Saarland University

The Elements of Stastical Learning

Assignement 2

Due Date: 15.11.2017

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Derive the variance formula:

$$Var(\frac{1}{k}\sum_{i=1}^{k}X_i) = \rho\sigma^2 + \frac{1-\rho}{k}\sigma^2$$

The R^2 statistic is a common measure of model fit corresponding to the fraction of variance in the data that is explained by the model. In general, R^2 is given by the formula

$$R^2 = \frac{TSS - RSS}{TSS} = 1 - \frac{RSS}{TSS}$$

The objective here is to show that for univariate regression, $R^2 = Cor(X,Y)^2$ Let's take first the RSS and TSS formula

 $RSS = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$ =amount of variability left unaccounted after the regression

$$TSS = \sum_{i=1}^{n} (y_i - \bar{y}_i)^2 = \text{total variance in Y}$$

TSS - RSS = amount of variance removed/explained by the regression

So we have

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}}{\sum_{i=1}^{n} (y_{i} - \bar{y}_{i})^{2}}$$

And the correlation formula

$$\widehat{Cor}(X,Y) = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

For an univariate linear regression, the approximation has the form (af+b) and we'll suppose an exact approximation with $(y-f)^2=0$. We will also assume that f is the model that minimize the square-error and that there is no shift of scaling that improve f.

We can write it like this

$$\sum_{i=1}^{n} (f_i - y_i)^2 \le \sum_{i=1}^{n} (af_i + b - y_i)^2$$

Consider the second part as $g(a,b) = \sum_{i=1}^{n} (af_i + b - y_i)^2$. As f minimizes the loss, g is optimized at g(1,0) and so it is the optimum. We can derive it

$$\frac{d}{da}g(a,b)_{(a=1,b=0)} = \sum_{i=1}^{n} 2(af_i + b - y_i)f_i = \sum_{i=1}^{n} 2(f_i - y_i)f_i = 0$$

So
$$yf - ff = 0 \rightarrow yf = ff$$

And

$$\frac{d}{db}g(a,b)_{(a=1,b=0)} = \sum_{i=1}^{n} 2(af_i + b - y_i) = \sum_{i=1}^{n} 2(f_i - y_i) = 0$$

So $\bar{y} = \bar{f} \to \text{Mean}$ is the normalized sum. We can simplify R^2 . From the derivative we have yf = ff and $\bar{f} = \bar{y}$. To simplify we assume \bar{y} and $\bar{f} = 0$

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}}{\sum_{i=1}^{n} (y_{i})^{2}} = 1 - \frac{yy - 2yf + ff}{yy}$$

Since we have yf = ff

$$R^2 = 1 - \frac{yy - ff}{yy} = \frac{ff}{yy}$$

For the correlation we have

$$\rho = \frac{\sum_{i=1}^{n} (f_i y_i)}{\sqrt{\sum_{i=1}^{n} f_i^2} \sqrt{\sum_{i=1}^{n} y_i^2}} = \frac{fy}{\sqrt{(ff)(yy)}} = \frac{ff}{\sqrt{(ff)(yy)}} = \sqrt{\frac{ff}{yy}}$$