

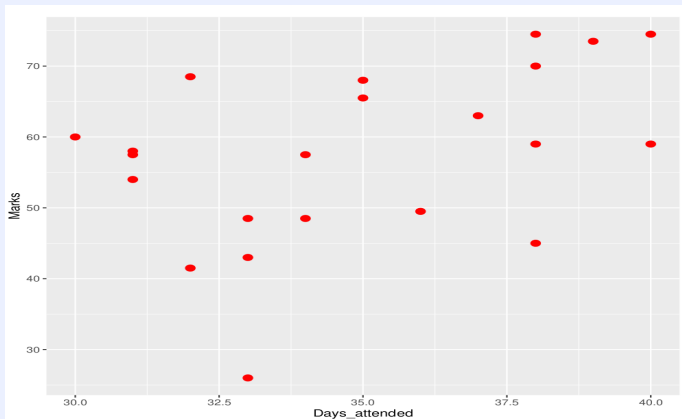
# STATISTICAL INFERENCE (MA862)

## Lecture Slides

### Topic 5: Linear Regression

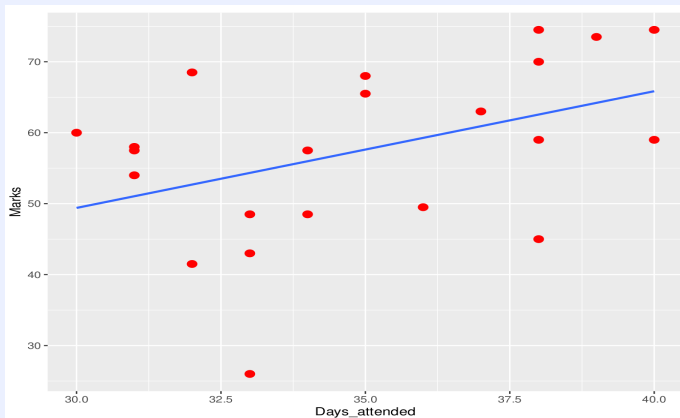
# Regression

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- Let's start with a real data from IITG which you can feel about it!!



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# Linear Regressions

- We have one particular variable that we are interested in understanding or modeling, such as sales of a particular product, sale price of a home, or voting preference of a particular voter. This variable is called the **target**, **response**, or **dependent variable**, and is usually represented by  $y$ .
- We have a set of  $p$  other variables that we think might be useful in predicting or modeling the target variable (for e.g. the price of the product, the competitor's price, and so on; or the lot size, number of bedrooms, number of bathrooms of the home, and so on; or the gender, age, income, party membership of the voter, and so on). These are called the **predicting**, **independent variables**, or **features** and are usually represented by  $x_1, x_2, \dots, x_p$ .

# Linear Regressions

- Thus, we have

$$y = f(\mathbf{x}; \boldsymbol{\beta}) + \varepsilon,$$

for some real valued function  $f$ , where  $\mathbf{x}$  is vector of predictors,  $\boldsymbol{\beta}$  is the vector of parameters, and  $\varepsilon$  is error.

- If  $f$  is linear in the parameters vector  $\boldsymbol{\beta}$ , then the regression is called linear regression.

# Examples and Role of Transformations

- $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_p x_p$  is a linear model.
- $y = \beta_0 + \beta_1 x + \beta_2 x^2$  is a linear model, because it is linear in  $\beta$  (even though not in  $x$ ).
- $y = \beta_0 + \beta_1 x^{\beta_2}$  is a non-linear model, as it is not linear in  $\beta$ .
- $y = \beta_0 x^{\beta_1}$  is not a linear model, but  $\ln y = \ln \beta_0 + \beta_1 \ln x$  is.
- $y = \frac{e^{\beta x}}{1 + e^{\beta x}}$ , where  $y \in (0, 1)$
- $y = \frac{1}{\beta_0 + \beta_1 x_1 + \beta_2 x_2}$ .

# Main use of Linear Regressions

Typically, a regression analysis is used for one (or more) of three purposes:

- ① modeling the relationship between  $x$  and  $y$ ;
- ② prediction of the target variable (forecasting);
- ③ testing of hypotheses.

# Simple Linear Regression

- Just one predictor  $x$ , i.e.  $p = 1$ .
- The model for the **simple linear regression** is given by

$$y = \beta_0 + \beta_1 x + \epsilon,$$

where  $y$  is the outcome variable (random),  $x$  is the independent/predictor variable (non-random) and  $\epsilon$  is the random error term.  $\beta_0$  (intercept) and  $\beta_1$  (slope) are model parameters (unknown constants).

- Equivalently, the model can be written for  $i = 1, 2, \dots, n$  number of observations  $(x_1, y_1), \dots, (x_n, y_n)$  as

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i, i = 1, \dots, n.$$

- How do you interpret  $\beta_0$  (intercept) and  $\beta_1$  (slope)?



# Least Squares Estimation

- Goal: To estimate  $\beta_0, \beta_1$  by minimizing error in some sense (e.g. squared error)
- One reasonable way is to use the principle of Least Squares, i.e. minimize the objective function

$$Q(\beta_0, \beta_1) = \sum_{i=1}^n \epsilon_i^2 = \sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i)^2$$

with respect to  $\beta_0, \beta_1$ .

- Differentiate  $Q(\beta_0, \beta_1)$  with respect to  $\beta_0, \beta_1$  and equate the partial derivatives to zero to get the estimates  $\hat{\beta}_0, \hat{\beta}_1$ .
- The resulting equations are called **normal equations**:

$$\sum_{i=1}^n (y_i - \beta_0 - \beta_1 x_i) = 0 \text{ and } \sum_{i=1}^n x_i (y_i - \beta_0 - \beta_1 x_i) = 0$$

# Least Squares Estimation

- The solution is given by

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x} \quad \text{and} \quad \hat{\beta}_1 = S_{xy} / S_{xx}$$

where

$$S_{xx} = \sum_{i=1}^n (x_i - \bar{x})^2 \quad \text{and} \quad S_{xy} = \sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}).$$

- $\hat{\beta}_0$  and  $\hat{\beta}_1$  are called the **least squares estimator (LSE)** of  $\beta_0$  and  $\beta_1$ , respectively.