Nonparametric Bayesian Inference for Topical Collocation Models

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Joint work with Lan Du, Massi Ciaramittra, Zhendong Zhao and Mark Steedman
Outline

Introduction
Probabilistic context-free grammars
Topic models as PCFGs
Adaptor grammars: a non-parametric extension of PCFGs
Segmentation with adaptor grammars
Finding topical collocations with adaptor grammars
Efficient implementation with boundary indicator sampling
Experimental evaluation
Conclusions and future work
Beyond bags of words

• Traditional information retrieval and extraction models treat documents as *bags of words*

• But isolated words can be misleading, especially in *technical domains* such as biomedicine, finance, etc.
  ▶ a *wash sale* isn’t about cleaning anything
  ▶ the *New York Times* isn’t new, and doesn’t have anything to do with arithmetic
  ▶ a *neural net* is not a (e.g., fishing) net, and doesn’t have much to do with brains

• Many collocations are *topic-specific*
  ▶ the *white house* is non-compositional collocation in *politics*, but a compositional phrase in *real-estate*
Prior work on collocations and topic models

- **Pipeline approaches** identify collocations in corpus in a preprocessing step, and uniformly replace each collocation in corpus with a single token (e.g., *neural net* ⇒ *neural_net*) before topic modelling (e.g., Lau et al., 2013)
  - scales well to large corpora
  - collocations are not topic-dependent

- **Extensions to LDA** jointly find topics and collocations
  - **LDACOL** generates each word either from a document-dependent topic, or from the preceding word (Griffiths et al., 2007)
  - **The Topical N-gram model** (TNG) generates each word either from a document-dependent topic, or from a combination of the preceding word and its topic (Wang et al., 2007)
    - the algorithms generally don’t scale to large corpora
    - collocations aren’t topic-dependent in LDACOL

- Our work *jointly infers topics and collocation*, and the inference algorithm is parallelisable and scales to large corpora
Outline of our approach

- We extend *sequence segmentation* models to learn *topical collocations*
  - LDA topic models can be expressed as PCFGs (Johnson 2010)
  - *Adaptor grammars* (Johnson et al 2007) are a non-parametric Bayesian generalisation of PCFGs that can express both segmentation models and topic models
  - Goldwater et al (2006) introduced a non-parametric Bayesian approach to *word segmentation* that uses *point-wise sampling over boundary indicator variables*

- Here we take a *topical collocation model* initially defined as an adaptor grammar, and:
  - reparameterise it using a generalisation of Goldwater’s *boundary indicator variables*, and
  - develop an efficient, *parallel sampler* that exploits *topic and word sparsity* (Yao et al, 2009; Newman et al., 2009)
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Probabilistic Context-Free Grammars

- Probabilistic context-free grammars (PCFGs) define *probability distributions over trees*
- Each *nonterminal node* expands by
  - choosing a rule expanding that nonterminal, and
  - recursively expanding any nonterminal children it contains
- Probability of tree is *product of probabilities of rules* used to construct it

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$Pr(\text{Tree}) = \frac{7}{68}$
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\[ \Pr(\text{Tree}) = 1 \times \]
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Pr(Tree) $= 1 \times 0.7 \times$
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\[
\Pr(\text{Tree}) = 1 \times 0.7 \times 1 \times 0.8 \times 0.3
\]
Simple PCFGs like this are *not very good models of natural language syntax*

- PCFGs aren’t good parameterisations of natural language
- accurate PCFGs need thousands of nonterminal symbols and hundreds of thousands of rules
  - smoothing is an essential “black art”
  - unsupervised estimators of PCFGs perform very poorly *even when initialised with correct parses*

But PCFGs can model many other interesting things!
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**Topic models as PCFGs**

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Conclusions and future work
• Topic models **cluster words and documents into topics**
  ▶ usually *unsupervised* (i.e., topics aren’t given in training data)
• Important for document analysis and information extraction
  ▶ Example: clustering news stories for information retrieval
  ▶ Example: tracking evolution of a research topic over time
Mixture versus admixture topic models

- In a **mixture model**, each document has a **single topic**
  - all words in the document come from this topic
- In **admixture models**, each document has a **distribution over topics**
  - a single document can have multiple topics (number of topics in a document controlled by prior)
  - can capture more complex relationships between documents than a mixture model
- Both mixture and admixture topic models typically use a “**bag of words**” representation of a document
Annotating an unlabeled dataset is one of the bottlenecks in using supervised learning to build good predictive models. Getting a dataset labeled by experts can be expensive and time consuming. With the advent of crowdsourcing services . . .

The task of recovering intrinsic images is to separate a given input image into its material-dependent properties, known as reflectance or albedo, and its light-dependent properties, such as shading, shadows, specular highlights, . . .

In each trial of a standard visual short-term memory experiment, subjects are first presented with a display containing multiple items with simple features (e.g. colored squares) for a brief duration and then, after a delay interval, their memory for . . .

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Example (cont): mixture topic model

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Example (cont): admixture topic model

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This paper’s goal: Collocation topic models

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Mixture versus admixture models

• Admixture models are more complex than mixture models
  ⇒ Admixture models often require more data to learn

• Mixture models can describe shorter documents (phrases, clauses or single sentences) fairly well, where one topic per document assumption is not too bad
  ▶ e.g., Twitter posts

• Admixture models are better for longer documents, which are likely to have more than one topic
  ▶ e.g., long news articles
Mixture topic models as PCFGs (1)

- Idea: Design PCFG so that:
  - non-deterministic rules implement generative steps in topic model
  - deterministic rules propagate information to appropriate place

Sentence $\rightarrow$ Topic$_i'$  \[ i \in 1, \ldots, \ell \]
Topic$_i'$ $\rightarrow$ Topic$_i'$ Topic$_i$  \[ i \in 1, \ldots, \ell \]
Topic$_i'$ $\rightarrow$ Topic$_i$  \[ i \in 1, \ldots, \ell \]
Topic$_i$ $\rightarrow$ $w$  \[ i \in 1, \ldots, \ell \]
\[ w \in \mathcal{W} \]
Mixture topic models as PCFGs (2)

- Choose a topic for sentence (non-deterministically)

Sentence $\rightarrow$ \text{Topic}'$_i$ $\quad i \in 1, \ldots, \ell$

\text{Topic}'$_i$ $\rightarrow$ \text{Topic}'$_i$ \text{Topic}_i $\quad i \in 1, \ldots, \ell$

\text{Topic}'$_i$ $\rightarrow$ \text{Topic}_i $\quad i \in 1, \ldots, \ell$

\text{Topic}_i $\rightarrow$ $w$ $\quad i \in 1, \ldots, \ell$

$w \in \mathcal{W}$
Mixture topic models as PCFGs (3)

- Copy sentence topic to each word (deterministically)

Sentence $\rightarrow$ Topic$_i^\prime$  \hspace{1cm} $i \in 1, \ldots, \ell$
Topic$_i^\prime$ $\rightarrow$ Topic$_i^\prime$ Topic$_i$  \hspace{1cm} $i \in 1, \ldots, \ell$
Topic$_i^\prime$ $\rightarrow$ Topic$_i$  \hspace{1cm} $i \in 1, \ldots, \ell$
Topic$_i$ $\rightarrow$ $w$  \hspace{1cm} $w \in \mathcal{W}$
Mixture topic models as PCFGs (4)

- Generate each word from sentence topic (non-deterministically)

Sentence → Topic\(_i\)  
Topic\(_i\) → Topic\(_i\)  
Topic\(_i\) → Topic\(_i\)  
Topic\(_i\) → w 

Sentence → Topic4'  
Topic4' → Topic4'  
Topic4' → Topic4'  
Topic4' → w

w ∈ \(\mathcal{W}\)
Admixture topic models as PCFGs

- Admixture topic models are usually applied to entire documents.
- Standard PCFG parsing algorithms require time proportional to $t^3$ of sentence length.
  - while PCFGs can generate full documents, with standard parsing algorithms they would be unacceptably slow.
  - see Luong et al. (2013) for a predictive parsing algorithm for very long strings.
- *Document ids* let us break a document into several smaller chunks.
  - a document id is a special nonterminal identifying the document this input came from.
Admixture topic models as PCFGs (1)

• Prefix strings from document \( j \) with a *document identifier* “\(_j\)”

\[
\begin{align*}
\text{Sentence} & \rightarrow \text{Doc}'_j \quad j \in 1, \ldots, m \\
\text{Doc}'_j & \rightarrow \_j \quad j \in 1, \ldots, m \\
\text{Doc}'_j & \rightarrow \text{Doc}'_j \text{ Doc}_j \quad j \in 1, \ldots, m \\
\text{Doc}_j & \rightarrow \text{Topic}_i \quad i \in 1, \ldots, \ell \\
\text{Topic}_i & \rightarrow w \quad i \in 1, \ldots, \ell \\
\text{Topic}_i & \rightarrow \_w \quad i \in 1, \ldots, \ell \\
\text{Doc}_j & \rightarrow \text{Topic}_j \quad j \in 1, \ldots, m \\
\end{align*}
\]
Admixture topic models as PCFGs (2)

- Spine deterministically \textit{propagates document id up through tree}

\[
\begin{align*}
\text{Sentence} &\rightarrow \text{Doc}_j' & j \in 1, \ldots, m \\
\text{Doc}_j' &\rightarrow _j & j \in 1, \ldots, m \\
\text{Doc}_j' &\rightarrow \text{Doc}_j' \text{ Doc}_j & j \in 1, \ldots, m \\
\text{Doc}_j &\rightarrow \text{Topic}_i & i \in 1, \ldots, \ell \\
\text{Topic}_i &\rightarrow w & i \in 1, \ldots, \ell \\
\end{align*}
\]
Admixture topic models as PCFGs (3)

- \( \text{Doc}_j \rightarrow \text{Topic}_i \) rules nondeterministically map documents to topics
Admixture topic models as PCFGs (4)

- \( \text{Topic}_i \rightarrow w \) rules nondeterministically map *topics to words*

Sentence \( \rightarrow \) Doc\(_j^\prime\)  \( j \in 1, \ldots, m \)

Doc\(_j^\prime\) \( \rightarrow \_j \) \( j \in 1, \ldots, m \)

Doc\(_j^\prime\) \( \rightarrow \text{Doc}^\prime_j \text{Doc}_j \) \( j \in 1, \ldots, m \)

Doc\(_j\) \( \rightarrow \text{Topic}_i \) \( i \in 1, \ldots, \ell \)

\( \text{Topic}_i \rightarrow w \) \( i \in 1, \ldots, \ell \)

\( w \in \mathcal{W} \)
Why are these reductions interesting?

• *Not* claiming that topic modelling should be done using PCFGs
  ▶ PCFG parsing takes time proportional to *cube* of document length
  ▶ standard topic model algorithms take time *linear* in document length

• The PCFG reductions suggest *new kinds of models that merge grammars and topic models*
  ▶ easily implemented and evaluated (on small corpora at least)

• Grammars are good at:
  ▶ grouping words into hierarchically-structured larger units
  ▶ tracking relative ordering of these units
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Motivation for adaptor grammars

- PCFGs are *parametric models*
  - a PCFG can be viewed as a set of multinomials (one for each nonterminal)
    - learning a PCFG $\Rightarrow$ setting the rule probabilities
- But in some cases *the rules* themselves have to be learnt
- One way to formulate this:
  - there is an *infinite set of possible rules*
    - but *only finitely many have non-zero probability*
- In an adaptor grammar, the *possible rules are the yields of the trees generated by a PCFG*
  - adaptor grammars formalise this by using a PCFG to define the base distribution of a *Dirichlet Process* or a *Pitman-Yor Process*
  - recursion in the PCFG $\Rightarrow$ *hierarchical Dirichlet Processes*
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Unsupervised word segmentation

- **Word segmentation** task: *segment utterances into words* (Elman 1993, Brent 1996)
- Input: phoneme sequences with *sentence boundaries*
- Task: identify *word boundaries*, and hence words

\[
\text{you \ want \ to \ see \ the \ book}
\]

- Ignoring phonology and morphology, this involves *learning the pronunciations of the lexical items* in the language
CFG models of word segmentation

Words → Word
Words → Word Words
Word → Phons
Phons → Phon
Phons → Phon Phons
Phon → a | b | ... 

• CFG trees can describe segmentation, but

• PCFGs can’t distinguish good segmentations from bad ones
  ▶ PCFG rules are too small a unit of generalisation
  ▶ need to learn e.g., probability that bUk is a Word
Towards non-parametric grammars

Words → Word
Words → Word Words
Word → all possible phoneme sequences

- Learn probability Word → b U k
- But infinitely many possible Word expansions
  ⇒ this grammar is not a PCFG
- Given fixed training data, only finitely many useful rules
  ⇒ use data to choose Word rules as well as their probabilities
- An adaptor grammar can do precisely this!
Unigram adaptor grammar (Brent)

Words → Word
Words → Word Words
Word → Phons
Phons → Phon
Phons → Phon Phons

• Word nonterminal is adapted

⇒ To generate a Word:
  ▶ select a previously generated Word subtree with probability \( \propto \) number of times it has been generated
  ▶ expand using Word → Phons rule with probability \( \propto \alpha_{\text{Word}} \) and recursively expand Phons
Adaptor grammars as a non-parametric extension of PCFGs

- An adaptor grammar reuses previously-generated subtrees $T_A$ of adapted nonterminals $A$
- This is equivalent to adding a rule $A \rightarrow w$ to the grammar, where $w$ is the yield of $T_A$
  - for implementation efficiency, adaptor grammars constrain $w$ to only consist of terminals
  - Fragment Grammars (O’Donnell 2009) lift this restriction
- If the base CFG generates an infinite number of trees $T_A$ for $A$, then the adaptor grammar is non-parametric
- But any set of sample parses for a finite training corpus only contains a finite number of number of adapted subtrees
  - sampling methods (e.g., MCMC) are a natural approach to learning and parsing adaptor grammars
  - in implementation terms, an adaptor grammar is like a PCFG with a constantly changing set of rules
Computation with adaptor grammars

- Adaptor grammars are *strictly more expressive than PCFGs*
  - non-parametric ⇒ can’t be represented by a finite parameter vector
- But the *posterior predictive distribution* can be *approximated by a PCFG* where *the rules vary depending on the data*

⇒ Metropolis-within-Gibbs MCMC sampler (Johnson et al., 2007)

repeat forever:
  - randomly pick a string from training data
  - compute approximating PCFG for posterior predictive distribution given parses for other sentences
  - *sample a parse from approximating PCFG*
  - use a Metropolis-Hastings accept-reject step to correct for approximation

- The parsing step is usually the slowest (cubic in length of string)
- Cohen et al. (2010) have developed a mean-field variational Bayes inference algorithm for adaptor grammars
Unigram model of word segmentation

- Unigram “bag of words” model (Brent):
  - generate a *dictionary*, i.e., a set of words, where each word is a random sequence of phonemes
    - Bayesian prior prefers smaller dictionaries
  - generate each utterance by choosing each word at random from dictionary
- Brent’s unigram model as an adaptor grammar:

Words → Word⁺
Word → Phoneme⁺

• Accuracy of word segmentation learnt: *56% token f-score*
  (same as Brent model)
• But we can construct many more word segmentation models using AGs
Adaptor grammar learnt from Brent corpus

• **Initial grammar**

1  Words → **Word** Words  
1  **Word** → Phon 
1  Phons → Phon Phons  
1  Phon → $D$  
1  Phon → $A$

1  Words → **Word** 
1  Word → Phon  
1  Phons → Phon Phons  
1  Phon → $G$  
1  Phon → $E$

• **A grammar learnt from Brent corpus**

16625  Words → **Word** Words  
1575  **Word** → Phons  
4962  Phons → Phon Phons  
134  Phon → $D$  
180  Phon → $A$  
460  **Word** → (Phons (Phon $y$) (Phons (Phon $u$)))  
446  **Word** → (Phons (Phon $w$) (Phons (Phon $A$) (Phons (Phon $t$))))  
374  **Word** → (Phons (Phon $D$) (Phons (Phon $6$)))  
372  **Word** → (Phons (Phon $&$) (Phons (Phon $n$) (Phons (Phon $d$))))
More complex adaptor grammar models of word segmentation

• Because adaptor grammar models generalise PCFGs, we can combine the topic model grammars and word segmentation grammars
  ▶ non-linguistic context does improve word segmentation
  ▶ social cues do not improve word segmentation (as far as we can tell)
• We can learn the internal structure of words too
  ▶ words are a sequence of syllables
  ▶ learn syllable structure jointly with word segmentation
  ▶ we can learn different structures for word-peripheral and word-internal syllables
  ⇒ the best reported accuracy for unsupervised word segmentation (89% f-score)
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Topical collocation models

Annotating an unlabeled dataset is one of the bottlenecks in using supervised learning to build good predictive models. Getting a dataset labeled by experts can be expensive and time consuming. With the advent of crowdsourcing services...

The task of recovering intrinsic images is to separate a given input image into its material-dependent properties, known as reflectance or albedo, and its light-dependent properties, such as shading, shadows, specular highlights, ...

In each trial of a standard visual short-term memory experiment, subjects are first presented with a display containing multiple items with simple features (e.g., colored squares) for a brief duration and then, after a delay interval, their memory for ...

Many studies have uncovered evidence that visual cortex contains specialized regions involved in processing faces but not other object classes. Recent electrophysiology studies of cells in several of these specialized regions revealed that at least some ...
Topic model with collocations

- Combines *PCFG for admixture topic model* and *segmentation adaptor grammar*

Sentence → Doc$_j$ \( j \in 1, \ldots, m \)

Doc$_j$ → $\_j$ \( j \in 1, \ldots, m \)

Doc$_j$ → Doc$_j$ Topic$_i$ \( i \in 1, \ldots, \ell; \)

\( j \in 1, \ldots, m \)

Topic$_i$ → Words \( i \in 1, \ldots, \ell \)

Words → Word

Words → Words Word

Word → $w$ \( w \in W \)
Data preparation in Griffiths et al (2007)

- Documents are papers from NIPS proceedings (~ 3 million words)
- Case normalised
- Segmented at *punctuation* and *function words*

annotating an unlabeled dataset is one of the bottlenecks in using supervised learning to build good predictive models. Getting a dataset labeled by experts can be expensive and time consuming. With the advent of crowdsourcing services ... the task of recovering intrinsic images is to separate a given input image into its material-dependent properties, known as reflectance or albedo, and its light-dependent properties, such as shading, shadows, specular highlights, ...
Finding topical collocations in NIPS abstracts

- Run topical collocation adaptor grammar on NIPS corpus
- Run with $\ell = 20$ topics (i.e., 20 distinct Topic$_i$ nonterminals)
- Corpus is segmented by punctuation
  - terminal strings are fairly short
  - inference is fairly efficient
- Used Pitman-Yor adaptors
  - sampled Pitman-Yor $a$ and $b$ parameters
  - flat and “vague Gamma” priors on Pitman-Yor $a$ and $b$ parameters
Sample output on NIPS corpus, 20 topics

- Multiword subtrees learned by adaptor grammar:
  
  \[ T_0 \rightarrow \text{gradient descent} \]
  \[ T_0 \rightarrow \text{cost function} \]
  \[ T_0 \rightarrow \text{fixed point} \]
  \[ T_0 \rightarrow \text{learning rates} \]
  \[ T_3 \rightarrow \text{membrane potential} \]
  \[ T_3 \rightarrow \text{action potentials} \]
  \[ T_3 \rightarrow \text{visual system} \]
  \[ T_3 \rightarrow \text{primary visual cortex} \]
  \[ T_1 \rightarrow \text{associative memory} \]
  \[ T_1 \rightarrow \text{standard deviation} \]
  \[ T_1 \rightarrow \text{randomly chosen} \]
  \[ T_1 \rightarrow \text{hamming distance} \]
  \[ T_{10} \rightarrow \text{ocular dominance} \]
  \[ T_{10} \rightarrow \text{visual field} \]
  \[ T_{10} \rightarrow \text{nervous system} \]
  \[ T_{10} \rightarrow \text{action potential} \]

- Sample skeletal parses:
  
  \[ _3 \ (T_5 \text{ polynomial size}) \ (T_{15} \text{ threshold circuits}) \]
  \[ _4 \ (T_{11} \text{ studied}) \ (T_{19} \text{ pattern recognition algorithms}) \]
  \[ _4 \ (T_2 \text{ feedforward neural network}) \ (T_1 \text{ implements}) \]
  \[ _5 \ (T_{11} \text{ single}) \ (T_{10} \text{ ocular dominance stripe}) \ (T_{12} \text{ low}) \ (T_3 \text{ ocularity}) \ (T_{12} \text{ drift rate}) \]
Some collocations found in NIPS corpus

<table>
<thead>
<tr>
<th>Count</th>
<th>Topic</th>
<th>Collocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>T0</td>
<td>unites states israeli binational science foundation bsf</td>
</tr>
<tr>
<td>2</td>
<td>T5</td>
<td>batch k-means empty circles online gradient</td>
</tr>
<tr>
<td>12</td>
<td>T1</td>
<td>partially observable markov decision processes</td>
</tr>
<tr>
<td>12</td>
<td>T2</td>
<td>defense advanced research projects agency</td>
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<tr>
<td>7</td>
<td>T5</td>
<td>radial basis function rbf network</td>
</tr>
<tr>
<td>5</td>
<td>T6</td>
<td>analog vlsi neural network chip</td>
</tr>
<tr>
<td>4</td>
<td>T12</td>
<td>national science foundation graduate fellowship</td>
</tr>
<tr>
<td>3</td>
<td>T10</td>
<td>globally optimal on-line learning rules</td>
</tr>
<tr>
<td>3</td>
<td>T12</td>
<td>radial basis function rbf units</td>
</tr>
<tr>
<td>3</td>
<td>T13</td>
<td>non-parametric multi-scale statistical image model</td>
</tr>
<tr>
<td>3</td>
<td>T15</td>
<td>weight vector estimate requires knowledge</td>
</tr>
<tr>
<td>3</td>
<td>T17</td>
<td>orientation bands intersect ocular dominance</td>
</tr>
<tr>
<td>3</td>
<td>T18</td>
<td>optimal brain damage le cun</td>
</tr>
<tr>
<td>3</td>
<td>T6</td>
<td>normalized mean squared prediction error</td>
</tr>
<tr>
<td>47</td>
<td>T5</td>
<td>markov chain monte carlo</td>
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<tr>
<td>43</td>
<td>T12</td>
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<td>41</td>
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<tr>
<td>23</td>
<td>T12</td>
<td>radial basis function network</td>
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### Some collocations found in NIPS corpus (cont.)

<table>
<thead>
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<th>Count</th>
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<th>Collocation</th>
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</thead>
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<td>T11</td>
<td>principal components analysis pca</td>
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<td>16</td>
<td>T11</td>
<td>hidden markov models hmm</td>
</tr>
<tr>
<td>14</td>
<td>T18</td>
<td>artificial neural network ann</td>
</tr>
<tr>
<td>13</td>
<td>T15</td>
<td>optimal brain damage obd</td>
</tr>
<tr>
<td>12</td>
<td>T4</td>
<td>kanerva sparse distributed memory</td>
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<tr>
<td>11</td>
<td>T14</td>
<td>hybrid monte carlo method</td>
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<tr>
<td>11</td>
<td>T19</td>
<td>artificial neural networks ann</td>
</tr>
<tr>
<td>10</td>
<td>T0</td>
<td>mean square error mse</td>
</tr>
<tr>
<td>10</td>
<td>T12</td>
<td>radial basis functions rbfs</td>
</tr>
<tr>
<td>10</td>
<td>T16</td>
<td>markov decision process pomdp</td>
</tr>
<tr>
<td>10</td>
<td>T11</td>
<td>hidden markov model hmm</td>
</tr>
<tr>
<td>10</td>
<td>T3</td>
<td>atr human information processing</td>
</tr>
<tr>
<td>10</td>
<td>T18</td>
<td>artificial neural networks anns</td>
</tr>
<tr>
<td>10</td>
<td>T9</td>
<td>spin spin correlation function</td>
</tr>
<tr>
<td>9</td>
<td>T2</td>
<td>naive mean field approximation</td>
</tr>
<tr>
<td>9</td>
<td>T0</td>
<td>mean squared error mse</td>
</tr>
<tr>
<td>9</td>
<td>T7</td>
<td>support vector machines svms</td>
</tr>
<tr>
<td>9</td>
<td>T8</td>
<td>owl sound localization system</td>
</tr>
<tr>
<td>8</td>
<td>T1</td>
<td>compatible lateral bipolar transistors</td>
</tr>
<tr>
<td>8</td>
<td>T13</td>
<td>nsf presidential young investigator</td>
</tr>
<tr>
<td>8</td>
<td>T14</td>
<td>basic differential multiplier method</td>
</tr>
</tbody>
</table>
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Boundary indicators in word segmentation models

\[ y \triangle u \triangle w \triangle a \triangle n \triangle t \triangle t \triangle u \triangle s \triangle i \triangle D \triangle 6 \triangle b \triangle U \triangle k \]

"you want to see the book"

- Boolean *boundary indicator variables* are located between each adjacent pair of elements
- Isomorphism between assignments to boundary indicator variables and sequence segmentations
- Goldwater et al. (2006) word segmentation model samples possible segmentations by Gibbs sampling the boundary indicator variables
  - each Gibbs step only requires the *ratio of the probabilities of segmentations with the boundary present and without the boundary present*
  - \( \Rightarrow \) no difficult-to-compute partition function!
Boundary indicator representation of topical collocations

- Boundary indicator variables range over possible topics, plus a special “null topic” $0$

  \[
  \text{polynomial } \hat{0} \text{ size } \hat{5} \text{ threshold } \hat{0} \text{ circuits } \hat{15}
  \]

- An assignment to the boundary indicator variables uniquely determines a parse tree for the string

- We use Gibbs sampling over these boundary indicators instead of sampling parse trees
  \[\Rightarrow\] avoids cubic time complexity of PCFG parsing
Boundary sampling algorithm for topical collocation models

- Because of the isomorphism between adaptor grammar parses and boundary indicator variable assignments, we can sample parses by sampling boundary indicator variable values.

- Gibbs sampling algorithm for boundary indicator variables:
  repeat forever:
  ▶ pick a random boundary indicator variable
  ▶ compute relative probabilities of all parses corresponding to possible values of variable
    – most of parse tree is fixed ⇒ strictly local computation
  ▶ sample a new value for boundary indicator variable according to these relative probabilities

- Basically same as Griffiths et al. (2004) Gibbs sampler for LDA, except for the “null topics”
Because our sampler is so similar to standard LDA sampler, we can use most of the implementation tricks developed for LDA.

Document → topic and topic → word distributions are sparse ⇒ use sparse sampling techniques of Yao et al. (2009) that divide topic probabilities into three “buckets”:

- **Smoothing only** bucket: base distribution
- **Document topic** bucket: non-zero count document-topic pairs
- **Topic word** bucket: non-zero count topic-word pairs

We parallelise our inference algorithm by generalising the multi-threaded algorithm used in Distributed LDA (Newman et al., 2009)

- we improve their algorithm by parallelising the reduction operation
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Overview of experiments

• We evaluate our model in four ways:
  ▶ *Document classification:* evaluates how well topics are assigned to documents
  ▶ *Topic coherence:* evaluates how well topics are assigned to words
  ▶ *Information retrieval:* evaluates how well topics are assigned to both documents and words
  ▶ *Efficiency:* measures how fast an implementation is

• We compare the Topical Collocation Model (TCM) to the following models:
  ▶ LDA (Mallet implementation)
  ▶ Pipeline Approach (PA) (Lau et al., 2013)
  ▶ The LDA collocation model (LDACOL) (Griffiths et al., 2007)
  ▶ Topic N-gram model (TNG) (Wang et al., 2007)
  ▶ The Adaptor Grammar topical collocation model (AG-colloc) (Johnson, 2010)

Only the first two models can be run on larger data sets.
Document classification and information retrieval on small corpora

<table>
<thead>
<tr>
<th>Task</th>
<th>Classification accuracy</th>
<th>IR MAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dataset</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MReview</td>
<td></td>
<td>SJMN-2k</td>
</tr>
<tr>
<td>Mallet-LDA</td>
<td>71.30</td>
<td>18.85</td>
</tr>
<tr>
<td>LDACOL</td>
<td>71.75</td>
<td>19.03</td>
</tr>
<tr>
<td>TNG</td>
<td>71.40</td>
<td>19.06</td>
</tr>
<tr>
<td>PA</td>
<td>72.74</td>
<td>19.16</td>
</tr>
<tr>
<td>AG-colloc</td>
<td><strong>73.15</strong></td>
<td><strong>19.37</strong></td>
</tr>
<tr>
<td>Non-sparse TCM</td>
<td><strong>73.14</strong></td>
<td><strong>19.30</strong></td>
</tr>
<tr>
<td>Sparse TCM</td>
<td><strong>73.13</strong></td>
<td><strong>19.31</strong></td>
</tr>
</tbody>
</table>

- The **movie review** (MReviews) corpus (Pang and Lee, 2012) consists of 1,000 positive and 1,000 negative movie reviews
- The **San Jose Mercury News** (SJMN-2k) corpus consists of 2,000 news articles
- All non-boldface scores are significantly different ($p < 0.05$) to best
Classification accuracy on larger corpora

<table>
<thead>
<tr>
<th></th>
<th>Mallet-LDA</th>
<th>PA</th>
<th>TCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Politics</td>
<td>89.1</td>
<td>89.2</td>
<td>89.2</td>
</tr>
<tr>
<td>Comp</td>
<td>86.3</td>
<td>87.4</td>
<td>87.9</td>
</tr>
<tr>
<td>Sci</td>
<td>92.0</td>
<td>93.2</td>
<td>93.4</td>
</tr>
<tr>
<td>Sports</td>
<td>91.6</td>
<td>91.7</td>
<td>92.6</td>
</tr>
<tr>
<td>Reuters-21578</td>
<td>97.3</td>
<td>97.5</td>
<td>97.6</td>
</tr>
</tbody>
</table>

- The *Politics, Comp, Sci* and *Sports* are subsets of the 20 Newsgroups corpus with 4,891, 3,952, 1,993 and 2,625 documents respectively.
- The *Reuters-21578* corpus has 21,578 Reuters news stories.
- Evaluation procedure:
  - find document → topic assignments for each model and corpus
  - randomly split corpus into train (80%) and test (20%)
  - train SVM to predict document label
Information retrieval on larger corpora

<table>
<thead>
<tr>
<th></th>
<th>Mallet-LDA</th>
<th>PA</th>
<th>TCM</th>
</tr>
</thead>
<tbody>
<tr>
<td>SJMN</td>
<td>20.7</td>
<td>20.9</td>
<td>21.2</td>
</tr>
<tr>
<td>AP News</td>
<td>24.0</td>
<td>24.5</td>
<td>24.8</td>
</tr>
</tbody>
</table>

- The **SJMN** corpus has 90,257 documents
- The **AP News** corpus has 242,918 documents
- Experimental procedure:
  - use the Wei and Croft (2006) information retrieval system, where the topic model is used (together with a unigram language model) to predict the probability of the query given the document
  - for the collocation models, the query is retokenised using collocations
  - we report Mean Averaged Precision (MAP) scores
# Topic coherence evaluation

| Models    | $p(w|t)$ | $p(t|w)$ |
|-----------|----------|----------|
| Mallet-LDA| 71.9     | 73.2     |
| PA        | 72.8     | 76.7     |
| TCM       | **73.2** | **79.7** |

- The *intrusion detection* task detects how well Mechanical Turkers can spot “intruders” in lists of topical words (Chang et al., 2009)
  - train models on the San Jose Mercury News corpus
  - select 10 words or collocations that maximise $p(w|t)$ or $p(t|w)$
  - randomly select a high-probability word or collocation from another topic
  - measure the accuracy with which the Turkers spot the intruder
Running time per iteration

<table>
<thead>
<tr>
<th>Dataset</th>
<th>MReview</th>
<th>SJMN-2k</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Topics</td>
<td>100</td>
<td>800</td>
</tr>
<tr>
<td>AG-colloc</td>
<td>84.9</td>
<td>1305</td>
</tr>
<tr>
<td>Non-sparse TCM</td>
<td>13.8</td>
<td>233</td>
</tr>
<tr>
<td>Sparse TCM</td>
<td>0.28</td>
<td>0.35</td>
</tr>
</tbody>
</table>

- The non-sparse TCM sampler performs each iteration about *6 times faster* than the adaptor grammar sampler
  - but blocked samplers (e.g., the adaptor grammar sampler) often need fewer iterations than pointwise samplers (e.g., the TCM sampler)
- The *sparse sampler* is more than 50 times faster!
Evaluating the parallelisation speedup

- Experiments on a machine with 80 Xeon E7-4850 processors (2.0GHz) and 96 GB memory.

Figure: Plot of speedup in running time for the Mallet-LDA and our TCM.
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Conclusions

• Grammars can encode topic models and a wide range of generalisations of them
  ▶ The *topical collocation model* jointly identifies topics and collocations

• By re-expressing the models in terms of *boundary indicator variables* we can derive a fast, parallelisable Gibbs sampler for the Topical Collocation Model (TCM)
  ▶ we have also used boundary indicator sampling in *document segmentation* and *phonology induction* models

• The TCM performs well on *document classification*, *information retrieval* and *topic coherence* evaluations.

• The *sparse sampler* significantly speeds inference for topical collocations
Future work

• Can we exploit sparsity more generally in the adaptor grammar sampler?
  ▶ the adaptor grammar sampler uses *block sampling*, which samples an entire parse at a time, rather than the *point-wise sampling* used in LDA and here

• Investigate other structural sensitivity in topical collocations
  ▶ Johnson (2010) uses adaptor grammars to learn and classify named entities
    ▶ perhaps topical collocations also have an asymmetric structure?

• Learn and exploit latent feature representations for words and collocations