Final Project Presentations and Wrap-Up

Ivan Corneillet

Data Scientist

Here's what's happening today:

- Final Project Presentations
- What models did we learn in this class? Which one(s) should I choose?
- The dataset has a lot of features. What should I do?
- What else did we learn in this class?
- What's next?

Final Project Presentations

Wrap-Up

What models did we learn in this class?

Regression

- k-Nearest Neighbors
- Linear Regression
- Regression Trees (Decision Trees and Random Forests)
- AR, MA, ARMA, and ARIMA

Classification

- k-Nearest Neighbors
- Logistic Regression
- Classification Trees (Decision Trees and Random Forests)

What models did we learn in this class? We've also took an advanced look on the following topics:

- Closed-form solution for Linear Regression
- Ordinary Least Squares (OLS) and Loss Functions
- Gradient Descent
- Regularization
- Principal Component Analysis (a.k.a., PCA)

What models did we learn in this class? We've also made a foray in unsupervised learning:

- k-Means Clustering

What model(s) should I use? Ask yourself the following questions:

- Do I have an output or not?
  - If yes, you need to use a supervised learning technique (really the focus of this class); otherwise, you will use an unsupervised technique (e.g., k-Means for clustering)
- Assuming you have a supervised learning problem, is your output a quantitative variable or qualitative
  - If it is quantitative you will use one of the regression methods; otherwise you will use a classification algorithm

What model(s) should I use? Is your goal interpretation or prediction?

- Interpretative regression models are:
  - Linear Regression
  - Simple Regression Decision Trees
- Predictive regression models are:
  - k-Nearest Neighbors
  - Regression Random Forests
  - AR, MA, ARMA, and ARIMA. Low order of models are relatively interpretable but higher order are not. This is mainly why they are usually only used for prediction

What model(s) should I use? Is your goal interpretation or prediction? (cont.)

- Interpretative classification models are:
  - Logistic Regression
  - Simple Classification Decision Trees
- Predictive classification models are:
  - Classification Random Forests

I have a lot of features. What should I do?

- Coming up with features is difficult, time-consuming, requires expert knowledge. "Applied machine learning" is basically feature engineering – Andrew Ng
- Consider the following techniques to help you reduce the dimensionality of your dataset:
  - Lasso (Regularization/Feature Selection)
  - Principle Component Analysis (a.k.a, PCA)
  - Feature Importance (using Random Forests)

What else did we learn in this class? (cont.)

- Over the course, we improved our Python fluency
  - *pandas* DataFrames and other Python data structures (e.g., dictionaries)
  - Write basic functions to simplify our life and avoid code duplication (e.g., transforming variables on the training set then on the testing set)

What else did we learn in this class? (cont.)

- We are no longer afraid of statistics! You should feel at home now with:
  - (Two-Tail) Hypothesis Testing
  - Normal, Student's t-, and F-distributions
  - t-values and p-values

What else did we learn in this class?

- We discussed how important it was to tidying up data
  - Tidying data is one of the most fruitful skill you can learn as a data scientist. It will save you hours of time and make your data much easier to visualize, manipulate, and model

What else did we learn in this class? (cont.)

- The importance of validating your models and the k-fold cross-validation techniques
  - Divide your dataset into a train and a test sets. Train with training Data and Test it with test data
  - Divides your train set into chunks. Then train your model on all groups but one, and then test it on the one chunk left out. Repeat on all groups. This way, you are not wasting any data. Especially useful when you have a small dataset

What else did we learn in this class? (cont.)

- Git/GitHub
  - GitHub has become such a staple amongst the open-source development community that many developers have begun considering it a replacement for a conventional resume and some employers require applications to provide a link to and have an active contributing GitHub account in order to qualify for a job

What's next?

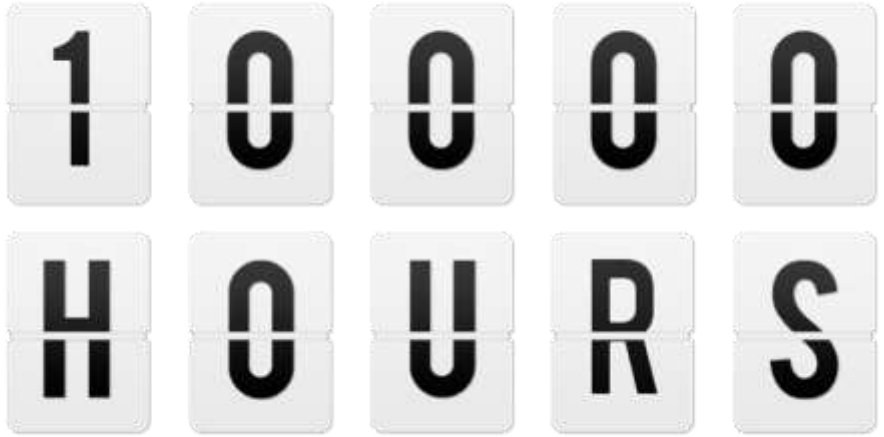
- A lot!
- This course was just an introduction to Data Science
- We focused on learning just a handful on models but learning them well. There are of course many more…

In the short term, consider spending time learning or doing a deep dive on the following machine algorithms:

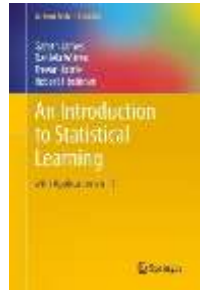
- Boosting (on Decision Trees) (regression/classification)
- Naive Bayes (classification)
- Support Vector Machines (a.k.a., SVM) (classification)
- Ensemble Learning (regression/classification)

Get your Hands Dirty, a.k.a., Practice, Practice, Practice…

- Kaggle (http://www.kaggle.com) competitions are a great way to practice everything we've learned in this class. And it's fun too!
  - Azi, Jeremiah, and Ivan are spending way too much time in this site…
  - You can compete by yourself but your can also team up with your fellow GA classmates!
- If Kaggle is not your thing, you should consider joining a study group if you haven't done so already



Longer term, consider the following resources



- An Introduction to Statistical Learning: with Applications in R (by James et al.). The e-book is available free-of-charge here

- A MOOC (Massive Open Online Courses) called Statistical Learning covering the book above is usually offered by Stanford also free-of-charge once a year during the winter. (now self-paced!) Check it out here

- For a more advanced treatment of these topics, check out The Elements of Statistical Learning: Data Mining, Inference, and Prediction (by Hastie et al.). And yes, the e-book is also free… (here)