Improving Text Analysis Using Sentence Conjunctions and Punctuation

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# Challenges in understanding consumers

- Ambiguous language
- Ratings scales
  - Yeah and nay-saying
  - Haloing
  - Pre-define statements
- Choice-based analysis
  - Conjoint: incentive alignment
  - Revealed demand: short purchase histories

# Customer review data

- Unstructured
- Use of dummy-variable regression
  - Valence
  - Appearance of words
  - Applied to intent, experience, conversion, attributes, sales
- Difficulty with high-level interactions
  - 1,000 unique terms are usual
  - Variable selection

# Topic modeling

- Topics are comprised of word vocabularies (words and probabilities).
- A review or articles is associated with many potential topics.
- Words are thought to appear after choosing a topic, and then a word from the topic vocabulary.
- Word and topic probabilities are estimated from the observed word counts across documents.
- Topics can be related to other data, such as customer ratings on a fixed-point scale.

# Büschken and Allenby (2016)

- Sentence-based analysis
- Predict customer ratings of products

"The hotel was really nice and clean. It was also very quiet. There was a thermostat in each room so you can control the coolness. The bathroom was larger than most hotels. The breakfast was sausage and scrambled eggs, or waffles you make yourself on a waffle iron. All types of juice, coffee, and cereal available. The breakfast was hot and very good at no extra charge. The only problem was the parking for the car. The parking garage is over a block away. It is \$15.00 per day. You don't want to take the car out much because you can't find a place to park in the city, unless it is in a parking garage. The best form of travel is walking, bus, tour bus, or taxi for the traveler. The hotel is near most of the historic things you want to see anyway. I would return to this hotel and would recommend it highly."

# LDA model

The  $n^{th}$  word appearing in review d,  $w_{dn}$ , is thought to be generated by the following process in the LDA model:

1. Choose a topic  $z_{dn} \sim \text{Multinomial}(\theta_d)$ .

2. Choose a word  $w_{dn} \sim \text{ from } p(w_{dn}|z_{dn}, \Phi)$ .

 $p(\theta_d) \sim \text{Dirichlet}(\alpha)$ 

 $p(\phi_t) \sim \text{Dirichlet}(\beta)$ 

# Ratings sub-model

Cut-point model for ratings:

$$r_d = k$$
 if  $c_{k-1} \le \tau_d \le c_k$ 

Latent regression on topic probabilities:

$$\tau_d \sim N(\theta_d'\beta, \sigma)$$

Topic probabilities for each review

# Latent regression results

Table 6: Pseudo  $R^2$  from Rating-based Topic Models

Model	Midscale Hotel	Upscale Hotel	Italian Restaurant
LDA-Rating SC-LDA-Rating	$egin{array}{c} 0.375 \ (0.05) \ 0.531 \ (0.08) \end{array}$	$\begin{array}{c} 0.559 \ (0.04) \\ 0.601 \ (0.09) \end{array}$	$\begin{array}{c} 0.628 \ (0.04) \\ 0.692 \ (0.08) \end{array}$

# What about conjunctions and other punctuation?

- Introduce an autocorrelated topic model where topic carryover is more generally driven by conjunctions (and, but, because) and punctuation (periods, exclamation marks, commas).
- These syntactic elements are routinely stripped out of text analysis because they are content-neutral.
- Our model assumes that a reviewer stays with a topic for some time before switching to another. The probability of topic change is a function of these elements of speech.

# Illustration

but

Bedroom was fine, staff were helpful. Hotel frontage very unimpressive and street slightly dingy but in general hotel offered good value for the money.

- 1) bedroom fine staff helpful hotel frontage unimpressive street slightly dingy general hotel offered good value money.
- bedroom fine staff helpful hotel frontage unimpressive street slightly
  and
  dingy general hotel offered good value money.

for

Original review

Arrows indicate covariates for topic carryover

# Autocorrelated Topic LDA (AT-LDA)

$$\zeta_n = 1 : z_n = z_{n-1}$$
  
 $\zeta_n = 0 : z_n \sim \text{Multinomial}(\theta_d)$ 

Either stay with the topic or not

$$\zeta_n \sim \text{Binomial}(\psi_n | z_{n-1})$$
$$\psi_n | z_{n-1} = \frac{\exp[\delta_{0, z_{n-1}} + \tilde{x}'_n \delta]}{1 + \exp[\delta_{0, z_{n-1}} + \tilde{x}'_n \delta]}$$

Pr(stay) = f(topic constant, speech)

# Topic changepoint model (TCPM)

1. draw  $\{\theta_d\}$ :  $\theta_d \sim Dirichlet(\alpha)$ , IID  $\forall d$ 

2. draw  $\{\phi_t\}$ :  $\phi_t \sim Dirichlet(\beta)$ , IID  $\forall t$ 

3. draw { $\lambda_t$ }:  $\lambda_t \sim Gamma(\delta)$ , IID  $\forall t$ 

# Topics runs from a Poisson distribution

- 4. For r = 1, i.e. the first topic run in d = 1 (and omitting subscript d in the following for clarity):
  - (a) draw topic  $z_{r=1}$ , the topic assignment of the first run r = 1:

 $z_{r=1} \sim Multinomial(\theta_d)$ 

- (b) draw  $l_{r=1}$ , the run length (i.e. number of words) of r = 1:
  - $l_1 \sim Poisson(\lambda_{z_1}).$

The Poisson distribution generating  $l_1$  has lower bound 1 and upper bound  $N_d$ .

This is simply because the length of the first topic run cannot exceed  $N_d$ .

(c) draw  $l_1$  words from  $Multinomial(\phi_{t=z_1})$  IID. If  $l_1 = N_d$ , stop.

	Restaurants	Camping Tents	Luxury Hotels	Dog Food
Number of reviews	$2,\!351$	7,973	$3,\!481$	6,018
Corpus size	171,385	364,761	79,377	94,165
<b>•</b>	· · ·	,	· · ·	,
Number of unique terms	$1,\!531$	$3,\!664$	1,060	$1,\!980$
Number of words per review				
Mean	72.9	45.7	24.7	15.7
SD	83.5	58.1	19.8	22.7
Max	606	792	205	536
Number of sentences per review				
Mean	13.4	6.2	4.9	3.0
SD	14.1	6.8	3.0	3.1
Consumer rating (5pt scale)				
Mean	3.75	4.19	4.42	4.38
SD	1.41	1.23	0.88	1.21

#### Table 1: Descriptive statistics of data sets (after pre-processing).

Table 2: Incidents of conjunctions and punctuation in the data sets. Conjunctions appearing less 200 times (e.g. provided, until), are omitted to reduce clutter. Total occurences include ommitted covariates.

	Restaurants	Camping Tents	Luxury Hotels	Dog Food
Conjunctions				
for	4,439	9,274	1,796	2,929
and	$13,\!683$	$21,\!683$	5,912	6,929
$\operatorname{but}$	$3,\!258$	5,374	1,083	$1,\!629$
or	933	1,868	278	529
SO	1,878	3,819	550	1,321
after	737	1,090	165	445
as	1,725	3,292	550	1,114
because	512	1,138	148	482
before	472	737	102	208
even	620	$1,\!155$	199	299
if	1,260	2,509	430	484
now	264	696	23	425
once	226	652	41	101
since	341	441	60	385
$\operatorname{than}$	615	1,244	212	453
that	3,867	6,042	904	1,772
$\operatorname{though}$	217	483	71	93
when	1,303	1,912	370	515
where	326	541	114	68
which	1,091	983	310	331
while	407	586	83	134
who	384	308	83	223
what	909	732	155	372
Punctuation				
,	15,316	20,660	5,762	$6,\!130$
	$27,\!674$	38,463	12,710	10.794
;	855	$1,\!175$	318	249
;	1,774	3,201	0	$1,\!123$
?	309	317	48	100
&	330	335	2	210
(	1,168	2,391	532	716
)	1,151	2,445	538	718
Total occurrences	88,651	136,756	33,853	41,606
Number of documents	2,351	7,927	3,215	6,018
Covariates per document	37.7	17.3	10.5	6.9
Covariates per word	0.52	0.37	0.43	0.44

#### Fit results

Topic Carry-over AT-LDA w/o covariates Bay of Words Nodel (Jateony Topic (Jumin AT-LDA w covariates -916,784 (10) - 1,731,181 (16) - 347,884 (10) Study (PP( 1)) Stidy VIII Mode -1,004,005 (6) -1,022,057 (8) -1,052,217 (8) -1,052,217 (8) -1,052,217 (8) -900,380 (10) 1,001,007 (6) -963,344 (10) Restaurant Deview ) -1,310,546 (15) -411,002 (11) -301,274 (8) -1,743,012 (16 -1,949,083 (14) -2,002,006 (14) 2,151,200 (14) -2,104,102 (14) -2,006,406 (14) Camping Tent Nerrens 341,457 (10) JUXUIY HOLE 369,832 (10) -10,000 (10) -10,000 (10) -10,000 (10) -409,896 (10) Reinell -449,457 -459,477 -400,477 -40 Dog Flood Nerrens

# Predictive fit results

Topic Carry-over	Topic Chunking	Bag of Words	Model Category
Topic Carry-over AT-LDA w/o covariates AT-LDA w covariates	SC LDA Sticky SC LDA OPC LDA Sticky OPC LDA TOPM		Model
-221,600 -220,661	-221,709 -221,640 -221,594 -221,671	-221,900	Restaurant
-478,753 -475,974	478,655 478,655 478,663	-481,607	Restaurant Camping Tent Luxury Hotel Dog Food Reviews Reviews Reviews Reviews
-92,976 -92,785	-92,962 -92,962	-93,614	Luxury Hotel Reviews
-129,307 -129,307	-129,550 -129,265 -129,247	-129,378	Dog Food Reviews

# Topic chunking

Model	Parameter	Restaurants	Camping Tents	Luxury Hotels	Dog Food
AT-LDA TCPM	$\psi \ \lambda$	$0.42 \ (0.19; \ 0.66) \\ 4.2 \ (2.5; \ 9.0)$	$\begin{array}{c} 0.47 \; (0.29; \; 0.65) \ 4.9 \; (2.5; \; 9.6) \end{array}$	$\begin{array}{c} 0.48 \ (0.36; \ 0.59) \ 3.7 \ (2.0; \ 6.9) \end{array}$	$egin{array}{l} 0.40 & (0.11; \ 0.56) \ 2.9 & (2.3; \ 4.1) \end{array}$

# Change in topic change probability

Structural covariate		,	?	!	)	"Because"	"But"	"And"	"once"
Present Absent	$0.509 \\ 0.043$		$\begin{array}{c} 0.460 \\ 0.211 \end{array}$		$0.462 \\ 0.063$		$0.465 \\ 0.009$	$0.464 \\ 0.391$	$0.460 \\ 0.140$

#### Topic uniqueness – term overlap frequency



# Topic coherence – KL divergence









#### Topic response latency - word cloud stimuli



naximum of 12 words), which summarizes the cloud.

I III AIA

# Topic response latency - results



# Distribution of topic probabilities



# Example customer reviews

[1] "unprofessional. I was charged on both of my credit cards by the 11 am manager and yet she said my cards did not go through. my bank card companies showed transactions approved on their system. the manager did not take the time to cancel the transaction and try again. my experience was very unpleasant. the cashier did not know what was wrong with the transaction so she asked the manager for help. the manager is apparently very unqualified being that she did not know how to handle the transaction. she just kept sliding the cards over and over. there are many places to eat in Roswell and with poor customer service like this I will not return to this place. I was charged \$17 and cents on my cards and was told that my cards had a problem. I did ask for a customer service card and that too was refused. I wonder why?"

[2] "the food at this place is okay, but I found the service to be terrible. the managers are impossible to contact for complaints, and their associates actually tried to bully me! I was called names and hung up on several times when I tried to call the manager. they told me I was 'simple' and 'low' and 'stupid'. nobody has ever said such things about me. it ruined my meal, and my day. I don't care if their food is even excellent (which it's not). I will never eat there again. as of today, I still cannot get hold of the manager to voice my complaints, after leaving multiple messages. I never expected this experience with a pizza place. don't eat there if you don't want insults with your pizza!"

[2] "These are my observations in camping in this tent for a week. PROS: The tent did set up very easily and was very roomy with enough room for two queen size air mattresses and gear. We liked the number of windows and the size, it let you get a good breeze through the tent. CONS: This tent is heavy and quite bulky,as you would expect with any instant tent but I found it very cumbersome. I also found the door design a tad bit awkward and kept tripping over the bottom zipper when getting in and out, also with no rain fly when you open the door to get in and out in rain all of the water pours in the tent. That leads me to the biggest issue that I had with the tent, it LEAKED... and definitely not just condensation, humidity or moisture in the tent. I have had plenty of other tents and I know what normal condensation and humidity is and this was definitely rain leaking through at the roof seams. This left us in a damp tent for the better part of a week and made it quite uncomfortable and miserable. Ultimately the cons outweighed the pros for me and I will be searching for a different tent for our next trip."

[3] "Spacious tent, good ventilation. It is NOT WATER prof, had it in the rain, if you touch the inside of the tent with a finger, there will be a drip in that spot. The one would expect waterproof fabric for the money spent. However, if you don't touch it form the inside, it will not drip, so it can be managed. The big pro is that it is EASY to set up. It sets up in seconds."

Restaurant Topic 3

Camping Tent Topic 1

# Restaurant topics

Rank	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6	Topic 7	Topic 8	Topic 9	Topic 10
1	really	pizza	food	menu	cheese	food	us	bar	go	$\operatorname{night}$
2	good	best	service	salad	sauce	great	came	room	will	times
3	$\overline{\mathrm{got}}$	italian	restaurant	ordered	$\operatorname{chicken}$	service	waitress	dining	back	dinner
4	just	new	one	wine	fries	good	table	restaurant	$\operatorname{can}$	$\operatorname{time}$
5	like	chicago	just	good	$\operatorname{sandwich}$	place	minutes	tables	place	years
6	little	style	said	also	meat	atmosphere	order	area	time	lunch
7	pretty	place	bad	pasta	flavor	$\operatorname{staff}$	$\operatorname{took}$	back	$\operatorname{get}$	day
8	one	restaurant	like	$\operatorname{dessert}$	bacon	friendly	back	street	$\operatorname{try}$	$\operatorname{rib}$
9	burger	barbecue	never	$\mathbf{best}$	barbecue	restaurant	$\operatorname{get}$	$\operatorname{right}$	eat	many
10	ordered	$\operatorname{crust}$	manager	dinner	bread	experience	asked	parking	$\operatorname{make}$	last
11	much	home	ordered	large	fresh	$\mathbf{excellent}$	drinks	building	one	breakfast
12	sandwich	ever	experience	salads	$\operatorname{pork}$	nice	$\operatorname{got}$	$\operatorname{lot}$	going	year
13	menu	pizzas	husband	dishes	came	always	food	near	never	restaurant
14	went	great	will	$\operatorname{chicken}$	burger	recommend	$\operatorname{time}$	$\operatorname{small}$	say	went
15	fries	york	good	delicious	served	prices	brought	table	like	2
16	also	cheese	$\operatorname{told}$	$\operatorname{fresh}$	salad	wait	$\operatorname{drink}$	front	sure	several
17	$\operatorname{meal}$	places	owner	one	$\operatorname{hot}$	wonderful	bill	inside	definitely	people
18	said	one	however	items	sweet	well	take	around	know	party
19	$\operatorname{still}$	$\operatorname{good}$	$\operatorname{steak}$	$\operatorname{dish}$	taste	pleasant	wait	side	want	$\operatorname{sunday}$
20	lot	family	nothing	house	onion	reasonable	seated	located	$\operatorname{visit}$	week

# Ratings sub-model

Cut-point model for ratings:

$$r_d = k$$
 if  $c_{k-1} \le \tau_d \le c_k$ 

Latent regression on topic probabilities:

$$\tau_d \sim N(\theta'_d \beta, \sigma)$$

Topic probabilities for each review

# Predicting ratings

Model category	Model	Restaurants	Camping Tents	Luxury Hotels	Dog Food
Bag-of-words	LDA	0.631	0.603	0.441	0.626
Topic chunking	SC-LDA CPC-LDA TCPM	$0.652 \\ 0.628 \\ 0.720$	$0.683 \\ 0.694 \\ 0.674$	<b>0.656</b> 0.559 0.626	<b>0.782</b> 0.750 0.743
Carry over	AT-LDA	0.794	0.714	0.658	0.736

# Restaurant regression

Parameter	Topic	Posterior Mean	CL
Covariates			
$eta_0$	Intercept	0.249	0.662
$\beta_1$	Really good sandwich	-1.133	0.924
$\beta_2$	This is the best pizza place	0.922	0.894
$eta_3$	People wanted to talk to manager or owner	-7.911	1.000
$eta_4$	Things ordered	1.013	0.875
$eta_5$	Various items on menu	0.424	0.707
$eta_6$	Food and service very good	5.600	1.000
$\beta_7$	Frustration with waitress	-3.425	1.000
$\beta_8$	Layout of restaurant	$0^*$	—
$eta_9$	Will not go back	-1.570	0.966
$\beta_{10}$	First dinner at this restaurant	-0.612	0.753
Cut-points			
$c_1$		-1.643*	—
$c_2$		-1.163	1.000
$c_3$		-0.578	0.998
$c_4$		$0.128^{*}$	—
$R^2$		0.794	

# Camping Tent regression

Parameter	Topic	Posterior Mean	$\operatorname{CL}$
Covariates			
$\beta_0$	Intercept	0.865	0.990
$\beta_1$	Problems with water leaks and rainfly	-5.443	1.000
$\beta_2$	Tent has plenty of room for people	4.503	1.000
$\beta_3$	I can't recommend this tent	-1.774	0.996
$\beta_4$	Returned tent to Amazon	-7.335	1.000
$\beta_5$	Needs better instructions	-2.136	1.000
$\beta_6$	Issues with porch and screen	-0.563	0.795
$\beta_7$	Very nice tent	0.021	0.520
$\beta_8$	Issues with door, zipper or window	-2.928	1.000
$\beta_9$	Occasion tent was used	-3.000	1.000
$\beta_{10}$	Heavy weather with winds and storm at night	-1.474	0.980
$\beta_{11}$	Tent can be set up easily	3.098	1.000
$\beta_{12}$	Poles and stakes broke	-8.542	1.000
$\beta_{13}$	Great tent, good price	8.159	1.000
$\beta_{14}$	Tent kept dry inside during rain	-0.110	0.607
$\beta_{15}$	Number of people	1.596	0.991
$\beta_{16}$	"I love it"	0*	-
Cut-points			
$c_1$		-1.773*	-
$c_2$		-1.306	1.000
$c_3$		-0.922	1.000
$c_4$		-0.286*	-
$R^2$		0.714	

# Next steps

- Other research
  - Incorporation into choice models
  - GoM models and extremes