Introduction to Modern Regression and Predictive Modeling

Merlise Clyde

8/30/2017

Coordinates

- Instructor: Merlise Clyde

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- TAs:

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  - Main http://stat.duke.edu/courses/Spring17/sta521

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  - Github https://github.com/STA521-F17

Grading

Component	Percentage
Participation	5%
Homework	25%
Midterm 1	20%
Midterm 2	20%
Data Analysis Part I	15%
Data Analysis Part II	15%

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- Team based data analysis assignments

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  - Individual contribution evaluated by peer assessment
  - You may help each other, but submitted work must be your own

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- 2 In-Class Midterms

Reproducible Research / Data Analysis

- R + RStudio + JAGS

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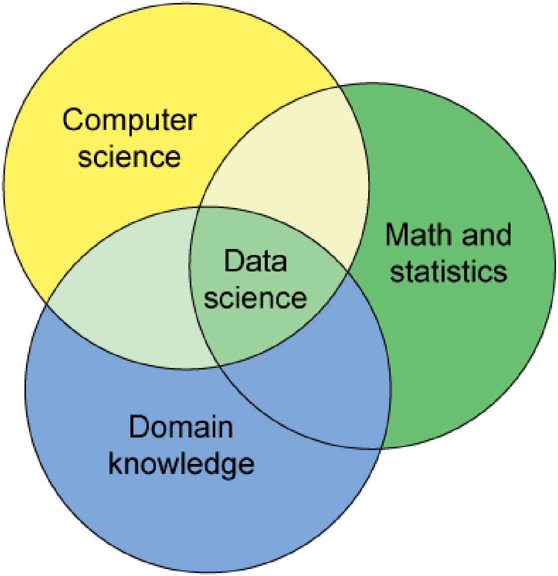
- Complete the course survey (email link next week)

Data Science



See (Bin Yu's IMS Presidential Address 2014)[http://bulletin.imstat.org/2014/10/ims-presidential-address-let-us-own-data-science/]

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  - Model Based Statistical Learning

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- interpretation of results for non-statisticians

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- Other Topics: Nonparametric Regression, Time Series, Neural Networks

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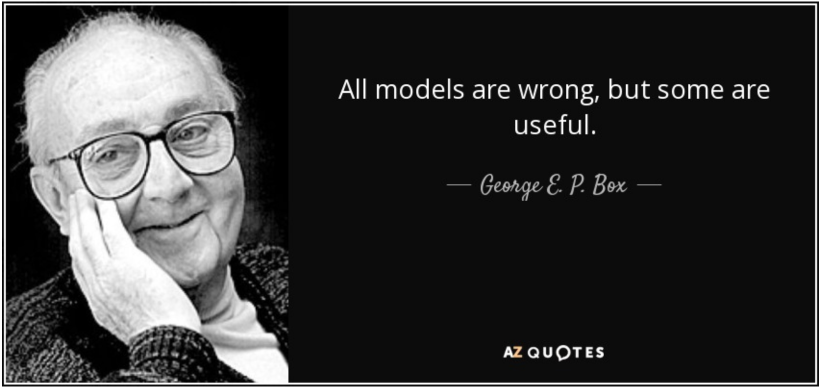
- Bayesian versus Frequentist ?

Tradeoffs. . .


All models are wrong, but some are useful.
— George E. P. Box —
AZ QUOTES

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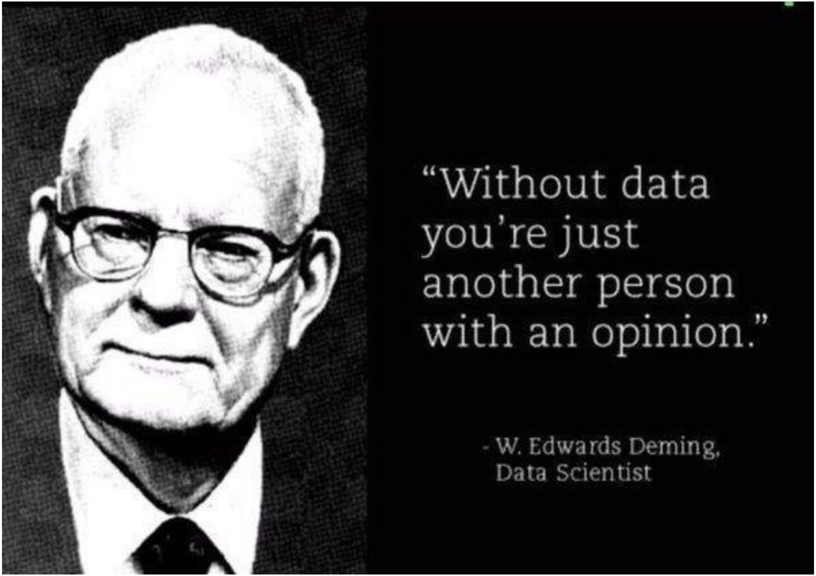
  - uncertainty after seeing data

Got Data?


"Without data
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with an opinion."
- W. Edwards Deming,
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- Important to understand advantages and problems of each perspective!

Statistical and Machine Learning ?

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- EDA, Model Building, and Predictive Checking crucial!