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Combining Latent Topics with Document Attributes in Text Analysis

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Abstract

This paper introduces a variant to existing models of multinomial regression for text analysis. Using the base model introduced by Taddy (2013a), we extend the data-generating model to incorporate topics not explained by metadata. In doing so, we seek to increase the prediction accuracy over existing techniques, bridge the gap between multinomial regression and standard topic models, and investigate methods for discovering new topics in a corpus. We explore computational aspects of our approach, provide software for parallelization of the algorithm, and conclude by proposing areas of future research.

Contents

Introduction

Motivation

The analysis of data contained in natural language text is referred to as text mining or text analysis. The field has grown rapidly in popularity since the seminal 1963 Mosteller and Wallace paper that analyzed the word usage patterns of James Madison and Alexander Hamilton to determine the authorship of disputed federalist papers. More recently, through the advent of inexpensive computation and increasingly accessible digital information, widespread applications for text analysis have been developed in automated advertisement placement, business intelligence, finance, and national security (Belsky, 2012, and Taddy, 2013c). Finally, the increasing size of digitally-stored text data have created a need for computationally-efficient models that can categorize text or make inferences on authorship or other factors relevant to the text's composition.

Modeling Text Data

A common technique for modeling text data is the use of multinomial models on word 'stems' derived from the original document. Typically, text information is naturally grouped by documents, and each document is represented by counts of words, or "tokens". A document might be a single written text (e.g. an academic article), or a collection of works by the same author (e.g. all of the lyrics of an album by the Rolling Stones) A token is often a single word (called a unigram) but may also be a sequence of two or more words (e.g.'good swimmer' is a bigram, and 'I eat cheese' is a tri-gram). The word components of tokens are often reduced to'stem' form by removing suffixes (e.g. 'illuminated', 'illumination' and 'illuminating' all become 'illuminate'), using the popular Porter stemming algorithm (Porter, 1980).

Since the number of unique words that appear in a large number of documents can be extensive, we often restrict the number of tracked tokens, p, to words or phrases that occur in at least two documents. If the total number of documents n is large, we may also remove common tokens that add little meaning and are found in almost all documents (i.e. 'the' or 'of').

A trivial example of such content might be student's answers to the question 'What did homework assignments involve?', with the following four responses:

Table 1: Example of text data from course reviews

Document	Content
1	Some computation and formula proving, a lot of R code
2	Problems, computation using R
3	Some computations and writing R code
4	Proofs, problems, and programming work

These tokens are then aggregated by document: For i in $1, ..., n$, the vector $x_i = [x_{i1}, x_{i2}, ..., x_{ip}]$ contains the number of occurrences of first, second, $\ldots$ p th token in the ith document, where p is the total number of unique tokens in all documents. This forms the complete count matrix $X = [x_1, x_2, ..., x_n]^T$, where each x_{ij} is the number of occurrences of word j in document i.

Continuing with the example in Table 1 by removing common words and stemming the remaining words produces the count matrix X in Table 2.

Table 2: Creating a word-count matrix from text

Document	Some	comp	formula	prov	R	code	use	problem	writ	program	work
1	1	1	1	1	1	1	0	0	0	0	0
2	0	1	0	0	1	0	1	1	0	0	0
3	1	1	0	0	1	0	0	0	1	0	0
4	0	0	0	1	0	0	0	1	0	1	1

Multinomial Model

We then model each document x_i as the realization of a multinomial distribution. That is,

$$x_i \sim MN(q_i, m_i)$$

where q_i is the vector $[q_{i1}, \ldots q_{ip}]$ of token probabilities for document x_i and m_i is $\sum_{j=1}^{p} x_{ij}$, or the total number of tokens in document i

It is trivial to show that the maximum likelihood estimator of q_i is $f_i = x_i/m_i$, but by imposing structure on q_i, we can model features of the data. The two most common techniques for creating structure are *topic models* and *metadata*.

Topic Models

Under a topic model, each document is the realization of a linear combination of K topics, where each topic $l = 1, .., K$ represents a distribution, or vector of probability weights $\omega_l = [\omega_{l1}, ..., \omega_{lp}]$, over words. As a simple example, we can imagine a fitness store that primarily sells books on biking, running, and swimming. We can see that a probability distribution of these topics would have high probability weights on the terms (“pedal”, “helment”) for biking, (“stride”) for running, and (“breath”, “stroke”, “water”) for swimming. By denoting the proportion of topic l as θ_l, we can imagine each document as being generated by a linear combination of topics $\theta_1\omega_1 + \theta_2\omega_2 + \theta_3\omega_3$, described as the following data-generating process:

1. Choose the number of words N

2. Choose $\theta = \theta_1, ...\theta_K$, the proportion of topics. (i.e., a book completely about swimming would have $\theta = (1, 0, 0)$, a book about triathalons might have $\theta = (1/3, 1/3, 1/3)$).

3. For each word w_i:

   (a) Choose topic l with probability θ_l

   (b) Choose a word w_i with the topic word-weighting vector ω_l

Traditionally, the topic model proportions are given a Dirchlet prior, and the model is also known as Latent Dirichlet Allocation, or LDA. For a thorough introduction to topic models, we refer the reader to Blei, Ng, and Jordan (2003).

Metadata

Text data is frequently accompanied by information, or metadata, about the text itself. For example, metadata on an academic article could include the number of times the article has been cited, and the journal in which the article has been published. We then seek to model the relationship between metadata and the composition of the text. For example, given a database of written movie reviews and final rating out of five $y \in (1, 2, 3, 4, 5)$, we might want to predict the movie rating from the text content of the review.

Metadata and Unigram Models

If the support Y of metadata y takes discrete values $y^{(1)}, y^{(2)}, \ldots, y^{(m)}$ with few unique observations (m small), we can 'collapse' the token counts over levels of metadata for simplification and computational gains. That is, each dataset of n ordered (text, metadata) pairs

$$\Big[(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\Big] \tag{1}$$

can be expressed, as m collapsed observations:

$$\Big[(\sum_{x_i:y_i=y^{(1)}} x_i), (\sum_{x_i:y_i=y^{(2)}} x_i), \ldots, (\sum_{x_i:y_i=y^{(m)}} x_i)\Big] \tag{2}$$

Then, a simple log-link model allows us to express document x with given metadata rating y, denoted x_y, as $x_y \sim MN(q_y, m_y)$, with

$$q_{yj} \sim \frac{exp[\alpha_j + y\phi_j]}{\sum_{l=1}^{p} exp[\alpha_l + y\phi_l]} \tag{3}$$

The coefficient ϕ is referred to as the *distortion vector.* Intuitively, it *distorts* the base frequency of words α by the effect of the metadata y. For example, if we had text information on college course evaluations written by students, and metadata of a value, from one to ten, representing the student's evaluation of the class, we would expect the distortion vector ϕ to have high loadings, or coefficients, on terms such as 'interesting', 'engaging', and 'useful', and low loadings on the words 'difficult', 'boring' and 'sleepy'.

Theory and Approach

Mixture models and cluster membership

We now turn our attention to the main purpose of this paper, which is to incorporate latent topics across documents while maintaining the computational simplicity of a collapsable multinomial model. To do so we will restrict our model by assuming that every document is a member of one and only one topic. In order not to confuse our approach with traditional topic models, where each topic can take a weight $\theta \in (0, 1)$, we refer to the model in which a document can only belong to one topic as a *cluster membership model*. This terminology also emphasizes the theoretical relationship between our model and finite mixture models, where every data point is generated by a specific mixture component.

As a simple motivating example, we might imagine a corpus of movie reviews written by several bloggers. After accounting for text information explained by the rating (e.g. relating a 5-star rating to 'good plot'), the remaining heterogeneity in the movie review content could be related traits of the blogger (e.g. gender, or home city). We may be interested in predicting traits of bloggers given their movie reviews, and also in determining how movie review content changes across these traits. For example, we could examine how movie reviews written by female bloggers differ from movie reviews written by male bloggers.

Model Specification

Denoting the word count of a document as the vector x_i, we propose that words in a document are distributed as a multinomial with a log-link to document metadata and cluster membership. That is:

$$x_i \sim MN(q_{ij}, m_{ij}); \quad q_{ij} = \frac{exp(\alpha_j + y_i\phi_j + u_i\Gamma_{kj})}{\sum_{l=1}^{p} exp(\alpha_l + y_i\phi_l + u_i\Gamma_{kl})} \tag{4}$$

In our notation, y_i and u_i are the metadata and cluster membership associated with document i. u_i is an $n \times 1$ vector, and y_i is a $n \times N_m$ matrix, where N_m is the number of metadata variables. α is the vector that correspond to a baseline or intercept of word frequencies. Using the same terminology introduced earlier, the coefficients ϕ_j and Γ_{kj} are the distortion vectors for metadata and cluster membership, respectively.

We use the subscript k for cluster membership to denote that each document x_i is considered a member of one of $k = 1, .., K$ clusters, with their own distortion vectors $\Gamma_1, .., \Gamma_K$

By collapsing over metadata, we can express the the distribution of a document x given metadata y, x_{yk}, with

$$x_{yk} \sim MN(q_{yk}, m_{yk}), \quad q_{yk} = \sum_{i:y_i=y, u_i=k} \Big[\sum_{j=1}^{p} x_{ij}\Big] \tag{5}$$

and

$$q_{yk} \sim \frac{exp[\alpha + y\phi + u_k\Gamma_k]}{\sum_{l=1}^{p} exp[\alpha_j + y\phi_j + u_k\Gamma_{kj}]} \tag{6}$$

Estimation of Parameters via Maximum a Posteriori

The negative log likelihood of a multinomial distribution can be written as

$$\ell(\alpha, \phi, \Gamma, u) = \sum_{i=1}^{N} x_i^{\top}(\alpha + \phi v_i + u_i\Gamma_{kj}) - m_i log(\sum_{j=1}^{p} exp\Big[\alpha + \phi v_i + u_i\Gamma_{kj}\Big]) \tag{7}$$

Following previous literature on text regression (Taddy 2013a), we specify Laplace priors and a gamma hyperprior on coefficients, as well as a gamma lasso penalty on coefficients Φ and Γ). This procedure leads us to minimize the sum of log likehood with the gamma lasso penalty.

$$\ell(\alpha, \Phi, \Gamma, u) = \sum_{j=1}^{p} (\alpha_j/\sigma_\alpha)^2 + c(\Phi, \Gamma) \tag{8}$$

The procedure to fit the coeffecients of a multinomial with gamma lasso penalty are documented in Taddy (2013b). We now briefly detail the fitting of the cluster membership via Bayesian estimation:

$$\boldsymbol{u}^*_{MAP} = \arg\max_{\mathbf{u}} \; P(\mathbf{u}|X) \tag{9}$$

$$= \arg\max_{\mathbf{u}} \; \frac{P(\mathbf{u}|X)\, P(\boldsymbol{u})}{P(X)} \tag{10}$$

$$= \arg\max_{\mathbf{u}} P(\mathbf{u}|X)\, P(\boldsymbol{u}) \tag{11}$$

And under the assumption that the $P(u_i) = P(u_j)$ for any two cluster vectors u_i, u_j, we eliminate $P(\boldsymbol{u})$:

$$\boldsymbol{u}^*_{MAP} = \arg\max_{\mathbf{u}} P(\mathbf{u}|X) \tag{12}$$

Although the likelihood function cannot be solved analytically, the discrete support for $\mathbf{u}$ makes it trivial to check the entire parameter space.

The algorithm we use to fit coefficients α, ϕ, Γ and cluster memberships u_i is two main steps iterated until convergence:

Algorithm for Cluster Membership Model with Gamma Lasso Penalty

1. Initialize u_i for $i = 1, \ldots, n$
2. Determine parameters α,ϕ, Γ by fitting a multinomial regression on $y_i|x_i, u_i$ with a gamma lasso penalty
3. For each document i, determine new cluster u_i membership as $argmax_{k=1,..,K}\Big[\ell(u_i|\alpha, \phi, \Gamma)\Big]$
4. Check if current cluster assignment is different from previous cluster assignment, $(\mathbf{u}^{(t)} = \mathbf{u}^{(t-1)})$. If so, return to step 2. If not, end algorithm.

By alternating between the first two steps, we aim to converge to optimal parameter estimates α, ϕ, Γ as well as optimal cluster memberships $\mathbf{u}$.

In practice, the algorithm converged after less than 20 iterations for all three datasets that we tested, with between 5 and 20 clusters. To address possible issues of cycling or non-convergence, an option for a maximum number of iterations was included in the code. If the algorithm does not converge within the maximum number of iterations, the program would stop and return the current parameter estimates, as well as notifying the user of non-convergence.

Computation

As noted previously, a property of multinomial regression is the ability to collapse observations across levels of metadata without losing information. This attractive property is preserved in the cluster membership model.

In step (2) of the algorithm, we can increase the speed by only evaluating portions of the likelihood function relevant to u_i and $\Gamma_k j$ by eliminating first two terms from the full likelihood and penalty equation.

$$\ell(u_i|\alpha, \phi, \Gamma) = \sum_{i=1}^{N} x_i^\top (u_i \Gamma_{kj}) - m_i log(\sum_{j=1}^{p} exp\Big[\alpha + \phi v_i + u_i \Gamma_{kj}\Big]) \tag{13}$$

In addition, the rightmost term does not depend on x_i and can be precalculated for each cluster u_i. This will lead to an order-of-magnitude speed-up as long as the number of clusters is relatively small compared to the number of documents.

Initializing Cluster Membership

We begin our algorithm by initializating $\mathbf{u}$, that is, assigning each document u_i to a cluster. Because each document can only be a member of one topic (unlike a traditional topic model), we want to investigate how important the cluster member initialization is to the final coefficients. For this paper, we initialize cluster membership using one of the three following methods:

1. Random Initialization
2. K-means on the word count data X
3. K-means on the residual of the word count data after incorporating metadata y (that is, given predicted word count $\hat{X}$, clustering on $X - \hat{X}$

Application and Evaluation of Algorithm

We applied the Cluster Membership model to two datasets: Congressional Speech records, most famously used to investigate media slant (Gentzkow and Shapiro, 2010) and a corpus of restaurant reviews collected by the website we8there.

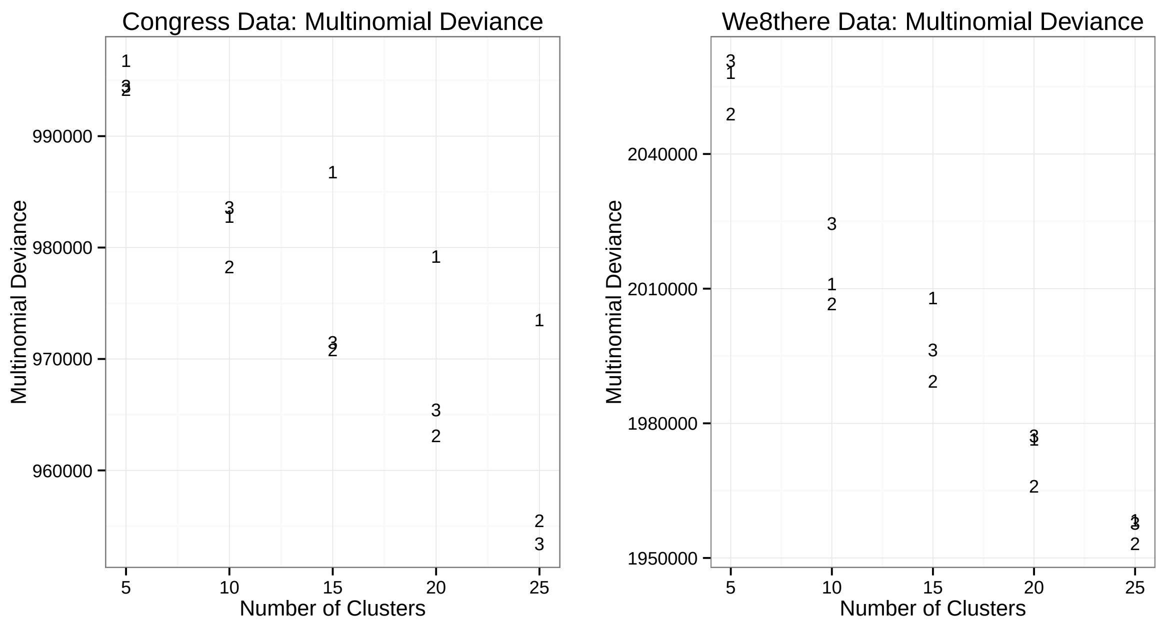
Congressional Speech

We first investigate the performance of the algorithm on the congressional speech data. The data consists of text from 579 speeches of the members of the 109th Congress. For the analysis, party membership was regressed onto speech data. The algorithm was run for 5, 10, 15, 20, and 25 clusters, each over the 3 different initialization methods described in the previous section. We then report the multinomial deviance, or two times the negative log likelihood, in figure 1.

We note that, for any given number of clusters, a better-fitting model is almost always obtained by initializing the cluster memberships on the text data, compared to assigning each document to a random cluster. We also note that initializing the cluster memberships to the residuals of the text data regressed on the outcome variable (in this case, GOP party membership) usually produced a worse-fitting model than simply initializing membership on the original text data.

Previous research (Taddy 2012) has shown that the optimal number of topics for a topic model on this dataset is around 10. This fact is not shown in our data for a couple of reasons. First, the cluster membership model is much less flexible than a standard topic model, and would likely need many more clusters to model the same lexical variation. Second, we are possibly over-fitting the data, since these models are not run under cross-validation.

Figure 1: Multinomial Deviance from fitted model cluster membership model



1 : random cluster initialization, 2 : K Means, 3 : K means on residuals

Interpretation of Topics

An essential aspect of topic modeling is determining the overall theme from the loadings vector. Previous research shows that correctly-specified topic models allow for rich interpretation of themes that can change over time, as well as model relationships between themes (Blei and Lafferty, 2006, and Blei and Lafferty, 2006b).

Of particular importance in our model is that our extreme simplification of topic weights does impede the ability to discover common themes across documents. If the topics produced by our method bear no relation to the topics produced by more complex topic modeling approaches, then there is little benefit of our model, regardless of computational improvements and model simplicity.

To test topic fit, we compare topics produced from our method with the topics produced by fitting a topic-only model, via MAP, with 12 topics on the Congressional Data (Gentzkow and Shapiro, 2010). Fortunately, we find that topics from our model are, in many cases, similar to topics obtained by traditional methods. As an example, table 4 shows a "stem cell" topic found by our method, compared to a similar topic found using the topic-only model mentioned above. The table consists of, for both models, the words with the highest loadings, or weight, in that topic, in decreasing order. This is equivalent to a list of the words with the highest components of cluster coefficient Γ_j.

Table 3: Comparison of top word loadings on a stem-cell topic

Cluster Membership	Topic Model (LDA)*
umbilic.cord.blood	pluripotent.stem.cel
cord.blood.stem	national.ad.campaign
blood.stem.cel	cel.stem.cel
adult.stem.cel	stem.cel.line

*Results reported in Taddy (2012)

Interpretation of results

We first evaluate our model by comparing the coefficients predicting GOP to a gamma lasso regression without any topic models. The words with the highest loading for determining party affiliation are illustrated in Table 4. This is equivalent to the list of words with the highest components in β. We see that some phrases have high loadings on GOP affiliation for both models, like 'weapon grade plutonium' and 'speaker table' (A stemmed version of 'Speaker of the table'). These are words that are, on general, used by many Republicans. Phrases such as 'People Middle East', which appears in the model without cluster memberships but is not as strongly indicative of GOP affiliation once cluster topics are added, are evidence that some terms are better explained by a particular topic than by party affiliation as a whole. Finally, we note that the coefficients in Table 4 are higher for the Cluster Membership model than for the multinomial model without clusters. This is because the addition of clusters to the model allows more flexible modeling that enables a closer fit. In this sense, too many clusters will cause over-fitting. General guidelines on the number of topics to be included in a model are well-documented by Taddy (2012).

Table 4: Words with highest loadings for predicting Republican-party affiliation

	Cluster Membership*		Multinomial Regression	
	term	loading	term	loading
1	ready.mixed.concrete	9.25	un.official	5.47
2	driver.education	7.34	people.middle.east	5.47
3	speaker.table	7.2	speaker.table	5.47
4	medic.liability.reform	6.85	term.care.insurance	5.47
5	near.retirement.age	6.42	weapon.grade.plutonium	5.46
6	weapon.grade.plutonium	6.23	national.homeownership.month	5.46
7	death.tax.repeal	5.98	nation.oil.food	5.45
8	commonly.prescribed.drug	5.72	united.nation.oil	5.45
9	national.ad.campaign	5.69	national.heritage.corridor	5.44
10	national.homeownership.month	5.37	feder.air.marshal	5.42

*Mixed model fit with 15 topics, each topic initialized with K-means on the word count matrix

The theory behind our mixed topic model regression predicts that the topics should be able to incorporate a specific theme important to a group of individuals, leaving behind the more general predictors of party-affiliation to the regression coeffecient. We can test this prediction by examining terms that are significant for a Multinomial Regression without topics, but decrease in importance once topic models are added. For a simple illustration, we choose the phrase "nation oil food", which predicts affiliation with the Republican party. The term is strongly associated with a topic we might call "domestic issues" topics, whose most likely words are displayed in Table 5.

Table 5: Top word loadings of the "domestic issues" topic (Congress data)

	term	loading
1	nation.oil.food	20.09
2	united.nation.oil	12.09
3	liberty.pursuit.happiness	8.11
4	life.liberty.pursuit	8.11
5	minority.women.owned	6.73
6	universal.health	6.67
7	white.care.act	6.64
8	ryan.white.care	6.6
9	universal.health.care	5.99
10	growth.job.creation	5.39
11	drilling.arctic.national	5.3
12	tax.relief.package	5.29
13	judge.john.robert	5.26
14	fre.enterprise	5.07
15	arctic.refuge	4.93

One cluster from a model fit with 20-clusters, each having been initialized with K-means on the residuals of metadata regression

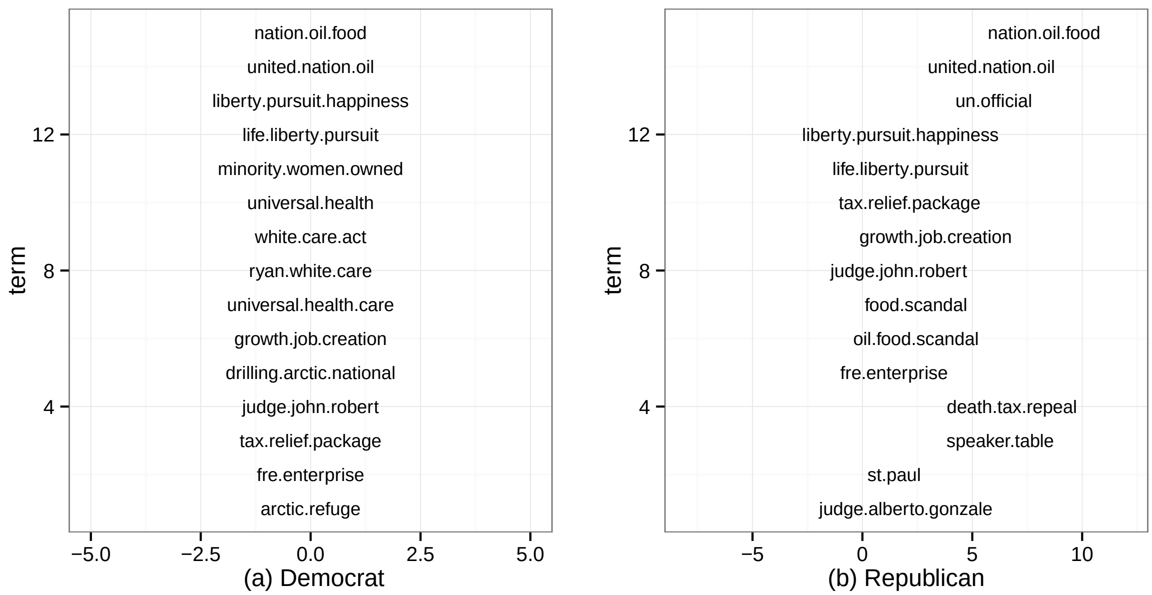
We also notice that the members of this cluster (by our simplification, each observation can only be a member of one topic) are 3 Republicans and 8 Democrats. The ability to group observations that may have different metadata (in this case, political party) is a benefit of our mixed regression-topic model approach. Under standard multinomial regression, observations cannot be grouped by topics.

Comparison to Blei's Inverse Regression Topic Model

As mentioned in Rabinovich and Blei (2014), the addition of latent topics to a model of text data with attributes is the ability to gain an intuitive concept to how metadata affects the distribution of a given topic. To demonstrate this effect, we use the graphical model presented in the Rabinovich and Blei paper to show the Democrat/GOP distortion to the 'domestic issues' topic shown mentioned previously.

The algorithm detected a cluster of words, commonly mentioned together, and the graph shows, on the left panel, this cluster as used by Democrats, in order from most used (top) to less used (bottom). On the right panel, the same cluster is distorted by the coefficient for Republican-party affiliation, where the value of the coefficient is displayed by the horizontal position of the word. Like the left panel, the vertical ordering of the words depicts the most used (top) to less used (bottom) words, and we see that the order has changed for some words that have a strong Republican connotation. For example, Republicans are much more likely to mention the noun phrases 'un official' or 'death tax repeal'.

Figure 2: Congress 109: Cluster word loadings with covariate distortion



A cluster from the Congressional data. On the left are, from highest (top) to lowest (bottom) , terms with the largest Democratic word loadings. On the right are the words with the highest Republican word loadings, also sorted. The horizontal position indicates the value of ϕ, or distortion on word distribution predicted by being a Republican.

Restaurant Reviews: We8there Data

We briefly illustrate the results of the cluster membership model on the we8there corpus of restaurant reviews with a table of word loadings for a selected cluster, as well as a distortion graph of that topic. As with the Congress data, we note that despite the simplicity of our model, we obtain meaningful clusters. Table 6 illustrates a cluster we might label as 'pizza diner'.

As with the Congressional data, we also show the effect of metadata regression on the topic weights. However, the analysis for the food reviews data is different from the congressional data: instead of a binary response for party affiliation, the covariate in the we8there data is the overall food review score, from 1 (low) to 5 (high). Phrases with high β coefficients are predictive of a higher review score.

Table 6: Top word loadings of the "pizza diner" topic (we8there data)

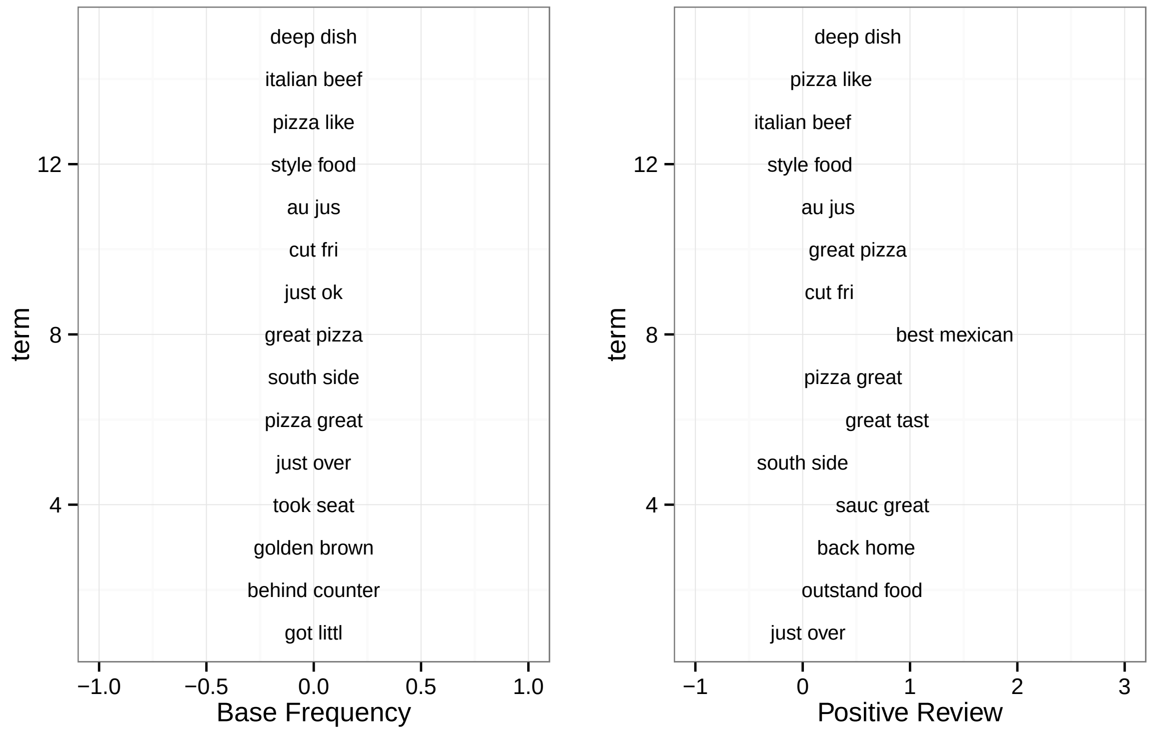
	term	loading
1	deep dish	7.76
2	italian beef	7.07
3	pizza like	6.85
4	style food	6.69
5	au jus	6.33
6	cut fri	6.16
7	just ok	6.01
8	great pizza	5.96
9	south side	5.94
10	pizza great	5.82
11	just over	5.75
12	took seat	5.72
13	golden brown	5.61
14	behind counter	5.58
15	got littl	5.52

One cluster from a model fit with 15 clusters , each having been initialized with K-means on the original text

A brief interpretation of the results is as follows: The algorithm grouped the documents into clusters, one of which is characterized by high usage of the words displayed on the left panel of Figure 3. This fitted cluster is not related to the restaurant rating. However, we can visualize what a highly positive review of the food in the cluster might look like by adding the rating coefficient, which we do on the right panel. The change in vertical ordering from the left panel to the right shows how the most common words we would expect to see changes when the review is positive, while the horizontal position shows the weight of each word's coefficient on a review being positive. Preprocessing of the data makes it less easy to reconstruct the exact phrases, but we can see that the phrases 'pizza great' (originally 'pizza is/was great'), 'great taste', and 'deep dish' are associated with positive reviews.

The presence of the term 'best mexican' in the 'pizza diner' cluster distorted by a positive review illustrates one fundamental drawback of our model. Because we do not model relationship between cluster word loadings and covariate distortion word loadings, combining the two will predict collections of terms that may never appear together in the actual data. The shortcoming is also mentioned in other work on text analysis and metadata (Rabinovich and Blei, 2014), and possible solutions will be mentioned in the next section.

Figure 3: we8there: Cluster word loadings with and without metadata distortion



A cluster from the we8there restaurant reviews dataset. On the left are, from highest (top) to lowest (bottom), terms with the largest word loadings in this given cluster. On the right are the word loadings of the cluster altered by a positive review. The horizontal position indicates the value of ϕ, or distortion on word distribution predicted by a positive review.

Extension

Feature Allocations

A promising extension of the cluster membership model is the generalized 'feature allocation' (Broderick 2013), where each observation can be attributed multiple features. This setup is an intermediary between our cluster membership model and a traditional topic model. The algorithm provided in this paper could be extended to incorporate a feature allocation, although the order of step 3 of the algorithm increases from linear $\mathcal{O}_{cluster} = n_k$ to $\mathcal{O}_{feature} = 2^{n_k}$, where n_k refers to the number of clusters/features in the model. This increase in complexity may be reduced through changes to the algorithm, and the model would still enjoy the ability to collapse observations across unique features.

Cross Validation and Prediction

One drawback of our model is that, in order to train cluster membership, the values of the metadata are required (see algorithm pseudocode in previous section). This hinders the ability to use the method for prediction (where, presumably, we hope to predict missing metadata from the text), and impeded our ability to perform cross validation. One possible solution would be to use k-nearest neighbors or other appropriate algorithm to assign each document of the test data to a cluster, after fitting a model with training data. However, this approach would be difficult to combine with the feature allocation extension proposed above, since the n observations would be separated into 2^{n_k} partitions, instead of n_k.

Modeling relationships between clusters and metadata

As noted in a previous section, one drawback of our model is the lack of relationship between clusters and metadata distortion vectors. Previous work on topic models allowed for correlation between topics (Blei & Lafferty 2006) and has successfully applied these models to complicated datasets (Blei & Lafferty 2007). Other authors have noted this problem (Rabinovich & Blei 2014), and possible solutions include allowing a range of metadata distortion vectors with varying relationships to each cluster or topic.

Conclusion

In this paper, we have reviewed the theory behind topic modeling and regression on metadata in text data. We introduce an algorithm that combines the metadata regression techniques developed by Taddy (2013a, 2013b) with a simple adaptation of the classic topic model. We then applied our algorithm to two large, sparse text datasets and report the results, noting that the simple cluster membership is able to identify similar topics found in more complex LDA models. We conclude by suggesting possible extensions of our approach to assist with generalizing and comparing the cluster membership model to alternative models for topic and metadata analysis.

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