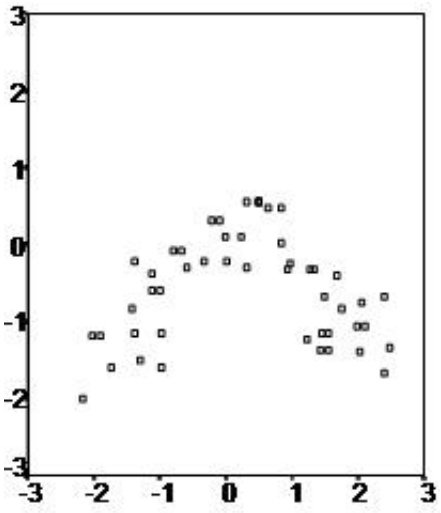
Assumptions of Linear Regression

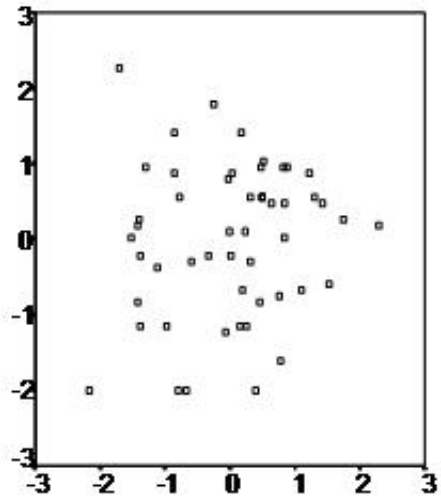
Linear regression makes several key assumptions:

- Linear relationship
- Multivariate normality
- No or little multicollinearity
- No auto-correlation
- Homoscedasticity

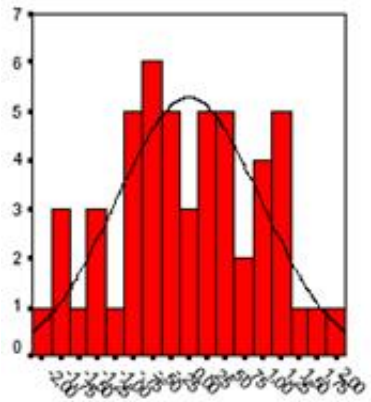
Linear regression needs at least 2 variables of metric (ratio or interval) scale. A rule of thumb for the sample size is that regression analysis requires at least 20 cases per independent variable in the analysis.

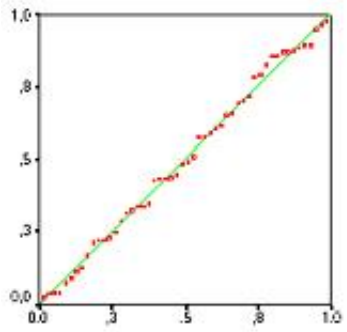
Firstly, linear regression needs the relationship between the independent and dependent variables to be linear. It is also important to check for outliers since linear regression is sensitive to outlier effects. The linearity assumption can best be tested with scatter plots, the following two examples depict two cases, where no and little linearity is present.





Secondly, the linear regression analysis requires all variables to be multivariate normal. This assumption can best be checked with a histogram and a fitted normal curve or a Q-Q-Plot. Normality can be checked with a goodness of fit test, e.g., the Kolmogorov-Smirnof test. When the data is not normally distributed a non-linear transformation, e.g., log-transformation might fix this issue, however it can introduce effects of multicollinearity.





Thirdly, linear regression assumes that there is little or no multicollinearity in the data. Multicollinearity occurs when the independent variables are not independent from each other. A second important independence assumption is that the error of the mean has to be independent from the independent variables.

Multicollinearity might be tested with 4 central criteria:

1) Correlation matrix – when computing the matrix of Pearson's Bivariate Correlation among all independent variables the correlation coefficients need to be smaller than 1.

2) Tolerance – the tolerance measures the influence of one independent variable on all other independent variables; the tolerance is calculated with an initial linear regression analysis. Tolerance is defined as $T = 1 – R^2$ for these first step regression analysis. With T

3) Variance Inflation Factor (VIF) – the variance inflation factor of the linear regression is defined as VIF = 1/T. Similarly with VIF > 10 there is an indication for multicollinearity to be present; with VIF > 100 there is certainly multicollinearity in the sample.

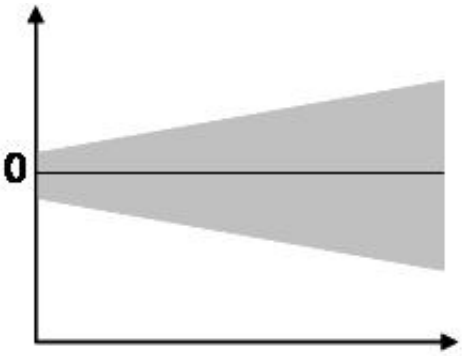
4) Condition Index – the condition index is calculated using a factor analysis on the independent variables. Values of 10-30 indicate a mediocre multicollinearity in the linear regression variables, values > 30 indicate strong multicollinearity.

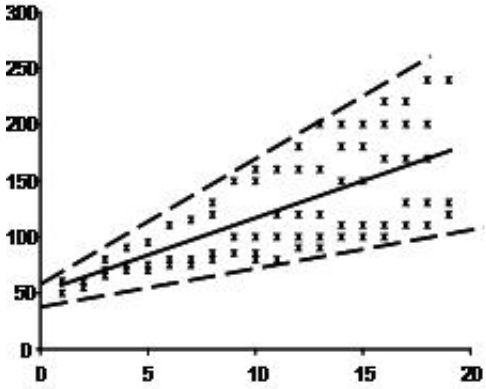
If multicollinearity is found in the data centering the data, that is deducting the mean score might help to solve the problem. Other alternatives to tackle the problems is conducting a factor analysis and rotating the factors to insure independence of the factors in the linear regression analysis.

Fourthly, linear regression analysis requires that there is little or no autocorrelation in the data. Autocorrelation occurs when the residuals are not independent from each other. In other words when the value of y(x+1) is not independent from the value of y(x). This for instance typically occurs in stock prices, where the price is not independent from the previous price.

While a scatterplot allows you to check for autocorrelations, you can test the linear regression model for autocorrelation with the Durbin-Watson test. Durbin-Watson's d tests the null hypothesis that the residuals are not linearly auto-correlated. While d can assume values between 0 and 4, values around 2 indicate no autocorrelation. As a rule of thumb values of 1.5

The last assumption the linear regression analysis makes is homoscedasticity. The scatter plot is good way to check whether homoscedasticity (that is the error terms along the regression are equal) is given. If the data is heteroscedastic the scatter plots looks like the following examples:





The Goldfeld-Quandt Test can test for heteroscedasticity. The test splits the data in high and low value to see if the samples are significantly different. If homoscedasticity is present, a non-linear correction might fix the problem.

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