

# STAT151A Homework 2.

Your name here

This homework is due on Gradescope on **Sunday September 29th at 9pm.**

## 1 Ordinary least squares in matrix form

Consider simple least squares regression  $y_n = \beta_1 + \beta_2 x_n + \varepsilon_n$ , where  $x_n$  is a scalar. Assume that we have  $N$  datapoints. We showed directly that the least-squares solution is given by

$$\hat{\beta}_1 = \bar{y} - \hat{\beta}_2 \bar{x} \quad \text{and} \quad \hat{\beta}_2 = \frac{\overline{xy} - \bar{x} \bar{y}}{\overline{xx} - \bar{x}^2}.$$

Let us re-derive this using matrix notation.

**(a)**

Write simple linear regression in the form  $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$ . Be precise about what goes into each entry of  $\mathbf{Y}$ ,  $\mathbf{X}$ ,  $\boldsymbol{\beta}$ , and  $\boldsymbol{\varepsilon}$ . What are the dimensions of each?

**(b)**

We proved that the optimal  $\hat{\boldsymbol{\beta}}$  satisfies  $\mathbf{X}^\top \mathbf{X} \hat{\boldsymbol{\beta}} = \mathbf{X}^\top \mathbf{Y}$ . Define the “barred quantities”

$$\begin{aligned}\bar{y} &= \frac{1}{N} \sum_{n=1}^N y_n \\ \bar{x} &= \frac{1}{N} \sum_{n=1}^N x_n \\ \overline{xy} &= \frac{1}{N} \sum_{n=1}^N x_n y_n \\ \overline{xx} &= \frac{1}{N} \sum_{n=1}^N x_n^2,\end{aligned}$$

In terms of the barred quantities and the number of datapoints  $N$ , write expressions for  $\mathbf{X}^\top \mathbf{X}$  and  $\mathbf{X}^\top \mathbf{Y}$ .

**(c)**

When is  $\mathbf{X}^\top \mathbf{X}$  invertible? Write a formal expression in terms of the barred quantities. Interpret this condition intuitively in terms of the distribution of the regressors  $x_n$ .

**(d)**

Using the formula for the inverse of a  $2 \times 2$  matrix, find an expression for  $\hat{\beta}$ , and confirm that we get the same answer that we got by solving directly.

**(e)**

In the case where  $\mathbf{X}^\top \mathbf{X}$  is *not* invertible, find three distinct values of  $\beta$  that all achieve the same sum of squared residuals  $\boldsymbol{\varepsilon}^\top \boldsymbol{\varepsilon}$ .

## 2 Probability and matrices

For this problem, assume that  $y_n = \beta_0 + x_n \beta_1 + \varepsilon_n$  for scalar  $x_n$  and some fixed  $\beta_0$  and  $\beta_1$ . Assume that

- The residuals  $\varepsilon_n$  are IID with  $\mathbb{E}[\varepsilon_n] = 0$  and  $\text{Var}(\varepsilon_n) = \sigma^2$ .
- The regressors  $x_n$  are IID with  $\mathbb{E}[x_n] = \mu$  and  $\text{Var}(x_n) = \nu^2$ .
- The residuals are independent of the regressors.

**(a)**

Evaluate the following expressions. (You may need to remind yourself of the definition of conditional expectation and variance.)

- $\mathbb{E}[y_n]$
- $\text{Var}(y_n)$
- $\mathbb{E}[y_n | x_n]$
- $\text{Var}(y_n | x_n)$

**(b)**

Compute the following limits using the LLN, or say that the limit does not exist or is infinite.

- $\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=1}^N \varepsilon_n$
- $\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=1}^N \varepsilon_n^2$
- $\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=1}^N x_n$
- $\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=1}^N x_n^2$
- $\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=1}^N x_n \varepsilon_n$
- $\lim_{N \rightarrow \infty} \frac{1}{N} \sum_{n=1}^N x_n y_n$

**(c)**

Compute the following limits using the CLT, or say that the limit does not exist or is infinite.

- $\lim_{N \rightarrow \infty} \frac{1}{\sqrt{N}} \sum_{n=1}^N \varepsilon_n$
- $\lim_{N \rightarrow \infty} \frac{1}{\sqrt{N}} \sum_{n=1}^N y_n$
- $\lim_{N \rightarrow \infty} \frac{1}{\sqrt{N}} \sum_{n=1}^N (y_n - (\beta_0 + x_n \beta_1))$

**(d)**

Noting that this is simple linear regression, let  $\mathbf{X}$ ,  $\mathbf{Y}$ , and  $\boldsymbol{\varepsilon}$  be as in the solution to question one above. Evaluate the following limits, or say that the limit does not exist or is infinite.

Here,  $(\mathbf{A})_{ij}$  denotes the  $i, j$ -th entry of the matrix  $\mathbf{A}$ . Let the regressor  $x_n$  be in the second column of  $\mathbf{X}$ .

- $\lim_{N \rightarrow \infty} \frac{1}{N} \mathbf{1}^\top \boldsymbol{\varepsilon}$
- $\lim_{N \rightarrow \infty} \frac{1}{\sqrt{N}} \mathbf{1}^\top \boldsymbol{\varepsilon}$
- $\lim_{N \rightarrow \infty} \frac{1}{N} (\mathbf{X}^\top \mathbf{X})_{11}$
- $\lim_{N \rightarrow \infty} \frac{1}{N} (\mathbf{X}^\top \mathbf{X})_{12}$
- $\lim_{N \rightarrow \infty} \frac{1}{N} (\mathbf{X}^\top \mathbf{X})_{22}$
- $\lim_{N \rightarrow \infty} (\mathbf{X}^\top \mathbf{X})_{11}$
- $\lim_{N \rightarrow \infty} \frac{1}{N} (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^\top (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})$
- $\lim_{N \rightarrow \infty} \frac{1}{\sqrt{N}} (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})^\top (\mathbf{Y} - \mathbf{X}\boldsymbol{\beta})$

Hint: Write the matrix expressions as sums over  $n = 1$  to  $N$ .

### 3 One-hot encoding

Consider a one-hot encoding of a variable  $z_n$  that takes three distinct values, “a”, “b”, and “c”. That is, let

$$\mathbf{x}_n = \begin{cases} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} & \text{when } z_n = a \\ \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} & \text{when } z_n = b \\ \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} & \text{when } z_n = c \end{cases}$$

Let  $\mathbf{X}$  be the regressor matrix with  $\mathbf{x}_n^\top$  in row  $n$ .

**(a)**

Let  $N_a$  be the number of observations with  $z_n = a$ , and let  $\sum_{n:z_n=a}$  denote a sum over rows with  $z_n = a$ , with analogous definitions for b and c. In terms of these quantities, write expressions for  $\mathbf{X}^\top \mathbf{X}$  and  $\mathbf{X}^\top \mathbf{Y}$ .

**(b)**

When is  $\mathbf{X}^\top \mathbf{X}$  invertible? Explain intuitively why the regression problem cannot be solved when  $\mathbf{X}^\top \mathbf{X}$  is not invertible. Write an explicit expression for  $(\mathbf{X}^\top \mathbf{X})^{-1}$  when it is invertible.

**(c)**

Using your previous answer, show that the least squares vector  $\hat{\beta}$  is the mean of  $y_n$  within distinct values of  $z_n$ .

**(e)**

Suppose now you include a constant in the regression, so that

$$y_n = \alpha + \beta^\top \mathbf{x}_n + \varepsilon_n,$$

and let  $\mathbf{X}'$  denote the regressor matrix for this regression with coefficient vector  $(\alpha, \beta^\top)^\top$ . Write an expression for  $\mathbf{X}'^\top \mathbf{X}'$  and show that it is not invertible.

**(f)**

Find three distinct values of  $(\alpha, \beta^\top)$  that all give the exact same fit  $\alpha + \beta^\top \mathbf{x}_n$ .

## 4 Correlated regressors

Suppose that  $y_n = \mathbf{x}_n^\top \beta + \varepsilon_n$  for some  $\beta$ . Suppose that  $\mathbb{E}[\varepsilon_n] = 0$  and  $\text{Var}(\varepsilon_n) = \sigma^2$ , and  $\varepsilon_n$  are independent of each other and the  $\mathbf{x}_n$ .

Let  $\mathbf{x}_n \in \mathbb{R}^2$ , where

- $\mathbf{x}_n$  is independent of  $\mathbf{x}_m$  for  $n \neq m$ ,
- $\mathbb{E}[\mathbf{x}_{n1}] = \mathbb{E}[\mathbf{x}_{n2}] = 0$ ,
- $\text{Var}(\mathbf{x}_{n1}) = \text{Var}(\mathbf{x}_{n2}) = 1$ , and
- $\mathbb{E}[\mathbf{x}_{n1}\mathbf{x}_{n2}] = \rho$ .

**(a)**

If  $|\rho| < 1$ , is  $\mathbf{X}^\top \mathbf{X}$  always, sometimes, or never invertible?

**(b)**

If  $|\rho| = 1$ , is  $\mathbf{X}^\top \mathbf{X}$  always, sometimes, or never invertible?

**(c)**

What is  $\lim_{N \rightarrow \infty} \frac{1}{N} \mathbf{X}^\top \mathbf{X}$ ? When is the limit invertible?

**(d)**

State intuitively why there is no unique  $\hat{\beta}$  when  $\rho = 1$ . When  $\rho = 1$ , give two distinct values of  $\beta$  that result in the same fit  $\beta^\top \mathbf{x}_n$ .

## 5 Matrix square roots

In the last homework, we proved that if  $\mathbf{A}$  is a square symmetric matrix with eigenvalues  $\lambda_p$  and eigenvectors  $\mathbf{u}_p$ , then we can write  $\mathbf{A} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^\top$ , where  $\mathbf{U} = (\mathbf{u}_1 \dots \mathbf{u}_p)$  has  $\mathbf{u}_p$  in its  $p$ -th column, and  $\mathbf{\Lambda}$  is diagonal with  $\lambda_p$  in the  $p$ -th diagonal entry. We also have that the eigenvectors can be taken to be orthonormal without loss of generality.

We will additionally assume that  $\mathbf{A} = \mathbf{X}^\top \mathbf{X}$  for some (possibly non-square) matrix  $\mathbf{X}$ .

Define  $\mathbf{\Lambda}^{1/2}$  to be the diagonal matrix with  $\sqrt{\lambda_p}$  on the  $p$ -th diagonal.

- Prove that, since  $\mathbf{A} = \mathbf{X}^\top \mathbf{X}$ ,  $\lambda_p \geq 0$ , and so  $\mathbf{\Lambda}^{1/2}$  is always real-valued. When the eigenvalues are non-negative, we say that  $\mathbf{A}$  is “positive semi-definite.” (Hint: using the fact that  $\lambda_p = \mathbf{u}_p^\top \mathbf{A} \mathbf{u}_p$ , show that  $\lambda_p$  is the square of something.)
- Show that if we take  $\mathbf{Q} = \mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{U}^\top$  then  $\mathbf{A} = \mathbf{Q}\mathbf{Q}^\top$ . We say that  $\mathbf{Q}$  is a “matrix square root” of  $\mathbf{A}$ .
- Show that we also have  $\mathbf{A} = \mathbf{Q}\mathbf{Q}$  (without the second transpose).
- Show that, if  $\mathbf{V}$  is any orthonormal matrix (a matrix with orthonormal columns), then  $\mathbf{Q}' = \mathbf{Q}\mathbf{V} \neq \mathbf{Q}$  also satisfies  $\mathbf{A} = \mathbf{Q}'\mathbf{Q}'^\top$ . This shows that the matrix square root is not unique. (This fact can be thought of as the matrix analogue of the fact that  $4 = 2 \cdot 2$  but also  $4 = (-2) \cdot (-2)$ ).
- Show that if  $\lambda_p > 0$  then  $\mathbf{Q}$  is invertible.
- Show that, if  $\mathbf{Q}$  is invertible, then the columns of  $\mathbf{X}\mathbf{Q}^{-1}$  are orthonormal. (Hint: show that  $(\mathbf{X}\mathbf{Q}^{-1})^\top(\mathbf{X}\mathbf{Q}^{-1})$  is the identity matrix.)