

COMBINING LATENT TOPICS WITH DOCUMENT ATTRIBUTES IN TEXT ANALYSIS

Nelson Auner

Advisors: Prof. Matt Taddy & Prof. Stephen Stigler

University of Chicago

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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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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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Table: Creating a word-count matrix from text

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1	1	1	1	1	1	1	0	0	0	0	0
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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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B	Problems, computation using R
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C+	Proofs, problems, and programming work

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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 \Rightarrow "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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- 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

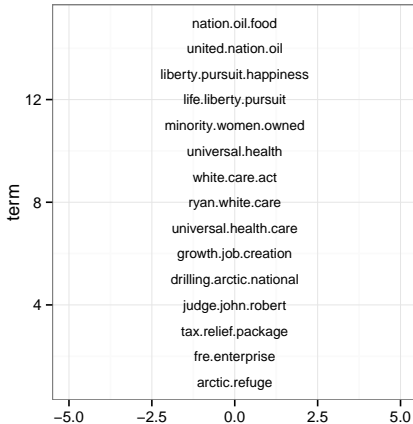
Good news: We are able to recover similar topics with our model:

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

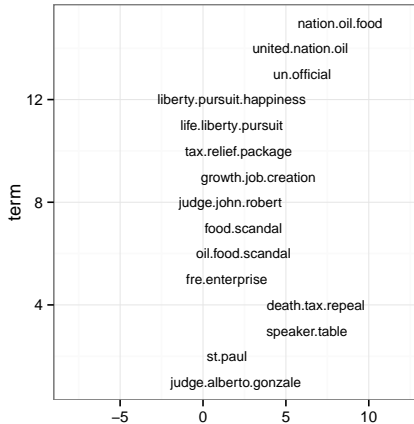
Cluster Membership	Topic Model (LDA)*
umbilic.cord.blood	pluripotent.stem.cel
cord.blood.stem	national.ad.campaign
blood.stem.cel	cel.stem.cel
adult.stem.cel	stem.cel.line

*Results reported in Taddy (2012)

Incorporating metadata: Congressional Speech



(a) Democrat

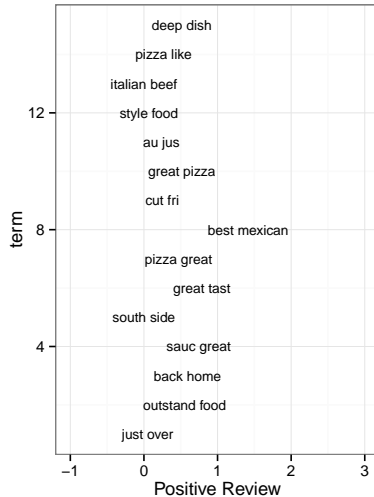
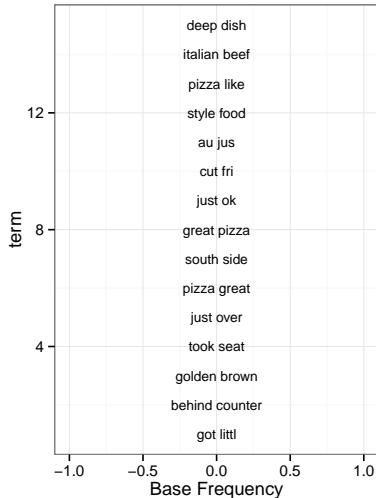


(b) Republican

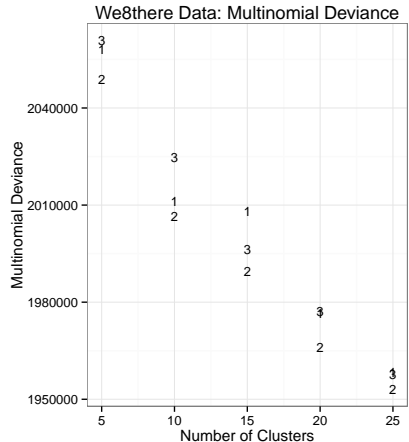
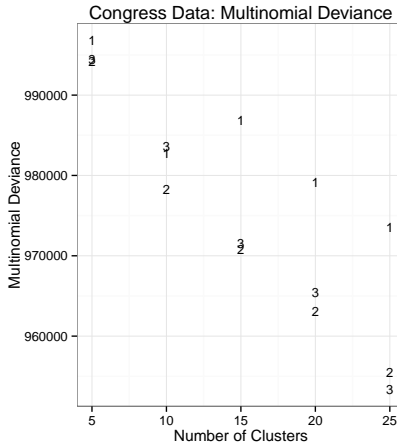
Example Topic from Restaurant Review

	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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- ② Feature Allocations: Allow an observation to be a member of multiple clusters

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- ③ Prediction and Cross Validation

Imma Let you Finish, but the Dirichlet was the greatest prior of all time!

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The screenshot shows the rapgenius.com website interface. At the top is the 'rapgenius' logo and a search bar. Below the logo are navigation links: 'ADD NEW SONG', 'FORUMS', 'VERIFIED ARTISTS', and 'RAP STATS'. The main content area is titled 'Kanye West – Stronger Lyrics'. Below the title, it says 'Produced By: Kanye West, Mike Dean & Timbaland' and 'Track 3 on Graduation'. There are statistics for the song: '216,684 views', '2 viewing', '31 annotations', and a 'Locked' status. Below these are social media sharing buttons for 'PYONG!' (23), 'Like' (150), and 'Tweet' (28), along with 'Embed' and 'Follow' buttons. A link 'How do I create annotations?' is also present. The lyrics are displayed below, starting with '[Produced by Kanye West, Mike Dean, and Timbaland]' and '[Hook]'. The visible lyrics are: 'N-now th-that that don't kill me', 'Can only make me stronger', 'I need you to hurry up now', 'Cause I can't wait much longer', 'I know I got to be right now', and 'Cause I can't get much wronger'.

rapgenius Search: rapper, song title, or lyrics

ADD NEW SONG FORUMS VERIFIED ARTISTS RAP STATS

Kanye West – Stronger Lyrics

Produced By: Kanye West, Mike Dean & Timbaland

Track 3 on Graduation

216,684 views 2 viewing 31 annotations Locked

PYONG! 23 Like 150 Tweet 28 Embed Follow

How do I create annotations?

[Produced by Kanye West, Mike Dean, and Timbaland]

[Hook]

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Can only make me stronger
I need you to hurry up now
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Results

Results

	term	loading
1	yeezus	5.48
2	constel	3.79
3	homm	3.79
4	preach	3.79
5	bound	3.6
6	thoma	3.38
7	thirti	3.32
8	rocka	3.31
9	rowland	3.25
10	jamaican	3.23
11	blocka	3.22
12	movement	3.22
13	unlik	3.08
14	vknow	3.08

Thank You

Thank You

