# Problem Set 1

## Due Sep 12, before class

### 1. The simplest OLS

Show that the sample mean equals

$$\bar{y} = \underset{\mu}{\operatorname{arg \, min}} n^{-1} \sum_{i=1}^{n} (y_i - \mu)^2.$$

### 2. Univariate OLS without intercept

Find

$$\hat{\beta} = \arg\min_{\beta} n^{-1} \sum_{i=1}^{n} (y_i - \beta x_i)^2.$$

## 3. Pairwise slopes

Given  $(x_i, y_i)_{i=1}^n$  with univariate  $x_i$  and  $y_i$ , show that

$$\hat{\beta} = \sum_{(i,j)} w_{ij} b_{ij},$$

where the summation is over all pairs of observations (i, j),

$$b_{ij} = \frac{y_i - y_j}{x_i - x_j}$$

is the slope determined by two points  $(x_i, y_i)$  and  $x_j, y_j$ , and

$$w_{ij} = \frac{(x_i - x_j)^2}{\sum_{(i',j')} (x_{i'} - x_{j'})^2}$$

is the weight proportional to the squared distance between  $x_i$  and  $x_j$ . In the above formulas, we define  $b_{ij} = 0$  if  $x_i = x_j$ .

#### 4. Invariance of OLS

Assume that  $X^TX$  is non-degenerate and  $\Gamma$  is a  $p \times p$  non-degenerate matrix. Define  $\tilde{X} = X\Gamma$ . From the OLS fit of Y on X, we obtain the coefficient  $\hat{\beta}$ , the fitted value  $\hat{Y}$ , the residual  $\hat{\epsilon}$ , and the hat matrix  $\hat{H}$ ; From the OLS fit of Y on  $\tilde{X}$ , we obtain the coefficient  $\tilde{\beta}$ , the fitted value  $\tilde{Y}$ , the residual  $\tilde{\epsilon}$ , and the hat matrix  $\tilde{H}$ .

(a) Prove that

$$\hat{\beta} = \Gamma \tilde{\beta}, \quad \hat{Y} = \tilde{Y}, \quad \hat{\epsilon} = \tilde{\epsilon}, \quad \hat{H} = \tilde{H}.$$

(b) In a treatment-control experiment with m treated and n control units

$$X = \begin{pmatrix} 1_m & 1_m \\ 1_n & 0_n \end{pmatrix},$$

show that  $H = \text{diag}\{m^{-1}1_m1_m^T, n^{-1}1_n1_n^T\}.$ 

## 5. Full sample and subsample OLS

Partition the full sample into K subsamples:

$$X = \begin{pmatrix} X_{(1)} \\ \vdots \\ X_{(K)} \end{pmatrix}, \quad Y = \begin{pmatrix} Y_{(1)} \\ \vdots \\ Y_{(K)}, \end{pmatrix}$$

where the k-th sample consists of  $(X_{(k)}, Y_{(k)})$  with  $X_{(k)} \in \mathbb{R}^{n_k \times p}$  and  $Y_{(k)} \in \mathbb{R}^{n_k}$  being the covariate matrix and outcome vector. Let  $\hat{\beta}$  be the OLS coefficient based on the full sample, and  $\hat{\beta}_{(k)}$  be OLS coefficient based on the k-th sample. Show that

$$\hat{\beta} = \sum_{k=1}^K W_{(k)} \hat{\beta}_{(k)},$$

where the weight matrix equals

$$W_{(k)} = \left(\sum_{k'=1}^{K} X_{(k')}^{T} X_{(k')}\right)^{-1} X_{(k)}^{T} X_{(k)}.$$