IS 6489: Statistics and Predictive Analytics

Class 1

Jeff Webb

Tonight's agenda

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- Conceptual framework for the course
- Class 1 script: Set up RStudio and get started with R

What is this course about?

Course topics

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  - Communicate your results to non-experts as solutions to business problems.
- You will gain experience taking an analysis from raw data to finished product, and along the way will learn to use efficient workflows and make your research reproducible.

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- With these models we can:
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  - create a model to **predict** unknown values of the outcome variable given known inputs.
- Regression models are easy to fit and extremely powerful. Yet even for experts complicated models *are easy to misuse and misinterpret*.

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- These are important questions. We'll set them aside for now to focus on the *analytical problem* of identifying customers likely to churn.

Telcom dataset (first six rows, selected columns)

gender	SeniorCitizen	Dependents	tenure	Churn
Female	0	No	1	No
Male	0	No	34	No
Male	0	No	2	Yes
Male	0	No	45	No
Female	0	No	2	Yes
Female	0	No	8	Yes

Let's create a simple model of churn

```
## glm(formula = Churn ~ gender + SeniorCitizen + tenure, f
##     data = churn)
##                coef.est coef.se
## (Intercept)   -0.11     0.05
## genderMale    -0.04     0.06
## SeniorCitizen  1.05     0.07
## tenure        -0.04     0.00
## ---
##   n = 7043, k = 4
##   residual deviance = 6998.6, null deviance = 8150.1 (di
```

Questions

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- How would we know if adding or removing variables improved the model?

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- Does this model violate any of the mathematical assumptions of logistic regression?

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- **Using modern statistical software to fit models is easy, but understanding, validating, improving and communicating your results can be a challenge.**
- This course will equip you for that challenge.

Who should take this course?

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- Some preparation is essential since students with little (or barely remembered) statistics knowledge, or who have no R programmming experience, tend to struggle.
- If your statistics and/or programming skills are weak then consider doing some preparatory course work and delaying this course. Your learning experience will be vastly better.

Course elements

Main course texts

- **Datacamp.** Students have free access to all of the content at Datacamp through the end of the semester. (Email me if you have not received an invitation to the IS 6489 group at Datacamp or experience problems with your account.)

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- James, G., Witten, D., Hastie, T., and Tibshirani, R. (2013). **An introduction to statistical learning**. Springer. This is the main textbook for the course. It is available to download for free at the above link (look in the upper right corner of the page: "Download the book PDF"). The print book is available from Amazon.

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- We'll plan to take a break at about 7:15 PM.

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- **Weekly quizzes.** To ensure that you have understood the material in the labs, there will be short weekly quizzes covering the same material.

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- There will be an interim report due midway through the semester to ensure that you're making progress on the project, and a final report due a week after the last class.

Methods of instruction

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- The script created during live coding will be posted to Canvas afterwards for your reference.

Data Science

Why data science? Free and ubiquitous data.

"The ability to take data — to be able to understand it, to process it, to extract value from it, to visualize it, to communicate— will be a hugely important skill in the next decades, because now we really do have essentially free and ubiquitous data. So the complimentary scarce factor is the ability to understand that data and extract value from it. **I keep saying the sexy job in the next ten years will be statisticians**."

Hal Varian, Google Chief Economist and UC Berkeley Professor, *The McKinsey Quarterly*, January 2009

Why data science? A trend of more and more data.

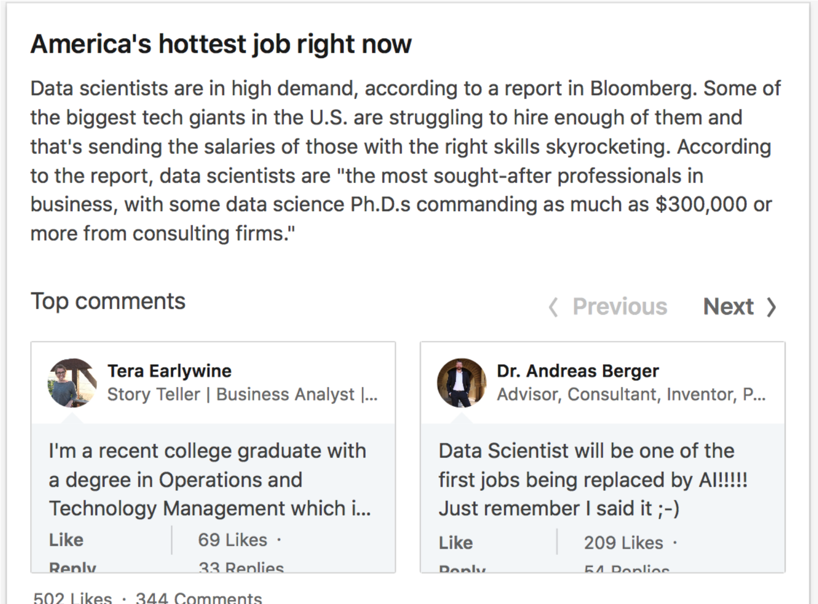
From 2011:

"By 2018, the United States alone could face a shortage of 140,000 to 190,000 people with deep analytical skills as well as 1.5 million managers and analysts with the know-how to use the analysis of big data to make effective decisions."

Mckinsey & Company, *Big data: The next frontier for innovation, competition, and productivity* (2011).

Why data science? Shortage of talent.

From LinkedIn, May 2018:



America's hottest job right now

Data scientists are in high demand, according to a report in Bloomberg. Some of the biggest tech giants in the U.S. are struggling to hire enough of them and that's sending the salaries of those with the right skills skyrocketing. According to the report, data scientists are "the most sought-after professionals in business, with some data science Ph.D.s commanding as much as $300,000 or more from consulting firms."

Top comments

‹ Previous Next ›

Tera Earlywine
Story Teller | Business Analyst |...

I'm a recent college graduate with a degree in Operations and Technology Management which i...

Like | 69 Likes ·
Reply | 33 Replies

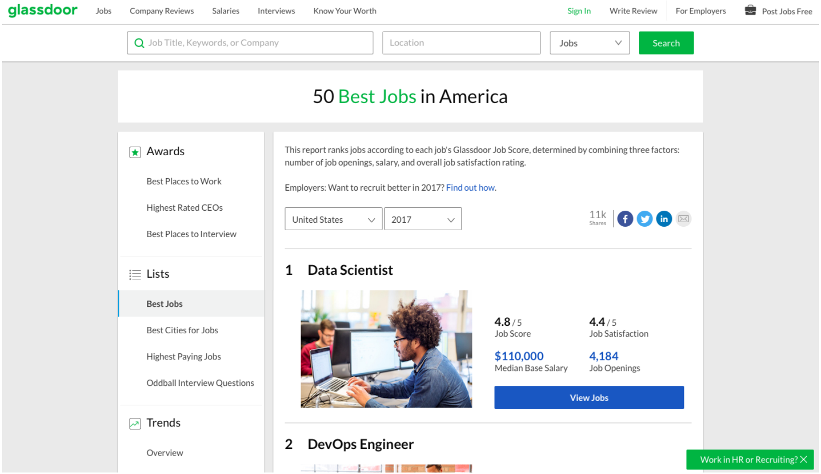
Dr. Andreas Berger
Advisor, Consultant, Inventor, P...

Data Scientist will be one of the first jobs being replaced by AI!!!!! Just remember I said it ;-)

Like | 209 Likes ·
Reply | 54 Replies

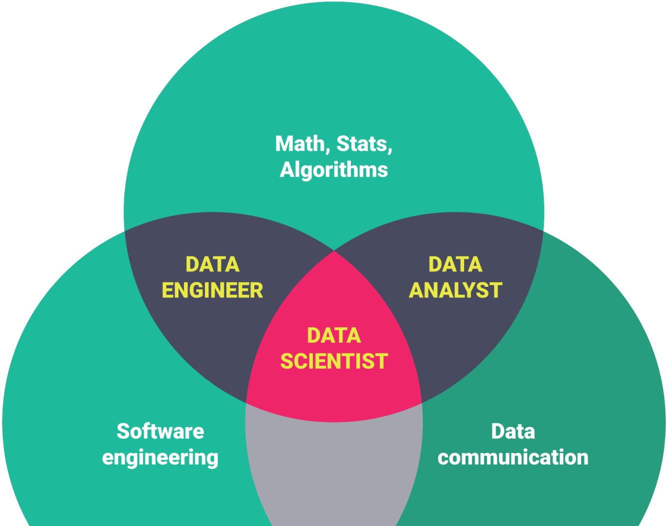
502 Likes · 344 Comments

Why data science? Interesting work.



What is a data scientist?

Data scientists extract, visualize and communicate insights from data. They are skilled at statistics, programming and telling stories.



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  2. Recommend an incentive program based on your analysis of the cost of the program compared to the benefit of retaining customers.
  3. Make a case for your recommendation with compelling visualizations and clear explanations.

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- The tidyverse collection of packages: dplyr, ggplot2, tidyr . . . .

Introductions

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- My last industry job was directing the data science team at Salt Lake Community College.

You

- Form groups of 2 or 3 with those sitting near you.

You

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- Introduce yourselves and have a conversation for 5 or 10 minutes:

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  - What is your educational and professional background?
  - Why are you interested in studying analytics?

Conceptual Framework for the Course

Statistical learning

From *An Introduction to Statistical Learning*:

"Statistical learning refers to a vast set of tools for understanding data. These tools can be classified as supervised or unsupervised. Broadly speaking, supervised statistical learning involves building a statistical model for predicting, or estimating, an output based on one or more inputs. . . . With unsupervised statistical learning there are inputs but no outputs; nevertheless we can learn relationships and structure from such data." (1)

Conceptual framework

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- Prediction vs. description

Example dataset: mtcars (first six rows)

	mpg	cyl	hp	wt
Mazda RX4	21.0	6	110	2.620
Mazda RX4 Wag	21.0	6	110	2.875
Datsun 710	22.8	4	93	2.320
Hornet 4 Drive	21.4	6	110	3.215
Hornet Sportabout	18.7	8	175	3.440
Valiant	18.1	6	105	3.460

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- `cyl`, `hp` and `wt` are the *predictors* (also known as independent variables, inputs, features or fields).
- The goal in supervised learning is to use the recorded relationships between the predictors and the outcome to develop (or "learn") a model that can be used for prediction or description.

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- In this course we consider only *supervised learning*.

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- For regression we will use linear regression and K-nearest neighbors (KNN) regression.
- In *classification problems* the outcome is binary and the goal is to learn a model of class membership denoted by categopries such as 0/1 or no/yes or passed/failed.
- For classification we will use logistic regression, KNN classification and support vector machines.

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- An example. . . .

Prediction

	mpg	wt
Mazda RX4	21	2.620
Mazda RX4 Wag	21	2.875
Datsun 710	22.8	2.320
Hornet 4 Drive	21.4	3.215
Hornet Sportabout	18.7	3.440
Valiant	18.1	3.460
Duster 360	?	3.570
Merc 240D	?	3.190
Merc 230	?	3.150

- *Predictive goal*: Learn a model that will fill in the missing outcome values.

Description

	mpg	wt
Mazda RX4	21	2.620
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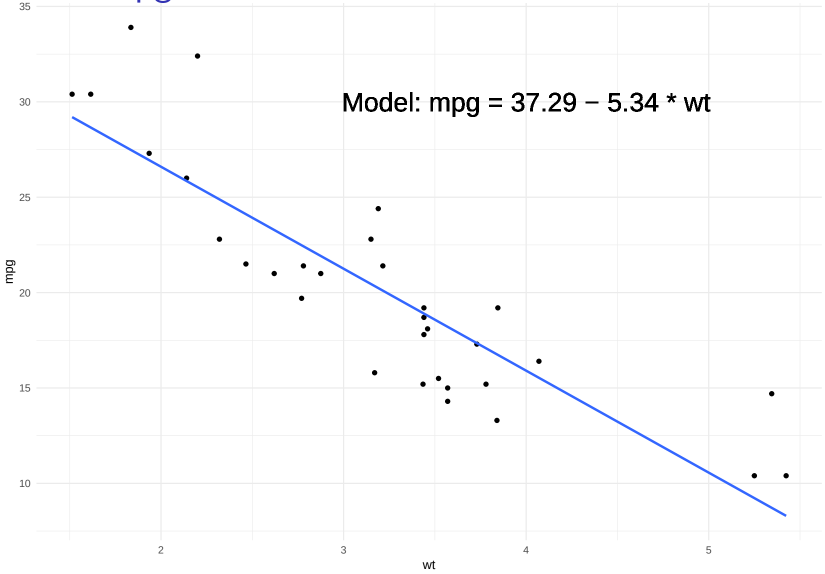
- *Descriptive goal*: Learn a model that will describe the relationship between mpg and wt.

Model of mpg



- **Description**: wt increases by 1, mpg declines by 5.34.

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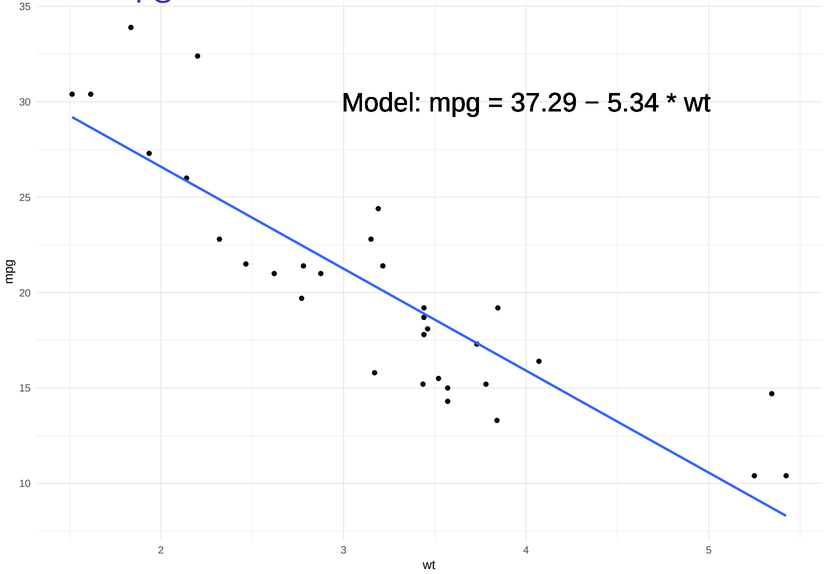

- **Description**: wt increases by 1, mpg declines by 5.34.
- **Prediction**: when wt = 4.5, mpg = 37.29 - 5.34 * 4.5.