In multiple linear correlation and regression we use additional independent variables (denoted *X1*, *X2*, ..., and so on) that help us better explain or predict the dependent variable (Y). Almost all of the ideas we saw in simple linear correlation and regression extend to this more general situation. However, the additional independent variables do lead to some new considerations. Multiple regression analysis can be used either as a descriptive or as an inferential technique

Multiple Regression and Correlation Analysis

The dependent variable Y is related to independent variables $X_1, X_2, ..., X_k$ and the error term e through the linear relationship

 $Y=a_0+a_1X_1+a_2X_2+\ldots+a_kX_k+e$

where a_0, a_1, \dots, a_k are unknown population parameters.

• There is no linearity among X₁,...,X_k (no collinearity assumption)

- The error term *e* has normal distribution with expectation (E*e*=0) (normality)
- Variance of *e* does not depend on *X*₁,...,*X*_k (homoscedasticity)
- In cross-sectional data analysis we infer about the unknown parameters using random sample

 $(Y_1, X_{11}, \ldots, X_{1k}), (Y_2, X_{21}, \ldots, X_{2k}), \ldots, (Y_n, X_{n1}, \ldots, X_{nk})$

Multiple Regression and Correlation Analysis

$$Y=a_0+a_1X_1+a_2X_2+\ldots+a_kX_k+e$$

The parameters are estimated by the least squares method. The least square relationship is written as

$$\hat{Y} = \hat{a}_0 + \hat{a}_1 X_1 + \hat{a}_2 X_2 + \ldots + \hat{a}_k X_k$$

Steps in multivariate regression analysis

- Preliminary variable selection: if the correlation absolute value between any two continuous explanatory variables exceeds 0.7 skip one of them - the one having smaller correlation with Y
- 2. Check whether loglinear model gives better correlations
- 3. Check model's validity verifying the hypotheses.

 $H_0: a_1 = a_2 = \ldots = a_k = 0, \ H_1: some \ a_i \neq 0$

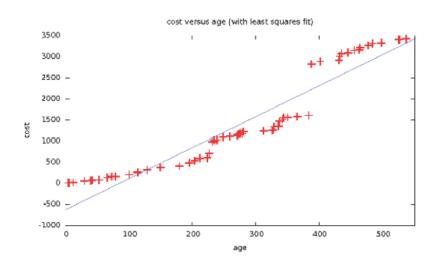
4. Skip non significant independent variables using t-test

 $H_0:a_i=0\ H_1:a_i\neq 0$

- 5. Redo the least squares for the final model
- 6. Verify model assumptions (homoscedasticity and normality)
- 7. Check if there are influential outlying observations influential outliers.

Laboratory example

DATA3-7: Data for a Toyota station wagon (57 observations) cost = cumulative repair cost in actual dollars (11 - 3425) age = age of car in weeks of ownership (Range 5 - 538) miles = miles driven in thousands (Range 0.8 - 74.4)



Add logarithms of variables (Gretl:Add\logs of selected vars) and compute correlation matrix

Correlation Coefficients, using the observations 1 - 57 5% critical value (two-tailed) = 0.2609 for n = 57		
cost 1.0000	5-	miles 0.9265 cost 0.9965 age 1.0000 miles
Correlation Coefficients, using the observations 1 - 57 5% critical value (two-tailed) = 0.2609 for n = 57		
l_cost 1.0000	l_miles 0.9711 1.0000	l_age 0.9822 l_cost 0.9971 l_miles 1.0000 l_age

We choose model with logarithms.

	Model 1: OLS, using observations 1-57. Dependent variable: l_cost			
	coefficient std. error t-ratio p-value			
	const -0.898719 0.199045 -4.515 3.38e-05 *** l_age 1.41680 0.0365646 38.75 1.30e-041 ***			
R-squared 0.964662, F test P-value(F) =1.30e-41 White's test for heteroscedasticity - Null hypothesis: heteroscedasticity not present				

with p-value = P(Chi-square(2) > 32.2411) = 9.97572e-008

Make diagnostic plots:

Graphs\Fitted actual plot\against l_age

Graphs\Residual plot\against l_age

Conclusion: First observation is an outlier and it should be removed

After outlier removal

Model 3: OLS, using observations 2-57 (n = 56) Dependent variable: l_cost coefficient std. error t-ratio p-value const -1.49829 0.186139 -8.049 8.21e-11 *** l_age 1.52391 0.0339184 44.93 1.85e-44 *** R-squared 0.973946 Adjusted R-squared 0.973463 F(1, 54) 2018.580 P-value(F) 1.85e-44 White's test for heteroskedasticity - Null hypothesis: heteroskedasticity not present with p-value = P(Chi-square(2) > 9.91542) = 0.00702901

Your task

Choose multivaraite data of your interest

and

make a complete data analysis using multivariate regression model