

# 1 Linear Regression

Setup:

- Start with a random vector  $X^T = (X_1, \dots, X_p)$  and random variable  $Y$ .
- Will approximate regression function  $Y = f(X)$  where  $f(x) = E(Y|X = x)$  with linear function  $f(x) = \sum_{j=1}^p \beta_j X_j$
- let  $\mathbf{X}$  be the  $n \times p$  matrix of observations of  $X$ , and  $y$  be the observations of  $Y$ .
- easy to show that minimizing squared error loss function yield the following estimate  $\hat{\beta}$

$$\hat{\beta} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T y$$

- now, from ESL book: “In order to pin down the sampling properties of  $\hat{\beta}$ , we now assume that the observations  $y_i$  are uncorrelated and have constant variance  $\sigma^2$ , and that the [observations]  $x_i$  are fixed (non-random)”

Results:

- first, from solution for  $\hat{\beta}$  we can prove that

$$VAR(\hat{\beta}) = (\mathbf{X}^T \mathbf{X})^{-1} \sigma^2$$

This is relatively straight forward. Can prove  $VAR(AZ) = A VAR(Z) A^T$  for constant matrix  $A$  and random vector  $Z$ . And uncorrelated, constant variance implies  $VAR(Y) = \mathbf{I}_n \sigma^2$ .

- second: the typical estimate of  $\sigma^2$  is

$$\hat{\sigma}^2 = \frac{1}{N - p - 1} \sum_{i=1}^N (y_i - \hat{y}_i)^2.$$

This estimator is unbiased - that is:  $E(\hat{\sigma}^2) = \sigma^2$ .

I cannot prove this. But ESL simply brush past it, because I assume it is a very well known (and perhaps very easy) result. **This is what I need help with.**

- Then they say: “To draw inferences about the parameters and the model, additional assumptions are needed” - they assume:
  - the conditional expectation of  $Y$  really is linear in the  $X$
  - the deviations of  $Y$  around its expectation are additive and gaussian, hence

$$Y = E(Y|X_1, \dots, X_p) + \epsilon \tag{1}$$

where  $\epsilon \sim N(0, \sigma^2)$

Now it is easy to show

$$\hat{\beta} \sim N(\beta, (\mathbf{X}^T \mathbf{X})^{-1} \sigma^2)$$

to do this, think of each observation  $y_i$  as a random variable  $Y_i$ , which by assumption is  $Y_i = E(Y|X = x_i) + \epsilon_i$ , where the  $\epsilon_i$  are i.i.d  $N(0, \sigma^2)$ . Plugging this in, yields said result.