

## Lecture 1: Simple Linear Regression

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## 1.1 Motivating Example: MLB Batting Averages

Suppose we have access to each MLB player's 2020 and 2021 batting averages and no other information. How would we predict a player's 2021 batting average from their 2020 one?

Generally, a good idea is to start with exploratory data analysis. Let's plot the data and see what we learn.

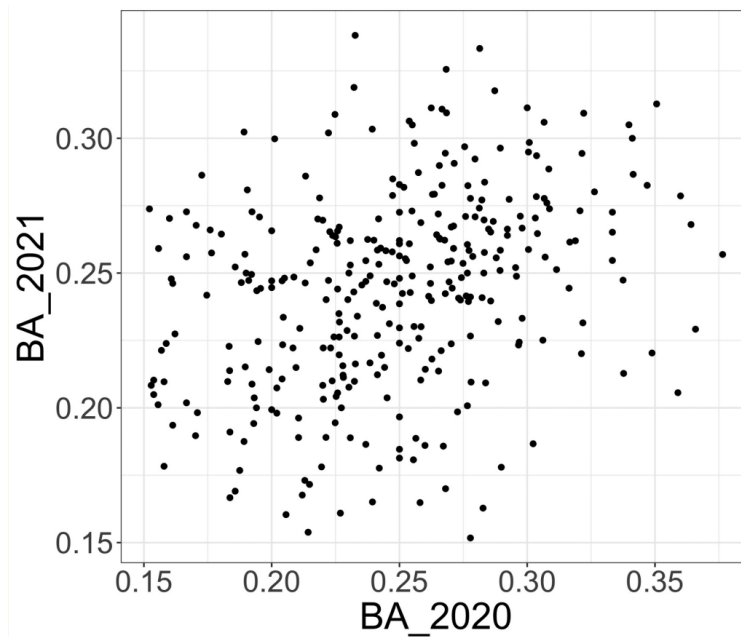


Figure 1.1: Batting Averages for MLB Players in 2020 and 2021

What does the relationship look like?

- Somewhat linear with a positive slope
- Positive relationship: you'd expect that a higher 2020 BA is associated with a higher 2021 BA
- You might imagine drawing a best fit line through the points

Let's plot that line of best fit!

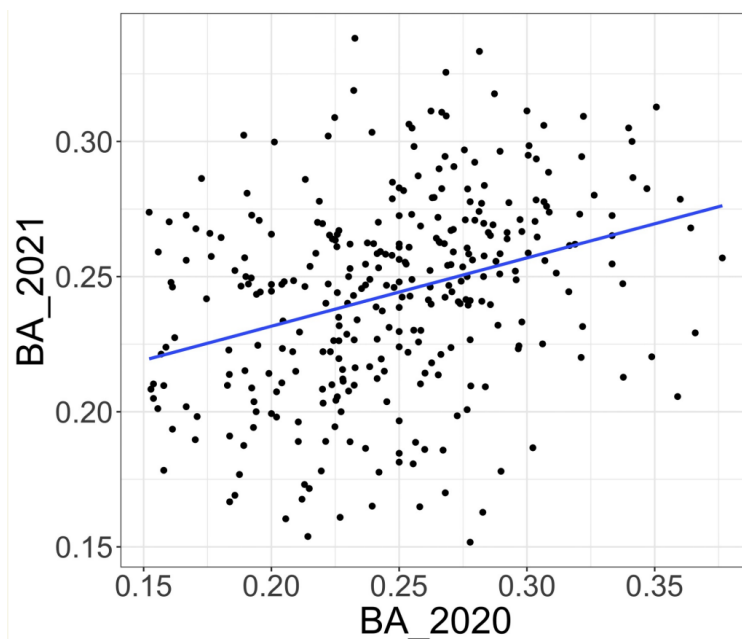


Figure 1.2: Line of Best Fit for MLB Batting Averages

This relationship isn't perfect, there's certainly some correlation but a lot of noise in the data. Still the question remains: how did we get this line? We **set up a model** to define this mathematically.

## 1.2 Setting Up the Model

Index each baseball player by  $i = 1, \dots, n$ . Let  $X_i = BA_i^{(2020)}$  be our independent (predictor) variable and  $Y_i = BA_i^{(2021)}$  be our dependent (response) variable. Assuming a **linear relationship** between each  $X_i$  and its corresponding  $Y_i$ , we can write:

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad (1.1)$$

where  $\beta_0$  is an unknown constant intercept,  $\beta_1$  is an unknown constant slope, and  $\epsilon_i$  is a random, independent, and identically-distributed error (or noise) term with mean 0 and constant variance  $\sigma^2$ . Mathematically, we can write

$$\epsilon_i \text{ i.i.d., } \mathbb{E}[\epsilon_i] = 0, \text{ and } \mathbb{E}[\epsilon_i^2] = \sigma^2 \quad (1.2)$$

We are interested in the conditional expectation of  $Y_i$  given  $X_i$ , or

$$\mathbb{E}[Y_i | X_i] = \beta_0 + \beta_1 X_i \quad (1.3)$$

This represents the "true" underlying line, but we don't know the values of  $\beta_0$  and  $\beta_1$ . How do we **obtain estimates for these parameters** to obtain the "best fit" line?

## 1.3 Estimating Model Parameters

**Definition 1.1** (Ordinary Least Squares). Find the values  $\hat{\beta}_0$  and  $\hat{\beta}_1$  that minimize the **Residual Sum of Squares (RSS)**, or the mean squared error.

**Definition 1.2** (Residual Sum of Squares).

$$\begin{aligned} RSS(\beta_0, \beta_1) &= \sum_{i=1}^n (Y_i - \mathbb{E}[Y_i | X_i])^2 \\ &= \sum_{i=1}^n (Y_i - (\beta_0 + \beta_1 X_i))^2 \end{aligned} \quad (1.4)$$

Visually, we can think of the RSS as the sum of the squared vertical distances between the observed points and the fitted line (or the squared residuals). In Figure 1.3, we plot the residuals for each point.

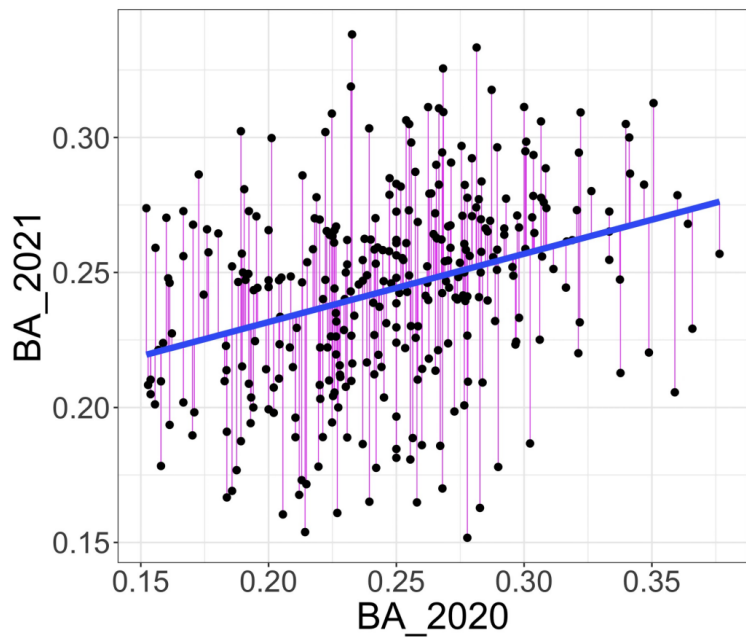


Figure 1.3: Residuals for MLB Batting Averages

Our objective is to find the intercept ( $\beta_0$ ) and slope ( $\beta_1$ ) which minimize the sum of squares of the lengths of the pink line segments. Mathematically, we write:

$$\begin{aligned} \hat{\beta}_0, \hat{\beta}_1 &= \arg \min_{(\beta_0, \beta_1)} RSS(\beta_0, \beta_1) \\ &= \arg \min_{(\beta_0, \beta_1)} \sum_{i=1}^n (Y_i - (\beta_0 + \beta_1 X_i))^2 \end{aligned} \quad (1.5)$$

We can solve this with calculus, setting the partial derivatives with respect to  $\beta_0$  and  $\beta_1$  to zero.

$$\begin{aligned} \frac{\partial}{\partial \beta_0} RSS(\beta_0, \beta_1) &= \sum_{i=1}^n -2(Y_i - (\beta_0 + \beta_1 X_i)) = 0 \\ \implies \frac{1}{n} \sum_{i=1}^n \beta_0 &= \frac{1}{n} \sum_{i=1}^n (Y_i - \beta_1 X_i) \\ \implies \hat{\beta}_0 &= \bar{Y} - \hat{\beta}_1 \bar{X}^a \end{aligned} \quad (1.6)$$

$$\begin{aligned}
\frac{\partial}{\partial \beta_1} \text{RSS}(\beta_0, \beta_1) &= \sum_{i=1}^n -2X_i(Y_i - (\beta_0 + \beta_1 X_i)) = 0 \\
\Rightarrow -\frac{1}{n} \sum_{i=1}^n X_i Y_i + \beta_0 \frac{1}{n} \sum_{i=1}^n X_i + \beta_1 \frac{1}{n} \sum_{i=1}^n X_i^2 &= 0 \\
\Rightarrow \beta_1 \left( \frac{1}{n} \sum_{i=1}^n X_i^2 - \bar{X} \right)^2 &= \frac{1}{n} \sum_{i=1}^n X_i Y_i - \bar{X} \bar{Y} \\
\Rightarrow \hat{\beta}_1 &= \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^n (X_i - \bar{X})^2}
\end{aligned} \tag{1.7}$$

So we have closed-form expressions for  $\hat{\beta}_0$  and  $\hat{\beta}_1$ . But what do these coefficients mean?

## 1.4 Interpreting Model Coefficients

### 1.4.1 Covariance

**Definition 1.3** (Covariance). *The covariance between two random variables  $X$  and  $Y$  is defined as*

$$\sigma_{XY} = \text{Cov}(X, Y) = \mathbb{E}[(X - \mathbb{E}[X])(Y - \mathbb{E}[Y])] \tag{1.8}$$

*Note that if  $\mathbb{E}[X] = \mathbb{E}[Y] = 0$ , then  $\sigma_{XY} = \mathbb{E}[XY]$ .*

- Positive covariance: If when  $X$  is positive,  $Y$  tends to be positive (and when  $X$  is negative,  $Y$  tends to be negative), then  $\sigma_{XY} > 0$
- Negative covariance: If when  $X$  is positive,  $Y$  tends to be negative (and when  $X$  is negative,  $Y$  tends to be positive), then  $\sigma_{XY} < 0$

We proceed with some theorems that you will prove in your homework.

**Theorem 1.4.** *If  $X$  and  $Y$  are independent, then  $\sigma_{XY} = 0$ .*

**Theorem 1.5.** *The **sample covariance** between  $X$  and  $Y$ , defined as*

$$S_{XY} = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y}) \tag{1.9}$$

*is an unbiased estimator of  $\sigma_{XY}$ .*

**Theorem 1.6.** *The **sample variance** of  $X$ , defined as*

$$S_X^2 = \frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X})^2 \tag{1.10}$$

*is an unbiased estimator of  $\sigma_X^2 = \text{Var}(X)$ .*

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<sup>a</sup>  $\bar{X} = \frac{1}{n} \sum_{i=1}^n X_i$  and  $\bar{Y} = \frac{1}{n} \sum_{i=1}^n Y_i$  are the sample means of the predictor and response variables, respectively.

<sup>b</sup>  $\beta_0 \frac{1}{n} \sum_{i=1}^n X_i = \beta_0 \bar{X} = (\bar{Y} - \hat{\beta}_1 \bar{X}) \bar{X} = \bar{X} \bar{Y} - \hat{\beta}_1 \bar{X}^2$ , from Equation 1.6

## 1.4.2 Correlation

**Definition 1.7** (Correlation). *The correlation between two random variables  $X$  and  $Y$  is defined as*

$$\rho_{XY} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y} \quad (1.11)$$

*It is a normalized version of the covariance, and is always between  $-1$  and  $1$ .*

**Definition 1.8** (Sample Correlation). *The sample correlation between  $X$  and  $Y$  is defined as*

$$r_{XY} = \frac{S_{XY}}{S_X S_Y} = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \quad (1.12)$$

We can use the sample correlation to measure the strength of the linear relationship between  $X$  and  $Y$ . Consider our estimate  $\hat{\beta}_1$  from Equation 1.7:

$$\begin{aligned} \hat{\beta}_1 &= \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^n (X_i - \bar{X})^2} \\ &= \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2} \sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}} \cdot \frac{\sqrt{\sum_{i=1}^n (Y_i - \bar{Y})^2}}{\sqrt{\sum_{i=1}^n (X_i - \bar{X})^2}} \\ &= r_{XY} \cdot \frac{S_Y}{S_X} \end{aligned} \quad (1.13)$$

We can also reciprocally express the sample correlation in terms of  $\hat{\beta}_1$ :

$$r_{XY} = \hat{\beta}_1 \frac{S_X}{S_Y} \quad (1.14)$$

So if  $X$  and  $Y$  have the same scale (or sample variance), then the sample correlation is simply the slope of the linear regression line!

## 1.5 Remarks on Correlation

### 1.5.1 Correlation Can Be Misleading

Correlation is a measure of **linear association** between two variables. Figure 1.4 shows four plots with equal correlation, but they have **very** different relationships. What does this tell us?

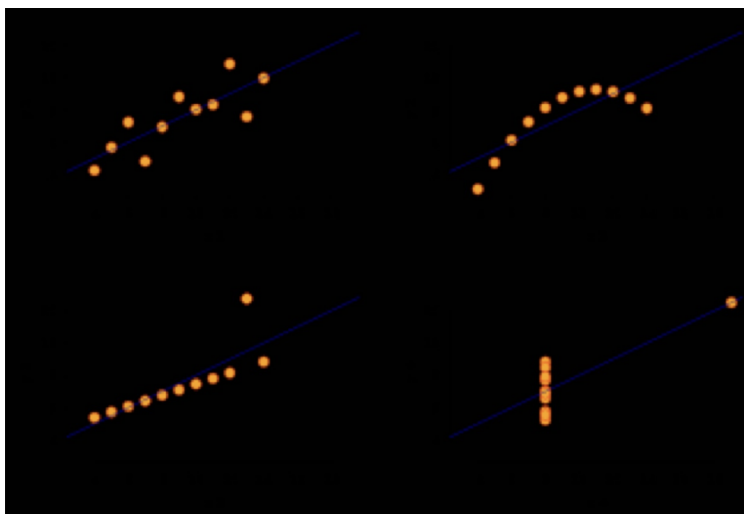


Figure 1.4: Four scatter plots with equal correlation

Correlation can be **meaningless** if:

- The relationship is not linear at all
- There are extreme outliers in the data.

It is best to use correlation to describe data whose scatter plots are roughly elliptical (football-shaped). The lesson? **ALWAYS PLOT YOUR DATA!**

### 1.5.2 Case Study: In-Play Batting Average vs Batting Average

In Figure 1.5 below, we plot the MLB season averages for in-play batting average vs overall batting average for each season. It's clear when we plot the data that there is a different relationship between IPBA and BA before 1951 vs after 1951. We should consider splitting the data into two for our analysis.

**Scatterplot of IPBA (In Play Batting Average) and Average (seasonal data)**  
**Red < 1951 Blue > 1950.**  
**Correlation = 0.36**

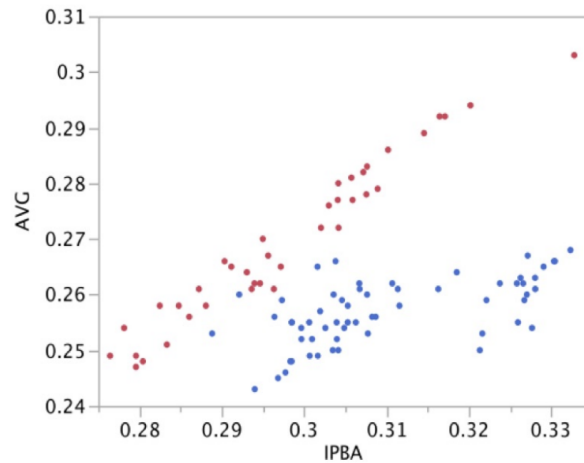
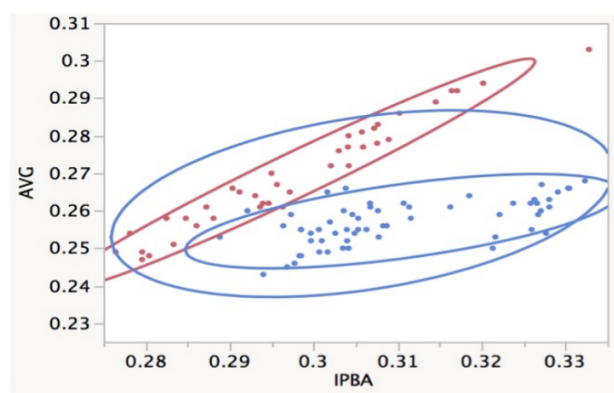


Figure 1.5: The relationship between in-play batting average and overall batting average is clearly different before and after 1951

In Figure 1.6, you can see that the data is much more tightly clustered in an elliptical shape when it is separated. Generally, this shape indicates the best type of data for prediction.

**Scatterplot of IPBA (In Play Batting Average) and Average (seasonal data)**



**Overall:  $r = .36$**   
**Red:  $r = .97$  Blue:  $r = .91$**

Figure 1.6: The correlation is much higher when the data is split

Notice that the correlation for either data (red or blue) is almost 3 times larger than the two together (0.97 and 0.91 vs 0.36).

## 1.6 Back to Our Batting Average Model

In Section 1.2, we defined our model as

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i \quad (1.15)$$

where  $Y_i$  is the dependent variable,  $X_i$  is the independent variable,  $\beta_0$  is the intercept,  $\beta_1$  is the slope, and  $\epsilon_i$  is the error term. Letting  $X = BA^{(2020)}$  and  $Y = BA^{(2021)}$ , we now know that  $\hat{\beta}_1$  is a measure of how correlated  $BA^{(2020)}$  is with  $BA^{(2021)}$ .

We use **R** to fit our linear regression model.

```
model = lm(BA_2021 ~ BA_2020, data = ba_data)  
summary(model)
```

From this summary output, we can see that  $\hat{\beta}_1 = 0.25$ . This means that a batting average increase of 0.020 in 2020 is associated with a predicted batting average increase of 0.005 in 2021.

## 1.7 Regression to the Mean

If  $X_i > \bar{X}$ , then  $X_i = \bar{X} + \delta$ , with  $\delta > 0$ . Then it follows that:

$$\begin{aligned} \hat{Y}_i &= \hat{\beta}_0 + \hat{\beta}_1 X_i \\ &= (\bar{Y} - \hat{\beta}_1 \bar{X}) + \hat{\beta}_1 X_i \\ &= \bar{Y} + \hat{\beta}_1 (X_i - \bar{X}) \\ &= \bar{Y} + \hat{\beta}_1 \delta \end{aligned} \quad (1.16)$$

$$(1.17)$$

In our example,  $\hat{\beta}_1 = 0.25$ , therefore

$$\hat{Y}_i = \bar{Y} + \frac{\delta}{4} \quad (1.18)$$

This is an example of **regression to the mean**.  $BA_i^{(2020)}$  is  $\delta$  greater than  $\bar{BA}^{(2020)}$ , but  $\widehat{BA}_i^{(2021)}$  is only  $\frac{\delta}{4}$  greater than  $\bar{BA}^{(2021)}$ . In other words, our prediction of player  $i$ 's 2021 batting average is somewhere between their 2020 BA and the mean BA in 2021.