

Assumptions of L.R.

① Assumption of Linearity: We assume that the data can be predicted using a straight line (hyperplane). It means the independent variables (features) & the target variable should have linear relationship.

② No multicollinearity:

What is collinearity?

Ans: Suppose we have two features f_1 & f_2 and if

$$f_1 = a_2 f_2 + a_1 \text{ then } f_1 \text{ \& } f_2 \text{ are colinear}$$

Multicollinearity: Multiple features are colinear:

$$f_1 = a_1 + a_2 \cdot f_2 + a_3 \cdot f_3 \Rightarrow f_1, f_2 \text{ \& } f_3 \text{ are multi-collinear.}$$

How is it a problem?

Suppose we found out \vec{w} as $[1, 2, 3]$ & $w_0 = 5$

$$\therefore \hat{y} = w_1 x_1 + w_2 x_2 + w_3 x_3 + w_0$$

$$\therefore \hat{y} = x_1 + 2x_2 + 3x_3 + 5$$

Now suppose x_1 & x_2 are colinear and their collinearity

is described as: $x_2 = 1.5 x_1$

$$\therefore \hat{y} = x_1 + 2(1.5 x_1) + 3x_3 + 5$$

$$\hat{y} = 4x_1 + 3x_3 + 5 \therefore \text{our classifier } (\vec{w}) = [4, 0, 3]$$

will be same as $\vec{w} = [1, 2, 3]$

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But we know that higher the value of w_i , more important the feature is. \therefore According to original $\vec{w} [1, 2, 3]$, feature 24 was least imp. but with the new $\vec{w} [4, 0, 3]$, it becomes the most imp. feature!

\therefore We will not be able to identify feature importance

How to deal with multicollinearity?

Ans: VIF (Variance Inflation Factor)

- ① To calculate VIF, we first consider one of the factors as 'y' and the others as 'x'

f_1	f_2	f_3	...	f_d
← x →				← y →

- ② Then we train a Linear Regression model for these new X & y.

- ③ After training the model, we compute the R^2 score of the model. We will call this as R_j^2 (R^2 score of feature f_j)

- ④ Then we calculate VIF as :

$$VIF = \frac{1}{1 - R_j^2}$$

Range of VIF: $[0, \infty]$

$$\text{if } R^2 = -\infty \Rightarrow VIF = \frac{1}{1 - (-\infty)} = 0$$

$$\text{if } R^2 = 1 \Rightarrow VIF = \frac{1}{0} = \infty$$

But In most cases, values of R^2 will be between 0 to 1

\therefore case-1: $R_j^2 \approx 1$

$\Rightarrow VIF \approx \infty$

\rightarrow High R_j^2 means the Feature is highly colinear

$\rightarrow \therefore$ we can drop this feature

case-2: $R_j^2 \approx 0$

$\Rightarrow VIF \approx 1$

\rightarrow Low R_j^2 means the feature is not highly colinear

$\rightarrow \therefore$ Don't remove this feature

We do this process for each feature. (calculate the VIF of each feature & based on VIF we will either drop that feature or keep it.)

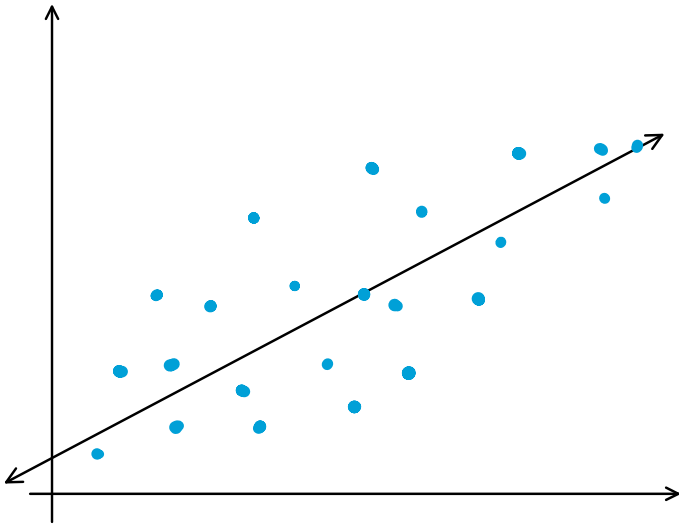
\rightarrow Practically,

$VIF > 10$: Highly colinear feature (drop)

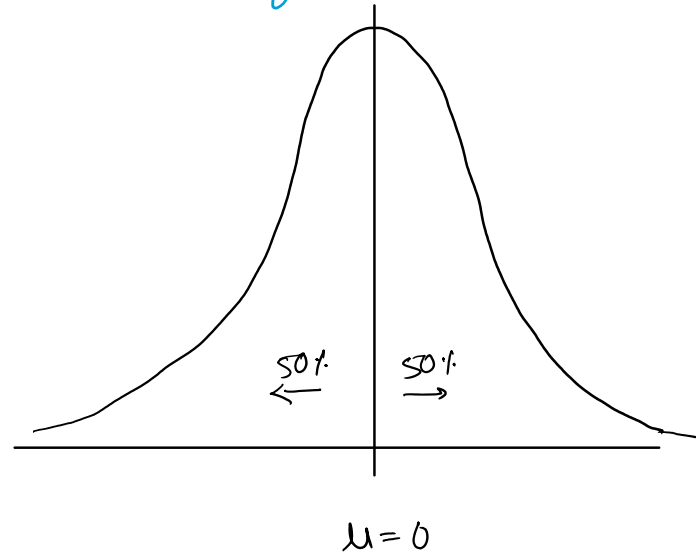
$5 \leq VIF \leq 10$: Highly colinear feature (think about the other aspects and then decide whether to remove or to keep)

$VIF < 5$: Low multicollinearity (Don't remove it)

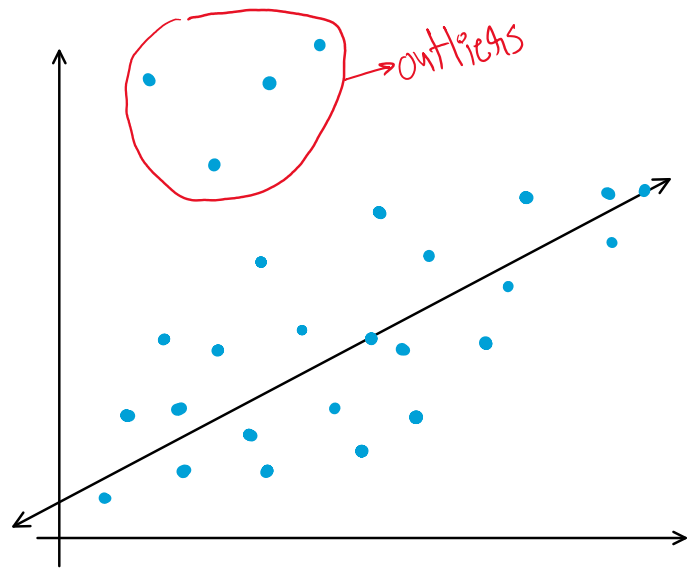
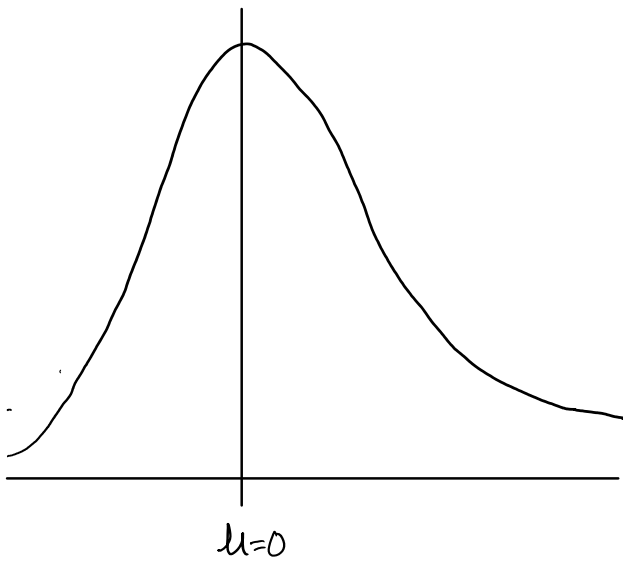
③ Normality of Residuals: The histogram of errors must exhibit normal distribution.



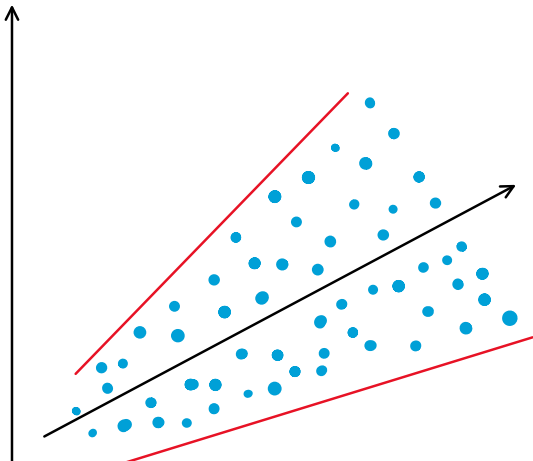
Histogram of errors

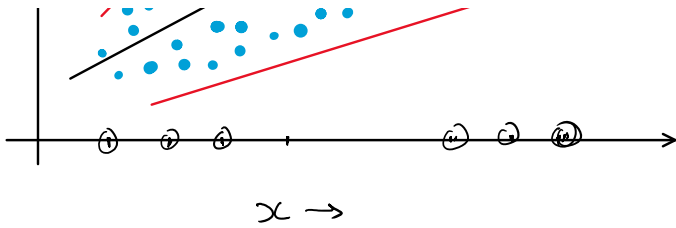


Case-2: Right skewed.

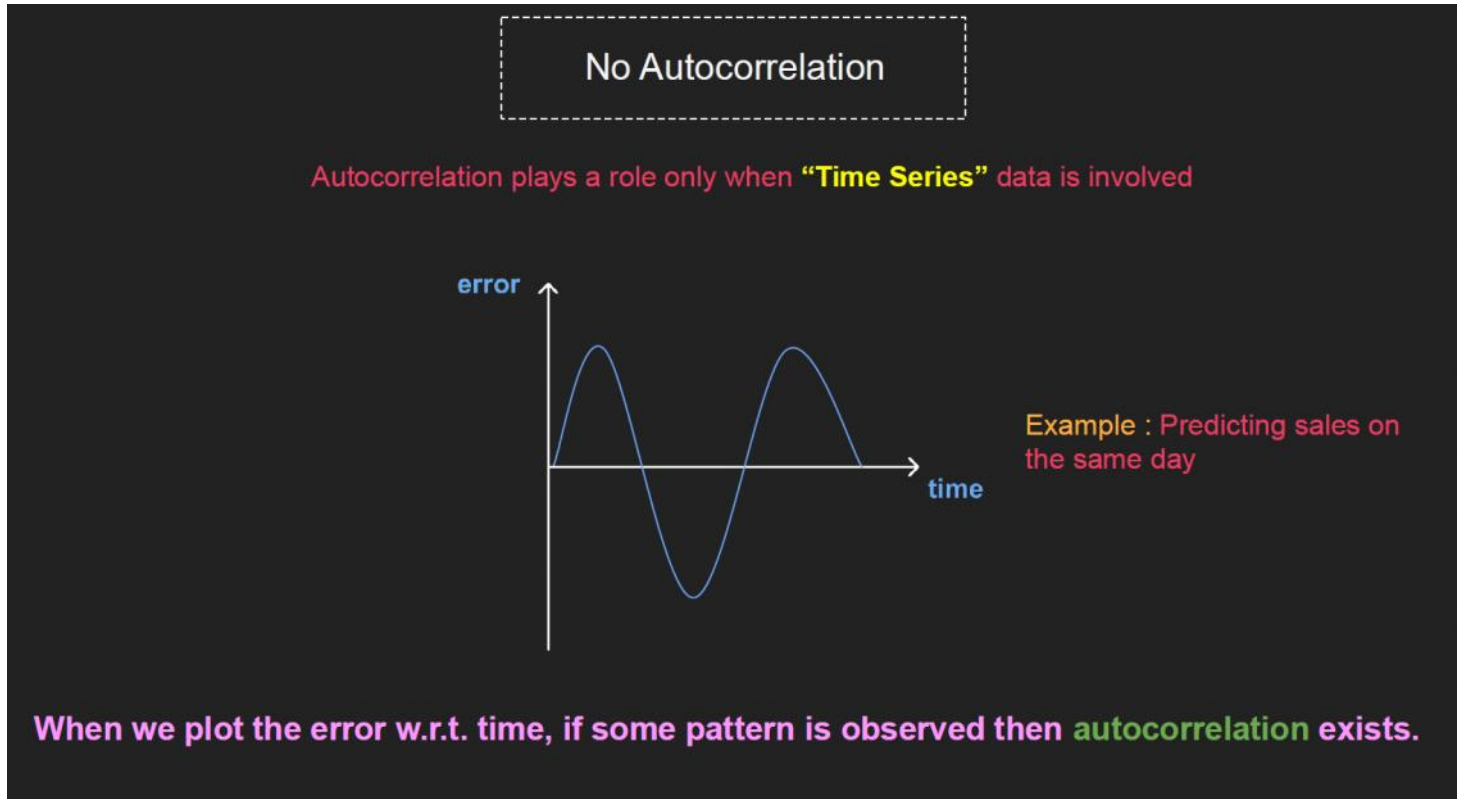


④ No Heteroskedasticity





⑤ No Autocorrelation (seasonality):



- Examples:-
- ① Predicting evening sales of a restaurant from the data of morning sales & afternoon sales
 - ② Predicting sales of umbrellas in January based on sales data from June to Dec.