

CHE384, From Data to Decisions: Measurement, Uncertainty, Analysis, and Modeling

Lecture 51 Addressing Multicollinearity

Chris A. Mack
Adjunct Associate Professor

<http://www.lithoguru.com/scientist/statistics/>

© Chris Mack, 2016 Data to Decisions 1

What to Do About Multicollinearity

- If we only care about prediction, **restrict the scope** of the model to coincide with the range of predictor variables that exhibit the same pattern of multicollinearity
- Drop some correlated predictor variables (ones with the highest VIF)
- Add data** cases that break the pattern of multicollinearity
- Measure some coefficients in a separate experiment (then fix those coefficients)
- Use **Ridge Regression**
- Use **Principal Component Analysis (PCA)**

© Chris Mack, 2016 Data to Decisions 2

Adding Data to Break Collinearity

Two possibilities:

1. We have no data because we did not collect it
2. We have no data because they do not exist

© Chris Mack, 2016 Data to Decisions 3

What to Do About Multicollinearity

- Use **Ridge Regression**
 - Add a small bias to the estimators to help break the correlations and reduce variance
 - Find the minimum of

$$S = \sum_{i=1}^n \left(y_i - \beta_0 - \sum_{j=1}^p \beta_j x_{ji} \right)^2 + k \sum_{j=1}^p (\beta_j)^2$$

penalty
 - The penalty shrinks our coefficients
 - We generally scale and center (standardize) our data before we perform the regression

© Chris Mack, 2016 Data to Decisions 4

Ridge Regression

- To perform ridge regression, just add $p-1$ rows to the standardized data, with 0 for the y -values and $\sqrt{k}I_p$ for the x -values (predictor values), then do a standard OLS regression
- How to pick k , the ridge coefficient?
 - Plot the fit coefficients versus k (called a *ridge trace*), pick the smallest k at which the coefficients start to level off (don't change much)
 - Using a validation data set, find k that minimizes validation SSE

© Chris Mack, 2016 Data to Decisions 5

Properties of Ridge Regression

- The ridge regression model coefficients are biased smaller, but have smaller variance
 - As $k \rightarrow 0$, $\hat{\beta}_{ridge} \rightarrow \hat{\beta}_{OLS}$
 - As $k \rightarrow \infty$, $\hat{\beta}_{ridge} \rightarrow 0$
 - For orthonormal design matrix, $\hat{\beta}_{ridge} = \hat{\beta}_{OLS} / (1 + k)$
- Even for perfect multicollinearity, the ridge regression solution will always exist
- There is always a value of k where the MSE of the ridge coefficients are smaller than for OLS

© Chris Mack, 2016 Data to Decisions 6

