

COMBINING LATENT TOPICS WITH DOCUMENT ATTRIBUTES IN TEXT ANALYSIS

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Outline

- 1 Text as Data
 - Multinomial Models
 - Metadata and Computation
 - Topic Models
- 2 Cluster Model
 - Algorithm
 - Cluster Initialization
- 3 Application
 - Congressional Speech Data

Text as Data

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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

Multinomial Models

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Table: 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

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A+	Some computation and formula proving, a lot of R code
B	Problems, computation using R
B	Some computations and writing R code
C+	Proofs, problems, and programming work

Metadata and Computation

- n documents with metadata that takes m discrete values:
- Normally, $n \gg m$
- \Rightarrow "Collapse" by outcome variables.
- Model as m observations, instead of n

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Reality: There are thousands of course reviews

Topic Models

In a topic model, documents are the realizations of mixtures of topics.

A topic is a distribution of words.

- A book about triathlon training $\sim \theta_1 \text{ Running} + \theta_2 \text{ Biking} + \theta_3 \text{ Swimming}$
- Problem: We can no longer collapse observations, must use all n observations

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Stroke, Air, Water

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Cluster Model

Goal

- Want to use the Topic Model but incorporate Metadata
- Also want computational ease

Approach

- Restrict each document to only one topic \Rightarrow "cluster"
- Can collapse observations over unique (metadata, cluster) combination

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

Algorithm for Cluster Membership Model with Gamma Lasso Penalty

- 1 Initialize u_i for $i = 1, \dots, n$
- 2 Determine parameters α, ϕ, Γ by fitting a multinomial regression on $y_i | x_i, u_i$ with a gamma lasso penalty (Taddy 2013)
- 3 For each document i , determine new cluster u_i membership as $\operatorname{argmax}_{k=1, \dots, K} [\ell(u_i | \alpha, \phi, \Gamma)]$
- 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.

How do we initialize the clusters?

We test three different approaches:

- Randomly assign each observation to a cluster
- Group documents by k-means, then assign clusters
- Regress metadata on text, then group residual's by k-means to clusters
- We'll look at the efficacy of each approach.

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Congressional Speech and Restaurant Reviews

- We apply the algorithm to two datasets:
 - Congressional Speech records, most famously used to investigate media slant (Moskowitz and Shapiro, 2010)
 - A corpus of restaurant reviews called we8there.
- Can this simple model capture the variation explained by a topic model?
- How does choice of cluster initialization affect the fit?

Comparison with the Topic Model

Good news: We are able to recover similar topics with our model:

Table: 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)

An Example Cluster

	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

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Incorporating metadata

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