

# R Notebook

Code ▼

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1. Probability that a recombination event occurs between two adjacent base pairs is small, on the order on  $10^{-8}$ ...also approximately 3 billion base pairs where recombination can occur

A. Assume there are 3B positions where recombination can occurs and the probability for it is  $10^{-8}$ ... recombination events are independent of each other...total # of recombination events during once instance of meiosis is binomially distributed

i. Use `dbinom` with parameters `size = 3000000000`, `prob = 0.00000001` and plot the PMF for the number of recombination rates per meiosis

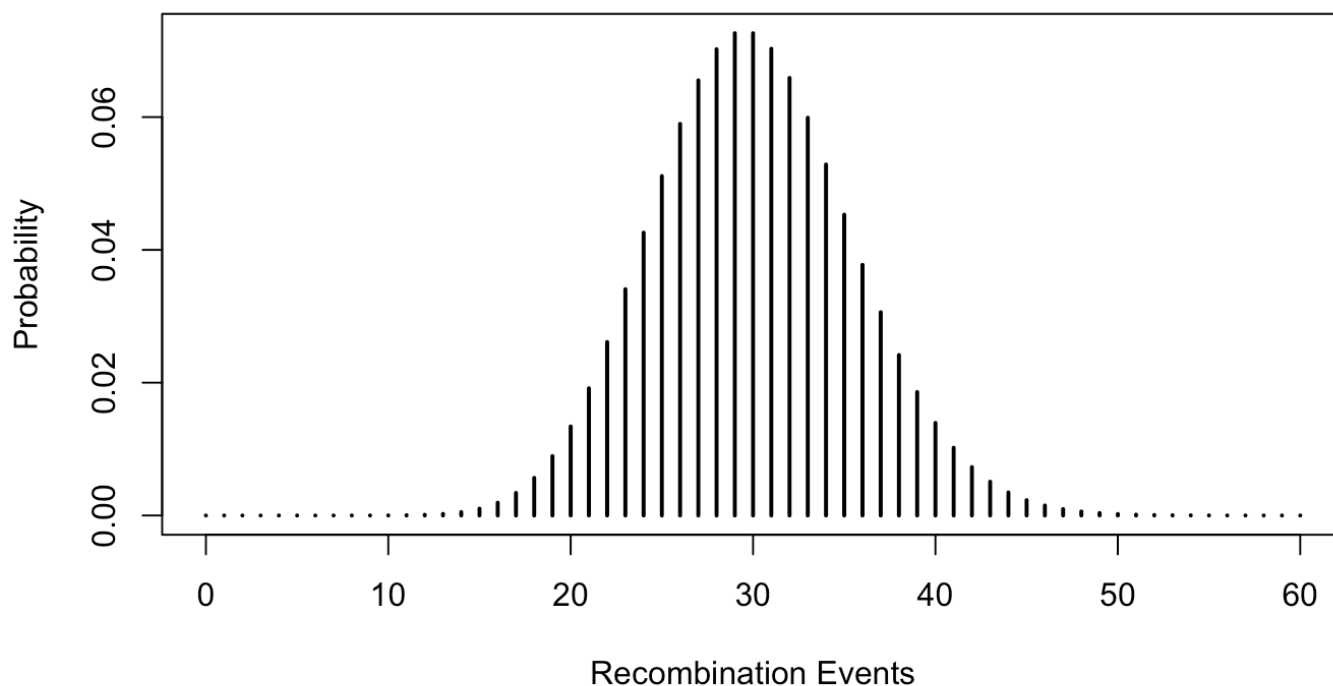
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```
size <- 3000000000
prob <- 0.00000001
lambda <- 30

x <- seq(0, 60, by=1)
y <- dbinom(x, size, prob)

plot(x, y, type="h", lwd=2, main="Binomial PMF", xlab="Recombination Events", ylab="Probability")
```

## Binomial PMF



ii. Use `pbinom` with the same parameters to calculate the probability that the number of recombination events per meiosis is 20 or less

[Hide](#)

```
pbinom(20, size, prob)
```

```
[1] 0.03528462
```

iii. Use `pbinom` with the same parameters to calculate the probability that the number of recombination events per meiosis is 40 or more

[Hide](#)

```
1 - pbinom(39, size, prob)
```

```
[1] 0.04625304
```

iv. Use `qbinom` with the same parameters to calculate the 1st percentile

[Hide](#)

```
qbinom(0.01, size, prob)
```

```
[1] 18
```

v. Use `qbinom` with the same parameters to calculate the 99th percentile

[Hide](#)

```
qbinom(0.99, size, prob)
```

```
[1] 43
```

B. Approximate the binomial in part A with the Poisson with parameter  $\lambda = 30 \dots 30 = 3 \text{ billion} \times 10^{-8}$

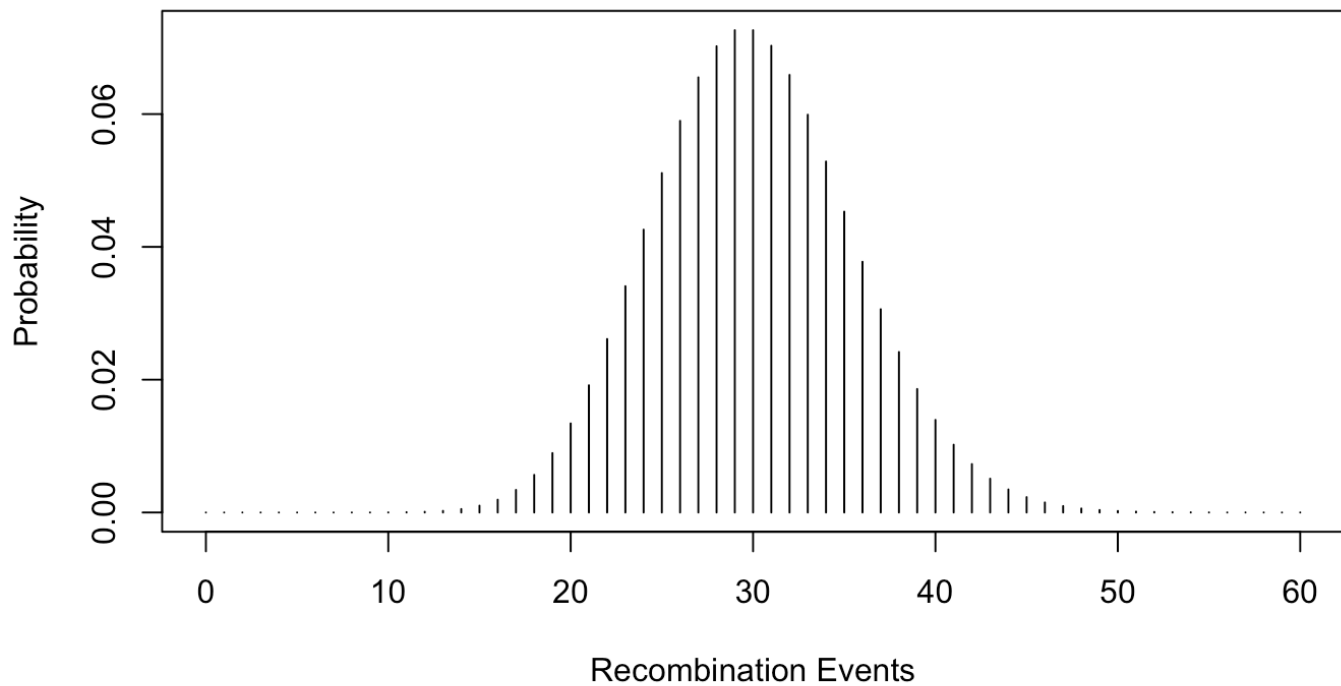
i. Use `dpois` with parameter `lambda = 30` and plot the PMF for the number of recombination events per meiosis

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```
y <- dpois(x, lambda)
```

```
plot(x, y, type="h", main="Poisson PMF", xlab="Recombination Events", ylab="Probability")
```

## Poisson PMF



ii. Use `ppois` with the same parameters to calculate the probability that the number of recombination events per meiosis is 20 or less

[Hide](#)

```
ppois(20, lambda)
```

```
[1] 0.03528462
```

iii. Use `ppois` with the same parameters to calculate the probability that the number of recombination events per meiosis is 40 or more

[Hide](#)

```
1 - ppois(39, lambda)
```

```
[1] 0.04625304
```

iv. Use `qpois` with the same parameters to calculate the 1st percentile

[Hide](#)

```
qpois(0.01, lambda)
```

```
[1] 18
```

v. Use `qpois` with the same parameters to calculate the 99th percentile

[Hide](#)

```
qpois(0.99, lambda)
```

```
[1] 43
```

vi. Does Poisson appear to be a good approximation to the binomial for this problem?  
Yes, the results are identical so the Poisson approximation is valid

2. The exponential density function is (see pdf)...expected value (same as random variable mean) is  $1/\lambda$ .  
Use the `dexp` function with parameter `rate = 1` (corresponds to  $\lambda = 1$ ) to plot the density function. Let  $n = 100$

A. i. Simulate  $n$  exponential random variables (use `rexp` with `rate = 1`) and take their sample mean...repeat this 1,000 times

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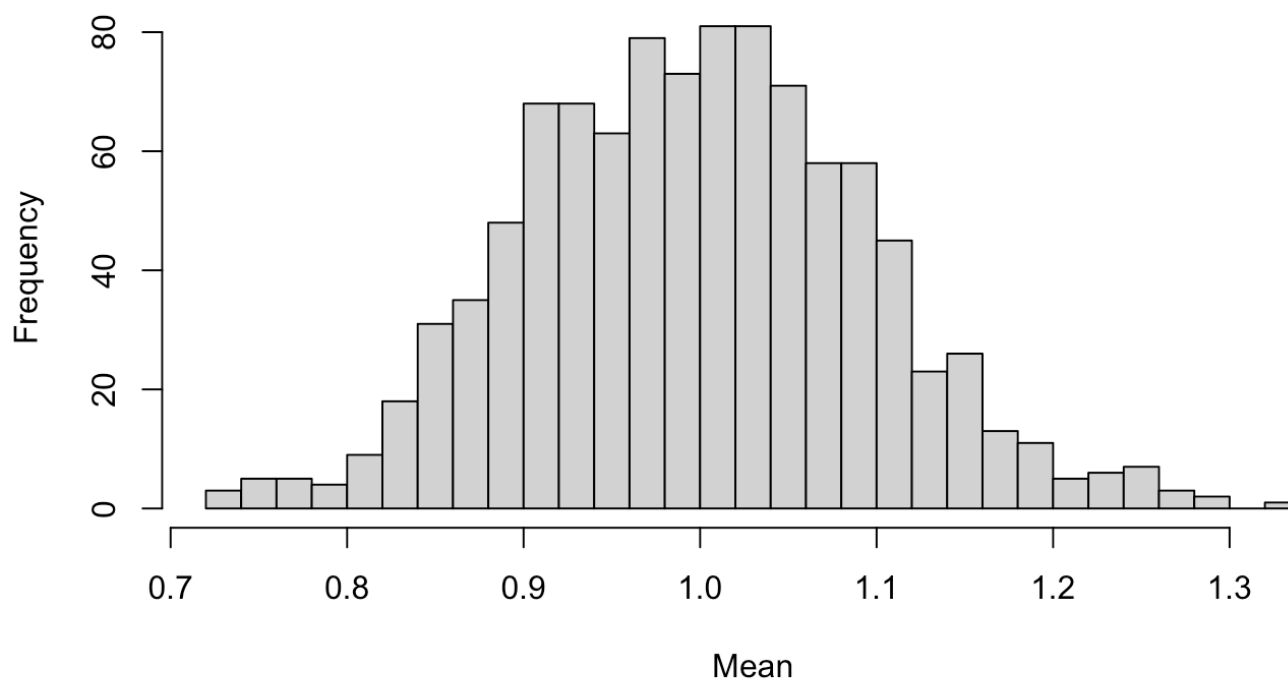
```
set.seed(123) # reproducibility
n <- 100
sample_means_100 <- replicate(1000, mean(rexp(n, rate = 1)))
```

ii. Plot the histogram of the 1,000 sample means from i

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```
hist(sample_means_100, breaks = 30, main="Sample means (n = 100", xlab="Mean")
```

## Sample means (n = 100)



iii. Calculate the min, mean, an the max of 1,000 sample means from i

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```
summary(sample_means_100)
```

```

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.7228  0.9271  0.9984  0.9975  1.0617  1.3202

```

iv. Repeat steps i – iii for n = 1000 and n = 10000. Does the sample mean appear to converge?

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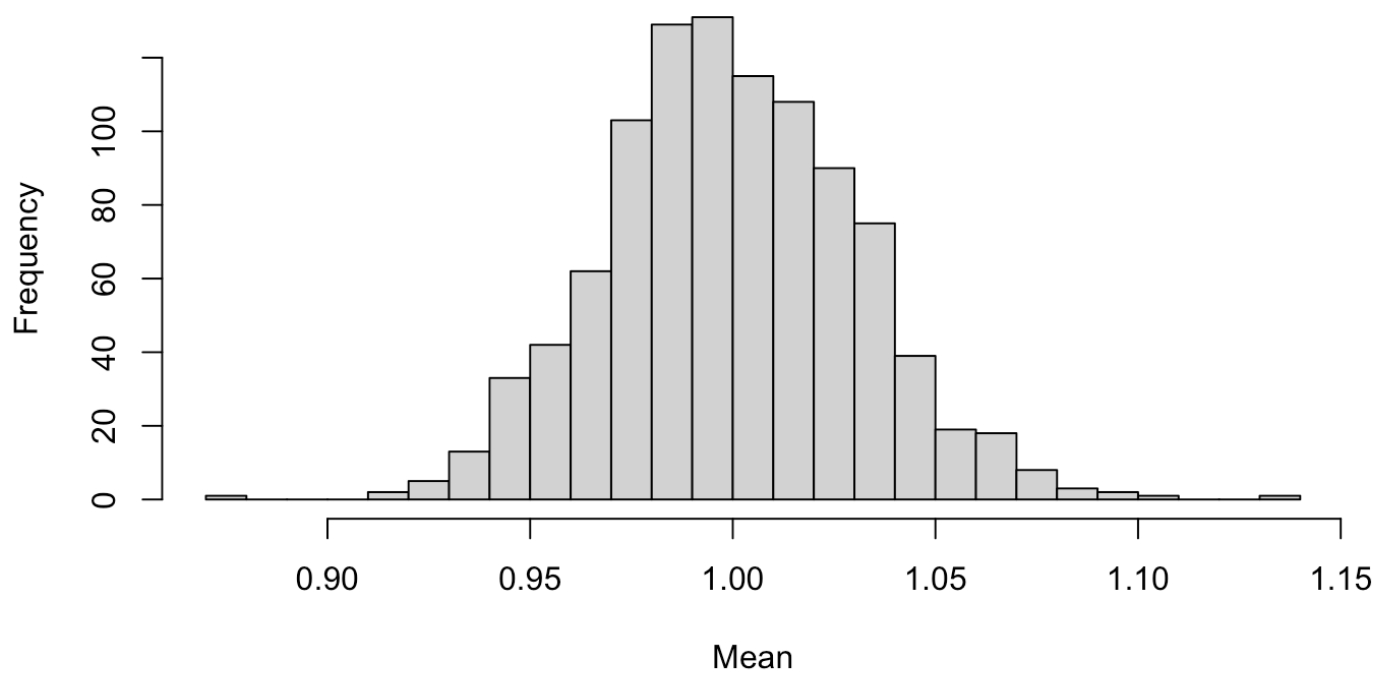
```

n <- 1000
sample_means_1000 <- replicate(1000, mean(rexp(n, rate = 1)))

hist(sample_means_1000, breaks = 30, main="Sample Means (n = 1000)", xlab="Mean")

```

## Sample Means (n = 1000)

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```
summary(sample_means_1000)
```

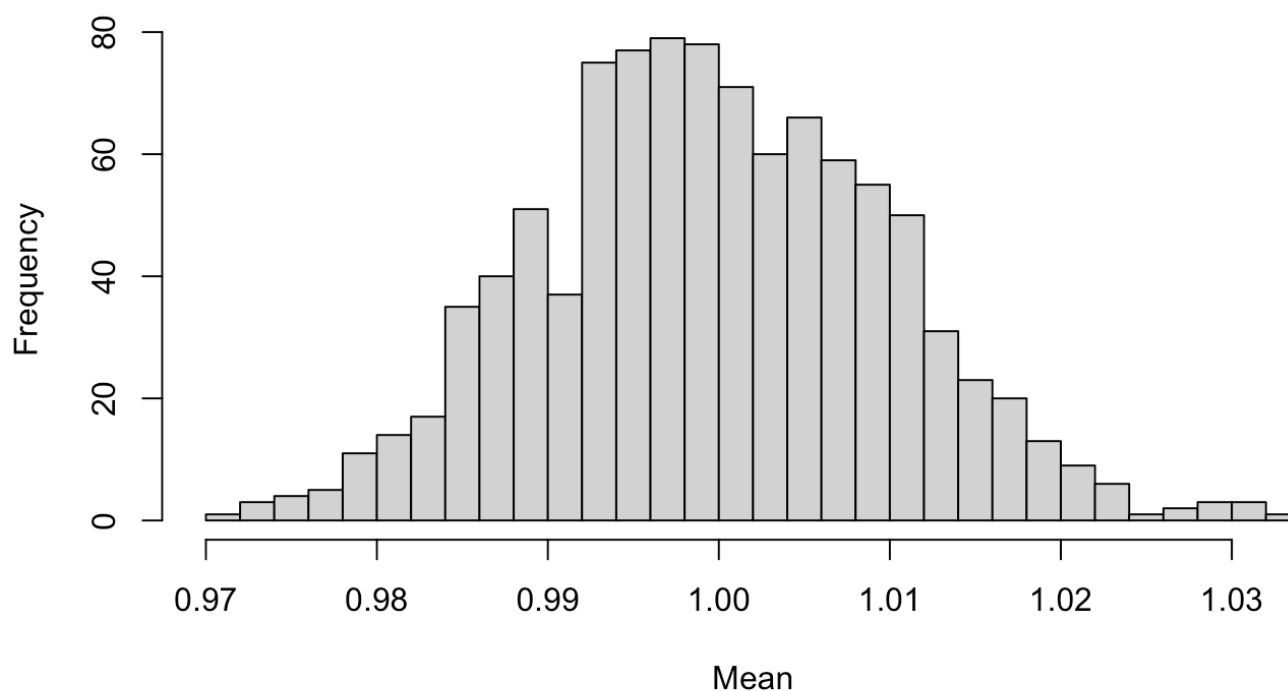
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.8733	0.9791	0.9980	0.9997	1.0210	1.1317

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```
n <- 10000
sample_means_10000 <- replicate(1000, mean(rexp(n, rate = 1)))

hist(sample_means_10000, breaks = 30, main="Sample Means (n = 10000)", xlab="Mean")
```

## Sample Means (n = 10000)


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```
summary(sample_means_10000)
```

```

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
0.9719  0.9930  0.9993  0.9997  1.0071  1.0335

```

The sample mean stabilizes around 0.97 – 1.0 as n increases and the spread of the histogram decreases.

B. The pareto distribution is (see pdf)...isn't the standard in R...need to install.packages("EnvStats")...when a = 1 the expected value is undefined (or infinity)...recall the Law of Large Numbers and the Central Limit Theorem

i. Simulate n Pareto random variables (use rpareto with location = 1, shape = 1) and take their sample mean. Repeat this 1000 times

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```

#install.packages("EnvStats") # hash after running once
library(EnvStats)

set.seed(123) # for reproducibility
n <- 100
sm_pareto_100 <- replicate(1000, mean(rpareto(n, location = 1, shape = 1)))

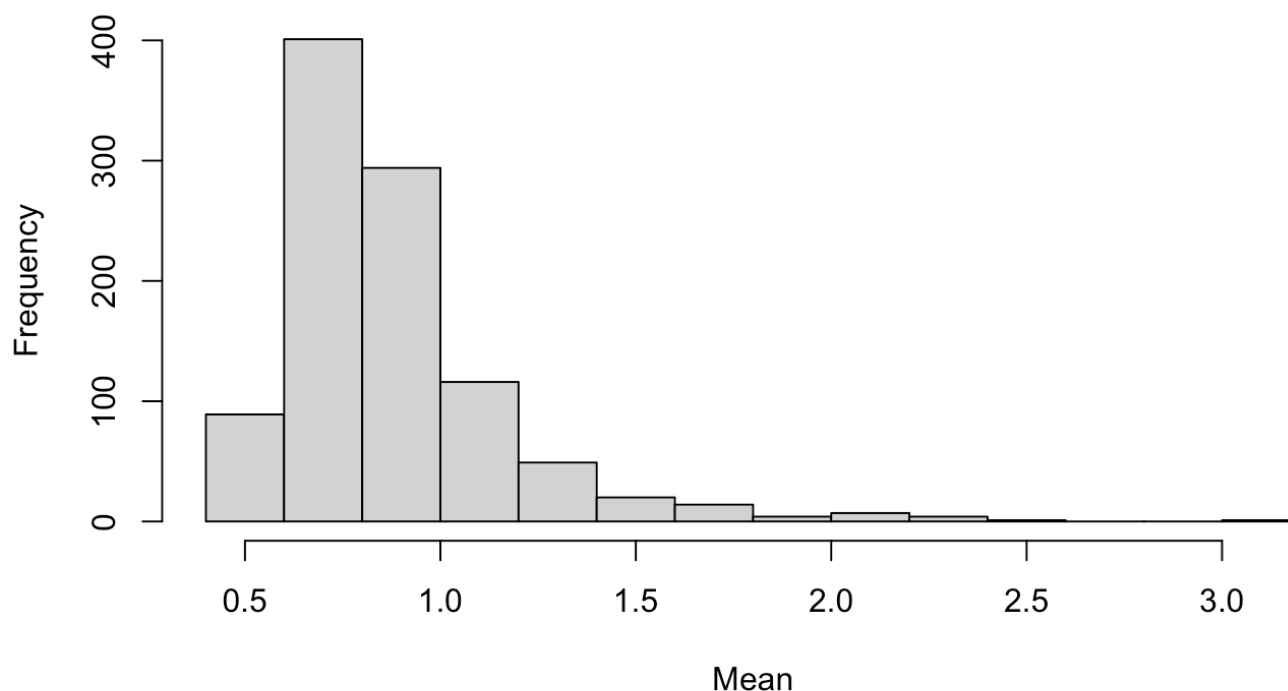
```

ii. Plot the histogram of the 1000 sample means from i

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```
hist(log10(sm_pareto_100), breaks=10, main="Pareto Sample Mean (n = 100)", xlab="Mean")
```

### Pareto Sample Mean (n = 100)



iii. Calculate the min, mean, and the max of 1,000 sample means from i

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```
summary(sm_pareto_100)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
3.005	4.886	6.391	11.980	9.274	1303.628

iv. Repeat steps i - iii for  $n = 1000$  and  $n = 10000$ . Does the sample mean appear to converge?

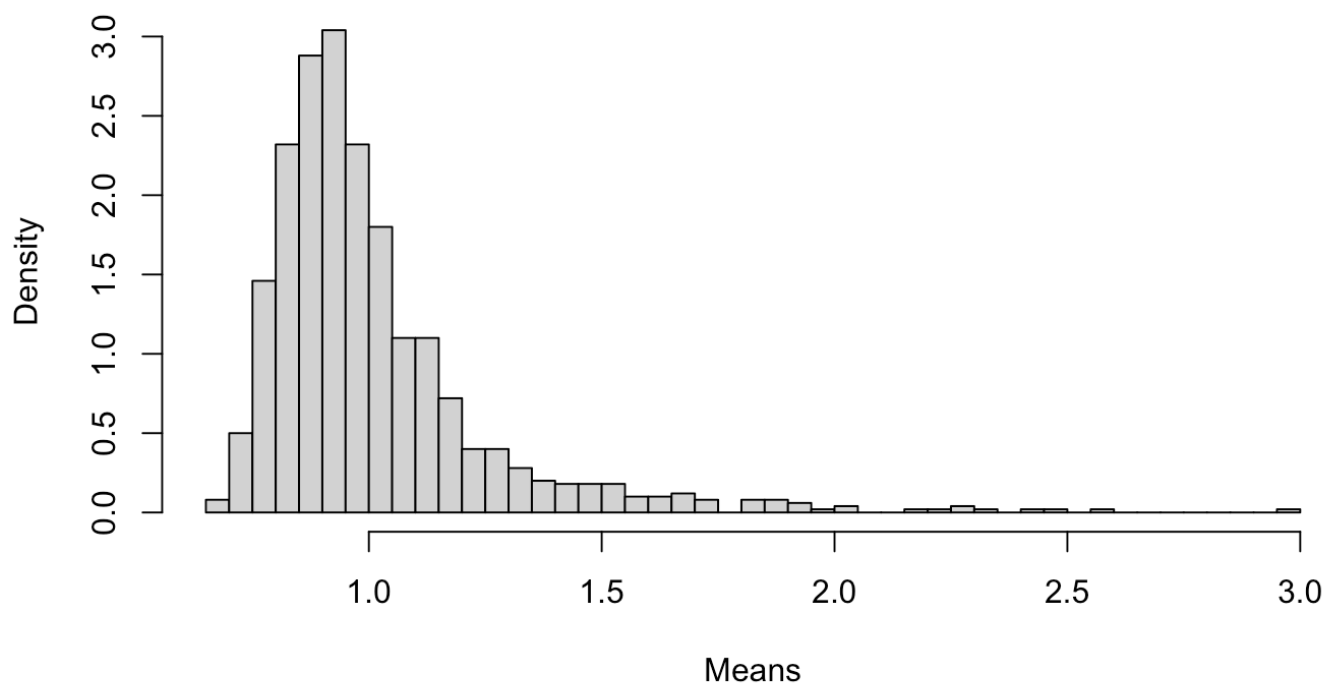
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```
n <- 1000
sm_pareto_1000 <- replicate(1000, mean(rpareto(n, location = 1, shape = 1)))

hist(log10(sm_pareto_1000), breaks = 50, main="Pareto Sample Means (n = 1000)", xlab="Means", probability=TRUE)
```



## Pareto Sample Means (n = 1000)


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```
summary(sm_pareto_1000)
```

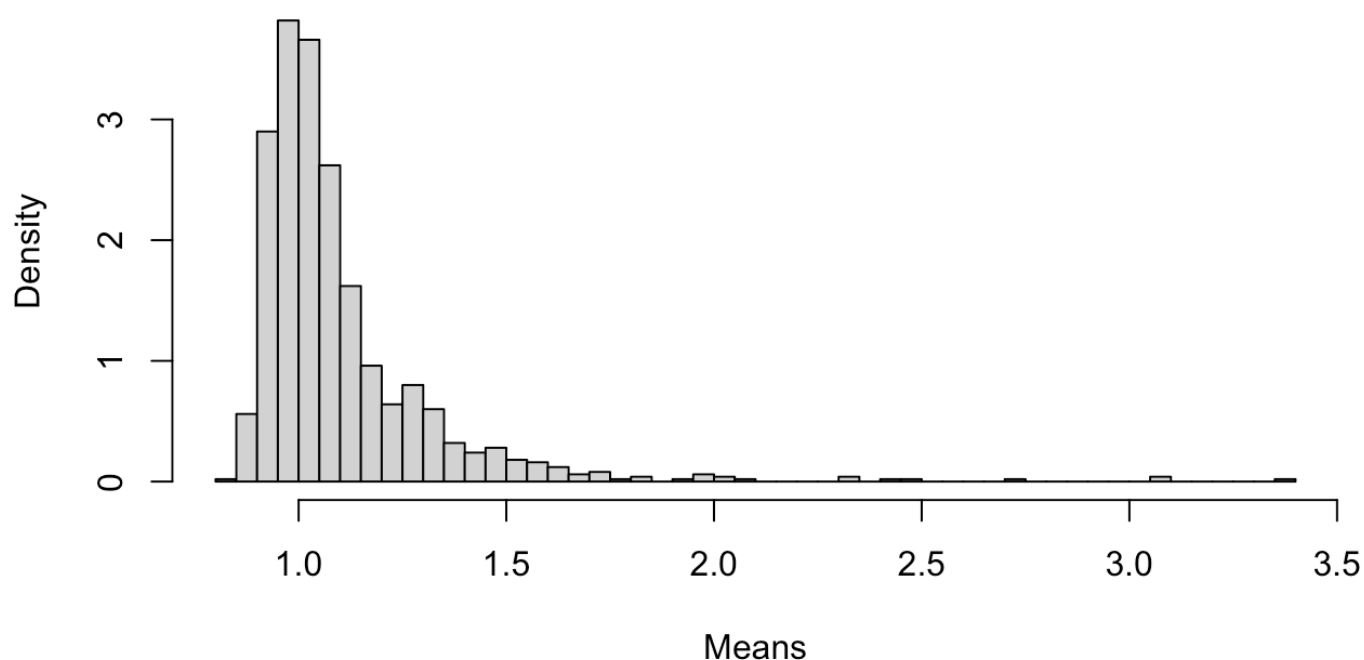
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
4.560	7.263	8.816	14.507	11.947	900.052

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```
n <- 10000
sm_pareto_10000 <- replicate(1000, mean(rpareto(n, location = 1, shape = 1)))

hist(log10(sm_pareto_10000), breaks = 50, main="Pareto Sample Means (n = 10000)", xlab =
"Means", probability=TRUE)
```

## Pareto Sample Means (n = 10000)


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```
summary(sm_pareto_10000)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
6.885	9.296	10.862	19.833	13.900	2358.245

3. Consider the simple model for father and son heights. Let  $X$  be a normal random variable with mean 70 and sdev  $\sigma$ , let  $e_1$  be a normal random variable with mean 0 and sdev  $\tau$ , and let  $e_2$  be a normal random variable with mean 0 and sdev  $\tau$ . Further assume  $X$ ,  $e_1$ , and  $e_2$  are independent. Define  $F = X + e_1$  and  $S = X + e_2$ ... idea is that if  $F$  and  $S$  are father and son heights, respectively, they both have the same  $X$  due to genetics and independent 'disturbance' terms  $e_1$  and  $e_2$

A. Calculate the covariance of  $F$  and  $S$

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```
set.seed(123)
n <- 10000

sigma <- 3 #sdev of genetic component
tau <- 2 #sdev of environmental variation

X <- rnorm(n, mean = 70, sd = sigma) # Genetic
epsilon_F <- rnorm(n, mean = 0, sd = tau) # Random effect father
F <- X + epsilon_F # father's height
epsilon_S <- rnorm(n, mean = 0, sd = tau) # Random effect son
S <- X + epsilon_S # son's height

# Covariance calculation
cov(F, S) # should be close to sigma^2
```

```
[1] 9.119239
```

B. Calculate the correlation of F and S

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```
cor(F, S) # Should be <1 due to regression
```

```
[1] 0.6940373
```

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```
expected_corr <- sigma^2 / (sigma^2 + tau^2)
expected_corr
```

```
[1] 0.6923077
```