Tracking Theoretical Shifts over Time

A Natural Language Processing Analysis of

Cass R. Sunstein

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Introduction

Related Work

Introduction

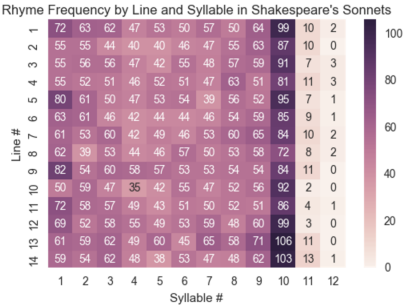
Applying NLP to law and economics:

- *Five reasons for the use of network analysis in the history of economics* [Catherine and Doehne, 2018]
- *What topic modeling could reveal about the evolution of economics* [Ambrosino et al., 2018]
- *Forty Years of Behavioral Economics* [Truc, 2021]

A Unique Approach

Introduction

- Ideological analysis over time
- Single-author corpus?
  - Literature only [Culpeper and Archer, 2020]



Application - 1/2

Introduction

- Chicago school of economics (neoclassical economics)
- *Homo economicus* $\rightarrow$ perfect rationality
- Psychologists (Amos Tversky, Daniel Kahneman) in the 1960s
- Behavioral economics: bounded rationality, heuristics, biases
- Prospect theory (losses $\neq$ gains)

Application - 2/2

Introduction

- Cass R. Sunstein (born 1954)
- University of Chicago Law School
- Republicanism (not the Republican party)
- Libertarian paternalism, *Nudge* in the 2000s

Working Hypotheses

Introduction

In Sunstein's articles:

- Can we detect a transition from republicanism to behavioral economics? When?
- How to represent subtopics of republicanism (citizenship, civic virtue...) over time?
- How to model the interaction between global topics (poverty, autonomy...)?

Methodology

Introduction

Three main phases:

- Corpus acquisition and cleaning
- Frequentist, statistical analysis (mostly supervised)
- Machine learning analysis (mostly unsupervised)

Perspectives

- Semi-supervised, ”objective” text interpretation
- Field orthogonal to ours, with an expert in economics

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Corpus acquisition and processing

Selection and retrieval

Corpus acquisition and processing

- Two sources: JSTOR[1] and Chicago Unbound[2]
- 1987-2005: 215 + 415 = 620 articles
- Duplicates/quality filtering: working versions?
- Final list: 231 PDF files

[1] https://www.jstor.org/
[2] https://chicagounbound.uchicago.edu/

Text extraction

Corpus acquisition and processing

- Three main OCR tools
- LAPDFText > CERMine > Tesseract/OCRmyPDF (for our use)

Manual cleaning

Corpus acquisition and processing

Duration: 40-60 hours.

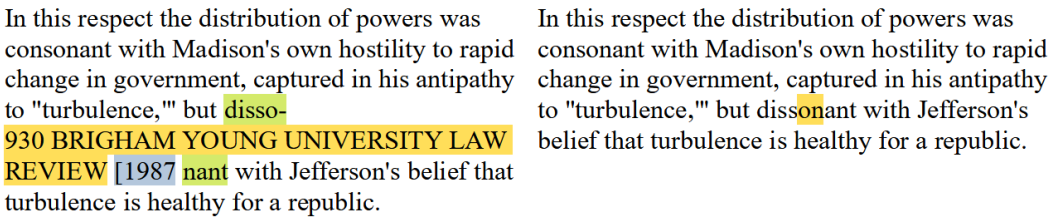


Figure 1: Cleaning of a page/line break (green), page footer (yellow) and header (blue).

Not pictured: missing pages (usually a few), structured data (figures, tables).

Automatic cleaning

Corpus acquisition and processing

Duration: 15-20 hours.

Judicial control of regulatory behavior has come in the form of the "hardlook" doctrine, initi- ally developed by the United States Court of Appeals for the District of Columbia CIrCUIr, 2 and subsequently endosred by the Supreme Court.3 3 The hard-look doctrine has both procedural and substantive elements. Procedurally, it requires regulatory agencies to generate detailed explanations for their decisions-to consider reasonable alternatives.'"	Judicial control of regulatory behavior has come in the form of the "hard-look" doctrine, initially developed by the United States Court of Appeals for the District of Columbia Circuit, and subsequently endorsed by the Supreme Court. The hard-look doctrine has both procedural and substantive elements. Procedurally, it requires regulatory agencies to generate detailed explanations for their decisions — to consider reasonable alternatives.

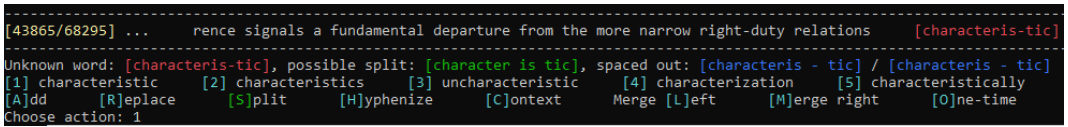
Figure 2: Cleaning of footnote numbers (yellow), typographical/OCR errors (green), bad de-hyphenation (blue) and dash-hyphen confusion (red).

Automatic cleaning - The Monster

Corpus acquisition and processing

Automatic cleaning - The Monster

Corpus acquisition and processing



Automatic cleaning - The Monster

Corpus acquisition and processing

Type	Number of items learned
Unknown words	11,648
Word substitution rules	2,078

Table 1: Statistics obtained using the Monster.

Resulting Corpus

Corpus acquisition and processing

- 231 text files
- 43 thousand paragraphs
- 2.8 million words
- 17.5 million characters

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NLP for validating hypotheses

TF-IDF

NLP for validating hypotheses

Term Frequency-Inverse Document Frequency (TF-IDF)

- Basic statistical method, extracts words specific to each document
- Counts word frequencies in each document (year) and over the whole corpus
- Applies the following formula for each year

$$\text{tfidf}(t, d, D) = \frac{f_d(t)}{\sum_{w \in D} f_d(w)} \log\left(\frac{|D|}{|\{d \in D : t \in d\}|}\right)$$

- The bigger the TF-IDF at time t, the more important the word

Results

NLP for validating hypotheses

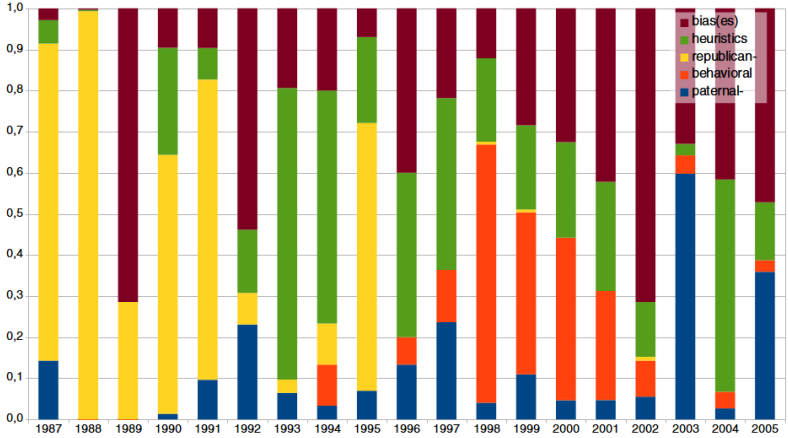
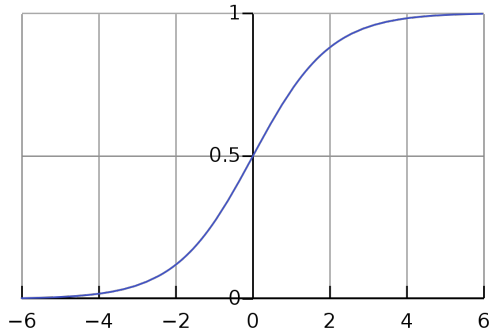


Figure 3: The normalized TF-IDF of selected words over time.

Transition Modeling

NLP for validating hypotheses

$$h(x) = \frac{1}{1 + e^{-x}}$$



Why the sigmoid?

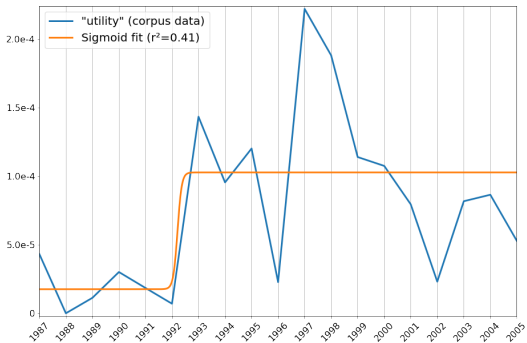
NLP for validating hypotheses

$$f(L, k, x, x_0, b) = \frac{L}{1 + e^{-k(x-x_0)}} + b$$

- Organic approximation
- Helps us filter words
- Visualizes intensity of change and length

Word selection

NLP for validating hypotheses



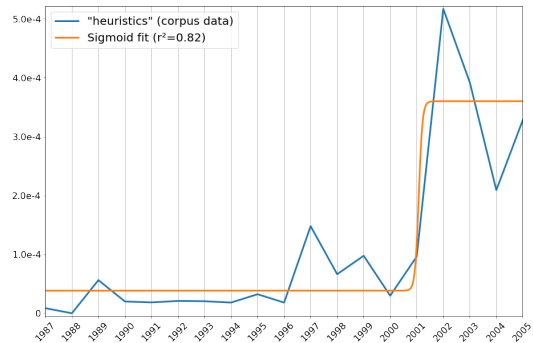
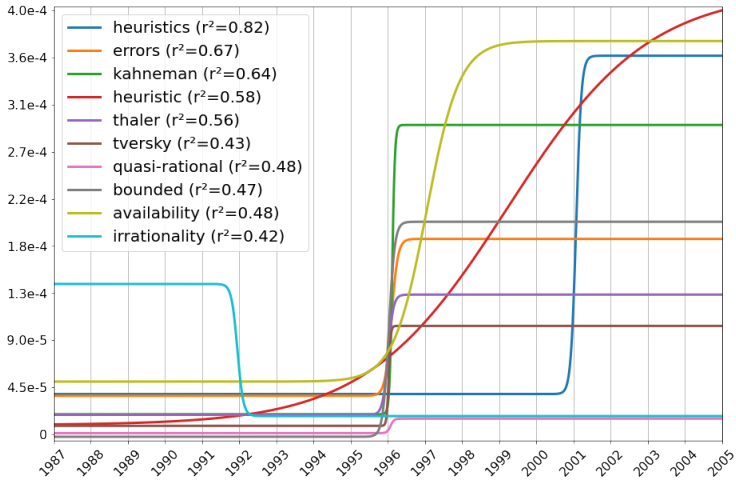


Figure 4: Observed versus fitted data for a low (left) and a high (right) value of r^2.

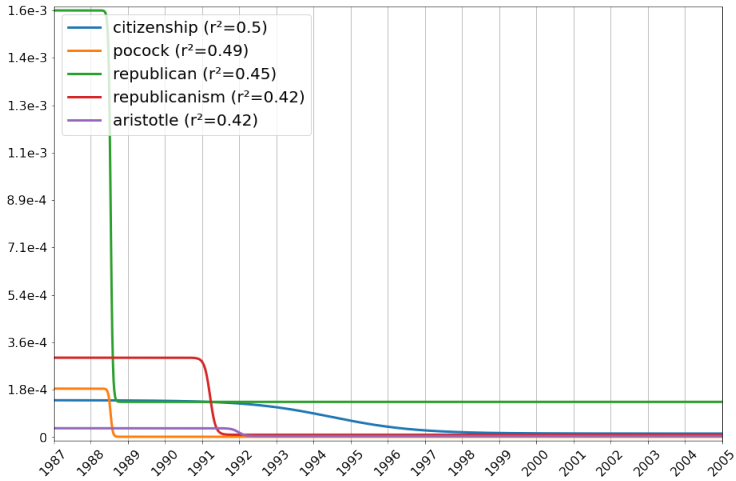
Results 1/2

NLP for validating hypotheses



Results 2/2

NLP for validating hypotheses

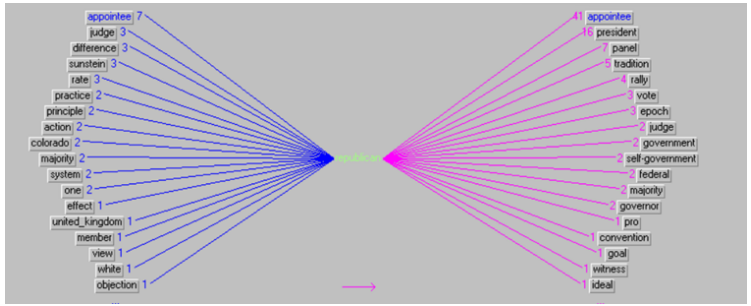


Semantic Analysis with Tropes

NLP for validating hypotheses

Semantic Analysis with Tropes

NLP for validating hypotheses



Results

NLP for validating hypotheses

Figure 5: "Heuristic" before and after 1994.

Results

NLP for validating hypotheses

Figure 6: ”Preferences” before and after 1994.

Results

NLP for validating hypotheses

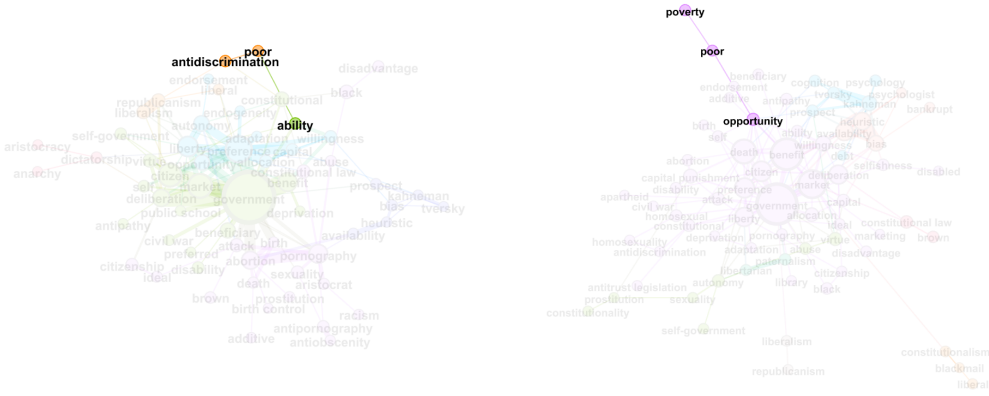


Figure 7: ”Poor” before and after 1994.

Results

NLP for validating hypotheses

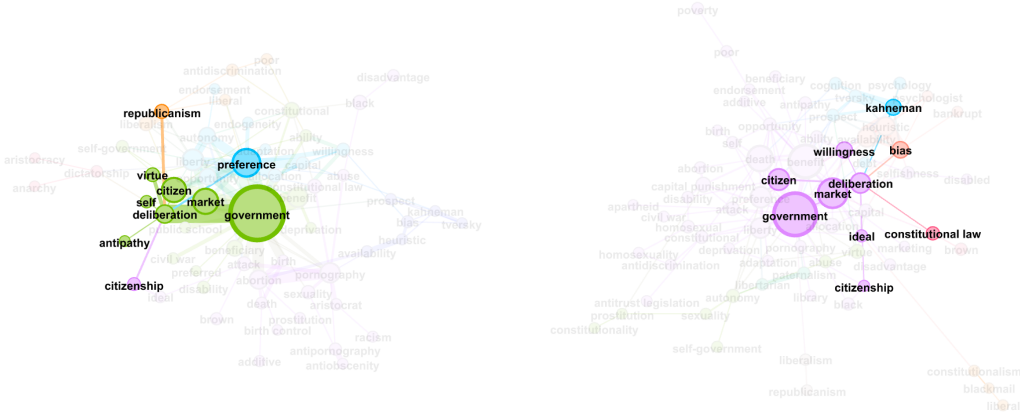


Figure 8: ”Deliberation” before and after 1994.

Global results: 1987-1993 / 1994-2005

NLP for validating hypotheses

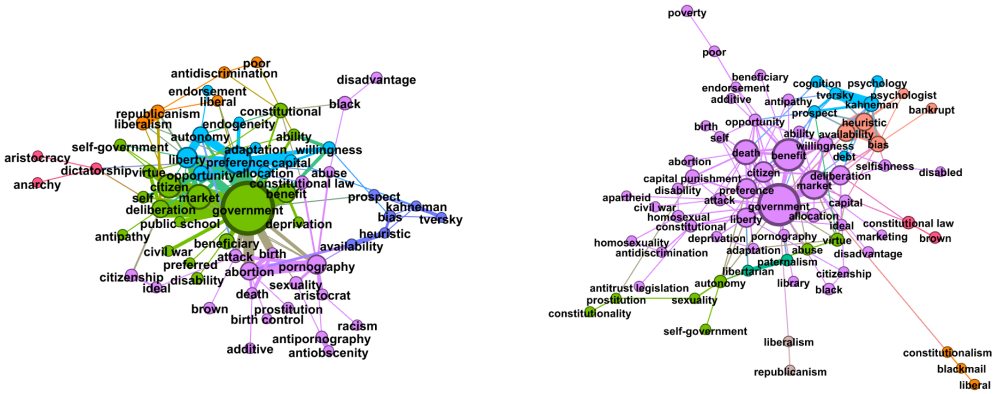


Figure 9: The entire graph before and after 1994.

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NLP tools as a source of new hypotheses

What is topic modeling?

NLP tools as a source of new hypotheses

- Extraction of main themes
- Topics
- Weights

Latent Dirichlet Allocation

NLP tools as a source of new hypotheses

LDA [Blei et al., 2003] solves this problem:

- One of the first unsupervised methods
- Words that appear in the same context are part of the same topic
- We can select the number n of topics

Results

NLP tools as a source of new hypotheses

1987 (topics 1 and 2)	
.011*power	.017*state
.008*administrative	.014*court
.008*judicial	.012*statute
.008*understanding	.010*regulatory
.008*contract	.010*private
.006*state	.009*democracy
.006*agency	.009*protection
.006*justice	.009*provide
.006*lochner	.009*discrimination
.006*system	.009*agency

1995 (topics 1 and 2)	
.020*right	.009*lawyer
.011*people	.007*theory
.009*rule	.007*social
.008*category	.006*people
.008*constitutional	.006*constitutional
.007*political	.006*political
.007*particular	.006*general
.006*might	.005*right
.006*think	.005*rule
.006*change	.005*agreement

2005 (topics 1 and 2)	
.009*would	.014*precautionary
.008*people	.013*principle
.008*paper	.010*discount
.007*activity	.008*risk
.006*agency	.007*regulation
.006*perhaps	.007*supra
.006*engage	.006*benefit
.006*relatively	.020*sunstein
.006*procedure	.011*market
.006*likely	.011*posner

Cons

NLP tools as a source of new hypotheses

This method still has flaws:

- Still relies on expert input
- Not consistent
- Depends on the n value

Dynamic and Embedding Topic Modeling

NLP tools as a source of new hypotheses

- [Blei and Lafferty, 2006] introduces Dynamic Topic Modeling (DTM)
- [Dieng et al., 2020] also upgrades topic modeling to Embedding Topic Modeling (ETM)

While we did not use either, it led us to a great discovery...

Bertopic

NLP tools as a source of new hypotheses

BERTopic [Grootendorst, 2022]: topic modeling algorithm using word embeddings (through BERT) to represent the evolution of topics.

What is BERT?

NLP tools as a source of new hypotheses

Bidimensional Encoder Representations from Transformers (BERT)

- Series of large transformer models
- Shown to perform very well in a large array of NLP tasks
- Internally relies on word embeddings

Better results!

NLP tools as a source of new hypotheses

Topic #	Words
0	punitive, awards, damages, jury, juries, dollar, judgments, punishment, punitive damages, outrage
1	speech, amendment, free, first amendment, pornography, first, government, free speech, expression, viewpoint
2	id, see id, see, id id, id 38, 38, 28 id, id 535, id 67, 66 id
3	discrimination, affirmative, affirmative action, action, racial, race, caste, equality, black, principle
4	president, executive, power, congress, presidential, framers, powers, control, authority, independent
5	us, 1976, see, 1973, usc, united, cir, 424, eg, 410
6	epa, air, pollution, clean, environmental, act, standards, clean air, emissions, air act
7	risk, risks, people, probability, slovic, availability, heuristic, fear, availability heuristic, information
8	interpretation, statutory, interpretive, statutes, meaning, principles, courts, norms, legislative, text
9	standing, injury, plaintiff, article, injury fact, suit, court, congress, iii, article iii

Groups of topics

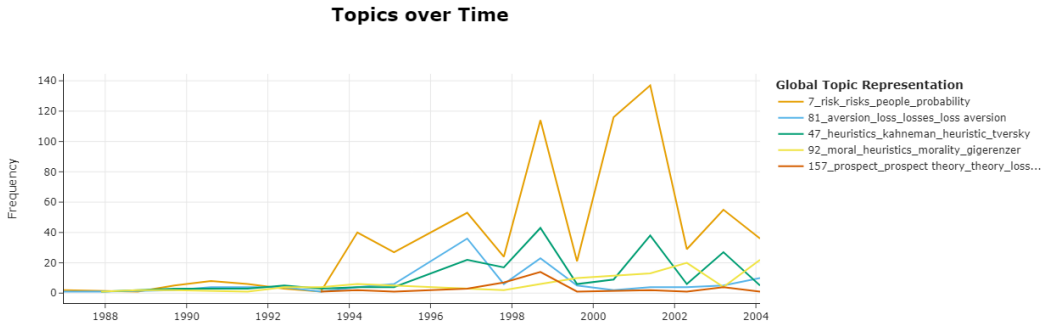
NLP tools as a source of new hypotheses

Category	Topics
Political philosophy	36, 40, 44, 51, 75, 130
Economic approaches	24, 146
Ethics	125, 134
Judicial interpretations	19, 33, 39, 50, 155
Libertarian paternalism	13, 74
Moral philosophy	3, 13, 18, 35, 61, 74, 121
Behavioral economics	7, 47, 81, 92, 157
Endowment effect	65
Miscellaneous	12, 55

Table 2: Groups of topics extracted from BERTopic, labeled by prof. Ferey.

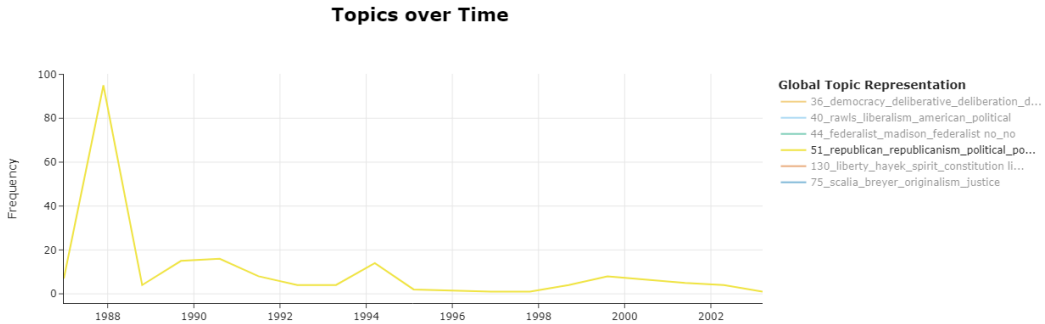
Example of frequency analysis

NLP tools as a source of new hypotheses



Example of frequency analysis

NLP tools as a source of new hypotheses



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Conclusion

Results and interpretation

Conclusion

- The hypothesis seems true, through multiple methods
- Republican $\rightarrow$ Behavioral economics
- Sub-topics: poverty, deliberation, preferences
- Objective text interpretation?

Takeaways?

Conclusion

- Applying many methods from the master's
- Customer - consultant relationship
- Good preparation for interdisciplinary work - common in NLP

Q&A

Thank you for listening!
Your feedback will be highly appreciated.

References I

Conclusion

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SSRN Scholarly Paper ID 3762621, Social Science Research Network, Rochester, NY.

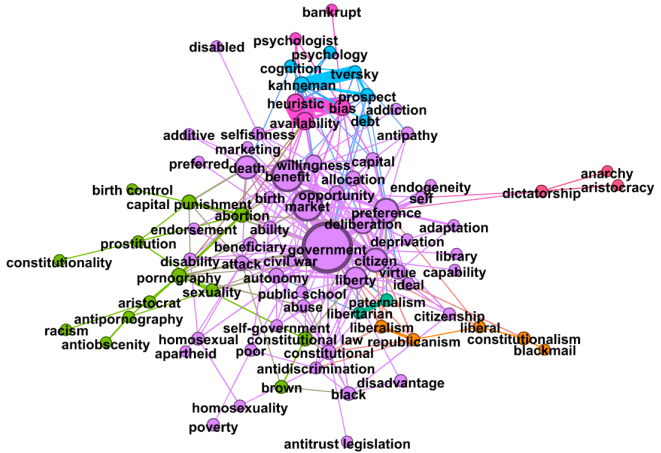
What would we change?

Conclusion

- Rely more on existing work (literature)
- Corpus cleaning: start automation earlier
- Give ourselves more deadlines

Global results: 1987-2005

Conclusion



Text extraction

Conclusion

- Question of footnotes, de-hyphenation?
- Mostly LAPDFText (80%), manual footnote insertion
- CERMine for the remaining articles (more footnote work)
- 4 bad articles: OCRmyPDF + manual de-hyphenation

Text extraction

Conclusion

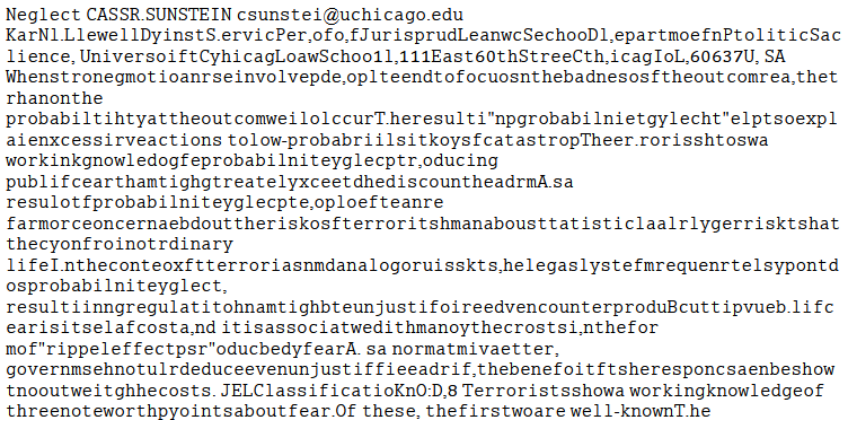


Figure 10: An article requiring the use of OCRmyPDF.

Corpus evaluation

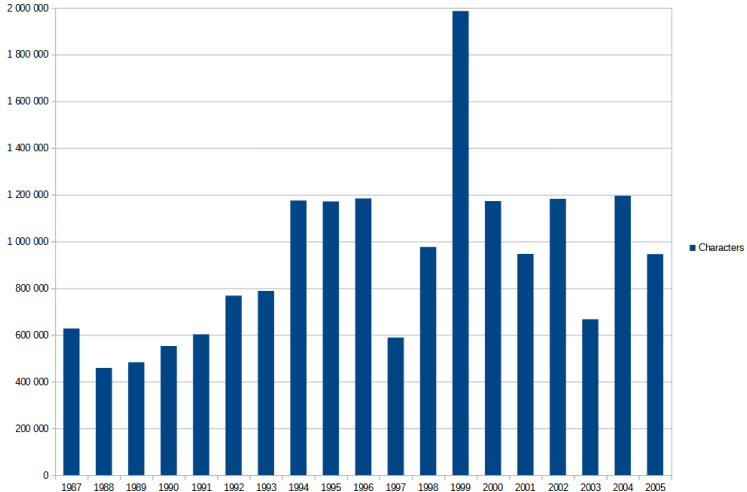
Conclusion

Corpus	Minimum	Maximum	Average	Std. deviation
CERMine	11.618	269.665	22.057	20.778
LAPDFText	11.018	39.360	18.418	3.315
Manual cleaning	10.995	23.275	17.085	2.268
Manual + auto. cleaning	10.495	22.130	16.705	2.151

Table 3: Statistics about the average sentence perplexity computed over all articles.

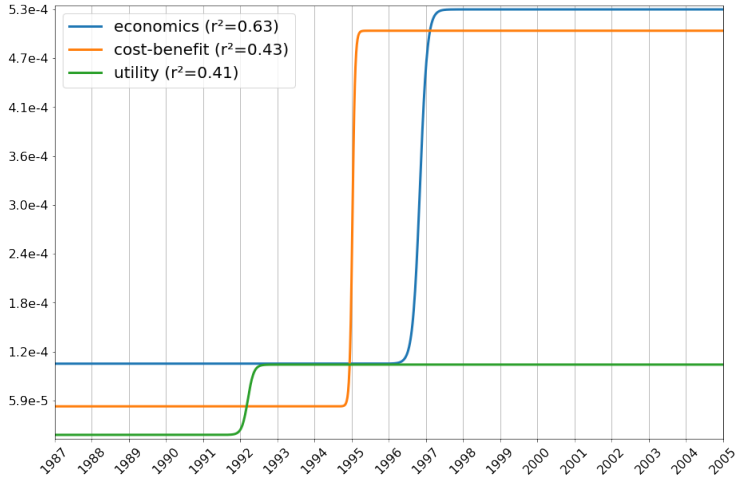
Resulting corpus

Conclusion



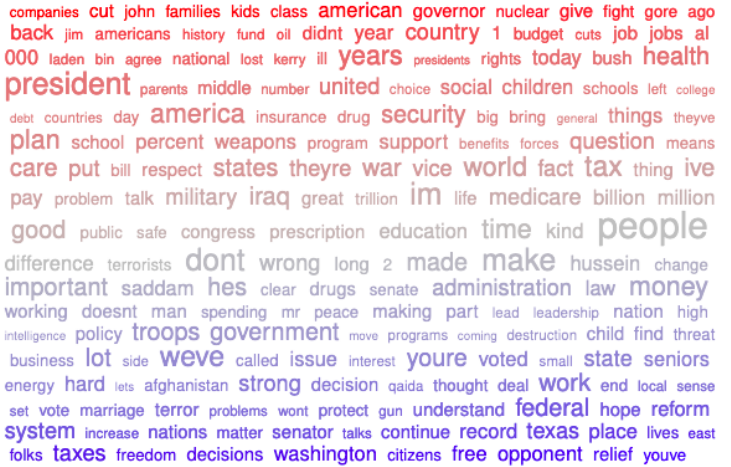
Results 3/3

Conclusion



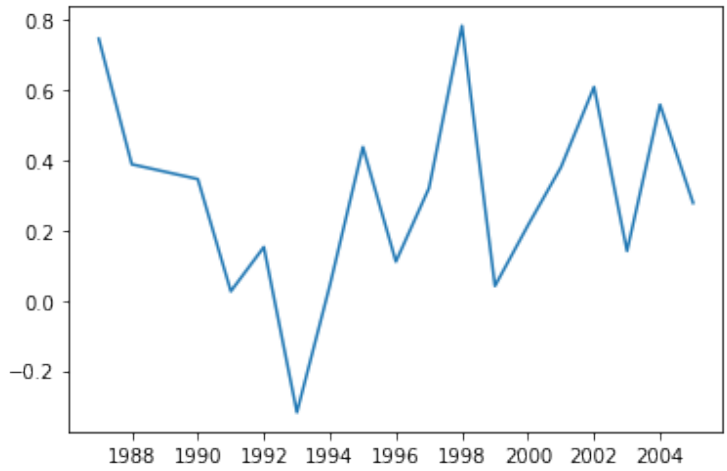
Supervised approaches

Conclusion



Sentiment Analysis with NLTK

Conclusion



Future work

Conclusion

- Posner-Becker blog
- [Jelveh et al., 2018]
- [Ahmed and Xing, 2010]