

# Linear Regression Assumptions

- Linearity
- Constant Variance
- Independence
- Normality



# How to check?

Using Residual Analysis.

*Residual = Observed – Predicted*

$$\hat{e} = y - \hat{y}$$

We need to use the standardized residuals  $r_i$  for assessing the model assumptions.

$$r_i = \frac{\hat{e}}{\hat{\sigma} \sqrt{1 - h_{i,i}}}$$

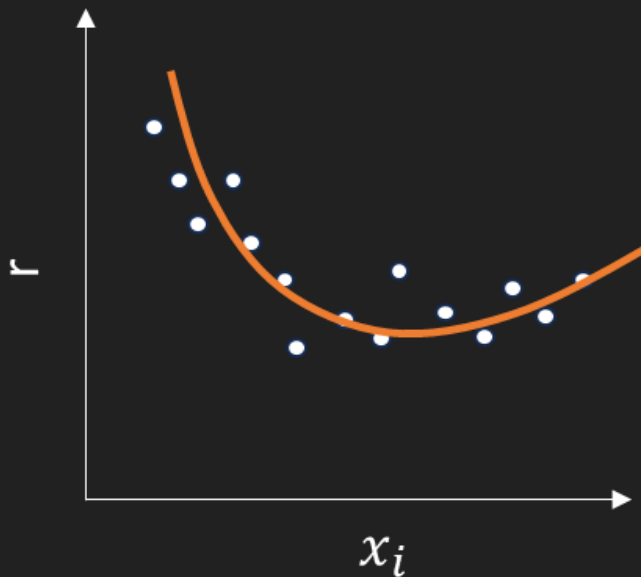
Where:

- $\hat{\sigma}$ : standard deviation of the residuals.
- $h_{i,i}$ : leverage value for observation.



# Linearity / Mean zero Assumption

The relationship between the response and each predicting variable is linear.



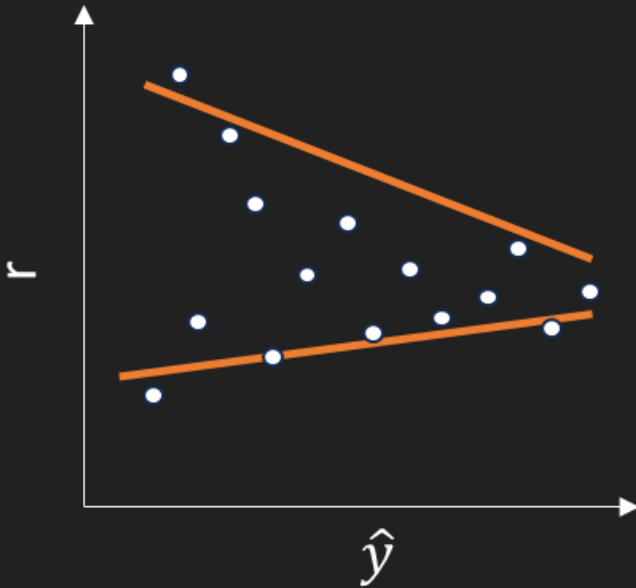
How to check: Plot residuals against each predicting variable.

The plot shows there might be a **non-linear** relationship between “ $y$ ” and “ $x_1$ ”



# Constant Variance Assumption

Also called a **homoscedasticity** check. Linear regression assumes the variance of the residuals is constant.



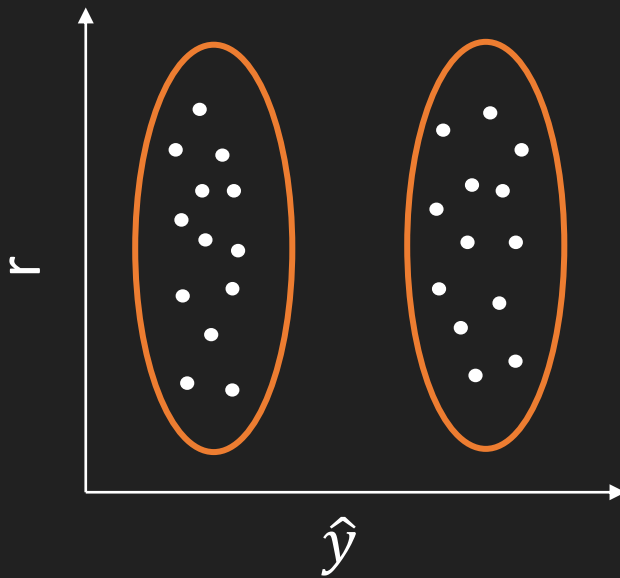
**How to check:** Plot residuals against fitted values.

The above plot is an example of **heteroscedasticity**.



# Independence Assumption (1/2)

Complicated to check. When using residual analysis we are checking for **uncorrelated** errors, not **independence**.



**How to check:** Plot residuals against fitted values.

The above plot shows clusters of residuals which can be interpreted as **correlated**.



# Independence Assumption (2/2)

We can also use the Durbin-Watson test to check for **autocorrelation** at lag 1 of the residuals.

**How to check:** Calculate the Durbin-Watson statistic "d". If  $1.5 < d < 2.5$ , we can conclude there is **NO** first-order correlation between the residuals.

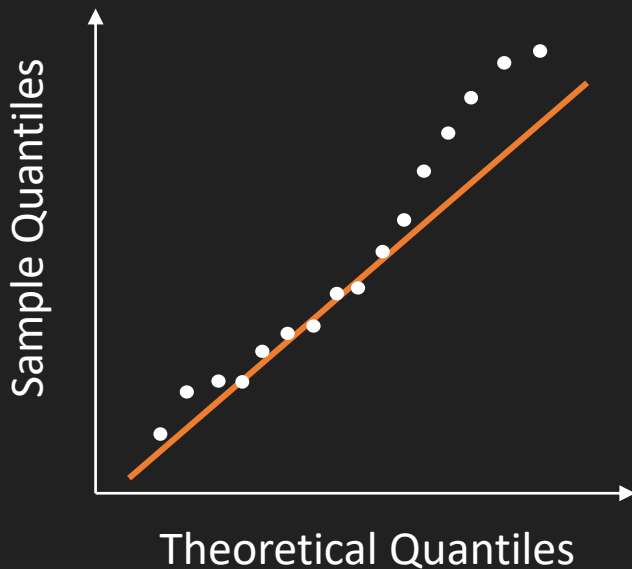
If  $d < 1.5$ , there is presence of **positive autocorrelation**.

If  $d > 2.5$ , there is presence of **negative autocorrelation**.



# Normality Assumption

Important especially when it comes to t-tests / F-test (hypothesis testing) and confidence intervals.



How to check:  
Create a normal  
Q-Q plot of the  
residuals.

The residuals should follow the **straight line** if they are normally distributed.



# What's next??

In the next post, we'll see how to check these assumptions using Python!

```
#### 1. Linearity Assumption
```

```
fig, axes = plt.subplots(nrows=3, ncols=4, figsize=(15, 10))
```

```
for i, ax in enumerate(axes.flatten()):
```

```
    if i < len(X.columns) - 1: # Exclude the constant term
```

```
        sns.scatterplot(x=X.iloc[:, i + 1], y=standardized_residuals, ax=ax)
```

```
        ax.set_xlabel(X.columns[i + 1]) # Skip constant column
```

```
        ax.set_ylabel('Standardized Residuals')
```

```
        ax.axhline(0, color='r', linestyle='--')
```

```
plt.tight_layout()
```

```
plt.show()
```

