

And β is a $K \times 1$ vector of regression coefficient and ϵ is $n \times 1$ vector of random error components and ϵ is assumed to follow a multivariate normal distribution with mean vector 0 and covariance matrix $\sigma^2 I$. Now this is our basic model, and now in order to do the forecasting, we assume that suppose a set of n_f observation on the same set of k explanatory variables are available and corresponding observations on y are to be predicted.

So we have here two sets of observation, the first set of observation consisting of n observations on x and y and there is another set of n_f observation in which only the value of x are known but the values of y 's are unknown. So we assume that for this additional n_f observation, the same model continues and we assume that such n_f observations also follow the same model that is $y = x\beta + \epsilon$, but now there is a difference between this model and earlier model.

So we try to denote it by here y as y_f , x here as x_f and ϵ as ϵ_f where now y_f is a $n_f \times 1$ vector of values on Y that are unknown which has to be predicted, which has to be forecasted and x_f is a matrix of order $n_f \times k$ and β is $k \times 1$ vector and ϵ_f is a $n_f \times 1$ vector of random error components and we can assume that ϵ_f also has got the similar properties like as in the earlier case it is following a multivariate normal distribution with mean vector 0 and covariance matrix $\sigma^2 I$.

And further we also assume that the elements in ϵ and ϵ_f are mutually independent. Okay, one thing we have to keep in mind that the variables in matrices x and x_f they are the same, same x_1, x_2, \dots, x_k okay. So let us call this model as model number 1 and this model as model number 2. Now we have to do the forecasting the forecasting in the case of outside sample case is done in two steps, the first step is to use n observations in the model number 1 to obtain the estimate of β as $\hat{\beta} = (x^T x)^{-1} x^T y$.

And in the second step use $\hat{\beta}$ to forecast y_f in model number 2 as we try to construct the predictor p_f which is $x_f \hat{\beta}$ and this is $x_f (x^T x)^{-1} x^T y$. So now we are going to use this same predictor for average value forecasting and actual value forecasting.

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Average value forecasting

Prediction error $p_f - E(y_f) = x_f \hat{\beta} - x_f \beta$
 $= x_f (\hat{\beta} - \beta) = x_f (x'x)^{-1} x' \epsilon$

$E[p_f - E(y_f)] = x_f (x'x)^{-1} x' E(\epsilon) = 0$
 $\Rightarrow p_f$ provides unbiased prediction for $E(y_f)$

Predictive covariance matrix
 $Cov_m(p_f) = E[(p_f - E(y_f))(p_f - E(y_f))']$
 $= E[x_f (x'x)^{-1} x' \epsilon \epsilon' x (x'x)^{-1} x_f']$
 $= \sigma^2 x_f (x'x)^{-1} x_f' \leftarrow$

Predictive variance
 $PV_m(p_f) = \text{tr}[Cov_m(p_f)]$
 $= \sigma^2 \text{tr}[(x'x)^{-1} x_f' x_f] \leftarrow$

So now we consider the first situation in which we are considering the average value forecasting. Now we try to adjust the statistical properties of predictor p_f when it is used for average value forecasting and in order to do so first of all we find its prediction error, so as we have done in the earlier case we are trying to use the predictor p_f to forecast expected value of y_f .

So the prediction error is given by $p_f - \text{expected value of } y_f$ this $= x_f \hat{\beta} - x_f \beta$ and this can be written as $x_f \hat{\beta} - \beta$, and that $= x_f x \text{ transpose } x \text{ whole inverse } x \text{ transpose } \epsilon$, right. You may recall that $\hat{\beta} - \beta = x \text{ transpose } x \text{ whole inverse } x \text{ transpose } \epsilon$ okay. Now we try to find the expected value of prediction error and we notice that this is $\text{expect } x_f x \text{ transpose } x \text{ whole inverse } x \text{ transpose } \text{expected value } \epsilon$ this $= 0$.

So this implies that p_f provides unbiased prediction for expected value of y_f that is in forecasting the average value in case of outside sample prediction. Now we have to find the predictive variance. In the earlier lecture we had found the predictor variance directly, but in this lecture just for the sake of illustration we will find the predictive covariance matrix first and then we will try to take its trace to find out the predictive variance.

So let us try to find out the predictive covariance matrix say this is defined as covariance of p_f when it is used for mean value denoted by m and this is expected value of $p_f - \text{expected value of } y_f$ and $p_f - \text{expected value of } y_f$ and its transpose. We already have obtained these

expressions, so we can write down here directly this is x_f , x transpose x whole inverse x transpose ϵ , ϵ transpose x x transpose x whole inverse x_f transpose.

Now when we bring the expectation operator inside the bracket, the expected value of ϵ , ϵ transpose is $\sigma^2 I$ and so this can be further simplified as $\sigma^2 x_f x$ transpose x whole inverse x transpose f , and now from here we can find the predictive variance as PV of p_f when it is used for mean value forecasting is equal to trace of covariance matrix of p_f when it is used for mean value prediction and this is nothing but trace of σ^2 times trace of x transpose x whole inverse x_f transpose x_f .

So now we observe that both these expressions of covariance matrix of p_f as well as the predictive variance of p_f they are depending on the unknown value of σ^2 .

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Estimates of $Cov_m(p_f)$ and $PV_m(p_f)$
 Replace σ^2 by $\hat{\sigma}^2 = \frac{SS_{res}}{n-k}$ (Anova)
 $\hat{Cov}_m(p_f) = \hat{\sigma}^2 x_f (x'x)^{-1} x_f'$
 $\hat{PV}_m(p_f) = \hat{\sigma}^2 \text{tr} [(x'x)^{-1} x_f' x_f]$
 Prediction interval for $G(y_f)$
 σ^2 known 100(1- α)% prediction interval for $G(y_f)$
 $[p_f - z_{\frac{\alpha}{2}} \sqrt{PV_m(p_f)}, p_f + z_{\frac{\alpha}{2}} \sqrt{PV_m(p_f)}]$ $z_{\frac{\alpha}{2}} : N(0,1)$
 σ^2 unknown 100(1- α)% prediction interval for $G(y_f)$
 $[p_f - t_{\frac{\alpha}{2}, n-k} \sqrt{\hat{PV}_m(p_f)}, p_f + t_{\frac{\alpha}{2}, n-k} \sqrt{\hat{PV}_m(p_f)}]$
 $t_{\frac{\alpha}{2}, n-k} : \text{table of } t \text{ probabilities}$

So we would like to estimate them on the basis of given sample of data and we would like to obtain the estimates of covariance matrix p_f and predictive variance of p_f , okay so in order to obtain the estimate the rule is very simple, simply replace σ^2 by $\hat{\sigma}^2$ and that is obtained from the analysis of variance by $SS_{residual}$ divided by $n - k$. Okay now once I try to do it, then an estimate of the covariance matrix of p_f and it is used for mean value prediction is obtained as $\hat{\sigma}^2 x_f x$ transpose x whole inverse x_f transpose.

An estimate of predictive variance of p_f when it is used for mean value prediction this is obtained as $\hat{\sigma}^2$ and trace of x transpose x whole inverse x_f transpose x_f . Now we obtain the prediction interval for expected value of y_f . The prediction interval can be

obtained exactly in the same way as we have done in the earlier lecture. So we will try to consider here two possible cases when sigma square is known.

And In this case the 100(1 - alpha) percent prediction interval for expected value of yf is obtained as say here $p_f - z_{\alpha/2} \text{se}(p_f)$ and $p_f + z_{\alpha/2} \text{se}(p_f)$ when it is used for mean value prediction and here this value $Z_{\alpha/2}$ they are obtained from normal distribution tables.

And similarly in other case we assume that sigma square is unknown, and in this case 100(1 - alpha) % prediction interval for expected value of yf is obtained as $p_f - t_{\alpha/2, n-k} \text{se}(p_f)$ and $p_f + t_{\alpha/2, n-k} \text{se}(p_f)$ when it is used for mean value, okay and here this value $t_{\alpha/2, n-k}$ they are obtained from tables of t probabilities.

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Actual value prediction (y_f)
 $p_f = x_f \hat{\beta}$
 Prediction error $p_f - y_f = x_f \hat{\beta} - (x_f \beta + \varepsilon_f)$
 $= x_f (\hat{\beta} - \beta) - \varepsilon_f$
 $E[p_f - y_f] = 0 \Rightarrow p_f$ provides unbiased prediction for y_f .
 Predictive covariance matrix

$$\begin{aligned} \text{Cov}_a(p_f) &= E[(p_f - y_f)(p_f - y_f)'] \\ &= E[\{x_f(\hat{\beta} - \beta) - \varepsilon_f\} \{x_f(\hat{\beta} - \beta) - \varepsilon_f\}'] \\ &= x_f V(\hat{\beta}) x_f' + E(\varepsilon_f \varepsilon_f') \quad \left| \begin{array}{l} V(\hat{\beta}) = \sigma^2 (X'X)^{-1} \\ E(\varepsilon_f \varepsilon_f') = \sigma^2 I_{n_f} \end{array} \right. \\ &= \sigma^2 [x_f (X'X)^{-1} x_f' + I_{n_f}] \end{aligned}$$

 Predictive variance

$$PV_a(p_f) = \text{tr}[\text{Cov}_a(p_f)] = \sigma^2 [\text{tr}(x_f (X'X)^{-1} x_f' + I_{n_f})]$$

So this is all about the average value prediction in case of outside sample prediction and now we try to consider the actual value prediction in the case of outside sample prediction. So here we are essentially interested in forecasting the value yf and for that we are using the predictor pf that is equal to xf beta hat. So now first of all we try to find out the prediction error.

So we are trying to find or predict yf using pf, so the prediction error is given by pf-yf and this is nothing but xf beta hat-xf beta+epsilon f, so this is xf beta hat - beta-epsilon f, okay.

So now we try to take its expectation and we find that expected value of $y_f - \hat{y}_f$ this comes out to be null vector because expected value of $\hat{\beta} = \beta$ and expected value of $\epsilon_f =$ null vector.

So this implies that \hat{y}_f provides unbiased prediction for y_f . Next we try to find out its predictive covariance matrix, and this is obtained as we denote it say covariance matrix of \hat{y}_f when it is used for actual value a , okay. So this is defined as expected value of $(y_f - \hat{y}_f)(y_f - \hat{y}_f)^T$ and when we try to solve it this is $X^T(\hat{\beta} - \beta) - \epsilon_f$ and its transpose.

And when we try to open it, and we try to take the expectation of an inside this comes out to be nothing the covariance matrix of $\hat{\beta}$ times X^T + expected value of $\epsilon_f \epsilon_f^T$ which is nothing but the covariance matrix of ϵ_f . Since we already have derived that the covariance matrix of $\hat{\beta}$ is given by $\sigma^2 X^{-1}$.

So I can substitute this value here and I can obtain it say $X^T X^{-1} X^T + \sigma^2 I$ which is identity matrix of order say $n_f \times n_f$. Now using this result we can find out the predictive variance. So we will denote the predictive variance of \hat{y}_f when it is used for actual value forecasting this is simply the trace of covariance matrix of \hat{y}_f when it is used for actual value forecasting and this is simply the σ^2 times trace of $X^T X^{-1} X^T + I$,

n_f because trace of identity matrix of order n_f . So now we obtain here the predictive covariance matrix and predictive variance of \hat{y}_f , but we can again see that these two expressions are depending upon σ^2 that is unknown.

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Estimates of $Cov_a(p_f)$ and $PV_a(p_f)$

Replace σ^2 by $\hat{\sigma}^2 = \frac{SS_{res}}{n-k}$ (Anova)

$$\hat{Cov}_a(p_f) = \hat{\sigma}^2 [X_f (X'X)^{-1} X_f' + I_{n_f}]$$

$$\hat{PV}_a(p_f) = \hat{\sigma}^2 [t_{\alpha/2} (X'X)^{-1} X_f' X_f + n_f]$$

Prediction intervals

σ^2 known : 100(1- α)% prediction interval

$$[p_f - z_{\alpha/2} \sqrt{PV_a(p_f)}, p_f + z_{\alpha/2} \sqrt{PV_a(p_f)}] : z_{\alpha/2} \rightarrow N(0,1)$$

σ^2 unknown : 100(1- α)% prediction interval

$$[p_f - t_{\alpha/2, n-k} \sqrt{\hat{PV}_a(p_f)}, p_f + t_{\alpha/2, n-k} \sqrt{\hat{PV}_a(p_f)}]$$

So now we try to find out estimates covariance matrices and predictive variance, estimates of covariance matrix of pf and predictive variance of pf and they are used for actual predication. So in order to obtain them we simply have to replace sigma square by sigma square hat which is obtain by sum of square due to residual divided by degrees freedom and this some of a square due to residual that is obtain from the analysis of variance table.

So, once I try to do it here then the estimate of covariance matrix of pf when it use for actual value predication this comes out to be sigma square hat, and $X_f X_f'$ transpose X whole inverse X_f' transpose plus identity matrix of order n_f and estimate of predictive variance of pf when it is used for actual value prediction comes out to be sigma square time trace of X transpose X whole inverse X_f' transpose $X_f + n_f$,

Now our next objective is to find out the predication interval. So the prediction intervals can be found exactly in the same way as we have done in the earlier cases, so we will have here two cases one is sigma square is known and in this case the hundred one minus alpha % predication interval is obtain as $p_f - z_{\alpha/2}$ square root of predictive variance of pf when it use for actual value and $p_f + z_{\alpha/2}$ square root of prediction variance of pf when it is used for actual value.

And where the values of $z_{\alpha/2}$ are obtained from the tables of normal 0 1 probabilities, similarly the second case here will be when sigma square is assume to be unknown and in this case the 100 1- alpha % prediction interval is obtained as $p_f - t_{\alpha/2, n-k}$ and standard

error of \hat{y} when it is used for actual value prediction and $\hat{y} \pm t_{\alpha/2, n-k}$ and standard error of predictive variance that is \hat{y} when it is use of actual value.

So now you can see that we have considered the outside sample predication in this lecture we constructed a predicated based on the ordinary least square estimator and we have implied it for the average value forecasting and actual value forecasting, next question which have I would like to address is a following, in this lecture and in the earlier lecture we had use only the ordinary least square estimation for forecasting.

This possibly will give you and impression that possibly only the ordinary least square estimator can be used for forecasting this is not correct, one can actually use any estimator for forecasting the only difference is going to be that we will replace the ordinary least square estimator by the corresponding estimator, but we have to clear full after that the properties of the predictors there test of hypothesis, there prediction interval will also be changed accordingly.

Sometimes it may easy to find such properties and sometime it may be difficult to find such properties. So now we are going to stop here the only question which is left is that we have developed the theoretical properties in this lecture and the earlier lecture on forecasting, but how to use them on a real set of data, so that we would try to address in the next lecture, till then good bye.