Machine Learning for Social Sciences

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Machine Learning in the Social Sciences

- Discovery
- Measurement
- Causal Inference

Machine learning $\rightsquigarrow$ powerful, but important to recognize limitations

Online Advertisements

- Online ads: billions of revenue
- Last click attribution: ads “get credit” if last thing you see before you buy
- Goal: optimize probability my ad is the last one clicked

Optimized, but for the task you choose

Voter Targeting Decisions

Campaigns: exert effort to mobilize voters

- Voter lists, consumer data, and proprietary surveys to target
- Hersh 2015: limitations to voter file, depends on state
- Merge: hard to combine data from different sources
- Clean: hard to know if someone has moved or just not voting
- Target: hard to run experiment during campaign to determine who to target

You work with the data you have

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Subsequent work (not with experiment) shows effects on politeness, tone on twitter

Machine Learning and "Bias"

Machine learning methods can mitigate bias in decision making

- Kleinberg et al "Human Decisions and Machine Predictions" $\rightsquigarrow$ Make better bail decisions using machine learing
- Bansak et al $\rightsquigarrow$ machine learning places refugees in better areas

Machine learning methods can inherent (and amplify) biases in decision making

- Caliskan et al "Semantics derived automatically from language corpora contain human-like biases" $\rightsquigarrow$ machine learning can inherent human biases

Machine learning is not a panacea for human biases

Text and Political Science

A pre-2000's view of text in social science

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    - Statistical methods/algorithms, computationally intensive

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- Foreign news sources, treaties, sermons, fatwas, ...

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What automated text methods don't do:

- Develop a comprehensive statistical model of language
- Replace the need to read
- Develop a single tool + evaluation for all tasks

Texts are Deceptively Complex

`We've got some difficult days ahead. But it doesn't matter with me now. Because I've been to the mountaintop. And I don't mind. Like anybody, I would like to live a long life. Longevity has its place. But I'm not concerned about that now.`

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Texts $\rightsquigarrow$ high dimensional, not self contained

Texts are Surprisingly Simple

(Lamar Alexander (R-TN) Feb 10, 2005)

Word	No. Times Used in Press Release
department	12
grant	9
program	7
firefight	7
secure	5
homeland	4
fund	3
award	2
safety	2
service	2
AFGP	2
support	2
equip	2
applaud	2
assist	2

Texts are Surprisingly Simple (?)

`US Senators Bill Frist (R-TN) and Lamar Alexander (R-TN) today applauded the U S Department of Homeland Security for awarding a $8,190 grant to the Tracy City Volunteer Fire Department under the 2004 Assistance to Firefighters Grant Program's (AFGP) Fire Prevention and Safety Program...`

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Machine Learning methods can help with even small problems

Course Plan

- Preliminaries: Acquiring Text and Feature Engineering
- Discovery
  - Regular Expressions and Vector Space Model of Text
  - Unsupervised Clustering
  - Topic Models
  - Embeddings
  - Fictitious Prediction Problems
- Measurement
  - Hand Coding
  - Dictionary Methods
  - LASSO and Ridge
  - Naive Bayes and ReadMe
  - Boosting, Bagging, and Ensembles
  - Structural Topic Models for Measurement
- Causal Inference
  - Text as Intervention
  - Text as Response and as Covariate

Course Evaluation Plan

Three (Equal) Parts to Evaluation

1) 5 homeworks.
   - Collaborate with folks in class
   - But write up your own work
   - Goal: (1) deeper understanding of the statistical methods (2) develop programming skills and (3) learn how to apply techniques from class to your own work
2) Class Participation
3) Poster Session + Paper

Poster Session + Paper

Goal: create *publishable* research output
Work in groups (2-3 people), apply methods from the class
Sequence:

- Initial project selection/question: April 16th.
- Data set collected, ready to analyze: May 7th
- Initial analyses/Write Up: May 16th
- Final Meeting with me to discuss project: May 28th
- Poster Session: June 4th
- Paper due by the end of final exam period

I want to work with you to make publishable research

Opportunity for Faculty Collaboration

Anna Grzymala-Busse "Looking for fairly simple sentiment analysis of official pronouncements and declarations (bulls) of the Catholic popes from about 8th to the 21st century. Im specifically looking for how official church views on the state have changed over time: how the church views the claims of rulers/ monarchs, its views on different forms of government (monarchy/ subsidiarity/ democracy etc), and when and how it sees the state as a rival or a complement in areas such as administration, the naming of clerics, education, taxes, health care, poverty relief, etc. How consistent are the Churchs views? How do they change in response to threats such as the Black Plague or the Reformation? "

Course Content

Prerequisites:

1) Must have: Linear Regression, Mathematical Statistics, background in `R`, `Python` or related language
2) (Very) Nice to have: Likelihood Theory, Causal Inference, and related courses

Technical class:

- Hard work: time spent on programming, problem sets, and research
- Time consuming: please set aside time to work on this class
- Everyone can succeed

Questions: Smartest person in the room rule

Thursday: Feature Representations