DATA SCIENCE 11 WEEK PART TIME COURSE

Week 3 - Model Evaluation Wednesday 6th January 2016

- 1. Motivation
- 2. How do we know if we have a good model?
- 3. What is the Bias-Variance tradeoff?
- 4. Lab
- 5. Homework Review

WHATIS A GOOD MODEL?

Q: What's wrong with training error?

Thought experiment:

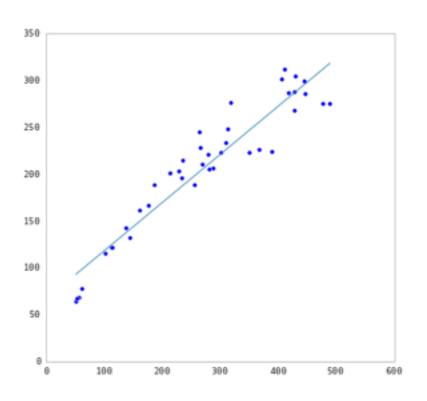
Suppose we train our model using the entire dataset.

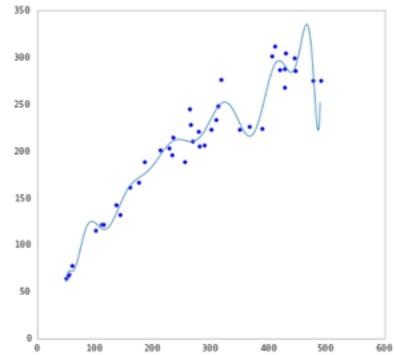
Q: How low can we push the training error?

- We can make the model arbitrarily complex (effectively "memorizing" the entire training set).

A: Down to zero!

TRAINING ERROR 5





TRAINING ERROR

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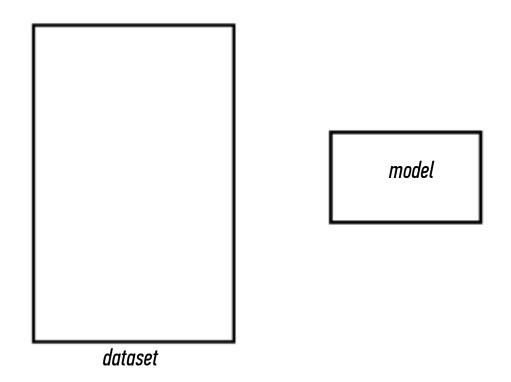
A: Down to zero!

A: Training error is not a good estimate of accuracy beyond training data.

WHY THIS MATTERS

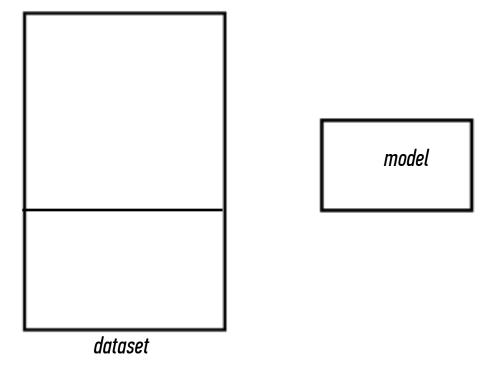
The data that we are given for prediction won't always be the end of the data we are interested in! We may not have access to all the data of interest

We will gather data and build and iterate over models however a main reason for building the model was to predict unseen test cases.

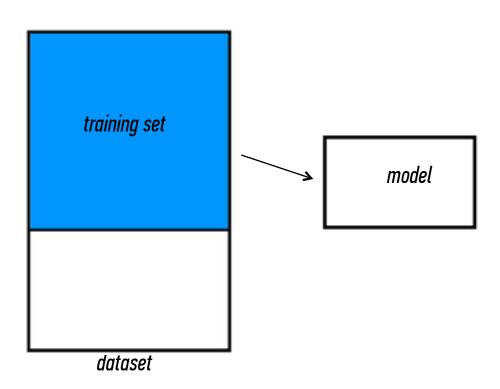


Q: How can we make a model that generalizes well?

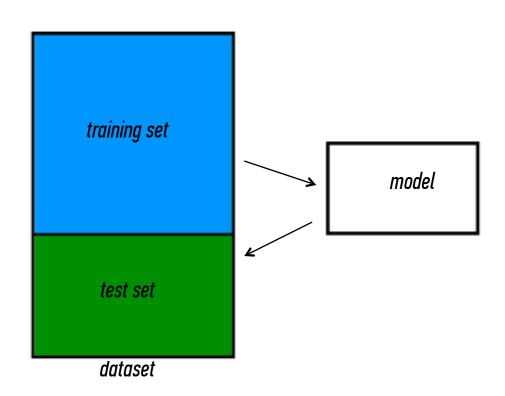
1) split dataset



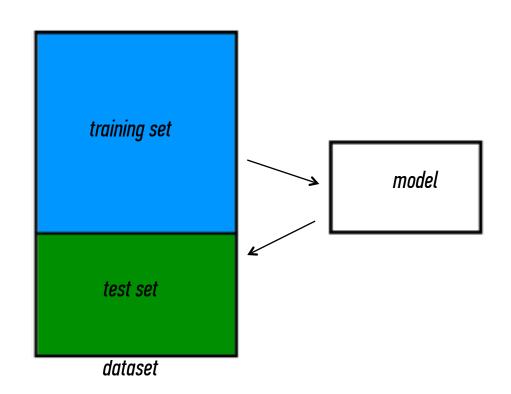
- 1) split dataset
- 2) train model



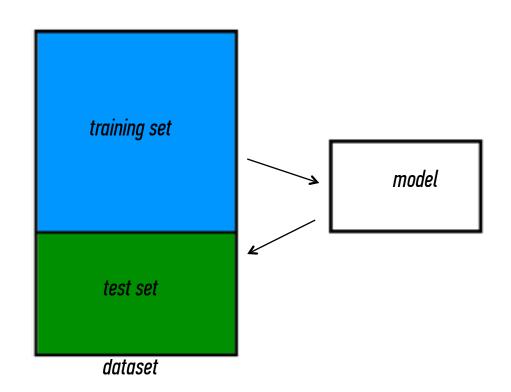
- 1) split dataset
- 2) train model
- 3) test model



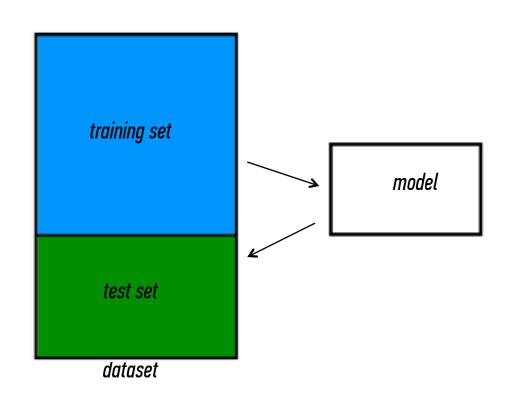
- 1) split dataset
- 2) train model
- 3) test model
- 4) parameter tuning



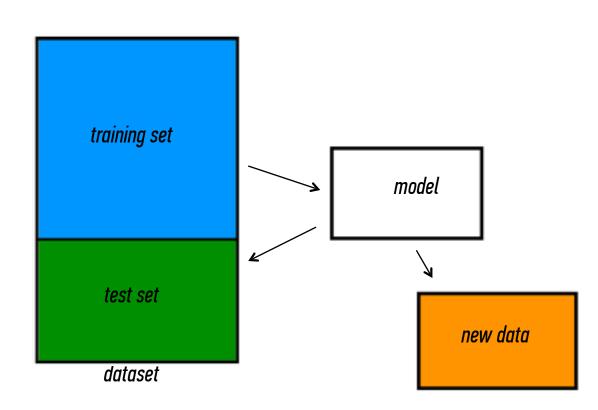
- 1) split dataset
- 2) train model
- 3) test model
- 4) parameter tuning
- 5) choose best model



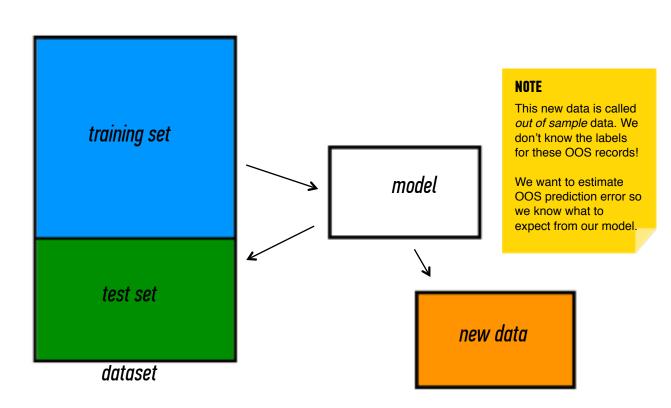
- 1) split dataset
- 2) train model
- 3) test model
- 4) parameter tuning
- 5) choose best model
- 6) train on all data



- 1) split dataset
- 2) train model
- 3) test model
- 4) parameter tuning
- 5) choose best model
- 6) train on all data
- 7) make predictions on new data



- 1) split dataset
- 2) train model
- 3) test model
- 4) parameter tuning
- 5) choose best model
- 6) train on all data
- 7) make predictions on new data



Suppose we do the train/test split. Q: How well does test set error predict OOS?

Thought experiment:

Suppose we had done a different train/test split.

Q: Would the test set error remain the same?

A: Of course not!

A: On its own, not very well.

Suppose we do the train/test split. Q: How well does test set error predict OOS?

Thought experiment:

Suppose we had done a different train/test split.

Q: Would the test set error remain the same?

A: Of course not!

A: On its own, not very well.

NOTE

The test set error gives a high-variance estimate of OOS accuracy.

Something is still missing! Q: How can we do better?

Thought experiment:

Different train/test splits will give us different test set errors.

Q: What if we did a bunch of these and took the average?

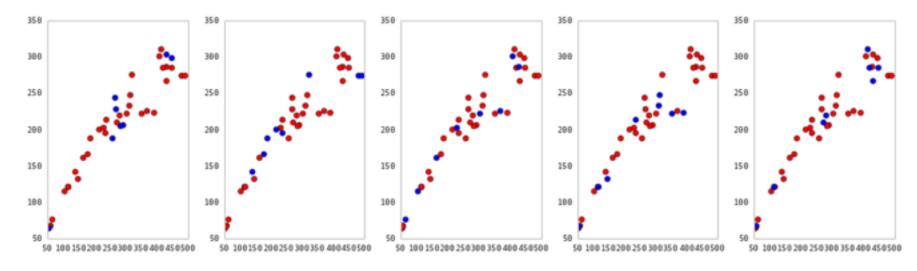
A: Now you're talking!

A: Cross-validation.

Steps for K-fold cross-validation:

- 1) Randomly split the dataset into K equal partitions.
- 2) Use partition 1 as test set & union of other partitions as training set.
- 3) Calculate test set error.
- 4) Repeat steps 2-3 using a different partition as the test set at each iteration.
- 5) Take the average test set error as the estimate of OOS accuracy.

CROSS VALIDATION 21



5-fold cross-validation: red = training folds, blue = test fold

CROSS VALIDATION

Features of K-fold cross-validation:

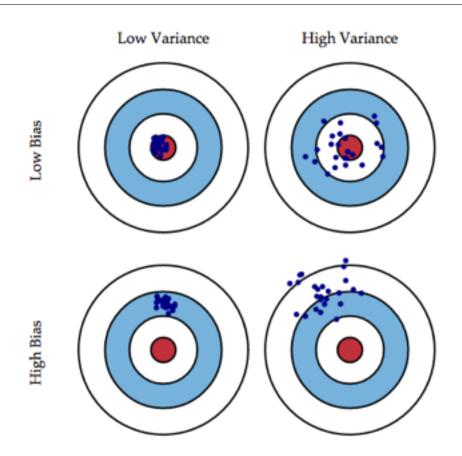
- More accurate estimate of OOS prediction error.
- More efficient use of data than single train/test split.
 - Each record in our dataset is used for both training and testing.
- Presents tradeoff between efficiency an computational expense.
 - 10-fold CV is 10x more expensive than a single train/test split
- Can be used for parameter tuning and model selection.

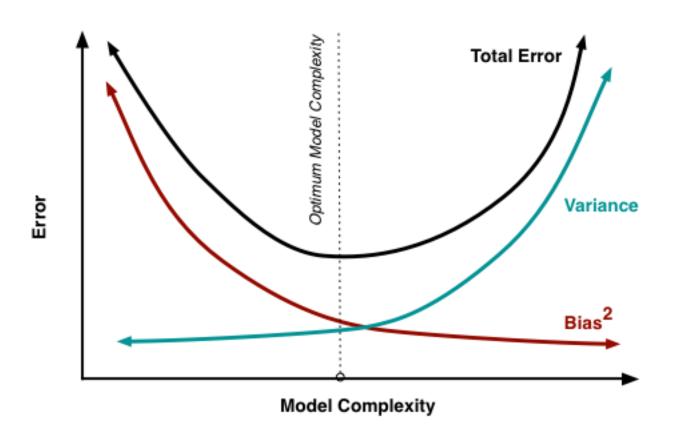
Errors due to Bias

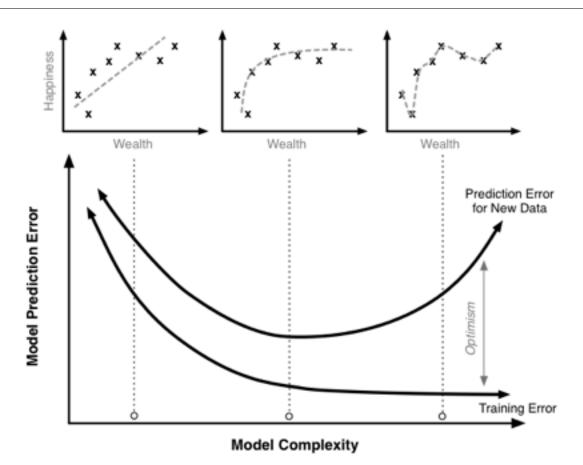
When we are training over multiple data sets we will have different errors. Bias measures how far off we are in general the predictions are from the actual values

Errors due to Variance

This is how variable our model is for a given data point. The variance calculates how much the predicted are from the actual values

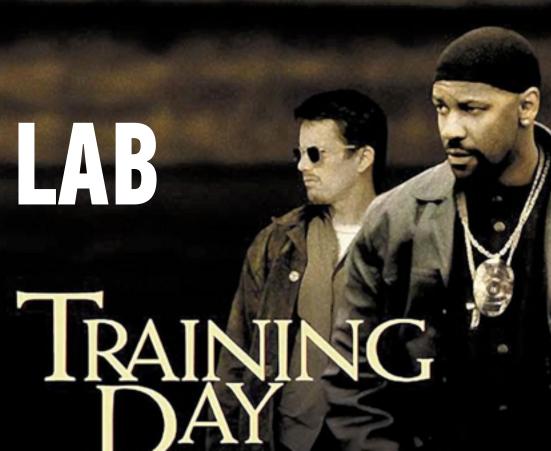






DATA SCIENCE PART TIME COURSE





DISCUSSION TIME

- Questions from previous lesson?
- ▶ Further Reading for Model Evaluation
- Check in with homework
- > Tasks for next week

WEEK 3 Monday

QUESTIONS

- What are we trying to do when we use Logistic Regression?
- ▶ Why use it instead of Linear Regression for classification?
- Evaluating a logistic Regression model

DATA SCIENCE - Week 3 Day 2

DISCUSSION TIME

An Introduction to Statistical Learning

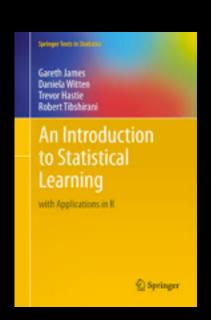
▶ Chapter 5 - Resampling Techniques

Logistic Regression applied to loan applications

https://github.com/nborwankar/LearnDataScience

Odds Ratio in Logistic Regression

http://www.ats.ucla.edu/stat/mult_pkg/fag/general/odds_ratio.htm



DATA SCIENCE - Week 3 Day 2

Tasks for Monday 11th January (< 30 mins)

□Have a git Repository setup with a Project Outline in the README.md
igspace Read and work though the code on this website on your own machine (copy and run)
http://www.datarobot.com/blog/regularized-linear-regression-with-scikit-learn/
☐Write out your computer specs (RAM, Hard Drive and CPU)
☐ If you are interested in doing kaggle competition send me your username so I can add you
□Fill in a Class Survey / Exit Ticket
CEND ME VIA CLACK DRODE DE TUE ADOVE