

# Modul 4: Regression

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# Module Overview

## Topics

- Regression Analysis
- Type of Regression
- Simple Linear Regression
- Multiple Linear Regression

## Activities

- Group Discussion
- Coding Practice

# Module Objectives

- Understand what is Regression Analysis
- Create Regression Model using Python
- Use regression analysis to predict future values

# What is Regression?

- Regression analysis is a tool for building statistical models that characterize relationships among a dependent variable and one or more independent variables.

# Purpose of Regression

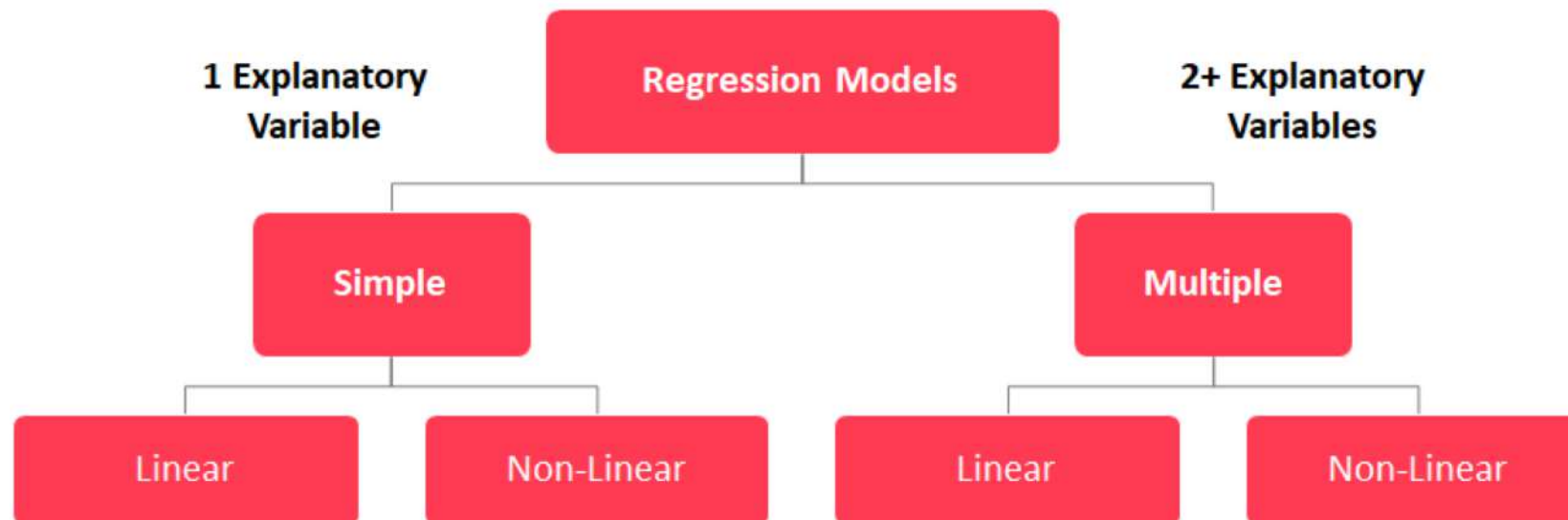
- The purpose of regression analysis is to analyze relationships among variables.
- The analysis is carried out through the estimation of a relationship and the results serve the following two purposes:
  - Answer the question of how much  $y$  changes with changes in each of the  $x$ 's ( $x_1, x_2, \dots, x_k$ ),  $Y$  is the dependent variable
  - Forecast or predict the value of  $y$  based on the values of the  $X$ 's.  $X$  is the independent variable

# Step of Regression Analysis

A regression analysis can be broken down into 5 steps.

- Step 1 : state the hypothesis.
- Step 2 : test the hypothesis (estimate the relationship).
- Step 3 : interpret the test results. This step would enable us to answer the following questions,
- Step 4 : check for and correct common problems of regression analysis.
- Step 5 : evaluate the test results.

# Type of Regression



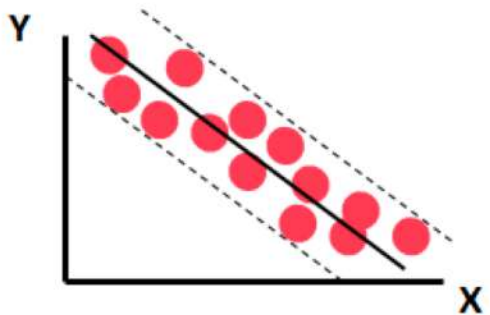
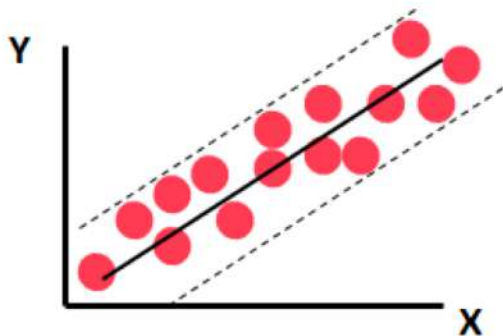
# Simple Linear Regression

- Only one independent variable,  $X$
- Relationship between  $X$  and  $Y$  is described by a linear function
- Changes in  $Y$  are assumed to be related to changes in  $X$

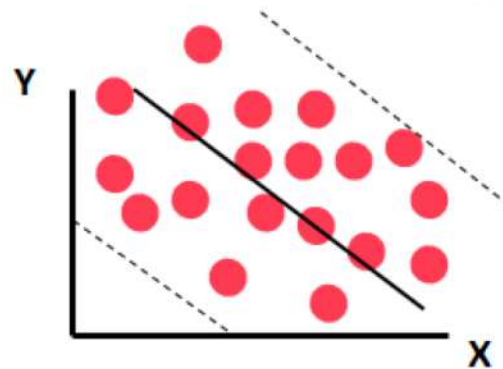
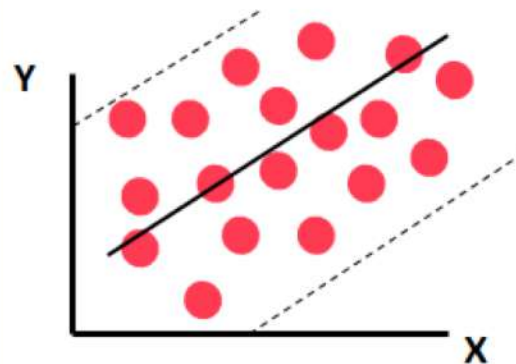


# Types of Relationship

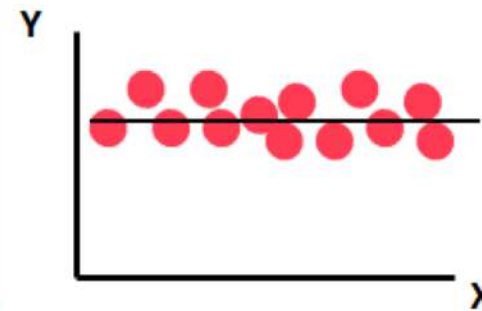
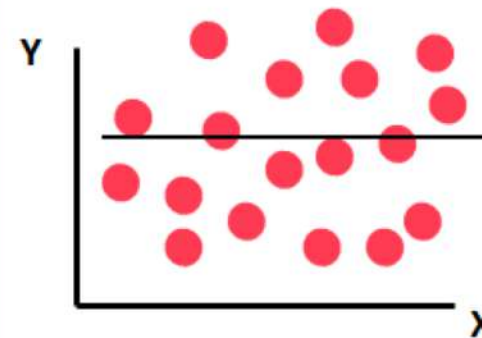
Strong relationships



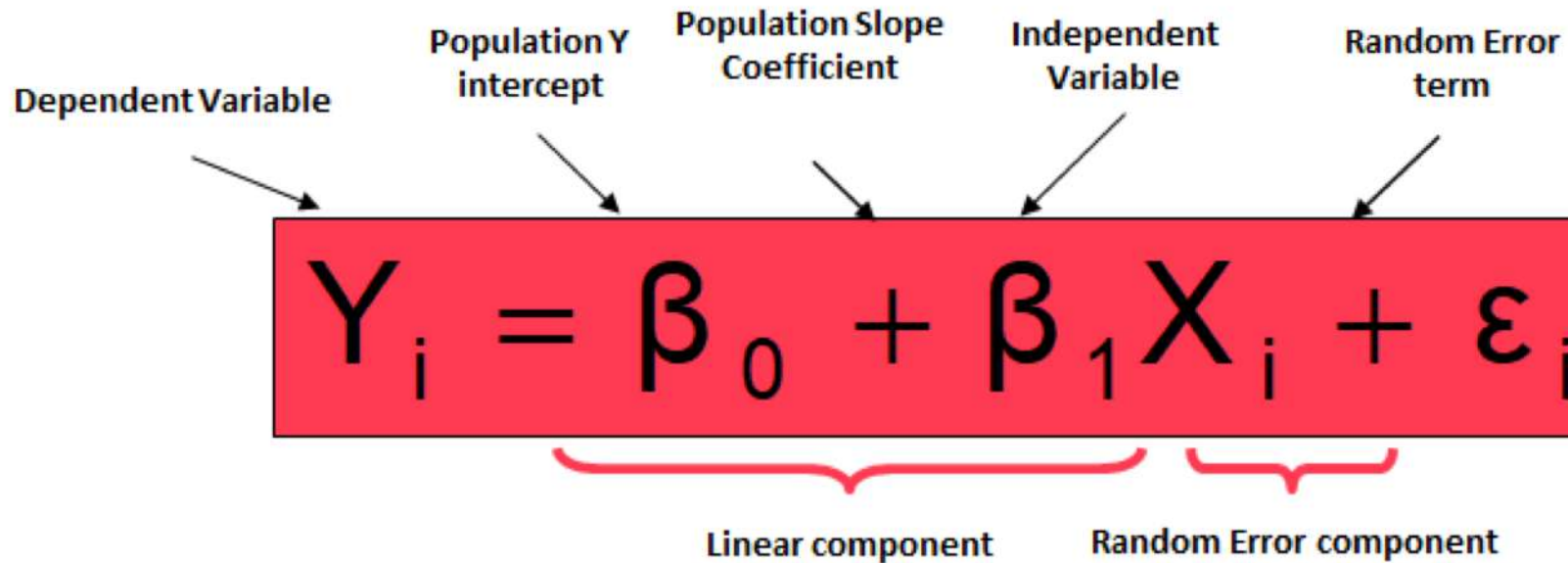
Weak relationships



No relationship



# Simple Linear Regression Model



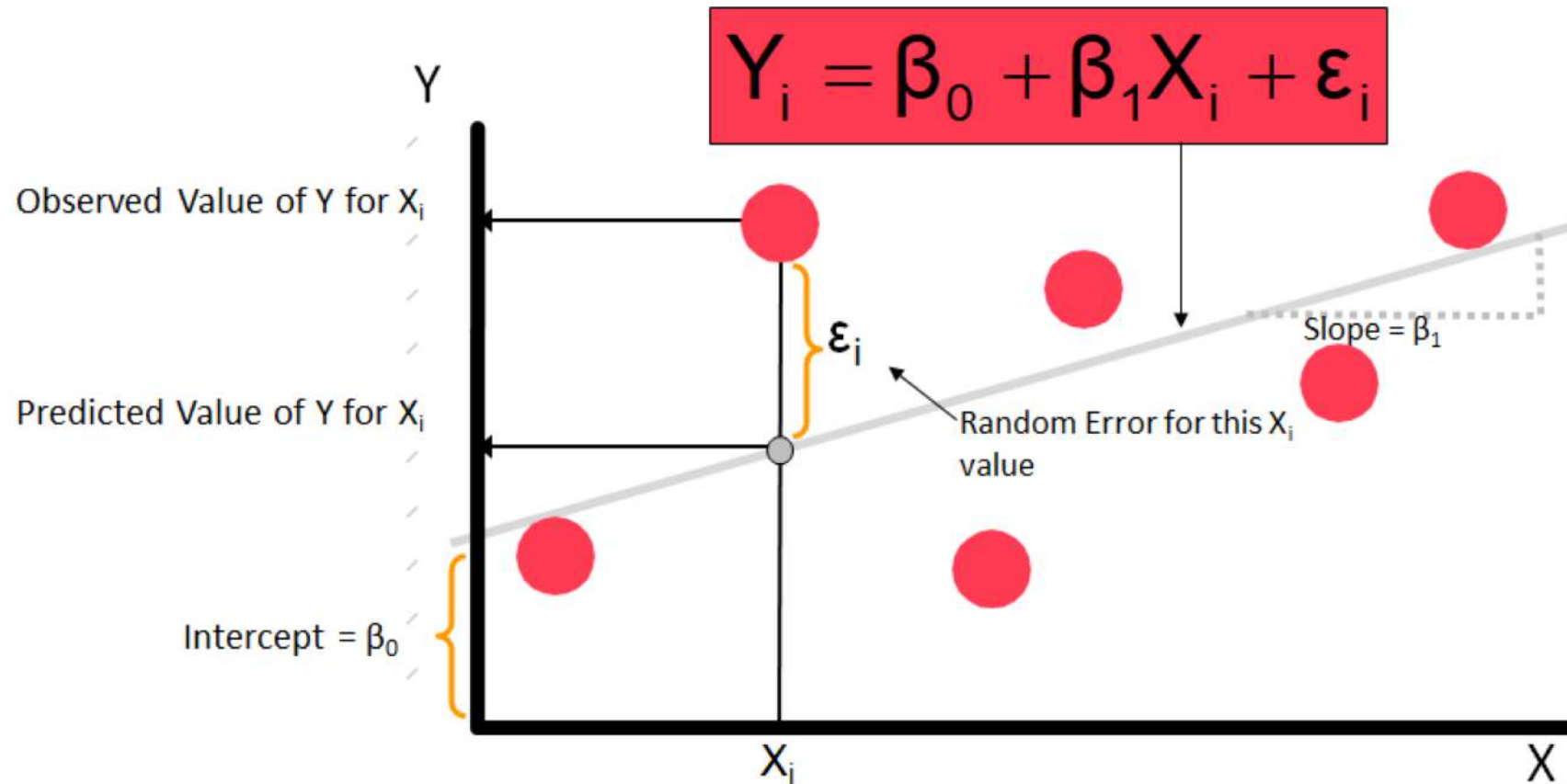
The diagram illustrates the Simple Linear Regression Model equation,  $Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$ , with labels and components:

- Dependent Variable:**  $Y_i$
- Population Y intercept:**  $\beta_0$
- Population Slope Coefficient:**  $\beta_1$
- Independent Variable:**  $X_i$
- Random Error term:**  $\epsilon_i$

The equation is divided into two components:

- Linear component:**  $\beta_0 + \beta_1 X_i$
- Random Error component:**  $\epsilon_i$

# Simple Linear Regression Model



# The Least Squares Method

- $b_0$  and  $b_1$  are obtained by finding the values of that minimize the sum of the squared differences between  $Y$  and  $\hat{Y}$  :

$$\min \sum (Y_i - \hat{Y}_i)^2 = \min \sum (Y_i - (b_0 + b_1 X_i))^2$$

# Finding the Least Squares Equation

- The coefficients  $b_0$  and  $b_1$ , and other regression results in this chapter, will be found using python

# Interpretation of Slope and Intercept

- $b_0$  is the estimated average value of  $Y$  when the value of  $X$  is zero.
- $b_1$  is the estimated change in the average value of  $Y$  as a result of a one-unit change in  $X$ .



# Example: Simple Linear Regression

- A real estate agent wishes to examine the relationship between the selling price of a home and its size (measured in square feet)
- A random sample of 10 houses is selected
  - Dependent variable (Y) = house price in \$1000s
  - Independent variable (X) = square feet

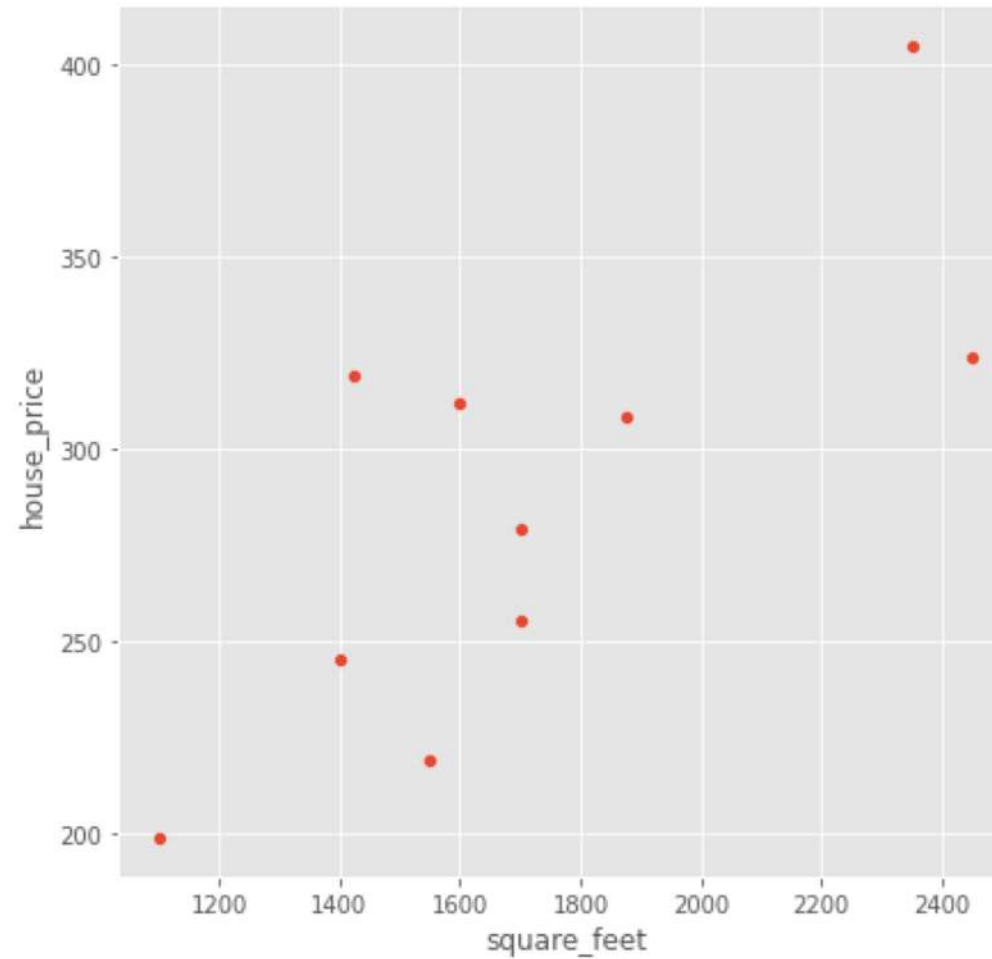


# Example: Data

|   | house_price | square_feet |
|---|-------------|-------------|
| 0 | 245         | 1400        |
| 1 | 312         | 1600        |
| 2 | 279         | 1700        |
| 3 | 308         | 1875        |
| 4 | 199         | 1100        |
| 5 | 219         | 1550        |
| 6 | 405         | 2350        |
| 7 | 324         | 2450        |
| 8 | 319         | 1425        |
| 9 | 255         | 1700        |



# Example: Scatter Plot

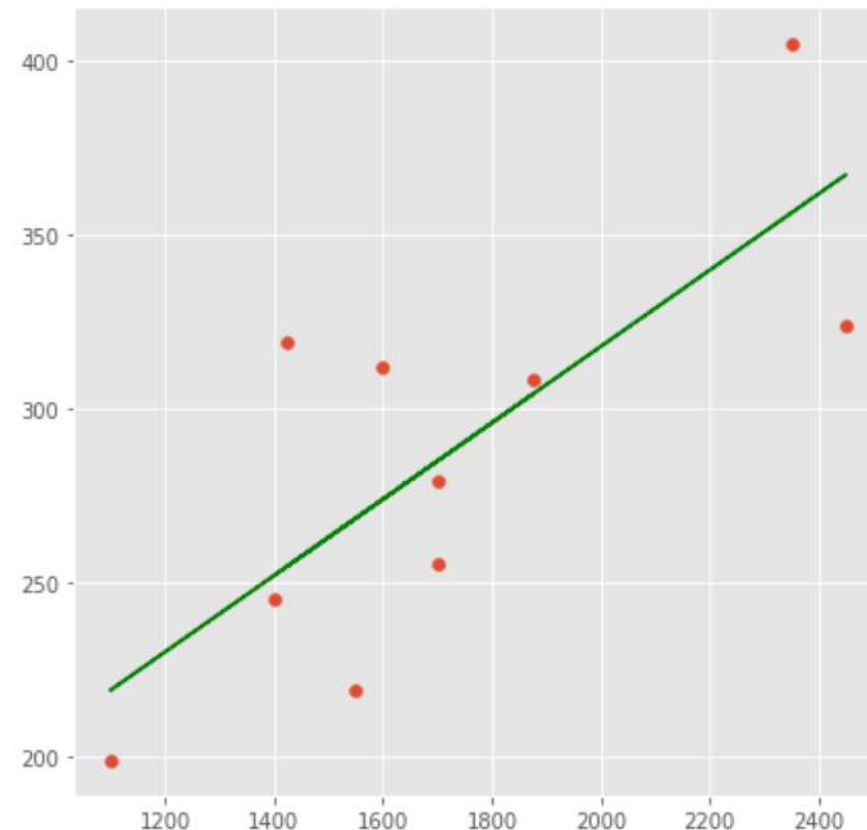


# Example: Regression Equation

- Regression equation from Python
- **Slope** = 0.10976774
- **Intercept** = 98.24832962138078

```
print('Intercept: \n', regr.intercept_)  
print('Coefficients: \n', regr.coef_)
```

Intercept:  
98.24832962138078  
Coefficients:  
[0.10976774]



## Example: Interpretation of $b_0$

- $b_0$  is the estimated average value of  $Y$  when the value of  $X$  is zero (if  $X = 0$  is in the range of observed  $X$  values)
- Because a house cannot have a square footage of 0,  $b_0$  has no practical application

# Example: Interpretation of $b_1$

- $b_1$  estimates the change in the average value of  $Y$  as a result of a one-unit increase in  $X$
- Here,  $b_1 = 0.10977$  tells us that the mean value of a house increases by  $.10977(\$1000) = \$109.77$ , on average, for each additional one square foot of size

# Example: Making Predictions

- Predict the price for a house with 2000 square feet:
- House price  $= 98.25 + 0.1098(\text{square feet})$   
 $= 98.25 + 0.1098 (2000)$   
 $= 317.85$
- The predicted price for a house with 2000 square feet is  $317.85(\$1,000\text{s}) = \$317,850$

# Measures of Variation

Total variation is made up of two parts:

$$SST = SSR + SSE$$

Total Sum of  
Squares

$$SST = \sum (Y_i - \bar{Y})^2$$

Regression Sum  
of Squares

$$SSR = \sum (\hat{Y}_i - \bar{Y})^2$$

Error Sum of  
Squares

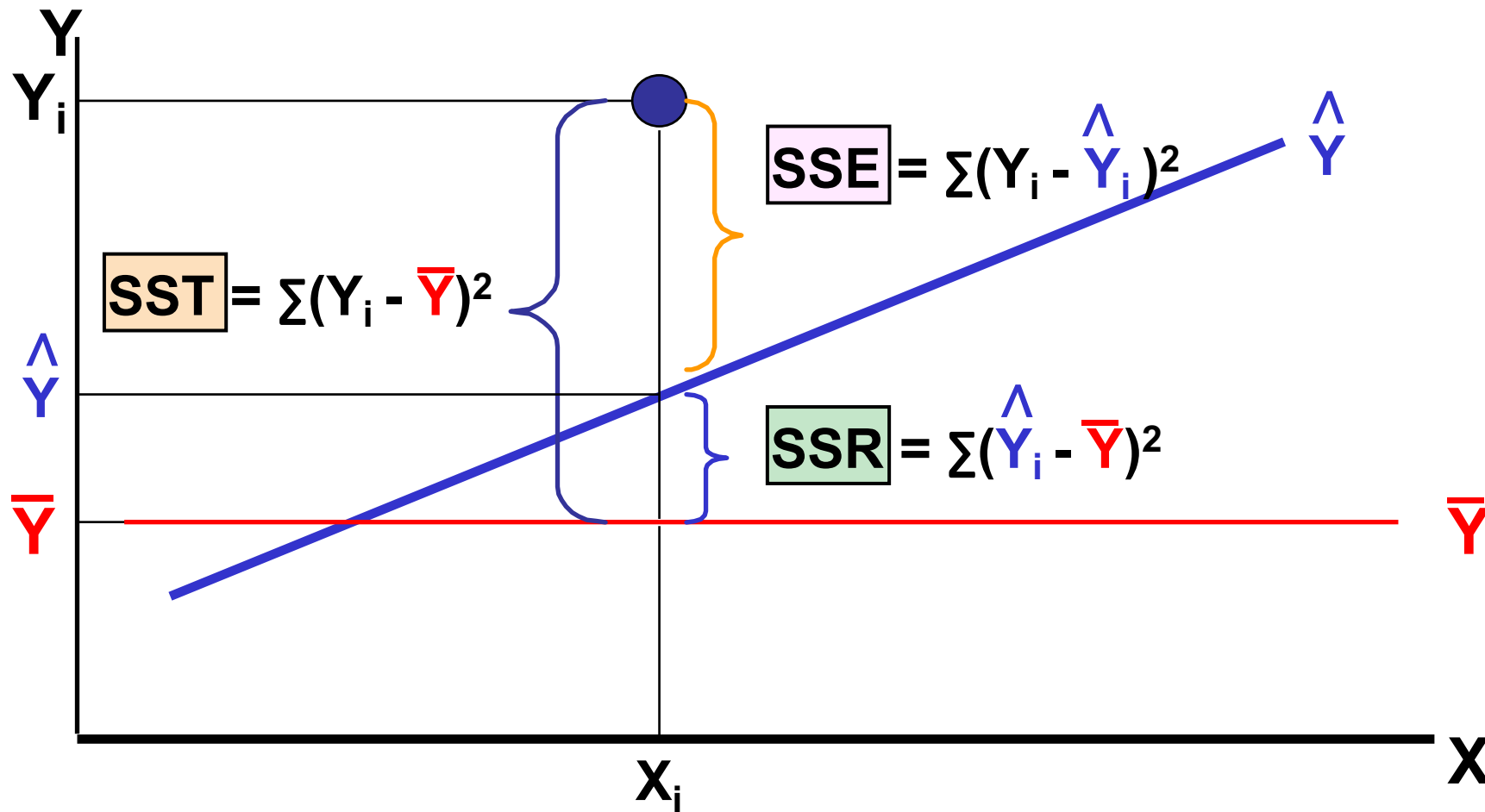
$$SSE = \sum (Y_i - \hat{Y}_i)^2$$

# Measures of Variation

- **SST = total sum of squares (Total Variation)**
  - Measures the variation of the  $Y_i$  values around their mean  $\bar{Y}$
- **SSR = regression sum of squares (Explained Variation)**
  - Variation attributable to the relationship between X and Y
- **SSE = error sum of squares (Unexplained Variation)**
  - Variation in Y attributable to factors other than X



# Measures of Variation





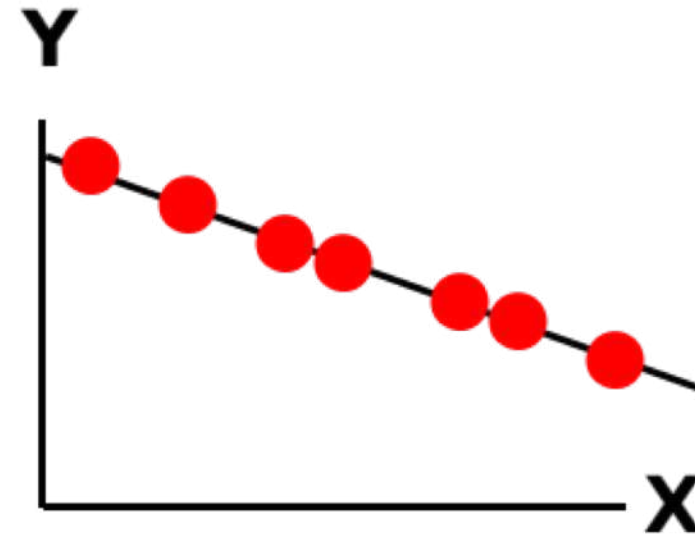
# Coefficient of Determination, $r^2$

- The coefficient of determination is the portion of the total variation in the dependent variable that is explained by variation in the independent variable
- The coefficient of determination is also called r-squared and is denoted as  $r^2$
- Note  $0 \leq r^2 \leq 1$

$$r^2 = \frac{SSR}{SST} = \frac{\text{regression sum of squares}}{\text{total sum of squares}}$$

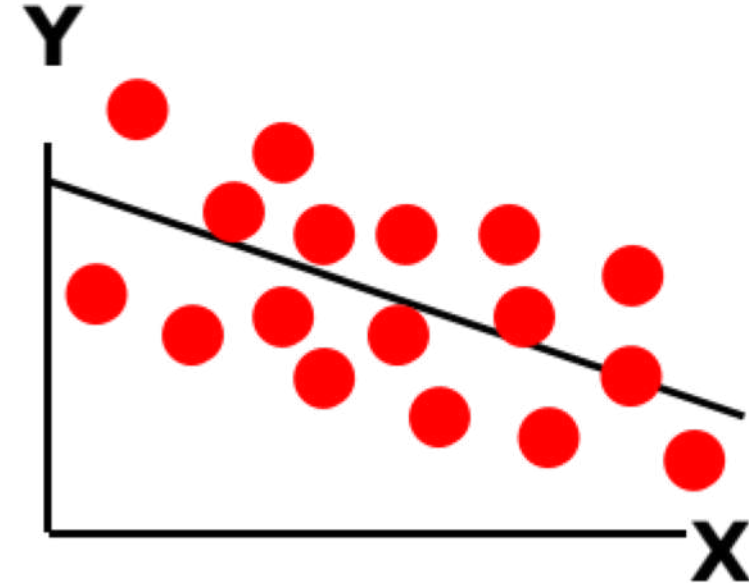
# Examples of Approximate $r^2$ Values

- $r^2 = 1$
- Perfect linear relationship between X and Y:
- 100% of the variation in Y is explained by variation in X



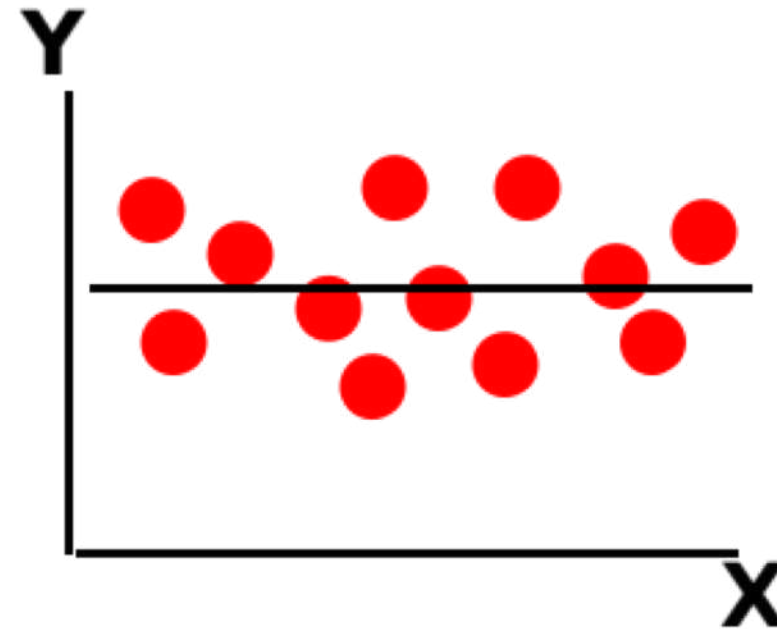
# Examples of Approximate $r^2$ Values

- $0 < r^2 < 1$
- Weaker linear relationships between X and Y:
- Some but not all of the variation in Y is explained by variation in X



# Examples of Approximate $r^2$ Values

- $r^2 = 0$
- No linear relationship between X and Y:
- The value of Y does not depend on X. (None of the variation in Y is explained by variation in X)



# r2 in Python

```
model = sm.OLS(Y, X).fit()
predictions = model.predict(X)

print_model = model.summary()
print(print_model)
```

OLS Regression Results

```
=====
```

|                   |                  |                     |         |
|-------------------|------------------|---------------------|---------|
| Dep. Variable:    | house_price      | R-squared:          | 0.581   |
| Model:            | OLS              | Adj. R-squared:     | 0.528   |
| Method:           | Least Squares    | F-statistic:        | 11.08   |
| Date:             | Wed, 14 Oct 2020 | Prob (F-statistic): | 0.0104  |
| Time:             | 16:28:58         | Log-Likelihood:     | -50.290 |
| No. Observations: | 10               | AIC:                | 104.6   |
| Df Residuals:     | 8                | BIC:                | 105.2   |
| Df Model:         | 1                |                     |         |
| Covariance Type:  | nonrobust        |                     |         |

```
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```

|             | coef    | std err | t     | P> t  | [0.025  | 0.975]  |
|-------------|---------|---------|-------|-------|---------|---------|
| const       | 98.2483 | 58.033  | 1.693 | 0.129 | -35.577 | 232.074 |
| square_feet | 0.1098  | 0.033   | 3.329 | 0.010 | 0.034   | 0.186   |

```
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```

|                |       |                   |          |
|----------------|-------|-------------------|----------|
| Omnibus:       | 1.066 | Durbin-Watson:    | 3.222    |
| Prob(Omnibus): | 0.587 | Jarque-Bera (JB): | 0.779    |
| Skew:          | 0.399 | Prob(JB):         | 0.677    |
| Kurtosis:      | 1.890 | Cond. No.         | 7.82e+03 |

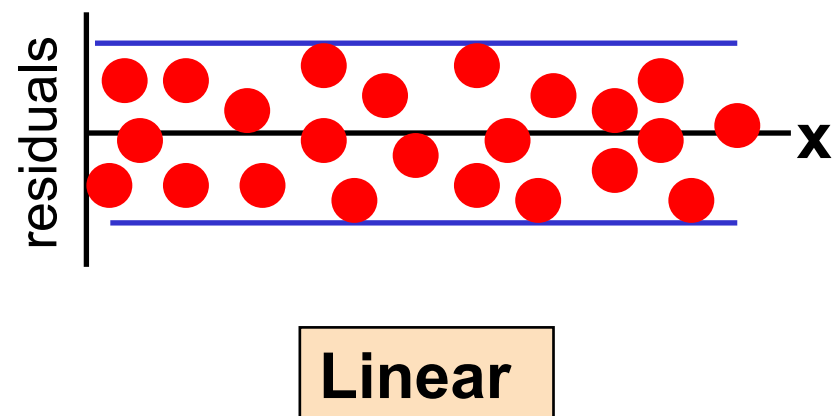
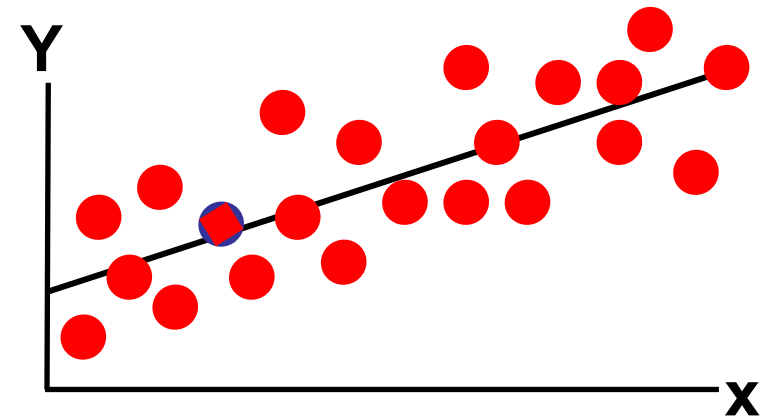
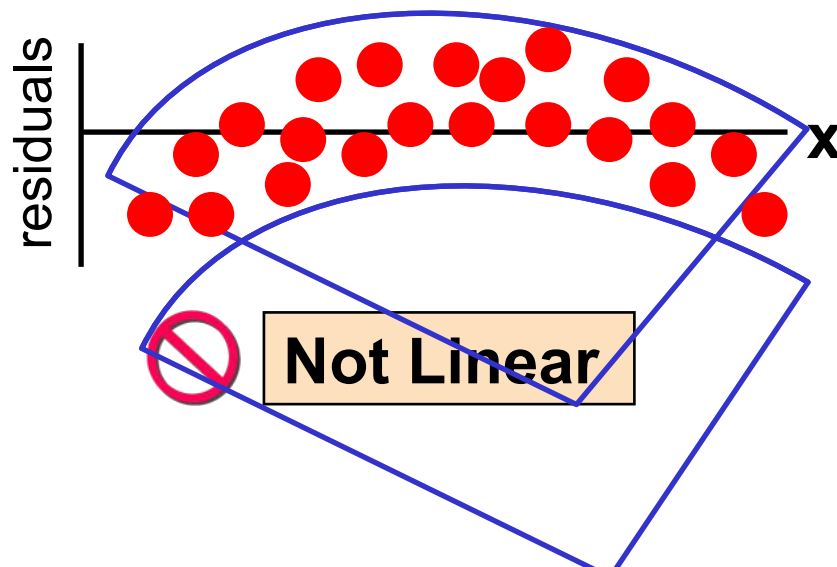
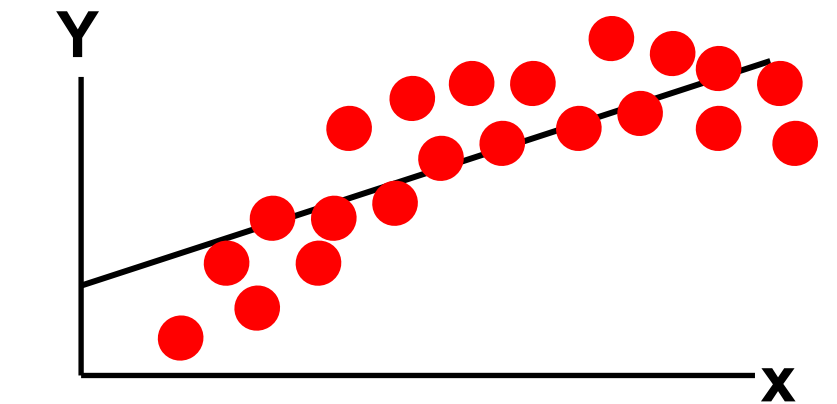
```
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```

# Residual Analysis

- The residual for observation  $i$ ,  $e_i$ , is the difference between its observed and predicted value
- Check the assumptions of regression by examining the residuals
  - Examine for linearity assumption
  - Evaluate independence assumption
  - Evaluate normal distribution assumption
  - Examine for constant variance for all levels of  $X$  (homoscedasticity)



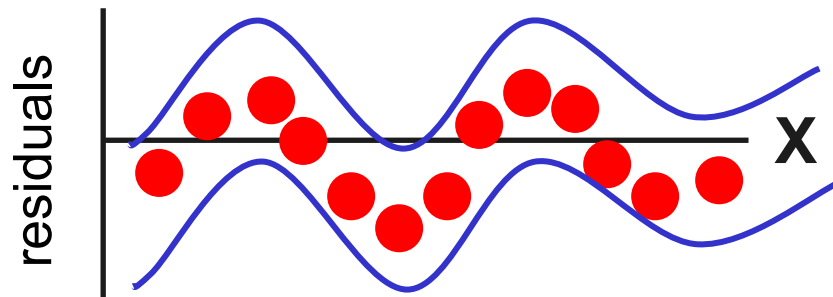
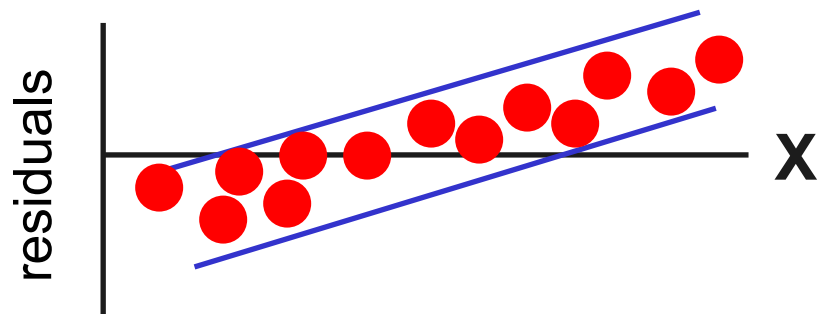
# Residual Analysis for Linearity



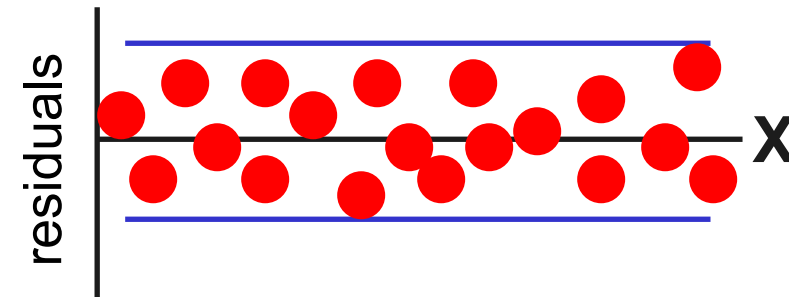
# Residual Analysis for Independence



**Not Independent**



**Independent**



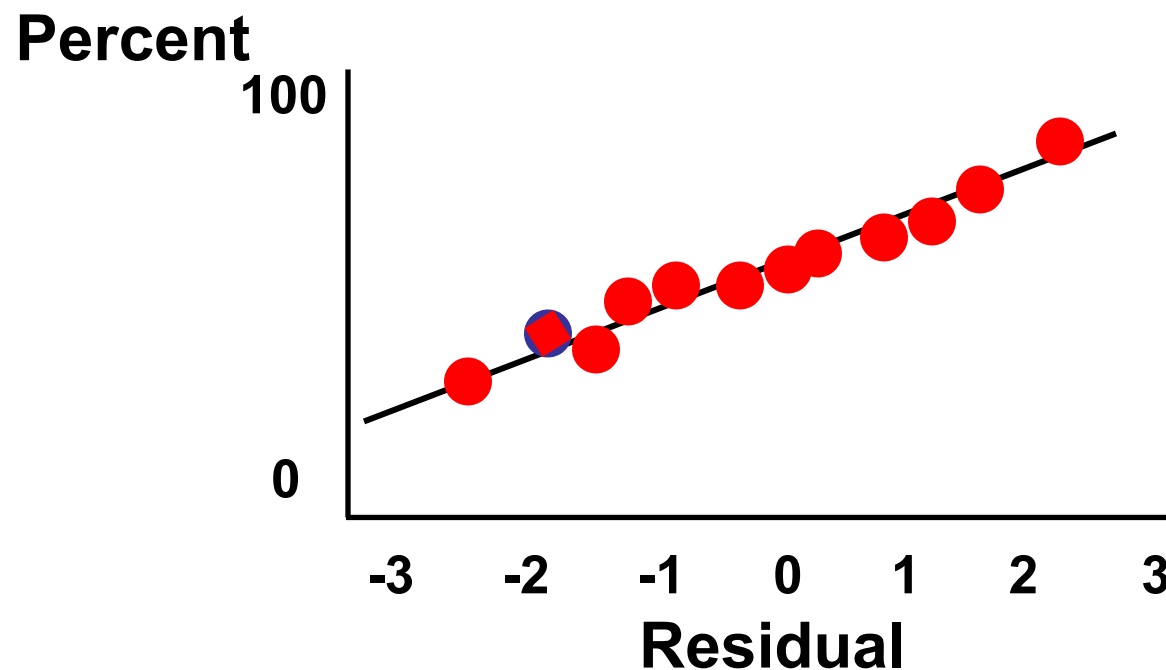


# Checking for Normality

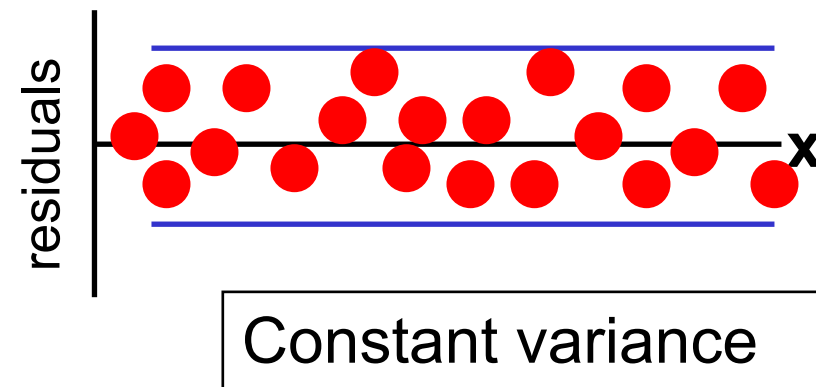
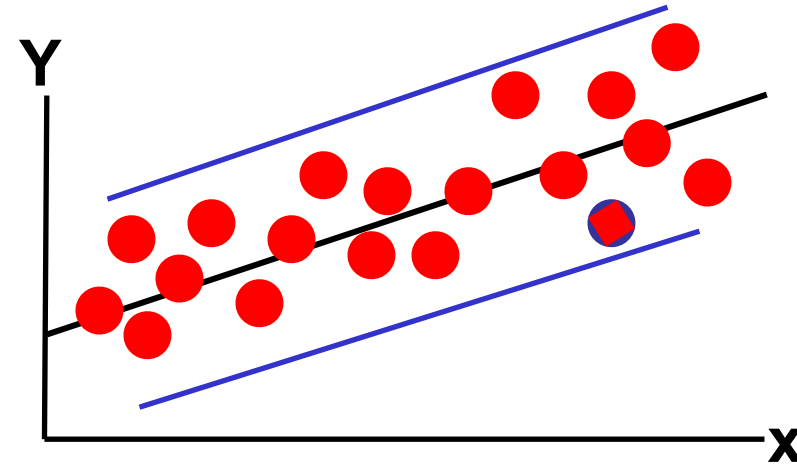
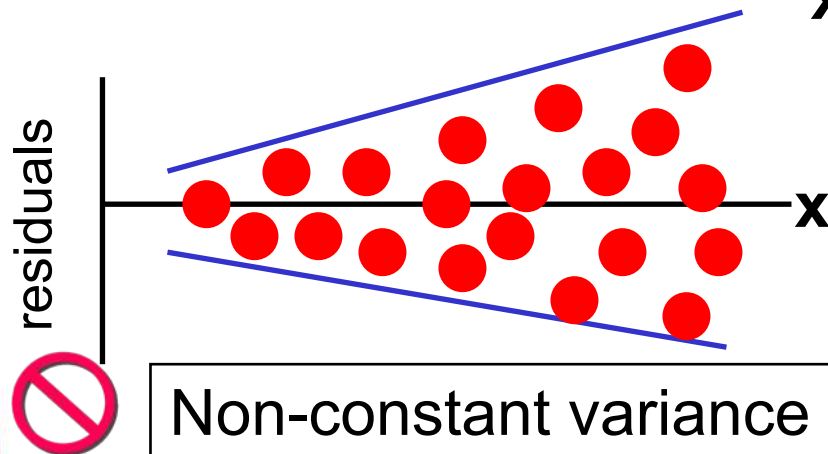
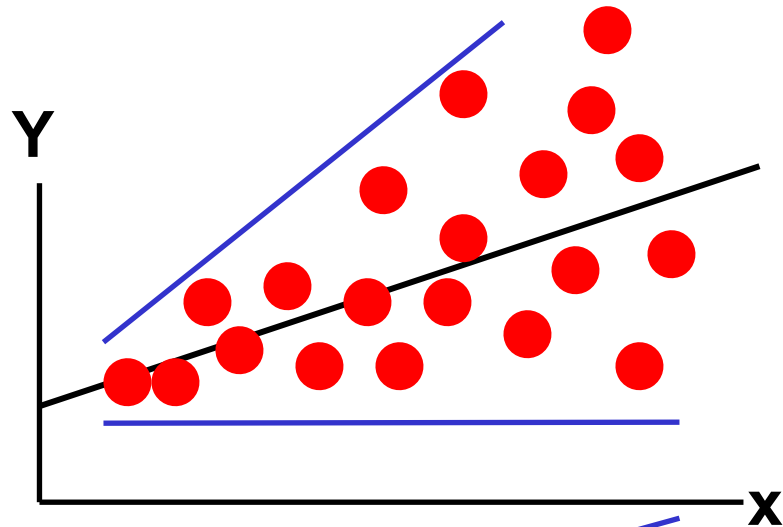
- Examine the Stem-and-Leaf Display of the Residuals
- Examine the Boxplot of the Residuals
- Examine the Histogram of the Residuals
- Construct a Normal Probability Plot of the Residuals

# Residual Analysis for Normality

- When using a normal probability plot, normal errors will approximately display in a straight line.



# Residual Analysis for Equal Variance

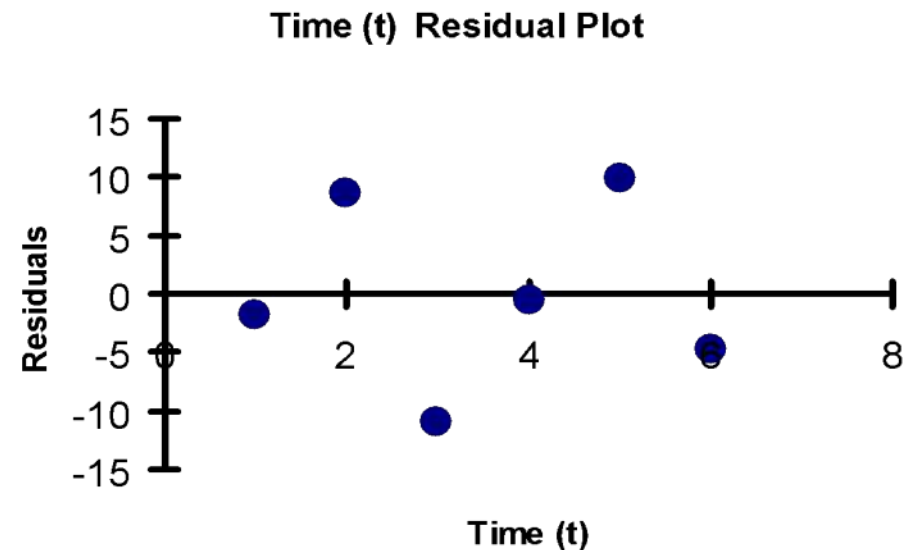


# Measuring Autocorrelation

- Used when data are collected over time to detect if autocorrelation is present
- Autocorrelation exists if residuals in one time period are related to residuals in another period

# Autocorrelation

- Autocorrelation is correlation of the errors (residuals) over time
- Here, residuals show a cyclic pattern, not random. Cyclical patterns are a sign of positive autocorrelation
- Violates the regression assumption that residuals are random and independent



# The Durbin-Watson Statistic

- The Durbin-Watson statistic is used to test for autocorrelation
- $H_0$ : residuals are not correlated
- $H_1$ : positive autocorrelation is present

$$D = \frac{\sum_{i=2}^n (e_i - e_{i-1})^2}{\sum_{i=1}^n e_i^2}$$

- The possible range is  $0 \leq D \leq 4$
- $D$  should be close to 2 if  $H_0$  is true
- $D$  less than 2 may signal positive autocorrelation,  $D$  greater than 2 may signal negative autocorrelation

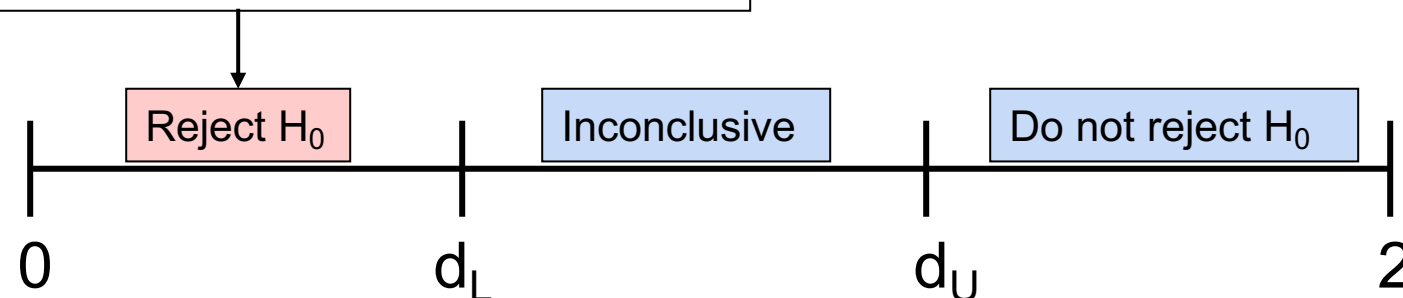
# Testing for Positive Autocorrelation

$H_0$ : positive autocorrelation does not exist

$H_1$ : positive autocorrelation is present

- Calculate the Durbin-Watson test statistic =  $D$ 
  - (The Durbin-Watson Statistic can be found using Excel or Minitab)
- Find the values  $d_L$  and  $d_U$  from the Durbin-Watson table
  - (for sample size  $n$  and number of independent variables  $k$ )

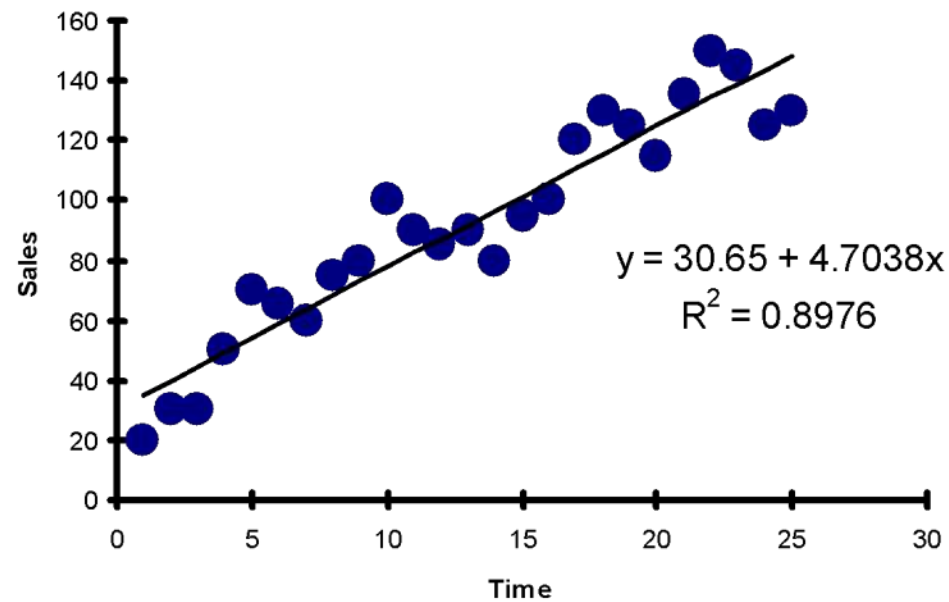
Decision rule: reject  $H_0$  if  $D < d_L$





# Testing for Positive Autocorrelation

- Suppose we have the following time series data:
- Is there autocorrelation?

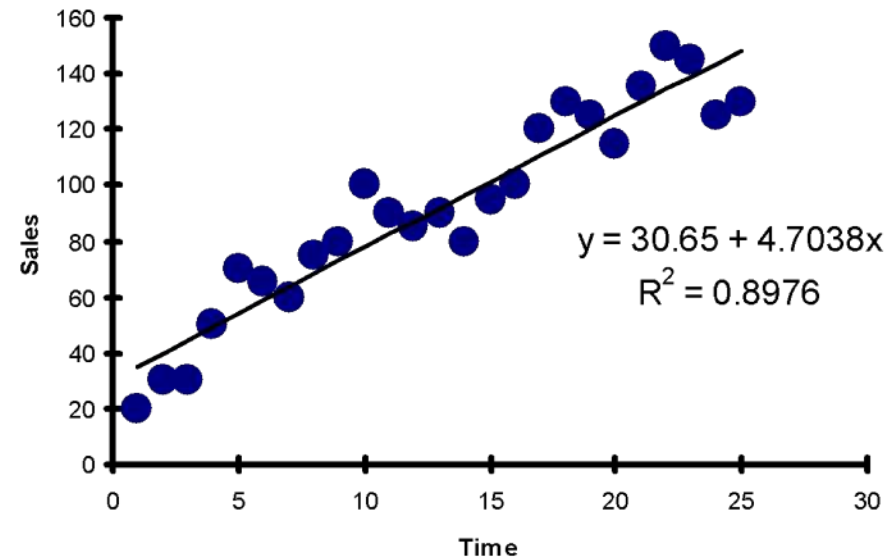




# Testing for Positive Autocorrelation

- Example with  $n = 25$ :

| Durbin-Watson Calculations             |                |
|--|----------------|
| Sum of Squared Difference of Residuals | 3296.18        |
| Sum of Squared Residuals               | 3279.98        |
| <b>Durbin-Watson Statistic</b>         | <b>1.00494</b> |



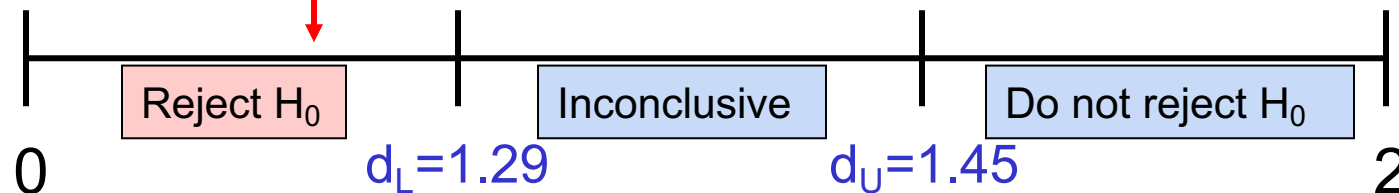
$$D = \frac{\sum_{i=2}^n (e_i - e_{i-1})^2}{\sum_{i=1}^n e_i^2} = \frac{3296.18}{3279.98} = 1.00494$$

# Testing for Positive Autocorrelation

- Here,  $n = 25$  and there is  $k = 1$  one independent variable
- Using the Durbin-Watson table,  $d_L = 1.29$  and  $d_U = 1.45$
- $D = 1.00494 < d_L = 1.29$ , so reject  $H_0$  and conclude that significant positive autocorrelation exists

Decision: **reject  $H_0$**  since

$$D = 1.00494 < d_L$$



# Inferences About the Slope

- The standard error of the regression slope coefficient ( $b_1$ ) is estimated by

$$S_{b_1} = \frac{S_{YX}}{\sqrt{SSX}} = \frac{S_{YX}}{\sqrt{\sum (X_i - \bar{X})^2}}$$

where:

$S_{b_1}$  = Estimate of the standard error of the slope

$$S_{YX} = \sqrt{\frac{SSE}{n-2}}$$

= Standard error of the estimate

# Inferences About the Slope: t Test

- t test for a population slope
  - Is there a linear relationship between X and Y?
- Null and alternative hypotheses
  - $H_0: \beta_1 = 0$  (no linear relationship)
  - $H_1: \beta_1 \neq 0$  (linear relationship does exist)
- Test statistic

$$t_{\text{STAT}} = \frac{b_1 - \beta_1}{S_{b_1}}$$

$$\text{d.f.} = n - 2$$

where:

$b_1$  = regression slope  
coefficient

$\beta_1$  = hypothesized slope

$S_{b_1}$  = standard  
error of the slope

# Inferences About the Slope: t Test Example

|   | house_price | square_feet |
|---|-------------|-------------|
| 0 | 245         | 1400        |
| 1 | 312         | 1600        |
| 2 | 279         | 1700        |
| 3 | 308         | 1875        |
| 4 | 199         | 1100        |
| 5 | 219         | 1550        |
| 6 | 405         | 2350        |
| 7 | 324         | 2450        |
| 8 | 319         | 1425        |
| 9 | 255         | 1700        |

## Estimated Regression Equation:

$$\text{house price} = 98.25 + 0.1098 (\text{sq.ft.})$$

The slope of this model is 0.1098

Is there a relationship between the square footage of the house and its sales price?

# t Test Example

- $H_0: \beta_1 = 0$
- $H_1: \beta_1 \neq 0$

|             | coef    | std err | t     | P> t  | [0.025  | 0.975]  |
|-------------|---------|---------|-------|-------|---------|---------|
| const       | 98.2483 | 58.023  | 1.693 | 0.129 | -35.577 | 232.074 |
| square_feet | 0.1098  | 0.033   | 3.329 | 0.010 | 0.034   | 0.186   |

$b_1$

$S_{b_1}$

$$t_{\text{STAT}} = \frac{b_1 - \beta_1}{S_{b_1}} = \frac{0.10977 - 0}{0.03297} = 3.32938$$

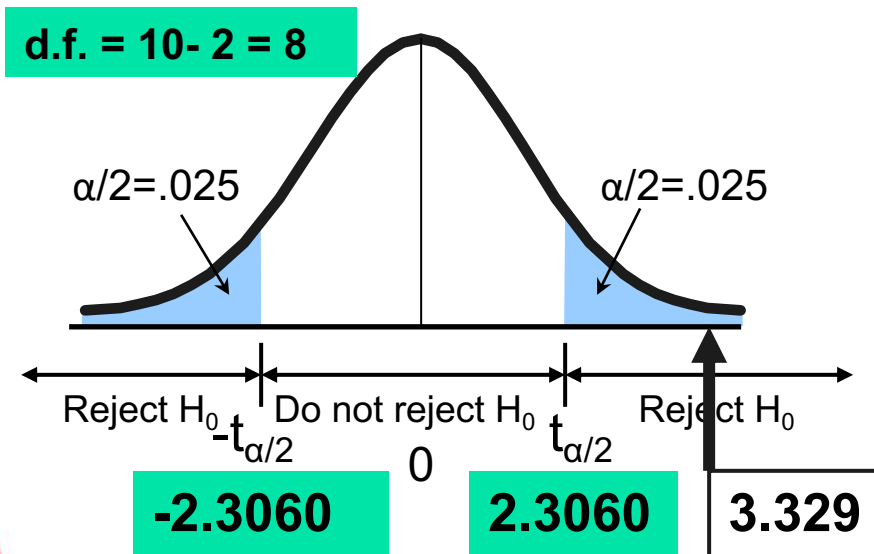


# t Test Example

Test Statistic:  $t_{\text{STAT}} = 3.329$

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$



Decision: Reject  $H_0$

There is sufficient evidence that square footage affects house price



# Multiple Linear Regression

|             | coef    | std err | t     | P> t  | [0.025  | 0.975]  |
|-------------|---------|---------|-------|-------|---------|---------|
| const       | 98.2483 | 58.033  | 1.693 | 0.129 | -35.577 | 232.074 |
| square_feet | 0.1098  | 0.033   | 3.329 | 0.010 | 0.034   | 0.186   |

p-value

Decision: Reject  $H_0$ , since  $p\text{-value} < \alpha$

There is sufficient evidence that square footage affects house price.

# Multiple Linear Regression

- Idea: Examine the linear relationship between
- 1 dependent ( $Y$ ) & 2 or more independent variables ( $X_i$ )

# F Test for Significance

OLS Regression Results

|                   |                  |                     |         |
|-------------------|------------------|---------------------|---------|
| Dep. Variable:    | house_price      | R-squared:          | 0.581   |
| Model:            | OLS              | Adj. R-squared:     | 0.528   |
| Method:           | Least Squares    | F-statistic:        | 11.08   |
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| Df Model:         | 1                |                     |         |
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| Skew:          | 0.399 | Prob(JB):         | 0.677    |
| Kurtosis:      | 1.890 | Cond. No.         | 7.82e+03 |

With 1 and 8 degrees of freedom

p-value for the F-Test

$$F_{\text{STAT}} = \frac{\text{MSR}}{\text{MSE}} = \frac{18934.9348}{1708.1957} = 11.0848$$

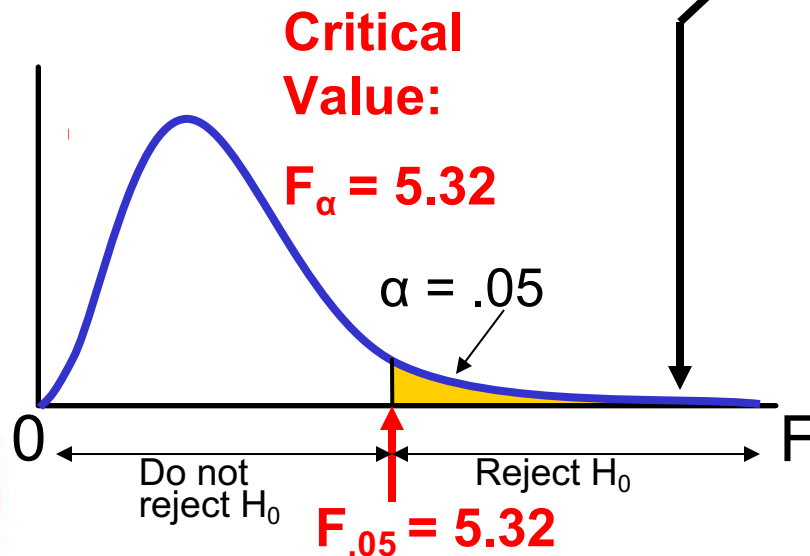
# F Test for Significance

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$

$$\alpha = .05$$

$$df_1 = 1 \quad df_2 = 8$$



## Test Statistic:

$$F_{\text{STAT}} = \frac{MSR}{MSE} = 11.08$$

## Decision:

Reject  $H_0$  at  $\alpha = 0.05$

## Conclusion:

There is sufficient evidence that house size affects selling price

# Confidence Interval Estimate for the Slope

- Confidence Interval Estimate of the Slope:

$$b_1 \pm t_{\alpha/2} S_{b_1} \quad \text{d.f.} = n - 2$$

|             | coef    | std err | t     | P> t  | [0.025  | 0.975]  |
|-------------|---------|---------|-------|-------|---------|---------|
| const       | 98.2483 | 58.033  | 1.693 | 0.129 | -35.577 | 232.074 |
| square_feet | 0.1098  | 0.033   | 3.329 | 0.010 | 0.034   | 0.186   |

At 95% level of confidence, the confidence interval for the slope is (0.0337, 0.1858)



# Confidence Interval Estimate for the Slope

|             | coef    | std err | t     | P> t  | [0.025  | 0.975]  |
|-------------|---------|---------|-------|-------|---------|---------|
| const       | 98.2483 | 58.033  | 1.693 | 0.129 | -35.577 | 232.074 |
| square_feet | 0.1098  | 0.033   | 3.329 | 0.010 | 0.034   | 0.186   |

Since the units of the house price variable is \$1000s, we are 95% confident that the average impact on sales price is between \$33.74 and \$185.80 per square foot of house size

This 95% confidence interval **does not include 0**.

**Conclusion:** There is a significant relationship between house price and square feet at the .05 level of significance

# t Test for a Correlation Coefficient

- Hypotheses
  - $H_0: \rho = 0$  (no correlation between X and Y)
  - $H_1: \rho \neq 0$  (correlation exists)
- Test statistic
  - (with  $n - 2$  degrees of freedom)

$$t_{\text{STAT}} = \frac{r - \rho}{\sqrt{\frac{1 - r^2}{n - 2}}}$$

where

$$r = +\sqrt{r^2} \text{ if } b_1 > 0$$

$$r = -\sqrt{r^2} \text{ if } b_1 < 0$$



# t Test for a Correlation Coefficient

Is there evidence of a linear relationship between square feet and house price at the .05 level of significance?

$H_0: \rho = 0$  (No correlation)

$H_1: \rho \neq 0$  (correlation exists)

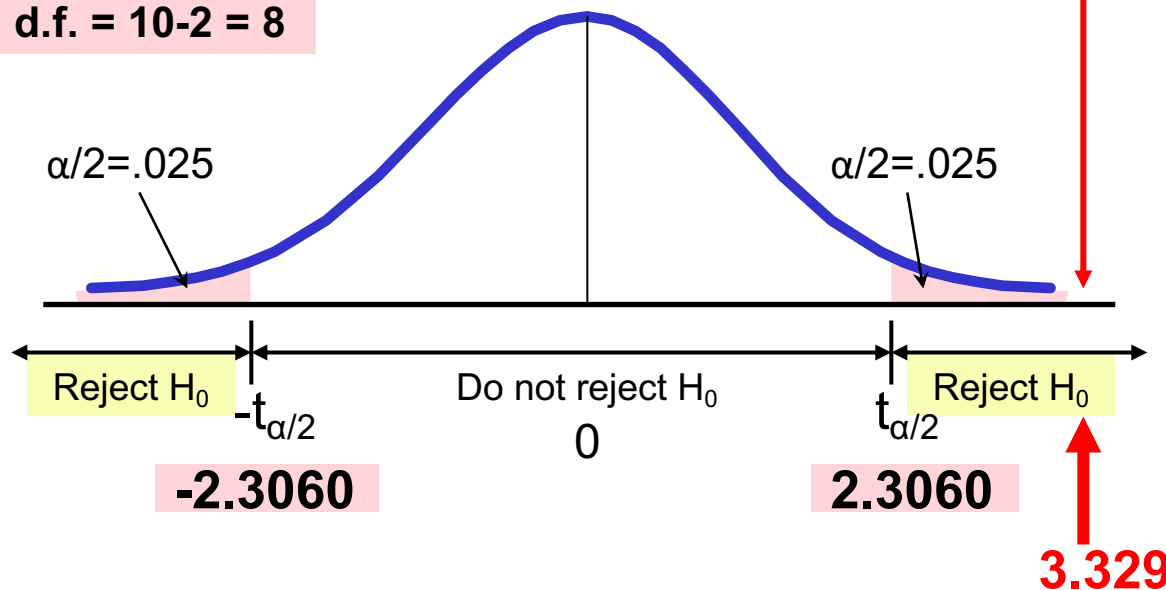
$\alpha = .05$  ,  $df = 10 - 2 = 8$

$$t_{\text{STAT}} = \frac{r - \rho}{\sqrt{\frac{1 - r^2}{n - 2}}} = \frac{.762 - 0}{\sqrt{\frac{1 - .762^2}{10 - 2}}} = 3.329$$

# t Test for a Correlation Coefficient

$$t_{\text{STAT}} = \frac{r - \rho}{\sqrt{\frac{1 - r^2}{n - 2}}} = \frac{.762 - 0}{\sqrt{\frac{1 - .762^2}{10 - 2}}} = 3.329$$

d.f. = 10 - 2 = 8

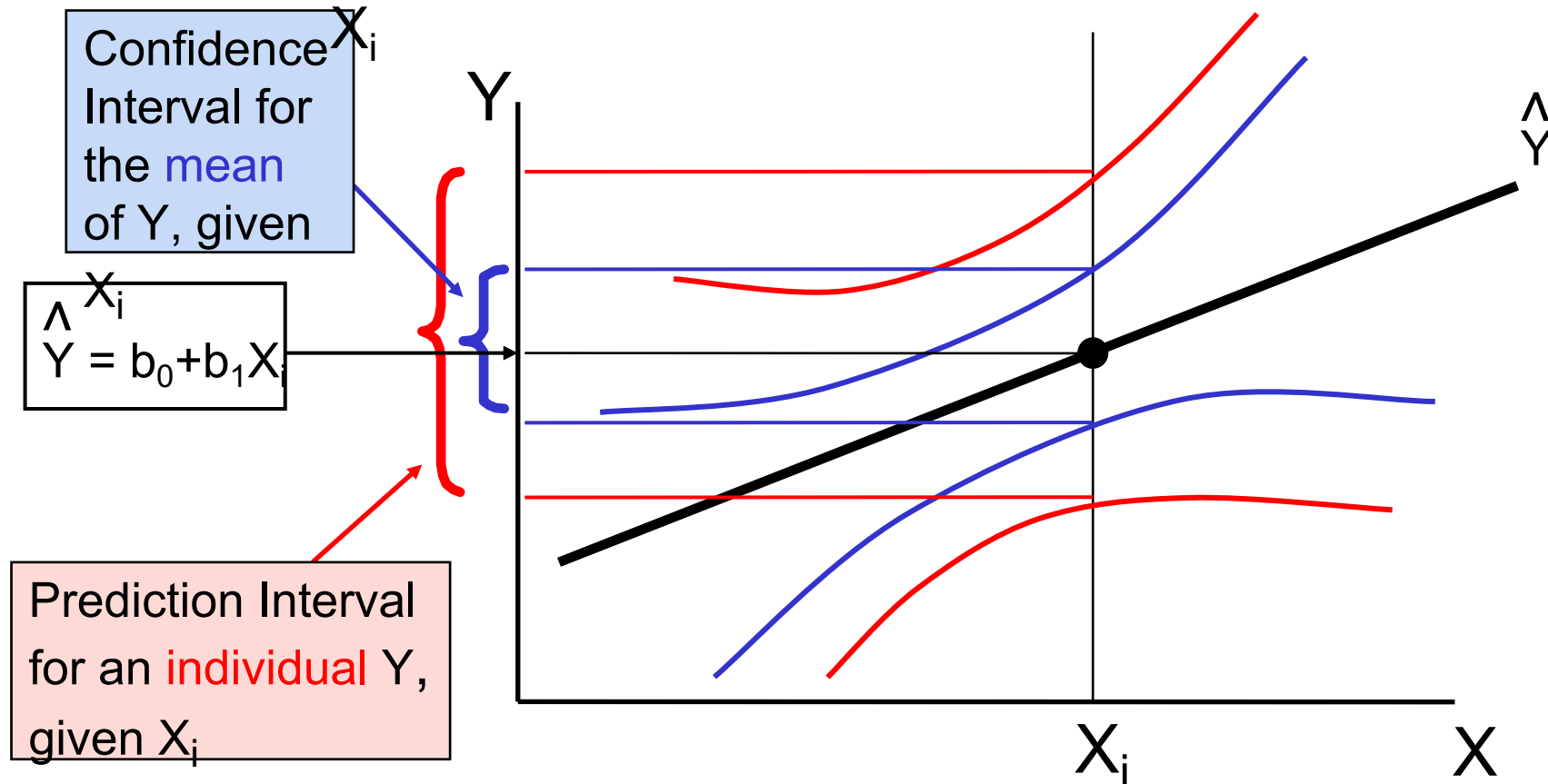


**Decision:**  
Reject H<sub>0</sub>

**Conclusion:**  
There is **evidence** of a linear association at the 5% level of significance

# Estimating Mean Values and Predicting Individual Values

Goal: Form intervals around  $\hat{Y}$  to express uncertainty about the value of  $Y$  for a given



# Confidence Interval for the Average Y, Given X

Confidence interval estimate for the **mean value of Y** given a particular  $X_i$

Confidence interval for  $\mu_{Y|X=X_i}$  :

$$\hat{Y} \pm t_{\alpha/2} S_{YX} \sqrt{h_i}$$

Size of interval varies according to distance away from mean, X

$$h_i = \frac{1}{n} + \frac{(X_i - \bar{X})^2}{SSX} = \frac{1}{n} + \frac{(X_i - \bar{X})^2}{\sum (X_i - \bar{X})^2}$$

# Prediction Interval for an Individual Y, Given X

Confidence interval estimate for an  
**Individual value of Y** given a particular  $X_i$

Confidence interval for  $Y_{X=X_i}$  :

$$\hat{Y} \pm t_{\alpha/2} S_{YX} \sqrt{1 + h_i}$$

This extra term adds to the interval width to reflect  
the added uncertainty for an individual case

# Estimation of Mean Values: Example

## Confidence Interval Estimate for $\mu_{Y|X=X}$

Find the 95% confidence interval for the mean price of 2,000 square-foot houses

Predicted Price  $Y_i = 317.85$  (\$1,000s)

$$\hat{Y} \pm t_{0.025} S_{YX} \sqrt{\frac{1}{n} + \frac{(X_i - \bar{X})^2}{\sum (X_i - \bar{X})^2}} = 317.85 \pm 37.12$$

The confidence interval endpoints are 280.66 and 354.90, or from \$280,660 to \$354,900



# Estimation of Individual Values: Example

## Prediction Interval Estimate for $Y_{X=X}$

Find the 95% prediction interval for an individual house with 2,000 square feet

Predicted Price  $\hat{Y}_i = 317.85$  (\$1,000s)

$$\hat{Y} \pm t_{0.025} S_{YX} \sqrt{1 + \frac{1}{n} + \frac{(X_i - \bar{X})^2}{\sum (X_i - \bar{X})^2}} = 317.85 \pm 102.28$$

The prediction interval endpoints are 215.50 and 420.07, or from \$215,500 to \$420,070



# Multiple Linear Regression

- Idea: Examine the linear relationship between
- 1 dependent ( $Y$ ) & 2 or more independent variables ( $X_i$ )

# Multiple Linear Regression

Idea: Examine the linear relationship between  
1 dependent ( $y$ ) & 2 or more independent variables ( $x_i$ )

**Population  
model:**

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \varepsilon$$

Annotations for Population model:

- Y-intercept:  $\beta_0$
- Population slopes:  $\beta_1, \beta_2, \dots, \beta_k$
- Random Error:  $\varepsilon$

**Estimated  
multiple  
regression  
model:**

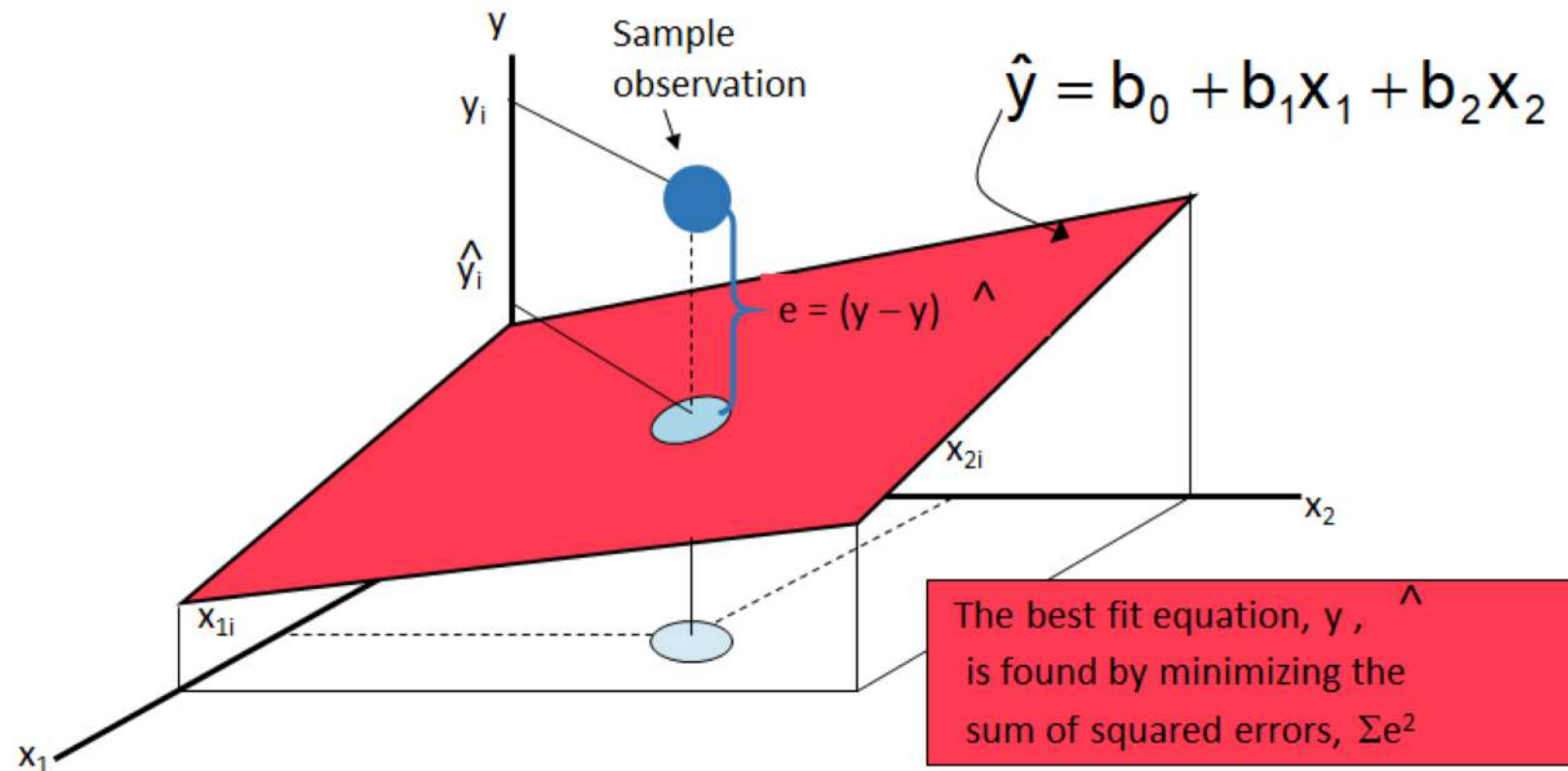
$$\hat{y} = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_k x_k$$

Annotations for Estimated multiple regression model:

- Estimated (or predicted) value of  $y$ :  $\hat{y}$
- Estimated intercept:  $b_0$
- Estimated slope coefficients:  $b_1, b_2, \dots, b_k$

# Multiple Linear Regression

## Two variable model



# Example: Multiple Linear Regression

- A distributor of frozen dessert pies wants to evaluate factors thought to influence demand
- Dependent variable: Pie sales (units per week)
- Independent variables: Price (in \$), Advertising (\$100's)
- Data are collected for 15 weeks



# Example: Data

|    | week | pie_sales | price | advertising |
|----|------|-----------|-------|-------------|
| 0  | 1    | 350       | 5.5   | 3.3         |
| 1  | 2    | 460       | 7.5   | 3.3         |
| 2  | 3    | 350       | 8.0   | 3.0         |
| 3  | 4    | 430       | 8.0   | 4.5         |
| 4  | 5    | 350       | 6.8   | 3.0         |
| 5  | 6    | 380       | 7.5   | 4.0         |
| 6  | 7    | 430       | 4.5   | 3.0         |
| 7  | 8    | 470       | 6.4   | 3.7         |
| 8  | 9    | 450       | 7.0   | 3.5         |
| 9  | 10   | 490       | 5.0   | 4.0         |
| 10 | 11   | 340       | 7.2   | 3.5         |
| 11 | 12   | 300       | 7.9   | 3.2         |
| 12 | 13   | 440       | 5.9   | 4.0         |
| 13 | 14   | 450       | 5.0   | 3.5         |
| 14 | 15   | 300       | 7.0   | 2.7         |

$$\widehat{\text{Sales}} = b_0 + b_1 (\text{Price}) + b_2 (\text{Advertising})$$



# Example: Regression Equation

$$\text{Sales} = 306.526 - 24.975(\text{Price}) + 74.131(\text{Advertising})$$

where

Sales is in number of pies per week

Price is in \$

Advertising is in \$100's.

**$b_1 = -24.975$** : sales will decrease, on average, by 24.975 pies per week for each \$1 increase in selling price, net of the effects of changes due to advertising

**$b_2 = 74.131$** : sales will increase, on average, by 74.131 pies per week for each \$100 increase in advertising, net of the effects of changes due to price

# Example: Making Predictions

Predict sales for a week in which the selling price is \$5.50 and advertising is \$350:

$$\begin{aligned}\text{Sales} &= 306.526 - 24.975(\text{Price}) + 74.131(\text{Advertising}) \\ &= 306.526 - 24.975(5.50) + 74.131(3.5) \\ &= 428.62\end{aligned}$$

Predicted sales  
is 428.62 pies

Note that Advertising is  
in \$100's, so \$350  
means that  $X_2 = 3.5$



# Adjusted $r^2$

- $r^2$  never decreases when a new  $X$  variable is added to the model
  - This can be a disadvantage when comparing models
- What is the net effect of adding a new variable?
  - We lose a degree of freedom when a new  $X$  variable is added
  - Did the new  $X$  variable add enough explanatory power to offset the loss of one degree of freedom?

# Adjusted r2

- Shows the proportion of variation in Y explained by all X variables adjusted for the number of X variables used

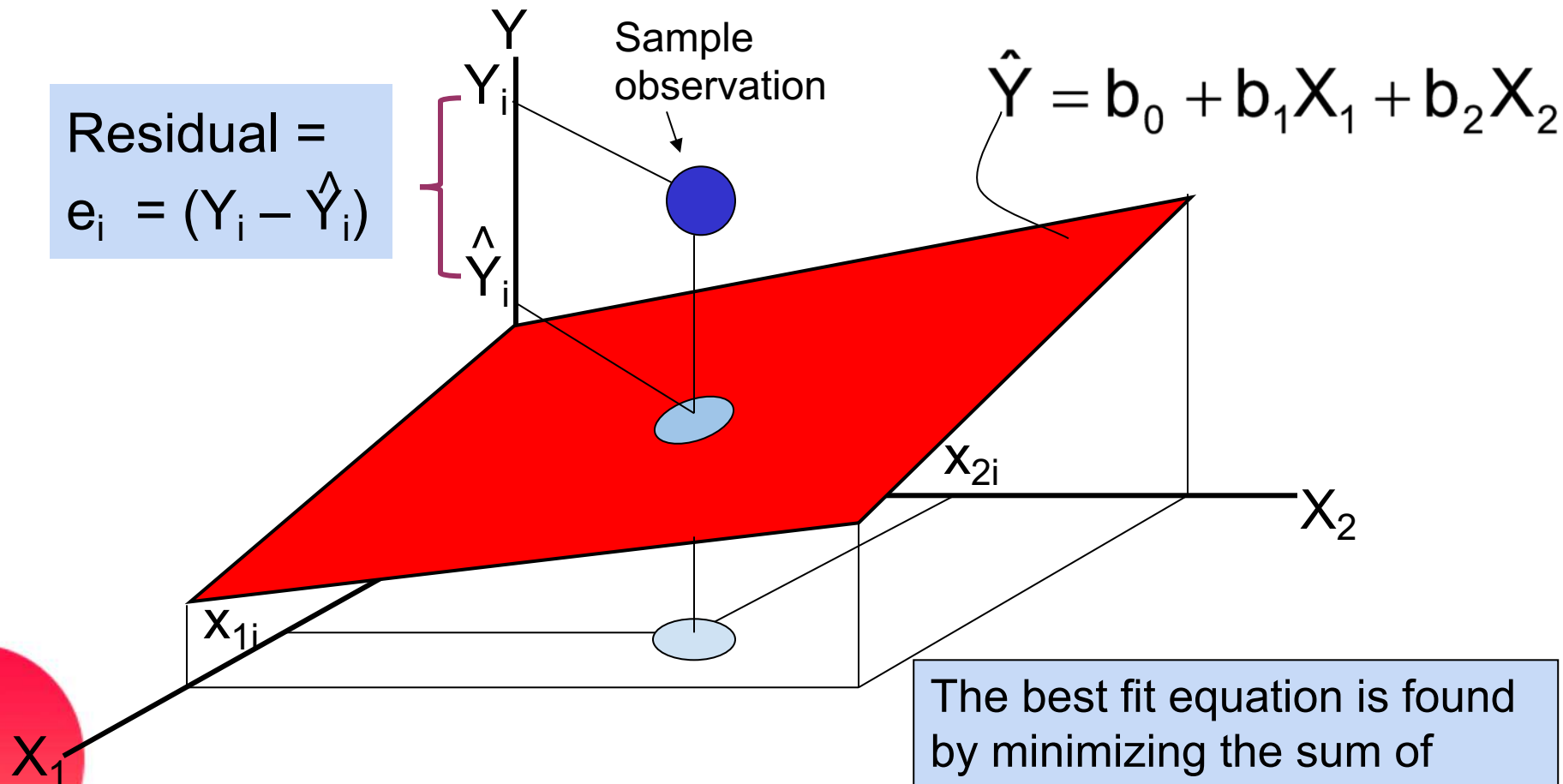
$$r_{adj}^2 = 1 - \left[ (1 - r^2) \left( \frac{n - 1}{n - k - 1} \right) \right]$$

(where n = sample size, k = number of independent variables)

- Penalize excessive use of unimportant independent variables
- Smaller than r2
- Useful in comparing among models

# Residuals in Multiple Regression

Residual =  
 $e_i = (Y_i - \hat{Y}_i)$



The best fit equation is found by minimizing the sum of squared errors,  $\sum e^2$

# Pitfalls of Regression Analysis

- Lacking an awareness of the assumptions underlying least-squares regression
- Not knowing how to evaluate the assumptions
- Not knowing the alternatives to least-squares regression if a particular assumption is violated
- Using a regression model without knowledge of the subject matter
- Extrapolating outside the relevant range

# Strategies for Avoiding the Pitfalls of Regression

- Start with a scatter plot of  $X$  vs.  $Y$  to observe possible relationship
- Perform residual analysis to check the assumptions
- Plot the residuals vs.  $X$  to check for violations of assumptions such as homoscedasticity
- Use a histogram, stem-and-leaf display, boxplot, or normal probability plot of the residuals to uncover possible non-normality

# Strategies for Avoiding the Pitfalls of Regression

- If there is violation of any assumption, use alternative methods or models
- If there is no evidence of assumption violation, then test for the significance of the regression coefficients and construct confidence intervals and prediction intervals
- Avoid making predictions or forecasts outside the relevant range

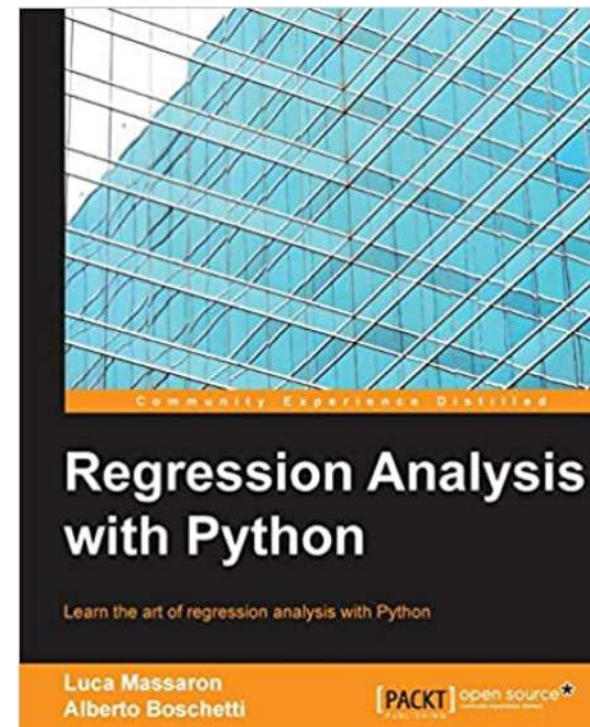
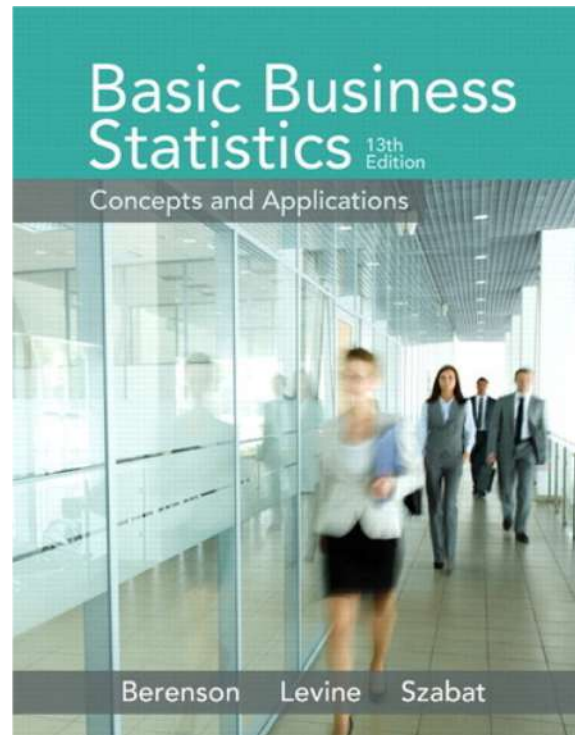


# Practice with Python

- Practice Link: <https://github.com/rc-dbe/dti>

# References/Additional Resources

- Basic Business Statistics 13th Edition by Mark Berenson
- Regression Analysis with Python by Luca Massaron



# Assignment Week 4

- Create a multiple linear regression model using pie sales data in <https://github.com/rc-dbe/dti>
- Use Google Collab (or Jupyter Notebook if you want)
- Put the code in your github
- Make it informative as possible

# Assignment Week 4

