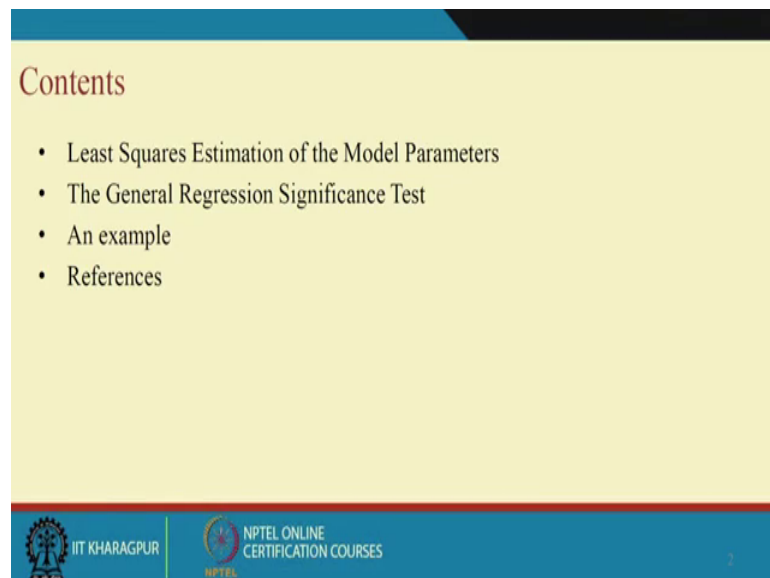


Design and Analysis of Experiments
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Lecture – 24
Regression Approach to ANOVA

Welcome. Today we will discuss the regression approach to ANOVA.

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You have gone through ANOVA analysis of variance.

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ANOVA.

One way analysis of variance.

$y_{ij} = \mu + \tau_i + \epsilon_{ij}$ ← One way ANOVA.

Treat	1	2	...	j	...	n _i
→ 1						
2						
...						
i						
...						
a						

(a+1) parameters to be estimated.

$L = SSE = \sum_{i=1}^a \sum_{j=1}^{n_i} \epsilon_{ij}^2 = \sum_{i=1}^a \sum_{j=1}^{n_i} (y_{ij} - \mu - \tau_i)^2$

$N = an$

$\frac{\partial L}{\partial \mu} = 0; \frac{\partial L}{\partial \tau_i} = 0 \quad i=1, 2, \dots, a$

One way analysis of variance, one way we will discuss in term with reference to one way analysis of variance one of the way ANOVA and the model we have given y_{ij} general model is $\mu + \tau_i + \epsilon_{ij}$ that is for one way ANOVA.

Here it is the general observation and our data was something like this that the factor or the treatment levels 1, 2, i to a levels and these side the observations or replications to n. When we have gone for balanced one and some way are here if it is a somewhere y_{ij} is there and this is the general model. So, how many parameters to be estimated? One is μ another one is a number of τ_i . So, total a plus 1 parameters to be estimated. So, in today's lecture we will see that how regression is used to estimate this a plus 1 parameters and how the SS R, SS E and SS T can be estimated using the regression approach.

Further what I will show you I will show one example and then we will see that the ANOVA results versus our regression result for the model adequacy test, although the parameters level comparison also possible. So, essentially we will see that least square estimation of model parameters, the general regression significant test example and few references.

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Least Squares Estimation of the Model Parameters

Single-factor ANOVA fixed-effects model $y_{ij} = \mu + \tau_i + \epsilon_{ij}$




The least squares estimators of μ and τ_i SS of Error: $L = \sum_{i=1}^a \sum_{j=1}^n \epsilon_{ij}^2 = \sum_{i=1}^a \sum_{j=1}^n (y_{ij} - \mu - \tau_i)^2$

Simultaneous equation:

$$\frac{\partial L}{\partial \mu} = 0$$

$$\frac{\partial L}{\partial \tau_i} = 0 \quad i = 1, 2, \dots, a$$

$$-2 \sum_{j=1}^n (y_{ij} - \hat{\mu} - \hat{\tau}_i) = 0$$

$$-2 \sum_{j=1}^n (y_{ij} + \hat{\mu} - \hat{\tau}_i) = 0 \quad i = 1, 2, \dots, a$$




Let us see this model what is the fixed effect one way model is $y_{ij} = \mu + \tau_i + \epsilon_{ij}$. You require to estimate μ and τ_i . So, what is the procedure in least square method? Least square (Refer Time: 02:52) method procedure is you minimize the sum of squares error, sum squares errors SS E, you minimize SS E. So, a minimize SS E. Now in this equation what is ϵ_{ij} is the error term, this is $y_{ij} - \mu - \tau_i$.

Now, if I sum it over i and j j equal to 1 to n , i equal to 1 to a then you sum it j equal to 1 to n , i equal to 1 to a , but what we are saying sum square that mean you first make it square. So, this square and then sum it. So, this is your SS E, this is your SS E. So, we say this is the its denote that this is the function of L , a L is this function not function of L . L is noted by this function, then what you require to do, you require to find out $\frac{\partial L}{\partial \mu}$ and put it to 0 and $\frac{\partial L}{\partial \tau_i}$ then put it to 0, i equal to 1 to like a . So, what it will give you? It will give you one equation here and here are number of equation. So, you will be having a plus 1 number of equations simultaneous equation which to be solved. So, let us see the slides.

What are the simultaneous equation? So, $\frac{\partial L}{\partial \mu}$ given this is 0 and $\frac{\partial L}{\partial \tau_i}$ given this is 0. So, the first one if you take derivative of these with respect to μ you will get this equation. Now if you do the same with respect to τ_i you will get this equation. So, this equation and this equation here i equal to, so how many equations you have? You have a plus 1 equations that is what we are seeing here.

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Least Squares Estimation of the Model Parameters (Contd.)

$$\begin{array}{rcl}
 N\hat{\mu} + n\hat{\tau}_1 + n\hat{\tau}_2 + \dots + n\hat{\tau}_a & = & y_{..} \\
 n\hat{\mu} + n\hat{\tau}_1 & = & y_{1.} \\
 n\hat{\mu} & + & n\hat{\tau}_2 & = & y_{2.} \\
 & & \vdots & & \vdots \\
 n\hat{\mu} & & & + & n\hat{\tau}_a & = & y_{a.}
 \end{array}$$

- The $(a+1)$ equations in $(a+1)$ unknowns are called the **least squares normal equations**.
- If the last a normal equations be added, the first normal equation can be obtained.
- The normal equations are not linearly independent, and no unique solution for $\mu, \tau_1, \tau_2, \dots, \tau_a$ exists.
- The effects model is **overparameterized**

$$\sum_{i=1}^a \hat{\tau}_i = 0 \qquad \begin{array}{l} \hat{\mu} = \bar{y}_{..} \\ \hat{\tau}_i = \bar{y}_{i.} - \bar{y}_{..} \quad i = 1, 2, \dots, a \end{array}$$

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How this equation is coming $n\hat{\mu}$ all this? Suppose you just think of this equation equal to 0. So, sum total of y_{ij} across j and i will give you $n\hat{\mu}$ will give you this one $y_{..}$ double dot there is a grand total and then μ here n times, n mean the total number of observation. So, n equal to $a \times n$ that n times μ cap and for every τ there will be what is the how many observations are there; for every τ , τ_1 n observation, τ_2 n observation, like τ_i n observation, but for μ grand mean total observation is N n equal to a into n . So, as a result when you put the of the number of observations into equation then what happen this will be n , sum of all $n y_{ij}$ which is nothing, but $y_{..}$ total. What is $y_{..}$ total? $y_{..}$ dot dot, that is what we have computed earlier. So, let me repeat this case again.

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	1	2	...	i	...	n	Total
1							y _{1.}
2							y _{2.}
...							...
i							y _{i.}
...							...
a							y _{a.}
							y _{...}

I have 1, 2, i, a treatments and you have 1, 2, j, n your applications, then if I write total here this will give you y 1 total, y 2 total, y i total, y a total and if you find out the grand total this is y dot dot, grand total is total of all those things. This is nothing but grand total means sum of j equal to 1 to n, i equal to 1 to i y ij.

So, what is our first equation? First equation is minus 2 i equal to 1 to a j equal to 1 to n, y ij minus mu cap minus tau i cap equal to 2; obviously, given that there tau i cap. So, in this equation what I mean to say if I remove the sum this minus 2 will also be canceled then what will happen if I write this portion this positions, this is what this was n time total of y ij that mean y double dot bar this portion gives you this. Now, minus, minus this 1 i equal to 1 to a j equal to 1 to N in capital, total is N times mu cap. Now, plus this what is happening tau 1 will be for small n types because there are n observation. So, minus n tau 1 cap minus n tau 2 cap like this minus n tau a cap this will become 0, this will become 0. So, then we are getting this equation first equation. N mu cap plus n tau 1 n tau 2 like this small one this is giving you this equation.

Now, come to the second formula. What is the second formula? So, from this formula we have first formula we are getting N mu cap plus n tau 1 cap n tau 2 cap plus n tau a cap this equal to y double dot this is our equation number 1.

From the second formula second formula is equation is y j equal to 1 to n then y ij minus plus mu cap minus tau i this becomes 0, suppose you are making doing that minus minus

this. So, what is happening here then this is minus. So, using this equation what you are getting? You are basically supposed for here i equal to 1 to a . If I put i equal to 1 what I will get this will go out. So, it is n times μ n times μ cap plus what you will get here this τ_1 that that will also be n times τ_1 cap equal to y_1 dot because this is the first row this will this quantity will give you first row total.

So, in this manner, in this manner you are getting first row total form the first equation, second equation, second row this. So, you will be having such $n+1$ least square normal equations. So, what is the constraint here? Constant is that if you sum up a number of equations starting from the second one starting from this one to the last one that is a number of last 2 equations if you sum up you will get the first equation. So, as a result effectively you have unique a number of equations. But you want to you have to estimate a plus 1 parameters. So, as a result what happened you have a constraint it is your over parameterize model. So, you have a constraint that i equal to 1 to τ_i cap equal to 0 this constant. Using this constant, so what happen and all these a plus 1 equation you will be able to estimate the parameters. How?

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The image shows handwritten mathematical derivations on a grid background. In the top right corner, there is a small logo for 'CET IIT KGP'. The derivations are as follows:

①
$$N\hat{\mu} + n\hat{\tau}_1 + n\hat{\tau}_2 + \dots + n\hat{\tau}_a = y_{..}$$

$$\Rightarrow N\hat{\mu} + n(\hat{\tau}_1 + \hat{\tau}_2 + \dots + \hat{\tau}_a) = y_{..}$$

$$\Rightarrow N\hat{\mu} + n \sum_{i=1}^a \hat{\tau}_i = y_{..}$$

$$\Rightarrow N\hat{\mu} = y_{..}$$

$$\Rightarrow \hat{\mu} = \frac{y_{..}}{N} = \bar{y}_{..} \leftarrow$$

②
$$n\hat{\mu} + n\hat{\tau}_1 = y_{1.}$$

$$\Rightarrow \hat{\mu} + \hat{\tau}_1 = \frac{y_{1.}}{n} = \bar{y}_{1.}$$

$$\therefore \hat{\tau}_1 = \bar{y}_{1.} - \hat{\mu} = \bar{y}_{1.} - \bar{y}_{..} \leftarrow$$

$$\therefore \hat{\tau}_2 = \bar{y}_{2.} - \bar{y}_{..}$$

So, what we got? We got $N\hat{\mu}$ $n\hat{\tau}_1$ $n\hat{\tau}_2$ cap like this small n τ_a cap equal to $y_{..}$ dot dot that is the total grand total. Then this is nothing, but $N\hat{\mu}$ cap plus if we take in common this is τ_1 plus τ_2 all caps are there plus τ_a equal to $y_{..}$ dot dot this is nothing, but $N\hat{\mu}$ cap plus n sum of τ_i cap i equal to 1 to a equal to $y_{..}$

double dot now this is 0 because of the constraint. So, we can write $N \mu \hat{c}$ equal to y double dot other way $\mu \hat{c}$ is y double dot by n ; that means, grand total by total number of observations this is nothing, but \bar{y} and this is what we have done in ANOVA also that is what is the grand total average this is from average formula that sum of all observation divided by that total number of observations. So, this is fantastic.

Now, if I take the second equation this is my first equation then second normal equation this is $n \mu \hat{c} + n \tau_1 \hat{c} = y_1 \cdot$, then a second one $\mu \hat{c}$ is known because already $\mu \hat{c}$ is estimated. So, if I write $\tau_1 \hat{c}$ now that that mean $\mu \hat{c} + \tau_1 \hat{c} = y_1 \cdot / n$ this is nothing, but \bar{y}_1 average. So, as a result $\tau_1 \hat{c}$ is nothing, but \bar{y}_1 average, \bar{y}_1 average minus $\mu \hat{c} = \bar{y}_1$ average minus \bar{y} that is average. So, here \bar{y}_1 this average. So, this is what you have seen earlier also. That we said that for every row average if you can recall we found out that overall average and then the tau then we found out the average here, this is \bar{y}_1 average, \bar{y}_2 average, \bar{y}_i average, like \bar{y}_a average then we say that what is the effect of first level that these average minus this average.

What is the effect of i th level? \bar{y}_i average minus \bar{y} that this grand average. So, that means, in general from this equation we can say $\tau_i \hat{c} = \bar{y}_i$ that is the average i th average minus by this average this is the estimate you have seen earlier; now, from here if I know that all the tau and mu estimates then the residuals also will be known from the primary equations $y_{ij} = \mu + \tau_i + \epsilon_{ij}$ this.

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The General Regression Significance Test

□ Rules for normal equations for any experimental design:

- **RULE 1.** There is one normal equation for each parameter in the model to be estimated.
- **RULE 2.** The right-hand side of any normal equation is just the sum of all observations that contain the parameter associated with that particular normal equation.
- **RULE 3.** The left-hand side of any normal equation is the sum of all model parameters, where each parameter is multiplied by the number of times it appears in the total on the right-hand side.

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So, this is the rules. Now, for normal equation that there are three rules. Rule one is there is one normal equation for each parameter in the model to be estimated. So, we have in one factor one way ANOVA, we have a levels for a treatments levels and grand mean.

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One-way ANOVA
a treat / p

a+1 parameters
(a+1) eqns.

Goodness of fit / ANOVA Test

Full model: $y_{ij} = \mu + \tau_i + \epsilon_{ij}$

Reduced model: $y_{ij} = \mu + \epsilon_{ij}$

$H_0: \tau_i = 0, i = 1, 2, \dots, a$

$SS_T = SS_{\text{treatment}} + SS_{\text{error}}$

$SS_T = SSR + SSE$

ANOVA Reg

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So, as a result a plus one parameters to be estimated that I told you I am repeating the same thing. So, that for every parameter there will be a normal equation a plus a 1 equations will be there and it is seen. Then the right hand side of any normal equation is just the sum of all observations that contain the parameter associated with that particular

normal equation. See here, right hand side is what sum of all observations because this is a this equation with respect to μ this is a equation right hand side sum of all parameters, sorry sum of all observations sum of all observations second one you see with respect to τ_1 sum of the observations. So, like this, the right hand side of n normal equation is just sum of all observations that contain the parameter associated with that particular normal equation.

Rule 3, the left hand side of any normal equation is sum of all the model parameters where each parameter is multiplied by the number of times it appears in the total on the right hand side. You see, suppose you this one you consider this one if you consider you see that this is \bar{y}_2 it is n times the right hand left hand side a n times it appears for a particular row number of n times the number of observations you have got n application is there. So, these parameters in this equation the parameters are multiplied by that number of observations that is n . So, in the regression approach you are (Refer Time: 18:57) there will be as many equation as many parameters we have. And the general rule is that three rules are there, if you apply this three rule you will be able to get all the equations even if you do not go by the least square that traditional mathematical procedure.

Now, once you have the general equation the normal equations you are in a position to estimate all the parameters which are nothing, but the way we have seen in one way ANOVA lecture. Similar, same thing is coming to obvious. Now, I will show you the important one there that is means that goodness of fit measures, goodness of fit as well as I can say that the test ANOVA test, overall test. So, what happened we have seen that the corner we ANOVA partitioned the total sum square total into sum square treatment plus sum square error.

Now, using regression approach how do you compute these things? SS_E and $SS_{treatment}$ if we say $SS_{treatment}$ in if and in regression you have seen this is in ANOVA one way ANOVA and regression what you have seen you have seen that SS_T equal to SS_R plus SS_E . What is the SS_R ? Sum square regression. So, this sum square regression and sum square treatment, ultimately it is a partitioning the total variability into 2 parts. So, they will be almost same maybe because of the approach. There will be some variability is some difference in the calculated values may be am, but approaches are same; that means, SS_R here is nothing, but equivalent to a $SS_{treatment}$.

So, let us see then using ANOVA regression approach for how to compute that SS R SS E, SS E and we get the earlier results what we have already used. So, here we are using, we will be using to the concept of full model full model mean if hours is a one way ANOVA case then y_{ij} equal to $\mu + \tau_i + \epsilon_{ij}$ that is full model.

Another one is reduced model. Reduced model means suppose then this factor is not contributing in any way then this model can be written like this $\mu + \epsilon_{ij}$ when $\tau_i = 0$, $i = 1$ to a is true it is true then this model is nothing, but this is reduced model. That means, the treatments are not at all contributing to the response or that the independent variable in terms of regression is not contributing to the overall variability of the y the response variable. So, we use these 2 and then we will apply certain rules to find out that the sum squares for total, sum square for error and sum square for treatment or regression. Let us see what is this rule.

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The General Regression Significance Test
 The reduction in the unexplained variability is always the sum of the parameter estimates, each multiplied by the right-hand side of the normal equation that corresponds to that parameter. For example, in a single-factor experiment, the reduction due to fitting the **full model** $y_{ij} = \mu + \tau_i + \epsilon_{ij}$ is

$$R(\mu, \tau) = \hat{\mu}y_{..} + \hat{\tau}_1y_{1.} + \hat{\tau}_2y_{2.} + \dots + \hat{\tau}_ay_{a.}$$



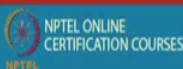
$$= \hat{\mu}y_{..} + \sum_{i=1}^a \hat{\tau}_i y_{i.}$$

$$SS_E = \sum_{i=1}^a \sum_{j=1}^n y_{ij}^2 - R(\mu, \tau)$$

$$R(\mu, \tau) = \hat{\mu}y_{..} + \sum_{i=1}^a \hat{\tau}_i y_{i.}$$

$$= (\bar{y}_{..})y_{..} + \sum_{i=1}^a (\bar{y}_{i.} - \bar{y}_{..})y_{i.}$$

$$= \frac{y_{..}^2}{N} + \sum_{i=1}^a \bar{y}_{i.}y_{i.} - \bar{y}_{..} \sum_{i=1}^a y_{i.}$$

$$= \sum_{i=1}^a \frac{y_{i.}^2}{n}$$




Rule is that the reduction in the x unexplained variability is always the sum of the parameter estimates in the sense that each multiplied by the right hand side of the normal equation that corresponds to that parameter. For example, in a single factor experiment the reduction we have seen already the single factor experiment. Now, if we say the reduction is $R(\mu, \tau)$ then this is basically how many parameters are there here μ and a number of τ $a + 1$ parameters. You see each of the parameter estimates are multiplied by the right hand side value of the normal equation. So, what is the estimate

of mu? That is mu cap. So, what is there in the right hand side of the normal equation? Grand total multiplied by grand total.

What is the second one? Tau 1 right hand side y 1 total; like this tau 2 cap y 2 total tau a cap y a total. So, this is now this correspond equivalent to mu cap y double dot plus i equal to a equal to 1 to a tau i cap, y i dot, y i dot. So, this is what is the reduction of variability from of y reduction over a very variability that is if you use the full model.

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Handwritten mathematical derivations on a grid background. The equations show the relationship between SSE, $R(\mu, \tau)$, and the sum of squares of observations. Key equations include:

- $SSE = \sum_{i=1}^a \sum_{j=1}^n y_{ij}^2 - R(\mu, \tau)$
- $R(\mu, \tau) = \hat{\mu}_0 + \sum_{i=1}^a \tau_i y_{i.}$
- $y_{ij} = \mu + \tau_i + \epsilon_{ij}$
- $\epsilon_{ij} = y_{ij} - \mu - \tau_i$
- $y_{ij} = \mu + \epsilon_{ij}$
- $\sum \epsilon_{ij} = (y_{j.} - \mu)^2$
- $SSE = \sum_{i=1}^a \sum_{j=1}^n y_{ij}^2 - \frac{\sum_{i=1}^a y_{i.}^2}{n}$
- $R(\mu) = \sum_{i=1}^a \frac{y_{i.}^2}{n}$

Now, if we assume that is from SS some square point of view; that means, the sum square of all the observations we are not talking about some square deviation some square of all the observation j equal to 1 to n, i equal to 1 to a and if this is subtracted by R mu and tau. What is this? This is what is the reduction of variability if the ANOVA model is used say in them the difference is giving you some square errors. That means, this is the variability in y and this one is here mu is included. So, this one is the variability including mu means what I mean to say y ij equal to y ij equal to mu plus tau i plus epsilon ij, I am taking square of this.

Suppose then and this, this one this one ultimately we want this. So, y ij is a equal to epsilon ij equal to y ij minus mu minus tau i. So, that sense if I square this and then take the sum you will get this and this one is coming here and whatever this, this is what is the model part. So, this model part is coming here now you understand. So, as a result we

are saying this is SS E. Now, then what about this R mu and tau? That is we said that mu cap y double dot plus sum up sum of tau i cap y i dot i equal to 1 to a.

So, if you expand these you will get this one you see what you are getting if you expand this you are getting this mu i cap is nothing, but y grand average into this and into this and if you expand this, you will be getting that is nothing but y i dot square by n i equal to 1 to a y i dot square by capital N small n and square by more small n. Now that means, they say if I put in SS E then this is nothing, but j equal to 1 to n i equal to 1 to a y ij square minus sum of i dot square by n. So, this is your SS E.

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The General Regression Significance Test




The error sum of squares is $SS_E = \sum_{i=1}^n \sum_{j=1}^a y_{ij}^2 - R(\hat{\mu}, \hat{\tau})$
 $= \sum_{i=1}^n \sum_{j=1}^a y_{ij}^2 - \sum_{i=1}^n \frac{y_{i.}^2}{a}$

For the reduced model $y_{ij} = \mu + \varepsilon_{ij}$, there is normal equation, $N\hat{\mu} = y_{..}$ and the estimator of μ is $\hat{\mu} = \bar{y}_{..}$

$R(\hat{\mu}) = (\bar{y}_{..})y_{..} = \frac{y_{..}^2}{N}$

$R(\tau|\hat{\mu}) = R(\hat{\mu}, \hat{\tau}) - R(\hat{\mu})$
 $= R(\text{Full Model}) - R(\text{Reduced Model})$
 $= \frac{1}{a} \sum_{i=1}^n y_{i.}^2 - \frac{y_{..}^2}{N}$

$F_0 = \frac{R(\tau|\hat{\mu})/(a-1)}{\left[\sum_{i=1}^n \sum_{j=1}^a y_{ij}^2 - R(\hat{\mu}, \hat{\tau}) \right] / (N-a)}$

Now, this you are getting from the full model now if we do the same thing from the for the reduced model mu plus epsilon ij. Then epsilon ij is what? y ij minus mu if you t square you make square it and some of this then SS E what happened you will get from here. But rather we are interested in this R we are interested only R mu here mu and tau because for the full model and here these what is the procedure multiplied by. So, estimate is mu cap multiplied by its total, now this will give you y dot dot square by capital N you mean multiply do this you will get this.

So, as a result what happened now, now if I want to know what is the R value of the x factor. That factor one factor given mu what will happen then, this is nothing, but R mu tau minus R mu.

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$$\begin{aligned}
 R(y/\mu) &= R(\mu, y) - R(\mu) \\
 &= R(\text{Full model}) - R(\text{Reduced model}) \\
 &= \sum_{i=1}^a \frac{y_i^2}{n} - \frac{y_{..}^2}{N} \\
 F_0 &= \frac{SS_{\text{treat}}/\text{dof}}{SS_E/\text{dof}} = \frac{SS_R/\text{dof}}{SS_E/\text{dof}} = \frac{R(y/\mu)/a-1}{SS_E/N-a} \\
 &\sim \underline{\underline{F_{a, N-a}}}
 \end{aligned}$$

So, that mean R of full model minus R of reduced model. So, what do you got in R of full model we have already seen this is y_i dot square by n i equal to 1 to a minus what is the R of reduced model this square by N . What is this value? This is nothing, but the treatment effect contribution sum square treatments sum square R , this is R .

So, anyhow using all those things now what happened, you got SS_E using this formula you are getting the that factor contribution or SS_R or as a statement by this formula 1 by n of this formula. So, I think what I have done here. So, this one y by n is there fine 1 by n of this formula then you have you can find out that F_0 value, F_0 value is what? F_0 value is our $SS_{\text{treatment}}$ y a degree of freedom by SS_{error} by degree of freedom from ANOVA point of view from regression point of view SS_{bar} by degree of freedom by SS_E by degree of freedom. This is nothing, but now SS_{bar} a is here R_{tau} given μ divided by a minus 1 and then SS_E already you know the formula is given to you. So, I am not writing here further SS_E by N minus a . Now, if this follows same thing a N minus a and rest of the things known to you.

So, very quickly I will show you that in ANOVA for the power each read data we have seen SS_T is 72,000 all most, treatment 66, SS_{error} is 53 like this and then this is the ANOVA table and we found out that there is treatment effects.

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ANOVA-Example (Power data)

Power (W)	Observations (Etch rate)					Total	Averages
	1	2	3	4	5		
160	575	542	530	539	570	2756	551.2
180	565	593	590	579	610	2937	587.4
200	600	651	610	637	629	3127	625.4
220	725	700	715	685	710	3535	707

$$SS_T = \sum_{i=1}^4 \sum_{j=1}^5 y_{ij}^2 - \frac{y_c^2}{N}$$

$$= (575)^2 + (542)^2 + \dots + (710)^2 - \frac{(12,355)^2}{20}$$

$$= 72,209.75$$

$$SS_{\text{Treatments}} = \frac{1}{n} \sum_{i=1}^4 y_i^2 - \frac{y_c^2}{N}$$

$$= \frac{1}{5} [(2756)^2 + \dots + (3535)^2] - \frac{(12,355)^2}{20}$$

$$= 66,870.55$$

$$SS_E = SS_T - SS_{\text{Treatments}}$$

$$= 72,209.75 - 66,870.55 = 5339.20$$

Source of Variation	Sum of Squares	Degrees of Freedom	Mean Square	F_0	P-Value
RF Power	66,870.55	3	22,290.18	$F_0 = 66.80$	<0.01
Error	5339.20	16	333.70		
Total	72,209.75	19			

Now, we have used the same thing for regression. What we have done all there are 20 observations, then x value for first observation 200, 200 like this, then y values are there, then regression model is fit then y corrected sum square everything.

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Example in Regression format

Observation	X value	Y value	Avg Y	(Yi-Avg Y)	Sqr(Yi-Avg Y)	Y predicted	error	sqr(error)
1	200	629	617.75	11.25	126.5625	643.02	-14.02	196.5604
2	220	725	617.75	107.25	11502.5625	693.56	31.44	988.4736
3	220	700	617.75	82.25	6765.0625	693.56	6.44	41.4736
4	160	570	617.75	-47.75	2280.0625	541.94	28.06	787.3636
5	160	539	617.75	-78.75	6201.5625	541.94	-2.94	8.6436
6	180	590	617.75	-27.75	770.0625	592.48	-2.48	6.1504
7	200	600	617.75	-17.75	315.0625	643.02	-43.02	1850.72
8	160	530	617.75	-87.75	7700.0625	541.94	-11.94	142.5636
9	180	593	617.75	-24.75	612.5625	592.48	0.52	0.2704
10	200	610	617.75	-7.75	60.0625	643.02	-33.02	1090.32
11	220	685	617.75	67.25	4522.5625	693.56	-8.56	73.2736
12	220	710	617.75	92.25	8510.0625	693.56	16.44	270.2736
13	160	575	617.75	-42.75	1827.5625	541.94	33.06	1092.964
14	160	542	617.75	-75.75	5738.0625	541.94	0.06	0.0036
15	220	715	617.75	97.25	9457.5625	693.56	21.44	459.6736
16	180	579	617.75	-38.75	1501.5625	592.48	-13.48	181.7104
17	180	610	617.75	-7.75	60.0625	592.48	17.52	306.9504
18	180	565	617.75	-52.75	2782.5625	592.48	-27.48	755.1504
19	200	651	617.75	33.25	1105.5625	643.02	7.98	63.6804
20	200	637	617.75	19.25	370.5625	643.02	-6.02	36.2404
				SST=	72209.75		SSE=	8352.46

Now, SS T is 72.209.75 here 209.75, then SS E is 8352.46, but here it is less so maybe that is because of the rounding error and other things may be there. But whatever may be the thing, but ultimately total is same and then is the predicted values we have taken for

2 decimal. So, the error is also put 2 decimal maybe that may be the effect or may be the approach from the approach also there is little different values.

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Example in Regression format

From Regression analysis, we get,

$$SST = (y_i - \bar{y})^2 = 72209.75$$
$$SSE = (y_i - \hat{y})^2 = 8352.46$$

From ANOVA model, we get,

ANOVA				
	df	SS	MS	F
Regression	1	63857.29	63857.29	137.6159
Residual	18	8352.46	464.0256	
Total	19	72209.75		

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And then what happened we found out that from regression also the statistics is very high and we are saying that it is significant.

So, from ANOVA as well as from regression both case you are finding that the power has effect on the each eth. So, any one way you can go, but please keep in mind here the degree of freedom each number of parameters to be estimated minus 1. So, intercept plus the model that coefficient regression coefficient for power only for 2 minus 1 and then residual is more and that is basically this how. So, that is MSE is 464, now what about MSE here 333.

So, find out if you can find out that there is, there may be calculation error please tell me in the forum or if you find out that know that there is even further or much closer explanation for the 2 also discuss, all those things will come.

Thank you very much for your patient hearing.