

**Homework Assignment #1**

1. (5 points) For example 2 in lecture notes 1, what is the rank of the design matrix  $\mathbf{X}$ ? Assume  $n > p$ . You may have to describe cases. For cases where the rank is  $< p$ , describe what this means in “practical” terms – what does the scatterplot of the data look like?

Solution: Recall the model is

$$Y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \epsilon_i$$

where  $Y_i$  and  $x_i$  are the blood pressure and weight of subject  $i$ , respectively. The design matrix is

$$\mathbf{X} = \begin{bmatrix} 1 & x_1 & x_1^2 \\ 1 & x_2 & x_2^2 \\ \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 \end{bmatrix} = [\mathbf{1}_n \ (x_i)_n \ (x_i^2)_n]$$

With no constraints on the  $x$ 's, then  $\mathbf{X}$  could have rank 1, 2 or 3. If  $x_i$  are all equal, then all columns are the proportional to the first column  $\mathbf{1}_n$  so that  $\text{rank}(\mathbf{X}) = 1$ . If there are only two different values of  $x_i$ , a row reduced echelon form has two pivots so that  $\text{rank}(\mathbf{X}) = 2$ . Otherwise,  $\mathbf{X}$  has  $\text{rank}(\mathbf{X}) = 3$  (check this by row reduction). In “practical” terms, rank=1 means we would be trying to fit a quadratic term to data with one possible value of a covariate and there will be an infinite number of solution; rank=2 means we would be trying to fit a quadratic term to data with two possible values of a covariate and there will be an infinite number of solutions.

2. (5 points) For example 4 in lecture notes 1, what is the rank of the design matrix  $\mathbf{X}$ ? Assume  $n > p$ . You may have to describe cases. For cases where the rank is  $< p$ , describe what this means in “practical” terms – what does the scatterplot of the data look like?

Solution: The Inverse Square Law states that the force of gravity  $F$  between two bodies a distance  $D$  apart is given by

$$F = \frac{c}{D^\beta}$$

Taking logarithms on both sides yields the linear model

$$\log F = \log c - \beta \log D \Leftrightarrow Y_i = \beta_0 + \beta_1 x_i$$

with  $Y_i = \log F$ ,  $\beta_0 = \log c$  and  $x_i = -\log D$ . Hence if we have a sample  $(Y_1, x_1), \dots, (Y_n, x_n)$  where  $n > 2$  then the design matrix is  $\mathbf{X} =$

$$\begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{bmatrix}$$

The rank of  $\mathbf{X}$  could be 1 or 2. Using similar reasoning as problem 1,  $\text{rank}(\mathbf{X}) = 1$  implies that  $x_1 = \dots = x_n$ , that is, all the bodies in the sample are the same distance apart. The scatterplot in this case would look like the left side of figure 1.

**3.** (3 points) For example 5 in lecture notes 1, what is the rank of the design matrix  $\mathbf{X}$ ? Assume  $J \geq 2$ .

Solution: Recall the design matrix  $\mathbf{X}$  is

$$\begin{bmatrix} 1 & 1 & 0 \\ \vdots & \vdots & \vdots \\ 1 & 1 & 0 \\ 1 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 1 & 0 & 1 \end{bmatrix}$$

Note that the first column of  $\mathbf{X}$  is the sum of the second and third columns. The column space of  $\mathbf{X}$  is

$$\mathcal{R}(\mathbf{X}) = \text{span}\left\{ \begin{pmatrix} 1 \\ \vdots \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ \vdots \\ 1 \end{pmatrix} \right\}$$

hence  $\text{rank}\mathbf{X} = 2$ .

**4.** (3 points) For example 6 in lecture notes 1, what is the rank of the design matrix  $\mathbf{X}$ ? Assume  $K \geq 2$ .

Solution: Recall the design matrix  $\mathbf{X}$  is

$$\begin{bmatrix} 1 & 1 & 0 & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 1 & 0 & 0 & 1 \\ 1 & 0 & 1 & 1 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 1 & 0 & 1 \end{bmatrix} = \begin{bmatrix} \mathbf{1}_K & \mathbf{1}_K & \mathbf{0}_K & \mathbf{1}_K & \mathbf{0}_K \\ \mathbf{1}_K & \mathbf{1}_K & \mathbf{0}_K & \mathbf{0}_K & \mathbf{1}_K \\ \mathbf{1}_K & \mathbf{0}_K & \mathbf{1}_K & \mathbf{1}_K & \mathbf{0}_K \\ \mathbf{1}_K & \mathbf{0}_K & \mathbf{1}_K & \mathbf{0}_K & \mathbf{1}_K \end{bmatrix}$$

Performing elementary row operations, we can reduce the matrix to the echelon form

$$\begin{bmatrix} 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ \vdots & & & & \vdots \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}, \text{ thus } \text{rank}(X) = 3.$$

5. (5 points) Repeat the exercise on page 10 of lecture notes 2 for the dataset  $\{(x, y) = (1, 0), (1, 2), (0, 0)\}$ .

Solution: Here the design matrix is  $X = (1 \ 1 \ 0)^T$ , so  $\hat{\beta} = (X^T X)^{-1} X^T Y = 1$ . The fitted values are  $\hat{Y} = (1, 1, 0) = X$ . See figure 3 for the plots. In this case, there are three data points, so we must visualize the vectors in three dimensions. The dimension of  $\Omega$  is 1, while the dimension of  $\Omega^\perp$  is 2. The set  $\Omega^\perp$  is the set of all vectors perpendicular to a vector  $X = (1 \ 1 \ 0)^T$ , that is,  $\{c(1, -1, k) : c, k \in \mathbb{R}\}$ . See figure 4 for a scatterplot. If we fit the model  $Y_i = \beta_0 + \beta_1 x_i + \epsilon_i$  then the design matrix is

$$X^* = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 0 \end{bmatrix}$$

which has two linearly independent columns, hence in this case, the dimension of  $\Omega$  is 2, while the dimension of  $\Omega^\perp$  is 1. The set  $\Omega^\perp$  is the set of all vectors perpendicular to the plane  $\{c(1, 1, k) : c, k \in \mathbb{R}\}$  spanned by the two column vectors of the design matrix, that is,  $\{c(1, -1, 0) : c \in \mathbb{R}\}$ . Furthermore,  $\hat{\beta} =$

$$\begin{pmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \end{pmatrix}$$

So the intercept is zero and hence this model reduces to  $Y_i = \beta x_i + \epsilon_i$ , so the other previous answers do not change.

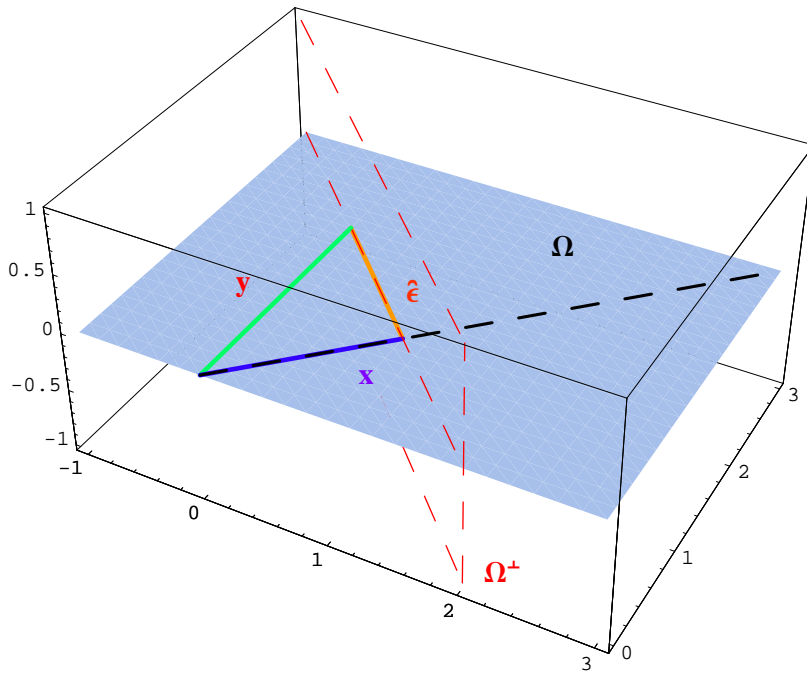


Figure 1: Visualization of problem 6

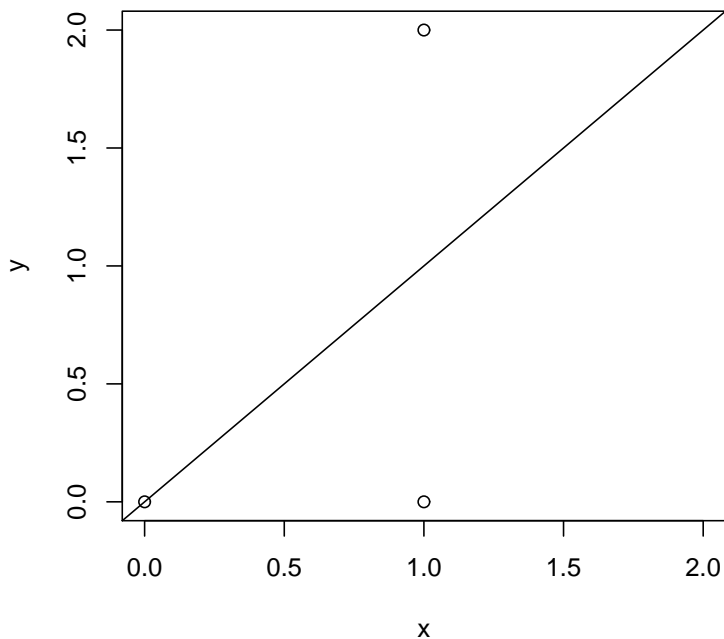


Figure 2: Scatterplot for problem 6

6. (5 points) Let  $\mathbf{P} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$  and  $\mathbf{Q} = \mathbf{I} - \mathbf{P}$  and assume that  $\mathbf{X}'\mathbf{X}$  is non-singular. Prove: (a)  $\mathbf{P}$  and  $\mathbf{Q}$  are symmetric and idempotent; (b)  $\mathbf{Q}\mathbf{X} = \mathbf{0}$  and  $\mathbf{X}'\mathbf{Q} = \mathbf{0}$ .

Solution: (a) Using the properties of matrix transpose,

$$[\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}']' = \mathbf{X}[(\mathbf{X}'\mathbf{X})^{-1}]'\mathbf{X}' = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$$

Moreover,

$$\begin{aligned} & [\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'][\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'] = \\ & \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}[\mathbf{X}'\mathbf{X}](\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}' \end{aligned}$$

proving that  $\mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'$  is symmetric and idempotent. As for  $\mathbf{Q}$ , note that matrix transpose distributes over sums,

$$(\mathbf{I} - \mathbf{P})' = \mathbf{I}' - \mathbf{P}' = \mathbf{I} - \mathbf{P}$$

since  $\mathbf{I}$  and  $\mathbf{P}$  are symmetric. Moreover,

$$(\mathbf{I} - \mathbf{P})(\mathbf{I} - \mathbf{P}) = \mathbf{I} - \mathbf{P} - \mathbf{P} + \mathbf{P}^2 = \mathbf{I} - \mathbf{P} - \mathbf{P} + \mathbf{P} = \mathbf{Q}$$

since  $\mathbf{P}$  is idempotent.

(b) By straightforward calculation,

$$\mathbf{Q}\mathbf{X} = (\mathbf{I} - \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}')\mathbf{X} = \mathbf{X} - \mathbf{X} = \mathbf{0}$$

Since  $\mathbf{Q}$  is symmetric, take transpose on both sides of the equation above to get

$$\mathbf{X}'\mathbf{Q} = \mathbf{0}$$

7. (3 points) Let  $\mathbf{J}_n$  be the  $n \times n$  matrix of 1's. Show  $\frac{1}{n}\mathbf{J}_n$  is idempotent.

Solution: Again, by straightforward calculation,

$$\frac{1}{n}\mathbf{J}_n\frac{1}{n}\mathbf{J}_n = \frac{1}{n^2} \begin{bmatrix} \mathbf{1}'_n\mathbf{1}_n & \cdots & \mathbf{1}'_n\mathbf{1}_n \\ \vdots & \ddots & \vdots \\ \mathbf{1}'_n\mathbf{1}_n & \cdots & \mathbf{1}'_n\mathbf{1}_n \end{bmatrix} = \frac{1}{n^2} \begin{bmatrix} n & \cdots & n \\ \vdots & \ddots & \vdots \\ n & \cdots & n \end{bmatrix} = \frac{1}{n}\mathbf{J}_n$$

8. (3 points) Let  $A$  be a symmetric  $n \times n$  matrix, let  $\lambda_i$  be its eigenvalues and let  $s$  be a nonzero integer. Prove  $\text{trace}(A^s) = \sum_{i=1}^n \lambda_i^s$

Solution: Since  $A$  is symmetric, applying the Spectral Theorem gives

$$A = T\Lambda T'$$

where  $T$  is an orthonormal matrix and  $\Lambda = \text{diag}(\lambda_1, \dots, \lambda_n)$ . Thus, we have

$$\begin{aligned} A^s &= (T\Lambda T')(T\Lambda T') \cdots (T\Lambda T') \\ &= T\Lambda(T'T)\Lambda T' \cdots T\Lambda T' \\ &= T\Lambda\Lambda T' \cdots T\Lambda T' \\ &= T\Lambda^2 T' \cdots T\Lambda T' \\ &\vdots \\ &= T\Lambda^s T' \end{aligned}$$

Hence

$$\begin{aligned} \text{trace}(A^s) &= \text{trace}(T\Lambda^s T') \\ &= \text{trace}(T'T\Lambda^s) \\ &= \text{trace}(\Lambda^s) \\ &= \text{trace}(\text{diag}(\lambda_1^s, \dots, \lambda_n^s)) \\ &= \sum_{i=1}^n \lambda_i^s. \end{aligned}$$