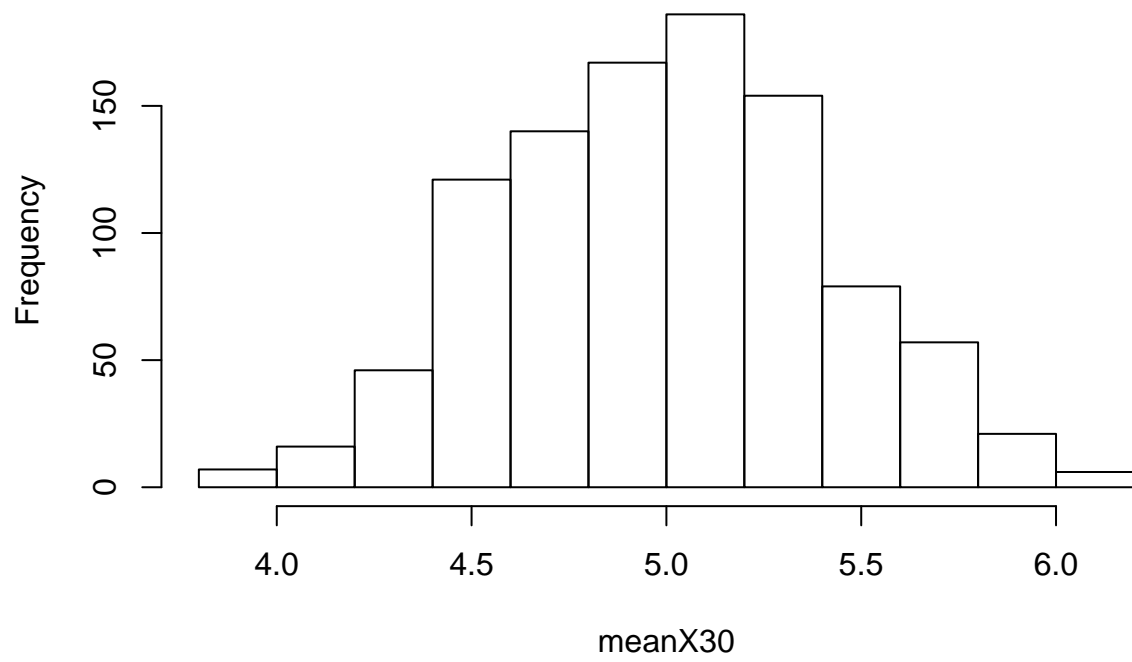


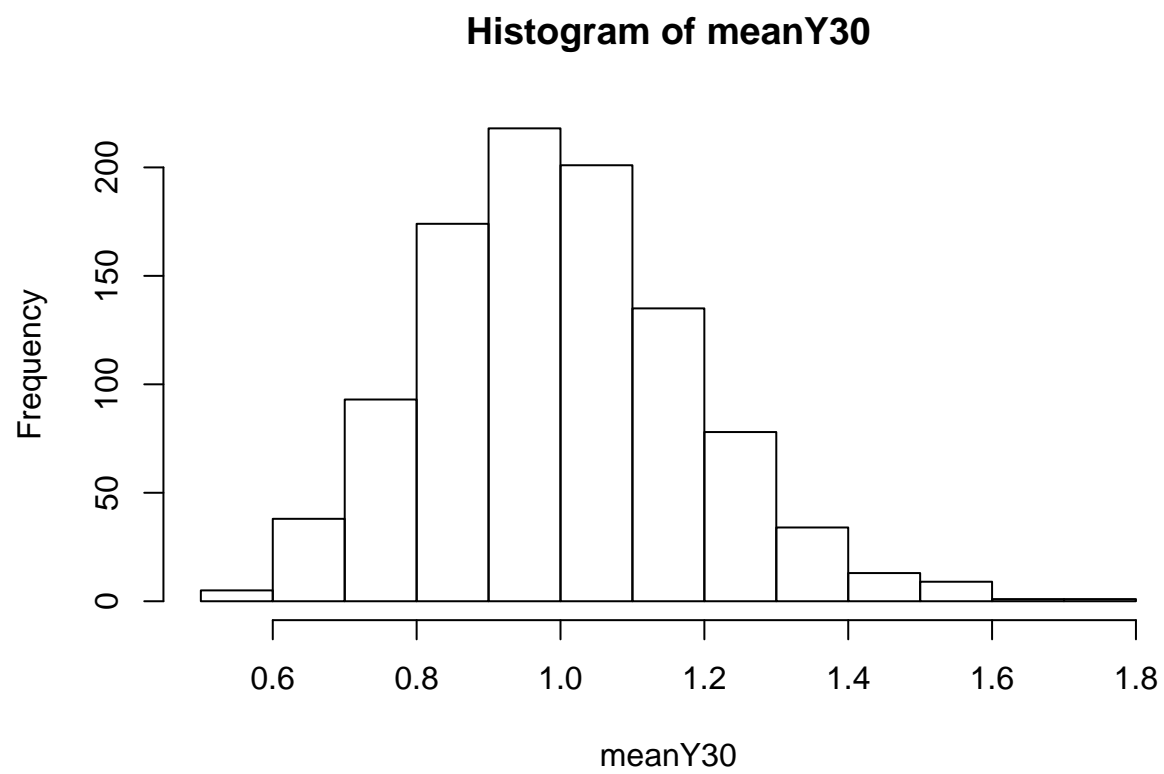


(3) kör 30, 100 och 1000 dragningar 1000 gånger och beräkna medelvärdet för varje 30, 100, 1000 dragningar. Sen visas medelvärdena som histogram.

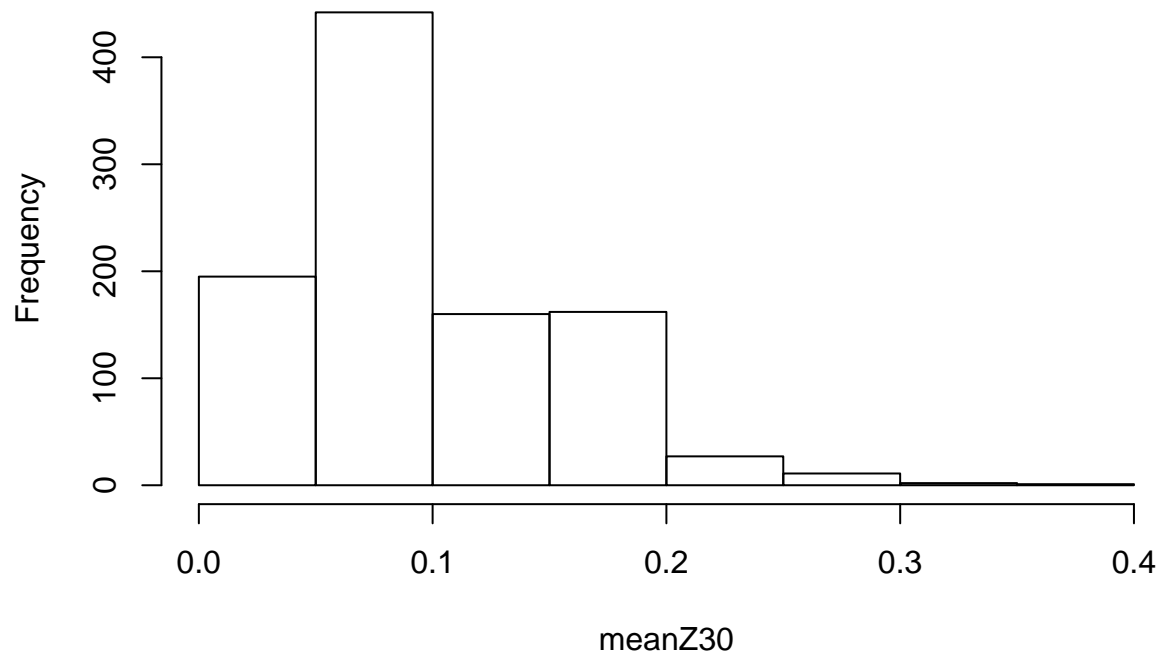
```
meanX30 <- numeric(0)
meanY30 <- numeric(0)
meanZ30 <- numeric(0)
for (i in 1:1000) {
  meanX30 <- c(meanX30, mean(rpois(30, 5)))
  meanY30 <- c(meanY30, mean(rexp(30, 1)))
  meanZ30 <- c(meanZ30, mean(rbinom(30, 10, 0.01)))
}
```

Histogram of meanX30



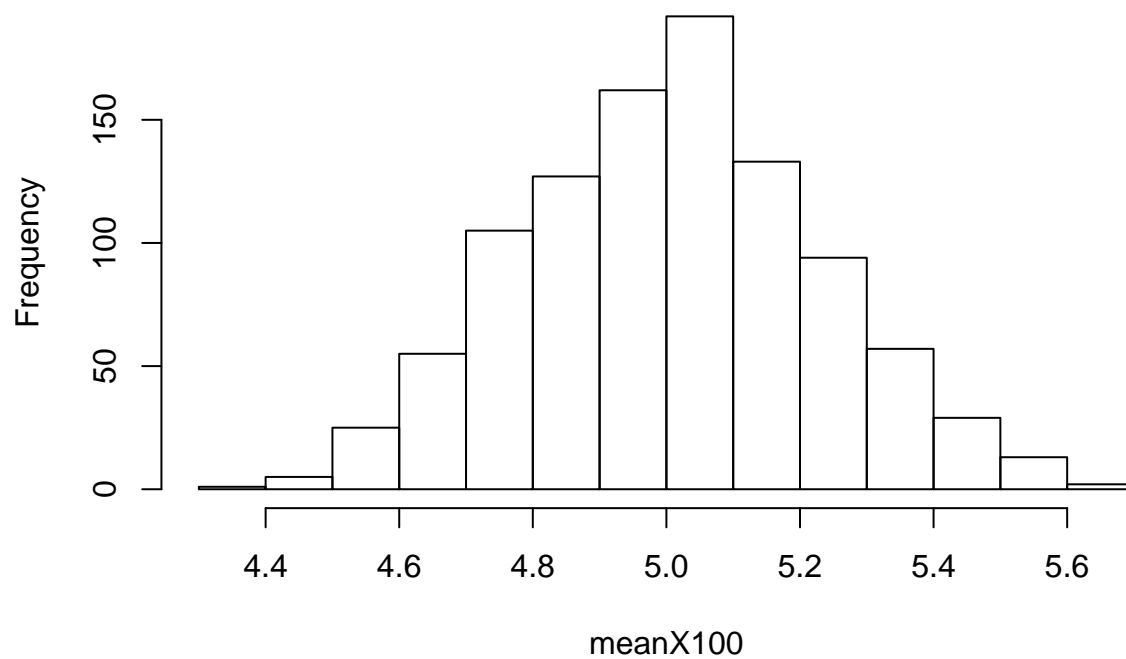


Histogram of meanZ30

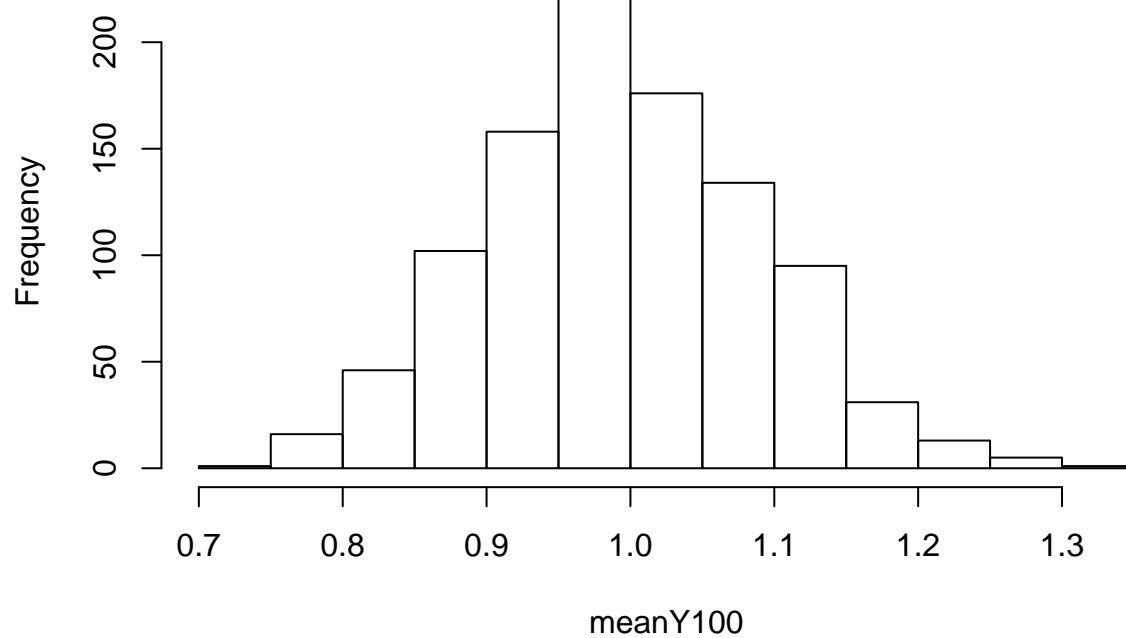


```
meanX100 <- numeric(0)
meanY100 <- numeric(0)
meanZ100 <- numeric(0)
for (i in 1:1000) {
  meanX100 <- c(meanX100, mean(rpois(100, 5)))
  meanY100 <- c(meanY100, mean(rexp(100, 1)))
  meanZ100 <- c(meanZ100, mean(rbinom(100, 10, 0.01)))
}
```

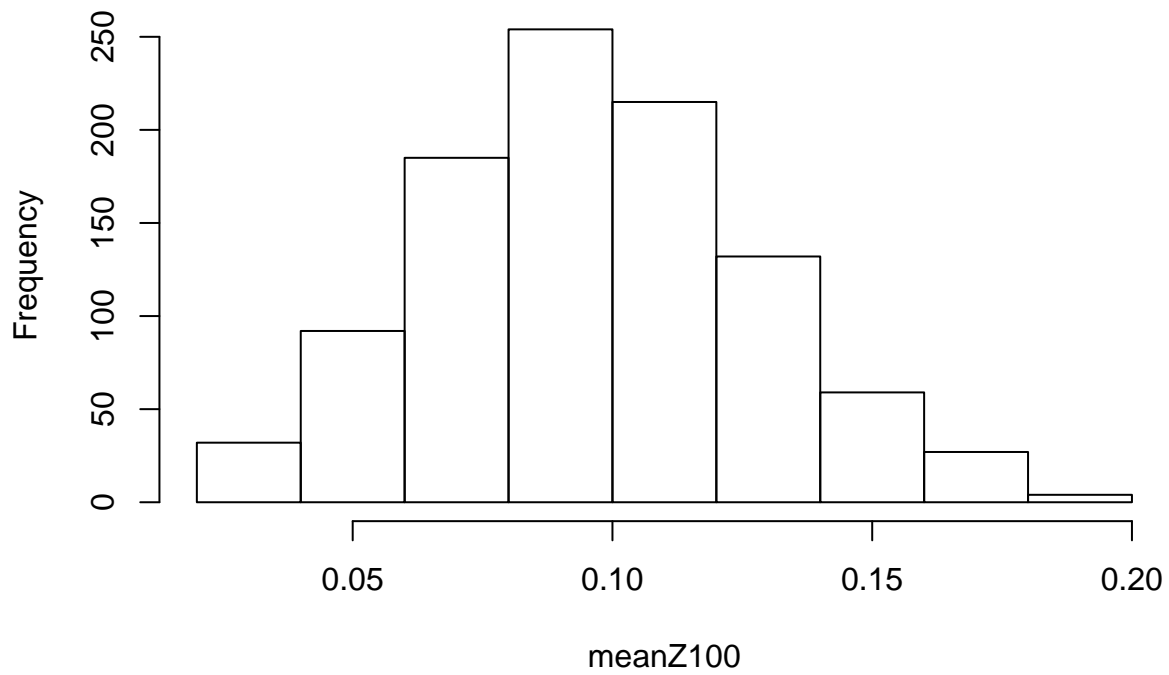

Histogram of meanX100



Histogram of meanY100

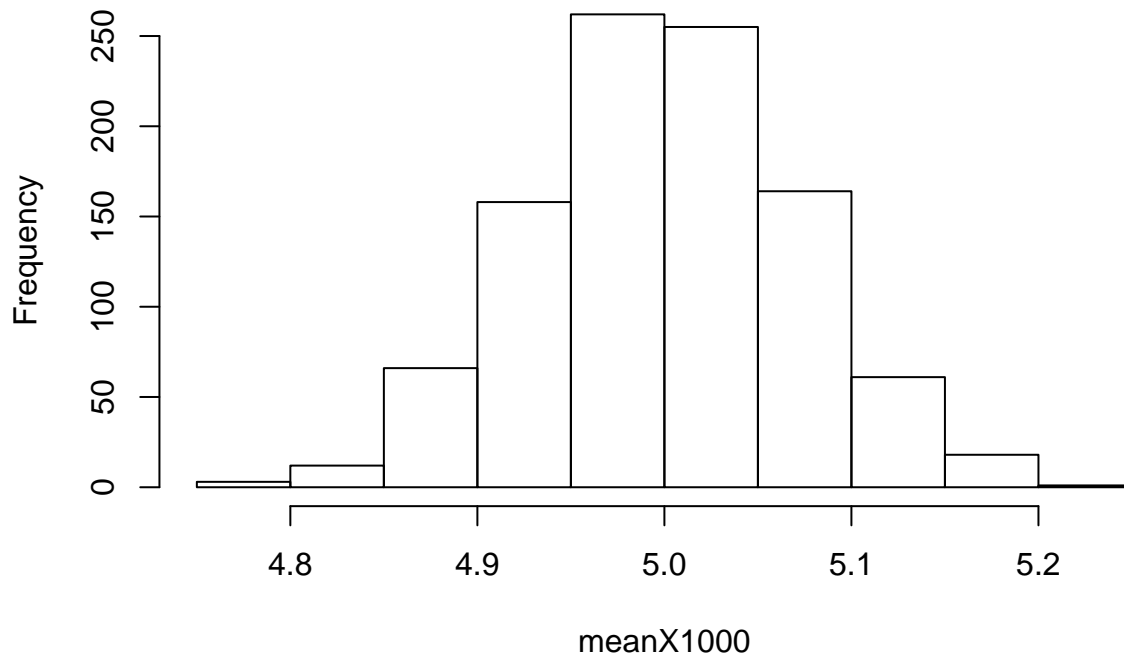


Histogram of meanZ100

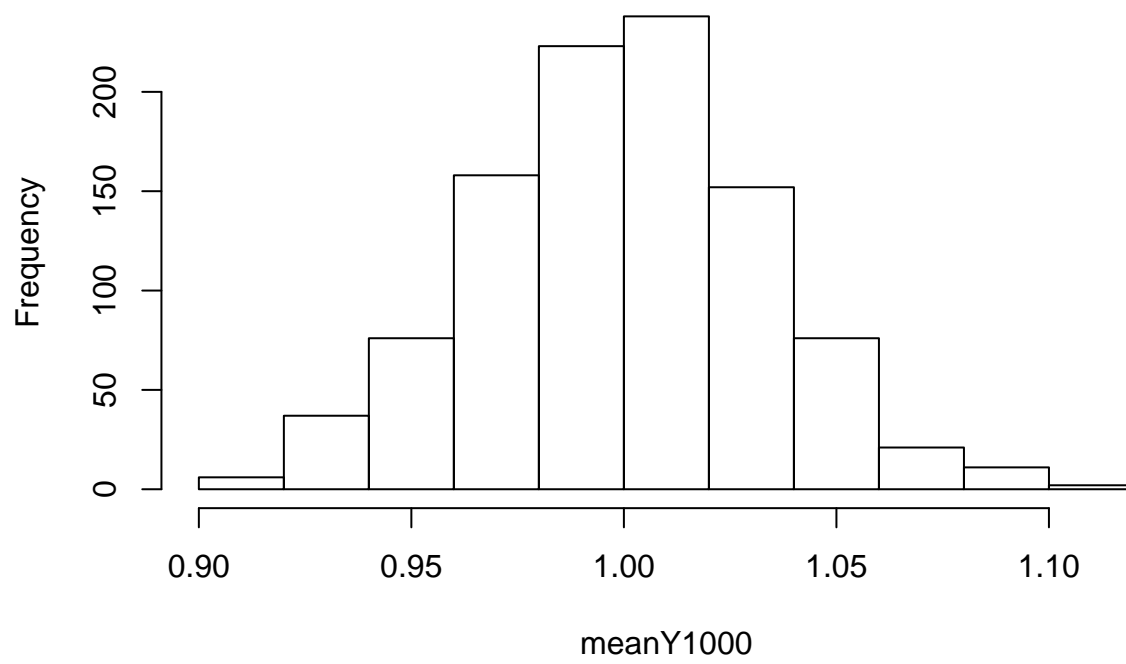


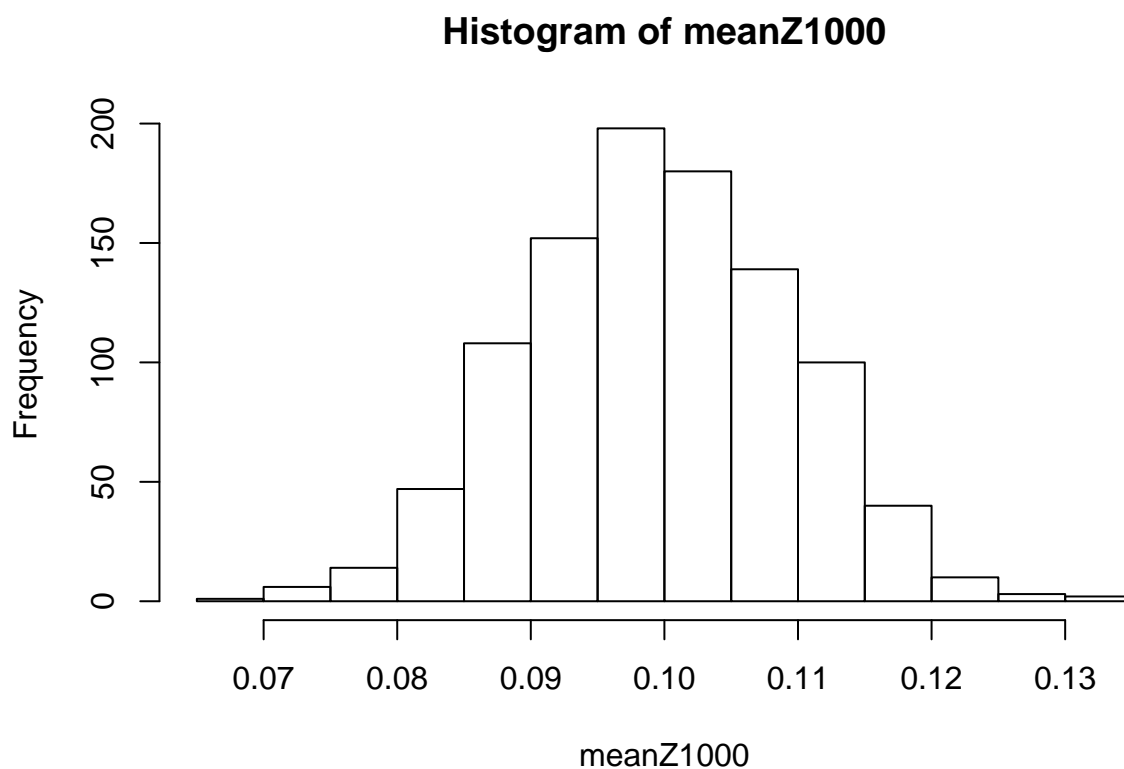
```
meanX1000 <- numeric(0)
meanY1000 <- numeric(0)
meanZ1000 <- numeric(0)
for (i in 1:1000) {
  meanX1000 <- c(meanX1000, mean(rpois(1000, 5)))
  meanY1000 <- c(meanY1000, mean(rexp(1000, 1)))
  meanZ1000 <- c(meanZ1000, mean(rbinom(1000, 10, 0.01)))
}
```

Histogram of meanX1000



Histogram of meanY1000





Centrala gränsvärdessatsen säger att medelvärdena konvergerar till en normalfördelning vilket de verkar göra.

Vid låg varians så minskar spridningen på medelvärdena vilket borde leda till att den konvergerar snabbare till en normalfördelning.

$$\text{Var}(X) = 5$$

$$\text{Var}(Y) = 1/(1^2) = 1$$

$$\text{Var}(Z) = 10 * 0.01 * 0.99 = 0.099$$

Detta borde då leda till att Z konvergerar snabbast mot en normalfördelning.