

# STATISTICAL DECISION THEORY - IX LINEAR MODELS AND DECISIONS

## THE GENERAL LINEAR HYPOTHESIS

OBSERVE RANDOM VECTOR  $\underline{Y}$  OF DIMENSION  $M$

$E(\underline{Y})$  ASSUMED TO LIE IN SUBSPACE OF DIMENSION  $N < M$  SPANNED BY COLUMNS OF KNOWN  $X$

THAT IS,  $E(\underline{Y}) = X\beta$  FOR SOME VECTOR OF LINEAR COMBINATION COEFFICIENTS OF DIMENSION  $N$

### ESTIMATION

$E(\underline{Y}) = X\beta \Rightarrow \underline{Y} = X\beta + \underline{\epsilon}$ ,  $\underline{\epsilon}$  A VECTOR (OF DIM  $M$ ) OF DEVIATIONS FROM THE MEAN (ERROR VECTOR)

GAME  $\langle \theta, A, L \rangle = \langle \beta, \text{SELECT } \beta, L \rangle$

A SELECTION (ESTIMATION) OF  $\beta$ , DESIGNATED  $\hat{\beta}$ , INDUCES  $\hat{\underline{Y}} = X\hat{\beta}$  AND  $\hat{\underline{\epsilon}} = \underline{Y} - \hat{\underline{Y}}$

THE STANDARD ESTIMATION CRITERION FOR SELECTING  $\hat{\beta}$  IN THE GENERAL LINEAR HYPOTHESIS

IS TO SELECT  $\hat{\beta}$  SO THAT THE LENGTH OF THE ERROR VECTOR,  $|\hat{\underline{\epsilon}}|$ , IS A MINIMUM (MINIMUM ERROR)

WITH THE STANDARD EUCLIDEAN INNER PRODUCT,  $|\hat{\underline{\epsilon}}| = \sqrt{\hat{\underline{\epsilon}}' \hat{\underline{\epsilon}}} = \sqrt{\sum \hat{\epsilon}_i^2}$ ; THUS, TO MINIMIZE THE LENGTH OF THE ERROR VECTOR IS TO MINIMIZE THE SUM OF THE SQUARES OF THE INDIVIDUAL ERRORS.

FROM THIS DERIVES THE NAME LEAST SQUARES

THE LEAST SQUARES ESTIMATE  $\hat{\beta}$  IS LINEAR IN  $\underline{Y}$ , UNBIASED, AND HAS MINIMUM VARIANCE AMONG ALL OTHER LINEAR UNBIASED ESTIMATES OF  $\beta$

SIMILARLY,  $\underline{P}\hat{\beta}$  IS AN MVU LINEAR ESTIMATE OF  $\underline{P}'\beta$  FOR ANY VECTOR  $\underline{P} \in \mathbb{R}^M$  A LINEAR FUNCTION OF  $\underline{Y}$  WITH EXPECTATION  $\underline{P}'\beta$ , OR, EQUIVALENTLY, IF  $\underline{P} \in \text{SPAN}(X')$ . — NOTE THAT, IF  $X$  IS OF FULL RANK, THEN ANY VECTOR  $\underline{P}$  OF LENGTH  $N$  (FOR  $\beta$  OF LENGTH  $N$ ) IS ACCEPTABLE — ALLOWS ESTIMATION OF LINEAR COMBINATIONS OF THE  $\beta_i$ 'S

FOR THE ASSUMPTION  $\underline{Y} \sim N(X\beta, \sigma^2 I)$ , THE LEAST SQUARES ESTIMATE OF  $\beta$  IS ALSO THE MAXIMUM LIKELIHOOD ESTIMATE (AND LIKEWISE FOR  $\underline{P}'\hat{\beta}$ )

FOR  $\underline{Y} \sim N(X\beta, \Sigma)$ , THE MAXIMUM LIKELIHOOD ESTIMATE FOR  $\beta$  WILL, IN GENERAL, BE EQUIVALENT TO A MINIMUM LENGTH ERROR VECTOR ESTIMATE FOR SOME NON-EUCLIDEAN INNER PRODUCT

### HYPOTHESIS TESTING ASSUME $\underline{Y} \sim N(X\beta, \sigma^2 I)$ — LIKELIHOOD RATIO TESTS

TESTS OF  $H_0: \beta_{k+1} = \dots = \beta_N = 0$  AGAINST THEIR NEGATIONS  $H_1: \beta_{k+1} = \dots = \beta_N \neq 0$  (I.E.,  $H_0: E(\underline{Y}) \in \text{SPAN}\{\text{FIRST } k \text{ VECTORS OF } X\}$ , RATHER THAN THE SPAN OF ALL OF  $X$ ) YIELD  $F$  STATISTICS

TESTS OF  $H_0: \beta = A$  OR  $H_0: \underline{P}'\beta = C$  YIELD  $t$  TESTS (WITH APPROPRIATE VARIANCE ESTIMATORS).