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

Drausin F. Wulsin[a], Emily B. Fox[c], Brian Litt[a,b]

[a] *Department of Bioengineering, University of Pennsylvania, Philadelphia, PA*
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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.

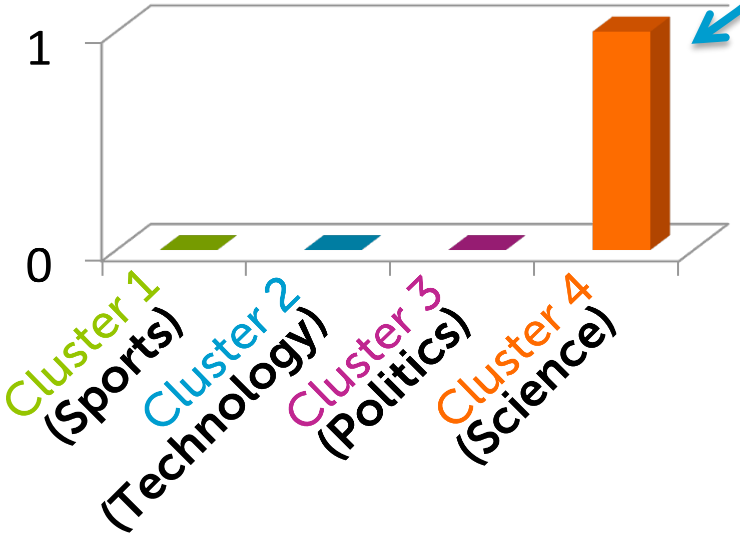
Keywords: Bayesian nonparametric, EEG, factorial hidden Markov model, graphical model, time series

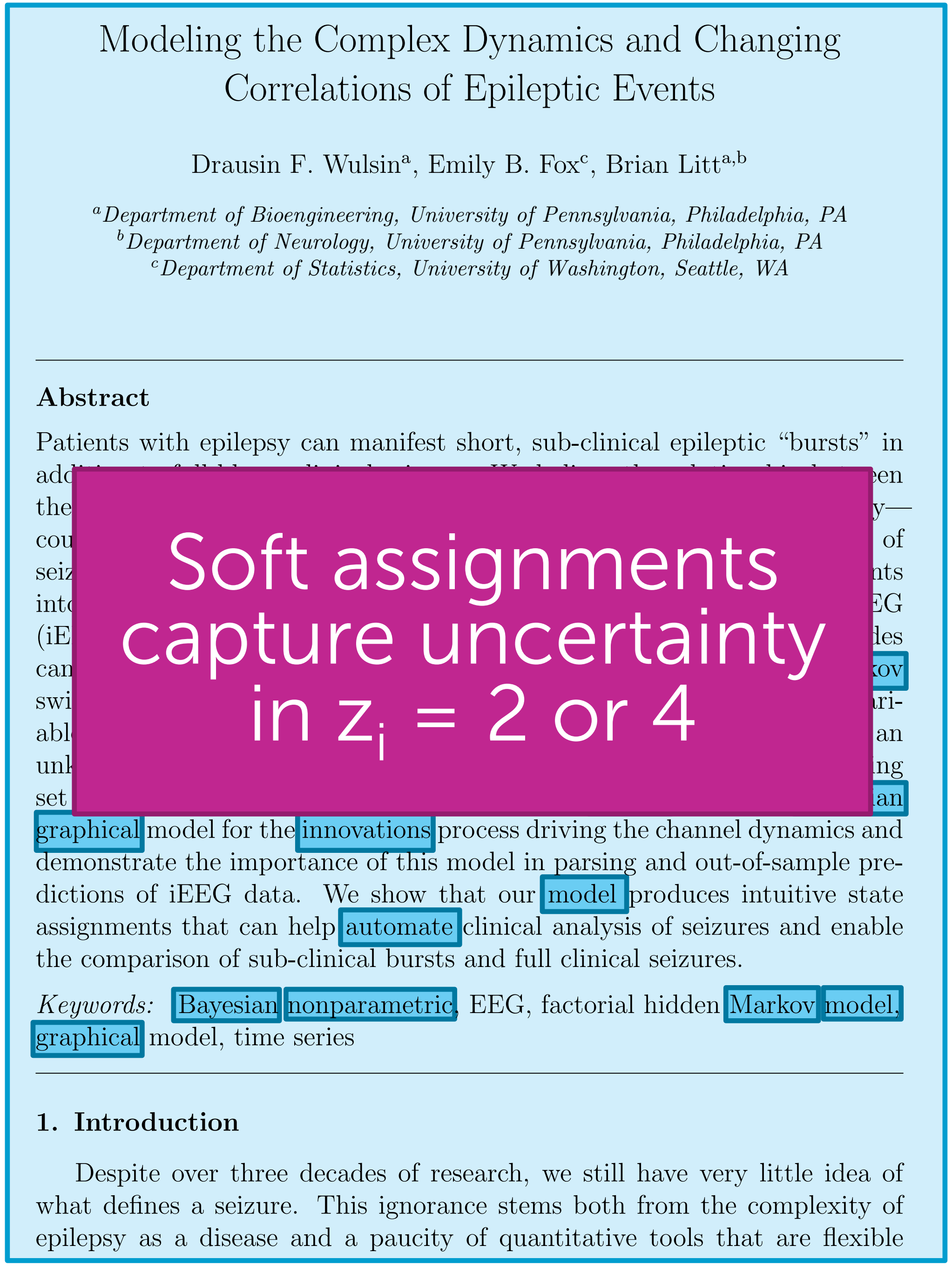
1. Introduction

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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Patients with epilepsy can manifest short, sub-clinical epileptic "bursts" in [illegible] 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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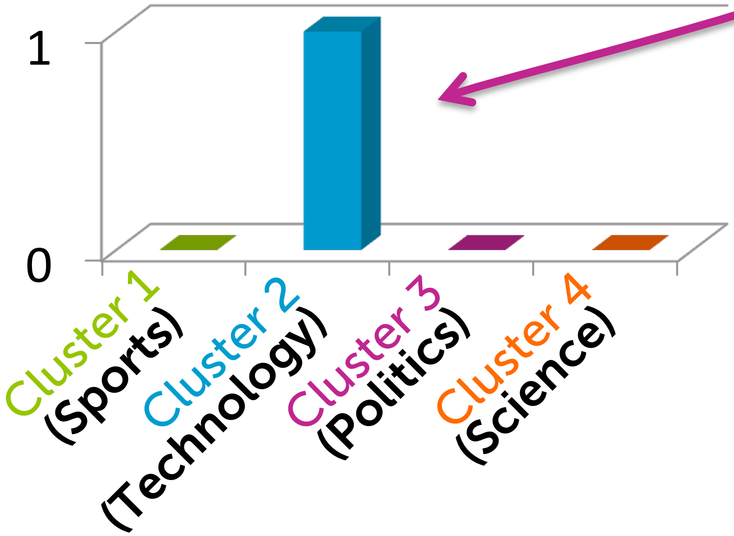
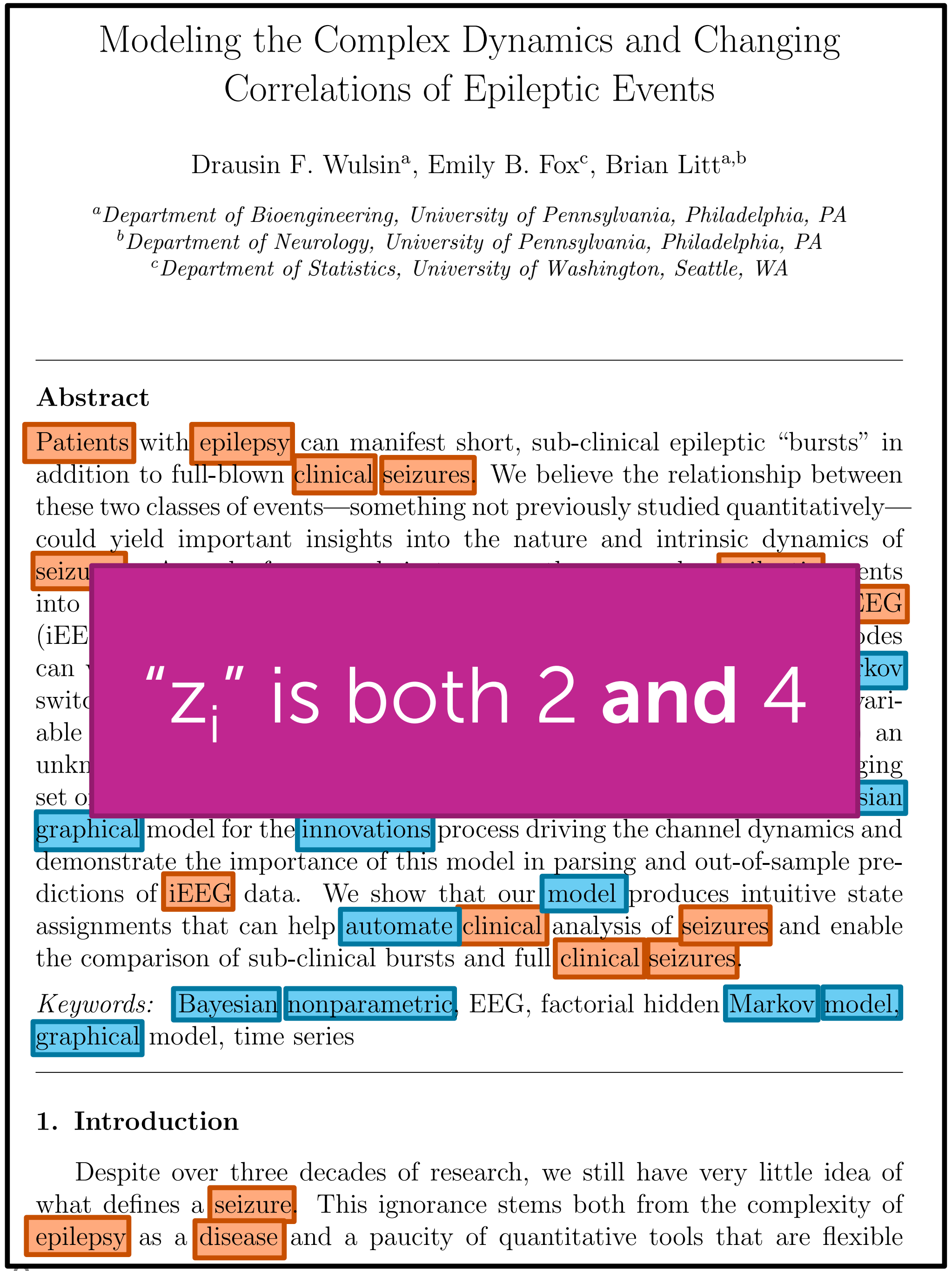
Soft assignments capture uncertainty in z_i = 2 or 4

Encoding of cluster membership z_i = 2

Or maybe cluster 2 (technology) is a better fit

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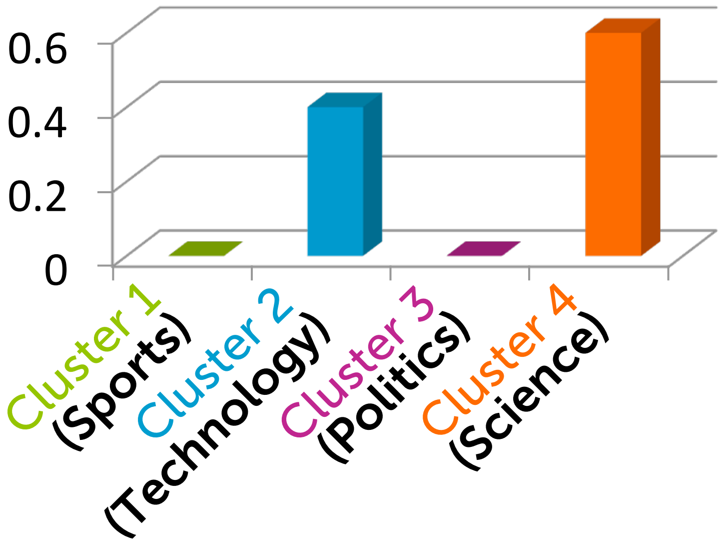
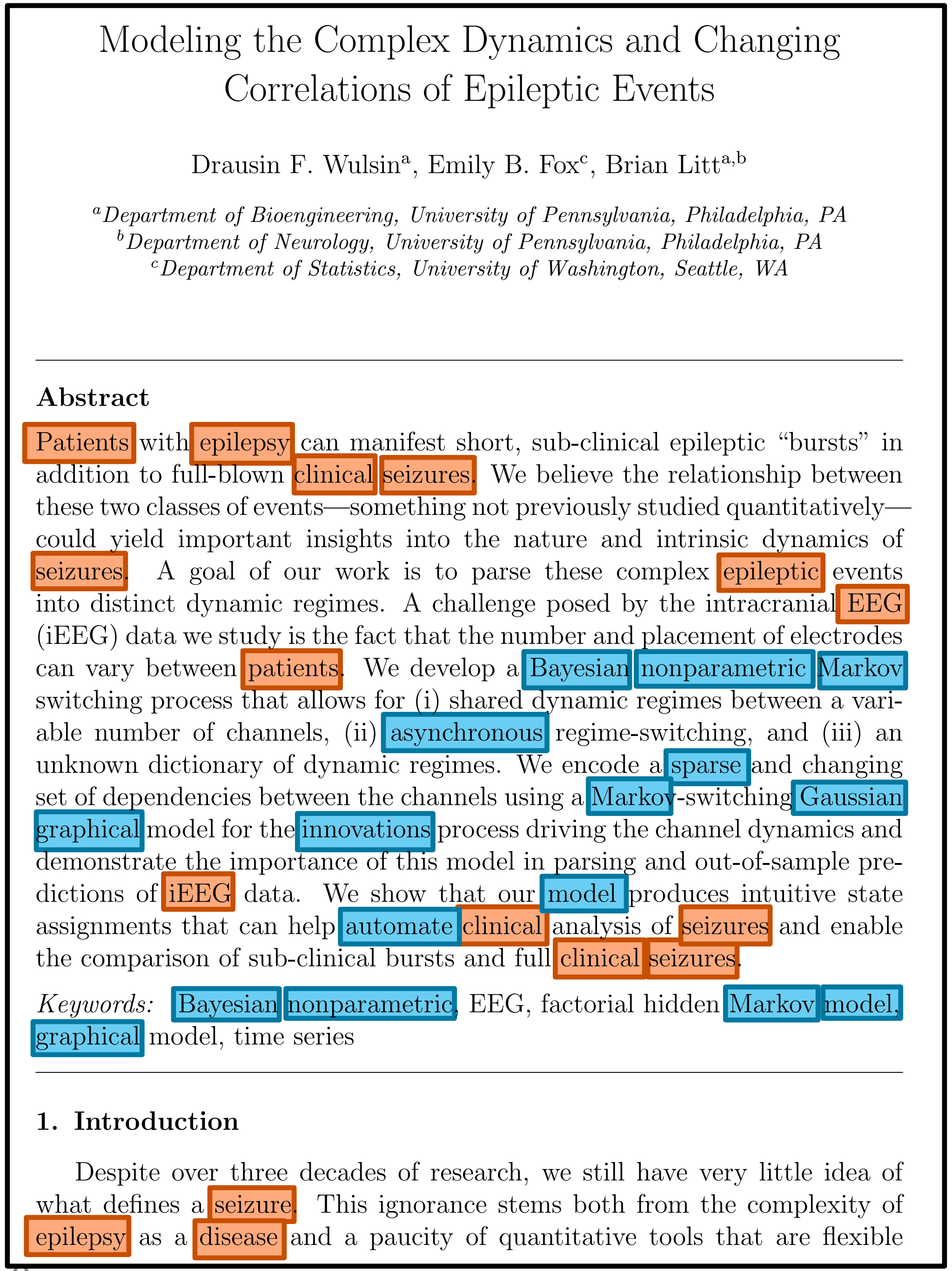
"z_i" is both 2 **and** 4

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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$\mathbf{x}_i =$

Bag-of-words representation

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epilepsy
modeling
complex
clinical
Bayesian

Bag-of-words representation

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$\mathbf{x}_i$ = {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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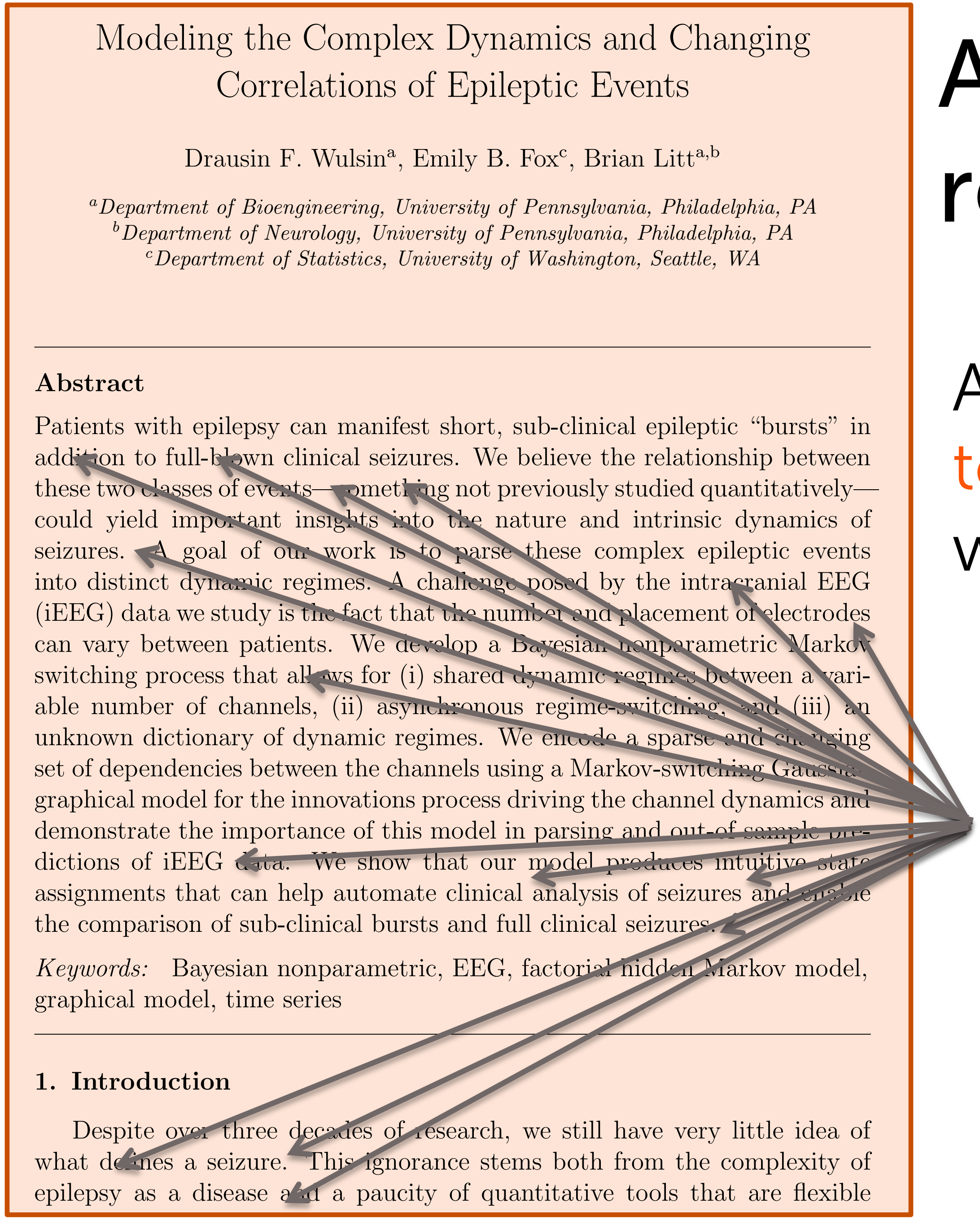
A model for bag-of-words representation

As before, the "prior" probability that doc i is from topic k is:

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

$\boldsymbol{\pi} = [\pi_1 \ \pi_2 \ldots \pi_K]$
represents corpus-wide topic prevalence

A model for bag-of-words representation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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
…	…

…

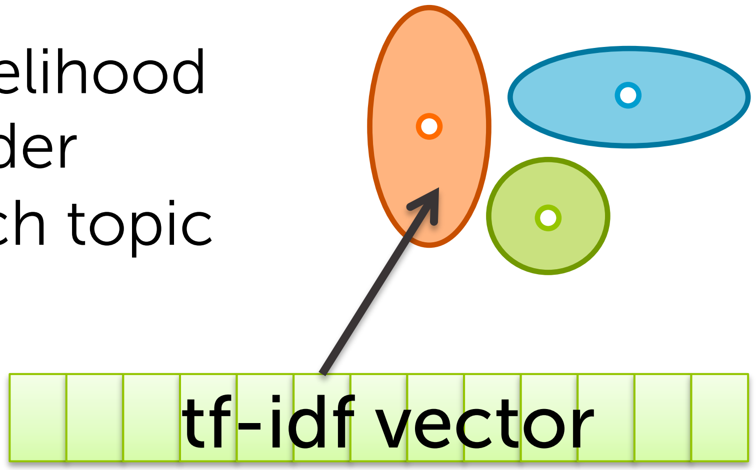
(table now organized by decreasing probabilities showing top words in each category)

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

Prior topic probabilities: $p(z_i = k) = \pi_k$

Likelihood under each topic:

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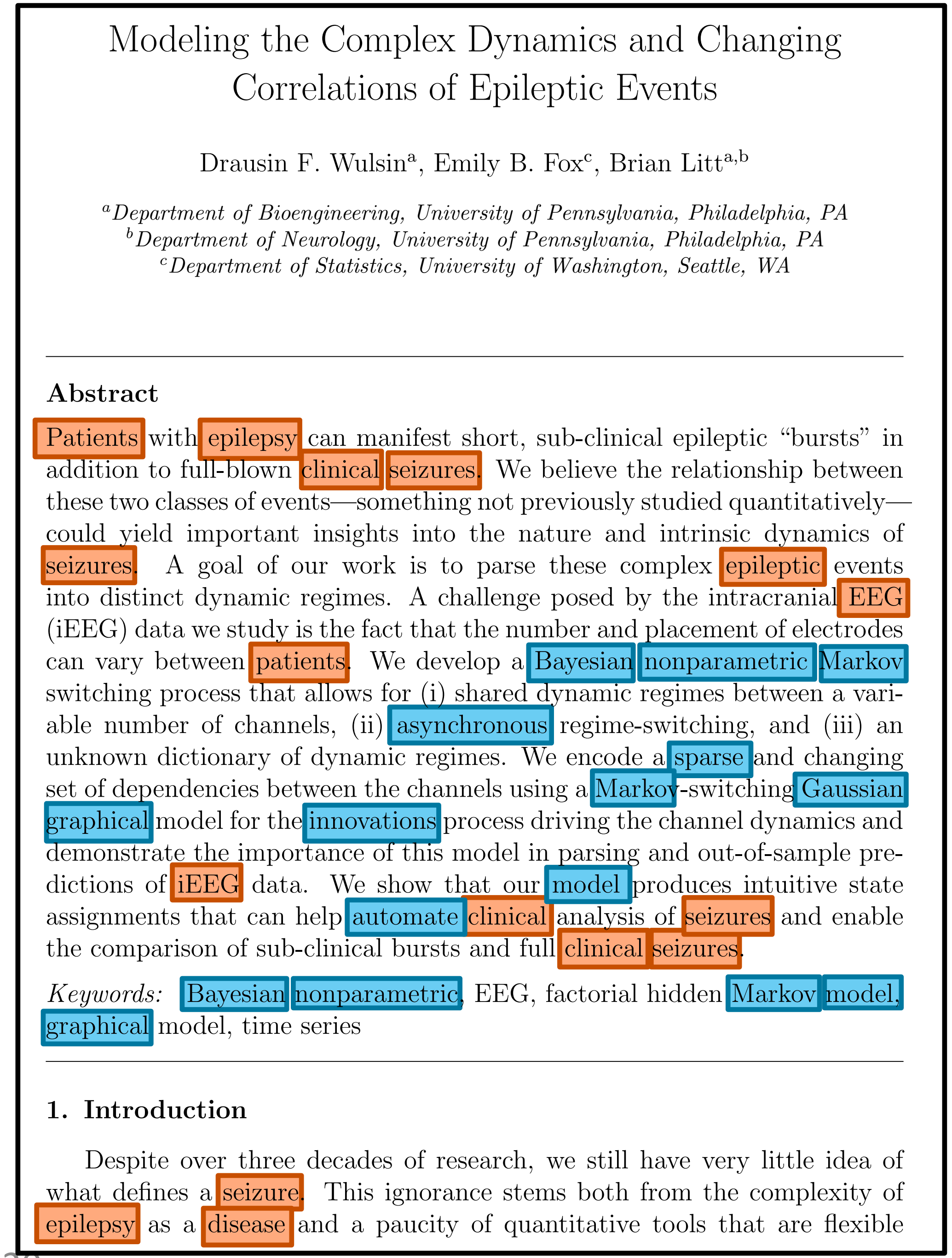
…

{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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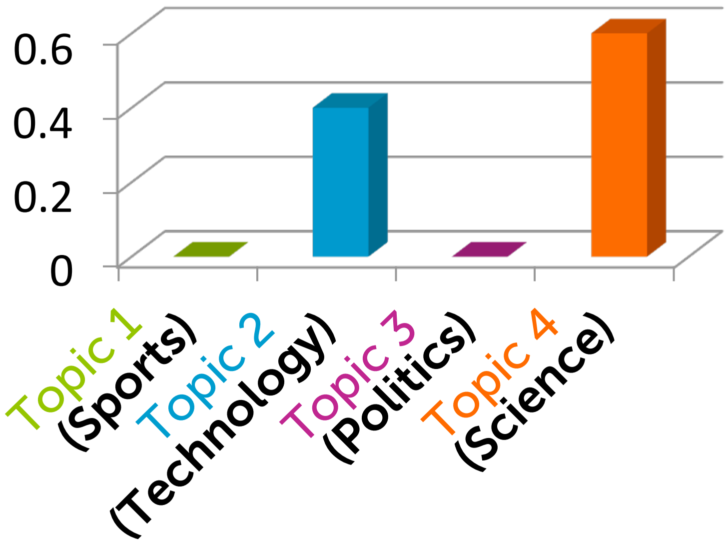
LDA is a mixed membership model

Want to discover a **set** of topics



Topic vocab distributions:

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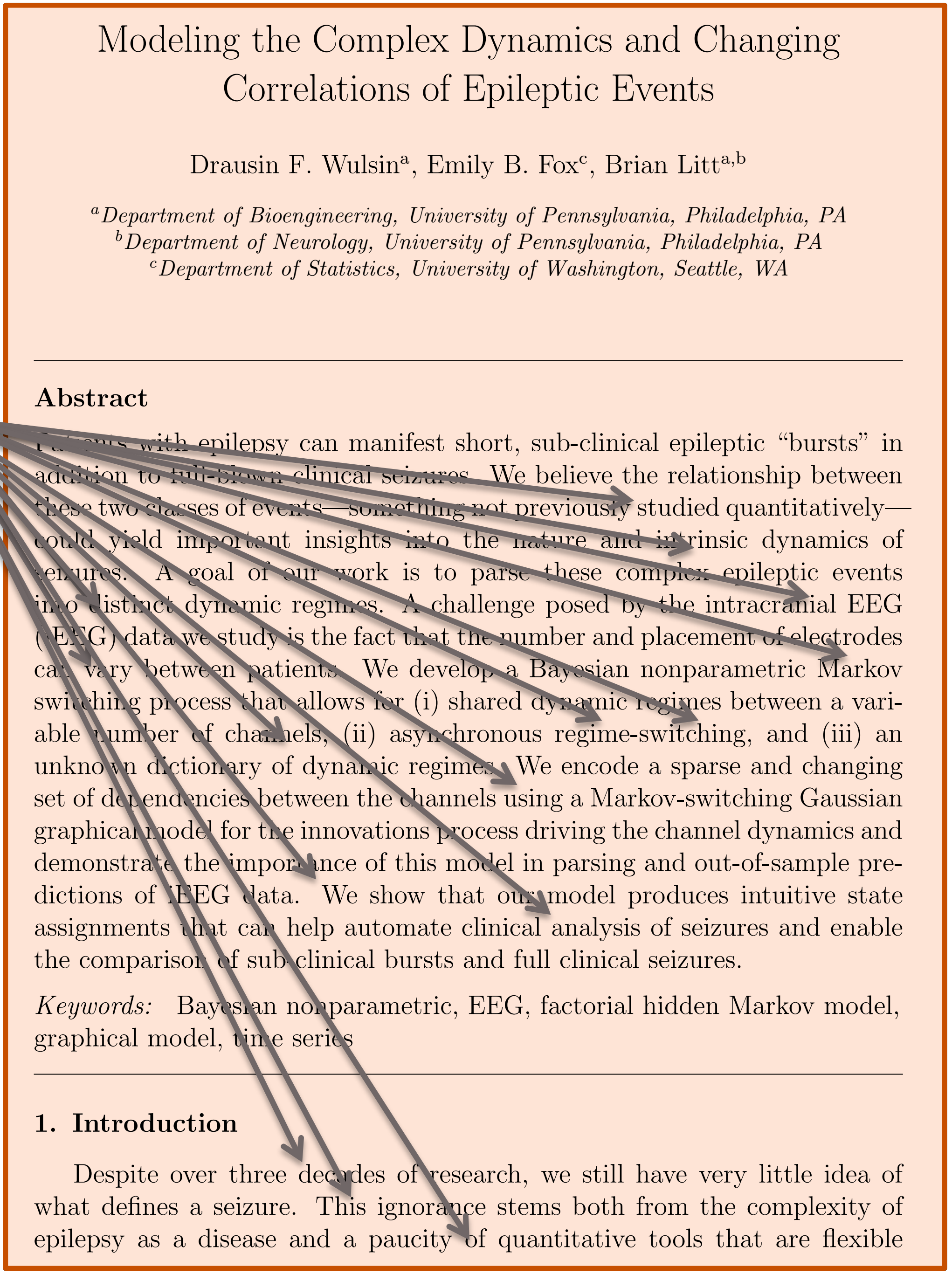
⋮



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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**

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

Same topic distributions:

SCIENCE	
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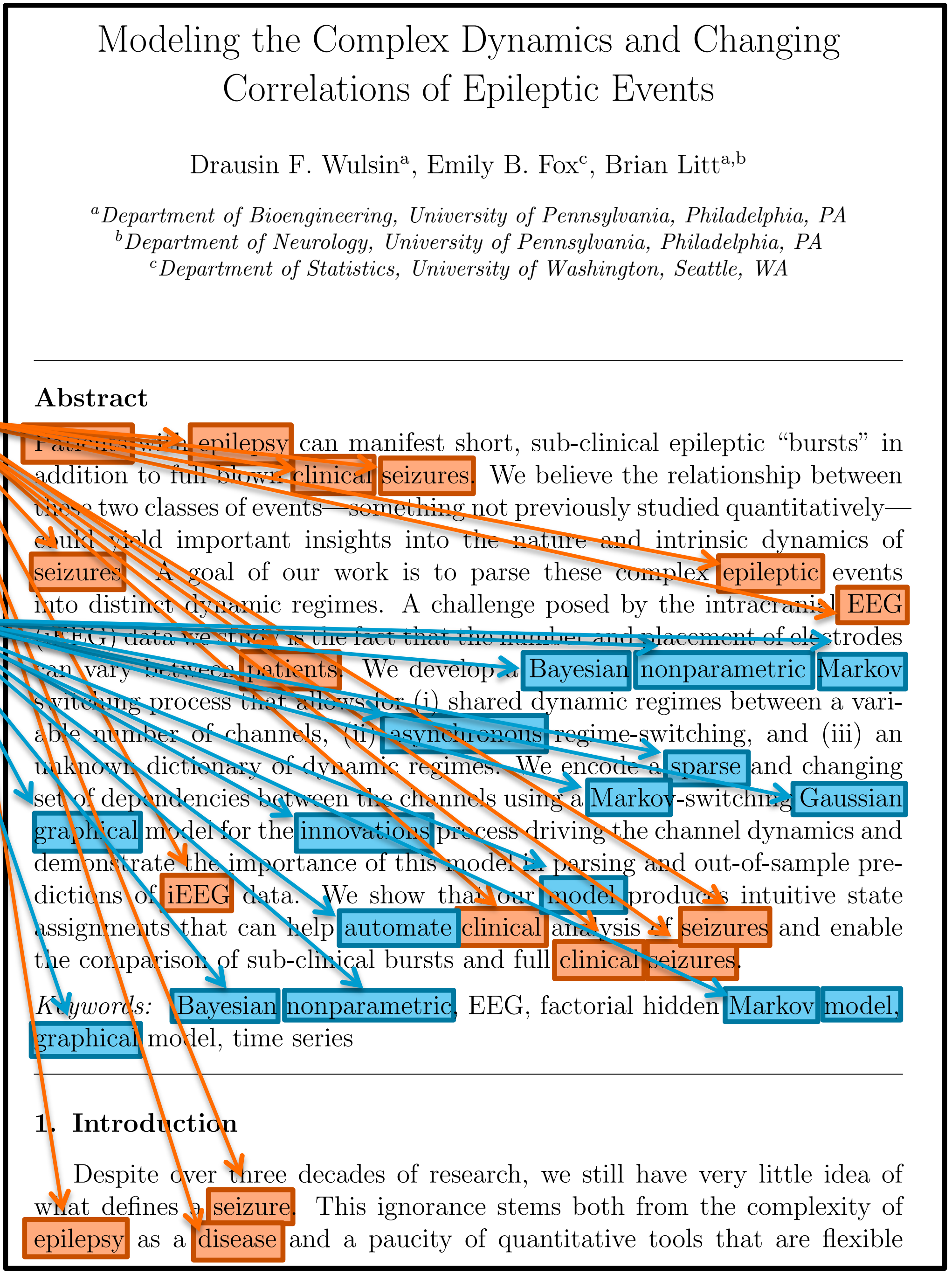

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In LDA:

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**

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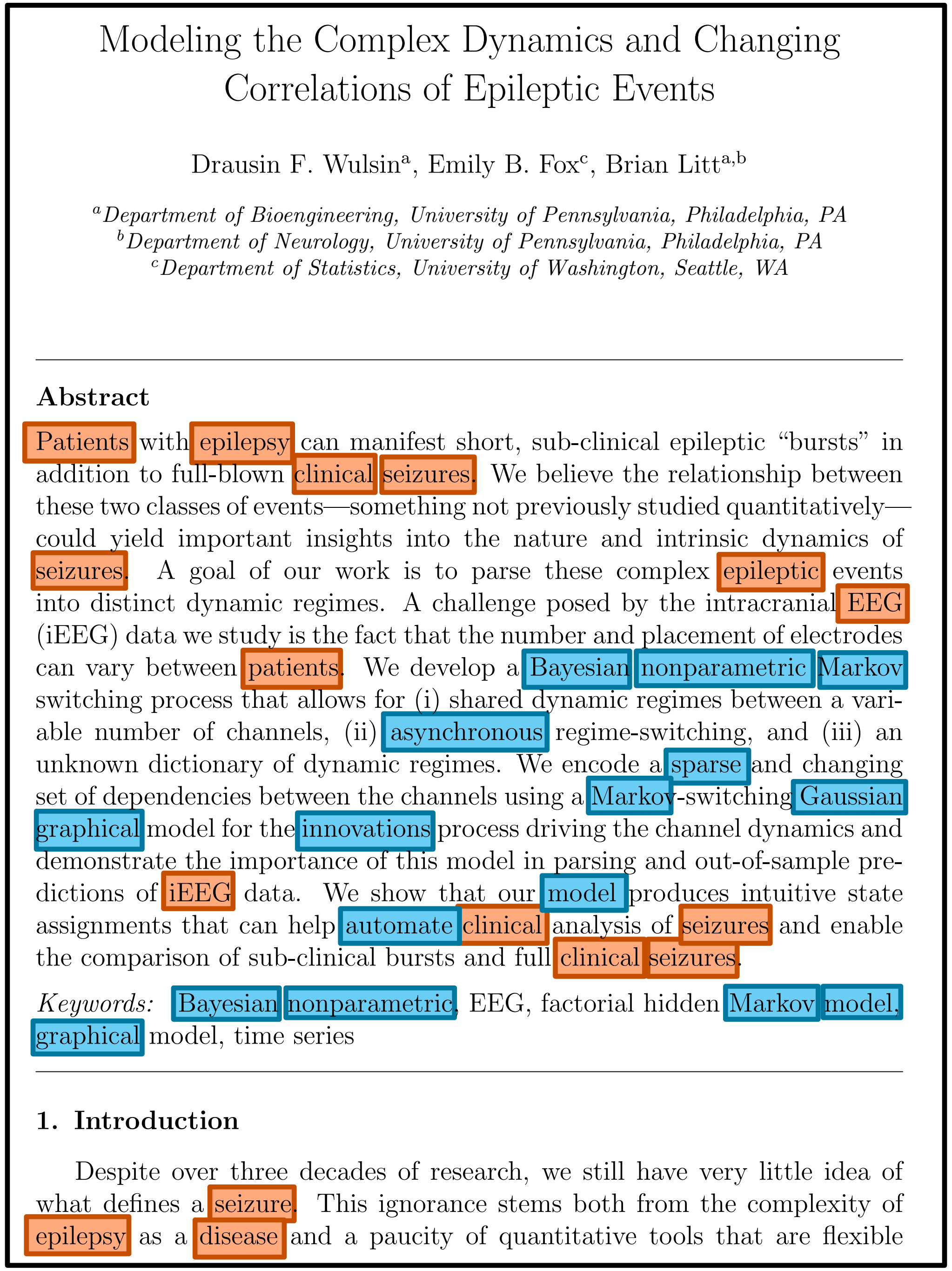

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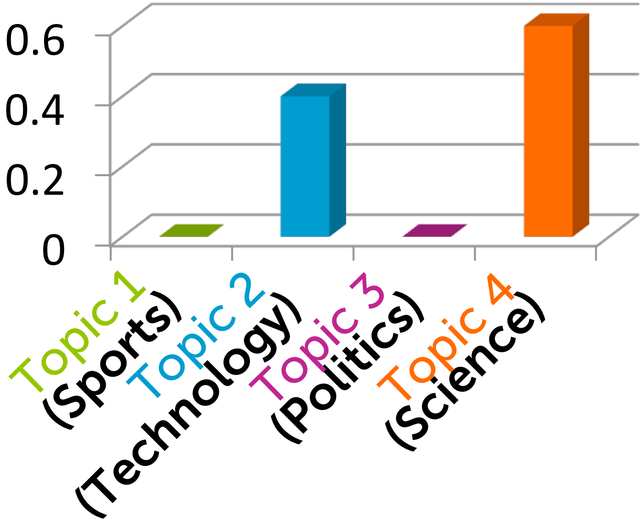
$$\pi_i = [\pi_{i1}\ \ \pi_{i2} \ldots \pi_{iK}]$$



Inference in LDA models

Topic vocab distributions:

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
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injury	0.01
…	…

⋮

Modeling the Complex Dynamics and Changing Correlations of Epileptic Events

Drausin F. Wulsin[a], Emily B. Fox[c], Brian Litt[a,b]

[a]*Department of Bioengineering, University of Pennsylvania, Philadelphia, PA*
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Keywords: Bayesian nonparametric, EEG, factorial hidden Markov model, graphical model, time series

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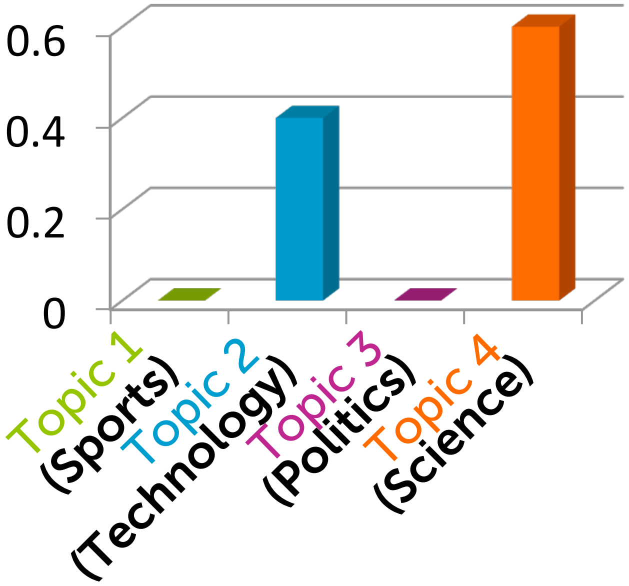

Topic vocab distributions:

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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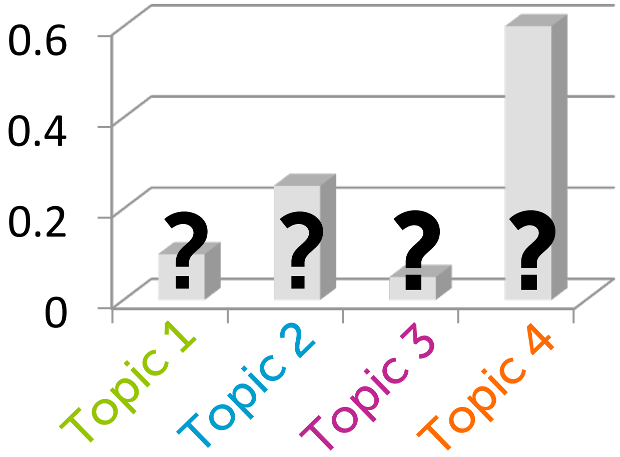

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Word 5	?
…	…

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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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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Interpreting LDA outputs

TOPIC 1	
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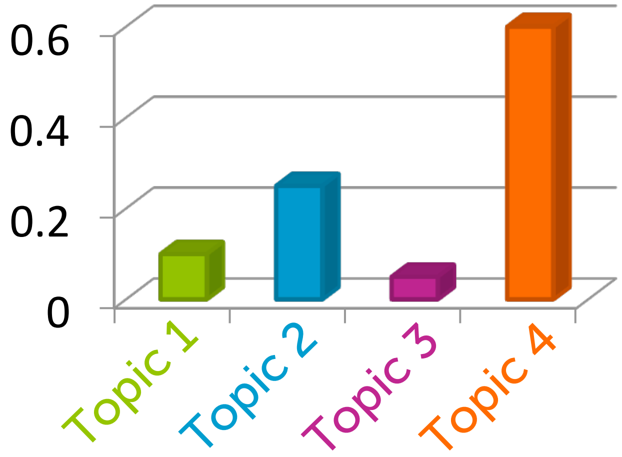

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TOPIC 1	
experiment	0.1
test	0.08
discover	0.05
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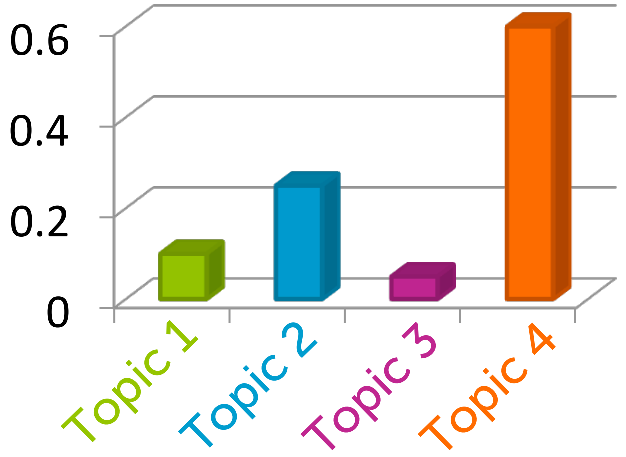

Examine **coherence** of learned topics

- 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

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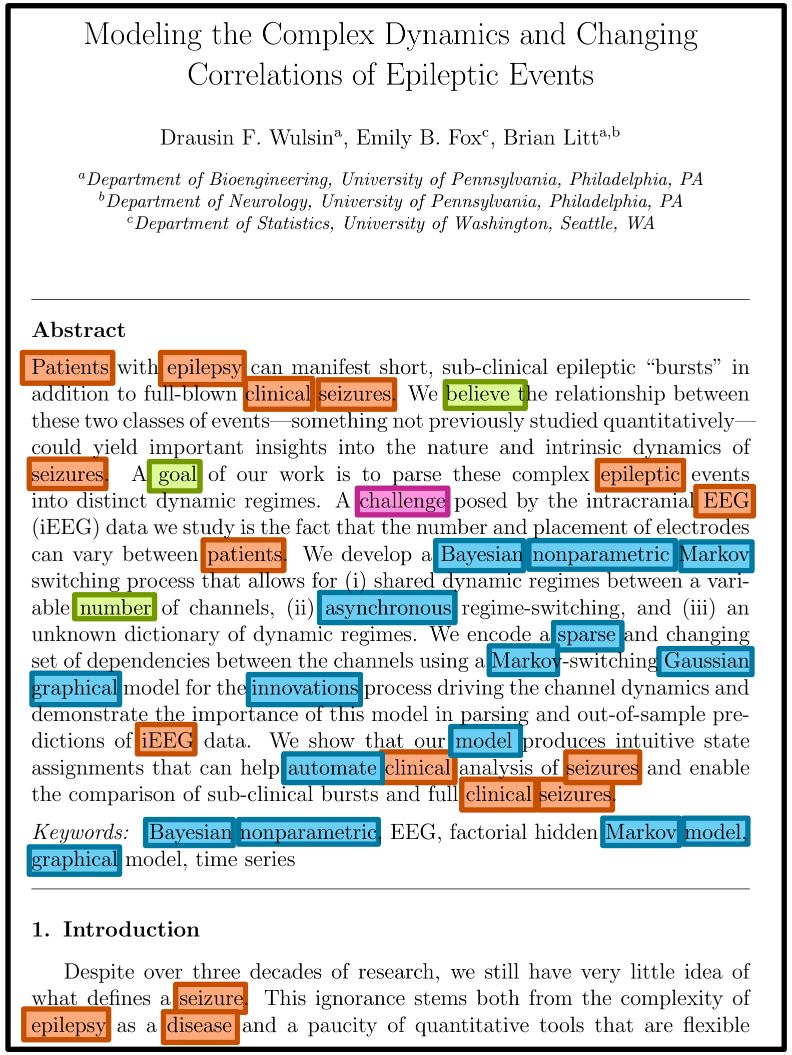
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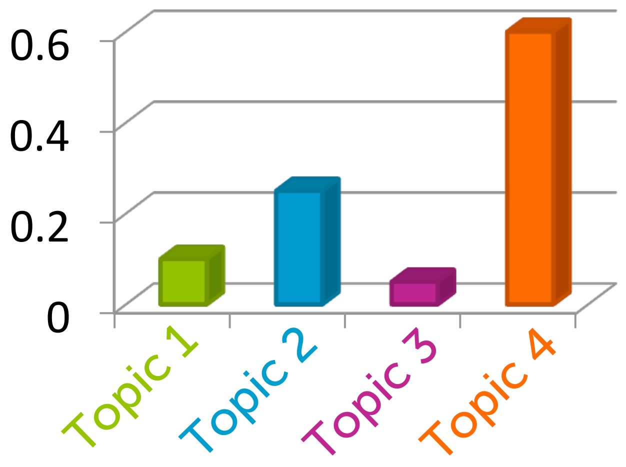

Doc-specific topic proportions can be used to:

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

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TOPIC 1	
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...	...

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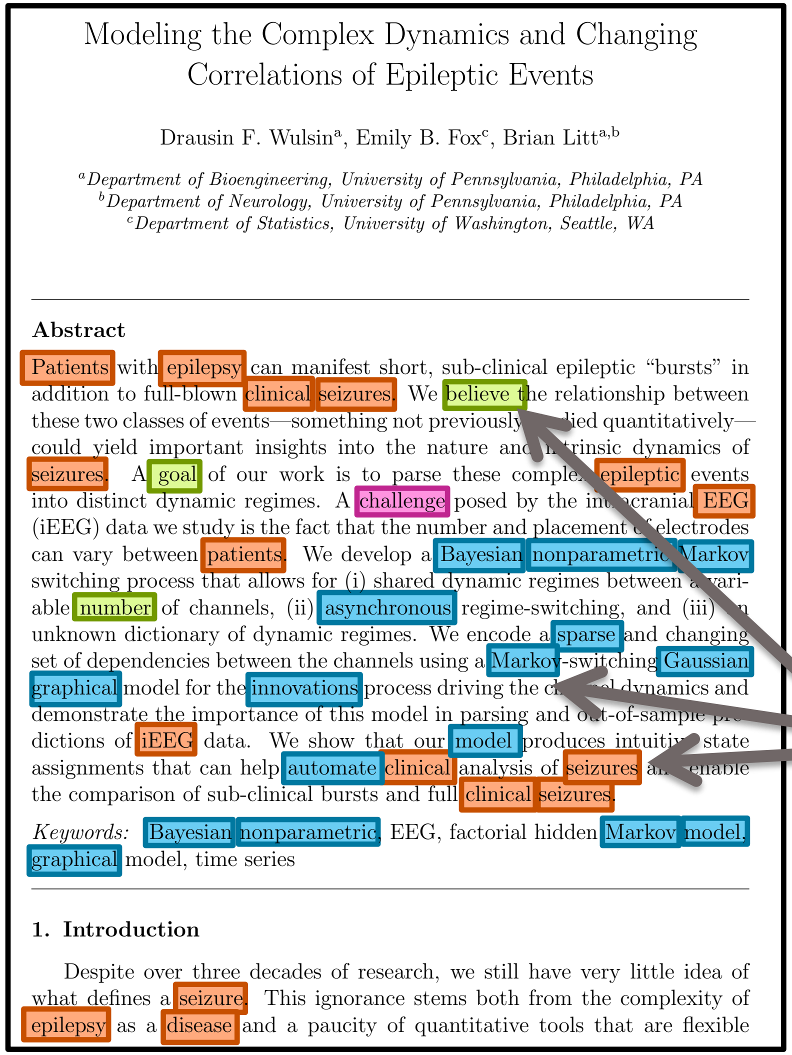
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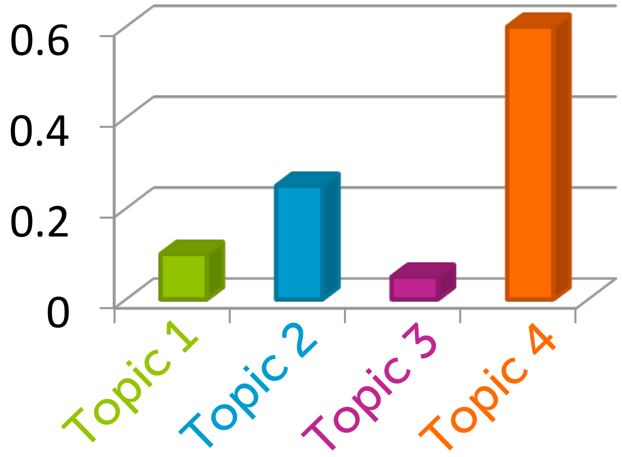

Typically **not** interested in word assignments

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

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

M-step: maximize likelihood over parameters

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

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
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⋮

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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**

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

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SCIENCE	
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test	0.08
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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
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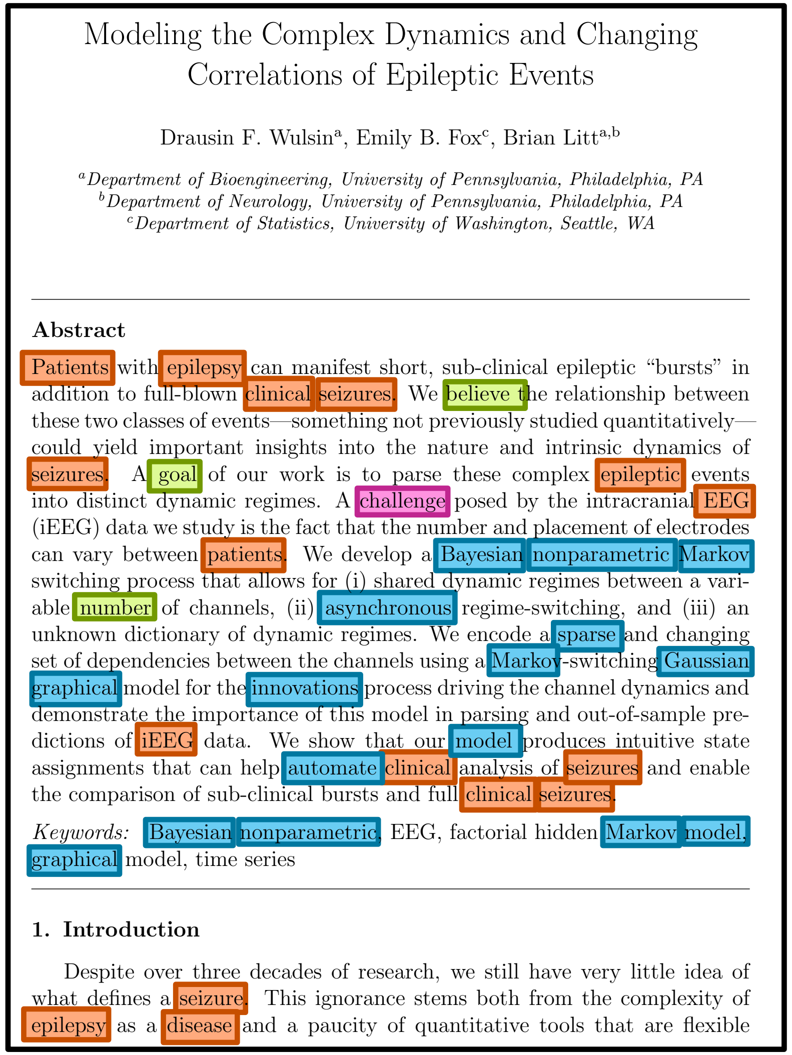

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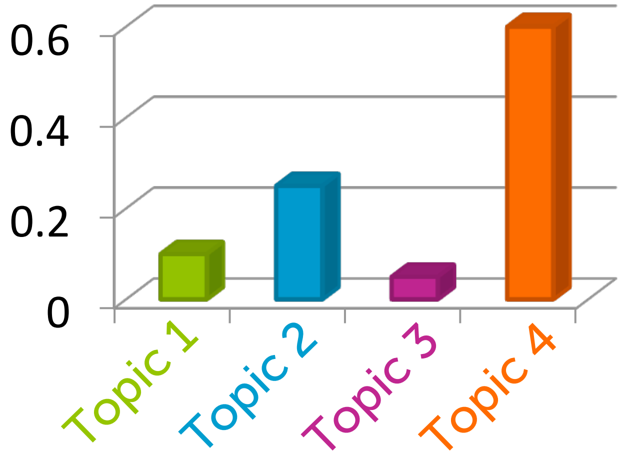

Can derive EM algorithm, but not common

(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
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injury	0.01
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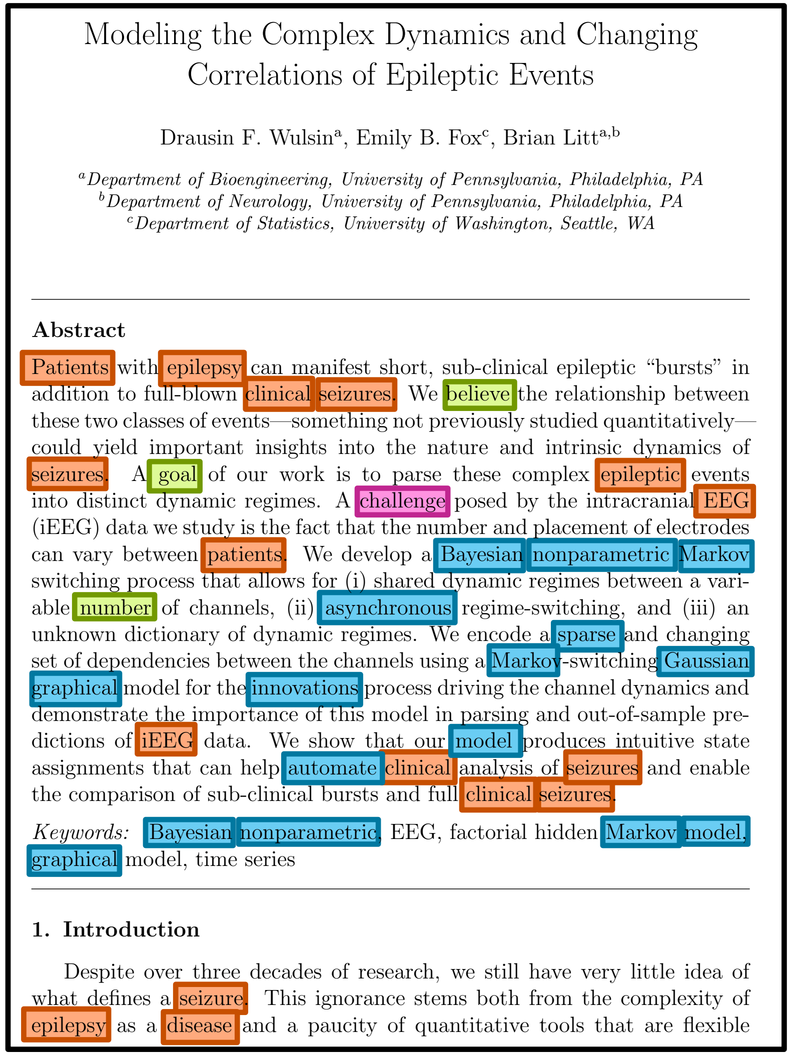
⋮



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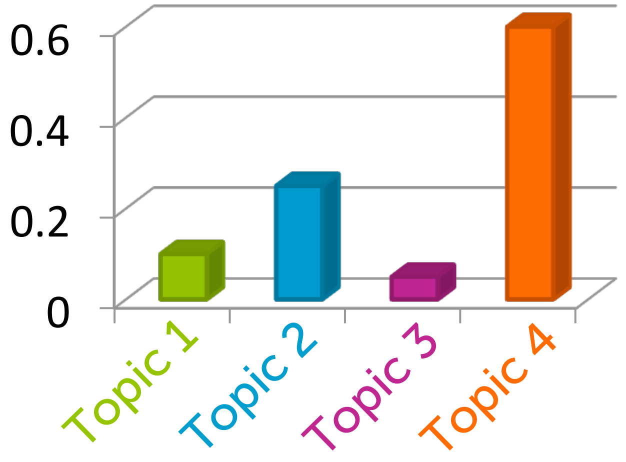


Current set of assignments

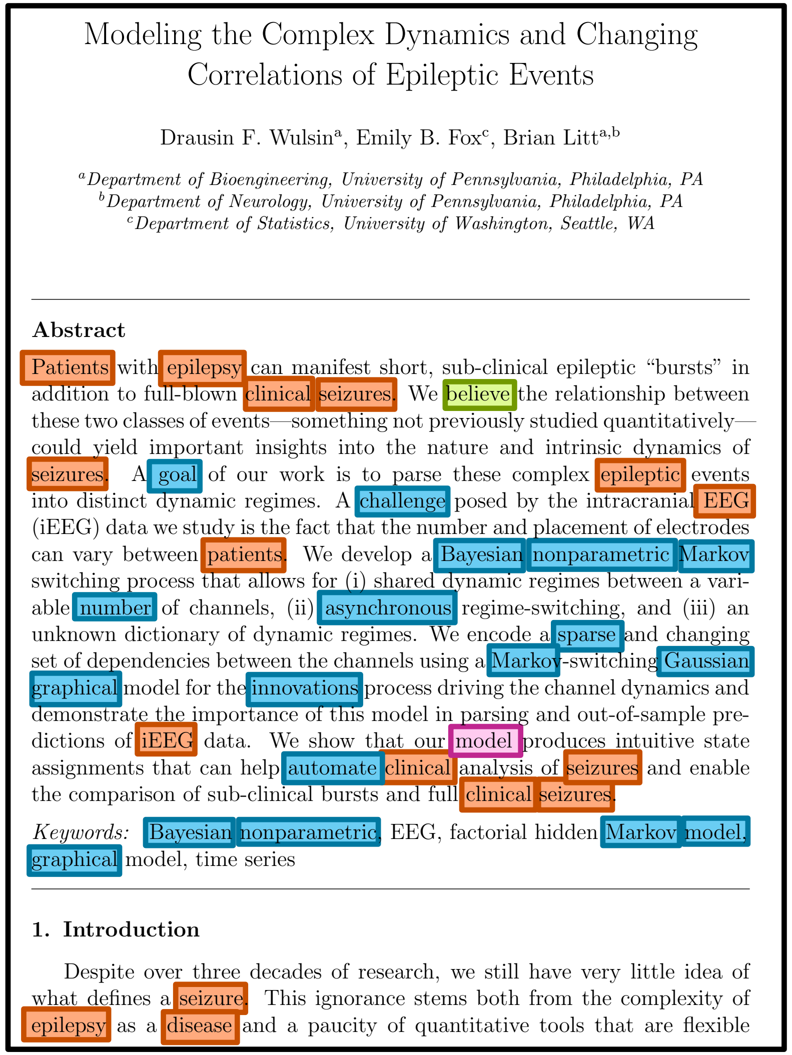
Random sample #10001

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
...	...

⋮



Modeling the Complex Dynamics and Changing Correlations of Epileptic Events

Drausin F. Wulsin[a], Emily B. Fox[c], Brian Litt[a,b]

[a]*Department of Bioengineering, University of Pennsylvania, Philadelphia, PA*
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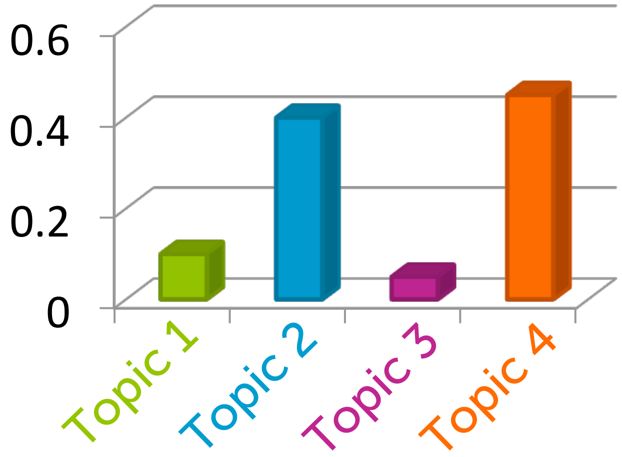

Current set of assignments

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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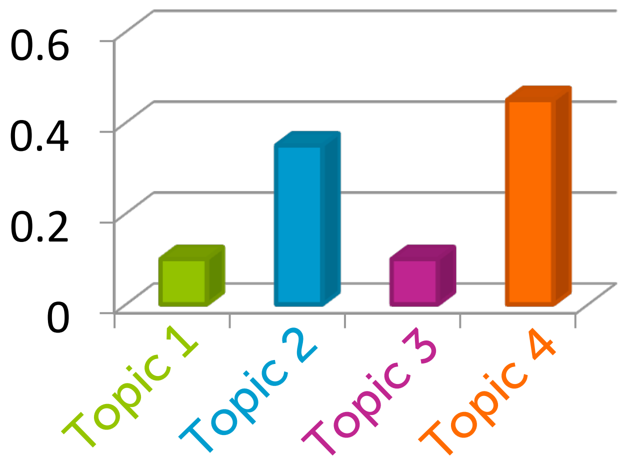
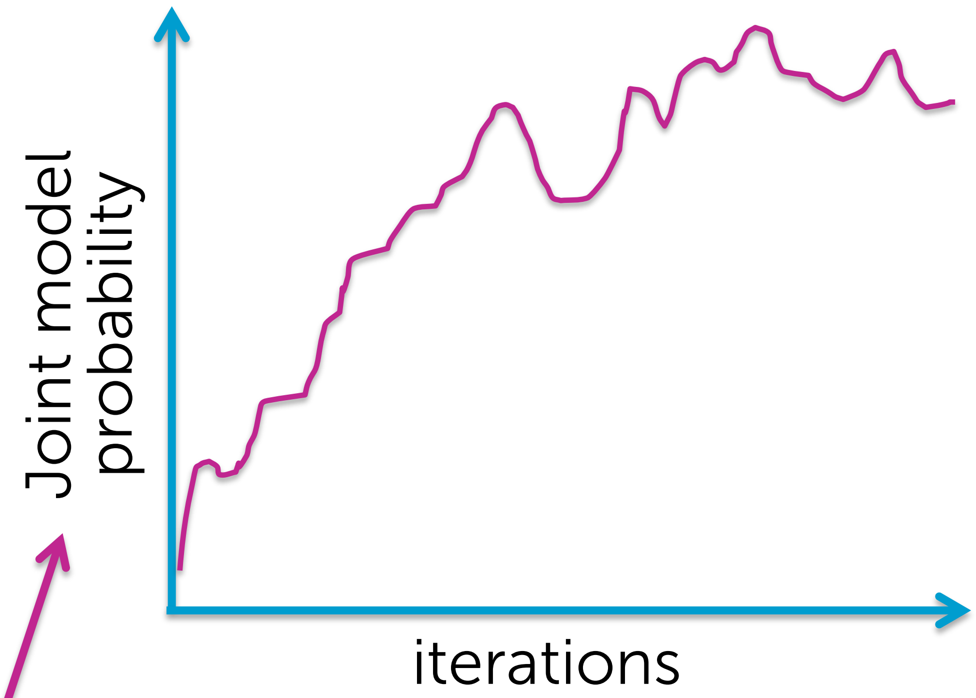


Current set of assignments

What do we know about this process?

Not an optimization algorithm



Eventually provides “correct” Bayesian estimates…

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

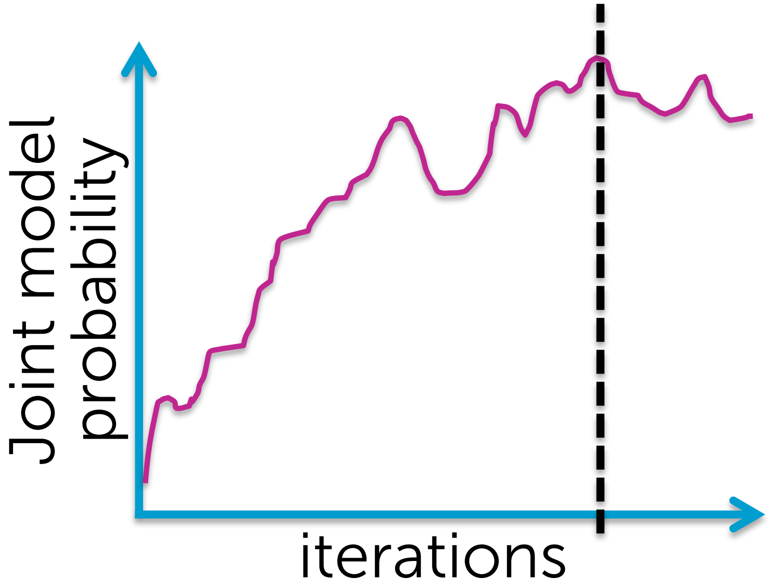
What to do with sampling output?

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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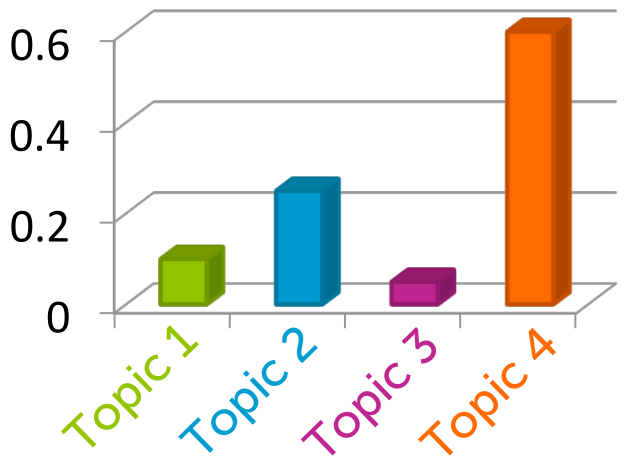

Current set of assignments

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

TOPIC 2	
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score	0.07
team	0.06
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...	...

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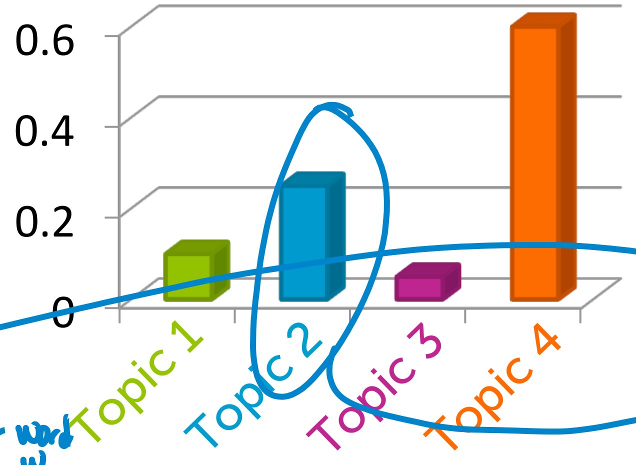
word w in doc i



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

$$r_{iw2} = \frac{\pi_{i2} \cdot p(\text{"EEG"} \mid z_{iw}=2)}{\sum_{j=1}^{K} \pi_{ij}\, p(\text{"EEG"} \mid z_{iw}=j)}$$

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

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

- doc topic proportions
- topic vocab distributions

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

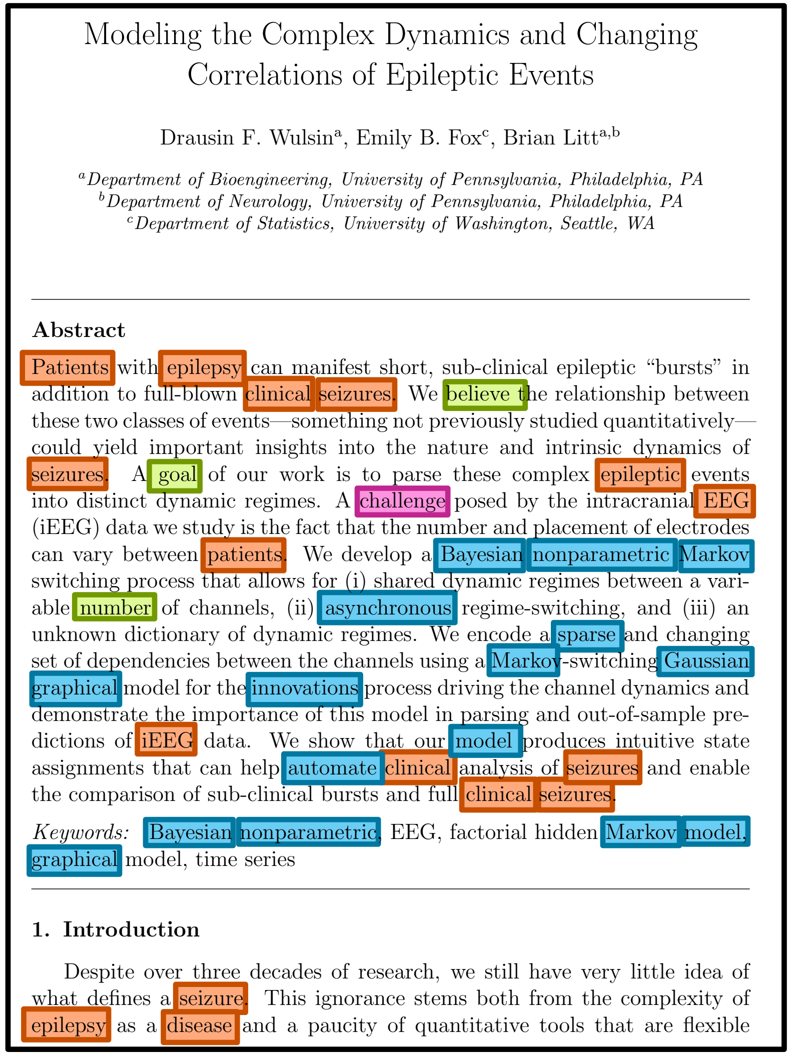
Gibbs sampling for LDA

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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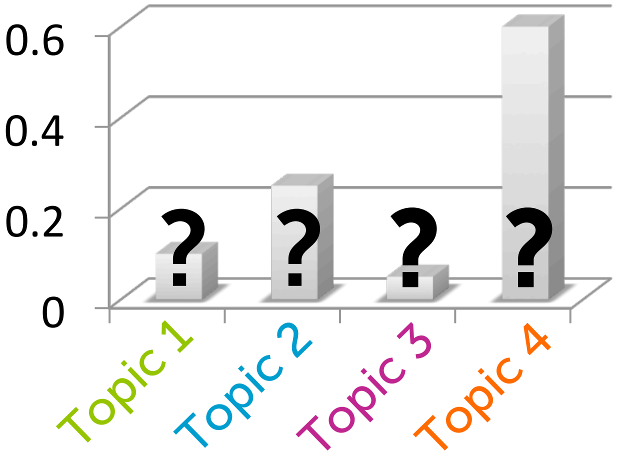


Step 2: Randomly reassign doc topic proportions based on assignments z_{iw} in **current doc**

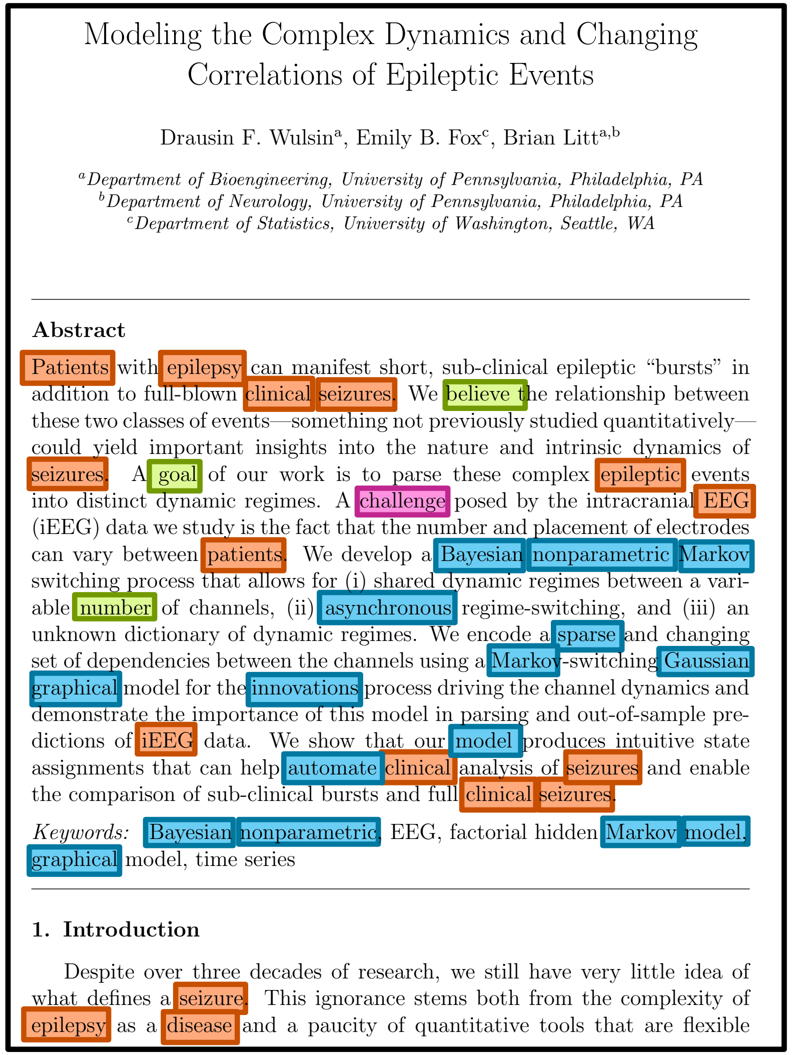
Gibbs sampling for LDA

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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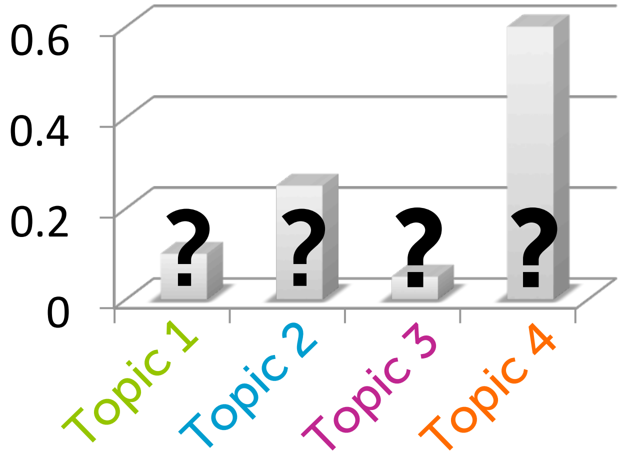


Step 3: Repeat for all docs

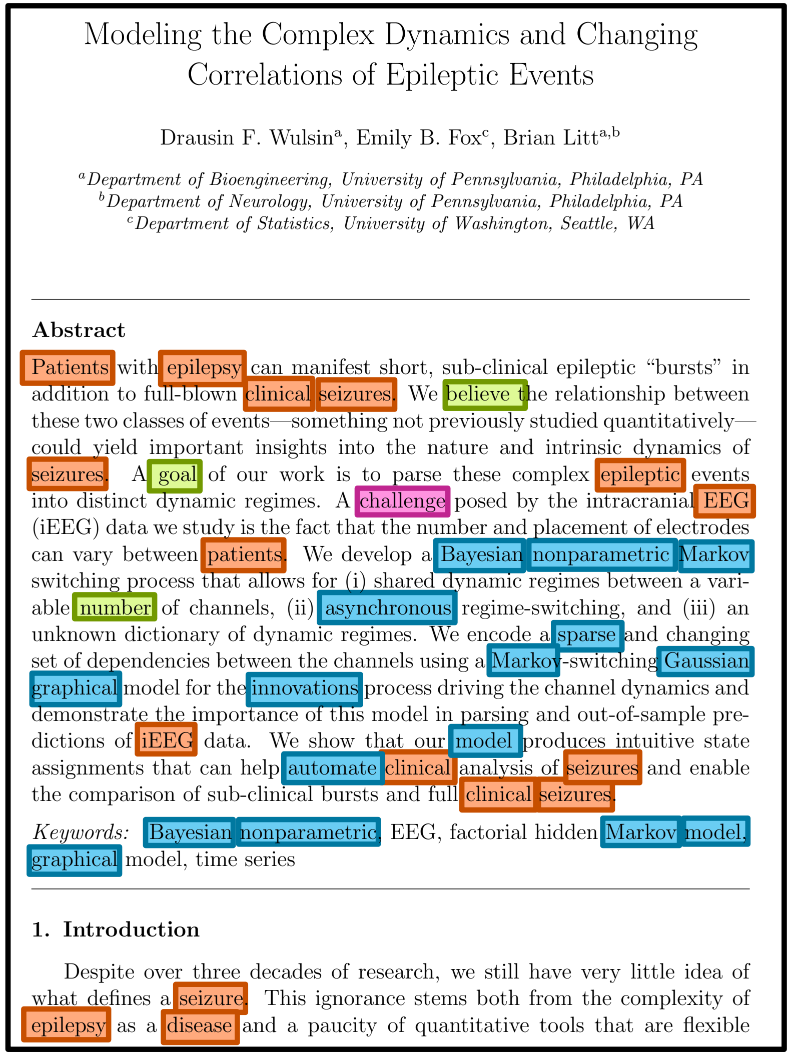
Gibbs sampling for LDA

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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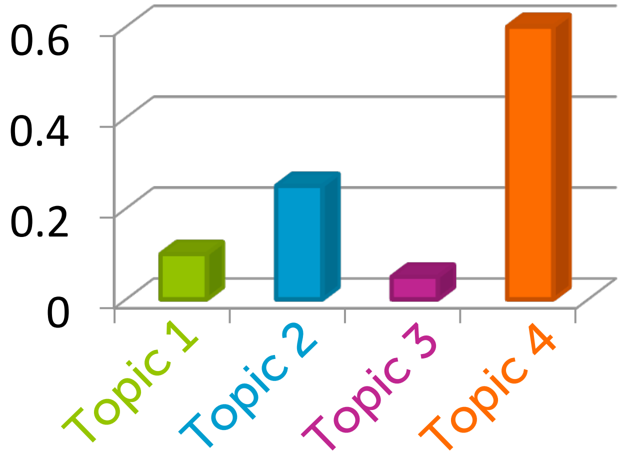

Step 4: Randomly reassign topic vocab distributions based on assignments z_{iw} in **entire corpus**

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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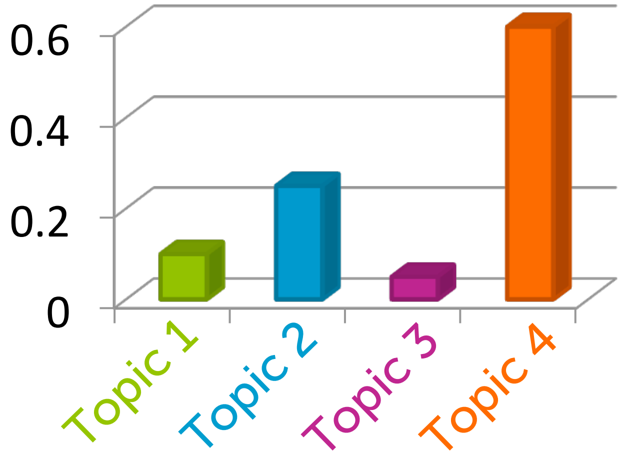


Repeat Steps 1-4 until max iter reached

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

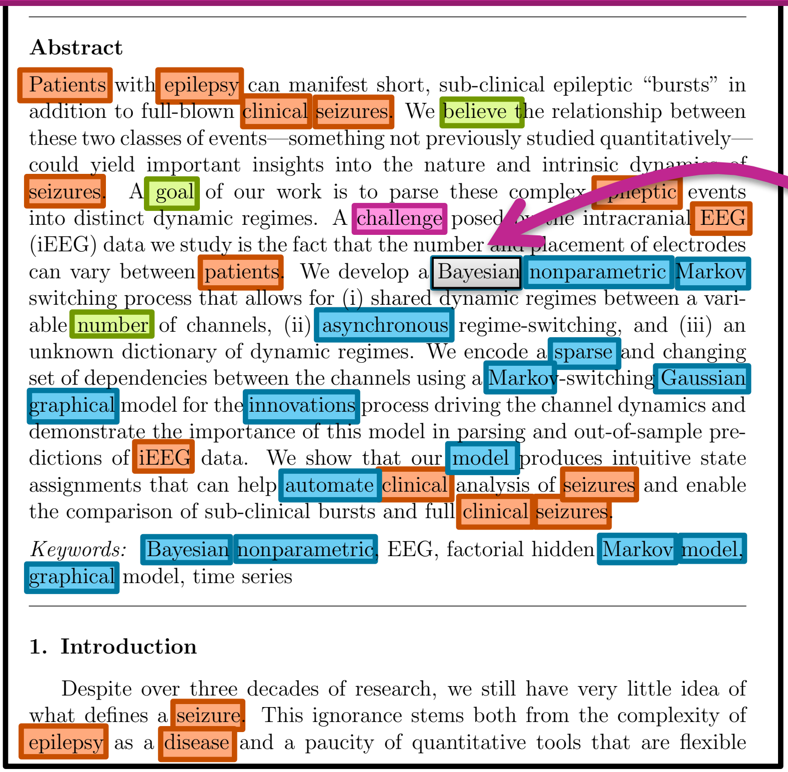
TOPIC 1	
experiment	0.
test	0.
discover	0.
hypothesize	0.
climate	0.
...	...

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
...	...

⋮

Never draw topic vocab distributions or doc topic proportions



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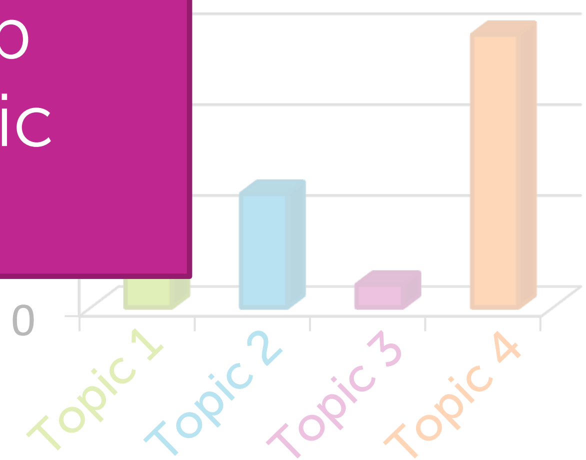


Randomly reassign z_{iw} based on current assignments z_{jv} of all other words **in document and corpus**

Select a document

epilepsy	dynamic	Bayesian	EEG	model

5 word document

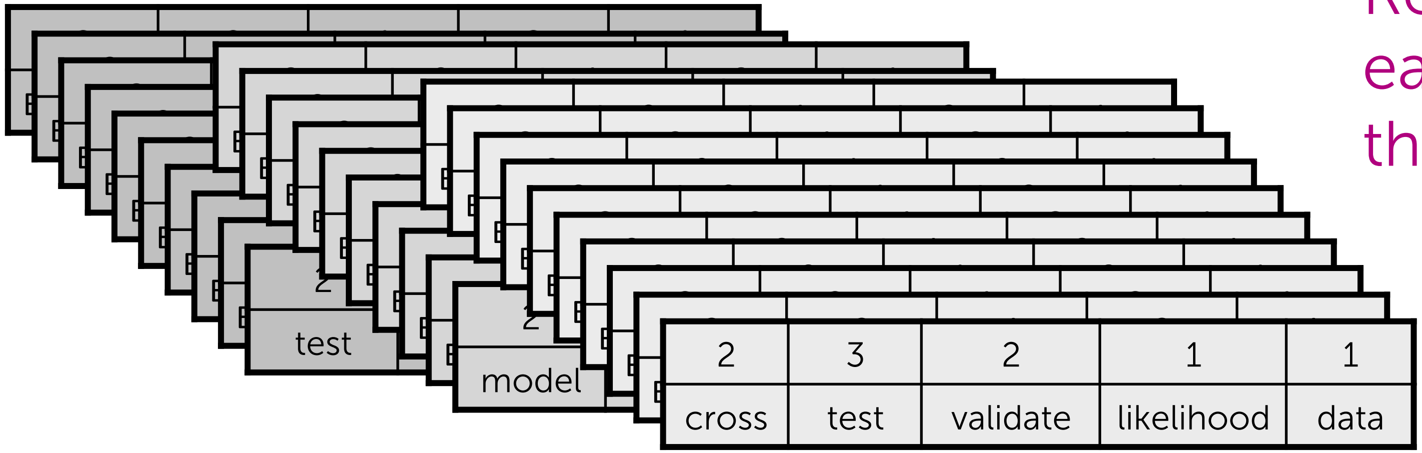
Randomly assign topics

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
Doc i	2	1	2

	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
…			

Total counts from **all** docs

Randomly reassign topics

3	$\cancel{2}$	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

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

	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
...			

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

Probability of new assignment

3	$\boxed{?}$	1	3	1
epilepsy	$\boxed{\text{dynamic}}$	Bayesian	EEG	model

reassign with probability

$p(z_{iw} \mid$ every other z_{jv} in corpus, words in corpus$)$

Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

Topic 1 Topic 2 Topic 3

How much doc "likes" each topic based on other assignments in doc

	Topic 1	Topic 2	Topic 3
Doc i	2	0	2

current assignments to topic k in doc i $\rightarrow$ n_{ik} ; smoothing param $\rightarrow$ α from Bayes prior

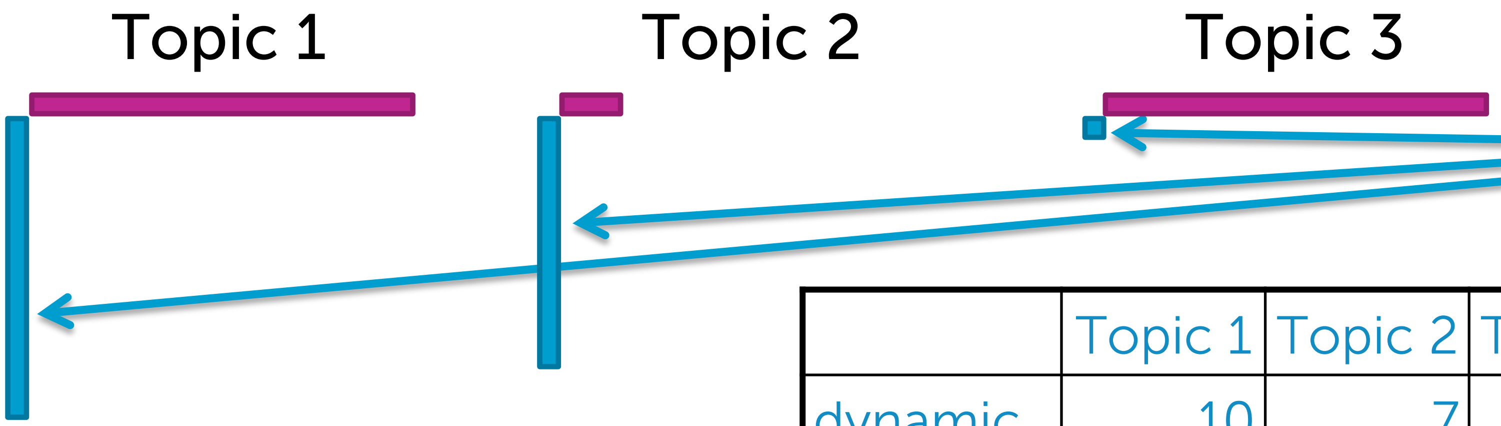
$$\frac{n_{ik} + \alpha}{N_i - 1 + K\alpha}$$

words in doc i $\rightarrow$ N_i

ignore current word

Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



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

	Topic 1	Topic 2	Topic 3
dynamic	10	7	1

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

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

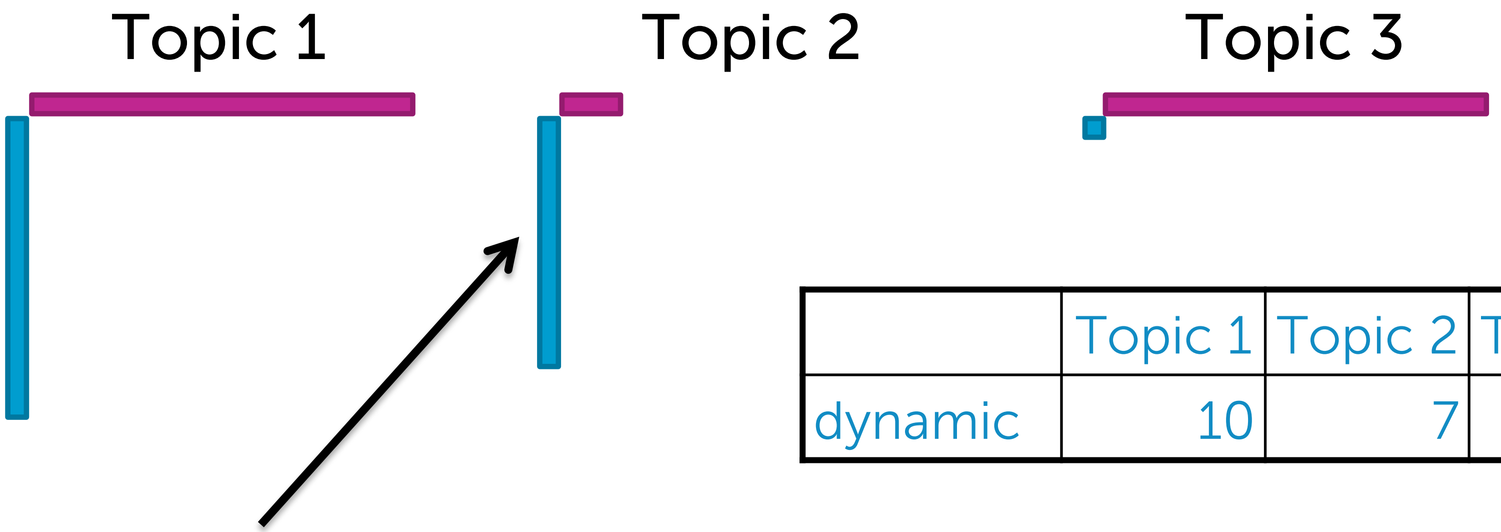
smoothing param

from Bayes prior

size of vocab

Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



	Topic 1	Topic 2	Topic 3
dynamic	10	7	1

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 2 | Topic 3

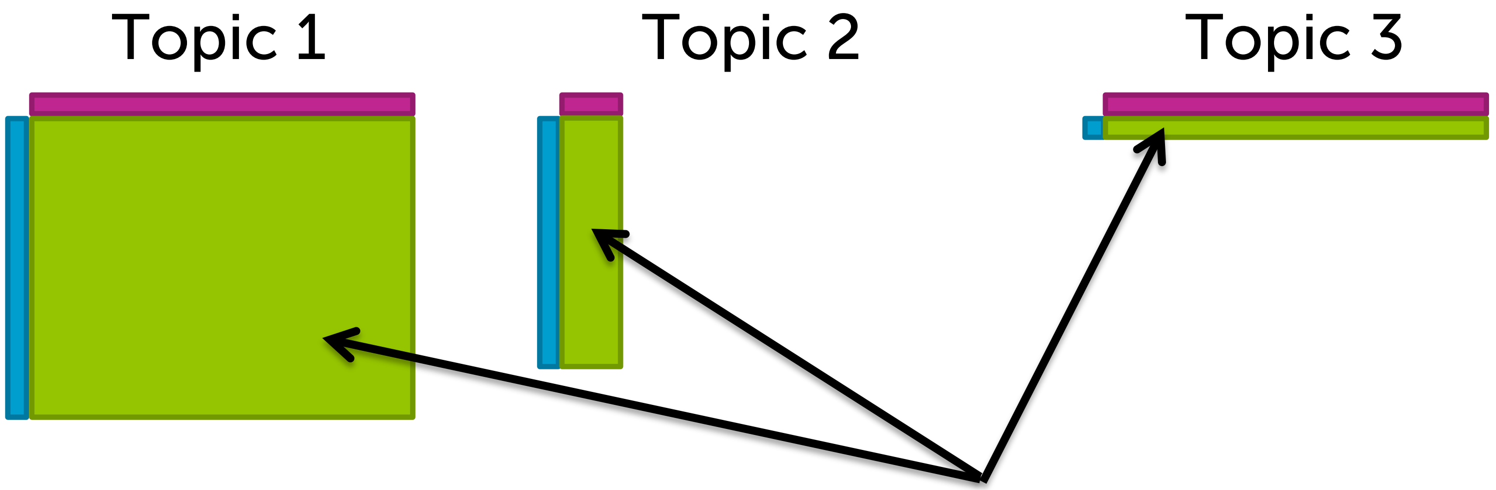
Topic fits word **and** document

Topic fits word, but not doc

Topic fits doc, but not word

Probability of new assignment

3	?	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



How much doc likes topic

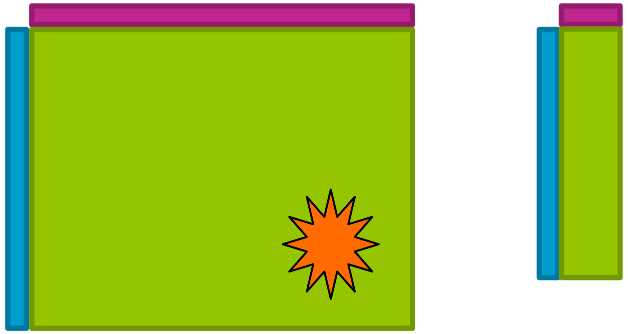
$$\frac{n_{ik}+\alpha}{N_i - 1 + K\alpha} \quad \frac{m_{\text{dynamic},k}+\gamma}{\sum_{w\in V} m_{w,k} + V\gamma}$$

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

Normalize this product of terms over K possible topics!

How much doc likes topic

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

How much topic likes word

Update counts

3	1	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

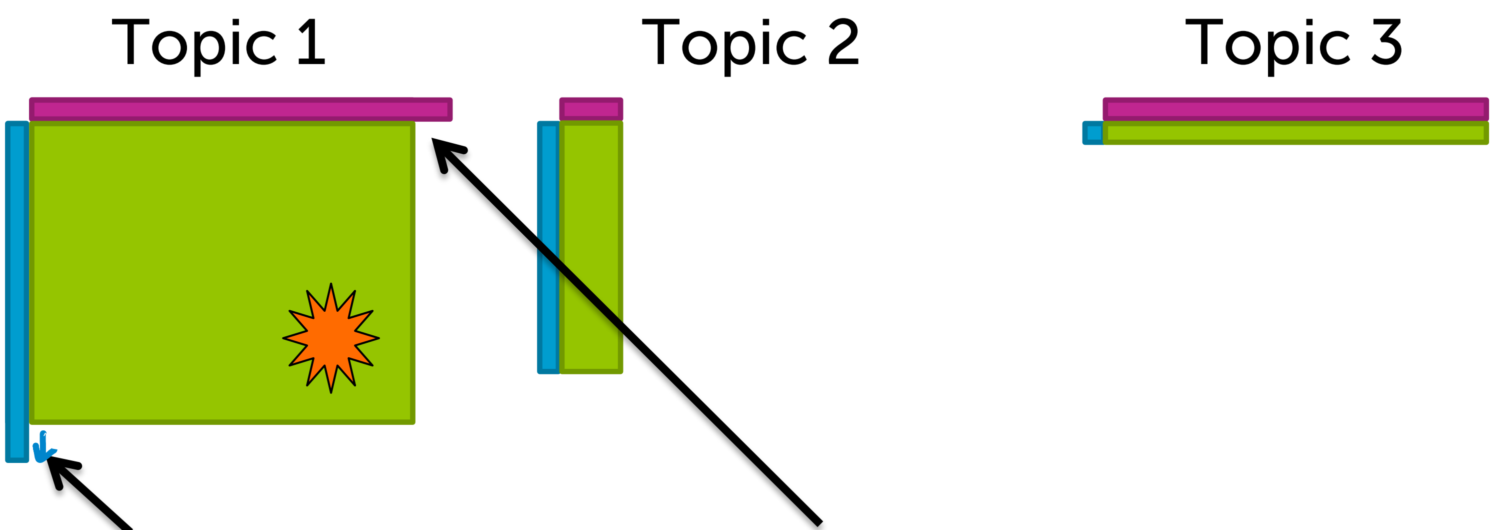
	Topic 1	Topic 2	Topic 3
epilepsy	1	0	35
Bayesian	50	0	1
model	42	1	0
EEG	0	0	20
dynamic	11 ~~10~~	7	1
…			

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

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

Geometrically…

3	1	1	3	1
epilepsy	dynamic	Bayesian	EEG	model



Increase popularity of "dynamic" in topic 1 (**corpus-wide**)

Increase popularity of topic 1 **in doc i**

Iterate through all words/docs

3	1	1	3	1
epilepsy	dynamic	Bayesian	EEG	model

	Topic 1	Topic 2	Topic 3
Doc i	2	0	2

	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
…			

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
goal	0.03
injury	0.01
...	...

⋮

Modeling the Complex Dynamics and Changing Correlations of Epileptic Events

Drausin F. Wulsin[a], Emily B. Fox[c], Brian Litt[a,b]

[a]Department of Bioengineering, University of Pennsylvania, Philadelphia, PA
[b]Department of Neurology, University of Pennsylvania, Philadelphia, PA
[c]Department of Statistics, University of Washington, Seattle, WA

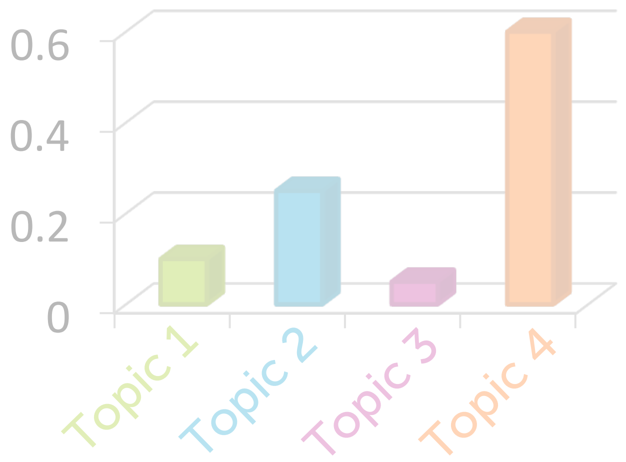
Abstract

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



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

What to do with the collapsed samples?

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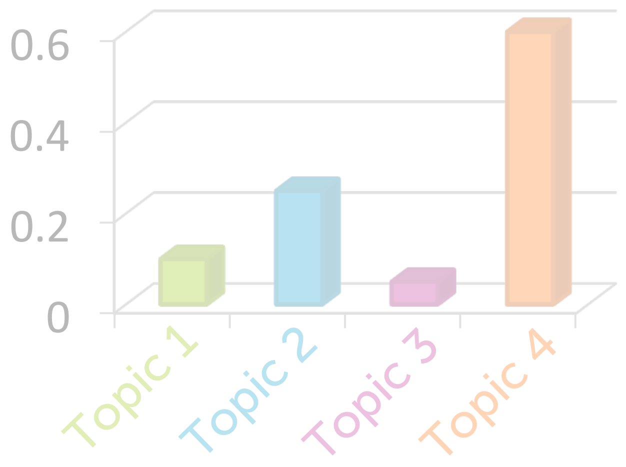

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1. Topics from conditional distribution…
   need corpus-wide info

What to do with the collapsed samples?

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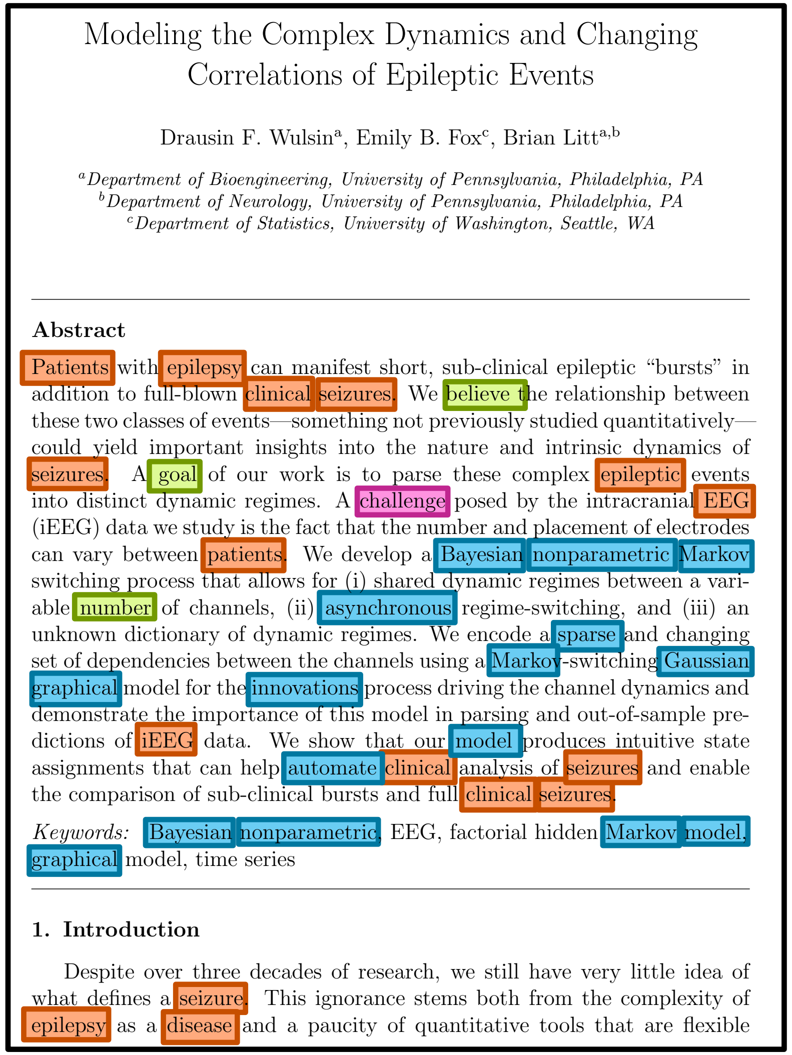

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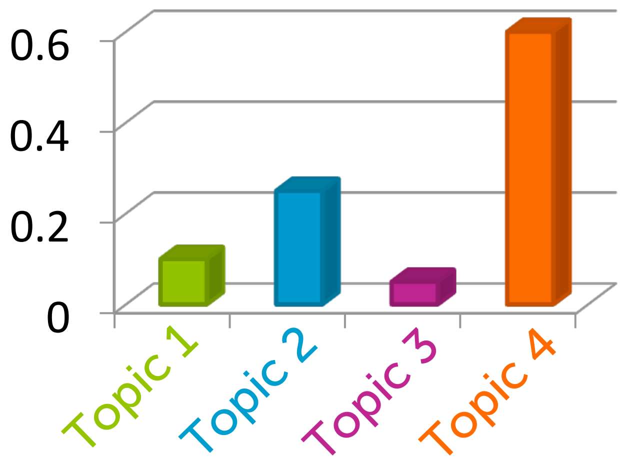

From "best" sample of $\{z_{iw}\}$, can infer:

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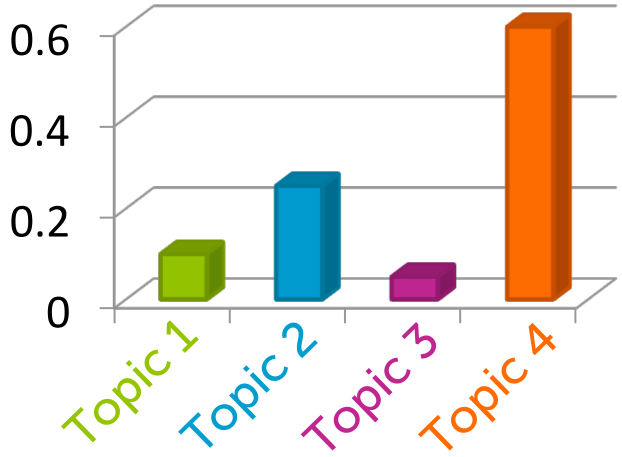

Simple approach:

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

Acknowledgements

Thanks to David Mimno (http://mimno.infosci.cornell.edu) for the collapsed LDA example outline