Regression Analysis

BUS 735: Business Decision Making and Research

Goals of this section

Specific goals

- Learn how to detect relationships between ordinal and categorical variables.
- Learn how to estimate a linear relationship between many variables.

Learning objectives

- LO2: Be able to construct and use multiple regression models (including some limited dependent variable models) to construct and test hypotheses considering complex relationships among multiple variables.
- LO6: Be able to use standard computer packages such as SPSS and Excel to conduct the quantitative analyses described in the learning objectives above.
- LO7: Have a sound familiarity of various statistical and quantitative methods in order to be able to approach a business decision problem and be able to select appropriate methods to answer the question.

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Correlation

- Pearson linear correlation coefficient: a value between -1 and +1 that is used to measure the strength of a positive or negative linear relationship.
  - Valid for interval or ratio data.
  - Not appropriate for ordinal or nominal data.
  - Test depends on assumptions behind the central limit theorem (CLT)
- Spearman rank correlation: non-parametric test.
  - Valid for small sample sizes (when assumptions of CLT are violated)
  - Appropriate for interval, ratio, and even ordinal data.
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Chi-Squared Test for Independence

- Used to determine if two categorical variables (eg: nominal) are related.
- Example: Suppose a hotel manager surveys guest who indicate they will not return:

	Reason for Not Returning		
Reason for Stay	Price	Location	Amenities
Personal/Vacation	56	49	0
Business	20	47	27

- Data in the table are always frequencies that fall into individual categories.
- Could use this table to test if two variables are independent.

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Test of independence

- **Null hypothesis**: there is no relationship between the row variable and the column variable.
- **Alternative hypothesis**: The two variables are dependent.
- Test statistic:

$$\chi^2 = \sum \frac{(O - E)^2}{E}$$

- O: observed frequency in a cell from the contingency table.
- E: expected frequency assuming variables are independent.
- Large χ^2 values indicate variables are dependent (reject the null hypothesis).

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Regression

- Regression line: equation of the line that describes the linear relationship between variable x and variable y.
- Need to assume that *independent variables* influence *dependent variables*.
  - x: *independent* or *explanatory* variable.
  - y: *dependent* variable.
  - Variable x can influence the value for variable y, but not vice versa.
- Example: How does smoking affect lung capacity?
- Example: How does advertising affect sales?

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Regression line

- Population regression line:

$$y_i = \beta_0 + \beta_1 x_i + \epsilon_i$$

- The actual coefficients β_0 and β_1 describing the relationship between x and y are unknown.
- Use sample data to come up with an estimate of the regression line:

$$y_i = b_0 + b_1 x_i + e_i$$

- Since x and y are not perfectly correlated, still need to have an error term.

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Predicted values and residuals

- Given a value for x_i, can come up with a **predicted value** for y_i, denoted $\hat{y}_i$.

$$\hat{y}_i = b_0 + b_1 x_i$$

- This is not likely be the actual value for y_i.
- **Residual** is the difference *in the sample* between the actual value of y_i and the predicted value, $\hat{y}$.

$$e_i = y_i - \hat{y} = y_i - b_0 - b_1 x_i$$

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Multiple Regression

- Multiple regression line (population):

$$y_i = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_2 + ... + \beta_{k-1} x_{k-1} + \epsilon_i$$

- Multiple regression line (sample):

$$y_i = b_0 + b_1 x_{1,i} + b_2 x_2 + ... + b_k x_k + e_i$$

  - k: number of parameters (coefficients) you are estimating.
  - ϵ_i: error term, since linear relationship between the x variables and y are not perfect.
  - e_i: residual = the difference between the predicted value $\hat{y}$ and the actual value y_i.

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Least Squares Estimate

- How should we obtain the "best fitting line".
- Ordinary least squares (OLS) method.
- Choose sample estimates for the regression coefficients that minimizes:

$$\sum_{i=0}^{n}(y_i - \hat{y}_i)^2$$

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Interpreting the slope

- Interpreting the slope, β: amount the y is predicted to increase when increasing x by one unit.
- When $\beta < 0$ there is a negative linear relationship.
- When $\beta > 0$ there is a positive linear relationship.
- When $\beta = 0$ there is no linear relationship between x and y.
- SPSS reports sample estimates for coefficients, along with...
  - Estimates of the standard errors.
  - T-test statistics for $H_0 : \beta = 0$.
  - P-values of the T-tests.
  - Confidence intervals for the coefficients.

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Example: Public Expenditure

- Data from 1960 about public expenditures per capita, and variables that may influence it.
- In SPSS, choose `Analyze` menu and select `Regression` and `Linear`.
- Select `EX` (Expenditure per capita) as your dependent variable. This is the variable your are interested in explaining.
- Select your independent (aka explanatory) variables. These are the variables that you think can explain the dependent variable. I suggest you select these:
  - ECAB: Economic Ability
  - MET: Metropolitan
  - GROW: Growth rate of population
  - WEST: Western state = 1.

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- **Sum of Squares Regression (SSR)**: measure of the amount of variability in the dependent (Y) variable that is explained by the independent variables (X's).

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2$$

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