Political Science 452: Text as Data

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  - Idiosyncratic to coders/researcher

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American Politics

- Policy Agendas Project
    - Congressional Bills Project
- LYDIA

Comparative Politics

- Legislative Speech Project
- Comparative Manifesto Project

International Relations

- Penn State Event Data Project

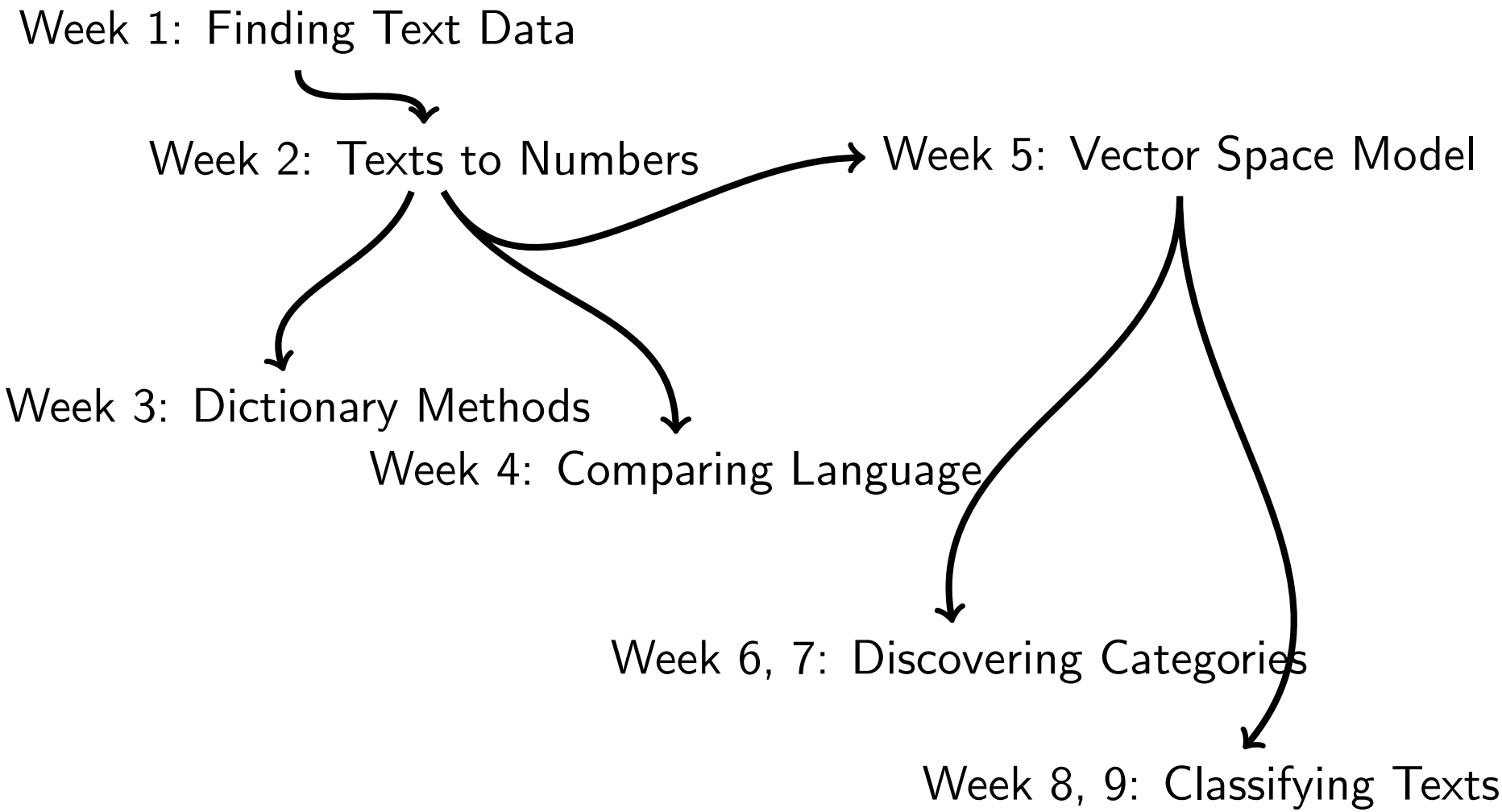
Why?

- 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
  - ...

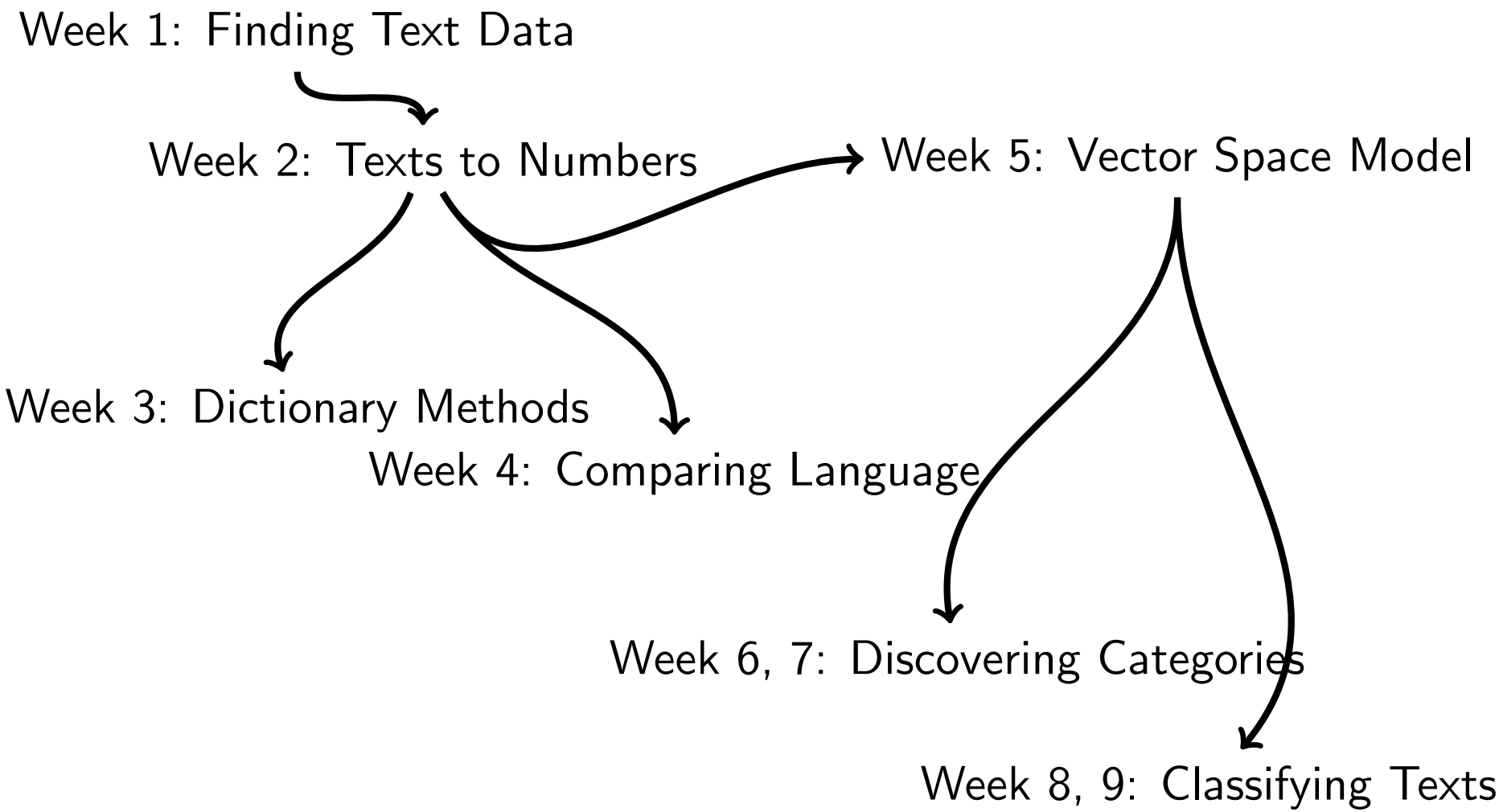
We will study a set of tools for the useful and principled analysis of massive text corpora

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



Plan for Course: Applied Focus



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

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

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```
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)

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

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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

Small Problems are harder than you think

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Automated methods can help with even small problems

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

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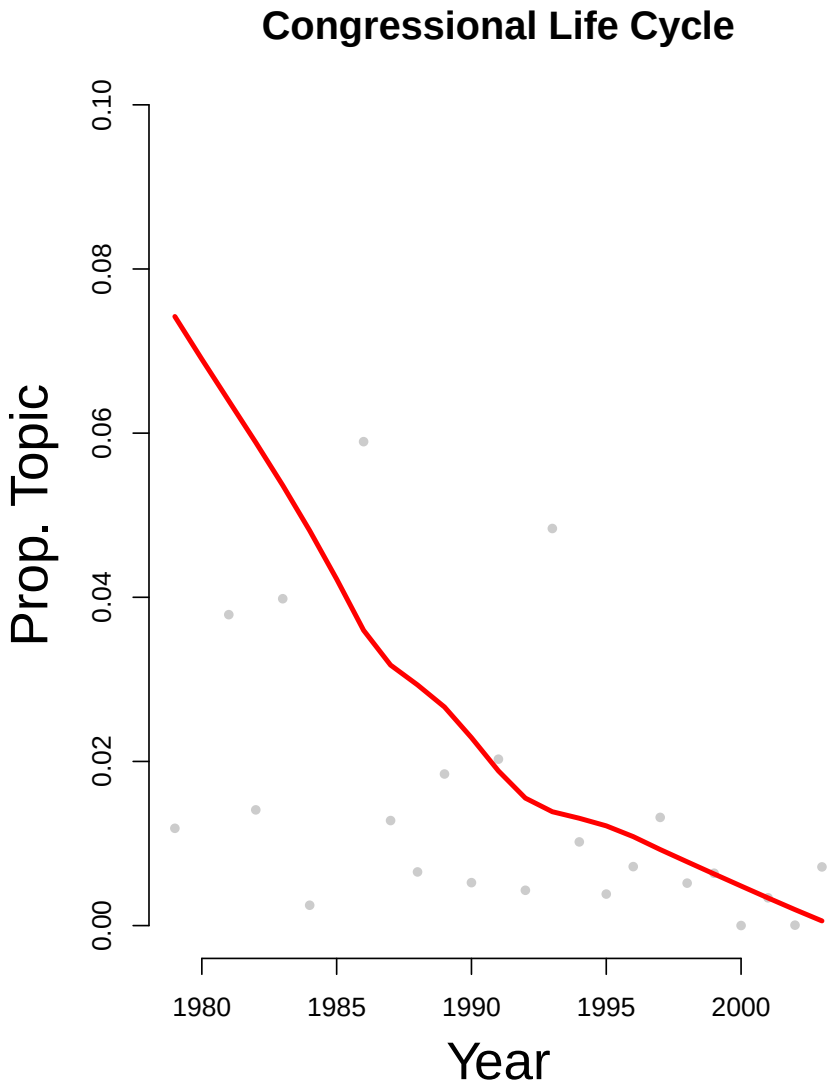
Literature reviews and analysis of concept development are difficult text problems

Automated Literature Reviews

JSTOR data, now available for download
`http://dfr.jstor.org`
Live example

History of Home Style



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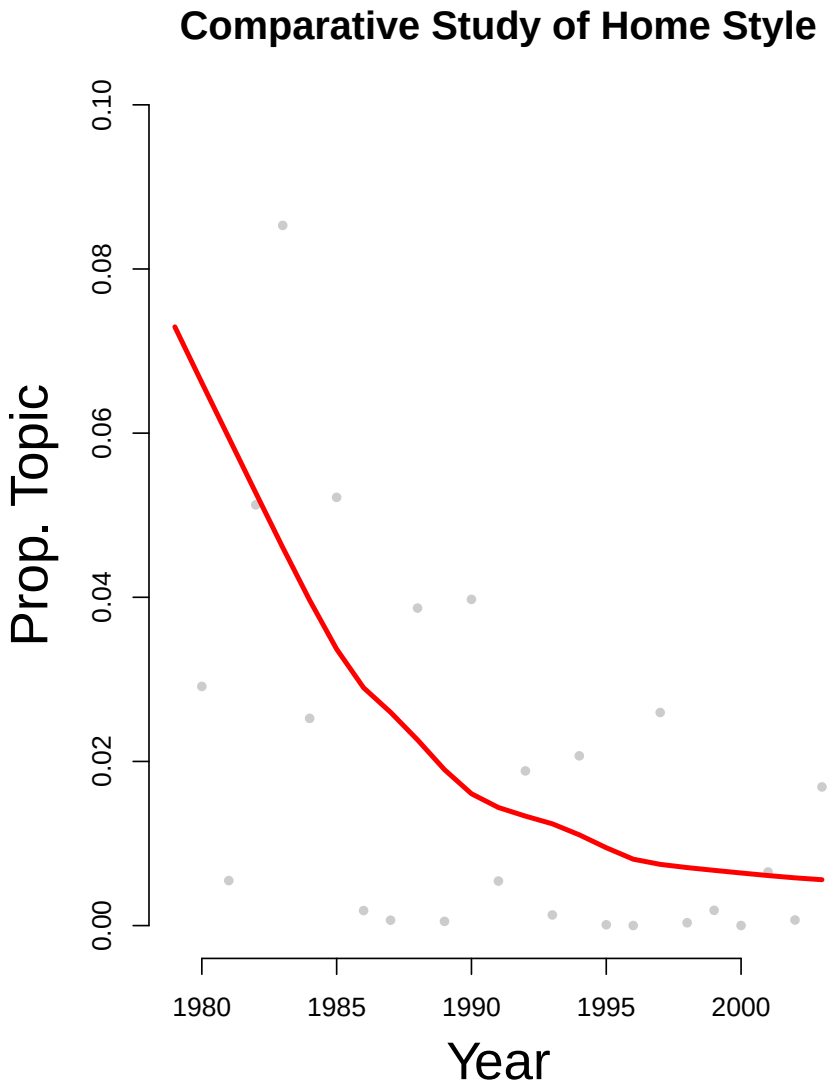

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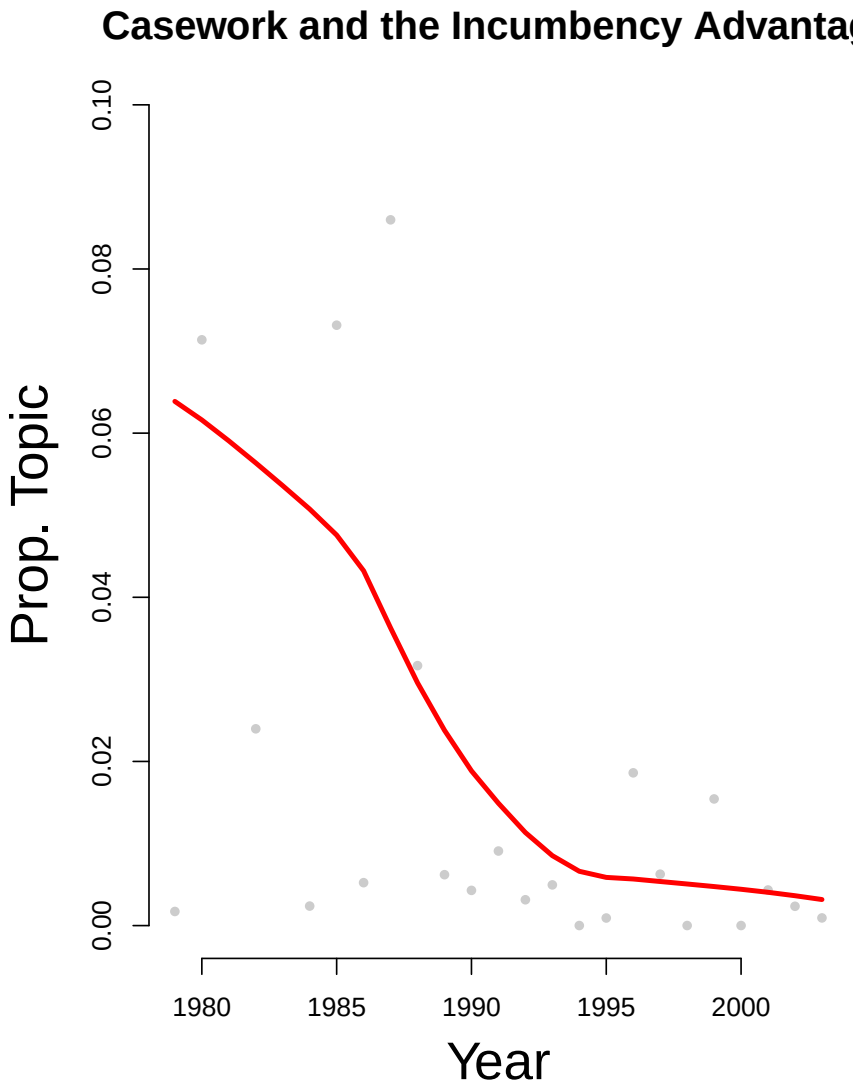

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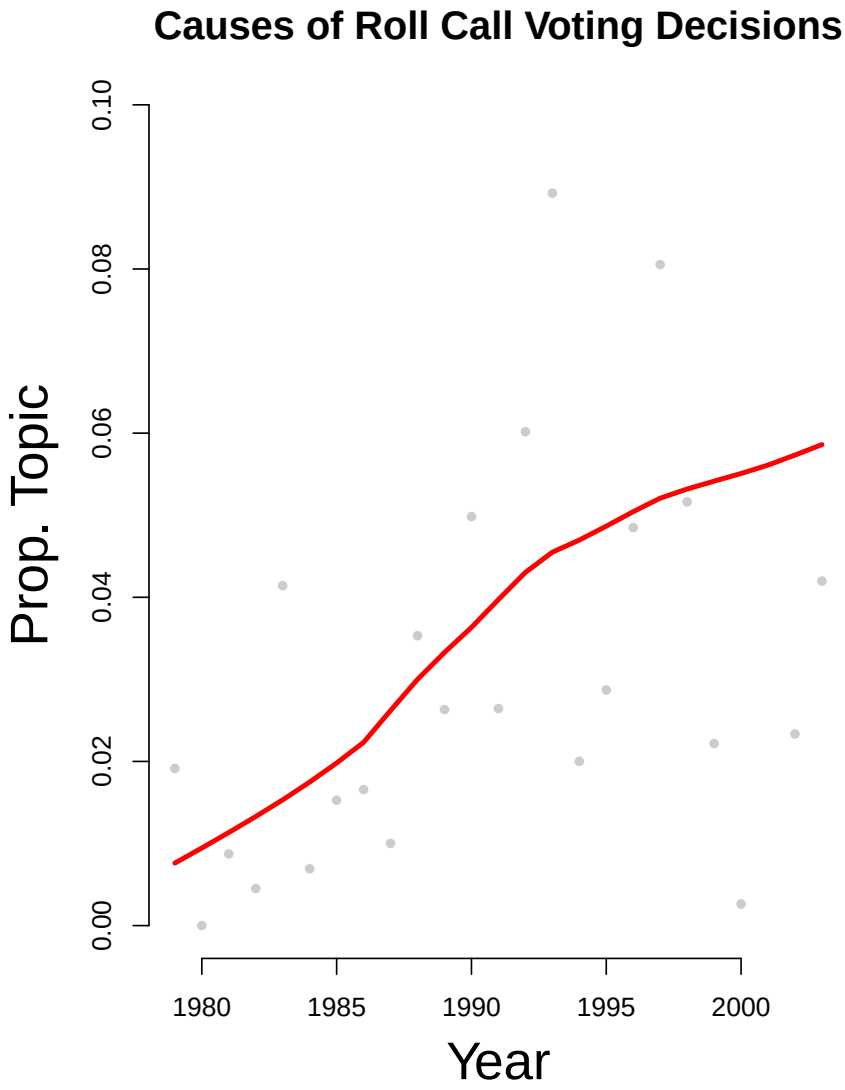

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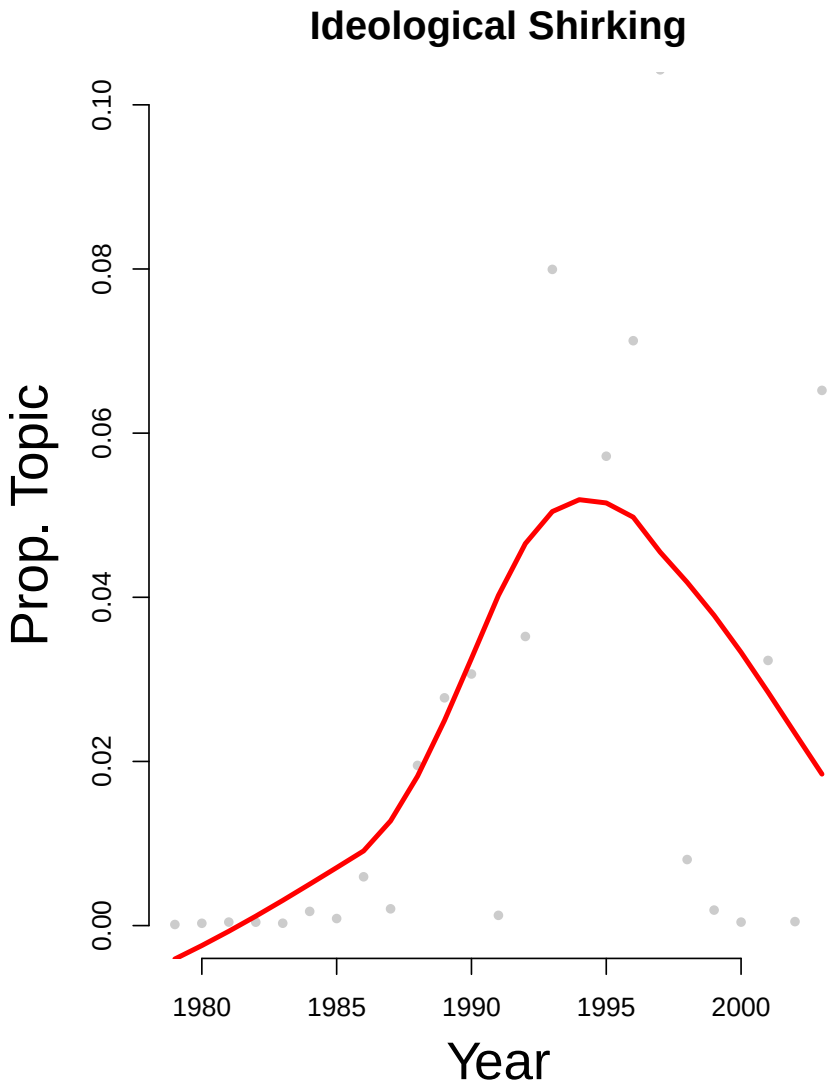

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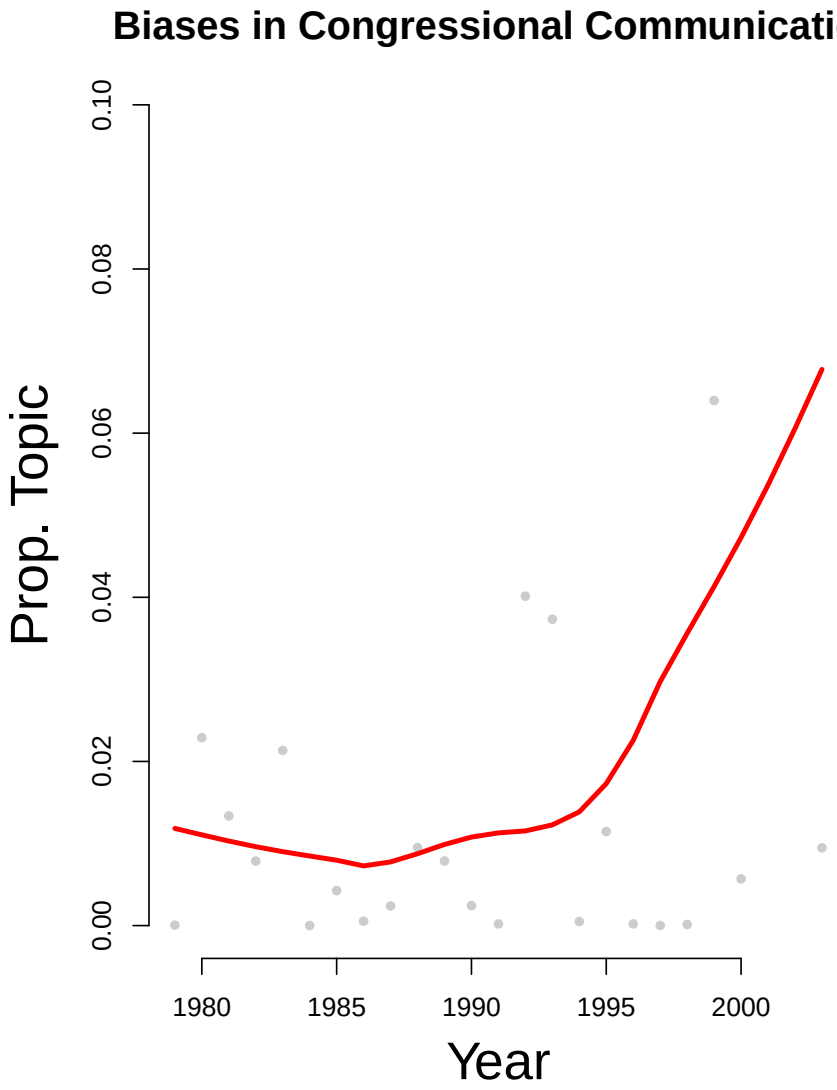

Intellectual History and Google Books

Scholars of political thought:

Live Example, Part 2.

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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

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Live Example 3: Paul Tonko (D-NY)

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- Requires some programming expertise

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

Other Data Sources/Acquisition

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