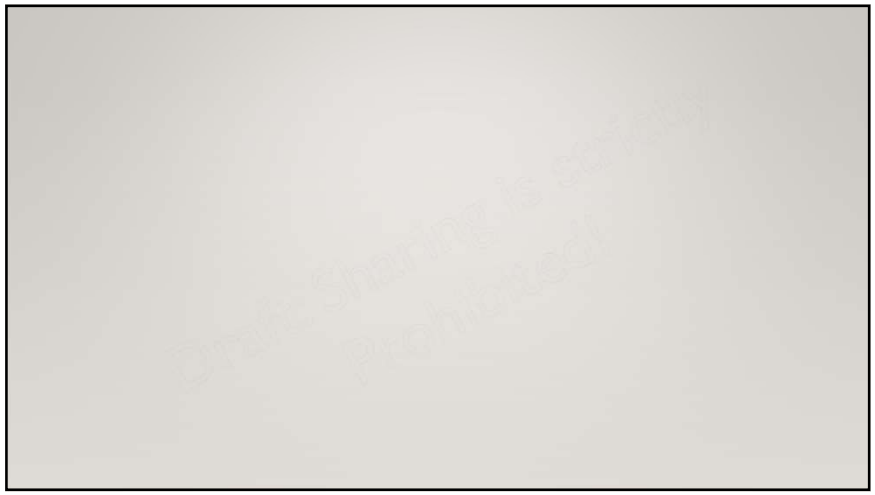

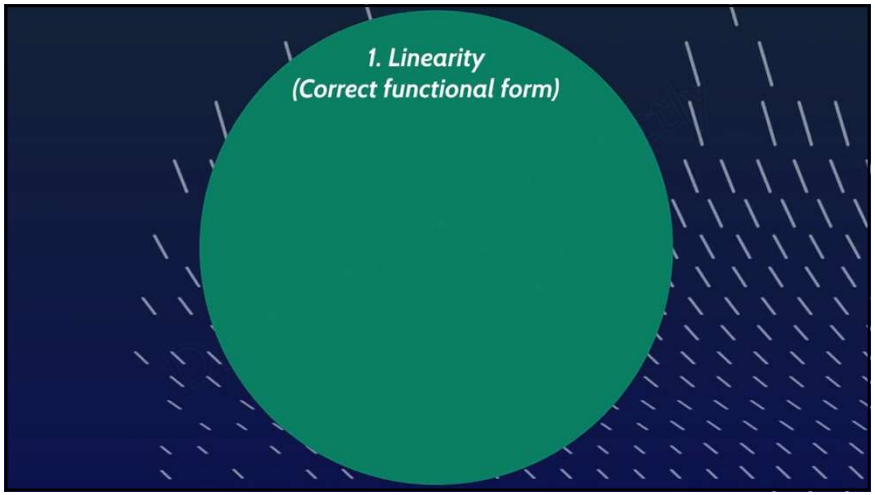
1. Linearity
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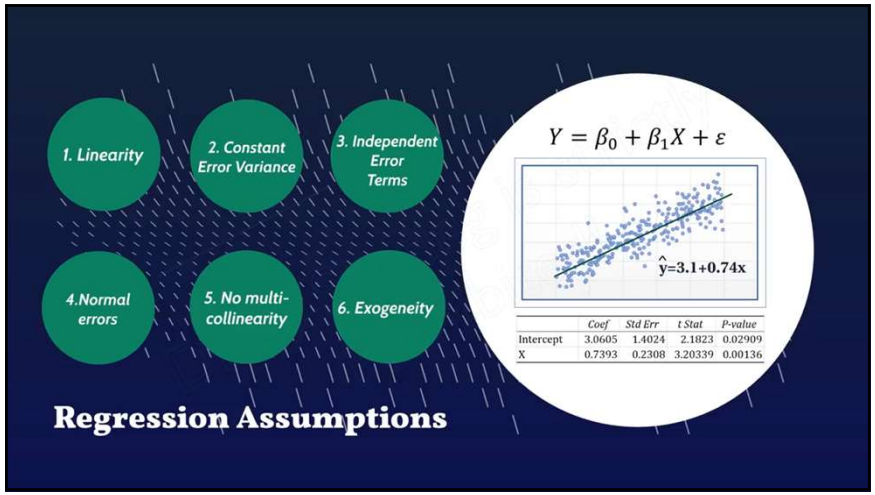
1. Linearity
2. Constant Error Variance
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$Y = \beta_0 + \beta_1 X + \varepsilon$
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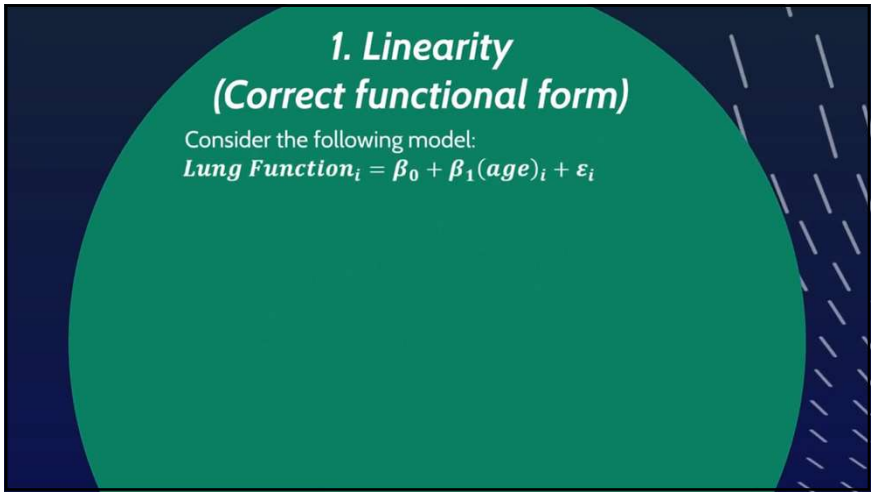
Coef Std Err t Stat P-value
Intercept 3.0605 1.4024 2.1823 0.02909
X 0.7393 0.2308 3.20339 0.00136
Regression Assumptions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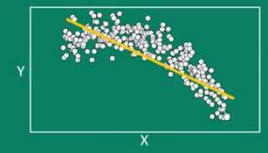

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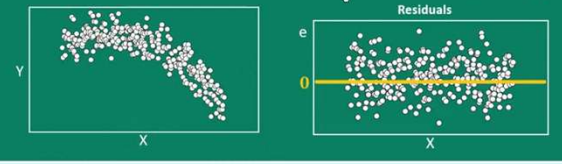

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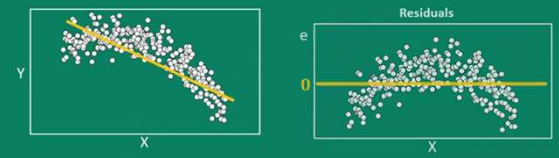

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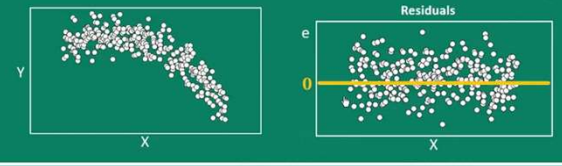

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- Residual plots
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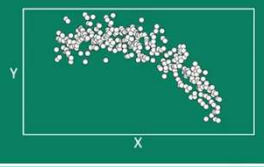

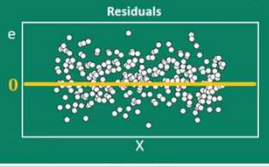

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Detection:

- Residual plots
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Remedies:

- Get the specification correct (trial and error)

Constant Variance
(no heteroskedasticity)

1. Linearity
2. Constant Error Variance
3. Independent Error Terms
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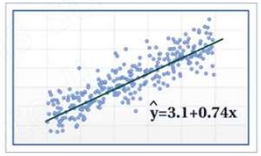
5. No multi-collinearity
6. Exogeneity

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



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Regression Assumptions

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Consider the following model:

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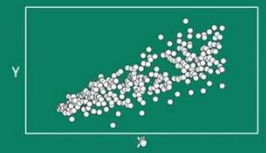

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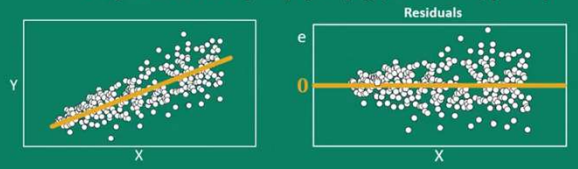

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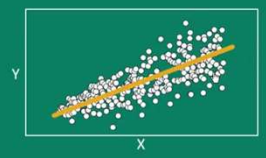

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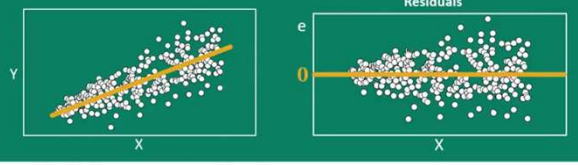

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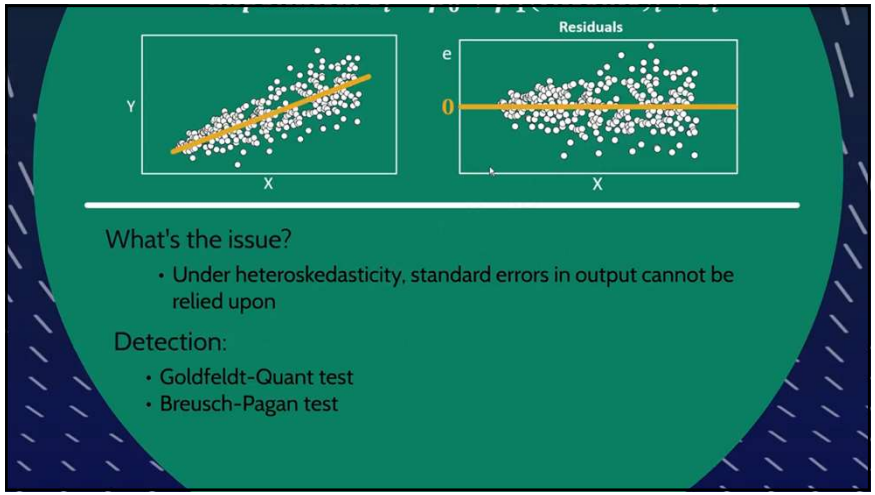

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- Goldfeldt-Quant test
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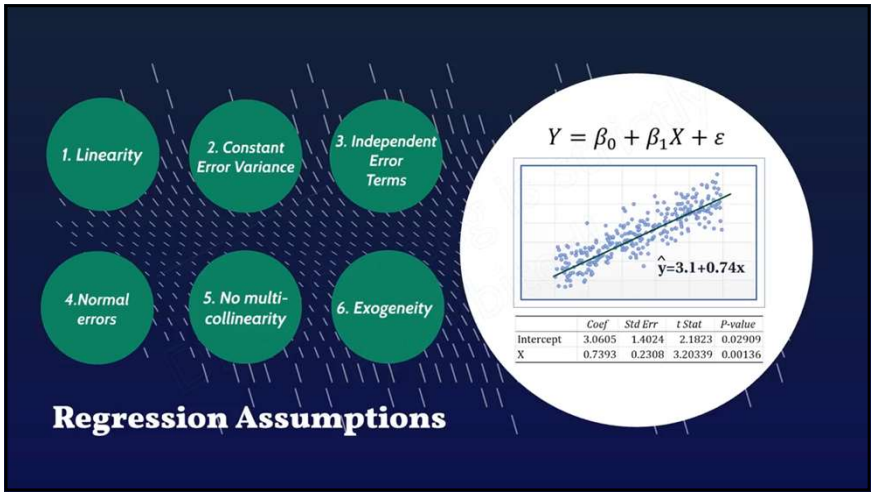

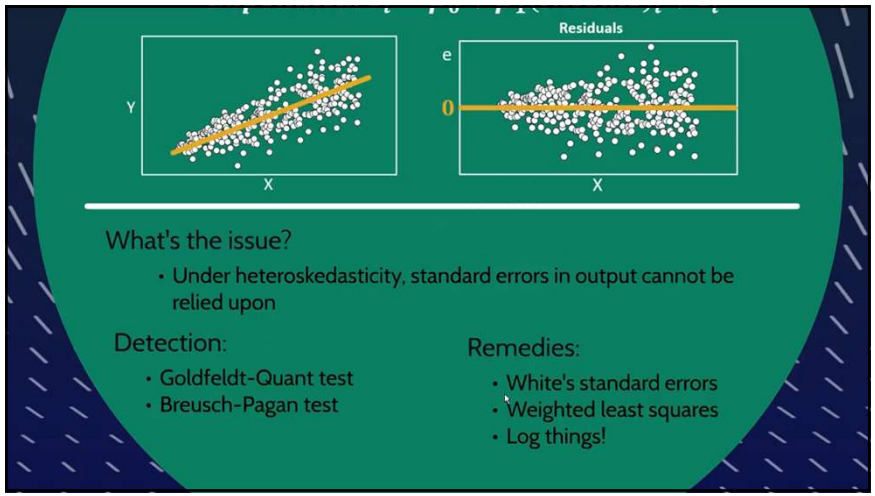

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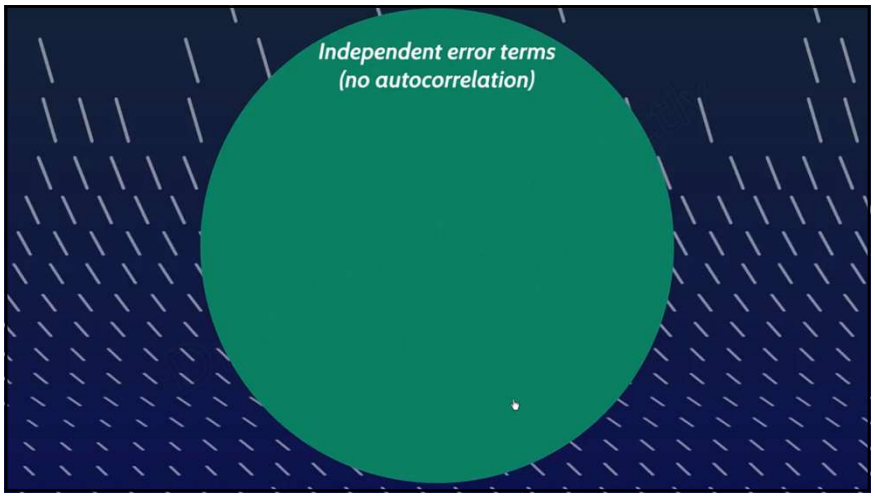
Remedies:

- White's standard errors
- Weighted least squares
- Log things!



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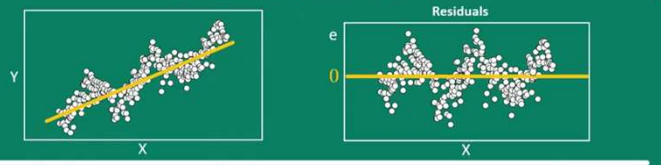

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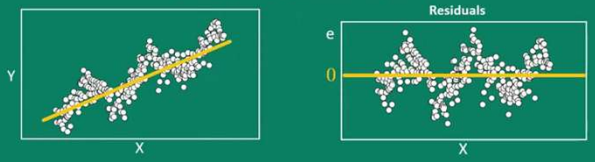

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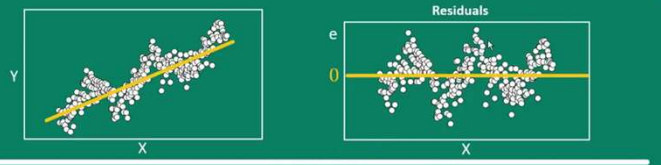

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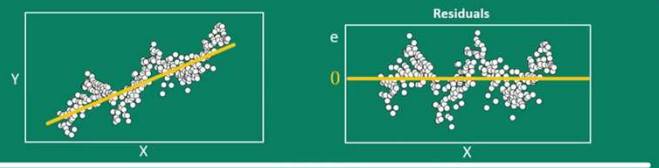

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- Durbin-Watson test
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Remedies:

- Investigate omitted variables
- Generalised difference equation (Cochrane-Orchutt or AR(1) methods)

Normality of errors

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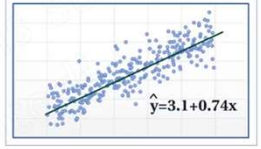

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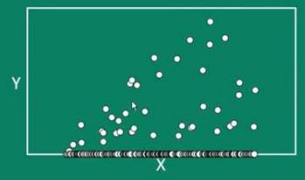

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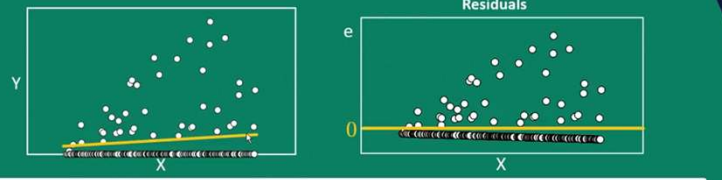

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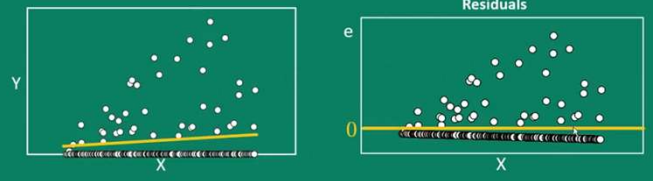

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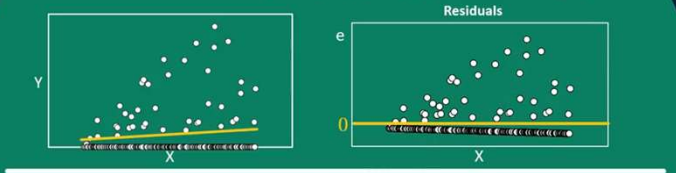

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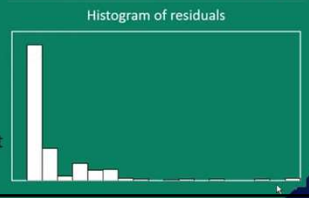

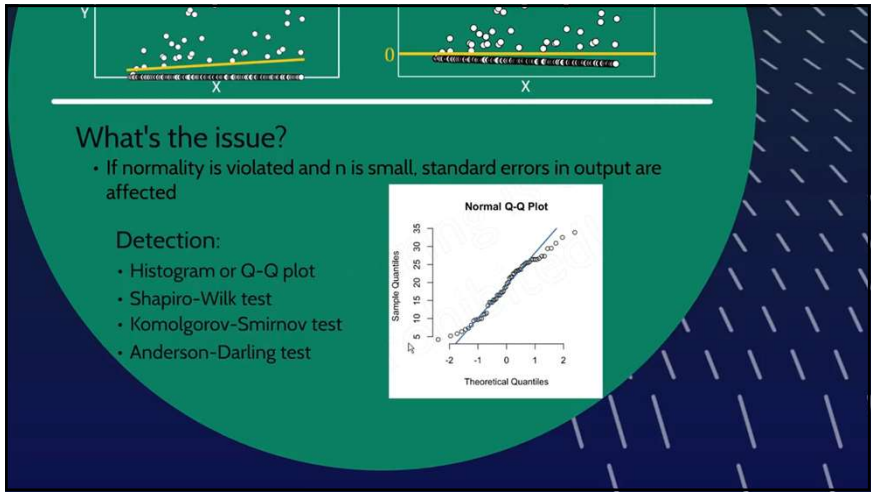

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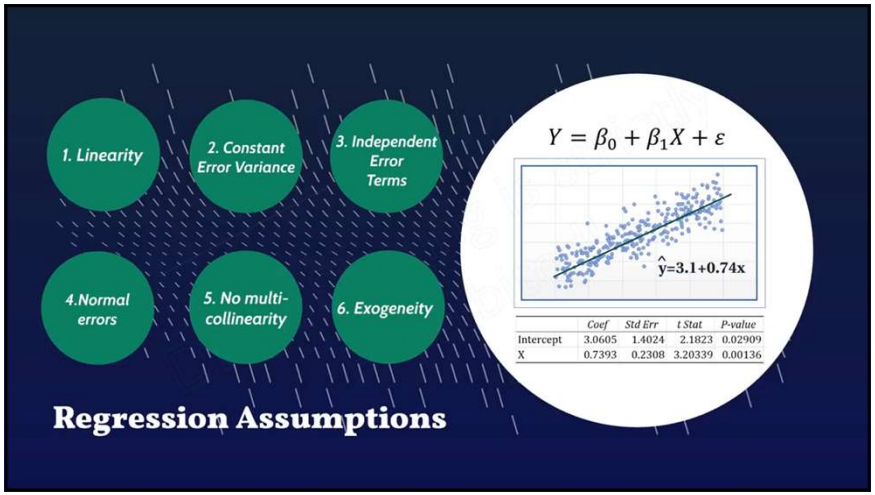

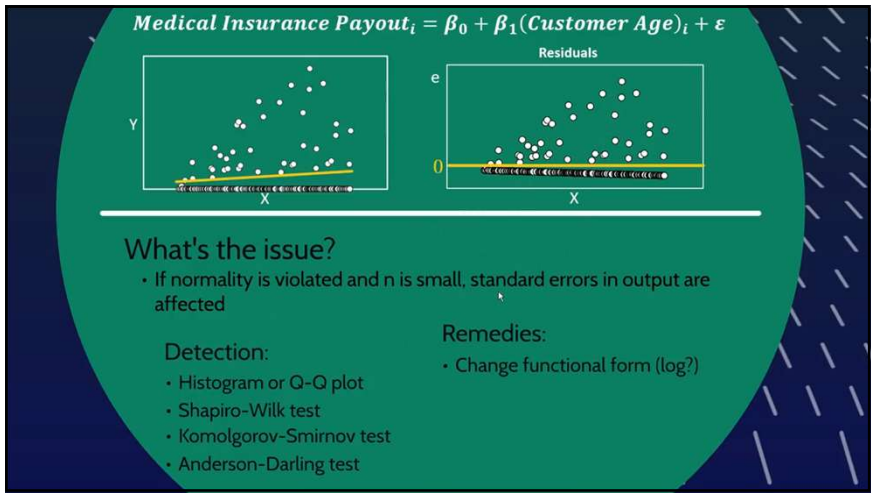

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Remedies:

- Change functional form (log?)

No multicollinearity

Consider the following model:

$$\boldsymbol{Motor\ Accidents}_i = \beta_0 + \beta_1(\boldsymbol{Num\ cars})_i + \beta_2(\boldsymbol{Num\ residents})_i + \varepsilon$$

$$i = suburb\ 1,2,3\ \ldots$$

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Remedies:

- Remove one of the variables

Exogeneity
(no omitted variable bias)

1. *Linearity*
2. *Constant Error Variance*
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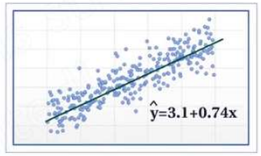
Regression Assumptions

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



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TECHNICALLY - Socio-economic status would affect ε_i in the model, thus, Education is no longer wholly exogenous as it can be explained in part by the error term.

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Detection:

- Intuition
- Checking correlations

Remedy:

- Using instrumental variables

THANK YOU!

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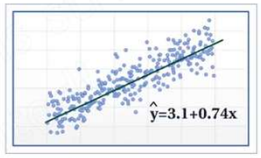

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