

Natural Language Processing for Law and Social Science

3. Dimensionality and Distance

Q&A Page

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- ▶ Both strategies amplify human effort, each in different ways.
- ▶ Distinctions are not clear-cut:
 - ▶ supervised learning models can be used to discover themes/patterns
 - ▶ unsupervised learning models can be used in service of prediction or known goals.

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4. Empirical analysis
 - ▶ Produce statistics or predictions with the trained model.
 - ▶ **Answer the research question.**

Outline

Document Distance

Dimensionality Reduction

Topic Models

Response Essays

Text Re-Use

- ▶ Text Re-Use algorithms (like “Smith-Waterman”) measure similarity by finding and counting shared sequences in two texts above some minimum length, e.g. 10 words.
 - ▶ useful for plagiarism detection, for example.
- ▶ precise but slow
 - ▶ shortcut: look at proportion of shared (hashed) 5-grams across texts

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 - ▶ that is, documents are rays, and similar documents have similar vectors.
- ▶ Can measure similarity between documents i and j by the cosine of the angle between x_i and x_j :
 - ▶ With perfectly collinear documents (that is, $x_i = \alpha x_j$, $\alpha > 0$), $\cos(0) = 1$
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Cosine similarity is computable as the normalized dot product between the vectors:

$$\text{cos_sim}(x_1, x_2) = \frac{x_1 \cdot x_2}{\|x_1\| \|x_2\|}$$

```
from sklearn.metrics.pairwise import
cosine_similarity
# between two vectors:
sim = cosine_similarity(x, y)[0,0]
# between all rows of a matrix:
sims = cosine_similarity(X)
```

Notes on Cosine Similarity

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Alternative distance metrics:

- ▶ dot product (sensitive to document length)
- ▶ Euclidean distance, $\|v_1 - v_2\|$
- ▶ Jensen-Shannon Divergence
- ▶ etc.

hopefully empirical results are not sensitive to choice of distance metric.

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(1) Legislative findings: the legislature finds that the best interest of a minor requires full parental involvement.

Figure 10: Match between Scott Walker’s bill and a highly similar bill from Louisiana. For a detailed view, please visit <http://dssg.uchicago.edu/lid/>.

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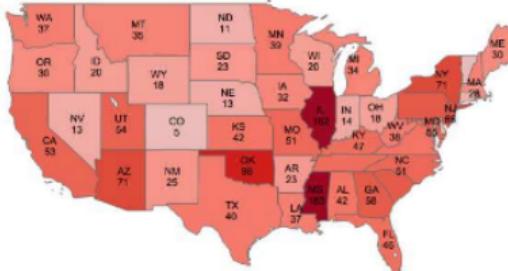


Figure 7: Introduced bills by state from ALEC model legislation

111 Legislative Findings. The legislature finds that the best overall outcome confirms the pain recognition function.

series of reviews, *Environment Canada*, 1973-1980. These documents have been present throughout the debate.

Paroxysmal nocturnal hematuria—In the later stages, atrophy, scarring, and calcification are seen throughout the kidney. The renal papillae are often lost, and the renal cortex is replaced by a dense, fibrous tissue. The kidney may become so contracted that it is hardly larger than a pea. After nephrectomy, hypertension, the urine color remains normal, and the patient is well until death. In the early stages, after kidney removal, hypertension, the urine color remains normal, and the patient is well until death.

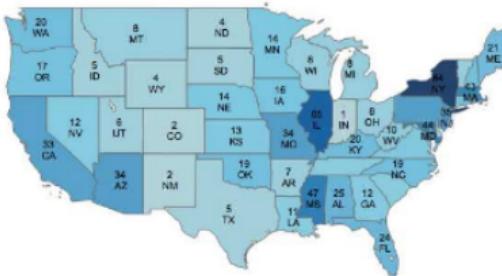


Figure 8: Introduced bills by state from ALICE model legislation

ABSTRACT

State legislatures introduce at least 45,000 bills each year. However, we lack a clear understanding of who is actually writing those bills. As legislators often lack the time and staff to draft each bill, they frequently copy text written by other states or interest groups.

However, existing approaches to detect text reuse are slow, biased, and incomplete. Journalists or researchers who want to know where a particular bill originated must perform a largely manual search. Watchdog organizations even hire armies of volunteers to monitor legislation for matches. Given the time-consuming nature of the analysis, journalists and researchers tend to limit their analysis to a subset of topics (e.g. abortion or gun control) or a few interest groups.

This paper presents the Legislative Influence Detector (LID). LID uses the Smith-Waterman local alignment algorithm to detect sequences of text that occur in model legislation and state bills. As it is computationally too expensive to run this algorithm on a large corpus of data, we use a search engine built using Elasticsearch to limit the number of comparisons. We show how LID has found 45,405 instances of bill-to-bill text reuse and 14,137 instances of model-legislation-to-bill text reuse. LID reduces the time it takes to manually find text reuse from days to seconds.

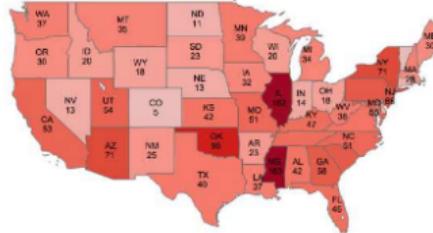


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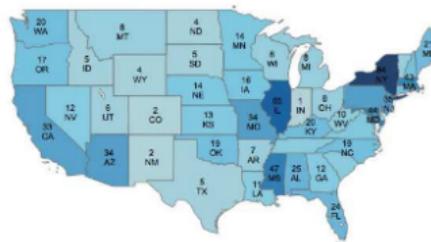


Figure 8: Introduced bills by state from ALICE model legislation

1. What is the research question?
2. Why is it important?
3. What is the problem solved?
4. What is being measured?
5. How does the measurement help answer the research question?

Outline

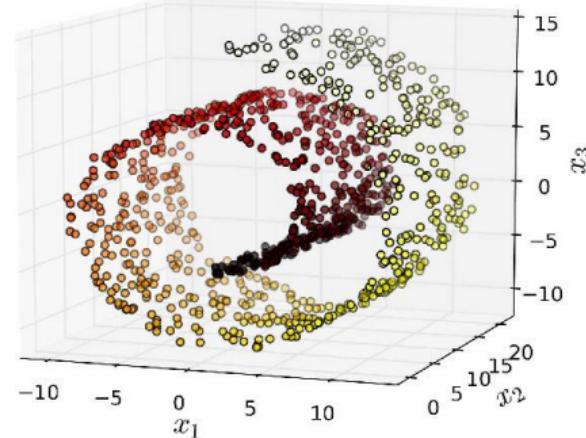
Document Distance

Dimensionality Reduction

Topic Models

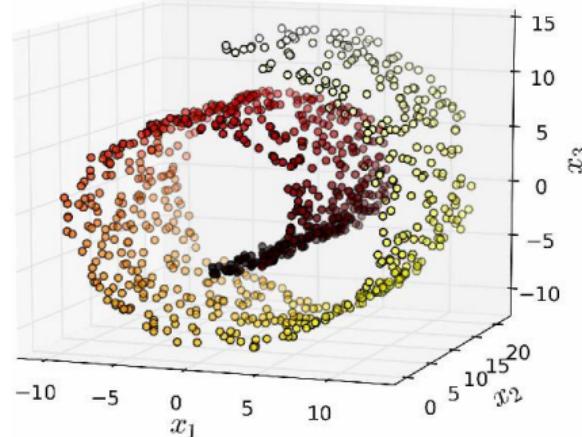
Response Essays

“The Swiss Roll”

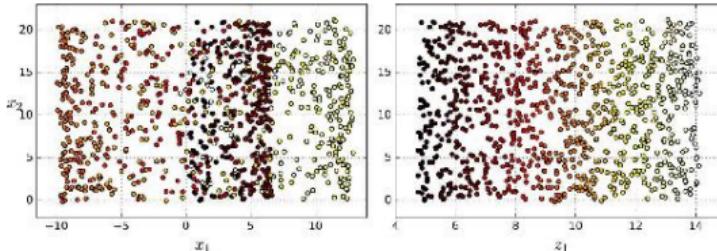


- ▶ Datasets are not distributed uniformly across the feature space.
- ▶ They have a lower-dimensional latent structure – a **manifold** – that can be learned.

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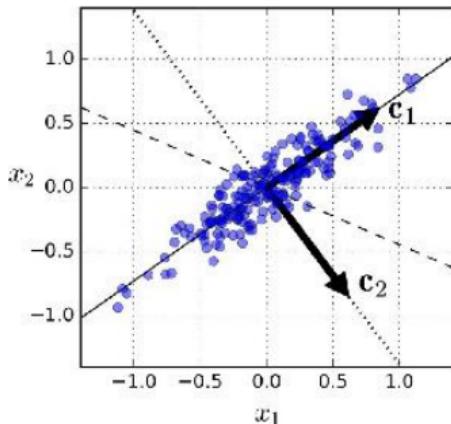


- ▶ **Dimensionality reduction** makes data more interpretable – for example by projecting down to two dimensions for visualization.
- ▶ improves computational tractability.
- ▶ can improve model performance.

What dimension reductions have we already tried?

PCA (principal component analysis) / SVD (singular value decomposition)

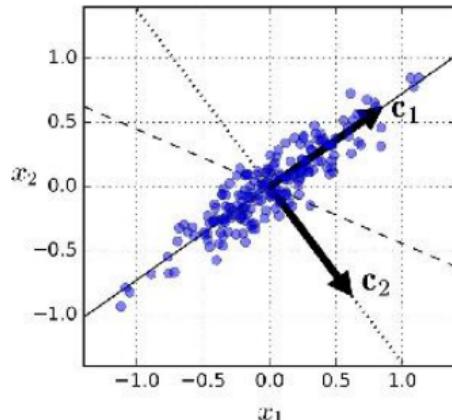
PCA (principal component analysis) / SVD (singular value decomposition)



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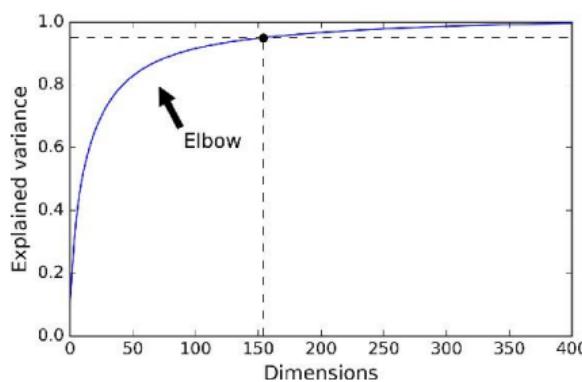
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- ▶ after the first component, subsequent components learn the (orthogonal) dimensions explaining most variance in dataset after projecting out first component.

PCA/NMF for Dimension Reduction

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 - ▶ compromise: use feature selection to keep strong predictors, and take principal components of weak predictors.
- ▶ PCA dimensions are not interpretable.
 - ▶ For non-negative data (e.g. counts or frequencies), **Non-negative Matrix Factorization (NMF)** provides more interpretable factors than PCA.

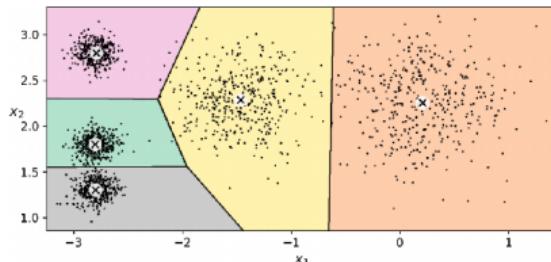
k -means clustering separates observations into k groups

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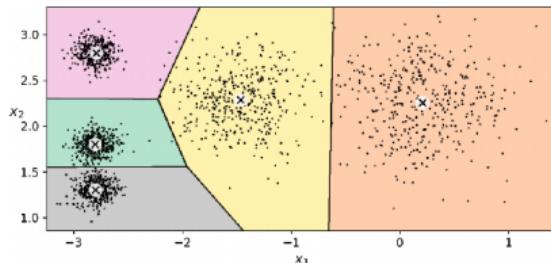


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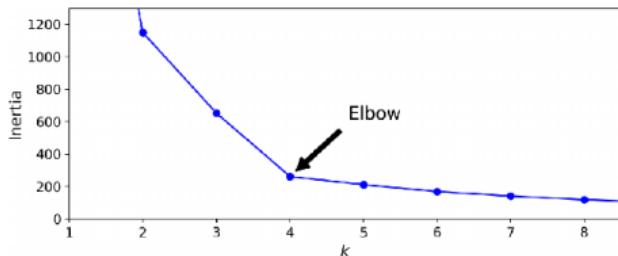
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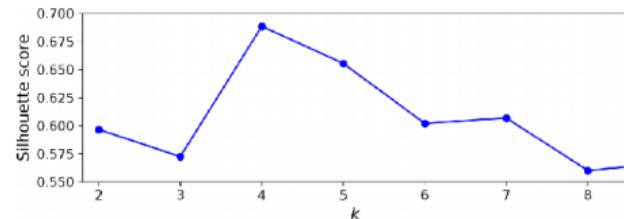
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k (number of clusters) is the only hyperparameter, can select using:



Selecting the number of clusters *k* using the “elbow rule”



Selecting the number of clusters *k* using the silhouette score

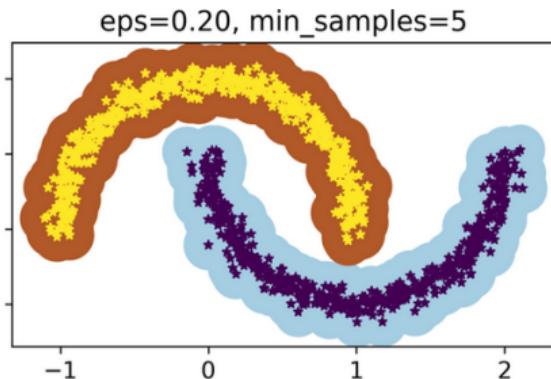
Other clustering algorithms

- ▶ “k-medoid” clustering use L1 distance rather than Euclidean distance; produces the “medoid” (median vector) for each cluster rather than “centroid” (mean vector).
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- ▶ DBSCAN defines clusters as continuous regions of high density.
 - ▶ detects and excludes outliers automatically



- ▶ Agglomerative (hierarchical) clustering makes nested clusters.

Applications

Ganglmair and Wardlaw, “Complexity, Standardization, and the Design of Loan Agreements”

- ▶ use k-medoid clustering to identify different types of debt contracts, and analyze customization.
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Hoberg and Phillips, “Text-Based Network Industries and Endogenous Product Differentiation”

- ▶ “business description” section from annual regulatory filings, preprocessed by extracting nouns, drop words appearing in more than 25% of documents.
- ▶ vector representation: binary for whether word appears (rather than counts)
- ▶ clusters of these vectors are “industries” – sets of firms with similar lists of nouns in their business descriptions.

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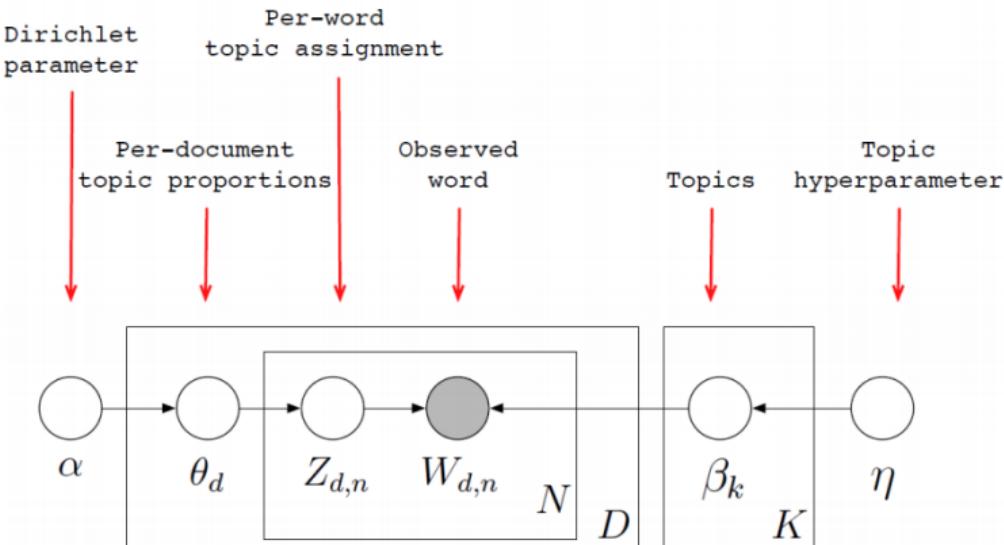
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- ▶ Social scientists use topics as a form of measurement
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 - ▶ tell a story not just about what, but how and why
 - ▶ **topic models are more interpretable** than other dimension reduction methods, such as PCA.

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- ▶ Assume: there are K topics (tunable hyperparameter, use coherence).
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Variational inference setup (Brandon Stewart slides).

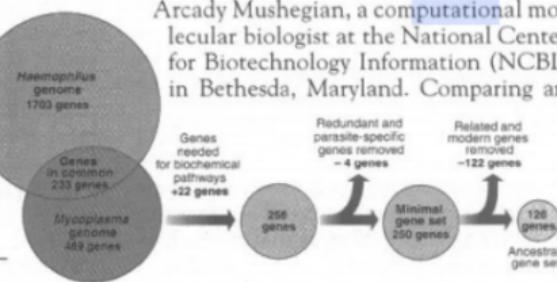
A statistical highlighter

Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions

"are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a genetic numbers game, particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Image from Hanna Wallach

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Can then use the topic proportions as variables in a social science analysis.

- ▶ e.g., Catalinac (2016) shows that after a Japanese political reform that reduced intraparty competition, candidate platforms reduced local pork and increased national policy.

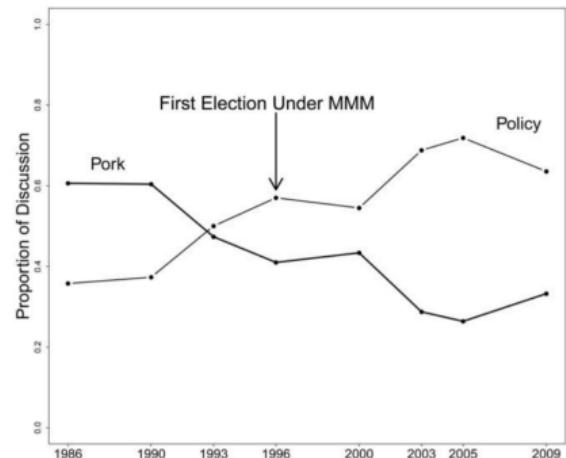


TABLE 1 A Summary of Common Assumptions and Relative Costs Across Different Methods of Discrete Text Categorization

A. Assumptions	Method				
	<i>Reading</i>	<i>Human Coding</i>	<i>Dictionaries</i>	<i>Supervised Learning</i>	<i>Topic Model</i>
<i>Categories are known</i>	No	Yes	Yes	Yes	No
<i>Category nesting, if any, is known</i>	No	Yes	Yes	Yes	No
<i>Relevant text features are known</i>	No	No	Yes	Yes	Yes
<i>Mapping is known</i>	No	No	Yes	No	No
<i>Coding can be automated</i>	No	No	Yes	Yes	Yes
B. Costs					
Preanalysis Costs					
<i>Person-hours spent conceptualizing</i>	Low	High	High	High	Low
<i>Level of substantive knowledge</i>	Moderate/High	High	High	High	Low
Analysis Costs					
<i>Person hours spent per text</i>	High	High	Low	Low	Low
<i>Level of substantive knowledge</i>	Moderate/High	Moderate	Low	Low	Low
Postanalysis Costs					
<i>Person-hours spent interpreting</i>	High	Low	Low	Low	Moderate
<i>Level of substantive knowledge</i>	High	High	High	High	High

Recommended: read this part of Quinn, Monroe, Colaresi, Crespin, and Radev (2010).

Topic modeling Federal Reserve Bank transcripts

Hansen, McMahon, and Prat (QJE 2017)

- ▶ Analyze speech transcripts from FOMC (Federal Open Market Committee).
 - ▶ private discussions among committee members at Federal Reserve (U.S. Central Bank)
 - ▶ 150 meetings, 20 years, 26,000 speeches, 24,000 unique words.

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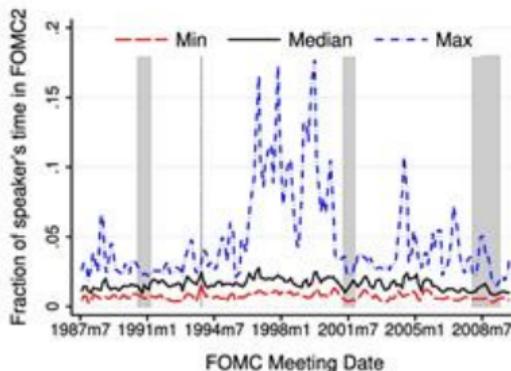
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- ▶ Pre-processing:
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- ▶ LDA:
 - ▶ $K = 40$ topics selected for interpretability / topic coherence.

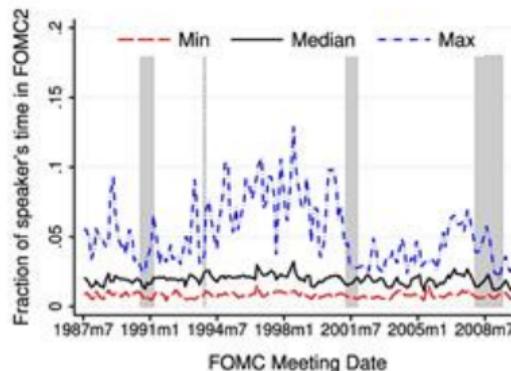
														Pro-cyclicality	
Topic0 ¹	product	increas	wage	price	cost	labor	rise	acceler	inflat	pressur	trend	compens	0.024	0.150	
Topic1 ^{1,2}	growth	slow	econom	continu	expans	strong	trend	inflat	will	recent	slowdown	moder	0.023		
Topic2 ²	inflat	expect	core	measur	higher	path	slack	gradual	continu	remain	view	suggest	0.017		
Topic3 ¹	percent	year	quarter	growth	month	rate	last	next	state	averag	california	employ	0.007		
Topic4	number	data	look	chang	measur	use	point	show	revis	estim	gdp	actual	0.007		
Topic5 ^{1,2}	polici	inflat	monetarpol	need	time	can	monetari	move	tighten	view	action	believ	0.005		
Topic6 ²	rate	term	expect	real	lower	increas	rise	level	declin	short	nomin	year	0.005		
Topic7	statement	word	chang	meet	languag	discuss	issu	want	read	sentenc	view	use	0.005		
Topic8 ²	chairman	support	mr	direct	recommend	agre	asymmetr	prefer	symmetr	move	toward	favor	0.004		
Topic9 ¹	employ	continu	growth	job	nation	region	seem	state	manufactur	greenbook	busi	bit	0.004		
Topic10	dollar	unitedstates	export	countri	import	foreign	japan	growth	abroad	trade	develop	currenc	0.003		
Topic11	model	use	simul	shock	effect	scenario	nairu	differ	rule	chang	baselin	altern	0.003		
Topic12 ²	risk	may	balanc	seem	side	uncertainti	possibl	econom	probabl	reason	upsid	much	0.003		
Topic13	forecast	greenbook	staff	project	differ	assumpt	littl	assum	somewhat	lower	end	period	0.002	0.100	
Topic14	period	committe	consist	econom	run	maintain	futur	read	slightli	stabil	expect	develop	0.002		
Topic15	invest	incom	spend	capit	household	consum	busi	hous	consumpt	sector	stock	stockmarket	0.002		
Topic16 ¹	month	report	increas	survey	expect	indic	remain	continu	last	recent	data	activ	0.002		
Topic17 ¹	project	forecast	year	quarter	expect	will	percent	revis	anticip	growth	next	recent	0.002		
Topic18	question	ask	issu	let	want	answer	rais	discuss	don	start	without	okay	0.001		
Topic19	peopl	talk	lot	much	comment	around	differ	number	reall	look	thing	hear	0.001		
Topic20	presid	ye	governor	parri	stern	vice	hoenig	minehan	kelley	jordan	moskow	mcteer	0.001		
Topic21	move	can	evid	signific	stage	inde	will	issu	econom	may	quit	clearli	0.001	0.075	
Topic22 ²	chairman	thank	mr	time	meet	laughter	comment	let	will	point	call	may	0.0		
Topic23 ¹	year	panel	line	shown	right	chart	expect	project	percent	middl	left	next	0.0		
Topic24	district	nation	area	continu	sector	construct	manufactur	report	activ	region	economi	remain	0.0		
Topic25	know	someth	happen	right	thing	want	look	sure	can	reall	anyth	els	0.0		
Topic26 ^{1,2}	polici	might	committe	market	may	tighten	eas	risk	action	staff	possibl	potenti	-0.001		
Topic27	year	continu	product	price	level	industri	will	sale	increas	auto	last	district	-0.001		
Topic28 ¹	inventori	product	sale	level	order	will	sector	come	good	quarter	much	adjust	-0.001	0.050	
Topic29	price	oil	increas	energi	effect	import	suppli	product	demand	will	market	oilprices	-0.002		
Topic30	term	might	point	can	sens	run	short	probabl	time	longer	tri	someth	-0.002		
Topic31	seem	may	time	certainili	bit	littl	quit	much	far	perhap	better	might	-0.003		
Topic32	money	aggred	borrow	seem	rang	reserv	rate	target	time	altern	suggest	million	-0.003		
Topic33 ²	move	market	point	will	fundsrate	rate	basispoints	need	fed	today	basi	time	-0.004		
Topic34 ¹	report	busi	compani	year	contact	firm	sale	worker	expect	plan	director	industri	-0.004		
Topic35	will	fiscal	ta	budget	cut	govern	effect	billion	state	spend	deficit	year	-0.005	0.025	
Topic36	will	econom	world	rather	problem	believ	can	situat	much	seem	view	good	-0.008		
Topic37	reall	look	side	thing	lot	problem	concern	littl	pretti	situat	kind	much	-0.012		
Topic38	bank	credit	market	loan	financi	debt	lend	fund	concern	financ	problem	spread	-0.018		
Topic39 ^{1,2}	economi	weak	recoveri	recess	confid	eas	neg	econom	will	turn	declin	period	-0.059		

Pro-Cyclical Topics

Hansen, McMahon, and Prat (QJE 2017)



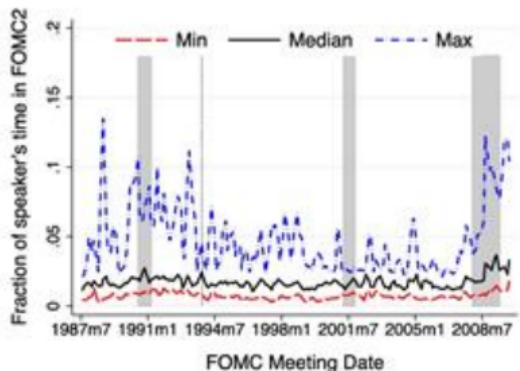
(A) TOPIC 0 'PRODUCTIVITY'



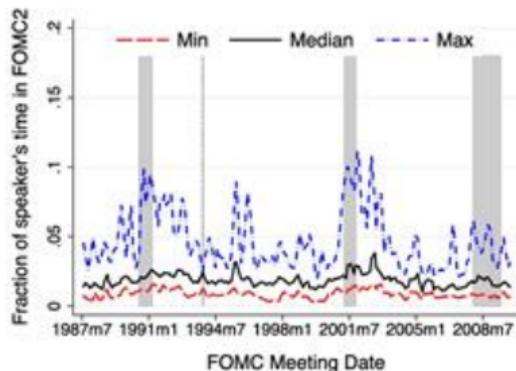
(B) TOPIC 1 'GROWTH'

Counter-Cyclical Topics

Hansen, McMahon, and Prat (QJE 2017)



(A) TOPIC 38 'FINANCIAL SECTOR'



(B) TOPIC 39 'ECONOMIC WEAKNESS'

TABLE IV
SUMMARY OF COMMUNICATION MEASURES (MEETING-SECTION-SPEAKER LEVEL)

Count measures		Topic measures	
Name	Description	Name	Description
Words	The count of words spoken	Concentration	The Herfindahl index applied to distribution over policy topics
Statements	The count of statements made	Quant	Percentage of time on data topics
Questions	The count of questions asked	Avg Sim (X) $X \in \{B, D, KL\}$ B = Bhattacharyya D = dot product KL = Kullback – Leibler	The similarity between a speaker's distribution over policy topics and the FOMC average, computed using metric X
Numbers	The count of numbers spoken	Pr (no dissent)	The fitted value for no voiced dissent from the LASSO for policy topic selection (only FOMC2)

Effect of Transparency

Hansen, McMahon, and Prat (QJE 2017)

- ▶ In 1993, there was an unexpected transparency shock where transcripts became public.

Effect of Transparency

Hansen, McMahon, and Prat (QJE 2017)

- ▶ In 1993, there was an unexpected transparency shock where transcripts became public.
- ▶ Increasing transparency results in:
 - ▶ higher discipline / technocratic language (probably beneficial)
 - ▶ higher conformity (probably costly)
- ▶ Highlights tradeoffs from transparency in bureaucratic organizations.

Structural Topic Model = LDA + Metadata

Roberts, Stewart, and Tingley

STM provides two ways to include contextual information:

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 - ▶ e.g. Republicans talk about military issues more than Democrats

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- ▶ The main implementation is in R. gensim has a light-weight version called “author topic model” (see this week’s notebook).

Objectives: Social-Science Research using Unsupervised Learning

1. **What is the research question?**
2. Corpus and Data:
 - ▶ obtain, clean, preprocess, and link.
 - ▶ Produce descriptive visuals and statistics on the text and metadata
3. Unsupervised learning:
 - ▶ **What are we trying to measure?**
 - ▶ Select a model and train it.
 - ▶ Probe sensitivity to hyperparameters.
 - ▶ Validate that the model is measuring what we want.
4. Empirical analysis
 - ▶ Produce statistics or predictions with the trained model.
 - ▶ **Answer the research question.**

Outline

Document Distance

Dimensionality Reduction

Topic Models

Response Essays

Response Essays

- ▶ Critically read and review an application paper.
- ▶ 300 words is the minimum for a passing grade (3+) but 500+ words would be expected for high grade (7+).
- ▶ Anonymize your submission – do not include your name anywhere in the document. Submit as TXT or PDF to EduFlow.

What can I write about?

- ▶ Any “Applications” reading from weeks 1 through 4 (see list in “Response Essays” page, linked from syllabus).

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 - ▶ dictionary methods, text complexity, n-grams, document similarity, topic models, machine learning.
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 - ▶ dictionary methods, text complexity, n-grams, document similarity, topic models, machine learning.
 - ▶ Please confirm off-syllabus readings with me by email.
- ▶ Note:
 - ▶ for conference-style articles 14 pages or shorter, you have to do two (shorter) response essays.
 - ▶ if a paper has an appendix, you are responsible for reading it!

What to think about

See response essays page.

- ▶ Example essays from previous years are available from homework page.
- ▶ We will continue to practice criticizing the required reading next week.