

# Homework 4 - bootstrap

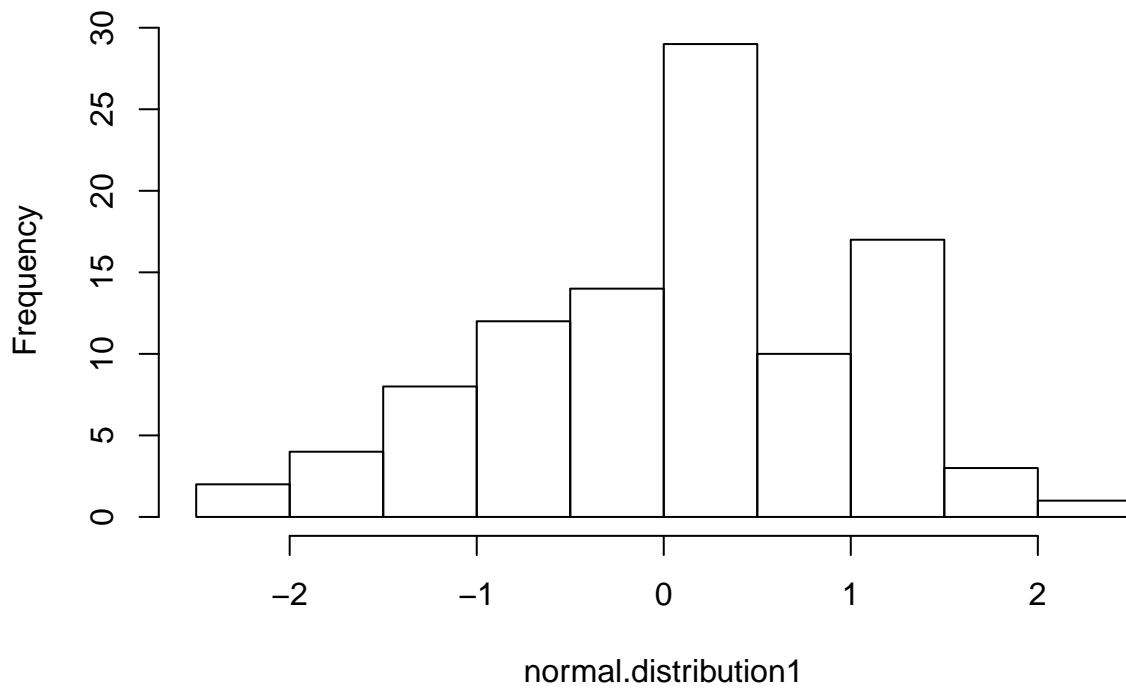
## Bootstrap Normal Distribution

First we create the two normal distributions called `normal.distribution1` and `normal.distribution2`.

```
normal.distribution1 = rnorm(100)
normal.distribution2 = rnorm(1000)
```

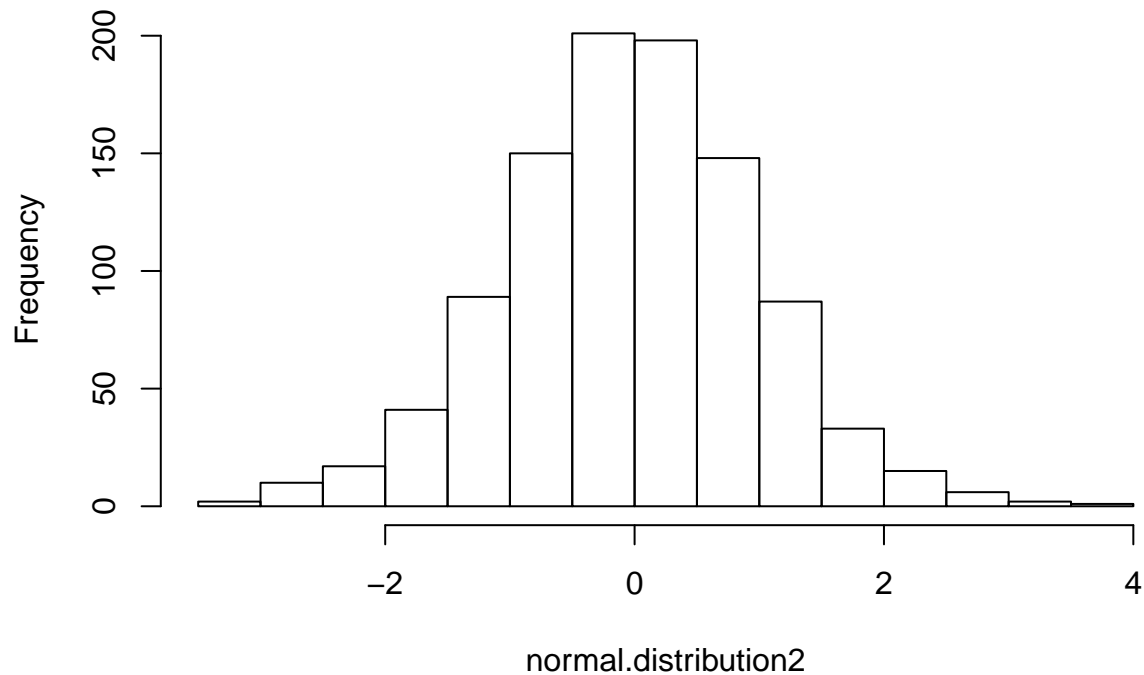
## Histograms of Normal Distributions

### Histogram of normal.distribution1



We would expect the first distribution to have a relatively normal distribution with 100 observations.

## Histogram of normal.distribution2



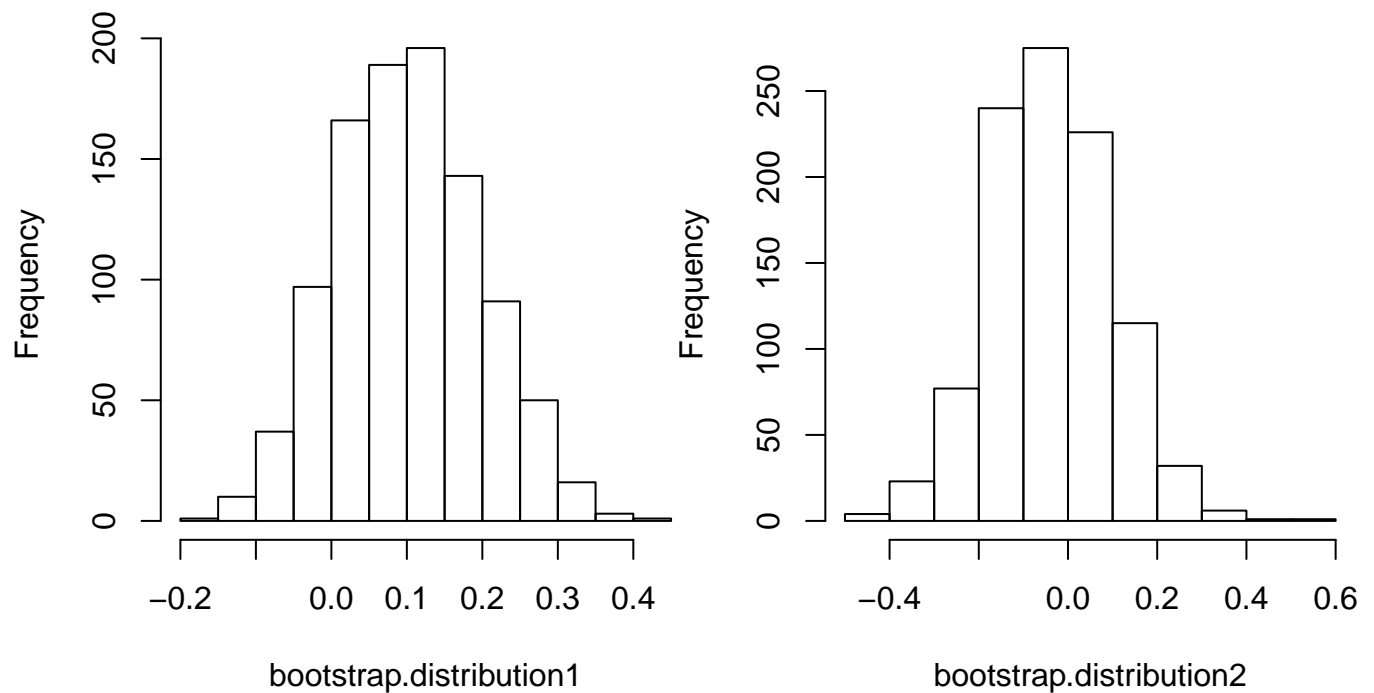
And the second distribution to be more normal than the first with 100 observations.

### Bootstrap function

Now we will introduce a bootstrap function that will take the `distribution` as its only argument and will return a new distribution based on creating 1000 means from 50 random samples out of the original distribution.

```
bootstrap = function(distribution) {  
  # sample size  
  n = 50  
  #number of simulations  
  nsim = 1000  
  lotsa.means = numeric(nsim)  
  for (i in 1:nsim) {  
    x = sample(distribution, 50)  
    lotsa.means[i] = mean(x)  
  }  
  
  lotsa.means  
}
```

Let's see what happens when we apply the `bootstrap` method against our `normal.distribution1` and `normal.distribution2` variables and graph the results:



As we can see, the bootstrap distribution is even more normal than the original and the amount of variance is much smaller in the bootstrap distribution

```
sd(normal.distribution1)
```

```
## [1] 0.9579179
```

```
sd(bootstrap.distribution1)
```

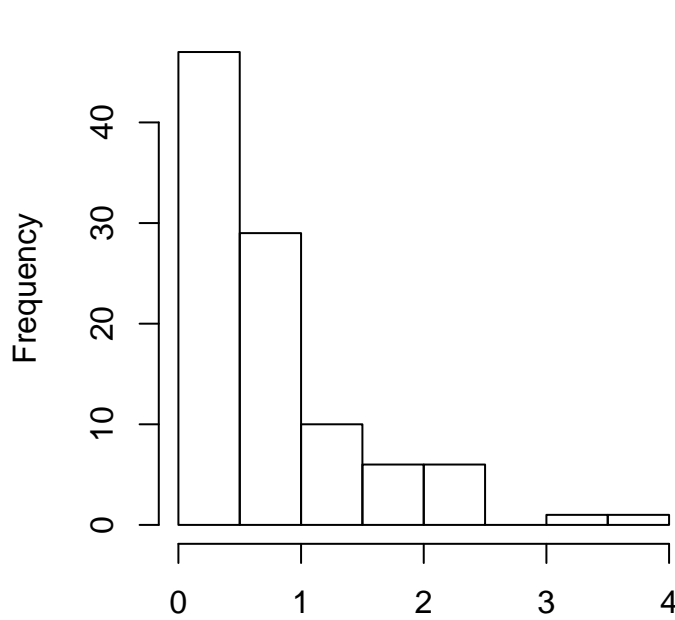
```
## [1] 0.09588992
```

## Bootstrap Exponential Distribution

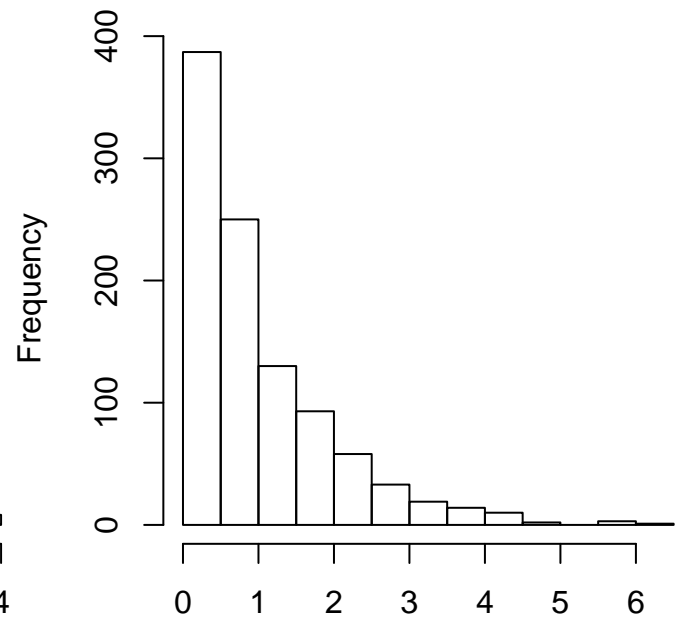
Now let's create two exponential distributions and apply the same steps that we did with the normal distributions above.

```
exp.distribution1 = rexp(100)
exp.distribution2 = rexp(1000)
```

As we can see, the data is heavily skewed with a strong, right-tailed distribution for both sets.



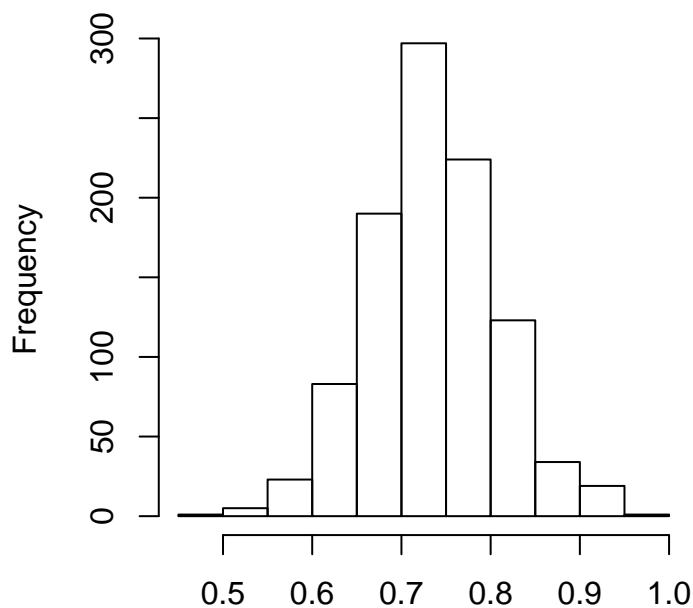
exp.distribution1



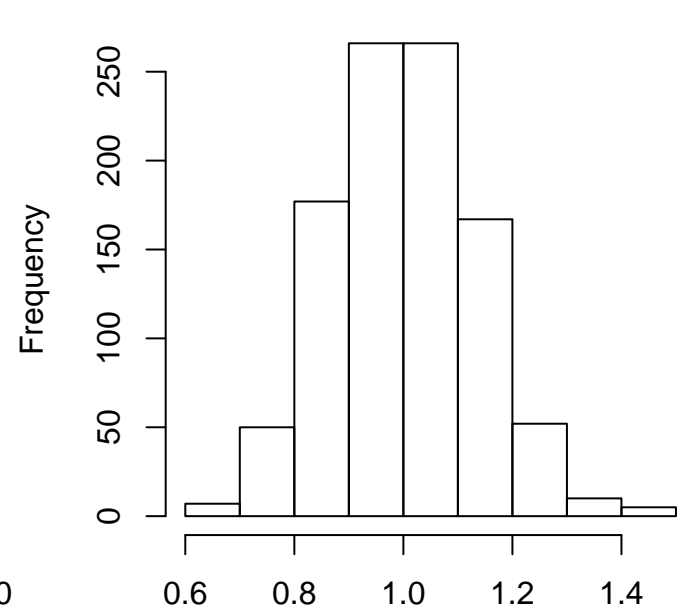
exp.distribution2

Applying the `bootstrap` method against our `exp.distribution` variables, we can see that the new distributions are almost completely normal... an amazing transformation from the original, right-tailed distributions.

```
exp.bootstrap.distribution1 = bootstrap(exp.distribution1)
exp.bootstrap.distribution2 = bootstrap(exp.distribution2)
```



exp.bootstrap.distribution1



exp.bootstrap.distribution2

Notice that the bootstrap distribution is centered around 1

```
mean(exp.bootstrap.distribution1)
```

```
## [1] 0.7342565
```

Finally, notice that the variance is much less within the bootstrap distribution

```
sd(exp.distribution1)
```

```
## [1] 0.7121581
```

```
sd(exp.bootstrap.distribution1)
```

```
## [1] 0.07165198
```

Thus, the true power of the Central Limit Theorem has been revealed and demonstrated.

The central limit theorem states that the sampling distribution of the mean of any independent, random variable will be normal or nearly normal, if the sample size is large enough. [stattrek.com](http://stattrek.com)