Combining latent topics with document attributes in text analysis

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Motivation

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Twitter Can Predict The Stock Market, If You're Reading The Right Tweets

In a world where one tweet can send Wall Street into a panic, social analytics company Dataminr tries to be there first, scanning all of Twitter to find individual messages with the right combination of language, context, and location that might end up being breaking–and money-making–news.

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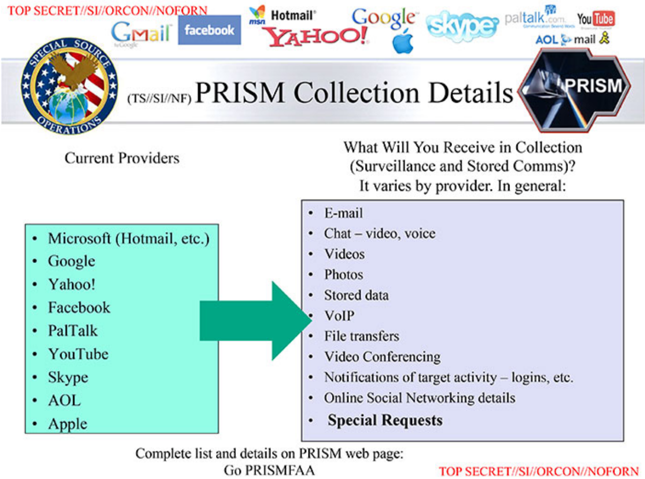
TOP SECRET//SI//ORCON//NOFORN
GMail
facebook
Hotmail
YAHOO!
Google
skype
paltalk.com
YouTube
AOL mail
SPECIAL SOURCE OPERATIONS
(TS//SI//NF) PRISM Collection Details
PRISM
Current Providers
Microsoft (Hotmail, etc.)
Google
Yahoo!
Facebook
PalTalk
YouTube
Skype
AOL
Apple
What Will You Receive in Collection
(Surveillance and Stored Comms)?
It varies by provider. In general:
E-mail
Chat – video, voice
Videos
Photos
Stored data
VoIP
File transfers
Video Conferencing
Notifications of target activity – logins, etc.
Online Social Networking details
Special Requests
Complete list and details on PRISM web page:
Go PRISMFAA
TOP SECRET//SI//ORCON//NOFORN

Outline

1. Text as Data
   - Multinomial Models
   - Metadata and Computation
   - Topic Models
2. Cluster Model
   - Algorithm
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

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

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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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- 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

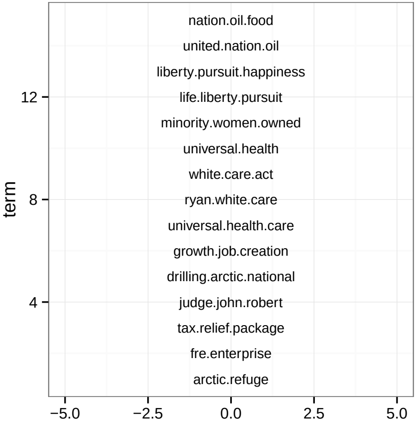
Good news: We are able to recover similar topics with our model:

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

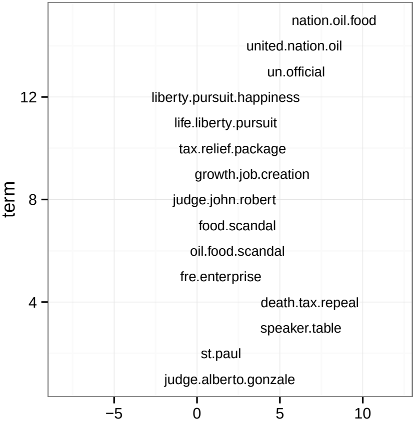
Cluster Membership	Topic Model (LDA)*
umbilic.cord.blood	pluripotent.stem.cel
cord.blood.stem	national.ad.campaign
blood.stem.cel	cel.stem.cel
adult.stem.cel	stem.cel.line

*Results reported in Taddy (2012)

Incorporating metadata: Congressional Speech



(a) Democrat

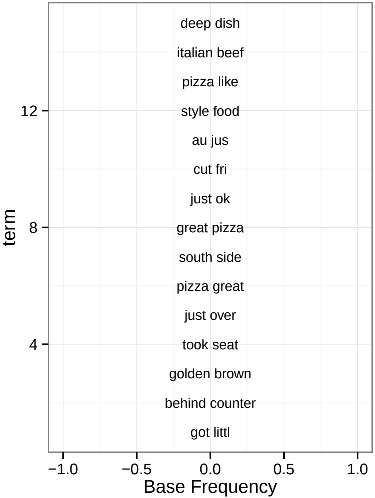


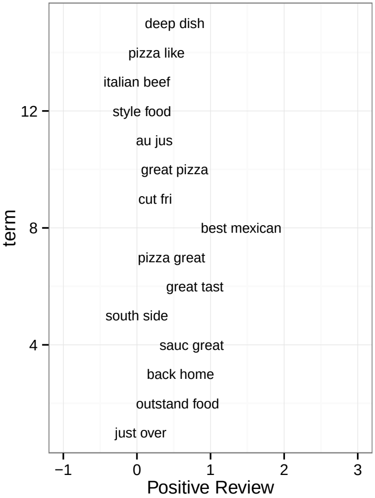
(b) Republican

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





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3. Prediction and Cross Validation

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Results

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	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	yknow	3.08

Thank You

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