

# Computer Assignment (CA) No. 10: Hypothesis Testing

## Problem Statement

This assignment is designed to introduce you to hypothesis testing. You will essentially build a computer simulation of Example 9.9 in the textbook:

### Example 9.9: ¶

The mean lifetime  $E[X]$  of the light bulbs produced by Lighting Systems Corporation is 1570 hours with a standard deviation of 120 hours. The president of the company claims that a new production process has led to an increase in the mean lifetimes of the light bulbs. If Joe tested 100 light bulbs made from the new production process and found that their mean lifetime is 1600 hours, test the hypothesis that  $E[X]$  is not equal to 1570 hours.

### The tasks to be accomplished are:

1. Create a function that generates  $n$  Gaussian distributed random variables:  $X = \text{gen\_grv}(\text{mean}, \text{stdev}, n)$
2. Compute the mean of  $X$ ,  $\bar{x}$ .
3. Create a function that tests whether the difference between the true mean and the estimated mean are statistically significant:  $\text{status} = \text{check\_significance}(\text{mean1}, \text{mean2}, \text{stdev}, n, \text{confidence})$
4. Create a function that determines the value of  $N$  for the difference between two means to be statistically significant:  $N = \text{determine\_significance}(\text{mean1}, \text{mean2}, \text{stdev}, \text{confidence})$

### Now, put this all together by doing the following:

1. Generate  $n$  random numbers with a mean of 1600 hours and a stdev of 120 hours for  $n = 10, 100, 1000$ .
2. Using your tools above, determine if the difference in the mean is significant for confidence levels of 0.8, 0.9, 0.95, 0.99, 0.999.
3. Determine the minimum value of  $n$  for which these differences would be statistically significant.
4. Repeat no. 2 for a standard deviation of 240 hours.
5. Find the maximum value of the variance for which the difference in the mean is significant for  $[n = 10, 100, 1000]$  and  $[\text{confidence} = 0.8, 0.9, 0.95, 0.99, 0.999]$ .

## Approach and Results

### A Quick Examination of Hypothesis Testing

#### Z-Score

The  $Z$  score, otherwise known as the standard score, is the "number of standard deviations an observation or datum is above the mean." Thus, it can be defined as

$$z = \frac{x - \mu}{\sigma}$$

where:  $\mu$  is the mean of the population,  $x$  is a sample, and  $\sigma$  is the standard deviation of the population.

This can also be applied to a random variable  $X$  or a sample mean  $\bar{X}$ , such that  $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$ . The  $Z$  score of the sample mean is equal to

$$Z = \frac{\bar{X} - E[X]}{\sigma_X / \sqrt{n}}.$$

where  $n$  is the number of samples in  $\bar{X}$ ,  $E[X]$  is the mean of the distribution of  $X$ , which we will denote as  $\mu_X$ , and the standard deviation of the sample mean is  $\sigma_{\bar{X}} = \sigma_X / \sqrt{n}$ .

## Confidence Limits



If  $\Phi()$  represents the CDF of the normal distribution and we are attempting to locate the confidence limits displayed in the graph (taken from the class text) for a two tail test!

$$P(-z_\alpha \leq Z \leq z_\alpha) = 1 - \alpha$$

Substituting the expression for  $Z$  above for a sample mean,

$$\begin{aligned} \Phi(z_\alpha) &= P(Z \leq z) = 1 - \alpha/2 \\ z_\alpha &= \Phi^{-1}(\Phi(z)) = \Phi^{-1}(1 - \alpha/2) \\ P\left(\bar{X} - z_\alpha \frac{\sigma}{\sqrt{n}} \leq \mu_x \leq \bar{X} + z_\alpha \frac{\sigma}{\sqrt{n}}\right) &= 1 - \alpha. \end{aligned}$$

Thus, the endpoints of the confidence interval are  $= \bar{X} \pm \Phi^{-1}(1 - \alpha/2) \frac{\sigma_x}{\sqrt{n}}$

## Process of Hypothesis Testing

1. Determine  $H_0$  and  $H_1$
2. Specify  $\alpha$ , the level of significance, which is the probability the sample means are different enough to reject  $H_0$ .
3. Calculate the test value  $z$ , or the standard score of the test value based on the collected data.
4. Find the confidence limits, or  $z_\alpha$ , given  $\alpha$
5. Reject or fail to reject  $H_0$

Thus, the rejection region is the region that lies outside the confidence interval; the confidence interval is the failure to reject region.  $H_0$  is failed to reject if  $z$  lies in the failure to reject region and it is rejected if  $z$  lies in the rejection region.

There are two methods to determine if  $H_0$  is rejected or failed to reject. For the first method, the random variable under test is normalized and if it is within  $\pm z_\alpha$ ,  $H_0$  is accepted. For the second method, the confidence limits are found by "de-normalizing"  $\pm z_\alpha$  and determining if the distribution's mean  $\mu_X$  is within the interval.

## Functions: gen\_grv, check\_significance, and determine\_significance

gen\_grv()

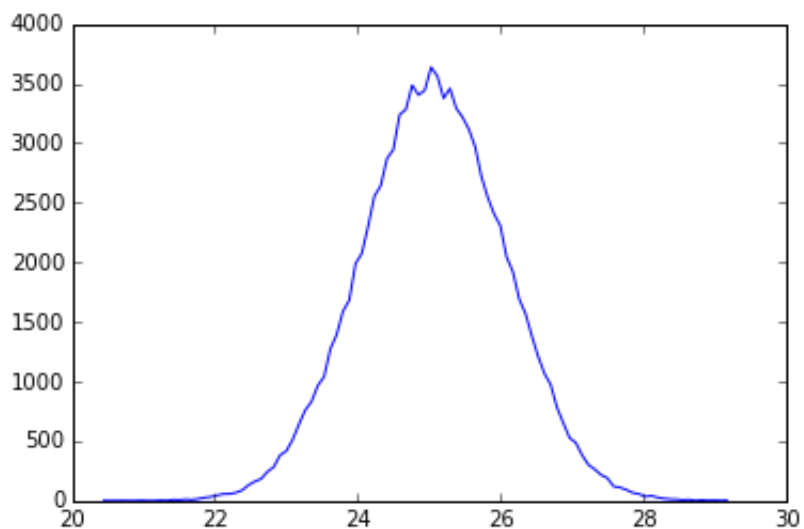
```
In [2]: %pylab inline
        from scipy.stats import norm
```

Populating the interactive namespace from numpy and matplotlib

```
In [3]: def gen_grv(mean, stdev, n):
        '''
           Generates n Gaussian random variables
        '''
        X = random.normal(mean, stdev, n)
        return X

        # TESTING
        x = gen_grv(25, 1, 100000)
        h = histogram(x, bins=100)
        plot(h[1][1:], h[0])
```

Out[3]: [<matplotlib.lines.Line2D at 0x7f7684c8b290>]



Generating a vector  $X$  consisting of 100,000 random variables which are normally distributed with a mean of 25 and a  $\sigma$  of 1 produces the figure above, which appears consistent with a normal distribution.

### check\_significance

The function utilizes the first method described above. The function returns true if  $H_0$  is failed to reject and false if  $H_0$  is rejected. The function is tested with the example provided in the problem statement.

```
In [4]: def check_significance(mean1, mean2, stdev, n, confidence):
    ...
        Preforms hypothesis test
        mean1 = the mean under test
        returns true when h_0 is accepted
        false when h_0 is rejected
    ...
    # normalize tested mean .... or z-score?
    Z = (mean1 - mean2)/(stdev/sqrt(n))

    # calculated x values of normal distribution which form the limits o
    f a confidence interval
    a = 1.-confidence
    z = norm.ppf(1 - a/2)
    return ((Z >= -z) and (Z <= z))

## Testing
mean1 = 1600
mean2 = 1570
stdev = 120
n = 100
confidence = [0.99, 0.95]
for c in confidence:
    print c, check_significance(mean1, mean2, stdev, n, c)

0.99 True
0.95 False
```

For the 0.99% confidence rating, or a significance level 0.01, the hypothesis  $H_0 : \mu_x = \mu_x$  is confirmed. For the 0.095% confidence rating or a significance level 0.05, the hypothesis  $H_0$  is rejected and  $H_1$  stating the mean is significantly different is failed to reject.

### determine\_significance

If the expression for a confidence interval is decomposed into a system of equations such that

$$\begin{aligned}\mu_x &\geq \bar{X} - z_\alpha \frac{\sigma_X}{\sqrt{n}} \\ \mu_x &\leq \bar{X} + z_\alpha \frac{\sigma_X}{\sqrt{n}},\end{aligned}$$

and the equations are individually solved for  $n$ , they both return the same answer,

$$n \leq \left( \frac{z_\alpha \sigma_X}{\mu_X - \bar{X}} \right)^2.$$

If  $n$  is not an integer, it will have to be rounded. The value of  $n$  derived from the equation above will denote the maximum number of samples the test value will still satisfy in the current confidence level. As the requirements for the function requested value of  $n$ , which concludes that the difference between the two means are significantly different,  $n$  is rounded up, as can be seen in the function below.

```
In [5]: def determine_significance(mean1, mean2, stdev, confidence):
    '''
        Description: Calculated the minimum value of n which would fit m
ean1 within the confidence interval for
        normal distribution of mean2 and stdev
    '''
    # find the normalized confidence limits
    a = 1 - confidence
    z_u = norm.ppf(1. - a/2) # inverse normal distribution
    z_l = -z_u
    n = (z_u*stdev/(mean2 - mean1))**2
    return ceil(n)

# TESTING
mean1 = 1600
mean2 = 1570
stdev = 120
n = 100
confidence = [0.99, 0.95]
for c in confidence:
    new_n = determine_significance(mean1, mean2, stdev, c)
    print "Confidence, New N, Sig Check, Old N, Sig Check"
    # Change new_n below
    print c, new_n, check_significance(mean1, mean2, stdev, new_n-1, c),
n, \
    check_significance(mean1, mean2, stdev, n, c)
```

```
Confidence, New N, Sig Check, Old N, Sig Check
0.99 107.0 True 100 True
Confidence, New N, Sig Check, Old N, Sig Check
0.95 62.0 True 100 False
```

The function is tested on the example in the problem statement again. If `new_n` is decremented after the commented line above, you can see the significance test will accept  $H_0$ .

## Tasks 1 to 4

1. Generate  $n$  random numbers with a mean of 1600 hours and a stdev of 120 hours for  $n = 10, 100, 1000$ .
2. Using your tools above, determine if the difference in the mean is significant for confidence levels of 0.8, 0.9, 0.95, 0.99, 0.999.
3. Determine the minimum value of  $n$  for which these differences would be statistically significant.
4. Repeat no. 2 for a standard deviation of 240 hours.
5. Find the maximum value of the variance for which the difference in the mean is significant for [ $n = 10, 100, 1000$ ] and [ $\text{confidence} = 0.8, 0.9, 0.95, 0.99, 0.999$ ].

```

In [6]: C = [0.8, 0.9, 0.95, 0.99, 0.999]
        N = [10, 100, 1000]
        S = [120, 240]

        mean2 = 1600 # true mean ...true, true mean. hint: cloud atlys
        ...
        DO EVERYTHING AT ONCE BECAUSE THERE ARE SO MANY ASSIGNMENTS
        Loop runs through parameters listed above utilizing functions genera
ted.
        ...

for s in S:
    print "Sigma = %d" %s
    print "=====
    for n in N:
        x = gen_grv(mean2, s, n) # generate n random variables
        print "The number of samples: %d, H_0, n required" %n
        print "-----"
        for c in C:
            print "The confidence level: %.3f %s %d" %(c, check_si
gnificance(mean(x), mean2, s, n, c), \
                                                    determine_signi
ficance(mean(x), mean2, s, c))
            print "\n"
        print "=====\\n"

```

Sigma = 120

```

=====
The number of samples: 10, H_0, n required
-----
The confidence level: 0.800 True 128
The confidence level: 0.900 True 210
The confidence level: 0.950 True 299
The confidence level: 0.990 True 515
The confidence level: 0.999 True 841

```

```

The number of samples: 100, H_0, n required
-----
The confidence level: 0.800 True 189
The confidence level: 0.900 True 311
The confidence level: 0.950 True 442
The confidence level: 0.990 True 763
The confidence level: 0.999 True 1244

```

```

The number of samples: 1000, H_0, n required
-----
The confidence level: 0.800 True 7816
The confidence level: 0.900 True 12875
The confidence level: 0.950 True 18281
The confidence level: 0.990 True 31574
The confidence level: 0.999 True 51525
=====

```

Sigma = 240

=====  
The number of samples: 10, H\_0, n required  
-----

The confidence level: 0.800	True	13
The confidence level: 0.900	True	21
The confidence level: 0.950	True	30
The confidence level: 0.990	True	51
The confidence level: 0.999	True	83

-----  
The number of samples: 100, H\_0, n required  
-----

The confidence level: 0.800	True	104
The confidence level: 0.900	True	171
The confidence level: 0.950	True	242
The confidence level: 0.990	True	418
The confidence level: 0.999	True	683

-----  
The number of samples: 1000, H\_0, n required  
-----

The confidence level: 0.800	True	26230
The confidence level: 0.900	True	43210
The confidence level: 0.950	True	61351
The confidence level: 0.990	True	105964
The confidence level: 0.999	True	172924

=====

## Task 5

This task is best solved with some math and a little bit of functions. Starting with the same system of equations derived for the generation of check\_significance,

$$\begin{aligned}\mu_x &\geq \bar{X} - z_\alpha \frac{\sigma_X}{\sqrt{n}} \\ \mu_x &\leq \bar{X} + z_\alpha \frac{\sigma_X}{\sqrt{n}},\end{aligned}$$

and isolated for  $\sigma_X$  yields again an identical expression,

$$\sqrt{n} \frac{\mu_X - \bar{X}}{z_\alpha} \leq \sigma_X.$$

Boom! An expression for  $\sigma_X$  which illustrates the required value given the  $n$ ,  $\mu_x$  and  $\bar{X}$ . Functionizing, combining with the ridiculous for-loop above and one questionable table layout follows.

```

In [7]: def find_sigma(mean1, mean2, n, confidence):
        '''
            find_sigma
            =====
            Determines the std. dev required for $H_0$ to fail.

            mean1: tested mean
            mean2: distribution mena
            n: # of samples
            confidence: the confidence level (WHATEVER THAT MEANS)
        '''
        a = 1. - confidence
        z_a = norm.ppf(1. - a/2)
        sigma = sqrt(n)*(mean2 - mean1)/z_a
        return abs(sigma)

C = [0.8, 0.9, 0.95, 0.99, 0.999]
N = [10, 100, 1000]
mean2 = 1600 # true mean ...true, true mean. hint: cloud atlys

'''
    DO EVERYTHING AT ONCE BECAUSE THERE ARE SO MANY ASSIGNMENTS
    Loop runs through parameters listed above utilizing functions genera
ted.
'''
for s in S:
    print "Sigma = %d" %s
    print "=====
    for n in N:
        x = gen_grv(mean2, s, n) # generate n random variables
        print "The number of samples: %d, H_0, n required, sigma requ
ired" %n
        print "-----
        -----"
        for c in C:
            print "The confidence level: %.3f, %s, %d, %.3f" %(c, che
ck_significance(mean(x), mean2, s, n, c), \
                determine_significance(mean(x), mean2, s, c), find_s
igma(mean(x), mean2, n, c))
            print "\n"
        print "=====\\n"

```

Sigma = 120

=====

The number of samples: 10, H\_0, n required, sigma required

-----

The confidence level: 0.800, True, 38, 61.810  
The confidence level: 0.900, True, 63, 48.158  
The confidence level: 0.950, True, 89, 40.416  
The confidence level: 0.990, True, 153, 30.752  
The confidence level: 0.999, True, 249, 24.073

The number of samples: 100, H\_0, n required, sigma required

-----

The confidence level: 0.800, True, 214, 82.035  
The confidence level: 0.900, True, 353, 63.915  
The confidence level: 0.950, True, 501, 52.640



The confidence level: 0.950, True, 501, 53.640  
The confidence level: 0.990, True, 865, 40.815  
The confidence level: 0.999, True, 1411, 31.950

The number of samples: 1000, H<sub>0</sub>, n required, sigma required

-----  
The confidence level: 0.800, True, 81234, 13.314  
The confidence level: 0.900, True, 133819, 10.373  
The confidence level: 0.950, True, 190002, 8.706  
The confidence level: 0.990, True, 328168, 6.624  
The confidence level: 0.999, True, 535540, 5.185

=====  
Sigma = 240  
=====

The number of samples: 10, H<sub>0</sub>, n required, sigma required

-----  
The confidence level: 0.800, True, 180, 56.678  
The confidence level: 0.900, True, 296, 44.159  
The confidence level: 0.950, True, 420, 37.060  
The confidence level: 0.990, True, 725, 28.199  
The confidence level: 0.999, True, 1183, 22.074

The number of samples: 100, H<sub>0</sub>, n required, sigma required

-----  
The confidence level: 0.800, True, 181, 178.602  
The confidence level: 0.900, True, 298, 139.154  
The confidence level: 0.950, True, 423, 116.782  
The confidence level: 0.990, True, 730, 88.860  
The confidence level: 0.999, True, 1191, 69.560

The number of samples: 1000, H<sub>0</sub>, n required, sigma required

-----  
The confidence level: 0.800, True, 4882, 108.625  
The confidence level: 0.900, True, 8042, 84.633  
The confidence level: 0.950, True, 11418, 71.026  
The confidence level: 0.990, True, 19721, 54.044  
The confidence level: 0.999, True, 32183, 42.306  
=====

## Conclusions

As the confidence level is increased, the confidence limits are widened, increasing the chance for the sample mean to be accepted. As a distribution's standard deviation increases, the confidence limits are also increased. The number of samples that compose the sample mean reduces the confidence limits.