Building a Robot Judge: Data Science for the Law

14. Measuring Polarization in Text

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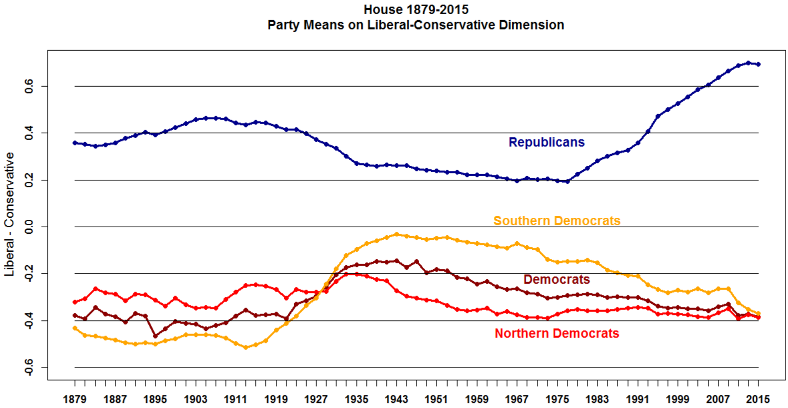
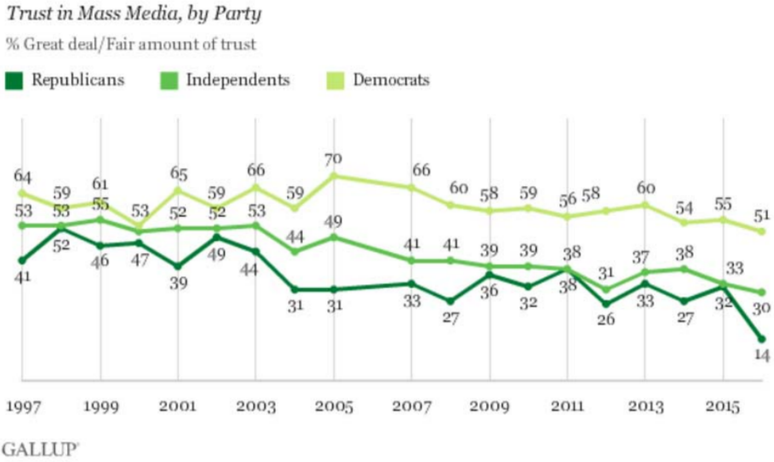
Polarization $\leftrightarrow$ Increasing Group Differences

- An important issue in public discourse across the world is **political polarization**.
  - That is, intensifying disagreement over the goals and means of government and society.
- In the U.S., Bernie Sanders on the Left an Donald Trump on the Right.
- In Europe, Five Star on the Left and Brexit on the Right.
- In Switzerland, the rise of the Swiss People's Party.



Source: Hans Noel.

Trust in Media



Gentzkow and Shapiro (2010)

- Corpora:
  - news text from large sample of US daily newspapers.
  - congressional text is 2005 Congressional Record.
- Pre-process text, stripping away prepositions, conjunctions, pronouns, and common words
  - get bigrams and trigrams
- Identify polarizing phrases using χ^2 metric. For each phrase w, let D_w be frequency for Democrats, R_w be frequency for Republicans. Let D_w^- and R_w^- be frequencies of *other* phrases.
- Then:

$$\chi_w^2 = \frac{(R_w D_w^- - D_w R_w^-)^2}{(D_w + R_w)(D_w + D_w^-)(R_w + R_w^-)(D_w^- + R_w^-)}$$

  - this is the test statistic for equality between parties of phrase use if they were both drawn from multinomial distributions.

TABLE I

MOST PARTISAN PHRASES FROM THE 2005 *CONGRESSIONAL RECORD*[a]

Panel A: Phrases Used More Often by Democrats		
Two-Word Phrases		
private accounts	Rosa Parks	workers rights
trade agreement	President budget	poor people
American people	Republican party	Republican leader
tax breaks	change the rules	Arctic refuge
trade deficit	minimum wage	cut funding
oil companies	budget deficit	American workers
credit card	Republican senators	living in poverty
nuclear option	privatization plan	Senate Republicans
war in Iraq	wildlife refuge	fuel efficiency
middle class	card companies	national wildlife
Three-Word Phrases		
veterans health care	corporation for public broadcasting	cut health care
congressional black caucus	additional tax cuts	civil rights movement
VA health care	pay for tax cuts	cuts to child support
billion in tax cuts	tax cuts for people	drilling in the Arctic National
credit card companies	oil and gas companies	victims of gun violence
security trust fund	prescription drug bill	solvency of social security
social security trust	caliber sniper rifles	Voting Rights Act
privatize social security	increase in the minimum wage	war in Iraq and Afghanistan
American free trade	system of checks and balances	civil rights protections
central American free	middle class families	credit card debt

TABLE I—*Continued*

Panel B: Phrases Used More Often by Republicans		
Two-Word Phrases		
stem cell	personal accounts	retirement accounts
natural gas	Saddam Hussein	government spending
death tax	pass the bill	national forest
illegal aliens	private property	minority leader
class action	border security	urge support
war on terror	President announces	cell lines
embryonic stem	human life	cord blood
tax relief	Chief Justice	action lawsuits
illegal immigration	human embryos	economic growth
date the time	increase taxes	food program
Three-Word Phrases		
embryonic stem cell	Circuit Court of Appeals	Tongass national forest
hate crimes legislation	death tax repeal	pluripotent stem cells
adult stem cells	housing and urban affairs	Supreme Court of Texas
oil for food program	million jobs created	Justice Priscilla Owen
personal retirement accounts	national flood insurance	Justice Janice Rogers
energy and natural resources	oil for food scandal	American Bar Association
global war on terror	private property rights	growth and job creation
hate crimes law	temporary worker program	natural gas natural
change hearts and minds	class action reform	Grand Ole Opry
global war on terrorism	Chief Justice Rehnquist	reform social security

[a] The top 60 Democratic and Republican phrases, respectively, are shown ranked by χ^2_{pl}. The phrases are classified as two or three word after dropping common "stopwords" such as "for" and "the." See Section 3 for details and see Appendix B (online) for a more extensive phrase list.

Consumers drive media slant (GS 2010)

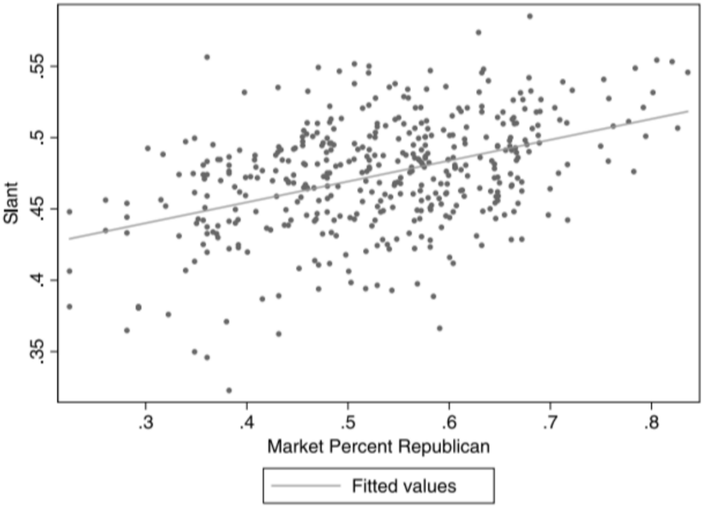


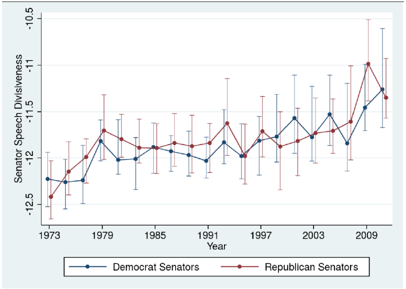
FIGURE 4.—Newspaper slant and consumer ideology. The newspaper slant index against Bush's share of the two-party vote in 2004 in the newspaper's market is shown.

Ash, Morelli, and Van Weelden (2017)

- Let f_{iwt} be the frequency of phrase w spoken by congressman i during session t, standardized within chamber-year to have mean zero and standard deviation one.
- Then the divisiveness of speech for congressman i at year t is defined as

$$Y_{it} = \log(\sum_{w} f_{iwt}\chi^2_{wt})$$

where the phrase-polarization measure χ^2_{wt} can vary by year.



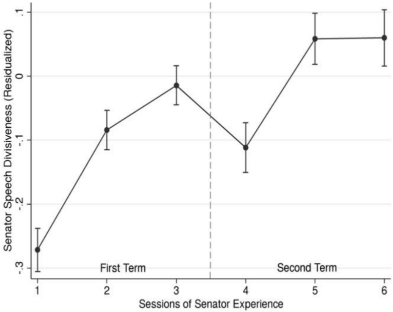


Figure 1. Senator speech divisiveness by election cohort. This figure plots average senator speech divisiveness over the course of the first two terms (six sessions, 12 years) of a senator's career. The values plotted are the mean residuals from a regression of senator speech divisiveness on a senator fixed effect, grouped by the first six sessions. This includes only senators who began their career in the first cohort (excluding senators appointed or elected to finish out an existing term). Error spikes indicate standard errors.

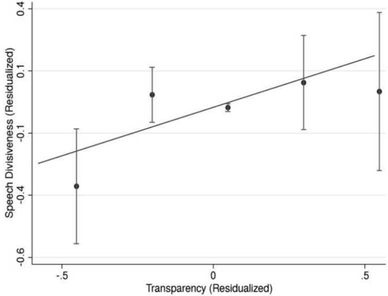
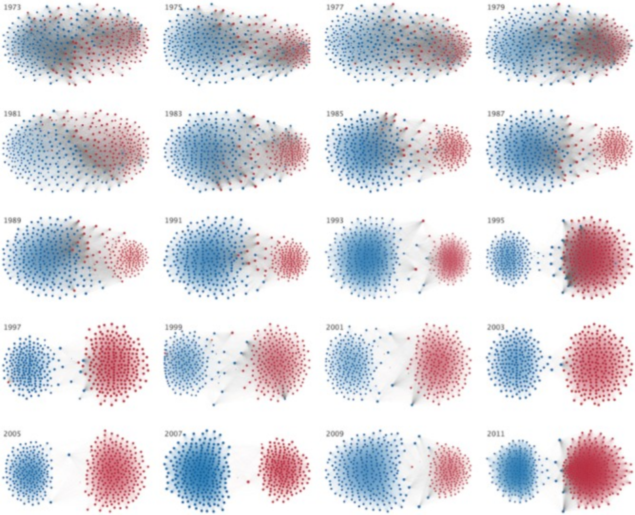


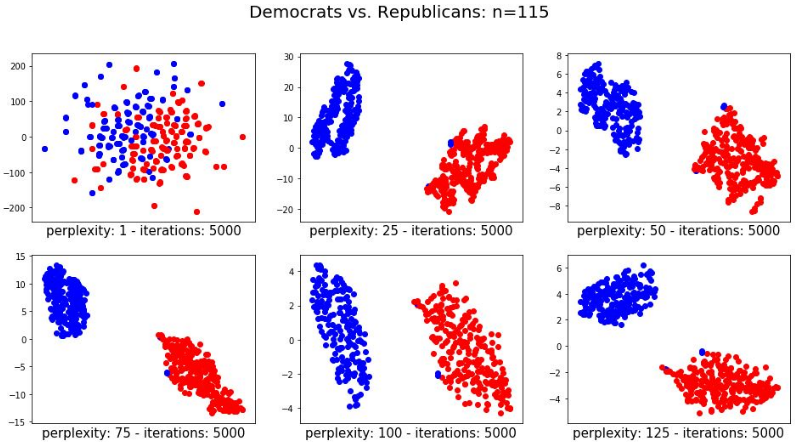
Figure 2. House member speech divisiveness by transparency level. This figure plots House member speech divisiveness against the transparency metric, after residualizing both on a party-year fixed effect, member fixed effect, and vote margin controls. Observations are grouped in bins of width .25. The trend line gives the linear fit. Error spikes indicate 95% confidence intervals.

Andris et al (2015)



"The Rise of Partisanship and Super-Cooperators in the U.S. House of Representatives." Plots of mutual agreement networks based on roll call votes, colored by party.

Congressman Embeddings



t-SNE plots of embedding vectors for each Congressman, trained to predict agreement on roll call votes. 115th Congress.

GST: Generative Model of Text

Gentzkow, Shapiro, and Taddy (*Econometrica* 2019)

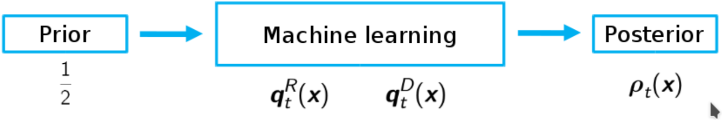
$\boldsymbol{c}_{it}^{p}$, vector of phrase frequences for speaker i at year t, by party $p \in D, R$, drawn from multinomial distribution

$$\boldsymbol{c}_{it}^{D} \sim \mathrm{MN}(\boldsymbol{q}_t^{D})$$
$$\boldsymbol{c}_{it}^{R} \sim \mathrm{MN}(\boldsymbol{q}_t^{R})$$

- $\boldsymbol{q}_t^{D}$ and $\boldsymbol{q}_t^{R}$ are party-specific vectors of probabilities

Bayesian Learning of Partisanship

Gentzkow, Shapiro, and Taddy (2019)



$\rho_{jt} = \frac{q_{jt}^R}{q_{jt}^R + q_{jt}^D}$, **posterior probability** that observer with neutral prior assigns to speaker being Republican if see phrase j in year t

- $\boldsymbol{\rho}_t$ is the vector of posteriors associated with each phrase

Define π_t = **partisanship** at time t:

$$\pi_t = \frac{1}{2}\boldsymbol{q}_t^R \cdot \boldsymbol{\rho}_t + \frac{1}{2}\boldsymbol{q}_t^D \cdot (1 - \boldsymbol{\rho}_t)$$

- Weighted average of posteriors – that is, is text informative of affiliation?

Language Choice Model

Gentzkow, Shapiro, and Taddy (2019)

- Let speaker i's "utility" from speaking phrase j at time t be

$$u_{ijt} = \alpha_{jt} + \boldsymbol{x}'_{it}\gamma_t + R_i\varphi_j$$

  - α_{jt}, baseline utility
  - γ_t, utility associated to speaker characteristics
  - R_i=Republican, so φ_j indexes party difference.

- If speaker chooses phrases to maximize utility u_{it} with respect to a choice-specific i.i.d. type 1 extreme value shock, then

$$q_{jt}(\boldsymbol{x}_{it}) = \frac{e^{u_{ijt}}}{\sum_l e^{u_{ilt}}}$$

Regularized cost function

Gentzkow, Shapiro, and Taddy (2019)

Learn $(\alpha_{jt}, \gamma_t, \varphi_j)$ to minimize

$$\sum_j \left\{ \sum_t \sum_i [\exp(\alpha_{jt} + \boldsymbol{x}'_{it}\gamma_t + R_i\varphi_j)m_{it} - (\alpha_{jt} + \boldsymbol{x}'_{it}\gamma_t + R_i\varphi_j)c_{ijt} + \lambda_j|\varphi_j|] \right\}$$

where $m_{it}=$ number of phrases spoken; $c_{ijt}=$ count for phrase j

- Approximate multinomial with Poisson model

$$c_{ijt} \sim \text{Pois}(\exp[\log(m_{it}) + u_{ijt}])$$

  allowing parallel computation across phrases.
- λ_j=phrase-specific lasso penalty, chosen to maximize information criterion.

Regularization and Permutation

Gentzkow, Shapiro, and Taddy (2019)

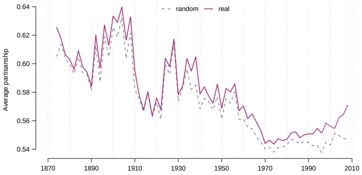
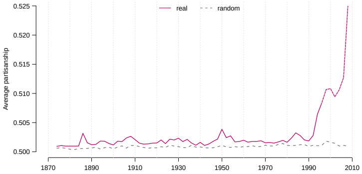
Maximum Likelihood Estimator	**Preferred (Penalized) Estimator**
	
Usual method: Plug-in MLE w/ Congress speech	Regularized method w/ permutation inference

Figure 3: Informativeness of Speech by Speech Length and Session

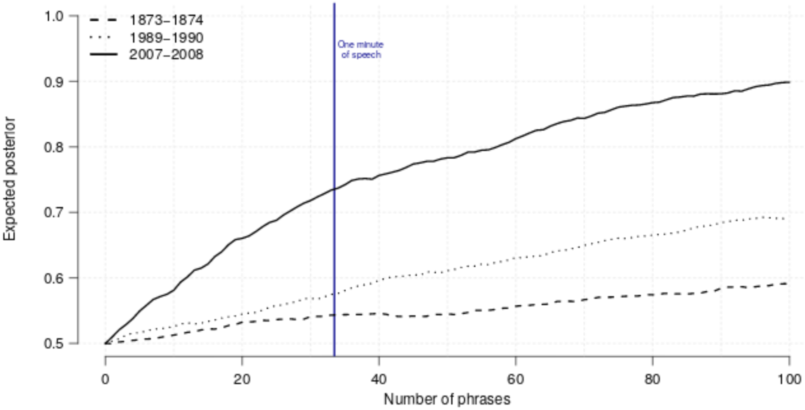
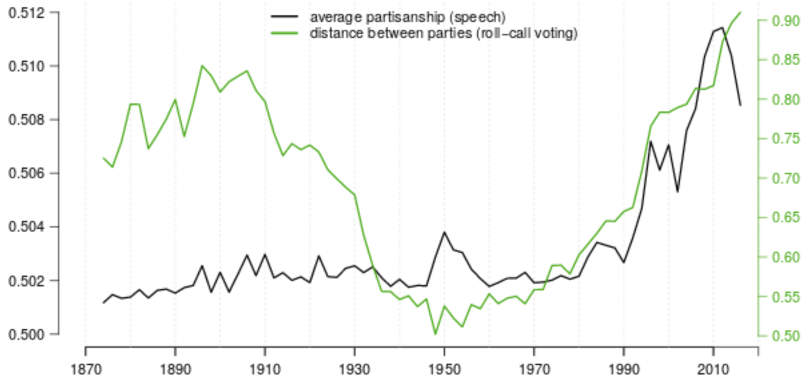


Figure 8: Partisanship vs. Roll-Call Voting

Panel A: Over Time

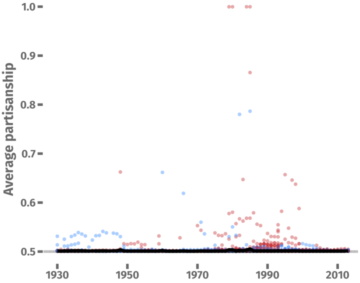


What about judges?

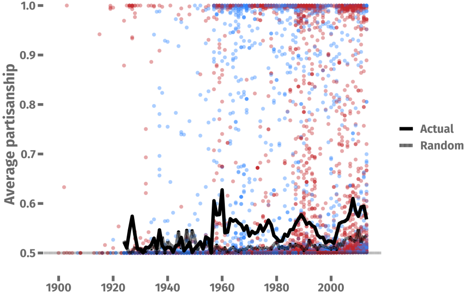
Ash, Chen, and Lu (2019)

- Apply the GST method to U.S. Circuit Courts, 1930-2013
- Look at polarization of language, as well as which previous cases are cited.

Polarization in Federal Judiciary



Phrases



Citations

Judicial prose (0.5) << Congress prose (0.515) << Precedent (0.6)