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
   - Restaurant Review Data
4. Extensions

Text as Data

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Table: What did homework consist of?

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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

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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
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Metadata and Computation

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

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Reality: There are thousands of course reviews

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- Problem: We can no longer collapse observations, must use all n observations

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Approach

- Restrict each document to only one topic ⇒ "cluster"
- Can collapse observations over unique (metadata, cluster) combination
- $x_i \sim MN(q_{ij}, m_{ij}); \quad q_{ij} = \frac{exp(\alpha_j + y_i\phi_j + u_i\Gamma_{kj})}{\sum_{l=1}^{p} exp(\alpha_l + y_i\phi_l + u_i\Gamma_{kl})}$

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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.

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3. Regress metadata on text, then group residual's by k-means to clusters

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- We apply the algorithm to two datasets:
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  - A corpus of restaurant reviews called we8there.
- Questions:
  - Can this simple model capture the variation explained by a topic model?
  - How does choice of cluster initialization affect the fit?

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

Comparison with the Topic Model

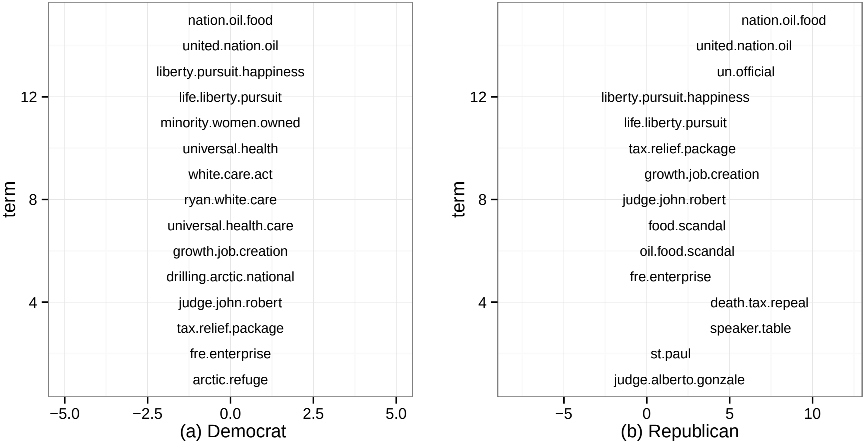
Good news: We are able to recover similar topics with our model:

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)

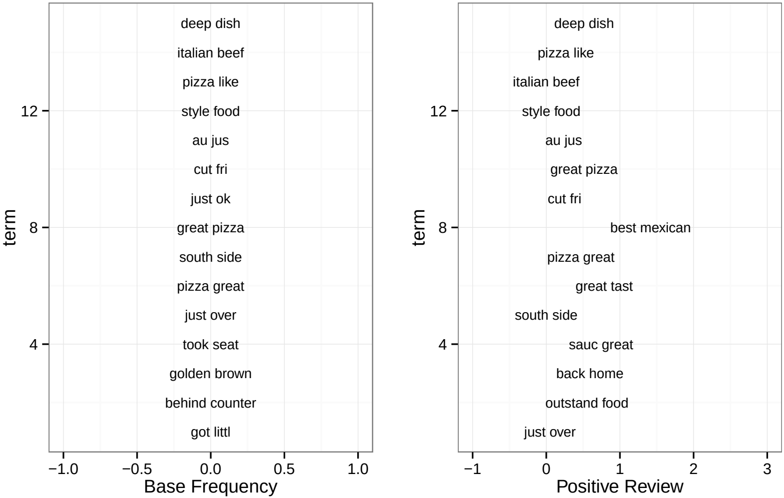
Incorporating metadata: Congressional Speech



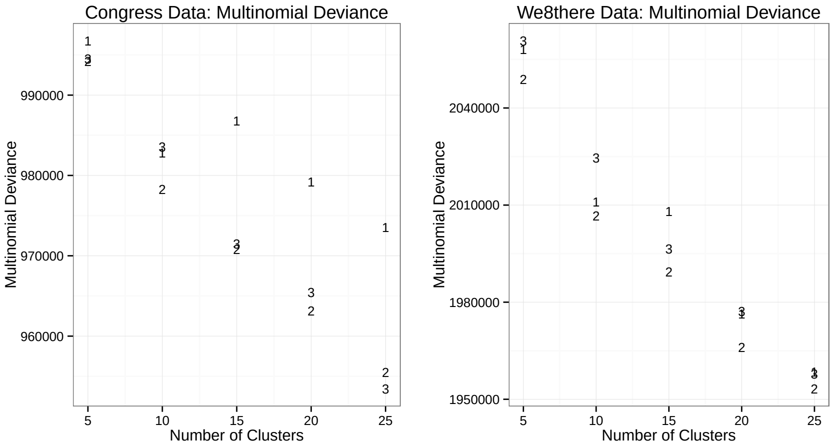
Example Topic from Restaurant Review

	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

Incorporating metadata: Restaurant Review



Evaluating Cluster Initialization



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3. Prediction and Cross Validation

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Results

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	term	loading
1	yeezus	0.36
2	challeng	0.3
3	dreamer	0.3
4	grass	0.3
5	loud	0.3
6	opportun	0.3
7	reduc	0.3
8	speak	0.3
9	frustrat	0.3
10	origin	0.3
11	perfect	0.29
12	rest	0.27
13	bound	0.23
14	seat	0.22

Thank You

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