9. Unsupervised Techniques III: Topic Models (flipped)

DS-GA 1015, Text as Data
Arthur Spirling

April 6, 2021

Housekeeping

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1 HW2 graded, back soon. HW3 on the way.

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2 Guide to final paper now in <Resources> folder.

Housekeeping

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2. Guide to final paper now in <Resources> folder.
3. No lecture/flipped session next week: will use lecture time (Tues, 11am-1250pm) as office hours.

Recap

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What is a topic, literally?

Recap

What is a topic, literally?

What is a topic, substantively?

Recap

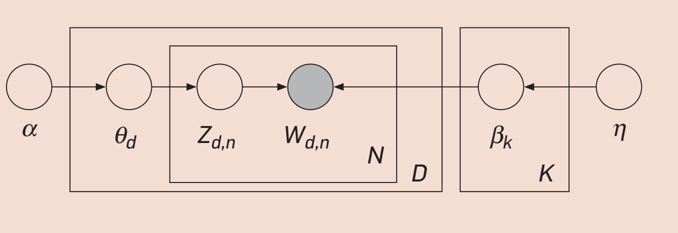
What is a topic, literally?

What is a topic, substantively?

What is a topic model for?

Plate Diagram for LDA

Plate Diagram for LDA



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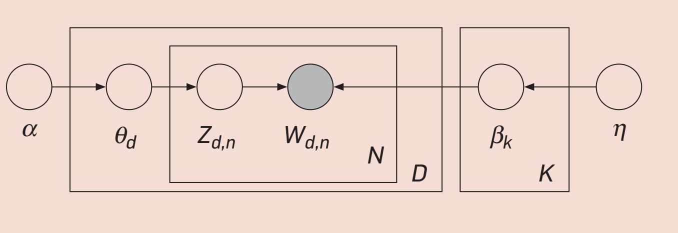

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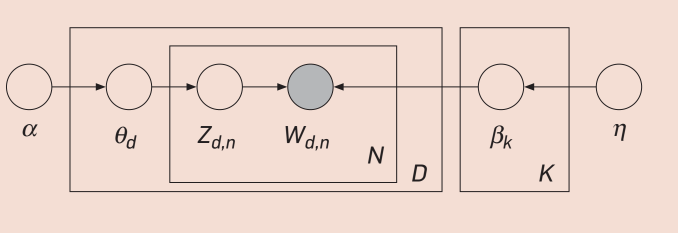

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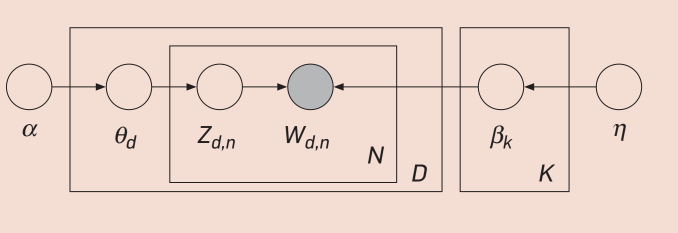

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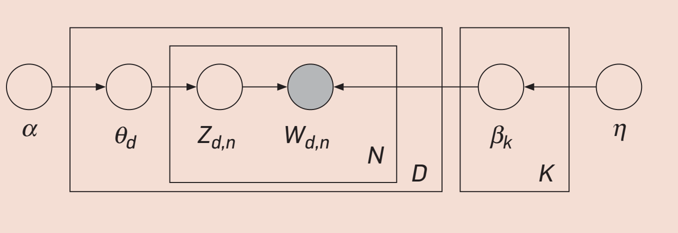

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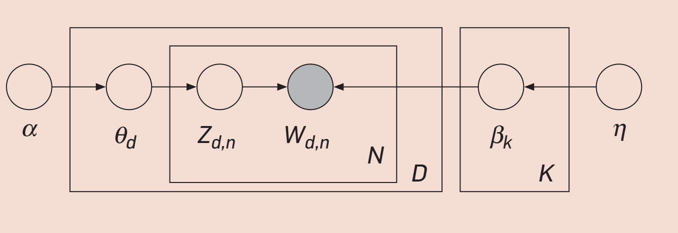

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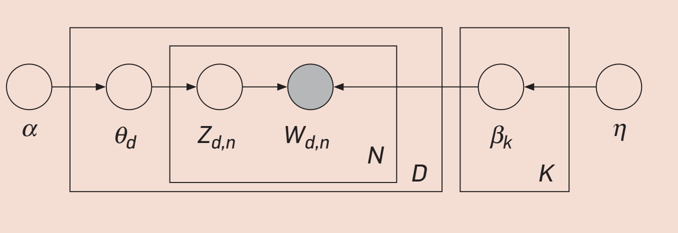

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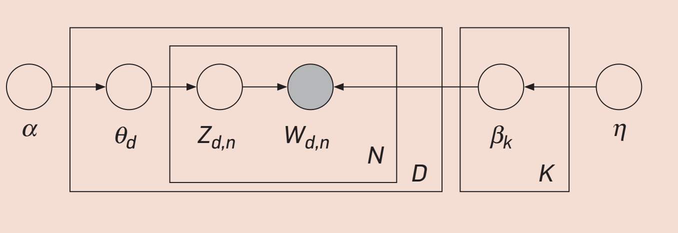

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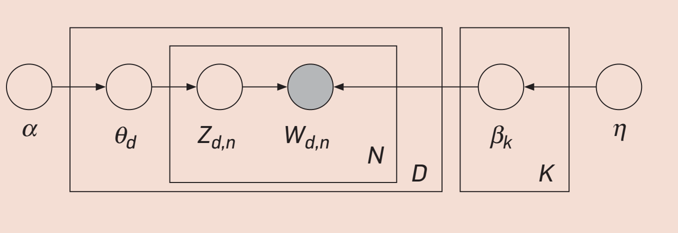

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What is z? θ? β?

$\rightarrow$ z is specific topic for this word in this document; θ is distribution over topics for this document; β is distribution over words (for this topic)

LDA...

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There are D documents in the corpus. There are V terms in these D documents. For now suppose we know the K topic distributions: there are K multinomials containing V elements each.

The multinomial distribution for the ith topic is denoted β_i, and $|\beta_i| = V$, meaning that the 'size' of this multinomial is equal to the number of different words in the corpus.

So, a little more formally...

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For each document. . .

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    2. Probabilistically draw one of the V words from β_j

Aside: Dirichlet distribution

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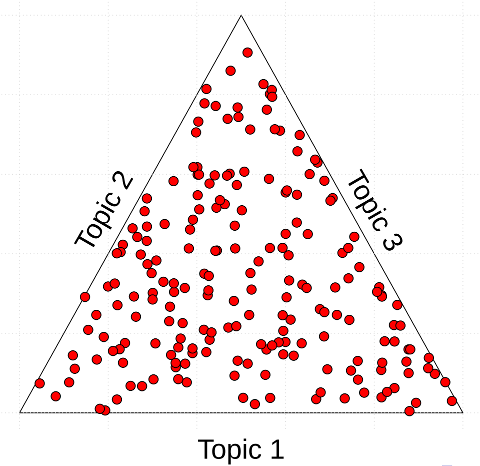
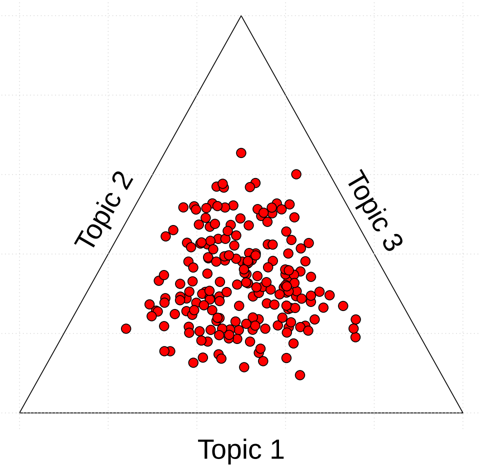
In terms of θ... larger values of α (assuming we are in symmetric case) mean we think (*a priori*) that documents are generally an even mix of the topics. If α is small (less than 1) we think a given document is generally from one or a few topics.

Example of Dirichlet

200 documents, 3 topics, $\alpha = 1$
(uniform)

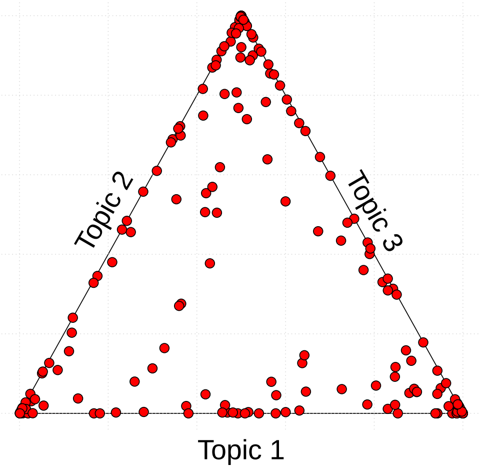


200 documents, 3 topics, $\alpha = 5$



Example of Dirichlet

200 documents, 3 topics, $\alpha = 0.2$



Exercise

Would you pick a high, low or uniform (i.e. $= 1$) α prior for the following:

1. State of the Union addresses
2. Sports news bulletins (e.g. headline summaries of results)
3. Tweets from `@NYUDataScience`
4. News stories from NYT

Answers?

Would you pick a high, low or uniform (i.e. $= 1$) α prior for the following:

1. State of the Union addresses

A larger than one– multiple topics covered

2. Sports news bulletins (e.g. headline summaries of results)

A lower than 1–mostly about one sport or other

3. Tweets from `@NYUDataScience`

A lower than 1–typically each document is about one topic

4. News stories from NYT

A symmetric–some stories talk about one thing, some touch on multiple issues

Varying Dirichlet prior for β

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Vocab: `essentially`, `tricks`, `fishing`, `charter`, `mainland`, `good`

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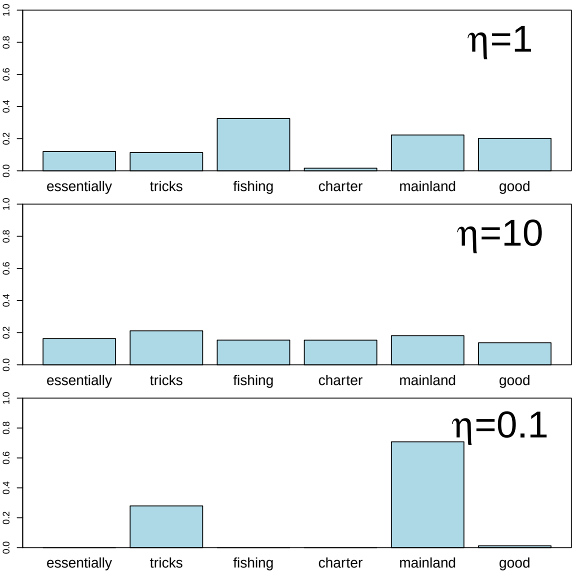

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For a user-selected k, a typical implementation of LDA will return...

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The word distribution for each topic.

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Results

For a user-selected k, a typical implementation of LDA will return...

The word distribution for each topic. (estimated βs)
The topic distribution for each document. (estimated θs)

Some implementations allow you to estimate e.g. α, in which case this is also returned. And perhaps some kind of fit statistic(s).

A Manifesto Example

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69 UK manifestos.

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The (some selected) word distributions for each topic. Sum down the columns is one.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
conservative	0.00188	0.00088	0.00185	0.00221	0.00168
party	0.00145	0.00067	0.00066	0.00577	0.00093
general	0.00073	0.00033	0.00018	0.00192	0.00040
election	0.00079	0.00053	0.00022	0.00235	0.00076
manifesto	0.00059	0.00078	0.00032	0.00099	0.00048
⋮	⋮	⋮	⋮	⋮	⋮

Continued. . .

Continued...

'Top' 6 most frequent words in each topic:

Continued...

'Top' 6 most frequent words in each topic: might help interpretation (!)

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
1	people	new	[markup]	new	must
2	local	government	people	labour	government
3	government	people	new	government	labour
4	new	continue	work	people	shall
5	tax	can	[markup]	shall	can
6	liberal	conservative	support	britain	policy

Continued...

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Meaningless 'junk' topics not unusual: debate as to whether one has to interpret every topic.

Exercise

This is the output for four topics (of a 100 topic model) produced for a sample of the Associated Press corpus (1988–1990).

Name/describe the topics.

New	Million	Children	School
Film	Program	Women	Students
Show	Tax	People	Schools
Music	Budget	Child	Education
Movie	Billion	Years	Teachers
Play	Federal	Families	High
Musical	Year	Work	Public
Best	Spending	Parent	Teacher
Actor	New	Says	Bennett
First	State	Family	Manigat
York	Plan	Welfare	Namphy
Opera	Money	Men	State
Theater	Programs	Percent	President
Actress	Government	Care	Elementary
Love	Congress	Life	Haiti

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"ARTS"	"BUDGET"	"CHILDREN"	"EDUCATION"
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In computer science, keep fitting until perplexity suggests otherwise.

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Q What does perplexity measure? (intuitively)

Ballpark k from Mimno & Blei, 2011

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Table 1: Statistics for models used as examples.

Name	Docs	Tokens	Vocab	Topics
News	1.8M	76M	121k	1000
Blogs	13k	2.2M	90k	100
Parliament	540k	55M	52k	300

Example: an "education" topic

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for $k = 5$

local
people
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education
ensure
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new
liberal
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for $k = 100$

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Q What is $p(\mathbf{z}|\mathbf{x})$, in terms of our topic model (intuitively)?

Variational Inference: the problem

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$$p(\mathbf{z}|\mathbf{x}) = \frac{p(\mathbf{z}, \mathbf{x})}{p(\mathbf{x})}$$

the denominator requires calculating $p(\mathbf{x}) = \int p(\mathbf{z}, \mathbf{x}) dz$.

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Q How and why does this differ to e.g. naive Bayes classification?

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3. Find an approximating distribution $q(\mathbf{z}) \approx p(\mathbf{z}|\mathbf{x})$. Iteratively improve the closeness between $q(\mathbf{z})$ and $p(\mathbf{z}|\mathbf{x})$. This is variational inference.

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A MCMC is guaranteed to get to the conditional you want. But much more slowly. So, use VI for larger data sets where we don't care as much about precision in the posteriors: e.g. topic modeling.

Evaluating Topic Models

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A From perspective of extrinsic evaluation,

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Basic idea: ask humans to evaluate different topic models in terms of coherence and relevance.

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→ "Traditional metrics are, indeed, *negatively* correlated with the measures of topic quality developed in this paper."

Topic Intrusion Example

6 / 10

DOUGLAS_HOFSTADTER

Douglas Richard Hofstadter (born February 15, 1945 in New York, New York) is an American academic whose research focuses on consciousness, thinking and creativity. He is best known for ", first published in

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student	school	study	education	research	university	science	learn
human	life	scientific	science	scientist	experiment	work	idea
play	role	good	actor	star	career	show	performance
write	work	book	publish	life	friend	influence	father