The effects of transitions of power on the contents of municipal government websites

Markus Neumann Bruce Desmarais Hanna Wallach

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Abstract

Websites have become a prominent source of data for automated text analysis in political science. However, extant research lacks common standards and often glosses over the details on how such analyses are conducted, exposing itself to potential pitfalls associated with this process and making replication difficult. We develop a set of guidelines and procedures to be followed in order to produce valid results. In order to develop a valid research design, the appropriate selection of cases and URLs is crucial. For the acquisition of website data, we cover several scraping methods and difficulties that can arise in the process. Pre-processing is a common step in text analysis, but when websites are concerned, additional measures need to be taken in order to guard against potential sources of bias. Finally, we cover several methods of analysis and validation appropriate for this kind of data. These steps are illustrated through our creation and exploitation of a new and innovative dataset - the websites of local governments in Indiana and Louisiana. We show that if our methodology is followed appropriately, an association between mayoral partisanship and the content of their cities' websites becomes visible.

1 Introduction

1.1 New Research Design

The analysis of entire websites has become more prominent recently, especially in the the text-as-data movement. We see great promise in this development, especially as it pertains to the study of governmental branches and agencies, which are often resilient to being studied by other methods. However, this line of inquiry comes with a set of particular challenges and pitfalls researchers need to be mindful of. We offer solutions to these problems at the four stages of such an analysis.

1. Design
   (a) Choosing the sample
   (b) Finding URLs
   (c) list of .gov websites
   (d) Finding supporting data
2. Scraping

(a) wget

(b) headless browser/Selenium

(c) Beautifulsoup/rvest

(d) APIs (httr)

(e) Wayback Machine

3. Pre-processing

    (a) Determining document filetype

    (b) File conversion

    (c) Conventional preprocessing (lowercase, numbers, punctuation)

    (d) Stemming and lemmatization

    (e) spellchecking

    (f) Dealing with duplicate text & html documents in particular

4. Analysis

    (a) LDA

    (b) Other topic models (structural, author, dynamic – maybe?)

    (c) SVM (+ other machine learning classifiers?)

    (d) Fightin Words

2 Background

Grimmelikhuijsen (2010) run an experiment in which citizens are exposed to randomly selected levels of information about local government council minutes. They find a negative relationship between the information level and perceptions of competence in the local government. This raises an interesting question regarding whether citizens or more likely to participate when they perceive competence or when they perceive incompetence.

Wang, Bretschneider and Gant (2005) present a widely cited 'model' for evaluating the accessibility of information on government websites. This is an important paper with which we should be familiar at a very detailed level as we use archived web content to assess the volume/accessibility of information provided by local governments.

Osman, Anouze, Irani, Al-Ayoubi, Lee, Balcı, Medeni and Weerakkody (2014) is less relevant, but they develop a multi-item measure to predict the level of citizen satisfaction with e-government services.

Grimmelikhuijsen and Welch (2012) conduct an enormously relevant study. Insofar as we analyze what predicts openness of government websites, we will be replicating and building upon this study. They focus on Dutch municipal websites, and their approach is fairly limited in scope and highly manual (which we can compliment). For example, one of the dependent variables "Decision-making transparency," is measured "using a discrete (1/0) indicator for whether the underlying principles or reasons for local air pollution policies were given on the Web site."

Names	Year	Journal	Findings	Important?
Benedictis-Kessner, Justin De Warshaw, Christopher	2016	JOP*	Regression discontinuity design. Democratic mayors spend more (but it is unclear on what, not the typical Democratic issue-areas), issue more debt, pay more interest	Yes
Caughey, Devin Warshaw, Christopher Xu, Yiqing	2015	Working Paper	Regression discontinuity design. Partisan composition of state governments affects state policy liberalism (composite index for the areas of social welfare, taxation, labor, civil rights, women's rights, moral legislation, family planning, environment).	Somewhat
Einstein, Katherine Levine Kogan, Vladimir	2015	Urban Affairs Review	Cities with more Democratic citizens spend more; more progressive (rather than regressive) forms of taxation; pursue intergov. aid more; spend more on police, fire, parks & recreation	Somewhat
Einstein, Katherine Levine Glick, David M.	2015	Working Paper	Survey of 72 mayors. Unlike Republican mayors, roughly half of Democrats seem to agree that cities should aim to reduce inequality. Democratic mayors also seem to favor redistribution to accomplish that goal.	Somewhat
Kiewiet, D Roderick Mccubbins, Mathew D	2014	Annual Review	City budgets have been severeley constrained since the Great Recession. Spending has thus decreased in general. Lack of funds means that there is not much discretion for partisanship.	Somewhat
Tausanovitch, Chris Warshaw, Christopher	2014	APSR*	Cities are responsive (taxes, expenditures, regressiveness of taxation) to citizens' conservatism/liberalism. Partisan elections do not make cities more or less responsive.	Yes
Guillamón, Ma Dolores Bastida, Francisco Benito, Bernardino	2013	European Journal of Law and Economics	Police spending in Spain. Conservative parties spend more on police. Spending is higher before elections. Also contains a useful overview of the literature.	Yes

Names	Year	Journal	Findings	Important?
Gerber, Elisabeth R.	2013	Cityscape	Partisanship of both citizens and elected city officials separately affect climate policy.	Yes
Solé-Ollé, Albert Viladecans-Marsal, Elisabet	2013	Journal of Urban Economics	Spanish cities. The authors "employ a regression discontinuity design to document that cities controlled by left-wing parties convert much less land from rural to urban uses than is the case in similar cities con- trolled by the right". Partisanship might also affect housing construction and price growth.	Yes
Gerber, Elisabeth R. Hopkins, Daniel J.	2011	AJPS	Regression discontinuity design. Democratic mayors spend less on public safety. All other policy areas (including taxation) are unaffected.	Yes
Trounstine, Jessica	2010	Annual Review	Race and ethnicity in local elections (not relevant to us). Partisan elections have higher turnout; non-partisan elections still tend to have some partisanship in them because voters learn about party of candidates from media. Non-partisan elections favor Republicans/upper class. Mixed evidence for whether partisanship of mayor is important for policy.	Somewhat
Palus, Christine Kelleher	2010	State and Local Government Review	Ideology (liberal/conservative) of citizen is well represented by gov. spending in five areas: (1) community development, housing, and conservation, (2) health and human services, (3) culture, the arts, and recreation, (4) environmental programs, and (5) transportation.	Somewhat
Ferreira, Fernando Gyourko, Joseph	2009	The Quarterly Journal of Economics	Regression discontinuity design. Null results for spending and city gov. size with regard to mayor partisanship.	Yes
Ansolabehere, Stephen Snyder, James M.	2006	Scandinavian Journal of Economics	Despite the journal, this is about the U.S. The important finding (for us) is the fact that counties whose government is controlled by the same party as the state government, receive more funding (county's share of state transfers, normalized by county pop.) from the state.	Somewhat
Murphy, Russell D.	2002	Annual Review	Not useful. Too philosophical; mostly cites papers written a hundred years ago. Also exclusively about larger cities.	No

Names	Year	Journal	Findings	Important?
Armstrong, Cory L.	2011	Government Information Quarterly	Comparison of county and school board websites in Florida (where the two align) with regard to transparency (presence or absence of public records). Manual content analysis (undergrads told to look around for 15 minutes). School board websites, more professional websites, and websites in Republican-dominated counties are found to be more transparent.	Yes
Cegarra-Navarro, Juan Pachón, José Cegarra, José	2012	International Journal of Information Management	Survey of Spanish municipal government officials (specifically, the city website managers). Respondents are asked about the features of their websites, the level of civic engagement and the size of their municipality. More sophisticated websites are correlated with greater civic engagement and greater use of e-government functions.	Yes
Dolson, Jordan Young, Robert	2012	Canadian Journal of Urban Research	Determinants of website content. Three categories: e-content (city information on website), e-participation, social media use. Tables on page 15 show frequencies of these categories across sites, and might be useful to inform our topics. Larger cities have better websites. Population growth and immigration are also tested, but the findings are somewhat inconclusive.	Yes
Feeney, Mary K. Brown, Adrian	2017	Government Information Quarterly	500 U.S. city websites at two points in time (2010-2014). Count model of website features regarding information, e-services, utilities, transparency and civic engagement. Having a larger population leads to more features. Relying on a website contractor leads to more information and transparency. The authors say that mayor-councils are negatively correlated with website sophistication, but their regression tables state the opposite.	Yes
Kaylor, Charles Deshazo, Randy Van Eck, David	2001	Government Information Quarterly	Model of best practices of e-government. Table 1 lists a number of possible ways this manifests, could be useful for our theory.	Somewhat
Ansolabehere, Stephen Urban, Florian	2002	Cities	Websites of 20 major cities across the world. Is website content correlated with city characteristics? Not particularly systematic, and the findings are inconclusive.	Somewhat
Jeffres, Leo W. Lin, Carolyn A.	2006	Journal of Computer-Mediated Communication	50 largest metropolitan areas in the U.S. Features include information about city, opportunities for citizen feedback, galleries of photos, links, etc. Purely descriptive analysis, doesn't contain anything that isn't covered in any of the other aricles.	No

There doesn't seem to be much literature on transitions of party control, if anything, that question is mostly phrased with regard to political representation. However, if we want to tie our paper to a larger theory, we could go with dynamic representation. Under dynamic representation, policy-makers are responsive to trends in citizens opinions, which mainly manifest/become apparent through election results, especially when incumbents are voted out of office. This fits our topic quite well. Also, of the few papers that do exist on the effects of partisan transitions, virtually all use regression discontinuity designs.

Why does the content of city websites matter? According to Mayhew (1974), politicians engage in advertising, credit claiming and position taking in order to get re-elected. Official city websites allow mayors to do all three. Their offices frequently take a prominent position on the frontpage, and many websites also feature a picture of the candidate. In local politics, where campaign funds are low, this lends the incumbent a crucial advantage in becoming more well-known among her constituents. Furthermore, municipal politics gives incumbents clear and tangible achievements they can point to, such as completed infrastructure projects, the acquisition of federal or state funding, or the hosting of city-wide events. City websites present an opportunity for local officials to brandish these accomplishments. Finally, they also give mayors a platform from which they can advertise their political beliefs. On municipal websites, this may not manifest in the form of brazen partisanship, but more subtle avenues are available. As noted by Einstein and Glick (2015), there are stark differences in the spending preferences of Democratic and Republican mayors. City websites can then be used to communicate the stance of a mayor on social or economic programs. Another advantage of websites with regard to communication is that unlike direct social interactions, officials have full control over them.

In addition to the use of city websites for the politicians that control them, variance in content also matters with regard to the people who visit them. Local residents likely rely on city websites to get news about events, hot-button political issues specific to their city, contact city officials or find out addresses or opening hours of city institutions. Visitors use city websites to look up local attractions, which are often described in great detail. Similarly, prospective residents looking to move, might rely on city websites to inform their decision on whether to relocate there. An inviting website emphasizing the city's receptiveness to new residents might make a real difference here. Finally, city websites frequently feature sections on business, but there is a lot of variance in this area: Some emphasize economic development, properties, or transportation, whereas others focus on undeveloped land and other business opportunities. Differences in websites likely say something about a city's economic profile, with potential repercussions for the political realm.

Website Analysis

The literature making use of scraped websites clusters into a number of categories. One, and most pertinent to our own endeavors, the e-governance literature which discusses the online presence of governments from a usability and public service point of view. For the most part, research in this category develops a classification scheme to rate websites in terms of accessibility, ease-of-use and function, and then hand-codes a set of websites according to these criteria (Urban 2002;

Armstrong 2011; Feeney and Brown 2017). As an example, Grimmelikhuijsen and Welch (2012) study local government websites with the goal of uncovering how they aid the goal of transparency. To this end, they analyze a set of Dutch municipalities in which air quality had deteriorated. The authors test whether local governments provide citizens with information about potential complications and solutions associated with this issue. Like most e-government studies however, this publication does not make any use of automated text analysis.

Websites have also played a major role in the field of media studies, as scholars have scraped and analyzed the online presence of newspapers, as well as the more diffuse world of online political blogs (Adamic and Glance 2005; Gentzkow and Shapiro 2010). Lin, Bagrow and Lazer (2011) provide a good example for a study which makes extensive use of automated content analysis - a necessity arising from its dataset of 66830 blog posts and 57221 online news articles. The authors estimate the political slant of these entities by counting the frequencies with which politicians of either side are mentioned and determine that blogs are generally more biased. Unfortunately for us, the authors don't go into the details of their text analysis, and offer no information on the acquisition and pre-processing of the data.

Another well-known example fitting into this area of study is the set of studies conducted by King et al. (King, Pan and Roberts 2013, 2014, 2017), in which the authors study censorship by the country's government on its lively blogosphere. However, the authors also provide no information on how their data was collected "our extensive engineering effort, which we do not detail here for obvious reasons [...]".

The websites of politicians and their parties have also fallen under scholarly scrutiny. Researchers have found that in order to identify the constituencies, motives and modes of communication of these actors, their websites can be very illuminating sources of information (Druckman, Kifer and Parkin 2009; Druckman, Hennessy, Kifer and Parkin 2010; Cryer 2017; Esterling, Lazer and Neblo 2011; Esterling and Neblo 2011; Norris 2003; Therriault 2010). Druckman, Kifer and Parkin (2009); Druckman et al. (2010) rely on the Mational Journal to find the websites, then hand-coded them. Cryer (2017) provides fairly little information, but does mention the fact that she relied on Archive-it, the webservice of the Internet Archive we discussed recently. Esterling, Lazer and Neblo (2011); Esterling and Neblo (2011) rely on hand-coded data by the Congressional Management Foundation, a nonprofit organization which aims to assist Congress. Therriault (2010) (a working paper) actually portends to use automated text analysis, and also has the most extensive overview of the associated methodology. However, the division of the website into sections (home page, topics, issues, details) is done by hand, and the actual analysis is incomplete. The author acquired the websites from the Library of Congress (which only collected them from legislators who actually consented, and Therriault notes that this causes nonrandom missingness).

Importantly for us, research analyzing and improving the scraping, pre-processing and analysis methods of this literature is scarce. Eschenfelder, Beachboard, McClure and Wyman (1997) provide something of an overview of how how federal websites should be assessed from an e-governance point of view, but they largely focus on the substantive criteria that should be fulfilled, rather than the technical aspects of website acquisition and analysis.

3 Data

The General Services Administration (GSA) maintains all .gov addresses, and provides a complete[1] list of all such domains to the public through GitHub[2]. This list is updated once per month - we rely on the version released on January 16, 2017. The data from the GSA contains the following variables: One, domain name, specifically, the all-uppercase version of domain and top-level domain (for example, 'ABERDEENMD.GOV'). Two, the type of government entity to which the domain is registered, such as city, county, federal agency, etc. Three, for federal agencies, the name is specfied. Finally, the city in which the domain is registered, is noted.

Here, we focus only on cities. As a first step, we use a webdriver-controlled browser (Firefox/Selenium/Geckodriver) to test whether all of the city websites actually work. Of the 2425 domains listed by the GSA as cities, 292 are not accessible. Furthermore, the .gov domain, as registered at the GSA, is frequently not the website a city actually uses. In many cases, these sites redirect to another address, sometimes not a .gov domain (in this case, we simply use this domain). We record these URLs, as they are required to retrieve the images websites stored in the Wayback Machine (WbM).

$T_1 + \beta_1$

In order to provide an overview of our coverage (as not all cities, towns and villages use .gov addresses), we merge this list with U.S. Census data[3]. Here, several limitations in the GSA data need to be accounted for: One, even though the GSA nominally separates websites of cities and counties, some of the domains categorized as cities actually belong to counties. The same is true for townships and boroughs. Ergo, we eliminate all websites belonging to these three types of entities by hand. Furthermore, the city name, as given by the GSA, refers to the city in which the domain is registered, which is not necessarily equivalent to the city the website serves. In many cases, a website of a larger city may be registered to one of its subdivisions (for example, the website of New York is registered to Brooklyn), or vice versa (for example, the website of Homecroftin, a small town within Indianapolis, is registered to the city as a whole). Consequently we fix mismatches between websites and cities manually. Finally, a number of cities are simply misspelled, which we also correct by hand.

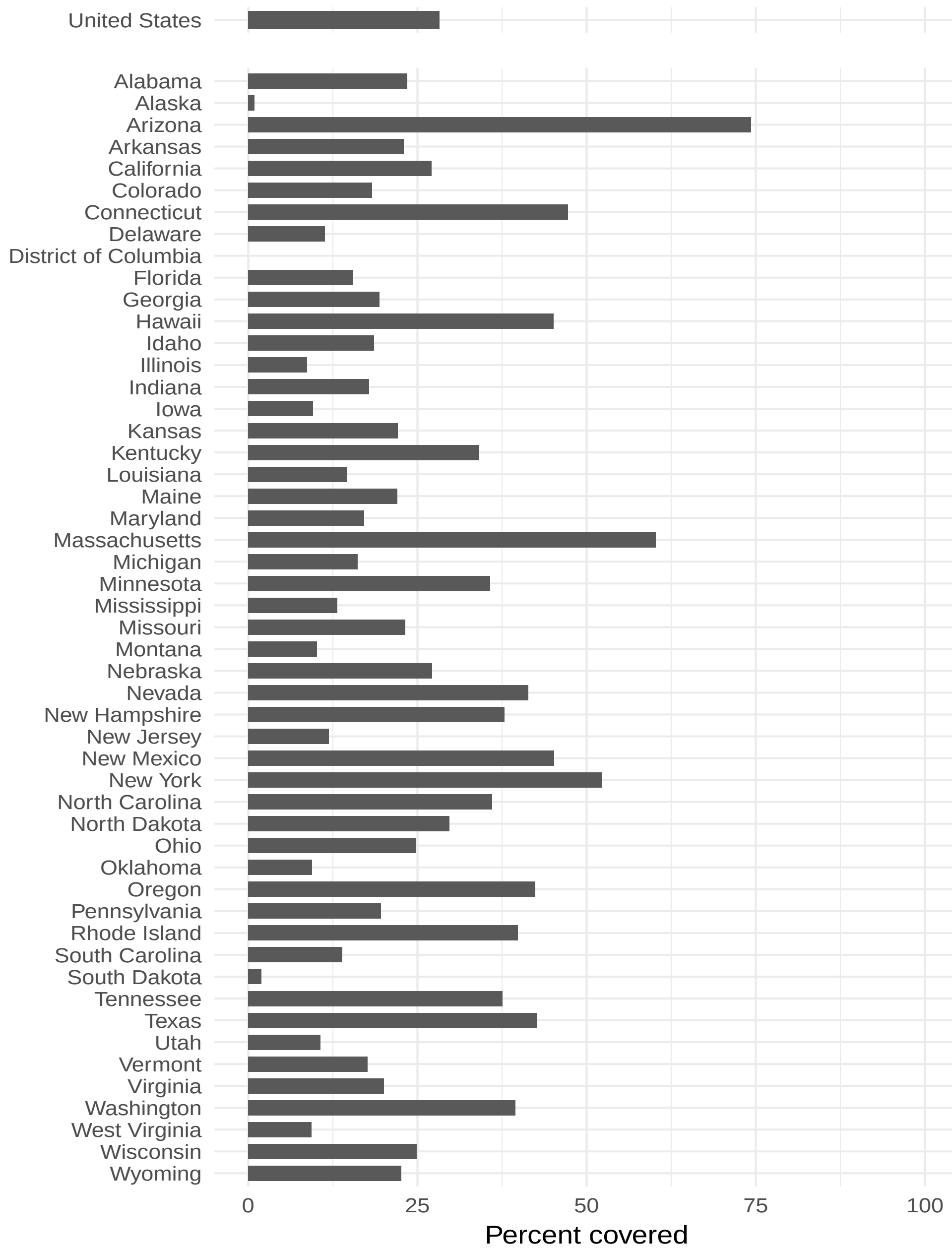
After the counties, townships and cities that cannot be matched to the Census data[4] and duplicate websites (some cities have more than one website) are removed, 1813 domains/cities remain.

These cities contain 90,616,865 people, and thus about 28% of the U.S. population (see figure 1).

We use the resulting list of websites to acccess their copies stored in the Internet Archive's Wayback Machine. To this end, we rely on the Ruby Gem 'Wayback Machine Downloader'[5] (WbMD). We supply the URL that each .gov website redirects to to the WbMD, which then downloads every

[1]Domains used for testing and internal programs are excluded.
[2]https://github.com/GSA/data/tree/gh-pages/dotgov-domains
[3]http://www2.census.gov/programs-surveys/popest/datasets/2010-2015/cities/totals/sub-est2015_all.csv
[4]There are five cities that are not contained in the Census data
[5]https://github.com/hartator/wayback-machine-downloader

Figure 1: Percentage of state population covered.



file present in the WbM from a snapshot in October 2016, or, if not available, as soon as possible after this point.

<Note: We have not actually done this last step for all websites (however, the R script which runs the Ruby package is already set up to do so once we need to). Instead 10 websites were randomly sampled from an older version of the GSA list, which still contained counties and townships, which is why one of the 10 websites is from Dutchess County, NY.>

Filetype	current	before	after
	51455	13866	19199
pdf	9646	5489	7544
jpg	5216	1988	3512
html	3767	17842	17596
aspx	2832	4356	3271
png	2714	2327	3684
gif	1068	664	1077
JPG	478	182	263
1	443	61	54
css	390	265	518
js	350	255	468
htm	264	295	256
docx	203	106	120
doc	167	70	130
asp	161	201	211
svg	87	55	69
php	83	157	241

Table 1: The most common file types in scraped websites

Website	current_size	current_files	before_size	before_files	after_size	after_files	size_change	files_change	control_change
attica-in.gov	61988	1417	7528	164	55956	1390	7.43	8.48	0.00
bedford.in.us	57628	560	27452	182	46388	525	1.69	2.88	0.00
cityofboonvilleindiana.com	9848	110	16996	172	20784	229	1.22	1.33	0.00
frankfort-in.gov	205368	2652	12208	242	138360	1077	11.33	4.45	0.00
warsaw.in.gov	298440	2117	26844	539	360400	2036	13.43	3.78	0.00
www.bloomington.in.gov	131128	2713	443360	14384	247096	9640	0.56	0.67	0.00
www.brazil.in.gov	43056	845	34472	625	55152	1214	1.60	1.94	0.00
www.carmel.in.gov	2270016	8727	1919344	5361	899900	2219	0.47	0.41	0.00
www.ci.auburn.in.us	183296	1025	21444	345	23564	211	1.10	0.61	0.00
www.cityoffortwayne.org	2136424	4378	266784	3582	233600	3018	0.88	0.84	0.00
www.cityofhobart.org	722000	2463	44192	650	62660	1037	1.42	1.60	0.00
www.evansvillegov.org	6345932	11844	290784	1281	1697224	6853	5.84	5.35	0.00
www.gary.in.us	373888	1227	121812	485	157140	719	1.29	1.48	0.00
www.huntingburg-in.gov	388680	2496	8644	213	375900	1953	43.49	9.17	0.00
www.jasperindiana.gov	561968	4013	55900	460	439072	2224	7.85	4.83	0.00
www.lakestation-in.gov	48	2	7724	84	257272	1097	33.31	13.06	0.00
www.linton-in.gov	32	1	24	2	24	2	1.00	1.00	0.00
www.madison-in.gov	531044	1848	36636	575	191624	1444	5.23	2.51	0.00
www.martinsville.in.gov	46792	1463	71628	1052	80944	800	1.13	0.76	0.00
www.monticelloin.gov	33656	753	18120	448	100680	2104	5.56	4.70	0.00
www.newhavenin.org	84364	626	2524	86	6792	334	2.69	3.88	0.00
www.richmondindiana.gov	250968	1042	217252	918	401672	2422	1.85	2.64	0.00
www.southbendin.gov	1264076	4749	454456	3286	1424136	2562	3.13	0.78	0.00
connersvillecommunity.com	170688	569	162316	815	187276	808	1.15	0.99	1.00
www.batesvilleindiana.us	166564	2348	39592	496	95696	1310	2.42	2.64	1.00
www.cityofrisingsun.com	994956	3311	321400	1268	80848	868	0.25	0.68	1.00
www.cityofrockport-in.gov	12068	98	5148	16	12068	98	2.34	6.12	1.00
www.elkhartindiana.org	1132828	2345	5588	123	6204	223	1.11	1.81	1.00
www.elwoodcity-in.org	224412	765	5000	123	139692	517	27.94	4.20	1.00
www.indy.gov	5726048	9675	6119260	10451	4984080	7981	0.81	0.76	1.00
www.northvernon-in.gov	272016	403	3132	112	289336	416	92.38	3.71	1.00
www.winchester-in.gov	364592	2480	6508	135	45488	567	6.99	4.20	1.00

Table 2: Number of files and size of websites

For some cities, whose websites make heavy use of JavaScript, this method does not lead to satisfying results. Consequently we restricted our corpus to cities with at least 3 documents.

4 Preprocessing

The documents are read in line by line, converted to UTF-8 and then stripped of dates, punctuation, numbers and words connected by underscores. At this point, the documents of one city still closely resemble one another in the form of boilerplate content, be it website elements (i.e. "You are here", "Home", "Directory" etc.) in html documents, or commonly used forms or phrases in pdfs, doc and docx files. This is an issue, because it clusters documents around the cities from which they originate in a way that has nothing to do with their actual content. In other words, the signal would be drowned out by the noise. Consequently we remove this content as following: Each line of every document is compared to every line in every other document belonging to the same city. We count how many times each line is duplicated for that city. We remove any line occuring more than our chosen threshold of 10.[6] This means that each document only retains the information that is particular about it. Preprocessing further includes setting every character to lowercase, as well as the removal of bullet points which frequently occur in html documents, extraneous whitespace, xml documents mislabeled as html files, and empty documents. Furthermore, some documents contain gibberish, often as a result of faulty or impartial OCR. To combat this problem, we employ two solutions. One, we use spellchecking, implemented through the hunspell R package, to remove all non-English words. However, hunspell does not cover everything, either because some tokens are not actual words (for example artifacts from defective encoding), or because random sequences of characters just so happen to form words that exist in a dictionary (for example "eh" or "duh"). Since we rely on a bag-of-words model in which syntax does not matter, we can ameliorate these problems by removing all text except for whitespaces and the characters that appear in the english alphabet. Since a lot of the nonsensical text tends to be quite repetitive, we also delete all documents in which the proportion of unique to total number of tokens is less than 0.15. Furthermore, hunspell does not spellcheck individual characters, so we remove all individual characters appearing as tokens except for "i" and "a". Since these pre-processing steps reduce documents which are largely unsuitable to only a few words of texts that don't make much sense, we also remove all remaining documents containing less than 50 tokens.

4.1 Indiana City Websites

It would be fine to focus on Indiana as a case. First, we need to answer some preliminary questions about the data.

1. For what percentage and number of IN cities can we find data from the WBM?

2. For how many election cycles can we find political leadership data for these matched cities?

[6] Empirically, lines tend to be duplicated either hundreds of times, or only once or twice, if at all.

3. In what number and percentage of cities is the local leadership majority Republican?

4. Relatedly, in a typical election cycle, for how many cities do we see a transition in party leadership (i.e., a shift from majority D (R) to majority (R) D).

1. 30 cities, with a combined population of 1,180,435. However, since only cities (as opposed to towns and villages) hold mayoral elections, only 16 of these, with a combined population of 1,094,383 can be matched to the election data.

2. 2015, 2011, 2007, 2003.

3. Of the 16 cities, 7 have Republican mayors after the 2015 elections.

4. In 6 cases, a shift of party control occurs, with 4 of these being Republican –> Democratic.

4.2 Research Design

Variable	Unit	Source
Population size	1000 people	Census
Population growth last 5 years	Percent	Census
Type of economy (agriculture/industry/services)	?	Census
Economic performance (GDP?)	$	Census
Party of mayor before election	Rep/Dem/(Ind)	in.gov/sos/elections/
Party of mayor after election	Rep/Dem/(Ind)	in.gov/sos/elections/
Change of party control	0/1	in.gov/sos/elections/
Presidential vote 2012 in county	Percent Rep	? (but I have the data)
Unemployment rate	Percent	Census
Broadband speed	Avg. Mbps DL	broadbandmap.gov

Table 3: List of covariates

1. Corpus:
    (a) Last snapshots before the election (November 3, 2015 in Indiana; tbd. in Louisiana (probably February))
    (b) First snapshot that is at least 2 months after the new government's inauguration (which is in January for Indiana, May for Louisiana)

2. Preprocessing:
    (a) restrict corpus to:
        i. documents belonging to cities in which a change of power occurred

   ii. documents that were added, deleted or changed between the two snapshots

   (b) words to lowercase
   (c) remove punctuation
   (d) stemming (Porter stemming algorithm?)
   (e) Remove stop words (regular list of stop words is enough, since we use an asymmetric prior)

3. Apply Grimmer's expressed agenda model to the corpus
   (a) Asymmetric prior
   (b) Each document can have only one topic (in contrast to the author-topic model)
   (c) Cities $i = 1, ..., n = 15$
   (d) Topic $k(k = 1, ..., K)$
   (e) Documents $j(j = 1, ..., D_i)$ from city i
   (f) Party covariate in the prior, where the deleted and unmodified documents are coded as from the first, and the added and modified documents from the second party

4. Results
   (a) Label topics using Grimmer's automatic cluster labeling method, based on most commonly used words in documents belonging to topic
   (b) Evaluate topics

Validation:

- Do the above for cities in which no change of power occurred.
- Check whether there is higher than average turnover around the new year by comparing changes to non-election years (and also Louisiana, where elections are later).
- Check how long documents stay on websites on average. Use websites with a lot of snapshots for this (these exist for both small and large cities).

Problem with using this model: Grimmer's expressed agenda model uses Senators as the actors. Senators is also who he is substantively interested in. For us, the equivalent to Senators is cities. However, we care about parties, not cities.

4.3 Survival model

The existence of individual documents on municipal government websites can be though of as a survival process. No document stays on a website forever, and it appears to be a reasonable assumption that as documents get older and thus less relevant, they get replaced. The factors determining the steepness of the survival curve are the topic - fire safety regulations likely stay up longer than a bulletin on the annual spring banquet - and the change of party control after an election.

> *H1*: The older a document, the more likely it is to be removed.

$S(t)$ has a downward slope. Admittedly, this is almost impossible not to be true. Also, test proportional, rising and falling hazard models.

> *H2*: Documents pertaining to administrative matters are less likely to be removed.

Introduce a categorical variable for the top 10(?) topics. A negative coefficient for administrative topics would support this hypothesis.

> *H3*: Documents introduced by the opposing party are more likely to be removed.

Introduce two variables into the survival model: One variable indicating which party has introduced a document, and a time-varying variable describing which party is currently in government. The hypothesis is tested through an interaction term between the two.

> *H4a*: Democrats are more likely to remove documents with topics pertaining to private enterprise, private schools.

Interaction term between party in power and categorical topic variable.

> *H4b*: Republicans are more likely to remove documents with topics pertaining to social justice, equality, taxes, public schools, etc.

Interaction term between party in power and categorical topic variable.

> *H5*: In line with their commitment to small government, Republicans are more likely than Democrats to remove documents.

Party in power variable.

This model will take up a lot of degrees of freedom. The rarity of snapshots for some cities might be a problem. Documents being changed and being removed can be modeled as competing risks.

$$
\begin{aligned}
Y = & \text{ Party that introduced the document} \\
& + \text{Party that is currently in power} \\
& + \text{Topic 1, topic 2, ..., topic k} \\
& + \text{Party that is currently in power} \times \text{Topic 1, topic 2, ..., topic k} \\
& + \text{Days since start of mayoral term (control)}
\end{aligned} \tag{1}
$$

4.4 Topic modeling

Note: this chapter is mostly a wordy and less coherent version of the above.

We hypothesize that a change in leadership from one party to the other will lead to a change in website content because the two parties have different agendas. Democrats have a predilection towards policies that promote social and economic equality, whereas Republicans like to emphasize small government as well as law and order. Documents uploaded to city websites are expected to be a reflection of these preferences.

The Latent Dirichlet Allocation (LDA) (Blei, Ng and Jordan 2003) is the most commonly used topic model. However, it is unable to account for the existence of two parties with very different policy agendas, translating to different preferred topics. There are two types of extensions to the LDA that fit our subject much better - the structural topic model, and the author-topic model.

The structural topic model, developed by Roberts, Stewart and Airoldi (2016) allows researchers to model a corpus as a function of metadata associated with its documents. Specifically, topic prevalence (the proportion of a document made up by a topic) and topical content (the rate at which words figure into a topic) are contingent on a set of covariates. In our case, the two most important covariates are (1) city and (2) authoring party (operationalized by whether a document was present before a change of power, or introduced afterwards). Furthermore, the population size of the city should be a predictor for both the number and kind of problems it faces, which thus need to be addressed on its website. Furthermore, city size also serves as an estimate for the budget and technical capacities of its staff in charge of maintaining the website[7]. Further demographic as well as economic data might also be useful to differentiate cities from one another. If we model the differences between cities properly, we might not have to/should not include city as a (categorical) variable, because it would probably interfere with these more meaningful covariates.

The author-topic model (Rosen-Zvi, Griffiths, Steyvers and Smyth 2004) would allow us to capture the fact that different authors have different topical preferences. Unfortunately, we have two types of 'authors' - cities, and parties. Given the largely divergent administrative needs of different types of cities, we would likely have to treat cities as the author. This would require us to capture the partisan authorship of different documents entirely on the basis of sub-sets of the website data - changed, added, or deleted documents. (Note: In the papers on author-topic models,

[7] Although this relationship is not exactly deterministic - when looking through .gov websites manually, I've noticed that a lot of websites of (presumably wealthy) towns of only a few thousand citizens often have extremely well-kept websites

the intention is often to analyze scientific articles. These articles are often co-authored. Would it be possible to have BOTH cities and parties as authors, so that a specific version of a website would then be 'co-authored' by its city and party?)

The critical element in this analysis is to accurately attribute authorship of documents to either party. Despite possible changes to websites due to a leadership transition, large parts of the content carry over. This means that unless the successor government decides to delete everything, some of the existing documents will be preserved, and in the model, also attributed to the new 'author'. But the reverse is not possible, because the predecessor government can't choose to retain documents from the future. *This is a very important point for municipal websites. We should investigate the possibility of modeling only the changes—documents that change, documents that are deleted, and documents that are added.*

Labeling newly added documents after a change of power is quite simple. As far as older documents are concerned, we would have to operate under the assumption that the incumbent didn't keep his or her successor's document's on the website for four years.[8] One problem here is the fact that the incumbent would have all the administrative topics assigned to them, simply because they have to have those on their website.

If we really do end up getting swamped with administrative terms in our topic models (and it does kind of look like that at the moment), we might be able to separate the signal from the noise by running a preparatory LDA once and using its results to create a new, corpus-specific list of stop words. After that, we run the actual model. This way, politically charged terms and topics, which likely are not as common, but present nevertheless, should be able to rise to the surface. It might be possible to refine this process by running an exploratory model on website data from cities in which party control never changes, and the incumbent always wins by large margins. 'Safe' cities like this should have fairly homogeneous populations, with little need for the incumbent to play politics on the municipal website. Hence, these websites should be filled with purely administrative content.

The use of asymmetric priors (Wallach, Mimno and Mccallum 2009) over the document topic distribution - i.e. the assumption that some topics, such as administrative content, are inherently more common - may be a more elegant way of dealing with this issue.

Another intervening factor is that for cities in Indiana, mayoral terms begin in January. Since a lot of clerical and administrative tasks tend to be year-specific, work tends to pile up around the new year. Thus it is possible that a spike in newly added documents is not due to a change in party control, but owed to a seasonal increase in activity. We can test for this by comparing election years to non-election years. Furthermore, since in Louisiana, mayors take office in May, we have another point of comparison.

Furthermore, if we only investigate cities in which control of government changes from one party to another, we may overestimate its effect. Not only does a transition in party control occur,

[8]Probably a safe assumption. However, we could, and probably should test how long documents tend to stay on a city website. Simple descriptive statistics (for example density plots) on the length of existance should likely be sufficient. If we want to be really fancy about it, we could create a duration model, with document topics as features. This would allow us to measure whether some documents tend to remain longer based on their topic (i.e. fire regulations are probably going to stay up longer than notes on a specific council meeting).

but the person in charge also changes. Parties are fairly homogeneous, so that two mayors from the same party may have very different policy preferences and managerial styles. To remedy this problem, we [could] utilize matching, pairing our cases with similar cities in which the incumbent does not run for re-election, but party control stays the same nevertheless.

In order to determine the optimal number of topics for our corpus, we utilize the measure developed by **?**. In contrast to other approaches such as **?** or **?**, this measure includes as much information about the model as possible by taking into account both the document-term matrix, as well as the word-topic matrix. We find 200 topics to be the best value (see figure 12).

4.4.1 LDA diagnostics

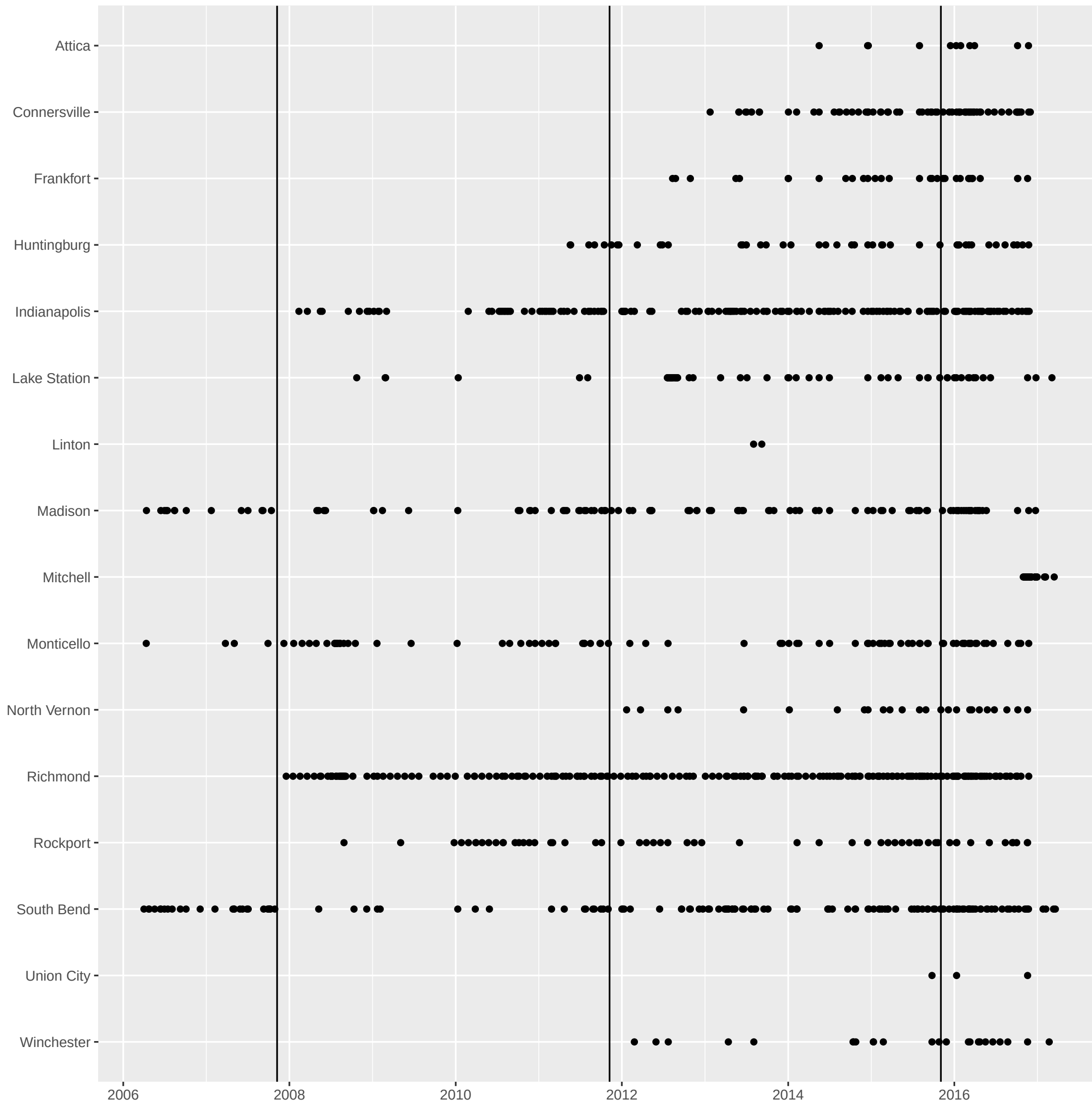
Figure 3 plots the densities of topic weights across documents, where each line represents a topic. Distributions with lower peaks near zero and flatter bodies indicate a topic that is present to varying degrees in multiple documents. This shape appears to be more common in documents from Republican cities. By contrast, a distribution with a high peak near zero and a very long tail is indicative of a topic that only appears in one specific document. This appears to be more common for documents in Democratic cities. The substantive conclusion then is that Democrats appear to be more prone to dedicating individual documents to one specific purpose, whereas Republicans produce general-purpose documents more often.

An alternative way to consider topic weights is to aggregate them across documents, in this case through their median or mean. Figure 4 shows this distribution of topic weights across topics. Most topics have a very low weight - meaning that they do not appear in a lot of documents. When aggregating across documents via the mean, this effect is more pronounced for Republicans, suggesting that most topics do not feature frequently (or even at all) in their documents. Democrats on the other hand appear to have a wider spectrum of topics from which they chose - supporting the hypothesis of Democrats as a 'big tent' party. However, this effect is reversed when using the median instead of the mean to aggregate across documents. Now, the the distribution has a higher peak and lower tail for Democrats. The cause for this stark divergence appears to lie in the fact the mean and median differ enormously - for the range displayed here, the mean is about a hundred times greater. Evidently, extremely large weights (i.e. some documents fitting specific topics perfectly) distort the picture. The median document is a better representation of the corpus as a whole, but the results do not fit our hypothesis. Their are however more consistent with figure 4.

Topics for which there are stark differences in their distribution across documents between Democrats and Republicans are of particular interest to us. To detect these topics, we take the absolute difference of the median document topic weights, and arrange them as a histogram, see figure 5. For the most part, differences are small. For a few topics however, a contrasts emerges.

Figure 6 displays the word-topic probabilities for the 10 topics with the largest partisan differences. Some of these, such as topic 82, with its focus on policing, safety and crime could be construed as politically charged. For the most part however, these topics focus on administrative matters.

Figure 2: Dates of Wayback Machine snapshots. The vertical lines are municipal elections.



To further investigate the topics with large partisan differences, figure 6 shows densities of topic weights just like figure 3, but reduced to only the topics with the largest differences. It appears that mere absolute differences between the medians (or some other measure of central tendency) obscures the fact that the distributions themselves are quite different.

To further investigate this issue, we look at the raw data itself - the document-topic matrices for Democrats and Republicans, displayed as heatmaps. Figure 8 shows that especially for Republicans (but also for Democrats, to a lesser extent), there appears to be extensive clustering for consecutive documents. Since the order of the documents in the corpus is dependent on the cities in which they appear in, it seems that topics are mere representation of city websites - each website 'owns' a number of topics, that appear across all of its documents, and hardly anywhere else. One possible cause for this type of clustering is the fact that documents frequently share common words, for example pertaining to navigation on the site, or standard forms that are shared throughout all documents.

4.4.2 Structural topic model

An ostensibly intuitive solution to topics clustering into cities in LDA is to include dummies for the cities in a statistical model of topics. This is facilitated by the structural topic model, which uses metadata on the document to account for variation in topics (Roberts, Stewart, Tingley, Lucas, Leder-Luis, Gadarian, Albertson and Rand 2014). However, figure 13 shows that if anything, the STM exacerbates the problem. Here, we plot the *p-values* of the coefficients for each city as well as the party variable across each topic. Under normal circumstances, plotting the p-values, as opposed to the fitted values, does not make much sense, but here it serves a diagnostic purpose. The plot shows that the party variable is never statistically significant at any conceivable level of confidence, nor is it even close to. Interestingly the same is true for a number of the cities as well. The topics cluster heavily into only about half of the cities, which does not present an improvement over LDA at all.

4.4.3 Prediction with SVM

An alternative approach to the problem is to ignore topics entirely, and go straight to predicting documents that are much more likely to be included on websites belonging to one or the other party. Classic machine learning techniques such as Naive Bayes, Linear Discriminant Analysis, or SVM should be expected to fare well in this context. Here, we rely on SVM, implemented with the SciKitLearn package in Python.[9] A grid search reveals the tf-idf representation of the document-term matrix to be better than pure word counts, unigrams to be superior to bi-grams, the application of an L2 penalty to be preferable to either L1 or elasticnet, and an alpha (a constant to multiply with the regularization parameter C) of 0.0005 to lead to the best results. Applying five-fold cross-validation to the (tf-idf) document-term matrix with the dimensions 16011x35000 leads to an average accuracy of 89%.[10]

However, Monroe, Colaresi and Quinn (2008) advise against using these types of methods in this context because they get the data generation process backwards: Our theory assumes that party

[9] We also implemented SVM in R through the packages kernlab and e1071 in R. However, neither of these provide a regularized version of SVM (NOTE: at least that is what I am gathering from the stack overflow error), which prevents us from using all of the features contained in our data. Instead, we ranked the features according to tf-idf and selected the top 5000. These methods are also quite slow, and provide a maximum accuracy of 82% in five-fold cross validation.

[10] Other methods used: Elastic-net in the glmnet package in R. Accuracy is 0.6924795 for in-sample prediction, so not worth bothering with.

leads to variation in writing, and yet we rely on the documents to predict party, in spite of the fact that we actually have perfect knowledge of it.

4.4.4 Informative Dirichlet model

Consequently we follow their recommendation to use the informative Dirichlet model they present in the paper (Monroe, Colaresi and Quinn 2008). This approach aims to account for the fact that some words naturally occur more than others by applying a Dirichlet prior based on the distribution of words in random text. Figure 14 shows the top words for both Democrats and Republicans - and accomplishes, to some extent, the goal of (Monroe, Colaresi and Quinn 2008) of banishing frequent words from this list and supplanting them by text with greater semantic, and in our case, partisan meaning. For Democrats, words related to public finances, such as 'fund', 'budget', or 'tax' are common - congruent with the party's greater willingness to raise and spend money publicly. Similarly, 'federal' 'funds' also appear among the Democratic top words. By contrast Republicans prefer to devote their attentions to purely local, and for the most part, logistic matters. 'Trees', 'water', 'street' and 'sign' appear on the list of Republican top words, suggesting that these mayors largely focus on city planning.

These top words also show some degree of overlap with those determined by aggregating over topics in LDA.

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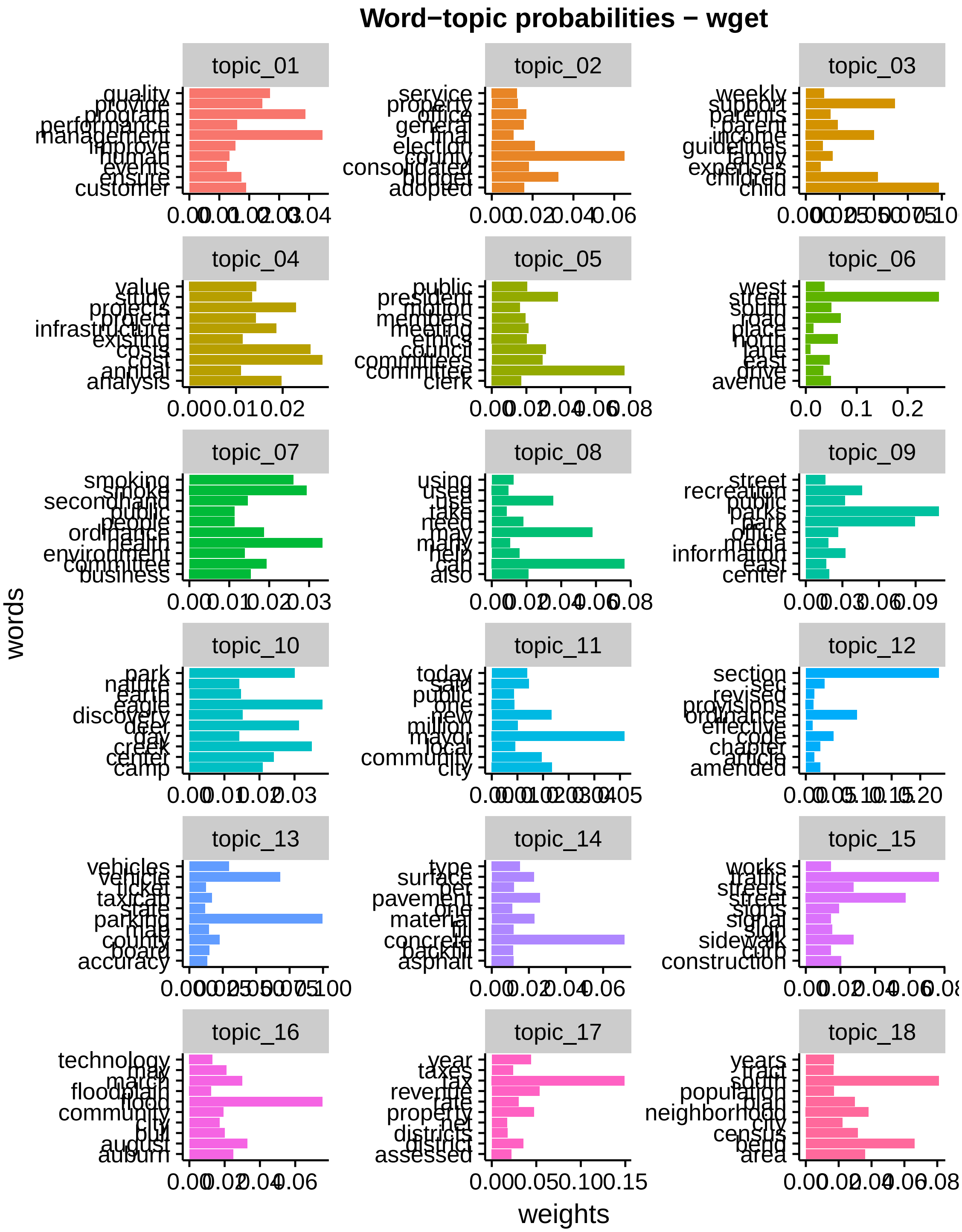
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topic_02
service property office general final election county consolidated budget adopted
topic_03
weekly support parents parent income guidelines family expenses children child
topic_04
value study projects project infrastructure existing costs cost annual analysis
topic_05
public president motion members meeting ethics council committees committee clerk
topic_06
west street south road place north lane east drive avenue
topic_07
smoking smoke secondhand public people ordinance health environment committee business
topic_08
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topic_13
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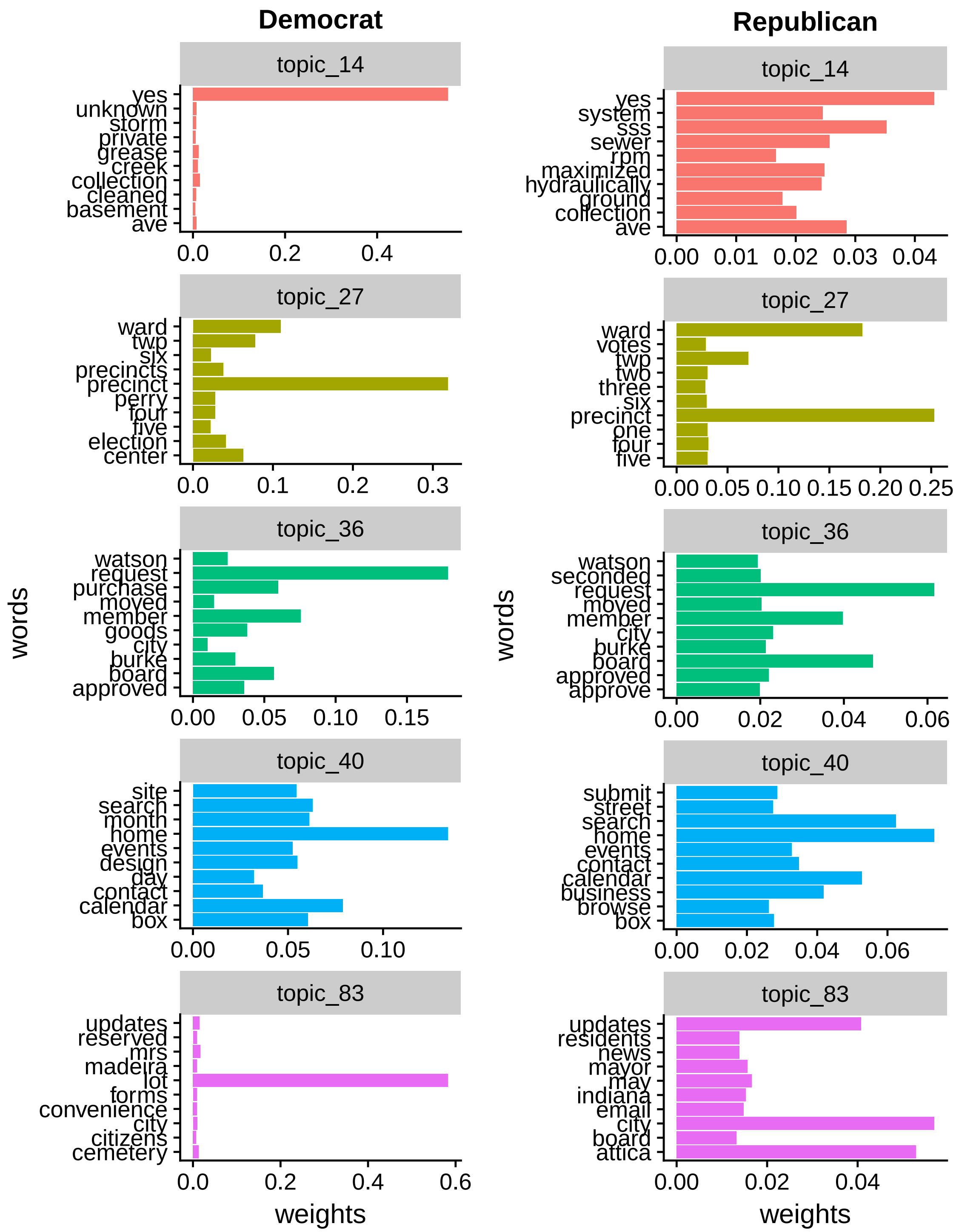

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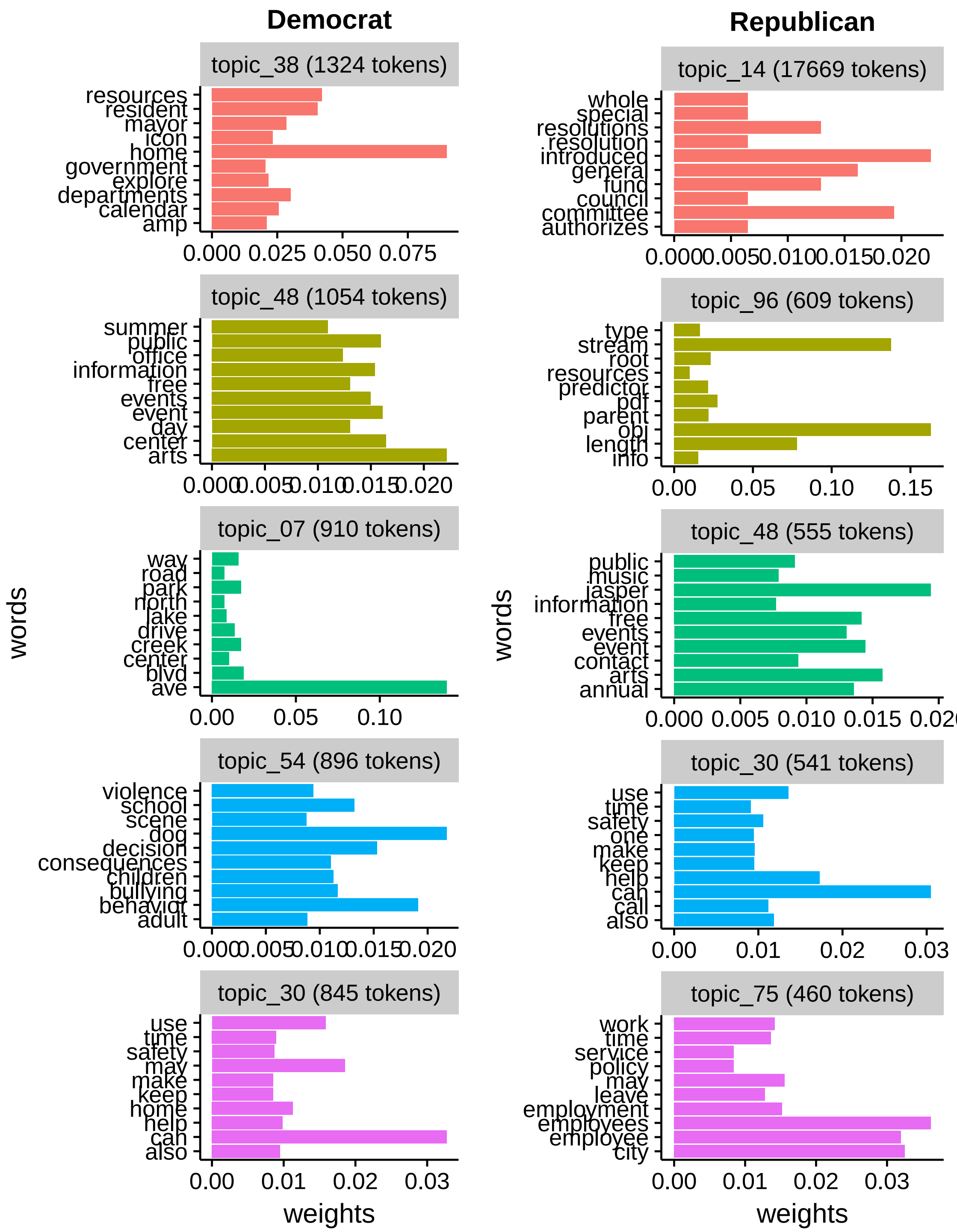
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Figure 3: Densities of topic weights for documents in Republican and Democratic cities.

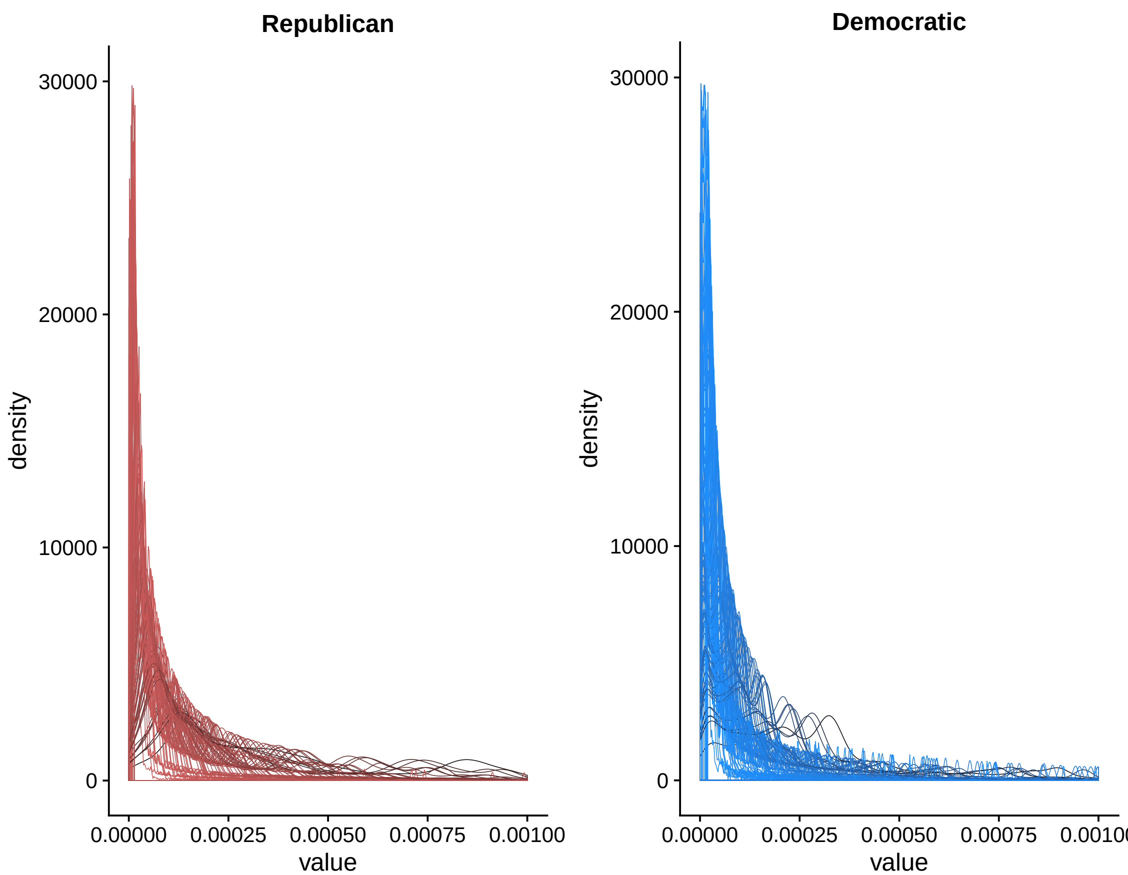


Figure 4: Densities of topic weights for documents in Republican and Democratic cities.

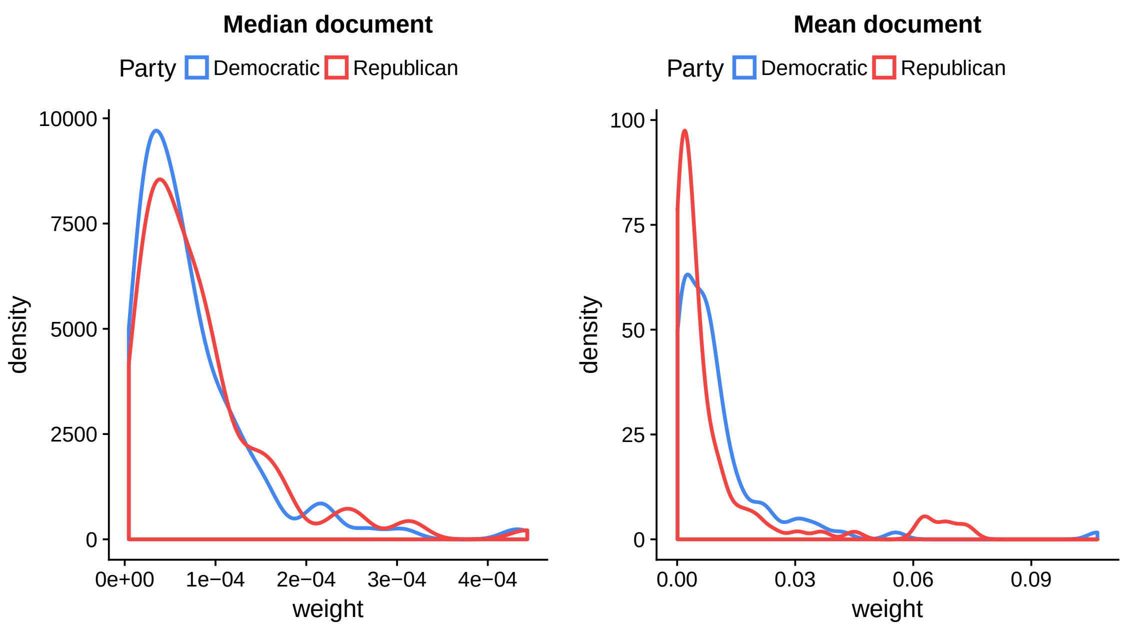


Figure 5: Word-topic probabilities for topics with big partisan differences

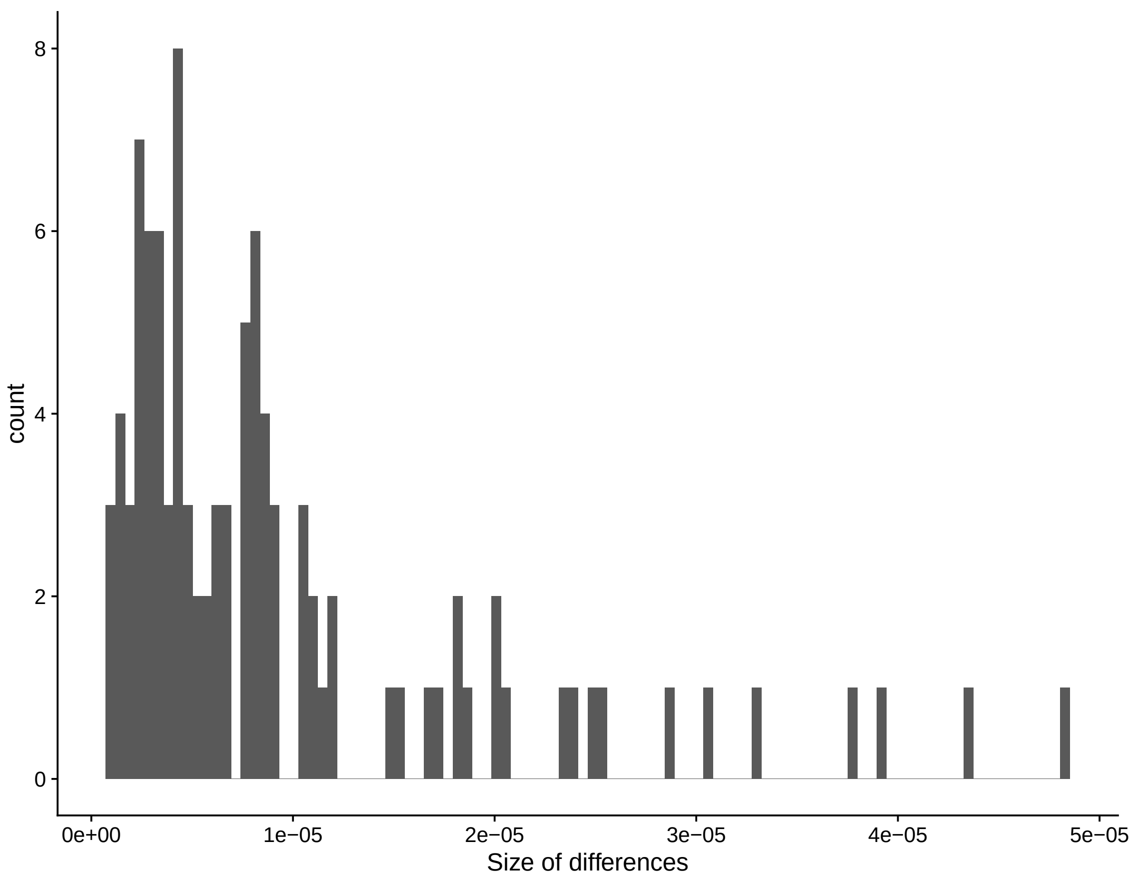


Figure 6: Word-topic probabilities for topics with big partisan differences

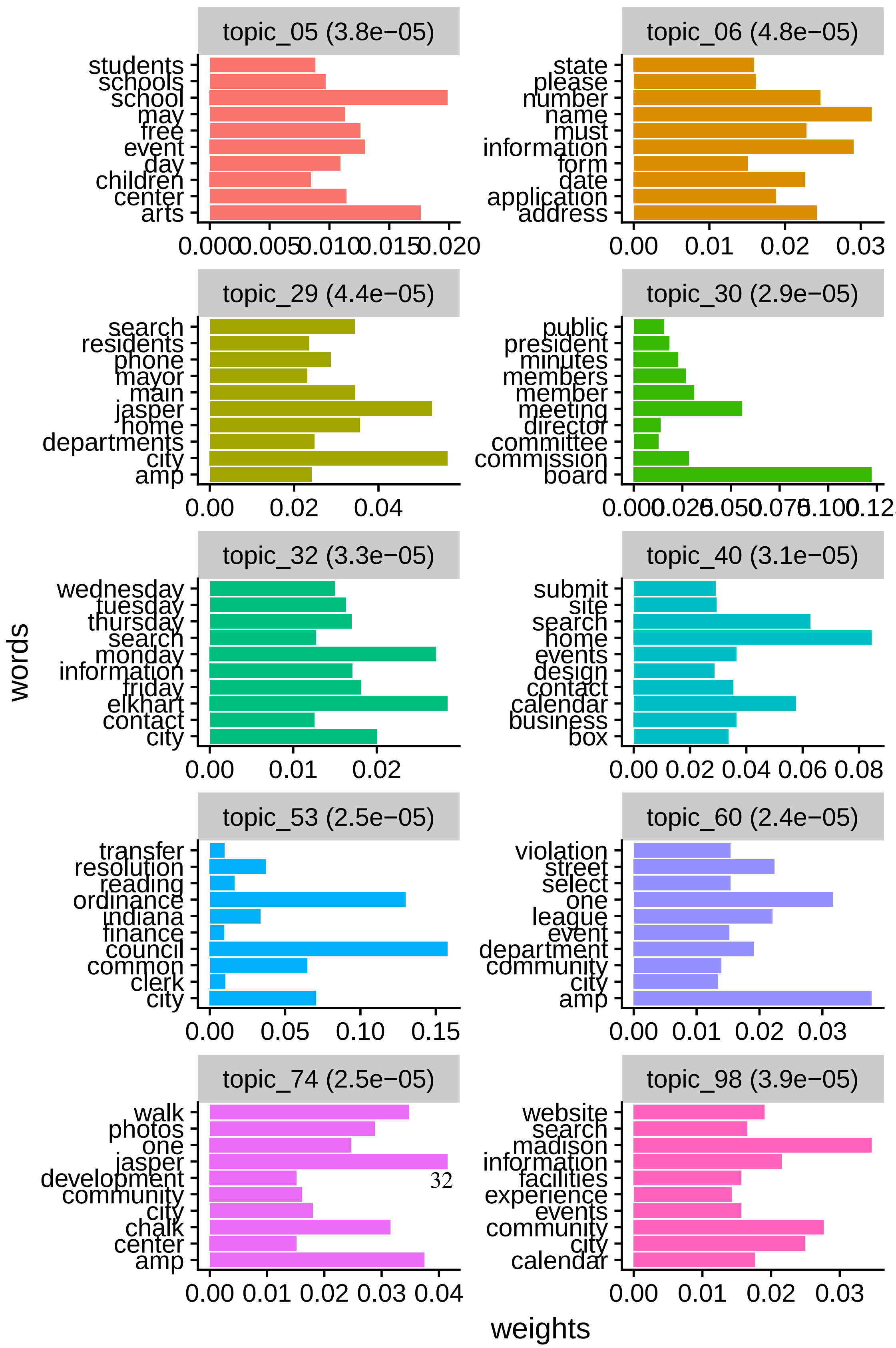


Figure 7: Word-topic probabilities for topics with big partisan differences

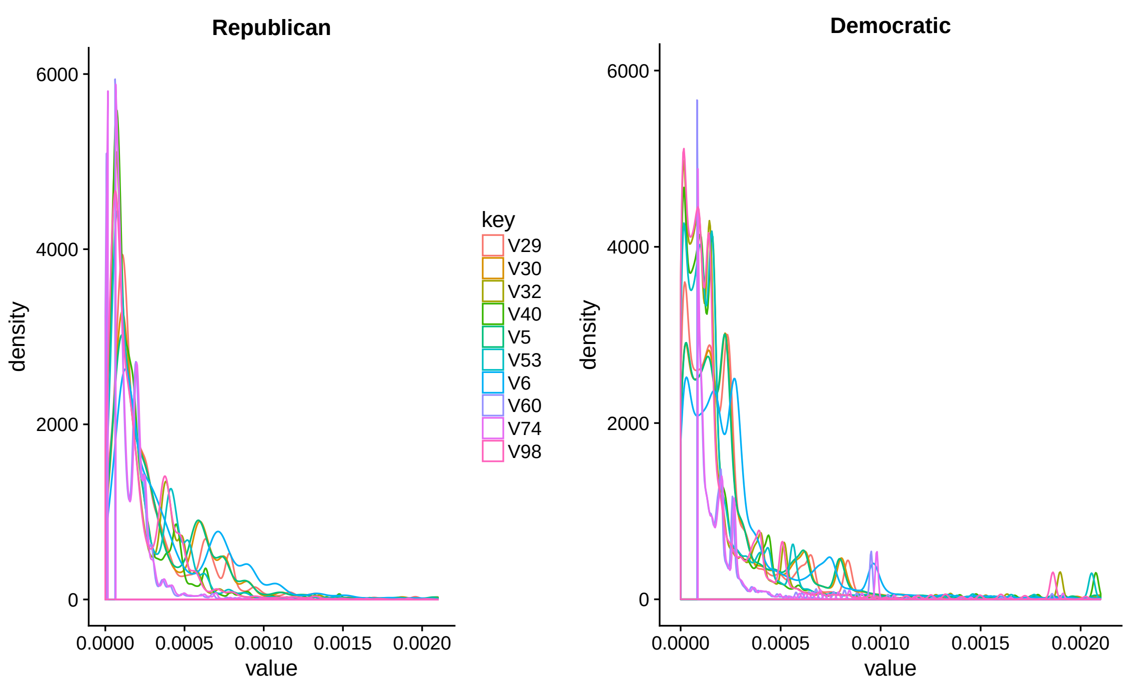


Figure 8: Word-topic probabilities for topics with big partisan differences

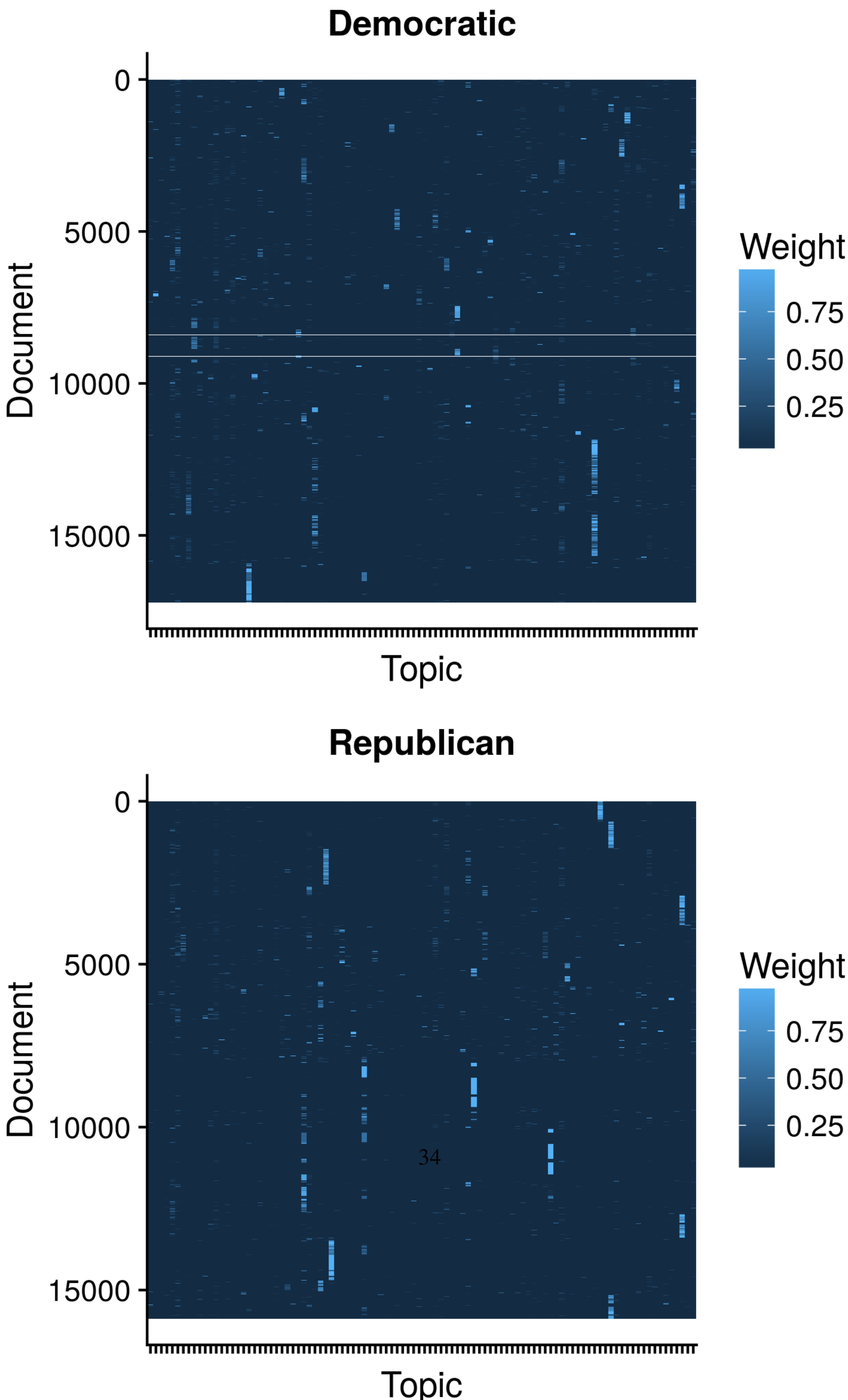


Figure 9: Topic coherence, varying the number of topics. The red line represents the mean topic coherence for each number of topics.

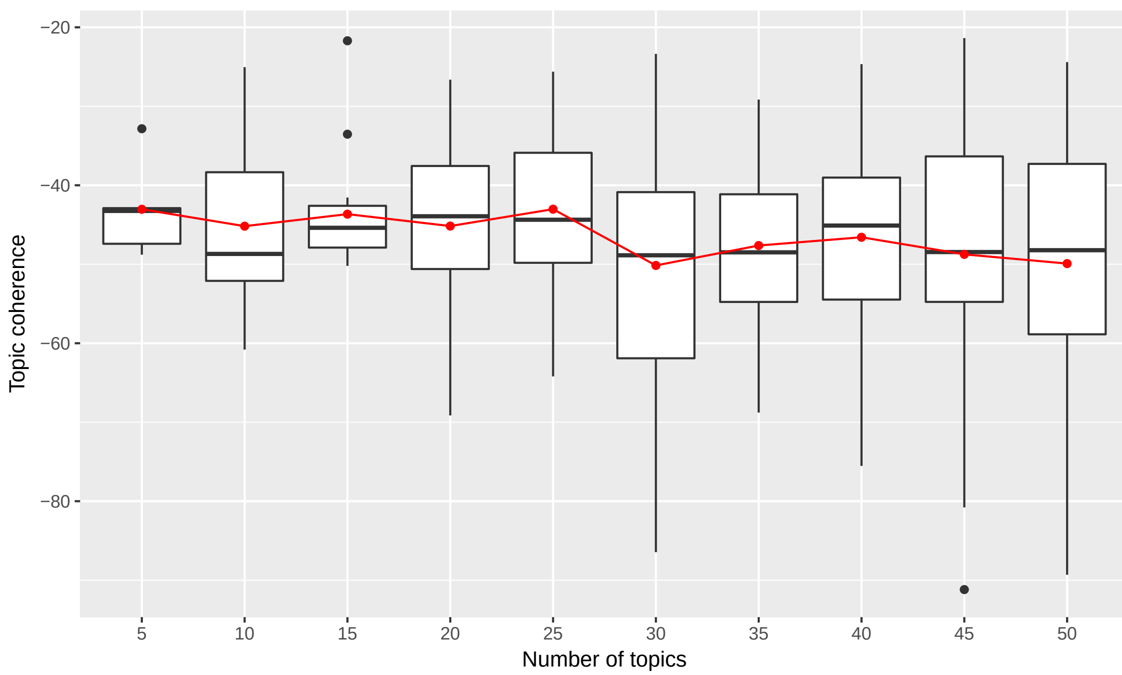


Figure 10: Cities in the corpus, by partisanship of mayor.

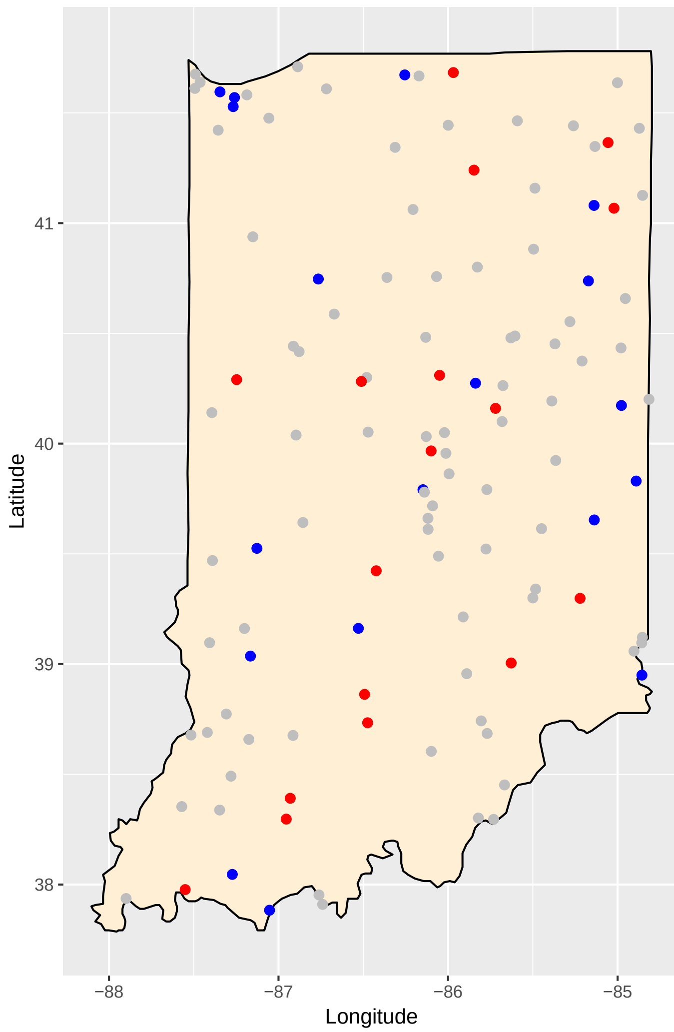


Figure 11: The most partisan topics. The number in parenthesis indicates how many times more the topic appears on average (measured through the number of words of the topic throughout the documents) in the respective party's corpus (indicated by the color).

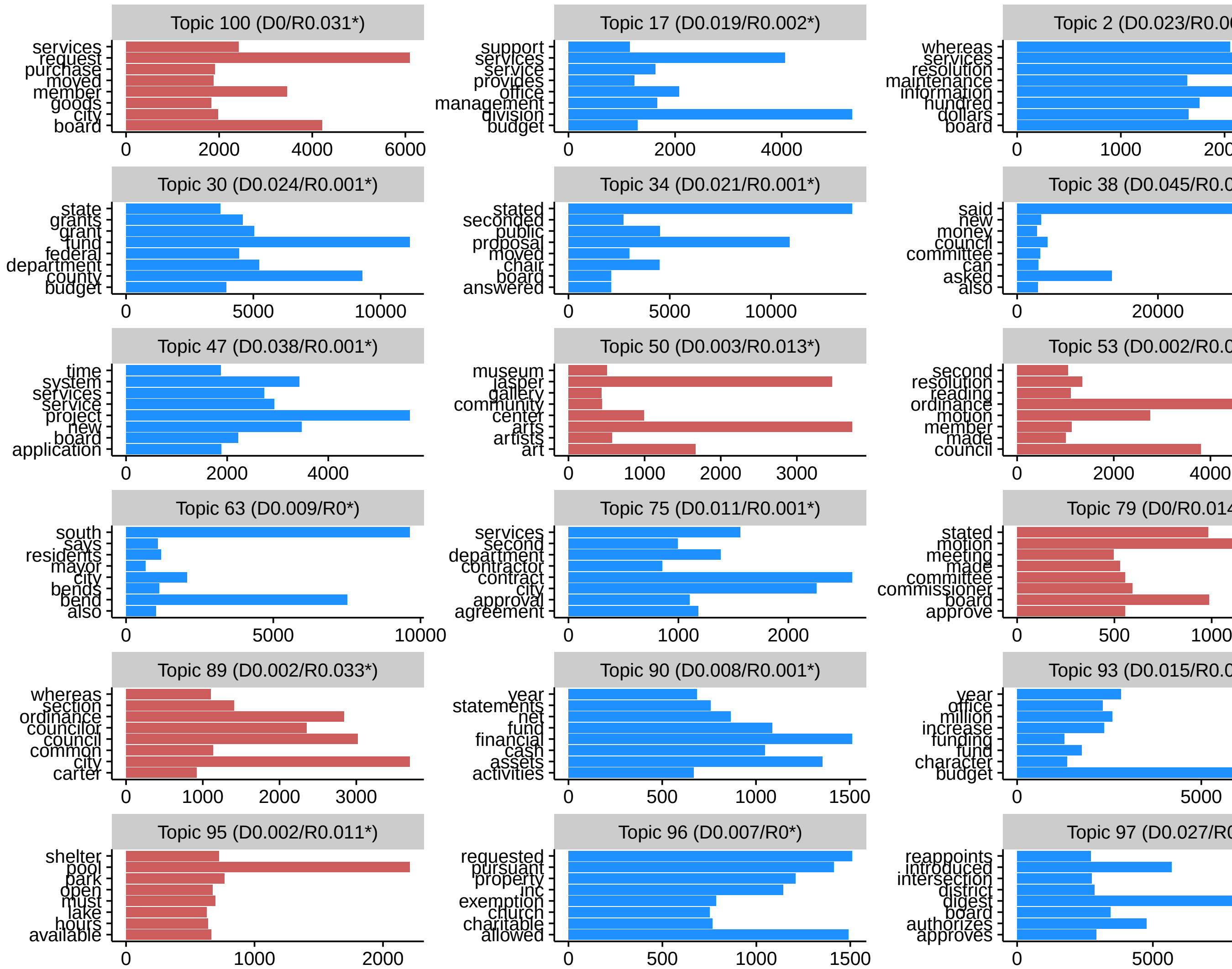


Figure 12: The optimal number of topics for our corpus. The measures of Grifffths 2004 and Cao 2009 indicate the best number of topics at their minimum, whereas the measure of Arun 2010 points to the best value at its maximum.

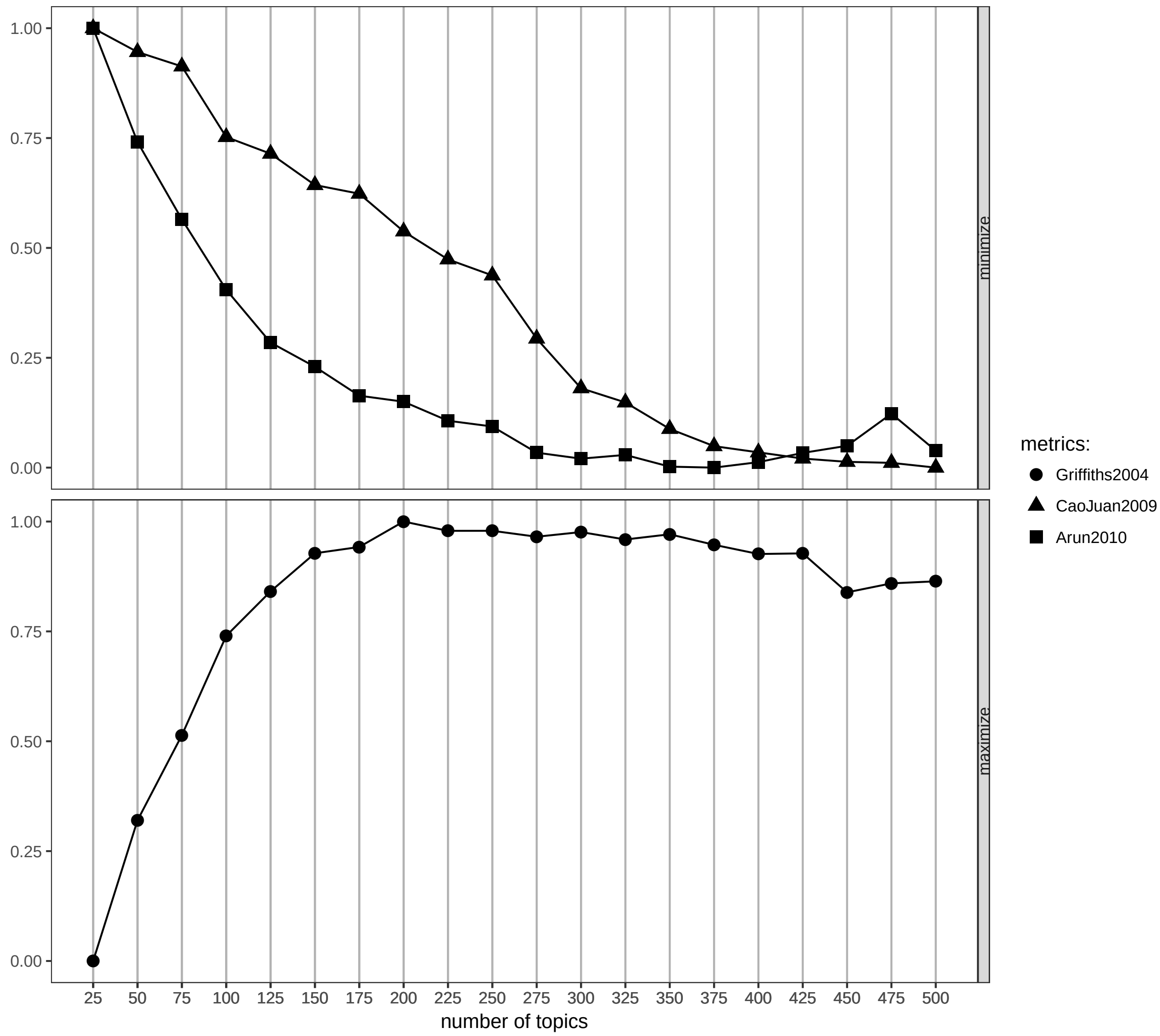


Figure 13: Results from a structural topic model, displayed as the p-values for each variable for each topic. This would normally be somewhat nonsensical, but here it illustrates why the model does not work.

Figure 14: Top democratic and Republican words (Indiana), according to the informed Dirichlet model of Monroe et al. (2008). Ordering is top to bottom for Democrats, and vice versa for Republicans.

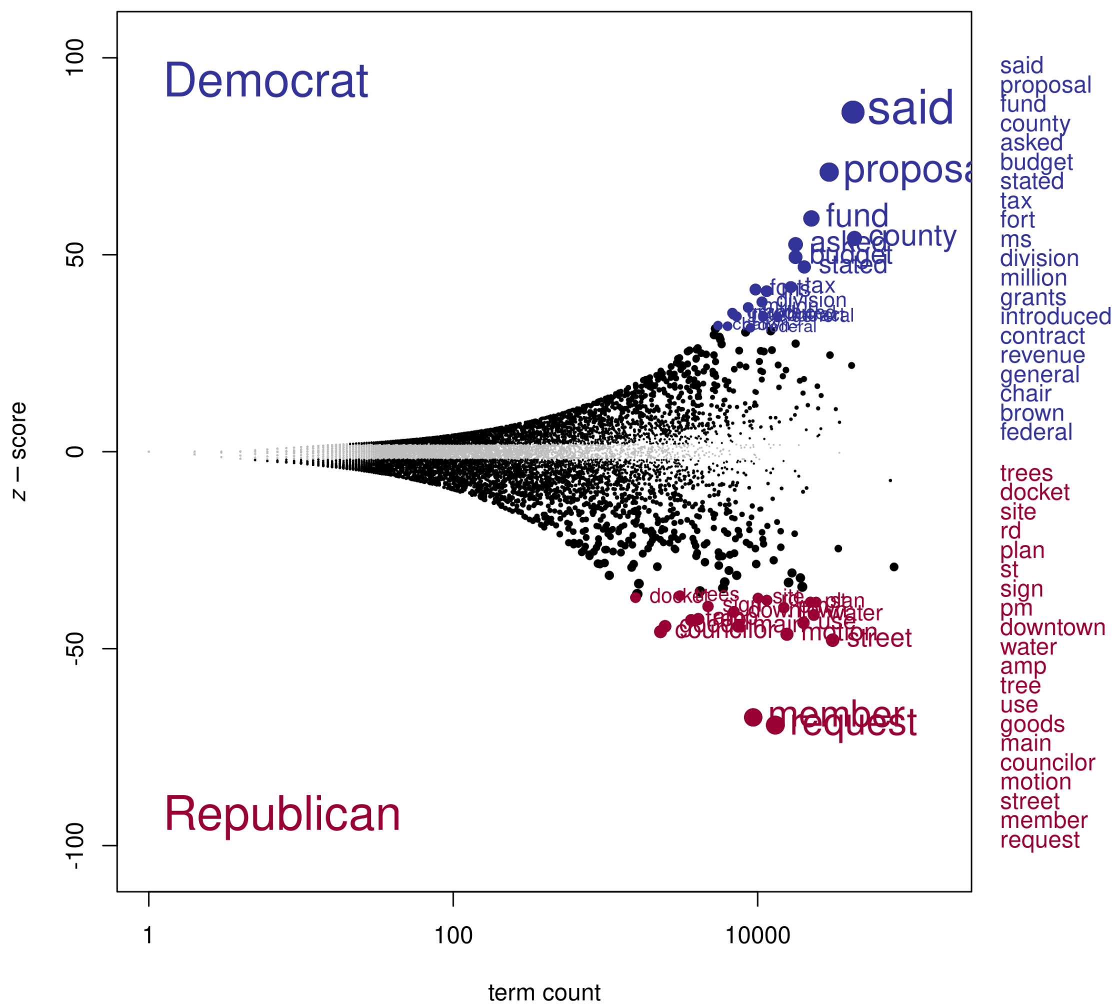
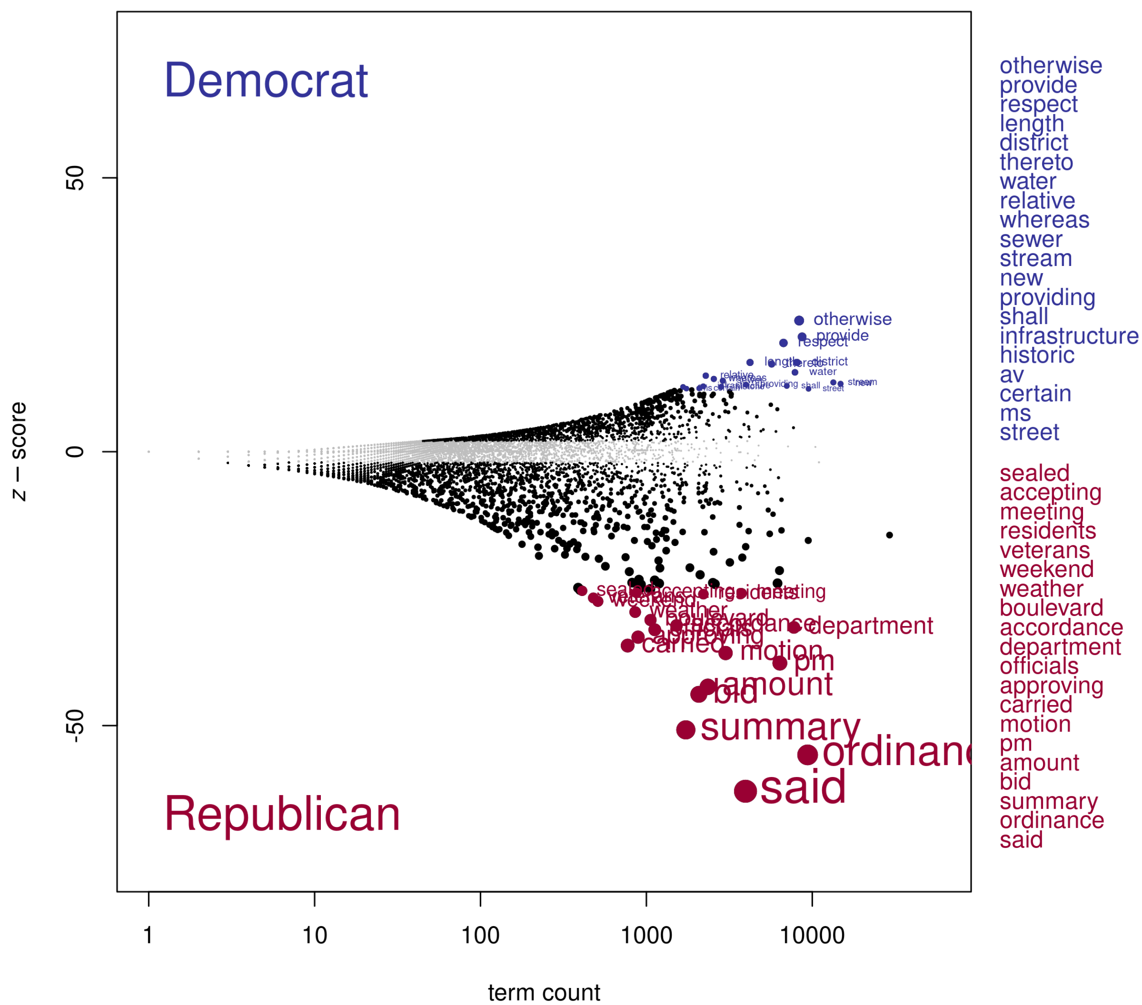


Figure 15: Top democratic and Republican words (Louisiana), according to the informed Dirichlet model of Monroe et al. (2008). Ordering is top to bottom for Democrats, and vice versa for Republicans.



Word (D)	Instances (D)	Word (R)	Instances (R)
city	42493	will	53761
said	40480	city	36210
county	39209	street	21207
proposal	29019	board	19496
public	27070	water	18637
council	23492	plan	18241
shall	23162	public	14327
department	22926	use	13233
services	22703	information	13062
fund	21661	development	12916
will	20697	department	11554
new	19000	area	11270
stated	18794	shall	11247
project	18538	fire	10861
property	18378	can	10748
budget	16631	must	10633
community	16236	park	10493
asked	16231	building	10356
tax	14549	motion	10168
board	14363	ordinance	9625
state	13964	request	9512
office	13818	council	9098
program	13536	community	9072
year	13376	meeting	8990
service	13312	ave	8555
provide	13138	service	8040
one	13066	construction	7999
section	12669	one	7885
work	11986	property	7741
information	11886	also	7492
development	11854	per	7442
committee	11802	required	7407
district	11584	home	7334
time	11466	center	7316
total	10965	made	7301
general	10731	site	7279
parks	10704	business	7222
system	10668	time	7157
digest	10481	services	7140
police	10474	housing	7111
management	10433	new	7006
park	10356	within	6910
also	10112	date	6818
division	9964	year	6768
street	9853	following	6754
resolution	9768	road	6629
contract	9763	member	6450
ordinance	9456	inc	6367
safety	9362	number	6360
code	9342	day	6254

Table 4: Top 50 Democratic and Republican words (Indiana), according to LDA. Topic ownership is determined by the ratio of Democratic to Republican tokens in it (both weighted by the total number of tokens per party). The instances of each token type are then summed across all topics owned by the party.

Word (D)	Instances (D)	Word (R)	Instances (R)
city	19306	city	9930
stream	13397	ordinance	4413
new	13001	information	3756
obj	10440	council	3422
otherwise	8271	said	3301
street	7990	plan	3194
provide	7647	department	2991
district	7449	state	2598
property	7031	public	2594
public	6864	meeting	2392
shall	6750	mayor	2258
respect	6698	one	2166
water	6085	application	2105
thereto	5686	development	2017
development	5124	parish	1809
use	5086	can	1807
ordinance	4963	new	1807
business	4763	water	1780
department	4757	program	1691
community	4705	project	1674
authorizing	4440	time	1648
located	4315	code	1641
mayor	4266	year	1560
length	4215	date	1556
project	3918	number	1548
section	3863	name	1516
service	3831	street	1504
councilman	3824	motion	1500
services	3782	day	1483
zoning	3771	park	1471
parish	3731	home	1469
providing	3641	address	1415
one	3636	office	1408
system	3617	amount	1392
building	3607	ave	1384
can	3557	budget	1382
code	3532	please	1375
office	3305	community	1334
drive	3223	area	1326
work	3171	contact	1319
permit	3165	emergency	1308
following	3153	summary	1282
within	3123	also	1271
must	3088	make	1265
plan	3064	two	1224
neighborhood	3048	work	1213
construction	3016	fire	1184
chapter	2973	bid	1134
ordinances	2885	planning	1124
fire	2878	people	1108

Table 5: Top 50 Democratic and Republican words (Louisiana), according to LDA. Topic ownership is determined by the ratio of Democratic to Republican tokens in it (both weighted by the total number of tokens per party). The instances of each token type are then summed across all topics owned by the party.

Word (D)	z-Score (D)	Word (R)	z-Score (R)
said	86.20	request	69.41
proposal	70.98	member	67.45
fund	59.22	street	47.84
county	54.15	motion	46.35
asked	52.62	councilor	45.69
budget	49.40	main	44.34
stated	46.90	goods	44.33
tax	41.79	use	43.43
fort	41.17	tree	42.77
ms	40.76	amp	42.48
division	38.01	water	41.45
million	36.62	downtown	40.66
grants	35.21	pm	39.60
introduced	34.85	sign	39.28
contract	34.36	st	38.23
revenue	34.33	plan	38.20
general	34.17	rd	37.71
chair	32.01	site	37.19
brown	31.86	docket	37.03
federal	31.46	trees	36.56
metropolitan	31.25	plat	36.15
management	30.69	old	35.44
agency	30.35	residential	34.65
approves	29.66	area	34.31
authorizes	29.11	variance	33.50
technology	28.45	th	33.20
provide	27.43	utility	33.11
dollars	27.30	ordinance	32.04
consolidated	26.29	carter	31.40
justice	25.93	approve	31.40
parks	25.79	building	30.78
lewis	25.73	feet	30.16
increase	25.66	news	29.37
digest	25.60	city	29.26
support	25.43	lots	29.19
oliver	25.43	lot	28.89
animal	25.02	aid	28.54
gray	24.72	overlay	28.53
capital	24.54	home	28.52
services	24.53	democrat	28.40
amends	23.84	republican	28.25
criminal	23.70	uses	28.05
enterprise	23.62	must	27.57
mayors	23.51	legal	26.64
court	22.90	zoning	26.53
township	22.86	councilors	26.50
controls	22.54	river	26.48
funded	22.28	stellar	26.40
referred	22.16	common	26.15
fiscal	22.10	rep	26.03

Table 6: Top 50 democratic and Republican words (Indiana), according to the informed Dirichlet model of Monroe et al. (2008).

Word (D)	z-Score (D)	Word (R)	z-Score (R)
otherwise	23.94	said	61.99
provide	20.97	ordinance	55.35
respect	19.86	summary	50.78
length	16.29	bid	44.29
district	16.29	amount	42.92
thereto	16.00	pm	38.59
water	14.49	motion	36.75
relative	13.88	carried	35.39
whereas	13.29	approving	33.86
sewer	12.96	officials	32.51
stream	12.65	department	32.08
new	12.40	accordance	31.71
providing	12.24	boulevard	30.73
shall	12.01	weather	29.28
infrastructure	11.94	weekend	27.32
historic	11.83	veterans	26.69
av	11.82	residents	26.01
certain	11.56	meeting	25.84
ms	11.52	accepting	25.77
street	11.48	sealed	25.39
bonds	11.29	responsive	25.23
et	11.18	regarding	25.09
urban	11.13	exceed	25.00
chapter	10.98	gathering	24.85
rs	10.96	hold	24.23
ll	10.96	emergency	24.16
green	10.95	works	24.06
pl	10.93	council	24.02
ct	10.78	contract	23.94
ca	10.76	approve	23.90
funds	10.53	purchase	23.47
housing	10.51	show	23.34
neighborhood	10.50	received	22.46
re	10.50	power	21.90
division	10.49	information	21.70
permits	10.48	recreation	21.24
iv	10.41	seconded	21.18
ft	10.27	esplanade	20.92
execute	10.22	park	20.21
communications	10.22	storm	19.87
feet	10.22	night	19.54
side	10.21	resolution	19.32
ch	10.18	progress	19.25
vi	10.15	playground	19.18
ad	10.15	furnish	19.02
db	10.13	lowest	18.81
permit	10.13	inc	18.26
amp	10.09	hall	18.07
revenue	10.04	heritage	17.83
id	10.00	evacuation	17.70

Table 7: Top 50 democratic and Republican words (Louisiana), according to the informed Dirichlet model of Monroe et al. (2008).

demTopic	demTopicCoeff	Democratic	repTopic	repTopicCoeff	Republican
59	-0.026	fort	28	0.024	motion
59	-0.026	citi	28	0.024	second
59	-0.026	ordin	28	0.024	made
59	-0.026	approv	28	0.024	approv
59	-0.026	purchas	28	0.024	mayor
59	-0.026	depart	28	0.024	present
59	-0.026	properti	28	0.024	state
59	-0.026	will	28	0.024	will
59	-0.026	resolut	28	0.024	citi
59	-0.026	contract	28	0.024	council
50	-0.019	propos	11	0.019	plan
50	-0.019	author	11	0.019	zone
50	-0.019	district	11	0.019	applic
50	-0.019	street	11	0.019	properti
50	-0.019	public	11	0.019	approv
50	-0.019	control	11	0.019	sign
50	-0.019	amend	11	0.019	site
50	-0.019	intersect	11	0.019	locat
50	-0.019	counti	11	0.019	commiss
50	-0.019	committe	11	0.019	file
42	-0.018	said	2	0.019	inc
42	-0.018	ask	2	0.019	electr
42	-0.018	state	2	0.019	build
42	-0.018	will	2	0.019	construct
42	-0.018	chair	2	0.019	home
42	-0.018	propos	2	0.019	street
42	-0.018	year	2	0.019	meridian
42	-0.018	move	2	0.019	servic
42	-0.018	need	2	0.019	west
42	-0.018	council	2	0.019	main
16	-0.018	prosecutor	27	0.016	request
16	-0.018	charg	27	0.016	board
16	-0.018	feloni	27	0.016	member
16	-0.018	counti	27	0.016	servic
16	-0.018	case	27	0.016	street
16	-0.018	crime	27	0.016	approv
16	-0.018	crimin	27	0.016	purchas
16	-0.018	offic	27	0.016	citi
16	-0.018	victim	27	0.016	move
16	-0.018	sentenc	27	0.016	good
13	-0.018	digest	35	0.016	council
13	-0.018	introduc	35	0.016	citi
13	-0.018	author	35	0.016	ordin
13	-0.018	counti	35	0.016	common
13	-0.018	appoint	35	0.016	councilor
13	-0.018	board	35	0.016	amend
13	-0.018	approv	35	0.016	resolut
13	-0.018	district	35	0.016	adopt
13	-0.018	fund	35	0.016	wherea
13	-0.018	street	35	0.016	approv

Table 8: Top 50 Democratic and Republican words (Indiana), according to STM. The words are the top words for the most Democratic/Republican topic, determined by the size (and significance) of the coefficient of the party covariate.

demTopic	demTopicCoeff	Democratic	repTopic	repTopicCoeff	Republican
1	-0.171	stream	49	0.095	event
1	-0.171	obj	49	0.095	music
1	-0.171	interpol	49	0.095	church
1	-0.171	baa	49	0.095	inform
1	-0.171	matrix	49	0.095	show
1	-0.171	metadata	49	0.095	park
1	-0.171	hum	49	0.095	market
1	-0.171	gym	49	0.095	visit
1	-0.171	rid	49	0.095	year
1	-0.171	yep	49	0.095	featur
15	-0.045	length	13	0.093	said
15	-0.045	root	13	0.093	work
15	-0.045	predictor	13	0.093	citi
15	-0.045	eye	13	0.093	depart
15	-0.045	word	13	0.093	airport
15	-0.045	acrobat	13	0.093	code
15	-0.045	adob	13	0.093	offici
15	-0.045	ash	13	0.093	resid
15	-0.045	rang	13	0.093	mayor
15	-0.045	vet	13	0.093	continu
57	-0.044	otherwis	56	0.064	ordin
57	-0.044	provid	56	0.064	summari
57	-0.044	respect	56	0.064	amount
57	-0.044	thereto	56	0.064	citi
57	-0.044	citi	56	0.064	bid
57	-0.044	author	56	0.064	depart
57	-0.044	ordin	56	0.064	motion
57	-0.044	amend	56	0.064	approv
57	-0.044	district	56	0.064	public
57	-0.044	locat	56	0.064	contract
41	-0.017	pdf	12	0.049	flood
41	-0.017	content	12	0.049	emerg
41	-0.017	type	12	0.049	storm
41	-0.017	width	12	0.049	disast
41	-0.017	text	12	0.049	weather
41	-0.017	resourc	12	0.049	hurrican
41	-0.017	parent	12	0.049	can
41	-0.017	filter	12	0.049	area
41	-0.017	font	12	0.049	busi
41	-0.017	page	12	0.049	inform
5	-0.017	polic	3	0.022	councilman
5	-0.017	crime	3	0.022	want
5	-0.017	offic	3	0.022	said
5	-0.017	investig	3	0.022	just
5	-0.017	arrest	3	0.022	know
5	-0.017	suspect	3	0.022	get
5	-0.017	victim	3	0.022	like
5	-0.017	report	3	0.022	citi
5	-0.017	block	3	0.022	can
5	-0.017	vehicl	3	0.022	come

Table 9: Top 50 Democratic and Republican words (Louisiana), according to STM. The words are the top words for the most Democratic/Republican topic, determined by the size (and significance) of the coefficient of the party covariate.

	Democratic	Republican
Cities	15	17
Documents	10257	5859
Tokens	6101752	2310072
Token assignments	6006202	2259362
Topics	103	97

Table 10: Descriptive statistics for Indiana. "Tokens" describes the number of words in each party's documents, "token assignments" the tokens assigned to each party in the topic model depending on the ratio of Democratic to Republican tokens in it (both weighted by the total number of tokens per party).

	Democratic	Republican
Cities	11	7
Documents	6287	1327
Tokens	1955198	322915
Token assignments	1789373	314628
Topics	143	57

Table 11: Descriptive statistics for Louisiana. "Tokens" describes the number of words in each party's documents, "token assignments" the tokens assigned to each party in the topic model depending on the ratio of Democratic to Republican tokens in it (both weighted by the total number of tokens per party).