

Applications: Prediction

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Introduction

- Methods map high-dimensional x to low-dimensional z

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- Three main uses of z
 - ① **Forecasting** (e.g., what will inflation be next month?)
 - ② **Descriptive analysis** (e.g., are there genes that predict risk aversion?)
 - ③ **Input into subsequent causal analysis** (e.g., as LHS var, RHS var, control, instrument, etc.)

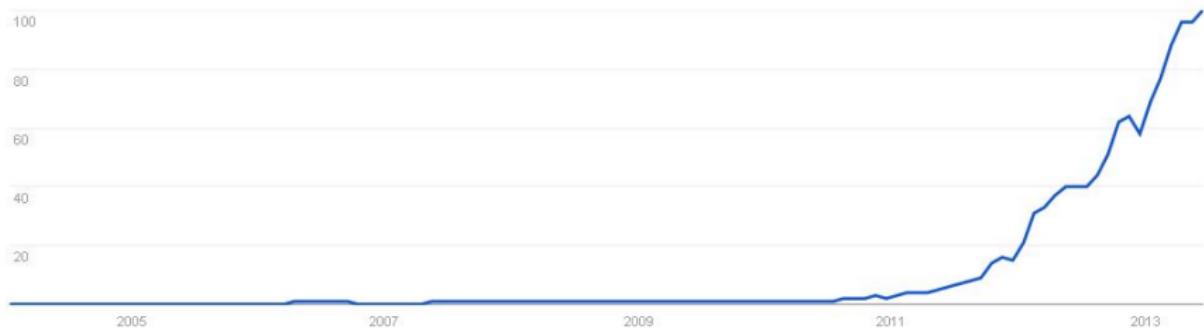
Outline

- Brief overview of data & applications
- Detailed discussion of text as data

Overview

Google Searches

“Big Data”



Google Searches

“Big Data”



0

100

Region | City

Google Searches: Applications

- **Prediction**

- Google flu trends (Dukik et al. 2009)
- Unemployment claims, retail sales, consumer confidence, etc. (Choi & Varian 2009, 2012)

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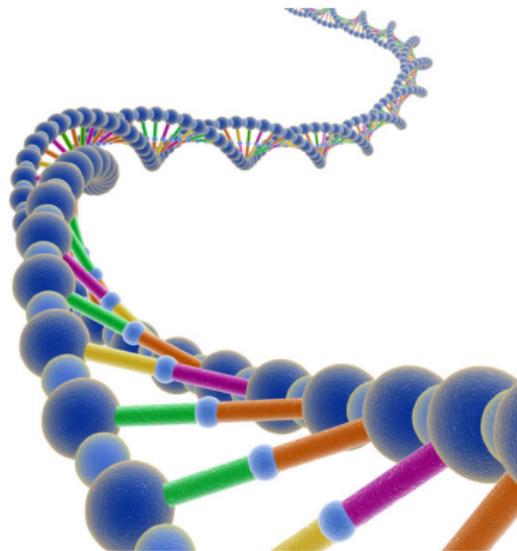
- **Descriptive**

- What searches predict “consumer confidence” (Varian 2013)

Google Searches: Applications

- Prediction
 - Google flu trends (Dukik et al. 2009)
 - Unemployment claims, retail sales, consumer confidence, etc. (Choi & Varian 2009, 2012)
- Descriptive
 - What searches predict “consumer confidence” (Varian 2013)
- Input to analysis
 - Saiz & Simonsohn (2013) → city-level corruption
 - Stephens-Davidowitz (2013) → racial animus & effect on voting for Obama

Genes



- Genetic data has been one of the main applications of high-dimensional methods
- LHS: Physical or behavioral outcome
- RHS: Single-nucleotide polymorphisms (SNPs)
- Typical dataset is $N \approx 10,000$ and $K \approx 2,500,000$

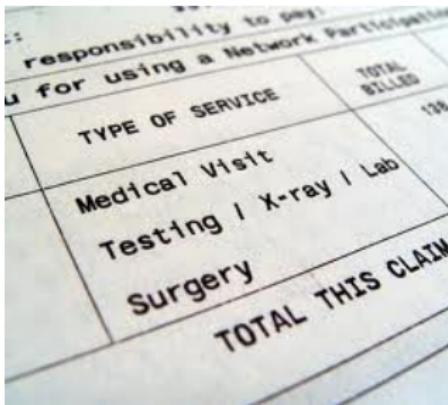
Genes: Applications

- **Descriptive:** look for genetic predictors of...
 - Risk aversion & social preferences (Cesarini et al. 2009)
 - Financial decision making (Cesarini et al. 2010)
 - Political preferences (Benjamin et al. 2012)
 - Self-employment (van der Loos et al. 2013)
 - Educational attainment, subjective well being (Rietveld et al. forthcoming)

Genes: Applications

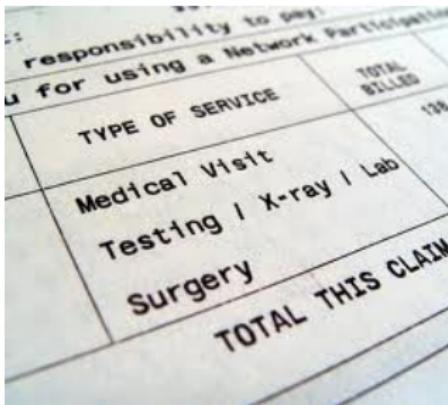
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 - Self-employment (van der Loos et al. 2013)
 - Educational attainment, subjective well being (Rietveld et al. forthcoming)
- Early reported associations have been shown to be spurious & non-replicable (Benjamin et al. 2012)

Medical Claims



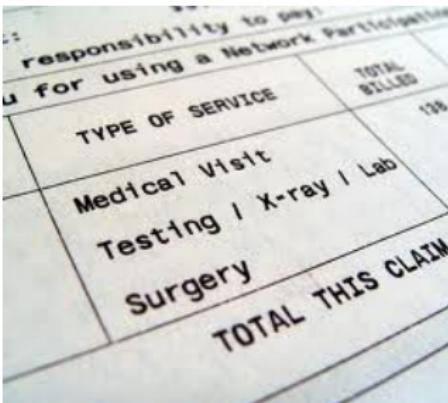
- Big and high dimensional
 - 10 years of Medicare data on the order of 100 TB
 - $(\text{patient} \times \text{doctor} \times \text{hospital} \times \text{treatment} \times \text{cost} \dots)$

Medical Claims



- Big and high dimensional
 - 10 years of Medicare data on the order of 100 TB
 - $(\text{patient} \times \text{doctor} \times \text{hospital} \times \text{treatment} \times \text{cost} \dots)$
- Dimension reduction: How to collapse data into a single-dimensional index of “health” or “predicted spending”
 - Medicare “risk scores” based on ad hoc criteria
 - Johns Hopkins ACG system uses proprietary predictive model

Medical Claims: Applications



- **Input into analysis**

- Numerous studies use Medicare risk scores as a control variable or independent variable of interest
- Einav & Finkelstein (forthcoming) use risk score as mediator of health plan choice
- Handel (2013) uses Johns Hopkins ACG score as measure of private information

Credit Scores



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- **Forecasting**
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- **Input into analysis**
 - Adams, Einav and Levin (2009) and Einav, Jenkins and Levin (2012) evaluate auto dealer's proprietary credit scoring algorithm
 - Rajan, Seru and Vig (forthcoming) look at market responses to using a limited set of variables in credit scoring

Online Purchases



- Amazon, Ebay, and other large Internet firms use purchase and browsing history to make recommendations, target advertising, etc.
- “Netflix Prize” contest for best algorithm to predict future user ratings based on past ratings

Congressional Roll Call Votes



- Poole & Rosenthal (1984, 1985, 1991, 2000, etc.) use factor analysis methods to project Roll Call votes into ideology scores
- Ask questions like
 - Are there multiple dimensions of ideology?
 - How has polarization changed over time?

Text as Data

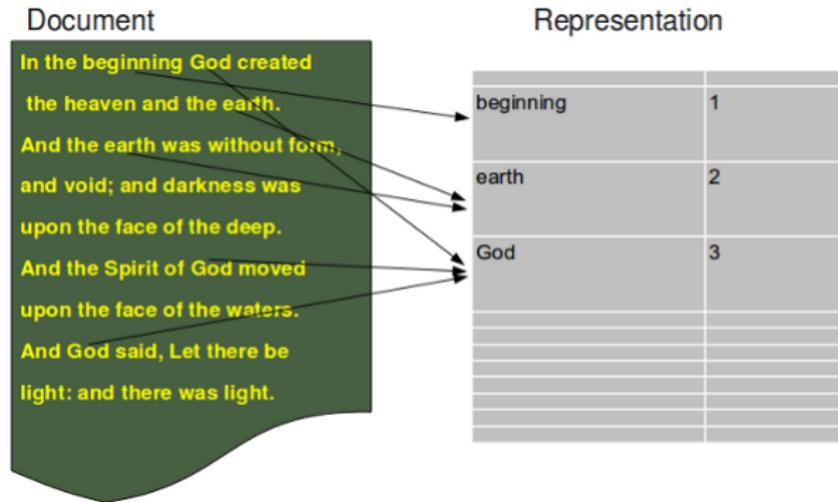
Sources

- News
- Books
- Web content
- Congressional speeches
- Corporate filings
- Twitter & Facebook

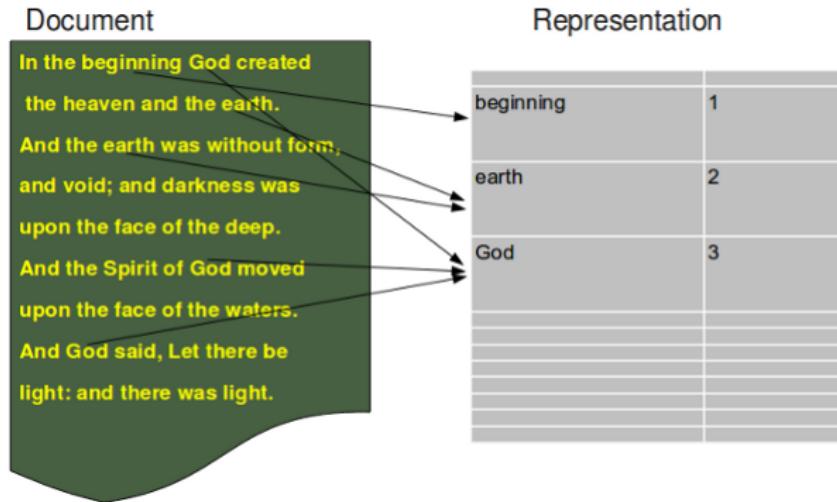
Less Obvious Sources

- Amazon and eBay listings
- Google search ads
- Medical records
- Central bank announcements

Bag of Words

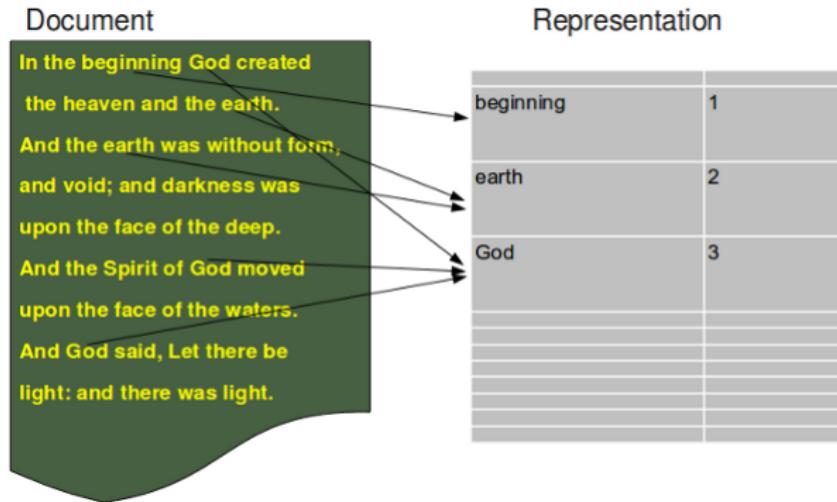


Bag of Words



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 - This seems crude, but it works remarkably well in practice, and gains to more sophisticated representations prove to be small

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- E.g.,
 - Keep only words occurring more than X times
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 - “Stem” words to combine, e.g., “economics,” “economic,” “economically”
 - Drop HTML tags

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 - “Stem” words to combine, e.g., “economics,” “economic,” “economically”
 - Drop HTML tags
- In fact, 90% of text analysis in economics does not automated dimension reduction at all
 - Saiz & Simonsohn (2013) → city name + “corruption”
 - Baker, Bloom, and Davis (2013) → “economic” + “policy” + “uncertainty”, etc.
 - Lucca & Trebbi (2011) → “hawkish/dovish,” “loose/tight,” + “Federal Open Market Committee”

Interfaces

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- Many researchers, however, can only access text via *search* interfaces (e.g., Google page counts, news archives, etc.)
 - This requires some external method of feature selection to narrow down vocabulary

Sentiment Analysis

Setup

- Outcome y_i
- Features x_i
- Data:

$$\underbrace{\{x_1, y_1\}, \{x_2, y_2\}, \{x_3, y_3\}, \dots, \{x_N, y_N\}}_{\text{Training set}}, \underbrace{\{x_{N+1}, ?\}}_{\text{Target}}$$

Spam Filter

- Outcome $y_i \in \{spam, ham\}$
- Human coder classifies N cases as *spam* or *ham*
- Must decide whether to deliver the $(N + 1)$ message or send it to the filter

Issues

- What features x_i do we use?
 - Counts of words?
 - Counts of characters?
 - Complete machine representation of e-mail?
- How do we avoid overfitting?
 - >1m words in English language
 - ASCII file with 100 printable characters has 95^{100} possible realizations

Applications

- Partisanship in the news media [TODAY]
 - Turn millions of words into an index of media slant or bias
- Sentiment in financial news [TODAY]
 - Classify news, chat room discussions, etc. as positive or negative
- Estimating causal effects [TOMORROW]
 - Turn a huge dataset into a low-dimensional control for endogeneity

Sentiment Analysis: *Partisanship in the News Media*

Overview

- Questions
 - How centrist are the news media?
 - What factors (owners, readers) predict how a newspaper portrays the news?
- Need measure of partisan orientation of news media
- Challenges
 - Training set: research assistants? surveys?
 - Dimensionality
 - Feature selection: words? phrases? images?
 - Parsimony: millions of possible words/phrases

Groseclose and Milyo (2005)

- Training set: US Congress
 - Assign members an ideology score y_i based on roll-call voting
- Dimensionality
 - Count frequency of citations to think tanks x_i in Congressional Record
 - Feature selection “by hand”: use *ex ante* criterion to control dimensionality

Groseclose and Milyo (2005)

[The Library of Congress](#) > [THOMAS Home](#) > Search the Congressional Record

Search the Congressional Record

105th Congress (1997-1998)

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[Congress-to-Year Conversion](#)

 [Help](#)

[Enter Search](#)

 SEARCH

 CLEAR

Exact Match Only Include Variants (plurals, etc.)

Member of Congress

Any Representative		
Abercrombie, Neil (HI-1)		
Ackerman, Gary L. (NY-5)		
Aderholt, Robert B. (AL-4)		

Any Senator		
Abraham, Spencer (MI)		
Akaka, Daniel K. (HI)		
Allard, Wayne (CO)		

Member speaking or mentioned All occurrences



Groseclose and Milyo (2005)

Mr. DORGAN. Mr. President, I come to the floor to speak first about the Congressional Budget Office, which last week released its monthly budget projection. And I noticed that this projection, this estimate, received prominent coverage in the Washington Post and in other major daily newspapers around the country last week....

A study by a tax expert at the **Brookings Institution** says if you have a national sales tax, the rates would probably be over 30 percent, and then add the State and local taxes, and that would be on almost everything. So say you would like to buy a house and here is the price we have agreed on, and then have someone tell you, oh, yes, you have a 37-percent sales tax applied to that price, 30 percent Federal, 7 percent State and local.



Speaker	Think Tank	Count
Dorgan, Byron (D-ND)	Brookings Institution	1

Groseclose and Milyo (2005)

- Count references to think tanks in news media

Groseclose and Milyo (2005)

- Let y_i be ADA score of senator i
- Let x_{ijt} be indicator for senator i cites think tank j on occasion t
- Then

$$\Pr(x_{ijt} = 1) = \frac{\exp(\alpha_j + \beta_j y_i)}{\sum_{j'} \exp(\alpha_{j'} + \beta_{j'} y_i)}$$

- Assume same model applies to news media m but treat y_m as unknown
- Estimate α_j, β_j, y_m via joint maximum likelihood

Groseclose and Milyo (2005)

- Dimension of data $p = 50$
 - Start with 200 think tanks
 - Collapse all but top 44 into 6 groups
- Dimension of data $n = 535$
 - Less those who don't cite think tanks

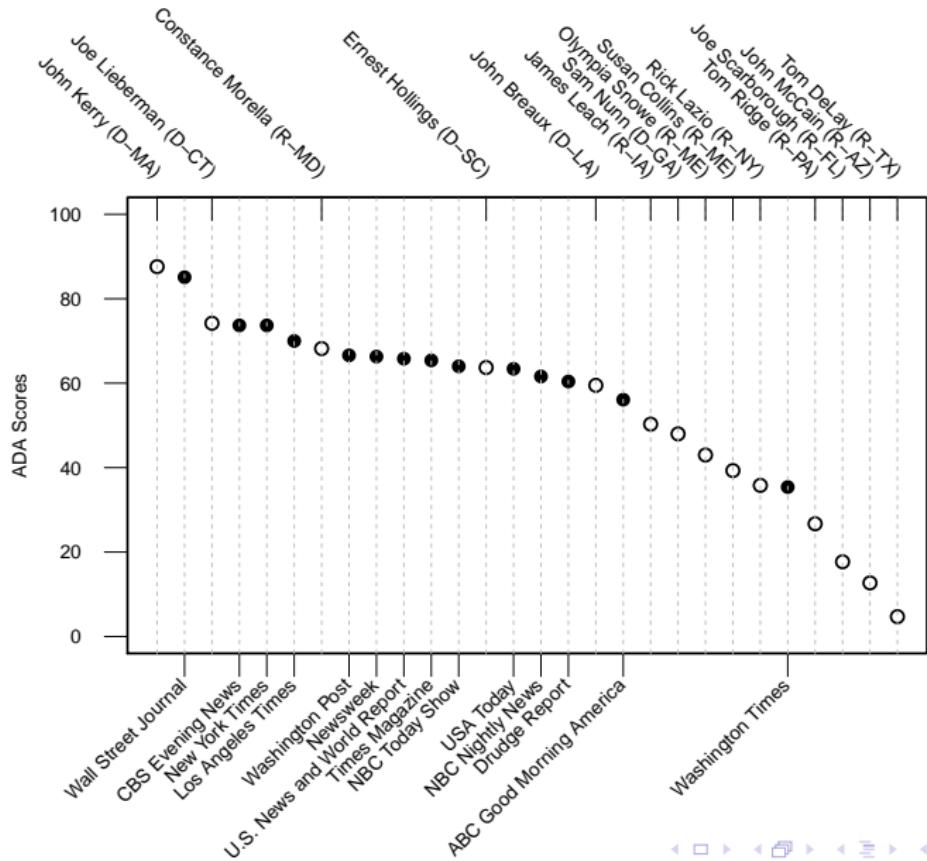
Groseclose and Milyo (2005)

Senator	Partisanship	News Outlet	Partisanship
John McCain	12.7	Fox News	
Arlen Specter	51.3	<i>USA Today</i>	
Joe Lieberman	74.2	<i>New York Times</i>	

Groseclose and Milyo (2005)

Senator	Partisanship	News Outlet	Partisanship
John McCain	12.7	Fox News	39.7
Arlen Specter	51.3	<i>USA Today</i>	63.4
Joe Lieberman	74.2	<i>New York Times</i>	73.7

Groseclose and Milyo (2005)



Gentzkow and Shapiro (2010)

- Text of 2005 Congressional Record
- Scripted pipeline:
 - Download text
 - Split up text into individual speeches
 - Identify speaker
 - Count *all* two-word/three-word phrases

- Training set: US Congress
 - Assign members an ideology score y_i based on partisanship of constituents
- Dimensionality
 - Compute frequency table of phrase counts by party
 - Compute χ^2 statistic of independence
 - Identify 1000 phrases with highest χ^2

Example: Social Security

- Memo to Rep. candidates: “Never say ‘**privatization/private accounts**.’ Instead say ‘**personalization/personal accounts**.’ Two-thirds of America want to personalize Social Security while only one-third would privatize it. Why? Personalizing Social Security suggests ownership and control over your retirement savings, while privatizing it suggests a profit motive and winners and losers.”

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- Congress: "personal account" (48 D vs 184 R); "private account" (542 D vs 5 R)

Top Phrases

Republicans: 2-word	Republicans: 3-word	Democrats: 2-word	Democrats: 3-word
stem cell	embryonic stem cell	private accounts	veterans health care
natural gas	hate crimes legislation	trade agreement	congressional black caucus
death tax	adult stem cells	american people	va health care
illegal aliens	oil for food program	tax breaks	billion in tax cuts
class action	personal retirement accounts	trade deficit	credit card companies
war on terror	energy and natural resources	oil companies	security trust fund
embryonic stem	global war on terror	credit card	social security trust
tax relief	hate crimes law	nuclear option	privatize social security
illegal immigration	change hearts and minds	war in iraq	american free trade
date the time	global war on terrorism	middle class	central american free
boy scouts	class action fairness	african american	national wildlife refuge
hate crimes	committee on foreign relations	budget cuts	dependence on foreign oil
oil for food	deficit reduction bill	nuclear weapons	tax cuts for the wealthy
global war	boy scouts of america	checks and balances	vice president cheney
medical liability	repeal of the death tax	civil rights	arctic national wildlife
highway bill	highway trust fund	veterans health	bring our troops home
adult stem	action fairness act	cut medicaid	social security privatization
democratic leader	committee on commerce science	foreign oil	billion trade deficit
federal spending	cord blood stem	president plan	asian pacific american
tax increase	medical liability reform	gun violence	president bush took office

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Other R: **personal accounts; social security reform; social security system**

Other D: **privatization plan; security trust; security trust fund; social security trust; privatize social security; social security privatization; privatization of social security; cut social security**

Top Phrases: Foreign Policy

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Other R: **saddam hussein, war on terrorism, iraqi people**

Other D: **funding for veterans health; war in iraq and afghanistan; improvised explosive device**

Top Phrases: Fiscal Policy

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Other R: **raise taxes; percent growth; increase taxes; growth rate; government spending; raising taxes; death tax repeal; million jobs created; percent growth rate**

Other D: **estate tax; budget deficit; bill cuts; medicaid cuts; cut funding; spending cuts; pay for tax cuts; cut student loans; cut food stamps; cut social security; billion in tax breaks**

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Custom List
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for: **Search** [advanced search](#) [new search](#)

return:

Search Hint: Connecting terms with AND narrows your search to give more precise results ...more on [search operators](#)

Results: 1 - 10 of 54

1 2 3 4 5 6 | Next

Show First Paragraph

1. The Washington Times - July 13, 1999

Tin ears on Social Security

You would think congressional leaders who wanted to advance a personal retirement account option to Social Security would offer a proposal that could at least be supported by the organizations and individuals who have been developing the idea for years now. But you would be wrong. House Ways and Means Committee Chairman Bill Archer, Texas Republican, and Social Security Subcommittee Chairman Clay Shaw, Florida Republican, have advanced a proposal that is a gross disfigurement of what...

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Washington Times (Company/Org) AND Moon, Sun Myung (Person) Washington Times (Company/Org) AND Washington DC (Place)

53 Results *

Search within

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Select 1-20

[Brief view](#) | [Detailed view](#)

1



[Tin ears on Social Security: \[2 Edition 1\]](#)

Ferrara, Peter. **Washington Times** [Washington, D.C] 13 July 1999: A17.

...who wanted to advance a personal retirement account option to Social Security
...worker's wages into a personal retirement account for the worker. These payments
...and proposed a sound personal retirement account plan. He would have granted

[Citation/Abstract](#) [Full text](#)

2



[Washington's financial miscreants sucker us](#)

Hurt, Charles. **Washington Times** [Washington, D.C] 05 Dec 2012: A.6.

...billions out of our personal retirement account to fund an obscene lavishness

[Citation/Abstract](#) [Full text](#)

3



[Brickbats blur Bush proposal for Social Security ; Plan backers say 'truth' obscured](#)

Lambro, Donald. **Washington Times** [Washington, D.C] 06 Feb 2005: A03.

... Mr. Bush's personal retirement account (PRA) plan has been attacked by

[Citation/Abstract](#) [Full text](#)

4



[Touching Social Security's hot third rail: \[2 Edition\]](#)

Lambro, Donald. **Washington Times** [Washington, D.C] 12 Dec 1996: A.17.

...Security taxes into their own personal retirement account. Mr. Forbes'

[Citation/Abstract](#) [Full text](#)



Example: Social Security

- "House GOP offers plan for Social Security; Bush's **private accounts** would be scaled back" (*Washington Post*, 6/23/05)
- "GOP backs use of Social Security surplus ; Finds funding for **personal accounts**" (*Washington Times*, 6/23/05)

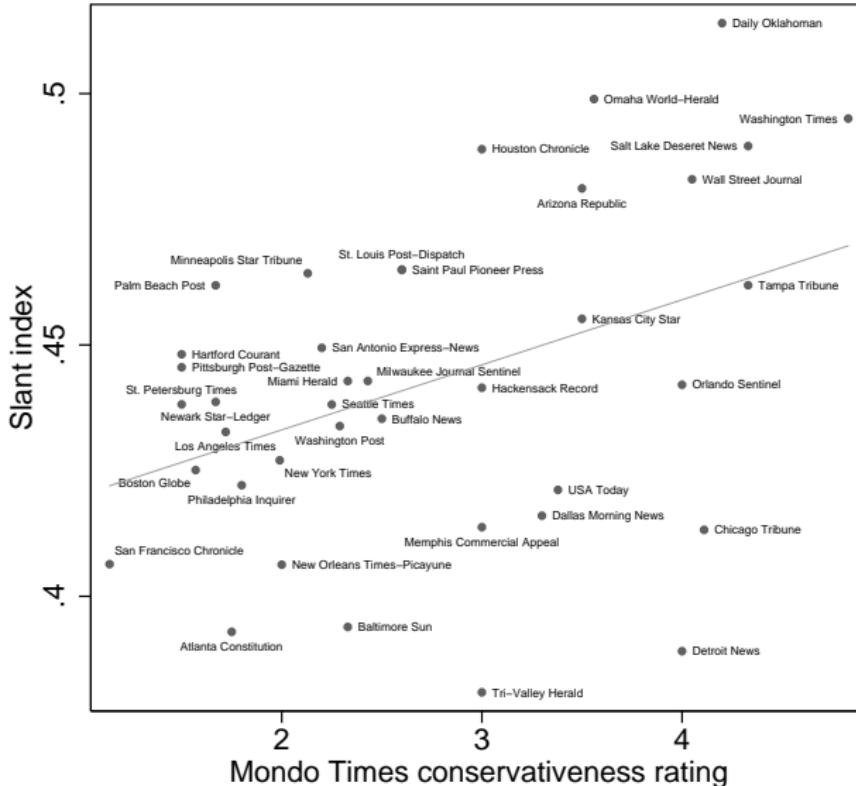
Linear Model of Phrase Frequency

- Let y_i be Republican vote share in senator i 's state
- Let x_{ij} be share of senator i 's speech going to phrase j

$$E(x_{ij}|y_i) = \alpha_j + \beta_j y_i$$

- Estimate via least squares
 - Procedure called *marginal regression*
- Apply same model to newspapers to infer y_m

Validation



How to Validate

- Newspaper rankings consistent with external sources
- Phrases make sense
- Sensitivity analysis
 - Change scores y_i (ADA, NOMINATE)
 - Change set of phrases
- Check agreement across sources
- Go look at the newspapers

Audit

TABLE A.I
AUDIT OF SEARCH RESULTS^a

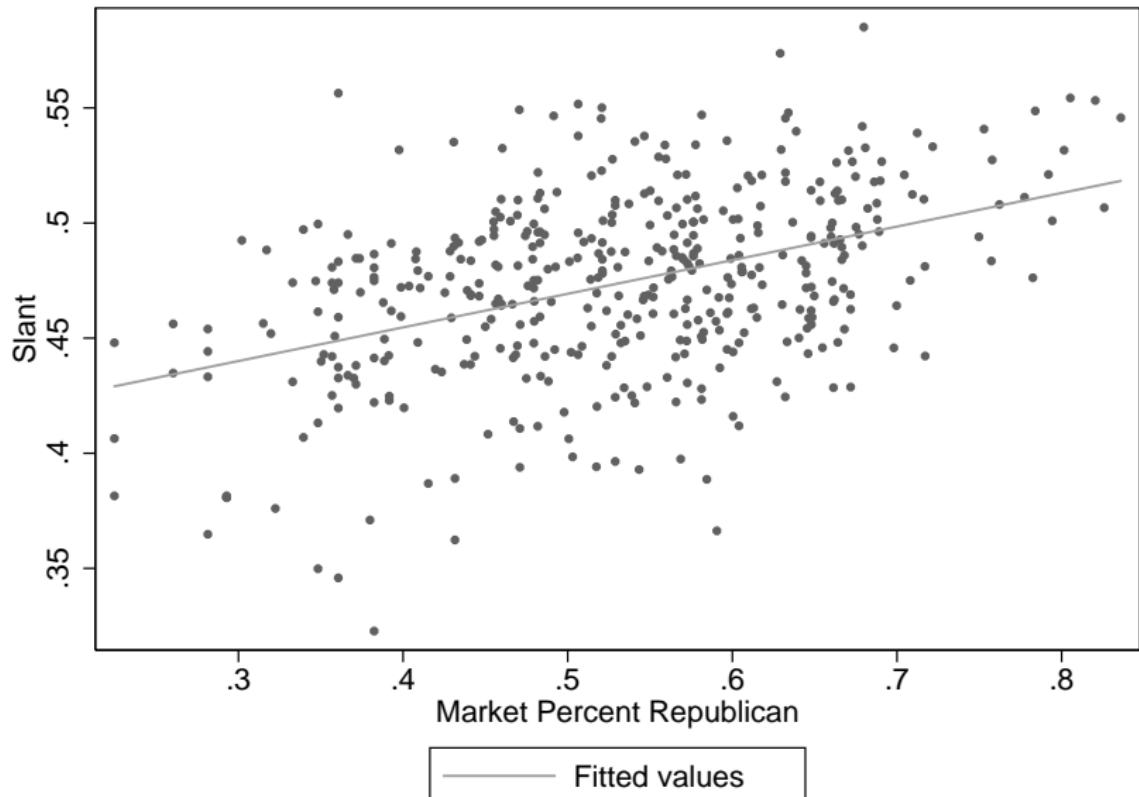
Phrase	Total Hits	Share of Hits in Quotes	Share of Hits That Are					
			AP Wire Stories	Other Wire Stories	Letters to the Editor	Maybe Opinion	Clearly Opinion	Independently Produced News
Global war on terrorism	2064	16%	3%	4%	1%	2%	10%	80%
Malpractice insurance	2190	5%	0%	0%	1%	3%	12%	84%
Universal health care	1523	9%	1%	0%	7%	8%	28%	56%
Assault weapons	1411	9%	3%	12%	4%	1%	25%	56%
Child support enforcement	1054	3%	0%	0%	1%	2%	11%	86%
Public broadcasting	3375	8%	1%	0%	2%	4%	22%	71%
Death tax	595	36%	0%	0%	2%	5%	46%	47%
Average (hit weighted)		10%	1%	2%	3%	3%	19%	71%

^aAuthors' calculations based on ProQuest and NewsLibrary data base searches. See Appendix A for details.

Economic Hypotheses

- Now that we have a measure, we can use it to model newspaper ideology
- Possible drivers
 - Consumer ideology
 - Owner ideology
 - Influence of incumbent politicians

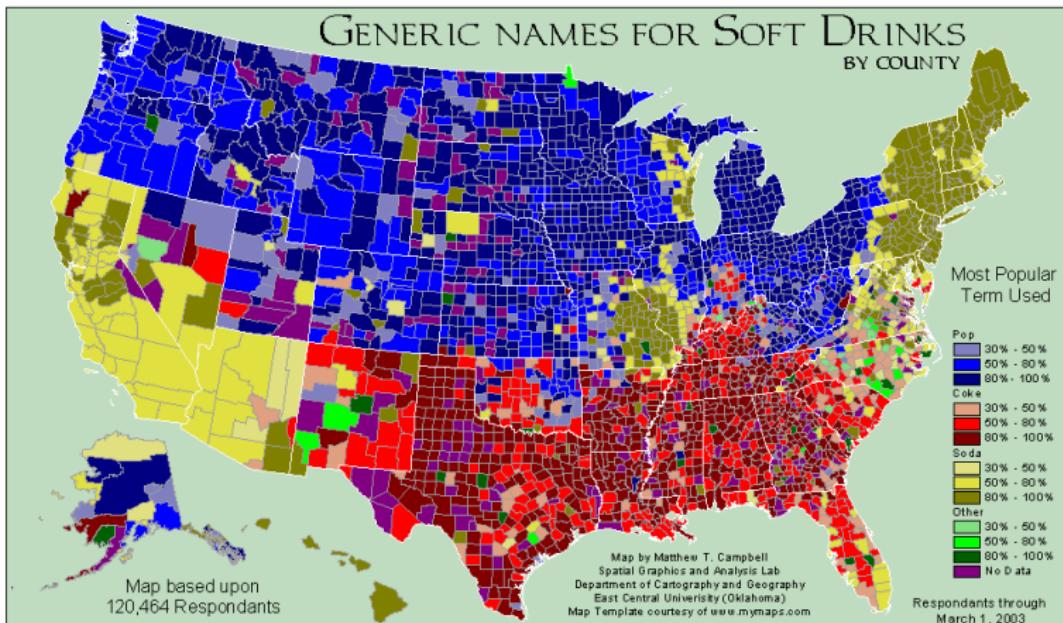
Role of Consumer Ideology



Possible Confounds

- Reverse causality
- Slant is proxying for other newspaper attributes (e.g. emphasis on sports vs. business)
- Slant is proxying for other market attributes (e.g. geography)

Soda vs. Pop



Solutions

- Control carefully for geography when relating slant to other variables
- Incorporate geography into predictive model
 - Predict the component of congressperson ideology that is orthogonal to Census division

Broader Lesson

- Can use predictive modeling as an aid to social science
- But
 - You get out what you put in
 - Consider possible sources of bias and misspecification

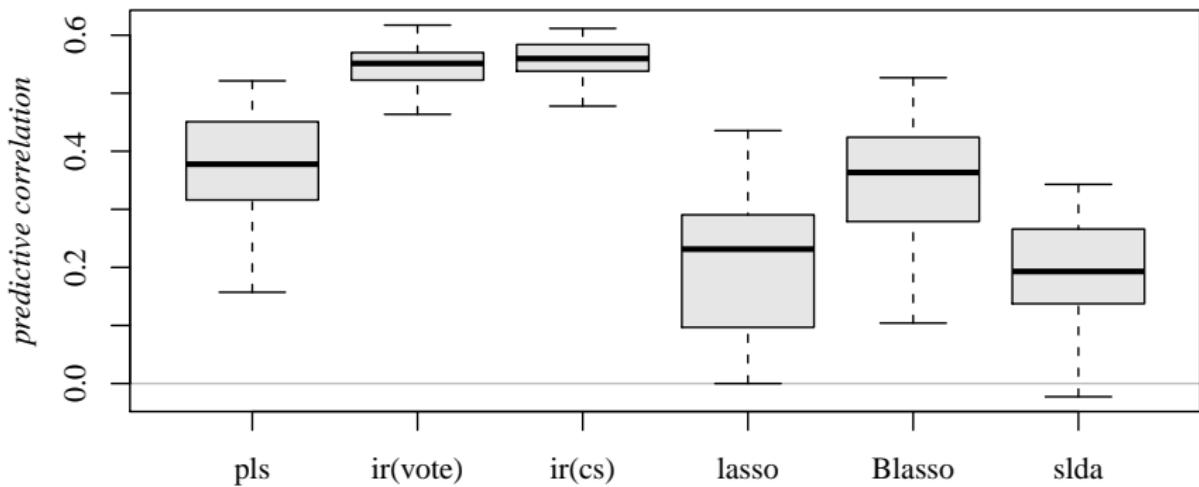
- Two main limitations of Gentzkow & Shapiro (2010)
 - Feature selection separate from model estimation
 - Linear model doesn't exploit multinomial structure of data

- Let y_i be Republican vote share in senator i 's state
- Let x_{ijt} be an indicator for senator i says phrase j at occasion t
- Then

$$\Pr(x_{ij} = 1) = \frac{\exp(\alpha_j + \beta_j y_i)}{\sum_{j'} \exp(\alpha_{j'} + \beta_{j'} y_i)}$$

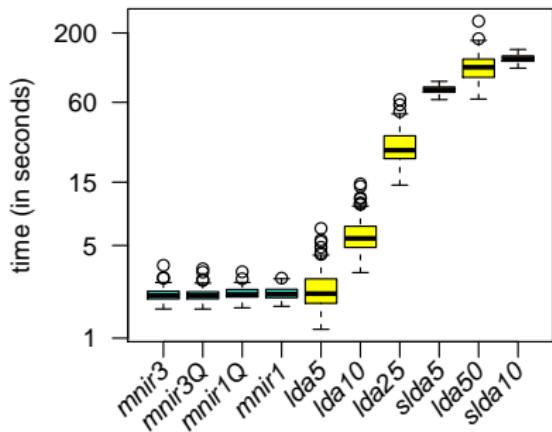
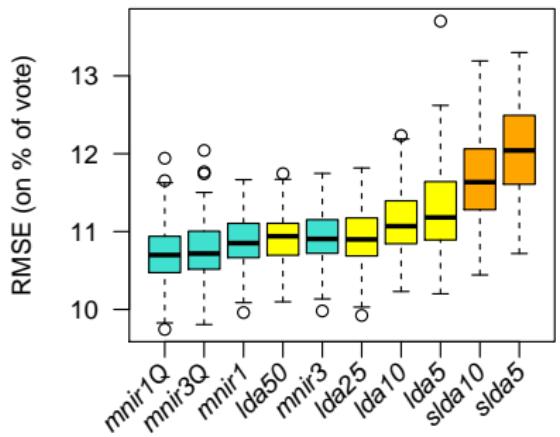
- Estimate via maximum likelihood
 - Uses log penalty for regularization
 - Uses novel algorithm for maximization
- Penalty imposes sparsity in β_j s
 - Means we can use a very large number of phrases p
 - Can think of this as a way to maximize performance subject to a phrase “budget”

Political Speech



- Note: LDA = latent Dirichlet allocation (stay tuned)

109th Congress Vote–Shares



Sentiment Analysis: *Financial News*

Overview

- Questions

- What explains time-series/cross-section of equity returns?
- Is there information beyond what is reflected in quantitative fundamentals (e.g. earnings)?

Tetlock (2007)

- Data: counts of words in WSJ “Abreast of the Market” column



Tetlock (2007)

- Features: Counts of words in each of 77 “Harvard-IV General Inquirer” categories
 - Weak
 - Positive
 - Negative
 - Active
 - Passive
 - etc.

List of entries in tag category:

Weak

List shows first 100 entries. Total number of entries in this category:

755

Entries for this category are shown with all tags assigned and sense definitions:

ABANDON

H4Lvd Negativ Ngtv Weak Fail IAV AffLoss AffTot SUPV

ABANDONMENT

H4 Negativ Weak Fail Noun

ABDICATE

H4 Negativ Weak Submit Passive Finish IAV SUPV

Tetlock (2007)

- Regressors
 - Weak words
 - Negative words
 - First principal component (“pessimism”)

Table II
Predicting Dow Jones Returns Using Negative Sentiment

The table data come from CRSP, NYSE, and the General Inquirer program. This table shows OLS estimates of the coefficient γ_1 in equation (1). Each coefficient measures the impact of a one-standard deviation increase in negative investor sentiment on returns in basis points (one basis point equals a daily return of 0.01%). The regression is based on 3,709 observations from January 1, 1984, to September 17, 1999. I use Newey and West (1987) standard errors that are robust to heteroskedasticity and autocorrelation up to five lags. Bold denotes significance at the 5% level; italics and bold denotes significance at the 1% level.

News Measure	Regressand: Dow Jones Returns		
	Pessimism	Negative	Weak
<i>BdNws_{t-1}</i>	-8.1	-4.4	-6.0
<i>BdNws_{t-2}</i>	0.4	3.6	2.0
<i>BdNws_{t-3}</i>	0.5	-2.4	-1.2
<i>BdNws_{t-4}</i>	4.7	4.4	6.3
<i>BdNws_{t-5}</i>	1.2	2.9	3.6
$\chi^2(5)$ [Joint]	20.0	20.8	26.5
<i>p</i> -value	0.001	0.001	0.000
Sum of 2 to 5	6.8	9.5	10.7
$\chi^2(1)$ [Reversal]	4.05	8.35	10.1
<i>p</i> -value	0.044	0.004	0.002

Antweiler and Frank (2004)

- Data: Message board contents on Yahoo! Finance and Raging Bull

```
-----  
FROM YF  
COMP ETYS  
MGID 13639  
NAME CaptainLihai  
LINK 1  
DATE 2000/01/25 04:11  
SKIP  
TITL ETYS will surprise all pt II  
SKIP  
TEXT ETYS will surprise all when it drops to below 15$ a pop, and even then  
TEXT it will be too expensive.  
TEXT  
TEXT If the DOJ report is real, there will definately be a backlash against  
TEXT the stock. Watch your asses. Get out while you can.  
-----  
FROM YF  
COMP IBM  
MGID 43653  
NAME plainfielder  
LINK 1  
DATE 2000/03/29 11:39  
SKIP  
TITL BUY ON DIPS - This is the opportunity  
SKIP  
TEXT to make $$$ when IBM will be going up again following this profit taking  
TEXT bout by Abbey Cohen and her brokerage firm.  
TEXT  
TEXT IBM shall go up again after today.  
-----
```

Antweiler and Frank (2004)

- Count words
- Create training set of 1000 messages hand-coded as buy, sell, hold
- Compute “naive Bayes classification:” posterior guess assuming words are independent

Table I
Naive Bayes Classification Accuracy within Sample and Overall Classification Distribution

The first percentage column shows the actual shares of 1,000 hand-coded messages that were classified as buy (B), hold (H), or sell (S). The buy-hold-sell matrix entries show the in-sample prediction accuracy of the classification algorithm with respect to the learned samples, which were classified by the authors (Us).

Classified: by Us	% 25.2 69.3 5.5 1,000 messages ^a All messages ^b	By Algorithm		
		Buy 18.1 3.4 0.2 21.7 20.0	Hold 7.1 65.9 1.2 74.2 78.8	Sell 0.0 0.0 4.1 4.1 1.3

^aThese are the 1,000 messages contained in the training data set.

^bThis line provides summary statistics for the out-of-sample classification of all 1,559,621 messages.

Antweiler and Frank (2004)

- Small amount of predictability in returns
- Messages predict volatility
- Disagreement (variable recommendations) predicts volume

Other Examples

- Li (2010): Uses naive Bayes to measure sentiment of forward-looking statements in 10Ks/10Qs
- Hanley and Hoberg (2012): Use cosine distance to measure revisions to IPO prospectuses

Topic Models

Factor Models

- “Unsupervised” methods (factor analysis, PCA) project high-dimensional data into low-dimensional measures, preserving as much variation as possible.

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 - Survey responses → “Big 5” personality traits

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 - Congressional roll call votes → “Common space” scores
 - Survey responses → “Big 5” personality traits
- Low dimensional measures are then inputs into subsequent analysis
- E.g.,
 - How has polarization in Congress changed over time? (Poole & Rosenthal 1984)
 - How does personality correlate with job performance (Tett et al. 1991)

Topic Models

- Topic models extend these methods to multinomial data such as text
- Relevant to measuring, e.g.,
 - What people talk about on social networks
 - What products share similar descriptions on Amazon / EBay
 - What “stories” are in the news today
 - What are economists studying

Purpose

- As with other unsupervised methods, topic models are of most interest to social scientists as an input into subsequent analysis

Purpose

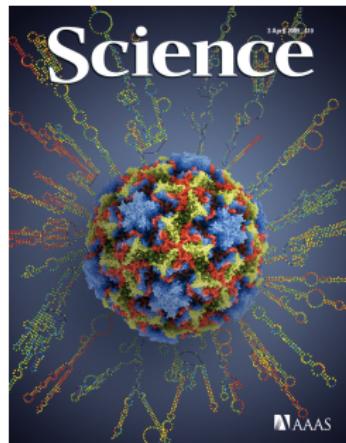
- As with other unsupervised methods, topic models are of most interest to social scientists as an input into subsequent analysis
- E.g.,
 - Do discussions of particular topics on Twitter predict stock movements?
 - Which products are close substitutes on EBay?
 - Is media slant driven by what you talk about or how you talk about it?
 - How has the distribution of topics in economics changed over time?

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- As with other unsupervised methods, topic models are of most interest to social scientists as an input into subsequent analysis
- E.g.,
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 - Is media slant driven by what you talk about or how you talk about it?
 - How has the distribution of topics in economics changed over time?
- A fair critique of topic modeling literature is that it hasn't progressed much beyond the measurement stage

Topic Models: *Blei & Lafferty (2006)*

Input



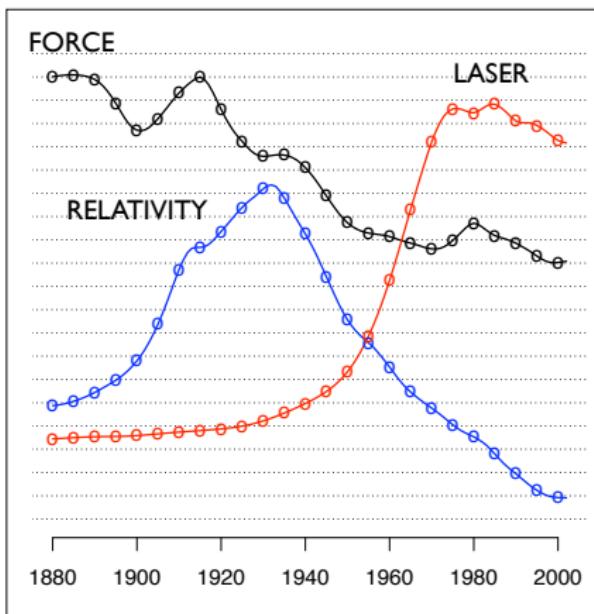
- OCR text of *Science* 1880-2002 (from JSTOR)
 - Count words used 25 or more times (after stemming and removing stopwords)
 - Vocabulary: 15,955 words
 - Total documents: 30,000 articles

Output

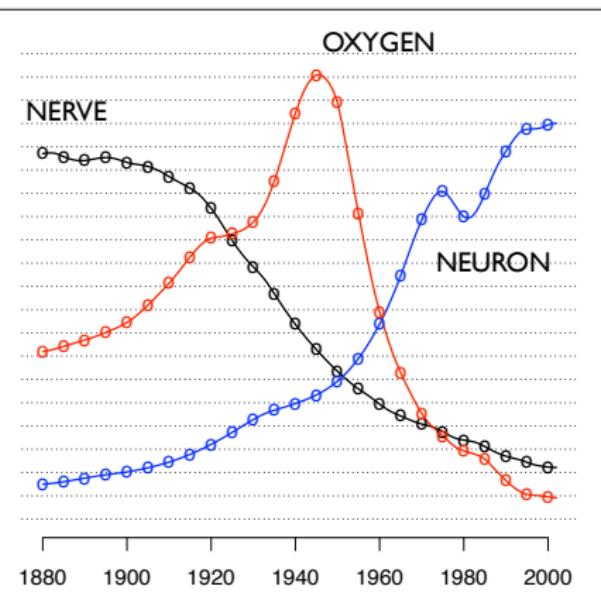
1	2	3	4
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

Output

"Theoretical Physics"



"Neuroscience"



Model: LDA

- Latent Dirichlet Allocation (LDA) introduced by Blei et al. (2003) as an extension of factor models to discrete data

Model: LDA

- Setup

- Documents $i \in \{1, \dots, n\}$
- Words $j \in \{1, \dots, p\}$
- Data \mathbf{x}_i is $(1 \times p)$ vector of word counts for document i

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- Data \mathbf{x}_i is $(1 \times p)$ vector of word counts for document i

- Factor model

- θ_{ik} is value of k -th **factor** for document i
- β_k is $(1 \times p)$ vector of **loadings** for factor k

$$E(\mathbf{x}_i) = \beta_1 \theta_{i1} + \dots \beta_K \theta_{iK}$$

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$$E(\mathbf{x}_i) = \beta_1 \theta_{i1} + \dots + \beta_K \theta_{iK}$$

- LDA

- θ_{ik} is weight on k -th **topic** for document i
- β_k is $(1 \times p)$ vector of **word probabilities** for topic k

$$\mathbf{x}_i \sim \text{Multinomial}(\beta_1 \theta_{i1} + \dots + \beta_K \theta_{iK})$$

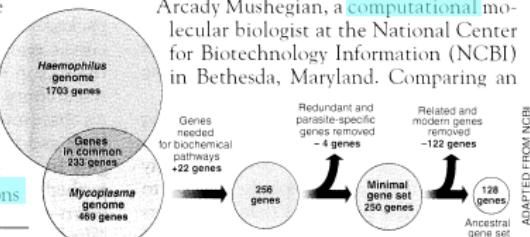
Model: LDA

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.

Model: LDA

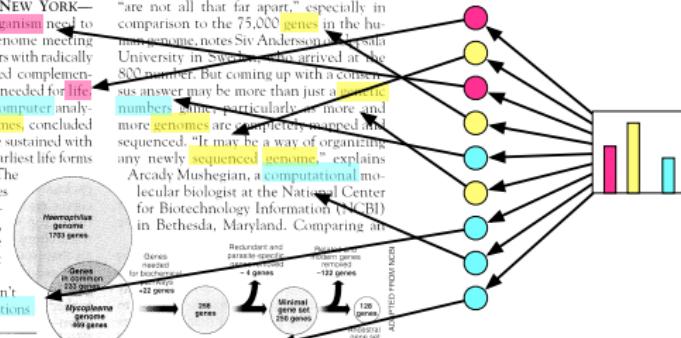
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Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes

Model: LDA

- For each document i ...
 - Draw topic proportions θ_i from Dirichlet distribution with parameter α
 - For each word j ...
 - Draw a topic assignment $k \sim \text{Multinomial}(\theta_i)$
 - Draw word $x_{ij} \sim \text{Multinomial}(\beta_k)$

Model: Dynamic

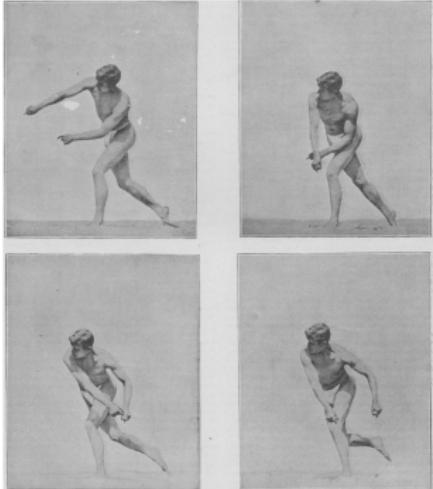
- One limitation of LDA is it assumes documents are exchangeable; in many settings of interest, topics evolve systematically over time

Model: Dynamic

"Instantaneous Photography" (1890)

Prestissi, who has taken thousands of pictures of flying birds, running horses, jumping men, etc., all subjects for their particular interest, and for the most artistic tour and sketches. He will be able to show his particular events in rapid motion, for instance, the horse-leaps of flying horses, which requires only security-two one-hundredths of a second, and in this short time make twenty-five pictures of the different positions in

walking man, or many views as possible in equal intervals of time, and he succeeded admirably in his undertaking. He was enabled to do this by means of a special event camera, for which with which the author has experimental knowledge. In this pictures the characteristic positions peculiar to different bodies are well presented. Many of them at first appear as-



INSTANTANEOUS PHOTOGRAPHS OF AN ATHLETE THROWING A JAVELIN.

long exposures, because the eye has never been able to observe these.

These pictures produced rich and important material for the study of motion, but Mr. Amesbury's success in making his exposures was due to the fact that he used a special device for giving the different phases of motion. He made it his object to get of one period of motion, for instance, of the step of a

giant interval. A dozen pictures showing the different phases of a position assumed by an athlete in throwing a javelin, reproduced from instantaneous photographs taken by Mr. Amesbury, now given on the right are the results of his work.

Mr. Amesbury's invention is a camera which automatically

gives the electric discharge, in which he was financially assisted by the German Government. In this instrument the series o-

"Infrared Reflectance in Leaf-Sitting Neotropical Frogs" (1977)

North American frogs, an examined *Rana catesbeiana*, *R. bergeri*, *R. catesbeiana*, *Rana pipiens* (*R. palustris*), *R. catesbeiana*, *Hyla cinerea*, *H. tigris*, and *H. versicolor* absorb infrared light and stand out sharply against foliage (Fig. 1).

Cole and Moore (1977) found that infrared frogs are infrared reflectors in the same way as are some Australian tree-frog *Hyla pusilla* (=Litoria carinata), the tree-frog *Litoria infrafrenata*, *A. maculatus*, and *A. cyanodactylus* described above all contain a newly dis-

covered red pigment and melanophores (*i*). Both *Brachycephalus* and *Phrynobatrachus* groups of *Cratoxenoidea* contain a purple pigment in their chromatophores (*i*). Whether these two skin colorations are related to infrared reflectivity and protective coloration is sparse. Both the eyes of birds and the pit organs of frogs are believed to be infrared receptors. In pigeons and chickens, the sensitivity maxima of the eyes are located at 700 nm, while the pit organs have these of 600 nm (*i*), and the snowy owl responds to infrared light (900 nm) (*S*). Visual sensitivity extending into the infrared may play a physiological role in

infrared vision. It is also known to use most green frogs on green leaves, although contrarians and physiologists believe that infrared vision is bad. Red and crimson pit organs are usually interpreted as thermal detectors, adaptations for thermoregulation, and are located at grey (*i*). In diurnal snakes, however, these receptors may be used to detect frogs that act as infrared sinks among leaves, and to identify the species of these wavelengths. The facial pits of crocodile snakes are directionally sensitive and respond to infrared radiation (*i*). Many species of birds and snakes are known to eat frogs and toad in their diet, and it is possible that snakes and snakes may have adapted for infrared cryptic coloration in tropical leaf-sitting frogs.

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South Florida, Tampa 33620

Rebeka and Nata

1. Knobell infrared stroboscopic film has a resolution

of 1000 frames per second (KIRK, 1974).

The dose condition (parts) are measured

as follows: 1000 nm = 1000 parts, 700 nm =

1000 parts, and 600 nm = 1000 parts.

2. The infrared reflectance of the frog skin is

not the same as the infrared reflectance of the

skin of the frog against the background

2. U. S. Gibson & R. Beckley, S. E. Werner,

3. U. S. Cole, Advances in Comparative Animal

Physiology, Vol. 1, Academic Press, San Diego, CA, 1974.

4. U. S. Cole, J. M. J. Stamps, *Proc. Roy. Soc. Lond. B Biol. Sci.* 197, 177 (1977).

5. U. S. Cole, *J. Physiol.* 274, 589 (1977).

6. U. S. Cole, *J. Physiol.* 274, 599 (1977).

7. U. S. Cole, *J. Physiol.* 274, 609 (1977).

8. U. S. Cole, *J. Physiol.* 274, 619 (1977).

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101. U. S. Cole, *J. Physiol.* 274, 1569 (1977).

102. U. S. Cole, *J. Physiol.* 274, 1579 (1977).

103. U. S. Cole, *J. Physiol.* 274, 1589 (1977).

104. U. S. Cole, *J. Physiol.* 274, 1599 (1977).

105. U. S. Cole, *J. Physiol.* 274, 1609 (1977).

106. U. S. Cole, *J. Physiol.* 274, 1619 (1977).

107. U. S. Cole, *J. Physiol.* 274, 1629 (1977).

108. U. S. Cole, *J. Physiol.* 274, 1639 (1977).

109. U. S. Cole, *J. Physiol.* 274, 1649 (1977).

110. U. S. Cole, *J. Physiol.* 274, 1659 (1977).

111. U. S. Cole, *J. Physiol.* 274, 1669 (1977).

112. U. S. Cole, *J. Physiol.* 274, 1679 (1977).

113. U. S. Cole, *J. Physiol.* 274, 1689 (1977).

114. U. S. Cole, *J. Physiol.* 274, 1699 (1977).

115. U. S. Cole, *J. Physiol.* 274, 1709 (1977).

116. U. S. Cole, *J. Physiol.* 274, 1719 (1977).

117. U. S. Cole, *J. Physiol.* 274, 1729 (1977).

118. U. S. Cole, *J. Physiol.* 274, 1739 (1977).

119. U. S. Cole, *J. Physiol.* 274, 1749 (1977).

120. U. S. Cole, *J. Physiol.* 274, 1759 (1977).

121. U. S. Cole, *J. Physiol.* 274, 1769 (1977).

122. U. S. Cole, *J. Physiol.* 274, 1779 (1977).

123. U. S. Cole, *J. Physiol.* 274, 1789 (1977).

124. U. S. Cole, *J. Physiol.* 274, 1799 (1977).

125. U. S. Cole, *J. Physiol.* 274, 1809 (1977).

126. U. S. Cole, *J. Physiol.* 274, 1819 (1977).

127. U. S. Cole, *J. Physiol.* 274, 1829 (1977).

128. U. S. Cole, *J. Physiol.* 274, 1839 (1977).

129. U. S. Cole, *J. Physiol.* 274, 1849 (1977).

130. U. S. Cole, *J. Physiol.* 274, 1859 (1977).

131. U. S. Cole, *J. Physiol.* 274, 1869 (1977).

132. U. S. Cole, *J. Physiol.* 274, 1879 (1977).

133. U. S. Cole, *J. Physiol.* 274, 1889 (1977).

134. U. S. Cole, *J. Physiol.* 274, 1899 (1977).

135. U. S. Cole, *J. Physiol.* 274, 1909 (1977).

136. U. S. Cole, *J. Physiol.* 274, 1919 (1977).

137. U. S. Cole, *J. Physiol.* 274, 1929 (1977).

138. U. S. Cole, *J. Physiol.* 274, 1939 (1977).

139. U. S. Cole, *J. Physiol.* 274, 1949 (1977).

140. U. S. Cole, *J. Physiol.* 274, 1959 (1977).

141. U. S. Cole, *J. Physiol.* 274, 1969 (1977).

142. U. S. Cole, *J. Physiol.* 274, 1979 (1977).

143. U. S. Cole, *J. Physiol.* 274, 1989 (1977).

144. U. S. Cole, *J. Physiol.* 274, 1999 (1977).

145. U. S. Cole, *J. Physiol.* 274, 2009 (1977).

146. U. S. Cole, *J. Physiol.* 274, 2019 (1977).

147. U. S. Cole, *J. Physiol.* 274, 2029 (1977).

148. U. S. Cole, *J. Physiol.* 274, 2039 (1977).

149. U. S. Cole, *J. Physiol.* 274, 2049 (1977).

150. U. S. Cole, *J. Physiol.* 274, 2059 (1977).

151. U.

Model: Dynamic

- Divide text into sequential slices (e.g., by year)
- Assume each slice's documents drawn from LDA model
- Allow word distribution within topics β and distribution over topics α to evolve via markov process

Estimation

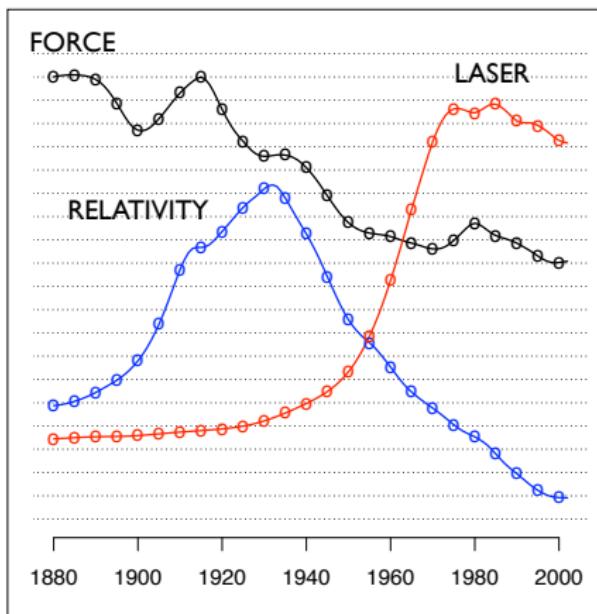
- Bayesian inference intractable using standard methods (e.g., Gibbs sampling)
 - Blei (2006) → variational inference
 - Taddy R package → MAP estimation
 - Current favorite → Stochastic gradient descent
- Main estimates are for 20 topic model

Results: LDA

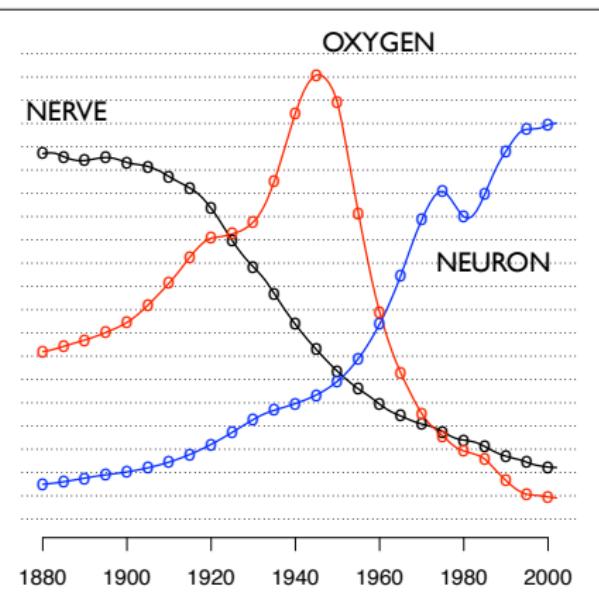
1	2	3	4
human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

Results: Dynamic

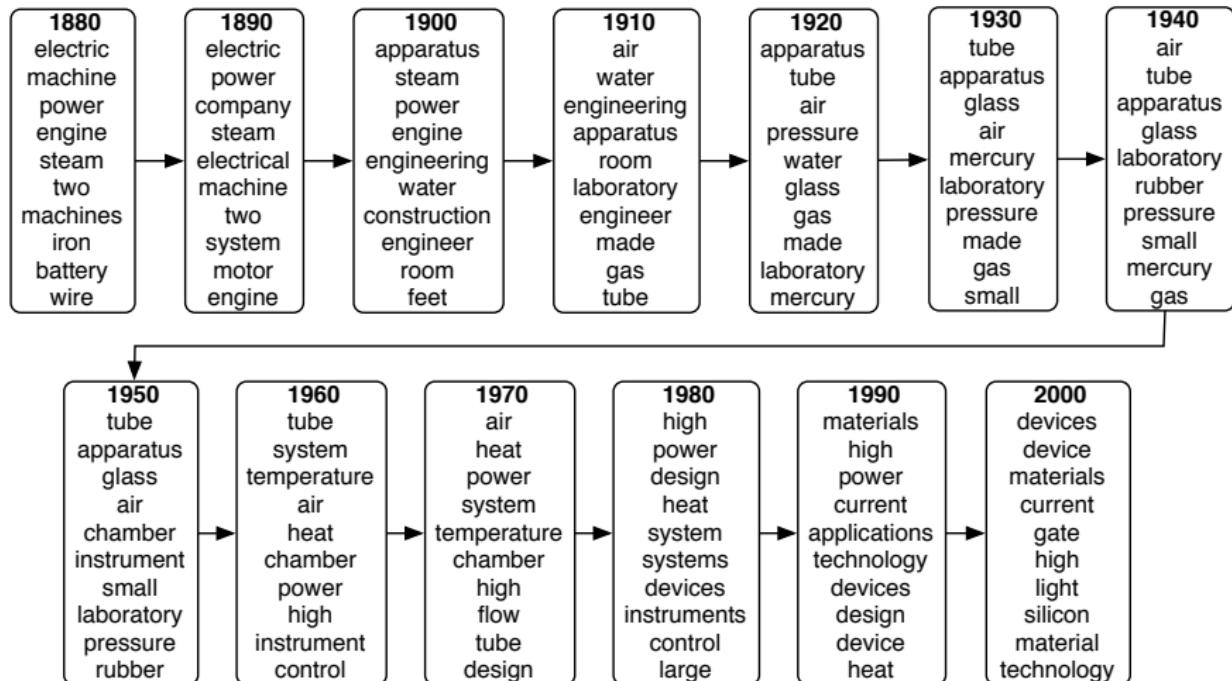
"Theoretical Physics"



"Neuroscience"



Results: Dynamic



Results: Dynamic

The Brain of the Orang (1880)

200

SCIENCE

Volume in these cases, which were submitted in a portion on the 1st of December last for correction or revision;—an objection being made not printed their exact number. After publication Professor Agassiz writes that the reports under his name are not addressed to him. We therefore request our readers to consider these withdrawns.

THE BRAIN OF THE ORANG

THE JOURNAL OF ENVIRONMENT & DEVELOPMENT

The basis of Schröder has been argued by Tiede, Maas, Sandfør, van der Kolk and Kuijper, Grootenhuis, Molenaar, etc., and the literature, however, of the last few years contains many other contributions to the subject. I recall myself of the opportunity of presenting some of my own results (Figs. 9 to 11), which were rejected by the referees of the first two papers of this series.



— 1 —

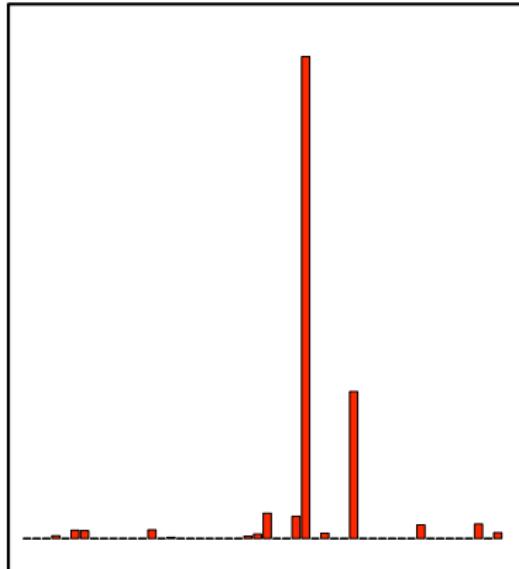
the basis of the Ossing, Charnier, and man are the same; there are certain minor differences, however, between them. The source of Sibylle is the Ossing river, or one of its tributaries, which is passing along a slightly backward direction; the water-basin is small. The source of Kielands is, on the other hand, quite apparent, is, however, situated slightly more forward in the Ossing than in man. It differentiates itself from the Ossing by the fact that the water-pipe is well marked, bordered externally by the fine sand of the delta; it descends suddenly on the distal side of the hemispheres, separating the parietal from the occipital lobes.

⁴ From the Proceedings of the Academy of Natural Sciences, Philadelphia.



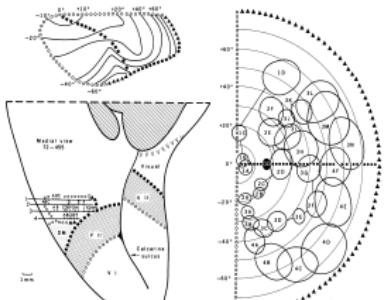
10

Incisor fissure: externally it is continuous with the dental lobes; as the first incisor grows, internally it is separated from the posterior central convolution more completely than is true, by a fissure which runs parallel with the dental fissure. These are the Ong's fissures running parallel with the pituitary, which separates the upper parietal lobule into inner and outer portions. The ponsoculus or the space on the same side of the parietal lobe between the pituitary-

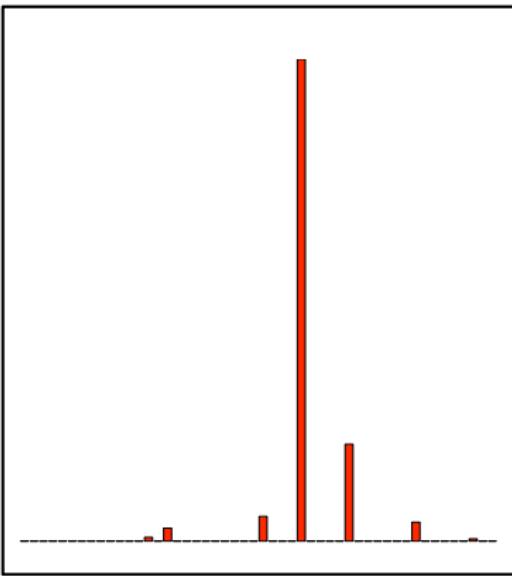


Results: Dynamic

Representation of the Visual Field on the Medial Wall of Occipital-Parietal Cortex in the Owl Monkey (1976)



57



Topic Models: *Quinn et al. (2010)*



United States
of America

Congressional Record

PROCEEDINGS AND DEBATES OF THE 106th CONGRESS, FIRST SESSION

Vol. 145

WASHINGTON, FRIDAY, FEBRUARY 12, 1999

No. 26

Senate

The Senate met at 9:36 a.m. and was called to order by the Chief Justice of the United States.

TRIAL OF WILLIAM JEFFERSON CLINTON, PRESIDENT OF THE UNITED STATES

The CHIEF JUSTICE. The Senate will convene as a Court of Impeachment. The Chaplain will offer a prayer.

of impeachment exhibited by the House of Representatives against William Jefferson Clinton, President of the United States.

THE JOURNAL

The CHIEF JUSTICE. If there is no objection, the Journal of proceedings of the trial are approved to date.

The majority leader is recognized. Mr. LOTT. Thank you, Mr. Chief Justice.

ORDER OF PROCEDURE

Under the consent agreement reached last night, following those votes, a motion relating to censure may be offered by the Senator from California, Senator FEINSTEIN. If offered, Senator GRAMM will be recognized to offer a motion relative to the Feinstein motion, with a vote to occur on the Gramm motion. Therefore, Senators may anticipate an additional vote or votes following the votes on the arti-

- Full text of speeches in US Senate 1995-2004
 - Count words appearing in 0.5% or more of speeches (after stemming)
 - Vocabulary: 3,807 words
 - Total documents: 118,065 speeches

Model

- Like Blei & Lafferty (2006), except
 - ➊ Each document is in exactly one topic
 - ➋ Dynamic distribution of topics, but topics themselves are static

Model

- Blei & Lafferty (2006)
 - $\mathbf{x}_i \sim Multinomial(\boldsymbol{\beta}_1\theta_{i1} + \dots \boldsymbol{\beta}_K\theta_{iK})$
 - $\boldsymbol{\theta}_i \sim F(\alpha)$
 - β and α both evolve over time
- Quinn et al. (2010)
 - $\mathbf{x}_i \sim Multinomial(\beta_{k(i)})$
 - $Pr(k(i) = j) = \alpha_j$
 - α evolves over time; β constant

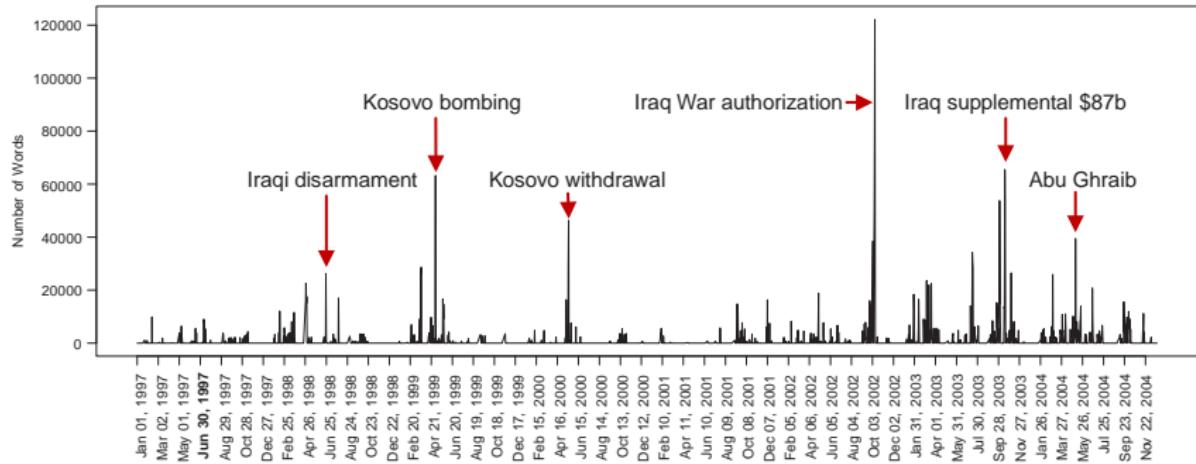
Estimation

- Estimate using ECM algorithm
- Main estimates are for 42 topic model (chosen based on “substantive and conceptual” criteria)

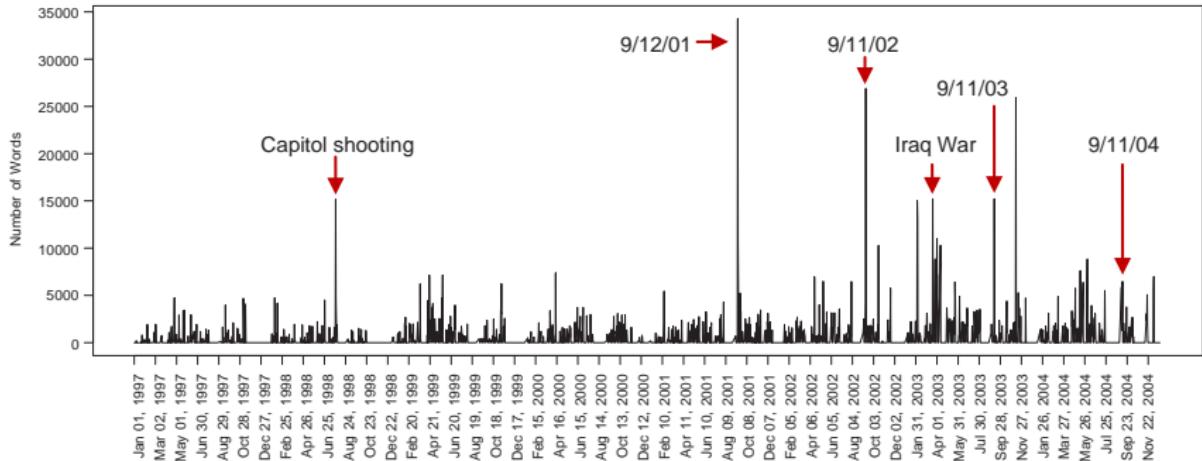
TABLE 3 Topic Keywords for 42-Topic Model

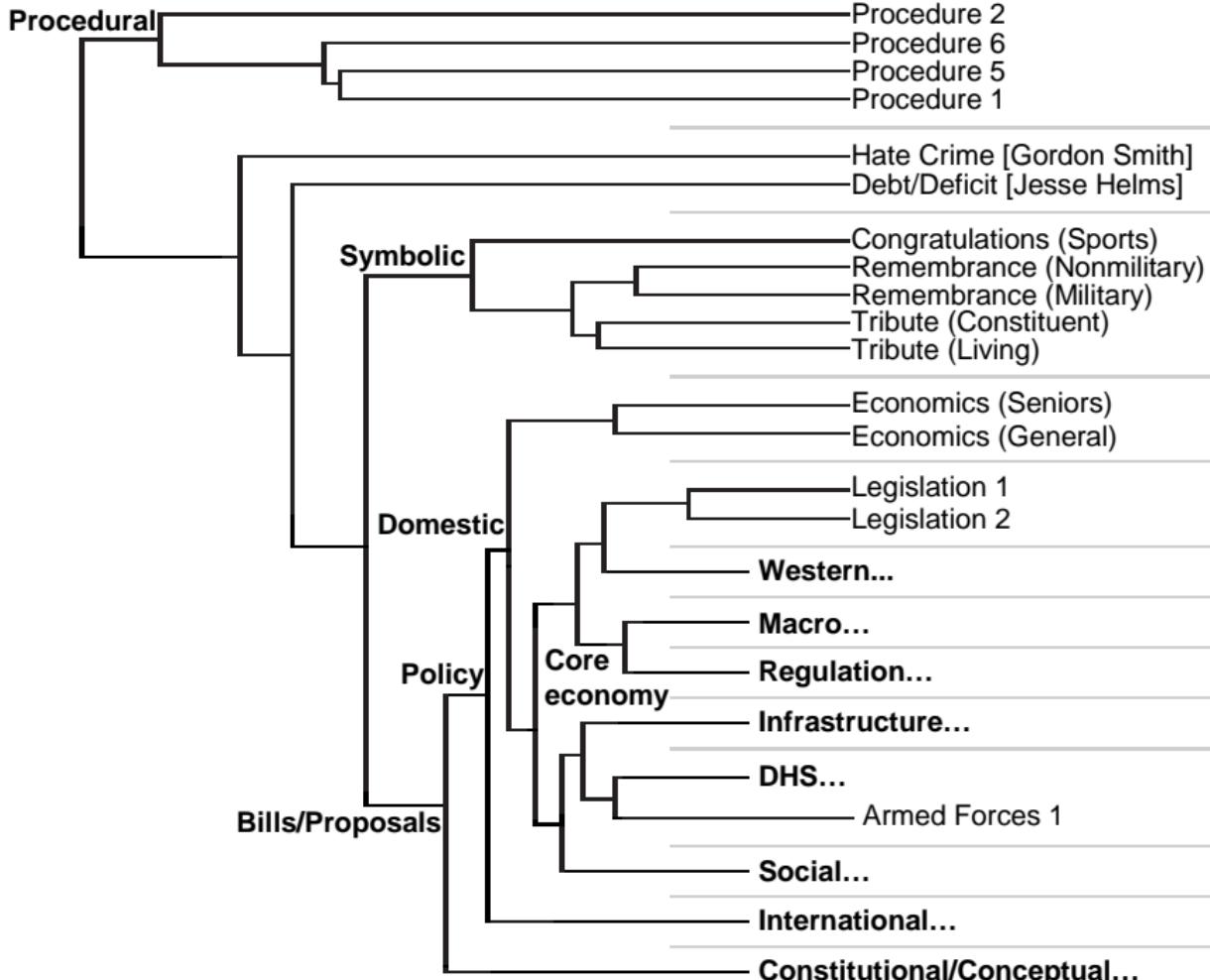
Topic (Short Label)	Keys
1. Judicial Nominations	nomine, confirm, nomin, circuit, hear, court, judg, judici, case, vacanc
2. Constitutional	case, court, attornei, supreme, justic, nomin, judg, m, decis, constitut
3. Campaign Finance	campaign, candid, elect, monei, contribut, polit, soft, ad, parti, limit
4. Abortion	procedur, abort, babi, thi, life, doctor, human, ban, decis, or
5. Crime 1 [Violent]	enforc, act, crime, gun, law, victim, violenc, abus, prevent, juvenil
6. Child Protection	gun, tobacco, smoke, kid, show, firearm, crime, kill, law, school
7. Health 1 [Medical]	diseas, cancer, research, health, prevent, patient, treatment, devic, food
8. Social Welfare	care, health, act, home, hospit, support, children, educ, student, nurs
9. Education	school, teacher, educ, student, children, test, local, learn, district, class
10. Military 1 [Manpower]	veteran, va, forc, militari, care, reserv, serv, men, guard, member
11. Military 2 [Infrastructure]	appropri, defens, forc, report, request, confer, guard, depart, fund, project
12. Intelligence	intellig, homeland, commiss, depart, agenc, director, secur, base, defens
13. Crime 2 [Federal]	act, inform, enforc, record, law, court, section, crimin, internet, investig
14. Environment 1 [Public Lands]	land, water, park, act, river, natur, wildlif, area, conserv, forest
15. Commercial Infrastructure	small, busi, act, highwai, transport, internet, loan, credit, local, capit
16. Banking / Finance	bankruptci, bank, credit, case, ir, compani, file, card, financi, lawyer
17. Labor 1 [Workers]	worker, social, retir, benefit, plan, act, employ, pension, small, employe

Defense [Use of Force]



Symbolic [Remembrance – Military]





Conclusion

Conclusion

- Today
 - Prediction with high-dimensional data
 - Applications
- Tomorrow
 - Estimating treatment effects with high-dimensional data
 - Application