

Outline

- Statistics Vs Machine Learning
- Assumptions of Linear regression
- Statistical Inference

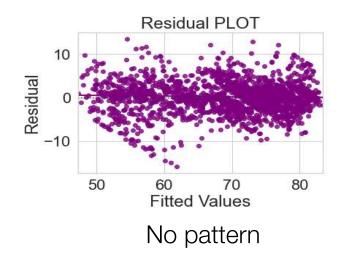
Linear Regression Assumptions

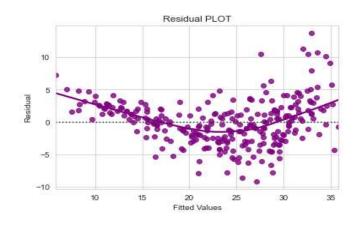
- Linearity: Independent and dependent variables are linearly related
- Independence: Residuals are independent
- Homoscedasticity: Equal Variance of residuals
- Normality: Residuals are normally distributed
- No (or little) Multicollinearity: Two or more independent variables have no (or little) correlation

If any of these assumptions are violated, then the forecasts, confidence intervals, and scientific insights yielded by the regression model may be seriously biased or misleading.

Linear Relationship

- After finding the best linear fit, a plot of the residuals will provide a good insight.
- If they don't follow any pattern, we say that the model is linear otherwise model is showing signs of non-linearity
- To deal with non-linearity, we can try transforming variables as per their relationship with target variable.





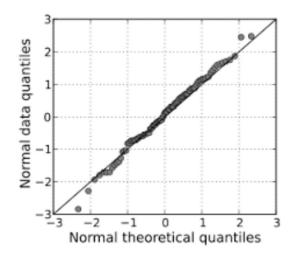
Some non-linearity

Normality

Histogram with Normal Curve

- Can be tested by plotting the distribution of residuals:

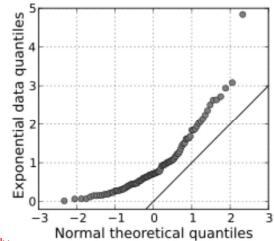
- Histogram
- Q-Q comparison plot
- Tests for normality, like the Shapiro's test.



Normal

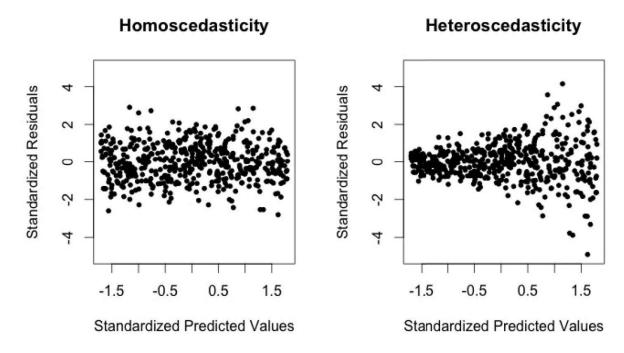
- When not normal
 - Transformations (log, exp etc.)
 of the dependent or
 independent variables can help

Not Normal



Homoscedasticity

- If the variance is not equal for the residuals across the regression line, then the data is said to be heteroscedastic.
- In this case the residuals can form a funnel shape or any other non symmetrical shape.
- Identifying the cause of hetroscedasticity is usually the best way to reason out ways to fix it



Statistical test: The Goldfeld–Quandt test

Multicollinearity

- Multicollinearity occurs when independent variables in a regression model are correlated with each other.
- When there is Multicollinearity, the relationship between any explanatory variable X and the response variable Y is not reflected by the coefficient of X

- Could simply look at the entire correlation matrix
- Variance inflation factors also help identify multicollinearity
- Simply eliminating the linearly related variables or other dimensionality reduction techniques (like PCA) help reduce or eliminate multicollinearity.

Variance Inflation Factor (VIF)

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

- R_j² is the R²-value obtained by regressing the j-th independent variable on the other independent variables
- Variance inflation factors (VIFs) >= 1
- Tells you what percentage of the variance is inflated for each coefficient.
- For example, a VIF of 1.7 tells you that the variance of a particular coefficient is 70% bigger than what you would expect if there was no multicollinearity, i.e., if there was no correlation with other predictors.

Statistical Inference

- Given the best estimates from the data, what can we say about the unknown true model?
 - The unkown parameter? confidence interval
 - Is there enough evidence in the data to say a coefficient is not zero? - hypothesis testing

Reviewing Linear Regression

OLS Regression Results							
Dep. Variable: Model: Method: Date: Time: No. Observations Df Residuals: Df Model: Covariance Type:	Wed, 0	OLS A Least Squares F Wed, 09 Dec 2020 F 12:48:42 L 278 A		R-squared: Adj. R-squared: F-statistic: Prob (F-statistic): Log-Likelihood: AIC: BIC:		0.814 0.809 147.3 1.20e-93 -734.21 1486. 1519.	
	coef	std err	t	P> t	[0.025	0.975]	
cylinders displacement horsepower weight acceleration	-0.3948 0.0289 -0.0218 -0.0074 0.0619 0.8369	5.549 0.423 0.010 0.016 0.001 0.118 0.064 0.704 0.705	-3.295 -0.933 2.870 -1.330 -8.726 0.524 13.149 -4.262 -0.860	0.001 0.352 0.004 0.185 0.000 0.601 0.000 0.391	-29.209 -1.228 0.009 -0.054 -0.009 -0.171 0.712 -4.388 -1.994	-7.358 0.439 0.049 0.010 -0.006 0.295 0.962 -1.615 0.782	
Omnibus: Prob(Omnibus): Skew: Kurtosis:		13.244 0.001 0.386 3.932	Jarque-Bera (JB): Prob(JB): Cond. No.		0.0 8.2	2.244 16.958 0.000208 8.26e+04	