

Problem Set 1

Due: October 19th, 2018

Problem sets are due at 5PM in the GSIs mailbox. You may work in groups, but each student should turn in their own write-up (including a printout of a narrated/commented and executed Jupyter Notebook if applicable). Please also e-mail a copy of any Jupyter Notebook to the GSI (if applicable).

1. Let \mathcal{H} be an Hilbert space and y a fixed vector within it. Show that for each $\epsilon > 0$ that there exists a $\delta > 0$ such that

$$|\langle h_1, y \rangle - \langle h_2, y \rangle| \leq \epsilon$$

for all $h_1, h_2 \in \mathcal{H}$ where $\|h_1 - h_2\| \leq \delta$ (HINT: use the Cauchy-Schwarz Inequality).

2. The linear regression of Y into X is

$$\mathbb{E}^*[Y|X] = X'\gamma_0, \quad \gamma_0 = \mathbb{E}[XX']^{-1} \times \mathbb{E}[XY].$$

Let $X = (1, W)'$, with W a $K \times 1$ vector of linearly independent random variables. Show that

$$\mathbb{E}[XX']^{-1} = \begin{bmatrix} 1 + \mathbb{E}[W]'\mathbb{V}(W)^{-1}\mathbb{E}[W] & -\mathbb{E}[W]'\mathbb{V}(W)^{-1} \\ -\mathbb{V}(W)^{-1}\mathbb{E}[W] & \mathbb{V}(W)^{-1} \end{bmatrix}$$

and hence also that

$$\gamma_0 = \begin{pmatrix} \alpha_0 \\ \beta_0 \end{pmatrix} = \begin{bmatrix} \mathbb{E}[Y] - \mathbb{E}[W]'\beta_0 \\ \mathbb{V}(W)^{-1}\mathbb{C}(W, Y) \end{bmatrix}.$$

You may assume that all the expectations and variances in the expression above are well-defined.

3. Let X be a $K \times 1$ vector of covariates with a constant as first element. Let W be a $J \times 1$ vector of additional covariates (excluding a constant). Consider the **long regression** of Y onto X and W :

$$\mathbb{E}^*[Y|X, W] = X'\beta_0 + W'\gamma_0.$$

Further consider the **short regression** of Y onto X alone

$$\mathbb{E}^*[Y|X] = X'b_0.$$

Finally consider the **auxiliary linear** (multivariate) regression of W given X

$$\mathbb{E}^*[W|X] = \Pi_0 X.$$

Here Π_0 is the $J \times K$ coefficient matrix $\Pi_0 = \mathbb{E}[WX'] \times \mathbb{E}[XX']^{-1}$. Let $U = Y - \mathbb{E}^*[Y|X, W]$.

(a) Use the Projection Theorem to show that $\mathbb{E}^*[U|X] = 0$.

(b) Use the Projection Theorem to show that $\mathbb{E}^*[X|X] = X$.

- (c) Use you the results from (a) and (b) above as well as linearity of the projection operator to further show that

$$\mathbb{E}^* [Y|X] = X' \beta_0 + \mathbb{E}^* [W|X]' \gamma_0$$

and hence that

$$b_0 = \beta_0 + \Pi_0' \gamma_0.$$

- (d) Interpret your result as an “omitted variable bias” (OVB) formula.
 (e) Further argue that you have shown the **law of iterated linear predictors**:

$$\mathbb{E}^* [Y|X] = \mathbb{E}^* [\mathbb{E}^* [Y|X, W]|X].$$

4. Show that

$$\mathbb{V}(Y) = \mathbb{V}(Y - \mathbb{E}^* [Y|X]) + \mathbb{V}(\mathbb{E}^* [Y|X]).$$

5. Let \mathbf{Y} be an $N \times 1$ vector of outcomes and \mathbf{X} and $N \times K$ vector of covariates (which includes a constant in column 1). The projection of \mathbf{Y} onto the column space of \mathbf{X} coincides with the least squares fit

$$\hat{\mathbf{Y}} = \mathbf{X} (\mathbf{X}' \mathbf{X})^{-1} \mathbf{X}' \mathbf{Y}.$$

Let $\hat{\mathbf{U}} = \mathbf{Y} - \hat{\mathbf{Y}}$ be the fitted residuals. Using vector space methods show that:

(a) $\mathbf{X}' \hat{\mathbf{U}} = 0$

(b) $\left(\mathbf{Y} - \frac{\mathbf{Y}' \mathbf{1}}{N}\right)' \left(\mathbf{Y} - \frac{\mathbf{Y}' \mathbf{1}}{N}\right) = \hat{\mathbf{U}}' \hat{\mathbf{U}} + \left(\hat{\mathbf{Y}} - \frac{\mathbf{Y}' \mathbf{1}}{N}\right)' \left(\hat{\mathbf{Y}} - \frac{\mathbf{Y}' \mathbf{1}}{N}\right)$

(c) $0 \leq R^2 \leq 1$ for $R^2 = 1 - \frac{\hat{\mathbf{U}}' \hat{\mathbf{U}}}{\left(\mathbf{Y} - \frac{\mathbf{Y}' \mathbf{1}}{N}\right)' \left(\mathbf{Y} - \frac{\mathbf{Y}' \mathbf{1}}{N}\right)}$

6. Compute the following exercises from Hansen (2018): 2.4, 2.16, 3.2, 3.3, 3.6 (using Projection Theorem argument), 3.8, 3.9