DS 100/200: Principles and Techniques of Data Science

Date: October 23, 2019

Discussion #9

Name:

Geometry of Least Squares

- 1. Consider the following diagram for the geometry of least squares. Fill in the blanks on the diagram with one of the following: (Note that $\hat{\beta}$ is the optimal β , and α is an arbitrary vector.)
 - set of all linear combinations of columns of X

 - X\vec{\alpha}
 - $\mathbb{X}\hat{\beta}$
 - $\vec{y} \mathbb{X}\hat{\beta}$ residual/error

note: Xa is just a linear combination of the columns of Discussion #9 2

2. Use the figure above, to explain why, for all $\alpha \in \mathbb{R}^p$,

$$\|\vec{y} - \mathbb{X}\alpha\|_{z}^{2} \ge \|\vec{y} - \mathbb{X}\hat{\beta}\|_{z}^{2}$$
 is as small as possible

3. From the figure above, what can we say about the residuals and the column space of X?

$$\vec{x}_{2}^{T}(y-X\hat{\beta})=0$$

$$\vec{x}_{2}^{T}(y-X\hat{\beta})=0$$

$$\vdots$$

 $X = \begin{bmatrix} 1 & 1 & 1 \\ \vec{x} & \vec{x}_2 & \vec{x}_p \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} & \vec{y} \\ \vec{x} & \vec{x}_2 & \vec{x}_p \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{x} & \vec{x}_2 & \vec{x}_p \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{x} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{x} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{x} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{y} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{y} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{y} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{y} & \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{y} & \vec{y} \\ \vec{y} & \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{y} & \vec{y} \\ \vec{y} \end{bmatrix} = \begin{bmatrix} \vec{$

4. Derive the normal equations from the fact above. That is, starting from the orthogonality of the residuals and column space of \mathbb{X} , derive $\mathbb{X}^t \vec{y} = \mathbb{X}^t \mathbb{X} \hat{\beta}$.

$$\chi^{T}y - \chi^{T}\chi \hat{\beta} = 0$$

$$\chi^{T}y = \chi^{T}\chi \hat{\beta}$$

5. What must be be true about \mathbb{X} for the normal equation to be solvable, i.e., to get a solution for $\hat{\beta}$? What does this imply about the rank of \mathbb{X} and the features that it represents?

$$\Rightarrow \hat{\beta} = (X^T \times)^{-1} \times^T Y$$

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Discussion #9

Dummy Variables/One-hot Encoding

In order to include a qualitative variable in a model, we convert it into a collection of dummy variables. These dummy variables take on only the values 0 and 1. For example, suppose we have a qualitative variable with 3 levels, call them A, B, and C, respectively. For concreteness, we use a specific example with 10 observations:

In linear modeling, we represent this variable with 3 dummy variables, \vec{x}_A , \vec{x}_B , and \vec{x}_C arranged left to right in the following design matrix. This representation is also called one-hot encoding.

We will show that the fitted coefficients for \vec{x}_A , \vec{x}_B , and \vec{x}_C are \bar{y}_A , \bar{y}_B , and \bar{y}_C , the average of the y_i values for each of the groups, respectively.

6. Show that the columns of X are orthogonal, (i.e., the dot product between any pair of column vectors is 0).

In each row: exactly one 1, rest zero

e.g.

$$X_1 \cdot X_2 = 1 \cdot 0 + 1 \cdot$$

Discussion #9

7. Show that

$$X^{t}X = \begin{bmatrix} n_{A} & 0 & 0 \\ 0 & n_{B} & 0 \\ 0 & 0 & n_{C} \end{bmatrix} = 1 \cdot 4$$

$$= 1^{2} + 1^{2} + 1^{2} + 0 + \dots + 0^{2}$$

$$= 1 \cdot 4$$

$$= 4 = 4 \text{ of points belonging}$$
to class $A = N_{A}$

note: x, x,

Here, n_A , n_B , n_C are the number of observations in each of the three groups defined by the levels of the qualitative variable.

matrix variable.

$$X^{T}X$$
, in general, is a matrix of dot products

 $X^{T}X = \begin{bmatrix} x_{1} & x_{1} & x_{2} & x_{1} & x_{3} \\ x_{2} & x_{1} & x_{2} & x_{2} & x_{3} \end{bmatrix} = \begin{bmatrix} n_{H} & 0 & 0 \\ 0 & n_{B} & 0 \\ 0 & 0 & n_{C} \end{bmatrix}$

8. Show that

9. Use the results from the previous questions to solve the normal equations for $\hat{\beta}$, i.e.,

Inverse of
$$X^TX = \begin{bmatrix} n_A & 0 & 0 \\ 0 & n_B & 0 \\ 0 & 0 & n_C \end{bmatrix}$$
 is $\begin{pmatrix} X^TX \end{pmatrix}^T = \begin{bmatrix} n_A & 0 & 0 \\ n_B & 1 \\ 0 & n_B & 1 \end{bmatrix}$

Then: $\hat{\beta} = \begin{pmatrix} X^TX \end{pmatrix}^{-1} X^T Y = \begin{bmatrix} n_A & 0 & 0 \\ 0 & 0 & n_C \end{bmatrix}$

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