Sum of Corrected Squares of
$$\chi_i$$
 $S_x^2 = \frac{1}{(n-1)} \sum_{i=1}^{\infty} \frac{1}{2(x_i - \bar{x})^2} = Sample$
Sections 2.2.2 and 2.2.3 of the textbook $\sqrt{ariance}$ of χ

Corver the
$$S_{xx} = \sum_{i=1}^{n} x_i^2 - \frac{(\sum_{i=1}^{n} x_i)^2}{n} = \sum_{i=1}^{n} x_i^2 - n \, \overline{x}^2 = \sum_{i=1}^{n} (x_i - \overline{x})^2 = \sum_{i=1}^{n} x_i (x_i - \overline{x}) = (n-1) \frac{S_x}{x}$$

Corver to
$$S_{xx} = \sum_{i=1}^{n} x_i - \frac{1}{n} = \sum_{i=1}^{n} x_i - n x^2 = \sum_{i=1}^{n} (x_i - x)^2 = \sum_{i=1}^{n} x_i (x_i - x)^2$$
Sum of

Cross

$$S_{xy} = \sum_{i=1}^{n} x_i y_i - \frac{\sum_{i=1}^{n} x_i \sum_{i=1}^{n} y_i}{n} = \sum_{i=1}^{n} x_i y_i - n \overline{x} \overline{y} = \sum_{i=1}^{n} (x_i - \overline{x}) (y_i - \overline{y})$$

Products of Y_i and Y_i are Y_i and Y_i and Y_i and Y_i are Y_i and Y_i and Y_i are Y_i and Y_i and Y_i are Y_i are Y_i and Y_i are Y_i and Y_i are Y_i are Y_i and Y_i are Y_i are Y_i and Y_i are Y_i and Y_i are Y_i are Y_i and Y_i are Y_i are

$$\sum_{i=1}^{n} (x_{i} - \overline{x})^{2} = \sum_{i=1}^{n} (x_{i} - \overline{x})(x_{i} - \overline{x}) = \sum_{i=1}^{n} x_{i}(x_{i} - \overline{x}) - \overline{x} \sum_{i=1}^{n} (x_{i} - \overline{x})$$

$$= \sum_{i=1}^{n} x_{i}(x_{i} - \overline{x}) - \overline{x} \sum_{i=1}^{n} x_{i}(x_{i} - \overline{x})$$

$$= \sum_{i=1}^{n} x_{i}(x_{i} - \overline{x}) - \overline{x} \sum_{i=1}^{n} x_{i}(x_{i} - \overline{x})$$

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$$= \sum_{i=1}^{n} x_{i}(x_{i} - \overline{x}) - \overline{x} \sum_{i=1}^{n} x_{i}(x_{i} - \overline{x})$$

$$\frac{\sum_{i=1}^{n} (x_i - \overline{x})(y_i - \overline{y}) = \sum_{i=1}^{n} x_i (y_i - \overline{y}) - \overline{x} \left(\sum_{i=1}^{n} (y_i - \overline{y}) = \sum_{i=1}^{n} x_i (y_i - \overline{y}) = \sum_{i=1}^{n} x_$$

Ex 2: Consider the following data set, in which the variables of interest are

$$x = \text{commuting distance (miles) and } y = \text{commuting time (min)}.$$

$$2x_{i}y_{i} = 176 \quad x \quad 5 \quad 10 \quad 15 \quad 20 \quad 25 \quad 2x_{i} = 75 \quad 2x_{i}^{2} = 1375$$

$$\Rightarrow x = \frac{2x_{i}}{N} = \frac{75}{5} = 15$$

$$y = \frac{75}{5} = 100$$

$$\hat{\beta}_1 = \frac{S_{\times Y}}{S_{\times \times}}$$
, $\hat{\beta}_2 = \hat{y} - \hat{\beta}_1 \hat{z}$
Sections 2.2.2 and 2.2.3 of the textbook $\hat{y} = \frac{\hat{y}_1 \hat{y}_2}{\hat{y}_1}$

Section 2.2.2: The properties of the least squares estimators:

1. They are linear functions of y_i . That is, they can be expressed as linear combinations of

$$\beta = \frac{S_{xy}}{S_{xx}} = \frac{\sum_{i=1}^{y_i} (x_i - \overline{x}) y_i}{S_{xx}} = \sum_{i=1}^{n} (\frac{x_i - \overline{x}}{S_{xx}}) y_i = \sum_{i=1}^{n} C_i y_i \text{ where } x_i - \overline{x}$$

$$\beta = \overline{y} - \beta_i \overline{x} = \frac{\sum_{i=1}^{n} (x_i - \overline{x}) y_i}{n} - (\sum_{i=1}^{n} C_i y_i) \overline{x} = \sum_{i=1}^{n} (\frac{1}{n} - \overline{x} C_i) y_i$$

2. They are unbiased estimators of regression coefficients.

A statistic T is an unbiased estimator of parameter θ if $E(T) = \theta$

$$E(\widehat{\beta_{0}}) = \beta_{0}$$

$$E(\widehat{\beta_{1}}) = \beta_{1}$$

$$E(\widehat{\beta_{1}}) = E\left[\sum_{i=1}^{n} C_{i} \vee_{i}\right] = E\left[\sum_{i=1}^{n} \left(\frac{\chi_{i} - \chi}{g_{xx}}\right) \left(\beta_{0} + \beta_{1} \chi_{i} + \varepsilon_{i}\right)\right]$$

$$= \sum_{i=1}^{n} \left(\frac{\chi_{i} - \chi}{g_{xx}}\right) E\left[\beta_{0} + \beta_{1} \chi_{i} + \varepsilon_{i}\right] = \sum_{i=1}^{n} \left(\frac{\chi_{i} - \chi}{g_{xx}}\right) \left(\beta_{0} + \beta_{1} \chi_{i} + \varepsilon_{i}\right)$$

$$= \sum_{i=1}^{n} \left(\frac{\chi_{i} - \chi}{g_{xx}}\right) \beta_{0} + \sum_{i=1}^{n} \left(\frac{\chi_{i} - \chi}{g_{xx}}\right) \beta_{1} \chi_{i} = \sum_{i=1}^{n} \left(\frac{\chi_{i} - \chi}{g_{xx}}\right) + \sum_{i=1}^{n} \chi_{i} \left(\chi_{i} - \chi\right)$$

$$= \left(\widehat{\beta_{1}}\right) = \beta_{1}$$
At home: Show $E\left(\widehat{\beta_{0}}\right) = E\left(\beta_{0}\right)$
and read section 2.2 of textbook.

(hapter)