

**MULTIVARIATE STATISTICS, Lesson 8-9.**  
**Multivariate Regression and ANalysis Of VAriance**

- **Linear regression:** given the expectation vector and covariance matrix of the random vector  $(Y, X_1, \dots, X_p)^T$ , we want to approximate  $Y$  (target variable) with a linear combination of the predictor variable  $\mathbf{X} = (X_1, \dots, X_p)^T$  in such a way that

$$\mathbb{E}(Y - \ell(\mathbf{X}))^2 = \mathbb{E}(Y - (a_1X_1 + \dots + a_pX_p + b))^2 = \mathbb{E}(Y - \mathbf{a}^T\mathbf{X} - b)^2 \rightarrow \text{minimum}$$

in the parameters  $\mathbf{a} = (a_1, \dots, a_p)^T$  and  $b$ .

1. *Theoretical solution:*  $\mathbf{a} = \mathbf{C}^{-1}\mathbf{d}$ ,  $b = \mathbb{E}(Y) - \mathbf{a}^T\mathbb{E}(\mathbf{X})$ , where  $\mathbf{C} = \mathbb{D}^2(\mathbf{X}) > 0$  and  $\mathbf{d}$  contains the cross-covariances between  $Y$  and  $X_i$ 's. If the expectations are 0's,  $\ell(\mathbf{X})$  and the error term  $\varepsilon := Y - \ell(\mathbf{X})$  are uncorrelated, hence

$$\mathbb{D}^2(Y) = \mathbb{D}^2\ell(\mathbf{X}) + \mathbb{D}^2\varepsilon = r_{Y\mathbf{X}}^2 \cdot \mathbb{D}^2(Y) + (1 - r_{Y\mathbf{X}}^2) \cdot \mathbb{D}^2(Y),$$

where  $r_{Y\mathbf{X}} = \text{corr}(Y, \ell(\mathbf{X}))$  is the **multiple correlation** between  $Y$  and  $\mathbf{X}$ . If  $Y_1 = \ell_1(\mathbf{X}) + \varepsilon_1$  and  $Y_2 = \ell_2(\mathbf{X}) + \varepsilon_2$ , then the **partial correlation** between  $Y_1$  and  $Y_2$  after eliminating the effect of  $\mathbf{X}$  is

$$r_{Y_1Y_2|\mathbf{X}} = \text{corr}(\varepsilon_1, \varepsilon_2) = \frac{\text{corr}(Y_1, Y_2) - \text{corr}(Y_1, \mathbf{X}) \cdot \text{corr}(Y_2, \mathbf{X})}{\sqrt{(1 - \text{corr}^2(Y_1, \mathbf{X})) \cdot (1 - \text{corr}^2(Y_2, \mathbf{X}))}},$$

where the last formula is applicable only in the  $p = 1$  case.

2. *Linear model:*  $\mathbf{Y} = \mathbf{X}\mathbf{a} + \underline{\varepsilon}$ , where measurements  $\mathbf{Y} = (Y_1, \dots, Y_n)^T$  are random variables due to the independent, zero expectation, homoscedastic measurement errors contained in  $\underline{\varepsilon} := (\varepsilon_1, \dots, \varepsilon_n)^T$  (the errors have the same variance  $\sigma^2$ ). The errors are added to a linear combination of given measurement points of the  $n \times p$  matrix  $\mathbf{X}$ . The parameter vector  $\mathbf{a} \in \mathbb{R}^p$  minimizing  $\|\mathbf{Y} - \mathbf{X}\mathbf{a}\|^2$  is obtained by solving the **Gauss normal equations:**  $\mathbf{X}^T\mathbf{X}\mathbf{a} = \mathbf{X}^T\mathbf{Y}$ . The solution is:  $\hat{\mathbf{a}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{Y}$ , if  $\text{rang}(\mathbf{X}) = p < n$ , otherwise we need generalized inverse:  $\hat{\mathbf{a}} = (\mathbf{X}^T\mathbf{X})^+\mathbf{X}^T\mathbf{Y}$ .
3. *Proclaim:* in the linear model, if  $\text{rang}(\mathbf{X}) = p < n$  and  $\underline{\varepsilon} \sim \mathcal{N}_n(\mathbf{0}, \sigma^2\mathbf{I}_n)$ , then  $\hat{\mathbf{a}} \sim \mathcal{N}_p(\mathbf{a}, \sigma^2 \cdot (\mathbf{X}^T\mathbf{X})^{-1})$ . In this case,  $\hat{\mathbf{a}}$  is also ML-estimate of  $\mathbf{a}$ .
4. **Gauss –Markov Theorem:** for any other unbiased linear estimate  $\tilde{\mathbf{a}}$  of  $\mathbf{a}$ :  $\mathbb{D}^2(\hat{\mathbf{a}}) \leq \mathbb{D}^2(\tilde{\mathbf{a}})$ , that is  $\hat{\mathbf{a}}$  is **BLUE** (Best, Linear, Unbiased) Estimate of  $\mathbf{a}$ .
5. *Testing the significance of the regression.* Under  $H_0 : \mathbf{a} = \mathbf{0}$

$$F = \frac{SSR}{SSE} \cdot \frac{n-p}{p} = \frac{SST - SSE}{SSE} \cdot \frac{n-p}{p} = \frac{R^2}{1-R^2} \cdot \frac{n-p}{p} \sim \mathcal{F}(p, n-p),$$

where  $SSR$ ,  $SSE$ , and  $R$  are sample estimates of  $\mathbb{D}^2(\ell(\mathbf{X}))$ ,  $\mathbb{D}^2(\varepsilon)$  and  $r_{Y\mathbf{X}}$ .

- **ANOVA models:**

1. *One-way ANOVA:*  $X_{ij} = m + a_i + \varepsilon_{ij}$  ( $j = 1, \dots, n_i; i = 1, \dots, k$ )
2. *Two-way ANOVA without interaction:* 1 observation/cell

$$X_{ij} = m + a_i + b_j + \varepsilon_{ij}, \quad (i = 1, \dots, k; j = 1, \dots, p)$$

3. *Two-way ANOVA with interaction:*  $n$  observations/cell

$$X_{ijl} = m + a_i + b_j + c_{ij} + \varepsilon_{ijl}, \quad (i = 1, \dots, k; j = 1, \dots, p; l = 1, \dots, n)$$

4. *Three-way ANOVA without interaction:* latin squares.