Introduction to Modern Regression and Predictive Modeling

Merlise Clyde

8/29/2018

▶ Instructor: Merlise Clyde

Instructor: Merlise Clyde

TAs:

Instructor: Merlise Clyde

TAs:

Jiurui Tang

- Instructor: Merlise Clyde
- TAs:
 - Jiurui Tang
 - ► Abbas Zaidi

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 - ► Github https://github.com/STA521-F18

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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 - You may help each other, but submitted work must be your own

Duke Community Standard

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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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Themes

- Interpretability versus predictive performance
- Bias-Variance Trade-off
- In sample versus out-of-sample
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- exact analysis versus approximation (computational scaling)
- understanding structure of data (relationships)
- Bayesian versus Frequentist ?

Tradeoffs...

Likelihood Based inference

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uncertainty after seeing data

Got Data?

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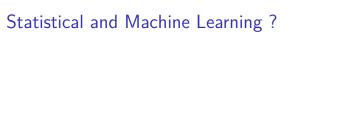
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- ▶ Bayesian methods sit on top of Frequentist Likelihood
- Important to understand advantages and problems of each perspective!



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- ▶ EDA, Model Building, and Predictive Checking crucial!