# Lecture 12: more Chapter 5, Section 3 Relationships between Two Quantitative Variables; Regression

Equation of Regression Line; Residuals
Effect of Explanatory/Response Roles
Unusual Observations
Sample vs. Population
Time Series; Additional Variables

## Looking Back: Review

## **4** Stages of Statistics

- Data Production (discussed in Lectures 1-4)
- Displaying and Summarizing
  - □ Single variables: 1 cat,1 quan (discussed Lectures 5-8)
  - □ Relationships between 2 variables:
    - Categorical and quantitative (discussed in Lecture 9)
    - Two categorical (discussed in Lecture 10)
    - Two quantitative
- Probability
- Statistical Inference

## Review

## □ Relationship between 2 quantitative variables

- Display with scatterplot
- Summarize:
  - **Form:** linear or curved
  - □ Direction: positive or negative
  - □ Strength: strong, moderate, weak
  - If form is linear, correlation *r* tells direction and strength.

Also, equation of least squares regression line lets us predict a response  $\hat{y}$  for any explanatory value x.

## Least Squares Regression Line

Summarize linear relationship between explanatory (x) and response (y) values with line  $\hat{y} = b_0 + b_1 x$  that minimizes sum of squared prediction errors (called *residuals*).

- □ Slope: predicted change in response *y* for every unit increase in explanatory value *x*
- **Intercept:** where best-fitting line crosses *y*-axis (predicted response for *x*=0?)

#### **Example:** Least Squares Regression Line

■ **Background**: Car-buyer used software to regress price on age for 14 used Grand Am's.

The regression equation is Price = 14690 - 1288 Age

- □ **Question:** What do the slope (-1,288) and intercept (14,690) tell us?
- **Response:** 
  - **Slope:** For each additional year in age, predict price

Intercept: Best-fitting line \_\_\_\_\_

#### **Example:** *Extrapolation*

■ **Background**: Car-buyer used software to regress price on age for 14 used Grand Am's.

The regression equation is Price = 14690 - 1288 Age

- □ **Question:** Should we predict a new Grand Am to cost \$14,690-\$1,288(0)=\$14,690?
- **Response:**

## Definition

Extrapolation: using the regression line to predict responses for explanatory values outside the range of those used to construct the line.

#### **Example:** *More Extrapolation*

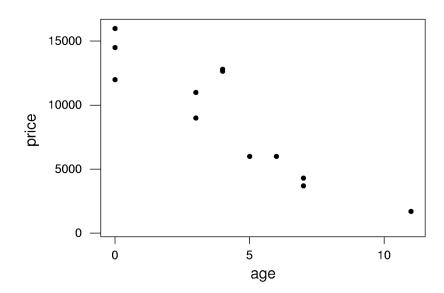
- □ Background: A regression of 17 male students' weights (lbs.) on heights (inches) yields the equation  $\hat{y} = -438 + 8.7x$
- Question: What weight does the line predict for a 20-inch-long infant?
- **Response:**

## Expressions for slope and intercept

- Consider slope and intercept of the least squares regression line  $\hat{y} = b_0 + b_1 x$
- □ Slope:  $b_1 = r \frac{s_y}{s_x}$  so if x increases by a standard deviation, predict y to increase by r standard deviations
- □ Intercept:  $b_0 = \bar{y} b_1 \bar{x}$  so when  $x = \bar{x}$ predict  $\hat{y} = b_0 + b_1 \bar{x} = (\bar{y} - b_1 \bar{x}) + b_1 \bar{x} = \bar{y}$
- → the line passes through the point of averages  $(\bar{x}, \bar{y})$

#### **Example:** Individual Summaries on Scatterplot

**Background**: Car-buyer plotted price vs. age for 14 used Grand Ams [(4, 13,000), (8, 4,000), etc.]



**Question:** Guess the means and sds of age and price? **Response:** Age has approx. mean yrs, sd yrs; price has approx. mean \$ , sd ©2011 Brooks/Cole, L12.17

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## Definitions

## ■ **Residual:** error in using regression line $\hat{y} = b_0 + b_1 x$ to predict y given x. It equals the vertical distance *observed minus predicted* which can be written $y_i - \hat{y}_i$

□ s: denotes typical residual size, calculated as  $s = \sqrt{\frac{(y_1 - \hat{y}_1)^2 + \dots + (y_n - \hat{y}_n)^2}{n-2}}$ 

*Note: s just "averages" out the residuals*  $y_i - \hat{y}_i$ 

## **Example:** Considering Residuals

**Background**: Car-buyer regressed price on age for 14 used Grand Ams [(4, 13,000), (8, 4,000), etc.].

The regression equation is

S = 2175

price = 14686 - 1290 age R-Sq = 78.5%

- **Question:** What does s = 2,175 tell us? П
- **Response:** Regression line predictions not perfect:
  - $x=4 \rightarrow \text{predict } y=$

actual  $y=13,000 \rightarrow \text{prediction error} =$ 

•  $x=8 \rightarrow \text{predict } \mathcal{Y}=$ 

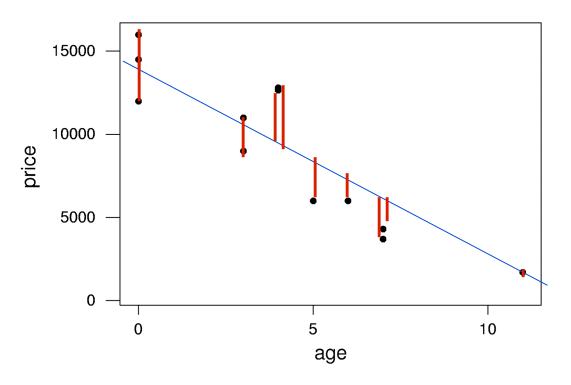
actual  $y=4,000 \rightarrow \text{prediction error} =$ 

Typical size of 14 prediction errors is

(dollars)

#### **Example:** Considering Residuals

Typical size of 14 prediction errors is s = 2,175 (dollars):
 Some points' vertical distance from line more, some less;
 2,175 is typical distance.

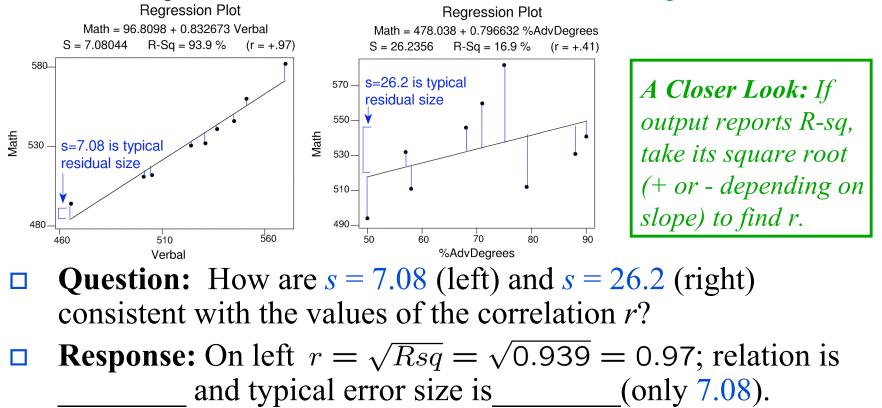


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#### **Example:** Residuals and their Typical Size s

**Background:** For a sample of schools, regressed

- average Math SAT on average Verbal SAT
- average Math SAT on % of teachers w. advanced degrees

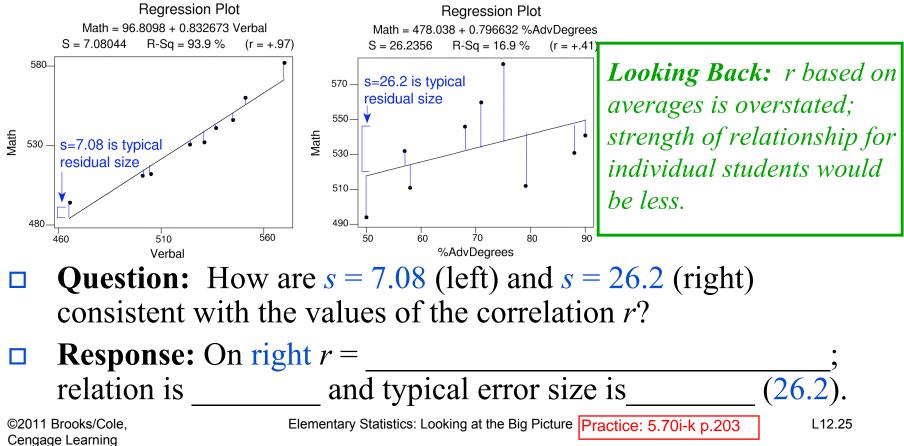


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#### **Example:** Residuals and their Typical Size s

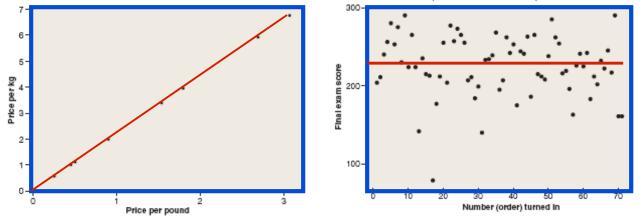
**Background:** For a sample of schools, regressed

- average Math SAT on average Verbal SAT *Smaller s*→*better predictions*
- average Math SAT on % of teachers w. advanced degrees



### **Example:** *Typical Residual Size s close to sy or 0*

- **Background**: Scatterplots show relationships...
  - Price per kilogram vs. price per lb. for groceries
  - Students' final exam score vs. (number) order handed in



Regression line approx. same as line at average y-value.

- **Questions:** Which has s = 0? Which has *s* close to  $s_y$ ?
- Responses: Plot on left has s = \_\_\_: no prediction errors.
   Plot on right: s close to \_\_\_\_. (Regressing on x doesn't help; regression line is approximately horizontal.)

#### **Example:** Typical Residual Size s close to $s_y$

#### **Background**: 2008-9 Football Season Scores

Regression Analysis: Steelers versus Opponents

The regression equation is

Steelers = 23.5 - 0.053 Opponents

S = 9.931

Descriptive Statistics: Steelers

Variable	N N	lean Median	TrMean	StDev	SE Mean
Steelers	19 22	2.74 23.00	22.82	9.66	2.22
Variable	Minimum	Maximum	Q1	Q3	
Steelers	6.00	38.00	14.00	31.00	

**Question:** Since s = 9.931 and sy = 9.66 are very close, do you expect |r| close to 0 or 1?

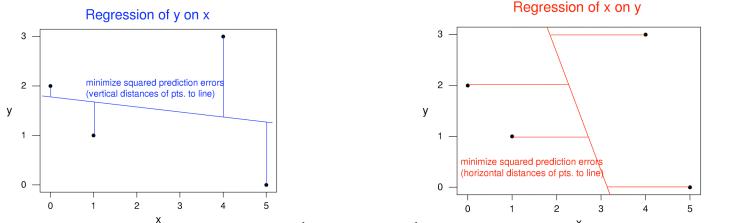
**Response:** *r* must be close to

## Explanatory/Response Roles in Regression

Our choice of roles, explanatory or response, does *not* affect the value of the correlation *r*, but it *does* affect the regression line.

# **Example:** *Regression Line when Roles are Switched*

**Background**: Compare regression of y on x (left) and regression of x on y (right) for same 4 points:



- **Question:** Do we get the same line regressing y on x as we do regressing x on y?
- **Response:** The lines are very different.
  - Regressing y on x:
  - Regressing *x* on *y*:

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Context needed;nt.consider variablesslopeand their rolesslopebefore regressing.

Practice: 5.60b p.198

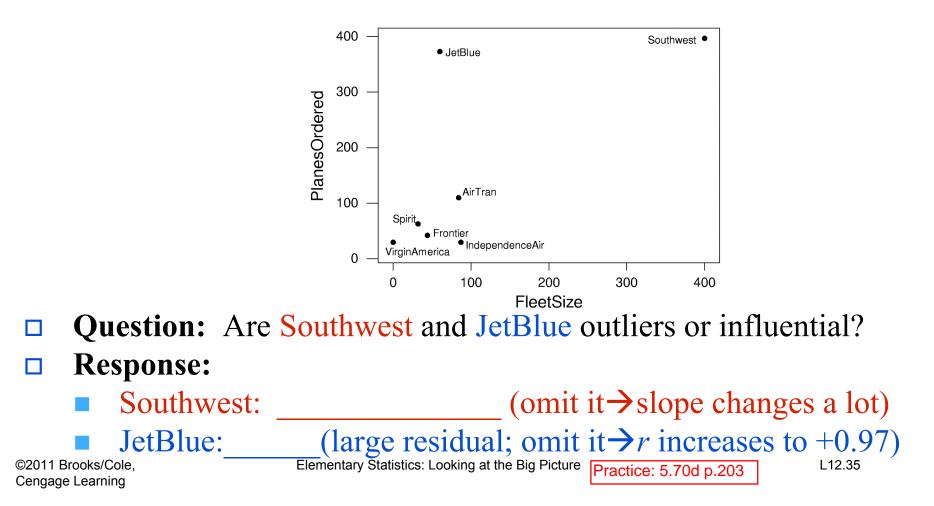
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## Definitions

- Outlier: (in regression) point with unusually large residual
- □ **Influential observation:** point with high degree of influence on regression line.

#### **Example:** Outliers and Influential Observations

**Background**: Exploring relationship between orders for new planes and fleet size. (r=+0.69)



### **Example:** Outliers and Influential Observations

**Background**: Exploring relationship between orders for new planes and fleet size. (r = +0.69)

Unusual Observations

Obs	FleetSiz	PlanesOr	Fit	SE Fit	Residual	St Resid
6	400	397.0	398.1	127.1	-1.1	-0.04 X
7	60	373.0	115.2	51.7	257.8	2.16R

R denotes an observation with a large standardized residual

X denotes an observation whose X value gives it large influence.

- **Question:** How does Minitab classify **Southwest** and **JetBlue**?
- **Response:** 
  - Southwest: (marked in Minitab)
    JetBlue: (marked in Minitab)

Influential observations tend to be extreme in horizontal direction.

## Definitions

- □ Slope  $\beta_1$ : how much response *y* changes in general (for entire population) for every unit increase in explanatory variable *x*
- □ Intercept  $\beta_0$ : where the line that best fits all explanatory/response points (for entire population) crosses the *y*-axis

*Looking Back: Greek letters often refer to population parameters.* 

Line for Sample vs. Population

Sample: line best fitting sampled points: predicted response is

$$\hat{y} = b_0 + b_1 x$$

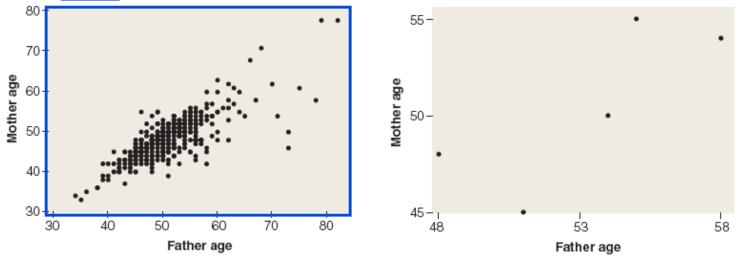
Population: line best fitting all points in population from which given points were sampled: mean response is

 $\mu_y = \beta_0 + \beta_1 x$ 

A larger sample helps provide more evidence of a relationship between two quantitative variables in the general population.

### **Example:** *Role of Sample Size*

**Background**: Relationship between ages of students' mothers and fathers both have r = +0.78, but sample size is over 400 (on left) or just 5 (on right):



- Question: Which plot provides more evidence of strong positive relationship in population?
- **Response:** Plot on

#### Can believe configuration on

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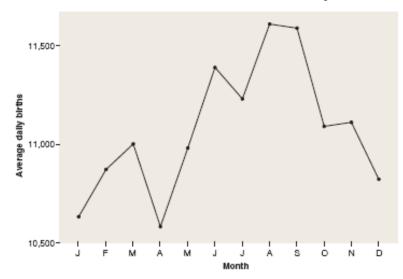
occurred by chance.

## Time Series

If explanatory variable is time, plot one response for each time value and "connect the dots" to look for general trend over time, also peaks and troughs.

#### **Example:** *Time Series*

■ **Background**: Time series plot shows average daily births each month in year 2000 in the U.S.:



Question: Where do you see a peak or a trough?
 Response: Trough in \_\_\_\_\_, peak in \_\_\_\_\_

#### **Example:** *Time Series*

**Background**: Time series plot of average daily births in U.S.



- **Questions:** How can we explain why there are...
  - Conceptions in U.S.: fewer in July, more in December?
  - Conceptions in Europe: more in summer, fewer in winter?
- **Response:**

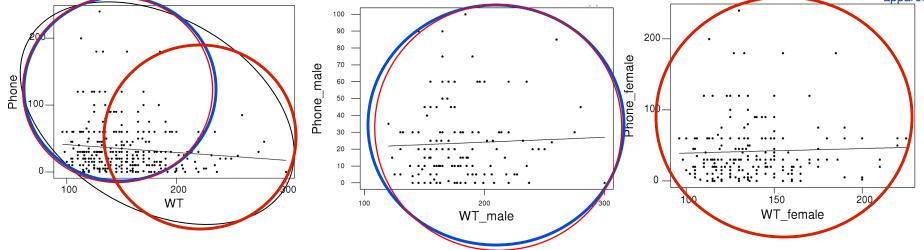
*A Closer Look:* Statistical methods can't always explain "why", but at least they help understand "what" is going on.

## Additional Variables in Regression

- Confounding Variable: Combining two groups that differ with respect to a variable that is related to both explanatory and response variables can affect the nature of their relationship.
- Multiple Regression: More advanced treatments consider impact of not just one but two or more quantitative explanatory variables on a quantitative response.

#### **Example:** Additional Variables

**Background**: A regression of phone time (in minutes the day before) and weight shows a negative relationship.



- Questions: Do heavy people talk on the phone less? Do light people talk more?
- □ Response: \_\_\_\_\_\_\_ is confounding variable → regress separately for \_\_\_\_\_\_ → no relationship

## **Example:** *Multiple Regression*

- **Background**: We used a car's age to predict its price.
- Question: What additional quantitative variable would help predict a car's price?
- **Response:**

## Lecture Summary (Regression)

- Equation of regression line
  - Interpreting slope and intercept
  - Extrapolation
- $\square$  Residuals: typical size is *s*
- □ Line affected by explanatory/response roles
- Outliers and influential observations
- □ Line for sample or population; role of sample size
- □ Time series
- □ Additional variables