# POIR 613: Measurement Models and Statistical Computing

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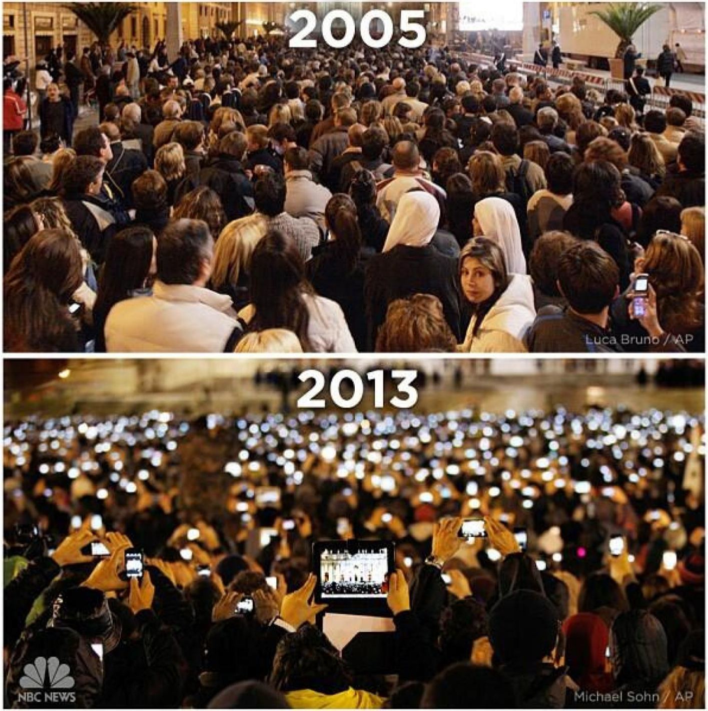
Course website:

pablobarbera.com/POIR613/

# Data is everywhere

243.26
Frosty
Krusty
TOMACCO
JUICE

Rx



Luca Bruno / AP

Michael Sohn / AP

NBC/Instagram

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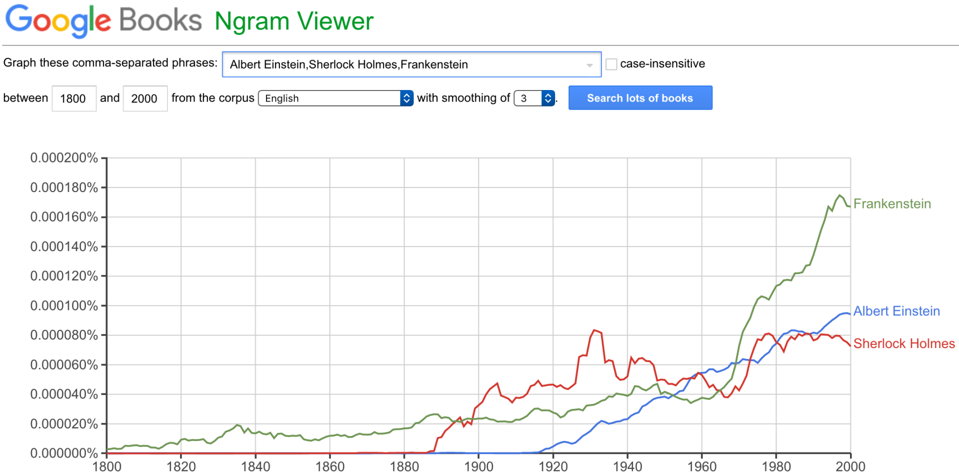


Google Books Ngram Viewer

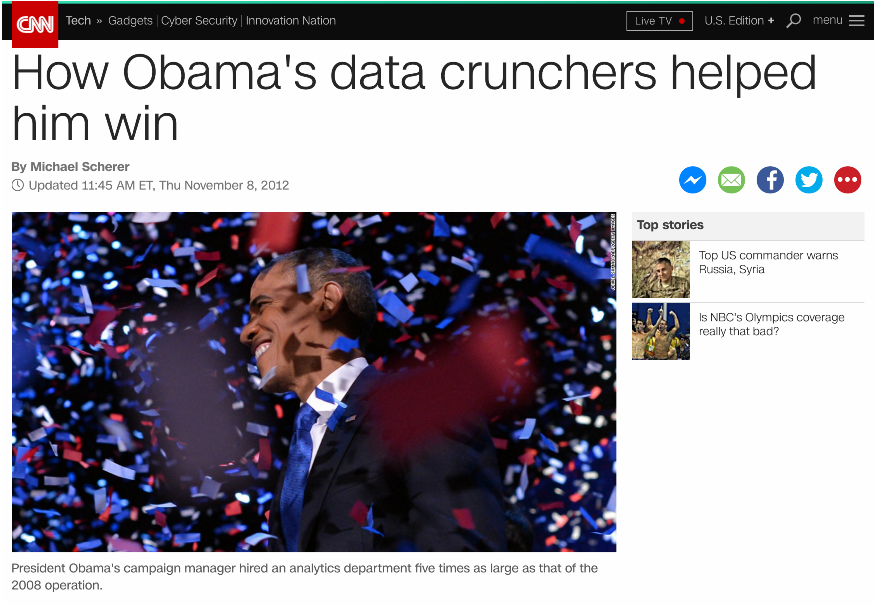
Graph these comma-separated phrases: Albert Einstein,Sherlock Holmes,Frankenstein ☐ case-insensitive

between 1800 and 2000 from the corpus English with smoothing of 3.

Search lots of books

Strongly agree
Agree
Disagree
ly disagree

# The Data revolution in election campaigns



CNN
Tech » Gadgets | Cyber Security | Innovation Nation
Live TV
U.S. Edition +
menu
JEWEL SAMAD/AFP/GETTY IMAGES

## How Obama's data crunchers helped him win

By Michael Scherer

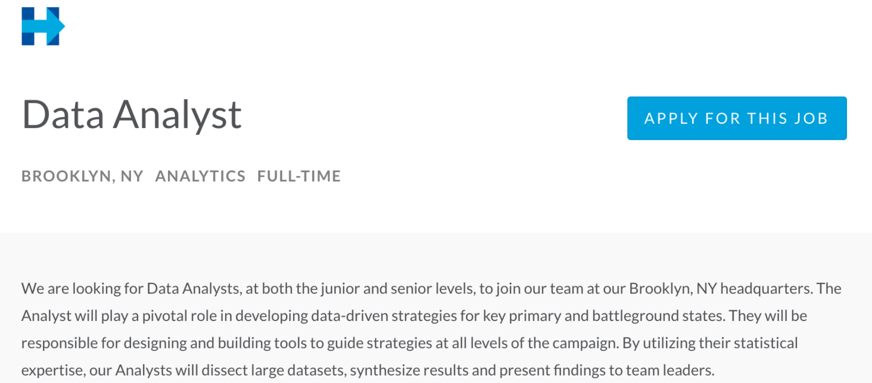
Updated 11:45 AM ET, Thu November 8, 2012

President Obama's campaign manager hired an analytics department five times as large as that of the 2008 operation.

**Top stories**

- Top US commander warns Russia, Syria
- Is NBC's Olympics coverage really that bad?

# The Data revolution in election campaigns

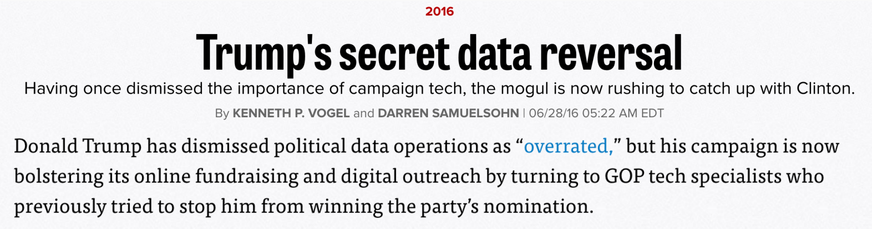


## Data Analyst

APPLY FOR THIS JOB

BROOKLYN, NY   ANALYTICS   FULL-TIME

We are looking for Data Analysts, at both the junior and senior levels, to join our team at our Brooklyn, NY headquarters. The Analyst will play a pivotal role in developing data-driven strategies for key primary and battleground states. They will be responsible for designing and building tools to guide strategies at all levels of the campaign. By utilizing their statistical expertise, our Analysts will dissect large datasets, synthesize results and present findings to team leaders.



2016

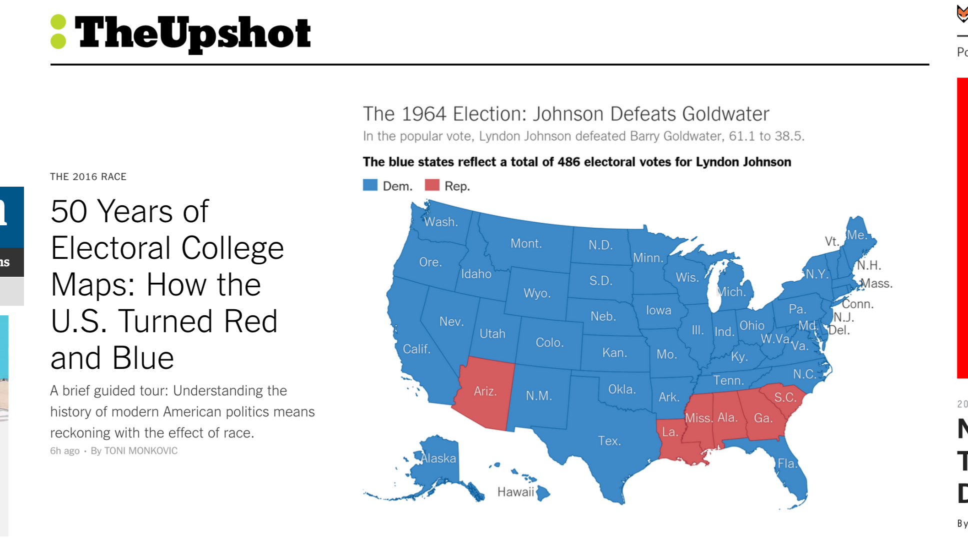
## Trump's secret data reversal

Having once dismissed the importance of campaign tech, the mogul is now rushing to catch up with Clinton.

By **KENNETH P. VOGEL** and **DARREN SAMUELSOHN** | 06/28/16 05:22 AM EDT

Donald Trump has dismissed political data operations as “overrated,” but his campaign is now bolstering its online fundraising and digital outreach by turning to GOP tech specialists who previously tried to stop him from winning the party’s nomination.

# Data Journalism



TheUpshot

THE 2016 RACE

## 50 Years of Electoral College Maps: How the U.S. Turned Red and Blue

A brief guided tour: Understanding the history of modern American politics means reckoning with the effect of race.

6h ago • By TONI MONKOVIC

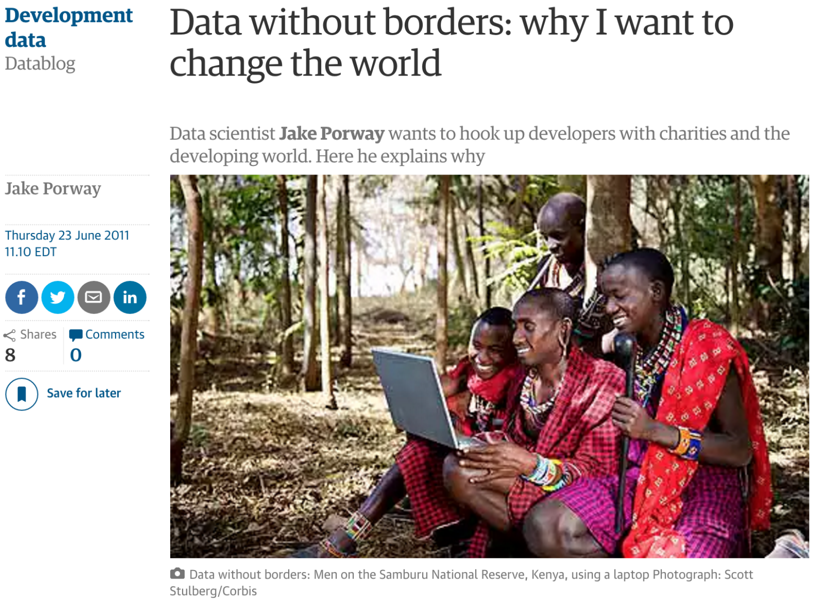
The 1964 Election: Johnson Defeats Goldwater

In the popular vote, Lyndon Johnson defeated Barry Goldwater, 61.1 to 38.5.

**The blue states reflect a total of 486 electoral votes for Lyndon Johnson**

🟦 Dem. 🟥 Rep.

# Non-profit sector



**Development data**
Datablog

## Data without borders: why I want to change the world

Data scientist **Jake Porway** wants to hook up developers with charities and the developing world. Here he explains why

Jake Porway

Thursday 23 June 2011
11.10 EDT

Shares
8

Comments
0

Save for later

Data without borders: Men on the Samburu National Reserve, Kenya, using a laptop Photograph: Scott Stulberg/Corbis

# Data Scientist:

## *The Sexiest Job of the 21st Century*

***Meet the people who can coax treasure out of messy, unstructured data.***

*by Thomas H. Davenport and D.J. Patil*

When Jonathan Goldman arrived for work in June 2006 at LinkedIn, the business networking site, the place still felt like a start-up. The company had just under 8 million accounts, and the number was growing quickly as existing members invited their friends and colleagues to join. But users weren't seeking out connections with the people who were already on the site at the rate executives had expected. Something was apparently missing in the social experience. As one LinkedIn manager put it, "It was like arriving at a conference reception and realizing you don't know anyone. So you just stand in the corner sipping your drink—and you probably leave early."

## How can we analyze *Big Data* to answer Political Science questions?

# POIR 613

**Goals**

- Read and evaluate research applying computational methods to political science problems
- Learn how to collect and manipulate quantitative data
- Develop skills necessary to analyze large and heterogeneous datasets

**Outline** (see detailed scheduled here)

- Weeks 1-2: Introduction. Ethics.
- Weeks 3-4: Surveys and experiments
- Weeks 5-8: Text as data methods
- Week 9-12: Social network analysis
- Weeks 12-13: GIS and A/V data

# Hello!

# About me

- Assistant Professor in International Relations at Univ. of Southern California
- As of January 2018, Assistant Professor in Computational Social Science at the LSE
- PhD in Politics, New York University (2015)
- Data Science Fellow at NYU, 2015–2016
- My research:
  - Social media and politics, comparative electoral behavior, corruption and accountability
  - Social network analysis, Bayesian statistics, text as data methods
  - Author of R packages to analyze data from social media
- Contact:
  - `pbarbera@usc.edu`
  - `www.pablobarbera.com`
  - Office hours: Wed 4pm-6pm (VKC 359A)

# Your turn!

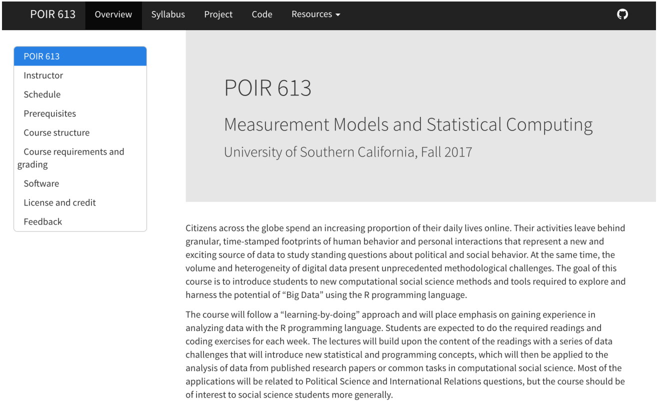
1. Name?
2. Department, year?
3. Research interests?
4. Previous experience with R?
5. Why are you interested in this course?

# Course philosophy

How to learn the techniques in this course?

- Lecture approach: not ideal for learning computational social science methods
- You can only learn by doing:
  - → Reading and criticizing research
  - → Applying methods to social science problems
- Structure of each session:
  1. Introduction to the topic (10-20 minutes)
  2. Discussion of research (60 minutes)
  3. Guided coding session (30-40 minutes)
  4. Coding challenges (30 minutes)
- You will continue working on the coding challenges after class and submit before beginning of next class

# Course website



POIR 613

Measurement Models and Statistical Computing

University of Southern California, Fall 2017

Citizens across the globe spend an increasing proportion of their daily lives online. Their activities leave behind granular, time-stamped footprints of human behavior and personal interactions that represent a new and exciting source of data to study standing questions about political and social behavior. At the same time, the volume and heterogeneity of digital data present unprecedented methodological challenges. The goal of this course is to introduce students to new computational social science methods and tools required to explore and harness the potential of "Big Data" using the R programming language.

The course will follow a "learning-by-doing" approach and will place emphasis on gaining experience in analyzing data with the R programming language. Students are expected to do the required readings and coding exercises for each week. The lectures will build upon the content of the readings with a series of data challenges that will introduce new statistical and programming concepts, which will then be applied to the analysis of data from published research papers or common tasks in computational social science. Most of the applications will be related to Political Science and International Relations questions, but the course should be of interest to social science students more generally.

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# Evaluation

- **Class participation**: 10%
  - Do all “readings for discussion” (required)
  - If unfamiliar with topic, also background reading
- **Referee reports and presentation**: 15%
  - TWO peer reviews (800-1000 words) of readings for discussion, due 8pm day before the class via Blackboard
  - 10-minute presentation in class (slides optional)
- **Coding challenges**: 25%
  - Not graded but submission (.Rmd + html/pdf files) via Blackboard is required before next class
- **Research project**: 50%
  - Original research paper (8,000 words) that employs computational methods in political science. Individual or group project (up to 3 people)

# Research project

**Goal:** demonstrate ability to conduct research that applies computational methods to political science questions.

**Constant progress** throughout semester:

| | |
|---|---|
| 09/15 | Project idea (one paragraph) |
| 10/02 | Project summary (2 pages) |
| 10/09 | Feedback from peers |
| 10/30 | Summary with descriptive statistics (5 pages) |
| 11/17 | First full draft (10-15 pages) |
| 11/28 | Student presentations (*) |
| 12/12 | Final paper |

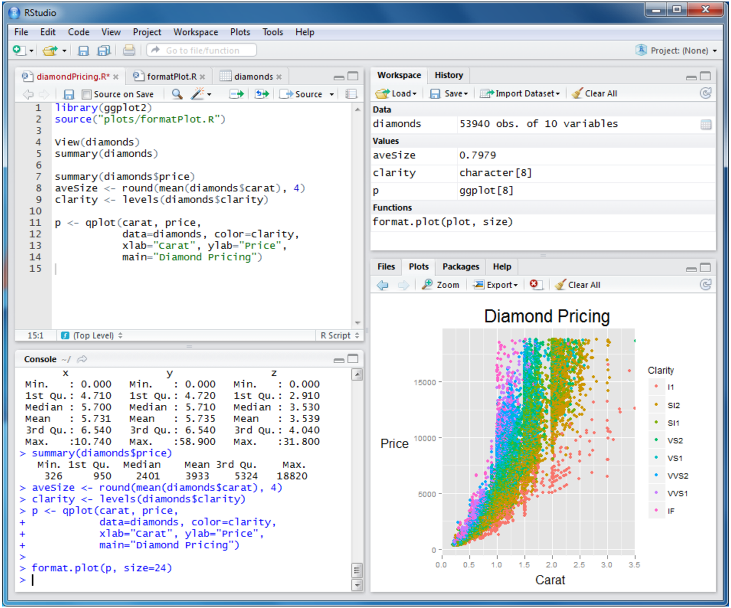
See course website for more information.

# Why we're using R

- Becoming *lingua franca* of statistical analysis in academia
- What employers in private sector demand
- It's free and open-source
- Flexible and extensible through *packages* (over 10,000 and counting!)
- Powerful tool to conduct automated text analysis, social network analysis, and data visualization, with packages such as quanteda, igraph or ggplot2.
- Command-line interface and scripts favors reproducibility.
- Excellent documentation and online help resources.

R is also a full programming language; once you understand how to use it, you can learn other languages too.

# RStudio Server



```r
library(ggplot2)
source("plots/formatPlot.R")

View(diamonds)
summary(diamonds)

summary(diamonds$price)
aveSize <- round(mean(diamonds$carat), 4)
clarity <- levels(diamonds$clarity)

p <- qplot(carat, price,
           data=diamonds, color=clarity,
           xlab="Carat", ylab="Price",
           main="Diamond Pricing")

```

**Data**

| | |
|---|---|
| diamonds | 53940 obs. of 10 variables |

**Values**

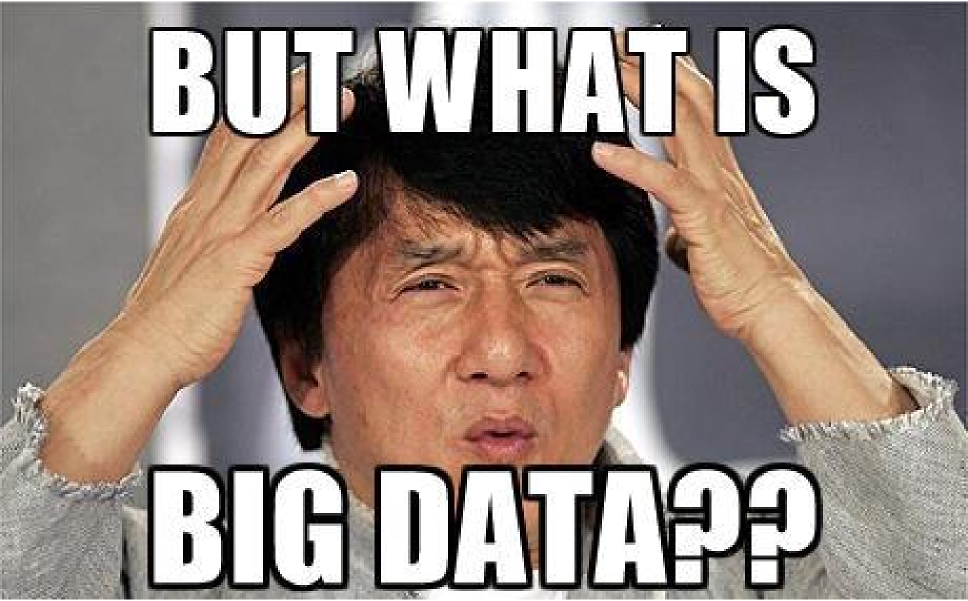
| | |
|---|---|
| aveSize | 0.7979 |
| clarity | character[8] |
| p | ggplot[8] |

**Functions**

format.plot(plot, size)

```
       x               y               z
 Min.   : 0.000   Min.   : 0.000   Min.   : 0.000
 1st Qu.: 4.710   1st Qu.: 4.720   1st Qu.: 2.910
 Median : 5.700   Median : 5.710   Median : 3.530
 Mean   : 5.731   Mean   : 5.735   Mean   : 3.539
 3rd Qu.: 6.540   3rd Qu.: 6.540   3rd Qu.: 4.040
 Max.   :10.740   Max.   :58.900   Max.   :31.800
> summary(diamonds$price)
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
    326     950    2401    3933    5324   18820
> aveSize <- round(mean(diamonds$carat), 4)
> clarity <- levels(diamonds$clarity)
> p <- qplot(carat, price,
+            data=diamonds, color=clarity,
+            xlab="Carat", ylab="Price",
+            main="Diamond Pricing")
>
> format.plot(p, size=24)
> |
```

# Big Data: Opportunities and Challenges


BUT WHAT IS
BIG DATA??

# The Three V's of Big Data

Dumbill (2012), Monroe (2013):

1. Volume: 6 billion mobile phones, 1+ billion Facebook users, 500+ million tweets per day...
2. Velocity: personal, spatial and temporal granularity.
3. Variability: images, networks, long and short text, geographic coordinates, streaming...

Big data: data that are so large, complex, and/or variable that the tools required to understand them must first be invented.

# Computational Social Science

> *"We have life in the network. We check our emails regularly, make mobile phone calls from almost any location ... make purchases with credit cards ... [and] maintain friendships through online social networks ... These transactions leave digital traces that can be compiled into comprehensive pictures of both individual and group behavior, with the potential to transform our understanding of our lives, organizations and societies".*
>
> ***Lazer** et al (2009) Science*

> *"Digital footprints collected from online communities and networks enable us to understand human behavior and social interactions in ways we could not do before".*
>
> ***Golder and Macy** (2014) ARS*

# Computational Social Science

Two different approaches in the growing field of computational social science:

1. Big data as a new source of information
   - Behavior, opinions, and latent traits
   - Interpersonal networks
   - Elite behavior
   - Affordable online experiments
2. How big data and social media affect social behavior
   - Collective action and social movements
   - Political campaigns
   - Social capital and interpersonal communication
   - Political attitudes and behavior

# Big data and social science: challenges

1. Big data, big bias?
2. The end of theory?
3. Spam and bots
4. The privacy paradox
5. Generalizing from online to offline behavior
6. Ethical concerns

# Computational **social** science

Challenge for social scientists: need for advanced technical training to collect, store, manipulate, and analyze massive quantities of semistructured data.

Discipline dominated by computer scientists who lack theoretical grounding necessary to know where to look.

Even if analysis of big data requires thoughtful measurement, careful research design, and creative deployment of statistical techniques (Grimmer, 2015).

New required skills for social scientists?

- Manipulating and storing large, unstructured datasets
- Webscraping and interacting with APIs
- Machine learning and topic modeling
- Social network analysis

# Good (enough) practices in scientific computing

Based on Nagler (1995) “Coding Style and Good Computing Practices” (PS) and Wilson *et al* (2017) “Good Enough Practices in Scientific Computing” (PLOS Comput Biol)

# Good practices in scientific computing

Why should I waste my time?

- Replication is a key part of science:
  - Keep good records of what you did so that others can understand it
- “Yourself from 3 months ago doesn’t answer emails”
  - More efficient research: avoid retracing own steps
  - Your future self will be grateful

General principles:

1. Good documentation: README and comments
2. Modularity with structure
3. Parsimony (without being too smart)
4. Track changes

# Summary of good practices

1. Safe and efficient data management
2. Well-documented code
3. Organized collaboration
4. One project = one folder
5. Track changes
6. Manuscripts as part of the analysis

# 1. Data management

- Save raw data as originally generated
- Create the data you wish to see in the world:
  - Open, non-proprietary formats: e.g. `.csv`
  - Informative variable names that indicate direction: `female` instead of `gender` or `V322`; `voted` vs `turnout`
  - Recode missing values to `NA`
  - File names that contain metadata: e.g. `05-alaska.csv` instead of `state5.csv`
- Record all steps used to process data and store intermediate data files if computationally intensive (easier to rerun parts of a data analysis pipeline)
- Separate data manipulation from data analysis
- Prepare README with codebook of all variables
- Periodic backups (or Dropbox, Google Drive, etc.)
- Sanity checks: summary statistics after data manipulation

# 2.Well-documented code

- Number scripts based on execution order:
  - → e.g. `01-clean-data.r`, `02-recode-variables.r`, `03-run-regression.r`, `04-produce-figures.R`...
- Write an explanatory note at the start of each script:
  - → Author, date of last update, purpose, inputs and outputs, other relevant notes
- Rules of thumb for modular code:
  1. Any task you run more than once should be a function (with a meaningful name!)
  2. Functions should not be more than 20 lines long
  3. Separate functions from execution (e.g. in `functions.r` file and then use `source(functions.r)` to load functions to current environment
  4. Errors should be corrected when/where they occur
- Keep it simple and don't get too clever
- Add informative comments before blocks of code

# 3. Organized collaboration

- Create a `README` file with an overview of the project: title, brief description, contact information, structure of folder
- Shared to-do list with tasks and deadlines
- Choose one person as corresponding author / point of contact / note taker
- Split code into multiple scripts to avoid simultaneous edits
- ShareLatex, Overleaf, Google Docs to collaborate in writing of manuscript

# 4. One project = one folder

Logical and consistent folder structure:

- `code` or `src` for all scripts
- `data` for raw data
- `temp` for temporary data files
- `output` or `results` for final data files and tables
- `figures` or `plots` for figures produced by scripts
- `manuscript` for text of paper
- `docs` for any additional documentation

# 5 & 6. Track changes; producing manuscript

- Ideally: use version control (e.g. GitHub)
- Manual approach: keep dates versions of code & manuscript, and a `CHANGELOG` file with list of changes
- Dropbox also has some basic version control built-in
- Avoid typos and copy&paste errors: tables and figures are produced in scripts and compiled directly into manuscript with LaTeX

# Examples

Replication materials for my 2014 PA paper:

- Code on GitHub
- Code and Data

John Myles White's ProjectTemplate R package.

Replication materials for Leeper 2017:

- Code and data

# For next week

1. Sign up for TWO peer reviews. Email with link will be sent tomorrow at 2pm.
2. Do readings for discussion: Kramer et al 2014 (and “Editorial Expression of Concern”) and Tufekci 2014. (Both short!)
3. New to CSS? Do background readings
4. Install most recent versions of R and RStudio