

# Qualitative Methods and Multi-Method Research

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# Pure Qualitative Research Is Fine!

# Integrative Research and Qualitative Methods

- Quantitative researchers sometimes, but not always, identify assumptions in the way that quantitative researchers do

# Integrative Research and Qualitative Methods

- Quantitative researchers sometimes, but not always, identify assumptions in the way that quantitative researchers do
- Other times, they talk about boundary conditions, limitations, challenges, needs in their research, etc.

# Some Ideas

- ① Enhance testing-based process tracing by reinforcing surprising steps in the process-tracing argument
- ② Enhance discovery-based process tracing by broadening the range of subject matters explored
- ③ Machine learning to help position texts within large collections
- ④ Quantitative components to help move between levels of analysis

# Enhance Surprising Process-Tracing Steps

- The best process-tracing evidence strongly supports one hypothesis but is very surprising under other hypotheses.
- This motivates people who accept those hypotheses to reinterpret.
- Adding additional evidence with different epistemological properties makes such reinterpretation harder, and therefore speeds up necessary theoretical change

# Party-System Collapse

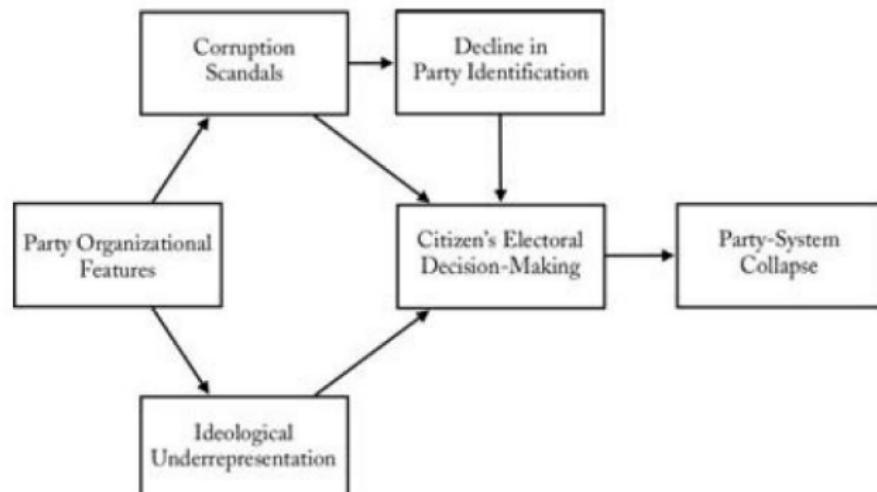


FIGURE 1.1. Causes of party-system collapse: overall structure of the argument

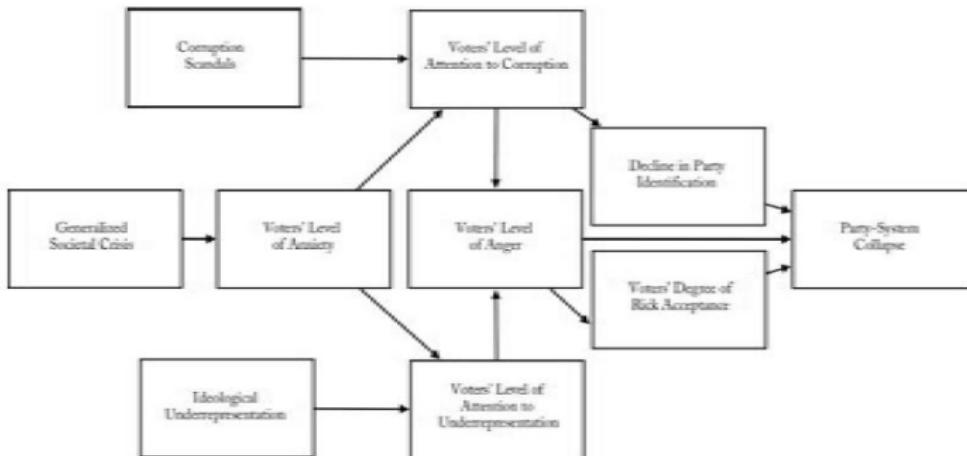


FIGURE 1.2. Voters and party-system collapse: refining the argument

TABLE 3.1. Economic performance of Latin American countries, 1980–2000 (percent)

<i>Country</i>	<i>Average Annual per Capita Growth</i>	<i>Average Annual Inflation</i>	<i>Average Unemployment</i>
Peru	-0.35	544.71	7.63
Venezuela	-1.08	32.72	10.08
Argentina	0.38	375.74	8.11
Bolivia	-0.31	663.83	5.31
Brazil	0.62	697.18	5.29
Chile	2.96	15.15	8.11
Colombia	1.22	23.21	11.64
Costa Rica	0.82	23.17	5.76
Dominican Republic	2.88	17.54	16.65
Ecuador	-0.55	1.09	8.69
El Salvador	0.50	5.18	9.01
Guatemala	-0.10	13.37	2.68
Honduras	-0.18	12.50	5.66
Mexico	0.86	42.47	3.34
Nicaragua	-2.09	1387.57	10.76
Panama	2.48	4.00	13.03
Paraguay	0.45	18.28	5.70
Uruguay	1.45	49.39	10.09

TABLE 3.2. Economic models of Latin American elections, 1980–2001

<i>Variable Name</i>	<i>Economics Only</i>	<i>Economics + Unemployment</i>
Intercept	0.596 (0.297)	1.044 (0.349)*
Last opposition vote share	0.339 (0.139)*	0.442 (0.145)**
Candidate from main opposition	-0.766 (0.217)**	-0.859 (0.216)**
Peru, 1985	-1.384 (0.469)**	-1.407 (0.462)**
Peru, 1990	1.262 (0.533)*	1.704 (1.049)
Venezuela, 1993	-0.833 (0.460)	-0.974 (0.457)*
Average inflation	-0.00244 (0.00041)**	-0.00232 (0.000508)**
Change in inflation	-0.0000821 (0.0000339)*	-0.0000835 (0.0000334)*
Current inflation	0.000551 (0.000119)**	0.000460 (0.000256)
Average growth	0.0965 (0.0386)*	0.119 (0.0409)**
Change in growth	0.0413 (0.0164)*	0.0390 (0.0165)*
Current growth	-0.0760 (0.0286)*	-0.0884 (0.0288)**
Per capita GDP	0.00000201 (0.0000302)	0.00000201 (0.0000308)
Unemployment		-0.0349 (0.0153)*
R <sup>2</sup>	0.744	0.763
Degrees of freedom	48	44

NOTES:

OLS regression estimates with all vote shares transformed via the logit function.

\*( $p < 0.05$ ) \*\*( $p < 0.01$ ).

TABLE 4.2. 1993 Model of Venezuelan traditional party identification

<i>Variable Name</i>	<i>Estimate (S.E.)</i>
Intercept	-1.048** (0.289)
Past party identification	0.790** (0.258)
Corruption concerns	-0.905* (0.428)
Economic concerns	-0.079 (0.128)
Preferred size of state	0.074 (0.080)

TABLE 5.4. 1998 model of Venezuelan presidential vote choice

<i>Variable Name</i>	<i>Acción Democrática (AD) Estimate</i>	<i>PVZ Estimate</i>	<i>Movimiento V República (MVR) Estimate</i>
Intercept	- 4.01 (1.40)**	0.39 (0.53)	- 1.47 (0.59)
Economic evaluations	- 0.18 (0.22)	- 0.08 (0.11)	0.21 (0.10)*
Corruption perceptions	0.65 (0.30)*	0.08 (0.15)	0.29 (0.14)*
Ideological leftist	- 0.93 (0.56)	- 0.23 (0.35)	1.02 (0.17)**
AD party ID	4.30 (0.34)**	0.49 (0.31)	- 1.71 (0.56)**
Social class "C"	0.29 (1.29)	0.12 (0.41)	0.98 (0.50)*
Social class "D"	1.75 (1.19)	- 0.06 (0.39)	0.74 (0.49)
Social class "E"	1.60 (1.20)	- 0.39 (0.40)	0.79 (0.49)

## NOTES:

Maximum-likelihood estimates of the parameters in a multinomial logit model of vote choice. Null deviance is 3831.08 on 4350 degrees of freedom; residual deviance is 3183.47 on 4320 degrees of freedom.

\*( $p < 0.05$ ) \*\*( $p < 0.01$ ).

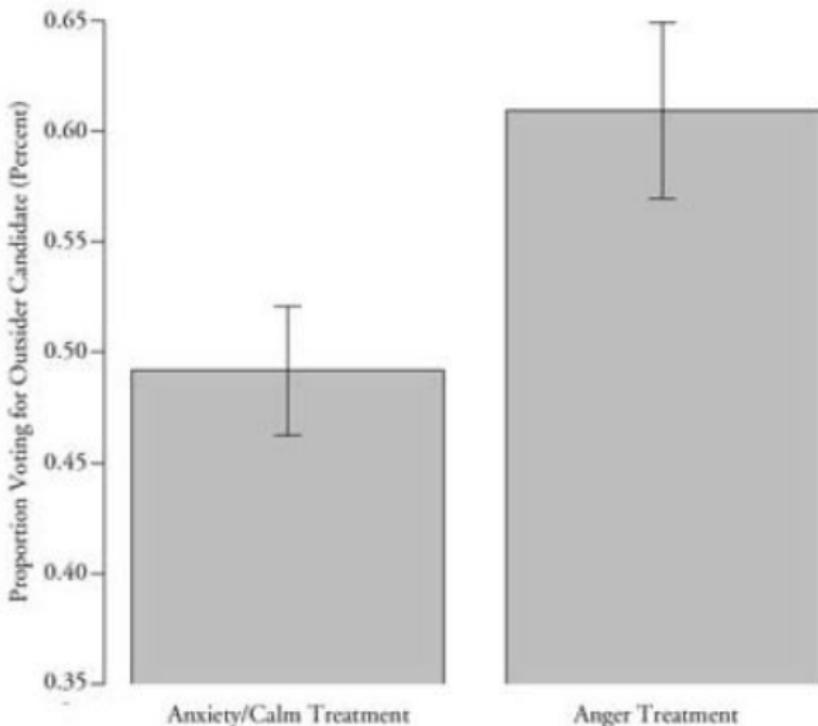


FIGURE 6.1. Affect and vote choice.

SOURCE: These data collected by the author in Lima and Cuzco, Peru, July–August 2009.

TABLE 7.2. Summary of parties' organizational traits

<i>Dimension</i>	<i>AD</i>	<i>COPEI</i>	<i>APRA</i>	<i>AP</i>	<i>IU</i>	<i>PJ</i>	<i>UCR</i>
Membership size	Large	Large	Medium	Small	Small	Medium	Medium
Leadership size	Large	Large	Medium	Medium	Medium	Small	Medium
Leadership experience	High	High	Medium	Low	Low	Low	Medium
Leadership pragmatism	Medium	Medium	Medium	Medium	Medium	Medium	Medium
Membership financing	Medium	High	Medium	Low	High	Medium	Medium
Leadership power in local nominations	High	High	High	Medium	Medium	Low	Low
Power of local units in national decisions	High	High	Medium	Medium	High	Low	Medium
Communication flows	Low	Medium	High	Medium	Medium	Medium	Medium
Civil-society ties	High	Medium	Medium	Medium	High	Low	Low
Particularistic benefits in activist recruitment	High	High	Medium	Medium	Medium	Low	Low
Autonomy from unions	Low	Medium	Medium	High	Medium	High	High



TABLE 7.3. Regression of local/national ideological distance on party organizational traits

<i>Variable</i>	<i>Estimate (SE)</i>	<i>P Value</i>
Intercept	- 0.27 (0.42)	0.53
Local voters' ideological distance from the national party	0.17 (0.05)	0.00
Membership size	0.04 (0.03)	0.16
Leadership size	- 0.02 (0.03)	0.60
Leadership experience	0.00 (0.04)	0.96
Leadership pragmatism	0.05 (0.09)	0.59
Membership financing	0.03 (0.03)	0.38
Leadership power in local nominations	- 0.11 (0.16)	0.47
Power of local units in national decisions	0.13 (0.06)	0.04
Communication flows	- 0.03 (0.07)	0.65
Civil-society ties	0.03 (0.04)	0.49
Particularistic benefits in activist recruitment	0.06 (0.12)	0.63
Autonomy from unions	- 0.04 (0.06)	0.50
Intra-party ideological diversity	0.51 (0.05)	< 0.01
Complexity of membership and outreach organizations	- 0.06 (0.05)	0.22
Importance of patronage	0.00 (0.04)	0.94
<i>R</i> <sup>2</sup>	0.51	

# Lacombe (2018)

The NRA deploys ideas to construct a politicized group social identity among gun owners, who are then easy to mobilize into political participation.

# Lacombe (2018)

- ① Archival research
- ② Structural topic models
- ③ Qualitative and quantitative content analysis
- ④ In-depth reading
- ⑤ Time-series analysis
- ⑥ Process tracing

**TABLE 1. Top Words Associated with Each Topic from *Rifleman Corpus***

Topic Label	Words
1 <i>Shooting Sports and Military Preparedness</i>	<i>FREX:</i> rifl, train, marksmanship, war, program, shooter, match, game, civilian, fire
	<i>High Prob:</i> nation, rifl, associ, shoot, program, train, will, war, time, servic
2 <i>Membership Programs and Benefits</i>	<i>FREX:</i> nra, member, membership, futur, generat, perri, editori, hold, help, nras
	<i>High Prob:</i> nra, member, year, can, one, take, now, will, million, come
3 <i>Gun Regulation</i>	<i>FREX:</i> citizen, registr, propos, possess, weapon, regist, purchas, honest, author, govern
	<i>High Prob:</i> firearm, citizen, state, arm, gun, use, govern, person, nation, weapon
4 <i>Crime, Self-Defense, and Guns</i>	<i>FREX:</i> law, feder, control, crime, handgun, crimin, bill, owner, legisl, court
	<i>High Prob:</i> gun, law, feder, legisl, control, polic, crimin, crime, bill, firearm
5 <i>Second Amendment</i>	<i>FREX:</i> citi, amend, vote, liberti, hous, presid, second, ban, magazin, declar
	<i>High Prob:</i> right, american, will, power, amend, peopl, citi, polit, constitut, bear
6 <i>Americanism and Guns</i>	<i>FREX:</i> hunt, men, safeti, board, respons, hunter, educ, cours, recreat, accid
	<i>High Prob:</i> america, will, men, hunt, american, safeti, peopl, hunter, respons, one

**Note:** Words are stemmed.

**TABLE 2. Identity-Forming Language in Gun Control Editorials and Letters to the Editor**

	Identity-Forming Language	In-Group Positive	Out-Group Negative
<i>NRA Editorials</i>	80% (338/422)	55% (232/422)	66% (280/422)
<i>Pro-Gun Letters</i>	64% (1366/2135)	43% (909/2135)	38% (813/2135)
<i>Anti-Gun Letters</i>	39% (401/1018)	7% (71/1018)	36% (362/1018)
<b>Note:</b> The “Identity-Forming Language” column depicts the portion of editorials or letters that discuss either in-group positive or out-group negative characteristics, or both. The “In-Group Positive” and “Out-Group Negative” are more specific and depict the extent to which each type of identity-forming language is used.			

The perceived opponents of gun rights consist of several distinct groups, the three most prominent of which are politicians, the media, and lawyers.

Politicians are described as: bureaucrat(ic), reformer(s), big city, urban, elitist, special interests, tyrannical, and “F” troop (politicians who have received “F” ratings from the NRA).

The media is described as: liar(s), coward(ly), elitist, phony, cynical, devious, shameless, and propaganda/propagandists.

Lawyers as: greedy, fat-cat, opportunist(s), big city, urban, elitist, phony, cynical, and liar(s).

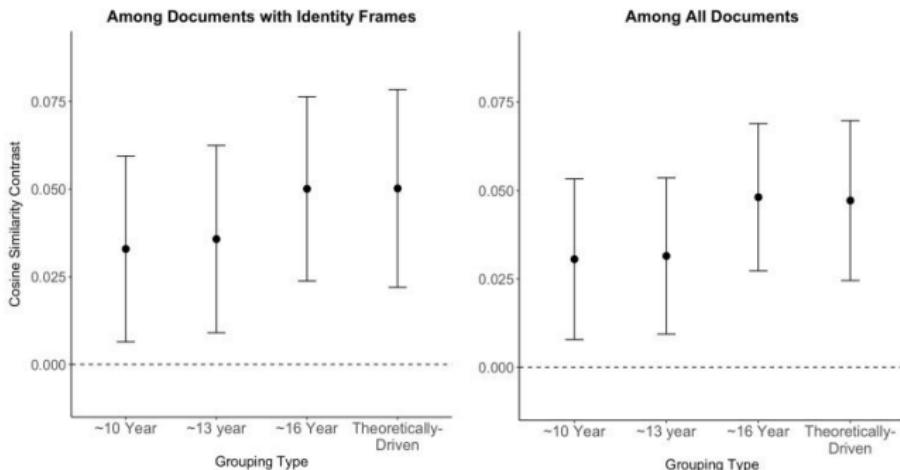
A set of more general characteristics is used to portray gun regulation proponents as un-American, including: fanatic(s), extreme/extremists, radical(s), hysterical, anti-liberty, Communist(s), tyrannical, globalist, and internationalist. Finally, gun control supporters are described as “anti-gunners” and “the gun ban crowd.”

**TABLE 3. Origination of Most Distinctive In-Group/Out-Group Phrases and Results of Lagged Linear Probability Model Predicting the Presence of Each Phrase in Pro-Gun Letters to the Editor**

Phrase	First appearance in an identity- framing document	Significant Effect in a Lagged Year	<i>Rifleman</i> 1 Year Lag	<i>Rifleman</i> 2 Year Lag	<i>Rifleman</i> 3 Year Lag
			Coefficient (p-value)	Coefficient (p-value)	Coefficient (p-value)
<i>Anti-gunners</i>	<i>American Rifleman</i> (December 1975)	✓	—	—	0.219 (0.020)
<i>Average citizens</i>	<i>American Rifleman</i> (February 1936)	✗	—	—	—
<i>Freedom-loving</i>	<i>American Rifleman</i> (May 1944)	✗	—	—	—
<i>Ordinary citizens</i>	<i>American Rifleman</i> (March 1948)	✓	—	0.303 (0.083)	—
<i>Law-abiding</i>	<i>New York Times</i> (September 1931)	✓	0.203 (0.050)	0.249 (0.020)	—

Note: Dependent variables are binary variables indicating whether a phrase appeared in a pro-gun letter to the editor in a given year for each year in the dataset (1930-2008). Separate models were estimated for each phrase. The independent variables presented in the table for each model are lagged binary variables indicating whether the phrase appeared in a *Rifleman* editorial in each of the three previous years. Also included in each model, as controls, was a binary variable indicating whether a phrase appeared in the *Rifleman* in the same year, as well as lagged binary variables indicating whether the phrase appeared in a pro-gun letter to the editor in each of the three previous years. All coefficients for variables included in the table that are significant at the p<0.1 level are included.

**FIGURE 1: Average Cosine Similarity Responsiveness**



Case studies showing that dissemination and textual influence include broad arguments and not just word-use patterns.

**TABLE 5. Logistic Regression Predicting Calls to Action**

	B (SE)	z-value	p-value
(Intercept)	-3.007 (0.551)	-5.454	<0.001
Threat	1.975 (0.324)	6.104	<0.001
Identity-Building Language	0.439 (0.366)	1.200	0.230
Policy Discussion	0.627 (0.496)	1.265	0.206

Null deviance: 551.58 on 421 degrees of freedom. Residual deviance: 475.88 on 418 degrees of freedom. AIC: 483.88.

Case studies of letters written to Presidents Johnson and Bush in response to NRA calls to action.

# Enhance Discovery-Based Process-Tracing

- It is much easier to add a new topic/theoretical theme to qualitative research before it begins than after data collection is complete.

# Enhance Discovery-Based Process-Tracing

- ① Collect some kind of data set related to the question of interest, that is as inclusive as possible.
- ② Use a machine-learning method to identify predictors related to the topics of interest.
- ③ Treat those predictors as clues about themes to explore in qualitative research.

# Example: Rise of the U.S. Alt-Right

- Alex Jones, InfoWars, and the Alt-Right
- It is likely that whatever is responsible for the growth of the alt-right has left traces in the discussions on InfoWars broadcasts.

```
library(tm)

infowarscorpus <- VCorpus(DirSource(directory="D:/Jan 6th/alexjonestranscripts/infowars", "UTF-8"))

ajmeta <- function(initialfilename){
  c(substr(str_split(initialfilename,"/")[[1]][5], 1,4),
    substr(str_split(initialfilename,"/")[[1]][5], 5,6),
    substr(str_split(initialfilename,"/")[[1]][5], 7,8),
    str_split(str_split(str_split(initialfilename,"/")[[1]][5],"_")[[1]][3],"\\\.")[[1]][1])
}

temp <- DirSource(directory="D:/Jan 6th/alexjonestranscripts/infowars", "UTF-8")

infometa.temp <- matrix(nrow=length(temp$filelist), ncol=4)

for (i in 1:length(temp$filelist)){
  infometa.temp[i,] <- ajmeta(temp$filelist[i])
}

meta(infowarscorpus, c("year", "month", "day", "show")) <- infometa.temp
```

20150104_Sun_Alex.mp3	2/2/2023 10:51 AM	Text Document	99 KB
20150105_Mon_Alex.mp3	2/2/2023 11:12 AM	Text Document	170 KB
20150106_Tue_Alex.mp3	2/2/2023 11:30 AM	Text Document	157 KB
20150107_Wed_Alex.mp3	2/2/2023 11:50 AM	Text Document	162 KB
20150108_Thu_Alex.mp3	2/2/2023 12:07 PM	Text Document	152 KB
20150109_Fri_Alex.mp3	2/2/2023 6:15 PM	Text Document	155 KB
20150111_Sun_Alex.mp3	2/2/2023 6:29 PM	Text Document	98 KB
20150112_Mon_Alex.mp3	2/2/2023 6:48 PM	Text Document	162 KB
20150113_Tue_Alex.mp3	2/2/2023 7:09 PM	Text Document	159 KB
20150114_Wed_Alex.mp3	2/2/2023 7:28 PM	Text Document	155 KB
20150115_Thu_Alex.mp3	2/2/2023 7:50 PM	Text Document	163 KB
20150116_Fri_Alex.mp3	2/2/2023 8:08 PM	Text Document	164 KB
20150118_Sun_Alex.mp3	2/2/2023 8:22 PM	Text Document	101 KB
20150119_Mon_Alex.mp3	2/2/2023 8:41 PM	Text Document	150 KB
20150120_Tue_Alex.mp3	2/2/2023 9:02 PM	Text Document	167 KB

```
infowarsprocessed <- tm_map(infowarscorpus,content_transformer(tolower))
infowarsprocessed <- tm_map(infowarsprocessed,removeWords,stopwords("english"))
infowars.dtm <- DocumentTermMatrix(infowarsprocessed)
```

```
library(gtrendsR)
library(dplyr)
library(tidyr)

extremism.trends1 <- gtrends(c("Alex Jones", "Infowars", "Oath Keepers",
                                "QAnon", "Proud Boys"), time="all")#since2004
```

```
extremismwords <- as.data.frame(as.matrix(infowars.dtm), col.names=infowars.dtm$dimnames$Terms)
extremismwords$date <- ISOdate(as.numeric(infowarsprocessed$dmeta$year), as.numeric(infowarsprocessed$dmeta$month),
                                as.numeric(infowarsprocessed$dmeta$day), hour=0)
extremismwords <- left_join(extremismwords, extremism.trends.daily, by=c("date"))
```

```
library(glmnet)
lambda <- 0.01
aj.lasso <- glmnet(extremismwords[1:292140], extremismwords$Alex.Jones, lambda=lambda,
                    family="gaussian",
                    intercept = T, alpha=1)
ajlassocoefs <- data.frame(varname = rownames(aj.lasso$beta), varcoef = as.numeric(aj.lasso$beta))
ajlassocoefs$varname[order(abs(ajlassocoefs$varcoef), decreasing=TRUE) [1:40]]
ajlassocoefs$varcoef[order(abs(ajlassocoefs$varcoef), decreasing=TRUE) [1:40]]
```

**Table:** Words and Coefficients Associated With Alex Jones and the Proud Boys

Outcome	Word	Coefficient
Alex Jones	Pappert	6.70
Alex Jones	Sanctimoniously	6.63
Alex Jones	87778925398777892539	4.34
Alex Jones	Bolsonaro	4.22
Proud Boys	Zionist	0.11
Proud Boys	loudmouth	0.08
Proud Boys	collusion	0.01

# Positioning Texts in a Collection

- Qualitative researchers often discuss texts drawn from large collections, as a way of characterizing both the individual text and the broader collection.

# Positioning Texts in a Collection

- ① Run a simple text-as-data model on the text collection as a whole.
- ② Summarize the topics selected from the model using qualitative readings of selected texts.
- ③ Use statistics related to the model to show how individual texts selected for close reading relate to the collection as a whole, and also to describe the overall population.

# Example: January 6th Legal Documents

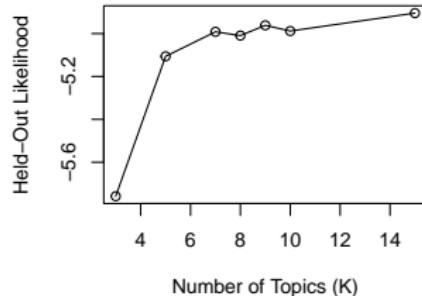
- The main DOJ Jan. 6th website lists about 2,700 documents related to cases against people involved with Jan. 6th.

```
processed_jan6th <- textProcessor(documents=db$text)
prep_jan6th <- prepDocuments(processed_jan6th$documents, processed_jan6th$vocab, processed_jan6th$meta)
```

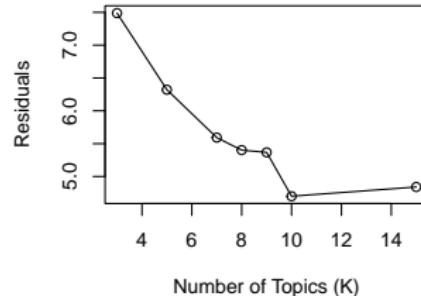
```
testmodelsize<-searchK(prep_jan6th$documents, prep_jan6th$vocab, K = c(3,5,7,8,9,10,15),  
                        verbose=FALSE)  
  
plot(testmodelsize)
```

## Diagnostic Values by Number of Topics

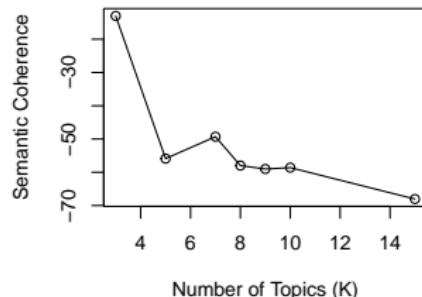
Held-Out Likelihood



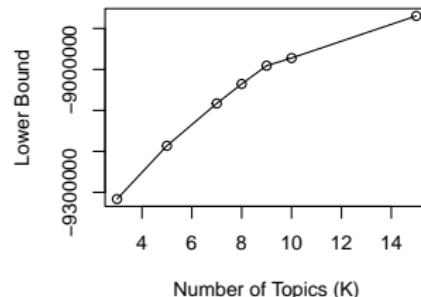
Residuals



Semantic Coherence



Lower Bound



```
jan6th8.stm <- stm(prep_jan6th$documents, prep_jan6th$vocab, 8)  
labelTopics(jan6th8.stm)
```

> `labelTopics(jan6th8.stm)`

Topic 1 Top Words:

Highest Prob: capitol, state, unit, build, defend, crowd, senat  
FREX: christensen, repair, expenditur, plea-, bartow, holli, linwood  
Lift: -cr--svh, check-congression, dennison, holli, repair, -cr---rbw, -law  
Score: crowd, presid, senat, chamber, christensen, member, short

Topic 2 Top Words:

Highest Prob: case, page, document, file, -cr--apm, -cr--bah, -cr--tjk  
FREX: -cr--bah, yyÿ, yyyy, -cr--abj, -cr--apm, -cr--rc1, rhr  
Lift: aiii, cda, ced, crl, deh, dlb, dtu  
Score: -cr--apm, file, document, page, -cr--bah, case, -cr--tnm

Topic 3 Top Words:

Highest Prob: wkh, dqq, dslwro, zlwk, wkdw, cramer, dqxdu  
FREX: dqq, dslwro, wkdw, dqxdu, waynick, munn, portlock  
Lift: "badass", "brian", "captain", "free", "gid", "group", "healion  
Score: dqq, wkh, dslwro, wkdw, zdv, iurp, rwkhu

Topic 4 Top Words:

Highest Prob: state, build, unit, conduct, capitol, restrict, usc  
FREX: rev, yazdani-isfehani, xxxxxx, loammi, xxxxxxxx, padilla, complaint  
Lift: -cr--kbj, -mj--, -mj--jeg, -offic, "bugziethedon", "chad", "elijah  
Score: disrupt, wkh, build, cordoned-, roxpeld, disord, vice

Topic 5 Top Words:

Highest Prob: capitol, build, state, video, januari, unit, senat  
FREX: witness-, bolo, afo', anonym, monm, affiant  
Lift: --job, 'm, 'fuck, "absolutely", "ami", "anthoni", "benjamin  
Score: affiant, presid, figur, fbi, crowd, chamber, individu

Topic 6 Top Words:

Highest Prob: januari, capitol, state, offic, messag, member, facebook  
FREX: denney, watkin, rhode, ashlock, crowl, niemela, -mj--rmm-zmf  
Lift: -destruct, -obstruct, -obstruct, "d, "assault, "certification", "destruct  
Score: watkin, messag, megg, denney, facebook, oath, parker

Topic 7 Top Words:

Highest Prob: page, case, file, document, imag, januari, capitol  
FREX: brodi, rockholt, mlynarek, cantrel, preller, balhorn, lovley  
Lift: "kyle, balhorn, bonenberg, brown-color, carhart, cronin, degregori  
Score: brodi, rockholt, preller, cantrel, mlynarek, lovley, balhorn

Topic 8 Top Words:

Highest Prob: client, agreement, sentenc, court, agre, right, will  
FREX: agreement, client', impos, guidelin, waiv, appeal, withdraw

```
db$filename_original[as.integer(names(prep_jan6th$documents[findThoughts(jan6th8.stm)$index$'Topic 1'[1]]))]
```

- Topics 3 and 7 are various kinds of judicial procedural documents, shared across various kinds of cases.
- Topic 2 is mostly plea bargains, while topic 5 is mostly charge sheets.

- For Topic 1, the most representative text is a stipulation of facts in the case of Jonathan Davis Laurens.

# The Atlanta Journal-Constitution

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## Selfie-taking Duluth man pleads to Jan. 6 charge



◀ Caption

Jonathan Davis Laurens laughed it off when friends on Facebook suggested he should not be inside the U.S. Capitol as a pro-Trump mob swamped the building on Jan. 6, 2021.

“We got into the capitol, walked around, chanted some slogans and stuff,” he wrote. “We weren’t there to tear (expletive) up, just disrupt the system. All in all, I had fun! LOL.”

Using security camera footage and Laurens' own social media postings, investigators were able to trace his route through the Capitol from the Senate side, through the Rotunda and Statuary Hall, and over to the House where he stood as a mob of rioters attempted to force their way into the House chamber. Then Laurens entered the Rayburn Reception Room near the House chamber where he snapped a selfie underneath a painting of George Washington.

- The most-representative document for topic 4 is an FBI affidavit about the activities of Brandon Nelson and Abram Markofski.

# Two more Wisconsin men — one of them a National Guard member — charged with entering U.S. Capitol during Jan. 6 riot



**Elliot Hughes**

Milwaukee Journal Sentinel

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After attending Trump's rally and arriving at the Capitol, the two men said police made no attempt to remove them from the building. Nelson said police were guiding people inside. Markofski told agents an officer said to him, "I can't make you guys leave. However, for your safety, you should leave."

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**milwaukee journal sentinel**

Surveillance cameras captured images of both men. They said they spent about 40 minutes inside the building and drove back to Wisconsin after leaving, according to the complaint.

- Topic 6 is most typically represented by a statement of offense for Daniel Ray Caldwell.

# North Texas man gets over 5 years in for assaulting Capitol officers during riot

Daniel Ray Caldwell doused a group of officers with bear spray during the Jan. 6 uprising at the U.S. Capitol, a prosecutor said.



Daniel Caldwell was caught on video spraying a chemical irritant at police officers defending the Capitol Building on Jan. 6, 2021. (Justice Department)

“During the riot, Caldwell taunted police officers by asking them to spray [pepper spray] and asking if they were ‘scared,’” Peterson said in a sentencing memo.

Later that day, Caldwell gave an interview to an undisclosed person in which he admitted to shouting at officers who were spraying rioters with chemical irritant, saying “Dude, do it again and we’ll spray you back,” Peterson said in the court filing.

They did and Caldwell sprayed the officers back. “I got like 15 of them,” he reportedly said in the interview.

Jenkins said his client was not involved in any organized plan to attack the Capitol. He asked for a four-year prison term.

- With respect to topic 8, the most representative document is a statement of offense for Matthew Capsel.

# Illinois man gets 18 months in prison for fighting with National Guard during Jan. 6 U.S. Capitol riot

Matthew Capsel was arrested just weeks after the Capitol riot for fighting with members of the National Guard. He later wrote on social media that "on the 6 good men had to do a bad thing."

By Jon Seidel | Dec 16, 2022, 5:03pm CDT



Federal authorities say this image depicts Matthew Capsel. | Federal court records

Capsel recorded TikTok videos while outside the Capitol on Jan. 6, 2021. In the videos, he said, “they only got so much mace and we got all these patriots we aren’t going to run out, they are going to run out. Hold the line, don’t run, go down with your eyes out and get some water to drink and hold your ground.”

He also joined a mob that ascended the stairs toward the inauguration bleachers on the building’s northwest side. He and others overcame officers there and stood on the bleachers.

Later, after a 6 p.m. curfew took effect, Capsel and a mob confronted a line of National Guardsmen. Capsel was at the front of the group that charged the troops, pushing against their riot shields. Capsel retreated only after the troops defended themselves with pepper spray.



Between the riot and his arrest in late January 2021, Capsel kept posting videos to TikTok and Facebook. In one, he made a slideshow featuring pictures of President Joe Biden, U.S. House Speaker Nancy Pelosi and Senate Majority Leader Chuck Schumer.

Music also played in the video, with lyrics that said, "Wish you would die, just f---ing die. Ever had a boss that was so damn bad, when you get to work it would drive you f---ing mad. If this place burned down it would be kind of sad. But to be away from him I would f---ing be kind of glad. To do all the work, he takes all the cred, about to blow up on this b-----."

- With this framework, we can answer questions about relative prevalence of different degrees of violence.

**Table:** Texts' Average Degree of Topic Membership

Topic	Average Membership
4 (Least Violence)	28%
1 (Near Violence)	10%
6 (Dramatic Violence)	3%
8 (Violence, Media)	9%

- We can also situate selected texts within the broader context. To pick an actually randomly selected example consider the statement of facts connected with Joseph Howe. The model tells us that Howe belongs in topic 8 (96% membership).

On Thursday, January 7, 2021, a tipster, who will be referred to as T-1, called the FBI's National Threat Operations Center (NTOC) to report information about individuals who participated in the riot at the U.S. Capitol. T-1 identified Michael Sparks (charged elsewhere, *see* D.D.C. Case No. 21-CR-87-TJK) as being the first individual to climb through a broken window into the U.S. Capitol building on January 6, 2021—that is, the very first rioter to breach the U.S. Capitol building. T-1 also knew that Sparks traveled to Washington, DC with co-workers from the Elizabethtown, KY area, including JOSEPH HOWE. (The agent who documented the tip and later interview incorrectly spelled the name "Howell," but he will be referred to throughout using his true name HOWE).

The next day, an FBI agent interviewed T-1 by telephone. T-1 explained that T-1 is an acquaintance of HOWE and overheard HOWE discuss plans with Sparks to travel to Washington, D.C. on January 6, 2021 to attend the pro-Trump rally. T-1 heard Sparks tell HOWE, "This time we are going to shut it down." After the incidents at the U.S. Capitol on January 6, 2021, HOWE's wife, who is also a co-worker of HOWE and Sparks, had a video of her husband being pepper sprayed at the U.S. Capitol.

On January 12, 2021, an FBI agent interviewed T-1 again. The agent provided T-1 with photographs of individuals inside the U.S. Capitol on January 6, 2021 to review, including a photograph of an unknown individual the agent believed at the time might be HOWE (though it was later determined that this photograph showed a different individual wearing similar clothing, including goggles and a dark beanie hat, but was not in fact HOWE). T-1 indicated that the man in the photograph "looks like Joe Howe." T-1 knew that HOWE sent photographs and videos of himself inside the U.S. Capitol to his wife, including one after being pepper sprayed.

On March 22, 2021, an FBI agent interviewed a witness, referred to as W-1. W-1 told the FBI that he traveled to Washington, DC with Sparks, HOWE, and others who worked at the same company in Elizabethtown, KY, in a vehicle rented by Sparks. Upon arriving near the U.S. Capitol on January 6, 2021, W-1 was separated from HOWE based on the large size of the crowd.

CO: You think we're getting in that building?

HOWE: We're getting in it.

CO: You think so?

HOWE: Oh yeah.

Unknown Male ("UM"): Tell you what, you go. We'll follow you.

HOWE: We're getting in it.

UM: [Unintelligible]

HOWE: We're getting in it.

At that point, another individual, who based on my review of the video and my knowledge of Sparks' voice I believe was Sparks, chimed in:

Sparks: All it's gonna take is one person go. The rest is following.

HOWE: Let it go south in there.





# Moving Between Levels of Analysis

- In any kind of research, it can be tough to move between levels of analysis.

# Moving Between Levels of Analysis

- In any kind of research, it can be tough to move between levels of analysis.
- Embedding a quantitative design component can sometimes save time, effort, and money in covering another level of analysis.

# Two More Challenging Designs

- ① Combining Game Theory and Qualitative Research
- ② Statistically Testing Generalizability of Qualitative Research