Modeling Social Annotation Data with Content Relevance using a Topic Model

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Introduction

- Context: social annotations, aka collaborative tagging or folksonomy
- Users freely annotate objects such as webpages, photos, blog posts, videos, music and scientific papers
- Examples: Delicious, Flickr, Technorati, YouTube, Last.fm, CiteULike

Introduction

- Problem: users often write *noisy*, or content-irrelevant annotations (e.g. "great", "to read")
- This paper proposes a generative model for topics and annotations that takes into account relevance/irrelevance of the annotations
- It is an extension of Blei and Jordan's Correspondence Latent Dirichlet Allocation (Corr-LDA), which assumes the annotations are always relevant

Proposed Method

• We have a set of *D* documents, and each consists of a pair of words and annotations $(\mathbf{w}_d, \mathbf{t}_d)$, where $\mathbf{w}_d = \{w_{dn}\}_{n=1}^{N_d}$ and $\mathbf{t}_d = \{t_{dm}\}_{m=1}^{M_d}$

	Table 1: Notation
Symbol	Description
D	number of documents
W	number of unique words
$T \\ K$	number of unique annotations
K	number of topics
N_{d}	number of words in the dth document
M_d	number of annotations in the <i>d</i> th document
Wdn	<i>n</i> th word in the <i>d</i> th document, $w_{dn} \in \{1, \cdots, W\}$
Zdn	topic of the <i>n</i> th word in the <i>d</i> th document, $z_{dn} \in \{1, \dots, K\}$
t_{dm}	with annotation in the <i>d</i> th document, $t_{dm} \in \{1, \dots, T\}$
Cam	topic of the <i>a</i> th annotation in the <i>d</i> th document, $c_{dm} \in \{1, \dots, K\}$
1'day	relevance to the content of the mth annotation of the dth document,
	$r_{dm} = 1$ if relevant, $r_{dm} = 0$ otherwise

Note: all tables and figures taken from the original paper

Proposed Method

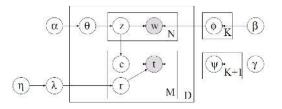


Figure 1: Graphical model representation of the proposed topic model with content relevance

• There are K + 1 annotation distributions (Ψ), since Ψ_0 is a topic-unrelated distribution that applies to irrelevant annotations

Proposed Method: Generative Model

- 1. Draw relevance probability $\lambda \sim \text{Beta}(\eta)$
- 2. Draw content-unrelated annotation probability $\psi_0 \sim \text{Dirichlet}(\gamma)$
- 3. For each topic $k = 1, \dots, K$:
 - (a) Draw word probability $\phi_k \sim \text{Dirichlet}(\beta)$
 - (b) Draw annotation probability $\psi_k \sim \text{Dirichlet}(\gamma)$
- 4. For each document $d = 1, \dots, D$:
 - (a) Draw topic proportions $\theta_d \sim \text{Dirichlet}(\alpha)$
 - (b) For each word $n = 1, \dots, N_d$:
 - i. Draw topic $z_{dn} \sim \text{Multinomial}(\boldsymbol{\theta}_d)$
 - ii. Draw word $w_{dn} \sim \text{Multinomial}(\phi_{z_{dn}})$
 - (c) For each annotation $m = 1, \dots, M_d$:
 - i. Draw topic $c_{dm} \sim \text{Multinomial}(\{\frac{N_{kd}}{N_{j}}\}_{k=1}^{K})$
 - ii. Draw relevance $r_{dm} \sim \text{Bernoulli}(\lambda)$
 - iii. Draw annotation $t_{dm} \sim \begin{cases} \text{Multinomial}(\psi_0) & \text{if } r_{dm} = 0 \\ \text{Multinomial}(\psi_{c_{dm}}) & \text{otherwise} \end{cases}$

Proposed Method: Inference

- The joint distribution is $P(\mathbf{W}, \mathbf{T}, \mathbf{Z}, \mathbf{C}, \mathbf{R} | \alpha, \beta, \gamma, \eta) = P(\mathbf{Z} | \alpha) P(\mathbf{W} | \mathbf{Z}, \beta) P(\mathbf{T} | \mathbf{C}, \mathbf{R}, \gamma) P(\mathbf{R} | \eta) P(\mathbf{C} | \mathbf{Z})$
- In the expression above, we have: $\mathbf{W} = \{\mathbf{w}_d\}_{d=1}^D, \mathbf{T} = \{\mathbf{t}_d\}_{d=1}^D, \mathbf{Z} = \{\mathbf{z}_d\}_{d=1}^D, \mathbf{C} = \{\mathbf{c}_d\}_{d=1}^D, \mathbf{c}_d = \{c_{dm}\}_{m=1}^{M_d}, \mathbf{R} = \{\mathbf{r}_d\}_{d=1}^D, \mathbf{r}_d = \{r_{dm}\}_{m=1}^{M_d}$

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• $\boldsymbol{\theta}$, $\boldsymbol{\Phi}$, $\boldsymbol{\Psi}$ and λ are marginalized out

Proposed Method: Inference

•
$$P(\mathbf{Z}|\alpha) = \prod_{d=1}^{D} \int P(\mathbf{Z}|\theta_d) P(\theta_d|\alpha) d\theta_d = \left(\frac{\Gamma(\alpha K)}{\Gamma(\alpha)^K}\right)^D \prod_d \frac{\prod_k \Gamma(N_{kd}+\alpha)}{\Gamma(N_{kd}+\alpha K)}$$

• $P(\mathbf{W}|\mathbf{Z},\beta) = \left(\frac{\Gamma(\beta W)}{\Gamma(\beta)^W}\right)^K \prod_k \frac{\prod_w \Gamma(N_{kw}+\beta)}{\Gamma(N_{kw}+\beta W)}$
• $P(\mathbf{T}|\mathbf{C},\mathbf{R},\gamma) = \left(\frac{\Gamma(\gamma T)}{\Gamma(\gamma)^T}\right)^{K+1} \prod_{k'} \frac{\prod_t \Gamma(N_{k't}+\gamma)}{\Gamma(N_{k't}+\gamma T)}$, where $k' \in \{0,\ldots,K\}$
• $P(\mathbf{R}|\eta) = \frac{\Gamma(2\eta)}{\Gamma(\eta)^2} \frac{\Gamma(M_0+\eta)\Gamma(M-M_0+\eta)}{\Gamma(M+2\eta)}$
• $P(\mathbf{C}|\mathbf{Z}) = \prod_d \prod_k \left(\frac{N_{kd}}{N_d}\right)^{M'_{kd}}$

Inference of the latent Z|W, T is done using collapsed Gibbs sampling

• The hyperparameters are estimated by maximizing the joint distribution, using a fixed-point iteration method

Proposed Method: Inference

• We have the following expressions, where j = (d, n), i = (d, m) and $\setminus j$ denotes the count excluding the *n*-th word in the *d*-th document

$$\begin{split} P(z_{j} = k | \boldsymbol{W}, \boldsymbol{T}, \boldsymbol{Z}_{\backslash j}, \boldsymbol{C}, \boldsymbol{R}) &\propto \frac{N_{kd \backslash j} + \alpha}{N_{d \backslash j} + \alpha K} \frac{N_{kw_{j} \backslash j} + \beta}{N_{k \backslash j} + \beta W} \left(\frac{N_{kd \backslash j} + 1}{N_{kd \backslash j}} \frac{N_{d} - 1}{N_{d}} \right)^{M_{kd}} \\ P(r_{i} = 0 | \boldsymbol{W}, \boldsymbol{T}, \boldsymbol{Z}, \boldsymbol{C}, \boldsymbol{R}_{\backslash i}) &\propto \frac{M_{0 \backslash i} + \eta}{M_{\backslash i} + 2\eta} \frac{M_{0\iota_{i} \backslash i} + \gamma}{M_{0 \backslash i} + \gamma T}, \\ P(r_{i} = 1 | \boldsymbol{W}, \boldsymbol{T}, \boldsymbol{Z}, \boldsymbol{C}, \boldsymbol{R}_{\backslash i}) &\propto \frac{M_{\backslash i} - M_{0 \backslash i} + \eta}{M_{\backslash i} + 2\eta} \frac{M_{c_{i}\iota_{i} \backslash i} + \gamma}{M_{c_{i} \backslash i} + \gamma T}, \\ P(c_{i} = k | r_{i} = 0, \boldsymbol{W}, \boldsymbol{T}, \boldsymbol{Z}, \boldsymbol{C}_{\backslash i}, \boldsymbol{R}_{\backslash i}) &\propto \frac{N_{kd}}{N_{d}}, \\ P(c_{i} = k | r_{i} = 1, \boldsymbol{W}, \boldsymbol{T}, \boldsymbol{Z}, \boldsymbol{C}_{\backslash i}, \boldsymbol{R}_{\backslash i}) &\propto \frac{M_{kt_{i} \backslash i} + \gamma}{M_{k \backslash i} + \gamma T} \frac{N_{kd}}{N_{d}}. \end{split}$$

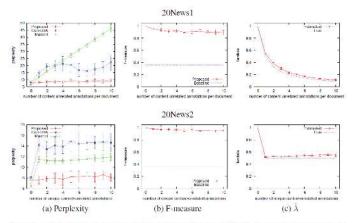


Figure 2: (a) Perplexities of the held-out content-related annotations, (b) F-measures of content relevance, and (c) Estimated content-related annotation ratios in 20News data.

Figure 2 (c) shows the content-related annotation ratios as estimated by the following equation, $\hat{\lambda} = \frac{M-M_0+n}{M+2\eta}$, with the proposed method. The estimated ratios are about the same as the true ratios.

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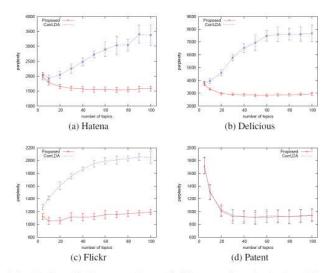


Figure 3: Perplexities of held-out annotations with different numbers of topics in social annotation data (a)(b)(c), and in data without content unrelated annotations (d).

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Table 2: The ten most probable content-unrelated annotations (leftmost column), and the ten most probable annotations for some topics (other columns), estimated with the proposed method using 50 topics. Each column represents one topic. The lower half in (a) and (b) shows probable words in the content.

unrelated	Topic1	Topic2	Topic3	Topic4	Topic5	Topic6	Topic7	Topic8	Topic9
toread web later great document troll # ? summary memo	programming development dev webdev php java software ruby opensource softwaredev	game animation movie Nintendo movie event xbox360 DS PS3 animation	economics finance society business economy reading investment japan money company	science research biology study psychology mathematics pseudoscience knowledge education math	food cooking gournet recipe cook life fooditem foods alcohol foodie	linux tips windows security server network unix mysql mail Apache	politics international oversea society history china world international usa news	pc apple iphone hardware gadget mac cupidity technology ipod electronics	medical health lie government agriculture food mentalhealth mental environment science
	development web series hp technology management source usage project system	game animation movie story work create PG mr interesting world	year article finance economics investment company day management information nikkei	science researcher answer spirit question human ehara proof mind brain	eat use omission water decision broil face input miss food	in setting file server case mail address connection access security	japan country usa china politics aso mr korea human people	yen product digital pc support in note price equipment model	rice banana medical diet hospital poison eat incident korea jelly

(a) Hatena

				(b) Defic	ious				
reference	money	video	opensource	food	windows	art	shopping	iphone	education
web	finance	music	software	recipes	linux	photo	shop	mobile	learning
imported	economics	videos	programming	recipe	sysadmin	photography	Shopping	hardware	books
design	business	fun	development	cooking	Windows	photos	home	games	book
internet	economy	entertainment	linux	Food	security	Photography	wishlist	iPhone	language
online	Finance	funny	tools	Recipes	computer	Art	buy	apple	library
cool	financial	movies	rails	baking	microsoft	inspiration	store	tech	school
toread	investing	media	ruby	health	network	music	fashion	gaming	teaching
tools	bailout	Video	webdev	vegetarian	Linux	foto	gifts	mac	Education
blog	finances	film	rubyonrails	div	ubuntu	fotografia	house	game	research
	money	music	project	recipe	windows	art	buy	iphone	book
	financial	video	code	food	system	photography	online	apple	legal
	credit	link	server	recipes	microsoft	photos	price	ipod	theory
	market	tv	ruby	make	linux	camera	cheap	mobile	books
	economic	movie	rails	wine	software	vol	product	game	law
	october	itunes	source	made	file	digital	order	games	university
	economy	film	file	add	server	images	free	pc	students
	banks	amazon	version	love	user	2008	products	phone	learning
	government	play	files	eat	files	photo	rating	mac	educatior
	bank	interview	development	good	ubuntu	tracks	card	touch	language

(b) Delicious

(c) Flickr

2008	dance	sea	autumn	rock	beach	family	island
nikon	bar	sunset	trees	house	travel	portrait	asia
canon	de	sky	tree	party	vacation	cute	landscape
white	digital	clouds	mountain	park	camping	baby	rock
yellow	concert	mountains	fall	inn	landscape	boy	blue
red	bands	ocean	garden	coach	texas	kids	tour
photo	music	panorama	bortescristian	creature	lake	brown	plant
italy	washingtondc	south	geotagged	halloween	cameraphone	closeup	tourguidesoma
california	dancing	ireland	mud	mallory	md	08	koh
color	work	oregon	natura	night	sun	galveston	samui

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