

**Dealing with Materials Data:
Collection, Analysis and Interpretation
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Lecture 73**


Hypothesis Testing VI

Hello and welcome to dealing with materials data course, we have come a long way in learning about hypothesis testing, all the way we have worked with the case in which we have considered normal distribution as the population distribution.

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Review

- Considered various cases of testing of null hypothesis $\mu = \mu_0$ under following alternatives
 - $H_A: \mu \neq \mu_0$
 - $H_A: \mu > \mu_0$
 - $H_A: \mu < \mu_0$
- The basic test statistics were two
 1. If population variance σ^2 is known then $Z = \frac{\bar{x} - \mu_0}{\sigma/\sqrt{n}}$
 2. If population variance σ^2 is unknown then $T = \frac{\bar{x} - \mu_0}{s/\sqrt{n}}$
- Under normal distribution assumption
 - $Z \sim N(0,1)$ if σ^2 is known
 - $T \sim t(n-1)$ if σ^2 is unknown



So, if we review it quickly, what we have seen is we have tested the null hypothesis, if the population is normal which mean μ and variance σ^2 .

- Considered various cases of testing of null hypothesis $H_0: \mu = \mu_0$ under following alternatives
 - $H_A: \mu \neq \mu_0$
 - $H_A: \mu > \mu_0$
 - $H_A: \mu < \mu_0$

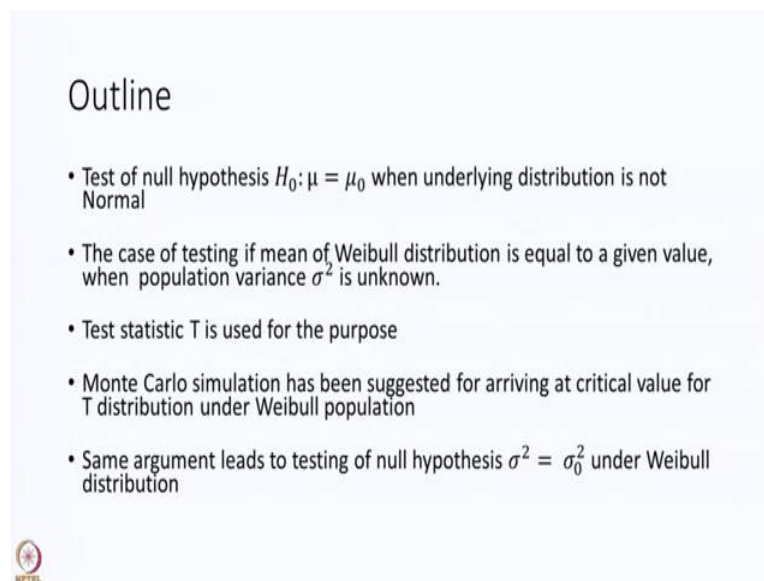
In both the cases, we found that if the population variance σ^2 is known, then it reduces down to testing a hypothesis using the test statistics Z , which is a standard normal variate. It is a normal variate with mean 0 and variance 1. In case we assume that σ^2 is unknown, then it reduces to a test statistic which is a student's T distribution statistic.

And it is distributed a students T distribution with N minus 1 degrees of freedom. The advantage of the two is that none of the two statistics distribution under H_0 , when you assume that null hypothesis is true, does not it does not depend on any other parameter then the value n or in case of Z it does not depend even in the size of the sample.

Something I have not shown here, but we also went through a testing of hypothesis process for testing that the sample, the population variance is equal to a given value σ_0^2 . And we found that Chi square that is N minus 1 sample variance divided by the sigma naught square is the Chi square variate and that variate if we call W then or we have called it Y probably that is the variate which has a test statistic, it becomes a Chi square distribution with N minus 1 degree of freedom.


So, it does not have any other parameter, only parameter is a known value depending on the sample size. And again, we tested the three alternatives and we found three critical regions in which we can reject the hypothesis when we assume that null hypothesis is true.

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Outline

- Test of null hypothesis $H_0: \mu = \mu_0$ when underlying distribution is not Normal
- The case of testing if mean of Weibull distribution is equal to a given value, when population variance σ^2 is unknown.
- Test statistic T is used for the purpose
- Monte Carlo simulation has been suggested for arriving at critical value for T distribution under Weibull population
- Same argument leads to testing of null hypothesis $\sigma^2 = \sigma_0^2$ under Weibull distribution



So, then comes what we want to do now, as I said before, we already made an assumption that the underlying population distribution is normal, but that may not be always the case. And as it was mentioned earlier also that in the material science and metallurgical engineering number of times the data do not follow a nice symmetric distribution like normal and we cannot really apply central limit theorem because the data size is not sufficiently large.

So, in this presentation today, in this session today, we would like to derive our test statistic to test the hypothesis, the same two hypotheses that the population mean is equal to a given value

versus its three alternatives. And population variance is equal to given value versus its three alternative, but the underlying population distribution will not be assumed to be normal. In this case, as a case we have assumed it to be Weibull distribution.

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Observation


- Observe that in testing the null hypothesis that $H_0: \mu = \mu_0$, the underlying test statistic is

$$Z = \frac{\bar{X} - \mu_0}{\sigma / \sqrt{n}}$$

If population variance is unknown then σ^2 gets replaced by sample variance S^2 , the test statistic takes form

$$T = \frac{\bar{X} - \mu_0}{S / \sqrt{n}}$$

- As $E(\bar{X}) = \mu$, $Var(\bar{X}) = \sigma^2/n$ and $E(S^2) = \sigma^2$ for any population distribution, above test statistics would be useful even to test the null hypothesis under non-Normal distribution
- Assumption of Normality simplifies the distributional aspects of the two test statistics Z and T
- Under distribution other than Normal the probability of critical region under $H_0: \mu = \mu_0$ may not have a closed form, and may need numerical calculations or Monte Carlo simulation.



We had mentioned it earlier, you just observe the test statistic that we found in testing the hypothesis that Mu is equal to Mu 0, when sigma square or the population variance is known is Z which depends only on X bar and rest of them are known parameters. If you say sigma square is unknown, then sigma square gets replaced by the sample variance.

So, T statistic is depends on X bar and S and otherwise Mu and Mu 0 and N which are all the known quantity. This X bar and S are very special statistics, because expected value of X bar is always Mu and variants of X bar is always sigma square over n no matter what the underlying population distribution.

Also, if you look at it, the expected value of S square is also sigma square, independent of what distribution, underlying distribution is it need not be normal. So, this actually indicates that the same Z and T can well be used as test statistics to test the same hypothesis Mu is equal to Mu 0 when sigma square is known, and Mu is equal to Mu 0 when sigma square is unknown.


And we can follow the practice only thing is assumption of normality makes life easy because the distributional aspect of the test statistics Z and T become very obvious, one is a standard normal distribution and the other is a T distribution with n minus 1 degree of freedom, which may not be the case when you deviate from the assumption of normality.

But well in that case, with the advent of computers and so much of computing facility and software, there always should be possible to find a numeric solution through either the numerical analysis or through Monte Carlo simulation and that is exactly what we are going to demonstrate or rather show it here. So, let us consider a case that we want to test the hypothesis μ is equal to μ_0 under Weibull distribution.

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Testing of $H_0: \mu = \mu_0$, under Weibull distribution

- Suppose that an indigenous engine component has been developed to replace an imported component.
- Also suppose that the low cycle fatigue life (LCF) is the property to be used to compare the indigenous component with the imported one.
- The developer has data on LCF of indigenous component, while he only knows the company provided mean LCF value of the imported component along with standard deviation
- Let X_1, X_2, \dots, X_n be a random sample of LCF values of indigenous components.
- The developer has analysed the data to find that LCF follows Weibull distribution.




So, here I have given you a situation in which such a problem can arise. Suppose, there is an indigenous engine component and this component is now need to be replaced where we earlier the manufacturer was using it important component. Now, the developers of the indigenous component have to show that its performance or the performance criteria that the important component meets is are also made by the indigenous component. And suppose the criteria is matching the low cycle fatigue life LCF life is the property we would like to compare.

So, assume that we have a data, sample data from the indigenous component X_1, X_2, X_3, X_n and we would like to, from this data we would like to show that the mean LCF value and the standard deviation of LCF value from this sample is same as what you would get from the important component. Remember, it is one can show that LCF values can follow closely Weibull distribution.

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Setting up the problem

- Want to test if LCF of indigenous component is same as that of imported component.
- For comparison we have two piece of information
 1. The LCF data X_1, X_2, \dots, X_n for indigenous components
 2. Mean LCF (μ_0) and standard deviation (σ_0) of imported components
- Let μ denote mean LCF of the indigenous components and σ denote standard deviation of the indigenous components
- Then the present case is the case of testing hypothesis
 - $H_0: \mu = \mu_0$Where the population distribution is Weibull.



So, let us set up the problem, we want to test if LCF of indigenous component is same as that of an important component. So, for comparison we have two pieces of information, we have an LCF data X_1, X_2, X_3, X_N which is a random sample of size N . And we have mean value of important component μ_0 and a standard deviation of important component σ_0 .

Let μ denote the mean value of LCF of indigenous component and σ denote the standard deviation of the indigenous component. Then, in the present case, we would like to test the hypothesis that μ is equal to μ_0 , where the population distribution is Weibull.

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3 parameter Weibull distribution


- Pdf for 3 parameter Weibull distribution can be given by

$$f(x) = \frac{c}{\beta} \left(\frac{x - \xi}{\beta} \right)^{c-1} \exp \left\{ - \left(\frac{x - \xi}{\beta} \right)^c \right\}$$

Where, ξ is location parameter, β is scale parameter and c is shape parameter

Transformed variable $W = \frac{x - \xi}{\beta} \sim Weib(0, 1, c)$ is called standard Weibull distribution

Mean of std Weibull distribution $\mu_W = \Gamma \left(\frac{1}{c} + 1 \right)$



In reality, we have to assume three parameter Weibull distribution. In the case of special random variable, we have given a very brief introduction to three parameter Weibull

distribution. So, we will revisit it here, the probability density function of three parameter Weibull distribution is given in this format,

$$f(x) = \frac{c}{\beta} \left(\frac{x - \xi}{\beta} \right)^{c-1} \exp \left\{ - \left(\frac{x - \xi}{\beta} \right)^c \right\}$$

where the ξ is called the location parameter β is called the scale parameter and C is called the shape parameter.

Now, let us take a transformed variable W, which is equal to

$$W = \frac{x - \xi}{\beta} \sim Weib(0, 1, c) \text{ is called standard Weibull distribution}$$

Weibull distribution with location parameter 0, scale parameter 1 and a shape parameter C. So, it means that this is this depends only now on one parameter which is called C, it is shape parameter.


This is also called a Standard Weibull distribution. Remember standard normal distribution does not depend on any parameter. Standard Weibull distribution depends on one parameter which is a shape parameter. The mean of standard Weibull distribution Mean of std Weibull distribution $\mu_W = \Gamma \left(\frac{1}{c} + 1 \right)$

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3 parameter Weibull distribution: transformed

- $W = \frac{x - \xi}{\beta}$
- $\Rightarrow X = \xi + \beta W \therefore E(X) = \xi + \beta E(W) \Rightarrow \mu = \xi + \beta \mu_W$
- Similarly $\sigma^2 = \beta^2 \sigma_W^2$
- Let X_1, X_2, \dots, X_n be random sample from Weib(ξ, β, c)
- Then W_1, W_2, \dots, W_n is a random sample from Weib(0, 1, c)

$$\bar{X} = \xi + \beta \bar{W}$$

$$S^2 = \beta^2 S_W^2$$


Now, if we transform the variable, the Weibull variable into

$$W = \frac{X - \xi}{\beta}$$

$$\Rightarrow X = \xi + \beta W \therefore E(X) = \xi + \beta E(W) \Rightarrow \mu = \xi + \beta \mu_W$$

$$\text{Similarly } \sigma^2 = \beta^2 \sigma_W^2$$

Let X_1, X_2, \dots, X_n be random sample from Weib(ξ, β, c)

Then W_1, W_2, \dots, W_n is a random sample from Weib(0, 1, c)

$$\bar{X} = \xi + \beta \bar{W}$$

$$S^2 = \beta^2 S_W^2$$


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The Weibull-t statistic

- Define statistic as

$$T = \frac{\bar{X} - \mu}{S/\sqrt{n}} = \sqrt{n} \frac{\bar{W} - \mu_W}{S_W}$$
- T is called Weibull-t statistic.
- Unlike student's t distribution, Weibull-t depends on one parameter c.
- Consider $H_0 : \mu = \mu_0$ with following three possible alternatives
 1. $H_1 : \mu \neq \mu_0$
 2. $H_2 : \mu > \mu_0$
 3. $H_3 : \mu < \mu_0$
- Assume variance σ^2 unknown
- Test Statistic T can be defined as

$$T = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} = \sqrt{n} \frac{\bar{W} - \mu_{W0}}{S_W}$$



Let us define Weibull T statistic that is our t statistic that we already know

$$T = \frac{\bar{X} - \mu}{S/\sqrt{n}} = \sqrt{n} \frac{\bar{W} - \mu_W}{S_W}$$

I call it T, but it would not follow the student's T distribution, whatever it may follow, I call it a Weibull t distribution and I call this a Weibull t statistic. T is called a Weibull t statistic and unlike T distribution Weibull t statistic also depends on one parameter, unknown parameter C, which is the shape of Weibull distribution.

So, it depends on of course, the degrees of freedom should be n minus 1 and because we have estimated X bar. So, with the degrees of freedom will be n minus 1, but it will also have another

parameter along with it which is C. Now, we consider the testing of hypothesis μ is equal to μ_0 against the three alternatives H_1, H_2, H_3 but there is a mistake here. Let us correct it so that the mistake does not continue.

- Consider $H_0 : \mu = \mu_0$ with following three possible alternatives

- $H_1 : \mu \neq \mu_0$

- $H_2 : \mu > \mu_0$

- $H_3 : \mu < \mu_0$

We straight away assume that sigma square is unknown. Then the T statistic as defined above

can be a T statistic $T = \frac{\bar{X} - \mu_0}{S/\sqrt{n}} = \sqrt{n} \frac{\bar{W} - \mu_{W0}}{S_W}$ for testing the hypothesis $H_0 : \mu = \mu_0$.

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Critical Region

- Let probability of type I error be fixed at α
- For the three alternatives the critical region, following the experience of Normal distribution, can be given as

- $H_1 : \mu \neq \mu_0$:
Reject H_0 if $|T| > t_w((1 - \alpha/2), n - 1)$
- $H_2 : \mu > \mu_0$:
Reject H_0 if $T > t_w((1 - \alpha), n - 1)$
- $H_3 : \mu < \mu_0$:
Reject H_0 if $T < t_w(\alpha, n - 1)$

Let us define what will be the critical region, you recall what we did in the past and we follow the same steps. So, if we fix the alpha and the type one error at alpha, then for the testing the null hypothesis against the three alternatives,

- $H_1 : \mu \neq \mu_0$: Reject H_0 if $|T| > t_w((1 - \alpha/2), n - 1)$

And of course, there will be a parameter I am sorry, of course, there will be a parameter C, which I have missed out. So, this is going to be your critical value, the alpha 1 minus alpha by

2 comes under the same argument, we are assuming that it is going to be symmetric. If it is not symmetric, then it has to have the two value I think it is, it would be more appropriate, if we write it that this can be written as

$$T < t_w\left(\left(1 - \frac{\alpha}{2}\right), n - 1\right) \text{ or } T > t_w\left(\left(1 - \frac{\alpha}{2}\right), n - 1\right)$$

This has to be either this or that.

Then, if we consider the rejection with the alternate hypothesis

2. $H_2 : \mu > \mu_0$ Reject H_0 if $T > t_w((1 - \alpha), n - 1, c)$
3. $H_3 : \mu < \mu_0$ Reject H_0 if $T < t_w(\alpha, n - 1, c)$


So, in other words like a Chi square distribution, we are assuming that this distribution will also be kind of asymmetric distribution. And then we are taking two values, this is t alpha by 2 and this is t 1 minus alpha by 2 and with the rest of the parameters, so that is n minus 1 and C, here also there is n minus 1 and C, this is the case with respect to this.

So, if you are looking for this situation, then you are going to look into this area to be alpha and therefore, this value is going to be t 1 minus alpha n minus 1 C. And if you are looking for the fourth case, if you are looking for this fourth case, then you will have to take some value here, where this value, this area is going to be alpha and therefore, this is going to be T Sub W alpha n minus 1 and C. I hope this is clear. So, these are going to be the critical region.

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Critical Value $t_w(\alpha, n - 1) = t_w(\alpha, n-1, c)$

- Weibull-t distribution depends on degrees of freedom (n-1) and shape parameter of Weibull distribution c.
- The Weibull-t distribution does not have any closed form of expression.
- Hence the critical values of Weibull-t distribution are simulated



So, how do we find any critical value and again I have to add a C here. I have to add a C here because it is actually, so this should be written as

$$t_w(\alpha, n - 1, c)$$

So, it is a Weibull t distribution depends on degrees of freedom n minus 1 and shape parameter of a Weibull distributions C. Therefore, Weibull t distribution does not have any closed form solution, the way we have defined it, it does not have a closed form solution hence the critical values of Weibull t are generally simulated, we will give you the here how to simulate it.

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Monte Carlo simulation for Weibull-t critical values

- Take μ_0
- Calculate using inverse gamma function $c_0 = \frac{1}{\Gamma^{-1}(\mu_0) - 1}$: $\mu_0 = \Gamma\left(\frac{1}{c_0} + 1\right)$
- Generate M number of samples of size n from Weib(0, 1, c_0),

$$W_{ji}, i = 1, 2, \dots, n; j = 1, 2, \dots, M$$
- For j = 1, 2, ..., M calculate \bar{W}_j and S_{Wj}^2
- Calculate Weibull-t statistic $T_j = \sqrt{n} \frac{\bar{W}_j - \mu_0}{S_{Wj}}$
- Sort the statistics T_j and $(1-\alpha)*M$ would give the Weibull-t critical value

Ref: Hina Gokhale, G.S. Reddy (2000), "Statistical analysis of mechanical properties of JFS castings", Technical Report No. DMRL/TR/2000268, March 2000.

So, this Monte Carlo simulation can be carried out that.

- Take μ_0
- Calculate using inverse gamma function $c_0 = \frac{1}{\Gamma^{-1}(\mu_0) - 1}$
- Generate M number of samples of size n from Weib(0, 1, c_0),

$$W_{ji}, i = 1, 2, \dots, n; j = 1, 2, \dots, M$$

- For j = 1, 2, ..., M calculate \bar{W}_j and S_{Wj}^2
- Calculate Weibull-t statistic $T_j = \sqrt{n} \frac{\bar{W}_j - \mu_0}{S_{Wj}}$
- Sort the statistics T_j and $(1-\alpha)*M$ would give the Weibull-t critical value

Once you have M capital M of T, j you sort them out from smallest to the largest. And if you take 1 minus alpha time M value of Tj that will be the alpha level critical value of Weibull t distribution depending on C0. So, what you really need to do is for different values of C0 you have to simulate this or as and when needed, you take what is your M 0, you convert it into your C0 and write a nice program, so that every time it generates this critical value and gives you, please remember when we do Monte Carlo simulation, it is very important to see the stability of it, make sure that the C that is given into it does not conflict with your Monte Carlo simulation process.


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Testing $\sigma^2 = \sigma_0^2$ in Weibull Population

- Under the assumption of Normal population testing

$$H_0 : \sigma^2 = \sigma_0^2$$
- Leads to test statistic

$$W = \frac{(n-1)S^2}{\sigma_0^2} \sim \chi^2(n-1)$$
- Observe the statistic W, when null hypothesis is true $E(S^2) = \sigma_0^2$ independent of the underlying population distribution
- Hence, W can also be test statistic for the present case.
- When population under concern is Weibull, the test statistic W is called Weibull- χ^2 statistic. And the distribution of the statistic is called Weibull- χ^2 distribution (χ_W^2)



If suppose now we want to test sigma square is equal to sigma naught square okay.

Under the assumption of Normal population testing

$$H_0 : \sigma^2 = \sigma_0^2$$

Leads to test statistic

$$W = \frac{(n-1)S^2}{\sigma_0^2} \sim \chi^2(n-1)$$

Just as in the previous case of testing Mu is equal to Mu 0 we find rather we observe that expected value of S square is sigma naught square or a sigma square independent of what is underlying population.

Hence, W can also be a test statistic for the present case. And when population under concern is Weibull, such a statistic is called a Weibull Chi square statistics and the distribution is called Weibull Chi square distribution.

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Weibull χ^2 statistic and Critical Region

- Let probability of type I error be fixed at α
- For the three alternatives the critical region, following the experience of Normal distribution, can be given as

1. $H_1 : \sigma^2 \neq \sigma_0^2$:
Reject H_0 if $W < \chi_W^2((\alpha/2), n - 1, c)$ or $W > \chi_W^2((1 - \alpha/2), n - 1, c)$
2. $H_2 : \sigma^2 > \sigma_0^2$
Reject H_0 if $W > \chi_W^2((1 - \alpha), n - 1, c)$
3. $H_3 : \sigma^2 < \sigma_0^2$
Reject H_0 if $W < \chi_W^2(\alpha, n - 1, c)$

Again, you can find the critical region. Here also please remember the statistic will depend on C . So, let me write it down everywhere. So, we will have this with C , here also there will be a C . So, if you are taking null hypothesis, $H_0 : \sigma^2 = \sigma_0^2$

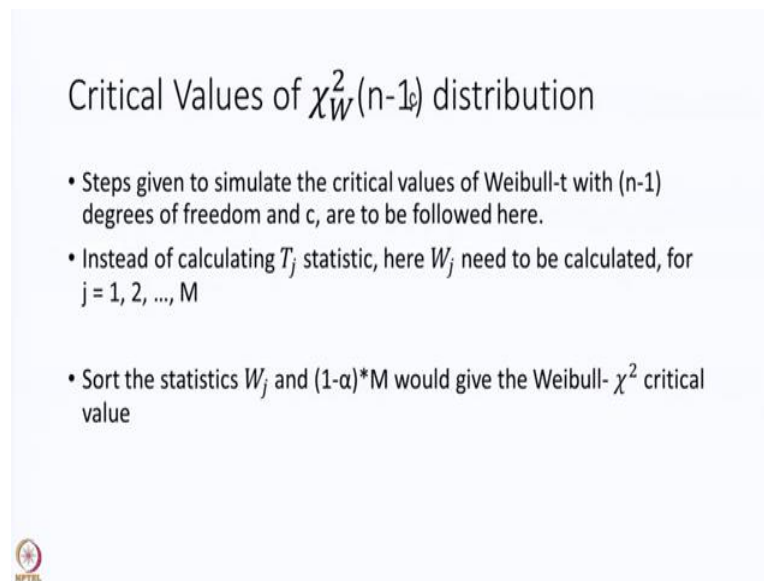
and your alternative

1. $H_1 : \sigma^2 \neq \sigma_0^2$: Reject H_0 if $W < \chi_W^2((\alpha/2), n - 1, c)$ or

$$W > \chi_W^2((1 - \alpha/2), n - 1, c)$$
2. $H_2 : \sigma^2 > \sigma_0^2$ Reject H_0 if $W > \chi_W^2((1 - \alpha), n - 1, c)$
3. $H_3 : \sigma^2 < \sigma_0^2$ Reject H_0 if $W < \chi_W^2(\alpha, n - 1, c)$

If your alternate is sigma square is greater than sigma 0 square, then we say that reject H_0 . If your Chi statistics W is greater than the Weibull Chi square with probability $1 - \alpha$ $n - 1$ degrees of freedom and nuisance parameter C . And if sigma square is less than sigma 0 square is your alternative, then the critical value is Weibull Chi square at alpha probability $n - 1$ degrees of freedom and nuisance parameter C .

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Critical Values of $\chi_W^2(n-1)$ distribution

- Steps given to simulate the critical values of Weibull-t with (n-1) degrees of freedom and c, are to be followed here.
- Instead of calculating T_j statistic, here W_j need to be calculated, for $j = 1, 2, \dots, M$
- Sort the statistics W_j and $(1-\alpha)*M$ would give the Weibull- χ^2 critical value

How do you find a critical values of Weibull Chi square distribution with n minus 1 degrees of freedom and nuisance parameters C, when we have to take the same steps as given to simulate the critical values instead of calculating test statistic, which is test statistic, which is T_j you calculate w_j and sort w_j from smallest to the largest and take 1 minus alpha times M th value which will give you Weibull Chi square critical value.

Please remember, here this value given is sigma naught square, so there will be a slight change in the beginning, he will take sigma naught square and from that you will calculate there is you have to find out the formula for sigma naught squared, which is given earlier and then you have to calculate the value of C naught and then do the simulation.

So, let us summarize it, we defined the testing of hypothesis process for testing μ is equal to μ_0 and sigma square is equal to sigma naught square under non normal distribution, in particular we took the case of Weibull. We did this because we found that the test statistics Z and T which we have chosen under normal population, their properties of choosing them for statistic is independent of what is the underlying population.

So, we decided that the same statistic can also be useful, we felt that it can also be useful to test the hypothesis under different population distribution. We did that with the Weibull distribution.

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Summary

- Weibull-t and Weibull- χ^2 statistic defined to test the null hypotheses

$$\mu = \mu_0$$

$$\sigma^2 = \sigma_0^2$$

- Critical region under the three alternative for both the above hypothesis discussed
- For both the cases steps to Monte Carlo simulate the critical values given



We found Weibull T and Weibull Chi square statistic, we found the critical region and we give the steps through Monte Carlo simulation to simulate the critical values. Please remember, there is nothing wholly about Weibull. This is just a case has been given to you, because when you said that distribution is not normal, there are too many possibilities come up. So, we have shown you one possibility, you can change it and see how the test procedure can develop as and when the need arises. Thank you.