Political Science 452: Text as Data

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April 6th, 2011
A pre-2000’s view of text in political science

- Political conflict often occurs in texts
Text and Political Science

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  - Difficult to store/search
  - Idiosyncratic to coders/researcher
A post-2000’s view of text in political science:
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Massive collections of texts are increasingly used as a data source in political science:
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Massive collections of texts are increasingly used as a data source in political science:

**American Politics**
- Policy Agendas Project
  - Congressional Bills Project
- LYDIA

**Comparative Politics**
- Legislative Speech Project
- Comparative Manifesto Project

**International Relations**
- Penn State Event Data Project
Why?
- Massive increase in availability of unstructured text (10 minutes of worldwide email = 1 LOC )
- Cheap storage: 1956: $10,000 megabyte. 2011: $0.0001 per megabyte (Unless you’re sending an SMS)
- Explosion in methods and programs to analyze texts
  - Generalizable: one method can be used across many methods and to unify collections of texts
  - Systematic: parameters/statistics demonstrate how models make coding decisions
  - Cheap: easily applied to many new collections of texts
- **Unchanged Demand**: Political conflict is expressed (or occurs over) texts
  - Laws
  - Treaties
  - News media
  - Campaigns
  - Political pundits
  - Petitions
  - Press Releases
  - ...
We will study a set of tools for the useful and principled analysis of massive text corpora

1) Methods for inferences about texts using pre-determined words/phrases
2) Methods for comparing language use across groups
3) Methods for discovering new organizations of text
4) Methods for efficiently classifying texts to a predetermined classification scheme
Plan for Course

Week 1: Finding Text Data

Week 2: Texts to Numbers

Week 3: Dictionary Methods

Week 4: Comparing Language

Week 5: Vector Space Model

Week 6, 7: Discovering Categories

Week 8, 9: Classifying Texts
Plan for Course: **Applied Focus**

Week 1: Finding Text Data

Week 2: Texts to Numbers → Week 5: Vector Space Model

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More on What Class is Covering

We’re not covering

- Machine Translation
- Word-sense disambiguation
- Collaborative Filtering
- Deep sentence parsing
- The IBM Jeopardy answer machine
- Self-aware machines (SkyNet...)

Examples/Methods draw heavily from what I find useful in my research
Enrolled Students and Motivated Auditors

Two components of evaluation:

1) 50%: Weekly assignments (on your own data)
2) 50%: A final paper analyzing text (broadly defined) using techniques from the class
Analyzing Text Can Be Hard (It Ain’t Magic)

Two simple problems: identify words and sentences in the following text
Analyzing Text Can Be Hard (It Ain’t Magic)

Two simple problems: identify **words** and **sentences** in the following text

At least $53 million in federal funds have gone to ACORN activists since 1994, and the controversial group could get up to $8.5 billion more tax dollars despite being under investigation for voter registration fraud in a dozen states. The economic stimulus bill enacted in February contains $3 billion that the non-profit activist group known more formally as the Association for Community Organizations for Reform Now could receive, and 2010 federal budget contains another $5.5 billion that could also find its way into the group’s coffers. A downloadable spreadsheet of the $53 million is posted on washingtonexaminer.com. Scott Levenson, ACORN’s national spokesman, said "we have received no significant federal funding." Michelle Bachmann (R-MN)
Analyzing Text Can Be Surprisingly Easy (It can seem magical)
(Lamar Alexander (R-TN) Feb 10, 2005)

<table>
<thead>
<tr>
<th>Word</th>
<th>No. Times Used in Press Release</th>
</tr>
</thead>
<tbody>
<tr>
<td>department</td>
<td>12</td>
</tr>
<tr>
<td>grant</td>
<td>9</td>
</tr>
<tr>
<td>program</td>
<td>7</td>
</tr>
<tr>
<td>firefight</td>
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<tr>
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<td>homeland</td>
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<td>fund</td>
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<td>award</td>
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</tr>
<tr>
<td>support</td>
<td>2</td>
</tr>
<tr>
<td>equip</td>
<td>2</td>
</tr>
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<td>applaud</td>
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What Can Text Methods Do?

Haystack metaphor:

- Improve Reading
  - Interpreting the meaning of a sentence or phrase
  - Analyzing a straw of hay
  - Humans: amazing (Straussian political theory, analysis of English poetry)
  - Computers: struggle
    - Comparing, Organizing, and Classifying Texts
      - Organizing hay stack
        - Humans: terrible. Tiny active memories
        - Computers: amazing
  - the subject of this course

What we won't do:

- Develop a comprehensive statistical model of language
- Replace the need to read
- Develop a single tool + evaluation for all tasks
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Small Problems are harder than you think

Manually develop categorization scheme for partitioning small (100) set of documents

Bell(1) = number of ways of partitioning n objects

Bell(2) = 2 (AB, A B)

Bell(3) = 5 (ABC, AB C, A BC, AC B, A B C)

Bell(5) = 52

Bell(100) ≈ 4.75 × 10^{115} partitions

Big Number: 7 Billion RAs

Impossibly Fast (enumerate one clustering every millisecond)

Working around the clock (24/7/365)

≈ 1.54 × 10^{84} × (14,000,000,000) years

Automated methods can help with even small problems
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A Brief Digression on Computing Languages

- Texts processing is active across many computer languages
- **Goal**: useful tools in R
- **Reality**: if you want automated texts to occupy a central part of research, you need to know a little
  - HTML
  - Python (or PERL)
  - If you knew JAVA or C, you’d be a step ahead
- We’ll talk about how to hire programmers to eliminate language gap
- I’ll post python code on course site [note: Kludgey Python Code]
Where and How to Find Text Data?

Internet and archives have massive stores of text data (and growing!)

- **Prepackaged Data**
- **Computer and Human intensive Web Scraping**
- **Archive Materials and Optical Character Recognition**

Goal: plan text (.txt) file. (UTF-8, ASCII)
An obvious plan for data acquisition

- Check prepackaged resources
  - Lexis-Nexis (Batch Downloads)
  - Proquest
  - Research Librarians

- Move to web based search
  - Before deciding to scrape a data set:
    - Is the HTML standardized? (Our example today: no [Xtreme webscraping])
    - Does the website allow you to scrape? (Not always)
    - Can you do it faster by hand? With Mturk?

- Archival research
  - Invest in a scanner that allows OCR
  - Before making plans to scan, be sure archives allows scanning
Two examples from prepackaged data sources
Automated Literature Reviews

How do we conduct literature reviews?

- Think about literature (ask graduate student working in area for help)
- Make an argument about the deficiency/gaps in that literature
- Cite the prominent articles, make an argument about "conventional wisdom" (which is always wrong), call it a day

Literature reviews and analysis of concept development are difficult text problems
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JSTOR data, now available for download
http://dfr.jstor.org
Live example
History of Home Style

Congressional Life Cycle

Year

Prop. Topic

Justin Grimmer (Stanford University)

Text as Data

April 6th, 2011
History of Home Style

Casework and the Incumbency Advantage

Year
Prop. Topic

0.00 0.02 0.04 0.06 0.08 0.10
History of Home Style

Causes of Roll Call Voting Decisions

Year
Prop. Topic

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History of Home Style

Ideological Shirking

Year

Prop. Topic

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Text as Data

April 6th, 2011 19 / 26
History of Home Style

Biases in Congressional Communication

Prop. Topic

Year

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Intellectual History and Google Books

Scholars of political thought:

Live Example, Part 2.
Scholars of political thought: Careful (manual) analysis of texts.
Scholars of political thought: Careful (manual) analysis of texts. Many books now available for download thanks to google

Live Example, Part 2.
Intellectual History and Google Books

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- books.google.com
- Advanced Search
- Full view only
- Download ”.epub”
- Use a converter

Live Example, Part 2.
Human and Computer Based Web Scraping
Mechanical Turk

- Mechanical Turk is an Amazon run marketplace for workers (humans).
- We can replicate this task by asking (bored, poor, bored & poor) workers to do the task.
- Distribute small tasks across workers.

Live Example 3: Paul Tonko (D-NY)
Mechanical Turk

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Live Example 3: Paul Tonko (D-NY)
A Brief Introduction to Web Scraping

How do we get other data?

Web pages are loaded with text data, but not necessarily prepared for download. Web scraping allows us to interact with HTML to extract text from web pages, which requires some programming expertise.
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Xtreme Web Scraping

- Congressional Web Sites and Press Releases
- Web Sites: Mix of professionals, capable amateurs, and horrible html writers
- No coherent structure across websites
- Difficult scraping problem: collecting press releases from a web site

Live Example 4, Paul Tonko (D-NY)
- Identify pages with press releases
- Extract press releases from page
Programming/Data Acquisition Help

- ODesk: submit programming tasks to coders (must be very specific)
- Elance: submit many small tasks to dedicated workers (don’t mind outsourcing work to India/OK with not paying minimum wage)
- Guru: “World’s largest online marketplace”
Conclusion

Today: Introduction and where to get text
Next week: how to represent text quantitatively