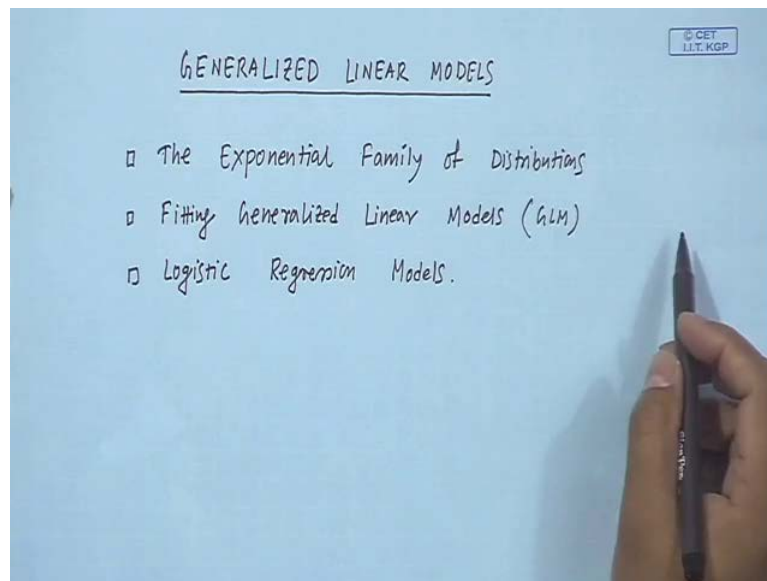


Regression Analysis
Prof. Soumen Maity
Department of Mathematics
Indian Institution of Technology, Kharagpur

Lecture - 30
Generalized Linear Models

Hi, so today, I will start a new module called generalized linear models.

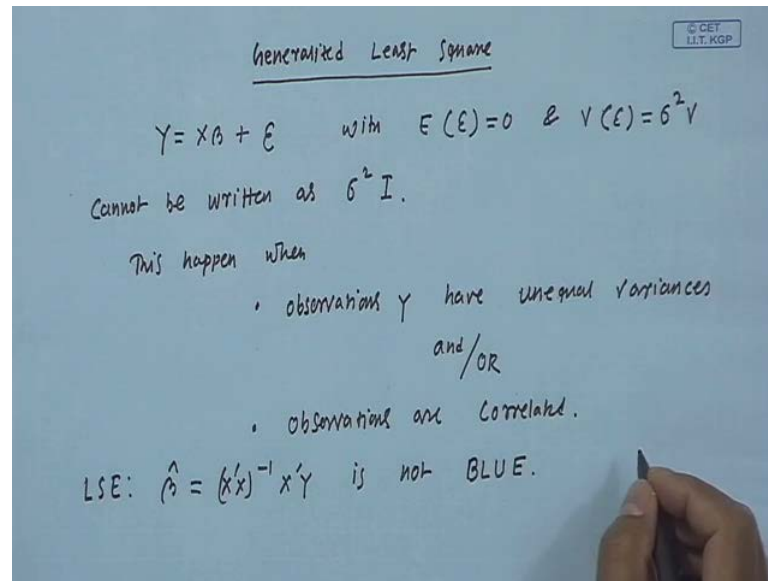
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And, here is the content of this module. 1st will talk about exponential family of distributions and then, fitting generalized linear models and logistic regression models ok. So, before I start this module I want to recall. We talked about a module called transformation and weighting to correct a model inadequacy. And there, we have started something called generalized least square of which weighted least square is a particular case. And, the generalized least square is concerned about the application of ordinary least square technique in situation where y equal to x beta plus epsilon. This is the model and exception of epsilon is equal to 0 but the variance of epsilon is equal to sigma square into v .

So, this v is the variance covariance matrix of the added term which cannot be written in the form of sigma square into i . So, let me write this thing in detail.

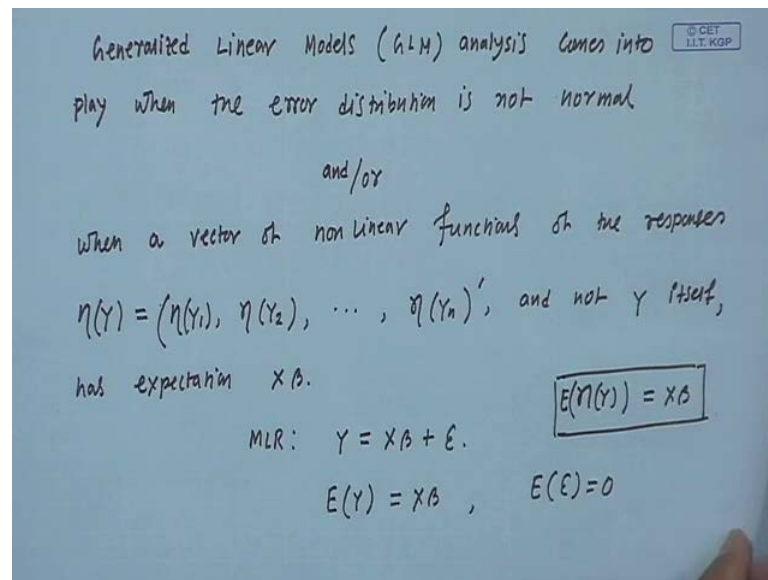
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So, the generalized least square so, this one is concerned about the application of ordinary least square technique in the situation where Y equal to X beat plus epsilon with exception of epsilon is equal to 0. And, variance of this epsilon is the variance, co variance matrix is equal to sigma square into V and this cannot be written as sigma square I ok. So, we have started that, you know this happen, when the observations Y have unequal variances and or observations are co related. That is why you know in this variance co variance matrix V the up diagonal elements are not equal to 0. So, in either case you know the conditions of gross mass of theorems are highlighted.

So, the least square estimate that is beta hat equal to X prime X inverse, X prime Y is not the best linear unbiased estimated. So, here you know we have started in the generalized least square, we have stared transformation on this module to get the best linear unbiased estimated. And also, in that module like, that is transformations and weighting to correct model inadequacy we talked about variance stabilization transformation, which deals with the situation when the response variable are having, you know inequality in variance ok.

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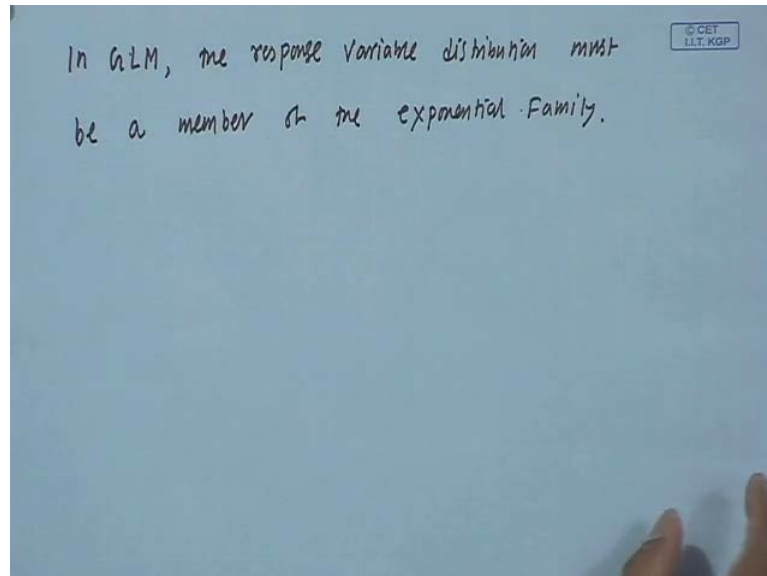
So, the generalized linear models, that is a G L M analysis comes into play when the error distribution is not normal. So, the distribution of error is not normal or which is equivalent to say that, the distribution of response variable is not normal. In that case, we need to use generalized linear model. So, you should understand the different between the generalized linear model and the generalized least square because generalized least square is used to deal with non constant variance in response variable. Or of course, when the observations are correlated whereas know this generalized linear model is used when the error distribution is not normal ok.

So, either the error distribution is not normal and or when a vector of non-linear functions of the response is, that is eta Y which is equal to: eta Y 1, eta y 2 and eta Y n. This vector and, not Y itself has exception X beta. So, I am not in position to explain this thing at this moment but what I can say here is that, in case of multiple linear regression model, we consider the model Y equal to X beta plus epsilon which is same as, we consider the model like expectation of Y is equal Y beta because of the fact that expectation of epsilon is equal to 0. So, in the usual linear model expectation of Y equal to X beta ok. So, that can be written in the linear combination of the regression coefficients but here you cannot. This is not true.

So here, instead of expectation of Y equal to X beta, there exist non-linear function, it is eta may be eta Y, expectation of eta Y is equal to X beta. Anyway, we will come to this

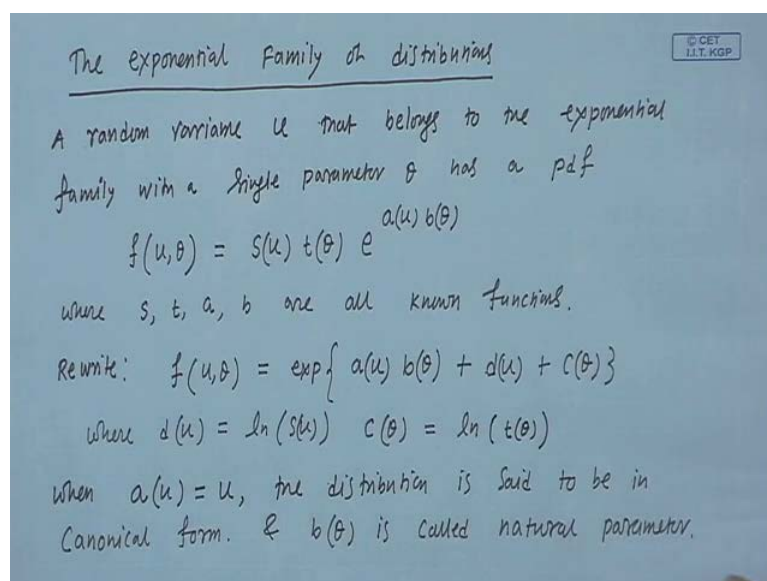
point at the end of this topic or module. So, let me mention one more thing. When we use, you know this generalized linear model.

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In generalized linear model G L M, the response variable distribution is not normal. That is what we know I mean, if it is not normal then we go for generalized linear model. But, the response variable distribution must be a member of the exponential family. So, next what will do is that we will learn, what you mean by this exponential family.

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So, the exponential family of distribution ok so, a random variable u . Here, we denote you know random variable by u , usually use the notation x or y , that belongs to the exponential family with a single parameter θ , has a probability density function $f(u, \theta)$, which is of the form $s(u) t(\theta) \exp\{a(u) b(\theta) + d(u) + c(\theta)\}$ ok. So, if the p d f of the random variable u is of this form then, we say that distribution in the exponential family where s, t, a, b are all known functions. So, let me rewrite this p d f. So, I can write this $f(u, \theta)$ as $\exp\{a(u) b(\theta) + d(u) + c(\theta)\}$ ok, where $d(u)$ is equal to $\ln s(u)$.

So, this is a log base e and $c(\theta)$ is equal to $\ln t(\theta)$, right ok. So, the p d f of random variable u which is exponential family can be written in this form and when $a(u)$ is equal to u , that is $a(u)$ is a identity function, the distribution if the distribution is said to be in canonical form and this is important. This $b(\theta)$ is called the natural parameter ok. And also, there could be you know several parameters in distribution like, if you consider as a binomial distribution it has 2 parameter: one is n which is the total number of trials and p , (Refer Time: 17:55) p is the probability of success in one trial. So, here we need to decide which one is correct parameter interest. If p is the parameter of interest then the other parameter n is called nuisance parameter. So, let me write it formally.

(Refer Slide Time: 18:21)

parameters other than the parameter of interest θ
are called nuisance parameters

Some Members of the exponential Family

1. Normal distribution $N(\mu, \sigma^2)$

$$f(u, \mu) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2} \left(\frac{u-\mu}{\sigma}\right)^2}, \quad -\infty < u < \infty$$

$$= \exp\left\{u \cdot \frac{\mu}{\sigma^2} + \left[\frac{-\mu^2}{2\sigma^2} - \frac{1}{2} \ln 2\pi\sigma^2\right] - \frac{u^2}{2\sigma^2}\right\}$$

$$a(u) = u, \quad b(\theta) = \frac{\mu}{\sigma^2}, \quad c(\theta) = \frac{-\mu^2}{2\sigma^2} - \frac{1}{2} \ln 2\pi\sigma^2, \quad d(u) = \frac{-u^2}{2\sigma^2}$$

So, parameters other than the parameter of interest θ are called nuisance parameters ok. So, let me talk about some members of the exponential family ok. So, the 1st one is

say normal distribution with a parameter μ and σ^2 right. So, you know that the p d f of, now see you know whether the p d f of normal distribution which is $f(u; \mu, \sigma^2)$. So, I am writing $f(u; \mu, \sigma^2)$ because u is the random variable and μ is the parameter of interest here and σ^2 is a nuisance parameter. So, let me see whether the p d f can be written in that form. So, this one is equal to $\frac{1}{\sqrt{2\pi\sigma^2}}$ $e^{-\frac{1}{2\sigma^2}(u-\mu)^2}$ and you know that this u is from minus infinity to plus infinity.

Now, whether I can write this in this form, say exponential you can check that this is $e^{-\frac{1}{2\sigma^2}(u-\mu)^2}$ into μ by σ^2 plus minus μ square by $2\sigma^2$ minus half $\ln 2\pi\sigma^2$ so, I will put this in bracket, minus u square by $2\sigma^2$ ok. So, this term is coming from here and this three are basically this exponent here ok. Now here, I need to indentify all minus a , u , b theta, c theta and d u . So, here I can see that a u is equal to u . This a u and b theta is μ by σ^2 and what is c theta? In fact c μ but, you know theta stands for parameter of interest so, here the parameter of interest is μ and this involve μ . So, c theta is equal to minus μ square by $2\sigma^2$ minus half $\ln 2\pi\sigma^2$ and d u is equal to minus u square by σ^2 .

So since, a u is equal to u so normal distribution is in canonical form and this is the natural parameter, μ is the μ by σ^2 is natural. I mean in fact μ is the natural parameter because μ is the parameter of interest ok. So, next will, I mean basically I will try to write down many distributions which are in the exponential family.

(Refer Slide Time: 24:19)

2. Binomial distribution $\text{Bin}(n, p)$

$$f(u, p) = \binom{n}{u} p^u (1-p)^{n-u}, \quad u = 0, 1, \dots, n.$$
$$= \binom{n}{u} \left(\frac{p}{1-p}\right)^u (1-p)^n$$
$$= \exp\left\{ u \ln\left(\frac{p}{1-p}\right) + n \ln(1-p) + \ln\binom{n}{u} \right\}.$$

$a(u) = u$, $b(\theta) = \ln\left(\frac{p}{1-p}\right) = \text{natural parameter.}$

$c(\theta) = n \ln(1-p)$, $d(u) = \ln\binom{n}{u}$

The next one is, see binomial distribution. So, you follow binomial distribution by parameter n and p and p is the parameter of interest and n is the nuisance parameter. So, here you call to mass function but, if u p as you know this is, n c u . So, here the u stands for the number of successes in n trials when, the probability of success is p ok. So, the probability mass function is n c u p to the power of u and into $1 - p$ to the power of $n - u$ and the u , the range of u is the number of successes would be: $0, 1$ and it could go up to n , out of n trials ok. Now, see whether this can be written in the exponential form, that the form you know I talk about. So, this is equal to n c u . I can write this as p by $1 - p$ to the power of u $1 - p$ to the power of n .

Now, let me write this as exponential $u \log p$ by $1 - p$ plus $n \log 1 - p$ plus $\log n$ c u ok. So, let me identify now. The functions a u here is equal to u b θ , which is the natural parameter, b θ is $\ln p$ by $1 - p$. I repeat again this natural parameter is important thing, we need to know what is the natural parameter for particular distribution. So, b θ is natural parameter which is $\ln p$ by $1 - p$, is the natural parameter. And of course, then c θ is $n \ln 1 - p$ and d u is equal to $\ln n$ c u . So, this does not involve any parameter of interest ok. So, c θ means it should involve parameter of interest in this function so the parameter of interest is p .

So, c θ is this quantity ok and also this binomial distribution is in the canonical form. Next, will talk about Poisson distribution.

(Refer Slide Time: 28:10)

3. Poisson Distribution $P(\lambda)$

$$f(u, \lambda) = \frac{e^{-\lambda} \lambda^u}{u!}, \quad u = 0, 1, \dots$$

$$= \exp \{ u \ln \lambda - \lambda - \ln u! \}$$

$a(u) = u$, $b(\theta) = \ln \lambda$, $c(\theta) = -\lambda$

↓
natural parameter.

$d(u) = -\ln u!$

Poisson distribution, with parameter lambda and you know that the probability density function for Poisson is $f(u, \lambda)$ is equal to $e^{-\lambda} \lambda^u$ divided by $u!$ and here, u is equal to: 0, 1 up to infinity. And, this can be written as exponential $u \ln \lambda - \lambda - \ln u!$ ok. So, it clearly, here my $a(u)$ is equal to u , so it is canonical form, my $b(\theta)$ is $\ln \lambda$. So, this is the parameter, this is natural parameter and my $c(\theta)$ is equal to $-\lambda$ and $d(u)$ is equal to $-\ln u!$ and here is the natural parameter. So, this is regarding the Poisson distribution. So, it is in the exponential family.

(Refer Slide Time: 30:10)

4. Gamma distribution with parameter θ or interest
& α as nuisance parameter.

$$f(u, \theta) = \frac{\theta^\alpha u^{\alpha-1} e^{-\theta u}}{\Gamma(\alpha)}, \quad \alpha, \theta > 0, \quad u > 0$$

$$= \exp \{ -\theta u + (\alpha \ln \theta - \ln \Gamma(\alpha)) + (\alpha-1) \ln u \}$$

$a(u) = u$, $b(\theta) = -\theta$

5. exponential distribution $f(u, \theta) = \theta e^{-\theta u}, \quad u > 0$
 $\theta > 0$

$$= \exp \{ -u\theta + \ln \theta \}$$

$b(\theta) = \theta = \text{natural parameter.}$

Next, let me talk about number 4, gamma distribution ok with parameter theta of interest and alpha as nuisance parameter. And, here is the p d f so, f u theta is equal to theta to the power of alpha u to the power of alpha minus 1 e to the power of minus theta u by gamma alpha. So here, all this alpha m theta, they are greater than 0 and u is greater than equal to 0. Now, you write it in the exponential form. So, exponential minus theta u plus alpha log theta minus log gamma alpha, you put them in one bracket because this basically (Refer Time: 32:00) b theta plus alpha minus 1 l n u, is coming from here right.

So, now you can identify the you know this is a u is equal to u b theta is equal to minus theta and this equal to c theta and d u ok. The next one is called exponential distribution. So here, the p d f of this exponential distribution f u theta which is obtained by just putting alpha equal to 1 here so, this is theta into e to the power of minus theta u. So, u is greater than equal to 0 and theta is greater than 0. So, this can be written as exponential minus u theta plus 1 n theta ok. So, you understood that you know the a u equal to u and b theta equal to theta and c theta equal to log n theta right. So, the natural parameter here, so here b theta is equal to theta which is natural parameter ok. So, you are almost done. Next, we will talk about one more distribution which is called negative binominal distribution.

(Refer Slide Time: 34:12)

6. Negative Binomial distribution

The variable u is the no. of failures observed to attain r successes in binomial trials with prob of success θ

$$f(u, \theta) = \binom{r+u-1}{r-1} \theta^r (1-\theta)^u, \quad u = 0, 1, \dots$$

$$= \exp \left\{ u \ln(1-\theta) + r \ln \theta + \ln \binom{r+u-1}{r-1} \right\}$$

$a(u) = u, \quad b(\theta) = \ln(1-\theta) \rightarrow$ Natural parameter.

$c(\theta) = r \ln \theta, \quad d(u) = \ln \binom{r+u-1}{r-1}$

So, negative binominal distribution so, I hope that you know you understand the experiment here. The variable u is the number of failures observed to attain r successes

in binomial trial with probability of success theta. And then, the probability mass function of this one can be written as $f(u, \theta) = \binom{r}{u} \theta^u (1-\theta)^{r-u}$. I hope you understand why this is, this is the probability mass function, theta to the power of r minus u, theta to the power of u. So u, the number of failure before to obtain r successes it can be it can start from 0, 1 anything ok. So, this can be, my concern is check whether this negative binomial distribution this, is in the exponential family or not. So, this is exponential $u \log(1-\theta) + r \log \theta + \ln \binom{r}{u}$.

So, you must understand that here my a(u) is equal to u, my b(theta) is equal to $\ln(1-\theta)$ so, the natural parameter this is the natural parameter. I am talking about every time because it is this is important to for the generalized linear model and my c(theta) is of course, $r \ln \theta$ and c'(u) is equal to $\ln \theta + u \ln(1-\theta)$. So, this shows that the negative binomial distribution is in the exponential family ok. So, next will talk about the expected value and variance of this a(u).

(Refer Slide Time: 38:14)

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Expected value & variance of $a(u)$

$$E(a(u)) = -\frac{c'(\theta)}{b'(\theta)} \quad \& \quad V(a(u)) = \frac{b''(\theta) c'(\theta) - c''(\theta) b'(\theta)}{[b'(\theta)]^3}$$

Example Binomial $a(u) = u, \quad b(\theta) = \ln\left(\frac{p}{1-p}\right), \quad c(\theta) = n \ln(1-p)$

$$b'(\theta) = \frac{1}{p(1-p)} \quad \left| \quad c'(\theta) = \frac{-n}{1-p}$$

$$b''(\theta) = \frac{2p-1}{[p(1-p)]^2} \quad \left| \quad c''(\theta) = \frac{-n}{(1-p)^2}$$

$$E(a(u)) = E(u) = \frac{n}{1-p} * p(1-p) = \frac{np}{1-p}, \quad V(a(u)) = V(u) = np(1-p).$$

So, expected value and variance of a(u) so, I am not going to derive it in terms of c(theta) and b(theta). So, you can check that this is E(a(u)), the expected value of function is minus c'(theta) by b'(theta) and the variance of a(u) is equal to b''(theta) c'(theta) minus c''(theta) b'(theta). So, this transfer the double durability of c(theta) with respect to theta so, b'(theta) by b'(theta) to the power of 3, just you know you believe me this is correct. I am just giving one example of say, binomial. In

case of binomial you just check that we had this a_u equal to u and we had b_θ , natural parameter that was $\log p$ by $1 - p$ and c_θ was $n \log n(1 - p)$ ok. Now, if you compute say, so you know b_θ so you can compute b'_{θ} that is, equal to $1/p - 1/(1 - p)$.

So, you can compute b''_{θ} , double derivative that is equal to $1/p^2 + 1/(1 - p)^2$ and similarly, you do for c_θ . So, c'_{θ} is equal to $-n/p + n/(1 - p)$, c''_{θ} is equal to $n/p^2 + n/(1 - p)^2$. So, now we can check that, you know that for binomial distribution expected of u is np so, you can check that expectation of a_u which is nothing but binomial it is expectation of u which is equal to $-c'_{\theta}$. So, that is $n/p + n/(1 - p)$ by p so, that is np . You know that for binomial distribution expected value is np and you can check that variance of a_u is equal to variance of u here which is equal to $np(1 - p)$. Just put log all this here ok.

So, this is sort of you know preparation for the generalized least square because, we told that you know generalized least square is used when distribution of response variable is not normal but it is distribution is from the exponential family. So, now we have you know idea about distributions are may be this is not interested list but, we know some distribution which are in the exponential family like: binomial, Poisson, normal, gamma, exponential, negative binomial. These are the example we just prove they are in the exponential family. Now, the thing is that suppose you have a set of observation like: x_i, y_i and the response variable y_i is not in normal and it is say from it is from the binomial distribution, why I follows binomial with parameter n_i, p_i .

So, p_i is the parameter of interest and n_i is the nuisance parameter. Then, how to deal with such situation because till now, we know that we talked about only if, y follow is normal using the Gauss Markov theorem normal also in the independent identical distribution. Then, by Gauss Markov theorem we know that the least estimate provide the best linear unbiased estimated for the regression coefficient. So, now will talk about how to fit a generalized in the situation when the response variable is not normal but, it is the distribution of the responsible variable is from exponential family ok.

(Refer Slide Time: 44:42)

Fitting Generalized Linear Model

Suppose we have a set of independent observations
 (Y_i, \tilde{x}_i') , $i=1(1)n$, $\tilde{x}_i' = (x_{i1}, x_{i2}, \dots, x_{ip})$ from
 some exponential type distribution of canonical form
 [i.e. $a(Y) = Y$]. The joint pdf is

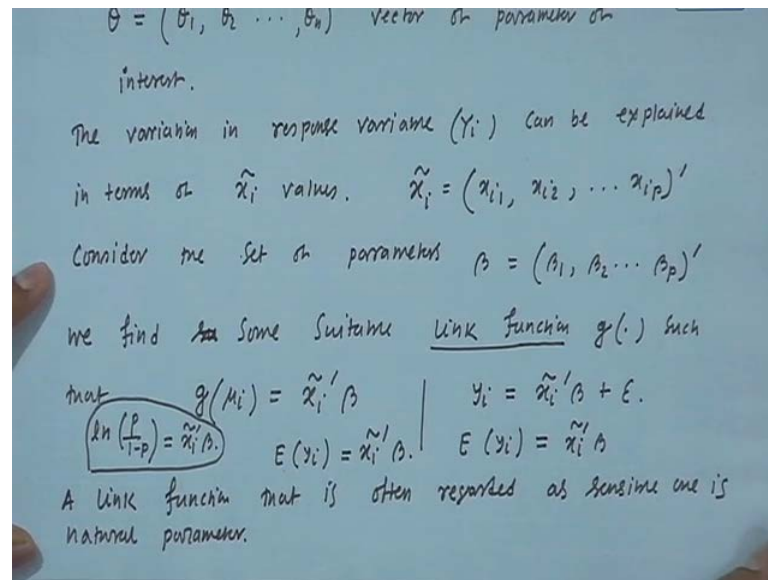
$$f(Y_1, Y_2, \dots, Y_n, \theta, \phi) = \exp \left\{ \sum_{i=1}^n Y_i b(\theta) + \sum_{i=1}^n c(\theta_i) + \sum_{i=1}^n d(Y_i) \right\}$$

where ϕ is a vector of nuisance parameters that occur
 within $b(\cdot)$, $c(\cdot)$, & $d(\cdot)$.

So, here is a fitting of fitting generalized linear model. As I told suppose, we have a set of independent observations. Suppose, my observations are: y_1, y_2, \dots, y_n . So, if you consider one regression then it is a simple regression but I can generalized, I can make it of vector. So, this is my i -th observation and then, this vector is say it has it consist of r regressors p regressors so, this is my observation for i equal 1 to n . So, I have n observation response variable y_i and there are several variable. Let me write this what is this x_i prime is that it is x_{i1}, x_{i2}, x_{ip} . That means it is a p component vector right and we have a set of independent observation from some exponential type distribution of canonical form. That means, that is a y_i is equal to y then the joint probability density function is so, I have n observation I just I have independent.

So, the joint probability density function is $f(y_1, y_2, \dots, y_n, \theta, \phi)$. So, this one is joint probability density function is nothing but the product of marginal's. So, this one is equal to you know that observation is exponential of the distribution. So, I can write as exponential $y_i b(\theta)$, I can write this because a y_i is equal to y that is why plus $c(\theta)$ plus $d(y_i)$. But, this is the pdf only for the i -th observation and once you multiple the marginal's here just have to put summation here, for i equal to 1 to n , i equal to 1 to n , i equal to 1 to n . So, where this ϕ is a vector of nuisance parameter that occur within b , c and d , ok.

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And, my theta is: theta 1, theta 2, theta n vectors of parameter of interest ok. Now, what we want is that, so we talked about the p d f and the variance in y in response variable y i can be explained in terms of x i values ok. Let me give some time. I will try to explain, what is the different between this generalized liner model and then linear model. So, here my x is regresses variable. So, this is basically x i 1, x i 2, x i p. So, I want to explain the variability in y using the regresses variable that is, what you find the relation between response variable and regression variable, this is the whole purpose of this course also. Consider the parameters that regression co efficient, consider the set of parameters beta which is equal to: beta 1, beta 2, beat p, prime ok.

Now, what we do is that we find some suitable link function. This is important link function, say g such that g of mu i is equal to x i prime beta ok. Let me just explain now, see in usual case what happen is that we consider that the model. So, what is that mu i, mu i is expectation of y i. So, in usual case what happen is that, we consider the model y i equal to say x i prime beta plus epsilon and then of course, expectation of y I, the ordinary case is equal to x i prime beta, that is all. But here, if the response variable is not in normal, if it is from some exponential family then x prime b, the regression variable explain the variability in g mu i. So, this is nothing but you know g of expectation of y i. So here, instead of writing expectation of y i is equal to x prime beta, we write g of expectation of y equal to x prime beta ok.

And, this link function, a link function that is often regarded as a sensible one is natural parameter. So, I will talk about this again in next class. But, let me say if this response variable is from is following binominal distribution then here, this link function will be there are the link function was what that will be the natural parameters. So, that is $\ln p$ by $1 - p$ which will equal to $x_i \beta$ and in case of normal distribution, we know the natural parameter is μ . So, in case of normal distribution this $g(\mu)$ is nothing but μ .

So, when we assume that y as followed that normal distribution, we can just write expectation of y_i is equal to, you can go with this model. But, for the other distribution we need to choose this g function, this link function which is nothing but natural parameter ok. So, we will be talking about this again in the next class. So, today we have to stop now.

Thank you.