

Probability and Statistics
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Lecture - 55
LSE, MME

Previous lecture I introduced certain criteria for estimation; that means, if we are taking an estimator what properties it must satisfy. There are various other properties and we will be discussing them in detail. But now let me introduce the methods for finding out estimators because it is alright to say that this estimator is unbiased or this is consistent, but how do we get them. So, I mentioned in the brief introduction to the history that the initial methods that were proposed were like method of least squares, the method of moments, the maximum likelihood estimation etcetera. Let me introduce these.

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Least Squares Estimation

$(x_1, y_1), \dots, (x_n, y_n)$

$y_i = \alpha + \beta x_i + \epsilon_i, \quad i=1, \dots, n$

Sum of Squares of Errors

$$S = \sum \epsilon_i^2 = \sum_{i=1}^n (y_i - \alpha - \beta x_i)^2$$

We want to determine α and β in such a way that S is minimized.

$$\frac{\partial S}{\partial \alpha} = -2 \sum (y_i - \alpha - \beta x_i) = 0$$
$$\Rightarrow \sum x_i - n\alpha - \beta \sum x_i = 0$$

In the least square methods; so here we assume that the data is obtained in the form of variables like $x_1 y_1, x_2 y_2, x_n y_n$. For example, this may be related to certain relationship like certain variables which are related in the sense that y_i 's could be the weights of the persons and x_i 's could be the heights, x_i 's could be the heights of the parents and y_i 's could be the heights of the office springs etcetera. So, there could be various kinds of things where they are related.

However, the relationship is to be determined in the form of a linear relationship such as y_i is equal to $\alpha + \beta x_i$. So, we assume that the actual observations will introduce certain error say ϵ_i 's. So, the purpose is that we should estimate the parameters of the model that is α and β in such a way that the sum of squares of errors that is $\sum (y_i - \alpha - \beta x_i)^2$; let me call it S . So, in the least square methods, we want to find out α and β such that this S is a minimum; excuse me, S is minimized.

Now, by looking at the nature of this function, it is easy to see that the minimizing choices of α and β will be obtained when the first order derivative of S with respect to α and β are equal to 0 because here it is a squared quadratic function and both α and β ; that means, its bowl shaped function and therefore, the minimization will be occurred when the first derivative is 0. So, $\frac{\partial S}{\partial \alpha}$ that is equal to $-2 \sum (y_i - \alpha - \beta x_i) = 0$, which we can write as $\sum y_i - n\alpha - \beta \sum x_i = 0$ or we can write it as $\bar{y} = \alpha + \beta \bar{x}$ that is the first equation.

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or $\bar{y} = \alpha + \beta \bar{x} \dots (1)$

$$\frac{\partial S}{\partial \beta} = -2 \sum (y_i - \alpha - \beta x_i) x_i = 0$$

$$\Rightarrow \sum x_i y_i = \alpha \sum x_i + \beta \sum x_i^2 \dots (2)$$

Equations (1) & (2) are called normal equations.

Solving (1) & (2), we get

$$\hat{\beta} = \frac{S_{yx}}{S_{xx}} \quad \text{and} \quad \hat{\alpha} = \bar{y} - \hat{\beta} \bar{x}$$

These are least squares estimates of α and β .

$$S_{yx} = \sum (x_i - \bar{x})(y_i - \bar{y})$$

$$S_{xx} = \sum (x_i - \bar{x})^2$$

Second equation is obtained by $\frac{\partial S}{\partial \beta} = 0$; that means, $-2 \sum (y_i - \alpha - \beta x_i) x_i = 0$. After simplification this is resulting in $\sum x_i y_i = \alpha \sum x_i + \beta \sum x_i^2$. Let me call it equation number 2. So, equations 1 and 2 are called normal equations. So, if we

solve equations 1 and 2 then we get the least square estimates of alpha and beta. So, for example, if we solve it we will get this solving 1 and 2, we get beta hat is equal to S_{yx} by S_{xx} and alpha hat is equal to \bar{y} minus beta hat \bar{x} . So, these are least squares estimates of alpha and beta.

Here S_{yx} is $\sum (x_i - \bar{x})(y_i - \bar{y})$ and S_{xx} is equal to $\sum (x_i - \bar{x})^2$. It can be shown that this alpha hat and beta hat are actually unbiased. Now for that we have to make certain assumptions on the model, we have assumed that y_i and x_i are related through this relationship and we have introduced a random error here ϵ_i . So, if we make ϵ_i 's are i.i.d and if I put normal 0 sigma square.

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Handwritten mathematical derivation on a whiteboard:

$$E(\hat{\beta}) = E\left(\frac{S_{yx}}{S_{xx}}\right) = \frac{1}{S_{xx}} E(S_{yx}) = \frac{\beta S_{xx}}{S_{xx}} = \beta$$

$$S_{yx} = \sum_{i=1}^n x_i y_i - n \bar{x} \bar{y}$$

$$E(S_{yx}) = \sum x_i E(y_i) - n \bar{x} E(\bar{y})$$

$$= \sum x_i (\alpha + \beta x_i) - n \bar{x} (\alpha + \beta \bar{x})$$

$$= n \bar{x} \alpha + \beta \sum x_i^2 - \alpha n \bar{x} - n \beta \bar{x}^2$$

$$= \beta S_{xx}$$

$$E(\hat{\alpha}) = E(\bar{y} - \hat{\beta} \bar{x}) = \alpha + \beta \bar{x} - \beta \bar{x}$$

So the least squares estimators $\hat{\alpha}$ & $\hat{\beta}$ are unbiased for α & β respectively.

Then it can be easily shown that expectation of beta hat, so that will be expectation of S_{yx} by S_{xx} that is equal to; now in this model S_{xx} I can keep out and when we are assuming here that ϵ_i 's are normal 0 sigma square then y_i follows normal α plus βx_i and sigma square.

If we make use of this it is related to expectation of S_{yx} . Now let me calculate this S_{yx} term. So, S_{yx} is equal to $\sum x_i y_i - n \bar{x} \bar{y}$. So, if I take expectation of this, this is equal to $\sum x_i$ expectation of y_i minus $n \bar{x}$ expectation of \bar{y} . So, that is equal to $\sum x_i$ alpha plus βx_i minus $n \bar{x}$. Now if I know the expectation of y_i if I substitute for each of them here I will get expectation of \bar{y} as alpha plus

beta x bar. So, this term after simplification becomes n alpha x bar plus beta sigma x i square minus alpha n x bar minus n beta x bar square. So, this is becoming beta S x x. So, if we substitute this value here, I will get beta S x x by S x x which cancels out that is equal to beta. This beta at least square estimate of beta is an unbiased estimate for beta.

Similarly if I look at expectation of alpha hat that is equal to expectation of y bar minus beta hat x bar; now expectation of y bar is alpha plus beta x bar and expectation of beta hat we have prove to be beta so this cancels out. So, the least square estimators of alpha and beta are unbiased for alpha and beta respectively. We may also consider after substitution an estimate for sigma square in this model.

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The image shows a handwritten derivation on a light blue background. At the top, it states: $\sum_{i=1}^n (y_i - \hat{\alpha} - \hat{\beta}x_i)^2 = \text{Error Sum of Squares} = \text{SSE}$. Below this, it shows the expansion of SSE: $\text{SSE} = \sum (y_i - \bar{y} + \hat{\beta}\bar{x} - \hat{\beta}x_i)^2$, which is then expanded into $\sum (y_i - \bar{y})^2 + \hat{\beta}^2 \sum (x_i - \bar{x})^2 + 2\hat{\beta} \sum (x_i - \bar{x})(y_i - \bar{y})$. This is further simplified to $\text{S}_{yy} + \frac{\text{S}_{yx}^2}{\text{S}_{xx}} - 2 \frac{\text{S}_{yx}}{\text{S}_{xx}} \cdot \text{S}_{yx}$, and then to $\text{S}_{yy} - \frac{\text{S}_{yx}^2}{\text{S}_{xx}}$. Finally, it states $E\left(\frac{\text{SSE}}{n-2}\right) = \sigma^2$ and $\text{MSE} = \frac{\text{SSE}}{n-2}$ is an unbiased estimator for σ^2 .

We may put y i minus alpha hat minus beta hat x i whole square what is this term our initial error some of a squares was y i minus alpha minus beta x i. Once I have estimated alpha and beta and I substitute then this is my estimated value of y I; this small y i is the actual value which has been observed, whereas from the model I can estimate it to be alpha hat plus beta hat x i. So, this is actually the error sum of squares which we call SSE. So, this is the value of this.

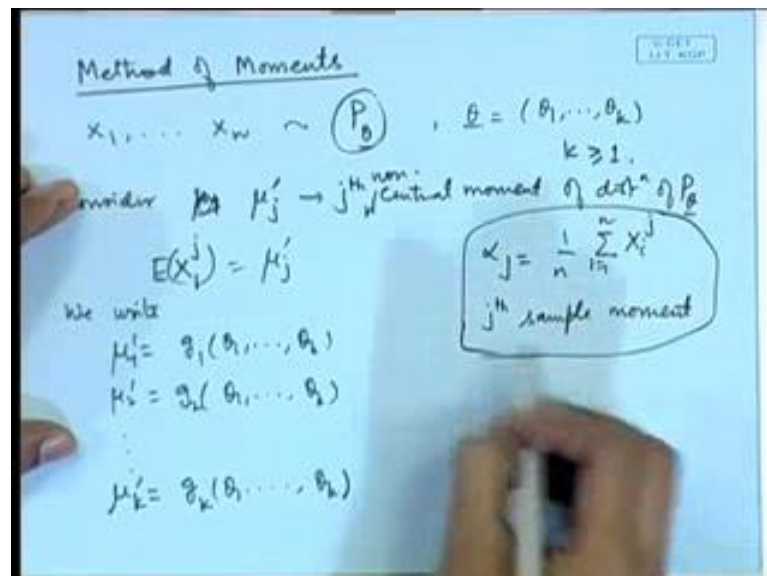
Now if I substitute this y i minus alpha hat. So, alpha hat is equal to y bar minus beta hat x bar minus beta hat x I, so this becomes plus here whole square. Let us simplify this term that is equal to sigma y i minus y bar whole square plus beta hat square sigma x i

minus \bar{x} whole square plus twice $\hat{\beta}_1(x_i - \bar{x}) - (y_i - \bar{y})$ summation with a minus sign here, I have taken the cross product term here.

This is equal to S_{yy} plus; now $\hat{\beta}$ is equal to S_{yx} by S_{xx} . So, this is S_{yx}^2 by S_{xx}^2 into S_{xx} minus twice S_{yx} by S_{xx} into S_{yx} . So, that is equal to S_{yy} minus S_{yx}^2 by S_{xx} . Then it can be shown that this will have expectation of SSE divided by $n - 2$ that will be equal to σ^2 . So, this we call MSE mean square error. This is an unbiased estimator. In modern statistics this particular analysis is coming under the topic of regression analysis where we study various kinds of relationships between given variables. So, suppose we are given variables x_1, x_2, \dots, x_k and y where y is the response variable and x_1, x_2, \dots, x_k are the explanatory variables then we fit various kinds of relationships between y and x_1, x_2, \dots, x_k .

And we derive the estimates of the parameters through least squares method. This methodology is also used for all types of linear models including those which are used in the analysis of variance. So, we will not perceive too much about this in this particular discussion.

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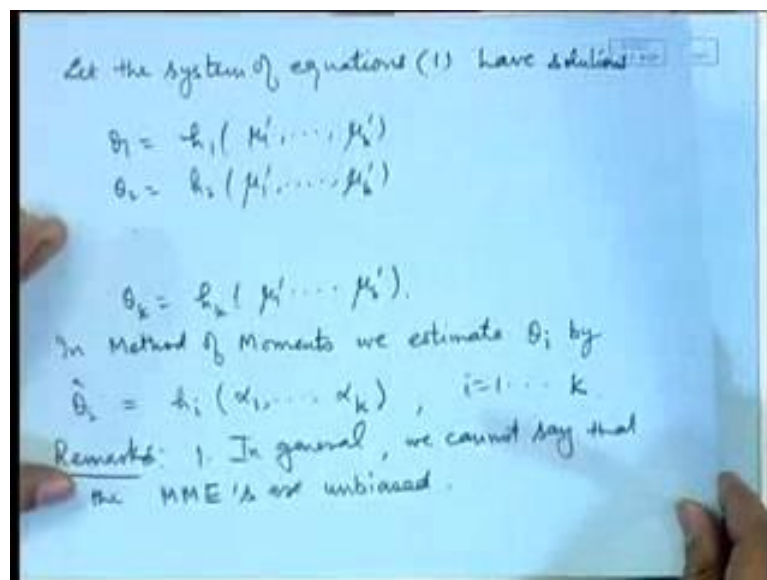


Next we consider the method of moments; this is attributed to Karl Pearson. The model is as follows, if we have a random sample say x_1, x_2, \dots, x_n from a population with parameter θ . So, θ may be in general 1 dimensional 2 dimensional or k

dimensional. So, here k is greater than or equal to 1, what we do? We consider μ_i or say μ_j prime that is the j th central moment sorry non central moment of distribution of p theta. That means, if I say that x_1, x_2, \dots, x_n is a random sample from here that at means expectation of x_1 to the power j that is actually μ_j prime.

In general these moments will be certain parametric functions; for example, I may have say μ_1 prime is equal to g_1 of $\theta_1, \theta_2, \dots, \theta_k$ μ_2 prime may be some function say g_2 of $\theta_1, \theta_2, \dots, \theta_k$. If I have k parametric function k parameters then I write up to k th. Now estimate let us write here I define α_j . So, α_j , I define to be $\frac{1}{n} \sum x_i$ to the power j i is equal to 1 to n ; that means, the j th sample moment. If we consider this let us write this system of equations as 1.

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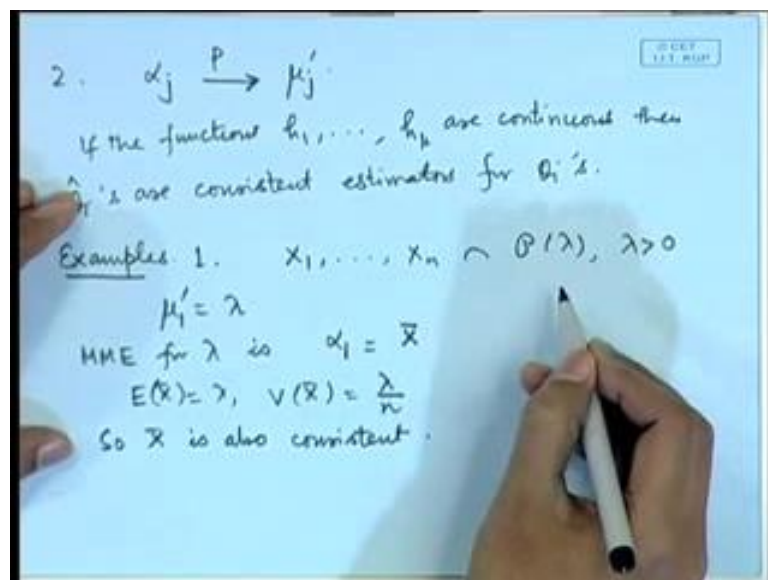
Let the system of equations 1 have solutions- say θ_1 is some function of h_1 of μ_1 prime, μ_2 prime, μ_k prime; θ_2 is some function h_2 of μ_1 prime, μ_2 prime, μ_k prime; θ_k is equal to some function of μ_1 prime, μ_2 prime, μ_k prime.

In method of moments we estimate θ_i by θ_i hat, let me call it h_i and in place of μ_1 prime, μ_2 prime, μ_k prime substitute $\alpha_1, \alpha_2, \alpha_k$ for i is equal to 1 to k . So, these are called method of moment's estimators of the parameters. So, basically what is the philosophy behind the method of moments? I am estimating the j th population moment by the j th central moment that is μ_j prime is estimated by α_j . So, whatever parametric function is coming to us for estimation, we substitute the

corresponding because the parametric functions will be sum functions of the moments and then whatever moment term is coming there we simply substitute the corresponding sample moment there.

In short this is the method of moments. So, like we had seen that the least square estimates are unbiased. But in general we cannot say that the method of moment's estimators, so I will use the word MME is in general they may not be unbiased. So, sometimes they may be unbiased, sometimes they may not be unbiased. However, consistency may be true.

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In particular we have say alpha j; this is consistent for mu j prime by the weak law of large numbers this convergence is valid. So, if the functions h 1, h 2, h k are continuous then theta i hats are consistent estimators for theta i is. So, consistency may be true and in most of the practical cases this may actually happen. However, unbiasedness is not guaranteed.

Let me explain this method by solving certain example, you may see that many time this is extremely simple, suppose I say x 1, x 2, x n follow Poisson lambda distribution. So, here you can see only 1 parameter is coming. So, we look at only the first moment mu 1 prime is lambda; that means, method of moments estimator for lambda is simply alpha 1 that is x bar. So, we had actually seen that x bar is here unbiased. In fact, it will be consistent also because variance of x bar will be expectation of x bar is lambda and

variance of \bar{x} will be actually λ by n because the variance of a Poisson distribution is same as the mean. So, variance will become λ by n .

So, \bar{x} is also consistent. So, you can see actually many times this method of moments estimator may be extremely simple.

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2. $X_1, \dots, X_n \sim N(\mu, \sigma^2)$

$$\begin{aligned} \mu_1' &= \mu & \mu &= \mu_1' \\ \mu_2' &= \mu^2 + \sigma^2 & \sigma^2 &= \mu_2' - \mu_1'^2 \end{aligned}$$

$$\hat{\mu}_{MME} = \bar{X}$$

$$\hat{\sigma}_{MME}^2 = \frac{1}{n} \sum X_i^2 - \bar{X}^2 = \frac{1}{n} \sum (X_i - \bar{X})^2 = \left(\frac{n-1}{n}\right) S^2$$

$$E(\bar{X}) = \mu, \quad E(\hat{\sigma}^2) = \left(\frac{n-1}{n}\right) \sigma^2$$

So $\hat{\sigma}^2$ is not unbiased.
However both are consistent.

Let me take another example say x_1, x_2, \dots, x_n follow normal μ, σ^2 , now this is a 2 parameter situation. So, we will write 2 moments. So, μ_1' is equal to μ , what is μ_2' ? μ_2' is $\mu^2 + \sigma^2$ that is a second moment. So, from here μ is equal to μ_1' the solution and σ^2 is equal to $\mu_2' - \mu_1'^2$. So, method of moments estimators will be for μ , it will be simply \bar{x} and for $\hat{\sigma}^2$ this will be $\frac{1}{n} \sum x_i^2 - \bar{x}^2$ that is $\frac{1}{n} \sum (x_i - \bar{x})^2$ which we can write as $\frac{1}{n} \sum (x_i - \bar{x})^2$.

You can also write it as $\frac{n-1}{n} S^2$. So, which is not S^2 , in fact, you can see expectation of \bar{x} is μ , but expectation of $\hat{\sigma}^2$ is $\frac{n-1}{n} \sigma^2$. So, this $\hat{\sigma}^2$ is not unbiased already I have proved that \bar{x} as well as $\hat{\sigma}^2$ they are consistent.

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3. $X \sim \text{Bin}(n, p)$
 If n is known
 $E\left(\frac{X}{n}\right) = p$, So $\hat{p}_{\text{MLE}} = \frac{X}{n}$
 However if n is also unknown.

$$\mu_1' = np$$

$$\mu_2' = np(1-p) + n^2 p^2 = np + n(n-1)p^2$$

$$p = \mu_1' - \mu_2' + \mu_1'^2$$

$$\mu_2' - \mu_1' = n(n-1)p^2$$

$$\mu_1' = np \Rightarrow \mu_1'^2 = n^2 p^2$$

$$\frac{\mu_2' - \mu_1'}{\mu_1'^2} = \frac{n-1}{n} = 1 - \frac{1}{n} \Rightarrow \frac{1}{n} = 1 - \frac{\mu_2' - \mu_1'}{\mu_1'^2}$$

Let us consider say x following binomial $n p$, now if n is known then you have expectation of x by n is equal to p . So, \hat{p}_{MLE} is simply x by n ; however, if n is also unknown there may be a situation where we do not know how many number of trials have been conducted in the binomial distribution and then I have to estimate both n and p , in that case then you may write the 2 moments you write μ_1' is equal to np and μ_2' is equal to $np(1-p) + n^2 p^2$.

From here, we solve for n and p . So, you can look at the solutions the values will turn out to be slightly combustion we get here p is equal to $\mu_1' - \mu_2' + \mu_1'^2$. So, you may just write down the values here p is actually np that is $np + n^2 p^2 - n$ that is $n(n-1)p^2$. So, $\mu_2' - \mu_1'$ is divided by is equal to $n(n-1)p^2$ and μ_1' is equal to np . So, this implies $\mu_1'^2$ is equal to $n^2 p^2$. So, we divide; if we divide, we will get $\mu_2' - \mu_1'$ divided by $\mu_1'^2$ is equal to $n-1$ by n that is $1 - \frac{1}{n}$.

This implies $\frac{1}{n}$ is equal to $1 - \frac{\mu_2' - \mu_1'}{\mu_1'^2}$.

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$$\Rightarrow \frac{1}{n} = \frac{\mu_1^2 + \mu_1' - \mu_2'}{\mu_1^2}$$

$$\Rightarrow n = \frac{\mu_1^2}{\mu_1^2 + \mu_1' - \mu_2'}$$

$$p = \frac{\mu_1^2 + \mu_1' - \mu_2'}{\mu_1}$$

So MME's for n & p are

$$\hat{n} = \frac{x^2}{x^2 + x - x^2} = x$$

$$\hat{p} = \frac{x^2 + x - x^2}{x} = 1$$

} absurd

This we can write as $\frac{1}{n}$ is equal to $\mu_1^2 + \mu_1' - \mu_2'$ prime by μ_1^2 . So, n is equal to μ_1^2 by $\mu_1^2 + \mu_1' - \mu_2'$ prime similarly p is equal to because from the first $\frac{1}{p}$ is equal to μ_1' by n . So, if n is already determined we just substitute there, so, μ_1' prime divided by this so that will give me $\mu_1^2 + \mu_1' - \mu_2'$ prime by μ_1' . So, method of moment's estimators for n and p are so for n , it will become now here I have taken only 1 observation x . So, we simply substitute x^2 divided by now this will lead to some peculiar problem which you can see $x^2 + x - x^2$.

This cancels out, you get only x , if you put p then you will get $x^2 + x - x^2$ divided by x which is canceling out and you get only one this is leading to absurd situation. Now why this is coming? Since I have here 2 observations, 2 parameters n and p it is not possible to estimate both of them with one observation; that means, I need to take a sample here. So, when n is known it is alright that is use x by n , but if n is unknown we need sample. So, let me say sample is x_1, x_2, \dots, x_N . So, in that case this situation can be resolved.

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$$\hat{\sigma}_{MME}^2 = \frac{\bar{x}^2}{\bar{x}^2 + \bar{x} - \frac{1}{N} \sum x_i^2} = \frac{\bar{x}^2}{\bar{x} - \frac{1}{N} \sum (x_i - \bar{x})^2}$$

$$\hat{\mu}_{MME} = \frac{\bar{x} - \frac{1}{N} \sum (x_i - \bar{x})^2}{\bar{x}}$$

4. $X_1, \dots, X_n \sim U(a, b), \quad a < b.$

$$\mu_1' = \frac{a+b}{2}, \quad \mu_2' = \frac{a^2 + b^2 + ab}{3}$$

$$a = \mu_1' - \sqrt{\frac{3}{2}(\mu_2' - \mu_1'^2)}, \quad \hat{a} = \bar{x} - \sqrt{\frac{3}{2} \sum (x_i - \bar{x})^2}$$

$$b = \mu_1' + \sqrt{\frac{3}{2}(\mu_2' - \mu_1'^2)}, \quad \hat{b} = \bar{x} + \sqrt{\frac{3}{2} \sum (x_i - \bar{x})^2}$$

So, here the MME is will be N hat MME is equal to now \bar{x} square divided by \bar{x} square plus \bar{x} minus $\frac{1}{n} \sum x_i^2$ which we can also write as \bar{x} square divide by \bar{x} minus $\frac{1}{n} \sum (x_i - \bar{x})^2$ whole square.

And $\hat{\mu}_{MME}$ will be equal to \bar{x} minus $\frac{1}{n} \sum (x_i - \bar{x})^2$ divided by \bar{x} . So, here you can see the form is quite complicated and the question of checking unbiasedness etcetera is ruled out because we cannot actually evaluate the expectations of ratios of this type of functions consistency, you can still be considered because \bar{x} will be consistent for μ and for σ^2 ; that means, if I considered \bar{x} by capital N then that will be consistent for μ etcetera. So, the consistency may hold, but the unbiasedness is totally ruled out. In fact, it cannot be even checked let us take another example, suppose we consider a 2 parameter uniform distribution, in a 2 parameter uniform distribution we have a and b as the parameters.

Now, let us consider say first moment here the first moment is $a + b$ by 2 and the second moment is $a^2 + b^2 + ab$ by 3, How many times you will see that when we have multi parameter situation the solutions of the equation may not be trivial because the equations need not be necessarily linear in general they may be non-linear equations as we have seen in the binomial case and same thing is true in the uniform distribution case also. So, if you solve these things, you will get a as μ_1'

minus $a\sqrt{3}$ into μ_2' minus $\mu_1'^2$ and b is equal to μ_1' plus $\sqrt{3}\mu_2'$ minus μ_1' square.

The method of moments estimators are obtained by substituting α_1 and α_2 forming μ_1' and μ_2' . So, I will get $\bar{x} - a\sqrt{3}$ by $\frac{1}{n} \sum x_i - \bar{x}$ and \hat{b} is equal to $\bar{x} + \sqrt{3} \frac{1}{n} \sum x_i - \bar{x}$ whole square. So in fact, you can see that many times the form of the method of moment's estimators may not be very convenient to handle. In fact, again if I ask here to check the unbiasedness expectation of \bar{x} may be $a + b/2$, but calculation of the expectation of this quantity is not that simple and therefore, in general the method of moments estimator does not seem to give very nice looking estimates.

In some of the situations of course, like in the Poisson distribution case are normal distribution case; we got nice solutions, but in many of the 2 parameter are more number of parameter situations that the method of modes estimators may not be always very nice.