

Latent Dirichlet Allocation: Mixed Membership Modeling

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Mixed membership models for documents

So far, clustered articles into groups



Doc labeled
with a topic
assignment

Clustering goal: discover groups of related docs

Are documents about just one thing?



Is this article
just about
science?



Soft assignments capture uncertainty



Soft assignment r_{ik} tells us this doc could be about [world news](#) **or** [science](#)

But, clustering model still specifies each doc belongs to **1 topic**

Modeling the Complex Dynamics and Changing Correlations of Epileptic Events

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Abstract

Patients with epilepsy can manifest short, sub-clinical epileptic “bursts” in addition to full-blown clinical seizures. We believe the relationship between these two classes of events—something not previously studied quantitatively—could yield important insights into the nature and intrinsic dynamics of seizures. A goal of our work is to parse these complex epileptic events into distinct dynamic regimes. A challenge posed by the intracranial EEG (iEEG) data we study is the fact that the number and placement of electrodes can vary between patients. We develop a Bayesian nonparametric Markov switching process that allows for (i) shared dynamic regimes between a variable number of channels, (ii) asynchronous regime-switching, and (iii) an unknown dictionary of dynamic regimes. We encode a sparse and changing set of dependencies between the channels using a Markov-switching Gaussian graphical model for the innovations process driving the channel dynamics and demonstrate the importance of this model in parsing and out-of-sample predictions of iEEG data. We show that our model produces intuitive state assignments that can help automate clinical analysis of seizures and enable the comparison of sub-clinical bursts and full clinical seizures.

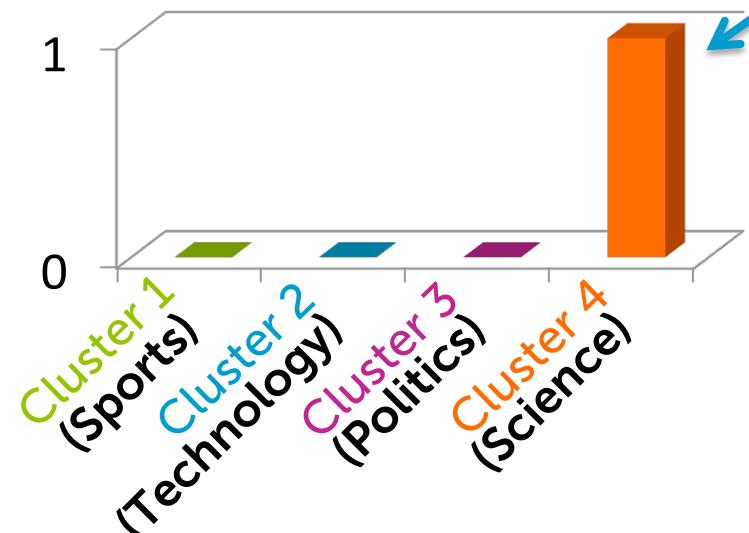
Keywords: Bayesian nonparametric, EEG, factorial hidden Markov model, graphical model, time series

1. Introduction

Despite over three decades of research, we still have very little idea of what defines a seizure. This ignorance stems both from the complexity of epilepsy as a disease and a paucity of quantitative tools that are flexible

Encoding of cluster membership $z_i = 4$

Based on science related words, maybe doc in cluster 4



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Soft assignments capture uncertainty in $z_i = 2$ or 4

graphical model for the innovations process driving the channel dynamics and demonstrate the importance of this model in parsing and out-of-sample predictions of iEEG data. We show that our model produces intuitive state assignments that can help automate clinical analysis of seizures and enable the comparison of sub-clinical bursts and full clinical seizures.

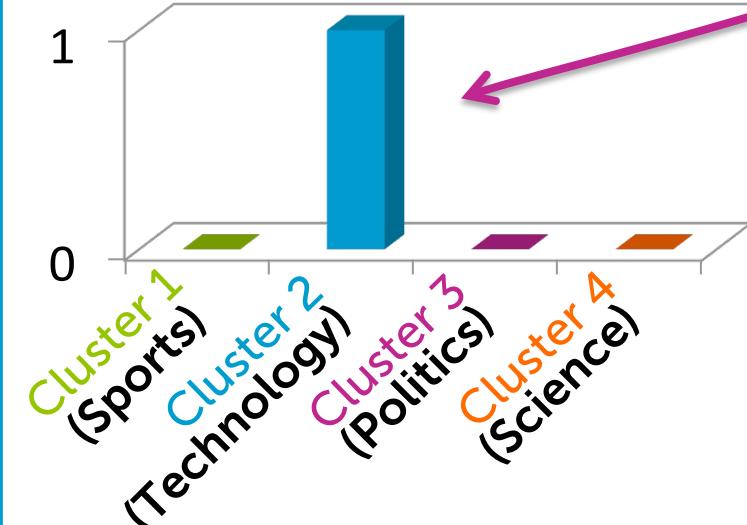
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Encoding of cluster membership $z_i = 2$

Or maybe cluster 2 (technology) is a better fit



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“ z_i ” is both 2 and 4

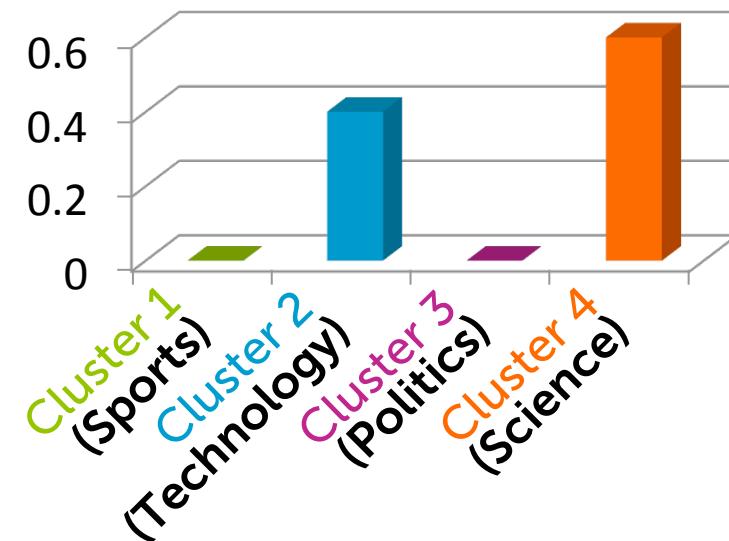
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Really, it's about science
and technology



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Mixed membership models

Want to discover a set of memberships

(In contrast, cluster models aim at discovering a single membership)

Building up to document mixed membership models

An alternative document clustering model



(Back to clustering,
not mixed
membership
modeling)



So far, we have considered...

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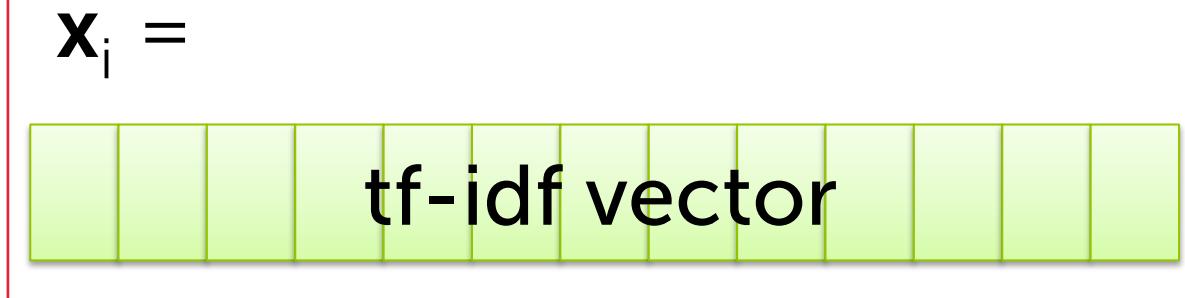
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Bag-of-words representation

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Bayesian

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$\mathbf{x}_i = \{\text{modeling, complex, epilepsy, modeling, Bayesian, clinical, epilepsy, EEG, data, dynamic...}\}$

multiset

= unordered set of words with
duplication of unique elements
mattering

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A model for bag-of-words representation

As before, the “prior” probability that **doc i** is from **topic k** is:

$$p(z_i = k) = \pi_k$$

$\pi = [\pi_1 \ \pi_2 \dots \ \pi_K]$
represents corpus-wide topic prevalence

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A model for bag-of-words representation

Assuming doc i is from topic k , words occur with probabilities:

SCIENCE	
patients	0.05
clinical	0.01
epilepsy	0.002
seizures	0.0015
EEG	0.001
...	...

words in vocab

Topic-specific word probabilities

Distribution on words in vocab for **each topic**

SCIENCE	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TECH	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

SPORTS	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

...

(table now organized by decreasing probabilities
showing top words in each category)

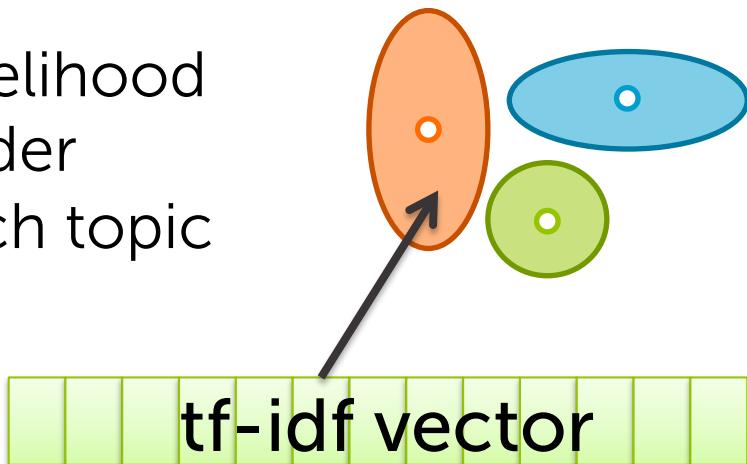
Comparing and contrasting

Previously

Prior topic probabilities

$$p(z_i = k) = \pi_k$$

Likelihood under each topic



compute likelihood of **tf-idf** vector under each **Gaussian**

Now

$$p(z_i = k) = \pi_k$$

SCIENCE	TECH	SPORTS
experiment 0.1	develop 0.18	player 0.15
test 0.08	computer 0.09	score 0.07
discover 0.05	processor 0.032	team 0.06
hypothesize 0.03	user 0.027	goal 0.03
climate 0.01	internet 0.02	injury 0.01
...

...

{modeling, complex, epilepsy,
modeling, Bayesian, clinical,
epilepsy, EEG, data, dynamic...}

compute likelihood of the
collection of words in doc
under each **topic distribution**

Latent Dirichlet allocation (LDA)

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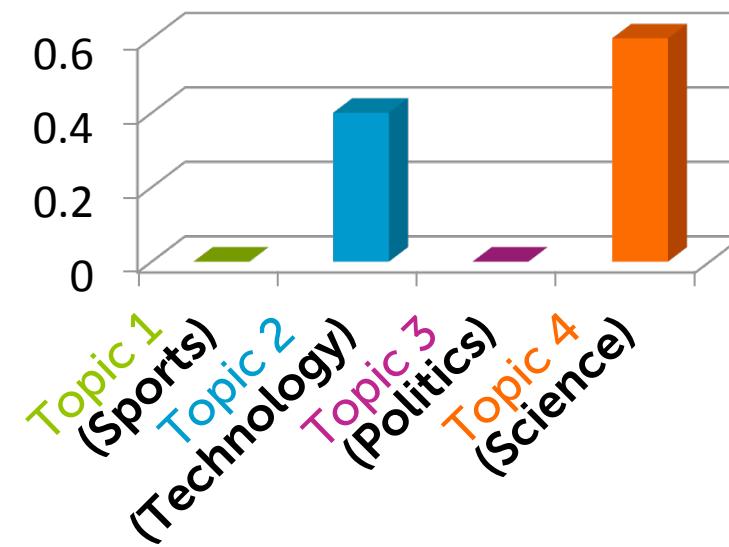
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LDA is a mixed membership model

Want to discover a set of topics



Topic vocab distributions:

SCIENCE	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TECH	
develop	0.18
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Clustering:

One topic indicator
 z_i per document i

All words come from
(get scored under)
same topic z_i

Distribution on
prevalence of
topics in corpus

$$\pi = [\pi_1 \ \pi_2 \ \dots \ \pi_K]$$

Same topic distributions:

SCIENCE	
experiment	0.1
test	0.08
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...	...

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In LDA:

One topic indicator
 z_{iw} per word in doc i

Each word gets scored under its topic z_{iw}

Distribution on prevalence of topics in document

$$\pi_i = [\pi_{i1} \ \pi_{i2} \ \dots \ \pi_{iK}]$$

Topic vocab distributions:

SCIENCE	
experiment	0.1
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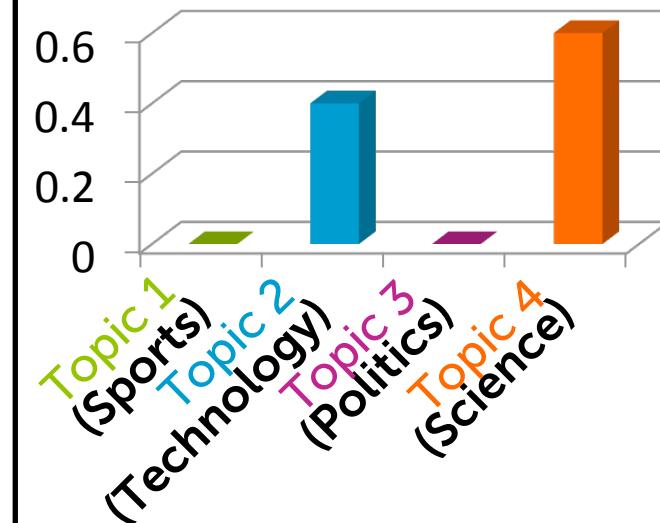
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Document topic proportions:

$$\pi_i = [\pi_{i1} \ \pi_{i2} \dots \ \pi_{iK}]$$



Inference in LDA models

Topic vocab distributions:

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test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

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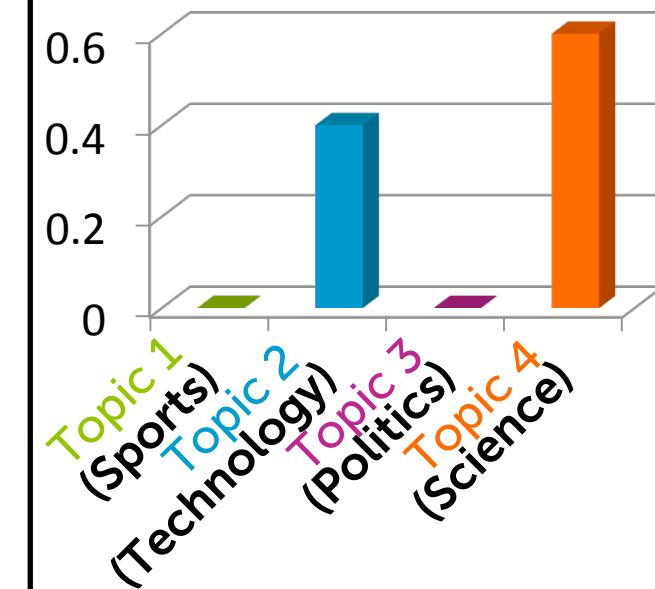
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Topic vocab distributions:

TOPIC 1	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 2	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 3	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

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Patients with epilepsy can manifest short, sub-clinical epileptic “bursts” in addition to full-blown clinical seizures. We believe the relationship between these two classes of events—something not previously studied quantitatively—could yield important insights into the nature and intrinsic dynamics of seizures. A goal of our work is to parse these complex epileptic events into distinct dynamic regimes. A challenge posed by the intracranial EEG (iEEG) data we study is the fact that the number and placement of electrodes can vary between patients. We develop a Bayesian nonparametric Markov switching process that allows for (i) shared dynamic regimes between a variable number of channels, (ii) asynchronous regime-switching, and (iii) an unknown dictionary of dynamic regimes. We encode a sparse and changing set of dependencies between the channels using a Markov-switching Gaussian graphical model for the innovations process driving the channel dynamics and demonstrate the importance of this model in parsing and out-of-sample predictions of iEEG data. We show that our model produces intuitive state assignments that can help automate clinical analysis of seizures and enable the comparison of sub-clinical bursts and full clinical seizures.

Keywords: Bayesian nonparametric EEG, factorial hidden Markov model, graphical model, time series

1. Introduction

Despite over three decades of research, we still have very little idea of what defines a seizure. This ignorance stems both from the complexity of epilepsy as a disease and a paucity of quantitative tools that are flexible

Document topic proportions:

$$\pi_i = [\pi_{i1} \ \pi_{i2} \dots \ \pi_{iK}]$$



Topic vocab distributions:

TOPIC 1	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 2	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 3	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

Modeling the Complex Dynamics and Changing Correlations of Epileptic Events

Drausin F. Wulsin^a, Emily B. Fox^c, Brian Litt^{a,b}

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^bDepartment of Neurology, University of Pennsylvania, Philadelphia, PA

^cDepartment of Statistics, University of Washington, Seattle, WA

LDA inputs:

- Set of words per doc for each doc in corpus

LDA outputs:

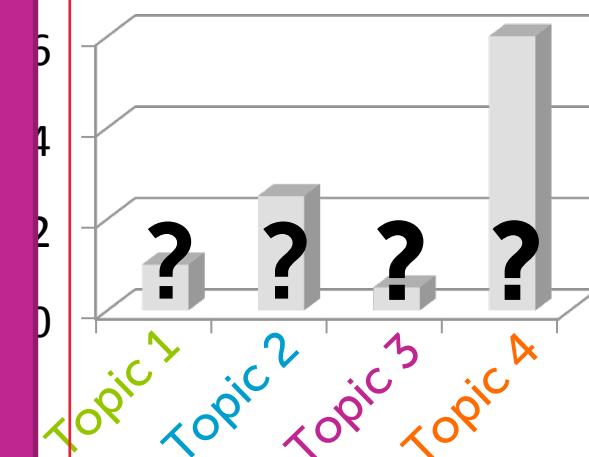
- Corpus-wide topic vocab distributions
- Topic assignments per word
- Topic proportions per doc

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Document topic proportions:

$$\pi_i = [\pi_{i1} \ \pi_{i2} \dots \ \pi_{iK}]$$



Interpreting LDA outputs

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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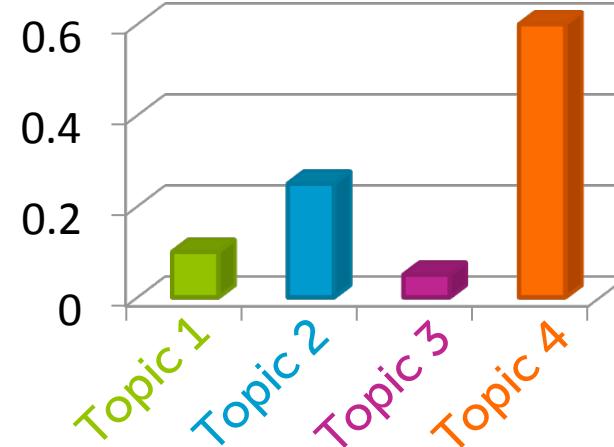
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climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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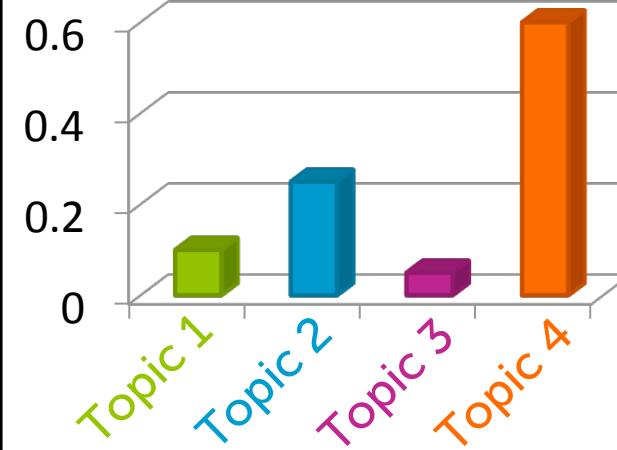
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Examine **coherence** of learned topics

- What are top words per topic?
- Do they form meaningful groups?
- Use to post-facto label topics (e.g., science, tech, sports,...)

Interpreting LDA outputs

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

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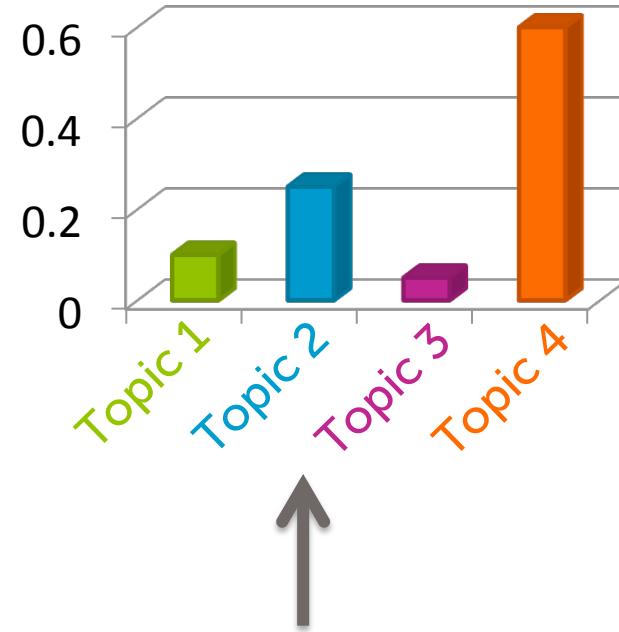
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Doc-specific topic proportions can be used to:

- Relate documents
- Study user topic preferences
- Assign docs to multiple categories

Interpreting LDA outputs

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

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develop	0.18
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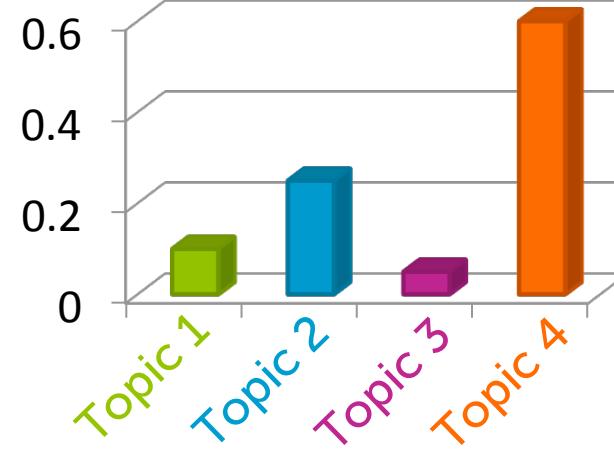
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Typically **not** interested in word assignments

An inference algorithm for LDA: Gibbs sampling

Clustering algorithms so far

k-means

Assign observations to closest cluster center

$$z_i \leftarrow \arg \min_j \|\mu_j - \mathbf{x}_i\|_2^2$$

Revise cluster centers

$$\mu_j \leftarrow \arg \min_{\mu} \sum_{i:z_i=j} \|\mu - \mathbf{x}_i\|_2^2$$

Iterative **hard** assignment
to max objective

EM for MoG

E-step: estimate cluster responsibilities

$$\hat{r}_{ik} = \frac{\hat{\pi}_k N(x_i | \hat{\mu}_k, \hat{\Sigma}_k)}{\sum_{j=1}^K \hat{\pi}_j N(x_i | \hat{\mu}_j, \hat{\Sigma}_j)}$$

M-step: maximize likelihood over parameters

$$\hat{\pi}_k, \hat{\mu}_k, \hat{\Sigma}_k | \{\hat{r}_{ik}, x_i\}$$

Iterative **soft** assignment
to max objective

What can we do for our bag-of-words models?

Part 1: Clustering model

SCIENCE	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TECH	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

SPORTS	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

:

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One topic indicator
 z_i per document i

All words come from
(get scored under)
same topic z_i

Distribution on
prevalence of
topics in corpus

$$\boldsymbol{\pi} = [\pi_1 \ \pi_2 \ \dots \ \pi_K]$$

What can we do for our bag-of-words models?

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SCIENCE	
experiment	0.1
test	0.08
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...	...

TECH	
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computer	0.09
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**Can derive
EM algorithm:**

- Gaussian likelihood of tf-idf vector



**multinomial likelihood
of word counts**

(m_w successes of word w)

- **Result:** mixture of multinomial model

What can we do for our bag-of-words models?

Part 2: LDA model

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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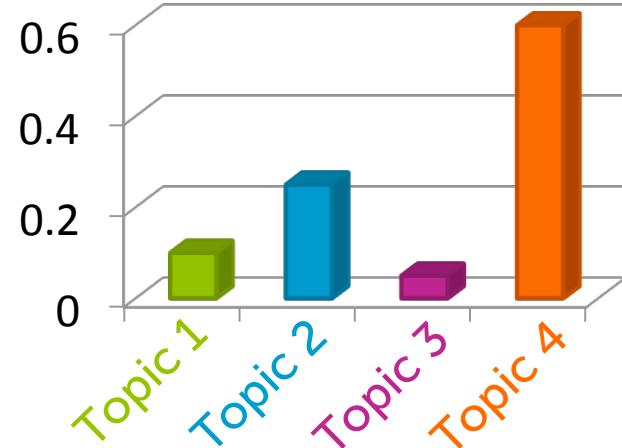
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Can derive
EM algorithm,
but not common
(performs poorly)

Typical LDA implementations

Normally LDA is specified as a **Bayesian model**
(otherwise, “probabilistic latent semantic analysis/indexing”)

- Account for **uncertainty in parameters** when making predictions
- Naturally **regularizes parameter estimates** in contrast to MLE

EM-like algorithms (e.g., “variational EM”), or...

Gibbs sampling for Bayesian inference

Gibbs sampling

Iterative **random** hard assignment!

Benefits:

- Typically intuitive updates
- Very straightforward to implement

Random sample #10000

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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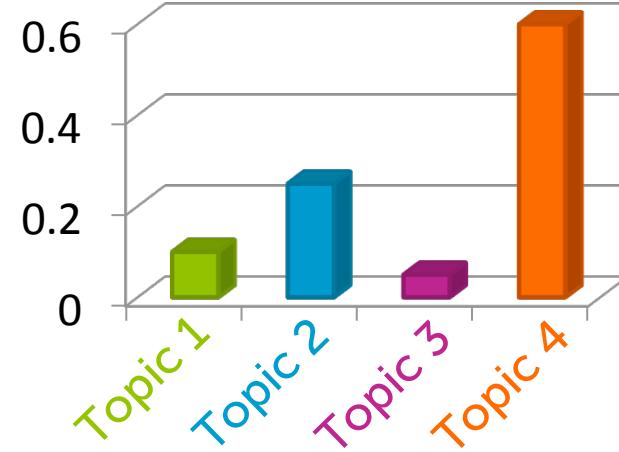
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Current set of assignments

Random sample #10001

TOPIC 1

experiment	0.12
test	0.06
hypothesize	0.042
discover	0.04
climate	0.011
...	...

TOPIC 2

develop	0.16
computer	0.11
user	0.03
processor	0.029
internet	0.023
...	...

TOPIC 3

player	0.15
score	0.07
team	0.06
offense	0.02
defense	0.018
...	...

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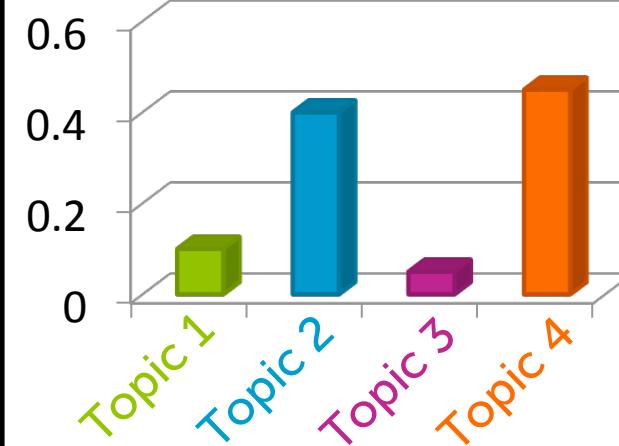
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Current set of assignments

Random sample #10002

TOPIC 1

experiment	0.10
discover	0.055
hypothesize	0.043
test	0.042
examine	0.015
...	...

TOPIC 2

computer	0.12
develop	0.115
user	0.031
device	0.022
cloud	0.018
...	...

TOPIC 3

player	0.17
score	0.09
game	0.062
team	0.043
win	0.03
...	...

⋮

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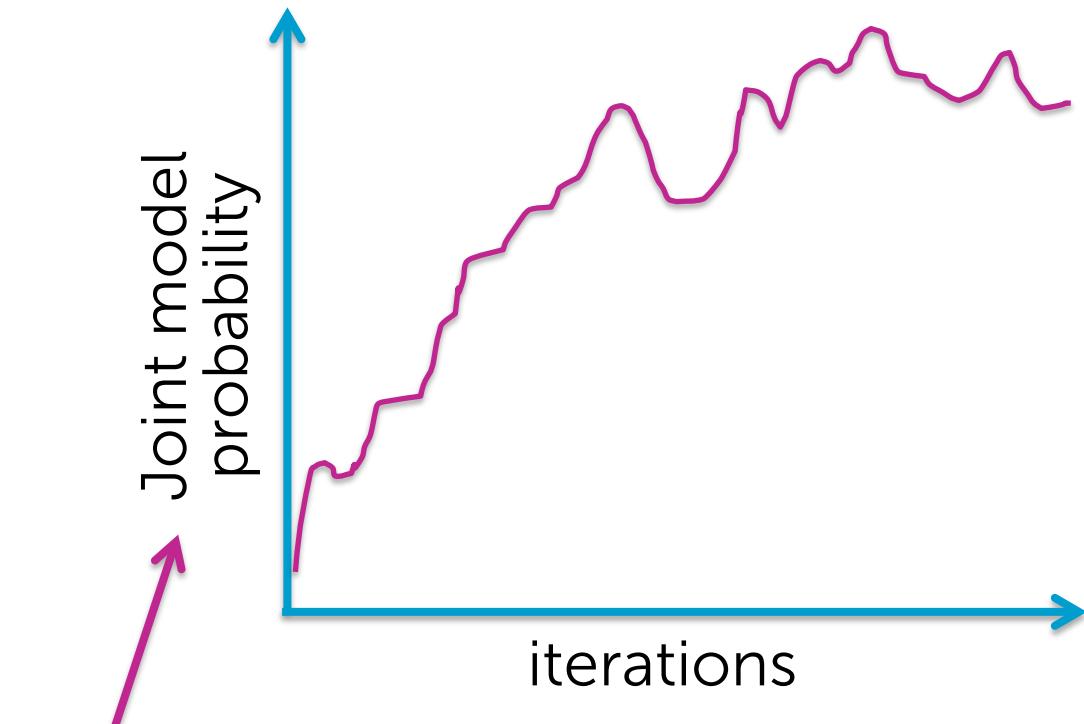
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Current set of assignments

What do we know about this process?

Not an optimization algorithm



probability of observations given variables/parameters
and probability of variables/parameters themselves

Eventually
provides
“correct”
Bayesian
estimates...

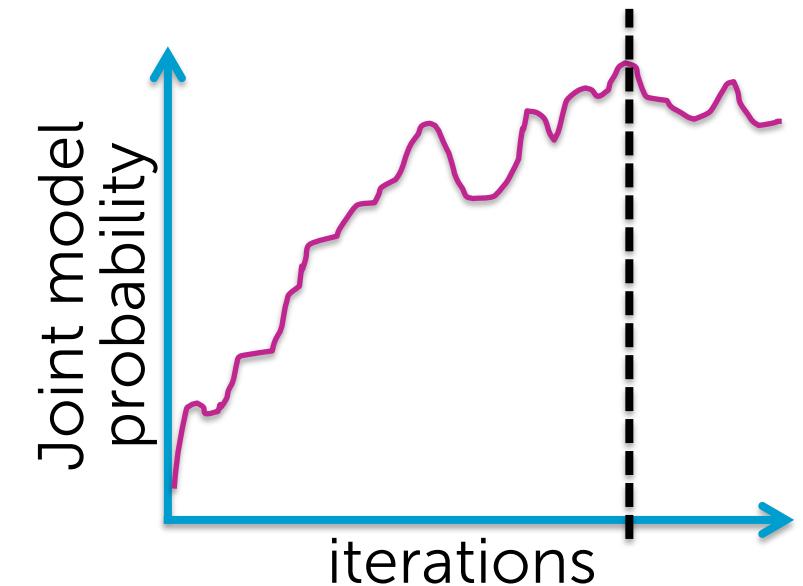
What to do with sampling output?

Predictions:

1. Make prediction for each snapshot of randomly assigned variables/parameters (full iteration)
2. Average predictions for final result

Parameter or assignment estimate:

- Look at snapshot of randomly assigned variables/parameters that maximizes “joint model probability”



Standard Gibbs sampling steps

Gibbs sampling algorithm outline

Iterative **random** hard assignment!

Assignment variables and model parameters
treated similarly

Iteratively **draw variable/parameter from
conditional distribution** having fixed:

- all other variables/parameters
 - values randomly selected in previous rounds
 - changes from iter to iter
- observations
 - always the same values

Gibbs sampling for LDA

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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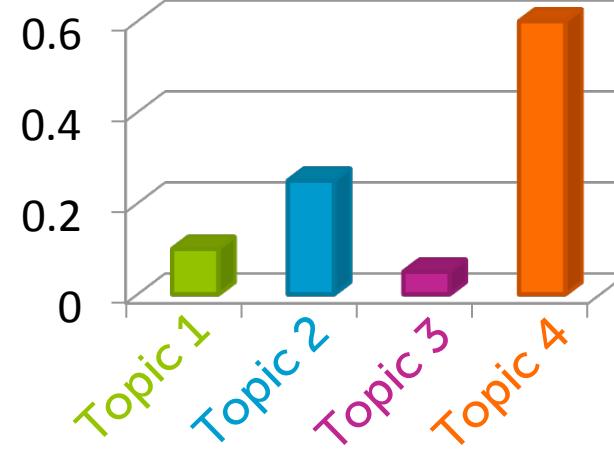
Abstract

Patients with epilepsy can manifest short, sub-clinical epileptic “bursts” in addition to full-blown clinical seizures. We believe the relationship between these two classes of events—something not previously studied quantitatively—could yield important insights into the nature and intrinsic dynamics of seizures. A goal of our work is to parse these complex epileptic events into distinct dynamic regimes. A challenge posed by the intracranial EEG (iEEG) data we study is the fact that the number and placement of electrodes can vary between patients. We develop a Bayesian nonparametric Markov switching process that allows for (i) shared dynamic regimes between a variable number of channels, (ii) asynchronous regime-switching, and (iii) an unknown dictionary of dynamic regimes. We encode a sparse and changing set of dependencies between the channels using a Markov-switching Gaussian graphical model for the innovations process driving the channel dynamics and demonstrate the importance of this model in parsing and out-of-sample predictions of iEEG data. We show that our model produces intuitive state assignments that can help automate clinical analysis of seizures and enable the comparison of sub-clinical bursts and full clinical seizures.

Keywords: Bayesian nonparametric EEG, factorial hidden Markov model, graphical model, time series

1. Introduction

Despite over three decades of research, we still have very little idea of what defines a seizure. This ignorance stems both from the complexity of epilepsy as a disease and a paucity of quantitative tools that are flexible



Current set of assignments

Gibbs sampling for LDA

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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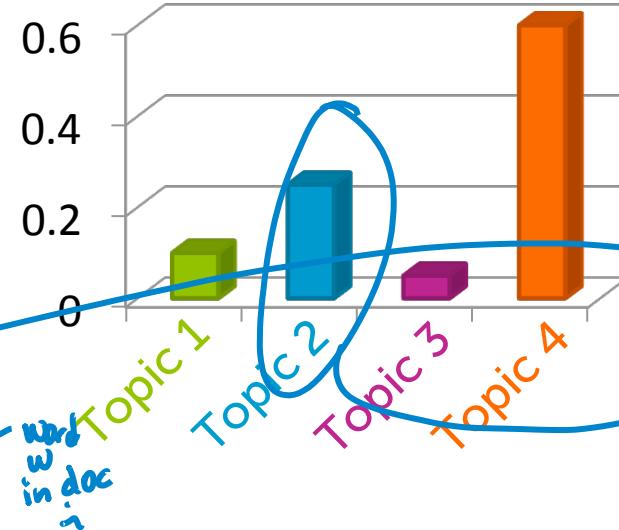
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Step 1: Randomly reassign all z_{iw} based on

- doc topic proportions
- topic vocab distributions

Draw randomly from responsibility vector
 $[r_{iw1} \ r_{iw2} \ \dots \ r_{iwK}]$

$$r_{iw2} = \frac{\text{prior prob. } z_{iw=2} \cdot P(\text{"EEG"} | z_{iw=2})}{\sum_{j=1}^K \text{prior prob. } z_{iw=j} \cdot P(\text{"EEG"} | z_{iw=j})}$$

prob. of assigning $z_{iw}=2$

Gibbs sampling for LDA

TOPIC 1

experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2

develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3

player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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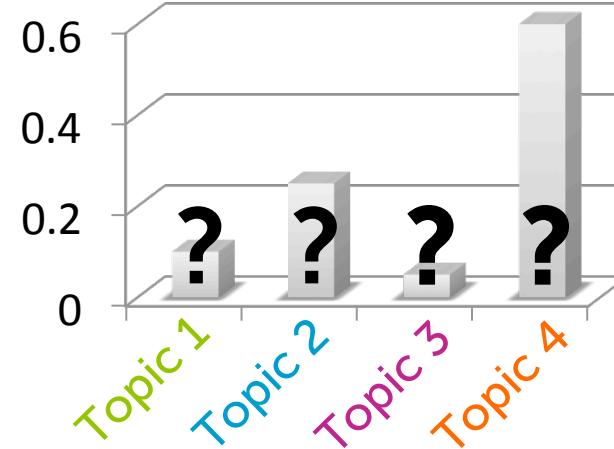
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Step 2: Randomly reassign doc topic proportions based on assignments z_{iw} in current doc

Gibbs sampling for LDA

TOPIC 1

experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2

develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3

player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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Step 3: Repeat for all docs

Gibbs sampling for LDA

TOPIC 1	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 2	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 3	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

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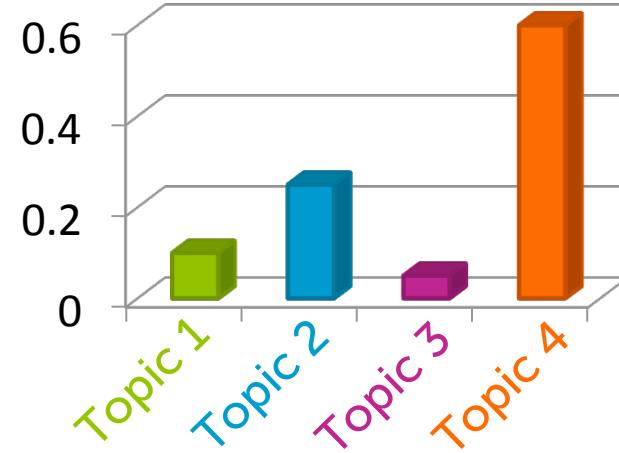
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Step 4: Randomly reassign topic vocab distributions based on assignments z_{iw} in entire corpus

Gibbs sampling for LDA

TOPIC 1

experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2

develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3

player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

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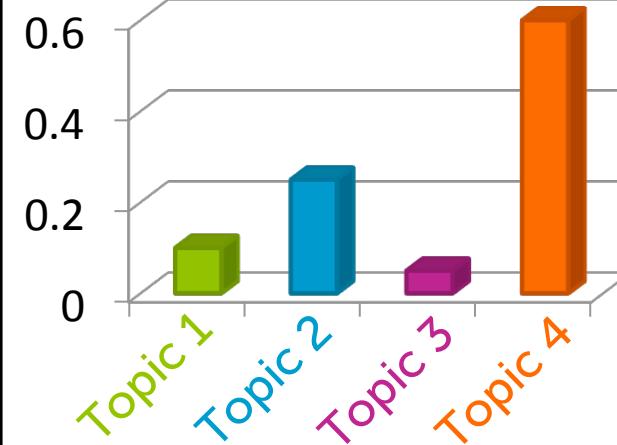
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**Repeat Steps 1-4 until
max iter reached**

Collapsed Gibbs sampling in LDA

“Collapsed” Gibbs sampling for LDA

Based on special structure of LDA model, can sample **just** indicator variables z_{iw}

- No need to sample other parameters
 - corpus-wide topic vocab distributions
 - per-doc topic proportions

Often leads to much better performance because examining uncertainty in smaller space

Collapsed Gibbs sampling for LDA

Never draw topic vocab distributions or doc topic proportions

TOPIC 1
experiment 0.
test 0.
discover 0.
hypothesize 0.
climate 0.
...

TOPIC 2
develop 0.18
computer 0.09
processor 0.032
user 0.027
internet 0.02
...

TOPIC 3
player 0.15
score 0.07
team 0.06
goal 0.03
injury 0.01
...

⋮

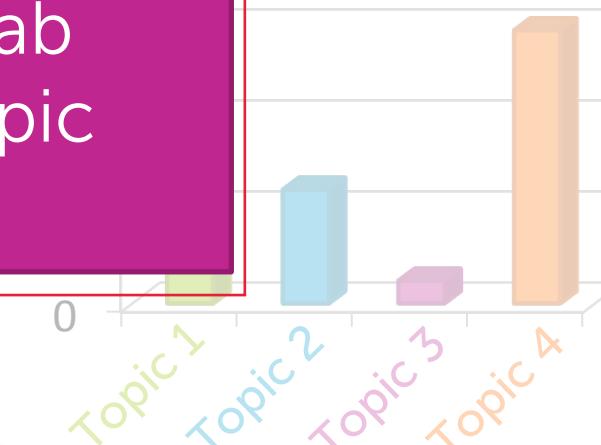
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Randomly reassign z_{iw} based on current assignments z_{jv} of all other words **in document and corpus**

Select a document

epilepsy	dynamic	Bayesian	EEG	model

5 word document

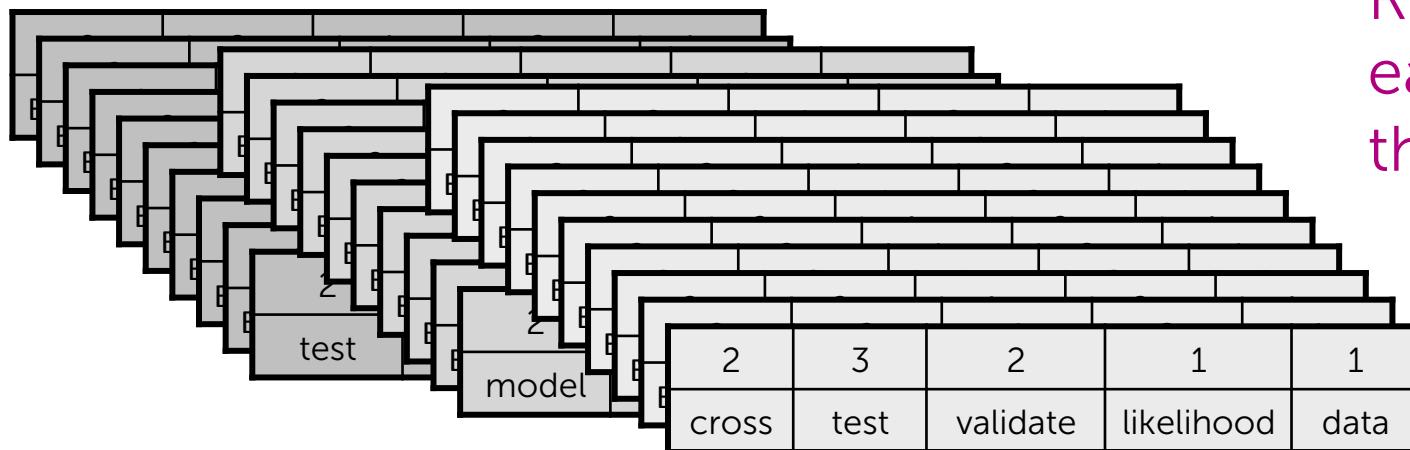
Randomly assign topics

3	2	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

(one possible approach)

Randomly assign topics

3	2	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



Repeat for
each doc in
the corpus

Maintain local statistics

3	2	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

	Topic 1	Topic 2	Topic 3
Doc i	2	1	2

Maintain global statistics

3	2	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

	Topic 1	Topic 2	Topic 3
epilepsy	1	0	35
Bayesian	50	0	1
model	42	1	0
EEG	0	0	20
dynamic	10	8	1
...			

	Topic 1	Topic 2	Topic 3
Doc i	2	1	2

Total counts from **all** docs



Randomly reassign topics

3	2	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

	Topic 1	Topic 2	Topic 3
epilepsy	1	0	35
Bayesian	50	0	1
model	42	1	0
EEG	0	0	20
dynamic	10	7 ⁸	1
...			

	Topic 1	Topic 2	Topic 3
Doc i	2	0 ¹	2

decrementing
counts
after removing
current assignment
 $z_{iw} = 2$

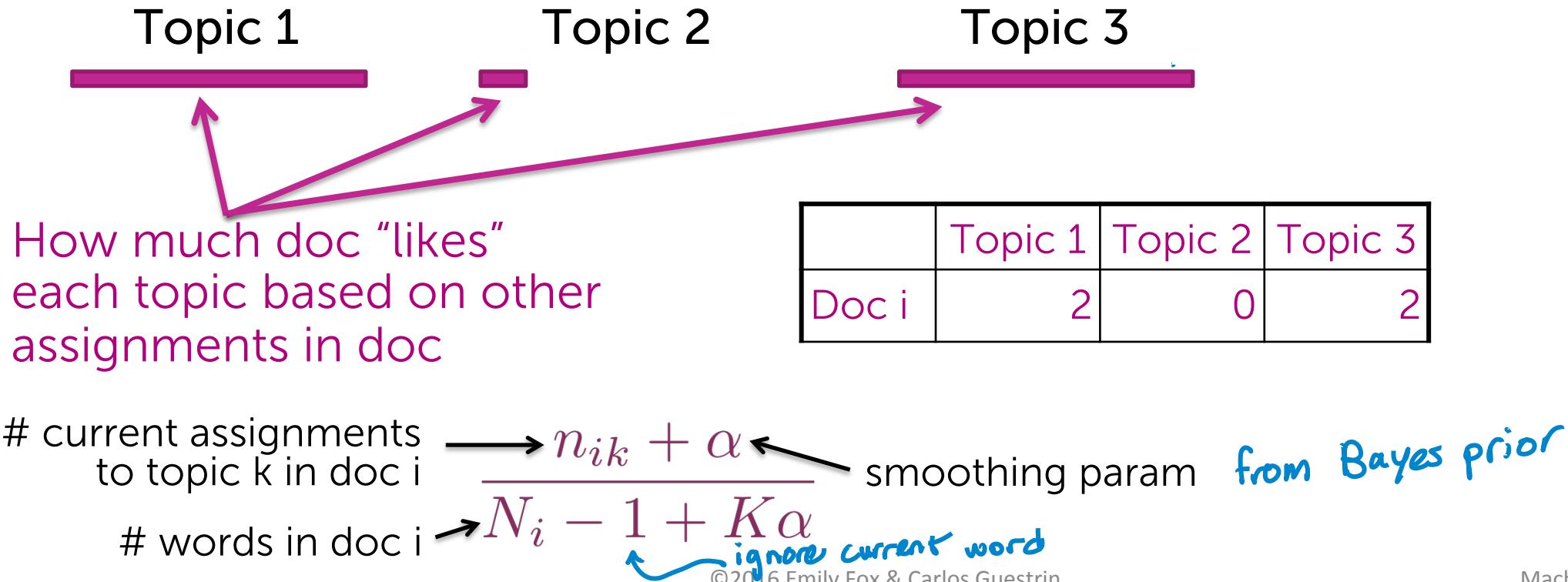
Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

Reassign with probability
 $p(z_{iw} | \text{every other } z_{jv} \text{ in corpus},$
 $\text{words in corpus})$

Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



Probability of new assignment

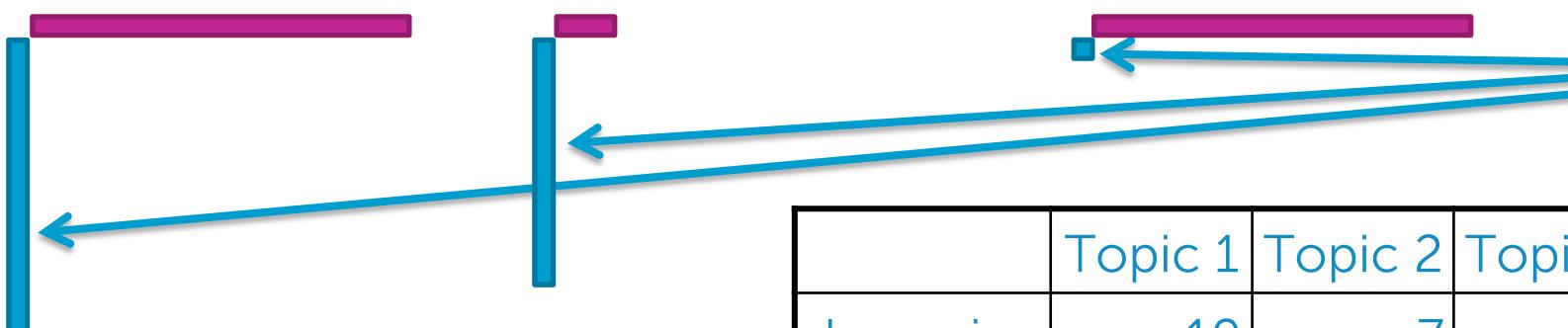
3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

Topic 1

Topic 2

Topic 3

How much each topic likes the word "dynamic" based on assignments in other docs in corpus



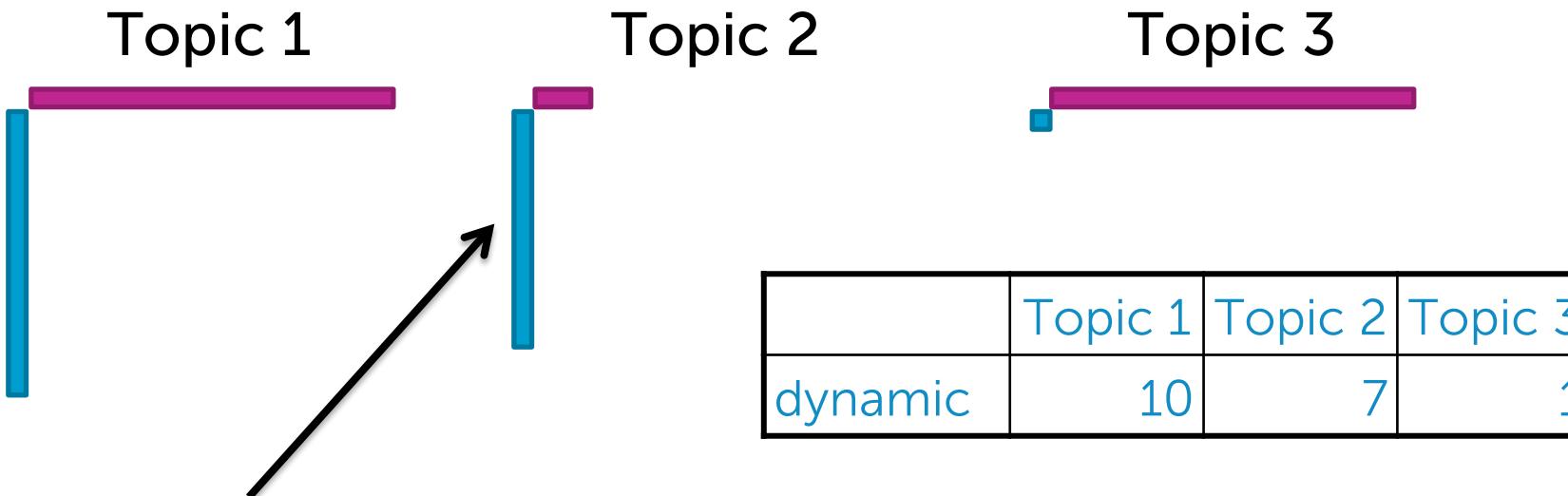
assignments
corpus-wide of
word "dynamic"
to topic k

$$\frac{m_{\text{dynamic},k} + \gamma}{\sum_{w \in V} m_{w,k} + V\gamma}$$

smoothing param *from Bayes prior*
size of vocab

Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



Topic 2 also really likes “dynamic”,
but in a different context...
e.g., a topic on fluid dynamics

Probability of new assignment

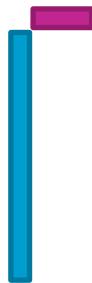
3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

Topic 1



Topic fits word
and document

Topic 2



Topic fits word,
but not doc

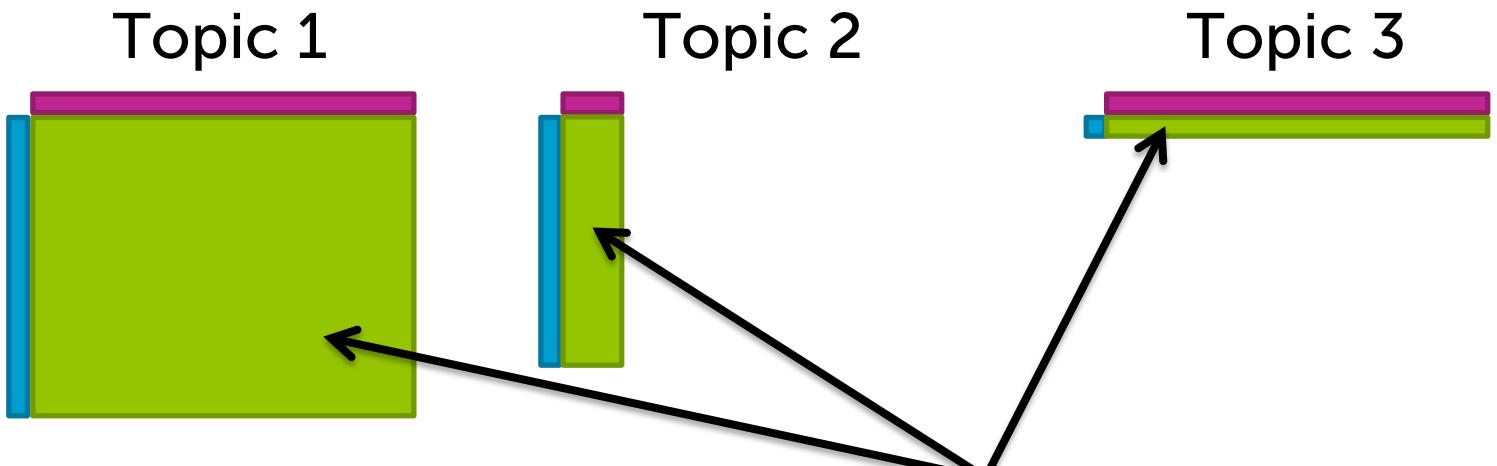
Topic 3



Topic fits doc,
but not word

Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



How much
doc likes topic

$$\frac{n_{ik} + \alpha}{N_i - 1 + K\alpha}$$

$$\frac{m_{\text{dynamic},k} + \gamma}{\sum_{w \in V} m_{w,k} + V\gamma}$$

How much
topic likes word

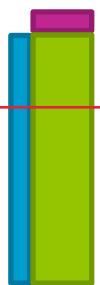
Randomly draw a new topic indicator

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

Topic 1



Topic 2



Topic 3



To draw new topic assignment (equivalently):

- roll K-sided die with these probabilities
- throw dart at these regions

How much
doc likes topic

$$\frac{n_{ik} + \alpha}{N_i - 1 + K\alpha} \quad \frac{m_{\text{dynamic},k} + \gamma}{\sum_{w \in V} m_{w,k} + V\gamma}$$

How much
topic likes word

Normalize this product of terms over K possible topics!

Update counts

3	1	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

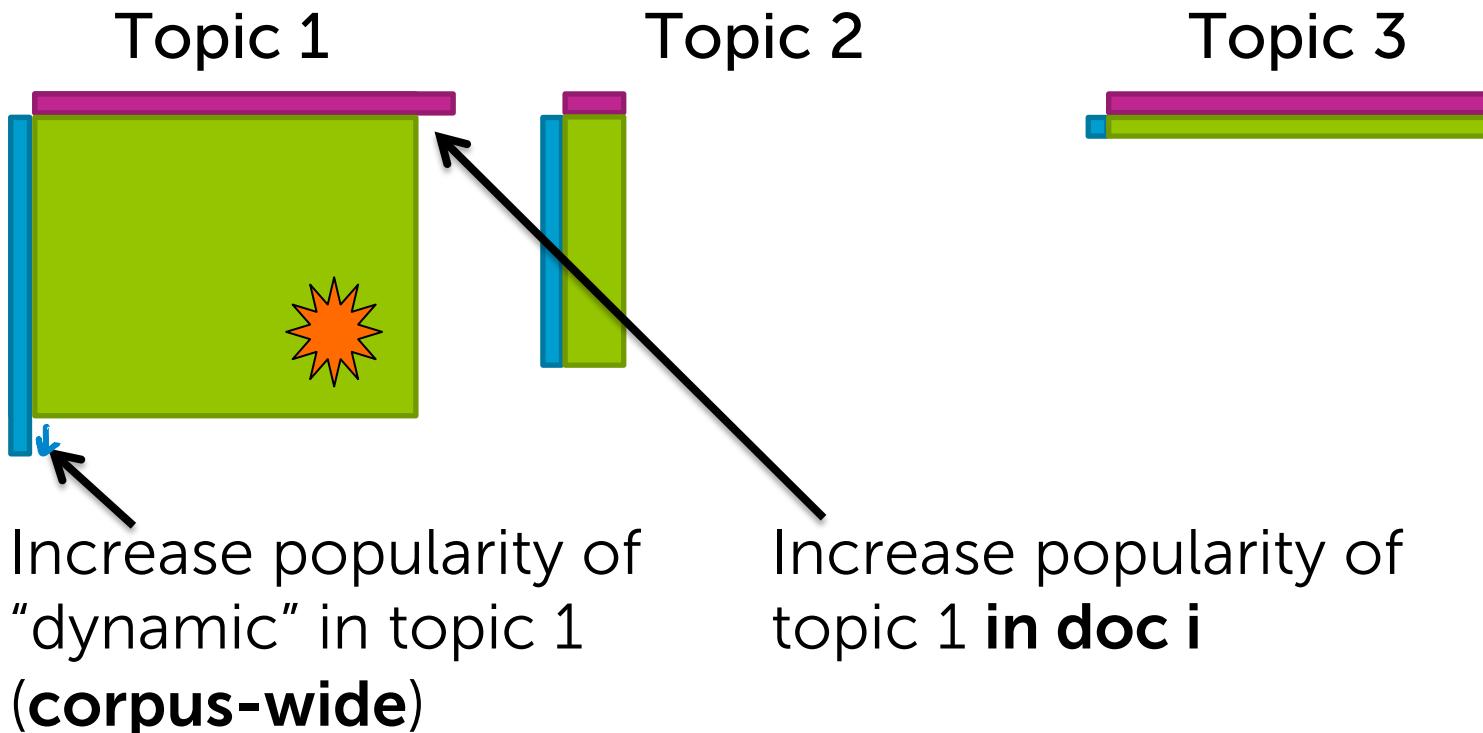
	Topic 1	Topic 2	Topic 3
epilepsy	1	0	35
Bayesian	50	0	1
model	42	1	0
EEG	0	0	20
dynamic	11	7	1
...			

	Topic 1	Topic 2	Topic 3
Doc i	3	2	0

increment counts
based on new
assignment of
 $z_{iw}=1$

Geometrically...

3	1	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



Iterate through all words/docs

3	1	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

	Topic 1	Topic 2	Topic 3
epilepsy	1	0	35
Bayesian	50	0	1
model	42	1	0
EEG	0	0	20
dynamic	10	7	1
...			

	Topic 1	Topic 2	Topic 3
Doc i	2	0	2

Using samples from collapsed Gibbs

What to do with the collapsed samples?

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	...

TOPIC 3	
player	0.15
score	0.07
team	0.06
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injury	0.01
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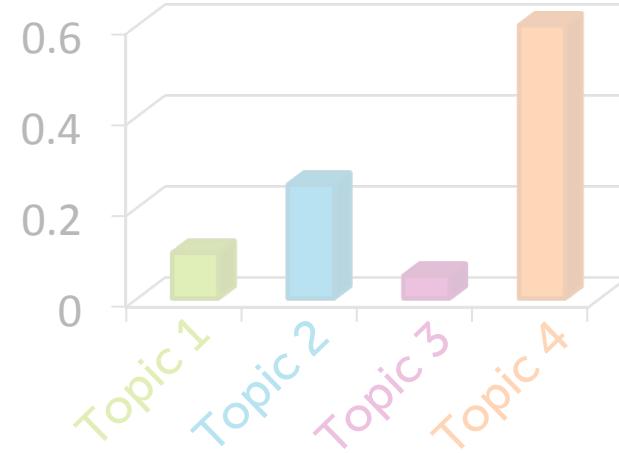
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From “best” sample of $\{z_{iw}\}$,
can infer:

What to do with the collapsed samples?

TOPIC 1

experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2

develop	0.18
computer	0.09
processor	0.032
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player	0.15
score	0.07
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...	...

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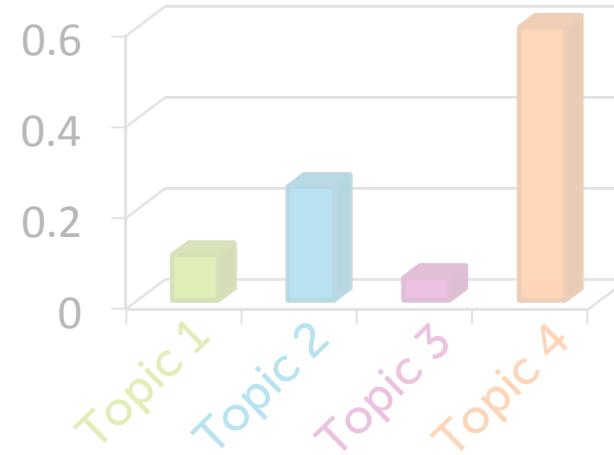
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From “best” sample of $\{z_{iw}\}$,
can infer:

1. Topics from conditional distribution...
need corpus-wide info

What to do with the collapsed samples?

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
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internet	0.02
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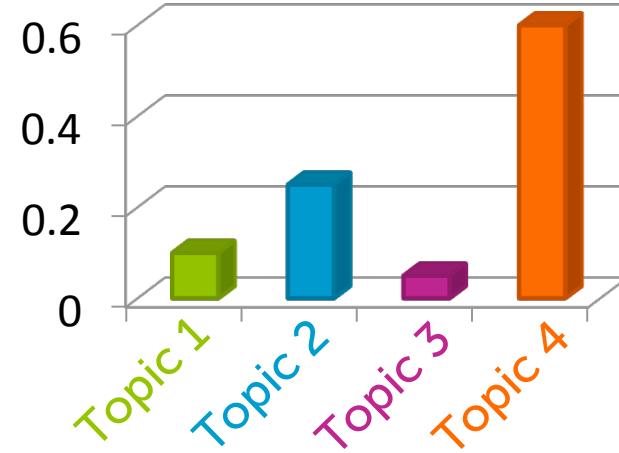
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Patients with epilepsy can manifest short, sub-clinical epileptic “bursts” in addition to full-blown clinical seizures. We believe the relationship between these two classes of events—something not previously studied quantitatively—could yield important insights into the nature and intrinsic dynamics of seizures. A goal of our work is to parse these complex epileptic events into distinct dynamic regimes. A challenge posed by the intracranial EEG (iEEG) data we study is the fact that the number and placement of electrodes can vary between patients. We develop a Bayesian nonparametric Markov switching process that allows for (i) shared dynamic regimes between a variable number of channels, (ii) asynchronous regime-switching, and (iii) an unknown dictionary of dynamic regimes. We encode a sparse and changing set of dependencies between the channels using a Markov-switching Gaussian graphical model for the innovations process driving the channel dynamics and demonstrate the importance of this model in parsing and out-of-sample predictions of iEEG data. We show that our model produces intuitive state assignments that can help automate clinical analysis of seizures and enable the comparison of sub-clinical bursts and full clinical seizures.

Keywords: Bayesian nonparametric EEG, factorial hidden Markov model, graphical model, time series

1. Introduction

Despite over three decades of research, we still have very little idea of what defines a seizure. This ignorance stems both from the complexity of epilepsy as a disease and a paucity of quantitative tools that are flexible



From “best” sample of $\{z_{iw}\}$, can infer:

1. Topics from conditional distribution...
need corpus-wide info
2. Document “embedding”...
need doc info only

Embedding new documents

TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
...	...

TOPIC 2	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
...	

TOPIC 3	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
...	...

⋮

Modeling the Complex Dynamics and Changing Correlations of Epileptic Events

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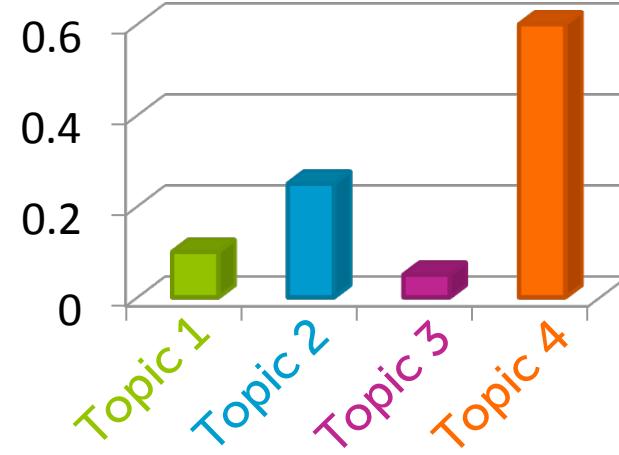
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Simple approach:

1. Fix topics based on training set collapsed sampling
2. Run uncollapsed sampler on new doc(s) only

Summary for LDA and Gibbs sampling

What you can do now...

- Compare and contrast clustering and mixed membership models
- Describe a document clustering model for the bag-of-words doc representation
- Interpret the components of the LDA mixed membership model
- Analyze a learned LDA model
 - Topics in the corpus
 - Topics per document
- Describe Gibbs sampling steps at a high level
- Utilize Gibbs sampling output to form predictions or estimate model parameters
- Implement collapsed Gibbs sampling for LDA

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