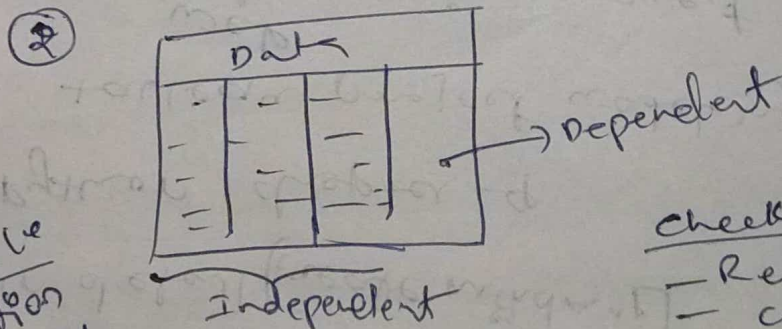
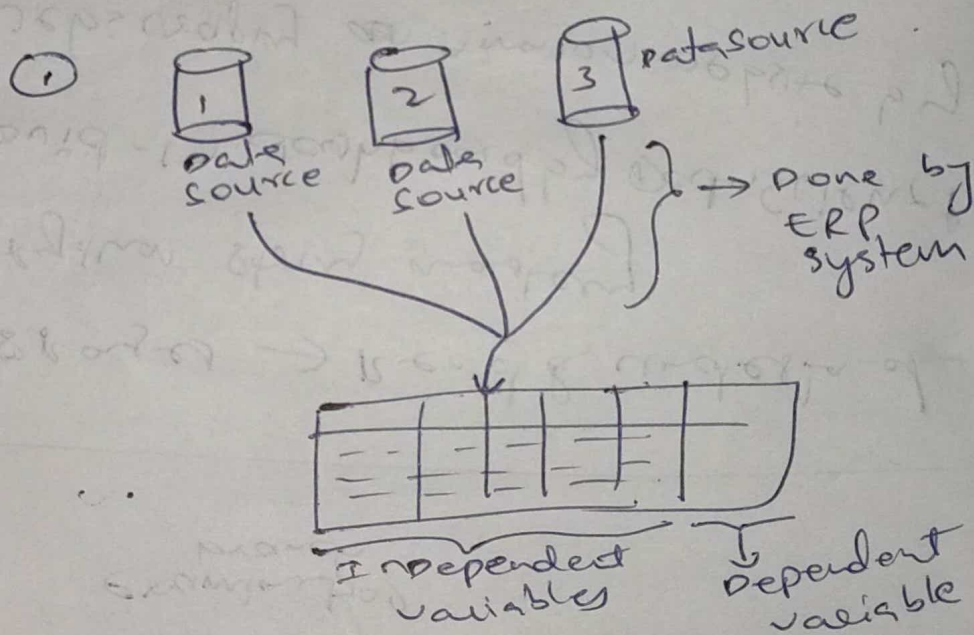


Dependent variable \rightarrow Independent variable
Association relationship

Linear Regression [supervised]
[Predictive Analytics]

8 steps in building CR-model

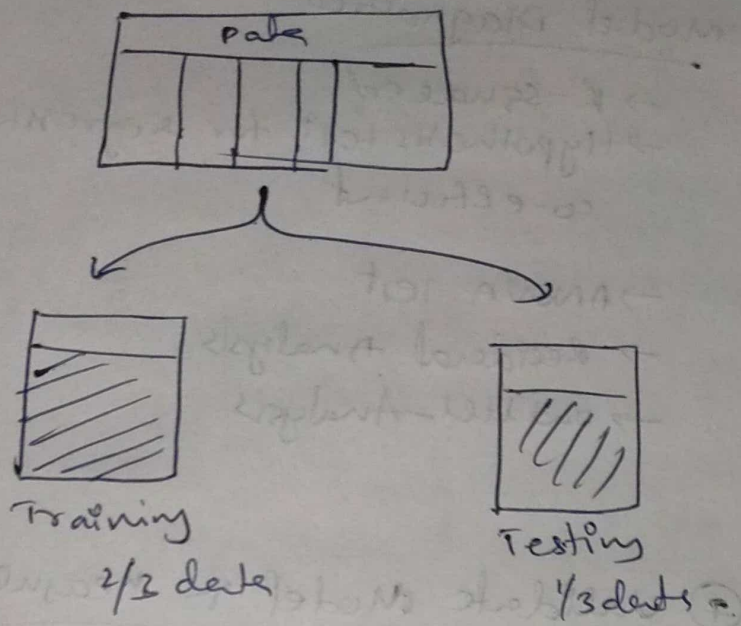
\rightarrow several iterations needed



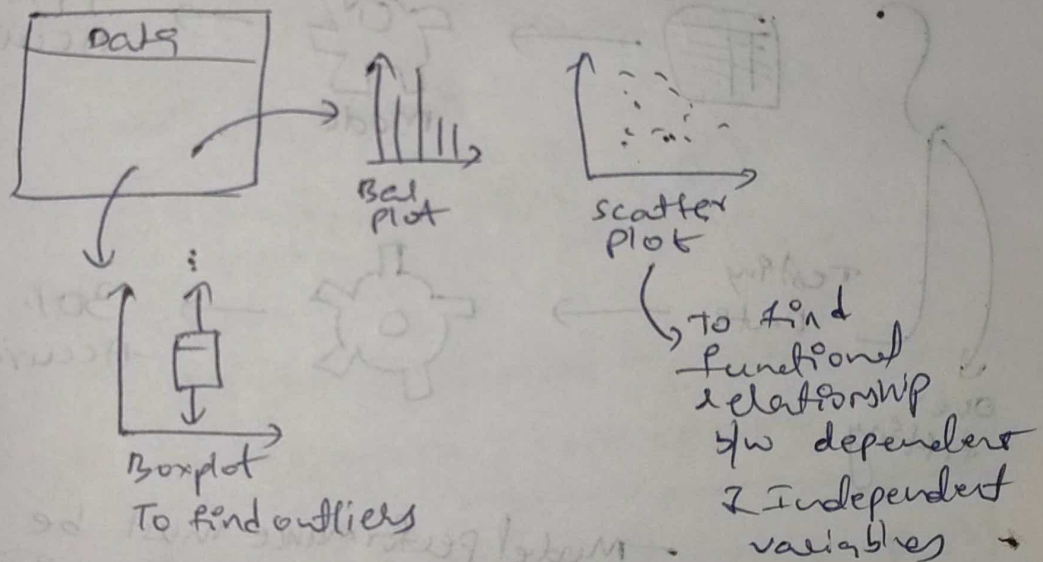
Techniques to handle
1) Data Imputation
2) new variables deriving
3) handle categorical data by encoding

check for
- Reliability
- completeness
- Accuracy
- missing data
- outliers

③



④



⑤

OLS → To find Regression Parameters

$$Y = \beta_0 + \beta_1 X + \epsilon$$

const
grade in 10th

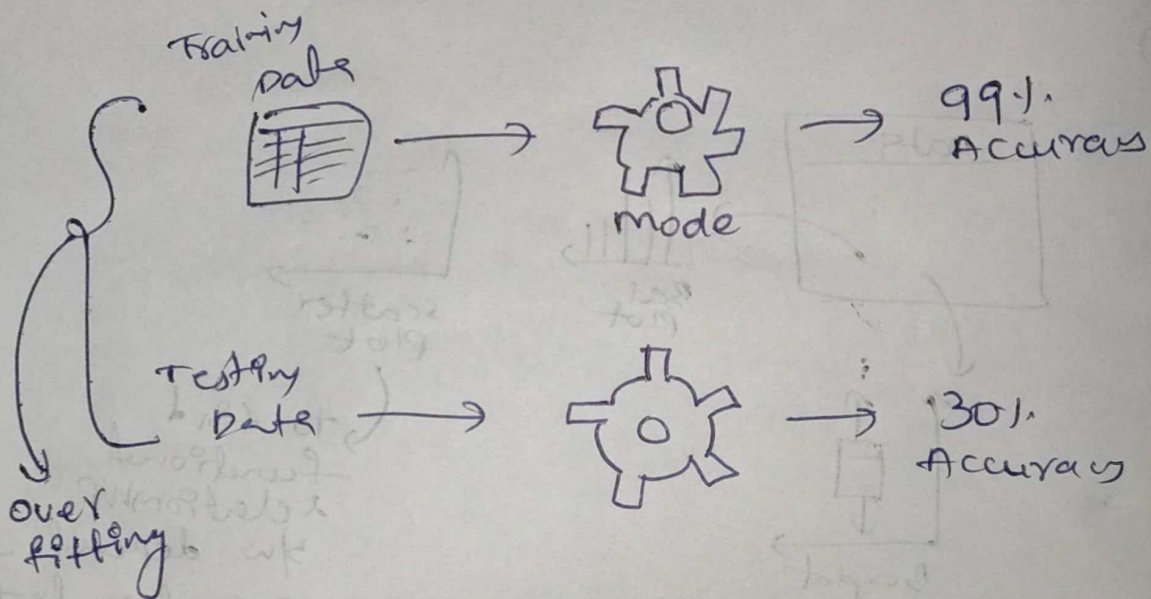
you will get β_0 & β_1

⑥ Model Diagnostics

- R-squared
- Hypothesis test for regression co-efficient

- ANOVA Test
- Residual Analysis
- outlier Analysis

⑦ Validate Model & Measure Accuracy



- Model performance must be consistent on both training & testing dataset

- cross validate the model using multiple training and test datasets

⑧ Deploy the model

- According to the Business rules

$$Y = \beta_0 + \beta_1 X + \epsilon$$

Y = Dependent Variable

(β_0, β_1) = Regression parameters

ϵ = Random Error

X = Independent variable

For n observations,

$$Y_i = \beta_0 + \beta_1 X_i + \epsilon_i$$

where $i = 1, 2, 3, \dots, n$

$$\epsilon_i = Y_i - \beta_0 - \beta_1 X_i$$

β_0 & β_1 can be estimated by minimizing sum of squared errors (SSE)

$$SSE = \sum_{i=1}^n \epsilon_i^2 = \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_i)^2$$

values of β_0 & β_1 are taken by partial derivatives of SSE

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^n (X_i - \bar{X})^2}$$

$$\hat{\beta}_0 = \bar{Y} - \hat{\beta}_1 \bar{X}$$

Above method is called as OLS method.

It yields BLUE (Best Linear Unbiased Estimator)

Myths

- Residuals follow Normal Distribution
- (ϵ_i) is constant for various independent variables
- ϵ_i & x are correlated
- functional relationship b/w outcome variable & feature is correctly defined.

Properties

- ① $\text{Mean}(y_i) = \hat{\beta}_0 + \hat{\beta}_1 x$
- ② y_i follows Normal Distribution with mean $\hat{\beta}_0 + \hat{\beta}_1 x$ & variance $\text{VAR}(\epsilon_i)$

$$\sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2 = \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i)^2$$

$$\frac{(\bar{y} - \hat{\beta}_0)(\bar{x} - \hat{\beta}_1)}{(\bar{x} - \hat{\beta}_1)} = \hat{\beta}_1$$

$$\bar{y} - \hat{\beta}_0 = \hat{\beta}_1$$

$$Y = \beta_0 + \beta_1 X + \varepsilon$$

constant
(1)

OLS API estimates (β_1) only to estimate β_0 a constant term need to be added as new feature.

$$Y_i = \beta_0 + \beta_1 X + \varepsilon$$

OLS gives $(\beta_0 \& \beta_1)$

$$Y_i = 30587.285652 + (3560.587 * 62.1)$$

For every 1% increase in grade '10' salary increases by 3560.587

Rahman
Abdullah