

# R-Based Statistical Distribution Analysis Toolkit

## Overall Summary for Sampling Distributions

The normality of the sampling distribution of a sample statistic depends on three key factors:

1. **Nature of the parent distribution** (e.g., symmetric like Normal, or skewed like Exponential).
2. **Type of statistic** (e.g., mean, median, IQR, standard deviation, etc.).
3. **Sample size (n)**, with larger sample sizes generally aiding convergence to normality.

## General Findings:

- **Statistics with Quick Normality:**
  - **Mean:** Achieves normality the fastest across most distributions, starting at small sample sizes ( $n \geq 10$  to  $n \geq 100$ ).
  - **Standard Deviation (SD):** Achieves normality relatively quickly ( $n \geq 50$  to  $n \geq 500$ ) for many distributions, but lags behind the mean.
  - **Median:** Achieves normality for symmetric distributions like Normal, but requires larger sample sizes ( $n \geq 50$  to  $n \geq 1000$ ) for skewed distributions like Exponential and Beta.
- **Statistics Requiring Larger Samples:**
  - **IQR:** Requires  $n \geq 500$  or more to approximate normality due to sensitivity to variability in distributions like Exponential and Beta.
- **Statistics That Rarely Achieve Normality:**
  - **Minimum and Maximum:** Consistently fail to achieve normality for most distributions due to their dependence on extreme values, especially in heavy-tailed distributions like Cauchy.
- **Parent Distribution Impact:**
  - Symmetric distributions (e.g., Normal, Beta with  $\alpha = \beta$ ) show faster convergence to normality for most statistics.
  - Skewed or heavy-tailed distributions (e.g., Exponential, Cauchy) delay or prevent normality for statistics like median, IQR, and extreme values.

## **Notable Situations:**

### **1. Cauchy Distribution:**

- Mean and SD never achieve normality which is opposite of others. Only the median and IQR converge at larger sample sizes.

### **2. Beta Distributions**

- Symmetric Beta distributions ( $\alpha=\beta$ ) show faster convergence to normality compared to highly skewed Beta distributions ( $\alpha\neq\beta$ ). For example:
  - $\alpha=2, \beta=2$ : Mean achieves normality at  $n\geq 10$ .
  - $\alpha=0.2, \beta=5$ : Mean require  $n\geq 1000$ .

### **3. Poisson Distribution:**

- Higher values of  $\lambda$  (e.g.,  $\lambda=25$ ) lead to faster convergence to normality for the mean and SD ( $n\geq 10$  to  $n\geq 50$ ), while smaller  $\lambda$  (e.g.,  $\lambda=0.001$ ) delays convergence significantly ( $n\geq 10,000$ )

### **4. Gamma Distribution:**

- Minimum achieved normality for  $n \geq 10$  but lose normality again after  $n = 1000$ , showing a non-monotonic pattern in convergence.

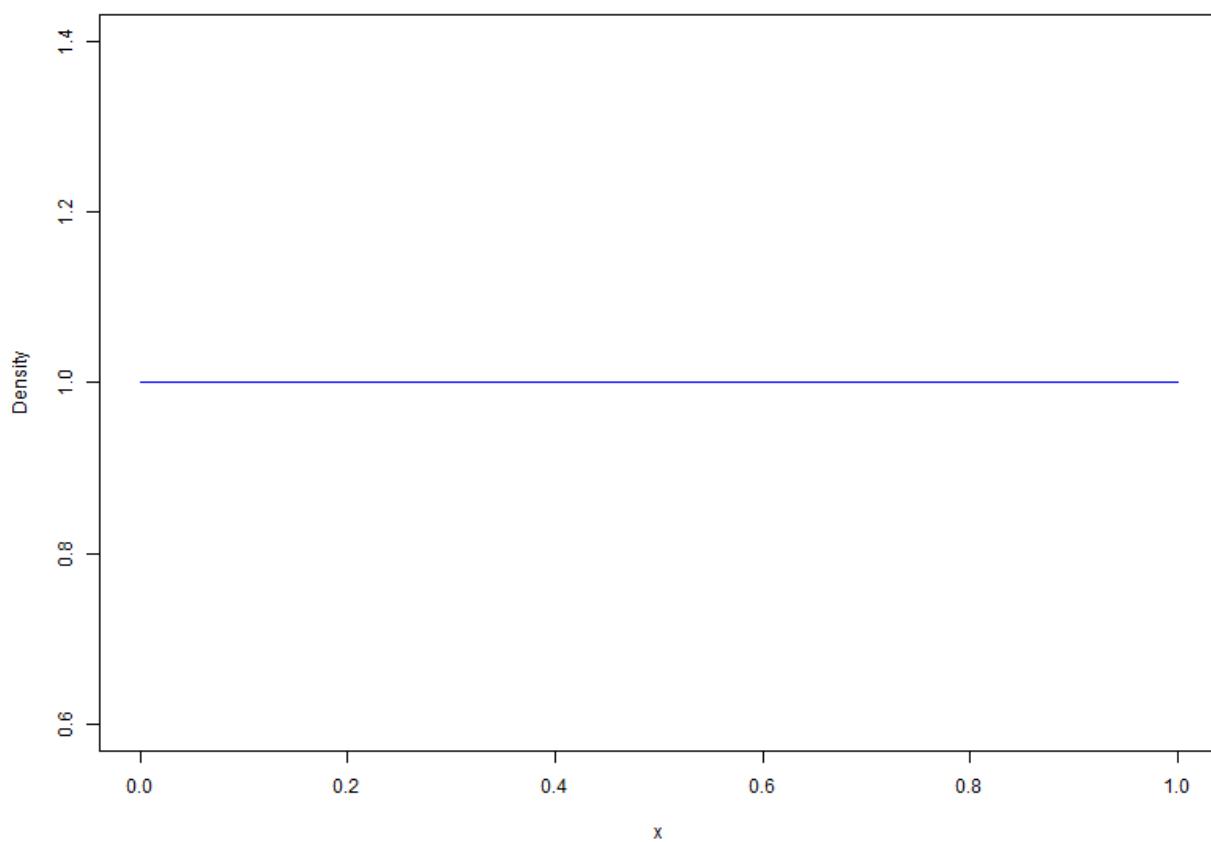
## **Summary of Key Results:**

- The mean is the most reliable statistic for achieving normality, converging quickly for symmetric and moderately skewed distributions.
- Extreme-value statistics like minimum and maximum almost never achieve normality.
- Distributions with higher symmetry (e.g., Normal, Beta with  $\alpha=\beta$ ) lead to faster and more consistent normality.
- Heavy-tailed distributions (e.g., Cauchy) or skewed distributions (e.g., Exponential, Beta with  $\alpha\ll\beta$ ) require much larger sample sizes for most statistics to approximate normality.

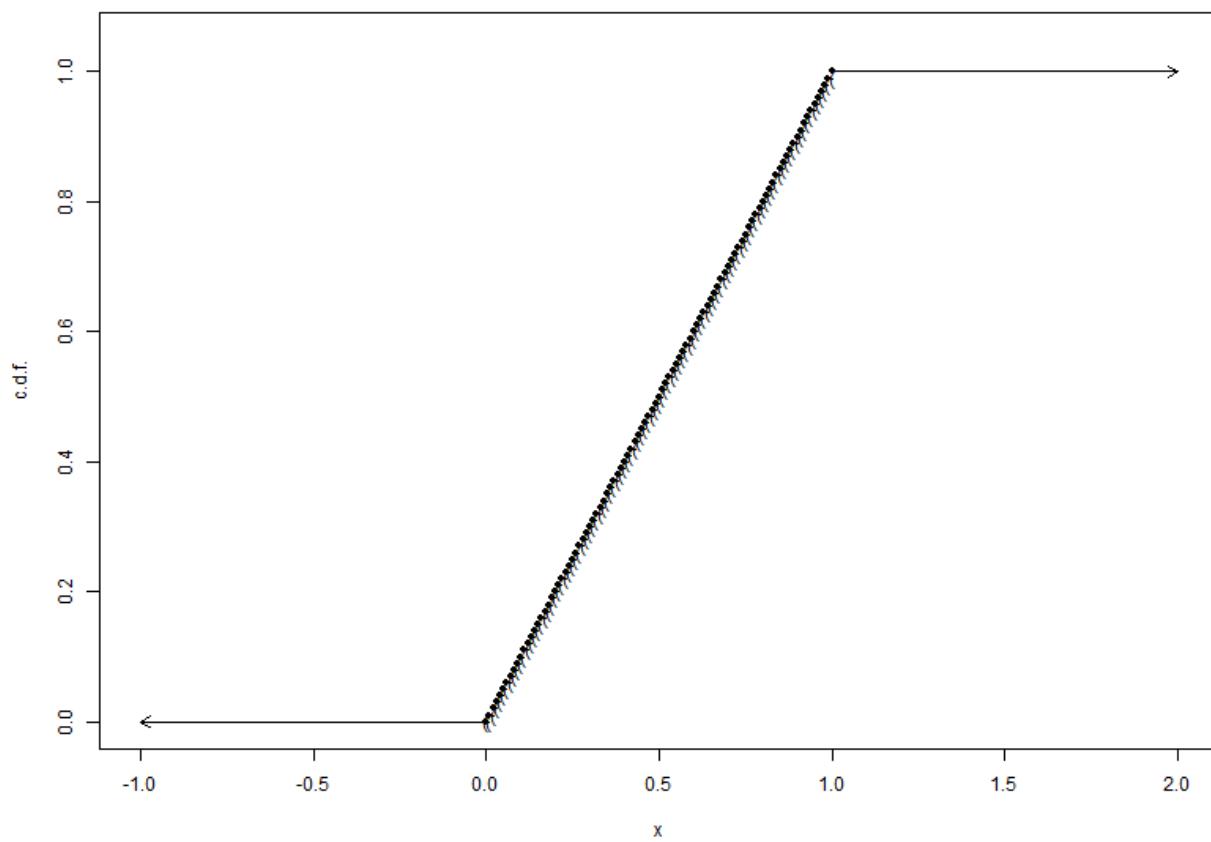
The detailed report and plots of distributions are on the following pages.

# UNIFORM DISTRIBUTION (0,1)

PDF of Uniform(0,1)



CDF of Uniform(0,1)



# UNIFORM DISTRIBUTION

	Values of n to achieve normality (nn=1000, a=0, b=1)								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Median	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Std Dev	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	

## Conclusion for Exponential Distribution

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 10$ , converging very quickly due to the Central Limit Theorem (CLT).
- **Median:** Achieves normality for  $n \geq 10$ , reflecting rapid convergence even in the presence of skewness.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 10$ , indicating strong consistency across sample sizes.
- **IQR:** Achieves normality for  $n \geq 10$ , showing fast convergence despite the Uniform distribution's variability.

### Normality Not Achieved:

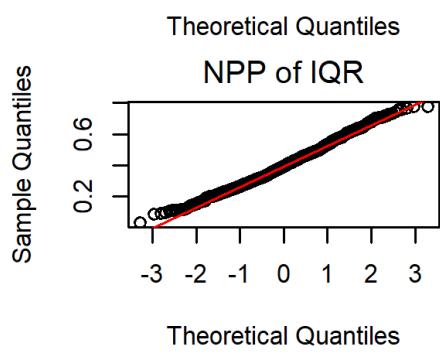
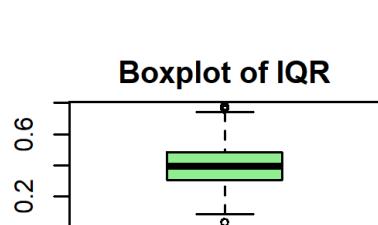
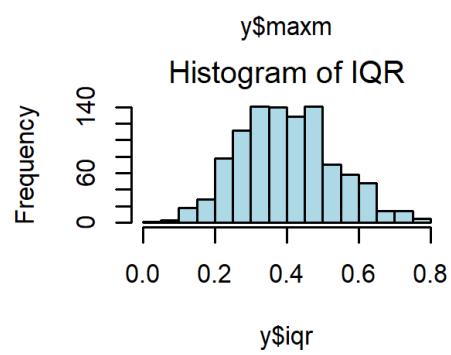
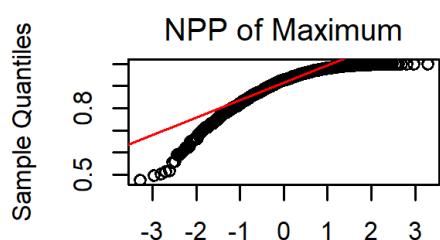
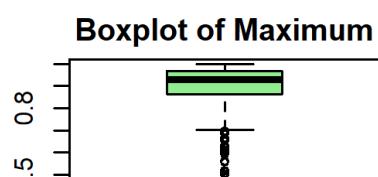
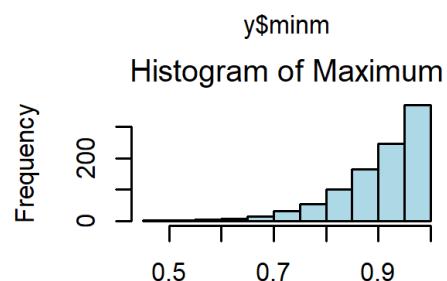
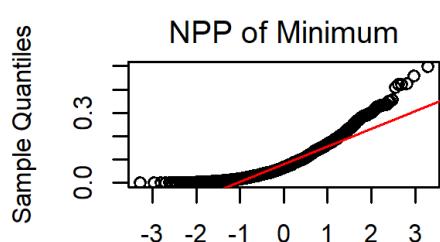
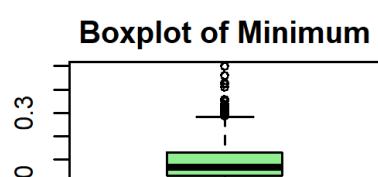
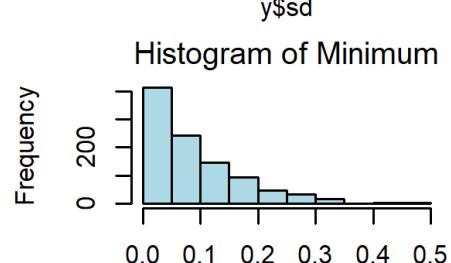
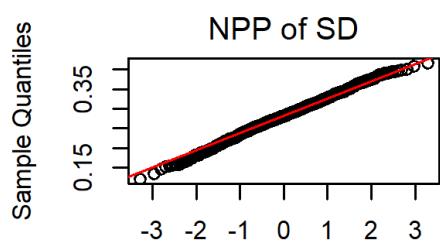
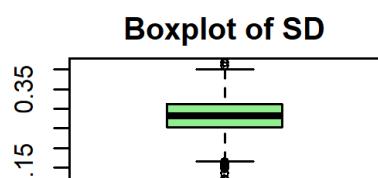
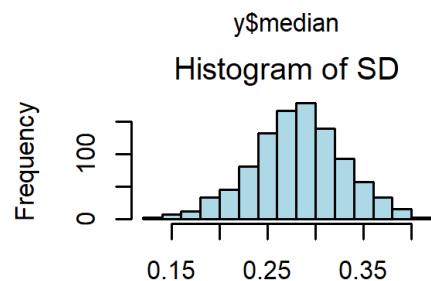
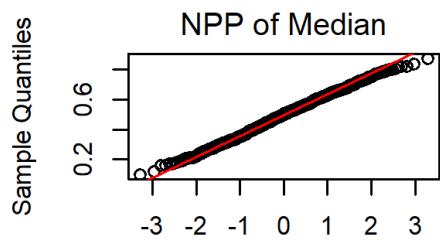
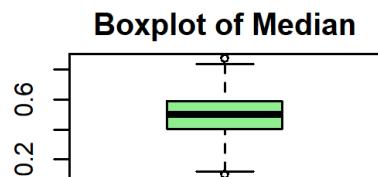
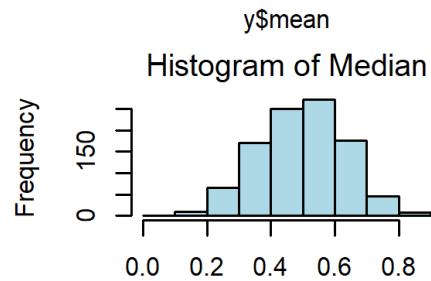
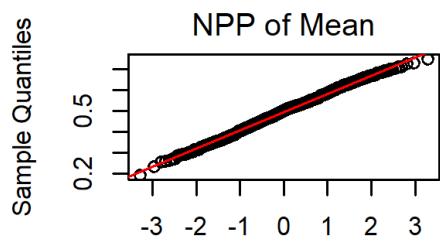
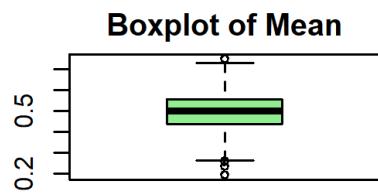
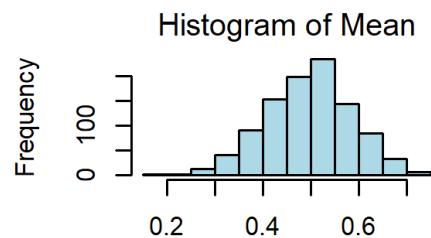
- **Minimum and Maximum:** Do not achieve normality for any  $n$ , as they are highly influenced by extreme values and the Uniform distribution's inherent asymmetry.

### Overall:

The mean, median, standard deviation, and IQR converge to normality extremely quickly, requiring only small sample sizes ( $n \geq 10$ ). However, the minimum and maximum fail to achieve normality due to their sensitivity to extreme values and the skewed nature of the Uniform distribution.

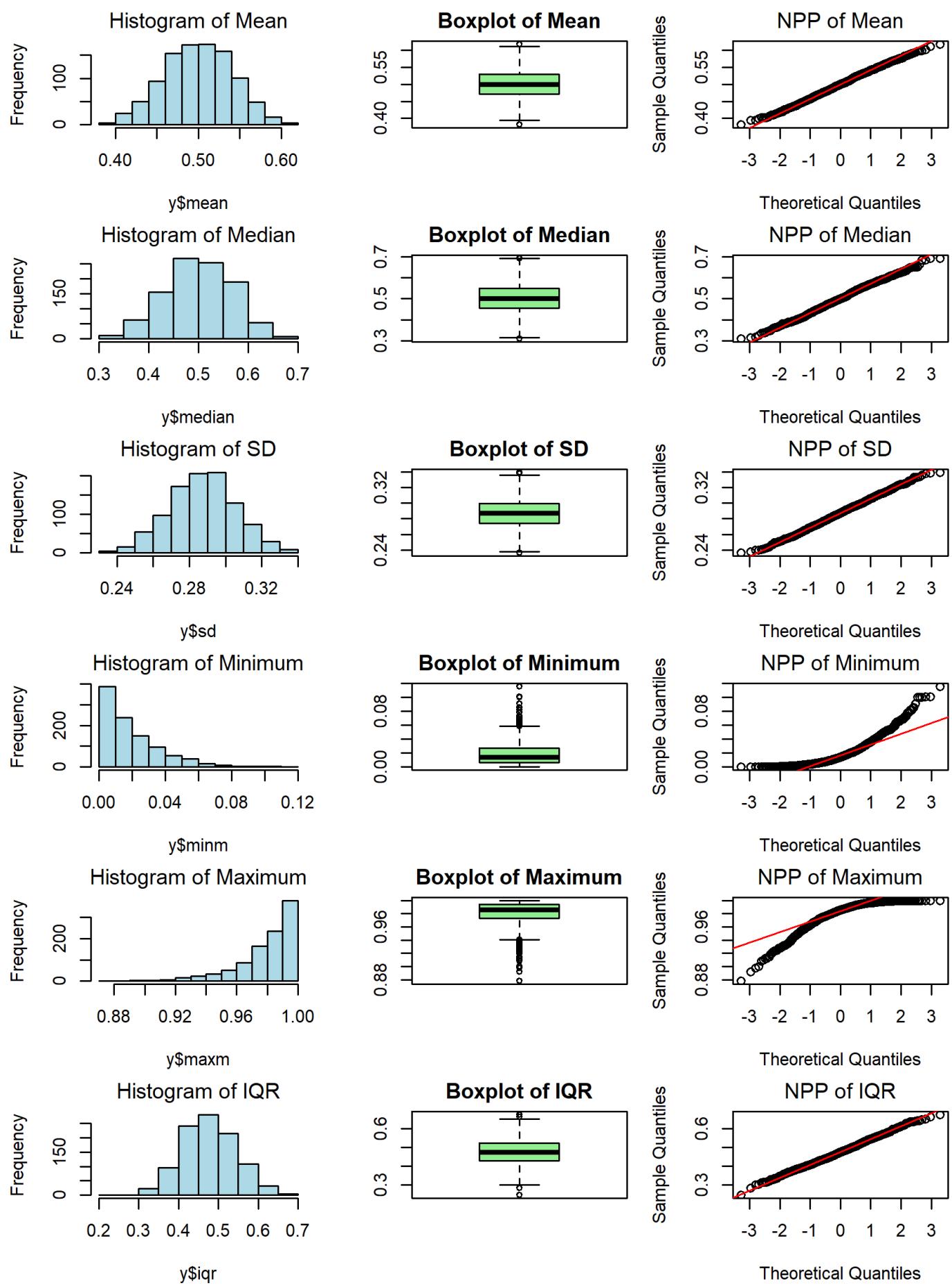
# UNIFORM DISTRIBUTION PLOT

(n=10, nn=1000, a=0, b=1)



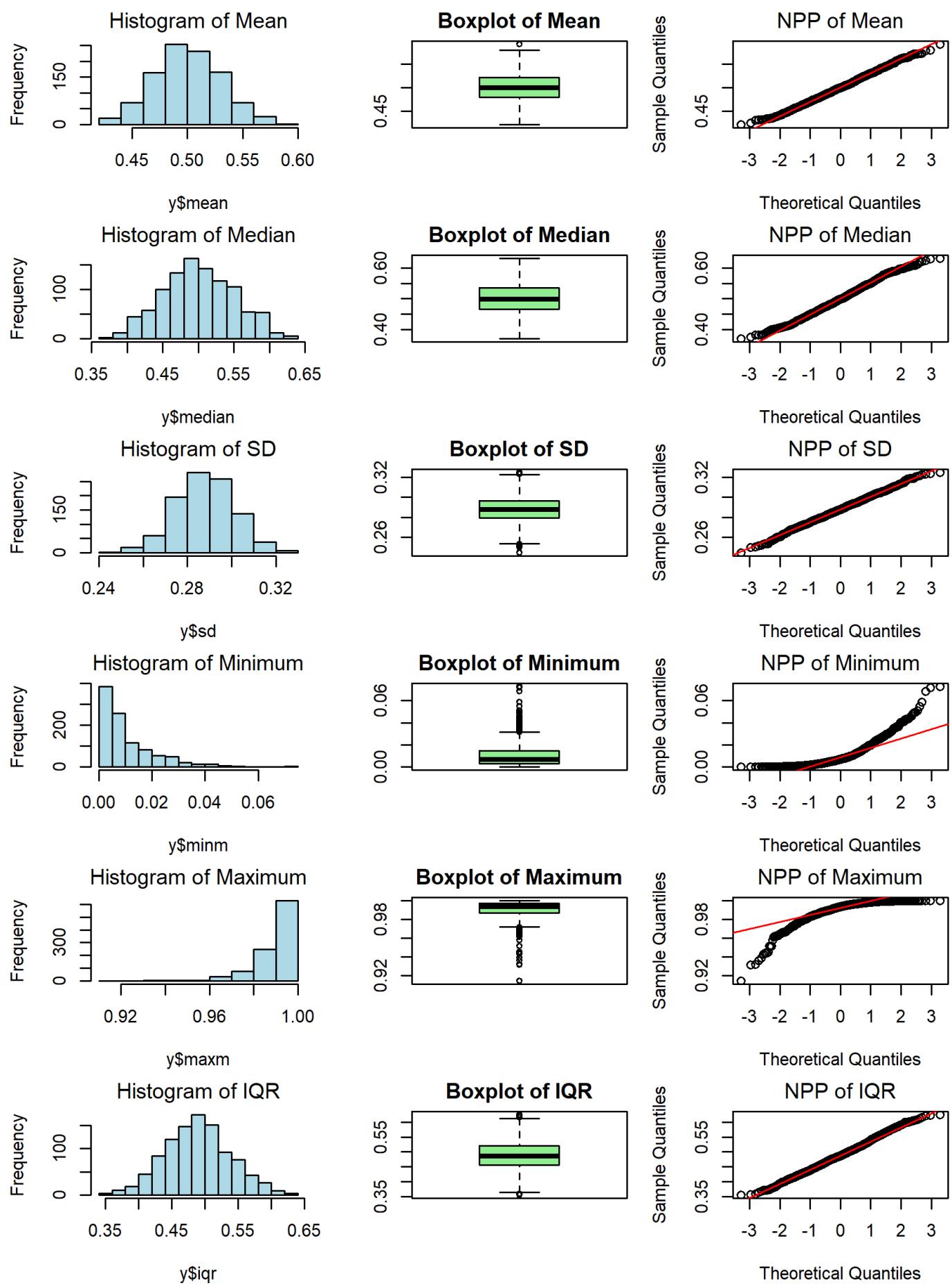
# UNIFORM DISTRIBUTION PLOT

(n=50, nn=1000, a=0, b=1)



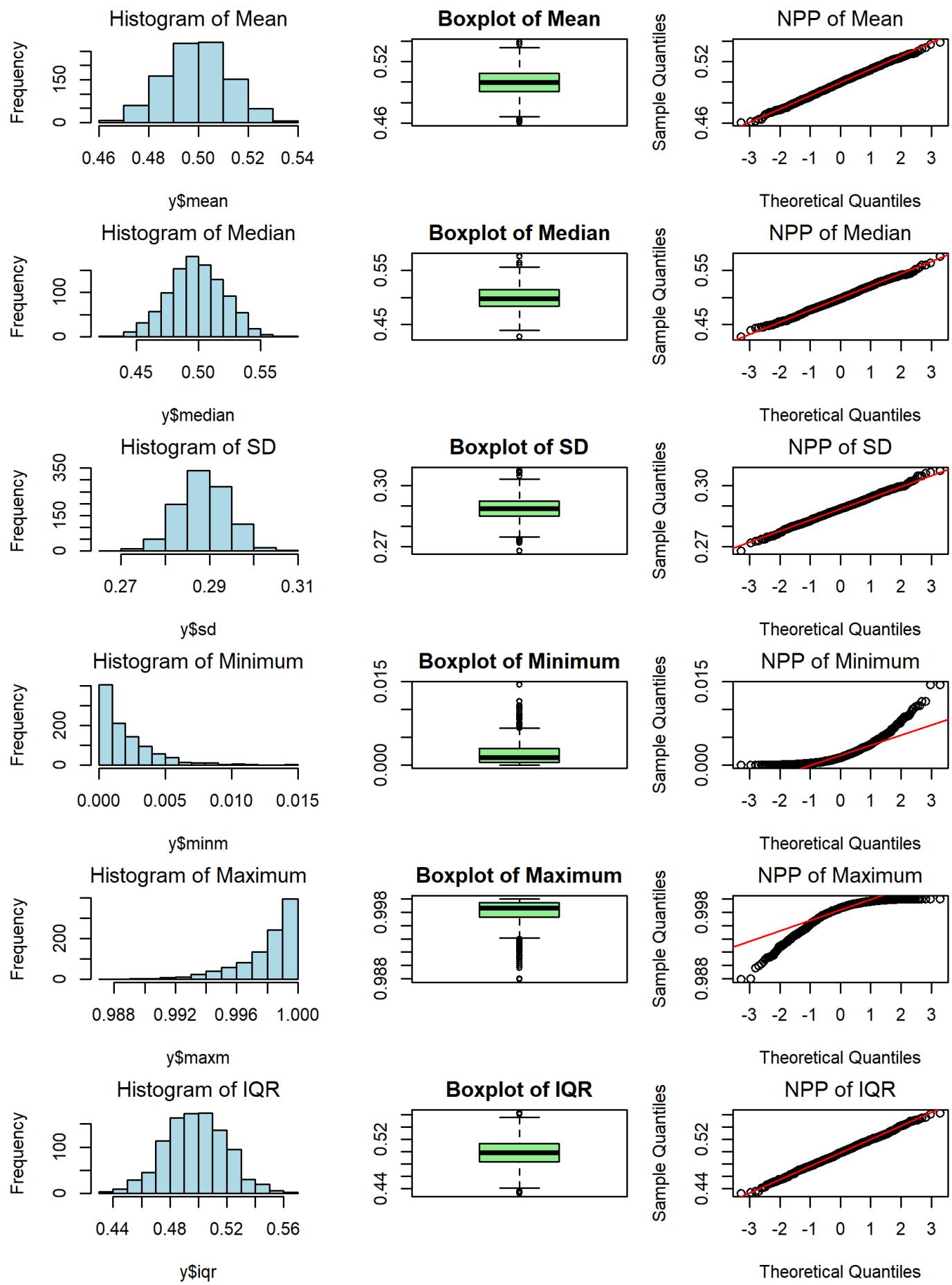
# UNIFORM DISTRIBUTION PLOT

(n=100, nn=1000, a=0, b=1)



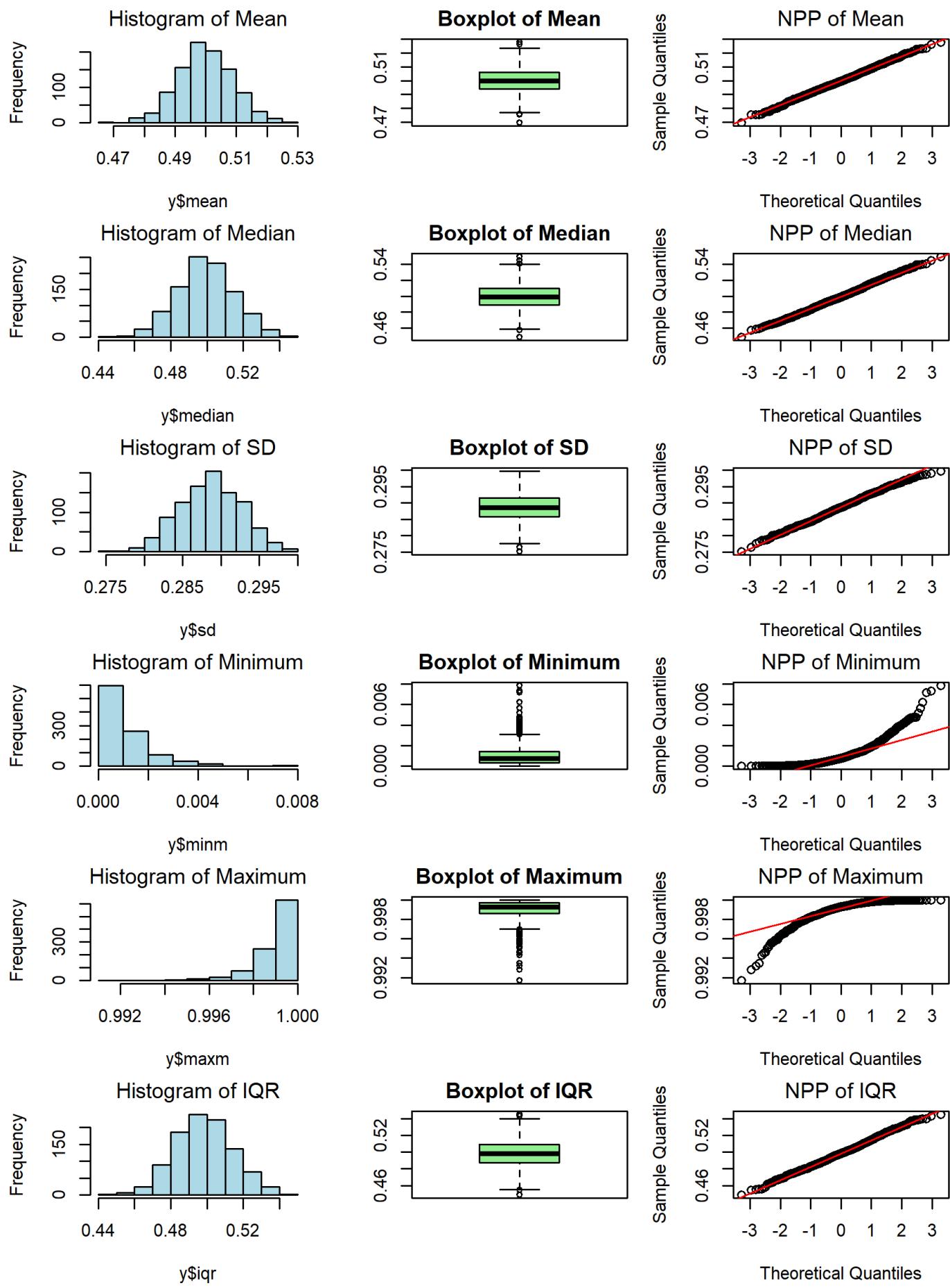
# UNIFORM DISTRIBUTION PLOT

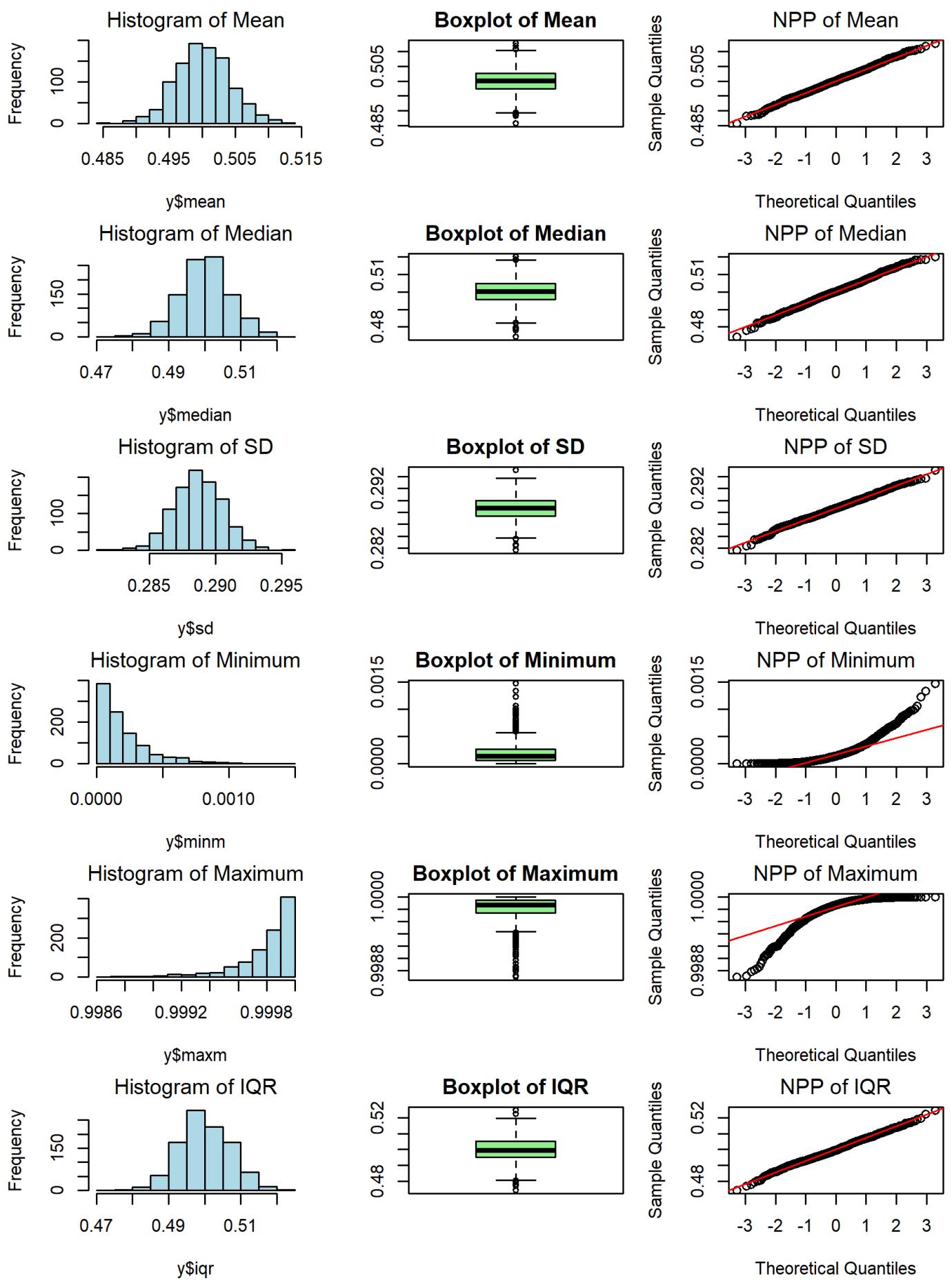
(n=500, nn=1000, a=0, b=1)



# UNIFORM DISTRIBUTION PLOT

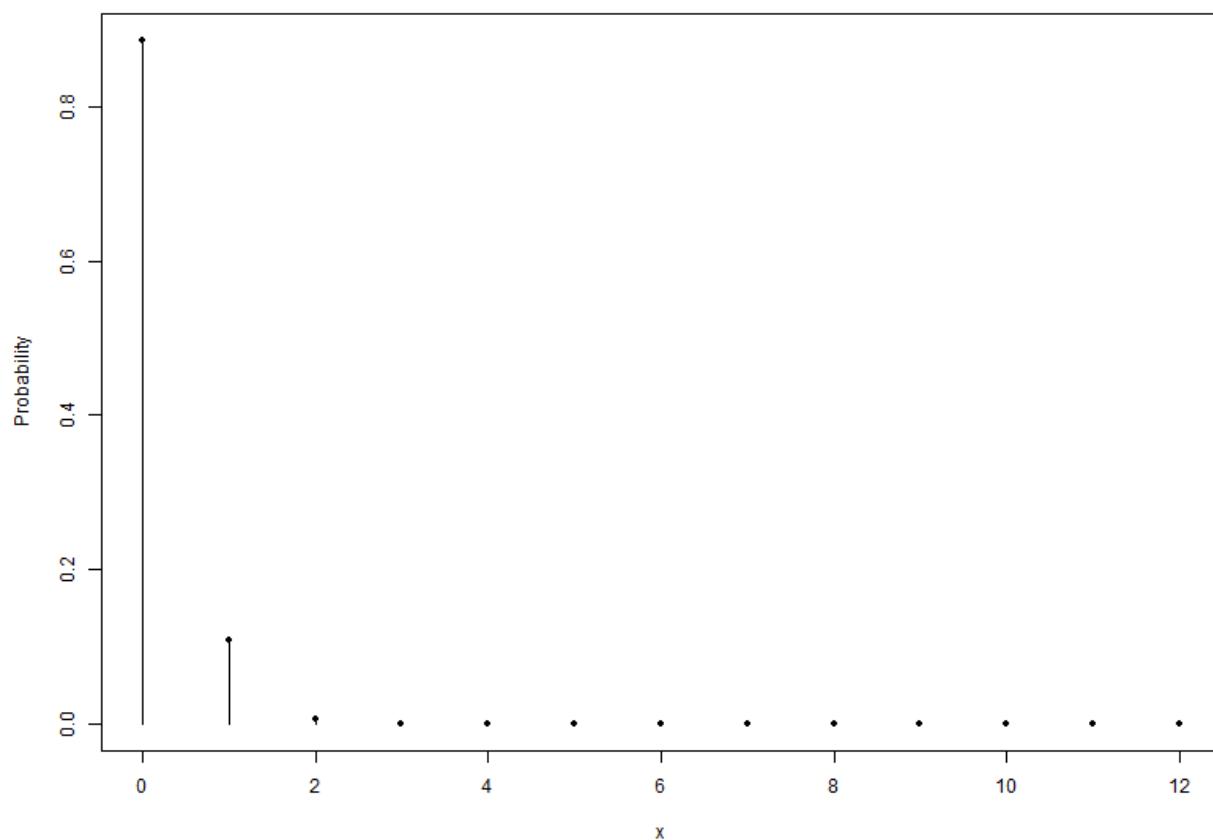
(n=1000, nn=1000, a=0, b=1)



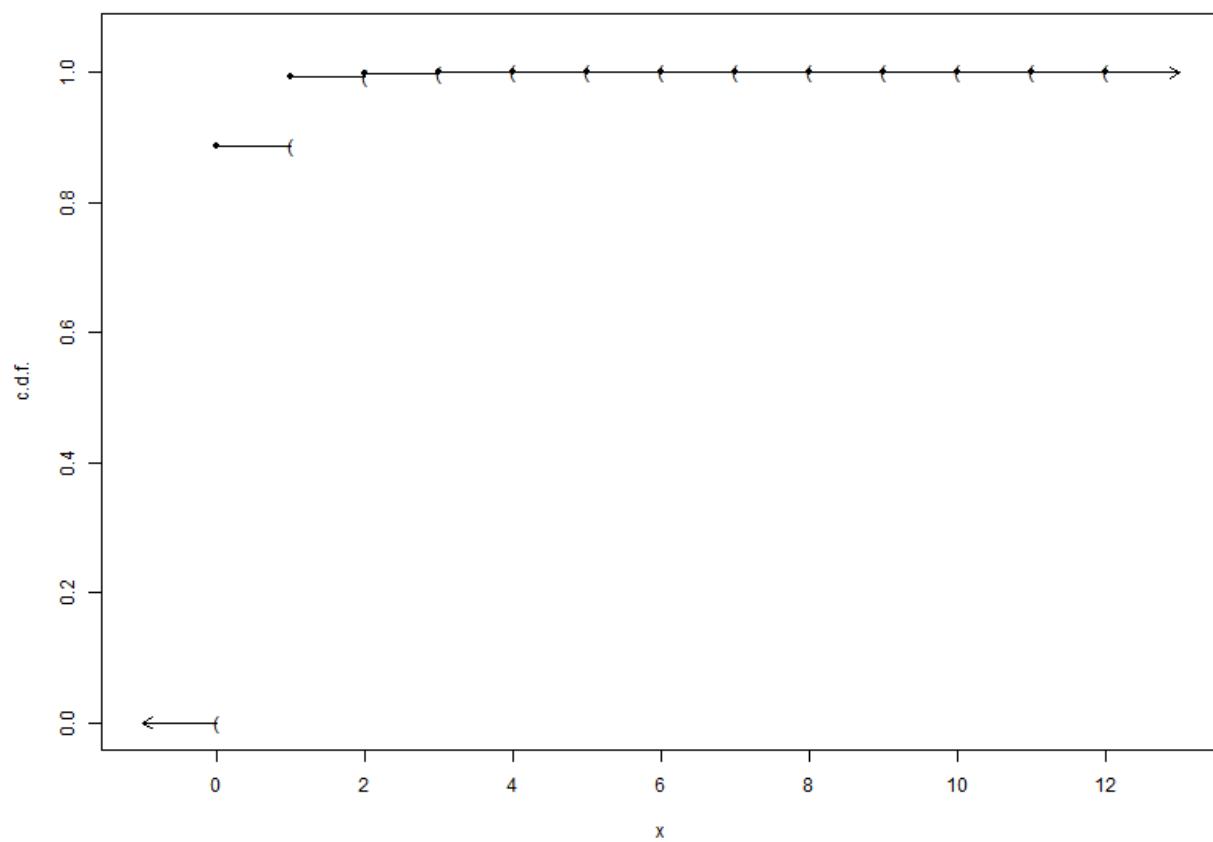


# BINOMIAL DISTRIBUTION (12,0.01)

PMF of Binomial(12, 0.01)



CDF of Binomial(12,0.01)



# BINOMIAL DISTRIBUTION

	Values of n to achieve normality (nn=1000, m=12, p=0.01)								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	No	No	Yes	Yes	Yes	Yes	500	
Median	No	No	No	No	No	No	No	NA	
Std Dev	No	No	Yes	Yes	Yes	Yes	Yes	100	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	No	No	NA	

## Conclusion for Binomial Distribution (m = 12, p = 0.01)

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 500$ , indicating that a moderately large sample size is necessary for the mean to approximate a normal distribution.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 100$ , converging faster compared to the mean.

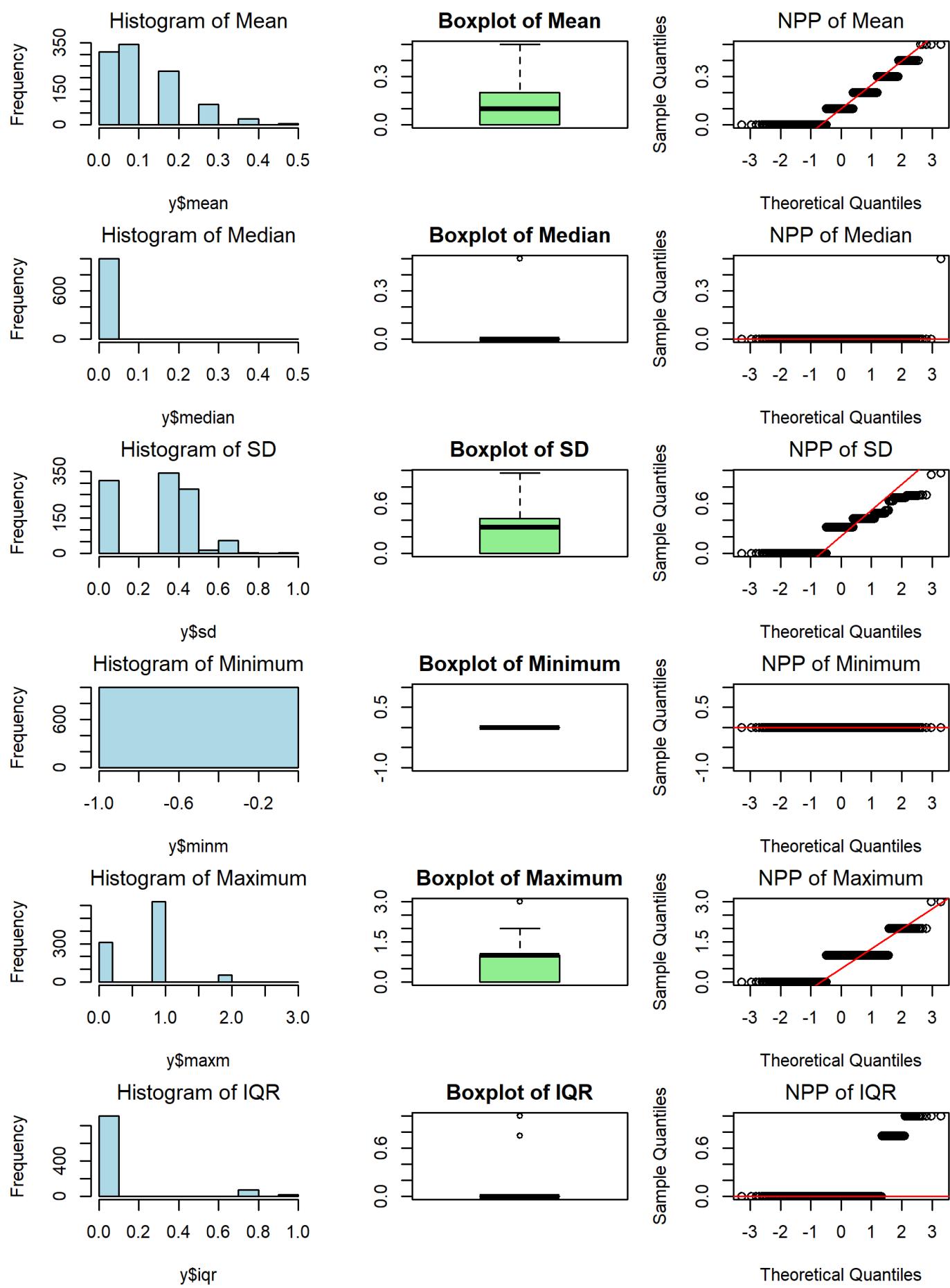
### Normality Not Achieved:

- **Median:** Does not achieve normality for any sample size, as it remains influenced by the discrete and skewed nature of the Binomial distribution.
- **Minimum and Maximum:** Do not achieve normality for any sample size due to their sensitivity to the extremes of the distribution.
- **IQR:** Does not achieve normality for any sample size, reflecting its dependency on the underlying discrete structure.

**Overall:** For the Binomial distribution with  $m = 12$  and  $p = 0.01$ , the mean and standard deviation are the only statistics that achieve normality. The standard deviation converges to normality faster ( $n \geq 100$ ), while the mean requires a larger sample size ( $n \geq 500$ ). The median, minimum, maximum, and IQR remain non-normal regardless of the sample size due to the distribution's discrete and highly skewed characteristics.

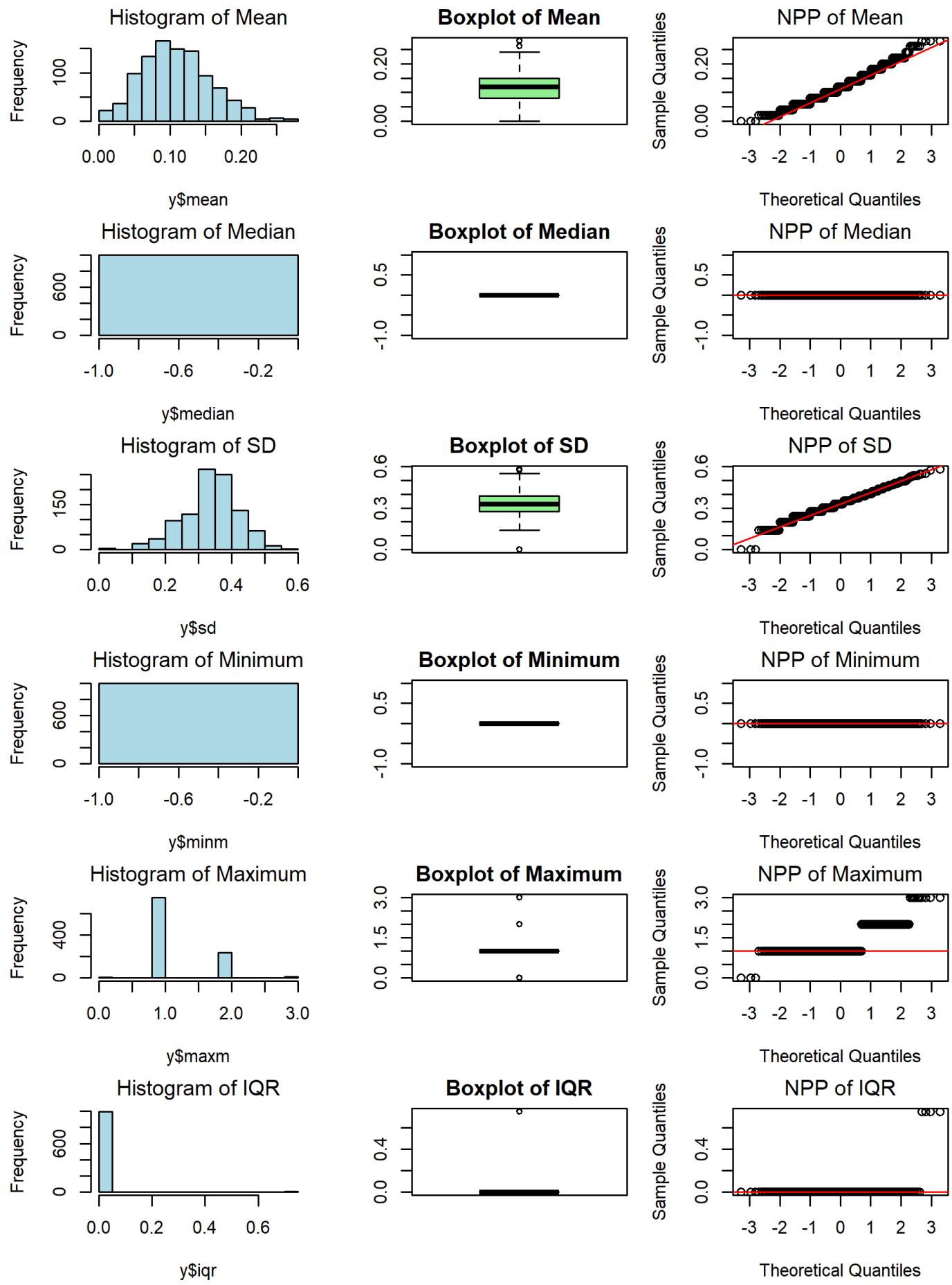
# BINOMIAL DISTRIBUTION PLOT

(n=10, nn=1000, m=12, p=0.01)



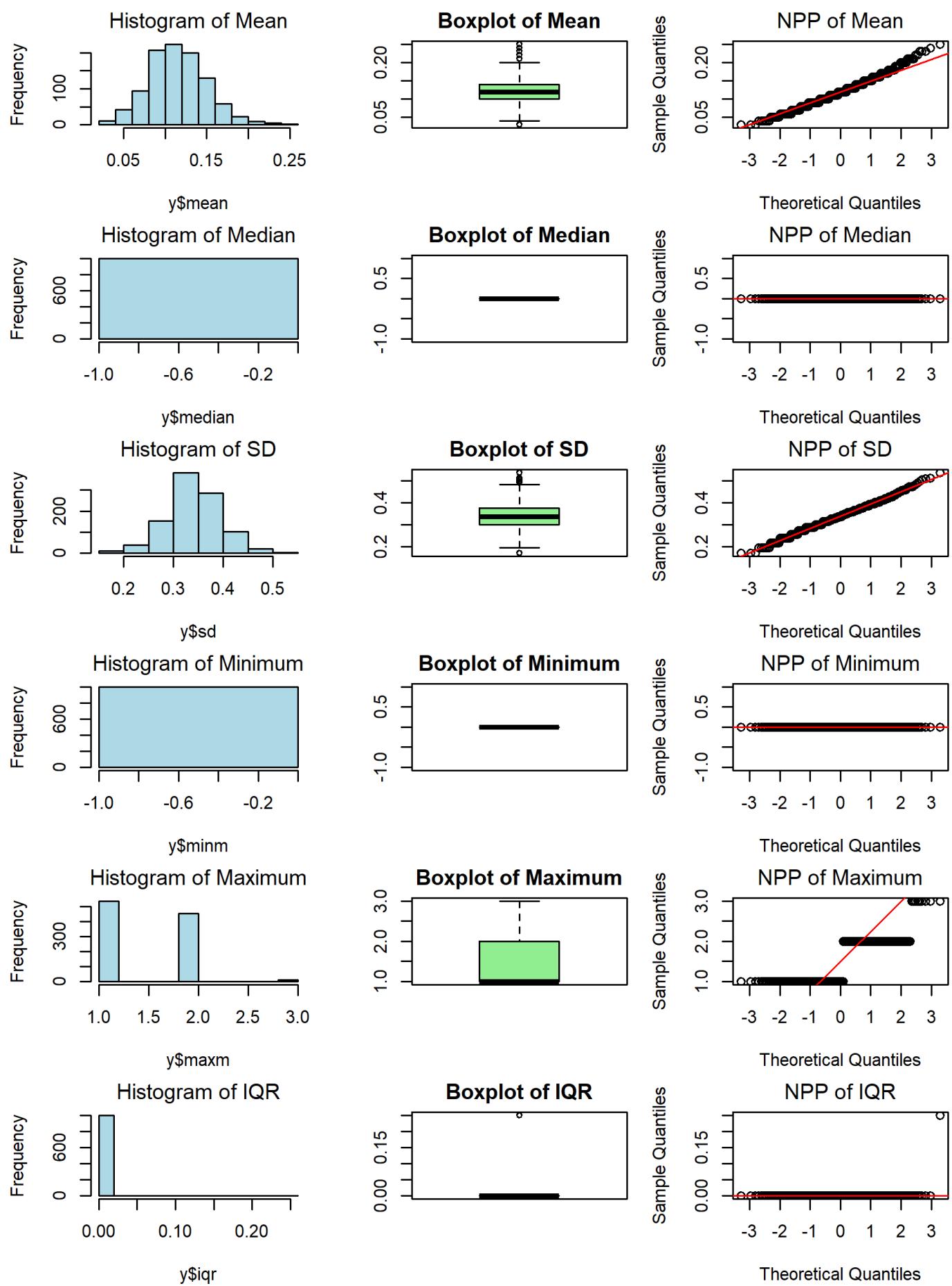
# BINOMIAL DISTRIBUTION PLOT

(n=50, nn=1000, m=12, p=0.01)



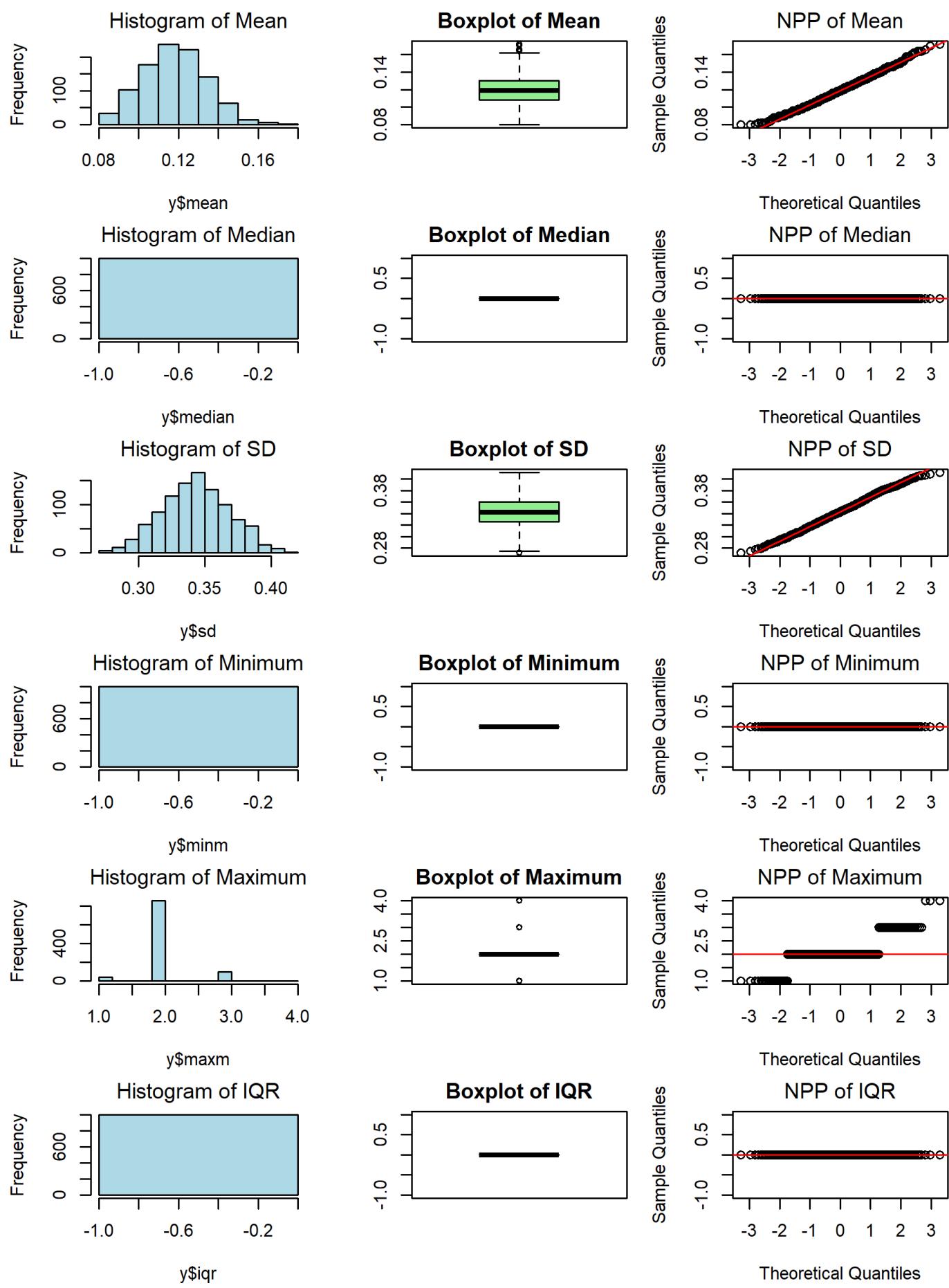
# BINOMIAL DISTRIBUTION PLOT

(n=100, nn=1000, m=12, p=0.01)



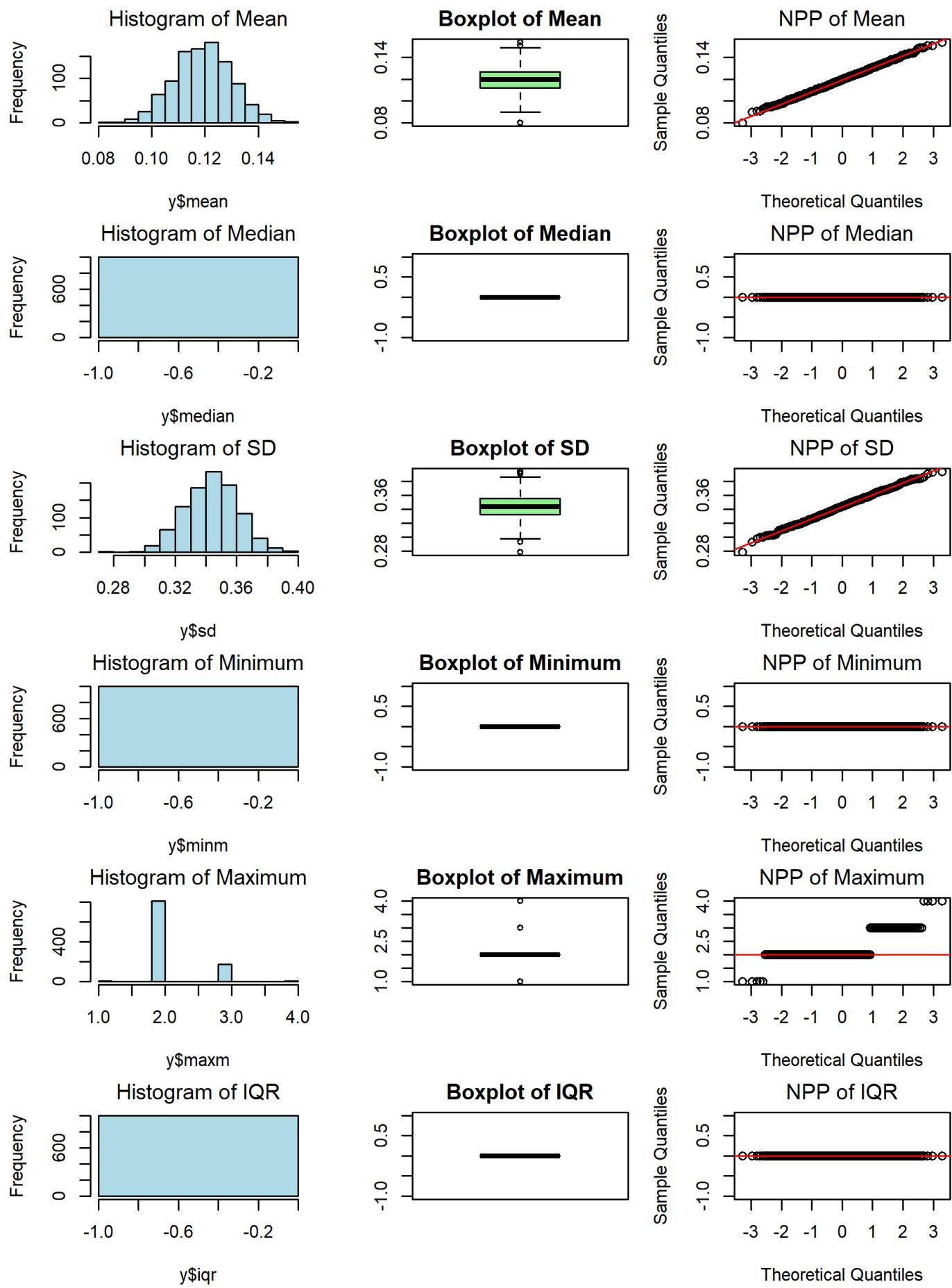
# BINOMIAL DISTRIBUTION PLOT

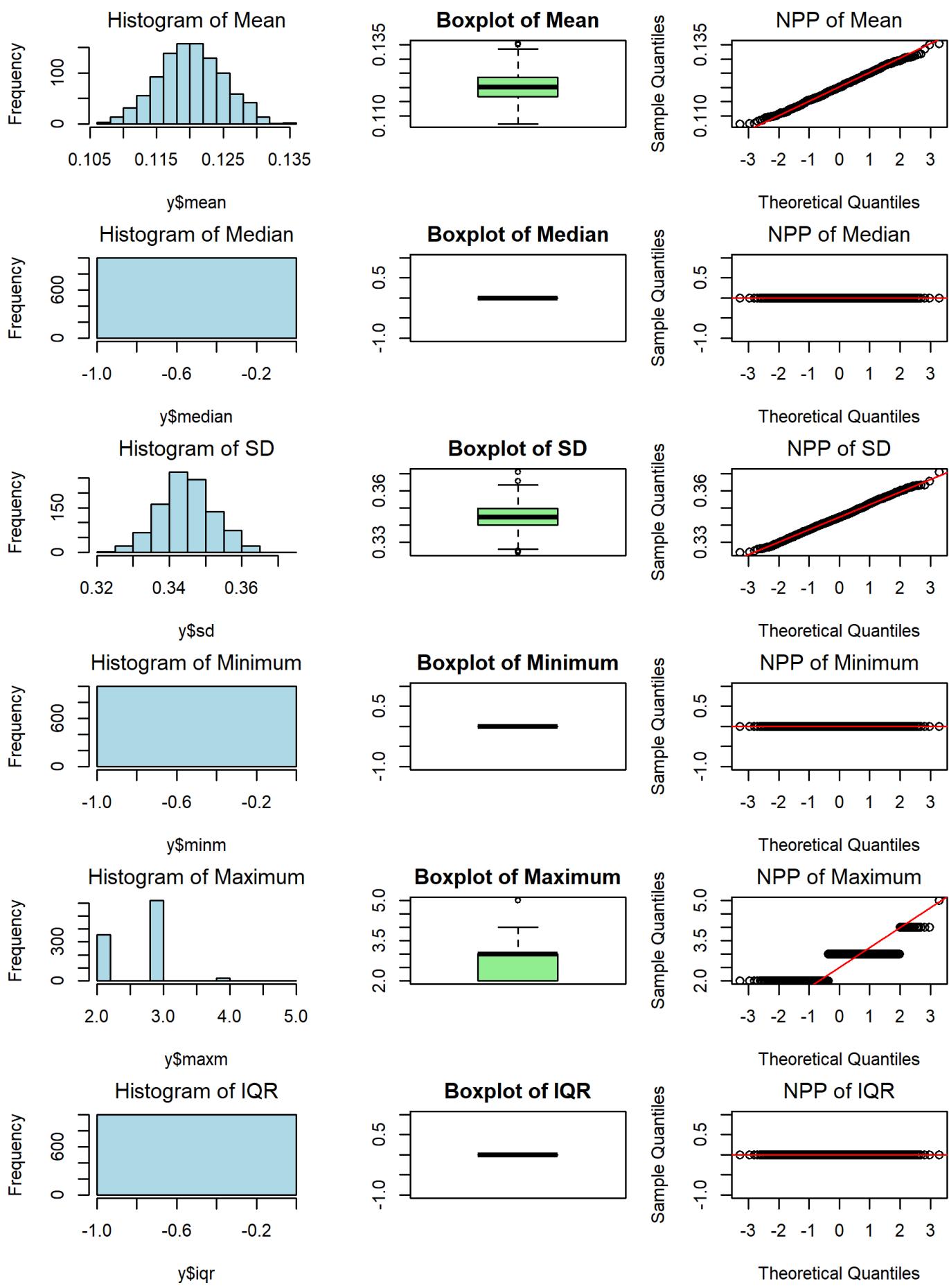
(n=500, nn=1000, m=12, p=0.01)



# BINOMIAL DISTRIBUTION PLOT

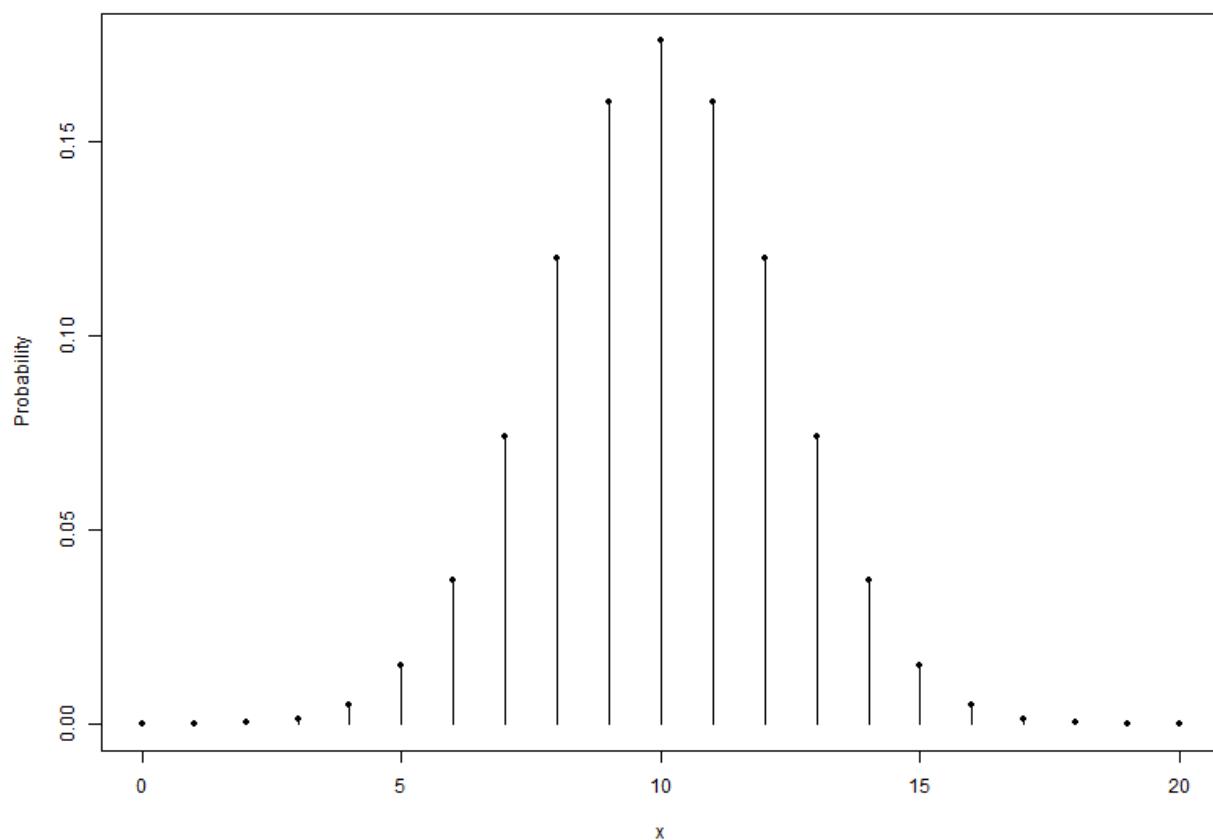
(n=1000, nn=1000, m=12, p=0.01)



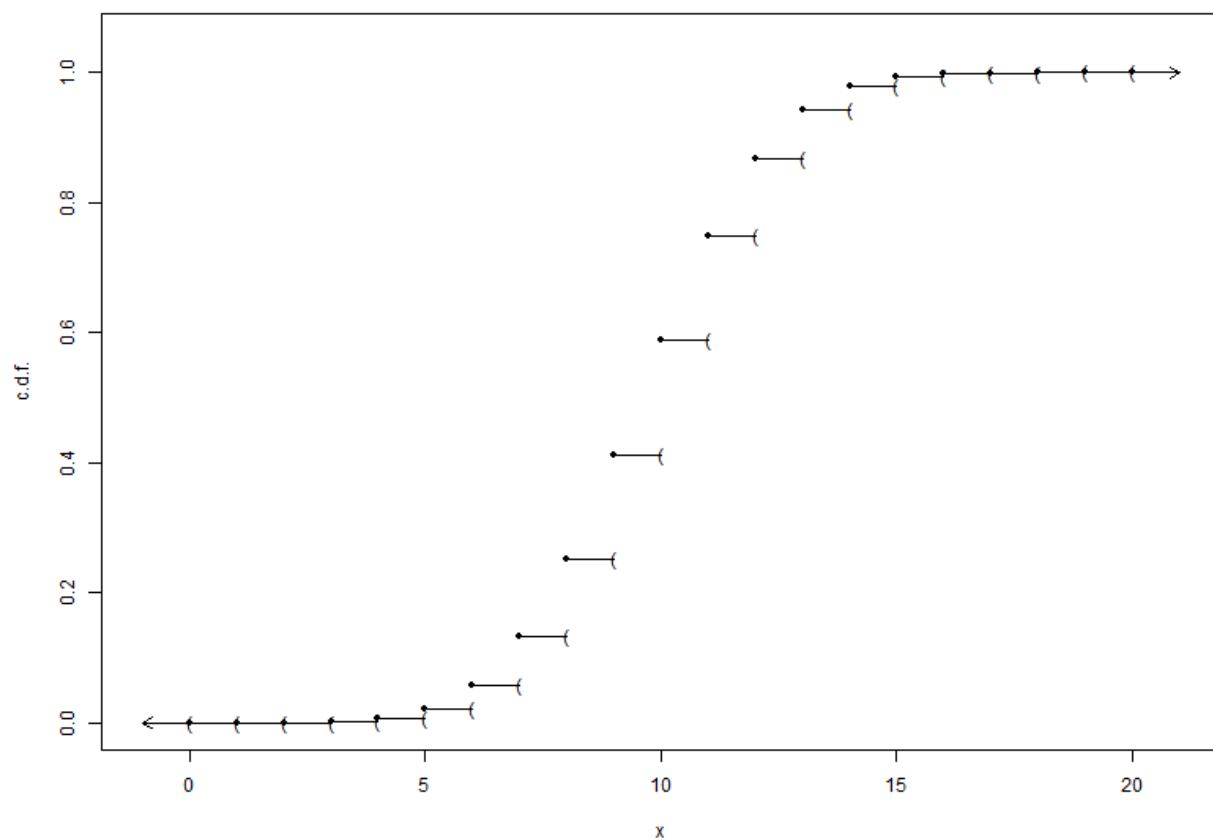


# BINOMIAL DISTRIBUTION (20,0.5)

PMF of Binomial(20, 0.5)



CDF of Binomial(20,0.5)



# BINOMIAL DISTRIBUTION

	Values of n to achieve normality (nn=1000, m=20, p=0.5)								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Median	No	No	No	No	No	No	No	NA	
Std Dev	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	No	No	NA	

## Conclusion for Binomial Distribution (m = 20, p = 0.5)

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 50$ , indicating that the mean converges to normality relatively quickly due to the symmetric nature of the Binomial distribution with  $p = 0.5$ .
- **Standard Deviation (SD):** Achieves normality for  $n \geq 50$ , showing a similar rate of convergence to the mean.

### Normality Not Achieved:

- **Median:** Does not achieve normality for any sample size, remaining non-normal due to the discrete characteristics of the Binomial distribution.
- **Minimum and Maximum:** Do not achieve normality for any sample size, as they are sensitive to the extremes of the distribution.
- **IQR:** Does not achieve normality for any sample size, reflecting its dependency on the underlying discrete structure.

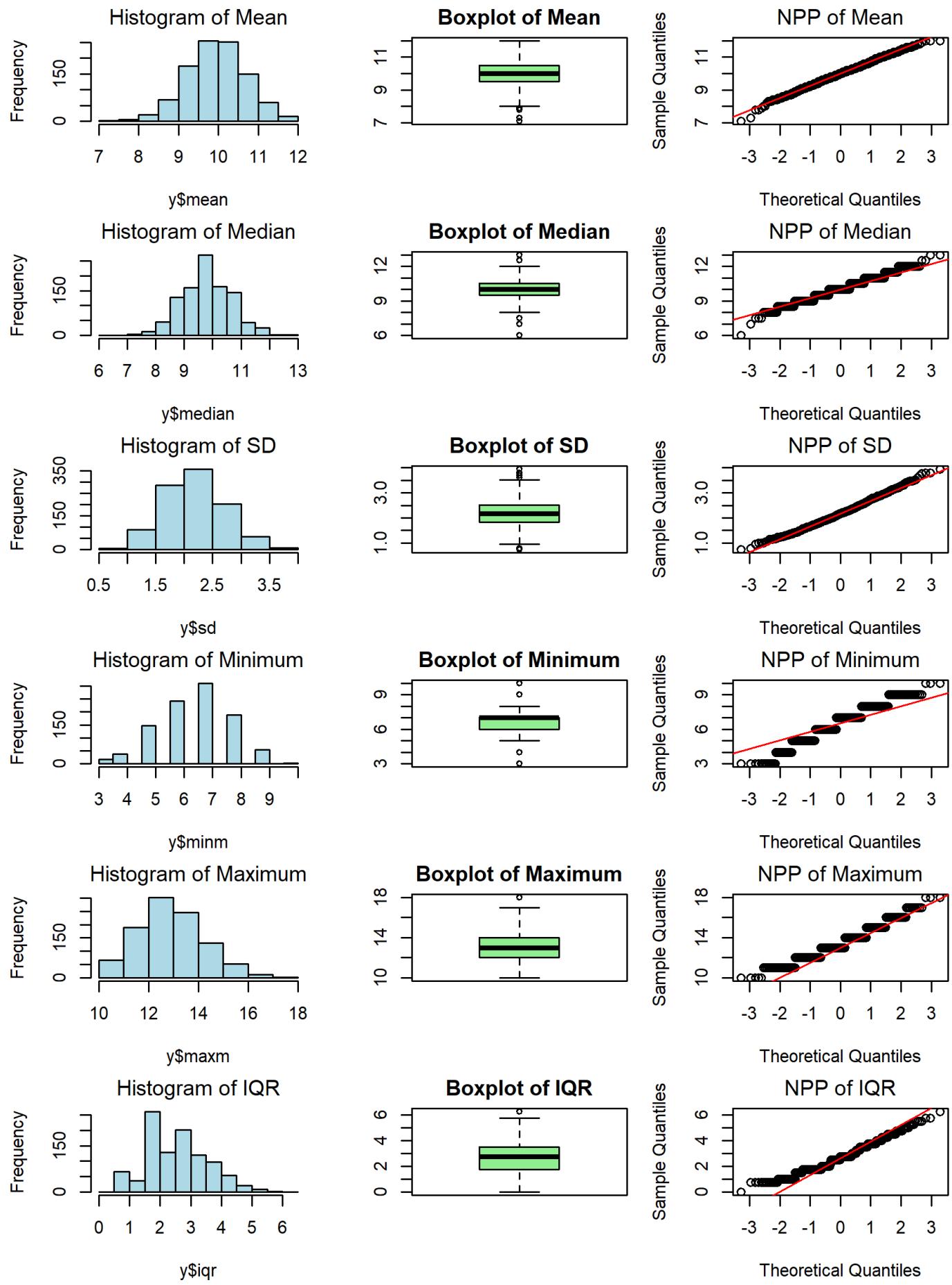
## Comparison with Binomial Distribution (m = 12, p = 0.01):

- For  $m = 20$  and  $p = 0.5$ , normality is achieved at smaller sample sizes ( $n \geq 50$ ) for both the mean and standard deviation compared to  $m = 12$  and  $p = 0.01$ . This faster convergence is due to the more symmetric and less skewed nature of the distribution when  $p = 0.5$ .

**Overall:** The mean and standard deviation achieve normality at  $n \geq 50$ , significantly faster than in the case of  $m = 12$  and  $p = 0.01$ . The median, minimum, maximum, and IQR remain non-normal regardless of sample size, consistent with the discrete nature of the distribution.

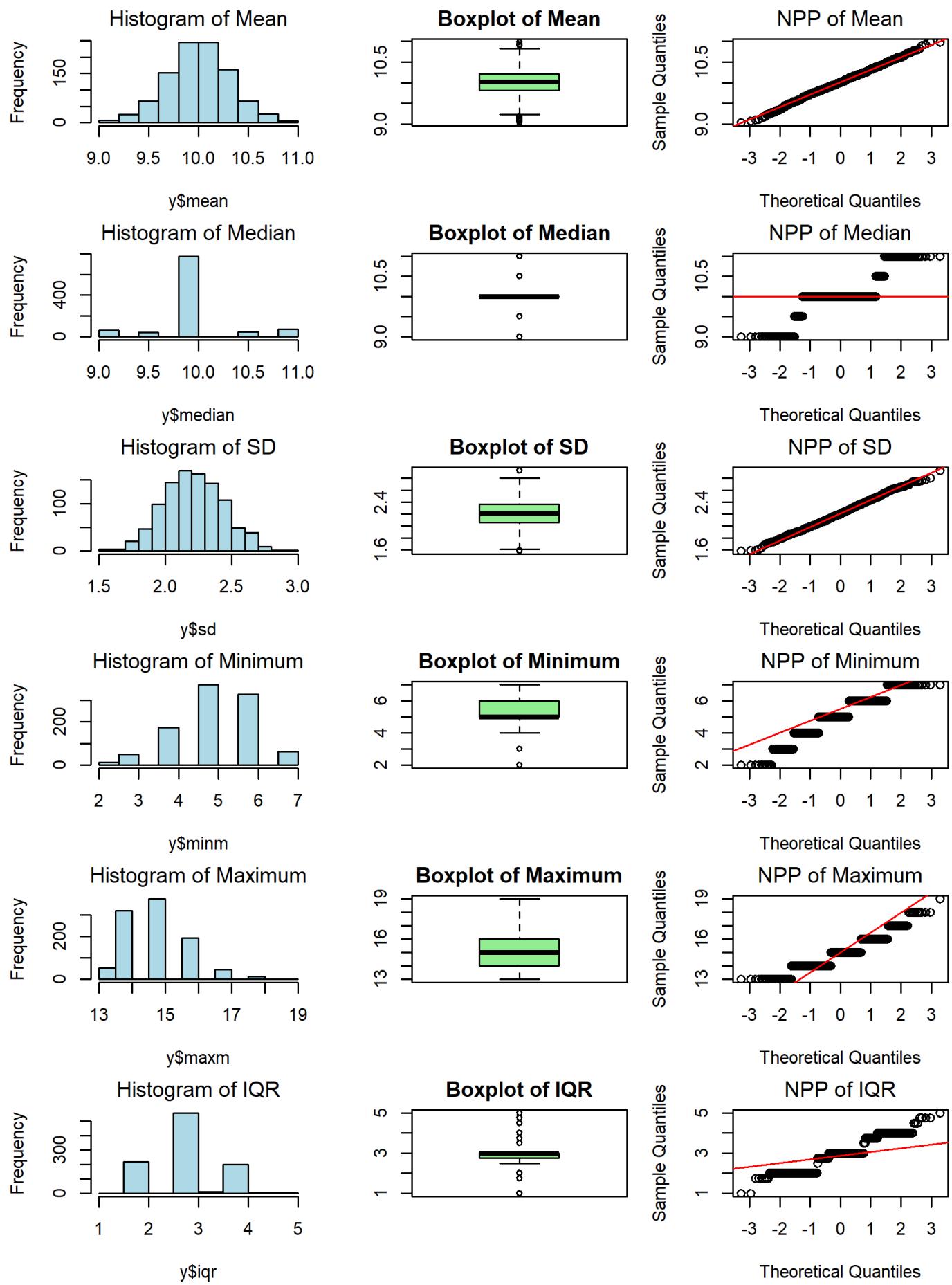
# BINOMIAL DISTRIBUTION PLOT

(n=10, nn=1000, m=20, p=0.50)



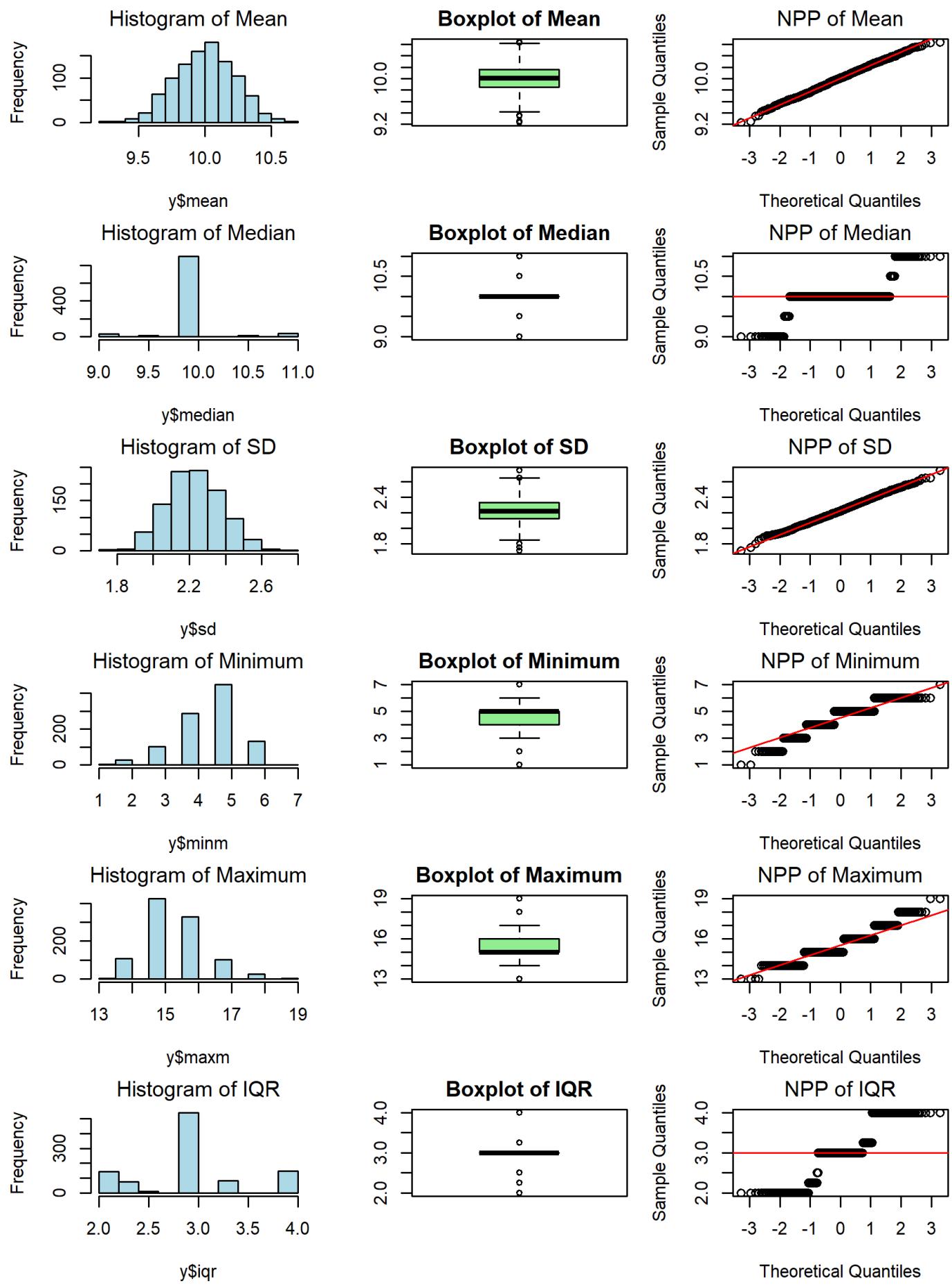
# BINOMIAL DISTRIBUTION PLOT

(n=50, nn=1000, m=20, p=0.50)



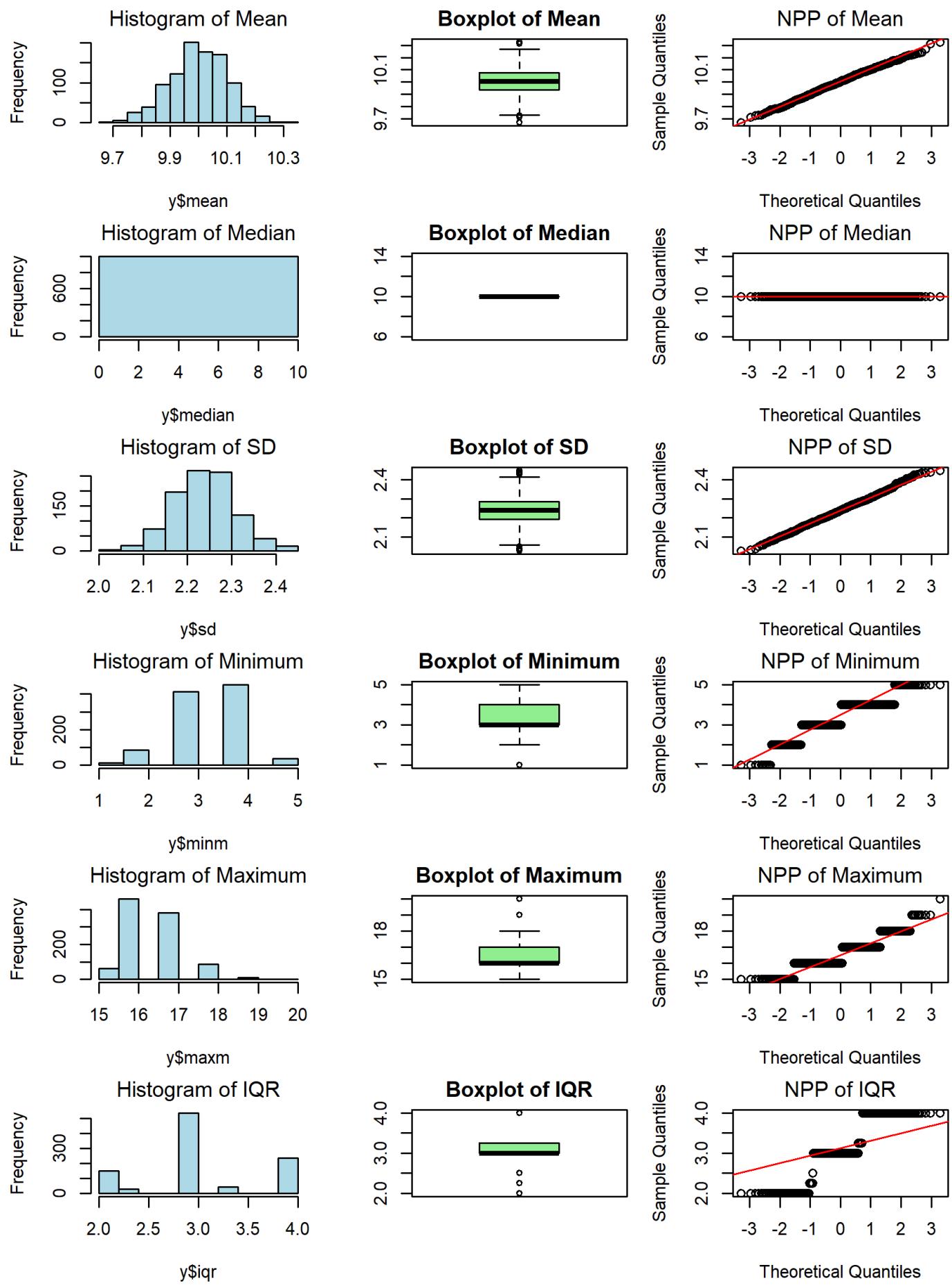
# BINOMIAL DISTRIBUTION PLOT

(n=100, nn=1000, m=20, p=0.50)



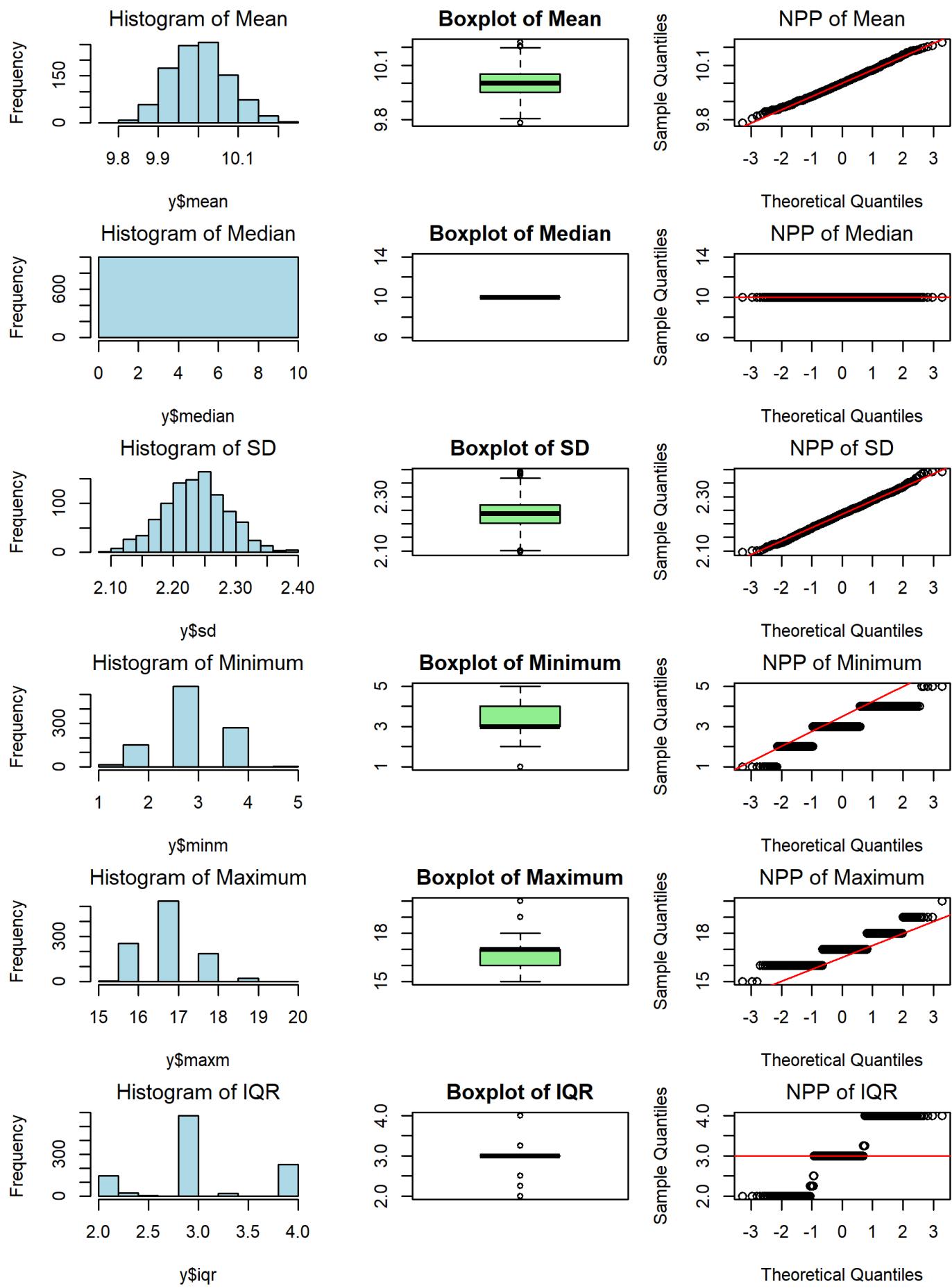
# BINOMIAL DISTRIBUTION PLOT

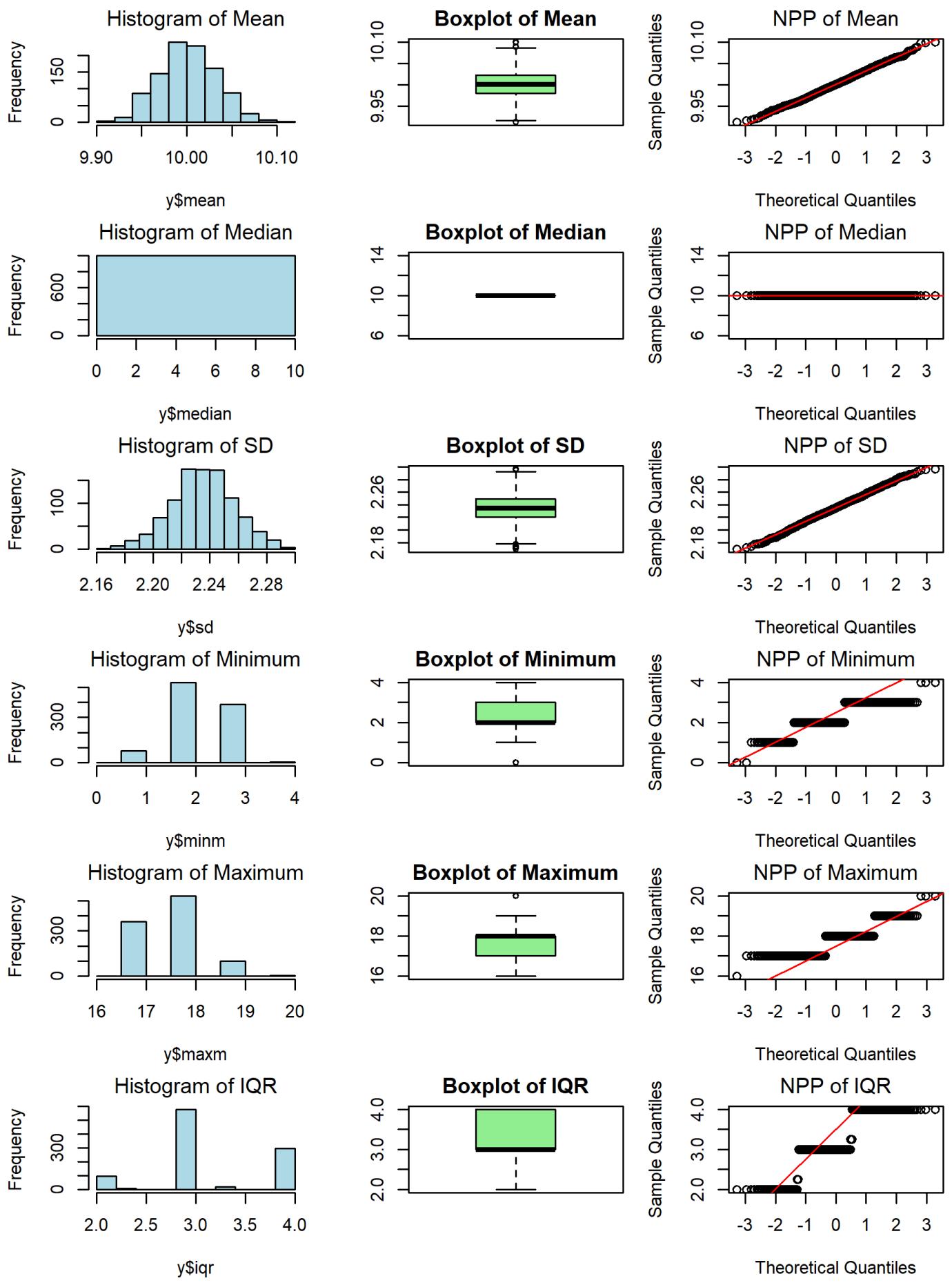
(n=500, nn=1000, m=20, p=0.50)



# BINOMIAL DISTRIBUTION PLOT

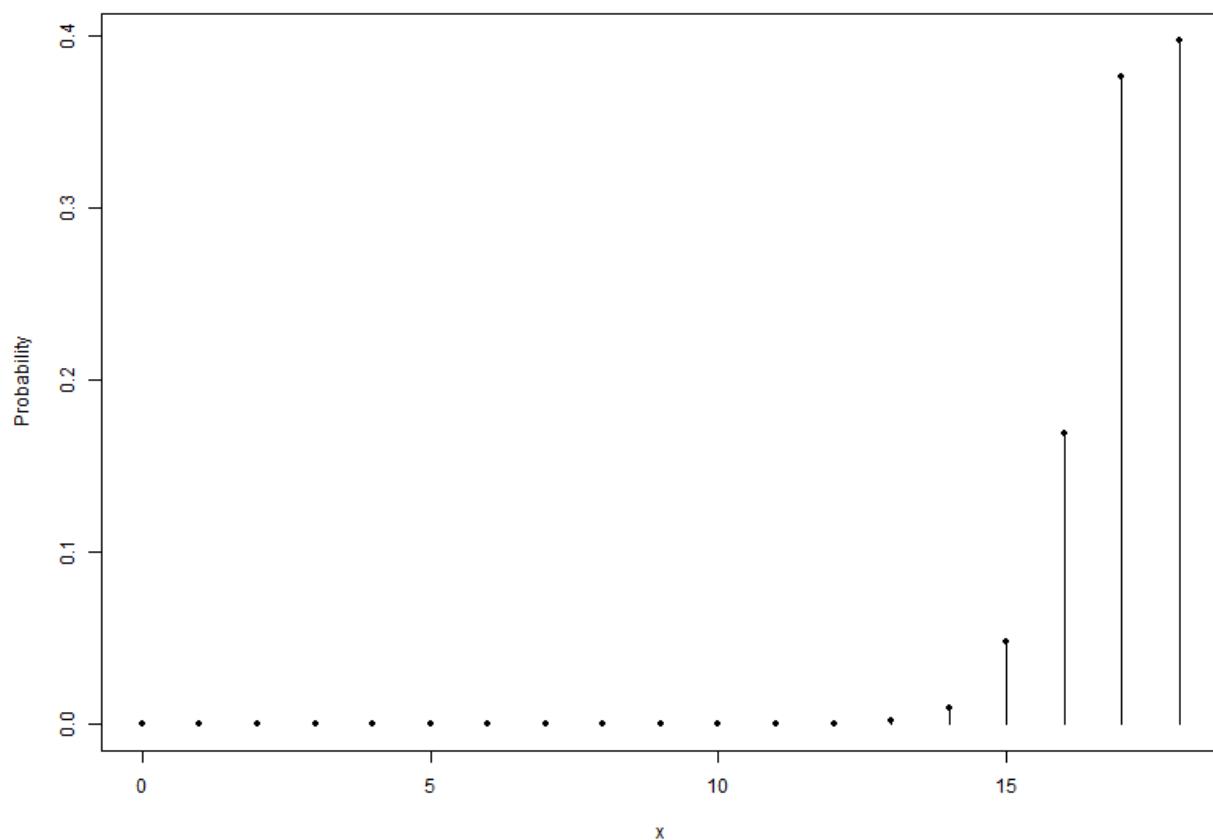
(n=1000, nn=1000, m=20, p=0.50)



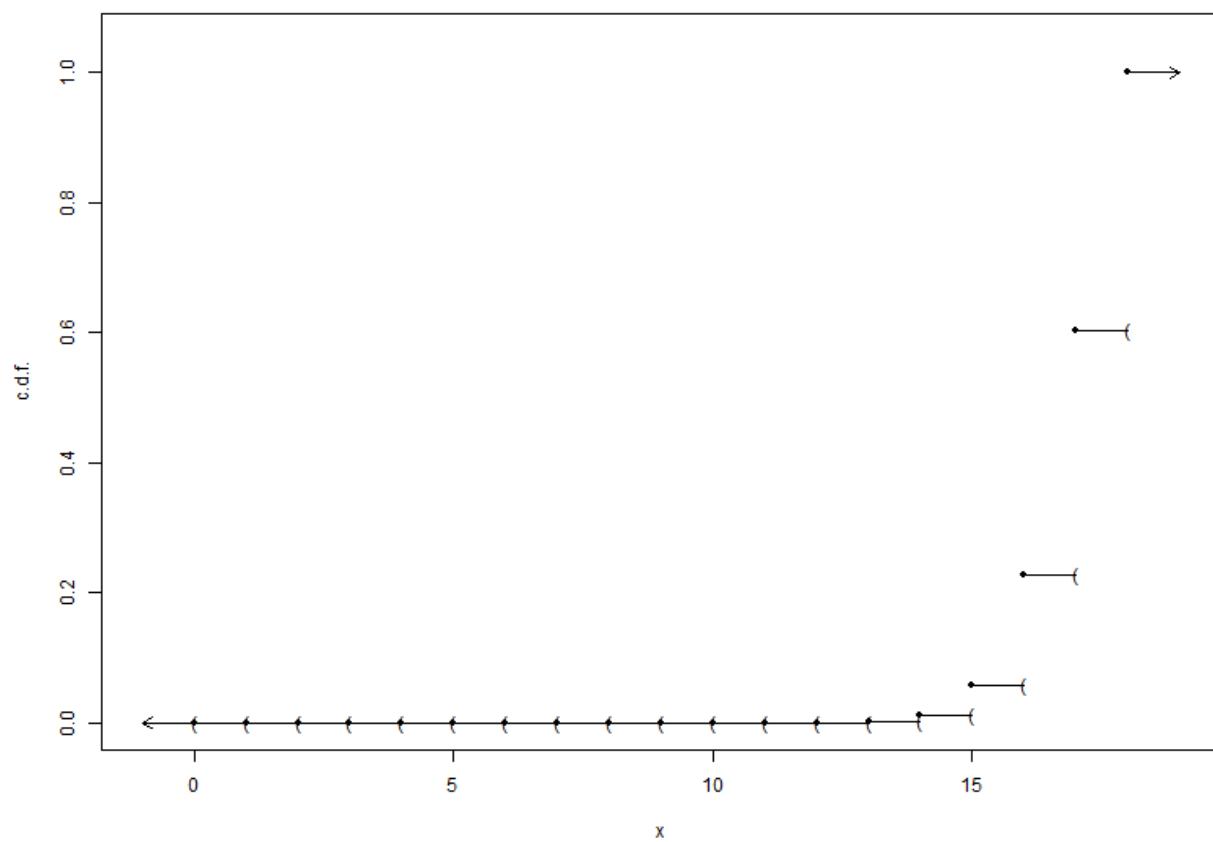


# BINOMIAL DISTRIBUTION (18,0.95)

PMF of Binomial(18, 0.95)



CDF of Binomial(18,0.95)



# BINOMIAL DISTRIBUTION

	Values of n to achieve normality (nn=1000, m=18, p=0.95)								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Median	No	No	No	No	No	No	No	NA	
Std Dev	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	No	No	NA	

## Conclusion for Binomial Distribution (m = 18, p = 0.95)

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 50$ , demonstrating relatively quick convergence due to the high probability of success ( $p = 0.95$ ) creating a concentrated distribution.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 50$ , with a convergence rate similar to the mean.

### Normality Not Achieved:

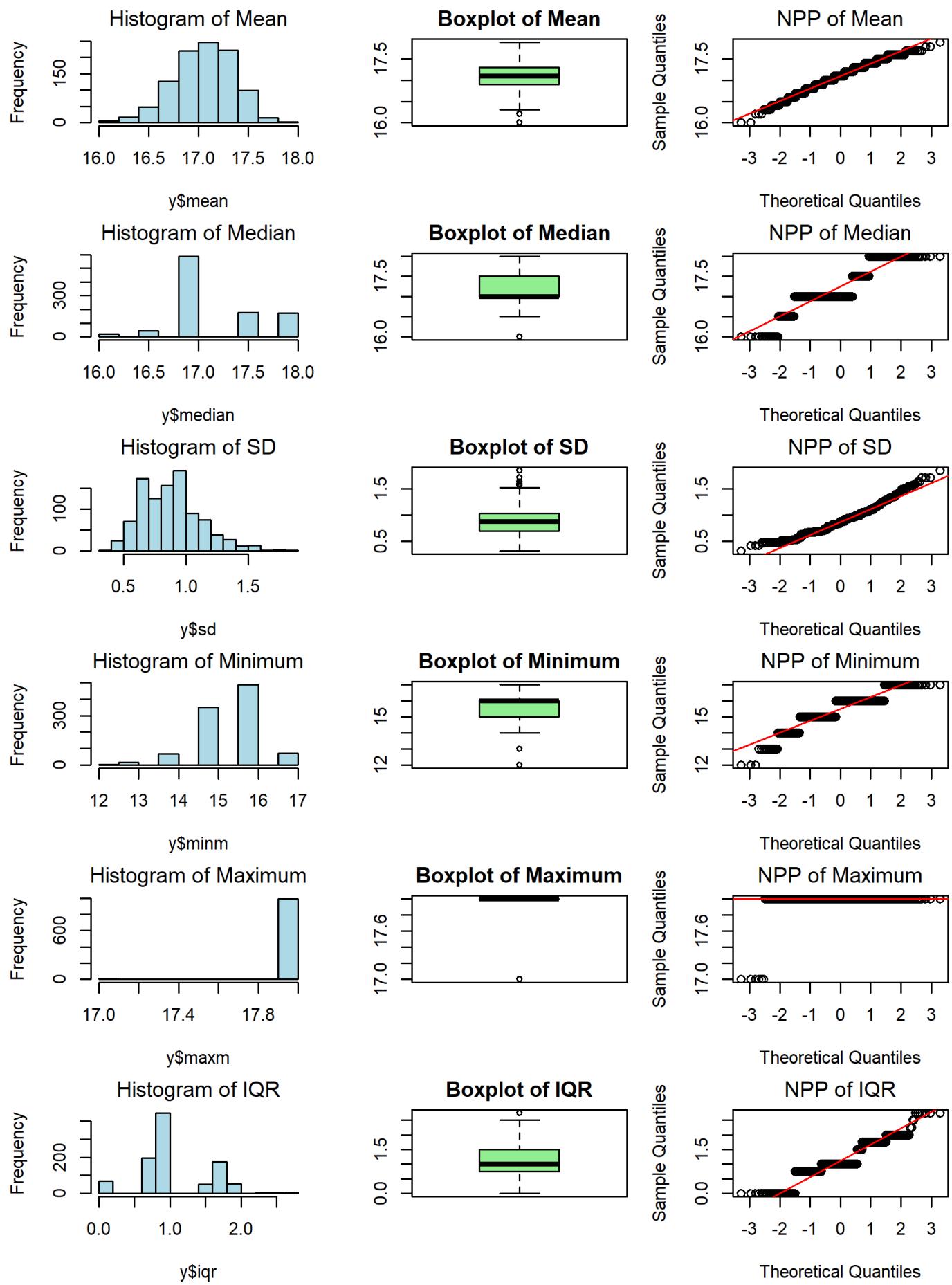
- **Median:** Does not achieve normality for any sample size, consistent with the discrete nature of the Binomial distribution.
- **Minimum and Maximum:** Do not achieve normality for any sample size, as they are strongly influenced by the extremes of the distribution.
- **IQR:** Does not achieve normality for any sample size, reflecting the dependency on the underlying discrete structure and skewness.

### Comparison with Other Parameters:

- Compared to **m = 20, p = 0.5**, the mean and standard deviation converge to normality at the same sample size ( $n \geq 50$ ). However, the distribution with **p = 0.95** is more skewed, making the normality less representative of the overall distribution characteristics.
- Compared to **m = 12, p = 0.01**, normality for the mean and standard deviation is achieved at much smaller sample sizes ( $n \geq 50$  vs.  $n \geq 500$  for the mean and  $n \geq 100$  for SD). This is due to the concentration of outcomes near the maximum for  $p = 0.95$ .

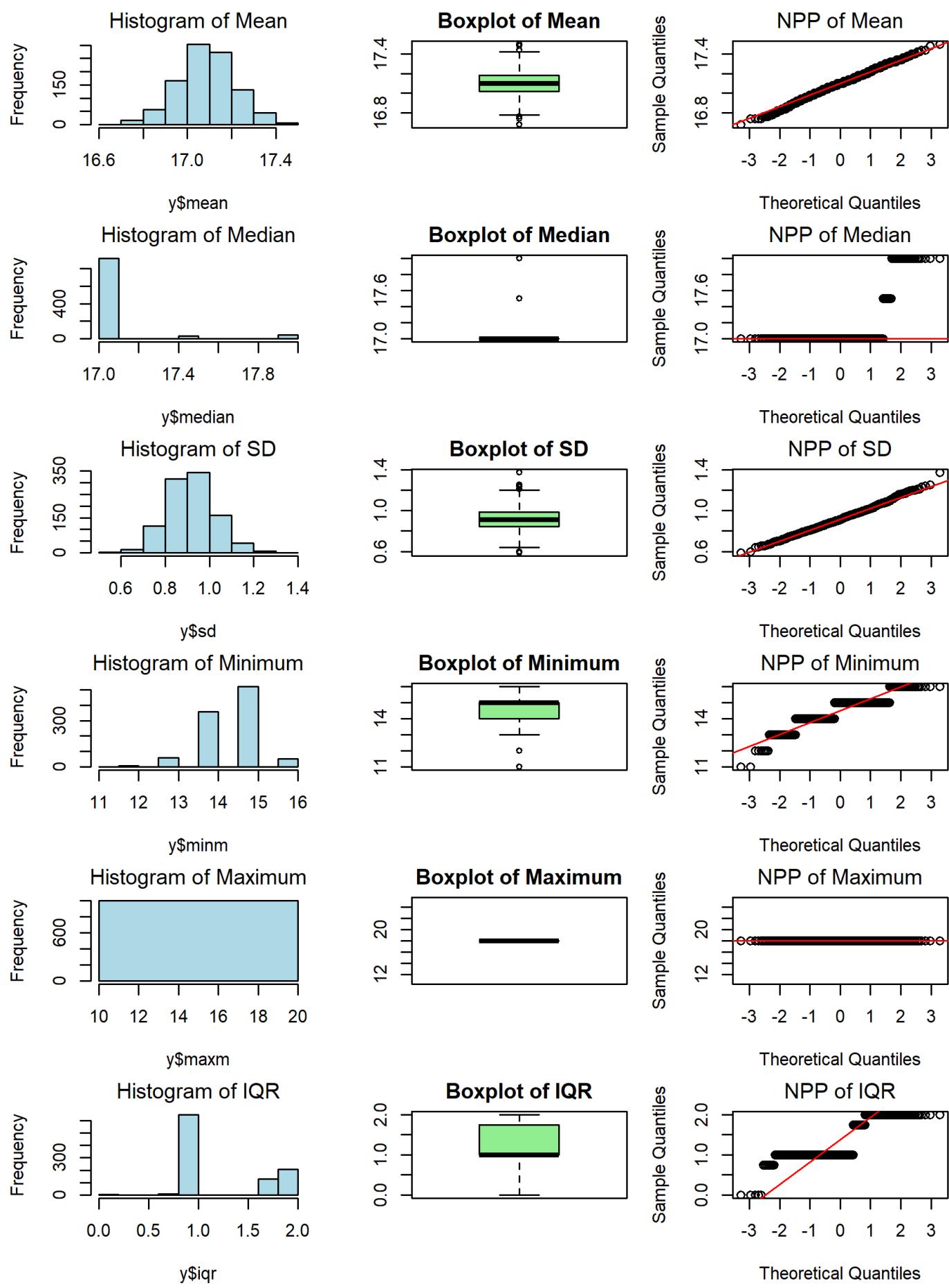
# BINOMIAL DISTRIBUTION PLOT

(n=10, nn=1000, m=18, p=0.95)



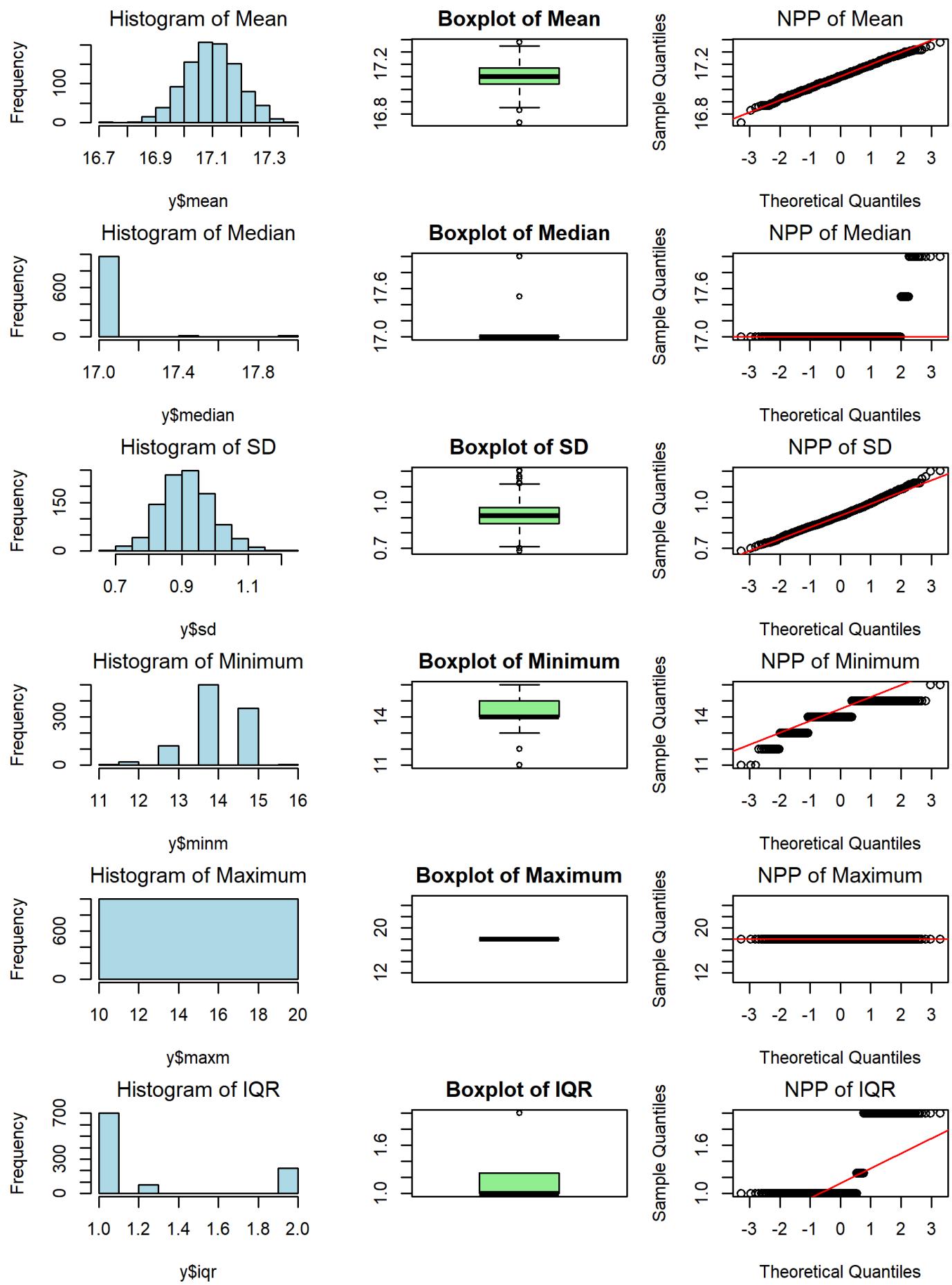
# BINOMIAL DISTRIBUTION PLOT

(n=50, nn=1000, m=18, p=0.95)



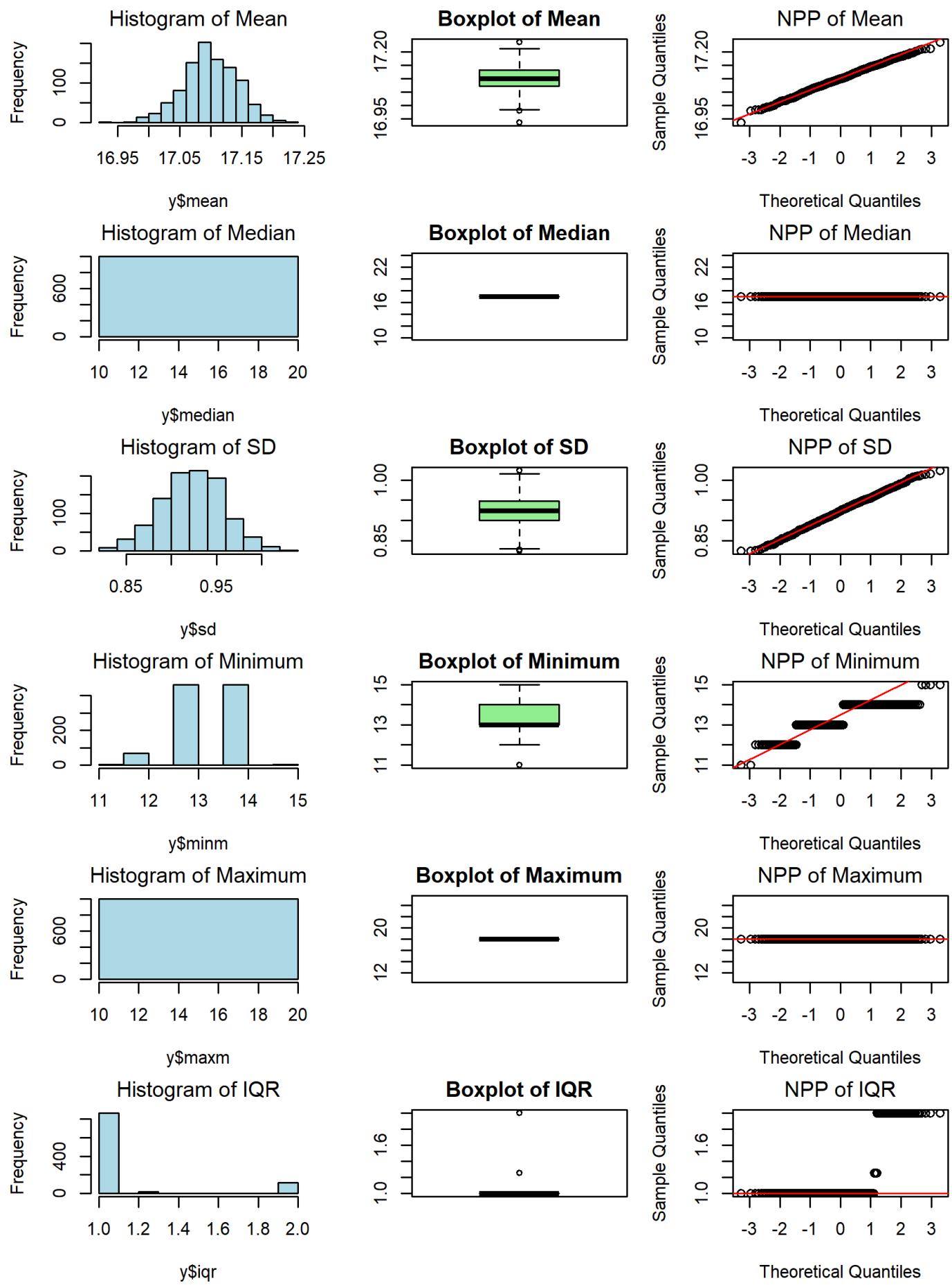
# BINOMIAL DISTRIBUTION PLOT

(n=100, nn=1000, m=18, p=0.95)



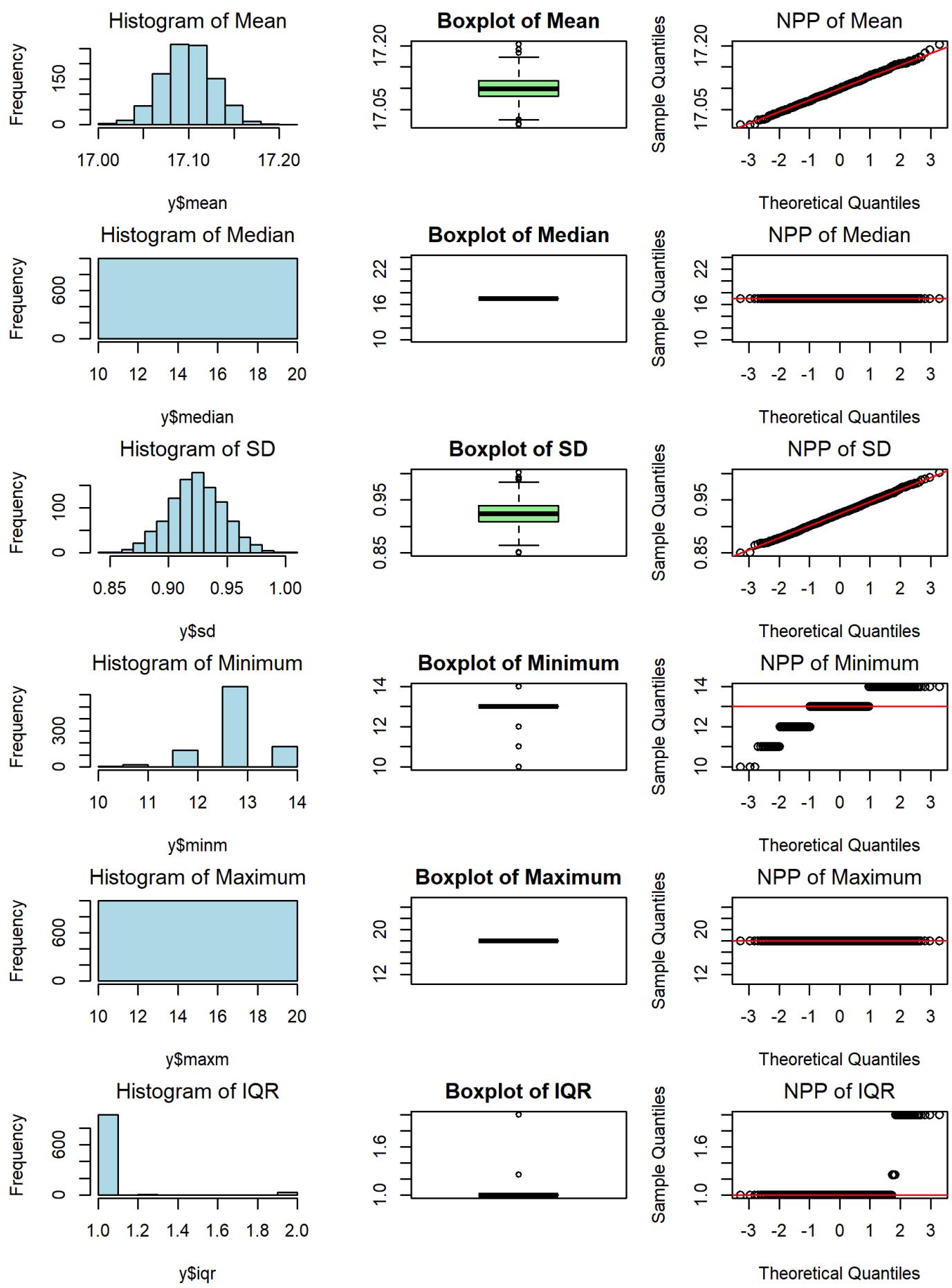
# BINOMIAL DISTRIBUTION PLOT

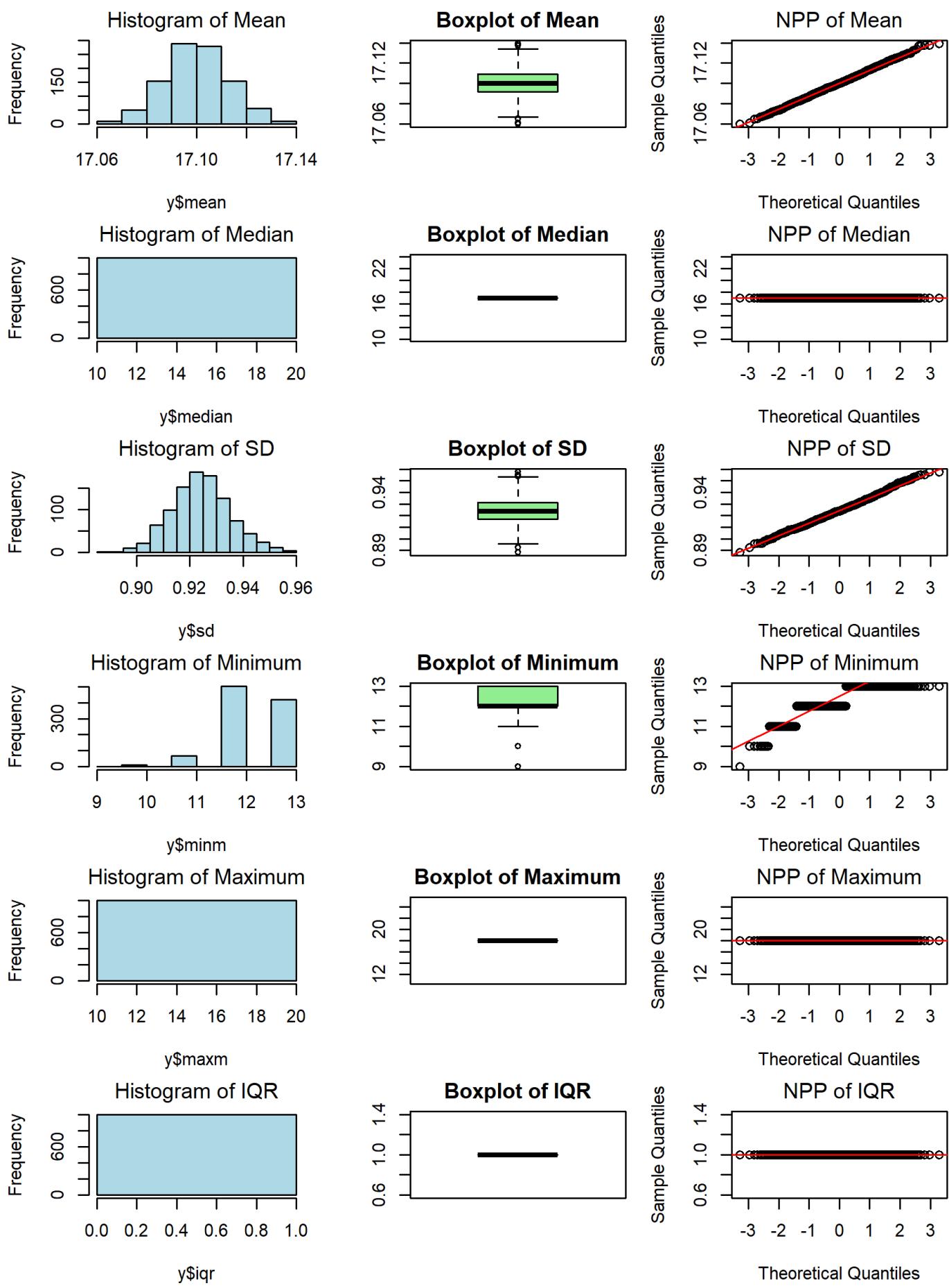
(n=500, nn=1000, m=18, p=0.95)



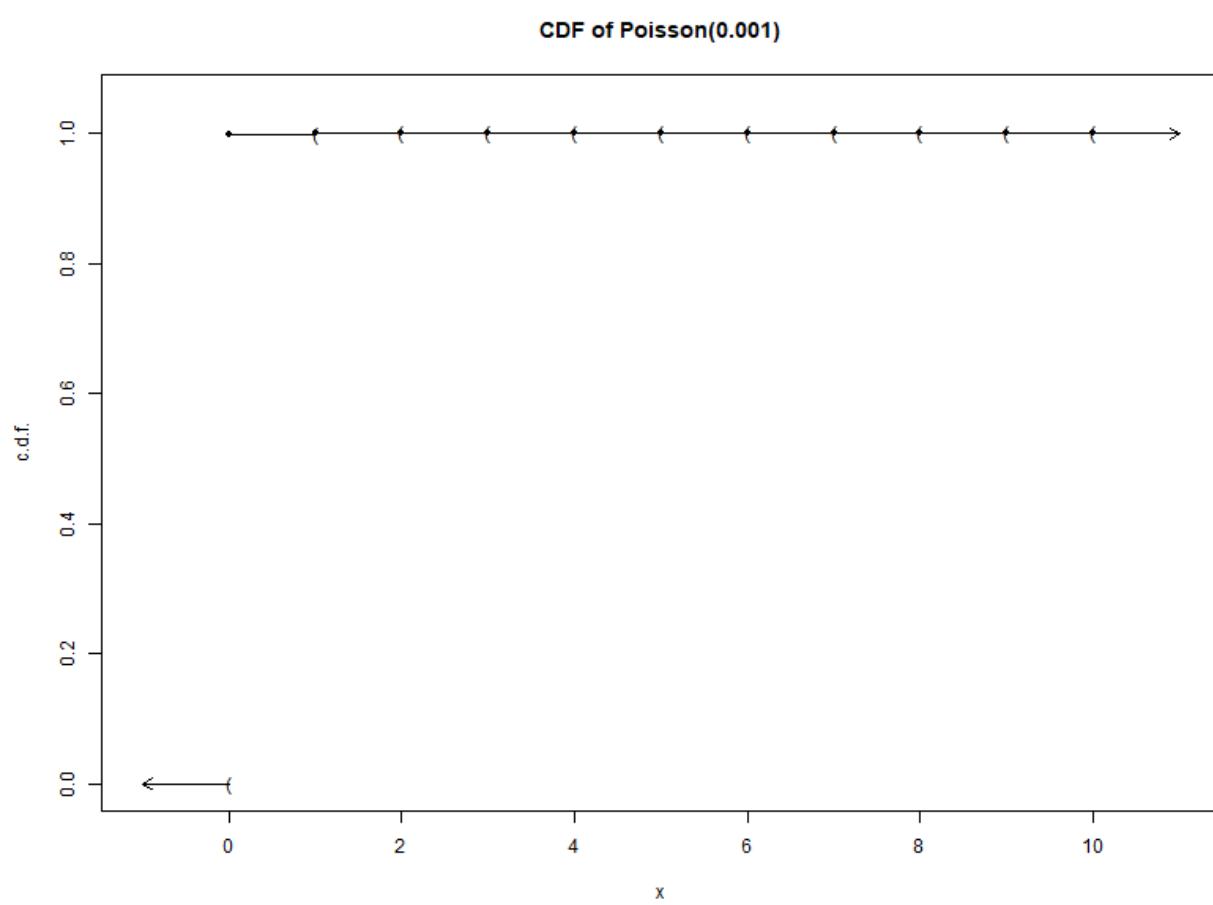
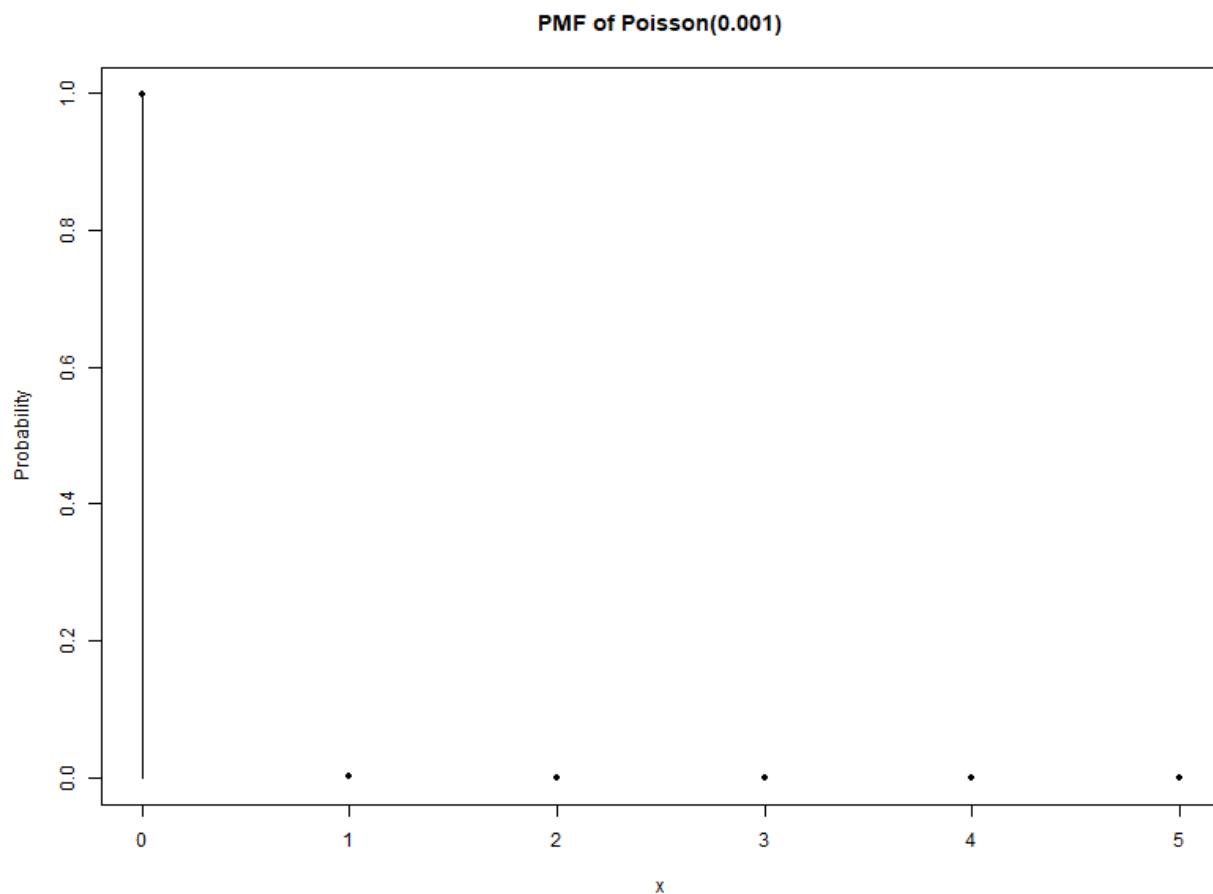
# BINOMIAL DISTRIBUTION PLOT

(n=1000, nn=1000, m=18, p=0.95)





# POISSON DISTRIBUTION (0.001)



# POISSON DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\lambda=0.001$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	No	No	No	No	No	Yes	10000	
Median	No	No	No	No	No	No	No	NA	
Std Dev	No	No	No	No	No	No	Yes	15000	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	No	No	NA	

## Conclusion for Poisson Distribution ( $\lambda = 0.001$ )

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 10,000$ , requiring a very large sample size due to the extremely low  $\lambda$ , which results in a highly skewed distribution.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 15,000$ , reflecting even slower convergence compared to the mean.

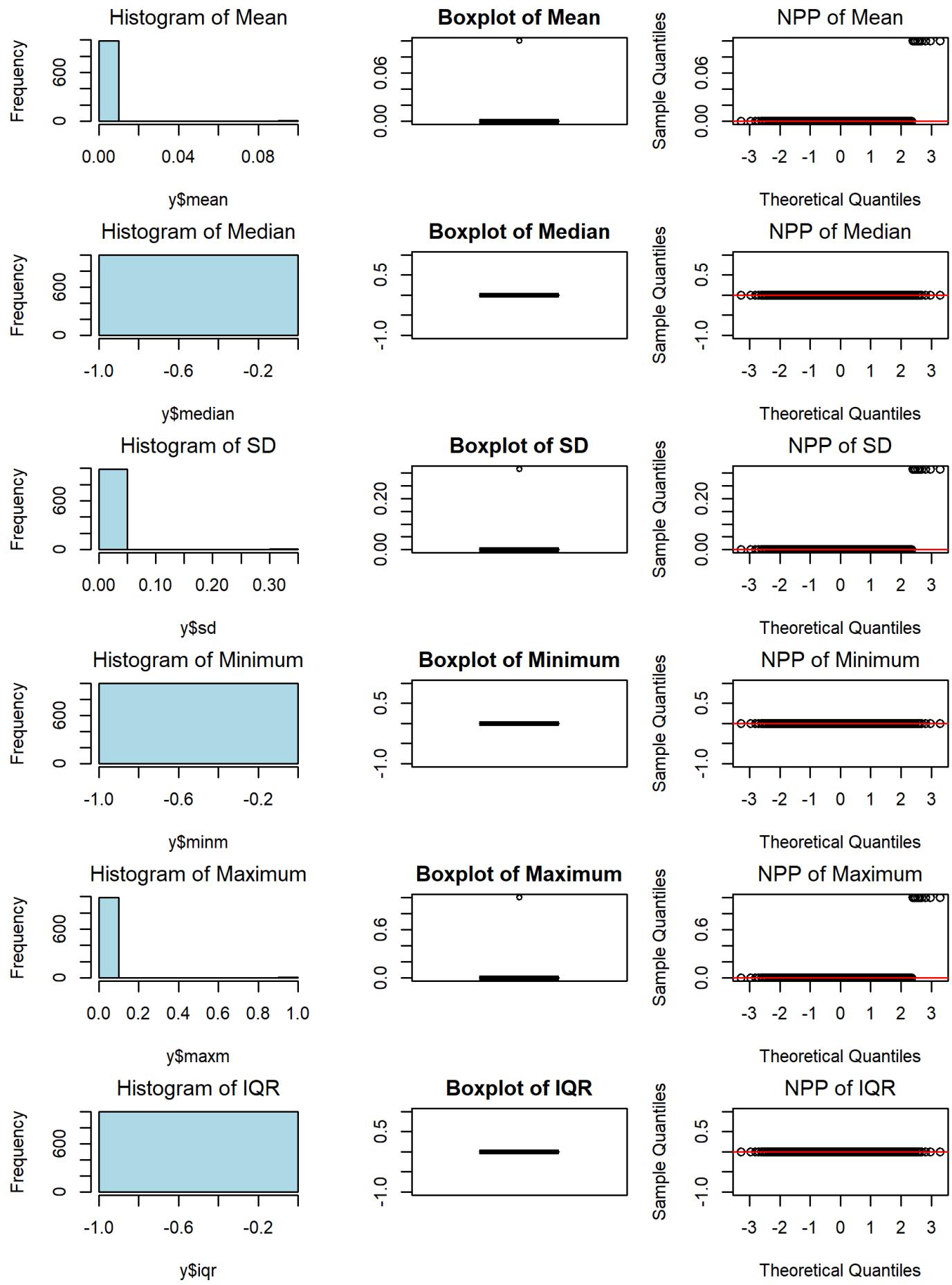
### Normality Not Achieved:

- **Median:** Does not achieve normality for any sample size due to the discrete nature of the Poisson distribution and the extreme skewness at  $\lambda = 0.001$ .
- **Minimum and Maximum:** Do not achieve normality for any sample size, as they are heavily influenced by the rarity of events in a distribution with such a low  $\lambda$ .
- **IQR:** Does not achieve normality for any sample size, as it remains tied to the structure of the underlying Poisson distribution.

**Overall:** For the Poisson distribution with  $\lambda = 0.001$ , achieving normality for the mean and standard deviation requires very large sample sizes ( $n \geq 10,000$  for the mean and  $n \geq 15,000$  for SD). This is significantly slower compared to Poisson distributions with larger  $\lambda$  values, where normality is achieved more easily due to reduced skewness. The median, minimum, maximum, and IQR remain non-normal, consistent with the highly discrete and sparse nature of the distribution at such a low  $\lambda$ .

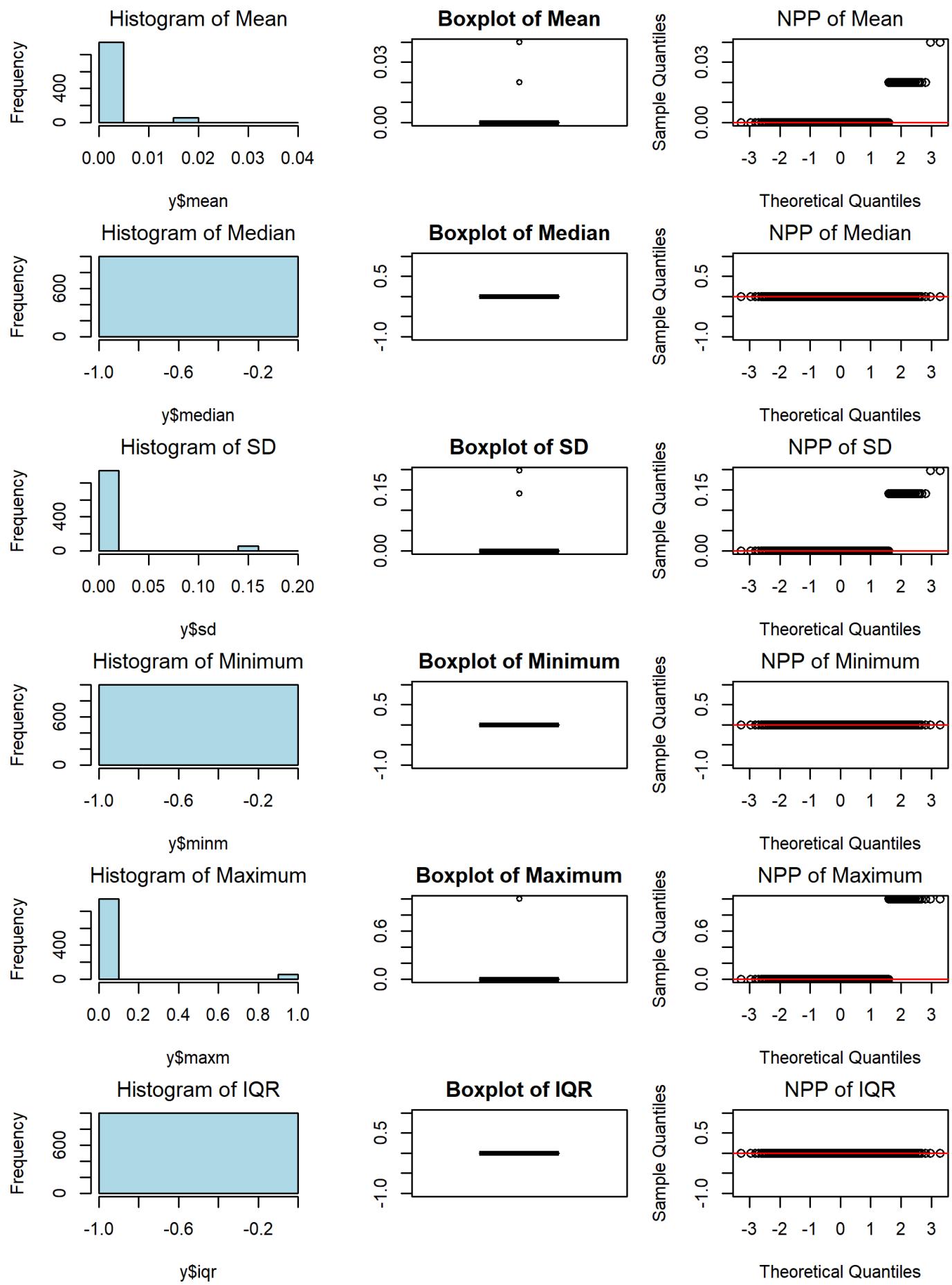
# POISSON DISTRIBUTION PLOT

(n=10, nn=1000,  $\lambda = 0.001$ )



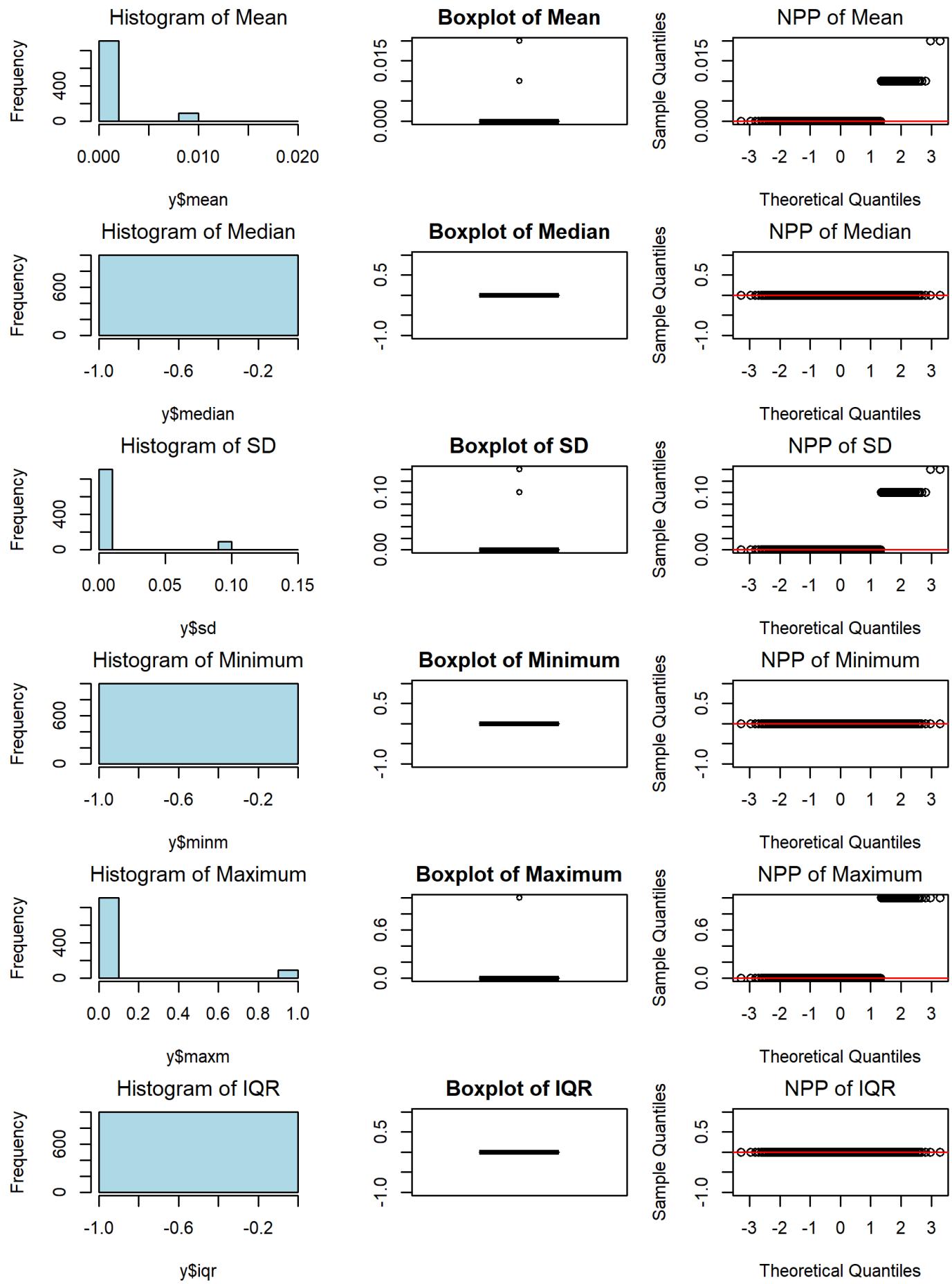
# POISSON DISTRIBUTION PLOT

(n=50, nn=1000,  $\lambda = 0.001$ )



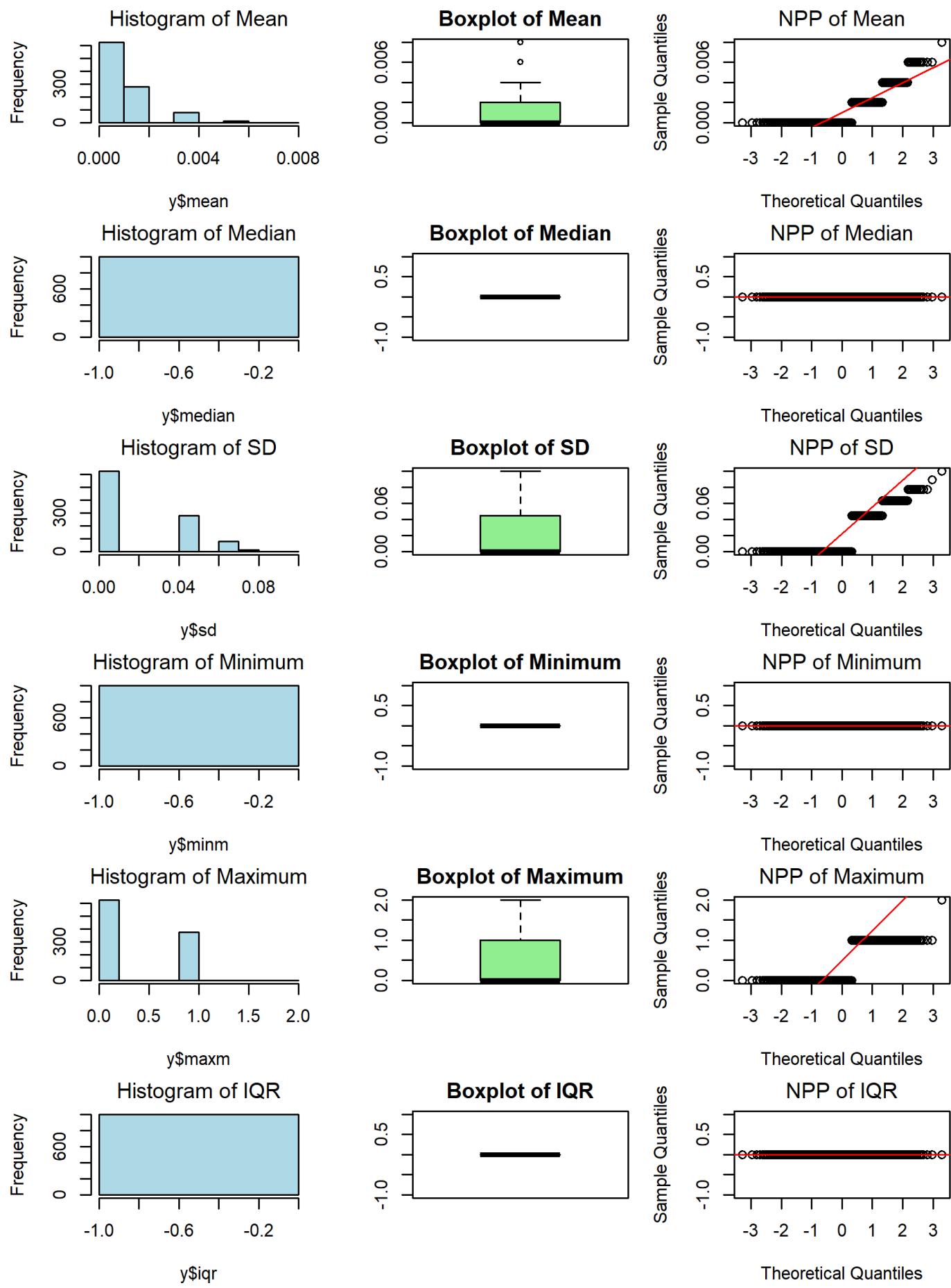
# POISSON DISTRIBUTION PLOT

(n=100, nn=1000,  $\lambda = 0.001$ )



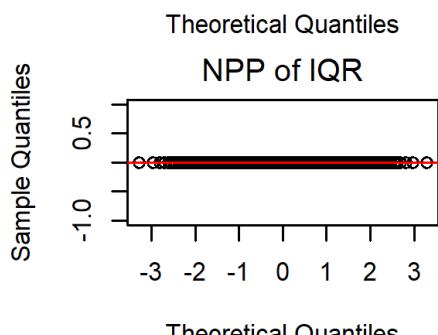
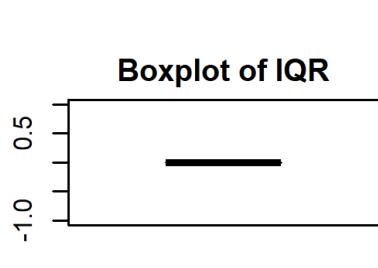
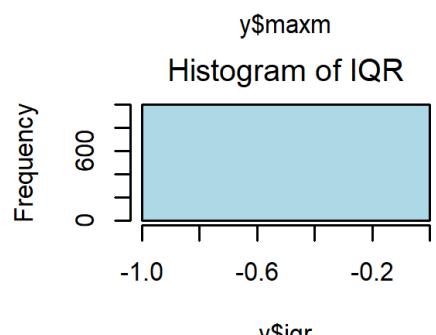
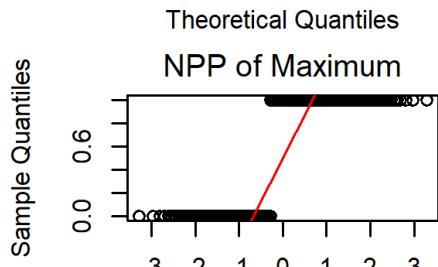
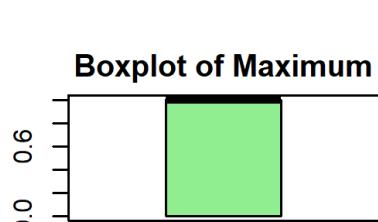
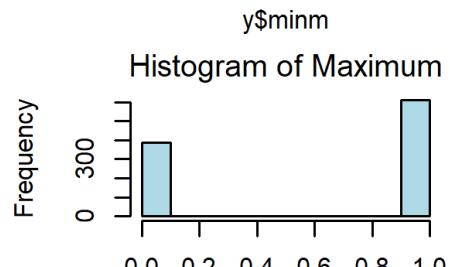
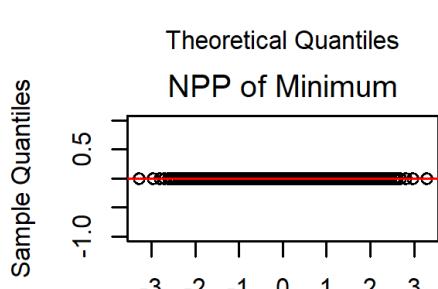
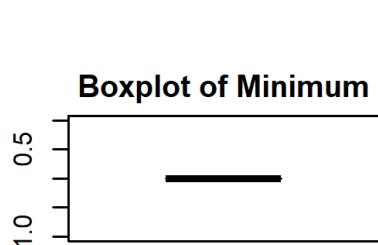
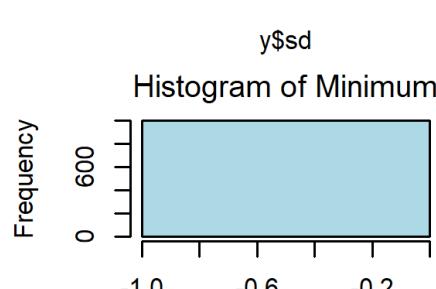
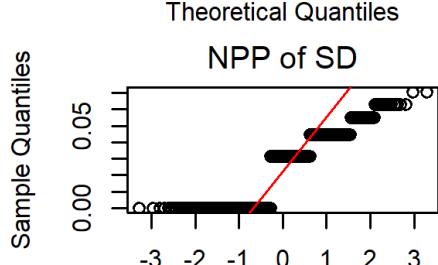
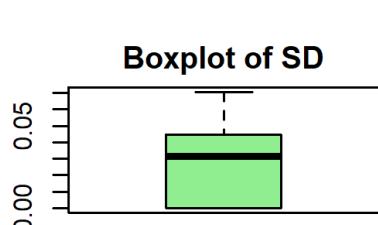
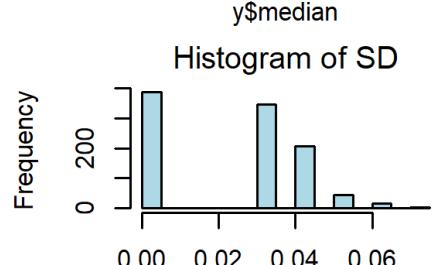
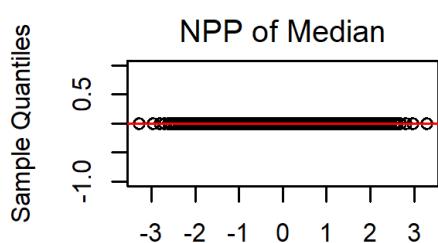
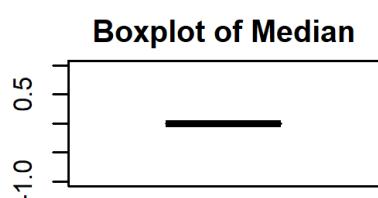
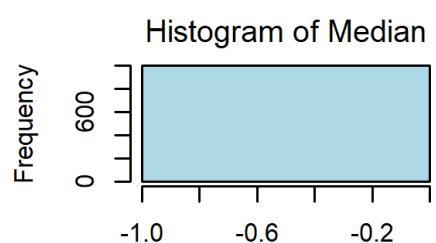
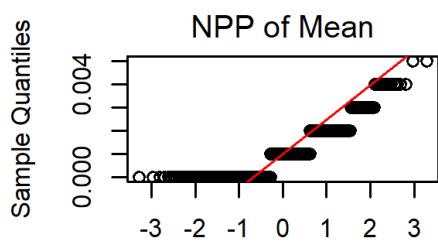
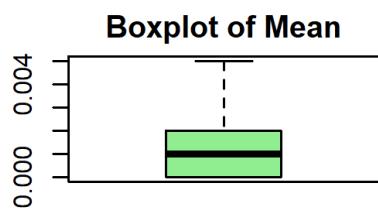
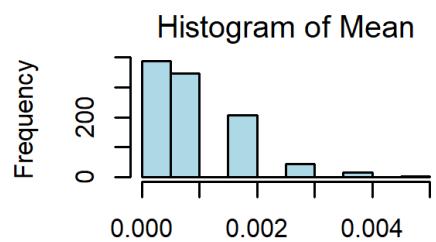
## POISSON DISTRIBUTION PLOT

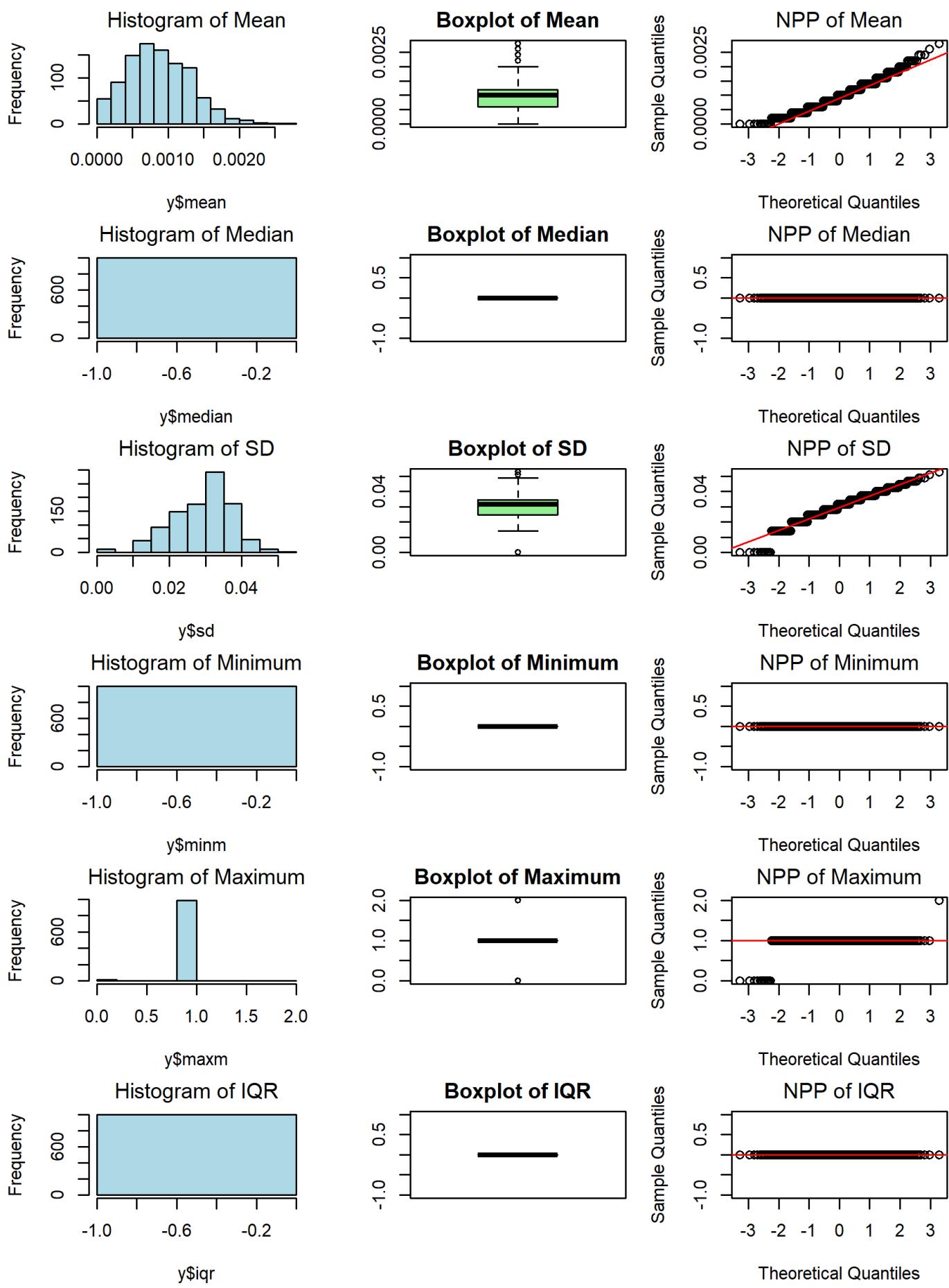
(n=500, nn=1000,  $\lambda = 0.001$ )



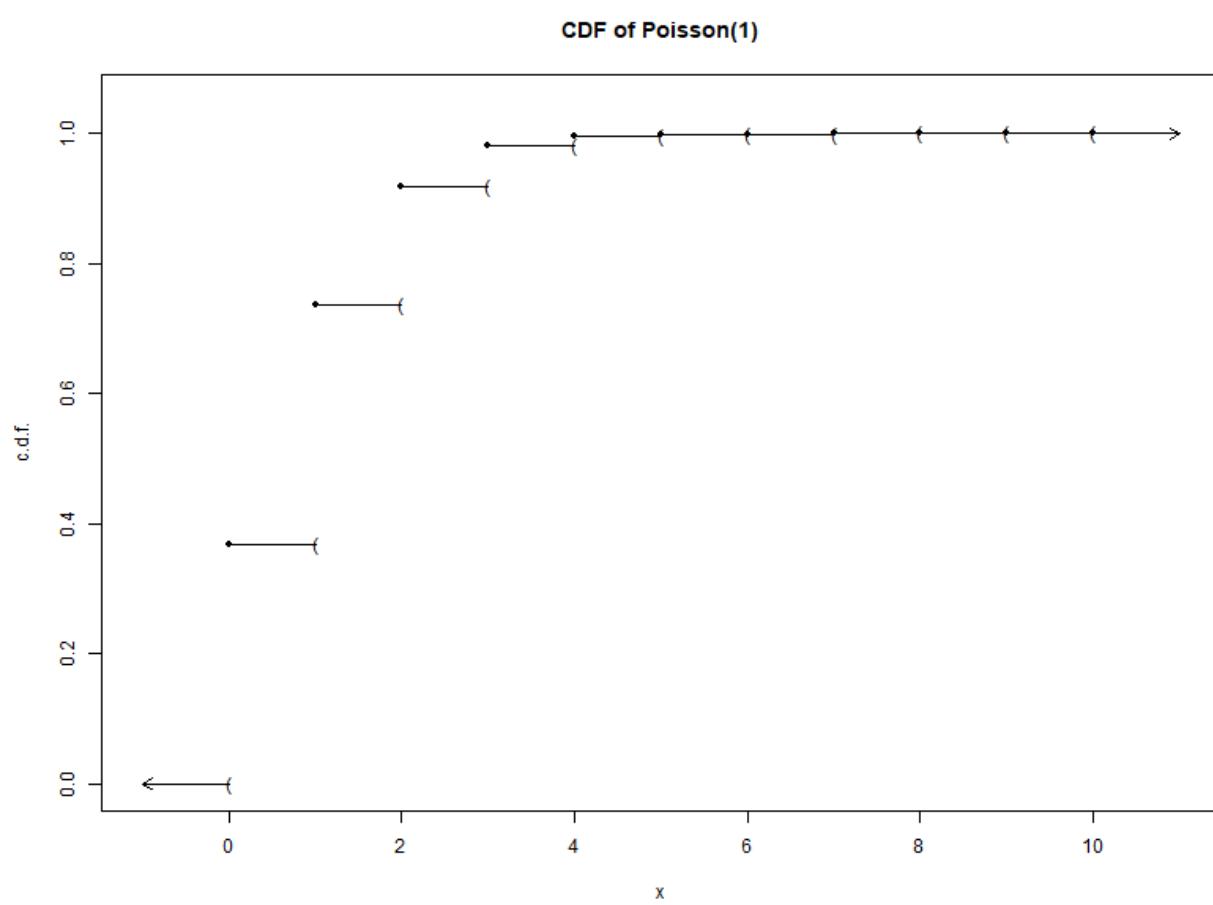
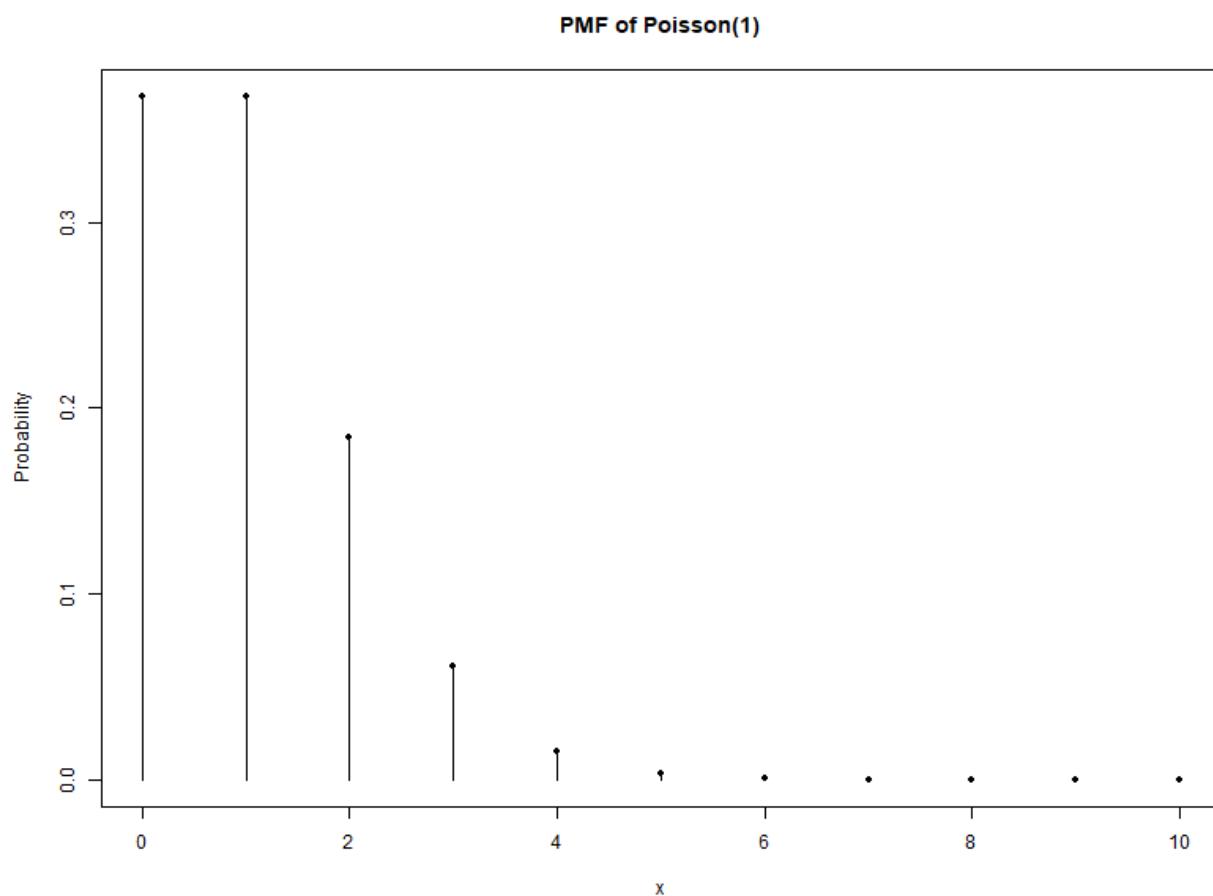
# POISSON DISTRIBUTION PLOT

(n=1000, nn=1000,  $\lambda = 0.001$ )





# POISSON DISTRIBUTION (1)



# POISSON DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\lambda = 1$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Median	No	No	No	No	No	No	No	NA	
Std Dev	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	No	No	NA	

## Conclusion for Poisson Distribution ( $\lambda = 1$ )

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 50$ , converging relatively quickly due to the moderate  $\lambda$  value, which reduces the distribution's skewness.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 50$ , matching the convergence rate of the mean.

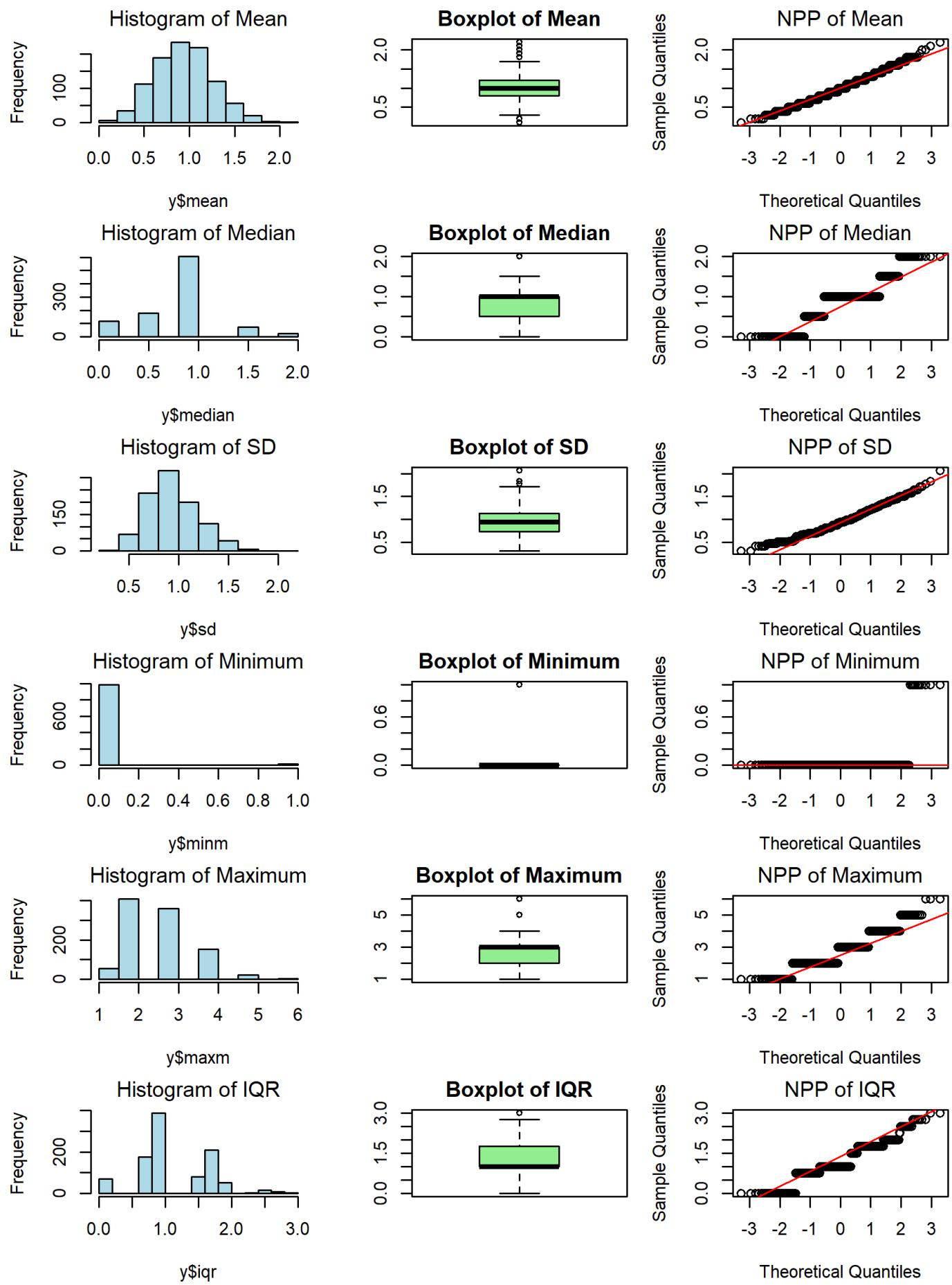
### Normality Not Achieved:

- **Median:** Does not achieve normality for any sample size, as the Poisson distribution remains discrete regardless of  $\lambda$ .
- **Minimum and Maximum:** Do not achieve normality for any sample size due to sensitivity to the extremes of the Poisson distribution.
- **IQR:** Does not achieve normality for any sample size, as it reflects the discrete and skewed nature of the distribution.

**Overall:** For the Poisson distribution with  $\lambda = 1$ , the mean and standard deviation achieve normality at  $n \geq 50$ , indicating a faster convergence compared to  $\lambda = 0.001$ . However, the median, minimum, maximum, and IQR remain non-normal, consistent with the characteristics of the Poisson distribution. This highlights that as  $\lambda$  increases, the convergence to normality for key statistics improves significantly.

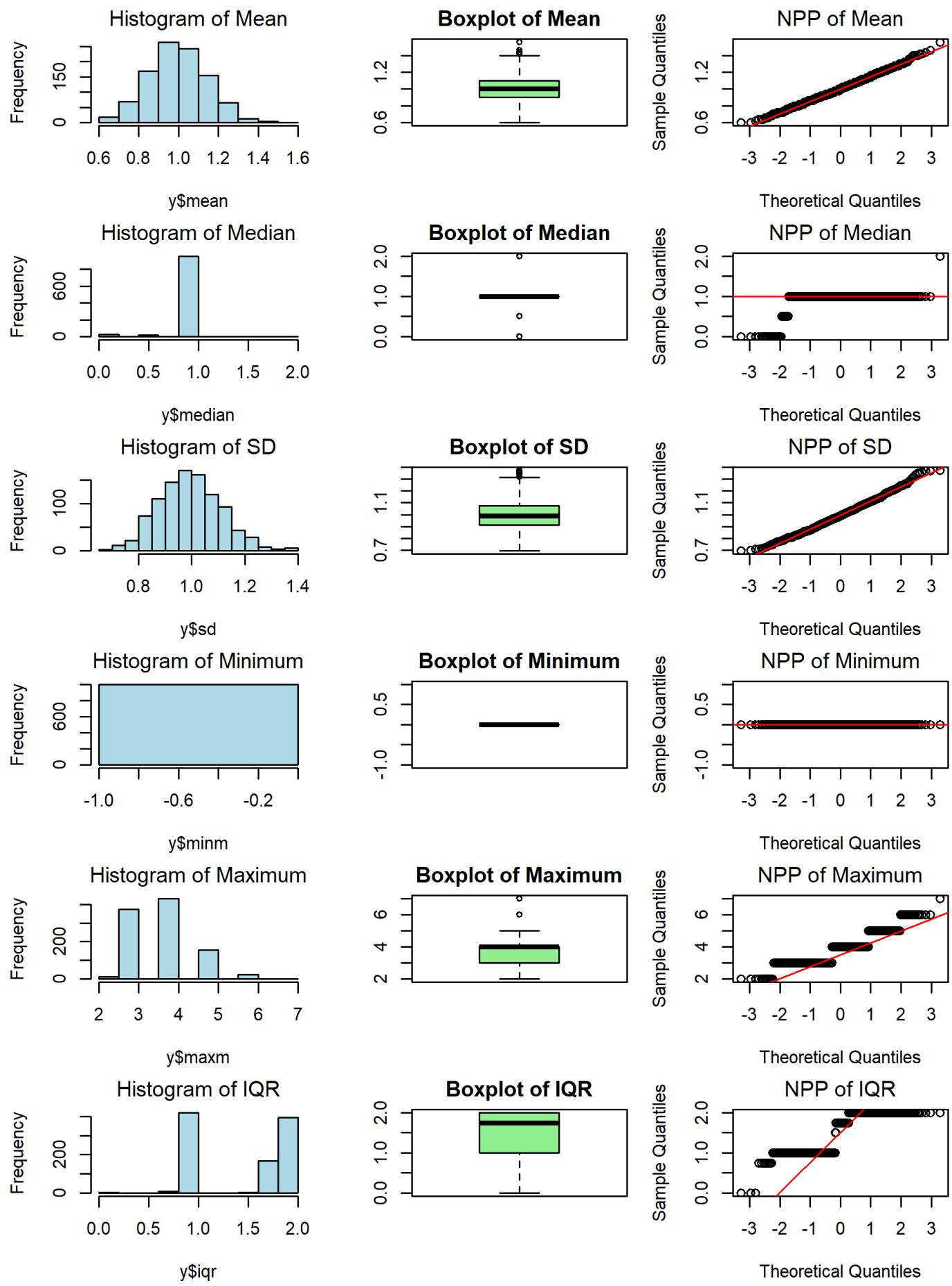
# POISSON DISTRIBUTION PLOT

(n=10, nn=1000,  $\lambda = 1$ )



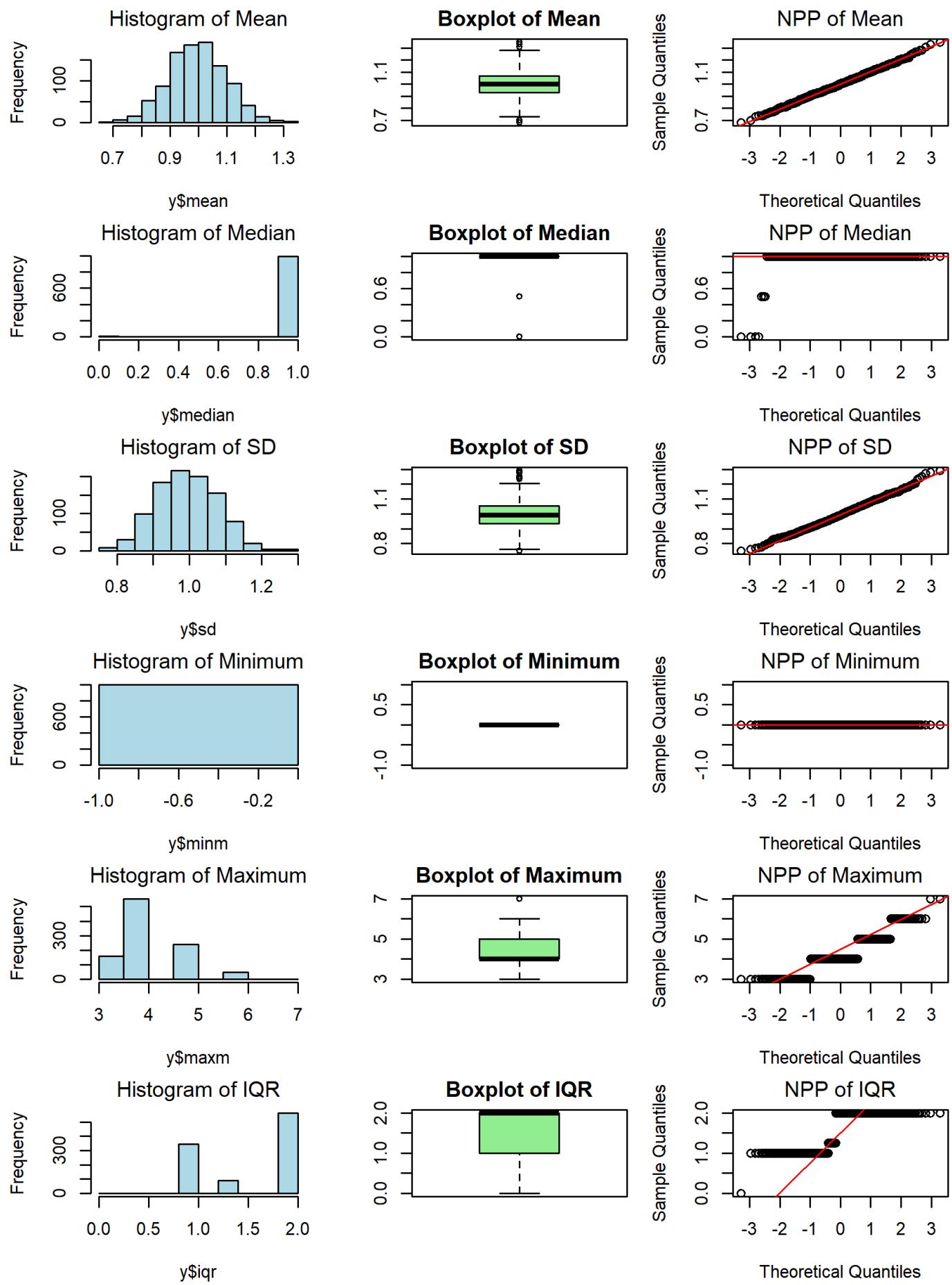
# POISSON DISTRIBUTION PLOT

(n=50, nn=1000,  $\lambda = 1$ )



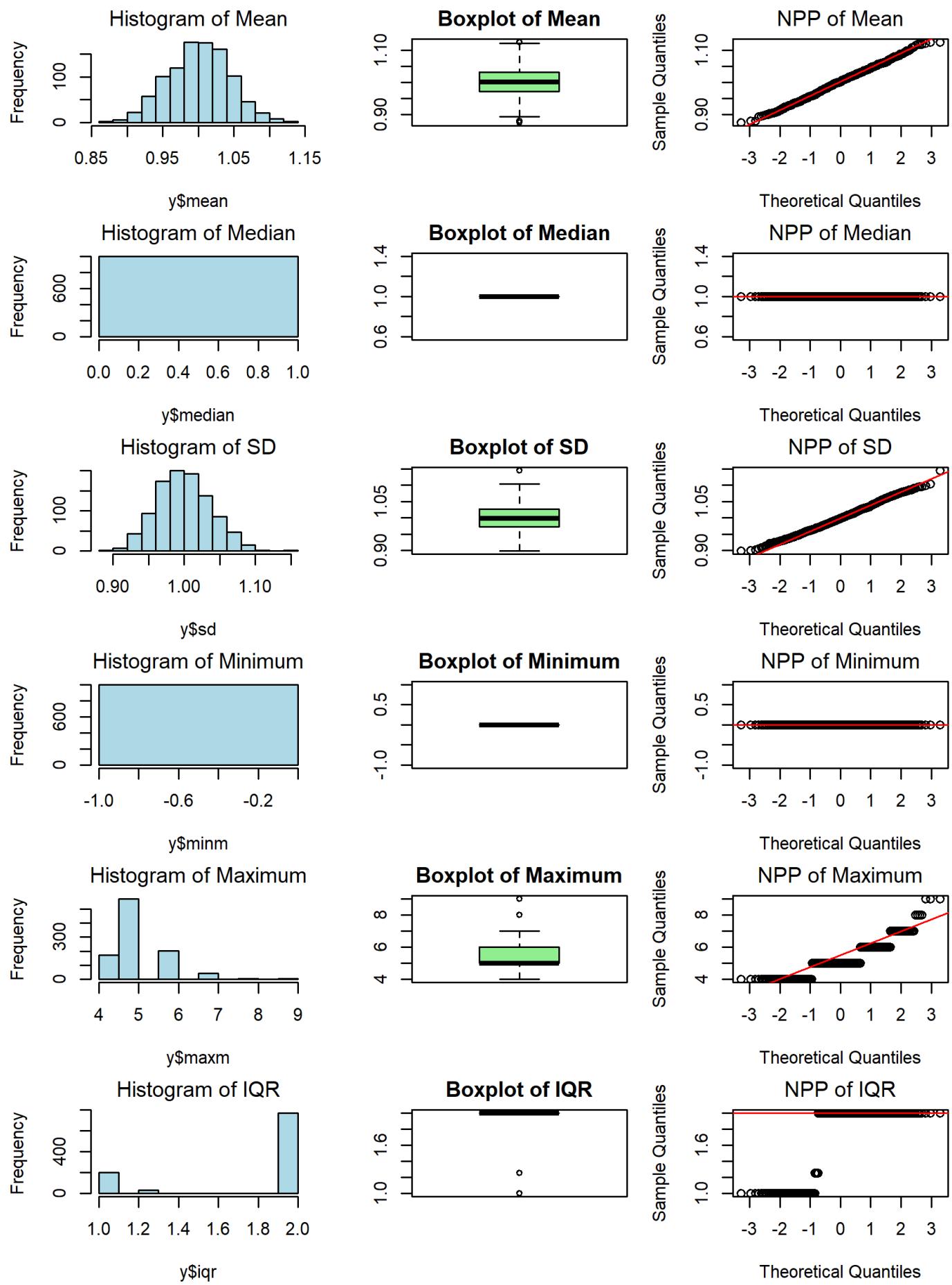
# POISSON DISTRIBUTION PLOT

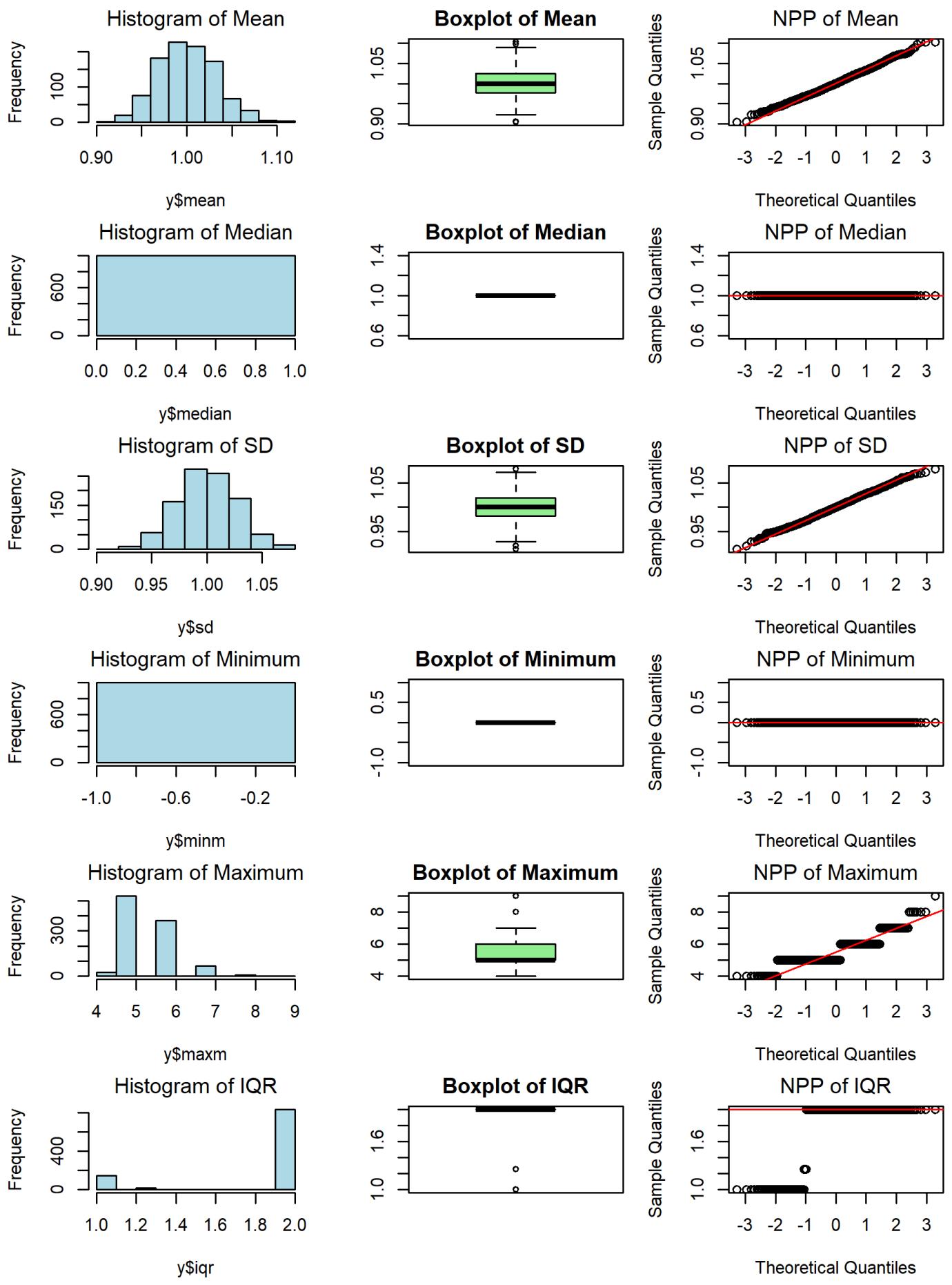
(n=100, nn=1000,  $\lambda = 1$ )

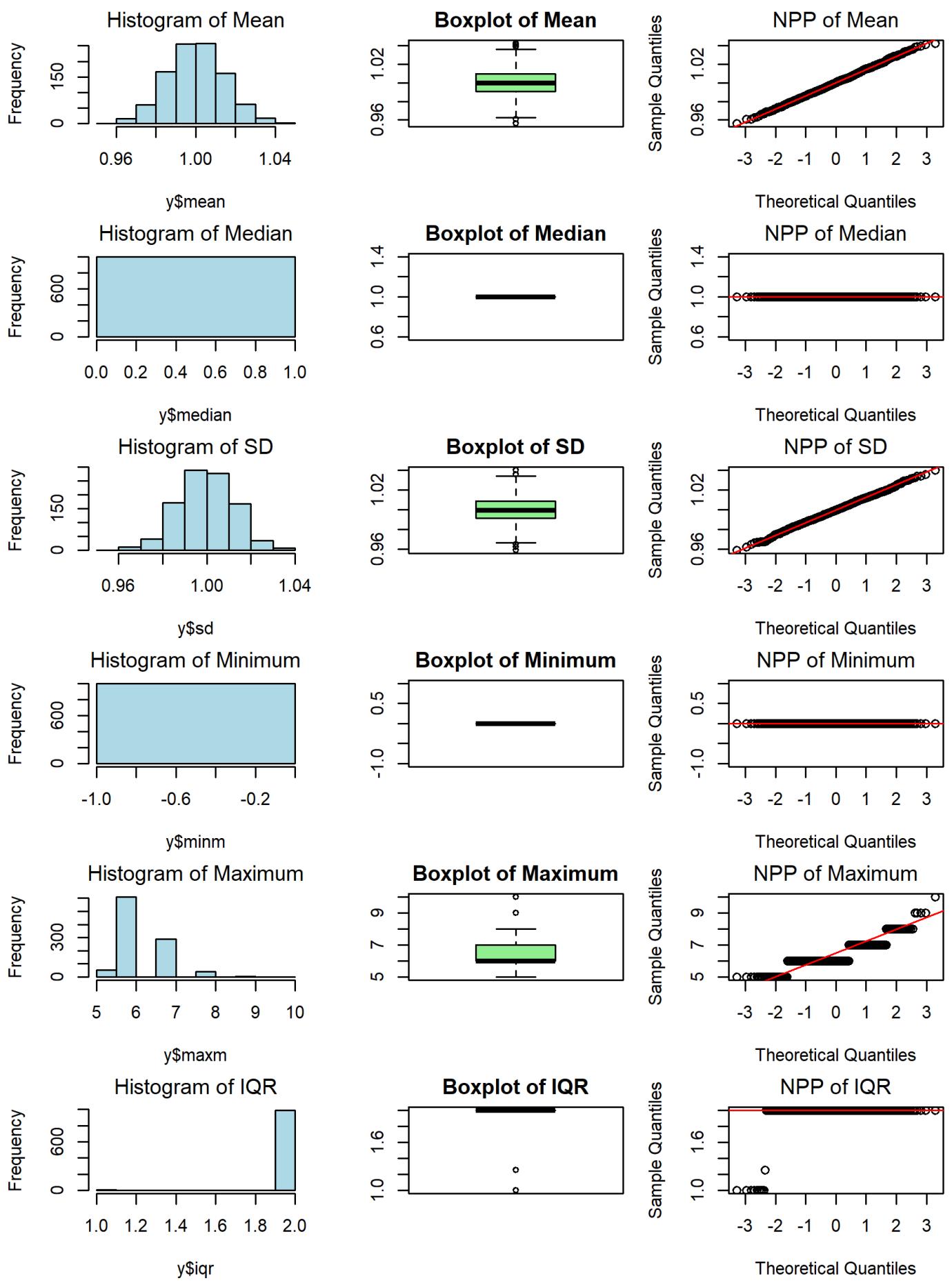


# POISSON DISTRIBUTION PLOT

(n=500, nn=1000,  $\lambda = 1$ )







# POISSON DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\lambda = 25$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Median	No	No	No	No	No	No	No	NA	
Std Dev	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	No	No	NA	

## Conclusion for Poisson Distribution ( $\lambda = 25$ )

### Normality Achieved:

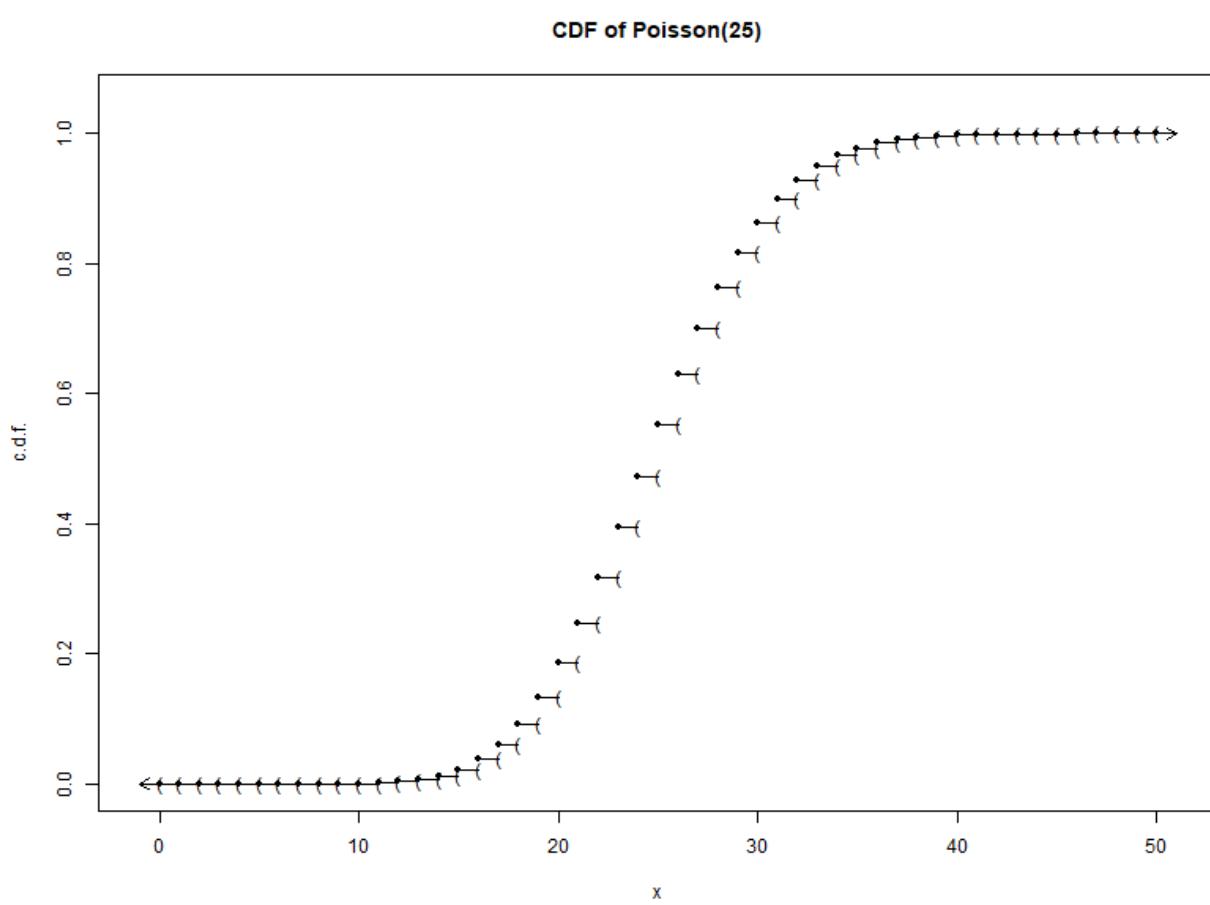
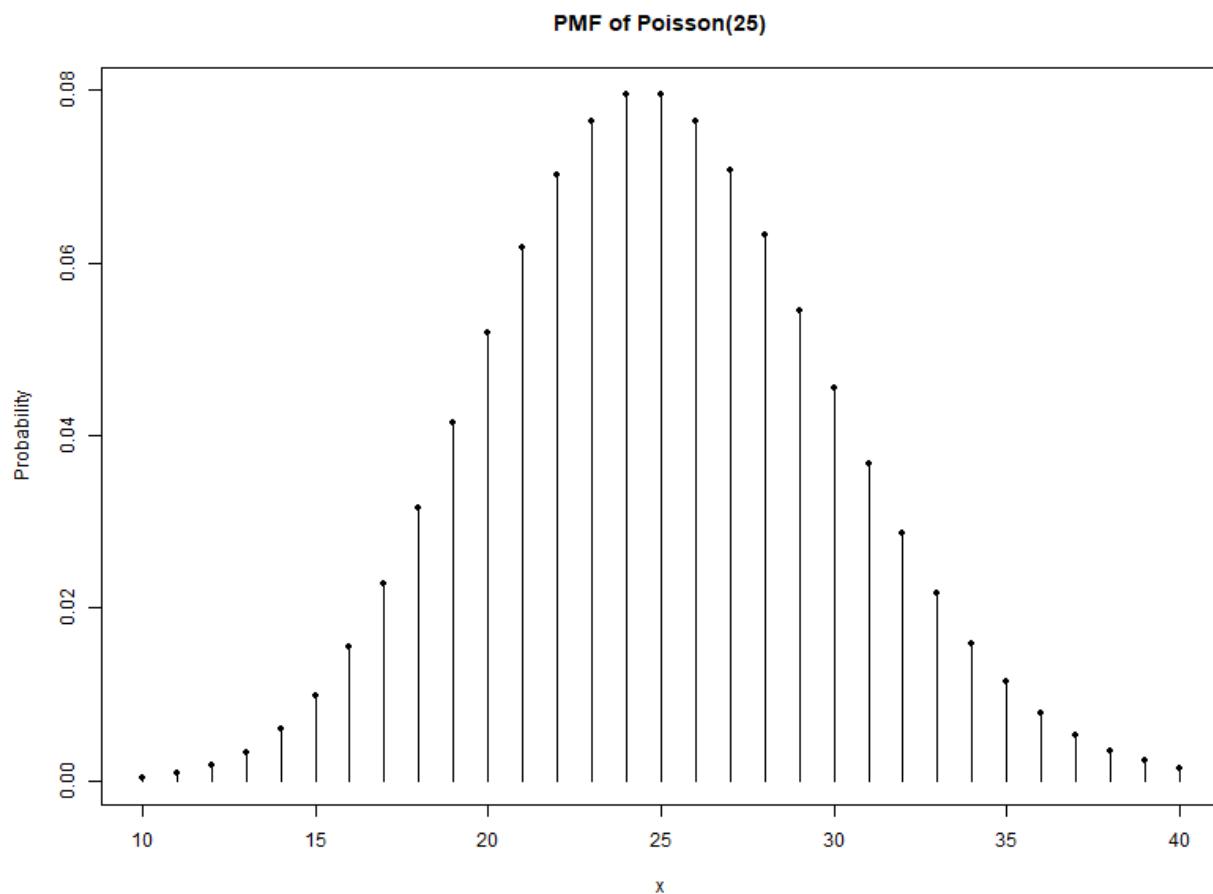
- **Mean:** Achieves normality for all sample sizes ( $n \geq 10$ ), as the higher  $\lambda$  value makes the distribution more symmetric and closer to the normal distribution even with smaller sample sizes.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 50$ , reflecting the rapid convergence due to reduced skewness at this higher  $\lambda$ .

### Normality Not Achieved:

- **Median:** Does not achieve normality for any sample size, as the Poisson distribution remains discrete despite the increased  $\lambda$  value.
- **Minimum and Maximum:** Do not achieve normality for any sample size, as they are influenced by the extreme tails of the distribution.
- **IQR:** Does not achieve normality for any sample size, indicating that interquartile properties are less affected by  $\lambda$  compared to the mean and SD.

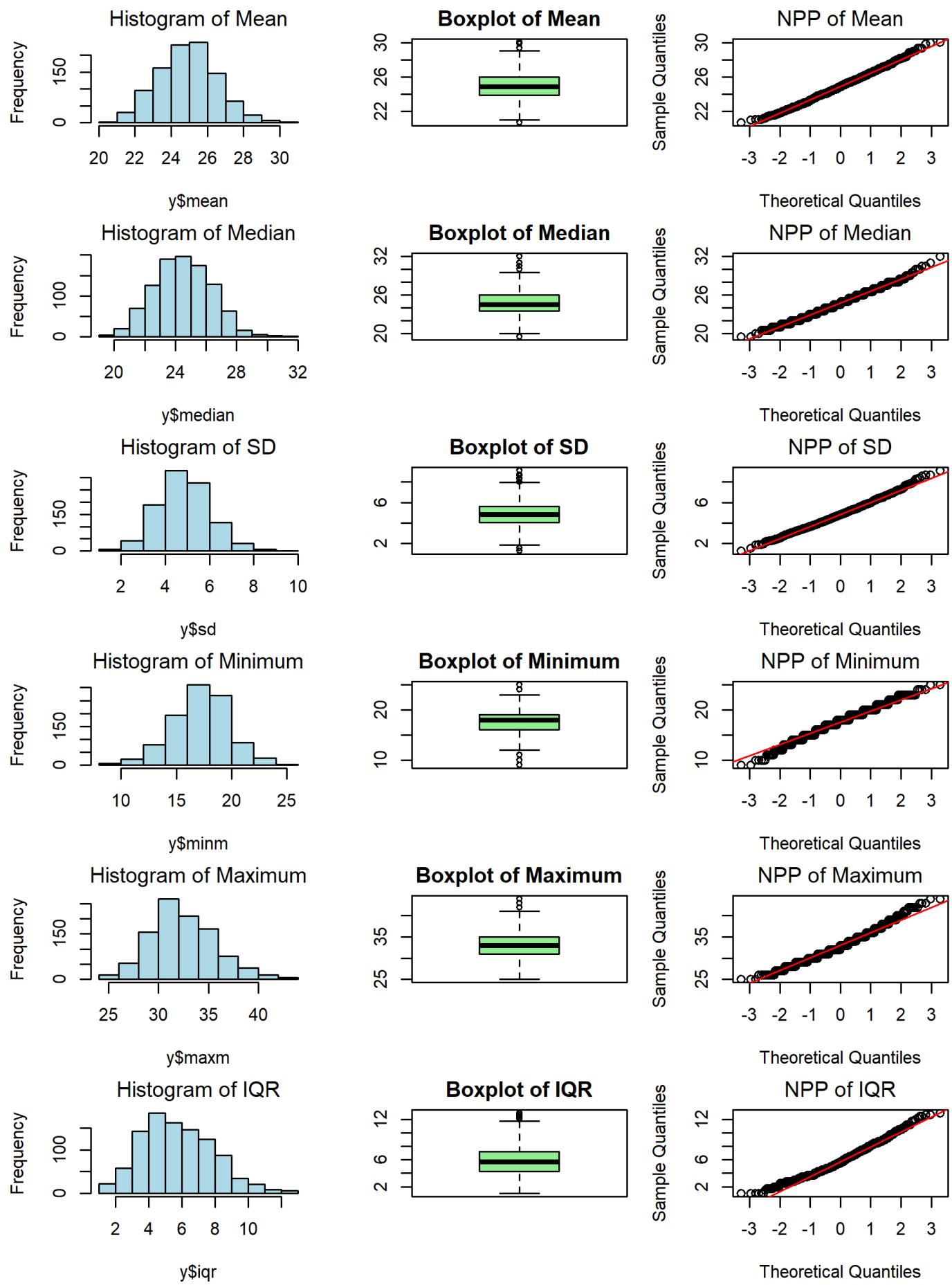
**Overall:** For the Poisson distribution with  $\lambda = 25$ , the mean achieves normality for all sample sizes, and the standard deviation follows closely at  $n \geq 50$ . This demonstrates the rapid convergence facilitated by the higher  $\lambda$  value. However, the median, minimum, maximum, and IQR remain non-normal, highlighting their resistance to convergence regardless of  $\lambda$ . The results underscore how larger  $\lambda$  values significantly enhance the normality of key statistics in the Poisson distribution.

# POISSON DISTRIBUTION (25)



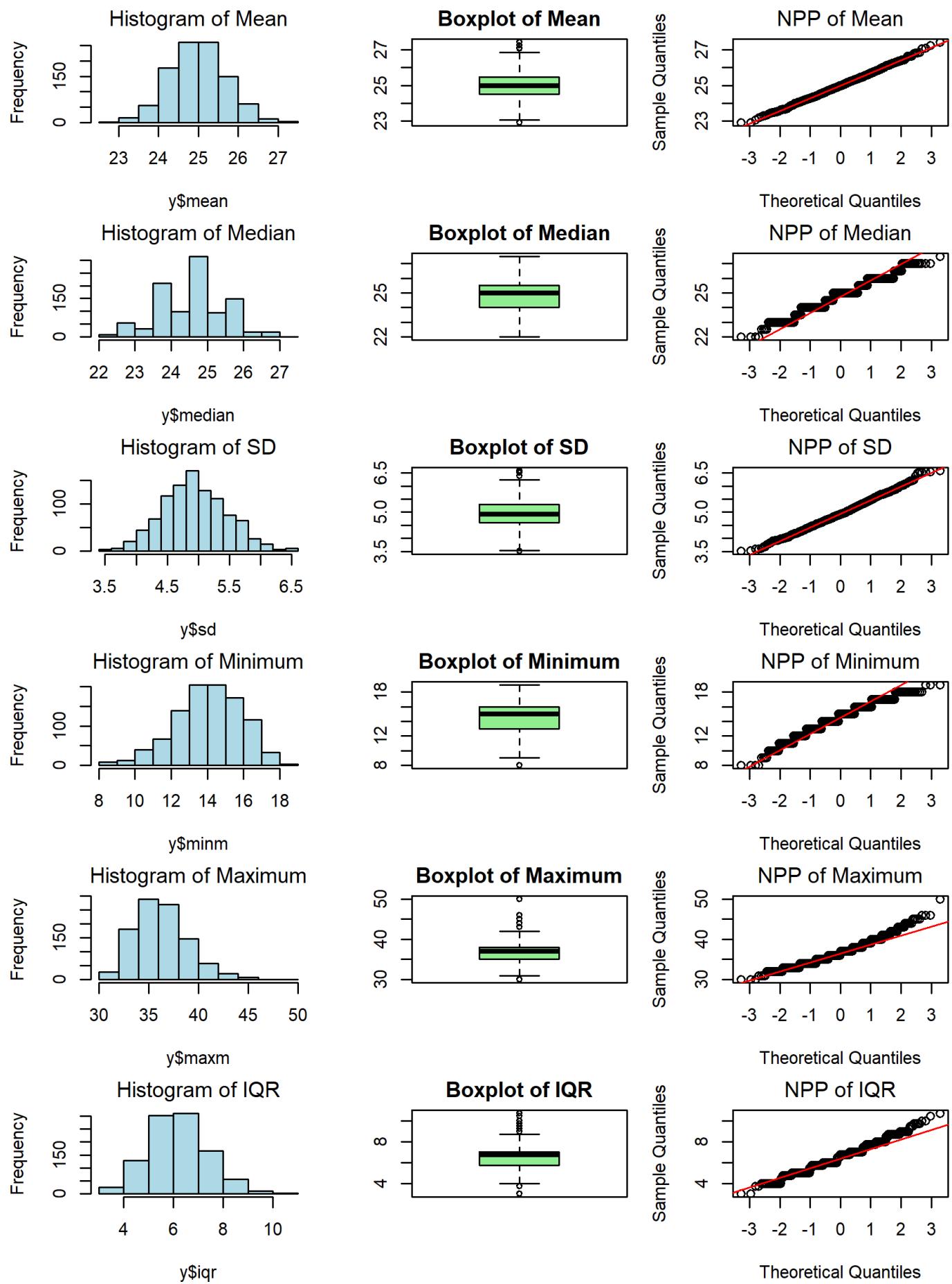
# POISSON DISTRIBUTION PLOT

(n=10, nn=1000,  $\lambda = 25$ )



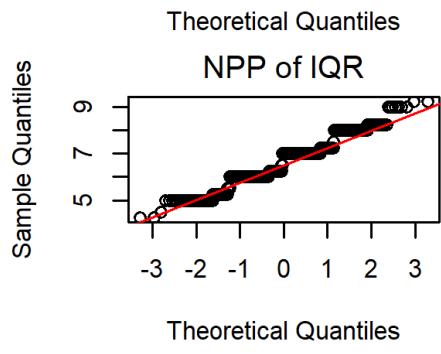
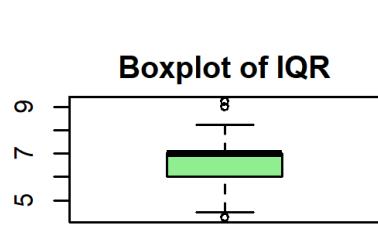
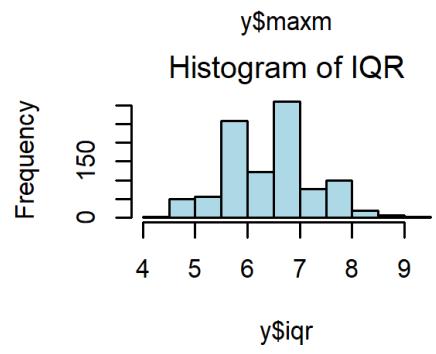
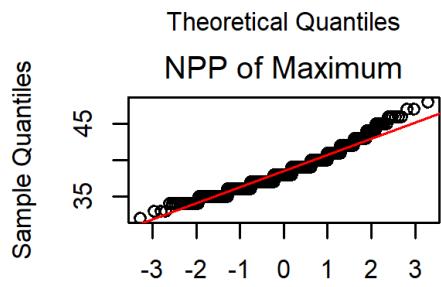
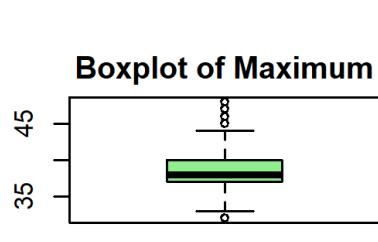
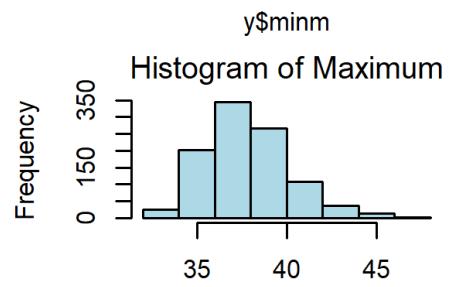
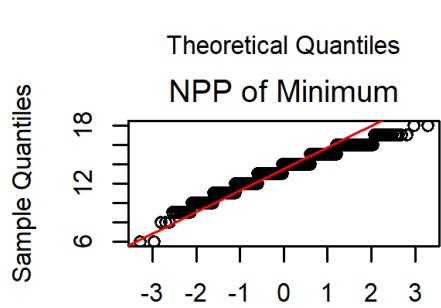
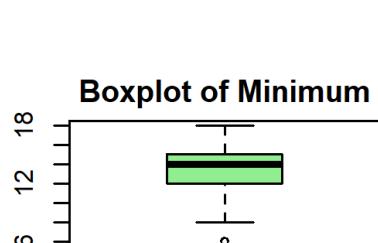
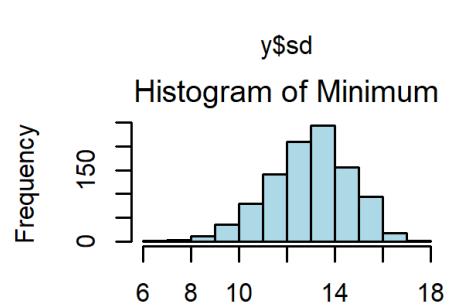
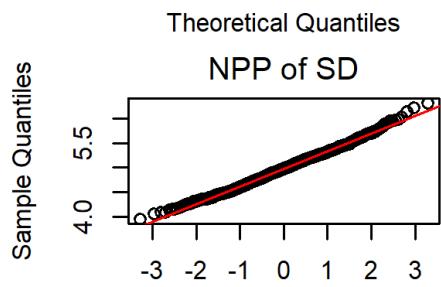
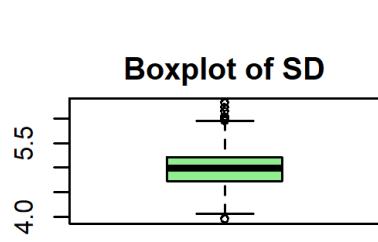
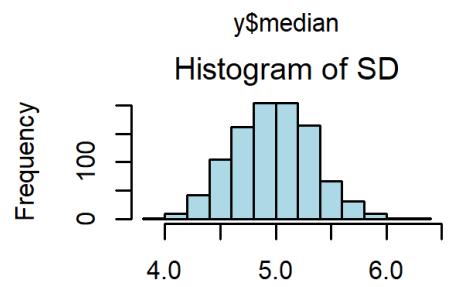
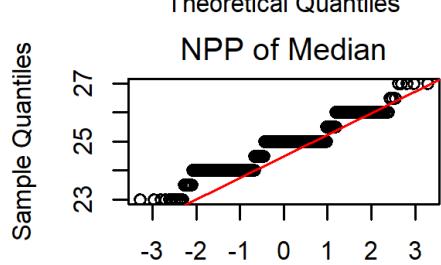
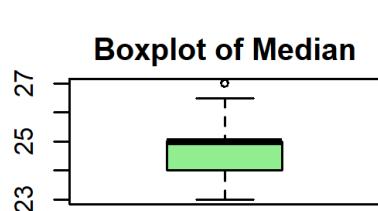
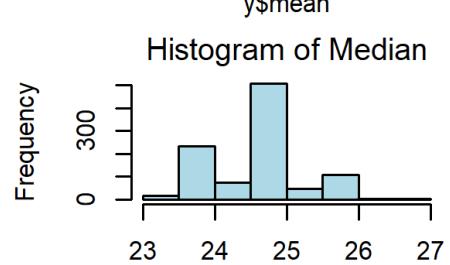
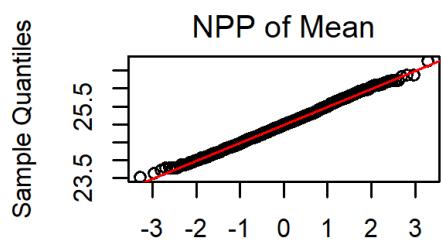
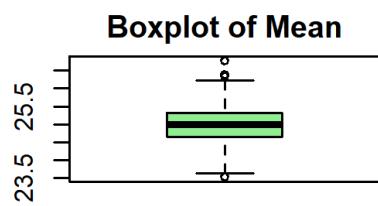
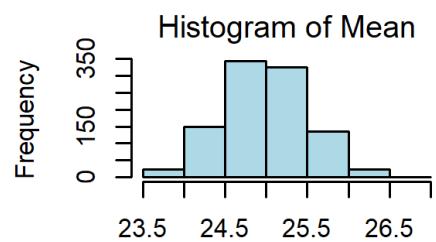
# POISSON DISTRIBUTION PLOT

(n=50, nn=1000,  $\lambda = 25$ )



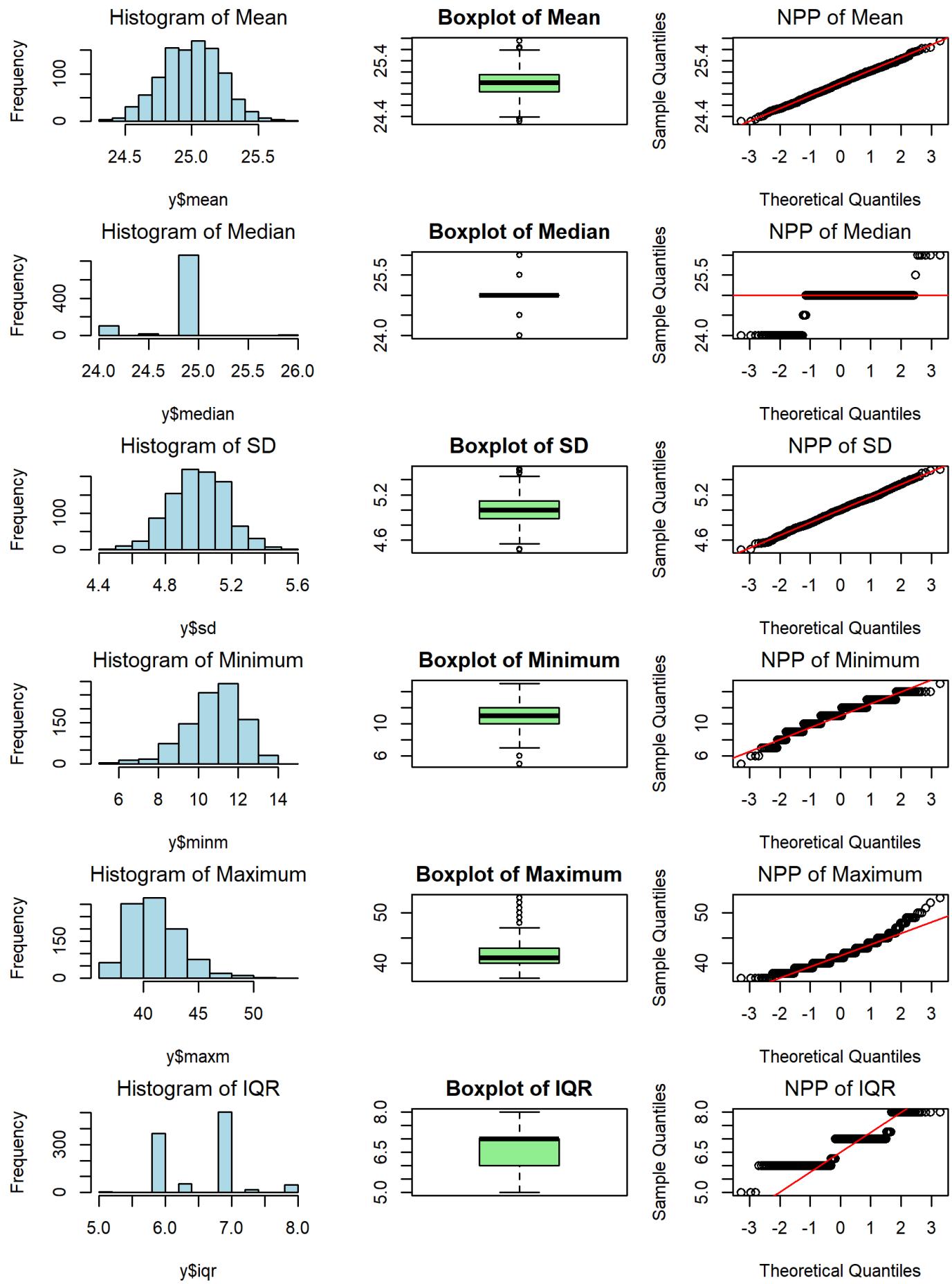
# POISSON DISTRIBUTION PLOT

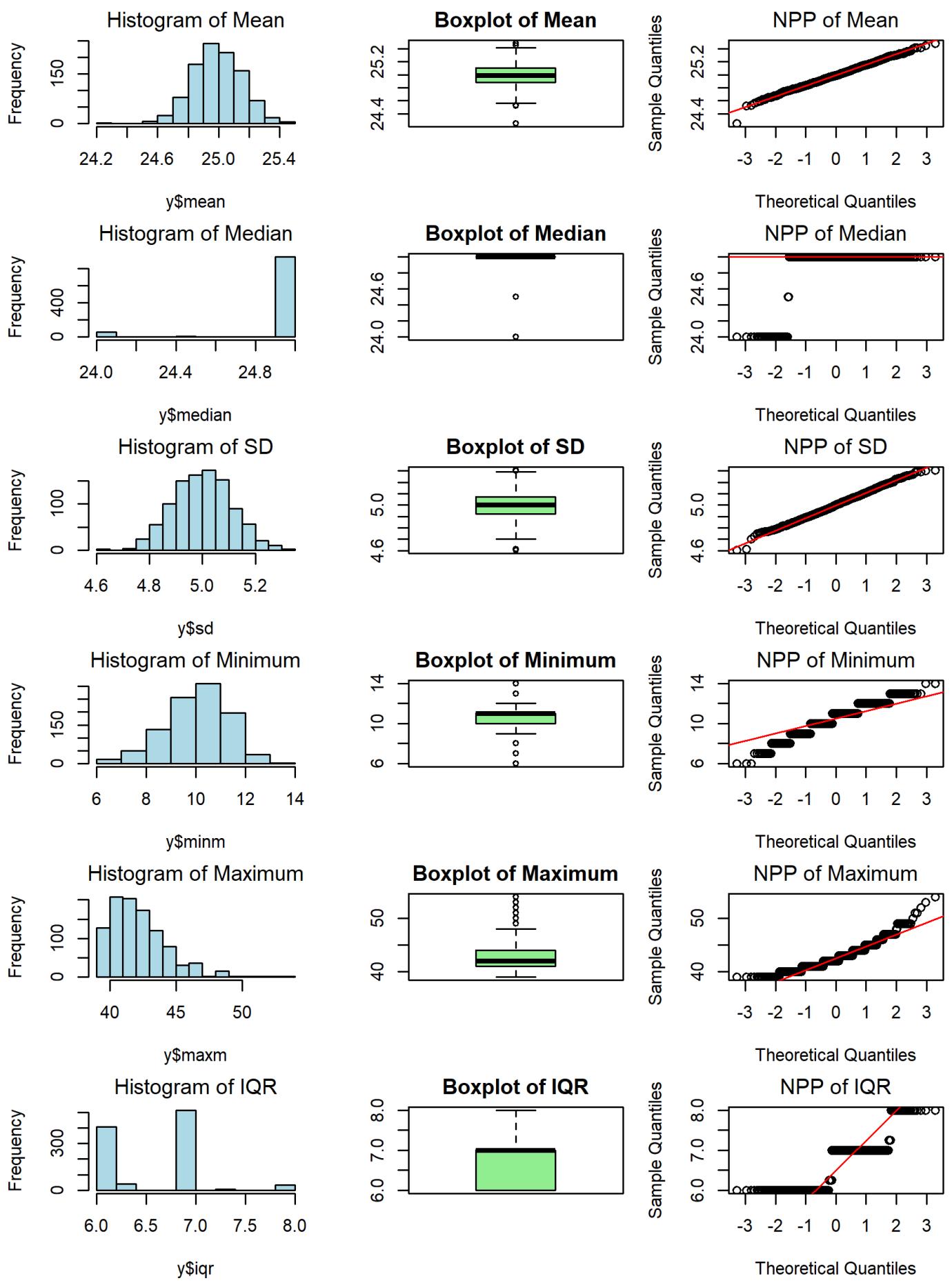
(n=100, nn=1000,  $\lambda = 25$ )

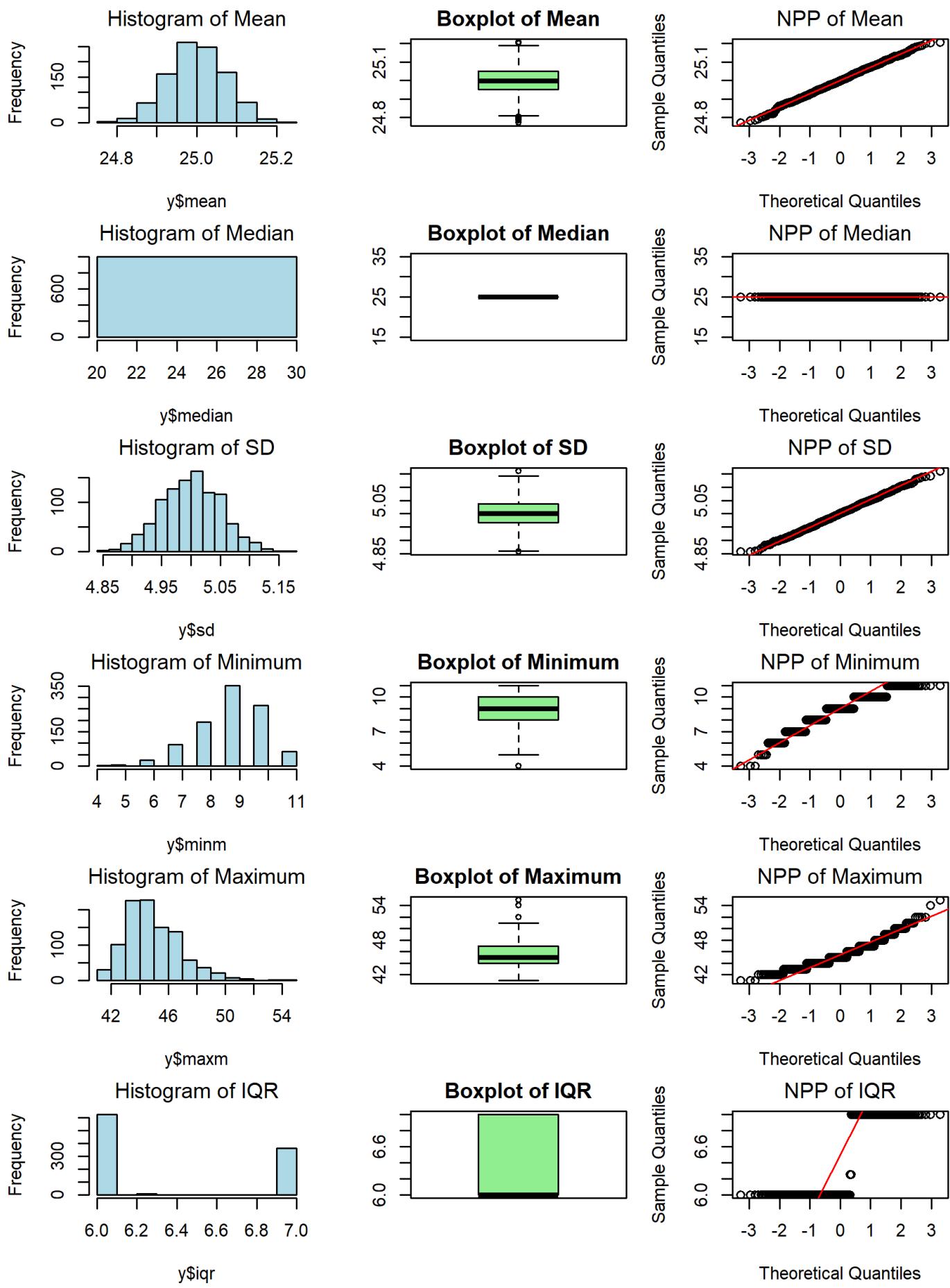


# POISSON DISTRIBUTION PLOT

(n=500, nn=1000,  $\lambda = 25$ )

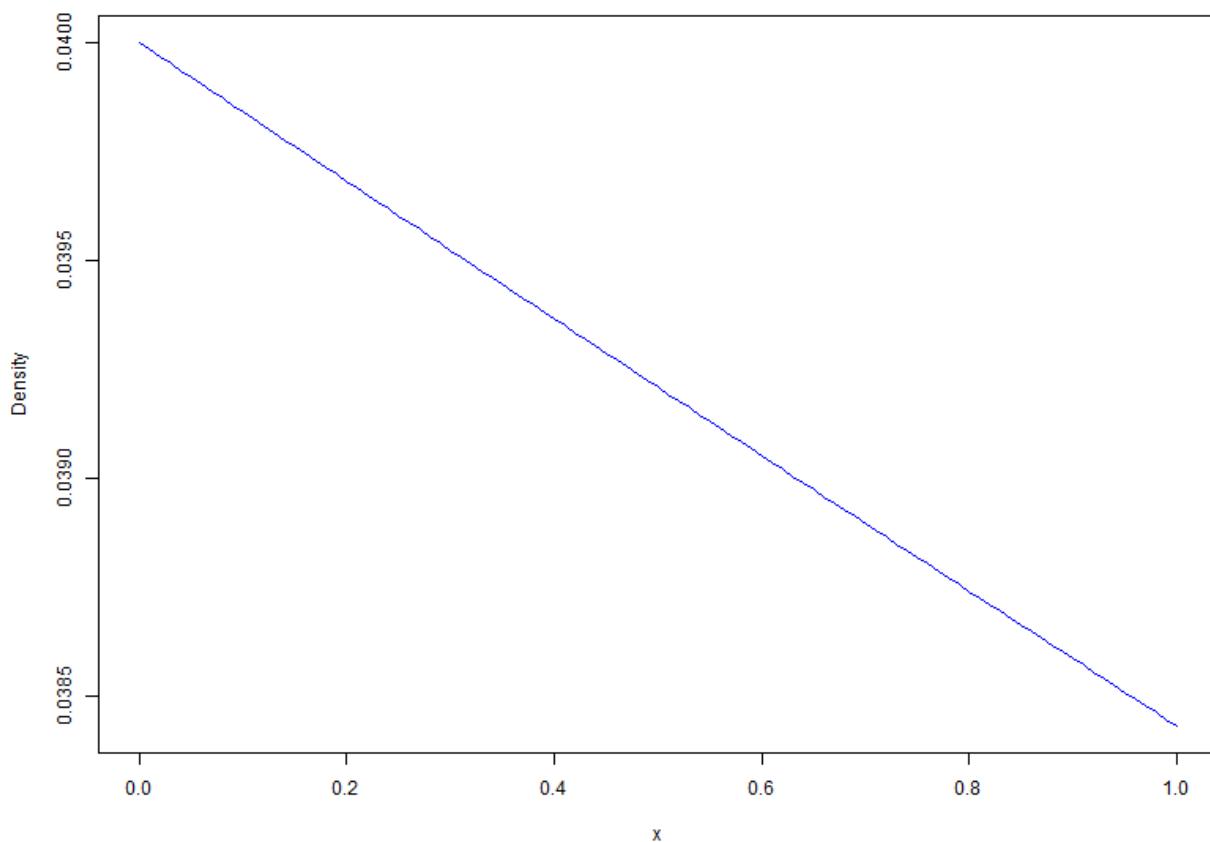




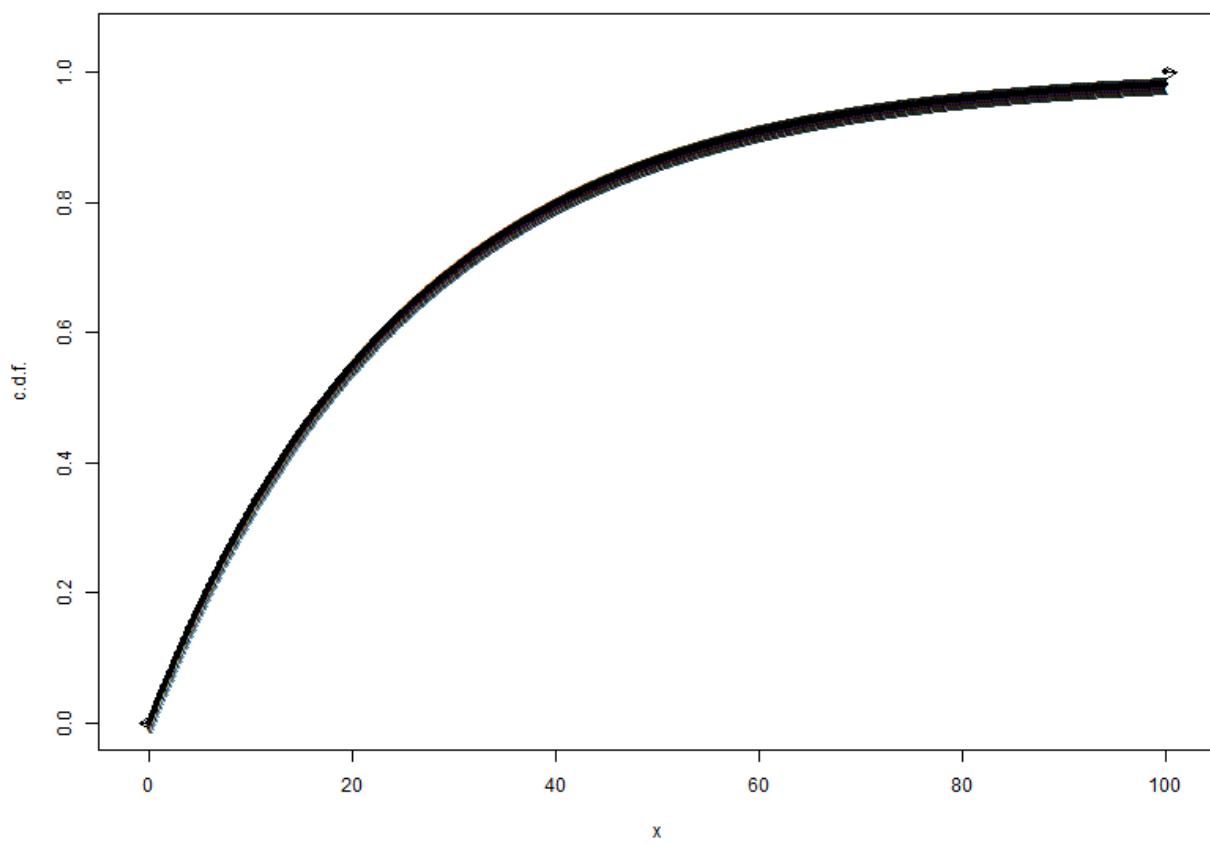


# EXPONENTIAL DISTRIBUTION (25)

PDF of Exponential(25)



CDF of Exponential(25)



# EXPONENTIAL DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\lambda=25$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Median	No	No	No	No	Yes	Yes	Yes	1000	
Std Dev	No	No	No	Yes	Yes	Yes	Yes	500	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	Yes	Yes	Yes	Yes	500	

## Conclusion for Exponential Distribution ( $\lambda = 25$ )

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 50$ , with a quicker convergence due to the relatively high  $\lambda$  value. This makes the distribution less skewed compared to lower  $\lambda$  values.
- **Median:** Achieves normality for  $n \geq 1000$ , with larger sample sizes required due to the distribution's skewness that reduces as  $n$  increases.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 500$ , reflecting a slower convergence due to the distribution's variability at smaller sample sizes.
- **IQR:** Achieves normality for  $n \geq 500$ , similar to the standard deviation, but with slower convergence than the mean.

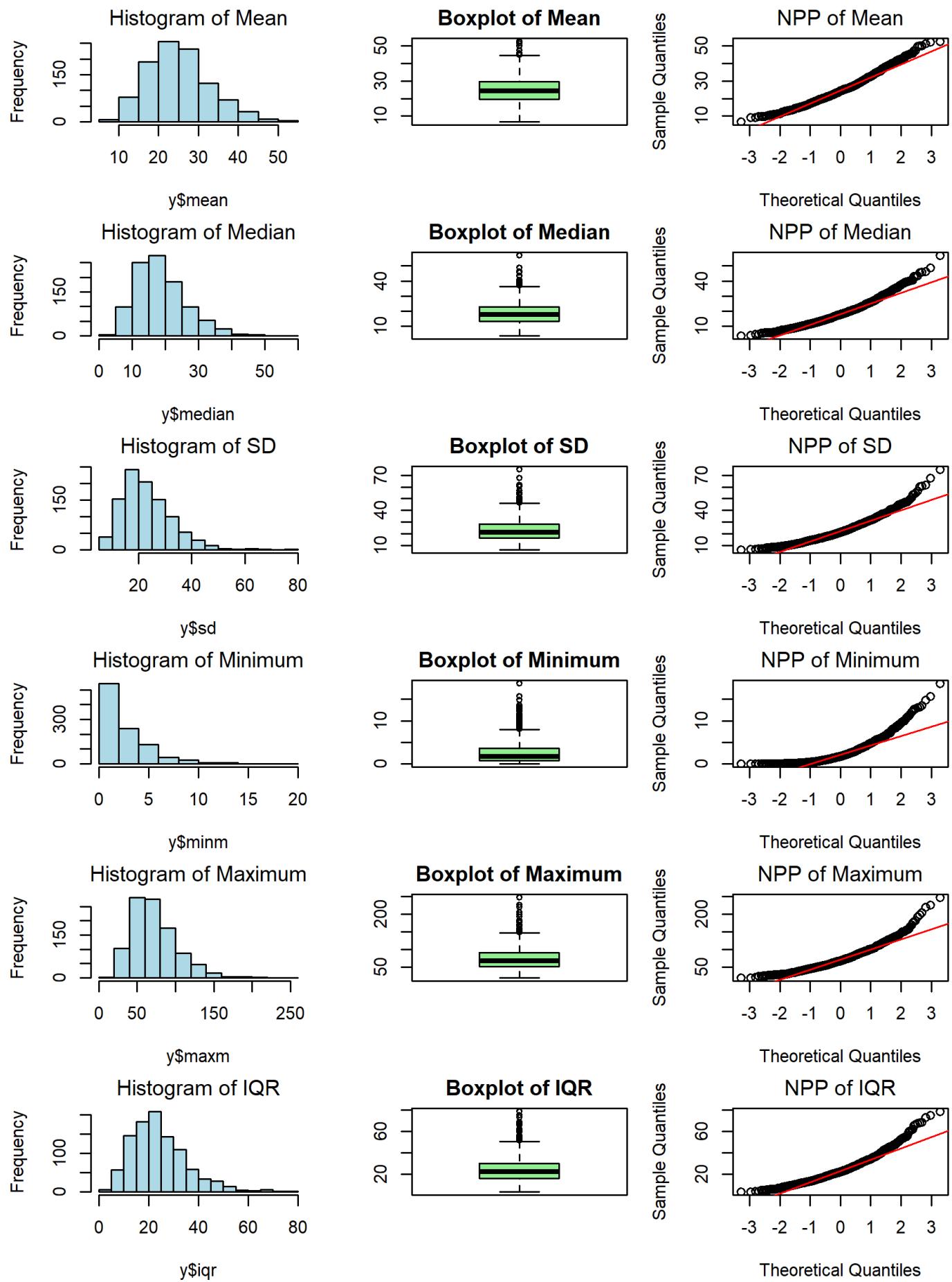
### Normality Not Achieved:

- **Minimum and Maximum:** Do not achieve normality for any sample size, as they are highly sensitive to the extreme values in the Exponential distribution.

**Overall:** For the Exponential distribution with  $\lambda = 25$ , the mean achieves normality quickly at  $n \geq 50$ , while the median, standard deviation, and IQR require larger sample sizes ( $n \geq 500$  to  $n \geq 1000$ ). The minimum and maximum remain non-normal due to the inherent skewness and extreme values in the distribution.

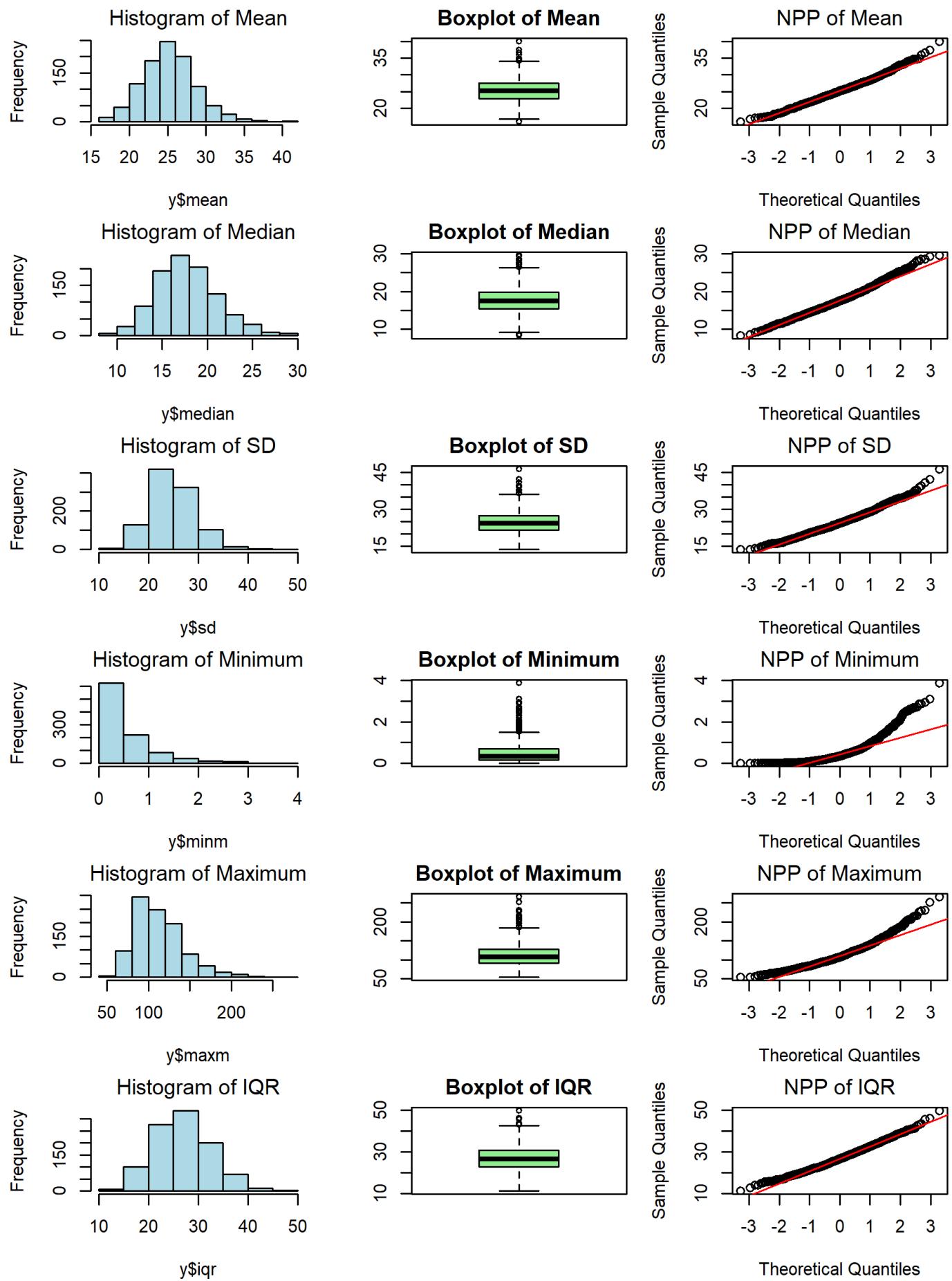
# EXPONENTIAL DISTRIBUTION PLOT

(n=10, nn=1000,  $\lambda=25$ )



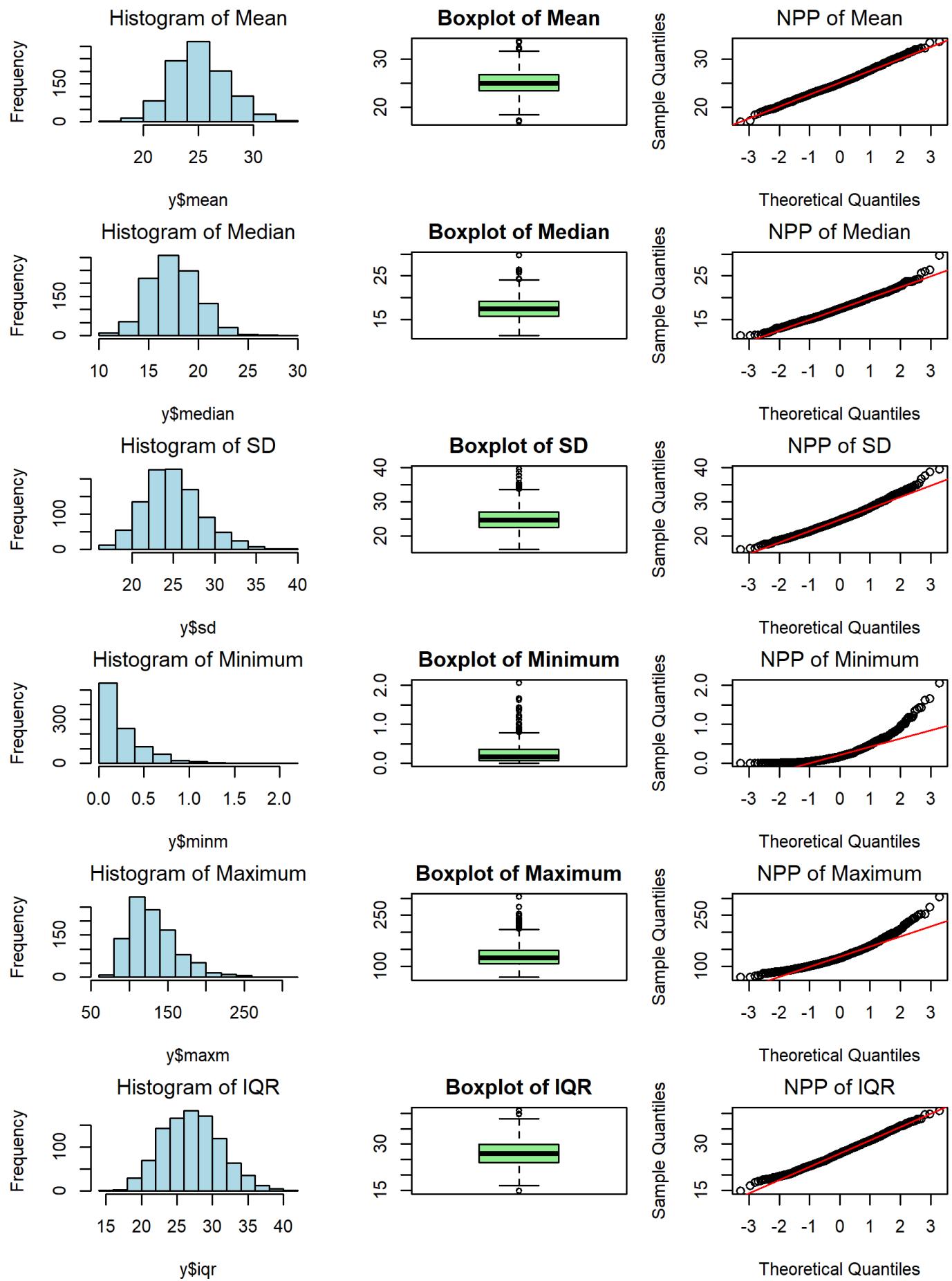
## EXPONENTIAL DISTRIBUTION PLOT

(n=50, nn=1000,  $\lambda$ =25)



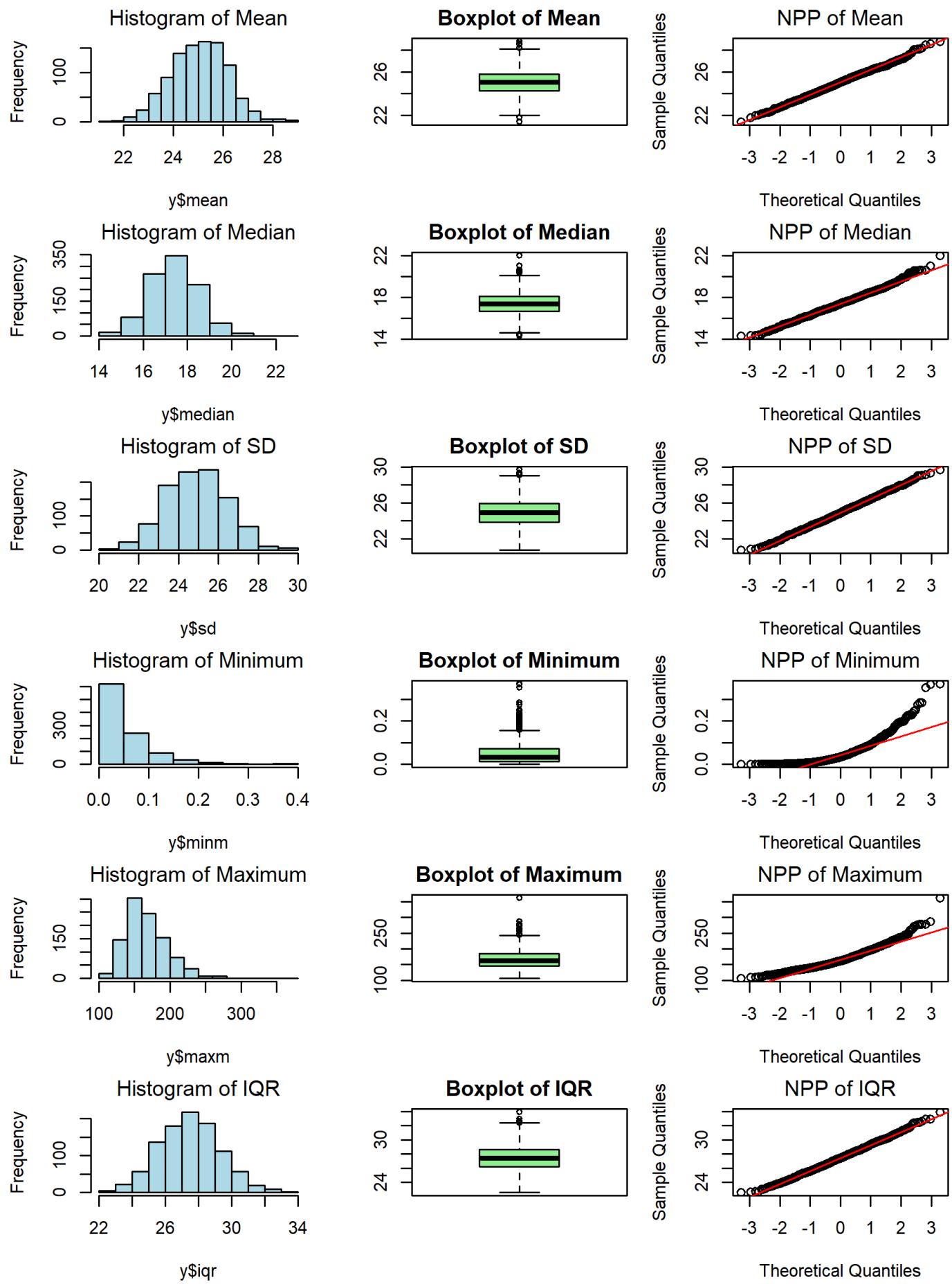
## EXPONENTIAL DISTRIBUTION PLOT

(n=100, nn=1000,  $\lambda$ =25)



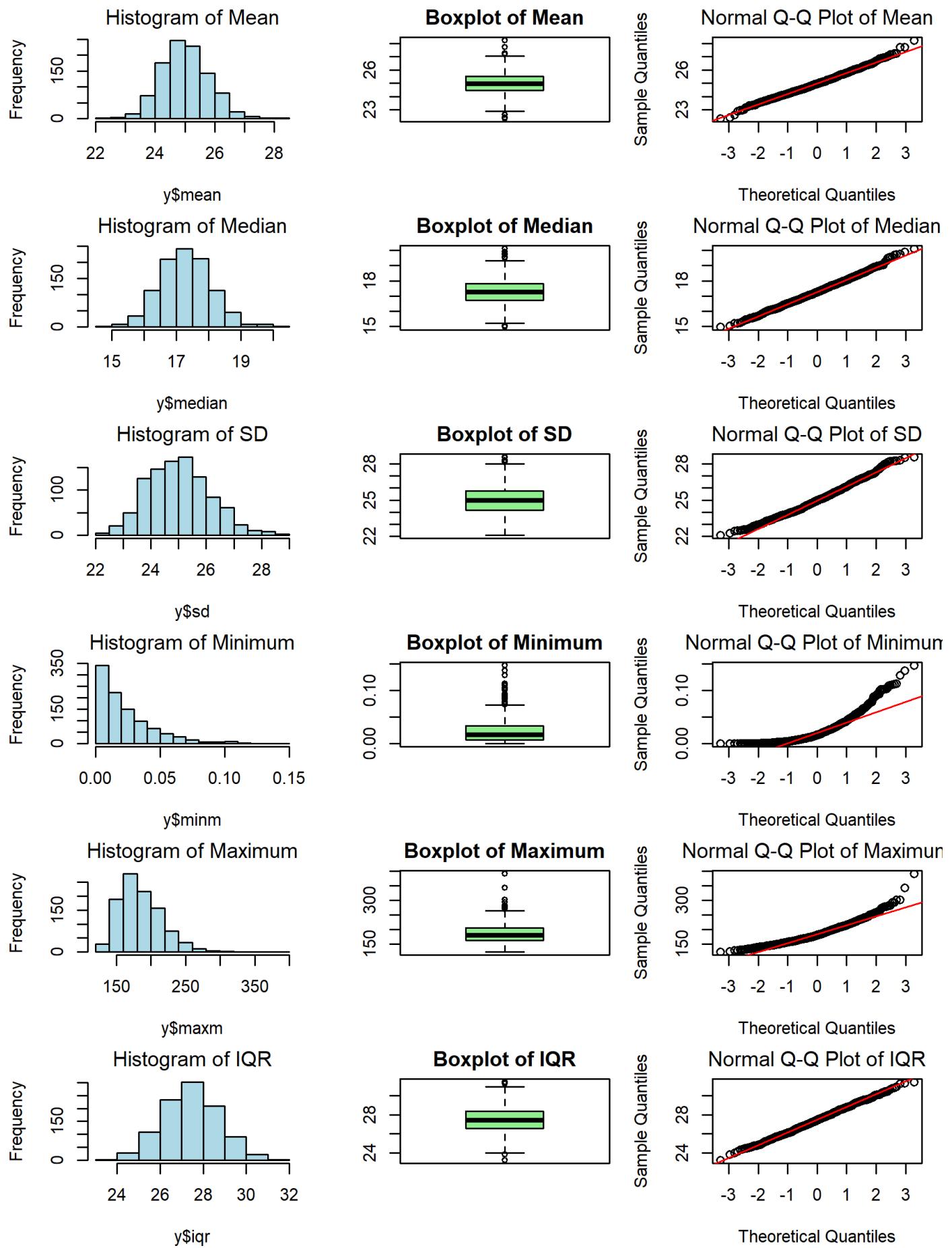
# EXPONENTIAL DISTRIBUTION PLOT

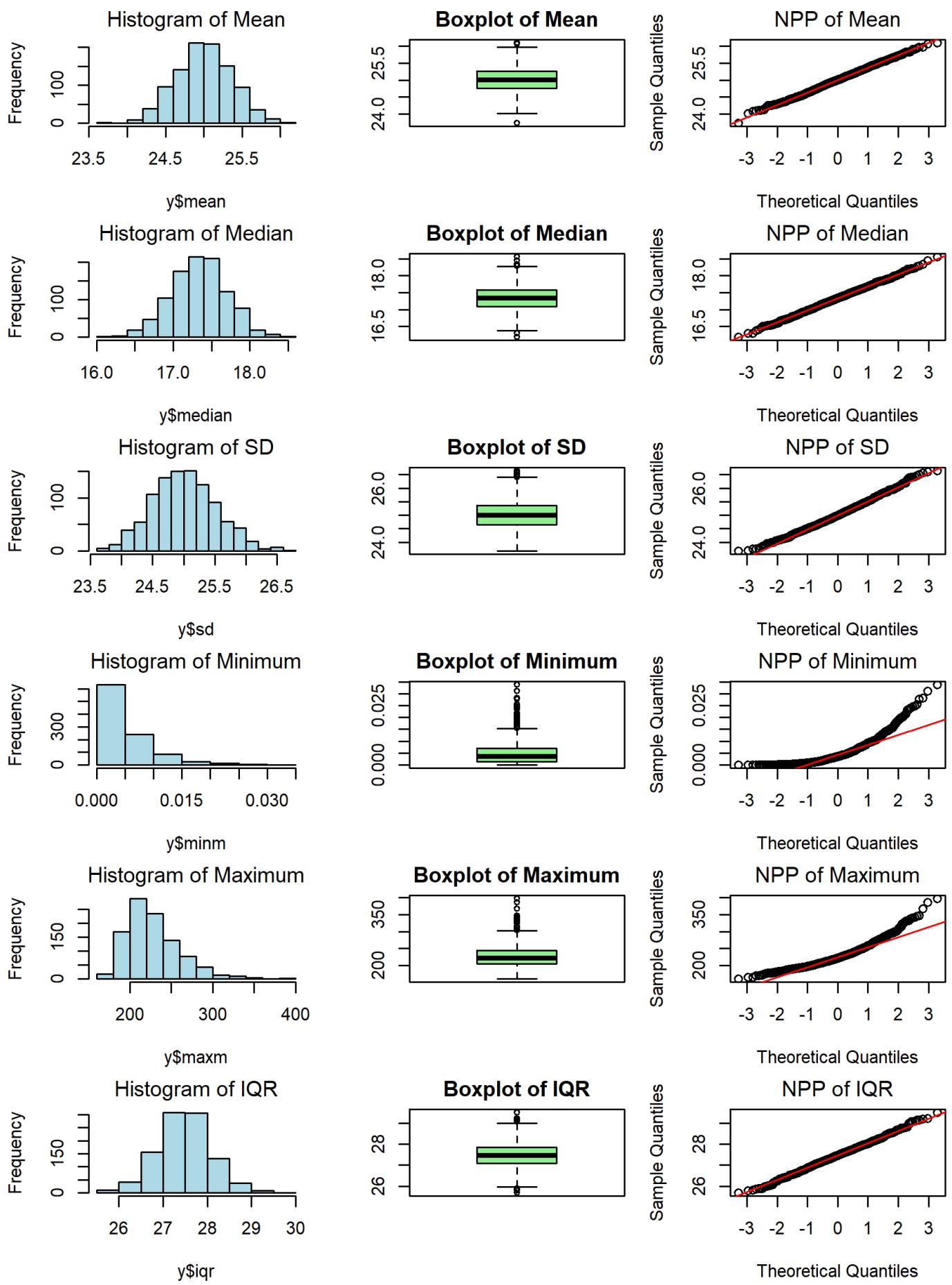
(n=500, nn=1000,  $\lambda=25$ )



## EXPONENTIAL DISTRIBUTION PLOT

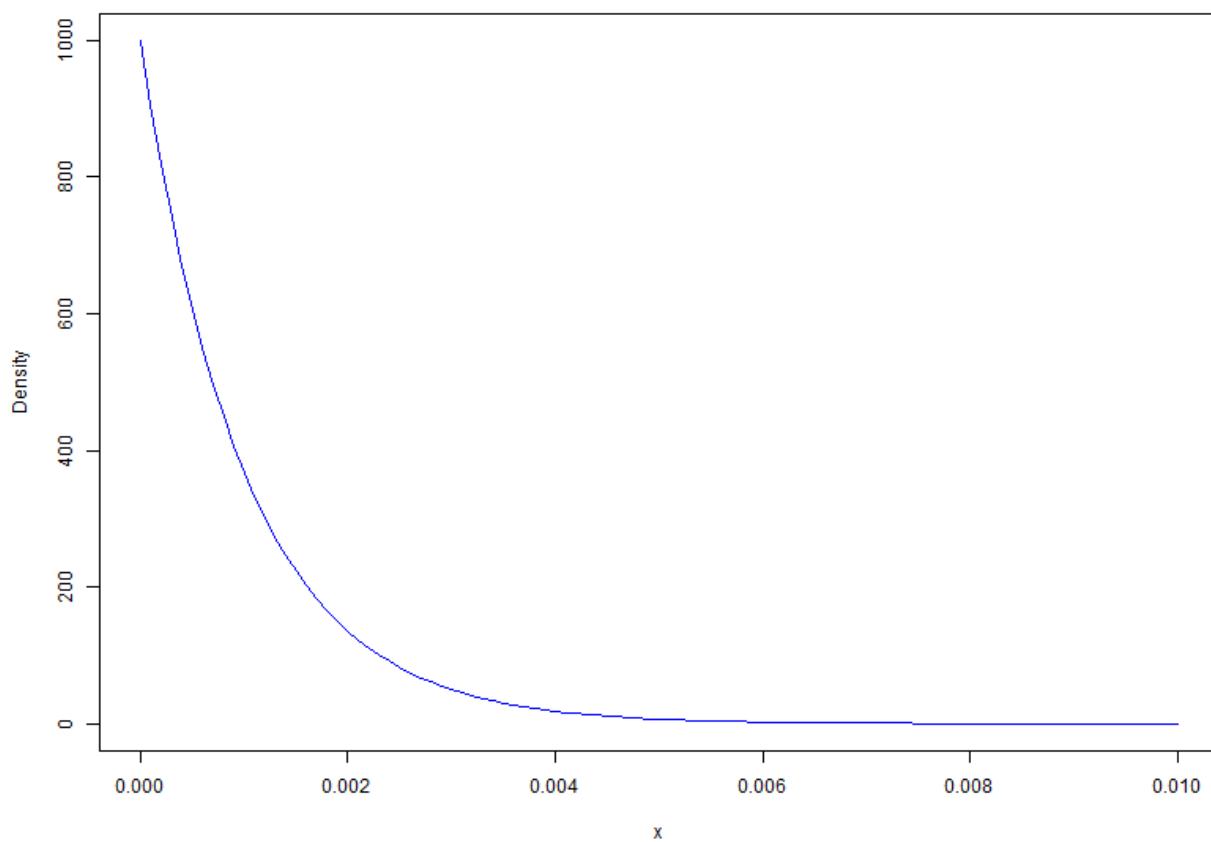
(n=1000, nn=1000,  $\lambda$ =25)



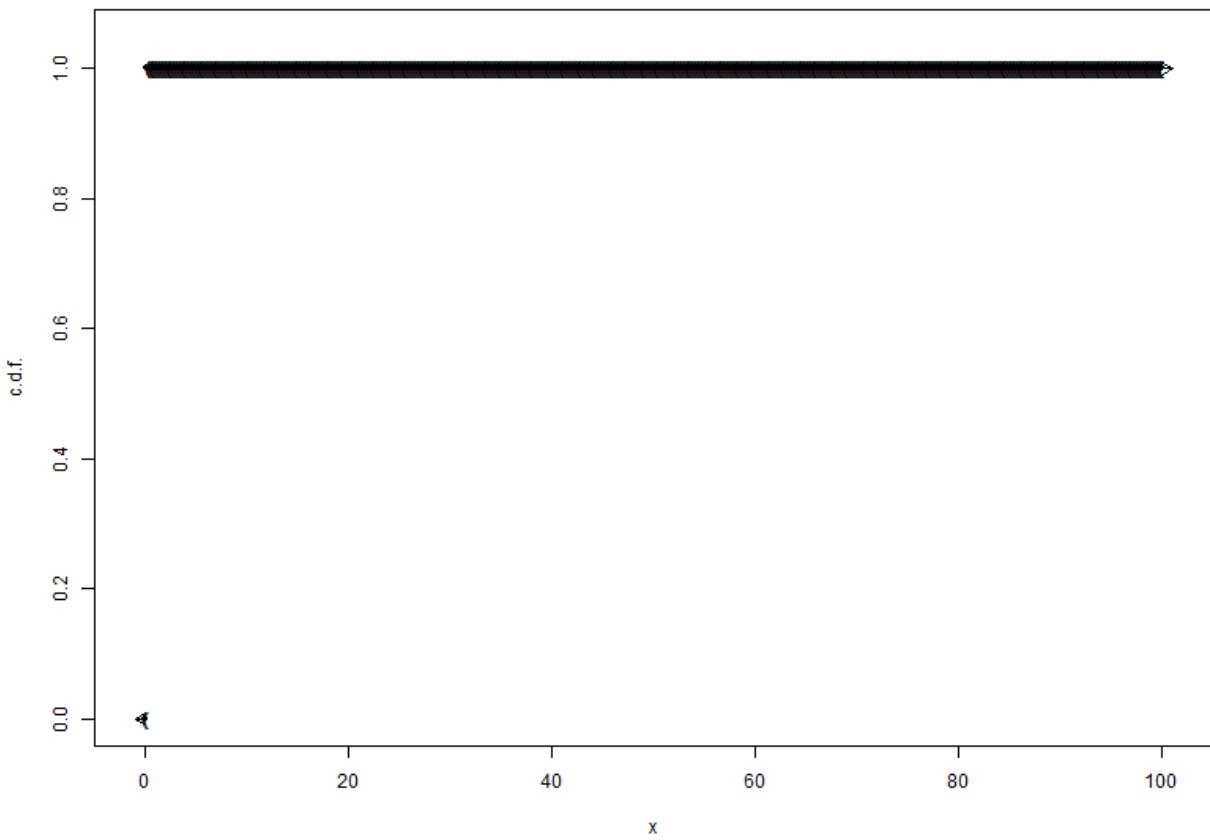


# EXPONENTIAL DISTRIBUTION (0.001)

PDF of Exponential(0.001)



CDF of Exponential(0.001)



# EXPONENTIAL DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\lambda=0.001$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	No	Yes	Yes	Yes	Yes	Yes	100	
Median	No	No	Yes	Yes	Yes	Yes	Yes	100	
Std Dev	No	No	Yes	Yes	Yes	Yes	Yes	100	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	Yes	Yes	Yes	1000	

## Conclusion for Exponential Distribution

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 100$ , reflecting moderate convergence due to the Central Limit Theorem (CLT).
- **Median:** Achieves normality for  $n \geq 100$ , with convergence similar to the mean despite the parent distribution's skewness.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 100$ , requiring comparable sample sizes to the mean and median for convergence.
- **IQR:** Achieves normality for  $n \geq 1000$ , showing slower convergence due to variability and sensitivity to skewness.

### Normality Not Achieved:

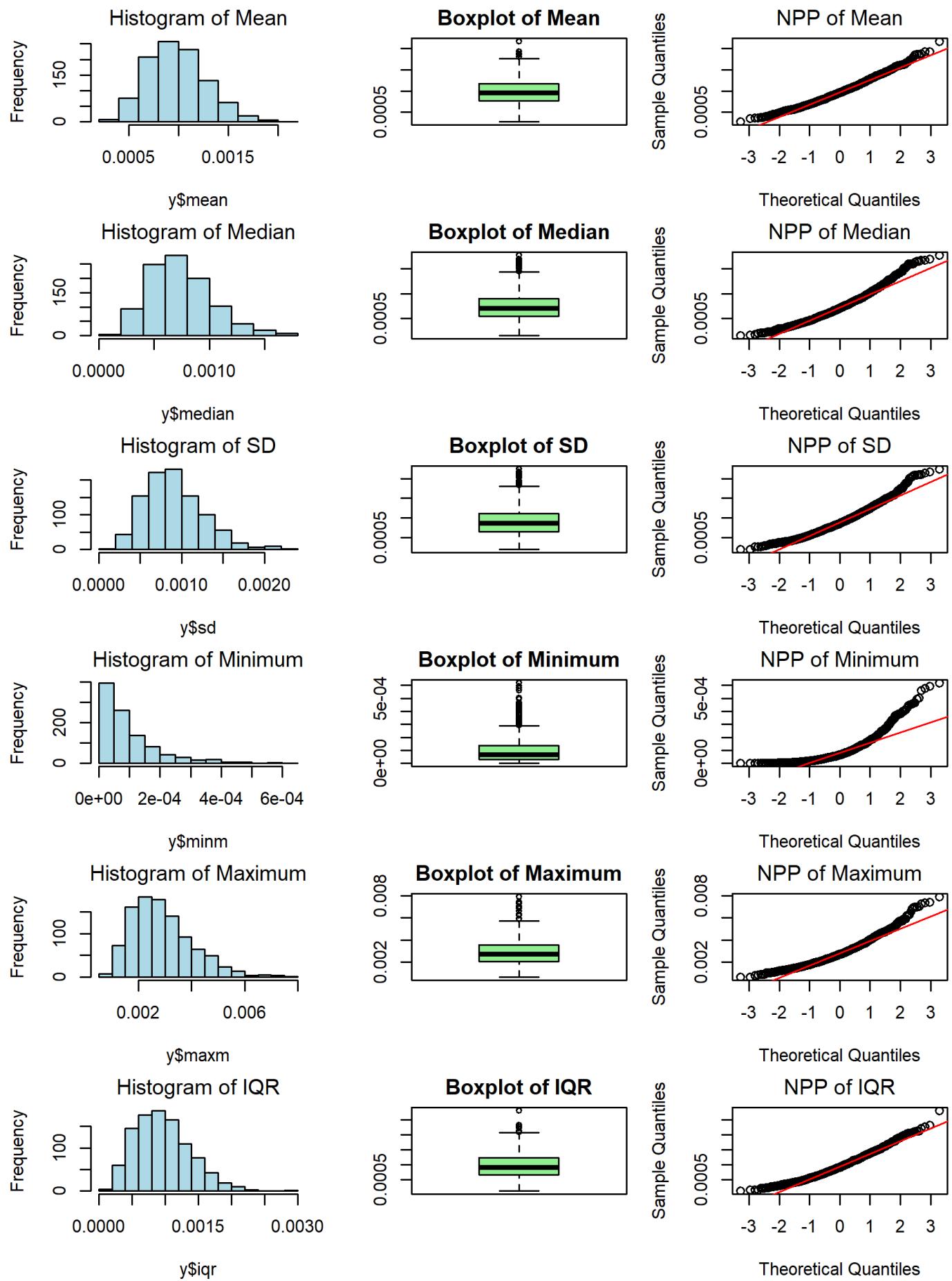
- **Minimum:** Does not achieve normality for any  $n$ , as it is highly influenced by extreme values and the Exponential distribution's asymmetry.
- **Maximum:** Does not achieve normality for any  $n$ , reflecting its sensitivity to extreme values in the parent distribution.

### Overall:

The mean, median, and standard deviation converge to normality for moderate sample sizes ( $n \geq 100$ ), making them reliable statistics. However, the IQR requires larger sample sizes ( $n \geq 1000$ ) to approximate normality, while the minimum and maximum never achieve normality due to the skewness and heavy tail of the Exponential distribution.

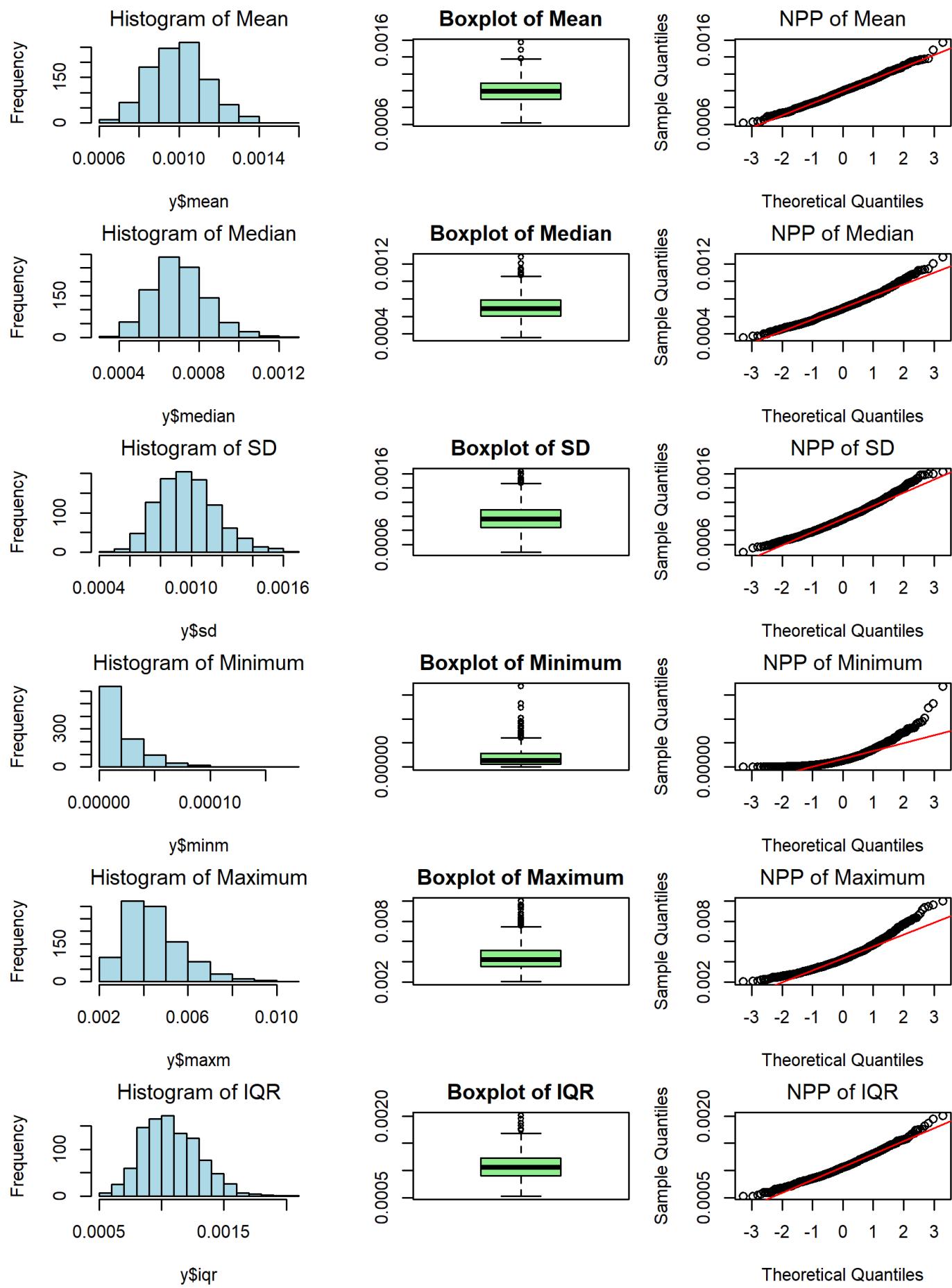
## EXPONENTIAL DISTRIBUTION PLOT

(n=10, nn=1000, λ=0.001)



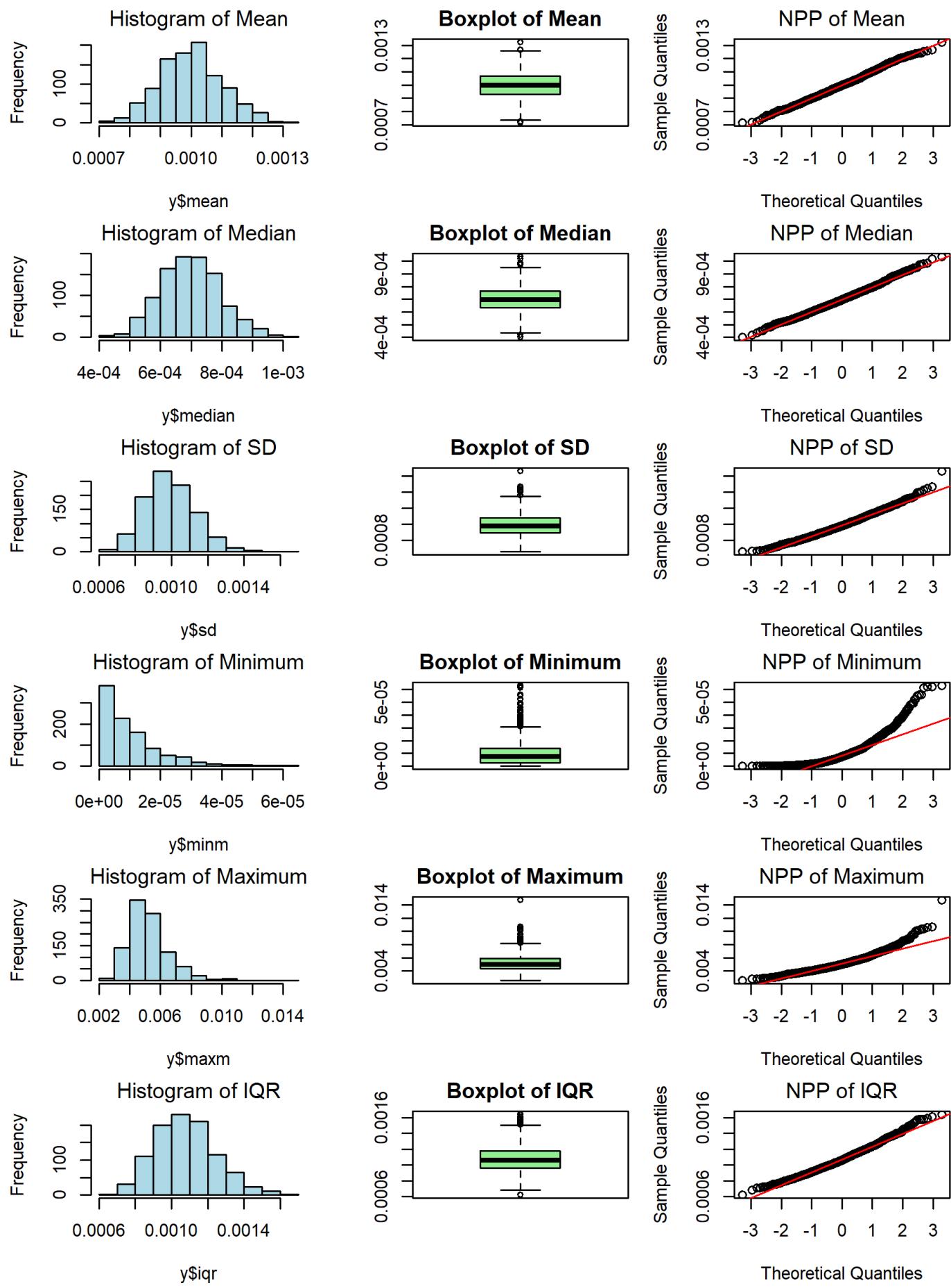
# EXPONENTIAL DISTRIBUTION PLOT

(n=50, nn=1000,  $\lambda=0.001$ )



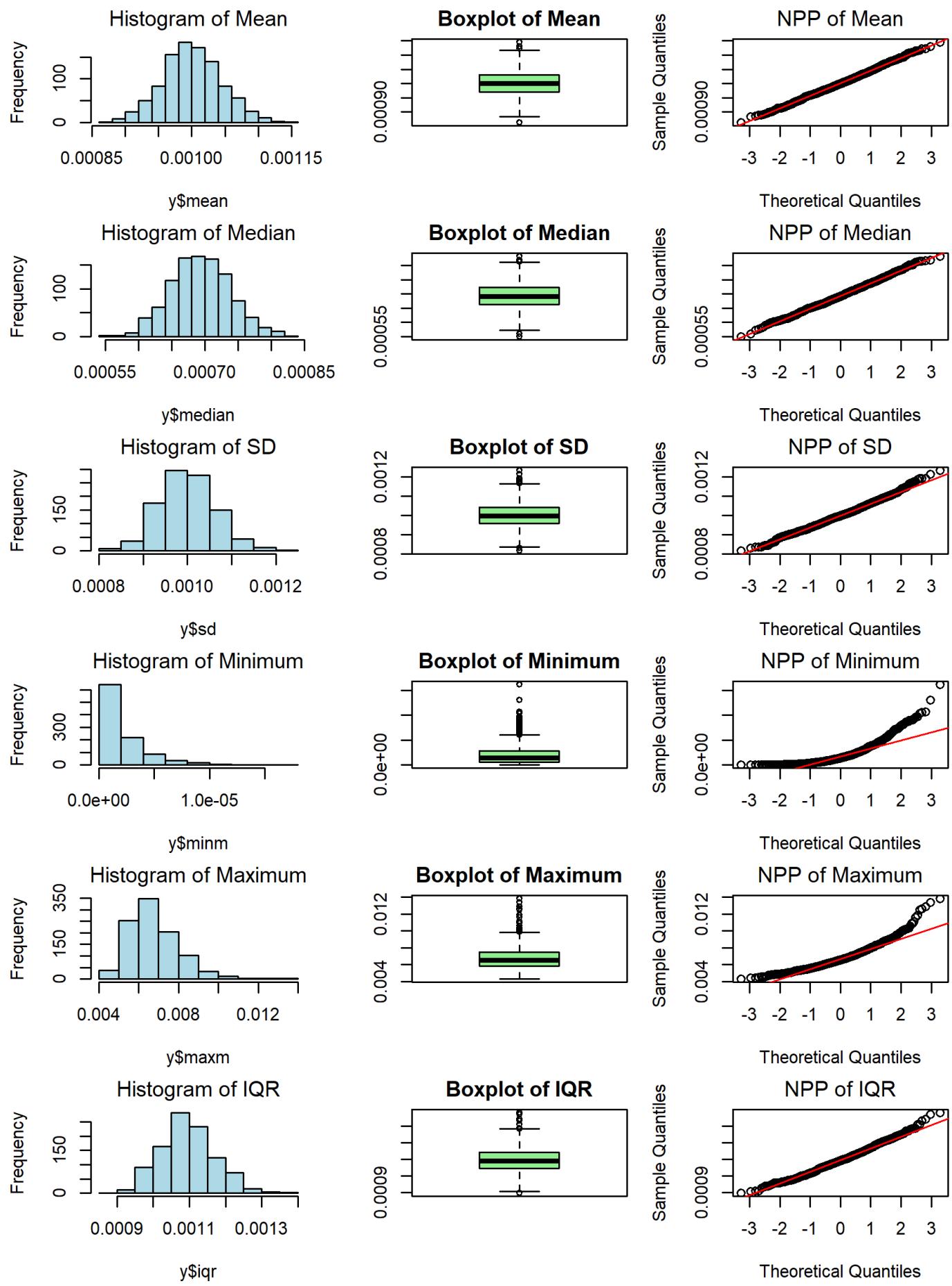
# EXPONENTIAL DISTRIBUTION PLOT

(n=100, nn=1000,  $\lambda=0.001$ )



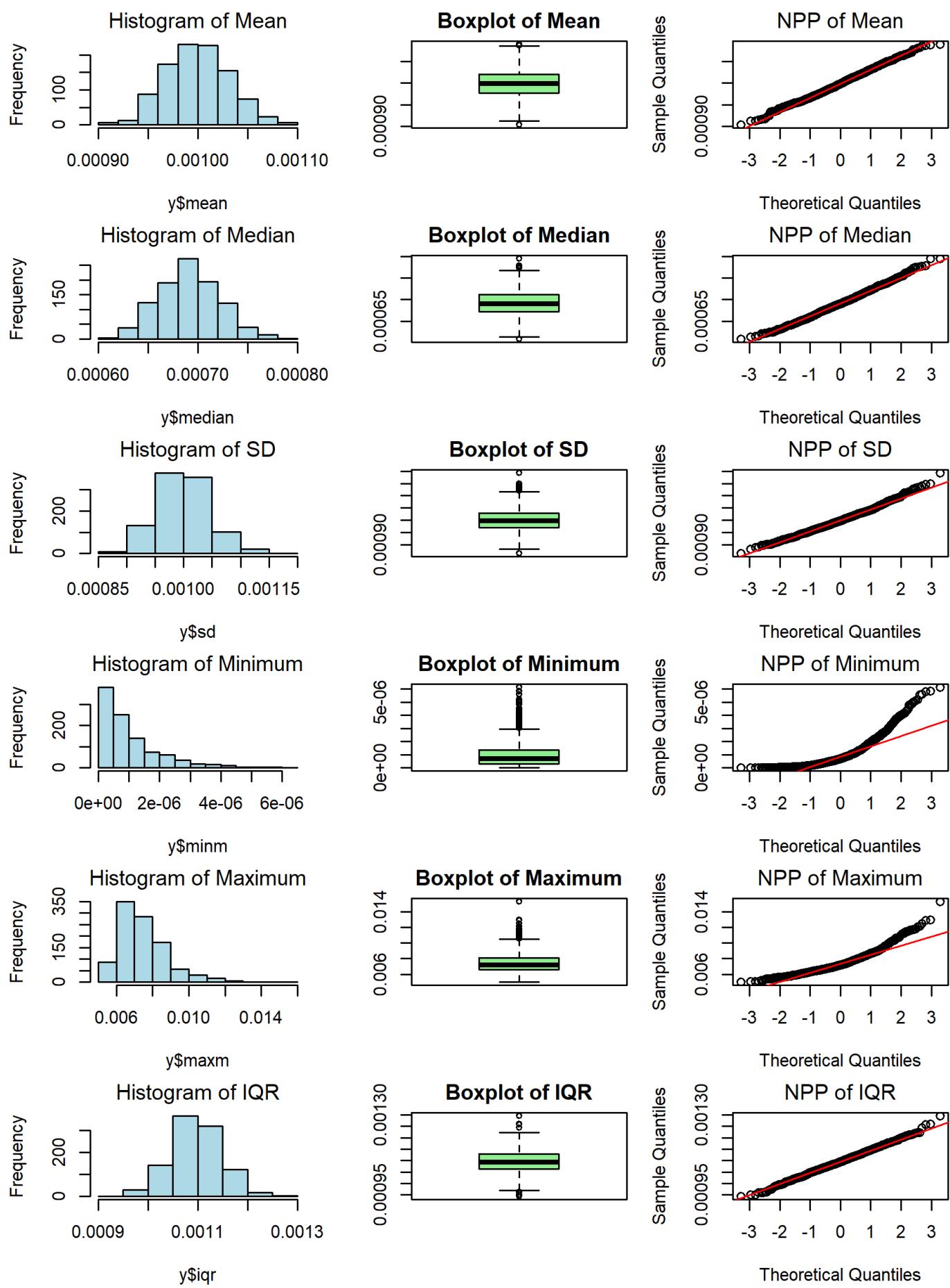
# EXPONENTIAL DISTRIBUTION PLOT

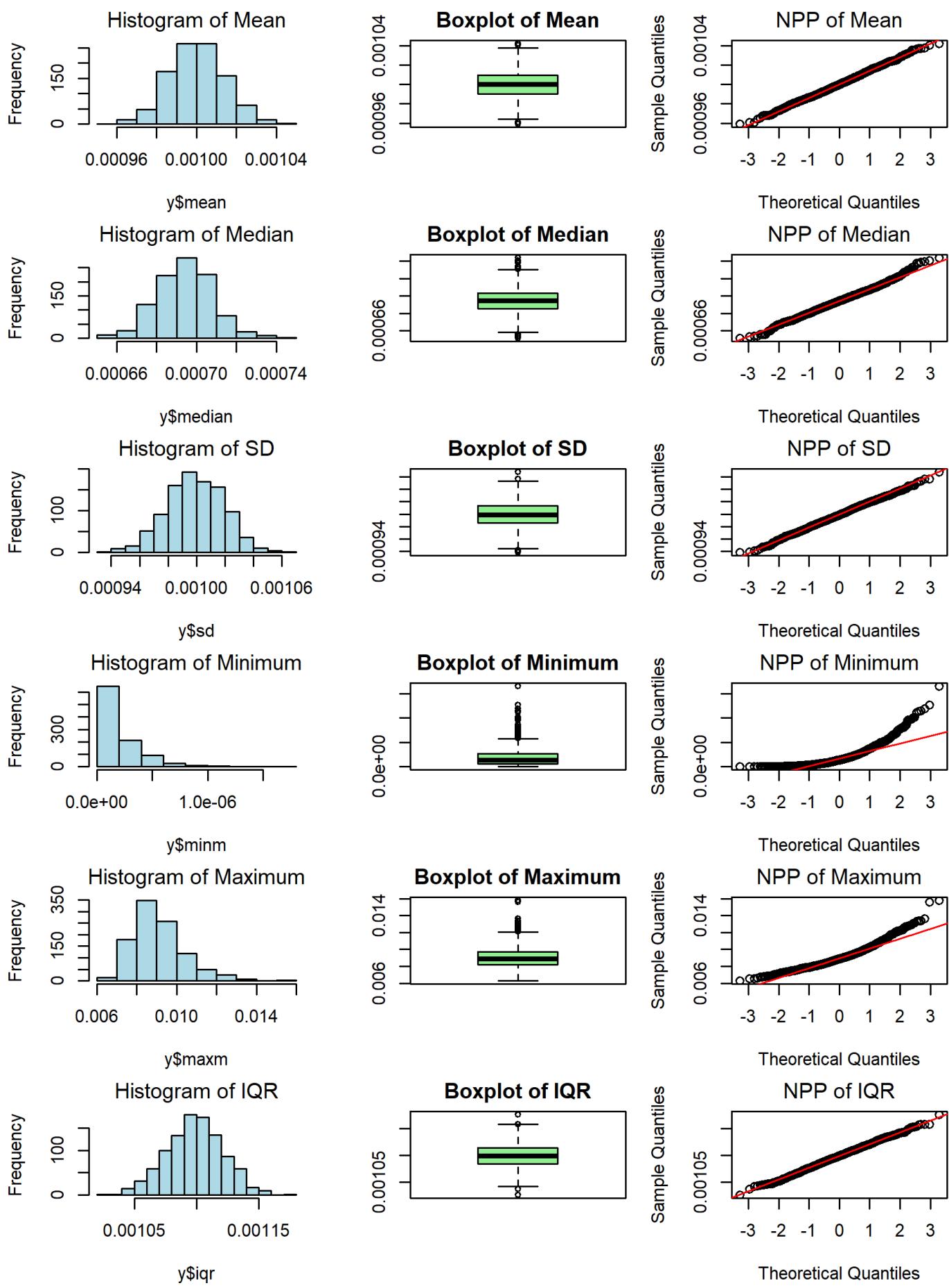
(n=500, nn=1000,  $\lambda=0.001$ )



# EXPONENTIAL DISTRIBUTION PLOT

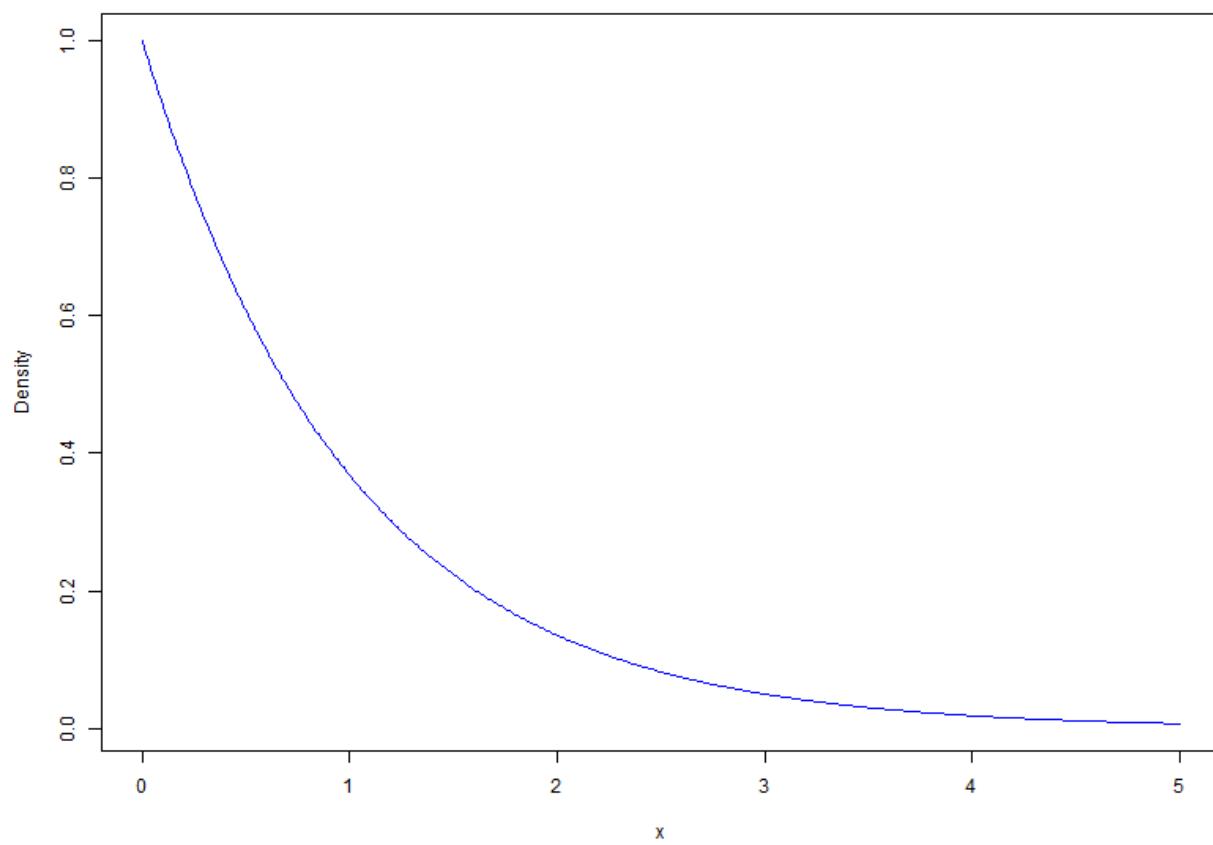
(n=1000, nn=1000,  $\lambda=0.001$ )



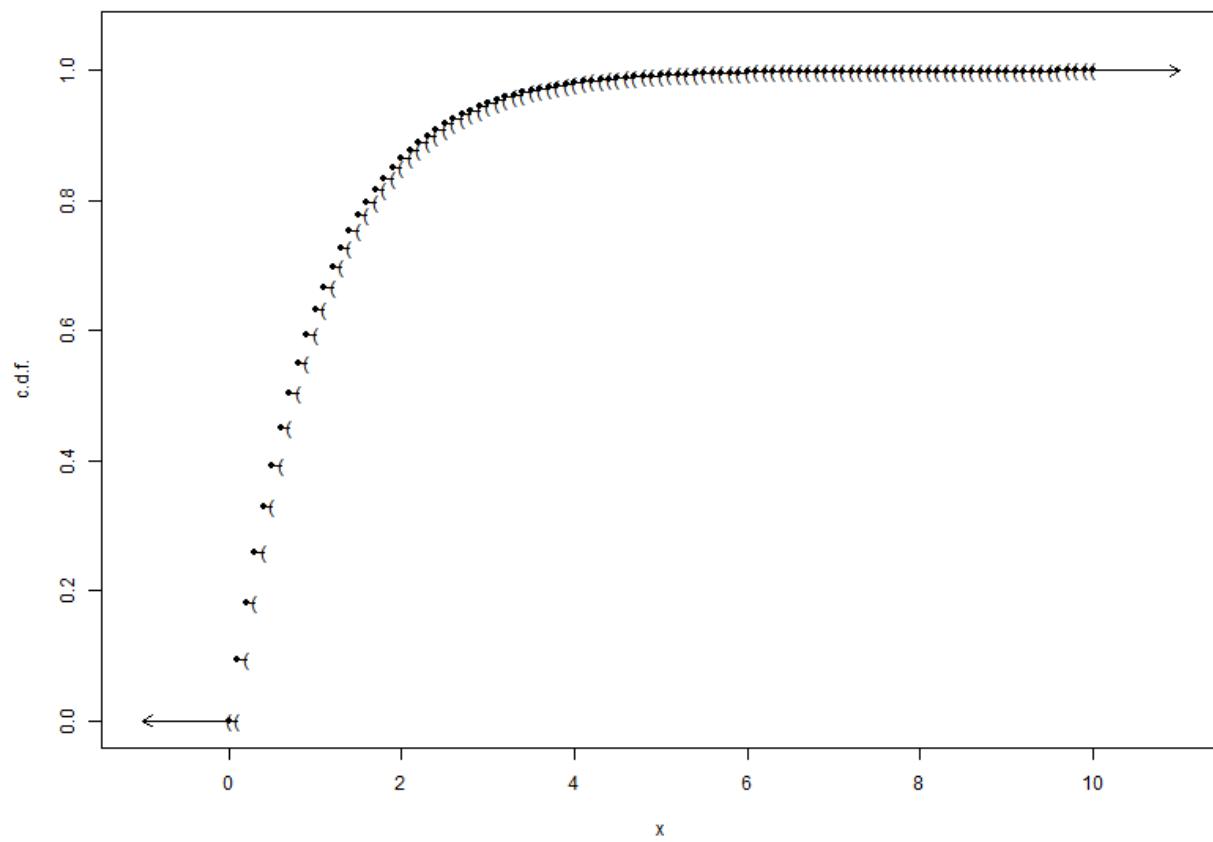


# EXPONENTIAL DISTRIBUTION (1)

PDF of Exponential(1)



CDF of Exponential(1)



# EXPONENTIAL DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\lambda=1$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Median	No	No	No	Yes	Yes	Yes	Yes	500	
Std Dev	No	No	No	Yes	Yes	Yes	Yes	500	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	Yes	Yes	Yes	Yes	500	

## Conclusion for Exponential Distribution

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 50$ , converging relatively quickly due to the Central Limit Theorem (CLT).
- **Median:** Achieves normality for  $n \geq 500$ , requiring larger sample sizes due to sensitivity to the distribution's skewness.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 500$ , reflecting a slower rate of convergence influenced by variability.
- **IQR:** Achieves normality for  $n \geq 500$ , indicating convergence similar to the standard deviation.

### Normality Not Achieved:

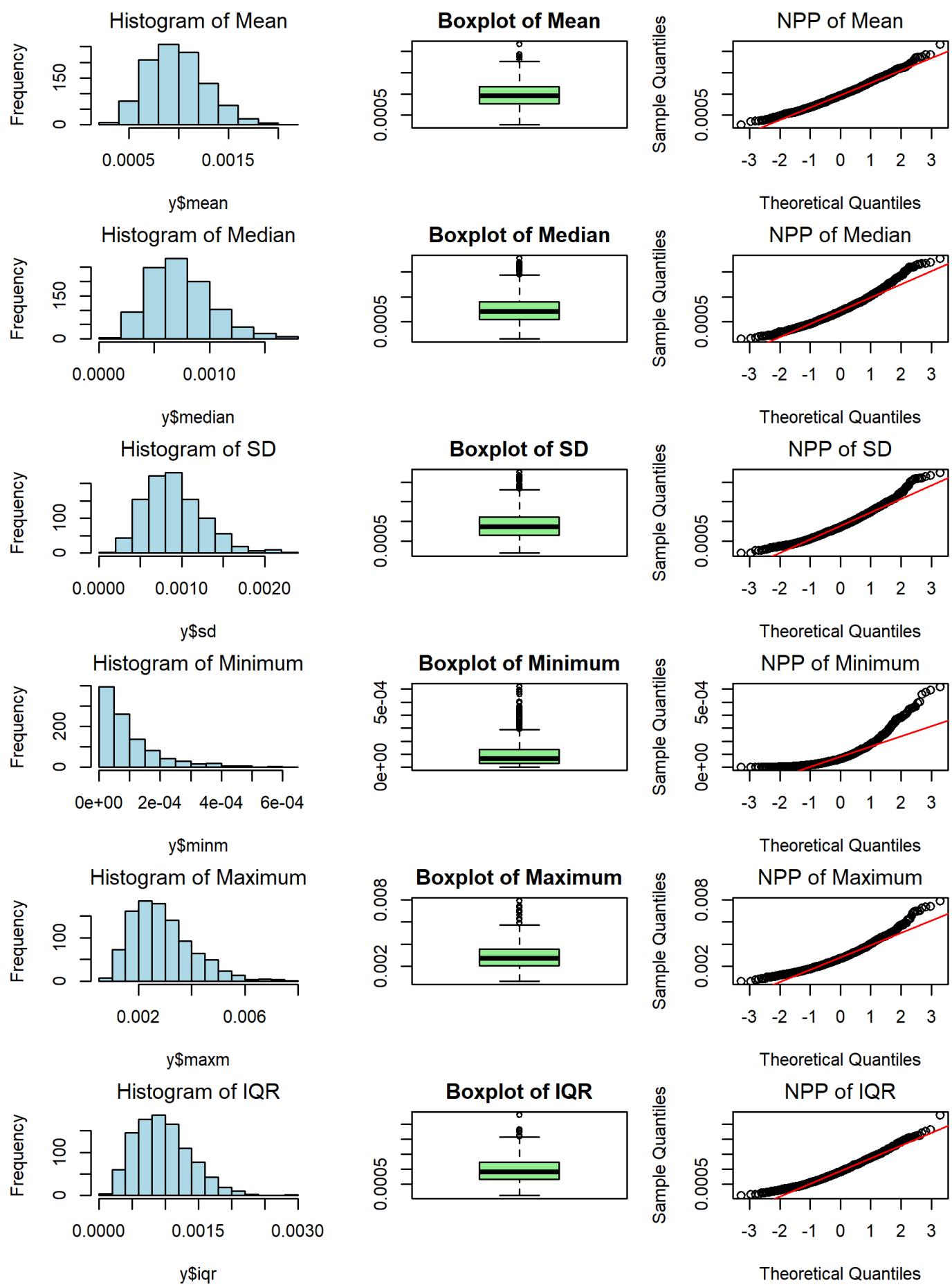
- **Minimum and Maximum:** Do not achieve normality for any  $n$ , as they are highly influenced by the Exponential distribution's extreme values and asymmetry.

### Overall:

The mean converges to normality fastest ( $n \geq 50$ ), making it the most reliable statistic for smaller sample sizes. The median, standard deviation, and IQR require larger sample sizes ( $n \geq 500$ ) due to the distribution's skewness and variability. The minimum and maximum remain non-normal regardless of the sample size.

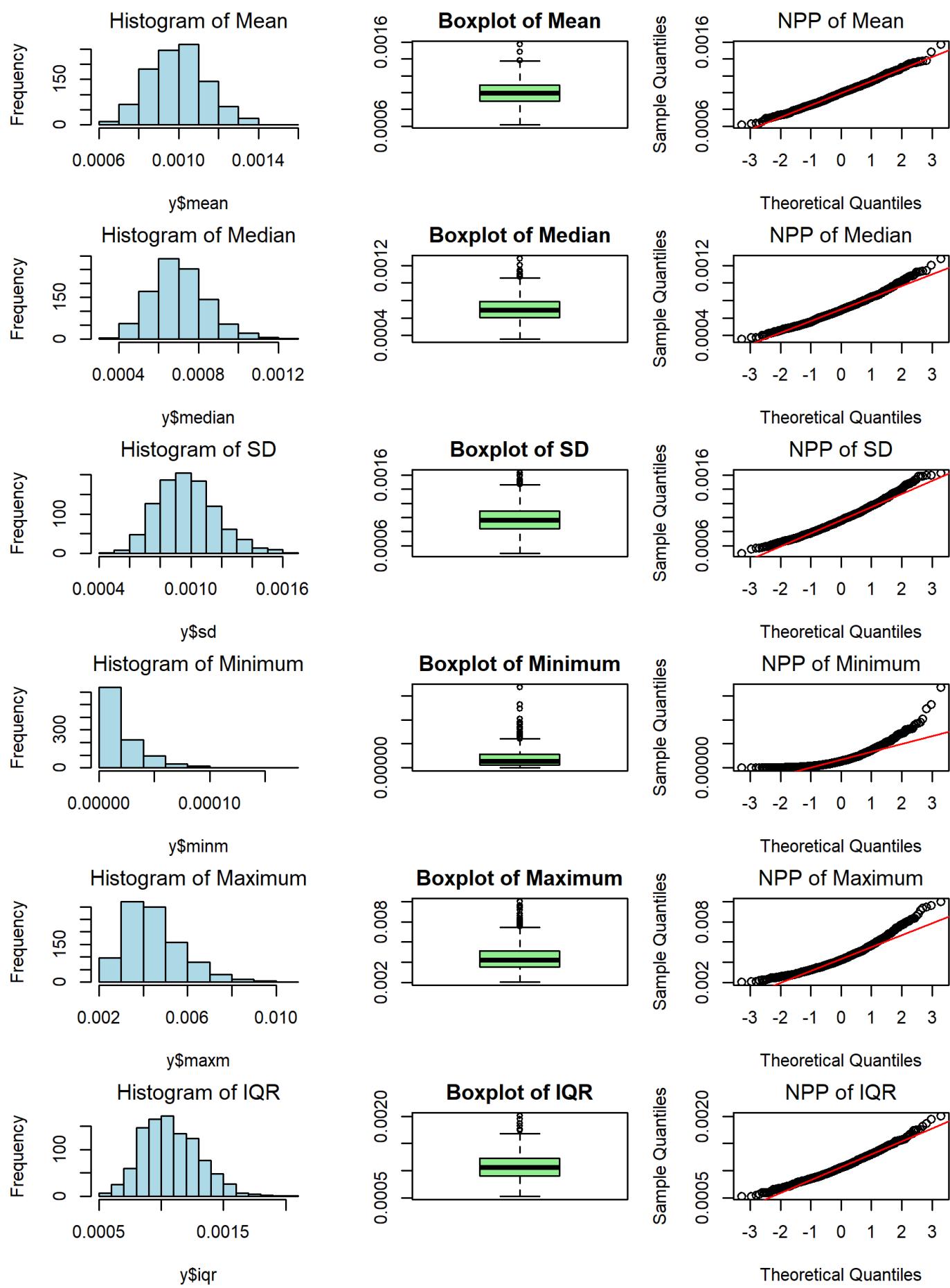
# EXPONENTIAL DISTRIBUTION PLOT

(n=10, nn=1000,  $\lambda=1$ )



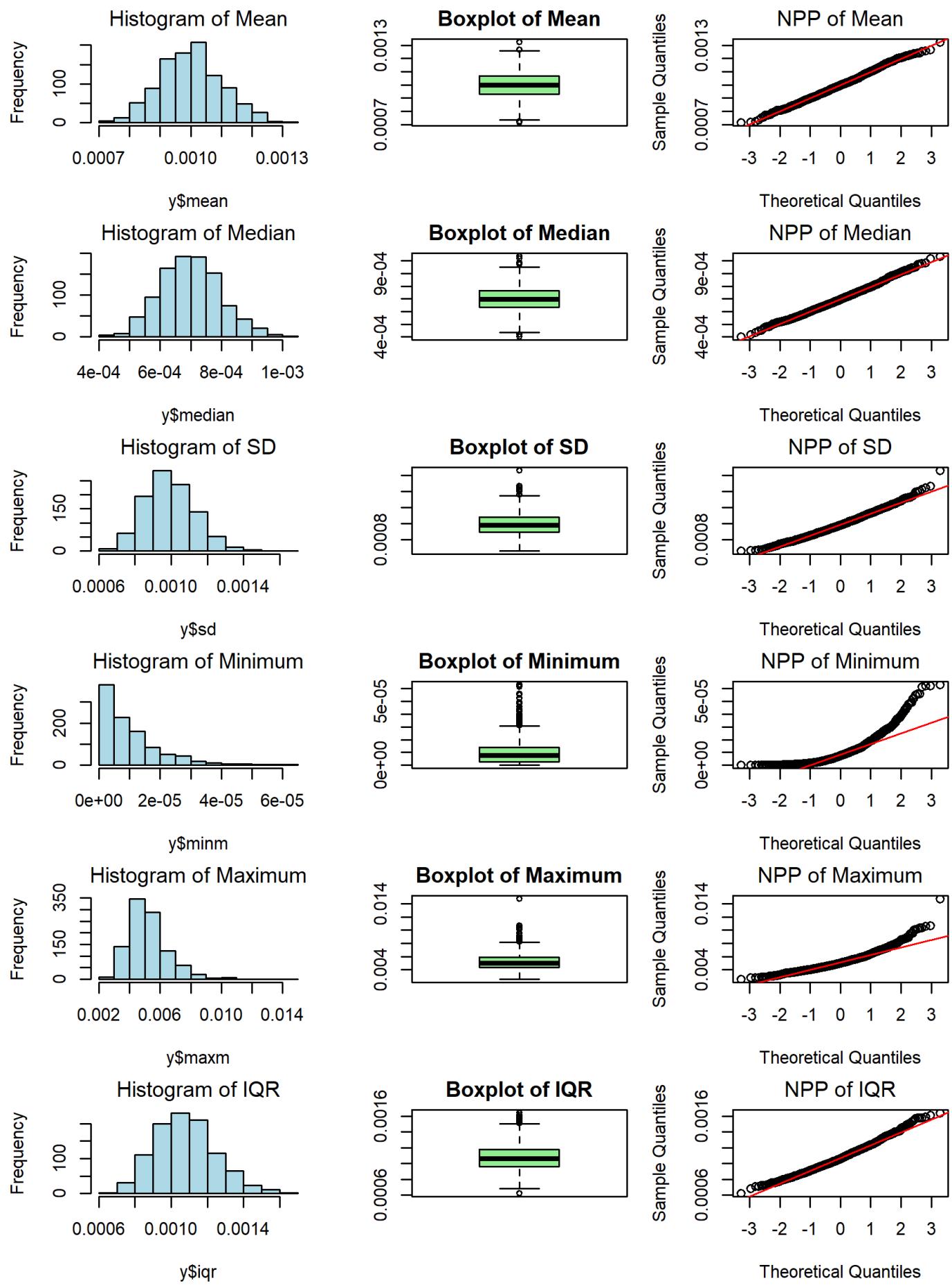
# EXPONENTIAL DISTRIBUTION PLOT

(n=50, nn=1000,  $\lambda=1$ )



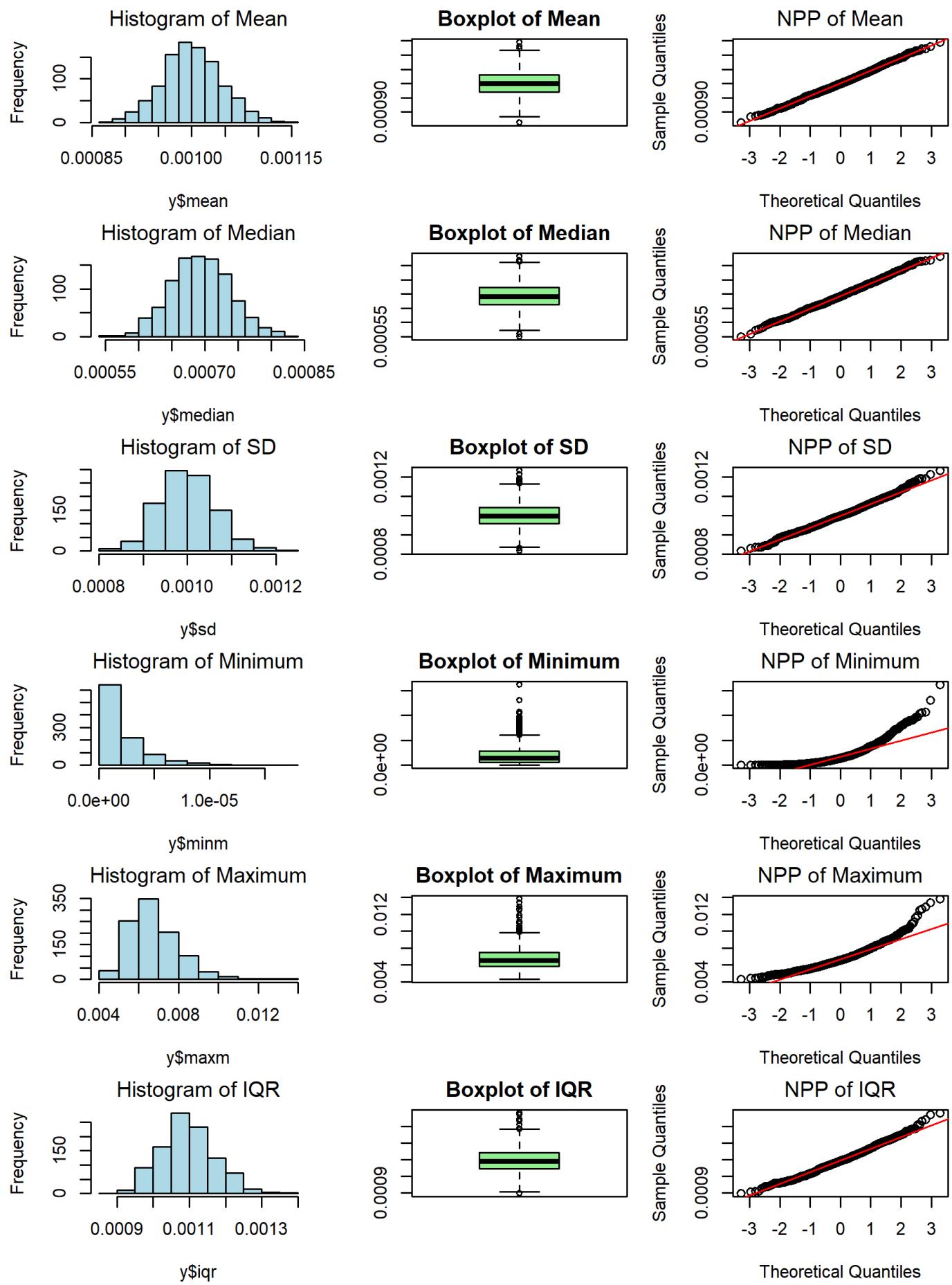
# EXPONENTIAL DISTRIBUTION PLOT

(n=100, nn=1000,  $\lambda=1$ )



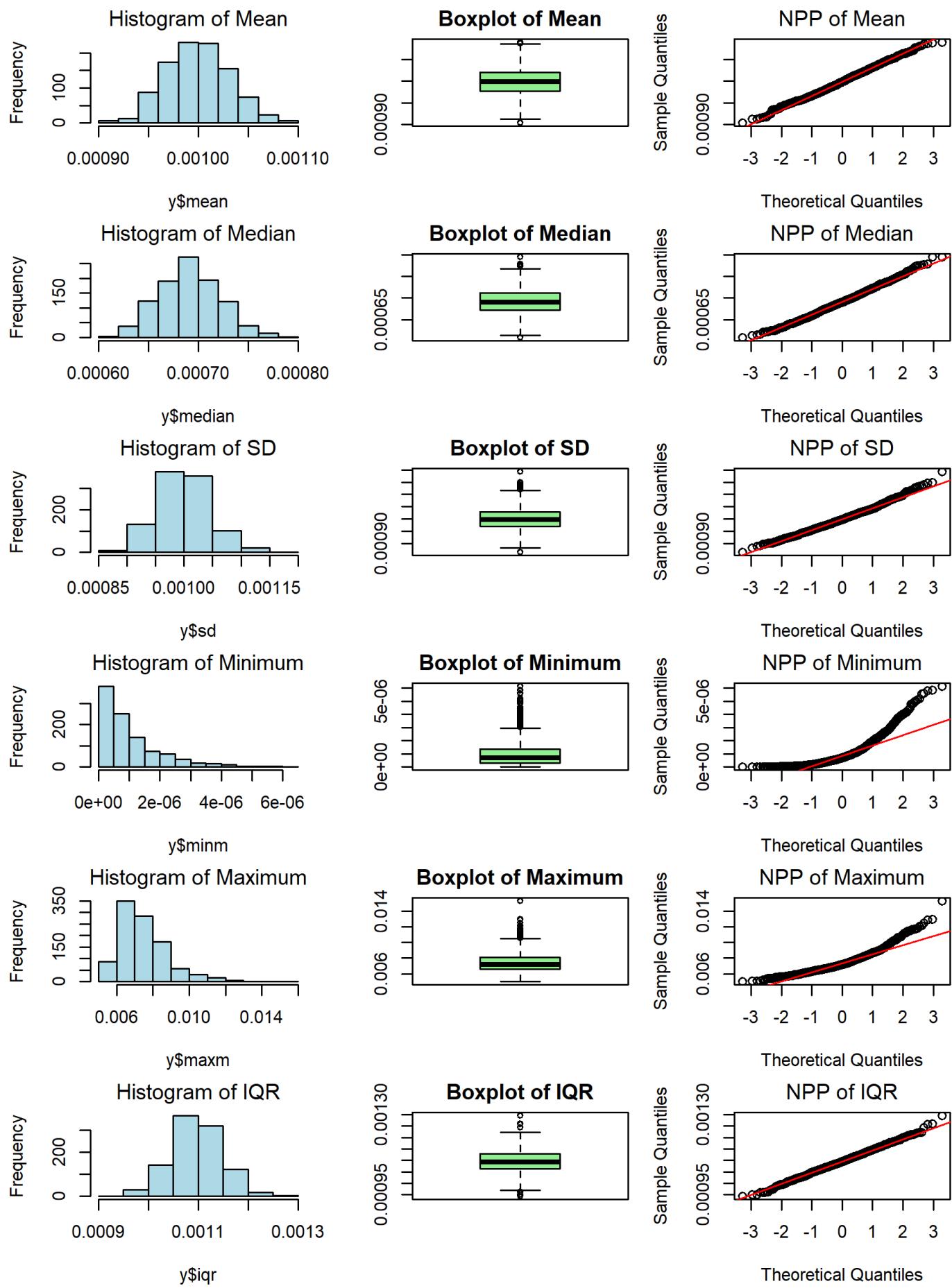
# EXPONENTIAL DISTRIBUTION PLOT

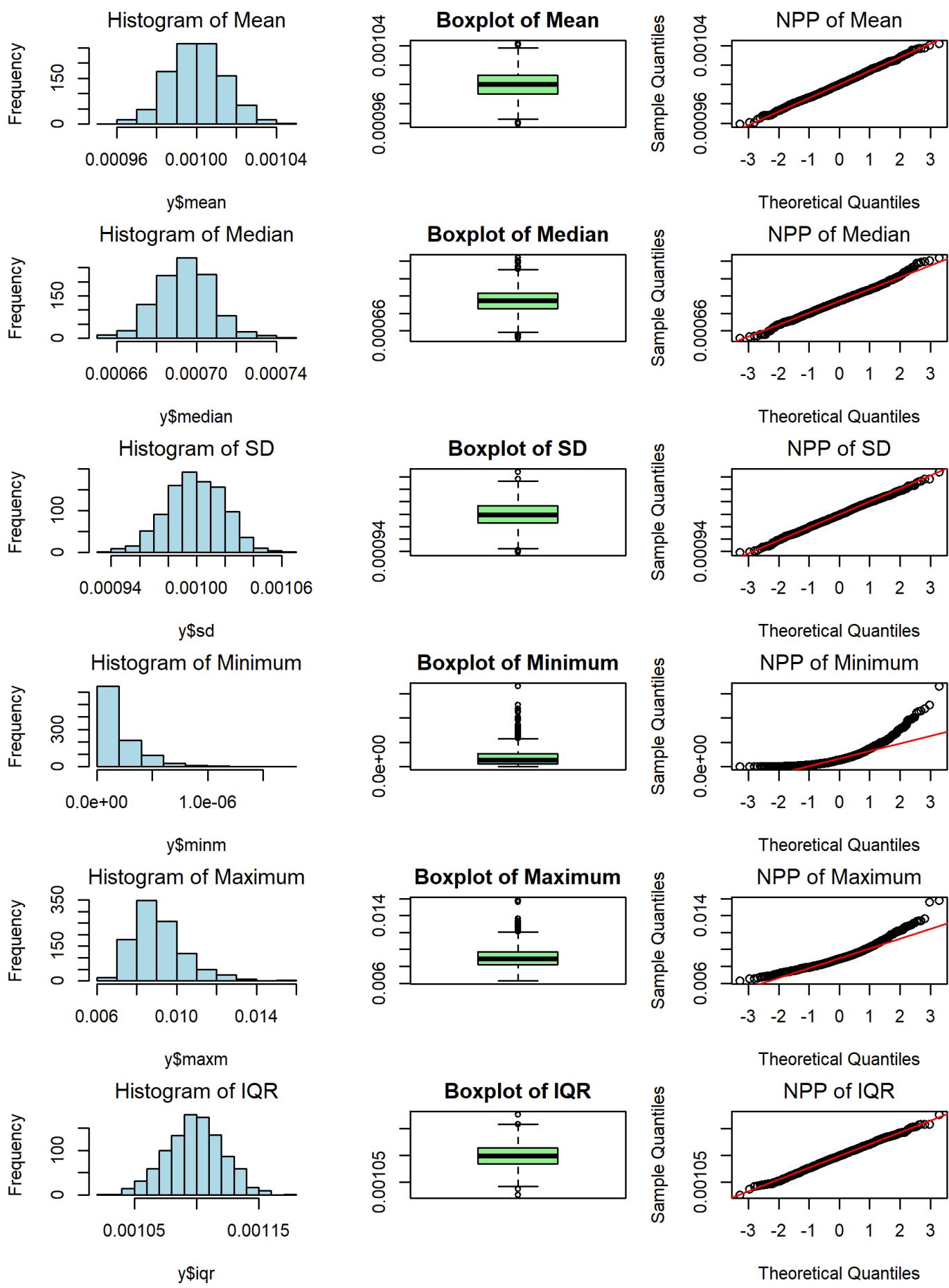
(n=500, nn=1000,  $\lambda=1$ )



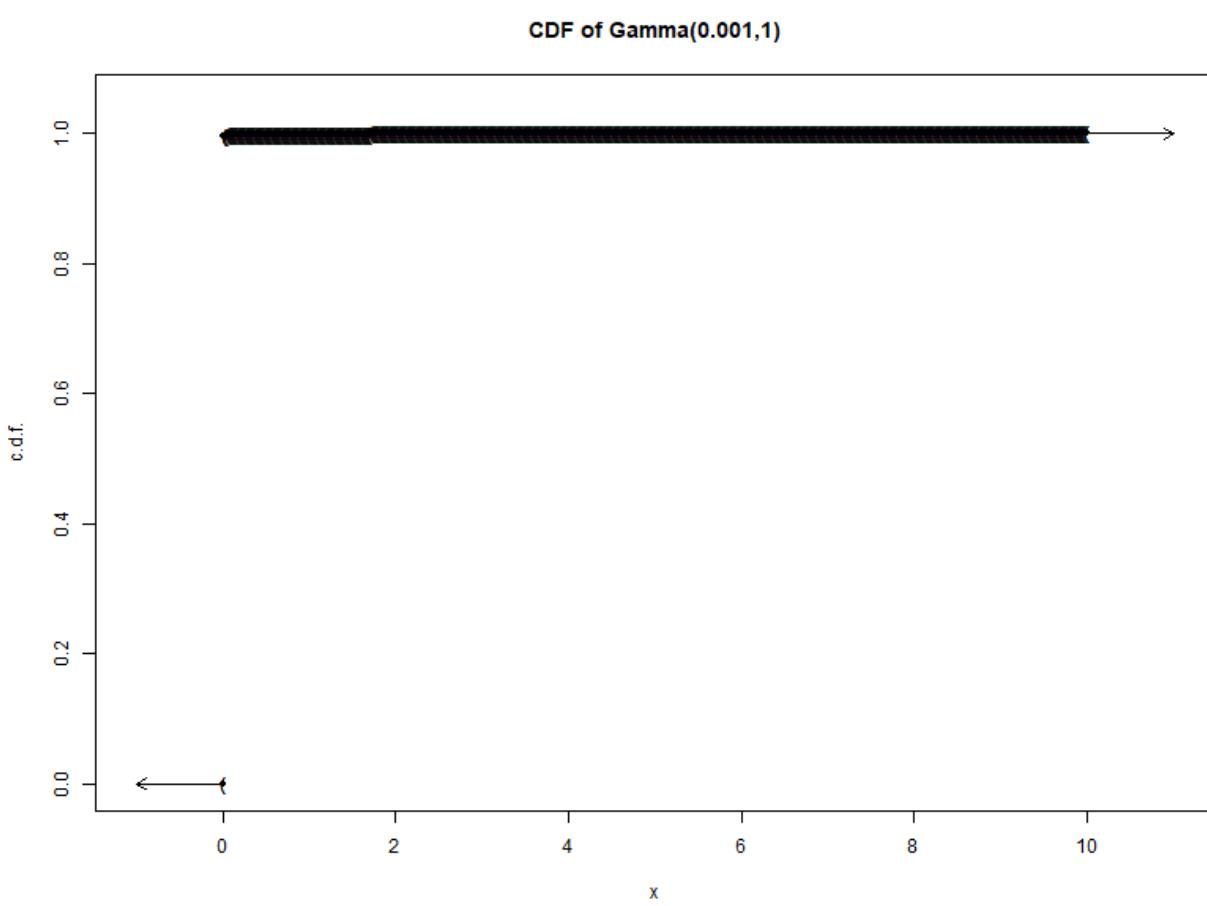
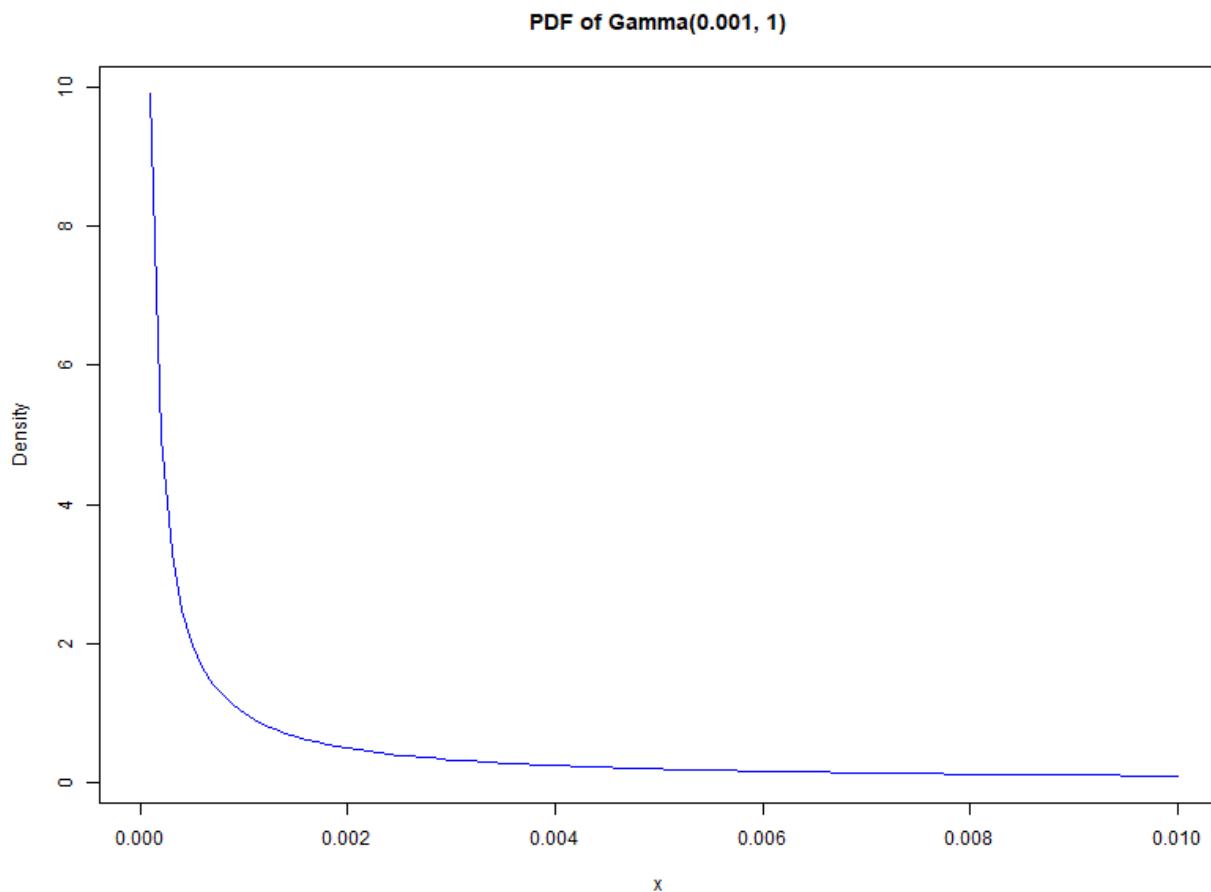
# EXPONENTIAL DISTRIBUTION PLOT

(n=1000, nn=1000,  $\lambda=1$ )





# GAMMA DISTRIBUTION (0.001,1)



# GAMMA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=0.001$ , $\lambda=1$ )								
Statistic	n=10	n=100	n=1000	n=5000	n=50e3	n=70e3	n=75e3	Min(n)	
Mean	No	No	No	No	No	No	Yes	75000	
Median	No	No	No	No	No	No	No	NA	
Std.Dev	No	No	No	No	No	No	Yes	75000	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	No	No	NA	

## Conclusion for Gamma Distribution

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 75,000$ , with convergence observed at larger sample sizes, indicating that higher sample sizes are necessary for the mean to approximate a normal distribution.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 75,000$ , showing a similar pattern of convergence as the mean with a high number of samples.

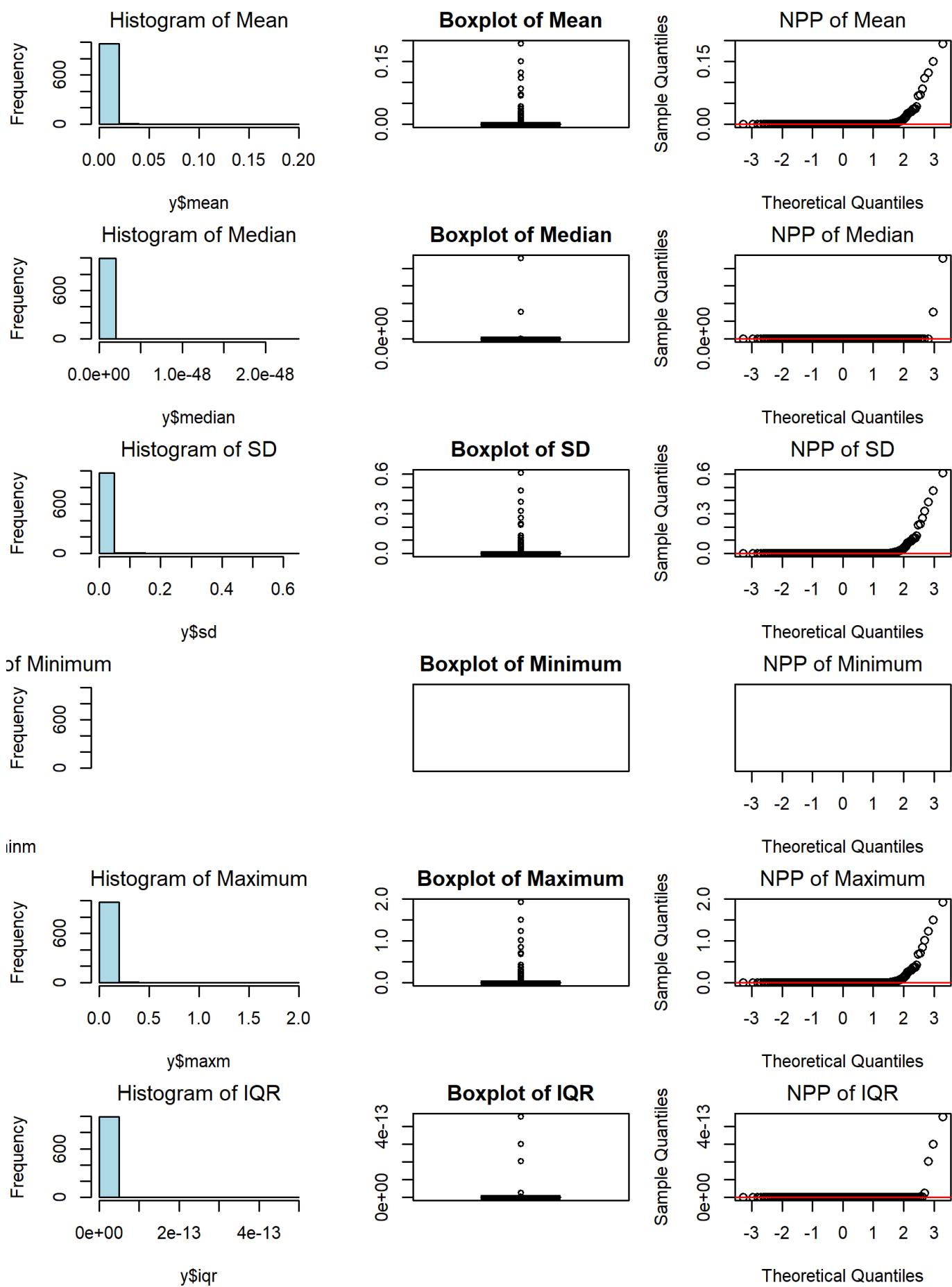
### Normality Not Achieved:

- **Median:** Does not achieve normality for any sample size, as it is still influenced by the shape of the Gamma distribution even with larger sample sizes.
- **Minimum and Maximum:** Do not achieve normality for any sample size, as these values are sensitive to the extreme values of the Gamma distribution.
- **IQR:** Does not achieve normality for any sample size, as it remains affected by the distribution's skewness and variability.

**Overall:** The mean and standard deviation are the most likely to achieve normality, but only for sample sizes  $n \geq 75,000$ . Smaller sample sizes ( $n < 75,000$ ) do not achieve normality for any of the statistics. The median, minimum, maximum, and IQR remain non-normal regardless of sample size due to the inherent characteristics of the Gamma distribution.

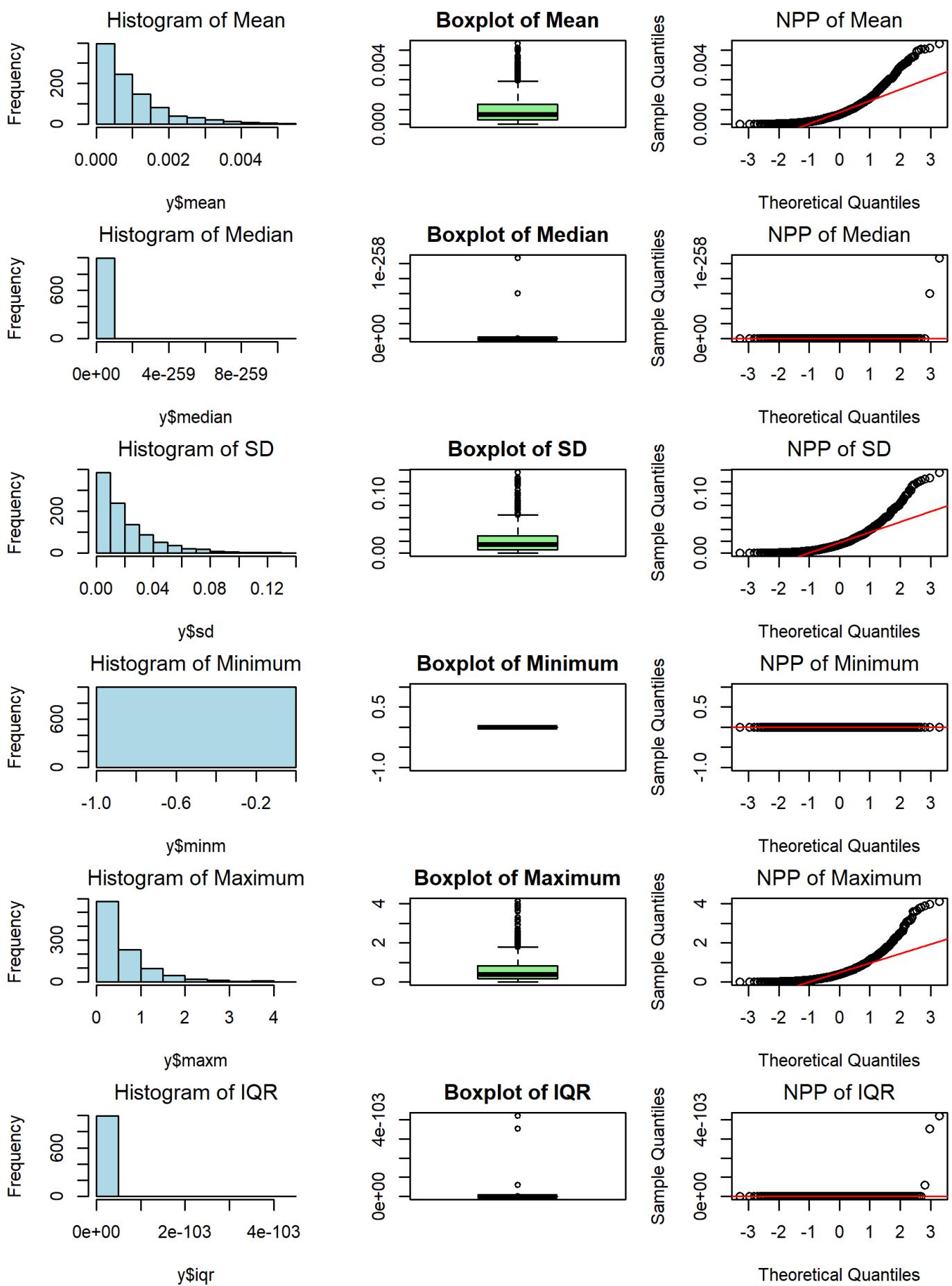
# GAMMA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=0.001$ ,  $\lambda=1$ )



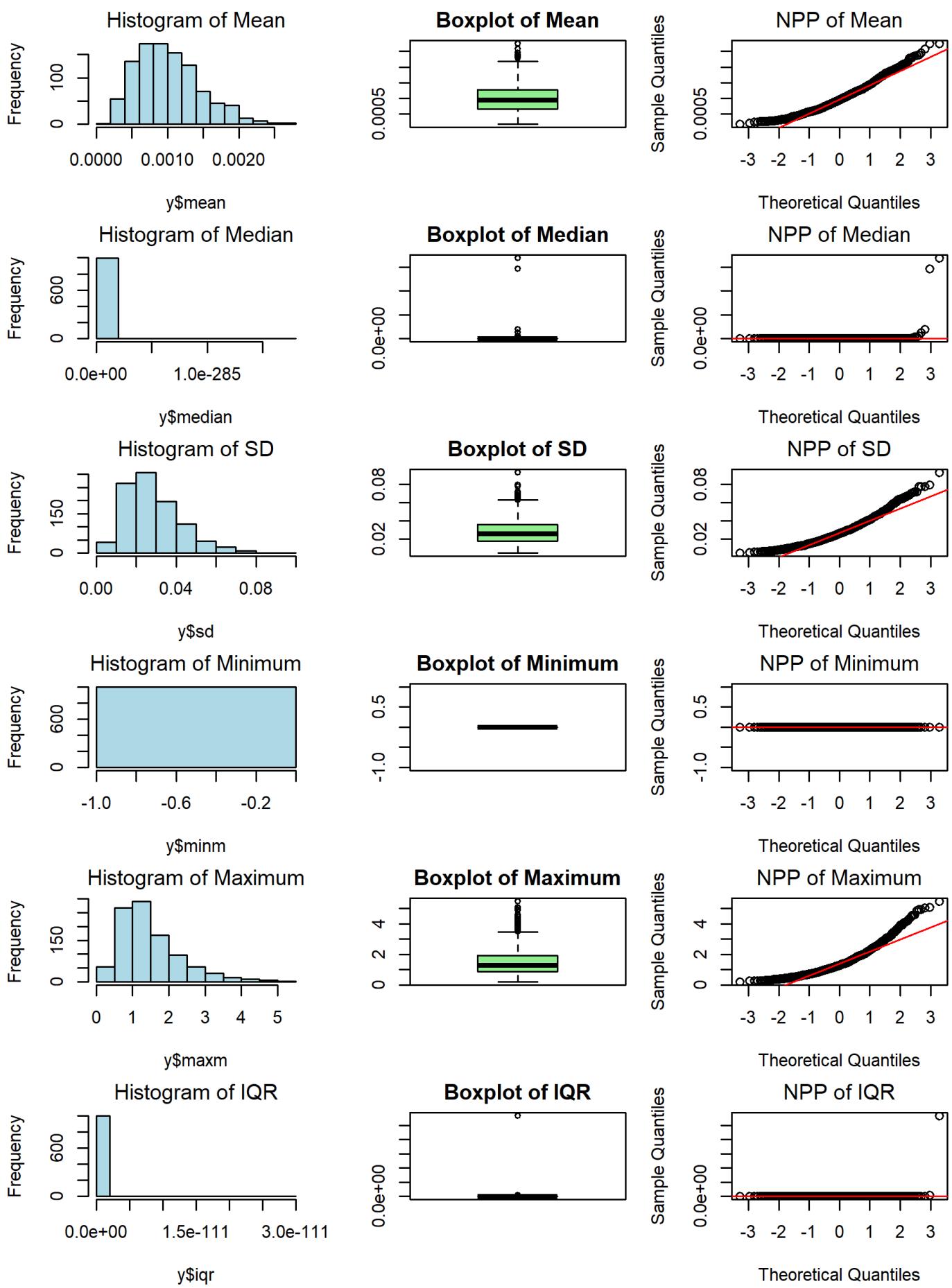
# GAMMA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=0.001$ ,  $\lambda=1$ )



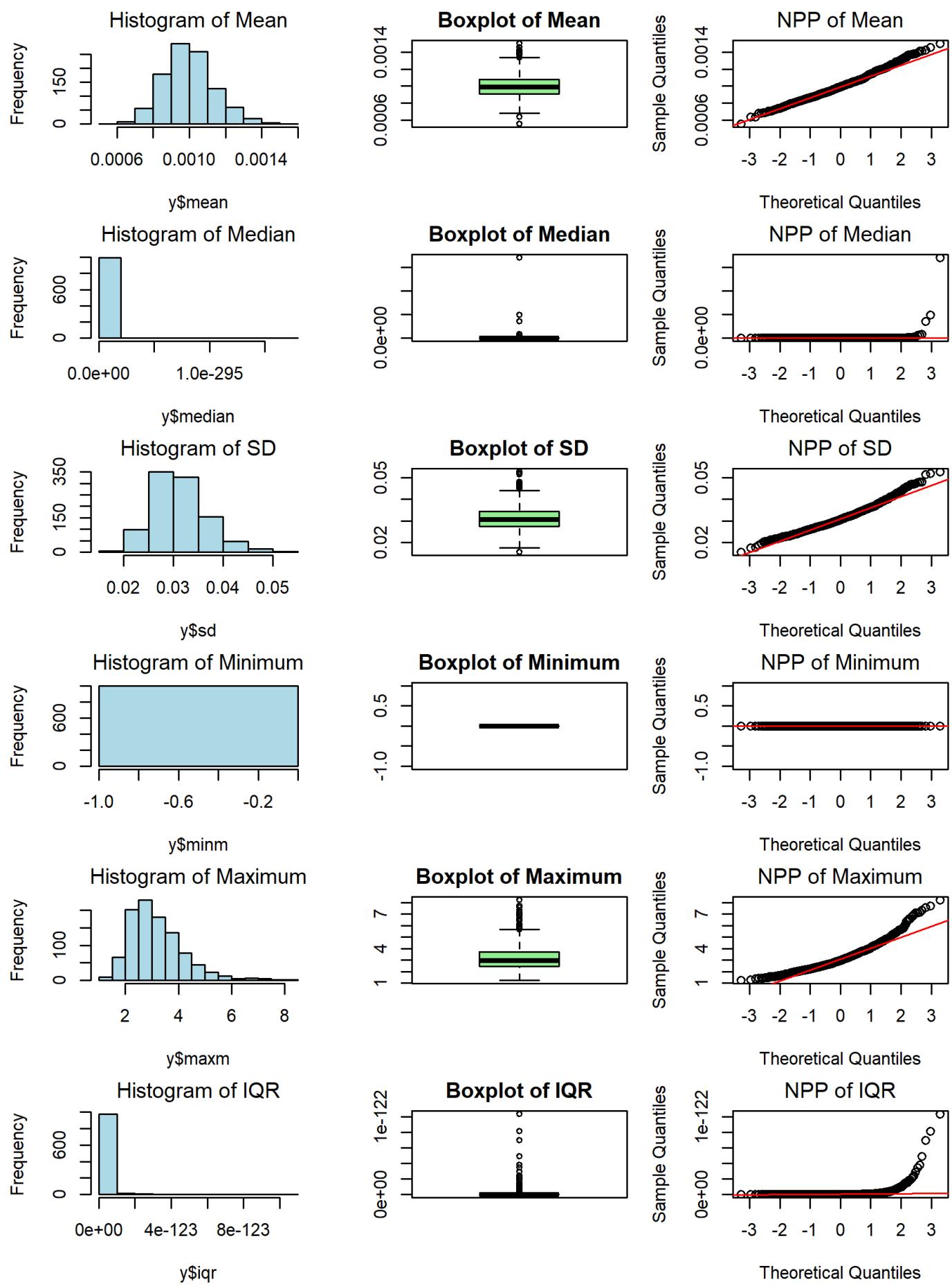
# GAMMA DISTRIBUTION PLOT

(n=5000, nn=1000,  $\alpha=0.001$ ,  $\lambda=1$ )



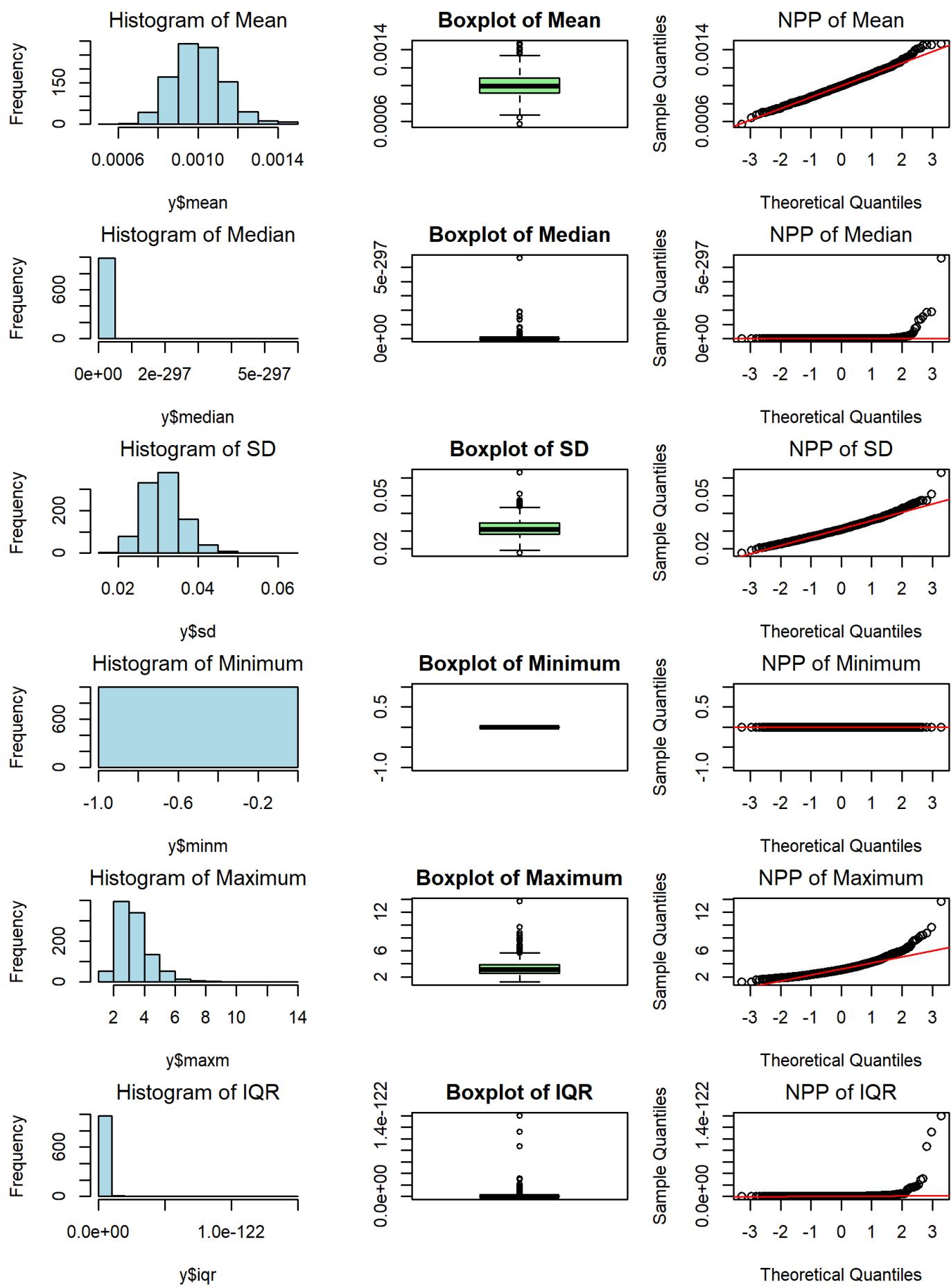
# GAMMA DISTRIBUTION PLOT

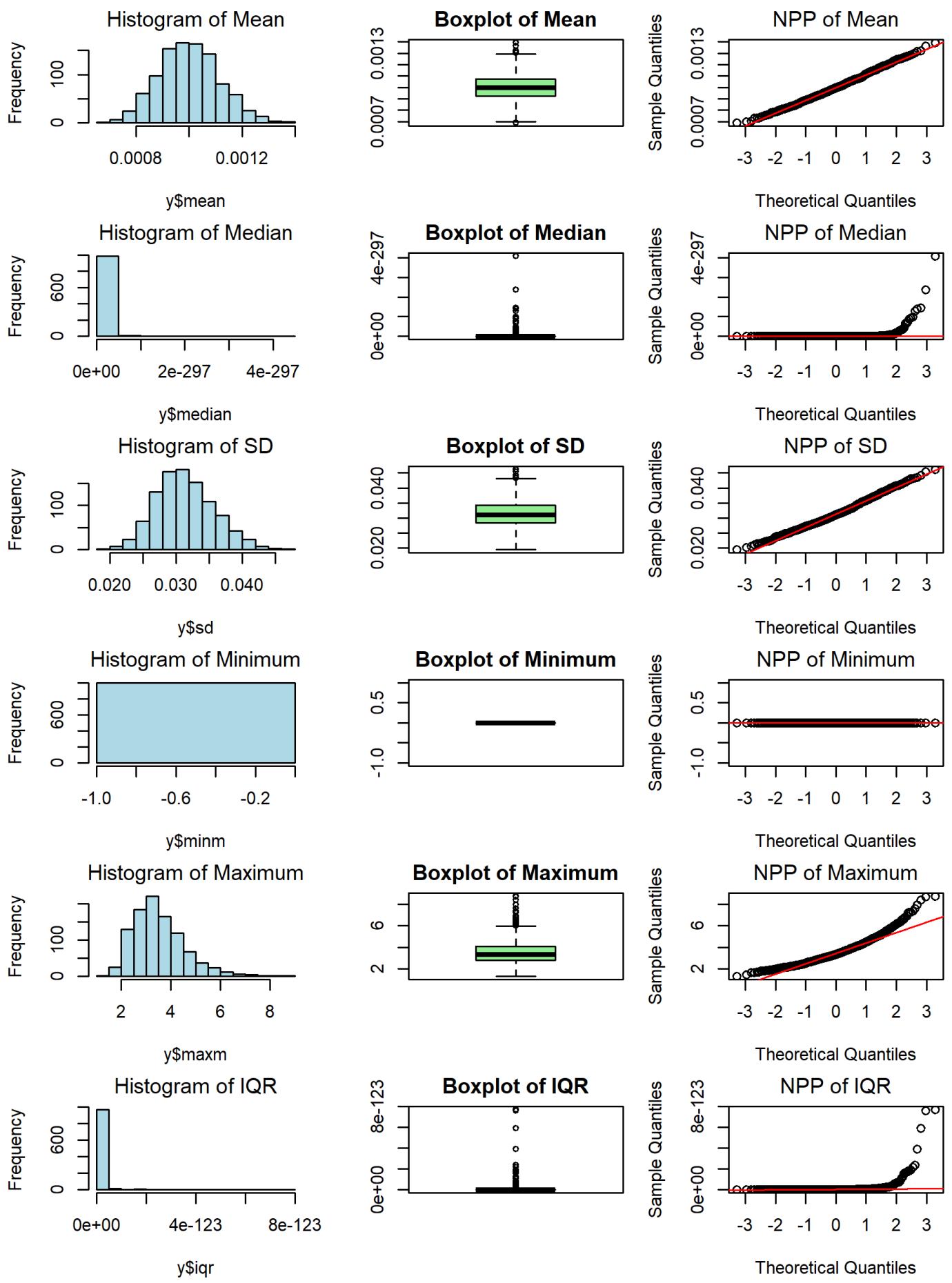
(n=50000, nn=1000,  $\alpha=0.001$ ,  $\lambda=1$ )



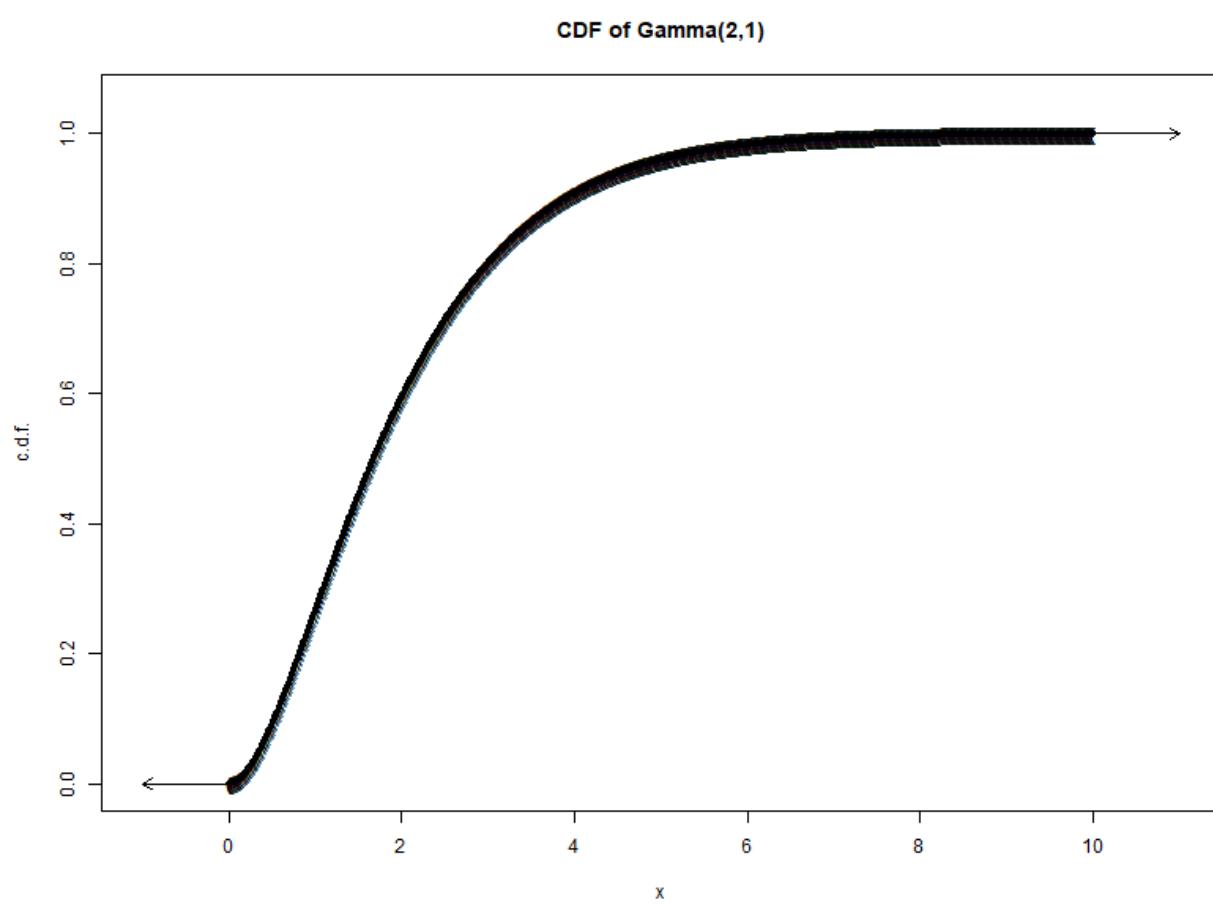
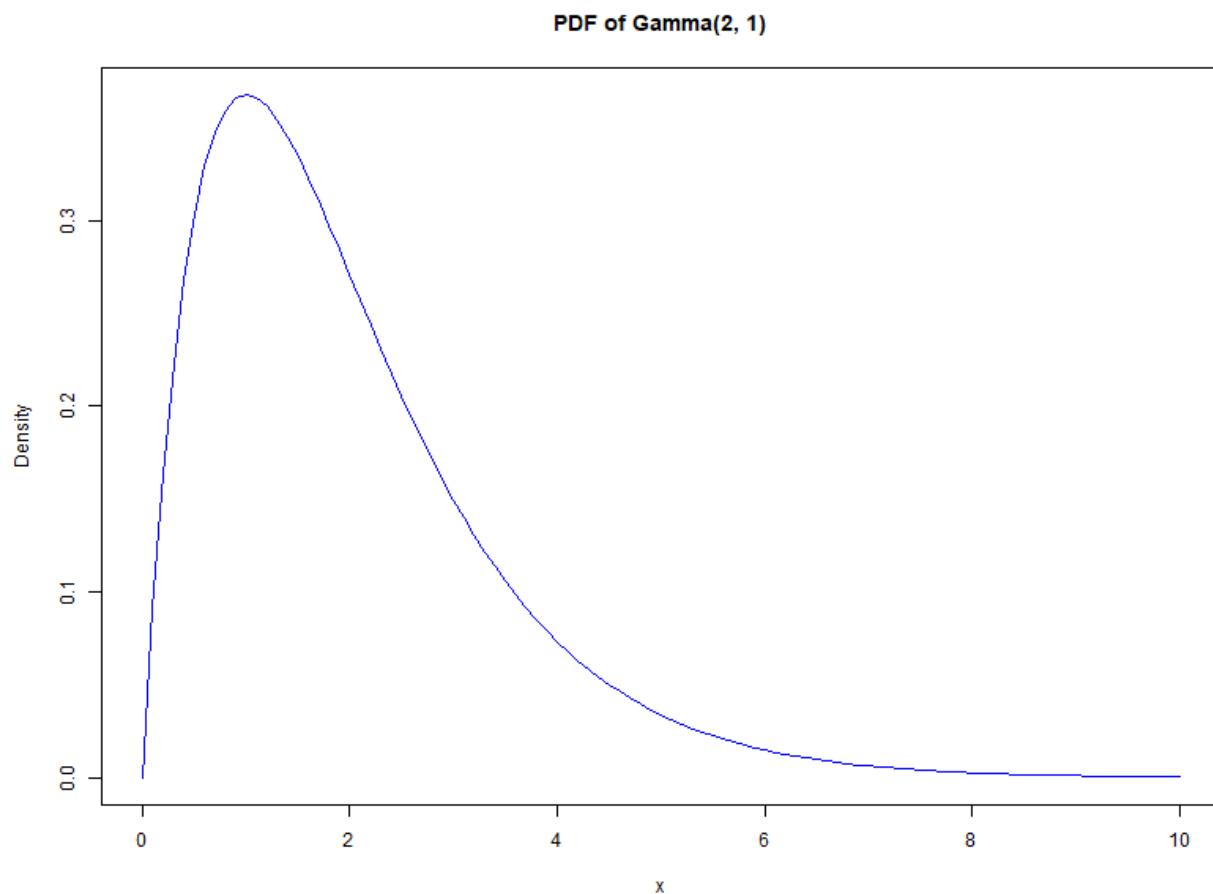
# GAMMA DISTRIBUTION PLOT

(n=70000, nn=1000,  $\alpha=0.001$ ,  $\lambda=1$ )





# GAMMA DISTRIBUTION (2,1)



# GAMMA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=2$ , $\lambda=1$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	No	Yes	Yes	Yes	Yes	Yes	100	
Median	No	No	No	Yes	Yes	Yes	Yes	500	
Std Dev	No	No	Yes	Yes	Yes	Yes	Yes	100	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	Yes	Yes	Yes	Yes	Yes	100	

## Conclusion for Gamma Distribution (with $\alpha = 2$ )

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 100$ , with convergence occurring relatively quickly as the sample size increases.
- **Median:** Achieves normality for  $n \geq 500$ , indicating that slightly larger sample sizes are necessary for the median to approximate a normal distribution.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 100$ , showing that the standard deviation converges to normality at smaller sample sizes compared to the median.
- **IQR:** Achieves normality for  $n \geq 100$ , with the IQR showing similar convergence patterns as the standard deviation.

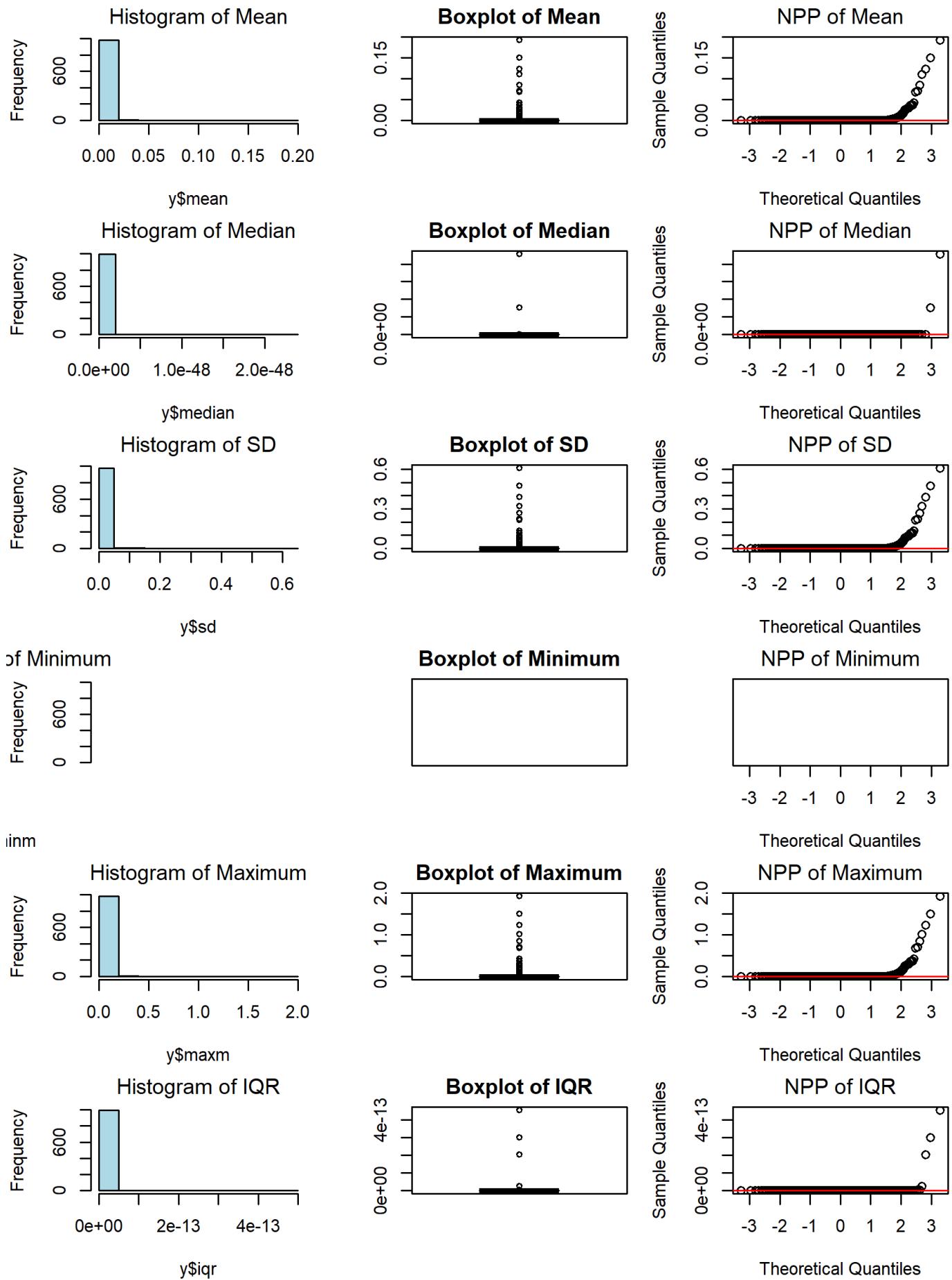
### Normality Not Achieved:

- **Minimum and Maximum:** Do not achieve normality for any sample size, as these values are still influenced by extreme values in the Gamma distribution.

**Overall:** For  $\alpha = 2$ , the mean, standard deviation, and IQR achieve normality at  $n \geq 100$ , which is much faster compared to  $\alpha = 0.001$ . The extreme values (minimum and maximum) still require large sample sizes ( $n \geq 500$ ) to approximate normality, and they remain non-normal for smaller sample sizes.

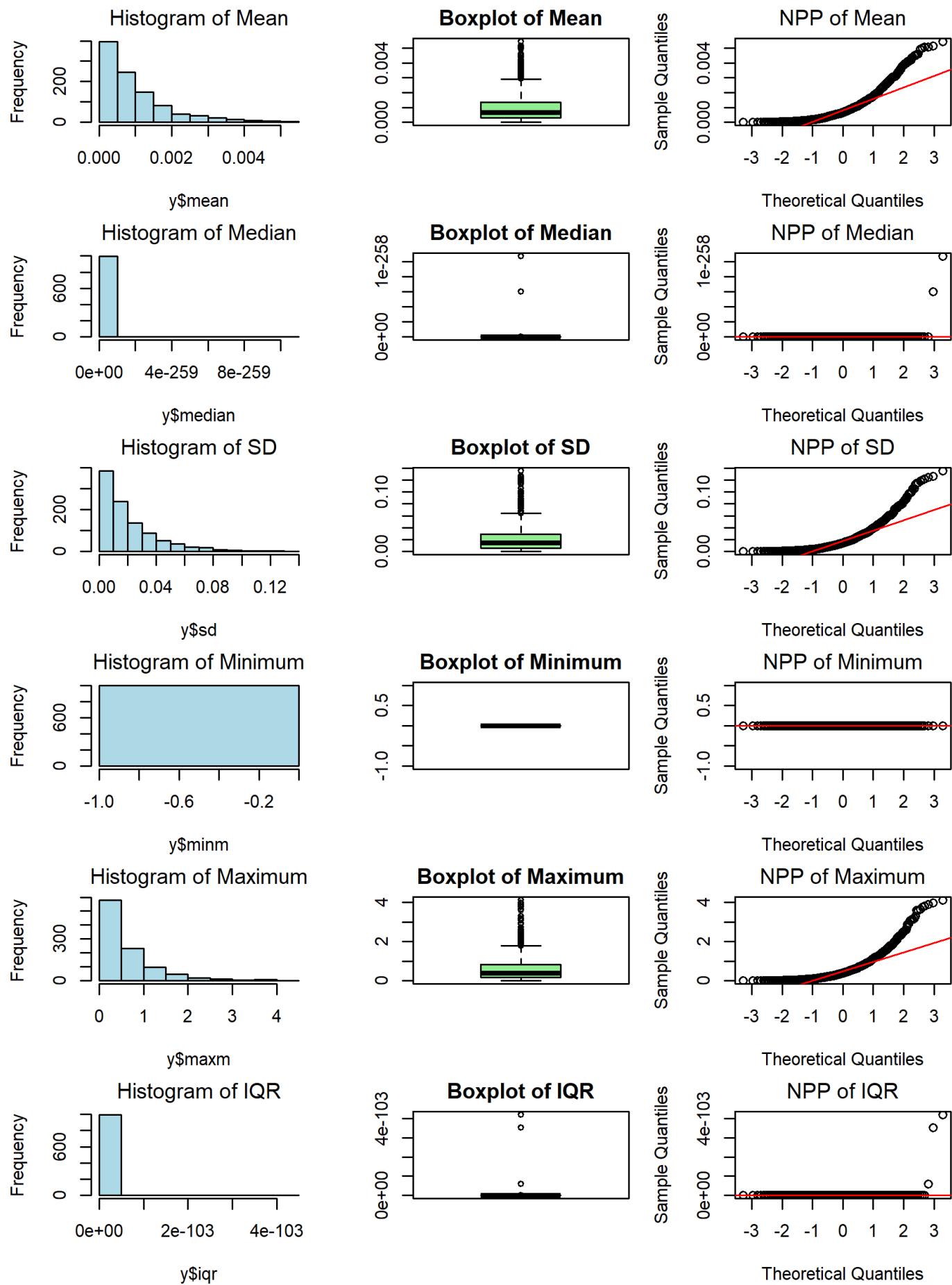
# GAMMA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=2$ ,  $\lambda=1$ )



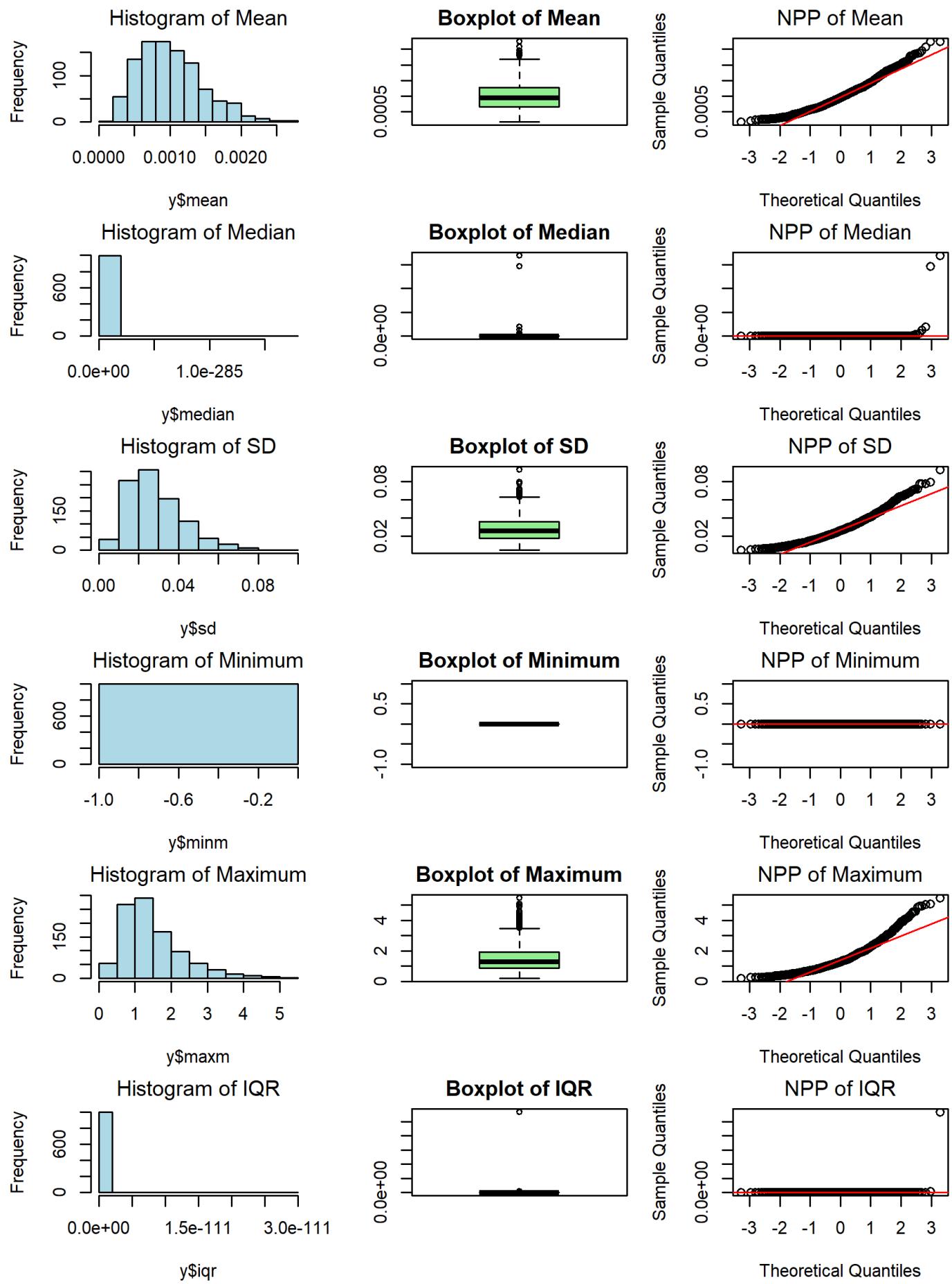
# GAMMA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=2$ ,  $\lambda=1$ )



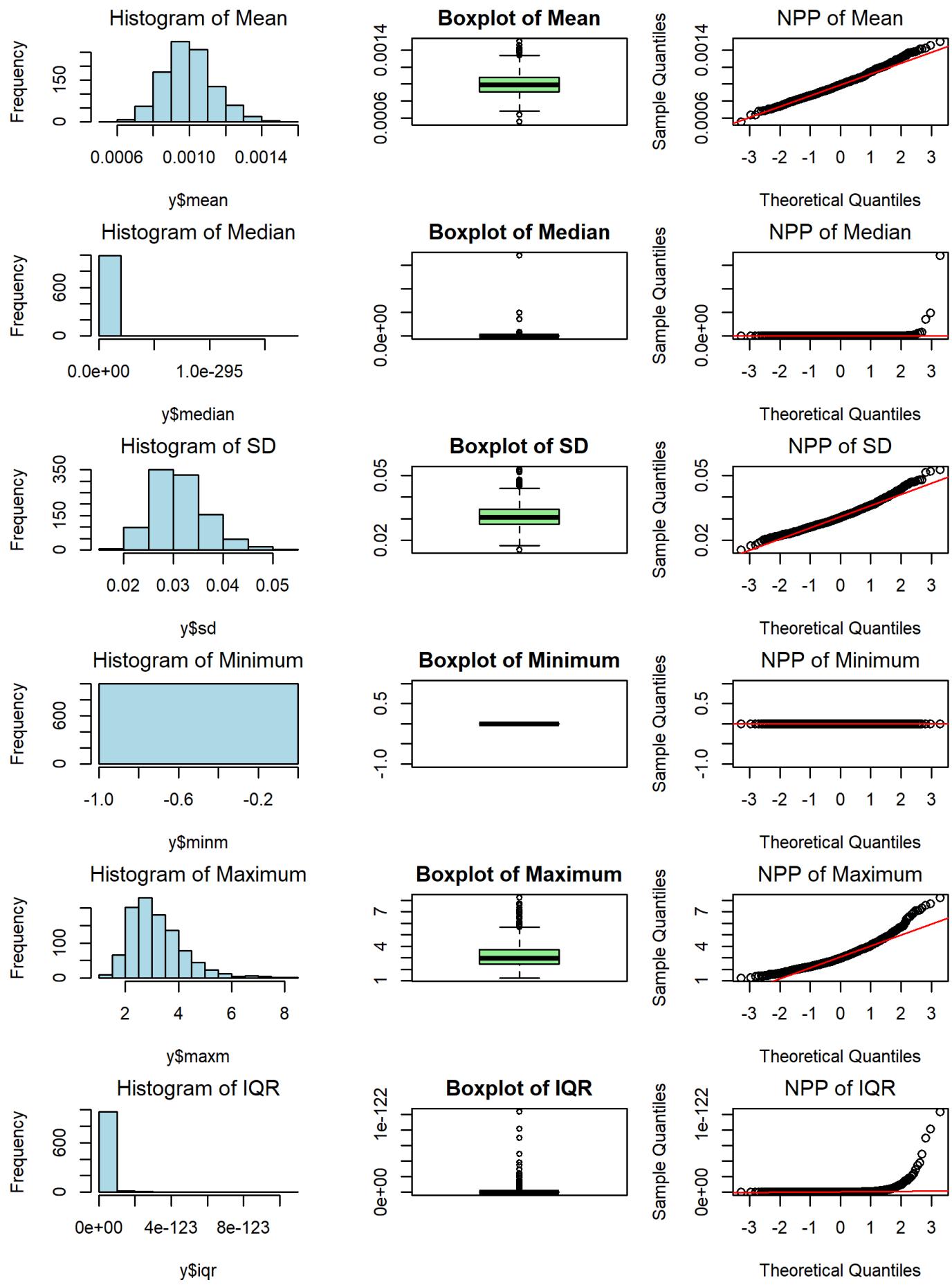
## GAMMA DISTRIBUTION PLOT

(n=5000, nn=1000,  $\alpha=2$ ,  $\lambda=1$ )



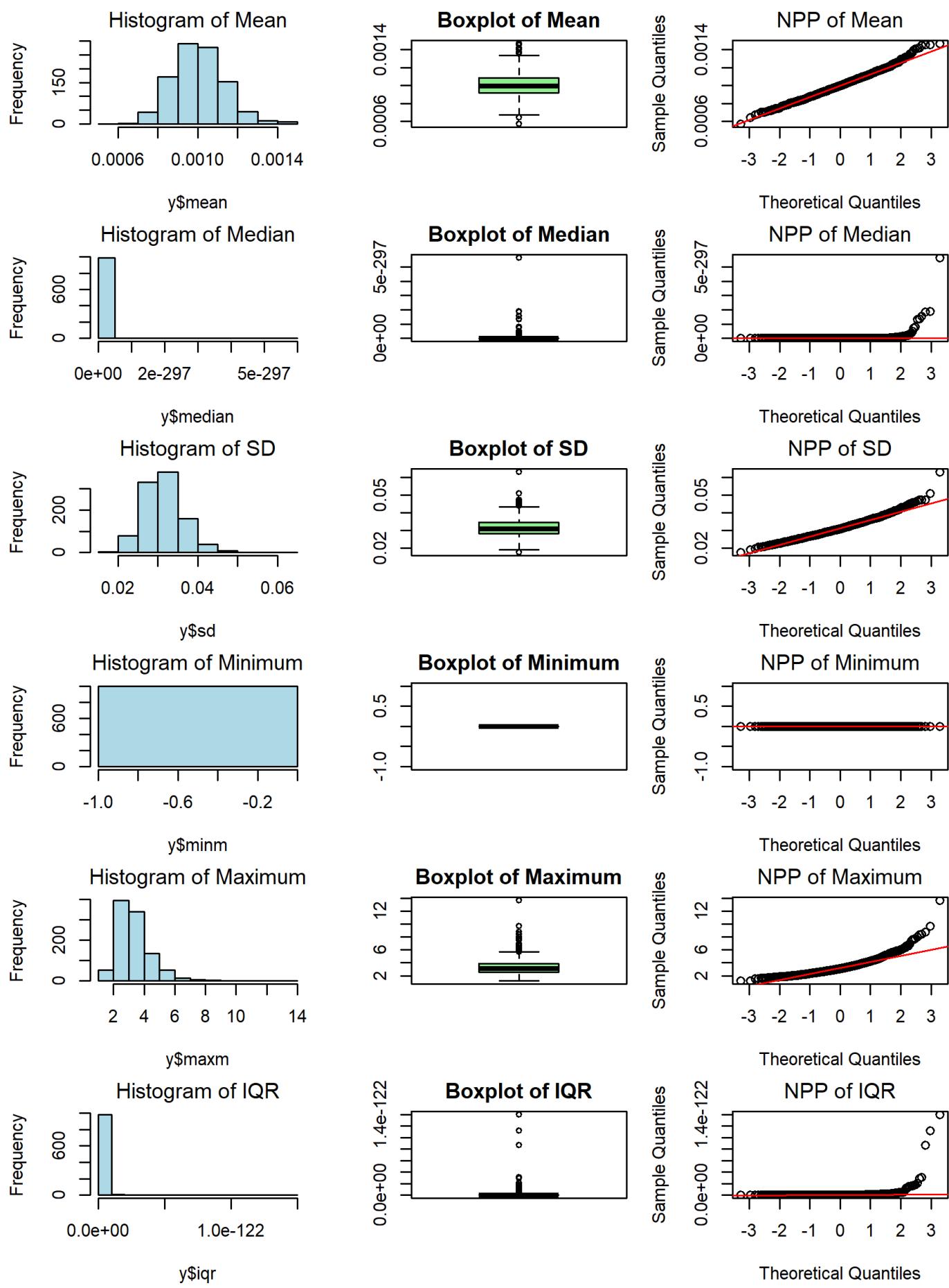
# GAMMA DISTRIBUTION PLOT

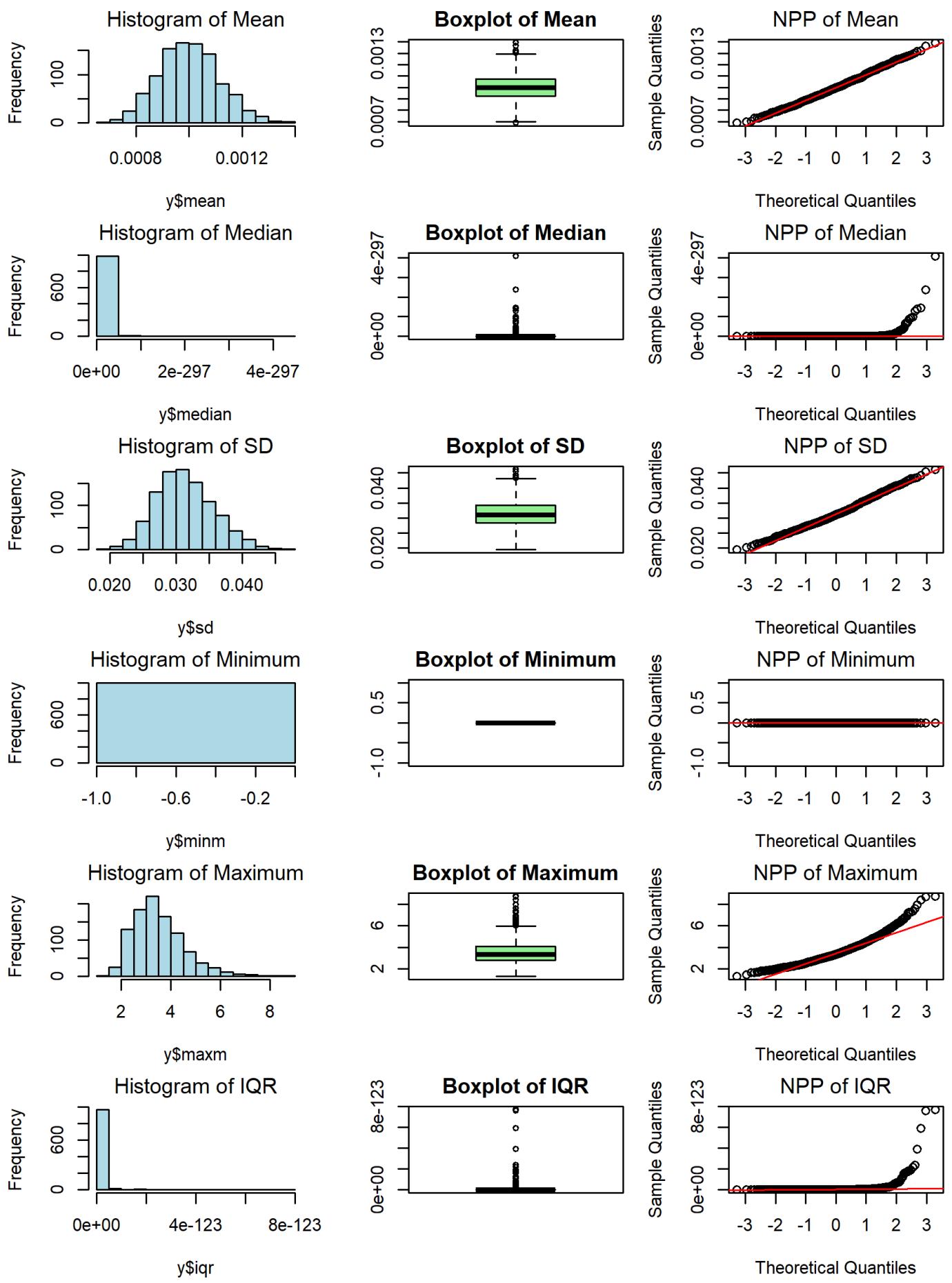
(n=50000, nn=1000,  $\alpha=2$ ,  $\lambda=1$ )



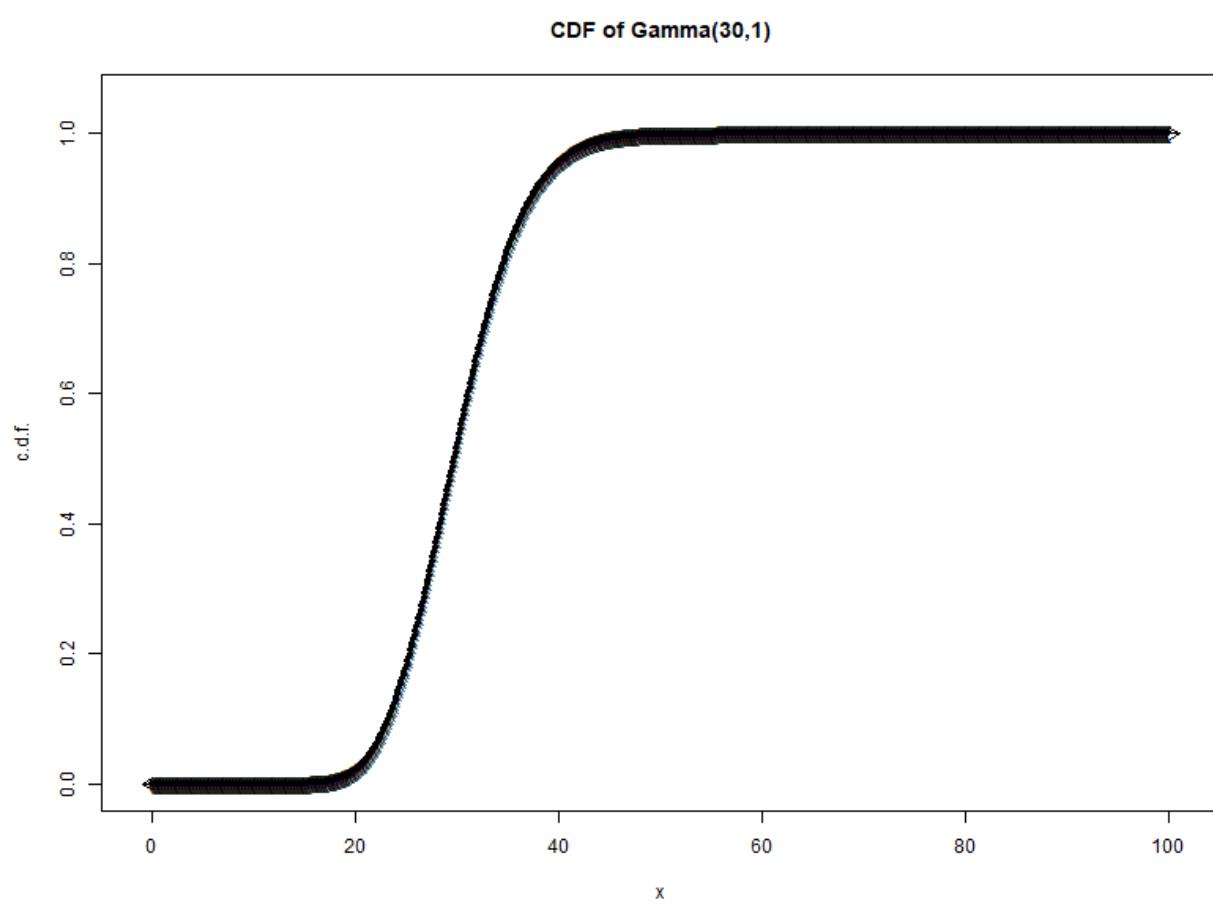
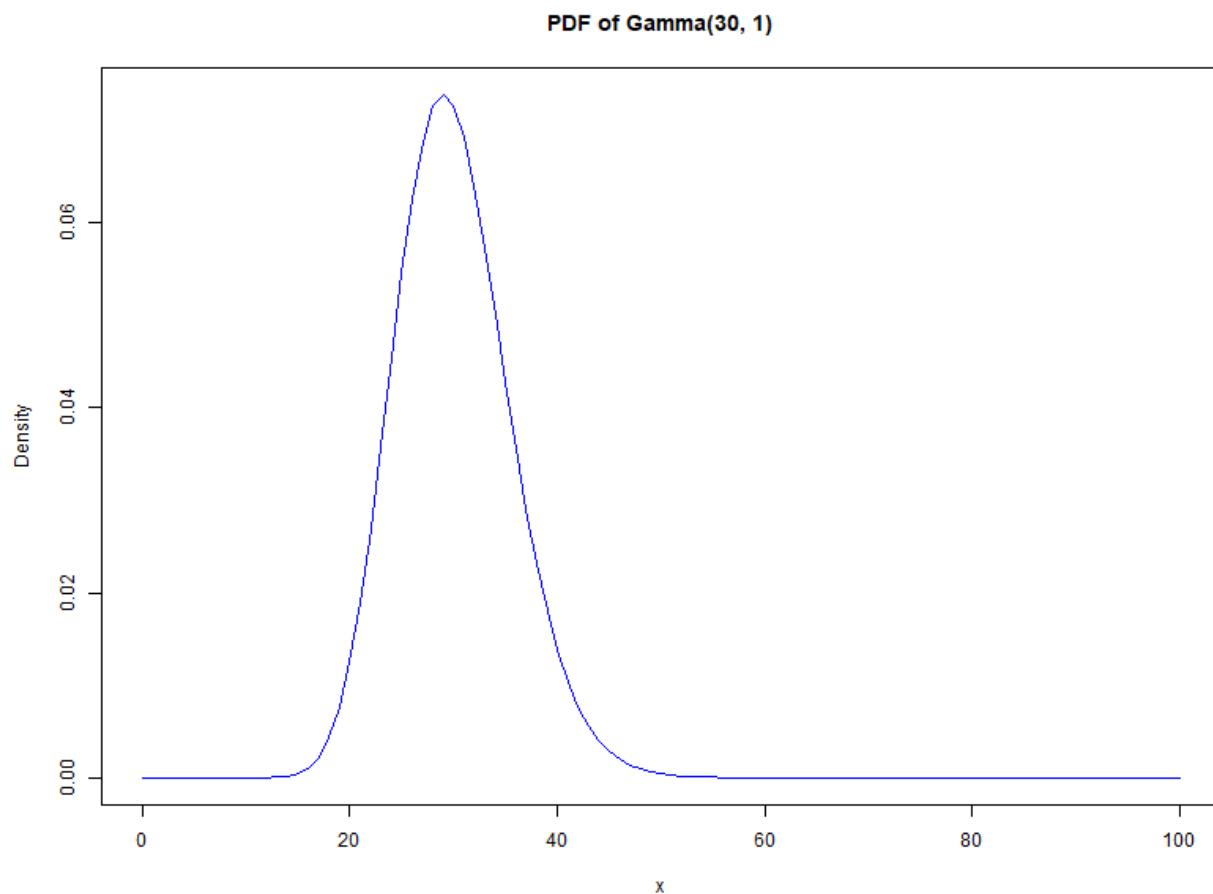
# GAMMA DISTRIBUTION PLOT

(n=70000, nn=1000,  $\alpha=2$ ,  $\lambda=1$ )





# GAMMA DISTRIBUTION (30,1)



# GAMMA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=30$ , $\lambda=1$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Median	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Std Dev	No	No	Yes	Yes	Yes	Yes	Yes	100	
Min	Yes	Yes	Yes	Yes	No	No	Yes	10	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	Yes	Yes	Yes	Yes	Yes	100	

## Conclusion for Gamma Distribution (with $\alpha = 30$ )

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 10$ , with quick convergence to normality as the sample size increases.
- **Median:** Achieves normality for  $n \geq 10$ , indicating a very fast convergence compared to lower values of  $\alpha$ .
- **Minimum:** Achieves normality for  $n \geq 10$  but loses normality again after  $n = 1000$ , showing a non-monotonic pattern in convergence.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 100$ , with convergence occurring at slightly larger sample sizes compared to the mean and median.
- **IQR:** Achieves normality for  $n \geq 100$ , with convergence following a similar pattern to the standard deviation.

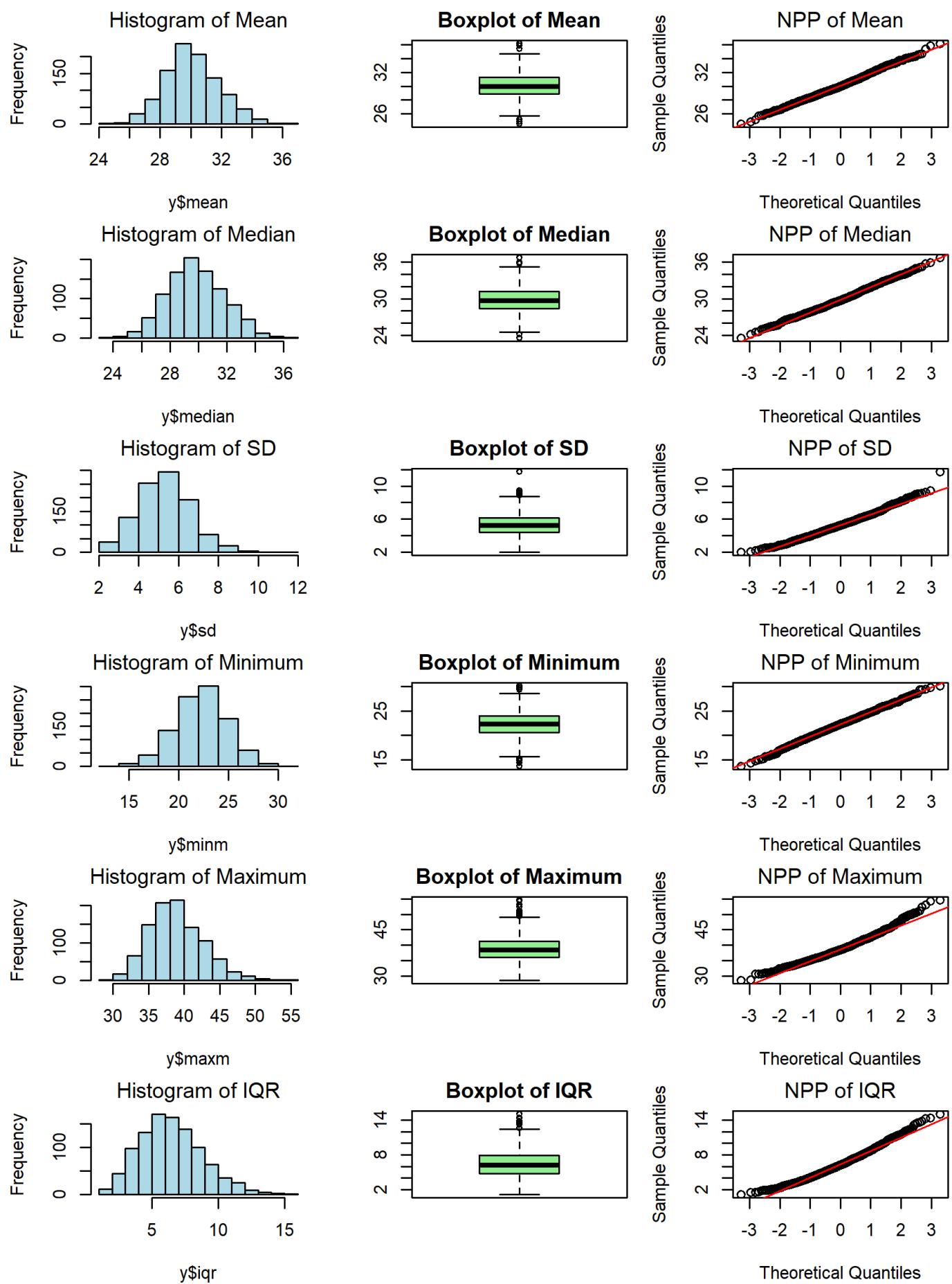
### Normality Not Achieved:

- **Maximum:** Does not achieve normality for any sample size, as it remains highly influenced by extreme values in the Gamma distribution.

**Overall:** For  $\alpha = 30$ , normality is achieved at very small sample sizes, especially for the mean, median, and minimum, where convergence is observed from  $n \geq 10$ . However, the minimum loses normality again after  $n = 1000$ . The standard deviation and IQR converge to normality at  $n \geq 100$ , showing faster convergence compared to lower values of  $\alpha$  (e.g.,  $\alpha = 0.001$  or  $\alpha = 2$ ). The maximum remains non-normal regardless of the sample size.

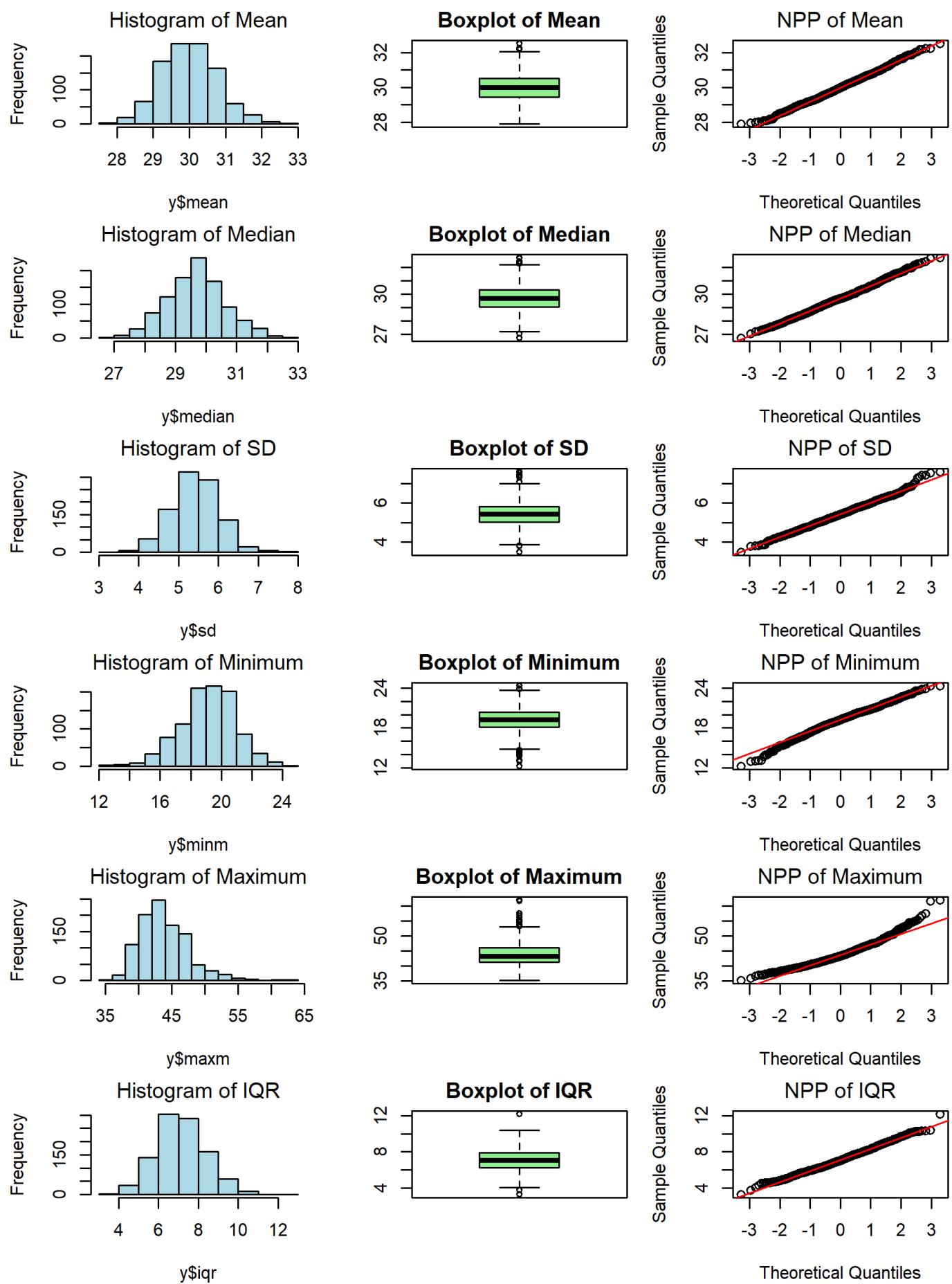
# GAMMA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=30$ ,  $\lambda=1$ )



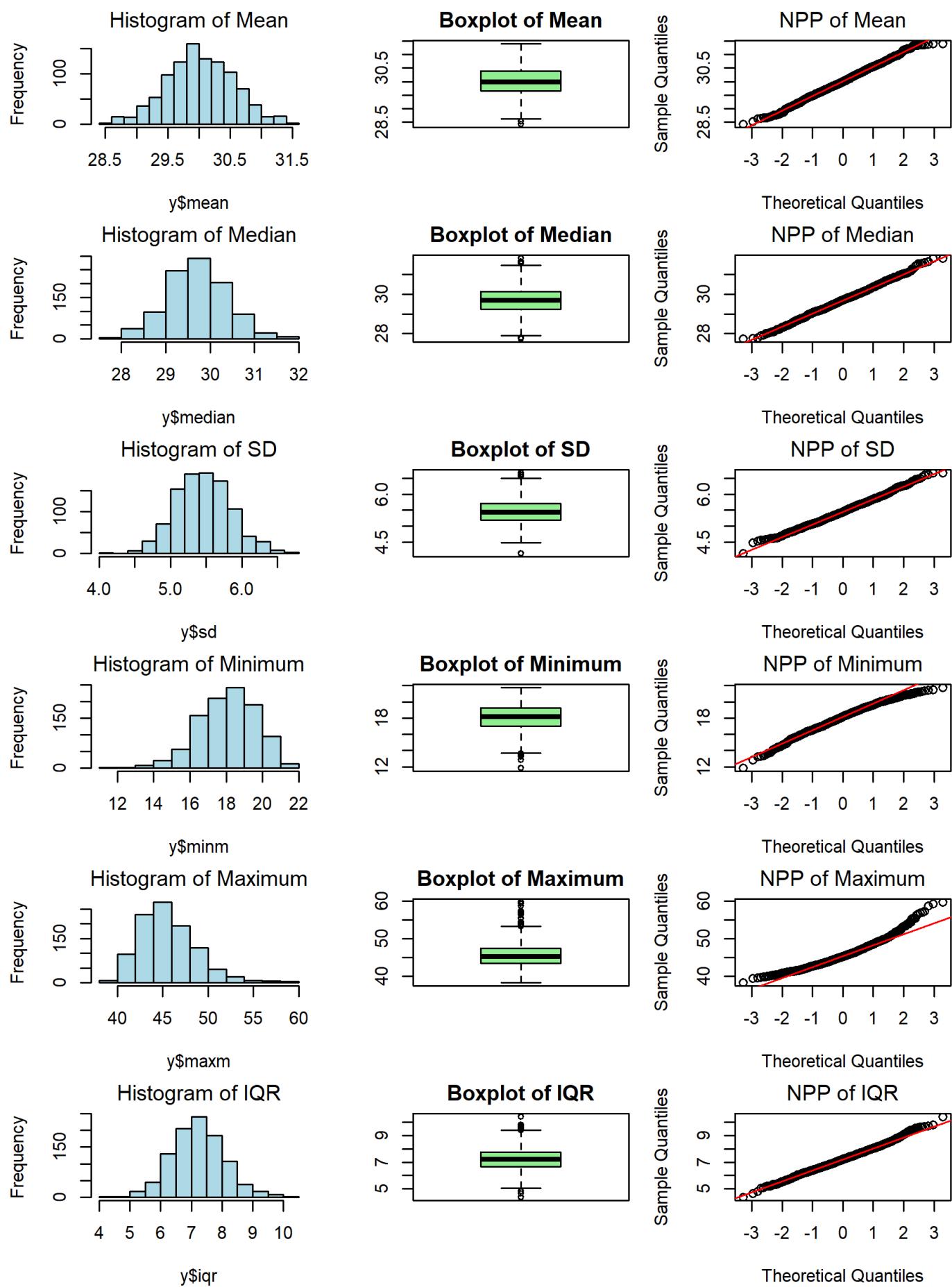
# GAMMA DISTRIBUTION PLOT

(n=50, nn=1000,  $\alpha=30$ ,  $\lambda=1$ )



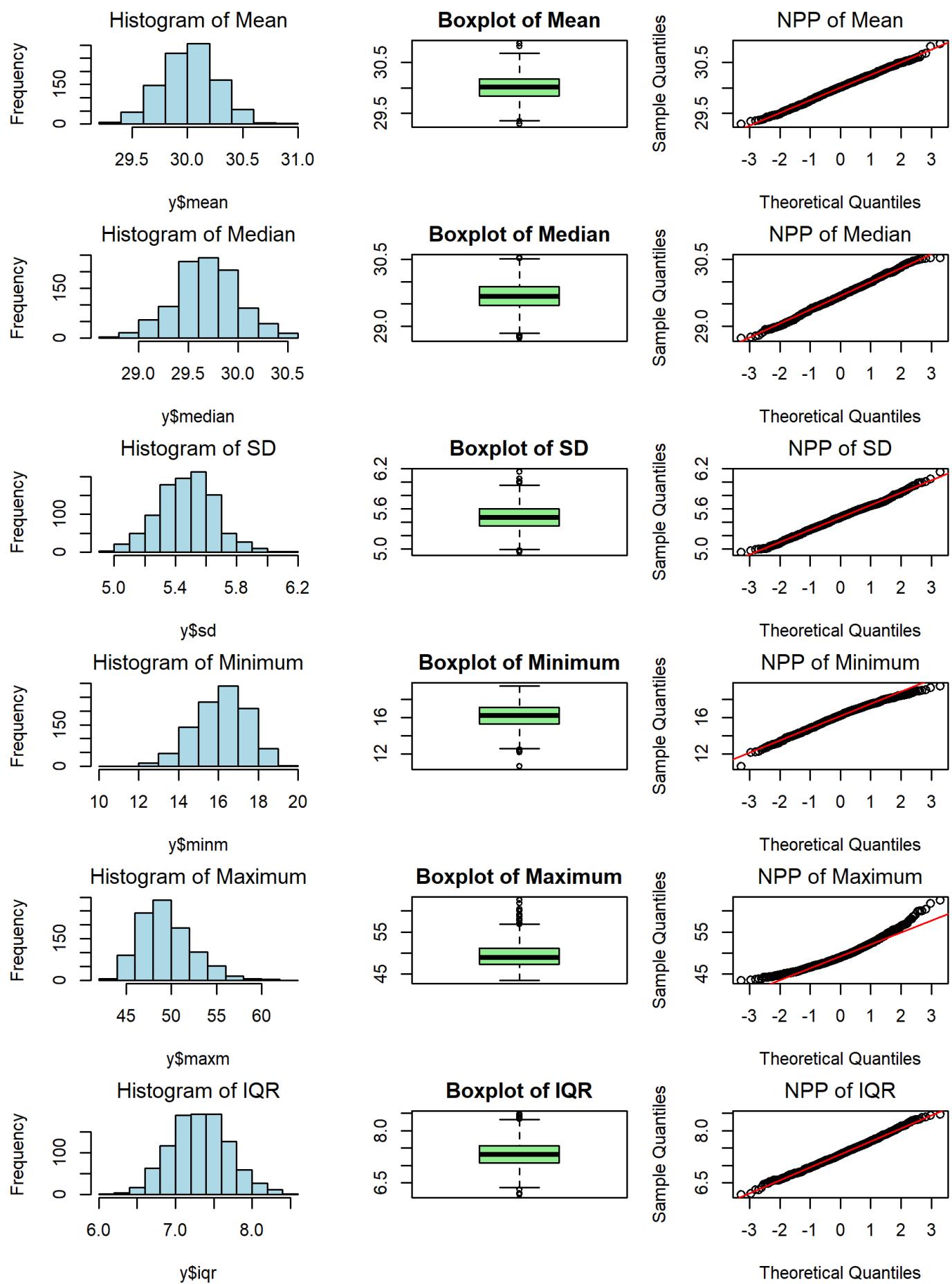
# GAMMA DISTRIBUTION PLOT

(n=100, nn=1000,  $\alpha=30$ ,  $\lambda=1$ )



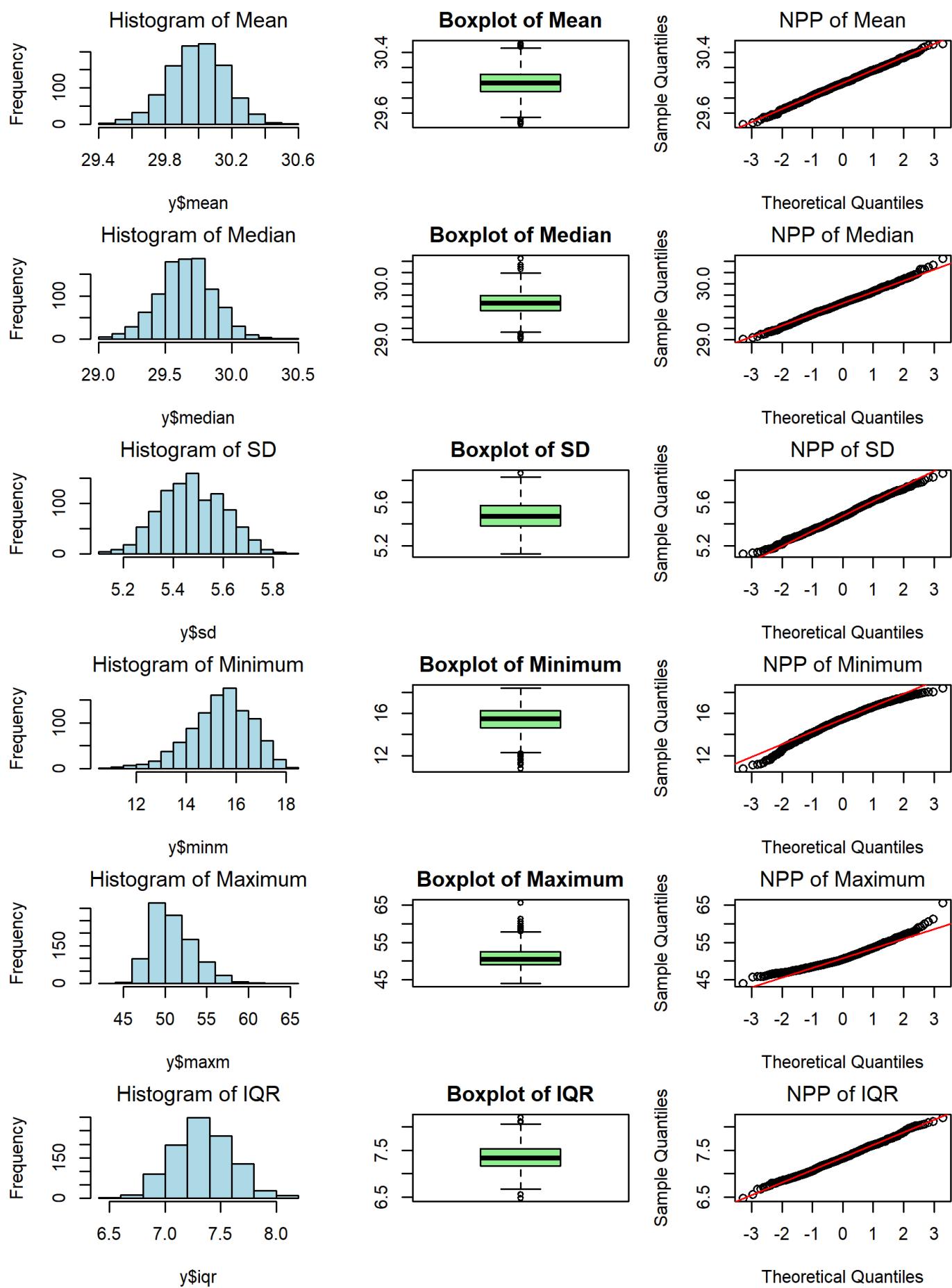
# GAMMA DISTRIBUTION PLOT

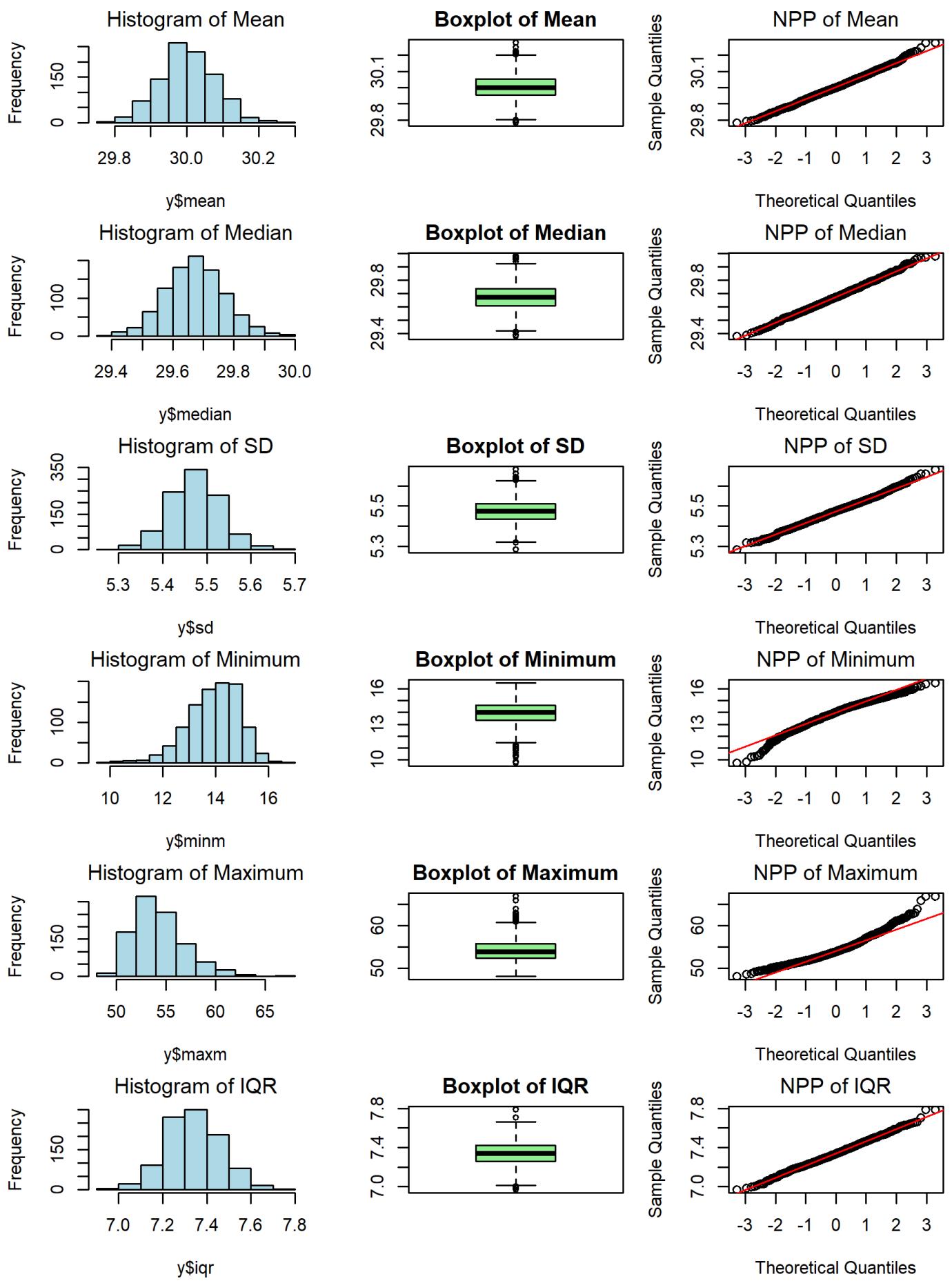
(n=500, nn=1000,  $\alpha=30$ ,  $\lambda=1$ )



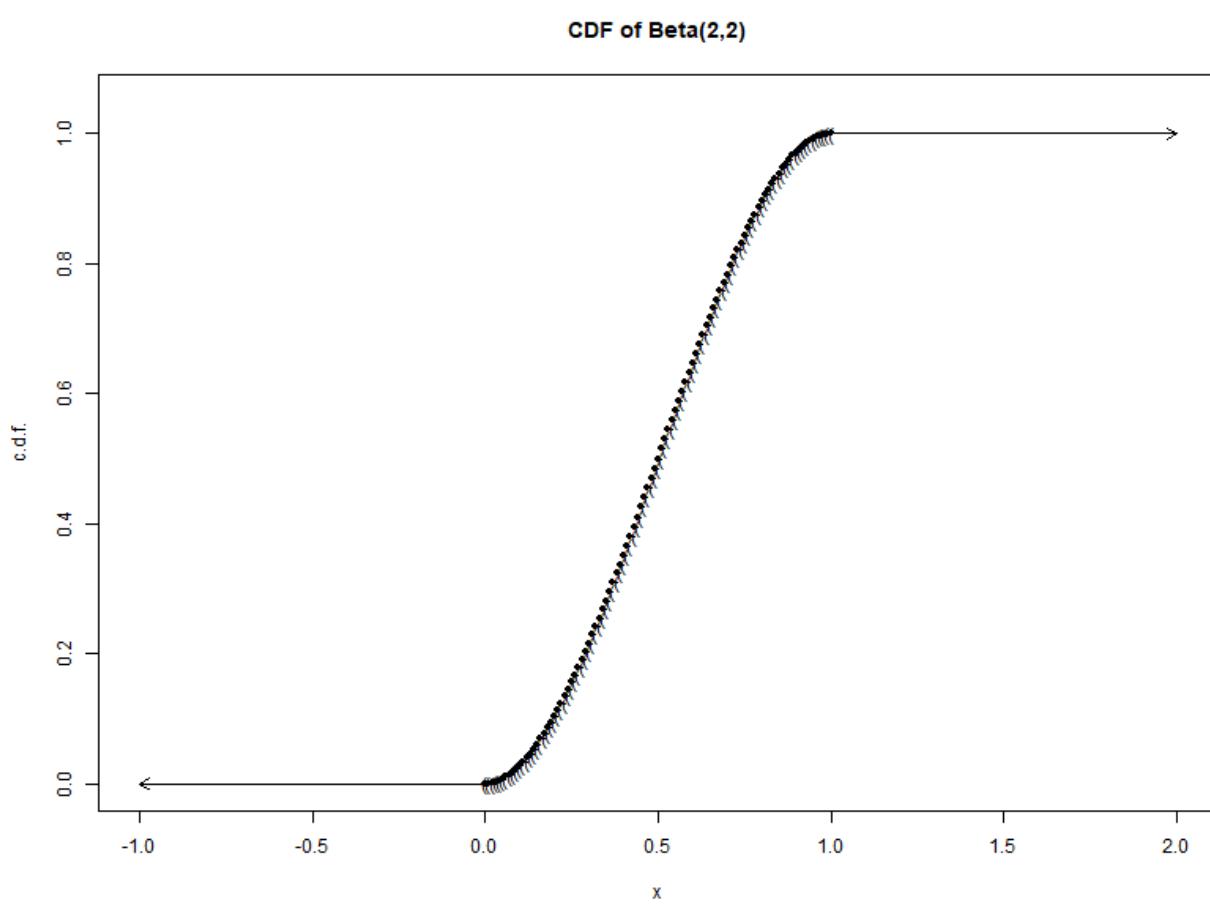
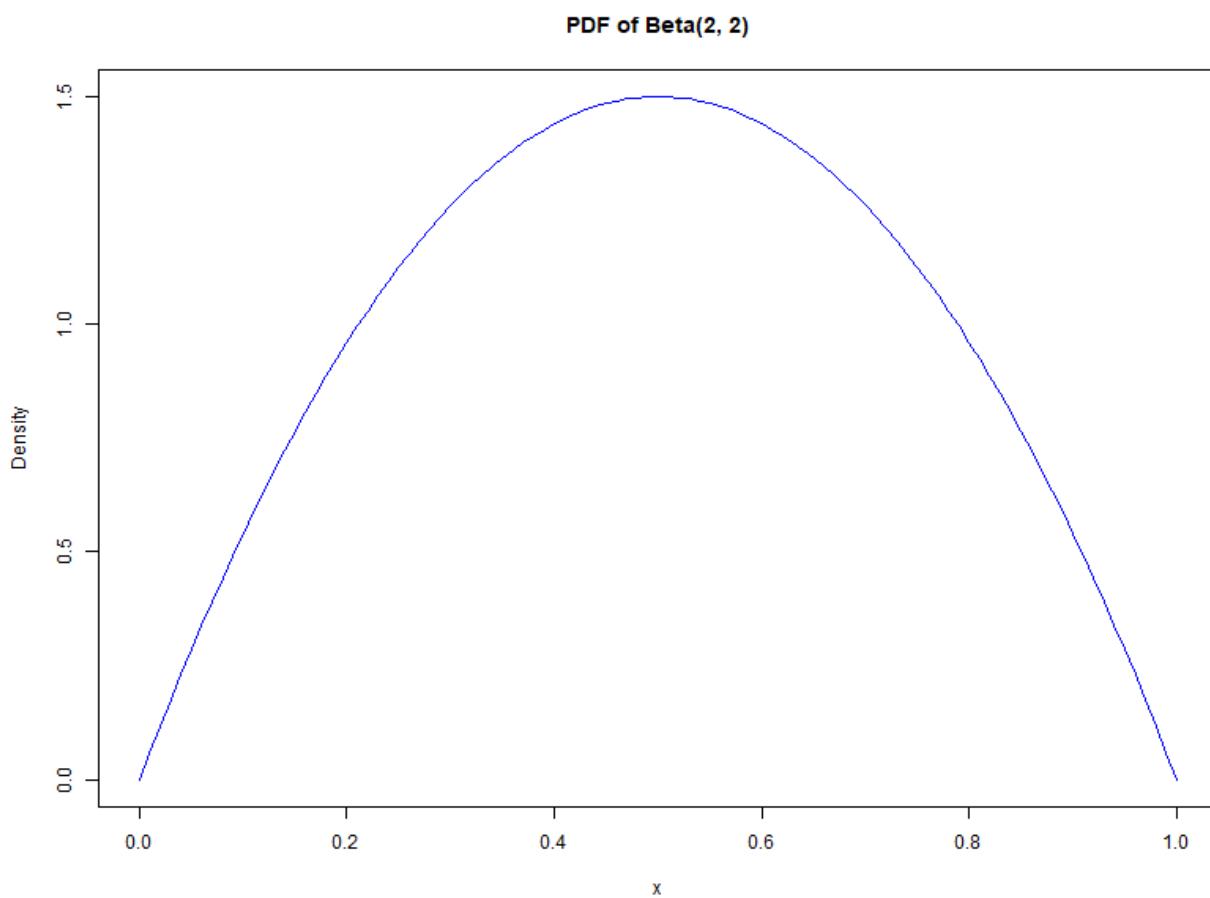
# GAMMA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=30$ ,  $\lambda=1$ )





# BETA DISTRIBUTION (2,2)



# BETA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=2$ , $\beta=2$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Median	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Std Dev	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	Yes	Yes	Yes	Yes	Yes	Yes	50	

## Conclusion for Beta Distribution ( $\alpha = 2$ , $\beta = 2$ )

### Normality Achieved:

- **Mean:** Achieves normality across all sample sizes ( $n \geq 10$ ), with normality reached relatively quickly due to the balanced parameters ( $\alpha = 2$ ,  $\beta = 2$ ) of the Beta distribution.
- **Standard Deviation (SD):** Achieves normality for all sample sizes ( $n \geq 10$ ), with convergence starting from very small sample sizes.

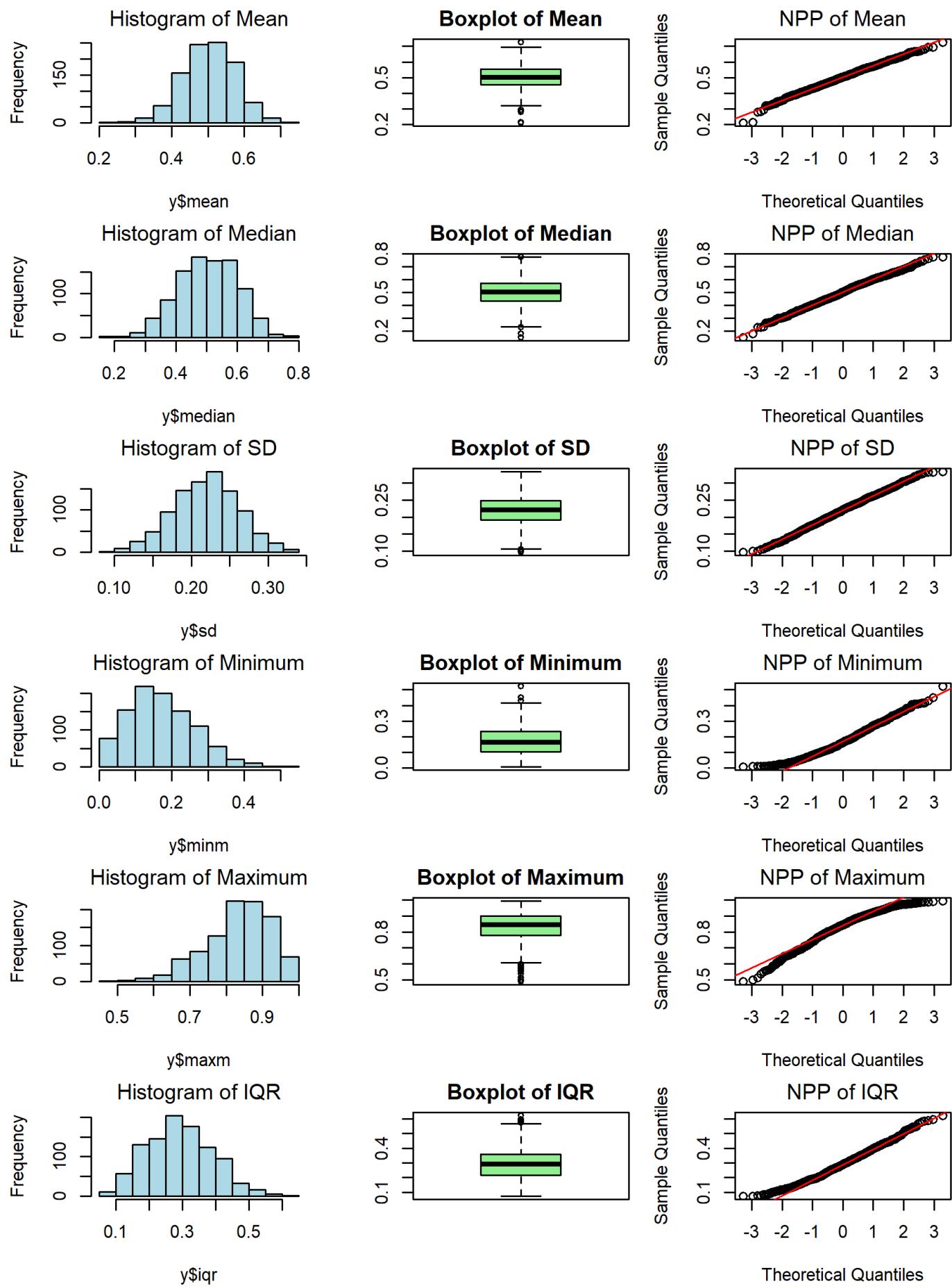
### Normality Not Achieved:

- **Median:** Achieves normality for  $n \geq 50$ , with smaller sample sizes ( $n \leq 10$ ) showing a more skewed distribution. Larger sample sizes help reduce the skewness.
- **IQR:** Achieves normality for  $n \geq 50$ , reflecting a similar trend to the median. The smaller the sample size, the more likely it is to deviate from normality.
- **Minimum and Maximum:** Do not achieve normality for any sample size due to their sensitivity to the extreme values in the Beta distribution.

**Overall:** The Beta distribution with  $\alpha = 2$  and  $\beta = 2$  shows the fastest convergence to normality for the mean, standard deviation, and IQR, even at smaller sample sizes ( $n \geq 10$ ). The median and IQR require larger sample sizes ( $n \geq 50$ ) to show normality. The minimum and maximum values do not show normality due to their inherent sensitivity to extreme values.

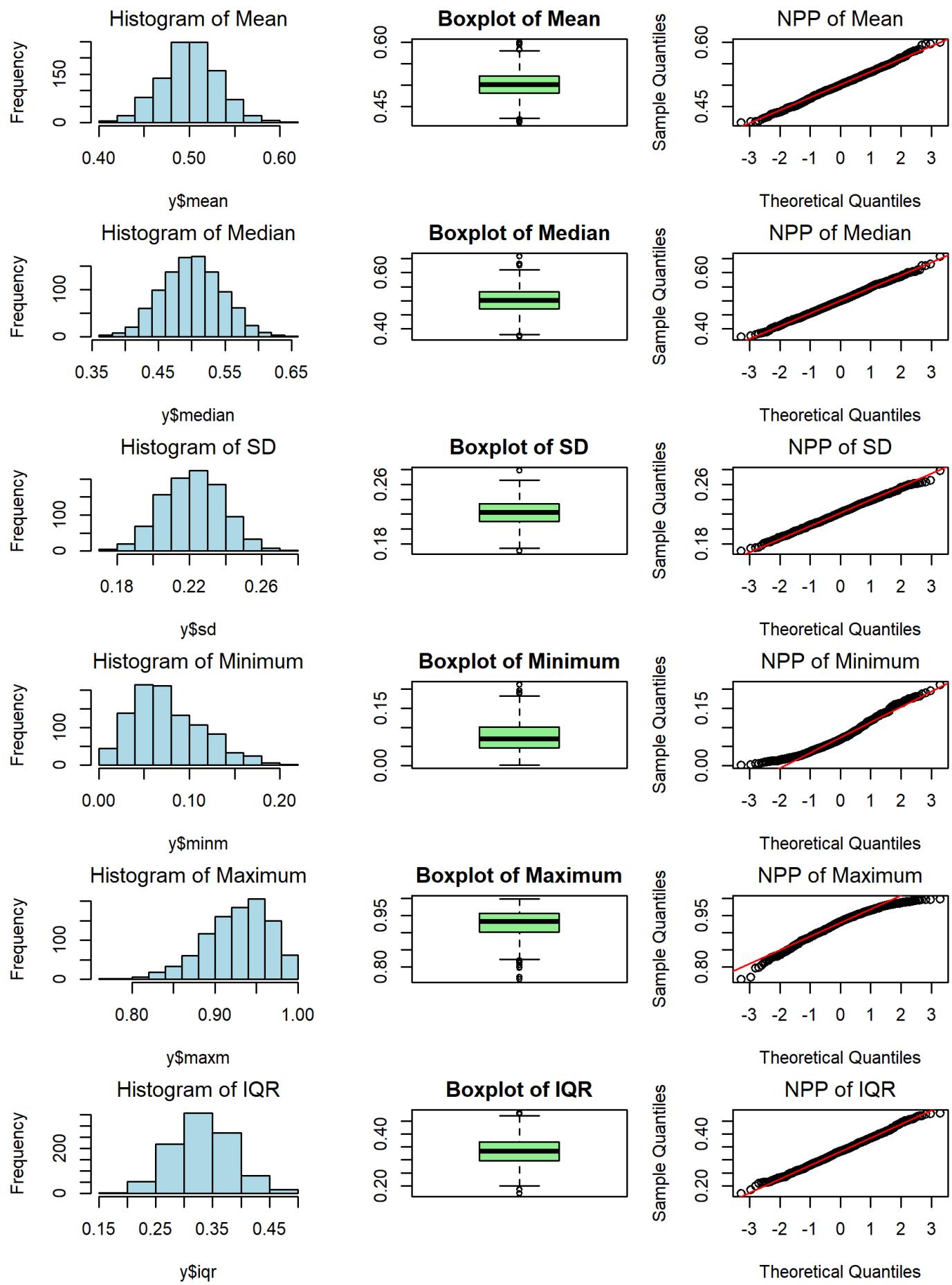
## BETA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=2$ ,  $\beta=2$ )



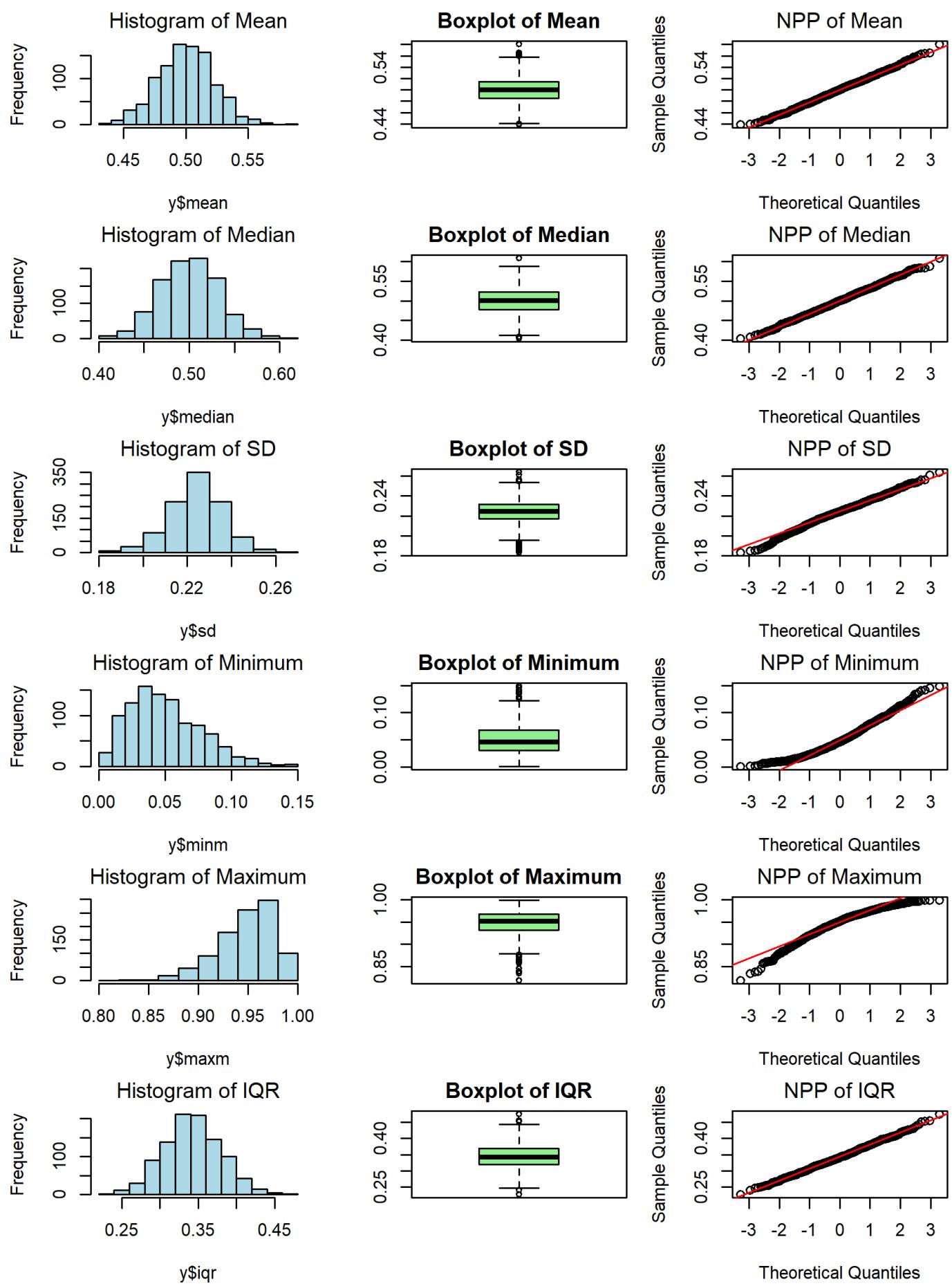
# BETA DISTRIBUTION PLOT

(n=50, nn=1000,  $\alpha=2$ ,  $\beta=2$ )



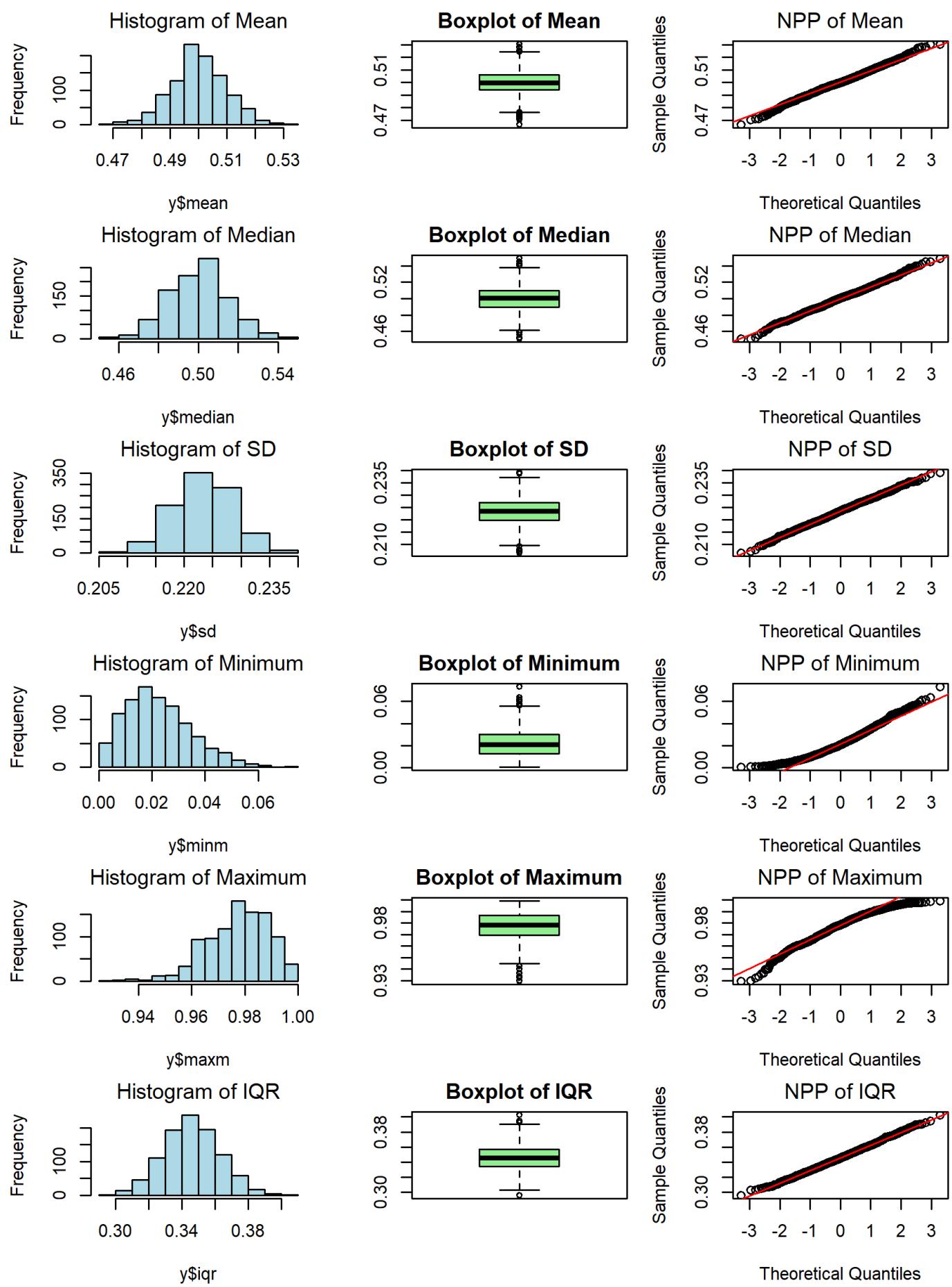
# BETA DISTRIBUTION PLOT

(n=100, nn=1000,  $\alpha=2$ ,  $\beta=2$ )



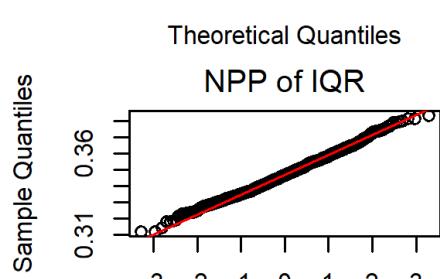
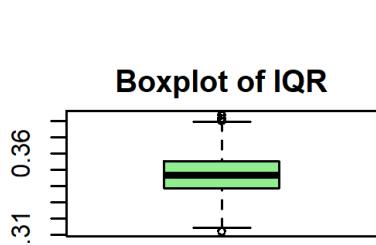
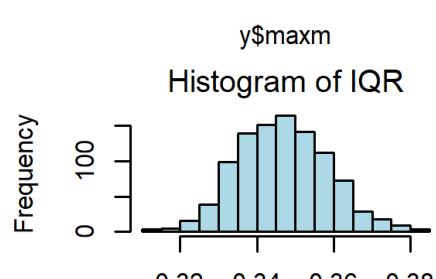
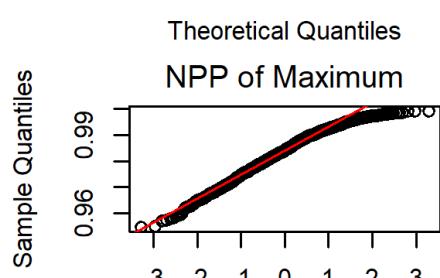
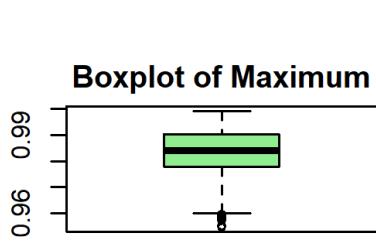
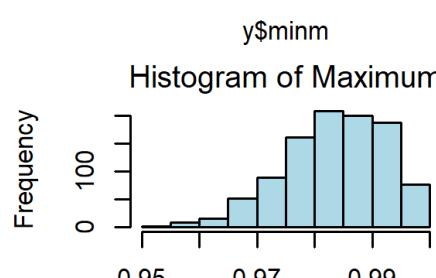
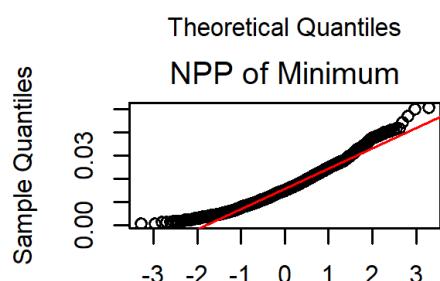
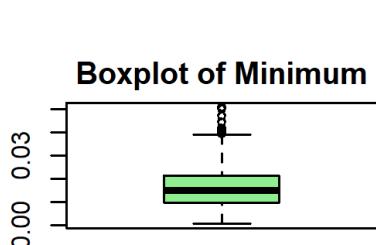
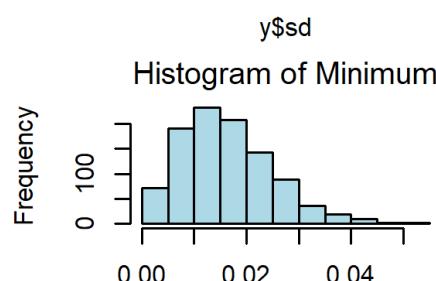
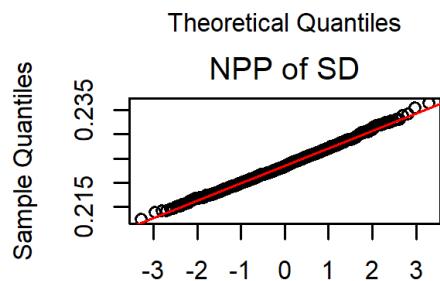
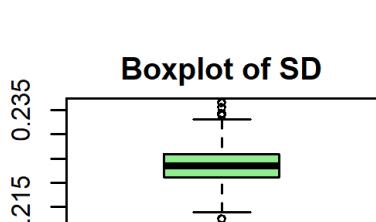
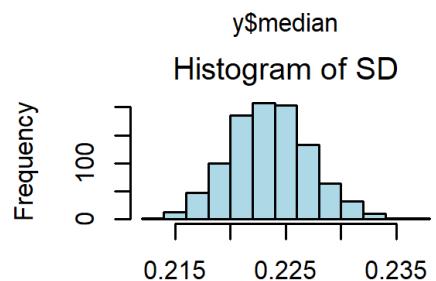
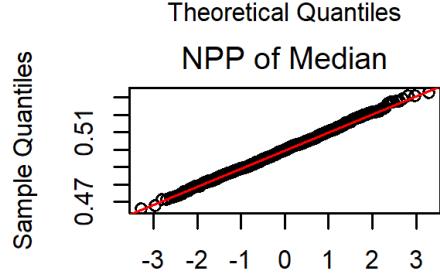
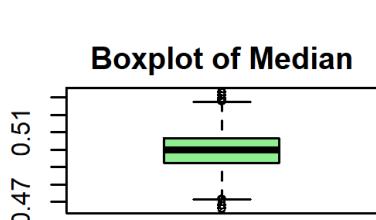
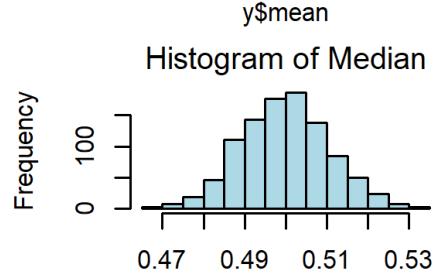
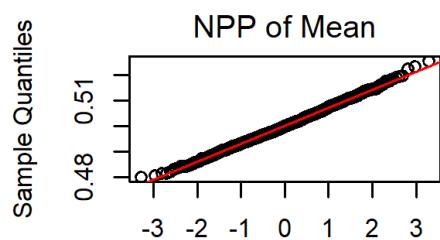
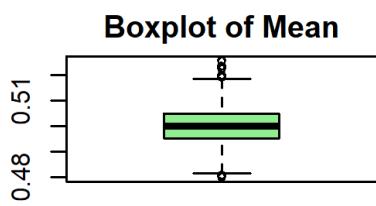
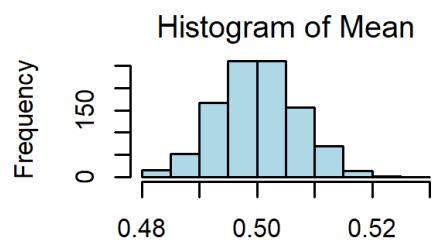
# BETA DISTRIBUTION PLOT

(n=500, nn=1000,  $\alpha=2$ ,  $\beta=2$ )



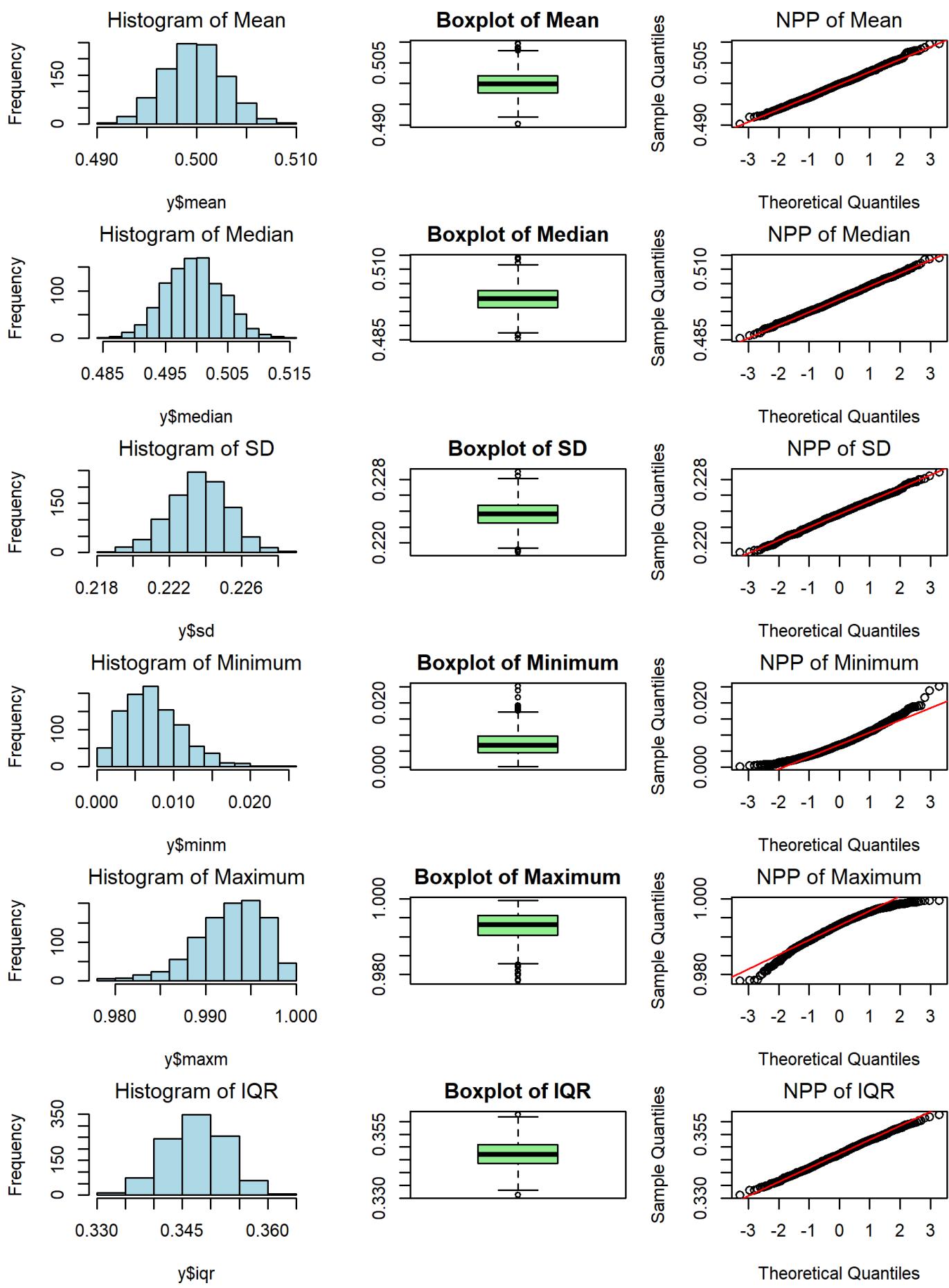
# BETA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=2$ ,  $\beta=2$ )



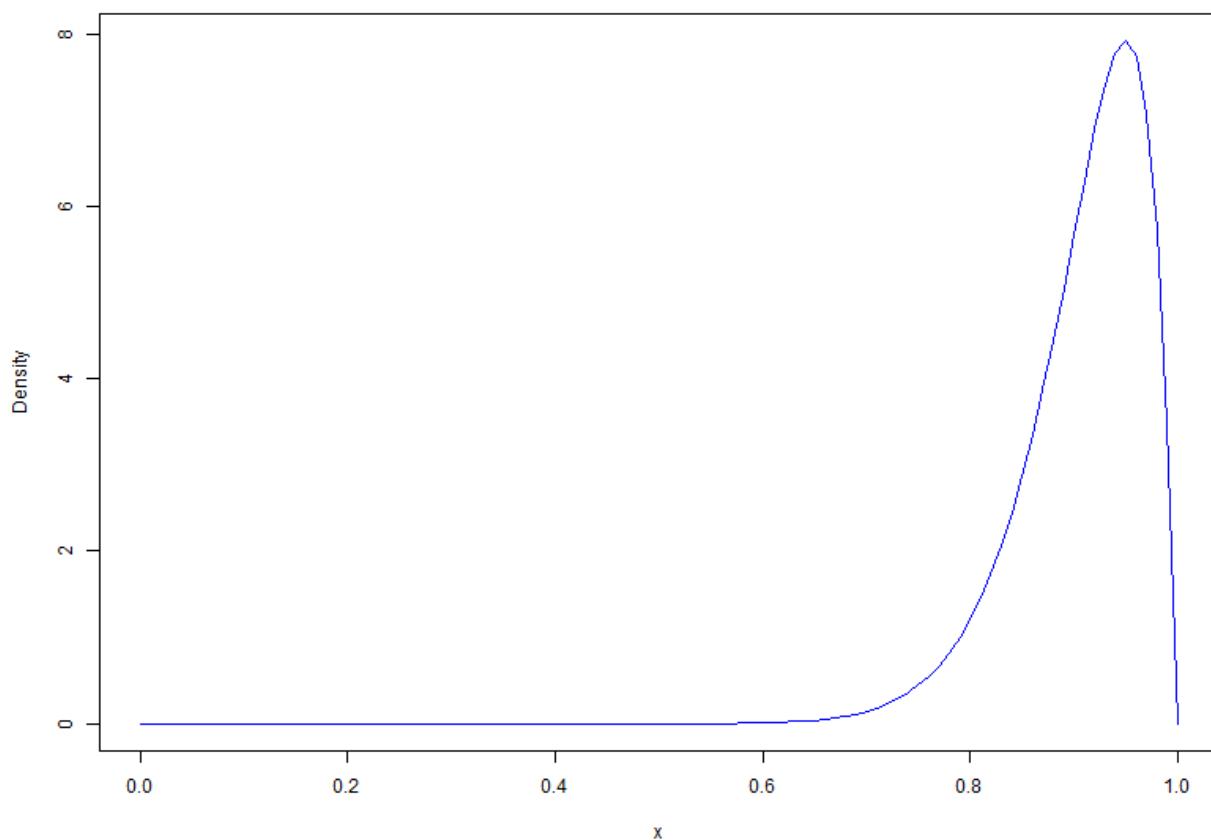
y*iqr*

Theoretical Quantiles

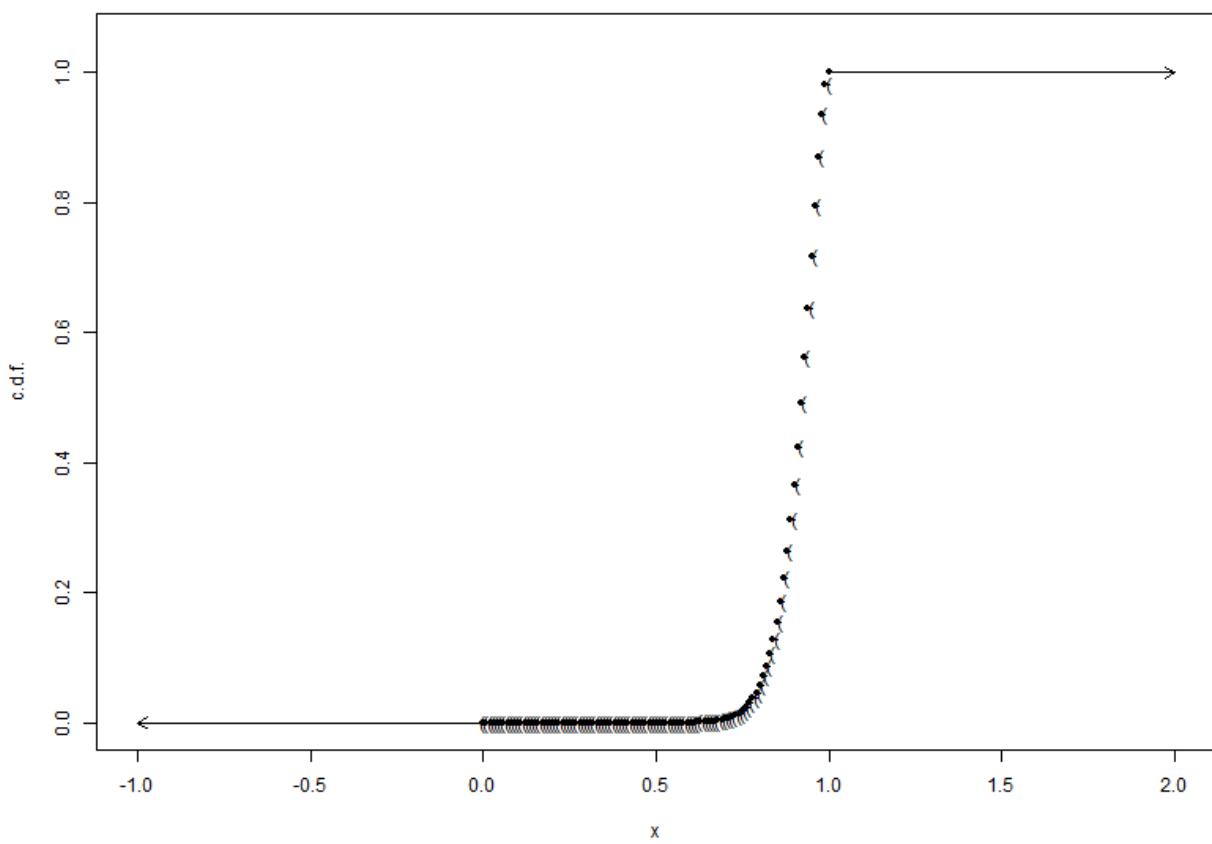


# BETA DISTRIBUTION (20,2)

PDF of Beta(20, 2)



CDF of Beta(20,2)



# BETA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=20$ , $\beta=2$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Median	No	No	Yes	Yes	Yes	Yes	Yes	100	
Std Dev	No	No	Yes	Yes	Yes	Yes	Yes	100	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	Yes	Yes	Yes	Yes	Yes	Yes	50	

## Conclusion for Beta Distribution ( $\alpha = 20$ , $\beta = 2$ )

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 50$ , with rapid convergence as sample size increases.
- **Median:** Achieves normality for  $n \geq 100$ , with smaller sample sizes ( $n \leq 50$ ) exhibiting more variability.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 100$ , showing increasing stability as sample size grows.
- **IQR:** Achieves normality for  $n \geq 50$ , with larger sample sizes reflecting a smoother distribution.

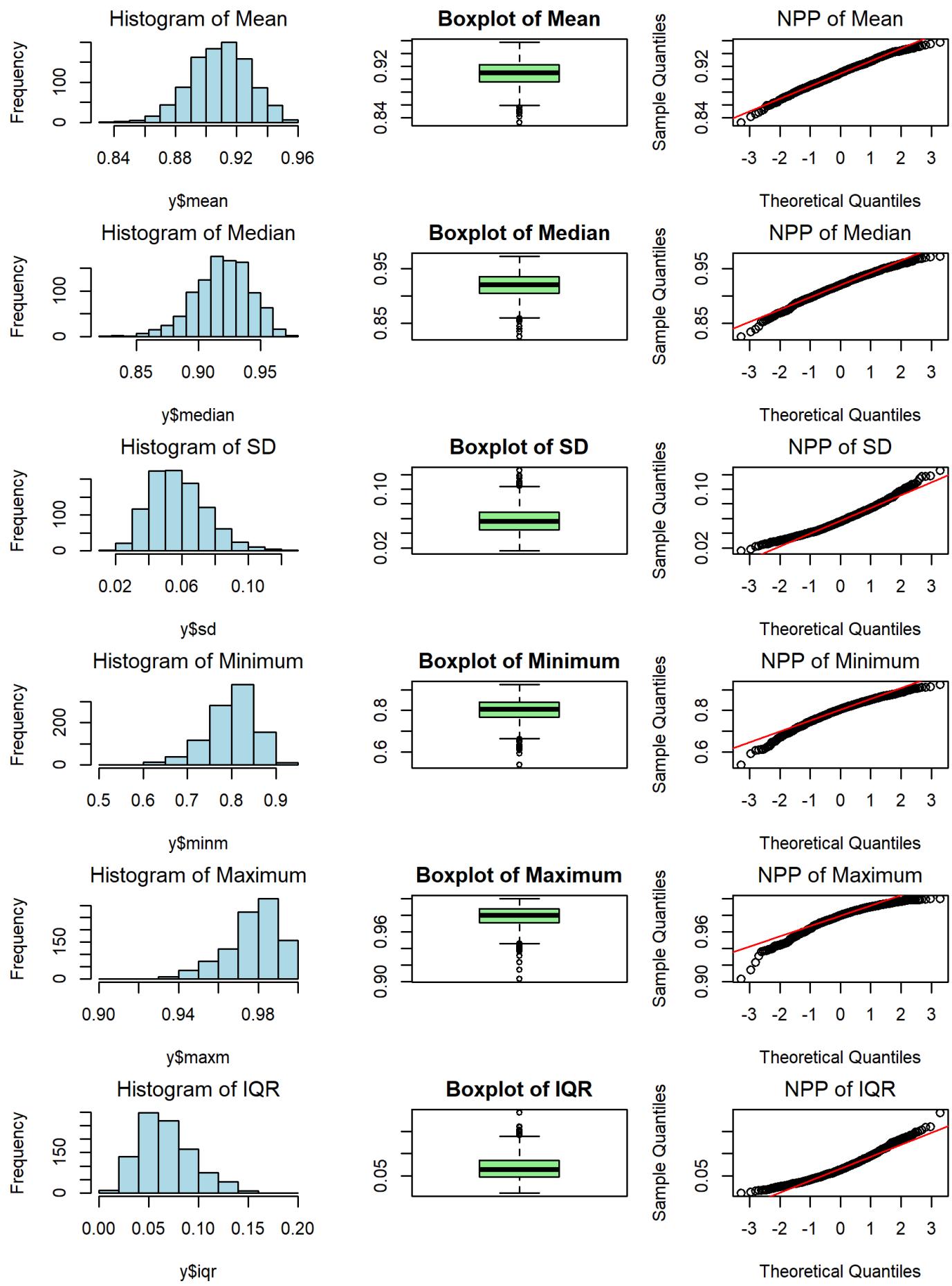
### Normality Not Achieved:

- **Minimum and Maximum:** Do not achieve normality for any sample size due to the distribution's skewness, especially at smaller sample sizes.

**Overall:** The Beta distribution with  $\alpha = 20$  and  $\beta = 2$  demonstrates the fastest convergence to normality for the mean, median, standard deviation, and IQR as the sample size increases, with  $n \geq 50$  being sufficient for the mean and  $n \geq 100$  for other statistics. The minimum and maximum values remain non-normal across all sample sizes due to the skewed nature of the distribution.

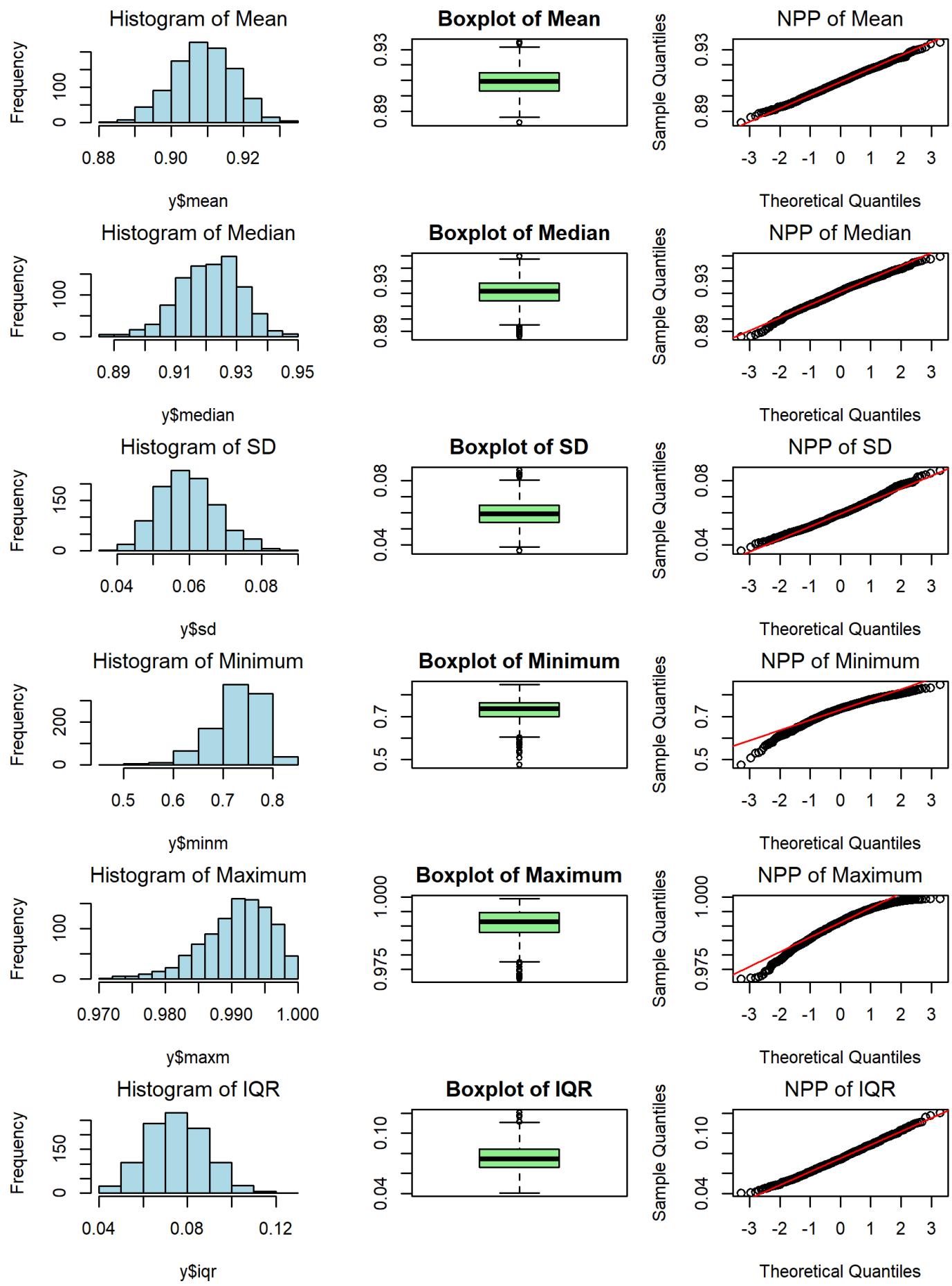
# BETA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=20$ ,  $\beta=2$ )



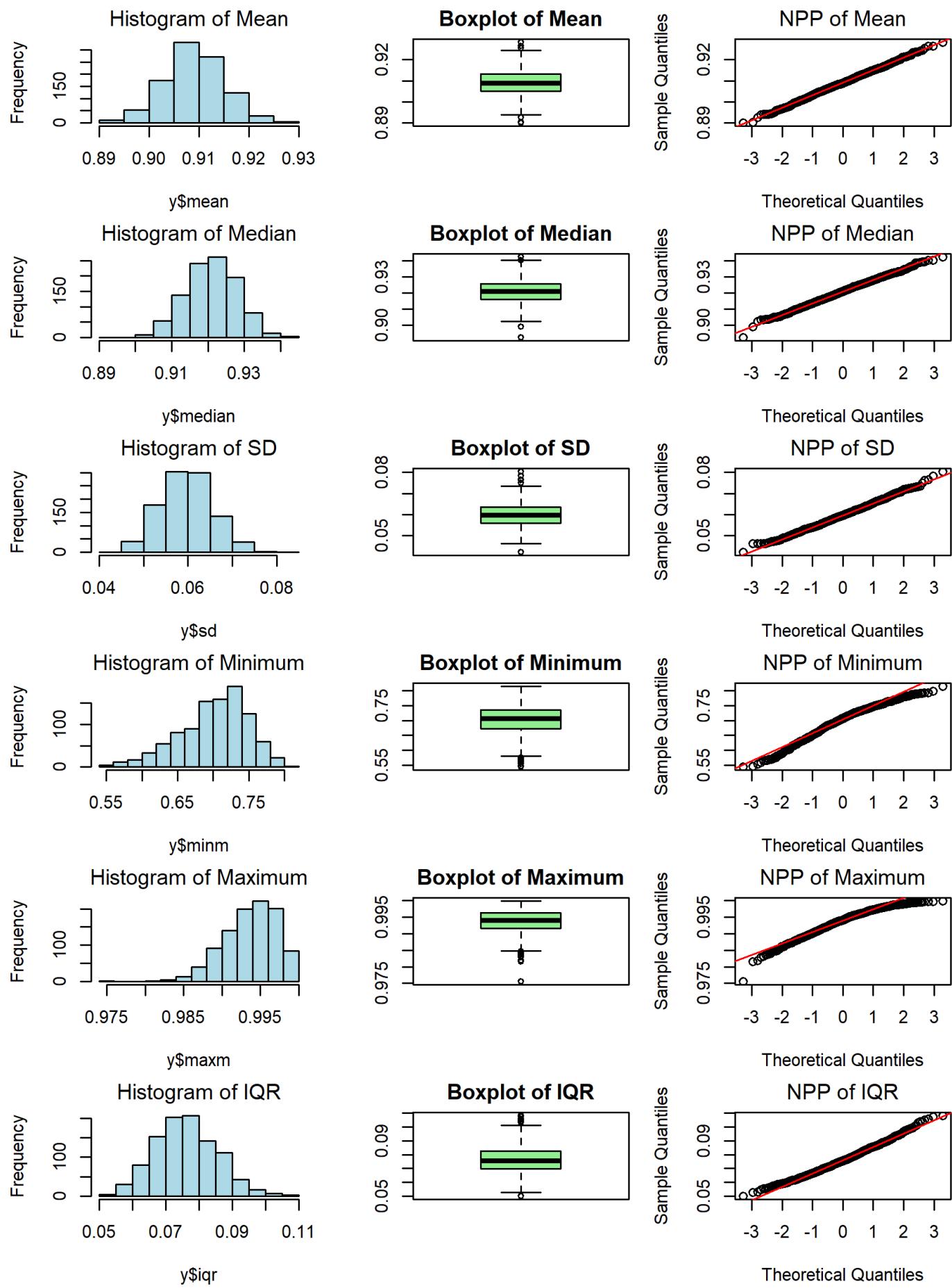
# BETA DISTRIBUTION PLOT

(n=50, nn=1000,  $\alpha=20$ ,  $\beta=2$ )



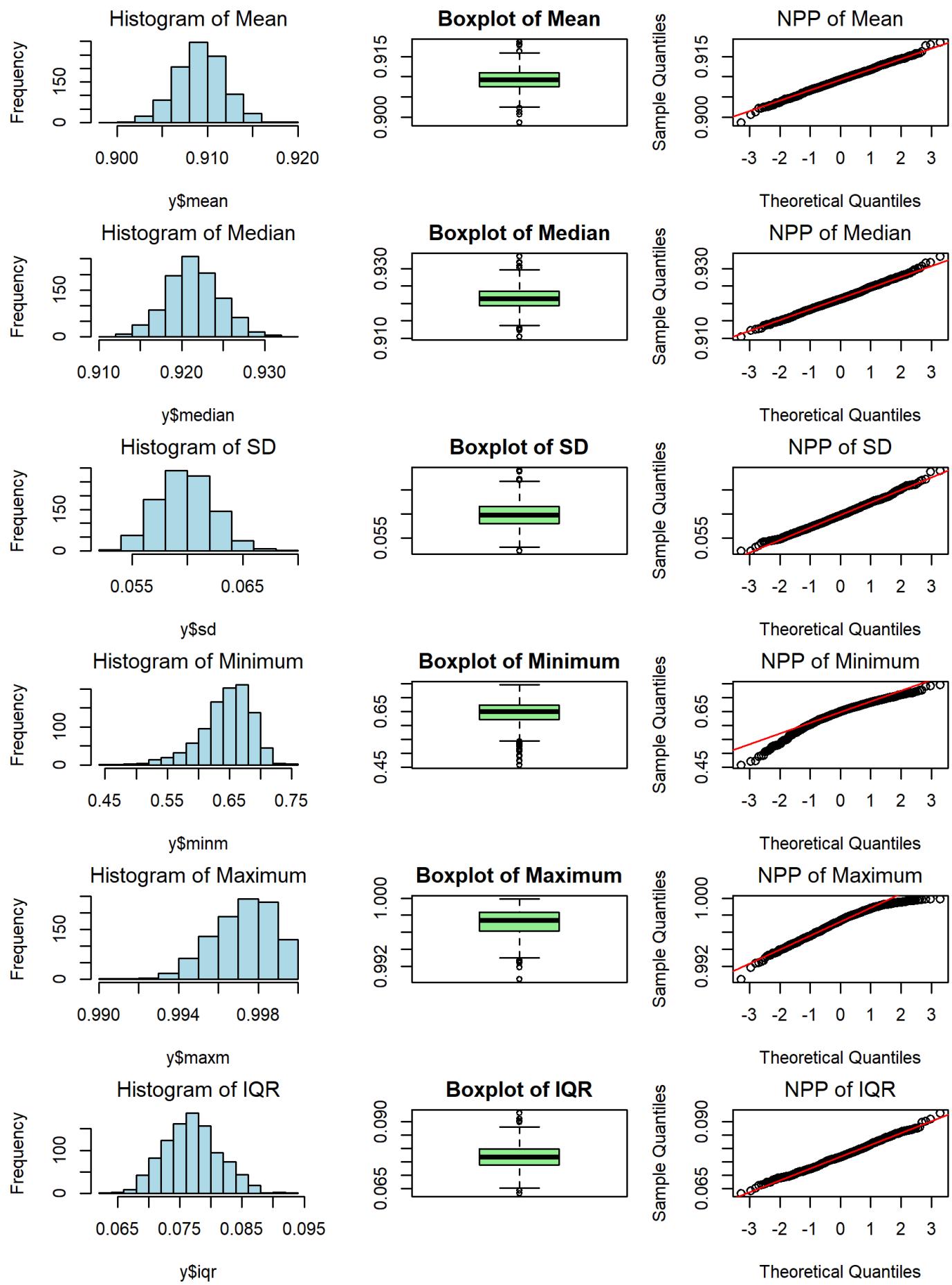
# BETA DISTRIBUTION PLOT

(n=100, nn=1000,  $\alpha=20$ ,  $\beta=2$ )



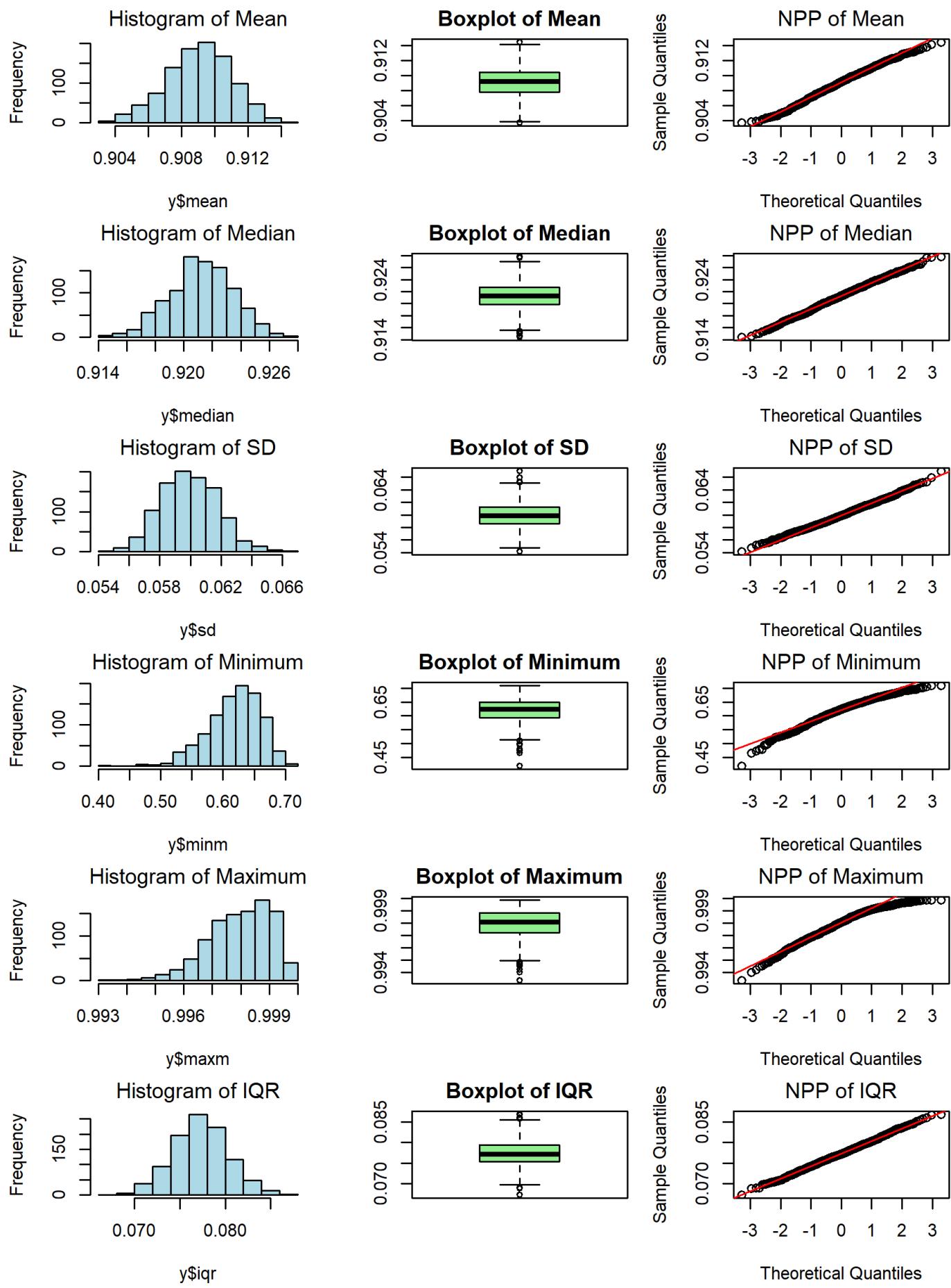
# BETA DISTRIBUTION PLOT

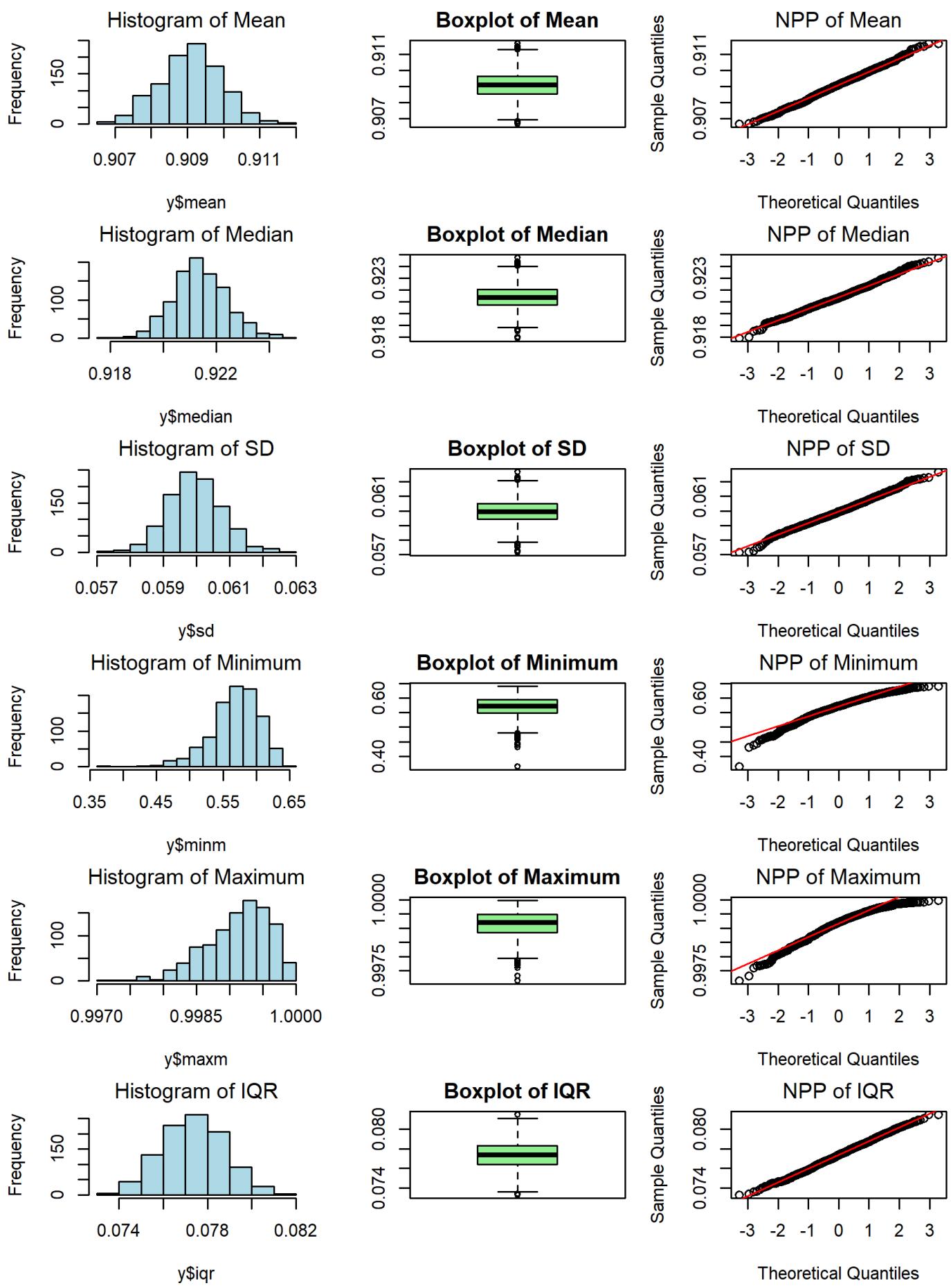
(n=500, nn=1000,  $\alpha=20$ ,  $\beta=2$ )



# BETA DISTRIBUTION PLOT

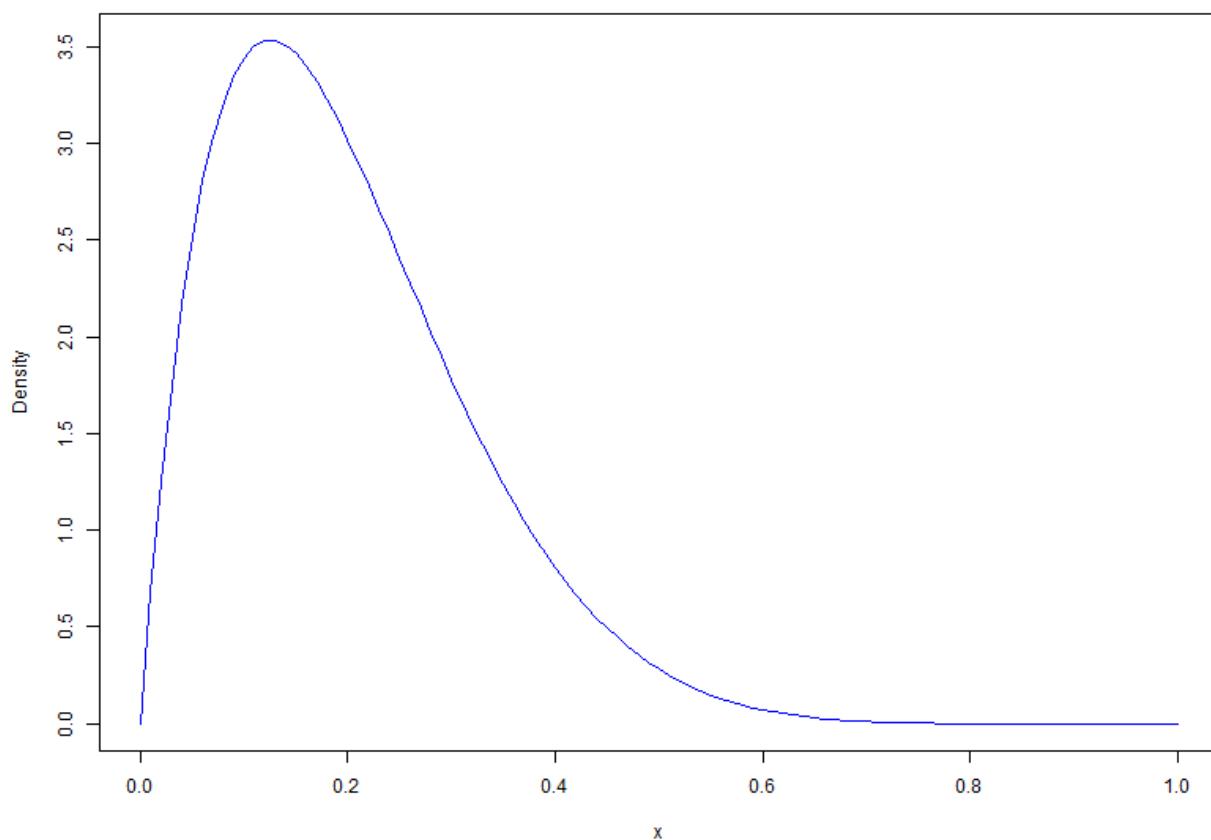
(n=1000, nn=1000,  $\alpha=20$ ,  $\beta=2$ )



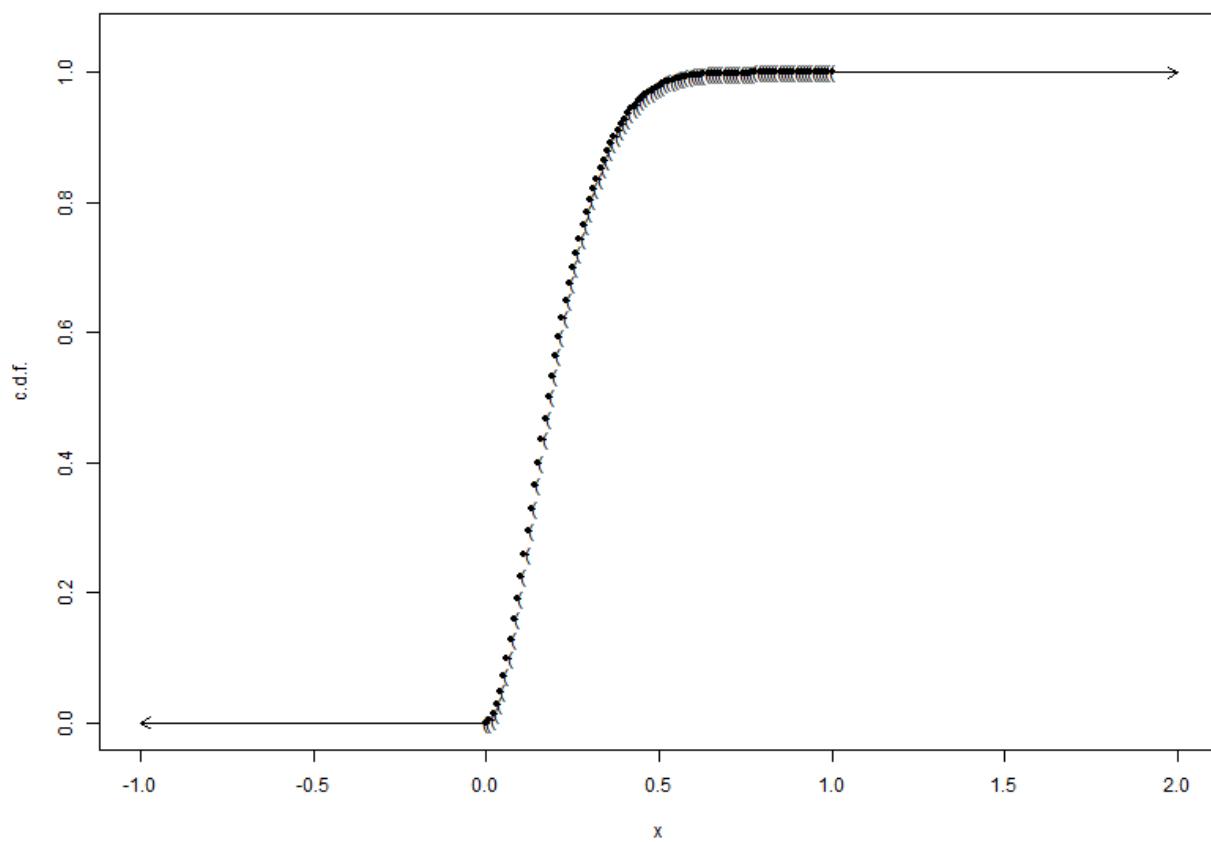


# BETA DISTRIBUTION (2,8)

PDF of Beta(2, 8)



CDF of Beta(2,8)



# BETA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=2$ , $\beta=8$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Median	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Std Dev	No	No	Yes	Yes	Yes	Yes	Yes	100	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	Yes	Yes	Yes	Yes	Yes	100	

## Conclusion for Beta Distribution ( $\alpha = 2$ , $\beta = 8$ )

### Normality Achieved:

- **Mean:** Achieves normality for all sample sizes ( $n \geq 10$ ), with fast convergence, making it the most reliable statistic across sample sizes.
- **Median:** Achieves normality for  $n \geq 50$ , with slower convergence compared to the mean.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 100$ , reflecting stabilization with larger sample sizes.
- **IQR:** Achieves normality for  $n \geq 100$ , with a noticeable trend toward convergence as sample size increases.

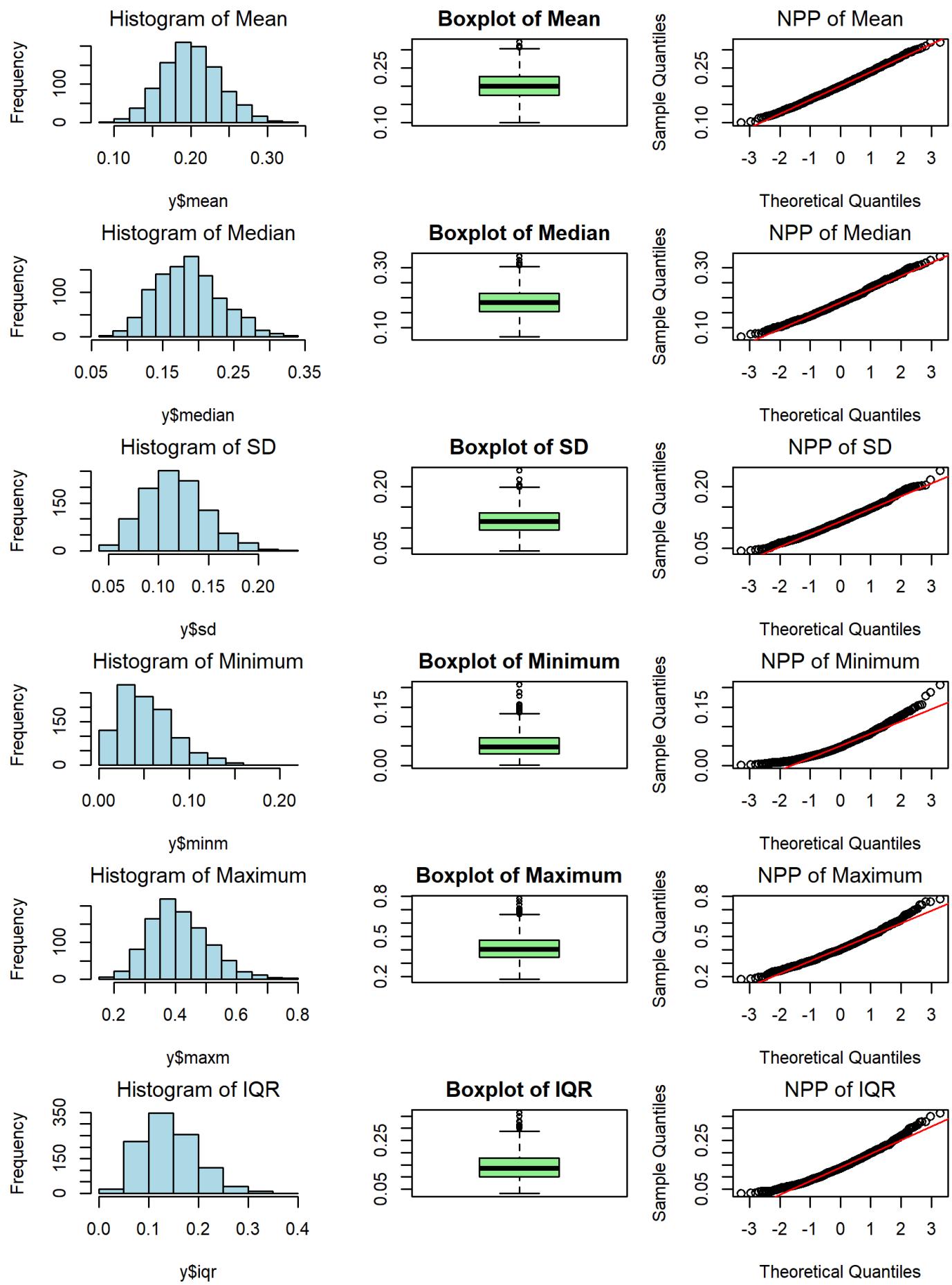
### Normality Not Achieved:

- **Minimum and Maximum:** Do not achieve normality for any sample size, as they are heavily influenced by the distribution's skewness, particularly at smaller sample sizes.

**Overall:** The Beta distribution with  $\alpha = 2$  and  $\beta = 8$  achieves normality for the mean at  $n \geq 10$ , with other statistics (median, standard deviation, and IQR) requiring larger sample sizes ( $n \geq 50$  for median,  $n \geq 100$  for SD and IQR) to stabilize. The minimum and maximum values remain non-normal across all sample sizes due to the skewed nature of the distribution.

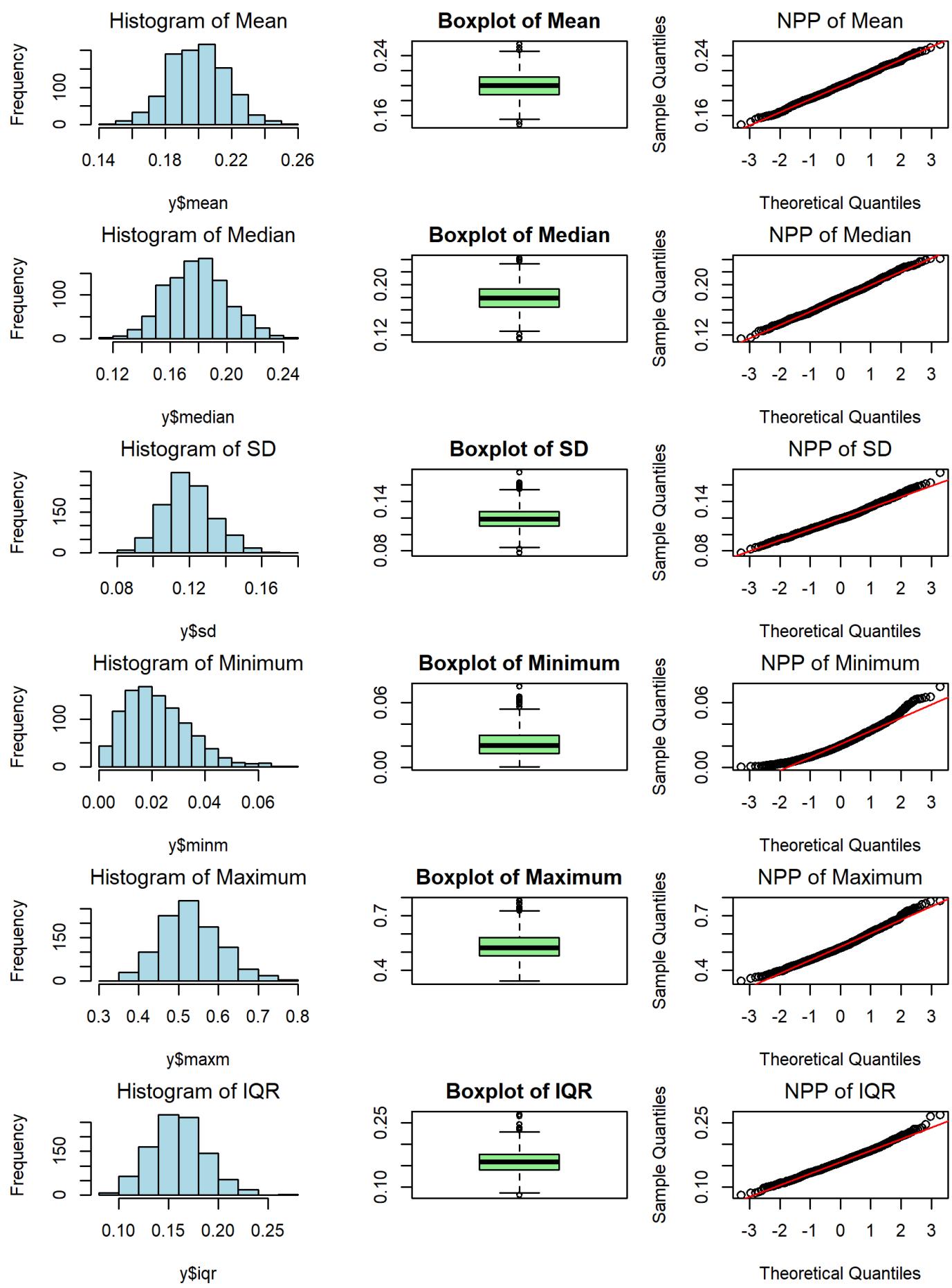
# BETA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=2$ ,  $\beta=8$ )



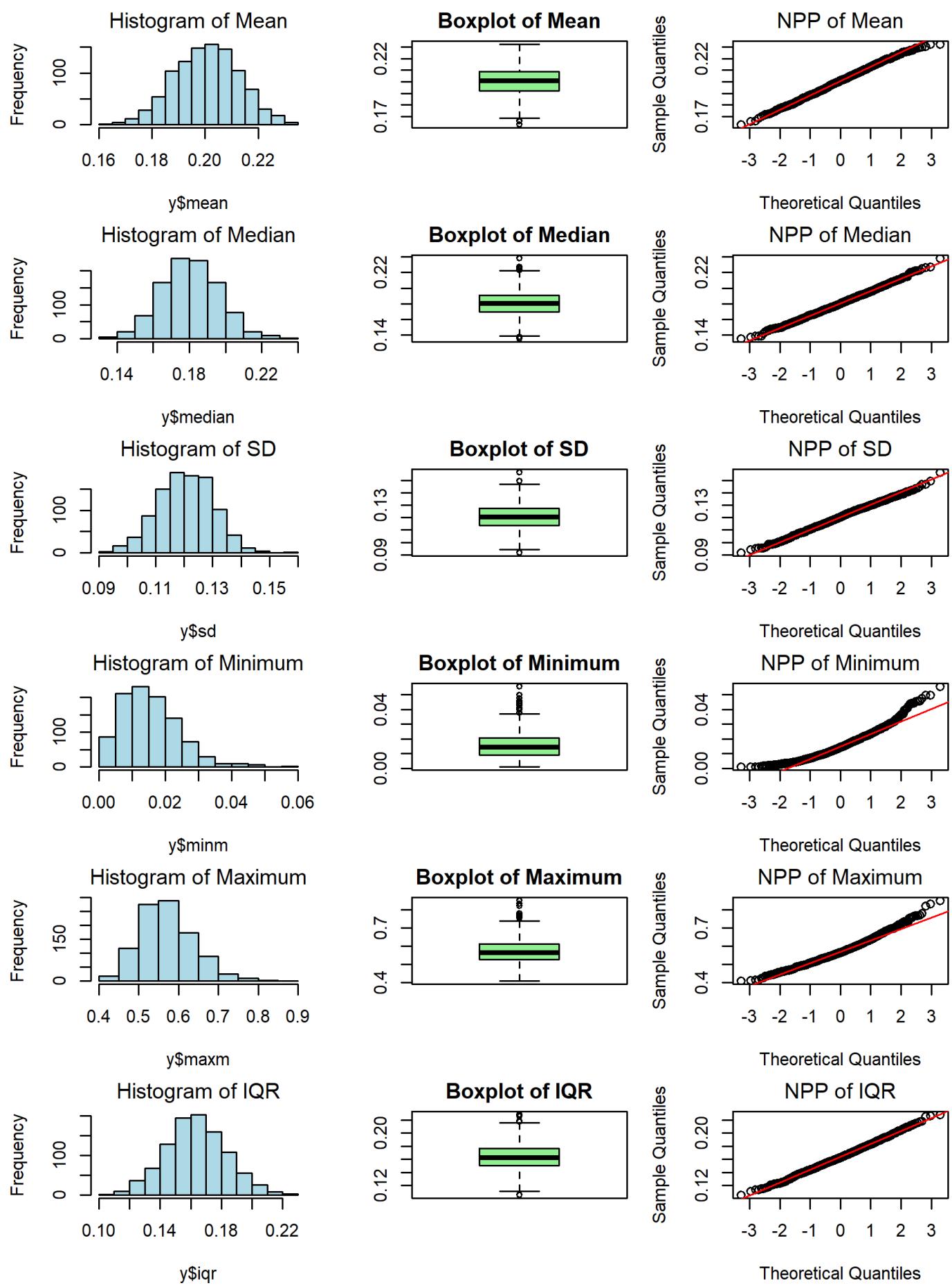
# BETA DISTRIBUTION PLOT

(n=50, nn=1000,  $\alpha=2$ ,  $\beta=8$ )



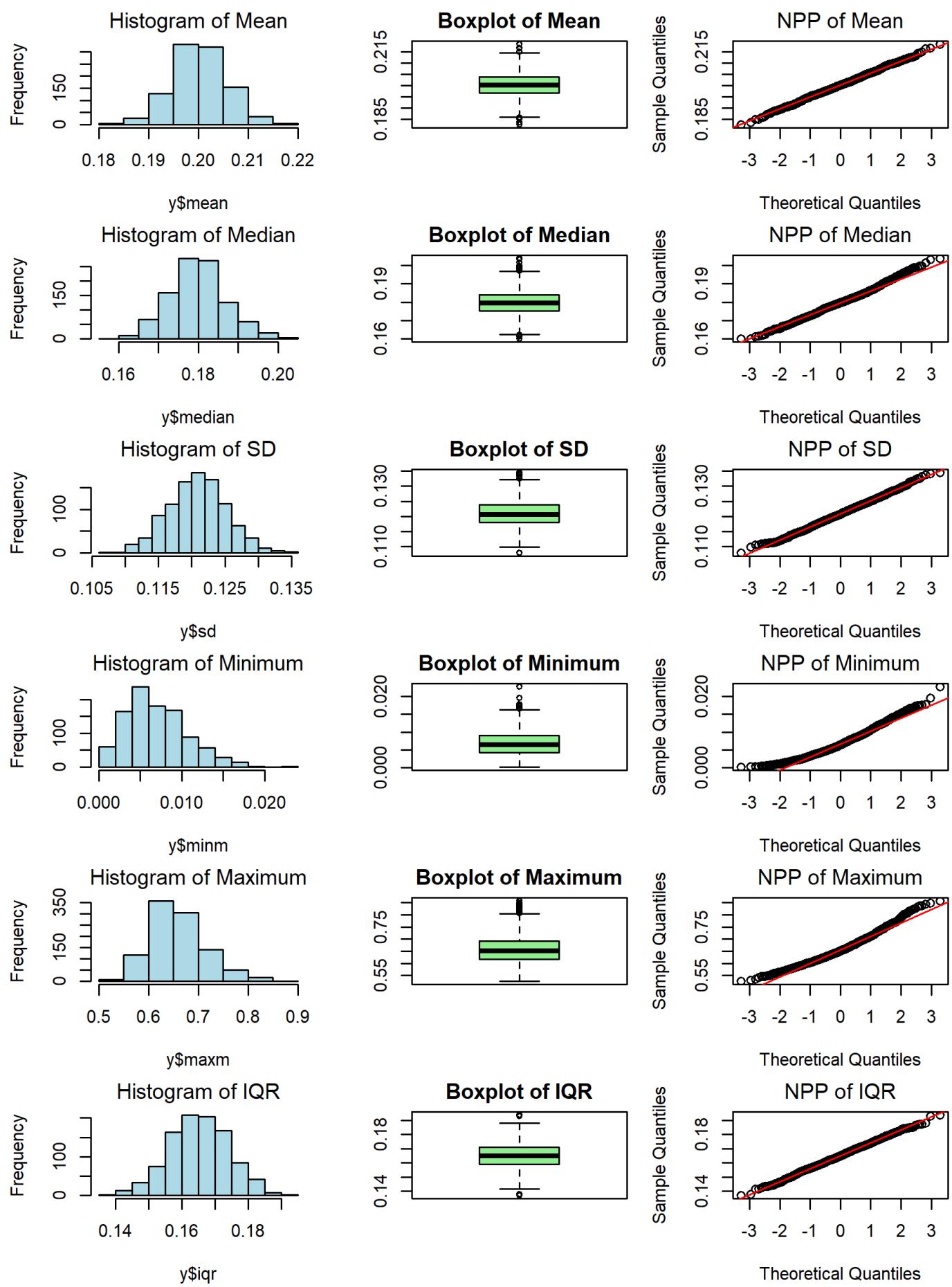
## BETA DISTRIBUTION PLOT

(n=100, nn=1000,  $\alpha=2$ ,  $\beta=8$ )



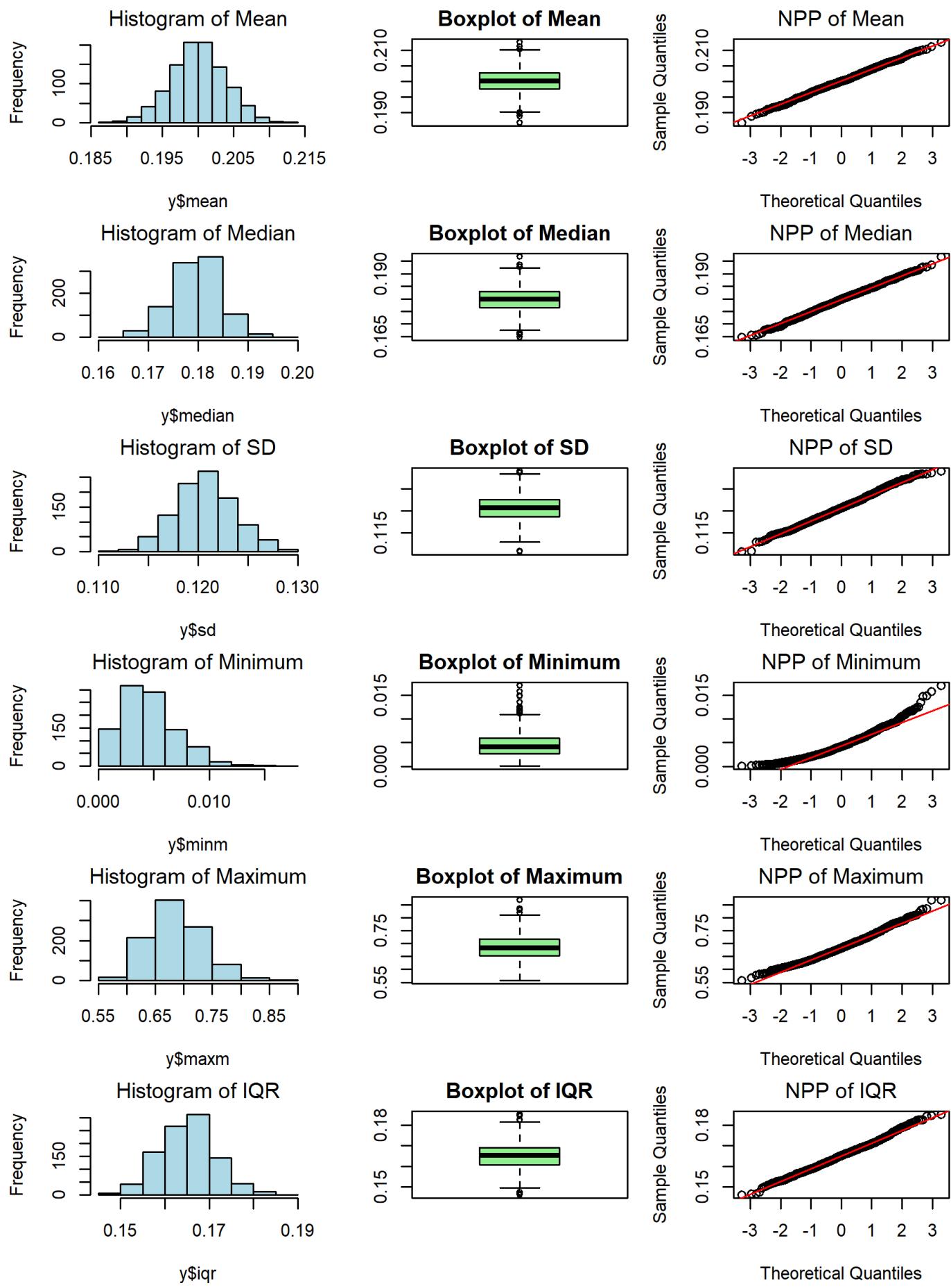
# BETA DISTRIBUTION PLOT

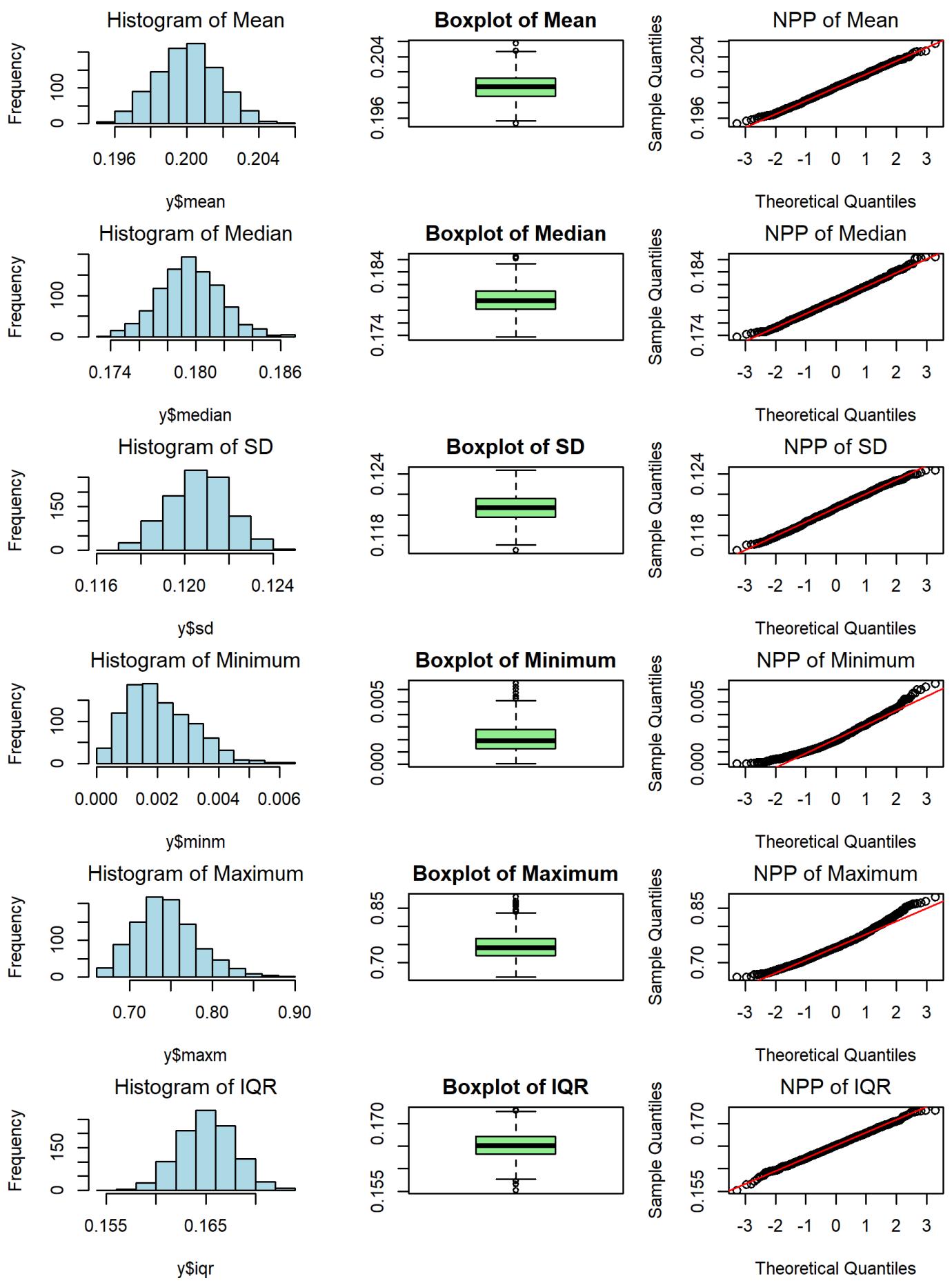
(n=500, nn=1000,  $\alpha=2$ ,  $\beta=8$ )



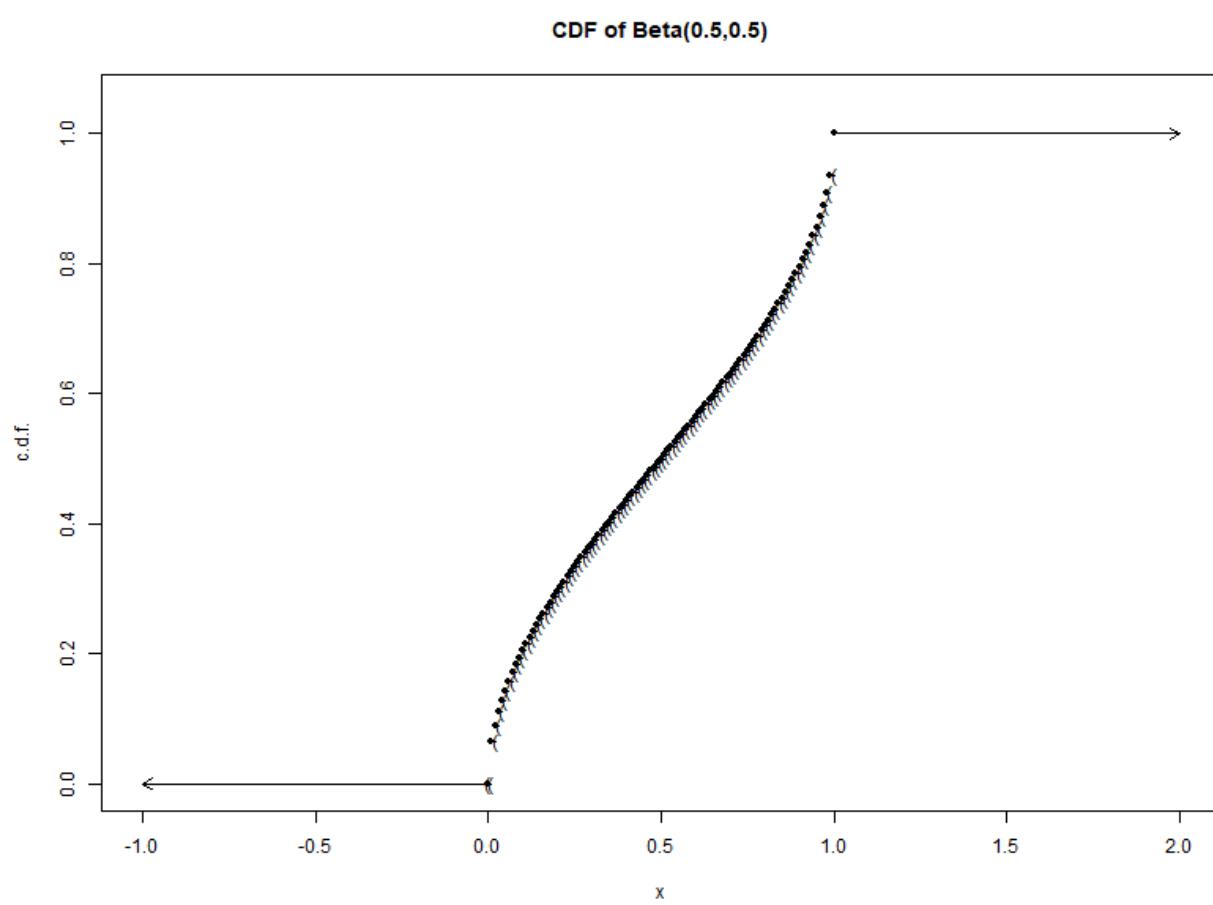
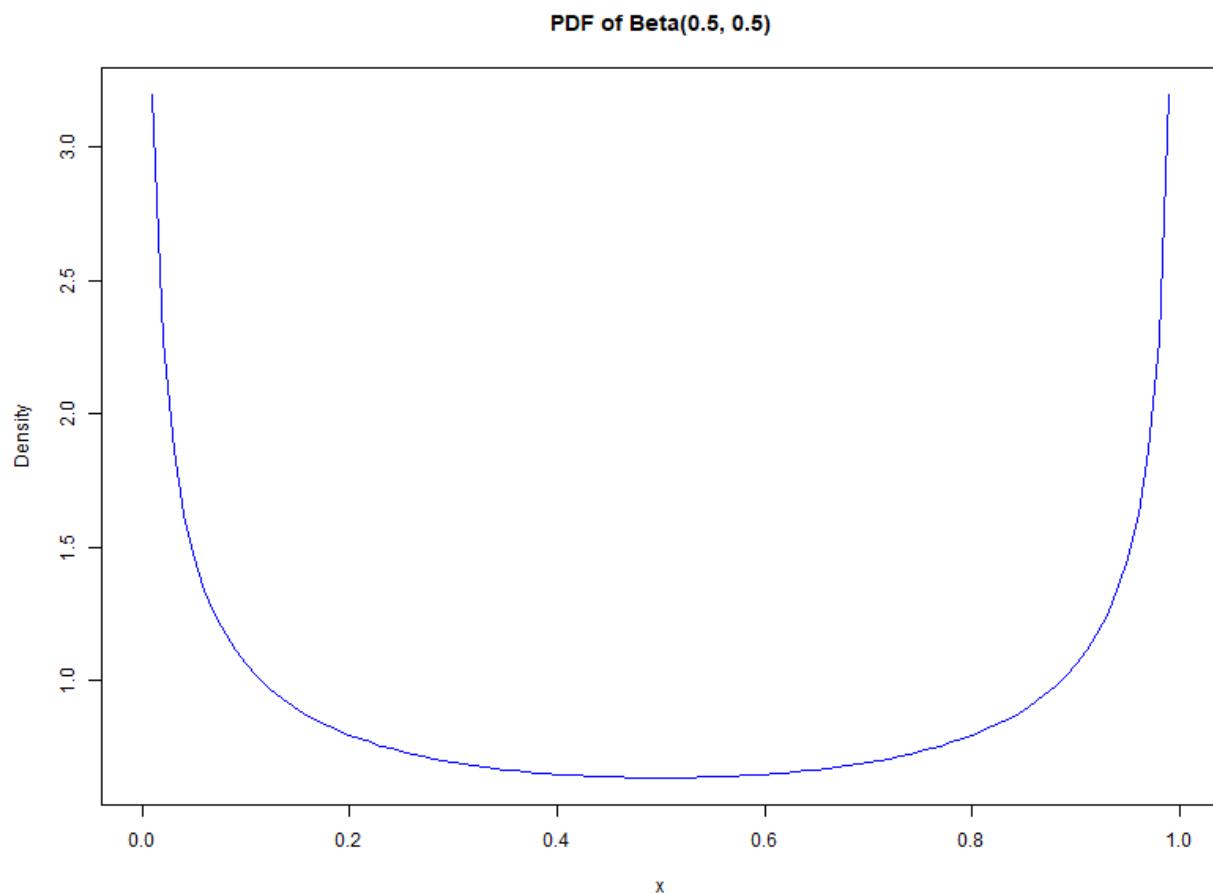
# BETA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=2$ ,  $\beta=8$ )





# BETA DISTRIBUTION (0.5, 0.5)



# BETA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=0.5$ , $\beta=0.5$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Median	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Std Dev	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	Yes	Yes	Yes	Yes	Yes	Yes	50	

## Conclusion for Beta Distribution ( $\alpha = 0.5$ , $\beta = 0.5$ )

### Normality Achieved:

- **Mean:** Achieves normality for all sample sizes ( $n \geq 10$ ), showing quick convergence for this statistic.
- **Median:** Achieves normality starting from  $n \geq 50$ , with gradual stabilization as the sample size increases.
- **Standard Deviation (SD):** Achieves normality from  $n \geq 50$ , indicating convergence to a stable distribution with increasing sample sizes.
- **IQR:** Achieves normality from  $n \geq 50$ , with more stable behavior as sample size increases.

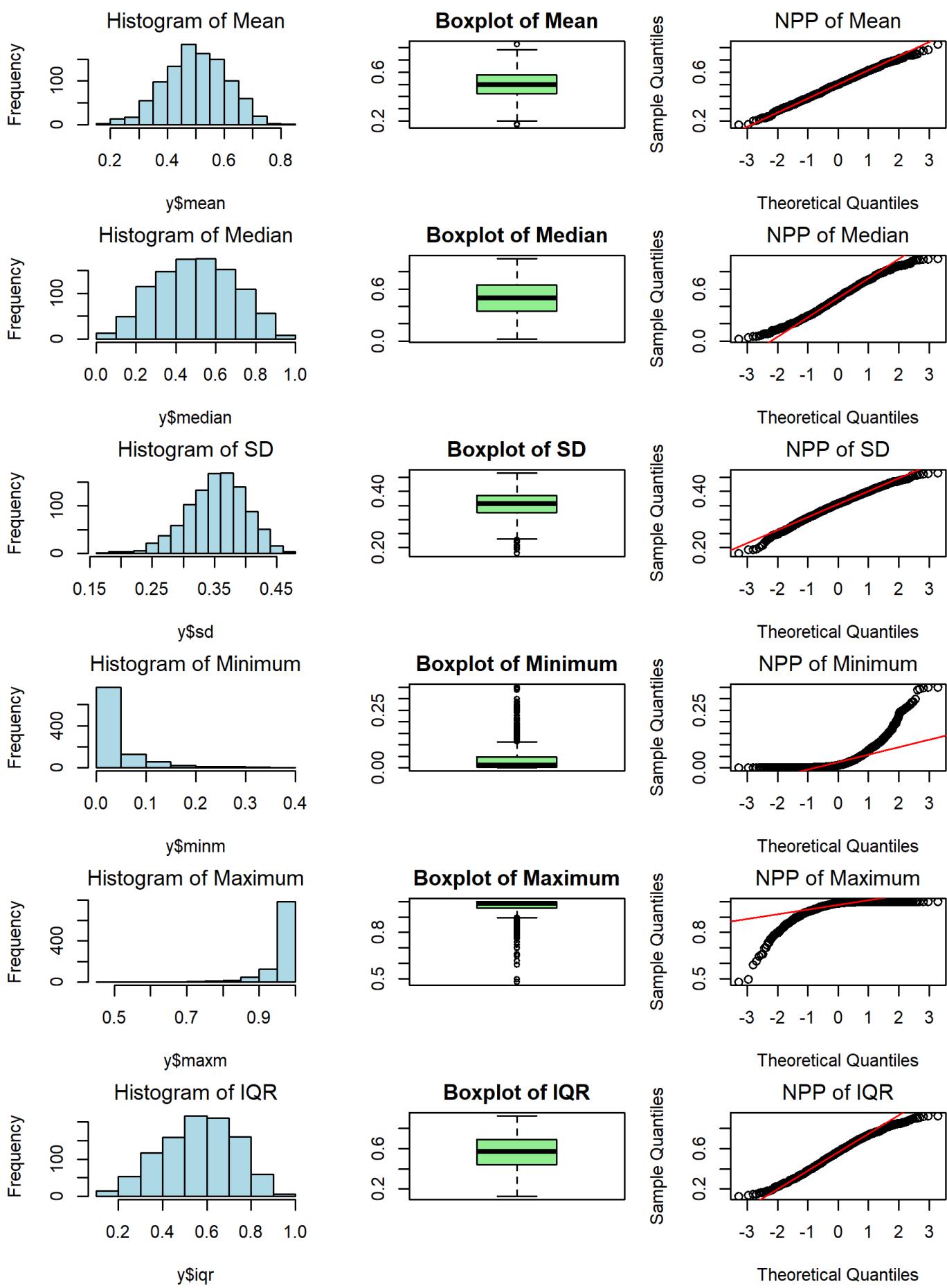
### Normality Not Achieved:

- **Minimum and Maximum:** Do not achieve normality for any sample size, as these statistics remain influenced by the highly skewed nature of the Beta distribution with  $\alpha = 0.5$  and  $\beta = 0.5$ .

**Overall:** The Beta distribution with  $\alpha = 0.5$  and  $\beta = 0.5$  shows quick convergence for the mean across all sample sizes, but other statistics such as median, standard deviation, and IQR start stabilizing only after  $n \geq 50$ . The minimum and maximum values remain non-normal at all sample sizes due to the pronounced skew of the distribution.

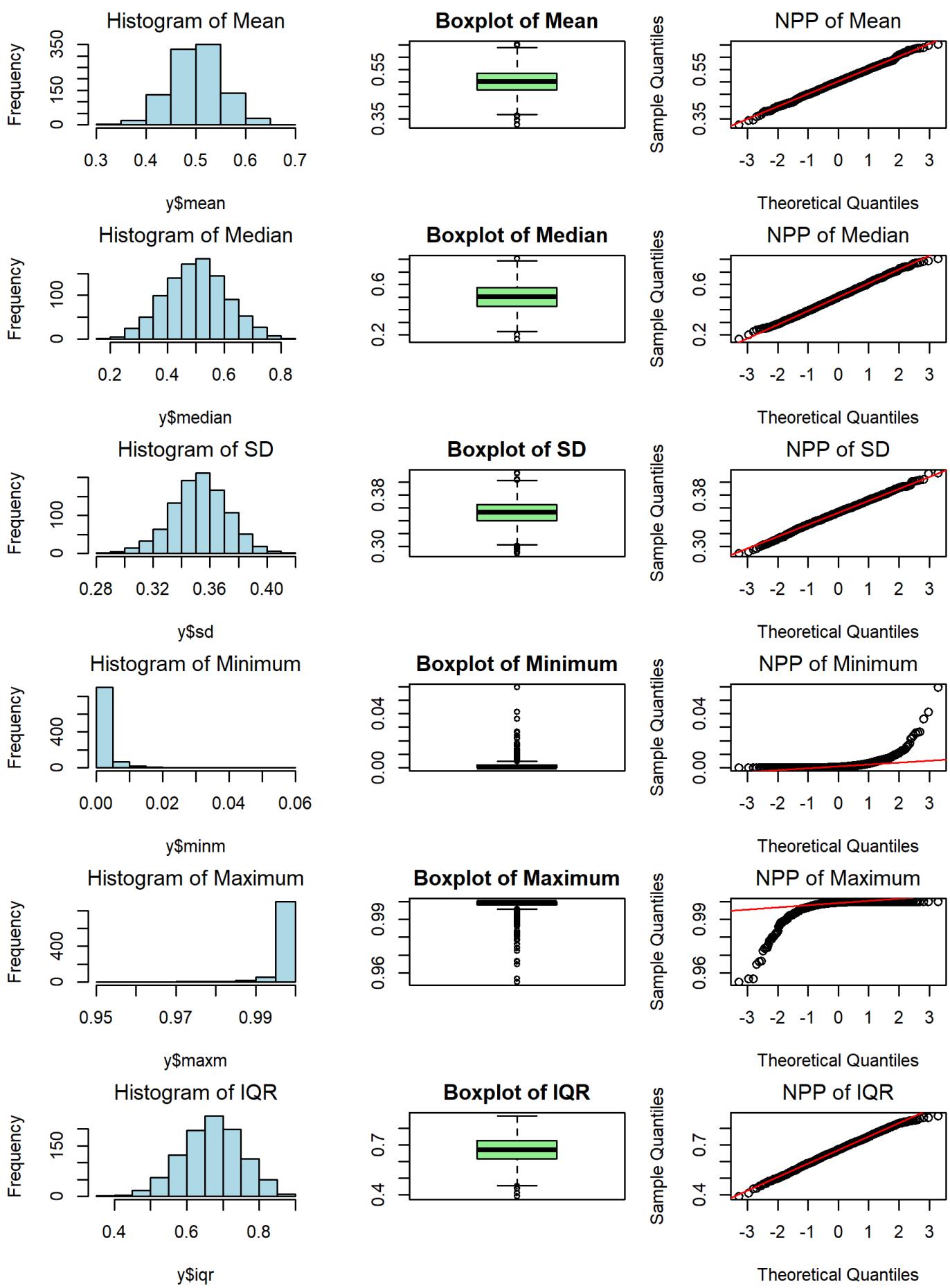
# BETA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=0.5$ ,  $\beta=0.5$ )



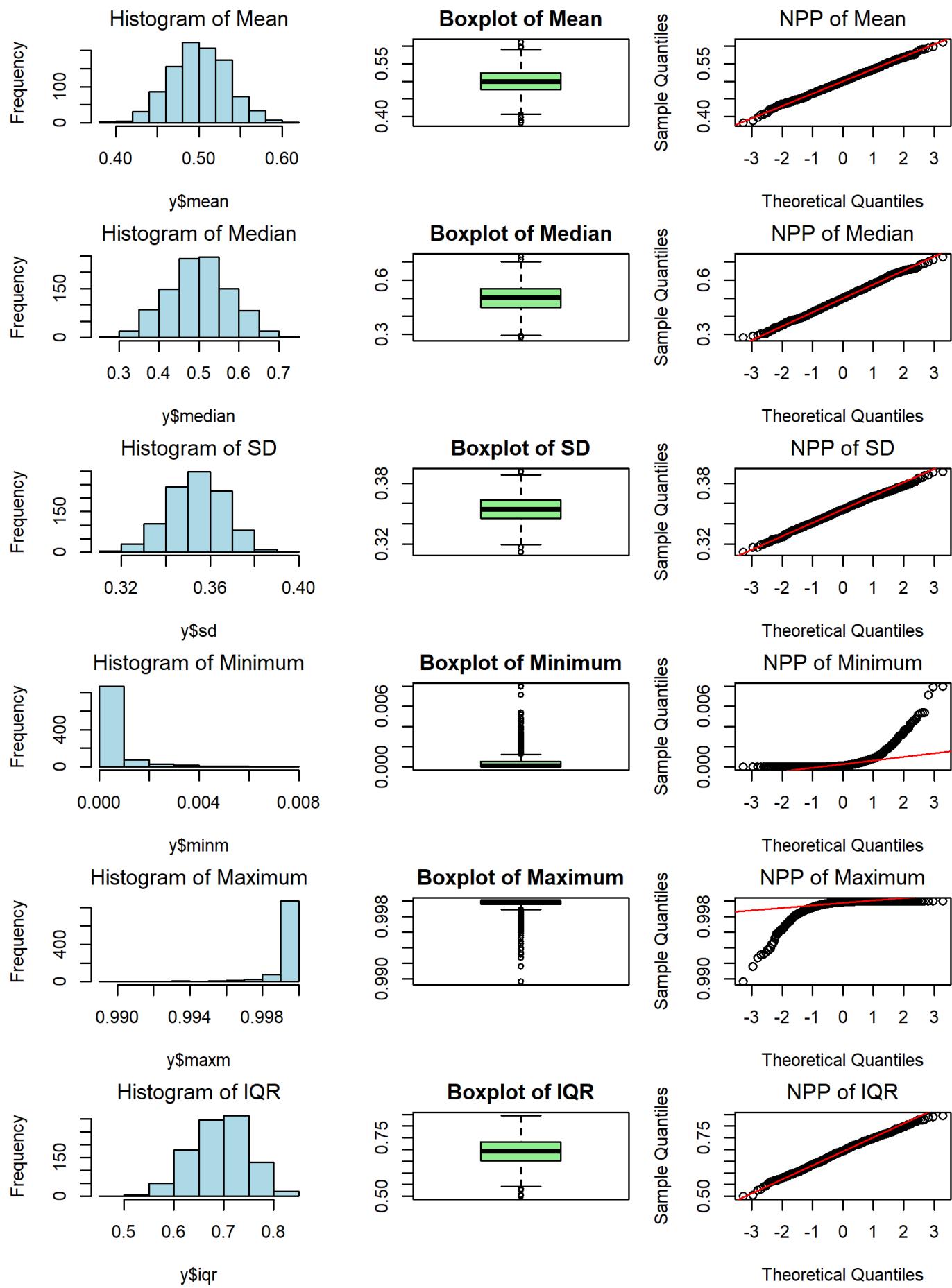
# BETA DISTRIBUTION PLOT

(n=50, nn=1000,  $\alpha=0.5$ ,  $\beta=0.5$ )



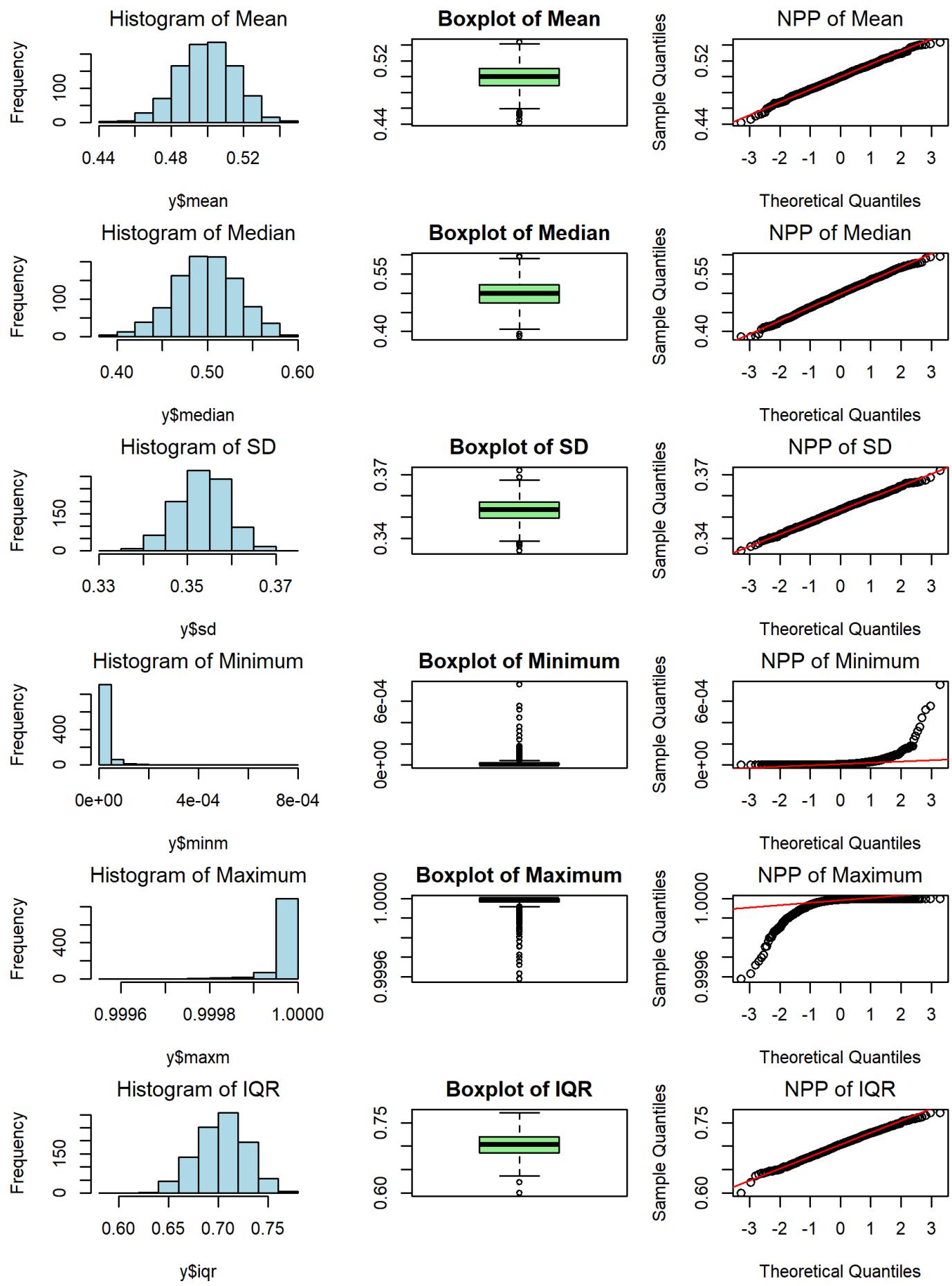
# BETA DISTRIBUTION PLOT

(n=100, nn=1000,  $\alpha=0.5$ ,  $\beta=0.5$ )



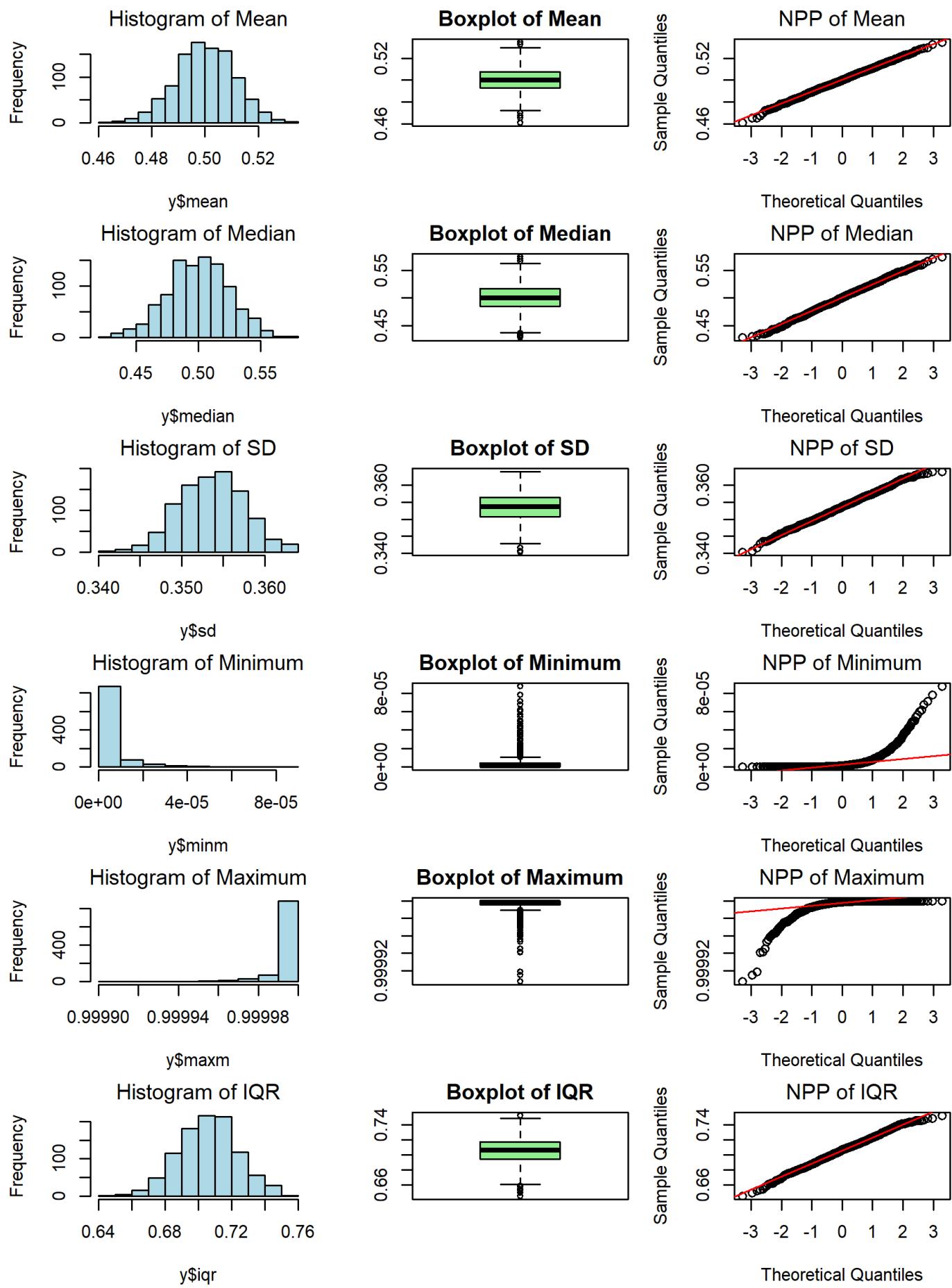
# BETA DISTRIBUTION PLOT

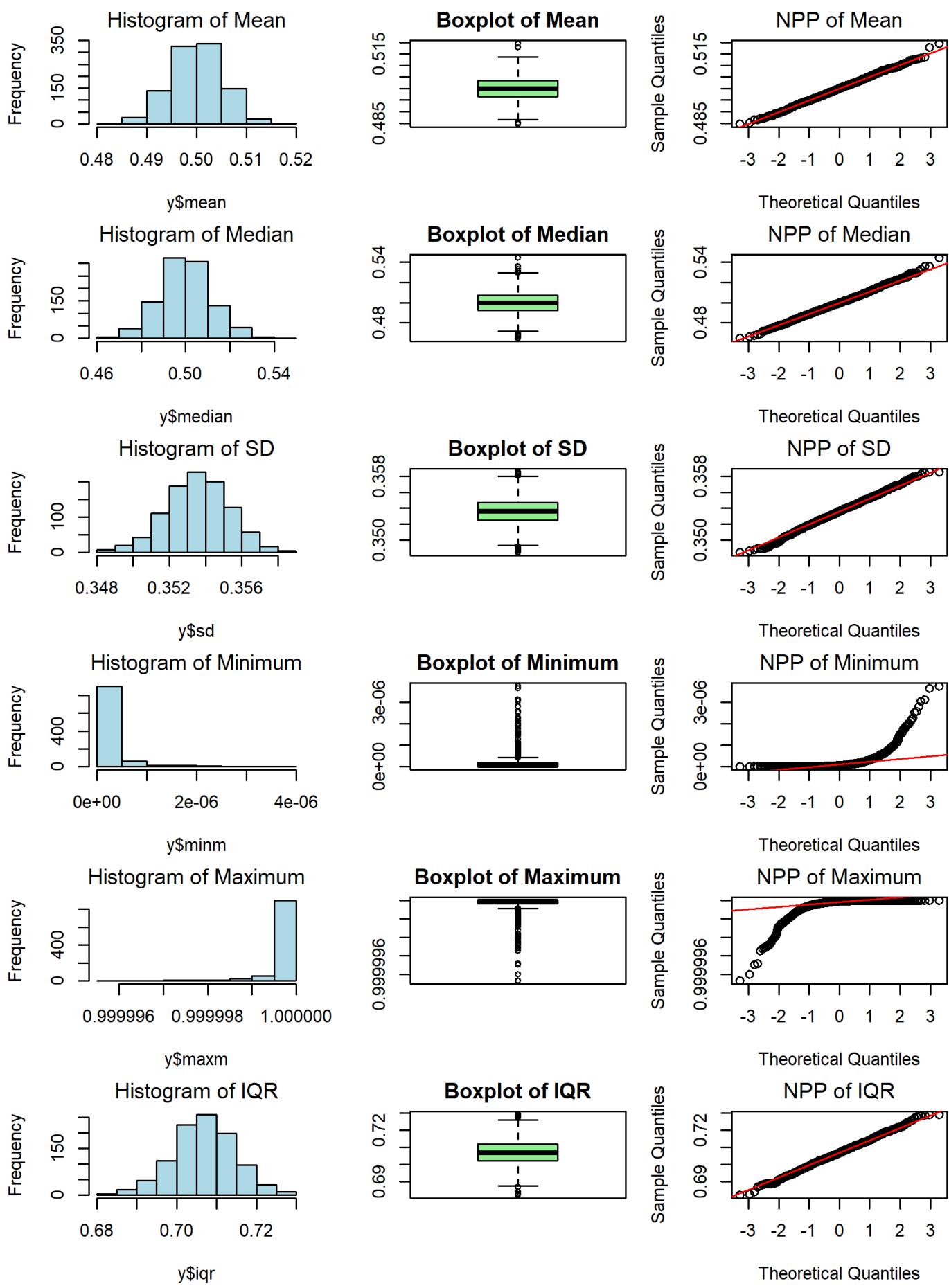
(n=500, nn=1000,  $\alpha=0.5$ ,  $\beta=0.5$ )



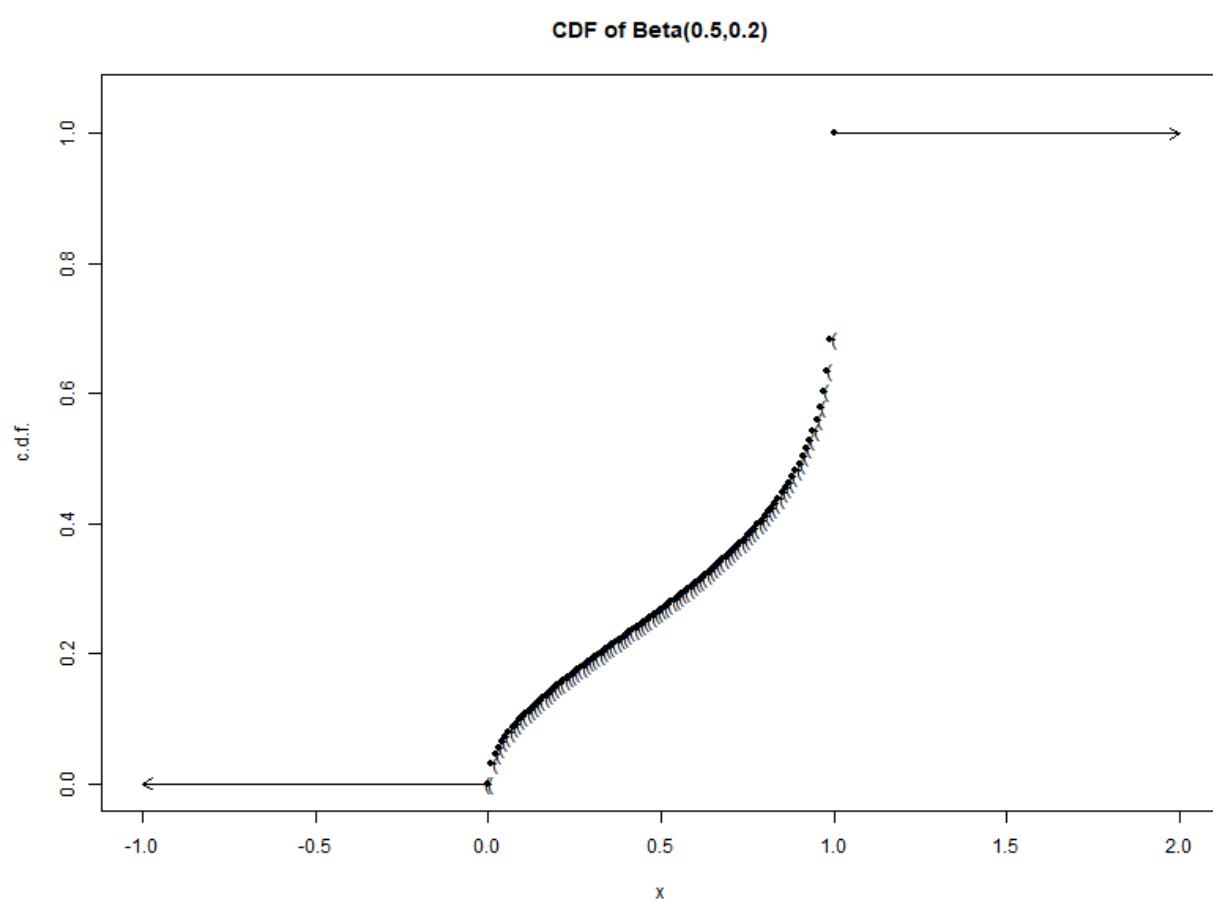
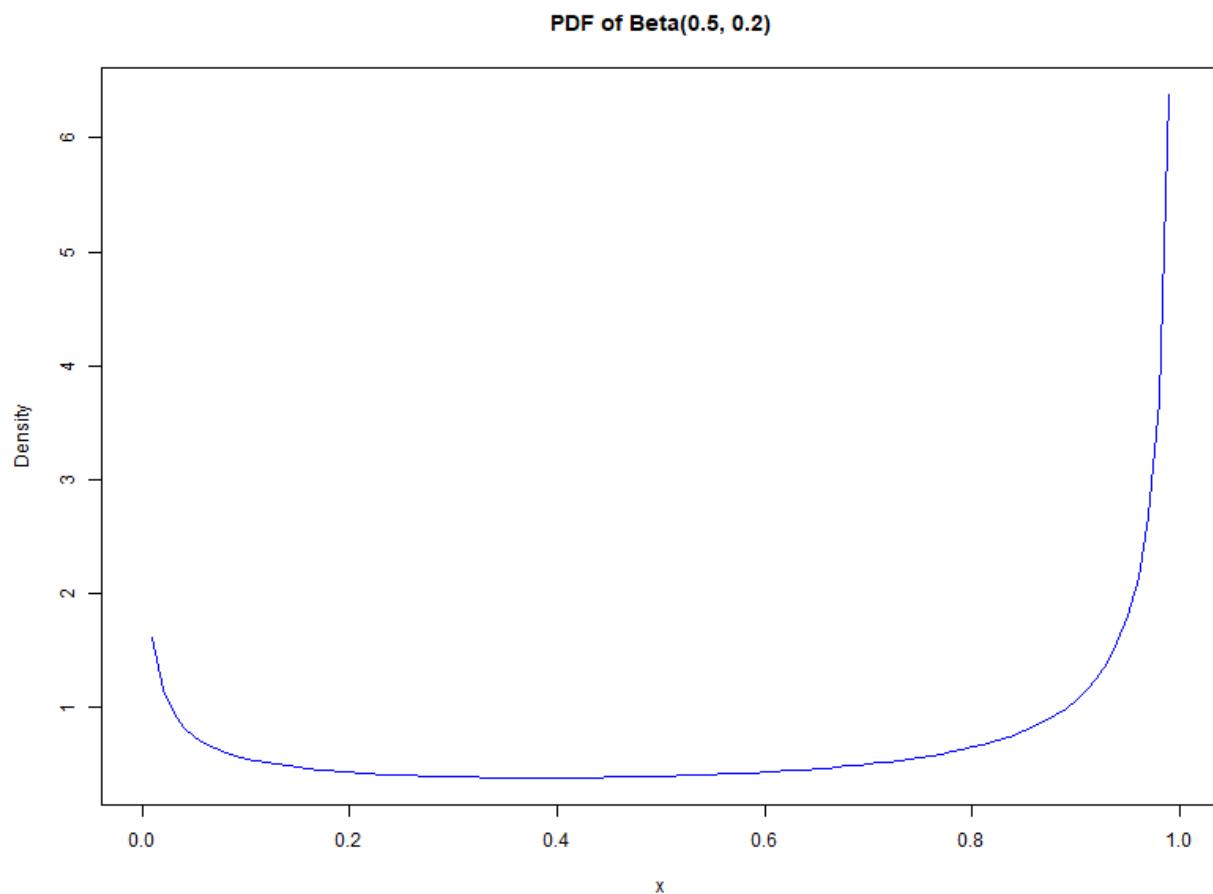
# BETA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=0.5$ ,  $\beta=0.5$ )





# BETA DISTRIBUTION (0.5,0.2)



# BETA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=0.5$ , $\beta=0.2$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	Yes	Yes	Yes	Yes	Yes	Yes	50	
Median	No	No	No	No	No	Yes	Yes	5000	
Std Dev	No	No	No	Yes	Yes	Yes	Yes	500	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	Yes	Yes	Yes	Yes	Yes	100	

## Conclusion for Beta Distribution ( $\alpha = 0.5$ , $\beta = 0.2$ )

### Normality Achieved:

- **Mean:** Achieves normality starting from  $n \geq 50$ , with gradual stabilization as sample size increases. The convergence is observed as the sample size grows.
- **Median:** Normality starts to appear only from  $n \geq 5000$ . For smaller sample sizes, the median remains highly influenced by the distribution's skew.
- **Standard Deviation (SD):** Achieves normality from  $n \geq 500$ , with more stable values as the sample size increases.
- **IQR:** Achieves normality from  $n \geq 100$ , with stabilization observed at larger sample sizes.

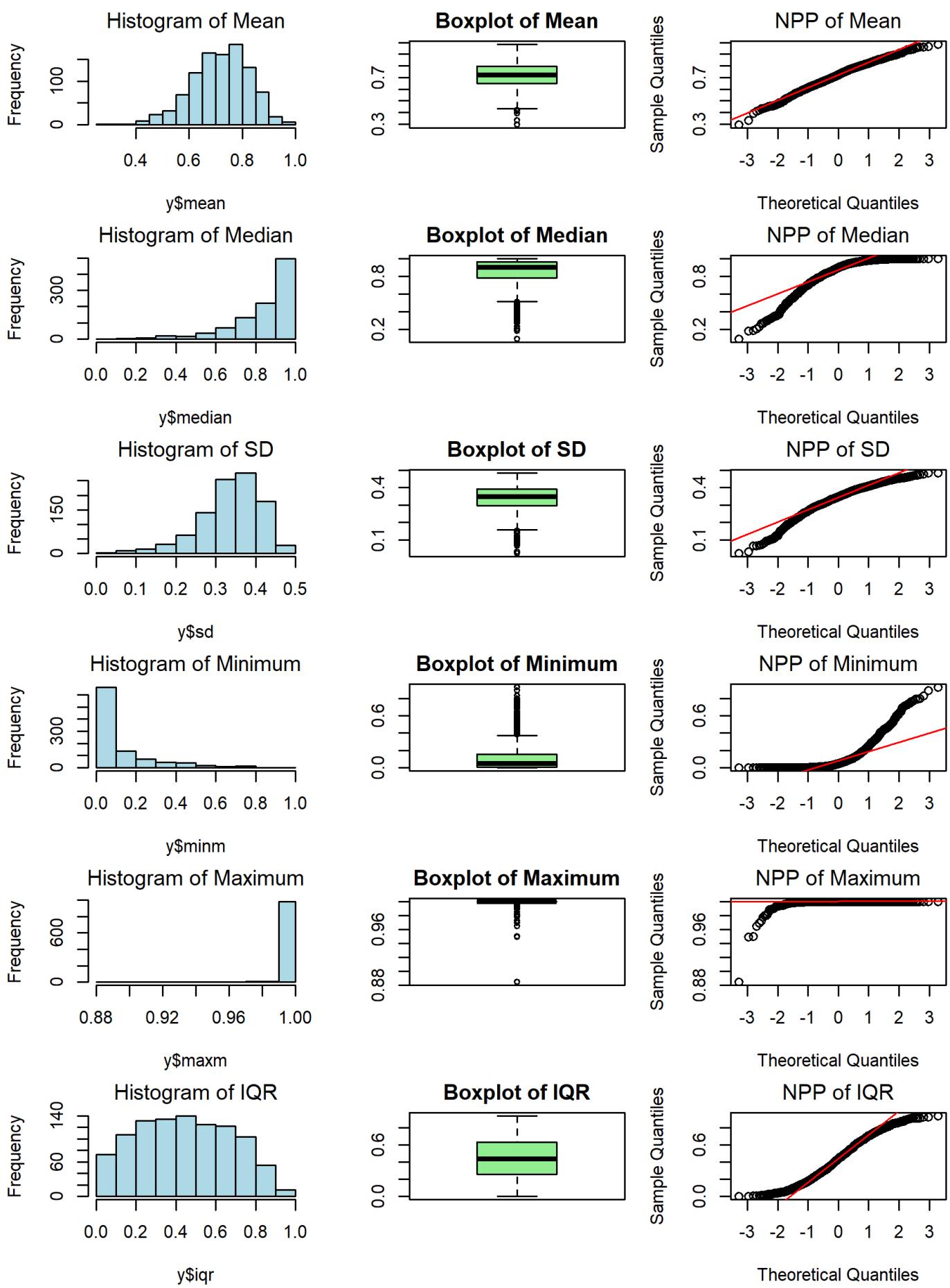
### Normality Not Achieved:

- **Minimum and Maximum:** These statistics do not achieve normality for any sample size due to the skewed nature of the Beta distribution with  $\alpha = 0.5$  and  $\beta = 0.2$ .

**Overall:** The Beta distribution with  $\alpha = 0.5$  and  $\beta = 0.2$  shows delayed convergence for the median, which only achieves normality at  $n \geq 5000$ . The mean, standard deviation, and IQR show earlier convergence to normality, starting from  $n \geq 50$ ,  $n \geq 500$ , and  $n \geq 100$ , respectively. However, the minimum and maximum values remain non-normal across all sample sizes due to the skewness of the distribution.

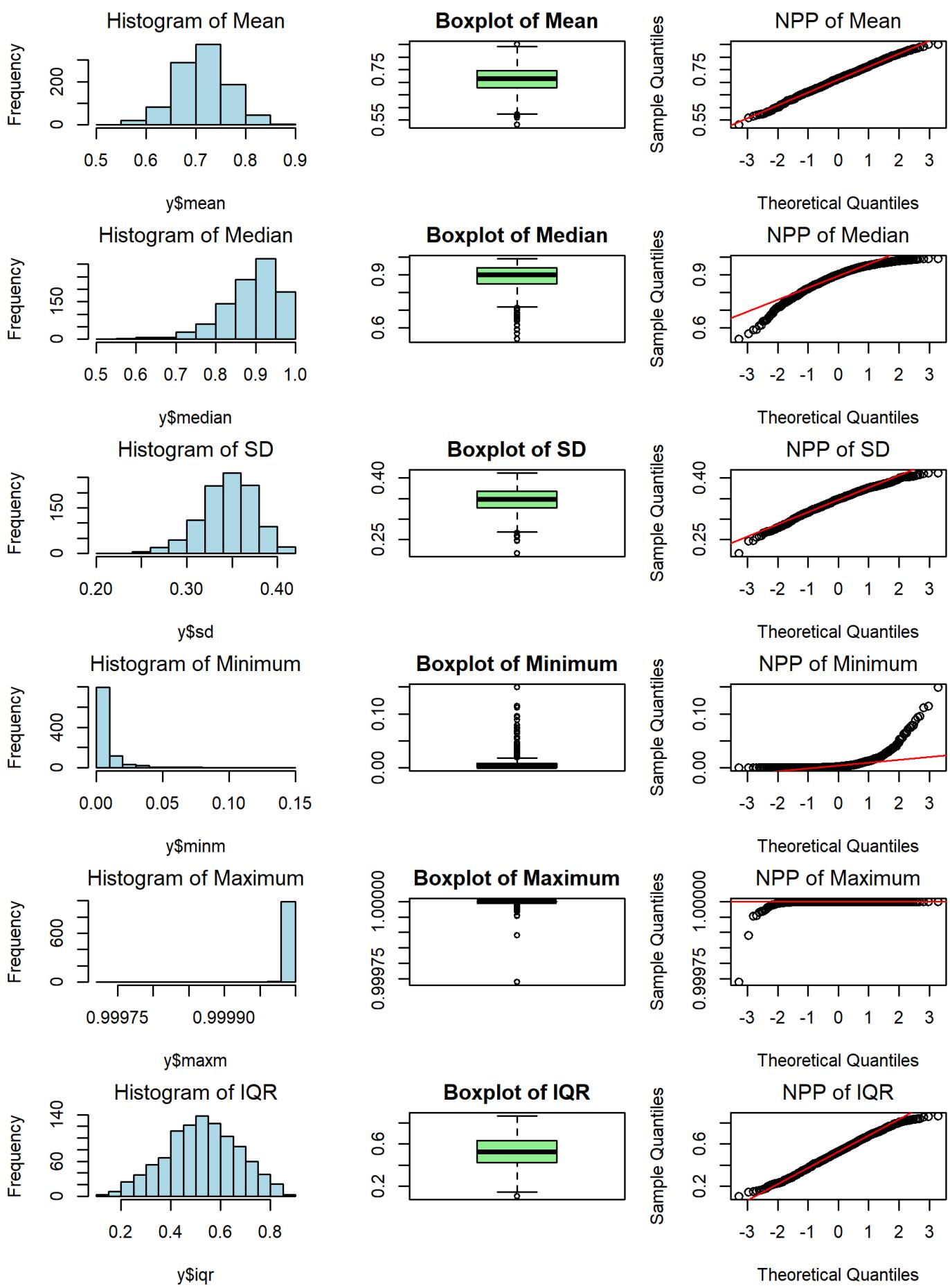
# BETA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=0.5$ ,  $\beta=0.2$ )



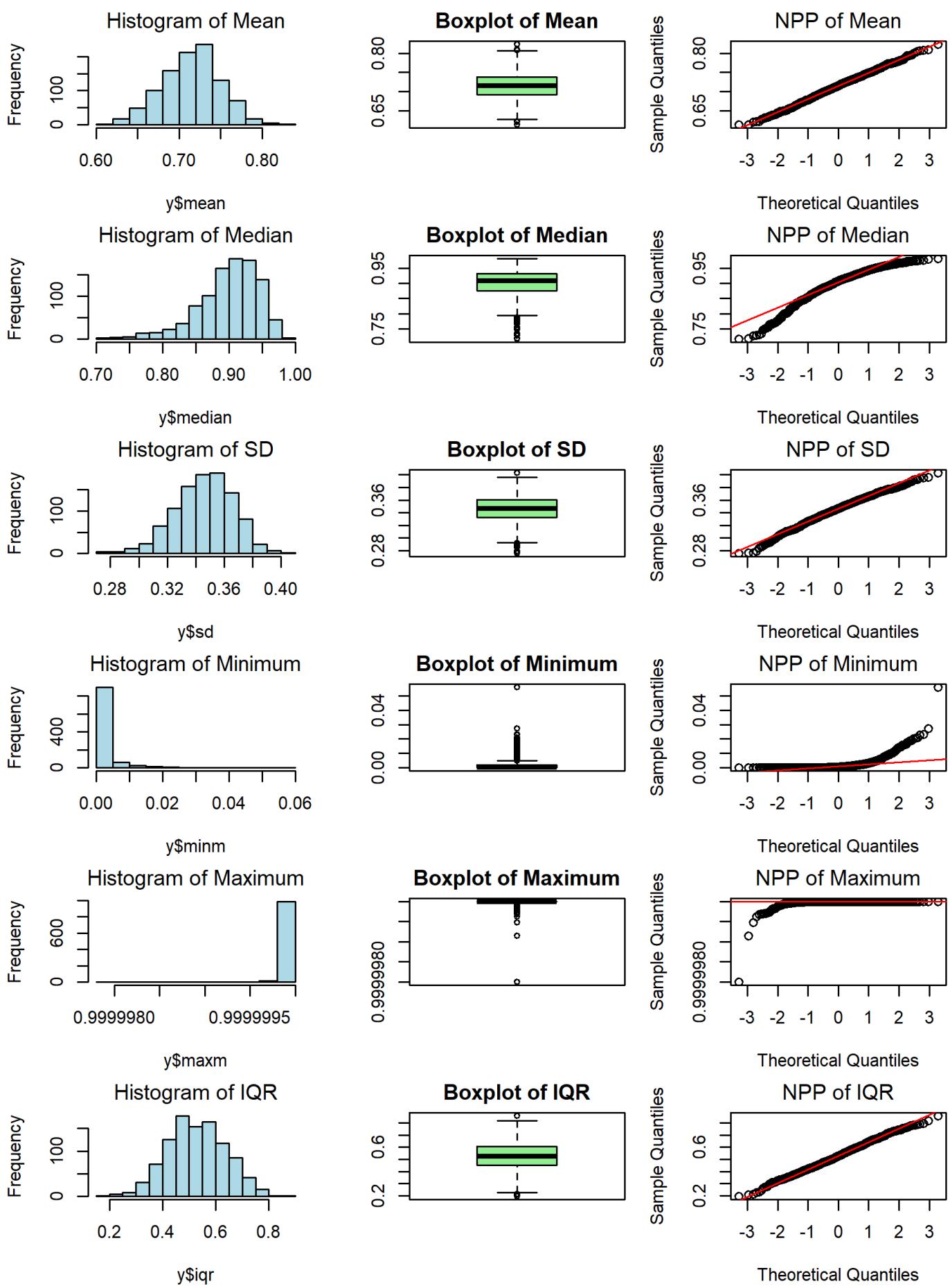
# BETA DISTRIBUTION PLOT

(n=50, nn=1000,  $\alpha=0.5$ ,  $\beta=0.2$ )



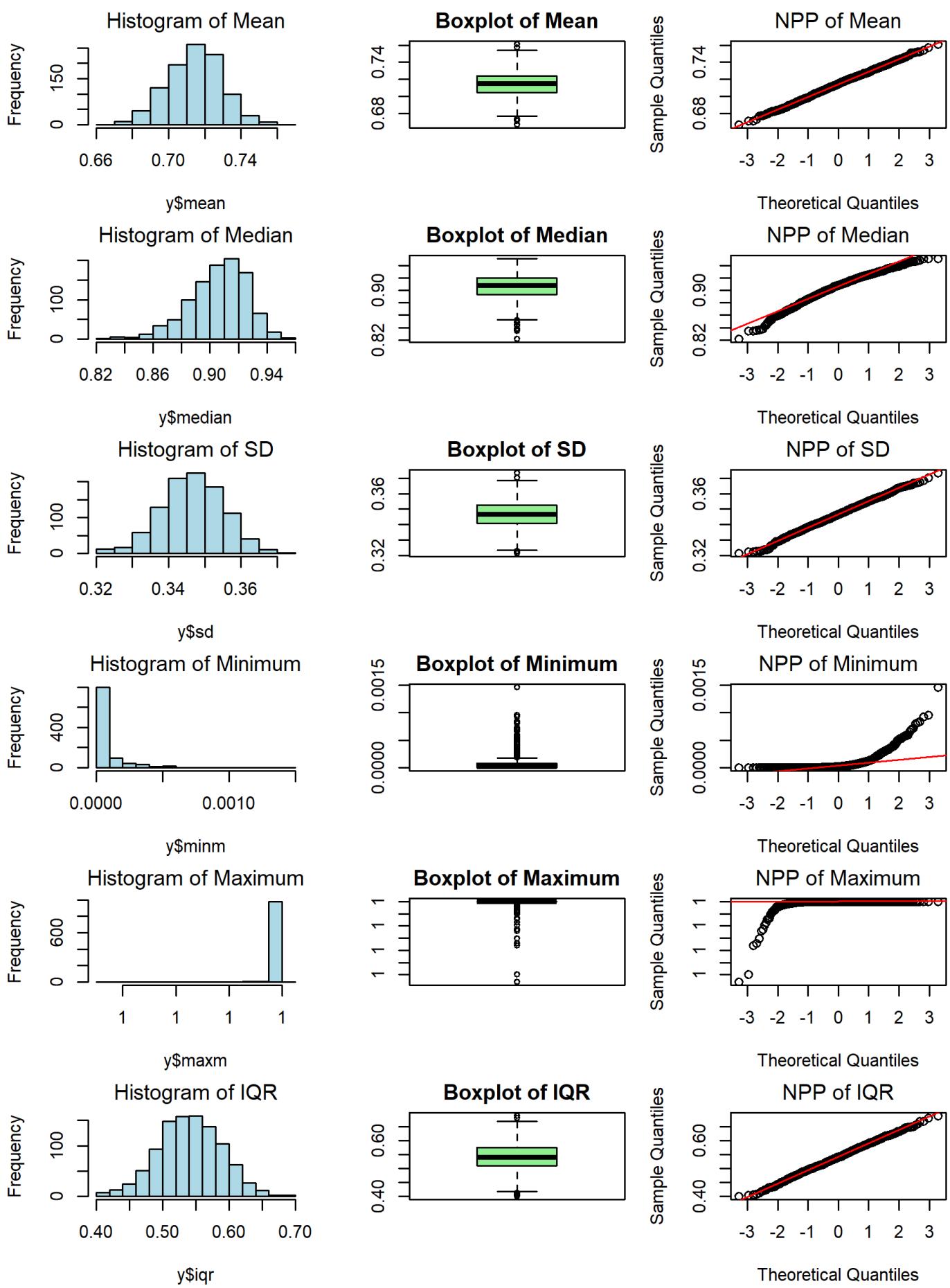
# BETA DISTRIBUTION PLOT

(n=100, nn=1000,  $\alpha=0.5$ ,  $\beta=0.2$ )



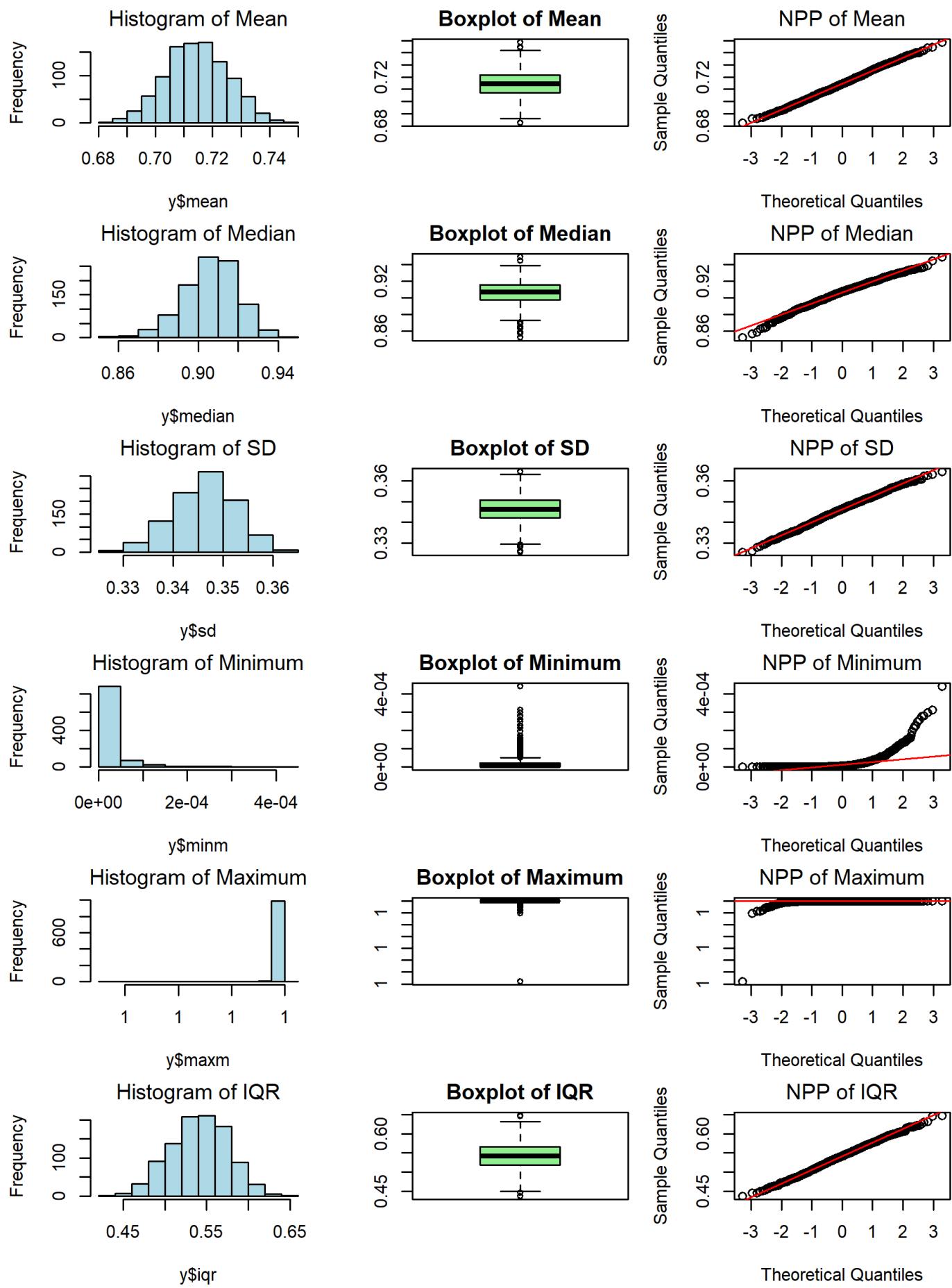
# BETA DISTRIBUTION PLOT

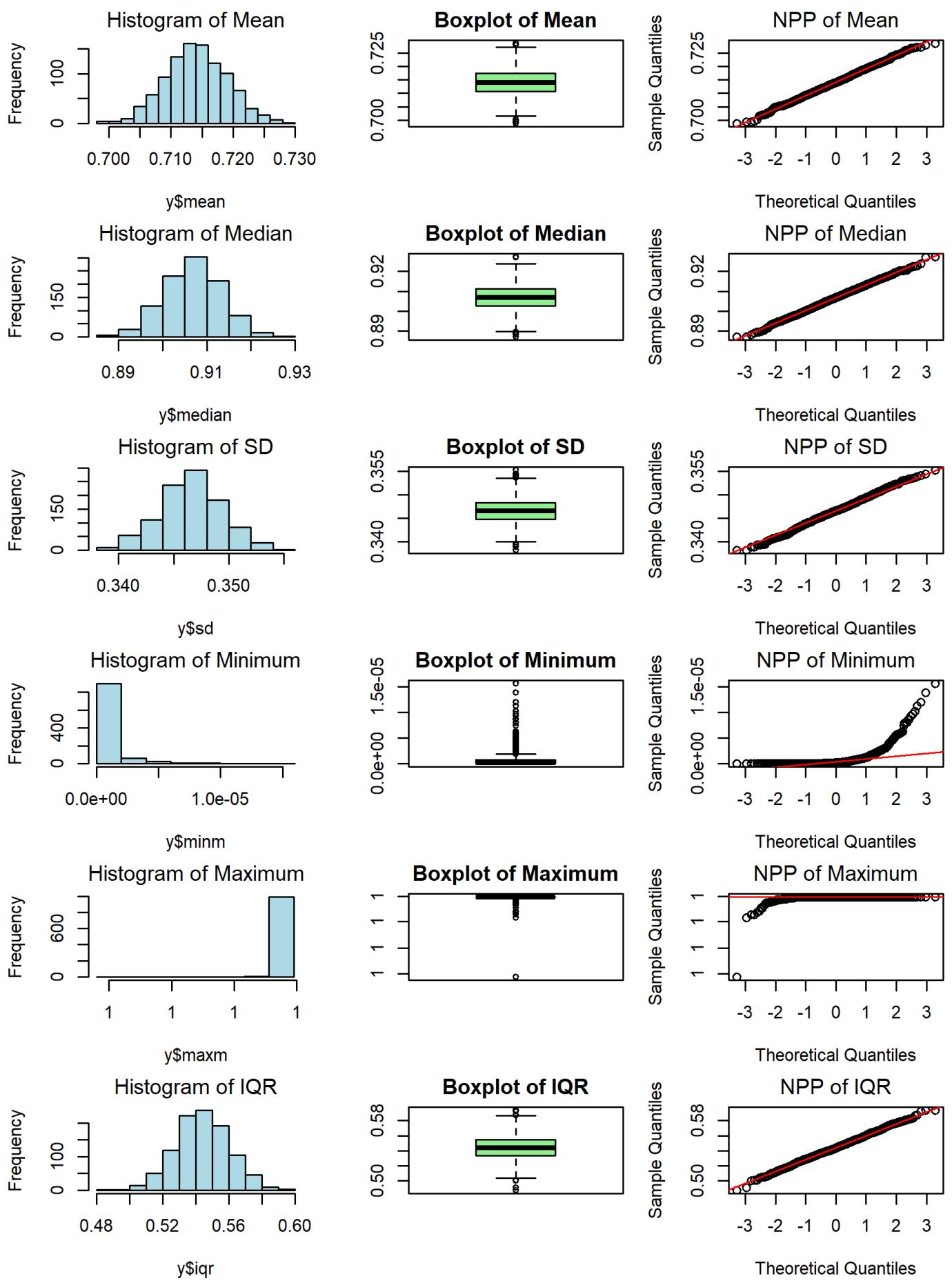
(n=500, nn=1000,  $\alpha=0.5$ ,  $\beta=0.2$ )



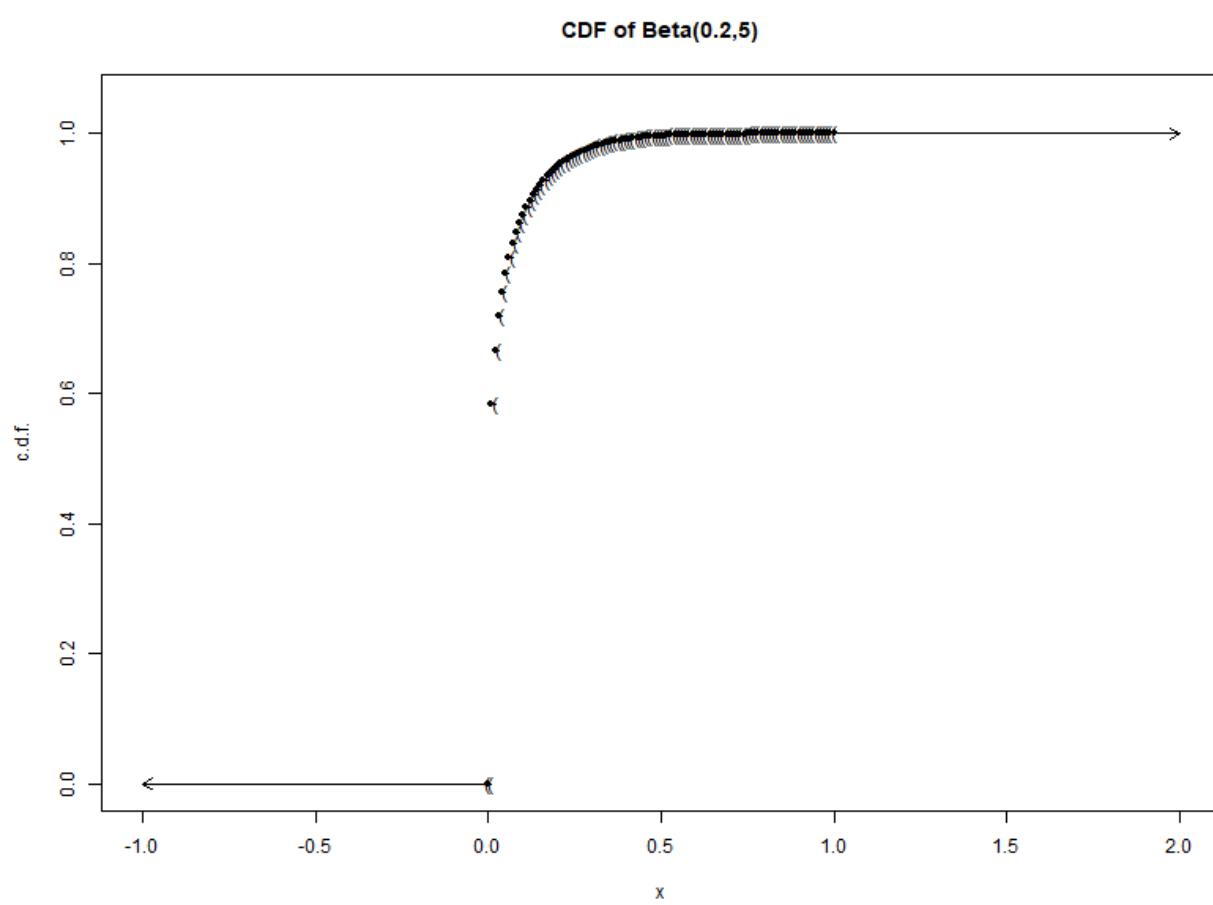
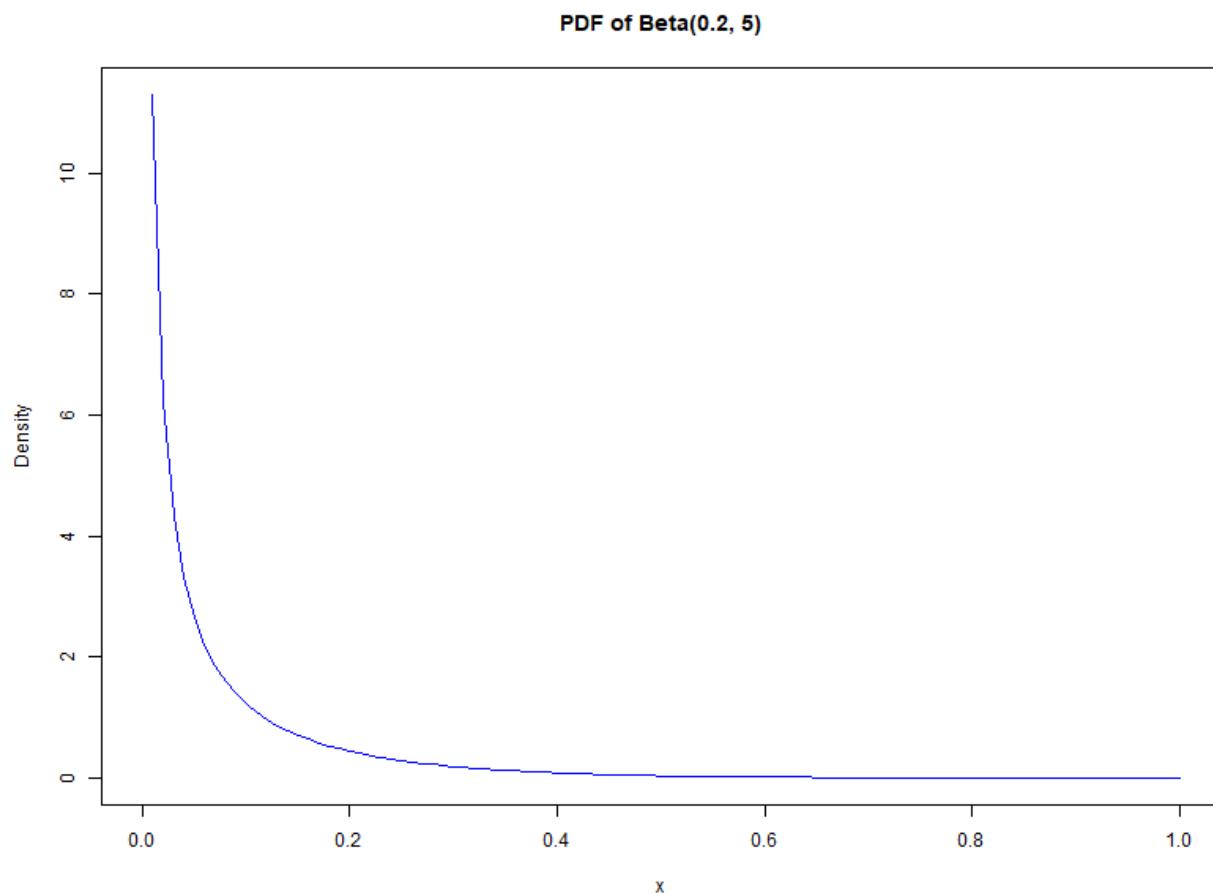
# BETA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=0.5$ ,  $\beta=0.2$ )





# BETA DISTRIBUTION (0.2, 5)



# BETA DISTRIBUTION

	Values of n to achieve normality (nn=1000, $\alpha=0.2$ , $\beta=5$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	No	No	No	Yes	Yes	Yes	1000	
Median	No	No	No	No	No	Yes	Yes	5000	
Std Dev	No	No	No	Yes	Yes	Yes	Yes	500	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	No	No	No	No	No	NA	
IQR	No	No	No	No	No	Yes	Yes	5000	

## Conclusion for Beta Distribution ( $\alpha = 0.2$ , $\beta = 5$ )

### Normality Achieved:

- **Mean:** Achieves normality starting from  $n \geq 1000$ , with stabilization as the sample size increases.
- **Median:** Achieves normality at  $n \geq 5000$ . Prior to that, it is still highly influenced by the skewed nature of the distribution.
- **Standard Deviation (SD):** Achieves normality starting from  $n \geq 500$ , becoming more stable as sample size increases.
- **IQR:** Achieves normality from  $n \geq 5000$ , with gradual stabilization for larger sample sizes.

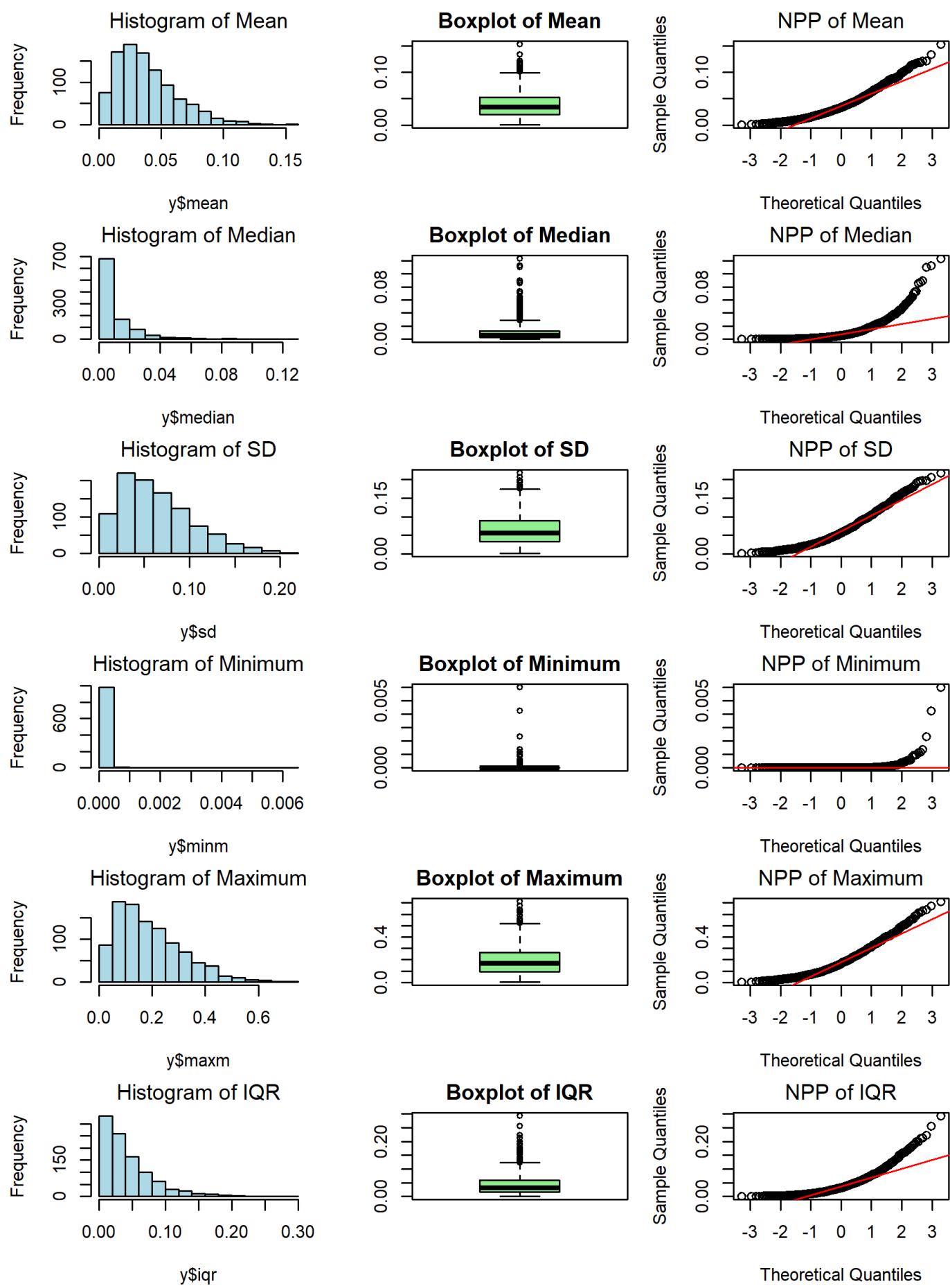
### Normality Not Achieved:

- **Minimum and Maximum:** These statistics do not achieve normality for any sample size due to the skewed shape of the Beta distribution with  $\alpha = 0.2$  and  $\beta = 5$ , where the distribution is highly skewed toward 0.

**Overall:** The Beta distribution with  $\alpha = 0.2$  and  $\beta = 5$  shows a delayed convergence to normality. The mean stabilizes around  $n \geq 1000$ , while the median and IQR only show normality at  $n \geq 5000$ . The standard deviation begins to stabilize at  $n \geq 500$ . As with other skewed Beta distributions, the minimum and maximum values do not achieve normality, reflecting the distribution's inherent skewness.

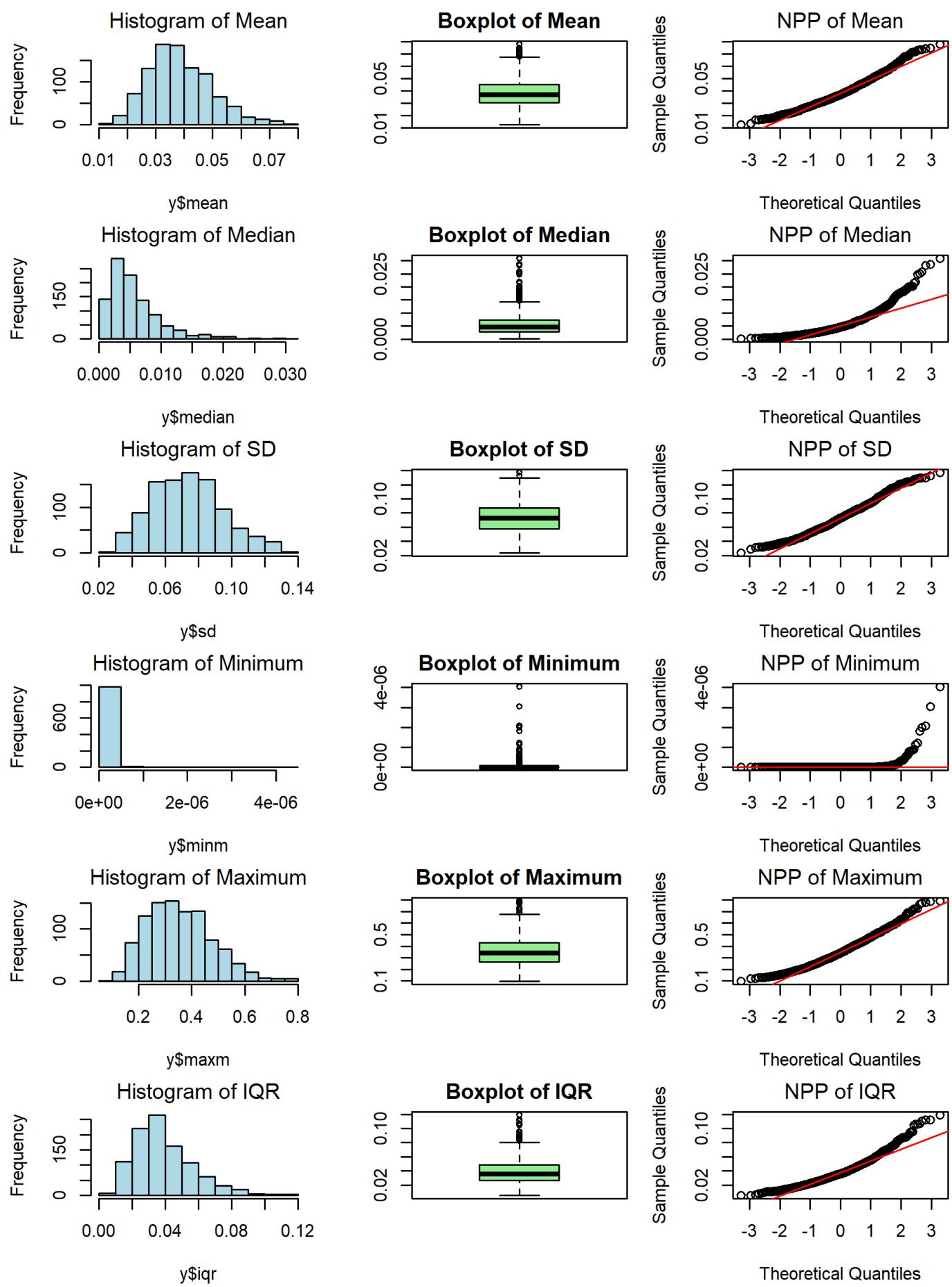
# BETA DISTRIBUTION PLOT

(n=10, nn=1000,  $\alpha=0.2$ ,  $\beta=5$ )



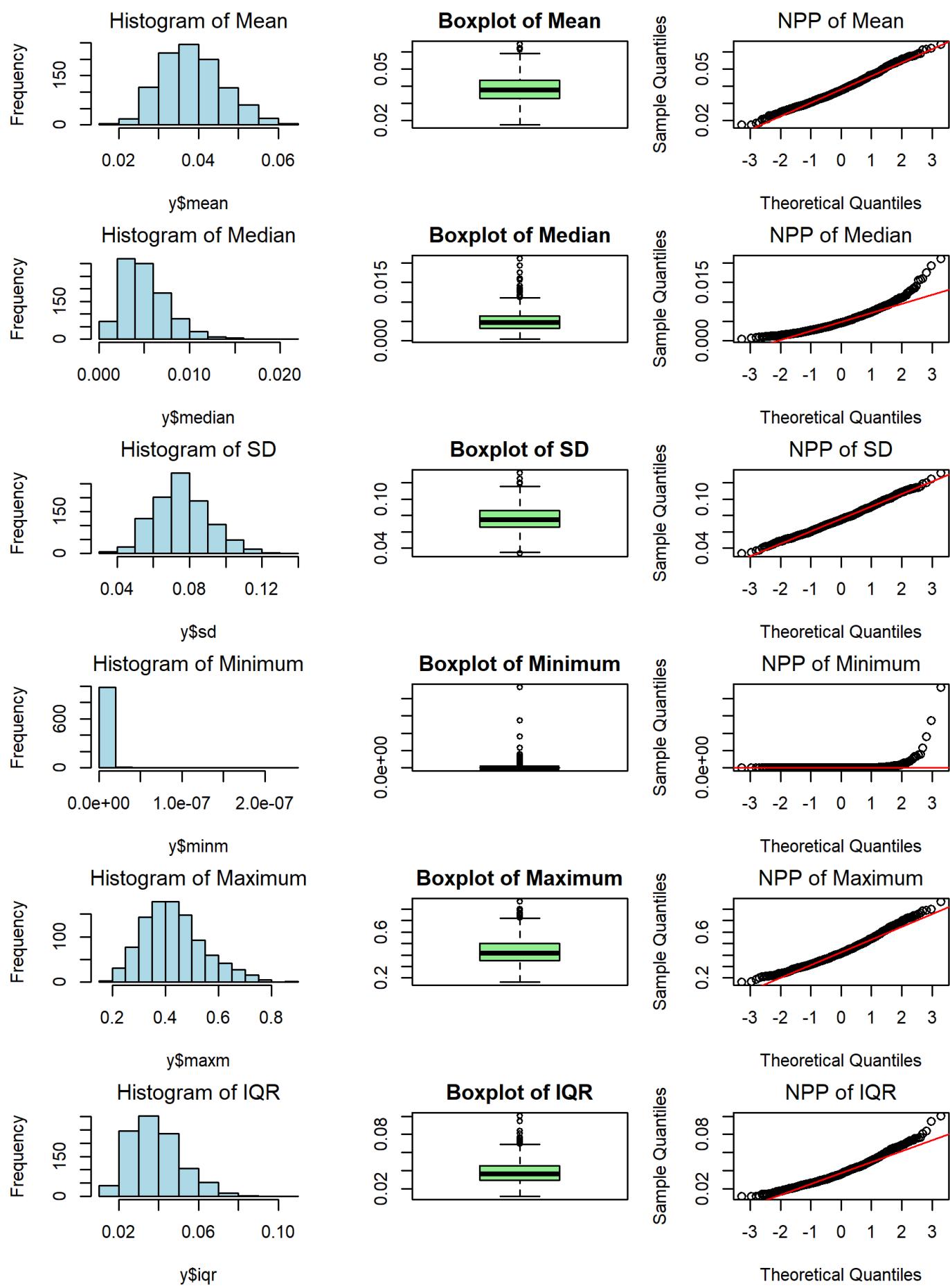
# BETA DISTRIBUTION PLOT

(n=50, nn=1000,  $\alpha=0.2$ ,  $\beta=5$ )



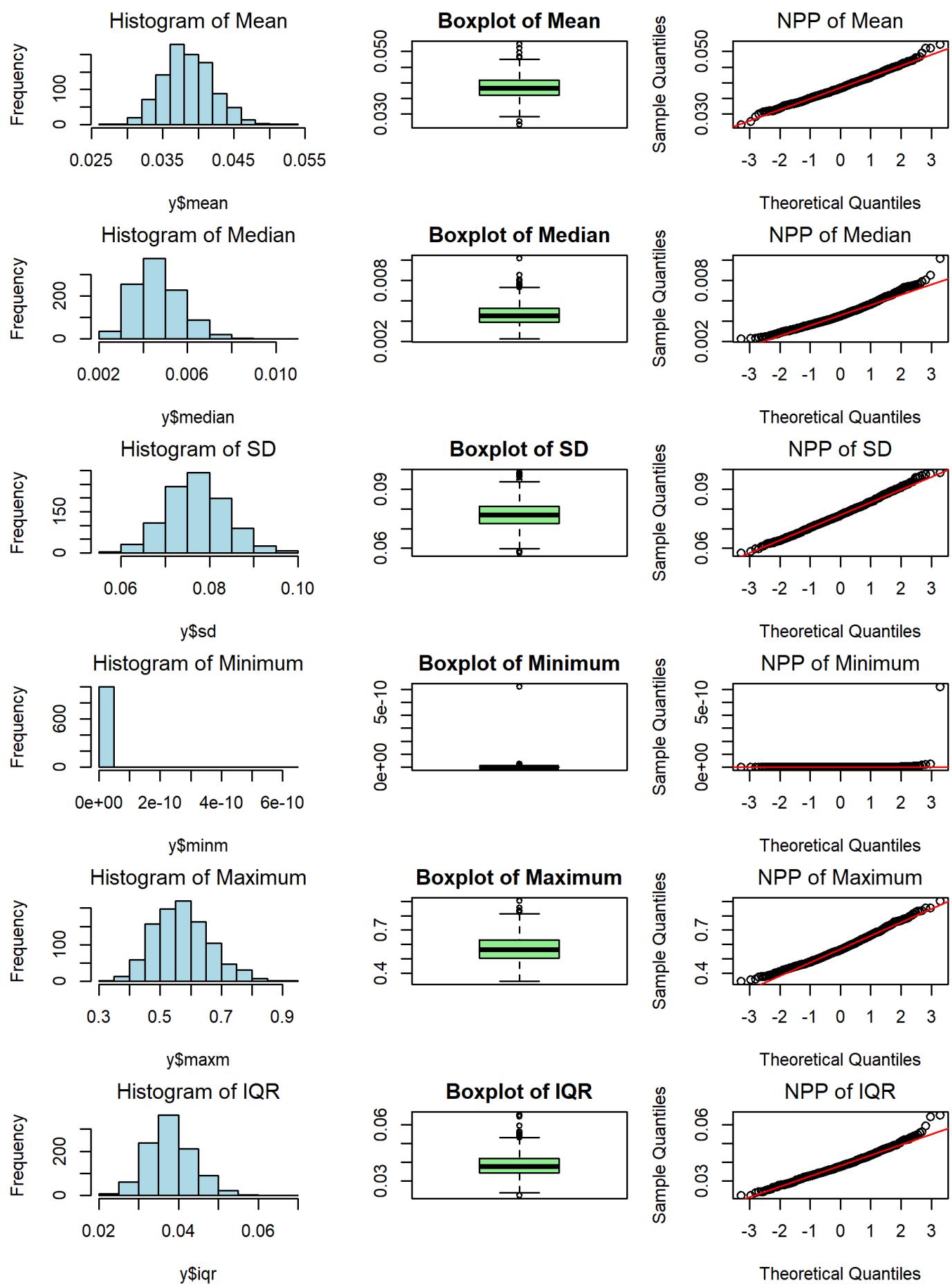
# BETA DISTRIBUTION PLOT

(n=100, nn=1000,  $\alpha=0.2$ ,  $\beta=5$ )



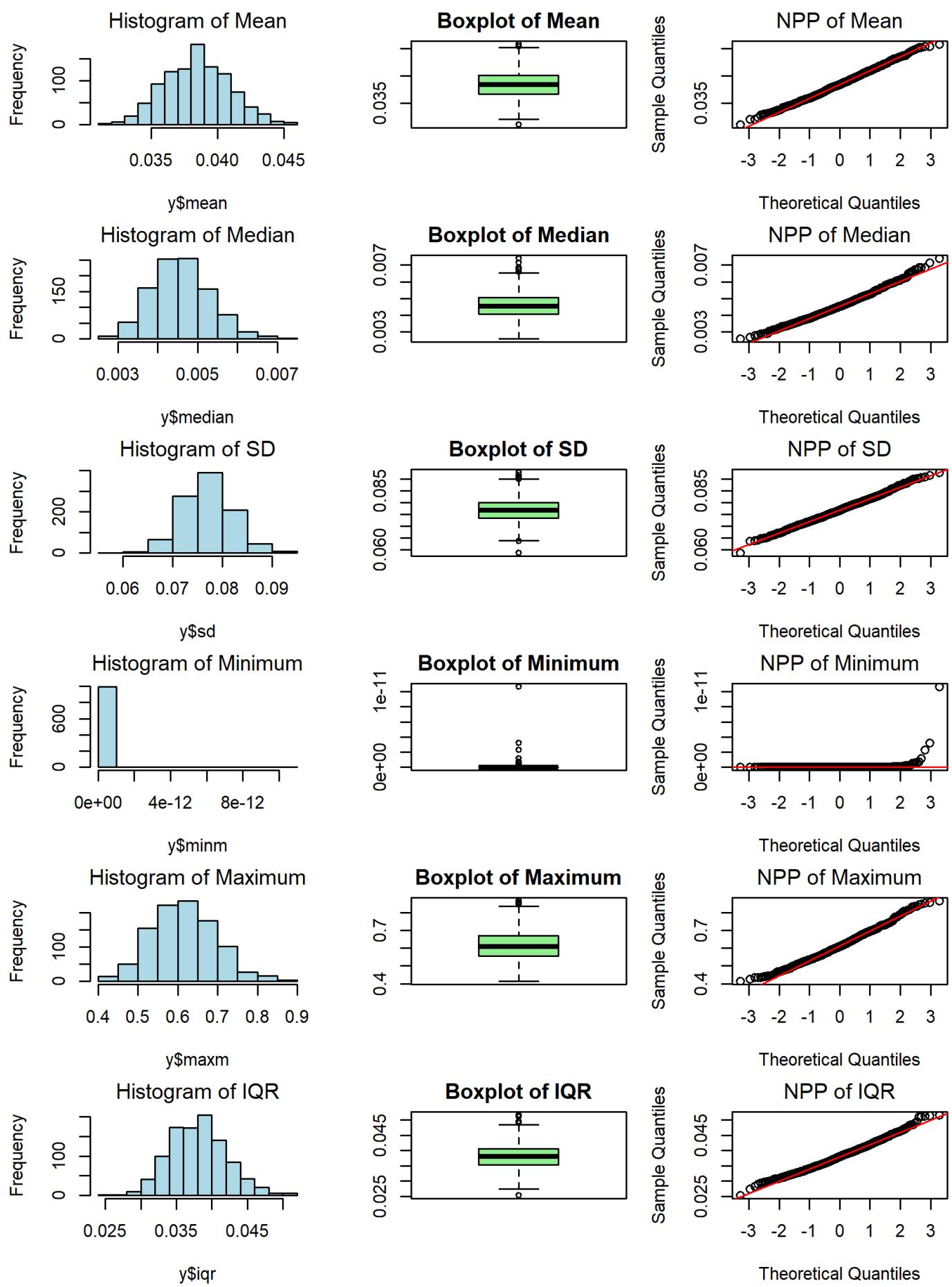
# BETA DISTRIBUTION PLOT

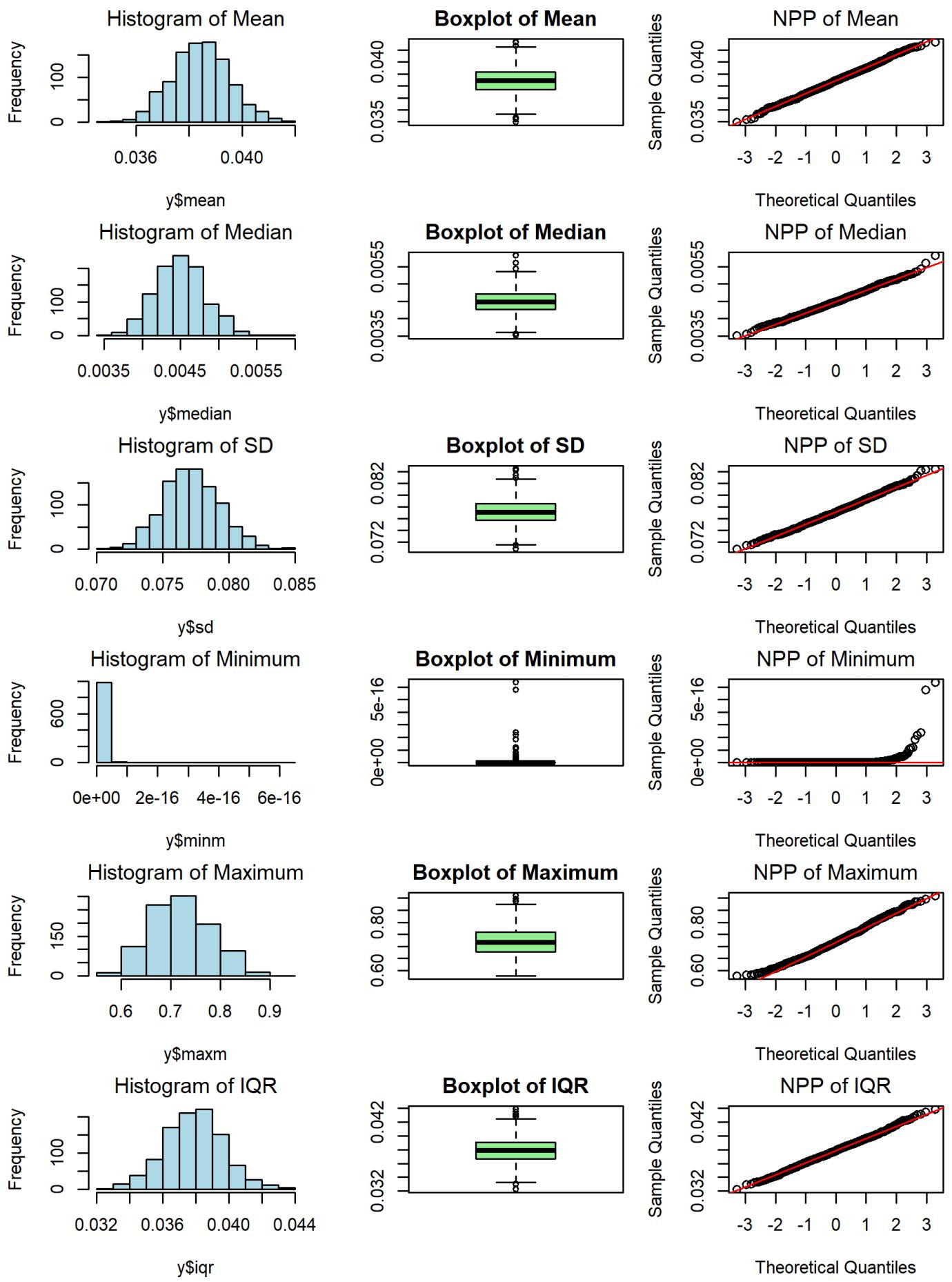
(n=500, nn=1000,  $\alpha=0.2$ ,  $\beta=5$ )



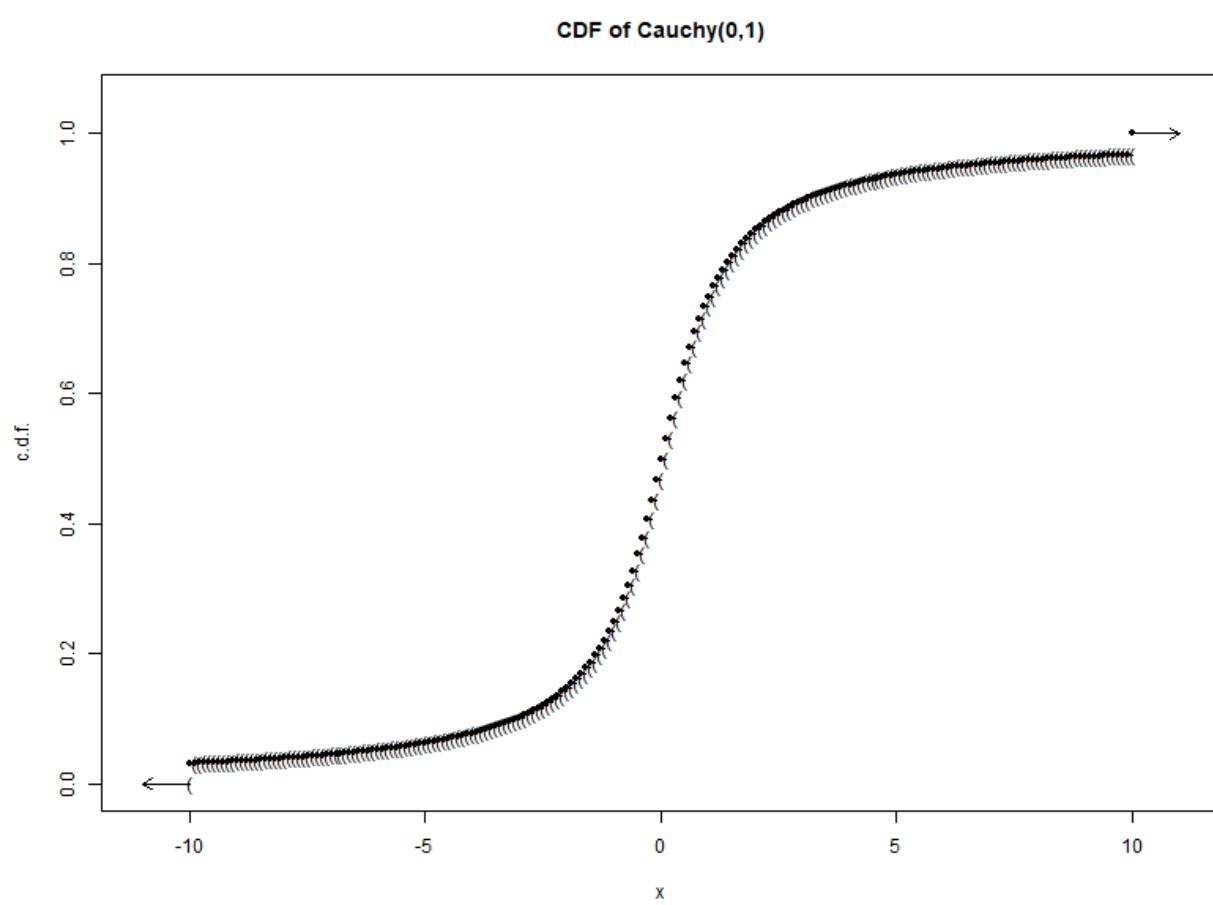
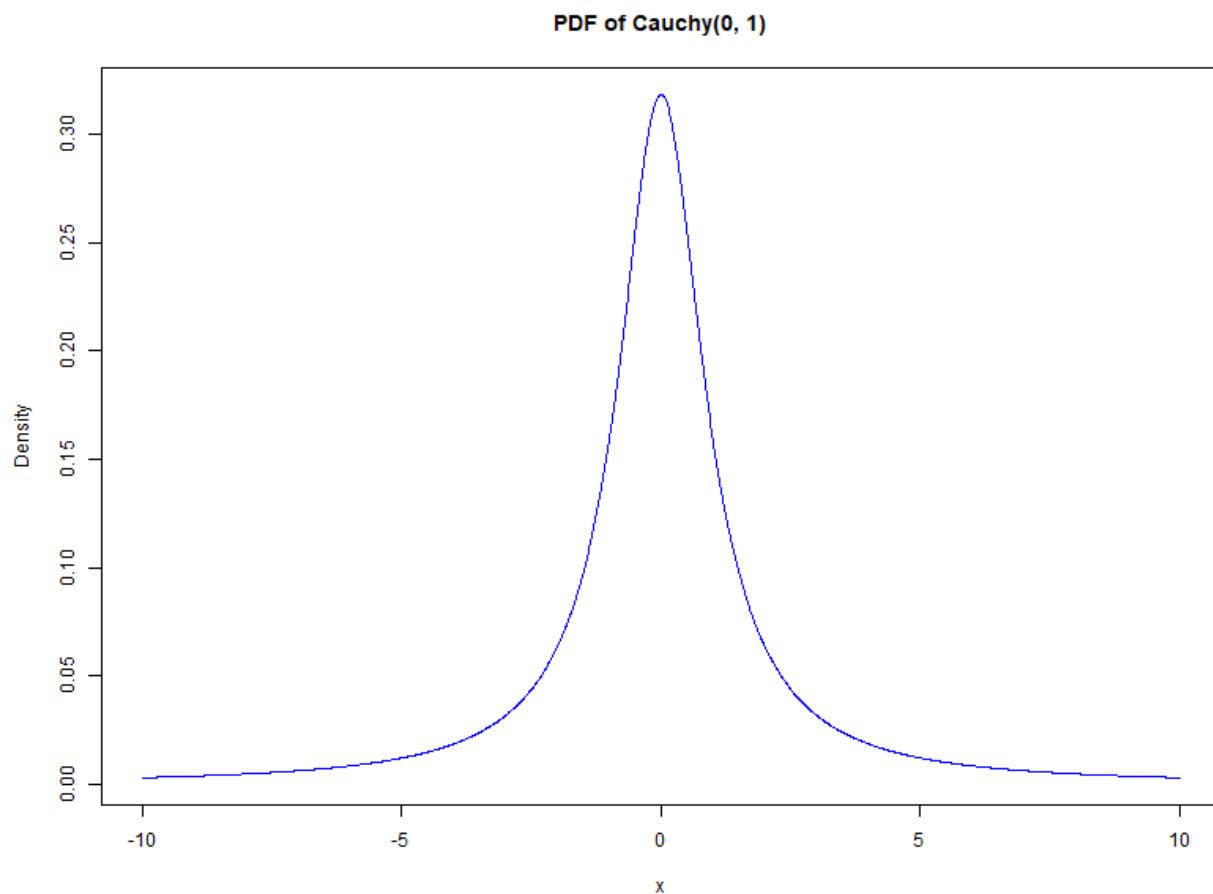
# BETA DISTRIBUTION PLOT

(n=1000, nn=1000,  $\alpha=0.2$ ,  $\beta=5$ )





# CAUCHY DISTRIBUTION (0,1)



# CAUCHY DISTRIBUTION

	Values of n to achieve normality (nn=1000, loc=0, scale=1)								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	No	No	No	No	No	No	No	No	NA
Median	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	50
Std Dev	No	No	No	No	No	No	No	No	NA
Min	No	No	No	No	No	No	No	No	NA
Max	No	No	No	No	No	No	No	No	NA
IQR	No	No	No	Yes	Yes	Yes	Yes	Yes	500

## Conclusion for Cauchy Distribution

### Normality Achieved:

- **Median:** Achieves normality for  $n \geq 50$ , converging relatively quickly despite the heavy tails of the Cauchy distribution.
- **IQR:** Achieves normality for  $n \geq 500$ , requiring larger sample sizes due to the variability introduced by the distribution's heavy tails.

### Normality Not Achieved:

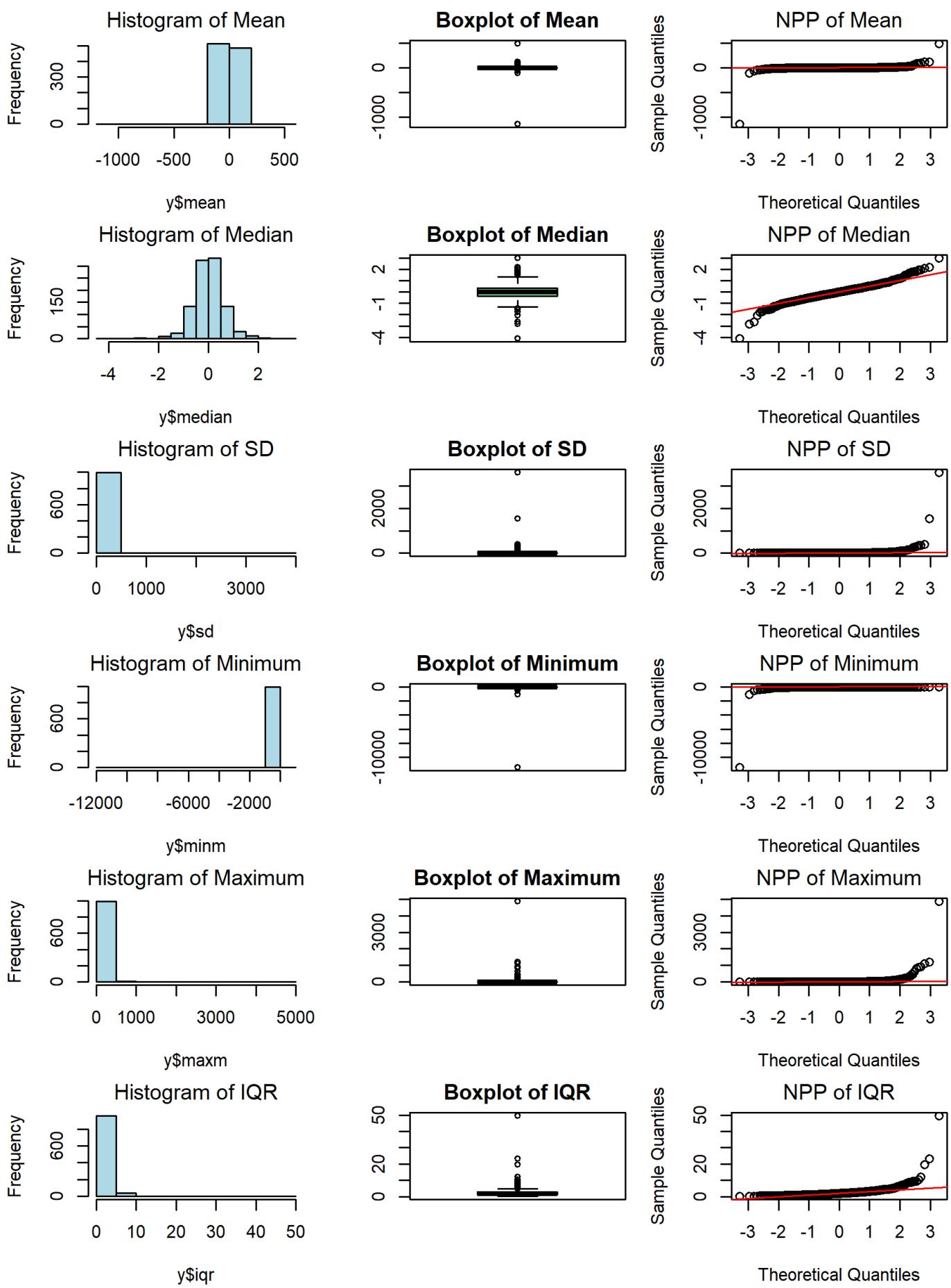
- **Mean:** Does not achieve normality for any  $n$ , as the Cauchy distribution lacks a finite mean, making the mean highly unstable.
- **Standard Deviation (SD):** Does not achieve normality for any  $n$ , reflecting the undefined variance of the Cauchy distribution.
- **Minimum and Maximum:** Do not achieve normality for any  $n$ , as they are heavily influenced by the extreme values inherent in the heavy-tailed nature of the Cauchy distribution.

### Overall:

The median and IQR are the only statistics to achieve normality, with the median converging faster ( $n \geq 50$ ). The mean, standard deviation, minimum, and maximum fail to achieve normality due to the Cauchy distribution's lack of finite moments and heavy-tailed properties.

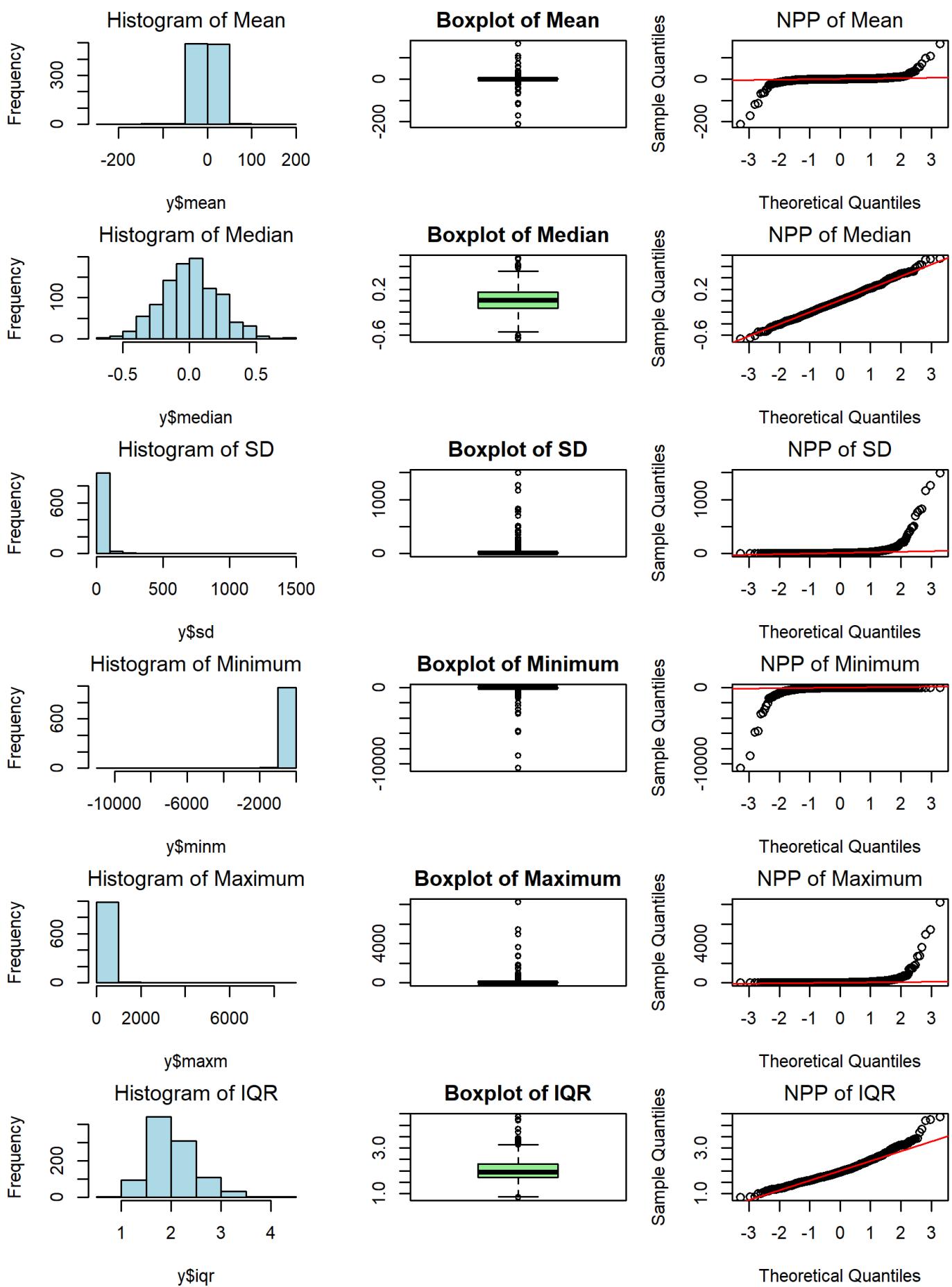
# CAUCHY DISTRIBUTION PLOT

(n=10, nn=1000, loc=0, scale=1)



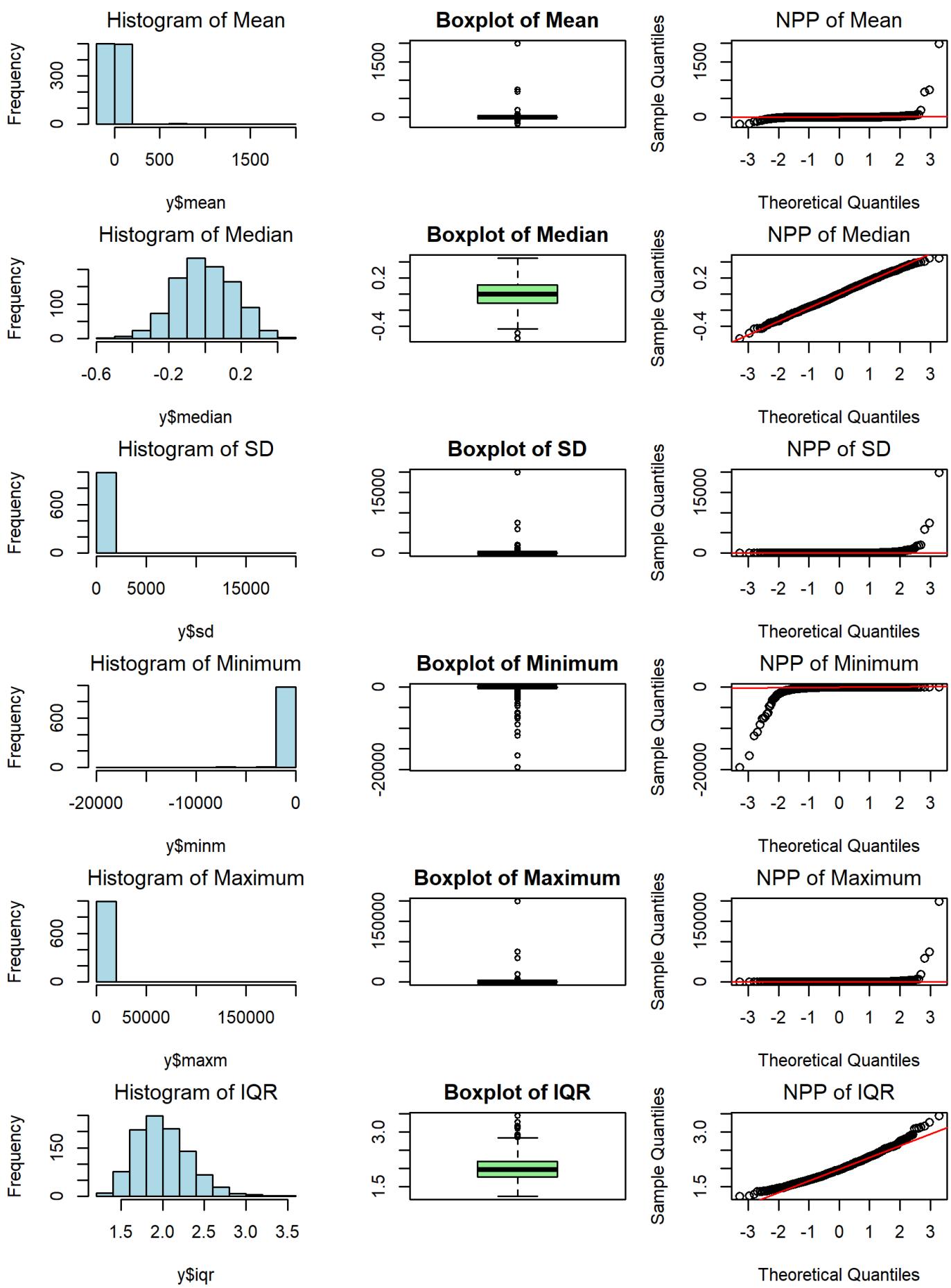
# CAUCHY DISTRIBUTION PLOT

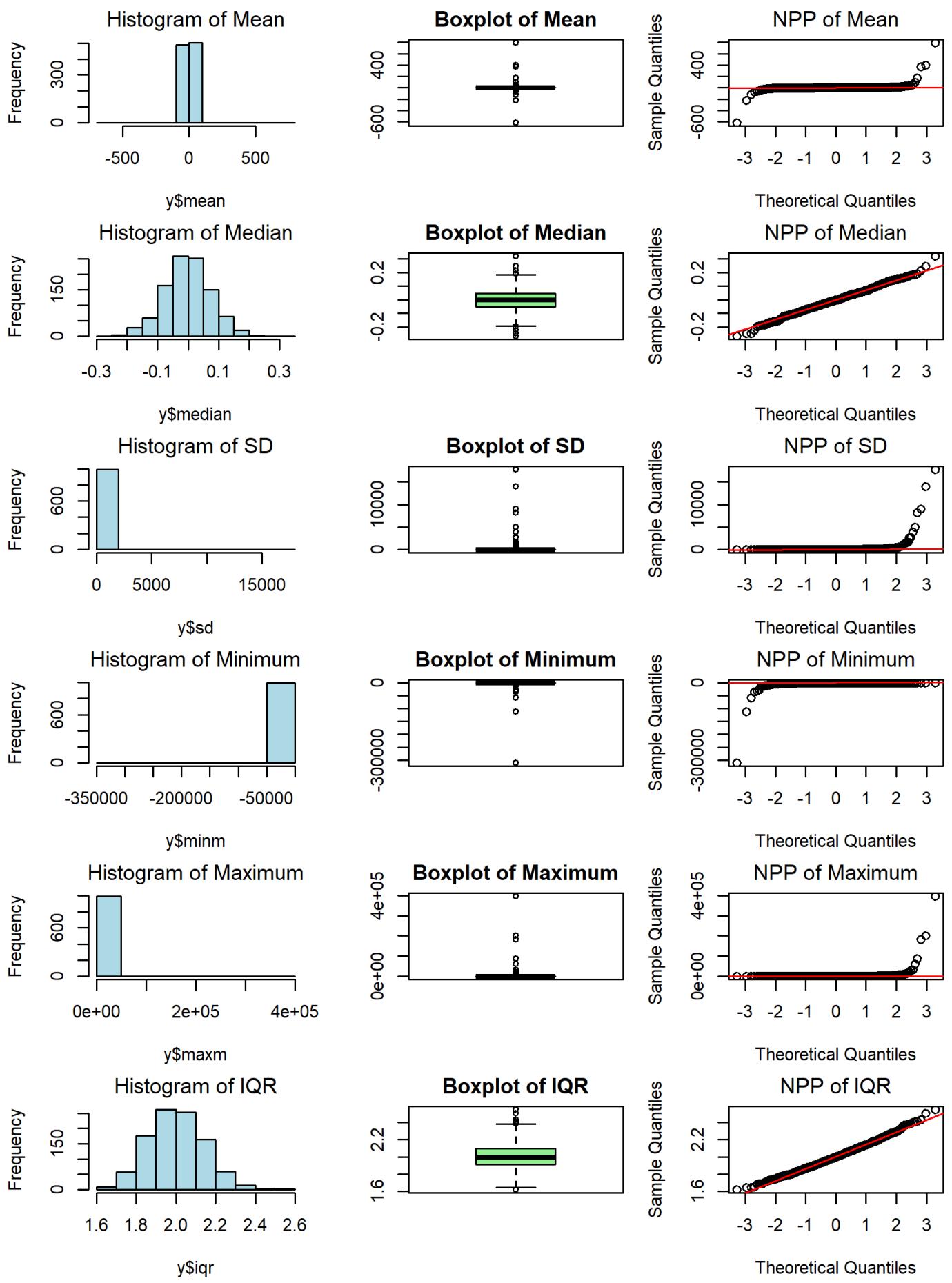
(n=50, nn=1000, loc=0, scale=1)



# CAUCHY DISTRIBUTION PLOT

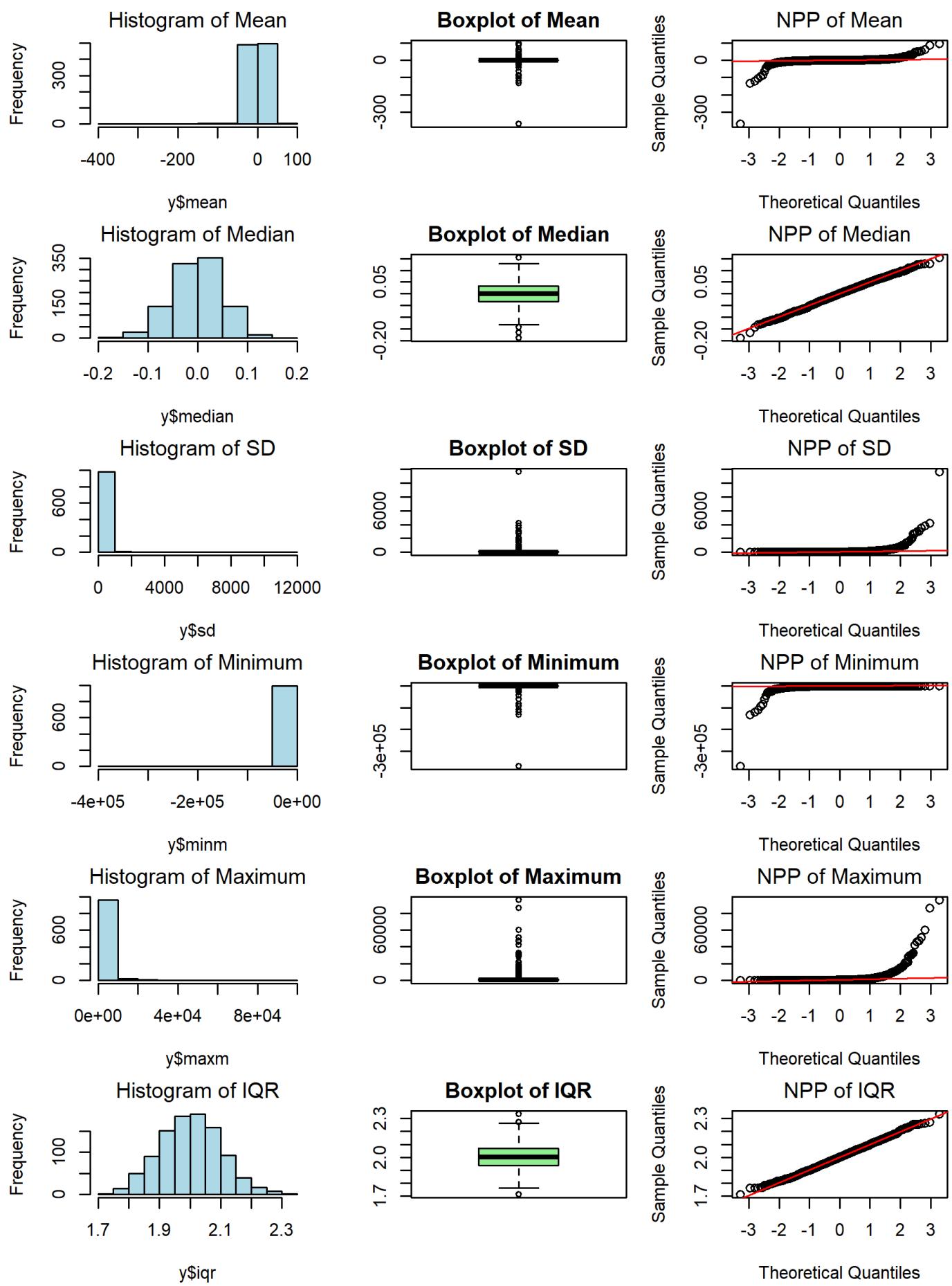
(n=100, nn=1000, loc=0, scale=1)

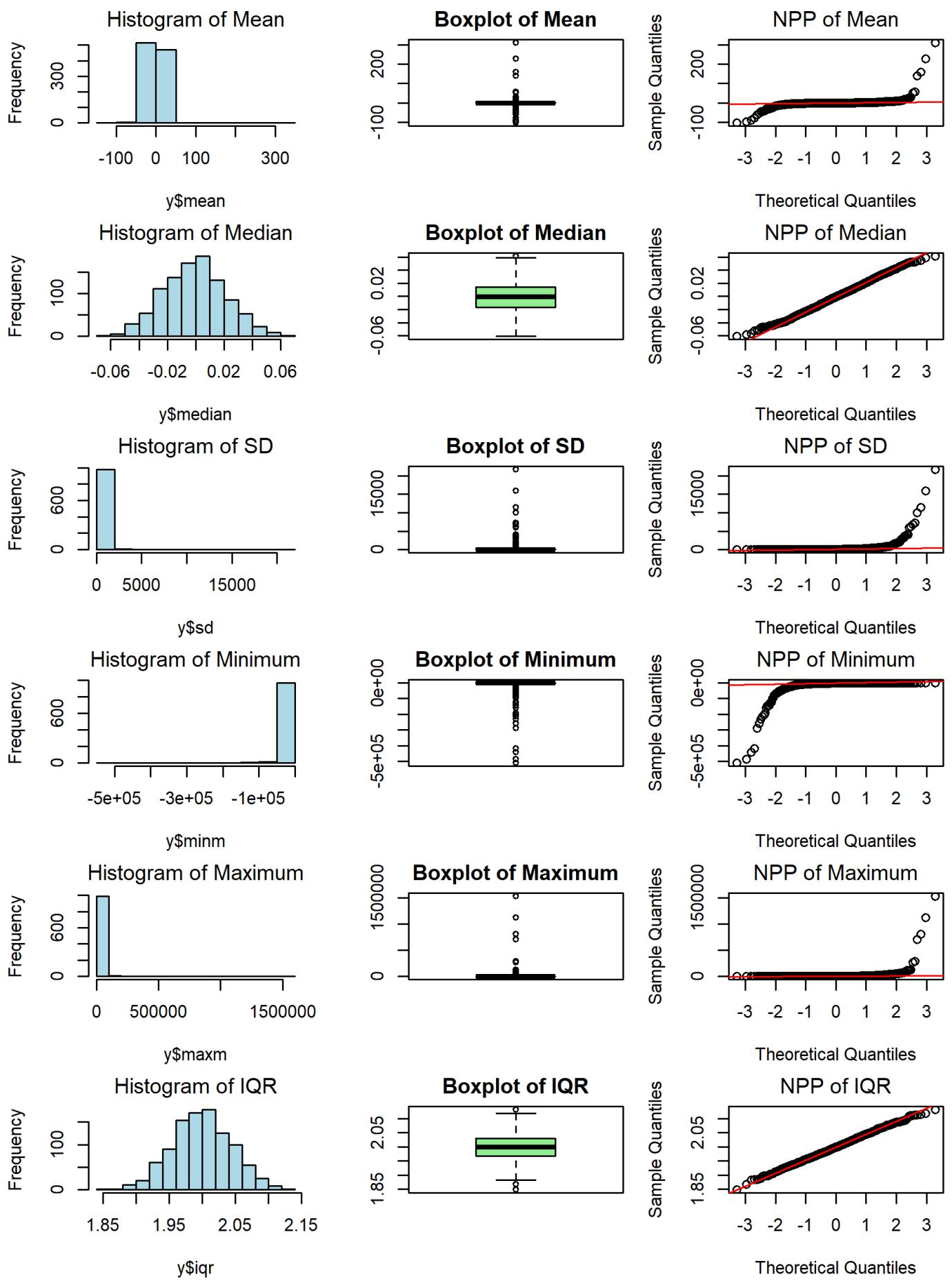




# CAUCHY DISTRIBUTION PLOT

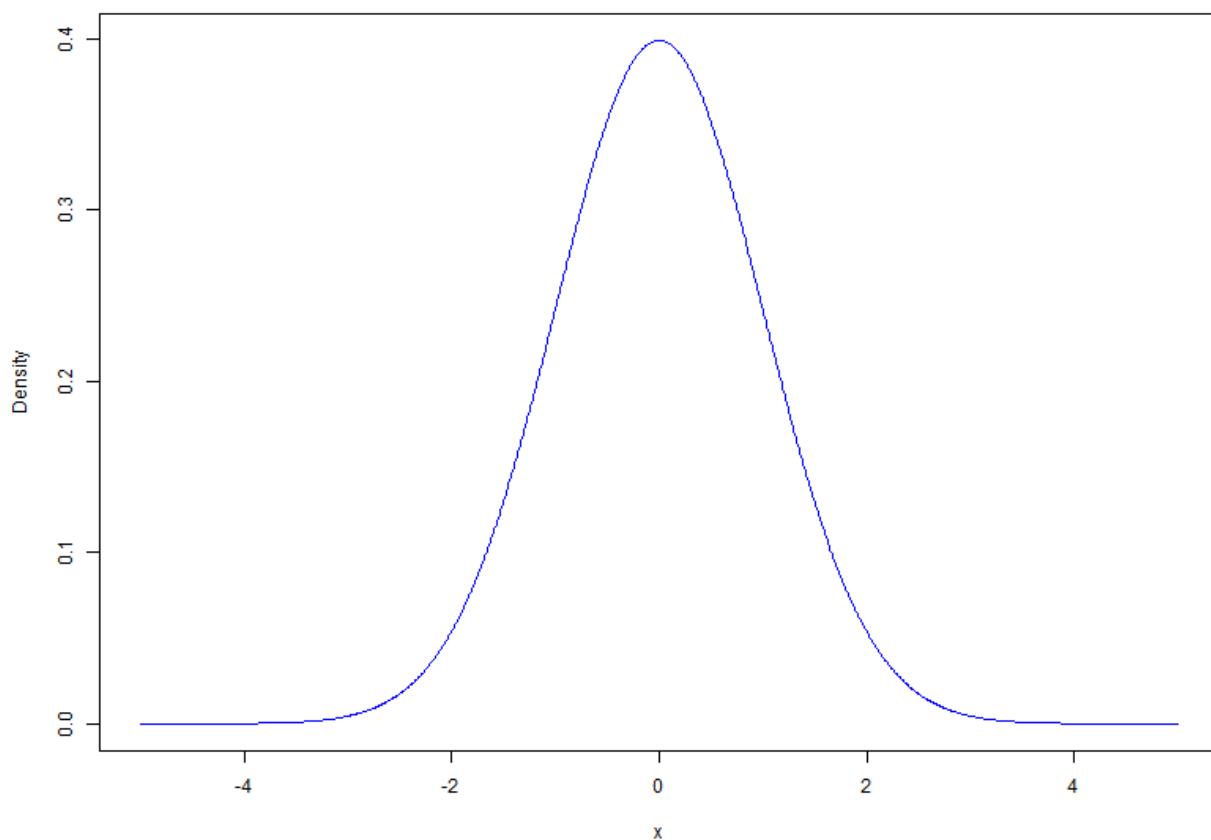
(n=1000, nn=1000, loc=0, scale=1)



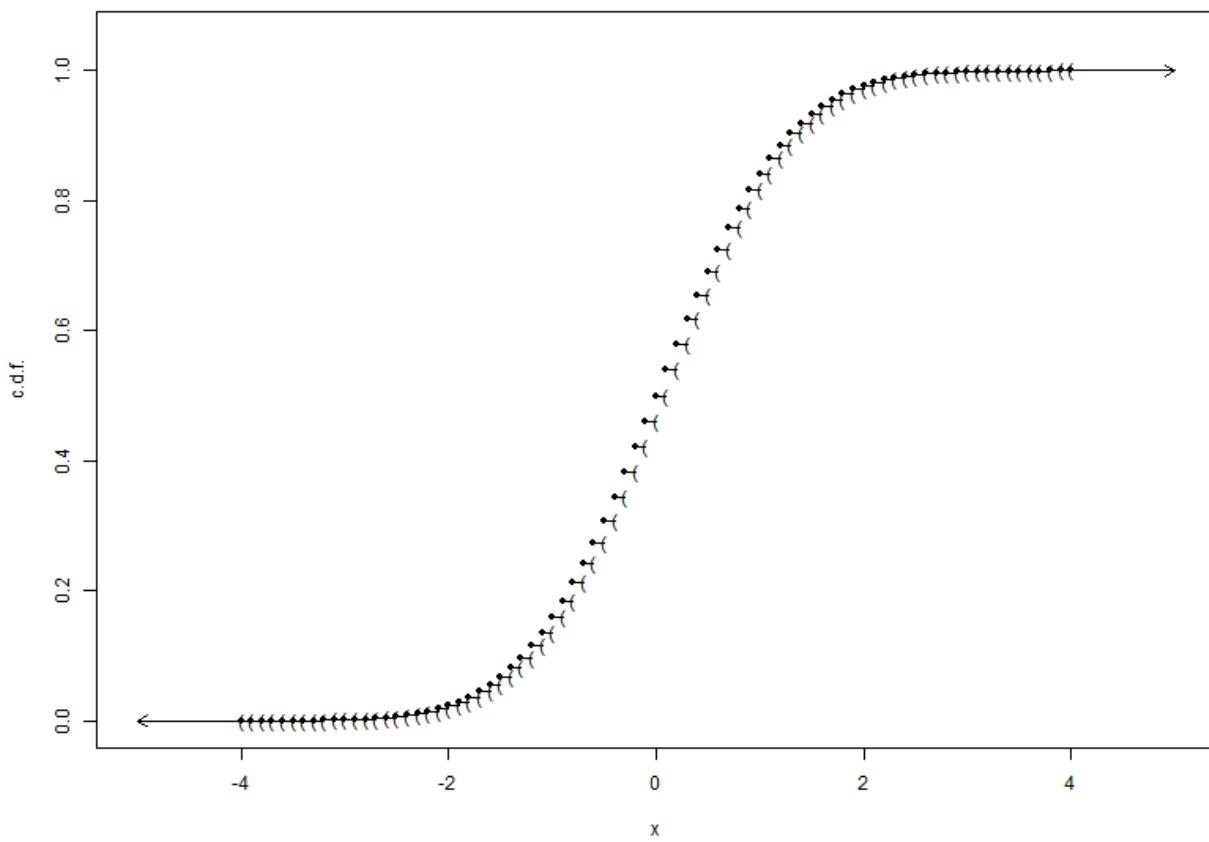


# NORMAL DISTRIBUTION (0,1)

PDF of Normal(0, 1)



CDF of Normal(0,1)



# NORMAL DISTRIBUTION

	Values of n to achieve normality ( $n=1000$ , $\mu=0$ , $\sigma=1$ )								
Statistic	n=10	n=50	n=100	n=500	n=1000	n=5000	Any n	Min(n)	
Mean	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Median	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Std Dev	Yes	Yes	Yes	Yes	Yes	Yes	Yes	10	
Min	No	No	No	No	No	No	No	NA	
Max	No	No	Yes	Yes	No	No	Yes	100	
IQR	No	No	No	Yes	Yes	Yes	Yes	500	

## Conclusion for Normal Distribution

### Normality Achieved:

- **Mean:** Achieves normality for  $n \geq 10$ , reflecting rapid convergence due to the Central Limit Theorem (CLT).
- **Median:** Achieves normality for  $n \geq 10$ , showing a faster convergence compared to skew-sensitive statistics.
- **Standard Deviation (SD):** Achieves normality for  $n \geq 10$ , demonstrating consistent behaviour across sample sizes.
- **IQR:** Achieves normality for  $n \geq 500$ , indicating moderate convergence influenced by the parent distribution's skewness.

### Normality Not Achieved:

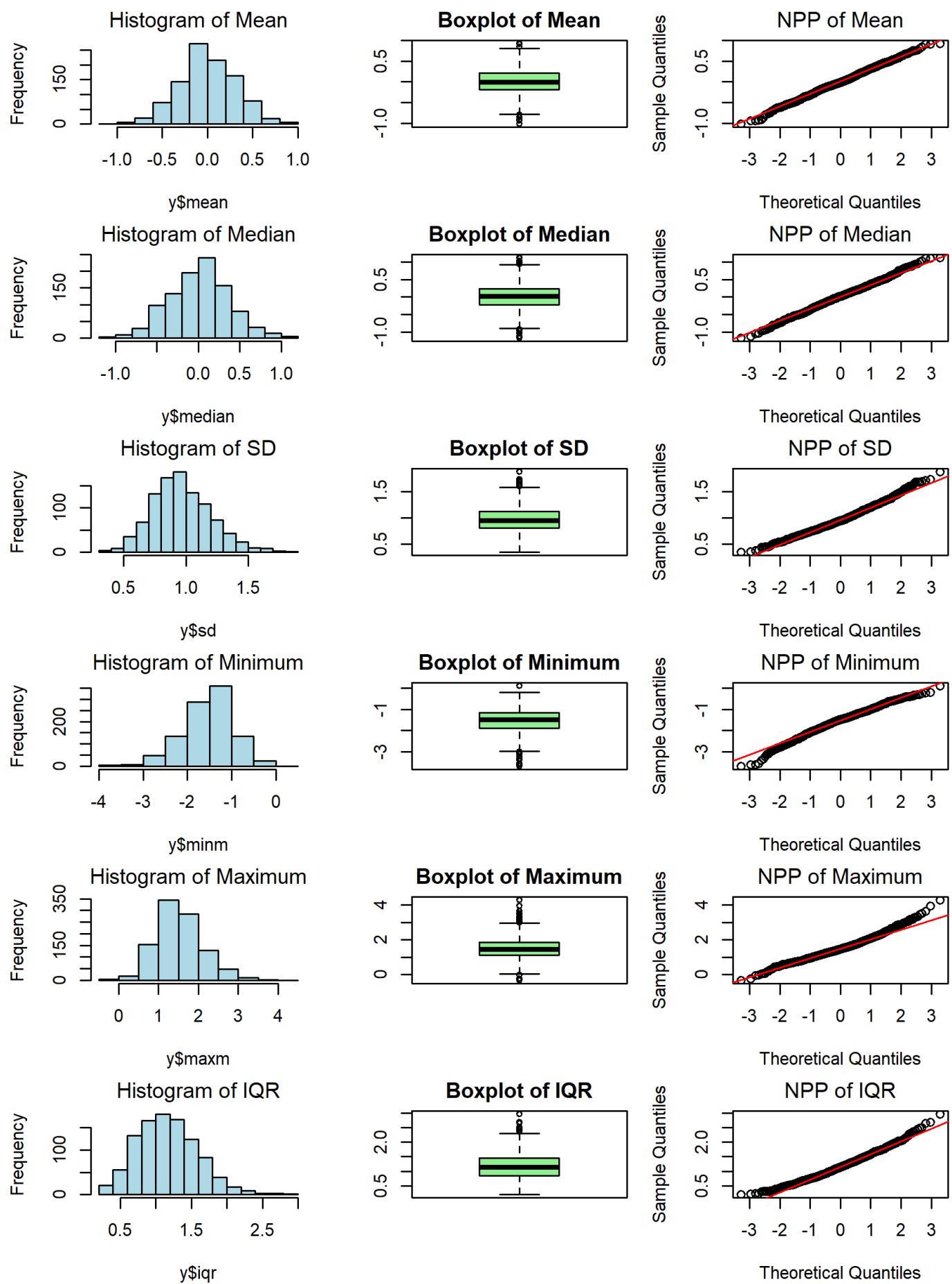
- **Minimum:** Does not achieve normality for any  $n$ , as it is highly sensitive to extreme values and the asymmetry of the Normal distribution.
- **Maximum:** Achieves normality only for  $n=100$  and  $500$ , but fails for larger sample sizes, likely due to variability in extreme values.

### Overall:

The mean, median, and standard deviation converge to normality quickly, making them reliable statistics for smaller sample sizes. However, skew-sensitive statistics like the minimum and maximum are less consistent, with the minimum failing to achieve normality entirely. The IQR requires larger sample sizes to approximate normality.

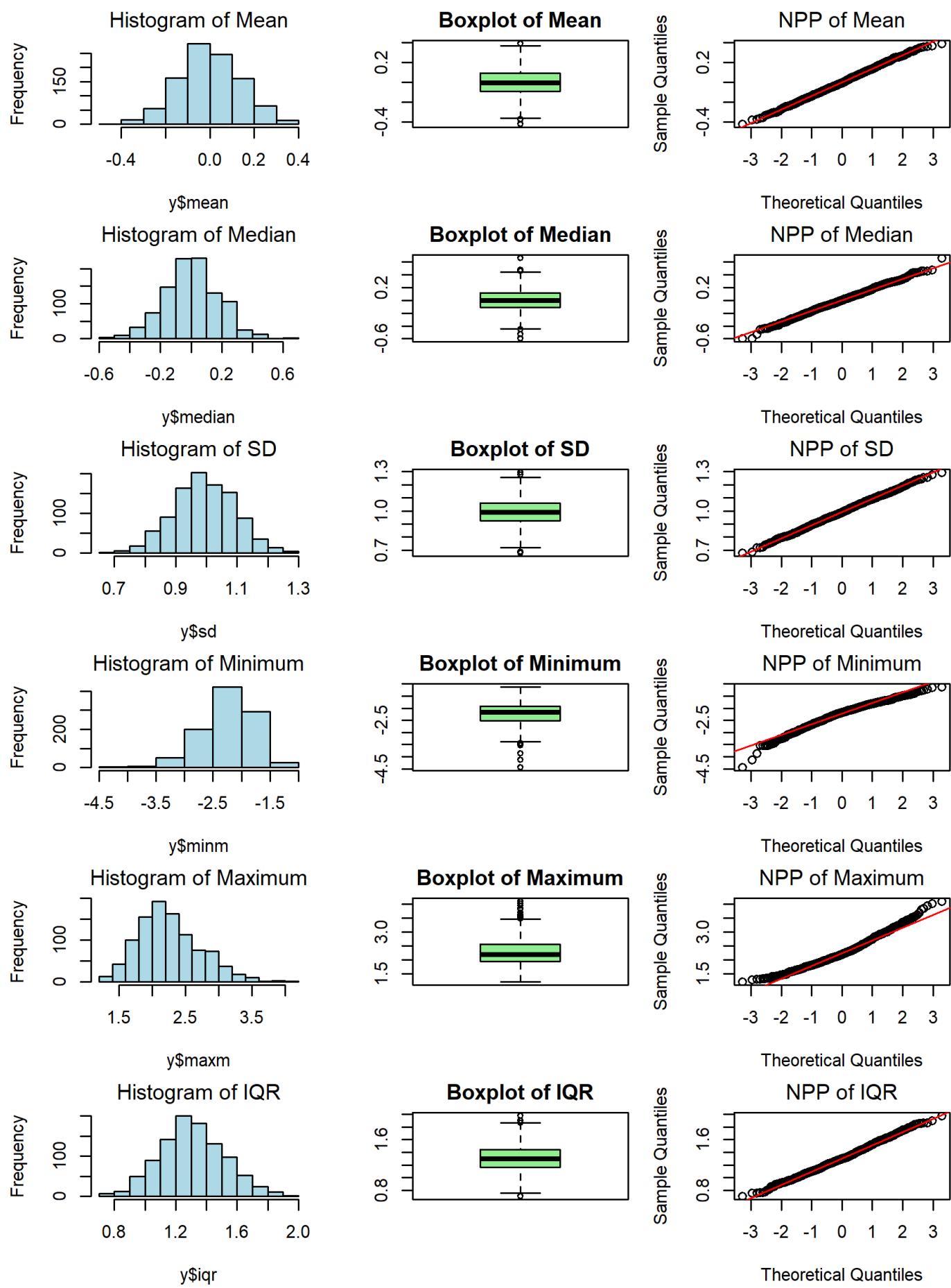
# NORMAL DISTRIBUTION PLOT

(n=10, nn=1000, μ=0, σ=1)



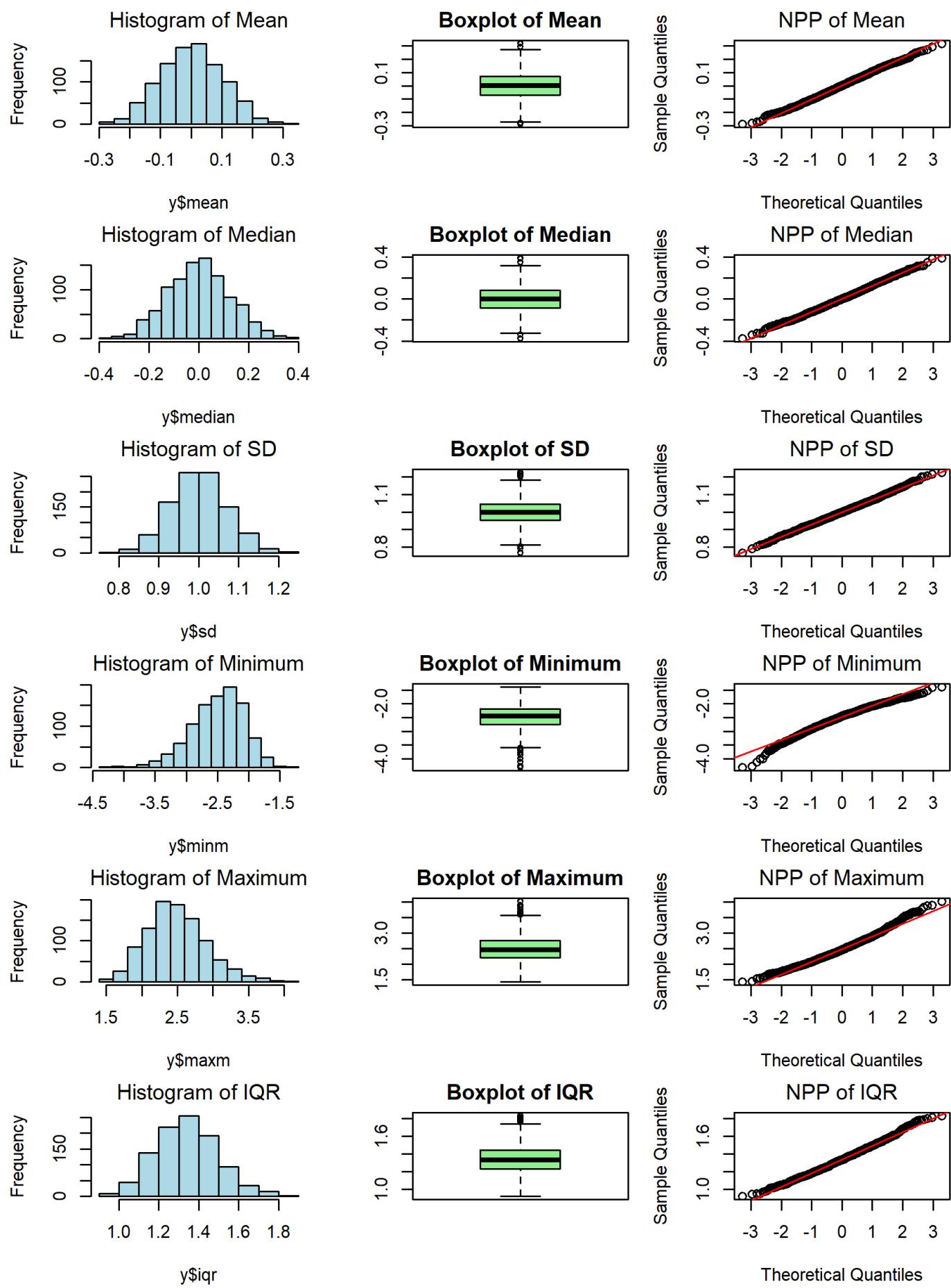
# NORMAL DISTRIBUTION PLOT

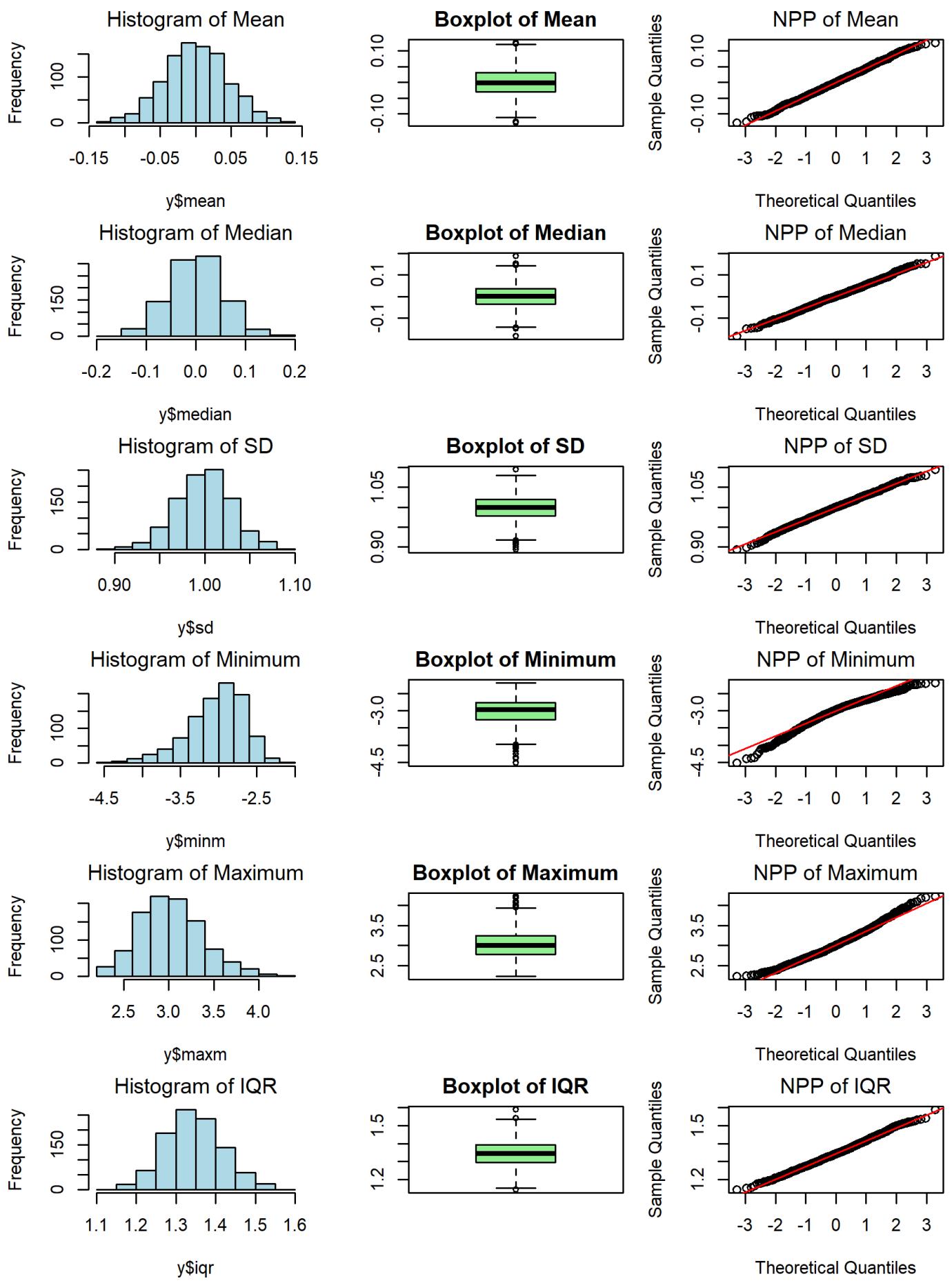
(n=50, nn=1000,  $\mu=0$ ,  $\sigma=1$ )



# NORMAL DISTRIBUTION PLOT

(n=100, nn=1000,  $\mu=0$ ,  $\sigma=1$ )





# NORMAL DISTRIBUTION PLOT

(n=1000, nn=1000,  $\mu=0$ ,  $\sigma=1$ )

