

# Lecture 3: Simple Linear Regression

Module 1: part 2

Spring 2024

# Logistics

- Lecture today will introduce linear regression with 1 covariate
- Labs Mon/Tues will cover fitting linear models in R
- Module 1 assessment will be posted before Monday Feb 3, due date is Tues Feb 9, 11:59pm

# Recap

- Population  $\rightarrow$  Data  $\rightarrow$  Statistic
- Mean, median, mode can be seen as minimizing certain criteria
- Correlation measures linear association between two variables

# Linear regression

## Parameters which govern a line

The equation for a line can be put into the following form

$$Y = b_0 + b_1X \quad (1)$$

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- $X$  and  $Y$  are variables
- $b_0$  is the **Y-intercept**. It is the value of the  $Y$  coordinate when  $X = 0$
- $b_1$  is the **slope**. It describes how  $Y$  changes as  $X$  changes.

# Wine vs Ratings

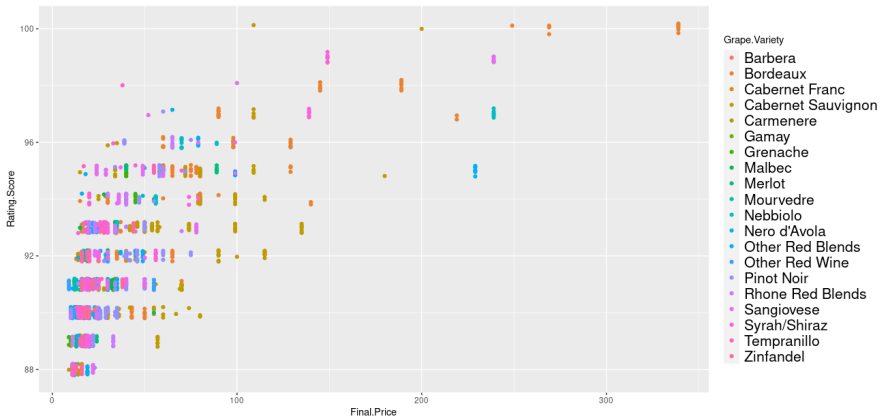


Figure: Data from Wine.com circa 2015

## Alternative way

Summarize a set of numbers  $\{2, 5, 8, 10\}$

- Let  $\hat{b}_0$  be a “candidate”
- The residual for  $x_i$  is  $x_i - \hat{b}_0$
- Measure how well the candidate summarizes the set by the *residual sum of squares*

$$RSS(\hat{b}_0) = \sum_i |x_i - \hat{b}_0|^2 = \sum_i |e_i|^2$$

- Suppose  $\hat{b}_0 = 6$

$x_i$	$x_i - \hat{b}_0$	$(x_i - \hat{b}_0)^2$
2	-4	16
5	-1	1
8	2	4
10	4	16

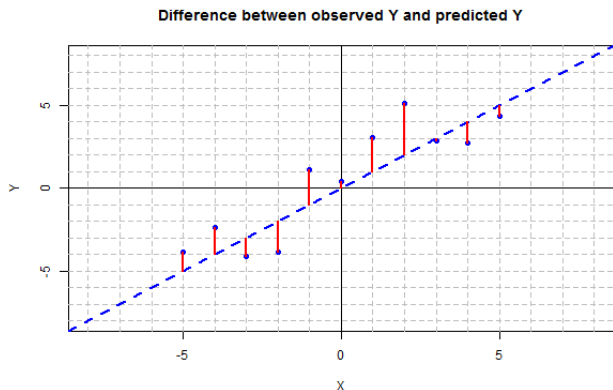


# Errors in Y

Suppose we observe  $(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)$ . To select a “best line” we consider the difference between the predicted point and observed value of  $y_i$ .

Predicted value:  $\hat{y}_i = \hat{b}_0 + \hat{b}_1 x_i$

Residual:  $e_i = y_i - \hat{y}_i$



## Selecting Regression Coefficient

How can we select a slope and intercept to minimize the sum of squared errors?

$$RSS(\hat{b}_0, \hat{b}_1) = \sum_i (y_i - \hat{y}_i)^2 = \sum_i (y_i - (\hat{b}_0 + \hat{b}_1 x_i))^2 \quad (2)$$

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Next few slides have math, which you can look through more carefully if you want, but is otherwise not necessary

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Take a derivative and set equal to 0!

$$\frac{\partial RSS}{\partial \hat{b}_1} = -2 \sum_i x_i (y_i - (\hat{b}_0 + \hat{b}_1 x_i)) = 0 \quad (3)$$

$$\frac{\partial RSS}{\partial \hat{b}_0} = -2 \sum_i (y_i - (\hat{b}_0 + \hat{b}_1 x_i)) = 0 \quad (4)$$

## Selecting Regression Coefficient: $\hat{b}_0$

$$\begin{aligned} 0 &= \frac{\partial \text{RSS}}{\partial \hat{b}_0} = -2 \sum_i (y_i - (\hat{b}_0 + \hat{b}_1 x_i)) \\ &= -2 \sum_i y_i + 2n\hat{b}_0 + \hat{b}_1 \sum_i x_i \end{aligned} \quad (5)$$

$$\Rightarrow \hat{b}_0 = \bar{y} - \hat{b}_1 \bar{x} \quad (6)$$

## Selecting Regression Coefficient: $\hat{b}_1$

$$\begin{aligned}\frac{\partial RSS}{\partial \hat{b}_1} &= -2 \sum_i x_i (y_i - (\hat{b}_0 + \hat{b}_1 x_i)) = 0 \\ &= \sum_i x_i (y_i - (\hat{b}_0 + \hat{b}_1 x_i))\end{aligned}\tag{7}$$

$$\hat{b}_1 = \frac{\frac{1}{n-1} \sum_i (x_i - \bar{x})(y_i - \bar{y})}{\frac{1}{(n-1)} \sum_i (x_i - \bar{x})^2} = \frac{s_{xy}}{s_x^2} = r_{xy} \frac{s_y}{s_x}\tag{8}$$

# Ordinary least squares regression

This procedure is called Ordinary least squares (OLS) or simple linear regression

$$\hat{y}_i = \hat{b}_0 + \hat{b}_1 x_i \quad (9)$$

- The best fit line passes through the centroid  $(\bar{x}, \bar{y})$
- $y_i - \hat{y}_i$  is called the **residual**
- The sum of the residuals for the best fit line is 0
- We say  $Y$  is “regressed onto”  $X$
- The estimated parameters are not symmetric. If we swap what is “ $x$ ” and what is “ $y$ ”, the line will change.

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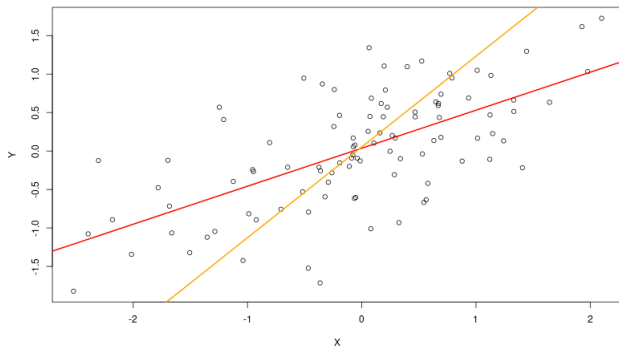


Figure: Red is  $Y$  regressed onto  $X$ ; Orange is  $X$  regressed onto  $Y$



# Outliers

# Outliers and Influential Points

You will see in the lab next week, that an outlier can drastically effect the results of a regression.

# Outliers and Influential Points

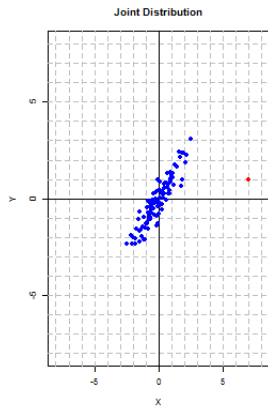
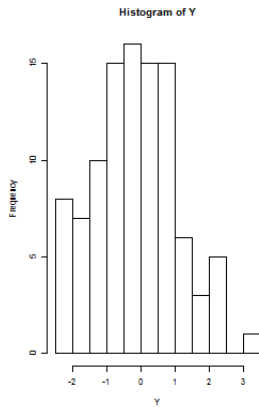
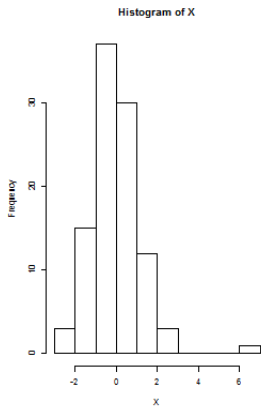
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Outliers are “unusual” observations. But what does it mean to be “unusual”?

- Unusual X value (marginal)
- Unusual Y value (marginal)
- Unusual X and Y value together (joint)
- Might be consistent with the trend, might be inconsistent with the trend

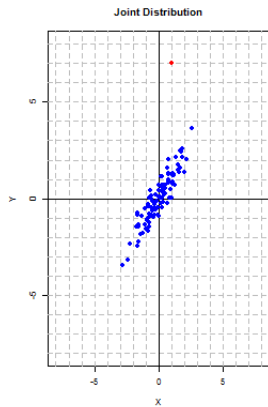
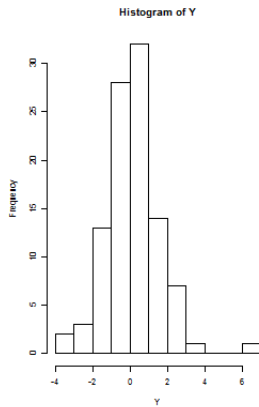
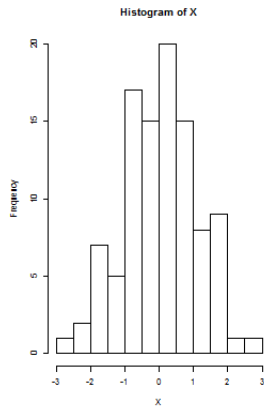
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## Unusual X Value



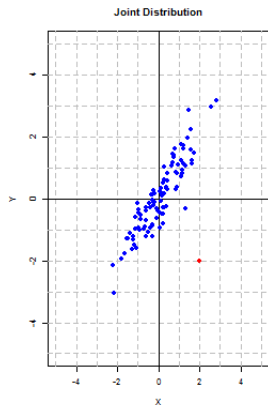
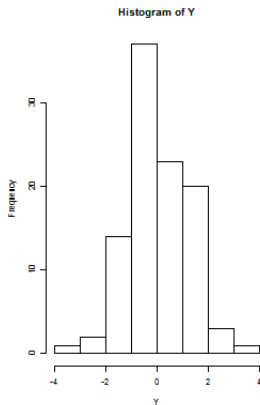
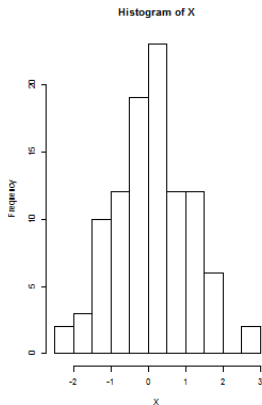
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## Unusual Y Value



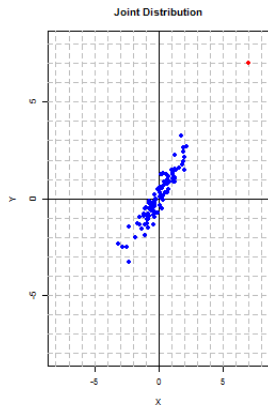
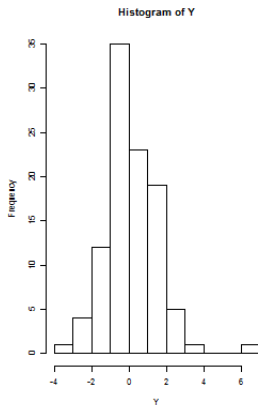
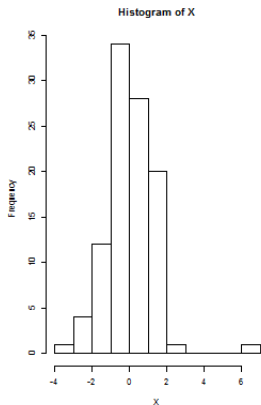
# Outliers and Influential Points

Unusual X and Y Value, inconsistent with the trend



# Outliers and Influential Points

Unusual X and Y Value, but consistent with the trend



# Outliers and Influential Points

Typically, we are most interested in the slope of a regression (rather than the intercept). The type of outlier changes the affect of the outlier on the slope.

$$\hat{b}_1 = \text{cov}(X, Y) / \text{var}(X) = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2} \quad (10)$$



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Outliers in the  $X$  direction affect the slope much more than outliers in the  $Y$  direction

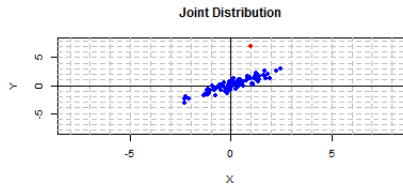
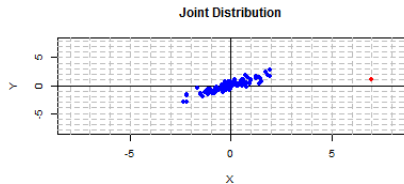
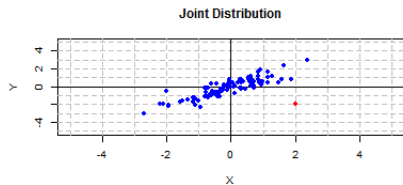
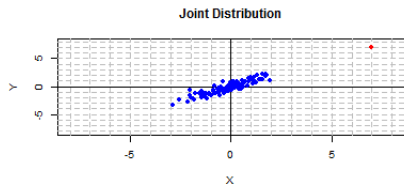
# Outliers and Influential Points

Outliers in the  $X$  direction can affect the slope much more than outliers in the  $Y$  direction

- Leverage- Points where the  $x_i$  is far from  $\bar{x}$  have high leverage
- Influence- Points whose inclusion/exclusion drastically change the regression slope. High leverage can increase influence. Depends on both  $X$  and  $Y$  values

# Outliers and Influential Points

Are the previous outliers we showed high leverage? high influence?



## Other estimators

- We motivated “Least Squares” regression as selecting the line (or the parameters of the line) which minimizes the RSS of the data
- But recall we could have defined other estimators ( $L_1$ )

$$(\hat{b}_0, \hat{b}_1) = \arg \min_{b_0, b_1} \sum_i |y_i - (b_0 - b_1 x_i)| \quad (11)$$

- The analogue of a “median line”
- Less affected by outliers
- Least absolute deviation estimator is a special case of what is called quantile regressions
- Will see example in lab

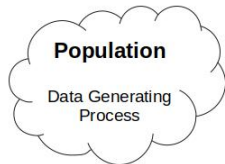
# Outliers and Influential Points

So what should we do with outliers?

- As with most thing in statistics... it depends
- What do we know about the outlier? What trend are we trying to capture?



# Sample data vs population distribution



**Data**

id	name	age	sex	height	weight	hair	eyes	skin	hair	eyes	skin
284	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
359	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
964	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
75	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
337	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
389	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
445	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
474	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
286	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
315	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
349	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
192	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
861	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
369	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
267	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
32	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
262	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
864	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
461	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
365	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84
834	Bob	22	M	183	80.9	Black	Blue	White	17	0.84	0.84



**Statistic**



## Wrap-up

- Introduce linear regression as procedure which minimizes the squared residuals
- Gave intuition for how outliers might effect resulting regression estimates