

TEXT CLASSIFICATION

Intent, topic, sentiment, etc.

Wongnai Challenge wongnai

- Predict star rating from review text

output



กวยเตี๋ยวอร่อย ราคาถูก นั่งทานในห้องแอร์

เมนูเด็ด: บะหมี่ต้มยำหมูแดง

input

ส่วนตัวชอบกวยเตี๋ยวต้มยำมากค่ะ รสชาติอร่อยไม่ต้องปูนเลย แต่ชุปเปอร์ตินไก่ใส่ถ่วงอกมาด้วย เหมือนเป็นเกาเหลาตินไก่มากกว่าชุปเปอร์ตินไก่ รสชาติก็ยังไม่กลมกล่อมเท่ากวยเตี๋ยวต้มยำ ตินไก่เปื่อยดี ทานง่าย

Wongnai challenge top model Accuracy 0.5844

Thai2fit (word embedding with adaptation) Accuracy 0.60925

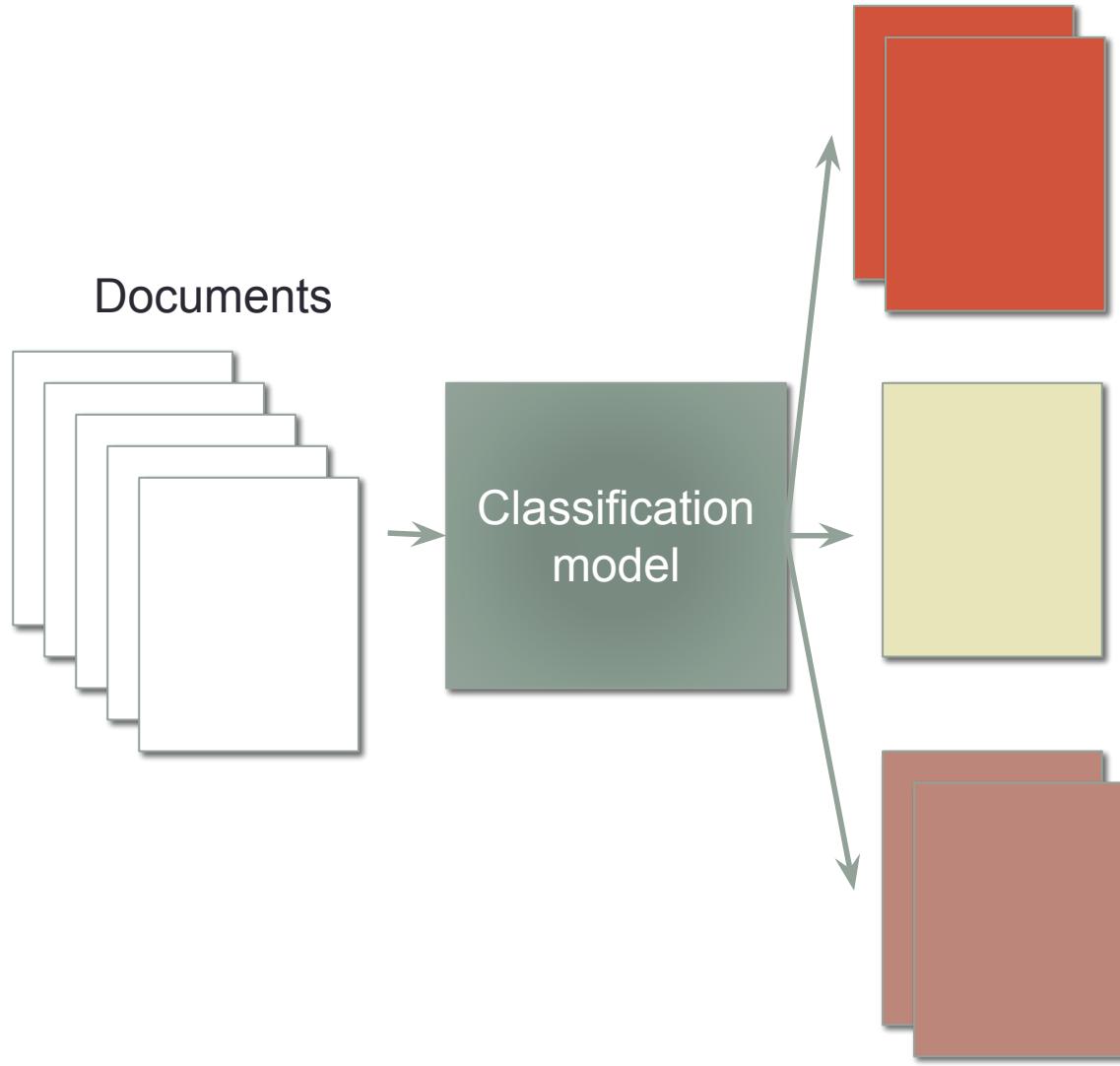
Thai2fit (on social media text) Accuracy 0.62580

Yelp reviews

Corpus	#docs	#s/d	#w/d	V	#class	Class Distribution
Yelp 2013	335,018	8.90	151.6	211,245	5	.09/.09/.14/.33/.36
Yelp 2014	1,125,457	9.22	156.9	476,191	5	.10/.09/.15/.30/.36
Yelp 2015	1,569,264	8.97	151.9	612,636	5	.10/.09/.14/.30/.37
IMDB	348,415	14.02	325.6	115,831	10	.07/.04/.05/.05/.08/.11/.15/.17/.12/.18

	Yelp 2013		Yelp 2014		Yelp 2015		IMDB	
	Accuracy	MSE	Accuracy	MSE	Accuracy	MSE	Accuracy	MSE
Majority	0.356	3.06	0.361	3.28	0.369	3.30	0.179	17.46
SVM + Unigrams	0.589	0.79	0.600	0.78	0.611	0.75	0.399	4.23
SVM + Bigrams	0.576	0.75	0.616	0.65	0.624	0.63	0.409	3.74
SVM + TextFeatures	0.598	0.68	0.618	0.63	0.624	0.60	0.405	3.56
SVM + AverageSG	0.543	1.11	0.557	1.08	0.568	1.04	0.319	5.57
SVM + SSWE	0.535	1.12	0.543	1.13	0.554	1.11	0.262	9.16
JMARS	N/A	–	N/A	–	N/A	–	N/A	4.97
Paragraph Vector	0.577	0.86	0.592	0.70	0.605	0.61	0.341	4.69
Convolutional NN	0.597	0.76	0.610	0.68	0.615	0.68	0.376	3.30
Conv-GRNN	0.637	0.56	0.655	0.51	0.660	0.50	0.425	2.71
LSTM-GRNN	0.651	0.50	0.671	0.48	0.676	0.49	0.453	3.00

Text/document classification



Document classification

Type	Focus	Example
Topic	Subject matter	Sports vs Technology
Sentiment/opinion	Emotion (current state)	Negative vs Positive
Intent	Action (future state)	Order vs Inquiry

Does Anne Hathaway News Drive Berkshire Hathaway's Stock?

ALEXIS C. MADRIGAL | MAR 18, 2011 | TECHNOLOGY



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Given the awesome correlating powers of today's stock trading computers, the idea may not be as far-fetched as you think.



A couple weeks ago, Huffington Post blogger Dan Mirvish noted a funny trend: when Anne Hathaway was in the news, Warren Buffett's Berkshire Hathaway's shares went up. He pointed to six dates going back to 2008 to show the correlation. Mirvish then suggested a mechanism to explain the trend: "automated, robotic trading programming are picking up the same chatter on the Internet about 'Hathaway' as the IMDb's StarMeter, and they're applying it to the stock market."

คืนนี้จะได้ดูตอนใหม่แล้ว #ขอเจ้า #อดใจไม่ไหว

Topic: บุพเพสันนิวาส

Sentiment: positive

Action: watch

อยากจะสั่งพิชช่าหน้ายาวยเอียนหน่อยครับ

Action: order_hawaiian

<https://www.theatlantic.com/technology/archive/2011/03/does-anne-hathaway-news-drive-berkshire-hathaways-st>

Other classification application

- Spam filtering
- Authorship id
 - Age id
 - Gender id
 - Native speaker id
 - First language id
- Auto tagging (information retrieval)
- Trend analysis
 - Patent landscape

Text classification definition

- Input
 - Set of documents: $D = \{d_1, d_2, d_3, \dots, d_M\}$
 - Each document is composed of words
 - $d_1 = [w_{11}, w_{12}, \dots, w_{1N}]$
 - Set of classes: $C = \{c_1, c_2, c_3, \dots, c_J\}$
- Output
 - The predicted class c from the set C

Rule-based classification

- Rules based on phrases or other features
 - Wongnai Rating
 - แมลงสาบ -> 2 ดาว
 - อร่อย -> 4 ดาว
 - ไม่อร่อย -> 2 ดาว
 - ...
 - What if the phrase is ไม่ค่อยอร่อย
 - New rule
 - อร่อย โดยที่ไม่มีคำว่า ไม่อยู่ແກງนั้น -> 4 ดาว
 - What if the phrase is ไม่ถูกแต่อร่อย
- This can yield very good results but...
- Building and maintaining rules is expensive!
- Or keep a word list of positive and negative words

Supervised text classification definition

- Input
 - Set of documents: $D = \{d_1, d_2, d_3, \dots, d_M\}$
 - And labels $Y = \{y_1, y_2, y_3, \dots, y_M\}$
 - Each document is composed of words
 - $d_1 = [w_{11}, w_{12}, \dots, w_{1N}]$
 - Set of classes: $C = \{c_1, c_2, c_3, \dots, c_J\}$
- Output
 - A classifier $H: d \rightarrow c$

What classifier?

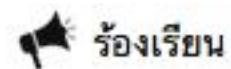
- Any classifier you like
 - k-NN
 - Naïve Bayes
 - Logistic regression
 - SVM
 - Neural networks 
- We use this kind of classifier before in last homework

Outline

- Naïve Bayes
- Topic Models
 - Latent topic models (LDA)
- LDA2vec

Bag of words representation

★★★☆☆ 1 check-in



กิวiy เดี่ยวอร่อย ราคาถูก นั่งทานในห้องแอร์

เมนูเด็ด: บะหมี่ต้มยำหมูแดง

ส่วนตัวชอบกิวiy เดี่ยวต้มยำมากค่ะ รสชาติอร่อยไม่ต้องปรุงเลย แต่ชุปเปอร์ตินไก่ใส่ถั่วงอกมาด้วย เหมือนเป็น
เกาเหลาตินไก่มากกว่าชุปเปอร์ตินไก่ รสชาติก็ยังไม่กลมกล่อมเท่ากิวiy เดี่ยวต้มยำ ตินไก่เปื่อยดี ทานง่าย

H

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= 3

Bag of words representation

H [ส่วนตัวชอบก็วยเดี่ยวตั้มยำมากค่ะ รสชาติอร่อยไม่ต้องปูรุงเลย แต่ชุบเปอร์ตินไก่ใส่ถังอกมาด้วย เหมือนเป็น
เกาเหลาตินไก่มากกว่าชุบเปอร์ตินไก่ รสชาติก็ยังไม่คลมกล่อมเท่าก็วยเดี่ยวตั้มยำ ตินไก่เปื่อยดี ทานง่าย] = 3

Bag of words on care the presence of words or features but ignore word position and context

H [ชอบ, อร่อย, ไม่, ไม่, คลมกล่อม, ทานง่าย] = 3

Bag of words representation

H [ส่วนตัวชอบก็วายเดียวต้มยำมากค่ะ รสชาติอร่อยไม่ต้องปูงเหลย แต่ชุปเปอร์ตินไก่ใส่ถั่วงอกมาด้วย เหมือนเป็น
เกาเหลาตินไก่มากกว่าชุปเปอร์ตินไก่ รสชาติก็ยังไม่คลมกล่อมเท่าก็วายเดียวต้มยำ ตินไก่เปื่อยดี ทานง่าย] = 3

Bag of words on care the presence of words or features but ignore word position and context

H [

Word	Count
ชอบ	1
อร่อย	1
ไม่	2
คลมกล่อม	1
ทานง่าย	1

] = 3

Bag of words for classification intuition

Test review

แมงสาบ
ใช้ได้
ถูก
อร่อย

1star

แมงสาบ
สกปรก
ແຍ່

3star

ใช้ได้
ถูก
อร่อย
คาดฝัน

5star

ເຫະ
ເໜີ
ອວ່ອຍ
ຍອດ

Bag of words for classification intuition

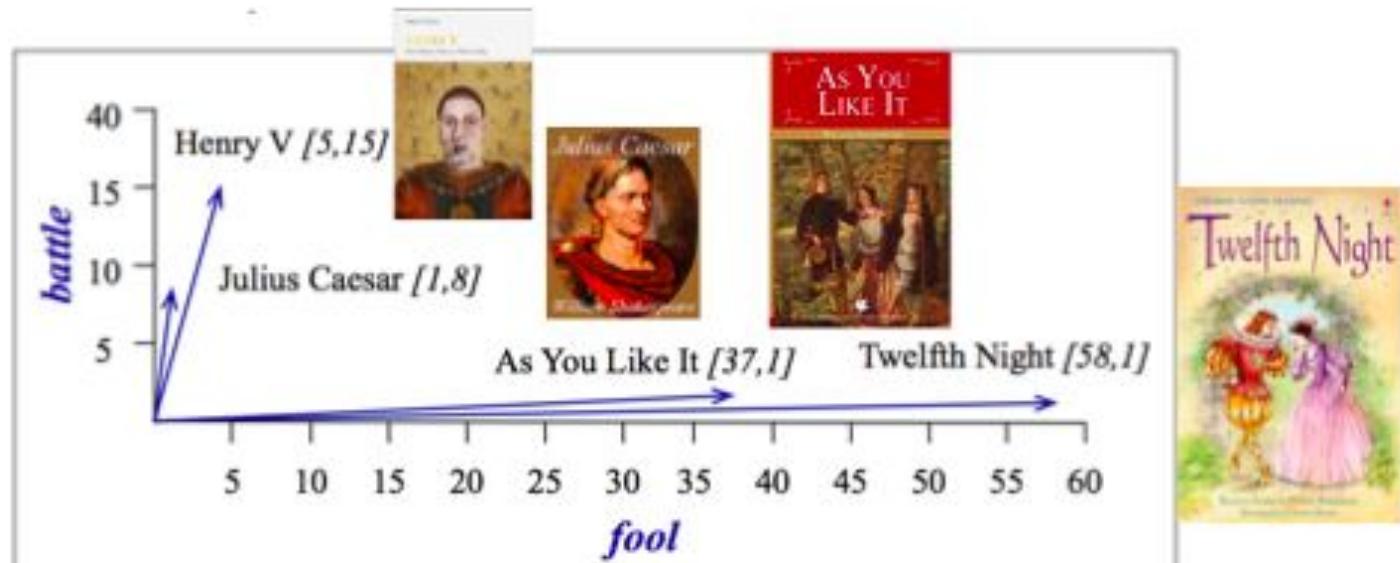


Figure 15.3 A spatial visualization of the document vectors for the four Shakespeare play documents, showing just two of the dimensions, corresponding to the words *battle* and *fool*. The comedies have high values for the *fool* dimension and low values for the *battle* dimension.

Reference: Jurafsky, Dan, and James H. Martin. Speech and language processing. 3rd edition draft, <https://web.stanford.edu/~jurafsky/slp3/>, August 2017

Bayes' Rule for classification

- A simple classification model
- Given document d, find the class c
 - $\underset{c}{\operatorname{Argmax}} P(c|d)$

$$= \underset{c}{\operatorname{Argmax}} \frac{P(d|c) P(c)}{P(d)}$$

Bayes' Rule

$$= \underset{c}{\operatorname{Argmax}} P(d|c) P(c)$$

P(d) is constant wrt to c

$$= \underset{c}{\operatorname{Argmax}} P(x_1, x_2, \dots, x_n | c) P(c)$$

The document is represented by features
 x_1, x_2, \dots, x_n

Bayes' Rule for classification

- A simple classification model
- Given document d , find the class c
 - $\underset{c}{\operatorname{Argmax}} P(c|d)$

$$= \underset{c}{\operatorname{Argmax}} \frac{P(d|c) P(c)}{P(d)}$$

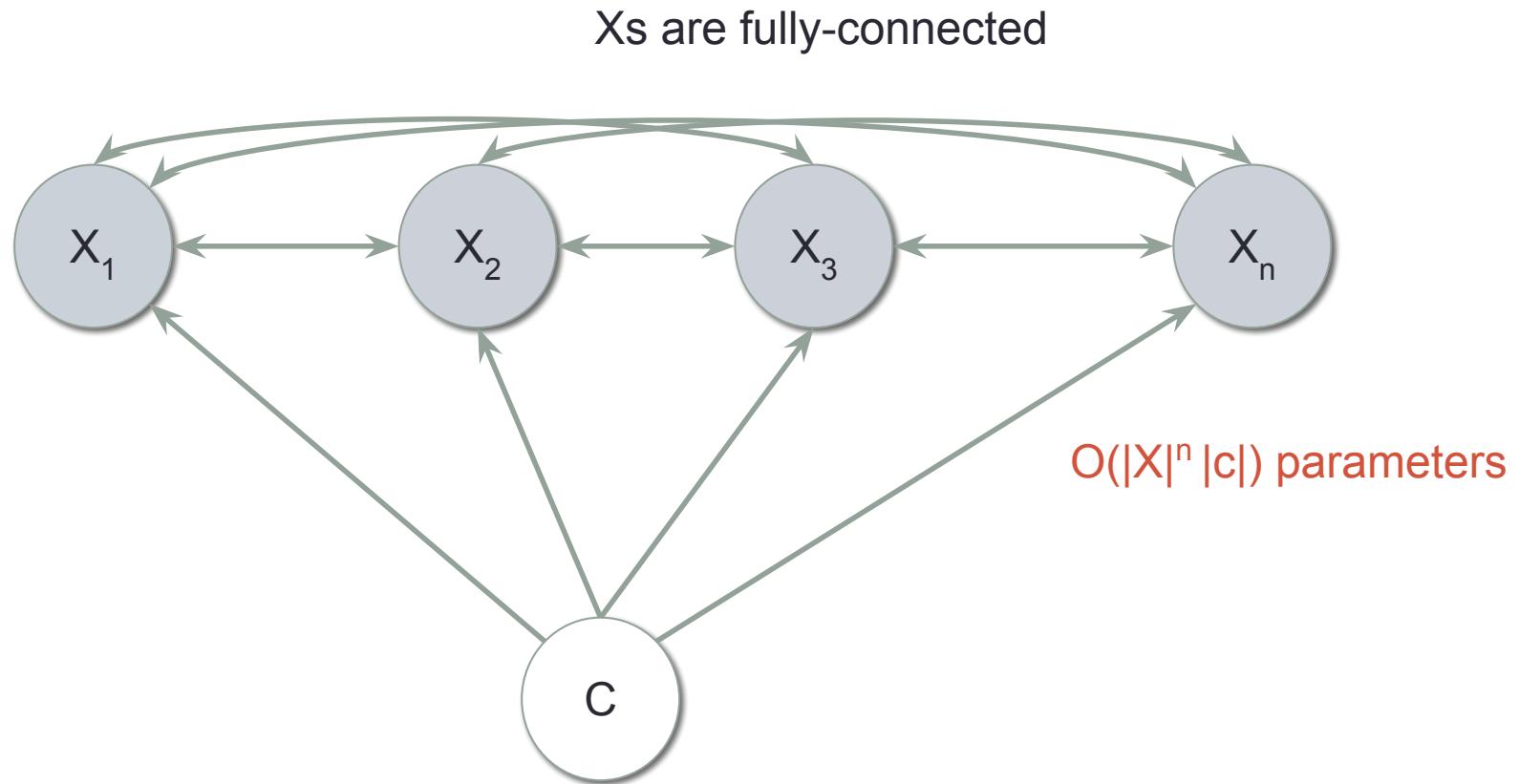
$$= \underset{c}{\operatorname{Argmax}} P(d|c) P(c)$$

$$= \underset{c}{\operatorname{Argmax}} P(x_1, x_2, \dots, x_n | c) P(c)$$

$P(x_1, x_2, \dots, x_n | c)$ requires $O(|X|^n |c|)$ parameters. Cannot train

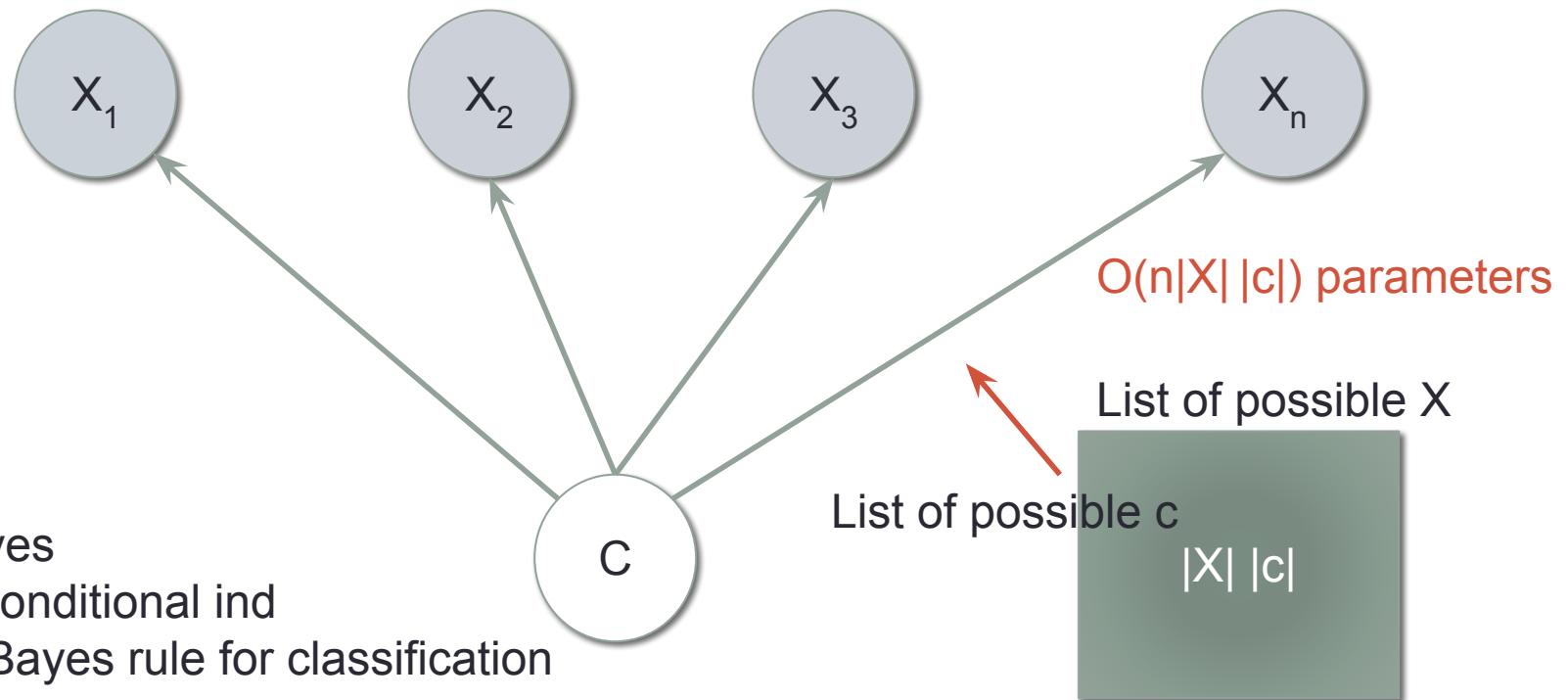
Graphical view

- $P(x_1, x_2, \dots, x_n | c) P(c)$



Bag of words assumption

- $P(x_1, x_2, \dots, x_n | c) P(c) = P(x_1|c) P(x_2|c) P(x_3|c) \dots P(x_n|c) P(c)$
 - Conditional independence



Learning the Naïve Bayes model

- As usual counts x_n is a feature that counts word occurrence
 x_1 how many times ຢອດ appear
- $P(x|c)$
- $P(x = “ຢອດ” | c=5) = \frac{\text{count}(x = “ຢອດ”, c = 5)}{\text{count}(c = 5)}$ List of possible counts
- $P(c)$ List of classes $|X| |c|$
- $P(c = 5) = \frac{\text{count} (c = 5)}{\text{count} (\text{all reviews})}$
- This is the Maximum Likelihood Estimate (MLE)

Learning the Naïve Bayes model

- What if we encounter zeroes in our table
 - $P(x|c)$
 x_n is a feature that counts word occurrence
 x_1 how many times ยอด appear
 - $P(x = “ยอด” | c=5) = \frac{\text{count}(x = “ยอด”, c = 5)}{\text{count}(c = 5)}$ List of possible counts
- List of classes $|X| |c|$
- $P(‘ร้าน นี่ ราด หน้า ยอด ผัก ไม่ อร่อย’ | c = 2)$
 $= P(x = “ร้าน” | c=2) * P(x = “นี่” | c=2) ... P(x = “ยอด” | c=2) * ...$
 $= 0$

Zero probability regardless of other words

One solution: add-1 smoothing (a hyperparameter to tune)

Naives Bayes

- Can use other features beside word counts
 - Feature engineering – restaurant name, location, price range, reviewer id, date of review
 - Tedious but very powerful
 - Features > 10000
- Pros: very fast, very small model
- Robust especially for small training data (hand-crafted rules)
- A good fast baseline. Always try Naive Bayes or logistic regression in model search.
- Even with lots of data and rich features, Naives Bayes can be very competitive and fast!

Naive Bayes vs Logistic regression

Generative vs Discriminative modeling

Given data x , predict y

- Naïve Bayes are generative models

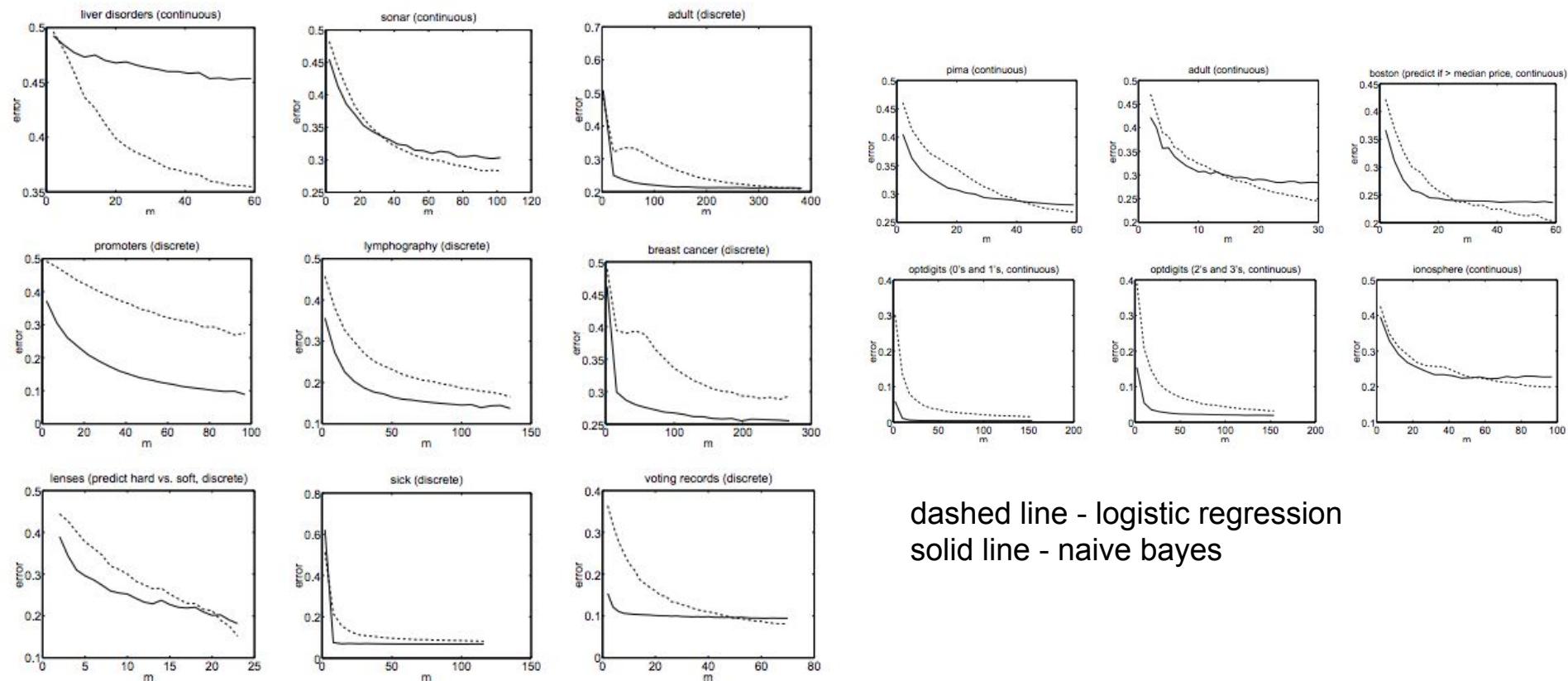
$$y^* = \operatorname{argmax}_y \frac{P(x|y)P(y)}{P(x)}$$

- Logistic regression are discriminative models
 - Note $P(y|x)$ can be any function that outputs y given x (a neural network)
- Logistic regression and Naive Bayes are linear models (linear decision boundary)
- They are quite interchangeable.

Naive Bayes vs Logistic regression

Generative vs Discriminative modeling

When training data is small, Naive Bayes performs better. When training data is large, Logistic regression performs better.



dashed line - logistic regression
solid line - naive bayes

Fast and good classification using n-grams

- Features: n-grams (bag of phrases)
- Model: logistic regression
- Very competitive results

Model	Yelp'13	Yelp'14	Yelp'15	IMDB
SVM+TF	59.8	61.8	62.4	40.5
CNN	59.7	61.0	61.5	37.5
Conv-GRNN	63.7	65.5	66.0	42.5
LSTM-GRNN	65.1	67.1	67.6	45.3
fastText	64.2	66.2	66.6	45.2

Table 3: Comparision with Tang et al. (2015). The hyper-parameters are chosen on the validation set. We report the test accuracy.

Fast and good classification using n-grams

- Features: n-grams (bag of phrases)
- Model: logistic regression
- Very competitive results

	Zhang and LeCun (2015)		Conneau et al. (2016)			fastText
	small char-CNN	big char-CNN	depth=9	depth=17	depth=29	$h = 10$, bigram
AG	1h	3h	24m	37m	51m	1s
Sogou	-	-	25m	41m	56m	7s
DBpedia	2h	5h	27m	44m	1h	2s
Yelp P.	-	-	28m	43m	1h09	3s
Yelp F.	-	-	29m	45m	1h12	4s
Yah. A.	8h	1d	1h	1h33	2h	5s
Amz. F.	2d	5d	2h45	4h20	7h	9s
Amz. P.	2d	5d	2h45	4h25	7h	10s

Table 2: Training time for a single epoch on sentiment analysis datasets compared to char-CNN and VDCNN.

Tag prediction

Model	prec@1	Running time	
		Train	Test
Freq. baseline	2.2	-	-
Tagspace, $h = 50$	30.1	3h8	6h
Tagspace, $h = 200$	35.6	5h32	15h
fastText, $h = 50$	31.2	6m40	48s
fastText, $h = 50$, bigram	36.7	7m47	50s
fastText, $h = 200$	41.1	10m34	1m29
fastText, $h = 200$, bigram	46.1	13m38	1m37

Table 5: Prec@1 on the test set for tag prediction on YFCC100M. We also report the training time and test time. Test time is reported for a single thread, while training uses 20 threads for both models.

Naïve Bayes tricks for text classification

• Domain specific features

- Count words after “not” as a different word

- I don’t go there. -> I don’t go_not there_not

- Upweighting: double counting words at important locations

- Words in titles
 - First sentence of each paragraph
 - Sentences that contain title words

Automatic text categorization using the importance of sentences
<https://dl.acm.org/citation.cfm?id=1072331>

Context-Sensitive Learning Methods for Text Categorization
https://www.researchgate.net/publication/2478208_Context-Sensitive_Learning_Methods_for_Text_Categorization

Information retrieval using location and category information
https://www.jstage.jst.go.jp/article/jnlp1994/7/2/7_2_141/_article

Different variants of Naive Bayes

- What we described was Multinomial Naive Bayes
 - Takes in word counts
 - Can also take in a binary version of word counts
- There's also Multi-variate Bernoulli Naive Bayes
 - Takes in binary version of word counts
 - Slightly different assumptions
- SVM-NB (SVM with NB as features)
- etc.

Additional readings

“Spam Filtering with Naive Bayes – Which Naive Bayes?”

http://www2.aueb.gr/users/ion/docs/ceas2006_paper.pdf

“Baselines and Bigrams: Simple, Good Sentiment and Topic Classification”

<http://www.aclweb.org/anthology/P12-2018>

Final words on text classification

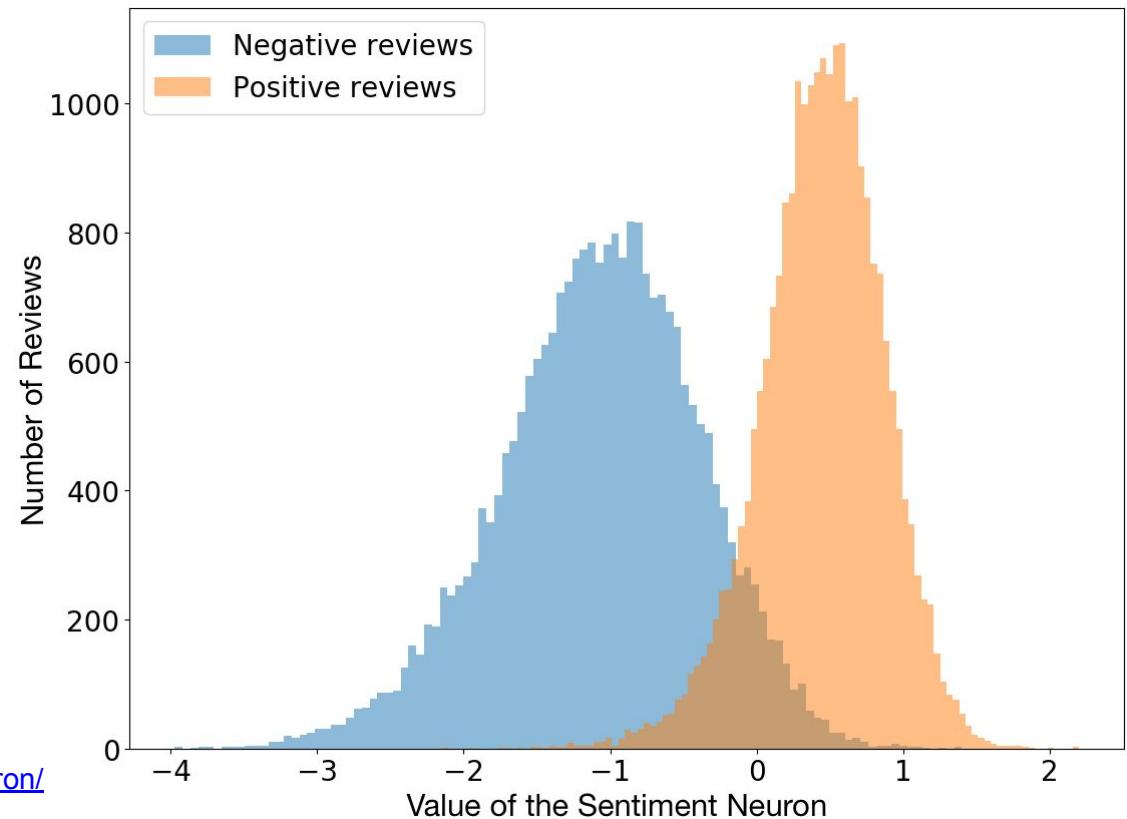
Current state-of-the-art are about learning representations
Unsupervised pre-training of text (Word2Vec, BERT,
ULMFit, etc)

Example Sentiment Neuron

Trained a LSTM network to predict next character from raw amazon reviews text (82 million reviews)

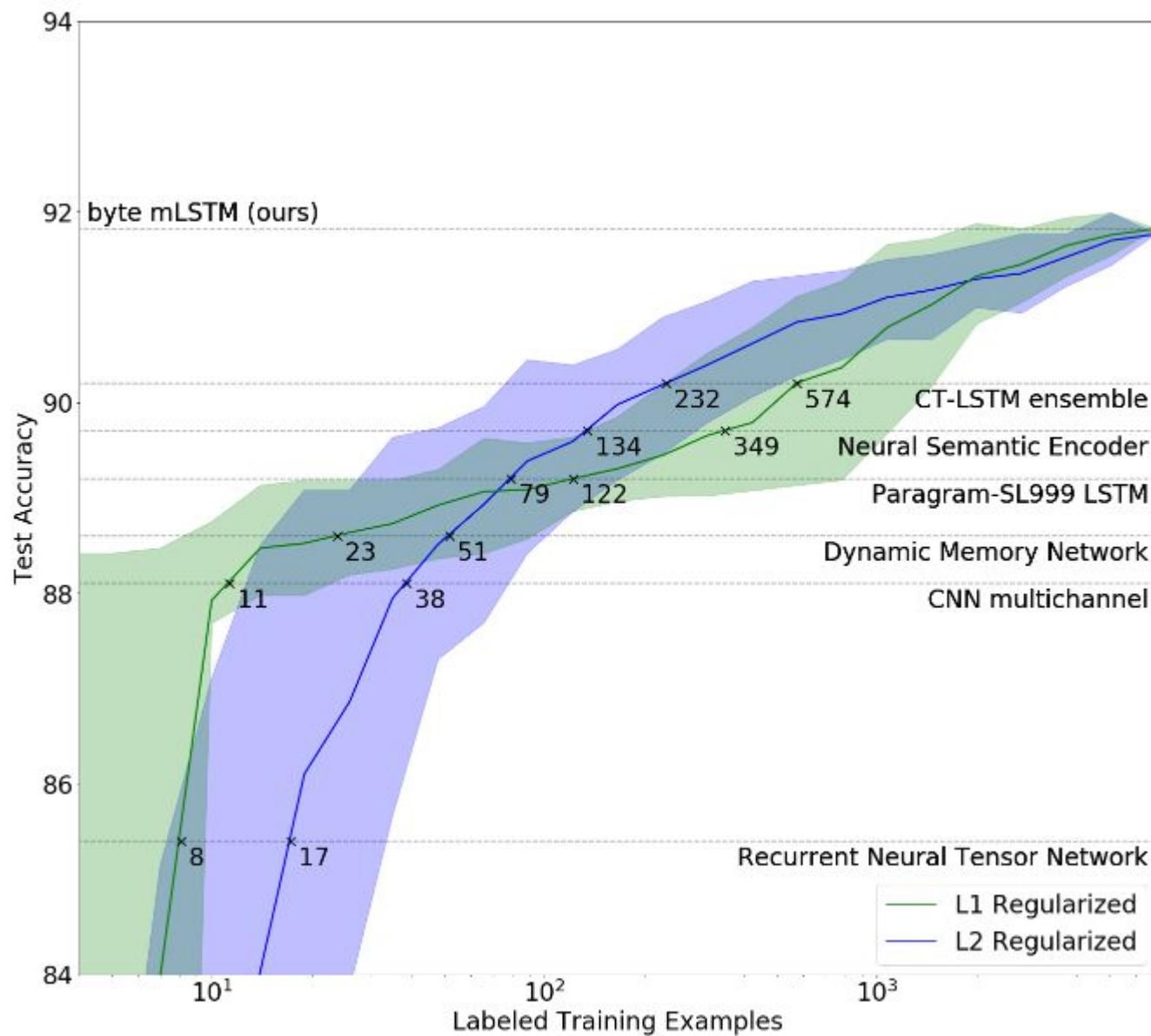
LSTM with 4096 hidden units

One unit seems to be learning sentiment



Sentiment neuron

This is one of Crichton's best books. The characters of Karen Ross, Peter Elliot, Munro, and Amy are beautifully developed and their interactions are exciting, complex, and fast-paced throughout this impressive novel. And about 99.8 percent of that got lost in the film. Seriously, the screenplay AND the directing were horrendous and clearly done by people who could not fathom what was good about the novel. I can't fault the actors because frankly, they never had a chance to make this turkey live up to Crichton's original work. I know good novels, especially those with a science fiction edge, are hard to bring to the screen in a way that lives up to the original. But this may be the absolute worst disparity in quality between novel and screen adaptation ever. The book is really, really good. The movie is just dreadful.



Relationship to language modeling

- $P(x|c)$ x_1 is a feature that looks at the first word
- $P(x = \text{ຍອດ} | c=5) = \frac{\text{count}(x = \text{ຍອດ}, c = 5)}{\text{count}(c = 5)}$ List of words
- $P(c)$ List of classes $|X| |c|$
- $P(c = 5) = \frac{\text{count}(c = 5)}{\text{count(all reviews)}}$

This looks like... n-grams, but instead of conditioning on the past, we condition on the topic –
bag of words model for topic modeling (unigram with topic)

Language modeling view

- Which class is this review
- $P(w|c)$

อร่อย แต่ ไม่ ถูก

Class= 1
อร่อย 0.01
แต่ 0.4
ไม่ 0.4
ถูก 0.03
...

Class= 5
อร่อย 0.4
แต่ 0.05
ไม่ 0.25
ถูก 0.15
...

$$P(s|c=1) = 0.01 * 0.4 * 0.4 * 0.03 = 0.000048$$
$$P(s|c=5) = 0.4 * 0.05 * 0.25 * 0.15 = 0.00075$$

Topic modeling

- Sometimes you want to model the topic of a document

Class=
บรรยายการคุย

อร่อย 0.01
แต่ 0.4
ไม่ 0.4
ถูก 0.03
...

Class= อาหาร

อร่อย 0.4
แต่ 0.05
ไม่ 0.25
ถูก 0.15
...

อาหารที่นี่ไม่ค่อยอร่อย แต่ขนม
ใช้ได้เลย ถ้าว่างอาจจะกลับมากิน
อีก แนะนำให้สั่งเค้กใบเตย

ด้านบรรยายการคุย มีเสียงก่อสร้างมา
จากตึกข้างๆ แต่นอกนั้นตกแต่ง
โอลิเวอร์ แต่ยังขาดอะไรไปหลายๆ
อย่าง

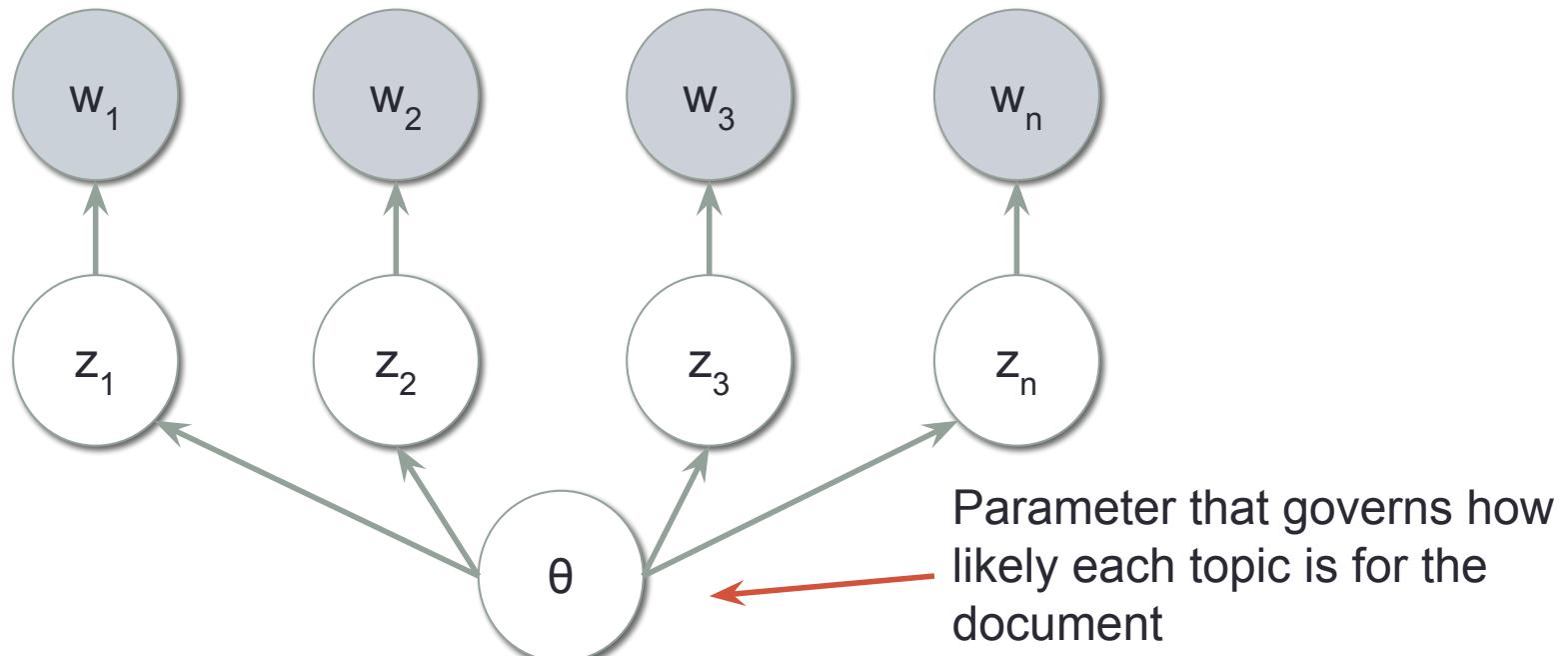
$$P(s|c=\text{บรรยายการคุย}) = ?$$
$$P(s|c=\text{อาหาร}) = ?$$

Naïve Bayes Topic modeling issues

- Most documents have multiple topics (multi-label).
 - Our model assumes 1 document 1 topic.
- Solution: Let a document be a mixture of topics (language model interpolation). Each word has its own topic, z .
 - $P(w) = P(w \text{ is topic A}) P(w | \text{topicA}) + P(w \text{ is topic B}) P(w | \text{topicB})$
 - $P(w \text{ is topic A}) + P(w \text{ is topic B}) = 1$

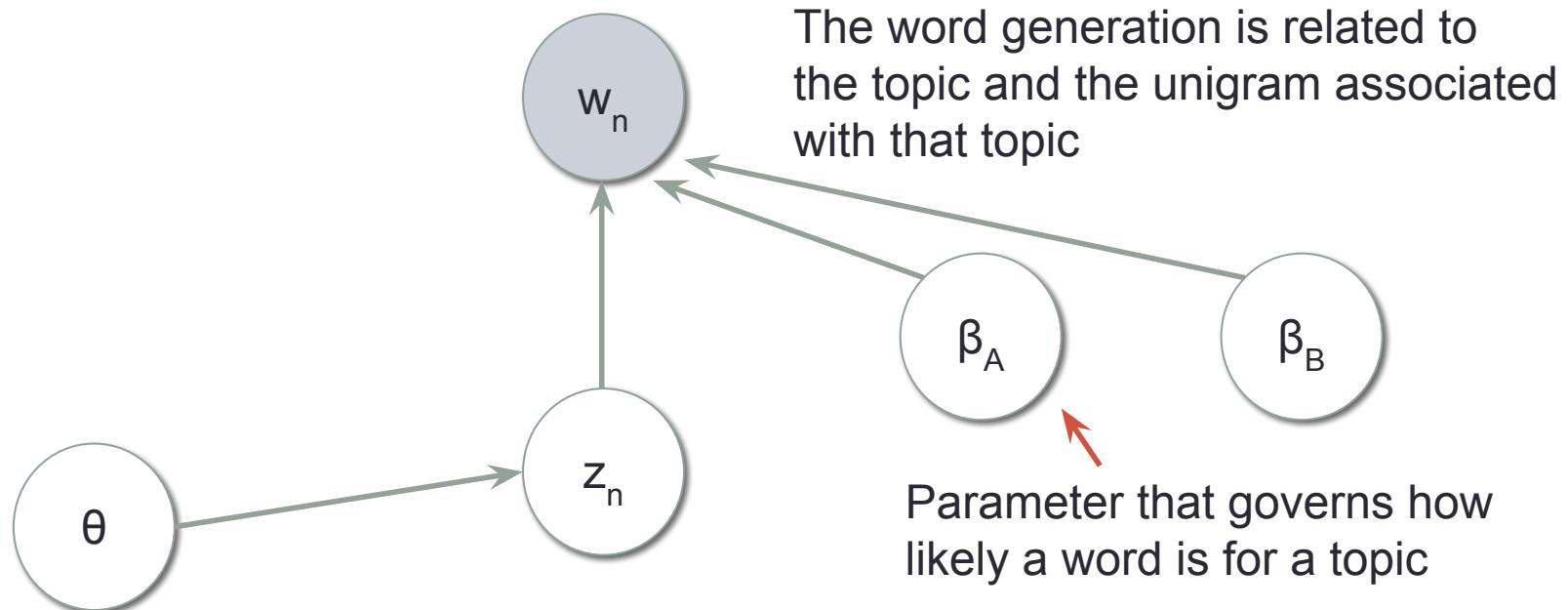
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 - $P(w) = P(z = A) P(w | z = A) + P(z = B) P(w | z = B)$
 - $P(z = A) + P(z = B) = 1, \quad \theta = P(z = A)$



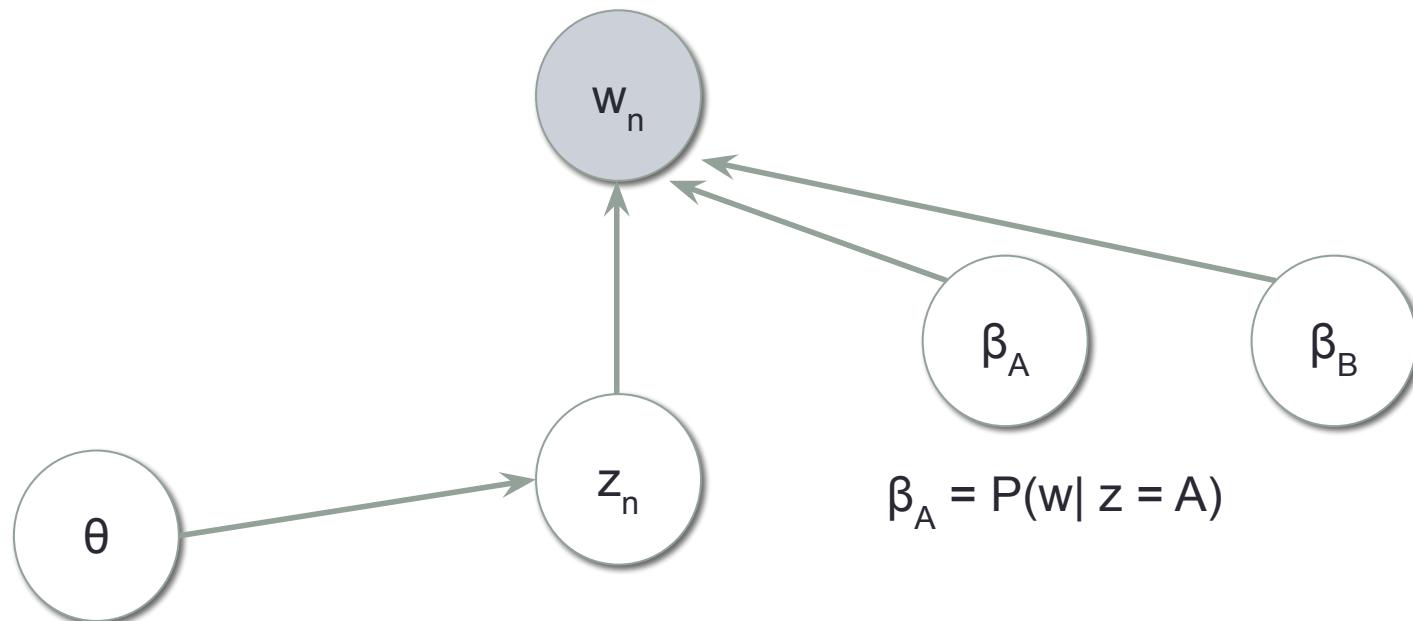
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 - Let a document be a mixture of topics (language model interpolation). Each word has its own topic, z .
 - $P(w) = P(z = A) P(w | z = A) + P(z = B) P(w | z = B)$
 - $P(z = A) + P(z = B) = 1, \quad \theta = P(z = A) \quad \beta_A = P(w | z = A)$



Graphical model and generation

- You can generate a sample from a graphical model by following the arrows



Graphical model and generation

- Given θ, β_A, β_B

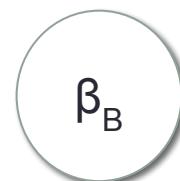


A = 0.3
B = 0.7

Cat = 0.5
Dog = 0.5

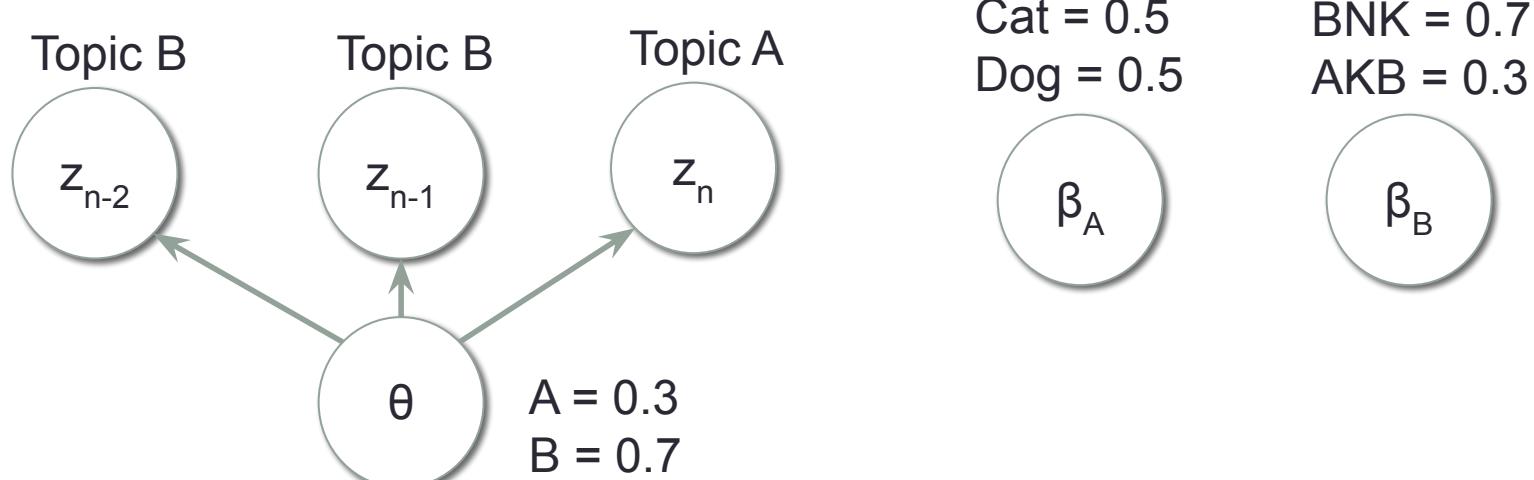


BNK = 0.7
AKB = 0.3



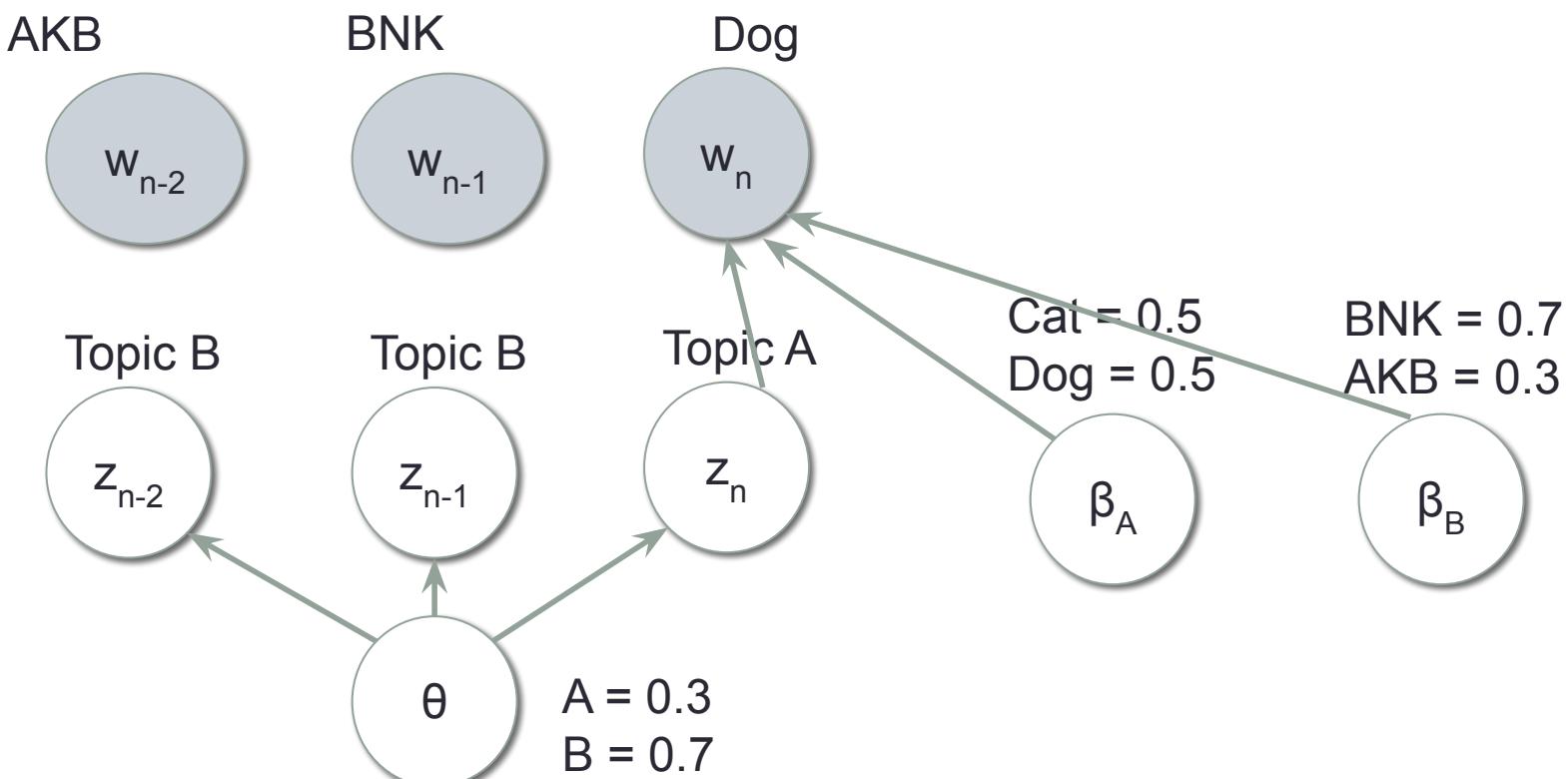
Graphical model and generation

- Given θ, β_A, β_B
- Generate (randomly create) z from θ



Graphical model and generation

- Given θ, β_A, β_B
- Generate (randomly create) z from θ
- Generate w_n from z_n, β_A, β_B



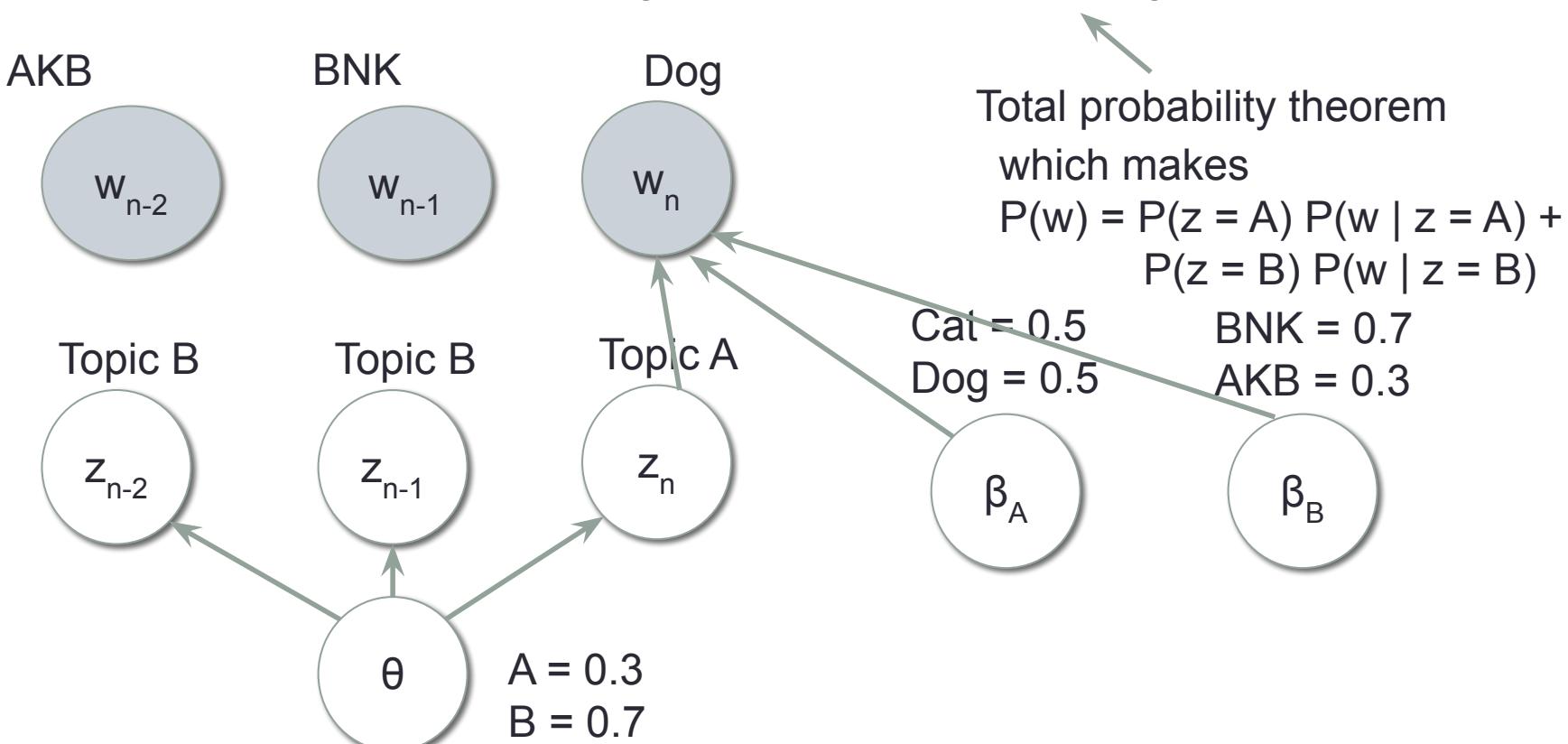
Graphical model and generation

How likely a sentence is likely to be generated follows this generation process

$$P(AKB, BNK, Dog, B, B, A) = P(B)P(B)P(A)P(AKB|B)P(BNK|B)P(Dog|A)$$

Note

$$\begin{aligned} P(AKB, BNK, Dog) &= P(AKB, BNK, Dog, A, A, A) + P(AKB, BNK, Dog, A, A, B) \\ &\quad P(AKB, BNK, Dog, A, B, A) + P(AKB, BNK, Dog, A, B, B) + \dots \end{aligned}$$



Graphical models and plate notation

- Sometimes you have too many relationships.

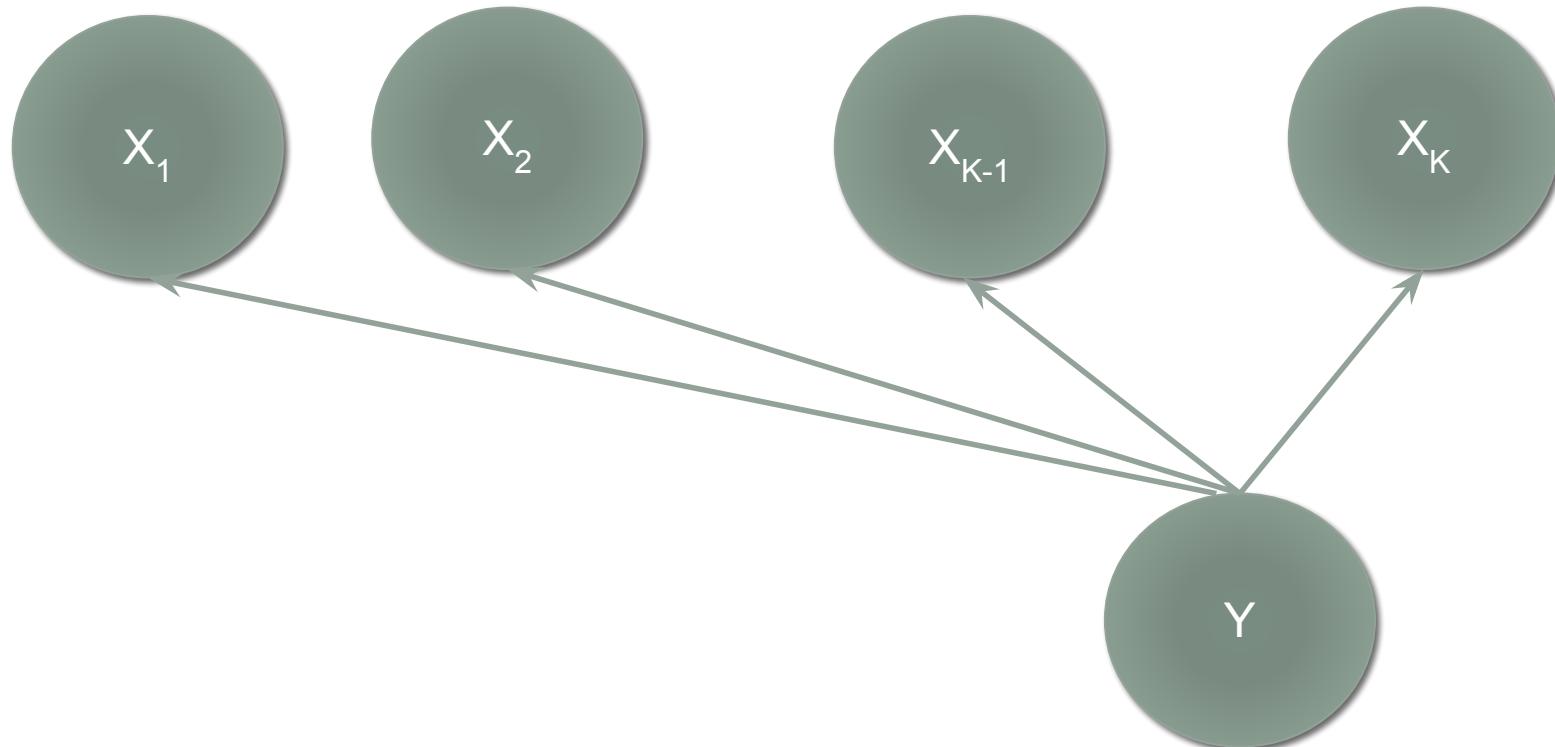
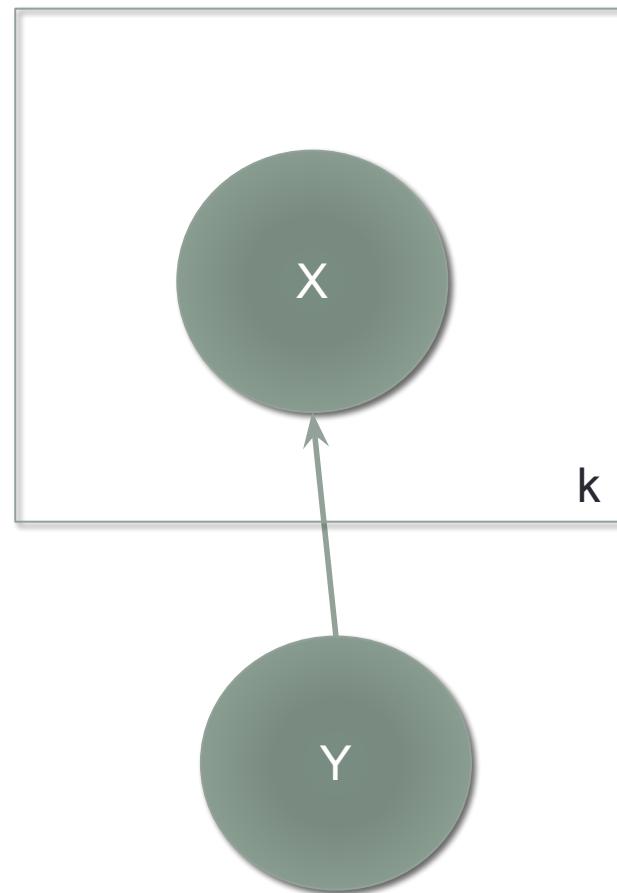
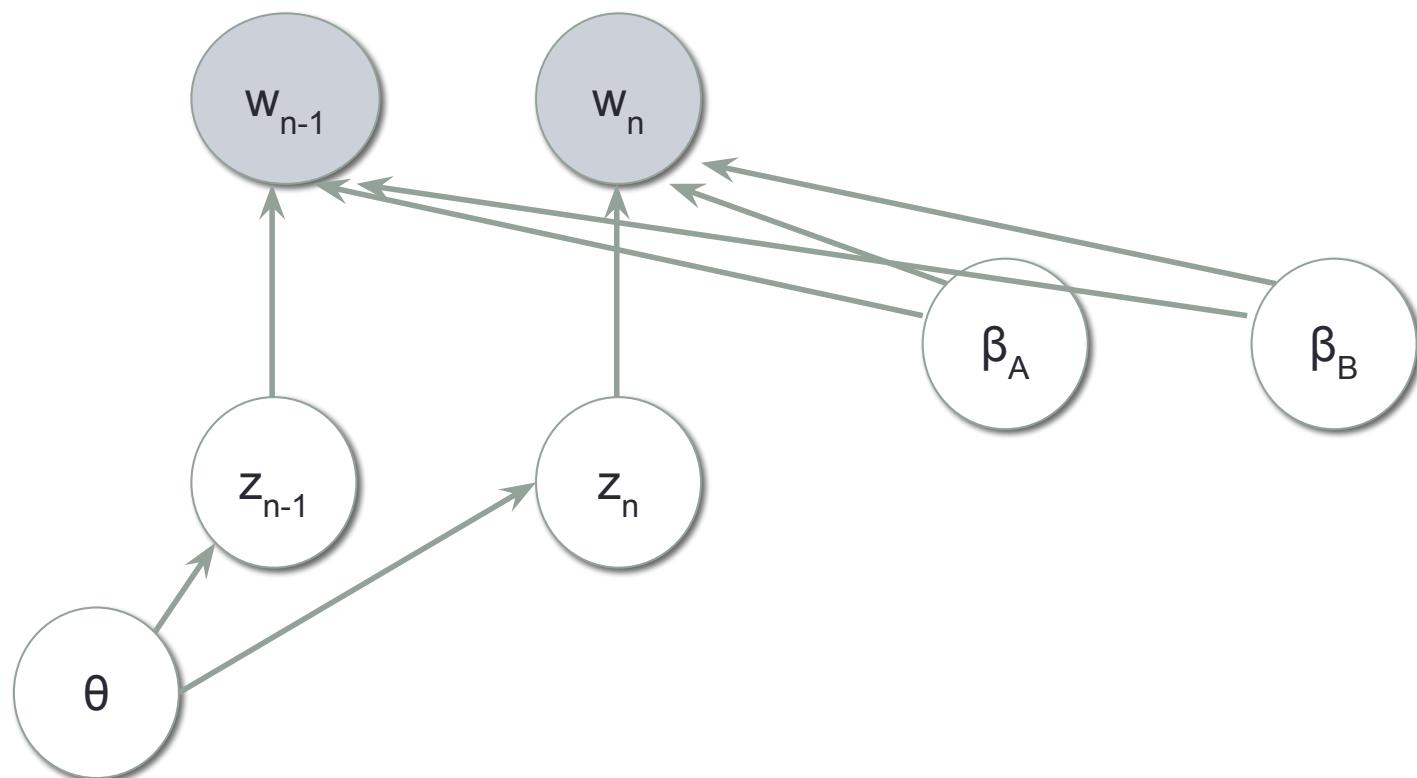


Plate notation

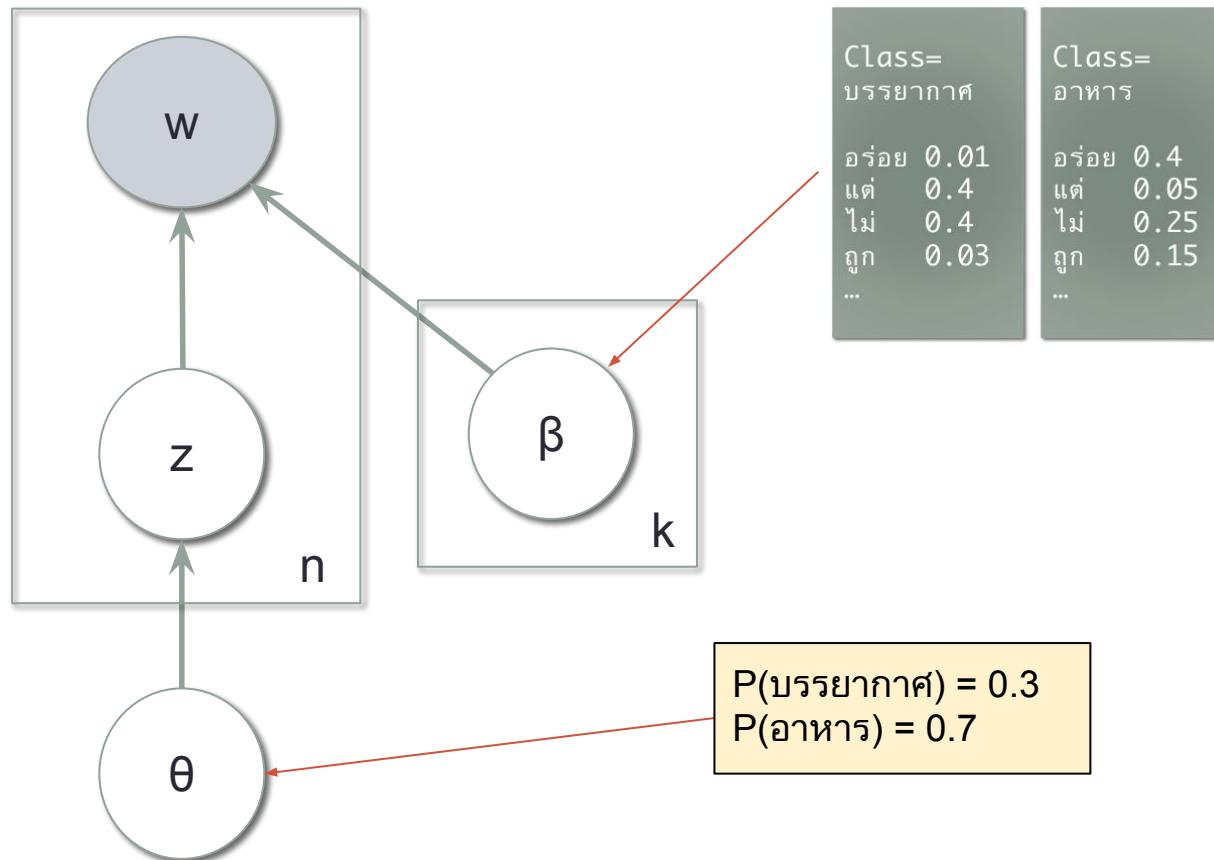
- Summarize by using a square box with number



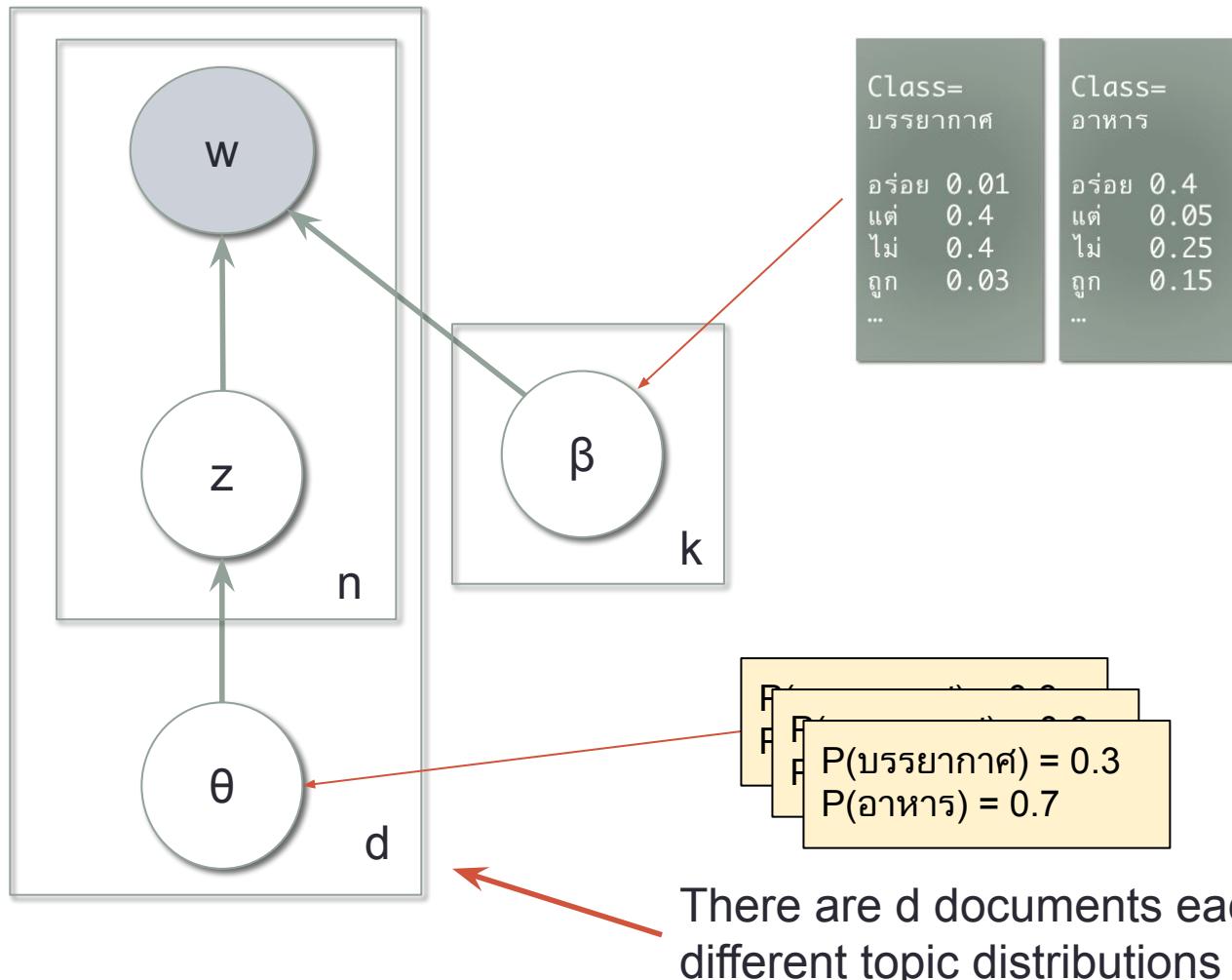
Topic modeling with plate notation



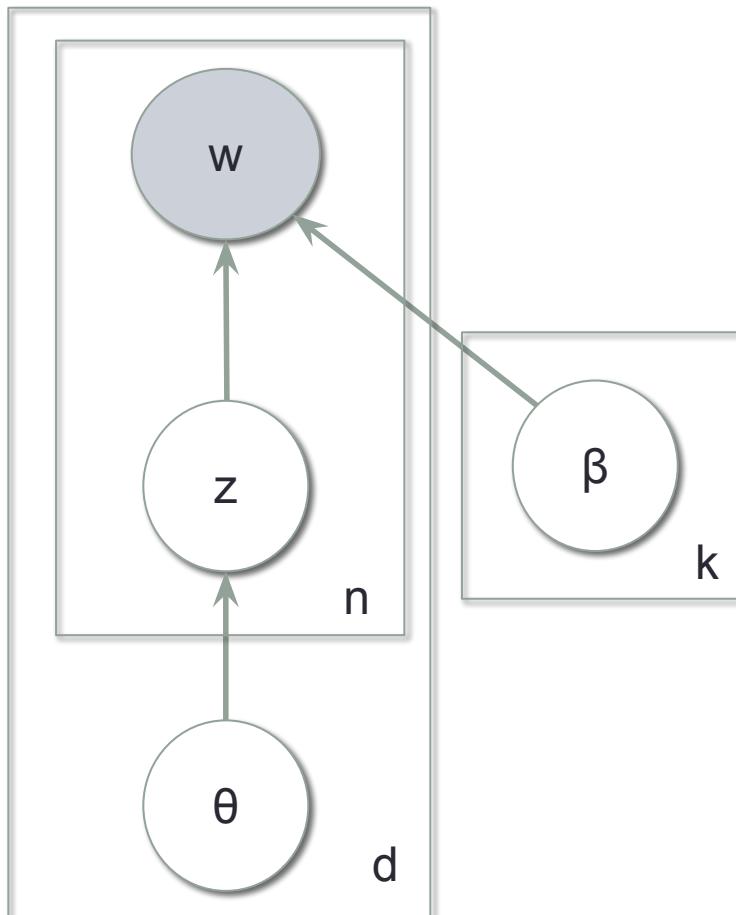
Topic modeling with plate notation



Topic modeling with plate notation

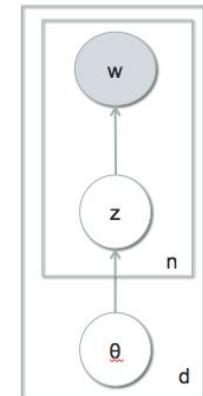


Topic modeling with plate notation



Called pLSA
probabilistic Latent Semantic Analysis

Note: if you look at other textbooks, you will see a slightly different picture



Learning topic latent model parameters

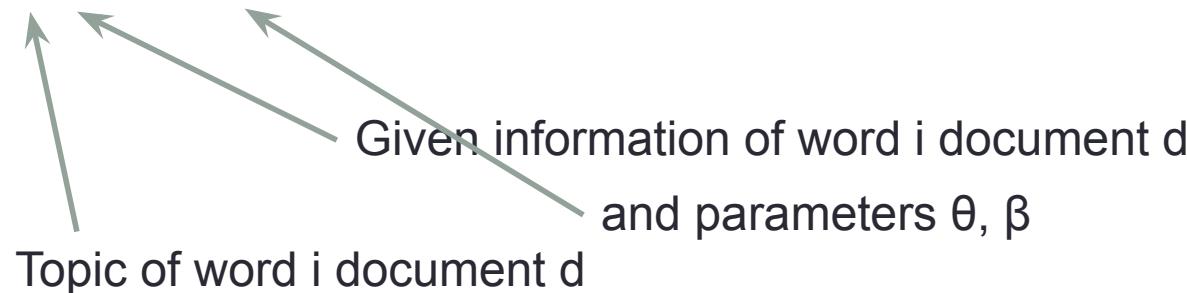
- How to find θ and β ?
 - “Cat,Dog,BNK”, “Cat, cat, cat, BNK”, “Dog, dog, BNK, dog, AKB”
- If we know, the latent topic z for each word we can use the counts
 - “Cat_A, Dog_A, BNK_B”
- $P(\text{Cat}|A) = \frac{\text{count}(\text{Cat_A})}{\text{count}(A)}$
- $P_1(A) = \frac{\text{count}(A)}{\text{count}(\text{all words in document 1})}$
- But we don't know the topic z for each word

Expectation maximization (EM)

- A method to iteratively maximize the likelihood of a model on training data
 - Expectation step (E step) – guess latent variables from model parameters (get soft counts)
 - Maximization step (M step) – re-estimate model parameters from latent variables (counts)

E-step

- Find an estimate for the latent variable given parameters θ, β
- $p(z_{di} | w_{di}, \theta, \beta)$



E-step

- Find an estimate for the latent variable given parameters θ, β

$$p(z_{di}|w_{di}, \theta, \beta) = \frac{p(z_{di}, w_{di}, \theta, \beta)}{\sum_{z'=1}^k p(z'_{di}, w_{di}, \theta, \beta)}$$

$p(w, \theta, \beta)$

E-step

- Find an estimate for the latent variable given parameters θ, β

$$p(z_{di}|w_{di}, \theta, \beta) = \frac{p(z_{di}, w_{di}, \theta, \beta)}{\sum_{z'=1}^k p(z'_{di}, w_{di}, \theta, \beta)}$$
$$= \frac{\theta_z|d\beta_w|z}{\sum_{z'=1}^k \theta_{z'}|d\beta_w|z'}$$

Index di for z and w dropped for clarity

E-step

- Find an estimate for the latent variable given parameters θ, β

$$p(z_{di}|w_{di}, \theta, \beta) = \frac{p(z_{di}, w_{di}, \theta, \beta)}{\sum_{z'=1}^k p(z'_{di}, w_{di}, \theta, \beta)}$$
$$= \frac{\theta_{z|d}\beta_{w|z}}{\sum_{z'=1}^k \theta_{z'|d}\beta_{w|z'}}$$


P(Word is from topic A | word is cat from document 1)
Probability that the word is from each topic. Use as counts

M-Step

- Instead of real counts use $P(z_{di})$ as the topic label
- $$P(\text{Cat}|A) = \frac{\text{count}(\text{Cat}_A)}{\text{count}(A)}$$
 - Sum $P(z_{di} = A)$ for all $w = \text{cat}$, all docs
 - Sum $P(z_{di} = A)$ for all words, all docs
- $$P_1(A) = \frac{\text{count}(A)}{\text{count}(\text{all words in document 1})}$$
 - Sum $P(z_{1i} = A)$ for all words doc 1

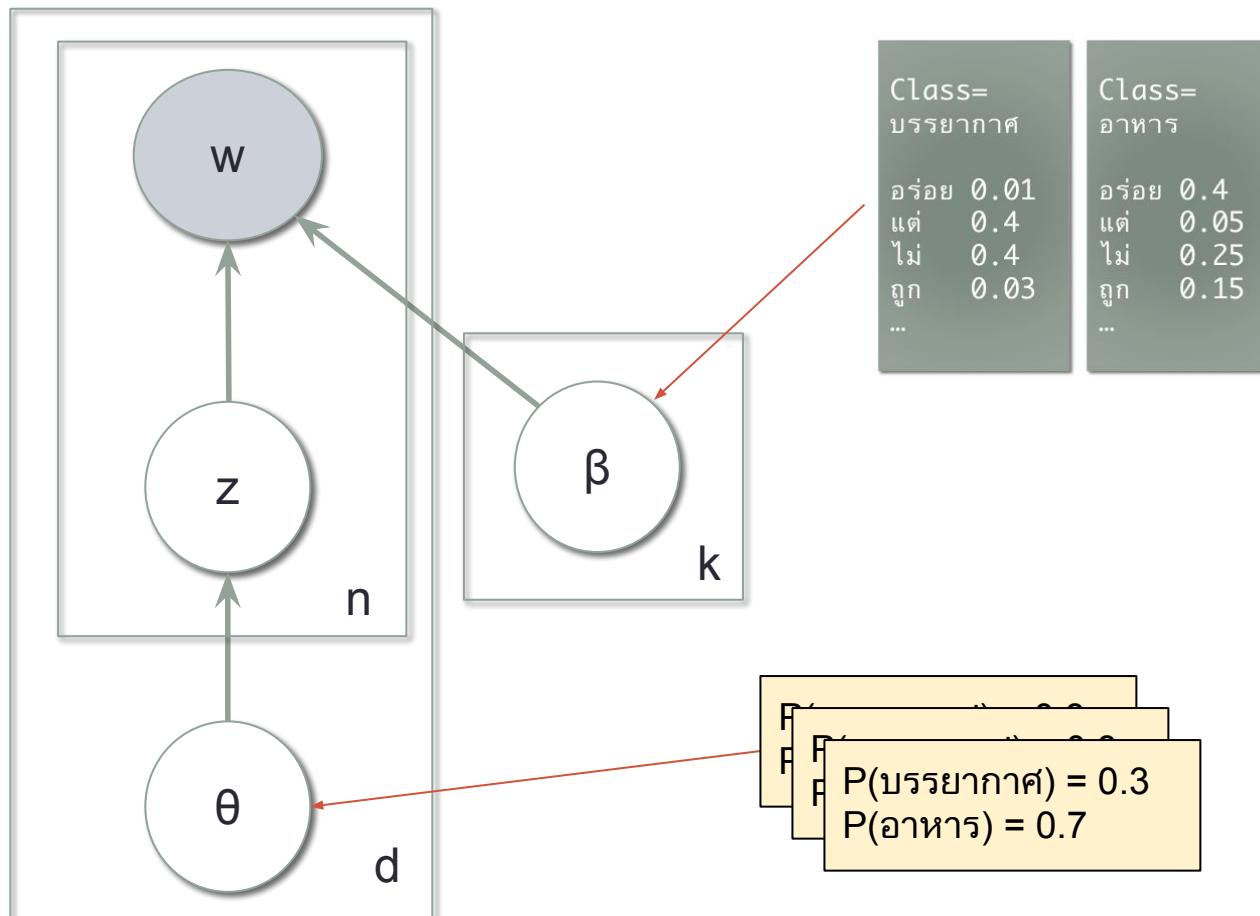
Expectation maximization (EM)

- Initialize θ, β
- Expectation step (E step) – guess latent variables from model parameters (get soft counts)
- Maximization step (M step) – re-estimate model parameters from latent variables (counts)
- Repeat E and M step until satisfied (Likelihood of the whole training set using the model does not change much)
- For more info on EM see pattern recognition lecture 6

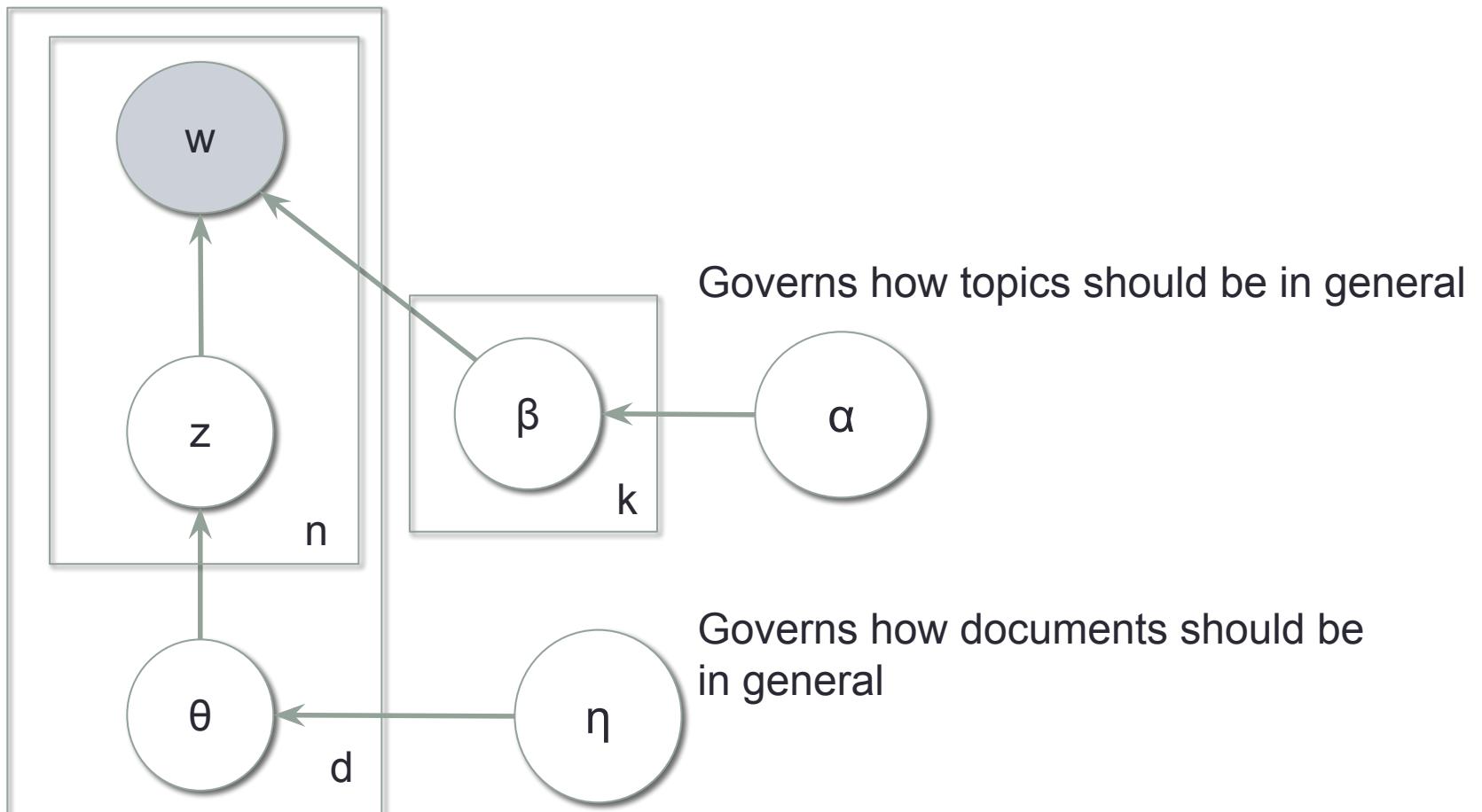
pLSA

- pLSA automatically clusters words into topic unigrams
 - Requires user to specify number of topics
- Automatically learn document representation based on the learned topics
 - $\text{DocA} = [0.7 \ 0.3]$ $\text{DocB} = [0.2 \ 0.8]$ $\text{DocC} = [0.5 \ 0.5]$
- Overfits easily to data outside of the training set
 - Nothing that ties all document together
 - A document from a document collection should be have topic distributions that are similar
- Solution: LDA (Latent Dirichlet Allocation)

pLSA



LDA



α and η

- α is a **Dirichlet distribution**
- Or a distribution of distributions...
- Example: rolling a die
- $P(x=1) = 0.3, P(x=2) = 0.1, \dots$
- This is a distribution. (**Multinomial distribution**)
- But what if I have a bag of dices, each with different distributions.
- α tells me the probability of what kind of die I will get

Dirichlet distribution

- pdf

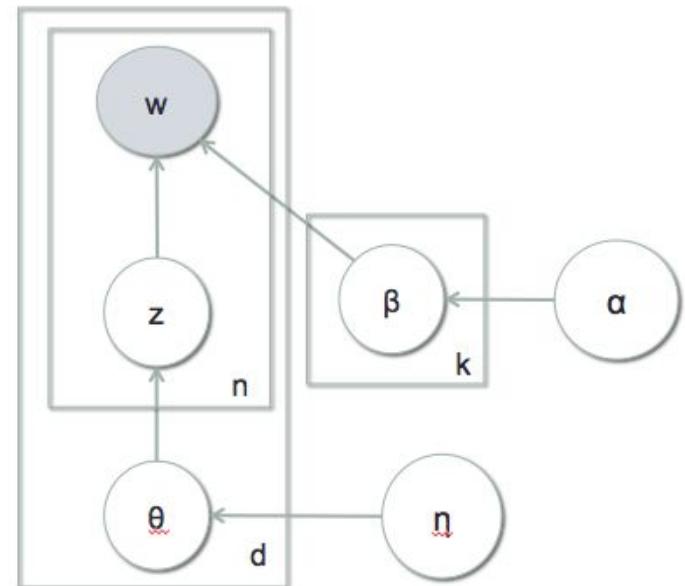
Parameters giving preference to each side of die/topic

$$f(x_1, \dots, x_K; \alpha_1, \dots, \alpha_K) = \frac{1}{B(\boldsymbol{\alpha})} \prod_{i=1}^K x_i^{\alpha_i - 1}$$

Probability of each side of die, probability of each topic

Generative process

- For each topic $k \in \{1, \dots, K\}$:
 - Draw word distributions $\beta_k \sim \text{Dir}(\eta)$
- For each document $d \in \{1, \dots, D\}$:
 - Draw topic proportions $\theta_d \sim \text{Dir}(\alpha)$
 - For each word in a document $n \in \{1, \dots, N\}$:
 - Draw a topic index $z_{dn} \sim \text{Mult}(\theta)$
 - Generate word from chosen topic
 - $w_{dn} \sim \text{Mult}(\beta_{zdn})$



Topics

gene 0.04
dna 0.02
genetic 0.01
...

life 0.02
evolve 0.01
organism 0.01
...

brain 0.04
neuron 0.02
nerve 0.01
...

data 0.02
number 0.02
computer 0.01
...

Documents

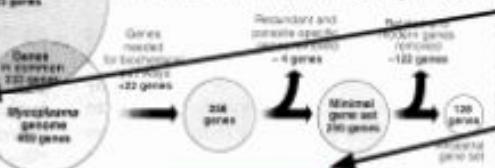
Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many genes does an organism need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for life. One research team, using computer analyses to compare known genomes, concluded that today's organisms can be sustained with just 250 genes, and that the earliest life forms required a mere 128 genes. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those predictions

* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

"are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Umeå University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a matter of numbers alone; particularly as more and more genomes are completely mapped and sequenced. "It may be a way of organizing any newly sequenced genome," explains Arcady Mushegian, a computational molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing all



Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

SCIENCE • VOL. 272 • 24 MAY 1996

Topic proportions and assignments

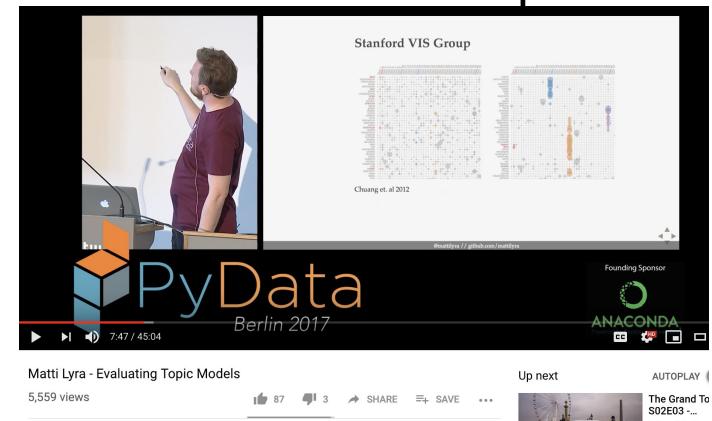


Parameter learning

- How do we actually learn these parameters and latent variables?
 - Gibbs sampling
 - Variational methods
- Totally beyond the scope of this class

LDA

- Automatically learns topics, and the word distribution of each topic
 - Just give a bunch of documents!
 - Each document is given a mixture of topics
 - Dirichlet prior prefers sparse topics – each document only have probability in few topics – easy for interpretability
- Requires user to pick number of topic
- **Requires user to make sense of the learned topics**
 - For more information on how to help visualize/evaluate unsupervised topic models
 - https://youtu.be/UkmlljRIG_M



Example usage

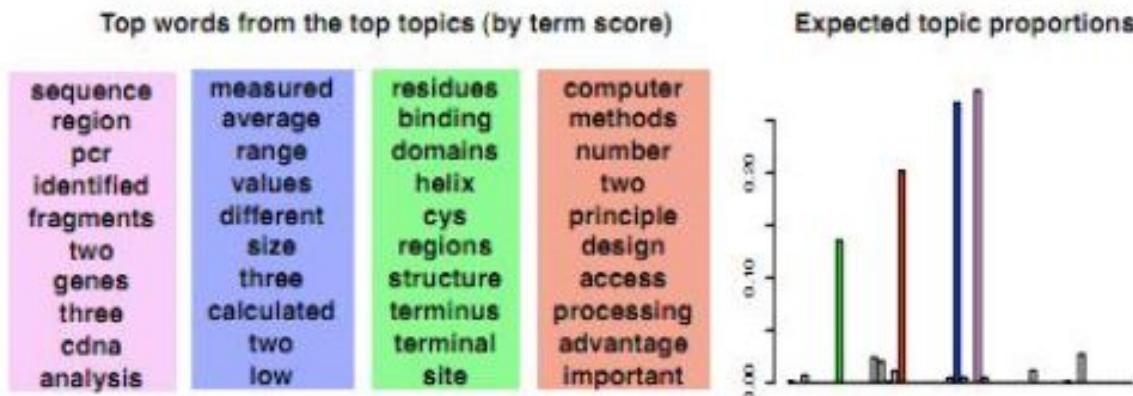
- Lots of lectures. Can we discover the topics? Can we classify the lectures? No topic labels given

Top 10 high probability nouns in word probabilities of Topics 3 ($\theta_{k=3}$), 15 ($\theta_{k=15}$), and 26 ($\theta_{k=26}$).

Topic 3 (~ classical mechanics)	Topic 15 (~astronomy)	Topic 26 (~ (time) unit)
m	Light	Percent
Energy	Degrees	Time
Force	Angle	Dollars
Mass	Frequency	Times
Point	Energy	Minutes
Velocity	Direction	Day
Direction	Waves	Bit
v	Sun	Year
Times	Star	Hour
Speed	Speed	Half

Chance and Statistical Significance in Protein and DNA Sequence Analysis

Samuel Karlin and Volker Brendel



Abstract with the most likely topic assignments

Statistical approaches help in the determination of significant configurations in protein and nucleic acid sequence data. Three recent statistical methods are discussed: (i) score-based sequence analysis that provides a means for characterizing anomalies in local sequence text and for evaluating sequence comparisons; (ii) quantile distributions of amino acid usage that reveal general compositional biases in proteins and evolutionary relations; and (iii) r-scan statistics that can be applied to the analysis of spacings of sequence markers.

Top Ten Similar Documents

- Exhaustive Matching of the Entire Protein Sequence Database
- How Big Is the Universe of Exons?
- Counting and Discounting the Universe of Exons
- Detecting Subtle Sequence Signals: A Gibbs Sampling Strategy for Multiple Alignment
- Ancient Conserved Regions in New Gene Sequences and the Protein Databases
- A Method to Identify Protein Sequences that Fold into a Known Three-Dimensional Structure
- Testing the Exon Theory of Genes: The Evidence from Protein Structure
- Predicting Coiled Coils from Protein Sequences
- Genome Sequence of the Nematode *C. elegans*: A Platform for Investigating Biology

Unsupervised topic modeling for real estate

Can we learn real estate characteristics from unstructured data?

คอนโดหุ้สไตร์ล้องกฤษ แห่งแรกในเข้า
ใหญ่ ที่ติด ถ.ธนารักษ์ มากที่สุด 1
ห้องนอน 1 ห้องน้ำ 1 ห้องนั่งเล่น
พร้อมห้องครัวแยกเป็นสัดส่วน

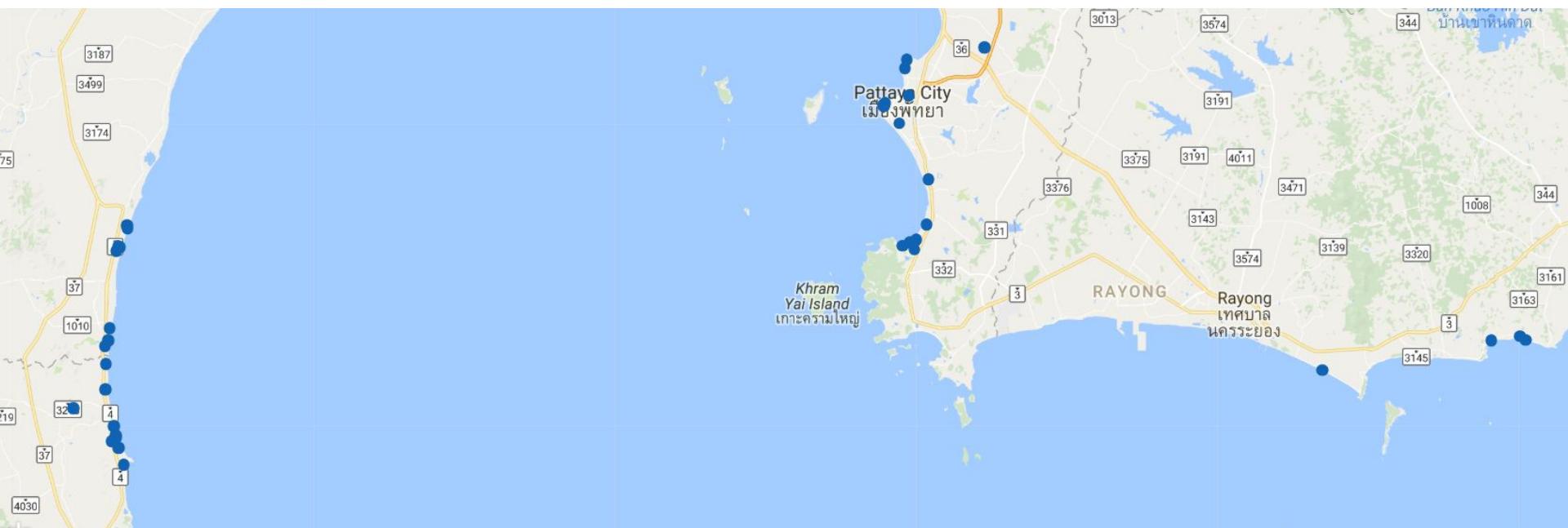
Just give it a bunch of descriptions



LDA Examples

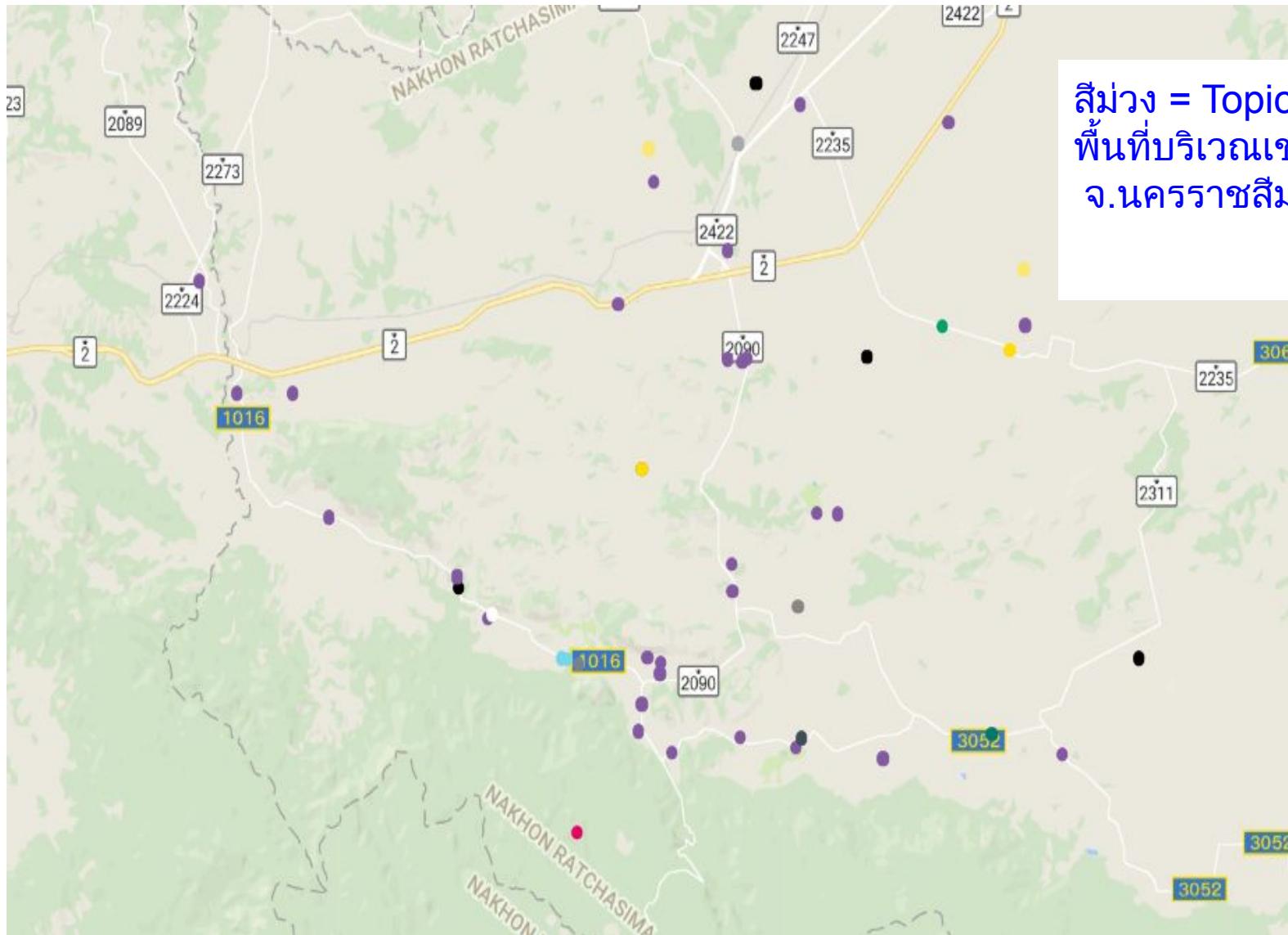
Topic 28

0.068*"วิว" + 0.058*"ทะเล" + 0.038*"คอนโด" + 0.029*"หัว" + 0.027*"คอนโดมิเนียม" + 0.025*"มองเห็น" + 0.023*"ทัศนียภาพ" + 0.022*"ชายหาด"



Topic 9

0.071*"ธรรมชาติ" + 0.031*"บรรยายกาศ" + 0.028*"ร่มรื่น" + 0.027*"บ้าน" + 0.025*"ท่ามกลาง" + 0.025*"สวน" + 0.025*"สัมผัส" + 0.021*"พื้นที่"



ลีม่วง = Topic 9
พื้นที่บริเวณเข้าใหญ่
จ.นครราชสีมา

Topic 40

0.115*"ระดับ" + 0.066*"เห็นอ" + 0.046*"หรู" + 0.031*"ทำเล" + 0.026*"ชีวิต" + 0.026*"ใช้ชีวิต" + 0.016*"สไตล์" + 0.016*"สะท้อน"

Topic 17

0.077*"พื้นที่" + 0.060*"ออกแบบ" + 0.045*"โล่ง" + 0.039*"โปร่ง" + 0.038*"ใช้สอย" + 0.020*"ประโยชน์" + 0.018*"ห้อง" + 0.017*"อาคาร"

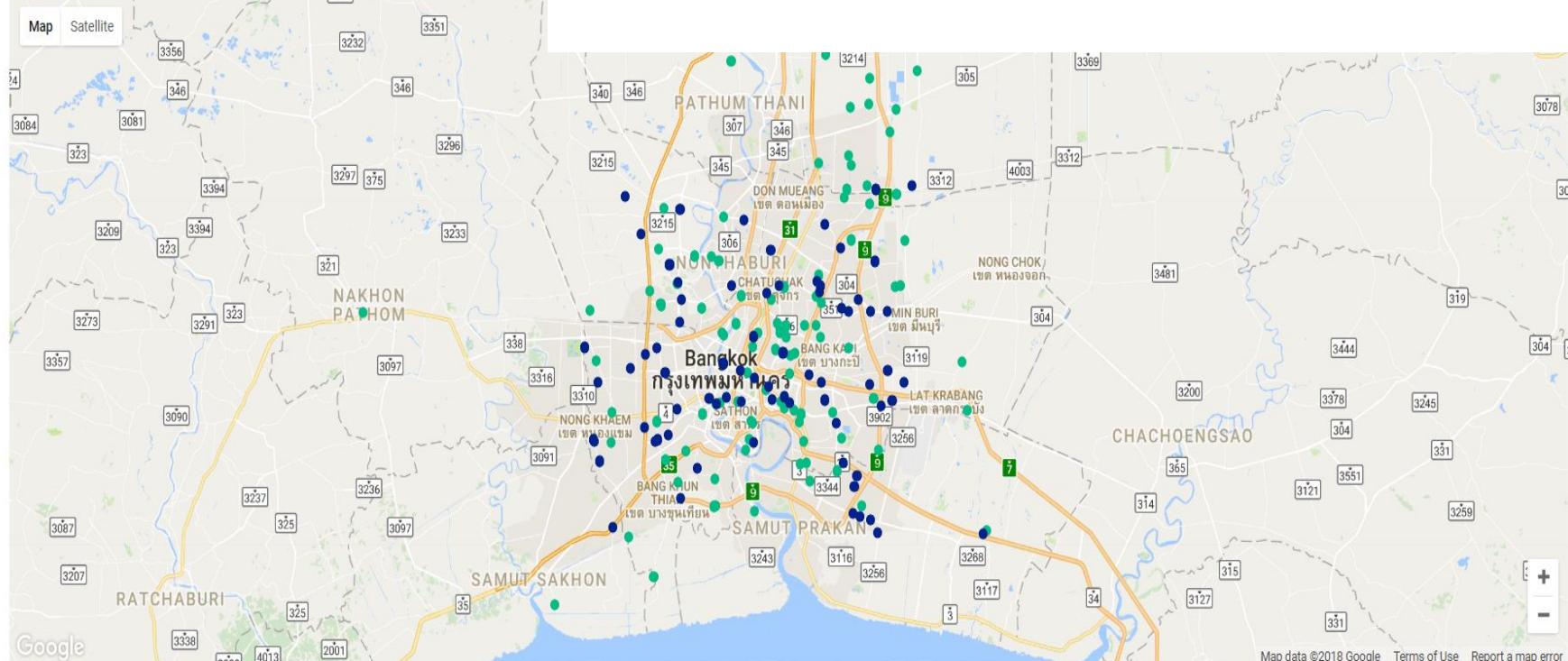


Select All Type Unselect All Type default

บ้านเดี่ยว บ้านแฝด ทาวน์เฮาส์ คอนโดมิเนียม อาคารพาณิชย์ โรงแรมพัฟฟิค ที่ดินเปล่า ทาวน์โฮม

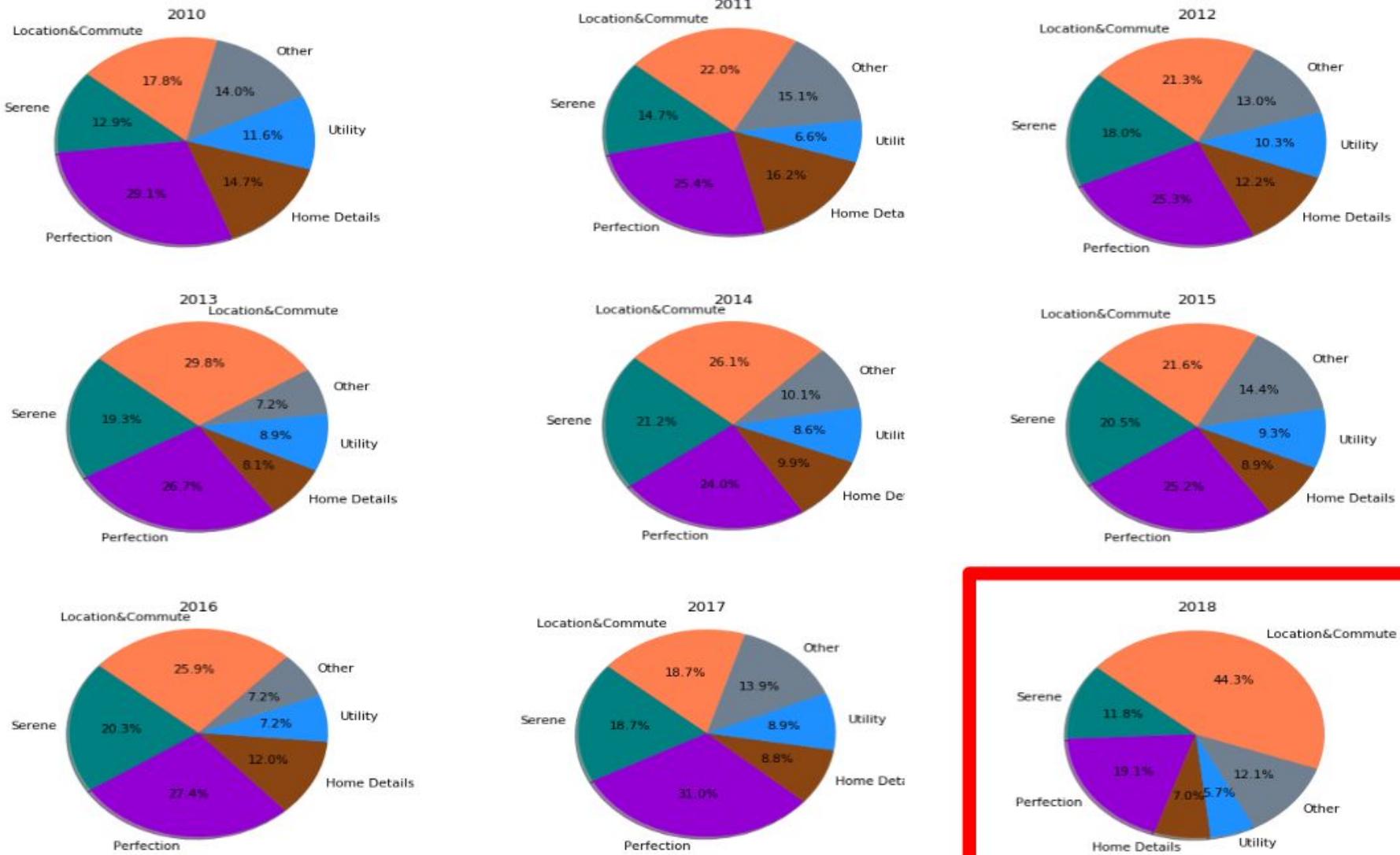
Select All Cluster Unselect All Cluster

cluster 0 cluster 1 cluster 2 cluster 3 cluster 4
 cluster 14 cluster 15 cluster 16 cluster 17 cluster 18
 cluster 27 cluster 28 cluster 29 cluster 30 cluster 31



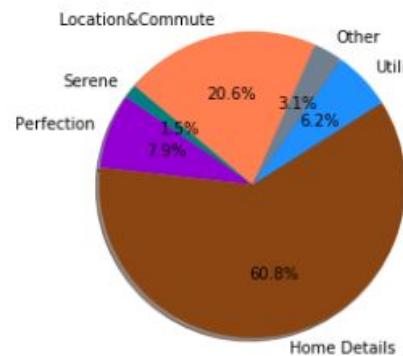
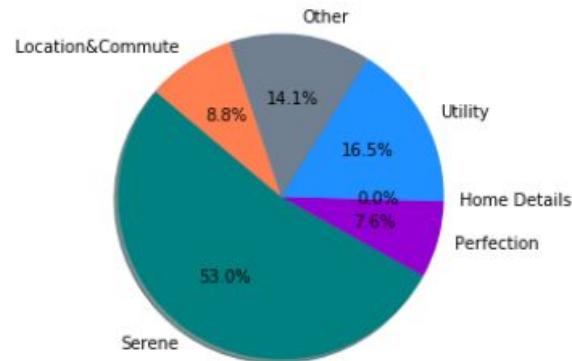
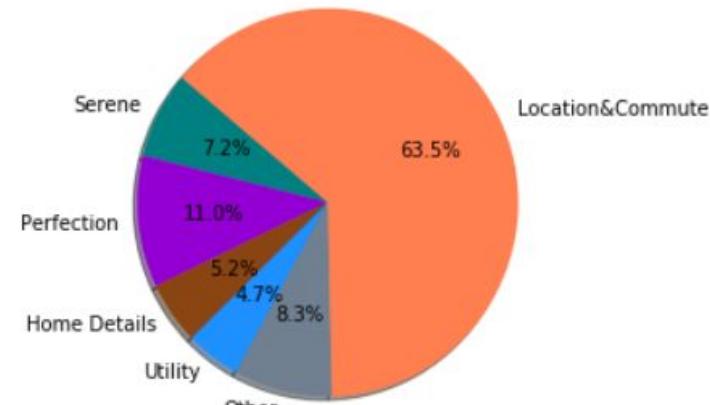
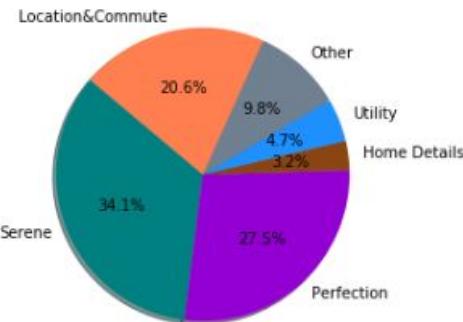
สิน้ำเงินเข้ม = โครงการที่มี Topic 40 อุดมมาก (หรู, ระดับ)
สีเขียว = โครงการที่มี Topic 17 (โครงการทั่วไป)

Time and advertising trends



Advertisement niche of each developer

Each real estate developer has its own style



More ideas

Uniting the Tribes: Using Text for Marketing Insight

Jonah Berger, Ashlee Humphreys, Stephan Ludwig, more...

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<https://doi.org/10.1177/0022242919873106>

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 Altmetric

17



Abstract

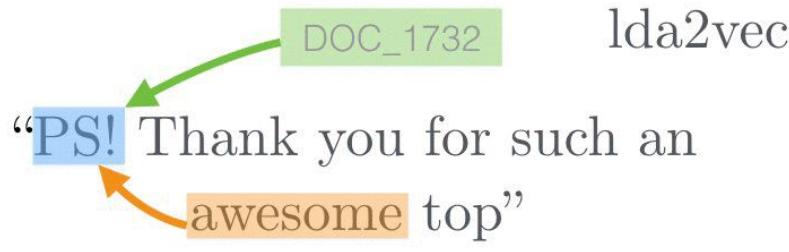
Words are part of almost every marketplace interaction. Online reviews, customer service calls, press releases, marketing communications, and other interactions create a wealth of textual data. But how can marketers best use such data? This article provides an overview of automated textual analysis and details how it can be used to generate marketing insights. The authors discuss how text reflects qualities of the text producer (and the context in which the text was produced) and impacts the audience or text recipient. Next, they discuss how text can be a powerful tool both for prediction and for understanding (i.e., insights). Then, the authors overview methodologies and metrics used in text analysis, providing a set of guidelines and procedures. Finally, they further highlight some common metrics and challenges and discuss how researchers can address issues of internal and external validity. They conclude with a discussion of potential areas for future work. Along the way, the authors note how textual analysis can unite the tribes of marketing. While most marketing problems are interdisciplinary, the field is often fragmented. By involving skills and ideas from each of the subareas of marketing, text analysis has the potential to help unite the field with a common set of tools and approaches.

LDA with deep learning

- LDA was developed on discrete inputs (words)
 - Modified to work with dense representation (word vectors)
 - “Gaussian LDA for Topic Models with Word Embeddings”
 - <http://www.aclweb.org/anthology/P15-1077>
- Modified network structure and loss function to include LDA traits
 - Use like a neural network(just like how we use crf in neural networks)
 - LDA2vec

LDA2Vec

- Word2Vec estimates words around a pivot word (local information)
- LDA estimates words from a document topic (global information)
- LDA2Vec estimates words using both information



word2vec

"PS! Thank you for such an
awesome top"



LDA2Vec

- Combines advantages from LDA and Word2Vec
 - Combine global info with local info
Word German + airline topic = Lufthansa
 - Dense word vector but sparse document vectors
Apple = [0.2 -1.2 -2.1 1.5]
 - Dense word vector but sparse document vectors
Doc1 = [80% 20% 0% 0%]
 - Mixture of topics for each document vector give interpretability for humans

sally said the fox jumped over the

Skip grams from sentences

fox

Word vector

-1.8	0.85	-0.6	-0.3	-0.5
------	------	------	------	------

Negative sampling loss

$$J_t(\theta) = \log \sigma(u_o^T v_c) + \sum_{i=1}^k \mathbb{E}_{j \sim P(w)} [\log \sigma(-u_j^T v_c)]$$

Context word

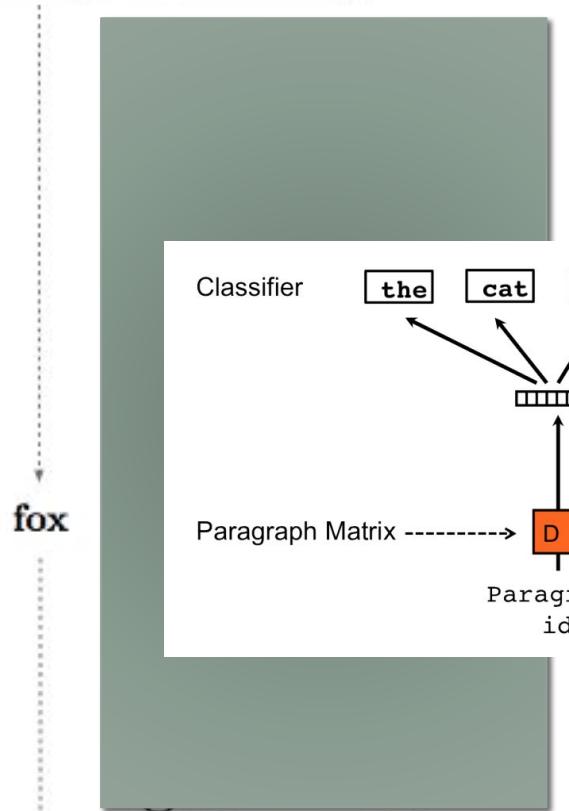
Negative samples

This is the negative sampling loss in the regular Word2vec

sally said the fox jumped over the

sally said the fox jumped over the

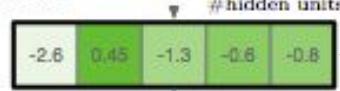
Skip grams from sentences



Word vector



Context vector



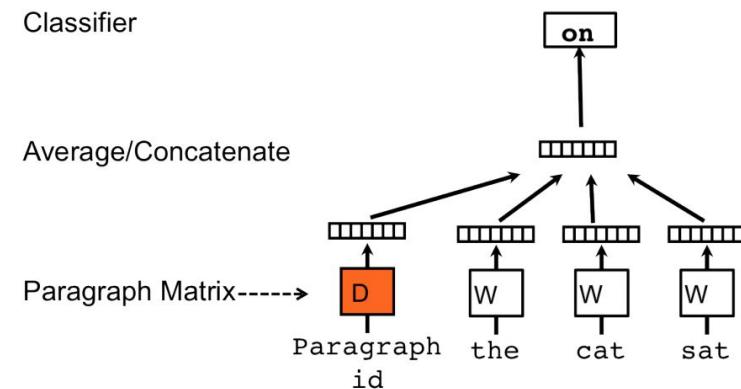
Negative sampling loss

sally said the fox **jumped** over the

Add global info by having a document vector (doc2vec)

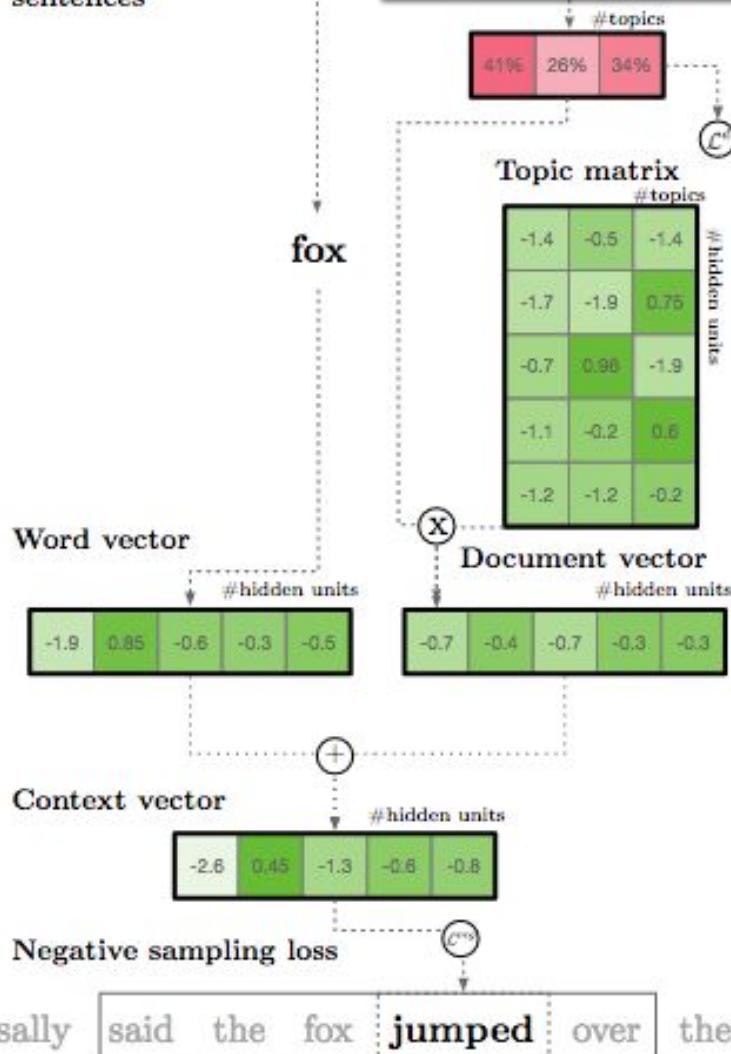
Document vector lies in the same space as word vector can add together, just like word2vec's king – queen + man

This vector (context vector) now has information more than just a single word. More on context vectors next lecture!



sally said the fox jumped over the

Skip grams from sentences



Just like how we model a topic mixture
 $p(w) = \sum p(\text{topic})p(w|\text{topic})$
We can model a document vector as
 $\sum p(\text{topic}) * \text{TopicVector}$

Topic vector lies in the same space as word vectors

Adding word vectors yields document vectors that lies in the word vector space

topic 2 = “politics” topic 1 = “religion”
Milosevic
absentee
Indonesia
Lebanese
Isrealis
Karadzic
Trinitarian
baptismal
Pentecostals
Bede
schismatics
excommunication

sally said the fox jumped over the

Skip grams from sentences

fox

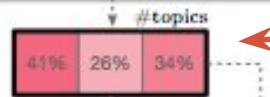
Word vector

	-1.9	0.85	-0.6	-0.3	-0.5
#hidden units					

Context vector

	-2.6	0.45	-1.3	-0.6	-0.8
#hidden units					

Negative sampling loss



This construction give explicit meaning to document vectors (valid probabilities)

Instead of a bunch of numbers

However, we further prefer sparse topic probabilities for even better interpretability

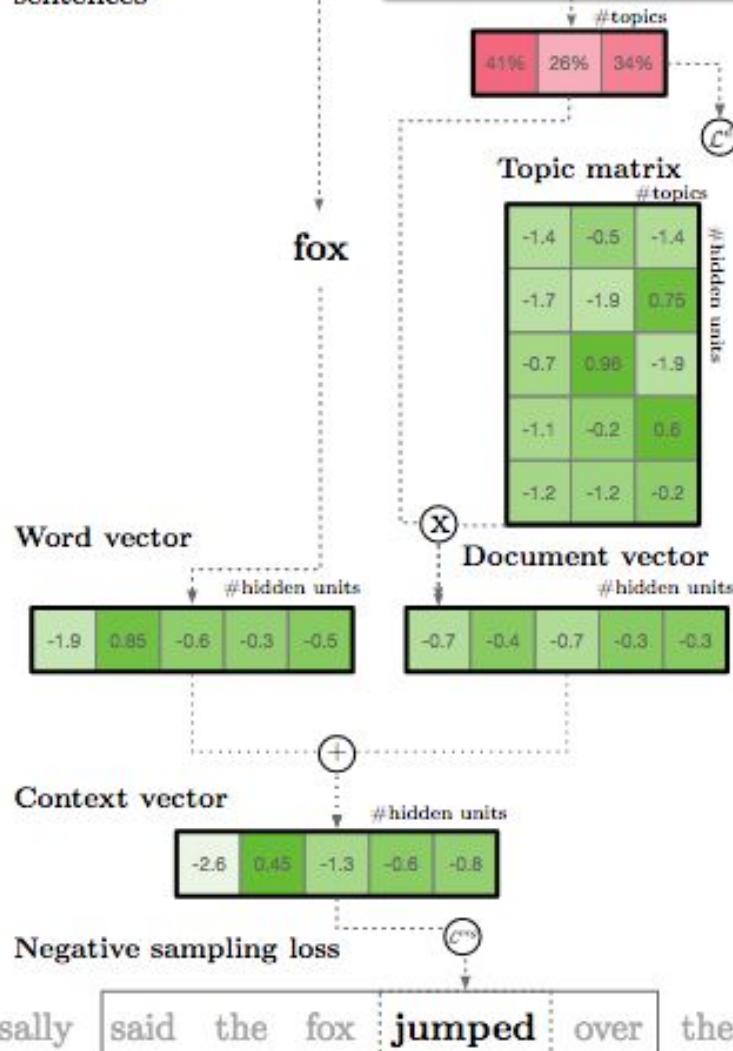
sally said the fox **jumped** over the

sally said the fox jumped over the

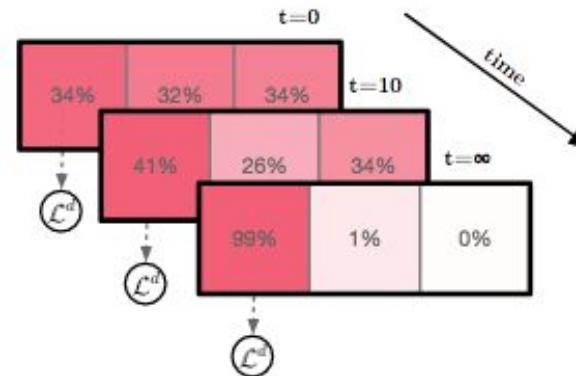
Skip grams from sentences



Add a loss term to include the Dirichlet loss which prefers sparse topics



Mixture prob becomes spares as training evolves



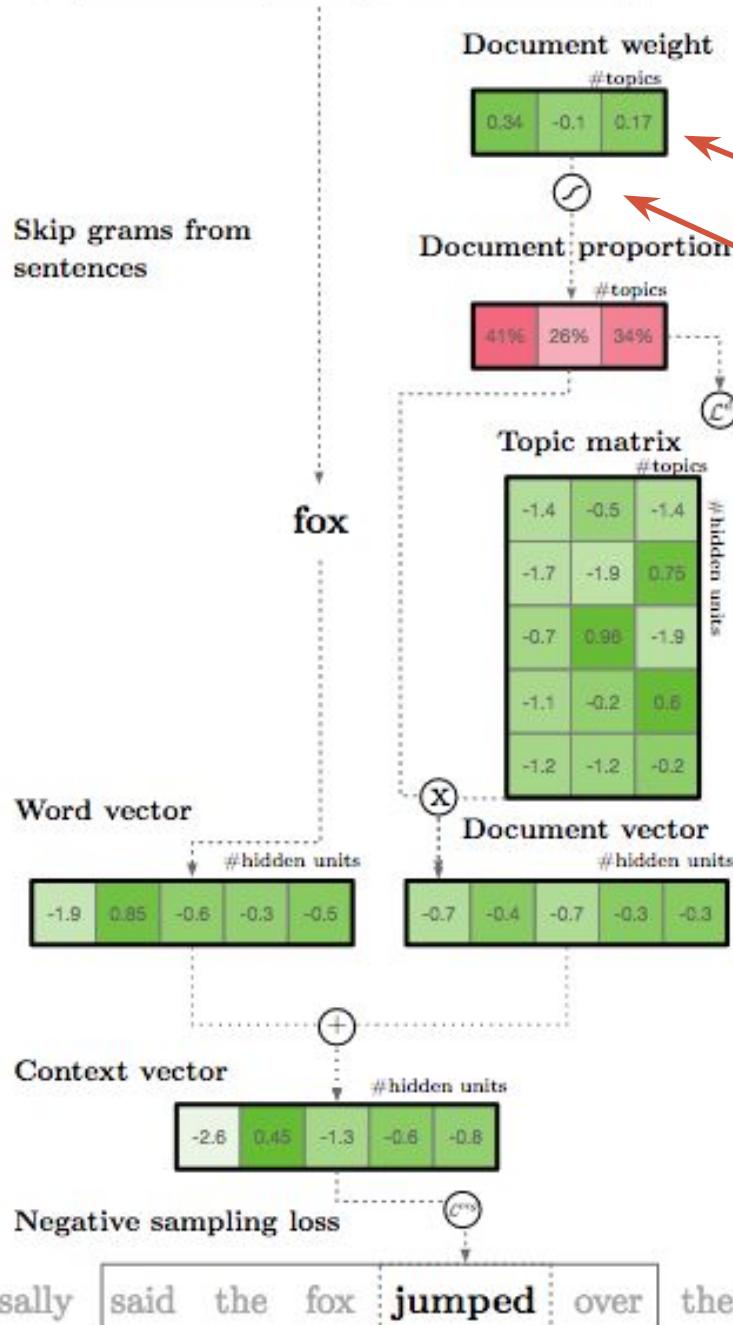
Sparse document proportions

$$\mathcal{L}^d = \lambda \sum_{jk} (\alpha - 1) \log p_{jk}$$
$$\alpha = n^{-1}$$

n is number of topics

This loss prefers a couple of high value p

sally said the fox jumped over the



To ensure the topics proportion is a prob,
Document weight is initialized and learned

The weight is transformed to prob using
a softmax

Overall loss function

- Loss from skip-gram and Dirichlet

Dirichlet loss

$$\mathcal{L} = \sum_{\text{word pairs } (i,j)} [\sigma(\vec{c}_j \cdot \vec{w}_i) + \sigma(-\vec{c}_j \cdot \vec{w}_{\text{negative}})] + \sum_{\text{documents } k} \log q(d_k | \alpha)$$

Skip-gram loss

$$\vec{c}_j = \vec{w}_j + \vec{d}_j$$

Context = word + document vector

$$\vec{d}_j = a_{j0} \cdot \vec{t}_0 + a_{j1} \cdot \vec{t}_1 + \dots$$

Document vector is mixture of topics

$$q(d_k | \alpha) = \sum_k (\alpha_k - 1) \log \alpha_k$$

Dirichlet likelihood term

LDA2Vec example

Selected Topic: 38

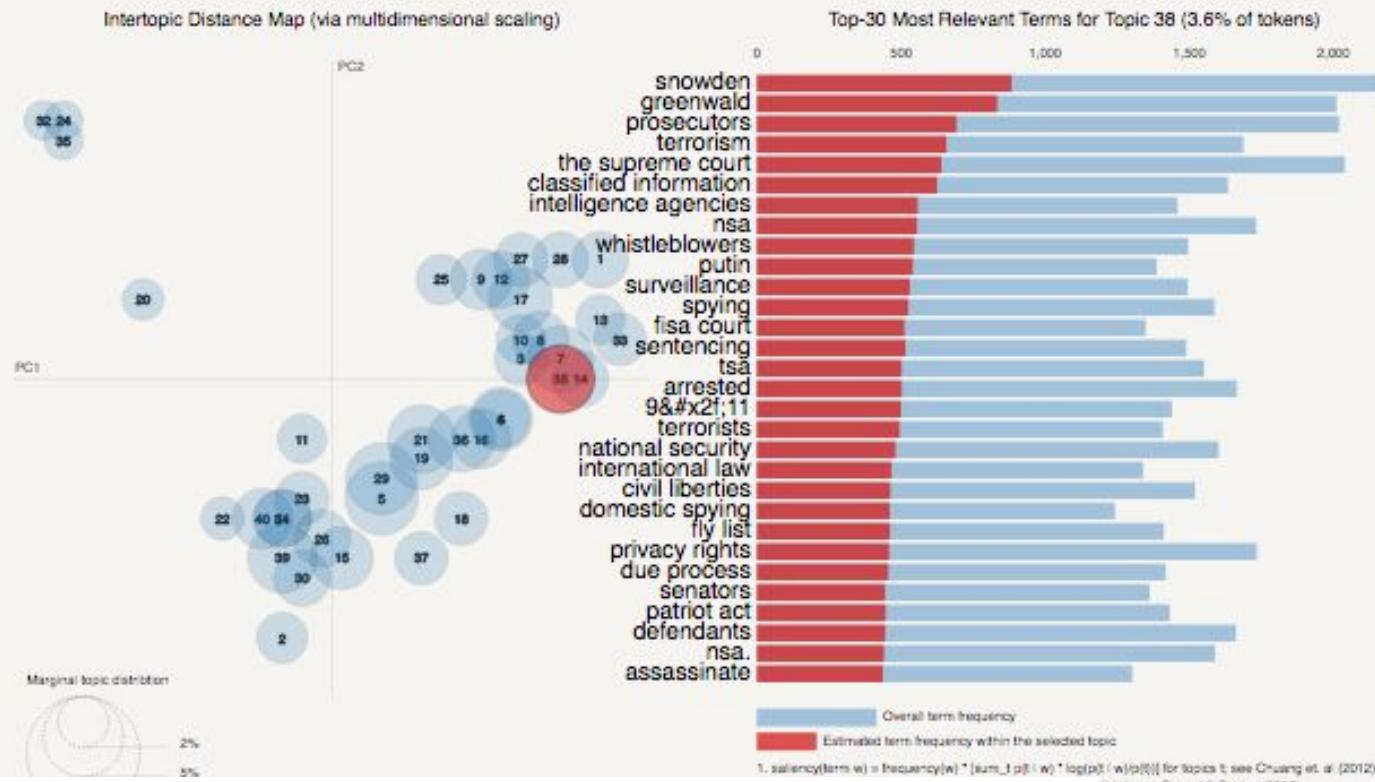
Previous Topic

Next Topic

Clear Topic

Slide to adjust relevance metric:(2)

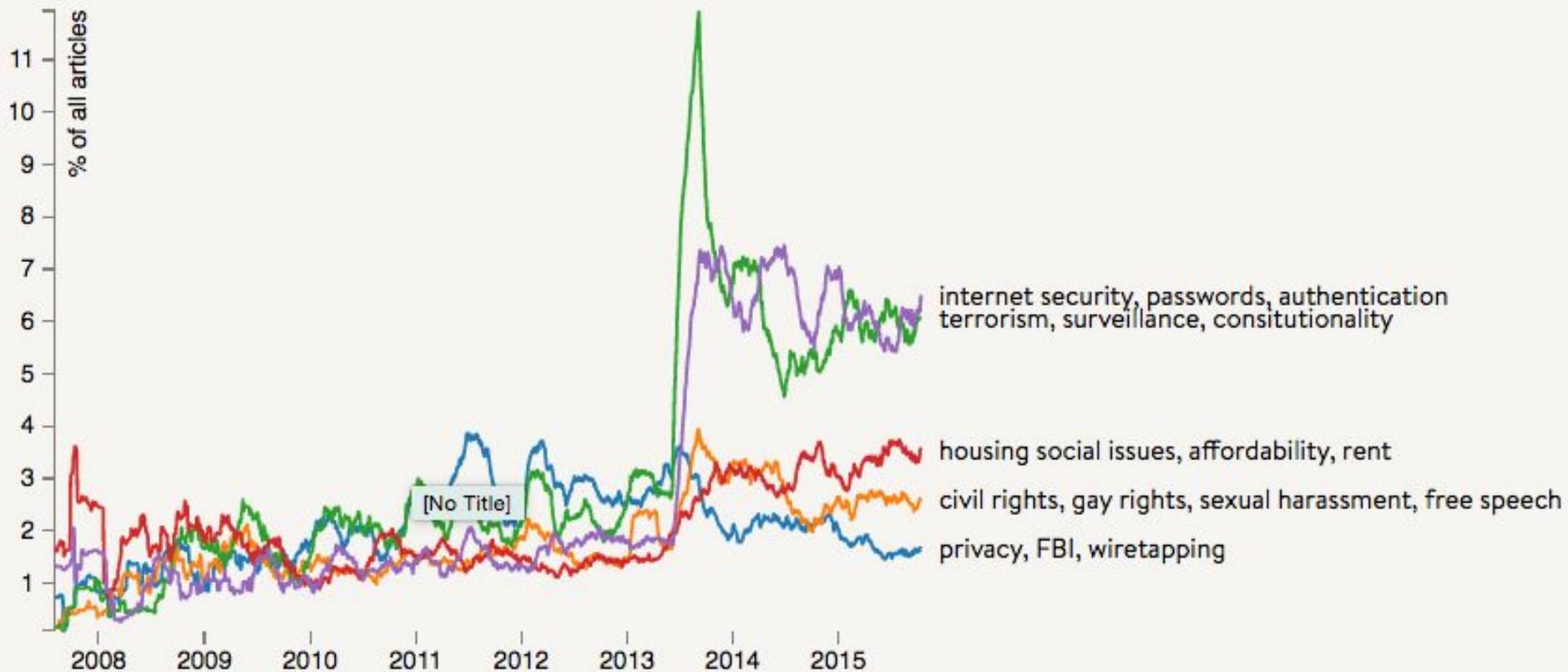
$\lambda = 1$



LDA2Vec example



Politics trend



LDA2Vec as a classification model

- Maybe not...
 - Model that offers human interpretability usually is worse
- But it's great for
 - Extract insights from trends by visualizations
 - Completely unsupervised model
 - Except for the need to specify number of topics and look through each topic words to determine the topic label
- This model gives a good example of
 - The design decisions for model building can be complex but logically motivated
 - Combining loss functions to get the desired behavior

Summary

- Text classification task
 - Bag of words model
 - Naïve Bayes
 - Topic Models
 - Latent topic models (LDA)
 - LDA2vec

- Context vectors
 - More next time

