MET3220C Computational Statistics

Linear Regression

(Chapter 6 of Wilk's book)

Key Points: 1) Determining best fit parameters 2) Determining uncertainty in best fit parameter 3) Working with uncertain observations

http://campus.fsu.edu/ bourassa@met.fsu.edu





Fitting Parameters for a Line

• The calculations for the y-intercept and slope are:

$$y\text{-intercept} = \frac{\left(\sum_{i}^{n} x_{i}^{2}\right)\left(\sum_{i}^{n} y_{i}\right) - \left(\sum_{i}^{n} x_{i}\right)\left(\sum_{i}^{n} x_{i} y_{i}\right)}{\Delta}$$
$$slope = \frac{n\left(\sum_{i}^{n} x_{i} y_{i}\right) - \left(\sum_{i}^{n} x_{i}\right)\left(\sum_{i}^{n} y_{i}\right)}{\Delta}$$
$$\Delta = n\left(\sum_{i}^{n} x_{i}^{2}\right) - \left(\sum_{i}^{n} x_{i}\right)^{2}$$

http://campus.fsu.edu/ bourassa@met.fsu.edu



The Florida State University



Linear Regression

Uncertainty Calculations

• The 'uncertainty in y' (Ω_y) is

$$\Omega_{y}^{2} = \frac{1}{n-2} \sum_{i}^{n} (y_{i} - mx_{i} - b)^{2}$$

• This can be used as error bars about your best fit line.

• The uncertainty in the slope and y-intercept are

$$\Omega_{slope}^{2} = n\Omega_{y}^{2} / \Delta$$
$$\Omega_{y-int}^{2} = \Omega_{y}^{2} \left(\sum_{i=1}^{n} x_{i}^{2} \right) / \Delta$$

http://campus.fsu.edu/ bourassa@met.fsu.edu





Example Correlation Between Pressure and Florida Winter Temperatures

Correlation Between SLP and Florida Temperature (DJF)



- A time series of
 average (of sorts)
 Winter temperature in
 Florida can be
 determined from
 station data.
- That time series can be correlated with modeled (analysis) pressure fields.
- The areas with high (positive or negative) correlation indicate teleconnections.

http://campus.fsu.edu/ bourassa@met.fsu.edu



The Florida State University



Selecting a Predictor



http://campus.fsu.edu/ bourassa@met.fsu.edu



The Florida State University

- It is somewhat safer to take predictors that are close to the location of interest.
- Less likely predictors can also have a good match. That is predictors with high correlations, but with a less obvious physical connection.
- The less likely predictors are more likely to fail in forecasts.
- Here it is assumed that a local pressure gradient is a good predictor.
- The pressure gradient explains >98% of variability in monthly temperatures.



Hypothesis Testing With Slopes

- Assume that we are interested in global warming. Why?
 - The consequences of rapid global warming could be dire.
 - The cost of attempting to prevent global warming could be huge.
 - If the cost is huge, it will come at the expense of other activities.
 - If the cost is huge, and the data does not support the existence of the problem, then much better things could be done with the money!
- We can calculate a rate of change of temperature with time (a slope).
 - How do we tell if the slope is statistically significant?
- We can assume (reasonably) that the null distribution (of values for slope) has a Gaussian distribution.
 - A z-value can be calculated by dividing the slope by the uncertainty in the slope.

http://campus.fsu.edu/ bourassa@met.fsu.edu





Cool Examples



• How Big a problem are outliers?

Cool graphics from http://www.statsoft.com/textbook/stbasic.html#Correlationsd

http://campus.fsu.edu/ bourassa@met.fsu.edu



The Florida State University



Linear Regression 7

A Problem:

Uncertainty In Paired Observations

- Linear regression assumes that uncertainty in the observations can be ignored.
 - This assumption is often not valid.
 - Results in (potentially large) errors in a slope and y-intercept!
 - Example: Uncorrupted data (left), and

• Added random error equal to a standard deviation (right).



Why Did Purely Random Noise Change The Slope?

- When we add noise we tend to add outliers, but we also distribute the data in a more random fashion.
- The distribution looks more like a sphere, and the slope tends to be closer to zero.
- Interestingly, if we exchange the axis, the slope also is decreased, which would seem to conflict with the previously determined slope.





One Solution To the Problem of Uncertainty In Paired Observations

- In many cases there is little bias in either of the paired observations, and the gain (proportionality) is equal to 1 (x = y).
- The uncertainty in both sets of data can be estimated by randomly adding Gaussianly distributed noise to a perfect fit, and modifying the standard deviations of the noise with the goal of match the observed curves of x(y) and y(x).
- Ideally a similar data distribution should be used in this approach. Fortunately, any ball park distribution will do!



