# Simple & Multiple Linear Regression Modelling and Interpretation

Vinay Kulkarni

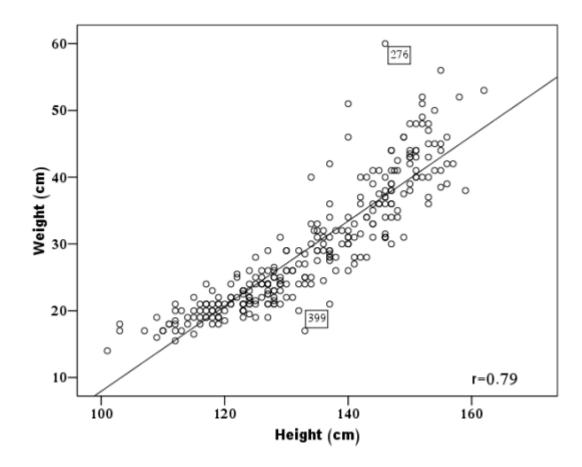
## Regression Analysis

- Are two given variables related to each other?
- Can we find a linear relationship between them?
- Can we predict the value of a random variable?
- These questions can be answered through Regression Analysis
- Regression
  - "Going back to mediocrity or average"

## Regression Analysis

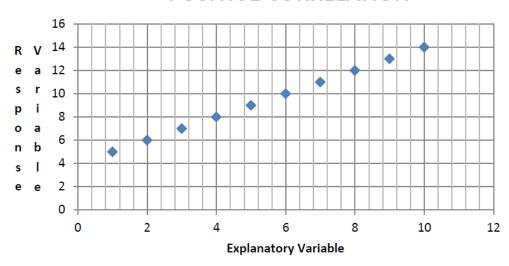
- Explanatory or Predictor or Independent variable(s)
- Response or Dependent variable
  - It is not always clear which variable is **predictor**, and which is the **response**!
- Types of regression analysis
  - Linear Regression
    - One Predictor, one response variable
  - Multiple Regression
    - Many Predictors, one response variable
- Other types of regressions:
  - Logarithmic, Exponential, Quadratic, Cubic

## First use Scatter Plot to assess the relationship

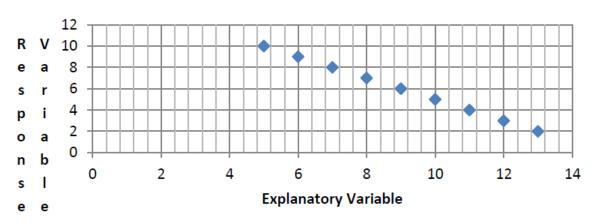


## First step: Use scatter plot

#### **POSITIVE CORRELATION**



### **NEGATIVE CORRELATION**



## Simple Regression Model

Simple regression model is of the form

$$-Y = \beta_0 + \beta_1 x + e$$

- Where
  - Y = Response variable
  - X = Regressor or explanatory variable
  - $-\beta_0$  is the y intercept
  - $-\beta_1$  is regression coefficient or slope
  - e is the random error
    - Has normal distribution
      - With mean 0
      - With variance  $\sigma^2$

## Least Squares Regression Line

Least squares regression line  $\hat{y} = b_0 + b_1 x$ It passes through the 'mean' point

$$\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n} \qquad \bar{y} = \frac{\sum_{i=1}^{n} y_i}{n}$$

Each point of the sample satisfies

$$y_i = \beta_0 + \beta_1 x_i + e_i$$

Where

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

Is the residual error, the square of which is minimized

## Least Squares Regression Line

SSE = 
$$\sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 = \sum_{i=1}^{n} (y_i - b_0 - b_1 X_i)^2$$

The values of coefficients are arrived at by minimizing the SSE. The results are as follows:

$$b_{1} = \frac{\left(\sum_{i=1}^{n} x_{i} y_{i} - \frac{(\sum_{i=1}^{n} x_{i})(\sum_{i=1}^{n} y_{i})}{n}\right)}{\left(\sum_{i=1}^{n} x_{i}^{2} - \frac{(\sum_{i=1}^{n} x_{i})^{2}}{n}\right)}, \text{ and } b_{0} = \overline{y} - b_{1} \overline{x}$$

Expressions derived in a separate document

## Partitioning the total variation

- After doing a (simple linear) regression analysis the variations in each value of the response variable (Y) can be tabulated as follows
  - Total variation = Variation explained by regression + Random variation
- Variation explained by regression
  - Attributable cause
- Random variation
  - Non-attributable causes
- If variation <u>explained by regression</u> is much higher than random variation
  - The response variable is said to be correlated to the explanatory variable

## Partitioning the total variation

- Total error = distance of point from the mean =
  - Distance of actual point from point on line +
  - Distance of point on line from mean
- If the distance of actual point from point on line is small
  - − → Fitness is good
- The measure of goodness of fit is known as
  - Coefficient of determination: R<sup>2</sup>
  - Closer this value is to 1, better the fit

## Partitioning of the Total Variation

$$Y_i = \overline{y} + (\hat{y}_i - \overline{y}) + (Y_i - \hat{y}_i)$$
, for i = 1, 2, 3, ..., n.

$$Y_i - \overline{y} = (\hat{y}_i - \overline{y}) + (Y_i - \hat{y}_i)$$
, for  $i = 1, 2, 3, ..., n$ .

Total deviation = Deviation due to regression + Deviation about regression

$$\sum_{i=1}^{n} (Y_i - \overline{y})^2 = \sum_{i=1}^{n} (\hat{y}_i - \overline{y})^2 + \sum_{i=1}^{n} (Y_i - \hat{y}_i)^2$$

$$SS_{total} = SS_{regr} + SS_{residuals}$$

$$SS_{\text{total}} = \sum_{i=1}^{n} (Y_i - \overline{y})^2 = \sum_{i=1}^{n} Y_i^2 - \frac{\sum_{i=1}^{n} Y_i^2}{n}$$

$$SS_{regr} = \sum_{i=1}^{n} (\hat{y}_i - \overline{y})^2 = b_0 \sum_{i=1}^{n} Y_i + b_1 \sum_{i=1}^{n} X_i Y_i - \frac{\sum_{i=1}^{n} Y_i^2}{n}, \text{ and}$$

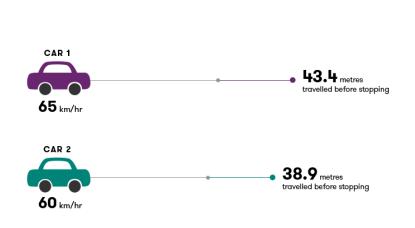
$$SS_{residuals} = SS_{total} - SS_{regr} = \sum_{i=1}^{n} Y_i^2 - b_0 \sum_{i=1}^{n} Y_i - b_1 \sum_{i=1}^{n} X_i Y_i$$
.

$$r^2 = SS_{regr} / SS_{total}$$

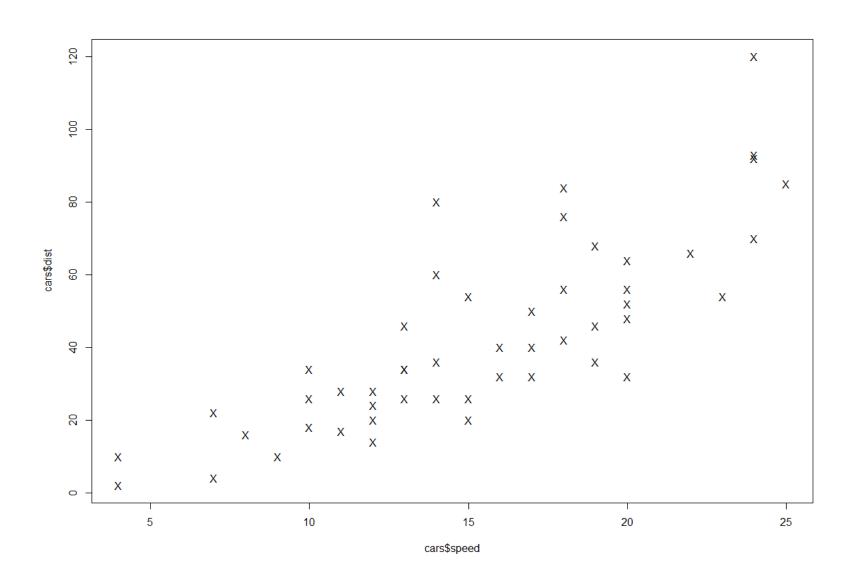
## Simple Linear Regression: Cars - Breaking Distance

Data: Speed v/s Breaking Distance

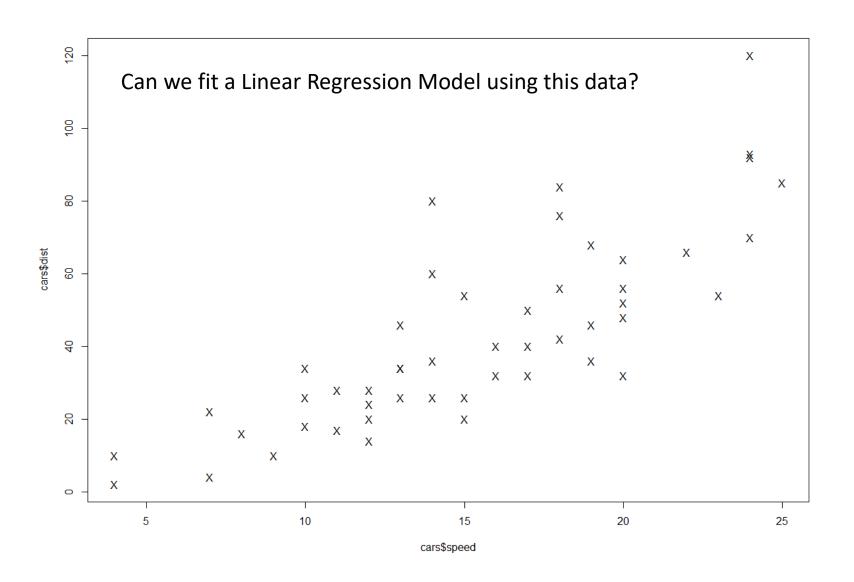
|    | speed | dist |    | speed | dist |
|----|-------|------|----|-------|------|
| 1  | 4     | 2    | 26 | 15    | 54   |
| 2  | 4     | 10   | 27 | 16    | 32   |
| 3  | 7     | 4    | 28 | 16    | 40   |
| 4  | 7     | 22   | 29 | 17    | 32   |
| 5  | 8     | 16   | 30 | 17    | 40   |
| 6  | 9     | 10   | 31 | 17    | 50   |
| 7  | 10    | 18   | 32 | 18    | 42   |
| 8  | 10    | 26   | 33 | 18    | 56   |
| 9  | 10    | 34   | 34 | 18    | 76   |
| 10 | 11    | 17   | 35 | 18    | 84   |
| 11 | 11    | 28   | 36 | 19    | 36   |
| 12 | 12    | 14   | 37 | 19    | 46   |
| 13 | 12    | 20   | 38 | 19    | 68   |
| 14 | 12    | 24   | 39 | 20    | 32   |
| 15 | 12    | 28   | 40 | 20    | 48   |
| 16 | 13    | 26   | 41 | 20    | 52   |
| 17 | 13    | 34   | 42 | 20    | 56   |
| 18 | 13    | 34   | 43 | 20    | 64   |
| 19 | 13    | 46   | 44 | 22    | 66   |
| 20 | 14    | 26   | 45 | 23    | 54   |
| 21 | 14    | 36   | 46 | 24    | 70   |
| 22 | 14    | 60   | 47 | 24    | 92   |
| 23 | 14    | 80   | 48 | 24    | 93   |
| 24 | 15    | 20   | 49 | 24    | 120  |
| 25 | 15    | 26   | 50 | 25    | 85   |



# First step: Visualization



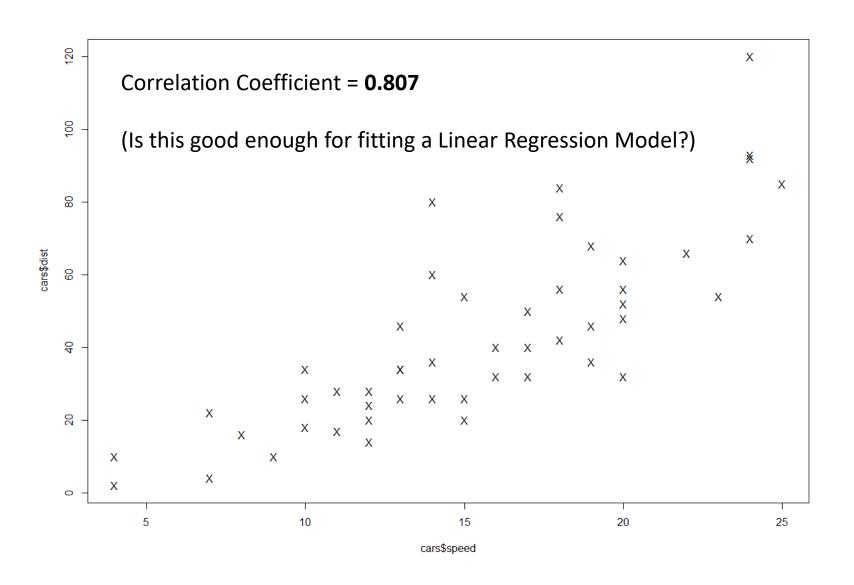
# Plot: Speed v/s Distance



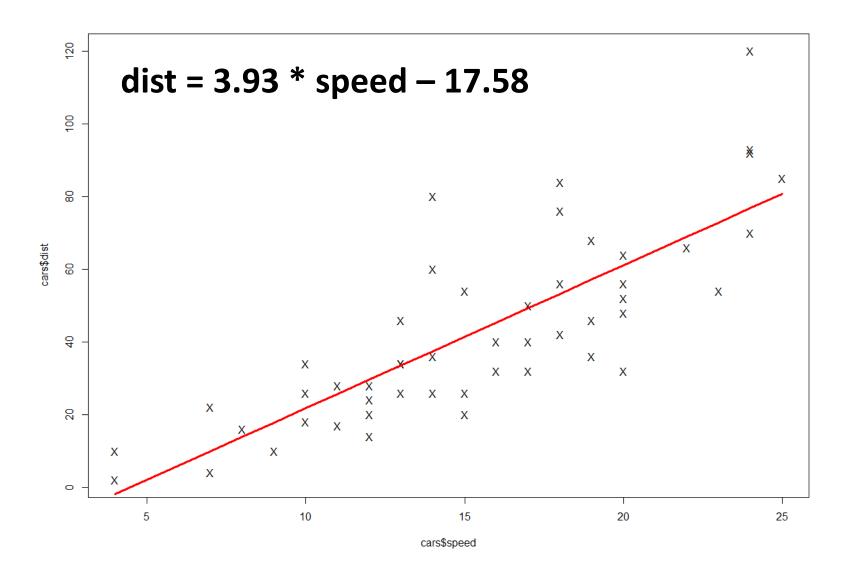
### **Correlation Coefficient**

- Is there a good enough reason to fit a Linear Regression model?
  - We need to check if the two variables in general have a linear relationship
  - Visual check is one method: works when only one predictor variable is involved
  - Finding out the correlation coefficient is another quick check
  - Correlation Coefficient:  $h_{xy} = \frac{1}{n} \sum_{k=1}^{n} \frac{\left(x_{1}^{n} \overline{x}\right)}{6x} \cdot \frac{\left(x_{1}^{n} \overline{y}\right)}{6y}$
  - Also:  $\beta_1 = \frac{1}{2} \alpha_1 \cdot \frac{6\gamma}{626}$

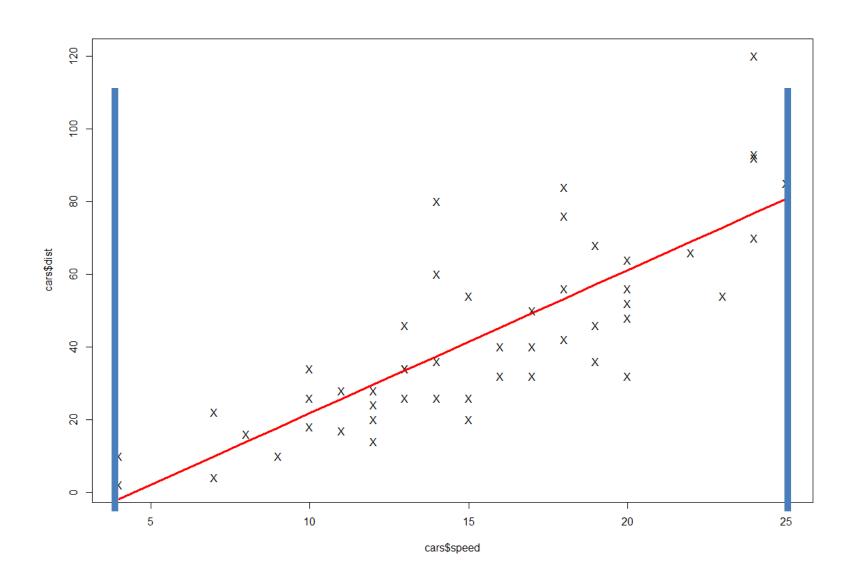
## Plot: Speed v/s Distance



## Linear Regression Model (based on LSE)



## Linear Regression Model: Validity



## **Linear Regression Model:**



## How good is the model?

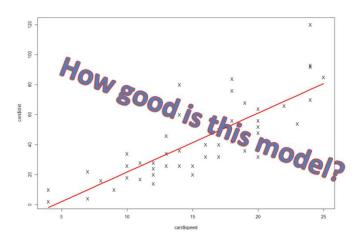
```
Residuals:
   Min
            1Q Median
                           3Q
                                  Max
-29.069 -9.525 -2.272
                        9.215 43.201
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
                    6.7584 -2.601
(Intercept) -17.5791
                                        0.0123 *
                       0.4155 9.464 1.49e-12 ***
speed
             3.9324
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 15.38 on 48 degrees of freedom
Multiple R-squared: 0.6511, Adjusted R-squared: 0.6438
F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12
```

Judged by analyzing various information generated during the process of Linear Regression



## Understanding the model: Residuals

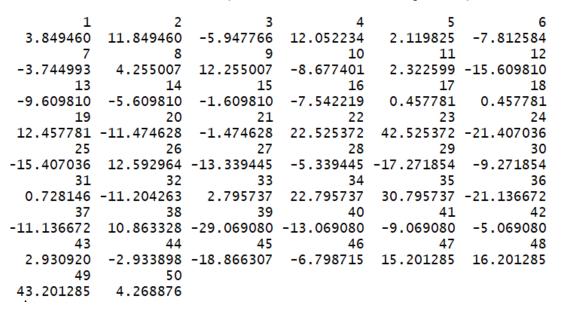
```
Residuals:
            10 Median 30 Max / RESIDUALS
25 -2.272 9.215 43.201
    Min
-29.069 -9.525 -2.272
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) -17.5791
                        6.7584 -2.601
                                         0.0123 *
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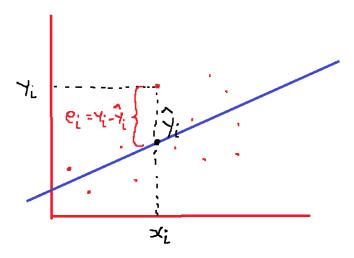


## Understanding the model: Residuals

### Residuals or Errors

Residuals (Cars example)





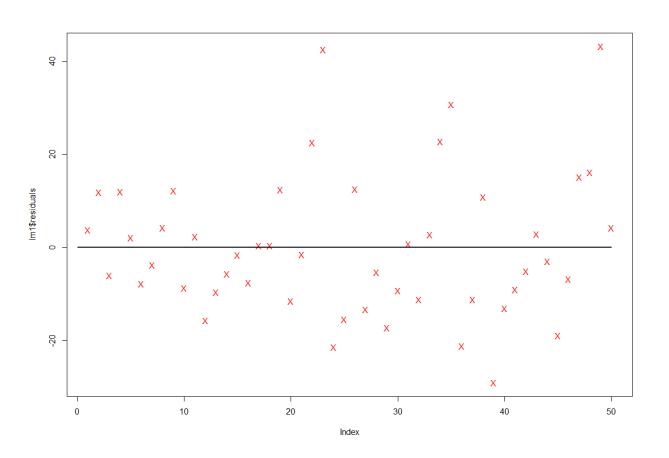
- Sum of errors = 0 (why?)
- Sum of square of errors = SSE =  $\sum_{i=1}^{\infty} = 11353.52$

## Understanding the model: Residuals

```
Residuals:
 Min 1Q Median 3Q Max - RESIDUALS -29.069 -9.525 -2.272 9.215 43.201
 Coefficients:
             Estimate Std. Error t value Pr(>|t|)
  (Intercept) -17.5791 6.7584 -2.601 0.0123 *
 speed
               3.9324 0.4155 9.464 1.49e-12 ***
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 Residual standard error: 15.38 on 48 degrees of freedom
 Multiple R-squared: 0.6511, Adjusted R-squared: 0.6438
  F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12
RESIDUAL STANDARD ERROR
                                             = \frac{1}{(50-2)} \cdot 1/353.52
     S = \sqrt{\frac{1}{n-2}} \cdot \sum e_i^2
                                               = 15.38
```

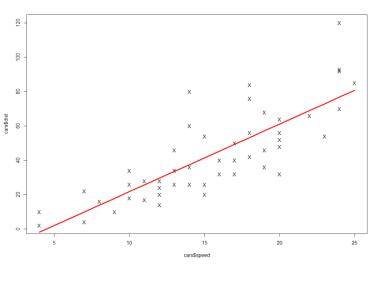
## Interpreting Residuals ...

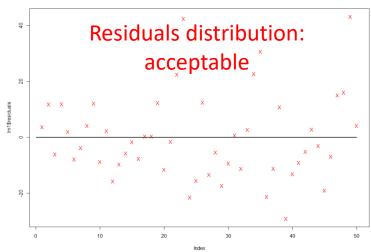
- Are they systematic or are they random?
- Good regression Residuals

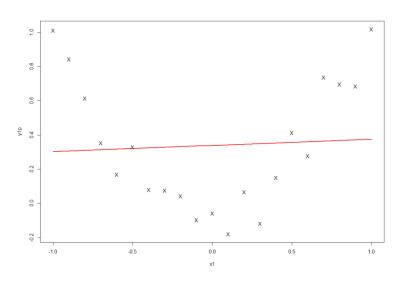


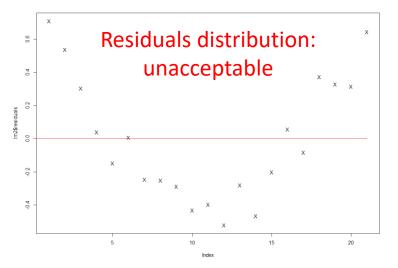
# Interpreting Residuals ...

- Are they systematic or are they random?
- Good regression ← Random Residuals









### **Estimates of the Coefficients**

```
Residuals:
     Min 1Q Median 3Q
                                           Max
-29.069 -9.525 -2.272 9.215 43.201
(Intercept) Std. Error t value Pr(>|t|) \beta_0 = -|7.579| speed 3.9324 0.4155 9.464 1.49e-12 *** \beta_1 = 3.9324
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 15.38 on 48 degrees of freedom
Multiple R-squared: 0.6511, Adjusted R-squared: 0.6438
F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12
           \beta_0 = \frac{\chi^2 - \overline{\chi} \cdot \chi_Y}{(\overline{\chi^2} - \overline{\chi}^2)}
```

$$\beta_1 = \frac{\overline{xy} - \overline{x}\overline{y}}{(\overline{x^2} - \overline{x}^2)} = h_{\overline{xy}} \cdot \frac{6y}{6x}$$
22 here  $h_{\overline{xy}} = \text{Correlation Coefficient}$ 

### **Coefficient Standard Errors**

```
Residuals:
    Min 1Q Median 3Q
                                     Max
-29.069 -9.525 -2.272 9.215 43.201
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -17.5791 6.7584 -2.601 0.0123 *
                                  9.464 1.49e-12 ***
              3.9324
                          0.4155
speed
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 15.38 on 48 degrees of freedom
Multiple R-squared: 0.6511, Adjusted R-squared: 0.6438
F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12
                       S = RESIDUAL STD. FRADR
                                            SEBI = SIN FOR
      SF_{p_0} = \frac{S}{\sqrt{n}} \cdot \left| 1 + \frac{\overline{\chi}^2}{\sqrt{2}} \right|
```

## t-value and p-value

```
Residuals:

Min 1Q Median 3Q Max

-29.069 -9.525 -2.272 9.215 43.201
```

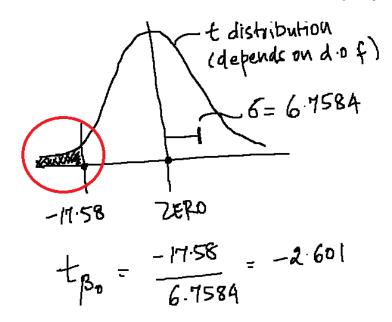
#### Coefficients:

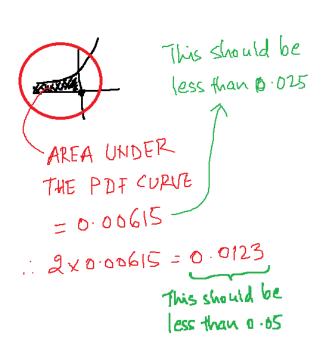
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Estimate Std. Error t value Pr(>|t|)
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```

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Residual standard error: 15.38 on 48 degrees of freedom Multiple R-squared: 0.6511, Adjusted R-squared: 0.6438

F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12





## t-value and p-value

```
Residuals:
```

```
Min 1Q Median 3Q Max -29.069 -9.525 -2.272 9.215 43.201
```

#### Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) -17.5791 6.7584 -2.601 0.0123 *
speed 3.9324 0.4155 9.464 1.49e-12 ***
```

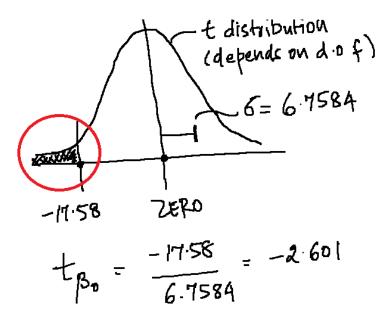
Derived value of a coefficient is acceptable iff it's corresponding p-val is less than 0.05

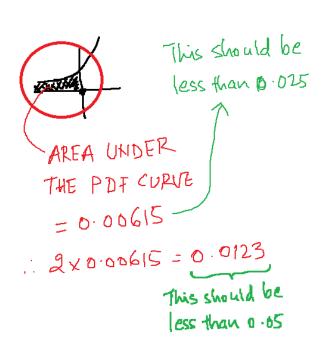
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.38 on 48 degrees of freedom

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F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12





### R-squared

```
Residuals:
     Min 1Q Median 3Q Max
-29.069 -9.525 -2.272 9.215 43.201
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -17.5791 6.7584 -2.601 0.0123 *
         3.9324 0.4155 9.464 1.49e-12 ***
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Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
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Multiple R-squared: 0.6511, Adjusted R-squared: 0.6438
F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12
 Y_i = \overline{y} + (\hat{y}_i - \overline{y}) + (Y_i - \hat{y}_i), for i = 1, 2, 3, ..., n.
 Y_i - \overline{y} = (\hat{y}_i - \overline{y}) + (Y_i - \hat{y}_i), for i = 1, 2, 3, ..., n.
  Total deviation = Deviation due to regression + Deviation about regression
  \sum_{i=1}^{n} (Y_i - \overline{y})^2 = \sum_{i=1}^{n} (\hat{y}_i - \overline{y})^2 + \sum_{i=1}^{n} (Y_i - \hat{y}_i)^2
  SS_{total} = SS_{regr} + SS_{residuals}
   r^2 = SS_{regr} / SS_{total}
```

### R-squared

```
Residuals:
```

Min 1Q Median 3Q Max -29.069 -9.525 -2.272 9.215 43.201

R-squared should be close to 1 for the regression to be considered good

#### Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) -17.5791   6.7584 -2.601   0.0123 *
speed   3.9324   0.4155   9.464   1.49e-12 ***
```

Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.38 on 48 degrees of freedom Multiple R-squared: 0.6511, Adjusted R-squared: 0.6438

F-statistic: 89.57 on 1 and 48 DF, p-value: 1.49e-12

$$Y_i = \overline{y} + (\hat{y}_i - \overline{y}) + (Y_i - \hat{y}_i)$$
, for i = 1, 2, 3, ..., n.

$$Y_i - \overline{y} = (\hat{y}_i - \overline{y}) + (Y_i - \hat{y}_i)$$
, for  $i = 1, 2, 3, ..., n$ .

Total deviation = Deviation due to regression + Deviation about regression

$$\sum_{i=1}^{n} (Y_i - \overline{y})^2 = \sum_{i=1}^{n} (\hat{y}_i - \overline{y})^2 + \sum_{i=1}^{n} (Y_i - \hat{y}_i)^2$$

$$SS_{\text{total}} = SS_{\text{regr}} + SS_{\text{residuals}}$$

$$SS_{\text{total}} = SS_{\text{regr}} + SS_{\text{total}}$$

$$SS_{\text{regr}} + SS_{\text{total}} = SS_{\text{regr}} + SS_{\text{total}}$$

## Multiple Linear Regression

 Multiple Linear Regression. Multiple linear regression attempts to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data (http://www.stat.yale.edu/Courses/1997-98/101/linmult.htm)

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik} + \epsilon_i, \quad i = 1, \dots, n$$

## Coefficients of Multiple Linear Regression

$$y_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik} + \epsilon_i, \quad i = 1, \dots, n$$

Can be written as :  $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$ 

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & x_{12} \cdots x_{1k} \\ 1 & x_{21} & x_{22} \cdots x_{2k} \\ \vdots & \vdots & \vdots \\ 1 & x_{n1} & x_{n2} \cdots x_{nk} \end{pmatrix} \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_k \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

## Coefficients of Multiple Linear Regression

$$\mathbf{y} = \mathbf{X}\beta + \epsilon$$
$$\sum_{i=1}^{n} \epsilon_i^2 = \epsilon' \epsilon = (\mathbf{y} - \mathbf{X}\beta)' (\mathbf{y} - \mathbf{X}\beta)$$

$$\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}}$$

$$\mathbf{X}'(\mathbf{y} - \mathbf{X}\hat{\boldsymbol{\beta}}) = 0$$

$$\mathbf{X}'\mathbf{y} - \mathbf{X}'\mathbf{X}\hat{\boldsymbol{\beta}} = 0$$

$$\mathbf{X}'\mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}'\mathbf{y}$$

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y}$$

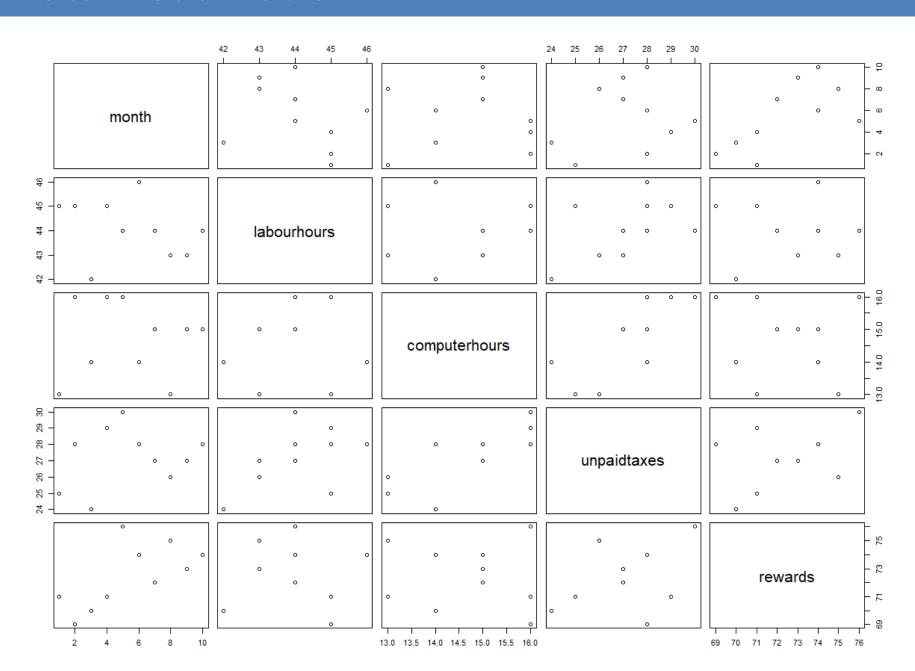
$$\hat{\mathbf{y}} = \mathbf{X}\hat{\boldsymbol{\beta}} = \mathbf{X}(\mathbf{X}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{y} = \mathbf{H}\mathbf{y}$$

## Multiple Linear Regression: Example

• Example: Data for multiple Linear Regression

| Х  | month | labourhours | computerhours | unpaidtaxes | rewards |
|----|-------|-------------|---------------|-------------|---------|
| 1  | jan   | 45          | 16            | 29          | 71      |
| 2  | feb   | 42          | 14            | 24          | 70      |
| 3  | mar   | 44          | 15            | 27          | 72      |
| 4  | apr   | 45          | 13            | 25          | 71      |
| 5  | may   | 43          | 13            | 26          | 75      |
| 6  | jun   | 46          | 14            | 28          | 74      |
| 7  | jul   | 44          | 16            | 30          | 76      |
| 8  | aug   | 45          | 16            | 28          | 69      |
| 9  | sep   | 44          | 15            | 28          | 74      |
| 10 | oct   | 43          | 15            | 27          | 73      |

## Data Visualization



## Multiple Linear Regression Model

- Model-1
- Assume that unpaid taxes are dependent on
  - Labour hours
  - Computer hours

```
Residuals:
    Min
              10 Median
                                      Max
-1.24668 -0.74702 -0.02321 0.51956 1.42706
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
                                 -1.037
                                        0.33411
(Intercept)
             -13.8196
                        13.3233
labourhours 0.5637
                         0.3033 1.859 0.10543
                         0.3131 3.511 0.00984 **
computerhours 1.0995
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1.071 on 7 degrees of freedom
Multiple R-squared: 0.7289, Adjusted R-squared: 0.6515
F-statistic: 9.411 on 2 and 7 DF, p-value: 0.01037
```

## Multiple Linear Regression Model

- Model-2
- Assume unpaid taxes are also dependent on regards
  - Labour hours
  - Computer hours
  - Rewards

```
Residuals:
                   Median
    Min
              10
                               30
                                       Max
-0.29080 -0.11604 -0.09998 0.09102 0.44452
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -45.79635 4.87765 -9.389 8.29e-05 ***
labourhours
            0.59697
                         0.08112 7.359 0.000323 ***
computerhours 1.17684
                         0.08407
                                  13.998 8.29e-06 ***
rewards
              0.40511
                         0.04223 9.592 7.34e-05 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.2861 on 6 degrees of freedom
Multiple R-squared: 0.9834, Adjusted R-squared: 0.9751
F-statistic: 118.5 on 3 and 6 DF, p-value: 9.935e-06
```

## Comparing the models ...

```
Residuals:
    Min
              10 Median
                               3Q
                                      Max
-1.24668 -0.74702 -0.02321 0.51956 1.42706
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -13.8196
                        13.3233 -1.037 0.33411
labourhours 0.5637 0.3033 1.859 0.10543
                     0.3131 3.511 0.00984 **
computerhours 1.0995
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1.071 on 7 degrees of freedom
Multiple R-squared: 0.7289, Adjusted R-squared:
F-statistic: 9.411 on 2 and 7 DF, p-value: 0.01037
```



MODEL-2

### Compare

- Residuals
- Residual Std. Error
- p-values
- R-squared
- F-Statistic & p-value

```
Residuals:
Min 1Q Median 3Q Max
-0.29080 -0.11604 -0.09998 0.09102 0.44452
```

#### Coefficients:

Residual standard error: 0.2861 on 6 degrees of freedom

Multiple R-squared: 0.9834, Adjusted R-squared: 0.9751 F-statistic: 118.5 on 3 and 6 DF, p-value: 9.935e-06

## Understanding Adjusted R-squared

```
Min
              10 Median
                               30
                                      Max
-0.29080 -0.11604 -0.09998 0.09102 0.44452
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)
             -45.79635 4.87765 -9.389 8.29e-05 ***
labourhours 0.59697 0.08112 7.359 0.000323
computerhours 1.17684 0.08407 13.998 8.29e-06 ***
rewards
         0.40511
                         0.04223 9.592 7.34e-05 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.2861 on 6 degrees of freedom
Multiple R-squared: 0.9834, Adjusted R-squared: 0.9751
F-statistic: 118.5 on 3 and 6 DF, p-value: 9.935e-06
```

$$R_{adj}^2 = 1 - \left\lceil \frac{(1-R^2)(n-1)}{n-k-1} \right\rceil$$
 Adjusted R-squared Penalizes the addition of insignificant independent variables

Residuals:

independent variables

## Understanding F-Statistic and its p-value

```
Residuals:
    Min
                  Median
              10
-0.29080 -0.11604 -0.09998 0.09102 0.44452
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)
             -45.79635 4.87765 -9.389 8.29e-05
labourhours
               0.59697
                         0.08112 7.359 0.000323
computerhours 1.17684 0.08407 13.998 8.29e-06
rewards
              0.40511
                         0.04223 9.592 7.34e-05 ***
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.2861 on 6 degrees of freedom
Multiple R-squared: 0.9834, Adjusted R-squared: 0.9751
F-statistic: 118.5 on 3 and 6 DF, p-value: 9.935e-06
```

Larger the value of F-statistic (coupled with p-value less than 0.05), better the Regression

For the Multiple Linear Regression to be valid:  $\beta_j \neq 0$  for at least one j

Alternately, the regression is invalid if:  $eta_1 = \cdots = eta_k = 0$ 

We need to check and ensure that second statement is not statistically true. This is done using the mechanism of statistical **Hypothesis Testing**. The following terms and ratios are calculated as part of this process:

$$SS_R = \sum_{i=1}^n (\hat{y}_i - \bar{y})^2 \qquad SS_{Res} = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \mathbf{y}'\mathbf{y} - \hat{\beta}'\mathbf{X}'\mathbf{y}$$

$$F = \frac{SS_R/k}{SS_{Res}/(n-k-1)} = \frac{MS_R}{MS_{Res}} \sim F_{k,n-k-1}$$

## Understanding F-Statistic and its p-value

```
Residuals:
    Min
                  Median
              10
-0.29080 -0.11604 -0.09998 0.09102 0.44452
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)
            -45.79635 4.87765 -9.389 8.29e-05 ***
labourhours 0.59697 0.08112 7.359 0.000323
computerhours 1.17684 0.08407 13.998 8.29e-06
rewards
              0.40511
                      0.04223 9.592 7.34e-05 ***
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.2861 on 6 degrees of freedom
Multiple R-squared: 0.9834, Adjusted R-squared: 0.9751
F-statistic: 118.5 on 3 and 6 DF, p-value: 9.935e-06
```

Larger the value of F-statistic (coupled with p-value less than 0.05), better the Regression

$$F = \frac{SS_R/k}{SS_{Res}/(n-k-1)} = \frac{MS_R}{MS_{Res}} \sim F_{k,n-k-1}$$

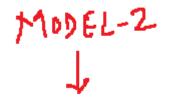
$$ss_r$$
 = 29.10818  
 $ss_{res}$  = 0.4912  
F =  $(ss_r / 3) / (ss_{res} / 6) = 118.50$ 

Using the F-Distribution chart, it can be established that p-value corresponding to F-statistic  $118.50_{(3,6)} = 9.935e-6$ 

## Comparing the models ... F-Statistic

F-statistic: 9.411 on 2 and 7 DF, p-value: 0.01037





#### Model-2

- Larger F-Statistic with p-value almost zero
- Lower RSE
- Better R-Squared
- Higher confidence on individual coefficient estimates

**Overall: A better model** 

```
Residuals:
    Min 1Q Median 3Q Max
-0.29080 -0.11604 -0.09998 0.09102 0.44452

Coefficients:
    Estimate Std. Error t value Pr(>|t|)
(Intercept) -45.79635 4.87765 -9.389 8.29e-05
```

Residual standard error: 0.2861 on 6 degrees of freedom

Multiple R-squared: 0.9834, Adjusted R-squared: 0.9751 F-statistic: 118.5 on 3 and 6 DF, p-value: 9.935e-06