

Lecture 11 – The Normal Equations



DSC 40A, Spring 2023

Announcements

- ▶ Discussion is tonight at 7pm or 8pm in FAH 1101.
- ▶ Homework 4 is out, due Tuesday at 11:59pm.
- ▶ Midterm 1 is **next Friday during lecture**.
 - ▶ Next Wednesday 7-9pm will be a mock exam and review session - save the date! No groupwork next week.
 - ▶ **Formula sheet** will be provided for the exam. No other notes.
 - ▶ More details coming soon.

Agenda

- ▶ Recap of Lecture 10.
- ▶ Minimizing mean squared error.
- ▶ Incorporating multiple features.

Recap of Lecture 10

Reframing regression using linear algebra

- ▶ Last time, we used linear algebra to reformulate our problem of fitting a linear prediction rule

$$H(x) = w_0 + w_1 x$$

- ▶ We defined a **design matrix** X , **parameter vector** \vec{w} , and **observation vector** \vec{y} as follows:

$$X = \begin{bmatrix} 1 & x_1 \\ 1 & x_2 \\ \dots & \dots \\ 1 & x_n \end{bmatrix}, \quad \vec{w} = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}, \quad \vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}$$

- ▶ Then we rewrote our prediction rule as a matrix-vector multiplication, defining the **hypothesis vector** \vec{h} as

$$\vec{h} = X\vec{w}$$

Minimizing mean squared error

- ▶ With our new linear algebra formulation of regression, our mean squared error now looks like:

$$R_{sq}(\vec{w}) = \frac{1}{n} \|\vec{y} - X\vec{w}\|^2$$

→ actual/observed

→ predicted

- ▶ Today, we will minimize this function using calculus.
- ▶ We already saw a sneak peek of the result. The optimal parameter vector \vec{w}^* is¹

$$\vec{w}^* = (X^T X)^{-1} X^T \vec{y}$$

- ▶ This gives the same w_0^* and w_1^* as our formulas from Lecture 6.

¹assuming $X^T X$ is invertible

Minimizing mean squared error, again

Some key linear algebra facts

If A and B are matrices, and $\vec{u}, \vec{v}, \vec{w}, \vec{z}$ are vectors:

✓ ▶ $(A + B)^T = A^T + B^T$

✓ ▶ $(AB)^T = B^T A^T$

✓ ▶ $\vec{u} \cdot \vec{v} = \vec{v} \cdot \vec{u} = \vec{u}^T \vec{v} = \vec{v}^T \vec{u}$

✓ ▶ $\|\vec{u}\|^2 = \vec{u} \cdot \vec{u}$

$$\|\vec{u}\| = \sqrt{u_1^2 + u_2^2 + \dots}$$

▶ $(\vec{u} + \vec{v}) \cdot (\vec{w} + \vec{z}) = \vec{u} \cdot \vec{w} + \vec{u} \cdot \vec{z} + \vec{v} \cdot \vec{w} + \vec{v} \cdot \vec{z}$

Goal

- ▶ We want to minimize the mean squared error:

$$R_{\text{sq}}(\vec{w}) = \frac{1}{n} \|\vec{y} - X\vec{w}\|^2$$

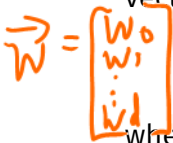
- ▶ Strategy: Calculus.

↖ function of a vector

- ▶ **Problem:** This is a *function of a vector*. What does it even mean to take the derivative of $R_{\text{sq}}(\vec{w})$ with respect to a vector \vec{w} ?

A function of a vector

- ▶ **Solution:** A function of a vector is really just a function of multiple variables, which are the components of the vector. In other words,


$$\vec{w} = \begin{bmatrix} w_0 \\ w_1 \\ \vdots \\ w_d \end{bmatrix}$$

$$R_{\text{sq}}(\vec{w}) = R_{\text{sq}}(w_0, w_1, \dots, w_d)$$

where w_0, w_1, \dots, w_d are the entries of the vector \vec{w} .²

- ▶ We know how to deal with derivatives of multivariable functions: the gradient!

²In our case, \vec{w} has just two components, w_0 and w_1 . We'll be more general since we eventually want to use prediction rules with even more parameters.

The gradient with respect to a vector

- ▶ The **gradient of $R_{sq}(\vec{w})$ with respect to \vec{w}** is the vector of partial derivatives:

$$\nabla_{\vec{w}} R_{sq}(\vec{w}) = \frac{dR_{sq}}{d\vec{w}} = \begin{bmatrix} \frac{\partial R_{sq}}{\partial w_0} \\ \frac{\partial R_{sq}}{\partial w_1} \\ \vdots \\ \frac{\partial R_{sq}}{\partial w_d} \end{bmatrix}$$

Partial derivs w.r.t. each component

where w_0, w_1, \dots, w_d are the entries of the vector \vec{w} .

$$\vec{a} \cdot \vec{x} = a_1 x_1 + a_2 x_2 + \dots + a_n x_n$$

Example gradient calculation

= fixed

Example: Suppose $f(\vec{x}) = \vec{a} \cdot \vec{x}$, where \vec{a} and \vec{x} are vectors in \mathbb{R}^n .
What is $\frac{d}{d\vec{x}} f(\vec{x})$?

vec \rightarrow f \rightarrow scalar Let $\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}$.

$$\frac{d}{d\vec{x}} f = \begin{bmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} = \vec{a}$$

Goal

- ▶ We want to minimize the mean squared error:

$$R_{\text{sq}}(\vec{w}) = \frac{1}{n} \|\vec{y} - X\vec{w}\|^2$$

- ▶ Strategy:
 1. Compute the gradient of $R_{\text{sq}}(\vec{w})$.
 2. Set it to zero and solve for \vec{w} .
 - ▶ The result is called \vec{w}^* .
- ▶ Let's start by rewriting the mean squared error in a way that will make it easier to compute its gradient.

Rewriting mean squared error

$$R_{\text{sq}}(\vec{w}) = \frac{1}{n} \|\vec{y} - X\vec{w}\|^2 = \frac{1}{n} \|\vec{e}\|^2 = \frac{1}{n} \vec{e} \cdot \vec{e} = \frac{1}{n} \vec{e}^T \vec{e}$$

Discussion Question

Which of the following is equivalent to $R_{\text{sq}}(\vec{w})$?

~~a) $\frac{1}{n} (\vec{y} - X\vec{w}) \cdot (X\vec{w} - y)$~~

~~b) $\frac{1}{n} \sqrt{(\vec{y} - X\vec{w}) \cdot (y - X\vec{w})}$~~

c) $\frac{1}{n} (\vec{y} - X\vec{w})^T (y - X\vec{w})$

d) $\frac{1}{n} (\vec{y} - X\vec{w})(y - X\vec{w})^T$

→ C

$\begin{bmatrix} \\ \\ \end{bmatrix} \begin{bmatrix} \\ \\ \end{bmatrix} \rightarrow \text{Scale}$
 $1 \times n$ $n \times 1$

$\begin{bmatrix} \\ \\ \end{bmatrix} \begin{bmatrix} \\ \\ \end{bmatrix} \begin{bmatrix} \\ \\ \end{bmatrix} = \begin{bmatrix} \\ \\ \end{bmatrix}$
 $1 \times n$ $n \times n$ $n \times 1$

Rewriting mean squared error

$$R_{\text{sq}}(\vec{w}) = \frac{1}{n} \|\vec{y} - X\vec{w}\|^2$$

$$= \frac{1}{n} (y - Xw)^T (y - Xw)$$

$$= \frac{1}{n} (y^T - (Xw)^T) (y - Xw)$$

$$= \frac{1}{n} (y^T - w^T X^T) (y - Xw)$$

$$= \frac{1}{n} (y^T y - \underbrace{y^T X w}_{(X^T y)^T w} - \underbrace{w^T X^T y}_{w \cdot X^T y} + w^T X^T X w)$$

$$= (X^T y)^T w = w \cdot X^T y$$

$$= X^T y \cdot w = X^T y \cdot w$$

$$= \frac{1}{n} (y \cdot y - 2 X^T y \cdot w + w^T X^T X w)$$

Rewriting mean squared error

$$R_{\text{sq}}(\vec{w}) =$$

Compute the gradient

$$\begin{aligned}\frac{dR_{\text{sq}}}{d\vec{w}} &= \frac{d}{d\vec{w}} \left(\frac{1}{n} [\vec{y} \cdot \vec{y} - 2X^T \vec{y} \cdot \vec{w} + \vec{w}^T X^T X \vec{w}] \right) \\ &= \frac{1}{n} \left[\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y}) - \frac{d}{d\vec{w}} (2X^T \vec{y} \cdot \vec{w}) + \frac{d}{d\vec{w}} (\vec{w}^T X^T X \vec{w}) \right]\end{aligned}$$

Compute the gradient

$$\begin{aligned}\frac{dR_{\text{sq}}}{d\vec{w}} &= \frac{d}{d\vec{w}} \left(\frac{1}{n} [\vec{y} \cdot \vec{y} - 2X^T \vec{y} \cdot \vec{w} + \vec{w}^T X^T X \vec{w}] \right) \\ &= \frac{1}{n} \left[\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y}) - \frac{d}{d\vec{w}} (2X^T \vec{y} \cdot \vec{w}) + \frac{d}{d\vec{w}} (\vec{w}^T X^T X \vec{w}) \right]\end{aligned}$$

- ▶ $\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y}) = 0$.
- ▶ Why? \vec{y} is a constant with respect to \vec{w} .

Compute the gradient

$$\begin{aligned}\frac{dR_{\text{sq}}}{d\vec{w}} &= \frac{d}{d\vec{w}} \left(\frac{1}{n} [\vec{y} \cdot \vec{y} - 2X^T \vec{y} \cdot \vec{w} + \vec{w}^T X^T X \vec{w}] \right) \\ &= \frac{1}{n} \left[\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y}) - \frac{d}{d\vec{w}} (2X^T \vec{y} \cdot \vec{w}) + \frac{d}{d\vec{w}} (\vec{w}^T X^T X \vec{w}) \right]\end{aligned}$$

- ▶ $\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y}) = 0$.
 - ▶ Why? \vec{y} is a constant with respect to \vec{w} .
- ▶ $\frac{d}{d\vec{w}} (2X^T \vec{y} \cdot \vec{w}) = 2X^T \vec{y}$.
 - ▶ Why? We already showed $\frac{d}{d\vec{x}} \vec{a} \cdot \vec{x} = \vec{a}$.

Compute the gradient

$$\begin{aligned}\frac{dR_{\text{sq}}}{d\vec{w}} &= \frac{d}{d\vec{w}} \left(\frac{1}{n} [\vec{y} \cdot \vec{y} - 2X^T \vec{y} \cdot \vec{w} + \vec{w}^T X^T X \vec{w}] \right) \\ &= \frac{1}{n} \left[\underbrace{\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y})}_{0} - \underbrace{\frac{d}{d\vec{w}} (2X^T \vec{y} \cdot \vec{w})}_{-2X^T \vec{y}} + \underbrace{\frac{d}{d\vec{w}} (\vec{w}^T X^T X \vec{w})}_{2X^T X \vec{w}} \right] = \vec{0}\end{aligned}$$

▶ $\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y}) = 0.$

▶ Why? \vec{y} is a constant with respect to \vec{w} .

▶ $\frac{d}{d\vec{w}} (\vec{2}X^T \vec{y} \cdot \vec{w}) = 2X^T \vec{y}.$

▶ Why? We already showed $\frac{d}{d\vec{x}} \vec{a} \cdot \vec{x} = \vec{a}.$

$$2X^T X \vec{w} = 2X^T \vec{y}$$

$$X^T X \vec{w} = X^T \vec{y}$$

▶ $\frac{d}{d\vec{w}} (\vec{w}^T X^T X \vec{w}) = 2X^T X \vec{w}.$

▶ Why? See Homework 4.

Compute the gradient

$$\begin{aligned}\frac{dR_{\text{sq}}}{d\vec{w}} &= \frac{d}{d\vec{w}} \left(\frac{1}{n} [\vec{y} \cdot \vec{y} - 2X^T \vec{y} \cdot \vec{w} + \vec{w}^T X^T X \vec{w}] \right) \\ &= \frac{1}{n} \left[\frac{d}{d\vec{w}} (\vec{y} \cdot \vec{y}) - \frac{d}{d\vec{w}} (2X^T \vec{y} \cdot \vec{w}) + \frac{d}{d\vec{w}} (\vec{w}^T X^T X \vec{w}) \right]\end{aligned}$$

The normal equations

- ▶ To minimize $R_{sq}(\vec{w})$, set gradient to zero and solve for \vec{w} :

$$-2X^T\vec{y} + 2X^TX\vec{w} = 0$$

$$\Rightarrow X^TX\vec{w} = X^T\vec{y}$$

general solution

- ▶ This is a system of equations in matrix form, called the normal equations.
- ▶ If X^TX is invertible, the solution is

$$\vec{w}^* = (X^TX)^{-1}X^T\vec{y}$$

- ▶ This is equivalent to the formulas for w_0^* and w_1^* we saw before!
 - ▶ Benefit – this can be easily extended to more complex prediction rules.

Incorporating multiple features

Incorporating multiple features

- ▶ How do we predict salary given **multiple** features?
- ▶ We believe salary is a function of experience *and* GPA.
- ▶ In other words, we believe there is a function H so that:

$$\text{salary} \approx H(\text{years of experience, GPA})$$

- ▶ Recall: H is a **prediction rule**.
- ▶ **Our goal:** find a good prediction rule, H .

Example prediction rules

$$H_1(\text{experience, GPA}) = \$2,000 \times (\text{experience}) + \$40,000 \times \frac{\text{GPA}}{4.0}$$

$$H_2(\text{experience, GPA}) = \$60,000 \times 1.05^{(\text{experience}+\text{GPA})}$$

$$H_3(\text{experience, GPA}) = \underbrace{\cos(\text{experience})} + \underbrace{\sin(\text{GPA})}$$

Linear prediction rules

- ▶ We'll restrict ourselves to **linear** prediction rules:

$$H(\text{experience, GPA}) = \underline{w_0} + \underline{w_1}(\text{experience}) + \underline{w_2}(\text{GPA})$$

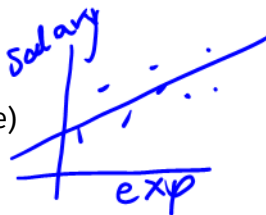
- ▶ As before, we can solve the **normal equations** to find w_0^* , w_1^* , and w_2^* . All we need to do is change the design matrix X .
- ▶ Linear regression with multiple features is called **multiple linear regression**.

Geometric interpretation

Question: The prediction rule

$$H(\text{experience}) = w_0 + w_1(\text{experience})$$

looks like a line in 2D.



1. How many dimensions do we need to graph

3 $H(\text{experience, GPA}) = w_0 + w_1(\text{experience}) + w_2(\text{GPA})$

2. What is the shape of the prediction rule?

plane

math: $z = ax + by + c$



Example dataset

- ▶ For each of n people, collect each feature, plus salary:

Person #	Experience	GPA	Salary
1	3	3.7	85,000
2	6	3.3	95,000
3	10	3.1	105,000

- ▶ We represent each person with a **feature vector**:

$$\vec{x}_1 = \begin{bmatrix} 3 \\ 3.7 \end{bmatrix}, \quad \vec{x}_2 = \begin{bmatrix} 6 \\ 3.3 \end{bmatrix}, \quad \vec{x}_3 = \begin{bmatrix} 10 \\ 3.1 \end{bmatrix}$$

The hypothesis vector

- ▶ When our prediction rule is

$$H(\text{experience}, \text{GPA}) = w_0 + w_1(\text{experience}) + w_2(\text{GPA}),$$

2 inputs

the hypothesis vector $\vec{h} \in \mathbb{R}^n$ can be written

$$\vec{h} = \begin{bmatrix} H(\text{experience}_1, \text{GPA}_1) \\ H(\text{experience}_2, \text{GPA}_2) \\ \dots \\ H(\text{experience}_n, \text{GPA}_n) \end{bmatrix} = \begin{bmatrix} 1 & \text{experience}_1 & \text{GPA}_1 \\ 1 & \text{experience}_2 & \text{GPA}_2 \\ \dots & \dots & \dots \\ 1 & \text{experience}_n & \text{GPA}_n \end{bmatrix} \begin{bmatrix} w_0 \\ w_1 \\ w_2 \end{bmatrix}$$

change design matrix to reflect prediction rule

Finding the optimal parameters

- ▶ To find the best parameter vector, \vec{w}^* , we can use the design matrix and observation vector

$$X = \begin{bmatrix} 1 & \text{experience}_1 & \text{GPA}_1 \\ 1 & \text{experience}_2 & \text{GPA}_2 \\ \dots & \dots & \dots \\ 1 & \text{experience}_n & \text{GPA}_n \end{bmatrix}, \vec{y} = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}$$

transposed feature vector

and solve the **normal equations**

$$X^T X \vec{w}^* = X^T \vec{y}$$

- ▶ Notice that the rows of the design matrix are the (transposed) feature vectors, with an additional 1 in front.

Notation for multiple linear regression

- ▶ We will need to keep track of multiple³ features for every individual in our data set.
- ▶ As before, subscripts distinguish between individuals in our data set. We have n individuals (or **training examples**).
- ▶ Superscripts distinguish between features.⁴ We have d features.
 - ▶ experience = $x^{(1)}$
 - ▶ GPA = $x^{(2)}$

³In practice, we might use hundreds or even thousands of features.

⁴Think of them as new variable names, such as new letters.

Augmented feature vectors

- ▶ The augmented feature vector $\text{Aug}(\vec{x})$ is the vector obtained by adding a 1 to the front of feature vector \vec{x} :

$$\vec{x} = \begin{bmatrix} x^{(1)} \\ x^{(2)} \\ \vdots \\ x^{(d)} \end{bmatrix} \quad \text{Aug}(\vec{x}) = \begin{bmatrix} 1 \\ x^{(1)} \\ x^{(2)} \\ \vdots \\ x^{(d)} \end{bmatrix} \quad \vec{w} = \begin{bmatrix} w_0 \\ w_1 \\ w_2 \\ \vdots \\ w_d \end{bmatrix}$$

- ▶ Then, our prediction rule is

$$\begin{aligned} H(\vec{x}) &= w_0 + w_1 x^{(1)} + w_2 x^{(2)} + \dots + w_d x^{(d)} \\ &= \vec{w} \cdot \text{Aug}(\vec{x}) \end{aligned}$$

The general problem

- ▶ we have n data points (or **training examples**):
 $(\vec{x}_1, y_1), \dots, (\vec{x}_n, y_n)$ where each \vec{x}_i is a feature vector of d features:

person 1

$$\vec{x}_i = \begin{bmatrix} x_i^{(1)} \\ x_i^{(2)} \\ \dots \\ x_i^{(d)} \end{bmatrix}$$

$\rightarrow \text{exp}$
 $\rightarrow \text{gpa}$
 \vdots

} vector of information for person 2

- ▶ We want to find a good linear prediction rule:

$$\begin{aligned} H(\vec{x}) &= w_0 + w_1 x^{(1)} + w_2 x^{(2)} + \dots + w_d x^{(d)} \\ &= \vec{w} \cdot \text{Aug}(\vec{x}) \end{aligned}$$

The general solution

- Use design matrix

$$X = \begin{bmatrix} 1 & x_1^{(1)} & x_1^{(2)} & \dots & x_1^{(d)} \\ 1 & x_2^{(1)} & x_2^{(2)} & \dots & x_2^{(d)} \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_n^{(1)} & x_n^{(2)} & \dots & x_n^{(d)} \end{bmatrix} = \begin{bmatrix} \text{Aug}(\vec{x}_1)^T \\ \text{Aug}(\vec{x}_2)^T \\ \dots \\ \text{Aug}(\vec{x}_n)^T \end{bmatrix}$$

Person 1
(row 1)
Feature 2
(gpa)

and observation vector to solve the **normal equations**

$$X^T X \vec{w}^* = X^T \vec{y}$$

to find the optimal parameter vector.

Interpreting the parameters

- ▶ With d features, \vec{w} has $d + 1$ entries.
- ▶ w_0 is the **bias**, also known as the **intercept**.
- ▶ w_1, \dots, w_d each give the **weight**, i.e. **coefficient**, of a feature.

$$H(\vec{x}) = w_0 + w_1 x^{(1)} + \dots + w_d x^{(d)}$$

- ▶ The sign of w_i tells us about the relationship between i th feature and the output of our prediction rule.

Summary

Summary

- ▶ We minimized the mean squared error for the prediction rule $H(x) = w_0 + w_1x$, which was

$$R_{sq}(\vec{w}) = \frac{1}{n} \|\vec{y} - X\vec{w}\|^2$$

- ▶ We found that the minimizing \vec{w} satisfies the **normal equations**, $X^T X \vec{w} = X^T \vec{y}$.
 - ▶ If $X^T X$ is invertible, the solution is:

$$\vec{w}^* = (X^T X)^{-1} X^T \vec{y}$$

- ▶ These same normal equations can be used to solve the **multiple linear regression** problem, where we use multiple features to predict an outcome. We simply need to adjust the design matrix X .