GENERAL ASSEMBLY

DATA SCIENCE

11 WEEK PART TIME COURSE

Week 4 - Regularization
Monday 11th January 2016

AGENDA

1. GUEST SPEAKER - Rainer Hillermann !
2. Motivation / Review
3. What is Regularization?
4. Why use Regularization
5. Lab
6. Discussion


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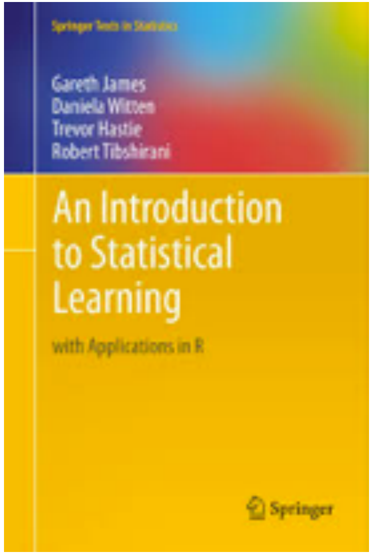
HOMEWORK

Two parts of the Homework related to this lesson

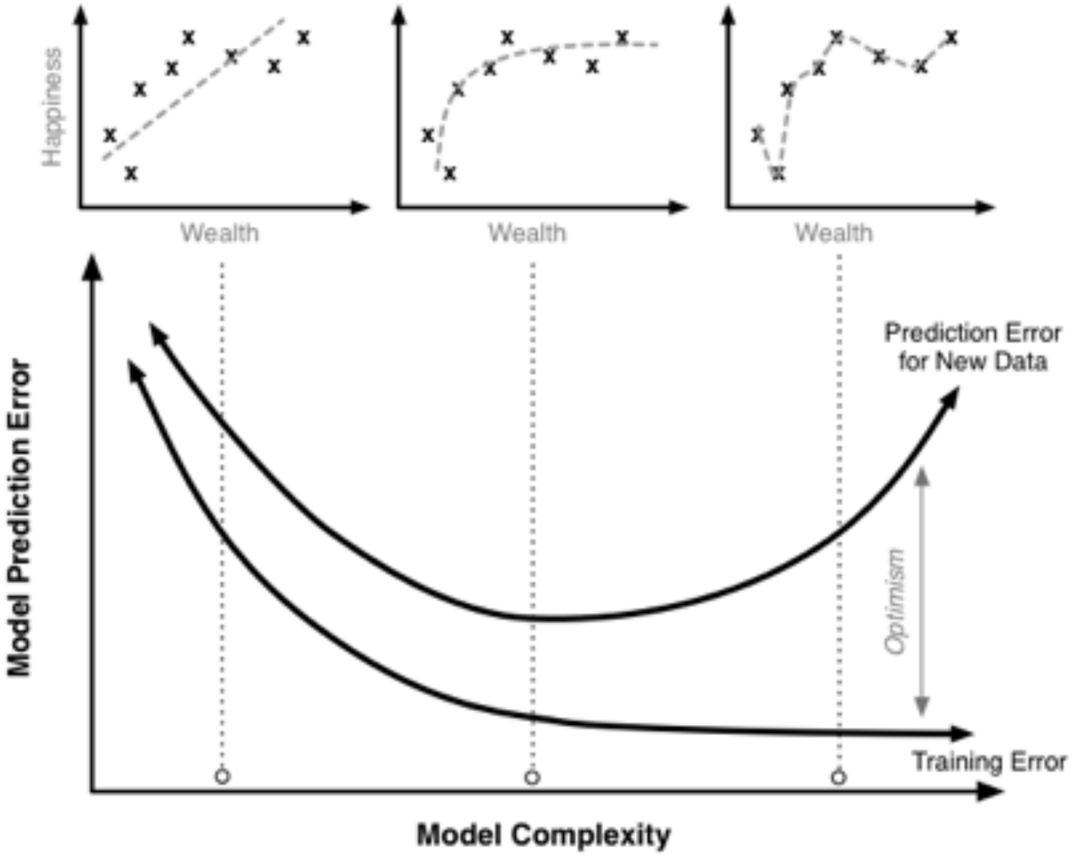
- Homework 2 - Chapter 6 of Introduction to Statistical Learning, Linear Model Selection and Regularization
- Task list - Data Robot Article, Regularized Linear Regression with scikit-learn

- Describe 3 ways we can select what features to use in a model?
- Why would we use regularization?



DataRobot

BIAS – VARIANCE TRADEOFF



We could fit a separate linear regression model for every combination of our features.

But what happens when we have a large number of features?

Computation time becomes a factor and we also need to consider that as we include more features we are increasing the chance we include a variable that doesn't add any predictive power for future data.

- A tuning parameter lambda (or sometimes alpha) imposes a penalty on the size of coefficients.
- Instead of minimizing the "loss function" (mean squared error), it minimizes the "loss plus penalty".
- A tiny alpha imposes no penalty on the coefficient size, and is equivalent to a normal linear model.
- Increasing the alpha penalizes the coefficients and shrinks them toward zero.

Recall from Week 2 that the least squares procedure estimates coefficients that minimise

$$\mathrm{RSS} = \sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2.$$

Regularization (or Shrinkage) is a way to constrain the estimates of beta to be close or equal to zero.

Ridge Regression is similar to least squares, except we include a penalty term,

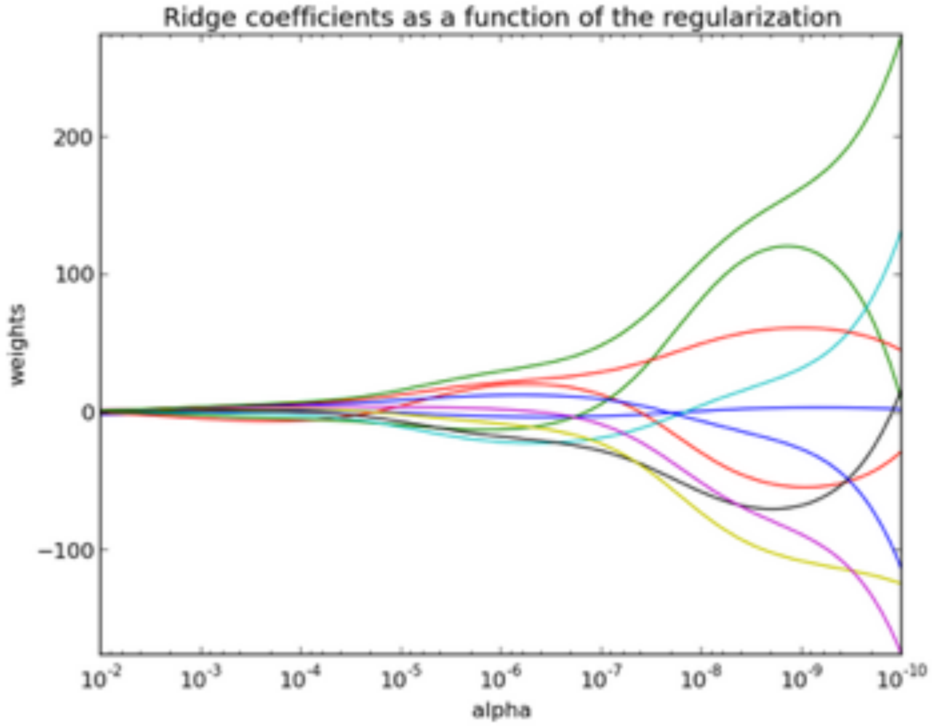
$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}\beta_j^2 = \mathrm{RSS} + \lambda\sum_{j=1}^{p}\beta_j^2,$$

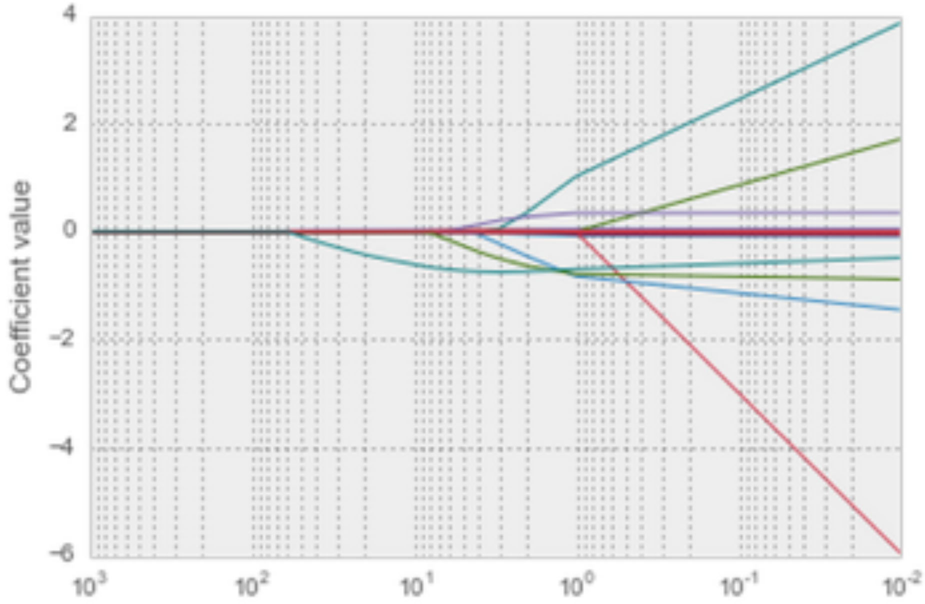
the λ term is a tuning parameter. When it is zero we get least squares, as it increases the term, $\lambda\sum_{j=1}^{p}\beta_j^2$ (the shrinkage penalty) has more of an impact and the coefficients will *approach* zero.

Lasso Regression is similar to Ridge Regression, except we have the absolute value of beta in our penalty term,

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j| = \text{RSS} + \lambda\sum_{j=1}^{p}|\beta_j|.$$

the λ term is a tuning parameter. When it is zero we get least squares, as it increases the term, $\lambda\sum_{j=1}^{p}|\beta_j|$ (the shrinkage penalty) has more of an impact and the coefficients will **equal** zero.


Ridge coefficients as a function of the regularization
200
100
0
−100
weights
10^{-2}
10^{-3}
10^{-4}
10^{-5}
10^{-6}
10^{-7}
10^{-8}
10^{-9}
10^{-10}
alpha


4
2
0
-2
-4
-6
Coefficient value
10^{3}
10^{2}
10^{1}
10^{0}
10^{-1}
10^{-2}

Lasso regularization is useful if we believe many features are irrelevant, since a feature with a zero coefficient is essentially removed from the model. Thus, it is a useful technique for feature selection.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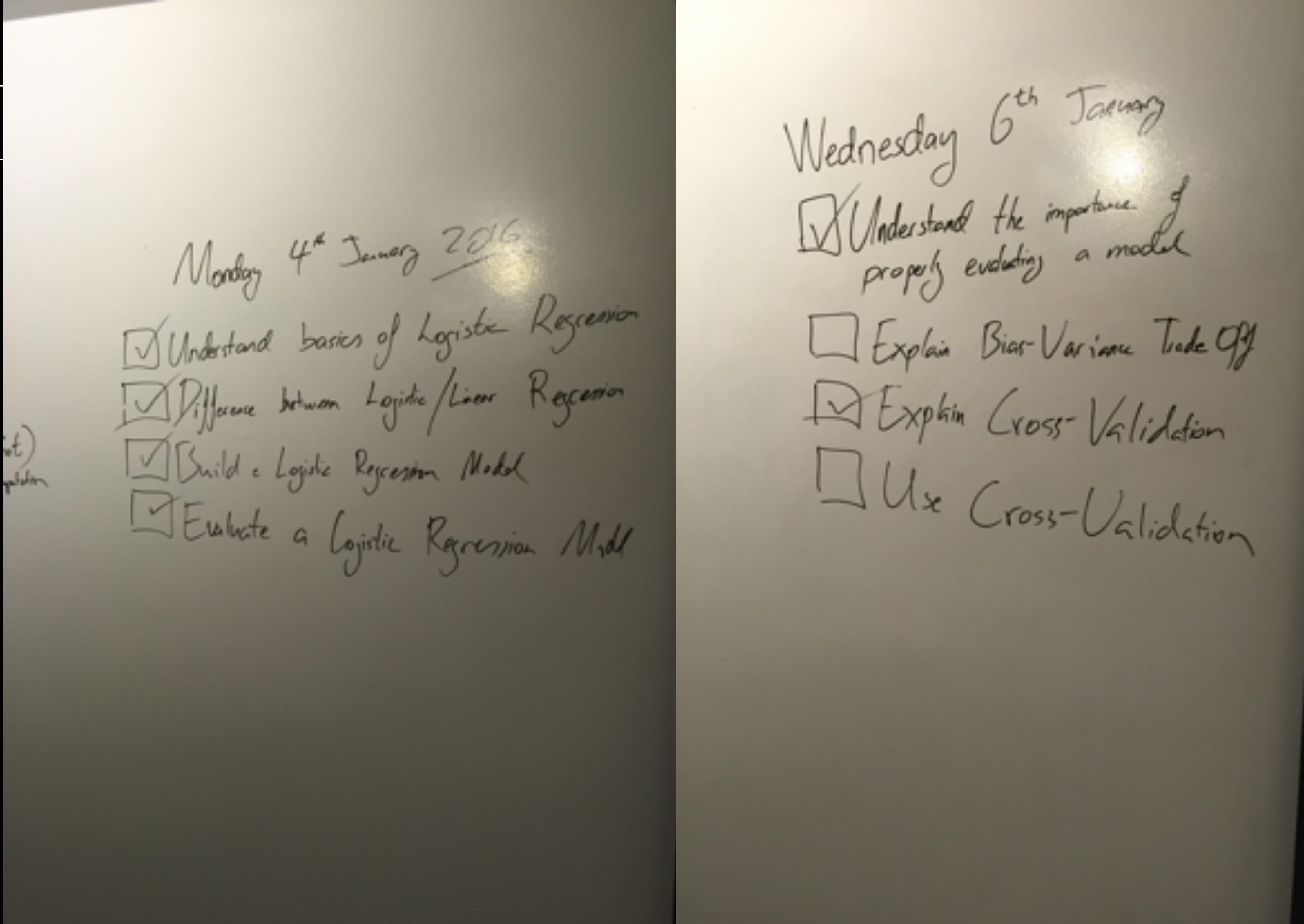
LAB

WEEK 3


Monday 4th January 2016
Understand basics of Logistic Regression
Difference between Logistic/Linear Regression
Build a Logistic Regression Model
Evaluate a Logistic Regression Model
Wednesday 6th January
Understand the importance of properly evaluating a model
Explain Bias-Variance Trade Off
Explain Cross-Validation
Use Cross-Validation

READINGS

Read the following before class on Wednesday

- Clustering Methods in Introduction to Statistical Learning, Chapter 10.3 (15 pages)
- Python Notebook on Clustering http://nbviewer.ipython.org/github/nborwankar/LearnDataScience/blob/master/notebooks/D1.%20K-Means%20Clustering%20-%20Overview.ipynb

DISCUSSION TIME

Free scope. Anything you would like to talk about? Can be anything, e.g.

- Software
- News Articles
- Things you'd like to cover in the course
- Things you've been thinking about trying out