# Spring 2015 Statistics 151 (Linear Models): Lecture Thirteen

## Aditya Guntuboyina

#### 05 March 2015

# 1 Regression Diagnostics

For regression diagnostics, we need to know about the following quantities:

- 1. Leverage
- 2. Standardized Residuals
- 3. Predicted Residuals
- 4. Standardized Predicted Residuals
- 5. Cook's Distance

We looked at Leverages in the last class.

### 2 Standardized Residuals

The residuals  $\hat{e}$  satisfy  $var(\hat{e}) = \sigma^2(I - H)$ . In particular, it is important to know that the residuals are correlated and have different variances.

For diagnostics, it is useful to look at standardized residuals; defined as

$$r_i = \frac{\hat{e}_i}{\hat{\sigma}\sqrt{1 - h_{ii}}}.$$

Under the assumption of normality on  $e_1, \ldots, e_n$ , we know that the residuals  $\hat{e} \sim N(0, \sigma^2(I - H))$ . Does the standardized residual  $r_i$  have a t-distribution? NO! because  $\hat{e}_i$  and  $\hat{\sigma}$  are not independent.

### 3 Predicted Residuals

How does one find outliers in the regression data? A first answer might be to look for subjects having large residuals. But the problem with this approach is that when the outlier also has a large leverage, then the residual will not be that large. Therefore, one needs to look at a combination of leverage and the value of the residual. It turns out that predicted residuals are a natural way of combining the residuals and the leverages.

The *i*th predicted residual is defined as follows. First throw away the *i*th subject and fit the linear model. Using that linear model, predict the value of  $y_i$  based on the explanatory variable values of the *i*th subject. The difference between  $y_i$  and this predicted value is called the *i*th predicted residual.

Let  $X_{[i]}$  denote the X-matrix with the *i*th row deleted. Also, let  $Y_{[i]}$  denote the Y-vector with the *i*th entry deleted and let  $x_i^T$  denote the *i*th row of the original X matrix.

The estimate of  $\beta$  after deleting the *i*th row is:

$$\hat{\beta}_{[i]} = \left(X_{[i]}^T X_{[i]}\right)^{-1} X_{[i]}^T Y_{[i]}.$$

The *i*th predicted residual is defined as

$$\hat{e}_{[i]} = y_i - x_i^T \hat{\beta}_{[i]}.$$

It might seem that to calculate  $\hat{e}_{[i]}$  for different i, one would need to perform many regressions deleting each subject separately. Fortunately, one can calculate these in a simpler way using the Sherman-Morrison formula from matrix algebra. I will do this in the next class.