

GROUP 17

ASSIGNMENT 1

TEAM MEMBERS:

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GROUP-17

Discrete Distributions:

BINOMIAL DISTRIBUTION:

A binomial random variable is the number of successes 'x' in 'n' repeated trials of a binomial experiment. The probability distribution of a binomial random variable is called a binomial distribution.

$$b(x; n, P) = {}^nC_x * P^x * (1 - P)^{n-x}$$

Example: flip a coin 2 times and count the number of times the coin lands on heads.

FIRST PART:

Parameters of distribution:

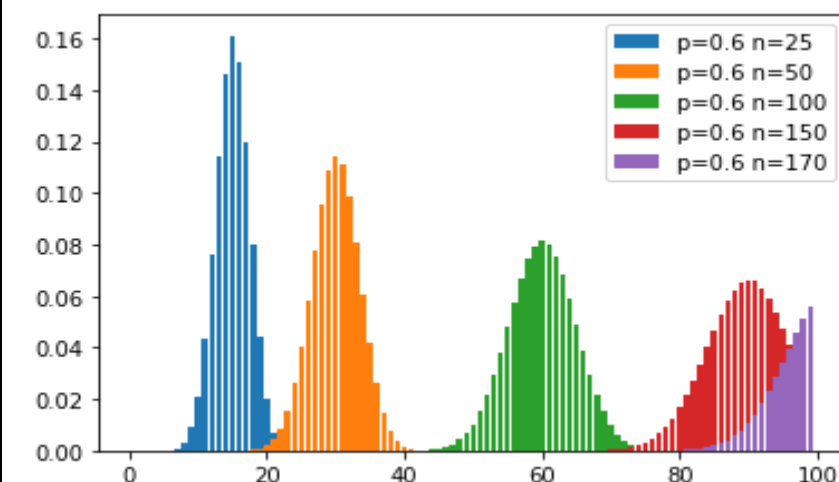
Parameters are n,p where n is number of trials and p is probability of success for each trial.

Distribution for different values of parameters:

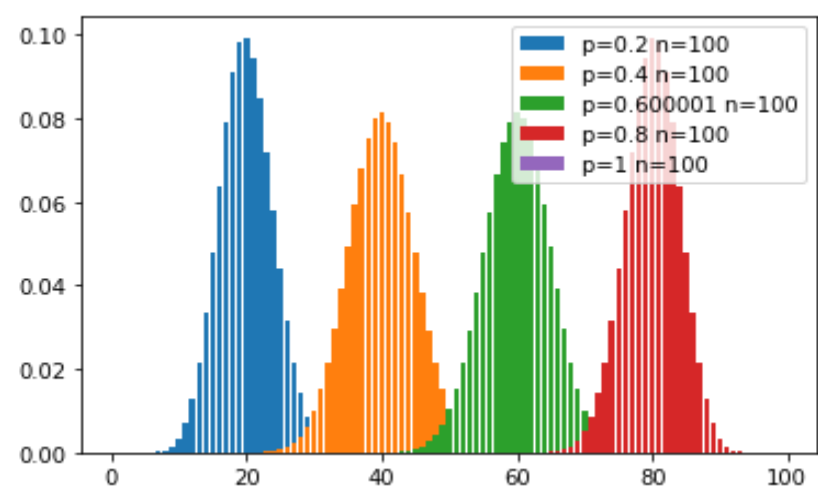
Considering $n=[25,50,100,150,170]$ for 5 different samples and $p=[0.2,0.4,0.600001,0.8,1]$ respectively

The distribution is as follows:

When n is varying and p is constant(i.e, $p=0.6$) :



When p is varying and n is constant(i.e, n= 100) :

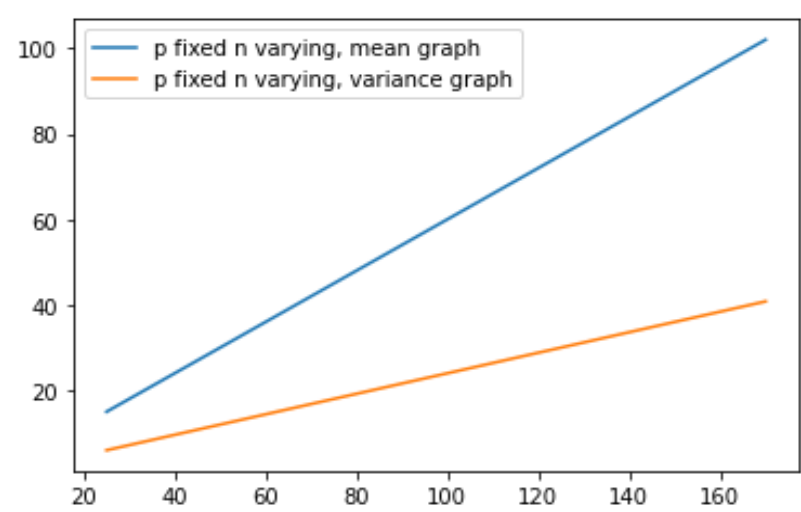


Mean and variance changes for different parameters:

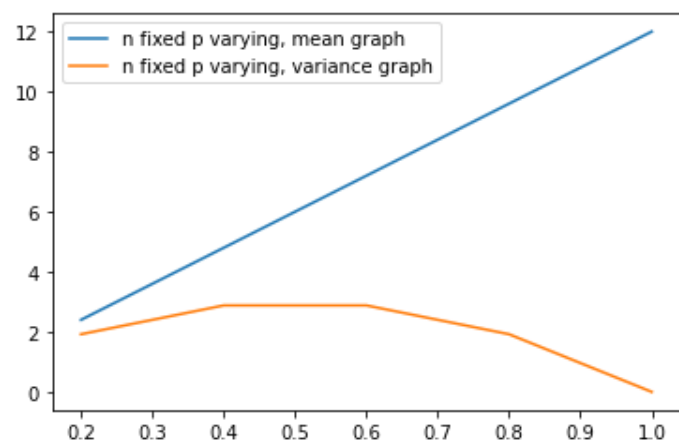
Mean= np

Variance= $np(1-p)$

When p is fixed and n is varying:



When n is fixed and p is varying:



SECOND PART:

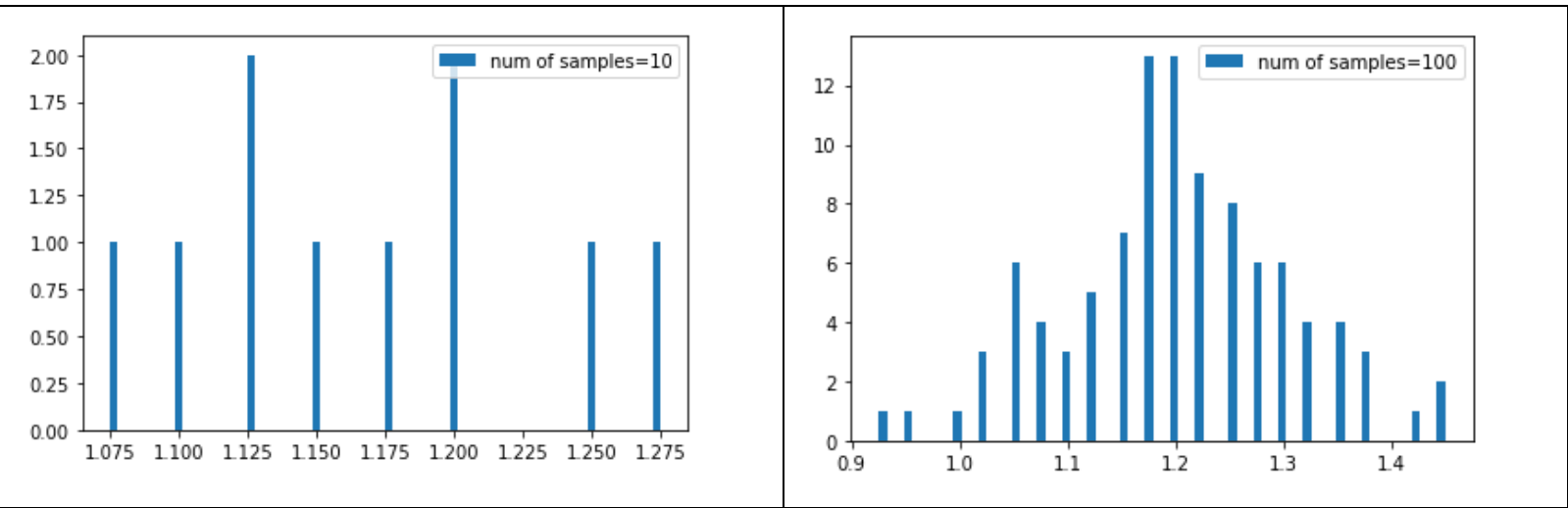
Mean of sample mean: 1.2000275000000002

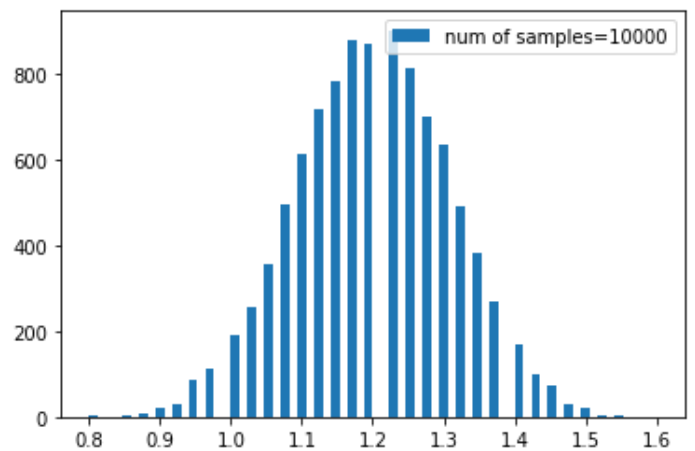
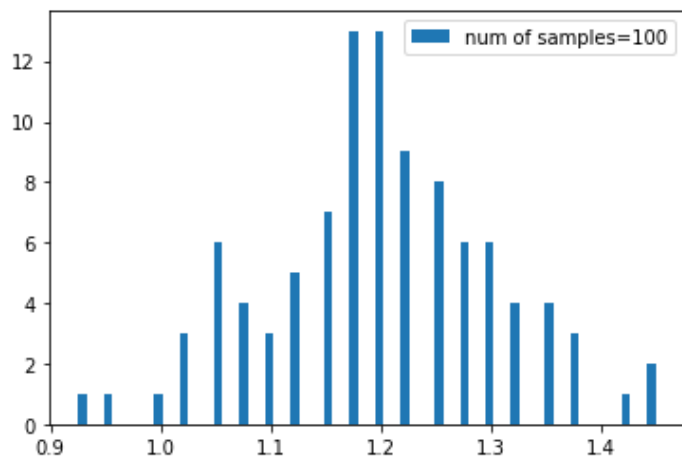
Variance of sample mean: 0.011927186743750002

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when $n=10000$,i.e 4th plot.,the curve is in the shape of bell.





GEOMETRIC DISTRIBUTION:

The geometric distribution is the probability distribution of the number of failures we get by repeating a Bernoulli experiment until we obtain the first success.

If X is a discrete random variable following geometric distribution with parameter p then

$f(x) = ((1 - p)^{(x-1)}) * (p)$ this is probability of success

Example: If we toss a coin until we obtain a head, the number of tails before the first head has a geometric distribution.

FIRST PART:

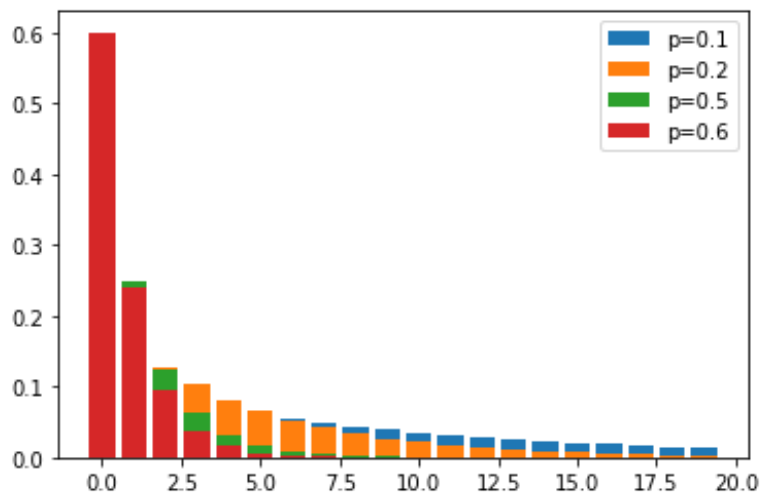
Parameters of distribution:

p is the parameter which represents the probability of success .

Distribution for different values of parameters:

Considering 4 different samples with $p = [0.1, 0.2, 0.5, 0.6]$ respectively

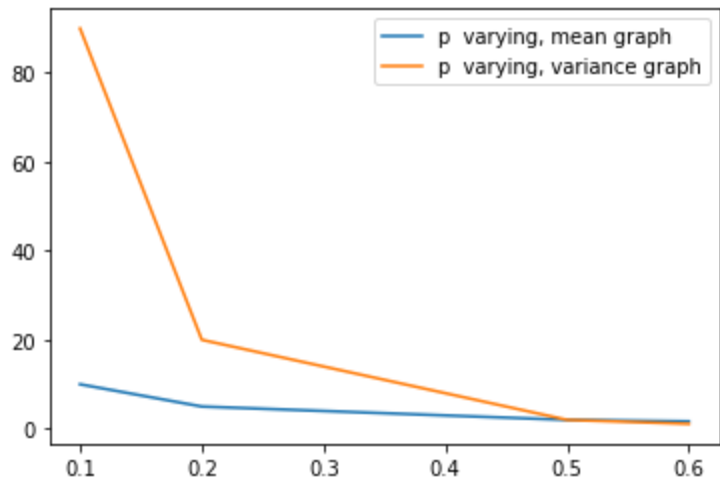
The distribution is as follows:



Mean and variance changes for different parameters:

Mean = $1/p$

Variance = $(1-p)/p \cdot p$



SECOND PART:

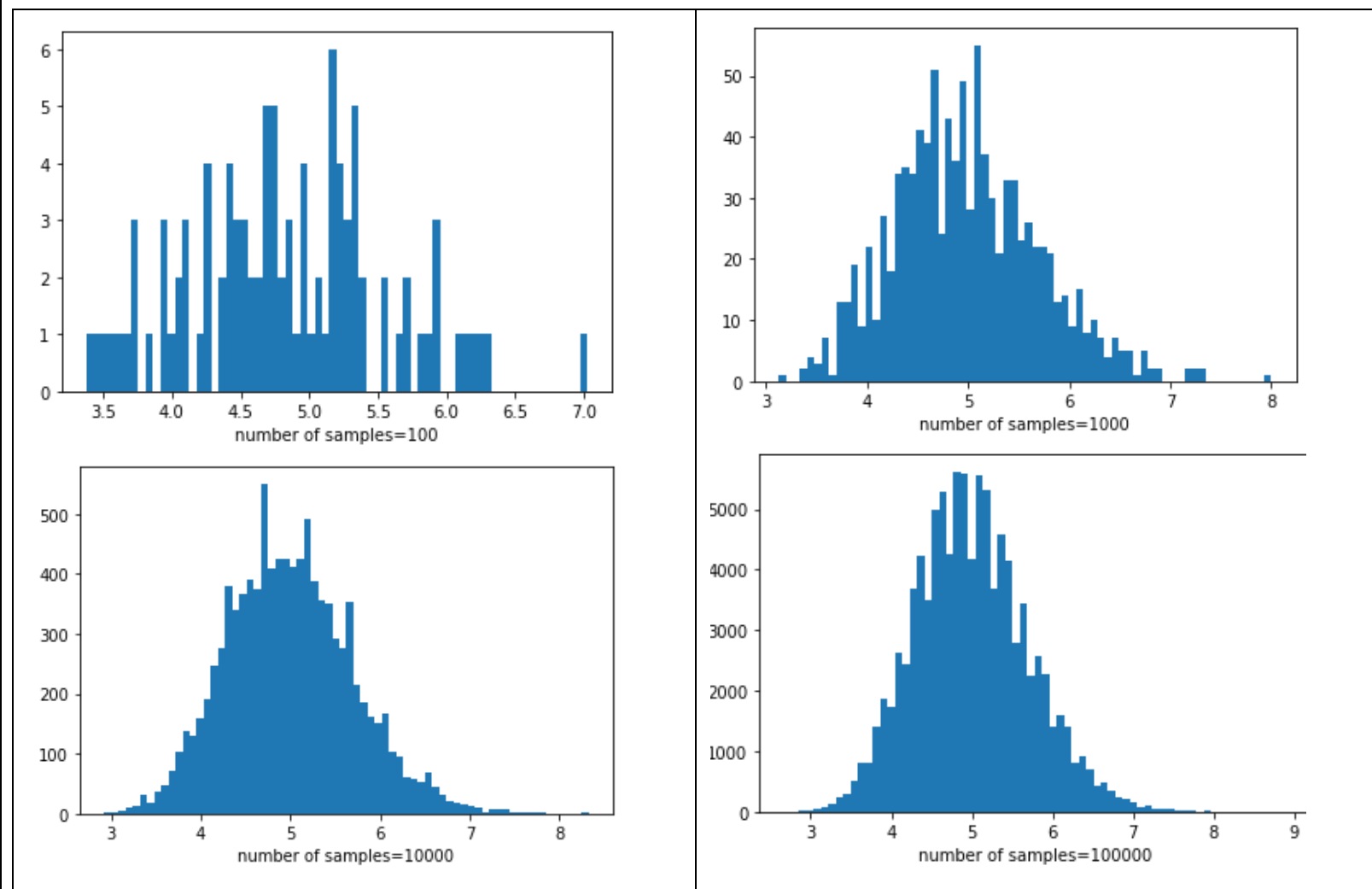
Mean of sample mean: 4.99326

Variance of sample mean: 0.49927032239999997

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when $n=100000$, i.e 4th plot ,the curve is in the shape of bell.



POISSON DISTRIBUTION:

Poisson distribution is a statistical distribution that shows how many times an event is likely to occur within a specified period of time. It is used for independent events which occur at a constant rate within a given interval of time.

$$f(x) = (e^{-\lambda} \lambda^x) / x!$$

Where , X is poisson random variable has parameter λ is average rate of value

Example: A video store averages 400 customers every Friday night. We can find the probability that 600 customers will come in on any given Friday night by poisson distribution.

FIRST PART:

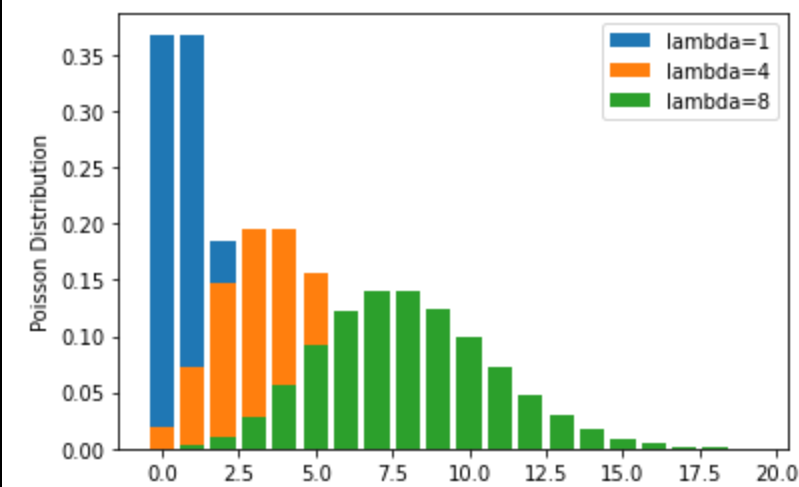
Parameters of this distribution:

- λ , which is the expected number of events in the interval (events/interval * interval length)

Distribution for different values of parameters:

Considering 4 different samples with $\lambda = [1, 3, 4, 8]$ respectively

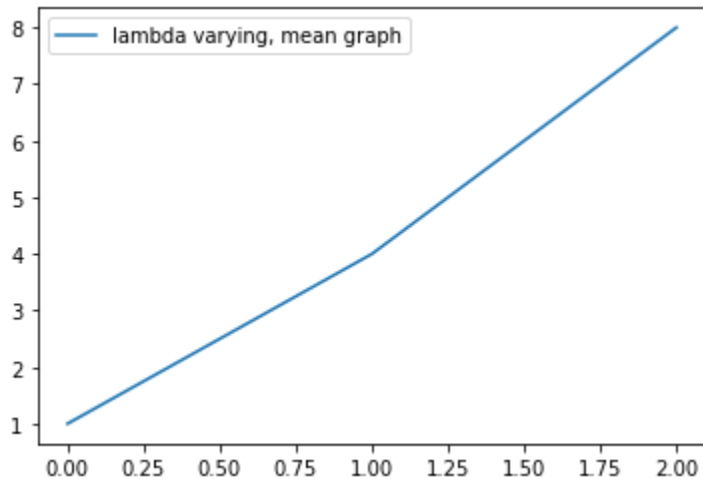
The distribution is as follows:



Mean and variance changes for different parameters:

Mean = λ

Variance = λ



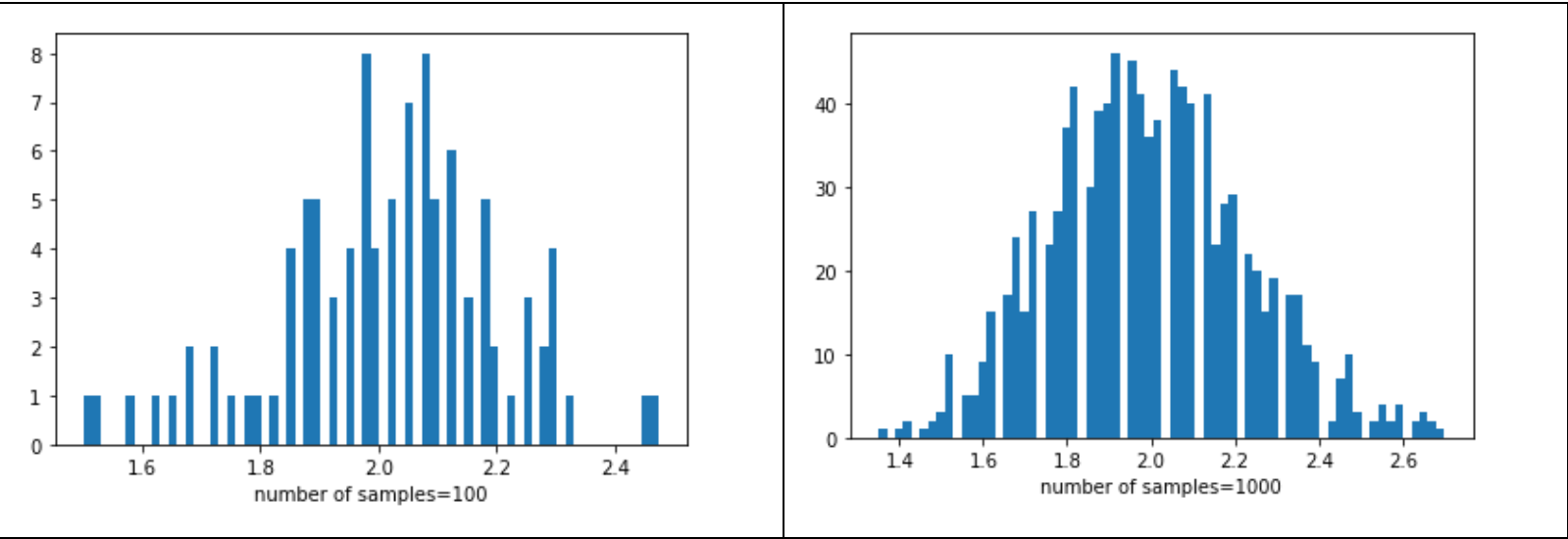
SECOND PART:

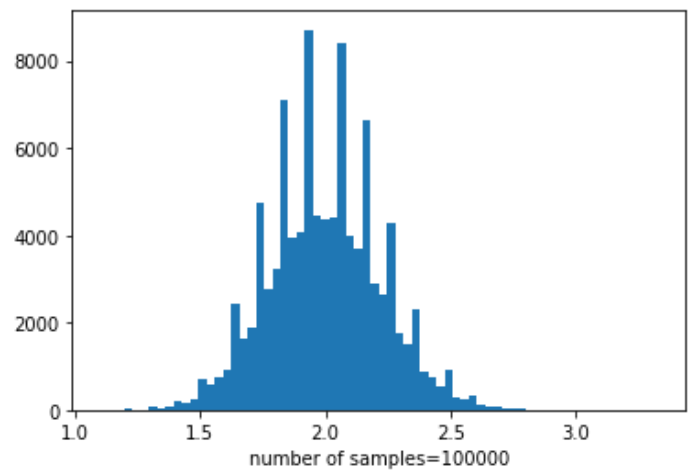
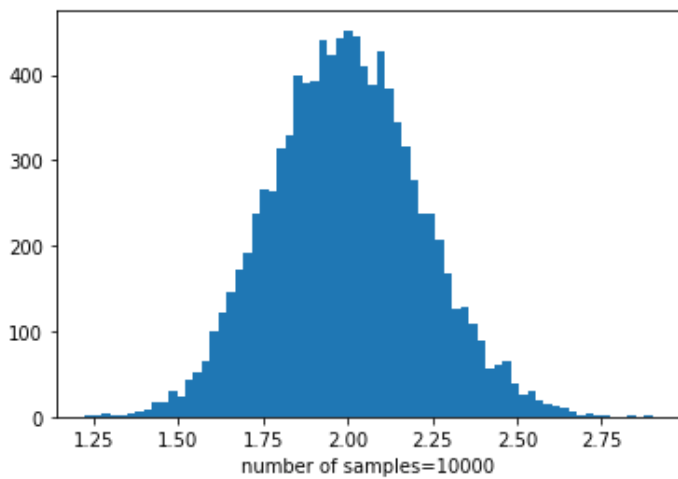
Mean of sample mean: 1.99862
 Variance of sample mean: 0.0503848456

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when $n=100000$, i.e 4th plot. The curve is in the shape of bell.





NEGATIVE BINOMIAL DISTRIBUTION:

The negative binomial experiment is almost the same as a binomial experiment with one difference: a binomial experiment has a fixed number of trials.

The random variable is the number of repeated trials, X , that produce a certain number of successes, r . In other words, it's the number of failures before a success.

$$nb(x; r, p) = \binom{x + r - 1}{r - 1} p^r (1 - p)^x \quad x = 0, 1, 2, \dots$$

Example:

Take a standard deck of cards, shuffle them, and choose a card. Replace the card and repeat until you have drawn two aces. Y is the number of draws needed to draw two aces. As the number of trials isn't fixed (i.e. you stop when you draw the second ace), this makes it a negative binomial distribution.

FIRST PART:

Parameters of distribution:

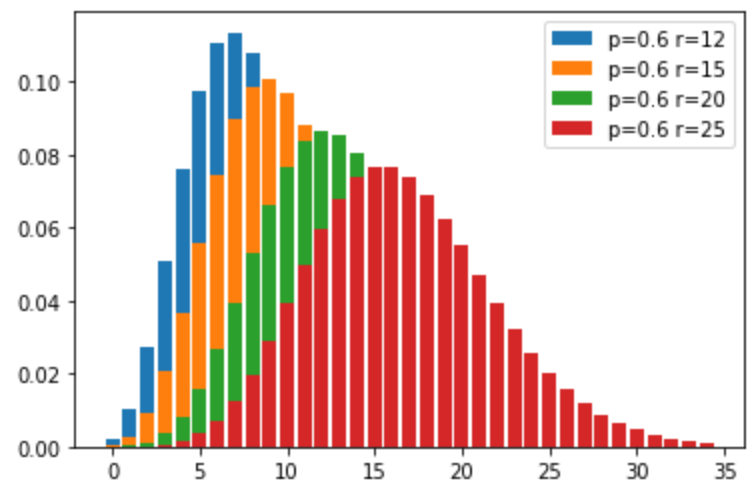
Parameters are r, p where r represents the number of failures before experiment is stopped and p represents success probability .

Distribution for different values of parameters:

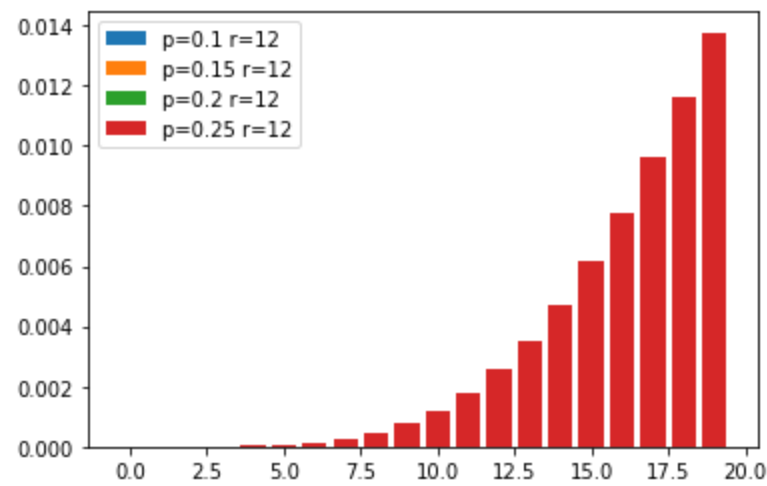
Considering $p = [0.1, 0.15, 0.2, 0.25]$ and $r = [12, 15, 20, 25]$ respectively.

The distribution is as follows:

When r is varying and p is constant(i.e, p=0.6):



When p is varying and r is constant(i.e, r=12):

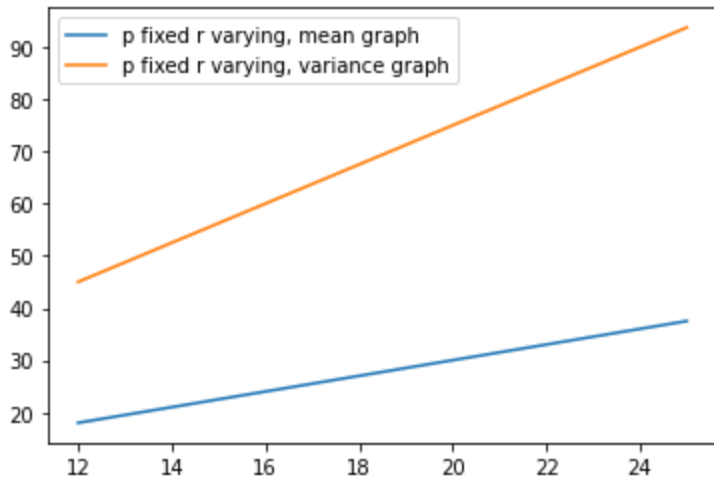


Mean and variance changes for different parameters:

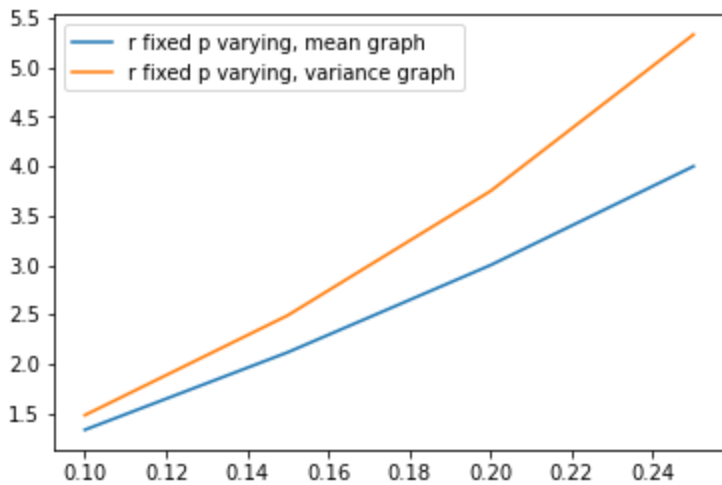
Mean = $(p \cdot r) / (1 - p)$

Variance = $(p \cdot r) / ((1 - p) \cdot (1 - p))$

When p is fixed and r is varying:



When r is fixed and p is varying:



SECOND PART:

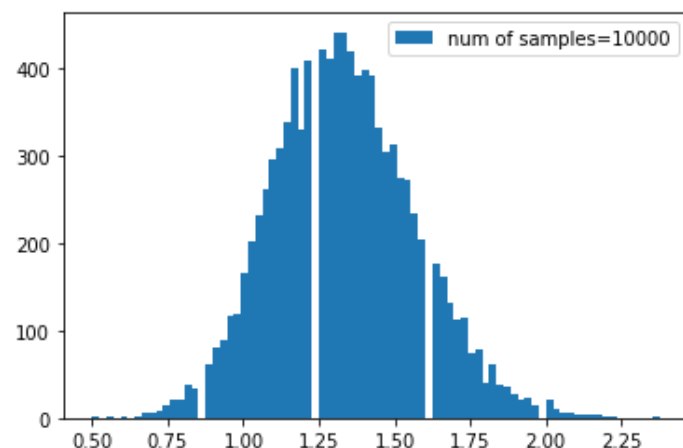
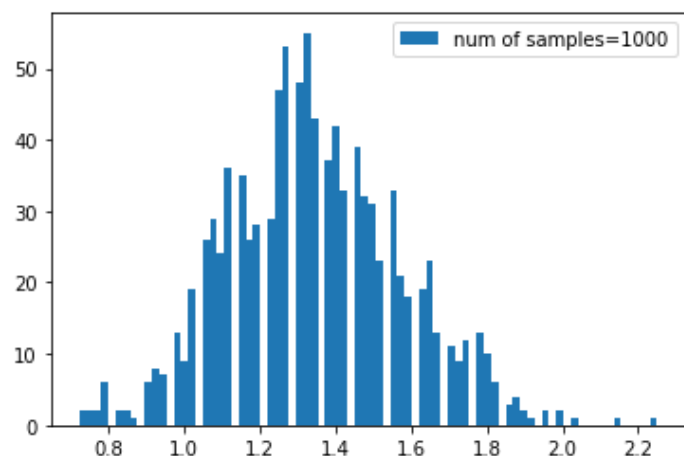
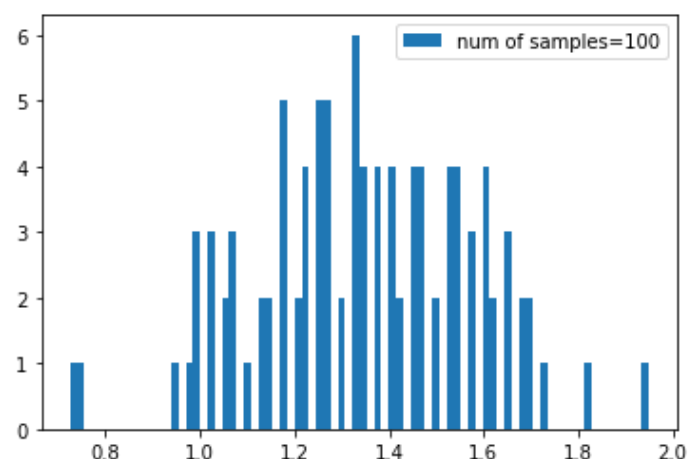
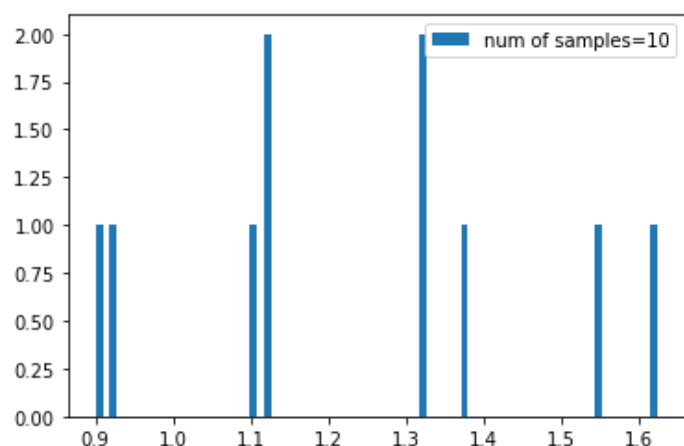
Mean of sample mean: 1.3295749999999997

Variance of sample mean: 0.056370944375

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when n=10000,i.e 4th plot.The curve is in the shape of bell.



DISCRETE UNIFORM DISTRIBUTION:

A random variable X has a discrete uniform distribution if each of the n values in its range, say x_1, x_2, \dots, x_n , has equal probability. Then, $f(x_i) = 1/n$ where $f(x)$ represents the probability mass function.

Suppose X is a discrete uniform random variable on the consecutive integers $a, a + 1, a + 2, \dots, b$ for $a \leq b$:

$$f(x) = 1/(b-a)$$

Example: Let X represent a random variable taking on the possible values of $\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$, and each possible value has equal probability

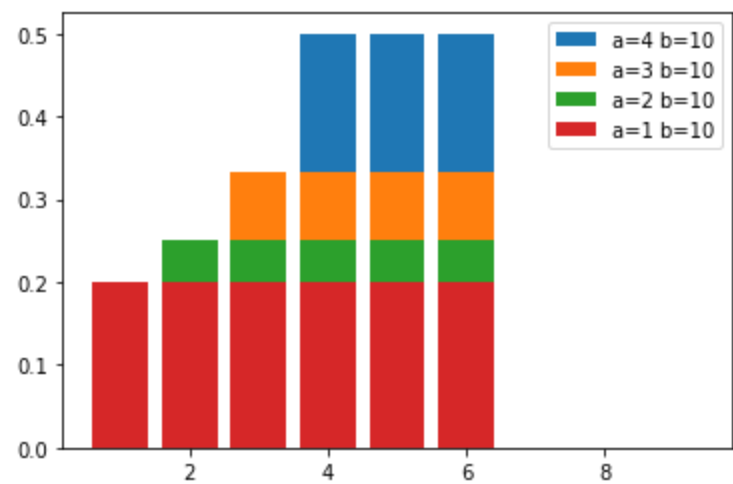
FIRST PART:

Parameters of the distribution: here a and b are the parameters

Distribution for different values of the parameters:

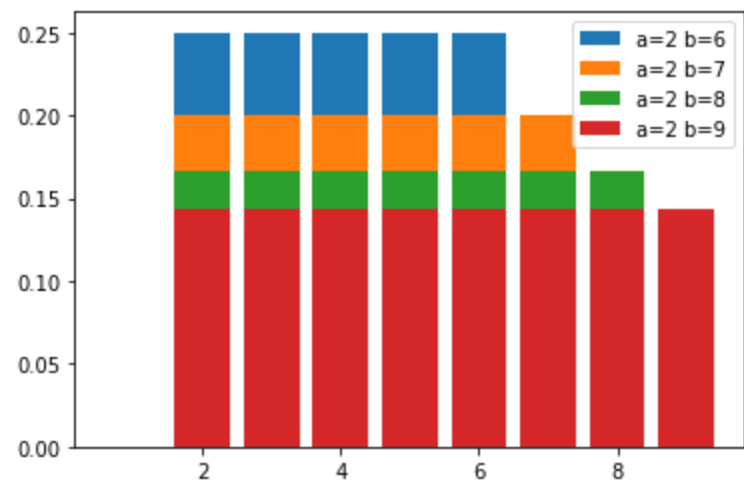
Considering different values for parameter $a=[4,3,2,1]$
Fixing the parameter b value: $b=6$ (we also have a condition : $a \leq b$)

The distribution is as follows:



Considering different values for parameter $b=[6,7,8,9]$
Fixing the parameter “a” value as $a=2$

The distribution is as follows:



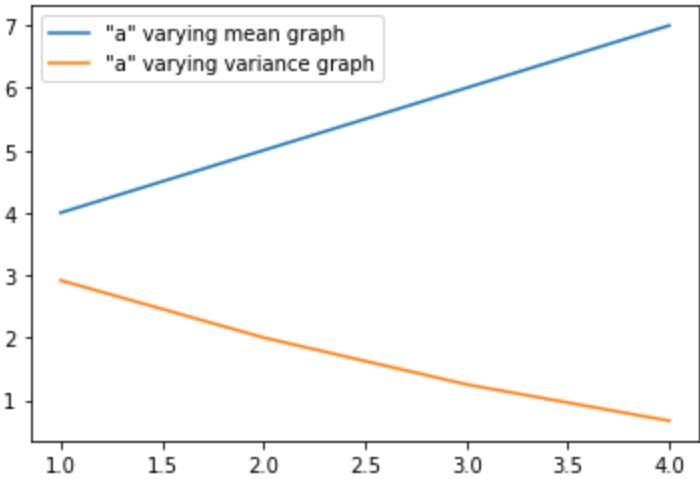
Mean and variance changes for different values of parameters:

Mean = $\mu = E(X) = b+a/2$

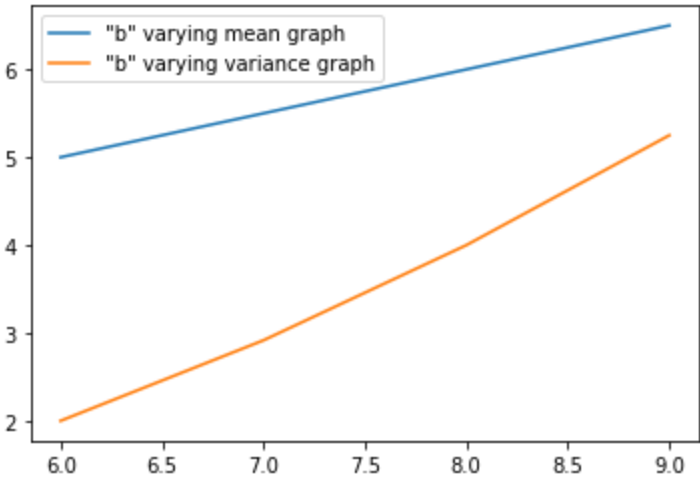
Variance = $\sigma^2 = ((b-a+1)^2-1)/12$

Considering different values for parameter a=[4,3,2,1]
Fixing the parameter b value:
b=6 (we also have a condition : a<=b)

The graph is as follows:



Considering different values for parameter b=[6,7,8,9]
Fixing the parameter "a" value as a=2
The graph is as follows:



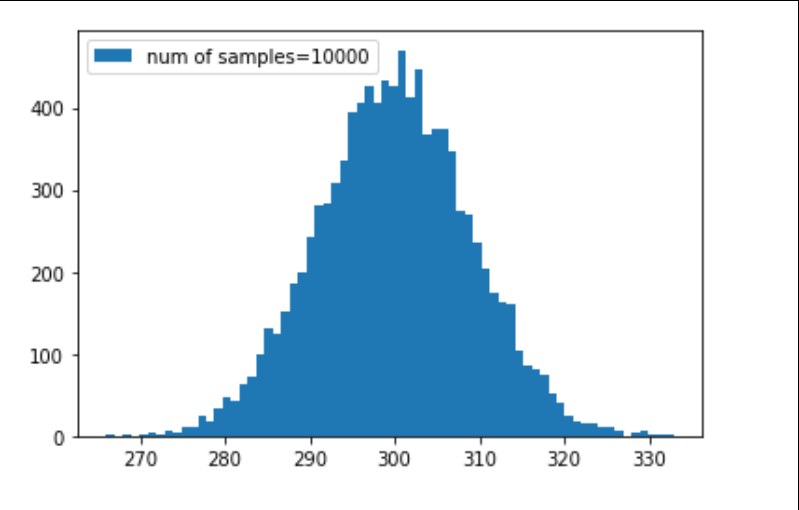
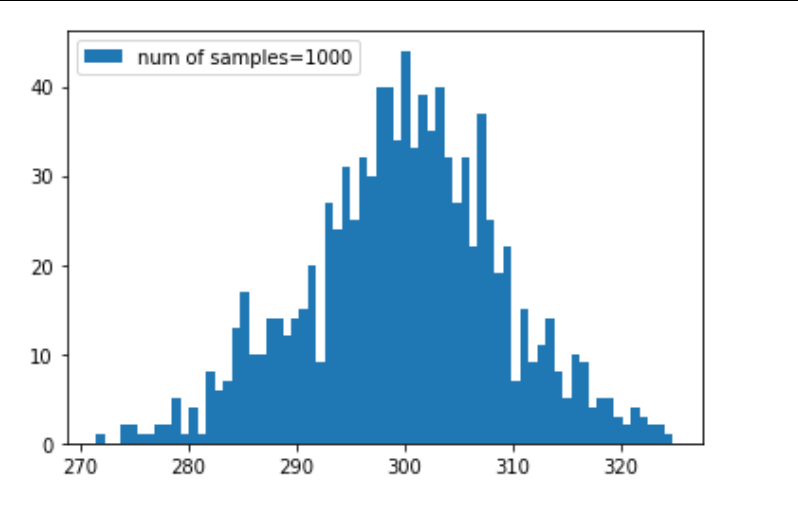
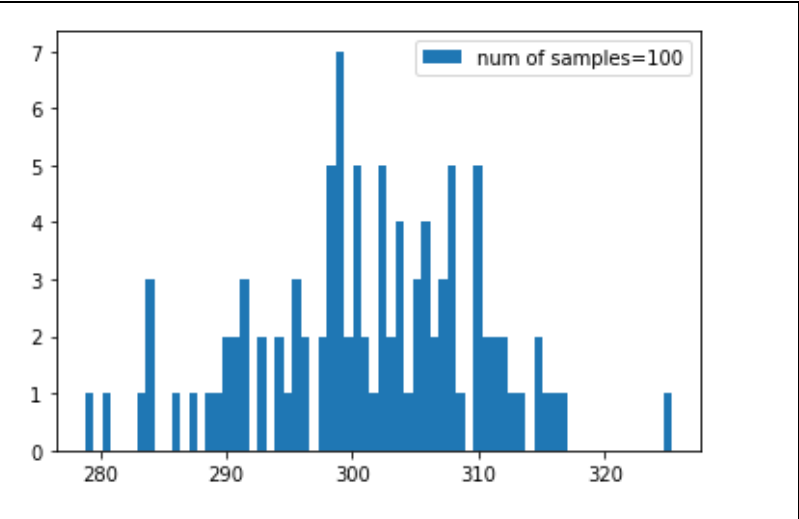
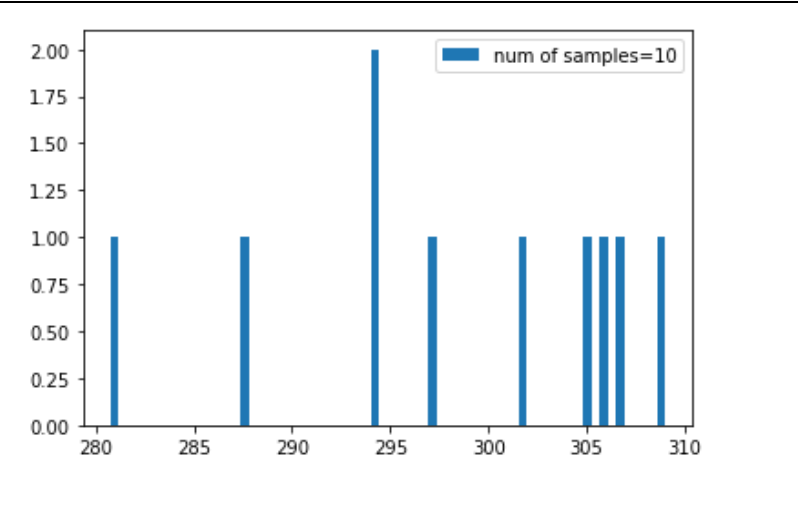
SECOND PART:

Mean of sample mean: 299.54300957565084
Variance of sample mean: 85.04151799402193

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when n=10000,i.e 4th plot.The curve is in the shape of bell.



Continuous Distributions:

NORMAL DISTRIBUTION:

A normal (or Gaussian) distribution is a type of continuous probability distribution for a real valued random variable

$$Y = \left\{ \frac{1}{\sigma \cdot \sqrt{2\pi}} \right\} \cdot e^{-\frac{(x - \mu)^2}{2\sigma^2}}$$

Example: Height of the population

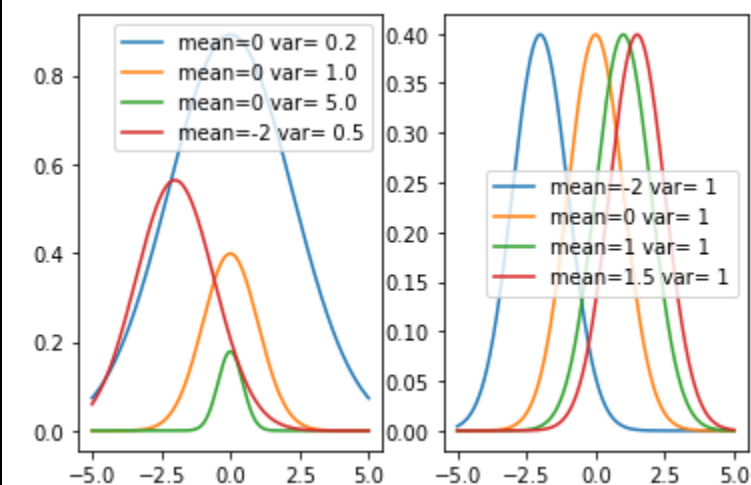
FIRST PART:

Parameters of the distribution: Parameters are Mean and variance

Distribution for different values of parameters:

Considering 4 different samples with mean= [-2,0,1,1.5] and variance =[0.2,1.0,5.0,0.5] respectively
The distribution is as follows:

Graphs when mean is varying and variance is constant (i.e, var=1) and graph when variance is varying and mean is constant (i.e, mean=0)



Mean and variance changes for different values of parameters:

Here mean and variance are the parameters itself ,so mean and variance change will not be there.

SECOND PART:

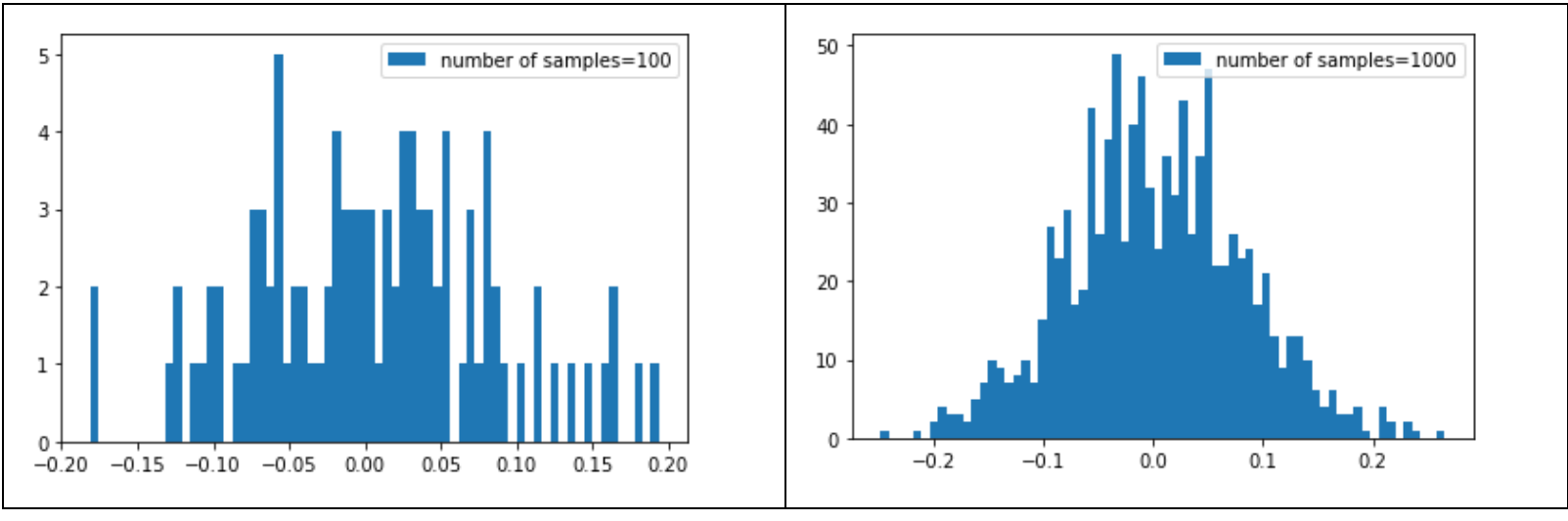
Mean of sample mean: 0.19964615013468887

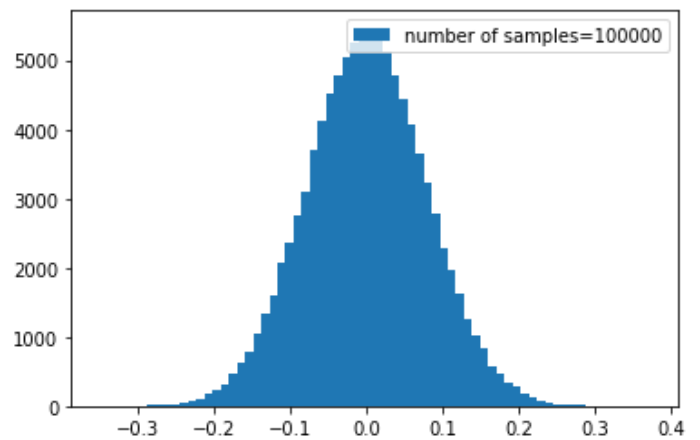
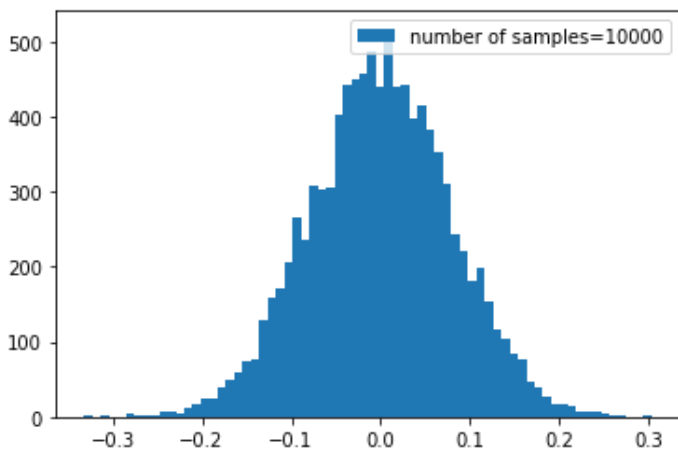
Variance of sample mean: 0.0009925562649594072

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when n=10000,i.e 4th plot.The curve is in the shape of bell.





EXPONENTIAL DISTRIBUTION:

The exponential distribution is a continuous probability distribution used to model the time we need to wait before a given event occurs.

$$f(x) = \lambda e^{-\lambda x}$$

Where X is Random Variable with parameter λ

Example: The amount of time (beginning now) until an earthquake occurs has an exponential distribution.

FIRST PART:

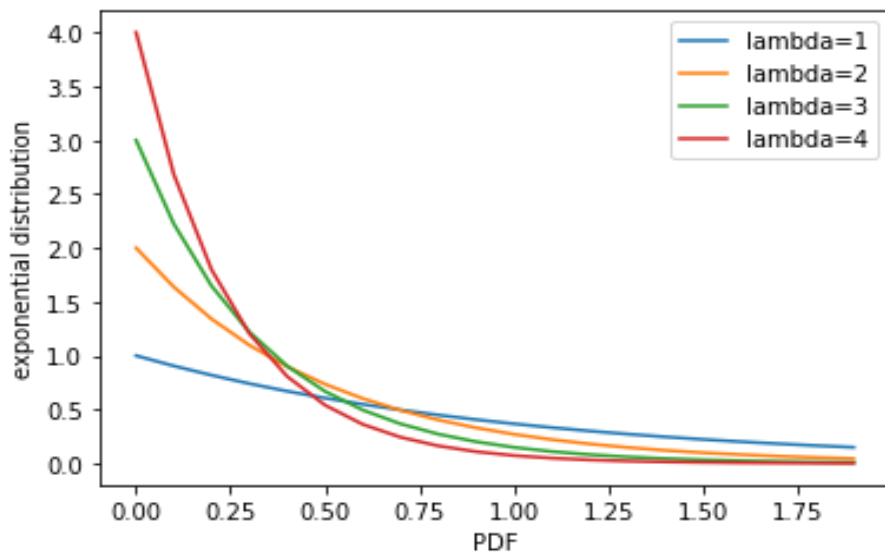
Parameters of this distribution:

$\lambda > 0$ is the parameter of the distribution, often called the rate parameter.

Distribution for different values of parameters:

Considering 4 different samples with $\lambda = [1, 2, 3, 4]$ respectively

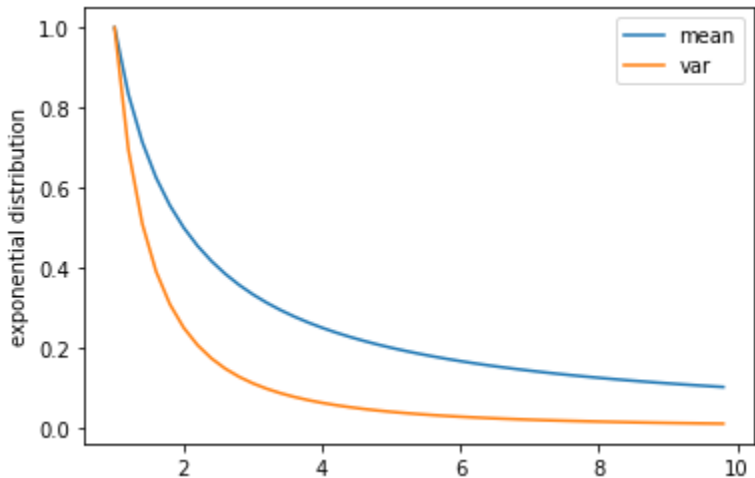
The distribution is as follows:



Mean and variance changes for different parameters:

Mean = $1/\lambda$

Variance = $1/(\lambda^2)$



SECOND PART:

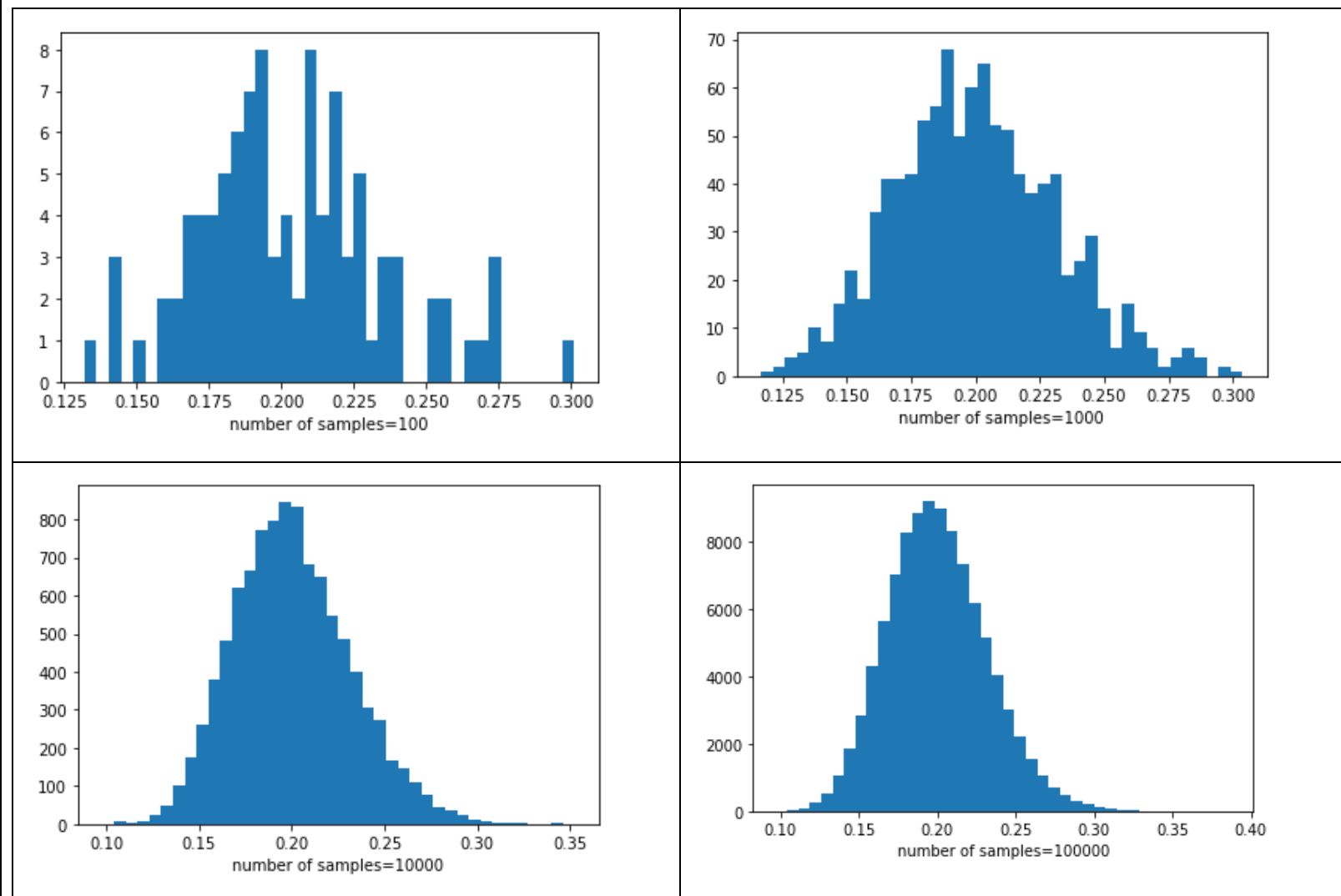
Mean of sample mean: 0.1996461501346887

Variance of sample mean: 0.0009925562649594072

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when $n=100000$, i.e 4th plot. The curve is in the shape of bell.



BETA DISTRIBUTION:

The Beta distribution is a type of probability distribution which represents all the possible values of probability. The most common use of this distribution is to model the uncertainty about the probability of success of a random experiment.

$$\frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha, \beta)}$$

Example: Suppose, if in a basket there are balls which are defective with a Beta distribution of $\alpha=5$ and $\beta=2$. For finding the probability of defective balls in the basket from 20% to 30% this distribution can be used.

FIRST PART:

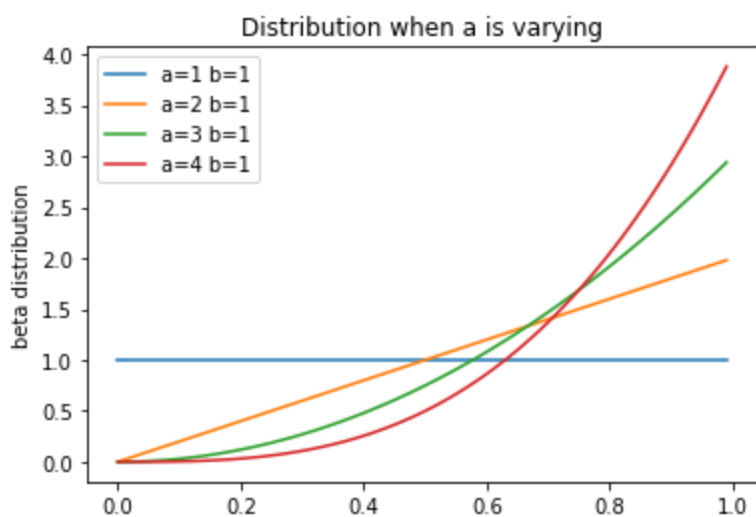
Parameters of distribution: Parameters are α and β where α is shape parameter and β is scale parameter.

Distribution for different values of parameters:

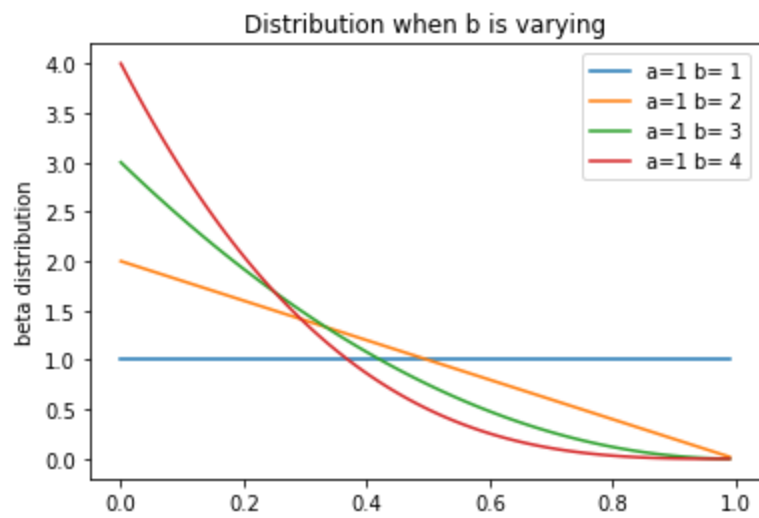
Considering $\alpha=[1,2,3,4]$ and $\beta=[1,2,3,4]$ respectively

The distribution is as follows:

When α is varying and β is constant (i.e, $\beta=1$):



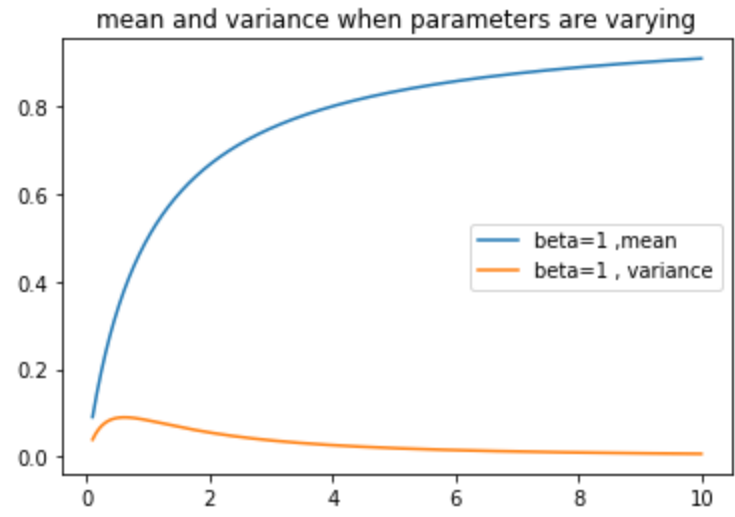
When β is varying and α is constant (i.e, $a=1$):



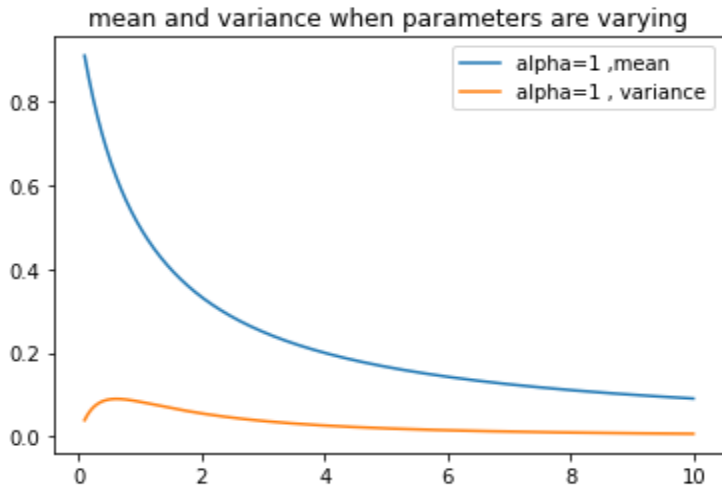
Mean and variance changes for different parameters:

Mean = $\frac{\alpha}{\alpha+\beta}$
 Variance= $\frac{(\alpha*\beta)}{((\alpha+\beta)**2) * (\alpha+\beta+1)}$

When alpha is varying and beta is constant(i.e, beta=1):



When beta is varying and alpha is constant:

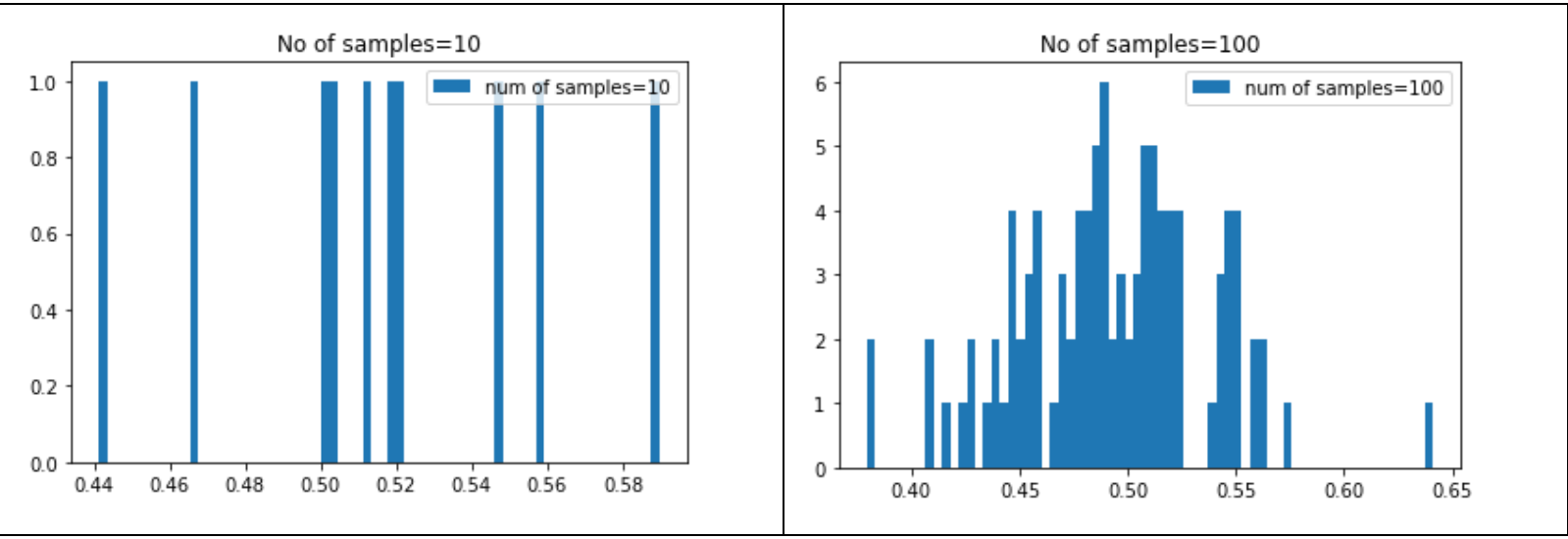


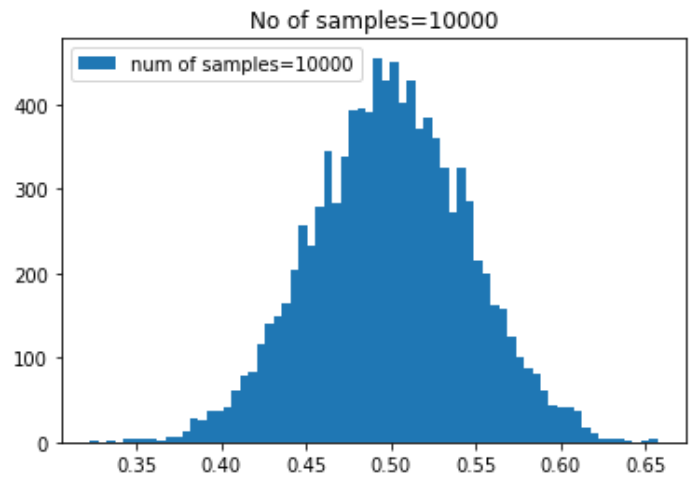
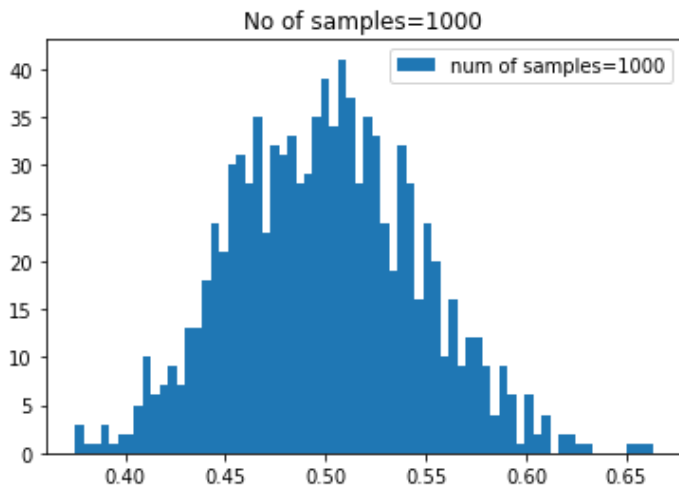
SECOND PART:
Mean of sample mean: 1.0008893537850958
Variance of sample mean: 0.010058793093934395

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when $n=10000$, i.e 4th plot. The curve is in the shape of bell.





GAMMA DISTRIBUTION:

The Gamma distribution describes the distribution of waiting times until a specific number of independent events (typically deaths) have occurred.

$$P(x) = \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\beta^{\alpha} \Gamma(\alpha)}.$$

Example: if the average mortality rate is one individual per five days (rate=1/5 or scale=5), then a Gamma distribution could be used to describe the distribution of expected waiting time before 10 individuals were dead.

FIRST PART:

Parameters of this distribution:

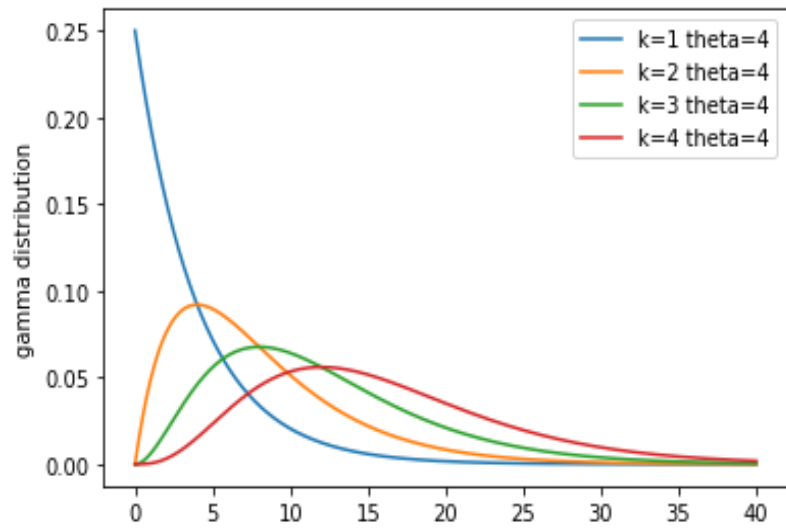
- θ : The rate of events happening which follows the Poisson process.
- k : The number of events for which you are waiting to occur.

Distribution for different values of parameters:

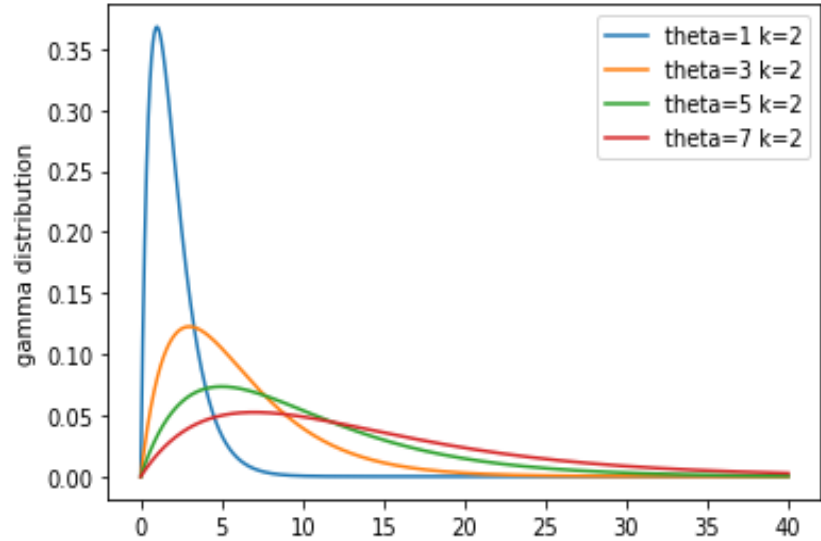
Considering $k=[1,2,3,4]$ and $\theta=[1,3,5,7]$ respectively.

The distribution is as follows:

When k is varying and θ is constant (i.e, $\theta=4$):



When θ is varying and k is constant(i.e, $k=2$):

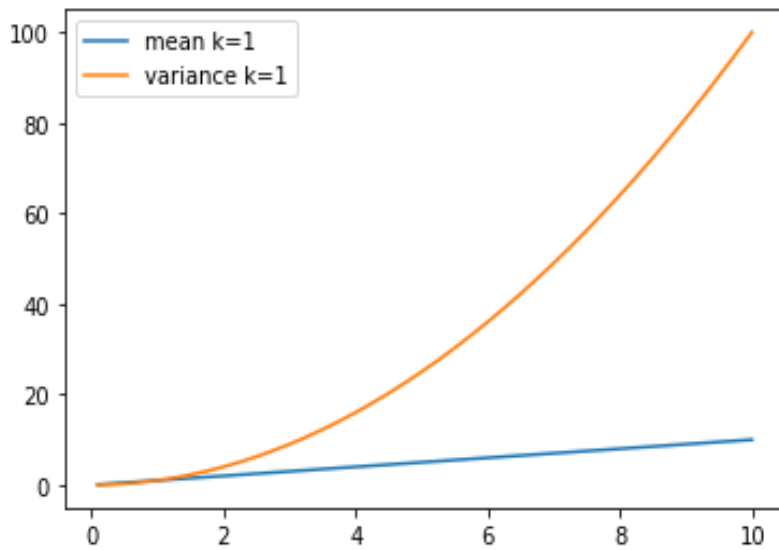


Mean and variance changes for different parameters:

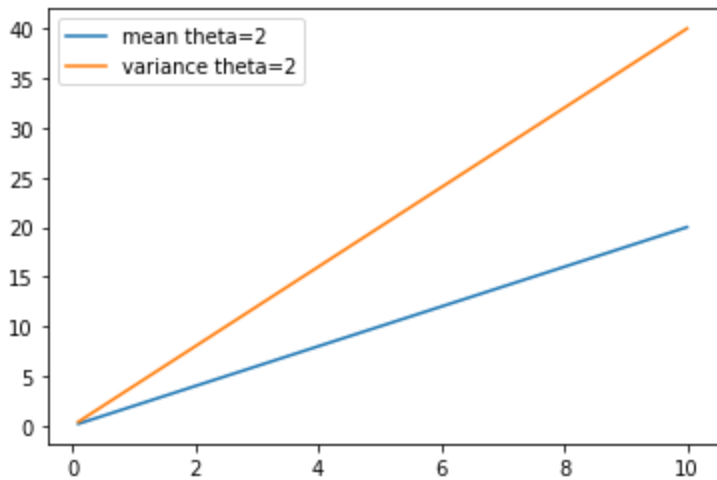
Mean = $k \cdot \theta$

Variance = $k \cdot \theta \cdot \theta$

When θ is varying and k is fixed i.e($k=1$):



When k is varying and θ is fixed i.e($\theta=2$):



SECOND PART:

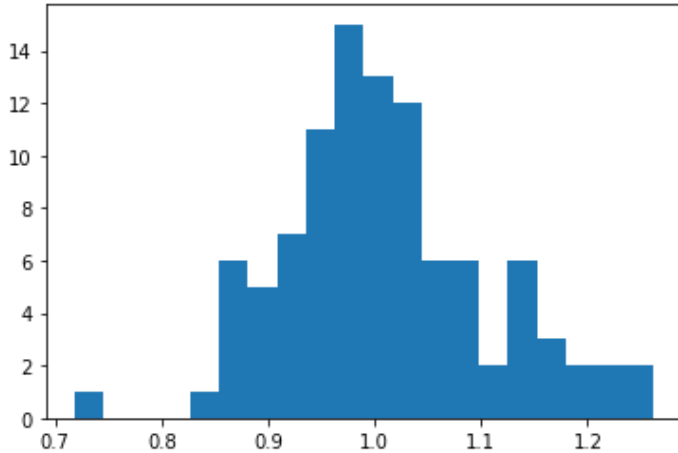
Mean of sample mean: 0.9981473035550558
 Variance of sample mean: 0.009875503021356773

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

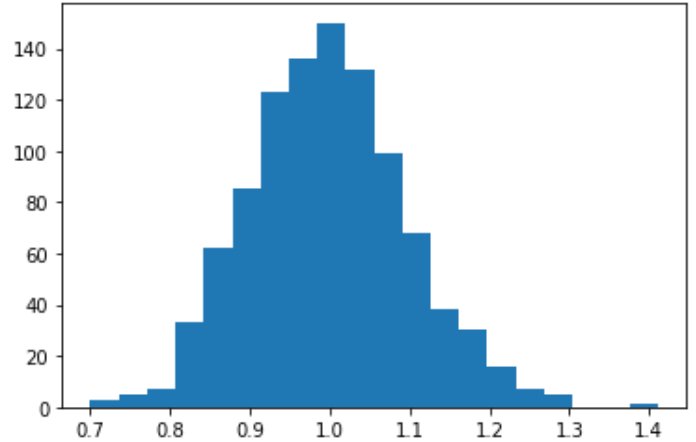
To prove CLT:

Here on plotting samples mean histograms by varying the number of samples every time, we can see that the graph slowly reaches and follows normal distribution . We can see that observation when $n=100000$,i.e 4th plot.The curve is in the shape of bell.

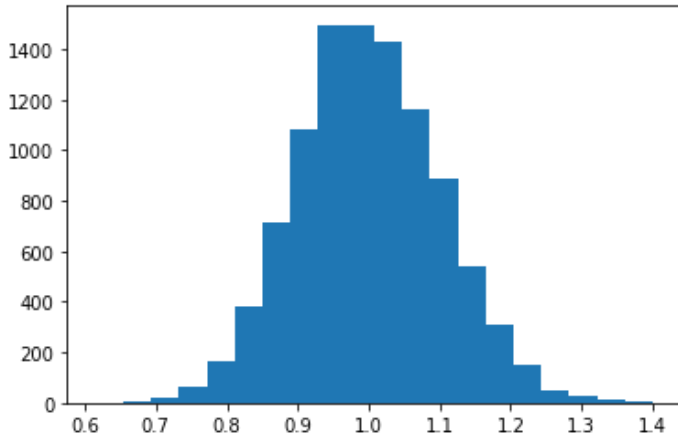
NUMBER OF SAMPLES =100



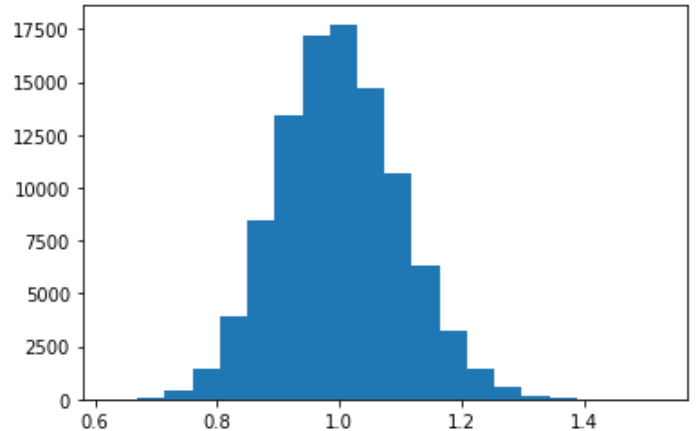
NUMBER OF SAMPLES =1000



NUMBER OF SAMPLES =10000



NUMBER OF SAMPLES =100000



LOGNORMAL DISTRIBUTION:

Log-normal (or lognormal) distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed. Thus, if the random variable X is log-normally distributed, then $Y = \ln(X)$ has a normal distribution.

$$\mathcal{N}(\ln x; \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp \left[-\frac{(\ln x - \mu)^2}{2\sigma^2} \right], \quad x > 0.$$

Example:growth rates or chemical concentrations might naturally operate on logarithmic or exponential scales.Consequently, when such data are collected on a linear scale, they might be expected to follow a log-normal distribution.

FIRST PART:

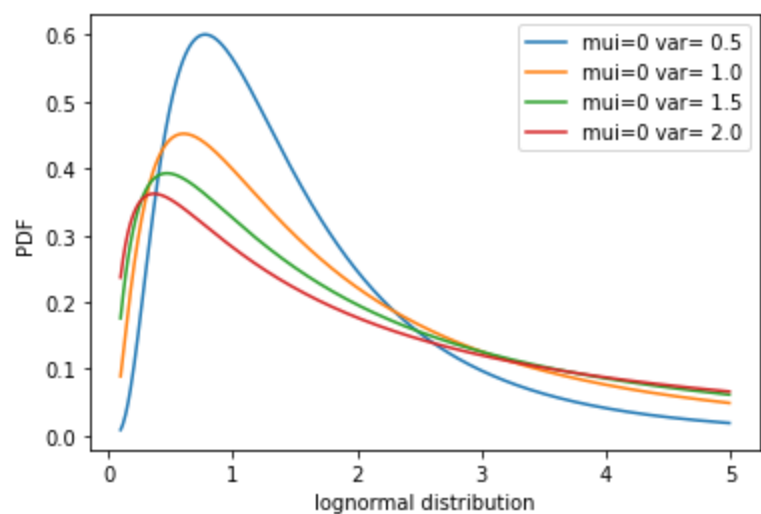
Parameters of this distribution:

- μ - the mean. This defines the center of the distribution, the location of the peak.
- σ^2 - the variance (or σ , the standard deviation) which defines the variability or spread of values around the mean.

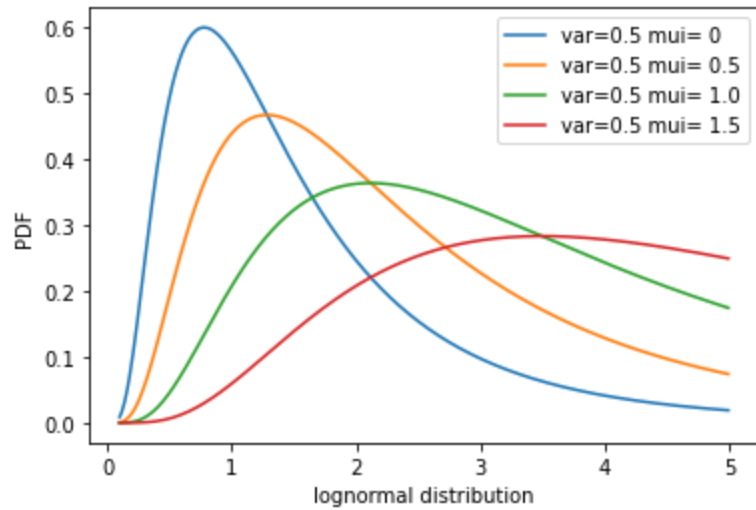
Distribution for different values of parameters:

Considering $\mu = [0,0.5,1.0,1.5]$ and $\sigma^2 = [0.5,1.0,1.5,2.0]$ respectively.
The distribution is as follows:

When σ^2 is varying and μ is constant(i.e, $\mu=0$):



When μ is varying and σ^2 is constant(i.e, $\sigma^2=0.5$):

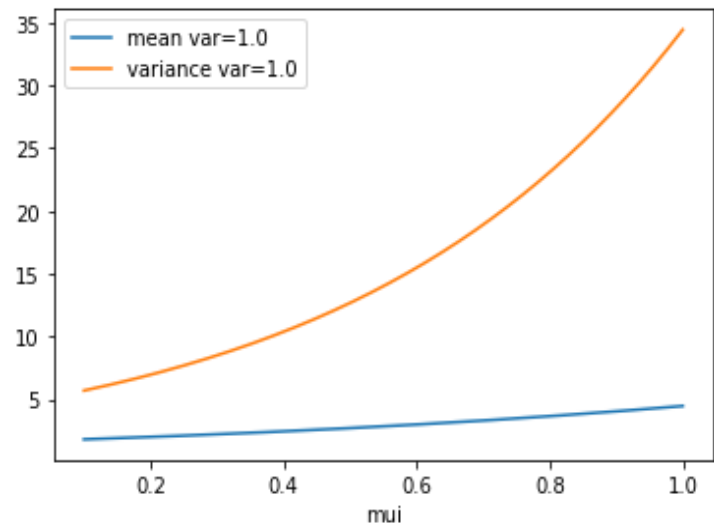


Mean and variance changes for different parameters:

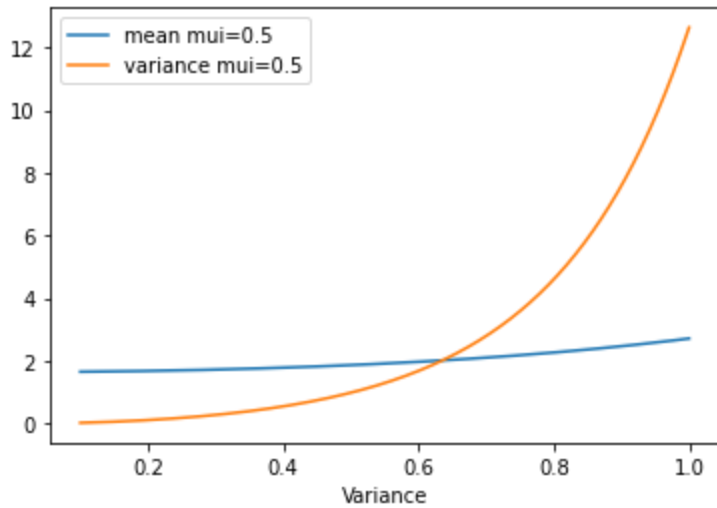
Mean = $\exp(\mu + \sigma^2/2)$

Variance = $(\exp(\sigma^2)-1)*\exp(2\mu + \sigma^2)$

When μ is varying and σ^2 is fixed i.e($\sigma^2=1.0$):



When σ^2 is varying and μ is fixed i.e($\mu=0.5$):



SECOND PART:

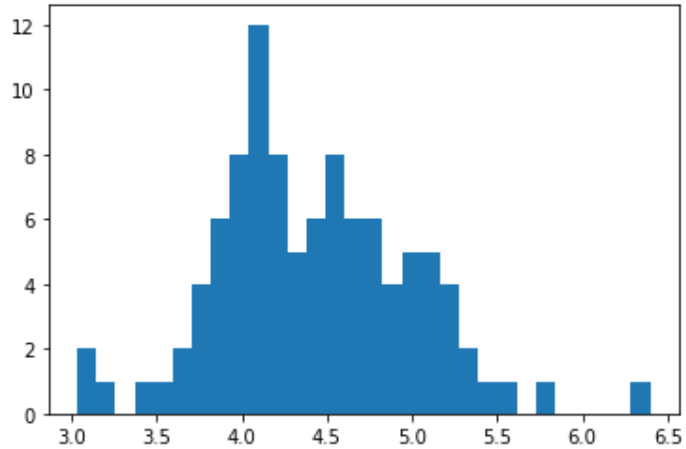
Mean of sample mean: 4.507422955127459
Variance of sample mean: 0.365882629909888

If the sample is random and sample size is large then the sample mean would be a good estimate of the population mean.

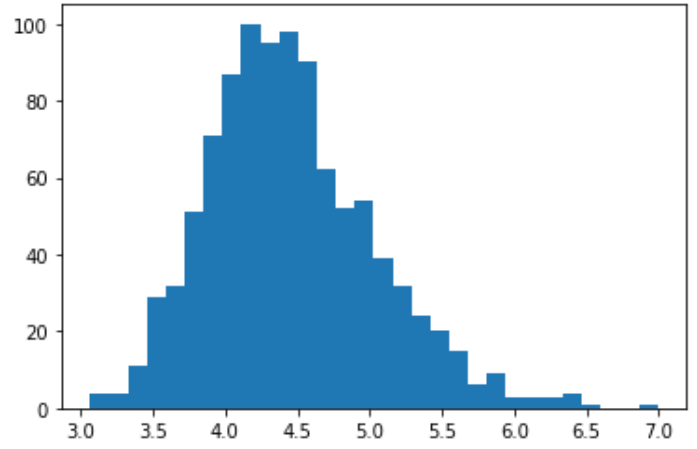
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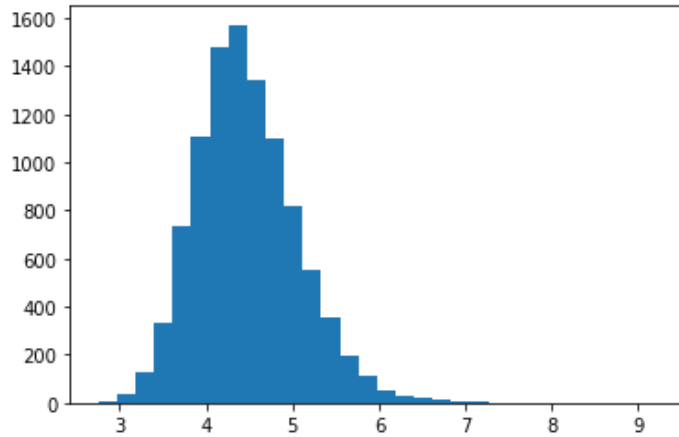
NUMBER OF SAMPLES =100



NUMBER OF SAMPLES =1000



NUMBER OF SAMPLES =10000



NUMBER OF SAMPLES =100000

